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Processing Medical Images Based on Text and Content

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Abstract

Text-based retrieval and content-based retrieval are two major approaches to image retrieval. The challenges to each of these two approaches have led researchers to use combined approaches and semi-automatic retrievals with user involvement in the recovery cycle, especially in medical issues. Accordingly, an image retrieval system is introduced in this article, which allows the user to use two types of query based on the keyword and sample image. The proposed system, after retrieving the initial results, makes semantically interactive image retrieval in a semi-automated manner using feedback received from the user and high-level semantic labels attributed to the images. This system, using a hierarchy of STs and doing some kind of learning from user feedback, is able to respond to various requests in the area of image retrieval. According to the tests, the proposed system has an acceptable accuracy.

Keywords: ST, image retrieval, learning, lung

INTRODUCTION

Image retrieval is an important research area that has attracted the attention of many researchers in recent years [1]. Two basic approaches to image retrieval are presented by researchers: text-based retrieval and content-based retrieval [3] [2]. In text-based retrieval, the retrieval process utilizes keywords and assigns them to images, and according to it, the query template is received from the user as words. Accordingly, the criterion for recognizing the similarity between images is the adaptation of the keywords attributed to them [4]. This approach faces two fundamental challenges [6] [3]:

- The time consuming and costly process of manually assigning keywords to images
- Personalization of keywords reflecting images by user.

Content-based retrieval is presented in response to the inadequacies in the above approach [4] [1]. In content-based retrieval, the retrieval process is performed based on low-level visual features such as color, texture and shape. The most important advantage of this method compared to previous one is the ability to automatically extract features' vector [4] [5]. This speeds up annotation of images dramatically. However, content-based retrieval is facing a serious challenge. The challenge is the existence of a semantic gap between the visual features of the lower level and the high level semantics in the images [5] [3]. The existence of this challenge has led the researchers to use combined approaches and semi-automatic retrieval with user involvement in the retrieval cycle [8] [7] [6]. Accordingly, the semi-automatic retrieval with the user's participation in the retrieval cycle and the use of a combination of keywords and visual features of the lower level to describe the images is considered to be the main topic of this research. The user's participation in the retrieval cycle, in the form of providing relevance feedback, leads to an increase in the accuracy and efficiency of the retrieval process [12] [11] [10].

In this paper, an image retrieval system is introduced that is semi-automatic, and semantically retrieves lung images with the help of users' relevance feedback and high-level semantic labels attributed to the images.

PROPOSED MODEL

The main components of the proposed system are ST, search engine and conceptual unit. The relationships in the article can be considered as generalized forms of the Rocchio formula [14] [16].

If the query is based on the keyword, the semantic search unit and if the query is based on the sample image, the content search unit will be launched by the search engine. After this stage, the retrieved images are displayed to the user and the user provides feedbacks for retrieved images based on close proximity to the requested semantic through the relevance feedback unit. The conceptual unit, first, splits the factors influencing the creation of a new query based on the type of primary inquiry, and provides to the query modification unit. For query based on the sample image, a set of positive and negative samples is feedback, and for querying by keyword, a set of positive and negative samples plus the initial query is used to create a new query. The query modification unit computes the ST images of the database with a new modified query according to the above mentioned factors and the system's information network, and thus retrieves new images that are more similar to the user-defined semantics. In fact, the query modification operation is dedicated to performing a kind of learning from user feedback to improve the results of the current retrieval meeting, as a valuation of database images based on ST's to the factors influencing the new query obtained from the previous relevance retrieval phase.

Semantic Tree (ST)

The ST used in the proposed method can be considered as a tree structure. The tree nodes are organized as a set of keywords with the same semantic and connections between nodes, based on the proper hierarchy of generalization-specialization relationships, so that the general concepts are at the highest level of the hierarchy and more specific concepts are placed at lower levels. In this ST, each node consists of several synonym words and each of the words in a node is assigned a membership grade or a certain weight to belong to that group. Figure (1) shows part of the ST used in this study.

