A Methodical Study of Content based Medical Image Retrieval in Current Days

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Abstract- Content-based image retrieval (CBIR) is standout amongst the most rich research fields in the area of computer vision & significant advancement has been made throughout the decade. CBIR is an image search methodology that changed the traditional text-based retrieval of images by utilizing various visual features, for example, color, texture, & shape, as criteria of search. In the area of medical, images, particularly digital images, are generated in constantly increasing quantities & utilized for diagnostics & therapy. Content based approaches into medical images to support in making clinical decision has been suggested that would simplify the management of clinical data & scenarios to incorporate the content-based approaches. As, the total quantity of data generated in diagnostic centers has increased, it leads to the utilization of CBIR in the daily routine of hospitals & clinics.

In this article, we recognized and talked about some of the issues exist in the area as numerous proposals for systems are made from the medical domain and research models are made in the department of computer science by utilizing medical datasets. Still, there are a small number of systems that appear to be utilized as a part of clinical practice. There is a needs to be expressed that the objective is not to change the text-based retrieval techniques as they exist right now but to enhance them with visual search tools. This article will provide a summary of available literature in the area of content based access to medical image data and on the method used in the area.

Keywords: content based image retrieval (CBIR), medical image retrieval, medical diagnostics, clinical reports and data.

I. Introduction to Image Retrieval

For the last 10 years, image retrieval has been a very active research field, however first review paper on access techniques in image databases was presented in the early 1980s. The subsequent review papers from different years describe the state-of-the-art of the corresponding years and comprise references to a large number of systems and explanation of the methodologies implemented. Enser presented a broad survey of image archives, numerous indexing techniques and basic searching tasks, utilizing typically text-based searches on annotated images. In 1997 a research paper presents an overview of the research domain about the past, present and future of image retrieval. An extensive overview of published systems is presented and an assessment of a subset of the systems is presented. Unfortunately, the assessment is very restricted and only for a little number of systems. Smeulders et al. presented abroad overview of methodologies to date. This paper depicts basic issues, for example, the semantic gap or the sensory gap and provides links to a large number of research papers describing the different techniques used in the field.

In this paper, section 2 covers overview of CBIR. Section 3 and section 4 describes briefly about necessity of CBIR system in medical field. Section 5 and 6 discuss about use of CBMIR in the relevant fields and finally future directions and conclusion of the paper.

II. An overview of Content-based Image Retrieval

CBIR is an image search technique intended to search images that are almost similar to a given query. This method enhance text-based retrieval by utilizing quantifiable &features of objective image as criteria of the search [1]. Basically, CBIR calculates the similarity between two images based on the similarity of the properties of their visual components, which can consist of the color, texture, shape, & spatial arrangement of regions of interest (ROIs). The non-dependence of CBIR on labels makes it perfect for large databases where it is not viable to manually assign keywords & other annotations. A selection of features utilized by CBIR imply that there is a possibility to display what images are similar & to describe why they are alike in an objective, non-qualitative way.

The main difficulties for CBIR comprise the application-specific definition of similarity (based on users' criterion), extraction of image features that are important to this definition of similarity, & sorting out these features into directories for fast retrieval from large databases [1, 2-4]. The selection of features is an important job during outlining a CBIR system as it is firmly correlated with the definition of similarity. Features fall into many classes. Common useful features can be extracted from nearly all images however are not essentially suitable for all applications, for example, color is not suitable for grayscale ultrasound images. Application-specific features are tuned to a specific issue & define characteristics unique to a specific

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problem domain; they are semantic features planned to encode a particular meaning [1]. Global features capture the overall characteristics of an image but unsuccessful to recognize essential visual characteristics if these characteristics take place in only a comparatively small part of an image. Local features defines the characteristics of a small set of pixels (possibly even one pixel), i.e., they signify the details. There has been a change towards using local features in current years, mostly driven by the certainty that more number of images are too complex to be defined in a general way; though, the combination of local & global features remains a research field of experimentation for practical computer vision applications [4].

A fundamental theory of most CBIR systems is that the selected image features used are adequate to define the image correctly. So, the selection of image features must be made to reduce two major constraints: the sensory gap & the semantic gap [1]. The sensory gap is the dissimilarity between the object in the world & the features selected from the image. It arises when an image is noisy, has low illumination, or incorporates objects that are partly blocked by other objects. The sensory gap is further compounded when 2Dimages of physical 3D objects are considered; some information is lost as the choice of view-point means an object might block part of itself. The semantic gap is the conflict between the purpose of the user & the images extracted by the algorithm. It happens as CBIR systems are not able to interpret images; they don't recognize the "meaning" in the images in the similar manner that a human does. Retrieval is executed based on the image features not image interpretations.

The similarity of image features can be measured in a number of ways. When the features are represented as a vector, distance metrics such as the Euclidean distance can be used. The idea of elastic deformation can be utilized to characterize similarity when subtle geometric dissimilarities between images are essential. Graph matching allows the comparison of images based on a combination of image features & the arrangement of objects in the images (or the relationships between them). At last, statistical classifiers can be trained to classify the query image into known classes. Classifier-based methodologies constitute an endeavor to overcome the semantic gap through training a similarity measure on recognized labeled data. A thorough discussion of different similarity measures can be found in [5].

The huge volume of modern image databases& high feature dimensionality of images has similarly added to challenges in effective real-time retrieval. In many situation, it is no more reasonable to compare a query with each element of the dataset. Effective indexing plans are important to store &divide the dataset so that the data can be accessed &pass through quickly, without demanding to visit or process unessential data. On the other hand, the search space can be trimmed by utilizing only a subset of the features or put on weights to features [4]. The large datasets additionally imply that accurate search paradigms, which look for images in the dataset that precisely fulfill all query norm, might no longer be feasible. This has led to the rise of approximated search methods, which rank the images in the dataset as per how well they fulfill every search criterion [1]. Possibly the most recognized estimated plan is k-nearest neighbor search, which retrieves the k most similar (highly ranked) images as calculated by distance from the query in the feature space.

There is a possibility that some of the images retrieved by approximate search models will be unsuccessful to meet the expectations of the users. Precision & recall are two quality measures defined to compute the precision of an approximate search model. Precision denotes to the proportion of retrieved images that are appropriate, i.e., the proportion of all retrieved images that the user was expecting. Recall is the proportion of all relevant images that were retrieved, i.e., the proportion of similar images in the dataset that were actually retrieved. The best case would be a retrieval system that accomplishes 100 % accuracy & 100% recall. Actually the thing is that the most current algorithms becomes unsuccessful to discover all similar images, &maximum of the retrieved images comprise different images (false positives).

