An efficient detection system of early blight disease on tomato leaf using shape metrics

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Under Supervision of

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To

My Beloved

Family

Approval

This thesis titled (**An efficient detection system of early blight disease on tomato leaf using shape metrics**) Submitted by Peash Ranjan Saha to the Department of Computer Science and Engineering, University of Chittagong, Bangladesh, has been accepted as satisfactory for the fulfillment of the requirements for the degree of B.Sc.(Engg.) in Computer Science and Engineering and approval as to its style and contents board examiners.

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Declaration

I declare that, except where otherwise stated, this thesis is entirely my own work and has not been submitted in any form to any where for any degree.

Peash Ranjan Saha
(Candidate)

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Abstract

Plant disease can cause significant reduction in both quality and quantity of agricultural products. Tomato is an important part of Chittagong region agricultural economy. Early blight caused by fungus *Alternaria solan*i is a major foliar diseases of tomato (*Lycopersicon esculentum Mill.*) . It affects the leaves, stems, and fruit of tomatoes . Early blight can also infect potato and eggplant .

Every year, large quantities of chemicals are used as fungicides to control this diseases thus evoking serious concern from environmentalists over deteriorating groundwater quality. Likewise, farmers are also concerned about the huge costs involved in these activities and severe profit loss. To remedy this situation various alternatives are being searched to minimize the application of these hazardous chemicals.

So automatic detection of early blight diseases on tomato leaves is an essential research topic as it may prove benefits in monitoring large fields of crops,and thus automatically detect the symptoms of disease as soon as they appear on leaves.

In this thesis , we propose and experimentally evaluate a software solution for automatic detection of early blight disease on tomato leaves. The developed processing scheme consist of five main steps, first color transformation structure for an input RGB image is created, then segmentation process is implemented, various image statistics are computed and statistics are analyzed using shape metrics for infected segments and finally extracted features are passed to trained classifier to identify the level of disease.

The proposed methodolgy can classify the examined disease with an accuracy of precision between 90% to 92%. Experiments on about 100 leaves with proposed statistical classifiers gave satisfactory results.

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Chapter-1
Introduction

Early blight of tomato is primarily a foliage disease, but may also cause fruit to rot near the stem in late fall [1] . Symptoms of early blight first appear on older leaves and are characterized by irregularly shaped brown spots with concentric rings as shown in Figure 1.

Figure 1.1 : Early blight disease infected leaf of tomato
(Original image courtesy of google image)

Manually the naked eye observation of experts is the main approach adopted in practice for detection and identification of early blight disease on tomato leaves. But, this requires continuous monitoring of experts which might be prohibitively expensive in large farms. Further, in some developing countries, farmers may have to go long distances to contact experts, this makes consulting experts too expensive and time consuming which has adverse effects in productivity.

We proposed a detection and classification system based on specific processing to extract the infected region and computing the texture statistics to evaluate the disease. Early blight disease of tomato can be broadly classified into four classes as following :

. Heavily infected
. Average infected
. Beginning stage
. Not infected

The main objectives of this research are to collect image data sets of early blight disease on vegetables,implement segmentation method to separate infected area,to compute statistics using shape metrics,development of various feature extraction technique by statistical analysis,development of classification algorithms to identify the level of disease,to experiment and compare the classification accuracies,eneralization of developed techniques to work with early blight disease of any vegetables.

The image datasets of the leaves selected for this study would be collected. Algorithms based on image processing techniques for color transformation and segmentation would be implemented. Manual feeding of the datasets, in the form of digitized RGB color photographs would be done for feature extraction and training the statistical classifier. After training the classifier, the test data sets would be used to analyze the performance of accurate classification. Comparison of the results obtained from the approaches would be completed and the best approach for the problem at hand would be determined.

Chapter-2

Literature review

Several key technologies incorporating concepts from image processing were developed by various researchers in the past to tackle this situation. The focus of these applications was to identify the disease in the early stages of infection so that selective application of the chemicals can adopt in field. Color-based classifiers, texture based classifiers and pattern based classifiers are some of the common method that have been tried in the recent past. The following sections will discuss some past work done using these methods.

Tian et al. (2000) developed a machine vision system to detect and locate tomato seedlings and weed plants in a commercial agricultural environment. Images acquired in agricultural tomato fields under natural illumination were studied extensively and an environmentally adaptive segmentation algorithm, which could adapt to changes in natural light illumination, was developed. The method used four semantic shape features to distinguish tomato cotyledons from weed leaves and a whole plant syntactic algorithm was used to predict stem location of whole plant. Using these techniques, accuracies of 65% for detection of tomato plants were reported.

Some of Color based techniques' work that is done past are:

Kataoka et al. (2001) developed an automatic detection system for detecting apples ready for harvest, for the application of robotic fruit harvesting. In this system, the color of apples was the main discriminating feature. The color of apples that were suitable for harvest and of those picked earlier than harvest time were measured and compared using a spectrophotometer. Both of these showed some differences in color. The harvest season's apple color and the color of apples picked before harvest were well separated based on Munsell color system, the L*a*b color space and XYZ color system. The threshold, which detects the harvest season apples, was produced based on the evaluation of these color systems.

Slaughter (1987), investigated the use of chrominance and intensity information from natural outdoor scenes as a means of guidance for a robotic manipulator in the harvest of orange fruit. A classification model was developed which discriminated oranges from the natural background of an orange grove using only color information in a digital color image. A Bayesian form of discriminant analysis correctly classified over 75% of the pixels of fruit in the natural scenes that were analyzed. Some of Texture based techniques' are given below:

In many machine vision and image processing algorithms, simplifying assumptions are made about the uniformity of intensities in local image regions. However, images of real objects often do not exhibit regions of uniform intensities. For example, the image of a wooden surface is not uniform, but contains variations of intensities which form certain repeated patterns called *visual texture*. The patterns can be the result of physical surface properties such as roughness or oriented strands, which often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface.

Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers. One immediate application of image texture is the recognition of image regions using texture properties. Texture analysis has been extensively used to classify remotely sensed images. Land use classification in which homogeneous regions with different types of terrains (such as wheat, bodies of water, urban regions, etc.) need to be identified is an important application.

Haralick et al. (1973) used gray level co-occurrence features to analyze remotely sensed images. They computed gray level co-occurrence matrices for a pixel offset equal to one and with four directions(0°, 45°, 90°, 135°). For a seven-class classification problem, they obtained approximately 80% classification accuracy using texture features.

Various techniques demonstrated by several authors are : H.ZulhaidiMohdShafri et al [2] demonstrated Self organizing maps & back propagation neural networks with genetic algorithms for optimization & support vector machines for diseases classification.

Mohammed Ei – Helly et al [3] uses image analysis integrated with the Central Laboratory of Agricultural Expert System (CLASE) diagnostic model. B. J. Woodford et al [4] identified the rate of browning within Braeburn apples and created an image recognition system to detect pest damage with the use of a wavelet based image processing technique and a neural network.

M.S. Prasad Babu et al [5] illustrated the use of a back propagation neural network. PanagiotisTzionas et al [6] used a combination of morphological features of leaves, image processing, feed forward neural network based classifier and a fuzzy surface selection technique for feature selection.

A. Meunkaewjinda et al [7] used a combination of image growing, image segmentation & a Zooming algorithm for the detection of plant diseases.

