An Automated System Design for Medical Image Storage and Distribution

By

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Declaration

I, the undersigned, declare that this thesis is my original work. It has never been presented for a degree in any other institution and that all sources of materials used in it have been duly acknowledged.

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This MSc thesis has been submitted for examination with my approval as an advisor.

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Certificate of Examination

This is to certify that the thesis prepared by Abdela Kemal Redi entitled '*An Automated System Design for Medical Image Storage and Distribution*' submitted in partial fulfillment of the requirements for the degree of Master of Science in Biomedical Engineering (Bioinstrumentation and Imaging) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Abstract

The advent of information and communication technologies (ICT) and their incorporation into the medical domain especially medical imaging have created opportunities to enhance medical services and provide improvement to patient care. To implement such services, the current medical system needs to be integrated to different imaging modalities and at the same time be available to health professionals and patients. Picture Archiving and Communication System (PACS) is one means of storing and uses a server for image transmission through a network. The images could be acquired using any given modalities like Computed Tomography (CT), Ultra Sound (US) or Magnetic Resonance Imaging (MRI) and stored digitally. Digital Imaging and Communications in Medicine (DICOM) and Health Level Seven (HL 7) are often standards used to exchange medical images and patient data within the health institutions and outside of the institution using public network (internet). The images taken from the different imaging modalities are often difficult to transfer over the internet because of their size. We could think of for example storing and transferring an isotropic MRI data set between systems even for few patients.

In order to transmit such slices of pictures via the internet, these images need to be compressed first. One of the primary obstacles in the development of a compression scheme is the loss of image resolution and contrast. However, we can improve the transmission time and also upload and download time. In the existing setup of the health facilities in Ethiopia, working medical image sharing systems are available only is some hospitals and function only within the hospitals. In low resource settings with chronic shortage of medical experts to examine the ever increasing amount of imaging data, there is always a need to locate a physician to consult and hence having a system that allows two ways communication remotely could be an enormous benefit.

This thesis focuses on the development of a working Medical Image File Storage and Distribution System (MIFSDS) for use in storage and exchange/sharing of medical images within and across hospitals. The system includes development of an image classification algorithm and design of a web page system for image distribution and communication. The image classification algorithm which has been developed based on higher order statistical image

feature extraction is shown to be accurate and robust while the system that has been developed for easy storage and transmission of imaging data allowing two way communication is proved to be simple and effective.

ACRONYMS

AI	Artificial Intelligence
AID	Adobe Illustrator Document
CLD	Color Layout Descriptor
CT	Computed Tomography
DBMS	Database Management System
DICOM	Digital Imaging and Communications in Medicine
EHD	Edge-Histogram Descriptor
EPS	Encapsulated Post Script
F_V	Features vector
GIF	Graphics Interchange Format
GLCM	Gray Level Co-occurrence Matrix
GUI	Graphical User Interface
HL 7	Health Level Seven
HTD	Homogeneous Texture Descriptor
ICT	Information and Communication Technologies
IP	Internet Protocol
JPEG/JPG	Joint Photographic Experts Group
k-NN	k-Nearest Neighbor
MIFSDS	Medical Image File Storage and Distribution System
MPEG	Moving Picture Experts Group
MR	Magnetic Resonance
MRI	Magnetic Resonance Imaging

NM	Nuclear Medicine
PACS	Picture Archiving and Communication System
PDF	Portable Document Format
PET	Positron Emission Tomography
PHP	Hypertext Preprocessor
PNG	Portable Network Graphics
RGB	Red Green Blue
SCAD	Simultaneous Clustering and Attribute Discrimination
SVM	Support Vector Machine
TCP	Transmission Control Protocol
US	Ultra Sound
WWW	World Wide Web
XAMPP	Cross-Platform Apache MySQL PHP Perl
XDS	Cross Enterprise Document Sharing
XR	X-ray

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Chapter One

1 Introduction

1.1 Background

The revolution in digital imaging has been accompanied by the adoption of a Picture Archiving and Communication System (PACS), which provides electronic storage, retrieval, distribution and presentation of medical images. PACS facilitates the handling of digital images so that they can be readily accessed and viewed by a variety of medical professionals in different locations and settings within a hospital [1] [3].

Digital Imaging and Communications in Medicine (DICOM) is a standard for storing and transmitting information in medical imaging. It includes a file format definition and a network communications protocol. DICOM enables the integration of scanners, servers, workstations, and network hardware from multiple manufacturers into a PACS and ensures the easy transmission of information between the different users [2] [3].

The primary functions of a Medical Image File Storage and Distribution System (MIFSDS) are to ensure timely distribution of, and access to, medical images of patients by the right physicians (specialists), and most healthcare organizations are implementing such technologies. To establish such a system and to successfully implement storage and distribution of medical images crossing the different hospitals, effective use of available standards such as HL7, DICOM and image compression, as well as appropriate technology and skilled technology partners are of paramount importance [1] [2] [3]. Other than the PACS, other schemes have also been proposed in the literature for effective storage and transfer of medical images within and across hospitals and health institutions.

There are a number of research institutions which make use of such facilities to effectively carry out their daily tasks. One widely used method in this regard is for example cloud computing. On one hand this scheme has already shown great promises in different areas of its implementation. On the other hand, having such a facility may require enough resources and be costly at times. This thesis focuses on development of a web based system for medical image storage and distribution through internet and also design of an automated system to classify medical images. The work investigates feasibility of an image classification scheme for use of storage, retrieval, and distribution of medical images. The system prototype is developed based on a XAMPP server and a graphical user interface (GUI). The system is tested on data available locally at selected public hospitals in Ethiopia as well as research image data acquired from freely available databases. System quality, performance and other related issues are also considered.

1.2 Statement of the Problem

As science and technology progressed, medicine became an integral part of the research. Gradually, medical science became an entirely new branch of science. In this regard, medical imaging has contributed a great deal while the technology behind it showing tremendous growth over the years. Effective and efficient imaging data handling and transmission is then a core issue that needs to be addressed.

Still being a developing nation, countries like Ethiopia have seen a tremendous growth of their health sector in the field of development of numerous large and small scale healthcare institutions. However, efficient data handling, particularly imaging data, is lacking. Paper based handling of imaging data still dominates in the current practices with all its drawbacks: challenging data back-up, long data access time, difficulty for editing and communication, and often result in data loss. The manual procedure is labor intensive at the same time requiring several personnel to handle imaging data particularly in areas with low resource settings with few health care providers available. Automated electronic systems allow easy back-ups, often instantaneous data access, efficient editing and communication, data security and efficient data handling.

The aim of this thesis project was to build a web application to store and distribute medical images between different parties with multitude of benefits for patients as well as health care providers. The proposed Medical Image File Storage and Distribution System (MIFSDS) is custom built to meet the specific requirements of the mid and large size hospitals across Addis Ababa. The modules and features have been particularly built to just fit into the listed requirements. Patient registration, doctor orders and prescriptions, patient scans, specialist reads and other pertinent information are stored and communicated between users based on different modules developed to do so. Four requirements are mostly considered while developing such systems: performance, efficiency, control and security which are all adopted in the current thesis work. The development of the system is assumed to decrease the time it takes for a medical image to reach the right expert for diagnosis and improve physician's performance and also health care workers continued exposure and experience in medical images so that they further develop subspecialized areas of interest or expertise as desired without changing their locations.

1.3 Objectives of the Study

1.3.1 General Objective

The major objective of this thesis is to design an automated system for use in efficient storage and distribution of medical images.

1.3.2 Specific Objectives

- ✓ To develop an algorithm that could be used in image modality classification;
- ✓ To develop a Medical Image File Storage and Distribution System (MIFSDS) that allows two way communication between parties;
- ✓ A prototype development of the proposed design;
- ✓ System performance evaluation.

1.4 Scope of the Study

Only three imaging modalities are considered in the current work: Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Ultra Sound (US) while other imaging modalities including nuclear medicine are not considered in the development of the proposed system in this thesis. A similar system design could be used for other modalities while the classification scheme ought to be modified to accommodate those. Also actual clinical validation of the system might need rigorous work and that has been omitted in the current study.

Organization of the Thesis

The rest of the thesis has been organized into four chapters. **Chapter Two** describes the details of related works that have been done in the past by various researchers in the literature. **Chapter Three** briefly explains the materials used along with the details of the methodology adopted in this thesis. **Chapter Four** presents the results obtained including discussions. Finally, the summary and conclusion of the thesis with recommendations leading to future work have been mentioned in **Chapter Five.**

Chapter Two

2 Medical Image Storage and Distribution Systems

2.1 Related Works

There have been many researches carried out in the literature for use in medical image storage and distribution applications. Some were focused on storage issues only, others on transmission while others tried both at the same time.

One study proposed a fuzzy rule-based medical image classification scheme for effective identification and communication of the images [4]. The authors used medical image data collected from the trauma centers and health centers in Jalgaon, India. The data was composed of: CT scans containing axial normal and abnormal images of the brain, MRI data containing T1 and T2 weighted axial, coronal, and sagittal brain images, X-ray data containing chest images, Ultrasound images as well as Microscopic images taken from stained samples on slides. Simple statistical measures including the mean, standard deviation and contrast were extracted from the images for the purpose of modality classification. A fuzzy based classifier was developed finally making use of these features following training and testing phases. The training phase was carried out in a number of steps including; (1) reading the medical image, (2) preprocessing the image using a median filter, (3) extracting the features and storing them into a feature database, (4) creating the member functions named contrast, mean, and standard deviation using the extracted feature values, and (5) defining the rule base for classification [5]. The features computed using the algorithm were used to build the membership functions of fuzzy quantities namely mean, standard deviation, and contrast of the medical images considered.

The testing phase includes (1) reading the medical image, (2) preprocessing of the image using a median filter, (3) extracting the features, (4) inputting these extracted features to the designed medical image classification system, and (5) classify result. The designed classification system evaluates these features using the defined knowledge base and maps the query image into the resultant image. The authors compared the performance of the proposed system with other classification approaches like Support Vector Machine (SVM) and k-nearest neighborhood (k-NN). The experiment was conducted on a total of 100 images: 20 images of each of the five modalities. Of these, 50 % of the data were used for training and the rest 50 % were used for testing purposes. The performance of the three classifiers was compared by computing a confusion matrix. Forty-one images out of fifty were correctly identified by the k-NN classifier which resulted in an accuracy of 82% with k = 5. Whereas SVM correctly classified forty-four images out of fifty which resulted in an accuracy of 88% making use of RBF kernel. Using the proposed fuzzy rule-based approach, forty-two images were correctly identified, four were misclassified, and four remained unclassified which resulted in an accuracy of 84% by the method. The performance of the SVM was better than the fuzzy system and the k-NN. But the SVM and k-NN are binary classifiers; they classify images into one of the defined classes so there is more risk of misclassification. The fuzzy system allows images to remain unclassified and the risk is minimized.

In another study, an image modality classification scheme was developed based on a clustering algorithm making use of the feature weighted clustering approach [6]. All features that are related to the cluster are given more weightage and the features that are not very relevant to the cluster are given lower weightage. The feature vectors are extracted from MPEG-7 Visual Feature Descriptors. MPEG-7 is an ISO/IEC standard developed by MPEG (Moving Picture Experts Group), was formally named "Multimedia Content Description Interface". As the name might suggest, this is a standard for describing the multimedia content data [7]. Visual section in the MPEG-7 system is used to describe an image specifically. Visual low-level descriptors included in the visual part of MPEG-7 are color, texture, shape and motion descriptors which describe different features of a related visual content. The method proposed in [6] made use of three MPEG-7 Visual descriptors that are found relevant: Color Layout Descriptor (CLD), Edge-Histogram Descriptor (EHD) and Homogeneous Texture Descriptor (HTD). After extraction of the feature vector, the authors focused on using EHD and proposed Simultaneous Clustering and Attribute Discrimination (SCAD) clustering technique for clustering the features and k-NN to match the modalities to the features. The authors used about 2600 medical images in the training and testing groups and a total of eight modalities: CT, GX (Graphics, typically drawing and graphs), MRI, Nuclear Medicine, PET (Positron Emission Tomography including PET/CT), PX (Optical imaging including photographs, micrographs and gross pathology), US (Ultrasound including color/Doppler) and X-ray (including X-ray angiography). The training group consisted of around 2380 medical images from all modality categories and the remaining were ground truth images used during the testing stage. They evaluate the performance of proposed classifier:

compare the accuracy of the classification by comparing the results of all the dataset classification done manually (ground truth) with the one done by the algorithm (proposed work).

Another study proposed a web-based medical diagnosis and prediction system composed of four main components: patients' databases (name, address, and other particular details and their illnesses), prediction module, diagnosis module and a user interface [8]. The prediction module utilizes a neural network technique to predict patient's illness or conditions based on previous similar cases. The diagnosis module consists of an expert system and fuzzy logic techniques to perform diagnosing tasks. A set of rules was defined using the patients-disease databases as well as the expert knowledge on the disease domain. The expert system uses the rules to diagnose patient's illness based on their current conditions or symptoms. In addition, fuzzy logic is integrated to enhance the reasoning when dealing with fuzzy data. The combination of the expert system and fuzzy logic that forms a hybrid (expert-fuzzy) system was meant to increase the system performance. They used multimedia and internet (or computer network) are two of the main tools that support the collaboration and distribution of information. Multimedia is a combination of media such as text, audio, visual and graphics can be used in medical application such as in image transmission (X-Ray images, pictures and etc.).

Another medical diagnostic system built over the World Wide Web (WWW) has also been proposed previously [9]. The web acted as the interface between users and the system. The model incorporated data collection (patient details and illness information), diagnosis, prediction and system administration. Information sharing, collaboration between medical practitioners, on-line discussion, on-line diagnosis and treatment were the main features of the system enabling doctors in different locations to share knowledge and expertise. Also centralized medical record allows doctors improve the quality of patients' diagnosis and treatment based on accurate patients' medical history. Such systems serve to improve the quality of medical decision-making, increases patient compliance and minimize iatrogenic diseases and medical errors. Employing the technology especially Artificial Intelligence (AI) techniques in medical applications could reduce healthcare cost enhancing time management and human expertise.

Another study they proposed sharing medical imaging over the cloud services the implementation was supported on the public cloud resources that are available on the Internet, creating the opportunity to exchange information between the medical devices inside the institutions with another devices located in another institution.

Despite of the advantages of the cloud computing, it also brings new challenges regarding the data privacy when the medical data are transmitted over different domains. Cloud computing is largely used to share files over the internet. Cloud providers offer a high quality of service, mainly in the availability and scalability. Their solution takes advantage of the cloud computing services to exchange information between different locations. The communication between the components of the digital medical laboratories was mainly used through DICOM. This protocol runs over TCP/IP protocol, but contains its own addressing model through the AETitle that identifies the medical device [50]. Due to the network filters restrictions (i.e. firewalls) this communication does not perform well in WAN (Wide Area Network) scenarios. To extend the communication to different institutions, the proposed approach takes advantage of the DICOM addressing mechanism to route the information to the correct location (i.e. AETitle is the DICOM address mechanism). The public cloud infrastructure is used as communication mechanism to support information forwarding among the involved entities through these routes. Furthermore, additional Cloud provider support is simplified due to a plugin-based system. To support abstraction with the cloud storage we developed a Cloud IO (Input/Output) stream mechanism [9].

2.2 Digital Images and Related Protocols

Two-dimensional (2D) image data could be classified into two primary categories: bitmap and vector.

A) **Bitmap images:** Bitmap images (also called raster images) can be represented as 2D functions f(x,y), where they have pixel data and the corresponding gray-level values stored in some file format. Raster is the most common category of images created and used within digitization projects. All scanners and digital cameras produce raster images and most output devices (print and screen) also use raster formats. Pixels have a defined proportion based on their resolution (high or low), and when the pixels are stretched to fill space they were not originally intended to fit, they get distorted resulting in blurry or unclear images. In order to retain pixel quality, one cannot resize raster images without compromising their resolution. As a result, it is important to remember to save raster files at the exact dimensions needed for the application. Most common examples of raster file formats are JPG, PNG, JFIF and GIF.

B) Vector images: These are a set of mathematical instructions that are used by a drawing program to construct an image. The common vector images include 2-D and 3-D architecture drawings, flow charts, logos and fonts. They consist of lines, curves and shapes with editable attributes such as color. Vector images are resolution independent; they can be reshaped or rescaled without losing quality. EPS (Encapsulated Post Script), AID and PDF are common examples that represent vector images.

2.2.1 Types of Digital Images

Binary Images

Binary images are the simplest types of images and can take on two values, typically black and white, or 0 and 1. A binary image is referred to as a 1-bit image because it takes only 1 binary digit to represent each pixel. Binary images are often created from gray-scale images via a thresh holding operation, where every pixel above the threshold value is turned white ('1'), and those below it are turned black ('0'), for example.

Gray-scale Images

Gray-scale images are referred to as monochrome (one-color) images. They contain gray-level information, no color information. The number of bits used for each pixel determines the number of different gray levels available. A typical gray-scale image contains 8bits/pixel data, which allows us to have 256 different gray levels (intensity ranges from 0 (black) to 255 (white)).

