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Content Based Image Retrieval Using Color, Shape and Texture

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Abstract: Our content based image retrieval (CBIR) system is capable of retrieving similar images from image database based on color, shape and texture. Color, texture and shape informations are primitive image descriptors and play a significant role in image retrieval purpose. CBIR systems extract these embedded image features from images and then utilize them to compare similarity between a query image and database images. The three fundamental bases in content-based image retrieval are features extraction, features matching, and retrieval of similar image for the matched features. In this work, we present a framework for the CBIR system providing color, texture and shape feature based image retrieval methods along with a combined retrieval method of all these three. In our CBIR system, as we observed, the retrieval efficiency is found to be satisfactory in terms of precision and recall.

Keywords: CBIR, Precision, Recall

I. INTRODUCTION

All manuscripts Content-based image retrieval (CBIR) plays a central role in the application areas such as multimedia database systems and has been used widely in recent years. In this chapter, we will discuss some introductory concepts related to CBIR.

A. Content Based Image Retrieval:

Content-based image retrieval (CBIR) is a technique used for retrieving similar images from an image database. It is also known as query by image content and content-based visual information retrieval.

CBIR is the application of computer vision to bring an efficient solution to the problem that arises in searching and retrieving of digital images from large image databases. Content-based means that the search makes use of the contents of the images (i.e., Color, texture and shape features) rather than relying on human-input metadata such as captions or keywords. In CBIR, each image that is stored in the image database has its features extracted and later on they are compared to the extracted features of the query image for retrieving similar images from the database. It involves two steps:

a. Feature Extraction: The first step in this process is to extract the image features to a distinguishable extent.
b. Feature Matching: The second step involves matching these features to yield a result that is visually similar.

The most challenging aspect of CBIR is to bridge the gap between low-level feature layout and high-level semantic concepts. Different CBIR systems have adopted different techniques. Few of the techniques have used global color and texture features where as few others have used local color and texture features.

B. Motivation:

The work presented in this report is motivated by the present spurt of research in the field of image classification and retrieval. Huge amount of multimedia content demands a sophisticated analysis rather than simple textual processing (metadata such as annotations or keywords).

Traditional methods for retrieving images are not very satisfactory or may not meet user demand. For example, in Google image search, typing ‘Apple’ returns the ‘Apple’ products as well as the apple fruit. Main reason is the ambiguity in the text language. Several other limitations are there.

Here, we will attempt to understand this broad field of Content based Image Retrieval and will try to design a new efficient CBIR framework & develop the system.

C. Objective of the Project:

Research and development issues in CBIR systems cover a range of topics, many shared with mainstream image processing and information retrieval. The main objectives of our project are as follows:

a. To study the CBIR Concepts.
b. To study the various existing techniques/algorithms in the area of CBIR.
c. Understanding the user’s needs and information-seeking behaviour in case of image retrieval.
d. Identification of suitable ways of describing image content and extracting such features from raw images.
e. Matching query image with database images in such a way that reflects human similarity judgments.
f. Efficiently accessing database images by content i.e., Color, Shape & Texture.
g. Providing a user friendly interface to CBIR system.

II. BACKGROUND CONCEPTS AND RELATED WORKS

In an image, embedded content features are mainly of three kinds- Color, Shape and Texture. Content based image

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retrieval (CBIR) systems use these features in its image retrieval purpose. In this chapter, we will elaborate the background concepts and related work done in the area of CBIR.

A. Challenges of Content Based Image Retrieval:

Present image retrieval techniques integrate both low-level visual features, addressing more detailed perceptual aspects, and high-level semantic features underlying more general conceptual aspects of visual data. Neither of these two types of features is sufficient to retrieve or manage visual data in an effective or efficient way. Although efforts have been devoted to combining these two aspects of visual data, the gap between them is still a huge barrier in front of researchers. Intuitive and heuristic approaches do not provide us with satisfactory performance. Therefore, there is an urgent need of finding and managing the correlation between low-level features and high-level concepts.

