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A Novel & Efficient Fusion Based Image Retrieval Model for Speedy Image Recovery

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Abstract

An efficient and novel image retrieval system is framed here, which retrieve images from massive datasets to overcome the constraints of efficiency and retrieval time. Thus to address this issue, an effective indexing technique is proposed on the hybrid system constituted by low level features of the image. Firstly, features are extracted from the combination color moment, LBP and segmentation to form a hybrid feature space. To reduce its dimensional space, principle component analysis is exercised which provide lesser and good quality features. On this space, two expedient indexing techniques are proposed: cluster based and similarity based. The approach that is proposed here is an innovative design of a hybrid content based image retrieval system, as in this framework all the skilled techniques are merged to form a competent and dynamic image retrieval system. Five touchstone datasets are used to test the performance of the system. Extensive experiments are carried out which shows that the system with cluster based indexing technique provides highlighted results as compared to similarity based technique and also surpasses the other latest state of art techniques in terms of precision and retrieval time

Keywords: Content based image retrieval, PCA, Clustering Based Indexing, Similarity-Based Indexing, Local binary pattern

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1. Introduction

Content-based image retrieval (CBIR): CBIR is a method to retrieve the query image from databases that utilizes the properties of an image as search terms which further returns the similar images rather than incorporating metadata like tags or descriptions associated with the image. This is required as the profound amount of complex images are being produced with the up gradation of image capturing devices. Prior to the usage of CBIR, the only way to query image databases was using text-based image retrieval (TBIR). TBIR is vastly employed in various search engines including Yahoo, Google etc. [1]. However, there are various limitations to this approach as it's highly labor-intensive and requires manual annotation of images with tags. Also, this is an infeasible task in large-scale and heterogeneous collections of images because of certain errors that are brought into by the influence of human perception [2].One solution to TBIR limitations is CBIR which is completely automatic and looks at the images on the basis of its visual features such as color, shape, texture, edges etc.

Image representation using the content is profoundly a very confronting task as most of the significant information that is required is extracted is from the image only, which is exhibited in lower dimensionality space. CBIR system retrieves the comparable images mostly on the basis of color, shape and texture by using different feature extraction techniques. This system is capable enough to see the colors in a particular way and then finding the images' color similarly. Besides all that, it is also capable of looking at the texture, although there's no such fixed definition of what texture means to a computer. The chosen texture descriptors are capable of representing the texture properly and also have the property of compensating variations such as rotation, scale changes because these kinds of variations can distort the original appearance of the images [3]. Like texture and color, this system also extracts the shape of an image by incorporating a boundary-based and region-based technique that traces pixels around the boundary of a shape and concentrations of pixels in a specific area. Once it gets these features, then it compares them with the same features of the other images in the database using some mathematical computations.

When the image is a complex one, only the use of primary feature or a single feature will not be sufficient. Because a single feature is not being able to capture the variable details present in the images. To overwhelm this problem combination of features are employed. However, eventually, it is capable of computing and returning images whose average difference from the original image is the smallest [3]. The basic block diagram of CBIR system is shown in Figure 1.

CBIR systems has many applications; One of its application is image mining used by the pathologists, that allows them to look at large samples of bacteria and instantly discover similarities between them which otherwise take quite a long time. Also, it is used by police for face identification purposes of the criminals that assists them in drawing sketches and take photos and then compare them with the mug shots' database. Content Based Image Retrieval (CBIR) is one of the most effective ways to store, manage, index, search, browse, mine or retrieve images from a voluminous image repository. Many researchers are developing an effective and precise image retrieval system keeping time and space constraints less for an intensely competitive environment [4].

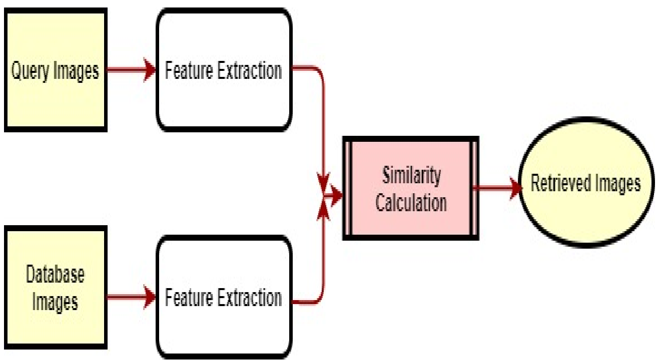

Figure 1. Block Diagram of a general CBIR System

The proposed framework here is different from others as it is a multi-model system with reduced time complexity. In this system, firstly the low level features are extracted from different techniques and a hybrid CBIR system is obtained. After this step, the PCA is practiced by which higher dimensional feature space is turned on to lower dimensions. Finally, indexing techniques are applied here for reducing the retrieval time and increasing the precision rate of the system. So the system that is designed here is ingenious and different from other state-of-the-art techniques as here all the finer or superior techniques are linked together in a proper way as described above to form a capable and efficient CBIR system. Moreover, the proposed framework provides the superior value of precision, recall and time as compared with other latest techniques.

