Dissertation on (Major Project-II)

"Improvement in Medical Image Retrieval through Color Histogram and Machine Learning"

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In

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By

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This is to certify that the thesis entitled **"Improvement in Medical Image Retrieval through Color Histogram and Machine Learning"** done by me for the Major project-II for the achievement of **Master of Technology** Degree in **Software Technology** in the **Department of Computer Science & Engineering**, Delhi Technological University, Delhi is an authentic work carried out by me under the guidance of Dr. Rajni Jindal.

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Abstract:

A Content Based Image Retrieval (CBIR) framework plays an undeniable critical job in the field of medical diagnoses of images produced from various medical modalities. The present thesis experiments with a new image recovery system with the point of enhancing the outputs of color histograms. Additionally, we aimed to look into how to quantify the feasibility of such strategies employed. Therefore, in research we suggested an strategy for retrieval image dependent on various image characteristics such as image HSV-color-histogram examination, extracting color values from the selected image. The proposed technique produced good test results. In spite of the fact, whichever strategy one selects for the execution of CBIR techniques and mark the performances, it is to be noted of this is where it is hard to achieve absolute results and truths. A number of methods might be surely adept at recovering particular set of images, yet they may perform inadequately on others.

Chapter-1

1.1 BACKGDROP

Recently, use of mainframe pictures is getting progressively mainstream. Popular across various divisions including scientific experiments, educational, medical, etc. Medical institution and hospitals are producing an extraordinary number of mainframe pictures like magnetic resonance imaging (MRI), X-ray, mammogram and computed tomography (CT scan) as part of their daily routine. These information speak to a rich wellspring of data that is significant for conclusion, treatment, recuperation, recovery, and so forth. Therefore, Various image having prepared are comprehensive image databases including X-ray, US (ultrasound), CT (computed tomography), MRI (magnetic resonance imaging) etc [1]. Intended image retrieval of queried image is the most significant structure in the IDM (Image Database Management) [2].

1.2 PROFOUND SOLUTION: CBIR

CBIR system has been one in most explicit investigation topic in the area of system retrieval image , and significant progressions have been achieved in past few period. Content in the present CBIR method might relate to different characteristic features of the image like textures, shapes, colors,or on the other hand whatever other data that can be gotten itself from the image. This system will return the utmost visibly similar and identical images as intended by the query image search. This method is object of study worldwide and there exist a great number of databases for the purpose. In case of issues relating to collecting the retrieval image based on huge data of images (CBIR) use to play an important role. And therefore a number of scholar suggested the application of CBIR in case of medical imaging diagnosis. So as to help the radiologists in deciphering the medical images, scientists have created developed supportive system such as

Content Based Image Retrieval (CBIR) systems and Computer Aided Diagnosis (CAD) system for purpose of diagnosis in medical imaging [3].

1.3 PROBLEM STATEMENT

Because of the consistently expanding quantity of medicinal images, methods for retrieval quickly and ordering strategies are required that all the while reduce the distance between the semantic importance of images and the numerical quality of features. The related researches report enlisted problems in existing research contributions:

- The present medical content based image retrieval systems chiefly depend on single selective feature.
- One of the challenges differentiating medical CBIR from general purpose multimedia applications is the granularity of classification.
- Improvement to the robustness of the system is required.
- Retrieval reliability necessary for biomedical images was not met by CBIR technique.
- The system's accuracy can be enhanced further by utilizing features that more refined and exact.
- The lack of interaction between medical and engineering experts, which is strongly related to usage and performance characteristics of CBIR systems.
- The dimension of feature highly affects the retrieval efficacy and quality.
- Efficiency of the retrieval system can be enhanced by employing a multi-dimensional indexing structure.

The realization of requirements in case of medical image retrieval can be achieved by colour as well as shape-based descriptors. But, still indirect correlates of the shape cue are getting used. This method are but not being capable of capturing the compulsory classification granularity and hence medical CBIR systems currently are not being able to utilize the best potential of the shape or colour information. This results into deficiency of assessment of retrieval attribute of CBIR systems when it comes to large medical image databases with undefined query topics and standards.

1.4 OUTLINE OF THE THESIS CONTENTS

Chapter 1: In the chapter one, we tried to give general idea of sentiment analysis while describing the methods that has been applied in natural language processing.

Chapter 2: Since there was lot of work done in this area, a comprehensive review of literature of CBIR and short focus on methodology is thrown

Chapter 3: describes the overview of the CBIR and medical CBIR.

Chapter 4: Discusses Medical Imaging System (MIS) and CBIR and Machine Learning

Chapter 5: In this chapter Medical Imaging System (MIS) CBIR and Machine Learning has been taken into consideration.

Chapter 6: Various components of experiment and the results are discussed in the chapter.

Chapter 7: This chapter concludes the research.

Chapter-2

2.1 LITERATURE REVIEW

2.1.1 HISTORY OF CBMIR

In the earliest Query By Image Content (QBIC) system was introduced in the early 1990s as one of the basic step in the methods of CBIR system by IBM [4].

Images of relevant contents were retrieved from the data-base by contrasting the numerical element or signature of the example with numerical element of images in repository. Toward the start, CBIR have secured the pictures inside enormous volumes of photo [5]. The initial computer-aided diagnosis (CAD) CBIR method in medicinal procedure was constrained to application like radio-graphs of spine, attractive reverberation imaging (MRI) of the head, photography of the skin, microscopy. In view of research medical image highlight included geometric and spatial data[6-8]. The highlights of pictures were accomplished from shape, surface and colour. Muller [9] directed a thorough audit of investigations of CBIR system in medical application. The doctor depicts the neurotic region of interest (ROI) physically by utilizing the choice motor and programmed search when an example picture is gone into the database [10]. The general structure of medical CBIRframeworks depend on GNU image searching tool through apparatus (MedGIFT), additionally image recovery in medical applications (IRMA) explore that was created in 2001 and 2002 individually [11-12]. Other approaches such as IBrowse and KMeD have begun to improve since 10 years ago. However, in various early stages of content-based retrieval of medical images, manual annotations were inaccurate, time consuming and unreproducible [13].

2.1.2 MAJOR WORKS

Various technical literatures consistently give an account of exploratory executions of CBIR algorithms and different model frameworks, however, the use of CBIR methods for either routine clinical application or bio-medical researches seems, by all means, to be constrained.

Muller et al. [14,15] led a complete survey of investigations of CBIR framework in medical application. The underlying computer-aided diagnosis (CAD) CBIR strategy in medical procedure was constrained to application like, magnetic resonance imaging (MRI) of the head, microscopy, radio-graphs of spine, photography of the skin (see figure1).

Oliveira et al. [16] used CBIR clinically and revealed that the computation time in CBIR systems can be reduced by the application of Grid computing. To illustrate it My-Grid architecture is installed in a hospital system. The low level speciality based CBMIR methods [17,18] achieve the activity of medical image retrieval as per the similarities found among low-level image features [19]. Wang et al. [20] assigned local descriptors to visual words by quadratic programming (QP) task. They gauged the visual words by the boosting strategy and utilized the upgraded Jensen-Shannon uniqueness as the comparability measure to improve discriminative force.

Ballerini et al., [21] removed low level highlights, inclusive of shading co-variance-based highlights, surface highlights, and utilized the Bhattacharyya separate metric and Euclidean separation to quantify similitude of those highlights, individually. Rahman et al. [22] mapped low-level highlights, including shading and surface minute based highlights, to semantic ideas, and included the connections and basic connections between the particular optic ideas to build new highlights. At that point they processed the Euclidean separation of the particular advanced highlights as their similitudes to recover medicinal pictures. Suganya et al. [23] connected the SVM (Support Vector Machine) to order semantic ideas, for example, typical liver, alcoholic, carcinoma, liver sore and cirrhosis. The returned outcomes are the pictures having the equivalent semantic idea with the inquiry one. André et al. [24] changed visual words into semantic marks by utilizing their natural Fisher based technique for endomicroscopy video recovery [25].

The anatomy of the visual framework clarifies from the structure perspective that why visual data is so vital to human cognition. The psychological capacities that such a framework must help incorporate the ability to recognize among objects, their situations in space, movement, sizes, shapes, and surface. A portion of these natives can be utilized as descriptors of picture content in machine vision look into.

