Smart Agricultural Technology 8 (2024) 100480

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Feature engineering to identify plant diseases using image processing and artificial intelligence: A comprehensive review

Seyed Mohamad Javidan [a], Ahmad Banakar [a,*], Kamran Rahnama [b], Keyvan Asefpour Vakilian [c], Yiannis Ampatzidis [d]

[a] Department of Biosystems Engineering, Tarbiat Modares University, Tehran, Iran
[b] Department of Plant Protection, Faculty of Plant Production, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran
[c] Department of Biosystems Engineering, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran
[d] Agricultural and Biological Engineering Department, Southwest Florida Research and Education Center, University of Florida, 2685 FL-29, Immokalee, FL 34142, USA

ARTICLE INFO

Keywords:
Textural features
Feature extraction
Machine learning
Symptoms

ABSTRACT

Plant diseases can significantly reduce crop yield and product quality. Visual inspections of plants by human observers for disease identification are time-consuming, costly, and prone to error. Advances in artificial intelligence (AI) have created opportunities for the rapid diagnosis and non-destructive classification of plant pathogens. Several machine vision techniques have been developed to identify and classify plant diseases automatically based on the morphology of specific symptoms. The use of deep learning models has achieved acceptable disease classification results, but they require large datasets for training, which can be labor-intensive, time-consuming, and computationally costly This problem can be solved, to a point, by using data augmentation techniques and generative AI in order to increase the size of the datasets. Furthermore, a combination of deep feature extraction and classification by machine learning was used for accurate disease detection and classification. In some cases, traditional base classifiers trained with small datasets including basic shape, color, and texture features can be feasible for the efficient identification of plant diseases. The performance of such classifiers depends primarily on the features extracted from images; therefore, feature extraction plays a vital role in identifying diseases. Feature engineering, a process to identify the most relevant variables from raw data in order to develop an efficient predictive model, is explored in this paper.

1. Introduction

Plants display physical changes as a response to pathogens, which are known as "symptoms" of diseases. Most plant diseases appear with their characteristic symptoms, which are clearly manifested in the host's body. A plant disease symptom can be defined as a visible abnormality including changes in shape, color, and texture on a plant or internal symptoms that later become visible. Most of the symptoms of plant diseases are visible and are caused by biological or non-biological factors [1]. The symptoms that occur in the plant are usually the result of morphological and physiological changes or damage to the plant tissue and then the cell due to interference in the plant's metabolism [2]. All the basic structures of vascular plants are exposed to the attack of pathogenic agents. Typically, the appearance of a viable symptom indicates a relatively late stage of infection and/or colonization of a pathogen. Disease symptoms can be caused by living and non-living factors alone or in combination [3].

The presence of diseases and the symptoms they cause can take some time to develop, but luckily, there is a window of opportunity for early disease detection and control. Symptoms that humans can see with the naked eye are often morphological or physiological changes in the tissues or organs of the plant. The primary origin of a plant disorder is typically cellular, and a wide range of factors can contribute to plant dysfunction, including pathogens, insects, parasitic plants, toxins, environmental stress, and human activities. Effective and timely management of diseases requires awareness of the presence and spread of insects, as well as recognition of visual symptoms of disease. Early diagnosis and intervention are crucial to preventing disease spread and reducing plant and crop damage [4,5].

Although multiple factors can generate similar symptoms, an efficient diagnostic technique must be able to identify correctly the primary cause [6]. Correctly identifying the main cause of symptoms is crucial

* Corresponding author.
E-mail address: ah_banakar@modares.ac.ir (A. Banakar).

https://doi.org/10.1016/j.atech.2024.100480
Received 6 April 2024; Received in revised form 26 May 2024; Accepted 27 May 2024
Available online 28 May 2024

for linking them to the responsible agent and determining the affected plant [7]. Symptoms affect the performance of the plant, and several plant functions can be undesirably impacted by either biotic or abiotic factors and cause visible symptoms. Understanding these functions is essential for accurate diagnoses of plant disorders [8,9].

Plant disease symptoms could be changes in the color, shape, or function of various parts. For instance, leaf wilting is a sign of *Verticillium* wilt, a fungal disease. Browning and necrotic lesions on bean leaves are another example of a symptom of bacterial blight. A disease in a plant is not the pathogen itself but the effect of the organism on the plant, i.e. a symptom [3]. Table 1 provides examples of symptoms of various diseases and their pathogenic groups.

Symptoms of the diseases are evident in different parts of the plant; however, the leaves of the plant as the most important parts of the photosynthesis mechanism are usually used to diagnose the disease [11]. There have been significant advances in computer vision that enable intelligent detection and classification of plant diseases. These advances can improve the accuracy and efficiency of disease identification, allowing for better management of plant health. While human inspection remains a critical component of disease detection, computer vision technology offers additional tools for quick and accurate identification of plant diseases, which can lead to better outcomes for agriculture and the environment. In the automatic detection of plant diseases, a classifier that is trained using a labeled dataset detects diseases by extracting input features from plant images.

Accuracy is the main criterion that researchers use to calculate the performance of a classification model [12]. Feature extraction, which is an important step in automatic identification of plant diseases, can improve the accuracy of the classifier and lead to more accurate disease diagnosis [13]. Feature engineering is a process to identify and select the most relevant variables from raw data to develop a reliable predictive model. Fig. 1 shows the different steps of diagnosis and classification of plant leaf diseases. As the figure shows, feature extraction is an essential part of such diagnosis. This study aims to review the features that have been usually extracted from plant leaves in recent studies for plant disease diagnosis. Moreover, since an efficient disease segmentation in the images is required for reliable image feature extraction, available segmentation methods are also reviewed and discussed in this study.

2. Plant disease segmentation

Plant disease segmentation is a crucial task in plant disease detection and analysis. The goal is to automatically segment disease lesions from healthy tissues in an image that may contain both plant tissues and other unrelated objects. To achieve this goal, several segmentation techniques have been developed over time, including thresholding, region growing, watershed algorithm, edge-based segmentation, regional methods, and clustering techniques [14].

Thresholding is one of the most common and simple methods of image segmentation. This method relies on the brightness difference between the disease lesions and the healthy tissues. The brightness difference allows to differentiate the disease regions from the healthy regions by setting a threshold value [15]. The threshold value is determined by Otsu's method also called the global thresholding method, which calculates the threshold value that minimizes the intra-class variance. This method is simple and fast, but it may be sensitive to the noise in the image and can result in inaccurate segmentation [16].

Region growing is another technique that can be used for disease segmentation. The region-growing method works by starting with a seed pixel that contains a known disease region and then growing the region through consecutive pixels that have the highest probability of being a disease pixel. The region-growing process is performed iteratively until no more pixels of the same class can be added to the region [17].

The watershed algorithm is another popular segmentation technique that can be used for disease segmentation. It works by finding the contours between regions that are based on the gradient of the input image [18]. The input image is first converted into a topographic map, in which each pixel represents a surface with a certain height. The higher the pixel, the steeper the surface. The algorithm then finds the contours that divide the surface into catchment areas, which correspond to the diseased regions [19].

Edge-based segmentation is a technique that uses edge information, which is based on intensity changes between pixels, to define the boundaries of the disease regions. This technique can be useful in segmenting the disease regions from other objects in the image. One widely used edge-based segmentation technique is the Canny edge detection, which uses a combination of first and second-derivative filters to detect the edges in the image [20].

The regional methods, also known as region-merging algorithms, are a class of segmentation techniques that are used in image processing to extract object boundaries from images [21]. These algorithms are based on the assumption that the boundaries between different regions in an image are represented by an image gradient or edge map. One of the popular regional methods for image segmentation is the active contours model (ACM) or the snake model. The ACM is a region-merging algorithm that relies on the edges of the input image to automatically separate different regions. The algorithm works by minimizing an energy function that is based on the length of the contour and the image intensity [22]. The algorithm is iterative, and it starts with a random curve that traces the edges in the image. The curve is iteratively adapted to minimize the energy function, which results in the contour moving toward the disease regions [21,23]. Another popular regional method for image segmentation is the level set technique. It is a geometric approach used for finding the boundaries between two regions in an image. The level set is a parameterized curve that moves in space to minimize the boundary energy function. The algorithm is iterative, and it starts with a random curve that traces the edges in the image. The curve is iteratively adapted to minimize the energy function, which results in the curve moving toward the disease regions [24].

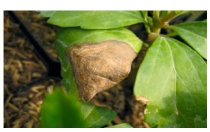
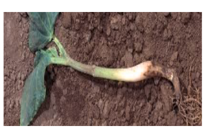
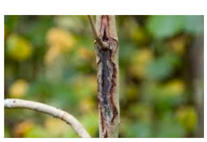
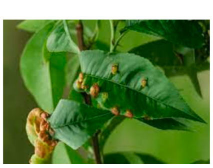
Clustering is a technique that groups data points based on their similar characteristics. It is a powerful tool for image segmentation and can be used to segment a large number of regions in an image. There are several clustering algorithms for image segmentation, such as *K*-means clustering, hierarchical clustering, and non-hierarchical clustering [25]. *K*-means clustering is the most commonly used technique for image segmentation. It works by iteratively dividing the input image into a set of *K* clusters, where *K* is a positive natural number. At each iteration, the algorithm assigns one point to the cluster and then adjusts the center of each cluster based on the assigned points. This process is repeated until either a user-specified number of iterations or a certain convergence criterion is achieved [26]. Table 2 compares the popular methods of segmenting plant disease areas.

While each segmentation method has its own merits in terms of speed and accuracy, it is important to consider the specific requirements available in each task [27]. Threshold-based, clustering-based, and regional methods are effective in specific scenarios when dealing with large amounts of data or more complex geometries, providing high accuracy with low computational cost [28]. On the other hand, region-growing and edge-based segmentation algorithms work well with images with noisy backgrounds or high contrast. Therefore, it's essential to select the appropriate method for each application to achieve acceptable results [29].

3. Feature extraction techniques

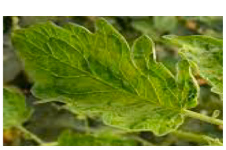
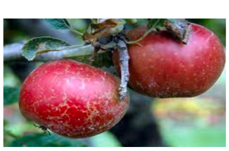
Feature extraction is an essential part of computer vision and machine learning and helps to identify and describe objects in images [30]. Disease symptoms in plant images are placed in their own group based on the extracted features including color, texture, and shape, which are used for model training [31]. Acquiring significant information from raw images is essential for machine learning models to detect diseases in plants. Feature extraction aims to produce meaningful information from

Table 1
Symptoms description of various plant diseases and their relation with pathogenic groups.

