

DETECTION AND CLASSIFICATION OF PLANT LEAF DISEASES

S. Ananthi*

S. Vishnu Varthini*

ABSTRACT

Images form important data and information in biological sciences. Plant diseases have turned into a dilemma as it can cause significant reduction in both quality and quantity of agricultural products. Automatic detection of plant diseases is an essential research topic as it may prove benefits in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves. The proposed system is a software solution for automatic detection and computation of texture statistics for plant leaf diseases. The developed processing scheme consists of four main steps, first a color transformation structure for the input RGB image is created, then the green pixels are masked and removed using specific threshold value, then the image is segmented and the useful segments are extracted, finally the texture statistics is computed. From the texture statistics, the presence of diseases on the plant leaf is evaluated. Experimental results on a database of about 500 plant leaves of 30 different plants confirm the robustness of the proposed approach.

Keywords: HSI, Color Co-occurrence Matrix, Texture, Plant Leaf Diseases.

*Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Sivakasi

1. INTRODUCTION

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. It, therefore, has many applications in biology [1].

Plant diseases cause periodic 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. Since the effects of plant diseases were devastating, some of the crop cultivation has been abandoned. It is estimated that 2007 plant disease losses in Georgia (USA) is approximately \$653.06 million [2]. In India no estimation has been made but it is more than USA because the preventive steps taken to protect our crops are not even one-tenth of that in USA.

The naked eye observation of experts is the main approach adopted in practice for detection and identification of plant diseases. 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 [3] and moreover farmers are unaware of non-native diseases. Automatic detection of plant diseases is an important research topic as it may prove benefits in monitoring large fields of crops, and thus automatically detect the diseases from the symptoms that appear on the plant leaves. This enables machine vision that is to provide image based automatic inspection, process control and robot guidance. Comparatively, visual identification is labor intensive, less accurate.

Kim et.al, have classified the grape fruit peel diseases using color texture features analysis. The texture features are calculated from the SGDM and the classification is done using squared distance technique. Grape fruit peel might be infected by several diseases like canker, copper burn, greasy spot, melanose and wind scar [4]. The classification accuracy achieved is 96.7%. Helly et.al developed a new method in which HSI transformation is applied to the input image, and then it is segmented using Fuzzy C-mean algorithm. Feature extraction stage deals with the color, size and shape of the spot and finally classification is done using neural networks [5]. Real time specific weed discrimination technique using multilevel wavelet decomposition was proposed by Siddiqil et.al. In this histogram equalization is used for preprocessing, features are extracted from wavelet decomposition and

finally classified by Euclidean distance method [6]. The classification accuracy obtained is 97%.

Al-Bashish, Braik and Bani Ahmed developed a fast and accurate method in which the leaf diseases are detected and classified using k-means based segmentation and neural networks based classification [7]. Automatic classification of leaf diseases is done based on high resolution multispectral and stereo images [8]. Sugar beet leaves are used in this approach. Segmentation is the process that is carried out to extract the diseased region and the plant diseases are graded by calculating the quotient of disease spot and leaf areas. An optimal threshold value for segmentation can be obtained using weighted Parzen-window [9]. This reduces the computational burden and storage requirements without degrading the final segmentation results.

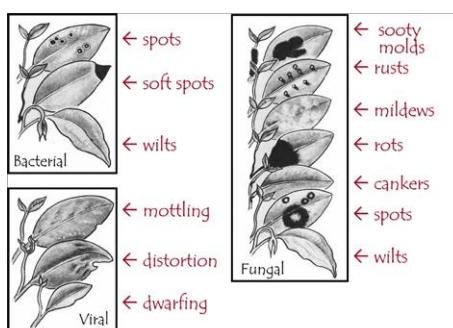


Figure 1: Types of diseases

In this paper, detection and classification of leaf diseases has been proposed, this method 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. Plant diseases may be broadly classified into three types. They are bacterial, fungal and viral diseases. Some of the diseases are shown in Figure 1.

The paper is structured as follows. The next section discusses the Proposed Method. The Section 3 gives the Recognition Results. Finally, Section 4 gives the Discussion and Conclusion of the Proposed Method.

2. THE PROPOSED APPROACH

First, the images of various leaves are acquired using a digital camera. Then image-processing techniques are applied to the acquired images to extract useful features that are necessary for further analysis. Figure 2 depicts the basic procedure of the proposed vision-based detection algorithm in this paper.

