*A Progress Report*

*on*

# Detection of Infectious Patterns on Tomato Leaves due to Pathogens using Image Processing Techniques.

*carried out as part of the course CS1634 Submitted by*


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In

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**Abstract**

Using typical digital colour pictures, a method for locating and measuring leaf symptom is shown. Because it was designed to be totally automated, it removes the possibility of human error, cutting down on the time it takes to assess the severity of the disease. The technology can handle photos with many infection sites, reducing the amount of time it takes to detect them. According to studies, the results are more accurate when the infected area and veins have the same tone and colour characteristics. The algorithm has one constraint: the background must be as dark as feasible. According to studies, the methodology provided accurate estimates in a wide range of conditions, including differences in leaf size, shape, and colour, symptoms, and leaf veins. Many external factors influence the outcome, such as image capture methods and file compression on different platforms.

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## 1 Introduction

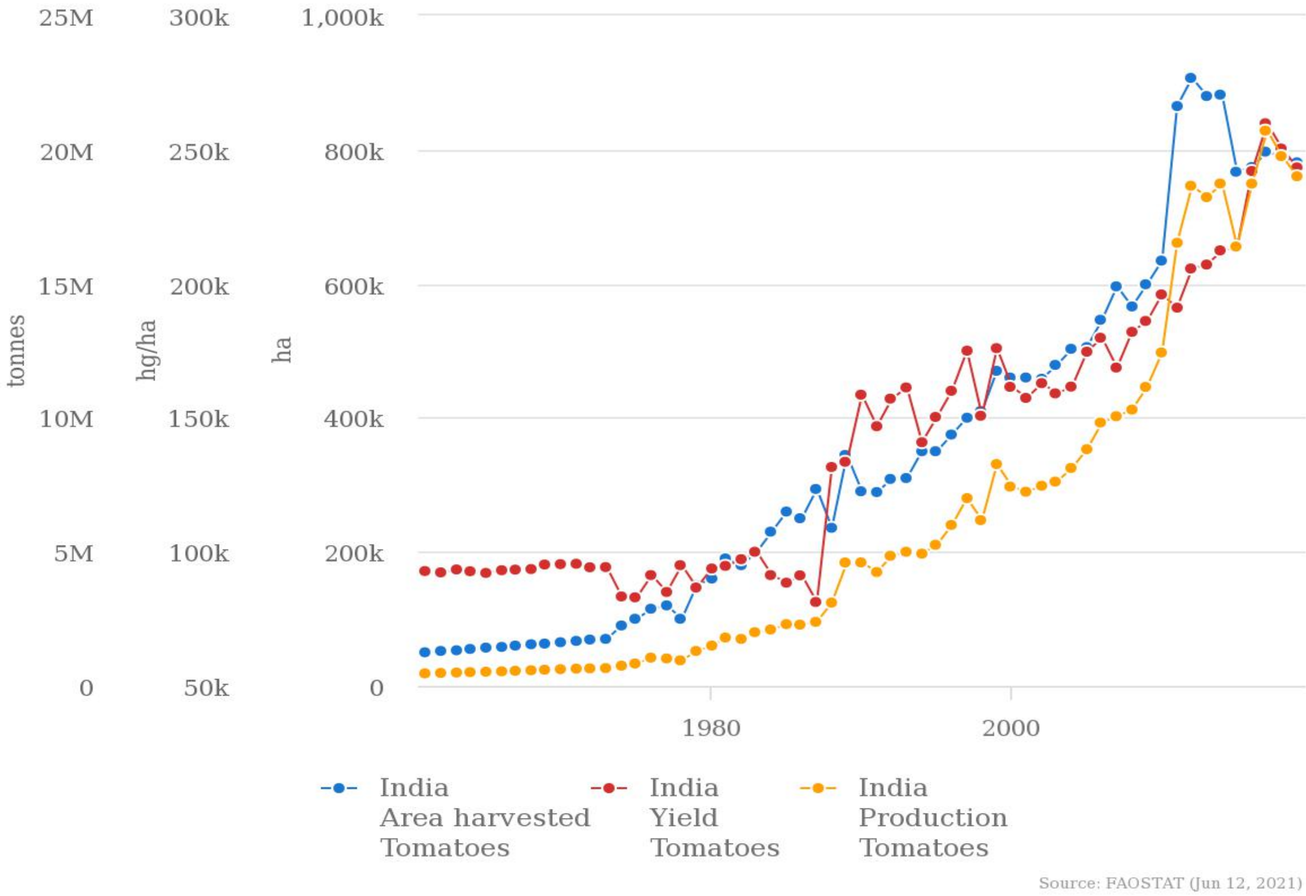



Figure.1 Timeline of Production, area harvested and yield of Tomato crop from 1961 to 2019(FAOSTAT statistical database)

Tomatoes are one of the world's most popular vegetables, with an annual market value of approximately 6 trillion INR. According to the data presented above, crop production has been declining since 2014. This tendency could be caused by plant pathogens. Pathogens reduce crop production and have an impact on system sustainability. Environmental, agricultural, social, and economic factors all contribute to food insecurity. These points of view must be reconciled in order to gain a more comprehensive understanding of the multifaceted consequences of plant diseases and their inferred implications.

One of the world's most infamous pests, two spotted spider mites, has a host range of over 200 crops and is one of the most common pests. Pesticide sales alone account for over $400 million in annual control expenses. The bug develops resistance to more than a hundred chemical compounds, making it one of the most resilient arthropods (Michigan State University 2019). Plant diseases can be detected using a specialised procedure, reducing the amount of surveillance needed on large plant farms and allowing for proper response in the early stages, such as when symptoms appear on plant leaves

## 1.1 Motivation

Agriculture is the backbone of the Indian economy and one of the most important livelihoods of India. It provides approximately 52% of the available jobs in india and according to the economic data of the financial year 2006-07 agriculture contributes around 18.1% to the GDP.( Arjun, K. M. 2013)

Hence it is of great importance that no damage is done to the crops. The two major factors that may damage the harvest are climate and plant diseases. Therefore along with favourable climate prevention of plant diseases is very important. For this detection of plant diseases plays an important role. Detecting the symptoms in a timely manner can help evaluate the seriousness of the disease and in turn help in choosing the best approach in dealing with the disease.