Color Images

Color images can be modeled as three-band monochrome image data, where each band of data corresponds to a different color. The actual information stored in the digital image data is the gray-level information in each spectral band. Typical color images are represented as red, green, and blue (RGB images). Using the 8-bit monochrome standard as a model, the corresponding color image would have 24-bits/pixel (8-bits for each of the three color bands red, green, and blue).

Multispectral Images

Multispectral images typically contain information outside the normal human perceptual range. This may include infrared, ultraviolet, X-ray, acoustic, or radar data. These are not images in the usual sense because the information represented is not directly visible by the human visual system. However, the information is often represented in visual form by mapping the different spectral bands to RGB components.

2.2.2 What is DICOM

DICOM stands for Digital Imaging and Communications in Medicine. DICOM is a standard that establishes rules that allow medical images and associated information to be exchanged between imaging equipment from different vendors, computers, and hospitals. A CT scanner produced by vendor A and a magnetic resonance imaging (MRI) scanner produced by vendor B can send images to a PACS from vendor C using DICOM as a common language.

DICOM image differs from other image formats since the DICOM file consists of a header with data sets and an image packed into a single file. Header information is organized as a regular and standardized series of tags. By accessing the information, data on patient, device, imaging parameters, etc. become readily available. When DICOM images are transmitted over the internet for educational and other purposes, it is necessary to remove all personal information that can be used to identify the patient.

2.2.3 Evolution of Digitalization and DICOM Standard

Evolution of data sharing in radiology started from digitalization of radiological exams in 1970. The main incentive to digitalize medical images was to replace labour intensive and inefficient analogue film reading environment in radiology department with computerized images to optimize the increasing workload. Evolution of information technology also opened new horizons for diagnostic image processing after their acquisition. The first digital images were produced by nuclear medicine, angiography and CT equipment [10]. Introduction of new imaging modalities increased considerably the number of diagnostic exams and consequently required establishing a proper storage environment. At the early stage of digitalization, radiology images were stored in a proprietary format close to the individual imaging modality.

The lack of common standards in digital imaging hindered establishment of universal image archives. It also appeared that stand alone computer workstations did not facilitate the overall efficiency in image reporting because different modalities demanded specific workstations. This evolution motivated academic radiologists to work out universal standard for digital images in medicine which could allow archiving and retrieval of different exams and communication of image data, where the universal standard for images was not dependent on the equipment vendor.

The initial version of standardized terminology was created in the mid of 1980 and the DICOM standard was published in 1993 [11]. This initiative allowed vendors to elaborate and manufacture multimodality archiving and communication systems – picture archiving and communication system (PACS). Today, DICOM is the main technical and interoperable standard for data sharing in medical imaging. It defines the rules for digital imaging and communication of diagnostic and therapeutic information in disciplines that use digital images and associated data. In addition to the digitalization of medical images, the digitalization of patient's administrative and clinical data demanded healthcare providers to address interoperability issues where data was stored in different non-communicable information systems inside the same healthcare organization [12]. The lack of clinical and administrative communication required interfacing of digital imaging technology with other information systems.

Once images are digitalized, PACS is used to acquire, store, query, retrieve, display and process medical images and associated data originating from different imaging modalities. PACS integrates these sub-systems by digital networks and software applications [13]. It allows effective communication, for patient care, of DICOM images. As a separate medical imaging technology, it is a prerequisite for image sharing and shared workflow. PACS provides a platform for a single point of access for images and related data and also integrates images from other healthcare information systems. To achieve digitalization of the whole imaging pathway, digital images should be accompanied by patients' digital data, including administrative data. For medical documentation, the most widely used interoperability standard is Health Level Seven (HL7). It provides a comprehensive framework and related standards for the exchange, integration, sharing, and retrieval of electronic health information that supports clinical activity and the management, delivery and evaluation of health services [14]. HL7 covers a wide range of healthcare processes while DICOM concentrates mainly on medical imaging and the related exchange of data.

2.2.4 Evolution of Cross-organizational Data Sharing

Along with the development of interoperability standards in medical imaging, the integration of databases evolved in consecutive stages. Data sharing between healthcare providers started with point-to-point integrations followed by simultaneously accessible central databases, and most recently, by many-to many connections [15][16].

Point-to-point connection allows healthcare professionals located in one institution access medical data collected and stored in another institution. In this case, two organizations would agree about the technical standards for data sharing, organizational and security rules, etc. There can be more organizations that are connected to the same database and use the data simultaneously. However, technical interoperability and contractual relations remain bilateral between two healthcare providers. Every new connection demands new agreements between collaborating parties.

However, neither point-to-point connections nor shared databases are effective if the user needs to share more than one database. To support simultaneous access to different databases, a more effective many-to-many approach is used [17]. This setting uses a central integration platform which communicates with different databases. Each healthcare organization is assumed to have only one integration to the central platform. There is no need for multiple agreements between different healthcare providers and databases. All data exchange issues are covered using technical integration and by a contract between the healthcare provider and the integration platform.

Many-to-many database integration is achieved by using the Integrating the Healthcare Enterprise (IHE) standard profiles, particularly cross-organization data sharing profiles like the Cross Enterprise Document Sharing (XDS). XDS is not a standard itself but a set of technical and organizational agreements which describe how to use international standards like DICOM and HL7 most effectively in the shared healthcare environment.

2.3 Applications of Digital Image Analysis

Digital image analysis is a process of manipulating images to enhance or extract something deemed useful. The type of analysis could be categorized into low level, mid-level or high level. Digital image analysis methods have been utilized in a variety of application domains. The main areas of applications include medical image processing, remote sensing, underwater image restoration & enhancement and computer vision. The role that digital images play varies depending upon the application. Some of the applications of digital image processing are discussed below:

Medical Image Analysis

Image analysis techniques have played an important role in several medical applications. In general, the applications involve the automatic extraction of features from the image which is then used for a variety of classification tasks, such as distinguishing normal tissues from abnormal tissues. Depending upon the particular classification task, the extracted features capture, for example, morphological properties, color properties, or certain textural properties of the image. Textural properties are closely related to the application domain to be used. In some diseases, such as breast cancer, changes in the X-ray images are texture changes as opposed to clearly delineated lesions. In such applications, texture analysis methods are ideally suited to analyze the images [51].

Remote Sensing

Remote sensing is basically an acquisition of small or large scale information signals from an object or phenomenon, by using various real-time sensing devices that are wireless in nature, or not in physical or direct contact with the object (such as aircraft, spacecraft, satellite or ship). Practically remote sensing is a collection of different data signals using variety of devices for gathering information on a given object or area [18].

Underwater Image Restoration & Enhancement

In underwater image processing, the basic physics of light propagation in the water medium comes into extinction. When the light enters into water, it exponentially attenuates with the depth of water level; therefore the visibility distance is affected and is limited. Underwater images suffer from different problems such as blurring, non-uniform lightening, noise, low contrast, etc.

Therefore, restoration & enhancement of underwater images is an essential area of research. Various filters are used in the enhancement methods to improve the image quality, to suppress the noise, to preserve the edges in an image and for smoothening of the image [19] [20].

Computer Vision

Computer vision is a kind of automated watchdog, which uses both science and technology. Being a discipline from science, computer vision is related to theory for design of artificial systems that can acquire information from images. The image input may be of many formats, such as a video signal sequence, or multiple views from different cameras, or data input from a medical scanning machine. Examples of applications of computer vision include systems for controlling processes such as an industrial robot or an autonomous vehicle; for detecting events such as in visual surveillance or people counting; for organizing information such as for indexing databases of images and image sequences; for modeling objects or environments such as industrial inspection, medical image analysis or topographical modeling; and for interaction such as the input to a device for interaction between a computing machine and human [21].

2.4 Image Texture Analysis and the Gray Level Co-occurrence Matrix (GLCM)

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. There exist various definitions of texture in the literature. Intuitively texture dictates coarseness, smoothness or similar other properties of objects, i.e. it contains important information about the structural arrangement of surfaces. The textural features based on gray-tone spatial dependencies have a general applicability in image classification. The three fundamental pattern elements used in human interpretation of images are spectral, contextual and textural features [22]. Comparing the three, spectral features describe the average tonal variations in various bands of the visible and/or infrared portion of an electromagnetic spectrum. Contextual features contain information derived from blocks of pictorial data surrounding the area being analyzed. Textural features contain information about the spatial distribution of tonal variations within a band.

Texture analysis can be used to quantify and detect structural information in different images. The approaches to texture analysis are usually grouped into: Structural or syntactic; Model-based; Signal processing or transform based and Statistical. In this thesis work, focus was given to statistical approaches of texture analysis which are described in the subsequent sub sections.

2.4.1 Statistical Approaches for Texture Analysis

Statistical methods are the most widely used approaches for analyzing medical images. Statistical texture analysis methods define textures based on describing the spatial distribution of gray values through computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. Local features are defined by the combination of intensities at specific position relative to each point in the image. Extracted statistics are classified as first, second or higher order statistics according to the number of points which define the local features [22] [23].

The simplest statistics are the gray level first-order statistics. They describe the gray level histogram of an image. In first order statistics, image properties depend on individual pixel values. A group of statistical measures which describe the histograms can be calculated from the gray level values of individual pixels in an image, including mean gray level of pixels, variance and their standard deviation, and signal-to-noise ratio. A further characterization of the histogram includes skewness and kurtosis. Skewness is a measure of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.

In the current thesis work, we are concerned with second-order statistics, such as the co-occurrence matrix and the gray level difference, which describe the spatial relationships between image pixels. In second order statistics, the image properties depend on pixel pairs. Second order statistics is described in the following section. Higher order statistics, including run length measures and the autocorrelation function, can also be measured for texture analysis.

Second Order Statistical Measures

Second-order texture measures are mainly based on the joint gray level histogram of pairs of geometrically related image points.

Gray Level Co-occurrence Matrices

The Gray Level Co-occurrence Matrix (GLCM) method has become one of the most well-known and widely used texture measures [22]. Image texture is one of the important characteristics used in identifying the objects or the regions of interest in an image. The textural features based on gray level spatial dependencies have a general applicability in image classification. Textural features contain information about the spatial distribution of tonal variations within a band and all the texture information is contained in the GLCM. Hence all the textural features are extracted from the GLCM.

GLCM is also called Gray Level Dependency Matrix. It is defined as a two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship. GLCM of an image is computed using a displacement vector d, defined by its radius δ and orientation θ. Consider for example a 4x4 image represented by Figure 2.1 with four gray-tone values 0 through 3. A generalized co-occurrence for that image is shown in Figure 2.2 where #(i,j) stands for number of times gray tones i and j have been neighbors satisfying the condition stated by displacement vector d [27][44].

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

Figure 2.1: 4 x 4 image with four gray tone values from 0 to 3.

GRAYTONE

		0	1	2	3
	0	#(0,0)	#(0,1)	#(0,2)	#(0,3)
GRAYTONE	1	#(1,0)	#(1,1)	#(1,2)	#(1,3)
	2	#(2,0)	#(2,1)	#(2,2)	#(2,3)
	3	#(3,0)	#(3,1)	#(3,2)	#(3,3)

Figure 2.2: General form of any gray tone spatial dependence matrix for image with gray tone value 0-3 and # (i, j) stands for number of times (frequency) gray tones i and j have been neighbors.

4	2	1	0
2	4	0	0
1	0	6	1
0	0	1	2

(a) GLCM for δ=1 and θ= 0°

6	0	2	0
0	4	2	0
2	2	2	2
0	0	2	0

(c) GLCM for δ=1 and θ= 90°

4	1	0	0
1	2	2	0
0	2	4	1
0	0	1	0

(b) GLCM for δ=1 and θ= 45°

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

(d) GLCM for δ=1 and θ= 135°

Figure 2.3: a-d: GLCM for δ=1 and θ=0°, 45°, 90°, 135° respectively.

The four GLCMs for orientations equal to 0°, 45°, 90° and 135° and radius equal to 1 (counting symmetric co-occurrences) are shown in Figure 2.3.

These are symmetric matrices hence evaluation of either upper or lower triangle serves the purpose. Frequency normalization can be employed by dividing values in each cell by the total number of pixel pairs possible. Hence the normalization factor for 0° would be (Nx-1) x (Ny-1) where Nx represents the width and Ny represents the height of the image. The quantization level is an equally important consideration for determining the co-occurrence texture features. Also, neighboring co-occurrence matrix elements are highly correlated as they are measures of similar image qualities.

Choice of radius δ

Various research studies show δ values ranging from 1, 2 to 10. Applying large displacement value to a fine texture would yield a GLCM that does not capture detailed textural information. From the previous studies, it has been concluded that overall classification accuracies with $\delta = 1$, 2, 4, 8 are acceptable with the best results for $\delta = 1$ and 2 [27, 44]. This conclusion is justified, as a pixel is more likely to be correlated to other closely located pixel than the one located far away. Also, displacement value equal to the size of the texture element improves classification.

Choice of angle θ

Every pixel has eight neighboring pixels allowing eight choices for θ, which are 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°. However, taking into consideration the definition of GLCM, the co-occurring pairs obtained by choosing θ equal to 0° would be similar to those obtained by choosing θ equal to 180°. This concept extends to 45°, 90° and 135° as well. Hence, one has four choices to select the value of θ. Sometimes, when the image is isotropic, or directional information is not required, one can obtain isotropic GLCM by integration over all angles.

Gray level quantization

The number of gray levels Ng is an important factor in the computation of GLCM as the dimensions of matrix equals the number of gray levels. The fewer the number of gray levels, faster would be the computation. The crucial decision is to decide how many levels are needed to represent a texture successfully. The issue can be easily explained as the trade-off between computation time and information loss when choosing Ng. According to a previous study presented in [24], the greater Ng, the better the classification results.

GLCM is dimensioned to the number of gray levels Ng and stores the co-occurrence probabilities p (i,j) which assume numbers between 0 and 1. To determine the texture features, selected statistics are applied to each GLCM by iterating through the entire matrix. The textural features are based on statistics which summarize the relative frequency distribution which describes how often one gray tone will appear in a specified spatial relationship to another gray tone on the image.

Based on the appropriate GLCM parameters, we can derive first order statistics like: mean, variance, skewness, kurtosis and standard deviation from the images. These statistical features are concerned with properties of individual pixels. Where us the second order statistics of an image can be obtained from the GLCM which accounts for the spatial inter-dependency or co-occurrence of two pixels at specific relative positions. Co-occurrence matrices are calculated for a given distance d, gray level Ng and angles 0°, 45°, 90°, and 135°. For each matrix, we can get around fourteen features: Angular Second Moment (Energy), Contrast, Correlation, Sum of Squares or Variance, Inverse Difference Moment, Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance, Difference Entropy, Cluster Prominence and Cluster Shade.

2.5 Basics of a Web Page and its Components

2.5.1 Basic Softwares used to Design a Web Page

- **Front End** : PHP
- **Back End** : My SQL
- **Application Server** : XAMPP Server
- **Operating System** : Windows, Linux

Front End: PHP

PHP is a server-side, cross-platform, HTML-embedded scripting language. PHP (recursive acronym for PHP: Hypertext Preprocessor) is a widely-used open source general-purpose scripting language that is especially suited for web development and can be embedded into HTML [47].

Currently there are over half a million domains running PHP. Much of PHP's syntax is borrowed from C, Java and Pearl with a couple of unique PHP-specific features thrown in. The goal of the language is to allow web developers to write dynamically generated pages quickly. PHP eliminates the need for numerous small programs by allowing us to place simple scripts directly in our HTML files. It also makes it easier to manage large web sites by placing all components of a web page in a single HTML file.

PHP is mainly focused on server-side scripting language and it can be used on all major operating systems, including Linux, Microsoft Windows and Mac OS. PHP has also support for most of the web servers today. One of the strongest and most significant features in PHP is its support for a wide range of databases. Writing a database-enabled web page is incredibly simple using one of the database software specifically MySQL.

Back End: MySQL

MySQL is the world's most popular open source database software, with over 100 million copies of its software downloaded or distributed throughout its history. With its superior speed, reliability, and ease of use, MySQL has become the preferred choice because it eliminates the major problems associated with downtime, maintenance and administration for modern, online applications. MySQL is open source, very fast, reliable and flexible Database Management System. It provides a very high performance and it is multi-threaded and multi user Relational Database Management System. It is the world's most popular open source database system which is free and available on almost all platforms (works under UNIX, Windows and Mac OS). MySQL was primarily developed to manage large volumes of data at very high speed to overcome the problems of existed solutions. It can be used for variety of applications but it is mostly used for the web applications on the internet [48].

Application Server: XAMPP Server

XAMPP stands for Cross-Platform (X), Apache (A), MySQL (M), PHP (P) and Perl (P). It is a simple, lightweight Apache distribution that makes it extremely easy for developers to create a local web server for testing purposes. Everything you need to set up a web server – server application (Apache), database (MySQL), and scripting language (PHP) – is included in a simple extractable file. XAMPP is also cross-platform, which means it works equally well on Linux, Mac and Windows. Since most actual web server deployments use the same components as XAMPP, it makes transitioning from a local test server to a live server extremely easy as well. Web development using XAMPP is especially beginner friendly [25].

