Automated Plant Health Assessment Through Detection of Diseased Leaflets

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Abstract The diseases in plants have a great impact upon the yield and quality of agricultural products. The study of such diseases helps to ascertain the reasons of losses affecting the economy of a country's growth to a great scale. This helps to draw the attention toward the different visual patterns on plant leaves against various ailments to monitor the health for a sustainable agriculture output. It is indeed a great challenge to monitor the health and detect diseases on plants manually as it calls for tremendous amount of time, efforts and expertise. The proposed method focuses on techniques of image processing for detecting various diseases on plant leaves. Steps like image acquisition, feature extraction and segmentation help to classify the plants as healthy or unhealthy and alert the farmers also.

Keywords Image processing · Image capture · Segmentation · Feature extraction

1 Introduction

India is an agricultural country where majority of the population income depends mainly upon farming. Agriculture contributes as a large source of employment and source of earnings through exports. The plants, fruits and even medicinal herbs offer serviceable benefactions to the human race. Though farmers have wide range of options of sowing crops, yet a degradable performance is observed when the agricultural output is affected by various diseases [1]. It is estimated that 35–45% of the crop production is lost due to untimely detection of diseases in plant leaflets. Though most of the observations are strictly based upon the physical examination of the leaves, this leads to extensive delay in time and treatment [2]. Such approaches also produced results with low accuracy greatly affecting the economic growth of our country as well as a significant income drop in the income of the farmers [3]. With the advent of the technology and latest techniques, the detection of diseases

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in plants has been automated to improve food security [4]. These solutions have proved to as early and timely detection approaches with better accuracy than manual interventions [5, 6]. This paper helps to introduce techniques of image processing for detection of diseases in different plants.

2 Related Work

In this section, different methods of detection of plant diseases have been discussed using various image processing techniques.

In 2015, Rama Krishnan et al. [2] used the backpropagation algorithm for detecting the diseases in groundnut leaflets. Though colored images gave a higher accuracy, but limited diseases were detected. Padol et al. [4] used K-means clustering approach for detecting diseases in grape leaves in 2016. Though Support Vector Machine (SVM) was also used to classify the unhealthy leaves, the scope of accuracy improvement was also limited. Shaikh et al. [5] used Bi-level Thresholding technique with Gray-level Co-occurrence Matrix (GLCM) in Hidden Markov Model (HMM) for detecting diseases in citrus plant leaves. The results proved good accuracy in classifying and extracting the diseased parts. Kshir Sagar et al. [6] used MATLAB for implementing Multi-SVM and K-means algorithms for extracting feature from diseases of plants and fruits utilizing GLCM. Gandhi et al. [7] contributed solutions for detecting diseases in more than 150 crops using convolutional neural networks with Deep Learning approach in 2019. The model worked well with mobile and laptop mode but still required a physical intervention of farmers for image capturing. In 2020, Rama Thunnisa et al. [8] and Gomathy et al. [9] used SVM and clustering approaches, respectively, to detect diseases in vegetable plants. Saktidasan et al. [10] also used combination of Principal Component Analysis (PCA) and SVM with K-means algorithm to obtain better results. Singh et al. [11] to used latest approaches of Random Forest classifiers and Deep Learning for early plant disease detection with large datasets. But still, a limited accuracy was achieved in the results. A brief review of the recent work done is given below in Table 1.

3 Requirement of Hardware and Software

3.1 Components

- ESP-32 Microcontroller.
- Soil Moisture Sensor.
- DHT11 Temperature and Humidity Sensor.
- Submersible 3-6 V DC Pump.

