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Classification of Disease in Tomato Plants' Leaf Using Image Segmentation and SVM

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Abstract-Plant Disease recognition and classification play vital role in agriculture field. Product quality, quantity or productivity of plants is harshly affected by slight negligence in this domain. Huge amount of human work load for crops intensive care in vast farms can be reduced by automatic system accomplished of perceiving and classifying plant illnesses at early phases. This paper presents image processing framework for plant disease identification and classification. Our proposed workflow consists of three stages that are images segmentation, feature extraction and classification. For segmentation we use multi-thresholding then that of other common segmentation techniques. We used GLCM for feature extraction and Support Vector Machines for classification. We use GLCM texture feature as it gives pixel level information and SVM due to its robustness and optimality. Experiments were conducted on Tomato leaf dataset comprising of 4 different classes. Proposed framework achieved 98.3% overall accuracy with 10-fold cross validation.

Keywords-Disease Detection, Tomato Crop, Classification, GLCM, SVM.

I. Introduction

Agriculture has a main role in all aspect of human life, including clothing, food, medicine and employment, all over the world. It is a primary source of food for every country which is directly related to its economy as well. In the main categories of agriculture, tomato is the world's most being used vegetable, representing 16% of whole production of crops [i]. Overall, global tomato market is continually growing to indicate a noticeable increase in its demand and production. The market value improved at an average annual rate of +3.2% from 2007 to 2015. This rapid growing trend however indicates some noticeable fluctuations throughout the analyzed period. The growth pace was the most rapid in 2008, when the market profit increased by +8% from the previous year level. Over the period under review, the global tomato market attained its maximum profit of 200,014 million USD in 2014. Global tomato market income amounted to 189,229 million USD in 2015, decreasing by -5.4% against the previous year income [ii].

According to Food and Agriculture Organization statistics, Pakistan is ranked on 34thposition in the world for annual tomato production. Pakistan's total annual requirement of tomatoes is 890,434 tones. Out of total requirement, 67% tomatoes are produced locally while 33% are imported. Tomatoes are grown on an area of 62,930 hectare. Punjab produces 11% of country's total tomato yield [iii]. From 2015 to the end of the period under review, the total tomato market revenue failed to regain its former peak level. World's tomato production is presently around 130 million tons. 88 million of this production are planned for the active market while processed production is 42 million. China, US, India, EU and Turkey are world's top five producers [i]. They account for 70% of total production. The main point of this problem is that almost every year a huge amount of tomato crops is affected by different diseases. Due to improper care and lack of timely detection of diseases, theses crops are facing damage of quality, quantity and productivity as well. Diseases demolish the whole crops and affect the adjacent crops as well [iv]. It is found that the crops damaged by diseases result thousand billion dollars loss every year [v]. Plants diseases are very hard to control facing the challenge to detect the disease at right time in terms of as early as possible to reduce the loss and getting as increased production as possible.

The disease of tomato plant appears on plant stem, leaves or its fruit which makes it possible to detect the disease from its outer surface instead of study of plant DNA. This research is going to work on detection of diseases from their leaves by extensively studying the disease symptoms on leaves. This research aims at developing a vigorous framework for tomato crop, detecting their diseases and then classifying them. In this work we are targeting tomato plants as a primary victim and detecting their main diseases. The symptoms are in the form of various visible patterns or holes which are shown on leaves which will be the target to detect, observe and classify.

II. LITERATURE REVIEW

Diseases have potential to destroy large number of crops resulting in significant loss in terms of food shortages specially, if not detected and controlled in time. Diseases affect plant's leaves, stem and roots but leaves are more effective region to detect the disease. In past the plant diseases were observed by expert farmers and all the detection and cure processes were done manually facing lot of problems associated with these methods.