Otsu [8] illustrated segmentation, k-means clustering & back propagation feed forward neural network.RakeshKaundal et al [9] used support vector machines for developing weather based prediction models of plant diseases. H. Al-Hiary et al [10] designed airborne hyper-spectral imagery and the red edge techniques. Yan Li [11] proposed automatic spray a new method of pest detection and positioning based on binocular stereo to get the location information of the pest,which is used for guiding the robot to spray the pests with pesticides but his work did not make provision for invariance to distortion or angular transformation in the orientation of the pests on the crops. If there are changes in the orientation or position of the pests on the leaf, the robot is likely to miss the target and spray on areas not affected by the pest.

Paul Boissard [12] demonstrated a cognitive vision approach to early pest detection in greenhouse crops, his work concentrated on low infestation cases, which is crucial to agronomic decision making, particularly on white fly's. It was very good work for early detection of white fly but did not extend to more complex cases and on all forms or species of the pest, especially when the pest changes position or orientation. Recent research work has dwelled mostly on the detection of different crop diseases.

However, Di Cui [13] reported on how various sensing technologies have been developed for automatically detecting crop diseases whereas little or no attention is paid to the fundamental cause or the causal agent of the crop problems. The early detection of crop pests will help to evaluate the effect and the range of the existing pest populations before they become widespread in the environment. This facilitates their destruction by the introduction of predator species or other appropriate integrated pest management techniques, which delivers, according to the United States Environmental Protection Agency [14] , acceptable pest levels, preventive cultural practices, monitoring, mechanical controls, biological controls, and responsible pesticide use. Management is frequently contingent on identifying the existence of pest breeds whilst their populations are still restricted in size, it is important to recognize pest infestations before taking any control measure. Prevention of pest invasion is better than curing the effect that the pests have caused. Effective integrated pest management is achieved by having precise knowledge of the different pest species, and the related disease causal agents.

Having the knowledge of the pest before acting provides the opportunity to devise a suitable administrative strategy. The eradication of crop diseases has yielded unfavourable results because of incorrect procedures in handling pest control methods.

To facilitate one of the plant(tomato) disease control we try to propose an automatic disease detection system using k-means clustering in combination with some correspondence technique which are also investigated for detecting early blight disease on tomato leaves .

In the above we see that several authors applied various techniques like color based technique,texture based technique and we also see that they did not get accuracy above 80%. But in this paper we propose a different technique. Our proposed methodology that are described below can classify the disease with an accuracy between 90% to 92%.

Chapter-3
General terminologies

Color model :

Abstract mathematical model describing the way colors can be represented as tuples of numbers, typically as three or four values or *color components* (e.g. RGB and CMYK are color models) [15].

Color space :

Simply describes the range of colors, that a camera can see, a printer can print, or a monitor can display. Changes to lightness, hue, or saturation are applied equally to all the colors in the image [16] .

Color transformation :

Processing the components of a color image within the context of a single color model , as opposed to the conversion of those components between models (like the RGB-to-HSI and HSI-to-RGB conversion transformation) [17] .

Image segmentation :

Segmentation is a process that separates an image into regions . The goal of **segmentation** is to simplify and/or change the representation of an **image** into something that is more meaningful and easier to analyze [18] .

Feature extraction from images :

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately . Feature extraction is a special form of dimensional reduction. In other words feature extraction is the representation of various feature measurement of an image.

Shape metrics :

Shape metrics calculates different metrics that quantify a particular aspect of any kind of geometrical shape.

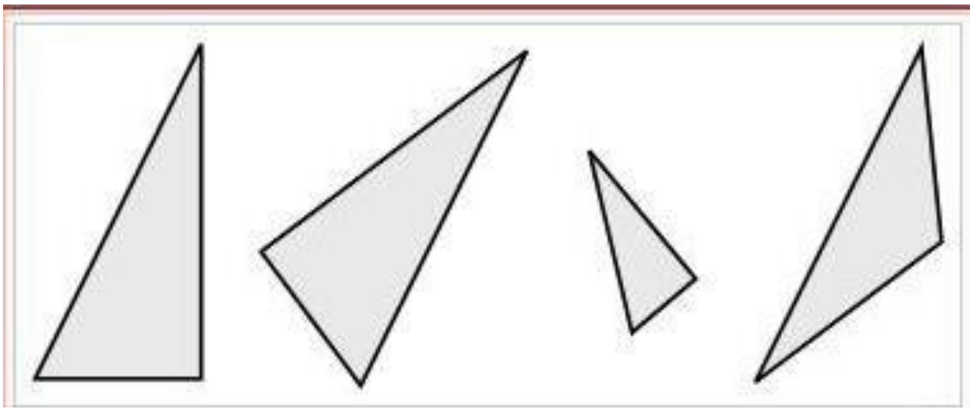


Figure 5.1 : An example of different triangular shape

Clustering :

A collection of data objects

- Similar to one another within the same cluster
- Dissimilar to the objects in other clusters

Chapter-4

Proposed Methodolgy

The overall concept that is the framework for any vision related algorithm of image classification is almost the same. First, the digital images are acquired from the environment . Then image-processing techniques are applied to the acquired images like segmentation to extract useful features that are necessary for further analysis. After that, several analytical discriminating techniques are used to classify the images according to the specific problem at hand. Figure 4.1 depicts the basic procedure of the proposed vision-based detection algorithm in this research.

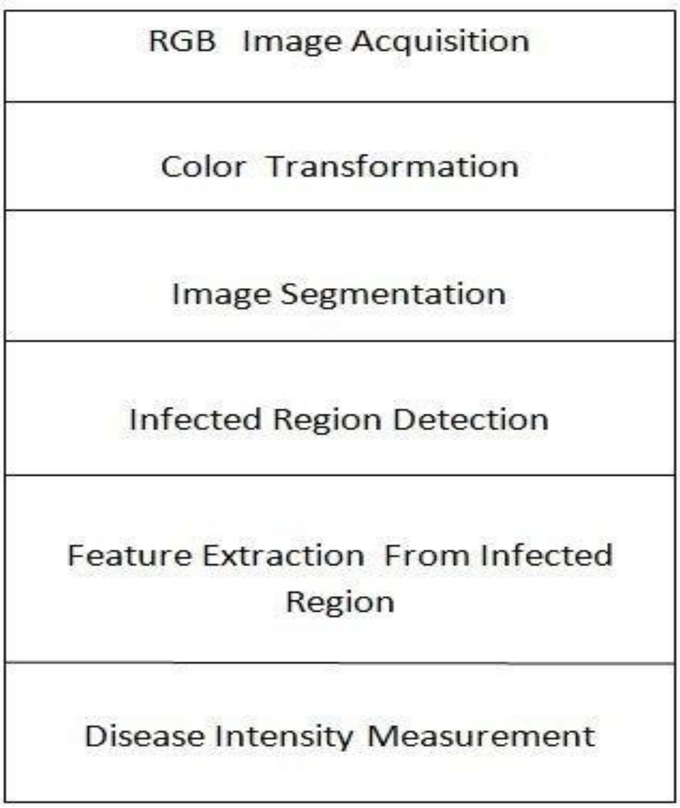


Figure 4.1 : Basic
flow diagram of proposed methodology

The proposed approach of early blight disease detection on tomato leaves is illustrated in algorithm 1. In the first step, RGB images of tomato leaf samples were collected.

Figure 4.2 shows some tomato leaf images infected by early blight disease. It is obvious from Figure 4.2 that leaves belonging to early blight, have significant differences in terms of color and texture.

Figure 4.2 : some sample leaf images infected by early blight disease (original image courtesy of google image)

In details, in step 2 a color transformation structure L*a*b for the RGB leaf image is created .

