Efficient Content Based Image Retrieval technique based on the Cuckoo Search Correlation Method

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***Abstract*—**Content-Based Image Retrieval (CBIR) is an challenging problem in the domain of digital data management. In this research, the Cuckoo Search Correlation based Content Based Image Retrieve (CSC-CBIR) is proposed. Initially, the input image is filtered with the help of the Laplacian of Gaussian (LoG) filter and this filtered images are used to extract the features. The features such as Histogram of Gradient (HOG), Scale Invariant Feature Transform (SIFT) and Gray Level Difference Matrix (GLDM) are extracted. Then the CSC method is used to select the relevant features from the image and order the retrieved images using correlation. These features are provided to the Support Vector Machine (SVM) to classify the relevant images from large dataset. The proposed method evaluated and compared with the existing method and this showed the effectiveness of the proposed method. The average precision value of the proposed model in the retrieval is 0.906, while exiting method obtained 0.8883.

Keywords*—Content-Based Image Retrieval, Cuckoo Search Correlation based Content Based Image Retrieve, Gray Level Difference Matrix, Histogram of Gradient, Laplacian of Gaussian, Scale Invariant Feature Transform and Support Vector Machine.*

I. INTRODUCTION

With rapid advances in Internet and multimedia technologies, the past decade has witnessed a tremendous growth in the number of Web images. The proliferation of images raises an urgent demand for smart image search technologies [1], [2]. As one of the emerging technologies to support fast and accurate image search, visual hashing has received great attention and became a very active research domain in the last decade [3]. As like any information retrieval system, the Content Based Image Retrieval (CBIR) system satisfy the user by retrieving relevant images to the user needs [4]. The main purpose of CBIR is to retrieve a number of similar images from the database to the user when the user provides an example image (i.e. query image) to the system [5]. A modern interactive CBIR system consists of the following main parts: feature extraction, feature reduction, ranking and relevance feedback [6]. Given the feature representations of the images to be searched and the query image, the output of the CBIR procedure includes a search in the feature space, in order to retrieve a ranked set of images in terms of similarity (e.g. cosine similarity) to the query representation [7].

Relevance feedback (RF) is a semi-automatic strategy that collects information from users and then exploits the information by either re-weighting the content similarity measurement or revising the query [8]. Due to large collections of images in the database, efficiency is an important factor for content-based image retrieval. Therefore, developing an efficient indexing method for content-based image retrieval is of great significance [9]. However, despite the continuous development of features, effectively and reliably measuring the similarity between images remains a challenging problem in image retrieval tasks [10]. This paper aims to improve the performance of the CBIR technique by proposing CSC model. The various features are extracted from the input images and the CSC method is used to measure the different features of the image. The SVM method is used to classify the relevant images from the large dataset and the Corel dataset is used to evaluate the performance. The average precision value of the proposed method is 0.906.

The organization of the paper is in the form of the literature survey is given in the section II, the proposed method is briefly explained in the section III and the experimental result is evaluated in the section IV.

II. LITERATURE SURVEY

The latest research involves in the CBIR were surveyed in this section and the several research using the indexing techniques is surveyed.

Pradhan, *et al.* [11] proposed a three-level hierarchical CBIR system/framework where, each level of the hierarchy uses either texture, shape or color image features to reduce the size of the image database by discarding the irrelevant images and at the final level of the hierarchy, it extract the most analogous images from the reduced image database. This method used adaptive Tetrolet transform to extract the texture features from the regions of interest of the images. They proposed a novel edge joint histogram to extract the shape features of the image that uses the orientation of the edge pixels and their distance from the origin together to create a novel joint histogram. This work also introduced another color channel correlation histogram for color feature extraction. The order of the three different feature extraction processes on each level of the hierarchy was not rigid because it is difficult to predict the proper order for the highest retrieval. The indexing of the retrieved image can be used to improve the efficiency of the image retrieval.

Qingyong Li, et al. [12] proposed a novel image retrieval system with implicit relevance feedback, named eye tracking based relevance feedback system (ETRFs). ETRFs is composed of three main modules: image retrieval subsystem based on bag-of-word architecture; user relevance assessment that implicitly acquires relevant images with the help of a modern eye tracker; and relevance feedback module that applied a weighted query expansion method to fuse users' relevance feedback. This method has the considerable performance and there are some degraded performance in the proposed method and have high computational cost.