Farmers are unable to conduct regular surveys for miles of fields at a time to observe each plant keenly. Moreover, in remote areas the lack of expert farmers always has been a problem for detection of diseases at right time. Many developing countries organize plant clinics for farmers at which they may educate about various pests and diseases. Moreover, plant pathologists can diagnose diseases from samples the farmers bring to these clinics. In addition to this, visits to the farms by Agriculture Extension Officers are also done. Now a days, using Fuzzy Logic, plants are classified as either diseased or healthy and if found diseased are also graded using the applications' like Fuzzy Inference System [v].

There are several methods discovered for attaining the diseased area from a leaf like multispectral and hyper spectral technologies, color images analysis, x-rays and ultrasound technologies etc. The researchers [vi] proposed an estimation technique for getting the real time RGB images from fields using a robot. Researcher used a greenhouse bell peppers as subject and observed for three months. They applied rectification, pixels sampling, severity estimation algorithm and other threshold algorithms. Finally, scientists gained the development graph of Powdery Mildew (PM) and Tomato Spotted Wilt Virus (TSWV). Gabor wavelet transform technique is used for extracting relevant features related to tomato leaf image. Support Vector Machines (SVMs) with substitute kernel functions, is then applied to perceive and recognize sort of disease that infects tomato plant [vii]. A computerized multi-class classification method for tomato ripeness measurement and assessment by examining and classifying diverse ripeness stages were used by authors [vii].

In this approach color features were used for classifying tomato ripeness stages. Principal Components Analysis (PCA) with Support Vector Machines (SVMs) and Linear Discriminant Analysis (LDA) algorithms are used as techniques for feature extraction and classification [viii].

Machine vision techniques as image processing based on two and three-dimensional information, and multispectral imaging are used for perceiving the exterior flaws of fruits [ix]. A novel approach is used due to its robustness for cucumber disease recognition which consists of three pipelined procedures, segmenting diseased leaf images by K-means clustering, extracting shape and color features from lesion information, and classifying diseased leaf images using sparse representation (SR) [x]. Researchers [xi] present an algorithm for image segmentation technique that detects diseases and classifies automatically. They applied genetic algorithm and neural networks for getting better results. Fuzzy C-means, as one typical clustering algorithm in pattern recognition, is used for image segmentation [xii]. Prohibitive demand for agricultural industry, effective growth and improved yield of fruit is necessary and important. For this reason, an efficient smart farming technique is necessary which will diagnose and classify external disease in fruits. Whereas system uses image processing techniques by implementing Open CV libraries. For image segmentation K-means clustering method is applied by [xiii], the images are arranged and plotted to their particular disease categories on basis of four feature vectors color, morphology, texture and structure of hole on the fruit. This structure uses two image databases, one for implementation of query images and the other for keeping fit of already stored disease images. ANN Artificial Neural Network concept is used for pattern matching and classification of diseases [xiv]. An image retrieval system using low-dimensional color feature vector containing only one image feature termed as weighted average of colorful image were proposed by researchers [xv]. For images recognition, the Euclidean distance between the feature vector of query image and each feature vector of database images is calculated.

Research [xvi] presented by authors detects the disease in mauls demoniacal by using k-mean clustering algorithm and RGB analysis. They use color patterns and texture features to detect and classify diseases and for classification they also use Byres classifiers. That research was for remote areas. Byres classifiers, k-means and principles components are good approach for disease detection and classification. The paper represents image processing neural network-based classification techniques to classify diseases & quick diagnosis can be carried out as per disease. In paper [xvii] author presents a robust algorithm for color images segmentation. Linear SVM and Otsu's thresholding method are used to categorize and grading of apples. The method for classification hyper plane requires minimum training with auto adjustable time. The problem due to the dissimilarities in lighting and color of fruit is also overcome by this method.

