ISSN 2250-3153

Content Based Image Retrieval in Biomedical Images Using SVM Classification with Relevance Feedback

Sukhada Aloni

Abstract- Content-based image retrieval (CBIR) framework for diverse collection of medical images of different imaging modalities, anatomic regions with different orientations and biological systems is proposed. Organization of images in such a database (DB) is well defined with predefined semantic categories; hence, it can be useful for category-specific searching. The proposed framework consists of machine learning methods for image pre-filtering, similarity matching using statistical distance measures, and a relevance feedback (RF) scheme.

In this framework, the probabilistic outputs of a multiclass support vector machine (SVM) classifier as category prediction of query and database images are exploited at first to filter out irrelevant images, thereby reducing the search space for similarity matching. Images are classified at a global level according to their modalities based on different low-level, concept, and key point-based features. It is difficult to find a unique feature to compare images effectively for all types of queries. Hence, a query-specific adaptive linear combination of similarity matching approach is proposed by relying on the image classification and feedback information from users. These images constitute an important source of anatomical and functional information for the diagnosis of diseases, medical research, and education. Effectively and efficiently searching in these large image collections poses significant technical challenges as the characteristics of the biomedical images differ significantly from other general purpose images.

Index Terms- Content Based Image Retrieval (CBIR), Medical Images, Support Vector Machine (SVM), Relevance Feedback (RF)

I. INTRODUCTION

Technique based on image or visual contents usually referred as features for the purpose of searching images with respect to request and interest of user from large image databases. In this paper content based image retrieval method is used as diagnosis aid in medical fields with the advent of imaging, clinical care could be significantly impacted with improved image handling. In recent years, rapid advances of software and hardware technology have made easy, the problem of maintaining large medical image collections Visual features as color, and shape and texture are implemented for retrieval of images. Traditional methods of image indexing have been proven neither suitable nor efficient in terms of space and time so it triggered the development of the new technique. It is a 2 step process where image features are extracted in first step to a distinguishable extent. In second step matching of features which are visually similar is done. The two retrieval systems namely, content and text based retrieval systems differ in the sense that the indispensable part of latter system is human interaction. High level features as keywords, text description uses by humans to measure similarity and image interpretation. Image retrieval system is an effective and efficient tool for managing large image databases. A content based image retrieval system allows the user to present a query image in order to retrieve images stored in the database according to their similarity to the query image [8][13].

Content based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content based image retrieval is opposed to concept based approached. “Content-based” means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term ‘content’ in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

The term Content-Based Image Retrieval (CBIR) seems to have originated in 1992, when it was used by T. Kato to describe experiments into automatic retrieval of images from a database, based on the colors and shapes present. Since then, the term has been used to describe the process of retrieving desired images from a large collection on the basis of syntactical image features.

Feature (content) extraction is the basis of content-based image retrieval. In a broad sense, features may include both text-based features (key words, annotations) and visual features (color, texture, shape, faces). However, since there already exists rich literature on text-based feature extraction in the data base management system and information retrieval research communities, we will confine ourselves to the techniques of visual feature extraction. Within the visual feature scope, the features can be further classified as general features and domain specific features [1][14].

Content-based image retrieval (CBIR) is the application of computer vision to the image retrieval problem, i.e., the problem of searching for digital images in large databases. “Content-based” means that the search makes use of the contents of the images themselves, rather than relying on textual annotation or human-input metadata. The visual features used for indexing and retrieval are classified in into three classes: primitive features that are low-level features such as color, shape and texture; logical features that are medium-level features describing the image by a collection of objects and their spatial relationships; and abstract feature that are semantic and contextual features. The obvious loss of information from image data to a representation by abstract features is called the semantic gap and constitutes nowadays a major research topic in this field. In order to close this semantic gap to improve retrieval performances, specialized retrieval systems have been proposed in literature[2]. Indeed, the more specialized the application is for a limited domain, the smaller the gap can be made using domain knowledge. Nonetheless, the concepts for medical image retrieval are limited to a particular modality, organ, or diagnostic study and, hence, usually not directly transferable to other medical applications.

