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ScienceDirect

Procedia Computer Science 165 (2019) 691–700

Procedia Computer Science

www.elsevier.com/locate/procedia

INTERNATIONAL CONFERENCE ON RECENT TRENDS IN ADVANCED COMPUTING 2019, ICRTAC 2019

Optimized Feature Integration and Minimized Search Space in Content Based Image Retrieval

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Abstract

The semantic gap between the user request and retrieval result is an important but unsolved problem in the content-based image retrieval (CBIR) systems. This paper introduces a new multi-level structure in a CBIR system to bridge the semantic gap using the combination of low-level visual contents of an image. The initial stage of the proposed system depends on the statistical information of the color images which gives the most prominent images for the further level of the process. In the next step, low-level features such as color and texture details are extracted using dominant color descriptor (DCD) and radial mean local binary pattern over the query and selected images. Subsequently, Particle Swarm Optimization (PSO) is applied over both the color and texture similarity measure between the query and selected images. Finally, this multi-level system is experimented on OT-scene and Corel-10k databases to assess the performance and it gives 78.43% and 52.34% average precision rate.

Keywords: Content-based image retrieval; Mean, Particle Swarm Optimization (PSO); Standard deviation.

1. Introduction

In recent years, digital image growth is tremendously increasing in different domains like web, medical, education, and remote sensing, etc. While searching for images in the huge image archive, content-based image retrieval (CBIR) system gives relevant images without the help of keywords generated by human experts [1]. The content based image retrieval system automatically extracts the details about the image and searches for similar details

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1877-0509
10.1016/j.procs.2020.01.065

around the whole image database. Once it finds the similar details, the image corresponding to those details is retrieved as the closely matched image which is placed at the top of the retrieval results. The image details are in the form of color, texture, shape and interest points, etc. [1]. Color is the significant low-level descriptor of an image because of its powerful differentiating behavior expressively used in the object identification task. Moreover, color is invariant to image size and orientation [2]. Color features can be expressed in the way of global and local using the following techniques such as color histogram [3], color moments [4,5], joint histogram [6], dominant color descriptors (DCD) [7], color correlograms [8], color coherence vector (CCV) [9] and the color layout descriptors [10], etc. The texture is also an influential descriptor for providing relevant results in CBIR systems with the help of structural arrangement and orientation details of pixels available in the object of an image. Most commonly used texture descriptors are gray level co-occurrence matrix (GLCM) [11], edge histogram descriptors (EHD) [12], local binary pattern (LBP) [13] and Gabor wavelet transform [14], etc. The CBIR system based on any one of the features among the three low-level features has less number of adequate results. Hence, the integration of more than one feature based CBIR system is introduced to improve the relevant retrieval [15-23]. However, the semantic gap still remains high, whereas the retrieval accuracy depends on the features and how much each feature contributes to similar image retrieval. The above-mentioned feature integrated CBIR systems assign an equal weight for each feature of the image. This reduces the retrieval accuracy of the CBIR system since every feature does not equally contribute to the image to give the discriminant feature representation. Moreover, the retrieval time of the CBIR system is proportional to the number of images present in the image database and the feature vector count of the extracted features. Thus, there is a need for an optimized weight assignment for each feature used to describe the image and relevant image selection method to reduce the search space of the retrieval system.

The proposed framework design supports the CBIR system in the form of integrating color, and texture features by giving optimized weight for each extracted features which improve the retrieval accuracy and uses the statistical measure of the image to reduce the search space of the retrieval system. This approach considerably reduces the size of the database used in the retrieval task which is directly proportional to the comparison space of the similar image retrieval system. Thus, the retrieval time of the proposed system is considerably less. Moreover, this framework is explored over two databases (Corel-10k and OT-scene) and the performance of this framework is compared with various existing multi-feature combined CBIR systems.

The structure of this paper is framed as follows: Related works are described in section 2, the proposed features of the integration technique are explained in section 3; Section 4 shows the experimental results and discussion. Section 5 gives the conclusion of this work.

