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Performance Analysis of Various Classifiers with Effective Dimensionality Reduction in Content-Based Image Retrieval

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Abstract- Content Based Image Retrieval (CBIR) is a technique, which is utilized for retrieving identical images from an image database. Dimensionality reduction of the feature space has a significant role in improving the classifiers' performance. For concerns involving storage and retrieval efficacy, dimensionality reduction in CBIR systems is essential. This research work introduces an efficient and new approach for improving the performance of CBIR based on Scale Invariant feature transform (SIFT) and local intensity order pattern (LIOP) descriptors. After this, bat algorithm is presented for dimensionality reduction, which considerably increases the classification accuracy. This paper provides the comparison of the classification efficacy of classifiers including Support Vector Machine (SVM), Classification and Regression Trees (CART) and Random Forest (RF) for CBIR. The experimental outcomes of the newly introduced classifiers are compared prior and after dimensionality reduction. The evaluation is performed on various image databases for showing the reliability of the newly introduced approach in terms of Precision, Recall, and Accuracy.

***Keywords*:** CBIR, Dimensionality Reduction, SIFT, Bat Algorithm, SVM, CART, RF, and Image Retrieval.

I. INTRODUCTION

In the past decade, the fast development of the internet has resulted in the exponential increase in the number of available image sets. The accumulation of these image groups (inclusive of art works, satellite and medical imagery) has gained the attention of more number of users in different professional domains for instance, geography, medicine, architecture, advertising, design, fashion and publishing. Image retrieval system yields a group of images from a set of images present in the database, which matches with the requirements of the user in similarity assessments like image content similarity, edge, and colour similarity. Previous image retrieval techniques obtained the required images through the matching of keywords, which are manually allocated to every image annotation, which is a highly cumbersome and time-taking process. Therefore, in the current scenario, content based image retrieval is getting into demand for an accurate and quick image retrieval**.**

CBIR system [1] performs the extraction of the image information, which is utilized for retrieving the relevant images from image database, which are a best match to the query image. In this procedure, various unique image features like colour, texture and shape or any other information are obtained from the images [2]. In CBIR systems, the image descriptors have the responsibility for evaluating the similarities amongst the images. The classification of the descriptors can be done based on the evaluation of the image characteristics. It is a known fact that several image descriptors are application based, which implies that their performance differ between applications. The dimensionality of image descriptors (feature vectors) utilized in image retrieval applications, generally, are very high. The common descriptor dimensions range between some tens and many hundreds. This high dimensionality exhibited by the feature vectors generates issues in the construction of effective data structures for conducting search and retrieval. To this end, there is substantial focus shown in the reduction of the dimensionality of the descriptors when maintaining the actual topology of the high dimensional space.

The earlier techniques examined for dimensionality reduction consists of Principal Component Analysis (PCA) Singular Value Decomposition (SVD), Self-Organizing Map (SOM), Fastmap and Multidimensional Scaling (MDS). SOM is very frequently employed for the classification and clustering of the feature vectors for limiting the search space. PCA or SVD account for the rotation of the coordinate axes of the high dimensional vector space such that projections onto the new axes lead to uncorrelated feature points. Dimensionality reduction is accomplished employing some rotated axes in the form of basis vectors [3]. In the case of MDS, the low dimensional representation is got by reducing few cost functions. In an ideal condition, for any certain query, the same set of adjacent neighbours in the lower dimensional space should be found as in the actual high dimensional space.

This paper introduces a new approach that depends on visual words merging in addition to the features merging of the Scale Invariant Feature Transform (SIFT) and Local Intensity Order Pattern (LIOP) feature descriptors depending on the bag-of-visual-words (BoVW) technique, for dealing with the aforementioned challenges. Scale Invariant Feature Transform (SIFT) [4], algorithm is utilized for defining the images' local features. SIFT is a technique used for the extraction of unique invariant features from images, which can be exploited for carrying out a trustable matching between various views of an object or scene. The features exhibit invariance to image scale and rotation, and are indicated to yield a reliable matching across a considerable range of affine distortion, variation in 3D viewpoint, addition of noise, and variation in illumination. The features are hugely unique, in the manner that one single feature can be rightly matched with a greater probability against a massive database consisting of features from several images [5]. After this Binary Bat Algorithm is introduced for handling the dimensionality problem. Also this paper analyses the performance of various classifiers namely the SVM classifier, Classification and Regression Trees (CART) and Random Forest (RF) for CBIR. This paper provides the comparison of the classification efficacy of classifiers Support Vector Machine (SVM), Classification and Regression Trees (CART) and Random Forest (RF) for CBIR.

