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Augment LTRP For Medical Image Retrieval (ALMIR) By Means of Ontology Based Annotation

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Abstract

In this work, an innovative image indexing and retrieval algorithm using Local Tetra Pattern (LTrP) and Texture features for content-based medical image retrieval (CBMIR) has been proposed. The main objective of the proposed work is to retrieve the accurate and related medical images from the stored database that resembles the query image. Here new technique is employed for reducing the semantic gap utilizing the ontology based annotation with semantic features as well as it reduces the sensory gap by extracting the entropy mass with the low level features. For texture classification and image retrieval co-occurrence matrix is calculated which is utilized to find texture features like Energy, Entropy, Variance and Correlation. Key value which acts as the index for enhancing image retrieval is got by the combination of all these features. The experiment results show that the proposed method has 82% recall at 45% precision and 70% recall at 35% precision compared to LTrP which has 60% recall at 45% precision and 40% recall at 35% precision and LBP which has 10% recall at 45% precision and 25% recall at 35% precision.

Keywords: CBMIR, Correlation, LTrP, ALMIR, COM

Introduction

Medical images are a significant information sources for clinical decision-making. Currently available information retrieval and decision making systems rely primarily on the clinical information from the medical images[1]. In general, three types of approaches for medical image retrieval are text-based, content-based and semantic based [2]. The Medical image representation is a central component of image classification or content-based image retrieval (CBIR). In this context, the design of visual features of medical image acts as major role in image classification [3].

The effectiveness of a CBIR approach greatly depends on feature extraction, which is its prominent step. The CBIR employs visual content of an image such as color, texture, shape and faces etc., to index the image database. Hence these features can be further classified as general (texture, color and shape) and domain specific (fingerprints, human faces) features [4][5][6].CBIR is performed in the feature space to find similar images to the example submitted by user [7]. The goal of content-based image retrieval (CBIR) is to return images similar to a user provided image query, most of the CBIR searches are employed in the medical field for medical image retrieval [8].

Medical imaging is fundamental to healthcare, and its widespread use has resulted in the creation of image databases for medical image segmentation and image retrieval. These image collections offer the opportunity for evidence-based clinical diagnosis, teaching, and medical research; for these applications, there is a requirement for appropriate methods to search the collections for medical images from the databases that have characteristics similar to user request. [9]CBIR has been proposed by the medical community for inclusion into picture archiving and communication systems (PACS) to provide an efficient search function to access the desired images. [10]

Related Works

SohailSarwara*et.al*[11] proposed an ontology based image retrieval framework from a corpus of natural scene images by imparting human cognition in the retrieval process. The proposed architecture addresses the issues of *keyword based image retrieval* and *content-based image retrieval* through the use of qualitative spatial representations over semantic image annotations. Domain ontology has been developed to model qualitative semantic image descriptions and retrieval, thereafter can be accomplished either using a natural language description of an image containing semantic concepts and spatial relations, or in a query by example fashion.

Yu-Gang Jiang *et.al*[12] proposed a novel and highly efficient approach that was semantic diffusion which utilizes semantic context for large-scale image and video annotation. Starting from the initial annotation of a large number of semantic concepts (categories), obtained by machine learning or manual tagging, the proposed approach refines the results using a graph diffusion technique. Different from the existing graph-based learning methods that model relations among data samples, the semantic graph captures context by treating the concepts as nodes and the concept affinities as the weights of edges. In particular, these approaches were capable of simultaneously improving annotation accuracy and adapting the concept affinities to new test data.

K.O. Cheng *et.al*in[13]addresses some fast feature extraction algorithms for joint retrieval of images compressed in JPEG and JPEG2000 formats. In order to avoid full decoding, three fast algorithms that convert block-based discrete cosine transform (BDCT) into wavelet transform are developed, so that wavelet-based features can be extracted from JPEG images as in JPEG2000 images. The first algorithm exploits the similarity between the BDCT and the wavelet packet transform. For the second and third algorithms, the first algorithm or an existing algorithm known as multi resolution reordering was first applied to obtain band pass sub bands at fine scales and the low pass sub band. Then for the sub bands at the coarse scale, a new filter bank structure was developed to reduce the mismatch in low frequency features.

Azizi Abdullah *et.al*[14] proposed fixed partitioning and salient point's schemes for dividing an image into patches, in combination with low-level MPEG-7 visual descriptor store present the patches with particular patterns. A clustering technique was applied to construct a compact representation by grouping similar patterns into a cluster code book. The code book will then be used to encode the patterns into visual keywords. In order to obtain high-level information about therelational context of an image, a correlogram was constructed from the spatial relations between visual keyword indices in animage. For classifying image,a k-nearest neighbors (k-NN) and a support vector machine (SVM) algorithms are used and compared.

