Classification of Textures Using a New Descriptor Circular and Elliptical-LBP (CE-ELBP)

K. Subba Reddy
Research Scholar, Jawaharlal Nehru Technological University, Anantapur, Ananthapuramu, Andhra Pradesh, India.
Associate Professor, Deparof CSE , RGMCET, Nandyal, Andhra Pradesh, India.

V. Vijaya Kumar
Dean, Department of Computer Science and Engineering & Informations Technology, Director-CACR, Anurag Group of Institutions (Autonomous), Hyderabad, India.

A.P. Siva Kumar
Professor, Department Computer Science and Engineering, Jawaharlal Nehru Technological University, Ananthapuramu, Andhra Pradesh, India.

Abstract
The Local binary Pattern (LBP) is a very simple and popular approach, and it played a vital role in many image processing applications. LBP captures isotropic structural information. The LBP completely fails in representing anisotropic information. Later, to represent anisotropic, horizontal elliptical LBP (H-ELBP) and vertical elliptical LBP (V-ELBP) are derived, however they derived only partial anisotropic information. To derive complete anisotropic information these two ELBPs are concatenated and it increases the feature vector size by two folds when compared to LBP. To capture both isotropic and anisotropic structural information, one needs to concatenate the histograms of LBP, H-ELBP and V-ELBP and this process increases the feature vector size into three folds when compared with LBP. We present a novel Feature Extraction method known as “circular and elliptical-LBP (CE-ELBP)” and a new variant of local binary pattern (LBP) and elliptical LBP (ELBP). The CE-LBP captures both isotropic and anisotropic structural information with a feature vector size equivalent to LBP. The CE-LBP quantizes/places the multi-structure information of LBP and ELBP (H-ELBP and V-ELBP) and derives a unique CE-LBP code that represents the complete set of micro patterns. The distinct advantages of CE-LBP are its ease in implementation, invariance to monotonic illumination changes and low computational complexity. The CE-LBP is tested on well-known databases i.e., Brodatz, UIUC and Outex using machine learning classifiers. The classification results are compared with conventional LBP, H-ELBP, V-ELBP and combination of these descriptors. The uniform patterns are also derived on CE-LBP and classification results are derived and compared. The results indicate the efficacy of the proposed method.

Keywords: Isotropic; Anisotropic; horizontal elliptical LBP; vertical elliptical LBP;

INTRODUCTION
Local Binary Patterns (LBP) have emerged as one of the most prominent and widely studied local texture descriptors in the field of computer vision and pattern recognition. This is mainly because of the merits of LBP i.e., simplicity, ability to capture image micro-structures, and robustness to illumination variations. A vast number of LBP variants were proposed for a diverse range of applications e.g., texture classification [1, 2, 3, 4], image retrieval [5, 6, 7], dynamic texture recognition [8, 9, 10], face image analysis [11] scene recognition [12-15], object detection [16, 17], human detection [18, 19], biomedical image analysis [20, 21], and many others [22-28].

As per our knowledge, only few authors carried out literature survey on LBP [5, 29, 30, 31, 32]. The literature surveys on LBP [29, 30], miss recent variants and do not include experimental investigations and where as the other papers [5, 6, 30, 31, 32] reviewed LBP variants and carried out experimental evaluation. In [5, 6, 7] the survey on LBP was carried out mainly based on its role in texture retrieval. The surveys on LBP [31, 32] were carried out on texture image classification. Recently, a more systematic survey on LBP with more number of variants and investigation on more number of data sets were carried out [33].A number of image descriptors were proposed by combining LBP with other descriptors. Gabor filters are used as preprocessing tools before LBP computation and these two provide complementary information: LBP captures small and fine details, while Gabor filters encode appearance information over a broader range of scales. The prominent work on this is, Local Gabor Binary Pattern (LGBP) [34].The CLBP descriptor [35] is derived by combining multiple LBP features i.e. CLBP_S, CLBP_M and CLBP_C. Based on the local differences in LBP two complementary components i.e., the Sign (CLBP_S) and Magnitude (CLBP_M) are derived. By using global threshold
and by considering the importance of grey level value of centre pixel in providing the discriminative information, the CLBP-C is derived. Later The CMLBP [36] approach are derived based on CLBP.

