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Cotton Leaf Disease Detection Using Image Processing

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Abstract

As a cash crop, cotton is the most important in India. Other than "White Gold," it's referred to among cash crops in the United States as "The King of Fibers". Cotton leaf diseases include Alternaria leaf spot, Cercospora leaf spot, Bacterial Blight, and Red spot. Cotton leaf disease detection and categorization are discussed in this article. Human eyes have difficulty identifying the specific kind of leaf disease that affects a plant's leaf. For a more accurate diagnosis of cotton leaf diseases, image processing and machine learning technologies may be helpful. Using a digital camera, I took images of a cotton field for this assignment. In the preprocessing stage, the backdrop is removed from the image using a background removal technique. Image segmentation is performed using the otsu thresholding method on images that have been cleaned of their backgrounds. Different segmented photos will be used to extract attributes such as color, form, and texture from the photographs. Classifiers will use them in the future to classify data.

Keywords: Leaf diseases; Image pre-processing; Image segmentation; Otsu’s thresholding; Support Vector Machine (SVM).

1. Introduction

Agriculture production is crucial to India's economy. More than 70% of rural households are dependent on agriculture. The agricultural sector employs more than 60% of the country's workforce and contributes to 17% of the country's GDP[1]. Early diagnosis of plant diseases is therefore vital in agriculture. From rice and wheat to cotton, India's agriculture produces a vast range of crops. Indian farmers also cultivate sugarcane, oilseeds, potatoes, and non-food commodities like coffee, tea, cotton, and rubber. Foliage and roots are essential to all these crops' survival. There are a variety of factors that cause various diseases in plant leaves, resulting in ruined harvests and, as a result, a negative impact on the country's economy. These large losses may be prevented by detecting plant illnesses early on. Detection of plant diseases accurately is necessary to strengthen our country's agriculture and economy. A plant's leaves may be killed by a variety of diseases. Farmers are having greater difficulty recognising these illnesses, and owing to a lack of information about these diseases, they are unable to take precautions on those plants. One of the areas used to identify plant illnesses is biomedical. Image processing techniques are an appropriate, efficient, and trustworthy area for disease diagnosis with the aid of plant leaf pictures in today's world. Farmers need quick and effective methods for detecting all kinds of plant diseases in order to save time. These systems may help to minimise pesticide usage and effort. Scientists have suggested several methods for measuring agricultural output using laboratory and technologies for effective detection of plant leaf diseases. There are numerous plant diseases and disease detection methods utilized by researchers, and the paper we've supplied is a survey of such methods.

2. Cotton Leaf Diseases

2.1. Bacterial Blight

This illness is caused by the bacteria "Xanthomonas Campestris pv. Malvacearum" [4]. Blight caused by bacteria manifests as an irregular, water-soaked area of 1 to 5 mm in diameter on leaves, bordered by an orange-brown color. Water-soaked parts appear first, then darken to black in color [6] [7, 8, 9]. Petioles and stems can be infected by spots on lesioned leaves that move to main veins of the leaf, causing premature leaf fall [12]. A leaf afflicted with Bacterial Blight is shown in Figure 1(a).

2.2. Alternaria

There are two common fungi that cause it: Alterneta and Alternaria macrospora. Symptoms of the disease are similar to those of bacterial leaf blight [11]. From 1-10mm in diameter at first develop little round spots that range in hue from brown to gray-brown. They later become dried out and lifeless with grey centers that break and fall off [11]. Old patches may sometimes meld together to form uneven dead zones. Alternaria infected leaf (Fig. 1(b)).

2.3. Cerespora

Cercospora Gossypina is the cause of Cercospora [12]. An infected leaf is characterized by two-centimeter-wide crimson spots on the leaves. Irregular-shaped dots with yellow-purple or black-purple borders and white centers [11]. Because lesion area is constrained by tiny leaf veins, the rakish leaf spot appears. This ailment affects the more mature leaves of developing plants. A Cerespora-infected leaf is shown in Figure 1(c).

