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Leaf Disease Detection and Vegetable Classification Using K-Means Clustering and SVM with Autonomous Robotic System using Deep Learning

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ABSTRACT:

Plant diseases in the field of agriculture can cause significant loss to the farmer. This leads to decline in the quality and quantity of the crop. Hence, it is very important to identify and recognize the type of plant disease in order to help the farmer. This information can help the farmer to take appropriate decision about increase in crop not compromising the quality. Manual methods which are currently being used to detect plant diseases are said to be time consuming, since it requires expert advice and requires enormous manual effort. In order to overcome these problems new technologies are being developed, which uses computer vision and image processing techniques to detect various diseases in plant. Results have shown that these methods can produce fast, accurate disease detection and have good economic importance. This proposed work presents automatic system for classification of three important plant diseases, namely Bacterial Blight, Leaf spot and Leaf Rust. This system uses K-means Clustering for segmentation and Support Vector Machine (SVM) classifier for classification.

Keywords: Agriculture, Plant Disease, Bacterial Blight, Leaf Spot and Leaf Rust, Computer Vision, Image Processing, K-means Clustering, SVM Classifier

I. INTRODUCTION

India is an agriculture country. 70% of Indian economy depends on agriculture but leaf infection phenomena causes the loss of major crops results in economic loss. Leaf infection is the invasion of leaf tissues by disease causing agents such as bacteria, virus, fungus etc leading to degradation of the leaf as well as plant. This can be characterized by spots on the leaves, dryness of leaves, color change in leaves and defoliation. The leaf infections may occur due to environmental condition changes such as huge rain fall, drastic changes in temperature or may be due to improper maintenance and some insects and pesticides.

Once the disease causing organisms such as bacteria, virus etc, entered into the leaf tissue, they starts multiplying and decreases the strength of the leaf and degradation starts. For instance it is seen that the outbreak of diseases which leads to large scale death and famine. It is estimated that the outbreak of helminthosporiose of rice in north eastern India in 1943 caused a heavy loss of food grains and death of a million people. In order to detect and diagnosis the leaf infection/disease various research works have been carried out and various methods or algorithms have been proposed. For example grapefruit peel diseases was analyzed by color texture features analysis. The texture feature analysis is intern categorized into structural, statistical, model based and transform method. Similarly in another method of analysis Hue Saturation Intensity [HSI] transformation is applied to the input image, Then it is segmented using K-means clustering algorithm. This algorithm is most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods. Although the conventional algorithm works well on most noise free images, feature extraction stage deals with the color, size and shape of the spot and finally classification is done using SVM classifiers.

In proposed project leaf infection detection is made through image processing technique because images form important data and information in biological sciences. Digital image processing and image analysis technology based on the advances in microelectronics and computers has many applications in biology and it circumvents the problems that are associated with traditional photography. This new tool helps to improve the images from microscopic to telescopic range and also offers a scope for their analysis. Therefore it has many applications in biology. The method for detection and classification of leaf diseases is based on masking and removing of green pixels, applying a specific threshold to extract the infected region and computing the texture statistics to evaluate the diseases using MATLAB.[1] .

II. EASE OF USE

Various techniques of image processing and pattern recognition have been developed for detection of diseases occurring on plant leaves, stems, lesion etc. by the researchers. The sooner disease appears on the leaf it should be detected, identified and corresponding measures should be taken to avoid loss. Hence a fast, accurate and less expensive system should be developed. The researchers have adopted various methods for detection and identification of disease accurately. One such system uses thresholding and back propagation network. Input is leaf image on which thresholding is performed to mask green pixels. Using K-means clustering segmented disease portion is obtained.

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One such system uses thresholding and back propagation network. Input is grape leaf image on which thresholding is performed to mask green pixels. Using Kmeans clustering segmented disease portion is obtained. Then ANN is used for classification. The other method uses PCA and ANN.PCA is used to reduce the dimensions of the feature data. to reduce the no. of neurons in input layer and to increase speed of NN. Sometimes threshold cannot be fixed and object in the spot image cannot be located.