L*a*b :

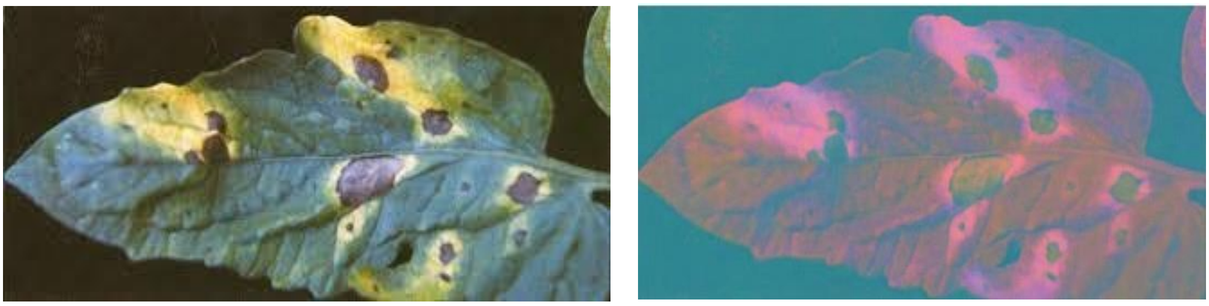
CIELAB system is device independent which is defined by the CIE to classify color according to the human vision. In the conversion process of an image from RGB color component to CIELAB color component, first RGB image is converted into CIEXYZ using following Equation.

$$X= 0.4014*R+0.356*G+0.1805*B$$
$$y = 0.2126*R+0.7152*G+0.722*B$$
$$z = 0.0193*R+0.1192*G+0.9505*B$$

Brightness and color information of LAB color model is independent of each other. In CIELAB color model, ‘L’ describes color brightness; ‘A’ describes the color ranging from green to red; ‘B’ describes the color ranging from blue to yellow. Conversion Formula for LAB color model is:

$$L = 0.2126*R+0.7152*G+0.722*B$$
$$A = 1.4749*(0.2213*R-0.3390*G+0.1179*B)+128$$
$$B = 0.6245*(0.1494*R+0.6047*G-0.8006*B)+128$$

L*a*b color transformation of an input image is shown in Figure 4.3.



a b

Figure 4.3 : (a) Input image from figure 1.1 (b) L*a*b color transformation of (a)

Algorithm 1 :

step 1 : RGB image acquisition

step 2 : Create the L*a*b color transformation structure

step 3 : Convert the color values in RGB to L*a*b color transformation structure.

step 4 : Apply k-means clustering segmentation algorithm using k=2

step 5 – 7 is for processing to detect infected region from object in cluster 1

step 5 : Calculate a threshold value using histogram from cluster 1

step 6 : Two-step masking to mask mostly green pixel

step 7 : Then perform image addition operation to remove green pixels from cluster 1 to separate infected region

step 8 – 10 is for extracting unique features

step 8 : Find the volume of infected region from new image generated in step 7

step 9 : Find & count all co-ordinate of infected regions pixels from object in cluster 2

step 10 : Apply KNNsearch algorithm to find the euclidean distance of a infected pixel From all the pixel found in step 9 .

step 11 : Image statistics computation

step 12 : Automated analysis of image statistics

step 13 : Perform classification to identify level of disease depends on analytical statistics

Then a device-independent color space transformation for the color transformation structure is applied in step 3. Steps 2 and 3 are inevitable to carrying out step 4.In this step the images at hand are segmented using the K-Means clustering technique.

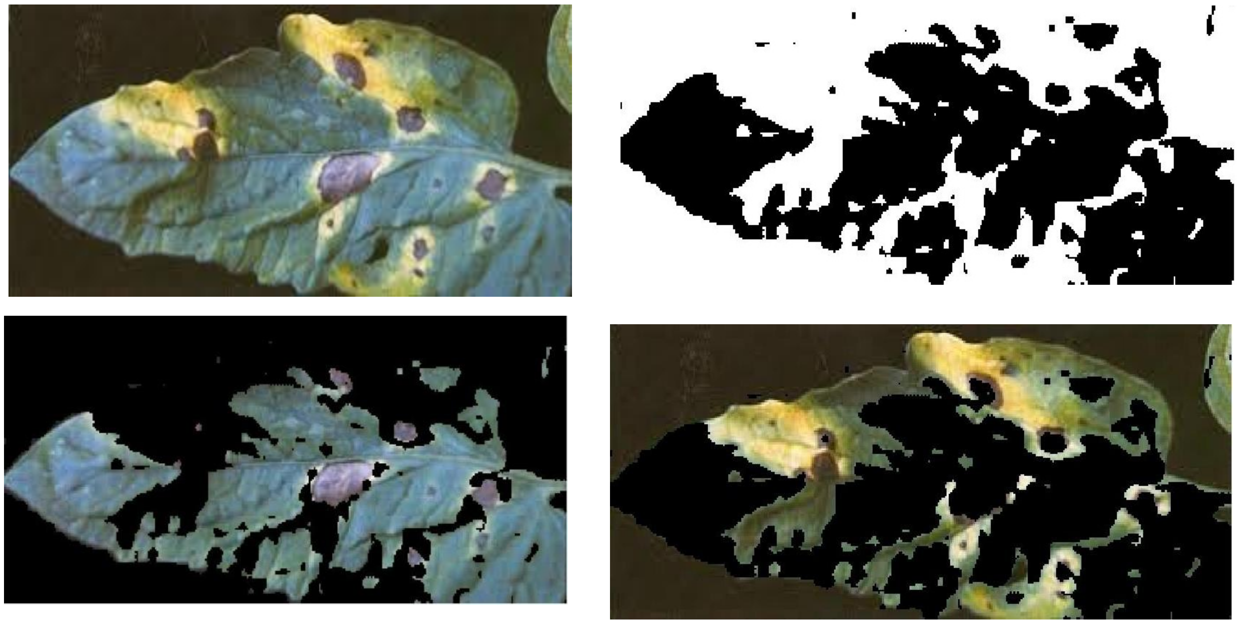
k-means clustering use euclidean distance metric to cluster the objects .

K-means :

k-means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster.

Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$), where each observation is a $d$imensional real vector, *k*-means clustering aims to partition the *n* observations into *k* sets ($k \leq n$) $\mathbf{S} = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS):