2.4. Grey Mildew

Mycosphaerella areola and Ramularia areola Atk. cause this fungus disease [11]. White patches of 3-4 mm in size appear on the leaves in the early stages of infection [11]. Sick leaves have uneven, angular, and pale translucent dots with diameters of about 1mm [8]. The diseased areas on the plant's leaves are a light to yellowish green color. The tiny spots fuse together to create larger spots as disease infection progresses, and the leaf tissues become reddish brown, with white frosty growth appearing on the bottom surface but not always on the top surface [8]. A grey Mildew-infected leaf is shown in Figure 1(d).

2.5. Fusarium Wilt

Fusarium oxysporum is the most common cause [12]. Cotton seedlings can be infected by the organism, but the illness usually appears in older plants [11]. Early symptoms include deeper green and reduced growth [4]. They are yellowing and the foliage is dwindling. They begin to show up on lower leaves just after the initial bloom, and as they crawl in, the leaf edges shrink, turning yellow at first, then brown. A Fusarium Wilt-infected leaf is shown in Figure 1(e).

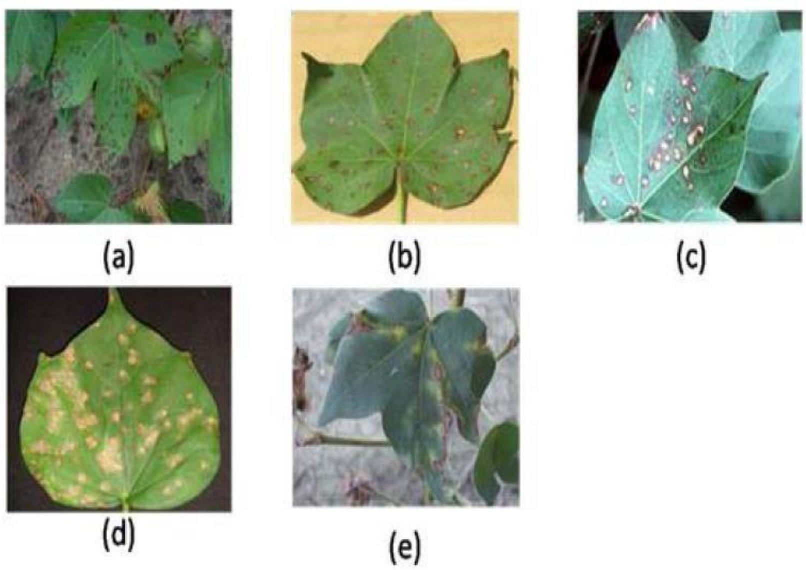

Fig 1. A sick leaf as an example (a) Leaf afflicted with Bacterial Blight[4] B) Alternaria infested leaf. (c)Leaf infested with Cerespora Grey [12] (d) Leaf infested with mildew [12] e) A leaf affected with Fusarium Wilt [2].

3. Literature Review

One of the most serious diseases of grapes is Downy Mildew and Powdery Mildew, which were discovered by Sanjeev Sannakki et al [7]. In addition, the images have been enlarged to 300x300px and the green pixels have been removed from them. Using Anisotropic Diffusion, the pictures are then enhanced five times in order to maintain the information about the damaged area. In addition to the K-mean clustering method, there is also the Grey Level Co-occurrence Matrix. When it comes to classification, a backpropagation neural network is used.

It was developed by Asma Akhtar et al. Otsu's approach is used to threshold data as part of the segmentation process. DWT and DCT features are retrieved from eleven Haralick texture properties. Support Vector Machines with DCT and DWT as classifiers produced a maximum accuracy of 94.45 percent.

An image recognition system was developed by G. Anthonys and N. Wickramarachchi [9] to identify illnesses in Sri Lankan rice fields. When identifying the image's edges, the Sobel approach is employed. The illness spot's texture, shape, and colour are retrieved and utilised to classify it. Rice blast was 80 percent accurate, Rice sheath blight was 60 percent accurate, and Brown spot was 85 percent accurate.