II. LITERATURE REVIEW

Liu, et al [6] tried to yield an elaborate survey of the current technical advancements in high-level semantic-based image retrieval. The current publications are included in this review encompassing various aspects of the research work in this area, inclusive of low-level image feature extraction, similarity measurement, and acquiring of high-level semantic features. Five important groups of the state-of-the-art methods are identified in slimming down the 'semantic gap': (1) making use of object ontology for defining the high-level concepts; (2) making use of machine learning techniques to relate the low-level features with query concepts; (3) employing relevance feedback for learning about the intention of the users; (4) creating a semantic template to guide the high-level image retrieval; (5) combining the evidences obtained from HTML text and the visual content present images for retrieving the WWW image.

Wang, et al [7] sought to evaluate three techniques generally employed in CBIR approaches and the techniques used for improving the technique's performance was investigated. A reference database consisting of 3000 Regions Of Interest (ROIs) was generated. Amongst them, 400 ROIs were chosen in random to create a testing dataset. Three technique, which include mutual information, Pearson's correlation and a multi-feature-based k-Nearest Neighbor (KNN) algorithm, were used for searching for the most identical reference ROIs to every testing ROI. The clinical relevance and visual similarity of the search results were assessed employing the areas under Receiver Operating Characteristic (ROC) curves (AZ) and average Mean Square Difference (MSD) of the mass boundary speculation level ratings between testing and chosen ROIs, correspondingly.

Bakar et al [8] studied about an alternate scheme for CBIR employing Scale Invariant Feature Transform (SIFT) algorithm for binary and grey scale images. The inspiration behind the usage SIFT algorithm for CBIR is because of the fact that SIFT exhibits invariance to scale, rotation and translation in addition to partial invariance to affine distortion and illumination variations. Motivated by these facts, the basic characteristics of SIFT used for robust CBIR are examined with the help of MPEG-7, COIL-20 and ZuBuD image databases. The proposed scheme makes use of the identified key points and its descriptors for matching between the query images and images acquired from the database.

Suharjito and Santika [9] developed a CBIR technique employing BoVW and multiclass SVM classifier. In the case of BoVW, Scale Invariant Feature Transform (SIFT) will be utilized in the form of the local features descriptor. This research work makes use of Gaussian Mixture Model (GMM) to be the technique for visual vocabulary creation and Fisher Vector (FV) to make the encoder. The multiclass SVM classifier employs linear kernel, Hellinger's kernel, and chi-square kernel for classification purposes. Once the query image class is available, the color histogram features will be acquired from query image and dataset that only comprises of image in the class similar to the query image. Datasets utilized in the paper include Corel and Guang-Hai Liu (GHIM-10K).

Giveki et al [10] studied about a novel approach for retrieving the images of various scenes through the introduction of a new image descriptor. The newly introduced descriptor operates with Scale Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Local Derivative Pattern (LDP), Local Ternary Pattern (LTP) and any other feature descriptor, which can be used on the image pixels. Since the newly introduced descriptor takes a set of pixels together, a greater degree of semantic is accomplished. In this research work, a novel image descriptor employing SIFT and LDP is presented, which is capable of finding the similarities and matches existing between images. The newly introduced descriptor generates highly distinguishing features for image content description.

Bama et al [11] introduced an effective computer-aided Plant Image Retrieval technique that is dependent on plant leaf images employing Shape, Colour and Texture features aimed chiefly for medical field, botanical gardening and cosmetic field. In this, HSV colour space is used for extracting the different features of leaves. Log-Gabor wavelet is used on the input image for extracting the texture feature. The Scale Invariant Feature Transform (SIFT) is included for extraction of the feature points of the leaf image. Scale Invariant Feature Transform converts an image into a huge group of feature vectors, each one of which exhibits invariance to image translation, scaling, and rotation, partial invariance to illumination variations and reliable to local geometric distortion. SIFT consists of four modules including identification of scale space extrema, local extrema detection, orientation assignment and key point descriptor.

III. PROPOSED METHODOLOGY

This section briefly provides the process involved in the proposed approach depending on visual words fusion in addition to the features fusion of Scale Invariant Feature Transform (SIFT) and Local Intensity Order Pattern (LIOP) and BAT descriptors for an efficient CBIR and classification process as illustrated in Figure 1.

