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Enhanced Image Texture Feature Extraction Method Using Local Tetra Patterns for Plant Leaf Classification System

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ABSTRACT

Image textures are groups of metrics computed to classify the captured texture of images. It reveals the information about the spatial orientation of color or gray level intensities in the images or specific regions of the images. The image texture classification of plant leaves is considered in this paper because of the extinction risk of various plants. An efficient plant leaf identification using image texture classification would aid in automatic recognition of the plant leaves. The existing image texture classification methods, namely, Local Tetra Patterns (LTrPs) are considered. LTrP considered only horizontal and vertical directions during the phasor difference computation stage. A Enhanced LTrP (ELTrP) is proposed in this paper by including the diagonal direction along with the horizontal and vertical directions in the LTrP. Then, features are extracted for the output image texture patterns. The features are classified using Support Vector Machine (SVM). 750 leaf images are trained from 50 classes, where each class consists of 15 leaves. 2500 leaf images are tested from 50 classes, where each class consists of 50 leaves. The proposed method ELTrP is analyzed in terms of classification accuracy with LBP, LTrP. Its performance is found to be satisfactory compared to LTrP.

***Index Terms*: **Content Based Image retrieval (CBIR), Local Tetra Pattern (LTrP),Enhance Local Tetra Patterns (MLTrPs), Phasor difference, and Support Vector Machine (SVM).

I. INTRODUCTION

IMAGE texture are groups of metrics computed to classify the captured texture of images. It reveals the information about the spatial orientation of color or gray level intensities in the images or specific regions of the images. The image texture classification of plant leaves is considered in this paper because of the extinction risk of various plants. An efficient plant leaf identification using image texture classification would aid in automatic recognition of the plant leaves.

The existing image texture classification methods, namely, Local Tetra Patterns (LTrPs) are considered. LTrP considered only horizontal and vertical directions during the phasor difference computation stage. A Enhanced LTrP (ELTrP) is proposed in this paper by including the diagonal direction along with the horizontal and vertical directions in the LTrP. The features are classified using Support Vector Machine (SVM) 750 leaf images are trained from 50 classes, where each class consists of 15 leaves. 2500 leaf images are tested from 50 classes, where each class consists of 50 leaves. The proposed method of ELTrP is analyzed in terms of classification accuracy with LTrP. Its performance is found to be satisfactory compared to LTrP of existing methods.

The remaining part of the paper is organized as follows: Section II involves the works related to the existing image texture classification methods using LBP and LTrP in various applications like health services,

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leaf texture analysis, and facial image analysis. Section III involves a brief description of the existing method LTrP. Section IV involves the description of the proposed method ELTrP for enhancing the classification accuracy. Section V involves the performance evaluation and comparison of ELTrP with existing techniques based on LTrP. The paper is concluded in Section VI.

II. RELATED WORK

Zhenhua and Zhang designed a complete modeling tool for the Local Binary Pattern (LBP) operator involved in image texture classification [1]. The complete model of LBP (CLBP) consists of a local region defined by a local difference sign-magnitude transform (LDSMT) and its center pixel. These center pixels characterize the image gray levels which are transformed into a binary code known as CLBP-Center (CLBP_C). LDSMT disintegrates the image local differences into two primitive parts (magnitude, sign) and two operators, such as CLBP-Magnitude (CLBP_M) and CLBP-Sign (CLBP_S). Constant texture classification is enhanced by using a combination of CLBP_C, CLBP_M, and CLBP_S.

Another novel feature descriptor for Content Based Image Retrieval (CBIR) was recently proposed by *Murala, et al* known as Local Tetra Patterns (LTrPs) [2]. Former features for texture classification like LBP and Local Ternary Pattern (LTP) encode the association between the referenced pixel and its neighboring pixels based on their gray-level difference. But, LTrP encodes this affiliation based on the orientations that are computed using the 1st order derivatives in horizontal and vertical orientations. A k^{th} order LTrP using $(k - 1)^{th}$ order vertical and horizontal orientations for effective CBIR is constructed.

