Optimization of Content Based Image Retrieval Using Hybrid Approach

Saqib Majeed[1,*], Muhammad Usman[1], Kashif Sattar[1], Saleem Iqbal[2], Jawaid Shabir[3]

[1]University Institute of IT, PMAS-Arid Agriculture University, Rawalpindi, Pakistan
[2]Department of Computer Science, Allama Iqbal Open University, Islamabad, Pakistan
[3]Department of Computer Engineering, SSUET, Karachi, Pakistan
[*]Corresponding author: saqib@uaar.edu.pk

Abstract

With the dawn of multimedia technology and the social web, retrieval from large image databases become possible. As a consequence of rising usage and incredible enthusiasm for inquiry about on Content-Based Image Retrieval (CBIR) systems, it needs improvement in the accuracy of CBIR systems in addition to the decline in monotonous results. Currently, the majority of research has focused on the representation and differentiation of images by an arrangement of low-level visual features. However, most of the retrieval systems produce repetitive or unnecessary retrieval results, termed a redundancy factor. In addition, content-based retrieval with reduced redundancy has a direct correlation with high-level semantics which is overlooked. Accurate content retrieval with reduced redundancy enables the user to focus on the actual problem in preference to nurture the retrieval results, augments the efficiency, and improves overall system performance. To enhance the retrieval accuracy and diminish the redundancy factor in image retrieval, we proposed an optimization-based technique that is blended with classification. In the proposed novel hybrid approach for CBIR, we used a two-tier architecture model. The first tier belongs to the feature extraction process via Particle Swarm Optimization with a Support Vector Machine as a classifier. On the way to reduce the redundancy factor, the K-Nearest Neighbor as a classifier is used with the Genetic Algorithm in the second tier. We noted a noteworthy increase in retrieval accuracy for images that is up to 25% (approx.). The proposed hybrid model is effective to enhance accuracy and reduce redundancy factors in CBIR systems. We used the WANG dataset for experimentation. Henceforward, improving the retrieval accuracy and reducing redundancy factor using unsupervised learning techniques is part of our future work.

Keywords—Content Based Image Retrieval, Genetic Algorithm, KNN, PSO, Redundancy Factor, Retrieval Accuracy, SVM

1 Introduction

FAST development in the area of smart compact mobile devices and access to higher bandwidth by everyone increases the use of new technologies and many applications. Particularly, social media apps have a strong influence on everyone's life. People are not only using these apps for daily chit-chat but also use for research and development activities. From school kids to research scientists and from entertainment to education, people of different ages are downloading and uploading images on daily basis. Doctors and researchers are also using images of X-ray s, CT, MRI, and PET scan in the medical field to identify diseases [1]. So the use of images increased in medical science with the help of machine learning techniques which helps in decision-making and disease anticipation [2]. This trend is increasing image databases exponentially in all areas of life with time. To handle such large databases we need effective and efficient methods to store and retrieve images with accuracy and on time [3]. A lot of research work has been done on image retrieval systems from keyword-based to Content-based, which try to get the required query image from large databases with accuracy and in a short time. In traditional methods, researchers used text descriptions and image captions, however, in new methods researchers are using features of images for image retrieval. These features can be shape, texture, and color, automatically extracted from images. As image retrieval is the need of almost every person, therefore this research area has been very dynamic since the 1970s. In new methods of image retrieval

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researchers are also using Artificial Intelligence (AI) for accuracy. Accuracy can be increased by using techniques of Genetic Algorithm [2], PSO, and Neural Networks. These AI techniques can be supervised learning-based or unsupervised learning based. In supervised learning, we use a method of classification whereas in unsupervised learning we use a method of clustering and no datasets are given.

1.1 Keyword Based Image Retrieval

The structure of Image retrieval by keyword based are introduced in the 1970s and they used catchphrases as descriptors to record a picture. Before pictures are ensured in the database, they are scrutinized physically, and doled out the keywords that are most fitting to depict their substance. These keywords are secured as an element of credits identified with the picture. A mid-question arranges the image retrieval will recognize from the client one or keywords that establish the pursuit benchmarks. Given keywords that match the images in search criteria are selected as the output image.