Hence authors proposed LTSRG-algorithm for segmentation of image. In cucumber leaf disease diagnosis, spectrum based algorithms are used .In the classification of rubber tree disease a device called spectrometer is used that measures the light intensity in electromagnetic spectrum. For the analysis SPSS is used .In citrus canker disease detection uses three level system. Global descriptor detects diseased lesion. To identify disease from similar disease based regions zone based local descriptor is used In last stage two level hierarchical detection structure identifies canker lesion.

For identification of disease on plant and stems first segmentation is carried using K-means clustering. An example shown by (Gavhale, Gawande, & Hajari, 2014) while developing an Automated System for Plant-level Disease Rating in Real Fields that, " k-means clustering is used to detect citrus anthracnose disease infected a citrus leaf; and basic clustering k-means algorithm is used for segmentation in textured images creating device independent color space conversion in which coordinates used to specify the color. The k-means clustering algorithm used to classify pixels based on a set of features. The classification achieved by minimizes the sum of squares of distances of the objects and the corresponding cluster. However, k- means clustering is used to separate the leaf image into different clusters if a leaf contains more than one disease and the suitable color group numbers lead to the better color extraction". The k-means clustering algorithm is used for segmentation of different plants' leaves to identify the diseases affected to them, the leaves of plants such as Rice, Cotton, Sugarcane and Grape and Apple etc. "The automatic system for recognition and classification of plants' diseases was projected before using k-means clustering method for segmentation and back propagation algorithm for classification to obtain the expected efficiency. The system for recognition of Ramularia disease, Bacterial Blight, scochyta Blight on cotton crop was developed in which input image is divided in various color channels like R, G, B, H, S, V, I, and grey levels then DWT is applied to each color channel and the wavelet energy is calculated for each sub-band and compose the feature vectors" (Rothe and Kshirsagar, 2014). "Using edge features and RGB pixel counting features the detection and classification of grey mildew, bacterial leaf blight, leaf curl, alternaria leaf's diseases on cotton was performed. An image recognition system for identification of diseases like Rice blast, Ricesheath blight and Brown spot in paddy fields of Sri Lanka was proposed in which Sobel method is used to detect the edges of the image and Texture, shape and color feature disease spot are extracted which are used for classification and accuracy of the system was 80% for Rice blast, 60% for Rice sheath blight and 85% for Brown spot. The color and texture features of diseased apple leaf were extracted.

The Kernel Principal Component Analysis (KPCA) based trait selection is carried out to identify the best characteristics. The classification model based KPCA and GA-SVM has found to have higher classification efficiency than the model based on PCA and GA-SVM" (Rothe and Kshirsagar, 2014). A proliferation of literature is available in plant leaf's disease detection and some of the key contributions of kmeans clustering are highlighted. In "Cercospora Leaf Spot (CLS) rater the goal of Codebook Generation Module (CGM) is to model the representative colors in three different types of regions.

In CGM, the diverse sets of superpixels into each of the three regions is manually labeled, to which k-means clustering is applied independently for generating the codewords of these three regions. In Rating Estimation Module (REM), superpixels are extracted from a set of images at four scales, where at each scale a novel feature representation is used to describe both the local and global image characteristics. Features at all scales are then fused and a regressor is earned from the selected features and the k-means clustering will extract codewords of each category for an Automated System for Plant-level Disease Rating in Real Fields" (Afridi, Liu, & McGrath, 2014).

