Received: 21 January 2019 | Revised: 9 April 2019 | Accepted: 17 May 2019
DOI: 10.1002/cpe.5368

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SPECIAL ISSUE PAPER

A dynamic wrapper-based feature selection for improved precision in content-based image retrieval

K. Sankar[1] | P. Uma Maheswari[2]

[1]Department of Computer Science and Engineering, Vivekanandha College of Engineering for Women, Tiruchengode, India
[2]Department of Computer Science and Engineering, College of Engineering, Guindy Campus, Anna University, Chennai, India

Correspondence
K. Sankar, Department of Computer Science and Engineering, Vivekanandha College of Engineering for Women, Tiruchengode-637 205, India.
Email: sankarkaliappan@gmail.com

Summary

The content-based image retrieval (CBIR) has been applied in the image processing as well as pattern recognition. A challenging task in the CBIR research has been through the feature extraction for decreasing any semantic gap that is an active research topic. Here, in this work, there is a texture feature that is extracted from an image, making use of a technique of curvelet transform. This curvelet is selected for a sparse representation that is quite critical for the estimation of images, which have been de-noised with some inversed problems. The wrapping-based curvelet transform will be even more robust as well as faster in the time of computation than the Ridge Transform. A technique of feature selection will be brought for selecting the optimal features. The correlation-based feature selection (CFS) method has been adapted for improving the accuracy of the CBIR systems. The non-deterministic polynomial (NP)–hard problems may be solved using the chemical reaction optimization (CRO) that has been motivated using the technique of chemical reaction. The benefits of proposed method is a necessity for marginal human intrusion for the purpose of retrieving the images needed from its database. The proposed mechanism has been again assessed depending on the Coral Database, and a performance study is ended using precision, f measure, and recall.

KEYWORDS

content-based image retrieval (CBIR), curvelet transform and chemical reaction optimization (CRO), wrapper feature selection

1 | INTRODUCTION

While performing search and retrieval in CBIR, the associated content is analyzed with the image. Based on descriptions that are low-level like color, texture or shape features are extorted.[1] Efforts are prepared by CBIR system to improve images, which are proper to the query image. Image classification contains image database, whose features need to be extorted as a preprocessing pace, similar to CBIR systems. For every database image, once the features have been extracted, these features subsequently can signify the image. Images are categorized based on such features through machine learning classifier. A query image is offered through the user for CBIR where features are taken out and is coordinated with the database feature to improve related images. As enormous computing power and memory are required to process and store visual data, efficient indexing is necessary to recover visual data from a huge image database. The images are classified into different classes that can enhance the performance and probing retrieval time.

A feature database is formed through the image vector. As the request image remains to this method, an initiation of the process of recovery takes place. The feature extraction methods for image database feature vector and internal demonstration of feature vector are transformed through query image. The measure of similarity comes in hand while calculating the distance among request image feature vector and target images in feature database. Depending on corresponding value, the images are ranked and are presented as output of CBIR system. Feature selection[2] plays a prime role in multiple areas of research, including data processing, data mining, pattern recognition, machine learning, classification issues, and so on. Different types of feature selection methods have been presented, and most of them use a heuristic search procedure or a novel technique to perform random search.

With regards to feature selection, various research works have been presented to identify significant educational features such as wrapper, filter, and hybrid approaches.[3] A machine learning algorithm is exploited through wrapper methods in evaluating the honesty of features or

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feature set, whereas, the latter technique, instead of using machine learning techniques to filter unrelated and unnecessary features, employs the basic attitude of the training data in evaluating the significance of features it has set through independent measures like distance, consistency, and correlation measures. Wrapper and filter approach are combined through hybrid method.

A multiscale directional transform is curvelet transform[4] that can be used in presenting the best non-adaptive sparse object image and contains optimum consequences for edge features. Lie-like edges are shown through most images or signals, which are discontinued through curves. Point singularity hypothesis of objects remains engaged through normal wavelet transform but did not regard as geometric features of structures. Because of this, in wavelet technique, edges and line regularity are not satisfied, and oscillation conditions are present for alignment of edges. In curvelet transform, to solve directional features, polar angled wedges or trapezoidal angular window is considered.

