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REVIEW

# Plant disease detection using computational intelligence and image processing

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**Abstract**
Agriculture is the most primary and indispensable source to furnish national income of numerous countries including India. Diseases in plants/crops are the serious causes in degrading the production quantity and quality, which results in economy losses. Thus, identification of the diseases in plants is very important. Plant disease symptoms are evident in various parts of plants. However, plant leaves are most commonly used to detect the infection. Computer vision and soft computing techniques are utilized by several researchers to automate the detection of plant diseases using leaf images. Various aspects of such studies with their merits and demerits are summarized in this work. Common infections along with the research landscape at different stages of such detection systems are discussed. The modern feature extraction techniques are analyzed for identifying those that appear to work well covering several crop categories. The study would help the researchers to understand the applicability of computer vision in plant disease detection/classification.

**Keywords** Phytopathology · Image processing · Plant disease · Detection and identification · Computer vision · Machine learning

## Introduction

The state of agriculture in a country depends on the products' (especially crops/plants) quality and quantity. In India, 58% of total population primarily depends on agriculture for their livelihood (Ministry of Agriculture & Farmers Welfare 2018). Factors such as weeds, pests, and diseases (disorders or dysfunctions) are responsible for crop production loss; specially, in India these factors are responsible for 15–25% loss of total crop production (Deshpande 2017). Nowadays, the demand for efficient farming processes in agriculture and food industries is increasing rapidly. Also, plants serve in balancing the environment by producing oxygen for living organisms. Plant leaves initiate the process of photosynthesis through which plants get their food. Diseases/disorders affect the leaves of plants so that they fail to provide adequate food for the plant, leading to bad health or death of the plant. Therefore, early detection, prevention, and management of plant diseases are very important. However, detection/identification of various diseases of plants in the large crop fields is a very complex task, which involves optical observation of leaves and expert manpower (Mokhtar et al. 2015; Verma et al. 2018; Poojary and Shabari 2018). It is a very difficult task for farmers/non-experts. The visual judgment of disease classification is intellectually driven, which may sometimes contain biases, optical misconceptions, and errors. The detection of plants' illnesses forced the researchers to use image processing tools to ease this challenging task (Rathod et al. 2013; Prajapati et al. 2016). From a set of diseases, a plant may have specific kind of infection depending on the cause, which increases the difficulties in the sense of proper detecting the disease through computer vision tools and techniques (Kulkarni and R.K. 2012; Nagasai and Rani 2015; Mg et al. 2017; Kumar et al. 2018). The objective of disease classification/detection system is to support the non-expert users, i.e., non-botanist and non-pathologist. In this context, several techniques have been developed for

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plant disease detection. Traditionally, modified Panchagavya mixture (MPG), deoxyribose nucleic acid (DNA)-based polymerase chain reaction (PCR), serological methods such as enzyme-linked immunosorbent assay (ELISA), molecular methods such as fluorescence in situ hybridization (FISH), immunofluorescence (IF) method, which is based on fluorescence microscopy, and flow cytometry (FC) method based on laser technique, etc., are used for diagnosis of plant diseases caused by several pathogens (Jahagirdar et al. 2003; Fang and Ramasamy 2015; Martinelli et al. 2015). All these techniques work in laboratory conditions. Remote sensing-based sensor applications and imaging techniques are innovatively used for automating the disease recognition process (Abdulridha et al. 2019b; Azadbakht et al. 2019). These techniques mitigate the need of expert manpower and work faster. Zhang and Meng (2011) proposed the automatic detection of canker disease in citrus leaves. This work stated accuracy of 87.99% using image processing, while human experts identified the disease with 86.88% accuracy. Camargo and Smith (2009b) utilized image processing along with machine learning to automatically detect cotton diseases caused by several pathogens. Thus, in this work, we discuss the applicability of image processing, machine vision, and machine learning techniques for plant disease detection.

Initiating from a discussion on various diseases in plants and plant pathology ("Plant pathology" section), a plant disease detection architecture is generalized ("Components of plant disease detection system" section). The accuracy and computational complexity of disease detection systems depend very much on feature extraction, selection of best applicable feature descriptors, and feature selection. Feature descriptors are the techniques/algorithms used to extract the feature vectors from plant leaf images. Features are known to play an important role in the domain of image processing. Due to this, various features, feature extractors, and existing feature extraction techniques are summarized in "Feature extraction: a review" section. Discussion on various aspects including limitations of available systems and difficulties in feature extraction module is given in "Summary and discussions" section. Further, the "Conclusion and future scope" section highlights some research trends and future scope. This review work would be helpful to researchers to identify appropriate techniques for developing their algorithms/systems for plant disease detection and diagnosis.

## Plant pathology

Plant pathology is a study concerned with plants and their diseases. In addition to this, it involves the study of responsible pathogens, their mechanism and methods to control or manage plant diseases and to reduce their impact on plants. Thus, it is a mechanism to deal with the life cycle of plant. It is also known as phytopathology (Phyto+Patho+Logo), which is a combination of three Greek words where Phyto means plant, Patho means diseases, and Logo means knowledge. There are four main objectives, as shown in Fig. 1, of plant pathology, viz. etiology (which is the study of origin, reasons, or causes (biotic/abiotic) of diseases), pathogenesis (which is the study of mechanism of disease development, i.e., process of infection, pathogen and host interaction), epidemiology (study of interaction between the pathogen and the diseased plants with respect to environmental condition, generally diseases in plant population, i.e., epidemics of plant diseases), and control/management (to develop management systems to reduce disease radiation and reduce the losses).

Phytopathology is a subdomain of agricultural sciences and comprises basic knowledge of plant anatomy, plant physiology, virology, mycology, nematology, botany, molecular biology, meteorology, genetic engineering, microbiology, and bacteriology as depicted in Fig. 2.

## Plant disease, its various types and symptoms

Plant disease is a problem occurs as a result of an abnormality in the form, physiology, or behavior of the plants. Diseases in plants are caused by infectious agents (pathogens like fungi, bacteria, or viruses) and noninfectious agents (like physiological factors such as sunburn, mineral deficiency, etc.) and depicted in Fig. 3 (Jim Isleib 2012). Diseases originated from infectious agents are biotic diseases. In contrast, abiotic diseases are because of the presence of noninfectious agents in plants. Abiotic diseases are less hazardous due to their nature of non-transmissibility; therefore, abiotic diseases are mostly avoidable. Thus, only the biotic diseases are considered in this manuscript and various categories of plant diseases are discussed and summarized. Figure 4 depicts various categories of plant biotic disease; leaf images of infected plants have been considered in this figure. In the literature, for a category of pathogens, a variety of research work is available for fungal and bacterial diseases; but virus infection not much focused. Blight, mildew, rust,

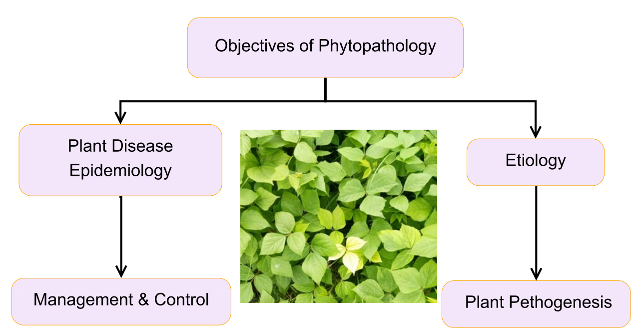


**Fig. 1** Objectives of phytopathology

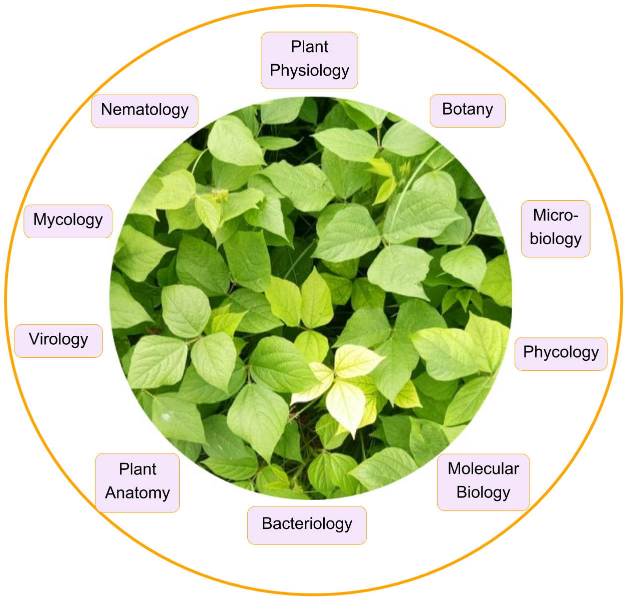


**Fig. 2** Subdomains of phytopathology

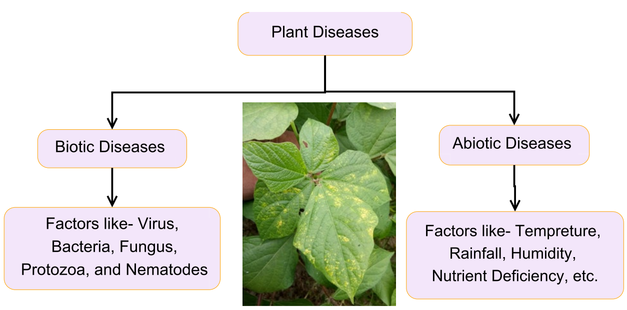


**Fig. 3** Plant disease classification and responsible factors

spots (due to the presence of fungal or bacterial), and canker are the most common diseases considered in the literature of plant disease classification and identification systems (Pujari et al. 2014, 2015; Thind et al. 2011). However, plant diseases due to nutrients deficiency and effects of nutrients deficiency on disease resistance and tolerance have also been explored for automation in the literature (Dordas 2008).

Performance of plant disease detection system using computer vision techniques is mostly depending on features and their extraction along with the type of classifiers used to classify the diseases. The type of features selected depends on diseases' symptoms. The symptoms of some common disease for a range of plant category are summarized in Table 1, which would help the researchers to identify the features.

## Components of plant disease detection system

Image processing techniques targeted to improve the crop production by contributing in crop field monitoring. Computer vision along with computational intelligent techniques/soft computing techniques has been utilized in several researches in the field of plant pathology (Sabrol and Kumar 2015; Singh et al. 2015a, b). This paper is focused on summarizing the articles that utilized the features of soft computing along with image processing. Therefore, the task of plant disease detection using image processing techniques along with soft computing is categorized in the following modules: image acquisition, image preprocessing, image segmentation and classification or identification. For accurate classification, proper training of a classifier on plant images is required; before these images of desired part of plant like leaves, roots, stems, and branches are captured and collected, in the next step various preprocessing techniques like transformation, contrast stretching, scaling, rotation, smoothening etc., are applied as per requirement; segmentation in the next phase is applied to get the desired spotted/lesion regions from the infected original image. In addition to this, feature sets are extracted from segmented lesion area and these features are used to train the classifier. During testing phase, the trained classifier identifies the disease present in test image, whether it is infected or healthy. Before this, the test images undergo all the steps used for train images, viz. preprocessing segmentation and feature extraction. In this paper, the necessity of all these steps is given and techniques proposed in the literature are also summarized.

The system is said to be effective and applicable if accuracy (classification rate/precision/success rate) is a performance measure to rate a system (Phadikar et al. 2012). Mean error time and prediction time are another performance measures (Kaur et al. 2018a). Meanwhile, the classification accuracy is greatly depending on good preprocessing, feature extraction, and feature vector preparation followed by selection of most suitable feature according to the problem.

### Image acquisition

For any computer vision system, this is the very first step. This includes retrieving images from certain databases/repositories and capturing images directly from the field. The accuracy of disease detection system is based on quality of images collected for the purpose of training: The quality of the captured images depends greatly on the camera used and its orientation. The real-time captured images consist of undesired data, i.e., noise, background, and shadow. The selection of images for a target disease is depending on the

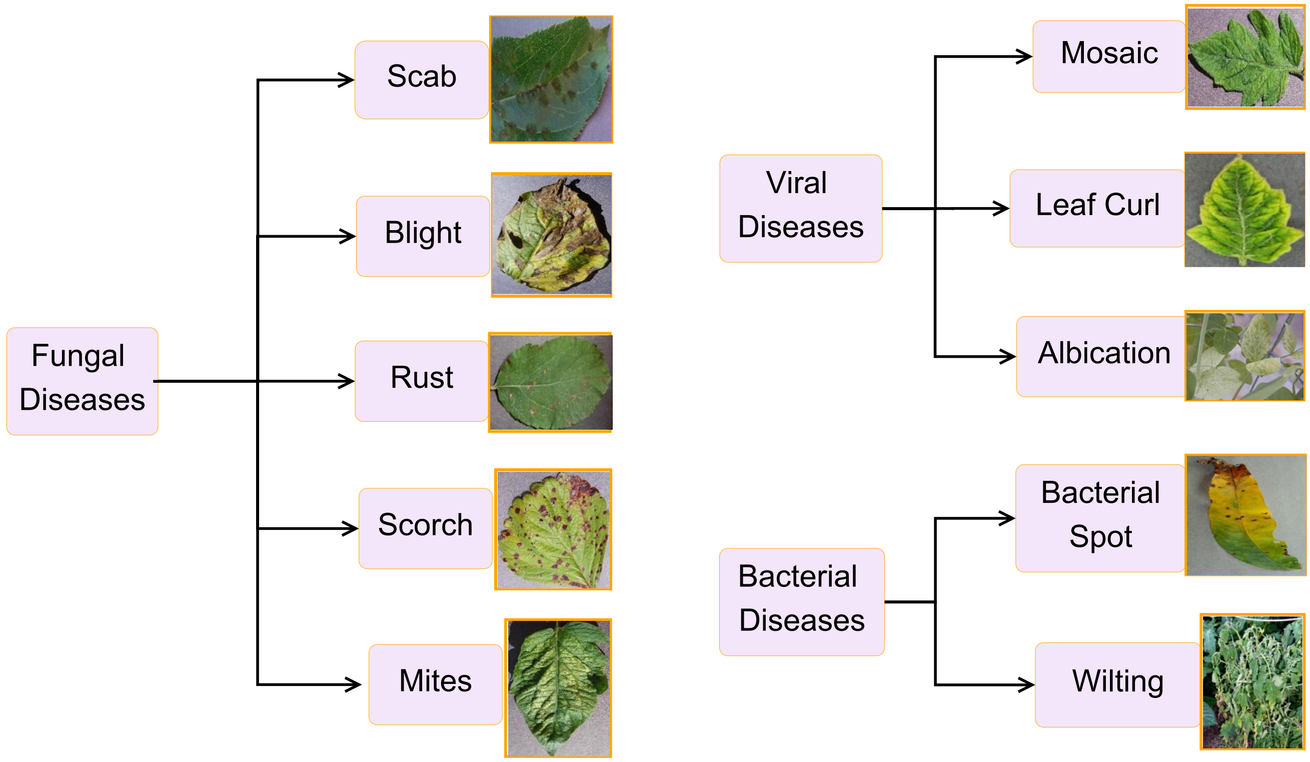


**Fig. 4** Various biotic infections in plants with their categories in various crops

aspect in which it is easy to extract/select a spotted region from the background. Therefore, much attention needs to pay for background removal, noise removal, and other improvements to increase the usability. In addition to this, specific devices are needed to capture fluorescent, thermal, hyperspectral images, although the same process is used for analysis of these images as of normal images. For the application of image processing in plant pathology, several researchers utilized some open accessible datasets like APS image dataset, PlantVillage image database, Cofi (Computers and Optics in Food Inspection) laboratory image dataset (citrus image infested with scale), and Digipathos images (Mohanty et al. 2016; Arnal Barbedo 2019). Some researchers used IRRI dataset and INIBAP leaf dataset for plant disease detection (Bashir et al. 2019; Camargo and Smith 2009b). Various researchers used self-created dataset collected either in real-time field condition or controlled laboratory environment through smartphones/digital cameras (Coulibaly et al. 2019; Pantazi et al. 2019; Karadağ et al. 2019; Fuentes et al. 2017; Shrivastava and Hooda 2014). In real-time field conditions, the complex background, lighting conditions, and illumination need special care because these promote the wrong extraction of pixel information and features. Few researchers worked on single culture instead of preparing a full dataset containing multiple crop sample images (Zhang and Meng 2011; Pydipati et al. 2006; Masazhar and Kamal 2018). Few researchers created and collected datasets from agricultural department of various universities (Deshapande et al. 2019; Pujari et al. 2016; Abed and Esmaeel 2018). On contrary, Analytical Spectral Devices (ASD) such as spectroradiometer have been utilized in the laboratory to find spectral reflectance and vegetation index of leaves (Azadbakht et al. 2019; Rothe and Kshirsagar 2015).