2. Related work

The image retrieval system based on the traditional color and texture feature extraction methods gives equal weightage for fusing the extracted features, which limits the retrieval accuracy of the CBIR system within a certain range [27]. On the other hand, the significant color and texture features of the image are extracted from Zernike chromaticity distribution moments and the Contourlet domain respectively. However, these features also share the same weight to give retrieval accuracy of the CBIR system around 70% over the Wang's databases [28]. The extracted feature of the images does not always have an equal probability of information about the image. Thus, feature selection approaches were introduced in the field of image retrieval. These feature selection methods give high weightage to the most prominent feature vectors among the other set of features extracted from the same image. Younus et.al [25] extracted four different features details (i.e.: color histogram, color moments, color co-occurrence matrix and wavelet energy) of the database images and performed clustering using the PSO based K-means clustering algorithm.

Then, the distance measure calculated between the query features and database image features cluster centers. This reduces the search space of the image retrieval system however the feature clustering the high dimensional feature vector takes more time for convergence. The color, texture and shape features of the database images are integrated using the PSO method which has high retrieval precision compared to the retrieval accuracy of each feature individually involved in the image retrieval process. However, image retrieval time based on this method is directly proportional to the number of images involved in the image retrieval process [26]. The image selection rule based on color mean and its standard deviation reduces the search space of the image retrieval system [28]. Even though it uses the image selection rule for reducing the search space, the integration of different kinds of features shares the same weight which is the drawback of this system. Like optimal weight assignment for the different kinds of feature, the feature extraction algorithm also plays an important role in CBIR since feature representation only holds discriminant details of the image. The popular color feature extraction method takes the dominant color information available in the image by quantizing the pixel intensities. There are two different kinds of image quantization techniques (i.e. (i) predefined range based image quantization (ii) clustering based image quantization) are available in color feature extraction. The clustering based image quantization represents the color details more approximately than the certain ranges involved in quantized color feature extraction. In texture feature extraction, the local structural arrangement of the image is extracted using the binary pattern available in the local region [13, 26]. Here, every raw pixel acts as a threshold for binary pattern creation. This representation is highly sensitive to a small amount of noise. To overcome this drawback, radial mean and angular mean local binary patterns are introduced [29]. These studies reveal that the optimized combination of image representation in the reduced subspace is still an active research area of CBIR.

This work concentrates to reduce the retrieval time of the CBIR system by selecting the set of prominent image's corresponding features for similarity measure calculation. Moreover, this work uses the discriminant details of the image in the compact representation and integrates them by assigning the optimal weight for them.

3. Proposed work

The standardized process of the optimized features integration based CBIR framework is depicted in Fig.1. The proposed CBIR framework is comprised of two-level of the process in a similar image retrieval task. Here, the first level fully depends on the statistical information of the images. Second level deals with the color and the texture information of the selected images.

The initial step of the proposed technique is to extract the statistical, color and texture feature of the database images. The following section gives details about the feature extraction techniques involved in this work.

3.1. Statistical information

The statistical information [28] such as mean and standard deviation are assessed separately from R, G, and B color channels of the RGB color space query image using Eqs. (1) and (2). Subsequently, image selection rule is formed by the combination of these two statistical measures.

$$Mean(I_c) = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} I_c(P_{ij}), c = \{R, G, B\} \tag{1}$$

$$Std(I_c) = \left(\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(I_c(P_{ij}) - Mean(I_c) \right)^2 \right)^{\frac{1}{2}}, c = \{R, G, B\} \tag{2}$$

where c is the color channel information of an image. M and N are the row and column size of a specific color channel of the image I_c. $I_c(P_{ij})$ indicates the value of the pixel in the i^{th} row and j^{th} column of the particular color channel image.