Proposed Work

The primary aim of Content Based Medical Image Retrieval System is efficient retrieval of medical images from the image database. The preprocessing and feature extraction of images should be done for the accurate retrieval of medical images for the requested input medical image. The retrieval of salient medical images will be done using streamlined semantic CBMIR by means of ontology based annotation. This system introduces new technique for reducing the semantic gap utilizing the ontology based annotation with semantic features as well as it reduces the sensory gap by extracting the lemma features and entropy mass with the low level feature. The system integrates two phases namely learning phase and retrieval phase. The learning phase consists of the steps namely preprocessing, feature extraction and semantic gap reduction. The feature extraction of the preprocessed images are carried out using LTrP method and then ontology based annotation with semantic method is used to find the indexing method which reduces the semantic gap. The following three layered system architecture close the well-known semantic gap problem. In the second phase an integrated retrieval model is introduced which combines textual, visual and high level features together.

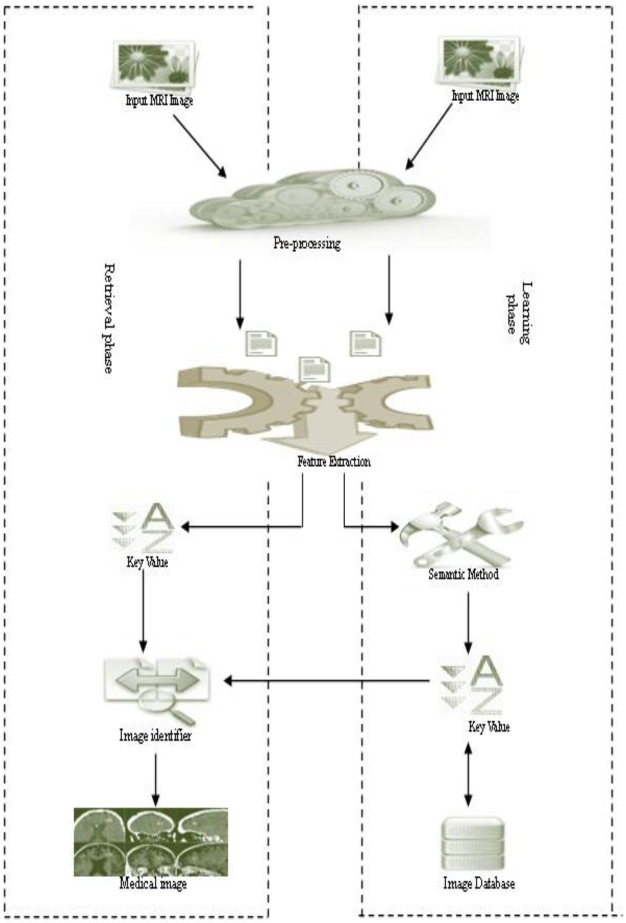

Figure. 1 Proposed Frame Work

The second phase is retrieval phase where the testing image is preprocessed and it's low-level and high level features are extracted and by using the suitable matching and indexing algorithm, the related images are retrieved. We can efficiently retrieve the medical images using the proposed system since it employs both the low level and high level features. The overall structure of the proposed method is illustrated in Figure 1.By the supervised machine learning approach, the images are classified as being relevant to an information need or not, and a pipeline information retrieval approach, images were retrieved using associated text and then re-rankedusing content-based image retrieval (CBIR) techniques. Medical images are essential in establishing diagnoses, analyzing and evaluating treatment results, and are useful for educational purposes in many clinical specialties.

Learning Phase

The Learning phase incorporates preprocessing, feature extraction and semantic method.The first step in this method is preprocessing. This step is an essential because noise will occur usually while capturing the images. These noises will reduce the quality of the image. The noises are cleared using preprocessing. In the next step, feature extraction, content of the image is represented using set of features.To avoid large input to the processing device the redundant features are reduced using LTrP[15] feature extraction method. After that the texture features are retrieved and finally the Semantic method is employed for semantic gap reduction. This method does the key value generation of images before they are stored in database. Hopefully, this will help to detect and retrieve medical images accurately during retrieval phase. The detailed process flow of the learning phase is illustrated as follows.

