

# Leaf Disease Detection Using Image Segmentation

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**ABSTRACT**

Around 70 percent of the Indian economy relies upon agriculture, so it is very important to improve the productivity and quality of agro- based products, for better production predicting disease effects on plants is essential. But prediction is very difficult in the manual process, till the disease raise can't be noticed easily. To predict initially required expert, and also require the excessive processing time. Therefore, image processing is employed for the detection of plant diseases. Disease infected area detection involves the sequence of methods like image acquisition, image pre-processing, image segmentation, feature extraction, and comparison. This paper discussed the methods used for the detection of plant diseases using their leaves images by discussing some segmentation and has an extraction algorithm utilized in disease detection. Our project is used to detect plant diseases and can help in knowing the solutions at the early stage. It helps to show the affected part of the leaf in percentage. It uses an enhanced thresholding algorithm to predict the infected area of the leaves. Thus, by using image processing and segmentation the detection of infected areas in terms of time complexity is effective and easier.

**Keywords:** Disease detection, Threshold algorithm, Morphological filters, Accuracy rate.

**INTRODUCTION**

Image processing deals with the system that works on an image. Image processing focuses on two major tasks they are the improvement of image data for human understanding and processing of image data for storing, transmitting, and representing automatic machine perception. Some focus on where image processing ends and fields like image analysis and computer vision start. The continuum from image processing to computer vision is usually choppy into low-, mid- and high-level processes.

Low Level Process	Mid Level Process	High Level Process
Input: Image Output: Image	Input: Image Output: Attributes	Input: Attributes Output: Understanding
Examples: Noise removal, image sharpening	Examples: Object recognition, segmentation	Examples: Scene understanding, autonomous navigation

**Fig-1: Types of Image level processes**

Phases of Image Processing:

1. Image Acquisition– It could be as simple as being given an image that is in digital form. The main work involves:
  - a) Scaling
  - b) Color conversion (RGB to Gray or vice-versa)
2. Image Enhancement– it's amongst the only and most appealing in areas of Image Processing it's also wont to extract some hidden details from a picture and is subjective.
3. Image Restoration– It also deals with appealing of a picture but its objective (Restoration is predicated on the mathematical or probabilistic model or image

degradation).

4. Color Image Processing– It deals with pseudo color and full-color image processing color models that apply to digital image processing.
5. Wavelets and Multi-Resolution Processing– It is the foundation of representing images in various degrees.
6. Image Compression-It includes preparing some functions to perform this operation. It focuses on image size or resolution.
7. Morphological Processing-It comprises tools for getting image components that are used for representing shape.
8. Segmentation Procedure-It includes partitioning a picture into its constituent parts or objects. Automatic segmentation is the toughest part of Image segmentation.
9. Representation & Description-It follows the output of the segmentation stage, choosing a representation is merely a part of the answer for transforming data into processed data.
10. Object Detection and Recognition-It may be a process that assigns a label to an object that supported its descriptor.

The agriculture industry is one of the most vital sectors for contributing to national income in many countries. Throughout the years, many agriculture components and processes have become automated to ensure faster production and to ensure products are of the highest quality standards. Because of the increased demand in the agricultural industry, agricultural produce must be cultivated using an efficient process. Diseases and defects found in plants and crops have a great impact on production in the agriculture industry and lead to significant economic losses. A loss of an estimated 33 billion dollars every year was the result of plant pathogens found in crops in the United States. Pathogenic species affect plants significantly, introducing diseases such as chestnut blight fungus and Huang long bing citrus disease. Insect infestation along with bacterial, fungal, and viral infections is another main contribution to diseases found in plants. Changes in climate and temperature are also a few factors that may contribute to the increase in diseases found in plants. Once a plant has been infected, symptoms develop on various segments of the plant, ultimately degrading the growth of the subsequent fruit or vegetable.

Mango production is one of a very large industry, especially in India. Mango tree infections do not only significantly reduce grade and yield, but can also affect the return bloom of the following season. These factors have a drastic impact on countries that rely heavily on their agriculture sector as their main method of income. To overcome these losses and issues of plant diseases, farmers tend to look to chemical pesticides as a remedy solution. This solution may be effective in eliminating plant diseases but has drastic drawbacks. As well as being costly, the increasing use of pesticides creates dangerous levels of toxic residue levels on agriculture products. This leads to concerns about wholesomeness and the healthiness of products raised by the public when

pesticides are commonly used in the products they purchase. Therefore, the use of pesticides must be controlled and used only when necessary. This controlled or monitored method of pesticide use is known as selective pesticide spraying.