B. Color Based Retrieval Concepts:

Several methods for retrieving images on the basis of color similarity have been described in the literature, but most are variations on the same basic idea. Each image added to the collection is analyzed to compute a color histogram [1] [2] which shows the proportion of pixels of each color within the image. The color histogram for each image is then stored in the database. At search time, the user can either specify the desired proportion of each color (75% olive green and 25% red, for example), or submit an example image from which a color histogram is calculated. Either way, the matching process then retrieves those images whose color histograms match those of the query most closely. The matching technique most commonly used, histogram intersection, was first developed by Swain and Ballard, in 1991. Variants of this technique are now used in a high proportion of current CBIR systems. Methods of improving on Swain and Ballard's original technique include the use of cumulative color histograms, combining histogram intersection with some element of spatial matching, and the use of region-based color querying. The results from some of these systems can look quite impressive.

C. Shape Based Retrieval Concepts:

The ability to retrieve image by shape is perhaps the most obvious requirement at the primitive level. Unlike texture, shape is a fairly well-defined concept – and there is considerable evidence that natural objects are primarily recognized by their shape. A number of features characteristic of object shape (but independent of size or orientation) are computed for every object identified within each stored image. Queries are then answered by computing the same set of features for the query image, and retrieving those stored images whose features most closely match those of the query. Two main types of shape feature are commonly used – global features such as aspect ratio, circularity and moment invariants and local features such as set s of consecutive boundary segments. Alternative methods proposed for shape matching have included elastic deformation of templates, comparison of directional histograms of edges extracted from the image, and shocks, skeletal representations of object shape that can be compared using graph matching techniques. Queries to shape retrieval systems are formulated either by identifying an example image to act as the query, or as a user-drawn sketch [3]. Shape matching of three-dimensional objects is a more challenging task – particularly where only a single 2-D view of the object in question is available. While no general solution to this problem is possible, some useful inroads have been made into the problem of identifying at least some instances of a given object from different viewpoints. One approach has been to build up a set of plausible 3-D models from the available 2-D image, and match them with other models in the database. Another is to generate a series of alternative 2-D views of each database object, each of which is matched with the query image. Related research issues in this area include defining 3-D shape similarity measures, and providing a means for users to formulate 3-D shape queries.

D. Texture Based Retrieval Concepts:

The ability to retrieve images on the basis of texture similarity may not seem very useful. But the ability to match on texture similarity can often be useful in distinguishing between areas of images with similar color (such as sky and sea, or leaves and grass). A variety of techniques has been used for measuring texture similarity; the best-established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity, or periodicity, directionality and randomness .Alternative methods of texture analysis for retrieval include the use of Gabor filters and fractals [4]. Texture queries can be formulated in a similar manner to color queries, by selecting examples of desired textures from a palette, or by supplying an example query image. The system then retrieves images with texture measures most similar in value to the query. A recent extension of the technique is the texture thesaurus, which retrieves textured regions in images on the basis of similarity to automatically-derived code words representing important classes of texture within the collection.

E. Related Work and Existing Systems:

A considerable number of image retrieval systems have been developed for commercial use and demonstration versions are in existence in the academic world. The commercial systems include IBM's QBIC [5], VIR image engine search from Virage Inc and Excalibur from Excalibur technologies. Several experimental systems exist in the academic arena, notable among them are Photobook system from Massachusetts institute of technology (MIT) [6], VisualSEEK system of Columbia University [6], MARS of University of Illinois [6] and NETRA of University of California [6]. But, here we will discuss only five CBIR systems whose systems of operation are most closely related to this project work. They are NETRA, RETIN developed by ENSA/University of Cergy-Pointoise, France [6], KIWI (Key-points Indexing Web Interface) of INSA Lyon, France [6], iPURE (Perceptual and User-friendly Retrieval of Images) developed by IBM India Research lab, New Delhi, India [6], and IMAGEMINER developed by Technologie-Zentrum Informatik, Uinversity of Bremen, Germany [6].

