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Comparative Analysis of Local Binary Patterns using Feature Extraction and Classification

Mandeep Kaur

M.Tech Scholar CSE Deptt.
SBBSIET, Padhiana, Jalandhar, Punjab, 144030, India

Er. Harpreet Kaur

A.P CSE Deptt.
SBBSIET, Padhiana, Jalandhar, Punjab, 144030, India

Abstract

CBIR (Content based image retrieval) deals with the retrieval of same image from the databases of image by utilizing the feature vector extracted from the image and that features basically describes the visual content presented in the image, like the color, texture, shape and the spatial relation among vectors. Herein, the concept of LBP (Local binary pattern) is used for the comparative analysis of CS-LBP and Block Based Division LBP. Histogram is being used for obtaining the parts of the image, for extracting the image, genetic algorithm is used and for the classification, neural network is used. The comparison is executed on the basis of different parameters, namely, Precision, Recall, Accuracy, Accuracy Retrieval Rate and Accuracy Precision Rate.

Keywords: CBIR, LBP, CS-LBP, Block Based Division LBP, Accuracy, Precision, Recall, Accuracy Retrieval rate, Accuracy Precision Rate

I. INTRODUCTION

In content-based image retrieval (CBIR) image databases [1] are indexed with descriptors derived from the visual content of the images. Most CBIR systems are concerned with approximate queries where the goal is to find images visually similar to a specified target image. CBIR presents a challenging problem since it has common elements with both the general image understanding problem (which seems to remain unsolvable for computers at least in the near future) and the field of general information retrieval [2].

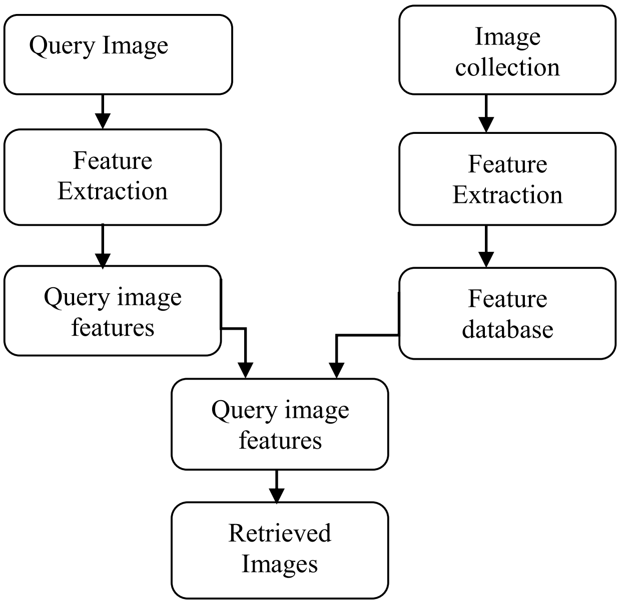

Figure 1: CBIR system architecture

When analyzing a field of technology, it is reasonable to look at the needs of the potential users. In the infancy of content-based image retrieval, the capabilities of the systems were so limited that a technology-driven approach may become sufficient. Now, as there is currently a considerable amount of research related to CBIR going on, it is more important to steer the development towards the needs of the users [3]. Modeling complex human behavior is a formidable task, however, and the current knowledge on the subject is relatively limited.

The local binary pattern (LBP) [4] feature has emerged as a silver lining in the field of texture classification and retrieval. Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by threshold the neighbourhood of each pixel and considers the result as a binary number and was introduced by Ojala et al. [5] The label operator has image pixels by thresholding the

3*3 neighbourhood of every pixel having centre value. The conversion of the results is by the binary number by utilizing the following equation:

$$LBP_{q,s} = \sum_{m=0}^{q-1} r\,(x_{s,m} - x_{0,0})^{2^n}$$

$$r(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

The original operator is being made in equation 2 with two extensions. Above mentioned LBP [6] for neighbourhood is for varied sizes that make it possible for handling the textures at variety of sizes. With the use of circular neighbourhood and bilinear interpolating, the value of pixels allows the radius with the pixel number in the neighbourhood. In the above equation, q sampling points are on the s radius circle. Second is defined as the uniform patterns like an LBP as uniform if it has mostly 0-1 or 1-0 transition when it is shown as a circular bit string. Neighbour's gray value does not lie precisely at the location of the pixels located being estimated by interpolation. Take M_N image I, in which $LBP_{q,s}(i,j)$ take LBP pattern of every pixel (i,j), therefore, the full texture image is shown by a histogram value j of length l:

$$j(l) = \sum_{i=1}^{M} \sum_{j=1}^{N} \partial\left(LBP_{p,r}(i,j) - l\right)$$

Where, $0 \leq l \leq L - 1$ and $L = 2^p$is known as the number of the LBP nodes. j has the properties being attractive: like, low complexity, power of satisfactory discrimination, gray scale invariance.

