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Abstract- The present paper proposes a new technique that extracts significant structural, texture and local edge features from images. The local features are extracted by a steady local edge response that can sustain the presence of noise, illumination changes. The local edge response image is converted in to a ternary pattern image based on a local threshold. The structural features are derived by extracting shapes in the form of textons. The texture features are derived by constructing grey level co-occurrence matrix (GLCM) on the derived texton image. A new variant of K-means clustering scheme is proposed for clustering of images. The proposed method is compared with various methods of image retrieval based on data mining techniques. The experimental results on Wang dataset shows the efficacy of the proposed method over the other methods.

Keywords: local binary pattern, local directional pattern, textons, GLCM features.

I. Introduction

The volume of digital images produced in the world wide has increased dramatically over the past 10 decades and the World Wide Web plays a vital role in this upsurge. This has created the availability of huge digital image databases or libraries. The handling and accessing of these data base images by human annotations is impractical and it has led to the automatic search mechanisms and it has created a demand for content based image retrieval (CBIR) models. CBIR is defined as a process that searches and retrieves images from a large database. The retrieval operation is performed on the basis of derived image features such as color, texture and shape. A good literature survey was conducted on CBIR and is available in [1-4]. The color is one of the significant feature of the CBIR and one of the simple color based CBIR is the color histogram [5].The retrieval performance of this generally limited due to its low discrimination power mainly on immense data. To improve this various color descriptors are proposed in the literature using neural networks [6], DCT-domain vector quantization [7], supervised learning [8] and color edge co-occurrence histograms [9].

The natural images are visualized by their rich content of texture mosaic and color. The texture descriptors are based on grey scale variation and they can also integrate with color component of image retrieval (IR). It is very difficult to give unique definition to texture and it is one of the significant and salient features for CBIR. The texture based image retrieval is reported in the literature based on the characteristics of images in different orientations [10, 11, 12, 13, 14, 15]. Extraction of texture features on wavelets [16], wavelet transform based texture features [16] and correlagrams [17] are also proposed for efficient IR. The performance of the correlograms [17] is further improved using genetic algorithms (GA) [18]. The integrated methods that combine the color histograms with texture features [19, 20] and correlograms with rotated wavelets [21] attained a good IR rate. Recently, the research focuses on CBIR systems that is fetching the exact cluster of relevant images and reducing the elapsed time of the system. For this purpose, various data mining techniques have been developed to improve the performance of CBIR system. Clustering is one of the vital techniques of data mining for quick retrieval of information from the large data repositories. Clustering is an unsupervised process, thus the evolution of clustering algorithm is important due to the extraction of hidden patterns [22, 23]. There are many applications in the real-world with clustering like credit card, mark analysis, web data categorization, image analysis, text mining, pattern recognition, market data analysis, weather report analysis [24].Data clustering explicitly divides the data into a set of k user specified number of groups by trying to minimize intra-cluster variance and maximize inter-cluster variance in an iterative manner [25, 26]. Various methods are proposed in the literature to improve the performance of the data clusters [27, 28, 29] in various applications. K-means [30] is one of the popular and efficient clustering algorithms. Later various variations to k-means algorithm are proposed to improve the efficiency [31, 32, 33].

A content-based image retrieval method using adaptive classification and cluster-merging is proposed for image retrieval to find multiple clusters of a complex

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image query [34]. This method [34] achieves the same retrieval quality, under linear transformations, regardless of the shapes of clusters of a query. A cluster-based image retrieval system by unsupervised learning (CLUE), is proposed for improving user interaction with image retrieval systems by fully exploiting the similarity information [35]. The CLUE retrieves image clusters by applying a graph-theoretic clustering algorithm and it is dynamic in nature. The CLUE retrieves image clusters instead of a set of ordered images. The principle of unsupervised hierarchical clustering is also used in CBIR [36]. The modified fuzzy c-means (MFCM) clustering scheme introduced fuzzy weights and it reduced the time of clustering and also used for image retrieval [37, 66]. A content-based parallel image retrieval system to achieve high responding ability is proposed and it is based on cluster architectures [38]. It has several retrieval servers to supply the service of content-based image retrieval. Many researchers used k-means clustering with variations and achieved a good image retrieval rate [39, 40, 41,42]. K-means clustering technique is helpful to reduce the elapsed time of the system.