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a. NETRA:

NETRA CBIR system use color, texture, shape and spatial location. The descriptor for the color is color histogram obtained using training set of images. Texture feature descriptor is the normalized mean and standard deviation of the Gabor wavelet transform of the images. Shape feature descriptors are the curvature function of the contour, the centroidal distance function of the contour and the complex coordinate function of the contour. Spatial location descriptor is bounding box. The system allows query by example. Similarity matching is carried out in the Euclidean space.

b. KIWI:

KIWI system like the RETIN system detects key points in an image rather than the entire image. It uses color and shape. The color descriptor is color histogram while the shape descriptors are computed with the aid of Gabor filters. The system allows query by example. Similarity matching is carried out in the Euclidean space.

c. iPURE:

iPURE system operates using color, texture, shape and spatial location. The system segments the image into regions before deriving the features. Color descriptor is the average color in CIE's (Comission Internationale de l'Eclairage) LUV color space. Texture descriptors are by means of WOLD decomposition. Shape descriptors are size, orientation axes and Fourier descriptor. The spatial location descriptors are centroid, and bounding box. The system accept query by example. Similarity matching is carried out in the Euclidean space.

d. IMAGE MINER:

IMAGE MINER system use color, texture and shape. Color descriptors is color histogram, texture description is grey level co-occurrence matrix. Shape description is carried out using image contour size, centroids and boundary coordinates. The system feature description has the capability to classify scenes and generate description of the scene with keywords and values. The system allows query by example. Special module within the system carries out similarity matching.

III. FRAMEWORK OF OUR CBIR TECHNIQUE

This chapter gives details of the framework of our CBIR system and the techniques we used in developing our system.