This paper is structured as follows: The Section 1 provides the introduction about Image Processing, Image Retrieval, CBIR technique, and an overview of the proposed approach. Section 2 discusses the literature work relevant to the proposed work of Hybrid and intelligent CBIR system. Section 3 gives the details about feature extraction technique, Indexing techniques that are used in the work. In the next section the main proposed work by an overall flow diagram, and algorithm is explained. Section 5 is the result and discussion section. In this section the outcomes of the indexed CBIR system are presented. In 6th part the performance of the proposed framework with the existing is tabulated and in the last section image retrieval results are displayed. After that, concluding summary is explained.

2. Related Work

This section gives the review on various previous works mainly on CBIR systems, hybrid systems, dimensional reduction methods and various indexing techniques. Different features extraction techniques that are used in these systems have their own pros and cons and when these features are properly selected and combined together the system become more compelling.

The most commonly used color descriptors in CBIR systems are color histograms. The color histogram of an image is represented in various color spaces such as CIE, RGB, XYZ etc. [5, 6]. Since, mostly the spatial organization of colors is not taken into consideration; this issue can become critical in CBIR for image collections on a large-scale. The descriptor for this was designed by this spatial knowledge over histograms which include MPEG-7, color layout descriptor (CLD), Dominant color descriptor (DCD) and color structure descriptor (CSD) [7]**.** In the field of recognition in visual object classes the new multi-scale LBP technique was employed as the simple LBP was not efficient while dealing with lighting changing conditions in images. This new operator had the property of photometric invariance and is multi-scale but at the expense of increased complexity. Moreover, the precision is also not very high [8]. Another advanced texture technique was framed called local tri-directional pattern which used the pixel's intensities in the three directions of its neighborhood. So, this method provides better features as compared with other techniques [9]. Another effective image retrieval method was designed based on the multiscale LBP technique for the retrieval of images from large databases. Different combination of LBP codes were evaluated by the integration of the eight neighbourhood pixels. Final feature vector was obtained from GLCM technique. The results were calculated from many benchmark datasets which proved to be much more effective than single scale LBP technique used for extracting texture of the images. This designed multi-scale LBP method was able to capture the most dominant features of the images that were not captured by normal LBP technique

[10] **.** Due to some close duplicate images the problems of infringement and redundancy of copyright in large image collections exists, so the solution to these problems was proposed that includes the concept of indexing. In this framework, the query image was enhanced followed by features' extraction based on SURF (Speeded up Robust Features) which was used for extracting the local invariant features. Afterwards, similarity measure was computed amongst the feature extracted images incorporating min-hash algorithm [11]. Pavithra et al. proposed a hybrid framework for a much more effective retrieval of the similar images by utilizing color, edge and texture features. The color moment technique here was used initially to filter out the images and after that the canny detector and LBP feature were integrated to make the hybrid system. The key components of this proposed research are the better feature extraction techniques along with the searching space reduction. To add up, the proposed methodology was implemented on the Wang's, Corel-5K and Corel-10K databases [12].The information of local relationship between pixels is not given by the raw images and that knowledge is required by the descriptors. So in order to overcome this issue or to gain information regarding this, new approach was designed. By this approach, patterns were extracted by multiple filtered images in which images were filtered using BoF and after that LBP technique was applied on every image [13]. Sadegh Fadaei et al. proposed the new CBIR scheme which was the optimization of color and texture features to improve the precision rate of the system. Dominant Color Descriptor (DCD) features were extracted from HSV color space and to extract texture features wavelet and curvelet were applied and finally these three features were combined optimally by optimization algorithm which is particle swarm optimization algorithms [14]. In [15] another hybrid CBIR system is framed composed of SURF and color moments to so that the accuracy of the system may be increased in applications related computer vision. For the indexing and similarity matching, KD-tree algorithm was used and at last the algorithm known as voting scheme was applied for ranking the retrieved images**.** A new system was proposed, based on three feature extraction techniques, Color and texture features are the main contents of the images which were extracted by color co-occurrence matrix (CCM) and difference between the pixels of scan pattern (DBPSP). The third image feature is based on color distribution, termed as color histogram for K-mean (CHKM) [16].

A capable system was designed by the integration of all the three features of the CBIR system for the achievement of better retrieval efficiency. In the first step, the image was predetermined by the algorithm called color quantization with the merging of clusters and afterwards an insignificant amount of dominating colors and their final percentages are achieved. Secondly, the spatial texture features were extracted by steerable filter decomposition. And after that, for the extraction of the shape pseudo-Zernike moments were integrated for the representation of the images [17]. Another CBIR was designed based on the integration of texture and color features. Color correlogram and coherence vector were used to extract color features and SURF features were also extracted. Multidimensional feature space was created and for the quantization purpose BoVW method was used. For enhancing the accuracy of the system multi-class SVM was used which works as a classifier for the big databases [18]. Another system based on identification and indexing of the duplicate images was proposed [19]. In this proposed method, firstly the image was enhanced and the features were extracted using SURF. For the evaluation of similarity between the images sim-hash algorithm was used. Local Sensitive hashing algorithm was used for indexing of near duplicate images. For decreasing the time of retrieval of images in large databases, another CBIR system was designed using only texture features. This texture descriptor was the combination of LTP and GLCM. In this approach, The LTP's of all the pixels are calculated and after that the relation between them is computed by GLCM technique. It is basically a texture based CBIR system [20]. In [21] different type of image retrieval system was designed using hashing based similarity search. It reduces the feature space and thus reduces the computational time and provides the good performance. Learning method that is joint binary codes was proposed which combines the image features to latent semantic features and is known as LSMH. An efficient hybrid CBIR system was proposed and tested on different distance measures such as Euclidean, manhattan, minkowski and many more. This was the combination of color and texture features using color moment, histogram, SWT and gabor wavelet techniques. For enhancing the precision value, various types of directivity descriptors were employed [22].

