Retrieval of Monuments Images Through ACO Optimization Approach

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Abstract - *Content Based Image Retrieval (CBIR) is an important research area in digital image processing. But, there is not much contribution of CBIR in monuments image retrieval. By using these kind of techniques it will be easy to identify and retrieve similar kind of monument images. This paper presents the monuments images retrieval system with Ant Colony Optimization (ACO) feature selection schema based on low level features of image. Low level features used are shape, texture and color. Shape feature is extracted using morphological gradients, texture feature is extracted using Improved Local Binary Pattern (ILBP) and color feature is extracted using Color Moments. Low level features are extracted then ACO is used for feature selection after that similarity metric is used for retrieving similar kind of images.*

Key Words: **CBIR, ACO, ILBP, Color Moments, Invariant Moments, Monument Image Retrieval**

1.INTRODUCTION

Images are the most common and convenient means of conveying or transmitting information. An image is worth a thousand words. Now a day numerous amount of images is being captured by different image acquisition techniques, these images database are used in many day to day applications for example military, remote sensing, engineering, medical field, crime prevention, environmental, astronomy, multimedia and many other applications.

For handling the gigantic amount of stored and exchanged image information some automatic image retrieval techniques are required. In case of database having less number of images, it is practicable to discover a required image simply by browsing while in case a database containing thousands of images it is not practicable to browse the desired image thus some more effective techniques are needed. Image retrieval is the procedure of finding the images having similar kind of content as query image given by the user based upon some similarity functions.

Image retrieval can be implemented based on following two methods:

a) Text Based Image Retrieval
b) Content Based Image Retrieval

Content Based Image Retrieval (CBIR) also known as Query by Image Content (QBIC) is the application of computer vision techniques to image retrieval problem that is problem of searching for digital images in large database.

As the CBIR is an automatic image retrieval process so the working is slightly different from Text Based Image Retrieval (TBIR) in some extent. CBIR is the process of retrieving images from a database or library of digital images according to the visual content of the images. In other words, it is the retrieving of images that have similar features such as colors, textures or shape. CBIR extracts the features from the image database and uses them to index images.