Table 1 Brief review of work done

Ref. No.	Year/ Authors	Tech. used	Advantages	Disadvantages	Application(s)
[1]	[2015], Sheng et al.	K-means	Faster extraction of affected areas with higher accuracy using Itti's method	Miscalculation under contrast conditions	Soybean leaves' disease detection
[2]	[2015], Rama Krishnan et al.	Backpropagation	Use of colored images with up to 97.41% of detection efficiency	Limited scope of detection	Groundnut leaves' disease detection
[3]	[2015], Bhange et al.	SVM and K-means	Two separate methods suggested	Almost 80% accuracy achieved	Pomegranate disease detection
[12]	[2015], M. Ranjan et al.	Artificial neural network (ANN), Hue saturation value features, backpropagation	Different colors were used to assign blocks for different diseases	Up to 80% accuracy achieved	Cotton leaves' disease detection
[13]	[2016], R. Patil et al.	K-means	Technique of segmentation and feature extraction was done on the basis of six clustering processes	Accuracy not mentioned in detection results	Detection of diseases in grape leaves
[14]	[2016], R. Anand et al.	K-means	ANN's used	Limited scope	Brinjal leaves' disease detection
[15]	[2017], Rukaiyya, P. Shaikh et al.	Bi-level Thresholding, Gray-level Co-occurrences Matrix (GLCM)	Hidden Markov Model (HMM)	Scope not extended beyond disease detection in citrus leaves	Citrus leaf unhealthy region detection
[16]	[2018], V. Sawarkar et al.	SVM, fuzzy classifier, color analysis, neural networks, KNN	SVM classifiers and ANN	Limited results	Rose plant disease detection
[6]	[2018], Kshirsagar, et al.	K-means, GLCM, multi-SVM	Technique works well with both leaves and fruit-related diseases	Limited set of leaves and fruits were used	General plants disease detection

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Table 1 (continued)

Ref. No.	Year/ Authors	Tech. used	Advantages	Disadvantages	Application(s)
[17]	[2019], Sharath D. M. et al.	Canny edge detection (CNN)	Calculation for the affected edges was done in pixels, and based on pixel count, the percentage of infection in fruits was determined	Large datasets for future scope	Disease detection in pomegranate plants for bacterial blight
[7]	[2019], R. Gandhi et al.	Convolutional neural networks using deep learning	Two model's inception and mobile net were deployed which could work in both mobile phone and computer	Physical deployment of farmers required	More than 152 crops solution possible
[18]	[2019], S. Vignesh wari et al.	SVM classifiers	Detail study on the diseases of rice plant, size of images in dataset, etc.	Limited methods were suggested	Machine learning (ML) techniques for rice plant disease detection in agricultural research
[19]	[2019], L. Annabel et al.	ANN, classification, disease detection, SVM, ML	A brief summary of various techniques used for classifying and detecting various bacterial, fungal and viral plant leaf diseases	Poor recognition rate and classification accuracy	Leaf disease detection in different plants
[8]	[2020], Rahama Thunnisa U. et al.	K-means clustering, SVM	Clustering algorithm helped in achieving highly accurate results in less time	Less datasets were used	Detection of vegetable diseases and classification
[9]	[2020], B. Gomathy et al.	Image segmentation, classification, neural network, clustering	A review of different techniques for detecting plant diseases was presented	Limited results with accuracy were mentioned	Plant diseases' detection and classification techniques

(continued)

Table 1 (continued)

Ref. No.	Year/ Authors	Tech. used	Advantages	Disadvantages	Application(s)
[10]	[2020], N. Vasudevan et al.	K-means clustering, Random Forest classification, image segmentation	Detection of the plant diseases in the early stage with comparison between two different algorithms for better results	Limited results with accuracy	Disease detection and recognition using K-means clustering
[11]	[2020], Singh D. et al.	Deep learning	Large datasets including 2598 data points	No accuracy mentioned	Visual detection of plant diseases
[20]	[2021], Sharma P. et al.	Application of internet of things	Water saving as irrigation is automated	Other sensors for measuring soil pH value, flow of air, fertilizer, etc. were not used	Irrigation automation

3.2 Software Utilized

- Blynk application.
- Arduino IDE.
- MATLAB.

4 Working

The circuit details of the project and its layout are shown in Figs. 1 and 2, respectively. The basic steps of the suggested methodology are given in Fig. 3. The flow description for the implementation steps is also shown in Fig. 4.