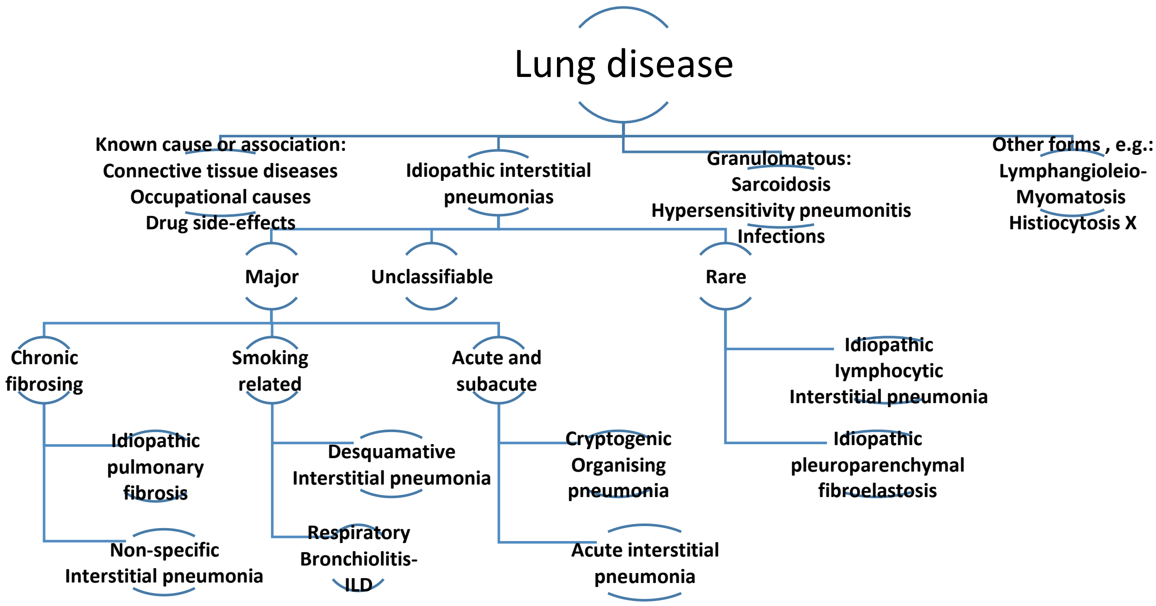

Figure 1: A hierarchical ST for lung diseases based on keywords

In the proposed method, each image is not assigned to as any of the keywords in the ST, but each image is associated with a specific weight with a node of the network, and, as noted, each node itself contains a set of synonymous words. Accordingly, in the proposed system, two weight sets are defined and used in this section:

• Weight values indicating the degree of membership and the validity of the synonymous keywords within each ST node.

• Weight values representing the relationship of each ST node with images inside the database, which indicates the power of describing a synonym set in the expression of semantic content of images.

The ST extension is performed in a semi-automated manner with the help of the user, which is used when the new word is entered, or if the keyword used in querying the ST structure does not exist, the user is requested to provide two keywords, one of which will be used as a generalization of the new word, and the other will be synonymous with it. If there is a synonym of the word in ST, the new word will be added as a new synonym at the corresponding node level, and if there is only a generalization of it, the word will be generalized as a new attribute of the semantic node and will be placed as the child in ST and all the relationships of the generalization node will be extended to the specialization node.

Semantic similarity (Q_St)

To retrieve related images, first, keywords are searched for in the ST, and after the nodes are acquired, the images associated with these nodes are ranked based on the weight.

Weight (I) = node (k) .value (i) * node (k) .image (j)

According to weight, to obtain the weight of each database image at the resemblance to the query, two weights of the node (k) .Image (j) node (k) .value (i) are used. In other words, the degree of membership of the keyword i in the corresponding node k and the relevance weight of the database image j with the semantic node k have a role in determining the similarity between image I and the keyword k. After calculating the value of all database images, all images are arranged in order of obtained values from top to bottom to retrieve the most valuable images according to the user-expressed numbers. Due to the use of an “Or” relationship, no constraint except for obtaining high value among images is imposed for retrieval. The final value of each image is calculated based on Rank.

