Content Based Medical Image Retrieval System using Multiple Classifier Framework

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ABSTRACT
Content Based Image Retrieval (CBIR) is the set of techniques for searching of similar images from an image database using automatically extracted image features such as color, shape and texture. Feature extraction is the fundamental step in the CBIR systems. In the proposed multiple classifier method best discriminating features are combined in order to improve the retrieval performance. In the proposed system three shape features and three texture features are combined. The best matched features are found using the Bipartite weighted graph and combined using the decision combination operators. The retrieval experiments were conducted on the large medical image database and the results show that the proposed multiple classifier system yields good retrieval performance than the retrieval systems based on the individual features.
Keywords:
CBIR, Shape features, Texture features, Medical images, Bipartite graph, retrieval.

1. Introduction

In this digital era, due to the rapid development of internet and information technologies, more and more images are generated and stored in digital form. This requires a great need for large image database management and effective image retrieval tools. The development of an automatic image retrieval system is thus a must to resolve the retrieval problem. With the advances in computer technologies in medical domain, there has been an explosion in the amount and complexity of digital data being generated, stored, transmitted, analyzed and accessed in hospitals. The huge amount of digital images generated in hospitals and health care centers leads to the need of automatic storage and retrieval of them.
The traditional approach to CBIR [2,7] represents each image in the database by a vector of feature values. For this approach, the choice of features to include for characterizing the images is the critical factor, which determines the ability to achieve high retrieval precision. Some common feature vectors will not perform well for medical domain because the features that are most effective in discriminating among images from different classes may not be the most effective for retrieval of images belonging to the same subclass within a class. For example in HRCT of the lungs, a query image may differ from other images within the same disease class on account of the severity of disease and other such factors. Unlike the general purpose images, medical images are more visually similar and hence will have similar visual features. The discrimination among similar medical images is difficult which will decrease the retrieval performance. To improve the retrieval performance of the medical image retrieval system, effective feature representation methods are needed to extract the discriminate salient features from the medical images.
A common approach to model an image retrieval system is to extract a vector of features from each image in the database and then use the similarity distance between those feature vectors as similarity measure for images. But the effectiveness of this approach is highly dependent on the quality of the features used. There are two ways to increase the efficiency of any pattern recognition system. One is to improve the performance of a single classifier; another is to combine the results of multiple classifiers [3]. It is difficult for a single classifier to achieve perfect solution. The multiple classifier method thereby becomes the best choice for solving pattern recognition problems. A multiple classifier method is superior to a single classifier method if the classifiers are selected carefully. The combination algorithm can take the advantages of each individual classifier to avoid its weakness.
Image retrieval system is an application of a pattern recognition system. To increase the performance of the system, rather than improving the performance of the single feature, it is best to combine the multiple features. The combination of various features can take the advantages of each individual feature. The performance of the retrieval system based on multiple features will be better if the features are selected carefully. In this paper a new framework for medical image retrieval system is proposed by combining multiple features. In this

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proposed method, for selecting the efficient features for the query image, the bipartite weighted matching problem (BWMP) [1] is used. The proposed medical image retrieval system yields a good retrieval performance because of the combination of salient features.

2. Proposed architecture

The proposed medical image retrieval system is based on the combination of the multiple classifiers.
The proposed multiple classifier method consists of six phases. They are

- Feature Extraction phase
  During this phase for each image in the database the shape features and the texture features are extracted and the feature vectors are stored in the database along with the image.

- Query phase
  In this phase, a query image is given as input and the shape and texture images.

- Shape classifier phase
  In this phase from the various shape features extracted, the shape similarity between the query image and the database images are found.

- Texture classifier phase
  In this phase using the various texture features, the texture similarity between the query image and the database images are found.

- Decision combination phase
  During this phase the shape similarity measure and the texture similarity measure are combined using the decision combination operator and the overall similarity distance between the query image and the database images are found.

- Output phase
  This phase ranks the images based on the overall similarity distance and displays the top most similar images.