LBP based two-dimensional texture analysis is used for the fault diagnosis of induction motors via texture analysis [3]. The detection of fault signatures at different operation modes in the presence of noise is a challenging task. The vibration signals in time domain are obtained from the motor and transformed into 2-D gray scale images. The LBP operator performs the feature extraction while a multi-class Support Vector Machine (SVM) is used to detect the faults through local feature descriptor analysis.

LBP is used extensively in health services. *Liu, et al* proposed an automated macular pathology diagnosis in retinal OCT (Optical Coherence Tomography) images based on LBP and multi-scale spatial pyramid in shape and texture encoding [4]. A major issue in the analysis of OCT images is the detection of the presence of normal macula based on macular hole, macular edema, and age-related macular retrogression pathologies. The multi-scale spatial pyramid was formed from the global image descriptors and the local binary pattern histograms form the local features. A robust performance is obtained by encoding the textures and shapes at multiple spatial scales and granularities. A 2-class SVM classifier detects the normal macula and other three pathologies. A fine differentiation of sub-divisions within a specific pathology can be observed with the help of full-thickness holes within the macular holes. *Sørensen, et al*. analyzed pulmonary emphysema using LBPs [5]. Large-scale analysis of emphysema in computed tomography (CT) scan images is performed by combining pixel posterior probabilities outputs. LBPs represent the texture features, while integrated LBP-intensity histograms defines the region of interests (ROIs). Texture classification is performed using a k nearest neighbor classifier based on histogram dissimilarity distance. The classification accuracy obtained for a set of 168 personally composed ROIs of normal, paraseptal emphysema, and centrilobular emphysema classes was 95.2%. Rotation invariant LBPs and genetic programming was integrated for the automatic detection and segmentation of bovine corpora lutea in ultrasonographic ovarian images [6]. A 3D version of LBPs was implemented in the texture analysis of neuroimages and diagnosis of Alzheimer's disease [7]. LBPs were also used as texture descriptors for medical image analysis [8] and they were also integrated with Haralick texture features and Haar wavelet features the classification of mammogram images using Artificial Neural Networks (ANNs) [9].

LBP is also used in the texture analysis of leaves. *Seiler, et al*. classified the habitat of aquatic life in the continental shelf of Tasmania using image-based mapping and automated data extraction methods [10]. The divisions of the aquatic life involve leaves, branches, corals, and reefs. This habitat classification involves LBP image textures to enhance the accuracy of the habitat prediction. The frequency of LBP is preferred to describe the texture because images with similar histograms may characterize different habitats. LBPs also possess rotation property defined by a combination of grey scale values of a circularly symmetric group of neighboring pixels in a local environment. The classification accuracy using LBP was estimated to be 78.5%. LBP is also used in the monitoring and grading of tea leaves [11]. Existing tools for tea quality monitoring include organoleptic techniques and instrument based methods. These schemes are expensive, laborious, time consuming, and less accurate. To overcome the inconsistency and inaccuracy, computer vision techniques such as LBP, signed differences, histogram intersection, and grey level co-occurrence matrix (GLCM) are applied. The image analysis is performed based on properties like granule color, size, shape, and texture.

LBP is majorly applied in facial image analysis. *Ylioinas, et al* constructed a gender classification model using an integrated approach of contrast information and LBP [12]. Gender classification was also extended to tedious real-world applications involving real-life faces [13]. LBP is used here to describe the faces, while the feature selection is performed by Adaboost algorithm. A classification accuracy of 94.81% was obtained using SVM classifier with boosted LBP features. LBP is a full gray-scale invariant texture operator used in face analysis supported by contrast information. Face recognition systems can be created using LBPs combined with decision trees [14]. For each facial region the most important LBP-like features are obtained by a generalized LBP in a supervised manner. A survey of the application of LBPs in facial image analysis is discussed in [15]. Several techniques use LBPs in tasks like recognition and detection of faces, demographic classification, facial expression analysis, and multi-view facial expression recognition [16]. An automatic facial expression recognition system was constructed in [17] based on the extraction of LBPs from image key points.

LBP was extended to pyramid transform domain known as PLBP [18]. The LBP details were cascaded in the form of hierarchical spatial pyramids based on the variations of the texture resolutions. LBPs was enhanced by considering non-uniform patterns in [19]. The non-uniform micropatterns of LBP are considered for feature extraction during the classification. A random subspace is utilized to overcome the constraints of non-uniform patterns such as, partial correlation, high dimension, and noise. Image security is important to conserve the integrity and authenticity of images, which is attacked by image splicing techniques.

