Content based Image Retrieval using Histogram and LBP

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Abstract-Image retrieval (IR) is a process of browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval is TBIR (Text Based Image Retrieval) which utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive; to address this, there has been a large amount of research done on automatic image annotation like CBIR. To improve existing CBIR performance, it is very important to find effective and efficient feature extraction mechanisms. This research aims to improve the performance of CBIR using Color and Texture features.

Keywords- *CBIR, Feature Extraction, Similarities measure, Feature vector, LBP.*

1. Introduction

In recent years, very large collections of images and videos have grown rapidly. In parallel with this growth, content-based retrieval and querying the indexed collections are required to access visual information. As a powerful technique, content-based retrieval systems have to provide easy-to-index data structures as well as faster query execution facilities. In order to index and answer the queries that the users pose to seek visual information, the contentof the images and videos must be extracted. Content-based image retrieval is a technique which uses visual contents to search images from large scale image databases according to users' interests. Content-based image retrieval uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. In typical content-based image retrieval systems Figure 1, the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. The visual content, or generally content, of images and video frames can be categorized as follows: spatial, semantic, and low-level. Since video data has a time dimension, the spatio-temporal content of a video data is also considered. However, extracting spatio-temporal content requires sophisticated techniques, thus do not included in the categorization. The spatial content of an image is the relative positioning of the objects residing in the image. The semantic content is the actual meaning of the image that a user captures when he/she looks at the image. The low-level content is formed by low-level features such as color, shape, and texture. These three features are considered important underlying primitives in human visual perceptions of the real world. Various methods exist in the literature for indexing the images based on these low-level features.

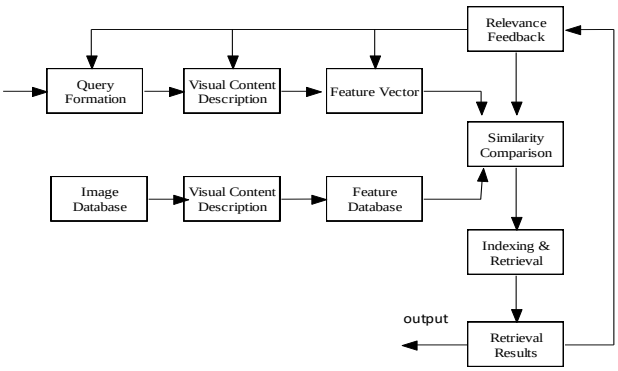

Figure1. Content-Based Image Retrieval System

II. Literature Review

A method for image indexing and comparison is proposed by approximating the statistical distribution of color histogram. Proposed method is capable of finding distance between two images, transition, scaling, and rotation [3, 14]. For organizing the images for CBIR, a neural network based

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method is proposed, which spectral histogram features are used. After this optimal combination of histogram features is calculated using optimal factor analysis to reduce dimension of features and maximize the discrimination. And these reduce feature are act as an input to a multiple layer perceptron to categorize image based on content using back propagation [4].

To avoid the problem like computational complexity and the retrieval accuracy, this paper proposed a new CBIR method by using color and texture feature.Finally texture moment is calculated through the ranklet images [5], more work has also done in color and texture feature [15, 17].

Two methods for describing the contents of images: First method characterizes images by global descriptor attributes, and the second is based on color histogram approach. Required time to compute feature vectors for global descriptor is much less as compared to color histogram. Hence cross correlation value & image descriptor attributes are calculated prior histogram implementation to make CBIR system more efficient [6]. Retrieval using color sometimes gives disappointing results because in many cases images with similar colors do not have similar content, for this problem a combining technique is produce in which both color and texture features of images are used to improve the retrieval performance. For this images in database are firstly ranked using color features and lastly top ranked images are re-ranked with their texture features [7].
There is also another algorithm of image retrieval which combines the multi-features like color, texture and shape and so on. After normalization retrieval is performed, and the multi-feature retrieval method is dividing into two methods: secondary i.e step by step carries on the retrieval another is separately extracting the features then unifies this feature for retrieval. And lastly the results are compare with Euclid distance metric [8, 18]. In the proposed scheme transfers each image to a quantized color code using the regulations of properties in compliance with HSV model. Simultaneously compare the images of database using these quantized color code. Because of this computational complexity is decreased [9].

An image retrieval system is proposed which uses color and shape descriptions information in the formation of feature vectors. And for feature or similarity matching Bhattacharyya distance and histogram intersection are used. Framework integrates the YCbCr color histogram which shows the global feature and Fourier descriptor as local descriptor to compute efficient retrieval results [10]. This paper introduce a region-based image retrieval system with high-level semantic color names defined for each region i.e a color name is assigned to each region. In the retrieval process, images of database those are having regions of same color name as that of the interested query region are selected, after selection images are further ranked based on their color and texture features. By this system decreases the semantic gap between numerical image features and the human semantics [11].

A composite feature measure is proposed, which combines the color and shape features of an image. By color quantization color features are generated and considered the spatial correlation with histogram matrix matching method. Supplement the color information using shape information with the improved moment invariants. This method is capable of handling situation like rotation images, translation images, noise added images etc. [12]. Integrated content based image retrieval is proposed using combined or multi-features and weighted similarity. Weights are determined on the bases of the accuracy of the individual feature-based queries based on automatic and semiautomatic method shows better results than manual method [13]. Also some work is done in by combing color with other feature [16, 19, 20, 21].

Among the spectral approaches of texture feature representation, multi-resolution simultaneous auto-regressive model (MR-SAR), wavelet transform, Gabor filters and Word decomposition have been found to be used in CBIR successfully [23].

The multi-resolution wavelet transform has been employed to retrieve images [11]. The wavelet features do not achieve high level of retrieval accuracy. Therefore, various methods have been developed to achieve higher level of retrieval accuracy using wavelet transform. Wavelet features computed from discrete wavelet coefficients are assigned weights to increase effectiveness in CBIR [25]. Features from lower resolutions are assigned higher weights as low resolution coefficients are likely to contain major energy portions of an image.

Some of the existing CBIR systems extract features from the whole image not from certain regions in it; these features are referred to as Global features. Histogram search algorithms [30] characterize an image by its color distribution or histogram. Many distances have been used to define the similarity of two color histogram representations. Euclidean distance and its variations are the most commonly used. The drawback of a global histogram representation is that information about object location, shape and texture is discarded. Color histogram search is sensitive to intensity variations, color distortions, and cropping. The color layout approach attempts to overcome the drawback of histogram search. In simple color layout indexing [30], images are partitioned into blocks and the average color of each block is stored. Thus, the color layout is essentially a low resolution representation of the original image. A relatively recent system, WBIIS [43], uses significant Daubechies' wavelet coefficients instead of averaging. By adjusting block sizes or the levels of wavelet transforms, the coarseness of a color layout representation can be tuned.

Hence, we can view a color layout representation as an opposite extreme of a histogram.

Region-based retrieval systems attempt to overcome the deficiencies of global feature based search by representing images at the object-level. A region-based retrieval system applies image segmentation to decompose an image into regions, which correspond to objects if the decomposition is ideal [44].

III. Querying by Color Content

Due to its broad fields of application in medical imaging, satellite photography, remote sensing, industrial quality inspection, etc., color has been a popular research area within image processing since early 70's.

Being of paramount importance in human visual perception, color constitutes one of the basic features on which content-based image retrieval is expected to operate. This chapter presents a content-based image retrieval system that can perform similarity matches on the color feature of images.

Color is one of the most important features of objects in image and video data. Each pixel in an image has a three-dimensional color vector and different color space approaches exist to represent color information. One of these color space models is the hardware-oriented Red-Green-Blue Model (RGB), where the color vector of a pixel p is the compound of red, green and blue channels v_p= (r; g; b). Another color space model is the Hue-Saturation-Value Model(HSV) that is based on color descriptions rather than individual color components v_p= (h; s; v). The RGB model has a major drawback: it is not perceptually uniform. Therefore, most of the systems use color space models other than RGB, such as HSV [26].