For the purpose to decrease losses found in defective plants many techniques have been introduced. Manual techniques, such as hand inspection and naked eye observation are very common methods used by farmers. Plant diseases are detected and characterized by observation from experts, which can be very expensive and time-consuming. Because these methods are very tedious it is prone to sorting errors and judgmental errors from different farmers. Therefore, disease detection systems have been introduced that tackle many of the issues faced with labor-intensive techniques.

**Existing System:**

1. The prevailing method for disease detection is just eye observation by experts through which identification and detection of plant diseases are done.
2. In doing so, an outsized team of experts also as continuous monitoring of plants is required, which costs very high once we do with large farms.
3. At the same time, in some countries, farmers do not have proper facilities or even ideas that they can contact experts. Due to which consulting experts even cost high also as time-consuming too.
4. Disease identification by the visual way may be a more laborious task and at an equivalent time, less accurate and may be done only in limited areas.

**PROPOSED METHODS**

**1. Image Acquisition:**

Leaf images are captured in the Image Acquisition method. Image acquisition is the start of any image processing technique, in which images are digitalized and stored. For this system, leaf sample images with visible disease spots can be either captured with a digital color camera with a uniform background on-site or can be retrieved from any online database. It is recommended that images retrieved from the internet have a uniform background. This will allow for more accurate segmentation results as the background area can be easily distinguished from the leaf area. The resolution of images retrieved from an external database does not need to be set to a specific value, but this will be amended in the pre-processing stage. As for images taken on-site, and digital RGB camera can be used. This camera provides high image capture detail with a resolution of 12 Megapixels. Another important feature of this camera is the low focal length of 4mm, which allows for a wider field of view. This aspect is vital for this system, as leaf images are taken at close range and the leaf area must be completely represented in the image.

**LITERATURE SURVEY**

TITLE	Advantage	Drawback
1. Image Processing In Agriculture For Pathogen Detection And Diagnose Of Mango Crop	1. Adaptive K-Means Clustering and Edge detection. 2. Normalization technique. 3. Robust and accurate	1. Normalizing is complex. 2. Focuses on two diseases only.
2. New Optimized Spectral Indices for Identifying and Monitoring Winter Wheat Diseases.	1. RELIEF-F algorithm 2. Develop new spectral indices (NSIs) 3. Percentage of diseases infected.	1. Difficult to implement the applications using RGB because of their range i.e. 0 to 255
3. An Empirical investigation of olive leave spot disease using auto-cropping segmentation and fuzzy c-means classification.	1. FCM algorithm with polygon auto-cropping segmentation. 2. Severity percentage is calculated. 3. Fuzzy c-means clustering.	1. Computationally complex. 2. Slow.
4. A novel algorithm for detecting bacterial leaf scorch (BLS) of shade trees using image processing.	1. Classification of algorithm. 2. Analyze shade leaves disease 3. High accuracy with less operational time.	1. Computationally complex to form convoluted clusters.
5. A New Method for Soybean Leaf Disease Detection Based on Modified Salient Regions	1. Morphology algorithm 2. Complicated farmland backgrounds. 3. Segmentation using threshold is performed.	1. Detection of diseases is improper.

A relatively low aperture of 1.8 allows for more light to enter the sensor, which can be beneficial in low light areas.

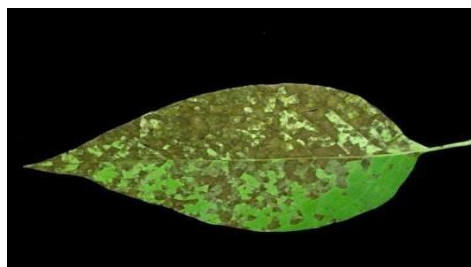


Fig-2: Input leaf image retrieved from plant

**2. Image Pre-Processing:**

It is the process of removing the noise from the image such as the captured image may contain dust, spores, and water drops. To remove the noise we use enhancement techniques and called image pre-processing. Also, the selection and conversion of the color space can be completed in this stage. In this case, the Lab color space is selected over the RGB color model due to multiple reasons. This is useful in cases where images are captured in areas with non-uniform lighting conditions. However, in practice, space is usually mapped onto a three-dimensional integer space for digital representation. The L\*a\*b\* space consists of a luminosity 'L\*' or brightness layer, chromaticity layer 'a\*' indicating where the color falls along the red- green axis, and chromaticity layer 'b\*' indicating where the color falls along the blue-yellow axis. There are no simple formulas for conversion between RGB and L\*a\*b\* because the sRGB color model is device-dependent. The sRGB values first must be transformed to the CIE1931 color space and then transformed into L\*a\*b\*.