Pre-processing

Image preprocessing is the first step of image retrieval to ensure accuracy of subsequent steps. The images acquired through different modalities cause many artifacts such as low resolution and noise which reduces the accuracy of acquired result. In order to overcome the above problem preprocessing of an image is required. These primitive methods along with reducing the noise, blur, the important and detailed structure necessary for subsequent steps. In order to increase the processing speed and to reduce the error probability of medical images, De-noising should be employed. It is one of the filtering processes. This type of filtering is applied to medical images to eliminate the noise in images. The advantage of this filter is to reduce the noise as well as to increase the contrast and intensity of an image.

The first step in the preprocessing is to convert the medical image into binary image by using a simple threshold. In reality, the input images are often corrupted with noise, as a result, the image obtained after threshold usually has noise around the shape boundary. The de-noising process eliminates those isolated pixels and small regions or segments.

De-Noising

In the pre-processing of MRI Brain images, the noise will be removed by employing the Non-local mean filter. Non-local smoothing filters are not like that of Local Smoothing filters. It does not update pixel value with an average like those of the pixels around it. Instead, it updates it by utilizing a weighted average of the pixels considered to be the most lineages. The weight of each pixel hinge on the distance between its intensity grey level vector and that of the target pixel is calculated. Each pixel x of the Non-local means De-Noised image is computed with the following formula:

$$D(x,y)=\sum_{y\varepsilon N} g(x,y)N(x,y) \qquad (1)$$

Where N is the Noisy image, D is the De-Noised image and Weights $g(x,y)$ meet the following conditions $0\leq g(x\ ,y)\leq 1$ and $\sum_{y} g(x,y) = 1$. Each pixel is a Weighted Average of all the pixels in the image. The Weights are based on the similarity between the Neighborhoods of pixels x and y.

Feature Extraction by Using LTrP

Feature extraction is the second step in the Learning phase. In feature extraction the de-noised medical images $[D(x, y)]$ are transformed into a set of features. For feature extraction, an excellent method LTrP should be employed here.The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel g_c.

It also encodes the relationship based on the direction of the center pixel and its neighbors, which are calculated by combining (n-1)th-order derivatives of the 0° and 90° directions. The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel g_c. Given image, I, the first-order derivatives along 0° and 90° directions are denoted as $I_{\theta}^{1}(g_p)|_{\theta=0^{o},90^{o}}$ where g_p is the gray value of the neighbouring pixel of g_c. Let g_c denote the center pixel in I, and let g_h and g_v denote the horizontal and vertical neighborhoods of g_c, respectively. Then, the first-order derivatives at the center pixel can be written as

$$I_{0}^{1^{o}}(g_h) - I(g_c) \tag{2}$$

$$I_{90}^{1^{o}}(g_c) = I(g_v) - I(g_c) \tag{3}$$

And the direction of the center pixel can be calculated as

$$I_{Dir}^{1^{o}}(g_c) = \begin{cases} 1, I_{0}^{1^{o}}(g_c) \geq 0 \; and \; I_{90}^{1^{o}}(g_c) \geq 0 \\ 2, I_{0}^{1^{o}}(g_c) < 0 \; and \; I_{90}^{1^{o}}(g_c) \geq 0 \\ 3, I_{0}^{1^{o}}(g_c) < 0 \; and \; I_{90}^{1^{o}}(g_c) < 0 \\ 4, I_{0}^{1^{o}}(g_c) \geq 0 \; and \; I_{90}^{1^{o}}(g_c) > 0 \end{cases} \tag{4}$$

From (4) it is evident that the possible direction of each central pixel can be 1, 2, 3 or 4 and eventually the image is converted into four directions.

Using the second order derivative, LTrP^2(g_c), 8-bit tetra pattern for each central pixel is obtained. All patterns are separated into four parts based on direction of center pixel. Finally the tetra patterns of each part (direction) are converted into three binary patterns. Similarly the other three tetra patterns for the remaining three directions of center pixels are converted to binary patterns. Thus, 12 (4 x 3) binary patterns are obtained.

The LTrP method used the 13th binary pattern (LP) which can be calculated by using the magnitudes of horizontal and vertical first-order derivatives:

$$M_{I^1(g_c)} = \sqrt{\left(I_{0^o}^{1}(g_c)\right)^2 + \left(I_{0^o}^{1}(g_c)\right)^2} \tag{5}$$

$$M_{I^1(g_p)} = \sqrt{\left(I_{0^o}^{1}(g_p)\right)^2 + \left(I_{0^o}^{1}(g_p)\right)^2} \tag{6}$$

$$Lp = \sum_{p=1}^{P} 2^{p-1} \left(M_{I^1(g_p)} - M_{I^1(g_c)}\right) \Big| P = 8 \tag{7}$$

After identifying the 13th binary pattern, their histogram is calculated and query image is compared with the images of the given database. During comparison, the n best images similar to query image are selected. The experimental results confirmed that LTrP outperforms the retrieval and is able to extract more detailed information from the image.

