VOL. 13, NO. 23, DECEMBER 2018 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

DECEASED LEAF IDENTIFICATION USING THE GEOMETRIC LOCAL BINARY PATTERNS (GLBP)

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ABSTRACT

Usage of classical Local Binary Pattern (LBP) for texture classification depending on the intensity changes of surrounding pixels around the each pixel in the image. Even though basic LBP is powerful, there are so many variations and applications by giving extensions and refinements to the basic LBP according to the requirement and nature of applications. But, in the proposed Geometric Local Binary Pattern (GLBP) technique instead of using closed neighbourhoods intensity oriented neighbourhoods intensity is considered. Actually, this is the one of the method which is variation of LBP and belongs to the family of Geometric Local Textural Patterns (GLTP). Here, the texture of the image classified by the help of GLBP histogram which is prepared from the occurrences of GLBP-codes obtained from the entire images. These type of identifications generally done by manually but it is time consuming and error prone. The major application of this process is to classify the images of leaves by considering the standard databases for identification of deceased leaves and observed better results.

Keywords: texture classification, local binary patterns (LBP), geometric local binary pattern (GLBP), geometric local textural patterns (GLTP).

INTRODUCTION

In the nature plants and trees are plays crucial role in our human life. The classification of the plants based on various criteria generally happens in the field of botanical sciences. In general, botanists classify the plants based on the fruits or flowers but they are seasonally or occasionally available. Majority of the researcher prefers classification of plants based on leaves because leafs are available irrespective of the seasons. Actually leaf classification by human inspection or by the manual procedures is the major challenge to the botanists and time consuming process because they compare and contrast the leaf based on the stored databases. By the new inventions arrived in the computer sciences especially in the field of Digital images processing or machine vision makes the above process very easy. Classification of tree leaf based on images is not new to the botanists. So many algorithms are available to search and find the leaf category [13] [14] [15].

In so many papers, Researchers introduce many number of novel techniques to classify the images of leaves based on their one of the important property called as "Texture". It is easy to identify but difficult to define. Surprisingly, until now there is no universally acceptable definition for Texture. But, it plays a important role in the classification and there are so many algorithms are developed. Roughly, we can understand the texture as distribution or repetitive arrangement of patterns (pixels) in a proper way. There are so many textures we can found in the nature for example surface of the water, leather of the animals (Tiger, Zebra), cross section of the trunk of the tree etc., bread slice, designed tiles and designed saris and cloths as some of the examples for artificially created textures.

Since the 1960's they are so many vide variety of techniques are developed for classify the textures based on certain criteria. There are four major categories of algorithms called statistical (or stochastic), mathematical, geometrical (structural), and signal processing methods proposed by Tuceryan and Jain [1]. Difference histogram and co-occurrence statistics are examples for statistical texture measures.

The second structured approach dealing with texture primitives (these are also called as textures or texons).these types of work well with macro textures.

CLASSIFICATION

The main purposes of the classification methods are divide the objects into most appropriate categories. Since there is no perfect classification method is there so we can take the help of probability concepts if need.

Actually there are two categories of traditionally classification techniques: parametric and non-parametric. In parametric classifier, make certain assumptions about the distribution of features. For example Bayesian classifier and Mahalanobis classifier. Where as in non-parametric classifiers can be used with arbitrary feature distribution of features and without assumptions about form of underlying densities for ex K-NN classifier.

A supervised classification process which involves two phases first one is the classifier must be presented with previously known training samples or other knowledge of feature distributions. The Local binary operator was first known as a complementary measure for local image contrast. The LBP operator worked with 8 neighbours of a pixel using the value of the central (middle one) pixel as the thresh hold value. An LBP for a neighbourhood was given by multiplying the threshold

value with weighted values given to the corresponding pixels and sum up the result.