Fig-3: Internet leaf image in L\*a\*b color space

**3. Image Segmentation**

The leaf image is partitioned into several parts called pixels and uses a Thresholding algorithm. Image segmentation is the process in which the digital image is partitioned into constituent regions so that the different regions can be easily distinguished and analyzed. Segmentation can be achieved by various techniques such as clustering methods, compression-based methods, and histogram-based methods. The first step is to accurately segment the region of interest from the background. In this case, the leaf area should be recognized and distinguished from the uniform background. Different thresholding techniques will be tested and compared to select the most appropriate for this system. Before implementing thresholding techniques, the original RGB image is converted into a greyscale image using a simple conversion method. The red, green, and blue channels represent a 2D array of pixel values ranging from 0 to 255. The greyscale conversion of the Internet leaf image and iPhone leaf image are shown in the below figure.

$$Greyscale\ value_{ij} = (0.2989 \times R_i) + (0.5870 \times G_i) + (0.1140 \times B_i)$$

Where  $i$  and  $j$  represent the pixel location in the matrices

$$\sigma_w^2(t) = w_b(t)\sigma_b^2(t) + w_f(t)\sigma_f^2(t)$$

$$\sigma_b^2(t) = w_b(t)w_b(t)[\mu_b(t) - \mu(t)]^2$$

$$w_b(t) = \sum_{i=0}^{t-1} p(i) \quad w_f(t) = \sum_{i=t}^{L-1} p(i)$$

$i=0$  to  $i=t$  Probability equation for background (left) and foreground (right)

$$\mu_b(t) = \sum_{i=0}^{t-1} ip(i) \quad \mu_f(t) = \sum_{i=t}^{L-1} ip(i)$$

$$b \quad i=0 \quad w_b \quad f \quad i=t \quad w_f$$

Mean equation for background (left) and foreground (right)

$$\sigma_b^2(t) = \sum_{i=0}^{t-1} (i - \mu_b)^2 p(i) \quad \sigma_f^2(t) = \sum_{i=t}^{L-1} (i - \mu_f)^2 p(i)$$

$$b \quad i=0 \quad b \quad f \quad i=t \quad f$$

Variance equation for background (left) and foreground (right)



**Fig-4: Internet leaf image after greyscale conversion.**

**Otsu Thresholding**- This algorithm is used to spot the disease region based on the calculation of the threshold value and identify the disease area.



**Fig-5: Internet leaf Otsu threshold background segmentation.**

#### 4. Feature Extraction

Image features like shape, area, texture and it uses morphological filters are known as feature extraction.

Morphological Techniques:

The first morphological method removes all connected components that have fewer than P pixels from the binary image. The value of P is chosen as the minimum area for an unwanted object in the image, anything below this area will be disregarded from the image. A structuring element of size P is passed over the image and objects smaller than the size of the structuring element is removed from the binary image.



**Fig-6: Binary conversion of the leaf after removing small areas.**

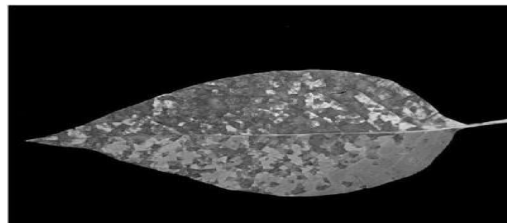
A circular flat morphological structuring element is then used to fill any gaps between small intersections. The figure illustrates how the diseased area is represented after removing small unwanted objects and after filling gaps to have a better representation of the overall leaf disease area.

