Department of Computer Science and Engineering (CSE)
Islamic University of Technology

Biomedical image retrieval with self organizing map and relative concept distance normalization(RCDN)

Authors
M Saiful Bari - 124441
and
Muhammad Usama Islam - 124414

Supervisor
Dr. Md. Hasanul Kabir
Associate Professor
Department of CSE
Islamic University of Technology

A thesis submitted to the Department of CSE
in partial fulfillment of the requirements for the degree of B.Sc. Engineering in CSE
Academic Year: 2015-16

November - 2016

Declaration of Authorship

This is to certify that the work presented in this thesis is the outcome of the analysis and experiments carried out by M Saiful Bari and Muhammad Usama Islam under the supervision of Dr. Md. Hasanul Kabir, Associate Professor, Department of Computer Science and Engineering (CSE), Islamic University of Technology (IUT), Dhaka, Bangladesh. It is also declared that neither of this thesis nor any part of this thesis has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

Authors:

M Saiful Bari
Student ID - 124441

Muhammad Usama Islam
Student ID - 124414

Supervisor:

Dr. Md. Hasanul Kabir
Associate Professor
Department of CSE
Islamic University of Technology

Acknowledgement

We would like to express our grateful appreciation for **Dr. Md. Hasanul Kabir**, Associate Professor, Department of Computer Science & Engineering, IUT for being our advisor and mentor. His motivation, suggestions and insights for this thesis have been invaluable. Without his support and proper guidance this research would not have been possible. His valuable opinion, time and input provided throughout the thesis work, from first phase of thesis topics introduction, subject selection, proposing algorithm, modification till the project implementation and finalization which helped us to do our thesis work in proper way. We are really grateful to him.

We are also grateful to **Mir Rayat Imtiaz Hossain**, MSc student, Department of Computer Science & Engineering, University of British Columbia, **Dr Mahmudur Rahman**, Assistant Professor, Department of Computer Science, Morgan State University and **Prof. Dr. Henning Muller**, University of Applied Sciences Western Switzerland, Sierre(HES-SO) for their valuable suggestions on our proposal of biomedical content based image retrieval.

We are very much grateful to ImageCLEF for providing us with necessary datasets to carry out the experiments. This research was supported by Department of Computer Science & Engineering , IUT . We are thankful to IUT Computer Center for making the resources available for smooth research work.

Abstract

Content based medical image retrieval is one of the most intriguing research area of modern image retrieval and biomedical image processing. In the biomedical domain the volume of information is rapidly increasing. For managing this huge amount of volume of information content based medical image retrieval techniques are indispensable. Medical researchers, physiotherapists, dentists and clinicians vividly use online databases to access the relevant biomedical bibliographic citations based on keyword search on different fields such as the main text, author, and date. However, a picture is worth a thousand words, and even more so in medical domain as images of diverse modalities constitute an important source of anatomical and functional information for the diagnosis of diseases, research, education. Researchers have proposed different methods to extract the meaningful information from images as well as retrieve images from query image. Though text based image retrieval is a well traversed approach, the efficient way of content based medical image retrieval is always preferred for bridging semantic gaps. We propose a novel approach for medical image retrieval where we represent the image with concepts which refers to distinguishable visual texture and shape definitions representing the visualness of an image. For concept learning we have used self-clustered weighted entropy based concept feature space trained by self-organizing map. We also proposed a new ranking procedure which is based on normalization of histogram of concepts. The hypothesis that such approaches would improve biomedical image retrieval is validated through experiments on ImageCLEFmed2009 IRMA data set, which is collected with official permission of IRMA.

Contents

List of Figures

Chapter 1

Introduction

1.1 Overview

The importance of medical images are enormous. They are vital for the diagnosis of disease and planning of the treatment. The production of medical image are increasing rapidly in quantity.[1]. From a recent study that was found in an European report that approximates medical images of all types occupied 30% of digital storage of the whole world in 2010[2]. With significant growth of scientific and research discovery, it became challenging to trace all these important and meaningful information at right place and right time within this huge volumes of literature. Doctors use images of past cases in comparison with current images to diagnose and provide potential treatment options of new patients. These images are also used for the purpose of teaching and research in the field of medical research.[3, 4]. Thus, the goal of a clinician or a doctor is often to solve a new problem by assessing previous similar cases or in this very case, medical images together with contextual information, by using information and knowledge from previous data.[5].

For successfully contributing to the process of information retrieval as a research field in biomedical domain, systematic as well as quantitative evaluation of activities using shared tasks on shared resources have been instrumental as an application area in the past few decades. Evaluation campaigns such as biomedical image data-sets, image retrieval competitions have enabled the comparative evaluation of new approaches, algorithms, theories and models through the use of standardized resources and common evaluation methodologies within regular as well as systematic evaluation cycles. The tasks organized over the years by ImageCLEF[6] have provided an evaluation platform and framework for evaluating the state of the art in biomedical image retrieval.

Medical articles and repositories contains various types of modalities such as distinct and multiple modalities to express information, the representation can be of text or graphics. The graphical representation is more important than that of textual representation as authors of journal articles often use illustrations to clarify the text, or to highlight or pinpoint special cases as interest points or region-of-interests (ROIs). These images often contain essential as well as important information in context and can assist in recognizing hidden visual patterns which is not contained in the article's text. Basically an image can compensate for thousands of texts. In medical domain a picture is worth a thousand words as images of diverse modalities constitute an important source of anatomical and functional information for the diagnosis of diseases, research and education. Overall, biomedical literature incorporates approximately 100 million figures, whereas the biomedical open access literature of PubMed Central (PMC) of National Library of Medicine (NLM) alone contained almost two million images back in 2014. So if we can have the in depth information of the images or the anatomical and functional information of this images instead of the thousands or millions of texts then that would act as more feasible in biomedical research domain.

The health care industry is expanding in a significant rate. Following the expansion, it becomes significantly important in technical domain to transform this massive volume of image and text data from biomedical articles into useful information and eventually to a form of actionable knowledge in the method of effective and efficient search process. However though in case of biomedical image retrieval it is a challenging task. The meaning of images cannot be understood by analyzing their content alone. However, only text information is sometimes insufficient in determining the usefulness of a publication. The importance of illustrations in scientific publications is well established.

Some retrieval systems in the medical domain searches the database according to their collateral text, such as captions, title, abstract, etc. to search for images within a collection of biomedical articles commonly represented and retrieve them., Some of the well-known examples of text based biomedical image retrieval systems are BioText, Goldminer, and Yale Image Finder (YIF).

Given that images are such a crucial source of information within the biomedical domain, content-based image retrieval (CBIR) has been gaining popularity. The goal of CBIR is to obtain from a possibly very large image database those images that are similar in content (e.g., color, texture, shape, edge, etc.) to an image of interest (the query image).

The importance of medical illustrations in journal articles has also motivated active research in content based image retrieval. However, after almost a decade of intensive research in medical image retrieval, progress has been slow due to the inability of image-processing algorithms to automatically identify the content of images in the manner that image retrieval and extraction systems have been able to do so with text. Biomedical image collections present unique challenges, where subtle differences determine retrieval accuracy between otherwise highly similar images. For example, a poster anterior (PA) chest x-ray of a tuberculosis patient appears overall very similar to a PA chest x-ray of a patient with interstitial lung disease, but retrieving both these images is incorrect for any request more specific than for a chest x-ray with pathology. The challenge is to find images that are semantically similar, and not merely similar in appearance. This gap, often referred to as the "semantic gap," is a significant hindrance to the practical use of CBIR systems.

In our approach of anatomy based biomedical image retrieval, we take an image data-set and manually select some suitable samples which are subset of the main image data-set. Then we have categorized them and divided them to 8x8 grid. Each grid is passed through unsupervised learning with the use of self-organizing maps (SOM) for clustering and dividing to 64 categories. These 64 categories are used as 64 concepts. In post processing step we provided an unique approach for image ranking using relative distance measurement and normalization of the feature vector.

1.2 Problem Statement

The primary goals of biomedical image retrieval system is to retrieve the correct set of images(with correct ranking) and to identify correctly the output image in biomedical domain from a given query image. Ideally, we want to identify these output set of biomedical images in the sample data-set from the given query image. However, massive research was done on text based image retrieval but in case of CBIR correctly identifying the feature vector is a challenge, from a large number of image data-sets of various anatomy. The truth value and identifying the effectiveness of features are little known and still covers a vast area of research. The ranking of images in post processing is already a difficult problem, complicated by anatomical repeats and orientation errors which may lead to high fragmentation of contiguous and miss-assembly. A plausible approach is to improve the performance of such assemblers is to take the relative distance of the concepts from input and output clustered grids present in the data-set before the assembly.

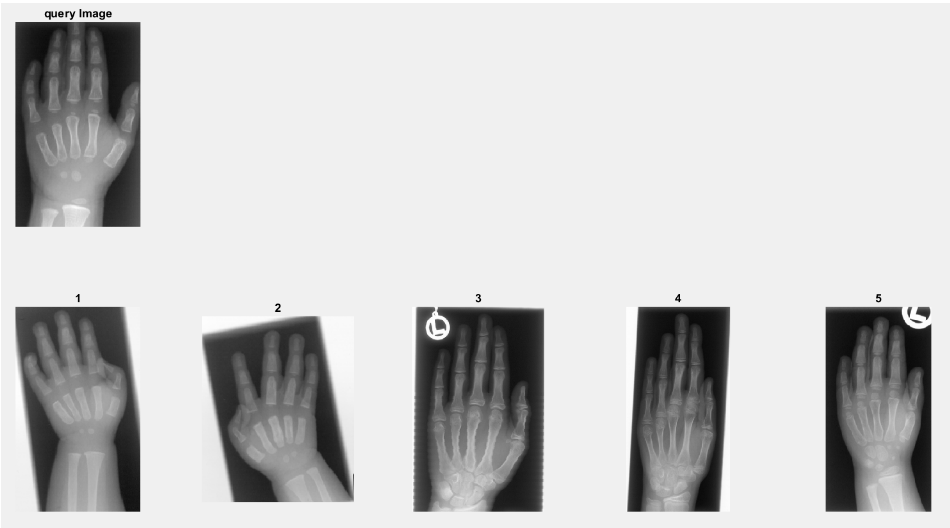

Figure 1.1: A sample retrieval example

1.3 Research Challenges

Biomedical images are very important due to the continued stable growth of the health care industry, it becomes significantly challenging in technical domain to transform of massive volumes of image and text data from biomedical articles into useful information and actionable knowledge in the form of effective and efficient search process. Until now, little attention is provided to the use of images in the articles as the meaning of images cannot be understood by analyzing their content alone. However, only text information is sometimes insufficient in describing the region of interest of an image.

Although different technologies have been developed, the characterization and identification of unknown query biomedical image remain challenging, mainly due to lack of perception of textual and shape features tools and the extremely similar nature of anatomical structure. Currently, the most commonly used approach to characterize and identify biomedical images in is to cluster into 8X8 grid and using multi-class SVM to train the data-set and generate features to cross check on the query images. There are some features which are effective in some of the image retrieval tools. However the well-researched arena is text based image retrieval. Some text based retrieval systems in the medical domain, such as BioText, Goldminer, and Yale Image Finder (YIF), search for images within a collection of biomedical articles commonly rep-resented and retrieve them according to their collateral text, such as captions, title, abstract, etc.

Given that images are such a crucial source of information within the biomedical domain, using visual image features (e.g., color, texture, shape, edge, etc.) in content-based image retrieval (CBIR) has been gaining popularity. The goal of CBIR is to obtain from a possibly very large image database those images that are similar in content (e.g., color, texture, shape, edge, etc.) to an image of interest (the query image). The challenge is to find images that are semantically similar, and not merely similar in appearance. This gap, often referred to as the "semantic gap," is a significant hindrance to the practical use of CBIR systems.

Various hospitals and other biomedical research institutions contain a large amount of data and this data are totally unstructured as we saw those data are collected directly from person. For processing biomedical image and finally finding valuable information from those we will be needing good feature set. However, most of the biomedical images are grayscale images. So the color information can't be utilized properly for creating the feature set.

The main idea is to bridge the semantic gap. The main research challenge is to bridge the semantic gap between the query image and the output images. In case of anatomical retrieval the semanticness is dependent on many factors such as texture, shape etc. This specific domain of selecting the feature set that properly bridge the semantic gap is also a big research area. However for a retrieval system is expected to provide a proper ranking of output images.