(Barbedo, J. G. A. 2014)The detection techniques can be divided into 3 types: manual, semi automatic and automatic.

Manual detection is done by pathologists using their expertise to distinguish between healthy and diseased tissues. Such a process takes time, is costly and is prone to errors due to fatigue and human negligence.

Semi automatic methods are carried out by using computer tools and image processing packages but still require human input and hence are prone to human error. Additionally at times they require complex adjustment which may take longer than manual methods.

Hence automatic detection becomes necessary because of its low cost, reduced time and removal of human errors.

Figure. 2 A tomato leaf infected with early blight(Plant Village Dataset,Kaggle)

# 2 Literature Review

## 2.1 Keywords Table

Table.1 Keywords Table

| Keyword | Methodology | Source |
|---|---|---|
| 1) colorspace | Conversion to L*a*b or HSV colorspace is required as RGB does not provide sufficient details for further image processing.<br>By applying further operations on H and a channels, infected tissues cam be differentiated from rest | Barbedo, J. G. A. (2016) |
| | Image is converted to another color space ,L*a*b and HSV are preferred in these case, and best results by provide by a channel of L*a*b color space which highlight infectious patterns. After applying mask, remaining pixel are turned black. | Barbedo, J. G. A. (2014). |
| | The colorspace transformation is applied on a image to assist it make extra apparent or explicit to point out some favored records which isn't seen in normal RGB colour space.<br>A two step process is required in which first RGB is changed to L*a*b color space, then L ,a ,b channels are individually separated. | Ali, H., Lali, M. I., Nawaz, M. Z., Sharif, M., & Saleem, B. A. (2017). |
| 2 )Thresholding | First we rescale the image and convert to grayscale, then by applying thresholding we generate a mask where all other pixels, except leaf was converted to 0.<br>The limitation of this algorithm was the variable background, which results in incorrect outcome, therefore segmented image is must for this separation technique | Barbedo, J. G. A. (2014). |
| | For selection of region of interest, a method is used which applies threshold according to energy difference and is known as Delta E.<br>Otsu thresholding can also be applied according to the outcomes. | Ali, H., Lali, M. I., Nawaz, M. Z., Sharif, M., & Saleem, B. A. (2017). |

| | | |
|---|---|---|
| | We can binarize intensity image by using otsu's thresholding. For extracting features of shape, boundary of leaf is required by 3x3 Laplacian operator. It also smoothen the surface and removes extra unwanted particles from the leaf. | Saleem, G., Akhtar, M., Ahmed, N., & Qureshi, W. S. (2019). |
| 3)Symptoms | 1)Softwares like Assess Software can also be used for measuring plant disease symptoms .<br>2)The a channel of L*a*b color space gave better results when , in low contrast images we segment extremely dark or extremely light patterns.<br>3) The h channel of HSV color space gave better results when due to infection, the whole leaf color was changing significantly | Barbedo, J. G. A. (2016). |
| | 1)Visualization of symptoms in the leaves also results in estimating spread of similar diseases in plants like tomato.<br>2)Leaf mold disease symptoms include gray spot under the leaf and a yellow area on top of leaf in infected area. | Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). |
| | 1)Any abnormal change in the tissue of leaf surface spread over different area are scattered small symptoms which are generally hard to detect.<br>2)We should keep only center leaf after removing background as we can more clearly see symptoms which may improve the overall outcome of the algorithm<br>3)One of the limitations of the algorithm is caused due to very small powdery symptoms or irregular leaf mottling. | Barbedo, J. G. A. (2019). |

## 2.2 Outcome of Literature Review

Table.2 Advantages and Disadvantages of different techniques

| Author | Method | Advantages | Disadvantages |
|---|---|---|---|
| Jayme Garcia Arnal Barbedo | Threshold the image with a value of 24 and 220 depending on weather the background is dark or white. The color space is changed to L*a*b and further a channel is used. Using masking, thresholding and morphological operations the viens, petiole and other such noise are removed. | Simple and Straightforward implementation, computationally lightweight, applicable in most situations, lighting conditions must be optimal, the algorithm was developed for the entire leaf hence results of portion of a leaf aren't accurate | The image must have a dark or white background, and the process is based on actual data rather than the mathematical and theoretical basis that machine learning and statistical techniques require.. |
| G. Saleem | Performed on Flavia dataset, By transforming the colour space to L*a*b, the ROI may be retrieved. The image is then binarized by computing the threshold using Otsu's technique (Otsu, 1975), and then processed with a Laplacian filter. Next feature extraction and dimensionality reduction is carried out. KNN classification is performed as last step. | Overcomes the limitations due to variety in leaf sizes by using various optimized features for classification, provide a very accurate and practical solution to the challenge of identifying plant types from raw leaves, which can be utilised in a mobile application to determine the plant class of a leaf by capturing a photograph, and best result is given by KNN classifier | At present works with images with non-cluttered background, can be improved to work with cluttered background by augmenting it with efficient segmentation |
| J. G. A. Barbedo | The method includes eroding the image before converting the image to different color channels of HSV amd L*a*b color space. A bright pixel correction is applied to the H channel. Then contrast enhancement is applied to both the channels and an histogram is created.This histogram is analyzed to find the threshold to binarize the image. Image is segmented on the basis of both the channels and the best out of the two is chosen by the user. | Deals with a wide variety of conditions due to the use of 2 channels. The technique is resilient to fluctuations in leaf colour and has a low rate of false positives and false negatives because it is a semi-automated technique. | It's a semiautomatic method and hence requires human intervention, Most errors were Venations are a source of inaccuracy because of colour channel restrictions, especially when the vein colour is yellow or brown rather than green. |

## 2.3 Problem Statement

Propose an algorithm to Detect Infectious Patterns on Tomato Leaves due to Pathogens using Image Processing and Machine Learning Techniques

## 2.4 Research Objectives

Agriculture is vital to developing country economies since it provides a large source of food, money, and work for rural residents. Two key elements that can jeopardise the yield are the weather and plant diseases. Pathogens diminish crop yields and threaten the system's long-term viability. Food insecurity is caused by a combination of environmental, agricultural, social, and economic factors.