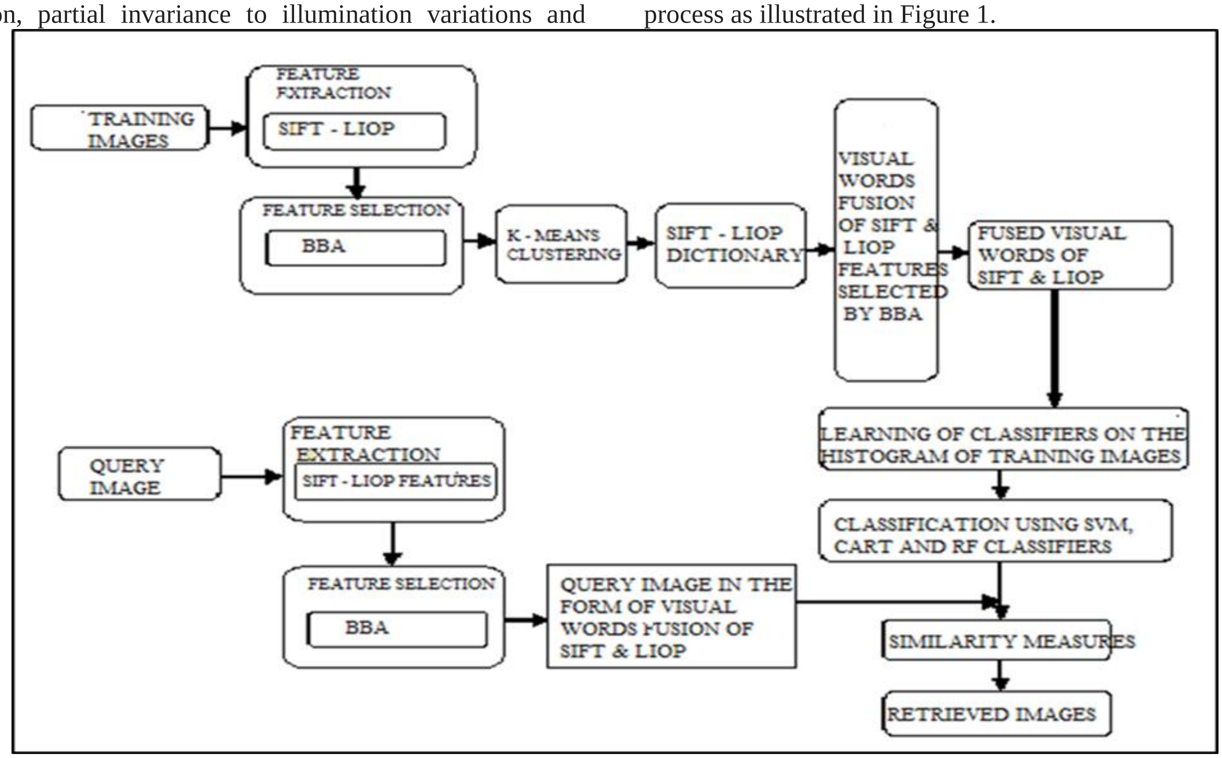


Figure 1: Block diagram of the proposed technique based on visual words fusion of SIFT, LIOP and Feature Selection using Binary Bat Algorithm (BBA)

The detailed process of the proposed approach is provided as below:

1. For each image in the training and test sets, SIFT and LIOP features are calculated.

2. The SIFT features [12] are calculated from every image over dense grid by using the mathematical equations below:

$$k_i(x)=\frac{1}{\sqrt{2\pi\sigma_{win}}}\exp\left(\frac{-1(x-x_i)^2}{2\sigma^2_{win}}\right)\omega\left(\frac{x}{m\sigma}\right), \qquad (1)$$

$$k_j(x)=\frac{1}{\sqrt{2\pi\sigma_{win}}}\exp\left(\frac{-1(y-y_i)^2}{2\sigma^2_{win}}\right)\omega\left(\frac{y}{m\sigma}\right), \qquad (2)$$

Where the side of the flat window is denoted by σ_{win}

3. The LIOP features are also calculated from every image by using the mathematical equation below:

$$LIOP\ descriptor = (des_1, des_2, \ldots\ldots, des_1) \qquad (3)$$

$$des_1 = \sum_{x\in bin_1} \omega(x) LIOP(x), \qquad (4)$$

Where $\text{LIOP}(x) = \varphi\left(\gamma\left(p(x)\right)\right)$,

$$p(x) = \left(I(x_1), I(x_2), \ldots\ldots I(x_n)\right) \in P^n \qquad (5)$$

$$\omega(x) = \sum_{i,j} sgni\left(\left|I(x_i) - I(x_j)\right| - T_{ip}\right) + 1 \qquad (6)$$

In the equation above, a sample point x_n, $I(x_n)$ denotes the intensity of the nth neighbouring sample, $P(x)$ refers to the N- dimensional feature vector of the intensities that indicates the Nneighbouring sample points of a point x in the local patch, the mapping γ orders the elements of the$N$-dimensional feature vector, pre-defined threshold is denoted by T_{lp}, sign function is indicated by sgn, $w(x)$ stands for the weighted function of the LIOP descriptor, the feature mapping function is indicated by φ, and i, j denote the coordinate position of the nth sample point x_n.

