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Employing Divergent Machine Learning Classifiers to Upgrade the Preciseness of Image Retrieval Systems

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Abstract**:** *Content Based Image Retrieval* (*CBIR*) *system is an efficient search engine which has the potentiality of retrieving the images from huge repositories by extracting the visual features. It includes color, texture and shape. Texture is the most eminent feature among all. This investigation focuses upon the classification complications that crop up in case of big datasets. In this, texture techniques are explored with machine learning algorithms in order to increase the retrieval efficiency. We have tested our system on three texture techniques using various classifiers which are Support vector machine, K-Nearest Neighbor* (*KNN*)*, Naïve Bayes and Decision Tree* (*DT*)*. Variant evaluation metrics precision, recall, false alarm rate, accuracy etc. are figured out to measure the competence of the designed CBIR system on two benchmark datasets, i.e. Wang and Brodatz. Result shows that with both these datasets the KNN and DT classifier hand over superior results as compared to others.*

Keywords**:** *Support vector machines, K-Nearest Neighbour* (*KNN*)*, Decision tree, Naïve bayes, False alarm rate.*

1. Introduction

With the up gradation of technology, huge image repositories are being constructed using different and advanced image capturing devices such as digital cameras, mobile phones, web cameras, etc. Hence saving and managing these voluminous databases is very compelling task. The seeking of a particular image from these vast image archives is categorized into two groups: Text Based Image Retrieval (TBIR) and Content Based Image Retrieval (CBIR) [1]. At the beginning, TBIR system was developed for retrieval of images. In these systems, the words that describe the image are entered into the system manually and after that these keywords are used by the system for the retrieval of the images. However, TBIR system is not very decisive and efficient as the keywords sometimes may not be able to describe the image properly especially in case of large datasets. Moreover, different persons can assign the different keywords for the same image and thereby the images retrieved are also not same [2].

So, to conquer this limitation of TBIR systems, CBIR were designed in which no human interference is required. In these systems the retrieval of images is performed automatically on the basis of their low level features which are color, shape and texture [3]. These low level features are extracted from the database images and feature vector is constructed for these images. Similar features are also extracted from the query image and feature vector is constructed. After that, the similarity between the query and database images is evaluated with the help of some distance metric. Various distance metrics can be used for the calculation such as Euclidean, city block, Manhattan, Minkowski, etc., [4]. Finally depending upon the distance value, the system retrieves the similar images. Lesser is the distance value, more is the similarity between the query and database image. After the step of feature selection and feature extraction another major step is dimensionality reduction. With the increase in the size of database, the feature size also increases. So there are various techniques which helps in decreasing the size of features and hence increasing the speed of image retrieval. Some of these techniques are Principal Component Analysis (PCA), Latent Dirichlet Allocation (LDA), etc., [5].

Sometimes, the results obtained after the similarity evaluation may not be accurate due to the semantic gap, which is the gap or difference between machine and human perception of images as CBIR systems works automatically without any human interference [6]. This critical issue in these systems can be overcome by the technique known as Relevance Feedback. In this mechanism the system is able to learn which image is of more interest to the user. So, it acts as an interface between user and the search engine. With these techniques the output retrieved images are refined depending upon the feedback from the user. The evaluations performed by the user are then interpreted to reform the aforementioned query for improving the performance of the complete system [7]. The complete CBIR system with relevance feedback is shown in Fig. 1.

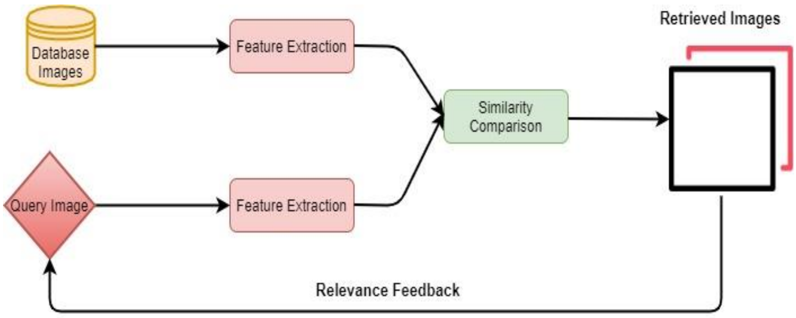

Fig. 1. CBIR system showing relevant feedback

For enhancing the performance of CBIR systems, machine-learning algorithms are now being used in which the image feature vectors act as input to the machine-learning algorithm. The novel techniques on image retrieval systems are being focused on these machine learning algorithms due to their simplicity, lesser complexity and higher swiftness [8]. These are categorized into four major groups, which are: supervised, unsupervised, semi supervised and reinforced learning.