Plant diseases can be detected using a specialised procedure, reducing the amount of surveillance needed on large plant farms and allowing for proper response in the early stages, such as when symptoms appear on plant leaves.
Detection techniques are classified into three types: manual, semiautomated, and automatic.
Because of their low cost, reduced time, and elimination of human errors, automatic detection approaches are addressed here .

# 3 Methodology and Framework

## 3.1 Algorithms, Techniques etc.

**Color Space Analysis**:

-**L*ab**

Lightness and the color-opponent dimensions a and b, which are based on compressed Xyz colour space coordinates, are used to define it

Lab is particularly notable for it's use in delta-e calculations

L – Lightness ( Intensity ).

a - a colour component that can range from green to red.

b - a colour component that ranges from blue to yellow in hue

In Lab color space, the L channel is independent of color information and encodes brightness only. The other two channels encode color.

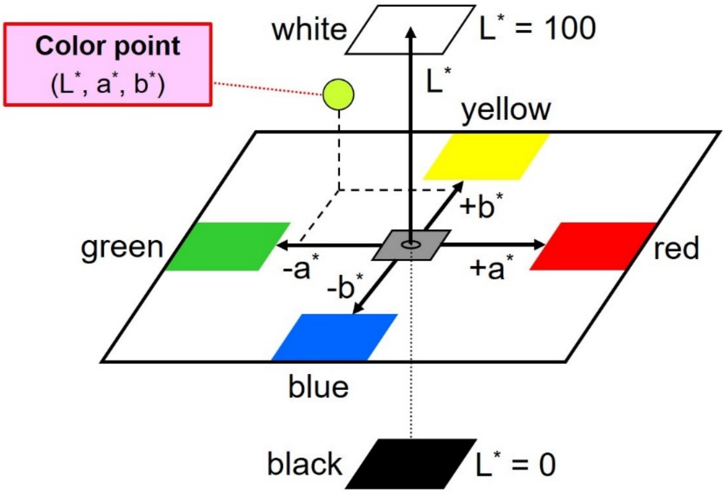
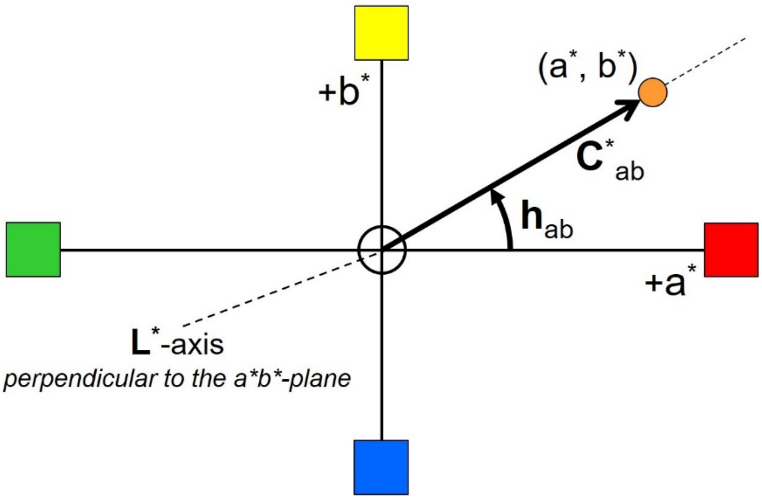



Figure. 3 Representation of L*a*b color space on 3-d axes

**Hue and Chroma**




**Hue**

The visible spectrum of fundamental colours that can be seen in a rainbow is referred to as hue. The three basic colours (red, blue, and yellow) and three secondary colours (orange, green, and violet) that occur in the colour wheel or colour circle make up hues

$$\boxed{h_{ab} = \arctan \frac{b^*}{a^*}}$$

### Chroma

The degree of vividness of a colour, or how pure it is relative to its colour wheel equivalent, is referred to as chroma. It refers to a color's brightness in relation to white.

$$\boxed{C^*_{ab} = \sqrt{(a^*)^2 + (b^*)^2}}$$

R, G, and B are transformed to floating-point representation and scaled to match the 0 to 1 range in 8-bit and 16-bit pictures

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \leftarrow \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$X \leftarrow X/X_n, \text{where} X_n = 0.950456$$

$$Z \leftarrow Z/Z_n, \text{where} Z_n = 1.088754$$

$$L \leftarrow \begin{cases} 116 * Y^{1/3} - 16 & \text{for } Y > 0.008856 \\ 903.3 * Y & \text{for } Y \leq 0.008856 \end{cases}$$

$$a \leftarrow 500(f(X) - f(Y)) + delta$$

$$b \leftarrow 200(f(Y) - f(Z)) + delta$$

where

$$f(t) = \begin{cases} t^{1/3} & \text{for } t > 0.008856 \\ 7.787t + 16/116 & \text{for } t \leq 0.008856 \end{cases}$$

and

$$delta = \begin{cases} 128 & \text{for 8-bit images} \\ 0 & \text{for floating-point images} \end{cases}$$

This outputs $0 \leq L \leq 100$, $-127 \leq a \leq 127$, $-127 \leq b \leq 127$. The values are then converted to the destination data type:

- 8-bit images

$$L \leftarrow L * 255/100, \quad a \leftarrow a + 128, \quad b \leftarrow b + 128$$

