CHAPTER 6

PROPOSED HYBRID MEDICAL IMAGE RETRIEVAL SYSTEM USING SEMANTIC AND VISUAL FEATURES

6.1 INTRODUCTION

Image representation schemes designed for image retrieval systems are categorized into two classes: Keyword (text) features and Visual features. The query scenario in image retrieval system based on keyword features (Chang and Hsu 1992; Shen et al. 2000) is Query by Keyword (QBK). Semantics of images can be accurately represented by keywords, as long as keyword annotations are accurate and complete. Although image retrieval techniques based on textual features can be easily automated, they suffer from the following problems:

1. Lack of uniform textual descriptions for common image attributes, severely limit the applicability of the keyword based systems.
2. When the size of the image database is large, manual annotations of keywords becomes a tedious and expensive process.
3. Because of the widespread synonymy and polysemy in natural language, the precision of keyword based image retrieval system is very low and their recall is inadequate (Furnas et al. 1987)

These facts limit the scale up of keyword-based image retrieval approaches. The content based image retrieval systems have been built to
address these problems. It relies on visual feature based representations such as color, texture and shape which can be extracted from images automatically. The query scenario in such a content based image retrieval system is query by image example (QBE).

The deep gap between visual features and high-level semantic (keyword) concepts is a major obstacle to more effective image retrieval. To improve the retrieval accuracy of the content-based image retrieval systems, research focus has been shifted from designing sophisticated visual feature extraction algorithms to reducing the semantic gap between the visual features and the richness of human semantics. Humans tend to use high-level semantic concepts when querying and browsing multimedia databases; there is thus, a need for systems that extract these semantic concepts and make available annotations for the image data.

There are two different modes of user interactions involved in typical retrieval systems. In one case, the user types in a list of keywords representing the semantic contents of the desired images. In the other case, the user provides a set of example images as the input and the retrieval system will try to retrieve other similar images. In most of the image retrieval systems, these two modes of interaction are mutually exclusive. Combining these two approaches allows them to benefit from each other which can yield a great deal of advantage in terms of both retrieval accuracy and ease of use of the system. Keeping this in mind a new hybrid framework is proposed here which combines the high level semantics and the low level visual features.

6.2 PROPOSED HYBRID IMAGE RETRIEVAL SYSTEM

In the proposed system, to reduce the gap between the low level visual features and high level semantic features, retrieval is performed by combining visual features and semantic information. In the literature, there
are some image retrieval system based on visual features and semantics. In such systems the annotation of the keywords or semantics is done by the supervised machine-learning approaches (Dina Demner-Fushman et al 2009). The drawback is that it needs a lot of training data set for image annotation. In the proposed approach, the image annotation is done by the semantic network, which is based on the user’s relevance feedback. Also the proposed system uses the DICOM information for representing the semantic features for performing the retrieval on medical images. The medical images generated in hospitals are represented by the DICOM format which consists of semantic information along with the images. These semantic features are extracted from the dataset values of the DICOM format. After the semantic information is extracted, the images are extracted from the DICOM format. The system uses a DICOM to jpeg converter to extract the images. From the images the visual features are extracted. In the proposed system the shape features and the texture features are used as visual features. In the proposed hybrid retrieval system the visual shape and textures features are combined with the semantic features to perform the retrieval. Figure 6.1 gives the architecture of the proposed hybrid framework for medical image retrieval system.

6.3 THE PROPOSED ALGORITHM

In this section, the algorithm for the proposed hybrid content based image retrieval framework is described. The retrieval system is integrated with relevance feedback and query expansion in which the semantic-based index and relevance feedback are integrated with those based on visual feature vectors. The framework supports both query by keyword through the semantic network and query by image example through the visual features.
Relevance feedback (Rui et al. 1997, Lee et al. 1998) is an online learning technique used to improve the effectiveness of the image retrieval system. The main idea of relevance feedback is to let the user guide the retrieval system. During the retrieval process, the user interacts with the system and rates the relevance of the retrieved images, according to his/her subjective judgment. With this additional information, the system dynamically learns the user’s intention and gradually presents better results. In the proposed hybrid system, the relevance feedback process refines the initial retrieval results which are obtained by the semantic features. Based on the feedback of the users, the semantic network is updated and semantic feature weightings in similarity measures are found.