II. PROPOSED METHOD

The objective of this paper is to develop and implement high-level methods for CBMIR with applications in medical-diagnosis tasks on radiological image archive. Based on a general structure for semantic image analysis that results in 6 layers of information modeling, Image Retrieval in Medical Applications (IRMA) is implemented with distributed system architecture suitable for large databases. And the main objective is to design a framework for classification driven biomedical image retrieval framework based on image filtering and similarity fusion by employing supervised learning technique. In our proposed method we have presented to evaluate the effectiveness of the proposed retrieval approach, exhaustive experiments were performed in a medical image collection. The collection comprises of 5 000 biomedical images of 30 manually assigned disjoint global categories, which is a subset of a larger collection of six different datasets used for retrieval evaluation campaign in Image CLEF 1 under the medical image retrieval track in 2007[4] [18]. In this collection, images are classified into three hierarchical levels. In the first level, images are categorized according to the imaging modalities (e.g., X-ray, CT, MRI, etc.). Next level is the image body part, and the final level is the orientation. The categories are selected based on analyzing the visual and some mixed-mode query topics during these three years (2005, 2006, and 2007) of Image CLEF campaign under the medical retrieval task. Around 80% of the images are gray level (e.g., X-ray, CT, and MRI) and 20% are color images (e.g., microscopic pathology, histology, dermatology) with varying resolutions[10].

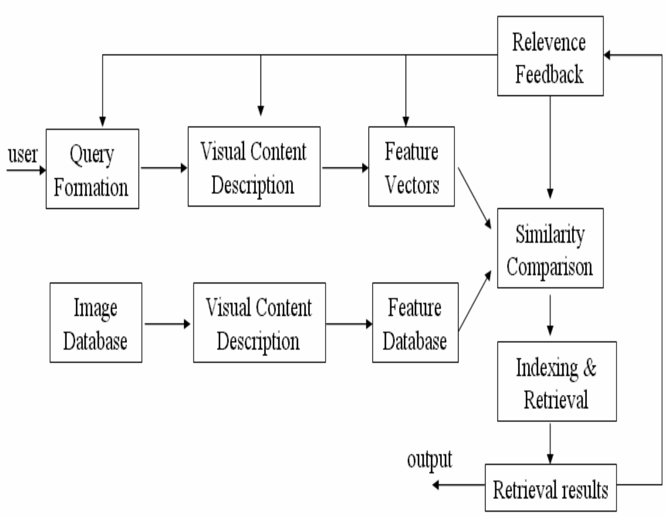

Fig 1: Content-Based Image Retrieval System.

A. Data Set

For the implementation of Content-Based Biomedical Image Retrieval Using SVM Classification and Relevance Feedback system a data set collected from different source for various class of Medical image is considered. Figure shows the database considered for the implementation. The collected Medical images are human body (or parts and function thereof) for clinical purposes (medical procedures seeking to reveal, diagnose or examine disease) or medical science (including the study of normal anatomy and physiology). Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are not usually referred to as medical imaging, but rather are a part of pathology and passed for implementation.

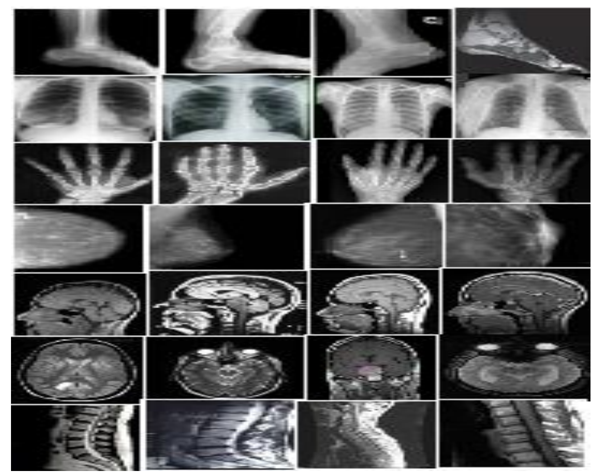

Fig.2: A Typical Example of the Used Bio Medical Images.

B. Content-Based Image Retrieval

In early days because of very large image collections the manual annotation approach was more difficult. In order to overcome these difficulties Content Based Image Retrieval (CBIR) was introduced. Content-based image retrieval (CBIR) is the application of computer vision to the image retrieval problem. In this approach instead of being manually annotated by textual keywords, images would be indexed using their own visual contents .The visual contents may be color, texture and shape. This approach is said to be a general framework of image retrieval [3][16].There are three fundamental bases for Content Based Image Retrieval which are visual feature extraction, multidimensional indexing and retrieval system design. The color aspect can be achieved by the techniques like averaging and histograms. The texture aspect can be achieved by using transforms or vector quantization .The shape aspect can be achieved by using gradient operators or morphological operators. Some of the major areas of application are Art collections, Medical diagnosis, Crime prevention, Military, Intellectual property, Architectural and engineering design and Geographical information and Remote sensing systems [1] [5].