The implementation of such image retrieval system depends hugely on pattern recognition. So we often need proper clustering methods, good region of interest (ROI) selection, multiclass SVM for training multiple concepts etc.

1.4 Thesis Objective

The objective of this thesis is to model an efficient content based image retrieval system. The whole model can be divided into several steps. In the first step we need to design a good image segmentation procedure where we divide the image to multiple segments to find region of interest. Each of the segments are used as a local information of that image. In the next step we need to perform clustering on this segments for that we need to generate a feature vector by extracting features from this local segments. Selecting a set of useful and meaningful features is always a tough challenge.

After performing the exact number of clustering we obtain multiple concepts which are used to mark the query image later on. All the images in the database are marked on the basis of their concepts and saved on the basis of clustering. When a query is performed the images are retrieved based on clustering. So the main objective remains as such that the retrieval of semantically closer image based on query image.

1.5 Thesis Contribution

We have developed a content based medical image retrieval system in an effectual way. Our procedure is inspired from a paper that focuses on biomedical image representation approach using visualness and spatial information in a concept feature space for interactive region-of interest-based retrieval. We have proposed an efficient way of extracting concept from a set of ideal images which can be used for any medical datasets rather than depending on few specific texture information of medical data. We have also used a proper segmentation methodology for working with region of interest. At the end in the retrieval process we worked on the ranking procedure while the procedure of ranking depends on the relative distance of the similar concepts. Our proposed ranking system proved to be computationally efficient and it reduces semantic gap to a significant level. We implemented some of the existing methods of content based medical image retrieval system to investigate their efficiency and also measure their accuracy. For experimental results, we implemented our proposed model and we have compared our model with the existing methods.

1.6 Organization of Thesis

In Chapter 1 we have discussed our study in a precise and concise manner. Chapter 2 deals with the necessary literature review for our study and there development so far. In Chapter 3 we have stated our proposed method, proposed algorithm and also the flowchart to provide a detail insight of the working procedure of our proposed Biomedical image retrieval system with self organizing map based on relative conceptual distance. Chapter 4 shows the results and comparative analysis of successful implementation of our proposed method. The final segment of this study contains all the references and credits used. We conclude our thesis and show the future prospects and research scopes of our proposed method.

Chapter 2

Literature Review

2.1 Research Review

2.1.1 Features

Color image descriptor is always been popular though most of the medical images are grayscale. Color histogram[44], color moments(CM)[45], color coherence vector(CCV)[46], color correlogram[47] are some popular color descriptor used as a feature. Yang et al.[48](in figure 2.1) discussed in brief about shape descriptor where shape representation is dependent on 6 different category named one-dimensional function for shape representation, Polygonal approximation, Polygonal approximation, Moments, Scale-space methods, Shape transform domains each having multiple descriptor.

B.verma et al.[20] worked on a novel fuzzy logic based approach for interpretation of color queries and for fusion of multiple quires. It is related to real world system and the quires of color are like mostly red, many green, and few red. Here integration image into database to store the image with keyword (or) text. Image retrieval is performed based upon the matching of query text or keyword. Medina et al.[22] worked on A fuzzy approach for image retrieval based on color feature. Here fuzzy database model is introduced to store and retrieve the image. Fuzzy HIS color space is used. Fuzzy object relational database system is used for flexible retrieval of the image. JuanMiguel medina et al.[23] worked on Fuzzy object relational database system are used to store the medical image with its parameters. This paper illustrate the capability of Fordbms, parameter cure are obtained from x ray image of patient's affected by scoliosis. The cob angle measurement is made to obtain the angle which help in image retrieval. S. Pradeep et al.[24] worked on CBIR system based image retrieval and segmentation of Medical image database with fuzzy value. This paper intend to retrieve by extracting most informative texture feature which can be extracted by using Gray-level –co-occurrence matrix (GLCM)[25]. GLCM has been popular feature for Medical CBIR system. Later on Yixiao Zhou et al[38] worked on GLEDCOM, set of 11 feature used as a shape and texture descriptor.

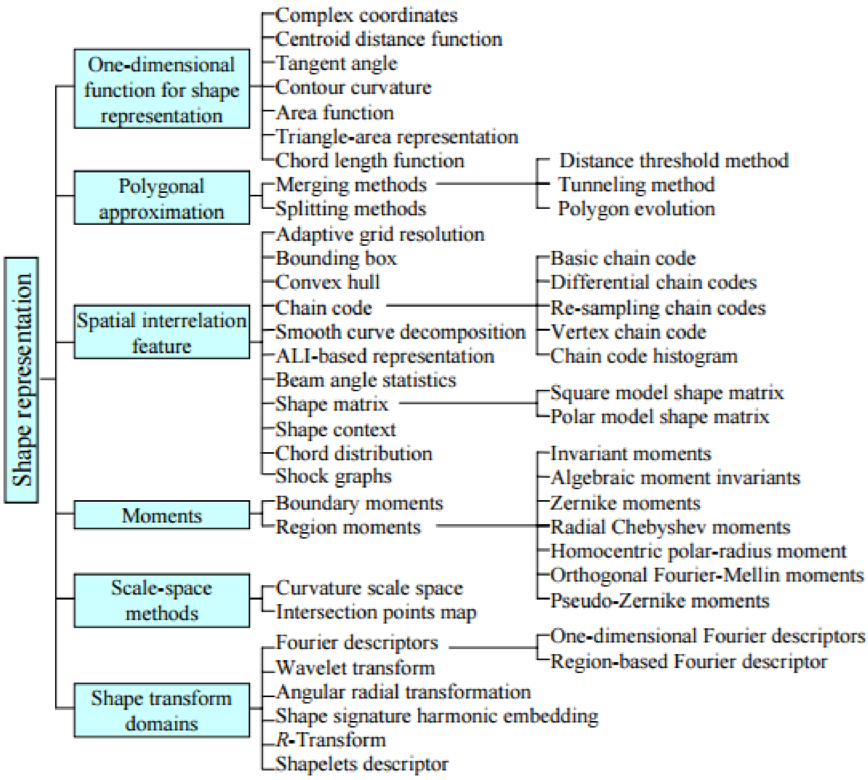

Figure 2.1: An overview of shape descriptors[48]

Muhammet Bastan et al[39] have done image and video retrieval based on MPEG-7 desctiptor. MPEG-7 have 7 descriptor named Color Structure Descriptor (CSD), Scalable Color Descriptor (SCD), GoF/GoP Color Descriptor (GoF/GoP), Color Layout Descriptor (CLD), Dominant Color Descriptor (DCD), Homogeneous Texture Descriptor (HTD), Edge Histogram Descriptor (EHD), Face Recognition Descriptor (FRD). Apart from that Savvas et al[40] proposed Color and Edge Directivity Descriptor named CEDD, a Compact Descriptor for Image Indexing and Retrieval. Savvas et al[41] also proposed Fuzzy color and texture histogram based low level feature for accurate image retrieval. B.Jyothi et al.[42] also extract texture feature using gabor filter in different orientation. They also used Chebichef moments as anouther visual feature. B. Ramamurthy et al[?] uses shape-based image Retrieval using canny edge(CA) Detection and k-means Clustering algorithms for Medical images.

2.1.2 Region of Interest

Content based image retrieval involves extraction of global and region features of images for improving their retrieval performance in large image databases. Region based feature have shown to be more effective than global features as they are capable of reflecting users specific interest with greater accuracy. Ying liu et al.[19] proposed "A survey of content based image retrieval", to improve the retrieval accuracy of an image and to reduce the semantic gap between the visual features of human semantics. To support query of high level semantic. Here region based image retrieval process is implemented for the process of image segmentation to a low level image features.

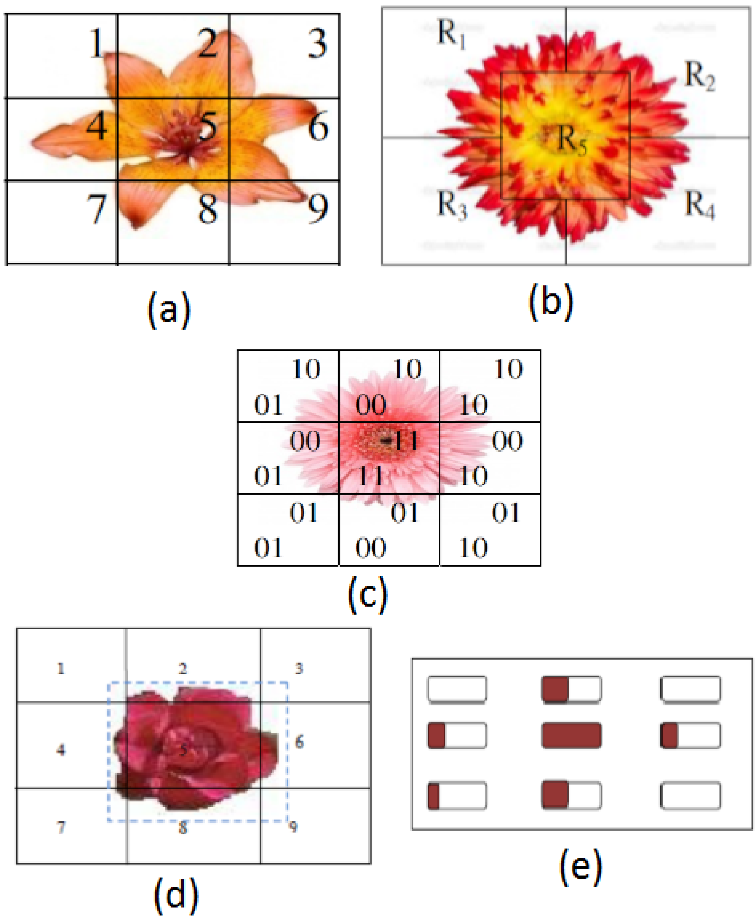

Figure 2.2: An overview of region of interest technique[62]

The Region Based Image Retrieval System(RBIR) utilizes features extracted from region or part of the image. Zhang et.al[53] proposed 32x32 segmentation of an image with size 4x4. Chan et al.[54] have proposed a ROI image retrieval method based on Color variances among adjacent objects (CVAAO) feature. Prasad et al. [55] in fig:3(a,d,e) uses the dominant colors of images to automatically extract regions. Huang et al[56] uses visual saliency in HSV color space for ROI extraction from color images. Shrivastava et al. [57] in fig:3(c) have proposed more effective approach considering relative locations of multiple ROI using binary region codes.Hsiao et al.[58] in fig:3(b) approach partitions images into a number of regions with fixed absolute locations. A novel approach to image indexing by incorporating a neural network model, Kohonen's Self Organising Map (SOM), for content based image retrieval is presented in [59]. When a user defines the ROI in the image the similarity is calculated by matching similar region in query and target images. The SOM algorithm is used to determine the homogeneous regions in the image adaptively. An unsupervised clustering and classification is used to group pixel level features without prior knowledge of data. To reduce the effect of noisy descriptors generated in ROI query Wang et al.[60] have proposed a new approach using a general bag of words and auxiliary Gaussian weighting scheme(AGW) for ROI based image retrieval system. Weight of each descriptor is assigned accoring to its distance from ROI query centre computed with the help of 2-D Gaussian window. The Simiarity score of database images is computed using AGW.In order to improve the object retrieval performance also in these difficult cases, Yang et al.[61] have suggested to use visual context of the query object to compensate for the inaccurate representation of query ROI. The context of the query object is determined using visual content surrounding it. Here ROI is determined as an uncertain observation of the latent search intent and the saliency map detected for the query image as a prior scheme. Rahman et al[51] divide the image into 5 overlapping region like (b) in figure 2.2 and he also divide the image into 8x8 grid for creating feature vector.

2.1.3 Classification

For general purpose image retrieval, Liu et al[34] applied a decision tree based learning algorithm (DT-ST) to make use of the semantic templates to discretize continuous-valued region features. Fei-Fei et al.[35] proposed an incremental Bayesian algorithm to learn generative models of object categories and tested it on images of 101 widely diverse categories. Methods based on relevance feedback[36] are also used to reflect the user intention using feedback loop in the retrieval process. For example in reference [36] query point movement algorithm is proposed for positive example scenario. To speed up the feedback process incremental clustering algorithm is used. Zhang et al.[37] proposed image translation into textual documents which are then indexed and retrieved the same way as the conventional text based search. Raghu krishnapuram et al.[21] worked on CBIR based on fuzzy approach to handle the usual exemplar-based queries and graphical sketch based queries. Here, LCR (leader clustering retrieval time by organizing (indexing), the database in term of group (cluster).