The literature studies show that the CBIR systems which are designed with the combination of low level features provides the preferable results as compared to that which are framed by using a single technique. Another major gap that is reported in the survey is the retrieval time and the complexity of the system. So the system designed here is the aggregation of color moment, LBP and shape features for the extraction of all the low level features so that an efficient CBIR is framed. Moreover, the retrieval time of images is also very less as the suitable indexing techniques are applied on the hybrid feature vector which makes the system more dynamic and simpler.

3. Main Contributions

The feature extraction techniques which are implemented in this work are color moment, Local binary pattern (LBP) and auto segmentation. The two indexing techniques that are utilized here are similarity based indexing and cluster based indexing. These techniques are explained in detail in the below headings.

3.1 Color moment for color feature extraction

Preferentially, color moment technique is opted to capture the images' details because of its lowest complexity and swifter response comparative to the other approaches including histogram based dominant color descriptor. Besides, it also escalates the overall effectiveness of the system [23]. It facilitates the statistical measures that are capable of expressing the crucial details which are present in the image. It avails the information related to the pixel distribution in the images in two compressed forms only [24].

The global computation of first and second order moments i.e. mean and standard deviation is done from RGB color space that are presented in Equations (1) and (2). Mean facilitates average information about the color in the image and standard deviation is the pixels' count that varies from the mean

$$\text{Mean (Ir)} = \frac{1}{XxY}\sum_{i=1}^{X}\sum_{j=1}^{Y} Pcij \quad \text{, r=[R, G, B]} \tag{1}$$

Ir = color channel information

X, Y= row and column size of image

$Pcij$=image pixel value in ith row and jth column

$$\text{Std }(I_r) = \left(\frac{1}{XxY}\sum_{i=1}^{X}\sum_{j=1}^{Y}(P_{cij} - Mean(I_r))^2\right)^{\frac{1}{2}}, \quad \text{r =[R, G, B]} \tag{2}$$

3.2 LBP for Texture Extraction

Texture is known to be one of the dominant features in CBIR systems to retrieve the relevant images. For texture, LBP feature extraction technique is used on a large scale for ample number of applications in image processing because of its simplicity, performance and implementation. Therefore, the designed hybrid CBIR system incorporates LBP for extracting the texture from the images [12].

The extensive usage of LBP texture descriptor is due to its illumination and rotational invariant properties. At first, pre-processing step is executed where the RGB image is transformed into grey scale followed by the division of image into smaller sub matrices of size 3×3 from which the feature extraction take place. All the extracted features procured from these smaller sub matrices are merged to form one feature histogram that represents the whole image [25].

Its working is based entirely on the variations between the centre value of the pixel and the neighbour pixel. The binary code for every pixel is generated from the step of thresholding of neighbour pixel along with the centre pixel as given in Equation (3) and Equation (4).

$$LBP_N = \sum_{i=0}^{N-1} f(P_i - CP)\, 2^i \tag{3}$$

$$\text{f (p)} = \begin{cases} 1; P \geq 0 \\ 0; P < 0 \end{cases} \quad \text{, N is total neighbouring pixels.} \tag{4}$$

$$Hist_k = \sum_{x=1}^{M}\sum_{y=1}^{M} f_2\,(LBP(x,y),k) \tag{5}$$

LBP is computed for the whole image followed by the framing of histogram that elucidates the entire texture of the image. Histogram of every individual bin is calculated using summation of the image pixel numbers as represented in Equation (5). LBP (x, y) is the value of x's row and y's column pixel position of the image. While computing the code of an image using LBP, all the undesired information of the edges is considered negligible in order to reduce the false information.

However, this operator is not specifically bounded up to eight neighbouring pixels as it can also uphold the relationship of pixels for greater distances from the centre pixel by assimilating some other thresholding values.