Retrieval Based on Color: Several methods for retrieving images on the basis of color similarity are being used. Each image added to the database is analyzed and a color histogram is computed which shows the proportion of pixels of each color within the image. Then this color histogram for each image is stored in the database. During the search time, the user can either specify the desired proportion of each color (for example, 75% olive green and 25% red), or submit a reference image from which a color histogram is calculated. The matching process then retrieves those images whose color histograms match those of the query most closely [17].

Retrieval Based on Structure: The ability to match on texture similarity can often be useful in distinguishing between areas of images with similar color. A variety of techniques has been used for Measuring texture similarity in which the best established rely on comparing values of what are known as second order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity, or periodicity, directionality and randomness. Alternative methods of texture analysis for retrieval include the use of Gabor filters and fractals. Texture queries can be formulated in a similar manner to color queries, by selecting examples of desired textures from a palette, or by supplying an example query image[17]. A recent extension of the technique is the texture thesaurus, which retrieves textured regions in images on the basis of similarity to automatically-derived code words representing important classes of texture within the collection.

Retrieval Based on Shape: The ability to retrieve by shape is perhaps the most obvious requirement at the primitive level. Unlike texture, shape is a fairly well-defined concept and there is considerable evidence that natural objects are primarily recognized by their shape. A number of features characteristic of object shape (but independent of size or orientation) are computed for every object identified within each stored image. Queries are then answered by computing the same set of features for the query image, and retrieving those stored images whose features most closely match those of the query. Two main types of shape feature are commonly used global features such as aspect ratio, circularity and moment invariants and local features such as sets of consecutive boundary segments. Alternative methods proposed for shape matching have included elastic deformation of templates, comparison of directional histograms of edges extracted from the image, and shocks, skeletal representations of object shape that can be compared using graph matching techniques. Queries to shape retrieval systems are formulated either by identifying an example image to act as the query, or as a user-drawn sketch.

Retrieval Based on Other Features: One of the oldest-established means of accessing pictorial data is retrieval by its position within an image. Accessing data by spatial location is an essential aspect of geographical information systems, and efficient methods to achieve this have been around for many years. Similar techniques have been applied to image collections, allowing users to search for images containing objects in defined spatial relationships with each other. Improved algorithms for spatial retrieval are still being proposed. Spatial indexing is seldom useful on its own, though it has proved to be effective in combination with other factors such as color and shape. Several other types of image feature have been proposed as a basis for CBIR. Most of these rely on complex transformations of pixel intensities which have no obvious counterpart in any human description of an image. Most such techniques aim to extract features which reflect some aspect of image similarity which a human subject can perceive, even if he or she finds it difficult to describe. The well-researched technique of this kind uses the wavelet transform to model an image at several different resolutions. Promising retrieval results have been reported by matching wavelet features computed from query and stored images. Another method giving interesting results is retrieval by appearance. The advantage of all these techniques is that they can describe an image at varying levels of detail (useful in natural scenes where the objects of interest may appear in a variety of guises), and avoid the need to segment the image into regions of interest before shape descriptors can be computed. Despite recent advances in techniques for image segmentation, this remains a troublesome problem.

C. Relevance Feedback (RF):

Relevance feedback is a significantly important algorithm which attempts to reduce the gap between the two levels of features, namely high and low. [7].

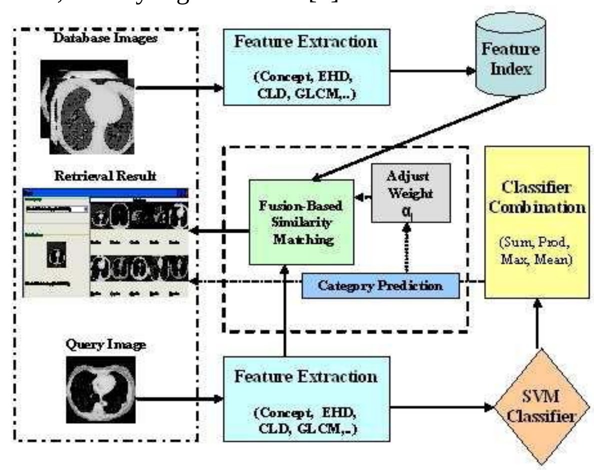

Fig 3: Block diagram of the classification-driven similarity fusion framework.