There are three steps involved in CBIR

a) Pre-processing
b) Feature Extraction
c) Similarity Measure

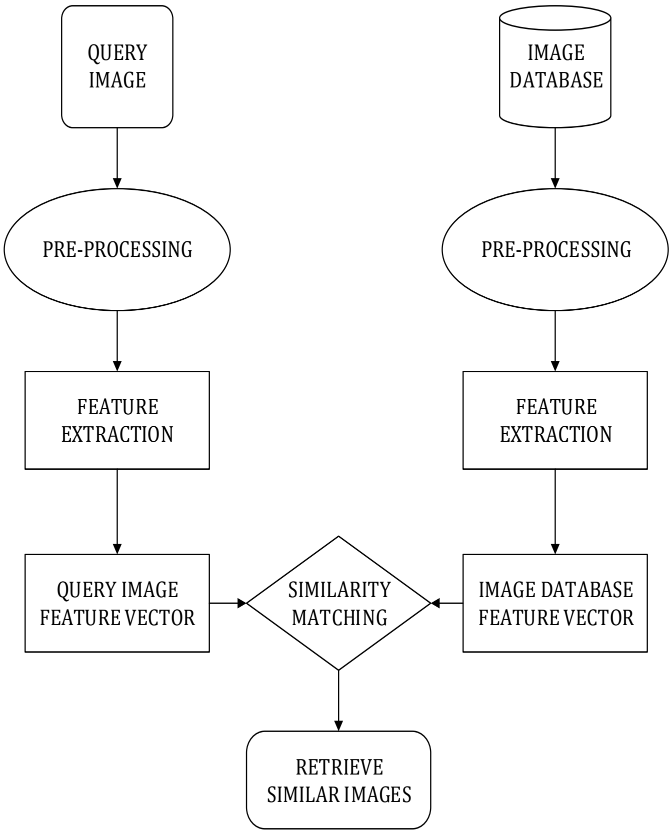

Fig -1: Basic Architecture of CBIR System

2. RELATED WORK

Table -1: Analysis of previous work

S. No.	Year	Author	Proposed work	Dataset used	Result analysis
1	2013	Padmashree Desai et al. [1]	Automatic classification of archaeological monuments using visual features. Morphological operators for shape feature and GLCM (gray level co-occurrence matrix) for texture feature.	Database consists of 500 monuments images with 5 categories 100 from each category.	Performance efficiency is calculated by using precision and recall.
2	2013	Shilpa Yaligar et al. [2]	Identification and retrieval of archaeological monuments images using visual descriptors based on color, texture and shape.	Database of 500 images containing different architecture monument images.	Retrieval performance is expressed using precision and recall graph.
3	2015	Malay S. Bhatt et al. [3]	Extracts genetic programming evolved spatial descriptor and classifies the indian monuments visited by tourists based on linear Support Vector Machines (SVM).	100 images from 4 different classes consisting 25 images of each class.	92.75% accuracy achieved
4	2016	A.Anandh et al. [4]	Proposed a technique for the generation of image content descriptor with three features viz., Color auto-Correlogram, Gabor Wavelet and Wavelet Transform.	Corel image database, Li image database and Caltech-101 image database.	Performance is measured using precision and recall.
5	2012	Shafimirza et al. [5]	Proposes an image retrieval method based on multi-feature similarity score fusion using genetic algorithm.	1000 images from Corel database of images, divided into 10 categories, each category has 100 images.	Precision and Recall values are calculated.
6	2010	Dr. H.B.Kekre et al. [6]	Presents a CBIR technique based on feature vectors as fractional coefficients of transformed images using DCT and Walsh transforms.	A database of 1000 divided into 11 categories is used.	Net average precision and recall are computed for all feature sets per transform
7	2016	Fuxiang Lu et al. [7]	Proposes an Improved Local Binary Pattern (ILBP) operator to describe local image texture more effectively.	Two texture datasets are used namely: RotInv_16_10 and Outex.	ILBP is computationally attractive and well suited for real- world applications because it can be realized with a few operators and a look-up table.
8	2015	Abdolreza Rashno et al.	Proposed a novel CBIR schema with wavelet and color features followed	10 categories of corel database are	All irrelevant and redundant features are dropped by ant

		[8]	by ant colony optimization (ACO) feature selection.	used	colony optimization which selects the most relevant features among feature set
9	2016	Rebika Rai et al. [9]	This paper focus on designing improved Swarm Computing methodology for content based image classification taking the full advantage of the solving power of Ant Colony Optimization (ACO) for Edge Detection, Support Vector Machines (SVM) as a base classifier, Discrete Wavelet Transform (DWT) for feature extraction and selection and Flower Pollination by Artificial Bee (FPAB) for optimization.	Total of seven categories are created each containing 30 images making a total of 210 images	A new technique, IAABO-TCI have been proposed and designed for classifying Imagery using swarm computing that has been visually and empirically tested to increase the accuracy of the output images in terms of PSNR value, Execution time, Kappa value and FOM.
10	2009	Akash Gautam et al. [10]	In this research, implement a new technique for CBIR by ant colony optimization (ACO) and Support vector machine (SVM) with dual tree complex wavelet transform (DTCWT) and color features	The experimental dataset contain 1000 images including horses, elephants, food, African people, etc.	In this work , a novel method for CBIR using ACO and SVM with DTCWT is implemented.

3. FEATURE EXTRACTION

3.1 Mathematical Morphology

The elementary notion of mathematical morphology explains use of structuring element of particular type to determine and elicit the relative shape in image to attain the intents of image analysis and identification [2]. In morphology, structuring element is applied on given image and output image is obtained. Distinct morphological operations such as Dilation, Erosion, Open and Close can be enforced on image with distinct structuring element [2].