Machine learning deals with programs that are developed, which learn from previous data. This arena of artificial intelligence deals with constructing adaptive computing systems, which can improve their work efficiency through the information got from experience. Machine learning is the study of generalization, construction, and analysis of algorithms. In many fields of studies involving machine learning, numerous classifier systems prove to be comparatively accurate and potent than an efficient single classifier as high classification accuracy cannot be reached through one single classification system.[5] Many studies are going on in the area of classifier combination as many theoretical and practical researches are showing positive results with reference to the advantages of mixture pattern over individual classifier models. Studies are going on actively relating to the designing of multiple classifier systems, which are popularly called classifier ensemble.

The efficiency of a "weak" classifier can be improved through a group of techniques called "boosting" with the help of ensemble structure, one of which is AdaBoost.[6] While conducting boosting, in a dataset, a set of weights are maintained across the objects; the objects that are difficult to classify require more weight, while subsequent classifiers focus on them. A learning algorithm is run time; the classifier is shared through the learner into a single composite classifier.

Section 2 presented the literature survey related to this work, Section 3 details the techniques and methods proposed here, Section 4 expands the consequences and the graph, and Section 5 explains the entire work and completes the research.

2 | LITERATURE SURVEY

Effective image classification utilizing low-level color and texture features are focused by Singh and Srivastava.[1] With regards to unknown images, it is well proven that the efficiency of classifier is good if alike images exist in the training set, whereas there cannot be any guarantee for images that are not similar from training set. This issue of classifier generalization prejudged the image recovery and explanation process. The design of this paper is to learn the differentiating ability for such varying class standard images. With regards to enhance image classification, specific low-level color and texture features were extracted from images. These aspects with color-based structures includes color percentile, moment and histogram, and texture features based on local binary pattern (LBP). Random forest classifier is used in overcoming simplification problem, which can handle over-fitting situation. The effectiveness of the proposed work is established by investigational examination of standard database.

A feature selection using binary gravitational search protocol was proposed by Rashedi and Nezamabadi-pour[7] so as to enhance the accuracy of CBIR systems. In the arena of pattern recognition, CBI is one the most disputed issues. The efficiency of CBIR system does not depend on features that are extracted from images. Higher accuracy is attained by choosing most appropriate features through modifying the semantic gap among features at high and low level. One of the most recent metaheuristic search algorithms is the gravitational search algorithm, and its power is evaluated with GA and binary PSO in feature selection. Corel database was used to evaluate the proposed technique. Significances verify the effectiveness of BGSA to amplify the accuracy of CBIR systems.

Sugamya et al[8] proposed CBIR where two techniques are used for a comparative analysis. The types of techniques decide the overall performance of comparative analysis used in extracting multiple features and the measures of similarity among query image and image database. Color features are extracted with the help of color histogram in the first technique, and fast discrete curvelet transform (FDCT) is employed by the second method for the same process. Chi-square distance is used in the initial method for color features of query and database images. For both images, color histograms were attained, and images with significant resemblances were exhibited. Next techniques comprise a set of features for computing the feature vector. When the calculation is done, comparison of database and query images are done to locate the top five comparable images, and consequences are exhibited.

The original purpose of curvelet was image de-noising and has done so excellently well in that field. A novel image feature, which was on the basis of curvelet transform, was put forth by Sumana et al.[9] On texture images, discrete curvelet transform was applied and low-order statistics was computed to transform the images. Extracted text features were utilized to represent images. Outcomes of retrieval showed that it outperformed the popularly used Gabor texture feature.

AdaBoost classifier was suggested as an ensemble to incorporate various classifier ensemble models was suggested by Novakovic and Veljovic[5] into classifier models to classify problems. The effect of various base classifiers in classification precision of AdaBoost classifier ensemble was evaluated. Five base classifiers were utilized on five medical dataset, and the result was related through indicating many kinds of decision tree algorithms for base classifier.

A real-coded CRO version (RCCRO) was presented by Lam et al[10] so as to explain continuous optimization issues. Its performance was compared with optimization methods on a huge standard set constant benchmark functions. The remaining were outdone through RCCRO on

an average. An adaptive scheme was put forth for RCCRO, which enhanced the presentation efficiently. This depicts that CRO is suited to solve issues in a continuous domain.