The rest of the paper organized as follows: The proposed method, local directional pattern (LDP),k-means and query matching are given in Section 2. Experimental results and discussions are summarized in section 3. Based on above work, conclusions are made in section 4.

II. Proposed Method

The present paper initially converts the color image into grey level image using HSV quantization. The present paper derives integrated features that significantly holds edge, shape and texture features, for this initially edge responses are obtained then shape features in the form of textons are evaluated. Then GLCM features are obtained. Images are clustered based on the two point perimeter K-means (TPP-KM) clustering scheme. A similarity measure in the form of Euclidian distance is used to retrieve the top most similarity images.

a) Algorithm for feature extraction

The features are extracted based on the following steps

Step 1: The color image is converted in to grey level images using HSV color space.

Step 2: Conversion of edge response image in to ternary pattern image. This is derived based on two sub steps 2(a) and 2 (b).

Step 2 a): The local features in the form of edge responses in eight directions are obtained on the grey level image based on local direction pattern (LDP) coded image.

The formation process of LDP is explained below.

The LDP is an eight bit binary code that describes the relative edge value of a pixel in different directions [43]. The present paper evaluates edge responses in eight directions on a central pixel of a 3 x 3 neighborhood using Kirsch masks [68].Out of eight (m_i/i=0, 1 ….7) only the k-most significant edges are given a value 1 and the remaining are set to zero. The three greatest responses, i.e. k=3 are considered in the present paper. The reason for this is the occurrence of corner or edge indicates a huge edge response value in a particular direction. The LDP code generation on a 3x3 neighborhood is shown below in Figure 1. The advantage of LDP over Local binary pattern (LBP) is, LDP can sustain the noise. And this is shown Figure 2. The Figure 2(b) corresponds to the noisy or fluctuated neighborhood of Figure 2(a). In this case the LBP code changes drastically whereas the LDP retains the same value.

			25	28	65			
			35	85	75			
			50	48	65			
Mask index	m_7	m_6	m_5	m_4	m_3	m_2	m_1	m_0
Mask value	331	131	-109	-293	-469	-229	171	467
Rank	2	4	5	7	8	6	3	1
Code bit	1	0	0	0	0	0	1	1
LDP code	131							

Figure 1: Transformation of LDP code for K=3

85	32	26	
53	50	10	LBP=00111000
60	38	48	LDP=00010011
(a)			

85	32	26	
49	50	10	
60	38	48	LBP=00101000
(b)			LDP=00010011

Figure 2: Stability of LDP vs. LBP (a) Original image (b) Image with noise

Step 2b): Conversion of LDP coded image in to ternary form, based on a threshold. This mechanism simplifies the extraction of textons that represent shape of the texture in the next step. This also makes the present process to be resistant to lighting effects, noise and other illumination changes. For this the neighborhood pixel (p_i) values of LDP coded image are compared with central pixel (P_c) using a lag limit value *'l'*. The neighborhood values are assigned one of the ternary values T_i. (Equation 1).

$$LDTP\ (T_i) = \begin{cases} 2 & P_i \geq (P_c + l) \\ 1 & |P_i - P_c| < l \\ 0 & P_i \leq (P_c - l) \end{cases} \qquad (1)$$

The process of generation of this is illustrated in Figure 3 with l=3. The proposed edge responses generate a total of 0 to K*(P-1) codes and this is considered as the main disadvantage. Here k is the number of greatest edge responses considered and p is the number of neighboring pixels. This is not considered as the disadvantage in the present paper, since we are not deriving LDP coded image and we are only deriving ternary patterns out of the LDP coded image. Further it is more convenient to derive shape feature (in the next step) on local ternary patterns (0 or 1 or 2) derived from edge responses.