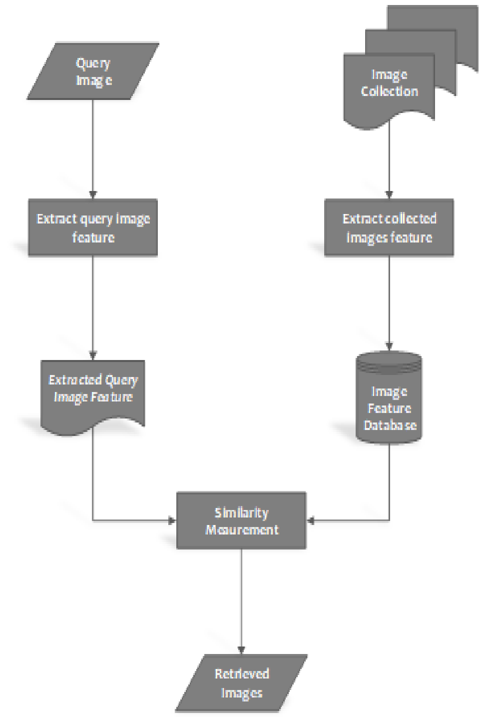

Fig. 1: Architecture of CBIR

1.2 Content-Based Image Retrieval

CBIR systems are one of the promising techniques to retrieve images from large databases. It is also an alternative to Keyword based systems. Unlike the keyword-based system, visual parts of the CBIR system are expelled from the picture itself. CBIR could be ordered in light of the kind of elements utilized for recovery which could be either low-level or high-level features. In the early years, low-level features incorporate color, shape, texture, or a blend of the above features were utilized. CBIR follows two major steps while processing, the first step is to extract the image feature, and the second step is to compute the similarity (Distance) between two extracted features. Commonly used low-level or content-based features are color, shape, and texture. The architecture of CBIR is shown in Fig. 1.

1.3 Semantic-Based Image Retrieval

Single components or a blend of various visual components could not catch abnormal state thoughts of images. In addition, because of the execution of Image Retrieval (IR) because low-level components are intimidating, there is a requirement for the standard of the exploration unites to recovery because of semantic importance by endeavoring to extricate the subjective idea of a human to delineate low-level features to the high-level concept of the semantic gap. What's more, representing the content of the image with semantic terms enables the user to find out images using text query that is natural, simpler, and favored by the front-end users to express the contrast in their mind and utilizing images. For instance, queries of users might be 'Discover sunset image as opposed to 'discover me an image contains red and yellow hues'. Hirwani proposed various semantic-based hybrid techniques and classified them using color, texture, and shapes [4]. Another research done by Ashok et al. [5] is text-based image retrieval using Natural Language Processing (NLP) technique. In this research, relevant documents are retrieved and finally, related images are retrieved from these documents.

2 Related Work

CBIR is one of the utmost promising and active exploration areas. Researchers present many papers on this do-main. CBIR can be helpful for users who need to search the image from a large dataset. A review of some papers is given below: Francisco presents a paper in which they used different medical images initially extract features and then use similarity measures using GA [2]. Their computational Time is much better as compared to others. Experimental results show Max. F-score CBIR 0.1731 CBIR without GA 0.1863

