International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-5, March 2019

Modified Local Binary Pattern Scheme using Row, Column and diagonally aligned Pixel's Intensity Pattern

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Abstract: ***This paper, suggested a novel method for texture feature descriptor using the row, column and diagonally aligned pixel intensity difference for efficient image retrieval based on image contents (CBIR). In Local Binary Pattern (LBP), a matrix of size 3x3 of an image is used, and then the central pixel of the window is subtracted from all its eight neighbours one by one pixel. LBP uses, 0 or 1 based on if the variance between central and neighbour pixel value is negative or positive respectively, to generate a binary pattern. Decimal value to this 0 and 1 binary string represents the binary value of the corresponding image pixel. By doing this, LBP ignores the effect of the row, column and diagonally aligned pixels of an individual pixel for its encoding to binary values and similarly for its texture explanation. This suggested texture descriptor is centered on the clue that row, column and diagonally aligned pixels of an individual pixel hold momentous quantity of data and this data that can be used for operational and proficient texture demonstration for CBIR. This method do not dependent only on the sign of the intensity values between central pixel and its neighbours as in pre-existing LBP methods, rather suggested technique measured the sign of variance between and its row, column and diagonally aligned pixels. Using this concept, in this paper we suggested a row, column and diagonally aligned pixels Intensity Pattern (RCDAPIP) based texture descriptor. This method considers the comparative intensity difference between a particular pixel and the center pixel by considering its row, column and diagonally aligned pixels and generate a sign (SRCDAP) and a magnitude pattern (MRCDA). Finally, both the patterns SRCDAP and MRCDAP are merged into single pattern (RCDAP) to produce a more proficient feature descriptor. The suggested technique has been tested on WANG database of one thousand images. The Euclidean and Manhattan distance are used for similarity measure. The precision % value and the recall % value is calculated on suggested technique are equated with existing local binary pattern (LBP). The suggested system indicated a momentous enhancement over pre-existing LBP technique.***

Index Terms: ***Feature Extraction, Local Binary Pattern, Pixel Intensity, Texture Feature, Texture Content based Image Retrieval.***

Manuscript published on 30 March 2019.
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I. INTRODUCTION

In the present era, because of the smart phones, digital scanners, and other digital storage devices are available on very short costs, many digital images are being clicked and uploaded each and every day. Because of this, a very huge image collections are being created and used and it has posed many challenging to manage and store this created data in a very effective and effectively manner. There are many applications in many fields for image search, some of them are like in medical fields, medical fields, farmer fields, entertainment fields etc. [1-2]. The main aim of image search is to recover mostly relevant images from an images database having many number of images. The database generally composed of thousands, lakhs of even more number of images in different orientations, occupying terabytes of space. This huge memory storage constraint has been enhanced by image compression method system to some level but, the whole collection of these terabyte memory space images makes it complicated for a person to search through the whole database for searching any image. This is the reason that we require an actual system for indexing as well as for retrieving required pictures from a huge pool of different images. [3] In earlier retrieval methods, pictures are characterized by simple text string and retrieval is centered on the text narrative. Meanwhile textual info may be varying with visual content, CBIR [4] is preferred and has been witnessed to make a great advance in recent years. It is normally approved that image recovery based on image feature is very much desirable for many applications in medical fields, farmer fields, entertainment fields etc. As an outcome, there is a requirement of a system that can first automatically fetch all the important features from the collection of images data sets and then to recover required images based on previously extracted features.

A. Content Based image retrieval

In this the search will examine the main information of the image other than the information data such as labels, keywords or interpretation linked with the image. The information states to colors and textures data that can be resulting from the image. The Content Based Image Retrieval has to turn into needed because many of the web-based engines for image searching are trust only on meta data and it yields a lot of false recognition in produced outputs [5].

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Any image contains three different types of contents namely color content, shape content and texture content [6]. In this paper we more focused on texture content.

B. Texture descriptor

Texture descriptor is a key feature of any image. Texture descriptor defines the visual pattern of the image pixels. There are two main categories of the representation of any texture first one is structural methods and the another method is statistical methods. In Structural methods we used only regular textures. [7]. SAR Model [8], Tamura features [9], Gabor Filter features [10], Wavelet Transform features [11], and Local Binary Pattern (LBP) [12] are regularly used and operative in existing CBIR systems for image retrieval. This paper is more focused on LBP.