38	39	101	100	20
20	25	33	67	109
53	65	43	111	117
65	132	125	145	36
120	100	65	42	144

(a) (a) neighborhood values

Sample (Intensity

49	146	26
44	37	7
41	100	138

(b) (b) LDP code of image (a)

2	2	0
2	1	0
2	2	2

(c) Ternary patterns on edge responses

Figure 3: Transformation of local edge responses image into ternary pattern image

Step 3: Derivation of local shape features in the form of textons on the ternary image. The method of deriving textons on ternary image is given in Figure 4. The basic unit of an image is pixels and its intensity and experiments based on this have not resulted any satisfactory results. In order to progress the performance the pattern and shape based methods are employed. A pattern and shape consists of group or set of neighboring pixels with similar intensity levels. One of such popular measure is "texton" proposed by Julesz [44]. Textons are defined as emergent patterns or blobs. These "textons" share a common property all over the image. The methods based on LBP and textons are very useful for texture analysis and classification [45, 46, 47] face recognition [48], age classification [49, 50, 51, 52], image retrieval [15] etc. Variousarray grammar models are proposed in the literature to represent patterns and shapes [53, 54]. Based on textons one can say whether texture is fine or coarse or in any other form. Textons can be derived on a 2x 2 or on a 3x3 or on any neighborhood window. The present paper utilized all texton patterns that forms only with two and four pixels on a 2×2 grid. This derives seven textons on a 2 x 2 grid. The derivation of texton image with the above 7 local shape features (textons) is shown below Figure 4.

3	1	1	2	1	3
3	2	3	2	3	1
1	2	4	2	4	2
1	3	1	3	2	1
2	2	2	1	3	2
2	2	3	1	3	1

(a)

3	1	1	2	1	3
3	2	3	2	3	1
1	2	4	2	4	2
1	3	1	3	2	1
2	2	2	1	3	2
2	2	3	1	3	1

(b)

3	1	1	2	1	3
3	2	0	2	3	1
1	2	0	2	0	2
1	0	0	3	2	0
2	2	2	1	3	0
2	2	0	1	3	0

(c)

Figure 4: Transformation of Texton process: a) Original image (b) Textons identification (c) Texton image

Step 4: Derivation of GLCM features. GLCM features are computed on the derived texton matrix.

The present paper evaluated four Haralick features [55] for effective image retrieval and they are listed below. The features homogeneity, energy, contrast and correlation are evaluated with an angle of 0°, 45°, 90° and 135° and the average value of this are considered as texture feature.

Homogeniety or Angular Second Moment (ASM):

$$\mathrm{ASM}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i,j)\}^2 \qquad (2)$$

ASM is a measure of homogeneity of an image. A homogeneous scene will contain only a few grey levels, giving a GLCM with only a few but relatively high values of P (i, j). Thus, the sum of squares will be high.

Energy :

$$\text{Energy} = \sum_{i,j} P(i,j)^2 \qquad (3)$$

Contrast :

$$\text{Contrast}=\sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j)\right\}, |i-j| = n \qquad (4)$$

This measure of contrast or local intensity variation will favor contributions from P (i, j) away from the diagonal, i.e. i ! = j.

Correlation :

$$\text{Correlation} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{iXj\}XP(i,j)-\{\mu_x X \mu_y\}}{\sigma_x X \sigma_y} \qquad (5)$$

Correlation is a measure of grey level linear dependence between the pixels at the specified positions relative to each other.

b) Clustering method

One of the commonly used and simplest algorithm for clustering is the K-means algorithm. K-means is one of the fundamental algorithms of clustering and it employs the square error criterion. The numbers of partitions are to be defined in K-means initially. The cluster centers are randomly initialized for predefined number of clusters. If the initial number of clusters is not properly chosen then the output of algorithm may converge to false cluster locations and completely different clustering result [58, 59]. This measure is often called the squared-error distortion [60,

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61] and this type of clustering falls into the general category of variance-based clustering [62, 63].