A new technique was scheduled by Li et al[11] to execute dependent group tasks for environments of computation that are heterogeneous. Two elements are present in the algorithm. First is an intellectual scheme in order to assign orders of implementation at task-by-task level, and the other is a distribution algorithm with its basis on chemical reaction-motivated metaheuristic named as chemical reaction optimization (CRO) to plan processors to tasks. The consequences of the study showed that the performance of CRO-based study was greater over heterogeneous earliest finish time (HEFT) and critical path on a processor (CPOP) deprived of abundant cost incurred on computation; this technique can have multiple runs in order to enhance search result.

The issue of imbalanced dataset is tackled through long-term learning approaches on the basis of random forest classifier ensemble which was proposed by Bhosle and Kokare.[12] The user feedback information was collected through extended-period learning relevance feedback approach to gain semantic knowledge of database images. Retrieval outcomes were enhanced by random forest (RF) classifier over these facts. It has been observed through experimental evaluation that there is sufficient classification accuracy when contrasted over existing method, which is accessible in the survey. Relevant feedback sowed a precision of 93% in nine iterations.

3 | METHODOLOGY

3.1 | Dataset

Corel-10 k dataset consists of 100 groups. Consider 10 000 images as of altered contents like sunset, beach, flower, building, car, horses, mountains, fish, food, door, etc. In all groups, there are 100 images of size 192 × 128 or 128 × 192 in the JPEG format. Corel-5 K dataset includes first 5000 images, and Corel-10 K dataset has 10-000 images. GHIM-10 k dataset comprises 20 groups. There are 10 000 images from many content like Corel dataset mentioned above. Individual group comprises 500 images of size 400 × 300 or 300 × 400 in JPEG format.[13]

3.2 | Curvelet transform for feature extraction

The limitations in wavelet transform can be overcome by a geometric transform called curvelet transform. It is a multi-scale multi-directional transform, with its basic function being needle-shaped. Wavelet transforms have isotropic functions, and so, it requires an increased number of coefficients in representing curve singularities. The basic function of curvelet transform is needle-shaped, and their directional sensitivity is high and is anisotropic. Parabolic scaling is done through curvelet such that they permit nearly sparse representation of curve singularities. The entire frequency space is covered with a different scale and direction span by the curvelet transform.[14] Various edges are signified by curvelet transform by additional singularities with curves than conventional transforms, ie, less factors are used for a definite re-establishment precision.

Curvelet transform is a ridge transform with binary square window that is curve is subdivided approximately straight to transmit on ridge transform. However, in the transform, there is big data redundancy. Thus, the curvelet transform first generation is transformed into second with very fast computation and fewer redundancies.[15] Initially, describe the variable x as space position parameter, was frequency domain parameter, and (r, θ) as polar frequency domain in the 2-dimentional space R2. $W(r)$ and $V(r)$ are smooth non-negative "radius window" and "corner window" correspondingly, and they should gratify as in Equation (1):

$$\begin{aligned} &\sum_{j=-\infty}^{\infty} W^2(2^j r) = 1, r \in \left(\frac{3}{4}, \frac{3}{2}\right) \\ &\sum_{j=-\infty}^{\infty} V^2(2^j r) = 1, r \in \left(-\frac{1}{2}, \frac{1}{2}\right). \end{aligned} \tag{1}$$

On behalf of all scales $j \geq j_0$, describe its Fourier frequency domain window as in Equation (2):

$$U_j(r, \theta) = 2^{-\frac{3j}{4}} W(2^{-j} r) V\left(\frac{2^{j/2}\theta}{\pi}\right). \tag{2}$$

Frequency domain curvelet transform is distinct as product of $\varphi_{j,l,k}$ and $f \in L^2(R^2)$

$$c(j, l, k) = \prec f, \varphi_{j,l,k}(x) \succ = \int_{R^2} f(x) \overline{\varphi}_{j,l,k}(x) \mathrm{d}(\mathrm{w}) \tag{3}$$

$$c(j, l, k) \coloneqq \frac{1}{(2\pi)^2} \int_{R^2} \hat{f}(x) \overline{\varphi}_{j,l,k}(x) \mathrm{d}(\mathrm{w}) = \frac{1}{(2\pi)^2} \int \hat{f}(x) U_j(R_{\theta_L} \mathrm{w} \exp\left[i \prec x_k^{(j,l)}, \mathrm{w}\right] \mathrm{dw}. \tag{4}$$

Curvelet consists of constituents on rough and fine scale, like wavelet theory.[16]

3.3 | Feature selection

Feature selection is a frequent method to progress the visual features performance and enhance the efficiency of the CBIR systems.