C. Traditional Local Binary Pattern (LBP) Texture feature

Local Binary Pattern (LBP) texture feature is most frequently used texture descriptor. In LBP, a matrix of size 3x3 of an image is used, and then the central pixel of the window is subtracted from all its eight neighbors' one by one pixel. LBP uses, 0 or 1 based on if the variance between central and neighbour pixel value is negative or positive respectively, to generate a binary pattern. Decimal value to this 0 and 1 binary string represents the binary value of the corresponding image pixel. [13-16]

D. Mathematically calculation of LBP value

Mathematically Local Binary Pattern can be calculated as [17]

$$LBP(N,R)=\sum_{i=1}^{N}2^{i-1}\times D(I_i,I_c) \tag{1}$$

$$D(I_i,I_c)=\begin{cases}1 & ,if\ I_i \geq I_C\\ 0 & ,Otherwise\end{cases} \tag{2}$$

Where N is representing number of neighboring pixels and R is representing radius. I_c and I_i is representing the intensity of central pixel and i^{th} neighbour pixel respectively. Calculation is LBP value is explained in figure 1.

I_6	I_7	I_8
I_5	I_c	I_1
I_4	I_3	I_2

(i)

51	38	51
41	40	47
32	49	38

(ii)

1	0	1
1		1
0	1	0

(iii)

32	64	128
16		1
8	4	2

(iv)

32	0	128
16		1
0	4	0

(v)

32	0	128
16	181	1
0	4	0

(vi)

Fig.1. Diagrams (i) to (vi) are presenting the calculation of Local Binary Pattern (LBP) value for a particular pixel (i) a 3×3 window with universal representations of the centered and its eight neighboring pixels (ii) an example of a 3x3 window with centered pixel's intensity 40 and eight neighboring pixel's intensities as shown (iii) pixels with centered and binary values 0 and 1 are assigned as a result based on sign of difference values (iv) specific weights binary digits 0 and 1 (v) multiplication with weights (vi) Addition of all the values to get LBP value.

In the same way LBP values of all the pixels of all the images in the data set is calculated and the same is matched with the LBP values of pixels of the query image to calculate the similarity index between query image and all the images available in the data set. But, LBP values are not unique. Two different pixels belonging to two different images can have same LBP values as shown in the figure 2.

I_6	I_7	I_8
I_5	I_c	I_1
I_4	I_3	I_2

51	38	51
41	40	47
32	49	38

46	26	37
39	30	35
28	45	29

1	0	1
1		1
0	1	0

1	0	1
1		1
0	1	0

32	0	128
16	181	1
0	4	0

32	0	128
16	181	1
0	4	0

Fig. 2: Example presenting equal Local Binary Pattern (LBP) value for the two different pixels belonging to two different images

The rest of the paper is presented as follows. In section 2, we have discussed the literature review. In section 3, we discussed the suggested technique. Section 4 briefly describes the suggested system framework. In Section 5 we discussed the used datasets and the results obtained. Last section describes the conclusion and the future scope.

II. RELATED WORK

For the content based features like texture, color, and shape are simple to extract therefor many researchers have explored many methods for this persistence. Loupias et al. [18] used discrete wavelet transform for texture feature analysis. Wavelet transform is to decompose the signal into a mutually orthogonal wavelet sets. For the improvements on this wavelet transform method many researchers done lots of work. Ojala et al. [19] suggested Local Binary Pattern (LBP) for image retrieval.