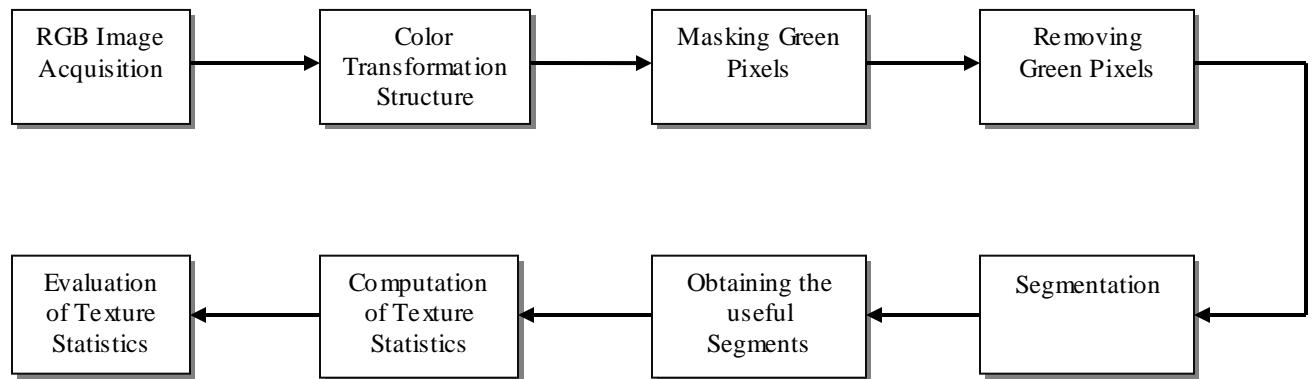


Figure: 2 Block Diagram of proposed approach

In the initial step, the RGB images of all the leaf samples were taken.

The step-by-step procedure of the proposed system:

1. *RGB image acquisition*
2. *Convert the input image from RGB to HSI format.*
3. *Masking the green-pixels*
4. *Removal of masked green pixels*
5. *Segment the components*
6. *Obtain the useful segments*
7. *Computing the features using color-co-occurrence methodology*
8. *Evaluation of texture statistics.*

Color Transformation Structure: First, the RGB images of leaves are converted into Hue Saturation Intensity (HSI) color space representation. The purpose of the color space is to facilitate the specification of colors in some standard, generally accepted way. HSI (hue, saturation, intensity) color model is a popular color model because it is based on human perception [10]. Hue is a color attribute that refers to the dominant color as perceived by an observer. Saturation refers to the relative purity or the amount of white light added to hue and intensity refers to the amplitude of the light. Color spaces can be converted from one space to another easily. After the transformation process, the H component is taken into account for further analysis. S and I are dropped since it does not give extra information. Figure 3 shows the H, S and I components.

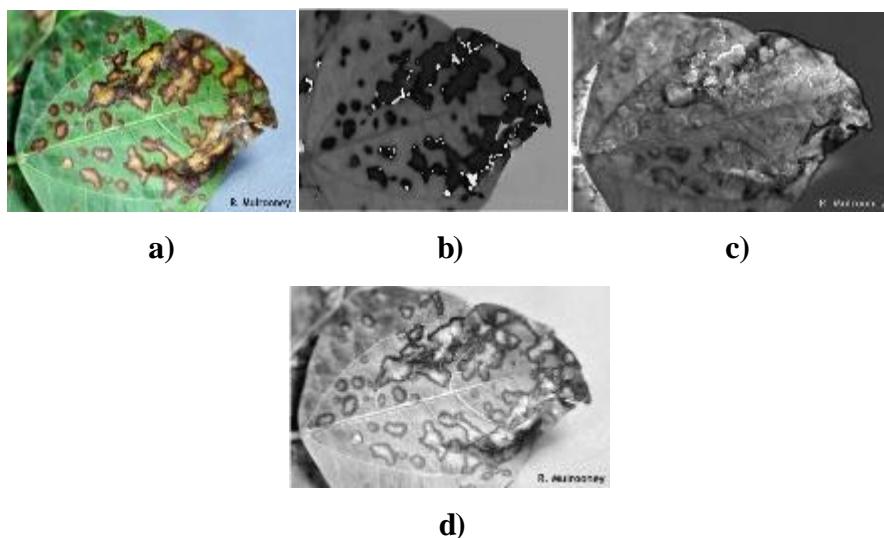


Figure 3: a) Input image infected by Bacterial Brown Spot b) Hue Component c) Saturation Component d) Intensity Component

Masking green pixels: In this step, we identify the mostly green colored pixels. After that, based on specified threshold value that is computed for these pixels, the mostly green pixels are masked as follows: if the green component of the pixel intensity is less than the pre-computed threshold value, the red, green and blue components of the this pixel is assigned to a value of zero. This is done in sense that the green colored pixels mostly represent the healthy areas of the leaf and they do not add any valuable weight to disease identification and furthermore this significantly reduces the processing time.