CBIR with GA 0.2268. Analoui introduces an approach Artificial Immune System (AIS) for analyzing the CBIR. Paper uses the TECNO-CBIR and Fuzzy Linking Histogram to retrieve image from noisy data set through AIS clustering Algorithms, their algorithm TECNO-CBIR improves strength, learning capabilities, scalability, and automatic scale assessment and they work on Color feature [6]. An experimental result on noisy images of dataset Cats, Green, sunset, etc. shows that the TECNO-CBIR approach decreased by 5-10Arai takes the dataset of Simulation and plankton and introduced a new approach to feature Shape by computing the distance between the centroid and object boundary. They utilize Multi-layer Centroid Contour Distance (MLCCD) [7]. Papers use the Shape feature. An experimental result shows approx. 8.67% improvement as compared to Centroid Contour Distance (CCD). Bulo uses CBIR with RFB Using Random Walks. Paper uses the Random Walks Algorithm and RFB which work on the Color feature [8]. Their technique is parameter-free, easy to implement, and scales well to huge datasets Oliva, Wang, and Caltech. An experimental result shows that using RFB performance improves by 95Chadha argued the Comparative Study and Optimization of Feature-Extraction Techniques for CBIR [9]. They compare different feature-extraction techniques Color Moments, Local/ Global Color Histogram, Co-occurrence, Geometric Moment, and Average RGB. In any case, independently these techniques result in poor execution. Along these lines, mixes of these techniques have likewise been assessed, and comes about for the most proficient mix of methods has been presented. They also proposed IR performance by Query modification through image cropping. They decreased time, increased accuracy, and try to reduce RF because most researchers neglected RF. They used WANG datasets and their results show before combined 42.05% before combined 91.51% optimization results in 81.69%. Chandy present a paper in which they proposed a Gray Level Statistical Matrix (GLSM) using four statistical texture features ROI (Regions of Interest), Preprocessing, Generation of GLSM, and Estimation of texture features [10]. In past no GLSM was used on MIAS then they decide to apply GLSM to MIAS Dataset. Experimental results show 85.10Chaudhry presents a paper in which they introduce a hybrid features technique for human activity acknowledgment. These features compute from the space-time 3D squares [11]. The Blocks or cubes are gotten through Interest Point Based feature extraction, at that point process kinematics include Principal Component Analysis (PCA) and an extraction algorithm has been utilized to decrease the feature vector' dimensionality. For order, they utilize artificial neural systems (ANNs). They use to analyze the KTH dataset. Experimental results show 88.61Gururaj purposed a Novel approach for Finding Fundus Images of the Eyes through Extracted Exudate for a CBIR System [12]. They proposed a novel approach for the detection of the Optical disk and the presence of any exudates. The paper shows the experimental setup in which they apply histograms on various numbers of Optical images with an accuracy of 92Imran takes the dataset of CORAL and applies PSO and SVM to it after that they apply RFB because only the performance of SVM or RFB is not better [13]. An experimental result shows 90Jeyakumar presents a paper in which they measure the performance of the IR system based on error metrics through the Human Visual System (HVS) and different mathematical functions [14]. They used homogeneous and heterogeneous datasets. Khan presents a paper in which they use feature fusion to combine different images (multifarious features) and user feedback for reduced semantic feedback for finding [15]. They compare the result precision is .40. They use it to analyze COREL. Latha uses CBIR Techniques in multilevel architecture for Vegetable Classification and they also used hybrid image features [16]. They proposed two levels. In the first level, they characterized color offered to analyze HSV (Hue, Saturation, and Value) color space from the database to recuperate the images with the lowest distinction expel. Second level Local Ternary Pattern (LTP) is offered on the initial level image. They increase accuracy and reduce time. Their success rate is 90%. If work as Multi-Layers and classification techniques are different then the success rate will be 100%. Lowanshi takes the COREL dataset and applies a multilayer classifier [17]. Initially used SVM then apply KNN-GA on it. An experimental result shows before combined 83.33% before combined (2tier) 97.33% on the same dataset. A PSO using the SVM method for Clustering and IR [18]. These hybrid techniques PSO using SVM are used to improve accuracy and efficiency. The paper shows the experimental setup in which they tested this hybrid technique for various numbers of Arabic numerals with an average accuracy of 90Majeed presents a paper in which they work on the Qualitative Semantics of any image and describe it (water, sky, snow, etc.) from one image [19]. Their architecture of SIREA is based on keyword-based image retrieval and CBIR through semantics. Their proposed model works on the transformation of human-understandable high-level features of image into RDF triple that contains information about the source image. Experimental results show 90% accuracy. They used natural scenes.

Mishra takes the dataset of Butterflies, flowers, and nature and applies Hybrid Swarm Intelligence Technique PSO and Artificial Bee Colony (ABC) [20]. Paper uses Color, Shape, and Texture features. An experimental result shows 80% but their improvement is too low because the average of ABC is 78% and PSO-ABC is 80%. Nugroho takes the dataset of Brain MRI and applies Zernike Moments Algorithm and R-Tree data structure. The initially used magnitude of Zernike then apply R-Tree on it. Papers use the Shape feature [21]. Using these methods the most valuable data from the dataset can be obtained. An experimental result shows 95.20Rao argued the CBIR using Exact Legendre Moments (ELM) and SVM. Paper uses ELM and SVM further improvement used Modified Moment Invariants and Stacked Euler Vector [22]. They proposed different moment techniques but they used ELM after that results are much better compared to MI, and ZM and they work on the Shape feature. They use to analyze Orthogonality and COIL-20 datasets. Experimental results show approx. 10-15% improvement as compared to others. Shamsi presents a paper in which they use the RFB approach for modernizing both the masses for a feature type and the masses for feature components [23]. They compare the result with Rui STL and CC STL methods then their result is effective. After 6 Iteration their method precision is .65, CC STL .63, and Rui STL .57. They use to analyze ImageCLEF 2007. Wang presents a paper in which they used a Color co-occurrence matrix to extract color through a mosaic dominate algorithm and extract texture features through a co-occurrence matrix, Similarity measure through Euclidean distance, and color IR through color-spatial feature [24]. The Paper compares the results in terms of accuracy and recall. They use to analyze natural image datasets. Experimental results show a 75-90% average of 82.94%. Rajamand introduces an approach for analyzing Region-Based Image Retrieval. The Paper uses the Semantic Cluster Matrix (SCM), RFB for retrieving semantic images for both untrained and trained classes [25]. An experimental result shows 91.80% and they use the Caltech dataset. Classification using GLCM features and texture-fused LBP variants was proposed by Garg and Dhiman [26]. This approach was applied to a CORAL dataset with the help of PSO based feature selector. Results showed improvement in most of the CORAL dataset classes. Anju and Shreelekshmi [27] proposed a semantic scheme using combined features. This scheme fused two visual descriptors of MPEG 7 which are extracted from images. It improved the precision level but the drawback is higher search time and storage requirement. Choe et al. [28] proposed a content-based image retrieval system using deep learning to assist in identifying lung disease without any requirement of experience level. Dataset used was CT images from Jan. 2000 to Dec. 2015 for a total of 288 patients categorized into four classes. the overall diagnostic accuracy improved (before CBIR, 46.1% [95% CI: 37.1, 55.3]; after CBIR, 60.9% [95% CI: 51.8, 69.3]; P ¡ .001).