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LBP is based on texture feature. LBP highly attracted the researchers because of its easy to use and the computational proficiency. LBP is also good in case of light changes. There are many application of LBP like image searching, image browsing, face detection etc. In Local Binary Pattern (LBP), a matrix of size 3x3 of an image is used,
and then the central pixel of the window is subtracted from all its eight neighbors one by one pixel. LBP uses, 0 or 1 based on if the difference between cental pixel values and neighbour pixel value is negative or positive respectively, to generate a binary pattern. Decimal value to this 0 and 1 binary string represents the binary value of the corresponding image pixel. By taking LBP as a standard many improvements have been done on it by many researchers. Shengcai Liao et al. [20] suggested Multi-scale Block Local Binary Pattern (MB-LBP), Wolf et al. [21] suggested three and four cluster LBP, B. Zhang et al. [22] suggested Local Derivative Pattern (LDP). Qian et al. [23] suggested Pyramid Local Binary Pattern (PLBP) for texture characterization by utilizing Gaussian and wavelet based low pass channels, Dubey et al. suggested Local Bit-plane Decoded Pattern (LBDP), Yao et al. [24] suggested Local Edge Pattern for Segmentation and Image Retrieval, He et al. [25] suggested Multi-structure Local Binary Pattern, Haralick et al. [26] used the model of Gray Level Co-occurrence matrix (GLCM) for classification of the image by texture feature extraction. To the best of our study, none of the existing methods measured the effect of the row, column and diagonally aligned pixels of a particular pixel in a 3×3 window of an image for its binary encoding and also for texture description. In this paper, we investigate the data contained in the row, column and diagonally adjusted pixels of a specific pixel for its binary encoding and furthermore for texture description. The suggested technique depends on the idea that row, column and diagonally adjusted pixels of a specific pixel hold noteworthy amount of data that can be utilized for proficient texture description for CBIR. This strategy don't depend just on the sign of the intensity contrast between central pixel and one of its neighbors just, rather this technique considered the sign of distinction esteems between and its row, column and diagonally adjusted pixels. Utilizing this idea, this paper built up another texture descriptor, named as row, column and diagonally aligned pixels Intensity Pattern (RCDAPIP) which considers the relative intensity distinction between a specific pixel and the inside pixel by thinking about its row, column and diagonally adjusted pixels and produce a sign and an magnitude design. At long last, both the patterns are connected into a solitary pattern to create a progressively proficient feature descriptor.

III. ROW, COLUMN AND DIAGONALLY ALIGNED PIXELS INTENSITY PATTERN

Suggested strategy don't reliant just on the sign of the intensity fluctuation between central pixel and one of its neighbors as in existing LBP, rather considered the sign of difference values between pixel and its row, column and diagonally adjusted pixels. Utilizing this idea, this paper created RCDAPIP texture descriptor which considers the relative intensity difference between a specific pixel and the central pixel by considering about its row, column and diagonally adjusted pixels and produce a sign (SRCDAP) and a magnitude pattern (MRCDA). At long last, both the examples are linked into a single pattern (RCDAP) to produce suggested feature descriptor. The row, column and diagonally aligned pixels of any pixel in 3 x 3 window is shown in the figure 3.