Feng, et al. [13] calculated the local curvature parameter of manifold utilizing the angle information in subspace to avoid local high curvature problems and then proposed a Warp Linear Local Tangent Space Alignment (WLLTSA) algorithm; furthermore, propose a U-Local Regression and Global Alignment (ULRGA) ranking algorithm to rank low dimensional image features. Curvature parameter was used in both WLLTSA and ULRGA to enhance robustness. A large amount of experimental results demonstrated the efficiency of CBIR system. Propose ULGRA took advantage of feedback information to improve the retrieval precision and ranking efficiency. The proposed method is not based on the object present in the image, so the region of interest method can provide better performance.

Guo, et al. [14] presented a simple approach to improve the image retrieval accuracy in the Void-and-Cluster Block Truncation Coding compressed domain. The proposed approach directly derived an image descriptor from the Ordered Dither Block Truncation Coding (ODBTC) data stream without performing the decoding process. The Color Histogram Feature (CHF) was generated from the two ODBTC color quantizer, while the Halftoning Local Derivative Pattern (HLDP) was constructed from the ODBTC bitmap image. The similarity between two images were measured from their CHF and HLDP features. Three schemes involved to improve the image retrieval accuracy, including the similarity weight optimization, feature reweighting, and user relevance feedback optimization. An evolutionary stochastic algorithm was exploited to optimize the similarity weight and feature weight in the nearest neighbor distance computation, as well as in the query update of relevance feedback optimization. The weighting factor need to improve for the better retrieval.

Guo, *et al*. [15] presented a new way to index a color image by exploiting the low complexity of the OrderedDither Block Truncation Coding (ODBTC) for generating the image features. The image content descriptor was directly constructed from two ODBTC quantizers and the corresponding bitmap image without performing the decoding process. The Color Co-occurrence Feature (CCF) derived from the ODBTC quantizers captured the color distribution and image contrast in block based manner, while the Bit Pattern Feature (BPF) characterizes image edges and visual patterns. The similarity between two images can be easily determined based on their CCF and BPF under a specific distance metric measurement. A metaheuristic algorithm, namely Particle Swarm Optimization (PSO), was employed to find the optimum similarity constants and improved the retrieval accuracy. The relevant feedback method can be added to the proposed method to increase the performance of image retrieval.

In order to overcome the above disadvantages, the CSC-CBIR model is proposed and evaluated with different databases. The correlated value of the cuckoo search algorithm is used to retrieve the images.

III. CONTENT BASED IMAGE RETRIEVAL MODEL

CBIR has attracted increasing interest in recent years. Given a query image, the image retrieval system obtains the images of the same object or scene from an image database. The input images are filtered using the LoG filter and the features are extracted from the images. The features such as HOG, SIFT and GLDM are extracted and the features are selected using the proposed CSC method. The SVM method is used to classify the relevant image using the query image.

A. Laplacian-of-Gaussian filter

The Laplacian-of-Gaussian (LoG) filter [16] is a well-known edge detector and the LoG filter minimizes the product of spatial localization and bandwidth. The input image was convolved with LoG mask and then, zero-crossings of the filtered image were detected as the edges. The LoG filter is defined in the Eq. (1), Where σ is the filter scale (space constant).

$$LoG(n,\sigma) = 1/\sqrt{2\pi\sigma^3}\,(1-\mathrm{n}^2/\sigma^2)\exp(-\mathrm{n}^2/2\sigma^2) \quad (1)$$

B. Feature Extraction

The different features such as HOG, SIFT and GLDM are extracted from the filtered images and these features are used to retrieve the relevant images. The HOG provides the gradient values of the images, and the color features of the images are extracted using the SIFT features. These features are considered as an effective in the CBIR and the description of the features are given in this section.