To identify Ramularia disease in cotton crops, as well as the Bacterial Blight and Ascochyta Blight that affect cotton crops in general, Alexandre A. They came up with a new way. To split a picture, color channels such as RGB, I3a, and I3b are employed. For each colour channel, the DWT method is applied, and the wavelet energy is determined for each sub-band in order to extract information from the image. For categorization, Support Vector Machines are utilized [9].

Mingyu Han and Jie Tian provided an automated system for identifying and classifying apple-leaf illnesses such as the mosaic virus, leaf spot, and rust. [11] Jie Tian et al. An apple leaf's color and texture are restored. In comparison to the PCA and GA-SVM model, the KPCA and GA-SVM model was found to be more efficient at classifying data than the former.

4. General Approach For Detection And Classification Of Leaf Diseases

Identifying leaf disease often involves two steps: With the use of machine learning, images may be processed and diseases classified. Photo acquisition, preprocessing, segmentation, and feature extraction are discussed in this section. Other ways of categorisation are also discussed.

4.1. Image Processing:

Some of the image processing techniques that can be used to identify illnesses include picture capture and pre-processing, image segmentation, and feature extraction.

a) Image Acquisition:

Assembling images from numerous sources is the process of acquiring images. A Canon A460 digital camera [1] was used by practitioners/researchers to capture leaf images, as was a mobile phone [7].

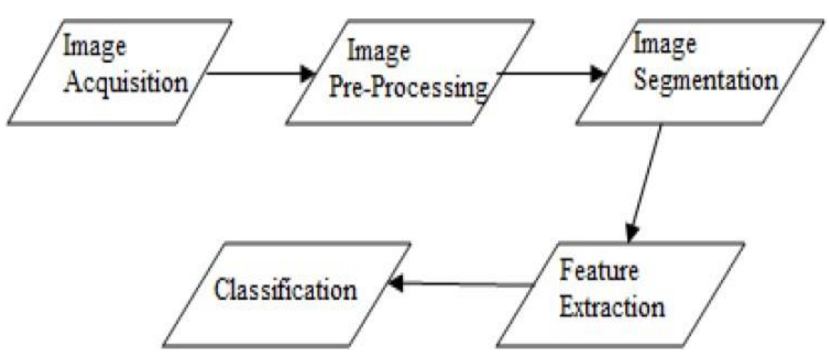

Fig 2. Disease Detection and Classification Methods for Leaves

b) Image Pre-processing:

By reducing unnecessary noise, this improves the image quality. As far as I know, there are very few academics who have worked on removing the image's background and shadow. There are a variety of noises, such as random and salt-and-pepper noise in the images, as an example. These sounds can be removed with the help of mean and median filters. One of the most frequently used picture pre-processing methods is histogram equalisation. The histogram equalisation method is used to boost the image's contrast. It's as simple as taking a noisy image and turning it into something that's clean or original. Image restoration filters include the Weiner, Wavelet, and Inverse filters, among others.

c) Image Segmentation:

This approach separates an image into several fragments. It may also be used to:

- Identify individual items inside an image;
- Locate an area of linked pixels with comparable characteristics;
- Locate the region's borders; and
- Remove undesirable regions.

Beyond K-means clustering and Otsu thresholding, there is also Canny and Sobel segmentation.

i.K-means Clustering: It is possible to segment photos using K-means clustering because it is the simplest unsupervised learning method available. "A cluster" is a set of things with similar attributes that are "dissimilar" from those in other clusters [6]. When using Kmeans clustering, you first select k initial centroids, the next step is to create k clusters by assigning all data points to the nearest centroid, and then recalculate each cluster's centroids. The flaw in the k-means method is that it may result in incorrect clustering with just a few samples of picture data [4]. K-means clustering with k=3 on a leaf disease image shows the foreground, background, and diseased portion of an image.

ii.In the Otsu thresholding technique, the object data is computed by iterating over all possible threshold values. Foreground or background pixels. Using the Otsu threshold method, you may find out what value gives you the least spread between foreground and background spreads. A grey diseased leaf image is subjected to Otsu thresholding which uses a single threshold value to distinguish foreground and background pixels, resulting in diseased section segmentation.