In [xviii] presented the work on perceiving pre-symptomatic existence of fungous related diseases using thermal imaging. Powdery fungus and gray mold illness on rose plants (Rosa hybrida L.) effects were examined by experiments in growth chamber. Selection of superlative thermal features with linguistic privet values was done for categorizing healthy and infected plants. For this classification two neuro-fuzzy classifiers were used [xix]. Authors [xx] uses Texture Features Analysis for recognizing Early Blight disease on Eggplant leaves. For this purpose, hyper spectral images were transformed in RGB, HSV and HLS images and GLSM based eight texture features (mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation) were extracted from gray images, RGB, HSV and HLS images, respectively.

III. EXPERIMENTAL METHODOLOGY

The architecture of the planned solution goals to model disease recognition, classification, and its grading system for tomato plant leaves. Various techniques were used in the system for preprocessing purpose. The proposed works under the steps follows as: image acquisition, preprocessing, feature extraction and classification. The procedural investigation of the work is presented graphically as follows in Fig 1. All this is done by using OpenCV and other Python libraries.

A. *Image Acquisition*

Acquiring image is the primary stage for any vision system. It is also defined as the digitization and storage of an image. There are different methods to acquire images in vision system to use for different processing purposes. After obtaining the images various method of processing are applied to perform a vision system task.

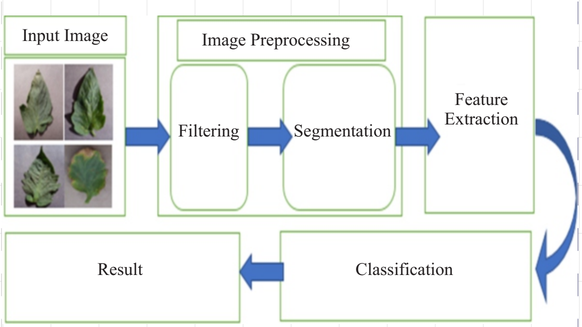

Fig. 1. Working Principle

B. *Image Pre-Processing*

Image processing is a 2D signal processing using an image as its input. Diverse computer algorithms related to digital image processing are used for performing various operation on an image to get the required results. Preprocessing procedures such as image resizing, filtering and segmentation are performed in this application. Initially, subject images are made noise free for supplementary operations such as segmentation and feature extraction as the noise may added during image acquisition or transmission.

C. *Image Segmentation*

Image segmentation is used for splitting an image into different regions or objects. This splitting depends upon the problem being resolved, where the segmentation should stop. The two elementary properties of pixel intensity values such as discontinuity and similarity are used to stop segmentation process. Segmentation through color thresholding is used to obtain regions having similarities. This thresholding can be achieved by setting the pixel intensity range value in the original image that chooses foregrounds pixels and rejects all others. Such an image is then converted to binary image and is masked with foreground to get in RGB [xxi]. Color based thresholding segmentation works under following procedure as shown below in Eq. 1.

$$|g(x,y)| = \begin{cases} 0, & f(x,y) < T \\ 1, & f(x,y) \geq T \end{cases} \quad (1)$$

Here 'T' represents the color threshold value, $f(x,y)$ denotes the original pixel value, and $g(x,y)$ is the resultant pixel value.

Eq. 1 encodes the input image into a true binary image. Fig. 2 further envision Equation 1as mappings of input grey level to yield grey level [xxii].

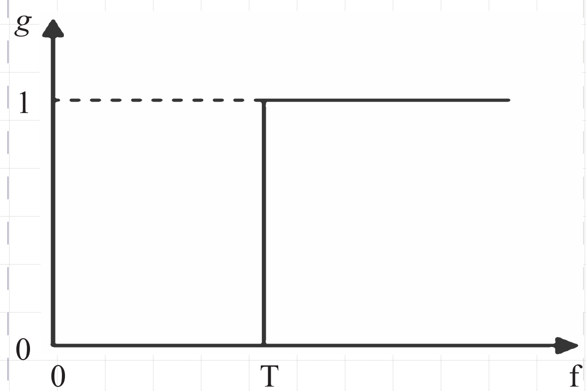

Fig. 2. Simplest Color Thresholding

Eq. 1 can be transformed into Eq. 2, if there exist more than one threshold values at a time

$$|g(x,y)| = \begin{cases} 0, & f(x,y) < T_1 \\ 1, & T_1 \leq f(x,y) \leq T_2 \\ 0, & f(x,y) > T_2 \end{cases} \quad (2)$$

Here 'T1' represents the lower threshold value, where 'T2' denotes the upper threshold value. Fig. 3 illustrates how thresholding with a pair of threshold is being done.