1.1.CS-LBP (Centre Symmetric LBP)

The concept was developed for the description of interest region. CS-LBP has an objective of producing small histograms with less number of LBP labels and can be best suited for region descriptors. It is being designed for the more stability in flat image regions [7].

The comparison of the pixel values with the centre pixels in not considered but it opposes the pixel symmetrically for the centre pixel [8]. Below figure is showing the description of right neighbor illustration:

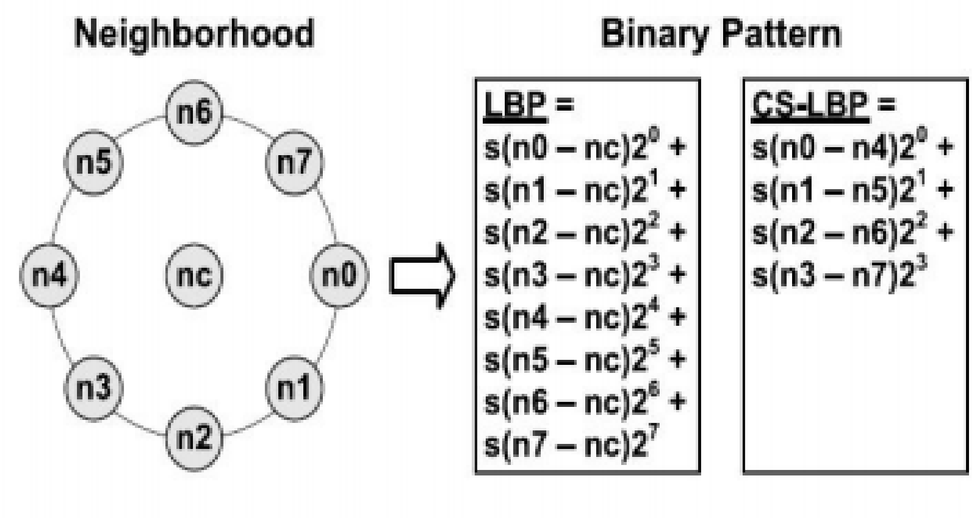

Figure 2: LBP and CS-LBP featured for 8 pixels neighborhood.

1.2.Block Based Division LBP

The mentioned approach is dependent on the sub-images for addressing the spatial image properties. It is basically utilized with histogram descriptors same as LBP [9]. The approach works as defined below:

i. Primarily, it divides the defined images in square blocks being arbitrary in size and overlap.
ii. The technique then calculates the LBP descriptors for every block and integrates the histogram in single vector of sub histograms showing the image.
iii. While in the query phase, the similar is done for the query images when the model is combined with the query by measuring the distance among every sub histogram.
iv. The last image dissimilarity D by means of classification is the calculation of less distances as shown in below equation 3:

$$D = \sum_{j=0}^{M-1} min_i \,(D_{j,i})$$

Above, M is the total amount of query image blocks with $D_{j,i}$ the distance among the jth query and ith model block histograms [10].

Histogram equalization is used to enhance contrast. It is not necessary that contrast will always be increase in this. There may be some cases were histogram equalization can be worse. In those cases, the contrast is decreased.