After calculating the final value of each image based on the value relationship of the image, the images that are of greater value represent a greater amount of user-defined semantic. In this way, images are ranked based on their values in order to be displayed to the user. Based on this, images that rank higher in the ranking, in general, contain a higher percentage of the semantic requested by the user.

Rank (j) = node (k) .rank (sum) / n

Content similarity

In this paper, two graphing and image processing methods are used to search content.

Graphing

The first step in drawing the image graph is done in two steps. The first step is to specify the boundary points of the graph, which uses points on the image edges. The second step is to find the edges between the points for which the least cost-based or MCP-based algorithms are used.

Boundary points

The images are marked in both (healthy and massive lungs) key points. For this purpose, the points on the edges of Fig. 2 are used. So that all the boundary points are first defined, then the points in the key areas are extracted from them. Of course, this phase of work is not done automatically, it is rather done by an expert.

Edges between points

At this stage, the points marked in the previous step are connected. To do this, different types of "MCP" based algorithms can be used. The algorithm used here is described below.

MCP (c)

L.insert (All points)

While (L)

M □ L

M.distance (all_remaining_points)

L.nearest_point

Exit (0)

Finally, the points are considered as vertices of the graph, and the distance between the two points as the weight of the edge between them. The final shape after applying the algorithm is shown in Fig. 2.

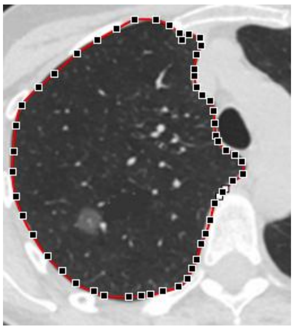

Figure 2: boundary points

Determination of the area of the mass

This part of the work consists of two steps. In the first stage, the boundary of the mass is determined by dots, and in the second stage the area of the specified region is calculated. These two steps are detailed below.

Mass Boundary

In the first stage, the center of the shape is determined and its distance is calculated to each vertex of the graph. The distances obtained are arranged in an array so that the highest point is considered as the starting point and its distance from the center of the shape is placed in the first house of the array. Then it is moved clockwise and the rest of the array values are obtained.

At the end of this step, two arrays are created in the form of two a, and b arrays, whose entries are the distance between the vertices of the graph and the center of both images (a healthy and massive lung). In the second step, the two arrays created in the first stage are compared, and if the difference between the two entries is greater than a threshold value, it is an indication of the presence of an abnormal mass in the lung. This threshold value is obtained by trial and error, which in our experiments is ultimately equal to 5.

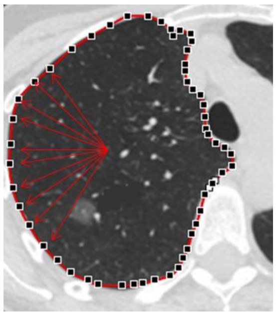

Figure 3: Distance between graph vertices and center of the mage

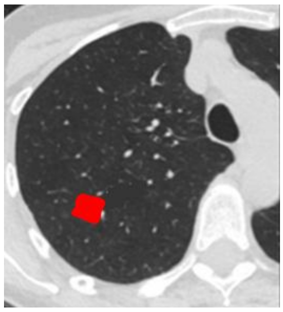

Figure 4: Determining the margin of the mass

Mass area

Triangulation has been used for this part of the work. The calculations are made on both the healthy and massive images, and therefore the area of both is calculated, and then the area of the mass is obtained from the difference between the two areas.

Image processing

Previous steps were performed using the graphing method and the area of the mass was computed. To determine exactly how accurately and precisely the work is done, the same processes is performed in the usual way in the processing images. In the end, the result of both are compared and the accuracy of the method is calculated.