IV. FEATURE SELECTION USING BINARY BAT ALGORITHM

Binary Bat Algorithm (BBA) is based on echolocation micro bats. BBA develops a discrete version of bat algorithm to solve feature selection problems and classifications. In BBA each artificial bats have a position, velocity and frequency vector. The position in BBA is either 0 or 1. The movement of bats results in updating their velocity, position and frequency using the following equations:

$$V_i(t+1) = V_i(t) + (X_i(t) - Gbest)F_i \qquad (7)$$

$$F_i = F_{min} + (F_{max} - F_{min})\beta \qquad (8)$$

Where V_i, X_i, and F_i are the velocity, position and frequency of i^{th} bat. β represents a random value between 0 and 1. The position of the Bat can be updated by sigmoid transfer function, is defined as:

$$S(V_i^j) = \frac{1}{1+e^{-v_i^j}} \qquad (9)$$

$$X_i^j = \begin{cases} 1 \; if\ sigmoid\ function > \sigma \\ o \;\; if\ sigmoid\ function < \sigma \end{cases} \qquad (10)$$

If the sigmoid function is greater than σ, then position of bat is 1; if the sigmoid function is less than σ, then position of bat is 0. σ is random value between 0 and 1. To reduce the loudness and increase the pulse rate the BBA can be updated as follows:

$$A_i(t+1) = aA_i(t) \qquad (11)$$

$$r_i(t+1) = r_i(0)[1 - \exp(-\gamma t)] \qquad (12)$$

Where $\alpha\ and\ \gamma$ are constant.

Binary Bat Algorithm [13]:

- Initialize the bat population
- Calculate fitness value of initial bats using sum of square error. The initial population bat which has minimum fitness is the global best (gbest).
- In all iteration, adjust velocity, frequency and the position as given in Eq. (7) (8) (1014) Calculate sigmoid transfer function Eq.(9)
- If the randomly generated is greater than the initial pulse rate (0.9), then the gbest is updated with the new bats. Calculate the fitness value of new bats.
- If the initial bat's fitness is less than the new bat's fitness and the random number is greater than the initial loudness (0.5) then the initial bat is updated.
- If the new bat's fitness is less than the gbest then update the gbest.
- Repeat step 4, until maximum iterations have been reached.

For the proposed technique based on visual words fusion of SIFT and LIOP descriptors, k-means clustering technique is applied to the extracted SIFT and LIOP features for which feature selection was done using the BAA. The features of SIFT and LIOP descriptors after feature selection produce two dictionaries. The resultant SIFT-based dictionary contains visual words of SIFT based features, while LIOP-based dictionary contains visual words of LIOP-based features. Both dictionaries are fused together in order to perform visual words fusion of SIFT and LIOP features. The dictionary of each descriptor is formulated by applying the following mathematical equation on the extracted features of each descriptor:

$$R = \sum_{i=1}^{k} \sum_{x_i \in s_i} (x_i - u_i)^2 \qquad (13)$$

Where$R$ represents the dictionary, u_i is the mean of all the points in the cluster s_i, and $x_l$represents the l th cluster or visual word.

After applying the clustering technique to extracted features of SIFT and LIOP descriptors, it produces two dictionaries that are represented by the following mathematical equations

$$D_{SIFT} = \{v_{s1}, v_{s2}, v_{s3,} \dots \dots, v_{sn}\} \qquad (14)$$

$$D_{LIOP} = \{v_{I1}, v_{I2}, v_{I3,} \dots \dots, v_{In}\} \qquad (15)$$

whereD_{SIFT} andD_{LIOP} are the resultant dictionaries that contain$n$ visual words (i.e., {V_{s1}, V_{s2}, V_{s3}, . . . , V_{sn}} and {V_{l1}, V_{l2}, V_{l3},. . . , V_{ln}}) of SIFT and LIOP-based features, respectively.

After computing dictionaries for SIFT and LIOP featured descriptors, both dictionaries are concatenated which results in visual words fusion of both descriptors, represented mathematically as follows:

$$D_R = \{D_{SIFT}; D_{LIOP}\} \qquad (16)$$

Where D_R is the resultant dictionary that contains SIFT and LIOP features in the form of fused visual words for more compact representation of image visual contents.