Relevance feedback was originally developed for improving the effectiveness of information retrieval systems. The main idea of relevance feedback is for the retrieval system to understand the user's information needs[15]. For a given query, the retrieval system returns initial results based on pre-defined similarity metrics. Then, the user is required to identify the positive examples by labeling those that are relevant to the query. The system subsequently analyzes the user's feedback using a learning algorithm and returns refined results. A typical relevance feedback mechanism contains a learning component and a dispensing component. The learning component uses the feedback data to estimate the target of the user. The approach taken to learn feedback data is key to the relevance feedback mechanism. In addition to the visual concept feature, we extract the global features. First one is , Color Feature: To represent the spatial structure of images, we utilize the Color Layout Descriptor (CLD) of MPEG- 7 [19]. The CLD represents the spatial layout of the images in a very compact form. It is obtained by applying the discrete cosine transformation (DCT) on the 2-D array of local representative colors in the YCbCr color space where Y is the luma component and Cb and Cr are the blue and red chroma components. Each channel is represented by 8 bits and each of the 3 channels is averaged separately for the 8 × 8 image blocks. In this work, a CLD with only 10 Y, 3 Cb, and 3 Cr, is extracted to form a 16-dimensional feature vector. Second One is Edge Feature: To represent the global shape/edge feature, the spatial distribution of edges are utilized by the Edge Histogram Descriptor (EHD) [9]. The EHD represents local edge distribution in an image by dividing the image into 4×4 sub-images and generating a histogram from the edges present in each of these sub-images. Third one is Texture Feature: We extract texture features from the grey level co-occurrence matrix (GLCM) of each image. In order to obtain efficient descriptors, the information contained in GLCM is traditionally condensed in a few statistical features[15]. Four GLCM's for four different orientations (horizontal 0◦,vertical 90◦, and two diagonals 45◦ and 135◦) are obtained and normalized to the entries [0,1] by dividing each entry by total number of pixels. Higher order features, such as energy, entropy, contrast, homogeneity and maximum probability are measured based on averaging features in GLCMs to form a 20-dimensional feature vector for an entire image Finally, two more features are extracted as Color Edge Direction Descriptor (CEDD) and Fuzzy Color Texture Histogram (FCTH) from the Lucene image retrieval (LIRE) library CEDD incorporates color and texture information into one single histogram and it requires low computational power in extracting comparing to MPEG7 descriptors. To extract texture information, CEDD uses a fuzzy version of the five digital filters proposed by the MPEG-7 EHD, forming 6 texture areas. This descriptor is appropriate for accurately retrieving images even in distortion cases such as deformation, noise and smoothing. In contrast, FCTH uses the high frequency bands of the Haar wavelet Transform in a fuzzy system, to form 8 texture areas [1][9].

Support Vector Machine (SVM) is a useful learning approach in relevance feedback. The dispensing component should provide the most appropriate images after obtaining feedback from the user. However, the dispensing component has two conflicting goals during each feedback round. On the one hand, the dispensing component has to provide as many relevant images as possible. On the other hand, the dispensing component, based on the information needs of the user, has to investigate the images of unknown relevance to the target. As the dispensing component returns more relevant images to the user, it has fewer images to mine the needs of the user at each round, and vice versa. A sensible strategy also plays an important role in relevance feedback. Hence, approaches to learning user feedbacks and dispensing strategies for returning the results both determine the performance of relevance feedback mechanisms.[14],

Relevance feedback is a feature of some information retrieval systems. The idea behind relevance feedback is to take the results that are initially returned from a given query and to use information about whether or not those results are relevant to perform a new query. We can usefully distinguish between three types of feedback: explicit feedback, implicit feedback, and blind or "pseudo" feedback.

D. *Support vector machine:*

A support vector machine (SVM) is a concept in statistics and computer science for a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The standard SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the input, making the SVM a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on[11][12].

