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Survey on Techniques and Image Modalities in Content Based Medical Image Retrieval

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ABSTRACT

The tremendous increase in medical images in the healthcare sector has given rise to the term CBMIR(Content-Based Medical Image Retrieval). CBMIR is said to ease the job of a physician in searching and retrieving similar images for a given query image. This helps in the detection and diagnosis of diseases in human body parts at the early stage. Due to the rapid increase in medical image databases searching and retrieving images similar to that of the query image from a huge database is a challenging task. A Survey on various CBMIR techniques that are used for retrieving biomedical images is given in this paper. This includes a literature survey of over more than 100 contributions to the field of content based medical image retrieval techniques. The major focus is on the techniques based on the representation of images visually in the medical field rather than annotated images.

Keywords: Content-Based Medical Image Retrieval, Medical image technologies

I. INTRODUCTION

Medical image technologies are in wide use due to the large collection of medical image databases getting generated across every corner of the world. From the traditional handcrafted way of retrieval techniques to the automatically learning models, CBMIR has evolved rapidly. Classic Medical imaging focused on the retrieval of annotated information about a patient's body parts. This gave rise to a significant advantage in the diagnosis of diseases in humans, detection, classification and segmentation [1]. X-ray medical imaging techniques started in 1895 [2], and then in 1950, nuclear medicine was possible. Later in the 1960s, ultrasound and diagnostic imaging came into existence, which gained popularity. Thereafter various medical imaging techniques such as CT, MRI, DICOM, and radiotherapy images were adopted. This collection of medical images increased rapidly and there was a need for storing and retrieving images efficiently. The time taken to extract useful information from the medical data was the most important field to many researchers. Image retrieval systems were either text-based or content-based. Content-based Image Retrieval became the widely used technique for medical image retrieval systems as it was more reliable.

One CBIR is a technique of searching images that are similar to the given query image and retrieving those images from a large database of images as shown in Fig. 1. CBIR uses visual features of an image such as shape, color, texture, and spatial arrangement of regions of interest (ROIs) features to extract useful information to match and retrieve similar images. Image retrieval is of two types: text-based and content-based, text-based retrieval analyzes content based on keywords, tags, annotations of images [3]. It is time-consuming to manually assign keywords and annotations to large repositories for text-based image retrieval. With CBIR it is eventually possible to show similar images by retrieval method. The main task in CBIR includes extracting features relevant to the specific application and finding similar images specific to the definition and grouping them for fast and efficient retrieval of images from a huge database of images [4-7]. The features selection in the CBIR system plays a major role in finding the similarity in the images [8, 9]. Features are of different types. For example, color features may not be sufficient to identify the content in an image specific to the application as in the case of medical images. Since medical images like x-ray, ultrasound, MRI are all grayscale images and require appropriate feature selection techniques to match the content of the query image with the database images. Domain-specific features are required to describe unique features specific to the application. Global features identify the entire image characteristics and fail to capture small portions of an image. whereas local features give the details of a small portion of pixels in an image. Local features are used in most of the investigations as it gives a detailed description of the specific region in an image [12]. The recent development is the use of deep learning models for CBIR tasks [10]. Image retrieval has also found its application in social media where real-time content sharing and publishing reports are increasing rapidly [11]. Due to the large storage space required to store the images as compared to text, the thought of moving the data to the cloud and then using it for their task was found in late 2016. Image encryption and watermarking techniques were used to provide privacy to sensitive data [13].

A. Content Based Medical Image Retrieval (CBMIR)

The huge collection of digital images generated in hospitals has led to the collection of a large database of medical images. Image retrieval system aims to provide efficient means to retrieve useful information from these large repositories. In the beginning, several text-based image retrieval systems were proposed [14-17]. Text-based retrieval was prone to error and required annotation of a large database which was a laborious task [18]. To overcome this drawback, CBIR was introduced. Query by image content(QBY) later known to be Content-based image retrieval was a topic of investigation for most researchers. With this CBIR found its application in medical image retrieval systems. CBMIR is a technique for extracting useful information from a huge database of medical images and recognizing similar case studies. This helps doctors in the diagnosis and treatment of different diseases [19, 20]. The application of CBMIR includes decision-making, education in the field of medicine, and research [21]. Visual features of medical images have a deep impact on diagnosis as seen in the clinical analysis [22]. Hence, decisions are made by looking into the case history and comparing them with current and past medical images [23]. This helps in finding images of the same category or detection of diseases of a similar kind [21]. CBMIR can be used to assist physicians who after finding abnormalities in the report can query the image and check the database to retrieve similar cases. This enables physicians to be more convinced with the diagnosis and may include pathological records which were not considered before. CBMIR provides evidence of case histories that are similar to his/ her decision along with the accurate class labels. Beginners with less experience can serve as an expert with the use of the CBMIR system and can diagnose better [24–26]. CBMIR can not only be used to retrieve similar images with the same diagnosis but also retrieves images that are visually similar but different diagnoses.