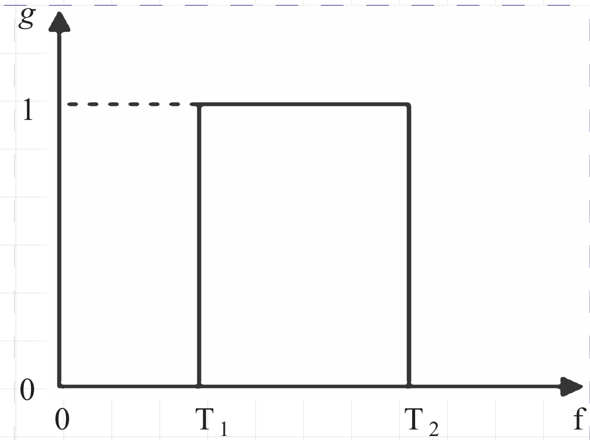

Fig. 3. Thresholding by setting pair thresh values

Characterizing each pixel in color images require more than one variable (one for each Red, Green, Blue), therefore multispectral thresholding is possible. However, it is difficult to set selection criteria for such type of images. Here, logical extension of thresholding is simply to place brightness thresholds on each image as described by [xxi, xxii] and then converting them to binary images individually. Afterwards, combing all of them by logically AND operator.

Color thresholding is the simplest and high resulting method of segmentation. The result of image segmentation using this method is shown in Fig. 4.

Fig. 4. Segmented Images

D. Feature Extraction

Extraction of features that results in some quantifiable data of interest is based on distinguishing one class object from another. Image feature usually includes texture, color and shape. In this work texture and color features are obtained for diseases identification [xxiii, xxiv].

E. Texture Feature Extraction Using GLCM

Special dependencies of gray levels in an image is calculated through Gray Level Co-occurrence Matrix(GLCM) [xxiv, xxv]. The quantity of gray levels in an image is closely correspondent to the number of columns and rows in GLCM. GLCM matrices are created in four special orientations (0^{o}, 45^{o}, 90^{o} and 135^{o}) [xxvi]. Another matrix is built as the average of earlier matrices. Suppose the Co-occurrence matrix is $L(i,j)$ and the matrix size is (N x N). Each element (i,j) denotes the frequency of pixel at gray level where(i) is spatially related to pixel with gray level (j).GLCM construction of a gray scale image is shown in Fig. 5.

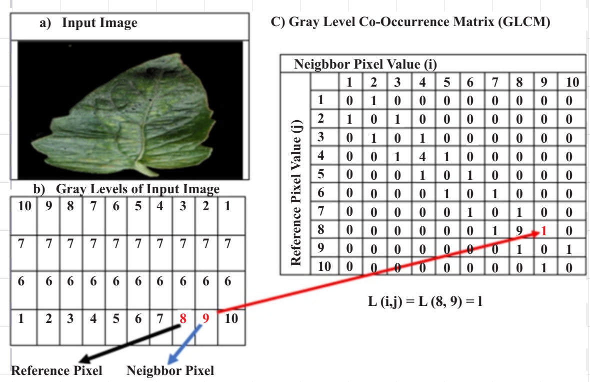

Fig. 5. GLCM

The input image sample consists of 10 gray levels and here the number of gray levels in the image determines the size of the GLCM. GLCM represents the relation between reference pixel (i) and neighbor pixel (j) in various orientations [xxvii, xxviii]. Relation between pixels is calculated horizontally at (0^{o}). Initial value in GLCM of each element (i,j) is zero. These element values were updated as per occurrence of pixels together. The texture feature such as Energy, Contrast, Dissimilarity, Homogeneity, Correlation, ASM, Mean and Standard Deviation using GLCM. Formulas for calculating these features are as follows.