Image classification is one of the important steps in image retrieval process because it saves more time while searching the images from huge volume of database. Image classification deals with grouping the same objects into the pre-defined classes for finding the class to which an object belongs. Categorization goes beyond the act of assigning the object to categories by adding other useful information for building metadata that systems use for the retrieval task.

For image classification, the Support Vector Machine (SVM) classifier is selected along with Classification and Regression Tree (CART) and Random Forest (RF) models.

V. SUPPORT VECTOR MACHINE (SVM)

Support Vector Machines (SVMs) are supervised learning techniques utilized for image classification. It considers the image database given to be two sets of vectors present in an 'n' dimensional space and builds an isolating hyper plane, which increases the margin between the images having relevance to query and the images with relevance to the query. Several pattern matching and machine learning tools and methods are available for clustering and classification of linearly differentiable and non-differentiable data. Support vector machine (SVM) is a considerably novel classifier and it is dependent on stringent base from the extensive field of statistical learning theory.

Support vector machines offer several benefits compared to other classifiers:

- They are computation wise quite efficient in comparison with other classifiers, particularly neural networks.
- Their functioning is good, even with high dimensional data and with lesser number of training data.
- They try to reduce the test error more than the training error.
- They are very reliable against noisy data.
- The problem of dimensionality and over fitting problems does not happen during the classification process.

Basically, SVM is a binary classifier, however it can be extended for multi-class problems also. The binary classification task can be indicated to be having, (x_i, y_i) pairs of data where $X_I, \exists X_P. AP$dimensional input space and yi Э [−1, 1] for both the output classes. SVM gets the linear classification function g(x) = w. x + b, which is associated with an isolating hyperplane w. x + b = 0, where w and b refer to the slope and intersection.

SVM generally includes the kernel functions for mapping the non-linearly differentiable input space onto a higher dimension linearly differentiable space. Several kernel functions are available like radial bases functions (RBF), Gaussian, linear, sigmoid etc.

The fundamental principle behind SVMs is a maximum margin classifier. Making use of the kernel technique, the mapping of the data can be first implicitly done to a high dimensional kernel space illustrated in figure 2. The maximum margin classifier is decided in the kernel space and the respective decision function in the actual space can be non-linear. The SVMs classify the non-linear data present in the feature space into linear data in kernel space.

The objective of SVM classification technique is to get an optimal hyper plane that separates the relevant and irrelevant vectors by increasing the margin size (between both classes). Image classification or categorization is basically a machine learning technique and can be considered to be a step employed for improving the speed of image retrieval in massive databases and to boost the retrieval accuracy.

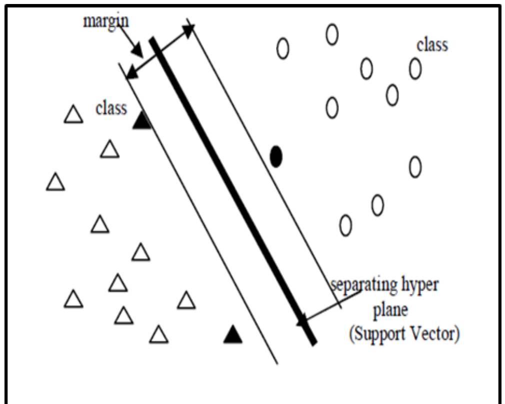


Figure. 2. SVM Classification of images

SVM retrieves all of the relevant images with success corresponding to the query image depending on minimum distance.

- Train the SVM by choosing the right samples of the database from every class. All of the classes of the image database are marked.
- Send the class labels and their features to the SVM classifier along with the selected kernel.
- Categorize all the images in the database by taking every image present in the database to be the query image [14].

A query image may be one among the database images. Then the processing of the query image is done for computing the feature vector. The distance $d^{c\,x}_{qi\,i}$is calculated between the query image ('q') and image from the database ('i'). Then the distances are sorted in ascending order and the nearest sets of images are then acquired. The topmost "N" retrieved images are utilized for performance computation of the algorithm proposed. The retrieval efficacy is measured through the counting of the number of matches.

VI. CLASSIFICATION AND REGRESSION TREE (CART) ALGORITHM

CART is a supervised decision tree induction technique. It recursively bifurcates the input into disjoint classes based on some attribute. Decision tree learning is practically simple and invariant to incomplete and noisy input features. Most of the decision tree approaches in the literature aim at improving the retrieval accuracy of the system. CART uses impurity as a measure to determine the best split. The splitting is terminated when further growth of the tree does not contribute to significant improvement in the results. Every image is assigned to some leaf node that emulates a class. CART makes use of a post-pruning process to arrive at a compromise between the size of the tree and the accuracy of the estimates [15].