Coloris the prominent visible properties of an image and each pixel of image contains a different value for color. As human vision perception can easily distinguish different colors, application of color features has widely been accepted in numerous CBIR applications. Before generation of a color descriptor, it is necessary to define a suitable color space. From the recent literature, we find HSV or HSL or HSB, YCrCb, CIE-L*u*v*, CIE-L*a*b* are popularly used in CBIR. Various color spaces have already been developed and used for different purposes in image processing. In some retrieval approaches, color features are combined with texture features to obtain a better performance. For convenience in color feature extraction process, color space conversion processes have been introduced. The transformation from RGB to HSV, HSB or HSL space is described in whereas RGB to CIE-L*u*v* or CIE-L*a*b* conversion is shown in. Among the color spaces, HSV is more useful in measuring perceptual similarity. Commonly used color descriptors include the use of the color histogram, color moments, the color coherence vector, and the color correlogram. Sometimes more than one color descriptors is used for image retrieval.

3.1.1 Preliminaries

Transformation and Quantization

The color regions are perceptually distinguishable to some extent. The human eye cannot detect small color differences and may perceive these very similar colors as the same color. This leads to the quantization of color, which means that some pre-specified colors will be present on the image and each color is mapped to some of these pre-specified colors. One obvious consequence of this is that each color space may require different levels of quantized colors, which is nothing but a different quantization scheme

(a) (b) (c)

Figure 3.1: Transformation, Quantization and Color Median Filtering of tiger Image. (a) Original image. (b) Image produced by applying RGB to HSV colortransformation and quantization. (c) Image produced after applying color medianfiltering.[27]

In Figure 3.1, the effect of color quantization is illustrated. Figure 3.1 (a) is the original image with RGB color space and (b) is the image produced after transformation into HSV color space and quantization. A detailed explanation of color space transformations (from RGB into HSV) and quantization can be found in [27].

3.1.2 Color Content Extraction

One of the widely used methods for querying and retrieval by color content is color histograms. The color histograms [28, 29] are used to represent the color distribution in an image or a video frame. Mainly, the color histogram approach counts the number of occurrences of each unique color on a sample image. Since an image is composed of pixels and each pixel has a color, the color histogram of an image can be computed easily by visiting every pixel once. By examining the color histogram of an image, the colors existing on the image can be identified with their corresponding areas as the number of pixels. One possible way of storing the color information is to use three different color histograms for each color channel. Another possible method is to have a single color histogram for all of the color channels. In the latter approach, the color histogram is simply a compact combination of three histograms and the empty slots can be discarded easily.

In [27], Smith and Chang proposed color sets as an opponent to color histograms. The color sets are binary masks on color histograms and they store the presence of colors as 1 without considering their amounts. For the absent colors, the color sets store 0 in the corresponding bins. The color sets reduce the computational complexity of the distance between two images. Besides, by employing color sets region-based color queries are possible to some extent. On the other hand, processing regions with more than two or three colors is quite complex.

The histogram approach is commonly used in most of the existing systems supporting query-by-color content. Figure 3.2 shows the color histogram of tiger image, which is first transformed into HSV color space and quantized. Each row is designated for a distinct color and corresponding number of pixels information is presented. Supplementary information about color for an image is the average color and it may be stored along with the color histogram for the sake of efficiency since it can be computed from the color histogram in one pass.

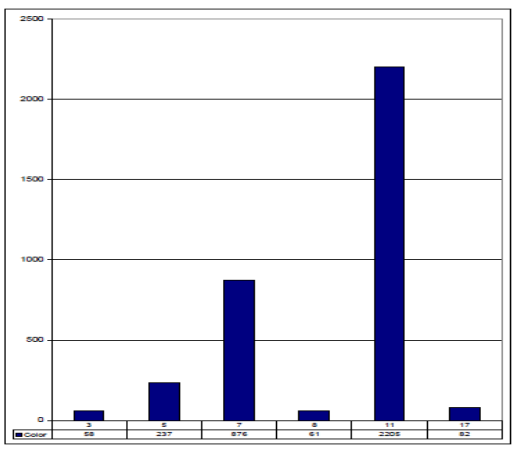

Figure 3.2: The Color Histogram Of Tiger Image In HSV Color Space[27]

Another image content storage and indexing mechanism is color correlogram [29]. It involves an easy-to-compute method and includes not only the spatial correlation of color regions but also the global distribution of local spatial correlation of colors. In fact, a color correlogram is a table each row of which is for a specific color pair of an image. The k-th entry in a row for color pair (i; j) is the probability of finding a pixel of color j at a distance k from a pixel of color i. The method resolves the drawbacks of the pure local and pure global color indexing methods since it includes local spatial color information as well as the global distribution of color information.

3.2 key factors affecting CBIR

We now describe the important issues of content based image retrieval system, which are:

3.2.1 Image Database Selection

To ensure the quality of research it is necessary to select a proper dataset as it plays animportant role in the CBIR performance. Based on the research objectives, choosing aproper database is necessary to establish a relevant analysis of various CBIR techniques.For any database, it is important to determine the ground truth, on the basis of whichretrieval is performed and performance is measured. Size and variety are other twoproperties of a database, which also affects the retrieval outcome. If the database size islarge consisting of multivariate images, a good retrieval result ensures the acceptance ofthe database as well as the implied method as a standard. Retrieval result variessignificantly by selecting different databases as the ground truth definition, size, andvariety of the databases are different.

3.2.2 Similarity Measurement

Once features are extracted, from all the database images and the query image, the similarity measurement becomes the crucial issue in content based image retrieval. Similarity measurement is the process of finding the difference or similarity between the database images and the query image using their features. The database image list is then sorted according to the ascending order of distance to the query image and images are retrieved from the database according to that order. There are various methods of calculating this distance, such as the Minkowski-Form distance, quadratic form distance, Mahalanobis distance, Kullback-Leibler divergence, and Jeffrey-Divergence [2].

3.2.3 Performance Evaluation Methods of CBIR

The level of retrieval accuracy achieved by a system is important to establish its performance. If the outcome is satisfactory and promising, it can be used as a standard in future research works. In CBIR, precision-recall is the most widely used measurement method to evaluate the retrieval accuracy. We have found some recent literature use this pair to measure the retrieval performance. Precision P is defined as the ratio of the number of retrieved relevant images r to the total number of retrieved images n, i.e., $P = r / n$. Precision measures the accuracy of the retrieval.

$$p = =$$

Recall is defined by R and is defined as the ratio of the number of retrieved relevant images r to the total number m of relevant images in the whole database, i.e., $R = r /m$. Recall measures the robustness of the retrieval.

$$R = =$$

3.2.4 Low-level Features in CBIR

A number of low-level image features can be extracted from an image. Detailed study on image features are presented in [1, 35]. Some commonly used low-level image features in recent literature includes the application of color, texture, shape, spatial location, etc. Some CBIR approaches use a combination of more than one low-level feature to improve retrieval performance. In this section we briefly describe the color features used in recent CBIR researches and their impacts.

IV. Querying by Texture Content

Texture, which refers to a characterization of the surface of an object or a collection of objects, has traditionally played an important role in the analysis of aerial, satellite, and medical images, among other image types. In recent years, it has found applications in content-based image retrieval systems as well. Texture recognition has been studied for many years; some of the typical methods include, but are not limited to, parametric statistical model-based techniques, structural techniques, techniques based on empirical second-order statistics and various transform-based techniques. Another major class of approaches for texture classification is based on the analysis of local properties of a texture sample by using either linear or nonlinear local operators [31].

V. Image Retrieval using Histogram and LBP

5.1 OVERVIEW OF SYSTEM USING HISTOGRAM

Within the framework of a statistical approach to the problem of text analysis, a content-based image retrieval system has been implemented to query upon digital images.Proposed retrieval method is divided into three steps: feature extraction of query and database images, similarities matching, and retrieving images.

(a) Feature Extraction: In this step all the images of database as well as the query image is quantized to 128 binsor 32 bins. And the output of extraction i.e name, histogram (128x128) & edges of the images is stored in a database.