Texture Analysis

Texture analysisdeals with texture analysis techniques to extract the powerful features of textures. In this work, we focus on texture feature extraction based on co-occurrence matrices.

Co-occurrence matrices

Several approaches exist for extracting texture features.In this work it focuses on the co-occurrence matrices (COM). This statistical approach is defined as the joint probability of occurrences of grey-levels i and j between pairs of pixels. Each value 'x' at coordinate (i, j) in the matrix reflects the number of occurrence of the grey-levels i and j separated by a given distance d (offset) along a given direction θ. The pair (d, θ) is the key of a COM. Formally; the definition for an N × M image f is as follows:

$$P_{d,\theta}(i,j)=\left|\left\{(n,m) \quad f(n,m)=i, \; f(n+d\cos\theta, m+d\sin\theta)=j\right\}\right| \quad (8)$$

Subsequently normalized:

$$P_{d,\theta}(i,j)=\frac{P_{d,\theta}(i,j)}{N\times M} \quad (9)$$

COM Selected Features

The Co-occurrence matrices are complicated and not helpful since no information can be drawn. For these reasons, we have chosen only four of them including energy, entropy, variance and correlation.

Energy:

It refers to global homogeneity of textures. A texture on high energy has a large number of homogeneous areas, whereas a texture on low energy has a small number. Energy (f_{eng}) is given as follows:

$$f_{eng}=\sum_{i=0}^{n}\sum_{j=0}^{n}P_{d,\theta}(i,j)^2 \quad (10)$$

where,$P_{d,\theta}(i,j)$ is the value of the point (i, j) of the co-occurrence matrix calculated for a distance d and an orientation θ.

Entropy:

Generally, entropy is a measure of the dispersion of a distribution. For textures, it refers to texture granularity which means the size and the number of texture primitives. A high value of entropy means a small number of large primitives, whereas a texture on low entropy has a large number of small primitives. Entropy (f_{ent}) is given as follows:

$$f_{ent}=\sum_{i=0}^{n}\sum_{j=0}^{n}P_{d,\theta}(i,j)\log P_{d,\theta}(i,j) \quad (11)$$

Variance:

Variance refers to the difference in intensity among neighboring pixels. A high value of variance means a large difference in intensity, whereas a texture on low variance has small difference. Variance is also referred to as contrast. Contrast (f_{con}) is given as follows:

$$f_{con} = \sum_{i=0}^{n} \sum_{j=0}^{n} (i - \mu)^2 P_{d,\theta}(i, j) \tag{12}$$

whereμ is the mean of co-occurrence matrix.

Correlation:

It measures the uniformity of grayscale distribution of pixels. A texture on high correlation has a uniform distribution, whereas a texture on low correlation is non-uniform. Correlation (f_{corr}) is given as follows:

$$f_{corr} = \frac{\sum_{i=0}^{n} \sum_{j=0}^{n} ijP_{d,\theta}(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{13}$$

where,μ_x, μ_y are respectively the mean of rows and columns of co-occurrence matrix and σ_x, σ_y are respectively the standard deviation of rows and columns of co-occurrence matrix. The use of the forth selected COM features in texture retrieval and semantic interpretation is very promising.

Semantic Method (Similarity)

The semantic gap is the main problem in image retrieval. The gap is between the high level image interpretations of the users and the low level image features stored for query indexing. The considerable differences between high level interpretation of the semantics of visual information and the low-level visual features are called as Semantic gap. CBMIR-based retrieval approaches is able to support semantic-based access. For reducing the semantic gap, ontology based annotation is employed.

Ontology Based Annotation

Ontology-based image retrieval is an effective approach to bridge the semantic gap because it is more focused on the semantic content which has the potential to satisfy the user need. A recent trend in ontology-based image retrieval is to fuse the basic modalities of images namely visual features and it is known as multi-modality ontology. Image annotation is to automatically associate semantic labels with images in order to obtain a more convenient way for indexing and searching images on the database.