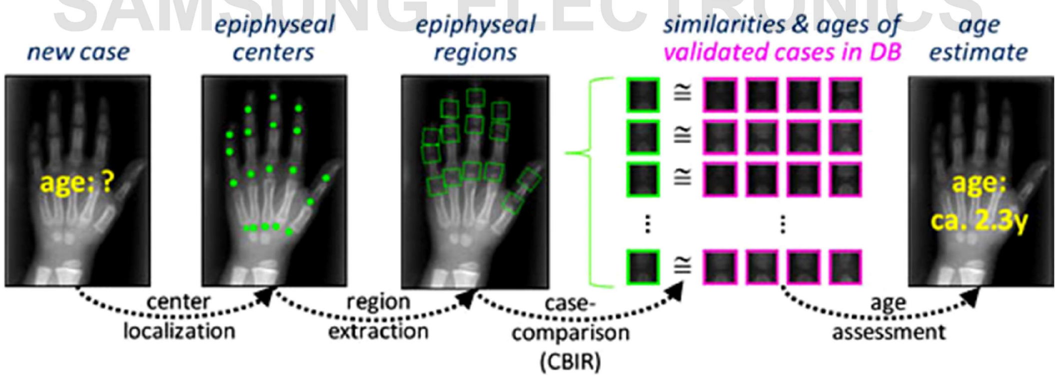


Figure 1: CBIR in similarity and age assessment

2.2 Methodology

Contrasting two images and choosing in the event that they are comparable or not is a generally simple activity for a human. Generating a program to do a similar thing successfully is anyway an alternate issue. A wide range of ways to deal with CBIR have been attempted and a considerable amount of these make the utilization of colour histograms.

It is easier for humans to visualize and compare two images to find the similarity or the differences but the same work for computers becomes complex. To resolve the complexities, a number of researchers utilized multiple forms of CBIR. All these multiple forms but have common feature of colour histograms. This project suggests some new, simple, methods to try and improve the results of standard colour histograms.

The Development is the main objective of the current effort a prototype of good (CBIR) structure for different medical images. The method follows two steps in which first is feature extraction and the second is image retrieving stage. Objective of the feature extraction is to acquire feature attributes from training datasets and then use it for the characteristic attribute derivation in the retrieving phase. An efficient medical content based image system retrieval is based upon effective color histogram and GLCM (Grey Level Co-occurrence Matrices) technique.

Principle component analysis (PCA) technique is utilized in extraction of unique features of the queried images that differentiates it from the other in the database images. Therefore, comparing the query image to the images in the database will produce a match that is similar. Here, the principle utilization of PCA method is dimensionality reduction of a datasets while sustaining much of the probable information.

Chapter-3

3.1 IMAGE RETRIEVAL

In a text based image searches (textual image retrieval) using search engines such as Google, Bing, yahoo, etc. is achieved by simply entering a few keywords related to the content of interest (i.e., a "query"), and then the outputs are produced based upon this query. But for a search by image, things work a little differently, in this text is not our query, instead its an image. Generally, there are three types of image based search systems:

i. query by meta-tags,

ii. query by example

iii. a hybrid approach consisting both.

The substance of picture is seldom being inspected amid the inquiry by meta-information frameworks. Rather, they depend on literary pieces of information, for example, manual comments and labeling performed by people alongside robotized logical insights, for example, the content that shows up close to the picture on a website page. Pursuit by model frameworks, then again, depend entirely on the substance of the picture, no watchwords are thought to be given. The picture is investigated, measured, and put away with the goal that comparative pictures are returned by the framework amid a pursuit. The picture seek frameworks that evaluate the substance of a picture are called CBIR (Content-Based Image Retrieval) frameworks. These sorts of structure will in general be to a great degree complex to assemble and scale, however consider a completely mechanized calculations to administer the inquiry and thus, no human intercession is required

3.2 CONTENT-BASED IMAGE RETRIEVAL (CBIR)

The CBIR system supplies an applicable way to retrieve similar the images of each type. A CBIR system uses visible contents to enable clients to peruse, look and recover comparable image from a database, in view of the users interest. Figure.2 shows a typical schematic diagram of working by CBIR system.Inquires about in CBIR were started back in mid 1990s to uphold the emergence of huge collection of image and to address the problem of retrieving relevant images from such databases [26]. The research area is becoming progressively dynamic with the headway of the accessibility in the medical business of multimedia technologies just as the progression in image processing and medical informatics [27].

Figure 2: Schema of data mining and information retrieval from database

Visual-based image retrieval have two main components are feature reduction and feature extraction with application of certain equality measurement. A group of minimum features are designated for the exception of specific data. PCA is an important method that includes changing the original information into a low dimension co-ordinate framework and makes another dataset. In CBIR systems, image content (feature vectors) includes the shape, texture, and color. They are extricated for ensuing uses during ordering and recovery process (as appeared in figure 3). Therefore, the greater part of the current CBIR system are region based where the features are removed uniquely from the Regions of Interest (ROI).

The calculations are some way or another constrained when managing bigger quantities of rich substance image in the database. Analysts, in beating these issues, have given resolutions to limit the semantic gap in retrieving the image through;

1. Different machine learning tools associating low-level features with query concepts, with machine-learning tools,
2. Ontology high-level concepts are defined by ontology,
3. Relevance feedback (RF) to promote consistent learning of user interest.

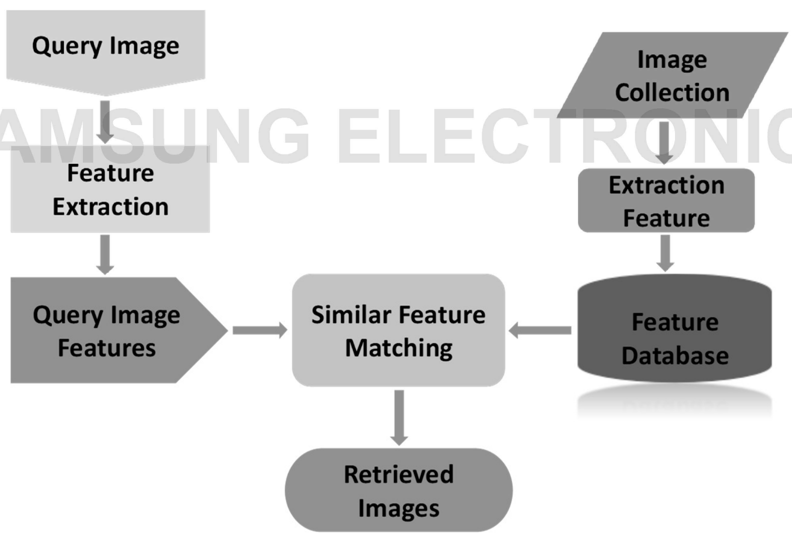


Figure 3: Flowchart of a typical architecture of CBIR system

3.3 CBMIR or Medical CBIR

Medicinal imaging is necessary in present day health-care. The far reaching use of medical imaging has brought about the formation of image databases, and also picture chronicling and correspondence frameworks. These vaults currently contain pictures from a various scope of modalities, multi-dimensional (3D, 4D or time changing) pictures, and co-adjusted multi-modality pictures [28]. These picture accumulations offer the open door for proof based analysis, instructing, and look into. Medicinal CBIR is a set up field of concentrate that is starting to acknowledge guarantee when connected to multi-dimensional and multi-modality therapeutic information. Imaging is a principal segment of present day prescription and is utilized generally for conclusion [29], treatment arranging [30], and evaluating reaction treatment [32].

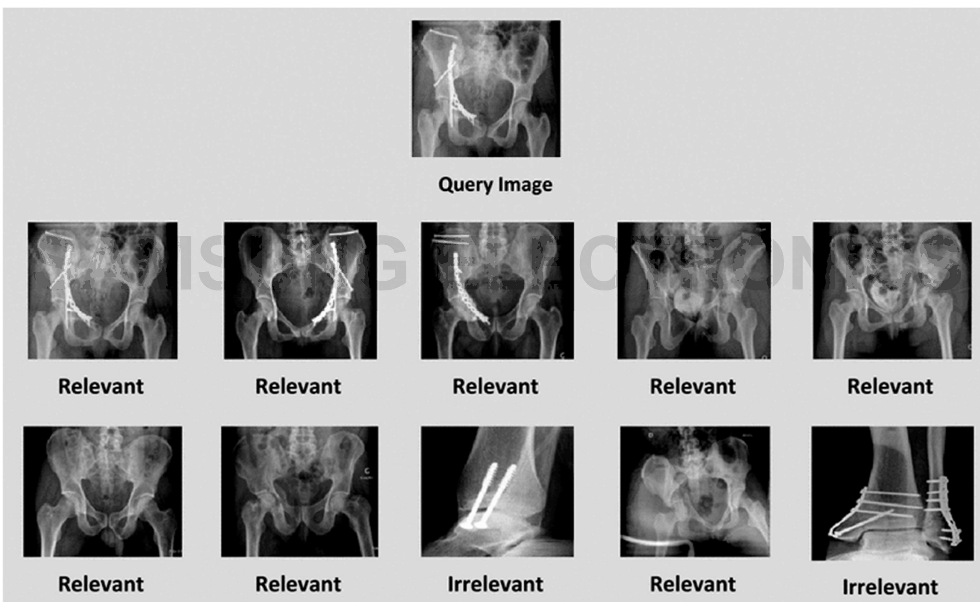


Figure 4: Result of CBIR system with relevant images to the query.