Erosion is given in equation (1)

$$(f\theta b)\ (x, y) = \min\{f(x+i, y+j) - b(i, j) \mid (x+i, y+j)\} \quad (1)$$

Dilation is given in equation (2)

$$(f\oplus b)\ (x, y) = \max\{f(x-i, y-j) + b(i, j) \mid (x-i, y-j)\} \quad (2)$$

Basic gradient = Image Dilated – Image Eroded

Internal gradient = Image Original – Image Eroded

External gradient = Image Dilated – Image Original

Five edge maps will be acquired for given image. Shape descriptors are acquired for each of the boundary images. These five edge maps as: basic gradient, internal gradient, external gradient, horizontal gradient and vertical gradients are used.

Figure 2. Depicts edge maps acquired after applying morphological gradients on input image.

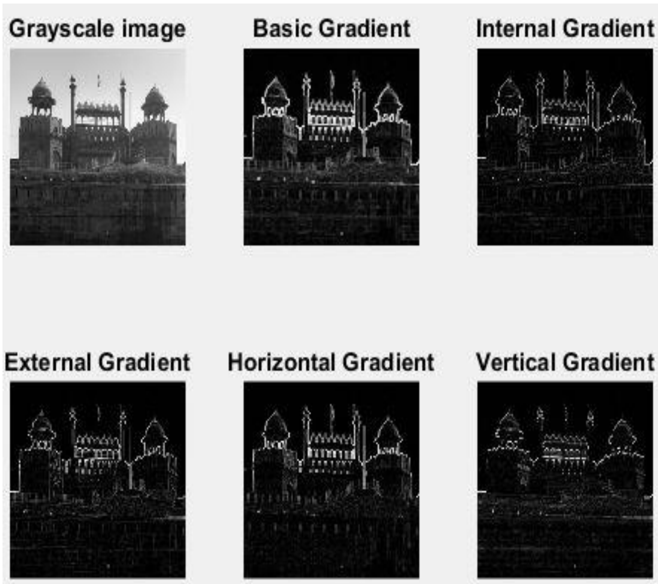

Fig -2: Morphological gradients of given image

3.2 Shape Feature

Seven 2-D invariant moments which are unaffected by rotation, mirroring, translation and change in scaling are shown in equation (3). There are 7 feature values in shape feature vector. These feature vectors are applied on 5 morphological gradients forming a total of 7*5=35 features.

$$\left.\begin{aligned}
I1 &= \eta_{20} + \eta_{02} \\
I2 &= (\eta_{20} - \eta_{02})^2 + 4\eta^2_{11} \\
I3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
I4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
I5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - \\
&\quad 3(\eta_{21} - \eta_{03})^2] + (3\eta_{21} - \eta_{03}) \\
&\quad (\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
I6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
I7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - \\
&\quad 3(\eta_{21} + \eta_{03})^2] - (\eta_{03} - 3\eta_{12}) \\
&\quad (\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned}\right\} \quad (3)$$

3.3 Texture Feature

Local Binary Pattern (LBP) feature for extraction of texture information was introduced by T. Ojala et al. [11] in 1996. This operator is stout against change in illumination and is characterised by a computational simplicity and capability to encode texture details. Every pixel in LBP feature is described by a binary code. Each pixel's (central) gray level is tested with its 8 neighborhood of size (size 3×3) [7]. If neighborhood pixels' value is greater than the central pixel then the result is fixed to one else to zero. For producing binary code multiply the results with weights given by 2's powers. For the central pixel (*x,y*) LBP code is defined as follows [3]:

$$LBP_{P,R} = \sum_{p=0}^{p-1} s\left(g_p - g_c\right) 2^p, \quad (4)$$

$$s(z) = \begin{cases} 1, & if\ z \geq 0, \\ 0, & otherwise \end{cases} \quad (5)$$

Where g_c is the value of intensity for the pixel in center (*x,y*), and p-th neighbor value is g_p. When a neighbor doesn't fall at integer coordinates, bilinear interpolation is used to determine its intensity value.

An extension of original LBP is called uniform LBP, denoted as $LBP^{u2}_{P,R}$.

$$U(LBP_{P,R}) = \sum_{p=0}^{p-1} \left| s\left(g_{p+1} - g_c\right) - s\left(g_p - g_c\right) \right|, \quad (6)$$

Where g_p is equal to g_0. If $U(LBP_{P,R}) \leq 2$ then LBP will be called as uniform.