A. Proposed System Architecture:

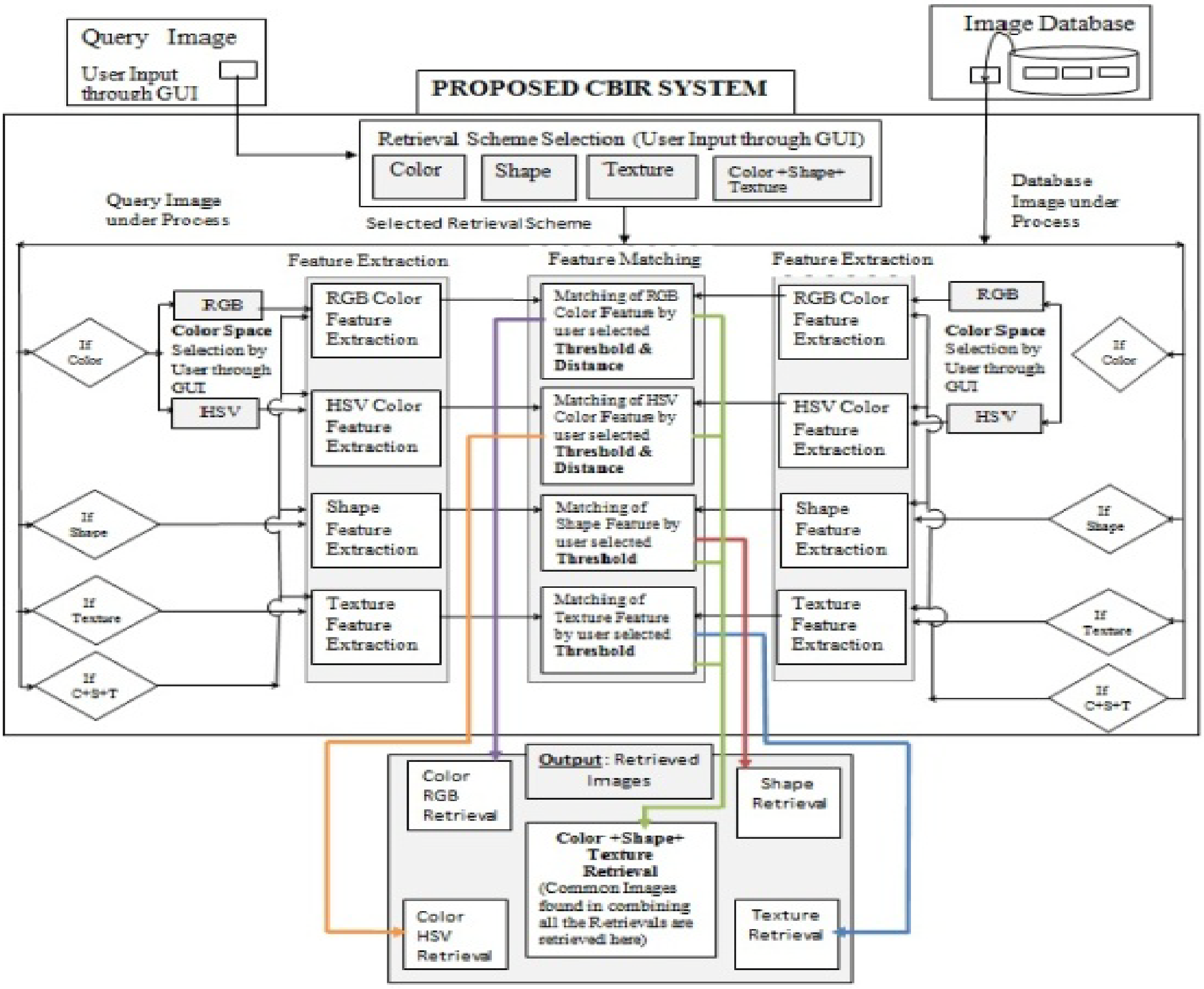

Figure 1: Architecture of proposed CBIR system

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B. Image Retrieval Technique Based on Color Feature :

Our CBIR system is capable of retrieving similar images by extracting the color features embedded in the images and uses a GUI for easy retrieval and parameter manipulation purposes. A stepwise representation of the retrieval process is given next.

First, the user inputs a query image. Let this query image be I(x, y).After loading the query image, pixel values are extracted either using RGB color space or HSV color space (here color space selection facility is given to the user through the system). Then these image pixel values are quantized into four color Bins (We used ranges from 0-63, 64-127, 128-191, and 192-255 for RGB color space & 0-0.2, 0.3-0.5, 0.6-0.8 and 0.9-1.0 for HSV color space).

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Once the query image has been quantized, images from the image database are taken one by one and the above procedure is followed for each of them till the quantization of image pixel values are over. Let J(x, y) represent the current database image, with which the query image I(x, y), has to be compared.

Let C_I^{Bn} be the number of quantized pixels in bin 'Bn' of the query image I(x, y) and C_J^{Bn} be the number of quantized pixels in bin 'Bn' of the database image J(x, y). Then to find the distance between the two images, Euclidean distance [] or Mahalanobis distance [] may be used. This distance selection feature is provided in our system through GUI. The distance may be computed by the formulae given below:

For Euclidian distance:

$$\text{Dist\_val}=\sqrt{\sum_{C=R,G,B \text{ or } H,S,V} \sum_{Bn=1}^{total\_bin} \left(c_I^{Bn} - c_J^{Bn}\right)^2}$$

For Mahalnobis distance:

$$\text{Dist\_val}=\sqrt{\sum_{C=R,G,B \text{ or } H,S,V} \sum_{Bn=1}^{total\_bin} \left(C_I^{Bn} - C_J^{Bn}\right)^t s_{Bn}^{-1} \left(C_I^{Bn} - C_J^{Bn}\right)}$$

Where s_{Bn}^{-1} is the Covariance matrix of the quantized pixel values in bin 'Bn'

In the final step, above computed Dist_val is compared with the threshold value (user selects through GUI) and for the nearest Dist_val with threshold, similar images are retrieved as per their rank of similarity.