iii.Edge detection methods Canny and Sobel: Many edge detection approaches have been developed, including Canny and Sobel. Images are segmented using the Canny algorithm, which detects edges. This device is also known as the Ideal edge detector (IED). This technique detects edges using a sobel approximation to derivatives. When Canny and Sobel segmentation is performed on a leaf image, the picture's edges are created.

d) Feature Extraction:

As a way to reduce the image's dimensionality, feature extraction can be used to extract the image's most informative parts. Color, shape, and texture are the three most common kinds of characteristics. TABLE I shows the various characteristics that may be retrieved from a picture.

4.2. Machine Learning:

There are now algorithms that learn from input data, provide predictions based on that data, and are being tested. For identifying or categorising illnesses, machine learning mostly uses classification methods. In terms of machine learning tasks, there are a variety of classification approaches available: The three types of learning are supervised, unsupervised, and reinforced.

a) Support Vector Machine (SVM):

Decision planes are used by the support vector machine to separate data. In SVM, the hyperplane is utilized to categorize data. In both linear and nonlinear ways, SVM can categorize data. Linear classification refers to the ease with which training samples/datasets may be categorised. Without linear classification, it is difficult to separate data from training samples. For binary and multiclass data, SVM can be employed.

b) K-Nearest Neighbor (K-NN):

Objects are classified using the KNN approach using the feature space's closest training samples. Among all machine learning methods, it is the most basic. A majority vote of its neighbours is used to classify an item. It is possible to assign objects to a particular class when k is equal to two, such as 2.1 or 1.9% [19].

c) Neural Network (NN):

When applied to external inputs, the neural network (NN) analyzes data by applying states to the inputs. It is a restriction of NN that the user has no knowledge what is happening in the classifier to categorize the dataset in a backpropagation neural network. In comparison to other types of NN, back propogation networks take longer to train [2].

5. Methodology

While utilizing Support Vector Machines, scientists classified Septoria leaf blight and downy mildew among others. In order to categorize and compare the accuracy of banana and lemon sunburn, frog's eye leaf spot, sunburn disease (fungal), early scorch (bacterial), and early scorch, it was decided to use an MDC with K-Mean SVM (fungal). As part of the segmentation process, a genetic algorithm was used.

It is a species of Phyllanthus. To classify wall leaf health, ANN was used [8] [9]. Images are first acquired from a database (see Figure 3). Using Kmeans clustering to segment the images, the ANN classifier is fed a set of features culled from the clusters. In Bilderfassung, photos from databases are gathered in order to create a single image.

The images were collected from the plant village's data bank. The images include tomato leaf spot, cotton leaf spot, and tomato leaf spot. In order to divide an image into discrete chunks or groups, the k-means clustering approach is used.