Besides relevance feedback, the proposed system supports cross-modality query expansion. From the retrieved images based on keyword search, the user inputs the positive images. The query is expanded by features
of these positive feedback images. In this way, the system is to extend a keyword-based query into feature-based queries to expand the search range. Figure 6.2 gives diagrammatic representation of the various steps involved in the proposed hybrid image retrieval system. The various steps involved in the proposed hybrid medical image retrieval system are given as follows:

Figure 6.2 Steps involved in the Proposed framework
Algorithm

Step 1: Input the Query Image

Step 2: Collect the query keywords from the DICOM header information.

Step 3: Retrieve the images based on the semantic keywords.

Step 4: Compute the feature vectors and the degree of relevance vector for the retrieved images using the query keyword only and input the result into the visual feature component.

Step 5: Collect positive and negative feedbacks from the user based on the initial retrieval results.

Step 6: Update the semantic network using the relevance feedback method.

Step 7: Compute the visual features and virtue probability based on the visual features.

Step 8: Compute the new hybrid ranking function for each image and sort the results.

Step 9: Display the images based on the hybrid ranking function.

Details of each processing step are presented in the subsequent sections.

6.3.1 Semantic Feature Extraction

The DICOM standard was created by the National Electrical Manufacturers Association (NEMA) to aid the distribution and viewing of medical images, such as CT scans, MRIs, and ultrasound. Imaging equipment used in hospitals generates medical images which are in DICOM format (Revet 1997). It is a standard format used to obtain, store and distribute medical images. DICOM comprise standardized textual descriptions of the
study, patient details, body region examined and the modality. A single DICOM file contains both a header as well as all of the image data. The header describes the text information about the scan. The header stores information about the patient's name, the type of scan, image dimensions, etc. The DICOM header size varies depending on how much header information is stored (Guild et al 2002).

DICOM files are composed by an image and tags describing the image. Tags are textual sequences of <attribute, value> pairs. The attribute describes the field of the text. The value gives the text information of the corresponding attribute. The textual information is considered as the semantic information. For all the DICOM files the image and the relevant tags are extracted and stored in the database. The extracted semantic information is stored in the database which is used during the retrieval process. The textual information extracted for the image is used as keyword annotations for that image.

In the keyword based image retrieval the major disadvantage is the manual annotation of keywords. In the proposed system this disadvantage is overcome by automatic annotation of keywords. The keywords extracted from the DICOM format is automatically annotated as keywords for each image. In the proposed method, for each image from the DICOM header the semantic information is extracted and this semantic information is attached as keywords for that image. These keywords are stored in the database as semantic information.

6.3.2 Construction of Semantic Network

In the proposed method, a semantic network (Ye Lu et al 2003) is used to associate the keywords and the images. The semantic network provides the information about the various keywords that can be associated
with an image. In this section, the method used to construct a semantic network from an image database is explained. The semantic network in the proposed system consists of a set of keywords having links to the images in the database. In the semantic feature extraction step, the various keywords associated with an image are found. The link between the keywords and the various images are found using the semantic network. Figure 6.3 gives the pictorial representation of the semantic network.

![Semantic network of the image database](image.png)

**Figure 6.3 Semantic network of the image database**

The links between the keywords and images provides the structure for the network. The weight on each link represents the degree of relevance of the keywords to the associated images’ semantic content. An image can be associated with multiple keywords, each of which with a different degree of relevance. Though, keyword associations may not be available at the beginning when the database is populated, there are several ways to obtain keyword associations. The straightforward method is to simply manually label images. This method may be expensive and time consuming, although already proved to be workable in many systems.