Ontology consists of entities and their relationships, which are organized hierarchically. It may be in the form of classes and subclasses where each class may consist of one or more instances. Ontology can be defined as an explicit specification of a conceptualization. For example, “cerebrum” is a subclass of class “brain”. Ontology is simply a knowledge representation method which provides the way to consolidate the information in a structured manner. It helps to associate semantics to any object or its image and provides a better way for image retrieval. For a better way for retrieval of image the image should be indexed before it is stored in the database. For indexing the images annotation could give hand to the ontology. From this ontology based annotation could be originated, thus this process employs an indexing process. In the proposed framework ontology based annotation act as the indexing of images thus the innovative work achieves better retrieval than existing retrieval methods. This frame work of ontology based annotation should be illustrated in the Figure 2.

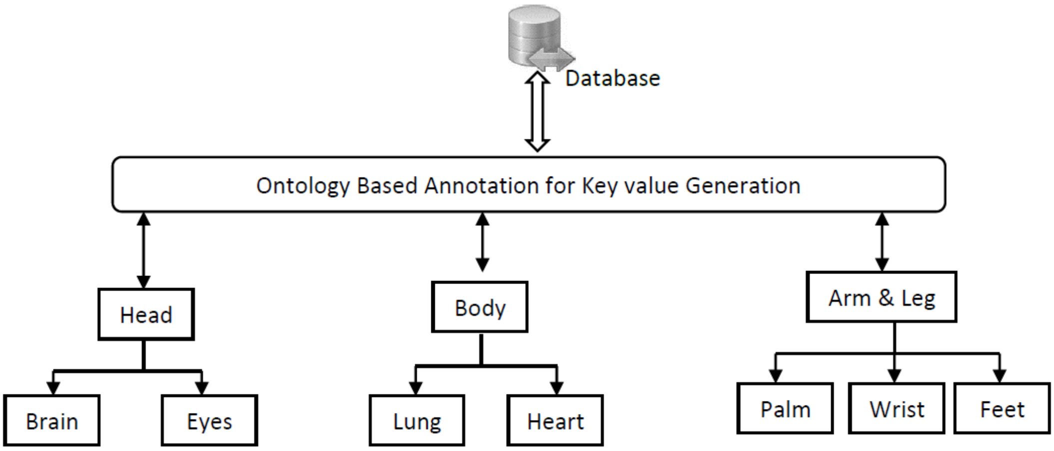

Figure 2: Ontology Based Annotation

From figure 2 the image could be indexed, the values needed for indexing could be gathered from feature extraction process. After the extraction of texture features the values are useful in the annotation of medical images. These values helps in the efficient image retrieval of the images learned in the database. After the extraction of texture features the annotation of image is done. The ontology based annotation is done by employing an effective method key frame generation.

Key frame generation from the extracted image for annotation.

Key frame generation method deals with the effective way to organize these LTrP values and texture values into a database to accelerate image retrieval process. For the retrieval of the images stored in database the Key frame generation method should be employed for fastest image retrieval.

Key frames describe important information from query images. The result from the feature extraction from the image given to the system in the learning phase is selected as the input for key frame module. Set of these key frames is given as input to the annotation part of the system as shown in figure 1.

The features of training images need to be extracted using LTrP, the extracted features are taken for key frame generation. For key frame generation, all the extracted features from the image are stored in new generated key“$fdb(i)$".

$$fdb(i) = LP + f_{eng} + f_{ent} + f_{cont} + f_{corr} \tag{14}$$

fdb Key value pair

i – Number of images

The annotation file created for all the three key frames have an ontology structure as shown in figure 2. During learning process all the images are indexed and saved by ontology based annotation and an image database is built. The image with the key value pair is stored in the database.

By using these key value generation the semantic gap between the high level image interpretations of the users and the low level image features are reduced. Thus more number of related images is retrieved.

Image Retrieval

Content-Based Medical Image Retrieval Systems (CBMIRS), on the other hand, allowbrowsing and retrieving from large image collections based on tetra pattern that are automatically extracted from the images. For a high resolution medical image diagnosis medically similar cases are often visually similar cases that can be found by CBMIRS depending strongly on Local tetra pattern of the images. The retrieval quality is sufficient for medical tasks and the automatic extraction of visual features is convenient, so the semantic gap between the low-level and high-level visual features are reduced.Thus user got exact and related image for a query image.