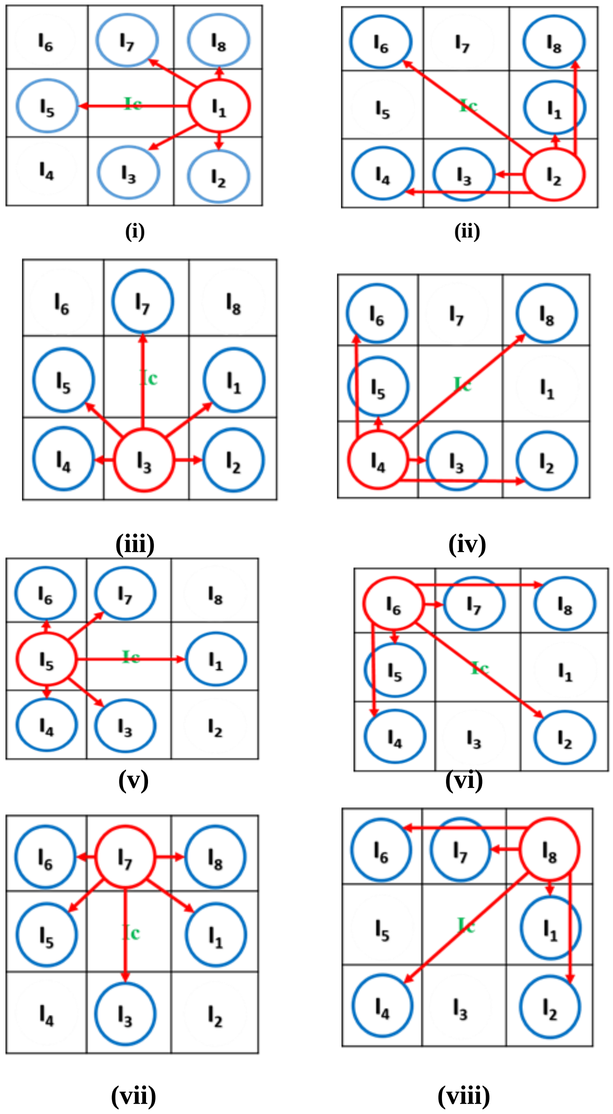

Fig. 3: Diagrams (i) to (viii) presenting the row, column and diagonally aligned pixels for each of the 8 neighbors pixels (Ii for all i = 1, 2, 3, 4, 5, 6, 7, 8) of central pixel Ic in a 3 x 3 window. All neighboring pixels has 5 pixels in row, column and diagonal. The set of row, column and diagonal pixels of Ii is denoted by Si

For the calculation SRCDAP we considered the sign of the difference values of the pixel Ii with its row, column and diagonally aligned pixels for all. For example when i = 1, set S_1 will contain five pixels I_2, I_3, I_5, I_7 and I_8 (eq 4) and when i = 2, set S_2 will contain five pixels I_3, I_4, I_6, I_7, I_1 and similar calculation for (eq 3)

$$S_i = \{I_{\mathrm{mod}(i+1,8)}, I_{\mathrm{mod}(i+2,8)}, I_{\mathrm{mod}(i+4,8)}, I_{\mathrm{mod}(i+6,8)}, I_{\mathrm{mod}(i+7,8)}\} \quad \forall i = 2,3,4,5,6,7,8 \tag{3}$$

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$$S_i = \{I_{\mathrm{mod}(i+1,8)}, I_{\mathrm{mod}(i+2,8)}, I_{\mathrm{mod}(i+4,8)}, I_{\mathrm{mod}(i+6,8)}, I_{i+7}\} \quad (4)$$

$$When, i = 1$$

Mathematically SRCDAP can be calculated as:

$B_{1,i}(k) = sign(S_i(k), I_i)$ Where, $k = 1,2,3,4,5$

(Set S containing five elements) (5)

$B_{2,i}(k) = sign(S_i(k), I_C)$ Where, $k = 1,2,3,4,5$

(Set S containing five elements) (6)

$$sign(a,b) = \begin{cases} 1 & , if a \geq b \\ 0 & , Otherwise \end{cases}$$

(7)

Here, a and b are two numbers. $B_{1,1}(1)$ is representing the bit code of the sign difference between $S_1(1)$ and I_1 and $B_{2,1}(1)$ is representing the bit code of the sign difference between $S_1(1)$ and I_c. $S_1(1)$ is the first element of the set S_1 and S_1 contains five elements those are row, column and diagonal neighbors of pixel

The calculation of SRCDAP value for the sample arrange as shown in figure 4.

I_6	I_7	I_8
I_5	I_c	I_1
I_4	I_3	I_2

(i)

46	26	37
39	40	35
28	45	29

(ii)

Fig. 4: Diagrams (i) and (ii) are presenting the arrangement of 8 neighbors of center pixel Ic in 3x3 window and one sample values for the calculation of SRCDAP value.

On applying the equations 5-7 on the sample values in figure 4, the values of $B_{1,i}(k)$ are shown in table 1 and that of $B_{2,i}(k)$'s are shown in table 2.

Table 1: The values of B1,i (k) on applying equations 5 - 7 on the sample window of size 3x3

i	K				
	1	**2**	**3**	**4**	**5**
1	0	1	1	0	1
2	1	0	1	1	1
3	0	0	0	0	0
4	1	1	1	1	1
5	1	0	0	1	0
6	0	0	0	0	0
7	1	1	1	1	1
8	0	0	0	1	0

The entries in the table for i = 1 are calculated as follows: For i = 1 the set S_1 will contains five values I_2, I_3, I_5, I_7 and I_8. On applying the equations 4 and 5 the required bit values are

$$B_{1,1}(1) = Sign(I_2, I_C) = Sign(29,35) = 0$$
$$B_{1,1}(2) = Sign(I_3, I_C) = Sign(45,35) = 1$$
$$B_{1,1}(3) = Sign(I_5, I_C) = Sign(39,35) = 1$$
$$B_{1,1}(4) = Sign(I_7, I_C) = Sign(26,35) = 0$$
$$B_{1,1}(5) = Sign(I_8, I_C) = Sign(37,35) = 1$$

The same calculations are done for all the remaining seven neighbours of the centered pixel I_c and the resultant values are stored in the table 1.