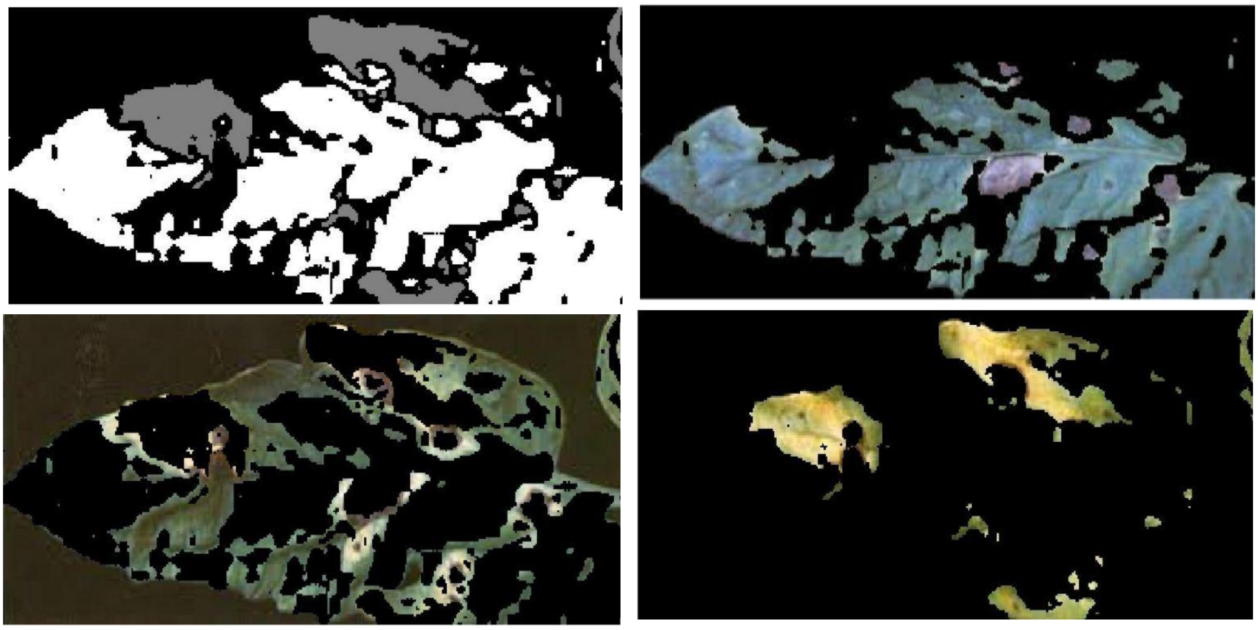
In k-means clustering technique k=2 has been set which determine the number of clusters . The reason to choose k=2 is that we need useful features in a single cluster. More the clusters the features are more separated. Symptoms of early blight disease which is mentioned earlier in (chapter 1- introduction) indicate that dark spots with concentric rings develop on older leaves first and the surrounding leaf area may turn yellow . In order to find this important feature in a single cluster after segmentation k=2 has been chosen. More illustration is shown in Figure 4.4.



a b
c d

Figure 4.4 : (a) Input image from figure 1.1 (b) input image labeled by cluster index by k-means (c) Objects in cluster 1 (d) Objects in cluster 2

from figure 4.4(d) , it can be seen that dark spot with concentric ring with surrounded yellow leaf area are in the same cluster which is most important in feature extraction in our proposed approach. As k increases these features are tends to be more separated. Figure 4.5 shows the result of k-means clustering for k=3. The separation of dark spot with concentric ring and surrounded leaf area can be seen in figure 4.5(c) and 4.5(d).



a b
c d

Figure 4.5 : (a) input image from figure 6.4(a) labeled by cluster index by k-means using k=3 (b) Objects in cluster 1 (c) Objects in cluster 2 (d) Objects in cluster 3

In step 5-7 mostly green pixel identification has been done from objects in cluster 1 by calculating automatic threshold value using image histogram function.

As these pixels determine the healthy area in tomato leaf and unnecessary for further computation these pixel are removed by two step pixel masking *Mask_1* and *Mask_2* and an image addition operation of this two mask.

An image pixel values consist of three channel namely redchannel (R), greenchannel (G) and bluechannel (B). Pixel value difference of these channels can be shown by an intensity plot or image histogram of these values. Figure 4.6 shows an intensity plot of objects in cluster 1 from figure 4.4(c) and figure 4.7 shows histogram of three channels of image from figure 4.4(c).

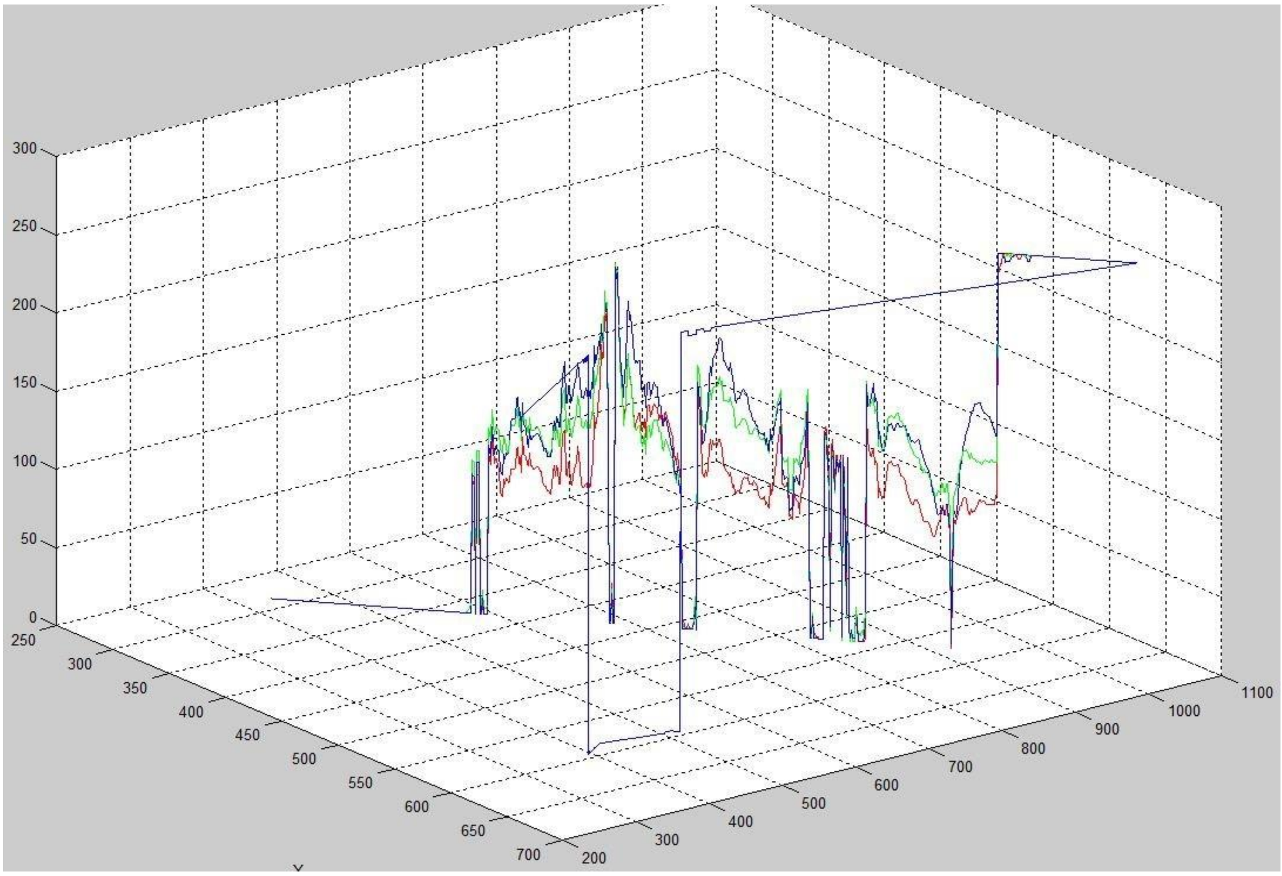
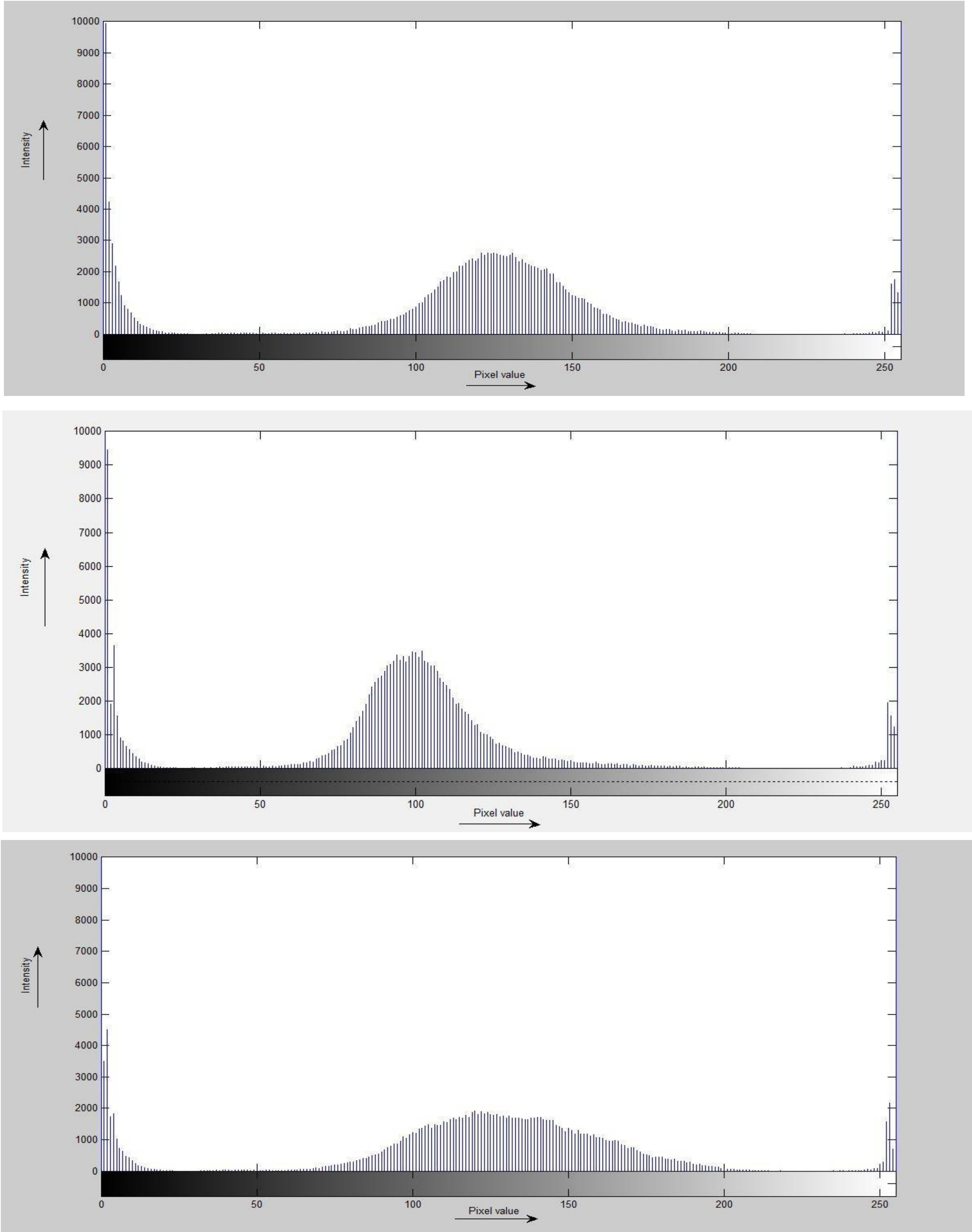