In case of CBIR systems mostly supervised machine learning algorithms are used whose function is to classify the input data. Various types of supervised machine learning algorithms exist which can be successfully applied on CBIR systems, i.e., Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT) and many more.

Behind the lucrative implementation of the CBIR systems, they can be used in different applications such as criminal face identification, medical disease diagnosis, textile industries, remote sensing and various others [9].

The main objective of this research article is to enhance the performance of different texture feature extraction techniques used in CBIR systems as these texture techniques are the most decisive features in these systems out of all the low level features. The conduct of these texture techniques can be bettered by deploying machine learning algorithms into them as a classifier. This in turn improves the performance parameters of the CBIR systems such as precision, recall, accuracy, false alarm rate etc. The maximum preferable texture techniques that can be employed in almost every type of images are Local Binary Pattern (LBP), Grey Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Waveform (DWT). So, here different types of supervised machine learning algorithms are employed over these techniques and their performance parameters are evaluated.

The remaining portion of the paper is constructed as: In the second section survey related to our research article is described by some latest articles. In the next section proposed framework is described which tells how the research is being done in this article. In the fourth section experimental set up and results are presented in detail. Finally, the concluding summary and the future work that can be explored here is described.

2. State-of-the-art techniques

Amongst all the low level features, texture is the most dominating and influential feature of an image. Basically, texture is the spatial arrangement of the visual pattern that is presented in the images. Numerous texture techniques based CBIR systems are proposed in the literature. Some of the latest are presented in this section.

Fadaei, Amirfattahi and Ahmadzadeh [10] schemed a novel texture technique for the retrieval of images from huge databases which was known as Local derivative radial pattern. It basically depends on the grey level difference between pixels and on their weighted combinations so the information loss there is not as big compared to other texture techniques. Another hybrid texture descriptor was proposed which was the combined approach of GLCM and LTP and is called as CoALTP. It combines the important properties of both techniques [11]. In the technique thus designed, firstly the pixel LTP's are evaluated and after that GLCM is used in all four directions and features are extracted. A different image hashing technique was proposed in [12] based on LBP basically used for identification of images. In this designed framework SVM was used as a classifier so as to increase the accuracy of the system. The ROC curve of the system tells that the execution of the system is much better and provides excellent results when compared with others [13].

A high level CBIR system was proposed in [14] having a capability of multiple object retrieval with the use of only visual attributes of the images. For the classification purpose C-SVC and Fisher vector classifier was used and these classified objects were stored for the searching task**.** An efficient CBIR system is framed in [15] in which DWT technique is used for extracting the texture features along with edge and color features and after that SVM is used as a classifier here for the classification of datasets so that the searching step becomes easier. Pham designed another system by extracting texture and color features both by representing the images using the local descriptors that are extracted from the key points present in the image. In this scheme, local extrema pixels are used as feature points and are called as LED, i.e., local extrema descriptor. For every key point color and texture information is generated by the combination of [16]. Almost in all CBIR systems, the similarity between the images is calculated by means of various distance metrics. But these metrics are of less tolerance and result in high sensitivity. Hence, to overcome this problem in [17] a novel texture feature based medical image retrieval technique was proposed known as texture block code tree. A new method of similarity evaluation was also proposed for fine grained and coarse grained.

In [18] a texture recognition technique was framed by the combination of Discrete Cosine Transform (DCT) and Fast DCT via wrapping which provides better results as compared to individually used DCT and FDCT in terms of recognition rate. Different machine learning classifiers have been used in the literature to enhance the capabilities of the system such as SVM, DT, KNN, etc. In [19] DT classifiers have been successfully used to detect the mischievous URLs for protecting them from cyber attacks.

In the next designed intelligent CBIR system [20] machine learning algorithm, i.e., KNN was used as a classifier so as to classify the input images. Color and texture features are extracted using color histogram and GLCM respectively and join together to form a single feature vector. After that, to increase the accuracy of the system KNN was applied on the integrated feature vector for classification purpose.

3. Proposed methodology

Smart and intelligent CBIR systems are designed here by deploying different supervised machine learning algorithms. As texture is one of the most influential and dominating feature of the images, so here the mostly used texture techniques are experimented individually on four different machine learning algorithms and performance parameters are compared on two touchstone CBIR datasets.