We have also reviewed CAD systems for the analysis of histopathological images, CBIR systems in medical image analysis, and hashing methods for large-scale image retrieval. Classifier-based CAD systems consist mainly of image preprocessing, detection and/or segmentation, feature extraction, machine learning-based classification, and postprocessing methods. We briefly review relevant work mainly according to the classification method, which is the focus of this paper. For example, Petushi et al[26]. employed adaptive thresholding and morphological operations to segment cells and represent high-density areas of different types of nuclei. These cells were then classified with linear discriminant analysis (LDA) and forward/backward search methods. Yang et al.[27] employed filter banks to model phenotypic appearance in histopathological images, which were classified via a gentle boosting mechanism. Caicedo et al.[28] proposed to use SIFT to detect key points and extract local descriptors, which are used to obtain a bag-of-words[29] and classified using a support vector machine (SVM) with kernel functions. Basavanhally et al.[30] proposed to detect locations of nuclei using a combination of region growing and Markov random fields. Three graphs (i.e., Voronoi diagram, Delaunay triangulation, and minimum spanning tree) are constructed to describe the arrangement of cells. SVM is then employed to classify the high or low presence of lymphocytic infiltration that can be used to evaluate phenotypic changes in breast cancer. Dundar et al.[31] proposed to segment cells using a Gaussian mixture model (GMM) and a watershed algorithm and to describe individual cells by their size, shape, and nucleoli. After that, multiple-instance learning (MIL) with SVM was used to identify and classify the stage of breast lesion. Most of these methods use one type of features to classify histopathological images. It is also possible to fuse multiple features in classifiers for comprehensive information. For instances, Tabesh et al.[32] aggregated color, texture, and morphometric cues at the global and histological object levels for k-nearest neighbors (kNN) and SVM-based classification. Doyle et al.[33] graded breast cancers with both graph-based and texture features for SVM-based classification. Rahman et al[51] worked with multi-class SVM based concept training where this concepts are used to mark images for query purpose.

2.2 Medical Image Retrieval System Review

The Goldminer®[7] searches figure captions to retrieve images from 11000 open-access peer-reviewed journal articles from the websites of American Roentgen Ray Society (ARRS), the American Society of Neuroradiology (ASN), the British Institute of Radiology (BIR), and the Radiological Society of North America (RSNA). It maps keywords in figure captions to concepts in NLM's Unified Medical Language System UMLS® metathesaurus and/or Medical Subject Heading (MeSH®) terms. Results are displayed in list or grid views. Users have the option to search by age/modality/sex derived from the caption text. It also allows searches using multiple keywords.

FigureSearch search engine developed at the University of Wisconsin at Milwaukee, is a component of the ask Hermes system[8], and is a tool devised to improve the quality of patient care by providing information to physicians at point of care. It uses the Lucene® text indexing and search technology to search online medical articles and generates a list view of results. Images are displayed on the left, while the title, authors, figure caption and summary are displayed on the right. The search engine separates itself from others with its ability to automatically generate summaries from papers (the purpose, experimental procedure, outcome and conclusion) using sentences from the main text.

BioText search engine[9] developed at the University of California at Berkeley, also uses the Lucene search engine to index over 300 open access journals and retrieves figures and text from online articles. Users can perform searches either on full-text or abstracts of journal articles. It is different from other search engines in that it can search table captions and retrieve part/expanded views of tables from online articles. Results can also be sorted by date and relevance.

Yottalook[10] performs multilingual search in thirty three languages to retrieve images from peer-reviewed journal articles on the Web. It uses Google's indexing technology and a proprietary software called iVirtuoso for natural query analysis, semantic ontology generation and determining relevance. Natural query analysis generates keyword from search queries. Yottalook uses an enhanced version of the RSNA's RadLex® medical ontology to identify relationships or synonymous terms. This is known as semantic ontology generation. Relevance is automatically derived using a relevance algorithm (part of the iVirtuoso software) and is used to rank the retrieved results. Results can be viewed as grid or list views and allows users to save their searches using their myRSNA accounts.

Yale Image Finder[11] developed at Yale University searches text within biomedical images, captions, abstracts, and title to retrieve images rom biomedical journal papers . It uses optical character recognition to recognize text in images in both landscape and portrait modes and then validates the extracted text against content extracted from corresponding full-text articles. A unique capability of YIF is that users can access related images from associated papers by directly comparing image content. It uses Lucene® technology to index, search and rank search results.

Image retrieval for medical applications (IRMA)[12] system, developed at Aachen University of Technology , Germany , aims to integrate text and image-based features for medical image retrieval. The system indexes images using visual features and a limited number of text labels. Images are classifies according to anatomy, biosystem ,imaging direction, and modality of the image (X-ray,CT,MRI etc.). It applies differential weighting of image features for computer aided diagnosis. The image features are derived from co registered training images. IRMA uses semantic layers to describe an image. These layers comprise multi-scale descriptions of the raw image data, extracted features, visual content and its spatial layout within the image. It supports text query as well as image query by example and has been tested on mammograms and bone x-ray images.

iMedline®[13] is a multimodal search engine under development at NLM with goals to retrieve images from biomedical literature relevant to text and image queries and linking evidence automatically extracted from clinical articles to patients cases. Along with the traditional elements of search results display, such as titles and author names, iMedline provides captions of the retrieved images and short summaries of the retrieved abstracts . For the document retrieval task, iMedline uses NLM's Essie s search engine. Essie is a phrase-based search engine with UMLS-based query expansion and probabilistic relevance ranking that exploits the document structure. The iMedline user interface provides the Essie search options and displays search results in grid or list views.

MIRAGE[43] is also an E-repository of Medical Images for Learning Biomedical Informatics: This paper proposed an E-repository for medical images that offers great facilities to learn about the biomedical informatics. The facilities of domain-based, atlas-based, and content-based retrieval (CBIR) techniques are implemented to search the images in this developed repository. The uniqueness of the system is CBIR system for 3D is developed and coupled with 3D visualization that has used for educational material and as well as tele-education in future.

There are several other systems that use image features to perform medical image retrieval but have not been evaluated here because they are not online systems. For example, MedGIFT[14] , VisMed[15] , ASSERT[16], and BRISC[18] . MedGIFT[19] was developed by the Viper group at the University of Geneva. It uses query by-example to perform visual search. VisMed uses a visual vocabulary based on color and texture features to perform medical image retrieval. It was developed by the Institute for Infocomm Research in Singapore. ASSERT is a prototype medical image retrieval system developed at Purdue University, West Lafayette, IN. BRISC is a prototype CBIR system for lung nodule images developed by DePaul University, Chicago, IL, and University of Maryland, College Park, MD.

Chapter 3

Proposed Method

3.1 Methodology of Proposed Method

In our approach of anatomy based biomedical image retrieval, we have taken an image data-set and manually selected some suitable images which are subset of the main image data-set. Then we have divided them to 8x8 grid. From each of the grid we extracted features and then created feature vector. Later on, we multiply the feature vector with the entropy of the grid. Then the feature vector is fed with SOM and and clustered into 64 shape and texture based concepts.

As we are using SOM now for each of the image in the database we divide them into 8x8 grid and mark each of the grid into one of the 64 concepts and create histogram of concepts of each images. Then save them to our clustered database to extract them quickly for a query.

For a query image we again prepare histogram of concepts in the same procedure. Then we extract the images form the cluster(database) based on the presence of the concepts and for each of histogram of concepts normalize them with our proposed method. Then we fed them in k-nearest-neighbour algorithm.

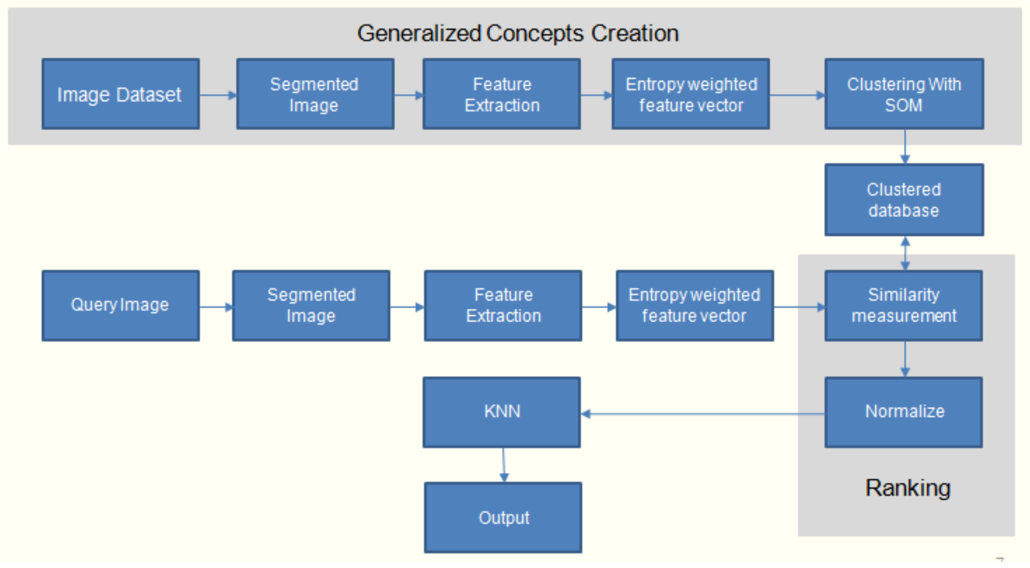

Figure 3.1: An overview of our proposed system

3.2 Feature Vector creation

"Bag-of-Concepts"-Based Image Representation

A major component of the proposed retrieval approach is the image representation in a visual concept feature space. By the term concept, we refer to the perceptually distinguishable image patches that are identified locally in image regions. For example, if we consider a CT image of lung or chest, which appears in many radiographic or medical-related journals, we observe several image regions with texturally different visual. patterns that are semantically distinguishable from each other For example, an area (ROI) of a CT scan having a slightly bright and hazy appearance can be mapped to the pattern"ground-glass opacity."

When the domain knowledge is available for these kinds of images, it would be effective to exploit it by utilizing any semi-supervised learning-based techniques. A semi-supervised learner can create a model of concepts to capture the variability's of the local patches by itself. In this context, an in-stance (e.g., local patch) in the training set can be represented by a feature vector along with its local concept- or category-specific labels.

Kohonen Self Organising Feature Maps (SOM) were originated by a man named Teuvo Kohonen, they provide a way of representing multidimensional data in much lower dimensional spaces - typically one or two dimensions. This progression, of reducing the dimensionality of vectors, is mainly a data compression technique known as vector quantisation. Besides that, the Kohonen technique makes a network that stores information in such a way that any topological links within the training set are maintained. The most important goal of an SOM is to change an incoming signal pattern of arbitrary dimension into a one or two dimensional discrete map, and to execute this transformation adaptively in a topologically arrangement way. Consequently SOM can be set up by placing neurons at the nodes of a one or two dimensional lattice. Higher dimensional maps are also feasible, but not so familiar. The neurons turn out to be selectively adjusted to various input patterns (stimuli) or classes of input patterns at some stage in the course of the competitive learning. The places of the neurons so tuned (i.e. the winning neurons) turn out to be generated and a meaningful coordinate system for the input features is generated on the lattice. The SOM consequently types they have need of topographic map of the input patterns. The self organization procedure involves four major components:
Initialization: All the connection weights are initialized with small random values.
Competition: For each input pattern, the neurons calculate their relevant values of a discriminated function which provides the basis for competition. The particular neuron with the smallest value of the discriminant function is declared the winner.
Cooperation: To be successful neuron discover out the spatial location of a topological neighbourhood of excited neurons, in that way as long as the basis for cooperation along with neighbouring neurons.
Adjustment: The excited neurons decrease their character values of the differentiated function in relation to the input pattern throughout appropriate adjustment of the combined connection weights, such that the comeback of the winning neuron to the subsequent application of a comparable input pattern is improved. The section proposed the implementation of bag of concepts with self organizing map which is an unsupervised learning algorithm.