C. Image Retrieval Technique Based on Shape Feature

In case of retrieving similar images by extracting the shape features embedded in the images, our CBIR system follow the stepwise process mentioned below:

a. First, the user inputs a query image. Let this query image be I(x, y).After loading the query image it is resized to a particular size (we take 150 × 150 as the resize window).
b. This resized image is then converted into grayscale image if it not in grayscale.
c. Now we perform Canny edge detection on the grayscale image. The points where edges are detected are termed as white points and all other points are termed as black points. We keep counts of the total white points using a counter TWI.
d. After the above step, images from image database are taken one by one and the above procedure is followed up to the detection of white and black points.
e. Now we check if the pixel positions of the white points of the current database image and that of the query image are same or not. If the pixels positions are found to be same, we term these pixel positions as matched points and also take a count of these total number of matched points by keeping a counter TMP('TMP' is initially assigned a value '0' before each matching of the images).

Mathematically, if I(x, y) and J(x, y) are the edge values (white points) at the pixel position (x, y) for the query image and the current database image respectively, then the images I and J may be shape compared as follows:

If I(x, y) =J(x, y) =1 (here'1' is assigned for matched points)

Then the TMP is incremented by 1. This process is continued for all pixels in the images to be compared.

f. Now total matched points percentage (TMPP) is calculated by the following formula:

$$\text{TMPP} = \frac{\text{TWI}}{\text{TMP}} \times 100\%$$

Here, TWI is the total white points in the query image I.

g. Finally, the TMPP value is compared with a standard threshold value (user selects this threshold value through GUI) and for the nearest TMPP with threshold, similar images are retrieved as per their rank of similarity.

D. Image Retrieval Technique Based on Texture Feature:

To retrieve similar images by extracting the texture features embedded in the images through our CBIR system, we have used the Invariant Color histograms [7] method.

Normally, color histograms are a very useful and simple descriptor for image regions. However, if the same region is viewed from different positions, we have different histogram results. Here, we have used the Invariant Color histogram method to create color histograms that are invariant under any mapping of the surface that is locally affine. This invariant color histogram is generated

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from an image surface is intimately tied up with the geometry i.e., texture of that surface, and the viewing position and thus a very wide class of viewpoint changes or deformations.

The procedure followed in invariant color histogram is given next.

a. First, the user inputs a query image. Let this query image be I(x, y).
b. Now red, green and blue values of each pixel for the image I(x, y) are extracted.
c. The red pixel values are assigned into a channel denoted by f and the average of green and blue values for each pixel are assigned into another channel g as follows:
   For each pixel (x, y),
   $f(x, y) = red(x, y)$
   $g(x, y) = \frac{1}{2}(\ green(x, y) + blue(x, y)\ )$

Now derivatives are to be calculated for the above cited two channels f and g. These derivatives are taken in the simplest possible way through the Convolution process using two filters [-1 0 1] and $\begin{bmatrix}-1\\0\\1\end{bmatrix}$ as follows:

f_x= Convolution (f , [-1 0 1])
g_x= Convolution (g , [-1 0 1])

$$f_y = \text{Convolution}\left(f\ ,\ \begin{bmatrix}-1\\0\\1\end{bmatrix}\right)$$

$$g_y = \text{Convolution}\left(g\ ,\ \begin{bmatrix}-1\\0\\1\end{bmatrix}\right)$$

d. After the above step, the weight for each pixel (x, y) of the image is calculated by the following formula:

$$\text{weight}(x, y) = |\ f_x(x,y) \times g_y(x,y) - f_y(x,y) \times g_x(x,y)\ |$$

e. Now a 3d array containing the histogram is allocated. Let this array be h of size 5×5×5. Here in this algorithm, 5 color bins are used in each of the three color channels, resulting in a total of 125 bins. While calculating the color invariant histogram using the 3d array h, the value of 'weight' is added to each of the pixel as it corresponds to the geometry of the image surface i.e., the texture.
f. Once the values of 'weight' for each pixel position (x, y) of the query image I and invariant color histogram 'h' are calculated by using the above procedure, these values are also calculated for the current database image J.
g. Now the difference between the values of invariant color histogram 'h' of the query image I and the current database image J are calculated and its mean value is taken. This mean value is compared with the threshold value (user selects this threshold value through GUI) and for the nearest difference with threshold, similar images are retrieved as per their rank of similarity.