## Color Space Comparison:

Figure. 5 Orignal Image

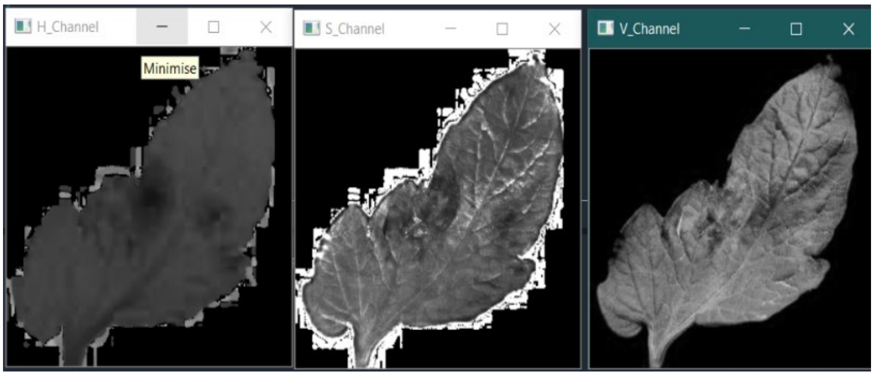



Figure. 6  H,S,V channels

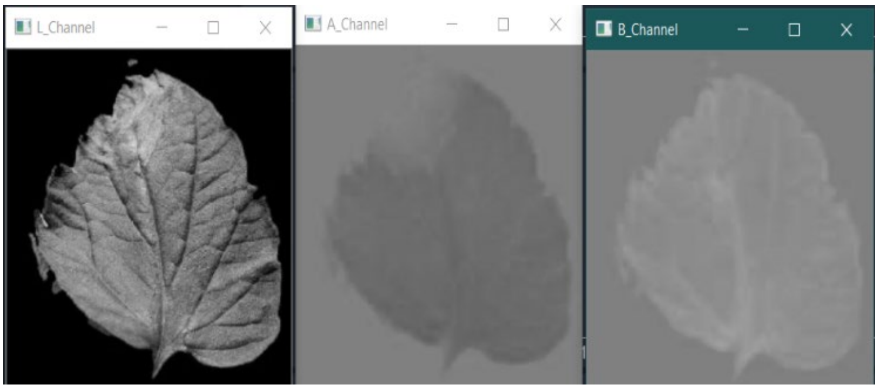



Figure. 7  L,a,b channels

**Contrast Stretching:**

Contrast stretching spreads the range of intensity values it contains over a chosen range of values to improve contrast. The enhancement is gentler than histogram equalisation because it can only apply a linear scaling function to image pixel values.

The transform function used here is:

P(out) = [P(in) - P(min)] / [ P(max) - P(min)] *255

**Thresholding:**

Thresholding is the most basic method of segmenting images in digital image processing. Thresholding is used to create binary pictures from grayscale images.

If the picture intensity is less than a given constant, the thresholding algorithm replaces each pixel in a picture with a black pixel, and if the image intensity is more than that constant, each pixel is replaced with a white pixel.

**Connected Component Labeling and Analysis:**

CCL (connected-component labelling) or CCA (connected-component analysis) is an algorithmic implementation of graph theory in which subgroups of linked components are labelled distinctively depending on a predefined criteria.

It is built on graph traversal algorithms. After finding the starting pixel of a connected component, all of that component's related pixels are named before moving on to the next image pixel.

After the labelling stage, the graph is divided into subsets, and then the data, such as centroid, area, etc can be recovered and analysed.

**Morphological Operations:**

Morphological transformations are done on binary images and requires two inputs: the original image, and the a structuring element or kernel that determines the operation's nature. The two basic operators are Erosion and Dilation with two variations namely Opening and Closing.

**1. Erosion**

A 2D convolution kernel slides through the image, eroding the foreground object's borders (white). If all of the pixels under the kernel are 1, the resultant pixel will be 1, else it will be 0.

Based on the kernel size, the pixels along the border are discarded. As a result, the width or scale of the foreground object reduces, or to put it another way, the white region in the image diminishes. It's useful for separating two joined objects and deleting minor white noises.

**2. Dilation**

This is inverse of erosion. A 2D convolution kernel moves through the image, dilating the edges of the foreground item (white colour). If at least one pixel under the kernel is one, the resultant pixel will be 1, else it will be 0. The size of the foreground object or the white region grows in this instance. This is used to reassemble shattered components.

**3. Opening**

The image is first eroded and then dilated, this is process is called opening. It is used to remove noise. Eroding it first removes the white noise but in the process shrinks the foreground object. Once the noise is gone the image is dilated to return the object to its original size.

**4. Closing**

The image is first dilated and then eroded, this is process is called closing. This is used to close holes and openings. Dilating it first fills the holes but increases the thickness of the object. Therefore it is eroded to bring it back to its original size.