The complete proposed system designed is framed here and is shown in Fig. 2.

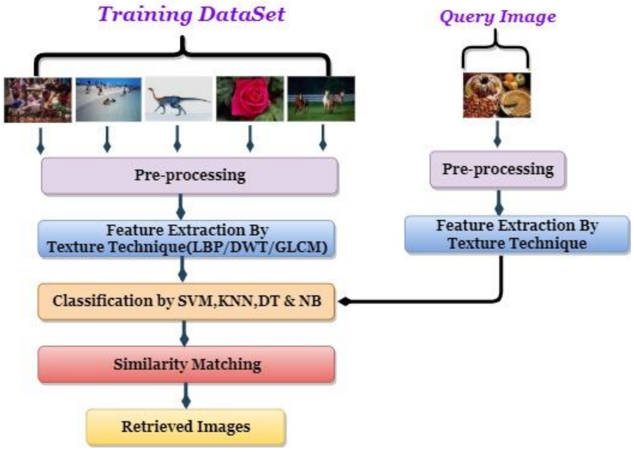

Fig. 2. Proposed block-diagram

The stepping of training and testing is given in two phases: training and testing phase.

Training phase:

- Texture features are extracted individually by LBP, DWT and GLCM techniques.
- SVM/NB/DT/KNN are trained and are modeled as a classifier and all are applied with every texture technique.
- Multiple classes are formed by these classifiers.

Testing phase:

- Similar feature is extracted from the query image.
- Query image is classified into the most pertinent class obtained by the classifier.
- Similarity of the query image is calculated from the images of its belonging class only not from the whole database.

Finally images are retrieved.

4. Experimental set up and evaluation parameters

The work has been implemented in MATLAB-15A, 4 GB memory and 64 bit Windows platform on two touchstone datasets. Wang and Brodatz databases are used here for conducting the experiments which are the two standard databases used for the analysis of CBIR systems. Wang database comprises of colored images and Brodatz is the collection of grey scale images. The Wang dataset contains total of 1000 images which are divided into 10 categories. Each category contains 100 images. The image is of size 256×384.

The second dataset, i.e., Brodatz contains total 1456 images which is formed by the combination of 13×16×7. Here, each image is divided into 16 images and every image is rotated into 7 different angles. 13 denotes the number of categories so the total images will be 1456 and the size of each image is 128×128. The sample images of both these databases are shown in Fig. 3 and Fig. 4.

Fig. 3. Images of Wang dataset

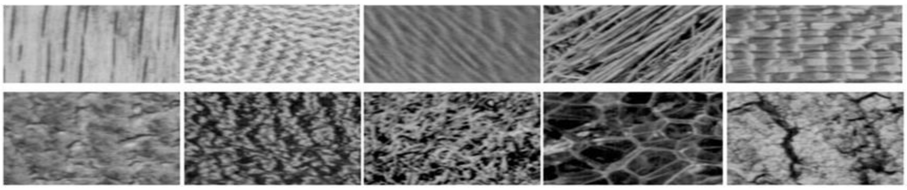

Fig. 4. Some images of Brodatz dataset

4.1. Evaluation parameters

In order to check out the competence of CBIR systems various parameters are evaluated and most important parameters in these systems are precision and recall. Here, in this designed framework in order to judge the performance of machine learning algorithms on different texture techniques different parameters are evaluated which are shown in below equations.

1. **Precision.** It is equal to the ratio of the relevant images retrieved to the total images retrieved,

(1) $$P = \frac{T_P}{N_t} = \frac{T_P}{T_P+F_P},$$

where T_P is the true positive, i.e., relevant images that are retrieved and F_P is referred as false positive which are misclassified as the relevant images.

2. **Recall.** It is the ratio of number of images retrieved that are relevant to the total number of relevant images that are present in the database,

(2) $$R = \frac{T_P}{N_D} = \frac{T_P}{T_P+F_N},$$

where F_N is false negative which means those images which are belonging to the relevant class but they are wrongly classified to the other class.