III. EXISTING METHODS FOR TEXTURE CLASSIFICATION

This section describes the existing methods for texture classification, namely LTrP.The conventional LTrP model computes a 2nd order LTrP based on the orientation of the pixels based on the pixels using horizontal (0°) and vertical (90°) derivatives [2]. The n^{th} order LTrP operator is estimated using $(n-1)^{th}$ order derivatives. LTrP is evolved from LBP, LTP (Local Ternary Pattern), and LDP (Local Derivative Pattern).

The first order derivatives of an image I along the horizontal and vertical directions are represented as $I_\theta^{\,1}(e_x)\,|_{\,\theta = 0°,\, 90°}$. e_m denotes the middle pixel in I, whereas e_h and e_v denote the horizontal and vertical environments of e_m respectively. The 1st order derivatives at the middle pixel are given as:

$$I_{0°}^{\,1}(e_m) = I(e_h) - I(e_m) \tag{1}$$

$$I_{90°}^{\,1}(e_m) = I(e_v) - I(e_m) \tag{2}$$

The orientation of the middle pixel is computed as:

$$I_{dir}^{1}(e_m)\ \lfloor\ \begin{cases} 1, I_0^1,(e_m) \geq 0\, and\ I_{90°}^1,(e_m) \geq \\ 2, I_0^1,(e_m) < 0\, and\ I_{90°}^1(e_m) \geq \\ 3, I_0^1,(e_m) < 0\, and\ I_{90°}^1(e_m) < \\ 4, I_0^1,(e_m) \geq and\ I_{90°}^1(e_m) < \end{cases} \tag{3}$$

The binary patterns (LPs) are estimated from the magnitude of the vertical and horizontal first order derivatives using the following equations (6) and (7), where X is the number of environments and (6) represents the magnitude LBP.

$$M_{I^1(e_x)} = \sqrt{\left(I^1_0,(e_x)\right)^2 + \left(I^1_{90^\circ},(e_x)\right)} \tag{4}$$

$$LP = \Sigma_{x^\circ 1}^{X} 2^x LBP\left(M_{I^1(e_x)} - M_{I^1(e_m)}\right)|_X \tag{5}$$

IV. ENHANCED APPROACH OF LTRP

First, the algorithm for the texture classification of ELTrP is explained, and then the structural architecture for the leaf image texture classification is explained in detail with respect to the former explained algorithm.

(A) Algorithm for Texture Classification

The proposed approach enhance the performance of Local tetra pattern technique [murala] by encodes the relationship between the centre pixel and its neighbors, based on the directions that are calculated using the first-order derivatives in vertical, horizontal and diagonal directions called as ELTrP.

The phasor differences for the middle pixel and the neighboring pixels in horizontal, vertical, and diagonal directions are checked according to Pseudocode 2. The difference between LTrP and ELTrP is the diagonal direction for checking the phasor differences. This process constitutes the derivative calculations. These functions of detecting the orientation of the middle pixel are given in (6) similar to (3).

$$I^1_{dir}(e_{m1}) \lfloor \begin{cases} 1, I^1_0,(e_m) \geq 0 \, and \, I^1_{90^\circ},(e_m) < 0 \, and \, I^1_{45^\circ}(e_m) < \\ 2, I^1_0,(e_m) < 0 \, and \, I^1_{90^\circ}(e_m) \geq 0 \, and \, I^1_{45^\circ}(e_m) \geq \\ 3, I^1_0,(e_m) \geq 0 \, and \, I^1_{90^\circ}(e_m) < 0 \, and \, I^1_{45^\circ},(e_m) < \\ 4, I^1_0,(e_m) < 0 \, and \, I^1_{90^\circ}(e_m) \geq 0 \, and \, I^1_{45^\circ}(e_m) < \\ 5, I^1_0,(e_m) < 0 \, and \, I^1_{90^\circ}(e_m) \geq 0 \, and \, I^1_{45^\circ}(e_m) \lfloor \\ 6, I^1_0,(e_m) < 0 \, and \, I^1_{90^\circ}(e_m) \geq 0 \, and \, I^1_{45^\circ}(e_m) < \\ 7, I^1_0,(e_m) < 0 \, and \, I^1_{90^\circ},(e_m) < 0 \, and \, I^1_{45^\circ},(e_m) < \\ 8, I^1_0,(e_m) \geq 0 \, and \, I^1_{90^\circ}(e_m) < 0 \, and \, I^1_{45^\circ},(e_m) < \end{cases} \tag{6}$$