## 3.2 Detailed Design Methodologies

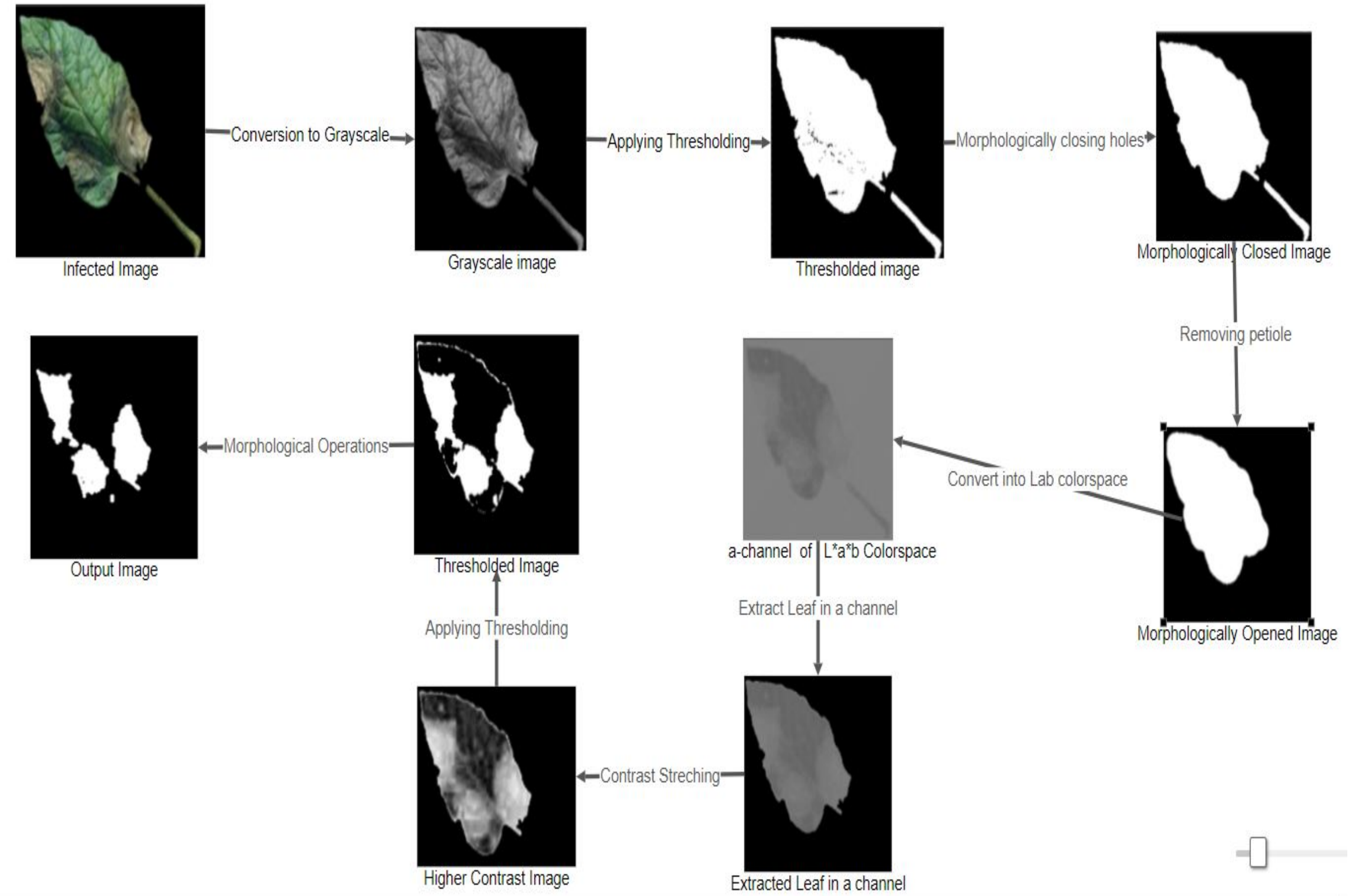



Figure. 8 Flow Chart

1.) First and foremost before processing the image it is resized such that its largest dimension is 800px. For this we use the opencv's resize function and then we use the fast NLM filter to remove the noise. This takes care of poorly taken images and bad lighting

Figure.9 Infected Image

2.) Next we create a mask for the leaf. For this first convert the image to grayscale and then threshold the image with a threshold value of 24.

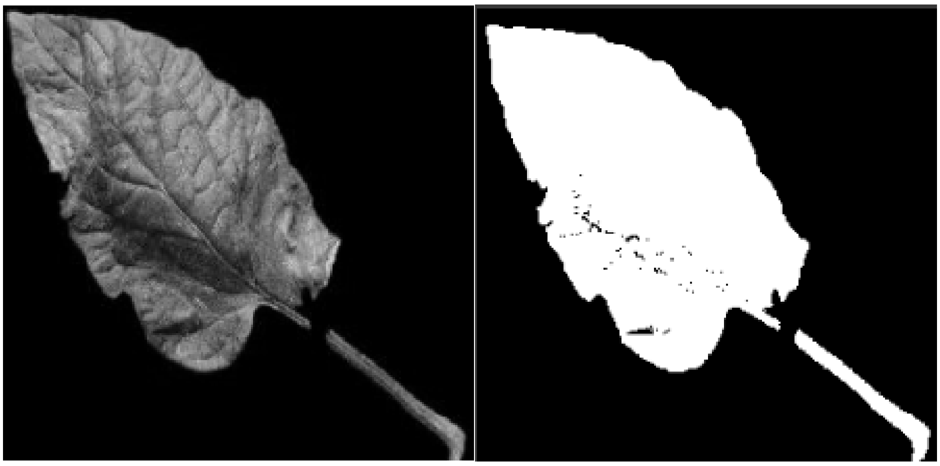


Figure 10. Grayscale image(L), Thresholded image(R)

The mask may contain some black dots(holes). These are removed by morphologically closing them using a kernel size of 5x5(using ellipse as the structuring element).

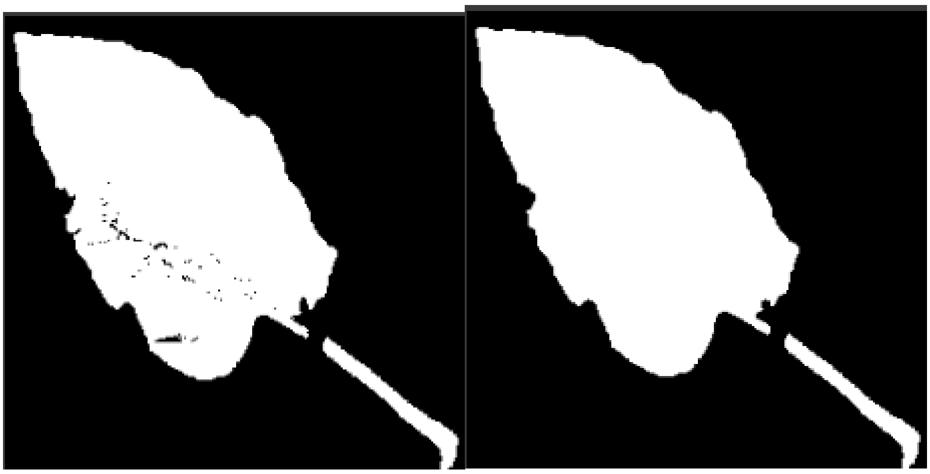


Figure.11 Image with Holes/Noise(L),Morphologically Closed Image(R)

3.) Next we want to remove the petiole. This is done by first morphologically opening the mask and then subtracting it with the original mask. What we obtain from this is the petiole with some outer edges of the leaf.