Symptom	Disease pictures [10]	Description	Plant pathogenic group					
			Fungi	Bacteria	Viruses	Nematodes	Phytoplasmas	Parasitic Plants
Blight		Rapid discoloration, wilting, and death of plant tissue	×	×				
Blotch		Blotch or large spot on leaves, shoots, or fruit	×	×				
Bronzing		Leaves or needles develop a bronze color	×			×		
Canker		Dead region on the bark of twigs, stems, or trunks, often discolored and either raised or sunken	×	×				
Chlorosis		An abnormal yellowing of plant parts	×	×	×	×		
Damping off		Decay of seeds in water logged soil or young seedlings shortly after emergence	×					
Decline		The gradual, often uniform, decline of plant health or death of plant tissue	×	×	×	×		×
Dieback		Progressive death of shoots, branches, or roots, generally starting at the tips	×	×	×	×		
Distortion		Irregular-shaped plant parts	×	×	×		×	
Flagging		Decline of a shoot or branch, while nearby branches remain healthy	×	×				
Gall		Abnormal, localized swelling on leaf, stem, or root tissue	×	×		×		

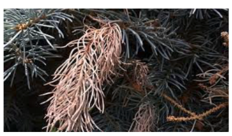
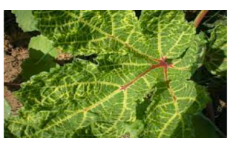
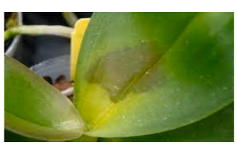
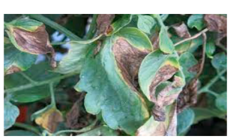
(*continued on next page*)

Table 1 (*continued*)

Symptom	Disease pictures [10]	Description	Plant pathogenic group					
			Fungi	Bacteria	Viruses	Nematodes	Phytoplasmas	Parasitic Plants
Gummosis		Production of a sticky gum that is exuded by the plant	×	×				
Leaf spot		Lesion on a leaf, may vary in color, shape and size	×	×	×			
Mosaic		Non-uniform foliage coloration, normally an intermingling of green color variations and yellowish patches			×			
Mummy		Hard, dried, diseased fruit	×					
Necrosis		Death of plant tissue	×	×				
Ring spot		A lesion with a dark outer ring and lighter center			×			
Rot		Decomposition and destruction of tissue	×	×				
Rugose		Wrinkled appearance to plant tissue	×		×			
Russet		Yellowish-brown or reddish-brown scar tissue on a fruit's surface	×					
Scab		Crust-like disease lesion	×	×				

(*continued on next page*)

Table 1 (*continued*)

Symptom	Disease pictures [10]	Description	Plant pathogenic group					
			Fungi	Bacteria	Viruses	Nematodes	Phytoplasmas	Parasitic Plants
Scorch		Browning and necrosis of leaf margins	×	×				
Shot-hole		Lesions where centers have fallen out	×	×				
Stunting		Reduced growth of a plant, where plant or plant parts are smaller than normal	×	×	×	×		
Tip blight		Death of tissue at the tip of a shoot	×	×				
Vein clearing		Leaf veins become yellow or clear			×			
Water Soaking		Wet, dark, or greasy lesions, usually sunken and/or translucent	×	×				
Wilt		Die back and drooping of necrosis leaves or other plant parts	×	×		×		
Witches' broom		Abnormal brush-like shoot development			×		×	×

the original data, avoid unnecessary redundant data, and focus on specific image properties [32]. Certain techniques utilize information on textures; others use shape, color, size, pattern, and edge to draw features. Selecting the suitable features for a particular application is critical in gaining desired results. Improper selection of features results in poor performance [33]. Extracting ideal features is fundamental and also challenging to develop an accurate disease diagnosis system [34].

Machine learning algorithms require a large number of features for accurate detection, but extracting reliable features in specific situations can be challenging [35]. Deep learning methods have improved this issue, but they still need big data, which is not available in most cases. Hence, selecting reliable features for effective detection of diseases is critical and challenging [36]. Furthermore, the performance of a feature on disease detection can be affected by various constraints or settings. For example, factors such as lighting and the distance of the camera from the plant leaves can make feature extraction not consistent and challenging [37]. Also, diseases may produce different symptoms in different plant growth stages. A particular feature may work well in one stage but not in another, which makes it challenging to select the right features for accurate disease diagnosis [29]. Hand-crafted feature selection requires a well-developed protocol of strategies to identify features for an optimal disease diagnosis system [38]. Table 3 shows the most common features used for plant disease detection along with their advantages and disadvantages.

Features including color, texture, and shape play a key role in detecting plant diseases based on their visual properties [12]. Selecting the proper set of features ensures that relevant information is extracted from the input images to perform the classification task. The feature extraction methods are generally classified into two kinds: hand-crafted and deep visual features. The term 'hand-crafted' refers to recognizing

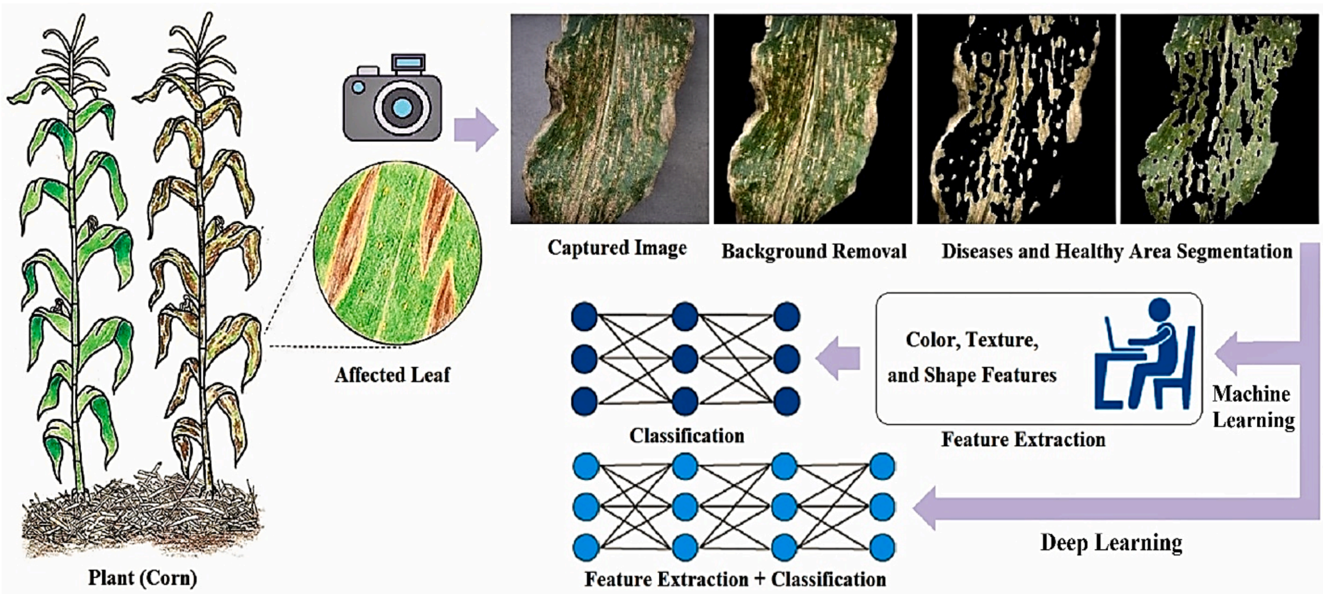


Fig. 1. Steps for diagnosis and classification of plant leaf diseases.

Table 2
A brief summary of some popular plant disease segmentation techniques with their advantages and disadvantages.

Methods	Advantages and Disadvantages
Thresholding	This is a simple and useful method for segmenting binary images based on a threshold value. It can handle images with poor contrast, and it's also computationally efficient. However, it may fail when the images contain noise which may lead to low accuracy in detecting the disease regions.
Region growing	This method starts from an initial pixel and searches its neighbors for pixels with similar intensity values. It then groups these pixels and continues the search until it has found the entire disease region. Its advantages include its simplicity and adaptability to various diseases. However, it may fail to identify diseases with complex geometries, and it may also suffer from the sensitivity of the cores used for the growing process.
Watershed algorithms	This method uses a watershed to segment the images into a set of catchment regions. This is done by using the edge map to find the boundaries between the different regions. Its advantages include its ability to work in complex geometries and its robustness in handling different light conditions and noise. However, it may fail in images where the disease regions are similar to the healthy ones.
Edge-based segmentation	This method segments images based on the detection of the edges. Its advantages include its high accuracy and its robustness in handling noisy and uneven backgrounds. However, it may fail when the edges are not distinct.
Regional methods	These methods use the regions as primitive elements for disease detection. These regions can be obtained from different techniques, including thresholding, region-merging algorithms, and clustering methods. Its advantages include its adaptability to complex geometries and its robustness in handling noisy and uneven backgrounds. However, it may fail to detect diseases with low or high intensity.
Clustering	These methods group the pixels based on their similarities. Its advantages include its ability to handle large amounts of data and its adaptability to complex geometries. However, it may fail in images with high noise levels and may require manual intervention to set the appropriate number of clusters.

valuable attribute vectors of the suitable object such as color, texture, and shape [39]. On the other hand, deep models offer state-of-the-art performance due to the automatic extraction of features through many connected layers [40]. However, as mentioned earlier, they require a dataset large enough for the algorithm to extract the significant features automatically. During the feature extraction phase, several factors should be considered including a potentially high number of significant features, irrelevant features, excessive computational time, similarity amongst features, a lack of robustness with scaling and rotation, and correlation among information [33,41]. The color, texture, and shape features, which are mostly extracted for plant diseases, are described in detail in the following section.

3.1. Detection of diseases using color features

Detecting plant diseases using color features refers to the use of the color information present in plant leaves for disease identification and analysis. Color pigment has been shown to be a powerful indicator of plant physiological and health status, as changes in color due to disease, stress, or other factors can provide valuable information for early diagnosis and disease management [42].