Figure 1 displays a generic CBIR model that can be considered for a particular applications. The dashed arrows specify the offline procedure that makes the search index, while the solid arrows indicate the online query process. The dashed line separate the offline & online procedures. At the time of the offline procedure, features are extracted from every images from the dataset. These features are then indexed for offline & online procedures. Note that feature extraction participates in both the offline & online procedures searching. At the time of online procedure, the same feature extraction procedure is executed on the query image. The query image's features are then compared to the features of indexed images using a defined similarity measurement algorithm. The measurements can then be used to rank the images in order of similarity or can be used to classify the images as "similar" or "not similar." This ranking is then displayed to the user. In some cases, the user can give feedback as weights or similarity indication to more enhance the search results. The feedback & retrieval procedure is repetitive till the user is fulfilled with the retrieved outcomes. The papers [1] &d [2-4] in the reference list give thorough overviews of general CBIR systems& components.
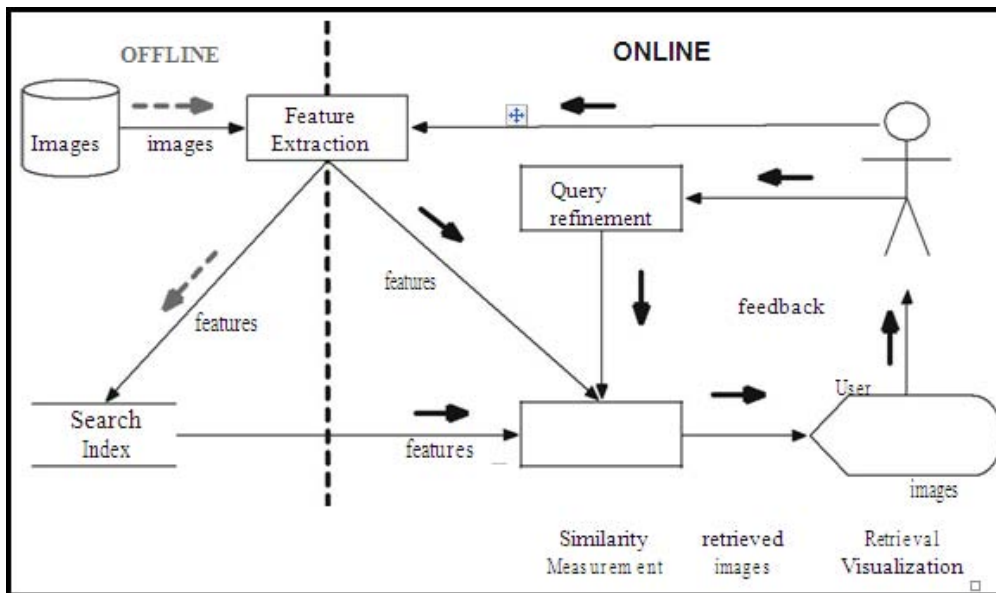
Figure 1 : A generic CBIR framework. The dashed arrows show the offline creation of the feature index from the image repository. The solid arrows show the online query process. The dashed line divides the offline and online processes. Note that feature extraction

Some examples of CBIR use are IBM's Query By Image Content (QBIC)system [6], which was used to search for famous artworks. Some others are Virage frame-work[7] & Photo book [8]. In recent times, Google Search by Image utilized the points, colors, lines, & textures in images uploaded by users to discover almost same type of images [9]. These new advancement simply that CBIR is a technology that is accessible to the masses.

Most recently, a shift in paradigm has changed the focus of CBIR research work in the direction of application-oriented, domain-specific technologies that would have more noteworthy effect on everyday life [4]. Because of developments in acquisition technologies, ongoing CBIR research work has moved towards images with an objective towards expanding image understanding. Present day medical imaging is one such field, where the retrieval of multidimensional & multimodal images from repositories of different data has possible applications in diagnosis, training, & research [10]. The content of medical images is complex: there is a high inconsistency in the detail of anatomical structures across patients; misalignment of structures can happen in volumetric and multimodality images; some imaging modalities experience the ill effect of low signal-to-noise ratios; & occlusion of structures is a common incidence. Moreover, there can be substantial variability among patients with the same health condition [11]. It is important that the qualities of specific medical images are considered when designing CBIR framework for them. The next segment presents a summary of the state of the art in medical CBIR.

III. The Need for Content-based Medical Image Retrieval

There are a few causes why there is a necessity for extra, alternative image retrieval techniques despite the gradually increasing rate of image production. It is critical to explain these requirements& to talk about potential technical & methodological enhancement and the resulting clinical benefits.

The objectives of medical information frameworks have frequently been defined to convey the required information at the right time, the right place to the right persons to enhance the quality &proficiency of care procedures [12]. Such an objective will most likely require more than a query by patient name, series ID or study ID for images. For the clinical decision-making procedure it can be helpful or even essential to find other images of the similar modality, the similar anatomic region of the similar disease. Even though part of this information is normally contained in the DICOM headers &numerous imaging devices are DICOM-compliant at this time, there are still a few issues. DICOM headers have shown to have a little bit high rate of errors, such as, for the field anatomical region, error rates of 16% have been described [13]. This can hamper the accurate retrieval of all wanted images.

Clinical decision support methodologies,for example, case-based reasoning [14] or evidence-based medicine [15,16] can generate a tougher need to retrieve images that can be important for supporting some of the diagnoses. It can even be imagined to have Image-Based Reasoning (IBR) as another discipline for diagnostic support. Decision support systems in

radiology [17] & computer-aided diagnostics for radiological practice as presented at the Radiological Society of North America (RSNA) [18] are growing & generate a necessity for powerful data & meta-data management & retrieval.

The general clinical advantage of imaging frameworks has already been presented in [19]. In [20], a technique is presented to recognize critical tasks for medical imaging based on their possible clinical advantages. It have to be expressed that the purely visual image queries as they are performed in the computer vision field will probably not be able to ever replace text-based techniques as there will always be queries for all images of some of the patient, yet there is a possibility to be a very good complement to text-based search based on their features. Still, the drawbacks & benefits of the technology have to be stressed to obtain acceptance and use of visual and text-based access methods up to their full potential. A situation for hybrid, textual & visual queries is presented in the CBIR2 system [21].

Other than diagnostics, teaching & research specifically are expected to improve through the use of visual access methods as visually interesting images can be chosen & can actually be found in the existing large repositories. The incorporation of visual features into medical studies is another fascinating point for many medical research fields. Visual features don't only let the retrieval of cases with patients taking similar diagnoses but also cases with visual similarity but distinctive diagnoses. In teaching, it can help teachers along with students to search educational image repositories & visually assess the out comes found. It may be a situation for directing in image atlases. Additionally, this can be utilized to cross-correlate visual & textual features of the images.