Figure 4.6 : R,G,B value difference in each pixels of image from figure 4.4(c) in a 3-D intensity plot.

In the above 3-D plot the lower plane indicates co-ordinates value and upper planes indicates the pixel values with different intensity of R,G,B.



a Figure 4.7 : Histogram of three channel of an image from figure 6.4(c)
b (a) R channel (b) G channel (c) B channel
c

According to the intensity plot and image histogram of each channel in our thresholding function *Mask_1* works with absolute difference of only redchannel and greenchannel and mask green pixels and *Mask_2* works with absolute difference of only redchannel and bluechannel and mask green pixels and then image addition operation of *Mask_1* and *Mask_2* is performed as illustrated in algorithm 2. A general threshold value is precomputed for every different image.

Algorithm 2 :

Step 1 - *Mask_1* : if (abs(redchannel – greenchannel) < computed threshold value) then red,green,blue component of this pixels is assigned to zero.

Step 2 – *Mask_2* : if (abs(redchannel – bluechannel) < computed threshold value) then red,green,blue component of this pixels is assigned to zero.

Step 3 – *Final_Mask = Mask_1 + Mask_2*

Figure 4.8 shows implementation of algorithm 2 of objects in cluster 1 from figure 4.4(c).

a b
c

Figure 4.8 : Algorithm 2 implementation of figure 4.4(c)
(a) Mask_1 (b) Mask_2 (c) Final_Mask

In the proposed approach, the method adopted for extracting the feature set is called the shape metrics . It is a method, shape of an image are taken into account, to arrive at unique features, which represent that image. Unique features are extracted from Final_mask by calculating the volume of each separated infected region .In other words calculation is done by counting all the pixels whose red,green,blue of a components has a value other than 255,255,255 respectively in each separated infected region.

Computation of image statistics is shown in algorithm 3:

Algorithm 3 :

step 1 : Find the volume of each separated region from Final_mask

step 2 : Find the summation of all volume to make a percentage of infected region

$$S = \sum_{K=0}^{k=i} V_k$$

where $V_1, V_2, V_3, \ldots\ldots, V_k$ is the volume of each separated infected region

step 3 : Calculate the percentage of whole infected area with respect to volume of leaf.

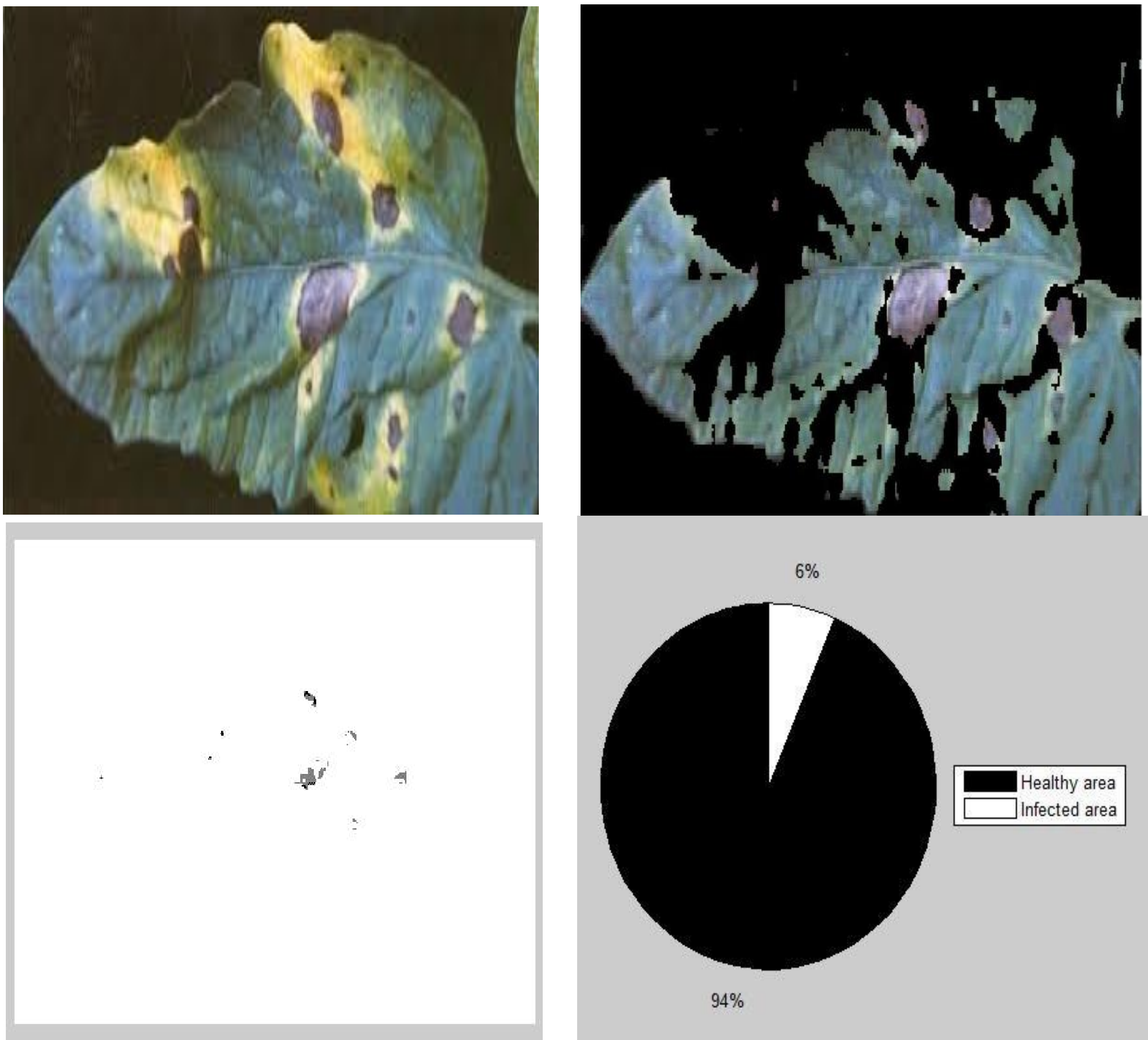
Other useful features are extraction method is : Find & count all co-ordinate of infected regions pixels from object in cluster 2 and apply KNNsearch algorithm to find the euclidean distance of a infected pixel From all the pixel found and image statistics are computed .