The advantage of LBP is, it can easily combine with other features to derive significant local texture information. To achieve rotation invariance globally, the LBP Histogram Fourier features (LBPHF) are derived by combining LBP with Discrete Fourier transform (DFT) [37]. LBPHF is combined with the CLBP_S and CLBP_M descriptors [35] to improve its distinctiveness further. Inspired by promising results of LBP and its variants, several researchers have developed local descriptors including LPQ [38], WLD [39], HGPP [40], LHS [41] and LFD [42, 43].

In the literature, different topologies were introduced on LBP, to capture different structural information. The Local Line Binary Pattern (LLBP) [44], which uses lines in vertical and horizontal directions for LBP computations. Other geometries, such as line and disk, were explored in local quantized pattern (LQP) [45]. The LQP allows larger local neighborhoods, and by this, it provides an increase in discriminative power with an increase in number of quantization levels and dimension. The “Elliptical local binary patterns (ELBP) [46], also generalized in [47] to parabolic, hyperbolic, and spiral neighborhood topologies, ELBP was proposed by Shu Liao et al. [46]. The ELBP, exploits elliptical patterns whereas the LBP derives circular patterns of the image.

The circular neighborhood of LBP, allows deriving rotation invariant features, however it misses to represent anisotropic structural information, which may be an important feature for many applications. To exploit anisotropic structure information, ELBP’s are derived. However, they completely fail in representing circular structures. This paper proposes, a new way to incorporate both isotropic and anisotropic information into LBP structure. For this, we extract design rule from handcrafted LBP and ELBP structures, i.e., computing the average gray values of two neighboring pixels as a single value.

The present paper is organized as follows. The section two describes the proposed method and section three presents’ results and discussions and the conclusions are presented in section 4.

DERIVATION OF ISOTROPIC AND ANISOTROPIC STRUCTURE INFORMATION USING A NEW VARIANT: CIRCULAR AND ELLIPTICAL-LBP (CE-LBP)

The basic LBP structure consists of a circular neighborhood (derived on a 3 x 3 neighborhood) with eight nearest neighbors [47] or d neighbors in a circle of radius ‘R=1”[46]. The advantage of circular neighborhood is that it achieves rotational invariance and preserves isotropic information [46]. The basic LBP was later extended with more number of sampling points (d), with different radius(R), different topologies and dimensions of the neighborhood but retaining the circular shape only. The isotropic structure of LBP may not be suitable for all applications. The anisotropic structural information is also an important feature for many image processing applications especially in face recognition, age classification etc., where the human eyes and mouth are basically anisotropic structures. To acquire this important feature, many researchers used elliptical local binary patterns (ELBP). LBP itself, is a special case of ELBP. The present paper derives a completely new variant of LBP and ELBP, called CE-LBP, to capture both isotropic and anisotropic structural information. The block diagram of CE-LBP is illustrated in Figure 2. The micro information of the texture in ELBP model is usually captured by using horizontal and vertical ELBP’s.

The conventional LBP[4] represents the spatial structure of the local texture. The local patterns are derived in LBP, by thresholding the 8-neighboring pixels of 3x3 neighborhood with the value of centre pixel(Figure 2).

\[
\text{LBP}_{d,R}(x,y) = \sum_{i=1}^{n} s(d_i - d) \cdot 2^{i-1}
\]

where \( s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \) (1)

Where \( d_i \) is the intensity value of centre pixel \((x,y)\), \( d \) corresponds to the intensities of \( d \)-neighboring pixels located on a circle of radius \( R \) centered at \( d \). In practice, the neighboring pixels are sampled on a circle. The neighboring pixels which do not fall exactly on the circle, are estimated by interpolation. The \( \text{LBP}_{d,R}(x,y) \) derives an unique decimal number ranges from 0 to \( 2^d-1 \). Figure 3 represents various
multi-resolution circular symmetric neighbors’ sets of LBP with different values of d and R.

\[ \text{angle - step} = 2 \times \pi / n \]  
\[ x_i = x_c + hR \times (\cos(i - 1) \times \text{angle - step}) \]  
\[ y_i = y_c + vR \times (\cos(i - 1) \times \text{angle - step}) \]

If \( hR = vR \), then ELBP becomes LBP, \( hR > vR \), then ELBP represents H-ELBP otherwise when \( hR < vR \) the ELBP becomes V-ELBP. The ELBP is denoted as \( \text{ELBP}^{d,hR,vR} \).