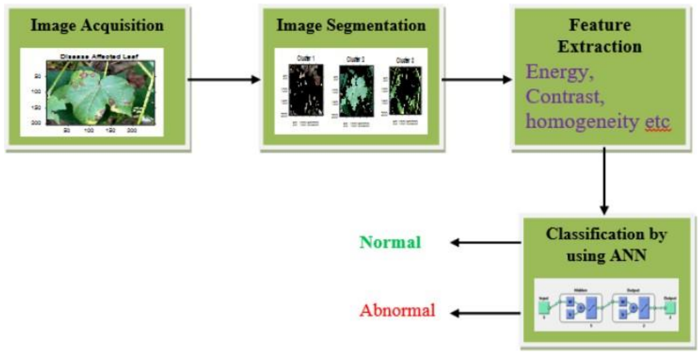

Fig 3. Discovery of disease using the proposed method

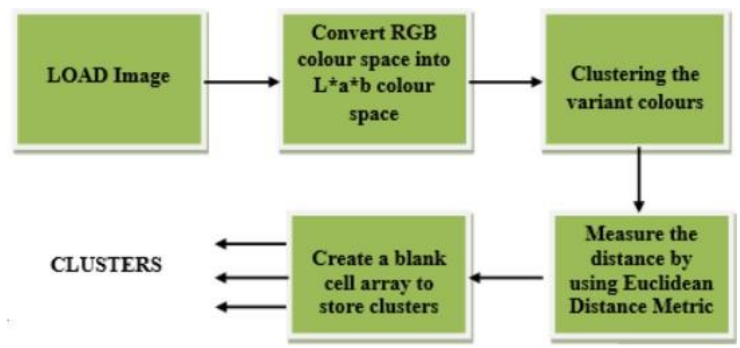

Fig 4. Using K-Means as a clustering method

In order to distinguish between the stained part and the healthy leaf region, K-means clustering is applied. Once you've loaded your database, you'll need MATLAB for the first step, which requires converting the image to L*a*b* color space. There are three different types of chromaticity layers: L* (lightness) and A* and B* (chromaticity). a* and b* layers contain all color data. In the next phase, you'll need to group the different colors. Because the total distances between pixels are reduced by reallocating each one to its closest cluster, the image is divided into three sections. There are different leaf segments in each cluster. Three clusters' index values and K means are utilized to label every pixel in the image. To store the clustering results, you'll have to construct a blank cell array.

Fig 5. Normal and Diseased Cotton Leaf

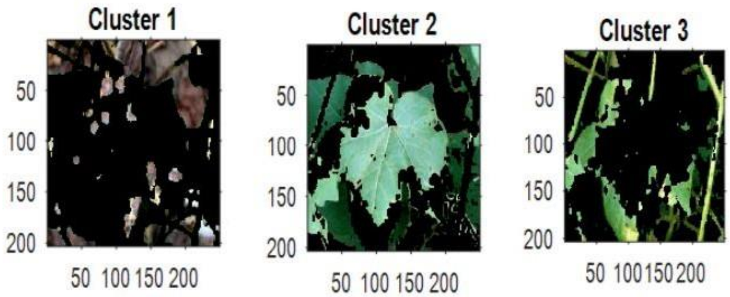

Fig 6. Cotton Leaf Clusters

5.1. Extraction of Feature

Segmented clusters are extracted in four processes, these are:
Stage 1: It is necessary for you to supply the cluster number of a diseased leaf portion in the first step of diagnosis.
Stage 2: If the image is RGB, convert it to grayscale.
Stage 3: During the third stage, a co-occurrence matrix with gray levels will be created (GLCMs).
Stage 4: From GLCM statistics (features) can be derived. There are two types of contrast: contrast and correlation, and energy and homogeneity. They are passed to the classifier for additional processing. The sick leaf cluster is the source of the features. Diagnose and classify leaf diseases with the help of these characteristics.

Table I Highlighted features for clusters 1 and 3

Features	Fig 4: Cluster-1	Fig 7: Cluster-3
Contrast	0.507885746067059	0.213265931372549
Correlation	0.865689782098393	0.782224239224636
Energy	0.582100315095136	0.863527567334379
Homogeneity	0.946855538655952	0.972392714898460
Mean	23.1548459849249	5.63678487141927
Standard Deviation	48.8486649473881	24.3246848498623
Variance	2229.83298033050	550.457989402222

5.2. Classification:

To classify the data in this study, we used the Neural Networks tool. Among the seven retrieved characteristics, the neural network receives the following as inputs: contrast, correlation, energy and homogeneity as well as mean, standard deviation, and variance. Use of back propagation and unifying neural networks was employed to classify the datasets under study. An error histogram and confusion matrix plot are provided after network training.