Automated analysis of image statistics are performed to classify and determine the level of disease. The training process while developing the proposed method has been executed by thoroughly matching with large dataset. By executing the matching process level of disease will be identified as one of the following four class :

. Heavily infected
. Average infected
. Beginning stage
. Not infected

Chapter-5
Experimental Results

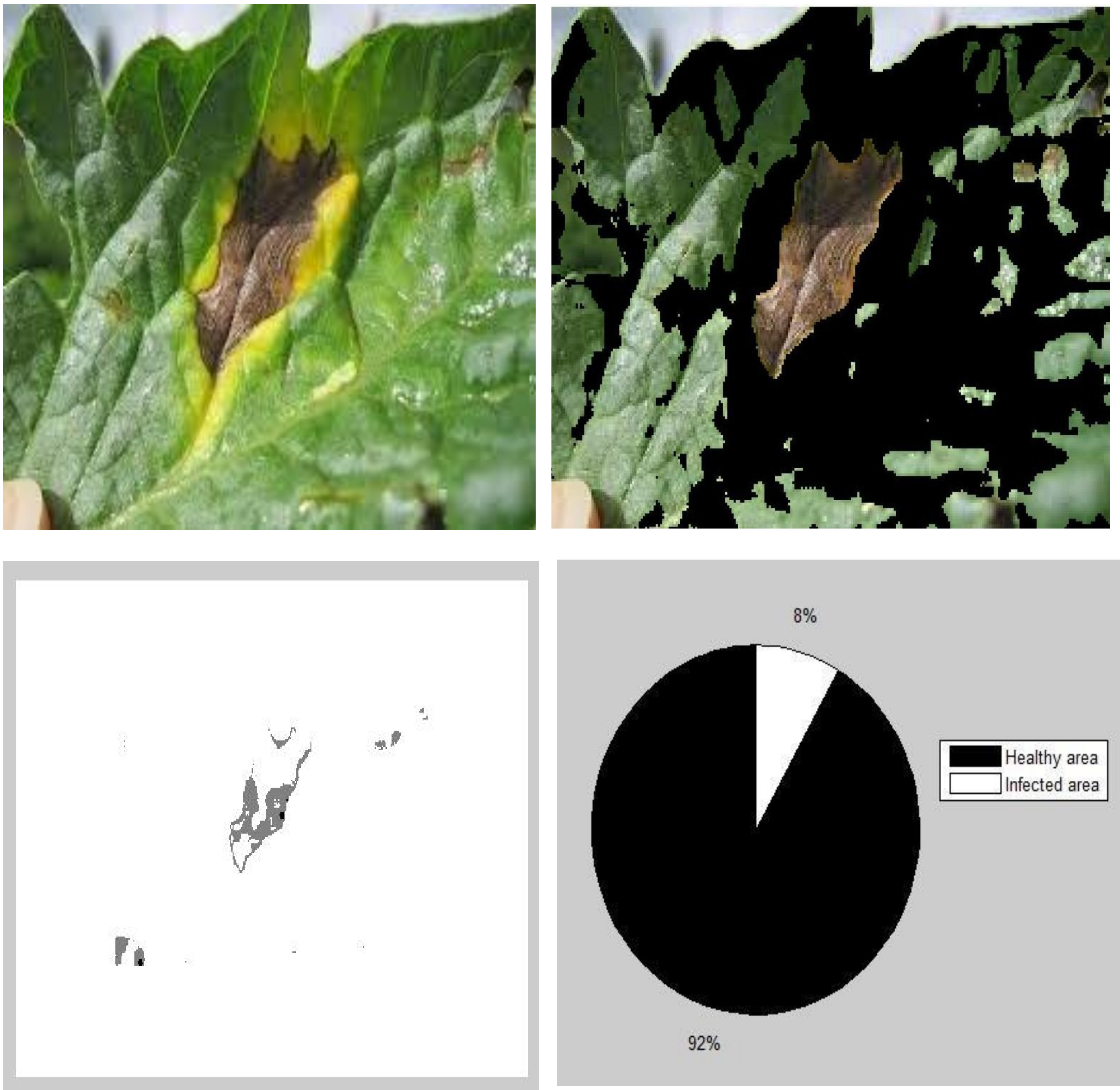
About 48 tomato leaves infected by early blight disease and 6 not infected leaves have been collected from google image to experiment and verification process of our approach. The results of our proposed methodology for testing samples of some images given in Figure 5.1 to Figure 5.4 . These results were obtained using automated analysis of image statistics.



a b
c d

Figure 5.1 : (a) Infected image (b) objects in cluster 1 by k-means clustering (c) Masking of cluster 1 to separate infected region (d) percentage of infected region