These steps are explained as:

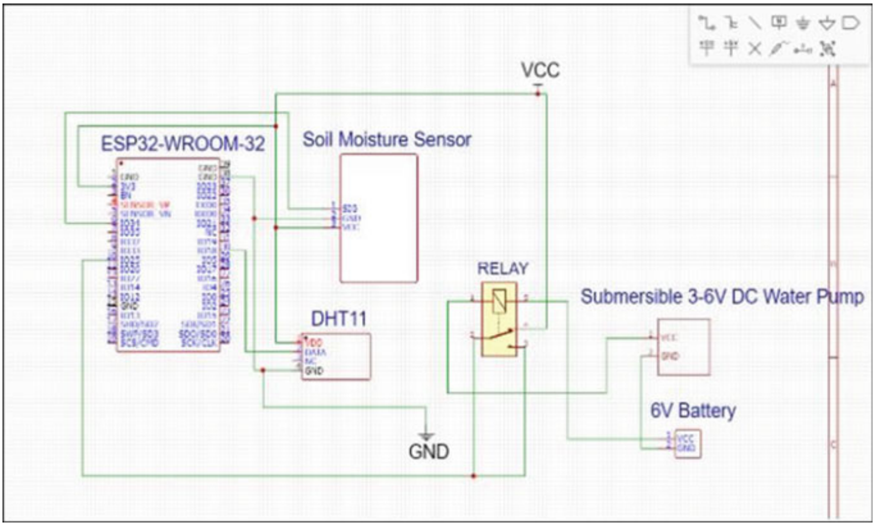


Fig. 1 Circuit details

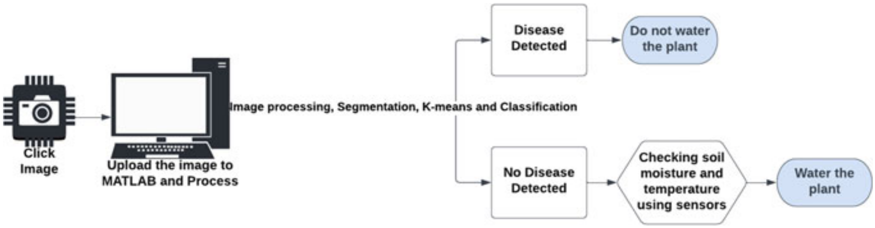


Fig. 2 Schematic representation

4.1 Acquiring the Image

First of all, colored images of the leaflets were taken through a high-resolution mobile camera. These were uploaded to a folder [13, 21, 22].

4.2 Initialization of the Image

This step is difficult as it is highly prone to noisy effects. The image is curtailed into size 256 × 256 using the Otsu technique of thresholding. This helps in classifying the given pixels into twin categories.