1) Histogram of oriented gradients

Histogram of Oriented Gradients (HOG) [17] feature descriptor is used in this work to extract the features. It is very effective to represent objects and is widely used in human and face detection. The first step is detecting all interest points of the image using the Harris detector. This operator is based on the auto-correlation matrix that describes the local structure of the image. Then compute the Gradient Orientation Histogram around the 16×16 pixel region of each interest point. First, the region is divided in 4×4 sub-region, for each sub-region the 8-bin gradient orientation $h(\mathrm{k})$, $k = 0$ *to* 7 are calculated which forms a feature vector of size 128 dimension $(4\times4\times8)$. The gradient oriented histogram is computed in the Eq. (2-7).

$$h(\mathrm{k}) = \sum_{d_{ij}} \in d_k m_{ij} \quad (2)$$

$$m_{ij} = \sqrt{dx^2{}_{ij} + dy_{ij}^2} \quad (3)$$

$$d_{ij} = \arctan(\mathrm{dy}_{ij})/\mathrm{dx}_{ij} - D \quad (4)$$

$$dx_{ij} = I_{ij} - I_{i+1,j} \quad (5)$$

$$dy_{ij} = I_{ij} - I_{i,j+1} \tag{6}$$

$$D = \arctan \frac{\sum_{ij} dy_{ij}}{\sum_{ij} dx_{ij}} \tag{7}$$

Where I_{ij} is the i, j pixel value of each sub-region, m_{ij} is the gradient magnitude of the pixel i, j, d_{ij} is the gradient direction at pixel $i, j, h(\mathrm{k})$ is the k^{th} dimension $h(\mathrm{k})$ of the gradient histogram represent the total intensity of the pixel gradient whose direction lies in the k^{th} direction bin $d_k, k = 0 to 7$. The direction bins are defined by the relative angle to the dominant gradient direction D of the image region. Finally, combing all the Gradient orientation Histogram of the interest point's area together to form a feature vector of size 128-dimension.

2) Scale-invariant feature transform

SIFT [18] is probably one of the most popular description schemes for extracting local features from image, and its excellent robustness have been assessed [19]. Given one image, SIFT first determines key points. Then it computes high dimensional vectors using the pixels surrounding each keypoint, considering scale. Image recognition is the result of the matching between the vectors of the query and the one extracted from the database images. This matching is based on distance as a k-Nearest Neighbor (k-NN) process is ran for each query vector. Eventually, a similarity score is computed from these neighbors.

More formally, keypoint detection relies on local extrema of the Difference-of-Gaussian function $D(\mathrm{x}, \mathrm{y}, \sigma)$, in the Eq. (8).

$$D(\mathrm{x}, \mathrm{y}, \sigma) = (\mathrm{G}(\mathrm{x}, \mathrm{y}, \mathrm{h}\,\sigma) - \mathrm{G}(\mathrm{x}, \mathrm{y}, \sigma)) \otimes \mathrm{I}(\mathrm{x}, \mathrm{y})$$

$$= \Delta G_{\sigma}(\mathrm{x}, \mathrm{y}) \otimes \mathrm{I}(\mathrm{x}, \mathrm{y}) \tag{8}$$

Where $\otimes$ is the 2D convolution operator, and $G(\mathrm{x}, \mathrm{y}, \sigma)$ is the kernel of the variable-scale Gaussian low-pass filter.

A keypoint is detected at the location and scale $x = (\mathrm{x}, \mathrm{y}, \sigma)^T$ if the following three conditions hold : (i) $D(\mathrm{x})$ is a local extrema over a neighborhood of x ; (ii) a sustainable contrast is present, i.e., $|\mathrm{D}(\mathrm{x})| > \mathrm{c}$ where C is a threshold hardcoded in the algorithm; (iii) the keypoint is not located on an edge, which can be detected by $tr(\mathrm{H})^2 / \det(\mathrm{H}) < \tau$, with H the 2×2 Hessian matrix of $D(\mathrm{x})$.

Each keypoint is subsequently used to generate high dimensional vectors, so-called local descriptors. The local descriptor V_x is an illumination-invariant 128-bin histogram of gradient orientations around the keypoint $x = (\mathrm{x}, \mathrm{y}, \sigma)^T$.

