# Digital Image Processing Techniques for Bacterial Infection Detection on Tomato and Crape Jasmine Leaves

R. Revathy, Dr. R. Roselin

**Abstract**— India is an agricultural country and plant disease plays key role in the production of agricultural products. Earlier detection will helps to improve the quality and quantity of the products. The proposed system is a detection of bacterial infection on tomato and crape jasmine leaves. Bacterial disease can be detected as brown-black colour spot and centre becomes dry. Tomato is a major agricultural crop and crape jasmine is an herb. The developed method consists of six steps: Image Acquisition, Colour Transformation, Filtering, Segmentation, Feature Extraction and Classification. The first step is image acquisition in which infected leaves are photographed. In colour transformation step an RGB image is converted into YIQ colour space. Then I channel alone taken for further analysis. After that, Median filter is applied for image smoothing and filtering. Next Otsu's thresholding is used to detect the infected disease spot. Over segmented image, the Haralick texture features are extracted and stored. Finally classification is done based on various types of classification algorithm. From that Scaled Conjugate Gradient algorithm on Tomato leaves provides 86% accuracy and 94% accuracy on Crape Jasmine leaves.

**Index Terms**— Median Filter, Otsu's Thresholding, Haralick Texture Feature and YIQ Colour Space.

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## 1 INTRODUCTION

Agriculture is the largest economic sector in India and plays a major role in socio-economic development. Crop cultivation depends on rainfall, quality of the soil and climatic conditions and short of any one of these leads to loss of crop. Diseases are major cause for loss of crop every year and really it is a challenge to control the diseases. Plant disease diagnosis is an art as well as science. The diagnostic process is inherently visual and requires intuitive judgment as well as the use of scientific methods. Plant diseases reduce both quantity and quality of plant products. Early detection of diseases is a major challenge in agriculture science [1].

Computer vision systems would help to tackle the problem. The following are some of the areas where image processing techniques are being applied in the field of agriculture:
1. Detection of weeds
2. To quantify affected disease spot
3. To find the nitrogen level of the plant
4. To find the chlorophyll level of the leaves
5. To identify the types of leaves.

In all these methods, digital images are acquired and image processing techniques are applied. The widely applied area of image processing is in plant protection which helps to produce quality product. Plant diseases may be broadly classified into three types. They are bacterial, fungal and viral diseases. Fungi are identified primarily from their morphology, with emphasis placed on their reproductive structures. Bacteria are considered more primitive than fungi and generally have sim-

pler life cycle. Viruses are extremely tiny particles consisting of protein and genetic material with no associated protein [2].

Infected leaf has dark water-soaked circular spots which are about 3 mm in sizes but may become larger when the temperature is right. The spots become angular and turn brown-black. Eventually, the centre of the spots may dry and leaf may drop prematurely. Infected young fruit has small black spots. As the bacteria further develop, the spots turn brown, slight sunken, scabby and sometimes surrounded by rings. Severe infestation gives the plant the appearance of blight.

Tomato is a warm-weather vegetable, it is very tender to frost and light freezes. The tomato is edible, often called as red fruit berry or solanum lycopersicum. The species originated in the South America. The tomato is consumed in diverse ways, including raw, as an ingredient in many dishes, sauces, salads and drinks. While it is botanically a fruit, it is considered a vegetable for culinary purpose. The plants typically grow to 1 – 3 meters in height and have a weak stem that often sprawls over the ground and vines over other plants.

Tabernaemontana divearicata (Crape Jasmine) commonly called pinwheel flower, is an evergreen shrub probably native to India. It is a common flowering, ornamental and medical plant of India and it is shrub type of plant. It is a small tree and it has a thin stem, this plant is blooming especially spring season, but in all year it blooms. It has sweet scent and it is used for medicine. The plant leaves milk is used as a medicine for wounds.

The method proposed by Sena et al. [3] aims to discriminate between maize plants affected by fall armyworm from healthy ones using digital images. They divided their algorithm into two main stages: image processing and image analysis. In the

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- R. Revathy, Research Scholar, Sri Sarada College for Women (Autonomous), Salem, E-mail: rvtymca@gmail.com
- Dr. R. Roselin, Assistant Professor, Sri Sarada College for Women (Autonomous), Salem, E-mail: roselinjothi@gmail.com

image processing stage, the image is transformed to a gray scale, thresholded and filtered. In the image analysis stage, the whole image is divided into 12 blocks. Blocks whose leaf area is less than 5% of the total area are discarded. For each remaining block, the number of connected objects, representing the diseased regions, is counted. The plant is considered diseased if this number is above a threshold, which, after empirical evaluation, was set to ten.