III. PREPARE YOUR PAPER BEFORE STYLING

3.1 Proposed Methodology

Many researchers have made an attempt for plant leaf disease identification. Some approaches identify the plants based on plant image color histogram, edge features and its texture information. They also classify the plants as trees, shrubs and herbs using complication classifier algorithms. But this proposed project work as seen in the figure 1 makes a simple approach by just considering leaf details using simple Support Vector Machine Classifier (SVM) for image classification without many complications. [2]

3.1.1 Image Acquisition

The images of the plant leaf are captured through the camera. This image is in RGB (Red, Green And Blue) form. Color transformation structure for the RGB leaf image is created, and then, a device-independent color space transformation for the color transformation structure is applied [3]

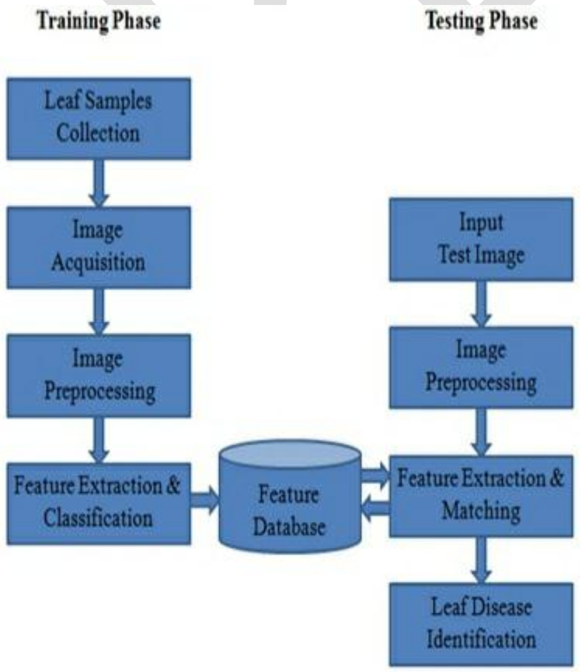

Figure 3.1: Block diagram of leaf disease detection and classification

3.1.2 Image Pre-processing

Pre-processing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. This pre-processing can reduce the infuence made by the background. The use of pre-processing is to reject some of the unwanted effects of the original image such as noise, etc. Maximize the conserve of image information and to minimize the real amount of data, thereby increase the accuracy and effectiveness of the feature extraction.

3.1.3 Feature Extraction

After pre-processing, in pattern recognition, the important and essential task is to measure the properties of an object because objects have to be detected based on these computed properties. In the feature extraction step, the task is to describe the regions based on chosen representation, e.g. a region may be represented by its boundary and its boundary is described by its properties (features) such as color, texture, etc. There are two types of representations, an external representation and internal representation. An external representation is chosen when the primary focus is on shape characteristics. An internal representation is selected when the primary focus is on regional properties such as color and texture. Sometimes the data is used directly to obtain the descriptors such as in determining the texture of a region, the aim of description is to quantify a representation of an object. This implies, one can compute results based on their properties such length, width, area and so on.

3.2 Equations

The equations are an exception to the prescribed specifications of this template. You will need to determine whether or not your equation should be typed using either the Times New Roman or the Symbol font (please no other font). To create multileveled equations, it may be necessary to treat the equation as a graphic and insert it into the text after your paper is styled.

Number equations consecutively. Equation numbers, within parentheses, are to position flush right, as in (1), using a right tab stop. To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in Note that the equation is centered using a center tab stop. Be sure that the symbols in your equation have been defined before or immediately following the equation. Use "(1)," not "Eq. (1)" or "equation (1)," except at the beginning of a sentence: "Equation (1) is ..."

IV. FEATURE EXTRACTION

After pre-processing, in pattern recognition, the important and essential task is to measure the properties of an object because objects have to be detected based on these computed properties. In the feature extraction step, the task is to describe the regions based on chosen representation, e.g. a region may be represented by its boundary and its boundary is described by its properties (features) such as color, texture, etc. There are two types of representations, an external representation and internal representation.

An external representation is chosen when the primary focus is on shape characteristics. An internal representation is selected when the primary focus is on regional properties such as color and texture. Sometimes the data is used directly to obtain the descriptors such as in determining the texture of a region, the aim of description is to quantify a representation of an object. This implies, one can compute results based on their properties such length, width, area and so on. Following are the algorithms used in feature extraction.

