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Review of image processing approaches for detecting plant diseases

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Abstract: There is intense pressure on agricultural productivity due to the ever-growing population. Several diseases affect crop yield and thus, effective control of these can significantly improve the production of food for all. In this regard, detection of diseases at an early stage and quantification of the severity, in general, has acquired urgent attention of the researchers. In this study, a summary of prevalent techniques and methodologies used for the detection, quantification and classification of diseases is presented to understand the scope of improvement. The study pays attention to critical gaps that exist in available approaches and enhance them for the early prediction of diseases. Diseases affect almost all parts of plants, e.g. root, stem, flower, leaf; a manifestation in different ways for different parts of the plant of the same disease presents a challenge for researchers. This study extends the review work published by JGA Barbedo in 2013, as there have been significant advances and numerous new techniques introduced since then. A novel approach of classifying and categorisation of the existing techniques based on pathogen types is a significant contribution by the authors in this study.

1 Introduction

There is a constant shortage of food and water for everyone due to the ever-increasing population, and the situation may become bleak in the future. Besides, global warming is also another significant problem impacting the environment and specifically agriculture production. Saving plants and trees and keeping them healthy can address the scarcity of food and environmental degradation. Researchers are trying to focus on these problems to come out with efficient and cost-effective solutions.

The occurrence of diseases in plants is of grave concern as the latter cause poor growth and reduced flowering, resulting in low yield. The diseases impact all parts of plants like roots, leaves, stem, seeds, and ultimately fruits. Thus, there can be many ways in which information about the health of plants can be gathered using various sensors supplemented by images which in turn can be further processed analytically for detection of preferably early signs of breaking of disease.

The reasons for onset of diseases are multifaceted and can be attributed to bad farming practices, deteriorating soil quality, worsening weather cycles and unfavourable climatic conditions. Farmers are still employing conventional methods in the majority of regions world-wide. Degradation in soil condition reduces the production potential of fields and thus poor yields of crops. In precision agriculture, variations in the temporal and spatial domains of the soil and crop are managed by a crop management system [1], but the rate of the development and deployment of the precision agriculture tools are not so rapid [2]. There is a gap between the existing techniques to handle diseases and the field protocols in practice [3].

This review paper identifies the gaps in knowledge and methodology employed in some of the areas highlighted above and details on techniques to address such gaps. We also touch upon dependable and economically viable plant health supervision and monitoring systems to detect potential diseases as early and as effectively as possible. Majority of such systems comprise of a multitude of sensors and necessary sub-systems, which together enable us to timely and efficiently capture the signatures and patterns of diseases reliably. These systems also include image and vision sensors and are much easier to deploy and use to benefit agricultural professionals and assist in use of technological advances. In this paper, we also try to illustrate the limitations and advantages of the various techniques previously adopted, the usefulness of results obtained and list possible future work suggested by the authors. A novel approach of categorising the techniques reported by previous authors has been evolved by us adding quite some value to understanding the diseases and suited techniques for them. The new approach makes use of pathogen types, causing various diseases, to classify the techniques and methodologies employed so as to make use of the latter more appropriately.

In this paper, we follow categorisation techniques employed similar to the one proposed by Arnal-Barbedo [4]; these techniques are categorised into three main groups, namely, (i) detection of diseases, (ii) quantification of disease severity, and (iii) classification, respectively. The paper has been organised into sections aligned with the above grouping.

It is worth mentioning that most diseases manifest themselves in the visible spectrum. In the vast majority of cases, the diagnosis, or at least a first guess about the disease, is performed visually by the trained raters. The human raters may be efficient in recognising and quantifying diseases; however, the subjectivity of their knowledge results into some disadvantages of the approach. Too much involvement of them may, however, only partially meet the end objectives. Since diseases in the plants generate some symptoms in the visible region of the spectrum, trained raters (or a person in charge of early detection) can be effectively utilised at least in the beginning stage. Manual raters are quite efficient and reliable in the detection and severity quantification of the supposed disease, but they still have some biases and imperfections which make the reading and detection an error-prone job.

Bock *et al.* [5] discusses some of the challenges faced by these manual raters in detail and summarised as: (i) tiredness found in raters and thus losing concentration leading to possibility of result inaccuracy, (ii) inter and intra-rater variability leading to subjectivity error, (iii) lack of standard area diagrams for right assessment, (iv) deficiency in regular quality training of raters, (v) degradation of sample quality due to transpiration of sample from field to lab, and (iv) last but not least, the expenses in hiring affordability of raters. These observations by Bock *et al.* [5] were observed after through experimentation and proper field trials. The challenges identified by Bock *et al.* [5] highlights some of the major problems of the human rater.

2 Background

In this section, for the sake of completeness, we have summarised a few significant papers mentioned by Arnal-Barbedo [4]. The summary of papers is presented the form of well-thought-out tables covering different aspects of the work done for detection, quantification and classification of the plant diseases through various image processing techniques.

Arnal-Barbedo [4] has very meticulously compiled the study and research carried out by several research workers on disease detection, quantification and classification of various plant species in the year 2013. The present paper is mainly concentrated on study and research beyond the period of Arnal-Barbedo [4].

As mentioned by Arnal-Barbedo [4], thresholding methods have been tried by several researchers to detect the diseases in various plants. Sena *et al.* [6] proposed a method based on thresholding to detect pest known as 'fall armyworm' found in maize plants. An empirical thresholded value differentiated healthy and diseased plants very well. Lindow and Webb [7] created a thresholding based technique to quantify the necrotic areas in tomatoes, bracken fern, sycamore and California buckeye. Martin and Rybicki [8] established a thresholding based system as described by Lindow and Webb [7] to quantify the severity of the infection caused by the maize steak virus on the maize plant. Škaloudova *et al.* [9] accomplished a disease quantification methodology to detect the extent of severity caused by a pest known as Tetranychus urticae Koch on bean plants. The results obtained by Škaloudova *et al.* [9] using the two-stage thresholding have been found better than the those of chlorophyll fluorescence method. Weizheng *et al.* [10] proposed a technique based on two-step thresholding to measure the lesion spread in the soybean plant. Price *et al.* [11] developed a method to quantify the amount of severity of leaf rust disease in coffee plants. They isolated the infected regions by simple thresholding. The developed system outperformed the manual raters in case of extreme spreading of the disease. Camargo and Smith [12] executed a method to quantify the lesion severity in bananas, maize, alfalfa, cotton and soybean plants, thresholding based on the histogram of intensities technique was used to classify healthy and infected regions. Camargo and Smith [12] found out that the texture feature can be used for discrimination of healthy and infected leaves. Macedo-Cruz *et al.* [13] developed a method to measure the damage extent of frost on oat crops and oat crop prediction. Their algorithm worked on images in CIELab colour space (a colour space expressing colour as luminance, chroma, and hue); they obtained the threshold for their algorithm by combining three primary thresholding techniques, namely, Otsu's method, isodata algorithm and fuzzy thresholding. Lloret *et al.* [14] created and deployed a wireless sensor network-based imaging system to find out the infected leaves and extent of severity caused due to nutrient deficiency, pest, disease or other harmful agents in a vineyard. They identified healthy and infected regions of the leaf by applying thresholding on RGB (Red-Green-Blue) as well as HSV (hue, saturation, value) colour spaces.

Abdullah *et al.* [15] developed a neural network-based method without using segmentation, to detect a typical disease known as Corynespora found in the rubber plant. Pydipati *et al.* [16] identified that classification techniques such as Mahalanobis statistical classifier and radial basis functions (RBFs) neural network classifiers trained with backpropagation algorithm were quite efficient for identifying diseases such as greasy spot, melanose, and scab in citrus plants. Performance of both the classification techniques was similar with best of four subsets containing ten texture features based on hue and saturation. Huang [17] presented a neural network and image processing method to detect and classify various diseases found in the seeds of moth orchids (phalaenopsis) such as bacterial soft rot, bacterial brown spot, and phytophthora black rot. The method achieved an accuracy of 89.6% with classification and 97.2% without classification. Sanyal *et al.* [18], Kai *et al.* [19] and Wang *et al.* [20] developed different neural network classification techniques to identify and classify various diseases in rice, maize, wheat and grapevines. Pagola *et al.* [21] and Contreras-Medina *et al.* [22] presented colour analysing techniques to quantify the disease severity caused due to the deficiencies in various plants, namely, barley, pumpkin, bean, pepper etc. Wiwart *et al.* [23] developed a colour-based classification method to identify the various deficiencies such as nitrogen, phosphorus, potassium and magnesium occurred in faba bean, pea and yellow lupine plants.