In this image retrieval process when a query image is given to the system,initially the query image is preprocessed. By these methods the noise in the query image is removed. Then the feature extraction process is continued by findingLTrP for the query image. After that the texture features of the image are extracted by co-occurrence matrix followed by extracting the energy, entropy, variance and correlation. Then from these extracted values the key pair for the image could be generated.

$$fq\left(\right) = LP + f_{eng} + f_{ent} + f_{cont} + f_{corr} \quad (15)$$

Image Identifier

Retrieval of similar images is based on similarity matching measures between features of query image with the database images features. In each method, two image feature values are verified from available database files, after that comparing equalities of query image (QI) and target image (TI). TI may be similar or equal or not equal. So based on the difference factor (DF), images are identified.

When the user of the system gives an image to the system as input, which is to be annotated automatically by the system, referred to as the Query Image X. The next task for the administrator is to find images in the downloaded dataset, that are visually similar to the query image X. To perform this task, state of the art content-based image retrieval engine is used that can extract visual features of a given image and return images that are visually similar to it. Higher similarity score implies that the image is more similar to the original query image. The images are ordered based on their similarity.Then the textual features (values) of all these similar images and the query image are checked and list of all the keywords are found. Finallythe most frequently occurring keywords in this list are found and these are taken as the tags for the query image X.

Similarity Comparison

Distance metric is the main tool for retrieving similar images from large medical databases. In proposed system, Euclidean distance is used for the purpose of similarity comparison.

$$ED=\sqrt{\sum_{i=1}^{N}\left(fq(i)-fdb(i)\right)^2} \tag{16}$$

Where $fq(i)$ stands for ith query image feature and $fdb(i)$ for corresponding feature vector database. Here N refers to number of images in database.From the equation (16) Euclidean distance between Query image and the images present in the database are compared. Thus from the distance of the calculated images in the database, images related to the query image is retrieved. Thus from the key value the similarity of the images are compared and most of the relevant images are retrieved.

Experimental Results

Experiments were conducted on MRI Brain images on a dataset of 500 images obtained from the open source databases TCIA and OSIRIX.

Performance Evaluation

De-noising

Here an input image is given into the system as input. The input image comprise of noise, so the removal of noise from the input image is illustrated in the Figure 3 by utilizing the de-noising process. Here various De-noising process done on medical images are shown.

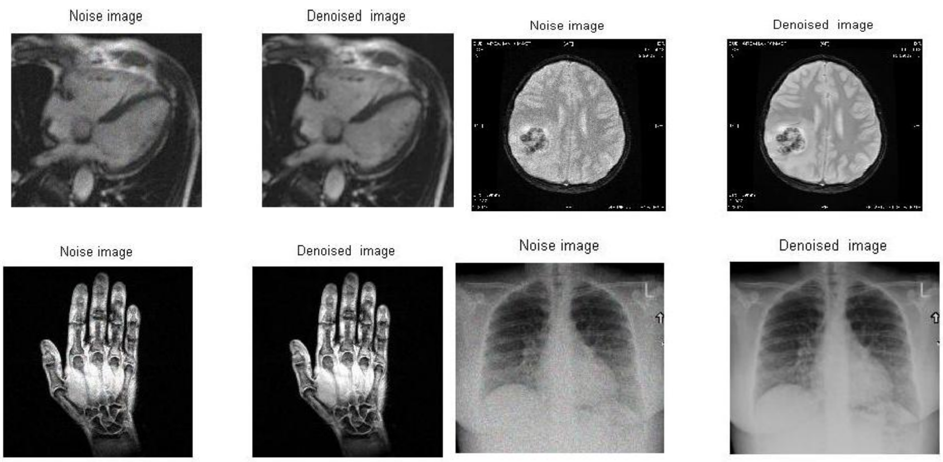

Figure 3: De-Noised Medical Images

Extracted Features

From the input images the feature values are extracted by using our proposed techniques. The proposed techniques comprise of the values extracted by using LTrp, Co-Occurrence matrix, and its texture features like Energy, Entropy, Variance and Correlation. These values are further employed for key value pair generation. The extracted feature values are shown in Table 1.

Table 1: Extracted Values of Various Features

Figures (Input)	Extracted Features					
	LTrP	COM	Energy	Entropy	Variance	Correlation
brain	510	1.01	814	5455.396	814	-0.07394
hand	276	1.13	7502	66939.78	7502	-0.10971
heart	284	2.60	2828	22475.04	2828	0.016394
lungs	510	5.55	2076	15856.9	2076	0.071347