E. *Image Content Descriptors:*

Generally speaking, image content may include both visual and semantic content. Visual content can be very general or domain specific. General visual content include color, texture, shape, spatial relationship, etc. Domain specific visual content, like human faces, is application dependent and may involve domain knowledge. Semantic content is obtained either by textual annotation or by complex inference procedures based on visual content. This chapter concentrates on general visual contents descriptions. Later chapters discuss domain specific and semantic contents. A good visual content descriptor should be invariant to the accidental variance introduced by the imaging process (e.g., the variation of the illuminant of the scene)[6].

However, there is a trade-off between the invariance and the discriminative power of visual features, since a very wide class of invariance loses the ability to discriminate between essential differences. Invariant description has been largely investigated in computer vision (like object recognition), but is relatively new in image retrieval. A visual content descriptor can be either global or local. A global descriptor uses the visual features of the whole image, whereas a local descriptor uses the visual features of regions or objects to describe the image content. To obtain the local visual descriptors, an image is often divided into parts first. The simplest way of dividing an image is to use a partition, which cuts the image into tiles of equal size and shape. A simple partition does not generate perceptually meaningful regions but is a way of representing the global features of the image at a finer resolution. A better method is to divide the image into homogenous regions according to some criterion using region segmentation algorithms that have been extensively investigated in computer vision. A more complex way of dividing an image, is to undertake a complete object segmentation to obtain semantically meaningful objects (like ball, car, horse). Currently, automatic object segmentation for broad domains of general images is unlikely to succeed. In this section, we will introduce some widely used techniques for extracting color, texture, shape and spatial relationship from images[7].

Color: Color is the most extensively used visual content for image retrieval. Its three-dimensional values make its

ISSN 2250-3153

discrimination potentiality superior to the single dimensional gray values of images. Before selecting an appropriate color description, color space must be determined first.

Color Space: Each pixel of the image can be represented as a point in a 3D color space. Commonly used color space for image retrieval include RGB, Munsell, CIE L*a*b*, CIE L*u*v*, HSV (or HSL, HSB), and opponent color space. There is no agreement on which is the best. However, one of the desirable characteristics of an appropriate color space for image retrieval is its uniformity

Color Moments: Color moments have been successfully used in many retrieval systems (like QBIC), especially when the image contains just the object. The first order (mean), the second (variance) and the third order (skewness) color moments have been proved to be efficient and effective in representing color distributions of images. Mathematically, the first three moments are

$$\mu_1 = \frac{1}{N}\sum_{J=1}^{N} fij \qquad (1)$$

$$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N} (fij - \mu_i)^2 \right)^{\frac{1}{3}} \qquad (2)$$

$$Si = \left(1/N \sum_{J=1}^{N} (f_{ij} - \mu_i)^3 \right)^{\frac{1}{3}} \qquad (3)$$

where fij is the value of the i-th color component of the image pixel j, and N is the number of pixels in the image. Usually the color moment performs better if it is defined by both the L*u*v* and L*a*b* color spaces as opposed to solely by the HSV space Using the additional third-order moment improves the overall retrieval performance compared to using only the first and second order moments. However, this third-order moment sometimes makes the feature representation more sensitive to scene changes and thus may decrease the performance. Since only 9 (three moments for each of the three color components) numbers are used to represent the color content of each image, color moments are a very compact representation compared to other color features. Due to this compactness, it may also lower the discrimination power. Usually, color moments can be used as the first pass to narrow down the search space before other sophisticated color features are used for retrieval.

Color Histogram: The color histogram serves as an effective representation of the color content of an image if the color pattern is unique compared with the rest of the data set. The color histogram is easy to compute and effective in characterizing both the global and local distribution of colors in an image. In addition, it is robust to translation and rotation about the view axis and changes only slowly with the scale, occlusion and viewing angle. Since any pixel in the image can be described by three components in a certain color space (for instance, red, green, and blue components in RGB space, or hue, saturation, and value in HSV space), a histogram, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component.

Color Coherence Vector: In previous work a different way of incorporating spatial information into the color histogram, color coherence vectors (CCV), was proposed. Each histogram bin is partitioned into two types, i.e., coherent, if it belongs to a large uniformly-colored region, or incoherent, if it does not. Let αi denote the number of coherent pixels in the ith color bin and βi denote the number of incoherent pixels in an image. Then, the CCV of the image is defined as the vector <(α1, β1), (α2, β2), …, (αN, βN)>. Note that <α1+β1, α2+β2, …, αN+βN> is the color histogram of the image. Due to its additional spatial information, it has been shown that CCV provides better retrieval results than the color histogram, especially for those images which have either mostly uniform color or mostly texture regions.