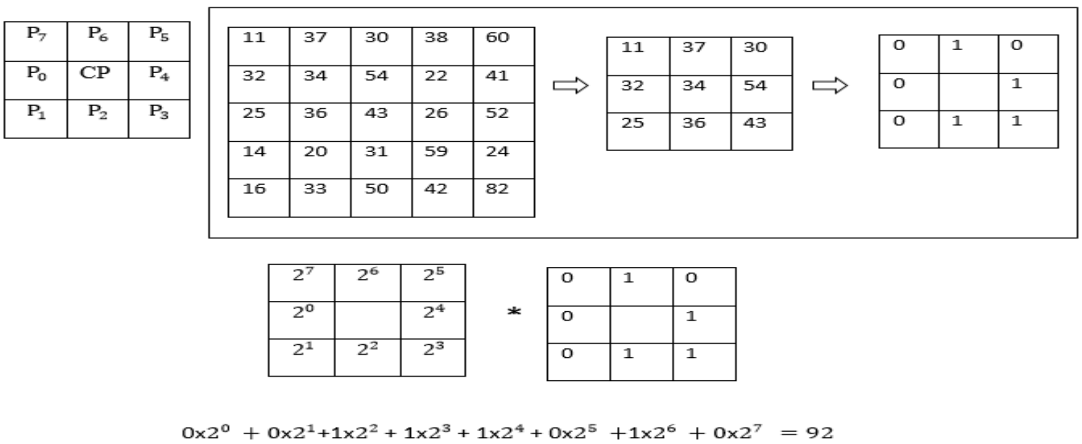

Figure 2. Calculation of Local Binary Pattern for every pixel

3.3 Shape feature Extraction

Very much like color and texture, shape is also one of the necessities and a considerable parameter when it comes to its integration with color and texture. Although, its extraction from the images is a very challenging task since in order to do so, one dimensional data is lost when a original 3-D object gets projected over the 2-D image plane [26]. Region area and contours are the primary source of shape features extraction. The models used for contours and areas are basically Fourier descriptors, spline fitting curves, gaussian curves etc. However, the bottlenecks with these models arise due to the missing out of boundary of shape information and when the performance of the system goes down [27, 17].

Shape extraction is done using different aspects with the calculation of various shape parameters such as mass, centroid, dispersion, solidity, variance, mean etc. These obtained parameters provide an approximate idea of the shape of the image. In this technique the image is segmented into classes. The most vital parameters of the shape include mass, centroid and dispersion are further evaluated and stored as a shape feature vector.

These are described in Equations (6), (7), (8) and (9). Mass is defined as the total number of pixels present in a single class.

$$\text{Mass}= \sum_{xy} m(a,b) \tag{6}$$

Where,

$$m = \begin{cases} 1, \; if \; i(a,b) \in c \\ 0, if \; i(a,b) \; \notin c \end{cases}$$

Centroid is the mask's centre where m is the mask of the cluster which is given as c, over the image i(a, b). The a_c and b_c are the co-ordinates which are given as

$$a_c = \frac{\sum_{ab} a * m(a,b)}{mass} \tag{7}$$

$$b_c = \frac{\sum_{ab} b * m(a,b)}{mass} \tag{8}$$

Dispersion is defined as the summation of all the regions of the class from the calculated centroid. For the measurement of this distance Euclidean measure is used.

$$D = \sum_i dist\left(d_c, d_{i,c}\right) \tag{9}$$

Where, dist $(d_c, d_{i,c})$ is the Euclidean distance
d_c Represents the centroid having class c
$d_{i,c}$ Represents the centroid of region of class c

3.4 Principle Component Analysis

In case of retrieval from large image datasets the features extracted are also very vast. So in those cases, the dimensional reduction is one of the main challenges in CBIR systems. Thus the features should be reprocessed by some efficient dimension reduction technique. These techniques are classified into unsupervised and supervised ones. In this paper, Principle Component Analysis [8] is used which is an unsupervised algorithm. PCA provides high image retrieval accuracy which has proved in the literature [28]. The basic principal features are extracted and mingled in a one module. The principal components which are extracted are also designated as eigen vectors.

For the calculations in PCA, the orthogonal transformation is used for the transformation of data into lower dimensional space.

Let the eigen vectors are $Z \in Y^{D \times N}$, where N is the number of features and D is the each eigen vector dimension. In this dimension reduction technique, projection matrix is used. $M = \{m_i\} \in Y^{D \times d}$, $(d < D)$ which reduces the dimension of features. The features of low dimensional inserted into the feature space is found in Equation (10)

$$W = M^T Z \tag{10}$$

For this, firstly the co-variance matrix is calculated as Equation (14)

$$\mu = \frac{1}{N_i} \sum_{i=1}^{N} f_i \tag{11}$$

$Cov = \sum_{i=1}^{N} (f_i - \mu)(f_i - \mu)^T$, where N is number of features $\{f_1, f_{2----} f_N\}$

μ= mean of image features

Eigen vector of M_{PCA} is an optional projection matrix which is estimated as in Equation (12)

$$M_{PCA} = \arg\max |X^T Cov\, X| \tag{12}$$

After that, Equation (10) is used for reduction of dimension of features

3.5 Similarity-Based Indexing

In case of similarity based indexing, the indexing of the database images is not done by making clusters. It is done by dividing the whole image dataset into the equal parts which is known as index. Every index has equal number of images. After that the index center is created by taking the mean of image features of every index which is described as index center features. The similarity based indexing technique is shown in Figure 3. Similarity between the query and database images is calculated by taking the difference between query image features and index centre features of all the dataset.

Below in the figure 3 the process of computing index centre for similarity based indexing is described where k is the index size:

- Partition feature matrix in K parts
- Calculate mean of each part as index center features

For every query image follow the steps mentioned:

- Check similarities of query image features to each index center features.

Pick the images whose difference is least from the index centre features.

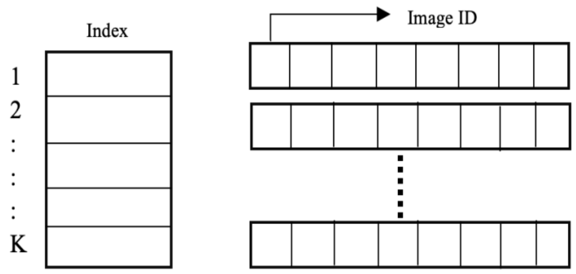

Figure 3. Indexing of images

However this technique provides the high efficiency and the precision rate but somehow the time taken by this indexing is higher than the clustering based technique because cluster based indexing runs automatically.