Annotation Design

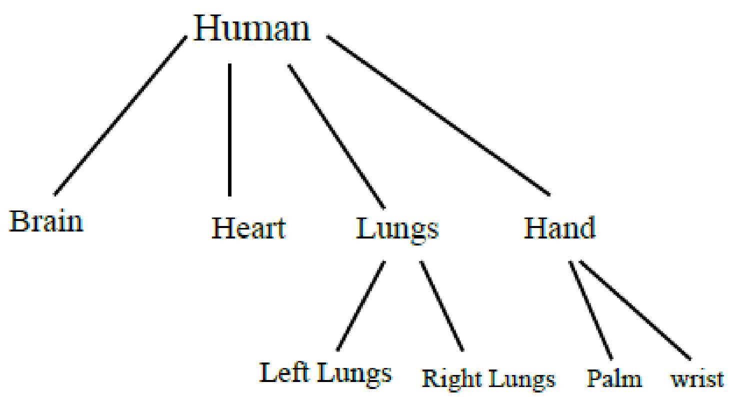

Figure 4: Ontology Based Annotation

In the annotation of medical images the proposed part annotates the image during learning phase. Each image could be annotated based on the key value pair generated based on the extracted features. Using the key value pair the images are annotated and stored in the database. Figure 4 shows the medical domain ontology which used for annotation. The main domain is Human body hence the root node is human. We have annotated four organs of human namely Brain, Heart, Lung and Hand. These organs are the leaf nodes which are recognized by the classifiers. Annotation file is created under the leaf nodes, which contains the object present in the image (leaf of the ontology) as well as all the parent nodes present in the ontology. For example, if the object identified in any frame is palm, the corresponding annotation image file will contain palm as well all its parent- Hand and root- Human.

Retrieval Phase

The images are retrieved based on the query image from the list of annotated images. Here a set of images retrieved while giving a query image is shown in Figure 5, Figure 6, Figure 7and Figure 8.

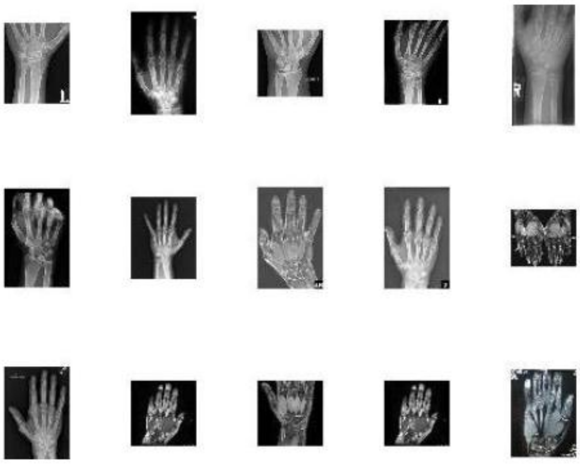

Figure 5: Retrieved results for hand image, with the top left image as the query image

Figure 6: Retrieved results for heart image, with the top left image as the query image

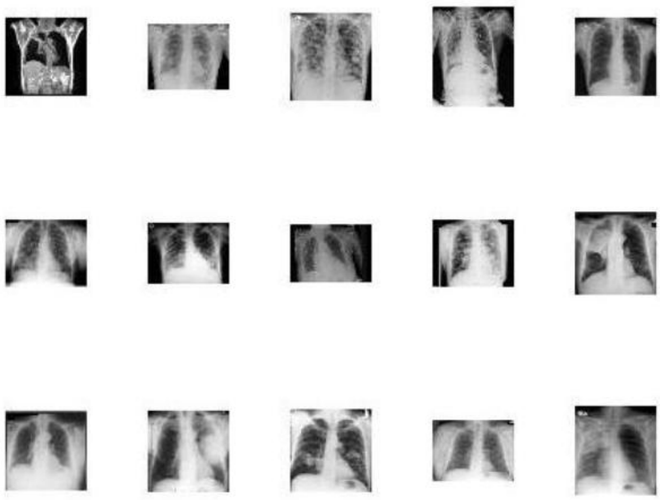

Figure 7: Retrieved Results For Lung Image, With The Top Left Image As The Query Image

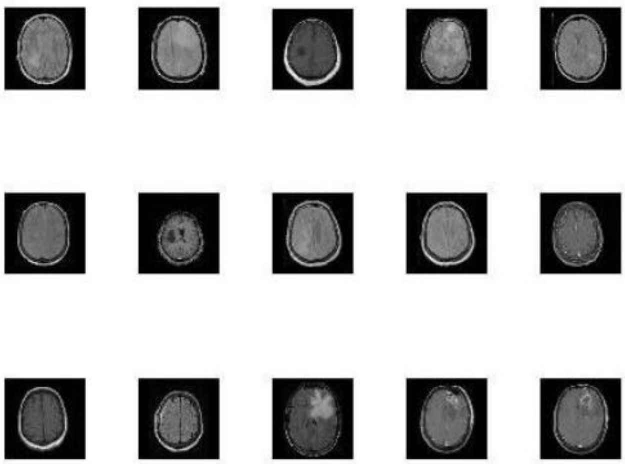

Figure 8: Retrieved Results For Brain Image, With The Top Left Image As The Query Image

Comparative Analysis

The performance of the proposed method can be identified by using precision and recall. Precision is the fraction of retrieved images that are relevant to the query image, while recall is the fraction of relevant images that are retrieved from the database. Both precision and recall are therefore based on an understanding and measure of relevance.

