Plant Leaf Species Identification Using LBHPG Feature Extraction and Machine Learning Classifier Technique

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Research Article

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Abstract

The paper presents the identification and classification of Indian agricultural crop species using a novel combined Local Binary Histogram Pattern of Gradient (LBHPG) image feature extraction technique. Initially, a partition of the leaf image background is done through the newly developed Fast Adaptive Fuzzy C-mean Clustering (FAFCM) technique. After that, leaf objects within the image are identified using the LBHPG method. For the classification, KNN, PNN, and SVM shallow machine learning classifiers are used for crop species identification. The performance evaluation is done by using LBP and HOG individually along with the new proposed LBHPG technique for classification using KNN, PNN, and SVM Classifiers. The performance evaluation is based on six metrics parameters of the confusion matrix, viz., accuracy, sensitivity, specificity, precision, recall, and F-measure. The experimental results show that the proposed novel LBHP feature extraction technique with PNN Classifier gives the highest accuracy of 94.58%.

1. Introduction

Species identification is an important task for obtaining robust and categorized characteristics from leaf images. When identifying the leaves of species from the spectrum, common visual characteristics such as green color, vein structure, shape, and dimensions are considered [1]. Plant species identification is essential as it provides valuable information on plant characteristics and categorization. From a visual perspective, most of the leaf images are generally characterized based on their veins and shape [2]. The perspective of such information is considered in the food industry, biotech, and pharmaceutical companies. The information charts prepared by taxonomists are used for identifying plant species using handy leaf-to-characteristics comparisons.

The process of comparison and identifying species is time-consuming and tedious. Also, the visual perception and interpretation abilities of humans affect the precision of identification. With the importance of species identification accuracy improvement, digital image processing (DIP) is used by taxonomists along with a pattern matching process. The DIP involves various stages such as preprocessing, segmentation and morphological operations, feature extraction and recognition. In view of the promising results of DIP-based recognition, a variety of methods have been developed by various researchers. The performance of identification is mainly affected by the extraction of characteristic features. Various methods have been developed so far, including mainly shape-based contour features. Computer-aided automatic leaf classification involves shape, color, and texture features as standard feature sets in several applications [3].

Wang et al. [4] have provided a method to extract shape contour features with eight different combinations. The moving median hypersphere classifier was developed by the authors to recognize 20 kinds of plant leaves with better results. Wu et al. [5] processed plant leaf images with morphological operations to obtain vein features for plant classification. The accuracy of the results is almost up to 90%

depending on the given input parameters, which include physiological length and width of leaf are required.

Begin, Cope et al. [6] obtained the plant leaf features using a combination of shape and texture features. The support vector machine (SVM), probabilistic neural network (PNN), and K-nearest neighbor (k-NN) are used to classify and compare the results among them. This work implements a novel technique to identify and classify plant leaf species based on digital leaf images. The optimized feature extraction is the main improvement seen in the work. The proposed technique is tested to classify using the Plant Village leaf dataset of soya, tomato, and potato plants.

2. Materials And Method

In this section, the details of the leaf image dataset and suggested image processing methods with a novel LBHPG feature extraction technique are discussed in suitable subheadings.

2.1 Database

The database is taken from the ICL Plant Village Image public database and contains soybean, tomato, and potato leaf images. The database is split into train (70%) and test (30%) to perform 2-fold analysis of the proposed algorithm and to avoid over-fitting. The distributed samples per class of the dataset are summarized in Table 2. 1.

Table 2.1
Database used for training and testing of classifier

Sr. No	Disease class	Training Samples	Testing Samples
1	Potato	80	40
2	Tomato	80	40
3	Soybean	80	40
Total		240	120

2.2 Proposed approach

In this research work, the algorithm was developed to automatically classify plant leaves with respect to species. The dataset was developed for soybean, potato, and tomato species. Also, the standard dataset Plant Village Image database is used for experimentation and validation of the algorithm. The temporal features are extracted using methods such as simple and morphological features, which include Area, Perimeter, Minor Axis Length, Major Axis Length, Convex Area, Aspect Ratio, texture features using local binary pattern (LBP), shape features using histogram of gradient (HOG), and a newly developed set of

Local Binary Histogram based Pattern of Gradient (LBHPG) features. The primary goal of LBHPG is to retrieve the shape and texture of a leaf along with the inclusion of characteristic features of serrations.

The feature values generated are, however, sensitive to the size and orientation of the leaf image. To make the mean variant subject to translation, scaling, and leaf object segmentation from the background, a preprocessing step is used to standardize these parameters before the features are extracted. The feature vectors are then provided as an input to train classifiers.

The SVM, KNN, and PNN classifiers are used for classification along with result comparison among them. The effectiveness of these algorithms was tested on Plant Village Image database datasets and ICL (Intelligent Computing Laboratory, Chinese Academy of Sciences) datasets [7].

2.3 Research Framework

The framework of the proposed leaf species identification system is shown in Fig. 2.1. The proposed work is divided into five phases: image acquisition; image preprocessing; image segmentation; feature extraction; and classification. In the image acquisition phase, various leaf image datasets are developed. In the preprocessing phase, the query leaf image is resized to have a standard and similar size for all. In the image segmentation phase, leaf area as a foreground area is segmented from the background using a fast-adaptive fuzzy C-means clustering (FAFCM) technique. Feature extraction consists of extracting the different shape and texture features from leaves using simple and morphological features using the LBP, HOG, and LBHPG methods.

These features become the input vector to KNN, PNN, and SVM in the classification stage that classifies the leaf species based on the extracted features.

The steps performed are outlined as follows:

II) Image Pre-processing includes a) Image Transformation, b) Image Segmentation, and c) Image Binarization. III) Feature extraction-a) Geometric and Morphological based Feature Extraction b) LBP-Texture based feature extraction c) HOG-Shaped-based feature extraction d) LBHPG-Feature optimization-based feature extraction IV) Classification-a) K-Nearest Neighbour (KNN), b) Probabilistic Neural Networks (PNN), c) Multiclass Support Vector Machine (SVM).

2.3.1 Processing Steps

The description of the process and steps involved are:

a. Image Acquisition

The purpose of this step is to obtain the image of a whole plant leaf from a defined image database so that analysis towards classification can be performed. The public as well as a self-developed image are used for the implementation of the algorithm. Plant leaf image databases of soybean, potato, and tomato were collected from plant village image databases [7]. While creating a self-developed soybean image database, the diseased soybean leaves are placed on a white background to remove background complexity. Then the plant leaf image is captured using a high-resolution mobile camera. Figure 2.2 shows acquired images of soybean, potato, and tomato healthy leaf samples from a defined image database.

b. Image Pre-Processing

Image preprocessing consists of Image Transformation, Image Segmentation, and Image Binarization.

c. Image Transformation

In image transformation, the input RGB leaf image is first converted into HSV image using the Equation (1) shown in Figure 2.3.

d. Leaf Image Segmentation

To extract leaf features, the input image used consists of background, which may affect the feature characteristics. The segmentation process consists of RGB to HSV color space conversion [8] or better contrast-based pixel identification for foreground and background. The background of the leaf is separated by using a threshold-based masking technique as shown in Fig. 2.4. The Fast Adaptive Fuzzy C-Means clustering (FAFCM) technique [9] is applied, which partitions the leaf object into 2 clusters, foreground, and background, as shown in Fig. 2.5. The leaf segmentation is achieved by a threshold algorithm with hue, saturation, and value features as follows:

The pixel value is within the range of 0 to 255, which is first converted into 0 to 1 using 255 as the dividing factor. The maximum contrast information C_{max} and the minimum contrast information C_{min} are obtained by selecting the minimum amongst red, green, and blue values. The range Δ is the difference between C_{max} and C_{min}. The ratio of Δ and C_{max} is calculated to get the value of sensitivity. Based on these sensitivity values, the foreground and background pixel identification is done.

The pixel belongs to foreground if $S > 0.2$; (S- sensitivity),

The image data type is set to unsigned integer 8 bit to get values within 0 to 255.