In case of similarity based indexing the similarity between the query image and database images any distance measure can be used like Euclidean, manhattan, sqeuclidean etc.

3.6 Clustering Based Indexing

Clustering is the type of an unsupervised machine learning algorithm. It is the technique of grouping unlabelled data in equal sizes based on the comparable features. Various types of clustering algorithms exist such as K-means, Fuzzy-C means, hierarchical and many more. Among these entire, K-means algorithm is uncomplicated, robust and fast learning algorithm [29]**.** In K-means clustering, complete dataset is classified into number of clusters say K of fixed sizes. After this, K centres defined one for every cluster. The centre points should placed in a proper way as different results are obtained on different locations. These points should be a long way from each other. Now associate each point of the dataset to its nearest centre by using the Euclidean distance between data points and centre which is given in Equation (13).

$$D(V)=\sum_{x=1}^{c}\sum_{y=1}^{c_i}\left(\|n_i - v_j\|\right)^2 \qquad (13)$$

Where,

c = cluster centers

c_i = data points in cluster i and $\|n_i - v_j\|$ is the Euclidean distance between n_i and v_j

After this step, a new centroid is computed from the given centres by the Equation (14) if data points are reassigned.

$$v_x = \left({}^{1}/_{c_i}\right)\sum_{j=1}^{c_i} n_i \qquad (14)$$

Then the distance is recomputed between the centroids and all the points in the dataset. The process is stopped if no points of dataset are reassigned, otherwise the process continues. Here dataset points refer to database images [30-32].

By using cluster based indexing technique, the query image is firstly compared with every cluster center. After that the ranking of these clusters is done depending upon the similarity measure with the query image. So, by using this type of technique the search area of the query image is reduced. Instead of searching from all the database images, the user is only concerned with the clustered images, which in turn decreases the retrieval time and increases the efficiency of the system.

4. Architectural Framework

In our proposed approach, an exclusive hybrid CBIR system has been described, which is the combination of color moment, LBP and auto segmentation technique. All these techniques of feature extraction are very superior as compared to others and connectedly provide prominent results as compared to individual ones. On this combined feature vector, PCA is applied so as to reduce the dimensions of the features and at last indexing techniques are applied on the PCA modified data. On these grounds, this approach is doubtlessly relevant and novel as in this system indexing techniques as well as PCA are applied along with the hybrid system. This complete system can be structured in 5 steps and is shown in Figure 4:

Step 1: Pre-processing: In this step, pre-processing of images is employed in which images are converted into required into desired color space such as RGB, HSV etc. All the images are indoctrinated to the fixed size in this phase.

Step 2: Feature Extraction and normalization: This step is based on the evulsions of the image features by LBP, color moment and shape parameters. The fused feature vector is obtained through min-max normalization method. With the process of normalization all the feature vectors comes to the common range. The features produced after this process is given as:

$$Normalized\ features = \frac{f - maximum}{maximum - minimum}$$

Where, f = feature value
maximum = uppermost value of every feature
minimum = lowest value of every feature

