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Medical Image Retrieval Based on Gray Cluster Co-occurrence Matrix and Edge Strength Levels

استرجاع الصور الطبية باستخدام مصفوفة الجوار للمجموعات الرمادية ومستويات قوة الحدود

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Abstract

In Content Based Image Retrieval (CBIR), the objective is to query image databases in order to retrieve images with specific desired meaningful features. Important types of features include texture features and shape features. A common approach is to divide retrieval process into two stages; the first one is based on high-level features followed by the second that is based on low-level features.

Within the previous mentioned general approach, methods vary in techniques they use. For each stage to extract features, and for matching feature sets based on these variations, existing methods perform differently in terms of precision, recall, and distance variance. In this research, we find that this variation in performance is an opportunity for us to propose a new method. We focus primarily on medical images, and follow the above approach but make the following two basic contributions: a) introduce the gray cluster co-occurrence matrix as texture feature extraction and use it as high-level features, and b) introduce edge strength levels as shape feature extraction and use it as low-level features.

The system is evaluated using images retrieval performance the evaluation precision and recall rate, and distance variance. Our proposed system suggests the precision rate was **94.90%** and recall rate was **89.72%**. The distance variance achieved lowest rate **(0.0022)** in images retrieval compared to each of partial systems individually and related works. Our method has better performance in retrieving the results than other related works and each of partial system individually.

Keywords: CBIR, medical image retrieval, texture features, shape features, Gray Cluster Co-occurrence Matrix.

ملخص البحث

يهدف المحتوى القائم على استرجاع المعلومات البصرية إلى البحث في قواعد البيانات البصرية من أجل إيجاد (استرجاع) صور محددة ذات مغزى وذات ميزات مطلوبة. تضم الأنواع المهمة من الميزات المطلوبة ميزة وضوح نسيج التركيب وكذلك ميزة الشكل.

أحد المناهج الشائعة لهذه العملية هو تقسيم الاسترجاع إلى مرحلتين تعتمد الأولى على الميزات رفيعة المستوى تليها الثانية التي تعتمد على الميزات منخفضة المستوى وفي إطار هذا النهج العام، تختلف الطرق في الأساليب التي يستخدمونها لكل مرحلة لاستخراج الميزات، ومطابقة مجموعات الميزات. وبناءً على هذه الاختلافات، تختلف الأساليب الحالية بشكل كبير في أداءها من حيث الدقة والاسترجاع والتباين البعدي، نجد في هذه الدراسة أن هذا الاختلاف في الأداء هو فرصة لنا لاقتراح طرق جديدة.

نركز في هذه الدراسة في المقام الأول على الصور الطبية، وإتباع النهج المذكور أعلاه ولكن بإضافة المساهمتين الأساسيتين التاليتين: أ) تقديم مصفوفة الجوار للمجموعات الرمادية لاستخلاص ميزة نسيج التركيب واستخدامها كميزة رفيعة المستوى. ب) تقديم مستويات قوة الحواف لاستخلاص ميزة الشكل واستخدامها كميزة ذات مستوى منخفض.

وقد قيم النظام أداء استرجاع الصور بناء على مقاييس التقييم مثل الدقة والارجاع وقياس متوسط الفرق في المسافة فقد حقق النظام دقة تصل إلى **٩٤,٩٠%** بينما نسبة الارجاع وصلت إلى **٨٩,٧٢%**. وحقق النظام المقترح متوسط التباين البعدي أدنى معدلاته حيث وصل إلى (**٠,٠٠٢٢**) مقارنة مع كل جزء من النظام على حدة وكذلك على صعيد الابحاث السابقة. هذه النتائج تشير إلى أن نظامنا فاق أداء كل جزء من النظام على حدة وكذلك فاق الدراسات السابقة المذكورة في البحث.

بسم الله الرحمن الرحيم

﴿قُلْ لَوْ كَانَ الْبَحْرُ مِدَادًا لِكَلِمَاتِ رَبِّي
لَنَفِدَ الْبَحْرُ قَبْلَ أَنْ تَنْفَدَ كَلِمَاتُ رَبِّي وَلَوْ
جِئْنَا بِمِثْلِهِ مَدَدًا﴾

[الكهف : ١٠٩]

Dedication

To my beloved Parents, for their constant prayers, their support, encouragement, and constant love have sustained me throughout my life.

To my Wife, for her relentless care and support. To my Children, with hope for a bright future.

Acknowledgment

First, I thank Allah for guiding me and taking Care of me all the time.

No acknowledgement would be sufficient without expressing my appreciation and thankfulness for my wife;

I can't refute her long lasting patience and support which she showed during this work and which was essential to accomplish it.

I would like to thank my family especially my parents and my children because they supported me all the time and suffered with me so much.

Also, I would like to take this opportunity to thank all my teachers and my research supervisor, Dr. Ashraf Al Attar for giving me the opportunity to work with him, guiding and helping me throughout this research and other courses.

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List of Abbreviations

CBIR	Content Based Image Retrieval
GUI	Graphical User Interface
CBVIR	Content-Based Visual Information retrieval
QBIC	Query by Image Content
GLCM	Gray Level Co-occurrence Matrix
CCM	Cluster Co-occurrence Matrix
GP-MI	Gradient Phase Mutual Information
MRI	Magnetic Resonance Imaging
CT	Computed Tomography
TFV	Texture Features Vector
PACS	picture archiving and communication systems
DICOM	Digital Imaging and Communications in Medicine
EDHD	Edge Density Histogram Descriptor
DWT	Discrete 2-D Wavelet Transform
EEWTA	Energy Efficient Wavelet Image Transform Algorithm
LL	Low-pass Vertical
LH	Low-pass Horizontal
HL	High-pass Vertical
HH	High-pass Horizontal
SIFT	Scale Invariant Features Transform

Chapter 1

Introduction

1. Introduction

In this chapter, we declare some definitions for abbreviations or terms which are related to our work, starting with CBIR definition, then we display problem statement, objective, scope and limitation, significance of thesis, and research format respectively.

1.1 Background and Context

In these days, the medical field benefits from modern devices like CT, X-Ray, MRI, etc. that capture pictures of patient's body, these pictures called medical images. Doctors use these medical images to diagnose diseases.

Similar to any other science, medical field has its own database that stores these medical images which are collected from hospitals and clinics. Now before doctors take decisions, they retrieve similar medical images from this database and consult other doctors about these images to help them to take more efficient diagnosis. Each record in this database contains the digital image and the corresponding extracted features.

The digital images contain many pieces of information called features, some of these features have meaningful data, more than that when stored in database and requested later, they will retrieve corresponding correct similar images. The selected approaches which are used to extract features in storing image in the database or retrieving images from the database lead to successful diagnosis.

1.1.1 Content Based Image Retrieval (CBIR)

The term "content-based image retrieval" seems to have originated in 1992 when it was used by T. Kato to describe experiments into automatic retrieval of images from a database, based on the colors and shapes present (Eakins, 1996). Since then, the term was used to describe the process of retrieving desired images from a large collection on basis of syntactical image features. The techniques, tools, and algorithms that are used originate from fields such as statistics, pattern recognition, signal processing, and computer vision (Lew, Sebe, Djeraba, & Jain, 2006).

The earliest commercial CBIR system was developed by IBM and was called QBIC (Query by Image Content) (Files, 2013). and also known as content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases (Lew et al., 2006). Content-based image retrieval is opposed to traditional concept-based approaches in as much concept-based image indexing, also variably named as "description-based" or "text-based" image indexing/retrieval, refers to retrieval from text-based indexing of images that may employ keywords, subject headings, captions, or natural language text (Ahmad, Tariq, Vrusias, & Handy, 2003; RASMUSSEN & Chen, 1999).

"Content-based" means that the search analyzes the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image. The term "content" in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself (Lew et al., 2006). CBIR is desirable because searches that rely purely on metadata are dependent on annotation quality and completeness. Having human manually annotate images by entering keywords or metadata in a large database can be time consuming and may not capture the keywords desired to describe the image. The evaluation of the effectiveness of keyword image search is subjective and has not been well-defined. In the same regard, CBIR systems have similar challenges in defining success.

The interest in CBIR has grown because of the limitations inherent in metadata-based systems, as well as the large range of possible uses for efficient image retrieval. Textual information about images can be easily searched using existing technology, but this requires humans to manually describe each image in the database. This can be impractical for very large databases or for images that are generated automatically, e.g. those from surveillance cameras. It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like "cat" as a subclass of "animal" can avoid the categorization problem, but will require more effort by a user to find images that might be "cats", but are only classified as an "animal". Many standards have been developed to categorize images, but all still face scaling and categorization issues (Lew et al., 2006).

Recently researchers turned toward automating extraction features using methods of Content-Based Image Retrieval (CBIR) to sorting and retrieving similar query image. This technique uses the automatically infers features as search criteria such as colors, shapes, and textures to extract image features for selecting the similarity measure function and so on.

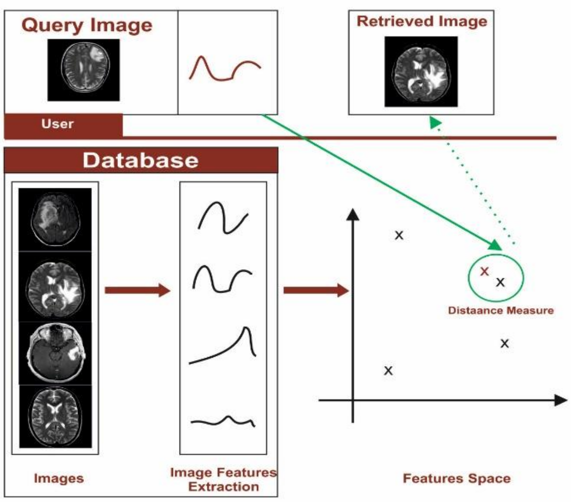


Figure (1. 1): Image retrieved biasd on Feture Extraction

1.1.2 Features Extraction

Power derived from transforming the image into important values as features, in machine learning, pattern recognition and in image processing to make decision. Feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction (Feature_extraction, n.d.).

When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a features vector). This process is called feature extraction. The extracted features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

1.1.2.1 Low level extraction

There have been many approaches to feature extraction, which combine a variety of features. It is possible to characterize objects by measures that we have already developed, by low-level features such as edges and corners (Nixon) . These can be grouped to give structure or shape and appearance of the object at particular interest points, and invariant to image scale and rotation. The motives for the earlier approaches that combine low-level features are the need to be able to search databases for particular images. This is known as content-based retrieval in image retrieval, which uses techniques from image processing and computer vision. Much of this material relates to whole applications and therefore can rely not just on collecting local features, shape, and texture but also on classifying objects in order not to allow object identification with high probability of mismatch.

1.1.2.2 High-level extraction

High-level algorithms are mostly in the machine learning domain. These algorithms are concerned with the interpretation or classification of a scene as a whole. Things like body pose classification, face detection, classification of human actions, object detection and recognition and so on (Li, Su, Fei-Fei, & Xing, 2010). These algorithms are concerned with training a system to recognize or classify something, then you provide it some unknown input that it has never seen before and its job is to either determine what is happening in the scene, or locate a region of interest where it detects an action that the system is trained to See for. You would have some sort of pre-processing stage where you have some high-level system that determines salient areas in the scene where something important is happening.

High-level algorithms are more in tune with how we classify objects in real life. For low-level feature detection algorithms, these are mostly concerned with finding corresponding points between images, or finding those things that classify as something even remotely interesting at the lowest possible level you can think of - things like finding edges or lines in an image (in addition to finding interesting points of course). In addition, anything dealing with pixel intensities or colors directly is what I would consider low-level too.

1.1.3 Cluster Analysis

Cluster analysis, also called segmentation analysis or taxonomy analysis, creates groups, or clusters, of data (Celenk, 1990). Clusters formed in such a way that objects in the same cluster are very similar and objects in different clusters are very distinct. Measures of similarity depend on the application.

K-Means Clustering is a partitioning method. The function k-means partitions data into mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, k-means clustering operates on actual observations (rather than the larger set of dissimilarity measures), and creates a single level of clusters (Fraley & Raftery, 1998). The distinctions mean that k-means clustering is often more suitable than hierarchical clustering for large amounts of data.

Clustering using Gaussian Mixture (GM) models form clusters by representing the probability density function of observed variables as a mixture of multivariate normal densities. Mixture models of the (GM) distribution class use an Expectation Maximization (EM) algorithm to fit data, which assigns posterior probabilities to each component density with respect to each observation (Figueiredo & Jain, 2002). Clusters assigned by selecting the component that maximizes the posterior probability. Clustering using Gaussian mixture models sometimes considered a soft clustering method. The posterior probabilities for each point indicate that each data point has some probability of belonging to each cluster. Like k-means clustering, Gaussian mixture modeling uses an iterative algorithm that converges to a local optimum(Figueiredo & Jain, 2002). Gaussian mixture modeling may be more appropriate than k-means clustering when clusters have different sizes and correlation within them.

1.1.4 Texture Features

Texture can be regarded as a similarity grouping in an image. Traditional texture analysis can be divided into four major issues: features extraction, texture discrimination, texture classification and shape from texture(Haralick,

Shanmugam, & Dinstein, 1973). For traditional features extraction, approaches are usually categorized into structural, statistical, model based and transform.
When feature extraction is applied on images, the texture features will be analyzed using statically methods, such as the image segmentation and important information of the relationship between neighborhoods (P. Zhang & Zhu, 2011).

- **Structured approach**

  A structured approach sees an image texture as a set of primitive Texel's in some regular or repeated pattern. This works well when analyzing artificial textures.

- **Statistical approach**

  A statistical approach sees an image texture as a quantitative measure of the arrangement of intensities in a region. In general this approach is easier to compute and is more widely used, since natural textures are made of patterns of irregular sub elements.

- **Model-based features**

  Models of two-dimensional random processes is one of number of random field models have been used for modeling and synthesis of texture. The parameters may provide a suitable feature set for classification and segmentation of the texture features when a model show is capable of representing and synthesizing a range of textures. These models must design a reasonably efficient and appropriate parameter estimation scheme, and it should be parsimonious. Popular random field models used for texture analysis include fractals, autoregressive models, fractional differencing models, and Markov random fields (Ahuja & Schachter, 1981; Reed & Dubuf, 1993).

- **Non-model-based features**

  The feature measures based on set of popular methods such as co-occurrence matrices, grey-level sum and difference histograms, Laws' masks, frequency domain methods, and Gabor filters.

  One of the basic methods is Gray Level Co-occurrence Matrix (GLCM) that captures numerical features of a texture using spatial relations of similar gray tones. (Haralick et al., 1973) Numerical features computed from the co-occurrence matrix can be used to represent, compare, and classify textures. this features as energy, entropy, contrast, homogeneity, correlation, Etc. (Lachmann & Barillot, 1992). All above reflecting comprehensive summary descriptor as semantic data will need it in retrieving images.

The rotation angle image and background region that influence in performance analytic image with (GLCM) used Gradient Phase Mutual Information (GP-MI) to compute the angle between two images(Mingquan, Guohua, & Shi, 2012).

- **Gray level co-occurrence matrix (GLCM)**

  A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix (Haralick et al., 1973; Thakare, Patil, & Sonawane, 2013). The texture filter functions, described in Texture Analysis cannot provide information about shape, i.e. the spatial relationships of pixels in an image.

- **Semantic Retrieval**

  Many CBIR systems therefore generally make use of lower-level features like texture, color, and shape. These features are either used in combination with interfaces that allow easier input of the criteria or with databases that have already been trained to match features (such as faces, fingerprints, or shape matching) (Lew et al., 2006). However, in general, image retrieval requires human feedback in order or statistical methods to identify higher-level concepts.

1.1.5 Shape Features

The edges are important features of images to extract image content and object recognition, because they contain contour important information such as gradient magnitude, angle direction and explanation of the object in images (Efford, 2000). So the Sobel, Prewitt and Canny descriptors can split the edge information as the target from the background, but the edge image in generally is complex and cannot compose image features , and there are a huge number of curves and lines that are difficult to be described by mathematical formula (Pentland, Picard, & Sclaroff, 1996).

1.1.5.1 Edge detection

Edge detection is the name for a set of mathematical methods which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. Edge detection is a fundamental tool in image processing, machine vision and computer vision, particularly in the areas of feature detection and feature extraction (Scott, 2011).

1.1.5.2 Sobel operator

The Sobel operator, sometimes called the Sobel-Feldman operator or Sobel filter, is used in image processing and computer vision. It is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function corresponding gradient vector or the norm of this vector (Sobel, 2014). The Sobel-Feldman operator is based on convolving the image with a small, separable, and integer valued filter in the horizontal and vertical directions and is therefore relatively inexpensive in terms of computations (Pentland et al., 1996). On the other hand, the gradient approximation that it is produces relatively crude, in particular for high frequency variations in the image. So, we will use Sobel kernels 3×3 to calculate gradient magnitude that describes the edge strength in images.

In this research we will introduce a new approach to retrieve medical images by extracting features which is combining gray cluster co-occurrence matrix as a texture features and edge strength levels as a shape features.

So we will use gray cluster co-occurrence matrix as image feature vector in high level features and achieved semantic classification (Wan & Chowdhury, 2003). Extracting a comprehensive semantic summary on the texture descriptor and storage(Manjunath, Ohm, Vasudevan, & Yamada, 2001). Calculating edge strength from a medical image is an approach of low level content features to judging it from any level strength. Our method describes 4 kinds of edge strength levels by applying Sobel kernels 3×3 to calculate gradient magnitude that describes the edge strength in images as shape features. The combination between two operations will improve accurate performance retrieve similar image.

1.2 The Research Problem

In these days, the medical field benefits from modern devices like CT, X-Ray, MRI, etc. that capture pictures of patient's body, these pictures called medical images. Doctors using these medical images to help them in making decisions of diagnose diseases.

Like any other science medical field has its own database that stores these medical images which are collected from hospitals and clinics. Before taking decisions, doctor retrieve similar medical images from this database and opinions of others doctors about these images to help them take more efficient diagnosis. Each record in this database contains the digital image and the corresponding extracted features.

The digital images contain many information called features, some of these features have meaningful data, more than that when stored in database and request later they will retrieve corresponding correct similar images. The selected approaches that used to extract features in storing image in the database or retrieving images from the database lead to successful diagnosis.

While our research does not claim to handle a shortcoming in previous research, our basic contribution is to add a method to the various techniques available for medical CBIR.

1.3 Objectives

This research has main and specific objectives through which we can achieve the solution to our problem.

1.3.1 Main objective

This research aims to develop a new CBIR method for medical image retrieval based on gray cluster co-occurrence matrix as texture features and edge strength levels as shape features. Also the research aims to investigate the advantages of our proposed method in enhancing the process of retrieving medical images. A large part of the research is dedicated to measure the effect of combining both methods in further enhancing the effectiveness of the image retrieval process.

1.3.2 Specific objectives

1- Collect real abnormality of MRI brain images from European Gaza Hospital.

2- Build a module for automate features extraction from medical images and store that images with corresponding features in a database.

3- Build matching feature modules to retrieve similar images.

4- Evaluate our method through comparing between our method and each of partial individually.

1.4 Significance of this thesis

- Accurate selecting features in medical images provide accurate high extracting features to distinct with other medical images.
- Enhancing performance in terms of accuracy to retrieve similar medical images set.
- Reducing semantic gap occurrences caused by using low-level features in extracting features.
- Extracting a Texture Features Vector (TFV) of semantic summary by statistical methods operations as high level features to reduce semantic gap.

- Can be used in various systems such as:
    - Medical Imaging Systems.
    - Diagnostic Helping Applications.
    - Researcher and Doctors Domain.

1.5 Scope and Limitations

This work expected to be developed under some constraints and limitations such as:

- Our experiments will take on medical images datasets.
- Difficulty in obtaining abnormality MRI brain images
- Our aim is to validate the effect of combining the gray cluster co-occurrence matrix and edge strength levels.
- Evaluating our model on gray color images only.

1.6 Research Methodology

The research methodology followed in this research in order to complete and achieve our goal is presented as:

- **Literature Review**

  Firstly, a review has done for current techniques used for handling the background cluttered and boundary concavities.

- **Study CBIR methods**

  CBIR methods are hard study. These types to explain the performance image retrieval methods.

- **Development our proposed solution**

  The proposed algorithm handle extraction features and reduces semantic gap problems.

- **Implementing the proposed algorithm**

  The proposed algorithm has implemented and tested in Matlap.

- **Evaluating and comparing results**

  The evaluation of the system has done using three metrics: recall, precision and MSE. These metrics has used to compare the proposed algorithm with related works.

1.7 Research Format

The research organized as follows. Chapter one is introduction, research problem, objectives, scope and significant. Chapter two is related work. Chapter three is technique and implementation. Chapter four is evaluation and discussion. Chapter five presents conclusions and future work.

Chapter 2

Literature Review

2. Literature Review

2.1 Background

In this chapter, we review a number of research works. We start with initial methods to retrieve images proposed based on content-based image retrieval methods, and discuss their limitations with respect to the problems of methods extraction features and semantic gap.