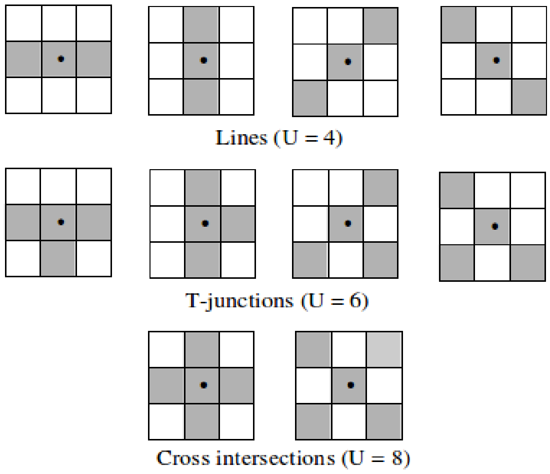

Fig -3: Basic primitives detected by gray and white rectangles relate to bit values 1 and 0 in binary forms.

ILBP can be defined as

$$ILBP^{ri}_{P,R} = \begin{cases} \sum_{p=0}^{P-1} s\left(g_p - g_c\right), & if\ U(LBP_{P,R}) \leq 2, \\ P - 1 + \frac{U}{2}, & otherwise, \end{cases} \quad (7)$$

Where *U* is defined in (6). By doing so, the $ILBP^{ri}_{P,R}$ operator has 3/2P different output labels.

3.4 Color Feature

Color features can be extracted from RGB, HSV, or other color spaces. Color histogram gives the color distribution of pixels of an image. But, different images may have same histograms because of inefficiency of color histograms to represent spatial information. Color moments are used as color moments can represent the color distribution along with color-based content [11]. Three central moments of an image's color distribution used here are Mean, Standard deviation and Skewness. Firstly R,G,B color channels of image are extracted then moments are calculated for each of these channels. Therefore total 3*3=9 color features are extracted [12].

4. ACO

Ant colony optimization (ACO) is a population-based metaheuristic that can be used to find approximate solutions to difficult optimization problems. In ACO, a set of software agents called *artificial ants* search for good solutions to a given optimization problem. To apply ACO, the optimization problem is transformed into the problem of finding the best path on a weighted graph. The artificial ants (hereafter ants) incrementally build solutions by moving on the graph. The solution construction process is stochastic and is biased by a *pheromone model*, that is, a set of parameters associated with graph components (either nodes or edges) whose values are modified at runtime by the ants.

5. PROPOSED SYSTEM

An efficient CBIR system is proposed in this paper for retrieving similar kind of monument images. In the first step of the proposed system low level features are extracted of images present in database and a feature vector is created then the query image is given to the system. Low level features of query image are also extracted and then ACO is applied for feature selection after that similarity metric is used for finding similar kind of images. In the final step similar kind of images are retrieved from the image database.