Figure 1 gives the overall architecture of the proposed multiple classifier image retrieval system.

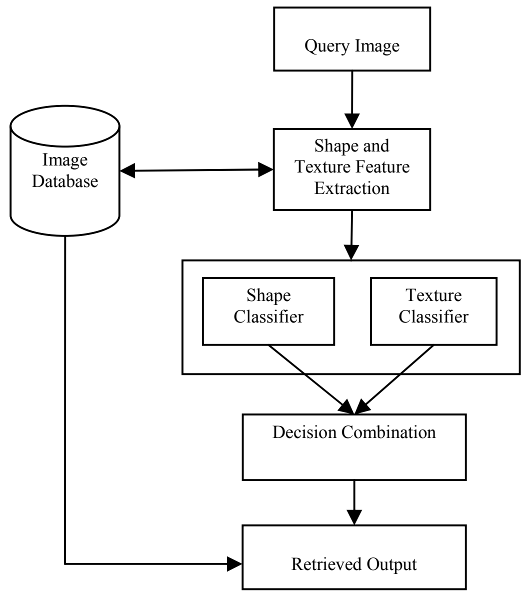


Fig 1 Architecture of the Proposed Multiple Classifier Retrieval System

3. Proposed algorithm

The algorithm of the proposed medical image retrieval system is as follows:

Algorithm

Step 1:
In the feature extraction phase for each image in the database extract the shape features using Zernike moments descriptor, Generic Fourier descriptor and the shape descriptor based on morphological operation. Store the extracted features of the shape classifier in the database.
Step 2:
Extract the texture features using the Gabor filter, homogeneous texture descriptor and the texture descriptor based on post processing Gabor filter. Store the extracted features of the texture classifier in the database during the feature extraction phase.
Step 3:
For the given query image Q, first extract the various shape features. For the query image Q and the database image D_i, the output of the shape classifier is found as follows:

a. Construct the bipartite weighted graph.
b. Compute the weights of the edges of the graph.
c. Find the optimal solution of the BWMP, which is the shape distance between the query image Q and the database image D_i.

d. The shape virtue probability between image Q and the database image D_i is calculated.

e. The above steps are repeated for every image D_i in the database, where i=1..N(the total number of images in the database).

Step 4:
For the given query image Q, the texture features are extracted. The output of the texture classifier is found by the same steps as given step (3) of the algorithm.
Step 5:
Find the overall virtue probability of the query image Q and the database image D_i, using the decision combination operator.
Step 6:
Sort the overall virtue probabilities according the descending order.
Step 7:
Rank the images according to the sorted virtue probabilities and display the top 20 ranked images.
The details of each step in the algorithm are explained in the subsequent sections.

4. Feature extraction and query phase

In content based image retrieval system, the images are retrieved based on the features extracted from the image. A feature is defined to capture a certain visual property of an image, either globally for the entire image or locally for a small group of pixels. The most commonly used features include those reflecting color, texture, shape, and spatial relation. In the proposed system the global extraction is used, where features are computed to capture the overall characteristics of an image. For the medical images the shape and the texture are the dominant features which can efficiently represent an image. In the proposed system during the feature extraction phase the shape and texture features are extracted for all the images in the database. During the query phase, the shape and texture features for the given query image is extracted.

4.1 Shape Feature Extraction

Based on the performance of the shape descriptor for medical image retrieval system, three shape descriptors are selected [10,11]. They are
i) Shape descriptor based on morphological operation
ii) Generic Fourier descriptor and
iii) Zernike moments
The shape features are extracted using these descriptors. The feature vectors are represented as follows:

$F_S(1)$ - Feature vector of shape descriptor based on morphological operation
$F_S(2)$ - Feature vector of Generic Fourier descriptor
$F_S(3)$ - Feature vector of Zernike moment descriptor

4.2 Texture Feature Extraction

From the performance study of various descriptors, three texture descriptors which gives good retrieval results for medical image retrieval system are selected [6, 8, 9]. They are
i) Texture descriptor based on post processing of Gabor filter
ii) Gabor filter and
iii) Homogeneous texture descriptor
The texture features are extracted from the images using these descriptors and stored in the database. Let $F_T(1)$ be the feature vector of the proposed texture descriptor. Let $F_T(2)$ be the feature vector of the Gabor filter and $F_T(3)$ be the feature vector of the Homogeneous texture descriptor.