In recent years, there is rapid growth of computerized medical image database using picture archiving and communication systems (PACS) in hospitals, and medical researchers. There is a focus to produce more efficient medical image applications of modalities every day to success rapid retrieval of images, and efficient access to visually similar images (Sudhakar & Bagan, 2011)

2.1.1 Text-based image retrieval

Retrieval idea has created in 1960 to retrieve text files that saved lastly. From that time many techniques in image retrieval are taken from this domain. Therefore, in 1970 (Long, Berman, & Thoma, 1996) suggested first idea to retrieved image depending on text information. It becomes clear that the combination of visual and textual retrieval has biggest potential. There are many things that are hard to express feelings, situations, (what is scary?), what is in the image, what is it about, what does it invoke?

The main problem is the goal of the annotation because that is depending on synonyms, hyponyms, and homonyms also the mistakes such as spelling errors, spelling differences (US vs. UK), and weird abbreviations particularly medical images.

Systems for medical image retrievals are text-based (Long, Berman, & Thoma, 1996; Long et al., 1997; H. J. Lowe, Antipov, Hersh, Smith, & Mailhot, 1999), strongly depending on human to manually input tags to refer on what are shows in medical images at diagnosis (Liu, Rothfus, & Kanade, 1998; Shyu et al., 1999). The different evaluation methods and clinical requirements make the extraction of medical images information to difficult task and large differences occurs in extraction the semantic features. For long time, huge human consumption and the lack of integrity and objectivity caused by manual achieved, but this can put import the visual features of images to retrieval result.

2.1.2 Content-based image retrieval

Recently researchers turned toward automate extraction features using methods of Content-Based Image Retrieval (CBIR) to sorting and retrieving similar query image. This technique uses the automatically infers features as search criteria such as colors, shapes, and textures to extract image features for selecting the similarity measure function and so on.

2.2 State of the Arts

We will review some of the previous work classified by approach retrieval method.

2.2.1 Image retrieval based on text-based without semantic concept

(Lehmann et al. (1999); Muller, Rosset, Vallée, and Geissbuhler (2003)) have proposed the medical CBIR system to add manually a target that constrains range of modalities. That are less flexible. Therefore, these research projects have developed recently with the goal to create CBIR systems for heterogeneous image collections.

(Long et al. (1996); Long et al. (1997); H. J. Lowe et al. (1999)) proposed systems for medical image based on text-based to retrieve images, these systems depending on human to manually input tags to refers on what is shows in medical images at diagnosis. The different evaluation methods and clinical requirements make the extraction of medical images information a difficult task and large differences accurate in extraction the semantic features. For long time, huge human consumption and the lack of integrity and objectivity caused by manual achieved.

2.2.2 Image retrieval based on DICOM as a semantic concept

Content-based image ret

rieval (CBIR) techniques use the features such as color, texture and shape as search criteria. These medical images contain semantic information can be used to retrieve the visual images (Annadurai, 2007). The most recent papers are to minimized gap between low-level features and high-level semantics concepts to more effective image retrieval.

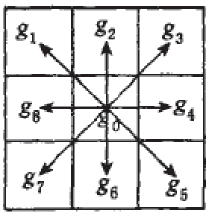
Annadurai (2007) Proposed a retrieval approach, which performed by combining the high-level semantics (DICOM features) and low-level content features (shape and texture). This application makes use of the Gabor wavelet for texture extraction. Similarity between the query image features and the features of the images in the database has calculated. He used The Digital Imaging and Communications in Medicine (DICOM). One image and tags describing the image compose DICOM files. Tags are textual or numerical sequences of <attribute, value> pairs. The textual information considered as the semantic information. Consequently, the DICOM format containing relevant information in image headers, those that are available in other formats lacks such header information. Hence, text annotations need to be included for their indexing.

2.2.3 Image retrieval based on statistical texture features as a semantic concept

Prasad, R. D., et al (2016) proposed image retrieval used dominant color and texture features. They used histogram of image to get normalized histogram of each pixel in the image and hence approximates to the probability distribution of pixel intensities. The next step is get a spatial relationship of pixels used a statistical method of texture that considers the gray-level co-occurrence matrix (GLCM). Image Indexing can be based on dominant color region in an image because it can be represented as a connected fragment of homogeneous color pixels, which is perceived by human vision. The segmented out dominant regions along with their features can be used as an aid in the retrieval of similar images from the image database. They used two algorithms Euclidean Distance Algorithm, K-Means Clustering Algorithm for similarity matched stage to decision making stage of CBIR system.

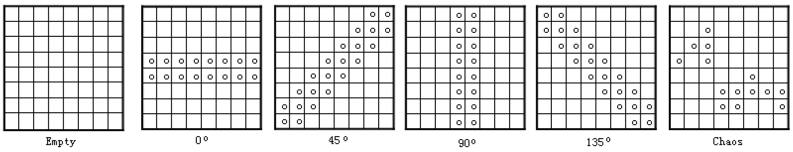
Mingquan et al. (2012) Proposed a new method of improved Gray Level Co-occurrence Matrix (GLCM) to overcome this shortcoming of traditional GLCM. In this method, they used Gradient Phase Mutual Information (GP-MI) to compute the angle between two images and use the method of masked image to remove the background of the image. In addition, they divide the image into several blocks equally and compute the GLCM of every block using Statistic the final GLCM of the direction of 0°, 45°, 90°and 135°. Moreover, they sum the GLCM of every block by different weights as the final texture feature.

P. Zhang and Zhu (2011) They proposed a method to calculate the gray-cell difference co-occurrence matrix of the gray image and the cell difference image by compare both image with texture structure methods and statistical methods.



Figure(2. 1): Clock mode to arrangement of the nine elements in the sliding windows

They used edge histogram to extracting shape features by divided each image to 4×4 sub regions in order to extract edge type.

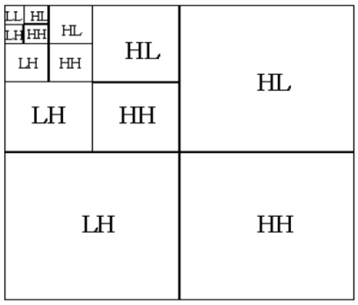


Figure(2. 2): Edge type corresponding discriminance

Li-dong and Yi-fei (2010) Proposed extended edge histogram method of WAN, combined local features with global shape features, combined edge of whole image with edge density of sub-images; it named as Edge Density Histogram Descriptor (EDHD). A multi-scale morphological gradient algorithm detected this image edges. The shape features were extract from the obtained edge image and edge-density histogram was constructed. They proposed the medical image retrieval and classification executed according on Euclidean distance and support vector machine. This method combines the global and local features of images, achieves content-based medical image retrieval and classification well. These approaches have been widely used in image retrieval due to their usually low computational costs and acceptable effectiveness.

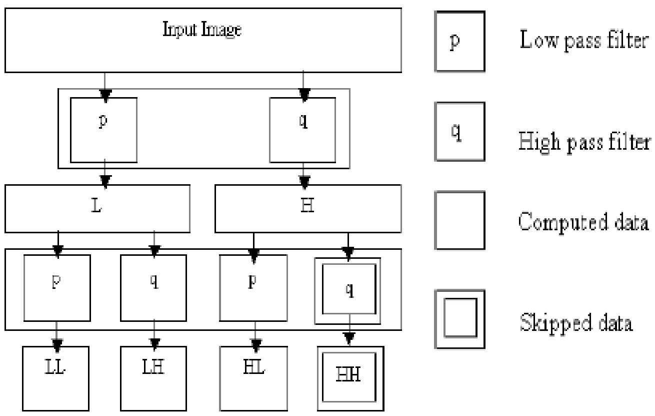
2.2.4 Image retrieval based on mapping algorithm as semantic

Jin, Hong, and Lianzhi (2009) Have proposed extracting low-level features using gray level co-occurrence matrix statistical features and wavelet statistical features. The discrete 2-D wavelet transform (DWT) can be implemented as a stage transformation. The output of each stage is then four sub-band images labeled LL, LH, HL, and HH, respectively.



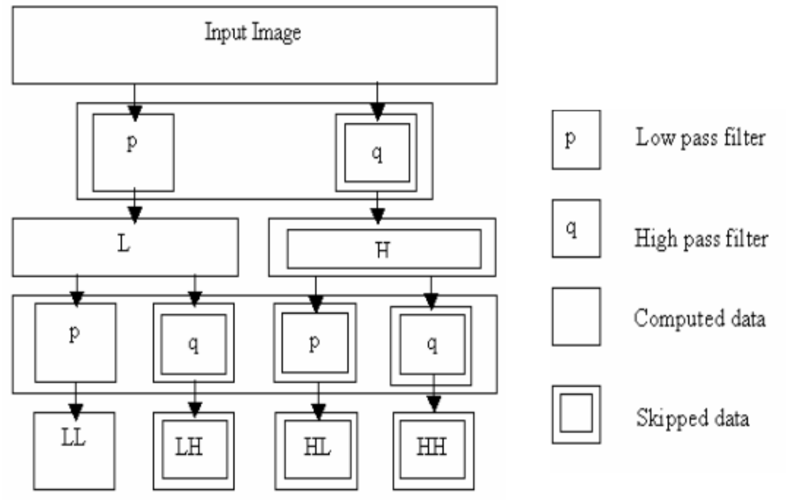
Figure(2. 3): Wavelet Decomposition

The semantic feature vector is the appearance number of a keyword in the report. They proposed mapping algorithm by a set of disjoint semantic concepts with visual appearance in medical images first selected to define a vocabulary based on medical knowledge representation. The low-level features extracted from medical image z to represent each vocabulary using GLCM Statistical Features and Wavelet Statistical Features as the retrieval feature. These low-level features used as training examples to build hierarchical semantic classifiers according to the semantic vocabulary. This paper need to define semantic feature vector that appearance as a keyword in the report.



Figure(2. 4): HH Elimination method of EEWTA

Rajakumar and Muttan (2010) Proposed medical retrieval system to extract features during the energy efficient wavelet by modified wavelet transformation used for Energy Efficient Wavelet Image Transform Algorithm (EEWTA). Implemented the HH elimination and H* elimination method that also employs the modified wavelet transformation and in this method it retains the most significant low pass sub band and eliminates all the high pass sub bands horizontal, vertical and diagonal sub bands. Each of which are associated with a feature vector derived directly from modified discrete wavelet transform.



Figure(2. 5): H* Elimination method of EEWTA

F. Zhang et al. (2014) Proposed approach to further capture the semantic association of the image pair based on the extracted Pair-LDA topics with direct topic structure, a correlation factor to represent this association. They proposed latent association assumes that the images are represented as the latent topics and generated in pairs from the correlation factor to distribution for one target image can be flexibly assigned. This idea makes to convert features to topics.
Not with standing, such mapping algorithm solutions fail on capturing some local features representing the details and nuances of the scenes.

2.2.5 Image retrieval based on clusters

Setia, Teynor, Halawani, and Burkhardt (2006) Proposed use relational features calculated over multiple directions and scales around these interest points.

Design issue is the choice of similarity measure to compare the bags of local feature vectors generated by each image, for which they proposed a novel approach by computed image similarity used cluster co-occurrence matrices of local features. This is major steps of algorithm proposed can be summarized as follow:

- **Preprocessing** Convert image to grayscale if needed, normalize gray values between 0 and 1.
- **Interest Points** apply an interest point detector (the Lupias Salient-Point Detector). Sort the obtained saliency map, and take the Ns points with the highest saliency values for further computation.
- **Local Relational Feature Generation** Evaluate a number of relational functions $\Re(x,y,r1,r2,\varphi,n)$. Each function gives for each interest point, a sub feature vector of length n. These are concatenated to get a local feature vector for each interest point.
- **Clustering** Take a random subset of local feature vectors from all training images. Cluster these feature vectors in Nc clusters according to some optimization criteria. Save the cluster centers for later use with test images.
- **Cluster Co-occurrence Matrix** The nearest cluster is calculated for all local feature vectors of the image. The complete local feature vectors are discarded the only retained information is the index of the nearest cluster. Consider all possible salient-point pairs. A cluster co-occurrence matrix of size Nc ×Nc is generated sector-wise used as the final feature vector for the image for use with an independent classifier. The main concerns are the many possibilities to choose various parameters, and the high dimensionality of the final feature vector.

Inoue and Urahama (2001) Improved an interactive Content-Based Image Retrieval (CBIR) system that allows searching and retrieving images from databases. Based on the fuzzy c-means clustering algorithm, the CBIR system fuses color and texture features in image segmentation. A technique to form compound queries based on the combined features of different images is devised. The proposed approach focus to improve quality of image segmentation, the RGB color space is converted to the CIELAB color space in this research. Next, for each image pixel, the color and texture features are extracted for segmentation by clustering. To extract the color feature, color median filtering is applied recursively to deemphasize noises. The extraction of texture feature, however, requires no filtering, and it is computed from the gray-scale version of the input image. After feature extraction, the pixel features are clustered into groups using the fuzzy c-means clustering algorithm. During the post processing steps, the region merging algorithm is applied recursively to combine over-segmented and un-dominant image regions. Finally, the well-defined regions are labeled for property extraction. This proposed depend on color images such as a skin cancer imagery database this used approaches rely on color and texture but our proposed not needing to RGB color because MRI and CT images are gray scale.

2.2.6 Image retrieval based on Scale Invariant Features Transform (SIFT)

Almeida, Torres, and Goldenstein (2009) Have presented discuss results obtained in several experiments proposed to evaluate the application of the SIFT in CBIR tasks. This approach relies on the choice of several parameters which directly impact its effectiveness when applied to retrieve images. the Detected locations that has invariant to scale or color change of the image can be accomplished by searching for stable features across all possible changes, using a continuous function of scale known as scale space showed that the SIFT approach is invariant to color channels. In addition, we have found that there is a trade-off between the size of the feature vector and its description quality in order to produce good results. Moreover, the use color information in the local-feature vector outperforms, but our proposal focused on gray scale medical images.

D. G. Lowe (2004) Proposed from the full set of matches, subsets of key points on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalized Hough transform. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches.

Many other feature types have been proposed for use in recognition, some of which could be used in addition to the features described to provide further matches under differing circumstances. Basri and Jacobs (1997) They have demonstrated the value of extracting local region boundaries for recognition. Other useful properties to incorporate include color, motion, figure-ground discrimination, region shape descriptors, and stereo depth cues. The local feature approach can easily incorporate novel feature types because extra features contribute to robustness when they provide correct matches, but otherwise do little harm other than their cost of computation.

SIFT relies heavily on the presence of strong edges. That it very accurate for objects where labeling is clearly visible but it poor accuracy when objects have little or no labeling visible.

2.3 Summary

As shown in this chapter, text-based techniques require extensive manual intervention and have limited capability in achieving practical image retrieval performance. On the other hand, there are various content-based methods with widely varying performance. This variation in techniques and performance opens a window of opportunity for us to make a contribution. We obtain a way to following commonly using CBIR approach depend on dividing features extraction phase into texture-features and shape features. Details of our approach follow in the next chapters.

Chapter 3

Research Methodology and Techniques

3. Research Methodology and Techniques

In this chapter we will present two sections. The first one is our technique which presents automatic retrieval similar query image from medical images database and overcomes many problems in extraction features images until reach the final goal. This goal is ranking closest distance similar images.

The second section presents the implementation structure for the main functions used to build the retrieval system. But before discussing these sections, we will present a research design and methodology to get brief details

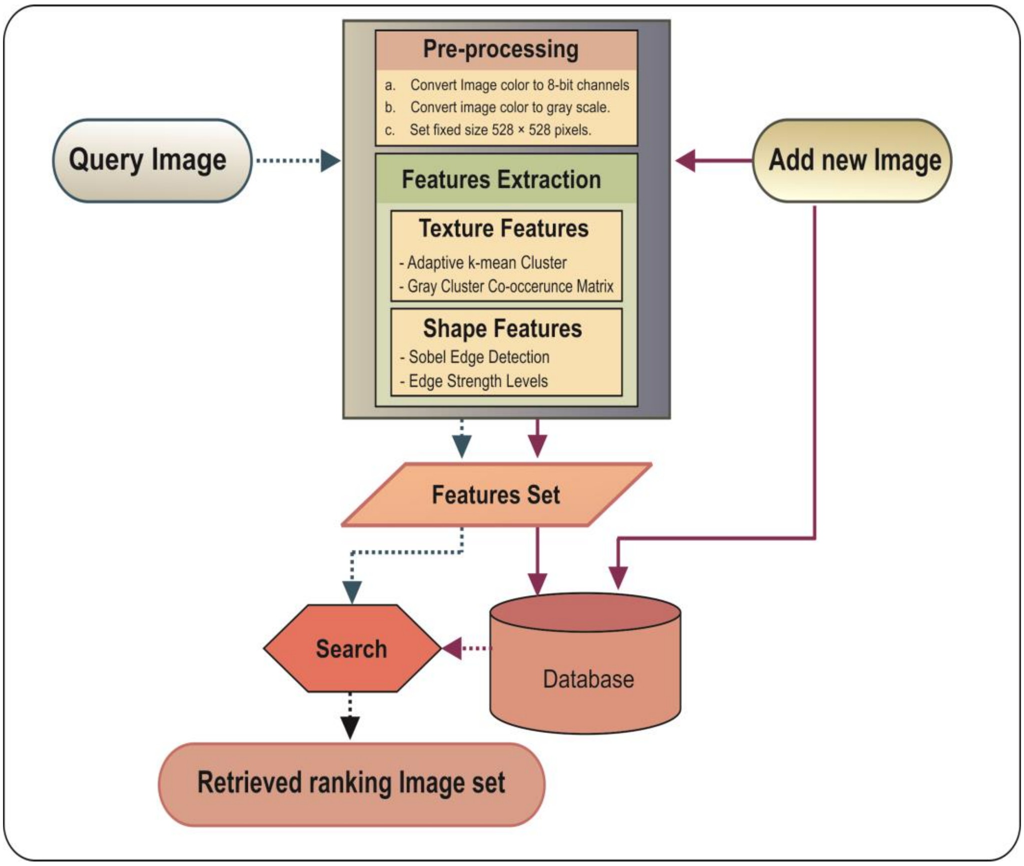
3.1 Research Methodology

Our research consists of four main stages: The first one is pre-processing medical images which presents automatic convert color Images to 8-bit channels, RGB color to gray scale and Set fixed size 528 × 528 pixels. This size is used to achieve the final goal.

The second stage presents the steps of extraction semantic data refers to texture features extraction from medical images through distributing gray level values in clusters and replace each gray value in image with centroid value cluster to compute gray level co-occurrence matrix equations into centered values. The final result of this section is getting values represent Texture Feature Vector (TFV). Euclidean distance that is metric tool to distance between TFV query image and each TFV image in database to sorting values closest distance.

The third stage presents the steps of extraction shape features to get some features from images such as visualized edges, strong edges and suggestion table (by experimental) contains strength edge levels. This operation refers to power edges in image with quantizing strength edges in the form tenderize levels (by experimental) to measure distance query image and other images in database. Trace distance is a function made to sum diagonal elements for each 2X2 sub-region image and sorting values closest distance.

Finally, to retrieve similar query image from database we need to combine second section and third section respectively to achieve high performance in medical image retrieval through combining high level features representing by semantic data which texture feature vector and low level features represented by strength edge levels. The result should show ranking in list by closest distance. We evaluate our developed model and integrate it into proposal system to evaluate its performance within the overall process. These stages and their details are depicted in (figure 3.1), and are further explained in the following two subsections.



Figure(3. 1): Proposal model for image retrieval design

3.1.1 Stage 1: Pre-processing images

In this stage we apply necessary processes on images. Like, (1) Convert color Images to 8-bit channels, (2) Convert RGB color to gray scale color, (3) Set fixed size 528 × 528 pixels.

3.1.1.1 Convert color Images to 8-bit channels

A ‘bit’ is a computer term for data storage. It can only contain two values, typically 0 or 1. 8-bit simply means the data chunk is 8 bits in total (or 2 to the power of 8, as each bit can be either '1' or '0'). This allows for numeric values ranging from 0 to 255.

Similarly 16-bit means the data size is 16 bits in total. (or 2 to the power of 16) This allows for numeric values ranging from 0 to 65535.

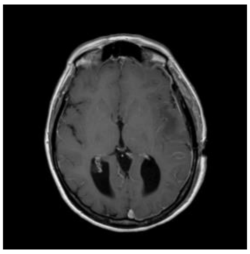
As long as we deal with images of gray scale, we need to convert color images to 8-bit channels toward reducing consume time in processes.

3.1.1.2 Convert RGB color to gray scale color

The medical images such as CT and MRI are gray scale images but when application machines are sorted in external hard disk then saved images as DCM or JPG that type RGB color.