Removing the masked cells: The pixels with zeros red, green, blue components were completely removed. This is helpful as it gives more accurate disease classification and significantly reduces the processing time.

Segmentation: From the above steps, the infected portion of the leaf is extracted. The infected region is then segmented into a number of patches of equal size. The size of the patch is chosen in such a way that the significant information is not lost. In this approach patch size of 32×32 is taken. The next step is to extract the useful segments. Not all segments contain significant amount of information. So the patches which are having more than fifty percent of the information are taken into account for the further analysis.

Color co-occurrence Method: The color co-occurrence texture analysis method is developed through the Spatial Gray-level Dependence Matrices (SGDM). The gray level co-occurrence methodology is a statistical way to describe shape by statistically sampling the way certain gray-levels occur in relation to other gray levels [11]. These matrices measure the probability that a pixel at one particular gray level will occur at a distinct distance and

orientation from any pixel given that pixel has a second particular gray level. The SGDM's are represented by the function $P(i, j, d, \theta)$ where I represent the gray level of the location (x, y) , and j represents the gray level of the pixel at a distance d from location (x, y) at an orientation angle of θ . SGDM's are generated for H image.

Texture Features: Texture features like Contrast, Energy, Local homogeneity, Cluster shade and Cluster prominence are computed for the Hue content of the image as given in Eqns.4 -8.

$$\text{Contrast} = \sum_{i,j=0}^{N-1} (i, j)^2 C(i, j) \quad (4)$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} C(i, j)^2 \quad (5)$$

$$\text{Local Homogeneity} = \sum_{i,j=0}^{N-1} C(i, j) / (1 + (i - j)^2) \quad (6)$$

$$\text{Cluster Shade} = \sum_{i,j=0}^{N-1} (i - M_x + j - M_y)^3 C(i, j) \quad (7)$$

$$\text{Cluster Prominence} = \sum_{i,j=0}^{N-1} (i - M_x + j - M_y)^4 C(i, j) \quad (8)$$

From the texture features, the plant diseases are classified into various types.

3. Experimental Results and Discussion:

About 500 plant leaves of 30 different native plant species of Tamil Nadu have been collected for analysis. The acquired leaf images are converted into HSI format. From the hue content, the co-occurrence features like contrast, energy, local homogeneity, shade and prominence are derived. The feature sets are used for analysis of disease type of particular species.

Samples of leaves with various diseases like early scorch, yellow spots, brown spots, late scorch, bacterial and fungal diseases are shown in Figure 4.



(a)



(b)

(c)

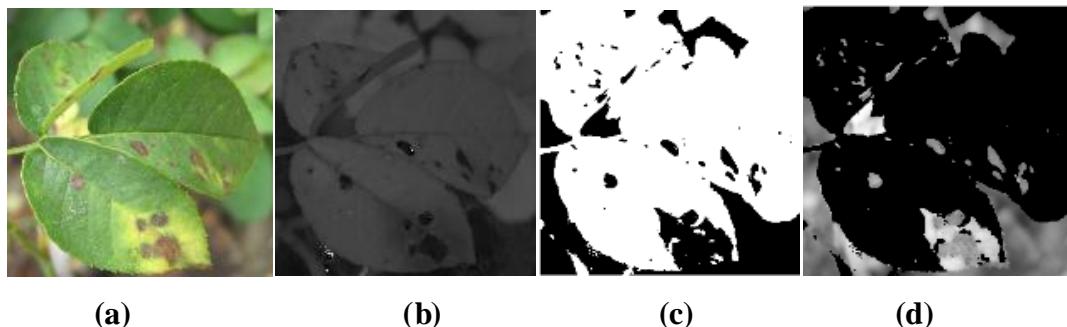


(d)

(e)

Figure 4: (a) Bacterial Disease in Rose and Beans Leaf (b) Sun Burn Disease in Lemon Leaf (c) Early Scorch Disease in Banana leaf (d) Late Scorch Disease in Beans Leaf (e) Fungal Disease in Beans Leaf

As a sample, a rose leaf that is infected by bacterial disease is taken as input to the algorithm. Fig 5.(a) shows the input image. Color transformation structure on the input image is performed. The hue content of the input image is shown in fig 5.(b). Then the green pixels are masked and removed using a specific threshold value. The thresholded image is shown in fig 5.(c). Then the R, G, B components are mapped to the thresholded image. The R component mapped to the thresholded image is shown in fig 5.(d).