For learning purpose we divide the each image with 8X8 grid. Each of the grid represents a concept C theoretically. Self organizing map is trained to cluster 64 categories among the selected images which is divided into 8X8 grid. Each of the grid is considered as an input. The feature vector of the input grid is based on shape and texture features. Later on for crating the feature vector for input and query images we use this trained som. Self organizing map in our case is used as to create concepts and mark concepts in the images. Later on the marked concepts are used to create histogram of concepts.

$$f_j^C = [f_{1j} \quad f_{2j} \quad ... \quad ... \quad f_{nj}] \tag{3.1}$$

each f_{ij} corresponds to the frequency of a concept c_i, 1 $\leq$i$\leq$64
f_j^C is the feature vector.

However, this representation scheme captures only a coarse distribution of the concepts and is analogous to the distribution of quantized color in a global color histogram

3.2.1 Feature selection

Gabor Feature: Gabor filters are used for analysis of the textures. They are sensitive to orientation. It is used widely as an edge detector. We modulate a complex sinusoid with Gaussian thus we obtain the gabor filter. Gabor features are constructed based on the responses obtained from the gabor filter. The Gabor texture features include the mean and the standard deviation of the magnitude of the Gabor wavelet transform coefficients. First the set of 50 dimensional Gabor vectors is extracted from all images from the database, then a partitioning of this set of Gabor feature vectors is created with a fixed number of clusters using one of the clustering algorithms. Finally, for each image a histogram from the cluster memberships of its Gabor feature vectors is created. The clustering algorithms allow us to obtain a different number of clusters and thus differently sized histograms.

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp[\frac{-1}{2}(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}) + 2\pi j W_x] \tag{3.2}$$

$$g_{mn}(x,y) = a^{-2m} g(x' + y'), ..a > 1 \tag{3.3}$$

where, W is the modulation frequency and σ_x^2, σ_y^2 represents variance in x and y directions. A set of self similar Gobor functions, $g_m n(x,y)$, are obtained by dilation and rotation of Gobar filter using the generating function.

Tamura Feature : In [63] the authors propose six texture features conforming to the visual perception of human, they are coarseness, contrast, directionality, line-likeness, regularity, and roughness. It is found that coarseness, contrast and directionality strongly correlate with the human perception. They are described below,

$$A_k(n_0,n_1) = \frac{1}{2^{2k}} \sum_{i=1}^{2^{2k}} \sum_{j=1}^{2^{2k}} X(n_0 - 2^{k-1} + i, n_1 - 2^{k-1} + j) \tag{3.4}$$

$$E_k^h(n_0,n_1) = |A_k(n_0 + 2^{k-1}, n_1) - A_k(n_0 - 2^{k-1}, n_1)| \tag{3.5}$$

$$E_k^v(n_0,n_1) = |A_k(n_0, n_1 + 2^{k-1}) - A_k(n_0, n_1 - 2^{k-1})| \tag{3.6}$$

$$S(n_0, n_1) = argmaxmaxE_k^d(n_0, n_1) \tag{3.7}$$

$$F_{crs} = \frac{1}{N_0 N_1} \sum_{n_0=1}^{N_0} \sum_{n_1=1}^{N_1} 2^{S(n_0,n_1)} \tag{3.8}$$

$$F_{con} = \frac{(\sigma)}{\alpha_4^z} \qquad with \qquad \alpha_4 = \frac{\mu_4}{\sigma^4} \tag{3.9}$$

$$\mu_4 = \frac{1}{N_0 N_1} \sum_{n_0=1}^{N_0} \sum_{n_1=1}^{N_1} (X(n_0, n_1) - \mu)^4 \tag{3.10}$$

Coarseness: The coarseness provides information about the size of the texture elements. The lower the coarseness value is, the smoother is the texture.
Contrast: Contrast stands for picture quality. It deals with dynamic range of gray-levels, polarization of the distribution of black and white on grey level histogram, sharpness of edges, period of repeating patterns.
Directionality: The orientation and the presence of orientation in the texture is very important. That is, two textures differing only in the orientation are considered to have the same directionality.

Global Texture Descriptor: [64] describes a texture descriptor to characterize complete images. The descriptor consists of five parts, where each part models different properties of the texture of the image. The parts are
Fractal dimension measures the roughness or the crinkliness of a surface. In this work it is calculated using the reticular cell counting method
Coarseness characterizes the grain size of an image. Here it is calculated depending on the variance of the image.
Entropy is a measure of unorderedness or information content in an image. Entropy is a well-known measure from information theory.
Spatial gray-level difference statistics (SGLD) describes the brightness relationship of pixels within neighborhoods. It is also known as co-occurrence matrix analysis.
Circular Moran autocorrelation function measures the roughness of the textures. For the calculation a set of autocorrelation functions is used.

Moments: This is a statistical measure where standard deviation and mean is used.

Wavelet transform: The wavelet transform is similar to the Fourier transform (or much more to the windowed Fourier transform) with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space. the Wavelet transform is in fact an infinite set of various transforms, depending on the merit function used for its computation.

GLCM : A GLCM Gray Level Co-occurrence Matrix is a histogram of co-occurring greyscale values at a given offset over an image. The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image.

GLEDCOM : utilizing the co-occurrence of both the texture and the shape features . The set of 11 features are T1 to T11. Here the equations are given.

$$T_1 = [\sum_{i=1}^{K_z}\sum_{j=1}^{K_h}\frac{p(i,j)}{j^2}] \tag{3.11}$$

$$T_2 = [\sum_{i=1}^{K_z}\sum_{j=1}^{K_h}p(i,j).j^2] \tag{3.12}$$

$$T_3 = \sum_{i=1}^{K_z}[\sum_{j=1}^{K_h}p(i,j)]^2 \tag{3.13}$$

$$T_4 = \sum_{j=1}^{K_h}[\sum_{i=1}^{K_z}p(i,j)]^2 \tag{3.14}$$

$$T_5 = \sum_{i=1}^{K_z}\sum_{j=1}^{K_h}[p(i,j)]^2 \tag{3.15}$$

$$T_6 = \frac{1}{\partial_1\partial_2}\sum_{i=1}^{K_z}\sum_{j=1}^{K_h}(i-\mu_1)(j-\mu_2)p(i,j) \tag{3.16}$$

$$T_7 = -\sum_{i=1}^{K_z}\sum_{j=1}^{K_h}p(i,j)\log_2 p(i,j) \tag{3.17}$$

$$T_8 = -\{\sum_{i=1}^{K_z}[\sum_{j=1}^{K_h}p(i,j)]\log_2[\sum_{j=1}^{K_h}p(i,j)]\} \tag{3.18}$$

$$T_9 = -\{\sum_{j=1}^{K_h}[\sum_{i=1}^{K_z}p(i,j)]\log_2[\sum_{i=1}^{K_z}p(i,j)]\} \tag{3.19}$$

$$T_{10} = \sum_{i=1}^{K_z}\sum_{j=1}^{K_h}(i-j)^2 p(i,j) \tag{3.20}$$

$$T_{11} = \sum_{i=1}^{K_z}\sum_{j=1}^{K_h}\frac{1}{1+(i-j)^2}p(i,j) \tag{3.21}$$

$$\mu_1 = \sum_{i=1}^{K_z}i.[\sum_{j=1}^{K_h}p(i,j)] \tag{3.22}$$

$$\mu_2 = \sum_{i=1}^{K_h}j.[\sum_{i=1}^{K_z}p(i,j)] \tag{3.23}$$

$$\partial_1 = \{\sum_{i=1}^{K_z}(i-\mu_1)^2[\sum_{j=1}^{K_h}p(i,j)]\}^{\frac{1}{2}} \tag{3.24}$$

$$\partial_2 = \{\sum_{j=1}^{K_h}(j-\mu_2)^2[\sum_{i=1}^{K_z}p(i,j)]\}^{\frac{1}{2}} \tag{3.25}$$

The features are used for training self organizing map to get 64 texture and shape based concepts that will be used to describe the local visualness.

3.2.2 Entropy Weighted Concept Vector

Measuring only the concept frequency in individual images might not be sufficient to determine their importance for.image representation. Additional information is necessary. In general, the popular TF-IDF term-weighting scheme is used, where the vector elements (feature attributes) are expressed as the product of local and global weights. This weighting scheme amplifies the influence of terms, which occur often in a document (e.g., tf factor), but relatively rare in the whole collection of documents (e.g.,idf factor). However, images are more complex than text documents and image patches contain more information about visual patterns of particular concepts than single keywords in text documents. To know which concept has visually discriminative power is important for image representation as the "bag of concepts." The visualness of a concept is generally defined as to what extent a concept has visual characteristics. To know which concept has visually discriminative power is important for image representation, especially refining the bag-of-concepts-based representation, since not all concepts are related to visual contents. An entropy of an image patch (e.g., concept) can be valuable to determine its importance of visualness for image representation. Entropy can be considered as the average number of bits one needs to represent a symbol in a stationary system, where the limited source symbols have fixed probabilities of occurrence.

In other words, an entropy is a quantity that is used to describe the degree of randomness of an image. Low entropy image patches will have very little contrast and a relatively uniform color information, such as those that appear in the background area of medical images, as shown in Fig. 5 for the concepts black and gray background. On the other hand, high entropy image patches such as the foreground image region have a great deal of contrast from one pixel to the next and are more important in capturing image content. We observe that in medical images, various regions in the foreground (such as the concepts honeycomb, bronchi, etc.) appear as rough or fractal. So the entropy of image patches is helpful for their separation from the uniform and smoothly varying background. The concepts in the part of background usually appear more frequently in images (similar to"stop-words" in documents) than those in the part of foreground. Hence, they are less effective in representing images for classification or retrieval. Thus, we use the entropy as a measure of concept importance similar to the key block entropy, which is the Shannon entropy of the patches based on pixel values. However, we only consider the intensity values of the gray-scale image patches instead of considering all three color channels in RGB space. The entropy of an image (patch) I is expressed as,

$$E = -\sum_{I=0}^{255} P(I) \log_2 P(I) \tag{3.26}$$

where P(I) is probability of occurrence of the intensity value (gray value) I appears in a patch. Now, to measure the entropy of each concept categories c_i in C, we select all the training patches in each category, sum up their entropy values and obtain the average values based on the number of training sample in each category as

$$e_i = \frac{\sum_{j=0}^{N_{ci}} E_j}{N_{ci}} \tag{3.27}$$

where E_j is the entropy of a patch x_j and N_{ci} is the number of training samples in concept category c_i. Finally, by using the entropy values of each concept categories, an image I_j is represented as a weighted-concept vector.

$$f_j^{wC} = e_i * [f_{1j} \quad f_{2j} \quad \dots \quad \dots \quad f_{nj}] \tag{3.28}$$

where $f_j wC$ is the feature vector that is being fed into self organizing map to train it to recognize 64 concepts.

3.3 Prepare and Query on the Image database

3.3.1 Image Representation

Once the neural network based self-organized-map is ready then we selects an image and mark them with this neural network(som). To do this work properly at first we divide the image into 8x8 grids. Then each of the grid is considered as a concepts. We create the texture and shape based feature vector of the grid and fed it to SOM. SOM decide the concept that a grid represents. We create a concept map of 8x8 grid of the image and also a histogram of concepts based feature vector(f_j^{wC}).