The question of image similitude has vital utilizations in the medicinal field on the grounds that symptomatic decision making has generally included utilizing evidences from the patient's data (non-image/image) combined with the doctor's previous involvements of such cases [33].

The concept of a CBMIR (Content Based Medical Image Retrieval) method is formulated to make programmed ordering by removing the substance of visual features by the utilization of low-level features for instance, shape, color, textures, etc., to furnish satisfactory informations. This method is known as QBE (Query By Image Example) that needs set of describing features and few similarity metrics to measure the database image with query image. In various literatures, different methods of CBIR have been published specifically intended to help medical work. Korn et al. depict a system for quick and viable retrieval of tumor shapes in mammogram x-rays[34]. This methodology has certain limitations on both the images (mammography only) and the features (tumor shapes only) which are supported by the system. the programmed search and determination motor with recovery instruments (ASSERT) works just on high resolution computed tomography of the lung [35]. It has been proposed that the dependence on imaging for different clinical work processes implies that entrance to applicable put away information will take into consideration more educated and compelling treatment [36]. Digitisation and the improvement of the picture documenting and correspondence frameworks (PACS) have empowered the capacity of therapeutic pictures in extensive computerized stores, which can be gotten to by clinical staff over a system. A doctor depicts the locale relating to a pathology and imprints an arrangement of anatomical tourist spots when the picture is gone into the database. PACS enables doctors to contemplate a patient's picture past by enabling them. PACS is to discover all pictures identified with a specific patient.

3.4 CBMIR INSIGHT WITH 'PACS'

CBIR has been proposed by the therapeutic network for consideration into correspondence frameworks and picture documenting. The possibility of PACS is to incorporate imaging modalities and interfaces with doctor's facility and divisional data frameworks with the end goal to deal with the capacity and conveyance of pictures to radiologists, doctors, experts, centers, and imaging focuses. A significant point in PACS is to give a proficient hunt capacity to get to wanted pictures. Picture seek in the computerized imaging and correspondence in medication (DICOM) convention is right now completed by the alphanumerical request of literary traits of pictures (appeared in figure 5).

Figure 5: PACS server and DICOM viewer in action

In any case, the data in which clients are keen on is the visual contents in the medicinal images instead of that dwelling in alpha-numerical organization. The substance of the images, is a ground-breaking and evident question which can be used to scan for different images containing in comparative component. Subsequently, content based access approaches are required to greatly affect PACS database management and health. Moreover, medicinal databases imaging that are detached with PACS can likewise acquire profits by CBIR technique. Figure 6 shows graphical representation of PACS-DICOM services and processes work-flow for image retrieval in various medical modalities.

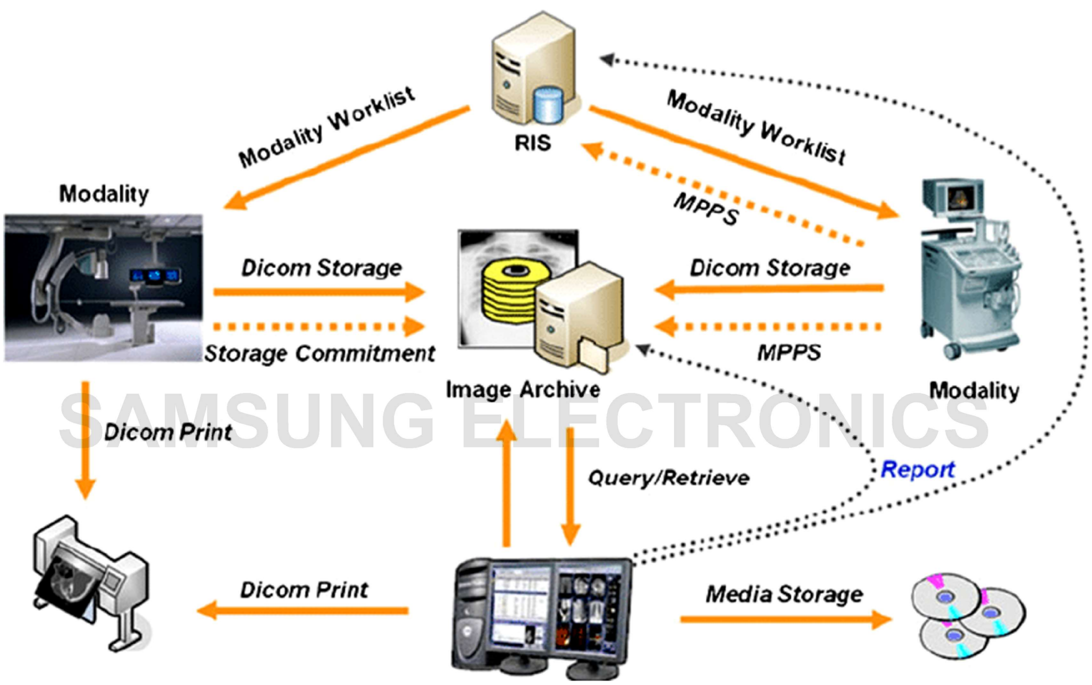


Figure 6: PACS-DICOM services and processes work-flow among medical modalities. (*source: Dicoogle)*

Subsequently, in medical domain analysts can utilize content-based image retrieval to discover images with comparative therapeutic zones and analyze their affiliation. In medicinal instruction, instructors can without much stress discover images with specific diagnostic qualities, as those traits can express specific illnesses.

Few of the current CBMIR frameworks happened to retrieve necessary images from the existing medical data-bases with the end goal of facilitating clinicians to take clinically approved decisions and with the end goal of medicinal research students to gain in their studies.

3.5 Ongoing CBIRS in Medical Application

1) Picture archiving and communication system
2) Spine pathology and image retrieval system
3) Spine x-ray images in the sagittal plane
4) Image retrieval for medical applications
5) Image Map
6) WebMIRS system
7) CervigramFinder system
8) Automatic Search and Selection Engine with Retrieval Tool
9) SPIRS-IRMA system

3.5.1 Overview of CBMIR applications

A. ASSERT (Automatic Search and Selection Engine with Retrieval Tools)

Important Features:

* The ASSERT framework utilizes a doctor in loop way to deal with recovering of lung HRCT images. The methodology expects clients to depict the pathological features, locales and recognize definite anatomical marking spots for each picture;

* This framework separates 255 highlights of surface, shape, colour, and dim scale features in pathological domain; A multidimensional hash table is developed to record the HRCT pictures.

B. medGIFT

Important Features:

* The medGIFT recovery framework removes worldwide and territorial shading and surface highlights, incorporating 166 hues in the HSV shading, and Gabour channel reactions in 4 ways each at 3 unique scales.
* Combining of literary marks and visual highlights are utilized for restorative picture recovery

C. IRMA (Image Retrieval in Medical Applications)

Important Features:

* This framework splits retrieval of the image process into seven consecutive steps, including registration, feature extraction, categorization, indexing, identification, feature selection and retrieval of images (figure-7).
* The IRMA framework is enforced as a platform for CBIR in medical domains;

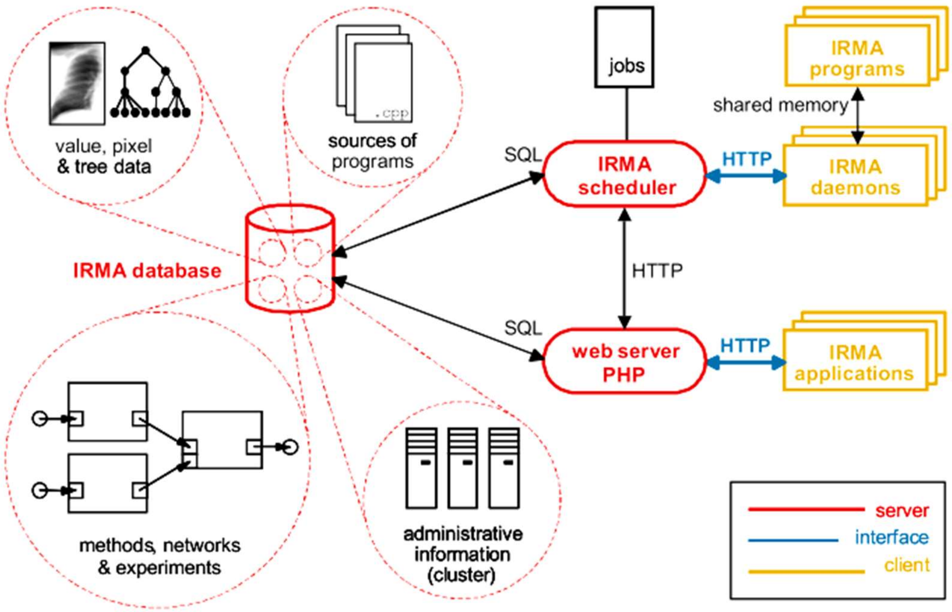


Figure 7: Systematic architecture of IRMA

D. National Health And Nutrition Examination Survey

Important Features:

- The ACS (Active Contour Segmentation) tool available in the system permits to generate templates by devising points over the vertebral columns. Once the template devision is established, location of next vertebra can be assessed. Henceforth, the template is placed on the image which further segment it.