Several color-based features have been used for detecting plant diseases, including RGB values, hue, saturation, and luminance [43]. RGB values are the simplest representation of color information, and they provide information on the red, green, and blue color channels present in the leaf color. Hue, saturation, and luminance, on the other hand, are derived from the RGB values and represent the perceived colors of the leaf. Hue is the perceived color, saturation is the measure of the intensity of the perceived color, and luminance is the measure of the luminosity or brightness of the perceived color [44]. These color-based features can be used to characterize the leaf's color properties and provide valuable information for plant disease detection and diagnosis. In addition to the RGB, hue, saturation, and luminance values, other color-based features such as the ratio of green to red color, yellow-green color, and green-red color, have been used for detecting plant diseases. The ratio of green to red color, for example, is useful for detecting chlorosis or chlorotic leaf, which is caused by an iron deficiency [45].

Generally, color-based features are widely used in plant disease detection due to their ability to provide information on the physiological and health status of the plant [46,47]. The development of robust and reliable color-based plant disease detection systems can help reduce plant crop losses and improve crop yields [48,49]. Table 4 shows the most commonly used features in order to diagnose plant diseases.

The mean is sensitive to the presence of noise in the image and is commonly used in conjunction with other features to improve the accuracy of the detection process [51]. The max is useful for identifying

Table 3
Advantages and disadvantages of most common features in plant disease detection.

Type of features	Method of extraction	Characteristics	Advantages	Disadvantages
Color features	Color moments	Based on statistical information such as mean, variance, and skewness.	Ability to overcome quantization effects, compact and robust.	No spatial information, can't describe all colors.
	Color Histogram	Based on color quantization and pixel counting for each color.	Easy computation, intuitive.	High noise sensitivity, no spatial information, high dimensional.
texture features	Gray-level co-occurrence matrix (glcm)	Based on the relative locations of pixels in the neighborhood.	Detecting texture variability efficiently, excellent performance in terms of processing speed and complexity.	Requires modeling in high correlation of Haralick features, high dimensionality of the matrix, and sensitivity in the processing of texture samples.
	Gabor Filter	A model of the human visual data processing system.	Defining the image structure using metrics of scale and orientation. Enables filtering in the spatial and frequency domains.	Non-orthogonality leads to redundant features at different scales.
	Local Binary Pattern (LBP)	Based on the variance in the gray level of pixels and its adjacent pixels.	Simple implementation, low computational cost, immune to scaling and rotational variations, and excellent performance due to a combination of statistical and structural analysis.	Non-adaptive pixel neighborhood, noise, and blurring sensitivity.
Shape features	Elliptic Fourier and discriminant analysis	Based on leaf disease boundary	Handle complicated shapes which may not be expressible as a unique function in polar coordinates.	Highly dependent on the segmented result of leaf images.
	Geometrical calculation + moment invariants	Based on algebraic invariant.	Computationally less expensive, invariant to scale, translation, and rotation. Ability to process smaller feature sets and represent global features.	Less resistive to occultation, Non-adaptive pixel neighborhood.

regions of intense color, such as disease-infected regions, as well as healthy regions where the plant is blooming [52]. High standard deviation values indicate regions of high color density variation, which may be caused by the presence of disease [47]. The median is useful for identifying regions of generally low intensity, such as healthy tissue, and can help to distinguish these regions from regions of high intensity, such as disease-infected regions [53].

3.2. Detection of diseases using texture features

Plant leaves have a unique surface texture that can be affected by various diseases, such as blight, mildew, and rust. These diseases cause changes in the texture of leaves, including color changes, brownish spots, and distorted patterns. The detection of these texture changes can provide an effective method for identifying plant diseases in a rapid, efficient, and cost-effective manner [54].

In recent years, texture-based features have become a common approach for plant disease diagnosis, and many researchers have identified texture in plant leaf images as the most effective feature in plant disease detection [55]. Texture features describe the surface patterns of plant leaves, which are directly related to their structural and chemical changes during disease progression [56]. These features include texture descriptors, such as Haralick features and neighborhood gray-level difference matrix (NGLDM), which capture the texture properties of the leaf surface and provide quantitative information about the changes in the texture patterns caused by diseases [57]. Texture features are often extracted from plant leaf images using image processing algorithms, such as Gabor filters, wavelet transforms, and fast Fourier transforms (FFT). These algorithms help to analyze the spatial frequency and local pattern information of the leaf surface, which can provide valuable information for detecting the presence and severity of plant diseases. Texture spectrum is a non-parametric texture descriptor that uses the frequency spectrum of the leaf image's texture to identify different texture patterns [58]. It captures the spatial frequency and energy information of the texture patterns and provides a detailed characterization of the various textural features present in the leaf image [29]. Table 5 summarizes the most common texture features used to diagnose plant diseases.

Each of the listed textural features plays a vital role in plant disease detection, providing researchers with valuable information about the health and state of the plant from the images. Contrast, measured by the variance of intensity values, is used to identify the brightness or darkness of the pixels in the image, which can be useful for detecting the presence of disease in the plant [60]. Correlation measures the linear association between the values of neighboring pixels and is useful for identifying regions in the image where the plant's tissue is similar in color or texture, which can be useful for identifying disease [61]. Energy measures the brightness and contrast of the image and is used to identify regions in the image where the plant's tissues are similar in brightness or contrast, which can be useful for identifying disease [62]. Homogeneity, measured by the variability of intensity values, is used to identify the level of intensity or color homogeneity in the image and is useful for identifying regions in the image where the plant's tissues are similar in color or intensity, which can be useful for identifying disease [63]. Entropy measures the disorder or randomness in the image and is used to identify regions in the image where the plant's tissues are similar in color or texture, which can be useful for identifying disease [64].

Root mean square (RMS) measures the intensity variability in the image and is used to identify the intensity variability of the plant's tissues, which can be useful for detecting the presence of disease in the plant [65]. Variance measures the spread of the intensity values and is used to identify the spread of the plant's tissue intensity values, which can be useful for identifying disease [66]. Smoothness measures the smoothness of the intensity values and is used to identify the smoothness of the plant's tissue intensity values, which can be useful for identifying disease [67]. Kurtosis is the heaviness of the intensity distribution in the

Table 4
Color features to diagnose plant diseases [50].

Features	Equation	Description
Mean	$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$	The sum of the observed results (gray values) divided by the total number of events (pixels).
Max	$M = \max(X) \text{ iff } \{a \in X \cap \ \forall x \in X, x \leq a\}$	Assigning the maximum gray value of a neighborhood to the central pixel.
Standard Deviation	$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x - \overline{x})^2}$	A measure of the spread of gray levels, showing how much individual values vary from the mean.
Median	$Med(X) = \begin{cases} X\left[\frac{n+1}{2}\right] & \text{if } n \text{ is odd} \\ \frac{X\left[\frac{n}{2}\right] + X\left[\frac{n}{2}+1\right]}{2} & \text{if } n \text{ is even} \end{cases}$	A measure of central tendency that provides a more robust and less sensitive measure than the mean that may contain extreme or outlier values. It's calculated by ranking all the gray values from low to high and selecting the middle one.

image and is used to identify the heaviness of the plant's tissue intensity distribution, which can be useful for detecting the presence of disease in the plant [68]. Skewness measures the degree of asymmetry in the image's intensity distribution and is used to identify the asymmetry of the plant's tissue intensity distribution, which can be useful for detecting the presence of disease in the plant [69].

3.3. Detection of diseases using shape features

Detecting plant disease using image shape features refers to the use of the shape and pattern of plant leaves for disease identification and analysis. An example of shape features commonly used in plant disease detection is the leaf outline [70]. The leaf outline is the contour of the leaf and can provide information on the size, shape, and structural patterns of the leaf. The leaf outline can be extracted using either manual or automatic methods such as edge detection algorithms or shape-matching algorithms [47]. The measurement of the leaf area is used to detect the presence and severity of leaf diseases, such as rust and mildew that can cause shriveling and reduction in leaf size. However, shape features like leaf area are scale-variant and can be affected by the distance of the camera from the leaf during image acquisition [71]. Other shape features such as leaf perimeter, aspect ratio, and compactness have also been used for plant disease detection [72]. The perimeter of the leaf is the sum of the center-to-center distance of neighboring pixels located at the leaf boundary, which reflects the shape of the leaf. The aspect ratio is the ratio of the width to the height of the leaf, and it can provide information on the shape and orientation of the leaf. The compactness of the leaf is a measure of the uniformity of the leaf shape, and it can be used to detect the presence of disease or damage [47].

Generally, shape features are useful in detecting the presence and severity of plant diseases, as they can provide information on the size, shape, and structure of the leaf [73]. By combining shape features with other image characteristics, such as color and texture, more accurate and comprehensive plant disease detection systems can be developed [74]. Table 6 shows the most common shape features used in order to diagnose plant diseases.

Shape features are crucial in analyzing the properties of objects, as they provide information about the object's physical properties [25]. In the case of plants, shape features can help researchers better understand the structure and characteristics of plant tissues, which can be used in studying plant diseases [70,77].

Area is a measure of the total amount of space occupied by an object in two-dimensional space. In plant disease detection, an area can help identify the size of the diseased region and measure the progress of the disease [37]. In plant disease detection, the perimeter can help identify the edges of the infected region and measure the extent of the disease [78]. Major and minor axis lengths can help identify the shape of the infected region and measure the progress of the disease [79,80]. The eccentricity index can help identify the shape of the infected region and measure the progress of the disease [81]. Circularity is a measure of how close an object is to being a perfect circle in two-dimensional space and it can help identify the shape of the healthy region and measure the progress of the disease [43,82]. The compactness index can help identify the extent of the infected region and measure the progress of the disease [83].

4. Available models to learn extracted features

Various plant disease datasets are developed to investigate the performance of machine learning-based classification models that can learn features extracted from plant leaf images for the prediction of plant leaf diseases. Table 7 shows some of the frequently used datasets by researchers who are working on image processing-based plant disease identification. According to the table, plant leaves of many horticultural products have been considered to create datasets reliable for image processing tasks. A summary of models used for plant leaf disease detection is brought in Table 8. The studies are sorted based on the time of publishing. Among the models, the support vector machines (SVM), random forest (RF), decision tree (DT), *k*-nearest neighbors (*k*-NN), naïve bayes (NB), and artificial neural networks (ANN) are the most conventional methods for learning the features extracted from plant leaves for plant disease identification. Deep learning methods, which involve non-handcrafted features, are also widely used for plant disease detection based on image processing. Some of these methods include compact binary descriptors (CBD), convolutional neural networks (CNN), GoogleNet, AlexNet, ResNet, DenseNet, MobileNet, and EfficientNet [84]. In particular, deep learning-based methods are robust and efficient compared to handcrafted features due to their independence of prior knowledge [85]. However, they have limitations as well. These limitations include low interpretability of the learned features, meaning that it is difficult to describe the learned features and difficulty in obtaining a larger dataset for model training.