I1(scan (H > s)) = (0….255)- Make foreground pixel on

I2(scan (S > s)) = (0….255)- Make foreground pixel on

I3(scan (V > s)) = (0….255)- Make foreground pixel on

Here, the (I) color image is shown in Fig. 2.5, where the foreground corresponds to the leaf region, and black pixels correspond to the background.

e. Fast Adaptive Fuzzy C-Means clustering (FAFCM)

The basic fuzzy c-means clustering (FCM) algorithm is sensitive to noise. The robustness of FCM is improved by using spatial information for image segmentation [9]. This improvement gives better segmentation but also increases computational complexity due to spatial information while calculating the distance between pixels within local spatial neighbours and clustering centroids. This issue can be solved by using an improved FCM algorithm based on morphological reconstruction and membership filtering (FRFCM) that is significantly faster and more robust than the FCM proposed in this research.

The modified objective function of these algorithms is given as follows:

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} u_{ki}^{m} \|x_i - v_k\|^2 + \sum_{i=1}^{N} \sum_{k=1}^{c} G_{ki}$$

(10)

Where, f = fx1; x2; x Ng represents a grayscale image, x_i is the grey value of the i^{th} pixel, v_k represents the prototype value of the kth cluster, and uki denotes the fuzzy membership value of the ith pixel with respect to cluster k. U = $[u_{ki}]$ cN represents the membership partition matrix. N is the total number of pixels in the image f, and c is the number of clusters. The parameter m is a weighting exponent on each fuzzy membership that determines the amount of fuzziness of the resulting classification. The fuzzy factor G_{ki} is used to control the influence of neighboring pixels on the central pixel. The Fast Adaptive Fuzzy C-Means clustering (FAFCM) technique is applied, which partitions the leaf object into 2 clusters, foreground, and background, as shown in Fig. 2.5.

f. Leaf Image Binarization

After that, the segmented image is converted into a binary image by using the global thresholding technique shown in Figure 2.6.

g. Feature extraction and description

Feature extraction refers to taking measurements, geometric or otherwise, of possibly segmented, meaningful leaf object regions in the image. The features vector describes the characteristics of the plant leaf captured in the images. In this research, a total of 9 features were extracted, out of which 6 for geometric and morphological shape-based features [10] and 3 for Local Binary Pattern (LBP) with Histogram of Oriented Gradients (HOG) formed a new developed Local Binary Histogram Pattern of Gradient (LBHPG) feature.

h. Local Binary Histogram Pattern of Gradient (LBHPG) feature

The LBHPG method is a combination of LBP and HOG. In this research, it was determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, the performance of detection is considerably improved on defined plant leaf image datasets.

i. Local Binary Pattern (LBP)

The texture feature extraction is done by using the LBP algorithm [11]. LBP features are extracted. The radius parameter is set to four pixels, and the binary number generator is set to eight pixels. The LBP-based feature extraction consists of an encoding mechanism in which at a time, a window of particular pixels, such as a 3 x 3 window, is considered for the process. The value of each pixel is subtracted from the center pixel value to get a positive and negative difference. The positive difference is considered as 1 and the negative as 0, along with the exact 0 as 0. After obtaining such 0 and 1 values, all values are collected in a clockwise manner to generate a binary number. The corresponding decimal value is obtained from this binary number to label the pixel. These numbers are called LBP codes. The example of the LBP operator is illustrated as shown in Fig. 2.7, and the results of LBP are shown in Fig. 2.8.

The LBP feature value for a pixel at (i_p, i_c) is calculated as,

$$LBPP, R(xc, yc) = \sum_{P=0}^{P-1} s\left(ip - ic\right) 2^{P}$$

(11)

Where i_c and i_p denote the grey level of pixel at the center of the window selected and the count of pixels in the radial region with radius R. The functional value of s (x) for binarization is calculated as,

$$s\left(x\right) = \begin{cases} 1, ifx \geq 0 \\ 0, ifx < 0 \end{cases}$$

(12)

$$(LBP)^{Ri} P, R = \min\{\mathrm{ROR} LBPP, R^{i} |, i = 0{,}1, \ldots, P - 1\}$$

13
The P number of pixels provides 2P values in 2P patterns using the operator LBP (P, R), given by,

LBP algorithm:

1. Select a window of 16x16 pixels.
2. Perform the subtraction process of pixels by selecting 8 pixels from the window.
3. Perform positive and negative values based on 0 and 1 labelling.
4. Collect 8 labelled values to generate a binary number.
5. Convert binary numbers to decimal values to label the pixels.

j. Histogram of oriented gradients (HOG)

The occurrence of gradient orientations is counted to obtain HOG features. HOG feature extraction has a variety of applications in image processing when applications such as object recognition are developed [12]. The process for computing HOG is given stepwise in the algorithm given below.

HOG Algorithm

Step 1. Normalize the leaf image for gamma and color.

Step 2. Compute gradients.

$$gp = g\left(x, y\right) = \sqrt{{\mathit{\Delta}x}^{2} + {\mathit{\Delta}y}^{2}}$$

(14)

where x and y are the locations of pixels and $\mathit{\Delta}$is the vector gradient.

The gradient direction is given by:

$$\theta \mathrm{p} = \theta (\mathrm{x}, \mathrm{y}) = arctan\frac{\mathit{\Delta}x}{\mathit{\Delta}y}$$

(15)

Step 3. Use weighted voting to build spatial and orientation cells.

Step 4. Perform contrast normalization for overlapping spatial blocks.

Step 5. Use histogram gradients to assemble the features' structure.

k. Local Binary Histogram Pattern of Gradient (LBHPG)
obtained the LBHPG features from combining the LBP texture feature with the HOG shape-based feature image [12] shown in Fig. 2.9.

LBHPG algorithm:

Step 1: Convert the RGB input image to HSV color space.

Step 2: Perform threshold segmentation to discard the background pixel information.

Step 3: Apply FAFCM for correct foreground segmentation.

Step 4: Extract geometrical features such as area, perimeter, minor and major axis length, convex area, axial ratio.

Step 5: Apply LBP to get binary texture features and obtain an LBP image.

Step 6: Extract HOG features from LBP image to obtain LBHPG features

l. Classification
In the classification step, 9 orthogonalize features are concatenated into a feature vector, which is then classified. The feature vector is used as input to KNN, PNN and SVM classifier to classify soybean, tomato, and potato plant leaf images.

m. Performance Analysis

The performance of the proposed LBHPG (leaf recognition model) is measured by a confusion matrix. The confusion matrix is used to measure true positive (TP), true negative (TN), false positive (FP), false negative (FN), sensitivity, specificity, precision, recall, and accuracy [13]. The performance is also analyzed using receiver operating characteristics (ROC) [14].

3. Results And Discussions

3.1 Evaluation Matrix: Machine Learning Statistics

In the following, various terms of machine learning statistics are explained in order to assess overall performance using the confusion matrix. The analysis is done for true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The description of TP, TN, FP, and FN is detailed in Table 3.1.

Table 3.1
Confusion matrix parameters

Parameter	Description
TP	Input is Tomato leaf and detected as Tomato
TN	Input is Tomato leaf and detected as non-Tomato
FP	Input is non-Tomato leaf and detected as Tomato
FN	Input is non-Tomato leaf and detected as non-Tomato

The analysis with confusion matrix parameters for potato and soybean is done in a similar manner as for tomato in Table 3.1. Using these confusion matrix parameters, sensitivity, specificity, precision, and accuracy are estimated. The formulae for these parameters are detailed in Table 3.2.

Table 3.2
Formulae for performance evaluation parameters

Parameter	Formula
Sensitivity	$\mathrm{TPR} = \frac{TP}{TP+FN}$
Specificity	$\mathrm{TNR} = \frac{TN}{TN+FP}$
Precision	$\mathrm{PPV} = \frac{TP}{TP+FP}$
Recall	$\mathrm{r} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$
Accuracy	$\mathrm{ACC} = \frac{TP+TN}{TP+TN+FP+FN}$
F-measure	$\mathrm{Fmeasure} = \frac{2*recall*precision}{\mathrm{recall+precision}}$

3.2 Confusion Matrix (Evaluation Matrix)

A total of 240 data samples for 3 classes of leaf species are used for training the PNN classifier. 120 data samples are considered for testing the performance of the system. The result consists of 77 correct and 25 incorrect classifications out of a total of 120 samples. Further detailed analysis shows that there are all correct classifications for class 1. Out of 24 incorrect classifications, 9 are for class 4 and 16 are for class 3. Based on the confusion matrix of the predicted and ground truth classes obtained using the PNN classifier, accuracy is 79.2%.