The present paper outlined a new variation to the existing K-means algorithm to reduce the number of iterations and to increase the overall retrieval rate. This new variation of K-means scheme is denoted as two point perimeter – K-means (TPP-KM) clustering scheme. The present scheme selects two points instead of one point in K-means and also a perimeter is also evaluated and the similarity is evaluated by using Euclidean distance.

c) Query matching and performance measure

The present retrieval model selects 20 top images from the database images that are matching with query image. This is accomplished by measuring the distance between the query image and database images. The present paper used Euclidean distance as the distance measure and as given below

$$Dist_s(T_n, I_n) = \left(\sum_{i,j=1}\left|f_i(T_n) - f_j(I_n)\right|^2\right)^{1/2} \tag{6}$$

Where T_n query image, I_n image in database;

The database image is used as the query image in our experiments. If the retrieved image belongs to the same category as that of query image we say that the system has suitably identified the predictable image otherwise the system fail to find the image. The performance of the present model is evaluated in terms of precision, recall rate and F-Measure as given in equation 7, 8 and 9.

$$Precision\ P = \frac{Number\ of\ relevant\ images\ retrieved\ (I_{RR})}{Number\ of\ retrieved\ images\ (I_{NR})} \tag{7}$$

$$Recall\ R = \frac{Number\ of\ relevant\ images\ retrieved\ (I_{RR})}{Total\ number\ of\ relevant\ images\ in\ the\ database\ (I_{TR})} \tag{8}$$

The algorithms that improve precession may degrade recall and vice versa. The present paper also evaluates another parameter called F-measure that is based on both precession and recall.

$$F - Measure = \frac{2*(precision\ *recall\ )}{(precision\ +recall\ )} \tag{9}$$

III. Results and Discussion

In order to efficiently investigate the performance of the present retrieval model, we have considered the Wang database [64]. Wang is a subset of Corel stock photo database of 1000 images. These images are grouped into 10 classes, each class contains 100 images. Within this database, it is known whether any two images are of the same class. Classification of the images in the database into 10 classes makes the evaluation of the system easy. The hefty size of each class and the heterogeneous image class contents made Wang data base as one of the popular database for image retrieval. The present paper considered 7-classes of images and 100 images per each class. For a query image the relevant images are assumed to be the remaining 99 images of the same class. The images from all other classes are treated as irrelevant images. The retrieval performance of the proposed method is judged in terms of precession, recall and F-measure. The proposed clustering method derived integrated novel features from edge responses, shapes in the form of textons and statistical parameters in the form of texture features (GLCM features). The average retrieval performance of the proposed method is compared with CBIR methods using data mining techniques [65, 66, 67] and the proposed method with K-means clustering method. The proposed method outperformed all the other methods in terms of precession, recall and F-measure and this is shown in the Figure 5, 6 and Figure 7. In the method [65] the features are extracted by GLCM features. In the existing method [67] fuzzy C-means clustering scheme is used with GLCM features and the method [66] used both color and statistical features with portioned clustering scheme. The advantage of the proposed method is the derivation of significant and powerful local features. Figure 8 shows seven examples of retrieval images, i.e. one image from each class, by the proposed method with 20-top most retrieved image.