CO-OCCURRENCE AND GRAY-LEVEL DIFFERENCES

The Local Binary Pattern (LBP) features which are invented by Ojala et [2] [5] [6] is a simple but plays an crucial role in texture classification. It comes under category of structural method. In 1970s, Haralik [3] introduced the gray level co-occurrence matrix representation of the texture. And there is still development in progress. For this purpose a set of grey level co-occurrence matrix (GLCM) is computed. This matrix represents the joint probability of the pairs of point separated by displacement operator. Since the co occurrence matrix considers information about pairs of pixels instead of single pixels it is called a second order statistics. Tamura [4] proposed six properties of visibility contrast, directionality, coarseness, regularity, line-likeness and roughness. Particularly LBP techniques are sustains due to its efficiency and low computational cost for classification tasks. Another advantage of these methods over others is tolerance against variations of illumination.

6	5	4		1	1	1
5	4	2		1		0
3	0	4		0	0	1
(a)				(b)		
1	2	4		1	2	4
8		16		8		0
32	64	128		0	0	128
(c)				(d)		

Figure-1. LBP Calculation LBP = 1 + 2 + 4 + 8 + 128 = 143.
(a) Neighbourhood pixels (b) Thresholds values
(c) Weighted values
(d) Multiplied corresponding values of (b) and (c)

Generally, with LBP techniques, consider intensity variations of neighbourhoods of the central pixels and derived with a number called LBP-code. The basic idea of LBP is to perform Boolean comparison of intensity value of the neighbourhood of a pixel with the intensity value of the pixel.

LBP AND ITS EXTENSIONS

A No of variants to the LBP operator are developed due to its flexibility and make it suitable according to various problem types and to increase its robustness and discriminative power, computational efficiency, illumination. Here, the present study presenting different variants under categories that describe their role in feature extraction. Some of the variant may come under more than one category [16].

Under category of neighbourhood topology, Elliptical binary Patterns (EBP) was developed used for face recognition. Elongated Quinary patterns (EQP) developed by using Quinary encoding in elliptical neighbourhood for the analysis of Medical images. Local line binary Patterns (LLBP) method uses lines in both vertical and horizontal directions for face recognition. Three-patch Local Binary Patterns (TPLBP) and four-patch Local Binary patterns (FPLBP) used for face analysis by using patch-based descriptor inspiration for this approach is CS-LBP.

Under Thresholding & encoding categories, Median Binary Patterns (MBP) method which uses the median value within the neighbourhood is used for thresholding used in texture classification. In improved version of LBP (ILBP) calculates the mean value of local neighbourhood used for thresholding. In Local Ternary Patterns (LTP) and Elongated Ternary Patterns (ELTP) three values (1, 0, -1) are used for encoding. The extension for the LTP is Scale Invariant Local Ternary pattern (SILTP) which handles illumination variations which is used in back ground subtraction. In Elongated Quinary Patterns (ELTP) deals with five values (-2, -1 , 0, 1, 2) which is used in Medical image analysis. Soft/Fuzzy Local Binary Patterns(S/FLBP) and probabilistic LBP thresholding values are replaced by a fuzzy membership function and probabilistic functions respectively. Transaction coded LBP (tLBP) used for car detection using encoding relation between neighbouring pixels and Direction coded LBP (dLBP) used for gender detection by related to CS-LBP, but it also uses central pixel for encoding.

In multi scale analysis category, Gaussian filtering is used for texture classification by multi scale low-pass filtering method before feature extraction. Cellular automata used for texture classification by compactly encoding several LBP operators at different scales. Multi-scale block LBP (MB-LBP) used for face recognition which compares average pixel values within small blocks. Pyramid-based multi-structure LBP used for texture analyses which applies LBP on different layers of image pyramid. Multi resolution uniform patterns used for gait recognition by implementing multi scaling points ordered according to sampling angle.

For handling rotation, Adaptive LBP (ALBP) used for texture classification by incorporated directional statistical information. LBP variance (LBPV) Build rotation variant LBP histogram and then apply a global matching used for texture classification.