The performance evaluation is done by replacing KNN with PNN and SVM classifiers. The performance of classification is shown in the confusion matrix and graphical presentation as shown in Figs. 2.10 and 2.11, respectively. The performance evaluation details are shown in Table 3.3.

Table 3.3
Machine learning Statistical Analysis of Accuracy for leaf identification

Feature	Accuracy	TPR (Sensitivity)	TNR (Specificity)	Precision	Recall	F-measure	Classifier
Only LBP feature							
LBP	84.17	91.11	80.00	73.21	91.11	81.19	KNN
LBP	89.58	97.50	80.00	61.90	97.50	75.73	PNN
LBP	85.42	87.88	83.69	79.09	87.88	83.25	SVM
Only HOG feature							
HOG	84.17	91.11	80.00	73.21	91.11	81.19	KNN
HOG	88.33	97.37	86.63	57.81	97.37	72.55	PNN
HOG	80.42	87.21	76.62	67.57	87.21	76.14	SVM
Combined HOG and LBP feature (LBHPG)							
LBHPG	86.67	94.62	81.63	76.52	94.62	84.62	KNN
LBHPG	**94.58**	**100**	**92.61**	**83.12**	**100**	**90.78**	**PNN**
LBHPG	90.42	90.74	90.15	88.29	90.74	89.50	SVM

The performance evaluation is done by using LBP and HOG individually along with a combination of the two, called LBHPG, for classification of species using KNN, PNN, and SVM classifiers. The overall analysis and comparison are as shown in the graphical presentation in Fig. 2.12.

From the graph in Fig. 2.12, it is observed that the LBHPG, along with the PNN classifier, shows better performance over other feature extraction and classifier methods.

3.3 Receiver Operating Characteristics (ROC)

Figure 2.13–2.15 shows the receiver operating characteristics of the KNN, PNN, and SVM classifiers. The ROC analysis mainly depends on the sensitivity and specificity.

From the results as in Table 3.3, the PNN classifier outperforms in terms of specificity, sensitivity, and accuracy over SVM and KNN for the identification of potato, tomato, and soybean plant leaf species. Hence, the area under the curve for PNN is dominating. In Figure ROC of the PNN classifier, the blue line shows the area covered by class 1 (potato), the red line shows class 2 (tomato), and partial coverage of the area in the green line by class 3 (soybean), having the highest values compared to KNN and SVM.

4. Conclusion

In the present work, Fast Adaptive Fuzzy C-means auto-segmentation with the proposed LBHPG feature extraction method applied with PNN, KNN, and SVM classifier technique were evaluated to validate their performance in leaf identification through leaf detection. The performance of the proposed PNN, KNN, and SVM classifiers was evaluated by 6 metrics for leaf identification through leaf detection, i.e., i) Sensitivity (SE), ii) Specificity (SP), iii) Precision (Pr), iv) Accuracy, v) Recall, and v) F-measures, confusion matrix, and Receiver operating characteristics (ROC) curve. The comparative leaf recognition analysis was evaluated by considering the plant leaves under consideration with classifier performance. We have applied the considered FAFCM clustering with LBHPG feature extraction method to the developed database. Based on comparison results in overall performance analysis, the combined (LBP + HOG) LBHPG and PNN classifier method performs best, with a 94.58% accuracy. The results elucidate that the proposed combined LBHPG feature extraction method outperforms individual LBP and HOG. The outcome of this work will help to precisely identify the soybean, tomato, and potato plant leaves and, hence, it will be useful for taxonomists for automatic leaf species identification.

Declarations

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Data Availability Statements:

The datasets analyzed during the current study are available in the [Plant Village Image Dataset: Kaggle] repository, https://www.kaggle.com/datasets/abdallahalidev/plantvillagedataset.

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Figures

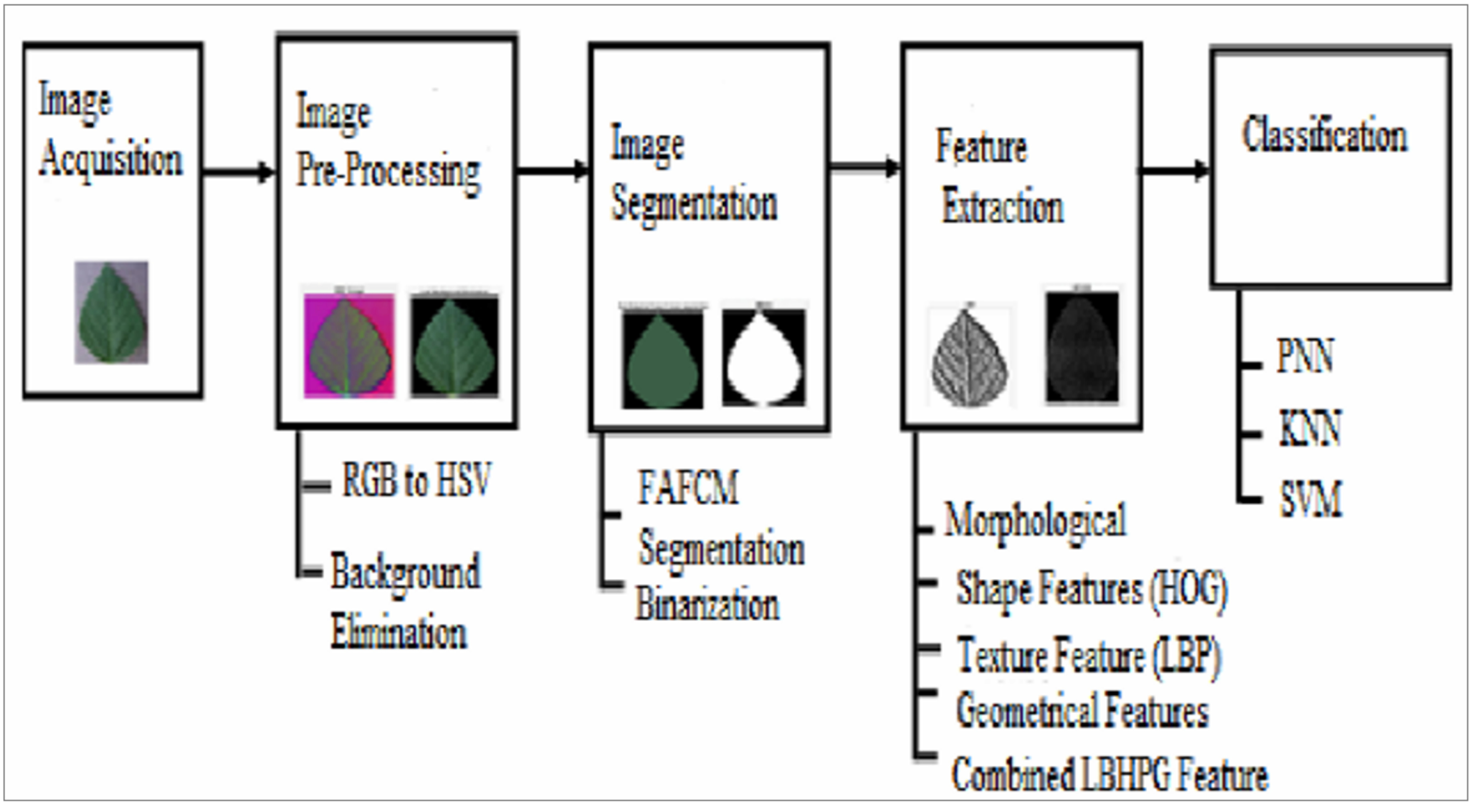


Figure 1

Framework of proposed leaf species Identification system.