The unique decimal code for \( \text{H-ELBP}^{d,hR,vR}(x_c,y_c) \) and \( \text{V-ELBP}^{d,hR,vR}(x_c,y_c) \) at each centre pixel \((x_c,y_c)\) is derived based on equation 5 and 6.

\[ \text{ELBP}^{d,hR,vR}(x_c,y_c) = \sum_{i=1}^{P} s(d_i^{n,hR,vR} - d_c) \times 2^{i-1} \]  
\[ S(x) = f(x) = \begin{cases} 1, & \text{if} \ x \geq 0 \\ 0, & \text{if} \ x < 0 \end{cases} \]

The decimal codes of conventional LBP, H-ELBP\textsuperscript{8,2,1} and V-ELBP\textsuperscript{8,2,1} ranges from 0 to 2\textsuperscript{24} (255). To capture the complete anisotropic structure information, we should concatenate the histograms of H-ELBP\textsuperscript{8,2,1} and V-ELBP\textsuperscript{8,2,1} codes. The dimension of these histograms ranges from 0 to 511, however, it completely misses the isotropic information. The LBP\textsuperscript{8,2,1} captures the complete isotropic information with a histogram bin range of 0 to 255. Therefore, to capture both isotropic and anisotropic information of the textures, one should integrate/concatenate both H-ELBP, V-ELBP with LBP. In this case, the number of bins of histogram ranges from 0 to 767 which increases the dimensionality to a huge extent. To overcome this dimensionality problem and to capture both isotropic and anisotropic structural information, the present paper derived elliptical and circular LBP(ELBP) or isotropic and anisotropic structural LBP (IA-LBP).

The following Figure 4 give the circular neighborhood and elliptical neighborhood (both horizontal and vertical) pixel windows.
The 12-neighborhood pixels (d_1, d_2, ..., d_7, d_8, d_11, d_21) around centre pixel d_c are required to form the basic LBP, H-ELBP and V-ELBP. Out of these, the diagonal pixels of LBP d_1, d_5, d_7 and d_11 are common among the three local patterns i.e. the LBP, H-ELBP and V-ELBP. The neighborhood pixels d_6 and d_8 are common among LBP and H-ELBP (Figure 4.b). The neighborhood sample points d_1 and d_8 are common among V-ELBP and LBP (Figure 4.a).

To capture both isotropic and anisotropic structural information, we need to consider all 12 sampling points around d_c, and in this case, the dimension of this structure ranges from 0 to 2^{12}-1 i.e. 0 to 4095 (Figure 5 (a)). However if one concatenates the histogram bins of LBP with H-ELBP and V-ELBP, the range of histogram bins will be from 0 to 767.

The aim of this paper is to derive circular and elliptical LBP(CE-LBP) that captures the total isotropic and anisotropic structure information with a minimum feature size. For this, the proposed CE-LBP quantizes, the total number of neighboring points around (x_c, y_c), that are required for LBP, H-ELBP and V-ELBP, into 8-neighboring points and derives a unique code for CE-LBP as shown in Figure 5 (b).