Coming to feature selection and Learning category, Dominant Local Binary Patterns (DLBP) used for texture classification make use of the most frequently occurred patterns of LBP. The Extended LBP Analyzes the structure and occurrence probability of non uniform patterns. LBP with hamming distance which is used for face recognition uses Non uniform patterns. FSC_LBP uses the method of Fisher separation criterion is used to find out the most prominent patterns types. By the method of fast correlation- based filtering use of fast correlation-based filtering to select LBP patterns for facial recognition and expression analysis.

The Decision tree LBP uses decision tree algorithms to learn discriminative LBP-like patterns for face recognition. AdaBoost algorithm is used for learning

discriminative LBP histogram bins and selecting the local regions and LBP settings for boosting LBP bins and histograms respectively. In Kernel Discriminative common vectors methods which are used for face recognition applied to Gabor wavelets and LBP features after PCA projection. Ada Boost-LDA method Select most discriminative LBP features from a large pool of multi-scale features for face recognition.

Other methods inspired by LBP developed for Texture analysis are Weber Law Descriptor (WLD) method codifies differential excitations and orientation components. Local Phase quantization (LPQ) method follows quantizing the Fourier transform phase in local neighbourhoods. GMM-based density estimator avoids the quantization errors of LBP for getting better performance.

MAJOR APPLICATIONS OF LBP

One of the major application areas is visual inspection of industrial products; the main goal is to classify products according to its quality. Detect the defective material according to their visual properties. By using human visualization it takes too much time and sometimes error prone. In visual inspection we can take help of texture features as supplement to color information. LBP is a good candidate for Computer vision used for the above application.

Wood inspection is another common application of the LBP, which the operator has been used with color and texture measures. Similarly, Paper quality inspection is a successful application area with the LBP. The LBP and GLCM texture feature features with a SOM based non-supervised segmentation method used for detecting defects in surface images.

Content based image retrieval (CBIR) used to retrieve the images according to content in a meaningful manner from the huge amount of images and video material which are not properly organized. A number of researchers have used LBP as the component of their CBIR systems. A new texture feature which is derived from LBP called "local edge Patterns" applied to an edge image instead of gray scale values directly give better retrieval rates as the results.

For image segmentation LBP/C with split-and-merge type unsupervised algorithm efficiently used for dividing large aerial images in the similarity regions. Similarly LBP/VAR operator is also another popular segmentation algorithm. Another most exotic useful application of LBP is detection of the person based on the hair .In this context LBP used as texture feature because of the real time nature of the problem.

GEOMETRIC LOCAL BINARY PATTERNS (GLBP)

Deceased leaf identification system going to apply the another new improvement of the LBP technique named Geometric Local binary Patterns (GLBP).This technique applies LBP-codes by evaluating "Oriented neighbourhood" instead of taking common circular neighbourhood around the pixel. The remaining part of this paper is separated as sections in the following way. In section 2 discuss the GLTP techniques. Present study explains implementation process in section 3.The experimental setup explained as section 4. Section 5 reports the results and discusses the findings. Finally, we completed with section 6 with conclusions and future scope.

THE GEOMETRIC LOCAL BINARY PATTERNS METHOD

In traditional LBP technique calculates the intensity values varies around each and every pixel in an image with a code number called LBP code [7][10][11]. And the histogram derived from these codes called LBP-histogram, Based on these occurrences of LBP code on each image used as a parameter to classify the global texture of the given images. But, in the process of geometric local binary patterns method current study focus on the Circular Neighbourhood around a Pixel.

Here, this paper defines the Interpolation Window (IW) as a square (grid) area, where corners are defined by centers of the four pixels on a 2x2 pixels neighbourhood. The current study represents values on the centre of gravity of 4 pixel values by $I_{i,j}$, $I_{i+1,j}$, $I_{i,j+1}$ and $I_{i+1,j+1}$.