In the proposed semantic network the keywords obtained from the DICOM format are used as initial keyword associations. More keywords can be learned from the user’s feedback. The relevance feedback mechanism is used to construct the keyword associations. Whenever the user feeds back a
set of images being relevant to the current query, input keywords are added into the system and link is created with these images. In addition, since the user tells that these images are relevant, confidently a large weight is assigned on each of the newly created links. Once the semantic network is built, it is updated using a simple voting scheme. The semantic network is updated in such a way that the keywords with a majority of user consensus will emerge as the dominant representation of the semantic content of their associated images.

6.3.3 Semantic Based Relevance Feedback

With the semantic network, semantic based relevance feedback can be performed. The basic idea behind it is a simple voting scheme, to update the weights associated with each link without any user intervention.

The weight updating process is described by the following algorithm:

Algorithm

Step 1) Initialize all weights to 1. That is, every keyword is assigned the same importance.

Step 2) Collect the user query and the positive and negative feedback examples corresponding to the query from the user.

Step 3) For each keyword in the input query, check to see if any of them is not in the keyword database. If so, add them into the database without creating any links.

Step 4) For each positive example, check to see if any query keyword is not linked to it. If so, create a link with weight 1 from each missing keyword to this image. For all other keywords that are already
linked to this image, increment the weight by some predefined values.

Step 5) For each negative example, check to see if any query keyword is linked with it. If so, decrease its weight in some way. In the proposed method the new weight is set to be one fourth of the original weight. If the weight on any link is less than 1, delete that link.

It can be easily seen that as more queries are inputted into the system, the system is able to expand its vocabulary. Also, through this voting process, the keywords that represent the actual semantic content of each image will receive a larger weight. The weight associated with each link of a keyword represents the degree of relevance in which this keyword describes the linked image’s semantic content. For efficient retrieval purpose, another aspect should also be considered. The importance of keywords that have links spreading over a large number of images in the database should be penalized. Therefore, in the proposed method the relevance factor $r_{ij}$ of the $i^{th}$ keyword association to the $j^{th}$ image is computed as follows:

$$r_{ij} = w_{ij} \left( \log_2 \frac{M}{d_i} + 1 \right)$$  \hspace{1cm} (6.1)

where $M$ is the total number of images in the database and $d_i$ is the number of links that the $i^{th}$ keyword has. The semantic relevance feature $\pi_i$ for the image $i$ is computed in equation (6.2).

$$\pi_i = \sum_{j=1}^{N} r_{ij}$$  \hspace{1cm} (6.2)

where $N$ is the number of query keywords linked with the image $i$ and $r_{ij}$ is the relevance factor of $i^{th}$ image with the $j^{th}$ keyword.
To illustrate the construction of semantic network and the semantic network based relevance feedback mechanisms, consider the following five sample images shown in Figure 6.4. In the proposed algorithm, initially the images are automatically annotated with the keywords that are extracted from the DICOM header of these images. For example Table 6.1 shows some of the keywords that are associated with the sample images.

![Sample Images](image)

**Figure 6.4  Sample Images**

**Table 6.1 List of Keywords extracted from the DICOM of the images**

<table>
<thead>
<tr>
<th>Images</th>
<th>Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image1</td>
<td>Lung, CT</td>
</tr>
<tr>
<td>Image2</td>
<td>Lung, Lung cancer, CT</td>
</tr>
<tr>
<td>Image3</td>
<td>Brain, Brain tumor, CT</td>
</tr>
<tr>
<td>Image4</td>
<td>Brain, Brain tumor, CT</td>
</tr>
<tr>
<td>Image5</td>
<td>Lung, Lung cancer, CT</td>
</tr>
</tbody>
</table>

The semantic network is constructed between the images and the keywords. There will be a link if the keyword is associated with the image as shown in Figure 6.5. Initially all the links have weight value as 1 and Table 6.2 gives the weights assigned to the links between the keywords and the images.
To illustrate the weight updating process in the semantic network through the relevance feedback, consider the keyword ‘Lung’ is given as input in the user query by keyword. A set of similar images will be displayed based on the keyword. From the images displayed, the positive and negative images are given by the user. For example the user selects image1 and image2 as positive examples. Image3 and image4 are selected as negative feedback images. The semantic network is updated using the algorithm given in section 6.3.3.