- In case of information portrayal, a polygonal estimation procedure is connected for removing immaterial structure highlights and diminishing the quantity of information points. The information acquired in the polygon approximation process characterize to the state of vertebra. At that point, the approximated bend of vertebra is changed over to digression space for equality estimation.

E. CervigramFinder

The CervigramFinder system [37] works on cervicographic images (additionally known as "cervigrams") and was stabilized by the communitarian attempts of the NLM (National Library of Medicine) and the NCI (National Cancer Institute) for the investigation of cancers related to female uterine cervix. This malignancy is firmly identified by the chronic infection of particular sorts of the HPV (Human Papilloma Virus).

Aceto-brightening marvel is cervicographic screening based: HPV infected abnormal tissue frequently it turns in white subsequent to being treated with 3-5% acidic corrosive. A cervigram is a 35 mm snapshot of the cervix taken roughly after one minute acidic corrosive introduction. NLM has made a cervigram database containing roughly 100,000 cervigrams taken between two noteworthy tasks in cervical malignant growth by NCI to examine the normal history (HPV) cervical neoplasia and contamination.

Chapter-4

4.1 MEDICAL IMAGING SYSTEM (MIS)

Medical image data-sets have regularly been utilized for retrieval systems. At the same time the medicinal domain is sequential referred to as one of the important application spaces for content-based access advancements as far as potential effect is concerned. Amid the following couple of years, significant changes are normal in computer and communication technologies that will offer the medical imaging systems industry a test to create progressed tele-medicine applications of more prominent exhibitions (figure 8). Medical industry, merchants, and masters need to concede to a general MIS structure that will give a pile of capacities, conventions and interfaces appropriate for coordination and the board of abnormal state image consults, reports and survey exercises. Most clinic imaging divisions need to computerize information systems in which quiet images and reports are to be put away. The put away information can be handled by two noteworthy sorts of medical applications, the incorporated Report and Review applications.

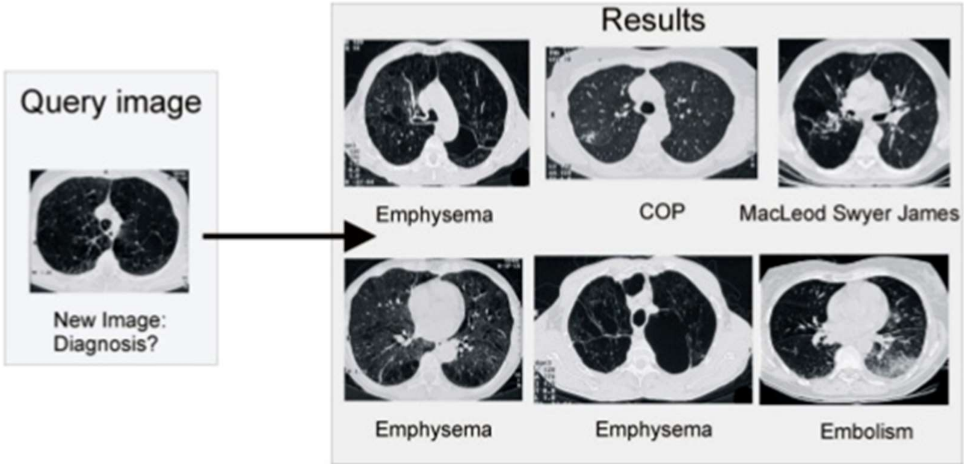


Figure 8: Example of medical diagnosis using image retrieval system

4.2 CBIR AND MACHINE LEARNING

Similarity measurement and feature representation are pivotal for the retrieval performance of CBIR system. It is along these lines been contemplated widely by scientists. An assortment of procedures have been proposed however and still, at the end of the day it stays as a standout amongst the most difficult issues in the continuous CBIR research. The fundamental purpose behind it is the semantic hole issue that exists between the low-level image pixels got by machines and elevated level semantic ideas seen by individuals. Such an issue presents central test of Artificial Intelligence from a high-level viewpoint that is the means by which to fabricate and prepare clever machines like human to handle genuine errands. Machine Learning is one promising system that endeavors to address this test in the long haul. In the ongoing years there have been imperative headways in machine learning strategies. Learning in Deep is an essential leap forward method, which incorporates a group of machine learning calculations that endeavor to show high-level deliberations in information by using deep architectures made out of numerous non linear transformations.

4.2.1 Deep Learning

DNNs (Deep Neural Networks) have generated new perspectives for Vision of Computer and have recently been applied for CBIR (Content-Based Image Retrieval). The observable pre-clinical structure changes gives a chance to AD early identification utilizing picture order devices, like Capsule Networks and CNN (Convolutional Neural Network).

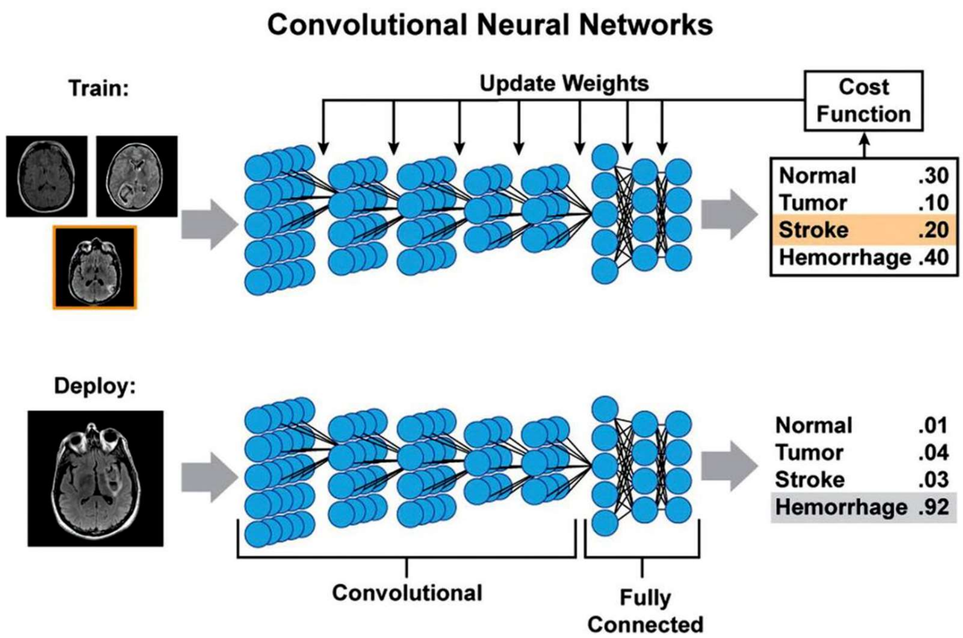


Figure 9: CNN in medical image classification

Deep learning expects to become familiar with numerous dimensions of portrayal and reflection that assist in gathering data from information, for example, pictures, recordings, sound, and content. It is making shocking additions in speech acknowledgment, computer vision, drug structuring and multimedia examination. Effect of deep learning is social and business spaces and broad on applications in restorative. Quickly, deep learning procedures have are two primary classes of : (1) unsupervised and semi-supervised learning algorithms, (2) absolutely supervised learning algorithms.

As a significant improvement for Boltzmann Machines (BM) was proposed by RBM. Let's give a brief background introduction on BM, RBM (Restricted Boltzmann Machines) and DBM (Deep Boltzmann Machines). In the following introduction, we will present the models under-mentioned terms and conventions introduced in initial research. Boltzmann Machines (BM) is a stochastic recurrent neural network and it is named after the Boltzmann dissemination in measurable mechanics. While accurate greatest probability learning in RBM is obstinate, new learning calculations, for example, Contrastive Divergence, has been proposed to complete the learning procedure proficiently.