The values of intensities of any point (p) within the IW can be calculated as follows:

$$I(p) = [x\ 1\text{-}x] \begin{bmatrix} Ii,y & Ii,j+1 \\ Ii+1,j & Ii+1,j+1 \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix}$$

Here, x, y belongs to [0, 1] are the corresponding Cartesian coordinates of the point.

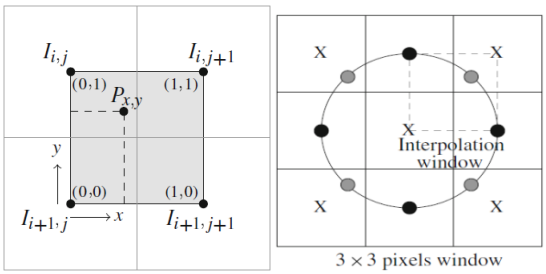

Figure-2. (a) Interpolation window (IW) (b) Points on a circle of radius 1 around a pixel.

In the fundamental GLTP techniques which are presented in [8] and [9]. The current work is going to follow characterizing the changes of insanity values around a pixel of an image by observing neighbouring points on concentric circles (circles with same centre with different radii). By the way of bilinear interpolation method we calculate the intensity of each of these points using the four surrounding neighbourhood pixels around the point. Geometrical Local Binary Pattern (GLBP) is simple way to perform Boolean comparisons, the point is assigned with a bit equal to one of its intensity value is higher than the value of its inner point else it is assigned with zero bit.

The connectivity of adjacent points, called as a path is defined as one point per circle, starts from the

centre one and ending on the outer circle. A neighborhood composed of one or more such type of paths is called an oriented neighborhood and it clearly defines a geometric pattern. The possible variations, rotated or mirrored, of geometric pattern around the central pixel defines set of symmetric patterns. For pattern around the pixel this work is going to calculate a Geometric Local Ternary Pattern code by the help of the bits of the points on the geometry. Patterns that are symmetric in nature are considered as same GLTP-code. There are so many variation of GLTP current study get by the way in which codes are computed and represent patterns of geometry differently. The major variations are (a) The Geometric Local with Derivative Patterns (GLDP) it is developed on the principle of first order local derivative which is introduced with the concept of local Derivative Pattern LDP technique. (b) Noise reduction by using threshold ie the sensitivity to noise can also be reduced by coding the difference in intensity between two points by using more than two levels.(c) The Geometric Local binary ,with Complement features, Patterns(GLCP) technique.(d)The LBP Derivative (LBPD) technique.

Calculation of neighbouring points for the GLTP:

Let us consider an odd square neighbourhood with size N greater than 3. Then, the central pixel on the neighbourhood can be calculated as

$I_c = ((N-1/2) +1, (N-1)/2+1))$

The no. of IWs are formed within the neighbourhood are (N-1) x (N-1).The no of circular neighbourhoods possible to create are (N-1)/2.

Figure-3. (a) a 6x6 Interpolation window (b) The set of 7x7 pixels (c) 6x6 interpolated points.

There are 36 interpolation windows are formed on 7x7 pixel windows they are numbered as 1 to 36 which can observed in Figure-2(a). Figure-2(b) shows the values of intensities are found as I_{11}, I_{12}, I_{13}…….I_{77}.The intensity values of a points within an Interpolation window are indicated by p_{11}, p_{12}, p_{13}…..p_{66} it is showed in Figure-2(c).

By using bilinear interpolation technique, we can calculate the intensity value for a particular point p_{ij} with the formula

$p_{ij} = I_{ij} + (I_{(i+1)j} - I_{ij})x + (I_{i(j+1)} - I_{ij})y + (I_{ij} + I_{(i+1)(j+1)} - I_{i(j+1)} - I_{(i+1)j})xy,$

Here, x, y values are called as Cartesian coordinates of the point within the interpolation window (IW).