To illustrate the proposed algorithm, consider the sample image given in figure 2. For the image first the various shape and textures are extracted according to the different shape and texture extraction techniques. In the proposed algorithm, 24 features are extracted for each feature descriptor. Table 1 gives the different shape and texture features for the sample image1. These extracted features are used by the shape classifier phase of the algorithm.

5. Shape classifier phase

The shape classifier retrieves the similar images according to the shape similarity between the query and template images. Five shape features extracted in the feature extraction stage are utilized by the shape classifier. The shape classifier finds the shape similarity of the query image and each image in the database. The matching problem between the query image and the database image in the shape classifier is to minimize the sum of distances of the matched features. This kind of matching problem are called bipartite weighted matching problem (BWMP). The proposed shape classifier uses the BWMP to find the best matching features.

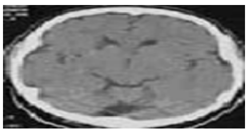


Figure 2 Sample Image1

Table 1 Shape and Texture features for the sample image1

Features	$F_S(1)$	$F_S(2)$	$F_S(3)$	$F_T(1)$	$F_T(2)$	$F_T(3)$
F_1	0.1461	0.3600	0.0502	4.1412	7.3945	2.0389
F_2	0.0283	6.3222	0.0283	6.2880	4.7891	4.0778
F_3	0.0283	2.8950	0.0721	7.2988	2.1836	6.1168
F_4	0.0173	4.8050	0.0871	7.8559	9.5782	7.1557
F_5	0.0156	4.4804	0.0229	9.2112	6.9729	8.1946
F_6	0.0721	0.2628	0.0885	10.6545	4.3673	11.2336
F_7	0.0431	0.0060	0.0190	6.9706	5.7619	7.2725
F_8	0.0572	0.3405	0.0532	14.3215	9.1564	12.3115
F_9	0.0871	2.7671	0.0457	9.4340	10.7651	10.0619
F_{10}	0.0631	0.3405	0.0148	11.9331	2.5303	8.1234
F_{11}	0.0207	0.3206	0.0365	10.4383	3.2955	14.1858
F_{12}	0.0269	8.8624	0.0502	10.1123	4.0607	14.2477
F_{13}	0.0222	6.0332	0.0695	15.4867	5.8259	13.3096
F_{14}	0.0672	6.1211	0.0104	10.5092	6.5911	8.3716
F_{15}	0.0229	3.3213	0.0596	9.2106	7.3562	7.4335
F_{16}	0.0885	6.2904	0.0096	6.4321	8.1214	8.4955
F_{17}	0.0244	6.0332	0.0117	7.3238	2.6835	10.0875
F_{18}	0.0690	4.6567	0.0120	9.5032	5.3670	13.1751
F_{19}	0.0727	0.3488	0.0367	15.3213	8.0506	11.2627
F_{20}	0.0320	0.3552	0.0345	12.3438	5.7341	15.3503
F_{21}	0.0190	2.7314	0.0414	9.3051	6.4177	12.4379
F_{22}	0.0043	2.5531	0.0414	7.4320	7.1012	10.5254
F_{23}	0.0226	1.3920	0.0165	9.5035	8.7848	8.6130
F_{24}	0.0664	0.1968	0.0389	11.2034	10.4683	14.7006