4.1 Spatial Gray Level Difference Method – SGLDM

SGLDM is based on second order conditional probability density function. SGLDM is a statistical method which constructs co-occurrence matrices to reflect the spatial distribution of gray levels in the region of interest . SGLDM is based on the estimation of the second order conditional probability density g(i, j, d, Θ). This means that an element at location (i, j) of the SGLD Matrix signifies the probability that two different resolution cells which are in a specified orientation Θ from the horizontal and specified distance d from each other, will have gray level values i and j respectively. The angle is used to evaluate the direction of texture, and the application of several distance values can provide a meaningful description of the size of the periodicity texture. Thus for different Θ and d values, different SGLD Matrices result. The angle Θ is usually restricted values of 0, 45, 90, and 135°, and the distance d is limited to values restricted to integral multiples of pixel size. The SGLDM matrix is formed by computing the number of occurrences of each pixel with gray level i that are away by distance d from any pixel with gray level j in a direction defined by angle θ. The choice of distance and angle combination, as well as the quantization level, is somewhat arbitrary. Fig.1 shows the co-occurrence for one pixel (yellow pixel) with d=3 pixel and θ {0, π/4, 2π/4, 3π/4}.

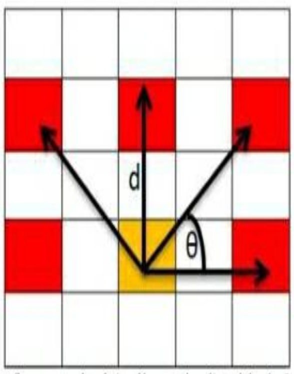

Fig.4.1 The Co-occurrence for one pixel (yellow pixel) with d=3 and θ{0, π/4, 2π/4, 3π/4}.

4.1.1 Contrast: It is a measure of the local variations of gray levels present in an image. Images with large neighbouring gray level differences are associated with high contrast. This parameter can also characterize the dispersion of the matrix values from its main diagonal. Contrast is defined as follows:

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j)$$

where p(i, j) corresponds to the elements of co-occurrence matrix, i.e. the probability of moving from a pixel with gray level i to a pixel with gray level j.

4.1.2 Homogeneity: This parameter, called also Inverse Difference Moment, measures the local homogeneity of an image. It assigns larger values to smaller gray level differences within pixel pairs. This parameter has opposite behaviour of the contrast. More the texture has homogeneous regions, more the parameter is high. Homogeneity is defined as:

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

4.1.3 Energy: This parameter is a measure of image homogeneity; it reflects pixel-pair repetitions. Homogeneous images have very few dominant gray tone transitions, which result into higher energy. Energy is defined as follows:

$$\text{Energy} = \sum_{i,j} p(i,j)^2$$

4.1.4 Correlation: Measures the correlation of a pixel to its neighbour. S

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$$

4.2 Run Difference Method – RDM

RDM is based on the estimation of the probability density function of the gray differences in an image.RDM is similar to SGLDM which extracts features that describe the size and prominence of texture elements in the image. RDM measures the pdf to p(r, gdif |θ) where gdif is the absolute difference between attenuation values of 2 pixels at a distance r away from each other in the direction of θ.

Three characteristic vectors that describe the texture description:

(i) DGD- Distribution of Gray level Differences

(ii) DOD – Distribution Of average Difference

(iii) DAD – Distribution of Average Distance

4.2.1 Features of RDM

With the above three characteristic vectors we define the following features of RDM.

LDE – Large Difference Emphasis measures the predominance of large gray level differences

$$LDE = \sum_{gdif=0}^{G-1} DGD(g_{dif}).\ln(2/g_{dif}).$$

Sharpness – measures contrast and definition of an image.

$$\text{Sharpness} = \sum_{gdif=0}^{G-1} DGD(g_{dif}).(g_{dif})^3$$

Second moment of DGD (SMG) – measures variation of gray level differences.

$$SMG = \sum_{gdif=0}^{G-1} \left(DGD(g_{dif})\right)^2.$$

Long Distance Emphasis (LDEL) – measures the prominences of large differences which are at a long distance from each other present in the matrix.

$$LDEL = \sum_{gdif=0}^{G-1} DAD(g_{dif}).(g_{dif})^2$$

4.3 Local Binary Pattern – LBP

This approach was introduced in 1996 by T. Ojala, M.Pietikainen and D. Harwood [4] as a basic binary operator. LBP features can provide robustness against variation in illumination . With LBP it is possible to describe the texture and shape of a digital image. This is done by dividing an image into several small regions from which the features are extracted. LBP is simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighbourhood of each pixel and considers the result as a binary number.