Contrast return a measure of the intensity contrast between a pixel and its neighbor over the whole image. That is mathematically can be written as, in Eq. 3. The contrast value is always remained zero for a constant image. On the other hand, correlation measures the similarities between a pixel to its neighbor over the whole image.

$$CONTRAST = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j) \right\}, |i-j| = n \quad (3)$$

$$ASM = \sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j)^2 \quad (4)$$

$$Correlation(\mathrm{COR}) = \frac{\sum_{i=1}^{G} \sum_{j=1}^{G} (i,\bar{x})(\mathrm{j},\bar{y}) P(i,j)}{\sigma_x, \sigma_y} \quad (5)$$

Where

$$\bar{x} = \sum_{i}^{G} i \sum_{j}^{G} P(i,j), \bar{y} = \sum_{j}^{G} j \sum_{i}^{G} P(i,j)$$

$$\sigma_{x^2} = \sum_{i}^{G}\left(i-\bar{x}\right)^2 \sum_{j}^{G} P(i,j)$$

$$\sigma_{y^2} = \sum_{j}^{G}\left(i-\bar{y}\right)^2 \sum_{i}^{G} P(i,j)$$

$$Diss = \sum_{i=0,j=0}^{G-1} P_{i,j}|i-j| \quad (6)$$

$$Energy = \sum_{i,j=0}^{G-1} P^2_{i,j} \quad (7)$$

$$Homg = \sum_{i,j=0}^{G-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (8)$$

$$Std \quad \sigma_i = \sqrt{\sigma_i^2}\ ,\ \sigma_j = \sqrt{\sigma_j^2} \quad (9)$$

$$Mean \quad \mu_i = \sum_{i,j=1}^{G} i\left(P_{i,j}\right), \mu_j = \sum_{i,j=1}^{G} j\left(P_{i,j}\right) \quad (10)$$

F. SVM Classification

In SVM data items are plotted in n-dimensional space in a coordinate according to its class. Classification is made by finding hyper-plane that discriminates the diverse classes as given in Fig. 6.

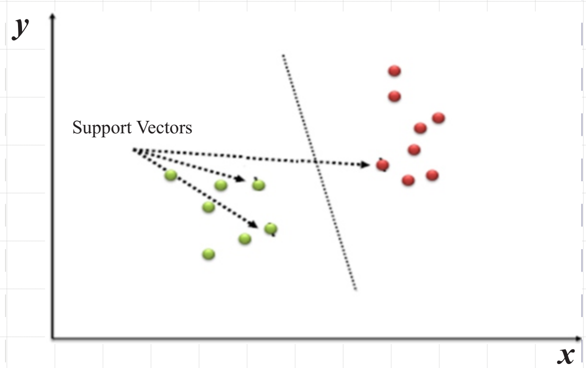

Fig. 6. SVM Working Principle

A training dataset with 'n' samples (a_1, b_1), (a_2, b_2),.....,(a_n, b_n). Where a_i is a feature vector with m-dimensional feature spaces and the labels $b_i \in$ -1, 1 belonging to either of two separable classes C_1 and C_2.

Following equations describes the solution of optimization problem using SVM algorithm which takes an optimal hyperplane with the maximal boundary to distinct two classes

$$\text{maximize} \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} \alpha_i \propto_j b_i b_j . K(a_i a_j)$$

$$Subject - to : \sum_{i=1}^{n} \propto_i b_i\ , 0 \leq \propto_i \leq C$$

Here $\propto_i$ is the allocated weight to the training sample a_i. If $\propto_i > 0$, a_i is called a supper vector. To achieve the superior generalization capability, C (as a regulation parameter) is used to tradeoff the model complexity and training accuracy.