- Constructing tree using the features color indexed image histogram and discrete wavelet
- Decomposition of the training images
- Classifying the input image using the decision tree
- Retrieving all the best matching images from the matching class of the input image using a simple distance metric.
- Image Feature Matching: For matching the input image features with the stored features of image data set, the simple Euclidean distance is used as a distance metric. The ranks of the matching images were calculated based on the Euclidean distance with the query image. In our evaluations, we only considered top 50 ranked matching images and calculated the precision by taking the average of precision of several runs with same category input query images.

VII. RANDOM FOREST (RF)

Random forests are recently proposed statistical inference tools, deriving their predictive accuracy from the nonlinear nature of their constituent decision tree members and the power of ensembles. Random Forest committees provide more than just predictions; model information on data proximities can be exploited to provide random forest features. Variable importance measures show which variables are closely associated with a chosen response variable, while partial dependencies indicate the relation of important variables to said response variable [16].

Random Forest generates multiple decision trees; the randomization is present in two ways: (1) random sampling of data for bootstrap samples as it is done in bagging and (2) random selection of input features for generating individual base decision trees. Strength of individual decision tree classifier and correlation among base trees are key issues which decide generalization error of a Random Forest classifier.

Random Forest is a classifier consisting of a collection of tree-structured classifiers $\{h(x,\theta_k)k = 1,2,\ldots.\}$ where the $\{\theta_k\}$ independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x.

Random Forest generates an ensemble of decision trees. To achieve diversity among base decision trees, Breiman selected the randomization approach which works well with bagging or random subspace method. To generate each single tree in Random Forest, Breiman followed following steps: If the quantity of records in the training set is N, then N records are examined at arbitrary however with substitution, from the first information, this is bootstrap test. This specimen will be the training set for developing the tree. On the off chance that there are M data variables, a number $m<<M$ is chosen such that at every node, m variables are chosen in arbitrary manner of M and the best part on these m attributes are utilized to split the node. The estimation of m is held constant within the development of forest. Each one tree is developed to the biggest degree conceivable.

In this way, multiple trees are induced in the forest; the number of trees is pre-decided by the parameter Ntree. The number of variables (m) selected at each node is also referred to as k. The depth of the tree can be controlled by a parameter node size (i.e. number of instances in the leaf node) which is usually set to one. Once the forest is trained or built as explained above, to classify a new instance, it is run across all the trees grown in the forest. Each tree gives classification for the new instance which is recorded as a vote. The votes from all trees are combined and the class for which maximum votes are counted (majority voting) is declared as classification of the new instance. Random Forest means the forest of decision trees generated using this process.

In the forest building process, when bootstrap sample set is drawn by sampling with replacement for each tree, about 1/3rd of original instances are left out. This set of instances is called OOB (Out-of-bag) data. Each tree has its own OOB data set which is used for error estimation of individual tree in the forest, called as OOB error estimation. Random Forest algorithm also has inbuilt facility to compute variable importance and proximities. The proximities are used in replacing missing values and outliers.

VIII. RESULT AND DISCUSSION

This section presents the performance measurements of the proposed technique. The performance is evaluated using precision, recall, and precision-recall (PR) curve parameters on Corel-A/1000, and Corel-B/1500 [17]. Image collections and the results are compared with the state-of-the-art CBIR techniques. All the results of the experiments are reported by performing each experiment 10 times.

The dictionary size and features percentages per image are two important parameters that affect the performance of the proposed technique. Increasing the size of the dictionary at some certain level for compact representation of the visual contents of the images increases the performance of the image retrieval, while larger sizes of the dictionary result in over fitting problem of CBIR. Similarly, in order to reduce the computational cost of the proposed technique that is slightly increased due to visual words fusion as well as the features fusion of SIFT and LIOP feature descriptors, performance analysis is carried out using different features percentages per image as reported in the subsequent sections.