For this the CE-LBP combines the two top pixels (d_2 and d_21), two bottom pixels (d_8 and d_8), two left pixels (d_6 and d_11) and two right pixels (d_1 and d_11) of d_c into one and represents the CE-LBP in a 3 x 3 neighborhood (Figure 5 (b)) using the following equations

\[
d_2 = \text{int}((d_2 + d_{21})/2) \\
\]

\[
d_8 = \text{int}((d_8 + d_{11})/2) \\
\]

\[
d_6 = \text{int}((d_6 + d_{11})/2) \\
\]

\[
d_1 = \text{int}((d_1 + d_{11})/2) \\
\]

Using the above the present paper derived a CE-LBP code of a pixel d_c with co-ordinate position (x_c, y_c) as

\[
\text{CE-LBP}_{(d_{R1}, R2)} = \sum_{i=1}^{8} S(d_i - d_c) \cdot 2^{i-1}
\]

with

\[
s(x) = \begin{cases} 
1, & \text{if } x \geq 0 \\
0, & \text{if } x < 0 
\end{cases}
\]

where d_i and d_c represent the intensity values of the centre and neighboring pixels; The R_1 corresponds to the ‘R’ of LBP, the ‘vR’ of H-ELBP and ‘hR’ of V-ELBP; The R_2 corresponds to ‘hR’ of H-ELBP and ‘vR’- of V-ELBP. The range of CE-LBP_{(8,1,2)} is from 0 to 255, with complete isotropic and anisotropic structural information.
anisotropic information. The working mechanism of CE-LBP
(8,1,2) is illustrated in Figure 6. We move the 5x5 block from
left-to-right and top-to-bottom throughout the image to
compute CE-LBP(8,1,2) code with 1 pixel as the step-length. In

Figure 6: Derivation of CE-LBP(8,1,2) from a 5x5x neighborhood.

In the literature after studying the conventional LBP trends on
number of texture and facial images, it is observed that certain
type of LBP represents more 90% of the windows. They are
termed as uniform LBP(ULBP) and they are considered as
fundamental units of textures. A pattern is uniform if the

RESULTS AND DISCUSSIONS

To investigate the classification accuracy, we have identified
three well known and popular texture databases i.e. Brodatz[48], UIUC[49] and Outex[50].The images of these
databases are captured under varying conditions like lighting,
illumination and varying sizes. Each database consists of
various classes and each class consists of various images. This
paper compared the proposed novel descriptors with LBP, H-
ELBP, V-ELBP and concatenation of H-ELBP and, V-ELBP
(HV-ELBP). Further, this paper also evaluated Uniform LBP
(ULBP) on the above descriptors and compared the
classification rates of the proposed novel CE-ULBP with
ULBP, H-EULBP, V-EULBP and HV-EULBP on the above
natural databases. This paper used the machine learning
classifiers Ibk, multilayer perceptron, and Liblinear for
classification purpose.

This paper selected 30 different homogeneous texture images
from Brodatz database with a dimension of 640 x 640 pixels.
The sample images are shown in Figure 7. This paper divided
each image into 25 non-overlapped texture images of size
128x128. This results a dataset of 750 images (30 x 25). The
proposed classifiers were trained by using 10 samples of each
class (30 x 10=300 images in total) and the remaining 15
samples per class were used for validation (30 x 15=450 images
in total).

Figure 7: Samples of the 30 classes randomly selected from
the Brodatz database.
The Oутex database contains two test suits: Oутex-ТС-10(TC12-000) and Oутex-ТС-12(TC12-001). Two subsets of the Oутex dataset, test suite TC10 (also known as Oутex_TC_00010 in [39]) and test suite TC12 (also known as Oутex_TC_00012 in [39]) are used for texture classification. Both TC10 and TC12 are composed of 24 texture classes of images under 128 x 128 resolutions for nine rotation angles (0°, 5°, 10°, 15°, 30°, 45°, 60°, 75°, and 90°) and on each rotation angle, there are 20 images. These images are captured under three illumination conditions namely 1. “inca” 2. t184 3. Horizon. The total number of images in TC10 and TC12 are 4320 and 9120, respectively. All images in TC10 are under the same illuminant inca, and this leads to 4320 (24 x 9 x 20 = 4320) images in total. There are 480 images in TC12 under inca in a single direction (24 x 20=480). There are 4320 t184 images and 4320 horizon images in TC12 under nine rotation angles (24 x 20 x 9=4320). This leads to a total of 9120 images in TC12. Both TC10 and TC12 share the same training dataset of the 480 “inca” images but use different test datasets.