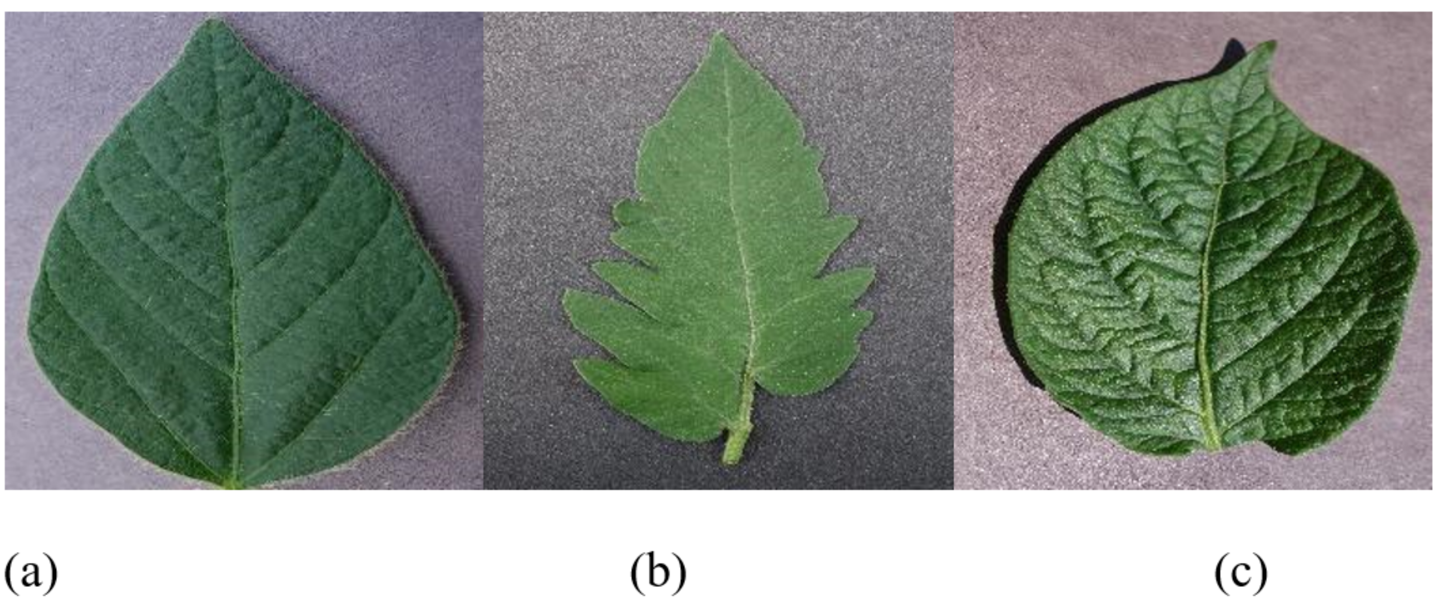
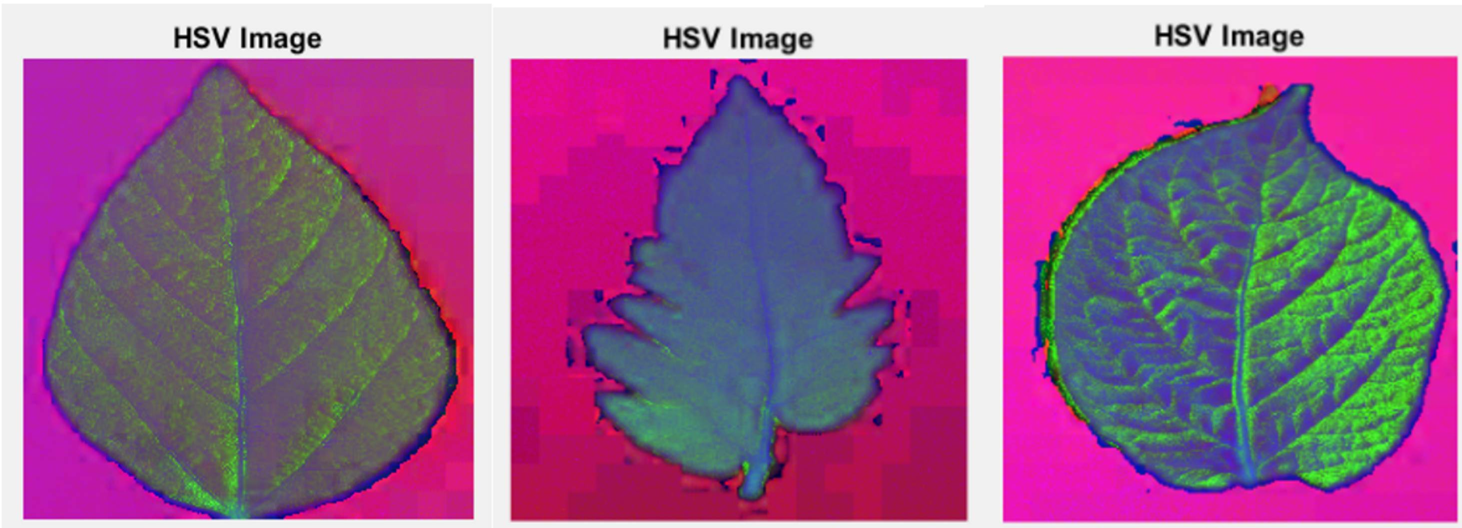


Figure 2

Samples of acquired healthy leaf images from database (a) Soybean (b) Tomato (c) Potato.



(a) (b) (c)

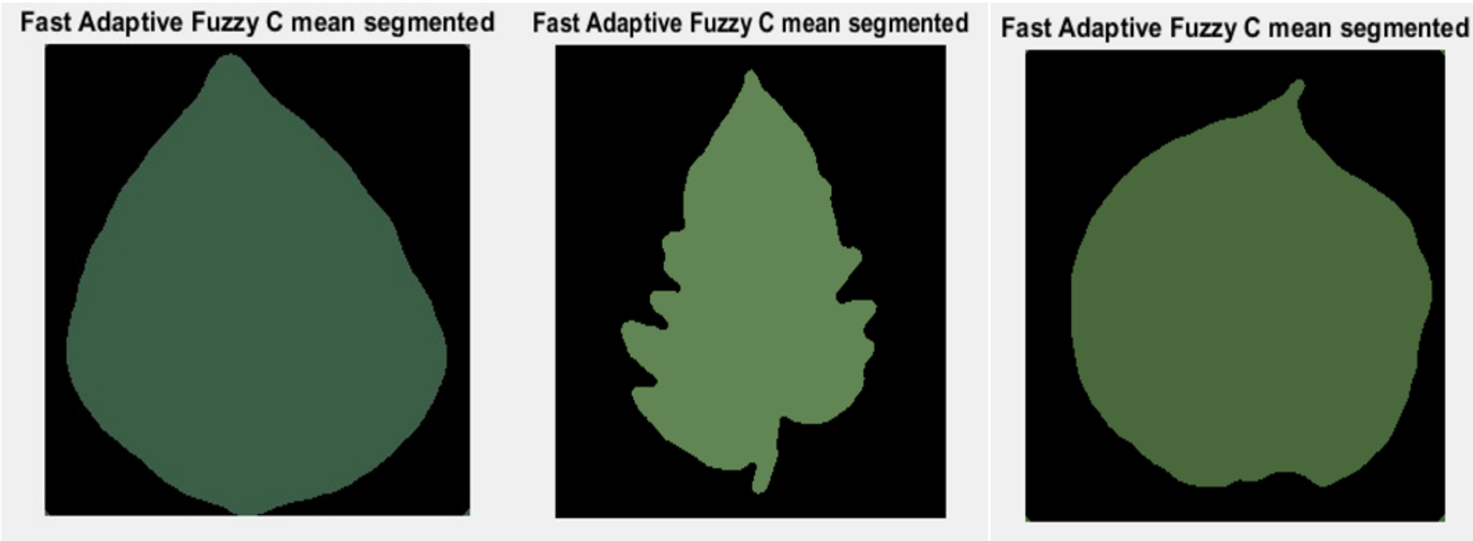
Figure 3

RGB to HSV Conversion of Input Image for (a) Soybean (b) Tomato (c) Potato.