E. Image Retrieval Technique Based on Combined Feature:

Our CBIR system is capable of retrieving similar images based on the combined procedure using the extracted color, shape and texture features embedded in the images. While retrieving, a user has to select thresholds and distance measure for each of color, shape and texture through the system GUI.

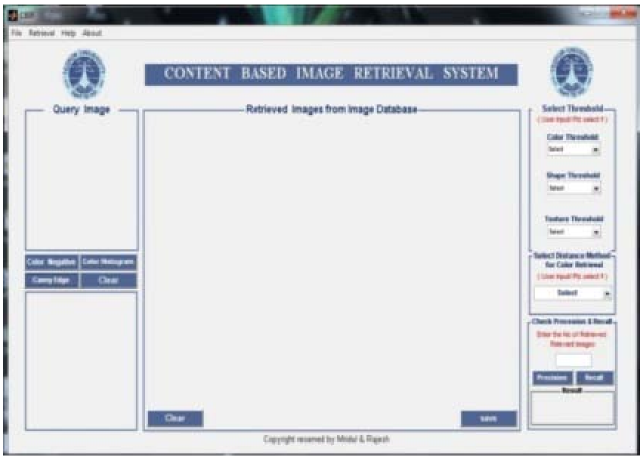
The procedure followed in Color+ Shape+ Texture retrieval is as follows:

a. First, the user inputs a query image. Let this query image be I(x, y).
b. Now all the three i.e., color, shape and texture feature based retrieval methods are used and three image retrieval queues are derived.
c. Finally, only the common images found in all the three retrieval queues are taken and retrieved which gives the most appropriate image match(s).

IV. RESULTS AND ANALYSIS

In this chapter, we present the experimental results with snapshots that were achieved through our CBIR system in retrieving images from an image database comprising of nearly about 100 different images. We have also analyzed the effectiveness of the developed CBIR system through the standard methods i.e., *Precision and Recall.*

A. Snapshots:



Figurw 2: CBIR System GUI

Figure 3: Output for Color RGB Retrieval

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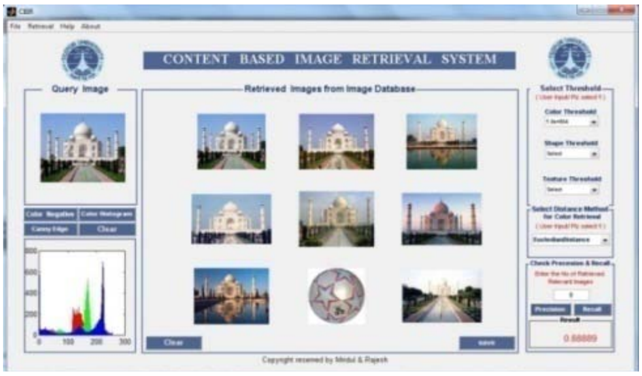

Figure 6: Output for Color HSV Retrieval

Figure 8: Output for Shape Retrieval

Figure 10: Output for Texture Retrieval

Figure 12: Output for C+S+T Retrieval

Figure 13: Some Portions of our Image Database

B. *Efficiency Analysis:*

In our CBIR system to assess the retrieval effectiveness, we have used the precision [8] and recall [8] as statistical comparison parameters .The standard definitions of precision and recall measures are given by following equations.

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of image retrieved}}$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the database}}$$

C. *Survey and Result Comparison:*

We have tested precision and recall of the images retrieved through different retrieval methods of our CBIR system. This test was carried over an image database comprising of 100 I mages. As per our observation, the retrieval efficiency of our CBIR system is found to be satisfactory in terms of precision and recall.