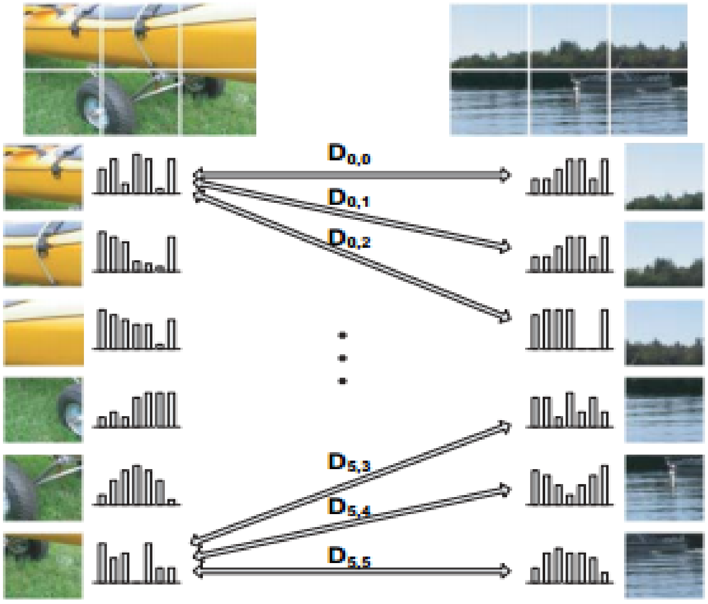

Figure 3: Block Based Division Method

Histogram equalization [11] redistributes intensity distributions. If the histogram of any image has many peaks and valleys, it will still have peaks and valley after equalization, but peaks and valley will be shifted. Because of this, "spreading" is a better term than "flattening" to describe histogram equalization. In histogram equalization, each pixel is assigned a new intensity value based on its previous intensity level.

Figure 3 is showing the histograms as the only examples not the exact LBP distributions of the image blocks [12].

This research has dealt with CS-LBP and Block Based Division LBP methods to provide the parts of images that would be obtained from histogram equalization. For the enhancement, Genetic algorithm will be applied. The extracted values would be trained using neural network to obtain better results. The features use to play a very important role in the image processing area. Before extracting features, the technique of image pre-processing like resizing is applied on the input image and, the features are obtained by different feature extraction techniques. These features are then utilized for classification and recognition of the objects in an image. The features are useful in terms of space utilization, efficiency in classification and obviously the time in processing the image, as they define characteristics of an image. Extracting effective features is the key for accurately detecting humans in images. Extracted features should be discriminative, failure resistant to various changes and easy to compute.

II. RELATED WORK

Shiv Ram Dubey et al. has presented new method for the description of an image with multichannel decoded LBPs. The authors have introduced adder- and decoder-dependent two schemas for the LBPs combination from more than one channel. The experiments related to image retrieval are performed for observing the efficiency of the proposed approaches. The approaches are compared with the existing ways of the techniques related to multichannel. The experiments are executed on 12 benchmark natural scene with color texture image databases, like Corel-1k, MIT-VisTex, USPTex, Colored Brodatz, and so on. It is being concluded that the introduced multichannel adder and decoder dependent LBPs enhancing the retrieval performance on every database and outperform another multichannel-based approaches by means of average precision and retrieval rate.

Melissa Cote et al. has presented new approach on texture classification which increases LBP-based methods robustness with respect to any intra-class variations type. The technique locally characterizes every pixel with histogram of LBP code and globally finds the textured image label by combining pixel labels via voting process. The proposed approach could be in principle given to some LBP version, as it focuses on the statistics being executed from the LBP codes. The authors has shown that the proposed pixel-based approach has improved traditional LBP block-based approaches by means of classification accuracy up to 5.1 p.p. on the public Outex database for the classic LBP by different neighborhoods with the different LBP extensions.

Shiv Ram Dubey et al. has given that LWP (local wavelet pattern) is resulted for every pixel of the CT image by using the relationship among centre pixel having the local neighboring information. The idea of this research is dependent on, encoding the information of local neighboring with the decomposition of local wavelet, executing LWP by utilizing the values of local wavelet decomposed with the values of transformed centre pixel. The author has tested the performance of proposed method on three CT image databases by means of precision as well as recall. The author has compared the given approach with the existing state of art descriptors of local image, the obtained results has shown that the proposed method has performed well as compare to another CT images retrieval.

Sadegh Fadaei et al. has proposed CBIR (Content-Based Image Retrieval) scheme dependent on the reliable combination of color as well as texture features for enhancing image retrieval precision. The findings has shown that not only the proposed wavelet, color and curvelet features performs better than the existing ones, but the combination has performed better in terms of accuracy as compare to the existing methods. The analysis has shown that the method being proposed has shown average precision from %67:85 upto %71:05 intended for DCD, %58:90 upto %65:43 used for wavelet and %53:18 upto %56:00 meant for curvelet utilizing Corel dataset. The proposed combination has also shown the average precision of %76:50 which is more as compare to another state of art methods.