(b) Matching: To calculate the difference between the query and all the images in database we use Euclidean Distance for both histogram and the edges. Euclidean distance or Euclidean metric is the "ordinary" distance between two points that one would measure with a ruler, and is given by the Pythagorean formula. By using this formula as distance, Euclidean space becomes a metric space. The Euclidean distance between two point's p and q can be calculated by the following formula. And after this similarities measure is calculated, similarities is calculated by finding mean and standard deviation of histogram and edges and then finally result is calculated by:

Euclidean distance,

The image *mean* is the average pixel value of an image. For a grayscale image this is equal to the average brightness or intensity. Let the image f(x,y) /be referred to using the shorthand f,the mean of this image, E[f] may be calculated using:

The *image variance*, Var[f], gives an estimate of the spread of pixel values around the image mean. It can be calculated using either Equation 2.2 or Equation 2.5. The latter has the advantage of requiring only one pass through the image. The *standard deviation* is simply.

Similarities = (similarities-)/s

Lastly summation of mean n standard deviation is done and summation is then sorted in increasing order i.e minimum to maximum. This sorting order shows images having minimum values are more accurate retrieved image.

(c) Retrieving images: Among the sorted list of images, 25images with minimum similarities are displayed. These 25 images are the best suited images those are extracted for the database or images with maximum similarities.

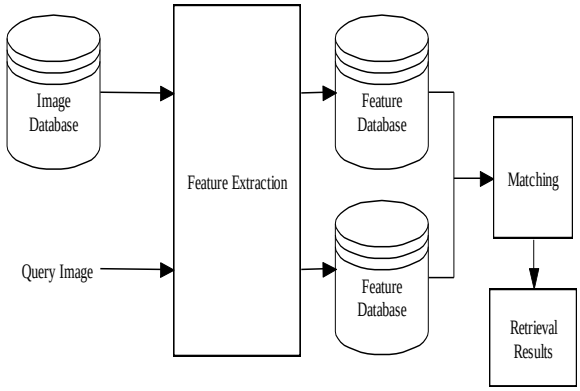

Figure5.1. Steps of Proposed Method

The Figure5.1 shows block diagram which represents the process of retrieval *i.e.* in feature extraction process features of image and that of query is extracted and stored in the feature database after that matching is perform between the features of query image and all the features of database images and lastly images which are match is then retrieved.

5.2 Overview of system using LBP

The local binary pattern operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image. These labels or their statistics, most commonly the histogram, are then used for further image analysis. The most widely used versions of the operator are designed for monochrome still images but it has been extended also for color (multi-channel) images as well as videos and volumetric data.

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5.2.1 Basic LBP

The basic local binary pattern operator was basedon the assumption that texture has locally two complementary aspects, a pattern andits strength. In that work, the LBP was proposed as a two-level version of the textureunit to describe the local textural patterns.

The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighborhood consists of 8 pixels, a total of 28 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood.

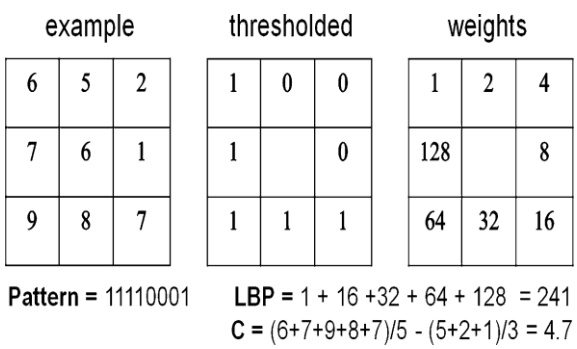


Figure5.2 Example of LBP [42]

5.2.2 Derivation of the Generic LBP Operator

In contrast to the basic LBP using 8 pixels in a 3 × 3 pixel block, this generic formulation of the operator puts no limitations to the size of the neighborhood or to the number of sampling points. The derivation of the generic LBP presented below:

Consider a monochrome image I (x, y) and let g_c denote the gray level of an arbitrary pixel (x, y), i.e. g_c = I (x, y). Moreover, let g_p denote the gray value of a sampling point in an evenly spaced circular neighborhood of P sampling points and radius R around point (x, y):

$$g_p = I(x_p, y_p),\ p = 0, \ldots, P-1 \text{ and}$$

$$x_p = x + R\cos(2\pi p/P),$$

$$y_p = y - R\sin(2\pi p/P).$$

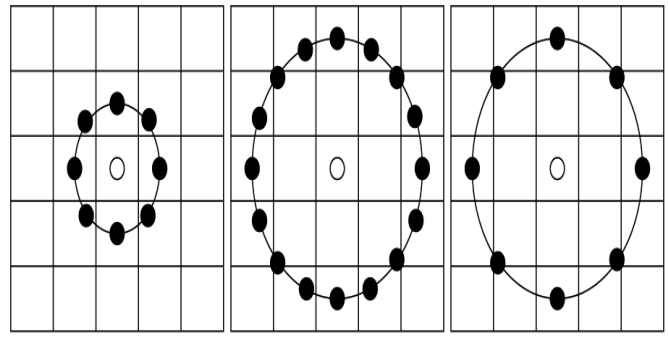


Figure5.3 The Circular (8, 1), (16, 2) And (8, 2) Neighborhoods. The Pixel Values Are Bilinearlyinterpolated Whenever The Sampling Point Is Not In The Center Of A Pixel [42]

Assuming that the local texture of the image I (x, y) is characterized by the joint distribution of gray values of P +1 (P > 0) pixels:

$$T = t(g_c, g_0, g_1, \ldots, g_{P-1})$$

Without loss of information, the center pixel value can be subtracted from the neighborhood:

$$T = t(g_c, g_0 - g_c, g_1 - g_c, \ldots, g_{P-1} - g_c)$$

In the next step the joint distribution is approximated by assuming the center pixelto be statistically independent of the differences, which allows for factorization ofthe distribution:

$$T \approx t(g_c)\, t(g_0 - g_c, g_1 - g_c, \ldots, g_{P-1} - g_c)$$

Now the first factor t (g_c) is the intensity distribution over I (x, y). From the point of view of analyzing local textural patterns, it contains no useful information. Instead the joint distribution of differences can be used to model the local texture

$$t(g_0 - g_c, g_1 - g_c, \ldots, g_{P-1} - g_c)$$

The learning vector quantization based approach still has certain unfortunate properties that make its use difficult. First, the differences $g_p - g_c$ are invariant to changes of the mean gray value of the image but not to other changes in gray levels. Second, in order to use it for texture classification the codebook must be trained similar to the other texton-based methods. In order to alleviate these challenges, only the signs of the differences are considered:

$$t(s(g_0 - g_c), s(g_1 - g_c), \ldots, s(g_{P-1} - g_c))$$

where s(z) is the threshold (step) function:

The generic local binary pattern operator is derived from this joint distribution. As in the case of basic LBP, it is obtained by summing the threshold differences weighted by powers of two. The $LBP_{P,R}$ operator is defined as:

means that the signs of the differences in a neighborhood are interpreted as a P -bit binary number, resulting in 2^P distinct values for the LBP code.

5.2.3 Mappings of the LBP Labels: Uniform Patterns

The uniform patterns allow seeing the LBP method as a unifying approach to the traditionally divergent statistical and structural models of texture analysis [45]. Each pixel is labeled with the code of the texture primitive that best matches the local neighborhood. The original operator uses called uniform patterns. For this, a uniformity measure of a pattern is used: U ("pattern") is the number of bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. A local binary pattern is called uniform if its uniformity measure is at most 2.In uniform LBP mapping there is a separate output label for each uniform pattern and all the non-uniform patterns are assigned to a single label. Thus, the number of different output labels for mapping for patterns of P bits is P (P − 1) + 3. For instance, the uniform mapping produces 59 output labels for neighborhoods of 8 sampling points, and 243 labels for neighborhoods of 16 sampling points.