(a) (b) (c)

Figure 4

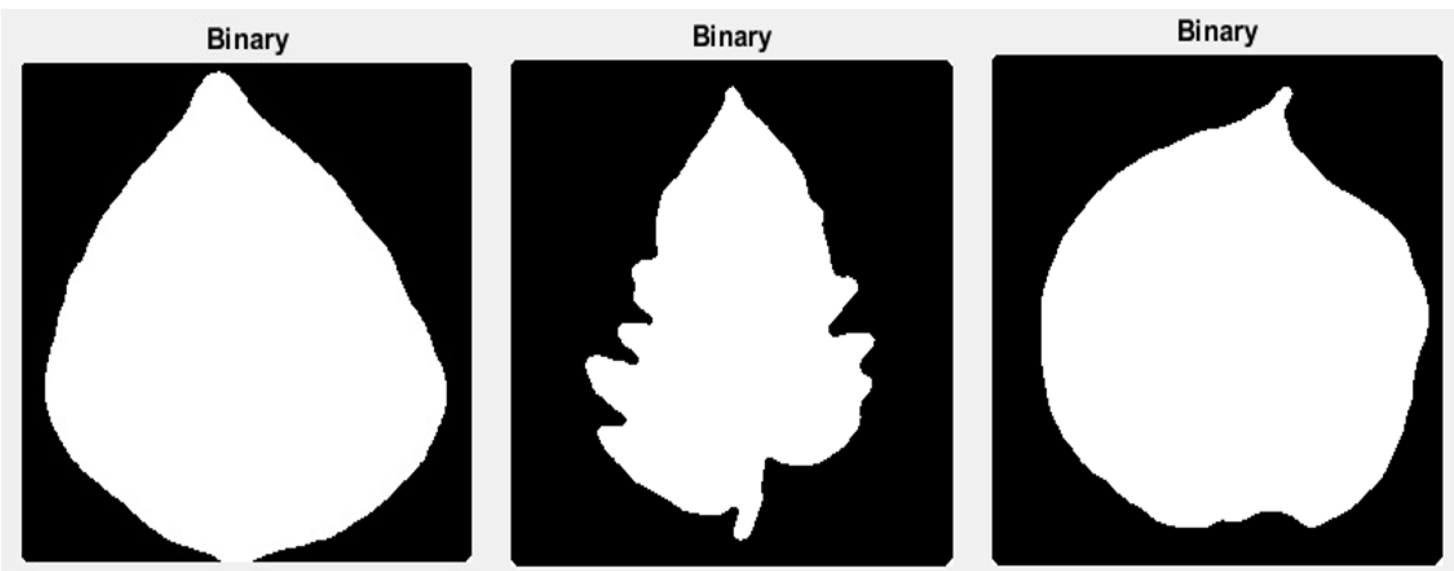
Samples of acquired healthy leaf images from database (a) Soybean (b) Tomato (c) Potato.



(a) Soybean (b) Tomato (c) Potato.

Figure 5

Segmented Image using Fast Adaptive Fuzzy C-Means clustering (FAFCM)



(a) Soybean (b) Tomato (c) Potato.

Figure 6

Binary image of (a) Soybean (b) Tomato (c) Potato plant leaf.

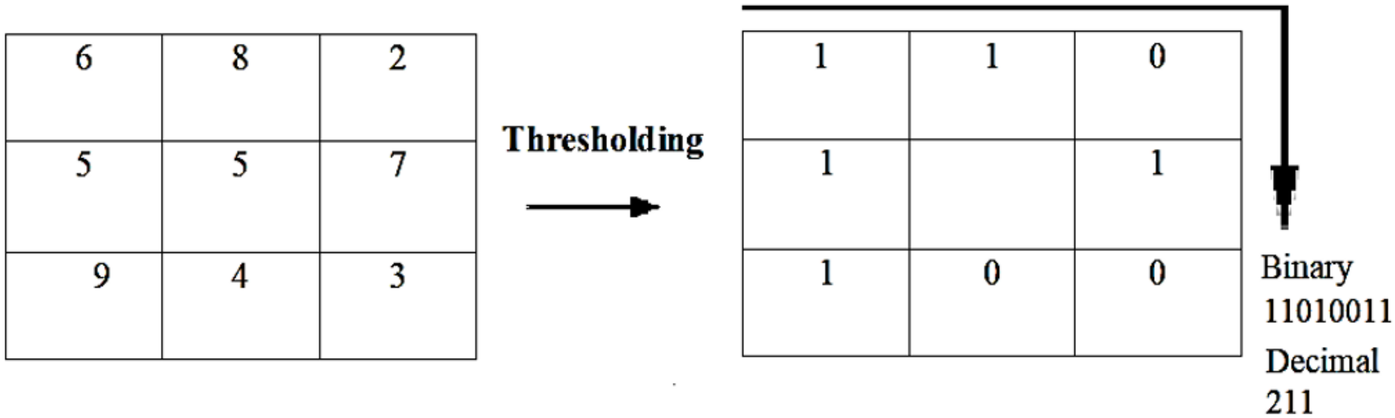


Figure 7

Example of LBP operator.

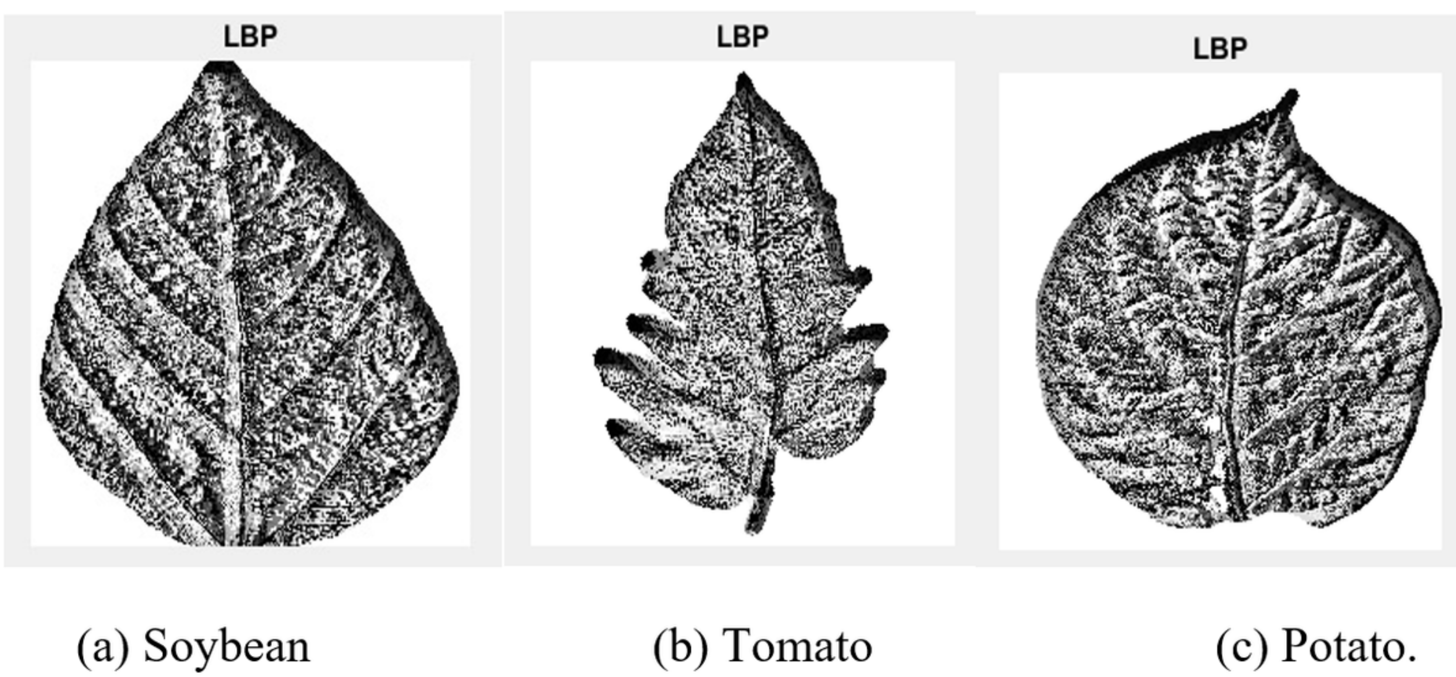
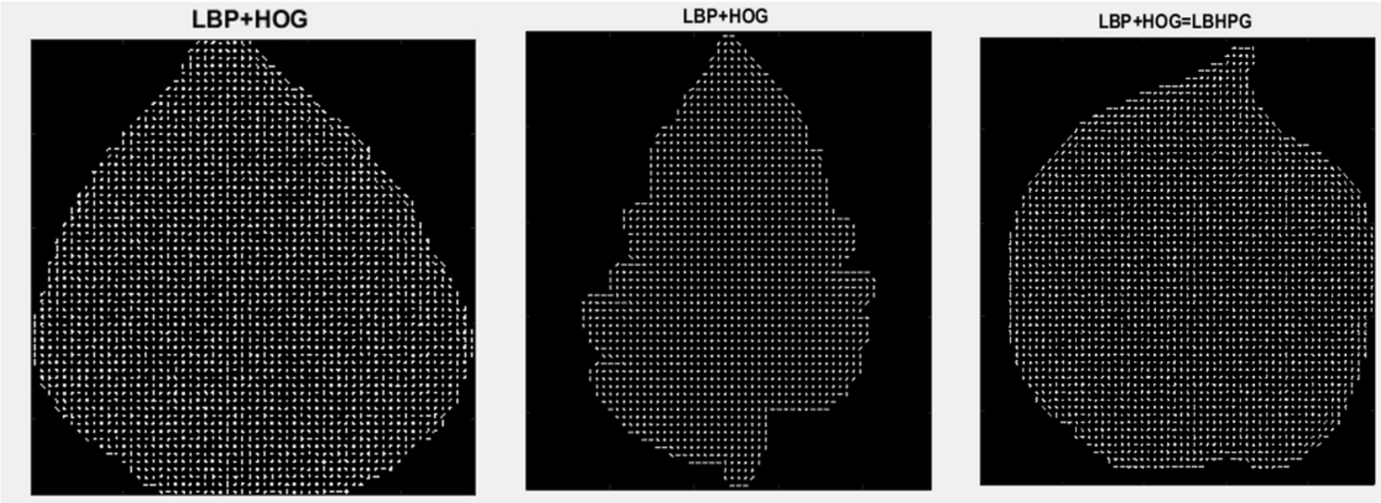