(a)

(b)

(c)

(d)

Figure 5: (a) Input Image (b) Hue Content. (c) Thresholded Image. (d) R Component Mapped Output

Table 1 lists the set of leaves that are infected by various diseases and the subsequent steps that are carried out to extract the diseased region of the leaf.

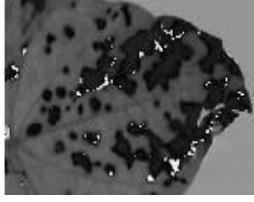
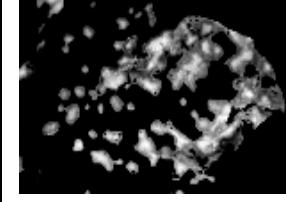
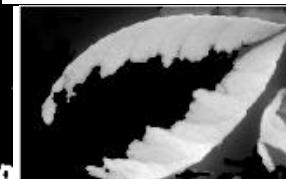
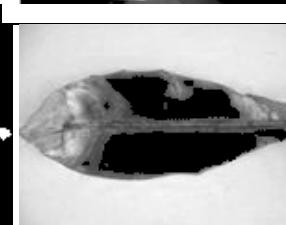
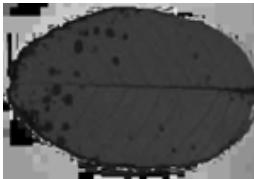
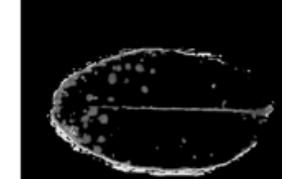
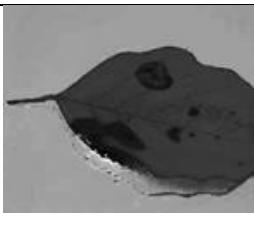
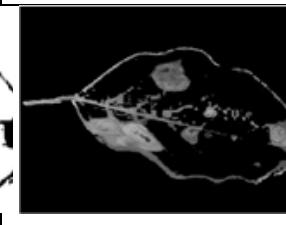
<i>Plant species</i>	<i>Input image</i>	<i>Hue content</i>	<i>Thresholded image</i>	<i>R component mapped output</i>
<i>Beans</i>				
<i>Lemon</i>				
<i>Banana</i>				
<i>Guava</i>				
<i>Jackfruit</i>				

Table 1: Detected Diseased Region of Various Leaves

After mapping the R, G, B components of the input image to the thresholded image, the co-occurrence features are calculated. The co-occurrence features such as contrast, energy, local homogeneity, cluster shade and cluster prominence are derived from the Co-occurrence matrix using the Eqns 4-8. The co-occurrence features for the H component of the leaf infected by various diseases are listed below.

Table 2: Co-occurrence feature for Beans leaf

<i>Category</i>	<i>Contrast</i>	<i>Energy</i>	<i>Homogeneity</i>	<i>Cluster shade</i>	<i>Cluster prominence</i>
<i>Normal</i>	932.7157	0.8412	0.9760	7.055×10^6	3.28×10^9
<i>Bacterial Brown Spot</i>	1.25×10^3	0.4787	0.7001	2.6749×10^6	0.869×10^9
<i>Fungal Disease</i>	1.75×10^3	0.5110	0.7479	3.8827×10^6	1.37×10^9

Table 3: Co-occurrence feature for Banana leaf

<i>Category</i>	<i>Contrast</i>	<i>Energy</i>	<i>Homogeneity</i>	<i>Cluster shade</i>	<i>Cluster prominence</i>
<i>Normal</i>	1301.1	0.9239	0.9697	1.8903×10^6	8.2097×10^8
<i>Early Scorch</i>	0.0230	0.7310	0.9885	-0.6528	1.4797

Table 4: Co-occurrence feature for Guava leaf

<i>Category</i>	<i>Contrast</i>	<i>Energy</i>	<i>Homogeneity</i>	<i>Cluster shade</i>	<i>Cluster prominence</i>
<i>Normal</i>	20.9861	0.9988	0.9994	1.5898×10^4	5.9122×10^6
<i>Chocolate Spot</i>	1738.5	0.6987	0.8613	3.9544×10^6	1.5568×10^9