5.1 Bipartite Weighted Matching Problem

Let G = (U, V, E = U x V) be a weighted complete bipartite graph. In the bipartite weighted graph, U represents the query image and V represents the template image in the database. In the proposed method, the nodes ui = { u1, u2, u3} of the query image represents the features $F_S(1)$ to $F_S(3)$ respectively. Similarly the nodes vj ={ v1, v2, v3} of the template image represents the shape features $F_S(1)$ to $F_S(3)$ respectively of the template (V) images. Let Wij be the weight of edge (ui,vj) which is the shape distance between the nodes ui and vj. Figure 3 depicts the bipartite weighted graph between the query image and a template image in the database. The bipartite weighted matching problem is to find a complete matching such that the sum of the weights of matching edges is minimum. The assignment problem (AP) are given n jobs and n works. Each assignment, assigning the ith job to the jth worker, has a fixed completion time or cost of the works is minimum. Therefore, the AP is a special case of the bipartite weighted matching problem when m = n. The AP can be formulated in linear programming standard forms as follows:

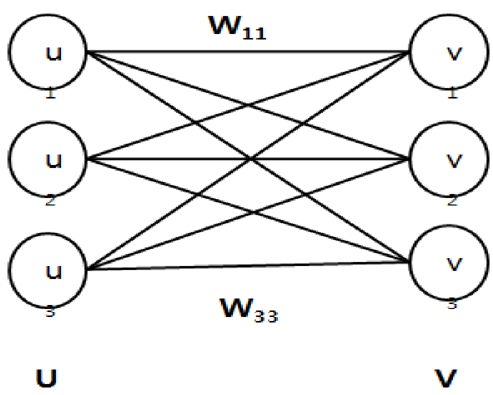


Figure 3 Bipartite weighted graph for shape classifier

$$Minimize \ \sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij} X_{ij} \qquad (1)$$

subject to

$$\sum_{i=1}^{m} X_{ij} = 1, \ for \ all \ 1 \le j \le m$$
$$\sum_{j=1}^{n} X_{ij} = 1, \ for \ all \ 1 \le i \le m$$
$$X_{ij} \in \{0,1\} \qquad (2)$$

In equation (1) and (2) $X_{ij} = 1$ if ui is matched with vj. The optimal solution of BWMP is obtained using equation (3)

Minimize

$$\sum_{i=1}^{m}\sum_{j=1}^{n} W'_{ij} X'_{ij} \qquad (3)$$

where

$$\sum_{i=1}^{m+n} X'_{ij} = 1 \ for \ all \ 1 < j < m+n$$

and

$$\sum_{j=1}^{m+n} X'_{ij} = 1 \ for \ all \ 1 < i < m+n$$

If X is a feasible solution of (1), its extension X' can be defined by

[1] for all $1 \le i \le m$, $1 \le j \le n$, $X'_{ij} = X_{ij}$;

[2] for all $i > m$, $j > n$, $X'_{ij} = X_{i-n,i-m}$;

[3] for all $1 \le i \le m$, $j>n$,

$$X'_{ij} = \begin{cases} 1, \text{if } i = j - n \text{ and } \sum_{k=1}^{n} X_{ik} = 0 \\ 0, \text{otherwise} \end{cases}$$

[4] for all $i > m$, $1 \le j \le n$,

$$X'_{ij} = \begin{cases} 1, \text{if } j = i - m \text{ and } \sum_{k=1}^{m} X_{kj} = 0 \\ 0, \text{Otherwise} \end{cases}$$

In the proposed work, weight matrix W'ij is obtained as follows

a) for all $1 \le i \le m$, $1 \le j \le n$,

$$W'_{ij} = shape\_dist(Q_i, D_j)$$

$$shape\_dist(Q_i, D_j) = \sqrt{\sum_{k=0}^{N}\left(F_{SQ}(k) - F_{SD}(k)\right)^2} \qquad (4)$$

where

$shape\_dist(Q_i, D_j)$ is the shape distance between shape feature i of the query image (Q) and shape feature j of a template image (D_j).