3.3.1 | Correlation-based feature selection (CFS)

A feature filtering technique such as CFS is used in locating the subset of features that is applicable potentially to a given task. CFS is heuristic in assessing the utility or value of a feature subset as provided in Equation (5). The usefulness of the individual features is shown in this heuristic to predict class label together with inter-correlation level among them.

$$Merits = \frac{k\bar{r}_{cf}}{\sqrt{k + k(k-1)\bar{r}_{ff}}}, \tag{5}$$

where Merits is the heuristic "merit" of a feature subset S containing k features, $\bar{r}_{cf}$ is the average feature class correlation, and $\bar{r}_{ff}$ is the average feature-feature inter-correlation. The irrelevant and redundant features are removed by this heuristic since they are poor class predictors. It is essential in computing the correlation between features. At first, numeric features are discretized by CFS using the Fayyad and Irani technique,[17] and symmetric uncertainty (SU) is used in evaluating the degree of relationship among discrete features. Entropy of Y before and after detecting X, where X and Y are discrete random variables, are given in Equations (6) and (7).

$$H(Y) = -\sum_{y \in Y} p(y)\log_2 p(y) \tag{6}$$

$$H(Y|X) = -\sum_{x \in X} p(x) \sum_{y \in Y} p(y|x)\log_2 p(y|x). \tag{7}$$

3.3.2 | Chemical reaction optimization (CRO)

Chemical reaction optimization (CRO), which is a chemical reaction, was recently proposed by Lam and Li in the year 2010.[18] A sequence of collisions takes place in a chemical reaction, by the reactants in a high-energy uneven state, which pass via some barriers, and a final product in low-energy unchanging conditions is formed. This driving high-energy molecule method is taken by CRO to constant states by numerous elementary reactions. CRO has been proven to be an effective optimization algorithm with multiple applications,[19] and mostly, they are combinatorial in nature. Alternately, the CRO existing version works in a discrete domain. Moreover, based on the no-free lunch theorem, all metaheuristics search for extreme remain similar while averaging in general possible objective functions. Thus, the same ability must be possessed by CRO to solve optimization problems as others.

Molecules

Molecules are the influenced agents. Individual molecule comprises a profile of numerous molecules, consisting of the molecular structure ω, (current) potential energy (PE), (current) kinetic energy (KE), and a few possible attributes. The optional qualities can be employed to build some CRO forms for certain issues offered that the executions convene the attributes of the elementary reactions. Users can eliminate any of these or append a few more to go with intends of their individual operators. The necessary meanings attributes in the profile are provided as:

- ***Molecular Structure:*** ω signifies the solution presently detained by a molecule. There is no exact necessity on the alignment of ω. It can be represented as a number, a vector, a matrix, or even a graph.
- ***Current PE****:* PE is the objective function value of the existing molecular configuration ω, ie, $PE\omega = f(\omega)$.
- ***Current KE****:* KE is the present molecule patience to hold of inferior quality molecular configuration with greater PE compared to the current one.

Elementary Reactions

Elementary reactions are of four types: on-wall unsuccessful collision, decomposition, intermolecular unsuccessful collision, and synthesis. Internal change in molecule is caused on effective achievement of elementary action subject to energy constraint activated by collisions.

3.4 | Classifier

3.4.1 | AdaBoost classifier

An important feature of classifier ensemble[1] is its diverse creating ability, and this can be called as the success of AdaBoost. Inaccurate classifiers are formed by constructing them, which focus on problematic object. The rest of the data are evaded and lead to large diversity that stimulated the ensemble performance frequently better than bagging. This leads us to accuracy dilemma, as there cannot be both very precise and diverse outputs. Next generation networks performances are analyzed in terms of data rate, signal-to-noise ratio, and bit error rate.[20-25]

The most popular ensemble technique is AdaBoost and can improve the prediction precision in order to generate a number of classifiers, thus building the best classifier. The algorithm's advantage is that less input features are required and much prior knowledge is not required about

weak learner. Moreover, there is high flexibility that is suitable to combine with other techniques to find weak hypothesis. This technique not only can predict classification tasks but also present self-rated confidence scores that can estimate the authenticity of the predictions. A reduced amount of knowledge computation is essential to improve accuracy of models over datasets.