2.5.2 What is Included in XAMPP?

XAMPP has four primary components. These are:

1) **Apache:** Apache is the actual web server application that processes and delivers web content to a computer. Apache is the most popular web server online, powering nearly 54% of all websites [49].
2) **MySQL:** Every web application, howsoever simple or complicated, requires a database for storing collected data. MySQL, which is open source, is the world's most popular database management system. It powers everything from hobbyist websites to professional platforms like Word Press [48].
3) **PHP:** PHP stands for Hypertext Preprocessor. It is a server-side scripting language that powers some of the most popular websites in the world, including Word Press and Facebook. It is open source, relatively easy to learn, and works perfectly with MySQL, making it a popular choice for web developers [47].
4) **Perl**: Perl is a high-level, dynamic programming language used extensively in network programming, system admin, etc. Although less popular for web development purposes, Perl has a lot of niche applications [49].

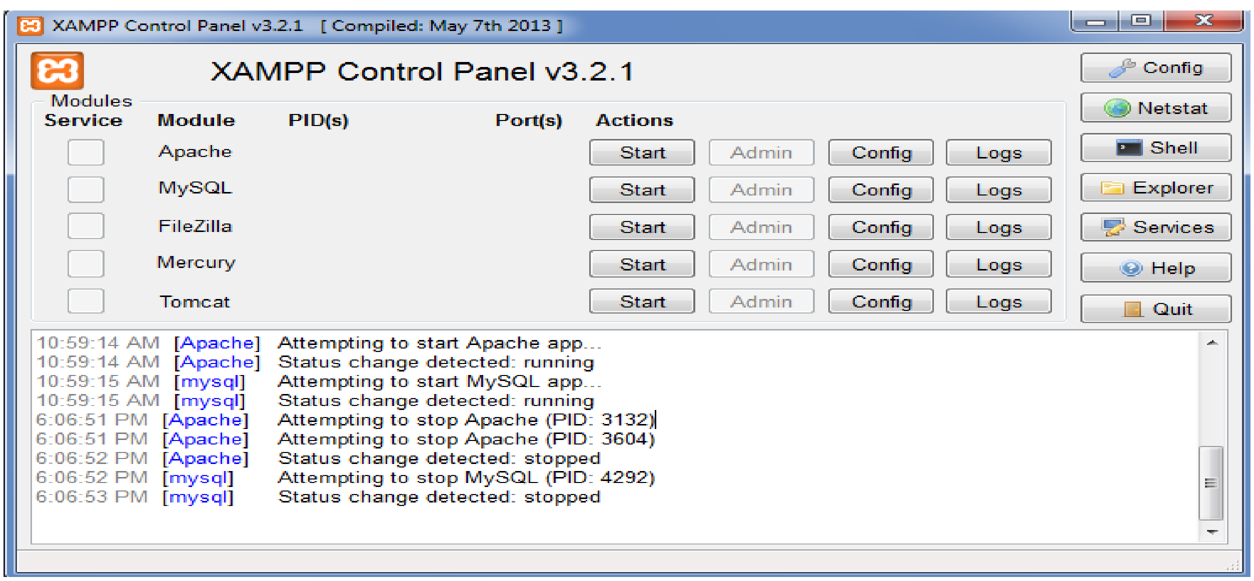

Figure 2.4: A snapshot of a XAMPP control panel V3.2.1.

Officially, XAMPP's designers intended it for use only as a development tool, to allow website designers and programmers to test their work on their own computers without any access to the internet. To make this as easy as possible, many important security features are disabled by default. In practice, however, XAMPP is sometimes used to actually serve web pages on the World Wide Web (WWW). A special tool is provided to password-protect the most important parts of the package. A snapshot of a XAMPP control panel version 3.2.1 is shown in Figure 2.4.

Chapter Three

3 Proposed Medical Image Storage and Distribution System

This chapter introduces the proposed medical image storage and distribution system that makes use of an automated system. It contains two major topics: a web page work environment and a method for medical image classification (image modality classification) based a tool developed using a digital image processing scheme with a complete GUI.

3.1 The Web Page Work Environment

The work environment for the current thesis project was chosen to be a notepad ++ V6.7.2 text editor as a console and XAMPP as a local host to connect Apache and MySQL database [45].

3.1.1 Algorithm and Short Description of the Web Page

The web design allows authenticated users (Receptionists /Nurse, Doctors, Physicians and Specialists) to exchange medical images and other data within and outside of the medical facilities. Users must first log into the system using authentication key (user name and password). For instance, if a physician wants to upload a patient's medical scans/images to the system database, he/she must first have privilege and sign into the system to have access. The web administrator registers users and gives privileges for those who are allowed to access the system. Registering to the system will grant the users to have an access; he/she can also upload, edit, comment, transfer and save in the system. The website, otherwise, will be available for a view by any user without requiring a registration. Access to basic information on the website such as list of public hospitals in Addis Ababa and the type of services they provide, useful links to other websites and the like does not require registration. A brief flowchart of the web page is depicted in Figure 3.1.

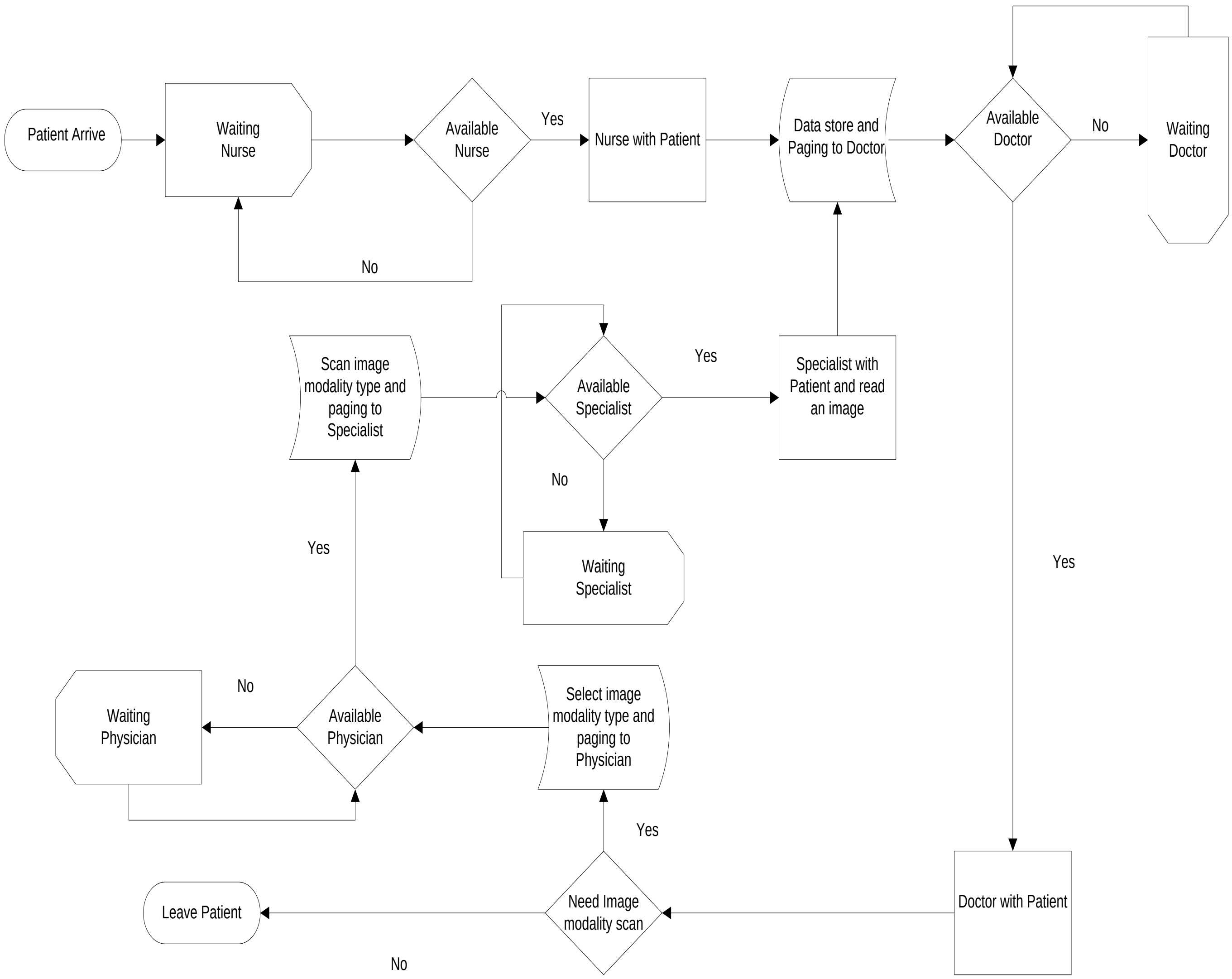

Figure 3.1 : A brief flowchart of the web page developed.

3.1.2 Implementation

The prototype was started by building a database in "phpMyAdmin" "localhost" server. In order to log in, XAMP control panel V3.2.1 has to be active/connected, which allow access to sign-in to "phpMyAdmin". Once the XAMP control panel V3.2.1 is successfully connected, it activates the Apache and MySQL server which are responsible for the storage and making use of data in the database. After connecting the Apache and MySQL server and the local host XAMPP control panel V3.2.1 successfully, we should browse the local host server (with URL "127.0.0.1/phpmyadmin" and log in as root, i.e. Username: "root", Password: ""). A snapshot of the XAMPP control panel while Apache and MySQL get activated is shown in Figure 3.2.

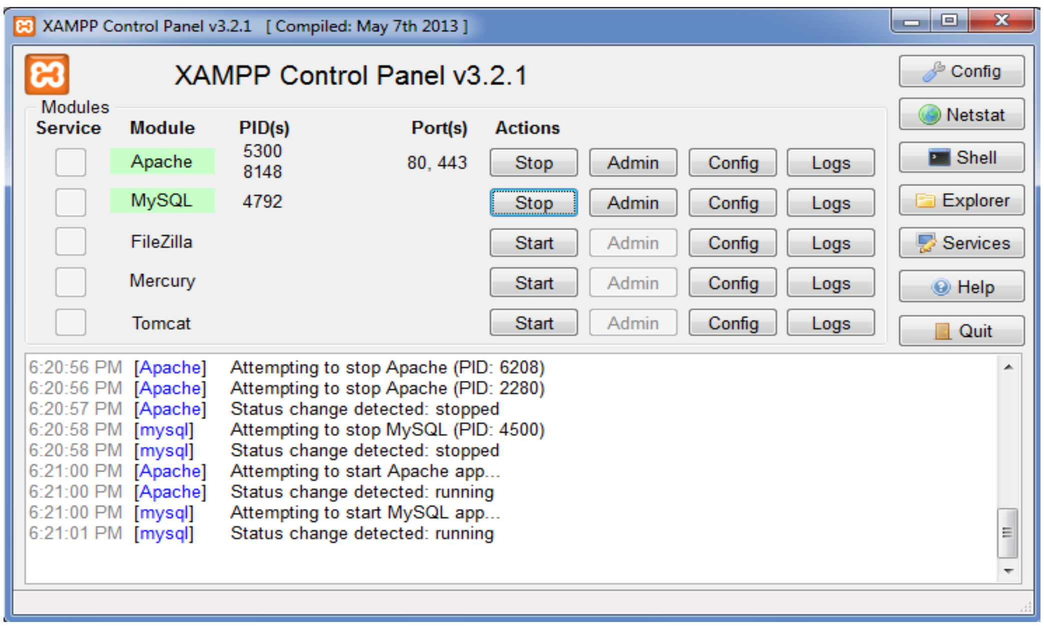

Figure 3.2: A snapshot of the XAMPP control panel while Apache and MySQL are being activated.

A relational root database named "databaseimage" was created containing several database tables for each specific application that are connected to each other. By definition a relational database is a database that has a collection of tables/Entities of data items, all of which are formally described and organized according to the relational model. Data in a single table/Entity represents a relation, from which the name of the database type comes. In typical solutions, tables/Entities may have additionally defined relationships with each other. In the relational model, each table/Entity schema must identify a column or group of columns, called the primary key, to uniquely identify each row. A relationship can then be established between each row in the table/Entity and a row in another table/Entity by creating a foreign key, a column or group of columns in one table/Entity that points to the primary key of another table/Entity. The relational model offers various levels of refinement of table organization and reorganization called database normalization. The database management system (DBMS) of a relational database is called an RDBMS, and is the software of a relational database [26].A brief explanation of Entity-Relationship Diagram database management system and their Attributes in Figure 3.3.

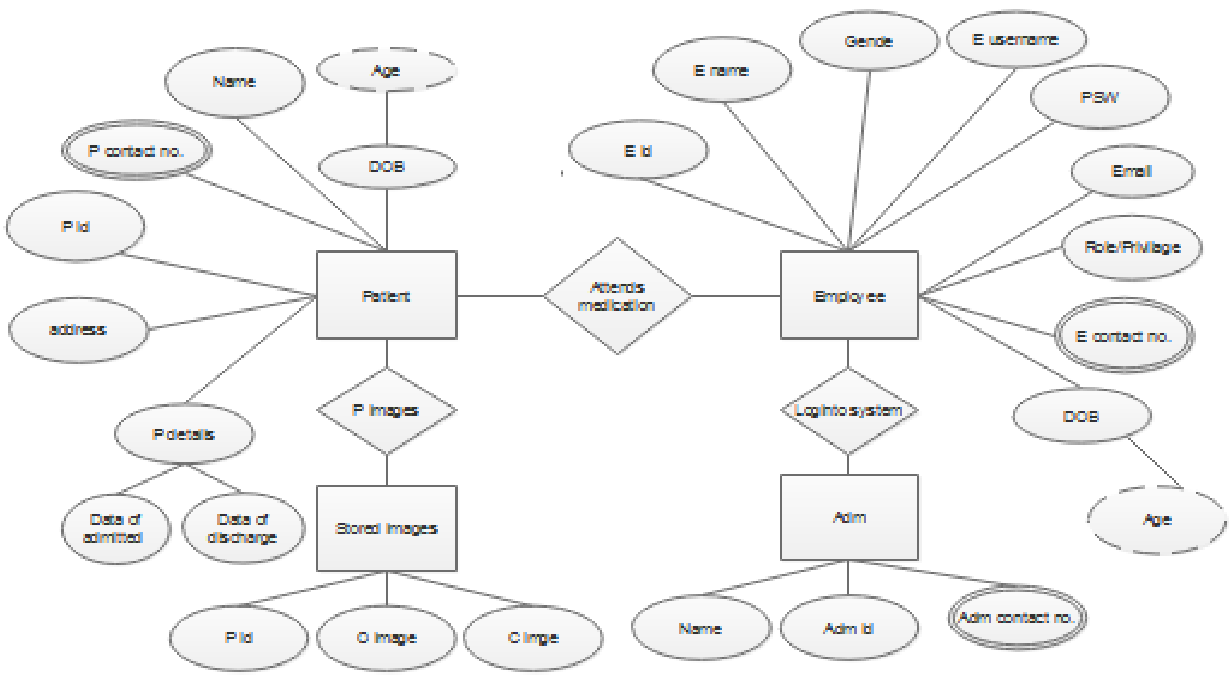

Figure 3.3: Entity-Relationship Diagram database management system and their Attributes.

The "databaseimage" relational database that was created contained three tables as per the model requirement (see also Figure 3.4):

1- Employee table

2- Patient table

3- Storedimage table which is related with primary key store table.

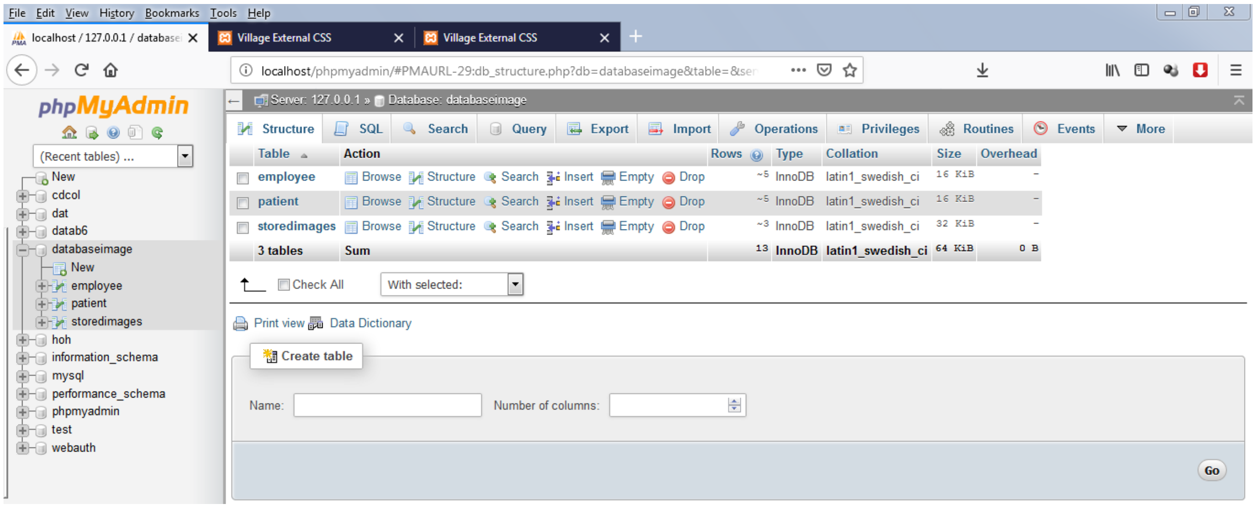

Figure 3.4: Databaseimage and its tables (employee, patient and storedimage).

The “employee” table was designed having the structural contents with ten attributes shown below in Figure 3.5.