Recently, few researches have been carried out on hyperspectral imaging for plant disease detection (Abdulridha et al. 2019a; Zhang et al. 2018a). Researchers also used android mobile for capturing leaf images in a hyperspectral manner (Shrivastava and Hooda 2014). CCD (charge-coupled device) color camera has been also utilized for capturing leaf images (Huang 2007; Yao et al. 2009). It is evident that processing of real-time/uncontrolled images is difficult as of laboratory environment condition due to the presence of complicated background, improper lighting, and presence of noise and shadow. The captured image quality and its details strongly depend on the equipment and techniques used. Therefore, the performance of entire system is influenced by the image acquisition phase.

**Table 1** Summary of common diseases and responsible pathogens for various plant categories

| Affected plant's name | Disease/infection/deficiency | Disease type (viral/bacterial/fungal) | Responsible pathogen | Symptoms |
|---|---|---|---|---|
| Apple | Scab | Fungal | Venturia inaequalis, Spilocaea pomi | Gray-brown or dull-black lesions on leaf |
| Apple | Black rot | Fungal | Botryosphaeria obtuse, Sphaeropsis malorum | Dark brown discoloration, rottenness of leaves |
| Apple | Cedar Rust | Fungal (Rust) | Gymnosporangium juniperi-virginianae | Small pale yellow spots on upper surface of leaves |
| Cherry | Powdery Mildew | Fungal | Podosphaera clandestina var. clandestina | Leaves covered with white-gray powder, fall of leaves or get brown |
| Corn | Cercospora spot (gray leaf spot) | Fungal (Foliar) | Cercospora sorghi, Cercospora zeae-maydis | Rectangular, brown to gray necrotic lesions, chlorosis, brown or black spots at foliage |
| Corn | Common rust | Fungal (rust) | Puccinia sorghi | Small flecks on leaves, small tan spots, brick-red pustules on both sides |
| Corn | Northern leaf blight | Fungal | Setosphaeria turcica | Long chlorotic, elliptical lesions, gray-green, tan or pale gray |
| Grape | Black rot | Fungal | Guignardia bidwellii | Initially small yellow spots, black fringe with brown to red borders |
| Grape | Esca (black measles) | Fungal | Phaeoacremonium aleophilum | Interveinal stripping, starts as dark red in red cultivars and yellow in white cultivars, dry and become necrotic |
| Grape | Isariopsis leaf spot (leaf blight) | Fungal | Mycosphaerella angulata, Cercospora brachypus | Irregular-shaped lesions, initially dull red to brown, and black later on (coalesce) |
| Peach | Bacterial spot | Bacterial | Xanthomonas arboricola pv. pruni | Dark small, clustered lesions at leaf tip, yellow area around lesions |
| Pepper bell | Bacterial spot | Bacterial | Xanthomonas campestris | Small water-soaked area on downside, slightly raised dark brown spots |
| Potato | Early blight | Fungal | Alternaria Solani | Small 1–2-mm black or brown lesions on leaves, foliage, tubers of potato |
| Potato | Late blight | Fungal | Phytophthora Infestans (Oomycetes) | Small light to dark green irregular-shaped water-soaked spots at lower leaf tips or edges. |
| Tomato | Bacterial spot | Bacterial | Xanthomonas Campestris pv. vesicatoria | Small yellow green lesions on young leaves, may get deformed or twisted, dark, greasy appearing spots on older |
| Tomato | Early blight | Fungal | Alternaria solani | Dark spots with concentric rings, with yellow on surroundings, leaves may die prematurely |
| Tomato | Leaf mold | Fungal | Fulvia fulva, Cladosporium fulvum | Usually with foliage, at upper side small pale green or yellowish spots with irregular margin |
| Tomato | Septoria leaf spot | Fungal | Septoria lycopersici | Wilting of tomato foliage, lowest leaves first, circular dark brown spots or gray dotted center with black specks |

**Table 1** (continued)

| Affected plant's name | Disease/infection/deficiency | Disease type (viral/bacterial/fungal) | Responsible pathogen | Symptoms |
|---|---|---|---|---|
| Tomato | Spider mites | Fungal | Tetranychus Urticae | Pale orange to red, feed on downside, sucking sap (shiny pale yellow marks on top of leaf) |
| Tomato | Target spot | Fungal | Corynespora Cassiicola | Small necrotic lesions with light brown centers, begin deep within tomato canopy |
| Tomato | Mosaic virus | Viral | Tomato mosaic virus (ToMV) | General mottling on foliage, light and darker green leaf mottle, distortion of younger leaves. |
| Tomato | Yellow leaf curl virus | Viral | Tomato yellow leaf curl virus (TYLCV) | Yellow (chlorotic) leaf edges, leaf cupping upward, small leaf size, leaf mottling |
| Tomato | Late blight | Fungal | Phytophthora Infestans (Oomycetes) | Water-soaked lesions with irregular shape, ring or lighter halo around spots |
| Orange | Citrus greening | Fungal | Motile Bacteria | Premature defoliation, mottling of leaves |
| Strawberry | Leaf scorch | Fungal | Diplocarpon earliana | Edges turn brown, curl and dry, bright red lesions may join together on raising |
| Squash | Powdery mildew | Fungal | Podosphaera xanthii | White color powdery spots both sides of leaves |

## Image preprocessing

Preprocessing involves the operations at lowest level of abstraction, for which input and output both are images only (Sonka et al. 1993). Image preprocessing phase is a fundamental step in computer vision and image processing. Due to the degradation of image quality from the presence of shadows, unspecified distortion, noise and complex backgrounds, preprocessing is the initial step to improve it and make it suitable for further processing (Bera et al. 2019). More often, in major datasets the images are collected in real-time conditions, containing inappropriate information. So before extracting features images are preprocessed to enhance computational accuracy of disease detection system. Processing time is also reduced by applying preprocessing operations like resize and crop.

Background elimination, enhancement, color space conversion, cropping, and smoothing are majorly used and popular preprocessing techniques present in the literature. Applicability of these operations varies with the quality of acquired images. Generally, color space conversion is followed by other preprocessing techniques like enhancement, filtering, background reduction, etc. (Kaur et al. 2018b). Various researchers utilized RGB, HSV, HSI, L*a*b*, grayscale, and YIQ color spaces (Pujari et al. 2014; Pydipati et al. 2006; Masazhar and Kamal 2018; Abed and Esmaeel 2018; Hallau et al. 2017; Zainon 2012; Ramesh et al. 2018; Khot et al. 2016; Dhingra et al. 2017; Cruz et al. 2018), but La*b* and HSV are majorly used color spaces in the literature (Pantazi et al. 2019; Deshapande et al. 2019; Kaur et al. 2018b; Rothe and Kshirsagar 2015; Vidyaraj and Priya 2016); HSV (H stands for hue, S stands for saturation, and V stands for value) provides colors which are closely related to human's color perception. A few researches were centric to YCbCr and CIE color spaces (Chaudhary et al. 2012; Kai et al. 2011; Joshi and Jadhav 2017). A new color space (H, I3a, and I3b) is also used in a research for automatically segmenting the lesions from infected leaf image after converting it from RGB color space (Camargo and Smith 2009a). Another research utilized the CIELuv color space; this color space is perceptually uniform, intuitive, and device independent; channels u and v store the color information (Ganeshan et al. 2017). A work used three separate color components a, u, and Cr from three different color spaces La*b*, Luv and YCbCr to reduce the illumination variability in images (Meunkaewjinda et al. 2008).

Apart from color space conversion, various image enhancement techniques and filters are applied to make the input leaf image more useful for further processing. In real-time captured dataset, generally noise is present in images; mean and median filters are utilized for denoising (Yao et al. 2009; Wang et al. 2012). Cropping is also used necessarily, if complex background is present when capturing in real-time environment. In the literature, top hat filter with

Gaussian function and min-max linear filter are utilized for contrast stretching and Laplacian filter and Gaussian filters for sharpening (Abed and Esmaeel 2018; Asfarian et al. 2013). Moreover, approaches like histogram equalization are used to maintain varying illumination (Mallika and Vasanthi 2017; Dange and Sayyad 2015; Khirade and Patil 2015).

Furthermore, preprocessing techniques like image flipping, noise injection, gamma correction, rotation, scaling, cropping, resize, zoom, random shift, and other transformations like affine, perspective and intensity transformations like brightness and contrast enhancement are applied for augmenting the dataset (Sladojevic et al. 2016; Goncharov et al. 2019). Augmentation is the process to generate more data by applying preprocessing techniques on existing data (Fuentes et al. 2017). In the application of deep neural network, it is desired to have higher data size; thus, data augmentation is pursued when existing/available data are not enough.

## Image segmentation

Segmentation is used for partitioning the image with the intent to find interested regions. It aims to separate the region having abnormalities: This simplified representation of the image is easy to analyze and more meaningful to differentiate the infected and non-infected regions. Image segmentation is the important part of almost all image processing or computer vision applications as a crucial technology and critical issue in image analysis (Chouhan et al. 2019; Mesejo et al. 2016; Zaitoun and Aqel 2015). However, process of image segmentation faces many challenges like the presence of complex background with green color pixels, improper boundaries of lesion/infected regions, varying illumination and presence of shadows (Barbedo 2016). The process of segmenting an image is generally categorized into two main categories: one is traditional approaches like edge detection based, region growing based, and thresholding based, whereas the other is soft computing/computational intelligence-based techniques which include segmentation with the help of soft computing approaches like genetic algorithm, fuzzy logic, neural network, etc.; the criteria of approach selection depend on author and problem being solved, but it is observed that computational intelligence-based approaches are generally used for image segmentation and these approaches performed better to traditional approaches for image segmentation. Segmentation process is important for the process of feature extraction.

In the literature, edge- and threshold-based segmentation is shown effective for plant disease detection applications. Edge-based segmentation techniques like Canny edge detector, Sobel operator, and Prewitt operator have been implemented in various research studies (Pydipati et al. 2006; Anthonys and Wickramarachchi 2009; Shinde et al. 2015; Bankar et al. 2014; Revathi and Hemalatha 2014b). In some studies, authors also applied thresholding-based techniques for lesion segmentation. Thresholding techniques like Otsu thresholding, adaptive intensity-based thresholding, and entropy-based thresholding are popularly used approaches (Phadikar et al. 2012; Pujari et al. 2016; Cruz et al. 2018; Khirade and Patil 2015; Phadikar and Sil 2008; Sengar et al. 2018; Pooja et al. 2018; Shen et al. 2008; Wang et al. 2014; Dey et al. 2016). An integrated approach of region growing technique with local threshold is also employed for efficient lesion segmentation (Pang et al. 2011; Singh et al. 2015a). Eventually, incorrect selection of threshold value may cause improper segmentation: Deciding the threshold value is very crucial step in thresholding-based segmentation approaches.

In addition, various studies utilized k-means clustering for diseased area segmentation and were found more efficient and suitable than edge-based segmentation approaches (Bashir et al. 2019; Masazhar and Kamal 2018; Abed and Esmaeel 2018; Kaur et al. 2018b; Wang et al. 2012; Khirade and Patil 2015; Zhang et al. 2017b; Sannakki et al. 2013; Bashish et al. 2011; Rastogi et al. 2015; Mainkar et al. 2015; Jadhav and Patil 2016). A few researchers preferred fuzzy c-means clustering for segmentation of infected area (Jagtap and Hambarde 2014; Bai et al. 2017). A study used super-pixel clustering, i.e., simple linear iterative clustering (SLIC) combined with k-means clustering to aid disease spot segmentation (Zhang et al. 2018b). Studies have also exploited GrabCut algorithm for lesion segmentation (Pujari et al. 2015; Pantazi et al. 2019). A study suggests a unique weighted lesion segmentation scheme over Otsu, expectation maximization (EM), active contour segmentation, and saliency segmentation approaches for efficient segmentation (Kim et al. 2014; Sharif et al. 2018). Fermi energy-based segmentation is also used based on color and grey-level intensity and performed better than Otsu and k-means approaches (Phadikar et al. 2013). Recently, few studies focused on segmentation using genetic algorithm for plant disease detection (Singh et al. 2015b; Meunkaewjinda et al. 2008; Singh and Misra 2017).

## Feature extraction and selection

Features represent relevant & discriminating attributes/information associated with objects, distinguishing one object from other objects. Features are helpful to identify objects and to assign the class label to an object. The feature extraction step is very important in constructing the classification/recognition model and aims at the extraction of relevant attributes characterizing each class (Kumar and Bhatia 2014). Generally, features like shape, color, size, corners, edges, etc., are considered for object recognition. In the literature, color, texture, and shape attributes of diseased area are used plant disease detection/classification;

segmenting the spotted/infected area from leaf image is of great importance. Depending on these attributes, various suitable feature extraction techniques have been employed in several researches of plant disease detection/classification. The performance of disease detection system greatly depends on feature extraction technique being employed. Therefore, choosing the features and feature descriptors is a serious issue in disease detection due to the similarity in disease characteristics (Chouhan et al. 2019). Color is usually described in terms of hue, saturation or chroma, luminance, histogram, moments etc.; attributes such as variance, contrast, and entropy are considered in texture features, whereas area, eccentricity, and roundness are characterized as shape features. Gray-level co-occurrence matrix (GLCM), wavelet transform, Haralick texture and Gabor transform, histogram of oriented gradients (HOG), and local binary patterns techniques are generally employed as feature descriptors/extractors in various studies (Mokhtar et al. 2015; Deshapande et al. 2019; Zhang et al. 2018b; Sharif et al. 2018).

Selection of irrelevant features causes critical performance issues: 1) Irrelevant features leads to higher computational cost, 2) the irrelevant features may cause overfitting of classifier. Thus, in machine learning and computer vision applications feature selection techniques are employed to find most relevant features from the feature vector. For this purpose, principle component analysis (PCA) score, entropy, and covariance of extracted features have been employed in a study (Sharif et al. 2018). Studies also utilized PCA, information gain (IG), and Relief-F feature evaluator, fuzzy curves and fuzzy surface, for selecting most suitable features (Sudha 2017; Gulhane and Gurjar 2011; Zhang et al. 2008). In addition to this, genetic algorithm and particle swarm optimization enhanced with skew divergence method are also utilized with the intent of selecting suitable color and texture features (Revathi and Hemalatha 2014b). “Feature extraction: a review” section presents a review/discussion of various feature extraction techniques employed in numerous studies for detecting plant diseases present in different plant cultures. On observing these techniques, an effort is made to find the most suited approach, most studied plant family.

## Disease classification

The classification step is the most prominent stage of plant disease detection using computer vision and image processing. With its much importance in disease detection, the performance of this phase depends on previous steps like data acquisition, the preprocessing step, the segmentation of infected area and final feature extraction and selection. On considering systems of plant disease detection using leaf images in this manuscript, it is clear to say that these systems work to classify images of plant leaves based on the infections and categorize them based on their symptoms, which is an application of soft computing or machine learning techniques. For this purpose, leaf image set is first employed to train the machine learning classifier model and after that the trained model is used to classify/recognize the test image set. As a result, the classifier should classify healthy and infected leaf images and also identify plant infections (Mokhtar et al. 2015; Sengar et al. 2018; Khirade and Patil 2015).