IV. Content-based Image Retrieval in Medicine

PACS & other hospital information systems store a huge amount of information, ranging from patient demographics & clinical measurements (age, weight, & blood pressure) to free text reports, test results, & images. The image types comprise of 2D modalities, for example, images of cell pathologies & plain X-rays, & volumetric images including CT, PET, & magnetic resonance (MR). Recent advances have introduced multimodality devices, e.g., PET-CT [22, 23]&PET-MR [24] scanners, which are capable of acquiring two co- aligned modalities during the same imaging session. Figure 2 presents a subset of the distinctive types of medical images.
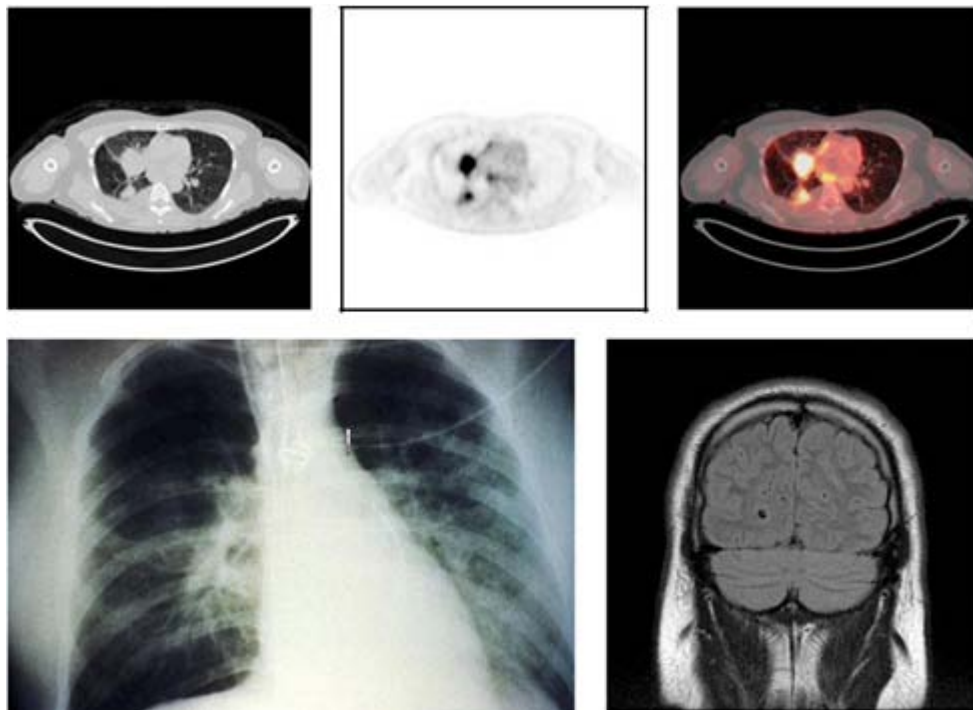

Figure 2 : A subset of the medical images available in many hospitals. Clockwise from the top left, they are axial CT slice, axial PET slice, axial fused PET-CT slice, coronal MR slice, and chest X-ray

Many research have already been done on the potential clinical advantages of CBIR in clinical applications. The ASSERT CBIR system utilized for High-Resolution CT (HRCT) lung images [25] exhibited an enhancement in the correctness of the diagnosis carried out by physicians [26]. Another research work for liver

CT showed that CBIR can deliver real-time decision support system [27]. Additionally, CBIR was presented to have advantages when utilized as part of a radiology teaching system [28].

In the next segment, we start our survey by presenting a summary of CBIR research for 2D medical images& inspect how these technologies have advanced & been applied to images with higher dimensions, e.g., volumetric CT scans, & images with a temporal dimension, e.g., dynamic PET. The incorporation of image with non-image data will then be discussed. Also, we will analyze how research works have dealt with the difficulties of retrieving images from datasets having images from various range of modalities. At last, we will present how multiple images from diverse modalities have improved medical CBIR abilities. Table 1 provides a brief summary of the studies that we will investigate in this review & the types of data utilized at the time of retrieval. Readers ought to refer to the appropriate article for further information, for example, figures demonstrating the retrieval results.

Table 1 : Studies divided by data types

Type of data	Studies
2D images	Radiographs: [35– 37]; spine X-rays: [38– 44]; cervicographs: [45, 46]; mammograms:[47– 49], [50, 51][a]; retinopathy: [49], [50, 51][a]
3D+ images	CT: [31, 32, 52], [33][a]; MRI: [53– 55]; dynamic PET: [56, 57][a]; PET-CT: [58– 69]
Non image Data	Text: [56, 57, 70– 76][b], [77, 78]; annotation or ontology: [33, 79, 80][b]; others: [50, 51][b]
Multiple Images	Image CLEF: [81–85]; pathology: [86]; general [87, 88]; PET-CT: [58– 69]
[a] Also used nonimage data	
[b] Also used image data	

a) 2D Image Retrieval

The most part of CBIR studies on 2D medical images has concentrated on radiographic images, for example, plain X-rays & mammograms. Our interest in this section is on techniques that mostly utilize conventional features, such as, shape & texture. These techniques will show how standard techniques in nonmedical CBIR [16] have been implemented in the medical field.

The Image Retrieval in Medical Applications (IRMA) project has been a continuous work in the CBIR of X-ray images for medical diagnosis systems. The IRMA methodology is separated into seven inter dependent phases [29]: (1) categorization based on global features, (2) registration by utilizing geometry & contrast, (3) local feature extraction, (4) category-dependent & query-dependent feature selection, (5) multiscale indexing, (6) identification of semantic knowledge, & (7) retrieval based on the earlier stages. The IRMA technique categories images into anatomical areas, modalities, & viewpoints & offers a generic system [30] that permits the derivation of flexible implementations that are enhanced for particular uses.

Other methods for radiograph retrieval have been tested to group features into semantically significant patterns. In one such kind of research work [31], multiscale statistical features were extracted from images by a 2D discrete wavelet transform. These features were then clustered into small patterns; images were represented as complex patterns comprising of sets of these smaller patterns. Experimentation outcomes find out that the technique had considerably higher precision & recall compared to two traditional methods: local & global gray-level histograms.

Various papers [32-38] have depicted experimentation into each component of CBIR for spine X-ray retrieval, comprising of feature extraction [39, 40, 37], indexing [38], similarity measurement [41, 44], & visualization & refinement [42]. The initial techniques of matching whole vertebrae shapes [33, 40] had a major shortcoming: in 2D X-rays, regions of the vertebrae that were not of pathologic interest could obscure dissimilarities between critical regions. Xu et al. [41] presented partial shape matching as an approach to manage with occlusion when comparing incomplete or distorted shapes. An application-centric feature, the nine-point landmark model utilized by radiologists & bone morphometrists in marking pathologies, was localized to enhance the computational performance of their algorithm for partial shape matching. In tests, their technique succeeded an accuracy>85 %. Although the users can apply weights to angles, lengths,& the cost to merge points on the model, it was tough to decide the effect these weights had on the retrieval outcomes, i.e., there was no feedback with respect to what every weight did to the shape.

This was solved in a later research work by Hsu et al. [42]; a web-based spine X-ray retrieval system

permit a user to alter the appearance of a shape & to assign weights to points on the shape to highlight their significance. The incorporation of relevance feedback further enhance the performance of the algorithm. Initially, 68% of the retrieved images were relevant (what the user expected); three iterations of feedback improved this by a further 22 %. Assigning weights to parts of the shape permitted the user to indicate why the images were similar. Moreover, the web-based shape retrieval algorithm was displayed to work with uterine cervix images; the system was able to differentiate between three tissue types with a precision of 64 % [45, 46].

The spine retrieval system was further enhanced with the introduction of several domain-specific features: the geometric & spatial relationships between adjacent vertebrae [43]. Merging these features with a voting consensus algorithm increased retrieval precision by about 8 %. To enhance the speed of the retrieval, Qian et al. [44] indexed the images by integrating the shapes in a Euclidean space. This index lead to a considerably faster retrieval time of 0.29 s compared to 319.42 s. Moreover, the integrated Euclidean distance measure was a decent calculation of the Procrustes distance used earlier; the initial 5 retrieved images were indistinguishable in both cases more than 100 queries.