$F_{SQ}(k)$ is the kth feature vector of the query image

$F_{SD}(k)$ is the kth feature vector of the database image

N is the length of the feature vector.

b) for all $1 \le i \le m$, $n+1 \le j \le m+n$,

$$W'_{ij} = S'_{i,j-n} = \begin{cases} shape\_dist(Q_i, D_j), if \ i = j - n \\ \infty, otherwise \end{cases}$$

c) for all $m+1 \le i \le m+n$, $1 \le j \le n$,

$$W'_{ij} = S'_{i,j-n} = \begin{cases} shape\_dist(Q_i, D_j), if \ i - m = j \\ \infty, otherwise \end{cases}$$

d) for all $m+1 \le i \le m+n$, $n+1 \le j \le m+n$,

$$W'_{ij} = 0$$

Once the value of the W'_{ij} and X'_{ij} are defined, the optimal solution of the bipartite weighted graph is found using the Hungarian method [4].

5.2 Shape Virtue Probability

The shape distance DS(Q, D_i) between image Q and the database image D_i, will be equal to the optimal solution of BWMP. Then, the shape virtue probability between image Q and image D_i can be defined in equation (6).

$$VP^s(Q, D_i) = 1 - D^S(Q, D_i) / D^s_{max} \quad (6)$$

where $VP^s(Q, D_i)$ represents the probability that image D_i could similar to image Q in the shape classifier and D^s_{max} is the maximum distance between the query and the template images in the database.
Physically the value of virtue probability is stretched from 0 (corresponding to the most dissimilar image) to 1 (corresponding to the completely similar image). Finally a list of sorted similar template images with descending shape virtue probabilities and rankings are output for decision combination.

6. Texture classifier phase

Texture classifier retrieves the similar images according to the texture similarity between the query and template images. Three texture features extracted in the feature extraction stage are utilized by the texture classifier.
The matching problem between two tested images in the texture classifier is to minimize the sum of distances of the matched features. Similar to the shape classifier, this kind of matching problem is solved using the bipartite weighted matching problem (BWMP).
In the bipartite weighted graph, U represents the query image and V represents the template image in the database. In the texture classifier the nodes ui = { u1, u2 ,u3} represents the texture features $F_T(1)$, $F_T(2)$ and $F_T(3)$ of the query image respectively. Similarly the nodes vj ={ v1, v2 ,v3} represents the texture features the database images. Wij is the weight of edge (ui,vj) which is the texture distance between ui and vj. The algorithm of bipartite weighted graph matching (BWMP) which is explained in section 5.1 is used for texture classifier. The optimal solution of the graph is found using the Hungarian method.

The texture distance between image i and image j, DT (i,j), will be equal to the optimal solution of BWMP. Then, the texture virtue probability between image Q and database image D_i can be defined as follows:

$$VP^T(Q, D_i) = 1 - D^T(Q, D_i)/D^T_{max} \quad (7)$$

where $VP^T(Q, D_i)$ represents the probability that image $D_i$could texture similar to image Q in the texture classifier and D^T_{max} is the maximum texture distance between the query and the template images in the database.
Physically the value of virtue probability is stretched from 0 (corresponding to the most dissimilar image) to 1 (corresponding to the completely similar image). Finally a list of sorted similar template images with descending texture virtue probabilities and rankings are output for decision combination.

7. Decision combination and output phase

The two main reasons for combining classifiers are to enhance the efficiency and accuracy. In the previous sections two classifiers have been designed. Each classifier outputs the ranking of the template images for the given query based on shape and texture features. The decisions by the classifiers are represented as the rankings of classes and the rankings can be combined by the methods [5] that either reduce or re-rank a given set of classes. The advantage of the combination methods based on ranking is the classifier independent property, i.e., these methods can weaken the inconsistency of the scales of different classifiers. On the contrary, the disadvantage of these methods is the tie problem. A tie problem will occur if more than two classes possess the same combined ranking. In the proposed multiple classifier method the set of sorted virtue probabilities are combined using product rule, sum rule and max rule in the decision combination stage. This measurement value dependent property not only can avoid the tie problem but also uplift the rankings of similar images in the output list. Hence, the retrieval accuracy and efficiency will be greatly improved.
The overall virtue probability is obtained from the shape virtue probability $VP^S(Q, D_i)$ and the texture virtue probability $VP^T(Q, D_i)$. These virtue probabilities can be combined by three different operators. They are