A survey report of tested precision and recall in our CBIR system in comparison to other's work is

Table 1: Survay report

IMAGE NAME		RGB COLOR	HSV COLOR	SHAPE	TEXTURE	C+S+T
apple1.jpg	TRHESHOLD(USER INPUT)	1.0e+004	1.0e+004	15	6	1.0e+004, 15,6
	DISTANCE METHOD	EUCLEDIAN DISTANCE	EUCLEDIAN DISTANCE	NA	NA	EUCLEDIAN DISTANCE
	PRECISION	0.888	0.777	0.800	0.555	1.000
	RECALL	1.000	0.875	0.500	0.675	0.125
ball1.jpg	TRHESHOLD(USER INPUT)	1.2e+004	1.2e+004	16	5	1.2e+004,16,5
	DISTANCE METHOD	EUCLEDIAN DISTANCE	MAHANLOBIS DISTANCE	NA	NA	MAHANLOBIS DISTANCE
	PRECISION	0.777	0.777	1.000	0.888	1.000
	RECALL	0.583	0.583	0.667	0.667	0.333
f2.jpg	TRHESHOLD(USER INPUT)	1.0e+004	1.2e+004	17	2	1.2e+004,17,2
	DISTANCE METHOD	EUCLEDIAN DISTANCE	EUCLEDIAN DISTANCE	NA	NA	EUCLEDIAN DISTANCE
	PRECISION	0.889	0.669	0.889	0.559	1.000
	RECALL	0.800	0.600	0.800	0.500	0.100
taj7.jpg	TRHESHOLD(USER INPUT)	1.4e+004	1.4e+004	16	4	1.4e+004,16,4
	DISTANCE METHOD	EUCLEDIAN DISTANCE	EUCLEDIAN DISTANCE	NA	NA	MAHANLOBIS DISTANCE
	PRECISION	0.667	0.889	1.000	0.556	1.000
	RECALL	0.462	0.615	0.615	0.384	0.076
um7.jpg	TRHESHOLD(USER INPUT)	1.6e+004	1.2e+004	15	4	1.2e+004,15,4
	DISTANCE METHOD	EUCLEDIAN DISTANCE	EUCLEDIAN DISTANCE	NA	NA	MAHANLOBIS DISTANCE
	PRECISION	0.222	0.333	1.000	0.556	1.000
	RECALL	0.153	0.230	0.692	0.384	0.076

Figure 14: Chart for tested precision and recall value in our CBIR system

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In our CBIR system, we have observed that, the average Precision value in % is = 78.76 and the average Recall value in % is = 61.00

Again the chart for tested precision and recall value in other's CBIR system [8] are given below:

Table 2: Precision and Recall values of different CBIR system

PRECISION AND RECALL VALUES IN %

Query Image	Color	Texture	EHD	All
1	21.8 28.0	50.0 15.0	23.6 34.1	35.2 60.0
2	100.0 98.0	75.0 62.0	87.0 68.0	100.0 78.0
3	74.6 59.0	20.0 10.0	65.0 37.0	42.8 90.0
4	91.7 24.0	75.0 33.0	85.6 34.9	92.0 28.0

In above, the average Precision value in % is = 64.98 and the average Recall value in % is = 47.43

So, after comparing our CBIR system's performance with the other one, it is clear that we have obtained better results.

V. CONCLUSION AND FUTURE WORK

Our Content-based image retrieval (CBIR) system utilizes three main embedded features in images i.e., Color, *Shape and Texture* to identify the similarity between a query image and the database image in purpose of image retrieval.

A user has been given the flexibility to select the any of the three feature based image retrieval method and to choose thresholds and distance method of his choice through a user friendly GUI in our developed CBIR system. Again one can easily analyze the efficiency in case of precision and recall which is also provided through our system GUI.

The results are found to be satisfactory for most of the query images and it is possible to improve it further by fine tuning the threshold and adding relevance feedback. Besides the already developed methods further approaches can be developed for better efficiency in the application of the image retrievals.

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