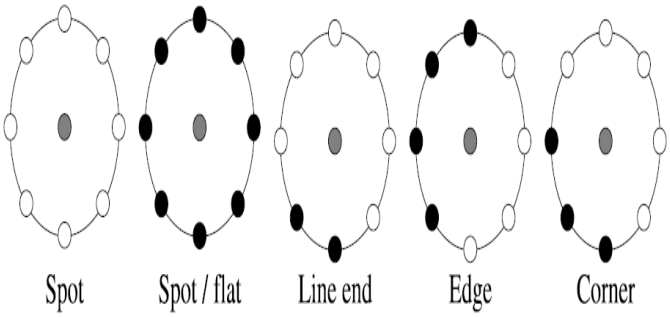


Figure5.4 Different Texture Primitives Detected By The LBP[42]

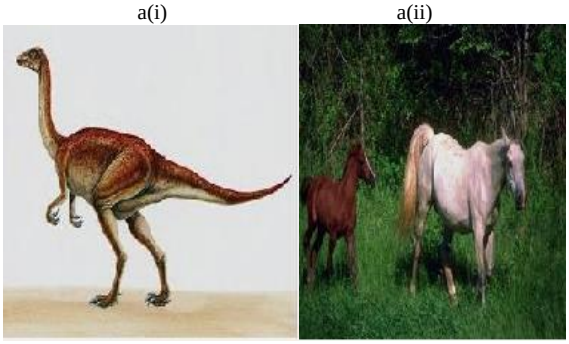
Local primitives detected by the LBP include spots, flat areas, edges, edge ends, curves and so on. Some examples are shown in Fig. 5.4 with the $LBP_{8,R}$ operator. In the figure, ones are represented as black circles, and zeros are white.

VI. Results and Discussion

To test the performance of our content-based image retrieval system on color and LBP similarity queries, we have used database containing more than 1600 jpg still images. All the images of database are resized to 256x256 jpg. In above discussed method histogram (128x128) is used rather (32x32) to decrease the processing time of retrieval. However hist32 shows more accurate result but our main aim to retrieve best images with less processing time. Retrieval process applies on huge database containing more than 1600 jpg images different categories like flowers, animals and nature's picture taken from http://wang.ist.psu.edu/docs/related/ [48].Figure6.1shows the two query images of each categories.

In the experiments, the query image is randomly picked from the database images or from the system, here we are dividing the query images in four categories Flower, Animal, Vehicle, and Natural Scene. And then its histogram 128x128 or 32x32 is calculated, but we prefer 128x128 since it reduces the processing time of retrieval with satisfactory results. After calculating the histogram of query image Euclidean distance is used to match the histogram from all the images in database. When similarities measure is calculated images are sorted in an increasing order and then finally first 25 images are displayed since they are the images which are best suited to the query image. And in case LBP firstly derivation of the generic LBP operator is done & than mapping is done here we are using uniform pattern for mapping. It also shows the 25 images in the results window.

a(i) a(ii)

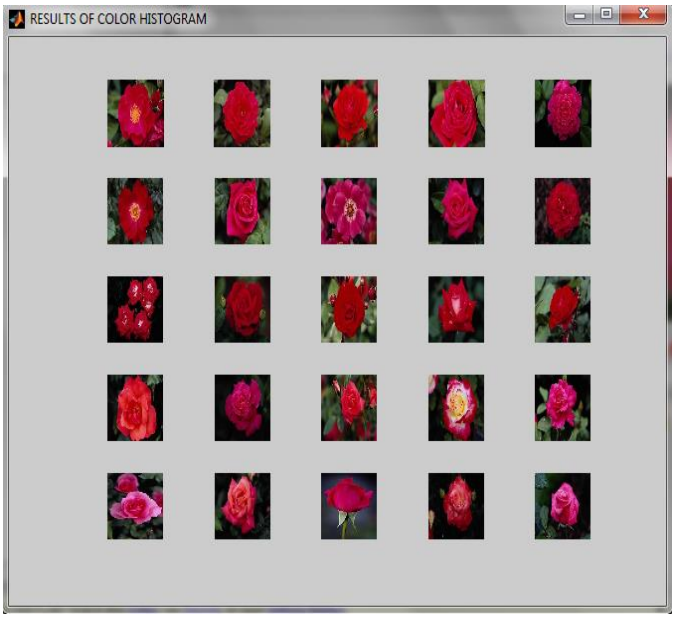


b(i) b(ii)

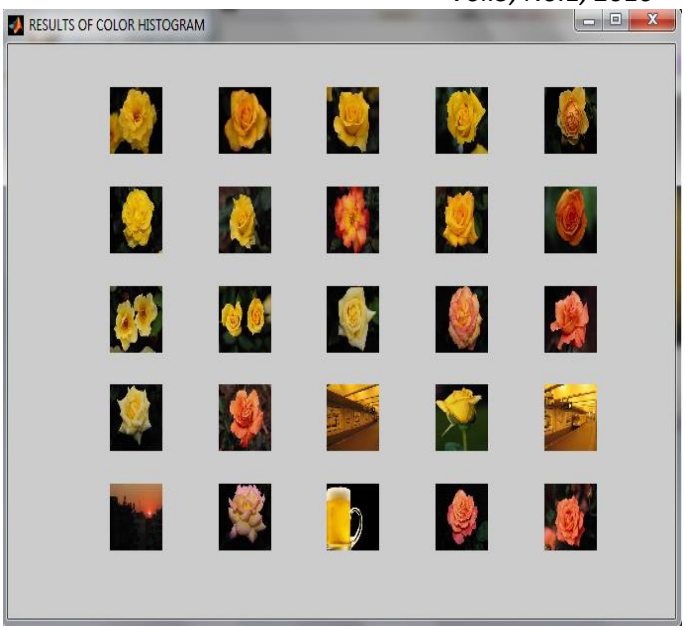
c(i) c(ii)

d(i) d(ii)

Figure6.1 Query Images Of Different Categories (A) Flower, (B) Animals, (C) Vehicles, (D) Natural Scene [48]

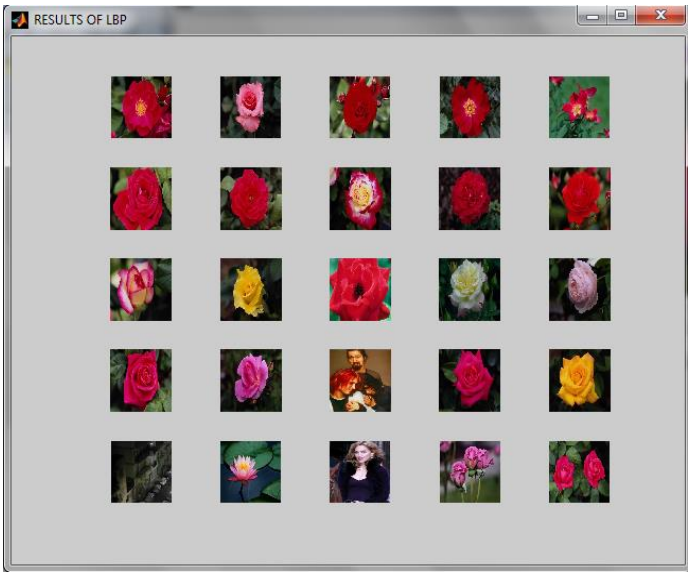


a(i)

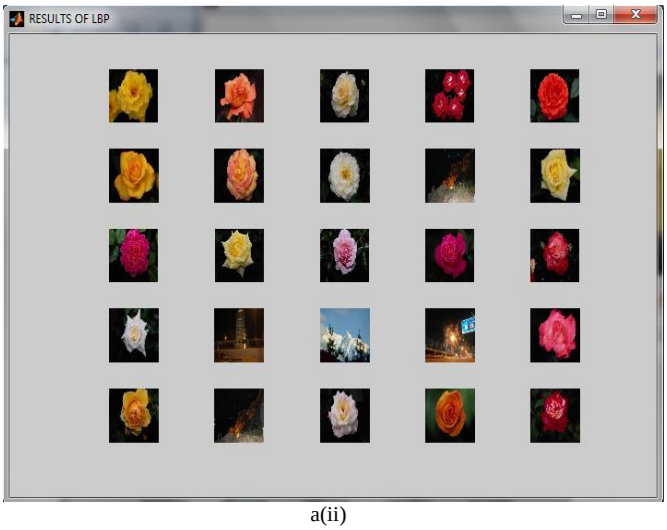


a (ii)