In summary, although existing techniques for feature extraction in computer vision are effective, there is a need for novel and cost-effective techniques that can automatically extract the most relevant features for image classification [123].

5. Challenges in the intelligent detection of plant diseases

Plant disease detection, especially early disease detection, is a major problem for farmers and farm managers, as it can lead to significant crop losses. Over the past decade, there have been significant advances in computer vision and machine learning that have improved the ability to detect and classify plant diseases from images. One of the main challenges in using these methods is the lack of high-quality labeled datasets that include sufficient examples of plant diseases and images that correctly represent real-world scenarios [124].

Table 5
Texture features to diagnose plant diseases [59].

Features	Equation	Description
Contrast	$\sum_{i,j}\lvert i-j\rvert^2 p(j,j)$	A measure of the difference in brightness between the lightest and darkest parts of an image, object, or feature. The higher the contrast, the more pronounced the differences between light and dark areas, which can help to highlight important features or details in an image.
Correlation	$\sum_{i,j}\frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i\sigma_j}$	It is used to determine the strength and direction of the linear relationship between two variables, which can help in understanding causality, predictive power, and relationship strength.
Energy	$\sum_{i,j}p(i,j)^2$	A statistical feature that describes the texture in an image. It measures the amount of variability or instability present in an image's texture and is calculated as the sum of the squared elements in the GLCM. The higher the energy value, the more variable or heterogeneous the texture is.
Homogeneity	$\sum_{i,j}\frac{p(i,j)}{1+\lvert i-j\rvert}$	It is defined as the homogeneity of the texture within a certain neighborhood around a pixel and is calculated as the variance of the GLCM. Homogeneity is a measure of the degree of similarity among neighboring pixels.
Entropy	$E = sum(p.*log2(p))$	A quantitative measure of the information content in the image in terms of its texture, representing the unpredictability of the texture elements. Higher entropy values indicate a higher degree of texture variations in the image, while lower entropy values indicate a more homogeneous texture.
Root Mean Square (RMS)	$X_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\lvert X_n\rvert^2}$	A statistical measure that represents the square root of the average of the squares of the differences between the observed and expected number of co-occurrences between two neighboring pixels. The higher the RMS value, the more heterogeneous the texture.
Variance	$\frac{1}{n}\left(\sum_{i=1}^{n}(X_i-\overline{X})^2\right)$	It is calculated as the second central moment of the statistical distribution of neighboring pixel values, and it measures the spread or variability of the texture around a certain pixel. High variance values correspond to more heterogeneous textures, while low variance values correspond to more homogeneous textures.
Smoothness	–	It is defined as the inverse of the standard deviation of the co-occurrence matrix and it estimates how smooth or homogeneous the texture in an image is. A greater smoothness value corresponds to smoother textures, while a lower smoothness value corresponds to more heterogeneous textures.
Kurtosis	$K = \frac{E(x-\mu)^4}{\sigma^4}$	A measure of the peakedness of the statistical distribution of neighboring pixel values, and it quantifies how far the distribution is from the normal distribution. High kurtosis values correspond to textures with a heavy tail behavior, while low kurtosis values correspond to textures with a more symmetric distribution.
Skewness	$S = \frac{E(x-\mu)^3}{\sigma^3}$	A measure of the asymmetry of the statistical distribution of neighboring pixel values, and it quantifies the degree to which the distribution is skewed. High skewness values correspond to textures with left- or right-skewed distributions, while low skewness values correspond to textures with more symmetric distributions.
Inventive Design Method (IDM)	–	A measure of the inventiveness of the texture pattern and is commonly used in image classification and segmentation tasks to distinguish between different regions of an image. The IDM is the difference between the actual and expected number of co-occurrences between two neighboring pixels. A positive IDM value implies that the texture pattern is more complex and intricate than expected.

Table 6
Shape features to diagnose plant diseases.

Features	Equation	Description	Refs.
Area	$a = \sum_{u=1}^{M}\sum_{v=1}^{N}A[u,v]$	The average of the number of pixels in each region or object found after running a segmentation algorithm on an image or image series.	Vishnoi et al. [33]
Perimeter	2 (length + width)	the sum of the center-to-center distance of neighboring pixels located at the leaf boundary The boundary pixels are the ones that separate the object from the background.	Vishnoi et al. [33]
Major axis length	$M = x_1 + x_2$	Length of the major axis of the ellipse	Vishnoi et al. [33]
Minor axis length	$m = \sqrt{\left((x_1+x_2)^2 - d\right)}$	Length of the minor axis of the ellipse	Vishnoi et al. [33]
eccentricity index	$\frac{Majoraxislength}{Minoraxislength}$	The eccentricity index is calculated as the difference between the lengths of the minor and major axes divided by the length of the major axis.	Vishnoi et al. [33]
Circularity	$\frac{4 \times pi \times area}{Perimeter^2}$	Defined as the ratio of the perimeter to the major axis length of a feature.	Vishnoi et al. [33]
Compactness index	$\frac{Area}{Perimeter^2}$	A measure of quantifying the shape of spatial objects in a way that reflects their relative spatial compactness.	Haug et al. [75]
Shape factors 1	$\frac{Majoraxislength}{Area}$	–	Bakhshipour and Jafari. [76]
Shape factors 2	$\frac{Area}{Majoraxislength^3}$	–	Bakhshipour and Jafari. [76]

Table 7
Datasets available for plant disease detection using computer vision.

Dataset name	Environment for image acquisition	Type of plant	Number of images	Number of classes	Refs.
PlantVillage	Laboratory	Multiple plants	54,305	38	Hughes and Salathe [86]
PlantDoc	Internet images	Multiple plants	2598	27	Singh et al. [87]
PDD271	Field	Multiple plants	220,592	271	Liu et al. [88]
PDDB	Laboratory and field	Multiple plants	1575	79	Barbedo [89]
PlantLeaf	Laboratory	Multiple plants	4503	12	Chouhan et al. [90]
Apple2020	Field	Apple	3642	4	Thapa et al. [91]
Cassava	Field	Cassava	21,397	5	Ramcharan et al. [92]
Citrus	Laboratory	Citrus	714	10	Rauf et al. [93]
BRACOL	Laboratory	Coffee	4407	4	Esgario et al. [94]
RoCoLe	Field	Coffee	1560	2	Parraga-Alava et al. [95]
JMuBEN	Field	Coffee	58,555	5	Jepkoech et al. [96]
MerlotGrape	Field	Grape	99	7	Abdelghafour et al. [97]
DiaMOS	Field	Pear	3505	4	Fenu and Malloci [98]
Rice5932	Field	Rice	5932	4	Sethy et al. [99]
Rice1426	Field	Rice	1426	9	Rahman et al. [100]
LWDCD2020	Field	Wheat spike	12,160	10	Goyal et al. [101]
Corn2018	Field	Corn	18,222	1	Wiesner-Hanks et al. [102]
Corn2022	Laboratory and field	Corn	7701	4	Qian et al. [103]
Field-PV	Field	Multiple plants	665	38	Gui et al. [104]
Black gram	Laboratory and field	Black gram	1000	5	Talasila et al. [105]

High-quality labeled datasets are essential for machine learning algorithms to learn accurate patterns and features from images [125]. Without sufficient datasets, the accuracy and reliability of the detection and classification models will be limited. This can lead to misdiagnoses, which can result in further financial loss for farmers [126]. Currently, the labeling process is time-consuming and labor-intensive, making it difficult to generate high-quality labeled datasets. Another challenge is that plant diseases can appear in different forms, depending on the type of disease, the stage of contamination, the plant growth stage, and the environmental conditions. Additionally, multiple diseases may infect a plant at the same time, making it difficult to accurately diagnose and treat the diseases [127]. Hence, obtaining high-quality images of infected plant leaves, including symptoms at different disease stages, is necessary for accurate diagnosis and classification [128–130]. This requires specialized equipment, such as high-quality cameras, lighting, and lenses, which can be expensive and difficult to access in remote areas.

Another challenge is the collection of diverse datasets that include a wide range of plant diseases, plant varieties, and environmental conditions. This can be difficult to access in remote or resource-constrained areas. There is a need for a large and diverse dataset to train machine learning models for plant disease detection. Shadowing can make it difficult to accurately identify and diagnose plant diseases, especially in field settings. To overcome this challenge, researchers are developing techniques for improving the quality and accuracy of imaging systems, as well as developing algorithms for image analysis and classification. Shadowing occurs when part of a leaf is obscured by another leaf (occlusion issue), reducing the amount of light that reaches the plant tissue. Shadowing and occlusion can lead to inaccurate identification and diagnosis of diseases.

Research is being conducted on techniques for controlling and optimizing environmental conditions such as temperature, humidity, lighting, and air quality to improve imaging system performance. Environmental conditions can impact imaging quality, and thus, diagnostic accuracy [131]. Factors such as air quality, humidity, and temperature can affect the plant tissue, reducing the ability to accurately capture and diagnose disease symptoms.

Finally, because plant diseases can develop more widespread symptoms over time, AI-enabled methods should be able to identify and classify disease severity and several disease development stages. This can help to improve the efficiency and accuracy of early disease diagnosis and control. Accurate and early disease diagnosis can enable farmers to take proactive measures to reduce the impact of a disease on plant health and productivity. Some methods for identifying disease development stages include assessing leaf color, texture, and size, and observing changes in the appearance, size, and distribution of the disease on the plant. Disease development stage identification can be challenging due to the complex nature of plant diseases and the variability in symptom presentation. In addition, other factors such as soil conditions, disease vectors, and pest pressures can also impact disease and symptom development.

6. Conclusion

This study critically reviewed techniques related to feature extraction for the development of smart plant disease detection and classification systems. Attention was focused on feature extraction, including different types of descriptors based on the spectral and spatial attributes of images, such as shape, texture, and color. Many image processing techniques have been developed utilizing single-type features as well as a combination of complementary features, which usually provide better detection accuracy. Furthermore, deep learning techniques have been effectively applied for automated feature extraction in various agricultural applications. These methods can simultaneously analyze both the color and the spatial characteristics of an image. However, deep learning techniques require large datasets, significant labor and time for labeling, and have high computational complexity and costs.