3. **Accuracy.** It is an important parameter to check the implementation of any experiment,

(3) $$A = \frac{T_P+T_N}{T_P+F_P+T_N+F_N}.$$

4. **False Alarm Rate (FAR).** It is defined as the number of the false positives to the total number of the non-events. It should be less for better implementation results,

(4) $$\text{FAR} = \frac{F_P}{F_P+T_N}.$$

5. Experimental results

5.1. Experiments conducted on Wang database

Initially, the Wang database is experimented and all the above parameters are evaluated on texture based image retrieval system using various machine learning algorithms. The most important and competent parameters of any CBIR system is precision and recall. The average value of precision is evaluated by every technique using all classifiers. Such as firstly, the average value of precision is calculated using simply LBP technique by taking all 1000 images of the database as the test images and all as training images. After that the average value of precision of LBP technique is evaluated by using four different machine learning classifiers which are: i) LBP with SVM, ii) LBP with KNN, iii) LBP with DT, and iv) LBP with NB. In all cases top five images are retrieved. Similar types of results are evaluated by other two texture techniques also which are DWT and GLCM. Their comparative analysis is graphically represented in Fig. 5.

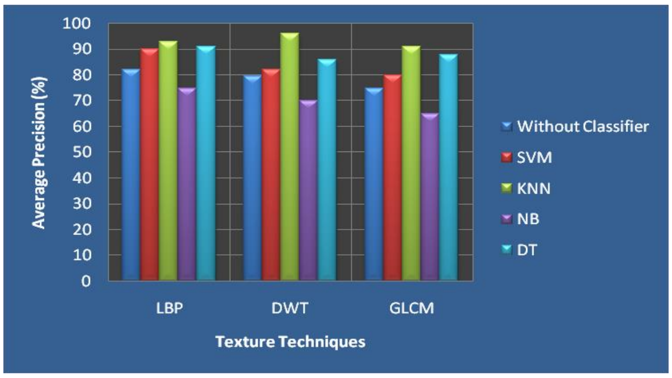

Fig. 5. Comparative analysis of average precision of texture technique with different classifiers

Here, in our experiments for calculating the similarity between the query and database images Euclidean distance measure is applied which is given as:

$$D_{\text{Euclidean}} = \sqrt{\sum_{i=1}^{n}(|Q_i - D_i|)^2}, \quad (5)$$

Q denotes the feature vector of the query image and D denotes the feature vector extracted for every image of the database. The lesser is the value of the distance the more is the similarity between the images. These values of precisions are calculated when top five images are retrieved in every case.

The numerous other parameters which are evaluated here for the three texture techniques on different machine learning classifiers are shown in Table 1.

From these obtained results it can be concluded that for Wang database the LBP technique provides highlighted results with almost all the classifiers. It is also observed from Fig. 6 that KNN classifier works prime with DWT technique. However, the NB classifier is not suitable with any texture technique. So it is clear that with Wang database which contains general categories of images such as human beings, flowers, and animals, etc., the NB classifier should not be used. On the other hand, when there is time constraint, then as per the above results DT algorithm is preferred over KNN classifier because it provides comparable results and KNN takes more time as compared with other classifiers.

Table 1. Comparative analysis of machine learning classifiers on texture techniques using different parameters on Wang database

Technique	Classifiers	FAR	Recall (%)	Accuracy (%)
LBP	SVM	1.1	86.8	96
	NB	3.37	65.6	92
	KNN	0.9	90.8	98
	DT	1.044	90.6	98
DWT	SVM	5.2	60	89
	NB	6.5	55	85
	KNN	0.88	90	98
	DT	1.76	84	96
GLCM	SVM	3.5	70	94
	NB	5.08	64.2	91
	KNN	0.89	92	99
	DT	1.47	87	98

5.2. Experiments conducted on Brodatz database

Similarly like the above case, the experiments are also analyzed on different database, i.e., Brodatz which comprised of grey scale images. Correspondingly, the precision values are computed by taking every image as query image and all as training images. So, 1456 values of precision are there and from this the average value of precision is calculated by every case like as above experiments. This value is calculated from every texture technique by using all four classifiers. The comparative analyses of average precision of all these techniques on all machine learning classifiers are shown in Fig. 6.