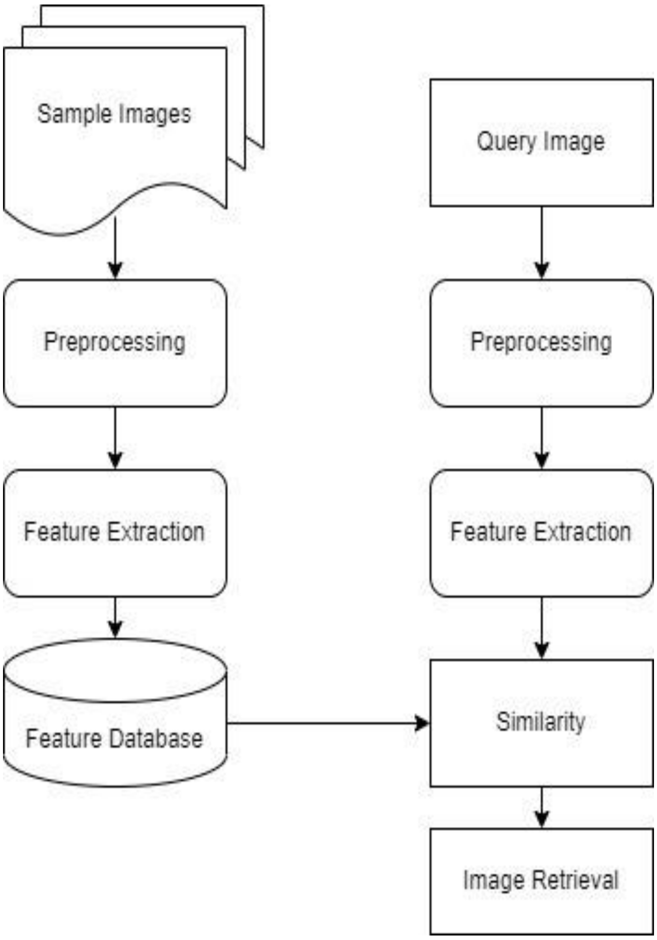

Figure 1: Architecture diagram of Content Based Image Retrieval system

II. TECHNIQUES

A. Descriptors

In Medical imaging, local texture features descriptors play a major role in differentiating visual features. Local binary pattern(LBP) was introduced for the first time and successful use of texture measures for various applications was proposed [27], and then, a generalized version of LBP was presented called a local ternary pattern(LTP) local texture descriptor for face recognition which was insensitive to noise and discriminate [28]. Representation of LBP is with 2-values '0' and '1' whereas LTP which is the extension of LBP is represented with 3-values '0', '1', and '-1'. Using the idea of a local quantized pattern(LQP) [29] and directional local extrema pattern (DLEP) [30], Rao and Rao [31] proposed a new feature descriptor called local quantized extrema patterns (LQEPs) for image indexing and retrieval, which first collects the direction quantized information from an image and then direction extrema is collected from the quantized data to integrate RGB color histogram with LQEP. Focusing on color features, local mesh quantized extrema patterns (LMeQEPs) was introduced again by Rao and Rao to improve the performance of the image retrieval system [32]. A novel descriptor called directional local ternary quantized extrema pattern (DLTerQEP) was proposed [33] for biomedical image indexing and retrieval. The results were measured by calculating the average precision and retrieval rate for this method and comparing it with the existing techniques: LBP, LQP, Binary Gabor pattern (BGP) for texture classification [34], and Weber law descriptor (WLD) [35].