Table 2: The values of B2,i (k) on applying equations 5 - 7 on the sample window of size 3x3

I	K				
	1	**2**	**3**	**4**	**5**
1	0	1	0	0	0
2	1	0	1	0	0
3	0	0	0	0	0
4	0	1	0	0	1
5	1	0	0	1	0
6	0	0	0	0	0
7	0	0	1	0	1
8	0	0	0	1	0

The entries in the table for i = 1 are calculated as follows: For i = 1 the set S_1 will contains five values I_2, I_3, I_5, I_7 and I_8. On applying the equations 5 and 6 the required bit values are

$$B_{2,1}(1) = Sign(I_2, I_C) = Sign(29,40) = 0$$
$$B_{2,1}(2) = Sign(I_3, I_C) = Sign(45,40) = 1$$
$$B_{2,1}(3) = Sign(I_5, I_C) = Sign(39,40) = 0$$
$$B_{2,1}(4) = Sign(I_7, I_C) = Sign(26,40) = 0$$
$$B_{2,1}(5) = Sign(I_8, I_C) = Sign(37,40) = 0$$

The same calculations are done for all the remaining seven neighbours of the centered pixel I_c and the resultant values are stored in the table 2. The structural change in the bit pattern is calculated by taking bitwise XOR operation between $B_{1,i}$ and $B_{2,i}$. XOR operating is described in table 3.

Table 3: XOR operation for two input A and B

A	B	XOR(A, B)
0	0	0
0	1	1
1	0	1
1	1	0

Form the table 3 it can be stated that for the similar input bits the XOR value is 0 and for dissimilar input bit the XOR value is 1. The structural change in the bit pattern of $B_{1,i}$ and $B_{2,i}$ is calculated by taking bitwise XOR operation. On XOR between $B_{1,i}$ and $B_{2,I}$ a pattern of 5 bits D_i is obtained and the total number of ones in D_i represents the total structural change. The number of ones in D_i may range from 0 to 5. Here ½(M+1) is considered as threshold where M is equal to 5. Therefore, the threshold value is 3. To generate the feature vector for SRCDAP the number of ones in.

D_i is compared with threshold value. If number of ones in D_i is greater than threshold value the feature vector has value 1 otherwise it has value 0. By doing this an eight bit feature vector for SRCDAP is calculated and the same has been converted to decimal value by using equation 8.

$$SRCDAP = \sum_{i=1}^{8} 2^{i-1} \times (FeatureVectorSRCDAP) \quad (8)$$

For the calculation MRCDAP we considered the magnitude of the difference values of the centered pixel with its row, column and diagonally aligned pixels.

In this we calculate mean M of the sum of the absolute difference between the pixel I_i with all its five row, column and diagonally aligned pixels for i = 1, 2, 3, 4, 5, 6, 7 and 8. T is also calculated as threshold value for the mean of the sum of the absolute difference between the pixel Ii and central pixel I_c. Then a feature vector of MRCDAP is generated based on equation 2. This feature vector is converted to decimal value using equation 9.

$$MRCDAP = \sum_{i=1}^{8} 2^{i-1} \times (FeatureVectorMRCDAP) \quad (9)$$

Finally, both the patterns SRCDAP and MRCDAP are concatenated into a single pattern (RCDAP) to generate suggested feature descriptor.

IV. SYSTEM FRAMEWORK

The suggested technique is portrayed in Fig. 5. The technique has been divided into two sections. In section 1, an image is taken as input and in the output, the feature vector is acquired after merging the SRCDAP and MRCDAP. In section 2, retrieval of image is performed utilizing SRCDAP and MRCDAP. Here, query image is taken as input and in output the retrieved images are obtained dependent on similarity measure of the feature vectors as in section 1. The suggested CBIR framework structure is represented in figure 5.