Pseudo code for AdaBoost classifier

```
Input: Training Data set with its labels
Initialize the weights of the training samples
Do While t=1, … T
        For each feature, train a classifier using a single
feature
        Calculate the error of weak classifier
        Choose the classifier with lowest error
        Update the weights of the training samples
Create a strong classifier
```

3.4.2 | Random forest classifier

Breiman[26] proposed an RF classifier, thus adding an additional layer of randomness to bagging a group or ensemble of simple tree predictors, where every tree can generate response, if presented with a predictor value set. Moreover, a different bootstrap sampling of data is used in constructing each tree utilizing multiple bootstrap data sample; RF alters the manner in which the classification or regression trees are constructed. Based on standard trees, each node is divided as optimal among all variables. In RF, individual node is fragmented as an optimal among subset of predictors, which are selected at random. Compared to many other classifiers, this approach turns to execute quite well in comparison to several other classifiers with discriminant analysis, SVM, and NNs and is active over-fitting.

Classification and regression issues are classified using RF classifier.[27] The input data class is definite through an ensemble classifier, ie, a group of classifiers that each classifier's decision remain shared. In the RF, every tree is accomplished with the help of a random vector that is tested autonomously from a training set with same distribution. Majority of votes determines the class of vector from all trees in the ensemble.

Assume T as the training set comprising of N labeled illustrations as$\{(x_1, y_1), (x_2, y_2), ..., (x_N, y_N)\}$. Vector $X = (x^1, x^2, \ldots, x^p)$ represents a vector with descriptive variables and $X\varepsilon\ \Re^p$. $Y\varepsilon(+1, -1)$ represents a class sample label. It aims to enterprise the classifier $\hbar$ which achieves the mapping $\hbar : \Re_p \rightarrow Y$. Random forest R is a group of m classifier, well-defined as in Equation (8):

$$R = \{\hbar(x, \Omega_k), \mathrm{k} = 1, \ldots\ \mathrm{m}\}, \tag{8}$$

where x is an n-dimensional arbitrary illustration of random vector X and Ω_k are the random vectors selected self-sufficiently from the training set T. Every tree is developed with an input variable sets that are designated arbitrarily with dimension $\check{n}$, from the bootstrapped training set of T, and so, $\check{n} < n$. The random vector $k\Omega$ for the kth tree is created with independent of preceding random vectors are $\Omega_1, \Omega_2\ \ldots\ , \Omega_{k-1}$. The classifier R is used for the input data classification.

4 | RESULTS AND DISCUSSION

For experiments, four classes and 750 images were considered. Table 1 and Figures 1-3 shows the Recall, Precision, and F Measure, respectively. Figure 4 shows the best fitness.

Table 1 and Figure 1 shows that the recall for CRO-AdaBoost performs better than CFS-random forest by 8.6%, than CFS-AdaBoost by 7.4%, and better than CRO-random forest by 2.8%. It is observed that the proposed CRO methods significantly improve the efficacy of the classifier with the optimal feature subset selected. When compared with CFS, the proposed CRO, as it iterates, keeps improving the feature subset.

Figure 2 shows that the precision for CRO-AdaBoost performs better than CFS-random forest by 8.6%, than CFS-AdaBoost by 7.34%, and better than CRO-random forest by 2.74%.

TABLE 1 Results

	CFS-Random Forest	CFS-AdaBoost	CRO-Random Forest	CRO-AdaBoost
Recall	0.835	0.844975	0.885	0.91
Precision	0.83515	0.84555	0.88535	0.909975
F Measure	0.83475	0.8451	0.88505	0.909975