Machine learning (ML) is an application of artificial intelligence (AI) which provides a system an ability to automatically learn, improve from experiences without being explicitly programmed and which has the capacity to make decisions (Al-Jarrah et al. 2014). Machine learning techniques have been classified generally into supervised and unsupervised machine learning (Kaur et al. 2018a). The supervised techniques work on labeled dataset, whereas unsupervised techniques work with unlabeled data by building inference on absent data labels during the training process. Another ML is known as semi-supervised, special supervised learning which utilizes both labeled and unlabeled datasets during training process. In the literature, various classification approaches have been utilized for plant disease detection, which is depicted in Fig. 5. But more often, support vector machine (SVM), artificial neural networks (ANNs), and k-nearest neighbor (k-NN) have been applied for this application machine learning techniques, while feature-based, fuzzy logic-based, and vegetation index-based techniques have been also utilized in few studies. Various models of ANN, viz. error back-propagation, feedforward neural network, multilayer perceptron (MLP), Kohonen’s self-organizing map (SOM), and probabilistic neural network (PNN), have been explored widely for plant disease detection using leaf images of various cultures, but the performance of MLP found better in comparison with the above-said competitive models (Karadağ et al. 2019; Pujari et al. 2016; Rothe and Kshirsagar 2015; Khirade and Patil 2015; Golhani et al. 2018; Majid et al. 2013; Guru et al. 2011; Mutalib et al. 2017; Orillo et al. 2014; Gharge and Singh 2016). In some studies, support vector machine, context-aware support vector machine (C-SVM), and one-class SVM have been employed for classification of plant diseases based on various features extracted from spotted region and evidently presented SVM better than ANN with respect to classification accuracy (Pantazi et al. 2019; Masazhar and Kamal 2018; Kaur et al. 2018b; Zhang et al. 2018b; Sharif et al. 2018; Dandawate and Kokare 2015; Raza et al. 2015; Waghmare et al. 2016). A study used unique sparse representation-based mechanism for classification of cucumber disease spots segmented using k-means clustering-extracted color and texture features, which entailed accuracy better than SVM (Zhang et al. 2017b). A research on detection of fungal diseases in maize leaves utilized k-nearest neighbor

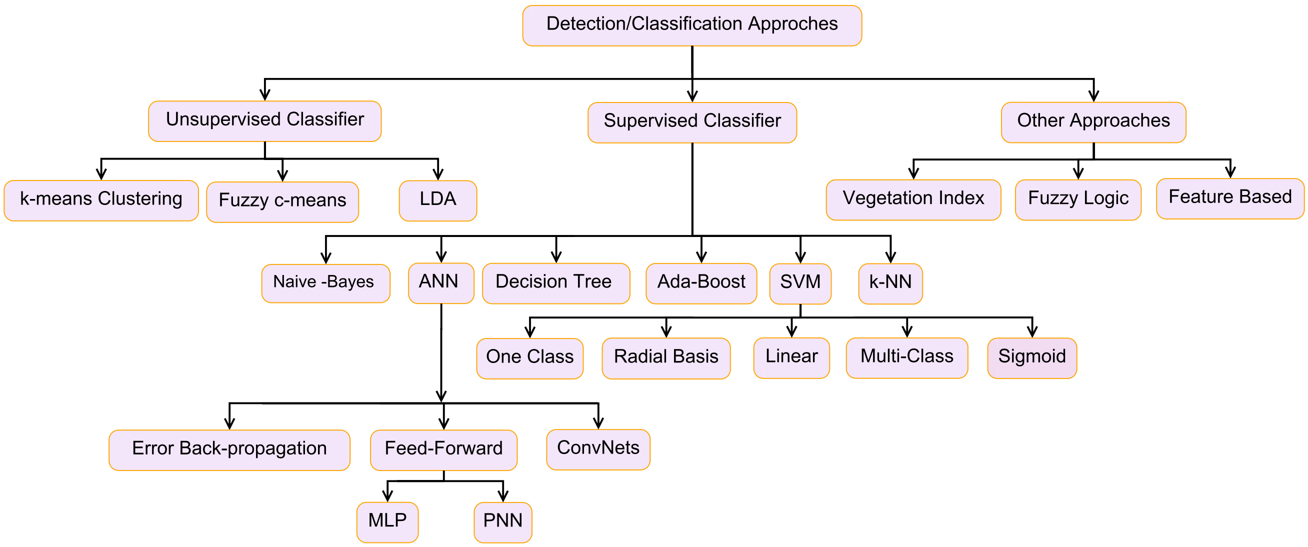


**Fig. 5** Various classifiers explored in studies for plant disease detection

(k-NN) and SVM for classification; the study entails better accuracy of SVM than k-NN (Deshapande et al. 2019). Apart from neural networks and support vector machine, fuzzy logic-based inference system and fuzzy rule-based system have also been employed for plant disease detection in some studies (Mainkar et al. 2015; Bin Mohamadazmi and Isa 2013; Mahajan and Dhumale 2018; Sabrol and Kumar 2016a; Reddy et al. 2019).

Recently, focus has been moved toward deep learning (DL) in the domain of computer vision and image processing (Cruz et al. 2018; Szegedy et al. 2015). To utilize the capabilities of deep neural networks in detection/classification of plant disease, some popular pre-trained networks, viz. AlexNet, GoogLeNet, ResNet, region-based convolutional neural network (R-CNN) and VGG, have been employed in various cultures (Mohanty et al. 2016; Arnal Barbedo 2019; Coulibaly et al. 2019; Fuentes et al. 2017; Kaya et al. 2019; Ferentinos 2018). A study applied convolutional neural network (CNN) to detect tomato diseases based on leaf images: CNN or ConvNet is deep feedforward ANN, which is most commonly applied to analyze visual imagery (Ashqar and Abu-Naser 2018).

In a study, Siamese neural networks with one-shot approach have been employed to explore data embedding and features in plant disease detection: Siamese neural networks are composed of twin networks both joined by a similarity layer through an energy function to determine embedding, i.e., representation of high-level features (Goncharov et al. 2019). In addition to this, a deep neural network consists of nine layers which are used on PlantVillage dataset for plant disease detection/classification; the study suggests to control overfitting of the deep neural networks (Geetharamani and Pandian 2019).

The performance of used classifiers is evaluated and validated on the basis of certain parameters, viz. accuracy, sensitivity, specificity, precision, and f1- score (Chouhan et al. 2019). Also, in some studies the performance of the proposed approaches is validated based on the interventions of human. Disease detection accuracy depends on classifier used. Thus, selection of classifier approaches for plant disease classification/detection is very crucial.

## Feature extraction: a review

The similarities in disease symptoms or infected area greatly affect correctness of plant diseases classification/detection; the performance of classifier used to identify/classify the infected leaves is directly influenced by such similarities. Thus, correct feature extraction is very crucial in disease classification. Therefore, this manuscript is focused on reviewing different feature extraction and feature selection techniques applied in the literature for various cultures/crops. Many researchers kept their study targeted on single cultures and their diseases, while a few worked on diseases instead of focusing on cultures. The visual features which are appeared to be better depending on the visual attributes of an image, either locally or globally, may be extracted (Bera et al. 2019). The following subsections summarize various feature extraction and feature selection techniques with respect to various features and their categories. In the literature, although maximum research work is focused on food grains (mainly wheat, rice, soybean, pea, and corn), but horticulture (mainly tomato, cucumber, chili, citrus, grape, and oil palm) and profit crops (mainly cotton, groundnut, sugar beet, and coffee) have also been the cultures of interest

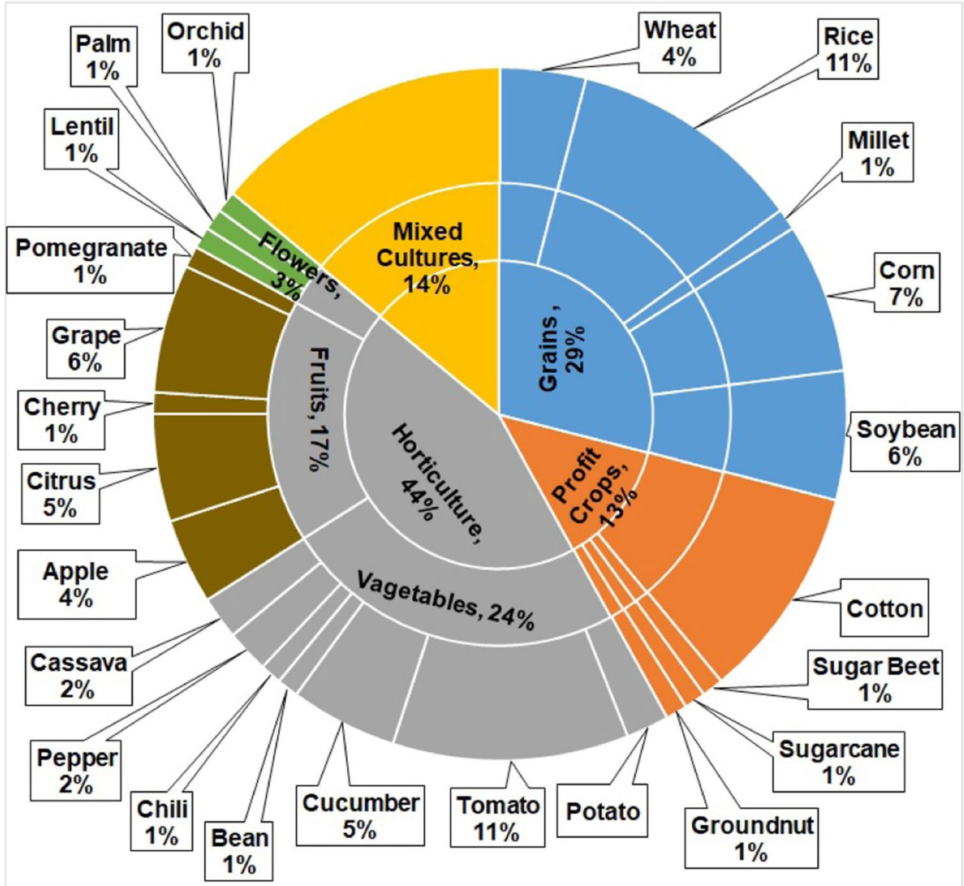


**Fig. 6** The present scenario of research in various crops explored during last 12 years (percentage of papers)

for some researchers. Figure 6 represents the present scenario of research work of disease detection using different image processing techniques in various crops. There are still many cultures to consider for detecting plant disease using leaf images through computer vision and machine learning technologies: The selection of crops for such research is driven by the availability of image datasets and experts.

## Texture features extraction

Image texture provides information about color patterns, local variation in image intensity and their spatial arrangements in a particular region of an image or entire image. In texture analysis, the two main issues are texture segmentation, i.e., determining the boundaries between various texture regions, and texture classification, i.e., identifying any given textured region based on the unique texture properties. Contrast, entropy, skewness, variance, homogeneity, and moment are some major features attached to texture of any image and used in classification of plant diseases. In studies, approaches like gray-level co-occurrence matrices (GLCM)/Haralick features, Gabor filters, shift-invariant feature transform (SIFT), discrete wavelet transform (DWT), and local binary patterns (LBPs) have been widely used for texture feature extraction.

### GLCM features

GLCM is 2-D matrix representing a set of image values in rows and columns (Sebastian V et al. 2012). It is being used to extract statistical/numeric features for compact representation of image texture. A study of disease detection in bean plant using leaf images employed the co-occurrence matrix to extract texture features from images. Grayscale image is utilized in order to extract total 13 GLCM features: contrast, correlation, mean, energy, homogeneity, variance, smoothness, root mean square, standard deviation, kurtosis, and inverse moment difference from train and test set images (Abed and Esmaeel 2018).

Another research focusing on classification of fungal diseases like common rust, northern leaf blight and healthy is conducted. The study explored Haar wavelet-based GLCM feature extraction which aimed to classify the fungal diseases through SVM (Deshapande et al. 2019). Further, a study of soybean disease detection and classification for downy mildew, frog eye, and septoria leaf blight utilized 14 Haralick texture features extracted through GLCM; this study suggested to use a combination of texture features and color that gives better accuracy instead of using single features (Kaur et al. 2018b). A study carried out on citrus leaves for detection and classification of anthracnose, black spot, canker, scab, greening and Melanose using machine vision explored 18 GLCM texture features, i.e., 14 Haralick features and 4 other features like cluster prominence, shade, homogeneity, and energy.

The study targeted to find better detection accuracy of citrus disease detection systems (Sharif et al. 2018). A disease-centric study irrespective of culture is carried out and explores the GLCM features with spatial gray-level dependence matrices (SGDM). The study utilized texture features, namely energy, entropy, homogeneity, contrast, inverse difference moment, maximum probability, and correlation, and aimed to classify diseases with SVM and ANN (Pujari et al. 2016). On reviewing various studies, it is found that GLCM is most used texture feature extraction mechanism. Many researches on various cultures, for disease detection using leaf images with machine vision applications, utilized GLCM for feature extraction (Ramesh et al. 2018; Khirade and Patil 2015; Bashish et al. 2011; Mainkar et al. 2015; Arivazhagan et al. 2013; Islam et al. 2017; Tian et al. 2013).

#### Scale-invariant feature transform (SIFT)

SIFT is the feature descriptor which represents local features of images in feature vectors; each feature is invariant to scale transformation (Lowe 1999). The local key features firstly extracted from a reference image and then a feature vector are prepared, and for recognition of an object in a test image, each feature of new image is compared to each feature of reference image. The finding of a match is on the basis of estimating Euclidean distance between the features. A study explored SIFT approach to extract texture features from rice leaf images for the classification and detection of brown spot, false smut, and bacterial leaf blight diseases; SIFT extracts a number of regions, and feature description is prepared for all the new images in order to predict the cluster to which they belong (Bashir et al. 2019). Another study used SIFT key features and correlation which is similar between a pixel and its neighbor pixels (Dandawate and Kokare 2015). It aimed to detect the infection in soybean leaf images using SVM two-class approach, which used the key attributes to distinguish the normal and infected leaves. For detecting and recognizing three diseases, namely leaf blast, brown spot, and bacterial blight in paddy plants, a research work employed SIFT feature extraction with classifiers (Mohan et al. 2016). This research aimed to detect paddy plant leaf diseases at early stage. Additionally, a research also utilized SIFT approach to prepare a range of descriptors from cassava plant leaves. This work is targeted to detect cassava mosaic disease using various classifiers, viz. SVM, Naïve Bayes, k-nearest neighbor, and two-layer MLP (Aduwo et al. 2010). Furthermore, a research used Haralick features extracted through GLCM for detecting plant diseases using machine learning approaches and suggested to use SIFT key attributes to improve detection accuracy (Ramesh et al. 2018). Moreover, a study of corn plant disease detection explores SIFT approach with other approaches of feature extraction. The study classifies gray leaf spot, common rust, leaf blight, and healthy leaves and evaluated features' performance through SVM, random forest, decision tree, and Naïve Bayes (Kusumo et al. 2019).

#### Local binary patterns (LBPs)

LBP is a visual descriptor which is used for classification in image processing and machine vision applications. LBP is discovered in 1994; it is grayscale invariant and texture based, which computes the difference of average grayscale level for all pixels either with value 1 or 0 in each neighborhood (Ojala et al. 1996). It is a synergetic method of texture analysis, i.e., detection accuracy increase when combined with other feature extraction approaches like histogram of gradients and pyramid HOG. Thus, LBPs have been a famous approach for texture analysis and feature extraction for many researchers. A unique study utilized the synergy of local binary patterns with one-class SVM classifier to detect powdery mildew, black rot, downy mildew, and healthiness of various plant species through their leaves; the approach focused on identification of disease rather on classification. An automatic detection system is proposed in a research to detect rust disease in lentil crop based on machine learning and computer vision techniques. The approach used microscopic leaf images of lentil, and LBP is applied after dividing the whole image into numerous regions, and these regions were further used to extract features (Singh et al. 2019). In addition, another study employed a unique technique opponent color LBP (OC-LBP) for texture feature extraction; the machine learning-based automatic system is proposed to detect grape diseases like downy mildew, powdery mildew, black rot, etc. (Waghmare et al. 2016). The opponent color LBP is joint color–texture feature extraction approach, developed in 1998, to compare grayscale and color–texture features (Jain and Healey 1998). The opponent color is the color that humans perceive as the opposite pair, i.e., yellow-blue and red-green; in OC-LBP, the local binary pattern which is used separately with each pair of color channels is used to obtain the opponent color patterns to extract neighborhood and neighborhood center pixels in dissimilar color channels (Maenpaa 2003). Furthermore, a work over apple fruit disease detection utilizes another form of LBP, i.e., complete local binary patterns, which considers both the magnitude and sign of local features along with gray-level value of center pixel of a neighborhood (Dubey and Jalal 2012).