Yingdong Ma et al. have introduced a system of pedestrian detection for extracting human objectives by utilizing an on-board monocular camera. The experiments are made on INRIA (Institut national de recherche en informatique et en automatique) dataset with the Caltech pedestrian detection benchmark showing novel system of pedestrian detection which is not compared to the relate pedestrian detectors, but it also executes at faster speed. The proposed novel system on the basis of pedestrian detection is being introduced with high efficiency and accuracy.

Jun Shang et al. has proposed object recognition based novel rotation invariant significant bit-planes-based local binary pattern. The author has categorized the image into number of sub regions as per intensity orders and divides the neighbor intensities. For improving the discriminative ability, the author has utilized multi-scale descriptor with average adjacent pixels containing more local spatial information and enhances the robustness to noise. The obtained results on the basis of recognition benchmarks has verified that the descriptor has performed better as compare to state of art binary descriptors with the SIFT descriptors.

III. SIMULATION MODEL

This section explains the analysis of LBP (Local Binary pattern), CS-LBP (Centre Symmetric LBP) with Block based division LBP.CS-LBP with Block based division LBP with feature extraction as well as with classification technique are compared. The comparison of the techniques is calculated on the basis of Accuracy, Recall, Precision, Accuracy Precision Rate and Accuracy Retrieval Rate.

The flow of the work by means of flowchart is being explained in the below diagram.

Step 1: For the training purpose, the images are uploaded.

Step 2: For CS-LBP (Center Symmetric-local binary pattern), the image is being concentrated. The same is implied to Block based division LBP.

Step 3: After the concentration of the images into the mentioned LBPs, the histogram is being developed for obtaining the values.

Step 4: For extracting the images for training feature, Concept of genetic algorithm is applied and for Classification, neural network is used.

Step 5: For testing of the uploaded images, histogram is obtained to get the values.

Step 6: Similarly, genetic algorithm is applied for extracting the features and for classification, neural network is used.

Step 7: The results are evaluated and compared in the end by using the mentioned parameters by using CS-LBP and Block based division LBP.