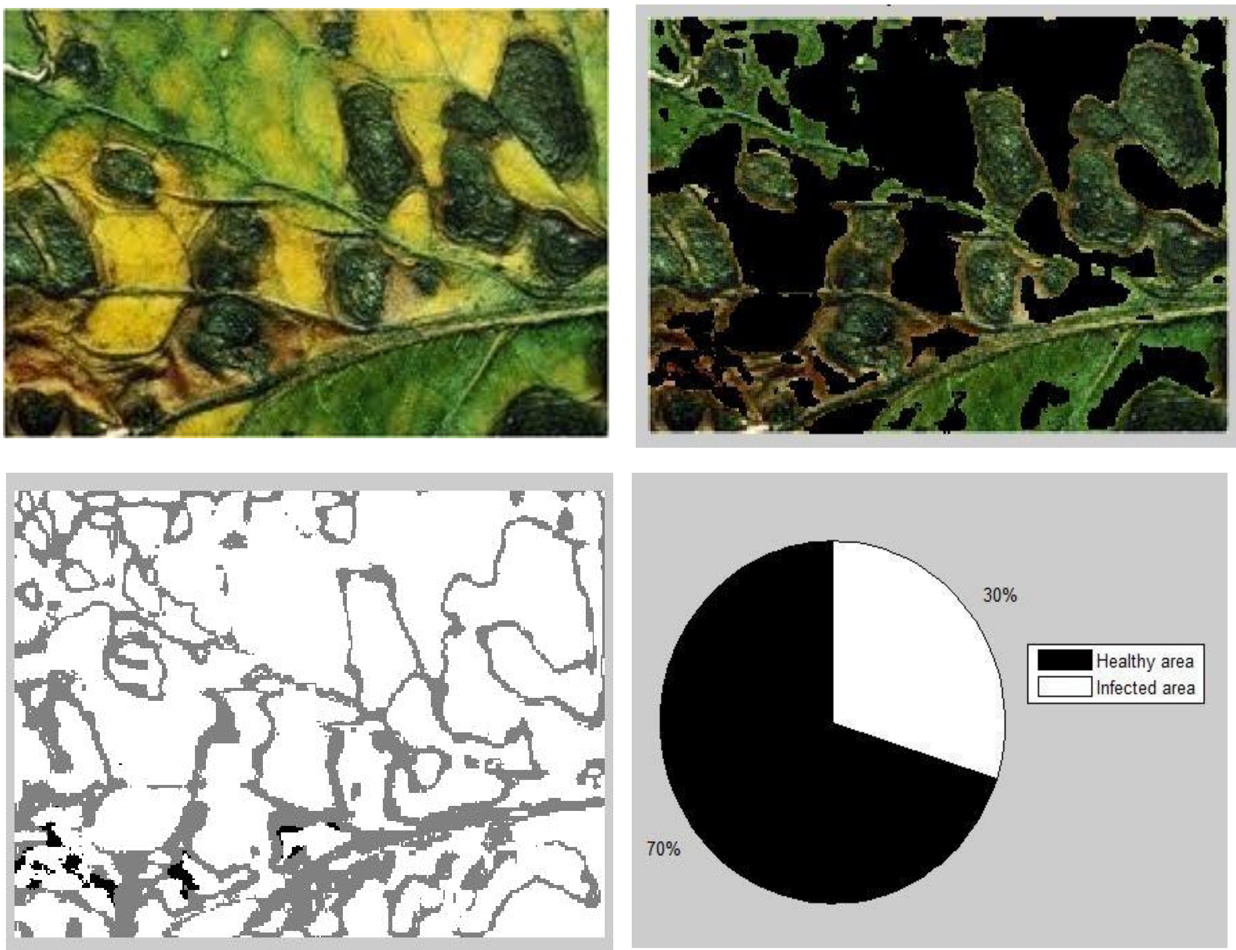
From figure 5.1(d) , it can be seen that percentage of infected area is 6% of leaves and according to automated analysis of this statistics and matching with dataset level of disease has been determined as Average Infected.



a b
c d

Figure 5.2 : (a) Infected image (b) objects in cluster 1 by k-means clustering (c) Masking of cluster 1 to separate infected region (d) percentage of infected region

From figure 5.2(d) , it can be seen that percentage of infected area is 8% of leaves and according to automated analysis of this statistics and matching with dataset level of disease has been determined as Average Infected.

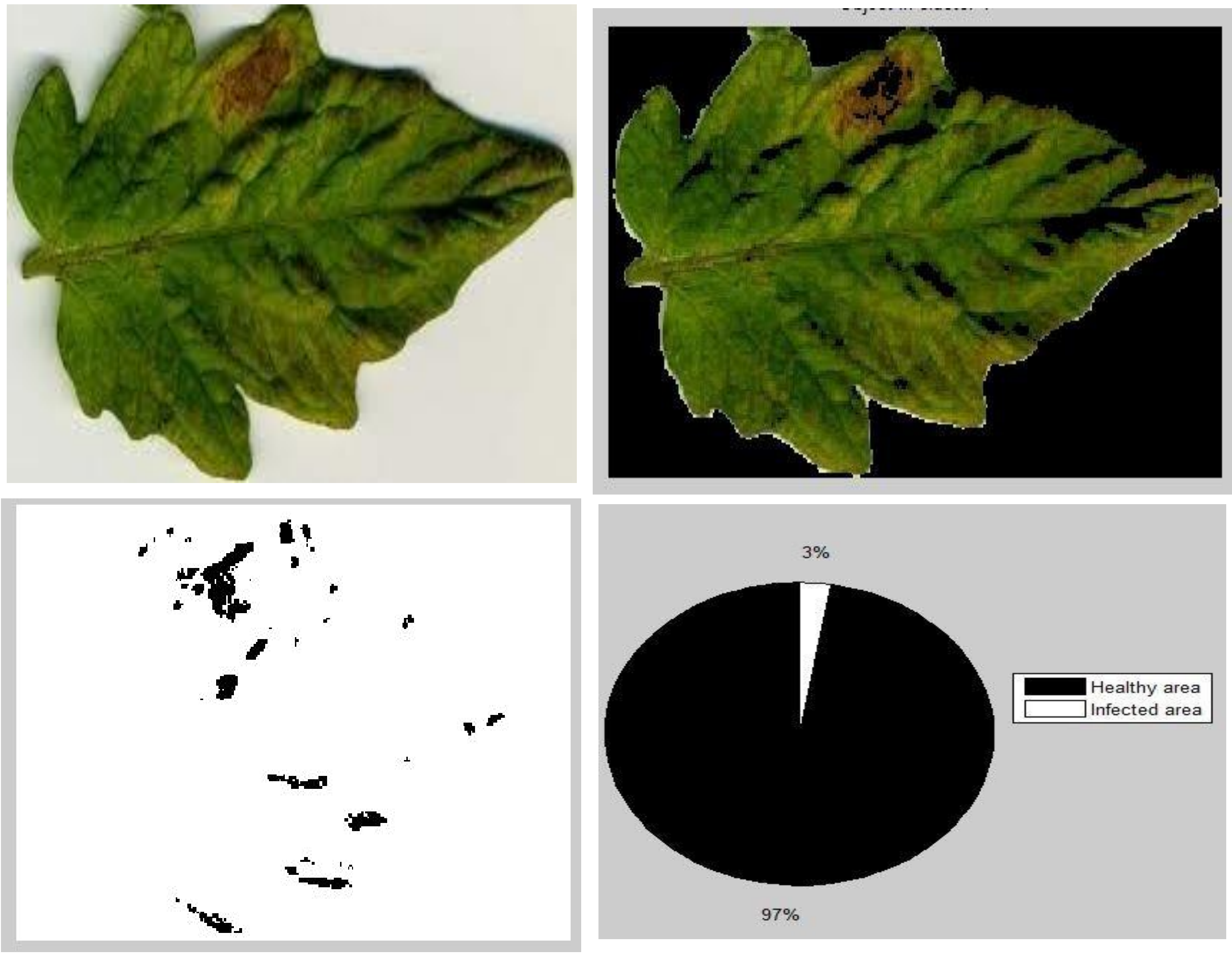


a b
c d

Figure 5.3 : (a) Infected image (b) objects in cluster 1 by k-means clustering (c) Masking of cluster 1 to separate infected region (d) percentage of infected region

From figure 5.3(d) , it can be seen that percentage of infected area is 30% of leaves and according to automated analysis of this statistics and matching with dataset level of disease has been determined as Heavily Infected.

Other useful features are extraction method such as finding & counting all coordinate of infected regions pixels from object in cluster 2 and apply KNNsearch algorithm to find the euclidean distance of a infected pixel from all the pixel found and image statistics are also has been computed .



a b
c d

Figure 5.4 : (a) Infected image (b) objects in cluster 1 by k-means clustering (c) Masking of cluster 1 to separate infected region (d) percentage of infected region

From figure 5.3(d) , it can be seen that percentage of infected area is 3% of leaves and according to automated analysis of this statistics and matching with dataset level of disease has been determined as Beginning stage. More experimental results can be seen in Appendix A.