A new binary wavelet decomposition technique was introduced in 1996 which presents the use of this method in lossless image coding [36-38]. For Image indexing and retrieval of medical images, a novel method of getting 8 binary bit planes by dividing the 8-bit grayscale image is carried out on each bit plane to extract binary images with multiple resolutions [39] and feature extraction using LBP [40]. Another method was proposed by murala using LTrPs(Local Ternary Patterns) [41] that calculated the first order derivative in the both(horizontal and vertical) directions to encrypt the association of the reference pixel with the neighborhood pixel. The proposed method was compared with LBP, local derivative pattern, and LTP and was found to have an improvement in the performance. A Local ternary co-occurrence pattern(LTrCoP) feature descriptor was presented by murala and Wu [42] that encodes the co-occurrence of similar ternary edges which were determined by the gray values of the center pixel and it's neighbor gray value pixels. They again proposed an algorithm using a local mesh pattern(LMeP) for medical image indexing and retrieval. This method encodes the relationship among the surrounding neighbor pixels with the given referenced pixel. Effectiveness is achieved by combining the algorithm with Gabor transform.Lumini A. Nanni introduced a new method to enhance the performance of a 2D descriptor [43]. An n-layer image was constructed using different preprocessing techniques to obtain multilayer descriptors as feature vectors and feed them for training with a support vector machine(SVM). Local binary pattern and local phase quantization were applied on both Color and gray-level images [44], and different variants of n-layer image. This method has shown that the combination of multilayer and texture descriptors outperforms the standard approaches. Murala and Wu [45] proposed a new algorithm for natural, texture, and medical image retrieval applications using a spherical, symmetric 3D local ternary pattern, which computed the relationship between the center pixel with the neighbor pixel in a 3D plan with five selected directions. This was generated using a multi-resolution Gaussian filter bank from a 2D image. Another feature descriptor called local peak valley co-occurrence patterns(LPVCoP) was proposed for medical image retrieval [46]. This method retrieves similar grayscale images by finding the relationship between the reference pixel and the neighbor pixel using the peak valley edges that were computed using directional derivatives. Amita and amol [47] proposed a new feature descriptor called the local neighborhood-based wavelet feature descriptor (LNWFD) for retrieving medical images based on the content of the image. Four sub-bands are acquired using a triplet half-band filter bank for single-level wavelet decomposition. In the next phase, the LNWEFD pattern is obtained using the relationship among wavelet coefficients on each of this sub-band from the 3x3 neighborhood window.

B. Barcodes

In recent days medical image indexing and retrieval are mainly using binary descriptors by most researchers. Annotation of barcode was first introduced by Tizhoosh for CBMIR [47,48]. He also proposed radon barcode (RBC) that produced a binary vector called “barcode” by projecting the image at different angles and binarizing the projections. Barcodes were also introduced on local binary patterns and local radon binary patterns (LRBPs) for CBMIR. Later a new radon barcode method called MinMax radon barcodes [49] was introduced since the previous method could lose a lot of useful information. In this algorithm, the smoothing function applies a moving average to separate small peaks (maximums)/valleys (minimums). Later, they found all the values that are on the way from min to max or vice versa. Then the corresponding values of zeros or ones were allocated to encode the projections.

As we now know radon barcodes are produced by binarization of radon projections, a new radon barcode [50] method called autoencoded radon bar-codes (ARBC) was proposed. Binarization is applied on the output of the hidden layer to autoencode radon projections on training images. Mina Nouredanesh et al. [51] introduced radon and Gabor transforms that were considered to be the most powerful techniques for shape-texture-based feature extraction. This combination of both radon and gabor features may be more powerful against variation in scaling or rotation, noise, and illumination. Gabor-of-Radon-Image Barcodes(GRIBCs) and Guided-Radon-of-Gabor Barcodes (GRGBCs) were two techniques proposed. Morteza Babauie et al. [52] proposed an image retrieval approach for a large dataset using radon barcodes. This technique called single projection radon barcode (SP-RBC) takes only a few radon single projections for all the images as global features.