Sekulska et al. [4] method aims to detect and quantify disease symptoms in pumpkin and cucumber leaves. The images used in the tests were captured using a flatbed scanner. The leaves were detached from the plants, treated and stained prior to the imaging. The authors used functions present in the MATLAB toolboxes to implement their ideas. The first step of the algorithm is the isolation of the leaf by thresholding. In the following, the image is transformed from RGB to HSV colour space. The brightness component (V) is discarded. Then, a Fuzzy c-means algorithm is applied in order to group the pixels into two main clusters, representing healthy and diseased regions.

Kurniawati et al. [5] proposed a method to identify and label three different kinds of diseases that affect paddy crops. As in many other methods, the segmentation of healthy and diseased regions is performed by means of thresholding. The authors tested two kinds of thresholding, Otsu's and local entropy, with the best results being achieved by the latter one. Afterwards, a number of shape and colour features are extracted. Those features are the basis for a set of rules that determine the disease that best fits the characteristics of the selected region.

Sonal et al. [6] used several task for the diagnosis for cotton leaf spot disease such as image acquisition, image enhancement, segmentation, shape feature extraction, colour based segmentation and classification. In image acquisition phase, the various disease leaves are taken using digital camera which is a BMP format image. The second phase is image enhancement in which RGB image is converted to a gray-scale image and image segmentation is done based on gray-level threshold value and finally binary image is gained. Camera flash acts as a noise, so median filter and morphological operators are applied to remove unnecessary spots. For shape feature extraction, blob analysis is used and features such as number of objects, area and perimeter are extracted. Next, SVM is used for classification. SVM is a popular classification tool used for pattern recognition and other classification purpose.

The method proposed by Al Bashish et al. [7] tries to identify five different plant diseases. The authors did not specify the species of plants used in the tests, and the images were captured in situ. After a preprocessing stage to clean up the image, a K-means clustering algorithm is applied in order to divide the image into four clusters. According to the authors, at least one of the clusters must correspond to one of the diseases. After that, for each cluster a number of colour and texture features are extracted by means of Colour Co-Occurrence Method, which operates with images in the HSI format. Those features are fed to a MLP Neural Network with ten hidden layers, which per-

forms the final classification.

## 2 EXPERIMENTATION

The proposed system is the detection of bacterial infection on Tomato and Crape Jasmine Plant. The steps involved in the implementation process are: Image Acquisition, Colour Transformation, Image Filtering, Segmentation, Feature Extraction and Classification. Implementation process is carried out through MATLAB. Fig 1 is block diagram of the proposed system which explains the steps carried out.

IMAGE ACQUISITION

COLOUR TRANSFORMATION

IMAGE FILTER

SEGMENTATION

FEATURE EXTRACTION

CLASSIFICATION
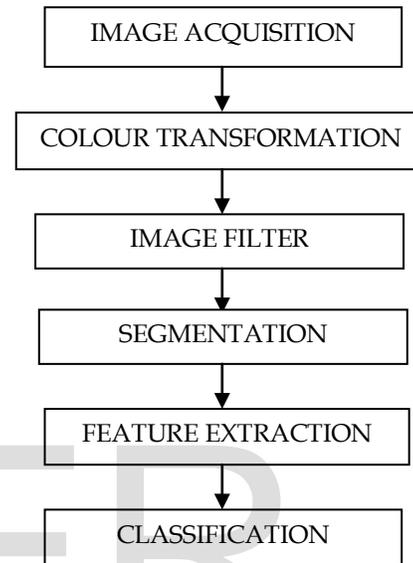
Fig. 1 Block Diagram of Proposed Approach

### 2.1 Image Acquisition

The first and foremost step in any image processing application is image acquisition which is carried out here also. The input images are in RGB color space. All crape jasmine and some tomato disease infection leaves are collected and captured through digital camera. Leaf images are in jpg file format. Fig 2 shows the captured image of tomato leaf and crape jasmine leaf with bacterical infection.