Figure6.2 Result of Color Histogram For flowers

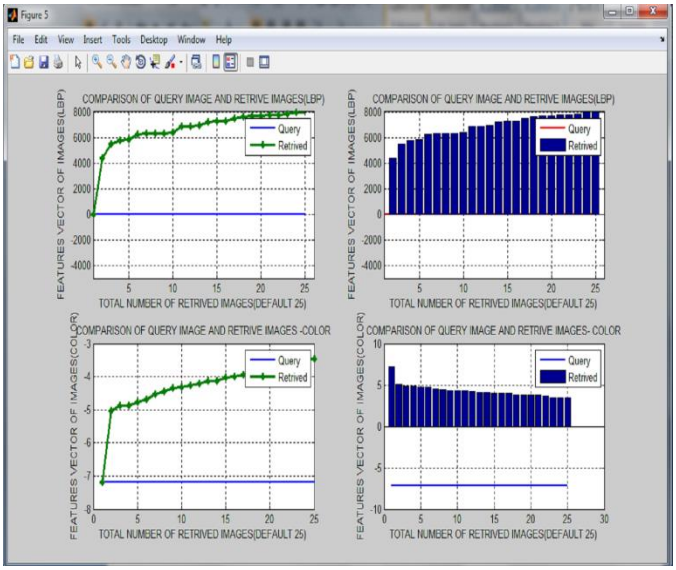


a(i)

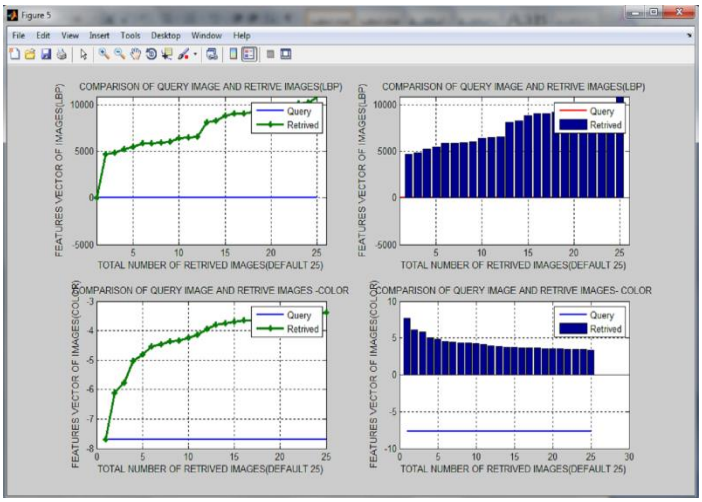


a(ii)

Figure6.3 Results of LBP for Flowers

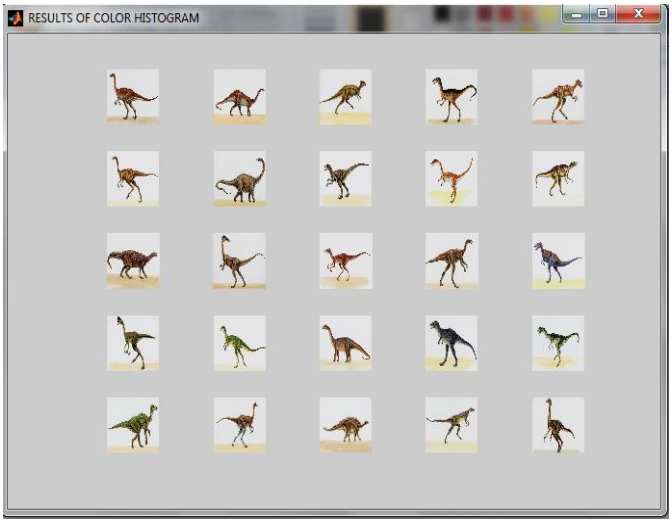


a(i)

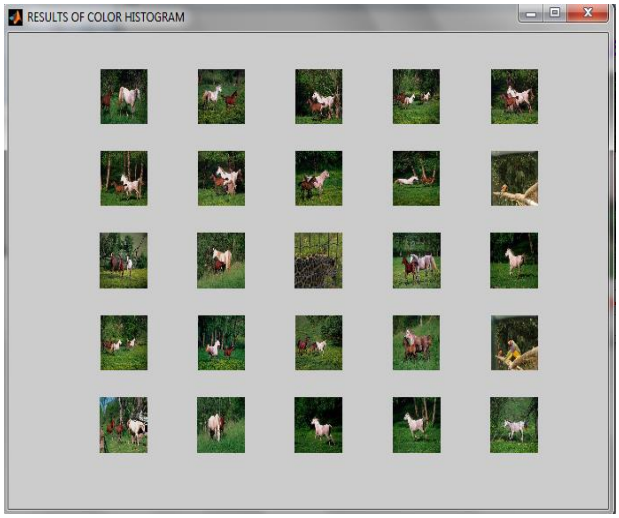


a(ii)

Figure6.4 Plots of ResultsforFlowers

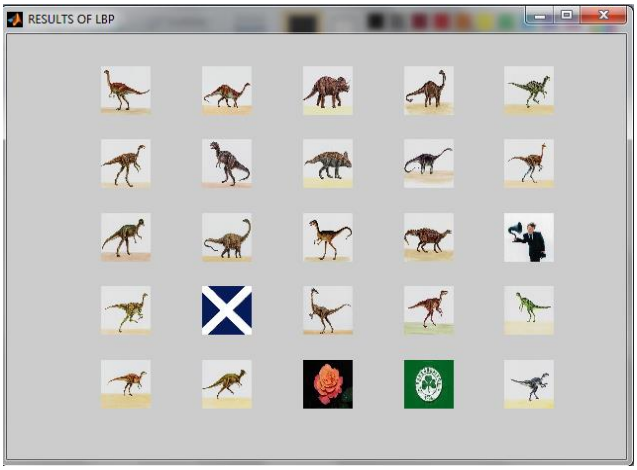


b(i)

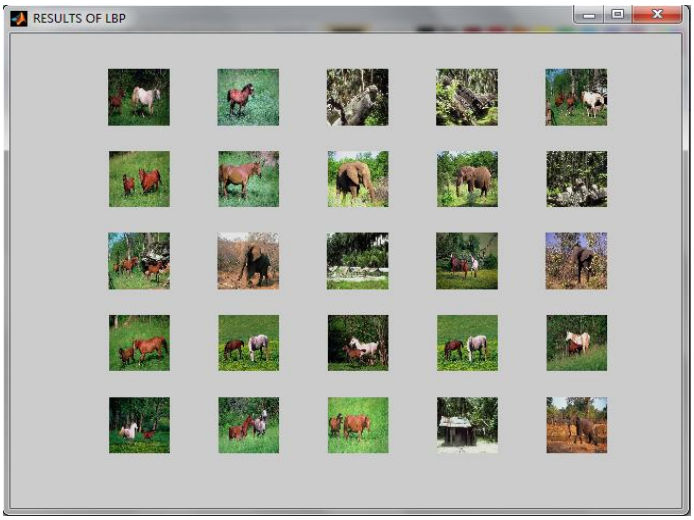


b(ii)