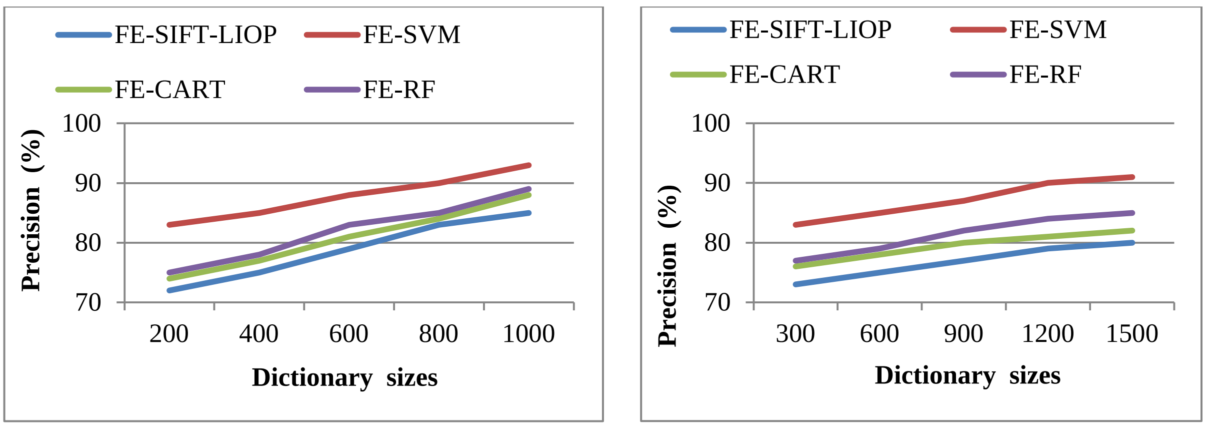
PRECISION AND RECALL:

The precision measures the specificity or accuracy while recall measures the sensitivity or robustness of the CBIR techniques. Both are mathematically represented by the following equations:

$$P \frac{I_r}{I_t}, \quad (17)$$

$$R \frac{I_r}{I_s}, \quad (18)$$

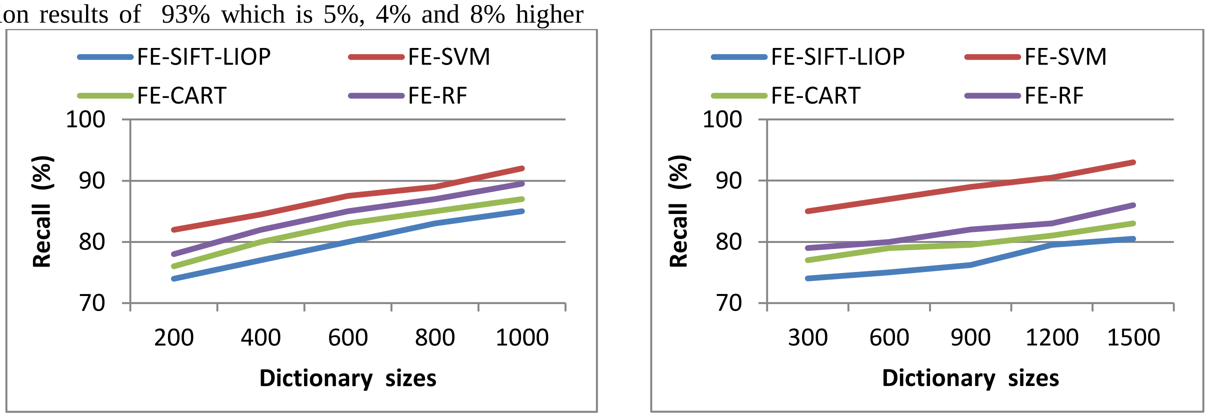
Where I_r represents the number of correctly retrieved images, I_t represents the total number of retrieved images, and $I_s$represents the total number of the images in a particular semantic category.



(a) Corel-A/1000 **(b) Corel-B/1500**

Figure 3. Precision results vs. classifiers

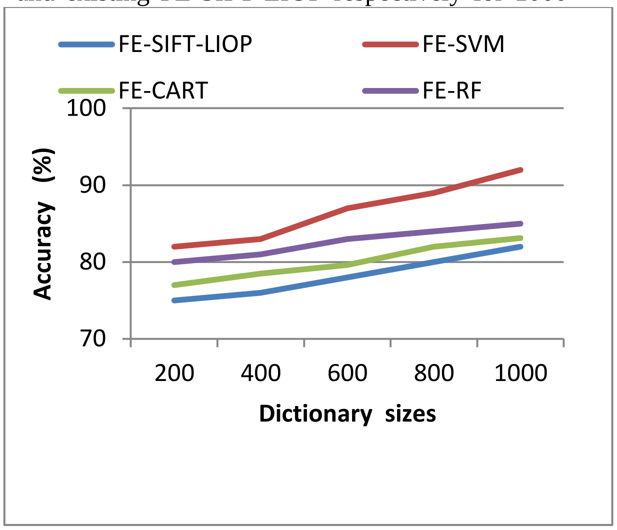
The figure 3 shows the precision results of the retrieval methods such as feature extraction with SIFT-LIOP (FE-SIFT-LIOP) , proposed feature extraction with SVM(FE-SVM), feature extraction with CART(FE-CART), and feature extraction with RF(FE-RF) methods. The results are shown in Corel-A/1000 and Corel-B/1500 dataset. Figure 3(a) shows the precision results of Corel-A database with respect to several classification methods. From the results it concludes that the proposed FE-SVM produce the higher precision results of 93% which is 5%, 4% and 8% higher when compared to FE-CART, FE-RF and existing FE-SIFT-LIOP respectively for 1000 dictionary sizes in Corel-A database. Figure 3(b) shows the precision results of Corel-B database with respect to several classification methods It concludes that the proposed FE-SVM produce the higher precision results of 91% which is 9%, 6% and 11% higher when compared to FE-CART, FE-RF and existing FE-SIFT-LIOP respectively for 1500 dictionary sizes in Corel B database.