Color Correlogram: The color correlogram was proposed to characterize not only the color distributions of pixels, but also the spatial correlation of pairs of colors. The first and the second dimension of the three-dimensional histogram are the colors of any pixel pair and the third dimension is their spatial distance.

Shape: Shape features of objects or regions have been used in many content-based image retrieval systems. Compared with color and texture features, shape features are usually described after images have been segmented into regions or objects. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to special applications where objects or regions are readily available. The state-of-art methods for shape description can be categorized into either boundary-based (rectilinear shapes, polygonal approximation, finite element models, and Fourier-based shape descriptors or region-based methods (statistical moments). A good shape representation feature for an object should be invariant to translation, rotation and scaling. In this section, we briefly describe some of these shape features that have been commonly used in image retrieval applications. For a concise comprehensive introductory overview of the shape matching techniques [18].

III. RESULTS

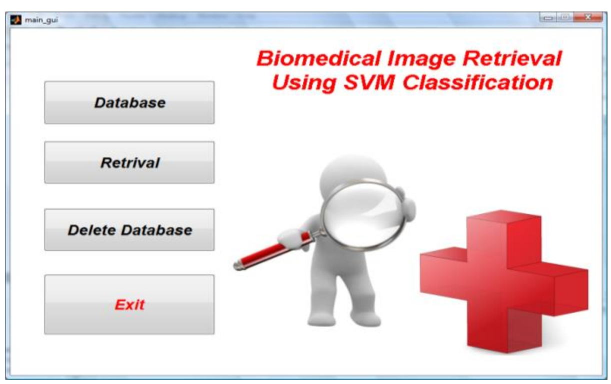

Fig 4: Initial GUI.

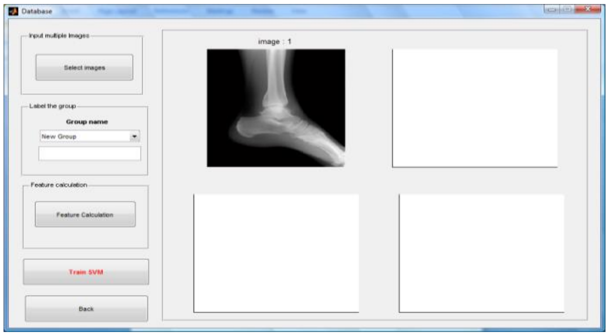

Fig 5: After Clicking Data Base.