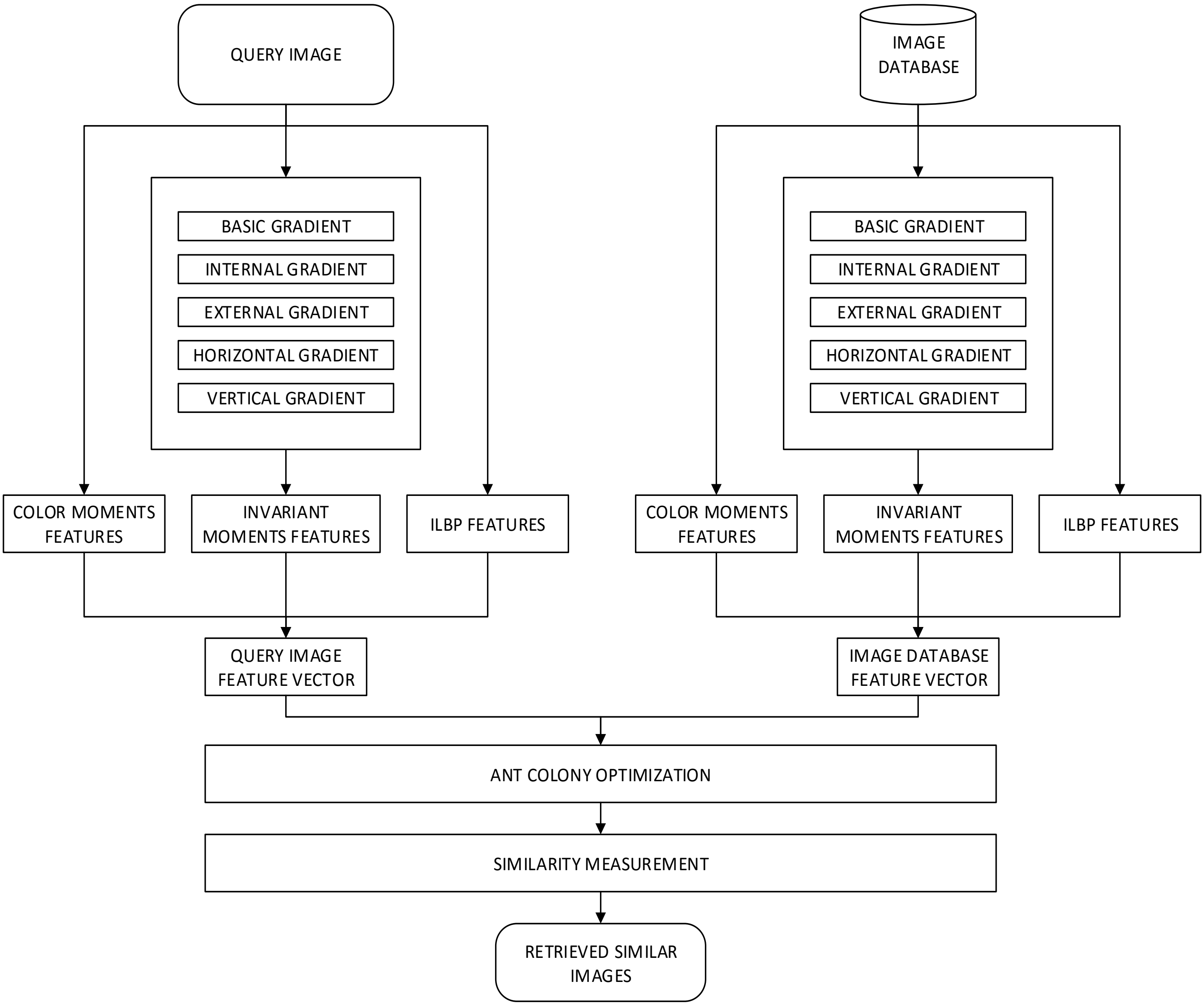

Fig -4: Proposed CBIR System

6. ANALYSIS AND OUTCOMES

6.1 Image Database

The most difficult task is the collection of data, no database is directly available of monument images for experimental purpose. The database present in this paper consist of 8 different categories are considered as: red fort, india gate, mansingh palace, humayun tomb, qutub minar, sun temple, tansen tomb, sanchi stupa. Figure depicts the sample images from database.

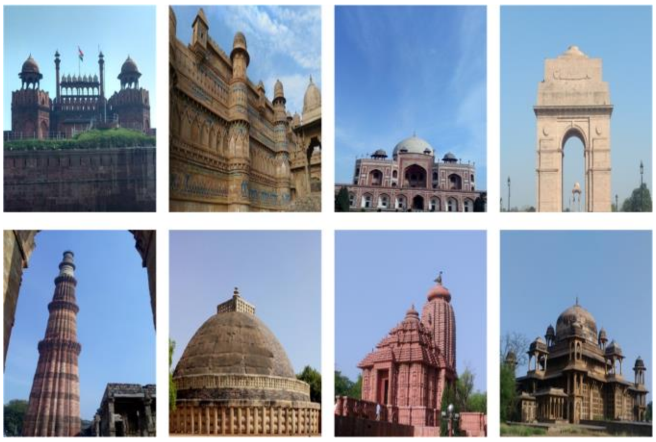

Fig -5: Database Images

6.2 Similarity Metric and Performance Evaluation

For calculating similarity between two images Standardized Euclidean Distance is used [13].