Figure.12 Morphologically Opened Image(L), Subtracted image containing the petiole and some outer edges(R)

4.) To extract the petiole from this image we use the concept of Connected Component Labeling and Analysis. What we do here is label each of the objects (in this case each all the white pixels that are connected is an object and is given a label) and then iterate over these labels and extract their stats in this case the area. The label with the largest area is selected which is the petiole and the rest are ignored. The extracted petiole is subtracted from the original mask of the leaf and stored. This will be the mask that we will use.

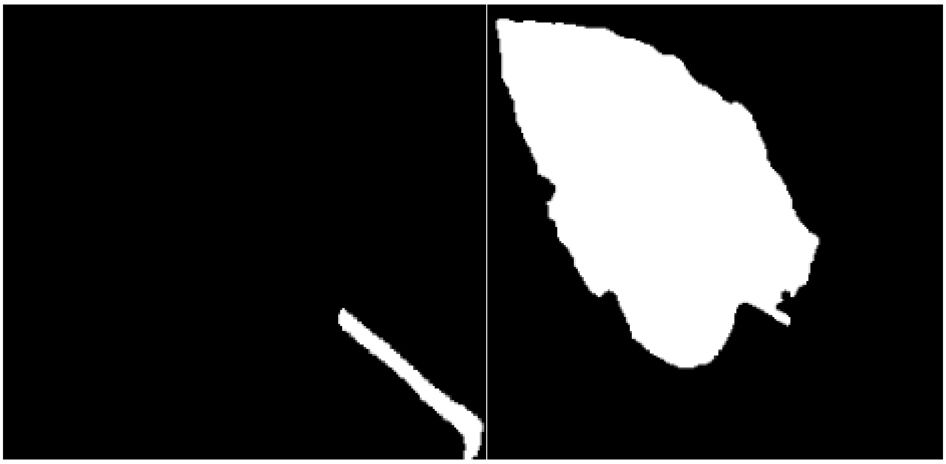


Figure.13 Extracted Petiole(L), Final Mask(R)

5.) Next we convert the image into lab colorspace and extract the alpha channel because the infected region is clearly visible in this channel. The extracted alpha channel is masked with the earlier created mask to remove the background.

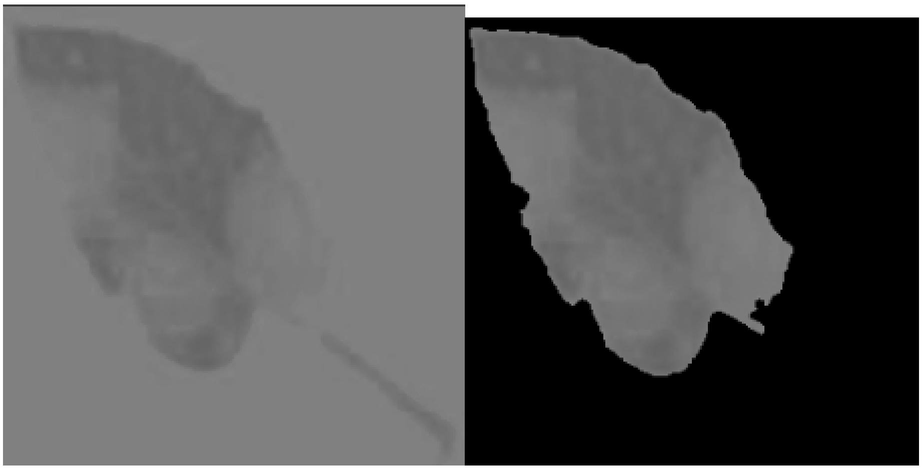


Figure.14 a-channel of L*a*b Colorspace(L), Extracted Leaf in a-channel(R)

6.) Next we improve the contrast of the image obtained in the previous step by applying contrast stretching. This will make the pixel values cover the entire range spreading it across the whole range irrespective of the image characteristics which helps with the visualization and use of a fixed threshold(experimentally calculated)

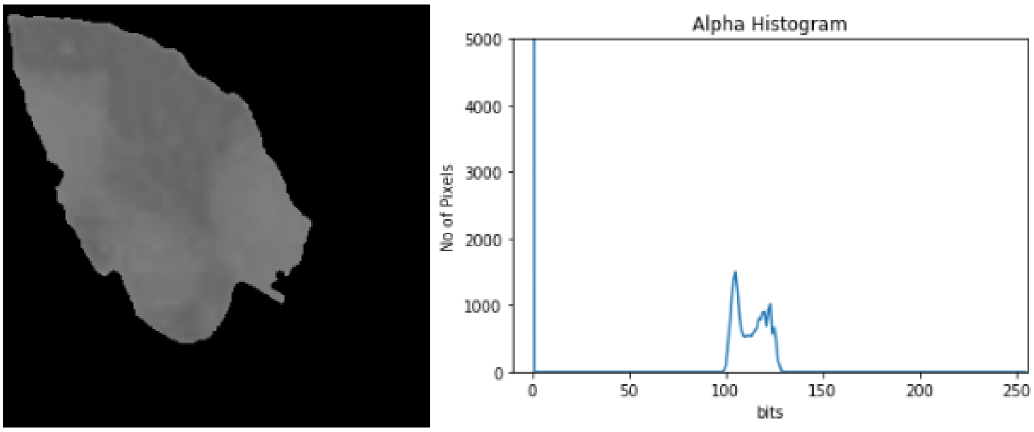



Figure.15 Lower Contrast Image(L), Histogram of the Low Contrast Image(R)