2.1 Previous Research Weakness

Exceptional perceptions in the survey of related works are as per the following:

1) There still have not been ideal depictions for semantic features. This is because of the decent variety of visual features, which generally exist in genuine uses of IR.
2) Old research implements one content feature and using one content feature cannot give the desired accuracy.
3) For more than one feature there is a need to calculate the weights so if we are using the equivalent weights then it cannot provide great results.
4) It is more appropriate and it has an incredible advantage to group the images into clusters to have the capacity to diminish the inquiry space in such web indexes. Data Clustering is frequently made as a stride for accelerating IR and enhancing exactitude, particularly from a vast database.
5) There are a considerable lot of strategies used to quantify the similarity between various elements, for ex-ample, data content, Dice coefficient, cosine coefficient, and distance-based measurements. In our thesis, a new approach is designed to calculate low-level features of the image and compute the similarity between two images based on the Euclidean distance.
6) All current CBIR systems suffer from insufficient generalization performance and accuracy. Constructing a generalized CBIR system is one of the profound current problems. When combining a few procedures like content-based, multi-feature extraction, artificial intelligence, and clustering to assemble the CBIR system, one can get nearer to speculation to an ever-increasing extent.

In some previous works, a combination of PSO, GA, and KNN was not used especially to optimize the main input. Our paper uses this combination but differently; hence it will use PSO and GA to optimize features' weights which contributes significantly to overall system performance.

3 Research Framework

To build up a productive algorithm for CBIR, a few issues must be illuminated. The primary issue is to choose the components is that to signify the images. Normally, with data and elements, the images are rich that can be utilized for IR. In any case, it should pick and concentrate on the most critical features that prompt a decent recovery result. The subsequent issue is the computational load to extricate image features and manage vast image databases. It needs to recall that bulky image databases are utilized for highlights extricating and IR, so it requires a framework with a fast and low computational load.

The structure of the proposed technique has been divided into distinct stages as illustrated in Fig. 2 and explained below:

i Initialization: Initially user query (search by image).
ii Preprocessing: Remove noise, Rescaling and Resize the image.
iii Feature Extraction: Extract global features from the image (Color, Texture, Shape).
iv Optimization: Optimize the extracted feature through a hybrid approach.
  a) 1st Layer: PSO using SVM.
  b) 2nd Layer: GA using KNN.
v Similarity Matching: Euclidean distance
vi Relevant Images: All relevant images are displayed if any redundant image is present then again optimize the features.
vii Relevant FeedBack (RFB): RFB uses for improvement purposes.
viii Result: Show the Image.

4 Proposed Work

In the proposed scheme, we follow the two-level classification architecture for more improvement purposes of the result, where PSO with SVM classifier is used in the first layer and KNN with GA is used as the second layer which takes input from the first processed classifier.

In the algorithm, the steps which we follow are:

1) Verify image database.
2) Read all training images from the image database.
3) Extract images RGB feature.
4) Stored all extracted features in separate single file each.
5) Now read the query image.
6) Repeat steps 3, and 4 for the query image.
7) Now apply Tier 1: PSO-SVM approach for training then the classification of images in a separate group, apply linear Kernel function
8) Then again extract the feature
9) Now apply Tier 2: GA-KNN approach for optimizing then the classification of images, for best-optimized retrieval results by applying the Easom function.
10) Calculate Distance: Compute distances between the feature vector(s) of the inquiry image and the database images through Euclidean distance through:

$$dist(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{1}$$

11) Calculate Redundancy Factor (RF):

$$RF = \frac{Total\ retrieved\ images\ =\ Total\ class\ images)}{Total\ class\ images} \tag{2}$$

if RF = 0 then Display the image
Else go to step 7

Algorithm 1: Extract features from the dataset
Input: Collected Image
Output: Image feature database
Initialization: Image dataset

1) Loop maximum iteration
2) **for** i = 1 to all images **do**
3) Extract image features
4) Store image features
5) End **for**
6) **return**