Chapter-5

5.1 MEDICAL IMAGING SYSTEM (MIS)

CBIR and Machine Learning

- The structure of different image document organizes typically has its root in the physical hardware usage that bolsters the imaging procedure, the motivation behind the image substance, and how the image is to be prepared. For instance, the raster portrayal of image is firmly identified with the advanced image testing and show mechanical assembly. Wavelet coefficient portrayal is utilized in a few frameworks that require constant transmission through PC connect with zooming ability. Since image documents require gigantic storage room, and request generous system transfer speed in crude pixel esteem organize, pressure is abundantly wanted in many events. More often than not, image pressure calculations can realize 10 overlay of decrease in the record measure without essentially influencing the visual quality. Then again, the pressure is at the cost of broad preparing and CPU control. The most ordinarily utilized pressure schedules more often than exclude some sort of change, for example, discrete wavelet change (DWT) and discrete cosine change (DCT), trailed by general pressure calculations, for example, run length encoding (RLE) and entropy encoding (i.e. Huffman encoding).

The image design is a critical factor in the image recovery, as it decides the essential image constituents that pass on the visual data content. They could be pixels, recurrence coefficients, shading histogram, idea terms.

5.2 MEDICAL IMAGING SYSTEM (MIS)

CBIR and Machine Learning

Extraction of Features is the first procedure of CBIR system. It is utilized to excerpt substantial images information like color, shape, texture, edges. Usually its desirable to eliminate the data contents that isn't fundamental or significantly counter-gainful for the specific recovery job that needs to be done. Therefore, feature extraction is the progression of separating important data from the original image content. The most basic properties to be examined for any sort of features are its data substance and in-variance to specific changes of the data information. Features of image might be grown from visual cues contained in a picture (figure 9). In various arrangements they are spoken to as alpha-numeric data, for example, charts or vectors. These stand as minimized surrogates. One can recognize two kinds of visual features:

i) Geometric feature: It makes utilization of shape based cues.

ii) Photo-metric features: It abuses shading and texture cues and they might be gotten specifically from crude pixel powers.

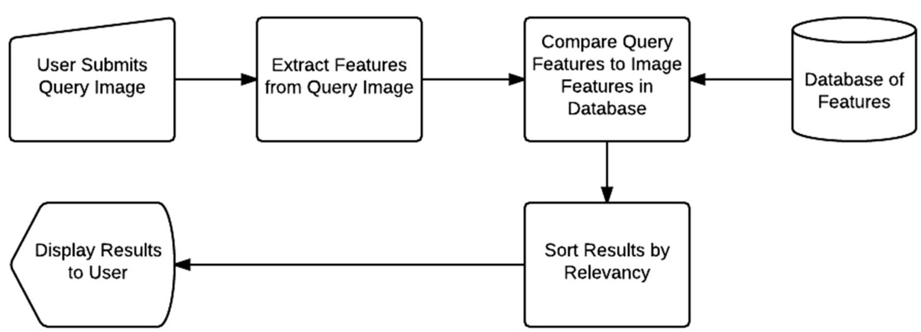


Figure 9: Scheme of CBIR systems and feature extraction

In underneath segment each element with their particular techniques for extraction has been examined. At that point, Neural network technique has been talked about which utilizes these highlights for classification of image.

5.2.1 Indexing

Ordering a data-set is the way toward measuring the data-set by using an image descriptor to extricate features from each picture. Features, then again, are the output of an image descriptor. Basically, features (or feature vectors) are only a rundown of numbers used to uniquely speak to and evaluate images. Figure 10 shows an image descriptor pipeline for the definition of feature vectors.

Figure 10 : Image descriptor pipeline for definition of feature vectors

By using a distance metric or similarity function, feature vector can be compared (figure 11). Similarity functions and distance metrics take two feature vectors as output and then input, a number that represents how “similar” they are”.

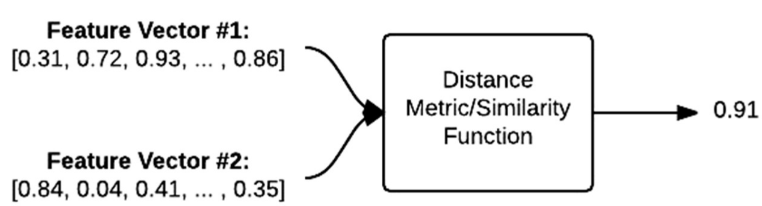


Figure 11: Quantifying feature vectors

5.2.2 Normalization

Normalization: The method results into distinctive elements within a class at the same time of normalization of other respective elements takes place. As for instance,For example, an image of an article could be meant have its center of gravity at a specific point, or pivoted to have its significant axis lined up with the horizontal axis of an image.

5.2.3 Shape

Shape: Here, numbers are arranged in such a way that it portrays a given shape feature. A descriptor tries to access shape in manners that agree with human nature. Usually utilized shape based procedures are mentioned below:

Fourier Descriptor: Fourier Descriptor is an old procedure and also supposed to be a legitimate depiction instrument. The depiction are easy to register. The standardized Fourier changed coefficients are known as the Fourier descriptor of the shape. FD is acquired by applying Fourier change on a shape signature.

$$a_n = \frac{1}{L\left(\frac{n2\pi}{L}\right)^2} \sum_{k=1}^{m} (v_{k-1} - v_k) e^{-jn(2\pi/L)^{l_k}}$$

Wavelet Transform: It leads to a various leveled planar curve descriptor which further got converted into components of different scales. This further helps in carrying the global approximation information and the local detailed information. There are multiple properties that a wavelength descriptor supposed to have as for example stability, spatial localization, uniqueness, multi-resolution representation and invariance.

Region-based Fourier Descriptor: It is also known as Generic FD (GFD). It has multiple applications. It is the application of MPFT (Modified Polar Fourier Transform) on shape images that results into GFD.

5.2.4 Texture Descriptor:

These are the Textures are intricate graphic designs made up of objects. These can be viewed as a similarity grouping.

Auto-correlation Based Texture Features: The literary character of an image relies upon the endemical size of surface natives. Huge natives offer rising to coarse surface and little natives give fare surface. An auto-relationship limit can be evaluated that gauges this coarseness.

GLCM (Gray Level Co-occurrence Matrix): It leads to extraction of textural characteristics of relating to an image statistically. So we can say that we are processing the tabulation of various groupings of pixel brightness value occurring in an image [38].

5.2.5 Local and Global Features

Local Features:

Local features characterize the picture with more subtleties [39]. Local feature is accomplished with the division of picture into little squares of pixels. Thus, in some CBIR frameworks, local features got qualified consequences of classification.

Global Features:

Global features give a diagram of the picture overall in content-based picture recovery frameworks. The advantage of global features is the capacity to concentrate and match in fast. Some CBIR frameworks utilize global shape or shading features to characterize the general thought of the pictures [40].

5.3 MEDICAL IMAGING SYSTEM (MIS)

CBIR and Machine Learning

The CBIR systems for separating some neighborhood features like shape, color or pictures utilized the strategy of division for pre-processing [41]. Division partitions the pictures into various locales. Figure 12 shows the example of picture division.

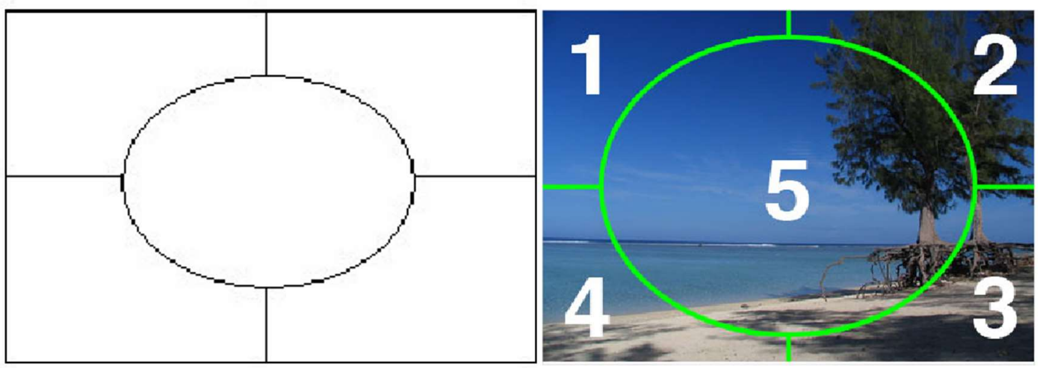


Figure 12: Image segmentation (in 5 parts)

5.3.1 Pixel Value and Colour Histogram

Pixel value is one of the more straightforward models of image features and it is the most immediate procedure for looking at inquiry in information base. Pixel value frequently doesn't accomplish sufficient outcome to look at two images [42]. Be that as it may, pixel value gives great outcomes when images are basic and there are scarcely any character acknowledgment or for grouping of two comparable images in medicinal examples.