Xu *et al.* [24] proposed a classification based technique for the identification of potassium deficiencies in tomato plants. Experimental implementation achieved an accuracy of 82.5%. Sannakki *et al.* [25], Sekulska-Nalewajko and Goclawski [26] and Zhou *et al.* [27] developed fuzzy-based methods to quantify the disease severity for pomegranate, pumpkin, cucumber and rice plants.

Story *et al.* [28] presented a detection method for deficiency in lettuce plant due to calcium. Early detection of deficiency in the plant is done with the help of dual segmented regression analysis. Meunkaewjinda *et al.* [29], Youwen *et al.* [30], Yao *et al.* [31] proposed a Support Vector Machine (SVM) based classifying method to identify and classify various diseases in grapevines, cucumber and rice plants. In Table 1 various features which are used in the majority in some techniques are summarised. Various techniques as discussed in this section are summarised based on pathogens, characteristics of the diseases caused by deficiency/ pathogen on the crop, colour space used, dataset and number of images used, accuracy and some other parameters can be seen in Table 2, respectively.

Table 1 Some of the features used commonly in various techniques

Paper name	Features extracted
Camargo and Smith [12]	Shape, texture, fractal dimension, lancunarity, dispersion, grey levels, grey histogram discrimination, Fourier descriptor
Abdullah *et al.* [15]	RGB colour variations and variegation
Pydipati *et al.* [16]	Colour texture features, texture features
Huang [17]	Colour and texture features, texture features such as entropy, energy, contrast
Sayal *et al.* [18]	Textural and colour features
Wang *et al.* [20]	Colour features, shape features and texture features

3 Categorical classification of algorithmic techniques

3.1 Major causes of diseases and deficiencies

In this section, we are first categorising and compiling the work carried out in the detection of plant diseases caused by various pathogens, such as bacteria, fungi, insects and nutritional deficiencies. Research works are arranged in respective tables categorised according to various parameters. The results are also compared and displayed in graphical forms for better understanding. In Section 3.1, recent work on detection of plant diseases is discussed, whereas in Section 3.2, work on quantification of plant diseases is compiled, and in the last Section 3.3, research works concerned with the classification of plant diseases are discussed. All of the works have been tabularised with well thought of columns for better understanding.

As shown in Fig. 1 there are many ways a plant might be affected by diseases/infections/pests/insects/deficiency. In this section, we summarise various techniques as per the effect of pathogens/infestations/deficiencies on plants. We have mainly focused on results aligned to bacterial, fungal, insects and deficiencies over several years.

While summarising the work according to various pathogens and deficiency, we focused on several parameters which we have used as table columns. The columns of the tables are, culture on which the infection is occurring, disease type, dataset and the accuracy obtained. By looking at these parameters, one can quickly get a clear idea of which techniques are more suitable for a specific type of diseases. By looking at the number of images/samples, it

Table 2 Summarising various techniques as mentioned in Arnal-Barbedo [4]

Paper name	Plant name	Pathogen	Diseases characteristics	Colour space	Total images	Classification	Accuracy
Sena *et al.* [6]	Maize	Fall Armyworm	Leaf holes	Grey scale	720	Thresholding	94.72%
Martin and Rybicki [8]	Maize	Maize streak virus	Leaf chlorotic area	Grey scale	140	Pixel thresholding	96.4%
Škaloudova *et al.* [9]	Bean	Two-spotted spidermite	Small pale spots, dry and silver leaves	grey scale	N.A.	Thresholding	N.A.
Weizheng *et al.* [10]	Soybean	Fungus	Leaf spot	HSI	N.A.	Ratio of lesion to leaf area	N.A.
Camargo and Smith [12]	Cotton	Southern green stink bug; Bacterial angular; Ascochyta blight	Spots, stains or strikes on leaves	RGB and HSV	117	SVM classifier	90%
Macedo-Cruz *et al.* [13]	Oat	Frost damage	Dried leaves	CIELab	2000	Unsupervised classification	96%
Lloret *et al.* [14]	Grapes	Deficiency, pest, disease	Anomalous pigmentation on leaves, leaf colour change	RGB	N.A.	Neural classifiers	N.A.
Abdullah *et al.* [15]	Rubber	Corynespora, bird's eye spot and collectotrichum	Leaf colour change, Leaf spots	RGB	700	Artificial neural network	70%
Huang [17]	Moth orchids	Various pathogens	Leaf spots, circular lesions	RGB	289	BP-neural network classifier	89.6%.
Sanyal *et al.* [18]	Rice	Nutrient deficiencies	Leaf colour and morphological changes s	RGB	N.A.	MLP classifiers	88.56%
Kai *et al.* [19]	Maize	Leaf blight, sheath blight, southern leaf blight	Leaf spots	YCbCr	10	BP neural network	98%
Wiwzart *et al.* [23]	Bean&pea	Nutrient deficiencies	Leaf colour changes	HSI& $L^*a^*b^*$	N.A.	Euclidean distances	N.A.

HSI, Hue Saturation Intensity; **RGB**, Red Green Blue; **HSV**, Hue Saturation Value; **CIELab**, CIE $L^*a^*b^*$ or Lab colour space; where L represents Luminosity and a^*, b^* represents colour hue and saturation; **CCM**, Colour Co-occurrence Matrix; **BP**, Back propagation; **GRNN**, General regression neural network; **MLP**, Multi layer perceptron; **BSR**, Bacterial soft rot; **BBS**, Bacterial brown spot; **PBR**, Phytophthora black rot.

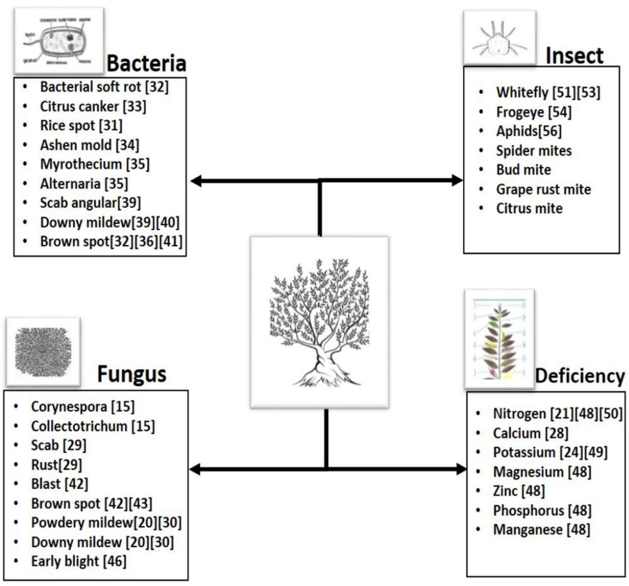


Fig. 1 *Various infections/diseases/pests/deficiency in plants*

gives a clear idea of how many images in the dataset is required to carry on the work for a particular disease in a specific plant/crop.

There are various plants which gets effected and are chosen by the researchers for their experiments, some of them over the years are summarised in Table 3. There are many diseases which occur due to bacteria in the plants, such as bacterial brown spot [17, 32–37], bacterial soft rot [17], citrus canker [38], rice spot [31], ashen mould [39], myrothecium [37], alternaria [37], scab angular [40], downy mildew [40, 41], leaf curl [42], bacterial blight [43]. Bai *et al.* [44], Zhang *et al.* [40, 41] worked on cucumber with 129, 300 and 420 images in their dataset.