Figure6.5 Results of Color Histogram for Animals

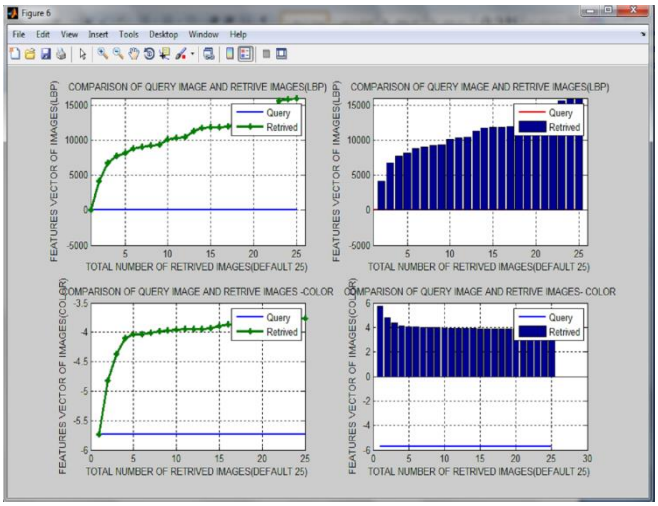


b(i)

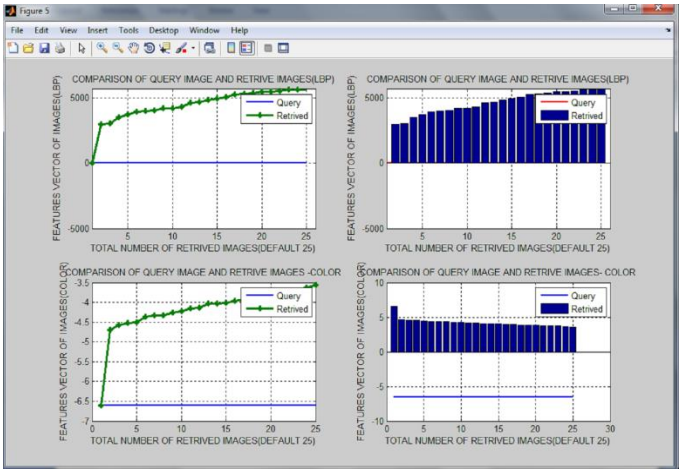


b(ii)

Figure6.6 Result of LBP for Animals

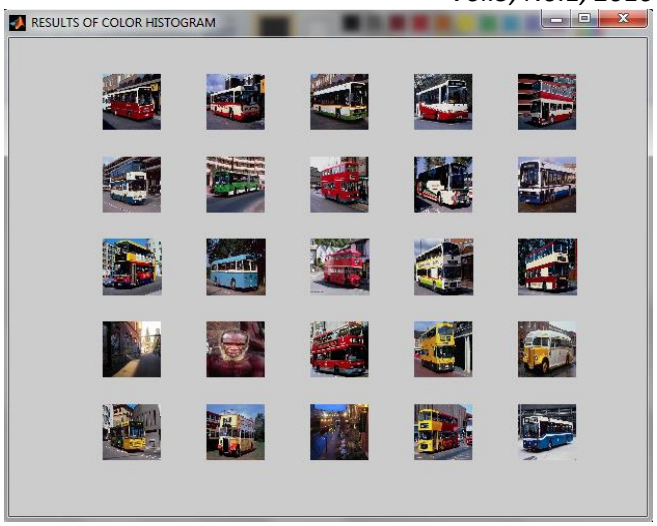


b(i)

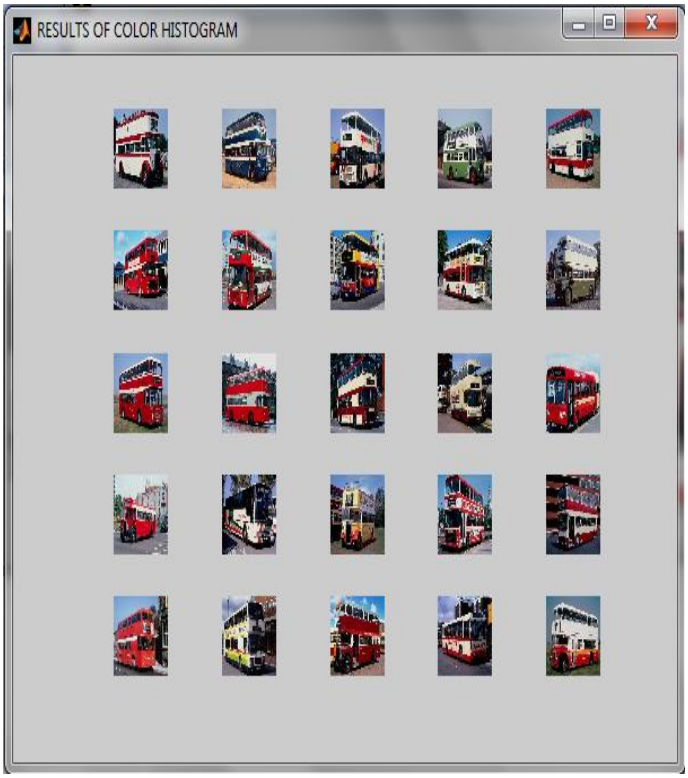


b(ii)

Figure6.7 Plots of Results for Animals

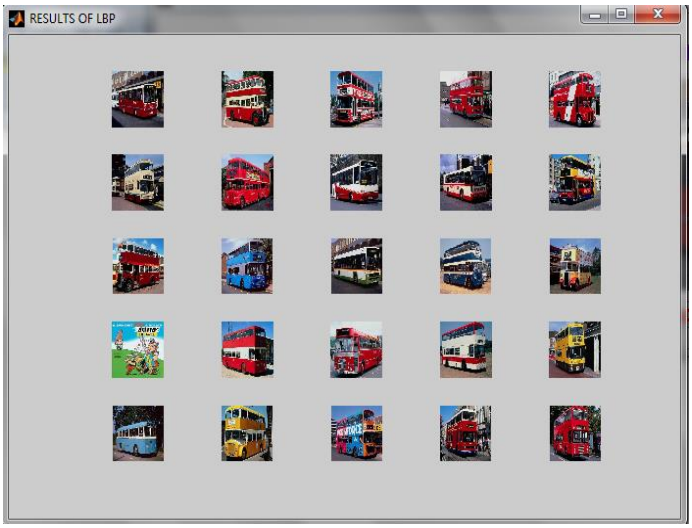


c(i)

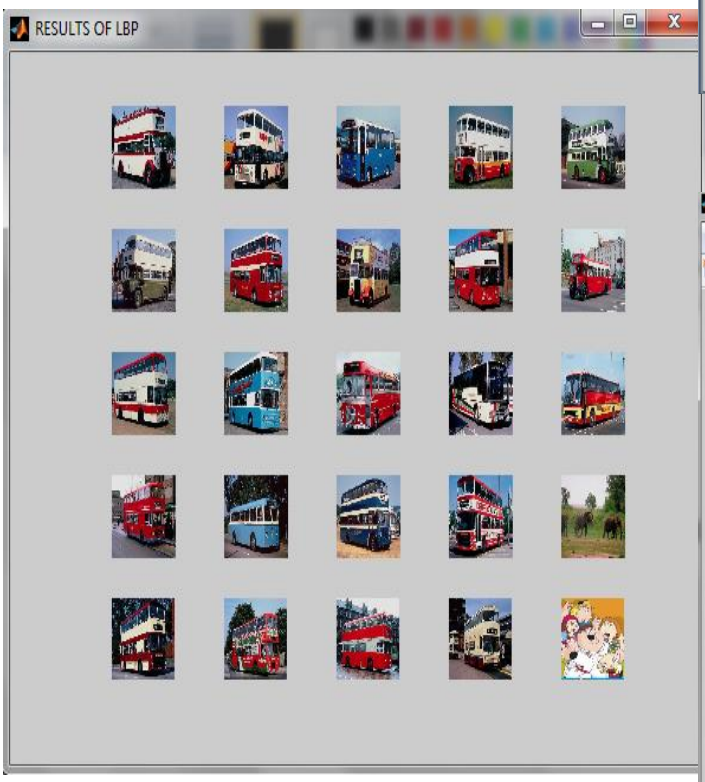


c(ii)