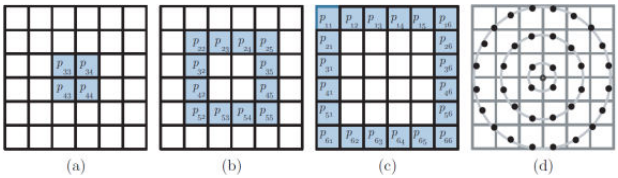

Figure-4. (a), (b), (c) shows some of the points (subsets) create Inner, Middle and Outer circular neighbourhoods respectively.

From the diagram 3(d) by the observation some of the points on circles are not located on the center of the Interpolation window. So, present work calculate the displacement of all points from the center as minimum as possible.

The X and Y Cartesian co-ordinates of the points within their corresponding Interpolation window taken as given below:

Table-1. First circle.

Point	Value of X coordinate	Value of Y coordinate
P34	0;5	0;5
P33	0;5	0;5
P43	0;5	0;5
P44	0;5	0;5

Table-2. For the second circle.

Point	X	Y	Point	X	Y	Point	X	Y
P25	0;37	0;37	P32	0;13	0;50	P54	0;50	0;13
P24	0;50	0;87	P42	0;13	0;50	P55	0;37	0;63
P23	0;50	0;87	P52	0;63	0;63	P45	0;87	0;50
P22	0;63	0;37	P53	0;50	0;13	P35	0;87	0;50

Table-3. For the third circle.

Point	X	Y	Point	X	Y	Point	X	Y	Point	X	Y
P16	0;10	0;10	P11	0;90	0;10	P61	0;90	0;90	P66	0;10	0;90
P15	0;35	0;65	P21	0;35	0;35	P62	0;65	0;35	P56	0;65	0;65
P14	0;46	0;93	P31	0;07	0;46	P63	0;54	0;07	P46	0;93	0;54
P13	0;54	0;93	P41	0;07	0;54	P64	0;46	0;07	P36	0;93	0;46
P12	0;65	0;65	P51	0;35	0;65	P65	0;35	0;35	P26	0;65	0;35

The Values of intensity of each point are compared to the closest inner point of same property including the central pixel. The point is marked as a bit equal to one if its intensity value is higher than its inner point else it is marked as zero as its bit value which is showed in Figure-4 (a).

Figure-4 (b) shows the result of the comparison is a set of bits. There are three paths identified as primary paths on these set of bits as shown in Figure-4(c), 4(d), 4(e), 4(f). The combination of two or more paths formed as a GLBP which is shown as Figure-4(g).By the assignment of weights denoting a power of 2 to the bits, we can obtained the GLBP code as shown in the Figure-4(h).

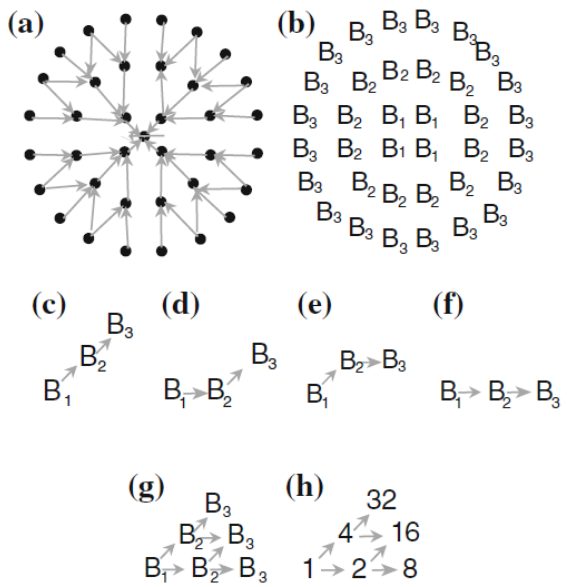

Figure-5. (a) Pair of points comparing intensity (b) The result comparing bits. (c)(d)(e)(f) The primitive paths (g) paths forming GLTP (h) GLTP code.

We can get variations of GLBP from the central pixel called symmetric GLBPs. from each GLBP can get one GLBP code for the fig 5(g) we can observed in Figure-6(a). And there are mirrored versions of GLBP can be found in Figure-6(b) for the Figure-5(g).