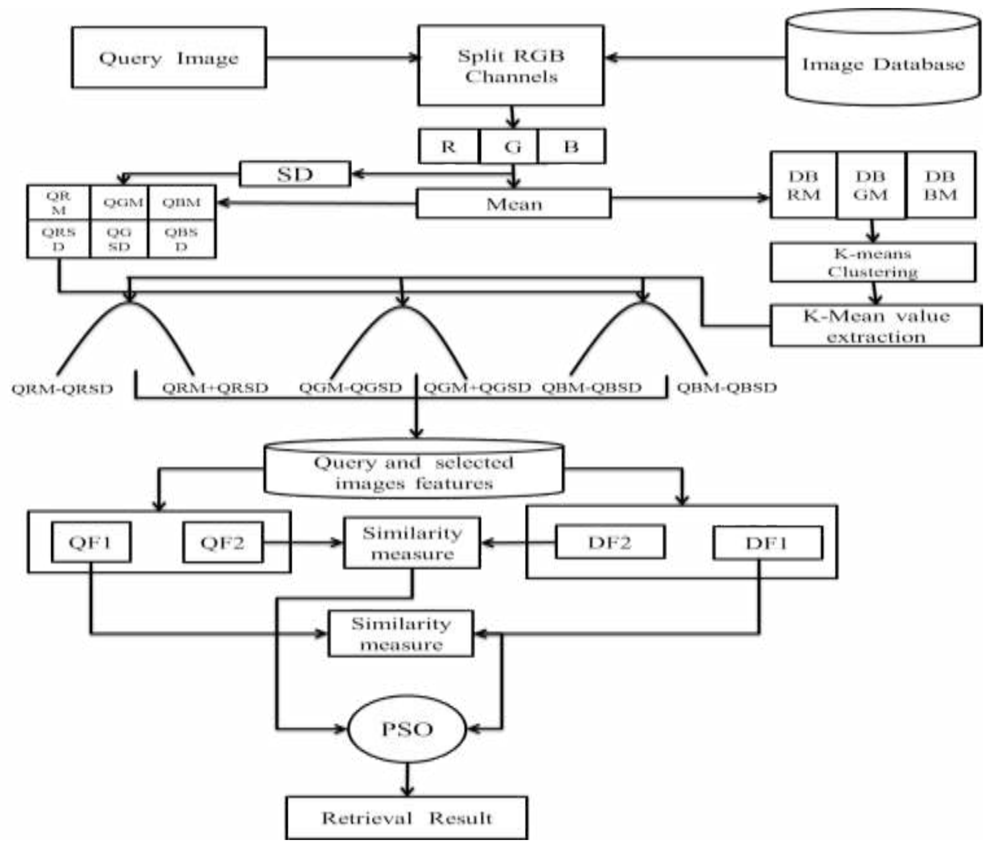

Fig. 1. Optimized feature integration based image retrieval.

3.2. Image selection

After the evaluation of the statistical information of the query image, low-threshold (LT) and high-threshold (HT) values are estimated through Eqs. (3) and (4) [34].

$$LT(I_C) = Mean(I_C) - Std(I_C), c = \{R, G, B\} \tag{3}$$

$$HT(I_C) = Mean(I_C) + Std(I_C), c = \{R, G, B\} \tag{4}$$

3.3. K-Means Clustering

First order color moment (Mean) of each image in the database is evaluated by Eq. (1). Then, the K-means clustering algorithm is applied over the first order (mean) statistical measure of the R, G, and B color channels of the database images.

If the calculated cluster mean information lies between the low-threshold and high-threshold from Eqs. (3) and (4). Then, the particular class images are selected for the next level of the process. This framework takes the features of these images for the retrieval process. This work forms 50 cluster means on the database images.

3.4. Color feature

The dominant color information of the image is extracted by applying K-means clustering over the HSV color channel of the image [30]. Here, the initial seed points of the K-means clustering algorithm is derived from the mean and maximum value of each channel. The dominant color information of the image is extracted by applying K-means clustering over the HSV color channel of the image [30]. Here, the initial seed points of the K-means clustering algorithm is derived from the mean and maximum value of each channel.

$$\text{Initial seed points}(c) = \frac{Ic_{mean}}{k} + (c-1) * \frac{Ic_{\max}}{k} \tag{5}$$

where, Ic_{mean} -Image channel mean. $Ic_{\max}$ - Image channel maximum. k – total number of cluster. c - indicates the cluster and it takes values from 1 to k. Based on the initial seed points the dominant color information of the image is extracted from the query and database images.

3.5. Texture feature

The structural arrangement information of the image is extracted from the radial mean value of the local region involved in texture feature extraction [29].

$$BP(I_c)_{p,r} = \sum_{l=0}^{p-1} s\left(\overline{I_{l,r_{1,..,n}}} - I_c\right)^{2^l}, s(d) = \begin{Bmatrix} 1, d \geq 0 \\ 0, d < 0 \end{Bmatrix} \tag{6}$$

where p indicates the number of equal distanced pixels considered in the circular neighbourhood in different radii (r=1,.,.,.,n). r holds the different radius values, I_c is the centre pixel value of the sub image and $\overline{I_{l,r_{1,..,n}}}$ gives mean value of the intensities I in the l^{th} pixel direction at different radii (i.e:1,.,.,n).