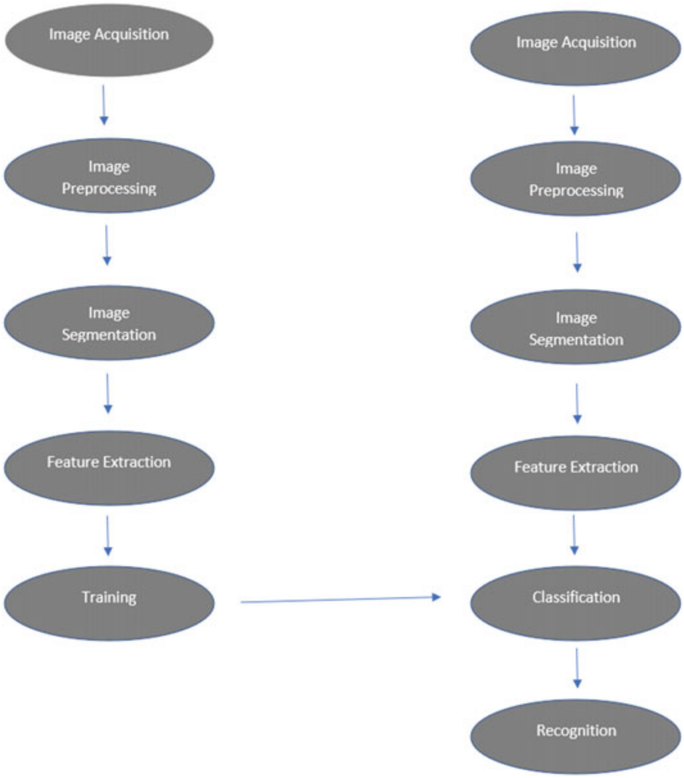


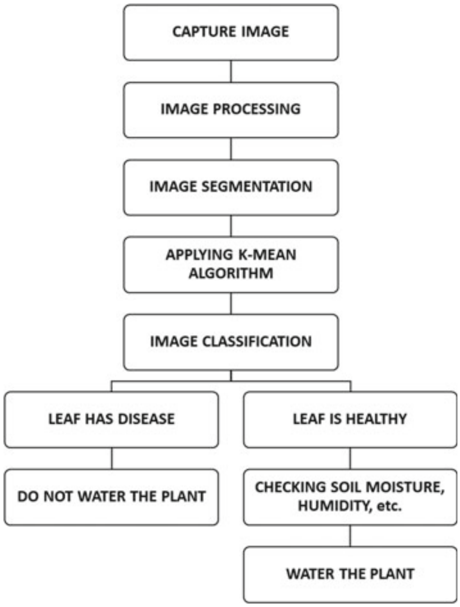
Fig. 3 Suggested methodology

4.3 Segmenting the Image

The information in the colored images is divided into three characteristics, namely ‘L’, ‘a’ and ‘b’, relating to light, red or green and blue or yellow values. After this conversion, K-means algorithm was utilized to segment the image into three clusters [5, 6, 14], as follows:

(a) The given data were assigned a number for cluster. Here K = 3.
(b) The mean was selected.
(c) The length amidst the points of data and mean were calculated utilizing Euclidean distance (utilizing the maximum distance as the criteria).
(d) The points of data nearer to the mean must be unchanged.
(e) The points of data closer to the mean value must be moved to adjoining cluster [9].

Fig. 4 Flow description of Implementation steps



4.4 Extraction of Features

Each cluster selected in the previous step is utilized for extracting the features. The colored or RGB images are converted into grayscale digital images to express the intensity of the leaf diseases in the range 0–1. Only a limited number of pixels are selected that are necessary and adequate to characterize the entire segment of an image. The contrived area within the histogram of data or the image is used to indicate its frequency of occurrence. The affected area (in %) in an image relates to the ratio of the region of plant disease to the total area of the leaf used and reflects the image quality of the healthy plants. A GLCM was used to describe the steadiness of an image using the dimensional connection from the pixels of the image. Features like such as contrast, energy, homogeneity, correlation, mean and skewness were reclaimed from the matrix [14]. These are given as:

(1) Contrast estimates the extremity between a picture element and its adjoining pel over a proper image. For a constant image, the value is zero.
(2) Energy quantifies the level of fidelity between squared elements totalized in a matrix with levels amidst zero and one. For a constant image the value is one.
(3) Homogeneity weighs the level of affinity amidst the pixels. For a constant image, the value is one.
(4) Correlation evaluates the relationship amidst a pel value with its nearby values betwixt −1 and 1. [15].

(5) Mean estimates the average of the samples over a finite number of samples.
(6) Skewness is a measure of lack of symmetry.

4.5 Classification

SVM has been used as a two-fold classifier for classifying the consistency in different pattern acknowledgement applications. The notion of SVM is to generate a hyper-plane betwixt sets of data for indicating the classes they belong to [14]. Specimens nearer to the brink are chosen for resolution of the hyper-plane, as shown in Fig. 5.