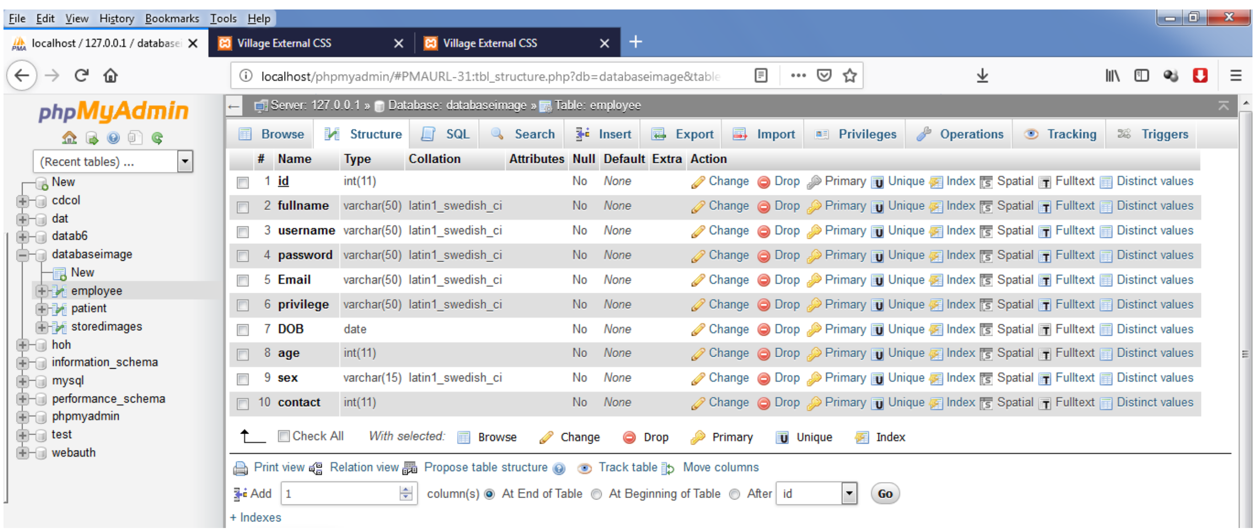

Figure 3.5: The “employ” table.

The “patient” table contained structural contents with fourteen attributes as shown below in Figure 3.6.

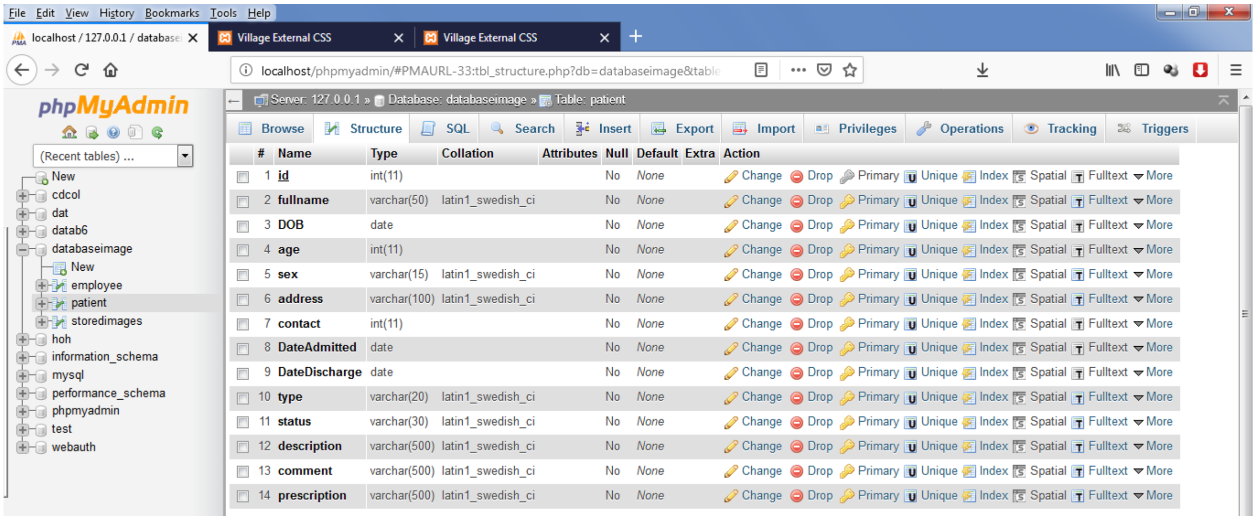

Figure 3.6: The “store” table.

Similarly, the “storedimage” table has three attributes as shown in the Figure 3.7 and this table is connected with primary key table store.

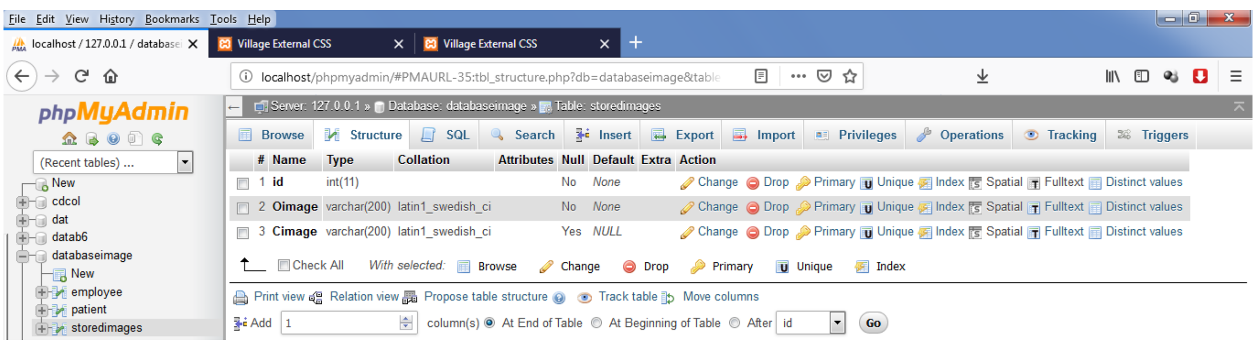

Figure 3.7: The “image” table.

Once the database system is created, users could login to it with their username and password to have access. Figure 3.7 shows the home page of the web based system (“MEDICAL IMAGE CENTER”) that has been developed where privileged users could login and have access to the system while any other user could browse to learn basics on public hospitals in Addis Ababa, their major services and other pertinent information. More detailed views of the system could be seen on Appendix A.

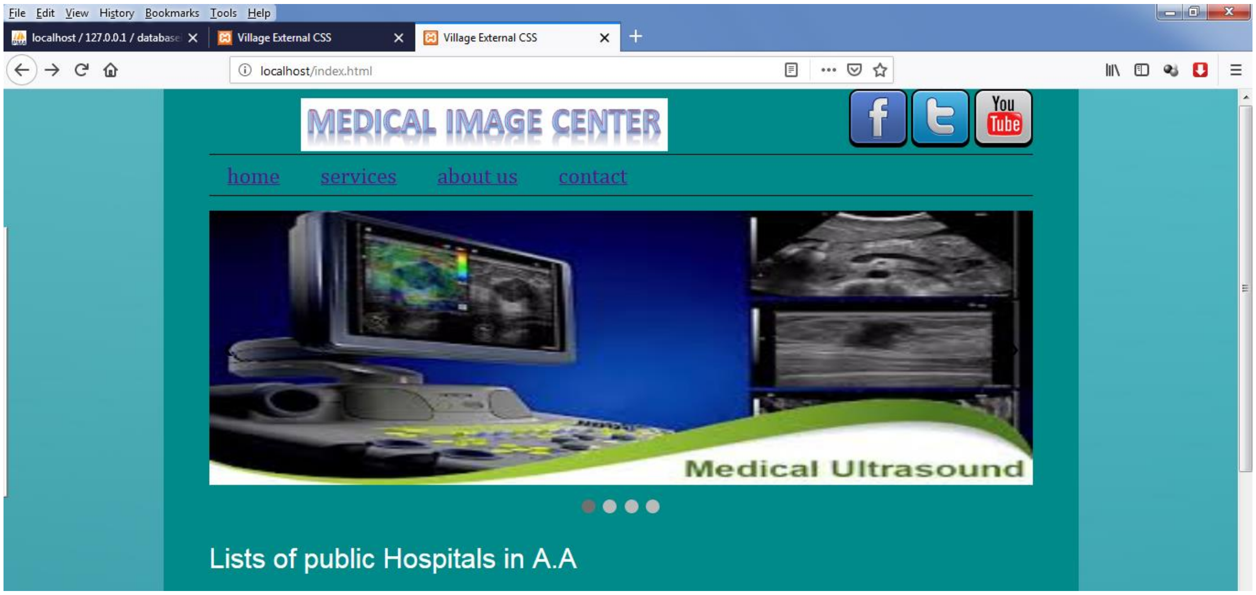

Figure 3.8: Home page of the designed medical images storage and distribution system.

3.2 Proposed Texture based Medical Image Classification Scheme

The second major part of this thesis work after the web design was to develop an image modality classification scheme that permits automatic recognition and transmission of the image/s to the party who has to do the image based diagnosis, for example. The scheme was developed based on texture analysis of digital medical images with various modalities. Figure 3.8 presents the block diagram of the steps followed. It includes image acquisition (data collection), image pre–processing, feature extraction, feature selection and a final classification scheme. The assumption was the images are all monochromatic (grayscale) and still images (not videos) and no color images are assumed even though the proposed method could be extended to accommodate colors.

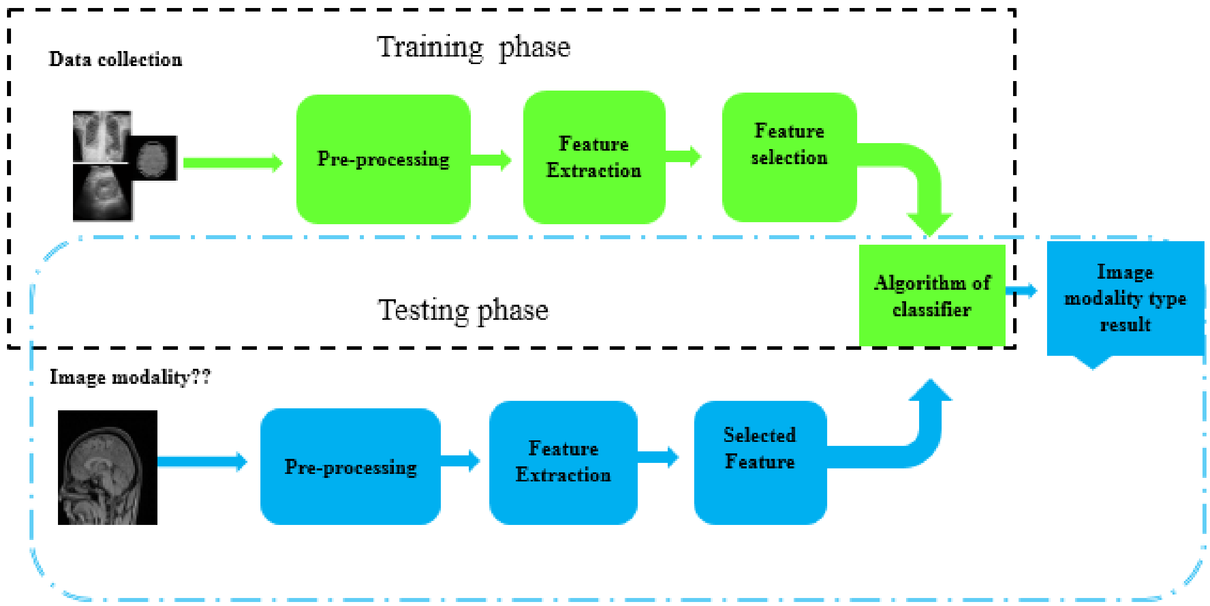

Figure 3.9: Block diagram of the proposed medical image classification scheme.

Data Collection

All the medical images in the current work were collected from Black Lion Hospital and St. Paul's Hospital, the two largest hospitals in Addis Ababa, Ethiopia. Experiments were conducted on 340 medical images having different sizes. Images include various anatomical structures and image orientations. Three imaging modalities were considered: US (32), MRI (124) and CT (184) and a database was created using these data sets. All images were monochromes (grayscales) and came in DICOM standard format. Note that the entire image classification scheme has been implemented on Matlab (Version R2013a). Typical size of the US images was 614x816, CT was 512x512 and MRI 256x256. Before further analysis, all images were brought into a common resolution (256x256) aiming a more effective feature extraction reducing the computational burden in the meantime.

3.2.1 Image Pre-processing

Usually images that are obtained may not be straight away suitable for identification and classification purposes because of certain factors, such as noise, lighting variations, poor resolutions, unwanted background and the like. The main goal of the pre-processing step is to improve the image quality to make it ready for further processing by removing or reducing the unrelated parts in the background of the medical images and optimal preparation of the data for post processing. In order to balance the trade-off between effective image pre-processing and the resulting loss of information, care must be taken when choosing a pre-processing scheme. In this thesis work, the median filter has been utilized as a pre-processing tool to get rid of some of the artifacts that come with the medical images before further feature extraction is carried out. Figure 3.9 presents US, CT and MRI images of human subjects and their appearance after the median filter is applied. Even though the visual appearance of the images before and after the application of the median filter is hardly different, the median filter removes certain artifacts that come with the images [52].

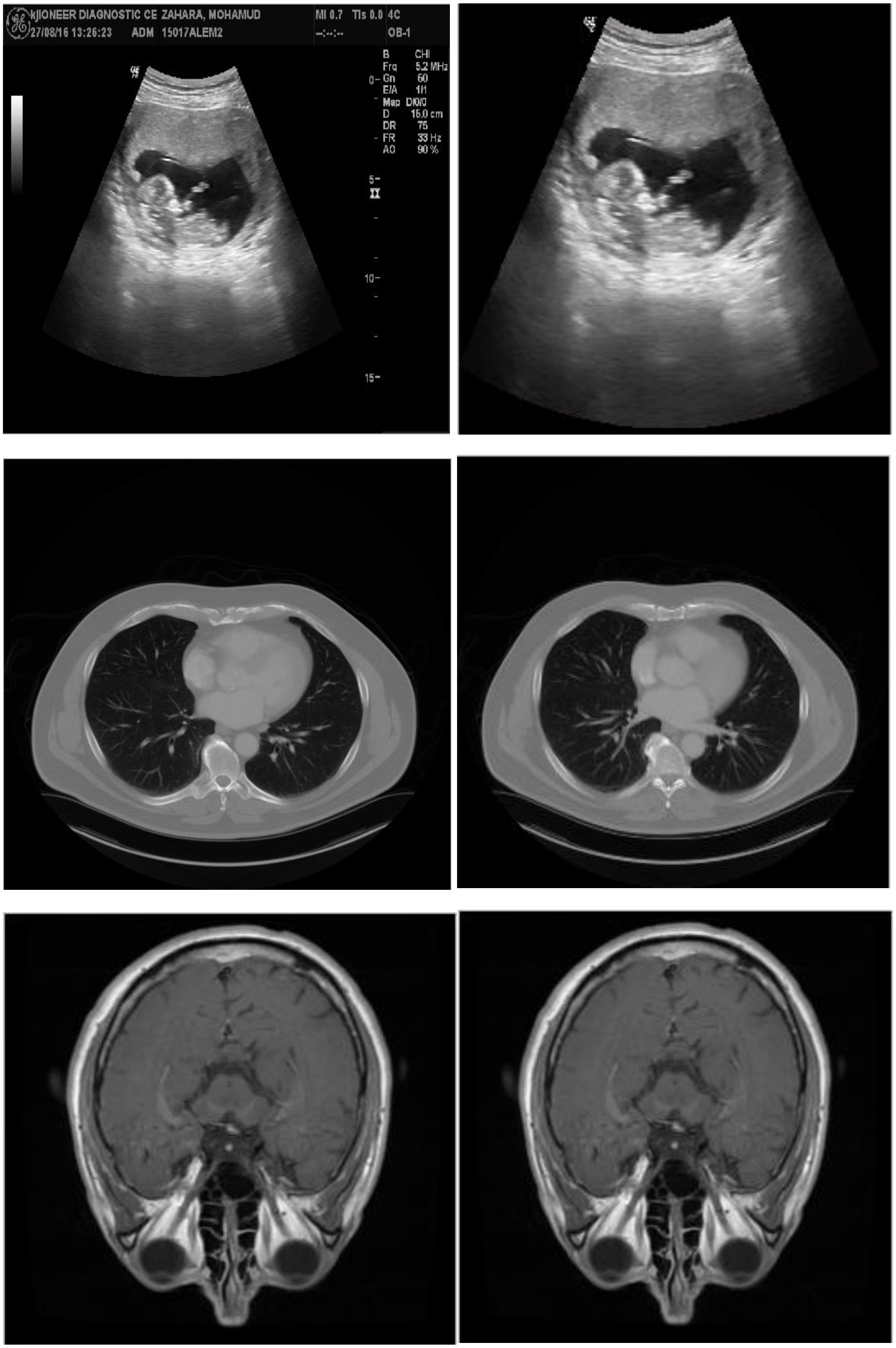

Figure 3.10: Left panel: Top-original US image (614x816), Middle-original CT image (512x512) and Bottom-original MRI image (256x256): Right panel: the respective pre-processed images using the median filter of size 3x3 after dimension reduction to 256.