Figure 6.5 Semantic Network

Table 6.2 Weights for the links between the keywords and the images

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Image1</th>
<th>Image2</th>
<th>Image3</th>
<th>Image4</th>
<th>Image5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lung</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brain</td>
<td></td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lung cancer</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Brain tumor</td>
<td></td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
The weights in the updated semantic network are given in Table 6.3. The image1 and image2 are given as positive examples and there is a link with weight 1. So the weight is incremented by one and thus the weight becomes 2. The image5 is not given in the feedback image and hence the weight of that link remains as 1. The updated weights for the links are given in Table 6.3. Similarly for another query keyword ‘CT’, from the retrieved images, the user has selected image1, image2 and image5 as positive examples and image3, image4 as negative examples. The updated weights for the links are given in Table 6.4. Here the weights of the link for the positive images are incremented to 2. At the same time the link between the CT keyword and the image3 is decremented since it is a negative example and the value becomes less than one and hence the link is removed. Similarly the link between the keyword CT and image4 is removed. The updated semantic network is depicted in Figure 6.6. The updated links are represented by dotted lines. The weight associated with each link of a keyword represents the degree of relevance in which this keyword describes the linked image’s semantic content.

Table 6.3 Updated weights for the links for the query keyword ‘lung’

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Image1</th>
<th>Image2</th>
<th>Image3</th>
<th>Image4</th>
<th>Image5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lung</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Brain</td>
<td></td>
<td></td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Lung cancer</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Brain tumor</td>
<td></td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 6.4 Updated weights for the links for the query keyword ‘CT’

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Image1</th>
<th>Image2</th>
<th>Image3</th>
<th>Image4</th>
<th>Image5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lung</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Brain</td>
<td></td>
<td></td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Lung cancer</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Brain tumor</td>
<td></td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 6.6 Updated Semantic Network

6.3.4 Visual Feature Extraction

During the visual feature extraction, the shape and texture features are extracted and the features are combined using the proposed multiple classifier architecture described in chapter 5. The shape and the texture features are used as visual features. In the multiple classifier system, the shape classifier retrieves the similar images according to the shape similarity between the query image and the database image. Texture classifier retrieves the similar images according to the texture features between the two tested images.
In the feature extraction phase, features are extracted from each image in the image database and the features are stored. From each image three shape features and three texture features are extracted. The shape features include Zernike moments, Generic Fourier descriptor and Proposed shape descriptor based on morphological operation. The texture features include Gabor filter descriptor, Homogenous texture descriptor and the Proposed texture descriptor based on post processing of Gabor filter.

The shape classifier finds the shape virtue probabilities which represent the shape distance and the texture classifier finds the texture virtue probability. In the decision combination the overall virtue probability is found by combining the shape and texture virtue probabilities. The images in the database are ranked according to the overall virtue probability.

6.3.5 Integration of Semantic Features and Visual Features

The main objective of the proposed hybrid content based image retrieval system is to integrate the high level semantics and the visual features. With the constructed semantic network, for the given query image, the relevance factor of the query image and the various semantic keywords are found. During the visual feature extraction, for the given query image the similarity of the query image with the database images are found by the virtue probability. To combine the high level semantic relevance features and the visual features, in the proposed system, a hybrid ranking measure function $G_{ij}$ between the query image i and the database image j is defined. This function measures the relevance of any image within the image database in terms of both semantic and visual feature content. The function is defined in equation (6.3).
\[ G_{ij} = \log(1 + \pi_i)D_{ij} + \frac{1}{N_R} \sum_{j \in N_R} \left[ \left( 1 + \frac{I_1}{A_1} \right)D_{ij} \right] - \frac{1}{N_N} \sum_{j \in N_N} \left[ \left( 1 + \frac{I_2}{A_2} \right)D_{ij} \right] \]

where \( \pi_i \) is the semantic relevance feature vector and \( D_{ij} \) is the virtue probability of the visual features between the query image \( i \) and database image \( j \). \( N_R \) and \( N_N \) are the number of positive and negative feedbacks respectively. \( I_1 \) is the number of distinct keywords in common between the image \( j \) and all the positive feedback images and \( I_2 \) is the number of distinct keywords in common between the image \( j \) and all the negative feedback images. \( A_1 \) and \( A_2 \) are the total number of distinct keywords associated with all the positive and negative feedback images respectively.