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Mass separation

For this, the separation method based on the use of colors is employed. So the color difference between the two healthy and massive image determines the mass. As shown in Figure 5, the dotted area of Figure 4 is completely separated from other parts by using the color separation method.

Figure 5: Separating the mass using the color separation method

Mass area

Given that the middle colors have been adjusted, the values of the entries of array in Figure 5 are all white or black points, and the middle and gray points are eliminated. As a result, counting the number of pixels in the white areas, the mass area is obtained.

Semantic similarity based on Keywords :

The methodology is that in the image database, images are ranked according to image locating based on current queries and relevance feedback in the form of related and unrelated labels provided by the user. According to this relationship, first, the highest ST is obtained between each image node associated with the semantic nodes of the image j, and then the average of the similarities is calculated for all of the related image nodes. Finally, the mean of semantic similarities between the total images of the related set for the first part of the relationship is obtained, and so for the unrelated set, this average value is calculated, and finally these two obtained values are summed up with the similarity value, which represents the similarity of the image j with user's query. In other words, the location relation addresses the calculation of the ST of the image j with the whole related and unrelated set, as well as all the words in the initial query in the mode of using the And operator.

$\text{Weight (I)} = \text{sum}_k (\text{sum}_j (\max (NA_{Ii,\ Kj} / \text{Depth}_{Max})(\text{Value}_{Ii} / \text{sum}(\text{Value}_{Ii}))\ \text{Value}_{Kj} / \text{sum}(\text{Value}_{Kj}))\ /m)/k - \text{Sum}_L (\text{sum}_j (\max (NA_{Ii,\ Kj} / \text{Depth}_{Max})(\text{Value}_{Ii} / \text{sum}(\text{Value}_{Ii}))\ \text{Value}_{Lj} / \text{sum}(\text{Value}_{Lj}))\ /m)/L + (i, Q)_{Similarity}$

Similarity weight

Similarly, similarity weight relationship shows the way in which the value of each database image is calculated in terms of their similarity to the initial query of the user.

The relation of the similarity weight shows the initial query filtering method and the calculation of the new value of each database image based on the above three components in the state of using the Or operator for combining the keywords.

According to this relationship, first, the highest ST of each node j from the image k in the related set and the semantic nodes attributed to the image j of the database is calculated, and then the maximum value among the similarities obtained for all the semantic nodes of the image k with the semantic of image J is calculated.

$\textit{Similarity} = \textit{Score} + \textit{Max}\ (NA_{Ii,\ Qi} / \textit{Max Depth})\ (\textit{Value}_{Ii} / \textit{Sum Value}_{I})\ (Q_i / \textit{Sum}_{Qi}))/\ \textit{Num}$

Finally, the most similarity between the entire image of the related set and the image j is obtained for the first part of the relationship, and so on in the second part of the relationship for the unrelated set. In other words, the relationship is based on calculating the value of image j based on ST on one of the images of related and unrelated sets through the similarity to even one of the concepts implied in images, as well as the ST to even one of the query keywords, which can be accountable when using the Or operator.

$(i, Q)_{Similarity} = \text{Max j (Max I} (NA_{Ii,\ Lj} / \text{Depth}_{Max})\ (\text{Value}_{Ii} / \text{sum}(\text{Value}_{Ii})\ (Q_i / \textit{Sum}_{Qi})$

In this case, for the Similarity section, the value of each of the database images can be calculated in terms of their similarity to the initial query of the user according to the re-weighting relationship.

$\text{Weight(I(} = \text{Max}_k (\text{Max}_j (\max_i (NA_{Ii,\ Kj} / \text{Depth}_{Max})(\text{Value}_{Ii} / \text{sum}(\text{Value}_{Ii}))\ \text{Value}_{Kj} / \text{sum}(\text{Value}_{Kj}))) - \text{Max}_L (\text{Max}_j (\max_i (NA_{Ii,\ Lj} / \text{Depth}_{Max})(\text{Value}_{Ii} / \text{sum}(\text{Value}_{Ii}))\ \text{Value}_{Lj} / \text{sum}(\text{Value}_{Lj}))) + (i, Q)_{Similarity}$

Symantec similarity based on user image :

In this case, the query by a sample image is replaced with a new query based on semantic search. In this section, there are two factors in determining the new value of each database image and sorting these images:

A) ST amount of each image to the related set.