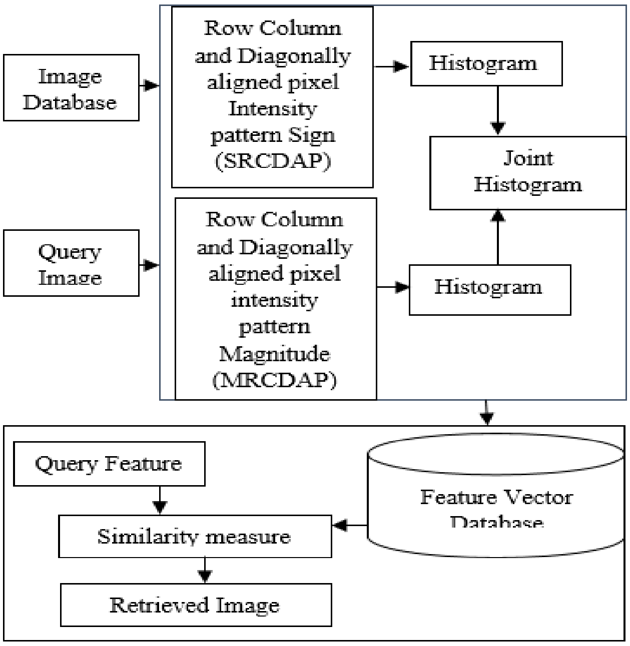

Fig. 5: Suggested CBIR system framework

To retrieve the images in CBIR systems, similarity measure also plays an important role. Following two distance measures are used for calculation of similarity matching.

A. Euclidean distance

$$D = \left(\sum_{i=1}^{N} | F_{di} - F_{qi} |^2\right)^{1/2} \quad (10)$$

B. Manhattan distance

$$D = \left(\sum_{i=1}^{N} | F_{di} - F_{qi} |\right) \quad (11)$$

V. DATASET AND RESULTS

The recommended system has been experienced for image retrieval on WANG dataset of one thousand images. Images are subdivided into ten classes to be specific class1 to class10 [27].Class1 comprising of images of Africans, class 2 comprising of images of beaches, class 3 comprising of images of Monuments, class 4 comprising of images of buses, class 5 comprising of images of dinosaurs, class 6 comprising of images of elephants, class 7 comprising of images of rose flowers, class 8 comprising of images of horses, class 9 comprising of images of snowy hills and class 10 comprising of images of foods. Distinctive classes of pictures have been shown in Figure 6 (a) – (j) and the equivalent has been depicted in table 4.

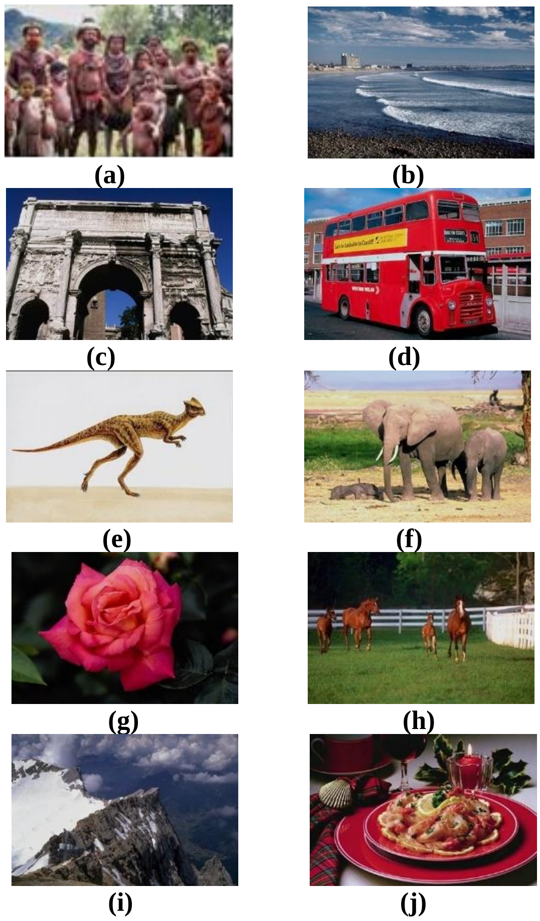

Fig. 6: Diagrams (a) to (j) presenting different categories of images in WANG dataset.

The different categories of images available in used dataset is described in table 4.