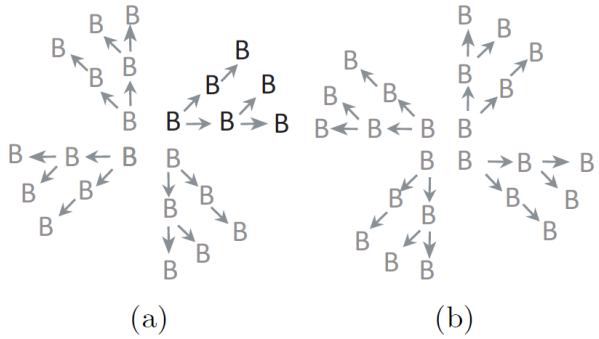

Figure-6. (a) Rotation version of the GLBP (b) Mirrored version of GLBP.

The codification in GLBP method is via Boolean comparison of intensity swaps between two points in the geometry. The point is marked as bit 1 if its intensity is greater than of that value to which it is compared; else it is considered as 0.

i.e. $S(x) = 1, x>0$ else
$= 0$

The variation among two images with respective of texture can be calculated as square root of double the value of Jensen-Shannon entropy called as k

$$k=\sqrt{2dJS(h1,h2)}$$

Where, h_1 and h_2 are two histograms with the same no of bins. The relative entropy given as

$$D(h_1\|h_2)=\sum_{i=1}^{n} h1(i)\log\frac{h1(i)}{h2(i)}$$

$$d_{js}(h_1, h_2) = 0.5D(h_1\|\frac{h1+h2}{2} + 0.5D(h_2\|\frac{h1+h2}{2}).$$

IMPLEMENTATION

For the implementation of GLBP algorithm current work consider to take grey scale images for simple and fast texture evaluation, because there is a need to perform 36 parallel bilinear interpolation and Boolean comparison operations. The performance of algorithm in terms of time complexity also taken into the consideration. Current work can obtain GLBP histogram as the result of the algorithm which represents the number of occurrences

of the possible GLBP on the images. The pseudo code is as given below.

Algorithm: **Geometric Local Binary Patterns (GLBP)**

Input to the algorithm: **size of the Block**

Output of the algorithm: **GLBP code and corresponding Histogram**

Begin
For the value m , from 1 to M in steps of 1
For the value n, from 1 to N in steps of 1

// accessing to 7 × 7 pixels neighbors
For the value, i , from − 3 to 3
For the value, j , from − 3 to 3

// padding of bits for image
I [i + 4, j + 4] := X[m + i ,n + j]
// from the pattern of Point in Figure-2(c)

For the value, i, from 1 to 6 in steps of 1
For the value, j, from 1 to 6 in steps of 1

// here x and y values are getting from the look up table
x, y = Get Cartesian Coordinates(i, j)
p[i , j] := Bil Int (I [i , j], I [i , j + 1],I [i + 1, j],
I [i + 1, j + 1], x, y)
// Bit values obtained from Fig 2(b)
For the value, i , from 1 to 6 in steps of 1
For the value, j , from 1 to 6 in steps of 1
//k and l values are obtained from a look up table
k, l = Get Point2Compare(i, j)
//S(x)=1, if x>0 else 0
B[i , j] := Signo (p[i , j], p[k,l])
// computation of histogram of GLBP
// Histogram index 'h'
For the value, h , from 1 to 8 in steps of 1
// Clear histogram of GLBP
For the value, b, from 1 to 64 in steps of 1
HistoGLBP[h][p] := 0
// for Computing GLBP code
Code:= 0
// g is bit index value in the GLBP
For the value, g, from 1 to 6 in steps of 1
Bit := GetBi t (h, g)
Code := Code + Bit * 2 pow g
HistoGLBP[h][Code] := HistoGLBP[h][Code] + 1
End .