For the experiment, a collection of normal and abnormal leaflets of Sigonia, Bhindi (Abelmoschus esculentus), Brinjal (Solanum melongena) and Karela (Momordica charantia) plants were taken. These are shown in Figs. 6 and 7, respectively, and denoted as plants P1, P2, P3, P4 and P5. Generally, the plants are affected by common diseases, such as Alternaria alternata, Anthracnose, Bacterial blight and Cercospora leaf spot. For detecting the most diseased plants, a mean of all pretentious areas was calculated for each plant to discriminate between the normal and damaged leaves in terms of accuracy of the algorithm used. The results helped to automatically water the healthy plants through the Blynk app software in the plant health tracking system once the soil parameters are checked using hardware components.

The complete project images are shown in Figs. 8a–d.

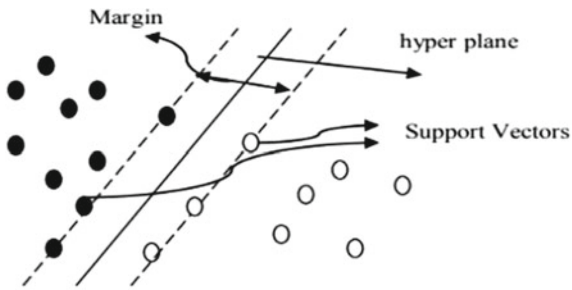


Fig. 5 Support Vector Machine classifier [10]

Fig. 6 Normal leaflets

Fig. 7 Damaged leaflets

5 Results

Highly pretentious diseased areas in plants were observed utilizing the k-mean clustering approach with SVM. The moisture, temperature and humidity parameters of the soil were continuously checked through the hardware components. The Blynk app successfully displayed the alerts for automatic watering of the plants. The detection of plant diseases with desirable accuracy is given in Table 2.

A brief comparison of the proposed technique with the existing methods is also summarized in Table 3 below.