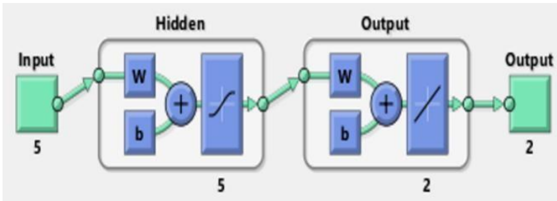

Fig 7. Proposed Classifier

Fig 8. Cotton Leaf Clusters

6. Results And Discussions

To carry out the tests, we use MATLAB. Foliage infected by ALSFD, GMCD, or the Rust Foliar Fungus Disease (RFFD) is the main source of the input (RFFD). We've built three clusters out of the original image. As shown in Figure 5, ALSFD, GMCD and RFFD disorders have been divided into clusters. ALSFD is shown in Figure 9(a), and the illness is identified in Cluster 2. GMCD is shown in Figure 9 (b), and illness is identified in Cluster 2. RFFD is seen in Fig 9 (c), and illness is found in Cluster 2. The following characteristics are extracted for three disorders from cluster 2:

For ANN & SVM, the classification results are shown in the tables 2. ANN classifier considers 3492 samples for three disorders. A total of 1032 samples are accurately identified as ALSFD, 98 samples are classed as GMCD, and 202 samples are labeled as RFFD. ALSFD has a 77.4 percent accuracy rate. A total of 900 samples have been correctly diagnosed, while 59 samples have been misclassified as ALFD and 69 samples have been classified as RFFD. It has an 88 percent accuracy rate. One thousand and twenty-one samples were correctly recognized as having RFFD, sixty-three as having GMCD, and forty-eight as having ALSFD. RFFD has an accuracy rate of 90.1 percent. ANN's algorithms have an average accuracy of 85,1%.

Table- 2: Features Extracted from Diseased Clusters

Features	Alternaria Leaf Spot Fungal Disease (ALSFD)	Grey-Mildew Cotton Disease(GMCD)	Rust Foliar Fungal Disease(RFFD)
Contrast	0.241187825	0.4295461	0.63732097
Correlation	0.898955824	0.8383667	0.8924959
Energy	0.784876	0.7957764	0.4945214
Mean	12.21319	13.564893	2.0560009
Standard Deviation	39.463444	40.286323	62.048908
Entropy	1.2980843	2.3965831	3.0200073
Variance	1428.2129	1481.1106	3535.5449
Kurtosis	15.13307	12.996019	5.3858371

Sample size for SVM classifier is 3490. ALSFD is correctly identified for 1123 samples, while GMCD and RFFD are incorrectly classified for 74 and 135 samples respectively. ALSFD has an accuracy of 84.3 percent. We successfully identified GMCDs in 1012 of the samples. We misidentified ALSFDs in four samples, whereas RFFDs were identified in nine samples. GMCD has an accuracy of 98.7%. While the RFFD classification is correct for 1056 tests, ALSFD and GMCD classifications are incorrect for 32 tests. RFFD has an accuracy of 93.2 percent. In total, 92.06 percent of the predictions are accurate.

Table- 3: Findings from the use of ANN Classifier

ANN Classifier	Alternaria Leaf Spot Fungal Disease (ALSFD)	Grey-Mildew Cotton Disease (GMCD)	Rust Foliar Fungal Disease (RFFD)	Accuracy in %
ALSFD	1032	98	202	77.4%
GMCD	59	900	69	87.8%
RFFD	48	63	1021	90.1%

Table- 4: A SVM Classifier's Classification Results

SVM Classifier	Alternaria Leaf Spot Fungal Disease (ALSFD)	Grey-Mildew Cotton Disease (GMCD)	Rust Foliar Fungal Disease (RFFD)	Accuracy in %
ALSFD	1123	74	135	84.3 %
GMCD	4	1012	9	98.7 %
RFFD	32	45	1056	93.2 %