Fig. 2 (a) Tomato Leaf          (b) Crape Jasmine Leaf

The RGB image in MATLAB as matrix will be:

$$Red = \begin{pmatrix} 150 & 150 & 150 \\ 150 & 150 & 150 \\ 150 & 150 & 150 \end{pmatrix} Green = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} Blue = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Fig. 3 RGB Image Representations in MATLAB

### 2.2 Colour Transformation

YIQ is the colour space used by the NTSC colour TV sys-

tem, employed mainly in North and Central America, and Japan. The YIQ colour space is a device-dependent colour space. In colour transformation step RGB color space is converted into YIQ colour space. Its purpose is to exploit certain characteristics of the human eye to maximize the utilization of a fixed bandwidth. The human visual system is more sensitive to changes in luminance than to changes in hue or saturation, and thus a wider bandwidth should be dedicated to luminance than to colour information. One of the advantage is gray scale information can be easily separated from YIQ colour space. The formula used to convert the RGB into YIQ colour space is follows:

$$Y = [0.299 * R + 0.587 * G + 0.114 * B]$$
$$I = [0.596 * R - 0.275 * G - 0.321 * B]$$
$$Q = [0.212 * R - 0.523 * G + 0.311 * B]$$

The result of the RGB to YIQ color space is shown in fig 4.

Fig. 4 RGB to YIQ Conversion of Tomato and Crape Jasmine Leaf

After the conversion process the RGB matrix will change into YIQ as follows:

$$Y = \begin{pmatrix} 44.85 & 44.85 & 44.85 \\ 44.85 & 44.85 & 44.85 \\ 44.85 & 44.85 & 44.85 \end{pmatrix} I = \begin{pmatrix} 89.4 & 89.4 & 89.4 \\ 89.4 & 89.4 & 89.4 \\ 89.4 & 89.4 & 89.4 \end{pmatrix} Q = \begin{pmatrix} 31.8 & 31.8 & 31.8 \\ 31.8 & 31.8 & 31.8 \\ 31.8 & 31.8 & 31.8 \end{pmatrix}$$

Fig. 5 YIQ Image Represenation as Matrix

Y, I and Q channels are separated after the transformation process is carried out. I channel alone taken for further processing and remaining Y and Q are left. The I channel image is shown in fig 6.

Fig. 6 I Channel Images of Tomato and Crape Jasmine Leaf

For further processing I channel value alone taken and its matrix form will be:

$$I = \begin{pmatrix} 89.4 & 89.4 & 89.4 \\ 89.4 & 89.4 & 89.4 \\ 89.4 & 89.4 & 89.4 \end{pmatrix}$$

Fig. 7 I Channel Matrix Represenation

## 2.3 Image Filtering

Usually there will be some noise in the image and even the camera flash also a type of noise in the image. In order to eliminate it filtering is used. The proposed system uses median filter which is a non-filtering. It is better at preserving sharp high-frequency details and also eliminates noise especially isolated noise spikes. The median m is a set of number and it is the midpoint of the sorted distributed value from the pixels in which half of the numbers are less than m and half are greater. It is more robust to outliers because, the median values are drawn from the pixel neighbourhood itself and it does not create any new unrealistic pixel value. This also helps in preventing edge blurring and loss of image details. It requires an ordering of the values in the pixel neighbourhood at every pixel location.

The step involved in median filter is as follows:
1.   Define the neighbourhood of the target pixel.
2.   Rank them in ascending order (first is lowest value,N x N$^{th}$ is highest value).
3.   Choose the median value of the filter
4.   Set the target pixel value to be equal to the value of the chosen median.

The fitler kernel value used in the proposed system is 3 x 3 matrix. This kernel value is slide over each and every pixel of the image to find the filtered image. The filtered image is shown in the below fig 8.

Fig. 8 Filtered Images of Tomato and Crape Jasmine Leaf

The filtered matrix of I channel value will become as follows:

$$\begin{pmatrix} 0 & 89.4 & 0 \\ 89.4 & 89.4 & 89.4 \\ 0 & 89.4 & 0 \end{pmatrix}$$

Fig. 9 Filtered I channel Matrix

## 2.4 Segmentation

Segmentation is a process in which the image is subdivided according to its constituent region or objects. Thresholding is an important technique in image segmentation applications. It

can be used in two ways: Manual thresholding and Automatic thresholding. Manual thresholding is very simple. The user manually chooses some threshold value such that pixels possessing values greater than the threshold are assigned to one region where those that fall below the threshold are assigned to another region. This approach is quite satisfactory and the appropriate threshold was chosen manually by trial and error. Many image processing tasks require full automation, and there is often a need for some criterion for selecting a threshold automatically.