Fig 6: Creation of Group

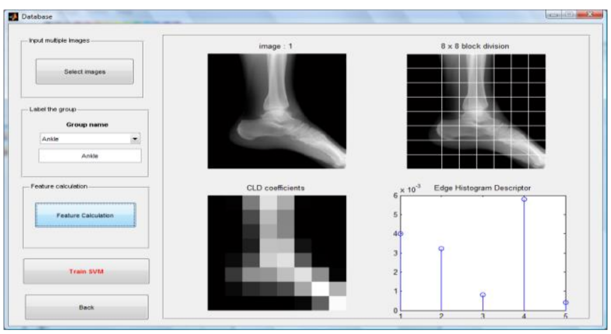

Fig 7: Feature Calculation

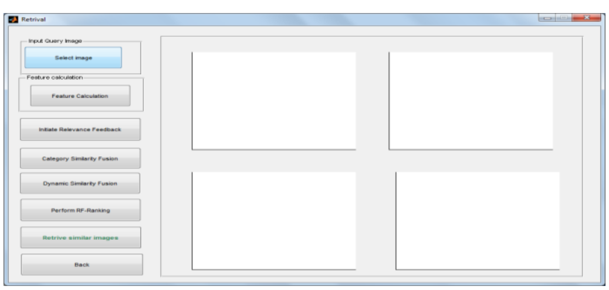

Fig 8: Retrieval window

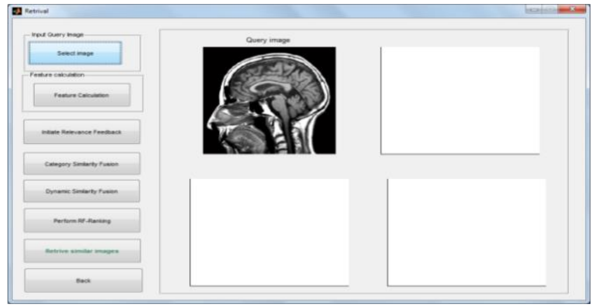

Fig.9: Input Image

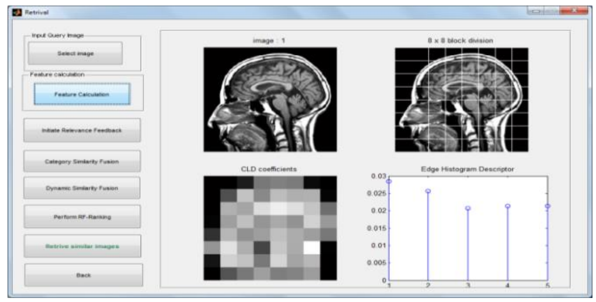

Fig.10: Estimation of Feature parameters

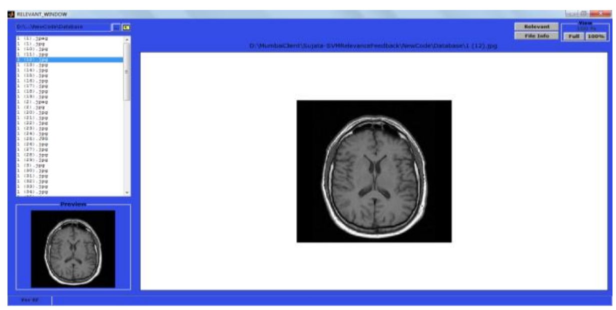

Fig.11: Relevant Selection Window for sample image-1

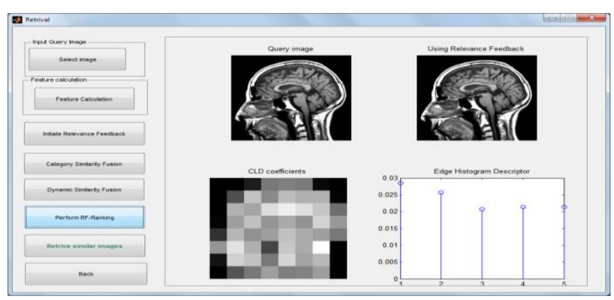

Fig. 14: Performing Final Similarity Match

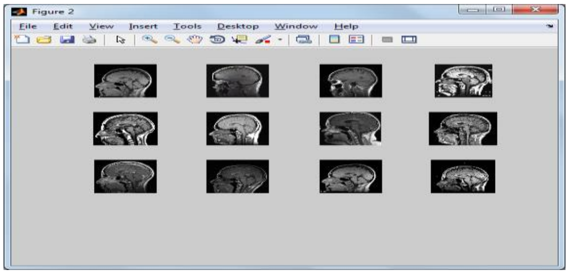

Fig.15: Final Output

IV. CONCLUSION

The goal of medical image databases is to provide an effective means for Organizing, searching, and indexing large collections of medical images. In this paper, a novel learning-based and classification-driven image retrieval framework is proposed for diverse medical image collections of different modalities. In our approach, we directly link classification to retrieval. In this framework, the image category information is utilized directly to filter out irrelevant images and adjust the feature weights in a linear combination of similarity matching. We use the RF-based technique to update the feature weights based on positive user feedback. Retrieval performance is promising and clearly shows the advantage of searching images based on similarity fusion and filtering in terms of effectiveness and efficiency. Overall, this retrieval framework is useful as a front end for large medical databases where a search can be performed in diverse images for teaching, training and research purposes.

REFERENCES

[1] Md Mahmudur Rahman, Sameer K. Antani, and George R. Thoma. "A Learning-Based Similarity Fusion and Filtering Approach for Biomedical Image Retrieval Using SVM Classification and Relevance Feedback". IEEE Transaction On Information Technology in Biomedicine Vol 15, NO. 4, July 2011.

[2] Haiying Guana, Sameer Antania, L. Rodney Longa, and George R. Thomaa "Minimizing the Semantic Gap in Biomedical Content-Based Image Retrieval Medical Imaging 2010: Advanced PACS-based Imaging Informatics and Therapeutic Applications", edited by Brent J. Liu, William W. Boonn, Proc. of SPIE Vol. 7628, 762807 · © 2010 SPIE.