3) Gray level difference matrix

The GLDM is based on the occurrence of two pixels which have a given absolute difference in gray level [20] and which are separated by a specific displacement δ . For any given displacement vector $\delta = (\Delta\,\mathrm{x}, \Delta\,\mathrm{y})$, in the Eq. (9).

Let

$$s(\mathrm{x}, \mathrm{y}) = |\,\mathrm{s}(\mathrm{x}, \mathrm{y}) - \mathrm{s}(\mathrm{x} + \Delta\,\mathrm{x}, \mathrm{y} + \Delta y) \tag{9}$$

The estimated probability-density function is defined in the Eq. (10)

$$(\mathrm{i}\,|\,\delta) = \mathrm{prob}(\mathrm{S}_0(\mathrm{x}, \mathrm{y}) = 1) \tag{10}$$

C. Cuckoo Search Correlation

Cuckoo search is a heuristic search algorithm that has been proposed recently by Yang and Deb [21]. The algorithm is inspired by the reproductive strategy of cuckoos. At the most basic level, cuckoos lay their eggs in the nests of other host birds, which may be of different species. The host bird may discover that the eggs are not it's own and either destroy the egg or abandon the nest all together. This has resulted in the evolution of cuckoo eggs that mimic the eggs of local host birds. To apply this as an optimization tool, ideal rules and algorithm are used [22]:

1) Each cuckoo lays one egg, which represents a set of solution co-ordinates, at a time and dumps it in a random nest;
2) A fraction of the nests containing the best eggs, or solutions, will carry over to the next generation;
3) The number of nests is fixed and there is a probability that a host can discover an alien egg. If this happens, the host can either discard the egg or the nest and this result in building a new nest in a new location. Based on these three rules, the basic steps of the Cuckoo search can be summarized as the pseudo code shown in the Table 1.

TABLE I. ALGORITHM FOR CUCKOO SEARCH CORRELATION

Cuckoo Search Correlation

Input: Population of the problem

Output: The best of solutions;

Objective function $f(\mathrm{x}), \mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, ..., \mathrm{x}_d)^T$

Generate initial population of n host nests x_i $(\mathrm{i} = 1, 2, ..., \mathrm{n})$

While $(\mathrm{t} < \mathrm{Max\,Generation})$ or (stop criterion)

Get a cuckoo randomly by Levy flight

Evaluate its quality/fitness F_i

Choose a nest among n(say, j) randomly

If $(\mathrm{F}_i > \mathrm{F}_j)$ replace j by the new solution;

A fraction (pa) of worse nests are abandoned and new ones are built;

Keep the best solution (or nests with quality solutions);

Rank the solutions and find the current best;

Pass the current best solutions to the next generation;

Measure the correlation for the outcomes;

End while

1) Correlation Coefficient

The correlation coefficient of the outcome of the cuckoo search algorithm is measured and the outcome of the cuckoo search algorithm is $A \& B$. The correlation coefficient is the measure of linear dependences, and then the Pearson's correlation coefficient is measured using the formula given in Eq. (11). Consider each variable has N scalar observations.

$$\rho(\mathrm{A},\mathrm{B}) = \frac{1}{N-1}\sum_{i=1}^{N}(\overline{\frac{A_i-\mu_A}{\sigma_A}})(\frac{B_i-\mu_B}{\sigma_B}) \quad (11)$$

Where μ_A and σ_A are the mean and standard deviation of A, respectively. The μ_B and σ_B are the mean and standard deviation of B . Alternatively, you can define the correlation coefficient in terms of the covariance of A and B , as shown in Eq. (12).

$$\rho(\mathrm{A},\mathrm{B}) = \frac{\mathrm{cov}(\mathrm{A},\mathrm{B})}{\sigma_A\sigma_B} \quad (12)$$

The correlation coefficient matrix of two random variables is the matrix of correlation coefficients for each pairwise variable combination, shown in Eq. (13).