3.1.1.3 Fixing the image size

The medical images vary in size. However, in order to make calculations easier, we have chosen zoom resize to obtain more enhanced retrieved images, we assume that all input images have got the same fixed size which has been chosen as 528×528 pixels. The reason we have chosen such a fixed size is because of its importance for the process of dividing the image into equally sized sectors which are necessary for convolution with Sobel kernel. This resize will not cause any confusion on images because the zooming on the pixel is not large



Figure(3. 2): Fixed size 528×528 Pixels

Algorithm1: preprocessing image

Input: colored image I
Output: 528 X 528 pixels gray scale image 8-bit channel

1. Convert I to 8-bit channel
2. Convert I to grayscale image
3. IMG = image after apply fixing size 528X528

3.1.2 Stage 2: Extracting texture features

Texture feature extraction consists of two steps: First, get the relation between neighborhood pixels through adaptive K-Mean cluster. Centroid value clusters from the original gray image. Second, extracting the texture features vector of centroid values through applied statistical method in Gray Cluster Co-occurrence Matrix.

3.1.2.1 Adaptive K-Mean Cluster

The problem faced in clustering is the identification of clusters in given data. A widely used method for clustering is based on K-means in which the data is partitioned into K number of clusters.

We chose adaptive K-means because it achieves the following:

1. Cluster a Gray single channel (0-255) as in k-means.
2. Not need to be specify the number of clusters.
3. Fast implementation.
4. Easy to understand.
5. Easy to modify the code according to your requirements.
6. No use of any Image Processing Tool Function.
7. Adaptive K-means uses same principle as in k-means, but here you do not need to define number of clusters.

In this method, clusters are predefined which is highly dependent on the initial identification of elements representing the clusters and focused on improving the clustering process. Jyothsna (2015) Proposed method advances an adaptive technique that grows the clusters without the initial selection of elements representing the cluster. It is found to be capable of segmenting the regions of smoothly varying intensity distributions. The technique has been used to achieve a notable accelerated search process.

The adaptive K means clustering algorithm starts with the selection of K elements from the input data set. These K elements form the seeds of clusters and are randomly selected. The properties of each element also form the properties of the cluster that is constituted by the element. The algorithm is based on the ability to compute distance between a given elements and cluster. This function is also applied to compute distance between two elements.

An important consideration for this function is that it should be able to account for the distance based on properties that have been normalized so that the distance is not dominated by one property or some property is not ignored while distance computation (Bandyopadhyay & Maulik, 2002).

The relationship between neighboring pixels in images is by replacing each pixel values with centroid cluster belongs as shown in (figure 3.3).

```
Algorithm 2: Adaptive K-mean Cluster
Input: IMG image to be clustered
Output: 528 X 528 cluster centers
        Copy value into an array.
        Initialize iteration Counters.
        while(true)
              Initialize seed Point.
              Increment Counter for each iteration.
          while(true)
              Initialize Counter for each iteration.
              Find distance between Seed and Gray Value.
              Find bandwidth for Cluster Center.
              Check values are in selected Bandwidth or not.
              Update mean.
              Condition for convergence and maximum iteration.
              Remove values which have assigned to a cluster.
              Store center of cluster.
              Update seed.
          end
          Check maximum number of clusters.
          Reset Counter.
        end
        Sort Centers.
        Find out Difference between two consecutive Centers.
        Find out Minimum distance between two cluster Centers.
        Discard Cluster centers less than distance.
        Make a clustered image using these centers.
        Replicate vector for parallel operation.
        Find distance between center and pixel value.
        Choose cluster index of minimum distance.
Reshape the labeled index vector.
```

n1	n1	n1	n1	n1	n1	n1	n1	n1
n1	n1	n2	n2	n2	nc	n2	n1	n1
n1	n2	n3	Nc	n3	n3	n3	n2	n1
n1	n2	n3	n3	Nc	nc	n1	n2	n1
n1	n3	n3	n2	n3	nc	n3	n2	n1
n1	n1	n2	n2	n3	n2	n3	n1	n1
n1	n1	n1	n1	n1	n1	n1	n1	n1

Figure(3. 3): visualizing the output matrix 528 x 528 centroid cluster values

3.1.2.2 Calculating Gray Cluster Co-Occurrence Matrix (GCCM)

We will use Gray Cluster Co-occurrence Matrix to extract texture features that are based on statistical co-occurrence matrix. These filters include mean, energy, homogeneity, contrast, entropy, and correlation. A setting for centroid quantization is available to reduce the number of shades of gray required representing the image as shown in (figure 3.3).

Applying equations from equation (3.2) to equation (3.7) to the normalized values of image are represented in matrix 528 x 528 (P. Zhang & Zhu, 2011).

We will use function (3.1) to normalize the matrix, making the sum of elements to be one.

$$P(i,j) = \frac{M(i,j)}{\sum_{i=0}^{L-1}\sum_{j=0}^{L_j-1} M(i,j)} \qquad \text{Eq. 3.1}$$

Where M(i,j) is centroid value in matrix 528 x 528, P(i,j) is normalized value.

We will use function from (3.2) to (3.7) to compute statistical features. Including Inertia, Energy, Correlation, Entropy, Homogeneity, Entropy, and Average of gray.

Inertia :

$$\mathrm{T}_1 = \sum_{i=0}^{528}\sum_{j=0}^{528} (i-j)^2\, P(i,j) \qquad \text{Eq.3. 2}$$

Energy :

$$\mathrm{T}_2 = \sum_{i=0}^{528}\sum_{j=0}^{528} [P(i,j)]^2 \qquad \text{Eq. 3.3}$$

Correlation:

$$T_3 = \frac{\left[\sum_{i=0}^{528}\sum_{j=0}^{528} ij\, P(i,j) - \mu_1\mu_2\right]}{\sigma_1\sigma_2} \qquad \text{Eq. 3.4}$$

where $\mu_1\mu_2$ *the means values* and $\sigma_1\sigma_2$ the standard deviations

Homogeneity :

$$T_5 = \sum_{i=0}^{528}\sum_{j=0}^{528} \frac{P(i,j)}{1+|i-j|} \qquad \text{Eq. 3.5}$$

Entropy:

$$T_4 = -\sum_{i=0}^{528}\sum_{j=0}^{528} lg\, P(i,j) \qquad \text{Eq. 3.6}$$

Average of gray:

$$T_6 = \sum_{i=0}^{528} i\left[\sum_{j=0}^{528} P(i,j)\right] \qquad \text{Eq. 3.7}$$

Finally, we will get a Texture Features Vector (TFV) of semantic summary from image as shown in (figure 3.4).

Algorithm 3: apply statistical method to extract Texture Features Vector (TFV)

Input: centroid clustered image
Output: texture feature victor
    Summation all element in matrix equal one
    Apply gray coprops function to get Contrast, Correlation, Energy, Homogeneity
    Apply entropy function
    Apply average function

T_1	T_2	T_3	T_4	T_5	T_6

Figure(3. 4): Texture Feature Vector (TFV)

Algorithm 4: Standardization TFV result

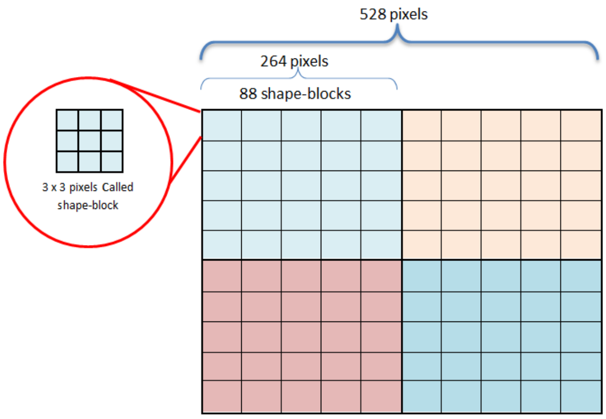
Input: texture feature vector (TFV)
Output: standardization result
    Online check min value from query image and all data
    Online check max value from query image and all data
        Normalize values by calculate tfv_query-mindata/maxdata-mindata

3.1.3 Stage 3: Shape Features Extraction

The shape features and the edges are important in retrieving process; in our research we will address the edge according to its strength.

3.1.3.1 Dividing image into shape-blocks

1. Separating image into 2×2 sub-regions based on (Nagabhushana, 2005), Each sub-region is 264×264 pixels. We believe this segmentation improves our approach because the features are distributed on the image on the four parts and each part has its pattern of edge strength levels.
2. Each sub-region 264×264 pixels is separated into 88 x 88 blocks called *shape-blocks*.
3. Each shape-block consists of 3×3 neighboring pixels, beginning from top left corner sub-region as shown in (figure 3.5).



Figure(3. 5): Visualizing separate image

3.1.3.2 Calculating Strength Levels for Shape-Blocks

1. **Generating gradient:** The Sobel kernel operator uses two 3×3 kernels which are convolution with the original image to calculate approximations of the derivatives-one for horizontal changes, and derivatives-one for vertical (Efford, 2000). A denotes at original image, Gx and Gy are two images which at each point contain the horizontal and vertical derivative approximations, the computations are as follows:

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * \mathbf{A} \qquad \text{Eq. 3.8}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * \mathbf{A} \qquad \text{Eq. 3.9}$$

Where * here denotes the 2-D convolution operation.

The two gradients are computed at each pixel can be regarded as the x and y components of a gradient vector:

$$G = \begin{bmatrix} G_x \\ G_y \end{bmatrix} \qquad \text{Eq. 3.10}$$

The x-coordinate is defined here as increasing in the "right"-direction, and the y-coordinate is defined as increasing in the "down"-direction.

At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using:

$$\boldsymbol{G} = \sqrt{G_x^2 + G_y^2} \qquad \text{Eq. 3.11}$$

So, the magnitude is sometimes approximated by:

$$\boldsymbol{G} = |G_x| + |G_y| \qquad \text{Eq. 3.12}$$

Thus, G measures the strength of an edge in gray level within the 3 x 3 neighborhood pixels.

Algorithm 5: edge Sobel detection

Input: IMG image
Output: gradient value
    Create gradient matrix 176X176
    Loop
    Convolution 3X3 neighborhood with Sobel operator X direction
    Convolution 3X3 neighborhood with Sobel operator Y direction
    Gradient absolute summation both convolution

2. **Quantizing gradients:** Note that we apply the quantization on each sub-region alone, each sub-region contains 88x88 shape-blocks that equals to 7744 shape-blocks of gradient values as in Table (3.1). We proposed (by experiments) the following rate of quantization: the lowest (10%) shape-blocks gradient values take rank 0, later (30%) values take rank 1, later (30%) values take rank 2, finally last (30%) values take rank 3. Now we have four matrices (88×88) shape-blocks as shown in (figure 3.6, figure 3.7) .

Algorithm 6: Quantization of gradient value

Input: gradient value

Output: quantizing value 0 – 3

Define quantize value (0 – 10% ranking 0, 10 – 40% ranking 1, 40 – 70% ranking 2, 70% – 100% ranking 3)

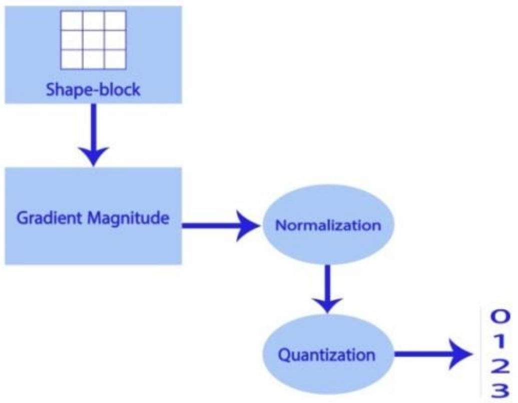
Separate gradient value to 2X2 sub-region each sub-region equal 88X88 shape-block

Find max value from each sub-region to select percentage value

Check gradient value from any rank

Table(3. 1): Proposal table of edge strength levels

Quantization	Range	Type
0	0-10%	Not Edges
1	10-40%	Weak
2	40-70%	Medium
3	70-100%	High



Figure(3. 6): Quantization shape_block

0	1	1	0	0	1	0	0	0	0
0	2	1	2	2	1	0	0	0	0
0	1	2	3	3	2	1	1	0	0
0	3	3	3	2	1	2	3	3	0
0	0	2	3	1	2	1	3	2	0
0	1	2	3	3	1	1	3	2	0
0	1	2	2	0	1	2	1	2	0
0	2	3	2	0	0	2	1	1	0
0	2	3	1	2	0	2	1	1	0
0	0	0	1	1	1	0	0	0	0

Figure(3. 7): Visualizing 2x2 sub_regions

We experimented more proposal tables to apply the best quantization on each sub-region alone, each sub-region contains 88x88 shape-blocks that equals to 7744 shape-blocks of gradient values as in the (table 3.1). We propose the following rate of quantization: the lowest (10%) shape-blocks gradient values take rank 0, later (30%) values take rank 1, and later (30%) values take rank 2, and finally last (30%) values take rank 3.

And we experimented other proposal tables to apply the best quantization on each sub-region alone, each sub-region contains 88x88 shape-blocks that equals to 7744 shape-blocks of gradient values as in the (table 3.2). We propose the following rate of quantization: the lowest (25%) shape-blocks gradient values take rank 0, later (25%) values take rank 1, and later (25%) values take rank 2, and finally last (25%) values take rank 3.

Table(3. 2): second proposal of edge strength levels to quarters

Quantization	Range	Type
0	**0-25%**	**Weak**
1	**25-50%**	**Medium**
2	**50-75%**	**Strong**
3	**75-100%**	**High**

Table(3. 3): result test for first proposal table

Q. IMG	Precision 3	Precision 5	Recall
Q1	100.00%	60.00%	77.78%
Q2	100.00%	100.00%	88.89%
Q3	100.00%	100.00%	100.00%
Q4	100.00%	100.00%	100.00%
Q5	100.00%	100.00%	80.00%
Q6	100.00%	80.00%	66.67%
Q7	100.00%	100.00%	80.00%
Q8	100.00%	100.00%	100.00%
Q9	100.00%	100.00%	100.00%
Q10	100.00%	100.00%	88.89%
Q11	100.00%	100.00%	100.00%
Q12	100.00%	100.00%	94.12%
AVG	**100.00%**	**95.00%**	**89.72%**

Table(3. 4): result test for second proposal table

Q. IMG	Precision 3	Precision 5	Recall
Q1	66.67%	60.00%	55.56%
Q2	100.00%	100.00%	88.89%
Q3	100.00%	80.00%	80.00%
Q4	100.00%	100.00%	90.00%
Q5	100.00%	100.00%	80.00%
Q6	100.00%	80.00%	66.67%
Q7	100.00%	100.00%	80.00%
Q8	100.00%	100.00%	100.00%
Q9	100.00%	100.00%	100.00%
Q10	100.00%	100.00%	77.78%
Q11	100.00%	100.00%	100.00%
Q12	100.00%	100.00%	83.33%
AVG	**97.22%**	**93.33%**	**83.52%**

Highest average precision and recall values are success in first proposal table (3.3). The precision rate in the first 3 images retrieval achieved (100.00%), the precision rate in the first 5 images retrieval achieved (95.00%), and the recall rate in last cases for images retrieval achieved (89.72%). So we decided to rely on the first proposal see table (3.1) due the results are better than the second proposal see table (3.4).

3.1.4 Stage4: Similarity Measurement

In stage 2, we calculate the final similarity by the Euclidean distance as the following:

$$D(I_q, I_d) = \frac{\sum_{i=1}^{N}\left(I_{qi} - I_{di}\right)^2}{N} \qquad \text{Eq. 3.13}$$

Where I_q is TFV vector from image query, I_d is TFV vector from images in database. The Euclidean Distance is suitable method which is widely used in image retrieval. The retrieval results are a list of images ranked by their similarities distance with the query image (Carson, Belongie, Greenspan, & Malik, 2002). The calculated distance is ranked according to closest similar; if the distance is less than a certain threshold, then this image is similar to the query image.

In stage 3, we calculate the final similarity by the trace distance. In linear algebra, the trace of an n-by-n square matrix A is defined to be the sum of the elements on the main diagonal (the diagonal from the upper left to the lower right) of A is following show:

$$\operatorname{tr}(A) = a_{11} + a_{22} + \dots + a_{nn} = \sum_{i=1}^{n} a_{ii} \qquad \text{Eq. 3.14}$$

Where a_{nn} denotes the entry on the n-th row and n-th column of A. The trace of a matrix is the sum of the (complex) eigenvalues, and it is invariant with respect to a change of basis. This characterization can be used to define the trace of a linear operator in general. Note that the trace is only defined for a square matrix ($n \times n$) see figure(3.8) to show summarize values for each image.

Algorithm 7: Similarity distance image

Input: gradient value
Output: distance similar image
    Calculate Euclidean distance from TFV
    Calculate trace distance from each sub-region (sum of diagonal elements)

sum of diagonal elements for sub_bregion1	sum of diagonal elements for sub_bregion2	sum of diagonal elements for sub_bregion3	sum of diagonal elements for sub_bregion4

Figure(3. 8): Summarize values for each image

3.1.5 Combining texture features and shape features

This operation is necessary to enhance and optimize image retrieval based on parallel combination of TFV vector by gray cluster co-occurrence matrix and average diagonal elements by edge strength level see figure (3.9). The displayed retrieval result images are those closest in distance to query image.

T_1	T_2	T_3	T_4	T_5	T_6	Avg of 4 values diagonal elements

Figure(3. 9): Combining texture features and shape features

Chapter 4

Results and Discussion

4. Results and Discussion

This chapter presents the study we conducted to assess our system with the following objective in mind: Assess the effectiveness of the medical image retrieval with combining texture feature extraction and shape feature extraction that offered by our system, and compare it with each of partial systems individually. The experiment were conducted to evaluate the system's service: the system was tested using a set of search queries (abnormality brain images) formulated by a domain expert. Search results were assessed in terms of precision and recall and distance variance, and then are compared with the results obtained by each of partial systems individually. The aim of this part is to explore the potential of our approach to improve medical image retrieval as compared to the each of partial systems individually. In the following sections, we present details about the experimental settings, annotations and query set used. Subsequently, the experimental procedures and results are discussed.

4.1 Experimental Settings

This section presents the implementation of this research, it describes both the software tools and hardware equipment used to build and test both the internal modules and the end user system, then it shows the experiments and procedures for the proposed methodology.

4.1.1 Software

Our work is implemented by MATLAB 2014. Our functions are pre-processing (), texture_feature_extraction(), and shape_feature_extraction(). The first functions are based filter that used to return a gray scale image 8-bit channel with fixed size 528 x 528. The second functions have cluster gray scale image and applied statistical method to extract features. These functions contain a set of steps to give Texture Feature Vector (TFV). The final functions have Sobel operator to calculate gradient value. Quantized operation depended on gradient value after separating the gradient value to 2 x 2 sub-region to extract shape features from images.

4.1.2 Hardware

The system will be tested using PC IBM with window 2010, and for more accurate results, the final version of the system will be tested on PC IBM based device with different storage and CPU capabilities.

4.1.3 Dataset

The real dataset used includes 127 images collected from European Gaza Hospital. The dataset includes abnormality brain scans as malignant tumors and benign, this dataset used in texture feature extraction and shape feature extraction. Firstly, the dataset features have been extracted and stored in a database using a MATLAB program.

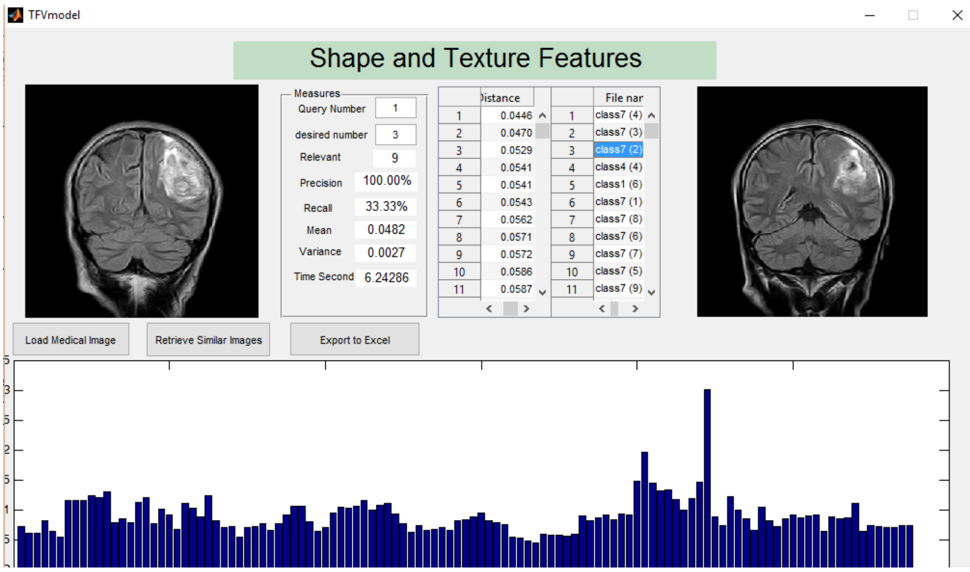
We used 115 images of MRI abnormality brain in database and 12 images queries for testing system. These images show abnormality brain such as benign tumors and malignant. The same dataset is also included in each of partial systems individually, our intention was to execute search queries over the same dataset and compare results generated by these systems and related works.