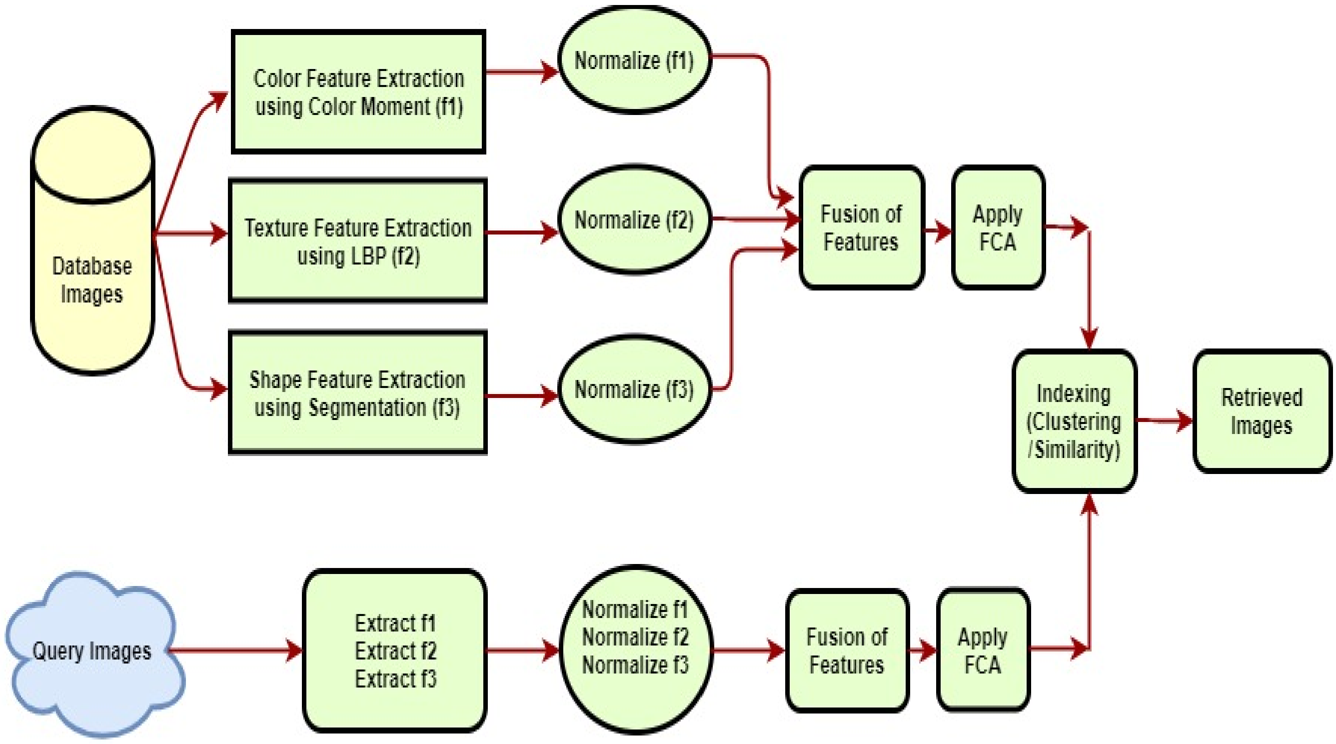

Figure 4. Proposed Framework

Step 3: Application of PCA: The next phase is the application of PCA on the fused feature vectors. These fused vectors are applied in the form of input to the PCA. It reduces the dimensions of the features produced by the above step so that the retrieval efficiency can be increased in large datasets also. In our proposed algorithm, the number of hybrid features that are generated are 80. But after the application of PCA these feature are reduced to 50.

Step 4: Indexing: In this step of designed architecture indexing techniques are analyzed which are similarity based and cluster based. By using these indexing techniques the similar type of images are maintained in particular index or clusters and the process of similarity calculation between the query and database images becomes a very untroublesome task. The retrieval time is deceased and accuracy is increased.

Step 5: Similarity matching & Retrieval: This is the last step of every image retrieval system. After the step of indexing, the indexes or clusters are formed of all the image databases used in the experiments. Now, according to the query image, similarity matching is performed between query image and the respective index/cluster to which it corresponds. The retrieved images are sorted in increasing order of the value of the used distance metric. Different types of distance metrics are there for the measurement of similarity, here in these experiments Euclidean distance is used which is given as:

$$D_E = \sqrt{\sum_{i=1}^{n} (|q_i - D_i|)^2}$$

Where, q_i and Di are the feature vectors of query and database image respectively.

4.1 Evaluation Metrics

The competence of these systems can be inspected in terms of various evaluation metrics. Most important parameters in these systems are precision and recall. They are defined in the below equations.

$$ARP = \frac{\text{No.of relevant images Retrieved}}{\text{Total No.of images Retrieved}}$$

$$ARR = \frac{\text{No.of relevant images retrieved}}{\text{No.of relevant images in database}}$$

Here, ARP is average rate of precision and ARR is average rate of recall.

5. Experimental Set Up and Results

5.1 Experimental Set Up

Experiments for the proposed system have been conducted on five benchmark datasets which are Corel-10K, 5K, 1K and GHIM-10K and Coil-100. The implementations are done on MATLAB-15A with 64 bit windows and 2GB memory. These are large datasets and contain different number and different type of images. All the three Corel datasets have same number of images in each category such as Corel-1K has 10 categories and each has 100 images, Corel-5K has 50 categories and each has 100 images and so on. The GHIM-10K dataset has 10,000 images divided into 20 categories. And the fifth dataset used here for the experiments is Coil-100 which comprises of 7200 images. The images in Coil-100 dataset are taken by the Computer Science Department in the Centre of Research on Intelligent Systems. The complete database contains total 100 objects with 72 poses of each object. The images of the 100 objects are taken at the 5 degrees pose internals. The sample images of all these datasets are shown in Figure 5.

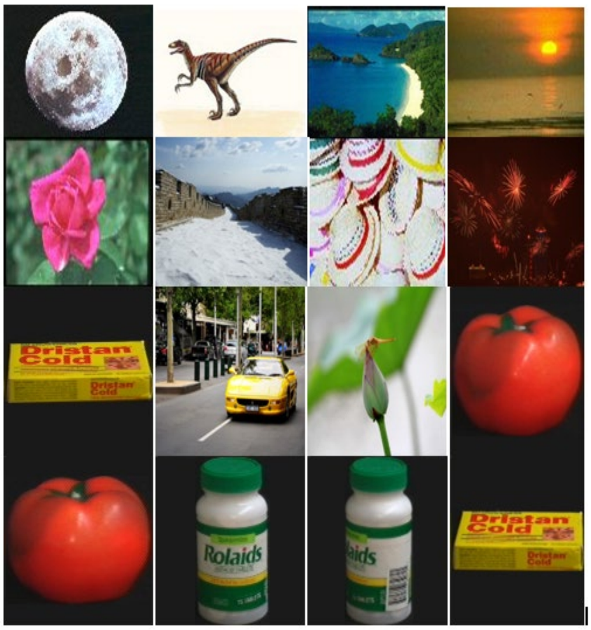

Figure 5. Sample images of all datasets

5.2 Experimental Results

By the above proposed framework, experiments are conducted on all the five databases for evaluating the performance parameters of the system by taking every image as the quey image and after that average value of precision is computed when top 10 images are retrieved. Precion, Recall and time is calculated for all the databases. The results of hybrid system with both indexing i.e cluster based and similarity based are displayed in Table 1 and Table 2.