Table 5: Co-occurrence feature for Lemon leaf

<i>Category</i>	<i>Contrast</i>	<i>Energy</i>	<i>Homogeneity</i>	<i>Cluster shade</i>	<i>Cluster prominence</i>
<i>Normal</i>	131.6131	0.9775	0.9905	3.74×10^5	1.36×10^8
<i>Sun Burn</i>	551.2493	0.2148	0.7527	52.504×10^5	21.642×10^8
<i>Bacterial Disease</i>	164.8886	0.9101	0.9592	8.7×10^5	2.66×10^8

<i>Late Scorch</i>	498.5613	0.4536	0.7102	42.28×10^5	14.858×10^8
--------------------	----------	--------	--------	---------------------	----------------------

Table 6: Co-occurrence feature for Mango leaf

<i>Category</i>	<i>Contrast</i>	<i>Energy</i>	<i>Homogeneity</i>	<i>Cluster shade</i>	<i>Cluster prominence</i>
<i>Normal</i>	246.3781	0.9882	0.9941	0.112×10^6	0.35107×10^8
<i>Brown Spot</i>	615.7240	0.6887	0.8390	2.73×10^6	8.2058×10^8
<i>Late Scorch</i>	409.6196	0.7497	0.8784	1.15×10^6	2.86×10^8

Based upon the Co-occurrence features obtained for different plant species (Table 2 to Table 6), it is inferred that the leaves which are affected by diseases shows significant differences in their co-occurrence features when compared to the normal leaf. Furthermore, the disease categories can also be easily categorized.

4. CONCLUSION

An application of texture analysis in detecting the plant diseases has been explained in this paper. Recognizing the disease is mainly the purpose of the proposed approach. The experimental results indicate the proposed approach can recognize the leaf diseases with little computational effort. The extension of this work will focus on developing algorithms and NN's in order to increase the recognition rate of classification process.

REFERENCES

1. Applications of image processing in biology and agriculture J. K. Sainis, Molecular Biology and Agriculture Division,R. Rastogi, Computer Division, and V. K. Chadda, Electronics Systems Division, BARC news letter.
2. Jean Williams-Woodward, Extension Plant Pathologist, (2009)-Georgia Plant Disease Loss Estimates, www.caes.uga.edu/publications.
3. H.Al-Hiary, S. Bani-Ahmad, M.Reyalat, M.Braik and Z.AlRahamneh, Fast and Accurate Detection and Classification of Plant Diseases, International Journal of Computer Applications (0975-8887), Volume 17-No.1.March 2011.
4. Dae Gwan Kim, Thomas F. Burks, Jianwei Qin, Duke M. Bulanon, Classification of grapefruit peel diseases using color texture feature analysis, International Journal on Agriculture and Biological Engineering, Vol:2, No:3,September 2009. Open access at <http://www.ijabe.org>.

5. Mohammed El.Helly, Ahmed Rafea and Salwa-El-Gammal, An Integrated image Processing System for Leaf Disease Detection and Diagnosis.
6. Muhammad Hameed Siddiqi1, Suziah Sulaiman, Ibrahima Faye and Irshad Ahmad, A Real Time Specific Weed Discrimination System Using Multi-Level Wavelet Decomposition, International Journal of Agriculture & Biology, ISSN Print: 1560–8530; ISSN Online: 1814-9596 ,09–118/YHP/2009/11–5–559–565 ,
<http://www.fspublishers.org>.
7. Al-Bashish, D., M. Braik and S. Bani-Ahmad, 2011. Detection and classification of leaf diseases using K-means-based segmentation and neural networks based classification. Inform. Technol. J., 10: 267-275. DOI:10.3923/itj.2011.267.275, January, 2011.
8. Sabine D. Bauer , Filip Korc, Wolfgang Forstner, The Potential of Automatic Methods of Classification to identify Leaf diseases from Multispectral images, Published online: 26 January 2011, Springer Science+Business Media, LLC 2011., Precision Agric (2011) 12:361–377, DOI 10.1007/s11119-011-9217-6.
9. Wang Jun, Wang Shitong, Image Thresholding Using Weighted Parzen Window Estimation. Journal of applied sciences 8(5):772-779, 2008, ISSN 1812-5654, Asian Network for Scientific Information, 2008.
10. Rafael Gonzalez, Richard E.Woods, Digital Image Processing, Third edition, Pearson Education, Prentice-Hall, Inc.
11. F.Argenti, L.Alparone and G.Benelli , Fast Algorithms for Texture Analysis using Co-occurrence Matrices, IEEE proceedings, Vol.137, No.6, pp. 443-448, 1990.