The magnitude ELTrP is estimated according to (7) similar to (4). The expression for magnitude binary patterns is given in (7).

$$M_{I^1(e_x)} = \sqrt{\left(I^1_0,(e_x)\right)^2 + \left(I^1_{90^\circ},(e_x)\right)^2 + \left(I^1_{45^\circ},(e_x)\right)} \tag{7}$$

The GLCM features [11] are extracted for the output image texture patterns. The features are classified using SVM [4] and the classification results are retrieved by comparing the testing data and the trained data.

(B) The Proposed ELTrP is Explained in the Following Seven Steps

STEP 1:

In the first step, we separate the image samples and convert it into gray scale image by using *rgb2gray* command. The converted image contains pixel information of input image.

STEP 2:

In this step, we separate the image into blocks as shown in Pseudocode 1, where I is the image, out is the image blocks, and N is the size of image.

Pseudocode 1: Separation of the image into blocks

```
For i is 3 to (N - 2),
For j is 3 to (N - 2),
    out{i, j} = I(I - 2 to I + 2, j - 2 to j + 2);
End
End
```

STEP 3:

The phasor differences from the center pixel to the neighboring pixels for angles of 0°, 45°, and 90° are checked as illustrated in Pseudocode 2.

Pseudocode 2: Check for phasor differences

```
For i is 1 to N
For j is 1 to N
    Temp = out{i, j};
    I0 = Temp(3, 4) - Temp(3, 3);
    I45 = Temp(2, 4) - Temp(3, 3);
    I90 = Temp(2, 3) - Temp(3, 3);
      If I0 >= 0 and I90 >= 0 and I45 >= 0
         Rule = 1;
      Else if I0 < 0 and I90 >= 0 and I45 >= 0
         Rule = 2;
      Else if I0 < 0 and I90 < 0 and I45 >= 0
         Rule = 3;
      Else if I0 >= 0 and I90 < 0 and I45 >= 0
         Rule = 4;
      Else If I0 >= 0 and I90 >= 0 and I45 < 0
         Rule = 5;
      Else if I0 < 0 and I90 >= 0 and I45 < 0
         Rule = 6;
      Else if I0 < 0 and I90 < 0 and I45 < 0
         Rule = 7;
      Else if I0 >= 0 and I90 < 0 and I45 < 0
         Rule = 8;
      End if;
    out(i, j) = Temp(Rule);
    Mag = sqrt(I0² + I45²+ I90²);
    Patt(i, j) = out(h) | (h=0,1,2,3,…,7)
```

ELTrP(i, j) = sum(2^{P-1} f(M_{gp} - M_{gc})) | P=1,2,…,8

End for;

End for;

STEP 4:

The texture pattern is extracted using the following line of code.

output = ELTrP;

STEP 5:

Classification is performed using SVM [4].

STEP 6:

The classification results are retrieved.

(C) Architecture for Texture Classification

The flow of the proposed system architecture of ELTrP is given in Fig. 1.