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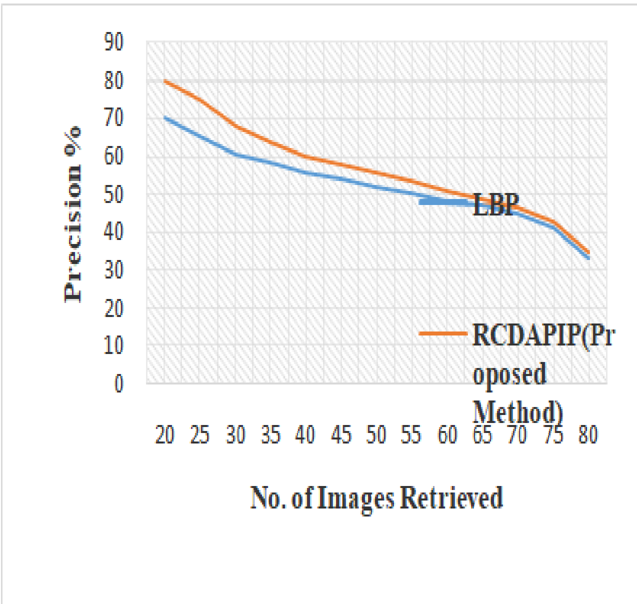
Table 4: Different types of classes and categories in WANG dataset

Sr. No.	Class #	Image Category
1	Class 1	African
2	Class 2	Beach
3	Class 3	Monument
4	Class 4	Buses
5	Class 5	Dinosaurs
6	Class 6	Elephant
7	Class 7	Rose
8	Class 8	Horse
9	Class 9	Snowy hills
10	Class 10	Food

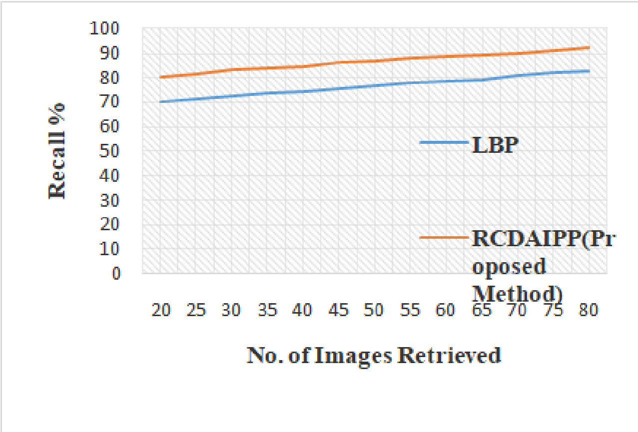
On applying the suggested method on WANG dataset for retrieving the query image and compared with existing LBP method. The performance of our suggested method is better that that of LBP method by 10.09 %. In our execution we initially retrieved 20 images and then gradually increased by 10 in each execution and maximum up to 80 images are retrieved. The results obtained as precision value and recall value using our suggested method on this dataset have been presented with the help of graphical plots shown in Fig. 7(a-b) and Fig. 8(a-b).

$$Precision = \frac{Total\ Number\ of\ Relevant\ Image\ Retrieved}{Total\ number\ of\ Images} \tag{12}$$

$$Precision = \frac{Total\ Number\ of\ Relevant\ Image\ Retrieved}{Total\ number\ of\ Relavent\ Images\ present} \tag{13}$$



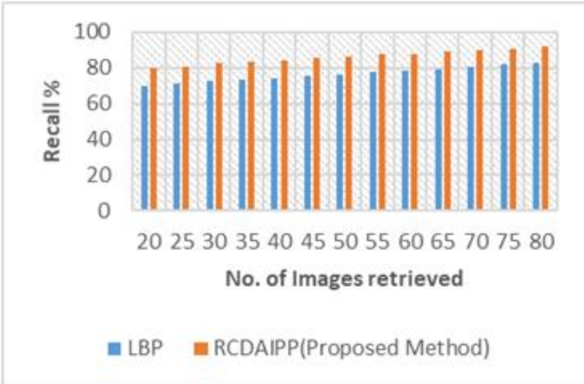
(a)



(b)

Fig. 7: Precision value % and Recall value %

(a)



(b)

Fig. 8: Precision value % and Recall value %

VI. CONCLUSION & FUTURE WORK

In this paper, we suggested a novel approach for texture feature descriptor using the row, column and diagonally aligned pixel intensity difference for effective image retrieval. Our suggested method is tested on WANG dataset of 1000 images divided into 10 categories with 100 images in each category. We verified suggested modified LBP technique on this dataset and compared with existing Local Binary Pattern technique. In our execution we initially retrieved 20 images and then gradually increased by 10 in each execution and maximum up to 80 images are retrieved.