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$$R = (\begin{matrix}\rho(\mathrm{A},\mathrm{A}) & \rho(\mathrm{A},\mathrm{B}) \\ \rho(\mathrm{B},\mathrm{A}) & \rho(\mathrm{B},\mathrm{B})\end{matrix}) \quad (14)$$

Since A and B are directly correlated to themselves, the diagonal entries are just 1, that is shown in Eq. (15).

$$R = \begin{pmatrix}1 & \rho(\mathrm{A},\mathrm{B}) \\ \rho(\mathrm{B},\mathrm{A}) & 1\end{pmatrix} \quad (15)$$

The features are given to the classifiers to find the similar images in the large dataset and the outcomes of the images are evaluated.

D. SVM Classification

Support Vector Machines (SVM) [23] is an approximate implementation of the Structural Risk Minimization (SRM) principle. It creates a classifier with minimized Vapnik Chervonenkis (VC) dimension. SVM minimizes an upper bound on the generalization error rate. The SVM can provide a good generalization performance on pattern classification problems without incorporating problem domain knowledge. Consider the problem of separating the set of training vectors belonging to two classes, as shown in Eq. (16).

$$\{(\vec{\mathrm{x}}_i,\mathrm{y}_i)\}_{i=1}^{N}, y_i = +1/-1 \quad (16)$$

Where x_i is an input pattern, and y_i is the label, +1 denotes positive example, -1 denotes the negative example. If those two classes are linearly separable, the hyperplane that does the separation can be easily calculated by Eq. (17).

$$\vec{w}^T\vec{x} + b = 0 \quad (17)$$

Where x is an input vector, w is a weight vector, and b is a bias. The goal of SVM is to find the parameters w_0 and b_0 for the optimal hyperplane to maximize the distance between the hyperplane and the closest data point, shown in Eq. (18) and (19).

$$w_0^T\vec{x}_t + b_0 \geq 1 \ \text{ for } \ y_i = +1 \quad (18)$$

$$w_0^T\vec{x}_t + b_0 < -1 \qquad \text{for } y_i = -1 \quad (19)$$

A linear separable example in 2D is illustrated in Fig. 1. If the two classes are non-linearly separable, the input vectors should be nonlinearly mapped to a high-dimensional feature space by an inner-product kernel function $(\mathrm{x},\mathrm{x}_i)$. Table 1 shows three typical kernel functions [24]. An optimal hyperplane is constructed for separating the data in the high-dimensional feature space. This hyperplane is optimal in the sense of being a maximal margin classifier with respect to the training data.

Once the features are extracted from the input images and the features are used by the SVM to classify the relevant image from the large datasets. The proposed CBIR model is evaluated and compared with other existing methods, as shown in the experimental result section.

IV. EXPERIMENTAL RESULTS

CBIR is one of the important technique to organize the large dataset and retrieve the relevant images. In this research, the CSC-CBIR method with the classifier is proposed to retrieve the relevant image from the large datasets. The feature extraction and feature selection from the filtered image and the data are fed to the SVM for the classifying the relevant images. The proposed method is evaluated in terms of different metrics and compared with the existing methods. The Corel dataset is used for evaluating the proposed method and there are 10,000 images present in the dataset. The proposed method is evaluated and dataset descriptions are given in this section.

A. Evaluation Metrics

Precision (specificity) refers to a measure of the capacity of the system in retrieving the images that are similar to the query image. Meanwhile, the Recall rate called the positive rate or sensitivity, gauges the capacity of CBIR systems in retrieving the image that is similar to the query images. The precision and

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recall values are measured using the formula shown in the Eq. (20) and (21). For the elaboration of the results, computation was made with precision and recall according to the number of query images (from the test dataset) and retrieved similar images from the corel image database.

$$recall = \frac{Number\ of\ similar\ image\ retrieved}{Total\ number\ of\ similar\ images\ in\ the\ database} \quad (20)$$

$$precision = \frac{Number\ of\ similar\ image\ retrieved}{Total\ number\ of\ images\ retrieved} \quad (21)$$

B. Corel image Dataset

The Corel dataset contains 10,908 images of the size 384 × 256 or 256 × 384 each. For this dataset, reported that the results in ten semantic categories having 100 images in each category. These semantic classes are namely: Africa, Buses, Beach, Dinosaurs, Buildings, Elephants, Horses, Mountains, Flowers, and Food. The reason for our choice to report the result on these categories is that: these categories are the same semantic groups used by most of the researchers who are working in the domain of CBIR to report the effectiveness of their work [25].