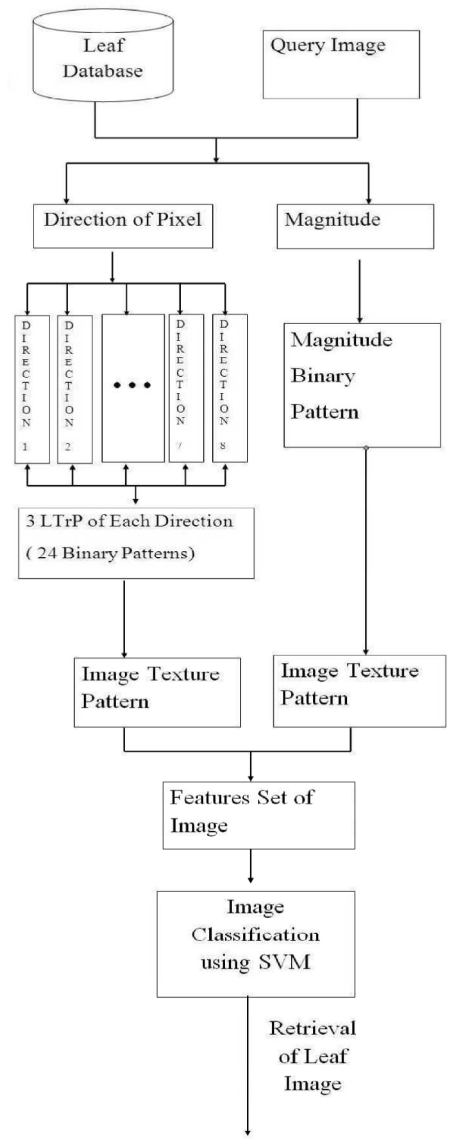

Figure 1: Proposed Flow of the System Architecture of Enhanced LTrP

The sample input plant leaf images were taken from Intelligent Computing Laboratory (ICL) [20]. A sample of four images from the dataset is shown in Fig. 2. The total set of images is separated into image samples. These image samples are segmented into blocks for texture classification according to Pseudocode 1.

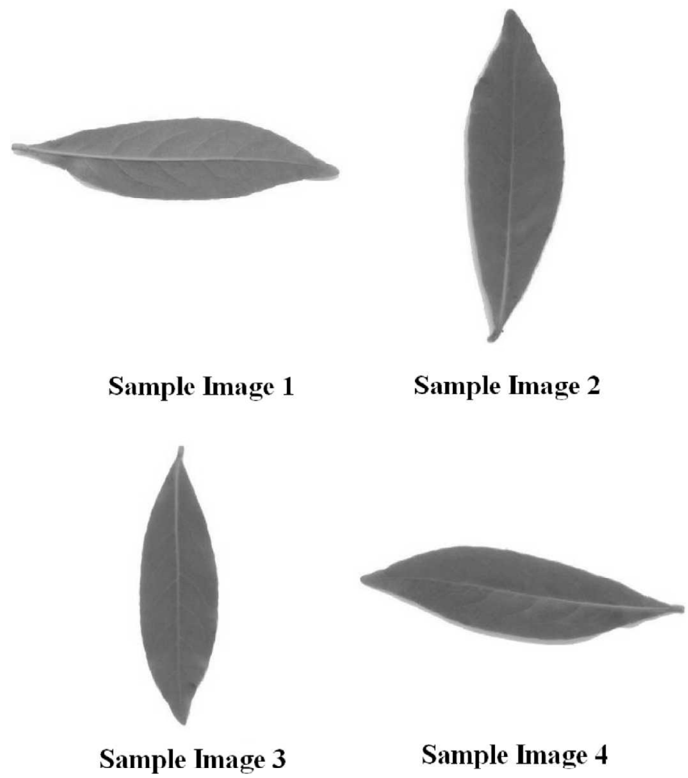

Figure 2: A Sample of Four Plant Leaf Images taken from the ICL Plant Leaf Dataset [20]

750 leaf images are trained from 50 classes, where each class consists of 15 leaves. 2500 leaf images are tested from 50 classes, where each class consists of 50 leaves.

V. PERFORMANCE ANALYSIS

A sample input color leaf image and the respective converted gray scale leaf image are shown in Fig. 3.

Figure 3: (a) Sample Input Color Leaf Image and (b) Transformed Gray Scale Leaf Image

The LTrp,ELTrP of a sample image block are given in Fig. 4.