- Sum (+) operator
- Product (x) operator and
- Maximum (MAX) operator

The overall virtue probability is defined as follows :

$$VP^{IR}(Q, D_i) = \begin{cases} VP^S(Q, D_i) * VP^T(Q, D_i), \text{when } OP = 'X' \\ \frac{[VP^S(Q, D_i) + VP^T(Q, D_i)]}{2}, \text{when } OP = '+' \\ Max\{VP^S(Q, D_i), VP^T(Q, D_i)\}, \text{when } OP = 'MAX' \end{cases}$$

(8)

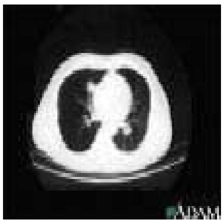
where

VPIR $VP^{IR}(i,j)$ is the probability that a template image D_i is similar to the query image Q in the overall system. OP represents the operator. From the experimental results it was found that the overall virtue probabilities found by sum operator is superior than the product and max operators.

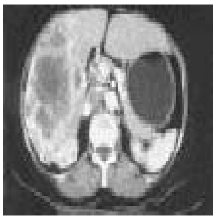
Finally, a list of sorted similar images with descending overall virtue probabilities is output. From the overall virtue probabilities the images are ranked and the top most similar images are retrieved. This proposed multiple classifier medical image retrieval system gives good retrieval performance because of the combined virtue probabilities.

8. Experimental results

To test the effectiveness of the proposed multiple classifier retrieval system for medical images, a large database which consists of 10,000 medical images which are acquired from the CT and MRI scans is used. The database consists of 3 different classes of images such as lung, liver and brain which are structurally similar. One image from each class of the database is given in the figure 4.



Class A : Lung



Class B : Liver

Class C : Brain

Figure 4 A sample image from each of the three classes of the Medical Image Database

The experiments were conducted by considering each image in the database as a query image. For each image 10 best matched images were retrieved from the database. The goal is to have all the retrieved images belonging to the same class and more similar to the query image. The following three different experimental results were discussed.

i) Retrieval results of Class A images
ii) Retrieval results of Class B images and
iii) Retrieval results of Heterogeneous database

First 20 different query images from class A database is selected and retrieval is performed with each query image. From the results the various performance measures were computed. The performance measures used for comparisons are

i) Mean average precision (MAP)
ii) R-Precision
iii) Precision@10
iv) Precision@20
v) Recall@10
vi) Recall@20

Figure 5-7(a,b) gives the retrieval results of the content based retrieval system using the proposed multiple classifier system for class A , class B and Heterogeneous database query images.

Table 2 gives the computed values of the various performance measures for the different proposed method for 20 different query images. From the table it was found that the proposed method is having good retrieval performance for the medical image retrieval system. The proposed multiple classifier system has highest MAP value (80%) for class A images. The proposed multiple classifier has MAP as 79% for class B images. The retrieval performance is good even for Heterogeneous database images also (MAP 78%). Figure 8-10 shows the precision vs recall graph of the proposed multiple classifier system for the class A, class B and heterogeneous images.

This high performance is due to the combination of the shape and texture features. Also in the proposed multiple classifier system, the shape classifier combines several shape features and the texture classifier combines different texture features. Table 3 gives the performance measures of the medical image retrieval system based on various individual features which are used in the proposed multiple classifier framework. From the experimental results conducted on the retrieval system which uses only single features, it was found that the multiple classifier system is more suitable for the content based image retrieval system for medical images than the system based on individual features. Figure 11 gives the precision vs recall graph of the various medical image retrieval systems.