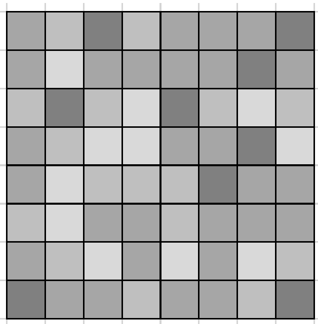

Figure 3.2: A gray scale image

C4	C2	C5	C2	C4	C3	C3	C5
C4	C1	C4	C3	C3	C5	C5	C4
C2	C5	C2	C1	C5	C2	C1	C2
C3	C2	C1	C1	C3	C4	C5	C1
C3	C1	C2	C2	C2	C5	C4	C4
C2	C1	C3	C3	C2	C5	C4	C3
C4	C2	C1	C3	C1	C3	C1	C2
C5	C3	C3	C2	C3	C4	C2	C5

Figure 3.3: Image is divided into multiple concept grid(concept map)

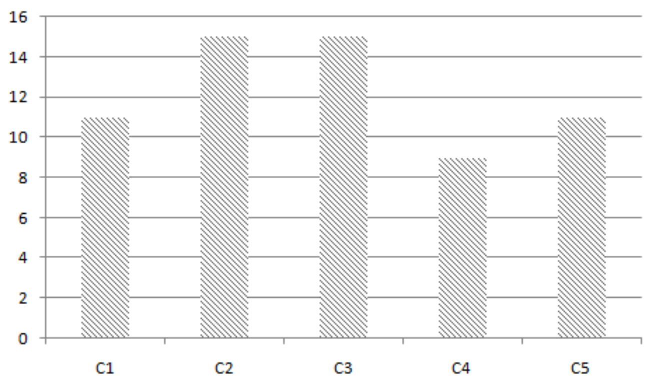

Figure 3.4: histogram of concepts

In this way we mark the whole database and crate histogram of concepts. The images are saved to a new database which is clustered into 64 category. Each of the cluster contains all the images that contains that individual concept. So for the worst case the redundancy of the database is 64 times of the original database. It's a trade off for fast query.

3.3.2 Query procedure

When a query image is given at first it is represented with the procedure described in section 3.3.1. Now when the query image is ready with f_j^{wC} feature vector, for each of the 64 bin if it's size is greater than 0 then we have extracted all the images of that respective cluster in our database. For each of the cluster image we have already created the concept map and histogram of concepts based feature vector. Now we need to normalize this feature vector. We called this procedure "Relative Concept Distance Normalization(RCDN)".

Before going to the procedure let's discuss about the problems of comparing the feature vectors without RCDN. There are two image below (a) and (c) which are different but maped to a single histogram of concepts.

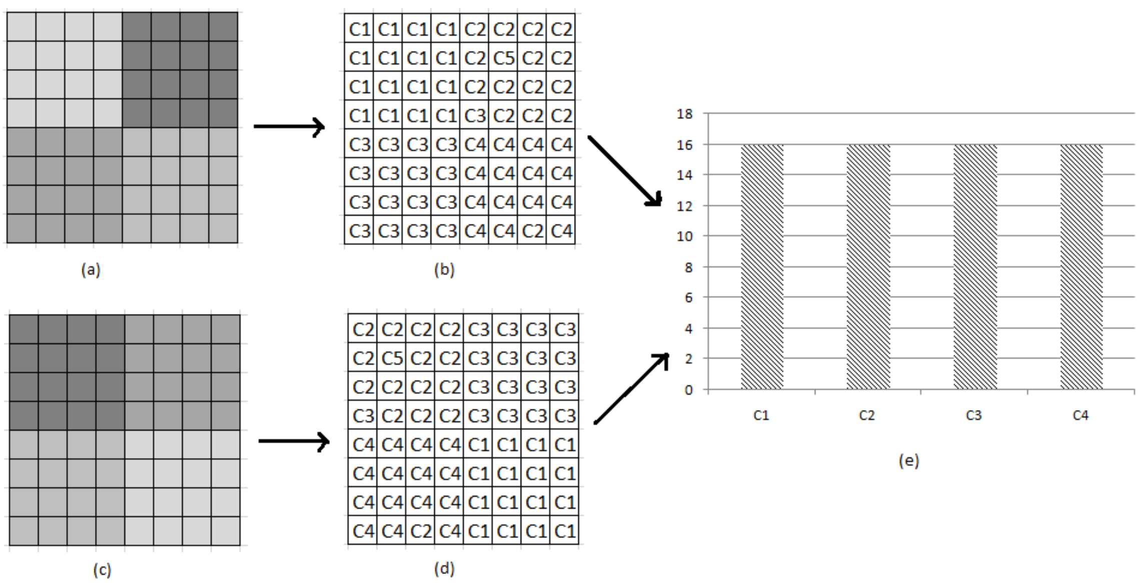

Figure 3.5: Two different image mapped to a same histogram of concepts

So for two different image there is one histogram. It's obvious from the figure that there is a collision and the collision could occur in many ways. So we normalize the feature vectors of the database in such a way so that they could not be same.

In database image, Normalize (divide) each of the concept of the histogram bin by the relative displacement of it's same nearest concept. For a position of the query image and database image if the two concept is same distance is 1 and the bin remains same. But if two concept is not same then we search for the concept of the query image in the database image. We have analyzed 3 different procedures.

1. Flow Network solution:

Each of the position of a specific concept of the input image is considered as a node which is connected to the source with infinite cost. Each of the position of that specific concept of the query image is considered as a node which is connected to the sink with infinite cost. Each off the connected node with the source are connected to the all of the nodes that are connected to the sink with cost p_{kj}. Here p_{kj} is the distance(manhattan) between the k^{th} connected node with the source to the j^{th} connected node of the sink. The min cut of this graph is the value with which the value of the histogram bin has been divided to normalize.

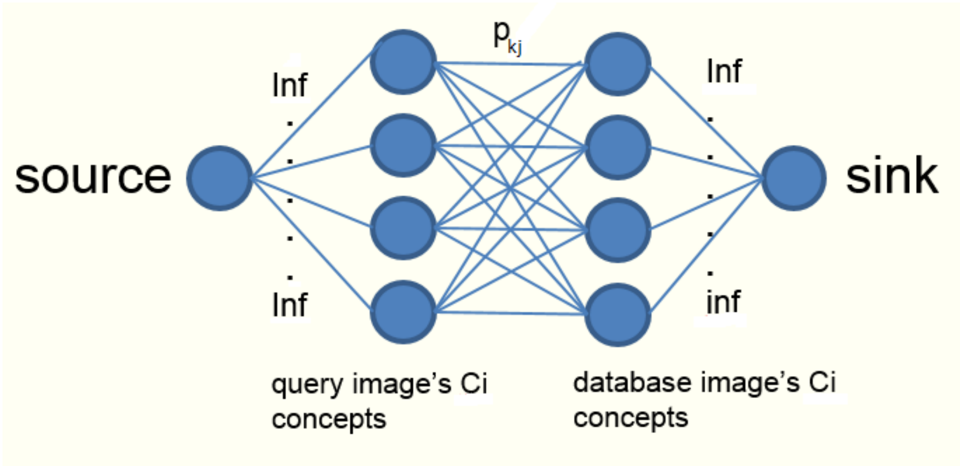

Figure 3.6: The Flow network

2.Relative Concept Distance Normalization(RCDN) with minimum distance:

In this procedure we have edited the **ford-fulkarson** algorithm. For each position if the two image(query and database) do not contain same concept we search for concept of the query image in database image and calculate the minimum distance(manhattan distance).

$$B_i = \frac{B_i}{\sum_{k=1}^{n_i^Q}(min\{d(p_{it}^Q, p_{ik}^C) + 1\})} \tag{3.29}$$

here B_i is the histogram bin value of the i^{th} concept. $d()$ is a function calculate the manhattan distance between 2 position. n_i^Q denotes number of i^{th} concept in the query image.p_{iQ}^Q and p_{iQ}^C are positions. Here superscript denotes whether the position is in the query(for Q) image or in the database(for C) image. the subscript ix denotes i^{th} concept of the query image which is the x^{th} number of i concept.

2.Relative Concept Distance Normalization(RCDN) with average distance:

in this case, for each position if the two image(query and database) do not contain same concept we search for concept of the query image in database image and calculate the average distance(manhattan distance) to normalize the feature vector.

$$B_i = \frac{B_i}{\sum_{k=1}^{n_i^Q}[avg\{\sum_{j=1}^{n_i^c} d(p_{iQ}^Q, p_{iQ}^C)\}]} \tag{3.30}$$

here B_i is the histogram bin value of the i^{th} concept. $d()$ is a function calculate the manhattan distance between 2 position. n_i^Q denotes number of i^{th} concept in the query image.n_i^Q denotes number of i^{th} concept in the database image. p_{iQ}^Q and p_{iQ}^C are positions. Here superscript denotes whether the position is in the query(for Q) image or in the database(for C) image. the subscript ix denotes i^{th} concept of the query image which is the x^{th} number of i concept. In our experiment RCDN with average distance provides better results.

After normalization of the feature vector we send perform a k-nearest-neighbour(KNN) algorithm and retrieve first k images based on the user input.

Chapter 4

Experiments, Result & Discussion

4.1 Dataset Evaluation

To evaluate the effectiveness of the proposed image representation approach, exhaustive experiments were performed in two different image collections. The first image collection consists of 12674 multi-modal biomedical images in 64 clustered disjoint global categories, which is a subset of a larger collection of six different data sets used for the medical image retrieval task in ImageCLEFmed'2008.In this collection the images are classified into IRMA codes. Each IRMA codes consists of four subcategories.

- T (technical) : image modality
- D (directional) : body orientation
- A (anatomical) : body region examined
- B (biological) : biological system examined

This allows a short and unambiguous notation (IRMA: TTTT – DDD – AAA – BBB), where T, D, A, and B denotes a coding or sub-coding digit of the technical, directional, anatomical, and biological axis, respectively. In addition, this notation avoids mixtures of one- and two-literal code positions.

4.1.1 Technical code for imaging modality

The T-code describes within a maximum of four positions the technical method. It starts with the physical source of image acquisition (e.g.: 1 ”x-ray”, 2 ”ultrasound”, 3 ”magnetic resonance imaging”, 4 ”optical imaging”, . . .) showing more details in the modality position (e.g.: 11 ”plain film projection radiography”, 12 ”fluoroscopy”, 13 ”angiography”, 14 ”computed tomography”, . . .). A third digit specifies the technique (e.g.: 111 ”digital”, 112 ”analog”, 113 ”stereometry”, 114 ”stereography”, . . .), and the fourth position of the T-code assesses sub-techniques (e.g.: 1111 ”tomography”, 1112 ”high energy”, 1113 ”low energy”, 1114 ”parallel beam”, . . .). A complete listing of the IRMA T-code is given in Appendix A. Note that the non-radiological part of this code (4 ”nuclear medicine”, 5 ”optical imaging”, 6 ”biophysical procedures”, 7 ”others”, 8 ”secondary digitization”) are not modeled completely.

4.1.2 Directional code for imaging orientation

This three-digit part of the IRMA-code incorporates a two-step orientation description starting with the common orientation (e.g.: 1 ”coronal”, 2 ”sagittal”, 3 ”transversal”, 4 ”other”) and giving a more detailed specification in the second position (e.g.: 11 ”posteroanterior (PA)”, 12 ”anteroposterior (AP) ”). Note that it is important to distinguish APand PA-directions since organs and bone structures might differ in scale, for instance, supposing plain x-ray chest imaging. Independent from the relative orientation of body region and imaging system, functional orientation tasks of the examination can also be described (e.g.: 111 ”inspiration”, 112 ”expiration”, 113, ”valsalva”, 114 ”phonation”, . . .).

4.1.3 Anatomical code for body region examined

The IRMA-code supports complete coding of the anatomical region. In total, nine major regions are defined (e.g.:1 ”total body”, 2 ”head/scull”, 3 ”spine”, 4 ”upper extremity”, . . .). The major region is followed by up to two hierarchical sub-codes (e.g.: 3 ”spine”, 31 ”cervical spine”, 311 ”dens”). The ten primary part of the anatomical code based on which we extracted images are, 0-unspecified, 1-whole body, 2-cranum, 3-spine, 4-upper extremity / arm, 5-chest, 6-breast, 7-abdomen, 8-pelvis, 9-lower extremity / leg.

4.1.4 Biological code for biological system examined

The B-code determines the organ system that is imaged. This axis is necessary because the body region examined insufficiently describes content and structure of images. For example, fluoroscopy of the abdominal region may access the vascular or the gastrointestinal system depending on the way the contrast agent is administered, which results in different image textures. On the top-level of this three digit IRMA-code, ten organ systems are specified (e.g.: 1 ”cerebrospinal system”, 2 ”cardiovascular system”, 3 ”respiratory system”, 4 ”gastrointestinal system”, . . .) each of which having up to three positions to exactly identify the organ in question (e.g.: 1 ”cerebrospinal system”, 11 ”central nervous system”, 111 ”mesencephalon”).