Future automated disease diagnosis systems should focus on developing AI-enabled techniques for detecting diseases at different disease development stages, with a focus on early disease detection and classification. Most existing studies have been focused on identifying late symptoms of plant diseases without considering disease progression. However, information on the severity of the disease is crucial for the early control of a disease. Efforts should be made to develop automated methods for disease severity estimation. Finally, techniques for detecting multiple factors (e.g., disease or disorders) that might affect a crop at the same time are needed. Plants may occasionally exhibit multiple infections simultaneously. Most current techniques can detect only one disease or disorder (e.g., nutrient deficiency) in a crop.

Funding

(Not applicable)

Availability of data and material

(Not applicable)

Table 8
Summary of models used for plant leaf disease detection.

Plant	Diseases	Features Extracted	Classifier	Accuracy	Studies
Rice	Bacterial leaf blight, Brown spot, Rice blast, Sheath rot	Mean, SD values of the lesion area, background pixels, and change of lesion color respective of background pixels in RGB planes and shape of disease spots	SVM NB SVM	94.40 % 79.5 %, 68.1 %	Phadikar and Sil [106]
Rice	Bacterial leaf blight, rice blast, Sheath rot	(entropy, contrast, uniformity, linear correlation, inverse difference) in 4-orientations and 3-spatial (HSV) system	SVM	88.00 %	Yao et al. [107]
Wheat	Leaf blight, Leaf rust, Powdery mildew	Shape, color, and texture features	SVM	95.16 %	Tian et al. [108]
Wheat	Powdery mildew, leaf rust, leaf blight, *Puccinia striiformis*	Lesion area ratio, compactness, seven invariant moments	SVM	60.59 %	Tian et al. [108]
Cucumber	Downy mildew, Bacterial angular, *Corynespora cassicola*, Gray mold, Scab, Powdery mildew, Anthracnose	Log frequency histogram color features in L*a*b* + shape features (Vector length)	SVM	85.70 %	Zhang et al. [109]
Rice	Bacterial leaf blight, Brown spot, Rice blast	area, mean value of RGB, HSV; SD of RGB color channels of the lesion	EBPNN	100 %	Orillo et al. [110]
Cotton	Bacterial blight, Leaf blight, Root rot, Micronutrient, Fusarium wilt, Verticillium wilt	Edge features + color texture features with PSO for feature selection	SVM, BPNN, Fuzzy classifier	91.00 %, 93.00 %, 94.00 %	Revathi and Hemalatha [111]
Corn	Gray leaf spot, Brown spot, Leaf blight	Shape, Color and Texture features	ANN optimized with PSO	93.30 %	Tao et al. [112]
Multiple crops	20 various diseases	RGB color features + 10 GLCM features	SVM, EBPNN	92 %, 87 %	Pujari et al. [113]
Apple	Black rot, Blotch, Scab, Healthy	Global histogram features	Random Forest	90 %	Samajpati and Degadwala [114]
Grape	Black rot, downy mildew, powdery mildew, healthy	HSV color features + texture features using OCLBP patterns	Multiclass SVM	89.30 %	Waghmare et al. [115]
Tomato	Bacterial leaf spot, Septoria leaf spot, Late blight, Bacterial canker, Leaf curl, Healthy	Mean, SD, and skewness for three color values of CIE XYZ color space and the correlation value of X and Y channels	Decision Tree	78 %	Sabrol and Kumar [116]
Soybean	Frog eye, downy mildew, bacterial pustule	Contrast, homogeneity, energy, difference variance, difference entropy, maximum probability, entropy for hue channel	3-Layer EBPNN	93.30 %	Gharge and Singh [117]
Sugar beet	Beet rust, Bacterial blight	RGB values & LBP of intensity and gradient, GLCM features	SVM	82 %	Hallau et al. [118]
Soybean	Septoria leaf blight, Frog eye, Downy mildew	Texture and Color features	SVM	85.65 %	Kaur et al. [71]
Cherry	Fungal infection	area Quantification of the diseased area using the lesion area ratio	KNN	99 %	Sengar et al. [119]
Corn	Common rust, northern blight, both diseases, healthy	Homogeneity, contrast, correlation, energy in 2-orientations and RGB spatial system	KNN, SVM	85 %, 88 %	Deshapande et al. [120]
PlantVillage Dataset	Frog eye, Downy mildew, Septoria leaf blight, Healthy	GLCM, complex Gabor filter, curvelet, and image moments	Neuro-Fuzzy Logic	93.18 %	Rao and Kulkarni [121]
Bell Pepper, Potato, and Tomato	Leaf Disease	LBP, GLCM, SIFT, and Gabor features	Ensemble learning	95.66 %	Kaur and Devendran [122]
Apple	Black spot, black rot or frog eye leaf spot, cedar rust, healthy	GLCM, color moment, and geometrical calculation	Slim mold optimization and RF	96.21 %	Javidan et al. [36]
Tomato	Bacterial spot, late blight, leaf mold, sectorial leaf spot, target spot, early blight, healthy	Shape, color, and texture features	Majority voting Ensemble learning	95.58 %	Javidan et al. [23]

Code availability

(Not applicable)

Ethical statement

The authors ensure that all procedures were performed in compliance with relevant laws and institutional guidelines. No human or animal subjects are involved in this research.

CRediT authorship contribution statement

Seyed Mohamad Javidan: Writing – original draft, Writing – review & editing, Methodology. **Ahmad Banakar:** Supervision, Writing – original draft, Writing – review & editing, Methodology, Conceptualization. **Kamran Rahnama:** Validation, Writing – review & editing, Supervision. **Keyvan Asefpour Vakilian:** Writing – review & editing, Methodology. **Yiannis Ampatzidis:** Writing – review & editing, Validation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] P.A. Nazarov, D.N. Baleev, M.I. Ivanova, L.M. Sokolova, M.V. Karakozova, Infectious plant diseases: etiology, current status, problems and prospects in plant protection, Acta Nat. 12 (3) (2020) 46–59, https://doi.org/10.32607/actanaturae.11026. Acta Naturae Ltd.
[2] K.M. Gold, Plant disease sensing: studying plant-pathogen interactions at scale, mSystems 6 (6) (2021) e01228. -21.
[3] S. Jahantigh, N.A. Oghaz, K. Rahnama, S. Hatamzadeh, Application of *Lactobacillus* spp. for the biological management of green mold (*Penicillium digitatum*) on sweet orange fruit under *in vitro* and storehouse conditions,

Biocontrol Sci. Technol. 33 (6) (2023) 567–581, https://doi.org/10.1080/09583157.2023.2208781. Informa UK Limited.

[4] Y. Ampatzidis, L. De Bellis, A. Luvisi, iPathology: robotic applications and management of plants and plant diseases, Sustainability 9 (6) (2017) 1010, https://doi.org/10.3390/su9061010.

[5] B. Khoshru, D. Mitra, K. Joshi, P. Adhikari, M.S.I. Rion, A.E. Fadiji, M. Alizadeh, A. Priyadarshini, A. Senapati, M.R. Sarikhani, P. Panneerselvam, P.K. D. Mohapatra, S. Sushkova, T. Minkina, C. Keswani, Decrypting the multi-functional biological activators and inducers of defense responses against biotic stresses in plants, Heliyon 9 (3) (2023) e13825, https://doi.org/10.1016/j.heliyon.2023.e13825. Elsevier BV.

[6] A.K. Mahlein, R.H.J. Heim, A. Brugger, K. Gold, Y. Li, A.K. Bashir, M.T. Kuska, Digital plant pathology for precision agriculture, J. Plant Dis. Prot. 129 (3) (2022) 455–456.

[7] J.M. Van Seventer, N.S. Hochberg, Principles of infectious diseases: transmission, diagnosis, prevention, and control. International Encyclopedia of Public Health, Elsevier, 2017, pp. 22–39, https://doi.org/10.1016/b978-0-12-803678-5.00516-6.

[8] A. Luvisi, Y. Ampatzidis, L. De Bellis, Plant pathology and information technology: opportunity and uncertainty in pest management, Sustainability 8 (8) (2016) 831, https://doi.org/10.3390/su8080831.

[9] P. Yang, L. Zhao, Y.G. Gao, Y. Xia, Detection, diagnosis, and preventive management of the bacterial plant pathogen pseudomonas syringae, Plants 12 (9) (2023) 1765, https://doi.org/10.3390/plants12091765. MDPI AG.

[10] B. Aglave, Handbook of Plant Disease Identification and Management, CRC Press, 2018, https://doi.org/10.1201/9780429504907.

[11] K. Asefpour Vakilian, J Massah, A farmer-assistant robot for nitrogen fertilizing management of greenhouse crops, Comput. Electron. Agric. 139 (2017) 153–163, https://doi.org/10.1016/j.compag.2017.05.012.

[12] K.M. Gold, P.A. Townsend, I. Herrmann, A.J. Gevens, Investigating potato late blight physiological differences across potato cultivars with spectroscopy and machine learning, Plant Sci. 295 (2020) 110316.

[13] S.K. Mathanker, P.R. Weckler, R.K. Taylor, G. Fan, AdaBoost and support vector machine classifiers for automatic weed control: canola and Wheat, in: Proceedings of the 2010 Pittsburgh, Pennsylvania, June 20-June 23, 2010, American Society of Agricultural and Biological Engineers, 2010, p. 1.

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

[15] X. Zhang, C. Cen, F. Li, M. Liu, W. Mu, CRFormer: cross-resolution transformer for segmentation of grape leaf diseases with context mining, Expert Syst. Appl. 229 (2023) 120324, https://doi.org/10.1016/j.eswa.2023.120324. Elsevier BV.

[16] N. Otsu, A threshold selection method from gray-level histograms, IEEE Trans. Syst. Man Cybern. 9 (1) (1979) 62–66, https://doi.org/10.1109/tsmc.1979.4310076. Institute of Electrical and Electronics Engineers (IEEE).

[17] R.K. Sarkar, A. Pramanik, Segmentation of plant disease spots using automatic SRG algorithm: a look up table approach, in: Proceedings of the 2015 International Conference on Advances in Computer Engineering and Applications, IEEE, 2015, https://doi.org/10.1109/icacea.2015.7194375, 2015 International Conference on Advances in Computer Engineering and Applications (ICACEA).

[18] H. Liu, W. Zhang, F. Wang, X. Sun, J. Wang, C. Wang, X. Wang, Application of an improved watershed algorithm based on distance map reconstruction in bean image segmentation, Heliyon 9 (4) (2023) e15097, https://doi.org/10.1016/j.heliyon.2023.e15097. Elsevier BV.

[19] L. Wang, J. Liu, J. Zhang, J. Wang, X. Fan, Corn seed defect detection based on watershed algorithm and two-pathway convolutional neural networks, Front. Plant Sci. 13 (2022), https://doi.org/10.3389/fpls.2022.730190. Frontiers Media SA.