#### Gabor filter transform

Gabor filter is a powerful approach for feature extraction and texture analysis. It is an implementation of Gabor wavelet transform (GWT, discovered by d. Gabor) with Gaussian window for spatial domain analysis (Gabor 1946). Gabor transform extracts features from various orientation and different scales. Thus, analysis of an image with Gabor filter is considered as similar to the perception in mammalian (human) visual system (Prasad et al. 2012). In the literature, Gabor filters have been employed for texture feature extraction in plant leaves to detect the present disease, a study of disease detection through analyzing image processing techniques and machine learning in the form of ANN. Being focused on three diseases anthracnose, bacterial blight, and Alternaria in pomegranate plant, the proposed approach employed Gabor filter to extract unichannel features (Kulkarni and R.K. 2012). In another unique study of disease detection in apple through fruit surface, Gabor filter is combined with LBP and Haralick features. The study, on the basis of performance of both approaches, uses local features with Gabor wavelet which leads to a powerful feature extraction algorithm (Jolly and Raman 2016). Similarly, a study of soybean disease detection employed Gabor features with color features and applied support vector machine with the intent to improve detection rate (Kaur et al. 2018b). In addition, Gabor transform has been also applied in a study of disease detection using leaf images; the work shows that Gabor wavelet transform is a robust and effective algorithm (Prasad et al. 2012). Furthermore, Gabor transform has been applied for color texture representation through opponent color features (Jain and Healey 1998). Another study proposed an approach to classify cotton diseases foliar leaf spot, curl gemini virus, bacterial blight, cercospora spots, and Alternaria. The study is proposed to use Gabor filter for classifying the disease on the basis of visual features (Gulhane and Gurjar 2011). Moreover, numerous researches employed Gabor wavelet transform for feature extraction in the plant disease detection system for detecting/classifying different diseases in various cultures (Mokhtar et al. 2015; Khot et al. 2016; Samajpati and Degadwala 2016).

#### Wavelet transform

Wavelet transform is a well-known technique and unified mathematical framework for texture feature extraction which is the input for texture classification. Numerous wavelets like discrete wavelet transform (DWT), Haar wavelet transform, etc., have been used in some studies for feature extraction (Gawali et al. 2017). The capability of discrete wavelet transform for multi-resolution analysis can be used to extract features of a picture in various scales (Akhtar et al. 2013). A study also used DWT, which decomposed the input leaf image into four regions, and from each, wavelet energy is extracted for texture feature analysis. The proposed work intended to identify foliar diseases—ramularia, bacterial blight, ascochyta blight, and some unknown disease in cotton plant using SVM (Bernardes et al. 2013). In addition, some studies have also used DWT for texture feature-based disease classification/identification for different diseases and various crops (Kaur et al. 2018b; Pujari et al. 2013, 2015; Sabrol and Kumar 2016a).

Another necessary technique of feature extraction based on wavelet is Haar transform which is offered by Alfred Haar in 1910 and not continuous (Haar 1910). Texture feature analysis using Haar transform has been utilized in a study of detecting fungal diseases in maize crops. The Haar filters generate four sub-bands for an image; in this work, Haar is applied on RGB image with the intent to find vertical, horizontal, and diagonal coefficients. As a result, it declares that Haar wavelet improves accuracy when used with SVM in comparison with other feature extraction techniques (Deshapande et al. 2019). In addition, a research also proposed Haar-like features to use for identifying paddy plant-diseased area using AdaBoost classifier. Feature extraction is done using rectangular Haar component to find horizontal and vertical variation with horizontal change and diagonal variation (Mohan et al. 2016).

#### Histogram of oriented gradients (HOG)

HOG is also one of the widely used feature extraction mechanisms in computer vision or image processing with the intent to detect the objects, infected region in leaf image (Ramesh et al. 2018). It is first explained and utilized in a study of pedestrian detection in still images and then extended the work for human and animal detection in captured images (Dalal et al. 2005). In a research, a comparative study is done for various features, viz. RGB, SIFT, and HOG, to detect corn diseases—common rust, northern leaf blight, and leaf spot gray spot. The study proposed that HOG features perform better with all machine learning approaches used: HOG features are extracted to find gradient orientation for localized sectors of an image and applied with various machine learning algorithms, viz. SVM, decision tree (DT), and k-NN (Kusumo et al. 2019). A study utilized HOG-based local descriptors for soybean crop disease identification using leaf images and demonstrated improvement in accuracy and correct classification for rust ten, mildew, and rust RB in soybean crop (Pires et al. 2016). A research proposed HOG features to be used with random forest classifier for detecting leaf image-based plant disease. The study suggested to use HOG due to its advantage of being operated at created cell area (Ramesh et al. 2018).

A variant of HOG, which is pyramid of histogram of oriented gradients (PHOG), is also used by some researchers in their studies. It is a pyramid extension of HOG feature descriptor and consists of HOG feature over each subregion of image at each scale (Bai et al. 2009). A study suggested to use PHOG features being fused with super pixel; the PHOG features are extracted, with number of pyramid=3, for each color channel of cucumber leaf images (Zhang et al. 2018b). Another research proposed by the same researchers employed logarithmic frequency PHOG to obtain lesion features which are used for cucumber disease classification through SVM (Sannakki et al. 2013).

In addition to the above feature descriptors, surveyed from the literature of plant disease detection systems, some local feature descriptors like bag of words (BOW), speed-up robust features (SURF), Oriented Fast, BRIEF, etc., also been utilized in few researches (Bashir et al. 2019; Aduwo et al. 2010; Kusumo et al. 2019). Texture features are key elements to describe the image either complete or a region from it. Therefore, this manuscript summarizes texture feature descriptors with their working behavior, which will help many researchers.

## Color features extraction

Color features represent object's surface depending on physical properties of colors and reflect various wavelength values. Color features have been demonstrated in various studies through different color spaces like HSI, RGB, HSV, HSL, YCbCr, etc. Color features are helpful to understand photometrical information such as shading, shadow, illumination, and optical density of different color channels (Afifi and Ashour 2012). Color features, either global or local, provide the information about color pattern either of the whole image or of the segmented region, i.e., diseased area in a leaf image. These features were first extracted and then used for disease detection/classification either through similarity measure or mapping through some machine learning algorithms. Therefore, the color feature descriptors can be applied on different color channels of the image; a simple color feature could be R, G, and B values to detect red, green, and blue objects in an image, respectively. Basically, colors are defined by moments and histograms (Kaur et al. 2018a). A work utilized color moments like mean, kurtosis, skewness, variance, and standard deviation as color features to classify soybean plant diseases (Kaur et al. 2018b). In various studies, color co-occurrence matrix and color histograms have been also utilized for plant disease detection based on computer vision/image processing (Guru et al. 2011; Dhaygude and Kumbhar 2013).

### Color co-occurrence matrix (CCM)

The color co-occurrence matrix (CCM) represents the color distribution in the form of a matrix for each of the color channels present (Chouhan et al. 2019). A study of citrus disease detection through color features utilized color co-occurrence matrix (CCM) to determine color features on hue, saturation, and intensity channels (Pydipati et al. 2006). In the proposed work, three CCMs are prepared based on SGDM for each channel in HSI color space having converted from RGB space to HSI; then, these matrices have been used to find various color features. Another research proposed a disease detection system to detect the diseases—early leaf spot and late leaf spot in groundnut crop, based on color and texture feature with back-propagation neural network (Ramakrishnan and Sahaya 2015); the local features, viz. entropy, contrast, energy, local homogeneity, and correlation, have been extracted using CCM for each channel of HSV color space. Moreover, several other research works utilized the color co-occurrence matrix for color feature extraction (Kai et al. 2011; Revathi and Hemalatha 2014b). Various researchers did their study on a range of color spaces and color channels for plant disease detection and classification (AI-Hiary et al. 2011).

### Color histogram

In some studies, color histogram is also utilized for color feature extraction. In computer vision/image processing, color histogram represents the color's distribution in an image, i.e., it represents the number of pixels for a set of possible colors. In a research work, color histograms have been employed for detecting plant diseases using machine learning and suggested to find color histograms for HSV leaf image due to its close alignment to human eye color representation (Ramesh et al. 2018). Another research to recognize plant types through the machine learning approaches used color histograms to find color features in red, green, and blue channels and obtained the best result in 10 bins of histograms after analyzing several bins (Caglayan et al. 2013).

## Shape features extraction

The shape features define the shape properties of any image or object based on some parameters. Shape features must have some properties like affine invariant, statistically independent, invariant to translation, rotation and scale operations and identifiability. The infected region in plant leaf can vary in shape, i.e., it depends on type of pathogen, disease types, and crop species. Thus, various shape features such as solidity, eccentricity, diameter, area, centroid, extent, minor axis length, major axis length, and convex hull of lesions, have been utilized in several studies of plant disease detection using leaf images in various cultures (Camargo and Smith 2009b; Bera et al. 2019; Wang et al. 2012; Phadikar et al. 2013).

A researcher proposed a research work for plant disease detection through machine learning based on shape features (Ramesh et al. 2018). The shape features have been extracted through Hu's moment which helped to define the outline of a particular leaf examined in their study; the Hu moment has been calculated after converting the color space from RGB to grayscale. In another study of disease detection, the researchers extracted zone-wise features to identify shape of lesions due to the presence of four diseases—bacterial blight, blast, brown spot, and sheath rot in rice crop; the shape descriptors like eccentricity, orientation, and context have been considered and calculated for leaf images (Joshi and Jadhav 2017).

Furthermore, a researcher used area, roundness, extending length, shape complexity, and concavity to form the shape features; the work concentrated on the exterior boundary of infected regions due to diseases like blast, sheath blight, and brown spot in rice crop (Anthonys and Wickramarachchi 2009). Moreover, a study using weighted segmentation of infected region employed geometric/shape features like area, filled area, aspect ratio, orientation, perimeter, extent, solidity, major axis, and minor axis to detect and classify anthracnose, black spot, canker, scab, and melanose disease in citrus plants (Phadikar et al. 2013). In addition, a researcher used a geometric feature—area of infected region to find similarity in infected and un-infected plant leaf images; the research was targeted to identify powdery mildew disease in cherry leaves (Sengar et al. 2018).

The summary of the research work reviewed in this section for the various food grains, profit crops, horticulture crops, and some mixed crops (assorted cultures) is provided in tabular form in "Appendix A."

## Summary and discussion

### Image acquisition and dataset size

It is very difficult to obtain/collect culture-specific plant leaf image dataset for any specific infection. It is observed that the experimental results/performance is greatly influenced by the kinds of dataset used in researches, i.e., real-time or laboratory condition (controlled) datasets. Thus, in the literature it is obvious to find limited size of leaf image dataset. Eventually, the larger datasets (in a range of thousand and more) have been observed during the survey only in very few previous studies (Barbedo 2016; Kaur et al. 2018b; Cruz et al. 2018; Sladojevic et al. 2016; Sharif et al. 2018; Geetharamani and Pandian 2019). This manuscript evidently represents through the survey that the larger datasets are mostly used in studies which employed convolutional neural networks (CNNs)/deep learning for plant diseases detection or classification. Also, a big difference in the size of train and test image datasets has been observed during the survey, i.e., generally train sets were found larger than test sets in most of the studies. Collecting leaf images in uncontrolled conditions (real-time) increases the complexity of the system, but it is of great significance in agriculture development and more acceptable in today's research. It is observed that few researchers utilized real-time acquired leaf images in their studies (Fuentes et al. 2017; Deshapande et al. 2019; Jagtap and Hambarde 2014; Zhang et al. 2018b). However, acquiring images through mobiles or cameras are more popular in the literature. Some concepts like sensor-based system to capture leaf images from both the side could also be an interested research work. However, some studies have gained attention to use hyperspectral image dataset to identity the disease. As a result, after the entire survey, the differences between selecting specific diseases are common to various cultures and various diseases for specific cultures.

### Approaches used for preprocessing and image segmentation modules

It has been observed that the selection of suitable techniques/approaches depends on the nature of acquired images. An appropriate approach, which is highly desired to serve the requirements, is selected from a range of techniques to perform specific task like acquisition, preprocessing, and segmentation. A large variation in schemes has been observed for these modules during the survey. Background elimination is found to be most desired and highly applicable preprocessing among others of its kind. Similar observations are made for segmentation module and a big variability has been found, i.e., standardization of segmentation approaches is still not achieved. Standardization of schemes in all modules is a difficult task in such systems because selection of appropriate approach highly depends on the nature of image set being used.

### Difficulties in feature extraction module

Several difficulties have been observed while extraction of features; similarity in the infected area leads first to the extraction of inappropriate features and then wrong classification based on irrelevant feature matching. Thus, feature to be extracted must be unique and must be insensitive to various transformation factors like scaling, rotation, affine, and orientation. If it is sensitive to such factors, then again it would raise complexity at preprocessing module. It is also observed that selection of inappropriate features could lessen the success of entire system in the sense of wrong classification of diseases (Sharif et al. 2018). Thus, it is necessary to select best set of features because each feature has a different importance level. So, some feature selection and reduction techniques have been seen in the literature to make performance of entire system higher (Sharif et al. 2018; Phadikar et al. 2013; Sudha 2017; Zhang et al. 2008).

Furthermore, convolutional neural networks could be a better feature extraction technique through utilizing its capabilities in feature extraction module.

### Techniques used for classification module and difficulties

A number of classification techniques have been explored and used for the task of classification and detection of plant diseases using leaf image. More often, support vector machine, artificial neural networks have been utilized for this purpose (Mokhtar et al. 2015; Masazhar and Kamal 2018; Kaur et al. 2018b; Zhang et al. 2017b, 2018b; Golhani et al. 2018). These classifiers have been used possibly for last 10 years. Another mostly used classifiers are feature based, which performs better followed by Naïve Bayes, backpropagation neural net, decision tree, K-nearest neighbor, and probabilistic neural net classifier. It has been observed through the survey that several researchers attentively tried to automate plant disease detection system. In some studies, performance is better with highly acceptable results and with small datasets for various cultures.

In addition, convolutional neural networks have been explored recently in multiple cultures incentive to make disease detection and classification more accurate. CNN's capability could be utilized for systems designed for single cultures. But the overfitting of CNN is seen as a major issue in system pertained for plant disease detection using deep neural net. Several techniques have been observed which can improve the efficiency of CNN-based classification system for single or multiple cultures.

### Weaknesses of available systems

It is found that system based on image analysis or hyperspectral imaging performed better than to rate disease severity visually, but some smart and intuitive solutions/goals are yet to achieve (Mahlein et al. 2018). Innovative techniques with improved precision are highly desired for plant protection and disease rating so that the forthcoming challenges could be addressed. An observation is made on the performance of the plant disease detection system and found that it greatly depends on the quality of acquired images, i.e., kind of training data. Furthermore, quality of acquired data is influenced by size of dataset acquired and features extracted from images. Thus, plant protection needs development of reliable data analysis system to deal with image annotations, pre-labeling of plant data for the early stage detection and prevention (Kuska and Mahlein 2018).

Moreover, it is found that all systems have a set of requirements to be fulfilled necessarily; if any requirement or constrained left unconsidered, then the proposed system provides inaccurate disease classification/detection. So in such cases, a researcher must design a versatile system with adjustable set of requirements instead of constant. The issue of overfitting/overtraining has been also observed which must be overcome; it disturbs the actual use of machine learning techniques like NN, deep NN, SVM, etc. So a highly adaptable and generalized system is to be developed for disease detection in several cultures. This domain is most popular due to availability of various strong machine learning tools and techniques, but these resources must not be compromised for accuracy.