The Experimental results of our approach also produce the result Not infected when the percentage of healthy area of a leaves is almost 100% or percentage of infected area is near 0%.

The results of our experiment on images of various level of diseases is shown in Table 1.

Level of disease	Number of Image	Successfully identified	Wrong identification
Heavily infected	17	16	1
Average infected	24	21	3
Beginning stage	7	7	0
Not infected	6	5	1
Overall image	54	49	5

Table 1 : Results of experiment of proposed approach

From the above table it can be seen that the percentage of successfully identification of level of disease is almost 91% as 49 out of 54 images have been successfully identified. Success and failure rate of proposed approach is shown in Figure 5.5.

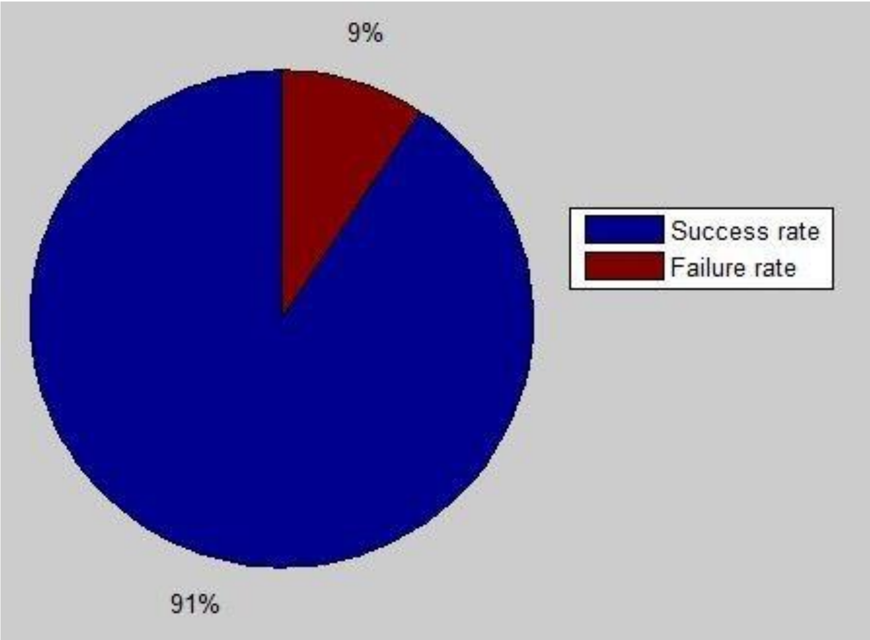


Figure 5.5 : Success and failure rate of proposed approach

Accuracy of proposed methodology can be increased with rigorous experiment on large scientific dataset and matching the results with experts opinion.

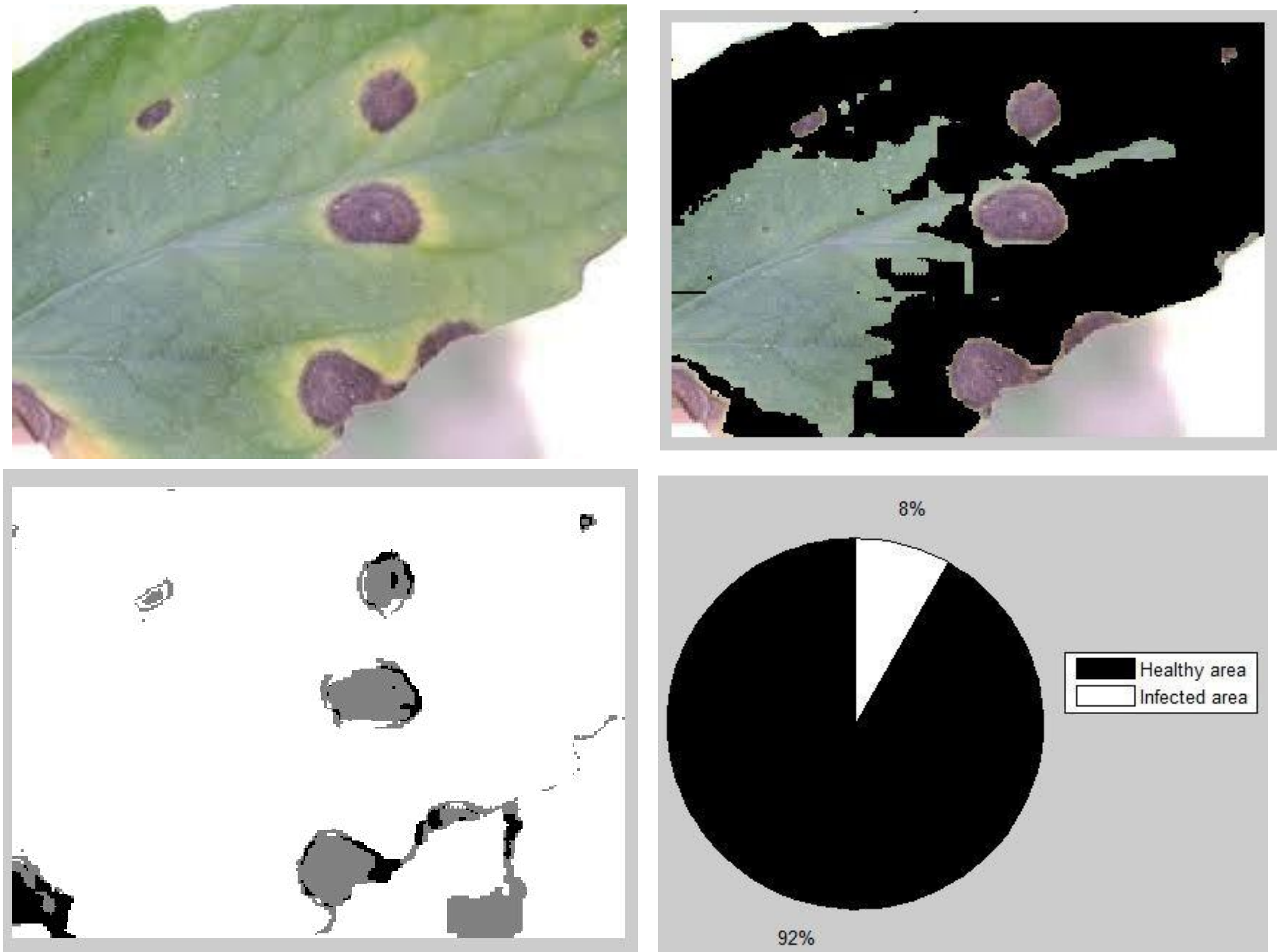
Chapter-6
Conclusion and Future work

An application of detecting early blight disease of tomato has been explained in this paper. Recognizing the determination of the intensity level of the disease is our main concern. From the experimental result section it can be seen that, the result based on combination of k-means clustering and image statistics is satisfactory. Hopefully the results of the proposed approach give better convergence when compared to conventional detection method.

In future we try to increase the training samples in order to improve disease dentification rate. Our proposed methodology only works on tomato leaf . Generalization of our technique to extend problem domain is our next concern. Our proposed methodolgy can classify the examined disease with an accuracy of precision between 90% to 92%. Proposed methodology can be extended to develop the rate of accurate detection.

Appendix-A

Experimental Results



a b
c d

Figure : (a) Infected image (b) objects in cluster 1 by k-means clustering (c) Masking of cluster 1 to separate infected region (d) percentage of infected region

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