For the TC10 dataset, with illumination condition “inca” with 0° of rotation (24 x 20=480 image), is used for training purpose in the present paper. The remaining images with other 8-rotations are used for testing (24 x 8 x 20=3840 images). For TC-12 dataset, the 24 x 20 images of illumination “inca” and rotation angle zero degrees are adopted for the training process. All the 24 x 20 x9 samples captured under illumination (t184 or horizon) are used as test data for TC12 dataset. The sample images from Oутex database are shown in Figure 8.

Figure 8: The sample images of 24 classes from Oутex database.

The sample images of UIUC database are shown in Figure 9. This database includes 25 classes and each class consists of 40 images. This results in total of 1000(25x40) texture images. The size of each image is 640x480. In our experiments we have partitioned 640 x 480 images into 15 non-overlapped images of size 128x128. This leads to a total of 15000 (25x 40 x 15) images and a total of 600 (40 x 15=600) images per class. In our texture classification experiments, 300 training images are randomly chosen from each class, while the remaining 300 images are used as test set.

Figure 9: Samples of the 25 classes from the UIUC database.

The texture classification results of the two proposed methods i.e. CE-LBP and CE-ULBP are compared with LBP and ELBP methods and listed in Table 1,2 and 3 for Brodtaz[48], UIUC[49] and Oутex[50] databases respectively. The following are noted down.

From Table 1 i.e. the classification results on the Brodtaz textures, the following findings are noted down. The proposed CE-LBP outperformed the LBP, H-ELBP, V-ELBP and concatenation of horizontal and vertical ELBP models. The basic reason for this, the CE-LBP captures the both isotropic and anisotropic structure information.

1. The isotropic structural model i.e. the LBP attained an average of 3% high classification rate than the partial anisotropic models: H-ELBP or V-ELBP.
2. The complete anisotropic structural information is obtained in the present paper by concatenating the H-ELBP and V-ELBP and this descriptor attained almost similar classification rate of LBP with an increase of dimensionality by two folds.
3. The proposed CE-LBP attained high classification rate of above 3%, 5% and 4% over LBP, partial anisotropic structures (H-ELBP and V-ELBP) and complete anisotropic structure HV-ELBP respectively.
4. The above trend is repeated on ULBP’s. The ULBP and concatenation of Horizontal and Vertical EULBP(HV-EULBP) attained almost same classification rate, however the feature vector size is doubled in the case of HV-EULBP descriptor. 
5. The proposed CE-ULBP descriptors achieved an average of 6% high classification rate than conventional ULBP and also on other ELBP’s.
6. The proposed CE-LBP and CE-ULBP have exhibited high classification rate on all three classifiers when compared to other conventional descriptors.

The experimental results on various variants of LBP on UIUC dataset using various classifiers are placed in Table 2 and the following are noted down.

1. The proposed CE-LBP attained a better classification rate on all three classifiers when compared to LBP and ELBP descriptors.
2. The isotropic structural descriptor attained an average 3% of high classification rate when compared to partial anisotropic structures; however the complete anisotropic structural descriptor (HV-ELBP) attained almost the same classification rate of LBP.
3. In case of uniform patterns, the CE-ULBP showed a 3% low classification rate when compared to CE-LBP. The CE-LBP has displayed an average of 5% high classification rate when compared to H-ELBP and V-ELBP and an average of 10% high classification rate when compared to ULBP and HV-EULBP.

The Table 3 displays the experimental results on the Outex dataset and from this the following are noted.

1. The partial anisotropic models: H-ELBP or V-ELBP exhibited a low performance of 1% when compared to LBP.
2. The HV-ELBP has shown slightly high classification rate than LBP model.
3. The proposed CE-LBP attained high classification rate of more than 5% and 6%, over LBP or HV-LBP and partial anisotropic structures (H-ELBP or V-ELBP) respectively.
4. The HV-EULBP attained slightly better classification rate than ULBP. And both these descriptors achieved a 2% higher classification rate when compared to H-EULBP or V-EULBP descriptors.
5. The proposed CE-ULBP descriptors achieved an average of 8% high classification rate than conventional ULBP and also on other ELBPs.