Figure6.8 Results of Color Histogram for Vehicles

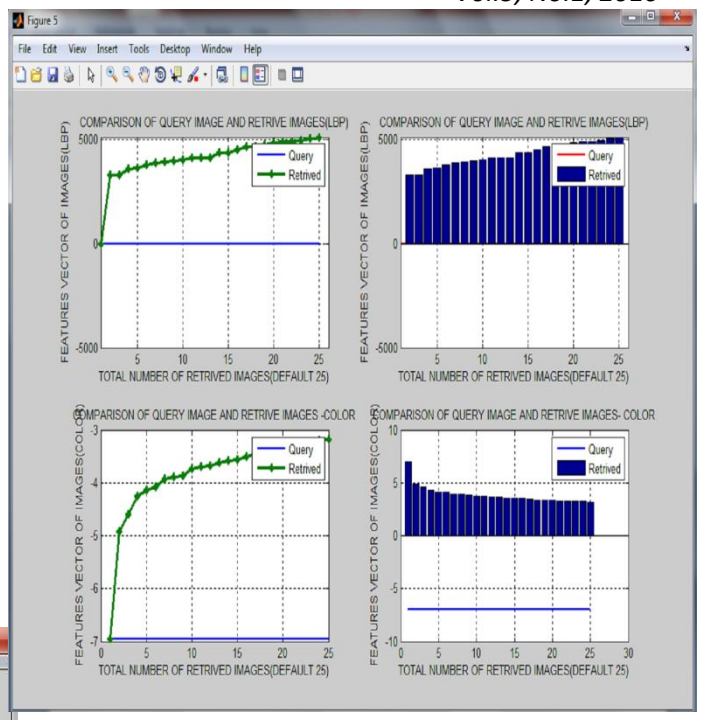


c(i)

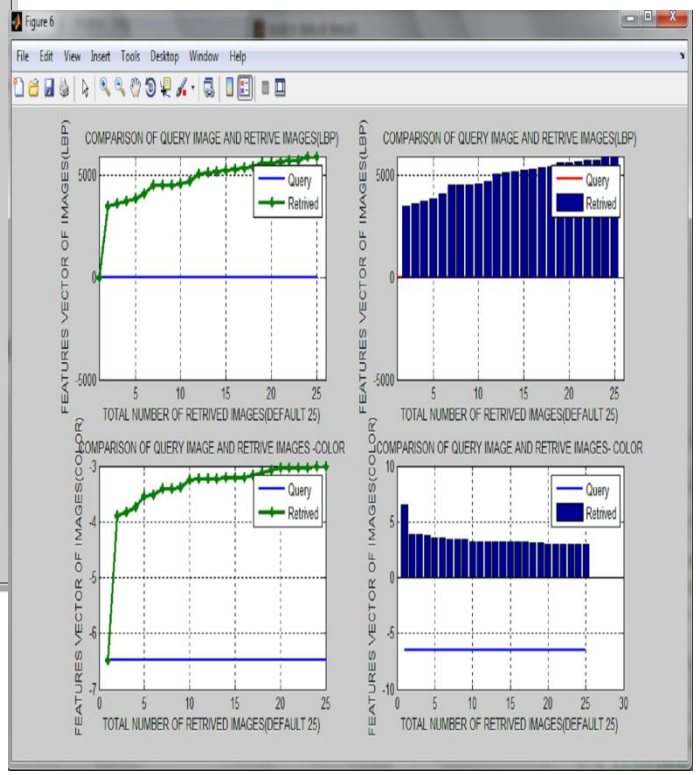


c(ii)

Figure6.9 Results of LBP for Vehicles

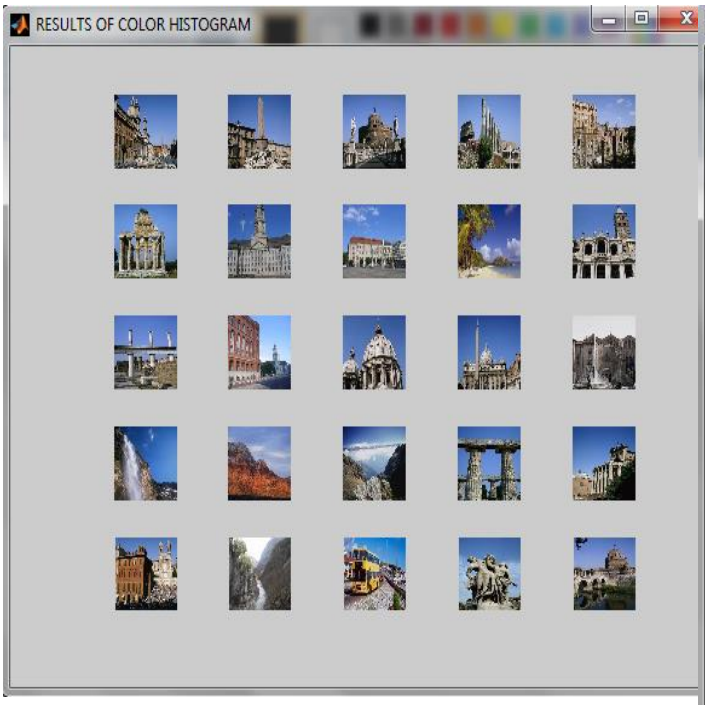


c(i)

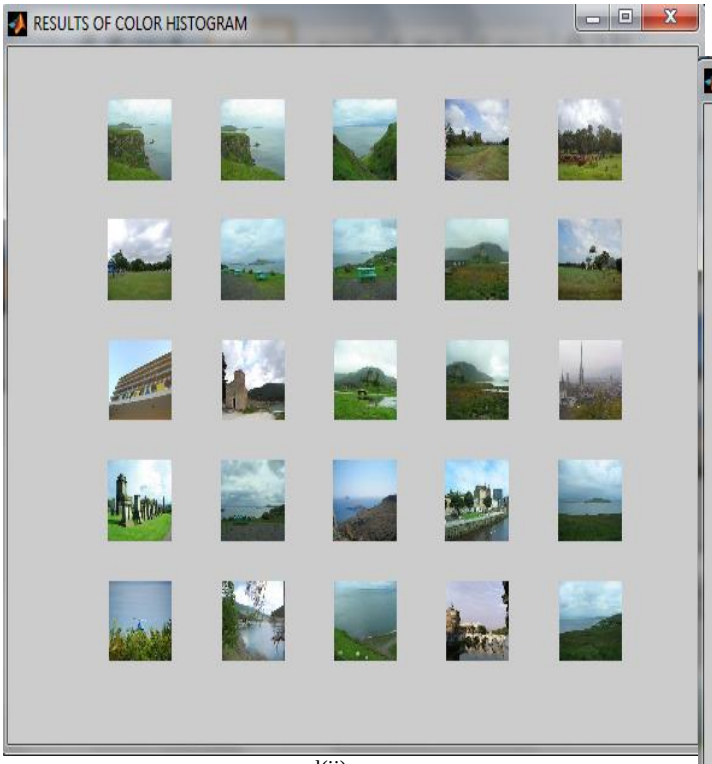


c(ii)

Figure6.10 Plots of Results for Vehicles

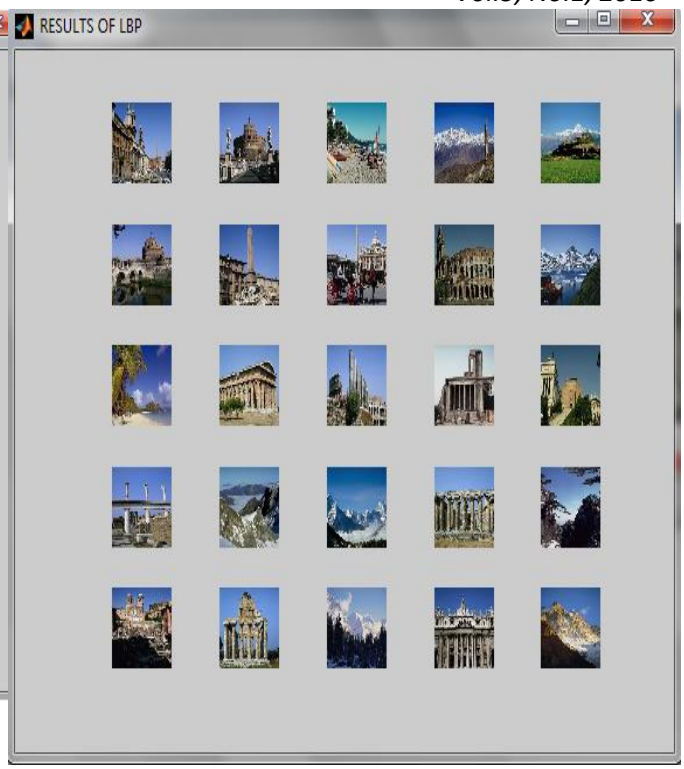


d(i)