Figure 8

Local binary Pattern (LBP) image of (a) Soybean (b) Tomato (c) Potato plant leaf.



(a) Soybean (b) Tomato (c) Potato.

Figure 9

Local Binary Histogram Pattern of Gradient (LBHPG) from LBP+HOG image.

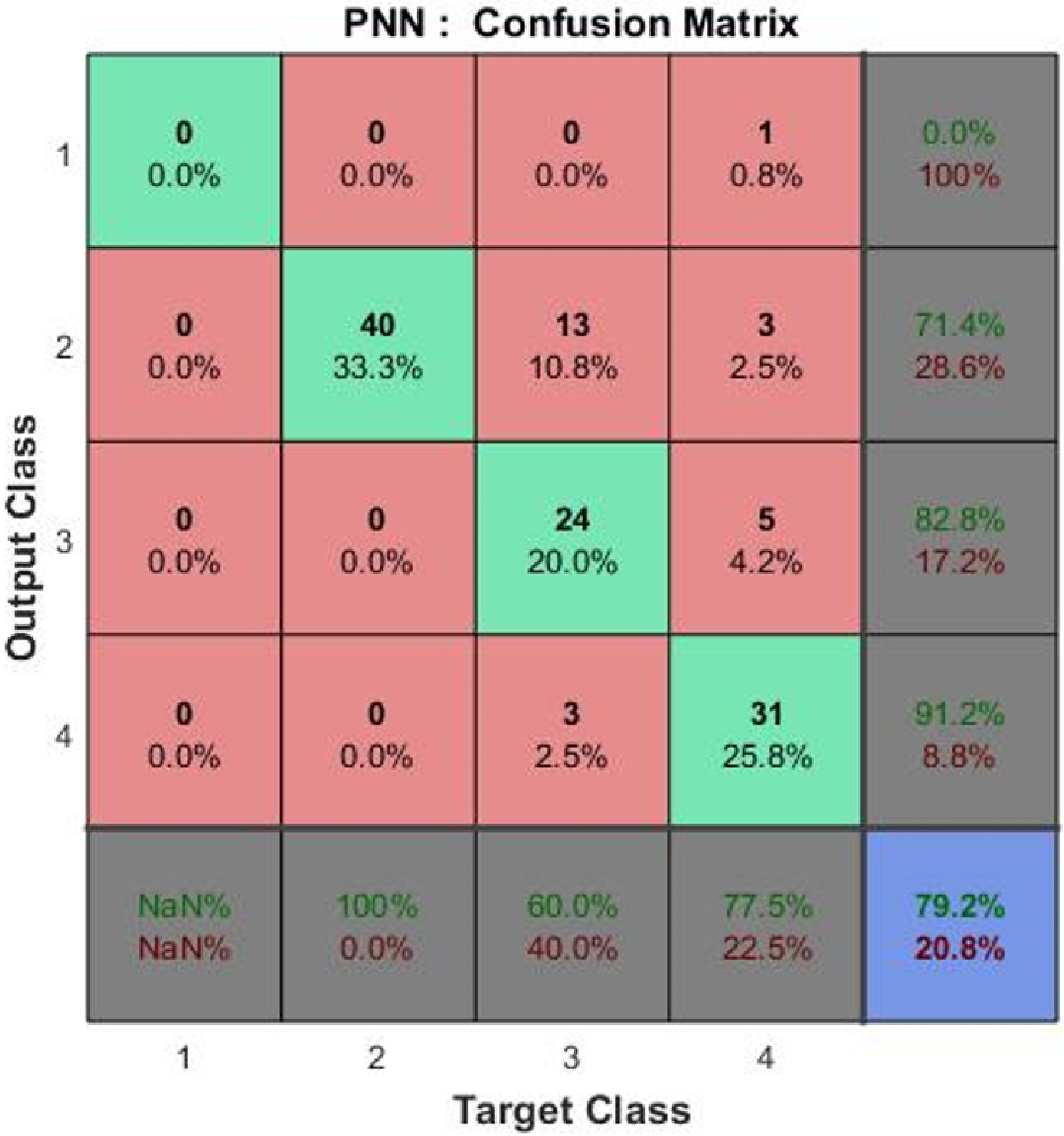


Figure 10

Confusion matrix for PNN classifier