These images sorted and read to store in the local database of our system. Then, texture feature extraction and shape feature extraction of these images were automatically linked to original images. Overall, these resulted separately into 12 cases depend on expert. (Table 4.1) shows details about the size of our types in database.

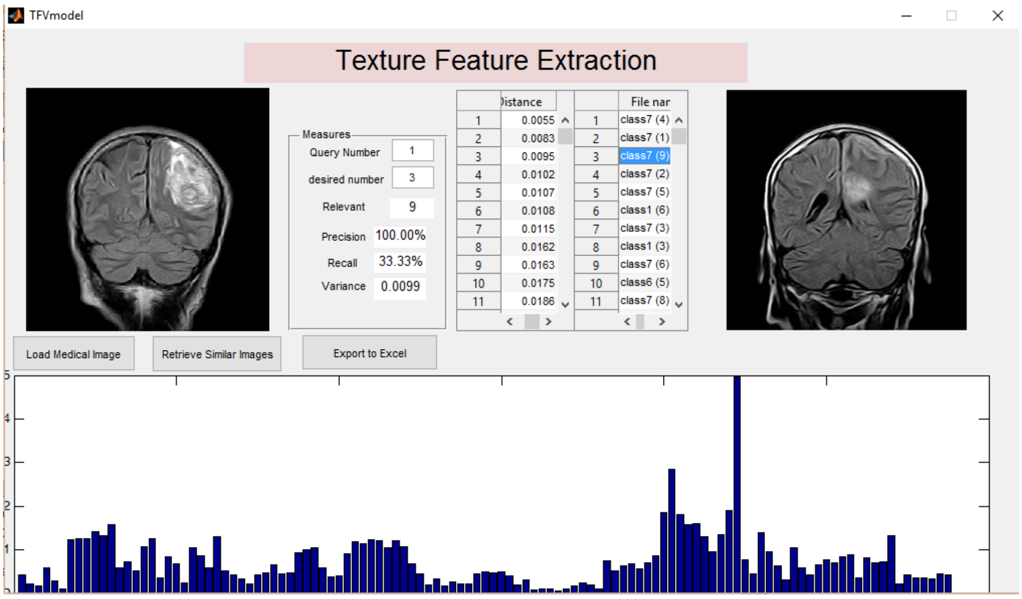
Table(4. 1): Data formation in dataset

Cases	Number
Case1	9
Case2	9
Case3	5
Case4	10
Case5	10
Case6	6
Case7	15
Case8	7
Case9	6
Case10	9
Case11	11
Case12	18
Sum	**115**

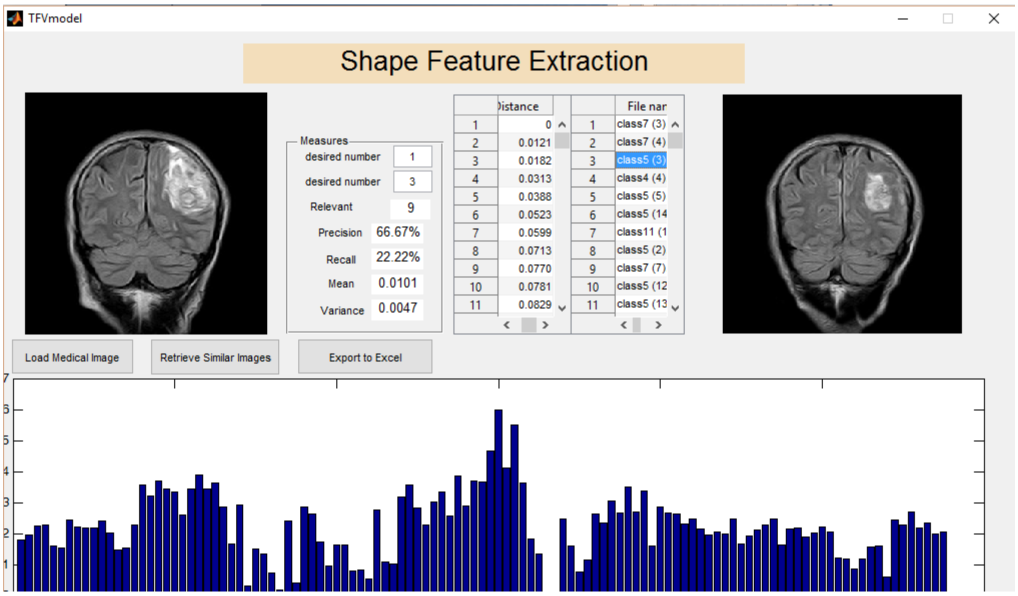
To make our system more efficient , we dedicated images search from MRI abnormality brain only (see Figure 4.1). We also excluded all images that were normal of MRI brain images. These images applied in each of part systems individually**.**



Figure(4. 1): The proposed model combine texure feature and shape feature



Figure(4. 2): texure feature extraction only



Figure(4. 3): shape feature extraction only

The dataset is contain 115 images of MRI abnormality brain images as applied in our application proposed were all introduced by a human expert. Then we asked him to retrieve sorting similar images in each cases (See Appendix 1 for the full list of queries.) to search in the domain in hand.

Based on these results, we asked the human expert in this domain to input queries to the system to validate the proposed and the accuracy image retrieved. Based on his experience in they formulated 12 queries that included various shapes and different patterns.

Note that only the medical images were used as search input. However, the images of queries were necessary to assess the relevance of the obtained results retrieved and whether they actually met the expert's queries.

4.2 Evaluation of retrieval result

The system was evaluated based on evaluation metrics such as precision and recall, distance variance, and consuming time retrieval.

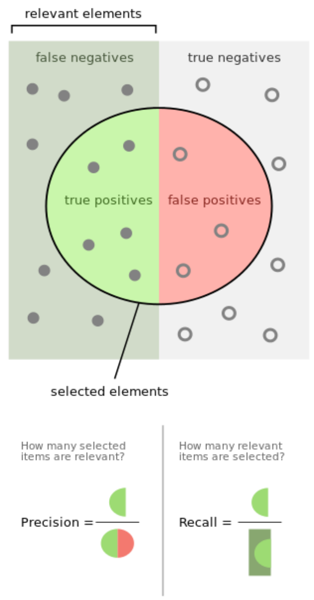
4.2.1 Precision and Recall

The measures of mean average precision which are defined as follows:

Precision measures the number of correctly identified items as a percentage of the number of items identified. Recall measures the number of correctly identified items as a percentage of the total number of correct items (Powers, 2011) (See Figure 4.4).

$$Precision = \frac{Number\ of\ relevant\ items\ retieved}{Number\ of\ retrieved\ items} \qquad \text{Eq. 15}$$

$$Recall = \frac{Number\ of\ relievant\ items\ retrieved}{Number\ of\ relevant\ items} \qquad \text{Eq. 16}$$

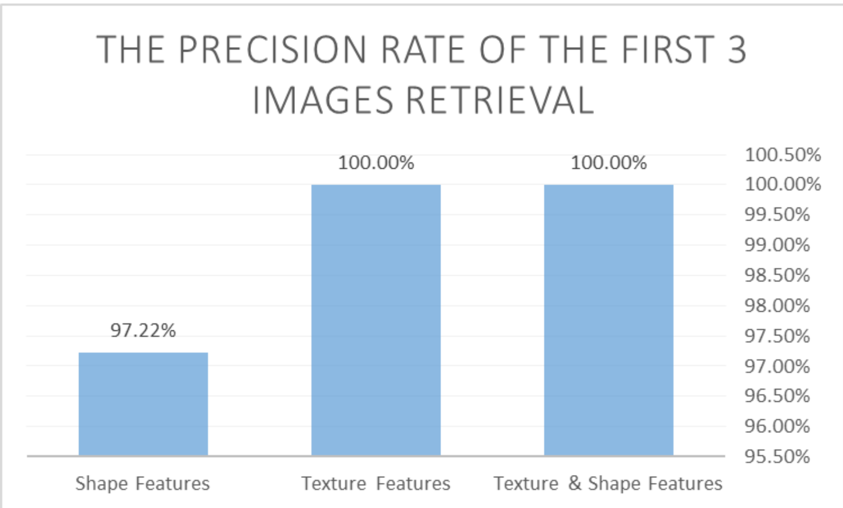


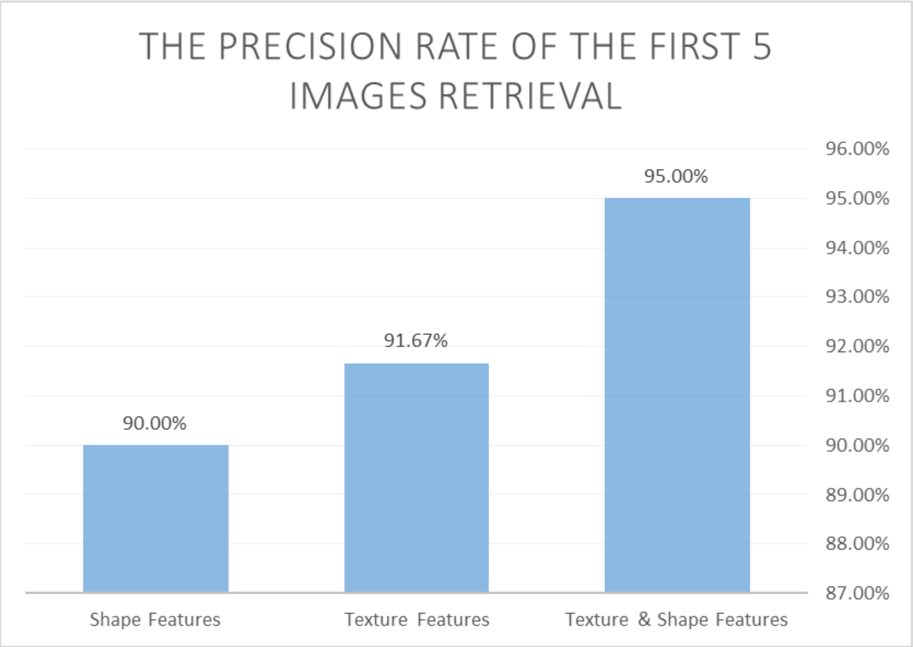
Figure(4. 4): Recall and Precision

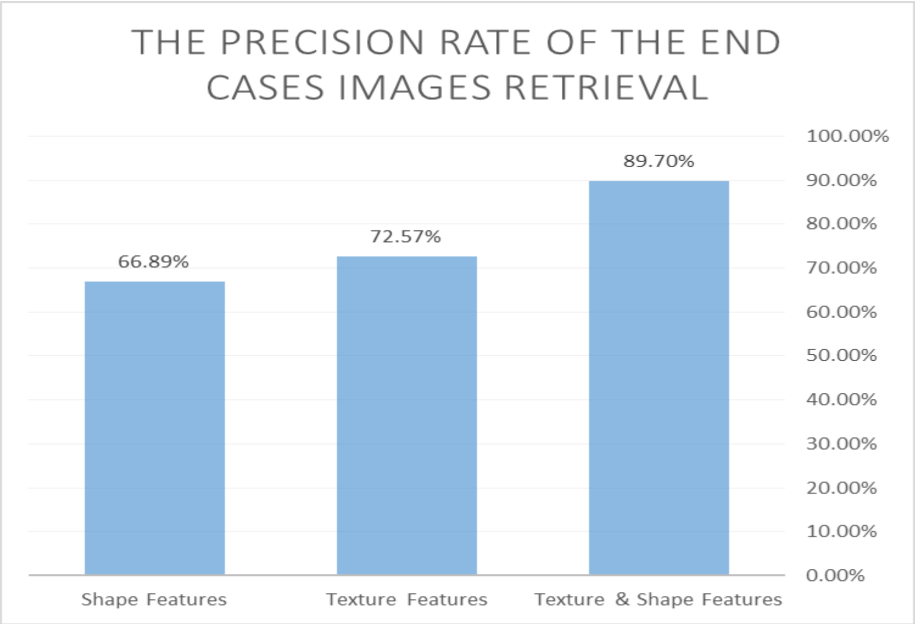
Results and discussion Table 4.2, Table 4.3, Table 4.4 illustrate the precision and recall evaluation results obtained over image based search and results obtained from retrieval based search in our system. (Refer to Appendix 1: explains how we compute recall, precision for images query).

Table(4. 2): depicts precision rate of the first 3, first 5, and the last case images for each case retrieval

Q Img.	Texture & Shape Features			Texture Features			Shape Features		
	3	5	last case	3	5	last case	3	5	last case
Q1	100%	60%	77.78%	100 %	100%	77.78%	66.67%	40%	33.33%
Q2	100%	100%	88.89%	100%	100%	66.67%	100%	100%	100%
Q3	100%	100%	100%	100%	80%	80%	100%	80%	80%
Q4	100%	100%	100%	100%	100%	80.00%	100%	100%	90.00%
Q5	100%	100%	80 %	100%	60%	70.00%	100%	100%	90.00%
Q6	100%	80%	66.67%	100%	60%	50.00%	100%	60%	50.00%
Q7	100%	100%	80%	100%	100%	73.33%	100%	100%	53.33%
Q8	100%	100%	100%	100%	100%	85.71%	100%	100%	85.71%
Q9	100%	100%	100%	100%	100%	83.33%	100%	100%	100%
Q10	100%	100%	88.89%	100%	100%	55.56%	100%	100%	42.86%
Q11	100%	100%	100%	100%	100%	81.82%	100%	100%	90.91%
Q12	100%	100%	94.12%	100%	100%	66.67%	100%	100%	72.22%
AVG	**100%**	**95.00%**	**89.70%**	**100%**	**91.67%**	**72.57%**	**97.22%**	**90.00%**	**66.89%**

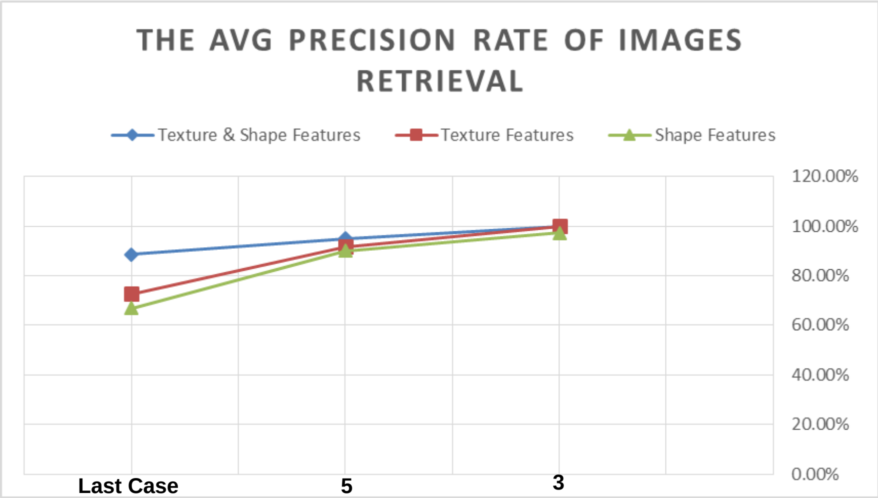






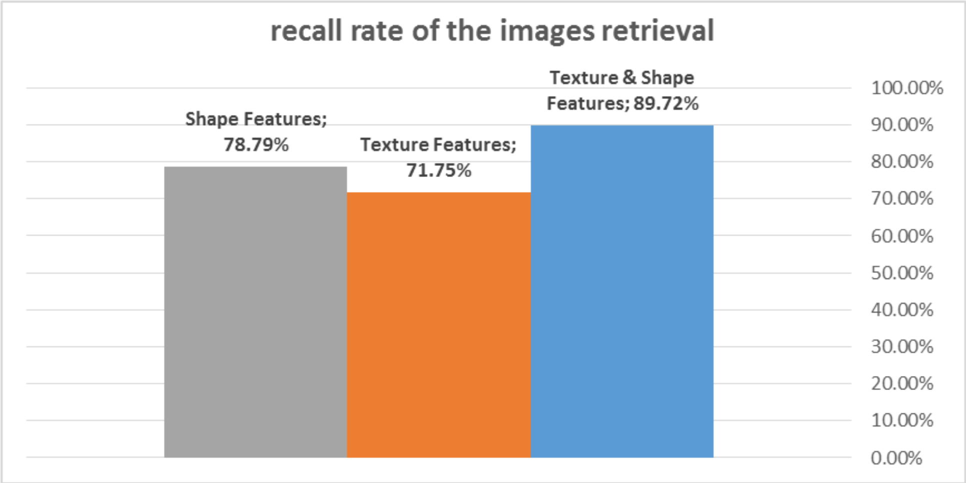
Table(4. 3): depicts average of the images retrieval of queries

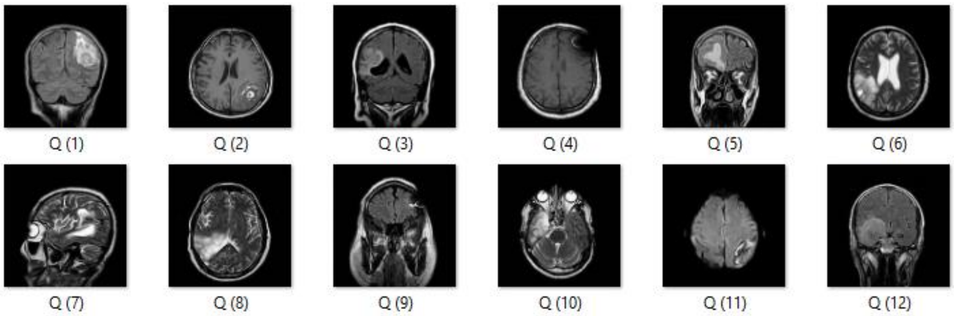
AVG Precision			
Q Img.	**Texture & Shape Features**	**Texture Features**	**Shape Features**
3	100.00%	100.00%	97.22%
5	95.00%	91.67%	90.00%
Last Cases	89.70%	72.57%	66.89%
AVG	**94.90%**	**88.08%**	**84.70%**



Table(4. 4): depicts recall rate of the images retrieval of queries

Q Img.	Texture & Shape Features	Texture Features	Shape Features
Q1	77.78%	77.78%	33.33%
Q2	88.89%	66.67%	100.00%
Q3	100.00%	80.00%	80.00%
Q4	100.00%	80.00%	90.00%
Q5	80.00%	70.00%	90.00%
Q6	66.67%	50.00%	50.00%
Q7	80.00%	73.33%	53.33%
Q8	100.00%	75.81%	85.71%
Q9	100.00%	83.33%	100.00%
Q10	88.89%	55.56%	100.00%
Q11	100.00%	81.82%	90.91%
Q12	94.44%	66.67%	72.22%
AVG	**89.72%**	**71.75%**	**78.79%**





Figure(4. 5): queries image

4.2.1.1 Results and Discussion

Our proposed system achieved higher average precision and recall rates compared to each of partial systems individually:

- For the first 3 images retrieved, our proposed system achieved the same precision rate for the individual texture feature system which equals (100.00%). While the individual shape feature system achieved the lowest average precision (97.22%).
- To ensure that our proposed system outperforms the individual texture feature system we also measured the precision for the first 5 images retrieved. The results showed that our proposed system achieved the highest average precision (95.00%).While the individual texture feature system achieved (91.67%) average precision and the individual shape feature system achieved (90.00%) average precision.

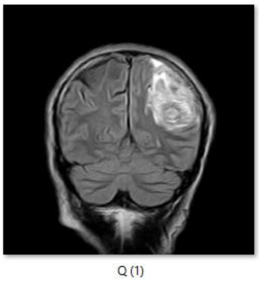
- In the last case, the average precision for our proposed system was (89.70%) while the individual texture feature system achieved (72.57%) average precision and the individual shape feature system achieved (66.89%). This result indicates that our method outperformed the proposed research.
- In the recall rate for measure correct images retrieved, our proposed system achieved the highest average recall (89.72%) while the individual texture feature system achieved (71.75%) average recall and the individual shape feature system achieved (78.79%) average recall.

Image retrieval process was improved by introducing semantic data from applying statistical method texture feature extraction on gray cluster co-occurrence matrix and strength edge by calculating gradient edges from shape feature extraction guidance for end user. The following example (See Figure 4.1) illustrated how the retrieval image approach resulted in better results as compared to the results: Given the query “Q1“ (See Figure 4.6). The result retrieves obtained from the system included all the images similar sorted from higher similar to lower similar. (See results in Figure 4.7).