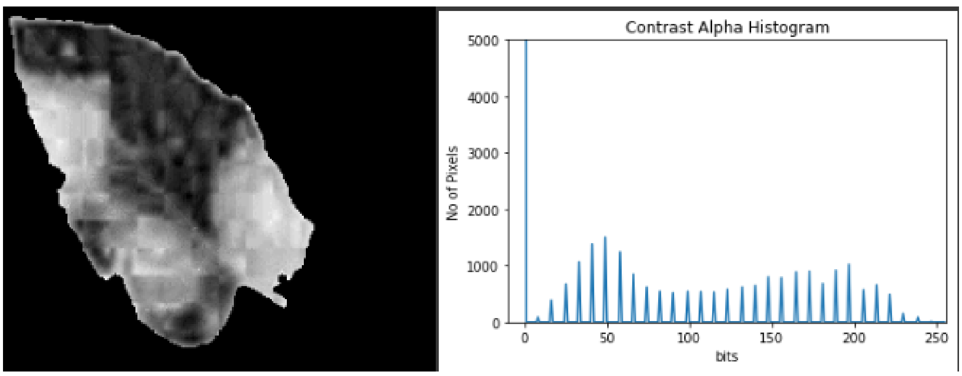



Figure. 16 Higher Contrast Image(L), Histogram of the High Contrast Image(R)

7.) The resulting image clearly shows the infected region. To extract them we threshold them with a threshold value of 128. Otsu's method of thresholding was tried but simple thresholding with a value of 128 gave better results.

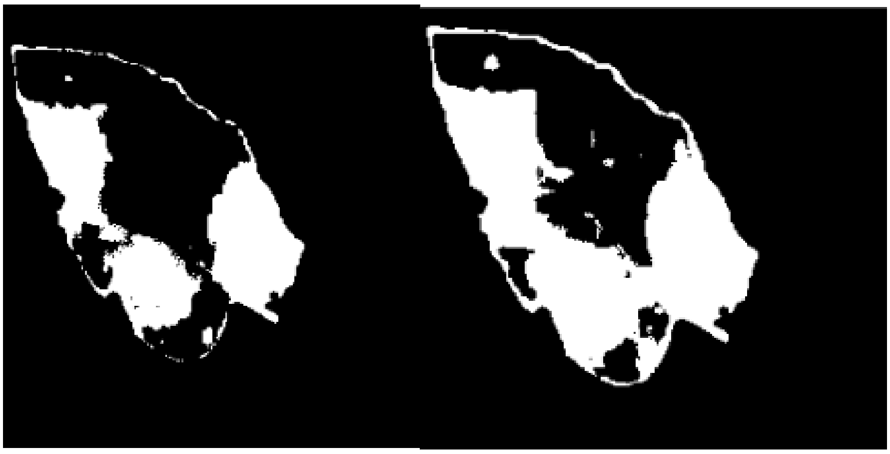


Figure.17 Thresholded Image with a value of 128, Thresholding using Otsu's Method

8.) The image shows the extracted region of interest but still has noise and holes that need to be removed and filled respectively. This binary image is morphologically closed using an ellipse as the structuring element and a kernel size of 3x3 followed by morphologically opening it using the same structuring element and a kernel size of 5x5. An extra process is followed to adjust for probable alterations to the symptoms. The picture is multiplied by a dilated replica of itself created with the same structuring element as the opening.

Figure.18 Image after Morphological Closing(L), Image after Morphological Opening(C), Image after subtracting Dilated Image(R)

# 4 Work Done

## 4.1 Gantt Chart

| | **Schedule for Research Work** | **Months/Weeks** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | February | | | | March | | | | April | | | | May | | | |
| | | W 1 | W 2 | W 3 | W 4 | W 1 | W 2 | W 3 | W 4 | W 1 | W 2 | W 3 | W 4 | W 1 | W 2 | W 3 | W 4 |
| 1 | Literature Review | | | | | | | | | | | | | | | | |
| 2 | Development environment & system setup | | | | | | | | | | | | | | | | |
| 3 | Research area identification | | | | | | | | | | | | | | | | |
| 4 | Formation of research statement and proposal | | | | | | | | | | | | | | | | |
| 5 | Design, development and implementation | | | | | | | | | | | | | | | | |
| 5.1 | Implement and compare existing solutions | | | | | | | | | | | | | | | | |
| 5.2 | Propose a novel solution | | | | | | | | | | | | | | | | |
| 5.3 | Formulation and acquisition of Dataset | | | | | | | | | | | | | | | | |
| 5.4 | Implement and comparison of solution with existing solutions | | | | | | | | | | | | | | | | |

The pipeline for the above methodology has been created and it went through the following phases.

1. Literature Review to understand the problem and its various solutions as a whole.

2. Choosing a color space for the model. The 2 main options were L*a*b and HSV. a-channel of L*a*b was chosen over the H-channel of HSV because The H- channel varies over all the hues whereas, the a-channel varies over the green chromatic axis hence the healthy tissues are easily distinguished from the infected tissues.

3. Creating a mask for the leaf. For creating the mask along with simple thresholding and using bitwise operations we had to find a method to locate the petiole. The Connected Component Labeling and Analysis, using-8 connectivity, best performed this task and was easily implemented. This task was tried by using DFS traversal and calculating the max area of the white regions but didn't give satisfactory results.

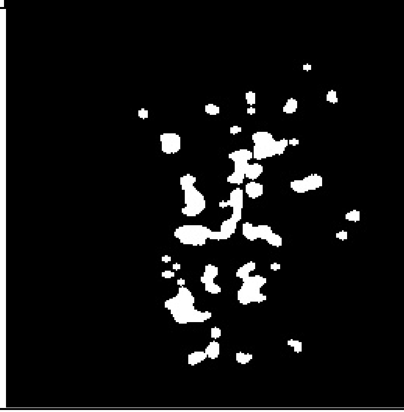
4. Improving the contrast. Various contrast transform functions(power law,etc) where implemented, along with histogram equalization but contrast stretching seemed to give the best result and made it possible to threshold it with fixed value at later stages.