When figuring a color histogram for an image, the diverse color axes are separated into a number of so-called bins [43]

Problem with colour histograms is deciding how many bins to use. Low number of bins decreases the storage space and time needed for indexing and retrieval, but also reduces the effectiveness. Therefore, an ideal three dimensional (8x8x8) RGB histogram in the HSV colour space (Hue, Saturation, Value) would therefore contain a total of 512 such bins (Fig. 13 and 14 below). When ordering the image, the colour of every pixel is found, and the relating bins tally is augmented by one. Commonly, images are represented as a 3-tuple of Red, Green, and Blue (RGB).

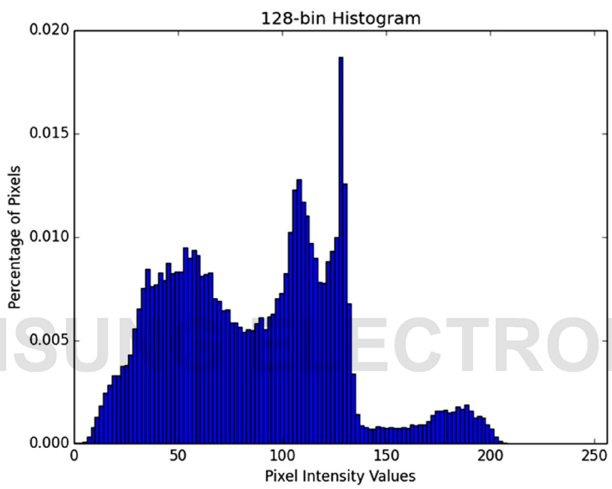


Figure 13: Pixel values in 128-bin histogram

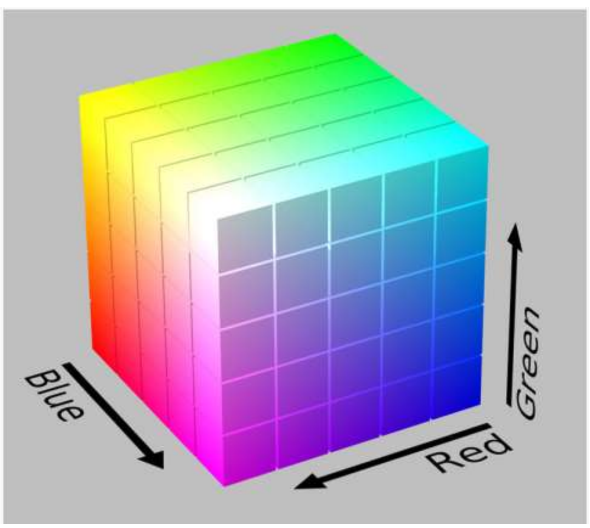


Figure 14: A 3-dimensional 8x8x8 RGB-histogram

Comparing all the colours in two images would however be very time consuming and complex, and so a method of reducing the amount of information must be used. One way of doing this is by quantizing the colour distribution into colour histograms. First introduced by Swain and Ballard [44], and used by many others, this is probably one of the more popular approaches to image retrieval today .

5.3.2 Comparing histograms

At the point when the images have been quantized into histograms, a technique for contrasting these is required. There are some of the popular histogram comparison metrics are the L1 (colour histogram intersection) and L2 (Euclidean distance) norms defined as:

$$L1 = \left|\sum_{i=1}^{n}\right| Q_i - I_i$$

$$L2 = \sqrt{\sum_{i=1}^{n} (Q_i - I_i)^2}$$

Where Qi is the value of bin i in the inquiry image and Ii is the relating bin in the database image. Figure 15 shows a comparison of distinct category of histogram equalization. A number of scholars have utilized the above stated L1 & L2 norms but it suffers some limitations. L1 has an issue of low recall in missing matching images, whereas L2 tends to give low accuracy retrieval.

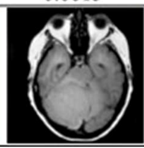
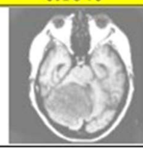
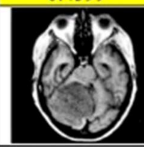
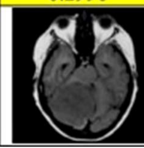
Dataset B 512× 512	OPT at J=4	Image Adjustment	Histogram Equalization	Adaptive Histogram Equalization	Matched Histogram	Matched Adaptive Histogram Equalization
Avg. G	10.7597	0.0424	0.0331	0.0543	0.0349	0.0526
Local C	0.8419	0.9344	0.3824	0.9170	1.0706	0.9125
STD	68.3716	0.2728	0.1911	0.2862	0.2163	0.2744
Edge I	109.7056	0.4387	0.3407	0.5567	0.3614	0.5392
E	6.7220	5.0743	3.9124	5.3889	5.4018	6.0080
PSNR (dB)	8.7355	75.1040	56.5905	69.8463	68.1138	70.1205
MI	0.7280	0.4516	0.2730	0.2757	0.3699	0.2833
$Q^{ab/f}$	0.0015	0.4948	0.1640	0.4399	0.2998	0.4190
Visual results						

Figure 15: Comparative histogram equalization

One feature of colour histograms that can be both an advantage and a disadvantage is their lack of spatial information. This can be an advantage as a given image's global histogram will remain the same when rotated or flipped (see Figure 16). This gives some spatial sensitivity, but increases the computing power and storage needed. One also looses the insensitivity to rotation we have in global colour histograms .

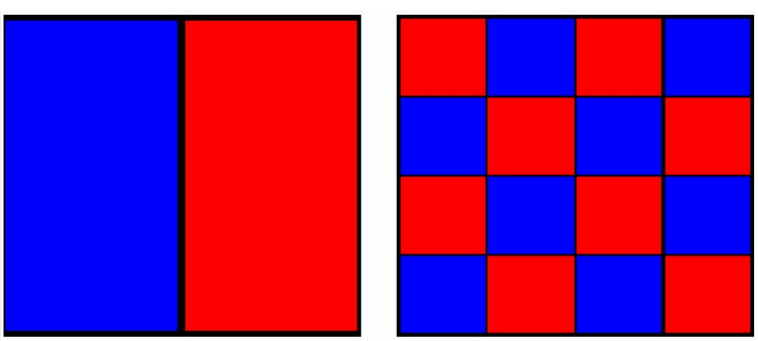


Figure 16: Images with equal colour distributions

5.4 Techniques Used For Image Quantification

Medical systems often-time utilize measurement approaches such as possible results; representing all images as feature vectors in an n-dimensional vector space and Euclidean vector space model or measuring distances between a query image represented by its features). Several other distance measures also exist for vector space model such as the city block distance; the Mahalanobis distance or a simple histogram intersection. Still, the use of high- dimensional feature spaces has shown to cause problems and great care needs to be taken with the choice of distance measurement in order to retrieve meaningful results. These problems with a similarity definition in high-dimensional feature spaces are also known as the curse of dimensionality and have also been discussed in the domain of medical imaging .

5.4.1 Feature Based

Primarily, an image is a portrayal of its objective object(s). Indeed an image has its substance, which catches the optical or mental properties of a question; with its arrangement shifting crosswise over various types of media. An image can be a variety of pixel esteems put away in uncompressed bitmap computerized image organize. In this organization, each esteem speaks to the shading power at discrete focuses or pixels. An image highlight can be characterized as the after effect of a calculation or a specialist assessment basis, performed to an objective image. For all intents and purposes, from the point of view of machine vision and mechanized substance based image recovery, we can characterize the substance of an image as the arrangement of every single conceivable component, or blend of essential highlights, of that objective image.

Query

An inquiry means that client's data is required. It can take various structures, going from Boolean question that is exceptionally compact, to an extremely point by point particular of the sort of records the client needs that traverses longer than the genuine archives themselves, to at least one example reports, (for example, images inquiries) that are set as models for the sort of wanted archives.