The basic idea of automatic thresholding is to select an optimal gray-level threshold value for separating objects of interest in an image from the background based on their gray-level distribution. While human beings can easily differentiate an object from complex background, image thresholding is a difficult task to separate them. The gray-level histogram of an image is usually considered as an efficient tool for development of image thresholding algorithms. Thresholding creates binary images from gray-level ones by turning all pixels below some threshold to 0 and all pixels above that threshold to 1. If $g(x,y)$ is a threshold version of $f(x,y)$ at some global threshold T, it can be define as:

$$g(x,y) = \begin{cases} 1 & if \ f(x,y) > T \\ 0 & otherwise \end{cases}$$

Otsu method is a type of global thresholding in which it depends on gray value of the image. Otsu method was proposed by Scholar Otsu in 1979. It is a global thresholding selection method, which is widely used because it is simple and effective. This method requires computing a gray level histogram before running [8]. The steps involved in Otsu's thresholding will be:

1. Compute the normalized histogram for the input image.
2. Compute the cumulative sums and means.
3. Find the global intensity threshold value for an image.
4. Based on the threshold value, separate the images into two parts representing 1 for foreground and 0 for background.

The filtered image is segmented using Otsu's threshold. Before finding the threshold value the histogram value is calculated and based on this histogram value an threshold value is found. Depending on that threshold value the image is converted to binary. The segmented binary image is shown in fig 10.



Fig. 10 Segmented Binary of Tomato and Crape Jasmin Leaf

The binary matrix for the filtered matrix will be:

$$\begin{pmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

Fig. 11 Binary Matrix

The Binary image which acts as a mask and it is multiplied with the RGB image to obtain the RGB disease infected spot alone as shown in the fig. 12.



Fig. 12 Segmented RGB Images of Tomato and Crape Jasmine Leaf

The Segmented RGB matrix will be:

$$R = \begin{pmatrix} 0 & 150 & 0 \\ 150 & 150 & 150 \\ 0 & 150 & 0 \end{pmatrix} G = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} B = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Fig. 12 Segmented RGB Matrix

For feature extraction the gray-level co-occurrence is generated which can be derived from the gray scale image. So RGB image needs to be converted into gray scale image for further processing. The RGB to Gray scale converted image is shown in fig. 13.



Fig. 13 Segmented Gray Scale Images of Tomato and Crape Jasmine Leaf

The segmented RGB to Gray scale converted matrix will be:

$$Gray = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

Fig. 14 Segmented Gray Scale Matrix

## 2.5 Feature Extraction

Feature extraction extracts some useful information from the image for the subsequent recognition or classification methods. The proposed system uses the texture feature extraction.

In 1973, Haralick [9] introduced the co-occurrence matrix and its texture features which are the most popular second order statistical features today. Haralick proposed two steps for texture feature extraction: the first is computing the co-occurrence matrix and the second step is calculating texture feature based on the co-occurrence matrix.

The co-occurrence matrix considers the relationship between two neighbouring pixels, the first pixel is known as a reference and the second is known as a neighbour pixel. Consider that I (x,y) denote an image, with G gray levels. The G X G gray level co-occurrence matrix $P_d^{\theta}$ for a displacement vector d=(dx,dy) and direction $\theta$ is defined as follows. The element (i,j) of $P_d^{\theta}$ is the number of occurrence of the pair of gray levels i and j which the distance between i and j following direction is d .