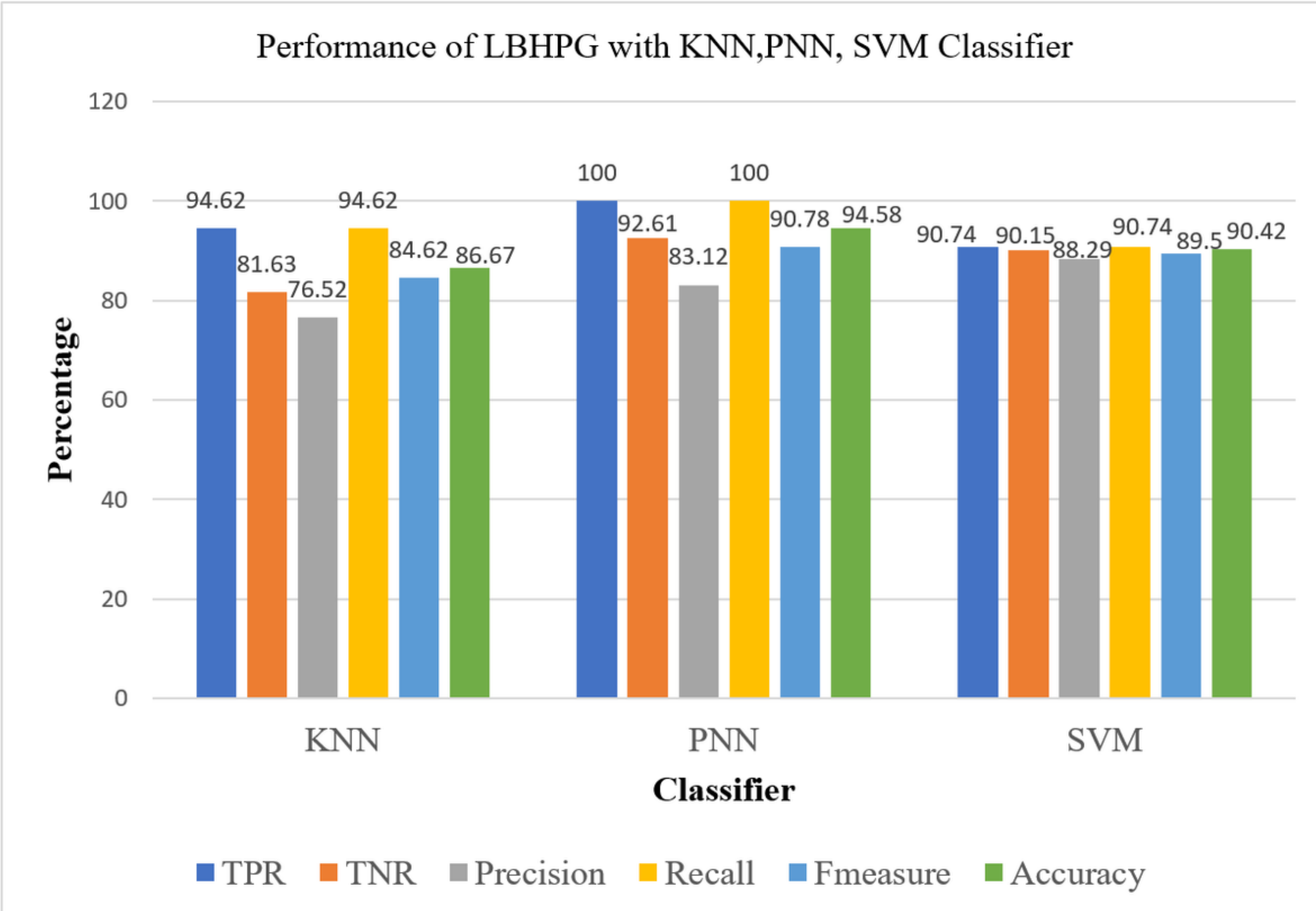


Figure 11

Result of LBHPG with KNN, PNN, SVM Classifier

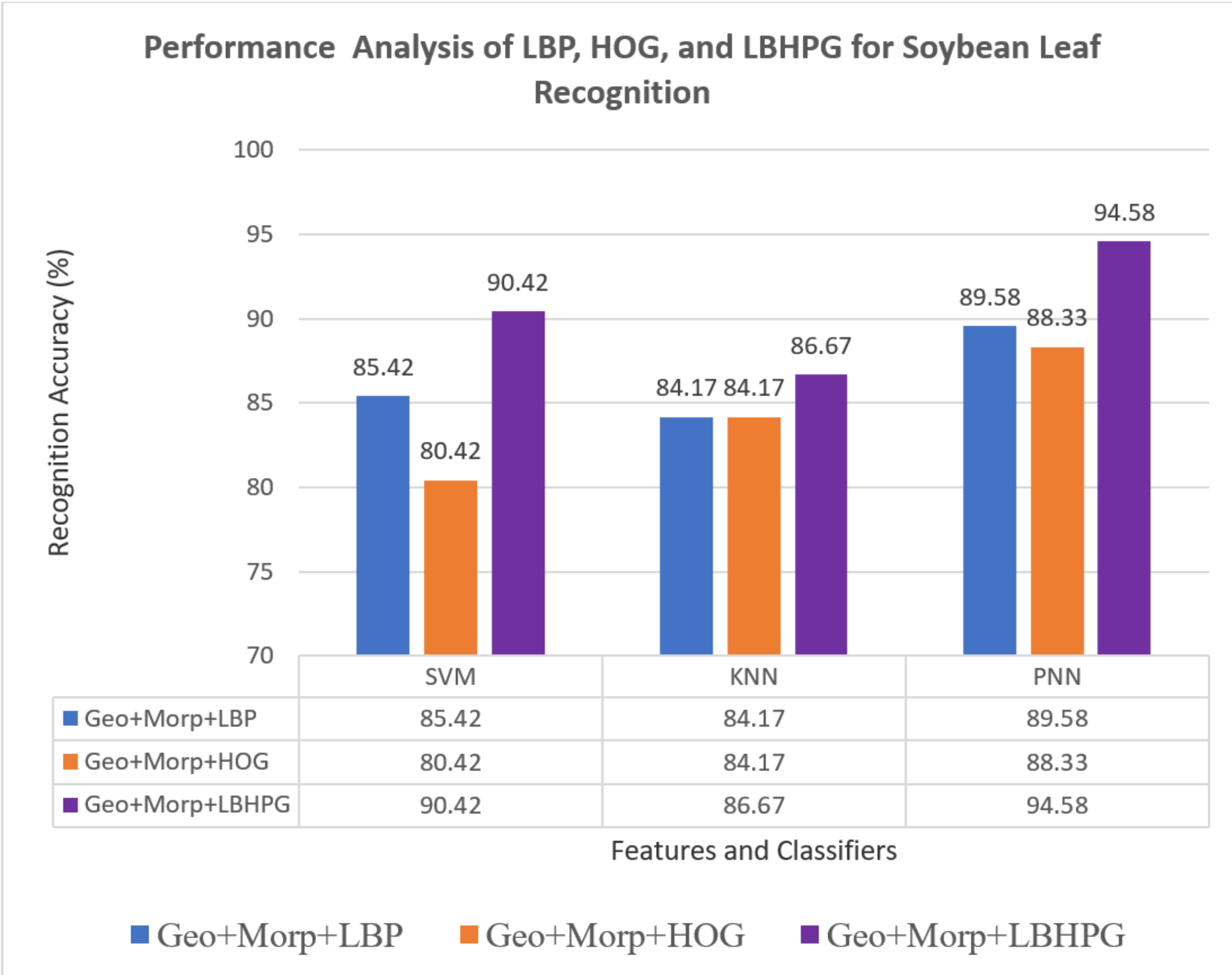


Figure 12

Result of Soybean Leaf Recognition

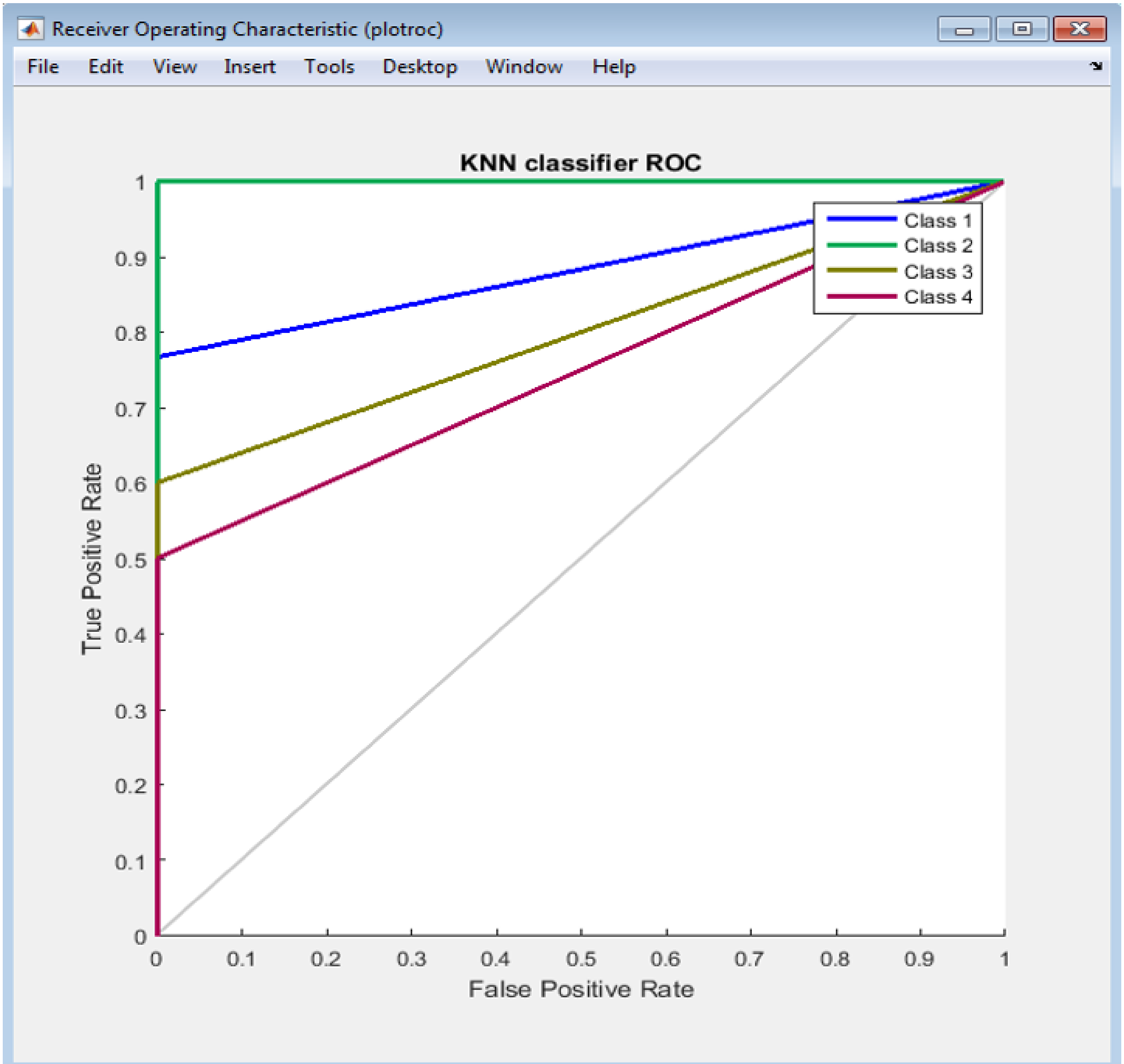


Figure 13

ROC of KNN classifier (TPR vs. FPR)