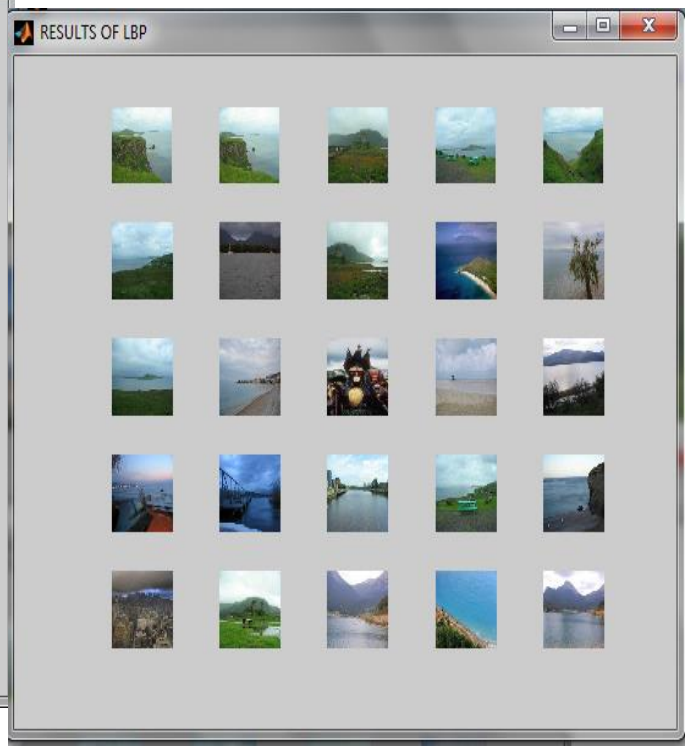


d(ii)

Figure6.11 Results of Color Histogram for Natural Scene

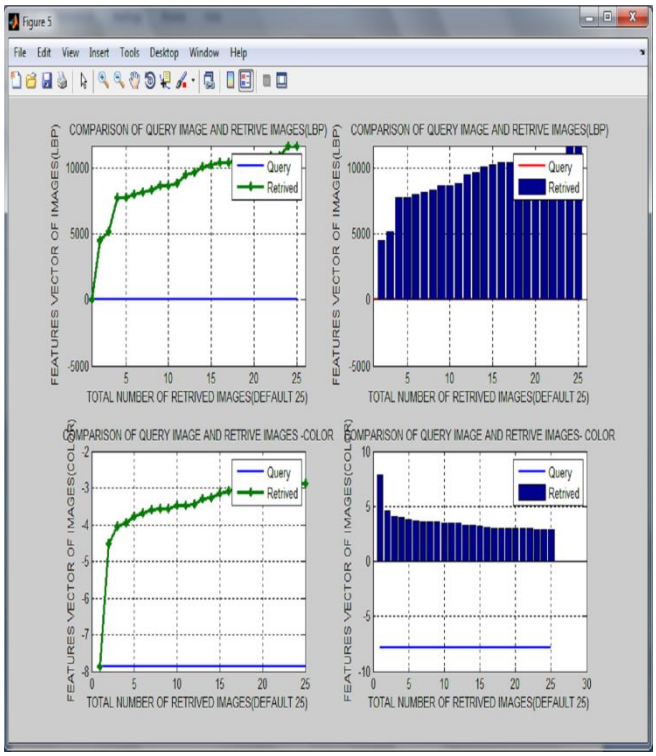


d(i)

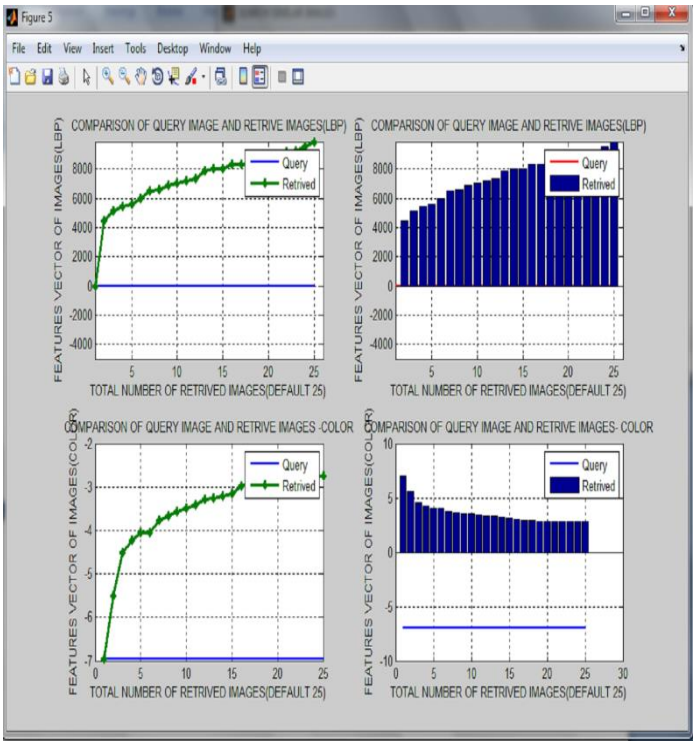


d(ii)

Figure6.12 Results of LBP for Natural Scene



d(i)



d(ii)

Figure6.13 Plots of Results for Natural Scene

Above are the results of histogram and LBP for each corresponding query image and also the plots of 25 images which shown how much retrieved images are similar to the query image. Figure6.1 shows the query images of different type, fig6.2, fig6.5, fig6.8 and fig6.11 are results for the color histogram method of query images which are shown in figure 6.1. The fig6.3, fig6.6, fig6.9 and fig6.12 are results for LBP.

6.1 Comparison of Color Histogram and lbp

From the above results shown, we have analysis that both of the methods given satisfactory result in different category like in case of animal and flower color gives the 99% precision while in case of vehicle LBP gives 99% precision but in case of natural scene both are given approximate the same precision percent. Precision is calculated by:

Image Category	Color		LBP	
	Precision	Error	Precision	Error
Flower	99%	1%	86%	14%
Animal	99.9%	0.1%	82%	18%
Vehicle	86%	14%	99%	1%
Natural Scene	82%	18%	86%	14%

Table 1 Precision percent of color and LBP method

VII. Conclusion and Future Work

We have designed and implemented a content-based image retrieval system that evaluates the similarity of each image in its data store to a query image in terms of color characteristics, and returns the images within a desired range of similarity. From among the existing approaches to color analysis within the domain of image processing, we have adopted the histogram approach to extract color features from both the query images and the images of the data store. Euclidean distance method has been used as the similarity measure between two feature vectors.

For the color content extraction, a well-known and powerful technique, color histograms, is used. The expressiveness of this technique is accelerated via color space transformation and quantization, and the images are smoothed by the help of color median filtering, a famous method for neighborhood ranking. The following section describes the contributions and major findings of the research.

Also we can enhance the retrieval percent by combining both the methodsi.e when color is merged LBP texture it can produce more than satisfactory result. For this we can do this in either two ways: both methods work simultaneously and (or) computation of one's result is followed by another.
From the result, we have found that histogram approach is more efficient and reliable in case of color feature is concerned. Also we have analyzed that histogram 32x32 give more accurate results than that of 128x128 but problem with 32x32 is that its processing time is high, therefore we

opted 128x128 to reduce the processing time and from the result it is clear that result are satisfactory. While when texture is concern LBP gives the better results as we can see from the above results

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