**Table 1:** Classification rate on Brodtaz dataset.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Name of the method</th>
<th>Liblinear</th>
<th>Multilayer Perceptron</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>LBP</td>
<td>90.02</td>
<td>91.82</td>
<td>90.92</td>
</tr>
<tr>
<td>2</td>
<td>H-ELBP</td>
<td>89.48</td>
<td>90.01</td>
<td>89.75</td>
</tr>
<tr>
<td>3</td>
<td>V-ELBP</td>
<td>88.28</td>
<td>89.24</td>
<td>88.76</td>
</tr>
<tr>
<td>4</td>
<td>H UV-ELBP</td>
<td>90.24</td>
<td>90.84</td>
<td>90.54</td>
</tr>
<tr>
<td>5</td>
<td>CE-LBP</td>
<td>93.72</td>
<td>94.68</td>
<td>94.20</td>
</tr>
<tr>
<td>6</td>
<td>ULBP</td>
<td>86.20</td>
<td>87.25</td>
<td>86.73</td>
</tr>
<tr>
<td>7</td>
<td>H-ULBP</td>
<td>85.44</td>
<td>84.23</td>
<td>84.84</td>
</tr>
<tr>
<td>8</td>
<td>V-ULBP</td>
<td>86.32</td>
<td>85.27</td>
<td>85.80</td>
</tr>
<tr>
<td>9</td>
<td>HUV –ULBP</td>
<td>87.21</td>
<td>87.28</td>
<td>87.25</td>
</tr>
<tr>
<td>10</td>
<td>CE-ULBP</td>
<td>92.48</td>
<td>93.25</td>
<td>92.87</td>
</tr>
</tbody>
</table>

**Table 2:** Classification rate on UIUC dataset.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Name of the method</th>
<th>Liblinear</th>
<th>Multilayer Perceptron</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>LBP</td>
<td>54.65</td>
<td>56.27</td>
<td>55.46</td>
</tr>
<tr>
<td>2</td>
<td>H-ELBP</td>
<td>52.25</td>
<td>53.89</td>
<td>53.07</td>
</tr>
<tr>
<td>3</td>
<td>V-ELBP</td>
<td>53.08</td>
<td>54.25</td>
<td>53.67</td>
</tr>
<tr>
<td>4</td>
<td>HV-ELBP</td>
<td>54.08</td>
<td>55.96</td>
<td>55.02</td>
</tr>
<tr>
<td>5</td>
<td>CE-LBP</td>
<td>60.72</td>
<td>62.88</td>
<td>61.80</td>
</tr>
<tr>
<td>6</td>
<td>ULBP</td>
<td>52.28</td>
<td>53.18</td>
<td>52.73</td>
</tr>
<tr>
<td>7</td>
<td>H-ULBP</td>
<td>49.97</td>
<td>52.16</td>
<td>51.07</td>
</tr>
<tr>
<td>8</td>
<td>V-ULBP</td>
<td>48.67</td>
<td>50.12</td>
<td>49.40</td>
</tr>
<tr>
<td>9</td>
<td>HUV –ULBP</td>
<td>53.67</td>
<td>55.27</td>
<td>54.47</td>
</tr>
<tr>
<td>10</td>
<td>CE-ULBP</td>
<td>57.21</td>
<td>60.02</td>
<td>58.62</td>
</tr>
</tbody>
</table>