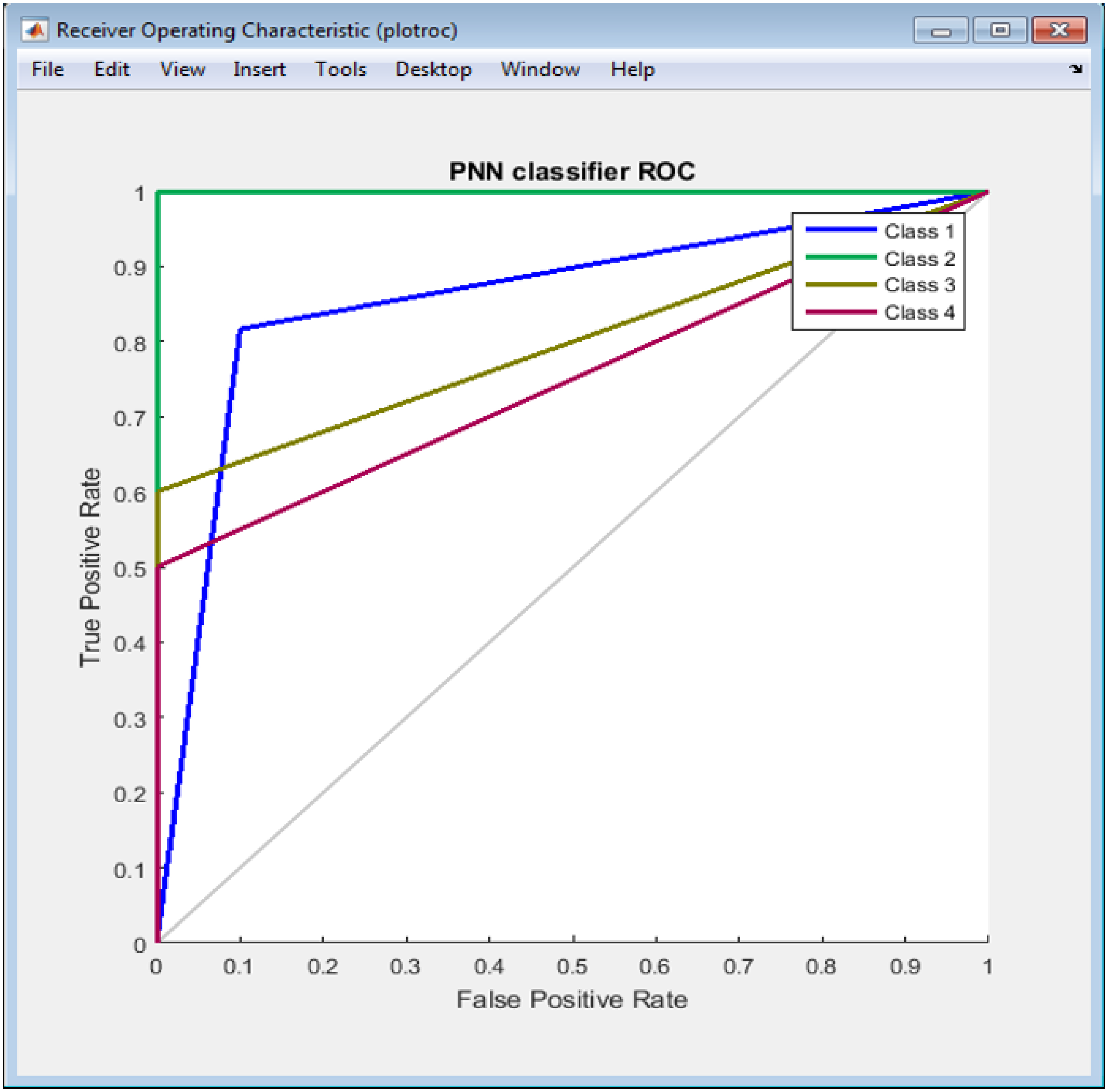


Figure 14

ROC of PNN classifier (TPR vs. FPR)

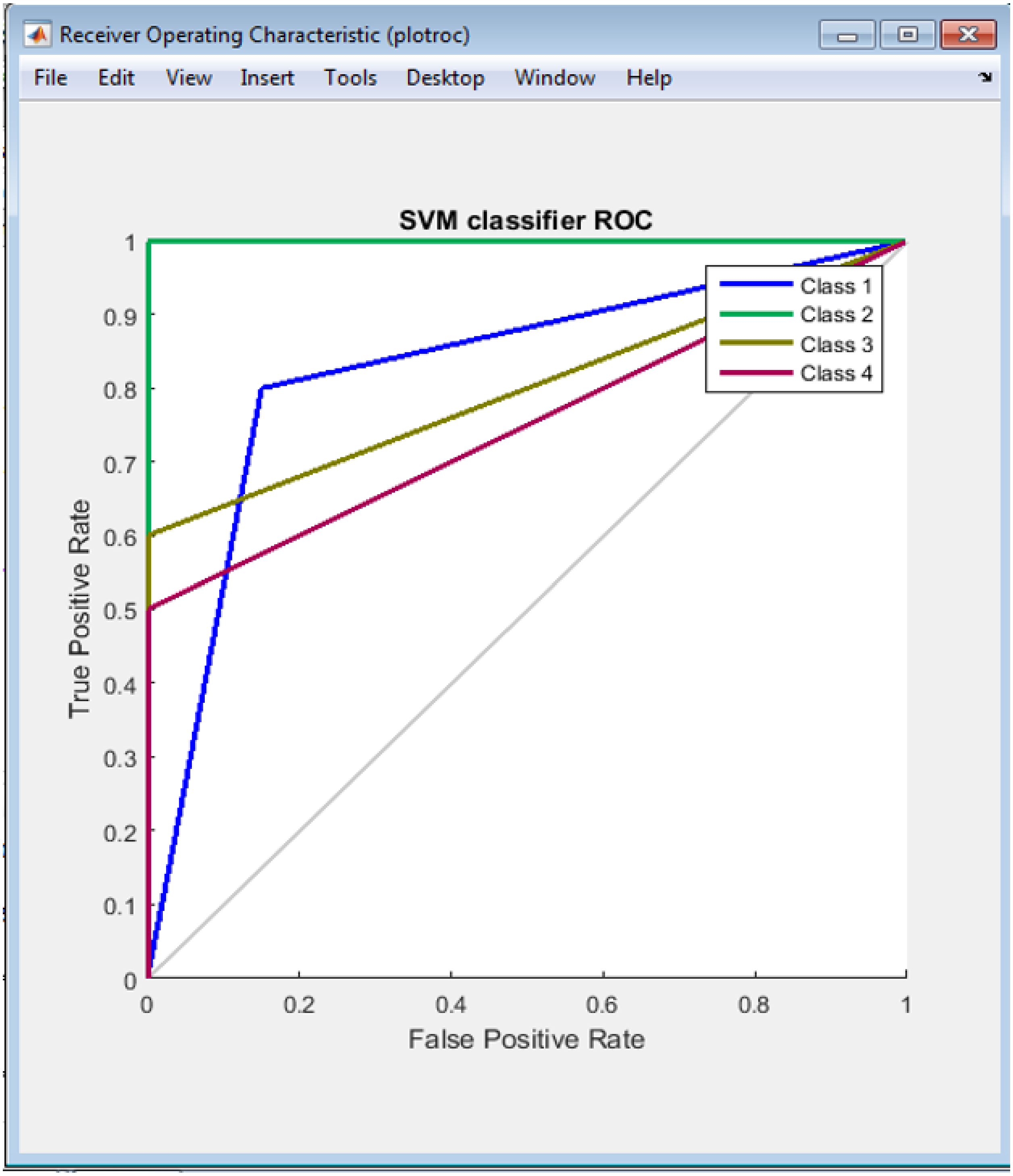


Figure 15

ROC of SVM classifier (TPR vs. FPR)