B) ST amount of each image to the unrelated set.

Valuing input image

According to two factors as well as the operation of valuing images based on ST as the smallest common ancestor of semantic sets of two images, the valuing relationship of input image shows operation of the conceptual unit in calculating the value of each database image in the state of query by a sample image. According to the relationship, first, the maximum value for the similarity between each semantic node of the related image with the semantic nodes of the j image of the database is obtained, and then the mean of these values is calculated for all of the related image semantics nodes. Finally, the most similarity between the related images and the image j is calculated as the first part of the relationship. For the second part, ST of the image with unrelated set is calculated. In fact, according to this relationship, the value of each database image is calculated based on the conceptual similarity to at least one of the images of related and unrelated sets, of course, by examining all the semantics in the corresponding image.

$$\text{Weight (I(} = \text{Max}_k \text{ (Sum}_j \text{ (max}_i \text{ (NA}_{Ii,\ Kj}\ /\text{Depth}_{Max})(\text{Value}_{Ii}/\ \text{sum(Value}_{Ii})) \text{ Value}_{Kj}/\ \text{sum(Value}_{Kj})/\text{i})) - \text{Max}_L \text{ (Sum}_j \text{ (max}_i \text{ (NA}_{Ii,\ Lj}\ /\text{Depth}_{Max})(\text{Value}_{Ii}/\ \text{sum(Value}_{Ii})) \text{ Value}_{Lj}/\ \text{sum(Value}_{Lj})/\text{i})) + \text{(i, Q)}_{Similarity}$$

IMPLEMENTATION AND TESTING

The lung image database consortium (LIDC) has a database containing CT images of the lung and information on the nodules shown in these images, including the physician's notes about the specific features of nodules: calcification, internal structure, subtlety, lobulation, margins, Sphericity coefficient, malignancy, texture, and spiculation.

All of these attributes are ranked in integer numbers from 1 to 5 (except for calcification, which is ranked on a scale of 1 to 6). Examining histogram charts for these features (Table 1) shows that several of them (calcification, internal structure, subtlety, and texture) are mainly in one or two main values. Therefore, when it is tried to find correlations between image attributes and physician rankings, these special rankings will not help much.

The data was split into 90 cases, each containing approximately 100 to 400 DICOM images (each 514KB) and an XML data file containing physician's notes. The XML data was extracted and centroid calculations were used to determine the images with the same nodule.

Subsequently, the nodule images were extracted from full-size CT scans of the lung. In this way, DICOM files were extracted from the nodules with a set of XML files with all feature data, physician notes, and metadata for each nodule image.

Table 1: histogram of images

Attribute	**Calcification**	**Internal Structure**	**Lobulation**	**Malignancy**	**Margin**	**Sphericity**	**Spiculation**	**Subtlety**	**Texture**
1	13	0	250	100	74	85	320	0	0
1.5	0	1000	150	150	200	0	250	100	0
2	0	0	200	350	195	320	120	110	100
2.5	0	0	0	0	0	0	0	115	0
3	8	0	150	200	200	360	110	0	0
3.5	0	0	200	250	480	0	125	150	400
4	100	80	250	275	500	260	154	595	746

All nodule images that were smaller than 5 × 5 pixels (about 3 x 3 mm) were removed because images that are so small cannot provide meaningful textual data (this minimum size was also used by Kim et al.).

After removing these images and images that had several lines, the final database contained 2,424 images of 141 unique nodules. The average image size is 15x15 in pixels and the actual image size is approximately 10x10mm. The smallest nodules are approximately 3 × 3 mm, while the largest of these are more than 70 × 70 mm. Eighty-eight percent of the images are below 20 × 20 mm.