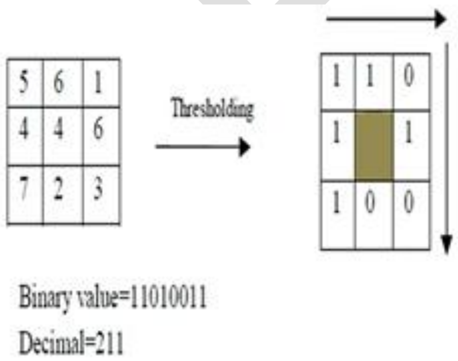

Fig 4.2: Original LBP Operator

The value of the centre pixel acts as a threshold which is compared with all its neighbouring pixel values, if the neighbours have value greater than or equal to the centre value then it is substituted with 1 else 0. Thus the image is divided into small regions from which the features are extracted which is concatenated and represented in a single feature histogram. Therefore, LBP-method can be applied on images to extract features which can be used to get a measure for the similarity between the images. The main idea is that for every pixel of an image the LBP-code is calculated. The occurrence of each possible pattern in the image is kept up. The histogram of these patterns, also called labels, forms a feature vector, and is thus a representation for the texture of the image. These histograms can then be used to measure the similarity between the images, by calculating the distance between the histograms. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity , which makes it possible to analyze images in challenging real-time settings.

V. K-MEANS CLUSTERING

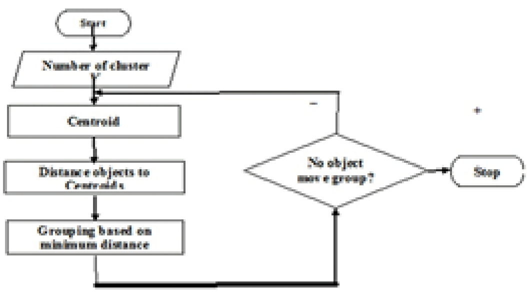

Figure 5.1: Flowchart of K-means clustering

The limitation of thresholding approach can be overcome by using region growing approach. K-means clustering is one of the popular algorithm in this approach and the flow chart is shown in figure 5.1. K-means clustering is a method for to classify a vector quantization which is familiar methods for cluster identification and analysis of images or data. K-nearest neighbor classifier is used to classify new data into the existing data on the cluster centers obtained by K-means. This is called as nearest centroid classifier or Rocchio algorithm. The K-means algorithm classifies the image (in this case pixel) based on a group of features into p number of classes. The classification is done by reducing the sum of squares of distances between the objects and mapping to corresponding clusters centroid. K-Means clustering algorithm extent to partition of q images into K clusters and each images belongs to the corresponding clusters with the centroid, mean intensity and area. This algorithm introduces a p different clusters. The good number of clusters p leading to give the separation (distance) is not known as a prior and it should be computed from the data set. The important of K-Means clustering is to reduce the total cluster variance or the square function. Algorithm: The procedure for K-Means Clustering is given below:

1) Classify the images into K number of groups where K should be known.
2) Mark K points at randomly in cluster centroid.
3) Mapping objects to their closest cluster centroid.
4) Calculate the mean, centroid or perimeter of all images in each cluster.
5) Repeat steps 2, 3 and 4 until the equal points are mapped to each cluster. K-means is the easiest algorithm that has detected many problem domains. The K-means clustering classification is the process to minimize the sum of squares of distance between the objects and the corresponding cluster or class centroid. However K-means clustering algorithm partitions the leaf image into four clusters in which one or more clusters contain the disease. An example of the output of K-means algorithm for a leaf affected by leaf spot disease is shown in figure. It is observed from figure 5.2 that cluster 1 contains healthy part of leaf. In figure 5.3 cluster 2 affected part of the leaf is shown.