[20] J. Canny, A computational approach to edge detection, IEEE Trans. Pattern Anal. Mach. Intell. PAMI-8 (6) (1986) 679–698, https://doi.org/10.1109/tpami.1986.4767851. Institute of Electrical and Electronics Engineers (IEEE).

[21] D. Mohamadzamani, S. Sajadian, S.M. Javidan, Detection of *Callosobruchus maculatus* F. with image processing and artificial neural network, Appl. Entomol. Phytopathol. 88 (1) (2020) 103–112, https://doi.org/10.22092/jaep.2020.341684.1324.

[22] M. Kass, A. Witkin, D. Terzopoulos, Snakes: active contour models, Int. J. Comput. Vis. 1 (4) (1988) 321–331, https://doi.org/10.1007/bf00133570. Springer Science and Business Media LLC.

[23] S.M. Javidan, A. Banakar, K. Asefpour Vakilian, Y. Ampatzidis, Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning, Smart Agric. Technol. 3 (2023) 100081, https://doi.org/10.1016/j.atech.2022.100081.

[24] J.A. Sethian, A review of level set and fast marching methods for image processing. Modern Methods in Scientific Computing and Applications, 2002, pp. 365–396. https://doi.org/10.1007/978-94-010-0510-4_10.

[25] S.M. Javidan, A. Banakar, K.A. Vakilian, Y. Ampatzidis, Tomato leaf diseases classification using image processing and weighted ensemble learning, Agron. J. (2023) 1–21, https://doi.org/10.1002/agj2.21293.

[26] K. Subramani, S. Periyasamy, P. Theagarajan, Double line clustering based colour image segmentation technique for plant disease detection, Curr. Med. Imaging 15 (8) (2019) 769–776, https://doi.org/10.2174/1573405614666180322130242. Formerly Current Medical Imaging ReviewsBentham Science Publishers Ltd.

[27] A. Mohammad-Razdari, D. Rousseau, A. Bakhshipour, S. Taylor, J. Poveda, H. Kiani, Recent advances in E-monitoring of plant diseases, Biosens. Bioelectron. 201 (2022) 113953, https://doi.org/10.1016/j.bios.2021.113953. Elsevier BV.

[28] M. Shoaib, B. Shah, T. Hussain, A. Ali, A. Ullah, F. Alenezi, T. Gechev, F. Ali, I. Syed, A deep learning-based model for plant lesion segmentation, subtype identification, and survival probability estimation, Front. Plant Sci. 13 (2022), https://doi.org/10.3389/fpls.2022.1095547. Frontiers Media SA.

[29] C. Jackulin, S. Murugavalli, A comprehensive review on detection of plant disease using machine learning and deep learning approaches, Meas. Sens. 24 (2022) 100441, https://doi.org/10.1016/j.measen.2022.100441. Elsevier BV.

[30] P.S. Thakur, P. Khanna, T. Sheorey, A. Ojha, Trends in vision-based machine learning techniques for plant disease identification: a systematic review, Expert Syst. Appl. 208 (2022) 118117, https://doi.org/10.1016/j.eswa.2022.118117. Elsevier BV.

[31] D.A.W.S. Ibrahim, D.B.A.K. Atya, Detection of diseases in rice leaf using deep learning and machine learning techniques, Webology 19 (1) (2022) 1493–1503, https://doi.org/10.14704/web/v19i1/web19100.

[32] J. Massah, K. Asefpour Vakilian, M. Shabanian, S.M. Shariatmadari, Design, development, and performance evaluation of a robot for yield estimation of kiwifruit, Comput. Electron. Agric. 185 (2021) 106132, https://doi.org/10.1016/j.compag.2021.106132.

[33] V.K. Vishnoi, K. Kumar, B. Kumar, A comprehensive study of feature extraction techniques for plant leaf disease detection, Multimed. Tools Appl. 81 (1) (2021) 367–419, https://doi.org/10.1007/s11042-021-11375-0.

[34] N. Nandhini, R. Bhavani, Feature extraction for diseased leaf image classification using machine learning, in: Proceedings of the 2020 International Conference on Computer Communication and Informatics (ICCCI), 2020, https://doi.org/10.1109/iccci48352.2020.9104203.

[35] K.A. Vakilian, M. Moreau, S.M. Javidan, An IoT-based smart biosensor for the measurement of nitrate concentration in liquid samples, in: Proceedings of the 2024 20th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP), IEEE, 2024, https://doi.org/10.1109/aisp61396.2024.10475236.

[36] S.M. Javidan, A. Banakar, K.A. Vakilian, Y. Ampatzidis, A feature selection method using slime mould optimization algorithm in order to diagnose plant leaf diseases, in: Proceedings of the 2022 8th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), IEEE, 2022, pp. 1–5.

[37] L. Zhang, Y. Sui, H. Wang, S. Hao, N. Zhang, Image feature extraction and recognition model construction of coal and gangue based on image processing technology, Sci. Rep. 12 (1) (2022), https://doi.org/10.1038/s41598-022-25496-5. Springer Science and Business Media LLC.

[38] Y. Atoum, M.J. Afridi, X. Liu, J.M. McGrath, L.E. Hanson, On developing and enhancing plant-level disease rating systems in real fields, Pattern Recognit. 53 (2016) 287–299, https://doi.org/10.1016/j.patcog.2015.11.021. Elsevier BV.

[39] A. Mathew, A. Antony, Y. Mahadeshwar, T. Khan, A. Kulkarni, Plant disease detection using GLCM feature extractor and voting classification approach, Mater. Today Proc. 58 (2022) 407–415, https://doi.org/10.1016/j.matpr.2022.02.350. Elsevier BV.

[40] K. Trang, L. TonThat, N.G. Minh Thao, Plant leaf disease identification by deep convolutional autoencoder as a feature extraction approach, in: Proceedings of the 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2020, https://doi.org/10.1109/ecti-con49241.2020.9158218.

[41] A. Beikmohammadi, K. Faez, A. Motallebi, SWP-LeafNET: a novel multistage approach for plant leaf identification based on deep CNN, Expert Syst. Appl. 202 (2022) 117470, https://doi.org/10.1016/j.eswa.2022.117470. Elsevier BV.

[42] M. Li, G. Zhou, A. Chen, L. Li, Y. Hu, Identification of tomato leaf diseases based on LMBRNet, Eng. Appl. Artif. Intell. 123 (2023) 106195, https://doi.org/10.1016/j.engappai.2023.106195. Elsevier BV.

[43] S. Hasan, S. Jahan, M.I. Islam, Disease detection of apple leaf with combination of color segmentation and modified DWT, J. King Saud Univ. Comput. Inform. Sci. 34 (9) (2022) 7212–7224, https://doi.org/10.1016/j.jksuci.2022.07.004. Elsevier BV.

[44] G. Xu, F. Zhang, S.G. Shah, Y. Ye, H. Mao, Use of leaf color images to identify nitrogen and potassium deficient tomatoes, Pattern Recognit. Lett. 32 (11) (2011) 1584–1590, https://doi.org/10.1016/j.patrec.2011.04.020. Elsevier BV.

[45] A. Abbas, Z. Zhang, H. Zheng, M.M. Alami, A.F. Alrefaei, Q. Abbas, S.A.H. Naqvi, M.J. Rao, W.F.A. Mosa, Q. Abbas, A. Hussain, M.Z. Hassan, L. Zhou, Drones in plant disease assessment, efficient monitoring, and detection: a way forward to smart agriculture, Agronomy 13 (6) (2023) 1524, https://doi.org/10.3390/agronomy13061524. MDPI AG.

[46] R.S. Krishnan, E.G. Julie, Computer aided detection of leaf disease in agriculture using convolution neural network based squeeze and excitation network, Automatika 64 (4) (2023) 1038–1053, https://doi.org/10.1080/00051144.2023.2241792. Informa UK Limited.

[47] W. Liang, K.R. Kirk, J.K. Greene, Estimation of soybean leaf area, edge, and defoliation using color image analysis, Comput. Electron. Agric. 150 (2018) 41–51, https://doi.org/10.1016/j.compag.2018.03.021. Elsevier BV.

[48] D. Mohammadzamani, S.M. Javidan, M. Zand, M. Rasouli, Detection of Cucumber fruit on plant image using artificial neural network, J. Agric. Mach. 13 (1) (2023) 27–39, https://doi.org/10.22067/jam.2022.73827.1077.

[49] N. Raj, S. Perumal, S. Singla, G.K. Sharma, S. Qamar, A.P. Chakkaravarthy, Computer aided agriculture development for crop disease detection by segmentation and classification using deep learning architectures, Comput. Electr. Eng. 103 (2022) 108357, https://doi.org/10.1016/j.compeleceng.2022.108357.

[50] M. Ashfaq, N. Minallah, Z. Ullah, A.M. Ahmad, A. Saeed, A. Hafeez, Performance analysis of low-level and high-level intuitive features for melanoma detection, Electronics 8 (6) (2019) 672, https://doi.org/10.3390/electronics8060672.