Table 1. Average precision of hybrid system with cluster based indexing

Datasets	Average Precision (%)
Corel-1K	97
Corel-5K	88.5
Corel-10K	79.6
GHIM-10K	93
Coil-100	98

Table 2. Average precision of hybrid system with similarity based indexing

Datasets	Average Precision (%)
Corel-1K	94
Corel-5K	86
Corel-10K	75
GHIM-10K	91
Coil-100	94

The comparative graph showing the average precision of both systems designed by the cluster based indexing and similarity based indexing is shown in Figure 6

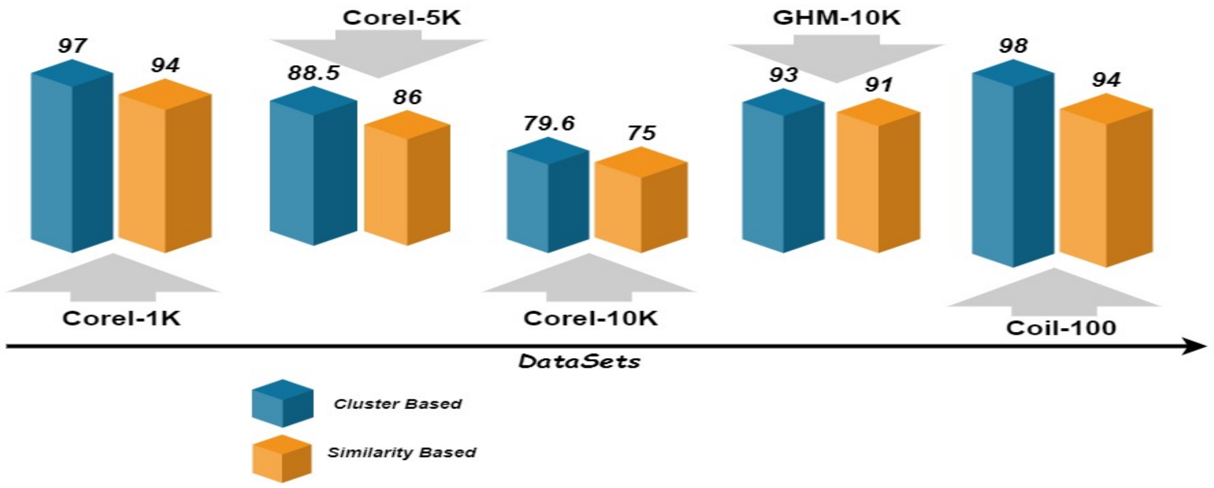

Figure 6. Comparison of average precision of both systems

Similarly like precision, time is also the most crucial parameter of the CBIR system. The collation of both the indexing techniques in terms of retrieval time of all the datasets are shown in Table 3. From the proposed image retrieval system, the time is calculated when top 10 images are retrieved matching with the query image.

Table 3. Time taken for retrieval of images in both indexing techniques (in seconds)

Datasets	Clustering Based	Similarity Based
Corel-1K	0.6	0.72
Corel-5K	0.75	0.82
Corel-10K	1.54	1.8
GHIM-10K	1.6	1.85
Coil-100	1.03	1.24

From the above experimental results shown in tables and figures, it has been proved that the proposed system with both the indexing techniques provide admirable precision rates and lesser retrieval time. However, it is also very undoubted from the above relative analysis that the hybrid system with cluster based technique provides a bit better results in terms of average precision as well as in case of retrieval time.

So finally the proposed CBIR system which is compared here with other latest techniques is by using the cluster based indexing technique.

6. Performance Comparison of the Proposed Method with other Techniques

The most decisive parameters to measure the overall efficiency of CBIR systems are precision and retrieval time. For authenticating the novelty in terms of precision and time of our proposed work, its comparison with other latest state-of-art methods is tabulated in Table 4 for Corel datasets Table 5 for GHIM-10K dataset and Table 6 for Coil-100 dataset.

The major critical issues that are reported in the literature studiesis the appropriate selection and combination of feature extraction techniques so that the framed CBIR system can provide prominent results in terms of precision, recall, f-measure etc. Another major concern that comes into action is the response time of designed CBIR system.

The designed framework in this manuscript overthrown all these constraints. First of all the hybrid system is designed by taking the combination of all the low level features by selecting suitable techniques. These are combined through the process of normalization. And to overcome the limitation of retrieval time fitting indexing technique is applied which makes the proposed CBIR system more efficient and divergent from others.