The Co-occurrence matrix can be calculated for the angle $\theta = 0, 45, 90 \ and \ 135$. If angle $\theta = 0$, then the co-occurrence matrix is generated by considering the nearest horizontal neighbouring pixel of the reference pixel. If $\theta = 90$, the reference pixel consider the nearest vertical pixel as neighbouring pixel. If $\theta = 45$ the neighbouring pixel will be diagonal left to the reference pixel and $\theta = 135$, the neighbouring pixel will be diagonal right to the reference pixel.
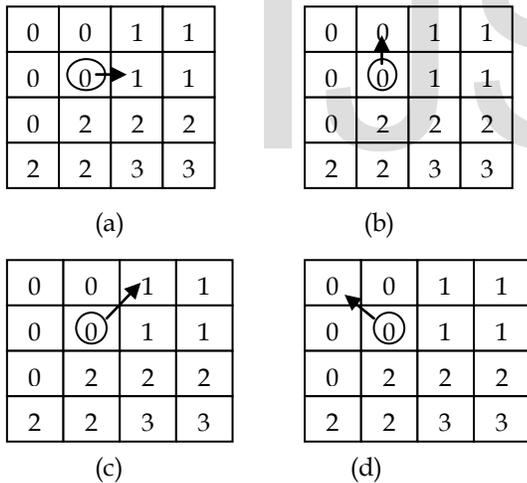


Fig. 15 Co-occurrence Matrix for Angle Values
(a) $\theta = 0$ (b) $\theta = 90$ (c) $\theta = 45$ (d) $\theta = 135$

The distance d is used to specify neighbouring pixel that is to be considered. If d=1, the neighbour pixel will be the immediate pixel of the reference pixel, d=2 the neighbour pixel will be second pixel of the reference pixel.
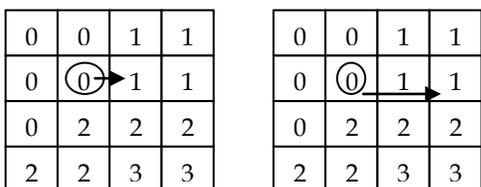


(a)                          (b)
Fig. 16 Co-occurrence Matrix for Distance Values
(a) d = 1 (b)  d = 2

Fig 17 is the representation of co-occurrence matrix generated for gray scale image with $\theta = 0 \ and \ d = 1$.
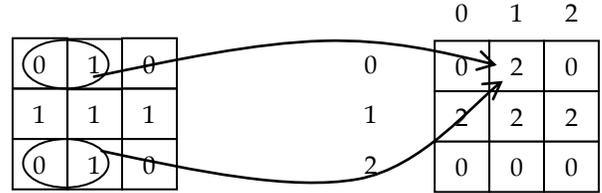


Fig. 17 Co-occurrence Matrix Generations

The co-occurrence matrix generated for the gray scale image will be:

$$\begin{pmatrix} 0 & 2 & 0 \\ 2 & 2 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Fig. 18 Gray Level Co-occurrence Matrix

Element (0,1) in the GLCM contains the value 2 because there is two instance in the image where two horizontally adjacent pixels have the values 0 and 0. Only horizontal adjacent pixel needs to considered, because here the angle taken is $\theta = 0$. Element (0,3) in the GLCM contains the value 1 because there are only one instance in the image where one horizontally adjacent pixel have the values 1 and 1. The same process continues to fill in all the values in the GLCM.

Finally the Co-occurrence matrix will be normalized by dividing each entry in the matrix with the dimension of the image. The normalized matrix of the above co-occurrence matrix will be:

$$\begin{pmatrix} 0 & 0.2222 & 0 \\ 0.2222 & 0.2222 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Fig. 19 Normalized Co-occurrence Matrix

After that haralick features are extracted which consists of 14 characteristics namely: Energy, entropy, variance, contrast, correlation, inverse difference moment, information measure of correlation – I & II, maximum correlation coefficient, sum average, sum variance, sum entropy, difference variance and difference entropy. The extracted values are stored in the excel sheet and used as a database for classification.

TABLE 1

HARALICK FEATURE EXTRACTION VALUES

| Characteristics | Values | Characteristics | Values |
|---|---|---|---|
| Energy | 0.1482 | Sum Entropy | 1.0022 |
| Contrast | 0.4444 | Entropy | 1.4466 |

| Correlation | 0.7099 | Difference Variance | 0.3539 |
|---|---|---|---|
| Variance | 1.9998 | Difference Entropy | 1.4466 |
| Inverse Difference Moment | 0.4444 | Information Measure of Correlation – I | 0.5566 |
| Sum Average | 2.2220 | Information Measure of Correlation – II | 0.9971 |
| Sum Variance | 0.9712 | Maximum Correlation Coefficient | 0 |

## 2.6 Classification

The final step is classification which aims to identify the correct class for the given values. Various classification algorithms are implemented using matlab and weka. The supervised classification method is used here and the accuracy of the algorithm is calculated using the correctly classified instance and incorrectly classified instance. The steps involved in all types of classification algorithms are:

1. Build the Classifier using Training Data
2. Test the classifier

For tomato leaves the classification algorithms used are Scaled conjugate gradient algorithm, back propagation algorithm, Logisitics algorithm, SPegasos algorithm and ADTree algorithm. In that Scaled conjugate gradient algorithm provides highest accuracy of 86% on classification.