Algorithm 2: Optimize feature of query image Layer 1
Input: Image
Output: Classified optimized image vector PSO-SVM
Initialization : Query image

1) **for** $i = 1$ to all image particles **do**
2) Extract image features
3) Store image features as Vector v
4) End **for**
5) **for** each particle
6) Initialize particle
7) End **for**
8) **do**
9) **for** each particle

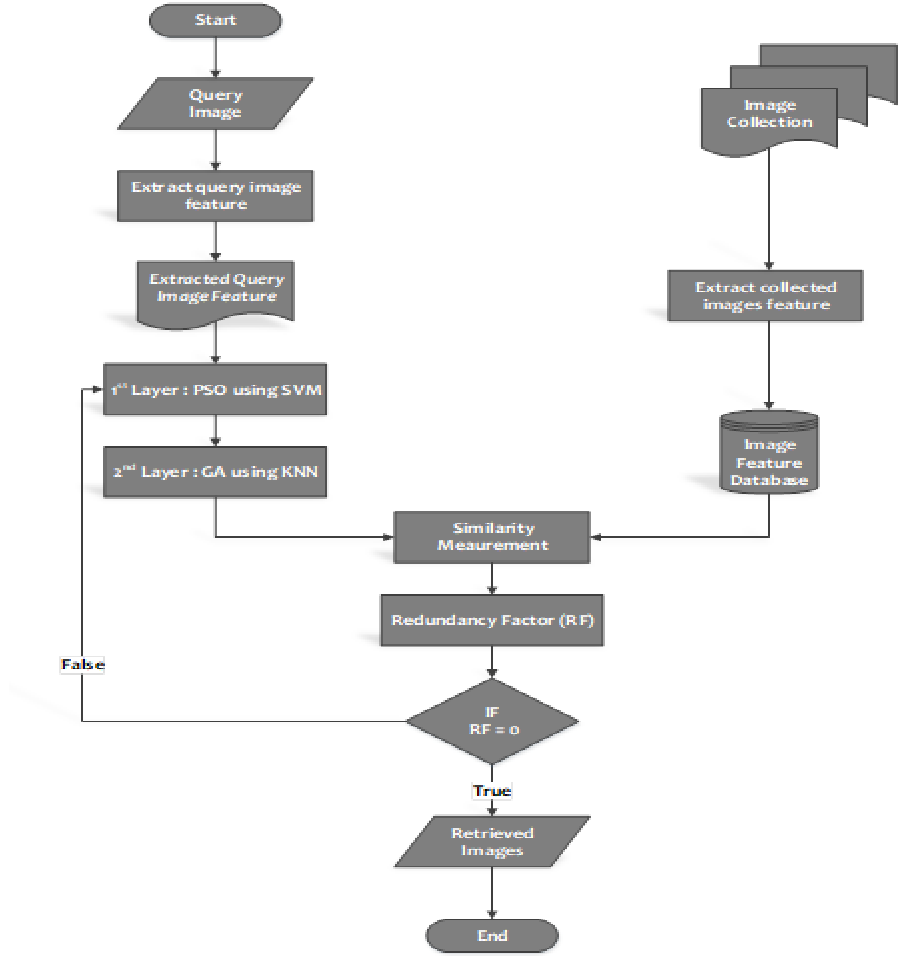

Fig. 2: Proposed framework

10) Calculate fitness value using linear kernel function, $k(x, y) = x^T y + c$
11) If the fitness value is better than the best fitness value ($pBest$) in history
12) set current value as the new $pBest$
13) End **for**
14) Choose the particle with the best fitness value of all the particles as the $gBest$
15) **for** each particle
16) $v[] = v[] + c_1 * rand() * (pbest[] - present[]) + c_2 * rand() * (gbest[] - present[])$
17) $present[] = present[] + v[]$
18) End **for**
19) Classify $(X, Y, v)//SVM$
20) **for** $j = 1$ to each optimized particle
21) Compute distance $d(X_j, v)$
22) End **for**
23) Compute set j containing indices for the j smallest distance $d(X_j, v)$
24) **Return**

Algorithm 3: Optimize feature of query image Layer 2

Input: Classified optimized image vector PSO-SVM

Output: Classified optimized image vector GA-KNN

Initialization : Query image

1) **for** each particle
2) Initialize particle
3) End **for**
4) **do**
5) **for** each particle
6) Evaluate the fitness of every particle using the Easom function:
7) $f(x) = -cos(x_1)\ cos(x_2)\ exp(-(x_1 - \pi)^2 - (x_2 - \pi)^2)$
8) End **for**
9) **repeat**
10) Select the *best particle* to be used by genetic operators