4.1.5 Dataset Extraction

In our experiment, dataset is extracted maintaining anatomical code which is divided into nine primary parts(excluding unspecifid). For experimental purpose we have used 85 percent data for training and 15 percent data for testing purpose. For concept model generation based on the SOM learning, 64 local concept categories are manually obtained from a training set of more than 5000x64 image patches.To generate the local patches, each image in the training set (we used only 2 percent images of entire data set) is resized to 512x512 pixels and partitioned into an 8x8 grid generating 64 non overlapping regions of size 32x32 pixels. Only the regions that conform to at least 5 percent of a particular concept category are selected and labeled with the corresponding category label.

4.2 Experimental Result

At first let's see the clustering results of self organizing map. The topology of self organizing map is hexagonal 8x8 grid shown below. The size of the feature vector is 62. So input size of the SOM is 62. There is 64 neuron in the SOM aligned in a squared shape. one neighbour is connected to it's six neighbour.

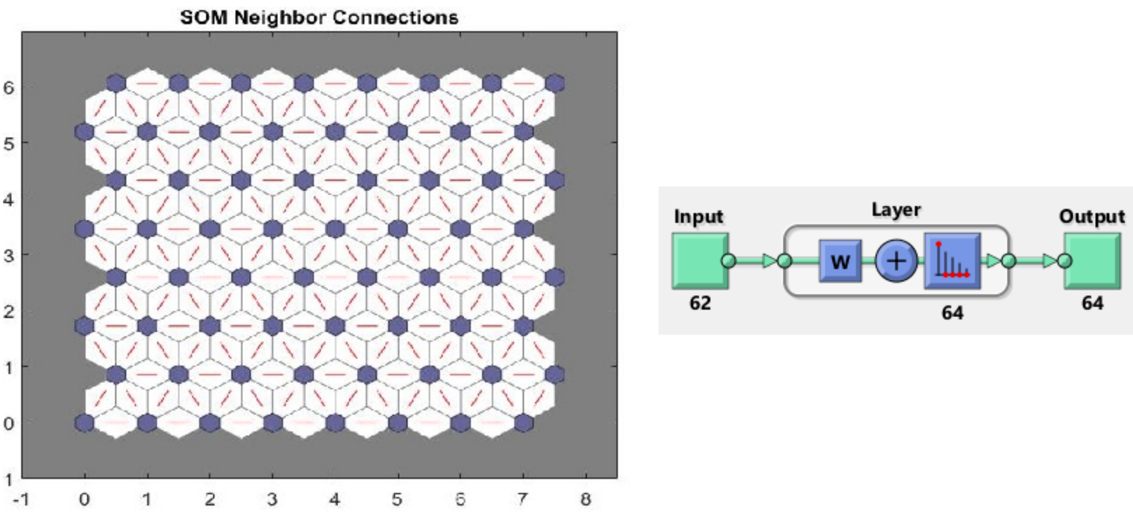

Figure 4.1: The grid connectivity of SOM

after clustering if we color the neighbouring weight the SOM connection looks like below,

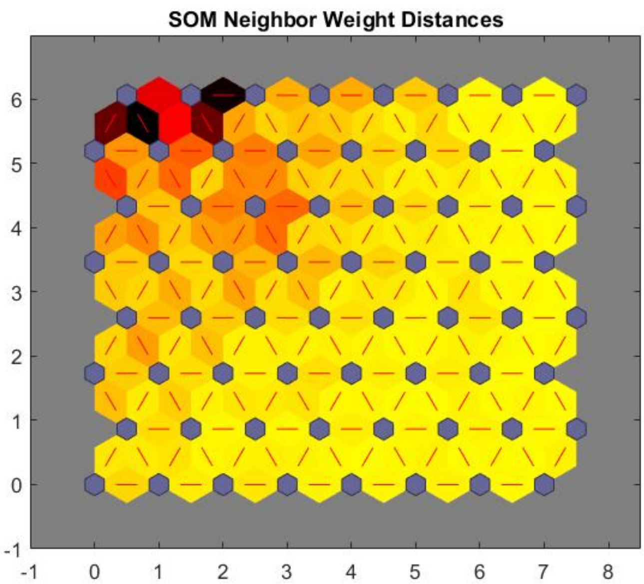

Figure 4.2: The weight distribution of SOM in color

it shows that there is not much more variation of distance. This is happened as because the dominance of black region in our image dataset.

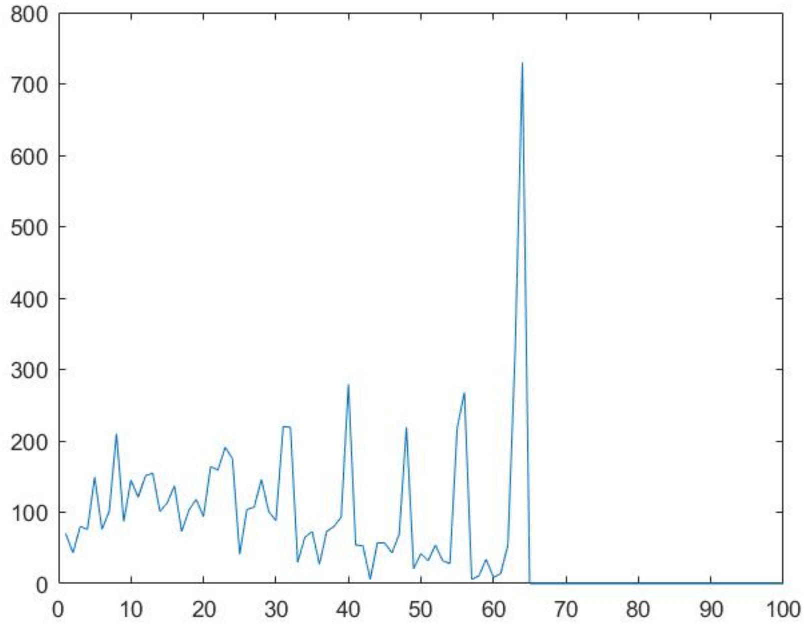

Figure 4.3: The frequency of concepts in value

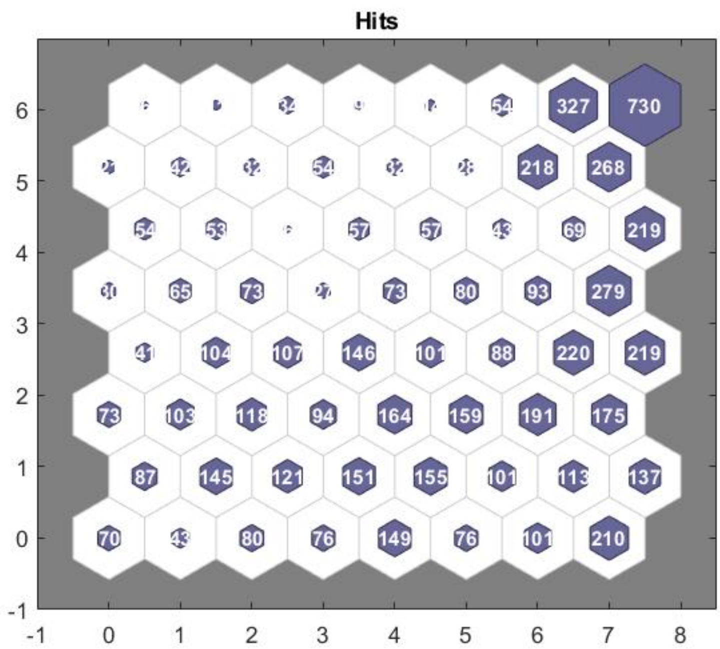

Figure 4.4: The frequency of concepts hitcount on neuron

figure 4.3 and 4.4 gives us the hit count of the clusters. Here from the first glance it seems obvious that the clustering is not so better. But if we see our research area and dataset, most of the images are consists of dark regions and together they made a dominance of dark region. So in the cluster there should be a neuron with much higher hit count which enables other neuron's low hit count. It is also a reminder that here we show result of a small subdatabase for better understanding.

Now let us discuss about the size of the self-organizing map. The som is performed better with 8x8 grid as here form the hit count we see that some of the clusters contains a small amount of hit count. For following case around 11-12 neuron contains a small amount of hits. After substituting we get around 52-53 active cluster. If we reduce the size of the network it reduces in square term. So a 7x7, 6x6 or 5x5 grid have around 37-39, 28-29, 19-20 active cluster which are not quite good amount of cluster to categorize 9 major anatomical data based on shape and texture feature. On the other hand if we increase size of the net, it increases by square term. So 9x9, 10x10, 11x11 gets 81, 100, 121 neurons which increases redundant data. For exhaustive clustering the same 2 category my turn into two different category.

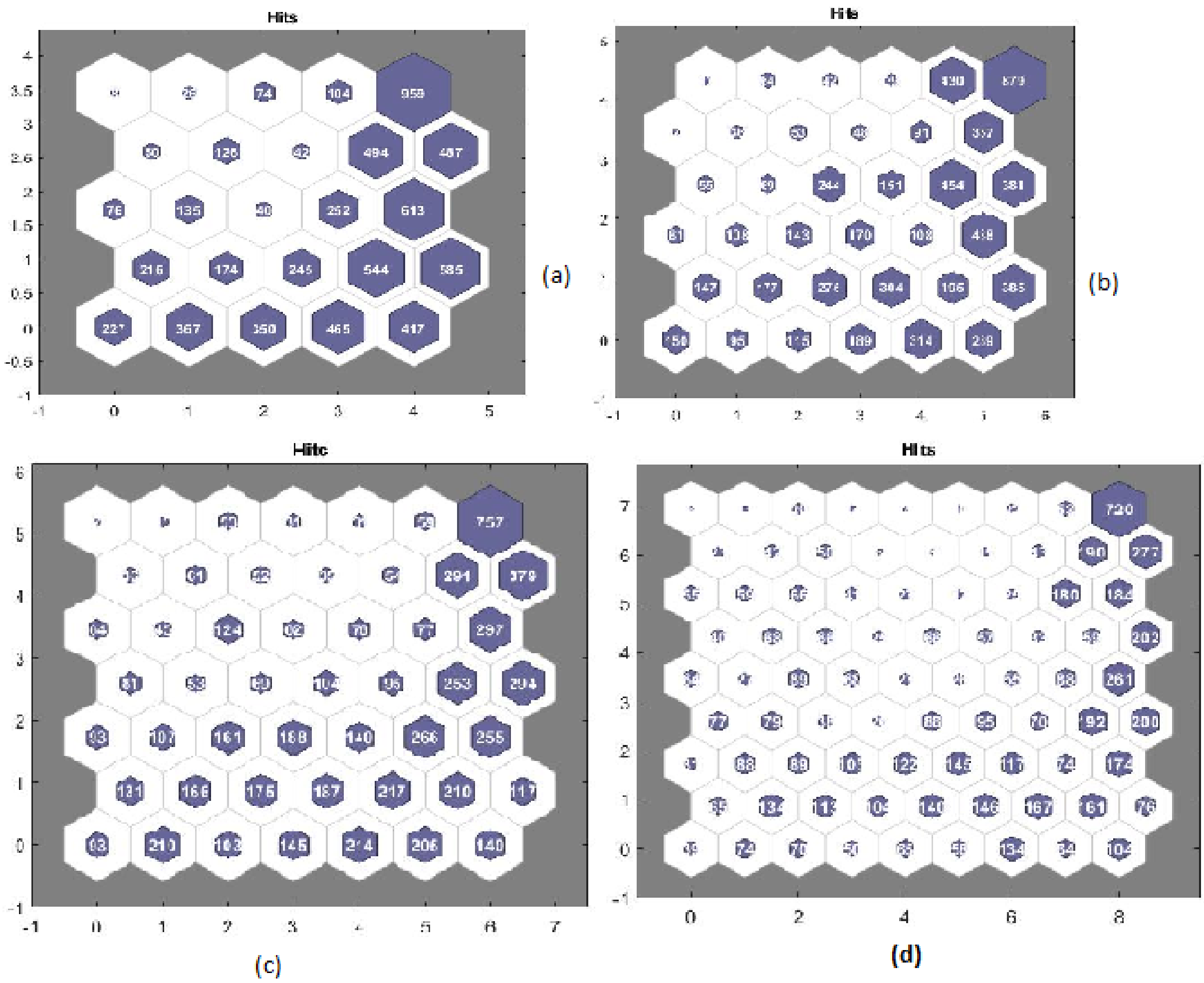

Figure 4.5: the hitcount for 5x5, 6x6, 7x7 and 9x9 grid

The use of entropy based weighted vector is shown below.