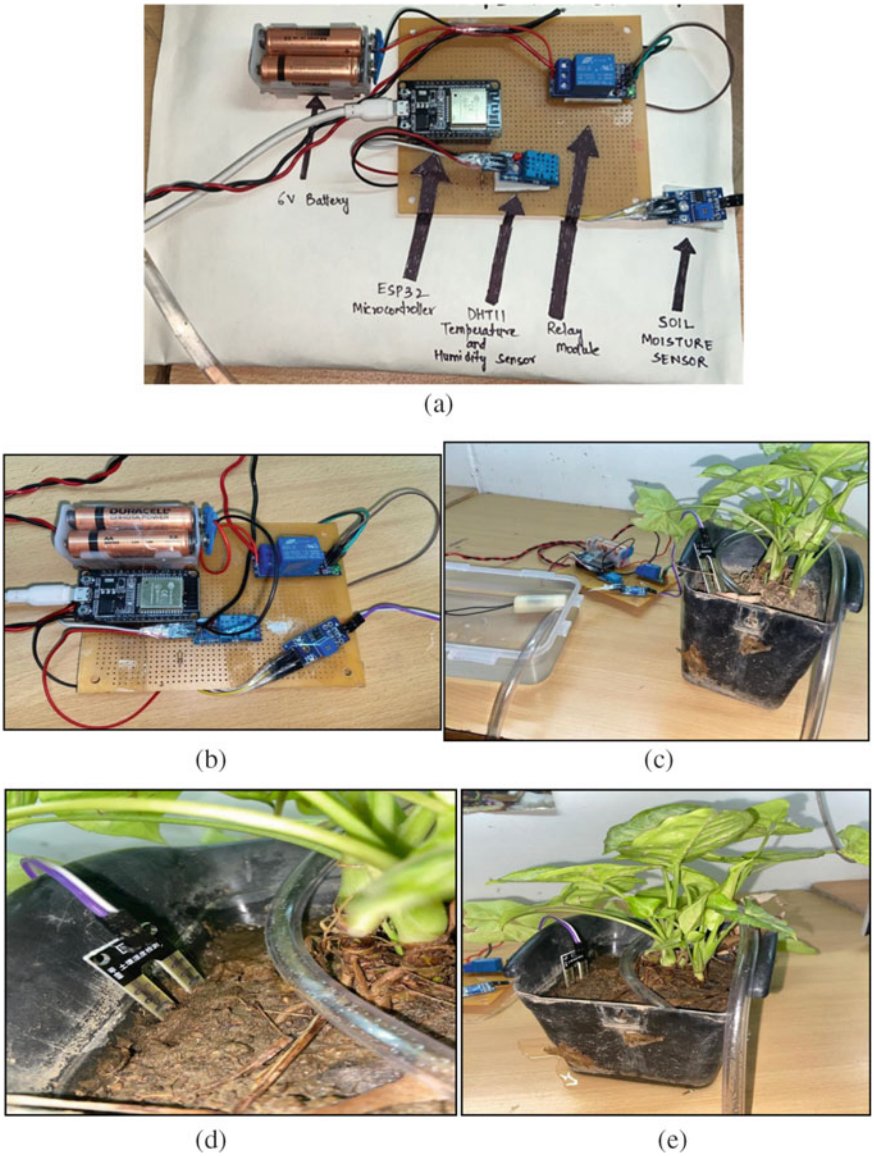


Fig. 8 **a**–**d** Complete project images

Table 2 Accuracy (in %) of the project for detecting diseases upon various abnormal leaves of plants

Plant No.	S. No.	Unhealthy plants (with disease)					Healthy plants
	Leaves tested	Alternaria alternata	Anthracnose	Bacterial blight	Cercospora leaf spot	Accuracy (%) in affected Areas (unhealthy plants)	
P1	L1	✓	✓			64.8063	
	L2		✓			41.33	
	L3		✓			30.27	
	L4						18.113
	L5						15.001
P2	L1				✓	50.8546	
	L2						15.0062
	L3			✓		50	
	L4	✓		✓		27	
	L5		✓	✓		69	
P3	L1						19.17
	L2	✓			✓	31	

(continued)

Table 2 (continued)

Plant No.	S. No.	Unhealthy plants (with disease)					Healthy plants
	Leaves tested	Alternaria alternata	Anthracnose	Bacterial blight	Cercospora leaf spot	Accuracy (%) in affected Areas (unhealthy plants)	
	L3		✓			48.5	
	L4		✓	✓		51.239	
	L5						17.301
P4	L1		✓		✓	47.23	
	L2	✓			✓	30.07	
	L3	✓		✓		27.93	
	L4						20.05
	L5			✓	✓	36.75	
P5	L1	✓		✓		28.87	
	L2	✓	✓		✓	47.41	

(continued)

Table 2 (continued)

Plant No.	S. No.	Unhealthy plants (with disease)					Healthy plants
	Leaves tested	Alternaria alternata	Anthracnose	Bacterial blight	Cercospora leaf spot	Accuracy (%) in affected Areas (unhealthy plants)	
	L3			✓	✓	52	
	L4	✓	✓	✓		51.239	
	L5						19.431

Table 3 Comparison of accuracy (in %) of the proposed technique with the existing techniques

	[9]	[10]	[17]	Proposed technique
Accuracy obtained	Good (range not mentioned)	Very limited	Less	40–60% approximately
Diseases detected	One	Two	Two	Four
Future scope	Large datasets needed	More agricultural plants can be used for detection	Other Vegetables can also be used	Technique may be utilized for testing diseases in more agricultural plants, vegetables and flowers

6 Conclusion

A nominal board utilizing sensors for detecting the real-time diseases in plants is introduced in the paper. A majority of common diseases in plants have been detected by the proposed technique with high accuracy. The technique currently limits the results obtained only from a few plants. Also, manual intervention of farmers is necessary for acquiring the images for calculating the detection accuracy.

However, the scope of the utility can be extended to other crops, fruits or vegetables also with the possibility of identification of more diseases utilizing better algorithms. The manual process of capturing the images may also be mechanized to extend the benefits of the proposed solution to a large part of the society and the country.

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