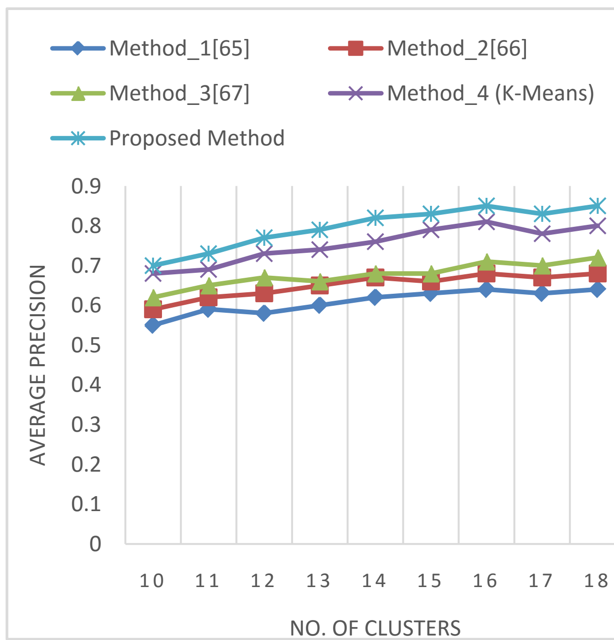

Figure 5: Average precision graph

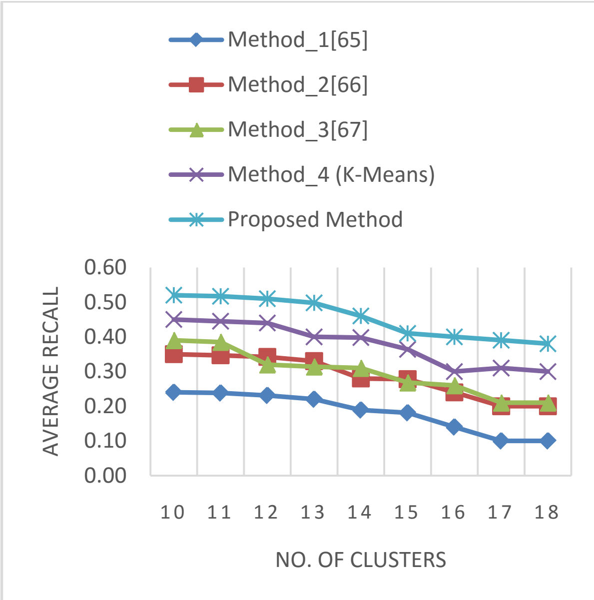

Figure 6: Average recall graph

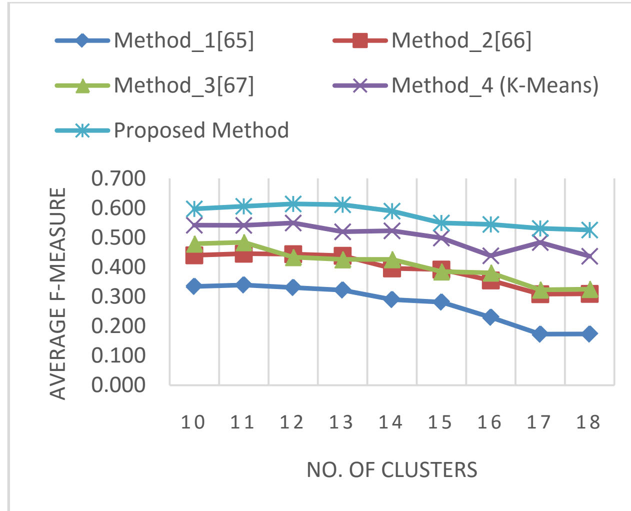

Figure 7: Average F-Measure graph

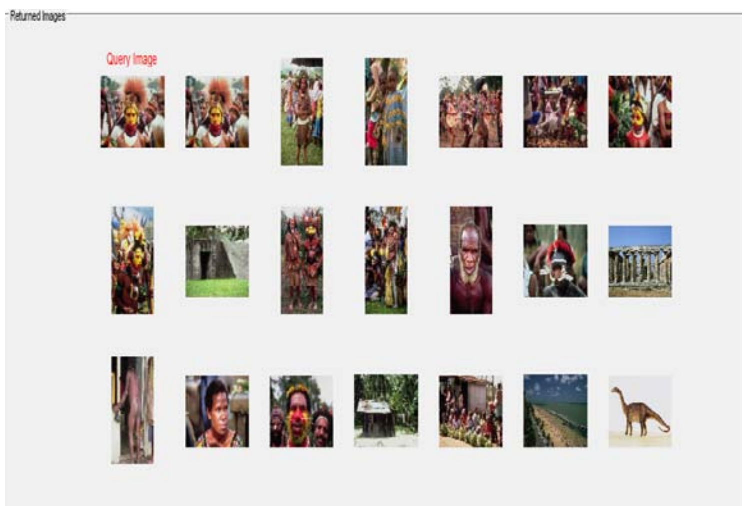

Figure 8(a): Retrieved African images

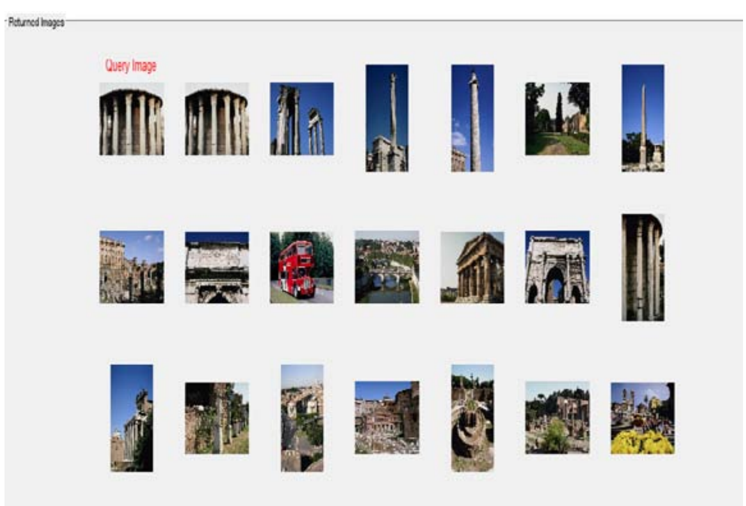

Figure 8(b): Retrieved monuments

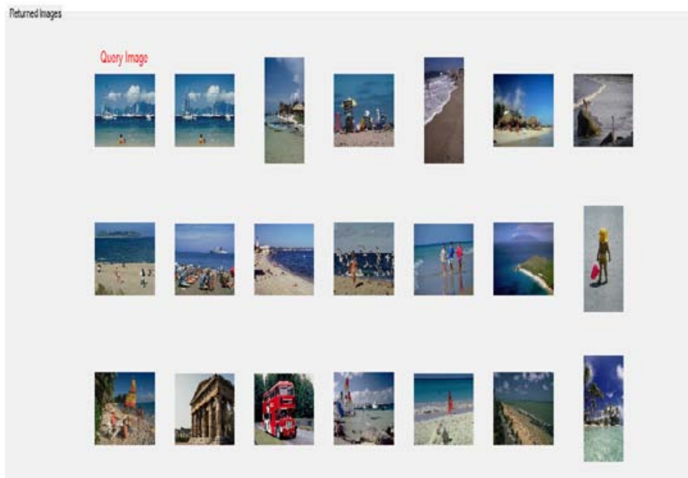

Figure 8(c): Retrieved beach sand images

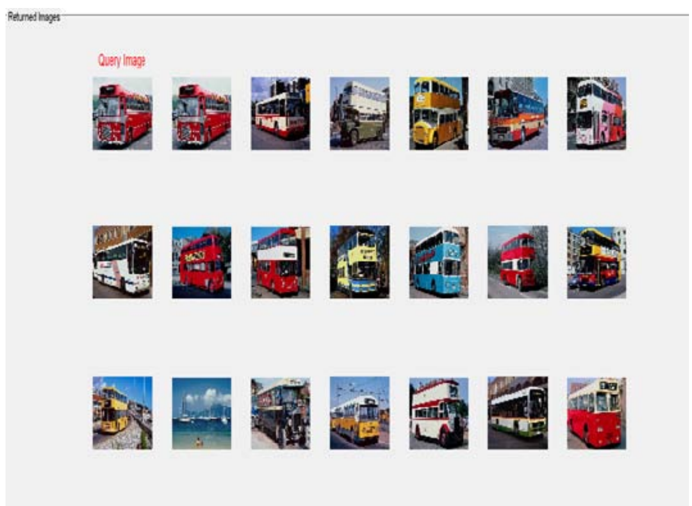

Figure 8 (d): Retrieved busses

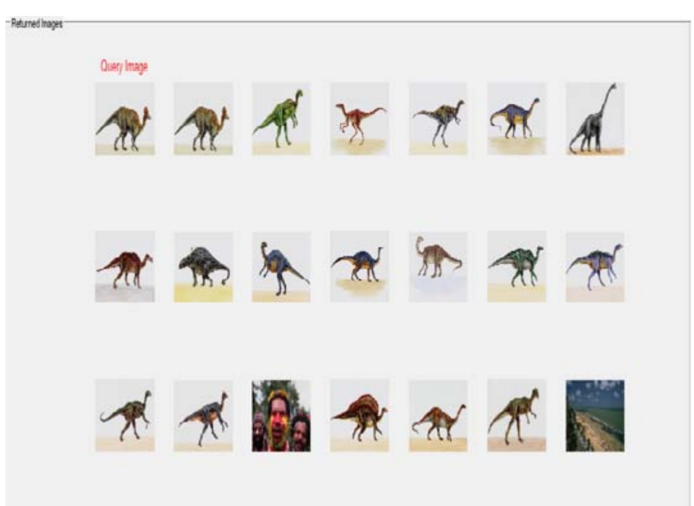

Figure 8(e): Retrieved dinosaurs