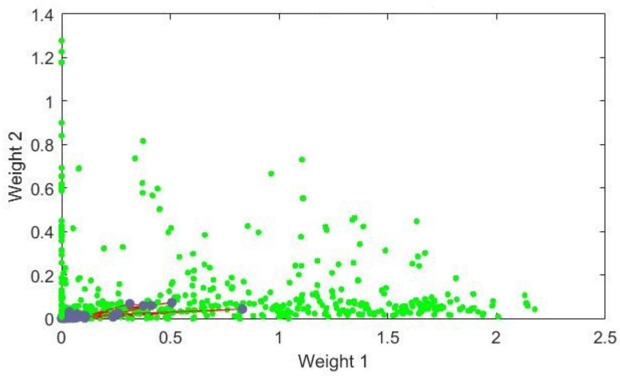

Figure 4.6: Sample points plotted in 2D grid with multiplying entropy(entropy weighted vector)

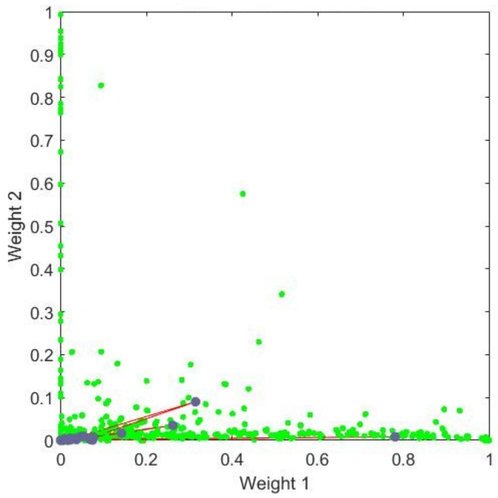

Figure 4.7: sample point plotted in 2D grid without multiplying entropy

Here for same number of point, we see that in case of entropy weighted vector the data points gets more distributed(in figure 4.6) than the original plot in figure 4.7

For evaluation of the effectiveness of the proposed approach based on retrieval performance, the concepts of Precision and Recall are used. Recall is the ratio of the number of relevant images returned to the total number of relevant images in the database. Precision is the ratio of the number of relevant images returned to the total number of images returned. So, when the top N (scope) images are considered and there are Q relevant images, the precision within top N . images is defined to be Precision(N) = QN, whereas recall will be Recall(N) = Q/R. Here, R is the number of all images that are relevant to the query image. A high Precision value means that there are few false alarms (i.e., the percentage of irrelevant images in the retrieval), while a high Recall value means that there are few false dismissals (the percentage of relevant images which failed to be retrieved). The average precision and recall are calculated over all the queries to generate the precision–recall (PR) curves in different settings. For a quantitative evaluation of the retrieval results, we selected all the images in the individual collections as query images and used "query-by-example" as the search method, where a query is specified by providing an example image to the system. A retrieved image is considered a correct match if and only if it is the same semantic category as the query image.

$$Precision = \frac{N}{Q} \tag{4.1}$$

$$Recall = \frac{Q}{R} \tag{4.2}$$

The ROC Curve of our experimental results are given below.

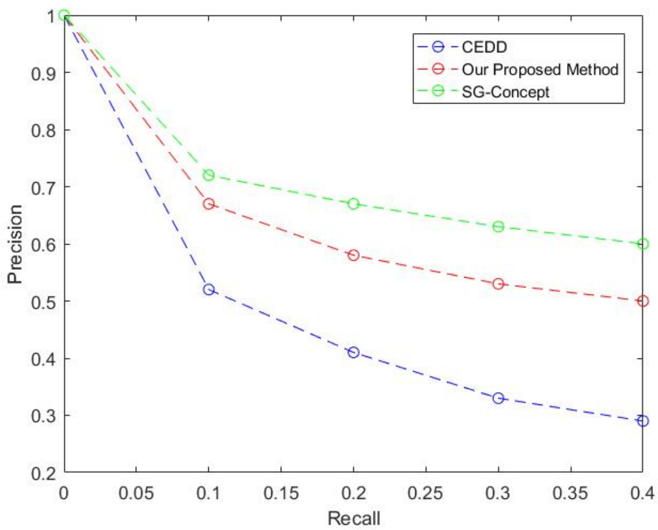

Figure 4.8: ROC curve for three different retrieval system

Here we have used the official software from CEDD publication. We have compare our dataset from that software. But the SG-concept experiment is not carried with our dataset. As we have very similar approach in solving the same problem, we have inputted their precision recall values. Here we see that our proposed approach is much better that the CEDD approach.

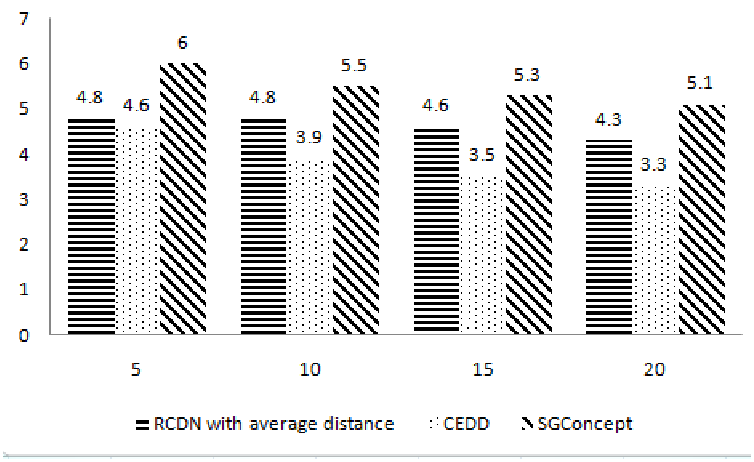

Figure 4.9: Precision value for k = 5,10,15,20 (with eq 3.30)

The Precision value for our system for fixed number of output is quite good. We have added precision value for here k=5,10,15,20. It is also important to say that we Have calculated CEDD precision with it's official software but we don't have any instance of SG-Concept executable. We just added their result for competitive purpose.

in this case it is worth mentioning that we have got the best results in our experiment using RCDN with average distance maintaining normalization equation 3.30. With normalize equation 3.29 we get the following results.

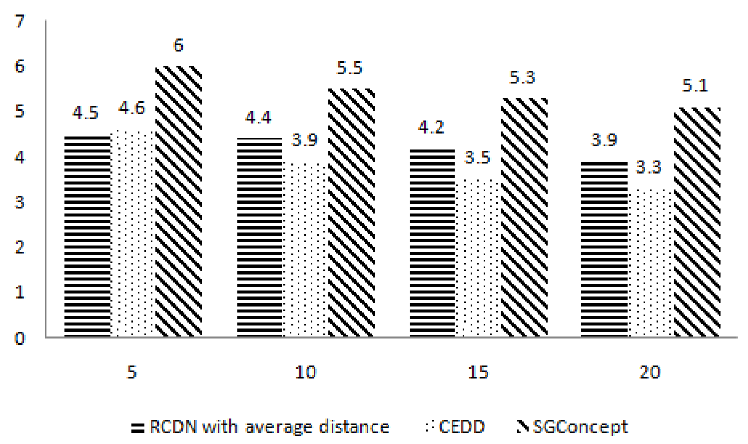

Figure 4.10: Precision value for k = 5,10,15,20 (with eq 3.29)

and with flow network we get following result.

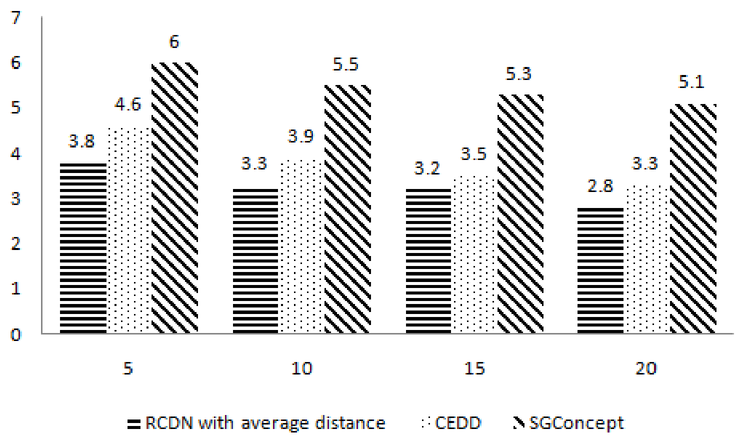

Figure 4.11: Precision value for k = 5,10,15,20 (for flow graph)

here in case of flow graph sometimes for overall optimization flow algorithm takes the longest path which creates wrong normalization for some position.

Chapter 5

Conclusion

This article introduces an approach for representing image with concepts and a generalized way to create concept using SOM. Each of the concept images are then converted to histogram histogram of concepts. Concept location information is also taken into account by dividing each image 16 non-overlapping grid. A spatial verification step can further refine the retrieval results based on similar overlapping region matching of query image ROI and the overlapping regions of database images. The search approach realizes semantic abstraction via prior learning and user interaction and improves retrieval effectiveness.

Bibliography

[1] C. Akgul, D. Rubin, S. Napel, C. Beaulieu, H. Greenspan, B. Acar, Content–based image retrieval in radiology: Current status and future directions, Journal of Digital Imaging 24 (2) (2011) 208–222.

[2] Unknown, Riding the wave: How europe can gain from the rising tide of scientific data, Submission to the European Commission, available online at http://cordis.europa.eu/fp7/ict/e-infrastructure/docs/hlg-sdi-report.pdf (October 2010).

[3] S. Montani, R. Bellazzi, Supporting decisions in medical applications: the knowledge management perspective, International Journal of Medical Informatics 68 (2002) 79–90.

[4] S. Montani, R. Bellazzi, Supporting decisions in medical applications: the knowledge management perspective, International Journal of Medical Informatics 68 (2002) 79–90.

[5] A. Aamodt, E. Plaza, Case-based reasoning: Foundational issues, methodological variations, and system approaches, AI communications 7 (1) (1994) 39–59.

[6] J. Kalpathy-Cramer, A. Garc'ıa Seco de Herrera, D. Demner-Fushman, S. Antani, S. Bedrick, H. Muller, Evaluating performance of biomedical image retrieval systems– an overview of the medical image retrieval task at ImageCLEF 2004–2014, Computerized Medical Imaging and Graphics.

[7] ARRS GoldMiner: http://goldminer.arrs.org/ , 1 Nov, 2016

[8] Y. Hong, C. Yong-gang, "Automatically Extracting Information Needs from Ad Hoc Clinical Questions", Proceedings of AMIA Symposium, pp. 96-100, 2008.

[9] M. A. Hearst, A. Divoli, H. Guturu, A. Ksikes, P. Nakov, M. A. Wooldridge, J. Ye, "BioText Search Engine: beyond abstract search", Bioinformatics, vol. 23, no.16, pp. 2196- 2197, 2007.

[10] Yottalook: http://www.yottalook.com/index_img.php, 3 Nov, 2016

[11] S. Xu, J. McCusker, M. Krauthammer, "Yale Image Finder (YIF): a new search engine for retrieving biomedical images," Bioinformatics, vol. 24, no. 17, pp. 1968-1970, 2008.

[12] IRMA: http://ganymed.imib.rwthaachen.de/irma/veroeffentlichungen_en.php, 1 Nov, 2016

[13] iMedline: http://archive.nlm.nih.gov/iti/, 1 Nov, 2016

[14] MedGIFT: http://medgift.hevs.ch/silverstripe/, 1 Nov, 2016

[15] MedGIFT: http://medgift.hevs.ch/silverstripe/, 3 Nov, 2016

[16] J. Lim, J. Chevallet, "VisMed: A Visual Vocabulary Approach for Medical Image Indexing and Retrieval", in proceedings of Asia Information Retrieval Symposium, pp. 84-96, 2005.

[17] ASSERT: http://cobweb.ecn.purdue.edu/RVL/Research/CBIR/index, 2 Nov,2016

[18] ASSERT: http://cobweb.ecn.purdue.edu/RVL/Research/CBIR/index, 2 Nov,2016

[19] Y. Liu, D. Zhang, G. Lu, and.-Y.Ma, "A survey of content-based image retrieval with high-level semantics," Pattern Recogn., vol. 40, no. 1, pp. 262–282, 2007.