Korn et al. [47] presented a tumor shape retrieval algorithm for mammography images. Specifically, the research work proposed application-centric features to model the "jaggedness" of the periphery of tumors; tumors were characterized by a pattern spectrum comprising of shape characteristics with high discriminatory power, for example, shape smoothness & area in different scales. This was carried out to differentiate benign & malignant masses, which are probably have higher fractal dimensions. Test on a simulated dataset found out that the proposed application-centric method succeeded 80 % accuracy at 100 % recall. Their utilization of pruning to diminish the search space brought about computational performance that was up to 27 times better than sequential scans of the full dataset.

Yang et al. [48] utilized a boosting framework to learn a distance metric that preserved both semantic & visual similarity at the time of medical image retrieval. At first, sets of binary features for data representation were found out from a labeled training set. To preserve visual similarity, sets of visual pairs (pairs of similar images) were utilized long with the binary features to train the distance function. The proposed method had higher retrieval precision than other retrieval techniques on mammograms & comparable accuracy to the best approach on the X-ray images from the medical dataset of the Cross Language Evaluation Forum's imaging track (Image CLEF). By learning dataset-centric features & distance functions, the retrieval system executed more

reliably than other state-of-the-art methods across various datasets.

b) 3D+ Image Retrieval

In current years, numerous image retrieval algorithms have been considered to use in 3D medical image retrieval. A basic method is to change a 3D image retrieval algorithm into an alternate problem. One such type of case is to choose key slices from the volume to decrease a complex 3D retrieval to a 2D image retrieval problem. Other methodologies include representing 3D features in domains where the dimensionality of the image is not a factor, e.g., graph representations. This portion depicted how such methods have been used for images with more than two dimensions.

The most well-recognized 3D image retrieval system is the ASSERT system [25], that retrieved volumetric HRCT images based on the key slices choose from the volumes. The system retrieved images with the same kind of lung pathology (such as, emphysema, cysts, metastases, etc.), preferably within the same lung lobe as the query. At the time of the query procedure, a physician would mark a pathology-bearing region in the HRCT lung slice; gray-level texture features and other statistics, were then extracted from these regions. Additionally, relational information about the lung lobes was achieved. In experimentation, the ASSERT system succeeded a retrieval accuracy of 76.3 % during matching the type of disease; this plunged into 47.3 % when the lobular location of the pathology was also taken into consideration. At the time of clinical evaluation [26], physicians used the ASSERT system to retrieve & display four diagnosed cases that were similar to an unknown case; this was demonstrated to enhance the precision of their diagnosis.

An enhancement in the ASSERT system included a two-phase unsupervised feature selection technique to "customize" the query [49]. In the first step, the features that best differentiated dissimilar classes of images were utilized to classify the query into the most applicable pathology class. During the second stage, the features that best differentiated between images within a class were utilized to detect the "subclass" of the query, i.e., to discover the most similar images within the class. The customized query method had an efficient retrieval accuracy of 73.2 % compared to 38.9 % using a single vector of all the features. The study demonstrated that finding images based on the class was suboptimal; there was a necessity to also discover the most similar images within a specific class.

Local structure information in ROIs was utilized for the retrieval of brain MR slices [50]. Two feature sets were compared for the representation of structural information. The first, local binary patterns (LBPs), treated every local ROI in the same way. On the other, Kanade-Lucas-Tomasi (KLT) feature points, provide

greater importance to the more salient regions. The out comes uncovered exciting insights about the trade-offs inherent in structure-based retrieval. LBPs were very dominant when spatial information was incorporated, & its precision was constantly higher than its rivals in experimentation including pathological cases or other anomalies. The tests also demonstrated that precision was degraded when KLT points were not matched.

Petrakis [51] proposed a graph-based technique to retrieve MR images. Every image was represented by an attributed graph; vertices presented ROIs, whereas edges represented relations between ROIs. Their outcomes demonstrated that a similarity measure on the basis of the idea of graph edit distance acquired the best retrieval accuracy, at the cost of computational effectiveness. Alajlan et al. [52] proposed a tree representation that attained enhanced computational performance by just indexing relations between ROIs that were incorporated (completely surrounded) within other ROIs.

Dynamic PET images comprise of a series of PET image frames obtained over time. Cai et al. [53] proposed a CBIR framework that use the temporal features in these images. They exploited the activity of pixels or voxels across different time frames by basing their retrieval on the similarity of tissue time–activity curves (TTACs) [54]. Cai et al. [55]also adopted three query input methods: textual attributes, definition of a query TTAC, & a combination of these features. Kim et al. [56] extended this retrieval to 4D (three spatial & one temporal) by processing 3D brain images to an anatomical atlas & defining the structures to search by utilizing the atlas' labels.

c) Retrieval Enhancement Using Non image Data

The greater part of image search in clinical field is performed by utilizing non image data. The abundance of non-image information stored in hospitals (clinical reports & patient demographics) implies that these data can improve the image retrieval procedure. In this portion, we concentrate on research work that present the use of non-image data to add semantic information to image features as a means of decreasing the semantic gap.

Text information is a basic add-on to image features [57], & medical CBIR research. Numerous examples of research consisting of non-image data have been described [53, 56]. Additionally, textual information has been utilized to complement many research work that were part of the Image CLEF medical challenge or used the same data [58-64].

A method to use text as the input query technique for image data together was proposed by Chu et al. [65]. The spatial properties of ROIs & the relationships among them were indexed in a conceptual model comprising of 2 layers. The 1st layer abstracted individual objects from images, whereas the 2nd layer modeled hierarchical, spatial, temporal, & evolutionary relations. The relationships represented the users' conceptual & semantic understanding of organs & diseases. Users made text queries by utilizing an SQL-like language; every query indicated ROI properties, like organ size, and relationships among ROIs. This retrieval method was expanded in [66] by incorporating a visual technique for query construction & by the addition of a hierarchy for grouping related image features.

Rahman et al. [63] introduced a method that utilized the correlation between text & visual components to implement the query. Their comparison of text, visual & combined methods shown that the text retrieval had a higher mean average precision than the purely visual method, while the combined method outpaced both text & visual features alone. This result could be observed in a comparison of different retrieval algorithms in [64] but could be described by the nature of the dataset that was utilized. The medical images in the Image CLEF dataset were very much annotated & this made text-based retrieval inherently simple compare to purely visual methods.

A comparison of text, images, & combined text & image features was carried out by Névéol et al. [67], by utilizing a dataset that was not as well annotated. The text features were extracted from the caption of the images in the document, as well as paragraphs referring to those images. The tests comprised of an indexing task that produced a single IRMA annotation for an image & a retrieval task that matched images to a query. The outcomes demonstrated that image analysis was better than text for both indexing & retrieval, however there were a few conditions where indexing executed better with text data. Additionally, the out comes shown that caption text gave more appropriate information than the paragraph text. Whereas combined image & text data appeared helpful for indexing, the retrieval precision was not considerably higher than that of using images alone.