3.6. Distance measure

The color feature distance [30] is calculated using the Eqs (7-9),

$$D(Q, DB) = \sum_{i=i}^{K} \min\left(\sum_{j=1}^{M} D(C_i, C_j) + D(H_i, H_j)\right) \tag{7}$$

Where, i and j takes the values from 1 to K and M respectively. C_i and Cj indicate dominant color of the query image and database images. H_i and H_j hold the query and the database images dominant color occurrence information.

$$D(C_i, C_j) = \sqrt{\left(CH_i - CH_j\right)^2 + \left(CS_i - CS_j\right)^2 + \left(CV_i - CV_j\right)^2} \tag{8}$$

$$D(H_i, H_j) = \sqrt{\left(H_i - H_j\right)^2} \tag{9}$$

where, CH_i , CS_i , CV_i , CH_j , CS_j and CV_j indicates the query and database images H, S and V channels dominant color information

The texture feature distance is calculated using the D1 distance measure given in Eq (10),

$$D1(qif, sif) = \sum_{s=1}^{m} \left| \frac{qif_s - sif_s}{1 + qif_s + sif_s} \right| \tag{10}$$

where, qif - query image feature, sif - selected image feature. s takes the value from 1 to length of the feature vector.

3.7. Normalization

Normalization limits the similarity measure of the selected images color and texture features to [0, 1]. The proposed framework implements the Min-Max normalization [32] to the color and texture similarity measure separately through the Eqs. (11).

$$ND(i) = \frac{D1_f(i) - \min(D1_f)}{\max(D1_f) - \min(D1_f)}, \quad i = 1,2,\ldots, L \tag{11}$$

where L is the total number of selected images. $D1_f\ (i)$ denotes the feature distance information of the i^{th} image in the selected images.

3.8. Optimal weight based feature integration

The Particle Swarm Optimization (PSO) algorithm emulates the mutual experience sharing the behaviour of the birds in the flock [24, 25, 31]. The PSO algorithm is applied over the similarity measure of the two different feature datasets (i.e.,color and texture) of the selected images, this improves the CBIR system performance in terms of retrieval precision. Here, PSO takes average precision as a fitness function and converge to achieve high precision rate. Before applying the PSO algorithm on the similarity measure of the selected image features, parameters involved in PSO needs to be initialized. The parameters of the PSO algorithms are the number of iteration (30), number of particles (20), dimensional of each particle (2), velocity, weight and acceleration coefficients. After each iteration, the local and global best position of the particle is stored in pbest, and gbest variable respectively and the velocity of each particle is obtained from Eq.(12) and the position of the particle is updated using the Eq.(13).

$$vl_i^{(t+1)} = w * vl_i^{(t)} + a1 * r1 * (pbest - p_i^{(t)}) + a2 * r2 * (gbest - p_i^{(t)}) \tag{12}$$

$$p_i^{(t+1)} = p_i^{(t)} + vl_i^{(t+1)} \tag{13}$$

where, $a1$ and $a2$ are the acceleration coefficients. Here, $a1$ and $a2$ are set to 2 which maintains the balance between particle's individual and social behavior. $r1$ and $r2$ are random variables which takes the value between 0 to 1. w - inertia weight which is fixed as 1.

The gbest value at the end of 30th iteration is taken as the optimal precision rate and its corresponding two dimensional particle position information acts as a weight for the color and texture feature respectively.

3.9. Performance measure

The average precision measure [28] on the retrieved results is evaluated using the Eqs (14-15).

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \quad (14)$$

$$\text{Average Precision} = \frac{\sum_{i=1}^{TDB} P(i)}{TDB} \quad (15)$$

where, $p(i)$ and TDB represents the precision and total number of images in the database.