The system user interface was written with C # using the .NET framework and served as a simple viewer to examine an image at the start, and then expanded to the comparison of two side-by-side images. After that, calculating the distance in the feature vector was added as a way to check the similarity between the images.

Next step: A complete CBIR program that allows the user to select a query image and a threshold. Then, the program analyzes all of these images, applies similarity criteria, and determines the closest images to the query image. All images that have a distance greater than the threshold value are put away and then the remaining images from the nearest image to the query image to the farthest image from the query image are ranked. This interface also allows the user to select a textual description that includes a feature vector.

Figure 6 shows that the number of retrieved items is changed, Gabor and Markov are almost identical, and when the item is retrieved, the best average accuracy is about 88%. Figure 6 also shows that when the number of retrieved items is less than five, Markov will have a similar function to Gabor. However, if five or ten images are retrieved, Gabor shows a significant improvement over Markov. When retrieving an item, the co-occurrence matrices with an average accuracy of only 29% are noticeably worse than Gabor and Markov. One possible explanation is that the co-occurrence model encodes the textual information globally, while Gabor and Markov are calculated at the pixel level.

Figure (7) shows the proposed retrieval system in responding to the query based on the keyword "Asthma". In this regard, Figure (7) shows the proposed system in query mode based on the sample image. In this case, images are retrieved based on a content search in the form of visual similarity to the query image.

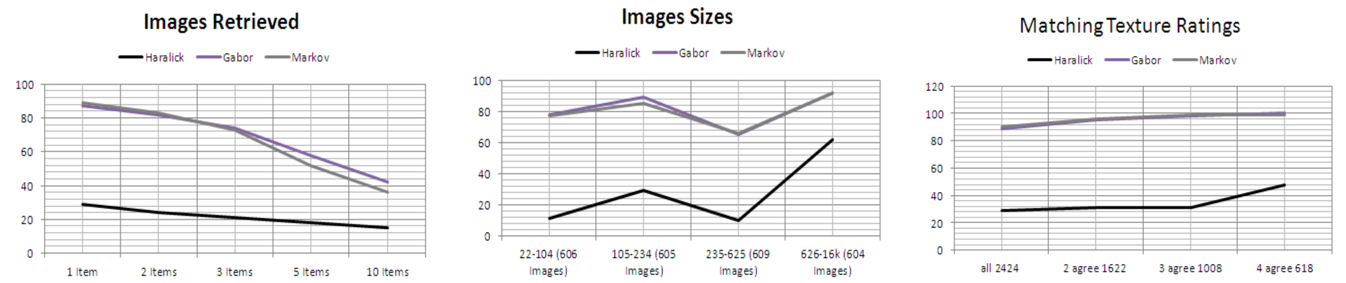


Figure 6: investigating of retrieval algorithms

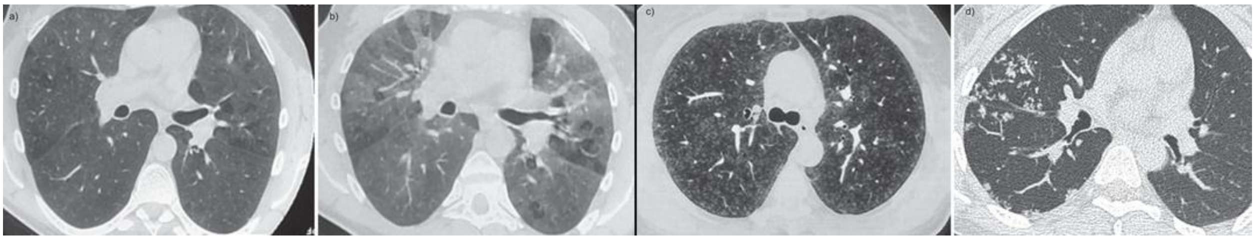


Figure 7: Proposed image retrieval system in the mode of query based on keyword

The function of the proposed system in a mode that begins with a keyword query and continues with a completely semantic mode based on the semantics associated with the images being sent through the conceptual unit is compared with the other mode of the system that begins by an image query and then is transferred by the conceptual unit of the visual domain and the visual content of the low level to the domain of semantic through the user feedback