A preliminary clinical study [27] assessed various features to retrieve the liver lesions in CT images. Especially, the study made a comparison among texture, boundary features, & semantic descriptors. Twenty-six distinctive descriptors, from a set of 161 terms from the RadLex terminology [68], were manually allotted by trained radiologists to the 30 lesions in the dataset; every lesion was given between 8 & 11 descriptors. The semantic descriptors were a feature that described why images were clinically similar. The similarity of a pair of lesions was described as the inverse of a weighted sum of dissimilarities of their corresponding feature vectors. The test results showed that the semantic descriptors beat the other features in precision & recall. Though, the highest accuracy was achieved during a combination of all the features was utilized or retrieval.

Quellec et al. [69] used unsupervised classification to index heterogeneous information (in the form of wavelets [49] & semantic text data) on decision trees. A committee was utilized to confirm that individual attributes (either text or image features) were not weighted too highly. A boosting algorithm was implemented to lessen the tendency of decision trees to be biased towards larger classes. The proposed algorithm succeeded an average precision at five retrieved items of about 79 % on a retinopathy dataset & of about 87 % on a mammography dataset. Without boosting, the results were lower, with 74 % for retinopathy&84 % for mammography. The method was robust to missing data, with an accuracy of about 60 % for the retinopathy data when <40 % of the attributes were available in the query images.

Likewise, in [71], wavelets were fused with contextual semantic data for case retrieval. A Bayesian network was utilized to evaluate the probability of unknown variables, i.e., missing features. Information from all features was then utilized to measure a correspondence between a query case & a reference case in the dataset, again utilizing conditional probabilities of a Bayesian network. An uncertainty component modeled the confidence of this correspondence. The highest precision was acquired during the use of all the features, however the Bayesian method alone outpaced Bayesian plus confidence information on a mammography dataset. On the retinopathy dataset, the highest accuracy was attained by the Bayesian plus confidence component.

d) Retrieval from Diverse Datasets

The various nature of medical imaging implies that CBIR abilities must have the capability to discriminate between modalities during searching for images. This drawback has been taken up by the medical image retrieval challenge at Image CLEF. Participants submit retrieval algorithms that are assessed on a large diverse medical image database [72]. General idea of submissions to the Image CLEF medical imaging task can be found in [73-75]. One key objective of the works incorporated is modality classification or annotation of regions, permitting successful retrieval on a subset of the various repository.

In 2006, Liu et al. [76] presented two techniques to solve this retrieval difficulties. The first method used global features such as the average gray levels in blocks, the mean & variance of wavelet coefficients in blocks, spatial geometric properties (area, contour, centroid, etc.) of binary ROIs, color histograms, & band correlograms. The second method divided the image into patches & used clusters of high dimensional patterns within these patches as features. Utilizing multiclass support vector machines (SVMs), they were able to accomplish a mean average accuracy of about 68 % when using visual features.

Tian et al. [77] utilized a feature set comprising of LBPs & the MPEG-7 edge histogram to analyze the impact of dimensionality reduction utilizing principle component analysis (PCA); the classification was executed by utilizing multiclass SVMs. The correctness of the dimensionally lessened feature set (80.5 % at 68 features) was not very different from the accuracy utilizing all features (83.5 % at 602 features). The maximum precision was succeeded by the feature set falling between these two extremes (83.8 % at 330 features).

Rahman et al. [78] presented a technique for the automatic categorization of images by modality & pre-filtering of the search space. They decreased the semantic gap by combining low-level global image features with high-level semantic categories utilizing supervised & unsupervised learning through multiclass SVMs & fuzzy c-means clustering. The retrieval efficiency was improved by utilizing PCA to decrease the feature dimension, whereas the learned category-zation & filtering decreased the search space. The tests on the Image CLEF medical dataset displayed that pre-filtering brought about higher precision & recall than executing queries on the whole dataset.

In a same kind of approach, the relationship between features in MPEG-7 format & anatomical ideas in the University of Washington Digital Anatomist reference ontology were utilized to annotate new, unlabeled images [79]. The most similar images, based on feature distance, were retrieved from the dataset based on the similarity of feature. The semantic annotation for the unlabeled image was derived from the annotations of the similar images. Experimentation on the Visible Human dataset [80] showed that their retrieval & annotation framework accomplished a precision of around 93.5%.

e) Retrieval of Multiple Images and Modalities

The storage of patient histories in PACS & the development of multimodality imaging devices have led challenges for the retrieval of several related images. The main challenge is utilizing complementary information from various images to execute the retrieval. The works described in this segment taken up this challenge by grouping images by the information they provide or by utilizing associations between features from various images.

A new research work [81] presented the utilization of several query images to augment the retrieval procedure. These images were of the similar modality: microscopic images of cells. Texture & color features were utilized in a two-tier retrieval method. In the first tier, SVMs were utilized to classify the most important disease type (same kind of approach used by [49]). The second tier was further divided into two

phases: the first level found the most similar images, whereas the second tier ranked individual slides by utilizing a nearest neighbor method for slide-level similarity. The slide-level similarity was weighted based on the distribution of the disease subtypes appearing on the slide & the frequency of that subtype across the entire dataset. The proposed technique achieved a classification accuracy of 93 & 86 % on two separate disease types.

Zhou et al. [82] proposed a case-based retrieval algorithm for images with fractures. The algorithm merged multi-image queries comprising of data from various imaging modalities to search a repository of different images. The cases in the repository incorporated X-ray, CT, MR, angiography, & scintigraphy images. The cases were represented by a bag of visual keywords & a local scale-invariant feature transform [83] descriptor. Retrieval was accomplished by measuring the similarity of each image in the query case with every image in the dataset to locate the set of most similar images (for a particular image in the query case). The list of all similar images was then converted to a list of unique cases in the dataset. Three feature selection strategies were assessed & it was showed that feature selection based on case offered the best performance & stability.

The studies explained before in this segment operated on multiple images or multiple modalities but were not intended to retrieve multimodality images that were achieved on a combined scanner. Devices, for example, the PET-CT & PET-MR scanners produce co-aligned images from two different modalities. The co-alignment of the various modalities provides opportunities for searches on the basis of the complementary features in the various modalities & spatial relationships between regions in either modality.

While clinical usage of co-aligned PET-CT has grown rapidly [84, 85], few studies have researched PET-CT CBIR [86-97]. Kim et al. [86] proposed a PET-CT retrieval system that allowed a user to search for images with tumors (extracted from PET) that were enclosed within a particular lung (extracted from CT) utilizing overlapping pixels. The research work presented the ability to search for tumors using their location or size. Song et al. [87] proposed a PET-CT retrieval technique utilizing Gabor texture features from CT lung fields & the SUV normalized PET image. Experimentations demonstrated that the technique which had higher accuracy than methods that used conventional histograms & Haralick texture features. A technique for matching tumors & abnormal lymph nodes by pair wise mapping across images was proposed in [90]. A weight learning method using regression for feature selection was proposed in [92]. Though the algorithms were limited to thoracic images, they showed promise for adaptation to entire body images.

Kumar et al. [93] presented a approach based on graph to PET-CT image retrieval by indexing PET-CT features on attributed relational graphs [51]; graph vertices represented organs extracted from CT & tumors extracted from PET. The methodology based on graph exploited the co-alignment of the two modalities to extract spatial relationship features [94] between tumors & organs; these were represented as graph edges. This permitted their graph representation to model tumor localization information, relative to a patient's anatomy. Retrieval was done by utilizing graph matching to make a comparison between the query graphs to graphs of images in the dataset. The method was extended to volumetric ROIs rather than key slices, thus allowing retrieval based on 3D spatial features [94]. Additionally, they presented that constraining tumors to the nearest anatomical structures by pruning the graph enhanced the retrieval procedure on simulated images [95]. In addition, they exploited their graph-based retrieval algorithm to describe the reason behind the retrieved images were similar to the query by designing user interfaces that allow the interpretation of the retrieved 2D PET-CT key slices [96]&3D PET-CT volumes [97].