5. Finally thresholding was done and simple thresholding with a value of 128 was preferred over Otsu's method of thresholding and Tozero threshold.

6. Finally morphological operations using an ellipse as the structuring element was used to remove the noise wherever required with small kernel size for small noises and larger kernel size to remove the petiole.

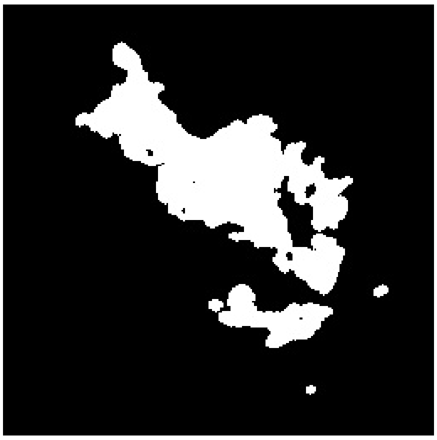
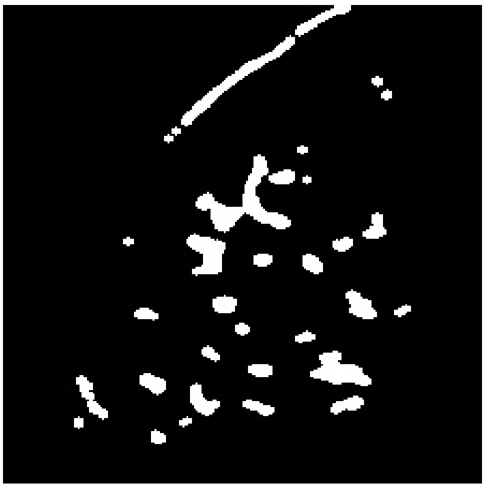
## 4.2 Results and Discussion

**Table 3 Tomatao Bacterial Spot:**

| | |
|---|---|
|  |  |
|  |  |

| | |
|---|---|
|  |  |

**Table 4 Tomato Early Blight**

| | |
|---|---|
|  |  |
|  |  |

| | |
|---|---|
|  |  |

**Table 5 Tomato Late Blight**

| | |
|---|---|
|  |  |

As we can see the above method clearly detects the infected area of the leaf but still it faces a few drawbacks in certain conditions:

1. Influence of leaf color and symptom color: The algorithm faces difficulty when the contrast between the healthy tissue and the infected tissue is very less. But in such cases sometimes it is even difficult for the human eye to distinguish between the two.

2. Influence of symptom size: Small symptoms may be removed due to morphological operations while debris and and other particles on the leaf may be mistaken as infected regions

3. Influence of leaf vein width: If the width is too large or has been artificially increased due to it casting a shadow it may be detected as an infected region.

4. Error sources and limitations: If the image wasn't taken in proper lighting it may have shadows which results in dark regions in the image. This dark regions may be misidentified as infected regions.

### 4.3 Individual Contribution of project members (in case of group project)

Viraj was responsible for Morphological Operations, contrast stretching, Connected Component Labeling and Analysis

Akshay was responsible for different color space and color channels selection , masking and thresholding implementation.

# 5 Conclusion and Future Plan

The aim was to extract the region of interest i.e. the region infected by pathogens. The ROI was done by using the 'a' chromatic axis (green / magenta) of the L*a*b color space. The alpha channel showed a clear distinction between the healthy green tissues and the infected brown tissues. This channel was masked with a mask created by thresholding the grayscale image of the original image and using Connected Component Labeling and Analysis to remove the petiole. The contrast of the image was improved by using contrast stretching. The final ROI extraction is done by thresholding the image by a value of 128 and improving the result by applying morphological operations.

Further improvements can be made by experimenting and fine tuning the parameters of thresholding and morphological operations. Further experimentation can be done to find a better method to improve the contrast and threshold the image. This method is yet to be tested on a large dataset, quantify the results and compare it with other methods.

# References

Book-Gonzalez, R. C., & Woods, R. E. (2002). Digital image processing.

Web page-Adrian Rosebrock (2018). " OpenCV Tutorial: A Guide to Learn OpenCV." https://www.pyimagesearch.com/2018/07/19/opencv-tutorial-a-guide-to-learn-opencv (July 19, 2018).

Arjun, K. M. (2013). Indian agriculture-status, importance and role in Indian economy. *International Journal of Agriculture and Food Science Technology*, *4*(4), 343-346.

Barbedo, J. G. A. (2014). An automatic method to detect and measure leaf disease symptoms using digital image processing. Plant Disease, 98(12), 1709-1716.

Barbedo, J. G. A. (2016). A novel algorithm for semi-automatic segmentation of plant leaf disease symptoms using digital image processing. Tropical Plant Pathology, 41(4), 210-224.

Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: classification and symptoms visualization. Applied Artificial Intelligence, 31(4), 299-315.

Barbedo, J. G. A. (2019). Plant disease identification from individual lesions and spots using deep learning. Biosystems Engineering, 180, 96-107.

Yigit, E., Sabanci, K., Toktas, A., & Kayabasi, A. (2019). A study on visual features of leaves in plant identification using artificial intelligence techniques. Computers and electronics in agriculture, 156, 369-377.

Saleem, G., Akhtar, M., Ahmed, N., & Qureshi, W. S. (2019). Automated analysis of visual leaf shape features for plant classification. Computers and Electronics in Agriculture, 157, 270-280.

Ali, H., Lali, M. I., Nawaz, M. Z., Sharif, M., & Saleem, B. A. (2017). Symptom based automated detection of citrus diseases using color histogram and textural descriptors. Computers and Electronics in agriculture, 138, 92-104.

## Appendix

Barbedo J. (2014). An Automatic Method to Detect and Measure Leaf Disease Symptoms Using Digital Image Processing. Plant disease, 98(12), 1709–1716. https://doi.org/10.1094/PDIS-03-14-0290-RE