[20] B. Verma and S. Kulkarni, "Fuzzy logic based interpretation and fusionof color queries," Fuzzy Sets Syst., vol. 147, pp. 99–118, 2004.

[21] R. Krishnapuram, S. Medasani, S.-H. Jung, Y.-S. Choi, and R. Balasubramaniam, "Content-based image retrieval based on a fuzzy approach,"IEEE Trans. Knowl. Data Eng., vol. 16, no. 10, pp. 1185–1199, Oct. 2004.

[22] J. M. Medina, S. Jaime-Castillo, C. D. Barranco, and J. R. Campa˜na,"Flexible retrieval of X-Ray images based on shape descriptors using afuzzy object-relational database," in Proc. Int. Fuzzy Syst. Assoc.–Eur.Soc. Fuzzy Logic and Technol., Lisbon, Portugal, Jul. 20–24, 2009, pp.903–908.

[23] J. Chamorro-Mart'Õnez, J. M. Medina, C. D. Barranco, E. Gal'anPerales, and J. M. Soto-Hidalgo, "Retrieving images in fuzzy object-relational databases using dominant color descriptors," Fuzzy Sets Syst., vol. 158,pp. 312–324, 2007

[24] S.Pradeep, Mrs.L.Malliga M.E., "Content based image retrieval and segmentation of medical image database with fuzzy value", ISBN No.978-1-4799-3834-6/14/, 2014 IEEE

[25] P. Mohanaiah, P. Sathyanarayana, L. GuruKumar, "Image Texture Feature Extraction Using GLCM Approach", International Journal of Scientific and Research Publications, Volume 3, Issue 5, May 2013, ISSN 2250-3153

[26] S. Petushi, F. U. Garcia, M. M. Haber, C. Katsinis, and A. Tozeren, "Large-scale computations on histology images reveal grade-differentiating parameters for breast cancer," BMC Med. Imag., vol. 6, no. 1, p. 14, 2006.

[27] L. Yang, W. Chen, P. Meer, G. Salaru, M. D. Feldman, and D. J. Foran, "High throughput analysis of breast cancer specimens on the grid," in Proc. Int. Conf. Med. Image Comput. Comput. Assist. Intervent., 2007, pp. 617–625.

[28] J. C. Caicedo, A. Cruz, and F. A. Gonzalez, "Histopathology image classification using bag of features and kernel functions," Artif. Intell. Med., pp. 126–135, 2009.

[29] J. Sivic and A. Zisserman, "Video Google: A text retrieval approach to object matching in videos," in Proc. IEEE Int. Conf. Comput. Vis., 2003, pp. 1470–1477.

[30] A. N. Basavanhally, S. Ganesan, S. Agner, J. P. Monaco, M. D. Feldman, J. E. Tomaszewski, G. Bhanot, and A. Madabhushi, "Computerized image-based detection and grading of lymphocytic infiltration in HER2+ breast cancer histopathology," IEEE Trans. Biomed. Eng., vol. 57, no. 3, pp. 642–653, Mar. 2010.

[31] A. N. Basavanhally, S. Ganesan, S. Agner, J. P. Monaco, M. D. Feldman, J. E. Tomaszewski, G. Bhanot, and A. Madabhushi, "Computerized image-based detection and grading of lymphocytic infiltration in HER2+ breast cancer histopathology," IEEE Trans. Biomed. Eng., vol. 57, no. 3, pp. 642–653, Mar. 2010.

[32] A. Tabesh, M. Teverovskiy, H.-Y. Pang, V. P. Kumar, D. Verbel, A. Kotsianti, and O. Saidi, "Multifeature prostate cancer diagnosis and Gleason grading of histological images," IEEE Trans. Med. Imag., vol. 26, no. 10, pp. 1366–1378, Oct. 2007.

[33] S. Doyle, S. Agner, A. Madabhushi, M. Feldman, and J. Tomaszewski, "Automated grading of breast cancer histopathology using spectral clustering with textural and architectural image features," in Proc. IEEE Int. Symp. Biomed. Imag., 2008, pp. 496–499.

[34] Liu, Y., Zhang, D., Lu, G.: Region-based image retrieval with high-level semantics using decision tree learning. Pattern Recognition 41, 2554–2570 (2008)

[35] Fei-Fei, L., Fergus, R., Perona, P.: Learning generative visual models from few training examples: an incremental Bayesian approach tested on 101 object categories. In: Proceedings of Computer Vision and Pattern Recognition, Workshop on Generative-Model Based Vision, pp. 178–185 (2004)

[36] Jing, F., Li, M.: Relevance Feedback in Region-Based Image Retrieval. IEEE Transactions on Circuits and Systems for Video Technology 14(5) (May 2004)

[37] Zhang, D., Islam, M.M., Lu, G., Hou, J.: Semantic Image Retrieval Using Region Based Inverted File. In: Proceedings of Digital Image Computing: Techniques and Applications, pp. 242–249 (2009)

[38] Yixiao Zhoua, Yan Huanga, Haibin Lingb and Jingliang Penga, "Medical Image Retrieval Based on Texture and Shape Feature Co-occurrence" , Medical Imaging 2012: Computer-Aided Diagnosis, edited by Bram van Ginneken, Carol L. Novak, Proc. of SPIE Vol. 8315, 83151Q · © 2012 SPIE · CCC code: 1605-7422/12/ , doi: 10.1117/12.911240 , Proc. of SPIE Vol. 8315 83151Q-1

[39] Muhammet Bastan, Hayati Cam, Ugur Gudukbay and Ozgur Ulusoy, "BilVideo-7: An MPEG-7 Compatible Video Indexing and Retrieval System", IEEE MultiMedia, vol. 17, no. 3, pp. 62-73, July-September 2010.

[40] Savvas A. Chatzichristofis, Yiannis S. Boutalis, "CEDD: Color and Edge Directivity Descriptor: A Compact Descriptor for Image Indexing and Retrieval", 6th International Conference, ICVS 2008 Santorini, Greece, May 12-15, 2008 Proceedings, DOI: 10.1007/978-3-540-79547-6_30

[41] Savvas A. Chatzichristofis and Yiannis S. Boutalis, FCTH: Fuzzy Color and Texture Histogram, A low level feature for accurate image retrieval.", Ninth International Workshop on Image Analysis for Multimedia Interactive Services, 978-0-7695-3130-4/08, 2008 IEEE, DOI: 10.1109/WIAMIS.2008.24

[42] B.Jyothi, B.Jyothi, P.G.Krishna Mohan. An Effective Multiple Visual Features for Content Based Medical Image Retrieval, "IEEE Sponsored 9th International Conference on Intelligent Systems and Control (ISCO)2015", 978-1-4799-6480-2/15/, 2015 IEEE.

[43] Xiaohong Gao, Yu Qian (2012); MIRAGE: An E-repository of Medical Images for Learning Biomedical Informatics, eTELEMED 2012: The Fourth International Conference on eHealth, Telemedicine, and Social Medicine, January 30, 2012 to February 4, 2012, ISBN: 978-1-61208-179-3, Valencia, Spain, 209 - 214

[44] A. K. Jain and A. Vailaya, "Image retrieval using colour and shape", Pattern Recognition, vol. 29, no. 8, (1996), pp. 1233-1244.

[45] M. Flickner, H. Sawhney, W. Niblack, et al., "Query by image and video content: the QBIC system", IEEE Computer, vol. 28, no. 9, (1995), pp. 23-32.

[46] G. Pass and R. Zabith, "Histogram refinement for content-based image retrieval", In Proc. Workshop on Applications of Computer Vision, (1996), pp. 96-102.

[47] J. Huang, S. Kuamr, M. Mitra, et al., "Image indexing using colour correlogram", In Proc. CVPR, (1997), pp. 762-765.

[48] M. Yang, K. Kpalma and J. Ronsin. "A survey of shape feature extraction techniques", Pattern Recognition, (2008), pp. 43-90.

[49] Jayashree Kalpathy-Cramer, Alba García Seco de Herrerab, Dina Demner-Fushmanc,Sameer Antani, Steven Bedric, Henning Müller, "Evaluating performance of biomedical image retrieval systems—An overview of the medical image retrieval task at ImageCLEF 2004–2013", Computerized Medical imaging and Graphics, Volume 39, Pages 55–61, 2014 Elsevier Ltd. DOI: http://dx.doi.org/10.1016/j.compmedimag.2014.03.004.

[50] Thomas M. Lehmann, Henning Schubert, Daniel Keysers,Michael Kohnen , Berthold B. Wein, "The IRMA code for unique classification of medical images", Medical Imaging 2003: PACS and Integrated Medical Information Systems: Design and Evaluation, H. K. Huang, Osman M. Ratib, Editors, Proceedings of SPIE Vol. 5033 (2003) © 2003 SPIE·1605-7422/03/

[51] Md. Mahmudur Rahman, Sameer K. Antani, Dina Demner-Fushman, George R. Thoma, "Biomedical image representation approach using visualness and spatial information in a concept feature space for interactive region-of-interest-based retrieval", Journal of Medical Imaging 2(4), 046502 (Oct–Dec 2015), 2329-4302/2015/ © 2015 SPIE.

[52] Jesus Martínez-Gómez,José A.Gámez,Alba García Seco de Herrera,Henning Müller, "Medical images modality classification using discrete Bayesian Networks", Computer Vision and Image Understanding · April 2016, DOI: 10.1016/j.cviu.2016.04.002

[53] Zhang, J., Yoo, C.-W., Ha, S.-W.: ROI Based Natural Image Retrieval using Color and Texture Feature. Fuzzy Systems and Knowledge Discovery (2007)

[54] Chan, Y.-K., Ho, Y.-A., Liu, Y.-T., Chen, R.-C.: A ROI image retrieval method based on CVAAO. Image and Vision Computing 26, 1540–1549 (2008)

[55] Prasad, B.G., Biswas, K.K., Gupta, S.K.: Region-Based Image Retrieval using Integrated Color, Shape and Location Index. In:Computer Vision and Image Understanding, vol. 94, pp. 193–233 (2004), http://dx.doi.org/10.1016/j.cviu.2003.10.016

[56] Huang, C., Liu, Q., Yu, S.: Regions of interest extraction from color image based on visual saliency. Journal of Supercomp., doi:10.1007/s11227-010-0532-x.

[57] Shrivastava, N., Tyagi, V.: Content based image retrieval based on relative locations of multiple regions of interest using selective regions matching. Inform. Sci. 259, 212–224 (2013), http://dx.doi.org/10.1016/j.ins.2013.08.043

[58] Hsiao, M.-J., Huang, Y.-P., Tsai, T., Chiang, T.-W.: An Efficient and Flexible Matching Strategy for Content-based Image Retrieval. Life Science Journal 7(1) (2010)

[59] Chen, T Chen: Colour Image Indexing Using SOM for Region-ofInterest Retrieval. Pattern Analysis & Applications 2, 164–171 (1999)

[60] Wang, Z., Liu, G., Yang, Y.: A New ROI Based Image Retrieval System using an auxiliary Gaussian Weighting Scheme. Multimedia Tools Application (2012), doi:10.1007/s11042-012-1059-3.

[61] Yang, L., Geng, B., Cai, Y., Hua, X.-S.: Object Retrieval Using Visual Query Context. IEEE Transactions on Multimedia 13(6) (December 2011)

[62] Nishant Shrivastava, Vipin Tyagi, "A Review of ROI Image Retrieval Techniques", S.C. Satapathy et al. (eds.), Proc. of the 3rd Int. Conf. on Front. of Intell. Comput. (FICTA) 2014, Vol. 2, Advances in Intelligent Systems and Computing 328, DOI: 10.1007978-3-319-12012-6_56, Springer International Publishing Switzerland 2015.

[63] H. Tamura, S. Mori, T. Yamawaki, "Textural Features Corresponding to Visual Perception. IEEE Transaction on Systems", Man and Cybernetcs, Vol. SMC-8, No. 6, pp. 460–472, June 1978

[64] B. Terhorst. Texturanalyse zur globalen Bildinhaltsbeschreibung radiologischer Aufnahmen. Research project, RWTH Aachen, Institute for Medizinische Informatik, Aachen, Germany, June 2003.

[65] A. R. Rao. A Taxonomy for Texture Description and Identification. Springer Verlag, 1990.