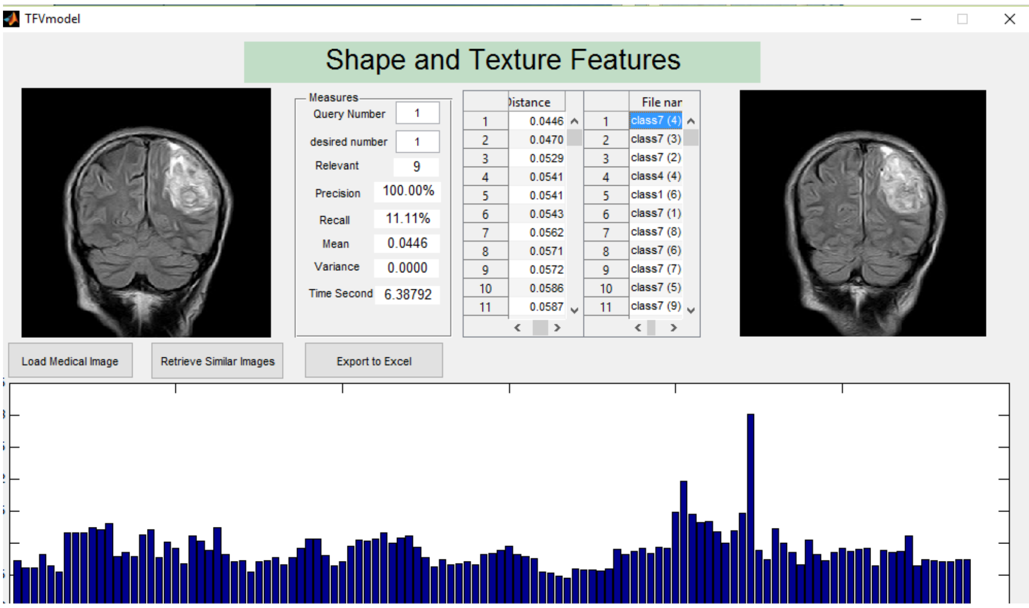
The result shown recall and precision rate in the proposed system (texture feature extraction and shape feature extraction) of higher measurements (See Table 4.5).

Table(4. 5): the prcision and recall results retrieval for query "Q1"

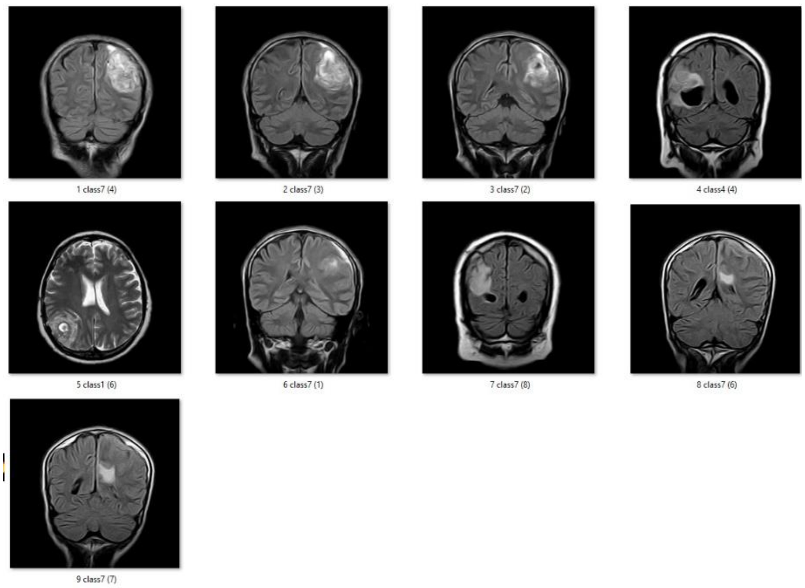
IMG. Retrieval	Precision rate
3	100.00%
5	60.00%
9 (Last Case)	77.78%
Recall rate	
77.78%	



Figure(4. 6): MRI image, Query "Q1"



Figure(4. 7): The images retrieval for "Q1" in the proposed system



Figure(4. 8): The images retrieval for query "Q1"

The system was able to retrieve the similar images. For other example "Q8" retrieve for the retrieval image approach as shown in (Figure 4.10).

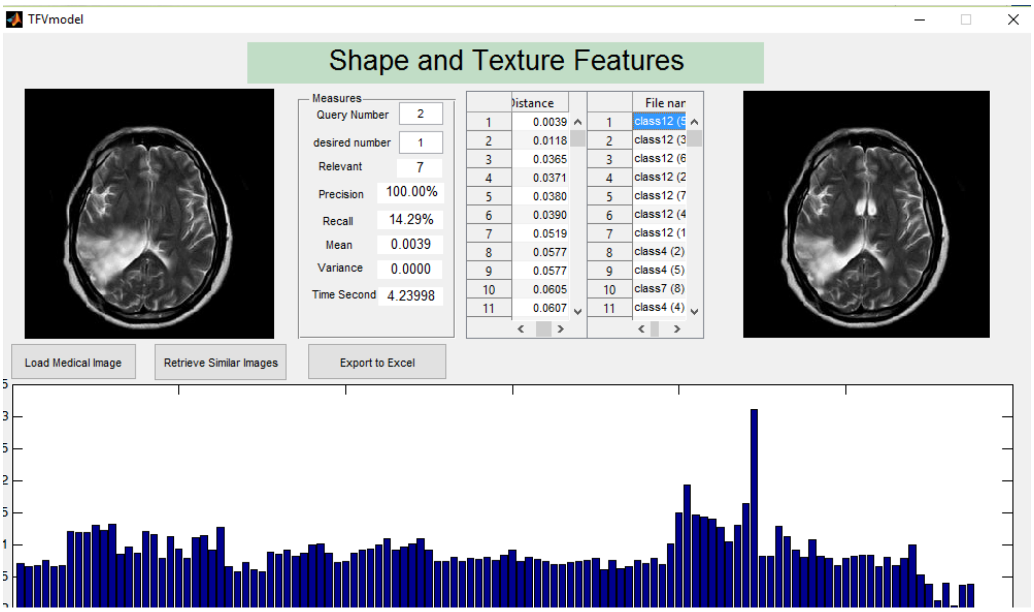
The result retrieves obtained from the system included all the images similar sorted from more similar to low similar. (See results in Figure 4.11).

The result achieved higher measurements for recall and precision rate in the proposed system (See Table 4.6).

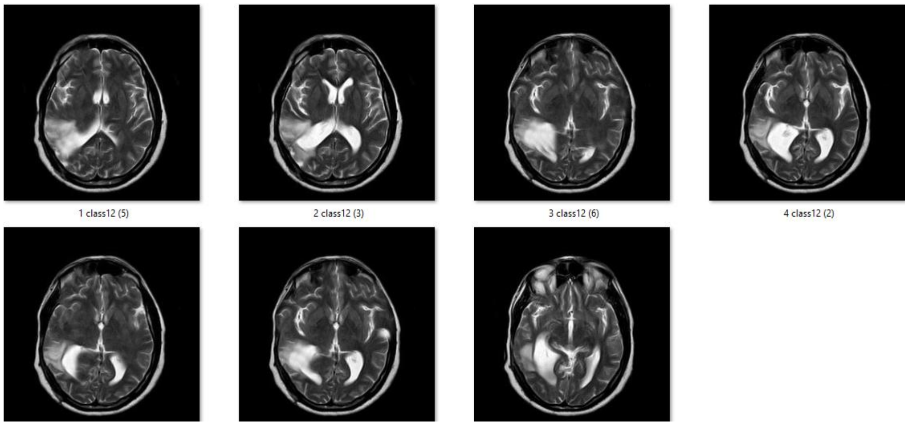
Table(4. 6): the prcision and recall results retrieval for query "Q8"

IMG. Retrieval	Precision rate
3	100.00%
5	100.00%
7 (Last Case)	100.00%
Recall rate	
100.00%	

Figure(4. 9): MRI image, Query "Q8"



Figure(4. 10): The images retrieval for "Q8" in the proposed system



Figure(4. 11): The images retrieval for query "Q8"

4.2.2 Distance variance

In probability theory and statistics, variance distance is the expectation of the squared of standard deviation of a random variable from its mean, and it informally measures how far a set of (random) numbers are spread out from their mean. The variance has a central role in statistics. It is used in descriptive statistics, Statistical inference, hypothesis testing, and amongst many others (Y. Zhang, Wu, & Cheng, 2012).

The variance is the square of the standard deviation, the second central moment of a distribution, and the covariance of the random variable with itself, and it is often represented by σ^2 or Var.(X).

The variance of a set of *n* equally likely values can be written as:

$$\operatorname{Var}(X) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2. \qquad \text{Eq. 4.1}$$

Where μ is the expected value, i.e.

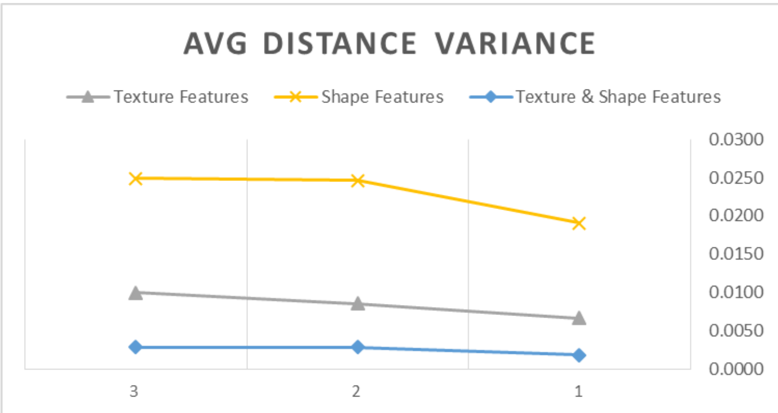
$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad \text{Eq. 4.2}$$

4.2.2.1 Results and Discussion

Retrieval performance is evaluated using the distance variance. Table 4.7 illustrates the evaluation results obtained over image based search in our method and each of partial system individually. Results obtained from retrieval based on extracting features using our system; we calculated the variance between the average distances and each retrieved images at the first 3, the first 5, and last case. The resulted distance variance for our system was very small (close to 0), which shows that our system outperforms each of partial systems individually refer to table 4.7 for the detailed values of average variance.

Table(4. 7): result distance variance for images retrieval

Q Img.	Texture & Shape Features			Texture Features			Shape Features		
	3	5	End Cases	3	5	End Cases	3	5	End Cases
Q1	0.0012	0.0015	0.0015	0.0066	0.0074	0.0099	0.0030	0.0051	0.0081
Q2	0.0001	0.0009	0.0007	0.0024	0.0095	0.0280	0.0001	0.0031	0.0074
Q3	0.0007	0.0017	0.0009	0.0037	0.0044	0.0030	0.0138	0.0222	0.0116
Q4	0.0009	0.0015	0.0020	0.0030	0.0053	0.0103	0.0116	0.0142	0.0167
Q5	0.0008	0.0012	0.0017	0.0081	0.0109	0.0147	0.0160	0.0193	0.0265
Q6	0.0003	0.0012	0.0015	0.0127	0.0159	0.0161	0.0353	0.0328	0.0308
Q7	0.0006	0.0008	0.0016	0.0042	0.0078	0.0172	0.0081	0.0088	0.0128
Q8	0.0046	0.0054	0.0056	0.0024	0.0034	0.0056	0.0414	0.0480	0.0464
Q9	0.0014	0.0022	0.0024	0.0150	0.0180	0.0190	0.0050	0.0160	0.0179
Q10	0.0048	0.0052	0.0051	0.0026	0.0083	0.0141	0.0405	0.0414	0.0345
Q11	0.0017	0.0033	0.0042	0.0175	0.0348	0.0618	0.0088	0.0146	0.0193
Q12	0.0049	0.0046	0.0031	0.0017	0.0021	0.0065	0.0454	0.0415	0.0276
AVG	**0.0018**	**0.0028**	**0.0028**	**0.0067**	**0.0085**	**0.0099**	**0.0191**	**0.0246**	**0.0249**



4.2.3 Consuming time

The system was evaluated based on consuming time in processes extraction features and retrieval images (See Table 4,8). Consume time is evaluated with the second time.

Table(4. 8): result consuming time of images retrieval

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	AVG
4.34	4.37	4.57	4.62	5.51	4.66	4.41	4.52	4.42	4.35	4.59	5.52	4.65

Finally, from our research exactly on how we could evaluate our work, we see that each worker evaluates his work in different ways depending on his job. Some of them use precision and recall rate (See Table 4.9). Other people use precision rate only (See Table 4.10). And some other can't be evaluated MRI brain. So, we made a comparison for precision and recall rates between our system and other related works. The precision rate in our system method was 89.72% and recall rate was 94.90% these results are better than related works. The precision rate in P. Zhang and Zhu (2011) was 72.50% and recall rate was 76.00% while the precision rate in Li-dong and Yi-fei (2010) was 76.50% and recall rate was 89.00% .

Table(4. 9): **Compare precision and recall with other related works**

Works	Precision	Recall
Our work	**89.72%**	**94.90%**
P. Zhang and Zhu (2011)	72.50%	76.00%
Li-dong and Yi-fei (2010)	76.50%	89.00%

Table(4. 10): **Average precision values only with other related works**

images retrieved	1	Last case
Our work	100.00%	89.70%
Annadurai, S. (2007)	100.00%	80.00%

4.3 Summary

The experimental results based on the Evaluation Metrics precision, recall, and distance variance shown that the system was better performance and accuracy in retrieving the results than each of partial system individually. The average precision rate in our proposed system achieved (89.72%) and average recall rate achieved (94.90%), also the system evaluated images retrieval performance based on the average distance variance suggest best lowest value for the images retrieved was (0.0027) , and the system evaluated based on consuming time was occupy 4.65 second.

Chapter 5

Conclusions and Future

5. Conclusions and Future Work

5.1 Conclusions

In content based image retrieval system, the reliability of retrieval results depends much on the image features used for measuring image similarity. In this paper, a new medical image retrieval method using gray cluster co-occurrence matrix as texture feature extraction, and edge strength levels as shape feature extraction.

We have evaluated our system and discussed the results image retrieval based on combination between texture features extraction and shape features extraction. This offered by our system was compared to each of partial systems individually. In this service the system was evaluated based on the Evaluation Metrics precision, recall, and distance variance. Average precision and recall values in our proposed system were higher compared to each of partial systems individually. This result indicated that our system outperformed each of partial systems individually in image retrieval. Also retrieval performance was evaluated with the distance variance to average distances where approach retrieval method had better variance in retrieving the results than each of partial systems individually.

5.2 Future Work

- Future research includes further contact with medical knowledge that will engage us in studying the classification, clustering and retrieval methods in medical images.
- We will combine the clinical data with images to study new methods to enhance the accuracy of similarity retrieval and classification.
- We intend to enhance the efficiency and portability of the algorithm by incorporating relevance feedback mechanism with our approach and developing a CBIR system which is platform independent that can be connected to PACS server.
- Thus the efficacy can be tested with a larger image collection of varying modalities.

The Reference List

The Reference List

Ahmad, K., Tariq, M., Vrusias, B., & Handy, C. (2003). *Corpus-based thesaurus construction for image retrieval in specialist domains*: Springer.

Ahuja, N., & Schachter, B. J. (1981). Image models. *ACM Computing Surveys (CSUR), 13*(4), 373-397.

Almeida, J., Torres, R. d. S., & Goldenstein, S. (2009). SIFT applied to CBIR. *Revista de Sistemas de Informacao da FSMA n, 4*, 41-48.

Annadurai, S. (2007). *Medical image retrieval by combining low level features and Dicom features.* Paper presented at the Conference on Computational Intelligence and Multimedia Applications, 2007. International Conference on.

Bandyopadhyay, S., & Maulik, U. (2002). Genetic clustering for automatic evolution of clusters and application to image classification. *Pattern recognition, 35*(6), 1197-1208.

Basri, R., & Jacobs, D. W. (1997). Recognition using region correspondences. *International Journal of Computer Vision, 25*(2), 145-166.

Carson, C., Belongie, S., Greenspan, H., & Malik, J. (2002). Blobworld: Image segmentation using expectation-maximization and its application to image querying. *Pattern Analysis and Machine Intelligence, IEEE Transactions on, 24*(8), 1026-1038.

Celenk, M. (1990). A color clustering technique for image segmentation. *Computer Vision, Graphics, and Image Processing, 52*(2), 145-170.

Eakins, J. P. (1996). *Automatic image content retrieval-are we getting anywhere?* Paper presented at the ELVIRA-PROCEEDINGS-.

Efford, N. (2000). *Digital image processing: a practical introduction using java (with CD-ROM)*: Addison-Wesley Longman Publishing Co., Inc.

Feature_extraction. (n.d., 30 November 2015, at 16:47). In Wikipedia. from https://en.wikipedia.org/wiki/Feature_extraction

Figueiredo, M. A., & Jain, A. K. (2002). Unsupervised learning of finite mixture models. *Pattern Analysis and Machine Intelligence, IEEE Transactions on, 24*(3), 381-396.

Files, M. H. (2013). Cluster Analysis.   Retrieved 18-05-2016

Fraley, C., & Raftery, A. E. (1998). How many clusters? Which clustering method? Answers via model-based cluster analysis. *The computer journal, 41*(8), 578-588.

Haralick, R. M., Shanmugam, K., & Dinstein, I. H. (1973). Textural features for image classification. *Systems, Man and Cybernetics, IEEE Transactions on*(6), 610-621.

Inoue, K., & Urahama, K. (2001). Fuzzy clustering based on cooccurrence matrix and its application to data retrieval. *Electronics and Communications in Japan (Part II: Electronics), 84*(8), 10-19.

Jin, L., Hong, L., & Lianzhi, T. (2009). *A mapping modelling of visual feature and knowledge representation approach for Medical Image Retrieval.* Paper presented at the Mechatronics and Automation, 2009. ICMA 2009. International Conference on.

Jyothsna, D. G. R. U. (2015). ADAPTIVE K-MEANS CLUSTERING FOR MEDICAL IMAGE SEGMENTATION. *International Journal of Technical Research and Applications*(Special Issue 31), 15-21.

Lachmann, F., & Barillot, C. (1992). *Brain tissue classification from MRI data by means of texture analysis.* Paper presented at the Medical Imaging VI.

Lehmann, T. M., Wein, B. B., Dahmen, J., Bredno, J., Vogelsang, F., & Kohnen, M. (1999). *Content-based image retrieval in medical applications: a novel multistep approach.* Paper presented at the Electronic Imaging.

Lew, M. S., Sebe, N., Djeraba, C., & Jain, R. (2006). Content-based multimedia information retrieval: State of the art and challenges. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 2*(1), 1-19.

Li-dong, F., & Yi-fei, Z. (2010). *Medical Image Retrieval and Classification Based on Morphological Shape Feature.* Paper presented at the Intelligent Networks and Intelligent Systems (ICINIS), 2010 3rd International Conference on.

Li, L.-J., Su, H., Fei-Fei, L., & Xing, E. P. (2010). *Object bank: A high-level image representation for scene classification & semantic feature sparsification.* Paper presented at the Advances in neural information processing systems.

Liu, Y., Rothfus, W. E., & Kanade, T. (1998). *Content-based 3d neuroradiologic image retrieval: Preliminary results.* Paper presented at the Content-Based Access of Image and Video Database, 1998. Proceedings., 1998 IEEE International Workshop on.

Long, L. R., Berman, L. E., & Thoma, G. R. (1996). *Prototype client/server application for biomedical text/image retrieval on the internet.* Paper presented at the Electronic Imaging: Science & Technology.

Long, L. R., Pillemer, S. R., Lawrence, R. C., Goh, G.-H., Neve, L., & Thoma, G. R. (1997). *WebMIRS: Web-based medical information retrieval system.* Paper presented at the Photonics West'98 Electronic Imaging.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International journal of computer vision, 60*(2), 91-110.

Lowe, H. J., Antipov, I., Hersh, W., Smith, C., & Mailhot, M. (1999). Automated semantic indexing of imaging reports to support retrieval of medical images in the multimedia electronic medical record. *Methods Inf Med, 38*(4), 303-307.

Manjunath, B. S., Ohm, J.-R., Vasudevan, V. V., & Yamada, A. (2001). Color and texture descriptors. *Circuits and Systems for Video Technology, IEEE Transactions on, 11*(6), 703-715.

Prasad, R. D., Kumar, B. S., Ram, K. S., & Manoj, B. V. (2016). Content Based Image Retrieval Using Dominant Color and Texture Features., *International Journal for Modern Trends in Science and Technology*, Volume: 2 | Issue: 04 | April 2016 | ISSN: 2455-3778.

Mingquan, W., Guohua, C., & Shi, Z. (2012). *Research on medical image retrieval based on texture feature.* Paper presented at the Signal Processing, Communication and Computing (ICSPCC), 2012 IEEE International Conference on.

Muller, H., Rosset, A., Vallée, J.-P., & Geissbuhler, A. (2003). Integrating content-based visual access methods into a medical case database. *Studies in health technology and informatics*, 480-485.

Nagabhushana, S. (2005). *Computer Vision and Image Processing*: New Age International.

Nixon, M. *Feature Extraction & Image Processing for Computer Vision* (3rd Edition ed.).