## Conclusion and future scope

This document presents a summary of various research works to automate the plant disease classification and identification system using computer vision and machine learning techniques. The efficient and automated system for plant disease detection is highly desired in India to overcome agriculture losses. The survey presents several well-acceptable techniques used for image acquisition, preprocessing module, approaches for lesion segmentation, feature extraction, and finally the classifiers. Various difficulties during feature extraction module have also been summarized. In addition, the limitation of existing systems has also been discussed with a vision to improve efficiency without compromising the present tools. This survey also presents various computer vision techniques highly accepted by several researchers in this domain and provides a demonstration of research in forthcoming time. The following are some points which would help the researchers in enhancing the performance of the state-of the-art systems.

### Recognition of stage of infection

After the survey, it has been observed that a plant could be infected by disease at any stage. Thus, identification of stage of infection is a leading factor for research in plant disease identification. Many researchers worked in this domain regardless to stage of the diseases in a plant, but it would be of great interest if the research is focused to detect the disease at a particular stage. Detection at early stage would forecast the disease which may help the farmers to take special care and to minimize agricultural losses. Thus, it is required to provide some special attention in identification of plant disease through the automatic systems with the potential to suggest special precautions stage-wise. Furthermore, estimating the infected area of a specific culture could be a work of interest in future at India which reduces and control the unmanaged usage of pesticides and would lead toward organic farming.

### Accurate classification

Development of systems to classify accurately the fungal, bacterial, and viral infections through leaf images must be focused. It is observed evidently that identifying a particular disease in a specific culture is easier than classification of multiple diseases through computer vision techniques and human experts as well. Even it is tough to state about grouping of leaves according to the infection with high confidence. Thus, developing effective system for the classification of diseases may be another interested area for research. Furthermore, it is again difficult to decide whether there is an infection or a mineral/nutrient deficiency in a plant. The future researchers may focus on this aspect of plant pathology.

### Development of new applications on real-time scale

In the literature, many researchers provided various solutions to this problem, but still corresponding systems are not available. A very few Web site solutions and mobile-based applications are available for online help. Applications like Plantix and Leaf Doctor are available as per best of our survey (Goncharov et al. 2019; Pethybridge et al. 2015). Thus, new online applications may be developed by considering it as a new research problem which would help the farmers in India and all around the world as well. At remote places, such applications would help the farmers in great extent in generating the "disease analysis reports" which can be sent to the expert to get assistance further.

In addition, development of real-time applications may be further a better research problem in this domain. It is observed from the literature during the survey that previous solutions proposed using leaf images are captured in laboratory conditions; none from them were on real-time conditions with well-acceptable results. So remote monitoring may be a better option and research problem in this domain to make farmers more aware about their crops by implementing real-time systems; in such studies, issues like memory requirements, sensory devices, high computational complexity, etc., would be the major problems.

### Reliability of detection systems

In the literature, various researchers focused to make disease detection fully automatic, but some check on results/accuracy must be made by an expert or plant pathologist to validate the reliability. Thus, instead of fully automatic systems, nowadays, some automation with experts interventions is required. This may be another concern for future researchers. Possibly, an expert system could be a better approach along with image processing and machine vision systems. Attempts to make such systems in future would also be a problem to consider for research in this domain.

### Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

## Appendix A. Summary of the research work for different crops

See Tables 2, 3, 4, 5, 6, 7, 8, 9, and 10.

**Table 2** Summary of grain (rice) culture

| (Reference) Year | Deficiency | Image dataset | No. of images | Feature extraction techniques | Classifier | Accuracy (in %) | Future work |
|---|---|---|---|---|---|---|---|
| *Rice* | | | | | | | |
| Orillo et al. (2014) | Leaf blight, Brown spot, Rice blast | Captured from IRRI Greenhouse, Los Banos, Philippines | 134 images, Training = 94 Validation = 20, Training =20 | Lesion area, mean value of RGB, HCV and SD of RGB color channel of diseased part | EBPN | 100 | Working with a big dataset, and more diseases and visual examination |
| Phadikar et al. (2013) | Leaf blight, Brown spot, Rice blast, Sheath rot | | | Mean, SD of infected pixels in RGB color channels and lesion shape | Rule-based classifier | 94.40 | Working with different features and more specific datasets as well as visual examination |
| Phadikar and Sil (2008) | Leaf blast, Brown spot | Captured by a camera from East Midnapur, South Bengal | | RGB of spots, FT of spots, and arbitrary rotation of spots | Self-organized Maps | 82% | Working with other databases and different diseases |
| Joshi and Jadhav (2017) | Leaf blight, Brown spot, Rice blast, Sheath rot | JPEG, collected from Agriculture Research Station, Lonawala | 115 images, Training =80, Testing = 35 | Color moments—mean and standard deviation in RGB planes, and shape features—eccentricity, extent, and orientation | MD classifier, k-NN classifier | 88.15 | Working with big datasets and other techniques to find more accurate result |
| Phadikar et al. (2012) | Brown spot, Leaf blast | Self-captured from agriculture fields using Nikon COOLPIX P4 | | Radial distribution of hue from center toward boundary used as a vector | Bayes' classifier and SVM | 79.5 68.1 | Working with more diseases, datasets, and other feature vectors |
| Yao et al. (2009) | Leaf blight, Rice blast, Sheath rot | Self-captured using CCD camera (NikonD80) from rice field of China National Rice Research Institute | 144 images, 72 samples of each disease | Shape features—area, perimeter, minimum enclosing rectangle, and texture features—entropy, contrast, uniformity, linear correlation, inverse difference | SVM | 97.20 | Working with other and larger datasets, examining visually |

**Table 2** (continued)

| (Reference) Year | Deficiency | Image dataset | No. of images | Feature extraction techniques | Classifier | Accuracy (in %) | Future work |
|---|---|---|---|---|---|---|---|
| Bashir et al. (2019) | Brown spot, Leaf blight, False smut, | Includes APS dataset and from RRI, Punjab Pakistan | 400 images, Training = 280, Testing = 120 | Local features using SIFT descriptors and preparing a vocabulary building using BoW technique | SVM | 94.16 | Working with more diseases and real-time datasets |
| Zhang et al. (2018a) | Sheath blight | Captured using unmanned aerial vehicle equipped with multispectral camera | | Color features of red, green and hue values | Vegetation index method | 63 | Employing the technique in other crops with more number of images |
| Mohan et al. (2016) | Leaf blight, Brown spot, Leaf blast | | 60 images | Haar features indicating vertical, horizontal, and diagonal variations of pixels, horizontal changes and SIFT | AdaBoost classifier, k-NN and SVM | 83.33 91.10 93.33 | Evaluate method using other features, and larger datasets |
| Asfarian et al. (2013) | Leaf blast, Leaf blight, Brown spot, Dan tungro | Collected from paddy fields of West Java, Indonesia | 40 images, 10 each disease | Fractal descriptors based on Fourier transform for texture analysis | PNN | 83 | Employing other methods and large image sets to get more accurate result |

**Table 3** Summary of grain (wheat and corn) cultures

| References | Deficiency | Image dataset | No. of images | Feature extraction techniques | Classifier | Accuracy (in %) | Future work |
|---|---|---|---|---|---|---|---|
| *Wheat* | | | | | | | |
| Tian et al. (2013) | Powdery mildew, Leaf rust, Leaf blight, Yellow rust | Self-captured with uniform black background using Nikon camera in Northern China | | Meta-level features (combined texture, color, shape) | SVM with ensemble learning | 95.16 | Working with different feature extraction methods |
| Wang et al. (2014) | Stripe rust, Powdery mildew | Collected from Precision Agriculture Base, Beijing | 200 images | Edge-oriented histogram features | Improved rotation kernel transformation based method | 95 | Deploying the research for different crops and diseases with more features and bigger image set |
| Azadbakht et al. (2019) | Leaf rust | Hyperspectral data collected at canopy level in fields of north west of Iran | | Leaf area index based | Regression methods | 95 | Deploying the same experimental setup/method and investigating with higher bandwidth value |
| *Corn* | | | | | | | |
| Kai et al. (2011) | | | | Spatial GLCM parameters (energy, entropy, moment of inertia, related and local stationary) | EBPN | 98 | Deploy the method with other dataset and evaluate with more features and number of images |
| Zhang et al. (2014) | Gray speck, Brown spot, Leaf blight | | 400 leaf images (175, 105, 120 of three classes) | Shape features (lesion area, geometrical center, minimum exterior rectangle, rectangle degree, roundness degree, figure complexity), color features—H component, GLCM features | 3-layer NN with PSO technique | 93.30 | Working with other optimization techniques with different classifiers |

**Table 3** (continued)

| References | Deficiency | Image dataset | No. of images | Feature extraction techniques | Classifier | Accuracy (in %) | Future work |
|---|---|---|---|---|---|---|---|
| Luo et al. (2015) | Leaf blight, Brown spot, Gray leaf spot, Rust spot, Curvularia spot | Collected from Institute of Crop Science, Chinese Academy of Agricultural Sciences | 744 leaf images (124 images for each disease) | Histogram features | Histogram matching | 94.44 | Working with different methods and databases |
| Kusumo et al. (2019) | Gray leaf spot, Common rust, Northern blight, Healthy | PlantVillage | 3823 images (513, 1192, 985 and 1162 images of four classes) | Local texture features (SIFT, SURF, Orient fast and rotated BRIEF) | SVM, DT, RF, Naïve Bayes' | 87 | Using hybrid features and a bag of features to increase the performance of the proposed methods |
| Deshapande et al. (2019) | Common rust, Northern blight, both diseases, Healthy leaf | Self-captured, using Samsung digital camera PL200, from Agriculture university Dharwad | 200 leaf images, 50 for each category | Six first-order histogram (mean, variance, kurtosis, skewness, energy, entropy) and GLCM features (contrast, correlation, energy, homogeneity) | k-NN with various distance metric, SVM with various kernel functions | k-NN: 85 SVM: 88 | Extending on more images of the same crop and deploying on different diseases and different plants |

**Table 4** Summary of grain (soybean and millet) cultures

| References | Deficiency | Image dataset | No. of images | Feature extraction techniques | Classifier | Accuracy (in %) | Future work |
|---|---|---|---|---|---|---|---|
| *Soybean* | | | | | | | |
| Shrivastava and Hooda (2014) | Brown spot, Frog eye | Self-captured, using Samsung mobile GT-S3770 digital camera from Soybean fields at Guna, India | 100 leaf images (50 samples of each category) | Shape features (perimeter and centroid) | k-NN: k = 1 and Euclidean distance metric | 75 | Working with other classifiers and more images with different crops and diseases |
| Gharge and Singh (2016) | Frog eye, Downy mildew, Bacterial pustule | IPM dataset | 30 images (10 images of each category) | GLCM of hue (contrast, homogeneity, energy, difference variance, difference entropy, maximum probability, entropy) | 3-layer EBPNN with 20 neurons in hidden layer | 93.30 | Real-time implementation and working with more than three diseases for the same crop |
| Pires et al. (2016) | Mildew, Rust tan, Rust RB | Captured at Soybean fields of Federal University, Brazil | 1200 scanned images | Local descriptors (SIFT, SURF, BOVW) and HOG, PHOW | SVM | 96.25 | Evaluation of other parts of BOVW and automation of the system at soybean fields |
| Jadhav and Patil (2016) | Leaf blight, Brown spot, Pod mottle | Self-captured | | Diseased area | Severity estimation using calculated area | | Evaluating with other datasets and expand the work in classification module |
| Kaur et al. (2018b) | Downy mildew, Frog eye, Septoria leaf blight | PlantVillage | 4775 leaf images | Color, texture, shape features and their combination | SVM | 84 | Implementing the method with real-time images for training and testing phases and can be extended to 3-D leaf images |
| *Millet* | | | | | | | |
| Coulibaly et al. (2019) | Yellowing, Malformation of ear, Plantule, Partial green ear, Healthy | Self-captured and some downloaded from Internet | 124 images (training& validation: 99; testing: 25) | Transfer learning | VGG16 model with early stopping technique | 89 | Working on other diseases and crops like corn, cottons, potatoes, etc. |

**Table 5** A summary of profit crops (cotton, sugar beet, groundnut, cane)

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| *Cotton* | | | | | | | |
| Gulhane and Gurjar (2011) | Scab rust | Self-captured | | Color features | EBPNN | 86.83 | Working with more images |
| Bernardes et al. (2013) | Ramularia, Bacterial blight, Ascochyta blight, Healthy | Collected from various phytopathologists at Embrapa cotton, Brazil | 420 leaf images | DWT energy ( for R, G, B, H, S, V, I3a, I3b, and Gray) | SVM | 89.50 | Deploy the method for other diseases and crops |
| Revathi and Hemalatha (2014b) | Bacterial blight, Leaf blight, Root rot, Micronutrient, Fusarium wilt, Verticillium wilt | Captured using Nokia Mobile camera from Tamil Nadu, India | 270 leaf images | Edge with color and texture features | SVM, BPNN, Fuzzy classifier | 92 | Working with larger datasets of different crops |
| Revathi and Hemalatha (2014a) | Root rot, Verticillium wilt, Fusarium wilt, Boll rot | Self-captured from fields | | RGB color features | Homogeneous Pixel counting technique | 98 | To develop disease prediction system with pest recommendation |
| Rothe and Kshirsagar (2015) | Bacterial blight, Alternaria, Myrothecium | Captured using Cannon A460 Digital Camera | | Hu's moments (invariant to translation, scale, rotation) | EBPNN | 85.52 | Developing a more robust system with more features and extending work on other crops like corn, maize, wheat, citrus, etc. |
| Sivasangari and Indira (2015) | Bacterial blight, Leaf blight, Root rot, Fusarium wilt, Verticillium wilt, Nutrient Deficiency | Self-captured using mobile phone camera | | Color and shape features | SVM | 99.30 | Deploy the method for different cultures |
| *Sugar beet* | | | | | | | |
| Hallau et al. (2017) | Cercospora leaf spot, Ramularia leaf spot, Phoma leaf spot, Beet rust, Bacterial blight | Captured using smart phone camera under controlled condition | 1400 images (720, 200, 30, 200, 250 of five categories) | Texture features with intensity, color and gradient values | SVM with radial basis kernel | 82 | Providing disease forecasting system using smartphone application |
| *Groundnut* | | | | | | | |
| Ramakrishnan and Sahaya (2015) | Cercospora Late leaf spot (LLS), Alternaris | | 100 leaf images of each category | CCM features (contrast, homogeneity, energy, correlation, and entropy) | EBPNN | 97.41 | To explore this method on more diseases and crops |
| *Cane* | | | | | | | |
| Pujari et al. (2013) | Leaf smut, Red rot | Collected from University of Agricultural Sciences, Dharwad, India | 2600 leaf images | Discrete wavelet transform | PNN | 86.48 | Extending the work for fruits, vegetables, cereals, etc., with other methods |

**Table 6** A summary of the mixed (Assorted) crops

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| Pujari et al. (2016) | Wheat leaf rust, Sunflower Powdery mildew, Grape Anthracnose, Maize Downy Mildew, Maize stalk rot, Cucumber bacterial wilt, Cotton angular leaf spot, Lime galls, Cucumber mosaic, Grape yellow virus, Tomato veinal chlorosis, Sugarbeet enations, Tomato Foliar nematode, Soybean cyst disease, wheat year cockle, Maize ear rot, sunflower boron deficiency, Citrus Zinc deficiency, Grapes magnesium deficiency, Tomato potassium deficiency | Captured using Sony color camera | 9912 leaf images | RGB color features (mean, SD, range and variance) and texture features (entropy, energy, homogeneity, correlation, contrast, maximum probability, inverse difference, mean, SD, sum of mean) | SVM and multilayer EBPNN | 92 and 87 | Working with other methods to enhance accuracy |
| Sladojevic et al. (2016) | 13 different plant diseases | Downloaded from Internet and other sources | 33469 leaf images (training: 30880 and testing: 2589) | | CNN | 95.80 | Spreading usage of the model on wider level and extending the work on more crops |