Figure 5.2: Cluster 1

Figure 5.3: Cluster 2

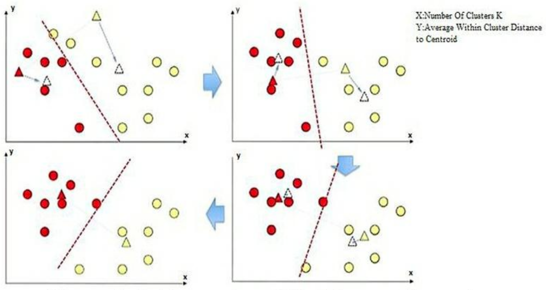

Figure5.4: Example of K- Means Clustering

VI. SUPPORT VECTOR MACHINE (SVM) CLASSIFIER

SVMs (Support Vector Machines) are a valuable system for information arrangement. Order errand as a rule includes isolating information into preparing and testing sets. Each occasion in the preparation set contains one "target esteem" (i.e. the class marks) and a few traits" (i.e. the highlights or watched factors). The objective of SVM is to deliver a model (in view of the preparation information) which predicts the objective estimations of the test information given just the test information characteristics. A Support Vector Machine (SVM) is a discriminative classifier formally characterized by an isolating hyperplane. At the end of the day, given marked preparing information (directed taking in), the calculation yields an ideal hyperplane which classifies new models. How about we think about the accompanying straightforward issue: We are given a lot of n focuses (vectors): x1, x2, x3, … .. xn with the end goal that xi is a vector of length m, and each have a place with one of two classes we mark them by "+1" and "- 1". So our preparation set is (X1,Y1),(X2,Y2),……(XN,YN) X i m,Yi {+1.-1} We need to discover an isolating hyperplane that isolates these focuses into the two classes. "The positives" (class "+1") and "The negatives" (class "- 1"). How about we acquaint the documentation utilized with characterize formally a hyperplane:F(X)=βO + βTX Where β is known as the weight vector and βo as the bias. For a linearly separable set of 2D points which belong to one of two classes, find a separating straight line. In Figure 6.1 you can see that there exist multiple lines that offer a solution to the problem.

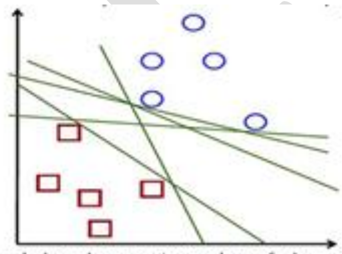

Figure 6.1: Green color hyperplane separating two classes of red squares and blue circles.

A line is awful in the event that it passes excessively near the focuses in light of the fact that it will be commotion touchy and it won't sum up effectively. Thusly, our objective ought to be to discover the line going beyond what many would consider possible from all focuses. At that point, the activity of the SVM calculation depends on finding the hyperplane that gives the biggest least separation to the preparation models. Twice, this separation gets the vital name of edge inside SVM's hypothesis. Along these lines, the ideal isolating hyperplane boosts the edge of the preparation information which is portrayed well in the Figure. The ideal hyperplane can be spoken to in a vast number of various courses by scaling of β and βo. As an issue of tradition, among all the conceivable portrayals of the hyperplane, the one picked is |βO + βTX|=1. Where χ symbolizes the preparation precedents nearest to the hyperplane. When all is said in done, the preparation models that are nearest to the hyperplane are called bolster vectors. This portrayal is known as the standard hyperplane. Figure 6.2: Finding an ideal hyperplane. The information as a rule contain clamors, which bring about covering tests in

example space, and there may deliver a few exceptions in the preparation informational index. So we have to expel these exceptions from the preparation informational index with the goal that a superior choice limit can be effectively framed. We here apply smoothening strategy to expel those focuses that don't concur with the larger part of their k closest neighbors. Specifically, by contrasting and the 1-NN and k-NN classifiers, it very well may be discovered that the SVM classifier can spare the storage room as well as diminish the order time under the instance of no giving up the characterization precision.