Let NR=Number of retrieved images relevant to the query image.

TR = Total Number of images retrieved.

TD = Total Number of Relevant images in the database.

$$\mathrm{Precision} = \frac{NR}{TR}$$

$$\mathrm{Recall} = \frac{NR}{TR}$$

From the Sensitivity Graph Fig.9, it is evident that the Accurate Retrieval capability of the proposed technique is higher than LBP and LTrP based Image Retrieval for medical Images.

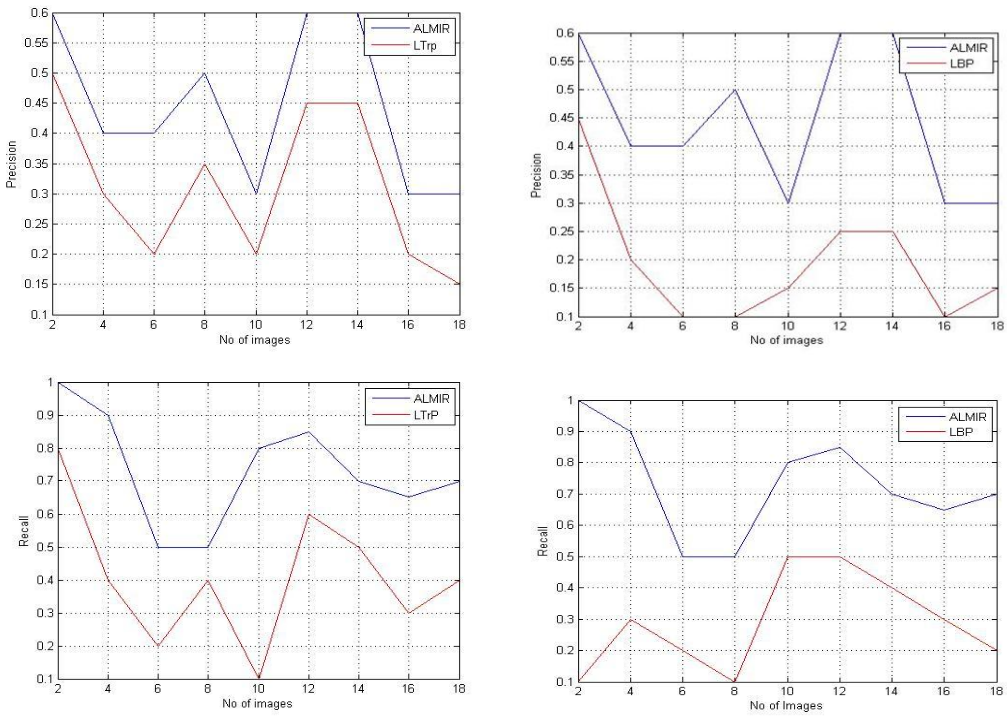

Figure 9: Comparison Evaluation Graph of the Proposed System with the LBP and LTrP

The performance measures of the proposed system are compared with LBP and LTrP in the Table 2.

Table 2: Comparison of performance measures with LBP and LTrP

Performance Measures	ALMIR	LBP	LTrP
F1-Score	**0.737672**	0.348937	0.529814
MAP	**0.444444**	0.194444	0.311111
P@10	**0.3**	0.15	0.20

Conclusion

In this paper, a new technique of Augment LTrP for Medical Image RetrievalSystem for medical images is presented. This paper also includes feature set calculation using Local Tetra Pattern technique and the analysis for Texture features like Energy, Entropy, Variance, Correlation by applying Co-occurance matrix. Experiments are carried out on Medical images for accurate image retrieval. Results show an improvement of precision and recall using ALMIR. It suggests that the proposed method is a brightly beaming and promising technique for medical image Learning and Image Retrieval in the Medical Imaging Applications. This Automated Image Retrieval system could be further used for retrieval of images with different types and varieties of images.

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