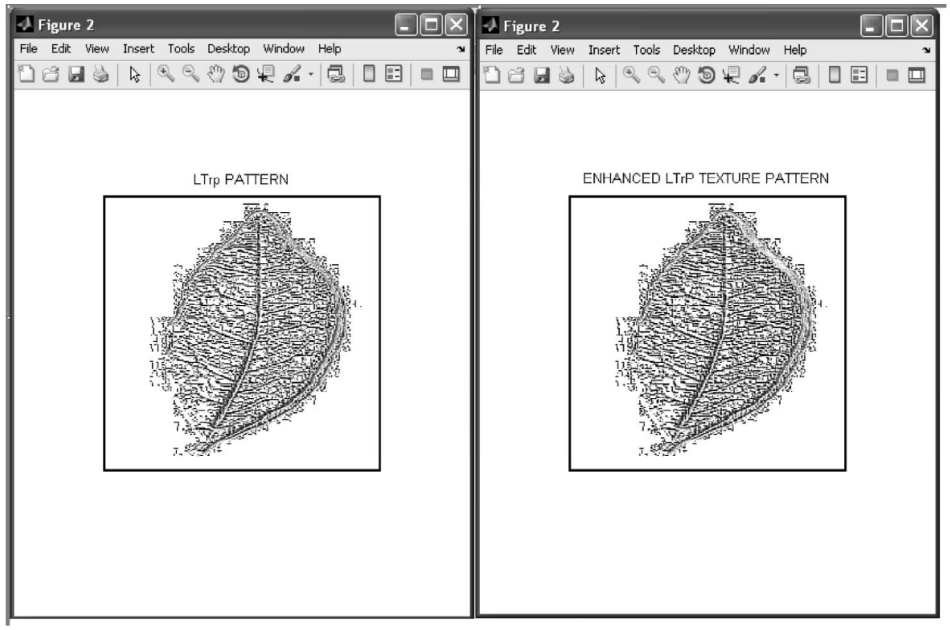

Figure 4: (a) LTrP (b) ELTrP.

The testing image class number displayed in first column as ac LEAF CLASS, number of image (like as name) taken from dataset in second colum as LEAF NUMBER and result of testing image in third colum as RETRIEVED CLASS shown in Fig. 4.

Fig. 5 and Fig. 6. Shows the confusion matrix. The confusion matrix function allows comparison of a classified image. A confusion matrix contains information about actual and predicted classifications done by a classification system. The performance of such systems is generally classified using the data in the matrix.

Table 1
Performance Measure LTrP and ELTrP

Name of Parameter	*LTrP*	*ELTrP*
Correct Rate	0.8723	0.9333
Error Rate	0.1277	0.0667
LastCorrectRate	0.8723	0.9333
LastErrorRate	0.1277	0.0667
InconclusiveRate	0.0600	0.1000
Classified Rate	0.9400	0.9000
Sensitivity	1	1
Specificity	0.9388	0.8980
PositivePredictiveValue	0.2500	0.1667
NegativePredictiveValue	1	1
PositiveLikelihood	16.3333	9.8000
Negative Likelihood	0	0
Prevalence	0.0200	0.0200
Accuracy	**87.234%**	**93.3333%**