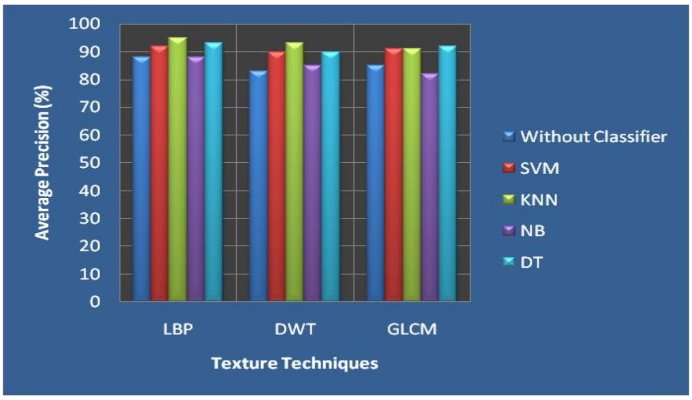

Fig. 6. Comparative analysis of average precision of texture technique with different classifiers

The other important parameters evaluated by these techniques are tabulated in Table 2.

Table 2. Comparative analysis of machine learning classifiers on texture techniques using different parameters on Brodatz database

Technique	Classifier	FAR	Recall(%)	Accuracy (%)
LBP	SVM	0.87	89	98
	NB	1.01	87	96
	KNN	0.56	96	98
	DT	0.42	94	97
DWT	SVM	0.91	88	96
	NB	1.12	85	91
	KNN	0.32	94	99
	DT	0.88	89	97
GLCM	SVM	0.99	91	97
	NB	1.05	85	96
	KNN	0.45	90	99
	DT	0.67	92	98

As observed from the above table, the results obtained from the Brodatz database are far better than Wang database. The Brodatz database contains grey scale images, so it is very clear that these texture techniques perform very well with these types of images. In this case also the KNN and DT classifier hand over some better results than other classifiers. It is also undoubted that, all these classifiers performs very well with Brodatz dataset which contains images such as bricks, raffia, grass, etc.

The experiments that are performed here will help the researchers how and when to use whichever type of machine learning algorithm on texture features for the retrieval of images in larger datasets. By exploiting the machine learning algorithms as classifiers after the feature extraction enhances the capability and accuracy of the CBIR system.

6. Image retrieval results

The Graphical User Interfaces (GUI's) of the images retrieved by taking a random image from Wang database using LBP technique is shown in Figs 7 and 8. In Fig. 7 the NB classifier is used with LBP technique and its precision comes out is 0.8 and in the second figure KNN classifier is used along LBP and in this case the value of precision comes out to be 1 which is 100%. The images are taken from the flower category and top five images are retrieved in both cases.

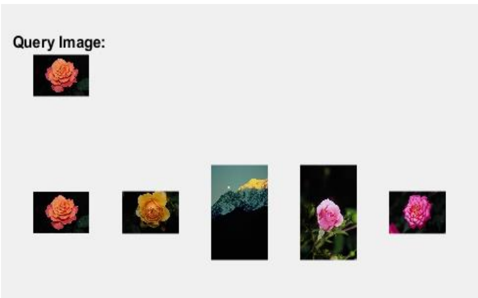

Fig. 7. Images retrieved by LBP technique using NB classifier

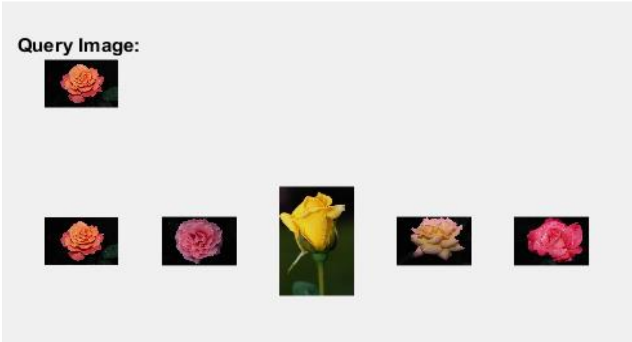

Fig. 8. Images retrieved from the similar image by LBP technique using KNN classifier

7. Conclusion

In this schemed framework, the pursuance of texture feature extraction techniques for image retrieval systems with different machine learning algorithms is examined. These supervised machine learning algorithms are trained as classifiers. Although there is a great swing towards deep learning algorithms but it is also very true that some of the applied algorithms with feature extraction techniques provide comparable results and are very swifter than trendy deep learning algorithms. The performances of four classifiers are correlated with three texture feature extraction techniques experimented on two datasets which are Wang and Brodatz. The different obtained texture based CBIR systems validate that for Wang database KNN and DT classifiers hand over superior results with LBP and DWT techniques. In case of Brodatz database which comprises of grey scale images DT provides highlighted results with all the three techniques. The NB classifies is not suggested to be used as a classifier with texture feature extraction techniques as it does not yield good result with any technique.

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