11) Generate new *particles* using crossover and mutation
12) Evaluate the fitness of the new *particles*
13) Replace the *worst particles* of the populations by the *best* new *particles*
14) **until**
15) Classify (X, Y, v) // KNN
16) **for** $k = 1$ for each particle
17) Compute distance $d(X_k, v)$
18) End **for**
19) Complete set k containing indices for the smallest distance $d(X_k, v)$
20) **Return**

Algorithm 4: Similarity Matching

Input: Classified optimized image vector GA-KNN and image featured database

Output: Image

Initialization : Image vector and image featured database

1) $dist = 0$
2) **for** i=1 to n
3) $dist(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$
4) End **for**
5) **if** *dist = minimum && Redundancy factor = 0*
6) **return** image
7) **else**
8) **goto** *Algorithm # 2*

4.1 Computational Complexity

The computational complexity is used to determine the time complexity of the proposed scheme. According to Algorithms 1,2 and 4 computational complexities are Big $O(n)$, and Algorithm 3 computational complexity is Big $O(n^2)$ so the overall computational complexity of the proposed technique is Big $O(n^2)$. If we compare it with the existing approach of OFET, it remains the same however on the other side our proposed scheme outperforms in all aspects.

4.2 Image Database

The image database that is used in our assessment is the WANG dataset. WANG dataset has 1000 images which is a subgroup of the Corel database. These images have 10 classes, every class contains 100 images. Inside this database identified whether any two images are of a similar class. There are 10 test images in each image class. Where the images in a similar row have a place with a similar class.

5 Performance Metrics

In this section, the proposed system outcomes are evaluated by using a confusion matrix, precision, recall graph, and RF table. These are defined and described respectively. The clustering accuracy is introduced in the confusion matrix by dealing with 10 observed and 10 real classes. An image sub-dataset of size 1000 of WANG database was extracted and it was classified into 100 images each for 10 different classes. The accompanying is the different class names utilized as a part of the image database.

1) Africans
2) Beach
3) Architecture
4) Buses
5) Dinosaurs
6) Elephants
7) Flowers
8) Horses
9) Mountains
10) Foods

Features are extracted for each conception in the database. Different features are normal and variations in Edge density, Boolean edge, density, RGB color space, and histogram.

5.1 Confusion Matrix

Confusion matrix for the 10 real classes and 10 experimental classes. Cluster accuracy is one of the ways of measuring the quality of a clustering solution. The accuracy is higher it shows that it is the better solution. The accuracy of each cluster is as shown in Table 1. From Table 1, it can be observed that Africans and buses are in the same class because of the similarity in color. Experimental classes of different sizes had different accuracy shown in Table 1. More than half of the clusters have an accuracy greater than 80%. For instance, for the experimental class value of 5 class, the accuracy is 100%. It is because of query image belongs to class 5.

5.2 Precise Graph

The precision between the Previous and Proposed approaches is calculated as shown in Tables, using the Equation as follows:

$$Precision\ (P) = \frac{No.\ of\ relevant\ images}{Total\ no.\ of\ retrieved\ images} \quad (3)$$

It is obvious from Table 2 and Table 3 that on average, the precision is increased by 20% using the proposed approach. Fig. 3, indicates the precision of each class independently. Dim bars demonstrate the precision of

TABLE 1: Classification report of the confusion matrix giving the Precision, Recall

Real/ Experimental Classes	1	2	3	4	5	6	7	8	9	10	Accuracy
1	42	1	2	0	0	1	1	0	0	3	84 %
2	2	31	3	2	1	3	0	1	5	2	62 %
3	4	2	33	3	0	3	1	1	3	0	66 %
4	2	1	1	39	0	0	0	0	5	2	78 %
5	0	0	0	0	50	0	0	0	0	0	100 %
6	0	0	0	0	0	47	0	1	2	0	94 %
7	0	0	1	0	3	0	45	0	0	1	90 %
8	0	0	0	0	1	1	0	48	0	0	96 %
9	1	9	5	1	0	3	0	0	31	0	62 %
10	6	0	1	1	0	0	0	0	0	42	84 %

TABLE 2: OFET (Previous Approach) Precision

Image Class	Image Retrieved	Relevant Image	Precision
1	298	32	0.11
2	6	6	1
3	7	4	0.57
4	6	6	1
5	56	50	0.89
6	9	7	0.78
7	45	45	1
8	54	48	0.89
9	10	6	0.60
10	373	31	0.8
Previous Approach Average:			**0.69**

TABLE 3: PSOGA (Proposed Approach) Precision

Image Class	Image Retrieved	Relevant Image	Precision
1	20	18	0.90
2	20	15	0.75
3	20	20	1
4	20	20	1
5	20	20	1
6	20	20	1
7	20	20	1
8	20	20	1
9	20	11	0.55
10	20	14	0.70
Proposed Approach Average:			**0.89**

going the preceding approach and dark bars exhibit the exactness of the proposed approach.