**Table 6** (continued)

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| Mohanty et al. (2016) | 14 crops and 26 diseases | Self-prepared dataset | Total 54,306 images | Transfer learning | AlexNet and GoogLeNet | 31.4– 9.35 | Extending the work for more crops and diseases and increase efficiency |
| Ferentinos (2018) | 25 different plants and 58 distinct diseases | Combined dataset (PlantVillage and self-captured) | Total 87,848 images | Transfer learning | AlexNet, Overfeat, GoogLeNet, VGG, AlexNetOWTBn | 33.27–99.53 | Working with real-time testing dataset and exploring the model to be a generic |
| Arnal Barbedo (2019) | 14 different plants and 59 distinct diseases | Self-prepared datasets—plant disease dataset before and after augmentation | 1575 images, on augmenting 46,409 leaf images | Transfer learning | GoogLeNet | 25–100 | Working on real-time large dataset with balance number of images, i.e., homogeneous dataset |
| Pantazi et al. (2019) | 18 different plant species with four disease classes (Powdery mildew, Downey mildew, Black rot, and healthy plants) | | 46 images | LBP for texture analysis | One-class SVM | 83.3–95 | Dataset not mentioned clearly, working with more images and different diseases |

**Table 7** A summary of horticulture crops—fruits (apple, citrus, cherry)

| (Reference) Year | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| *Apple* | | | | | | | |
| Dubey and Jalal (2012) | Apple scab, Apple rot, Apple blotch, Healthy apple | | 431 apple fruit images (100, 107, 104, and 120 images of four categories) | Global color histogram Color coherence vector Local binary pattern | Multiclass SVM | 93 | Working with leaf dataset and combining more features and use of different classifiers |
| Samajpati and Degadwala (2016) | Apple scab, Apple rot, Apple blotch, Healthy apple | | 80 Apple fruit images | Combined-global color histogram, LBP, local ternary features, complete LBP, Gabor features, and color coherence vector features | Random forest classifier | 95% | Fusing more than two color and texture features to find more accurate result |
| Jolly and Raman (2016) | Apple blotch, Apple scab, apple rot, Healthy | | 320 Apple fruit images | Haarlick and LBP with Kernel PCA for dimensionality reduction | SVM with nonlinear polynomial kernel (degree 3), k-NN (k = 10) | 96 | Extending the work with more images and other diseases in different crops |
| *Citrus* | | | | | | | |
| Zhang and Meng (2011) | Citrus canker, Healthy | Collected from citrus NRI, China | 3000 images (1000 and 2000 of the two categories) | LBP for hue value with 8 directions and Gabor features with 6 scales and 8 directions | modified AdaBoost classifier | 88 | Deploy the method in real time and extending the current work for other crops |
| Pydipati et al. (2006) | Melanose, Scab, Greasy spot, Normal citrus | Collected from the horticulture fields, Central Florida | 160 images (40 of each category) | CCM for texture features based on H, S, and I | SGDM based statistical classifier | 95 | Explore the method in outdoor conditions and work on combined leaf front and back images |
| Sharif et al. (2018) | Canker, Melanose, Scab, Greening, black spot, Anthracnose | Image Gallery dataset | 1000 citrus fruit images | Color, Geometric, and Texture features | Multiclass SVM compared with four other classifiers (DT, LDA, k-NN, and Ensemble Boosted Tree) | 95.80 | Construction of deep model and work on bigger citrus dataset |
| *Cherry* | | | | | | | |
| Sengar et al. (2018) | Powdery mildew | PlantVillage dataset | 50 healthy leaves and 50 infected by Powdery mildew | Lesion area | Quantification of diseased area using calculated lesion area ratio | 99 | Extending the work for different disease identification and quantification of other infected crops |

**Table 8** A summary of the horticulture crops—fruits (grape, pomegranate) and flowers (palm oil plants, orchid, and lentil)

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| *Grape* | | | | | | | |
| Meunkaewjinda et al. (2008) | Scab, Rust, Healthy | | 1593 images (Training: 497,489, 492 and Testing: 39,41, 35 of used classes) | Color and Gabor features | SVM | 86.035 | Making an agro product analysis system using unambiguous color information |
| Sannakki et al. (2013) | Downy mildew, Powdery mildew | | 33 images (17,16 of two classes) | CCM | Feed-forward EBPNN | 100 | Working with more images and disease in different cultures |
| Waghmare et al. (2016) | Black rot, Downy mildew, Powdery mildew, Healthy leaf | | 450 leaf images | HSV color features, Opposite-color LBP | Multiclass SVM | 89.30 | Providing decision support system to farmers for disease detection |
| Cruz et al. (2018) | Grapevine yellow | Self-captured and PlantVillage datasets | 272 self-captured, (PlantVillage: 3400 images) | | AlexNet, GoogLeNet, Inception-v3, ResNet-50&101, SqueezeNet | 98, 96, 98, 99, 99, 94 | Developing a tool for real-time field conditions |
| Goncharov et al. (2019) | Esca Black rot Healthy | PlantVillage dataset | 2986 leaf images | | Siamese network | 92 | To develop a prototype of Web interface and extending the work on more crops/diseases |
| *Pomegranate* | | | | | | | |
| Khot et al. (2016) | Bacterial blight, Anthracnose, Alternaria | | | HSI values, morphological and Gabor features | Minimum Distance classifier | | Working with benchmark datasets, no informatic work |
| *Palm Oil Plant* | | | | | | | |
| Masazhar and Kamal (2018) | Chimaera, Anthracnose | collected from Seed nursery, Negeri Sembilan | | GLCM (energy, homogeneity, contrast, entropy) | Multiclass SVM | 95 | Using different methods for the same culture |
| *Orchid* | | | | | | | |
| Bin Mohamadazmi and Isa (2013) | Healthy, Sick | collected using a camera (controlled conditions) | total 80 leaf images | lesion area, centroid and number of lesions | Fuzzy system | Leaves are sick to certain degree | To capture the dataset in real-time condition & to make system more smooth |
| *Lentil* | | | | | | | |
| Singh et al. (2019) | Rust, Healthy | Captured microscopic images with the camera | total 300 images | LBP | Visual examination | | Exploring other techniques with feature extraction and segmentation |

**Table 9** A summary of the horticulture crops—vegetables (potato, chili, bean, cassava, cucumber)

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| *Potato* | | | | | | | |
| Islam et al. (2017) | Late blight, Early blight, Healthy | PlantVillage | 300 leaf images | Color and texture feature (correlation, contrast, energy, entropy, kurtosis, homogeneity, mean, skewness, standard deviation, root mean square) | Multiclass SVM with linear kernel | 95 | Integrate more diseases from various cultures and estimating the severity of infection |
| Patil et al. (2017) | Late blight, Early blight | Collected from various sources including PlantVillage | 892 leaf images (300 of PlantVillage) | Texture features (inverse difference, contrast, difference variance, uniformity, homogeneity, maximum probability) | SVM, RF, ANN | 84, 79, 92 | Extending the work to more cultures |
| *Chili* | | | | | | | |
| Husin et al. (2012) | Healthy, Unhealthy | | 107 images (21 healthy & 86 unhealthy) | RGB color features | Histogram based | | Extending work on more crops |
| *Bean* | | | | | | | |
| Abed and Esmaeel (2018) | Brown spot, Powdery mildew | Collected from University of Florida & PlantVillage dataset | 100 images (Training: 60 & Testing: 40) | GLCM features | SVM | 100 | Working on cultures other than beans |
| *Cassava* | | | | | | | |
| Aduwo et al. (2010) | Mosiac, Healthy leaf | Captured from Research institute, Uganda with a digital camera | 101 mosiac infected and 92 healthy plants | hue histogram feature (HSV space), mean SIFT features, and mean SURF features | NB, SVM, MLP, k-NN | 98 | Implementing the method in real-time conditions and extend the classifiers' scope |

**Table 9** (continued)

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| *Cucumber* | | | | | | | |
| Vakilian and Massah (2013) | Downy mildew, Powdery mildew | Captured reflectance images using CCD digital camera | 300 images (Training: 250, Testing: 50) | Texture features (energy, local homogeneity, entropy) and thermal parameters (maximum temperature difference, leaf average temperature) | 3-Layer BPNN (5-20-2 nodes) | 88% | Extending the work to real-time detection of various viral and fungal diseases |
| Zhang et al. (2017b) | Powdery mildew, Scab angular, Scab, Anthracnose, Downy mildew | captured using Android phone camera from NAFU, China | 300 leaf images (60 images per category) | Log frequency PHOG features concatenated with L*a*b* values | SVM | 91.48 | Exploring deep learning techniques in cucumber disease detection and use of IOT |
| Zhang et al. (2017a) | Downy mildew, Bacterial angular, Corynespora cassiicola, Gray mould, Scab, Powdery mildew, Anthracnose | | | Log frequency histogram color features in L*a*b* space using FFT, shape features (vector length), and (their concatenation) | Sparse representation-based classification | 85.70% | Developing a structured sparse model for a large dataset |

**Table 10** A summary of the horticulture crops—vegetables (tomato, pepper bell)

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| *Tomato* | | | | | | | |
| Mokhtar et al. (2015) | Healthy, Infected | | | 4 GLCM at four angles (0, 45, 90, and 135 degree) and 9 texture features | SVM with various kernel functions | 99.83% (Linear kernel) | extending the work on different crops |
| Mainkar et al. (2015) | Septoria spot, Healthy | | | 4 GLCM texture parameters | Feed-forward BPNN | 94 | Finding better segmentation and feature extraction to use with different classifiers |
| Raza et al. (2015) | Powdery mildew, Healthy | Captured (in controlled conditions) at DCS, University of Warwick, UK | 71 plants (17 healthy plants and 54 infected plants) | Pixel values (a, b, C, Y channels, disparity and thermal intensity map) | SVM | 90 | To classify various biotic and abiotic disease like water stress |
| Vidyaraj and Priya (2016) | Healthy, Unhealthy | | | CCM (energy, contrast, homogeneity, correlation in H channel value | Least square SVM | | Result is not declared , working with other methods |
| Sabrol and Kumar (2016b) | Leaf spot, Septoria leaf spot, Late blight, Bacterial canker, Leaf curl, Healthy | | 598 leaf images | Mean, SD, and skewness (XYZ values), correlation (X,Y values) | DT classifier | 78 | Work with a combination of various features |
| Sabrol and Kumar (2016a) | Leaf spot, Septoria leaf spot, Late blight, Bacterial canker, Leaf curl, Health | collected using a digital camera from the tomato farms, Raipur, India | 180 leaf images | Color moments, histograms and coherence vector features | ANFIS, FIS (Sugeno subtractive clustering), FF-BPNN | 34.4, 86, 87.2 | Deploy to real-time applications, and extending to more diseases and crops |
| Sabrol and Kumar (2017) | Late blight, Healthy tomato | Collected using common digital camera | 106 leaf images (48 and 58 images of two classes ) | DWT (RGB feature vector) and Haar Wavelet (low and high frequencies of RGB values) | PCA, KPCA and ICA | 96.40 | Working with different classifiers |
| Fuentes et al. (2017) | Gray mold, Canker, Whitefly, Low temperature, Powdery mildew, Plague, Leaf mold, Nutritional deficiency | Captured (with background) using a camera from tomato farms, Korea | 5000 images | DWT (RGB color features), Haar wavelets (low and high frequencies of RGB values) | ResNet-50, VGG-16, ResNet-101, ResNet-152, ResNeXt-50 | 83.06 | Extending the work with deep neural to get more accurate result |

**Table 10** (continued)

| References | Deficiency | Image dataset | No. of images | Feature extraction technique | Classifier | Accuracy (%) | Future work |
|---|---|---|---|---|---|---|---|
| Ashqar and Abu-Naser (2018) | Yellow leaf curl virus, Early blight, Bacterial spot, Septorial leaf spot, Leaf mold, Healthy | PlantVillage dataset | 9000 leaf images | Transfer learning | CNN | 99.84 | Extending the work on different plants and crops |
| *Pepper bell* | | | | | | | |
| Xia et al. (2013) | | | | Shape features (boundary extraction and active shape) | MLP | 76 | Deploy the technique for other cultures |
| Karadağ et al. (2019) | Healthy, Fusarium, Mycorrhizal fungus, Both | Captured from ARI, Turkey | 80 leaf images | Wavelet transform (min, max, mean, SD) | ANN, NB, k-NN | 84 | Working with different methods |

## References


Abdulridha J, Ampatzidis Y, Kakarla SC, Roberts P (2019a) Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques. Precis Agric. https://doi.org/10.1007/s11119-019-09703-4

Abdulridha J, Ehsani R, Abd-Elrahman A, Ampatzidis Y (2019b) A remote sensing technique for detecting laurel wilt disease in avocado in presence of other biotic and abiotic stresses. Comput Electron Agric 156(October 2018):549–557. https://doi.org/10.1016/j.compag.2018.12.018

Abed S, Esmaeel AA (2018) A novel approach to classify and detect bean diseases based on image processing. In: ISCAIE 2018—2018 IEEE symposium on computer applications and industrial electronics, pp 297–302. https://doi.org/10.1109/ISCAIE.2018.8405488

Aduwo JR, Mwebaze E, Quinn JA (2010) Automated vision-based diagnosis of cassava mosaic disease. In: Industrial conference on data mining

Afifi AJ, Ashour WM (2012) Image retrieval based on content using color feature. ISRN Comput Graph 2012:1–11. https://doi.org/10.5402/2012/248285

Ministry of Agriculture and Farmers Welfare GoI (2018) Annual report 2018-19. http://agricoop.nic.in/annual-report. Accessed 15 June 2019

AI-Hiary H, Bani-Ahmad S, Reyalat M, Braik M, Alrahamneh Z (2011) Fast and accurate detection and classification of plant diseases. Int J Comput Appl 17(1):0975–8887

Akhtar A, Khanum A, Khan SA, Shaukat A (2013) Automated plant disease analysis ( APDA ): performance comparison of machine learning techniques. In: 11th international conference on frontiers of information technology (IEEE), pp 60–65. https://doi.org/10.1109/FIT.2013.19

Al-Jarrah OY, Siddiqui A, Elsalamouny M, Yoo PD, Muhaidat S, Kim K (2014) Machine-learning-based feature selection techniques for large-scale network intrusion detection. In: Proceedings—international conference on distributed computing systems 30-June–20(Ml):177–181. https://doi.org/10.1109/ICDCSW.2014.14

Anthonys G, Wickramarachchi N (2009) An image recognition system for crop disease identification of paddy fields in Sri Lanka. In: ICIIS 2009—4th international conference on industrial and information systems 2009, conference proceedings, pp 403–407. https://doi.org/10.1109/ICIINFS.2009.5429828

Arivazhagan S, Shebiah RN, Ananthi S, Varthini SV (2013) Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features. Int J Sci Eng Res 4(8):1777–1780

Arnal Barbedo JG (2019) Plant disease identification from individual lesions and spots using deep learning. Biosyst Eng 180(2016):96–107. https://doi.org/10.1016/j.biosystemseng.2019.02.002

Asfarian A, Herdiyeni Y, Rauf A, Mutaqin KH (2013) Paddy diseases identification with texture analysis using fractal descriptors based on Fourier spectrum. In: Proceeding—2013 international conference on computer, control, informatics and its applications: “Recent Challenges in Computer, Control and Informatics”, IC3INA 2013, pp 77–81. https://doi.org/10.1109/IC3INA.2013.6819152

Ashqar B, Abu-Naser S (2018) Image-based tomato leaves diseases detection using deep learning. Int J Acad Eng Res (IJAER) 2(12):10–16

Azadbakht M, Ashourloo D, Aghighi H, Radiom S, Alimohammadi A (2019) Wheat leaf rust detection at canopy scale under different LAI levels using machine learning techniques. Comput Electron