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The performance of our suggested method is better that that of LBP method by 10.09 %. In future we can work on this and can try to generate more texture feature descriptor for improving the existing performance of image retrieval systems based on contents.

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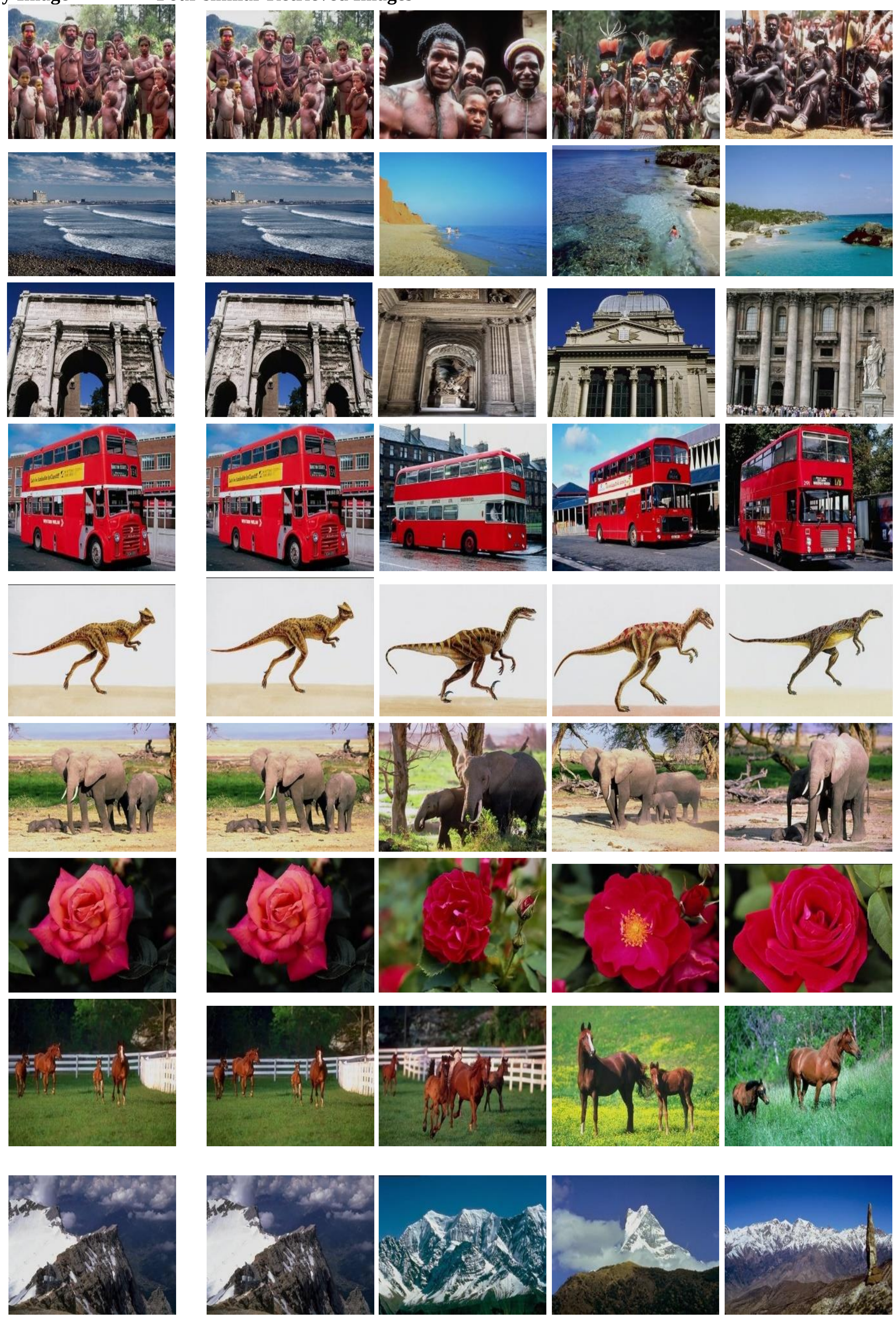
Appendix A

Retrieval Results

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

Query Image **Four similar Retrieved Images**



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