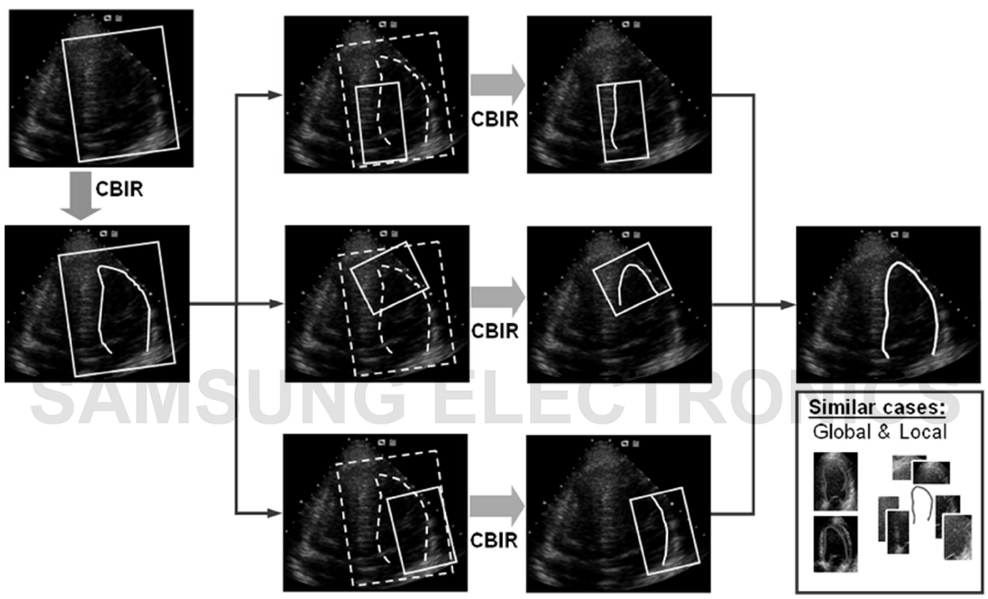


Figure 17: Similarity search

The component vectors of the image comprise an element data-set put away in the database. In network image recovery, client can present an inquiry model to the recovery framework looking for wanted images. The separations betwixt the component vectors of the question precedent and those of the media element data-set are then processed and positioned. Recovery is directed by applying an ordering plan to give a proficient method for looking through the image database. The framework speaks to this precedent with a component vector. At long last, the framework positions the list items and after that profits the outcomes that are most like the question models (figure 17).

Portrayal of pictures ought to consider for highlights which are most valuable for speaking to the substance of pictures. Notwithstanding it, the methodologies can sufficiently code the attributes of the pictures. Highlight eviction of the picture in the database is normally directed offline so calculation intricacy is definitely nope a noteworthy issue. Two highlights - texture and shading - are regularly used to remove the highlights of a picture.

Dimension Reduction

CBIR system may separate countless character from the content of an image to catch valuable image contents and to encourage successful questioning of database image . List of capabilities of high modality amplitude causes the "curse of dimension" issue where in the computational expense and multifaceted nature of the question increment exponentially with the quantity of dimensions [45].

To decrease the dimensionality of an extensive list of capabilities, the most broadly utilized system in image recovery is principal component analysis (PCA). The objective of principal component analysis is to determine however much fluctuation as could be expected with the most modest number of variables. Principal component analysis includes changing the first information into another coordinate system with low dimension, consequently making another arrangement of information. The new coordinate system evacuates the repetitive information, and the new arrangement of information may better speak to the fundamental data. Be that as it may, there is an exchange off between the effectiveness acquired through dimension decrease and the culmination of the data extricated. As information is spoken to bring down dimensions, the speed of recovery is expanded, however some imperative data might be lost during the time spent information change. In the exploration of therapeutic CBIR, Sinha and Kangarloo [46] exhibited the PCA application to the image arrangement of 100 hub cerebrum images .

Determination of similarity metrics directly affects the execution of CBIR. The sort of the feature vectors chose decides sort of estimation that will be used to look at their likeness [47]. “On the off chance that the features extricated from the images are exhibited as multi-dimensional focuses, the separations between relating multi-dimensional focuses can be determined. Euclidean separation is the most widely recognized measurement used to quantify the separation between two in multi-dimensional space”[48]. "Histogram intersection" was proposed [49, 50] to discover realized articles inside images utilizing shading histograms. Various different metrics, for example, "Mahalanobis Distance", "Minkowski-Form Distance", "Earth Mover's Distance", and "Corresponding Transportation Distance", have offered for explicit purposes. Antani et al., [51] utilized a few ways to deal with code the shape features for various classes of spine X-beams. Each class utilized a particular parallel metric to think about the separation betwixt two feature vectors.

Multi-Dimensional Indexing

“Retrieval of an image is usually based not only on the value of certain features, but also on the location of a feature vector in the multi-dimensional space Long” [52]. A retrieval query on a database of multimedia with multi-dimensional feature vectors usually requires fast execution of search operations. To support such search operations, an appropriate multi-dimensional access method has to be used for indexing the reduced but still high dimensional feature set. Popular multi-dimensional indexing methods include the R-tree and R*-tree. The R-tree, which is a tree-like data structure, is mainly used for indexing multidimensional data. Each node of an R*-tree has a variable number of entries. Each entry within a non-leaf node can have two pieces of data. The goal of the R*-tree is to organize the spatial data in such a way that a search will visit as few spatial objects as possible. Hence, the R-tree must be able to hold some sort of spatial data on all nodes. For high-dimensional features space, it is necessary to reduce the dimensionality using statistic multivariate analysis techniques such as the aforementioned principal component analysis (PCA).

Chapter-6

6.1 EXPERIMENTAL SETUP

Linux OS environment is used for the experimental setups and program implementations

Requirements: Python 2.7, NumPy, Scipy, matplotlib.pyplot, PIL libraries and OpenCV.

Description of work

A image can be viewed from multiple aspect. One among them is the colour used in the image which can be represented by global colour histogram. Many a time, it is the matching based on the region results into a precise finding. The images to be contrasted and each other are separated into sub-regions. It very well may be either as per a various levelled arrangement, for example, a quad-tree, or through image division process. The shading highlight of two images can be thought about by a separation or comparability measure as opposed to by including the quantity of pixels each shading container. This measure is then joined with the nearness of that shading in the image to shape the shading highlight descriptor. The descriptor can be of lower dimensionality than the shading histogram and proficiently ordered to encourage quick recovery execution.

6.1.1 General Steps

For this we have used some functions that extracted histogram bar values for each and every image. The generated image histogram is almost like a bar graph and that bar values (bins) varies from image to image depending on the colour, intensity and many other things related to that image.

Next we used image segmentation, as it is a standard method to fetch colour valuate images more accurately. Image segmentation divides image into different smaller regions. Here, the main objective of segmentation is to simplify the image representation for easier access and analysis. Collectively the segmented images correspond to the complete image in whole. Moreover, through segmentation various properties such as texture, colour, intensity, more over, can be easily manipulated, accessed and computed of an image. Additionally, after segmentation for each small region same matrix size as in image in pixels are received. Furthermore, manipulation of the segmented image's colour is more accurate and easier hence, colour values we receive have more accurate results.

After segmentation and feature extraction, we commit into training of the system. In the training stage we have to train our framework to perceive a picture legitimately by its excerpted values and properties. Whereas, the testing stage completely depends on the training stages. Better test values and precession are obtained by the better training of the framework.

The training set of images is composed of 200 images divided into 5 sub-sections. Thus, every sub-section involves 50 images. Furthermore, all of the feature values are concentrated for all the 200 images in that training vector. Similarly, for the testing purpose, all the feature values are extracted and contained in on place i.e. the testing vector. The set for testing images consists of 80 images, however, the image set is completely different though the training and testing images are almost identical. After training and testing phase is over, Euclidean distance is employed to compute the precision accuracies.

Following steps are executed for the retrieval of query results:

Step 1: The 3D (HSV) histogram of the query image is computed. Then, the number of bins in each direction (i.e., HSV space)is duplicated by means of interpolation.

For each image 'i' in the database:

Step 2: Load its histogram Hist(i). Use interpolation for duplicating the number of bins in each direction.

Step 3: For each 3-D hist bin, compute the distance (D) between the hist of the query image and the i-th database image.

Step 4: Keep only distances (D2) for which, the respective hist bins of the query image are larger than a predefined threshold T (let L2 the number of these distances).

6.1.2 Python and NumPy

Python is a clear and concise language with good support for input/output, numerics, images and plotting. The language has some peculiarities such as indentation and compact syntax that takes getting used to. When programming computer vision we need representations of vectors and matrices and operations on them. This is handled by Python's NumPy module where both vectors and matrices are represented by the array type [53].

The PIL (Python Imaging Library) gives general image dealing with and heaps of valuable fundamental image tasks like cropping, resizing, color conversion, rotating and much more. PIL is free and accessible from.