C. Deep Learning

Deep learning is part of artificial intelligence and machine learning that has made advances in the field of medicine for the past few years. Deep learning methods have seen wide application in the field of image searching and retrieval tasks. [53–55]. Techniques on deep learning are applied to many medical-related diagnoses and monitoring[56,57]. A convolution neural network (CNN) is used by most researchers in image analysis. CNN based visual pattern recognition was done in the late 1980s [58–65], and later in the 1990s CNN concept was o Deep learning techniques have outperformed in various computer vision problems. Ivakhnenko et al. [67] started the work on deep learning and after which several alternate techniques on deep learning were performed [68–70]. Nowadays deep learning methods are also applied on CBIR systems [71–73] and attained outstanding retrieval rates. In medical image analysis, the performance of deep learning was found effective. A convolutional neural network with five layers was designed for the classification of interstitial lung diseases by Anthimopoulos et al. [74]. A Convolutional restricted Boltzmann machine was introduced by Tulder [75] for lung texture classification and detection of airway in CT images was done using generative and discriminative learning objects for describing the training data and for classification. Segmentation of MR brain images using convolutional neural network was proposed, where the network uses multiple patch sizes and multiple convolution kernel sizes to obtain multi-scale information [76]. Later, Esteva et al. [77] classified skin lesions using a deep convolutional neural network at the dermatologist level. A deep neural network method was presented by Havaei et al. [78] for brain tumor segmentation. Here the CNN architecture uses both local and global contextual features and a fully connected layer that provides 40 fold speed up. This method involves a two-phase training procedure to resolve the imbalance of tumor labels. Singh et al. [79] presents a new fusion technique for CT and MR images. This method uses features of both nonsubsampled shearlet transform (NSST) and spiking neural network. Many works were carried out using deep learning in the field of medicine [80–84]. Later, deep learning techniques were applied for CBIR systems on medical images [85–87].

Chung et al. [88] proposed a deep Siamese CNN (SCNN) architecture, where only binary image pair information is trained and evaluated for CBMIR task. A combination of CNN transfer learning and radon projection pool method for medical image retrieval was proposed [89], which consists of two stages. In the first stage transfer learning via a convolutional neural network is adopted and in the second stage creation of a selection pool using radon projection is used for further reduct]ion. J Ahmad et al. [90] presents an efficient technique to compress convolutional features which is identified using optimal subset selection algorithm into a sequence of bits using Fast Fourier Transform(FFT). For image retrieval a parallel deep solution approach was proposed [91] which was based on convolutional neural networks and later followed by a local search was done using LBP, HOG and Radon features on IRMA dataset. Y cai et al. [92] proposed a new framework for medical image retrieval using CNN for feature extraction followed by hash mapping for dimensionality reduction of feature vectors. A skin lesion image retrieval system was developed [93] using Resnet-50 based transfer learning for classification of skin lesions and generation of ground truth.

Table I. Survey of Dataset and Techniques on CBMIR

Sl. No.	**Medical Image Dataset**			
	Dataset	**Image Modality**	**Technique (year)**	**Image Format**
1	OASIS, ILD, VIA/ECL AP-CT	MRI, CT	AIR-Net (2022) et al. [94]	DICOM
2	Kaggle Chest, Fundus, INbreast	X-ray, Fundus photography	CNN & Euclidean distance (2022) et al. [95]	jpg

Sl. No.	Medical Image Dataset			
	Dataset	Image Modality	Technique (year)	Image Format
3	IRMA ImageCLEF 2009	X-ray	SAE et al. (2020) [100]	png
4	EXACT-09, TCIA-CT	CT, MRI	Local lifting wavelet co-occurrence texture pattern (2021) et al. [102]	DICOM
5	LISS-CISs	CT	DCNN (2021) et al. [96]	DICOM
6	Kaggle DIARETDB1 MIAS	CT, MRI, X-ray Fundus Mammogram breast	OLWGP & CNN (2021) et al. [97]	jpg/png/jpeg
7	BreakHis	Histopathological	CNN (2021) et al. [98]	png
8	Kaggle Chest-Xray J. Cohen's Covid-19	X-ray, CT	CNN(2021) et al. [99]	jpg/png
9	Cancer Imaging Archive	CT, MR, PT, Pathology, etc,.	DCNN (2017) et al. [101]	DICOM, TIF

III. CONCLUSION

Many techniques have been applied in Content based medical image retrieval system with promising results. We have provided the different state-of-art methods in the field of medical image retrieval. Also have surveyed different medical dataset and image formats available in public repositories provided by different institutes for research work. As we can see the techniques have advanced from handcrafted methods to deep learning. Recently, there is a lot of research happening in Content based medical image retrieval tasks. Challenges in this application could be lack of medical data in specific format and modality as mentioned in many papers.

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