Experimentation from Table 4 and Table 5 using the Oliva database and multi-dataset shows that the precision is significantly increased and the redundancy factor is reduced. Fig. 4, indicates the accuracy of OFET (previous approach) and PSOGA (proposed approach). Dim bars demonstrate the accuracy of going the preceding approach and dark bars exhibit the exactness of the proposed approach.

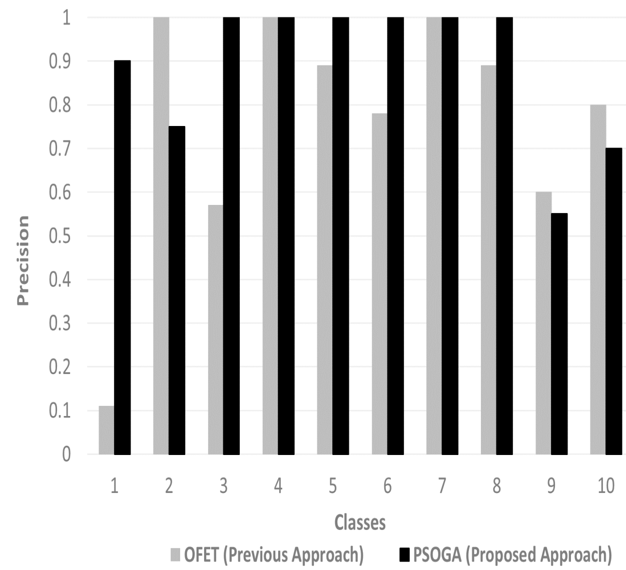

Fig. 3: Precision Graph

TABLE 4: Precision PSOGA (Proposed approach) Oliva Dataset

Image Class	Image Retrieved	Relevant Image	Precision	Redun -dancy Factor
1	20	15	0.75	-0.25
2	20	20	1	0
3	20	20	1	0.00
4	20	20	1	0
5	20	14	0.70	-0.30
6	20	17	0.85	-0.15
7	20	20	1	0
8	20	13	0.65	-0.35
		Average:	**0.87**	**-0.13**

5.3 Recall

The recall of the previous and proposed approaches is calculated using the equation as follows that shown in Table 6:

TABLE 5: Precision PSOGA (Proposed approach) Multi Dataset

Image Class	Image Retrieved	Relevant Image	Precision	Redun -dancy Factor
1	20	17	0.85	-0.15
2	20	18	0.90	-0.1
3	20	20	1	0.00
4	20	19	0.95	-0.05
5	20	20	1	0.00
6	20	18	0.90	-0.10
7	20	20	1	0
		Average:	**0.94**	**-0.06**

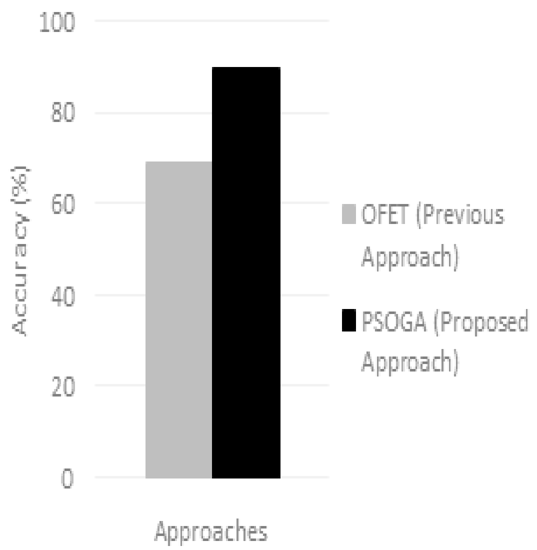

Fig. 4: Accuracy Graph

$$Recall\ (R) = \frac{No.\ of\ relevant\ images}{Total\ no.\ of\ relevant\ database\ images} \quad (4)$$

In Table 6, The correlation between recall and precision shows that the results are now more precise as compared to the previous approach.