Similarity between two samples measured using Kernel Function 'K'. Gaussian Radial Basis Function (RBF) is most widely used function among all available kernel functions. These kernels are used independent of the problem equally for both discrete and continuous data.

IV. RESULTS

In this article, experimental results are obtained on PC Intel core i7 @ 2.2 GHz CPU and 8GB memory. We used Python Open CV software on operating system Windows 10. The dataset used for this research was collected from online resources (https://plantvillage.org/). Dataset consists of total 200 images of tomato plant leaves which are divided into 4 classes. A few samples from dataset are shown in Fig._4. The classes are Healthy, Bacterial Spot Images, Early Blight Images, and Spider Mites.

The proposed work deployed different SVM kernels for feature classification includinglinear kernel, quadratic kernel, gaussian kernel and cubic kernel. For validation of results we used 70-30% training, testing and 10-fold cross validation schemes. Combined feature vector of GLCM Texture features named as Energy, Dissimilarity, Contrast, Correlation, homogeneity, Mean, Minpix, Maxpix, standard deviation and coefficient of Variance are used in this article. Fig. 7 and 8 show the scatter plots of GLCM features. Separation between different classes is clearly visible, which shows the strength of applied feature descriptors. Results of applying different SVM kernels are shown in Table I.

Confusion matrix representing the accuracy of individual classes in case of SVM classifier with Quadratic kernel is shown in Fig. 9,10 and 11. Three classes have 100% classification accuracy. Proposed framework achieves 98.3% accuracy for Tomato plant disease classification.

TABLE I
CLASSIFICATION RESULTS

Validation Scheme	SVM Kernel	Accuracy
70-30% Validation	Linear	95.0%
	Quadratic	**98.3%**
	Gaussian	78.3%
	Cubic	91.7%
10-Fold Cross Validation	**Linear**	**93.6%**
	Quadratic	93.2%
	Gaussian	91.5%
	Cubic	91.0%

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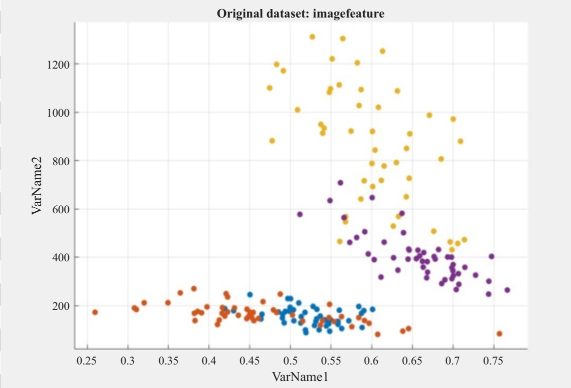