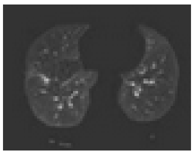
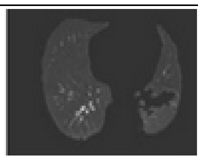
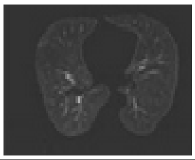
In order to compare the two methods of classification and color change, the accuracy of the work is measured. For this purpose, the calculated areas are compared by two methods, the result of which is shown in Table 2 and 3.

This difference is due to the low number of points considered as vertices of the graph in the first method. By increasing the number of points and closer the distance between the points selected, the calculated area becomes more accurate. Of course, as shown in Fig. 11, the larger the mass is, the greater its precision is. This algorithm works against low noise, does not require much memory, is so fast that it can be used in health care centers and has a good accuracy above 90%. The corresponding ROC chart is also shown in Figure 10. As it is clear, the graph of the first method is more uniform, indicating that it is better and the proposed method is more normal.

Table 2: ROC for both methods

First Method	Second Method
0	14400
0	16700
0	0
0	41000

Table 3: Results obtained from the proposed method for 4 sample images

Processed Image	Raw Image	Value
		0.11
		0.9
		0.8
		0.7

In order to complete the process of comparing the retrieval of images based on the semantic and visual content of the images, the function of the system is evaluated and compared in a different manner, all done based on content search. In this case, after the initial retrieval of images based on the low level feature of the color, the next interactive steps continue without regard to the semantics contained in the feedback images, based on the visual content of the images, as with other content-based systems. According to the obtained results, the precision-recall diagram of the proposed system can be displayed in several stages of semantic retrieval for the three modes mentioned in Table 4. As can be seen, in the mode of query based on keyword, the proposed method has an acceptable performance in image retrieval, and in the mode of query based on the sample image, the retrieval precision is located at the bottom of the provided precision-recall graph in the first step due to the low accuracy of content search for semantic retrieval of images. For the next steps, when images are retrieved based on semantic search, the accuracy of the results has increased, while for the other part of the graph, which is somehow the function of the retrieval systems based on content and is dedicated to image query and content-based processing for next steps of relevance retrieval, precision-recall diagram indicates a lack of reliability in content-based query for semantic image retrieval operation.

In other words, in the mode of query based on the keyword, because of the direct semantic referral to the query in the form of words, the system performance is of greater precision in all stages of retrieval in comparison with the query based on the sample image. Also, in the mode of query by the sample image, repeating the interaction steps based on the semantics in the feedback images will provide better results than content search using the visual features of the feedback images.

Table 4: The precision-recall diagram of the proposed system

	Keyword	Image	Keyword + Image
0.1	1	0.29	0.32
0.2	0.9	0.71	0.31
0.3	0.83	0.61	0.26
0.4	0.81	0.52	0.25
0.5	0.69	0.51	0.23
0.6	0.68	0.49	0.24
0.7	0.39	0.48	0.18
0.8	0.35	0.48	0.17
0.9	0.37	0.21	0.16
1	0.22	0.18	0.15

Table 5 and 6, respectively, show the precision-recall graphs for the number of retrieved images for the two query modes by the keyword and sample image. As can be seen, the performance of the system in relation to the query by keyword is superior to the query by the sample image and is of higher efficiency and accuracy. According to these diagrams, the precision and recall of the proposed system with respect to the number of images retrieved during an interactive retrieval meeting is acceptable for query based on the keyword. Also for query based on the sample image, where the user first presents the image as a query request, thus reducing the accuracy of the semantic retrieval results due to the nature of low-level visual features that do not have any semantic about the image, the precision-recall graphs of the proposed system are lower than the results for the query mode based on the keyword.