The fungi affects various plants as well, causing several forms of diseases, Table 4 summarises span of work over the years concentrating on detection of diseases caused by fungus. Various diseases which occur due to fungus are corynespora [15], bird's eye spot [15], powdery mildew [30, 47–50], downy mildew [20, 30, 51–53], scab [29],black spot [54], red spot [55], rust [20], anthracnose [56, 57], melanose [58], frogeye [59], curvularia leaf spot [60], wheat stripe rust [61], septoria leaf spot [62]. Dataset varies from 40 to 1500 images, with small dataset of 40 images Youwen *et al.* [30] achieved 100% accuracy in detecting powdery mildew, and with 1478 images Meunkaewjinda *et al.* [29] achieved an accuracy of 82.5 and 83.5% for detecting scab and rust diseases in grape. Various plants/crops as covered in Table 4 are rubber tree [15], cucumber plant [30], grapevine [29, 49, 51].

Nutrient deficiency is visible in the form of various symptoms which may be visual or internal, Nutrient deficiency affects the whole plant, and hence there is a direct effect on yield, quality and quantity of the crop. There are several characteristics which are related to specific nutrient deficiency, for example, calcium deficiency which deforms the leaf shape, nitrogen-deficient leaves become light green when they are on top of the plant and yellow when in the bottom of the plant, manganese deficiency cause elongated holes in between veins of the leaves, copper-deficient leaves become pale pink in between the veins. Table 5 summarises some of the work which is used to detect nutrient deficient plants using image processing techniques. Pagola *et al.* [21] identified nitrogen-deficient barley leaves using a manual inspection along with the developed algorithm and achieved a correlation of 0.95. Potassium deficiency in tomato is detected with an accuracy of 82.5% using 240 and 50 images as their dataset by Xu *et al.* [24]. Potassium deficiency in grapevine is detected using 50 images in dataset by with Rangel *et al.* [65]. Hairuddin *et al.* [66] worked on several deficiencies on palm leaves and detected nitrogen, phosphorous, potassium, boron, and several other deficiencies using 30 samples of leaves affected by each of the corresponding deficiency and achieved a good accuracy.

Insects also cause various forms of damages on plants/crops, detection of insects in greenhouses is critical and of urgent need, in this context Boissard *et al.* [69] developed an experiment to detect white-flies on rose plants, they measured the accuracy with manual counting of the flies on the plants. Damage of whiteflies on rose causes much financial loss. Soyabean is prominently affected by aphids, so many techniques have been identified to count and detect the aphid damage on soybean crop [70–72]. Various techniques are summarised in Table 6. In Fig. 2 detection accuracy of spot disease and mildew disease are represented over the years, we have included various spot diseases in Fig. 2*a*, such as brown spot, red spot, frogeye spot, various leaf spot diseases. In Fig.2*b* we have taken into account accuracy achieved by various researchers in detecting powdery and downy mildew over several years.

Various techniques as categorised in the sections of detection, quantification and classification of diseases are discussed in the following sections.

Table 3 Summary of work for the detection of bacterial diseases

Paper name & Year	Plant	Disease	Dataset	Accuracy
Huang 2007 [17]	Moth Orchids	Phytophthora black rot. Bacterial brown spot, Bacterial soft rot	289	88.8%, 90.09%, 88.8%
Bock *et al.* 2008 [38]	Grapefruit	Citrus canker	210	0.99, 0.96, 0.97(Correlation)
Yao *et al.* 2009 [31]	Rice	Rice spot	72	97.2%
Al Bashish *et al.* 2010 [39]	—	Early scorch, Tiny whiteness, Ashen mould, Cottony mould Late scorch	—	100%, 88%, 100%, 96%, 80%
Rothe and Kshirsagar 2015 [37]	Cotton plant	Bacterial Blight, Myrothecium and Alternaria	—	85%
Jagan *et al.* 2016 [36]	Paddy	Brown spot, leaf blast and bacterial blight	120	93.33%(k-NN) & 91.10%(SVM)
Sabrol and Kumar 2016 [45]	Tomato	Bacterial leaf spot, Septoria leaf spot, Bacterial canker and Leaf curl	598	78%
Bai *et al.* 2017 [44]	Cucumber	Leaf Spot	129	Average segmentation error 0.12%
Zhang *et al.* 2017 [41]	Cucumber	Scab angular, powdery mildew, downy mildew, anthrancnose and scab disease	300	91.48%
Zhang *et al.* 2017 [40]	Cucumber	Downy mildew, bacterial angular scab, greymould, anththracnose and powdery mildew	420	85.7%,
Shao *et al.* 2017 [46]	Tobacco	Wildfire, weather fleck and brown spot	324	92.5%

k-NN, K-nearest neighbours, a pattern recognition method used for classification and regression; SVM, Support Vector Machine, a supervised machine learning models used for classification and regression.

3.2 Detection of diseases

Detection of diseases is the first phase of the plant disease detection process. Various methods are reported for this purpose and are summarised below. Some of the common issues while detecting diseases are the proper isolation of the leaf from the complex background, varying lighting conditions in which the images are acquired as such images captured in variable lighting conditions produce many problems and difficulties in region of interest isolation.

Some disease symptoms cannot be adequately isolated as they are spread all over the infected part of the plant; this makes it hard to define a proper region of interest. Diseases manifest through various symptoms at different stages, so all these stages have to be considered while detecting the disease to increase the accuracy. Monitoring of the whole plant is a complicated task. Various diseases attack different sites, so this makes it difficult to isolate the type of disease. Sometimes symptoms generated by various diseases are visually similar, which makes it challenging to identify the disease and require more robust and sophisticated techniques to identify them.

3.2.1 Fuzzy logic-based approaches: Mao *et al.* [75] have applied fuzzy C-means clustering algorithm (FCM) technique on diseased leaf images of cotton plants. Authors were able to keep mean segmentation error down to 5%. When the background is complex, i.e. foreground and background are not distinct then it is tough to isolate the object, it is worth to mention that Bai *et al.* [44] were able to isolate cucumber leaves efficiently, and further the leaf spot disease from the complex background in a more efficient manner using the enhanced fuzzy c-means technique. The proposed technique involves five steps:

• Watershed algorithm was used for three iterations for the isolation of the target leaf on hue, saturation and intensity (HSI) colour space;
• Pixels with their corresponding clusters are identified and the distance between them are computed;
• The pixel neighbourhood's mean grey value, which constitutes a two-dimensional vector with greyscale information, is calculated as a sample point;
• Two-dimensional vector containing grey scale information is obtained by calculating the mean of grey values of the selected pixel's neighbourhood;
• Corresponding weights according to weight matrix are assigned to the obtained mean grey values and pixel grey values.

Tests were conducted to evaluate the sturdiness and accuracy of the proposed segmentation method on 129 cucumber disease images in vegetable disease database. It is of interest to mention that an average segmentation error of 0.12% was achieved through the technique discussed above for detection of cucumber leaf disease under complex background. The experimental tests showed that the method provided accurate estimates over a wide variety of conditions is robust to variation in size, shape, the colour of leaves, symptoms, leaf veins. The resulting accuracy is constrained by the similarity in shade and colour characteristics of the identified symptoms and leaf veins. Better results are obtained only with the black or white background.

Future scope: Potential future work may involve thorough work on pixel misclassification, which will further reduce the error and misclassification rate. Other than this, the image database used has to be expanded and optimised for more accurate results. This technique is scalable through exhaustive validation.

3.2.2 Optimisation approaches: Bello *et al.* [76] integrated ant colony optimisation with rough sets and were able to reduce the features but did not get satisfactory results in classification accuracy and execution time. Wang *et al.* [77] were able to achieve satisfactory results by obtaining an optimal number of features and quicker execution time by integrating particle swarm optimisation (PSO) with ant colony system. Guo *et al.* [78] integrated genetic algorithm (GA) with rough sets for optimal features selection.