Pentland, A., Picard, R. W., & Sclaroff, S. (1996). Photobook: Content-based manipulation of image databases. *International journal of computer vision, 18*(3), 233-254.

Powers, D. M. (2011). Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation.

Rajakumar, K., & Muttan, S. (2010). *Medical image retrieval using energy efficient wavelet transform.* Paper presented at the Computing Communication and Networking Technologies (ICCCNT), 2010 International Conference on.

RASMUSSEN, H.-L. E., & Chen, H. (1999). Intellectual access to images. *ILLINOIS*, 291.

Reed, T. R., & Dubuf, J. H. (1993). A review of recent texture segmentation and feature extraction techniques. *CVGIP: Image understanding, 57*(3), 359-372.

Scott, E. (2011). Digital image processing and analysis: human and computer vision applications with CVIPtools: CRC Press, Taylor & Francis Group, Boca Raton, FL.

Setia, L., Teynor, A., Halawani, A., & Burkhardt, H. (2006). *Image classification using cluster cooccurrence matrices of local relational features.* Paper presented at the Proceedings of the 8th ACM international workshop on Multimedia information retrieval.

Shyu, C.-R., Brodley, C. E., Kak, A. C., Kosaka, A., Aisen, A. M., & Broderick, L. S. (1999). ASSERT: a physician-in-the-loop content-based retrieval system for HRCT image databases. *Computer Vision and Image Understanding, 75*(1), 111-132.

Sobel, I. (2014). History and definition of the sobel operator. *Retrieved from the World Wide Web*.

Sudhakar, M., & Bagan, K. B. (2011). *A novel approach for retrieval of medical images in bit plane domain.* Paper presented at the Signal and Image Processing Applications (ICSIPA), 2011 IEEE International Conference on.

Thakare, V. S., Patil, N. N., & Sonawane, J. S. (2013). Survey on image texture classification techniques. *International Journal of Advancements in Technology, 4*(1), 97-104.

Wan, H.-L., & Chowdhury, M. (2003). Image semantic classification by using SVM. *Journal of software, 14*(11), 1891-1899.

Zhang, F., Song, Y., Liu, S., Pujol, S., Kikinis, R., Feng, D., & Cai, W. (2014). *Latent semantic association for medical image retrieval.* Paper presented at the Digital lmage Computing: Techniques and Applications (DlCTA), 2014 International Conference on.

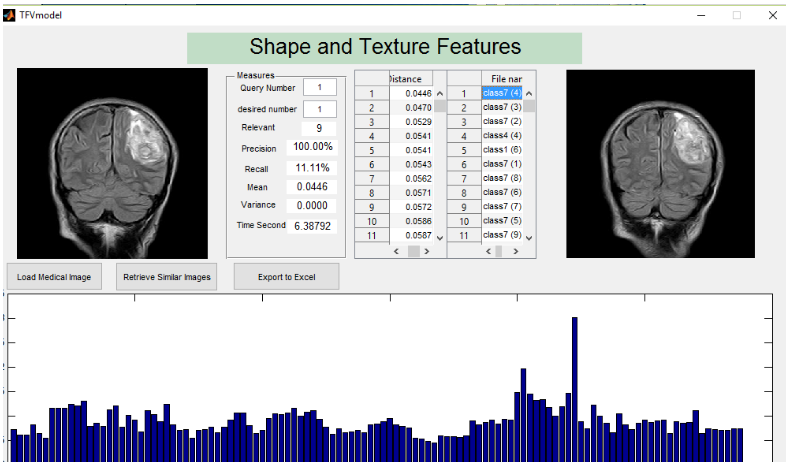
Zhang, P., & Zhu, H. (2011). *Medical Image Retrieval based on co-occurrence martix and edge histogram.* Paper presented at the Multimedia Technology (ICMT), 2011 International Conference on.

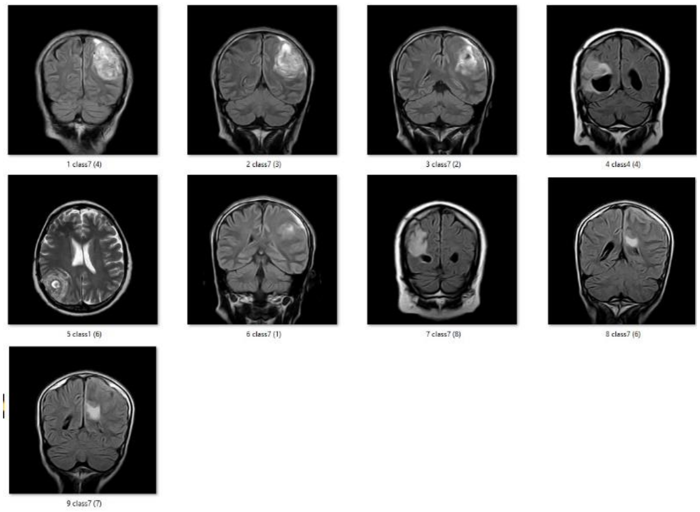
Zhang, Y., Wu, H., & Cheng, L. (2012). *Some new deformation formulas about variance and covariance.* Paper presented at the Modelling, Identification & Control (ICMIC), 2012 Proceedings of International Conference on.

Appendix 1
Query images and retrieval results

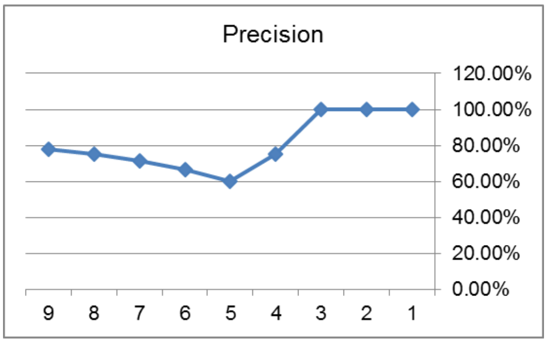
In our application method, we are present calculating recall, precision, and distance variance.

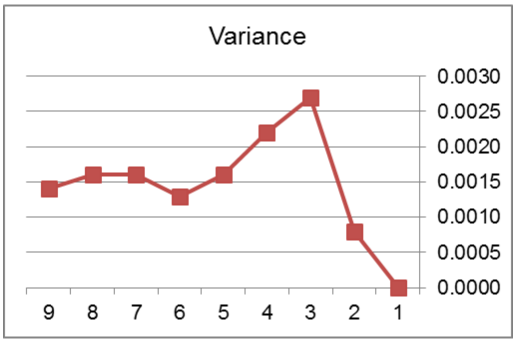
Q1:





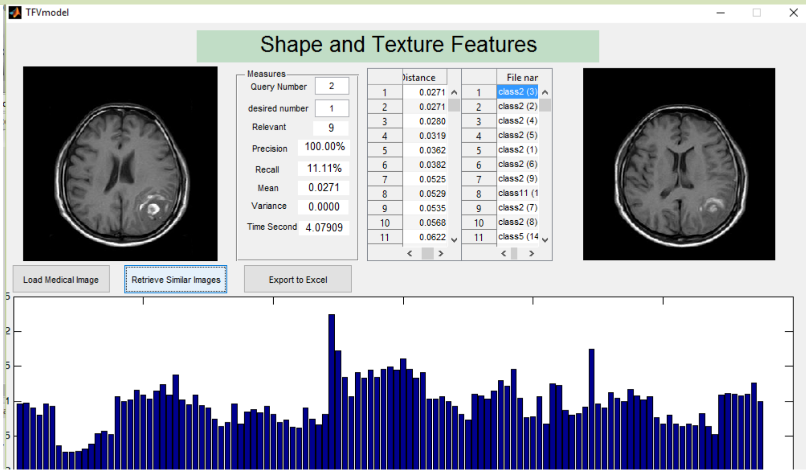
index	Precision	Mean	Variance
1	100.00%	0.0446	0.0000
2	100.00%	0.0458	0.0008
3	100.00%	0.0482	0.0027
4	75.00%	0.0497	0.0022
5	60.00%	0.0506	0.0016
6	66.67%	0.0512	0.0013
7	71.43%	0.0519	0.0016
8	75.00%	0.0525	0.0016
9	77.78%	0.0531	0.0014
recall	77.78%		



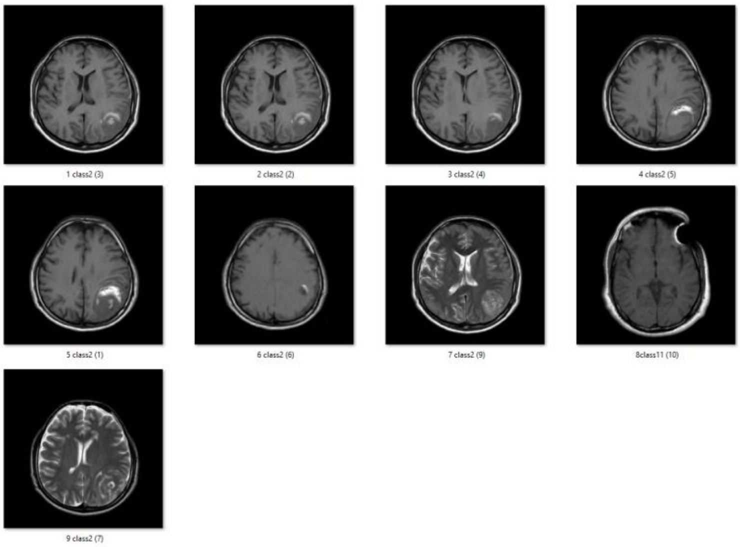


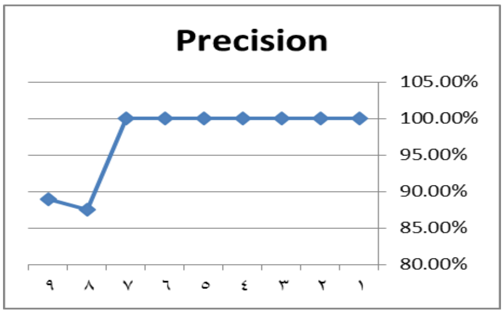
The results indicate that the first 3 image retrieved achieved precision 100% and recall rate in last case was 77.78%.

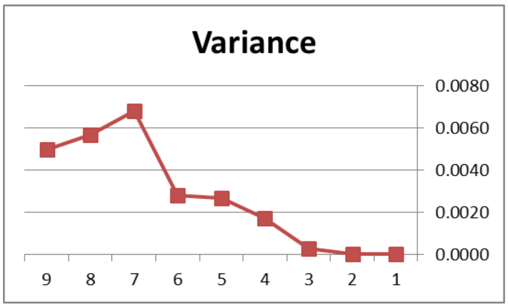
Q2



Index	Precision	Mean	Variance
1	100.00%	0.0271	0.0000
2	100.00%	0.0271	0.0000
3	100.00%	0.0274	0.0003
4	100.00%	0.0285	0.0017
5	100.00%	0.0300	0.0027
6	100.00%	0.0314	0.0028
7	100.00%	0.0344	0.0068
8	87.50%	0.0367	0.0057
9	88.89%	0.0386	0.0050
Recall	77.78%		

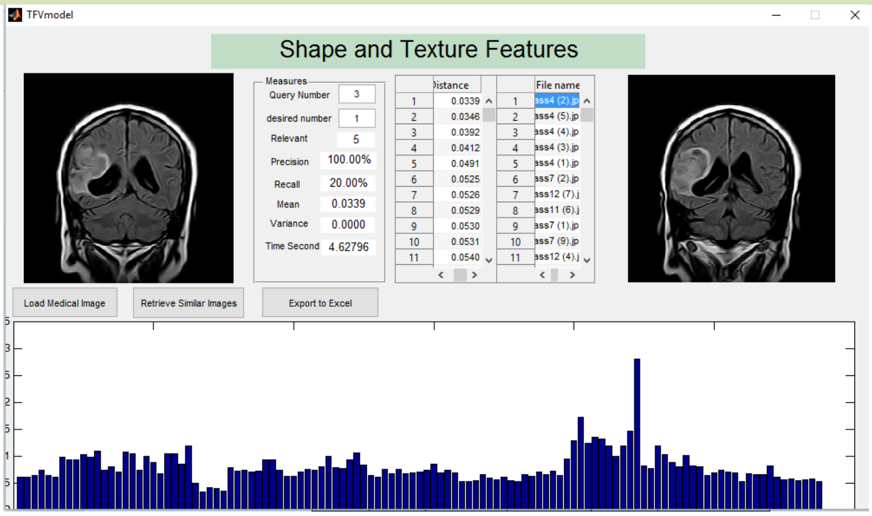






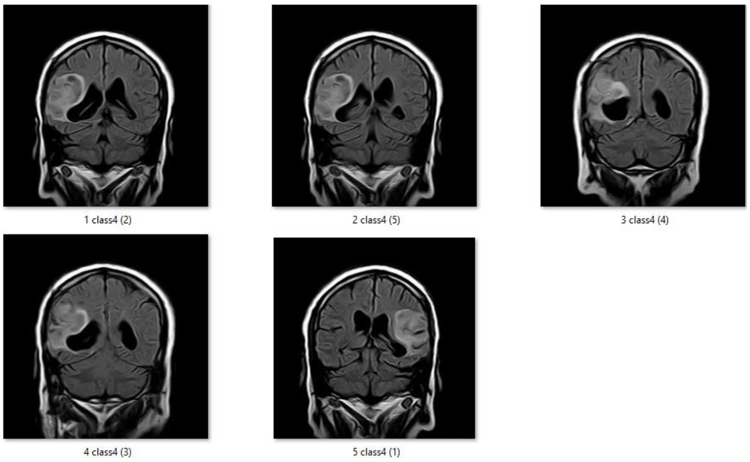
The results indicate that the first 7 image retrieved achieved precision 100% and recall rate in last case was 88.89%.

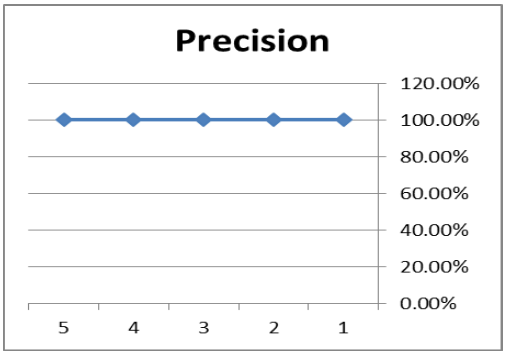
Q3

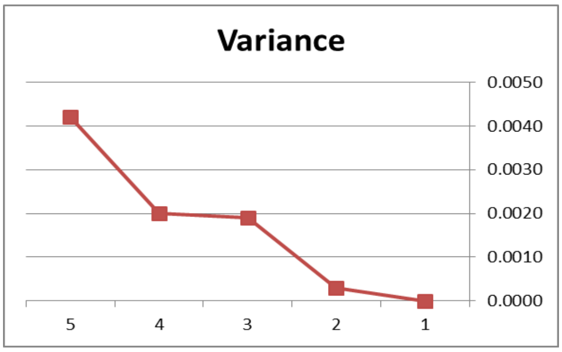


Index	Precision	Mean	Variance
1	100.00%	0.0339	0.0000
2	100.00%	0.0343	0.0003
3	100.00%	0.0359	0.0019
4	100.00%	0.0372	0.0020

5	100.00%	0.0396	0.0024
Recall	100.00%		

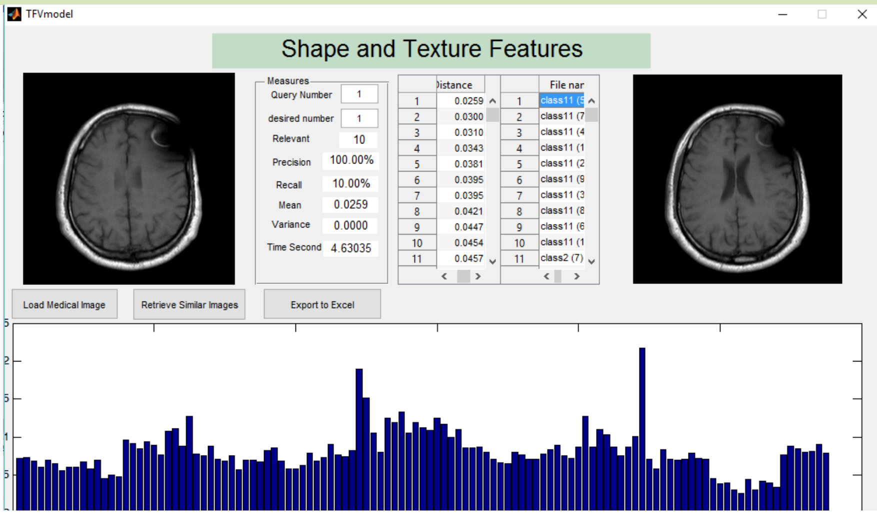






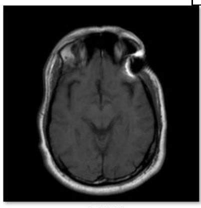
The results indicate that the all images retrieved in the case and achieved precision 100% and recall rate in last case was 100.00%.

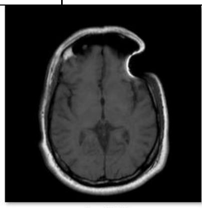
Q4

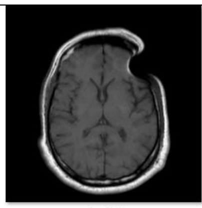


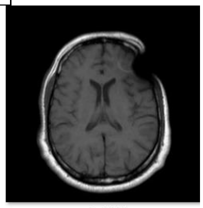
Index	Precision	Mean	Variance
1	100.00%	0.0259	0.0000
2	100.00%	0.0280	0.0014

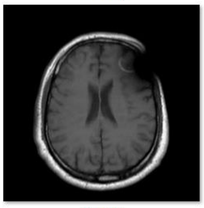
3	100.00%	0.0290	0.0012
4	100.00%	0.0303	0.0020
5	100.00%	0.0319	0.0028
6	100.00%	0.0331	0.0026
7	100.00%	0.0340	0.0021
8	100.00%	0.0350	0.0025
9	100.00%	0.0361	0.0028
10	100.00%	0.0370	0.0026
Recall	100.00%		

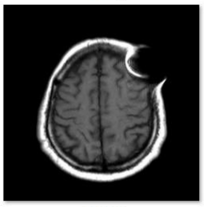

class11 (1)

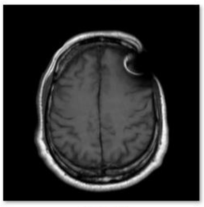

class11 (2)

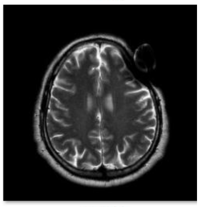

class11 (3)

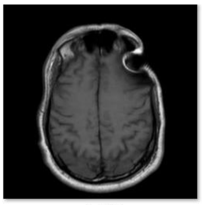

class11 (4)

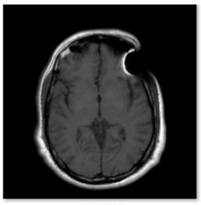

class11 (5)

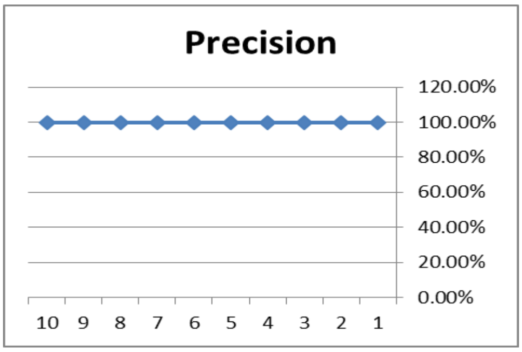

class11 (6)

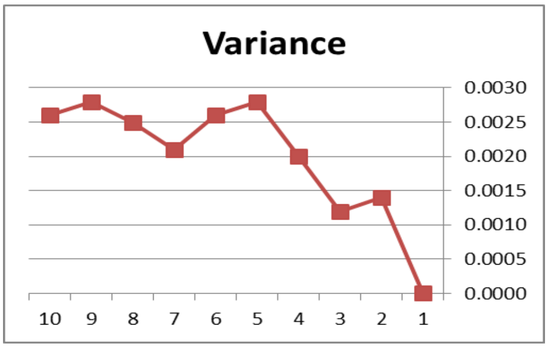

class11 (7)


class11 (8)


class11 (9)

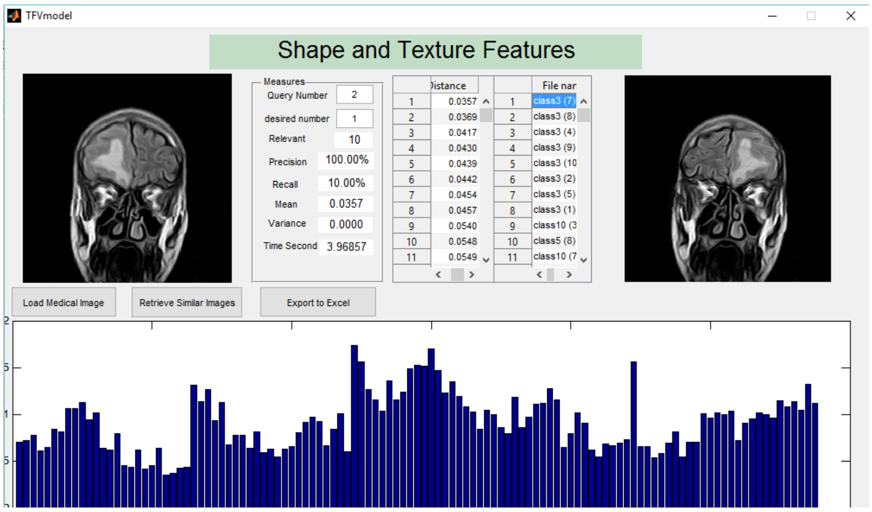

class11 (10)





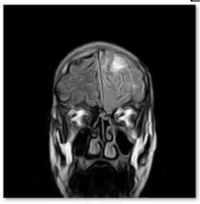
The results indicate that the all images retrieved in the case and achieved precision 100% and recall rate in last case was 100.00%.