Agric 156(September 2018):119–128. https://doi.org/10.1016/j.compag.2018.11.016
Bai X, Li X, Fu Z, Lv X, Zhang L (2017) A fuzzy clustering segmentation method based on neighborhood grayscale information for defining cucumber leaf spot disease images. Comput Electron Agric 136:157–165. https://doi.org/10.1016/j.compag.2017.03.004
Bai Y, Guo L, Jin L, Huang Q (2009) A novel feature extraction method using pyramid histogram of orientation gradients for smile recognition. Proc Int Conf Image Process ICIP 07118074:3305–3308. https://doi.org/10.1109/ICIP.2009.5413938
Bankar S, Dube A, Kadam P, Deokule PS (2014) Plant disease detection techniques using canny edge detection & color histogram in image processing. Int J Comput Sci Inf Technol 5:1165–1168
Barbedo JGA (2016) A review on the main challenges in automatic plant disease identification based on visible range images. Biosyst Eng 144:52–60. https://doi.org/10.1016/j.biosystemseng.2016.01.017
Bashir K, Rehman M, Bari M (2019) Detection and classification of rice diseases an automated approach using textural features. Mehran Univ Res J Sci Technol 38(1):239–250. https://doi.org/10.22581/muet1982.1901.20
Bashish DA, Braik M, Bani-Ahmad S (2011) Detection and classification of leaf diseases using K-means based segmentation and neura netwroks based classification. Inf Technol J. https://doi.org/10.1192/bjp.111.479.1009-a
Bera T, Das A, Sil J, Das AK (2019) A survey on rice plant disease identification using image processing and data mining techniques. Springer Singapore, https://doi.org/10.1007/978-981-13-1501-5, http://dx.doi.org/10.1007/978-981-13-1501-5_31
Bernardes AA, Rogeri JG, Oliveira RB, Marranghello N, Pereira AS, Araujo AF, Tavares JMRS (2013) Identification of Foliar diseases in cotton crop. In: Tavares JMRS, Jorge RMN (eds) Topics in medical image processing and computational vision, Lecture notes in computational vision and biomechanics. Springer, Dordrecht, pp 67–85. https://doi.org/10.1007/978-94-007-0726-9
Bin Mohamadazmi MT, Isa NM (2013) Orchid disease detection using image processing and fuzzy logic, pp 37–42
Caglayan A, Guclu O, Can AB (2013) A Plant Recognition Approach Using Shape and Color Features in Leaf Images. In: ICIAP 2013, Springer, Berlin, pp 161–170
Camargo A, Smith JS (2009a) An image-processing based algorithm to automatically identify plant disease visual symptoms. Biosyst Eng 102(1):9–21. https://doi.org/10.1016/j.biosystemseng.2008.09.030
Camargo A, Smith JS (2009b) Image pattern classification for the identification of disease causing agents in plants. Comput Electron Agric 66(2):121–125. https://doi.org/10.1016/j.compag.2009.01.003
Chaudhary P, Chaudhari AK, Godara S (2012) Color transform based approach for disease spot detection on plant leaf. Int J Comput Sci Telecommun 3(6):4–9
Chouhan SS, Singh UP, Jain S (2019) Applications of computer vision in plant pathology: a survey. Arch Comput Methods Eng. https://doi.org/10.1007/s11831-019-09324-0
Coulibaly S, Kamsu-Foguem B, Kamissoko D, Traore D (2019) Deep neural networks with transfer learning in millet crop images. Comput Ind 108:115–120. https://doi.org/10.1016/j.compind.2019.02.003
Cruz A, Ampatzidis Y, Pierro R, Materazzi A, Panattoni A, De Bellis L, Luvisi A (2018) Detection of grapevine Yellows symptoms in *Vitis vinifera* L. with artificial Intelligence. Comput Electron Agric 157:63–76
Pujari DJ, Yakkundimath R, Syedhusain Byadgi A (2013) Automatic fungal disease detection based on wavelet feature extraction and PCA analysis in commercial crops. Int J Image Graph Signal Process 6(1):24–31. https://doi.org/10.5815/ijigsp.2014.01.04
Dalal N, Triggs B, Europe D (2005) HistogramOfOrientedGradientsForHumanDetection.pdf. In: Proceedings of the 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)
Dandawate Y, Kokare R (2015) An automated approach for classification of plant diseases towards development of futuristic Decision Support System in Indian perspective. In: 2015 international conference on advances in computing, communications and informatics, ICACCI 2015, pp 794–799. https://doi.org/10.1109/ICACCI.2015.7275707
Dange DJ, Sayyad M (2015) Computer vision image enhancement and plant leaves disease detection. Int Jo Modern Trends Eng Res IJMTER 106–111
Deshapande AS, Giraddi SG, Karibasappa KG, Desai SD (2019) Fungal disease detection in maize leaves using Haar wavelet features. Springer, Singapore, https://doi.org/10.1007/978-981-13-1742-2, http://dx.doi.org/10.1007/978-981-13-1742-2_27
Deshpande T (2017) State of agriculture in India. PRS Legisl Res 113:1–29
Dey AK, Sharma M, Meshram MR (2016) Image processing based leaf rot disease, detection of betel vine (Piper BetleL.). Proc Comput Sci Elsevier Masson SAS 85:748–754. https://doi.org/10.1016/j.procs.2016.05.262
Dhaygude PSB, Kumbhar MP (2013) Agricultural plant leaf disease detection using image processing. Int J Adv Res in Electr Electron Instrum Eng 2(1):599–602
Dhingra G, Kumar V, Joshi HD (2017) Study of digital image processing techniques for leaf disease detection and classification. Mutimed Tools Appl. https://doi.org/10.1007/s11042-017-5445-8
Dordas C (2008) Role of nutrients in controlling plant diseases in sustainable agriculture: a review. Sustain Agric Agron Sustain 28:33–46. https://doi.org/10.1051/agro
Dubey SR, Jalal AS (2012) Detection and classification of apple fruit diseases using complete local binary patterns. In: Proceedings of the 2012 3rd international conference on computer and communication technology, ICCCT 2012, pp 346–351. https://doi.org/10.1109/ICCCT.2012.76
Fang Y, Ramasamy RP (2015) Current and prospective methods for plant disease detection. Biosensors 5(3):537–561. https://doi.org/10.3390/bios5030537
Ferentinos KP (2018) Deep learning models for plant disease detection and diagnosis. Comput Electron Agric 145(September 2017):311–318. https://doi.org/10.1016/j.compag.2018.01.009
Fuentes A, Yoon S, Kim SC, Park DS (2017) A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors (Switzerland). https://doi.org/10.3390/s17092022
Gabor D (1946) Theory of Communication. J Inst Electr Eng Part III Radio Commun Eng 93(26):58. https://doi.org/10.1049/ji-3-2.1946.0074
Ganeshan P, Sajiv G, L ML (2017) CIELuv color space for identification and segmentation of disease affected plant leaves using fuzzy based approach. In: Third international conference on science technology engineering and management (ICONSTEM)
Gawali PD, UKharat D, SHBodake P (2017) Plant leaf disease detection using image processing. Int J Recent Innov Eng Res 2(4):90–95
Geetharamani G, Pandian A (2019) Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Comput Electr Eng 76:323–338. https://doi.org/10.1016/j.compeleceng.2019.04.011

Gharge S, Singh P (2016) Image processing for soybean disease classification and severity estimation. Emerg Res Comput Inf Commun Appl. https://doi.org/10.1007/978-81-322-2553-9_44

Golhani K, Balasundram SK, Vadamalai G, Pradhan B (2018) A review of neural networks in plant disease detection using hyperspectral data Airborne Imaging Spectrometer for Applications. Inf Process Agric 5(3):354–371. https://doi.org/10.1016/j.inpa.2018.05.002

Goncharov P, Ososkov G, Nechaevskiy A, Uzhinskiy A (2019) Disease detection on the plant leaves by deep learning. Neuroinformatics 1:151–159. https://doi.org/10.1007/978-3-030-01328-8

Gulhane M, Gurjar A (2011) Detection of diseases on cotton leaves and its possible diagnosis. Int J Image 5:590–598

Guru DS, Mallikarjuna PB, Manjunath S (2011) Segmentation and classification of tobacco seedling diseases. In: COMPUTE'11, vol 1

Haar A (1910) On the theory of orthogonal function systems (translation). Math Ann 69(3):331–371

Hallau L, Neumann M, Klatt B (2017) Automated identification of sugar beet diseases using smartphones. Plant Pathol 67(2):399–410. https://doi.org/10.1111/ijlh.12426

Huang KY (2007) Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features. Comput Electron Agric 57(1):3–11. https://doi.org/10.1016/j.compag.2007.01.015

Husin ZB, Md Shakaff AYB, Abdul Aziz AHB, Mohamed Farook RBS (2012) Feasibility study on plant chili disease detection using image processing techniques. In: Proceedings—3rd international conference on intelligent systems modelling and simulation, ISMS 2012 pp 291–296. https://doi.org/10.1109/ISMS.2012.33

Islam M, Dinh A, Wahid K (2017) Detection of potato diseases using image segmentation and multiclass support vector machine. In: 2017 IEEE 30th Canadian conference on electrical and computer engineering (CCECE), pp 8–11

Jadhav SB, Patil SB (2016) Grading of soybean leaf disease based on segmented image using K-means clustering. IAES Int J Artif Intell IJ-AI 5(1):13. https://doi.org/10.11591/ijai.v5.i1.pp13-21

Jagtap MSB, Hambarde MSM (2014) Agricultural plant leaf disease detection and diagnosis using image processing based on morphological feature extraction. IOSR J VLSI Signal Process IOSR-JVSP 4(5):24–30

Jahagirdar S, Ravikumar MR, Siddaramaiah AL (2003) Traditional methods in the management of plant diseases—a review. Agric Rev 24(2):142–146

Jain A, Healey G (1998) A multiscale representation including opponent color features for texture recognition. IEEE Trans Image Process 7(1):124–128

Jim Isleib MSUE (2012) Signs and symptoms of plant disease: Is it fungal, viral or bacterial? https://www.canr.msu.edu/news/signs_and_symptoms_of_plant_disease_is_it_fungal_viral_or_bacterial. Accessed 15 Sept 2019

Jolly P, Raman S (2016) Analyzing surface defects in apples using gabor features. In: 2016 12th international conference on signal-image technology and internet-based systems analyzing, pp 178–185. https://doi.org/10.1109/SITIS.2016.36

Joshi AA, Jadhav BD (2017) Monitoring and controlling rice diseases using image processing techniques. Int Conf Comput Anal Secur Trends CAST 2016:471–476. https://doi.org/10.1109/CAST.2016.7915015

Kai S, Zhikum L, Hang S, Guo C (2011) A research of maize disease image recognition of corn based on BP networks. In: Third international conference on measuring technology and mechatronics automation, pp 246–249

Karadağ K, Tenekeci ME, Taşaltın R, Bigili A (2018) Detection of pepper fusarium disease using machine learning algorithms based on spectral reflectance. Sustain Comput Inf Syst. https://doi.org/10.1016/j.suscom.2019.01.001

Kaur S, Pandey S, Goel S (2018a) Plants disease identification and classification through leaf images : a survey. Arch Comput Methods Eng. https://doi.org/10.1007/s11831-018-9255-6

Kaur S, Pandey S, Goel S (2018b) Semi-automatic leaf disease detection and classification system for soybean culture. IET Image Process 12(6):1038–1048. https://doi.org/10.1049/iet-ipr.2017.0822

Kaya A, Keceli AS, Catal C, Yalic HY, Temucin H, Tekinerdogan B (2018) Analysis of transfer learning for deep neural network based plant classification models. Comput Electron Agric 158:20–29. https://doi.org/10.1016/j.compag.2019.01.041

Khirade SD, Patil AB (2015) Plant disease detection using image processing. In: Proceedings—1st international conference on computing, communication, control and automation, ICCUBEA 2015, pp 768–771. https://doi.org/10.1109/ICCUBEA.2015.153

Khot ST, Supriya P, Gitanjali M, Vidya L (2016) Pomegranate disease detection using image processing techniques. Int J Adv Res Electr Electron Instrum Eng. https://doi.org/10.15662/IJAREEIE.2016.0504008

Kim J, Han D, Tai YW, Kim J (2014) Salient region detection via high-dimensional color transform. In: Proceedings of the IEEE computer society conference on computer vision and pattern recognition, pp 883–890. https://doi.org/10.1109/CVPR.2014.118

Kulkarni A, Patil A (2012) Applying image processing technique to detect plant diseases. Int J Modern Eng Res IJMER 2(5):3661–3664. https://doi.org/10.1177/0958305X16685471

Kumar G, Bhatia PK (2014) A detailed review of feature extraction in image processing systems. In: International conference on advanced computing and communication technologies, ACCT, pp 5–12. https://doi.org/10.1109/ACCT.2014.74

Kumar SB, Nagaraja J, Venkatesan S (2018) An insight into plant disease detection using image processing—a review. Int J Eng Res Comput Sci Eng IJERCSE 5(4):120–127

Kuska MT, Mahlein AK (2018) Aiming at decision making in plant disease protection and phenotyping by the use of optical sensors. Eur J Plant Pathol 152(4):987–992. https://doi.org/10.1007/s10658-018-1464-1

Kusumo BS, Heryana A, Mahendra O, Pardede HF (2019) Machine Learning-based for automatic detection of corn-plant diseases using image processing. In: 2018 international conference on computer, control, informatics and its applications: recent challenges in machine learning for computing applications, IC3INA 2018—proceeding, pp 93–97. https://doi.org/10.1109/IC3INA.2018.8629507

Lowe DG (1999) Object recognition from local scale-invariant features. In: Proceedings of the international conference on computer vision

Luo J, Geng S, Xiu C, Song D, Dong T (2015) A curvelet-SC recognition method for maize disease. J Electr Comput Eng 8

Maenpaa T (2003) The local binary pattern approach to texture analysis—extensions and applications. Oulu. http://herkules.oulu.fi/isbn9514270762/

Mahajan V, Dhumale NR (2018) Leaf disease detection using fuzzy logic. Int J Innov Res Sci Eng Technol. https://doi.org/10.15680/IJIRSET.2018.0706067

Mahlein AK, Kuska M, Behmann J, Polder G, Walter A (2018) Hyperspectral sensors and imaging technologies in phytopathology: state of the art. Annu Rev Phytopathol 56(1):535–558. https://doi.org/10.1146/annurev-phyto-080417-050100

Mainkar PM, Ghorpade S, Adawadkar M (2015) Plant leaf disease detection and classification using image processing techniques. Int J Innov Emerg Res Eng 2(4):139–144