$$\text{Standardized value} = \frac{(\text{Original Value-Mean Value})}{(\text{Standard Deviation})} \quad (8)$$

$$d = \sqrt{\sum (1/s_i^2)(x_i - y_i)^2} \quad \text{for } i=1, 2, 3, 4, 5....n \quad (9)$$

Performance evaluation is done by using precision and recall. Average precision as well as recall is computed based on the number of retrieved relevant images. Basic methods of evaluating precision and recall are given by equations (10) & (11)

$$Precision = \frac{|\{Relevant\ images\} \cap \{Retrieved\ images\}|}{|\{Retrieved\ images\}|} \quad (10)$$

$$Recall = \frac{|\{Relevant\ images\} \cap \{Retrieved\ images\}|}{|\{Relevent\ images\}|} \quad (11)$$

Table -2: Precision and recall table

Image Category	Proposed System	
	Precision	Recall
Red fort	95	99
India gate	91	98
Mansingh palace	96	99
Humayun tomb	89	91
Qutub minar	98	97
Sun temple	92	93
Tansen tomb	88	90
Sanchi stupa	93	97

Table 2 depicts the precision and recall values for each category of images present in the database. Random image is selected from database as query image. Selected query image is then provided as query for calculating precision and recall values. For a given query image 50 similar kind of images are retrieved.

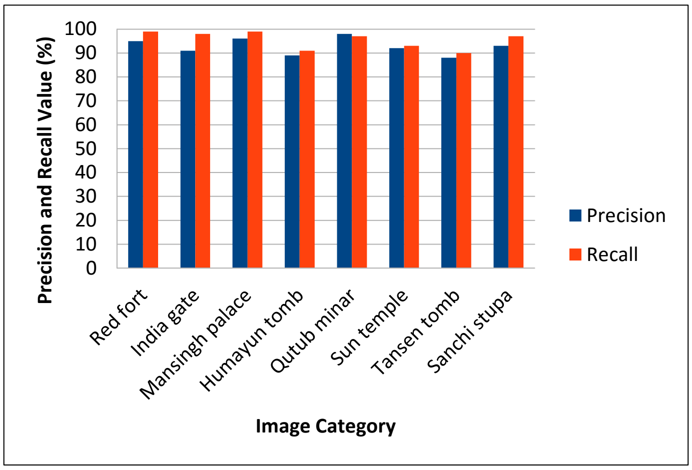

Fig -6: Precision and recall graph

6.3 Result Analysis

The results produced by proposed system are accurate, it can be seen in the precision and recall graph. 50 images are retrieved for the given query image then precision and recall table is formed. Some results with 20 images retrieved are shown in figure 7 and 8.