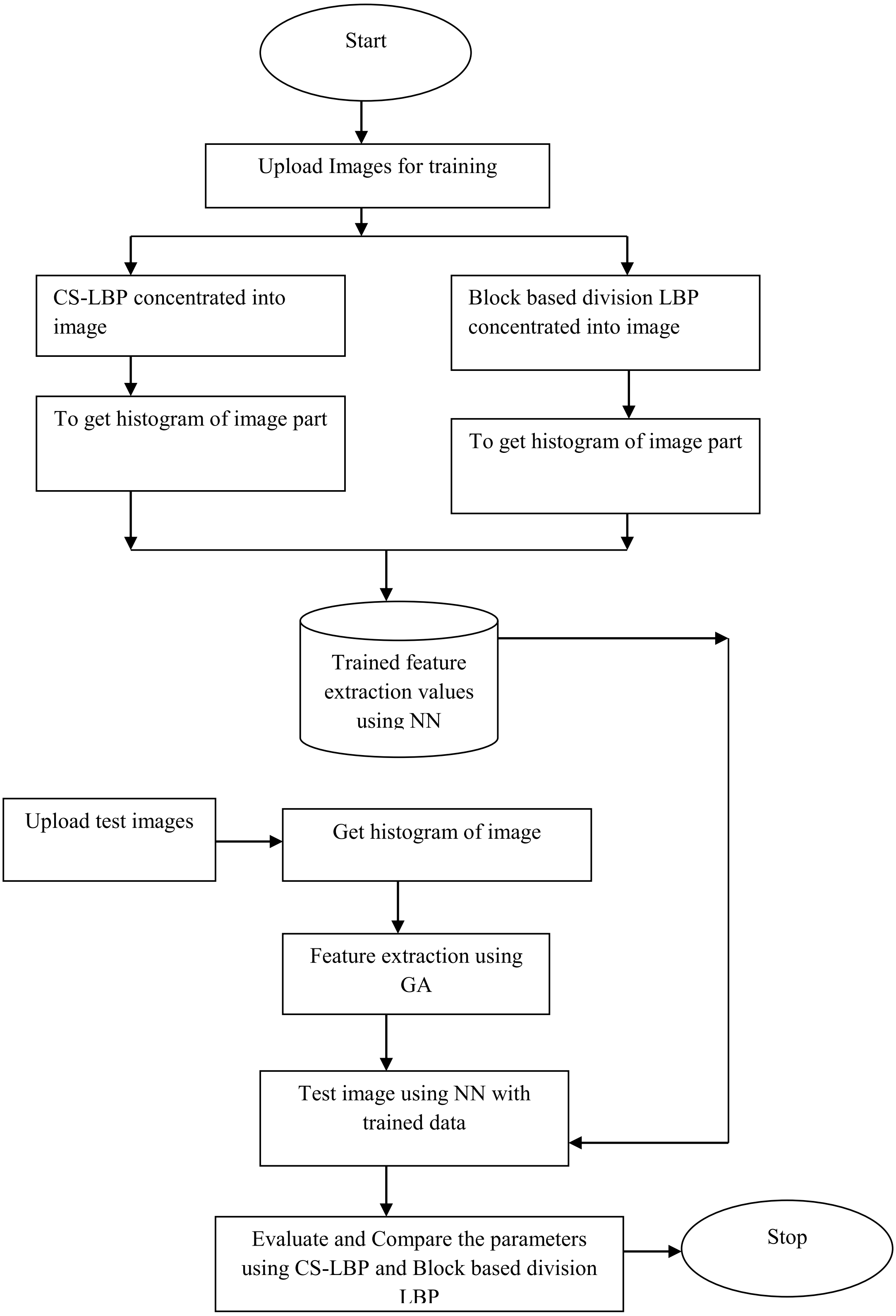

Figure 4: Methodology Flow Diagram

IV. SIMULATION RESULTS

This section explains the results obtained after the execution of the simulation model defined above. The results are calculated on the basis of Accuracy, Precision, Recall, Accuracy Precision Rate and Accuracy Retrieval Rate.

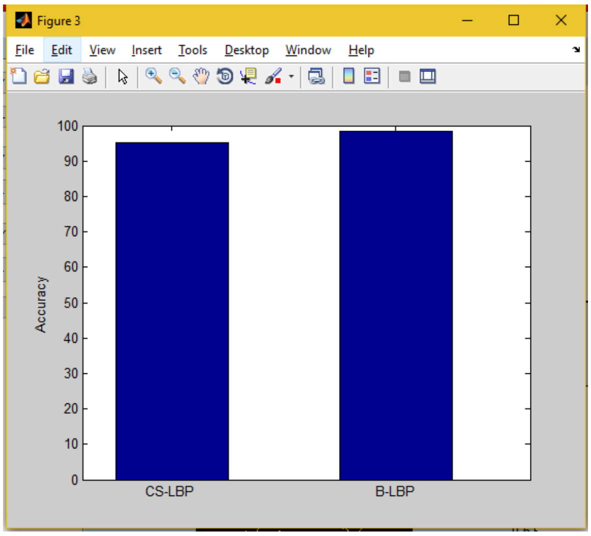

Figure 5: Accuracy Comparison

Above figure is explaining the comparison of accuracy for CS-LBP and Block based division LBP. X-axis of the above figure is defining the methods taken and y-axis is defining the accuracy. It is concluded from the above figure that the accuracy for block division LBP is higher as compare to CS-LBP.

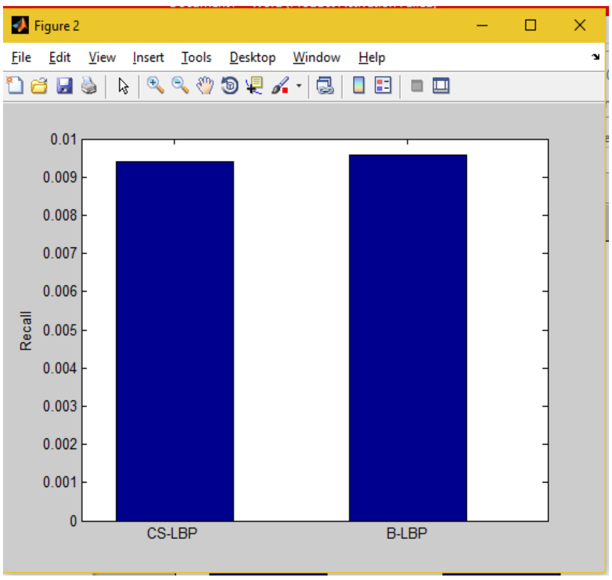

Figure 6: Recall Comparison

The above figure is explaining the comparison of recall rate for CS-LBP and Block based division LBP. It is defined as the division of documents appropriate to query being retrieved successfully. The recall rate for block based division LBP is slightly higher than the CS-LBP.