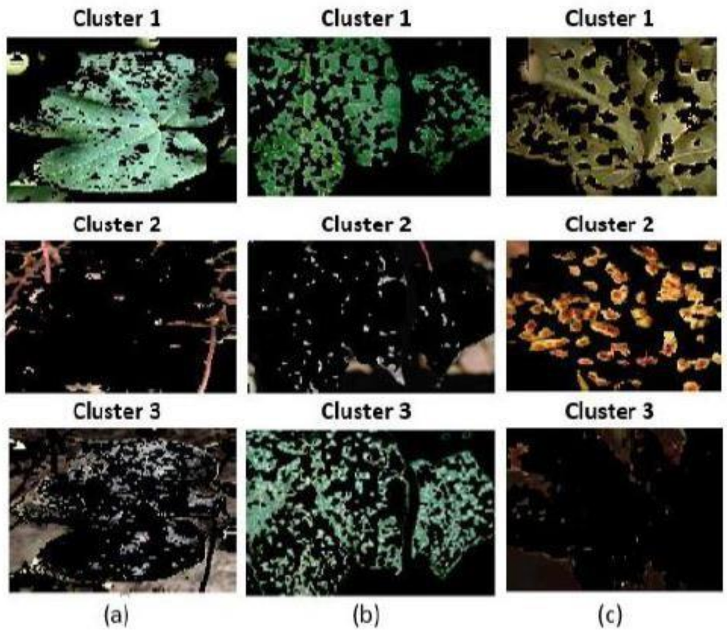

Fig 9. Isolating the three fungal diseases using K-Means Clustering Alternative Leaf Spot Fungal Disease (ALSFD) b. Grey Mildew Cotton Disease (GMCD) c. Rust Foliar Fungal Disease a (RFFD)

7. Conclusions

Automatic disease detection is achieved by means of image processing in this study. Using this method, leaf diseases can be detected quickly. Tests for Alternaria Leaf Spot Fungal Disease, Grey Mildew Cotton Disease, and Rust Foliar Fungal Disease are performed using this approach (RFFD). Using K-means clustering, leaf images may be segmented into clusters and characteristics extracted from the sick cluster. In addition to contrast and correlation, the sick cluster also has energy, mean, standard deviation, entropy, variation, and kurtosis. These collected characteristics are then fed into ANN and SVM classifiers at a later stage. Classification findings show that the SVM classifier is better at identifying illnesses than the ANN classifier when comparing the two. The ANN classifier has an overall accuracy of 85.1 percent, whereas the SVM has an overall accuracy of 92.06 percent.

References

1. Sukhvir Kaur, Shreelekha Pandey, Shivani Goel, Semi-automatic leaf disease detection and classification system for soybean culture, ISSN 1751-9659, IET Image Processing.
2. Davoud Ashourloo, Hossein Aghighi, Ali Akbar Matkan, Mohammad Reza Mobasheri and Amir Moeini Rad, "An Investigation into Machine Learning Regression Techniques for the Leaf Rust Disease Detection Using Hyperspectral Measurement" IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, pp.1-7, May 26, 2016.