For crape jasmine leaves Scaled conjugate gradient algorithm, back propagation algorithm, Naïve Bayes algorithm, Multi-layer Perceptron algorithm and Sequential minimal optimization algorithm are used for classification. In that Scaled conjugate gradient algorithm provides highest accuracy of 94% on classification.

## 3 RESULTS AND DISCUSSIONS

Datasets used for classification algorithms are Tomato leaves and Crape Jasmine leaves. Table 2 gives the dataset description in which 65 bacterial infected leaves are taken for Tomato and 67 bacterial infected leaves are taken for Crape Jasmine Leaves. Attributes mention the feature values which are extracted through haralick characterisitics and clusters indicate speices in bacterial infection.

TABLE 2
DATASET DESCRIPTION

| Dataset | No. of Leaves | No. of Attributes | No. of Clusters |
|---|---|---|---|
| Tomato Dataset | 65 | 14 | 2 |
| Crape Jasmine Dataset | 67 | 14 | 2 |

Table 3 shows the results of 65 tomato leaves with correctly classified, incorrectly classified instance with their classification accuracy percentage for various classification algorithms.

TABLE 3
RESULTS OF TOMATO LEAVES

| Method | Correctly Classified Instance | Incorrectly Classified Instance | Classification Accuracy |
|---|---|---|---|
| SCG | 56 | 09 | 86.15 |
| Back Propagation | 41 | 24 | 63.07 |
| Logistic | 52 | 13 | 80.00 |
| SPegasos | 53 | 12 | 81.53 |
| ADTree | 53 | 12 | 81.53 |

The following line chart explains the comparison of various algorithm results obtained by tomato leaves with correctly classified instance and incorrectly classified instances.
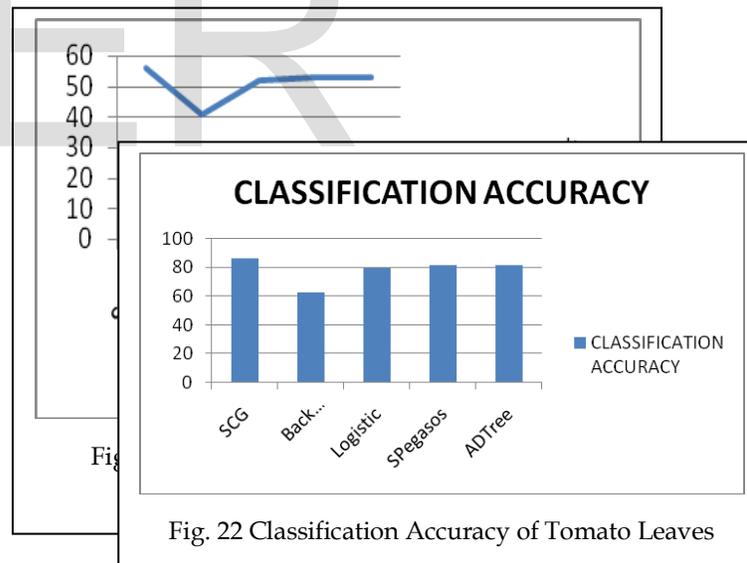


Fig. 22 Classification Accuracy of Tomato Leaves

Table 4 shows the results 67 crape jasmine leaves with correctly classified, in-
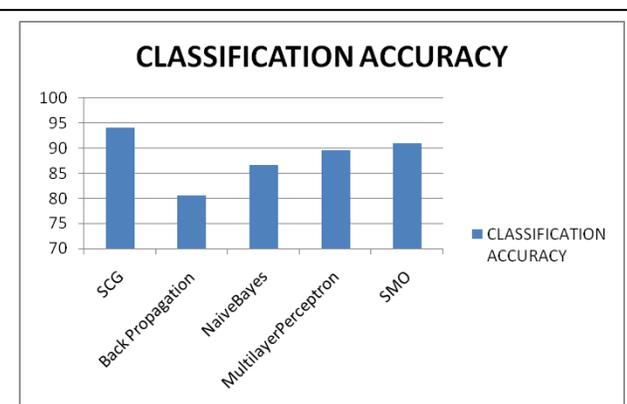


Fig. 23 Classification Accuracy of Crape Jasmine Leaves

correctly classified instance with their classification accuracy percentage for various classification algorithms.