EXPERIMENTAL SETUP

For the analysing the performance of the proposed GLTM algorithm we have taken the images of the leave in gray scale.(for the easy calculations we perform conversion from the color (RGB) images into greyscale images). For leaf classification we choose a challenging experimental setup. We have taken a sequence of experiments with the following datasets.

Austrian Federal Forest (AFF) datasets

The Experiments conducted on Austrian Federal Forest consists of nearly 134 pictures of leaves on pure white back ground. This database contains forty two varieties of leaves, with different shapes and colors. Here are some images along with their names.

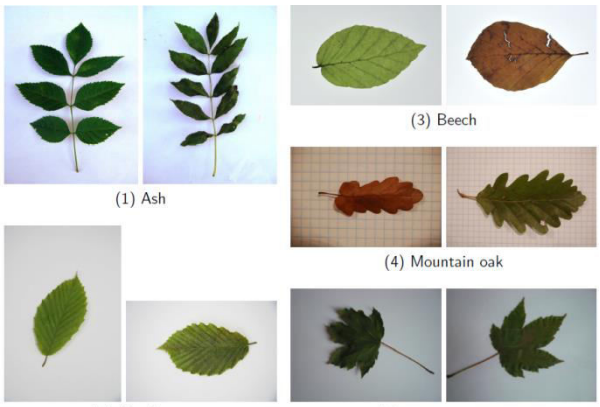

Figure-7. Sample leaves of Austrian Federal Forest (AFF) datasets.

This database contains 1097 varieties of leaves, with different shapes and colors from 32 plants. But in our experiments we have taken only 10 and 30 randomly selected images per class for test and training classes respectively. Here are some images along with their scientific names.

Figure-8. Sample leaves of Flavia leaf dataset.

Foliage dataset

This database contains forty two varieties of leaves, with different shapes and colors. The experiments consist of twenty five leaves per plant for the training set and another twenty for the testing purpose. Here are some names

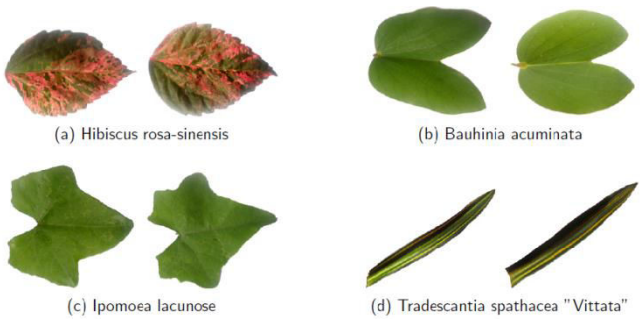

Figure-9. Sample leaves of Foliage dataset.

RESULTS AND DISCUSSIONS

We compare the performance of the proposed GLBP technique with LBP technique shows better performance while recognizing the texture modifications or changes. In our experiments, for leaf reorganization, we use one of the techniques called nearest-neighbor (NN) classifier with various distance measures.

Results for defects recognition

To compare the efficiency of the proposed geometric local binary patterns with the traditional local binary patterns we calculate for each category, the sensitivity and accuracy based on the following parameters: true positive(T+),True negative(T-),False positive(F+),False Negative(F-).

Table-4. Performance of the LBP System.

Category	T+	T-	F+	F-	Sensitivity	Specificity	Accuracy
Cat 1	47	290	3	2	93%	95.33%	96.77%
Cat 2	48	288	3	2	93%	95.23%	95.93%
Cat 3	35	262	14	14	71%	88.45%	84.87%
Cat 4	38	288	11	11	75%	92.00%	92.56%
Cat 5	51	296	0	0	98%	95.30%	94.76%

Table-5. Performance of the LBP System.

Category	T+	T-	F+	F-	Sensitivity	Specificity	Accuracy
Cat 1	49	292	8	0	100	97.67%	97.29%
Cat 2	48	290	6	1	98	96.23%	97.23%
Cat 3	38	276	22	10	78	91.77%	89.71%
Cat 4	47	288	15	2	95	94.56%	94.43%
Cat 5	50	301	15	0	99	100%	98.78%

ACKNOWLEDGEMENT

Authors would like to say thanks to their Family members, management, Principal, teaching and non-teaching staff and students for their continuous support and encouragement.