Table 4. Comparison of the average precision values of proposed method with other methods for Corel datasets

DataSet	Ref.[17]	Ref.[16]	Ref.[13]	Ref.[14]	Ref.[12]	Proposed
Corel-1K	67.2	72.7	65.4	76.5	83.2	97
Corel-5k	60.5	51.6	52	58.9	68.6	86.5
Corel-10k	49.22	24.6	36.7	49.78	59.9	72.6

Table 5. Comparison of the average precision values of proposed method with other methods for GHIM-10K dataset

DataSet	Ref.[21]	Ref.[10]	Ref.[8]	Proposed
GHIM-10K	52.02	76.99	32.79	90

Table 6. Comparison of average precision of proposed method with other methods for Coil-100 dataset

DataSet	Ref.[15]	Ref.[18]	Ref.[28]	Proposed
Coil-100	88	93	86	98

Along with the precision rate, the retrieval time of the proposed system shows much improvement as compared to other techniques. The comparison of retrieval time of the proposed method with other approaches on the 10 retrieval is graphically shown in Figure 7.

7. Image Retrieval Results

The GUI's of the retrieved images with clustering based indexing for the datasets GHIM-10K, Corel-1k and Coil-100 datasets are shown in are shown in Figures 8, 9 and 10 respectively by taking random query image from any category of the databases. These figures show the significance of the implemented work. In all these figures a random query image in entered in the designed system from the different databases and the top 10 images are retrieved. The retrieved images from the system show the efficacy of the proposed system.

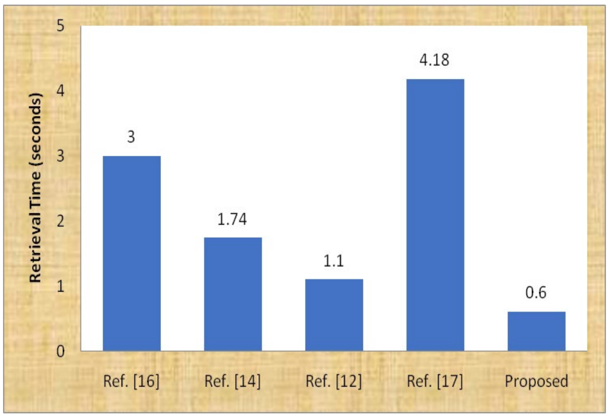

Figure 7. Comparison of retrieval time of the proposed method on Corel-1K database

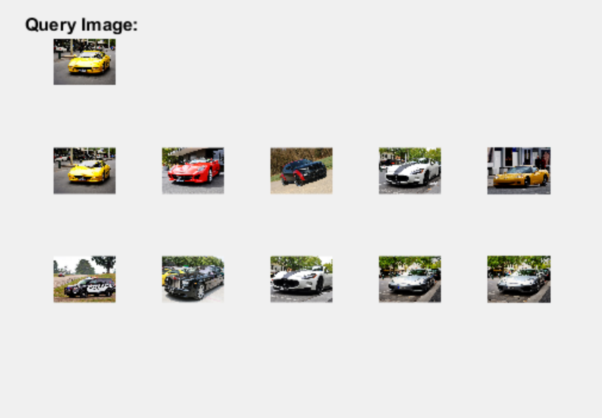

Figure 8. Retrieved top 10 images by proposed method from GHIM-10K dataset

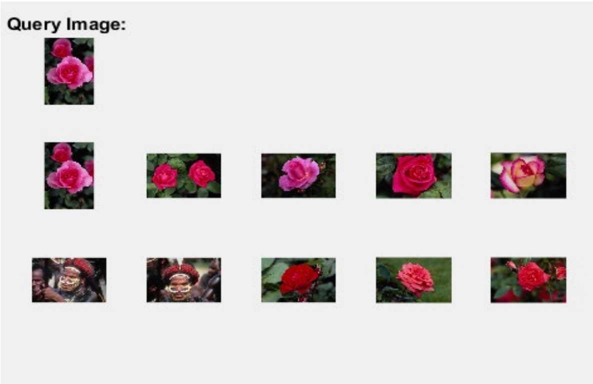

Figure 9. Retrieved top 10 images by proposed method from Corel-1K dataset

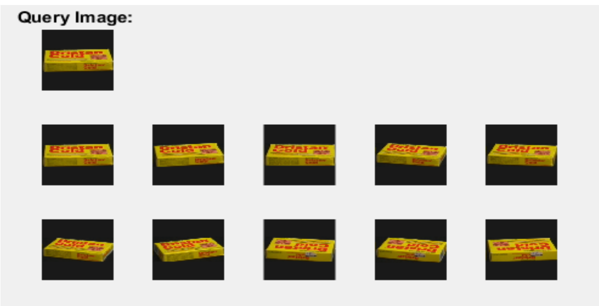

Figure 10. Retrieved top 10 images by proposed method from Coil-100 dataset

It is clearly observed from the above retrieval results that the images retrieved belong to almost from the same category of the query image.

8. Conclusion

A unique and innovative hybrid CBIR is devised in this paper so as to overwhelm the concern of retrieval time and efficiency of the system with larger datasets. The proper selection of features and searching space has the crucial role in these systems. Color, shape and texture features are extracted here for the formation of hybrid feature vector by the process of normalization. To decrease the dimensions of this feature space the PCA technique is applied so as the searching space is reduced. And finally, the clustering and similarity based indexing techniques are practiced so that the retrieval time and average precision is improved. At last, developed system is constructed with clustering based indexing as its performance is slightly better than similarity based technique. The complete system is implemented on Corel-10K, Corel-5K, Corel-1K, Coil-100 and GHIM-10K datasets and its performance is compared with other state of art methods which spectacles that it is much more competent and effective than other systems.

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