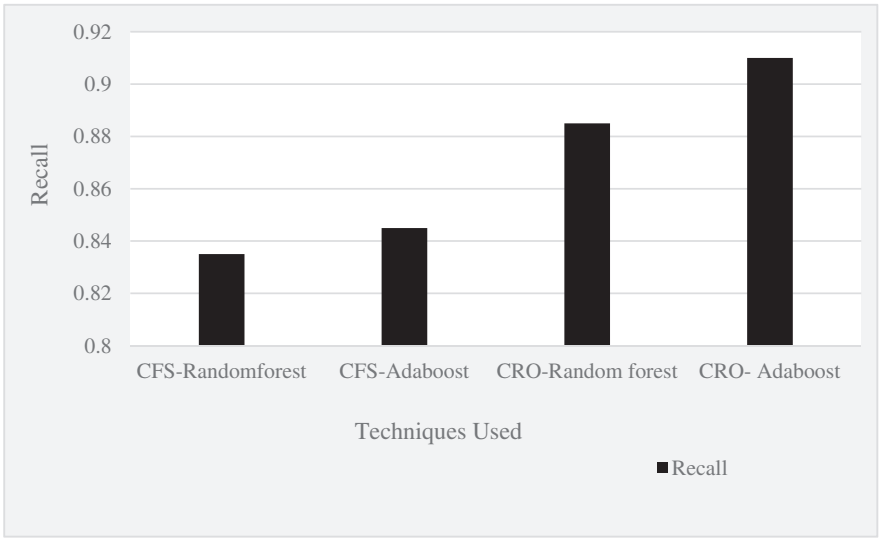


FIGURE 1 Recall for CRO-AdaBoost

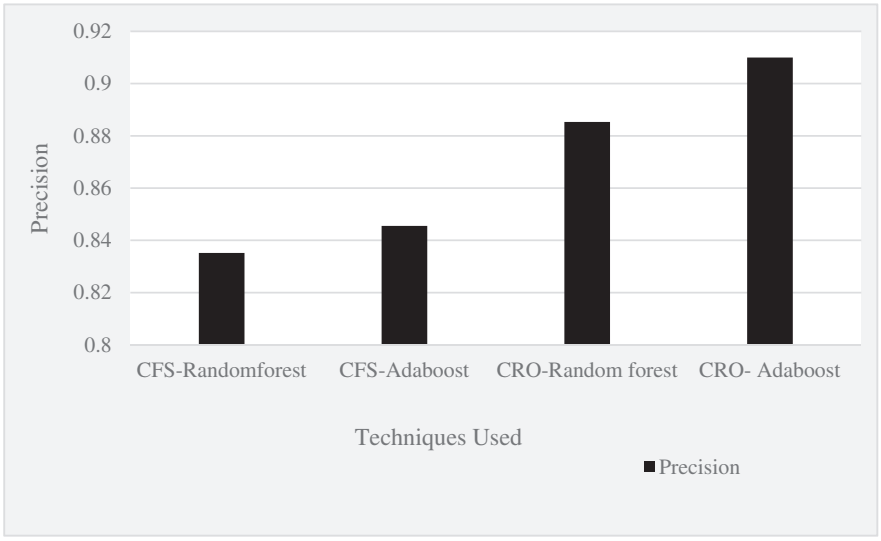


FIGURE 2 Precision for CRO-AdaBoost

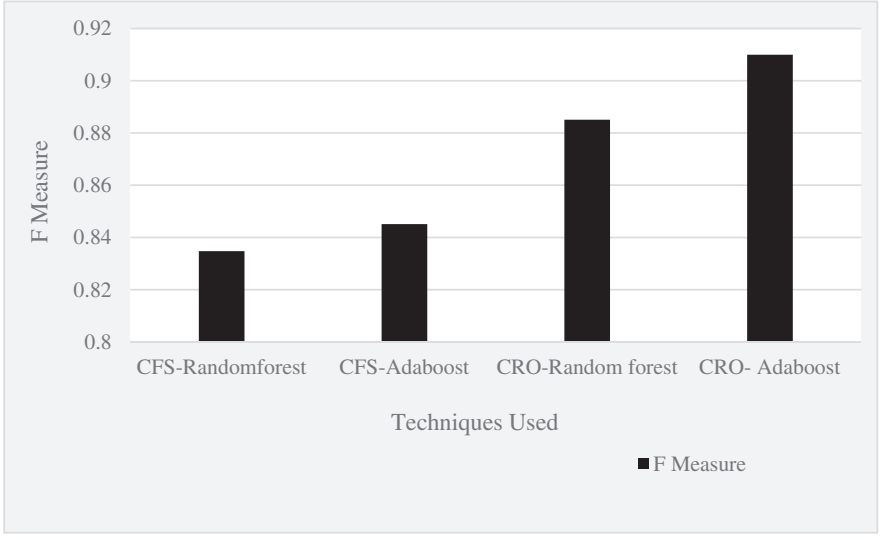


FIGURE 3 F measure for CRO-AdaBoost

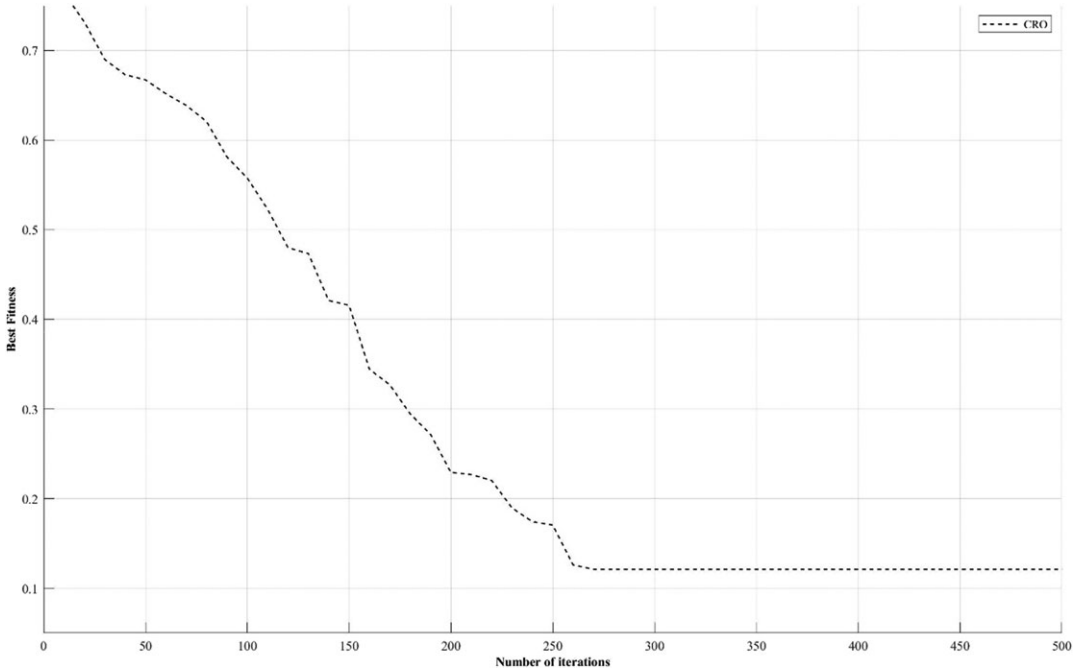


FIGURE 4 Best fitness for CRO

Figure 3 shows that the f measure for CRO-AdaBoost performs better than CFS-Random forest by 8.6%, then CFS-AdaBoost by 7.39%, and better than CRO-random forest by 2.78%. From Figure 4, it can be observed that the CRO achieves good performance for best fitness through varying number of iterations.

5 | CONCLUSION

The main concept of CBIR is to recover image, which is similar to some criteria such as color, texture, or shape. It can be deemed as a popular research area of one's interest. For this work, for the extraction of curvelet feature, there are the CFS and the CRO methods, which have been proposed, and the other classifiers, which may be the AdaBoost and the random forest method, have also been used. The curvelet transform will be for capturing even more information relating to respect orientation and for achieving the coverage of a spectral domain. The CFS will find the feature to be quite good in case it is found to be relevant to the class and will not be redundant to any of the other feature of such a class. Therefore, the feature is to be correlated highly to the class. There is a population-based CRO that is metaheuristic and imitates the molecular interactions that will drive to the minimum state of such free energy. In order to assign one, such predefined class label for sampling will be the classifier's basic function. This AdaBoost algorithm will be able to increase the accuracy of classification of the weak classifiers that are assigned randomly. The random forest will be a high-level classifier, and it is observed for over-fitting certain datasets that have noisy classification tasks. The outcome shows that the recall for the CRO-AdaBoost will achieve better result than the CFS-random forest by about 8.6%, than the CFS-AdaBoost by about 7.4%, and has to be better than the CRO-random forest by about 2.8%. The analysis of recall, precision, and f measure improves the classifiers performance in a better way.

In its future work, the Deep Neural Network (DNN) or a much more efficient technique of color extraction may be availed for improving the accuracy of image retrieval. This system may be further customized for a transfer learning.

ORCID

K. Sankar https://orcid.org/0000-0001-7934-6335

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How to cite this article: Sankar K, Uma Maheswari P. A dynamic wrapper-based feature selection for improved precision in content-based image retrieval. *Concurrency Computat Pract Exper*. 2019;e5368. https://doi.org/10.1002/cpe.5368