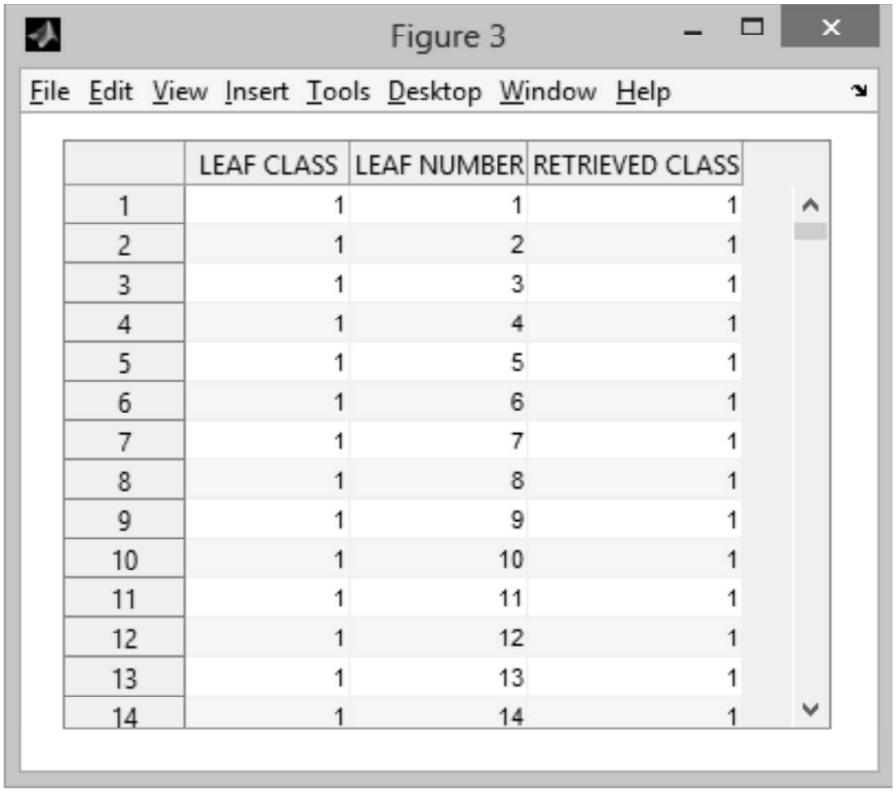

Figure 3

File Edit View Insert Tools Desktop Window Help

	LEAF CLASS	LEAF NUMBER	RETRIEVED CLASS
1	1	1	1
2	1	2	1
3	1	3	1
4	1	4	1
5	1	5	1
6	1	6	1
7	1	7	1
8	1	8	1
9	1	9	1
10	1	10	1
11	1	11	1
12	1	12	1
13	1	13	1
14	1	14	1