[3] Md Mahmudur Rahman, Sameer K. Antani, George R. Thoma. A Medical Image Retrieval Framework in Correlation Enhanced Visual Concept Feature Space U.S. National Library of Medicine, National Institutes of Health, Bethesda, MD, USA 2009 IEEE.

[4] Thomas M. Lehmanna1, Berthold Weinb, Jörg Dahmenc, Jörg Brednoa, Frank Vogelsangb, and Michael Kohnenb : "Content-Based Image Retrieval in Medical Applications: A Novel Multi-Step Approach:" Aachen University of Technology (RWTH), D - 52057 Aachen, Germany.

[5] Henning M¨uller12, Jayashree Kalpathy–Cramer3, Ivan Eggel1, Steven Bedrick3,Sa¨ıd Radhouani3, Brian Bakke3, Charles E. Kahn Jr.4, William Hersh31 University of Applied Sciences Western Switzerland (HES–SO), Sierre, Switzerland 2University Hospitals and University of Geneva, Switzerland: Overview of the CLEF 2009 medical image retrieval track.

[6] Aleksandra Mojsilovic and Jose Gomes IBM T. J. Watson Research Center, 30 Saw Mill River Road, Hawthorne, NY 10532: Sementic Based Categorization, Browsing and Retrieval in Mediacl Image Databases.

[7] Xiang Sean Zhou1,_, Thomas S. Huang2 Relevance feedback in image retrieval: A comprehensive review: Multimedia Systems 8: 536–544 (2003).

[8] Yong Rui□ Thomas S_ Huang□ Michael Ortega and Sharad Mehrotra: Beckman Institute for Advanced Science and Technology: Relevance Feedback□ A Power Tool for Interactive Content_Based Image Retrieval. IEEE Transactions 0n Circuits and Video Technology

[9] Md Mahmudur & RahmanSameer K. Antani. A Classification-Driven Similarity Matching Framework for Retrieval of Biomedical Images. National Institutes of Health, Bethesda, MD, USA MIR'10, March 29–31, 2010, Philadelphia, Pennsylvania, USA. 2010 ACM 978-1-60558-815-5/10/03.

[10] Roxana TEODORESCU and Daniel RACOCEANU. Prospective Study for Semantic Inter-Media Fusion in Content-Based Medical Image Retrieval: Med Imag Tech Vol.26 No.1 January 2008.

[11] Kai-Bo Duan & S. Sathiya Keerthi BioInformatics Research Centre, Nanyang Technological University, Nanyang Avenue, Singapore 639798. N.C. Oza et al. (Eds.): MCS 2005, LNCS 3541.

[12] Chih-Wei Hsu and Chih-Jen Lin : A omparison of Methods for Multiclass Support Vector Machines. IEEE Transactions 0n Neural Networks, VOL. 13, NO. 2, MARCH 2002.

[13] Chi-Ren Shyu, Carla E. Brodley, Avinash C. Kak, Akio Kosaka. ASSERT: A Physician-in-the-Loop Content-Based Retrieval System for HRCT Image Databases. Computer Vision and Image Understanding Vol. 75, Nos. 1/2, July/August, pp. 111–132, 1999.

[14] Pushpa B. PATIL, Manesh B. KOKARE: Relevance Feedback in Content Based Image Retrieval: Journal of Applied Computer Science & Mathematics, no. 10 (5) /2011.

[15] Henning M¨uller $ Jayashree Kalpathy Overview of the CLEF 2010 medical image retrieval track:Geneva University Hospitals and University of Geneva, Switzerland.

[16] Shrikant. B. Kale: Content Based Image Retrieval : Int. Jr. of Data Modelling and Knowledge Management Vol. 3 No. 1 January-June,2013.

[17] Chia-Hung Wei, University of Warwick, UK Chang-Tsun Li, University of Warwick, UK Roland Wilson, University of Warwick, UK : A Content-Based Approach to Medical Image Database Retrieval. 258 Wei, Li, and Wilson.

[18] Y. Fanid Fathabad & M.A. Balafar : CONTENT BASED IMAGE RETRIEVAL FOR MEDICAL IMAGES : International Journal on "Technical and Physical Problems of Engineering" (IJTPE), Iss. 12, Vol. 4, No. 3, Sep. 2012.

AUTHORS

First Author – Sukhada Aloni, B. Tech IT (ME Appeared), sukhada.aloni@gmail.com

Correspondence Author – Sukhada Aloni,, sukhada.aloni@gmail.com, +91 9920207720.