C. Performance Evaluation

The images are taken from the dataset and proposed method to retrieve the relevant images. The input image is preserved through the LoG filter and the filtered images are used to extract the features. The proposed CSC has been applied to the images to find the relevant features from the image. Based on the features selected from the images, SVM classifies the images related to the query images. The results acquired from the datasets based on the query images are shown in the Fig. 1 and 2.

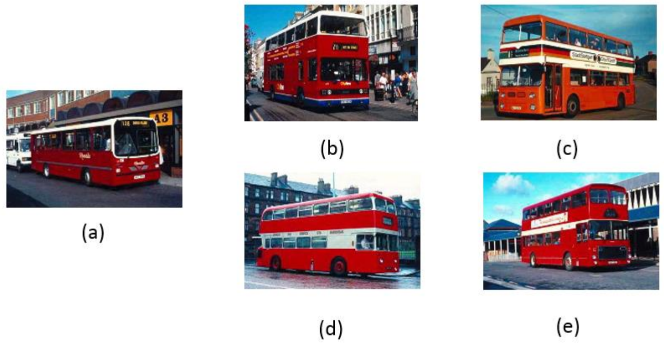

Fig. 1. Bus image (a) Query image, (b-e) Retrieved images

The input query image of bus is shown in the Fig. (1)(a) and the output retrieved images are shown in the Fig. (1)(b-e). The various features are extracted from the query image and based on the features selected by the CSC, the images are retrieved from the datasets. The query of bus image and retrieved images are shown in the Fig. (1). The parameters are measured from the output of different groups of images.

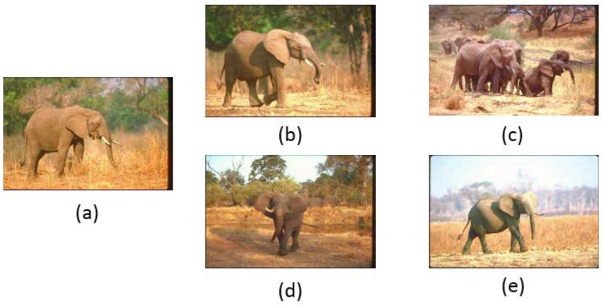

Fig. 2. Elephant image (a) Query image, (b-e) Retrieved images

The query image of the Elephant is shown in the Fig. (2) (a) and the retrieved images of Elephant are shown in the Fig. (2)(b-e). The features extracted from the query images are HOG, SIFT and GLDM and the CSC method is used to select the features from the query images. These features are fed to the SVM, so that it technique provide the relevant image from the database. The Elephant query image is shown in the Fig. (2)(a) and the all the retrieved images are elephant, as shown in the Fig. (2) (b). This shows that the proposed method provides the relevant images based on the query images.

TABLE II. PRECISION AND RECALL VALUE OF THE PROPOSED METHOD

Groups	Precision	Recall
Buses	0.97	0.78
Mountains	0.85	0.77
Beach	0.92	0.82
Elephants	0.84	0.64
Food	0.88	0.67
Flowers	0.97	0.72
Africa	0.86	0.76
Horses	0.97	0.86
Dinosaurs	0.99	0.78
Buildings	0.81	0.72

The precision and recall value of the CSC-CBIR model are measured and the values are shown in the Table 2. The outcome of the model is measured in terms of different metrics and this shows that the proposed model has the highest precision and recall value. The precision and recall values are measured for the different groups and the dinosaurs images have the higher precision value of 0.99 compared to other groups. The groups such as Busses, flowers and horses have the higher precision value of 0.97 and considerable recall values are acquired by the proposed model.