**Fig-7: Binary conversion of a leaf after filling gaps.**

#### 5. Comparison and accuracy

Compares the data with available data sets

and find out the disease exactly. In some cases, the

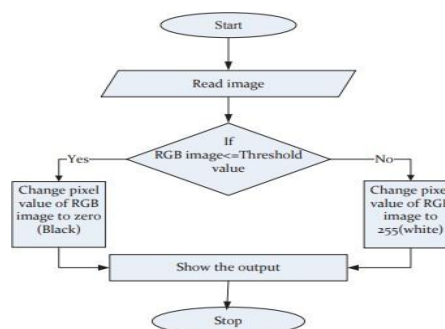


leaf may be infected with different diseases that are similar in color and could be clustered into the same cluster. The accuracy can be found out by iterating 500 times of the functions of code and then get an accurate percentage of disease- infected area in Matlab, and the leaf is compared to find the name of the disease.

#### ALGORITHM EXPLAINED

##### Otsu Thresholding

- It is used for the segmentation of infected areas.
- 1) According to the threshold, Separate pixels into two clusters with intensity values
  - 2) Apply threshold with particular pixel value to identify the spots of the leaf.
  - 3) Finds out the segmented area as per threshold values.



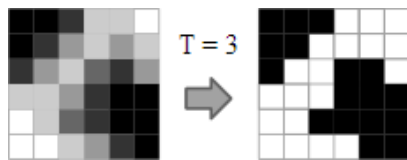
**Fig-8: Thresholding algorithm flowchart**

The greyscale image is then converted into a binary image according to the threshold set value. The output binary image replaces all pixels in the input image with luminance greater than the threshold value with the value 1 (white) and

replaces all other pixels with the value 0 (black). The threshold is set as a value between 0 and 255 where values closer to 0 signify a threshold value closer to lower greyscale values (black) and vice versa.

Threshold	T=1	T=2	T=3	T=4	T=5
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<b>Weight Background</b>	$w_b = 0.243$	$w_b = 0.5342$	$w_b = 0.5743$	$w_b = 0.8521$	$w_b = 0.9231$
<b>Mean Background</b>	$\mu_b = 0$	$\mu_b = 0.4890$	$\mu_b = 0.6652$	$\mu_b = 1.4561$	$\mu_b = 2.1421$
<b>Variance Background</b>	$\sigma^2 = 0$	$\sigma^2 = 0.2956$	$\sigma^2 = 0.4763$	$\sigma^2 = 1.5102$	$\sigma^2 = 2.6701$
<b>Weight Foreground</b>	$w_f = 0.8231$	$w_f = 0.5982$	$w_f = 0.8451$	$w_f = 0.3897$	$w_f = 0.1001$
<b>Mean Foreground</b>	$\mu_f = 3.0243$	$\mu_f = 3.5671$	$\mu_f = 3.7843$	$\mu_f = 4.2311$	$\mu_f = 4.0921$
<b>Variance Foreground</b>	$\sigma^2 = 1.9872$	$\sigma^2 = 0.7854$	$\sigma^2 = 0.4321$	$\sigma^2 = 0.3214$	$\sigma^2 = 0$
<b>Within Class Variance</b>	$\sigma^2 = 1.4365$	$\sigma^2 = 0.4321$	$\sigma^2 = 0.6543$	$\sigma^2 = 0.8791$	$\sigma^2 = 2.1432$
<b>Between Class Variance</b>	$\sigma^2 = 1.4612$	$\sigma^2 = 2.3142$	$\sigma^2 = 2.4423$	$\sigma^2 = 2.5612$	$\sigma^2 = 0.7405$



**Fig-9: Result of Otsu Thresholding at threshold value 3**

**EXPERIMENTAL RESULTS**

Otsu thresholding technique. The table illustrates the optimal threshold value found using the Otsu thresholding technique.

**Table-1: Otsu threshold values for leaf images**

Image	Otsu threshold greyscale (0-255)
Leaf image retrieved from internet	62.0734
Leaf image captured from	111.0234

If pixel greyscale > 62.0734 then pixel set to 1 (white) If pixel greyscale < 62.0734 then pixel set to 0 (black) The background segmentation result for the leaf image retrieved from the internet shown previously to show good promise on accurately highlighting the leaf area from the background.

**CONCLUSION**

The exact recognition and identification of the plant leaf disease at an early stage is significant for the effective development of yield and this is possible by utilizing image processing. By using thresholding and morphological filters we can easily identify the disease infected areas. Thus we can accurately identify and classify various plant diseases using image processing techniques.

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