This hybrid ranking measure is calculated for the given query image and also for each image in the database. This hybrid ranking measure combines the semantic similarity and the visual similarity. The images are ranked according to the hybrid ranking measure and the top most similar images are retrieved.

### 6.4 Experimental Results

The proposed framework for hybrid image retrieval system was implemented in the Medical Image Retrieval system (MedIR) which is the retrieval system developed for retrieving medical images. The system supports two modes of interaction: Query by keyword search and Query by image search. When the user enters a keyword-based query, the MedIR system retrieves the keyword similar images based on the semantic network. Figure 6.7 gives the user interface of a sample query by keyword search.

From the initially retrieved images based on the keywords, the user can select the positive and negative example images. In the MedIR interface
the user can enter the rank number of the images in the positive and negative text boxes. This feedback about the positive and negative images shows that the user is interested in which kind of images. Figure 6.8 shows the sample screenshot of the feedback given by the user.

![Figure 6.7 MedIR System- Query by Keyword](image)

Figure 6.7 MedIR System- Query by Keyword
Figure 6.8 MedIR System – Positive and Negative Feedback Images

When the user selects the query by image button, the new search results will be presented to the user. This new search results was based on the semantic and the visual features. Figure 6.9 shows the sample output of the MedIR system by combining the semantic and the visual information.
The retrieval experiments were conducted on large medical image database which consists of images acquired from CT, MRI and ultrasound scans. The database consists of three different classes of images: Class A, Class B and Class C which contains lung images, liver images and brain images respectively. Experiments were conducted by selecting 20 query images from each class. For each image first the query by keyword search is conducted. From the retrieved results the feedback about the positive and negatives images are given by the user.

To ensure the experiments were not biased, a group of 10 students were selected as users. These users were asked to select a subset of images
having the correct semantic content with respect to the current query image as positive feedbacks and those do not as the negative feedbacks. Once the feedback images were given, the query by image search was conducted which combines both the semantic content and the visual content of the image and the final retrieved results were given as output.

The experimental results of class A lung images are shown in Table 6.5. Figure 6.10(a-c) shows the sample output of a query image of class A images for the proposed multiple classifier system and the proposed hybrid retrieval system. This MedIR system based on the proposed hybrid retrieval method is compared with the MedIR system based on the proposed multiple classifier method. The performance measures used for comparisons are

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

From the Table 6.5, it was found that the proposed hybrid retrieval system outperforms the proposed multiple classifier system in the MedIR system. The proposed hybrid retrieval system has the mean average precision of 85% where as the proposed multiple classifier system has MAP as 80%. The precision for retrieving top 10 images (P@10) is nearly 99% in the proposed hybrid retrieval system. This high retrieval performance is due to the fact that the gap between the high level semantics and low level visual features have been reduced in the proposed hybrid system. Figure 6.11 gives the comparison chart of the various performance measures. Figure 6.12 gives the precision-recall graph in which the precision is recorded on the different levels of recall. From this graph also it was found that the proposed hybrid retrieval system accuracy is substantially improved than the proposed multiple classifier system.
Figure 6.10(a) Query Image from Class A

Figure 6.10(b) Results of MedIR system based on Multiple classifier for class A images

Figure 6.10(c) Results of MedIR system based on Hybrid retrieval for class A images
Table 6.5 Precision and Recall Measures for class A images

<table>
<thead>
<tr>
<th></th>
<th>MAP (%)</th>
<th>R-Prec (%)</th>
<th>P@10 (%)</th>
<th>P@20 (%)</th>
<th>R@10 (%)</th>
<th>R@20 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Multiple Classifier System</td>
<td>80.24</td>
<td>89.56</td>
<td>97.66</td>
<td>93.14</td>
<td>87.87</td>
<td>84.37</td>
</tr>
<tr>
<td>Proposed Hybrid Retrieval System</td>
<td>85.39</td>
<td>90.15</td>
<td>98.78</td>
<td>95.17</td>
<td>89.56</td>
<td>86.13</td>
</tr>
</tbody>
</table>