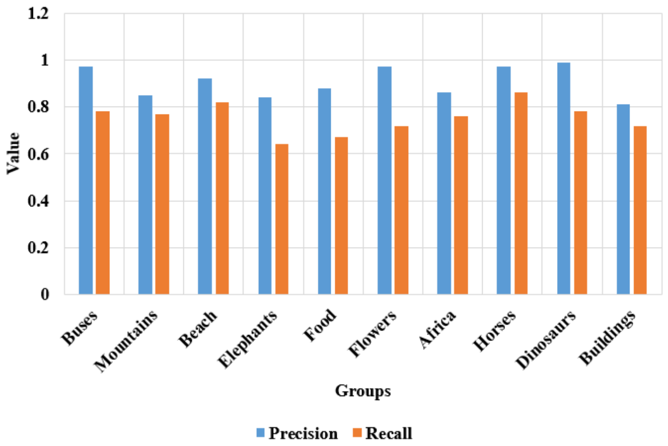

Fig. 3. Precision and Recall of different groups

The precision and recall value is measured for the proposed model and shown as the graph in Fig. (3). This shows that the proposed model has higher precision value and have considerable recall value in CBIR. The bus query image has the considerable precision and recall value and the dinosaur's image have the precision of 0.99. The recall value is low for some query images and considerable value is achieved for most of the images.

TABLE III. COMPARISON OF PRECISION VALUE

Groups	CSC	GA-ILS [26]	BTIR [25]
Buses	0.97	0.96	0.95
Mountains	0.85	0.82	0.75
Beach	0.92	0.9	0.7
Elephants	0.84	0.83	0.8
Food	0.88	0.87	0.75
Flowers	0.97	0.96	0.95
Africa	0.86	0.838	0.65
Horses	0.97	0.96	0.9
Dinosaurs	0.99	0.99	1
Buildings	0.81	0.755	0.75
Average	0.906	0.8883	0.82

The precision value measured for the CSC-CBIR model is compared with existing methods of [26] and [25]. The proposed and existing model has been processed using corel datasets and the performance are evaluated and compared with each other. This shows the effectiveness of the proposed model. The proposed CSC technique has higher precision value compared to the other two methods. The Bandelet Transform based Image Representation (BTIR) technique provide the considerable performance and genetic algorithm with Iterated Local Search (GA-ILS) method has better performance. The proposed method has the higher precision value compared to the other existing method due to the cuckoo search provides the relevant features in CBIR and the outcome of the cuckoo search are correlated to find the similar image in the database. The proposed method has the higher precision value compared to other techniques.

TABLE IV. COMPARISON OF RECALL VALUE

Groups	CSC	GA-ILS [26]	BTIR [25]
Buses	0.78	0.75	0.19
Mountains	0.77	0.75	0.15
Beach	0.82	0.815	0.14
Elephants	0.64	0.58	0.16
Food	0.67	0.62	0.15
Flowers	0.72	0.66	0.19
Africa	0.76	0.73	0.13
Horses	0.86	0.85	0.18
Dinosaurs	0.78	0.75	0.2
Buildings	0.72	0.62	0.15
Average	0.752	0.712	0.164

The recall value is compared to the other two existing methods in CBIR technique in the corel dataset and shown in the Table 4. The recall value is higher for the proposed method compared to the other two methods. The average recall value of the proposed CSC-CBIR model is 0.752 and for the existing method of GA-ILS method is 0.712. The BTIR method has the lower recall value compared to the other two methods and GA-ILS method has the considerable performance. This shows the effectiveness of the proposed model in the CBIR performance.

The proposed Cuckoo search method with correlated value provide the considerable performance in the CBIR technique. The effectiveness of the proposed method over the other method is shown in the result comparison. This shows that the proposed method can be applicable for the real-time system for effective retrieval.

V. CONCLUSION

CBIR refers to the process of obtaining images that are relevant to a query image from a large collection based on their visual content. The corel datasets is one of the standard datasets for evaluating the CBIR technique and this dataset is used in this research. In this context, the input image is filtered with the help of LoG filter and the filtered images are used to extract the features. The various features such as HOG, SIFT and GLDM are extracted from the images and the features are selected using the CSC method. The selected features are used by the SVM to classify the image as relevant to the query images. The proposed model is evaluated and compared with the existing methods. This showed that the proposed method has the highest performance compared to the other existing methods. The average precision value of the proposed model in CBIR is 0.906 and the average recall value is 0.752. In the future work, the relevance feedback can be included to improve the efficiency in terms of human requirement.

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