Fig. 7. Scatter Plot of Original Dataset

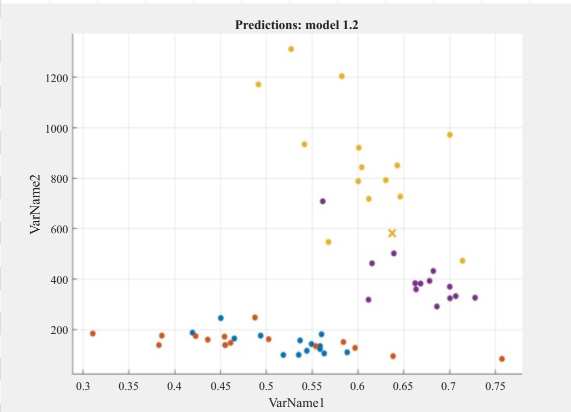

Fig. 8. Scatter Plot of Prediction over Quadric SVM

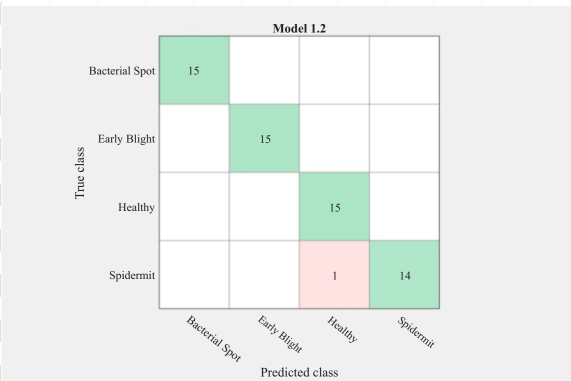

Fig. 9. Confusion Matrix for No. of observations

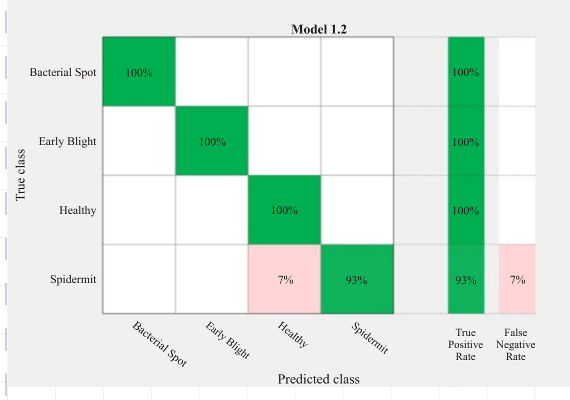

Fig. 10. Confusion Matrix for TP and FN rates

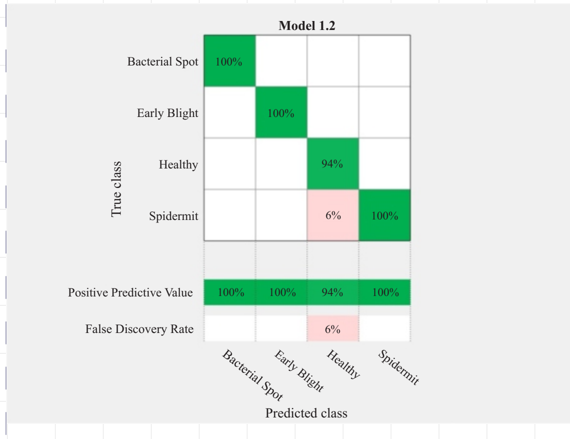

Fig. 11. Confusion Matrix of Positive Predictive values

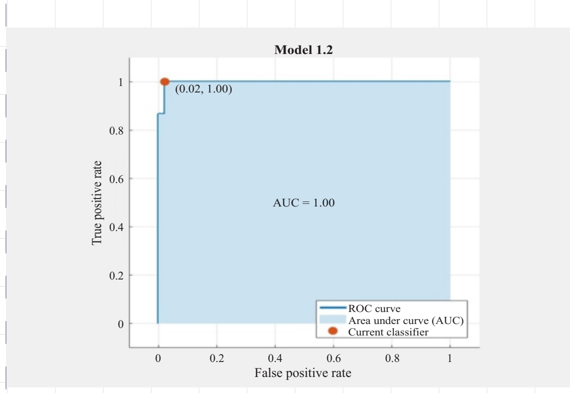

Fig. 12. ROC curve of Healthy leaves as Positive Class

V. CONCLUSION

The detection and classification of tomato crops disease becomes more effective for the farmers if done efficiently. Using image processing techniques, we made this task more robust and rapid. We used images of plant leaf that show visual symptoms of particular diseases. Our proposed framework can extract useful features from image and perform classification of disease type. The maximum average accuracy achieved during experimentation is 98.3%. Proposed system currently only utilizes texture features, but in future this work can be extended by including shape and color-based features along with texture features in order to get even better performance.

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