### TABLE 4
#### RESULTS OF CRAPE JASMINE LEAVES

| Method | Correctly Classified Instance | Incorrectly Classified Instance | Classification Accuracy |
|---|---|---|---|
| SCG | 63 | 04 | 94.03 |
| Back Propagation | 54 | 13 | 80.60 |
| NaiveBayes | 58 | 09 | 86.57 |
| Multilayer Perceptron | 60 | 07 | 89.55 |
| SMO | 61 | 06 | 91.04 |

The following line chart explains the comparison of various algorithm results obtained by crape jasmine leaves with correctly classified instance and incorrectly classified instances.
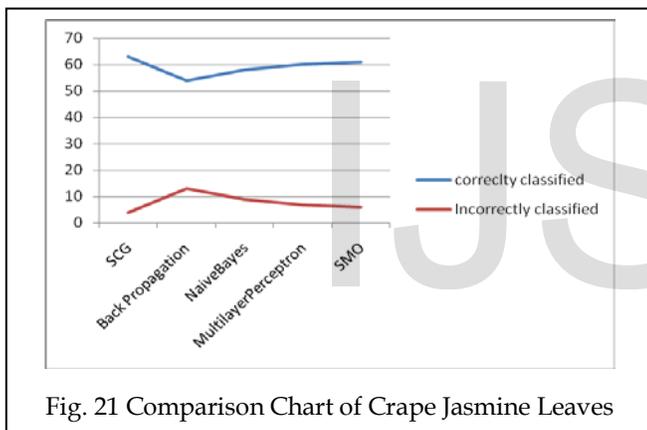


Fig. 21 Comparison Chart of Crape Jasmine Leaves

From the overall result it is concluded that,

- SCG classification on both Tomato and Crape Jasmine Leaves provides accuracy of above 86%
- Back Propagation classification on Tomato and Crape Jasmine Leaves provides an accuracy of above 63%
- Logistic, SPegasos and ADTree techniques on Tomato Leaves provides 80% classification accuracy.
- NaiveBayes, MulitlayerPerceptron and SMO techniques provides above 86% accuracy on Crape Jasmine Leaves.

The following fig 3 & 4 explains the accuracy percentage obtained for various classification algorithms for tomato and crape jasmine leaves.

## 4 CONCLUSION

The proposed system aims to find the bacterial infection on Tomato and Crape Jasmine Leaves. Foremost step is colour transformation in which the original RGB image is converted to YIQ colour space to acquire infected spot. Then channel separation is done on YIQ from that I channel alone is taken for further processing and remaining channels are left because it does not provide any additional useful information. In order to eliminate the noise in the image median filter is applied. Further thresholding is done on the image using Otsu method which provides a bacterial infection spot as a binary image.

Binary Image acts as a mask and it is multiplied with the RGB image to get infected spot. In order to extract the texture feature RGB image is converted into gray-scale image. Finally classification is done using SCG, Backpropagation, Logisitics, SPegasos, ADTree, Naïve Bayes and Multi-layer Perceptron algorithms.

It is concluded from the overall result that ADTree and SPegasos classification algorithm work much well in Tomato Leaves disease infection identification. In the case of Crape Jasmine Leaves disease identification, SCG and SMO method provides a better result. SCG algorithm provides highest accuracy on both the plants.

## 5 FUTURE WORK

The future scope of the work could be focused on finding all types of bacterial diseases on Tomato and Crape Jasmine Leaves. The future extension can be identifying viral and fungal disease on Tomato and Crape Jasmine Leaves. This work can be extended to find the bacterial disease infection on all types of plants. In order to improve classification accuracy more number of plant leaves can be collected and trained. For plant disease, there is no standard database is available so far. In future with expert judgment a proper database can be maintained with their disease species name. This helps many researches to propose various research ideas on agricultural image processing.

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