VII. RESULTS

In order to test the efficiency one can collect additional pictures of flowers present in the database and see if the system recognizes them. But to have significant results another set of suitable test images would have to be found. So a ground truth evaluation of the database has been conducted.

It consists of going through all the images in the database and search the second best match (the first one obviously being the same image). If the leaf image indicated is part of the same category as the leaf under test then it's a successful recognition. By doing this for the whole database, the performance of the system can be evaluated by establishing the recognition rate.

Loading the Image: Load the image from dataset

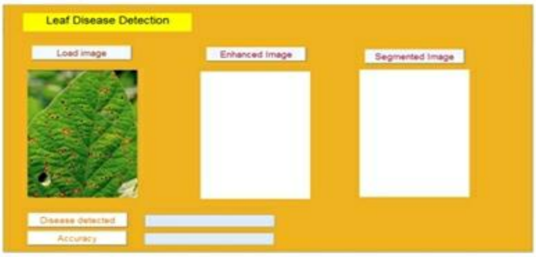

Figure 8.1: Load Image

Enhancing the Image: The image from database is enhanced so that results are more suitable for display or analysis. For example remove noise, sharpen or brighten an image.

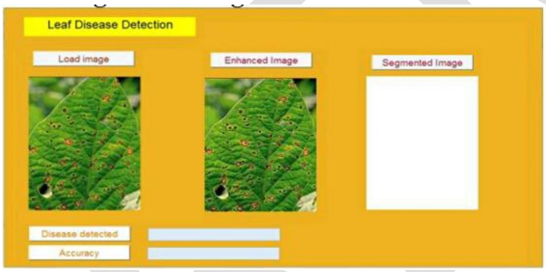

Figure 8.2: Enhanced Image

Segmentation of Image: This process is used for partitioning of digital image into multiple segments(set of pixels).The goal of segmentation is used to change representation

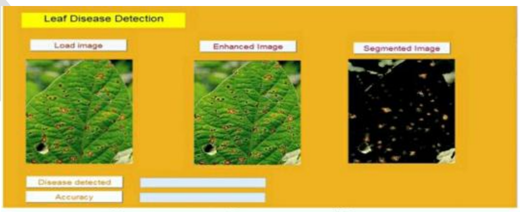

Figure 8.3:Segmented Image

Disease Detection and Accuracy: After the results of segmentation the disease is classified using SVM classifier and accuracy of the classifier is displayed.

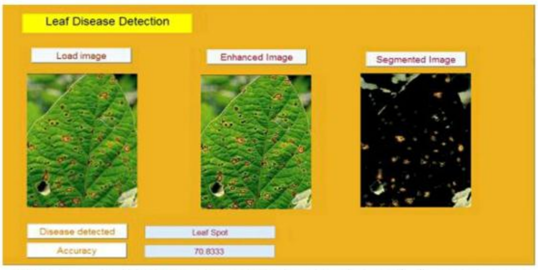

Figure 8.4: Disease Detected and Accuracy

VIII. CONCLUSION AND FUTURE WORK

The objective of the investigation work is to create advance programmed information handling framework which will decide the sickness influenced a piece of the leaf and to perceive the sort of infection. The item quality control is basically required to get the more esteem included items, the same number of studies demonstrate that prevalence of farming might be shortened from numerous infections. Hence, to enhance the yield and nature of the result of the leaves, the illness friendship can be diminished. The outcomes which are gotten will demonstrate the fruitful acknowledgment of leaf's illnesses, Bacterial Blight, Leaf Spot and Leaf Rust. The effectiveness of classifier dictated by dissecting 50 tests of leaves was observed to be 70%.

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