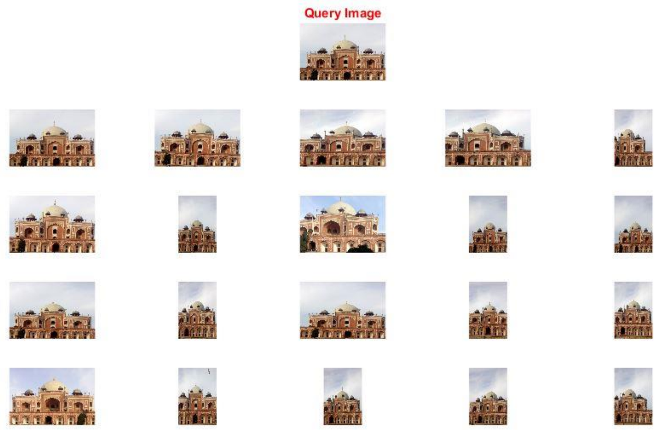

Fig -7: Retrieved similar images

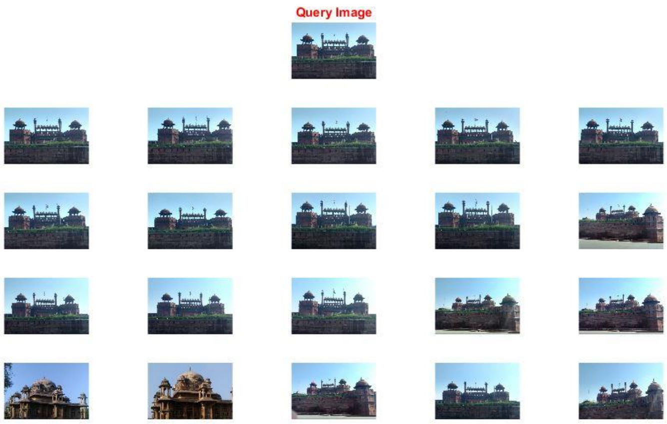

Fig -8: Retrieved similar images

7. CONCLUSION

The CBIR system proposed in this paper is an efficient approach to retrieve monument images. Shape feature of an image is extracted by using mathematical morphology and then invariant moments are applied, texture feature is extracted using ILBP and color feature is extracted using color moments. With the help of ACO optimization technique system is producing good results and is able to retrieve similar kind of images more accurately.

REFERENCES

[1] P. Desai, J. Pujari, N. H. Ayachit, and V. K. Prasad, “Classification of archaeological monuments for different art forms with an application to CBIR,” *Proc. 2013 Int. Conf. Adv. Comput. Commun. Informatics, ICACCI 2013*, pp. 1108–1112, 2013.

[2] S. Yaligar, S. Sannakki, and N. Yaligar, “Identification and Retrieval of Archaeological Monuments Using Visual Features,” 2013.

[3] M. S. Bhatt and T. P. Patalia, “Genetic programming evolved spatial descriptor for Indian monuments classification,” *2015 IEEE Int. Conf. Comput. Graph. Vis. Inf. Secur. CGVIS 2015*, pp. 131–136, 2016.

[4] A. A. Associate, “Content Based Image Retrieval System based on Semantic Information Using Color , Texture and Shape Features,” 2016.

[5] C. Engineering, “Retrieval Of Digital Images Using Texture Feature With Advanced Genetic Algorithm,” vol. 3, 2012.s

[6] H. B. Kekre, S. D. Thepade, and A. Maloo, “Image Retrieval using Fractional Coefficients of Transformed Image using DCT and Walsh Transform,” vol. 2, no. 4, pp. 362–371, 2010.

[7] “An Improved Local Binary Pattern Operator For Texture Classification" *Icassp 2016*, pp. 1308–1311, 2016.

[8] A. Rashno, S. Sadri, and H. SadeghianNejad, “An efficient content-based image retrieval with ant colony optimization feature selection schema based on wavelet and color features,” *Artif. Intell. Signal Process. (AISP), 2015 Int. Symp.*, pp. 59–62, 2015.

[9] R. Rai and R. Pradhan, “Swarm Computing Optimization techniques for Content based Image Classification,” pp. 1–9, 2016.

[10] A. Gautam and R. Bhatia, “A Novel Method For CBIR Using ACO-SVM With DTCWT And Color Features,” 2016.

[11] D. Srivastava, R. Wadhvani, and M. Gyanchandani, “A Review : Color Feature Extraction Methods for Content Based Image Retrieval,” vol. 18, no. 3, pp. 9–13, 2015.

[12] A. Malakar and J. Mukherjee, “Image Clustering using Color Moments , Histogram , Edge and K-means Clustering,” vol. 2, no. 1, pp. 532–537, 2013.

[13] Dr. Meenakshi Sharma, Anjali Batra ,”Analysis of Distance Measures in Content Based Image Retrieval”, Global Journal of Computer Science and Technology, Volume IV,2014.

[14] Ruchi Jayaswal and Jaimala Jha, “A hybrid approach for image retrieval using visual descriptor,” in ICCCA 2017 unpublished.

[15] Ravi Devesh and Jaimala Jha, " An Efficient Approach for Monuments Image Retrieval Using Multi-Visual Descriptors," in MCCS 2017 unpublished.