3.2.2 Image Feature Extraction

Feature extraction is most critical because the particular features made available for discrimination directly influence the efficacy of the classification task. The end result of the extraction task is a set of features, commonly called a feature vector, which constitutes a representation of the image. Features such as shape, texture, color, etc. are used to describe the content of images. In this study features derived from the GLCM (which was discussed in the previous chapter and revisited below) are used.

GLCM Textural Features

Image textures could be computed in various ways and statistical approaches are widely used methods in this regard. One such an approach makes use of image histograms, which is concerned about the distribution of image intensities. Measures of textures computed using histograms suffer from the limitation that they carry no information regarding the relative position of the pixels with respect to each other. One way to bring this type of information into the texture analysis process is to consider not only the distribution of the intensities but also the positions of pixels with equal or nearly equal intensity values. One such type of feature extraction procedure makes use of the GLCM [46].

The GLCM seems to be a well-known statistical technique for feature extraction. The GLCM is a tabulation of how often different combinations of pixel gray levels could occur in an image. The goal is to assign an unknown sample image to one of a set of known texture classes. Textural features can be scalar numbers, discrete histograms or empirical distributions [27] [28].

The GLCM texture method is a way of extracting second order statistical texture features from gray-level images. The GLCM is a matrix where the number of rows and columns is equal to the number of quantized gray levels, Ng, in the image. The matrix element p(i, j) is the set of second order statistical probability values for changes between gray levels i and j at a particular displacement distance (d) and angle (θ). To illustrate this method, suppose an image to be analyzed has Nx columns and Ny rows. The gray level appearing at each pixel is quantized to Ng levels.

Let $L_x = \{1, 2, \ldots, N_x\}$ be the columns,

$L_y = \{1, 2, \ldots, N_y\}$ be the rows, and

$G = \{0, 1, \ldots, N_g - 1\}$ be the set of Ng quantized gray levels.

The set $L_y \times L_x$ is set of pixels of an image ordered by their row and column designations. The image I can be represented as a function that assigns some gray level in G to each pixel or pair of coordinates in $L_y \times L_x$; i.e. $I: L_y \times L_x \rightarrow G$. The texture-context information is specified by the matrix of a relative frequency P(i, j). P(i, j) represents the number of occurrences of gray levels i and j within the window, at a certain (d, θ) pair. We use the following notation: Ng is the number of gray levels used, μ is the mean value of P, μx, μy, σx and σy are the means and standard deviations of Px and Py respectively. Px(i) and Py(j) are the entries in the marginal-probability matrix obtained by summing the rows and column of P(i,j) as shown in the equations below:

$$P_x(i) = \sum_{j=0}^{Ng-1} P(i,j)$$

$$P_y(j) = \sum_{i=0}^{Ng-1} P(i,j)$$

The means for the columns and rows of the matrix are, respectively, defined as

$$\mu_x = \sum_{i=0}^{Ng-1} i \sum_{j=0}^{Ng-1} P(i,j) = \sum_{i=0}^{Ng-1} i\, P_x(i)$$

$$\mu_y = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} j\, p(i,j) = \sum_{j=0}^{Ng-1} j\ P_y(j)$$

The variance for the columns and rows of the matrix are, respectively, defined as

$$\sigma_x^2 = \sum_{i=0}^{Ng-1} (i - \mu_x)^2 \sum_{j=0}^{Ng-1} P(i,j) = \sum_{i=0}^{Ng-1} (P_x(i) - \mu_x(i))^2$$

$$\sigma_y^2 = \sum_{j=0}^{Ng-1} (j - \mu_y)^2 \sum_{i=0}^{Ng-1} P(i,j) = \sum_{j=0}^{Ng-1} (P_y(j) - \mu_y(j))^2$$

$$P_{x+y}(k) = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P(i,j) \qquad i + j = k$$

For k = 0, 1, …, 2(Ng - 1)

$$P_{x-y}(k) = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P(i,j) \qquad |i - j| = k$$

For k = 0, 1, …, Ng - 1

Based on the above definitions the textural features are defined and six texture features are computed in this thesis for use in accurate classification of the images under consideration. These are all Haralick features [29]. Haralick actually computed many more features but some of the features were correlated to each other. The six computed here are assumed to be adequate for classification of the different imaging modalities considered.

Let P(i, j) be the (i, j)th entry in a normalized GLCM. Then the six features are computed using the following formulae:

1. **Autocorrelation** "U" is defined combination pairs as one point or one element, and describes the correlation of this point between other combination pair series.

$$\text{Autocorrelation} = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} (ij)P(i,j) \tag{3.1}$$

2. **Cluster Shade** Cluster shade is a measure of the skewness of the matrix and is believed to gauge the perceptual concepts of uniformity. A new "$i + j$" image is created, having a range of integer intensities from 0 to $2(N_g - 1)$. The u_{i+j} value is computed and stored for the first neighborhood of the image, and is subsequently updated as the neighborhood is moved by one pixel. When the cluster shade is high, the image is asymmetric.

$$\text{Cluster shade} = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \left(i + j - \mu_x - \mu_y\right)^3 P(i,j) \tag{3.2}$$

3. **Cluster Prominence** is also a measure of asymmetry. When the cluster prominence value is high, the image is less symmetric. In addition, when cluster prominence value is low, there is a peak in the GLCM matrix around the mean values. For an image, a low cluster prominence value indicates small variation in gray-scale.

$$\text{Cluster prominence} = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \left(i + j - \mu_x - \mu_y\right)^4 P(i,j) \tag{3.3}$$

4. **Sum of Squares (Variance)** It refers to the gray-level variability of the pixel pairs and is a measurement of heterogeneity. Variance increases when the gray-scale values differ from their means.

$$\text{Variance} = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} (i - \mu_x)^2 P(i,j) + \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \left(j - \mu_y\right)^2 P(i,j) \tag{3.4}$$

5. **Sum Average** Measures the mean of the gray level sum distribution of the image.

$$\text{Sum average} = \sum_{k=0}^{2(Ng-1)} iP_{x+y}(i) \tag{3.5}$$

6. **Sum of Variance** Measures the dispersion (with regard to the mean) of the gray level sum distribution of the image.

$$\text{Sum of variance} = \sum_{k=0}^{2(Ng-1)} \left(i - \left[\sum_{k=0}^{2(Ng-1)} iP_{x+y}(i)\right]\right)^2 \tag{3.6}$$

3.3 Feature Selection

In this thesis work, best features were selected based on their efficacy in accurately classifying medical images to the correct image modality type. There are many strategies available for such feature selection. However due to its fast and high level of accuracy in selecting the right feature to obtain the best achievable performance in classification, similarity and dissimilarity measurement technique has been used in the current study to quantify the classification accuracy. The similarity and dissimilarity measurement technique calculates the distance between any two group data as described in the following subsection.

3.4 Similarity and Dissimilarity Measures

Considering two sets of measurements X = {x1, x2,… xn} and Y = {y1, y2,... yn}, the similarity and dissimilarity between the two sets is a measure of quantifiable dependency or independency between the sets. Measurements of any two set points or phenomena can be represented by vectors X and Y with length of both vectors assumed to be ‘n’. The distance measures are also called as similarity measures or dissimilarity measures. Distances are measured using distance functions, which follow triangle inequality. The triangle inequality [31] states that for any triangle, the sum of the lengths of any two sides must be greater than the length of the remaining side as shown in Eq.3.7. Figure 3.10 shows a triangle where the lengths of the sides are given as X, Y and Z and should obey triangle inequality.

$$X + Y > Z \tag{3.7}$$

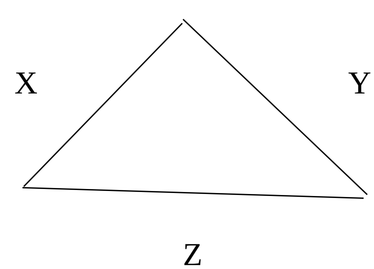

Figure 3.11: Triangle inequality.

There are a lot of applications and usages of similarity or dissimilarity measures like it helps in distinguishing one object from another; the objects can be grouped on the basis of similarity and dissimilarity; a new object can be classified into a group based on the behavior as per the similarity or dissimilarity measures; thus further actions and decisions can be planned based on the prediction and structural information of the data. In this study, three different similarity and dissimilarity measures, which are described below, are considered.

3.4.1 Bray-Curtis

The Bray-Curtis dissimilarity measure is named after J. R. Bray and J. T. Curtis [32]. It is a statistical approach, which is used for quantifying the compositional dissimilarity among two objects of different types. This quantitative approach is based on the number of counts at each object. It is a non-metric dissimilarity approach which is used for many applications and results are robust and reliable. Bray-Curtis dissimilarity is a modified way of the Manhattan dissimilarity measure, where the total summation of the differences among the variables is standardized with respect to the total summation of the object variables. Equation 3.10 shows the general equation of Bray-Curtis dissimilarity [32].

$$BC = \frac{\sum_{i,j=1}^{n} \left| X_i - Y_j \right|}{\sum_{i,j=1}^{n} \left| X_i + Y_j \right|} \tag{3.8}$$

The outcomes of Bray-Curtis dissimilarity range from zero to unity, where zero defines that the two objects have similar compositions and represent exactly same coordinates and unity defines that the two objects do not have any similarity. If both objects are at zero coordinates, then Bray-Curtis dissimilarity measure is not defined [33]. The Bray-Curtis dissimilarity is not a distance metric as it does not satisfy the triangle inequality.

3.4.2 Canberra

Canberra distance was introduced by Lance and Williams in 1966 and it was later refined in 1967 [34] [35]. It is a numerical measurement of the distance between two points in a vector space. It has been used for various purposes like a metric for comparison of ranked lists and also in computer security by using intrusion detection [36] [37]. It is similar to Manhattan distance metric and it is mathematically defined as the absolute difference among the variables of the objects concerned with respect to the summation of the absolute value of the variables before it is summed. Equation 3.9 gives the formula for the Canberra distance [37].

$$Can = \sum_{i,j=1}^{n} \frac{\left|X_i - Y_j\right|}{|X_i| + \left|Y_j\right|} \tag{3.9}$$

3.4.3 Cosine

Cosine similarity measure calculates the Cosine of the angle between two vectors present in an inner product space. The value of the Cosine of the angle ranges from -1 to 1. The Cosine measure at zero degree angle is 1 and it decreases at any angle other than zero. Thus, vectors of similar orientation have a Cosine similarity of 1, vectors at a right angle have a Cosine similarity of 0 and vectors which are exactly opposite to each other have a Cosine similarity of -1. But, generally Cosine similarity is used in positive space, so the values are bounded from 0 to 1. Cosine similarity is used for high dimensional positive spaces. Cosine similarity gives a measurement of similarity about two vectors with respect to each other [38].

$$Cosine = \frac{\sum_{i,j=1}^{n} X_i * Y_j}{\sqrt[2]{\sum_{i=1}^{n} X_i^2} * \sqrt[2]{\sum_{j=1}^{n} Y_j^2}} \tag{3.10}$$

This technique is used for the calculation of cohesion among the clusters in the field of data mining [39]. Equation 3.10 shows the mathematical formula for Cosine similarity [40].

3.5 Classification Model

After the completion of features selection, the next step is classification of medical images to their modality types. The main steps involved in medical images classification model are three. Those are features extraction from images, algorithm development and final classification. Figure 3.11 shows feature vectors arranged vertically. F_V represents feature vectors that are $F_1v_{...}$ F_1v_n, F_2v_1… F_2v_n, F_3v_1…F_3v_n, F_4v_1… F_4v_n, F_5v_1… F_5v_n and F_6v_1…F_6v_n. Accordingly, the six features computed in the current study namely Autocorrelation, Cluster shade, Cluster prominence, Sum of squares (variance), Sum average and Sum variance were arranged respectively.

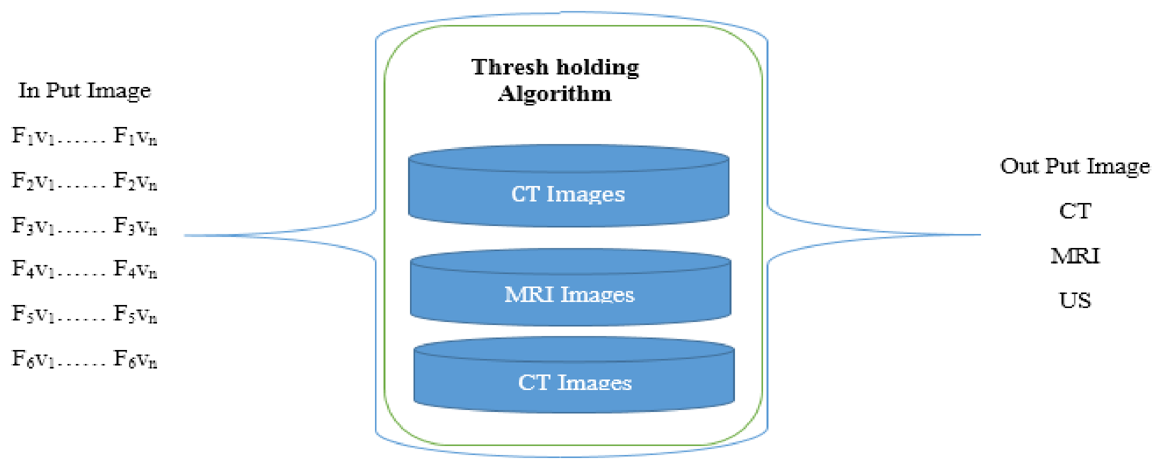

Figure 3.12: Graphical representation of input features and the output image modality.

Three image modality types are assumed in this thesis even though in principle the classification scheme developed could be extended to handle more number of imaging modalities.

3.6 The MATLAB Graphical User Interface

MATLAB is a software package for high-performance numerical computation and visualization. It stands for matrix laboratory, which indicates that most of the commands work with matrices. Developed by The Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++ and FORTRAN. It integrates computation, visualization and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation [41].

A graphical user interface (GUI) is a graphical display that contains devices, or components, that enable a user to perform interactive tasks. To perform these tasks, the user of the GUI does not have to create a script or type commands at the command line. Often, the user does not have to know the details of the task at hand. In MATLAB toolbox, a GUI can also display data in tabular form or as plots, and can group related components.

Each component, and the GUI itself, are associated with one or more user-written routines known as callbacks. The execution of each callback is triggered by a particular user action such as a button push, mouse click, selection of a menu item, or the cursor passing over a component. The creator of the GUI provides these callbacks. This kind of programming is often referred to as event-driven programming [43].

One can build MATLAB GUIs in two ways:

- Use GUIDE (GUI Development Environment), an interactive GUI construction kit, or
- Create code files that generate GUIs as functions or scripts (programmatic GUI construction).

The first approach starts with a figure that we populate with components from within a graphic layout editor. GUIDE creates an associated code file containing callbacks for the GUI and its components. GUIDE saves both the figure (as a .fig file) and the code file. Opening either one also opens the other to run the GUI. In the second approach, programmatic GUI-building approach, we create a code file that defines all component properties and behaviors; when a user executes the file, it creates a figure, populates it with components, and handles user interactions.

As a result, the code files of the two approaches look different. Programmatic GUI files are generally longer, because they explicitly define every property of the figure and its controls, as well as the callbacks. GUIDE GUIs define most of the properties within the figure itself [42]. They store the definitions in its .fig file rather than in its code file. The code file contains callbacks and other functions that initialize the GUI when it opens (see Appendix B).

Chapter Four

4 Results and Discussions

The present study was conducted with the aim of classifying medical images of three imaging modality types based on features extracted from them following the image processing scheme developed in the previous chapter.

4.1 Dataset

All the medical images in the current work were collected from Black Lion Hospital and St. Paul's Hospital, the two largest hospitals in Addis Ababa, Ethiopia. Experiments were conducted on 340 medical images having different sizes containing 32 Ultrasound (US), 124 Magnetic Resonance (MRI) and 184 Computed Tomography (CT) images. From these images, 234 images (22 US, 83 MRI and 129 CT) were used for training and 106 images (10 US, 41 MRI and 55 CT) for testing purposes.

4.2 Experimental Results and Discussion

The medical image classification algorithm developed in this thesis has been implemented in Matlab version R2013a.

4.2.1 Texture Features

The six texture features that were computed in the previous chapter were compared against each other for their ability to correctly classify the medical images into their respective imaging modality types. Before computing the six features, GLCM was computed for each image using the following parameters: gray level (L=8), radius (d=1) and four directions (0^0, 45^0, 90^0 and 135^0). Figures 4.1 through 4.6 present the raw values computed for the six features (Autocorrelation, Cluster prominence, Cluster shade, Sum of square (variance), Sum average and Sum variance). The best feature is then selected once distance matrices are computed, i.e. the distance between different classes (modalities) must be computed to pick the best texture feature.

Ideally we are looking for the feature that gives rise to maximum between class distance and minimum within class separation where class in our context refers to a given imaging modality.