SVM was used for finding out the performance of selected features. Hassanien *et al.* [50] proposed a moth flame optimisation algorithm which is based on rough sets for the detection of tomato diseases. In the proposed methodology, feature selection is made at the initial stages, which also help in the removal of data which is noisy, irrelevant, and redundant. The number of selected features from the initial stage plays a vital role in the next step, where the fitness function of the moth flame optimisation technique which is dependent on the rough sets dependency degree takes the features into consideration. Set of features for the maximisation was identified using moth flame optimisation and the rough sets. SVM was used for the identification of the features.

The mentioned algorithm Moth-Flame Optimisation and rough set was tested and bench-marked using the UCI machine learning data repository data sets. Performance of feature selection of the proposed method was compared with PSO and GAs along with rough sets. For checking the accuracy and effectiveness of the proposed algorithm, it was implemented to detect and classify tomato diseases such as powdery mildew and early blight. Data set was formed manually with diseased and healthy images, and the proposed method performed better by recall, precision, accuracy and FScore. There is a significant improvement in execution time for this proposed technique.

Future scope: Datasets with a more significant number of feature space dimensionality, a number of classes and varying size of the samples can be considered to test the mentioned algorithm for scalability, robustness and stability.

Table 4 Summary of work for the detection of fungal diseases

Paper name & Year	Plant	Disease	Dataset	Accuracy
Abdullah *et al.* 2007 [15]	Rubber tree	corynespora, bird's eye spot and collectotrichum	700	70%
Youwen *et al.* 2008 [30]	Cucumber	Powdery mildew and downy mildew	40	100%
Meunkaewjinda *et al.* 2008 [29]	Grape	Scab and rust	1478	83.5%, 82.5%
Kurniawati *et al.* 2009 [63]	Paddy crop	Blast, narrow brown spot, and brown-spot	94	94.7%
Patil *et al.* 2011 [64]	Sugarcane	Brown spot	90	98.6%
Peressotti *et al.* 2011 [51]	Grapevine	Downy mildew	760	—
Wang *et al.* 2012 [20]	Wheat and grape	wheat stripe rust, wheat leaf rust, grape downy mildew and powdery mildew	185	94.29%
Oberti *et al.* 2014 [49]	Grapevine	Powdery mildew	175	72%
Hassanien *et al.* 2017 [50]	Tomato	Powdery mildew and early blight	200	91.5%

Table 5 Summary of work for the detection of deficiency

Paper name & Year	Plant	Disease	Dataset	Accuracy
Boese *et al.* 2008 [67]	Eelgrass	leaf injury	—	—
Pagola *et al.* 2009 [21]	Barley	Nitrogen deficiency	160	0.95(R)
Story *et al.* 2010 [28]	Lettuce	Calcium deficiency	—	0.97(R^2)
Hairuddin *et al.* 2011 [66]	African oil palm	Nitrogen, phosphorous, potassium, boron, magnesium, manganese, and zinc	30 samples of each deficiency	—
Macedo-Cruz *et al.* 2011 [13]	Oat crops	Frost Damage	2000	91%
Xu *et al.* 2011 [24]	Tomato	Potassium deficiency	240	82.5%
Rangel *et al.* 2016 [65]	Grapevine	Potassium Deficiency	50	—
Wang *et al.* 2017 [68]	Wheat	Nitrogen concentration	339	0.73, 0.82, and 0.75(R^2)

R, Coefficient of correlation; **R**2, Coefficient of determination.

3.2.3 Machine learning methods: Researchers have recently given significant attention to deep learning techniques for the detection of diseases. Following paragraphs present some of the recent studies based on deep learning techniques in plant disease detection and prediction.

DeChant *et al.* [79] devised a convolution neural networks (CNNs) based approach to identify and detect the northern leaf blight (NLB) disease in maize plants using field-based imaging devices. The advantages of the proposed technique are given below:

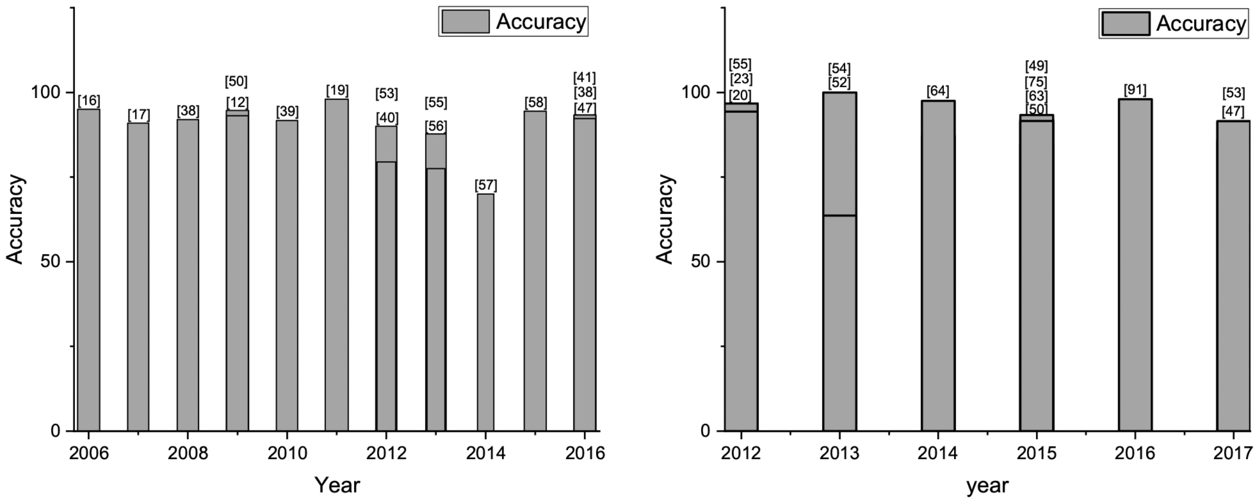
• By using CNN, data limitation and a large amount of noise in the plants grown in the field were handled efficiently.
• To detect the NLB lesions in a cropped image, various CNNs were trained to classify small regions and then a heat map was created which was further fed into a final CNN which in turn detected and classified the diseased image.
• An accuracy of 96.7% was achieved on several test set images which were not used in training.

Future scope: This approach is scalable and can be further used in other plants which exhibit visible symptoms and are rated or recognised by human experts as well. Further work can be carried out for improvement of replicability and accuracy of the quantification of the diseases.

Amara *et al.* [80] have proposed an automated method for detection of diseases in banana leaves using deep learning technique. Image data set is classified using the LeNet architecture as a CNN. Results obtained are very promising in the real working conditions in which there were many varying conditions such as illumination, complex background, mixed resolution, size, pose, and orientation of images as expected in actual field conditions. The feature extraction model is the part where the network learns to detect different high-level features from the input images, and this suited well for black Sigatoka, banana speckle diseases.

Future scope: Expansion of the current model for the detection of other diseases in various plants can be tried. Severity or the extent of the disease using an automated system may be explored, which may give further assistance to people handling the disease.