**Table 3:** Classification rate on Outex dataset.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Name of the method</th>
<th>TC-10</th>
<th>TC-12 't'</th>
<th>TC-12 ‘h’</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>LBP</td>
<td>LL</td>
<td>MLP</td>
<td>LL</td>
</tr>
<tr>
<td>2</td>
<td>H-ELBP</td>
<td>84.87</td>
<td>85.52</td>
<td>65.19</td>
</tr>
<tr>
<td>3</td>
<td>V-ELBP</td>
<td>84.02</td>
<td>85.67</td>
<td>63.76</td>
</tr>
<tr>
<td>4</td>
<td>HV-ELBP</td>
<td>85.05</td>
<td>86.36</td>
<td>64.28</td>
</tr>
<tr>
<td>5</td>
<td>CE-LBP</td>
<td>90.24</td>
<td>91.28</td>
<td>73.89</td>
</tr>
<tr>
<td>6</td>
<td>ULBP</td>
<td>79.98</td>
<td>81.21</td>
<td>61.90</td>
</tr>
<tr>
<td>7</td>
<td>H-ULBP</td>
<td>80.24</td>
<td>81.86</td>
<td>59.82</td>
</tr>
<tr>
<td>8</td>
<td>V-ULBP</td>
<td>81.03</td>
<td>82.34</td>
<td>58.74</td>
</tr>
<tr>
<td>9</td>
<td>HUV –ULBP</td>
<td>81.76</td>
<td>82.65</td>
<td>60.91</td>
</tr>
<tr>
<td>10</td>
<td>CE-ULBP</td>
<td>87.84</td>
<td>88.91</td>
<td>70.94</td>
</tr>
</tbody>
</table>

The graphs of Figure 10 and 11 displays the average classification rate of the proposed methods and existing methods. The graph of Figure 10 and 11 clearly indicates the proposed methods CE-LBP and CE-ULPB outperforms the existing methods on each database.
The following Table 4 gives the dimension of the existing and the proposed descriptors, with the type of information they capture.

**Table 4**: Description about the dimensions of proposed and existing descriptors.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Name of the descriptor</th>
<th>Dimension</th>
<th>Type of information</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Isotropic</td>
</tr>
<tr>
<td>1</td>
<td>LBP&lt;sub&gt;8,1&lt;/sub&gt;</td>
<td>256</td>
<td>Yes</td>
</tr>
<tr>
<td>2</td>
<td>H-ELBP&lt;sup&gt;8,2,1&lt;/sup&gt;</td>
<td>256</td>
<td>No</td>
</tr>
<tr>
<td>3</td>
<td>V-ELBP&lt;sup&gt;8,1,2&lt;/sup&gt;</td>
<td>256</td>
<td>No</td>
</tr>
<tr>
<td>4</td>
<td>H-ELBP&lt;sup&gt;8,2,1&lt;/sup&gt; U V-ELBP&lt;sup&gt;8,1,2&lt;/sup&gt;</td>
<td>512</td>
<td>No</td>
</tr>
<tr>
<td>5</td>
<td>LBP&lt;sub&gt;(8,1)&lt;/sub&gt; U UH-ELBP&lt;sub&gt;(8,2,1)&lt;/sub&gt; U V-ELBP&lt;sub&gt;(8,1,2)&lt;/sub&gt;</td>
<td>768</td>
<td>Yes</td>
</tr>
<tr>
<td>6</td>
<td>CE-LBP&lt;sub&gt;(8,1,2)&lt;/sub&gt;</td>
<td>256</td>
<td>Yes (total)</td>
</tr>
<tr>
<td>7</td>
<td>CE-ULBP&lt;sub&gt;(8,1,2)&lt;/sub&gt;</td>
<td>58</td>
<td>Yes (total)</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

The present paper derived a new variant to LBP and elliptical LBP. The proposed CE-LBP captures both isotropic and anisotropic structural information without increasing any dimension. The histogram bin sizes of various methods are listed in Table 4. From Table 4, it is clearly evident that the proposed CE-LBP captures LBP, H-ELBP and V-ELBP structural information with bin size same as the above three. The present paper is also derived ULBP on the proposed CE-ULBP and performed texture classification. The results clearly state the efficacy of the proposed method over the existing methods.

**REFERENCES**


[33] Li Liu, Paul Fieguth, Yulan Guo, Xiaogang Wang and Matti Pietikäinen, Local Binary Features for Texture Classification: Taxonomy and Experimental Study, Pattern Recognition, http://dx.doi.org/10.1016/j.patcog.2016.08.032


tabase.