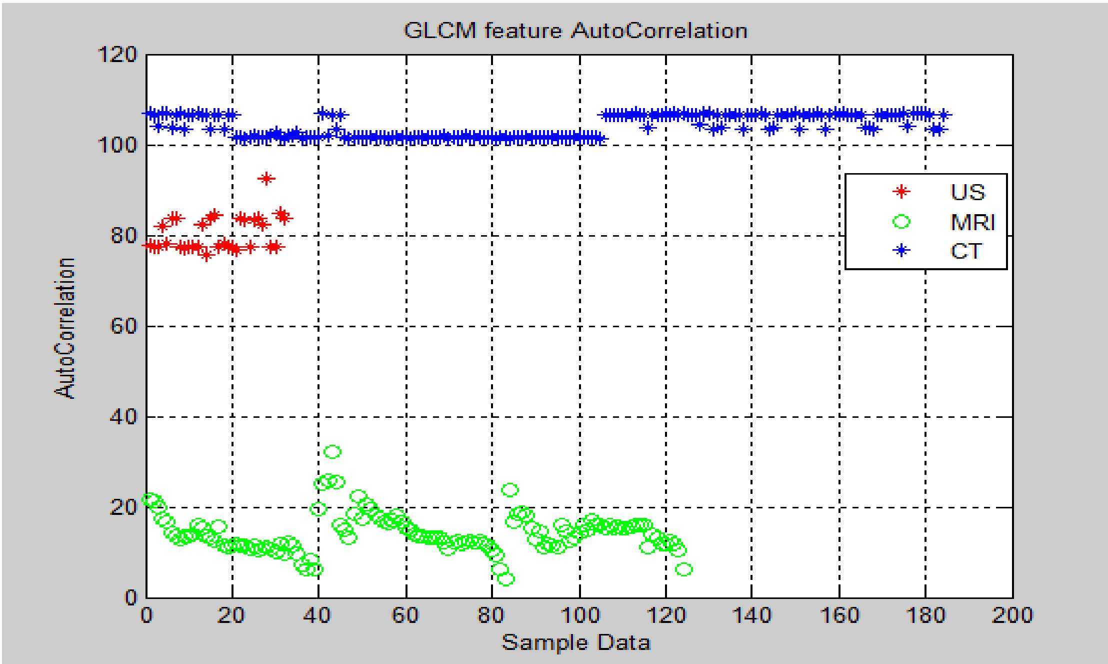

Figure 4.1: Medical image modality profile samples for Autocorrelation feature: top blue color (CT), middle red color (US) and bottom green color (MRI) sample images.

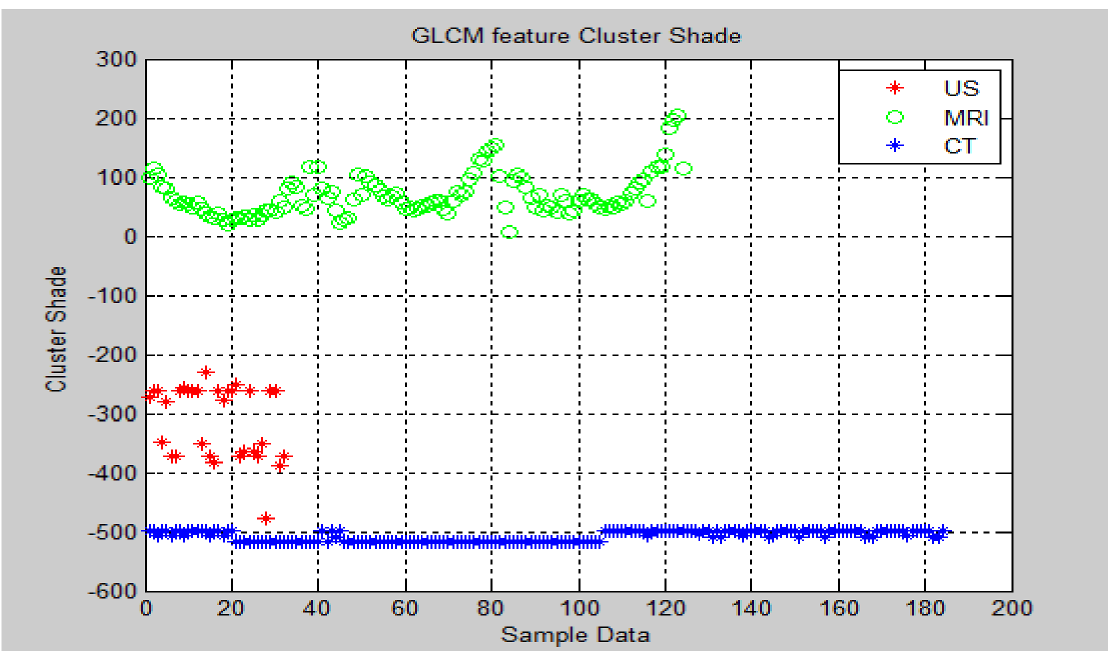

Figure 4.2: Medical image modality profile samples for cluster shade feature: top green color (MRI), middle red color (US) and bottom blue color (CT) sample images.

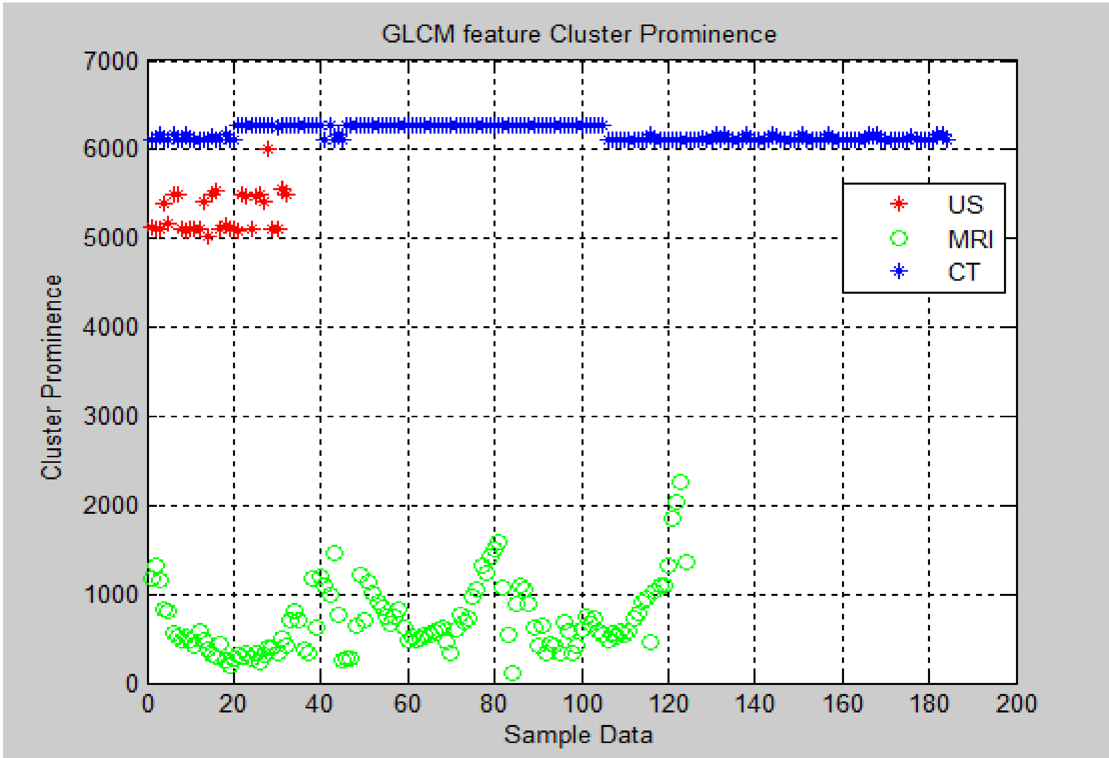

Figure 4.3: Medical image modality profile samples for cluster prominence feature: top blue color (CT), middle red color (US) and bottom green color (MRI) sample images.

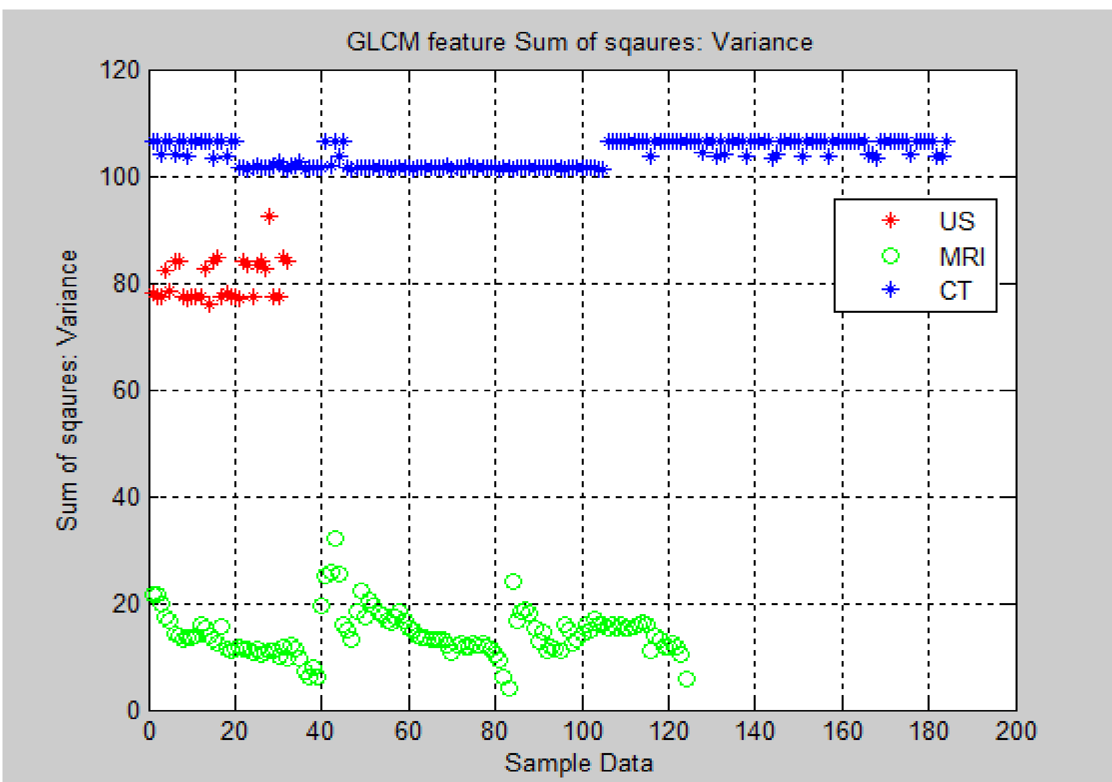

Figure 4.4: Medical image modality profile samples for sum of squares (variance): top blue color (CT), middle red color (US) and bottom green color (MRI) sample images.

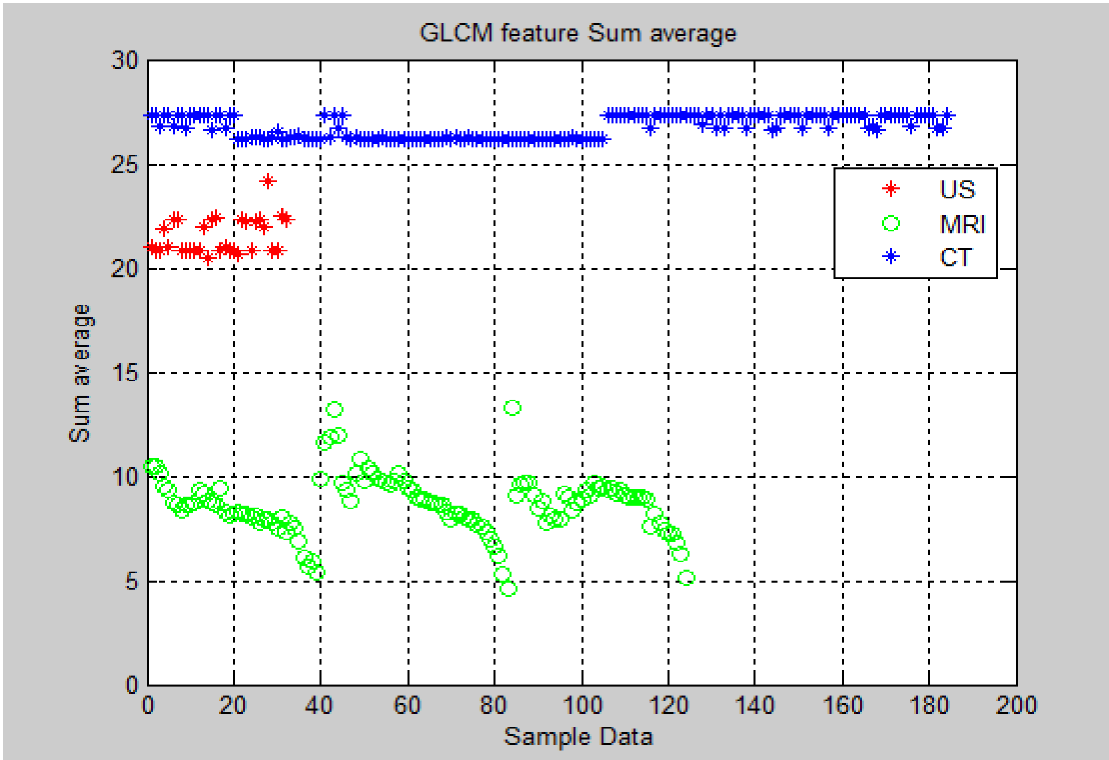

Figure 4.5: Medical image modality profile samples for sum of average feature: top blue color (CT), middle red color (US) and bottom green color (MRI) sample images.

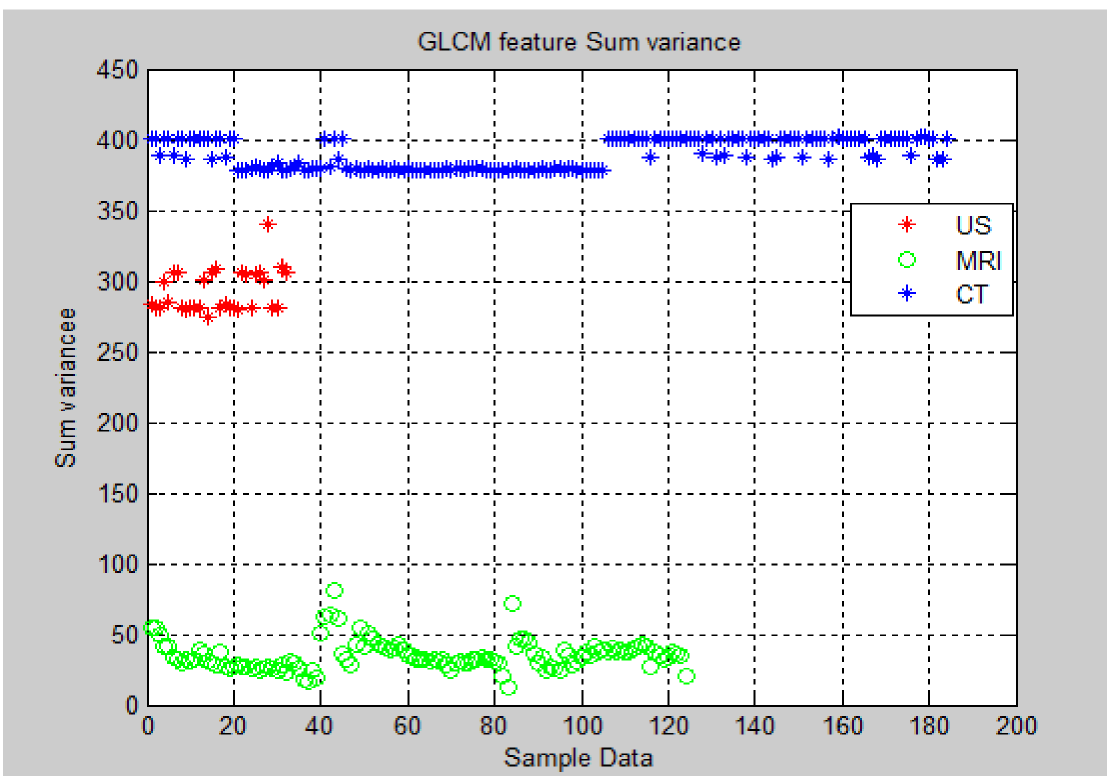

Figure 4.6: Medical image modality profile samples for sum of variance feature: top blue color (CT), middle red color (US) and bottom green color (MRI) sample images.

4.2.2 Classification Algorithm

Looking at the values of the features computed above, a simple thresholding (Min-Max) algorithm was developed to classify the images under consideration into their respective modalities. The Min-Max of each texture feature computed considering all 234 imaging samples (129 CT, 83 MRI and 22 US) is shown in Table 4.1. It was preferred to present those texture features that assume positive values and hence cluster shade feature was excluded as it assumes both positive and negative values. Different features assume different min and max value while their magnitude is substantially different from feature to feature.

Texture Features	**Image Modality Types**					
	CT		**MRI**		**US**	
	min	max	min	max	min	max
Autocorrelation	202.9	213.4	7.9	64	151.2	184.9
Cluster Prominence	12213	12565	239.3	4530.8	10059	12028
Sum of squares (Variance)	202.9	213.2	7.8	64.1	151.5	185.2
Sum Average	52.4	54.7	9.3	26.6	40.9	48.4
Sum Variance	756.6	802.8	26.2	162.5	549.4	680.9

Table 4-1: Computed texture features and their min and max values for different imaging modality types.