[51] G.K.V.L. Udayananda, C. Shyalika, P.P.N.V. Kumara, Rice plant disease diagnosing using machine learning techniques: a comprehensive review, SN Appl. Sci. 4 (11) (2022), https://doi.org/10.1007/s42452-022-05194-7. Springer Science and Business Media LLC.
[52] S.S. Harakannanavar, J.M. Rudagi, V.I. Puranikmath, A. Siddiqua, R. Pramodhini, Plant leaf disease detection using computer vision and machine learning algorithms, Glob. Transit. Proc. 3 (1) (2022) 305–310, https://doi.org/10.1016/j.gltp.2022.03.016. Elsevier BV.
[53] J. Dong, J. Lee, A. Fuentes, M. Xu, S. Yoon, M.H. Lee, D.S. Park, Data-centric annotation analysis for plant disease detection: strategy, consistency, and performance, Front. Plant Sci. 13 (2022), https://doi.org/10.3389/fpls.2022.1037655. Frontiers Media SA.
[54] J.F. Restrepo-Arias, J.W. Branch-Bedoya, G. Awad, Plant disease detection strategy based on image texture and bayesian optimization with small neural networks, Agriculture 12 (11) (2022) 1964, https://doi.org/10.3390/agriculture12111964. MDPI AG.
[55] H. Yu, J. Song, C. Chen, A.A. Heidari, J. Liu, H. Chen, A. Zaguia, M. Mafarja, Image segmentation of leaf spot diseases on maize using multi-stage Cauchy-enabled grey wolf algorithm, Eng. Appl. Artif. Intell. 109 (2022) 104653, https://doi.org/10.1016/j.engappai.2021.104653. Elsevier BV.
[56] M. Syifa, S.J. Park, C.W. Lee, Detection of the pine wilt disease tree candidates for drone remote sensing using artificial intelligence techniques, Engineering 6 (8) (2020) 919–926, https://doi.org/10.1016/j.eng.2020.07.001. Elsevier BV.
[57] C. Sarkar, D. Gupta, U. Gupta, B.B. Hazarika, Leaf disease detection using machine learning and deep learning: review and challenges, Appl. Soft Comput. 145 (2023) 110534, https://doi.org/10.1016/j.asoc.2023.110534. Elsevier BV.
[58] D. Zhang, M.M. Islam, G. Lu, A review on automatic image annotation techniques, Pattern Recognit. 45 (1) (2012) 346–362, https://doi.org/10.1016/j.patcog.2011.05.013. Elsevier BV.
[59] R.M. Haralick, K. Shanmugam, I. Dinstein, On some quickly computable features for texture, in: Proceedings of the Symposium of Computer Image Processing and Recognition, University of Missouri, Columbia 2, 1972, p. 12. -2.
[60] P. Bocca, A. Orellana, C. Soria, R. Carelli, On field disease detection in olive tree with vision systems, Array 18 (2023) 100286, https://doi.org/10.1016/j.array.2023.100286. Elsevier BV.
[61] N. Petrellis, C. Antonopoulos, G. Keramidas, N. Voros, Mobile plant disease classifier, trained with a small number of images by the end user, Agronomy 12 (8) (2022) 1732, https://doi.org/10.3390/agronomy12081732. MDPI AG.
[62] M. Keivani, J. Mazloum, E. Sedaghatfar, M. Tavakoli, Automated analysis of leaf shape, texture, and color features for plant classification, Trait. Signal 37 (1) (2020) 17–28, https://doi.org/10.18280/ts.370103. International Information and Engineering Technology Association.
[63] F. Mirjalili, J.Y. Hardeberg, On the quantification of visual texture complexity, J. Imaging 8 (9) (2022) 248, https://doi.org/10.3390/jimaging8090248. MDPI AG.
[64] E. Lhermitte, M. Hilal, R. Furlong, V. O'Brien, A. Humeau-Heurtier, Deep learning and entropy-based texture features for color image classification, Entropy 24 (11) (2022) 1577, https://doi.org/10.3390/e24111577. MDPI AG.
[65] R. Khakrangin, D. MohamadZamani, S.M. Javidan, Recognition of Fill and Empty Walnuts Using Acoustic Analysis and Fuzzy Logic, J. Nuts 12 (1) (2021), https://doi.org/10.22034/jon.2021.1918546.1103Amsini.
[66] C.H. Bock, K.S. Chiang, E.M. Del Ponte, Plant disease severity estimated visually: a century of research, best practices, and opportunities for improving methods and practices to maximize accuracy, Trop. Plant Pathol. 47 (1) (2021) 25–42, https://doi.org/10.1007/s40858-021-00439-z. Springer Science and Business Media LLC.
[67] D. Surya Prabha, J. Satheesh Kumar, Assessment of banana fruit maturity by image processing technique, J. Food Sci.Technol. 52 (3) (2013) 1316–1327, https://doi.org/10.1007/s13197-013-1188-3. Springer Science and Business Media LLC.
[68] T. Guo, Extreme precipitation strongly impacts the interaction of skewness and kurtosis of annual precipitation distribution on the Qinghai–Tibetan Plateau, Atmosphere 13 (11) (2022) 1857, https://doi.org/10.3390/atmos13111857. MDPI AG.
[69] J. Chen, D. Zhang, Y.A. Nanehkaran, D. Li, Detection of rice plant diseases based on deep transfer learning, J. Sci. Food Agric. 100 (7) (2020) 3246–3256, https://doi.org/10.1002/jsfa.10365.
[70] H. Wu, L. Fang, Q. Yu, J. Yuan, C. Yang, Plant leaf identification based on shape and convolutional features, Expert Syst. Appl. 219 (2023) 119626, https://doi.org/10.1016/j.eswa.2023.119626. Elsevier BV.
[71] S. Kaur, S. Pandey, S. Goel, Semi-automatic leaf disease detection and classification system for soybean culture, IET Image Process. 12 (6) (2018) 1038–1048, https://doi.org/10.1049/iet-ipr.2017.0822.
[72] M. Maray, A.A. Albraikan, S.S. Alotaibi, R. Alabdan, M.A. Duhayyim, W.K. Al-Azzawi, A. alkhayyat, Artificial intelligence-enabled coconut tree disease detection and classification model for smart agriculture, Comput. Electr. Eng. 104 (2022) 108399, https://doi.org/10.1016/j.compeleceng.2022.108399. Elsevier BV.
[73] V. Sathiya, M.S. Josephine, V. Jeyabalaraja, An automatic classification and early disease detection technique for herbs plant, Comput. Electr. Eng. 100 (2022) 108026, https://doi.org/10.1016/j.compeleceng.2022.108026. Elsevier BV.
[74] T. Hayıt, H. Erbay, F. Varçın, F. Hayıt, N. Akci, The classification of wheat yellow rust disease based on a combination of textural and deep features, Multimed. Tools Appl. (2023), https://doi.org/10.1007/s11042-023-15199-y. Springer Science and Business Media LLC.
[75] S. Haug, A. Michaels, P. Biber, J. Ostermann, Plant classification system for crop /weed discrimination without segmentation, in: Proceedings of the IEEE Winter Conference on Applications of Computer Vision, 2014, https://doi.org/10.1109/wacv.2014.6835733.
[76] A. Bakhshipour, A. Jafari, Evaluation of support vector machine and artificial neural networks in weed detection using shape features, Comput. Electron. Agric. 145 (2018) 153–160, https://doi.org/10.1016/j.compag.2017.12.032.
[77] C. Xia, J.M. Lee, Y. Li, Y.H. Song, B.K. Chung, T.S. Chon, Plant leaf detection using modified active shape models, Biosyst. Eng. 116 (1) (2013) 23–35, https://doi.org/10.1016/j.biosystemseng.2013.06.003. Elsevier BV.
[78] P. Siricharoen, B. Scotney, P. Morrow, G. Parr, Texture and shape attribute selection for plant disease monitoring in a mobile cloud-based environment, in: Proceedings of the 2016 IEEE International Conference on Image Processing (ICIP), IEEE, 2016, https://doi.org/10.1109/icip.2016.7532405, 2016 IEEE International Conference on Image Processing (ICIP).
[79] S.M. Javidan, Y. Ampatzidis, K.A. Vakilian, D. Mohammadzamani, A novel approach for automated strawberry fruit varieties classification using image processing and machine learning, in: Proceedings of the 2024 10th International Conference on Artificial Intelligence and Robotics (QICAR), IEEE, 2024, https://doi.org/10.1109/qicar61538.2024.10496652.
[80] J. Kotwal, D.R. Kashyap, D.S. Pathan, Agricultural plant diseases identification: from traditional approach to deep learning, Mater. Today Proc. 80 (2023) 344–356, https://doi.org/10.1016/j.matpr.2023.02.370. Elsevier BV.
[81] A. Sinha, R.S. Shekhawat, Review of image processing approaches for detecting plant diseases, IET Image Process. 14 (8) (2020) 1427–1439, https://doi.org/10.1049/iet-ipr.2018.6210. Institution of Engineering and Technology (IET).
[82] M.S.P. Ngongoma, M. Kabeya, K. Moloi, A Review of plant disease detection systems for farming applications, Appl. Sci. 13 (10) (2023) 5982, https://doi.org/10.3390/app13105982. MDPI AG.
[83] J. Kainat, S. Sajid Ullah, F.S. Alharithi, R. Alroobaea, S. Hussain, S. Nazir, Blended features classification of leaf-based cucumber disease using image processing techniques, S. Lakshmanan (Ed.), Complexity 2021 (2021) 1–12, https://doi.org/10.1155/2021/9736179. Hindawi Limited.
[84] X. Sun, G. Li, P. Qu, X. Xie, X. Pan, W. Zhang, Research on plant disease identification based on CNN, Cogn. Robot. 2 (2022) 155–163, https://doi.org/10.1016/j.cogr.2022.07.001. Elsevier BV.
[85] Y. Alqahtani, M. Nawaz, T. Nazir, A. Javed, F. Jeribi, A. Tahir, An improved deep learning approach for localization and recognition of plant leaf diseases, Expert Syst. Appl. 230 (2023) 120717, https://doi.org/10.1016/j.eswa.2023.120717. Elsevier BV.
[86] Hughes, David. P., & Salathe, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics (Version 2). arXiv. https://doi.org/10.48550/ARXIV.1511.08060.
[87] D. Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat, N. Batra, PlantDoc: a dataset for visual plant disease detection, in: Proceedings of the 7th ACM IKDD CoDS and 25th COMAD, 2020, pp. 249–253, https://doi.org/10.1145/3371158.3371196.
[88] X. Liu, W. Min, S. Mei, L. Wang, S. Jiang, Plant disease recognition: a large-scale benchmark dataset and a visual region and loss reweighting approach, IEEE Trans. Image Process. 30 (2021) 2003–2015, https://doi.org/10.1109/TIP.2021.3049334.
[89] J.G.A. Barbedo, Plant disease identification from individual lesions and spots using deep learning, Biosyst. Eng. 180 (2019) 96–107, https://doi.org/10.1016/j.biosystemseng.2019.02.002. Elsevier BV.
[90] S.S. Chouhan, U.P. Singh, A. Kaul, S. Jain, A data repository of leaf images: practice towards plant conservation with plant pathology, in: Proceedings of the 2019 4th International Conference on Information Systems and Computer Networks (ISCON), IEEE, 2019, pp. 700–707, https://doi.org/10.1109/ISCON47742.2019.9036158.
[91] R. Thapa, K. Zhang, N. Snavely, S. Belongie, A. Khan, The plant pathology challenge 2020 data set to classify foliar disease of apples, Appl. Plant Sci. 8 (9) (2020) e11390, https://doi.org/10.1002/aps3.11390.
[92] A. Ramcharan, K. Baranowski, P. McCloskey, B. Ahmed, J. Legg, D.P. Hughes, Deep learning for image-based cassava disease detection, Front. Plant Sci. 8 (2017) 1852, https://doi.org/10.3389/fpls.2017.01852.
[93] H.T. Rauf, B.A. Saleem, M.I.U. Lali, M.A. Khan, M. Sharif, S.A.C. Bukhari, A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning, Data Br. 26 (2019) 104340, https://doi.org/10.1016/j.dib.2019.104340.
[94] J.G. Esgario, R.A. Krohling, J.A. Ventura, Deep learning for classification and severity estimation of coffee leaf biotic stress, Comput. Electron. Agric. 169 (2020) 105162, https://doi.org/10.1016/j.compag.2019.105162.
[95] J. Parraga-Alava, K. Cusme, A. Loor, E. Santander, RoCoLe: a robusta coffee leaf images dataset for evaluation of machine learning based methods in plant diseases recognition, Data Br. 25 (2019) 104414, https://doi.org/10.1016/j.dib.2019.104414.
[96] J. Jepkoech, D.M. Mugo, B.K. Kenduiywo, E.C. Too, Arabica coffee leaf images dataset for coffee leaf disease detection and classification, Data Br. 36 (2021) 107142, https://doi.org/10.1016/j.dib.2021.107142.
[97] F. Abdelghafour, B. Keresztes, A. Deshayes, C. Germain, J.P. Da Costa, An annotated image dataset of downy mildew symptoms on Merlot grape variety, Data Br. 37 (2021) 107250, https://doi.org/10.1016/j.dib.2021.107250.
[98] G. Fenu, F.M. Malloci, DiaMOS plant: a dataset for diagnosis and monitoring plant disease, Agronomy 11 (11) (2021) 2107, https://doi.org/10.3390/agronomy11112107.