Another experiment was conducted on the heterogeneous database. This database consists of all type of images which belongs to various categories like lung, liver and brain. Fifty query images have been selected from these various categories and retrieval was conducted on the MedIR system with each query image. The various performance measures were computed based on the retrievals. The results are tabulated in the Table 6.6. Figure 6.13(a-c) shows the sample output of a brain query image using the proposed multiple classifier system and the proposed hybrid retrieval system. From the table, again it was found that the MedIR system based on the proposed hybrid retrieval system outperforms the proposed multiple classifier retrieval system. Also it was found that the Mean average precision is 83% for the hybrid system while it is 78% in the multiple classifier system. The precision is high and is 97% for the proposed hybrid system. From the experiments it was found clearly that combining the keyword features and the visual features yields significantly good retrieval performance in the MedIR system. Figure 6.14 shows the comparison chart of the various performance measures and Figure 6.15 gives the precision-recall graph. From this graph also it was found that the proposed hybrid retrieval system accuracy is high compared to that of the proposed multiple classifier system.
Figure 6.11  The performance comparison of the proposed multiple classifier with the hybrid retrieval system for class A images

Figure 6.12  Precision-Recall graph of the proposed multiple classifier and the hybrid retrieval system for class A images.
Table 6.6 Precision and Recall Measures for Heterogeneous images

<table>
<thead>
<tr>
<th></th>
<th>MAP (%)</th>
<th>R-Prec (%)</th>
<th>P@10 (%)</th>
<th>P@20 (%)</th>
<th>R@10 (%)</th>
<th>R@20 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Multiple Classifier System</td>
<td>78.13</td>
<td>85.11</td>
<td>94.16</td>
<td>92.17</td>
<td>84.12</td>
<td>82.37</td>
</tr>
<tr>
<td>Proposed Hybrid Retrieval System</td>
<td>83.13</td>
<td>89.12</td>
<td>97.23</td>
<td>95.79</td>
<td>88.16</td>
<td>86.89</td>
</tr>
</tbody>
</table>

Figure 6.13(a) Query Image from Heterogeneous Database

Figure 6.13(b) Results of MedIR system based on Multiple classifier retrieval for Heterogeneous Database
Figure 6.13(c) Results of MedIR system based on Hybrid retrieval for Heterogeneous Database

The performance of the hybrid retrieval system is much dependent on how the semantic network is constructed. The semantic network learns the relationship between keywords and images through the user queries and feedbacks. In order to make the voting procedure to be more effective, a significant amount of user queries and feedbacks are necessary. To avoid starting from scratch which slows down the learning rate of the system significantly, the MedIR system is initialized with keywords which are extracted from the DICOM information of the images. Ten users were asked to continuously use the MedIR system. From the experiments it was found that each query on average contains around five keywords initially. After the MedIR system was used several times, the system has learnt nearly all the commonly searched keywords and was able to produce accurate search results.
Figure 6.14  Performance comparison of the proposed multiple classifier with the hybrid retrieval system for Heterogeneous images.

Figure 6.15  Precision-Recall graph of the proposed multiple classifier and the hybrid retrieval system for Heterogeneous images.
6.5 CONCLUSION

In this chapter a new framework for the MedIR system is proposed. This system is based on the hybrid combination of the high level semantics and visual features. For extracting the high level semantics the DICOM information of the medical images are used. To the initially found keywords, the MedIR system learns additional keywords through the semantic network which is constructed from the user feedbacks. For extracting the visual features the multiple classifier system is used which combines the shape and texture features. In the proposed MedIR hybrid system semantic relevance and the visual similarity measures are combined using the new ranking measure. From the experimental results it was found that for a good retrieval system integration of the semantics and visual features is essential which yields a very high performance with MAP as 85.39% and has 5% of performance improvement over the proposed multiple classifier system.