In order to finally pick the best feature that does its purpose, we use the three similarity and dissimilarity measures were computed based on formulae presented in the previous chapter. Table 4.2 presents a summary of the computed distances per each imaging modality pair (a total of three pairs). Overall, cluster prominence and sum variance offered the best classification results with respect to all three distance matrices: Bray-Curtis, Canberra and Cosine. While sum variance performed slightly better than cluster prominence in most cases. Particularly, in differentiating CT and US images, sum variance feature outperformed all the other features in terms of the three computed distance matrices. As discussed in the previous chapter, both bray-curtis and cosine dissimilarity measures are bounded between 0 and 1 while Canberra distance could assume any positive value and the Canberra distance appears to be a better tool for quantifying the classification accuracies offered by the computed texture features. Particularly when the number of distinct imaging modalities we want to classify increases, the Canberra distance is assumed to be more informative than the rest, So we select the sum variance texture feature to develop an algorithm to classify image modality types.

Texture Features	CT - MRI			MRI - US			CT- US		
	Bray-Curtis	Canberra	Cosine	Bray-Curtis	Canberra	Cosine	Bray-Curtis	Canberra	Cosine
Autocorrelation	0.744	71.545	0.97028	0.683	65.768	0.96798	0.123	11.810	0.99852
Cluster Prominence	0.819	78.942	0.91364	0.790	76.200	0.91154	0.082	7.953	0.99914
Sum of Squares (Variance)	0.743	71.486	0.97030	0.683	65.752	0.96801	0.122	11.712	0.99854
Sum Average	0.489	47.074	0.99409	0.406	39.087	0.99301	0.104	9.979	0.99898
Sum Variance	0.827	79.449	0.96528	0.779	74.841	0.96296	0.135	12.982	0.99826

Table 4-2: Three distance matrices computed using the texture features per each imaging modality pair (a total of three pairs).

4.3 Experimental Results

All 106 images were correctly classified into their respective imaging modality types with 100% accuracy by all five features (excluding one that assumes negative values). The classification algorithm acts as a feature database that contains the predefined ranges (the feature min-max values) and assigns a given input image into one of the three imaging modality types. Table 4.3 presents the overall confusion matrix indicating a perfect classification by the algorithm.

Image Modality Types	CT	MRI	US	Total
CT	55	0	0	100%
MRI	0	41	0	100%
US	0	0	10	100%
Total	100%	100%	100%	100%

Table 4-3: The Confusion matrix developed after the application of the proposed algorithm on the medical images.

Two snapshots are depicted in Figures 4.7 and 4.8 showing the developed GUI while features are being computed and the inputted images are classified to their respective imaging modality types.

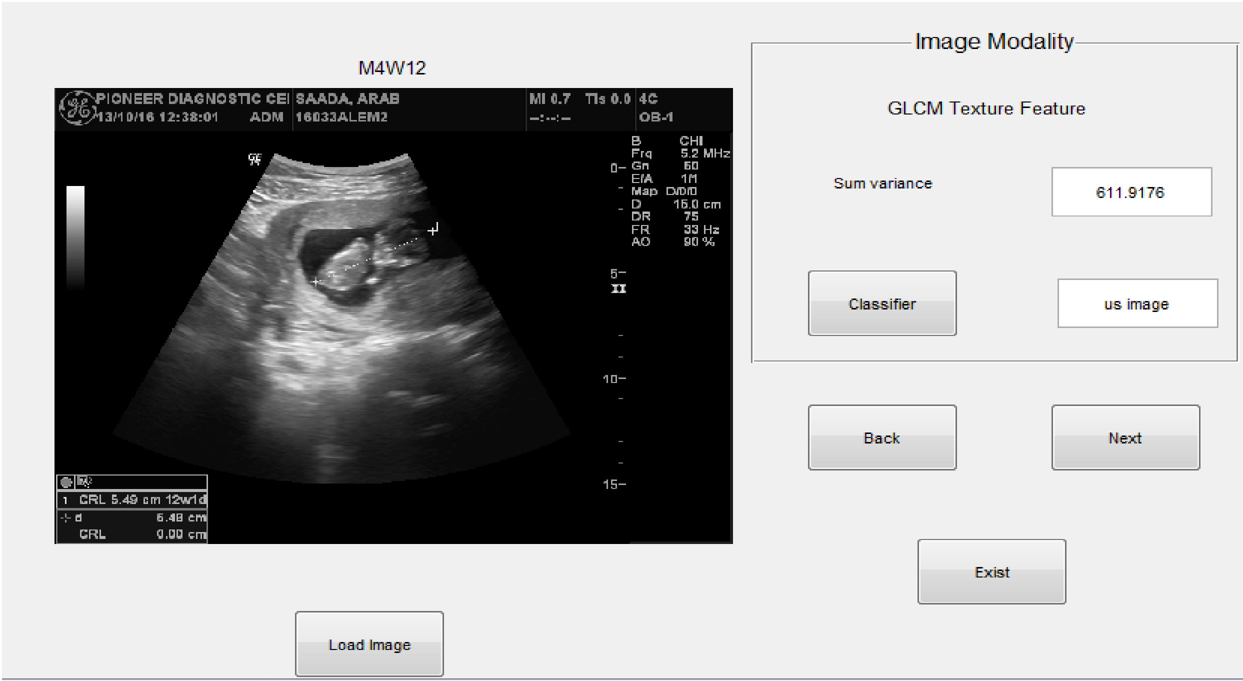

Figure 4.7: GUI snap shot for US image classification.

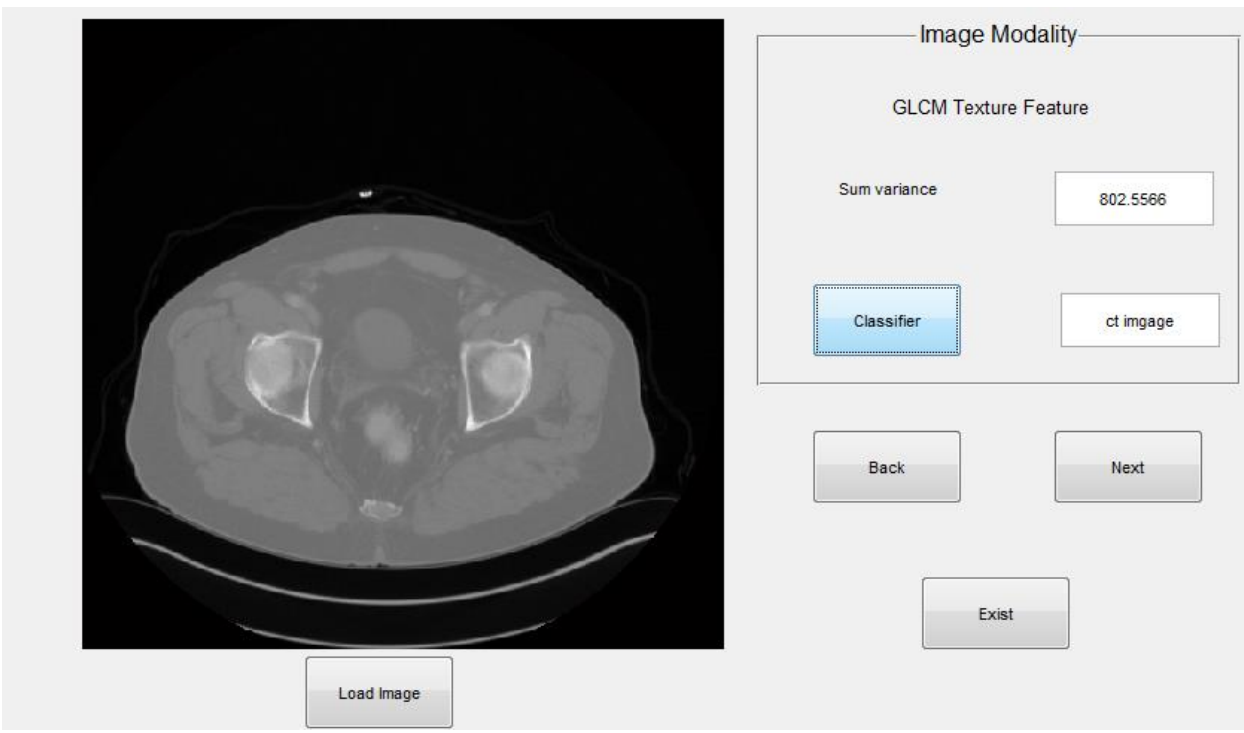

Figure 4.8: GUI snap shot for CT image classification.

4.4 Web Page

Snapshots of the developed web page system that allows two way communications for effective data storage and transmission of medical images have been included in Appendix A. The core of the system developed in this thesis is undoubtedly the automated scheme that is capable of identifying the modality type of a given medical image. Based on the outcome, the system is able to identify and communicate imaging data with the required imaging expert and receive feedbacks based on the flow pattern depicted in Chapter 3. Experts' feedbacks could be written diagnosis reports, abnormality delineations, suggestions and the like.

The existence of such a system has multiple advantages in the health care system that involves an imaging procedure. In low resource settings, number of available experts for an imaging procedure is often far from adequate with exaggerated patients to doctor ratio. Deploying such a system allows remote access to experts. Interpreting a given medical image is something that could be performed only by the right experts and optimal use of experts is a necessity. Misdiagnosis as a result of lack of experts is common in many clinics and becoming a pressing issue. Not only that, the imaging science is advancing tremendously and getting more sophisticated by day which allows only experts to deal with imaging data. Clinics in low resource settings could only sustain when such systems are available. The system also facilitates effective and economical imaging data storage, convenient access to images from multiple modalities and encourages imaging standardization, backup and archiving.

Chapter Five

5 Conclusion and Future Works

Effective image storage and transmission is required when economical imaging data storage, convenient access to images from multiple modalities as well as sharing of medical expertise is sought within or between health institutions or outside. In that regard, the development of a system that allows two way communications between different units is needed while an image classification scheme might be needed if remote disease diagnosis has to be performed or medical consultation is sought. The web based system ("MEDICAL IMAGE CENTER") that has been developed in this thesis for use in storage and transfer of medical images is proposed mainly to fill gaps that existed in clinics with low resource settings with no or inadequate medical imaging expertise. Remote assessment, delineation and other consultations are vital uses of the system. Tele radiology is one good example that could benefit from such a system.

The core of the system is an automated system that allows identification of imaging modality type so that the system could communicate images with the right expert/s found elsewhere. The automated system that has been developed in the current study does image modality classification based on second order statistical features extracted from the images. Three imaging modalities namely: CT, MRI and US were considered for developing the classification scheme while in principle the scheme could be extended to embrace other imaging modalities. Feature selection was carried out objectively based on computed distance matrices that show maximal separation between different imaging modalities.

Based on testing performed on the three imaging modality types, all testing images were correctly classified by the algorithm. A GUI was developed for a more interactive implementation of the system. The system is capable of two way communications between parties allowing consultations, remote discussion, image assessments, delineations, prescriptions and other medical procedures could be performed remotely between medical professionals within and outside of clinics. There is no need to overemphasize the need for such system particularly in low resource settings.

The system still has to be checked for its efficacy to work on more number of medical imaging modalities. Images come with different degrees of difficulties may be because of noise, illumination issues and other artifacts. When the number of imaging modality types increases, it is expected classification becomes more challenging and that might alter the feature selection procedure. For the three imaging modality types considered, a single feature, namely sum variance, was able to completely classify all the images into their modality types which may not work same if other image modality types are included. That might require hybridizing different features through some means and optimal combination of the features need carful investigation.

The developed storage and communication system is far from complete. It undoubtedly needs to include more features based on the need. A rigorous system trial must be performed to enhance the performance of the system. As it is a web based system, security is another issue that must be dealt with. Such systems dealing with patient image information must satisfy major security criteria before being deployed in the clinics. Also, it is assumed in this study that compressed images are stored and communicated and commonly used compression methods are used during image data coding and decoding. Developing a standalone lossless compression tool with better performance than existing tools might add a significant improvement for the developed system. These and similar other issues might need much further investigation.

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Appendices

Appendix A: A web page medical image storage and distribution proto type

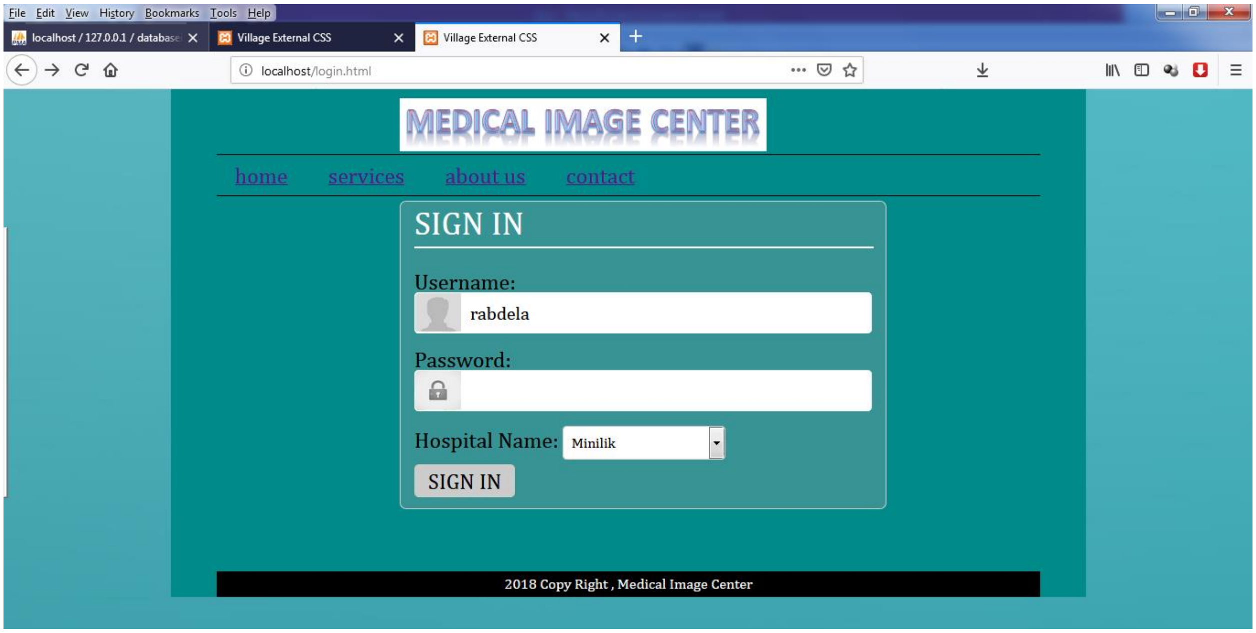


Figure A. 1: Login page.

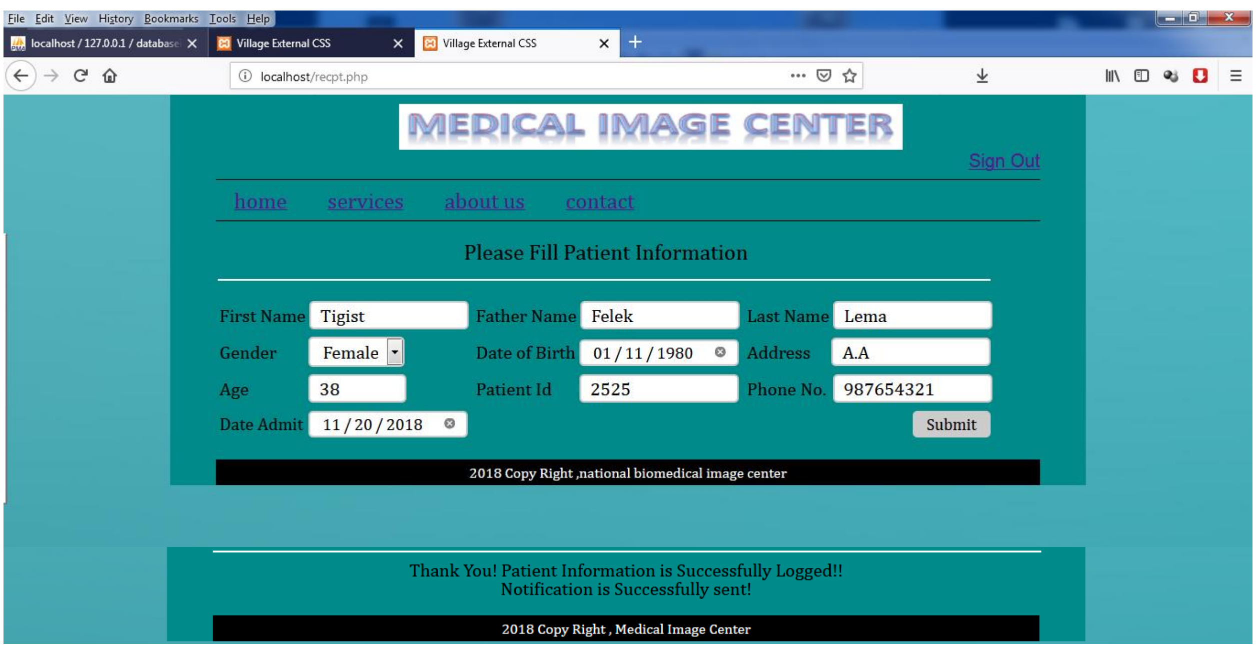


Figure A. 2: Receptions page.