[99] P.K. Sethy, N.K. Barpanda, A.K. Rath, S.K. Behera, Deep feature based rice leaf disease identification using support vector machine, Comput. Electron. Agric. 175 (2020) 105527, https://doi.org/10.1016/j.compag.2020.105527.
[100] C.R. Rahman, P.S. Arko, M.E. Ali, M.A.I. Khan, S.H. Apon, F. Nowrin, A. Wasif, Identification and recognition of rice diseases and pests using convolutional neural networks, Biosyst. Eng. 194 (2020) 112–120, https://doi.org/10.1016/j.biosystemseng.2020.03.020.
[101] L. Goyal, C.M. Sharma, A. Singh, P.K. Singh, Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture, Inform. Med. Unlocked 25 (2021) 100642, https://doi.org/10.1016/j.imu.2021.100642.
[102] T. Wiesner-Hanks, E.L. Stewart, N. Kaczmar, C. DeChant, H. Wu, R.J. Nelson, M. A. Gore, Image set for deep learning: field images of maize annotated with disease symptoms, BMC Res. Notes 11 (1) (2018) 1–3, https://doi.org/10.1186/s13104-018-3548-6.
[103] X. Qian, C. Zhang, L. Chen, K. Li, Deep learning-based identification of maize leaf diseases is improved by an attention mechanism: self-Attention, Front. Plant Sci. 13 (2022) 864486, https://doi.org/10.3389/fpls.2022.864486.
[104] P. Gui, W. Dang, F. Zhu, Q. Zhao, Towards automatic field plant disease recognition, Comput. Electron. Agric. 191 (2021) 106523, https://doi.org/10.1016/j.compag.2021.106523.
[105] S. Talasila, K. Rawal, G. Sethi, M.S.S. Sanjay, Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms, Data Br. 45 (2022) 108725, https://doi.org/10.1016/j.dib.2022.108725.
[106] S. Phadikar, J. Sil, Rice disease identification using pattern recognition techniques, in: Proceedings of the 11th International Conference on Computer and Information Technology, ICCIT 2008, ICCIT, 2008, pp. 420–423, https://doi.org/10.1109/ICCITECHN.2008.4803079.
[107] Q. Yao, Z. Guan, Y. Zhou, J. Tang, Y. Hu, B. Yang, Application of support vector machine for detecting rice diseases using shape and color texture features, in: Proceedings of the 2009 International Conference on Engineering Computation, ICEC 2009, 2009, pp. 79–83, https://doi.org/10.1109/ICEC.2009.73.
[108] Y. Tian, C. Zhao, S. Lu, Multiple classifier combination for recognition of wheat leaf diseases, Intell. Autom. Soft Comput. (2013) 37–41, https://doi.org/10.1080/10798587.2011.10643166. October 2014.
[109] S. Zhang, X. Wu, Z. You, L. Zhang, Leaf image based cucumber disease recognition using sparse representation classification, in: Computers and Electronics in Agriculture 134, Elsevier BV, 2017, pp. 135–141. https://doi.org/10.1016/j.compag.2017.01.014.
[110] J.W. Orillo, J. Dela Cruz, L. Agapito, P.J. Satimbre, I. Valenzuela, Identification of diseases in rice plant (*Oryza sativa*) using back propagation artificial neural network, in: Proceedings of the 2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2014, pp. 1–6, https://doi.org/10.1109/HNICEM.2014.7016248.
[111] P. Revathi, M. Hemalatha, Cotton leaf spot diseases detection utilizing feature selection with skew divergence method, Int. J. Eng. Sci. Technol. 3 (1) (2014) 22–30.
[112] J. Tao, A particle Swarm optimization algorithm for neural networks in recognition of maize leaf diseases, IFIP Adv. Inf. Commun. Technol. (2015) 495–505, https://doi.org/10.1007/978-3-319-19620-6_56.
[113] J.D. Pujari, R. Yakkundimath, A.S. Byadgi, SVM and ANN based classification of plant diseases using feature reduction technique, Int. J. Interact. Multimed. Artif. Intell. 3 (7) (2016) 6, https://doi.org/10.9781/ijimai.2016.371.
[114] B.J. Samajpati, S.D. Degadwala, Hybrid approach for apple fruit diseases detection and classification using random forest classifier, in: Proceedings of the International Conference on Communication and Signal Processing 2013, 2016, pp. 1015–1019.
[115] H. Waghmare, R. Kokare, Y. Dandawate, Detection and classification of diseases of grape plant using opposite colour local binary pattern feature and machine learning for automated decision support system, in: Proceedings of the 2016 3rd International Conference on Signal Processing and Integrated Networks (SPIN), 2016, pp. 513–518.
[116] H. Sabrol, S. Kumar, Fuzzy and neural network based tomato plant disease classification using natural outdoor images, Indian J. Sci. Technol. 9 (November) (2016) 1–8, https://doi.org/10.17485/ijst/2016/v9i44/92825.
[117] S. Gharge, P. Singh, Image Processing for Soybean Disease Classification and Severity Estimation, in: Emerging Research in Computing, Information, Communication and Applications, Springer, India, 2015, pp. 493–500. https://doi.org/10.1007/978-81-322-2553-9_44.
[118] L. Hallau, M. Neumann, B. Klatt, Automated identification of sugar beet diseases using smartphones, Plant Pathol. 67 (2) (2017) 399–410, https://doi.org/10.1111/ijlh.12426.
[119] N. Sengar, M. Kishore, C.M. Travieso, Computer vision based technique for identification and quantification of powdery mildew disease in cherry leaves, Computing 100 (11) (2018) 1189–1201, https://doi.org/10.1007/s00607-018-0638-1.
[120] A.S. Deshapande, S.G. Giraddi, K.G. Karibasappa, S.D. Desai, Fungal Disease Detection in Maize Leaves Using Haar wavelet Features, Springer Singapore, 2019, https://doi.org/10.1007/978-981-13-1742-2.
[121] A. Rao, S.B. Kulkarni, A hybrid approach for plant leaf disease detection and classification using digital image processing methods, Int. J. Electr. Eng. Educ. (2020), https://doi.org/10.1177/0020720920953126, 002072092095312.
[122] N. Kaur, V. Devendran, Ensemble classification and feature extraction based plant leaf disease recognition, in: Proceedings of the 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 2021, https://doi.org/10.1109/icrito51393.2021.9596456.
[123] J.G.A. Barbedo, A review on the main challenges in automatic plant disease identification based on visible range images, Biosyst. Eng. 144 (2016) 52–60, https://doi.org/10.1016/j.biosystemseng.2016.01.017. Elsevier BV.
[124] S.M. Javidan, A. Banakar, K. Asefpour Vakilian, Y. Ampatzidis, K. Rahnama, Diagnosing the spores of tomato fungal diseases using microscopic image processing and machine learning, Multimed. Tools Appl. (2024), https://doi.org/10.1007/s11042-024-18214-y. Springer Science and Business Media LLC.
[125] J. Ding, X. Li, An approach for validating quality of datasets for machine learning, in: Proceedings of the 2018 IEEE International Conference on Big Data (Big Data), IEEE, 2018, pp. 2795–2803, https://doi.org/10.1109/BigData.2018.8622640.
[126] P. Dhiman, V. Kukreja, P. Manoharan, A. Kaur, M.M. Kamruzzaman, I.B. Dhaou, C. Iwendi, A novel deep learning model for detection of severity level of the disease in citrus fruits, Electronics 11 (3) (2022) 495, https://doi.org/10.3390/electronics11030495.
[127] A.K. Mahlein, Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping, Plant Dis. 100 (2) (2016) 241–251, https://doi.org/10.1094/PDIS-03-15-0340-FE.
[128] J. Abdulridha, Y. Ampatzidis, J. Qureshi, P. Roberts, Identification and classification of downy mildew development stages in watermelon utilizing aerial and ground remote sensing and machine learning, Front. Plant Sci. 13 (2022) 791018, https://doi.org/10.3389/fpls.2022.791018.
[129] V.G. da Cunha, J. Hariharan, Y. Ampatzidis, P. Roberts, Early detection of tomato bacterial spot disease in transplant tomato seedlings utilizing remote sensing and artificial intelligence, Biosyst. Eng. 234 (2023) 172–186, https://doi.org/10.1016/j.biosystemseng.2023.09.002.
[130] L. Li, S. Zhang, B. Wang, Plant disease detection and classification by deep learning—A review, IEEE Access 9 (2021) 56683–56698, https://doi.org/10.1109/ACCESS.2021.3069646.
[131] S. Thomas, M.T. Kuska, D. Bohnenkamp, A. Brugger, E. Alisaac, M. Wahabzada, A.K. Mahlein, Benefits of hyperspectral imaging for plant disease detection and plant protection: a technical perspective, J. Plant Dis. Prot. 125 (2018) 5–20, https://doi.org/10.1007/s41348-017-0124-6.