Figure 4: Testing of Input Class and Result Class

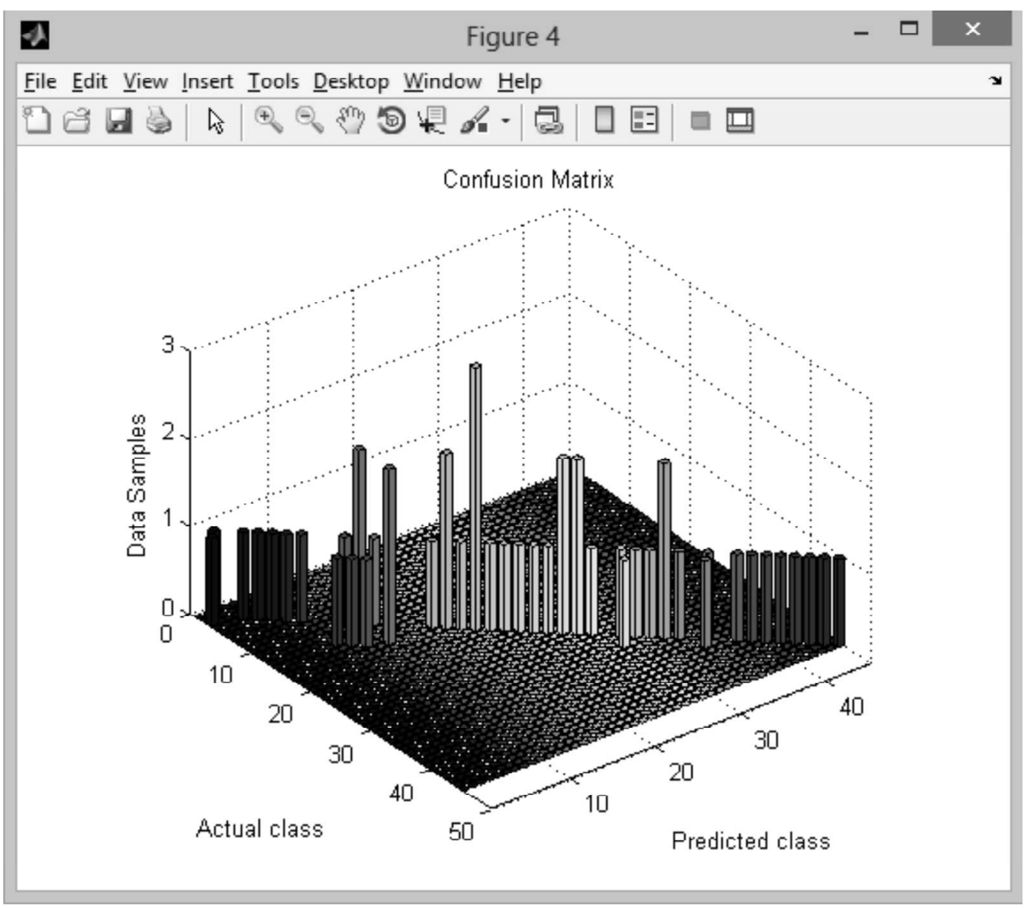

Figure 5: Comparison of Actual Class and Predicted Class

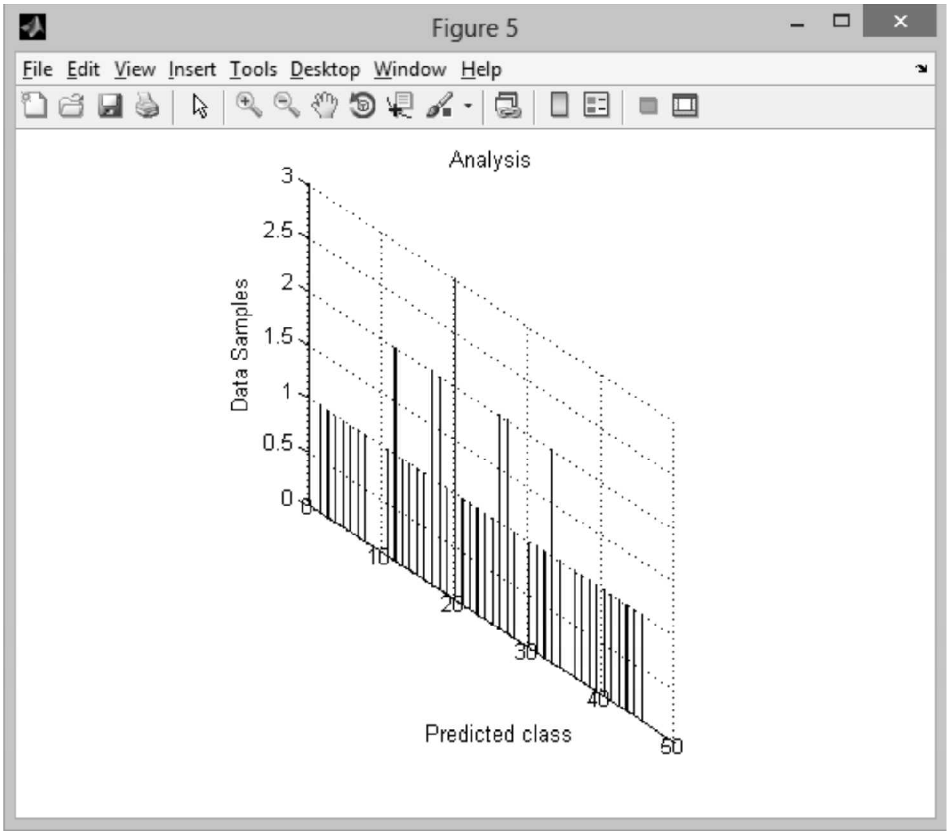

Figure 6: Input Data Sample with Predicted Class

The Performance Measure for LTrP and ELTrP are listed in Table 1. This comparison shows that our system has high accuracy and less computation due to the feature extraction. Hence the experimental results show that the accuracy results of proposed approach (ELTrP) are better than the LTrP. The proposed system accuracy is 93.333%.

VI. CONCLUSION

Image textures are groups of metrics computed to classify the captured texture of images. It reveals the information about the spatial orientation of color or gray level intensities in the images or specific regions of the images. The image texture classification of plant leaves is considered in this paper because of the extinction risk of various plants. An efficient plant leaf identification using image texture classification would aid in automatic recognition of the plant leaves. The existing image texture classification methods, namely, Local Tetra Patterns (LTrPs) are considered. LTrP considered only horizontal and vertical directions during the phasor difference computation stage. A Enhanced LTrP (ELTrP) is proposed in this paper by including the diagonal direction along with the horizontal and vertical directions in the LTrP. The features are classified using Support Vector Machine (SVM). 750 leaf images are trained from 50 classes, where each class consists of 15 leaves. 2500 leaf images are trained from 50 classes, where each class consists of 50 leaves. The proposed method ELTrP is analyzed in terms of classification accuracy LTrP. Its performance is found to be satisfactory compared LTrP. The proposed system accuracy is 93.333%. The future work of this plant leaf image texture analysis can be extended to the texture analysis with other method .

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