Majid K, Herdiyeni Y, Rauf A (2013) I-PEDIA: mobile application for paddy disease identification using fuzzy entropy and probabilistic neural network. In: ICACSIS, 2013 IEEE, pp 978–979
Mallika M, Vasanthi JJB (2017) Image enhancement techniques on plant leaf and seed disease detection. Int J Innov Res Comput Commun Eng 5(1):109–116
Martinelli F, Scalenghe R, Davino S, Panno S, Scuderi G, Ruisi P, Villa P, Stroppiana D, Boschetti M, Goulart LR, Davis CE, Dandekar AM (2015) Advanced methods of plant disease detection. A review. Agron Sustain Dev 35(1):1–25. https://doi.org/10.1007/s13593-014-0246-1
Masazhar ANI, Kamal MM (2018) Digital image processing technique for palm oil leaf disease detection using multiclass SVM classifier. In: 2017 IEEE international conference on smart instrumentation, measurement and applications, ICSIMA 2017 2017-Novem (November):1–6. https://doi.org/10.1109/ICSIMA.2017.8311978
Mesejo P, Ibáñez Ó, Cordón Ó, Cagnoni S (2016) A survey on image segmentation using metaheuristic-based deformable models: state of the art and critical analysis. Appl Soft Comput J 44:1–29. https://doi.org/10.1016/j.asoc.2016.03.004
Meunkaewjinda A, Kumsawat P, Attakitmongcol K, Srikaew A (2008) Grape Leaf disease detection from color imagery using hybrid intelligent system. In: Proceedings of ECTI-CON 2008, vol 0, pp 513–516
Mg A, Hanson J, Joy A, Francis J (2017) Plant leaf disease detection using deep learning and convolutional neural network. Int J Eng Sci Comput 7(3) http://ijesc.org/
Mohan KJ, Balasubramanian M, Palanivel S (2016) Detection and recognition of diseases from paddy plant leaf images. Int J Comput Appl 144(12):34–41
Mohanty SP, Hughes DP, Salathé M (2016) Using deep learning for image-based plant disease detection. Frontiers Plant Sci 7(September):1–10. https://doi.org/10.3389/fpls.2016.01419
Mokhtar U, El-Bendary N, EHassenian A (2015) SVM-based detection of tomato leaves diseases
Mutalib S, Abdullah MH, Abdul-Rahman S, Aziz ZA (2017) A brief study on paddy applications with image processing and proposed architecture. In: Proceedings—2016 IEEE conference on systems, process and control, ICSPC 2016 (December):124–129. https://doi.org/10.1109/SPC.2016.7920716
Nagasai S, Rani SJ (2015) Plant disease identification using segmentation techniques. Plant Dis 4(9):411–413. https://doi.org/10.17148/IJARCCE.2015.4988
Ojala T, Pietikainen M, Harwood D (1996) A comparative study of texture measures with classification based on feature distributions. Pattern Recognit 29(l):51–59
Orillo JW, Dela Cruz J, Agapito L, Satimbre PJ, Valenzuela I (2014) Identification of diseases in rice plant (oryza sativa) using back propagation Artificial Neural Network. In: 2014 international conference on humanoid, nanotechnology, information technology, communication and control, environment and management, HNICEM 2014—7th HNICEM 2014 joint with 6th international symposium on computational intelligence and intelligent in (November 2013). https://doi.org/10.1109/HNICEM.2014.7016248
Pang J, Bai ZY, Lai JC, Li SK (2011) Automatic segmentation of crop leaf spot disease images by integrating local threshold and seeded region growing. In: Proceedings of 2011 international conference on image analysis and signal processing, IASP 2011, pp 590–594. https://doi.org/10.1109/IASP.2011.6109113
Pantazi XE, Moshou D, Tamouridou AA (2019) Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. Comput Electron Agric 156(July 2018):96–104. https://doi.org/10.1016/j.compag.2018.11.005
Patil P, Yaligar N, Meena S (2017) Comparison of performance of classifiers—SVM, RF and ANN in potato blight disease detection using leaf images. IEEE Int Conf Comput Intell Comput Res ICCIC 2017:1–5. https://doi.org/10.1109/ICCIC.2017.8524301
Pethybridge SJ, Plant I, Pathology P, Pm Biology (2015) Leaf doctor : a new portable application for quantifying plant disease severity. Plant Disease Am Phytopathol Soc 99(10):1310–1316
Phadikar S, Sil J (2008) Rice disease identification using pattern recognition techniques. In: Proceedings of 11th international conference on computer and information technology, ICCIT 2008, Iccit, pp 420–423. https://doi.org/10.1109/ICCITECHN.2008.4803079
Phadikar S, Sil J, Das AK (2012) Classification of rice leaf diseases based on morphological changes. Int J Inf Electron Eng 2(3):460–463
Phadikar S, Sil J, Das AK (2013) Rice diseases classification using feature selection and rule generation techniques. Comput Electron Agric 90:76–85. https://doi.org/10.1016/j.compag.2012.11.001
Pires RDL, Gonçalves DN, Oruê JPM, Kanashiro WES, Rodrigues JF, Machado BB, Gonçalves WN (2016) Local descriptors for soybean disease recognition. Comput Electron Agric 125:48–55. https://doi.org/10.1016/j.compag.2016.04.032
Pooja V, Das R, Kanchana V (2018) Identification of plant leaf diseases using image processing techniques. In: Proceedings—2017 IEEE technological innovations in ICT for agriculture and rural development, TIAR 2017 2018-Janua(Tiar):130–133. https://doi.org/10.1109/TIAR.2017.8273700
Poojary H, Shabari SB (2018) A survey on plant disease detection using support vector machine. In: 2018 international conference on control, power, communication and computing technologies, ICCPCCT 2018, pp 292–295. https://doi.org/10.1109/ICCPCCT.2018.8574314
Prajapati BS, Dabhi VK, Prajapati HB (2016) A survey on detection and classification of cotton leaf diseases. Int Conf Electr Electron Optim Tech ICEEOT 2016:2499–2506. https://doi.org/10.1109/ICEEOT.2016.7755143
Prasad S, Kumar P, Hazra R, Kumar A (2012) Plant leaf disease detection using gabor wavelet. SEMCCO 2012. Springer, Berlin, pp 372–379
Pujari JD, Yakkundimath R, Byadgi AS (2014) Recognition and classification of produce affected by identically looking powdery mildew disease. Acta Technol Agric 17(2):29–34. https://doi.org/10.2478/ata-2014-0007
Pujari JD, Yakkundimath R, Byadgi AS (2015) Image processing based detection of fungal diseases in plants. Proc Comput Sci 46(Icict 2014):1802–1808. https://doi.org/10.1016/j.procs.2015.02.137
Pujari JD, Yakkundimath R, Byadgi AS (2016) SVM and ANN based classification of plant diseases using feature reduction technique. Int J Interact Multimed Artif Intell 3(7):6. https://doi.org/10.9781/ijimai.2016.371
Pydipati R, Burks TF, Lee WS (2006) Identification of citrus disease using color texture features and discriminant analysis. Comput Electron Agric 52(1–2):49–59. https://doi.org/10.1016/j.compag.2006.01.004
Ramakrishnan M, Sahaya ANA (2015) Groundnut leaf disease detection and classification by using back propagation algorithm. In: 2015 international conference on communication and signal processing, ICCSP 2015 (7092512506):964–968. https://doi.org/10.1109/ICCSP.2015.7322641
Ramesh S, Vinod PV, Niveditha M, Pooja R, Prasad Bhat N, Shashank N, Hebbar R (2018) Plant disease detection using machine learning. In: Proceedings—2018 international conference on design innovations for 3Cs compute communicate control, ICDI3C 2018, pp 41–45. https://doi.org/10.1109/ICDI3C.2018.00017
Rastogi A, Arora R, Sharma S (2015) Leaf disease detection and grading using computer vision technology and fuzzy logic. In: 2nd international conference on signal processing and integrated

networks, SPIN 2015, pp 500–505. https://doi.org/10.1109/SPIN.2015.7095350

Rathod AN, Tanawal B, Shah V (2013) Image processing techniques for detection of leaf disease. Int J Adv Res Comput Sci Softw Eng 3(11):397–399. https://doi.org/10.1186/cc14637

Raza SE, Prince G, Clarkson JP, Rajpoot NM (2015) Automatic detection of diseased tomato plants using thermal and stereo visible light images. PLoS ONE 10(4):1–20. https://doi.org/10.1371/journal.pone.0123262

Reddy NH, Kumar ER, Reddy M (2019) Bioinformatics and image processing-detection of plant diseases

Revathi P, Hemalatha M (2014a) Classification of cotton leaf spot diseases using image processing edge detection techniques. IEEE Proc Int Conf Emerg Trends Sci Eng Technol Recent Adv Sci Eng Innov INCOSET 2012:169–173

Revathi P, Hemalatha M (2014b) Cotton leaf spot diseases detection utilizing feature selection with skew divergence method. Int J Sci Eng Technol 3(1):22–30

Rothe PR, Kshirsagar RV (2015) Cotton leaf disease identification using pattern recognition techniques. In: 2015 international conference on pervasive computing: advance communication technology and application for society, ICPC 2015 00(c). https://doi.org/10.1109/PERVASIVE.2015.7086983

Sabrol H, Kumar S (2015) Recent studies of image and soft computing techniques for plant disease recognition and classification. Int J Comput Appl 126(1):44–55. https://doi.org/10.5120/ijca2015905982

Sabrol H, Kumar S (2016a) Fuzzy and neural network based tomato plant disease classification using natural outdoor images. Indian J Sci Technol 9(November):1–8. https://doi.org/10.17485/ijst/2016/v9i44/92825

Sabrol H, Kumar S (2016b) Intensity based feature extraction for tomato plant disease recognition by classification using decision tree. Int J Comput Sci Inf Secur IJCSIS 14(9):622–626

Sabrol H, Kumar S (2017) Recognition of tomato late blight by using DWT and component analysis. Int J Electr Comput Eng IJECE 7(1):194–199. https://doi.org/10.11591/ijece.v7i1.11531

Samajpati BJ, Degadwala SD (2016) Hybrid approach for apple fruit diseases detection and classification using random forest classifier. Int Conf Commun Signal Process 2013:1015–1019

Sannakki SS, Rajpurohit VS, Nargund VB, Kulkarni P (2013) Diagnosis and classification of grape leaf diseases using neural networks. ICCCNT 2013:3–7

Sebastian VB, Unnikrishnan A, Balakrishnan K (2012) Gray level co-occurrence matrices: generalization and some new features. Int J Comput Sci Eng Inf Technol IJCSEIT 2(2):151–157

Sengar N, Kishore M, Travieso CM (2018) Computer vision based technique for identification and quantification of powdery mildew disease in cherry leaves. Computing 100(11):1189–1201. https://doi.org/10.1007/s00607-018-0638-1

Sharif M, Attique M, Iqbal Z, Faisal M, Ullah MI, Younus M (2018) Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. Comput Electron Agric 150(May 2017):220–234. https://doi.org/10.1016/j.compag.2018.04.023

Shen W, Wu Y, Chen Z, Wei H (2008) Grading method of leaf spot disease based on image processing. Proceedings—International Conference on Computer Science and Software Engineering, CSSE 2008 6:491–494. https://doi.org/10.1109/CSSE.2008.1649

Shinde RC, Mathew CJ, Patil C (2015) Segmentation technique for soybean leaves disease detection. Int J Adv Res 3(5):522–528

Shrivastava S, Hooda DS (2014) Automatic brown spot and frog eye detection from the image captured in the field. Am J Intell Syst 4(4):131–134. https://doi.org/10.5923/j.ajis.20140404.01

Singh K, Kumar S, Kaur P (2019) Automatic detection of rust disease of Lentil by machine learning system using microscopic images. Int J Electr Comput Eng 9(1):660–666. https://doi.org/10.11591/ijece.v9i1 pp 660-666

Singh V, Misra AK (2017) Detection of plant leaf diseases using image segmentation and soft computing techniques. Inf Process Agric 4(1):41–49. https://doi.org/10.1016/j.inpa.2016.10.005

Singh V, Gupta S, Saini S (2015a) A methodological survey of image segmentation using soft computing techniques. In: Conference proceeding—2015 international conference on advances in computer engineering and applications, ICACEA 2015, pp 419–422. https://doi.org/10.1109/ICACEA.2015.7164741

Singh V, Varsha, Misra AK (2015b) Detection of unhealthy region of plant leaves using image processing and genetic algorithm. In: Conference proceeding—2015 international conference on advances in computer engineering and applications, ICACEA 2015, pp 1028–1032. https://doi.org/10.1109/ICACEA.2015.7164858

Sivasangari A, Indira K (2015) Cotton leaf disease detection and recovery using genetic algorithm. Int J Pure Appl Math 117:119–123

Sladojevic S, Arsenovic M, Anderla A, Culibrk D, Stefanovic D (2016) Deep neural networks based recognition of plant diseases by leaf image classification. Comput Intell Neurosci. https://doi.org/10.1155/2016/3289801

Sonka M, Hlavac V, Boyle R (1993) Image pre-processing. Image processing, analysis and machine vision, Springer, Boston, MA, chap 4:56–111. https://doi.org/10.1007/978-1-4899-3216-7_4

Sudha VP (2017) Feature selection techniques for the classification of leaf diseases in turmeric. Int J Comput Trends Technol 43(3):138–142

Szegedy C, Liu W, Jia Y, Sermanet P, Reed S (2015) Going deeper with convolutions. Explor Res 9th ed pp 95–111, https://doi.org/10.1109/CVPR.2015.7298594, arxiv:1409.4842

Thind T, Jain R, Sharma P, Khurana S, Aggarwal R (2011) Plant pathology in India Vision 2030. Indian Phytopathological Society, Division of Plant Pathology, Indian Agricultural Research Institute, New Delhi 110012, India

Tian Y, Zhao C, Lu S (2014) Multiple classifier combination for recognition of wheat leaf diseases. Intell Autom Soft Comput. https://doi.org/10.1080/10798587.2011.10643166

Vakilian KA, Massah J (2013) An artificial neural network approach to identify fungal diseases of cucumber (cucumis sativus l.) plants using digital image processing. Arch Phytopathol Plant Prot 46(13):1580–1588. https://doi.org/10.1080/03235408.2013.772321

Verma S, Chug A, Singh AP (2018) Prediction models for identification and diagnosis of tomato plant diseases. In: 2018 international conference on advances in computing, communications and informatics, ICACCI 2018, pp 1557–1563. https://doi.org/10.1109/ICACCI.2018.8554842

Vidyaraj K, Priya S (2016) Difference of Gaussian on frame differenced image. Int J Innov Res Electr Electron Instrum Control Eng 3(1):92–95. https://doi.org/10.17148/IJIREEICE

Waghmare H, Kokare R, Dandawate Y (2016) Detection and classification of diseases of grape plant using opposite colour local binary pattern feature and machine learning for automated decision support system. In: 2016 3rd international conference on signal processing and integrated networks (SPIN), pp 513–518

Wang H, Li G, Ma Z, Li X (2012) Application of neural networks to image recognition of plant diseases. In: 2012 international conference on systems and informatics, ICSAI 2012 (Icsai):2159–2164. https://doi.org/10.1109/ICSAI.2012.6223479

Wang L, Dong F, Guo Q, Nie C, Sun S (2014) Improved rotation kernel transformation directional feature for recognition of wheat stripe rust and powdery mildew. In: Proceedings—2014 7th international congress on image and signal processing. CISP 2014:286–291. https://doi.org/10.1109/CISP.2014.7003793

Xia C, Lee JM, Li Y, Song YH, Chung BK, Chon TS (2013) Plant leaf detection using modified active shape models. Biosyst Eng 116(1):23–35. https://doi.org/10.1016/j.biosystemseng.2013.06.003
Yao Q, Guan Z, Zhou Y, Tang J, Hu Y, Yang B (2009) Application of support vector machine for detecting rice diseases using shape and color texture features. In: 2009 international conference on engineering computation, ICEC 2009 pp 79–83. https://doi.org/10.1109/ICEC.2009.73
Zainon RB (2012) Paddy disease detection system using image processing. Thesis—Faculty of Computer Science and Software Engineering, pp 57–77
Zaitoun NM, Aqel MJ (2015) Survey on image segmentation techniques. Proc Comput Sci 65(Iccmit):797–806. https://doi.org/10.1016/j.procs.2015.09.027
Zhang D, Zhou X, Zhang J, Lan Y, Xu C, Liang D (2018a) Detection of rice sheath blight using an unmanned aerial system with high-resolution color and multispectral imaging. PLoS ONE 13(5):1–14. https://doi.org/10.1371/journal.pone.0187470
Zhang M, Meng Q (2011) Automatic citrus canker detection from leaf images captured in field. Pattern Recognit Lett 32(15):2036–2046. https://doi.org/10.1016/j.patrec.2011.08.003
Zhang S, Wu X, You Z, Zhang L (2017a) Leaf image based cucumber disease recognition using sparse representation classification. Comput Electron Agric 134:135–141. https://doi.org/10.1016/j.compag.2017.01.014
Zhang S, Zhu Y, You Z, Wu X (2017b) Fusion of superpixel, expectation maximization and PHOG for recognizing cucumber diseases. Comput Electron Agric 140:338–347. https://doi.org/10.1016/j.compag.2017.06.016
Zhang S, Wang H, Huang W, You Z (2018b) Plant diseased leaf segmentation and recognition by fusion of superpixel, K-means and PHOG. Optik Int J Light Electron Opt 157:866–872. https://doi.org/10.1016/j.ijleo.2017.11.190
Zhang YC, Mao HP, Hu B, Li MX (2008) Features selection of cotton disease leaves image based on fuzzy feature selection techniques. In: Proceedings of the 2007 international conference on wavelet analysis and pattern recognition, ICWAPR '07 1:124–129. https://doi.org/10.1109/ICWAPR.2007.4420649
Zhang Z, Li Y, Wang F, He X (2014) A particle swarm optimization algorithm for neural networks in recognition of maize leaf diseases. Sens Transducers 166(3):181–189