4. Experimental results

The proposed multiple features integrated CBIR framework is implemented in the MATLAB R2013a environment with the dual-core processor, 2 GB memory and 64 bit windows operating system and its performance is investigated over the Corel-10k[1] and OT_scene[2] databases. Figure. 2(a) shows sample images from the Corel database. Corel-10k contains 10000 images of resolution either 126×187 or 187×126 which are equally grouped into 100 classes. Therefore, each class has 100 images. OT-scene database has totally 2,688 images of 8 distinct groups such as coast, forest, intercity, highway, mountain, open country, tall buildings and street. In this database, all the images are in the resolution of 256×256, each group contain different number of images in to it and some of the images from this database is shown in Fig. 2(b).

(a) (b)

Fig.2. Sample images from the (a) Corel (b) OT scene database

In order to estimate the retrieval accuracy, each image of the database acts as a query to perform the similar image search. The retrieval precision of the color and texture feature involved in this proposed work is depicted in Fig.3.

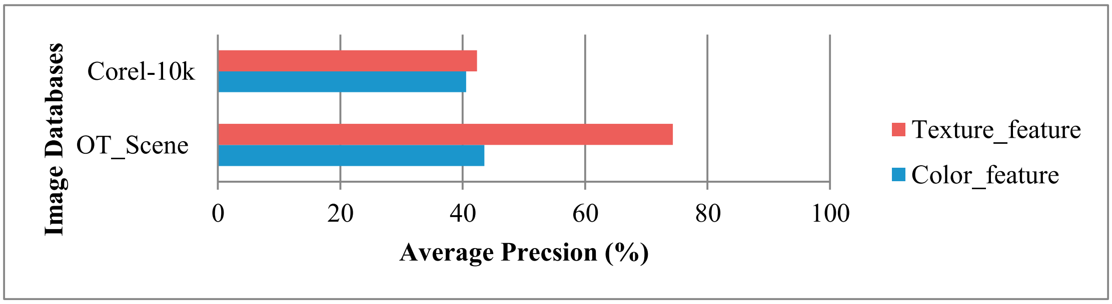

Fig.3. Average precision rate of the color [30] and texture feature [29] of the proposed work.

[1]Corel-10k Database: http://www.ci.gxnu.edu.cn/cbir/Dataset.aspx
[2]OTScence Database: http://cvcl.mit.edu/database.htm

The retrieval accuracy of the color feature extraction method used in Corel-10k and OT_scence database is low compared to the retrieval accuracy of the texture feature extraction method involved in this work. However, retrieval results obtained from color and texture feature extraction methods are not always the same. Thus, integration is needed between them. Figure 4 gives the results of assigning the same weight for each feature involved in feature integration and PSO based feature integration method.

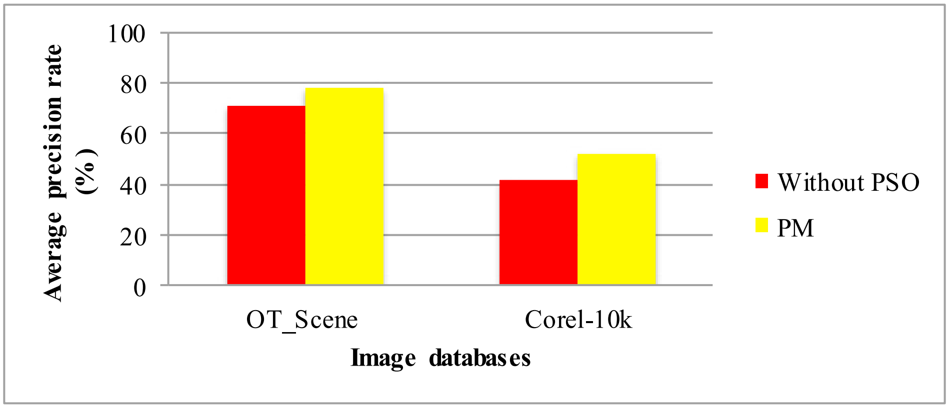

Fig. 4. Average precision rate of color [30] and texture feature [29] integration with equal weight (without_PSO) andwith PSO (PM)