Table 5: Precision diagram of the proposed system

	Keyword	Image	Keyword + Image
0.1	1	0.28	0.32
0.2	0.82	0.68	0.33
0.3	0.61	0.59	0.27
0.4	0.50	0.51	0.25
0.5	0.4	0.47	0.24
0.6	0.3	0.46	0.25
0.7	0.210.20	0.5	0.18
0.8	0.2	0.4	0.19
0.9	0.18	0.32	0.14
1	0.17	0.18	0.13

Table 6: Recall diagram of the proposed system

	Keyword	Image	Keyword + Image
0.1	0.3	0.2	0.05
0.2	0.36	0.28	0.03
0.3	0.4	0.32	0.1
0.4	0.5	0.38	0.21
0.5	0.52	0.51	0.32
0.6	0.56	0.56	0.4
0.7	0.6	0.67	0.44
0.8	0.7	0.71	0.45
0.9	0.81	0.72	0.51
1	0.89	0.88	0.59

It should be noted that according to the tests, the system's performance in providing a semi-automatic solution for semantic retrieval of images using ST includes high-level concepts both in terms of semantics and in the field of image transfer to semantics is of acceptable efficiency.

CONCLUSION

The proposed system uses a hierarchical ST in synonymous keywords collections, including high-level concepts such as facial expressions and human personality dimensions. During each learning step, the ST uses images for a more meaningful retrieval in both the “And”, and “Or” modes for query based on keyword, according to the query and the images presented as "related" and "unrelated". In addition, the proposed system replaces the content search of images by ST-based semantic search with feedback images, based on the sample image, after retrieving the initial results and for the subsequent relevance retrieval. In fact, the system provided, in a high-level and conceptual way, in both query modes based on the keyword and sample image, meets the semantic needs of users in the context in which learning is taken without regard for the low level visual characteristics and only based on the semantic content of the images. In this way, it has the ability to move the search from the content to semantic format. The implementation results show the acceptable accuracy for this system, so that under the conceptual unit operation, the results obtained in the mode of query based on the keyword and semantic search are much more semantic-oriented than the query mode based on the sample image and content search.

In this article, given the necessity of early and timely diagnosis of lung cancer, a novel method based on the processing of CT images is presented. This is done in three steps. In the first step, using the graphing method, the location of the mass is determined and its area is calculated. This phase of work is based on expert knowledge and non-automatic, but in the future, using neural networks or genetic algorithms, this step can also be done automatically. In the second step, using the image processing method, the location of the masses is determined and the masses are completely separated from the other parts of the image, and then the area of the segmented section is computed. In the final stage, the results of the two methods are compared together and the accuracy of the work is obtained.

The proposed method is very effective in reducing the human error in detecting the masses in the images. Several samples received by the presented model have been analyzed, resulting in a significant improvement in their results and speed and accuracy. In addition, the results are compared with the area detected by the radiologist and specialist. In this way, the efficiency of the software system detects masses in CT images with highly satisfactory precision (more than 90%). In the future, authors will try to reduce the amount of human intervention and error and increase precision by automatically detecting the points in the graph and creating a better graph.

SYMBOLS USED

n	The number of keywords in the user's query
K	Number of related set images
L	Number of non-related set images
I_i	Semantic i attributed to image j of database
K_j	Semantic j attributed to the k^{th} image of the related set.
L_j	Semantic j attributed to the L^{th} image of the unrelated set.
Q_j	Semantic j containing one of the query keywords
$Rank(I)$	Image j value (Coverage of all keywords by image j)
Max.Depth	Maximum depth in the hierarchy of semantics
NA	Depth of the closest common ancestor of i and j semantic sets in the hierarchy of semantics
node(k).value(i)	Value of image j
node(k).value(i)	Weight of the i keyword in the semantic node k
node(k).Image(j)	Relevance weight of image j with the semantic node k
node(k).rank(sum)	Value of image j for the K semantic node including a query word

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