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Figure 5(a) Query Image from class A

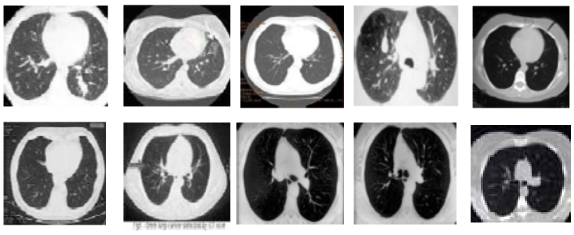

Figure 5(b) Retrieved results using the proposed multiple classifier retrieval system for class A images

Figure 6(a) Query Image from class B

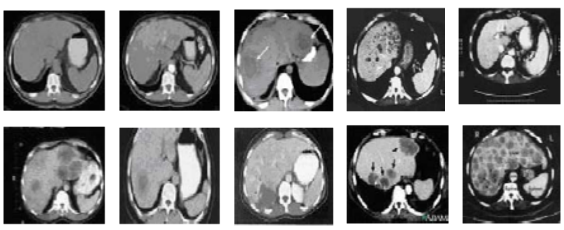

Figure 6(b) Retrieved results using the proposed multiple classifier retrieval system for class B images

Figure 7(a) Query Image from class C

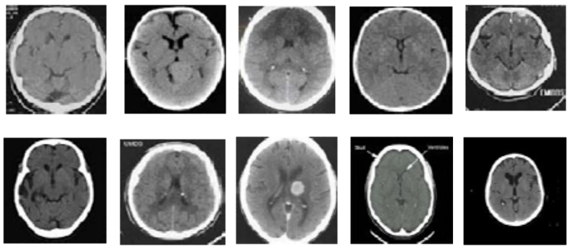

Figure 7(b) Retrieved results using the proposed multiple classifier retrieval system for Heterogeneous database

Table 2 Precision and Recall Measures of the Proposed Method

	MAP (%)	***R-Prec (%)***	***P@10 (%)***	***P@20 (%)***	***R@10 (%)***	***R@20 (%)***
For Class A Images	80.24	89.56	97.66	93.14	87.87	84.37
For Class B Images	79.32	87.15	95.76	93.78	85.67	83.27
For Heterogeneous Database Images	78.13	85.11	94.16	92.17	84.12	82.37