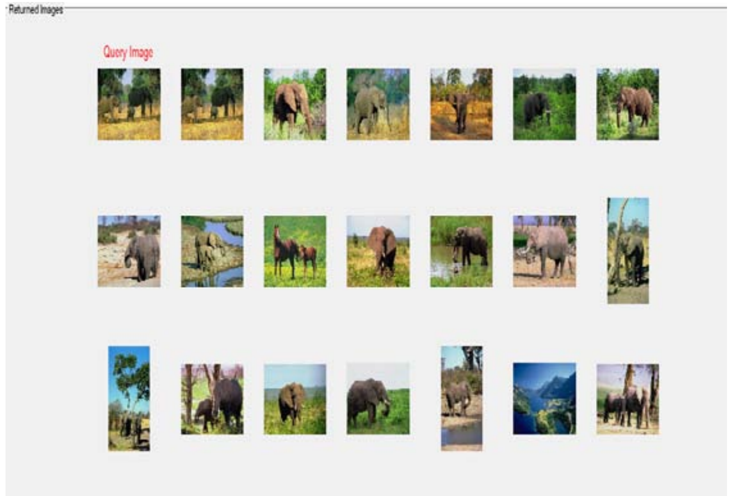

Figure 8 (f) : Retrieved elephant's images

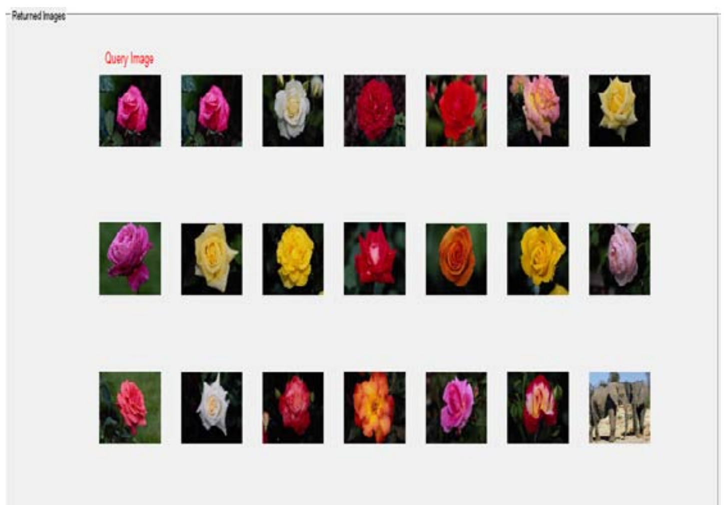

Figure 8(g): Retrieved flower images

IV. Conclusions

The present paper proposed a CBIR method using a data mining algorithm. The proposed method used a simple clustering scheme and achieved high retrieval rate when compared with the other existing methods because the proposed method extracted powerful and significant local features derived from edge responses, shape and textural properties. As with many other clustering algorithms, a limitation with our algorithm is that it requires the number of clusters to be known in prior. The advantage of edge responses is it can sustain with non-monotonic illumination variation and random noise. The shape features derived from textons are rotationally invariant. The texture features in the form of GLCM features with the help of clustering scheme retrieved the images in an accurate manner. The proposed method is experimented with one of the popular and heterogeneous dataset "Wang" and the experimental results indicates the superiority of the present method over the other existing methods.

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