Sladojevic *et al.* [81] developed a novel way for training and devised a new methodology which makes the whole system easy to implement in the real-world scenarios. The methodology developed is tested on 13 different plant diseases; it can identify the non-diseased leaves as well as isolate the leaves from the background. As per the authors claim, the methodology proposed is unique and a novel one in the current scenario. The paper details various steps to implement the proposed method for the recognition of the diseases; the databases created by them is thoroughly examined by the agricultural experts. Caffe, a deep learning framework developed by Berkley Vision and Learning Centre, was used to perform the deep CNN training. They worked on pear, cherry, and peach crops mainly detecting porosity and powdery mildew disease. In Fig. 3 the authors present the accuracy of each of the classes of plant diseases. The classes are healthy leaf of pear, cherry, peach affected by porosity, of peach affected by powdery



a *b*

Fig. 2 *Accuracy of spot and mildew diseases within span of years*
(a) Accuracy for the detection of Spot diseases(leaf) within span of years, ***(b)*** Accuracy for the detection of Mildew disease (powdery, downy) within span of years

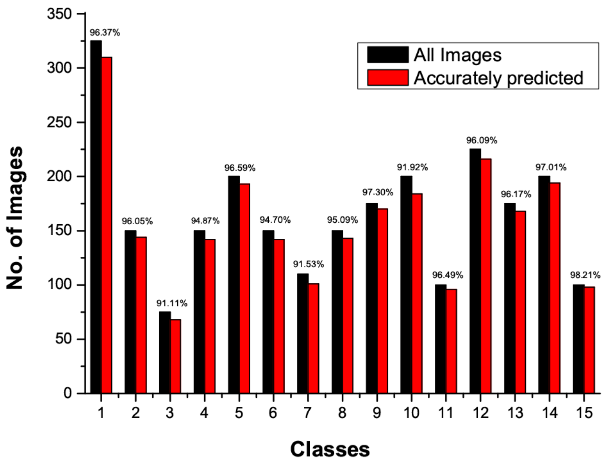


Fig. 3 *Prediction accuracy for each class separately [81]*

Table 6 Summary of work for the detection of damages due to insects

Paper name & Year	Plant	Disease	Dataset	Accuracy
Boissard *et al.* 2008 [69]	Rose	Whitefly	180	False positive rate(11%) and False negative rate(2.7%)
Husin *et al.* 2012 [73]	Chilli plant	living (biotic) and non-living (a biotic) agents	107	—
Barbedo 2013 [70]	Soybean	Whiteflies	475	87%
Gharge and Singh 2016 [74]	Soyabean	Frogeye, Downy mildew and Bacterial Pustule disease	30	93.3%
Momin *et al.* 2017 [71]	Soyabean	Defected beans, split beans and pods/stems	100	98%
Maharlooei *et al.* 2017 [72]	Soyabean	Aphids	96	0.96(R^2)

mildew, of peach affected by Taphrina deformans etc. Around 30,880 images were collected from various internet sources and out of which 4483 were original images and out of them 2589 images were used for validation. As we can see from the Fig. 3, classes with more number of images used for training dataset had slightly better accuracy. Peach leaves affected by powdery mildew disease class achieved the least accuracy of 91.1% and pear affected by gymnosporangium sabinae class achieved an accuracy of 97.3%.

The experimental results on the developed model achieved precision between 91 and 98%, for separate class tests, and an average of 96.3%.

Future scope: The proposed method can be improved by collecting a larger number of images to create much more diverse database. The inclusion of wide-angled images captured by drones covering a more extensive field area will make the database more robust. Combination of advanced and more powerful CNNs techniques along with object detection methods can further improve the accuracy and the confidence in the approach.

Mohanty *et al.* [82] developed a technique to classify healthy and diseased plant leaves by training two CNN architectures, namely AlexNet [83] and GoogLeNet [84] on publicaly available plant village dataset of 54,306 images containing various plant species ([82]). They used three versions of this dataset, i.e. colour, greyscale and leaf-segmented, out of which the colour version performed the best. In this process, they trained their respective CNNs to identify 14 different crop species and 26 diseases and found the best accuracy of around 98%; however, the accuracy was reduced to around 31% when the training was performed under different condition. Interestingly accuracy around 31% is far better than that (2.6%) obtained with the method based on random selection. This approach is good enough to predict diseases of various crops; however, the classification is limited to front-facing leaves in the noise-free and uniform background. Accuracy is more than 90% only when the testing and training are performed under similar conditions.

Future scope: Dataset can be enhanced with leaf samples under more diverse conditions. Furthermore, the approach should be able to classify the leaf samples in the real world scenario as well.

In some plants, the symptoms are not manifested predominantly and are not clearly visible, particularly in citrus plants, hence expert opinion is needed. If the plant is of sizeable commercial value, then the economic loss is enormous for the farmers. Keeping this aspect into consideration, Ali *et al.* [85] have attempted to solve this problem by applying DE (colour difference) algorithm. (Garcia-Ruiz *et al.* [86]) isolated the disease affected area and then identified the diseases through the hybrid feature set containing RGB, HSV, and LBPs (Local binary patterns) descriptors. RGB histograms and HSV as features give the rotation and illumination invariance. They classified various kinnow diseases such as citrus canker, gummosis, citrus greening, anthracnose and downy with much better accuracy.

Similarly, Ali *et al.* [85] have successfully applied their method to an economically significant plant 'Kinnow mandarin' which comprises 80% of citrus industry of Pakistan and successfully achieved overall 99.9% accuracy of disease detection with similar sensitivity. It is of much interest here to mention that the experiment was performed with the combination of colour and texture fixtures and similar results were achieved, as compared to individual channels. Further, for the reduction of feature set dimension, the principal component analysis (PCA) was performed. By using the state-of-art classifiers such as k-nearest neighbours (KNN), cubic SVM, boosted and bagged tree classifier, the reduced features were tested.

Ali *et al.* also found out that for the binary classification, HSV and LBP histogram features performed better when classified using bagged tree method. Also for classification of various diseases, features based on colour performed better. They successfully applied the developed method with reasonable accuracy on citrus plant having little variations in symptoms of diseases. It has the potential of application to other citrus plants species with different diseases along with the collaboration of the domain experts.

Future scope: The technique has the potential of application to other citrus plants species with different diseases with collaboration from domain experts. For further improvement in results, more training is needed along with the publically available datasets, comprising of diverse images with more variations of external factors. A portable platform-based solution can be developed to increase the portability and robustness of the proposed system.

3.2.4 Statistical inference method: Sannakki *et al.* [25] proposed an automatic infected region identification technique based on k-means clustering, by clustering the infected and healthy pixels. Siricharoen *et al.* [87] identified diseases by combining various features but did not emphasise on early symptom generations. Johannes *et al.* [88] developed a technique for automated diagnosis system for the detection of rust, septoria, and tan spots in wheat crop using a mobile device. The proposed technique involves a novel image processing algorithm based on candidate hot-spot detection in combination with statistical inference. The images were captured using seven mobile devices and resulted into more than 3500 images in two pilot sites located in Spain and Germany from 2014 to 2016.

Future scope: The method can be enhanced incorporating more steps to focus on measuring how this early-stage detection can help the user to react in time and plan for some preventive activities, e.g. crop protection application system.

3.2.5 Fusion method: Zhang *et al.* [40] developed a fusion method by combining superpixels, expectation maximisation (EM) algorithm, and logarithmic frequency pyramid of histograms of orientation gradients (PHOG), to recognise cucumber diseases. They first concentrated on some significant diseases of cucumber, e.g. scab angular, powdery mildew, downy mildew, anthracnose and scab diseases. In the proposed technique, they divided the diseased leaf into smaller regions using the superpixel operation. In the next step, they were able to identify the infected area of the diseased leaf at an accelerated speed as the superpixel operation increased the convergence rate of the EM algorithm. The authors identified the infected region of the leaf to obtain the logarithmic frequency PHOG features. Diseases were classified and identified using the SVM. They tested their algorithm on the database consisting of the diseased leaf images of the cucumber, and after experiments and some validation, the algorithm performed quite efficiently in identifying the cucumber diseases in practical and robust scenarios.

Future scope: Collection of Spatio-temporal, multi-channel and feature-rich images of the diseased leaves have become effortless due to the increase in the availability of cameras and the broad implementation of the internet of things framework in agriculture. Devices based on Internet of Things and framework can be incorporated to develop an efficient automatic crop disease recognition system.