REFERENCES

[1] Tuceryan, M., Jain, A.K.: Texture analysis. C.H. Chen, L.F. Pau, P.S.P. Wang, (eds.) 1998. The handbook of pattern recognition and computer vision. pp. 207-248: World Scientific Publishing Co., Singapore.

[2] Timo Ojala, Pietikainen, M., Maeenpaa T. 2002. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transaction Pattern Analysis Machine Intelligence. 24(7): 971-987.

[3] Haralick R.M., Shanmugam K., Dinstein I. 1973. Texture features for image classification. IEEE Transaction. Syst. Man Cybern. 3(6): 610-621.

[4] Tamura H., Mori S., Yamawaki Y. 1978. Textural features corresponding to visual perception. IEEE Trans. Syst. Man Cybern. SMC-8, 460-473.

[5] Timo Ojala, Matti Pietikainen, and D. Harwood. 11994. Performance evaluation of texture measures with classification based on kullback discrimination of distribution. In Proceedings of the 12th IAPR International Conference on Computer Vision and Image processing. 1: 582-585.

[6] Timo Ojala, Matti Pietikainen and Topi Manenpaa Computer Vision-ECCV 2000; 6th European conference on computer vision. In Springer Berlin Heidel Berg, Berlin, Heidelberg. 2000. Part Gray Scale and Rotation Invariant Texture classification with Local Binary Patterns. pp. 404-420.

[7] Ojala T., Pietikäinen M. 1996. A comparative study of texture measures with classification based on feature distributions. Pattern Recognition. 29(1): 51-59.

[8] Orjuela S.A, Rooms S.F., Philips W. 2010. Geometric local binary pattern, a new approach to analysis texture in images. In: 2010 International Conference on Topology and Its Applications: abstracts.

[9] Orjuela S.A., Triana J., Fernandez Gallego J.A., Alvarez J., Ortiz-Jaramillo B., Philips W. 2012. Fast texture evaluation of textiles using the GLBP technique in GPU architecture. In: Proceedings of the

Optics, Photonics, and Digital Technologies for Multimedia Applications II.

[10] M. Ojala, T. Pietik¨ainen and Z. Xu. 2000. Rotation-invariant texture classification using feature distributions. Pattern Recognition. 33(1): 43-52.

[11] S. A. Orjuela, R. Quinones, B. Ortiz-Jaramillo, F. Rooms, R. de Keyser, and W. Philips. 2011. Improving texture discrimination in the local binary patterns technique by using symmetry and group theory. In: 17th International Conference on Digital Signal Processing.

[12] S. A. Orjuela, F. Rooms, and W. Philips. 2010. Geometric local binary pattern, a new approach to analyses texture in images. In: 2010 International conference on Topology and its Applications: abstracts.

[13] M. Anil Kumar, Dr. U.Ravi Babu. 2017. Leaf Classification Using Completed Local Binary Pattern Of Textures. 2017 IEEE 7th International Advance Computing Conference, 6th, 7th January. pp. 871-874.

[14] M. Anil Kumar, S. Durga Bhavani and Dr. U. Ravi babu. 2017. A Completed Modeling of Local Binary Pattern Operator for Wood recognition System. International Journal of Innovations & Advancement in Computer Science IJIACS; ISSN 2347-8616; 6(6): 254-26.

[15] M. Anil Kumar, Dr. U. Ravi Babu. 2015. Textured Based Combined Approach for Plant Leaf Classification. International Conference on Emerging Trends in Science Technology Engineering and Management, 09th & 10th. pp. 387-389.

[16] M. Pietikainen *et al.* Computer Vision Using Local Binary Patterns. Computational Imaging and Vision 40, Chapter 2, Local Binary Patterns for Still Images. pp. 13-47.