V. The use in Various Medical Departments

The similar diversity that exists with regard to proposed applications exists similarly relating to the medical field where the utilization of content-based access techniques has been implemented or proposed. Apparently, most of the applications are based on the images generated in radiology departments, however there are additionally a few other departments where CBIRSs have been implemented. A group of images from numerous departments has been described in [51, 99]. A characterization of dermatologic images is described in [63,98,99]. Cytological specimens have previously been explained (in 1986, [100]) & also later on [101] although the search for 3D cellular structures followed later on [85].

Pathology images have been proposed over and over again for content-based access [43,102] as the color & texture characteristic can comparatively easy to be identify. The jobs of a pathologist when searching for reference cases similarly backings the use of an image retrieval system without only reference books. The utilization of tuberculosis smears is depicted in [103]. Ause of histopathologic images is presented in [104]&histological images are studied in [105,106,107]. In cardiology, CBIR has been utilized to find stenosis images. MRIs of the heart have been studied in [108].

In the radiology section, mammographies are a standout amongst the most frequent application parts with regard to classification & content-based search. The negative psychological impacts to remove tissue for false positive patients have been explained of one of the

main objective to be diminished. Diverse ultrasound images are utilized in [41].

Another active field is the categorization of High Resolution Computed Tomography (HRCT) scans of the lung as carried out by the Assert project [113,114]. A research on the diagnostic quality with & without utilizing the system exhibited a substantial enhancement of the diagnostic quality with utilizing a retrieval technique for finding related cases [115]. Also, a project using HRCT lung images is presented in [116, 117]. An explanation of use in this field is the hard decision-making job & the strong need of the diagnoses from texture properties. Explanations of HRCT lung images, their visual properties & their pathologies are presented in [118,119]. The utilization of thorax radiographies is presented in [18]. This will be a consider ably tougher job as quite a few layers are superposed & a lot of

factors except the pathology can impact on the visual content strongly.

Numerous different articles use medical images to show their algorithms but a clinical assessment of their utilization has rarely been carried out. In [50, 51, 120], magnetic resonance images (MRIs) of the brain are utilized to show the image search algorithms but the research papers don't discuss regarding any medical integration. [121,122] also utilize MRIs of the head to test their algorithms. CT brain scans to categorize lesions are utilized in [123]. The search for medical tumors by their shape characteristic (after segmentation) have been presented in [21]. Functional photon emission tomography (PET) images for retrieval are utilized in [124]. Spine X-rays are utilized in [21,126].

Table 2 displays an outline of a number of image types & the systems that are utilized to retrieve these images.

Table 2 : Images used-Name of the systems

Images Used	Names of the systems
HRCTs of the lung	ASSERT
Functional PET	FICBDS
Spine X-rays	CBIR2, MIRS
Pathologic images	IDEM, I-Browse,PathFinder, PathMaster
CTs of the head	MIMS
Mammographies	APKS
Images from biology	BioImage, BIRN
Dermatology	MELDOQ, MEDS
Breast cancer biopsies	BASS
Varied images	I²C, IRMA, KMed, COBRA,MedGIFT, ImageEngine

VI. The use in Fields Close to Medicine

There are several fields close to the medical domain where the utilization of content-based access techniques to visual data have been presented also or are already implemented. In the USA, a biomedical research network is going to be set up & the sharing of visual information & their management incorporate the utilization of similarity queries. Multidimensional biological images from different devices are used in the Bio Image project.

VII. Techniques Used in Medical Image Retrieval

This segment explains the different methods that are presently-used or that have been proposed for the utilization in medical image retrieval applications. Many of the methods are almost same to those used for general content-based retrieval but also methods that have not yet been utilized in medical applications are recognized. A specific objective centered on the data sets that are utilized to assess the image retrieval systems & on the measurements utilized for assessment. But, the performance assessment of systems is presently strongly ignored. Additionally,

machine learning in medical uses gets ever more importance & it is necessary to research numerous possibilities. Specialized work-shops exist for this area [164].

a) Features used

This portion explains the (visual) characteristic that are utilized in the different applications. In this segment text is added to examine whether this ought to be named content-based retrieval or rather not. As the formulation of similarity queries instead of text might be somewhat problematic, another subsection is added to depict the different prospects to formulate queries without text.

i. Query formulation

The query formulation with using entirely visual characteristics can be a huge issue. Maximum systems in CBIR use the query by example(s) (QBE) paradigm which require an proper starting image for querying. This problem of a sometimes missing starting image is well-known as the page zero problem.

If text is attached to the images, which is generally the case in medical applications, then the text can be utilized as a beginning stage & once visually relevant images have been found, further queries can be completely visual to discover visually similar cases not

able to be found by text or to sort the found cases by their visual resemblance. In the medical decision-making procedure, there are frequently images generated & accessible for the current case. At the beginning stage does not necessary to be further defined but the images of the case can be utilized directly. With regard to the segmentation of the images the user can additionally limit the query to some region of interest (ROI) in the image, which can lead to much more particular queries than if utilizing an image in its whole.

The use of human sketches has already been presented in basic image retrieval &it has additionally been presented for the utilization in medical applications. In view of the difficulty in exact drawing & the necessity for some artistic skills & time, this technique will only be appropriate for a very small subset of queries, for example, tumor shapes or spine X-rays, where sketches are possible directly in the image. For general image retrieval, sketches are excessively time-consuming & the retrieved results regularly not exact enough.

ii. *Text*

Numerous frameworks presented to utilize text from the patient record or studies to search by content. Others characterize a context-free grammar, a standardized vocabulary for image description [106] organ image definition language for the querying of images in image repositories utilizes text from radiology reports to change it into ideas in the UMLS meta thesaurus to then retrieve the images. The utilization of text for queries is undeniable efficient but the question is whether this can actually be called content-based queries as the text does not essentially define the image content. It rather puts the images into the context they have been taken in, so it ought to be called context-based queries as defined in [95]. The combination of textual with visual features or content & context of the images does have the most possibility to lead to good outcomes [21]. One can likewise be utilized to control the quality of the other or to get an improved recall of the retrieval results.

Other than the free text that is often used for retrieval, medical patient records like wise comprise extremely valuable structured information, for example, age, sex & profession of the patient. This information is just as significant as free text to put the images into a context.

iii. *Visual features*

Unfortunately, most articles that propose content-based queries don't clarify thoroughly which visual features have been utilized or are intended to be used. Some of the times, just a very vague depiction, for example, general texture & color or grey level features are given as in [51].