6.1.3 Python Code

NumPy is used for numerical processing, imutils (optional) to check OpenCV version and cv2 for OpenCV bindings. OpenCV represents RGB images as NumPy clusters, however in turn around request.

```
# import the necessary packages
import numpy as np
import cv2
import imutils

class ColorDescriptor:
    def __init__(self, bins):
        # store the number of bins for the 3D histogram
        self.bins = bins

    def describe(self, image):
        # convert the image to the HSV color space and initialize
        # the features used to quantify the image
        image = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
        features = []

        # grab the dimensions and compute the center of the image
        (h, w) = image.shape[:2]
        (cX, cY) = (int(w * 0.5), int(h * 0.5))

        # divide the image into four rectangles/segments (top-left,
        # top-right, bottom-right, bottom-left)
        segments = [(0, cX, 0, cY), (cX, w, 0, cY), (cX, w, cY, h),
            (0, cX, cY, h)]
```


Figure 18: Initial Code window: converting RGB to HSV and segmenting the image in 5 different parts.

The ColourDescriptor class (figure 18) epitomize all the vital rationale to extricate 3D HSV colour histogram from the pictures, while taking into consideration number of bin for the histogram. The *describe* method searches for an image, which is the image we need to portray for colour features. Inside of this we'll convert the RGB colour space (or rather, the BGR colour space), to the HSV colour space, followed by initializing list of features to quantify and represent images.

Next step is segmentation and feature extraction based on colour histogram.

```
        # loop over the segments
        for (startX, endX, startY, endY) in segments:
            # construct a mask for each corner of the image, subtracting
            # the elliptical center from it
            cornerMask = np.zeros(image.shape[:2], dtype = "uint8")
            cv2.rectangle(cornerMask, (startX, startY), (endX, endY), 255, -1)
            cornerMask = cv2.subtract(cornerMask, ellipMask)

            # extract a color histogram from the image, then update the
            # feature vector
            hist = self.histogram(image, cornerMask)
            features.extend(hist)

        # extract a color histogram from the elliptical region and
        # update the feature vector
        hist = self.histogram(image, ellipMask)
        features.extend(hist)

        # return the feature vector
        return features

    def histogram(self, image, mask):
        # extract a 3D color histogram from the masked region of the
        # image, using the supplied number of bins per channel
        hist = cv2.calcHist([image], [0, 1, 2], mask, self.bins,
            [0, 180, 0, 256, 0, 256])
```

Figure 19: Code for image segmentation and feature extraction

This actually masks the image regions based on the colour segmentation (figure 19). One simple method of adding some spatial information is dividing the image into four parts and then creating colour histograms from each of these. In this method each region of the query image is compared only to its corresponding region in the database images. The database is indexed before for unique identification of images (figure 20).


```
# construct the argument parser and parse the arguments
ap = argparse.ArgumentParser()
ap.add_argument("-d", "--dataset", required = True,
    help = "Path to the directory that contains the images to be indexed")
ap.add_argument("-i", "--index", required = True,
    help = "Path to where the computed index will be stored")
args = vars(ap.parse_args())

# initialize the color descriptor
cd = ColorDescriptor((8, 12, 3))

# open the output index file for writing
output = open(args["index"], "w")

# use glob to grab the image paths and loop over them
for imagePath in glob.glob(args["dataset"] + "/*.png"):
    # extract the image ID (i.e. the unique filename) from the image
```

Figure 20: Database indexing

Based on the segmentation and identifier, the image features are defined which in turn exploits the database for image retrieval using the *imagesearch* and calling the *colourdescriptor* and searcher class. Figure 21 shows the screenshot of search module.

```
# python search.py --index index.csv --query queries/103100.png --result-path dataset

# import the necessary packages
from imagesearch.colordescriptor import ColorDescriptor
from imagesearch.searcher import Searcher
import argparse
import cv2

# construct the argument parser and parse the arguments
ap = argparse.ArgumentParser()
ap.add_argument("-i", "--index", required = True,
    help = "Path to where the computed index will be stored")
ap.add_argument("-q", "--query", required = True,
    help = "Path to the query image")
ap.add_argument("-r", "--result-path", required = True,
    help = "Path to the result path")
args = vars(ap.parse_args())

# initialize the image descriptor
cd = ColorDescriptor((8, 12, 3))

# load the query image and describe it
query = cv2.imread(args["query"])
features = cd.describe(query)

# perform the search
searcher = Searcher(args["index"])
results = searcher.search(features)
```

Figure 21: Performing query image search

6.2 Results

In terms of memory consumption, results show that a structure which sizes up in Gigabytes can be effectively represented in a structure of just few tens of Megabytes. Table 1 shows an example of image files before and after the PCA dimension reduction and quantization has been performed. The first entry illustrates the dimension of the descriptors in the training set with PCA dimension reduction performed while the latter entry show the suitable representations for the entire data-set after product quantization.

This extreme shrinkage is due to substituting the vector representation of the images with a suitable algorithm .

In this project the images are divided into 10 columns and 8 colour bins. As a color feature we have taken 3 moments of HSV colour model. First of all we have converted RGB image to its equivalent HSV image. We have taken moment's upto its third order. Finally we have calculated three moments of each of the three components of H, S and V image. The method is tested both by itself and compared to results from the RGB histogram-method. The quantitative measure defined is average precision as explained below:

$$p(i) = \frac{1}{100} \sum_{1 \le j \le 1000,\ r(i,j) \le 100,\ ID(j) = ID(i)} 1$$

where *p(i)* is precision of query image *i*, ID*(i)* and ID*(j)* are category ID of image *i* and *j* respectively, which are in the range of 1 to 10. The *r i,(j)* is the rank of image *j* (i.e. position of image *j* in the retrieved images for query image *i*, an integer between 1 and 1000). This value gives the average percentile of images belonging to the category of image *i* in the first 100 retrieved images. Simply AMP can be calculated by :

$$AMP = \frac{(N - R)}{(N - 1)}$$

Where *N* is the number of images in the database and *R* is the rank of the returned image. This is calculated for each image and the results averaged.

Table 1. File dimensions and size after PCA reduction

File	Dimensions	Dimension (after PCA)	Size	Size (after PCA)
img1	1630x462	1630x210	900Kb	200Kb
img2	820x384	820x200	240Kb	110Kb

The best AMP results were achieved by the HSV histogram method with a score of 86%. RGB histograms came in a close second with 82%. However, HSV histograms do however perform consistently better than or equal to RGB. However, prior different approaches used different colour spaces and different techniques to define colour values. If the RGB colour space is used in some approach then researcher gives high priority to the red, green and blue values. And in case of HSV colour space, the hue, saturation and brightness takes the high priority level. For any other approaches different colour values get importance respectively.

CHAPTER 7

Conclusion and Future Scope

7.1 Conclusion

There are many types of medical images that can be stored on medical image databases. These images can be of MRI, nuclear medical imaging, X-ray, computed tomography scan, ultrasound (US), endoscopy, nuclear medical imaging, microscopy, and scanning laser ophthalmoscopy (SLO), etc. These databases helps in the retrieval of images with ease and high effectiveness. Finding images with this method is known as (CBIR), using information directly derived from the content of images themselves. The main objective of this thesis was to produce better outputs for image retrieval implementing colour histograms and machine learning methods using python programming script. Here, we explained a content based image retrieval system, use of colour histogram, feature extraction, dimensionality reduction and image segmentation process. The performance was found to be remarkably good and the results were near accuracy (greater number of relevant than irrelevant images). This is also evident that query by image technique is far better for image retrieval than textual based method as QBE focuses on the image contents, shape, colour, etc. which produces results relevant to the query image.

7.2 Further Objectives and Scope

This thesis intended to realize the problem of Content-Based Image Retrieval and its application in the biomedical field. The main goal of this thesis report was to propose an effective relevant QBE image search method in a large collection of biomedical images exploiting multimodal information found in such repositories .

The main goal of this work has been to build a strategy for image search that allows sample images as queries for the output results. This would provide the facility to search for images using example images, which in the medical domain could be associated with a diagnostic image for which we wish to obtain similar images as a reference. This paper also focuses on various efforts related :

- To adapt and implement image-processing methods through programming to extract the visual features that represent the image content .
- Accessing accurate and efficient retrieval of medical images of particular interest those are similar to a query image.
- To design and/or adapt a strategy to represent the contents of visual documents and images in a multimodality database .
- To implement a prototype system for medical image retrieval using the multimodal index.

The introduced CBIR system is using the present inbuilt functions of python and numpy. While colour histogram based method is most widely used, additionally, it is not essential that images containing same colours belong to the same space, therefore it is required to compare shape and texture too for the enhanced outputs. As image collections grow in size the system may take a lot of time, and eventually reduce the query-retrieval process.

This is an area that certainly warrants further research is that of measuring CBIR performances. As there has not been a lot of previous work the focus of most papers found seems to be on suggesting new and clever methods for image retrieval, not on how best to judge their effectiveness.

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