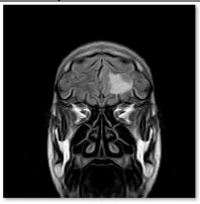
Q5:

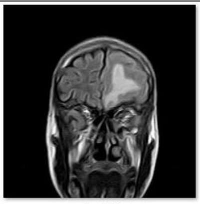


TFVmodel
Shape and Texture Features
Measures
Query Number 2
desired number 1
Relevant 10
Precision 100.00%
Recall 10.00%
Mean 0.0357
Variance 0.0000
Time Second 3.96857
Load Medical Image
Retrieve Similar Images
Export to Excel

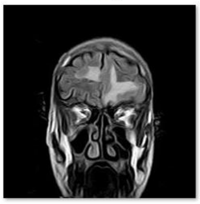
Index	Precision	Mean	Variance
1	100.00%	0.0357	0.0000
2	100.00%	0.0363	0.0004
3	100.00%	0.0381	0.0021
4	100.00%	0.0393	0.0018
5	100.00%	0.0402	0.0016
6	100.00%	0.0409	0.0013
7	100.00%	0.0415	0.0015
8	100.00%	0.0421	0.0013
9	88.89%	0.0434	0.0035
10	80.00%	0.0445	0.0032
Recall	80.00%		

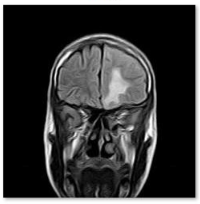

class3 (1)

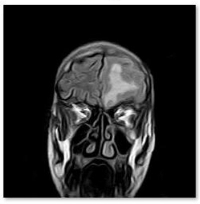

class3 (2)

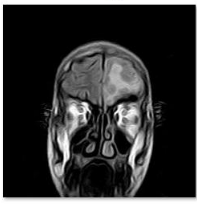

class3 (3)

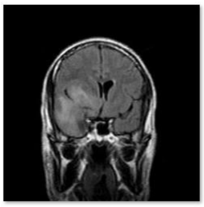

class3 (4)

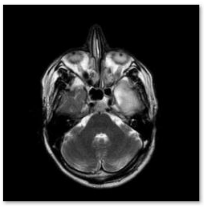

class3 (5)

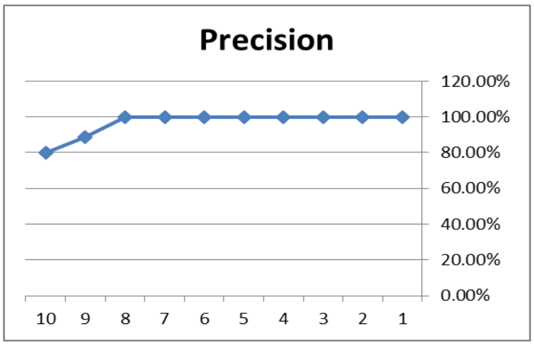

class3 (6)

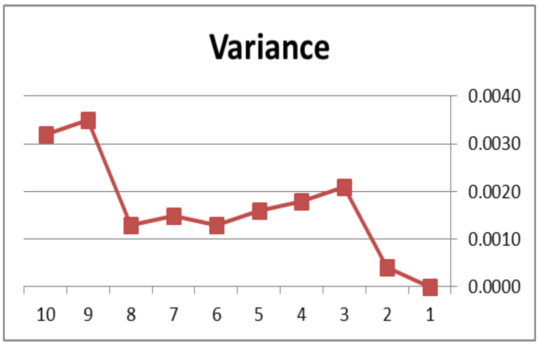

class3 (7)


class3 (8)


class5 (8)

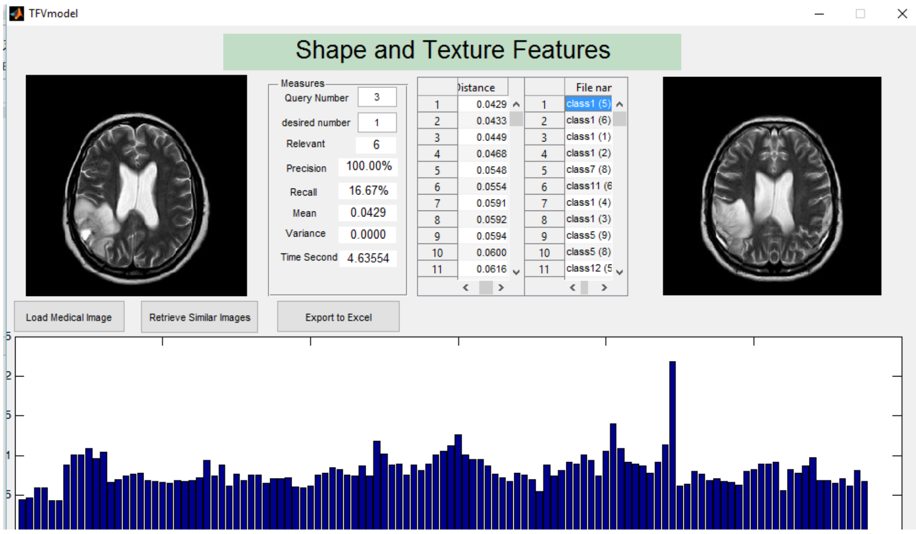

class10 (3)



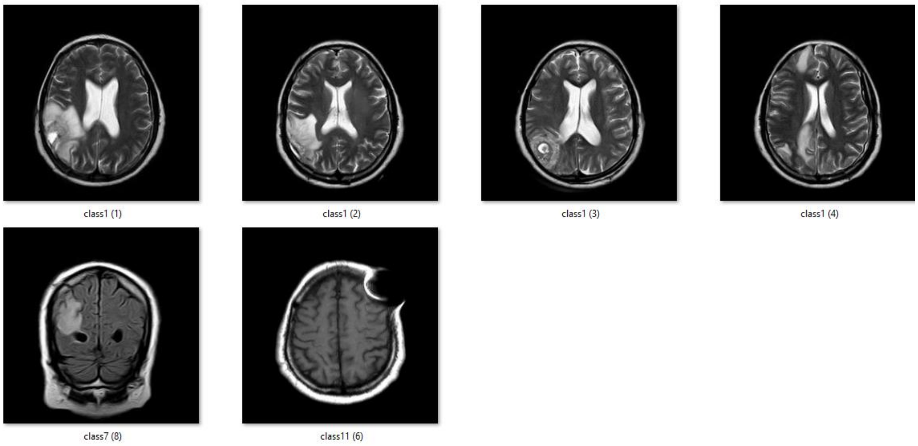


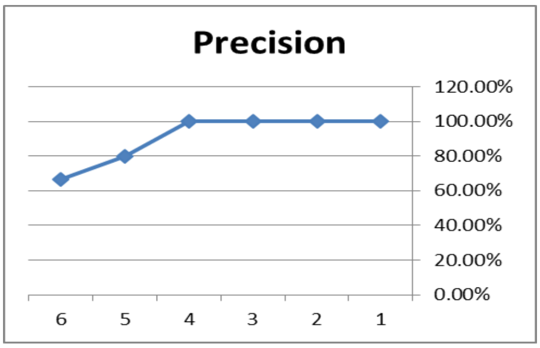
The results indicate that the first 8 image retrieved achieved precision 100% and recall rate in last case was 80.00%.

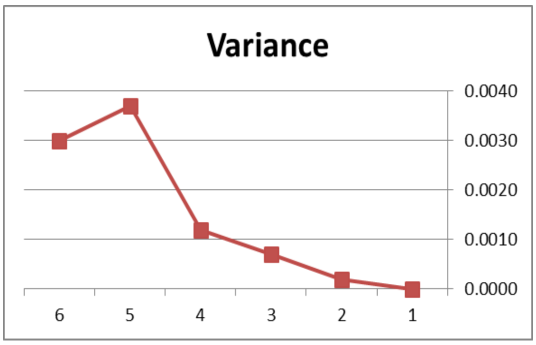
Q6



Index	Precision	Mean	Variance
1	100.00%	0.0429	0.0000
2	100.00%	0.0431	0.0002
3	100.00%	0.0437	0.0007
4	100.00%	0.0445	0.0012
5	80.00%	0.0465	0.0037
6	66.67%	0.0480	0.0030
Recall	66.67%		

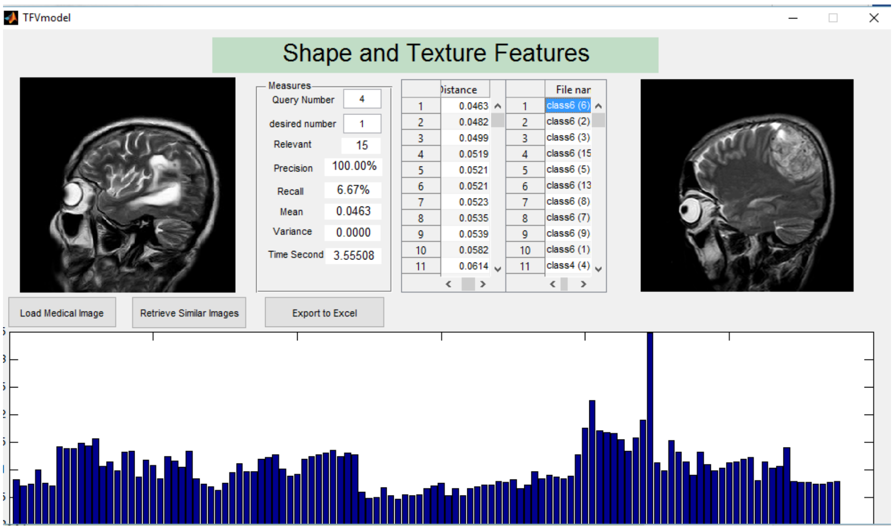




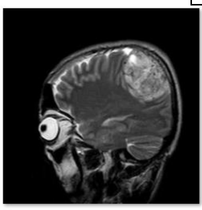


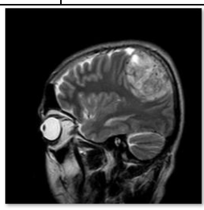
The results indicate that the first 4 image retrieved achieved precision 100% and recall rate in last case was 66.67%.

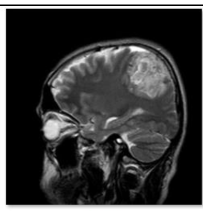
Q7



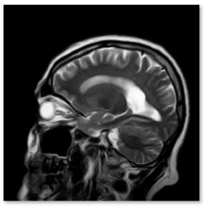
Index	Precision	Mean	Variance
1	100.00%	0.0463	0.0000
2	100.00%	0.0472	0.0007
3	100.00%	0.0481	0.0010
4	100.00%	0.0491	0.0014
5	100.00%	0.0497	0.0011
6	100.00%	0.0501	0.0008
7	100.00%	0.0504	0.0007
8	100.00%	0.0508	0.0010
9	100.00%	0.0511	0.0009
10	100.00%	0.0518	0.0020
11	90.91%	0.0527	0.0026
12	91.67%	0.0537	0.0032
13	84.62%	0.0546	0.0029
14	85.71%	0.0554	0.0027
15	80.00%	0.0561	0.0025
Recall	80.00%		

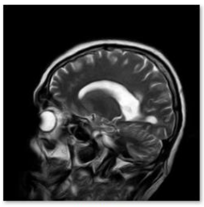

1 class6 (6)

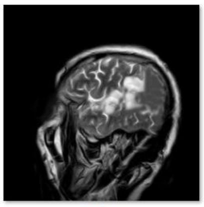

2 class6 (2)

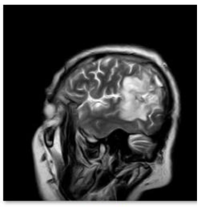

3 class6 (3)

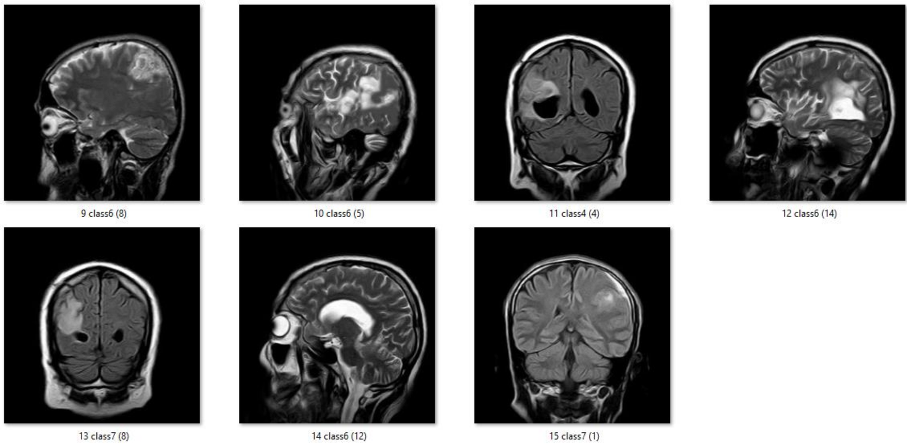

4 class6 (15)

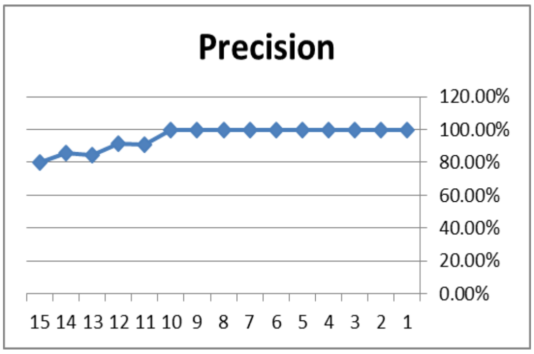

5 class6 (10)

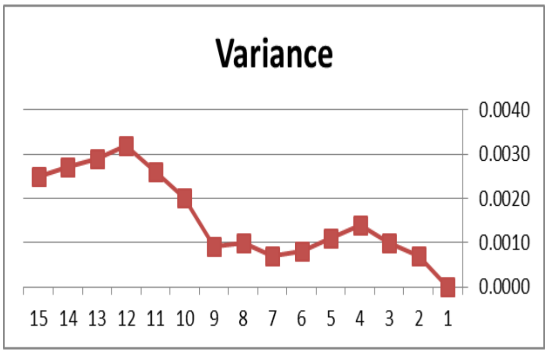

6 class6 (13)


7 class6 (7)


8 class6 (1)

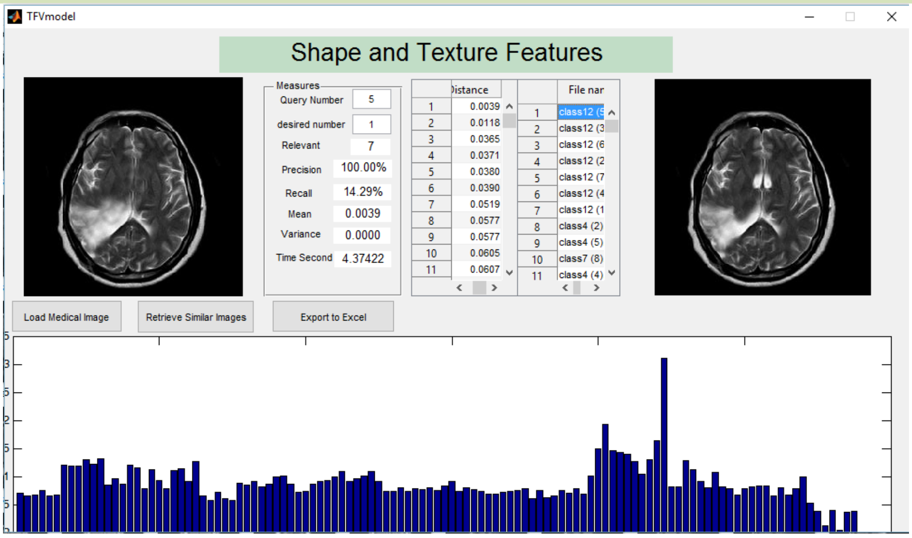






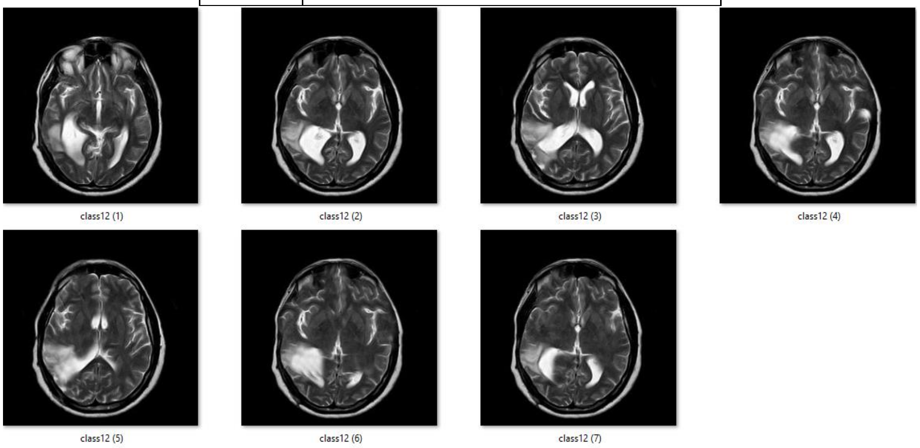
The results indicate that the first 10 image retrieved achieved precision 100% and recall rate in last case was 80.00%.

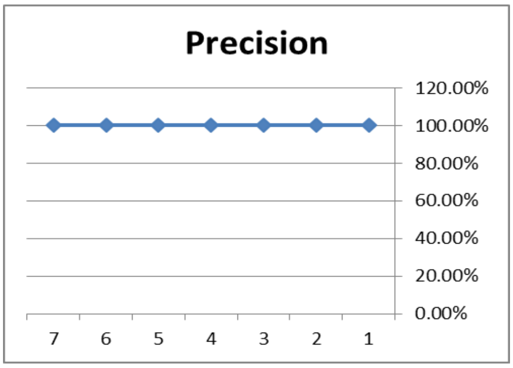
Q8

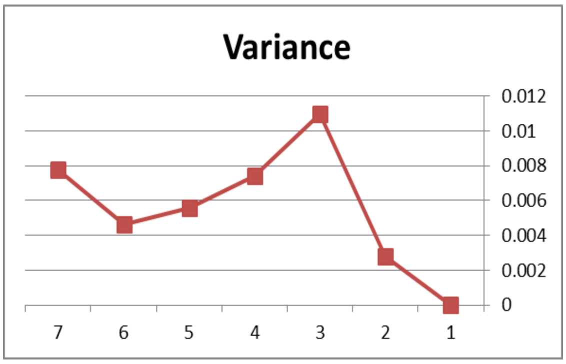


Index	Precision	Mean	Variance
1	100.00%	0.0039	0
2	100.00%	0.0079	0.0028
3	100.00%	0.0174	0.0110
4	100.00%	0.0223	0.0074
5	100.00%	0.0255	0.0056
6	100.00%	0.0277	0.0046

7	100.00%	0.0312	0.0078
Recall	100.00%		

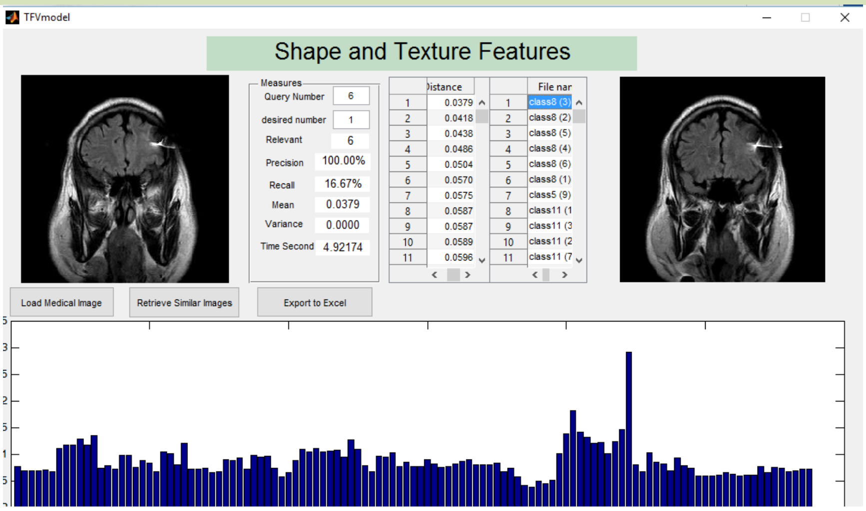






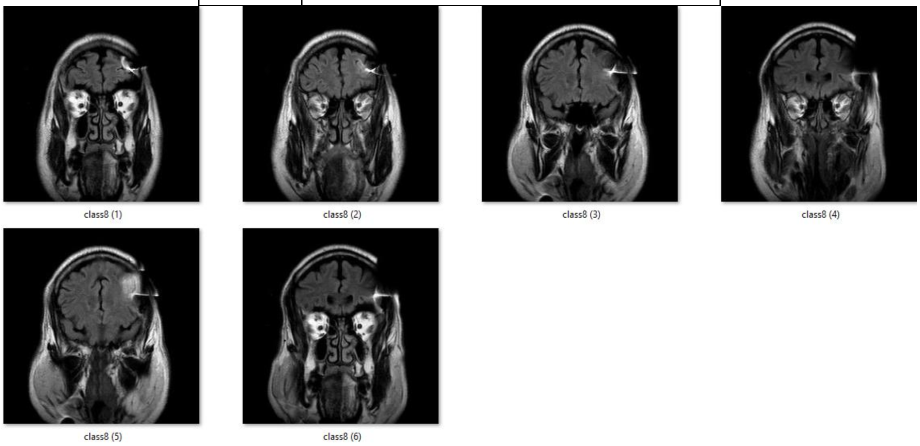
The results indicate that the all images retrieved in the case and achieved precision 100% and recall rate in last case was 100.00%.