3. Youssef Es-saady, Ismail El Massi, Mostafa El Yassa, Driss Mammass and Abdeslam Benazoun, “Automatic recognition of plant leaves diseases based on serial combination of two SVM classifiers” 2nd International Conference on Electrical and Information Technologies (ICEIT), IEEE, 2016.
4. Sonali Dash, K. Chiranjeevi, Dr.U.R. Jena and akula. Trinadh, “Comparative study of image texture classification technique”, International Conference on Electrical, Electronics, Signals, Communication and Optimization IEEE, 2015.
5. P. R. Rothe and R. V. Kshirsagar, “Cotton Leaf Disease Identification using Pattern Recognition Techniques”, International Conference on Pervasive Computing (ICPC) IEEE, pp. 1-6, 2015.
6. Yuanyuan Shao, Guantao Xuan, Yangyan Zhu, Yanling Zhang, Hongxing Peng, Zhongzheng Liu &Jialin Hou,” Research on automatic identification system of tobacco diseases”, vol. 65, no. 4, 252–259, Taylor & Francis, 2017
7. Vijai Singh, A.K. Misra,” Detection of plant leaf diseases using image segmentation and soft computing Techniques, “Information Processing in Agriculture 4 (2017) 41–49, science direct, 2017
8. Shanwen Zhang, Xiaowei Wuc, Zhuhong You, Liqing Zhang,” Leaf image-based cucumber disease recognition using sparse representation classification,” Computers and Electronics in Agriculture 135–141, science direct, 2017
9. Amar Kumar Dey, Manisha Sharma, M.R. Meshram,” Image Processing Based Leaf Rot Disease, Detection of Betel Vine (Piper BetleL.),” Procedia Computer Science 748 – 754, science direct, 2016
10. Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk and Darko Stefanovic,” Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification,” Hindawi Publishing Corporation Computational Intelligence and Neuroscience 2016, Article ID 3289801, 11 pages
11. Manisha Bhange, H.A. Hingoliwala,” Smart Farming: Pomegranate Disease Detection Using Image Processing,” Procedia Computer Science 280 – 288, science direct, 2015
12. Usama Mokhtar, Mona A. S. Ali, Aboul Ella Hassenian, Hesham Hefny,” Tomato leaves diseases detection approach based on support vector machines,” IEEE,2015
13. B. Adsule and J. Bhattad, “Leaves Classification Using SVM And NN For Disease Detection,” International Journal of Innovative Research in Computer and Communication Engineering Vol. 3, Issue 6, Pp. 5488–5495, 2015.
14. S. Vishnu, and A. Ranjithram, “Plant Disease Detection Using Leaf Pattern: A Review” International Journal of Innovative Science, Engineering & Technology, Vol. 2 Issue 6, June 2015.
15. M.Badnakhe, and P. Deshmukh, “Infected Leaf Analysis and Comparison by Otsu Threshold and k-Means Clustering” International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 2 Issue 3, March 2012.

16. D. Naik, and A. Vyavahare, “Disease Detection of Cotton crop using Image Processing Technique: A Survey,” International Journal for Research in Applied Science & Engineering Technology (IJRASET), Volume 3 Issue VI, 2015.
17. P. Warne and S. Ganorkar, “Detection of Diseases on Cotton Leaves Using K-Mean Clustering Method,” International Research Journal of Engineering and Technology (IRJET), Pp. 425–431, 2015.
18. G. Anthonys, N. Wickramarachchi “An image recognition system for crop disease identification of paddy fields in Srilanka”, fourth international conference on Industrial and Information system (ICIIS2009), 2009.
19. Alexandre A. Bernardes, Jonathan G. Rogeri, Roberta B. Oliveira, Norian Marranghello and Aledir S. Pereira, “Identification of Foliar Diseases in Cotton Crop” Springer Link Lecture notes in computational Vision and Biomechanics, Volume 8, pp.67-85,2013.
20. Jie Tian, Qiuxia Hu, Xiaoyi MA, Mingyu Han, “An improved KPCA/GA-SVM classification model for plant leaf disease recognition”, Journal of Computational Information Systems,8:18, pp.7737-7745, 2012.
21. P. R. Rothe, R.V. Kshirsagar (2014), “A study and implementation of Active Contour Model for Feature Extraction: With Diseased Cotton Leaf as Example”, International Journal of Current Engineering and Technology, Vol.4, No.2, pp. 812-816, April-2014.
22. Dheeb Al Bashish, Malik Braik, Sulieman Bani- Ahmad, “Detection and classification of leaf diseases using k-means based segmentation and neural network-based classification”, Information Technology Journal, ISSN 1812-5638, pp.267-275, 2011.
23. Rampf T., A. K. Mahlein, U. Steiner, E. C. Oerke, H.W. Dehne, L. Plumer, “Early detection and classification of plant diseases with Support Vector Machine based on Hyperspectral reflectance”, Computers and Electronics in Agriculture, Volume 74, Issue 1, ISSN 0168-1699, pp. 91-99, October2010.
24. Hillnhuetter C., A. K. Mahlein, “Early detection and localization of sugar beet diseases: new approaches”, Gesunde Pfianzen 60 (4), pp. 143-149, 2008.
25. Prasad Babu, Srinivasa Rao, “Leaves recognition using back-propagation neural network – advice for pest and disease control on crops”, Technical report, department of Computer Science and Systems Engineering, Andhra University, 2010.