3.2.6 Local descriptor method: Pires *et al.* [89] have proposed a novel approach for soybean disease recognition based on local descriptors and bag-of-visual-words technique. They experimented with five local descriptors (SURF, HOG, DSIFT, SIFT, and PHOW) applied over a broad set of digital images (greyscale and colour) acquired from a real-world soybean plantation in Brazil. The proposed approach is applied to scanned images (visible to the human eye), which does not require hyperspectral images and, therefore, can be used with commodity hardware such as smartphones. From the extracted features, they calculated a summary (lower-dimensional) feature vector using the technique Bag of Visual Words (BOVW). They tested their approach on a dataset consisting of 1200 scanned soybean leaves consisting of healthy samples, and samples with evidence of three diseases commonly observed in soybean crops namely, Mildew, Rust Tan, and Rust RB. The experimental results demonstrated better accuracy of the proposed approach and suggested that it can be easily applied to other kinds of crops.

Future scope: In future, the evaluation of the steps of BOVW can be done, such as the implementation of vocabulary construction and feature coding. Investigating diseases in their early stages and measuring their severity is also a potential future work.

3.2.7 Shape identification method: Momin *et al.* [71] developed a technique to detect deformity and anomaly in soyabean plant during its harvesting; the developed technique focuses on the detection of the materials-other-than-grain (MOGs). Several forms of the MOG such as infected beans, defected beans, split beans, and pods/stems, were detected by the algorithm. They tested the algorithm on front and backlit images acquired during the data-gathering phase. The image background was segmented and the dockage fractions were detected with the help of median blurring, morphological operators, watershed transformations and component labelling based on the projected area and circularity. The developed algorithm has been successfully applied and found to be reasonably satisfactory as dockage fractions were identified with an accuracy of 96% for spilt beans, 75% for contaminated beans and 98% for both defected beans and stem/pods. They mainly divided their algorithm for two different image types, one for front-lit and the other for back-lit leaf images.

Future scope: The method can be extended to integrate the proof of concept with a harvester. Computer vision feedback mechanism can be evolved for the operation of the gate to control the grain flow density.

3.2.8 Neural network: Shao *et al.* [46] proposed a technique to identify and detect various tobacco diseases; their methodology comprises of three stages, firstly, Otsu method was used to obtain disease location information, and the GrabCut function was initialised for extracting diseased area efficiently. Further, colour moments, disease contour and grey-level co-occurrence matrix (GLCM) were used to get colour, multi-contour and texture features. The back-propagation (BP) neural network was optimised by the genetic algorithm. The optimal initial weights and thresholds were then obtained, which shortened the training time and improved the accuracy of disease identification. Finally, BP neural network model-based tobacco diseases diagnosis system was established with the mobile client as input and the user services as output. The field experiments showed that the method could diagnose eight types of tobacco diseases effectively and automatically. Better disease recognition results in correspondence with different features sets, namely, (i) colour, contour feature, (ii) colour, contour, texture feature, and (iii) colour, multi-contour, texture feature were obtained. The average recognition accuracy rate of selected tobacco diseases was about 92.5%.

Future scope: Results can be further improved through the inclusion of multiple new features such as those related to colour, multi-layer contour and texture.

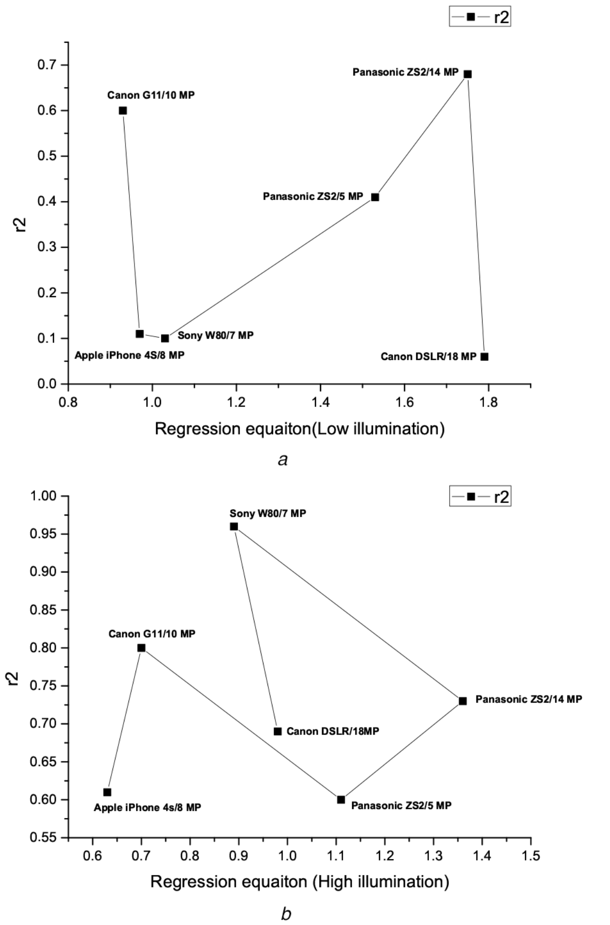


Fig. 4 *Regression equations and coefficient of determination r^2 for digital counting versus manual counting in different illumination conditions*
(a) Low Illumination, ***(b)*** High Illumination

3.3 Quantification

The methods categorised in this section check for the quantification of the disease severity. In quantification, the severity can be identified by two primary methods, one by calculating the total diseased area of the leaf, stem, bark, fruit etc. and the other method deals with how much the disease has penetrated the crop/plant. For this, feature analysis is done for colour and texture. Significant steps of the algorithms are the isolation of the symptoms using image segmentation which makes it more accessible for feature extraction and then a proper feature analysis for calculating the disease severity. They usually measure the performance and accuracy of the proposed algorithms according to the manual raters verdict and decisions, but the manual measurements always have a sense of imperfection and unreliability. Thus, we cannot rely entirely on these verdicts and should always keep this in mind while doing a performance measure. In determining the amount of severity or quantification of the disease, just on observation followed by analysis, is surely a challenging exercise even for the people who do it manually. Raters who are highly experienced in identification and determination of the diseases-based symptoms also face challenges and difficulties [5] in identifying and quantifying the diseases with required accuracy and are prone to errors such as:

• overestimation of observed diseases;
• proper estimation of disease severity;
• which part of the plant the disease has effected and also on the size of the plant;
• colour blindness in some manual raters;
• effect of mixed factors which may cause diseases and other abnormalities in plants.

3.3.1 Digital counting: Maharlooei *et al.* [72] developed a technique to quantify the extent of severity caused by an insect pest known as soybean aphid in soybean plants by counting the aphids present on the leaf. Four soybean varieties such as Sheyenne, Trail, Ashtabula, and Prosoy were used for experimentation for making the dataset more robust and diverse. Image data collection was done using mixed resolutions and illumination conditions to replicate external environmental factors.

The image processing steps include identification of the area of interest (AOI), segmentation, colour space transformation, image contrast adjustment, aphid identification and aphid counting, respectively. The image processing steps performed are (i) identification of AOI and is done by cropping the image manually; this helped in reducing time during the processing stage, (ii) segmentation of leaf image, performed by excess green method (Meyer *et al.* [90], Lamm *et al.* [91]), and (iii) segmentation process, performed on the HSI image to isolate the objects of interest from the leaf background image. The image was then converted to the one in HSI colour space and enhanced for proper segmentation of objects of interest by separating leaf as background. Selection criteria were decided by measuring the shape and area of three random aphid samples. The difference between counting methods under varying illumination conditions were analysed using mixed linear models.

There is a significant difference in the manual count and digital count under low-light illumination. Fig. 4 shows the correlation between manual and digital counting methods under high (Fig. 4*b*) and low (Fig. 4*a*) illumination conditions using different cameras. Regression coefficient varied according to the ISO sensitivity of the cameras, and during the study, the authors found out that the Sony cameras exhibited very high correlation between manual and digital counting methods with $r^2 = 0.96$ under high illumination conditions. The misclassification percentage was low for most cameras with different resolutions under high illumination conditions. One of the key findings of the work concluded that most cameras performed satisfactorily better even when the resolution was changing under bright light conditions.

Future scope: Overall, aphids along with brown spots and other noise can be removed with a more robust algorithm, and other environmental factors should be taken into account. The stronger robust segmentation process can be deployed to improve the segmentation time.