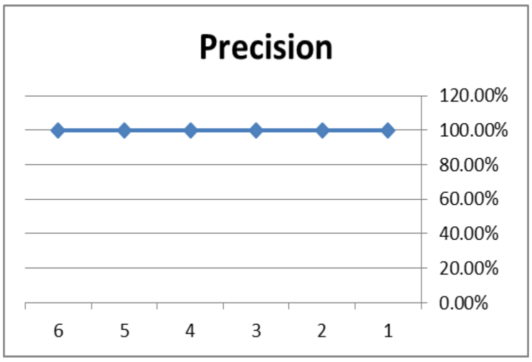
Q9

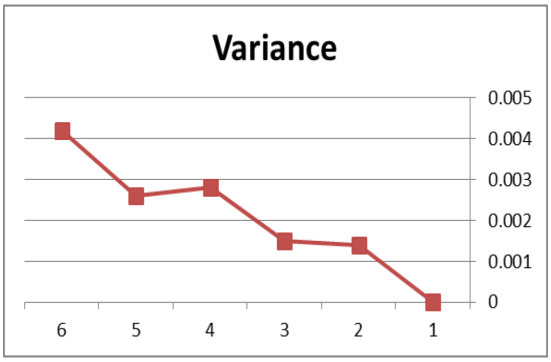


Index	Precision	Mean	Variance
1	100.00%	0.038	0
2	100.00%	0.04	0.0014
3	100.00%	0.041	0.0015
4	100.00%	0.043	0.0028

5	100.00%	0.045	0.0026
6	100.00%	0.047	0.0042
Recall	100.00%		

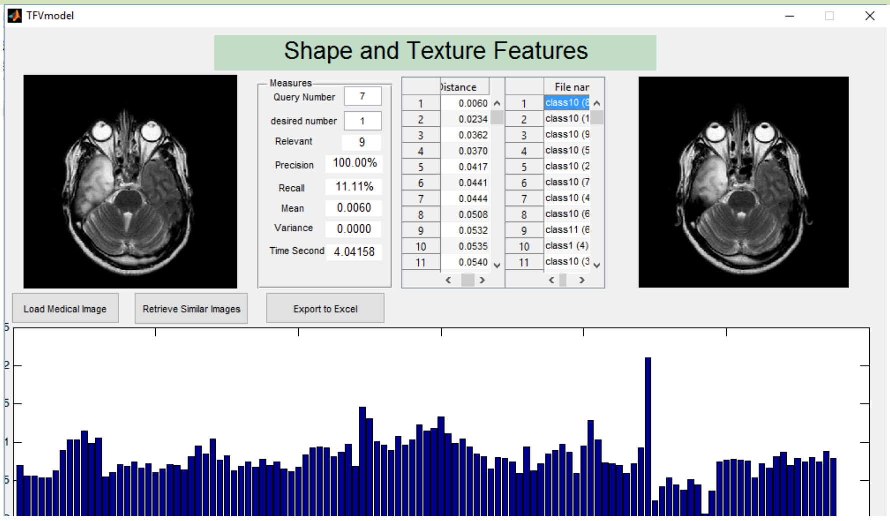






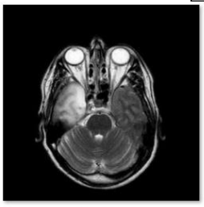
The results indicate that the all images retrieved in the case and achieved precision 100% and recall rate in last case was 100.00%.

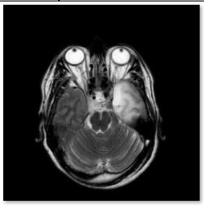
Q10

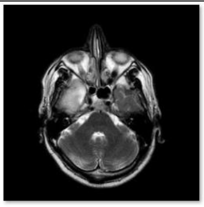


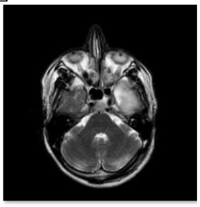
Index	Precision	Mean	Variance
1	100.00%	0.0060	0.0000
2	100.00%	0.0147	0.0062
3	100.00%	0.0219	0.0083
4	100.00%	0.0257	0.0057

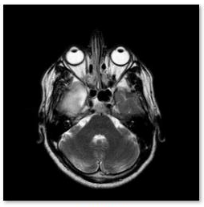
5	100.00%	0.0289	0.0057
6	100.00%	0.0314	0.0052
7	100.00%	0.0333	0.0042
8	100.00%	0.0354	0.0054
9	88.89%	0.0374	0.0052
Recall	88.89%		

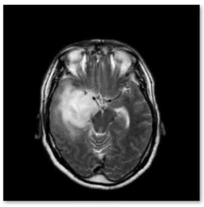

1 class10 (5)

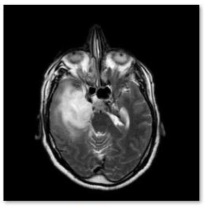

2 class10 (4)

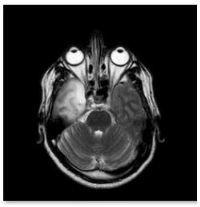

3 class10 (7)

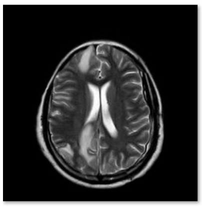

4 class10 (3)

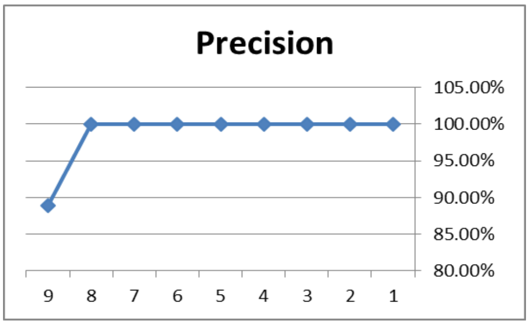

5 class10 (1)

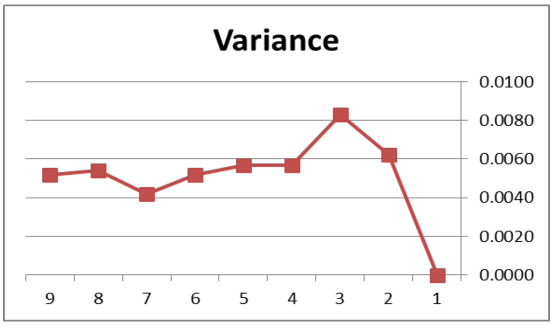

6 class10 (6)


7 class10 (2)


8 class10 (8)

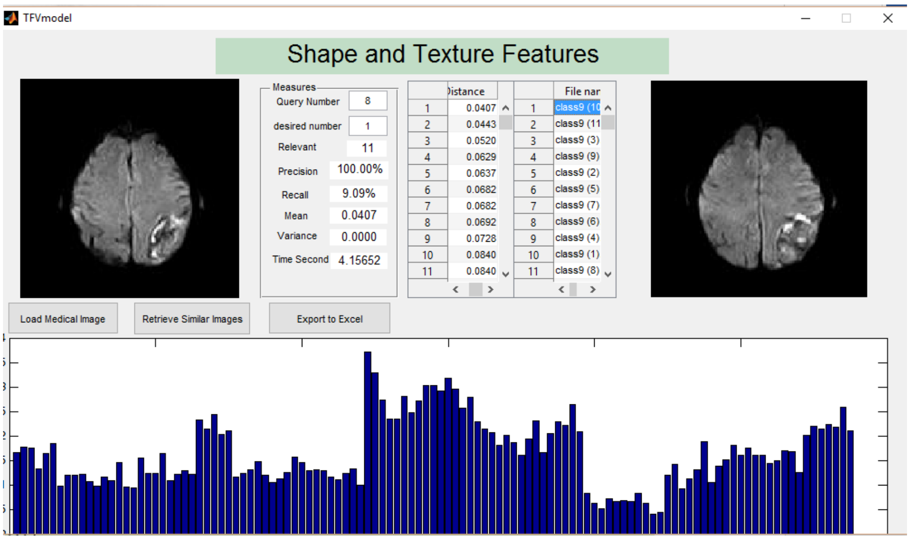

9 class1 (4)



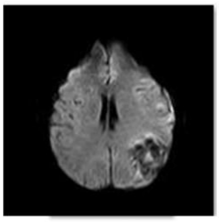


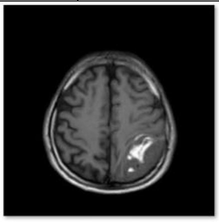
The results indicate that the first 8 image retrieved achieved precision 100% and recall rate in last case was 88.89%.

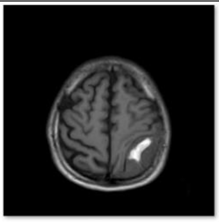
Q11

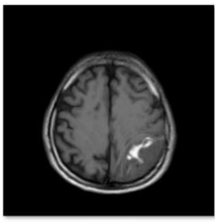


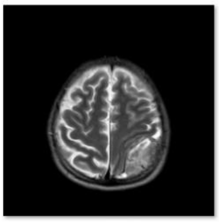
Index	Precision	Mean	Variance
1	100.00%	0.0407	0.0000
2	100.00%	0.0425	0.0013
3	100.00%	0.0457	0.0037
4	100.00%	0.0500	0.0065
5	100.00%	0.0527	0.0049
6	100.00%	0.0553	0.0053
7	100.00%	0.0572	0.0042
8	100.00%	0.0587	0.0037
9	100.00%	0.0602	0.0042
10	100.00%	0.0626	0.0068
11	100.00%	0.0646	0.0059
Recall	100.00%		

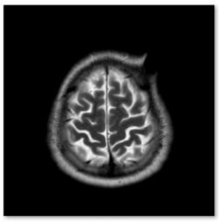

class9 (1)


class9 (2)

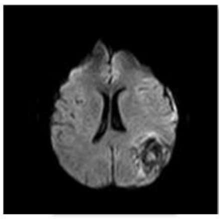

class9 (3)

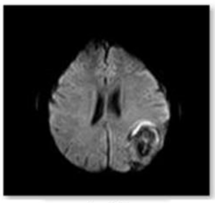

class9 (4)

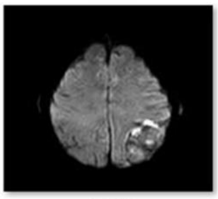

class9 (5)

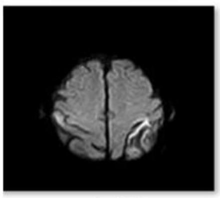

class9 (6)

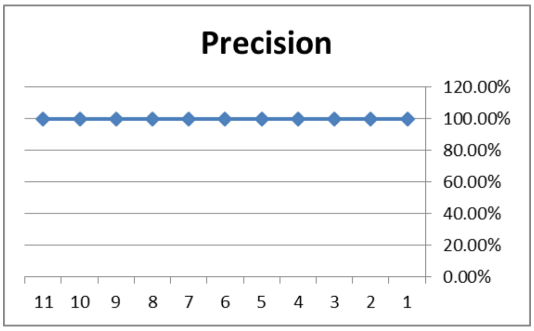

class9 (7)

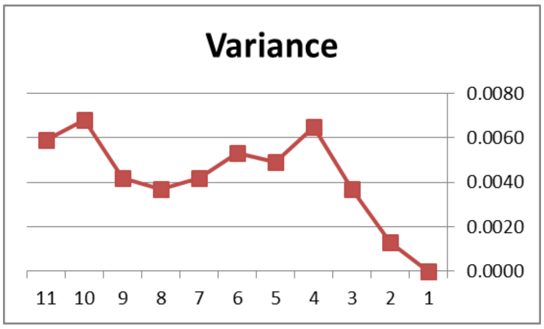

class9 (8)


class9 (9)


class9 (10)

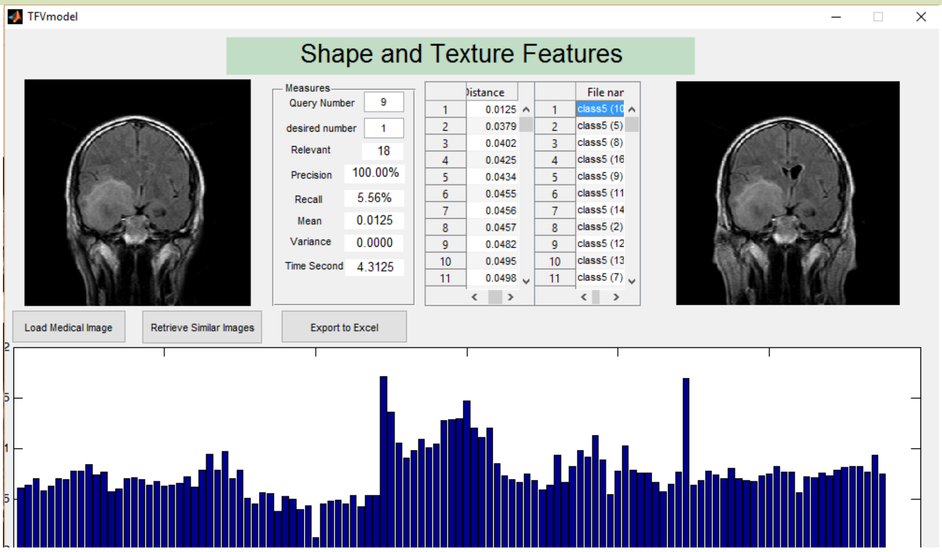

class9 (11)



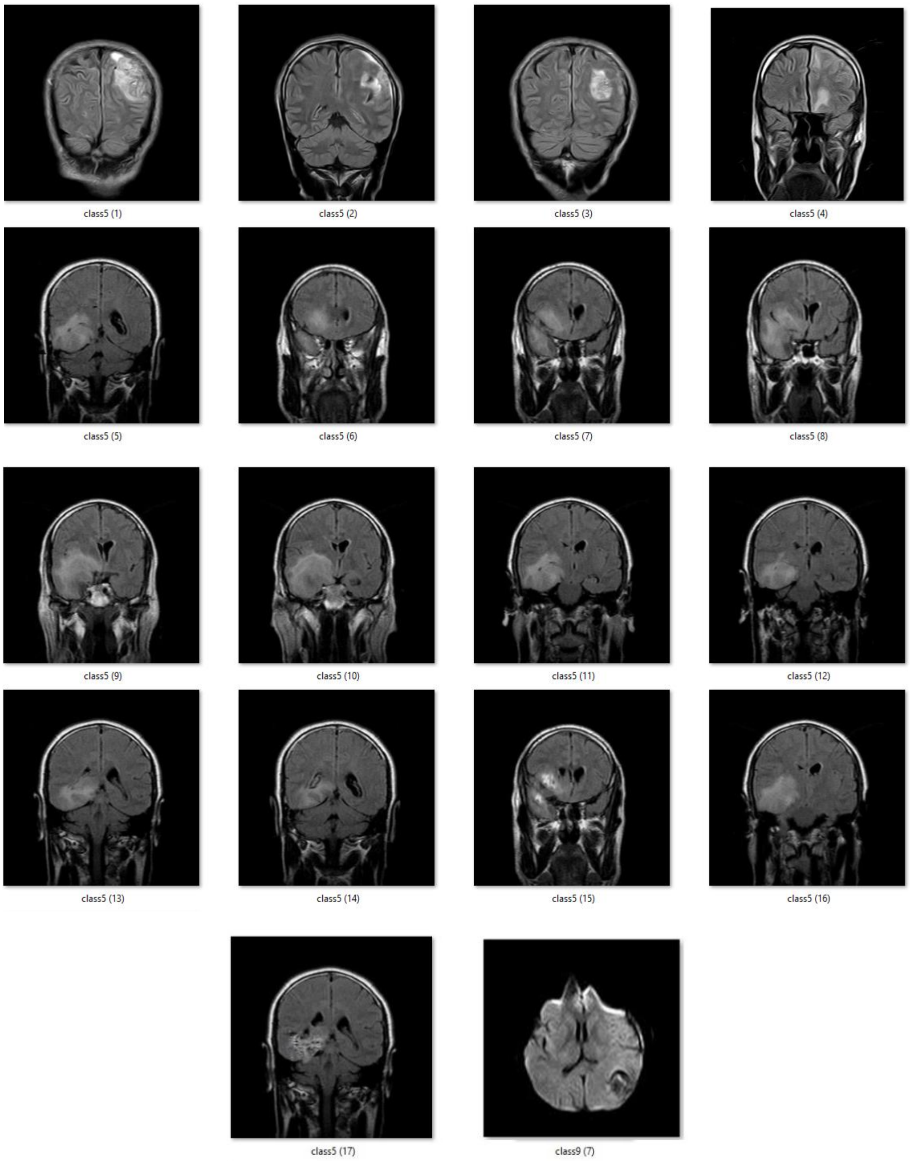


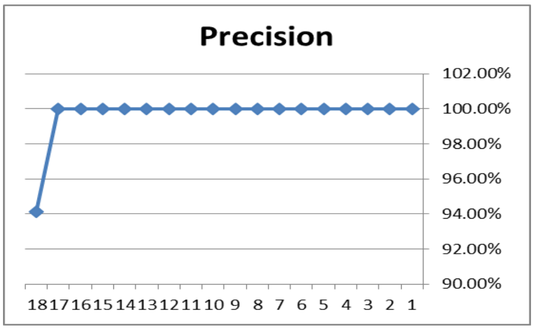
The results indicate that the all images retrieved in the case and achieved precision 100% and recall rate in last case was 100.00%.

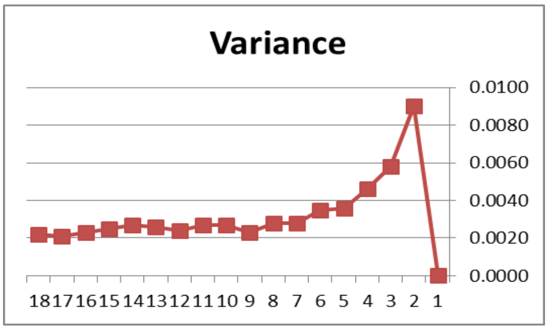
Q12



Index	Precision	Mean	Variance
1	100.00%	0.0125	0.0000
2	100.00%	0.0252	0.0090
3	100.00%	0.0302	0.0058
4	100.00%	0.0333	0.0046
5	100.00%	0.0353	0.0036
6	100.00%	0.0370	0.0035
7	100.00%	0.0382	0.0028
8	100.00%	0.0382	0.0028
9	100.00%	0.0392	0.0023
10	100.00%	0.0402	0.0027
11	100.00%	0.0411	0.0027
12	100.00%	0.0419	0.0024
13	100.00%	0.0427	0.0026
14	100.00%	0.0435	0.0027
15	100.00%	0.0442	0.0025
16	100.00%	0.0449	0.0023
17	100.00%	0.0454	0.0021
18	94.12%	0.0460	0.0022
Recall	94.44%		







The results indicate that the first 17 image retrieved achieved precision 100% and recall rate in last case was 94.44%.