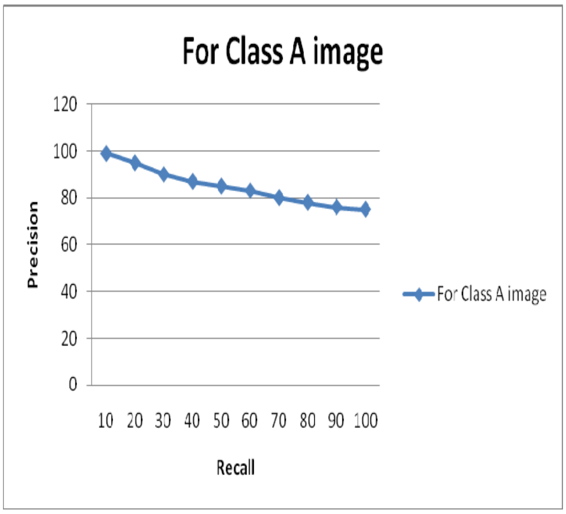

Figure 8 Precision vs recall graph for the 20 retrievals for the class A images

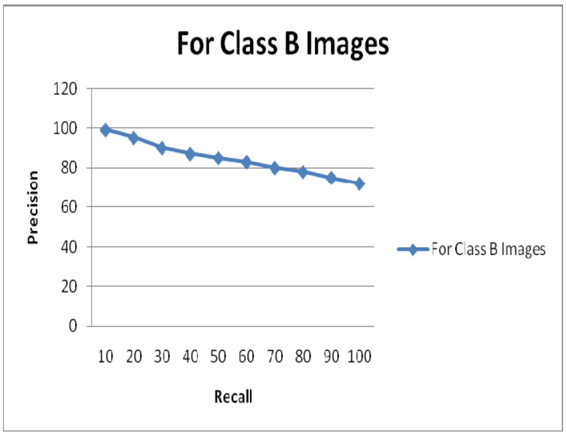

Figure 9 Precision vs recall graph for the 20 retrievals for the class B images

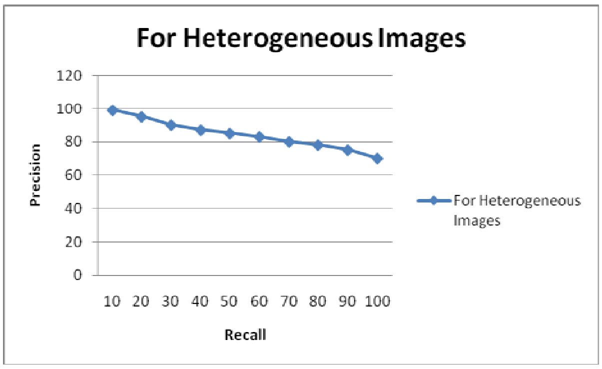

Figure 10 Precision vs recall graph for the 20 retrievals for the heterogeneous images

Table 3 Comparison of the Precision and Recall Measures for various methods

	MAP (%)	*R-Prec(%)*	*P@10(%)*	*P@20(%)*	*R@10(%)*	*R@20(%)*
Zernike Moments	48.28	55.52	79.79	77.41	65.33	63.11
Generic Fourier Descriptor	54.46	64.29	84.30	82.24	72.32	70.32

Shape Descriptor Based on Morphological operation	63.24	77.82	91.74	90.24	80.32	78.74
Gabor Filter	57.46	68.21	86.32	83.20	75.12	73.13
Homogeneous Texture Descriptor	48.28	55.27	69.50	66.26	56.44	54.54
Texture Descriptor Based on Post Processing Gabor Filter	74.24	82.52	93.64	91.24	84.12	81.77
Proposed Multiple Classifier System	80.24	89.56	97.66	93.14	87.87	84.37

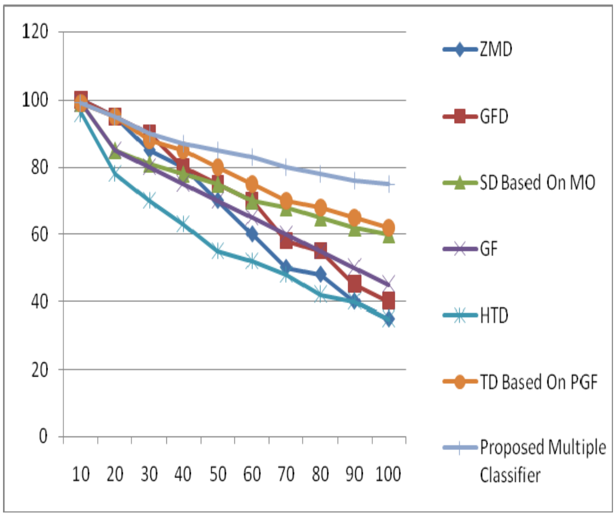

Figure 11 Precision Vs Recall – Comparison of various methods

9. Conclusion

In this paper a new framework for content based medical image retrieval system was proposed. This framework is based on the combination of multiple efficient classifiers. The shape classifier and texture classifier are used. In each classifier, multiple features are selected based on the Bipartite weighted matching problem. The shape distance and the texture distance are combined using the decision combination operator. The experimental results show that this multiple classifier retrieval system gives very good retrieval performance and the mean average precision measure is nearly 79.3%. The retrieval performance of the proposed multiple classifier system is 8% better than the texture descriptor based on post processing Gabor filter and 14% better than the shape descriptor based on morphological operation.

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