The retrieval precision of the feature integration method using the PSO gives more relevant result than the feature integration based on equal weight assignment. Moreover, Fig.4 reveals that the feature integration without the optimization techniques, results is improved compared to the retrieval result of the individual feature based CBIR system. It shows that the feature integration approach has a high impact on the individual feature based CBIR system. Moreover, the image does not have an equal probability of feature into it (i.e.: not all the features equally contribute in representing the image). Thus, PSO based feature integration system has achieved a high retrieval rate of 78.43% and 52.34% over OT_scence and Corel-10k database respectively in CBIR system. Figure 5 shows the retrieval results of the state-of-the-art CBIR techniques based on the combination of multiple features. The feature integration method suggested by Fadaei et.al [32] achieved 55.74% and 43.62% precision over the OT-Scence and Corel-10k. Even though PSO based integration is preferred in [32] this work, the choice of feature extraction methods is responsible for the result. Likewise, the color and texture features based on the PSO based clustering method limits the average precision of the OTscence and Corel-10k databases as 57.98% and 42.11% respectively. Moreover, Fig. 5 illustrates that the feature integration method [26] by sharing equal weight has low performance in CBIR system.

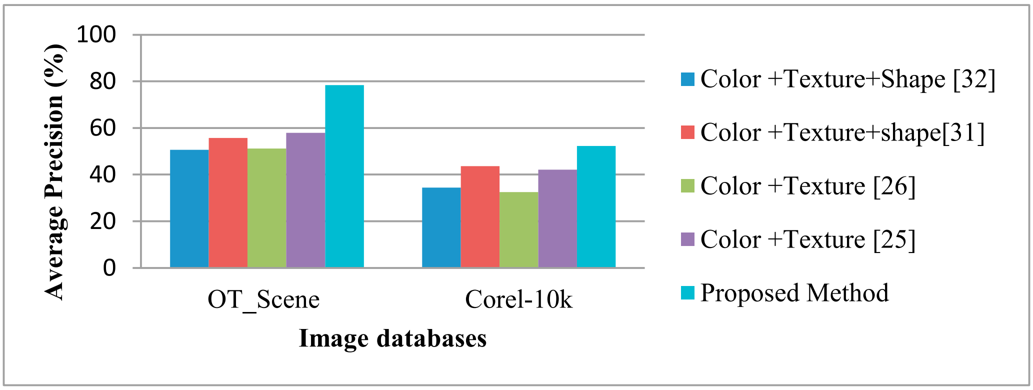

Fig. 5. Average precision rate of feature integrated methods [32],[31],[26],[25], and proposed method.

The effect of the image selection rule is studied and the corresponding results are given in Fig. 6. The number of images involved in the optimized CBIR is minimized by the mean and standard deviation based image selection rule used in the initial level of this work. Thus, the search space of a similar image search is narrow downed which increase the retrieval speed of the proposed CBIR system.

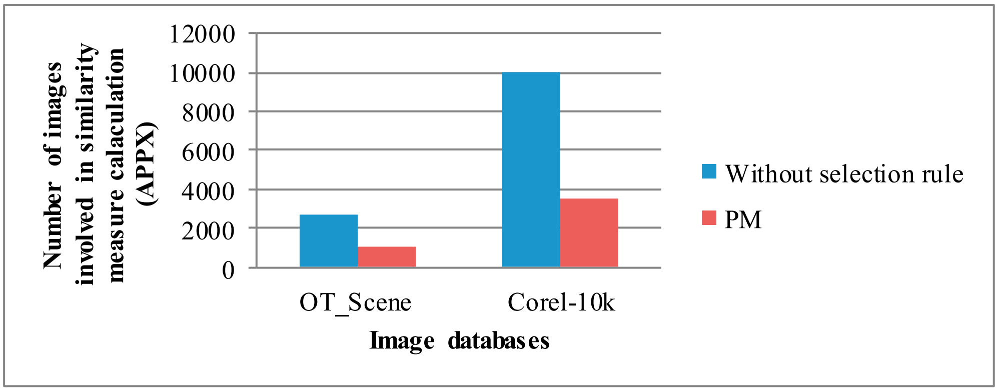

Fig. 6. Number of images involved in proposed and other CBIR system

5. Conclusion

The proposed work reduces the search space of the retrieval system based on the mean and standard deviation of the images involved in the retrieval task and clustered mean of the database images. Moreover, the proposed work achieved high retrieval accuracy over the OT-Scene and Corel-10k databases by integrating the prominent color and texture features of the image with the help of the PSO technique. The performance in the proposed work is high compared to the other state-of-the-art techniques of the CBIR systems.

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