3.3.2 Quantitative phenotyping: Divilov *et al.* [92] proposed a novel computational pipeline method to estimate the extent of severity by calculating the percentage area of grapevine leaf infected by the downy mildew sporulation. The pipeline method was applied on leaf images belonging to two different grapevine families, namely, (i) glabrous leaf (V. rupestris B38 x ‘Horizon’ [RH]), and (ii) trichomes-leaf (‘Horizon’ x V. cinerea B9 [HC]). Results obtained from the comparison between computer vision and manual inspection are found very encouraging in leaves belonging to RH and HC families, respectively. This method is very suitable to employ computer vision system before the sporulation stage of the plant to measure the leaf trichome area. Use of computer vision technique by a manual rater improves the accuracy with reduced time, and thus the phenotyping method can be enhanced to get better observation and evaluation of downy mildew disease resistance and also the leaf trichome density. The proposed method improves the accuracy even though slow in comparison with other similar machine vision-based techniques used for detection of plant diseases as it needs to use pipette inoculum separately on each leaf disc.

Future scope: The method can be scaled further to other plant species and diseases with images having a clear distinction in foreground and background.

3.3.3 Multiple kernel support vector regression: Wang *et al.* [68] tested and applied the Multiple-Kernel Support Vector Regression (MKSVR) algorithm for the estimation of leaf nitrogen concentration (LNC) level in wheat crop. Wang *et al.* [68] tested the MKSVR algorithm on remote sensing LNC data over the span of four years at different sites in Jiangsu province of China. The environmental disaster and environmental monitoring satellite system data collected by them were provided by Hongjian(HJ), data was provided in four different spectral bands. Preprocessing of all the data was done using a remote sensing image processing software known as ENVI4.7. HJ-CCD bands were used for the creation of vegetation indices.

Based on the training dataset, five methods for each stage were used in software to respectively establish a multiple linear regression (MLR) model, a partial least squares (PLS) model, an artificial neural network (ANN) model, a single kernel support vector regression(SK-SVR) model, and an MKSVR model. In each model, the vegetation indices were considered to be independent variables and LNC was the dependent variable.

They checked five different statistical techniques such as MLR, PLS, ANN, SK-SVR and MK-SVVR on the dataset. There is an imbalance in generalisation and learning ability due to the selection of the kernel, i.e. global or local in SVR. So multiple kernels SVR has the linear combination of the local and global kernels. Local kernel (RBF kernel), global kernel (polynomial kernel) and linearly combined multiple-kernel function which is the linear combination of both kernel functions are shown in (1)–(3).

Wang *et al.* [68] achieved better performance with MK-SVR than obtained with the other four models. LNC regression values were 0.73, 0.82, and 0.75 for the three stages, and the corresponding root-mean-square error (RMSE) values were 0.13, 0.21, and 0.20, and the relative RMSE values were 6.6, 7.7, and 6.5%

Future scope: Further calibration-validation procedures are needed for other wheat cultivars to test MK-SVR models. Additionally, other machine learning algorithms such as XY-fusion network, Random Forest, Boosting or Bagging can also be tested for obtaining better results for the prediction of crop parameters.

$$K(x, x')_{\mathrm{rbf}} = \exp(-\ \| x - x' \|^2 / \sigma^2) \tag{1}$$

$$K(x, x')_{\mathrm{poly}} = [(x \,.\, x') + 1)]^d \tag{2}$$

$$K(x, x')_{\mathrm{mix}} = \lambda \,.\, K(x, x')_{\mathrm{rbf}} + (1 - \lambda) \,.\, K(x, x')_{\mathrm{poly}} \tag{3}$$

where λ is the weight coefficient, x and x', are the feature vectors, σ is a free parameter, d is kernel parameter and K is kernel function as explained in [68].

3.3.4 Macro-based method: Laflamme *et al.* [93] developed a semi-automated method to quantify the extent of severity of chlorosis in a weed plant, Arabidopsis thaliana or the thale cress caused due to plant-pathogen, i.e. Pseudomonas syringae pv. tomato DC3000 and P. syringae pv. maculicola M6DE. PIDIQ applies an ImageJ-based macro to plant photos in order to distinguish healthy tissue from tissue that has yellowed due to disease. Laflamme *et al.* [93] made a macro to run on ImageJ(image processing program) which automated the process of cropping individual plants from the experimental testbed containing the set of plants arranged in a line. Their work required to save the details of chroma and pixels, so they saved the image in TIFF image file format. Green and yellow wavelengths were masked using empirically selected max and min values of hue and brightness. The ratio of the chlorotic and healthy leaves of plants was calculated and raw proportional values were arcsine-transformed and normalised for the removal of distribution bias.

3.4 Classification

Classification of diseases is a crucial aspect in plant leaf disease allowing one to categorise them through image processing techniques. The categorisation of diseases, according to pathogen groups, is a significant research domain and potentially a challenging area of work. Various classification techniques for single as well as multiple diseases are summarised in the following section. In classification, the primary focus is on the categorisation of various diseases and then the classification according to various pathogen groups.

Zhang *et al.* [41] have proposed a technique to identify and classify diseases in leaves of cucumber; they used sparse representation (SR) classification for the identification of the diseases. In their algorithm, Zhang *et al.* [41] there are mainly three stages, firstly K-means clustering was used for the segmentation of the diseased leaf. Zhang *et al.* [41] used JPEG images, converted images in L^*a^*b colour space, classified colours using a^*b^* values of the pixel and clustered by K-means clustering using Euclidean distance; then pixels are labelled corresponding to the cluster index acquired by k-means whereas the leaf is segmented according to colour. The lesion image is then selected from the cluster of images. Lesion cluster among the other four clusters is selected by mean values a^*b^* values of the cluster. After the experimentation values of the a^* b^* were determined, SR is followed as described in Bellavia [94]. The proposed SR-based disease recognition method is based on dataset creation with lesion selection from diseased images using the K-means algorithm. Colour features are extracted then compiled and normalised.

Shape features and colour features are joined together in a vector, features vectors are randomly selected from each class and then optimised to meet the termination condition, i.e. the ratio between two smallest residuals, for each class. SR-based classification happens according to the pre-defined decision rule.

Zhang *et al.* [41] worked on seven common diseases found in cucumber such as downy mildew, bacterial angular, corynespora cassiicola, scab, grey mould, anthracnose, powdery mildew. They were able to reduce the computational cost because they performed classification in the SR space. Zhang *et al.* [41] were able to achieve 85.7% overall accuracy in detection and classification of mentioned cucumber diseases. Hassanien *et al.* [50] classified two different aspects in their paper, firstly whether the tomato leaf is infected or not and then identify the disease infecting the plant. For this classification, they used SVM, and the specified feature vectors were used as the input. Two different tomato diseases were classified namely powdery mildew and the early blight, and for both the stages, SVM was used. Since the authors were dealing with a small dataset, k-cross-validation [95] is used to determine the performance of the predictive model and to check the classification results.

Barbedo *et al.* [96] proposed a disease classification algorithm which is quite practical to implement and tested on a wide range of diseased images. They classified 82 disorders caused by biotic as well as abiotic stress on 12 different plant/crop species such as common bean, cassava, citrus, coconut tree, coffee, corn, cotton, grapevines, passion fruit, soybean, sugarcane and wheat. They mixed their dataset with the real world as well as controlled environment images so as to make the algorithm more robust and achieved some impressive results.

Guided active contour method was used for isolation of the leaf from the background. Symptoms were segmented from the infected images, and then colour transformations were applied. They identified colour space channels such as H, S, V, l, a, b etc. which had their own correlations with the identified segmented symptoms. They then divided their algorithm into training for new disease classification and actual identification of disease. For classification they used pairwise classification [97]. They achieved an overall accuracy of 58% in identifying the disease, which is better than Camargo and Smith [12](53%) and Phadikar *et al.* [35] (53%) achieved.