Mostly all the systems that do give details use color & grey level features, typically in the form of a histogram [107, 108]. Local & global grey level features are utilized, in [99]utilized statistical distributions of grey levels for the classification of images & presents a brightness histogram. Since a number of images in the medical domain don't have colors or are taken under controlled conditions, the color properties are not in any way in the focus point of research & the same holds for invariants to lighting conditions. This can alter during using photographs, for example, in dermatology. Pathologic images will require to be normalized in some way as various staining techniques can generate diverse colors. In radiology, the normalization of grey levels between various modalities or even for the same modality can bring about problems when there is no definite reference point as is for the density of the CT.

As color & grey level features are of less significance in medical images with compare to in stock photography, the texture & shape features achieve in importance. Actually the majority of the standard methods for texture characterization are utilized from edge detection utilizing Canny operators [103] to Sobel descriptors [113]. [21,101,113] additionally utilized Fourier descriptors to classify shapes, [21] use invariant moments & [21] also scale-space filtering. Features derived from co-occurrence matrices are also regularly utilized [81, 118], along with responses of Gabor filter, wavelets & Markov texture properties. In mammography, denseness is utilized to find small nodules. It is intriguing to have a comparison of a few texture descriptors. A significant number of them model the same information & will probably deliver very similar results.

With regard to segmentation, the shape of the segments can be utilized as a powerful feature. Yet again, the exact nature of the shape features is not explained [112] which makes it impossible to define what exactly had been used. In [108] no segmentation has been carried out for the gaining of shape features but computer-assisted outlining. The segmentation of pathologic images is explained in [102]. In [122] even shape descriptors for 3D structures utilizing modal modeling are explained. Most common shape descriptors are Fourier descriptors [37,117,103] that simply permit to get invariant descriptions. The pattern spectrum is presented in [110] & morphological features are utilized in [110].

Utilizing segments in the images also permits utilizing spatial relationships as visual descriptors of the images. This is frequently proposed [111] but hardly any detail is given on how to obtain the objects/segments in the images, which does not allow to judge whether an implementation is possible. Another research paper shown interest on the issues of automatic segmentation.

The utilization of Eigen images for the retrieval of medical images in analogy to Eigen faces for face

recognition is presented in [62]. These features can be utilized for categorization when many images for every class exist. Still, the features are absolutely statistical & it is difficult to actually describe the comparability of two images on the basis of these features which can more effectively be carried out for a histogram intersection, for instance.

Like generic CBIR, semantic features are presented for visual similarity queries with medical images [107]. But then also, it comes down to simple textual labels attached to the images & a mapping between the text & the low-level features. A project to attach semantic labels automatically to images or regions is explained in [105]&in Project Image.

VIII. Summary and Future Directions

Various methodologies in the literature have been approved for various image modalities & clinical applications (breast cancer, spinal conditions, etc.). The multiplicity of 2D CBIR research has led to numerous 2D methodologies being implemented to images with higher dimensions, e.g., the representation of volumetric images using key slices.

The Image CLEF medical retrieval task has motivated research into retrieval from different datasets. The CBIR technologies made as part of the task are well positioned to to handle the difficulties in clinical environments where a variety of image modalities are obtained. Specifically, the Image CLEF task has prompted the improvement of methods for characterizing image modalities on the basis of features. In previous years, maximum of the images in the Image CLEF medical dataset were inherently 2D or 2D constructions of multidimensional data. The dataset is extending to incorporate volumetric, dynamic & multimodality images to motivate further research into the retrieval of such data.

The use of non-image features to complement image features has been broadly studied because all patients have some related textual data, for instance clinical reports & measurements. It has been shown that merging visual features together with text data enhance the precision of the search, however further research is important to make the contribution of this combination statistically significant [67].

In this survey, we have presented the evolution of CBIR towards the retrieval of multidimensional & multimodality images. While incredible advancement has been made, there are still a few difficulties to be solved. In the next portion, we explained particular areas for forthcoming research that ought to be pursued to enhance CBIR abilities for multidimensional & multimodality medical image retrieval from repositories comprising a different collection of data.

a) Visualization and User Interfaces

There has been inadequate research into visualization technique for CBIR framework, with maximum research work concentrating on enhancing retrieval accuracy & speed. Though, image retrieval tasks are generally done for a specific purpose. In medicine, these purposes can incorporate image-based reasoning, image-based training, or research. As such, a viable technique for demonstrating the images to the user is a critical part of CBIR systems.

Present research works that already discuss about these issues are frequently 2D or key slice CBIR systems, e.g. [127] for non-medical images. The introduction of multidimensional & multimodality data presents new visualization difficulties. CBIR systems require to have the ability to display multiple volumes or time series (one for every retrieved image), along with fusion information in the case of multimodality images. The systems need to improve hardware utilization, particularly when volume rendering is being utilized. Moreover, Tory & Moller [128] proposed many human factors that also need to be considered to facilitate the interpretation of visualized data by users. The visualization ought to exploit the retrieval procedure to show why the retrieved images are significant.

The development in the area of effective user interfaces is gaining interest, particularly if the CBIR systems are to be trialed in clinical settings. The guidelines of user inter face to search applications have to be pursued to guarantee that users can easily incorporate the CBIR system into their clinical workflow. Context-aware multimodal search interfaces, e.g. [129], ought to be followed to provide users the flexibility to solve the sensory & semantic gaps.

b) Feature Selection

The dimensionality has been a problematic area all the time for medical CBIR algorithms & stays significant as algorithms are developed for cutting edge medical images. Feature extraction & selection algorithms should develop a core component of retrieval techniques to guarantee that indexing & retrieval can be executed in an effective way. Methods that extract multidimensional local features from each pixel are no more viable for volume & types of images routinely gained in modern hospitals.

Moreover, the growing clinical usage of multi-modality images provides the chance to derive complementary information from various modalities, the combination of which will give extra multidimensional features that might not be obtainable from a single image type. Up coming research work should make full utilization of these features by characterizing similarity in terms of features from both modalities. Likewise, useful indexing features can potentially be extracted from the relationships between ROIs in diverse modalities. Feature selection algorithms should inspect the balance between features from individual modalities, along with relationship features between modalities.

c) Multidimensional Image Processing

Multidimensional images are currently developed as a routine part of clinical work processes. However, in spite of the predominance of volumetric images (CT, PET, MR, etc.) & time-varying images (4D CT, dynamic PET, & MR), some medical CBIR algorithms accept key slices to represent the complete set of multidimensional image data. While this has demonstrated viable in a few situations, it is exceptionally reliant on the selection of appropriate key slices; manual selection is subjective. In applications where key slices are still feasible, subjective determination can be kept away from utilizing a selection algorithm trained by unsupervised learning, as in [130]. In another cases, the utilization of key slices may not be possible as it may loss spatial information, for instance clinically relevant information (a fracture, multiple tumors, etc.) that is spread over numerous sites & slices. Several key slices, as in [91, 130], become less feasible in cases where the disease possibly spreads all through the body, e.g., cancer. As such, it is essential that upcoming medical CBIR research work do not depend on key slices & are enhanced to work directly on the rich multidimensional image data gained in modern hospitals.

The direct utilization of multidimensional images will need the incorporation of image processing methods (compression, segmentation, registration, etc.) that are intended for such images. The trend towards utilizing local features in general CBIR [4] shows that the improvement of correct segmentation algorithms will become important for the advancement of ROI-based CBIR solutions. The effectiveness of some present algorithms will additionally require to be enhanced for real-time operation. For instance, a new adaptive local multi-atlas segmentation algorithm [130] needs about 30 min to segment the heart from chest CT scans with a mean accuracy of about 87 %; this kind of processing times are not viable for rapid data access.