TABLE 6: Recall

Image Class	OFET (Previous Approach)		PSOGA (Proposed Approach)	
	Precision	Recall	Precision	Recall
1	0.11	0.32	0.90	0.18
2	1	0.06	0.75	0.15
3	0.57	0.04	1	0.2
4	1	0.06	1	0.2
5	0.89	0.50	1	0.2
6	0.78	0.07	1	0.2
7	1	0.45	1	0.2
8	0.89	0.48	1	0.2
9	0.60	0.06	0.55	0.11
10	0.8	0.31	0.70	0.14

TABLE 7: RF calculation for OFET (Previous approach)

Image Class	Image Retrieved	Relevant Image	Redundancy Factor
1	298	32	-0.89
2	6	6	0
3	7	4	-0.43
4	6	6	0
5	56	50	-0.11
6	9	7	-0.22
7	45	45	0
8	54	48	-0.11
9	10	6	-0.40
10	373	31	-0.92
Previous Approach Average			**-0.31**

TABLE 8: RF calculation for PSOGA (Proposed approach)

Image Class	Image Retrieved	Relevant Image	Redundancy Factor
1	20	18	-0.10
2	20	15	-0.25
3	20	20	0
4	20	20	0
5	20	20	0
6	20	20	0
7	20	20	0
8	20	20	0
9	20	11	-0.45
10	20	14	-0.30
Proposed Approach Average			**-0.11**

5.4 Redundancy Factor

The RF of the Previous and Proposed Approach is calculated as shown in Table 7 using the equation as follows:

$$RF = \frac{Total\ Retrieved\ Images - Total\ class\ images}{Total\ class\ images} \quad (5)$$

Table 7 and Table 8, By using the proposed approach on different datasets, the Redundancy factor is decreased. Fig. 5 and Fig. 6 show the redundancy factor of OFET (previous approach) and PSOGA (proposed approach) on a different dataset. Grayline (square) demonstrate the RF of going the preceding approach and the black line (triangle) exhibits the exactness of the proposed approach.

6 Conclusion

The several conclusions resulting from conducting this research are as follows:

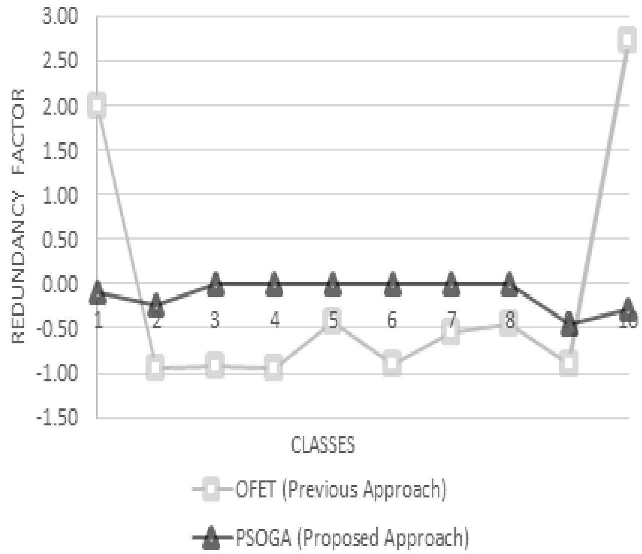

Fig. 5: Redundancy Factor Graph – Comparison

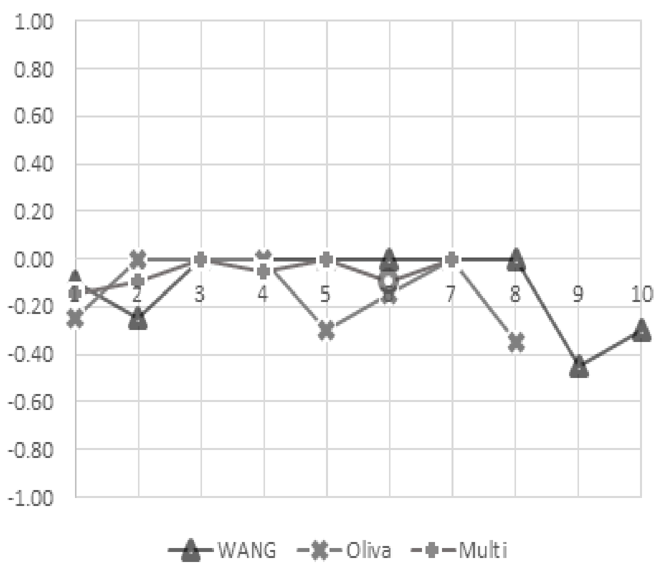

Fig. 6: Redundancy Factor Graph – Different Dataset

- Our novel approach to modeling the PSO with SVM as a classifier and GA with KNN as a classifier, together as a hybrid model is significant. It enhanced the RA and abated the RF of the CBIR.
- The WANG dataset is divided into 10 sub-classes. However, our proposed approach collectively dealt with sub-classes with a significant increase in the precision from 0.69 (existing approaches) to 0.90 (proposed approach).
- The collective influence of high-level features for example color, texture, and shape certainly augmented overall system performance.

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