4 Future prospects

Disease detection, quantification, classification and prediction are such challenging domains as they contain many varying parameters. Due to its vast, unpredictable nature inclusion of the latest machine learning and big data techniques will be a major improvement and an obvious evolution. Wolfert *et al.* [98] discussed the implementation of big data in farming practices which further improves the predictiveness of external environmental factors in farming and many others. There are many challenges still in the field of plant disease diagnosis using image processing and computer vision. In the recent review papers, we found out there are many potentials areas such as work on 3D images are still not so prevalent. Talking about deep learning, the predictive and probabilistic model generation from the already existing data is one of the significant advantages of it, and hence it is quite efficient regarding plant growth and disease prediction, identification, classification and quantification.

There are some publically available leaf datasets and disease libraries such as, PLANTIX, an AI-based mobile crop advisor application for the help of farmers and common people working in farming, which hosts a plant disease library which gives a proper visualisation and summary of many plant diseases [99], leaf snap dataset containing 23,147 images with 7719 images from the field itself [100], leaf classification dataset containing 1584 images from 99 different plant species [101], plant leaf dataset hosting website, supporting 22 different leaf datasets [102], plant village dataset containing approximately 50,000 images of healthy and infected plants [82]. Still, there is a need for ground truth backed public datasets for proper verification and validation of results obtained by the corresponding image processing techniques. Proper protocols are also needed for the formal (under lab conditions) and informal (field conditions) acquisition techniques. Lack of ground truth makes the verification quite hard and inaccurate, so the inclusion of agriculture experts and standardisation of plant disease symptoms for region-specific domains can be potential future work in this area. There is still a lack of proper public datasets in many crops, so the formation of datasets for crops is a possible future work; some of the technical points which can be covered in future aspects of various sub-domains for proper crop parameter prediction are machine learning algorithms such as XY-fusion network, random forest, boosting or bagging. Furthermore, multiple kernel support vector regression and fusion of various techniques, such as superpixel along with PHOG, can be explored. Better optimisation and segmentation techniques with newer evolutionary methods can be examined. Use of portable development boards such as Raspberry Pi, BeagleBone, Intel Galileo are still not so prevalent which can help in portability, cost-effectiveness and robustness of the system. The inclusion of IoT related framework will also boast the work and enhance the performance results.

Table 7 Further summarisation of latest techniques according to some more parameters

Paper name	Features extracted	ROI/AOI Techniques
Bai *et al.* [44]	Top projected canopy area (TPCA) as a morphological feature; RGB) and HSL values as colour features; and entropy, energy, contrast, and homogeneity as textural features	Marked-watershed algorithm
Hassanien *et al.* [50]	Gabor transform for textural pattern of diseased tomato leaves(402 features)	Gaussian mixture-based background/ foreground segmentation
Amara *et al.* [80]	Feature maps which lead to task specific powerful feature extractors	Not applicable
Ali *et al.* [85]	RGB histogram features, HSV histogram features and LBP as the textural descriptors	Delta E (DE), a colour difference-based algorithm for segmentation
Johannes *et al.* [88]	mean variance of a Gaussian weighting function, mean variance of the magnitude of the LBPs, flatness of the superpixel, maximum of the average of the b colour channel and average of the inverted a colour channel or intra-superpixel perceptual colour variance	Simple Linear Iterative Clustering (SLIC) [104], superpixel extraction algorithm
Zhang *et al.* [40]	logarithmic frequency pyramid of histograms of orientation gradients (PHOG) features	Fusion of superpixel clustering and expectation maximisation (EM) algorithm
Momin *et al.* [71]	HSI colour features	Morphological operations, boundary tracing, debridging, image subtraction
Shao *et al.* [46]	Colour moments, disease contour and GLCM were used to get texture features	GrabCut algorithm and Gaussian mixture model was used to describe the probability distribution of image pixels in foreground and background
Zhang *et al.* [41]	Shape and colour features	K-means-based segmentation followed by neural-network-based classification (KMSNN)

5 Conclusion

There have been significant advancements in the field of plant disease detection, quantification and classification though image processing techniques, the inclusion of recent work in alignment with the categories as mentioned above made the review more up-to-date and complete. This gives the future and current researchers a new and updated perspective on the work. There needs to be proper hand in hand collaboration between conventional farming techniques and technology to help the farmers and hence solve this never-ending problem. There are some farming practices in the picture, which gives a huge potential for future endeavours such as zero-budget farming [103]. With the use of open-source software development in the field of computer vision and machine learning along with the conventional and newly evolved farming practice, we may achieve fruitful results for the betterment of the society. Free distribution and sharing of the data will also benefit and facilitate the research work in this domain. The work covered in this paper is summarised in the form of tables according to well-thought parameters. Such as Table 7 shows the extracted features and techniques for identification of the area of interest/region of interest in some of the recent work and Table 8 summarises the work covered in this paper according to parameters such as disease type, pathogen type, culture, technique, colour space, and dataset.

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Table 8 Latest review of identification, detection and classification of techniques for plant diseases and its monitoring

Paper Name	Disease	Pathogen	Culture	Technique	Colour Space	Dataset
Bai *et al.* [44]	Leaf spot	Bacteria	Cucumber	Fuzzy logic	HSI	129 images
Zhnag *et al.* [41]	Downy mildew, bacterial angular scab, greymould, anththracnose and powdery mildew	Bacteria and fungus	Cucumber	Sparse representation	*L*a*b**	420 (60 images from each of the seven kinds of disease leaves)
Zhang *et al.* [40]	Scab angular, powdery mildew, downy mildew, anthrancnose and scab diseases	Bacteria and fungus	Cucumber	Fusion of super pixel expectation maximisation and PHOG descriptors	*L*a*b**	300 diseased leaf images with 60 images per class
Hassanein *et al.* [50]	Powdery mildew and early blight	Fungus	Tomato	Moth flame optimisation	HSV	UCI data repository
Laflamme *et al.* [93]	Pathogeneis associated	—	Tomato	Colour analysis	RGB	Not mentioned
Dechant *et al.* [79]	Northern leaf blight	Fungus	Maize	Deep learning	RGB	1834 images
Amara *et al.* [80]	Banana leaf speckle	Fungus	Banana	Deep learning	RGB and greyscale	3700 images from Plant village dataset [105]
Sladojevic *et al.* [81]	Porosity, powdery mildew	Fungus	Pear, cherry and peach	Deep learning	RGB	30,880 images for training and 2589 original images
Ali *et al.* [85]	Greening, downy mildew and anthrancnose	Fungus	Kinnow mandarin	Colour histogram and textural descriptors	*L*a*b**	199 images (99 are disease infected and 100 healthy)
Pires *et al.* [89]	Mildew, rust, tan and rust R8	Fungus	Soyabean	Local descriptors	RGB (1200 dpi resolution tiff format scanned images)	1200 scanned soybean leaves (divided into four classes, three of them attacked by fungi and one without diseases)
Momin *et al.* [71]	Defected beans, split beans and pods/stems	Infestation	Soyabean	MOGs (Material other than grains)	HSI	50 front and 50 black lit images
Mahrloei *et al.* [72]	Soyabean aphids	Infestation	Soyabean	Object counting	HSI	96 images
Shao *et al.* [46]	Wildfire, weather fleck and brown spot	Bacteria and fungus	Tobacco	Neural network	HSV	40 of Brown spot disease, 30 of angular leaf spot, 50 of wildfire, 40 for CMV, 50 for weather fleck, 38 for anthracnose, 45 for TMV and 31 for powdery mildew,
Divilow *et al.* [92]	Downy mildew	Fungus	Grapevine	Estimating the infected area	CIELAB	72 images
Johannes *et al.* [88]	Rust, septoria and tan spots	Fungus	Wheat	Candidate hot spot detection	RGB	3637 images (987 rust, 2505 containing septoria, 657 containing tan spot)
Wang *et al.* [68]	Leaf nitrogen concentration	—	Wheat	Multiple kernel SVM	Four spectral bands containing with a 30-m resolution	339 samples

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