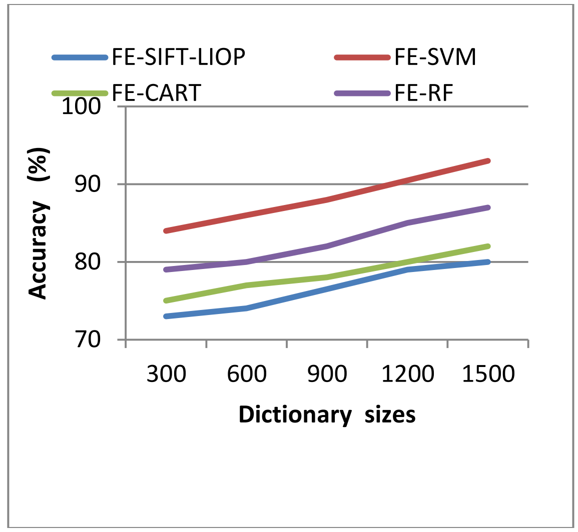
(a) Corel-A/1000 **(b) Corel-B/1500**

Figure 4. Recall results vs. classifiers

The figure 4 shows the recall results of the retrieval methods. The results are shown in Corel-A/1000 and Corel-B/1500 dataset. Figure 4(a) shows the recall results of Corel-A database with respect to several retrieval methods. From the results it concludes that the proposed FE-SVM produce the higher recall results of 92% which is 5%, 2.5% and 7% higher when compared to FE-CART, FE-RF and existing FE-SIFT-LIOP respectively for 1000 dictionary sizes in Corel-A database. Figure 4(b) shows the recall results of Corel-B database with respect to several retrieval methods It concludes that the proposed FE-SVM produce the higher recall results of 93% which is 10%, 7% and 12.5% higher when compared to FE-CART, FE-RF and existing FE-SIFT-LIOP respectively for 1500 dictionary sizes in Corel B database.



(a) Corel-A/1000



(b) Corel-B/1500

Figure 5. Accuracy results comparison vs. classifiers

The figure 5 shows the accuracy results of the retrieval methods. The results are shown in Corel-A/1000 and Corel-B/1500 dataset. Figure 5 (a) shows the accuracy results of Corel-A database with respect to several classification methods. From the results it concludes that the proposed FE-SVM produce the higher accuracy results of 92% which is 8.9%, 7% and 10% higher when compared to FE-CART, FE-RF and existing FE-SIFT-LIOP respectively for 1000 dictionary sizes in Corel-A database. Figure 5 (b) shows the accuracy results of Corel-B database with respect to several classification methods It concludes that the proposed FE-SVM produce the higher accuracy results of 93% which is 11%, 7% and 13% higher when compared to FE-CART, FE-RF and existing FE-SIFT-LIOP respectively for 1500 dictionary sizes in Corel B database.

XI. CONCLUSION

Content-Based Image Retrieval (CBIR) is a mechanism that is used to retrieve similar images from an image collection. In CBIR systems, the image descriptor responsible for assessing the similarities among images. High dimensionality of the feature vectors creates problems in constructing efficient data structures for search and retrieval. For this reason, there is considerable interest in reducing the dimensionality of the descriptors while preserving the original topology of the high dimensional space. In this work propose a novel technique based on Binary Bat Algorithm for dimensionality reduction after extracting the SIFT and LIOP features. Also the visual words fusion as well as features fusion of the SIFT and LIOP feature descriptors and fusion methodology is proposed in order to deal with the aforementioned issues. This work compares the classification efficiency of classifiers Support Vector Machine (SVM), Classification and Regression Trees (CART) and Random Forest (RF) for CBIR. Performance comparison shows that proposed FE-SVM produce the better accuracy.

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