Registration will be essential to retrieve multimodality images. Specifically, registration will be required to extract the relational features, segmentation tumors given anatomical priors, & fused visualization. Luckily, hybrid multimodality PET-CT & PET-MR scanners inherently provide co-alignment information that can be utilized for these reason.

d) Standardized Datasets for Evaluation

Most of the medical CBIR research work is assessed on the basis of private datasets that are collected for particular studies or purposes, for instance, retrieval of lung cancer images. These datasets are presented in the research work where they are utilized. This kind of datasets have the benefit of allowing CBIR that is enhanced for specific clinical applications or objectives. Additionally, it has the possibility to enhance the results by decreasing the number of variables that the algorithm must consider, e.g., by having fixed image acquisition protocols, devices, resolutions, etc. In this way, researchers can resolve a particular issue before generalizing their algorithms for a wider array of circumstances.

Though, the utilization of private datasets makes it hard to compare diverse CBIR algorithms across various research work. To ease this issue, there has been a push for the creation & utilization of huge & varied publicly accessible datasets with standardized gold standards or ground truth. We list a few such datasets in this segment.

The Image CLEF medical image dataset [72] have more than 66,000 images between 2005 & 2007. The collection was derived from many sources & contained radiology, pathology, endoscopic, & nuclear medicine images. In 2013, the Image CLEF medical image task had over 300,000 images comprising MR CT, PET, ultrasound, & combined modalities in one image.

The PEIR Digital Library [12] is a free pathology image database for medical education. Text descriptions have also been added to the images in this database as its main purpose was for the creation of teaching materials. These text descriptions can present the ground truth from which retrieval algorithms can be assessed.

The National Health & Nutrition Examination Surveys (NHANES)were a family of surveys carried out more than 30 years to monitor several health trends in the USA. The dataset comprise of spine X-ray images (as used in [35]), along with hand & knee X-rays. Though, just a portion of this dataset is freely accessible.

The Cancer Imaging Archive (TCIA) is a set of quite a few image collections, each of which was built for a specific reason, for instance the Lung Imaging Database Consortium (LIDC) [107] of chest CT & X-rays. The images in the TCIA collection comprised of several different image modalities, many subjects & several forms of supporting data.

To allow retrieval on huge collections, the VISCERAL project is a new initiative where main objective is to give 10 TB of medical image data for research & validation. Specifically, the project expects to hold challenges that exploit the knowledge stored in repositories for the improvement of diagnostic instruments. The VISCERAL dataset will be included two annotation standards: a gold corpus annotated by domain experts & a silver corpus annotated by deriving a consensus among research systems developed by challenge participants.

e) Clinical Adoption

There is a lack of clinical examples of CBIR us fullness in site of many years of CBIR research. This is partly because of the focus of most medical CBIR research: solving technical challenges (enhancing feature selection, similarity measurement) contrasted

with fulfilling a clinical goal. Likewise, the greater part of CBIR research is assessed only in nonclinical environments; association between physicians & computer scientists is generally limited to sharing data. Clinical assessment of CBIR will permit the examination of the advantages & downsides of current algorithms & will enable more prominent clinical importance in upcoming CBIR research.

The utilization of medical literature to guide CBIR design is another area that need research. Disease staging & classification schemes in cancer [109, 110] deliver contextual information that can be utilized to improve medical CBIR systems on the basis of the guidelines utilized by physicians. Moreover, the integration of medical terminology in ontologies like RadLex & the Unified Medical Language System [19] by learning correspondences between image features & text labels ought to be investigated for the case of multidimensional images.

Closer communication is required with clinical staff to guarantee that medical CBIR research has results that are relevant to health care. Clinical staff have to be involved in the design of CBIR systems; medical specialists should be consulted particularly if a domain-specific paradigm [4] is being adapted. An example of this kind of research is presented by Depeursinge et al. [2], who implemented three clinical work process to help students, radiologists, & physicians in the diagnosis of interstitial lung disease utilizing a hybrid detection-CBIR diagnosis system. The implementation of CBIR research as essential components of the clinical work process, compare to stand-alone applications, will enable its adoption in routine clinical practice [21].

In content based image retrieval, there are several problems that one can define to explain the variations between the growth of CBIR systems in the literature and the lack of their use in applications. The sensory and semantic gaps present in the image are the major problems to be eliminated as it may lead to lose of the information content in any image. Especially in medical images, which are complex to be retrieved form the database as it may contain more noises because of the uncertainty of defined features. To get rid of these problems and to develop a new idea in CBIR medical analysis, it is essential to analyze systems presented in the literature on their possibility to minimize the gaps.

The survey shows that many algorithms proposed earlier aims at reducing the seriousness caused by the feature gaps and to increase the accuracy and exactness of the retrieval process from the databases. Dealing with the two modalities such as 2D and 3D perspective view becomes active research in all of the developing algorithms. Generally, the multi-dimensional images are likely to be affected by the misclassification factor, which further reduces the clarities In addition, the reports generated by analysis of

algorithm depicts that all finds difficulty of measuring the similarities between the input image and images in the database, which further leads to occurrence of false positive data result. The level of precision and exactness is lost when more number of false positive data are generated by the algorithm. To satisfy this criteria, our system focuses on the iterative development of the similarity measurement to reduce the false positive maximum.

The other problem that affects the retrieval accuracy is noisy factors, which tend to appear in medical images as the center pixel is affected or hided by the surrounding pixels present in the features. The selection of suitable enhancement and filtering techniques to solve the invariance in pixels can be adopted in our method to eliminate the problems caused by noises. Thus, the factors affecting the retrieval of the multidimensional view of the medical image as discussed above are identified from the existing systems and the design of our proposed algorithm is promoted.

X. Conclusions

The large number of research publications in the field of content-based medical image retrieval especially in recent years shows that it is very active and that it is starting to get more attention. This will hopefully advance the field as new tools and technologies will be developed and performance will increase. Content-based visual information retrieval definitely has a large potential in the medical domain. The amount of visual data produced in medical departments shows the importance of developing new and alternative access methods to complement text. Content-based methods can be used on a large variety of images and in a wide area of applications. Still, much work needs to be done to produce running applications and not only research prototypes. When looking at most current systems, it becomes clear that few to none of them are actually in routine use.

In this review, we examined how state-of-the-art medical CBIR studies have been applied in the retrieval of 2D images, 3D images with multiple dimensions, and multimodality images from repositories containing a diverse collection of medical data. We also examined the manner in which non-image data were used to complement visual features during the retrieval process. The development of open toolboxes is another important factor for successful applications. Not only do interfaces for the communication with other applications need to be developed, also within the application it is important to stay modular, and so parts and pieces can be exchanged easily. This will help to reduce the number of applications developed and will make it possible to spend more time on the important tasks of integration and development of new methods and system optimizations.

It is clear that new tools and methods are needed to manage the increasing amount of visual information that is produced in medical institutions. Content-based access methods have an enormous potential when used in the correct way. It is now the time to create medical applications and use this potential for clinical decision-making, research and teaching.

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