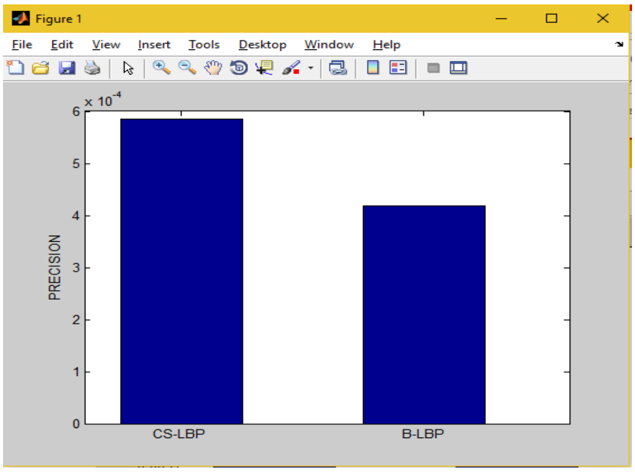

Figure 7: Precision Comparison

Above figure is depicting the comparison of Precision for both methods. Precision is the division of retrieved documents being relevant to the query which is successfully retrieved. From the above figure, it is clear that the precision rate for CS-LBP is higher as compare to Block based division LBP.

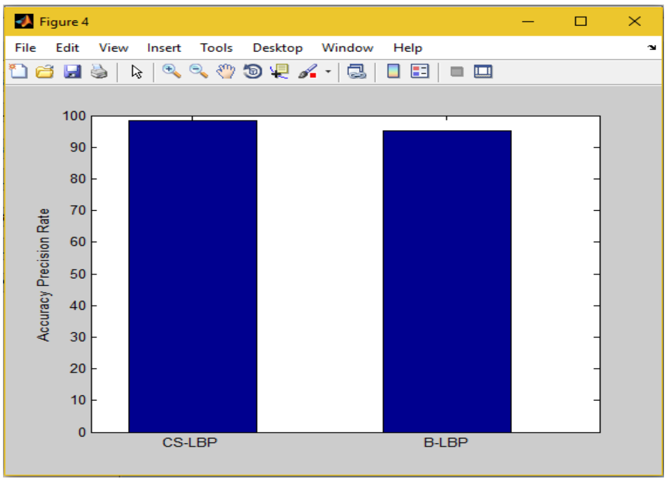

Figure 8: Accuracy Precision Comparison

The comparison of accuracy precision is shown in the above figure. X-axis is defining the methods undertaken and the Y-axis is defining Accuracy precision rate. From the above figure, it is clear that CS-LBP has obtained more accuracy precision as compare to block based division LBP.

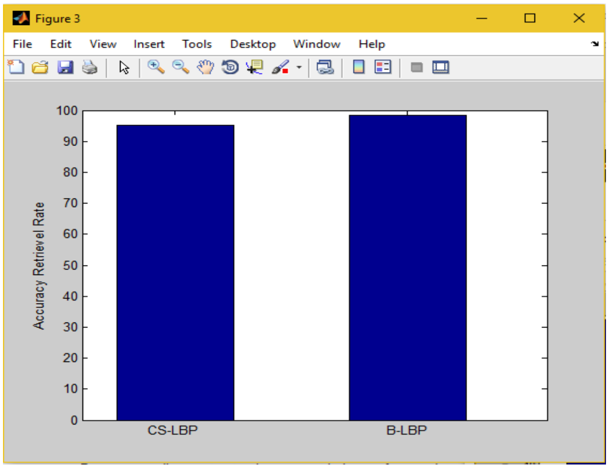

Figure 9: Accuracy Retrieval Comparison

Above figure is depicting the comparison of CS-LBP and Block based division LBP for accuracy retrieval rate. The accuracy retrieval rate for block based division LBP is more as compare to CS-LBP.

V. CONCLUSION

The concept of LBP is being adopted for the accurate description of the image feature with the simplicity. For defining the color image, it is necessary to combine LBPs from every image channel. In this research, the comparison of types of LBPs that is CS-LBP and Block based division is taken place with the usage of histogram equalization. For the extraction of the features, genetic algorithm is used for both the methods. Neural Network is used for the classification of the images. It is being concluded that the Block division LBP has performed better in every term as compare to CS-LBP.

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