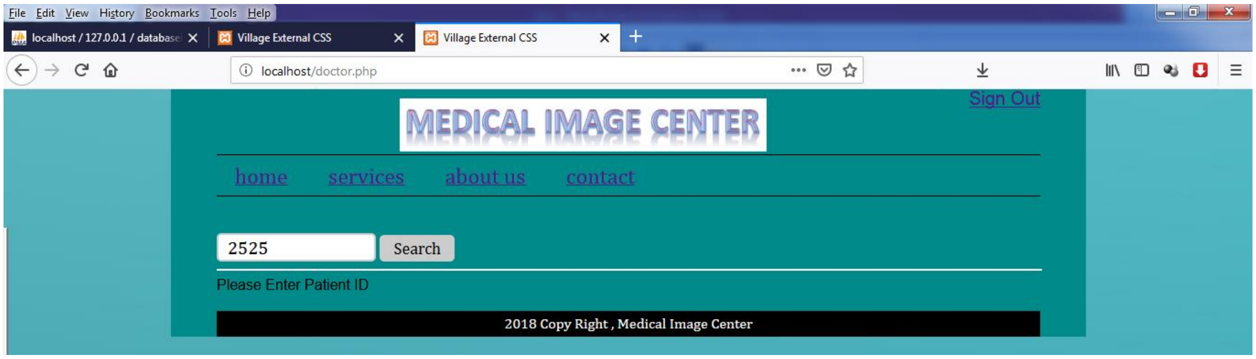


Figure A. 3: Search page (using patient Id) for doctors, physicians and specialist.

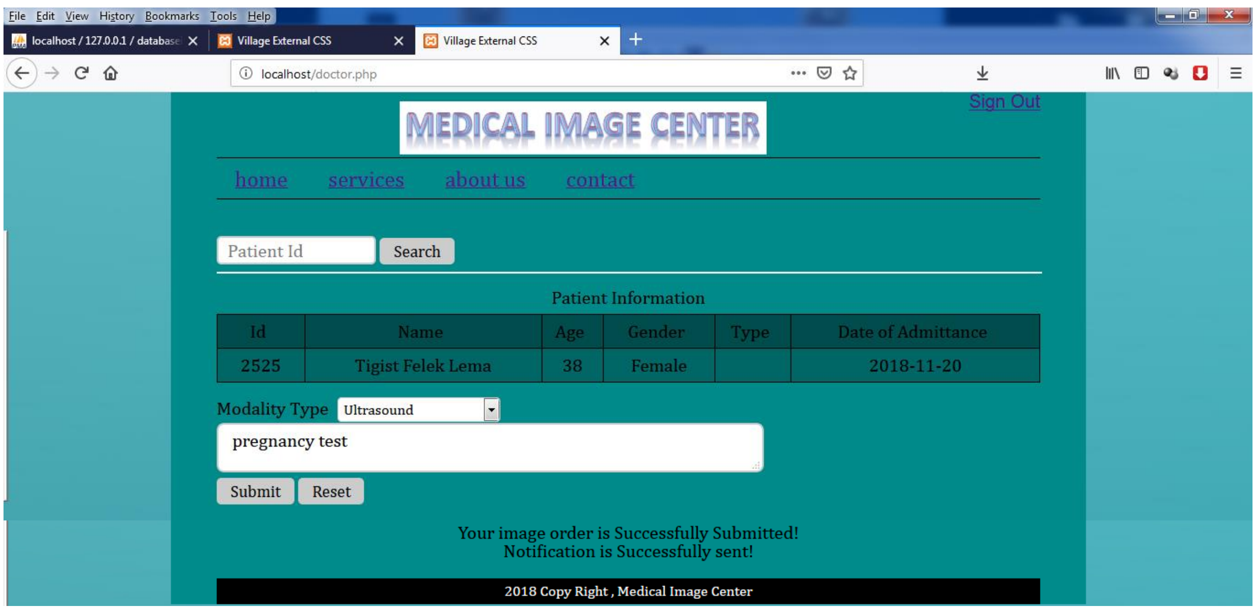


Figure A. 4: Doctors' page.

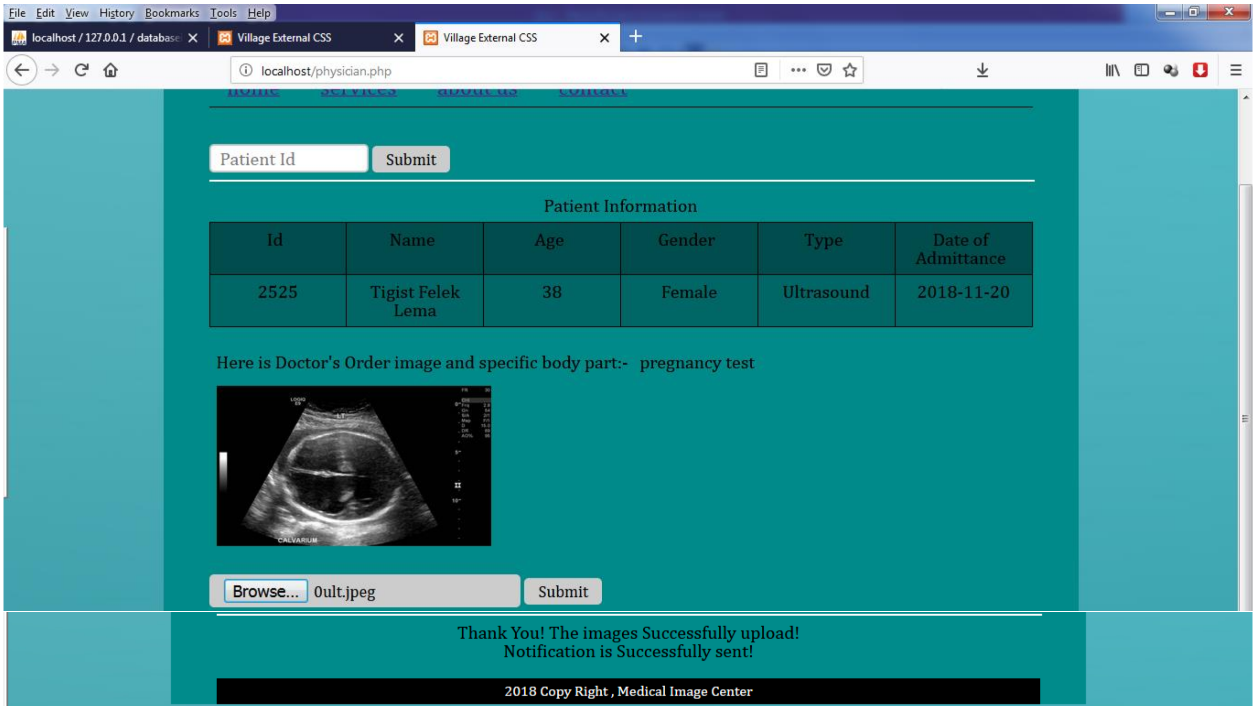


Figure A. 5: physicians' page.

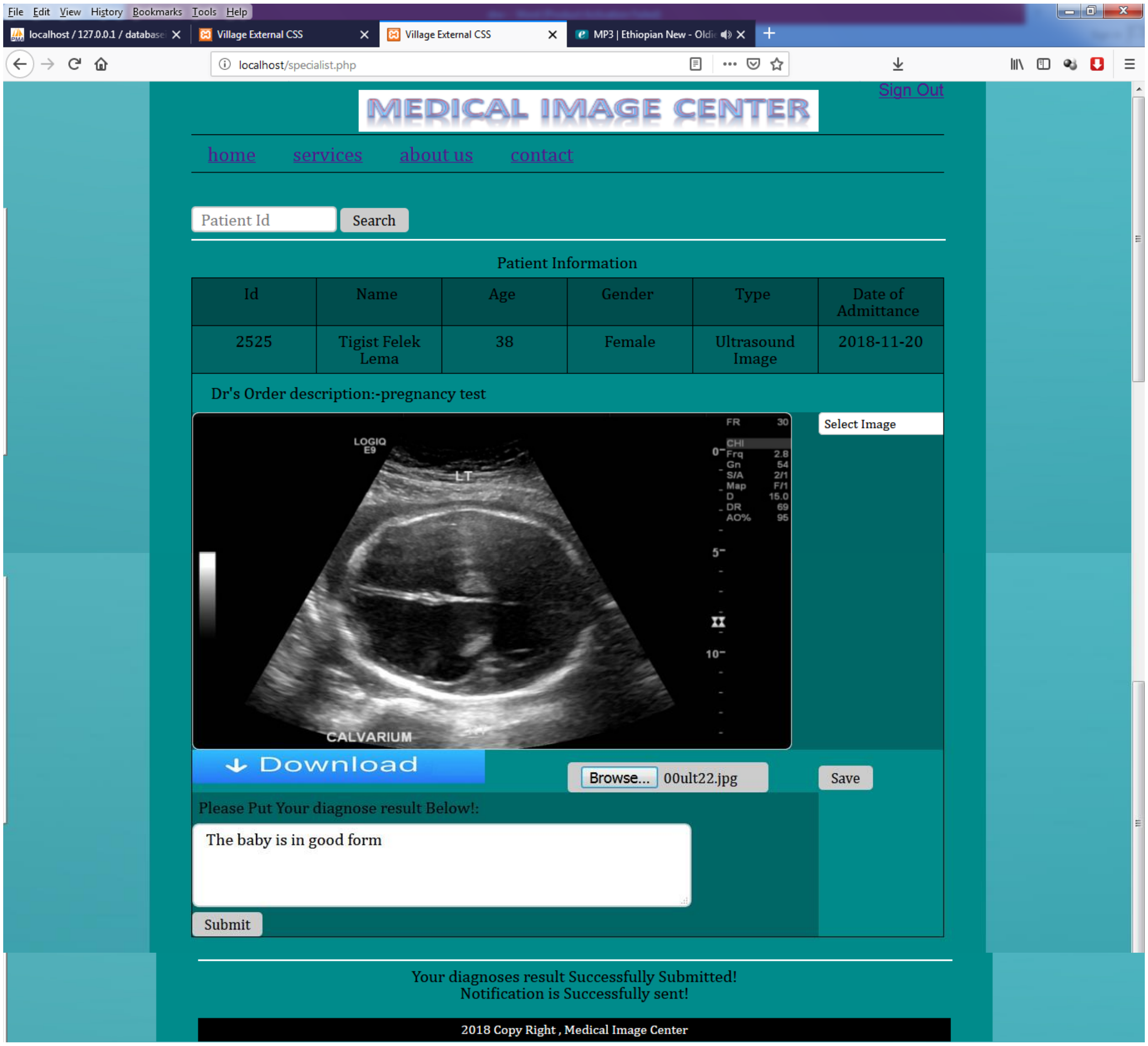


Figure A. 6: Specialists' page.

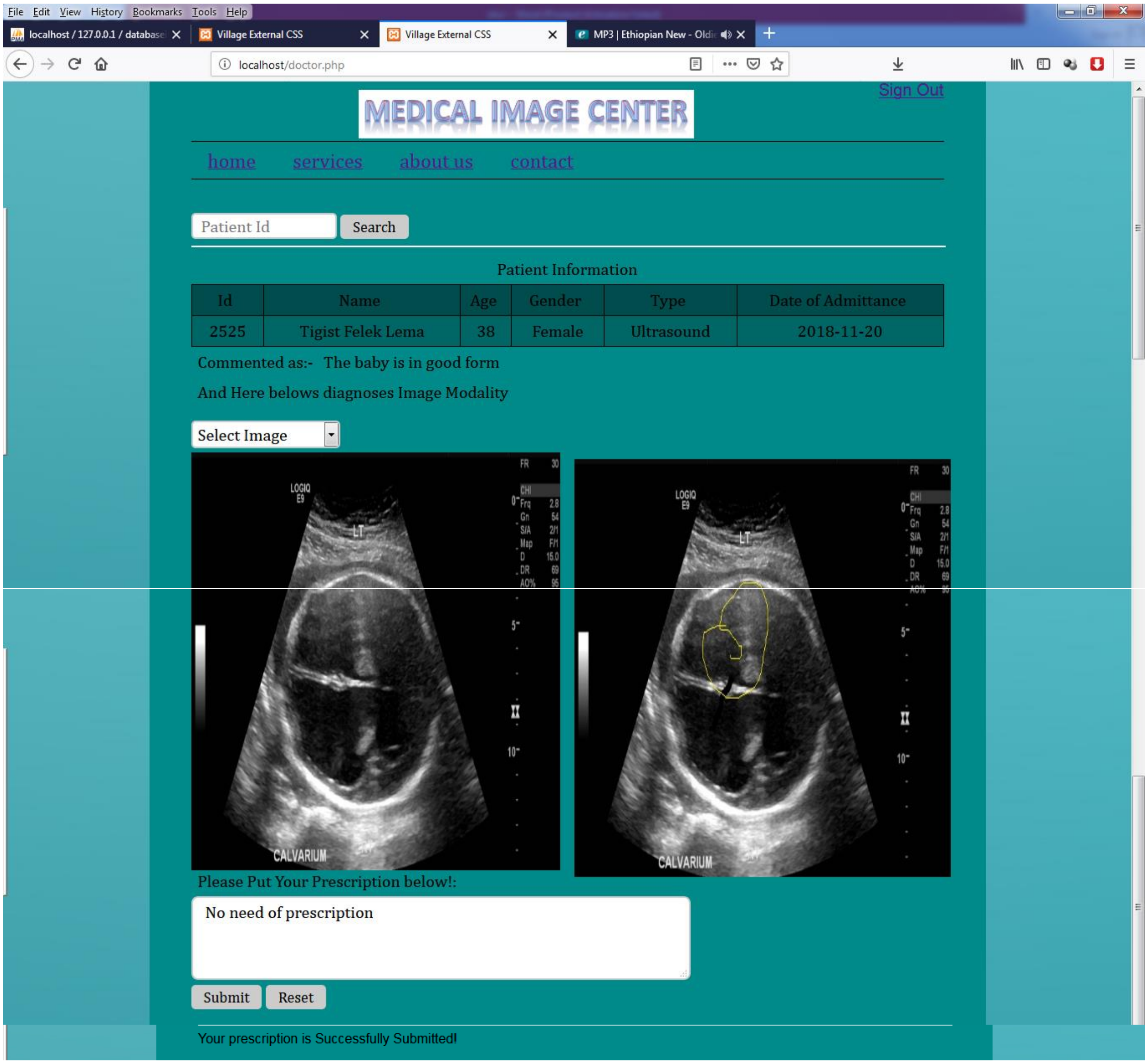


Figure A. 7: Doctors' page (assessment after assessment by a specialist).

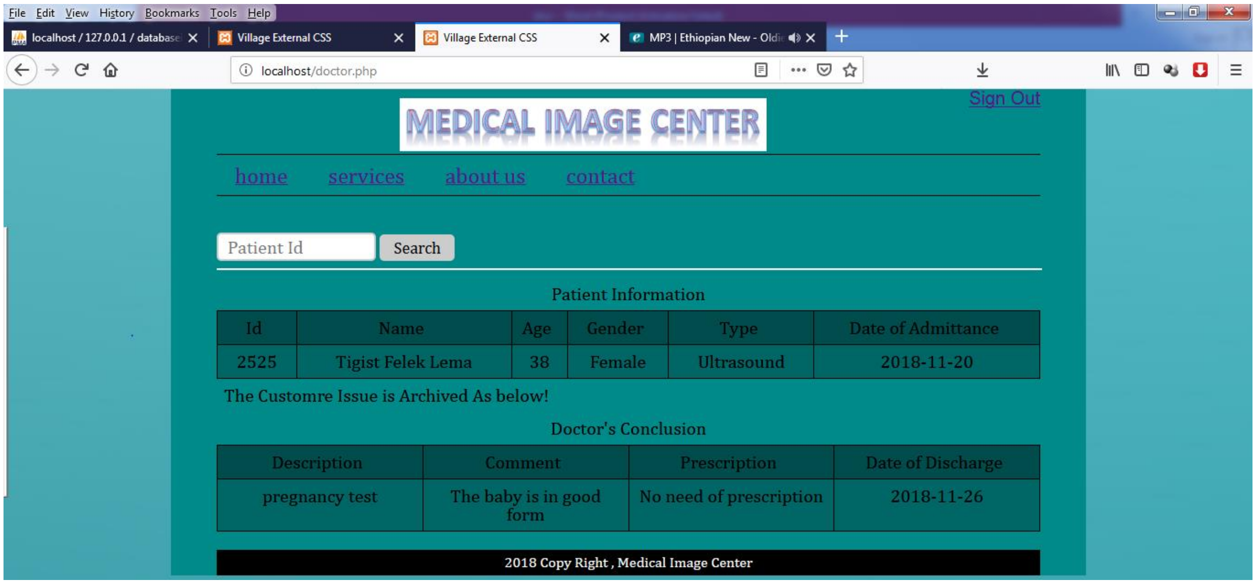


Figure A. 8: Doctors' page (summery of patient condition).

Appendix B: Graphical User Interface Development

As GUIDE is simpler method, it has been adopted to develop the GUI in this thesis. The basic steps required to create a MATLAB GUI are as follows:

1. Step 1

Make a rough layout of the components by hand on a piece of paper to implement the GUI. Figure B.1 presents a rough layout design of the GUI developed in this thesis.

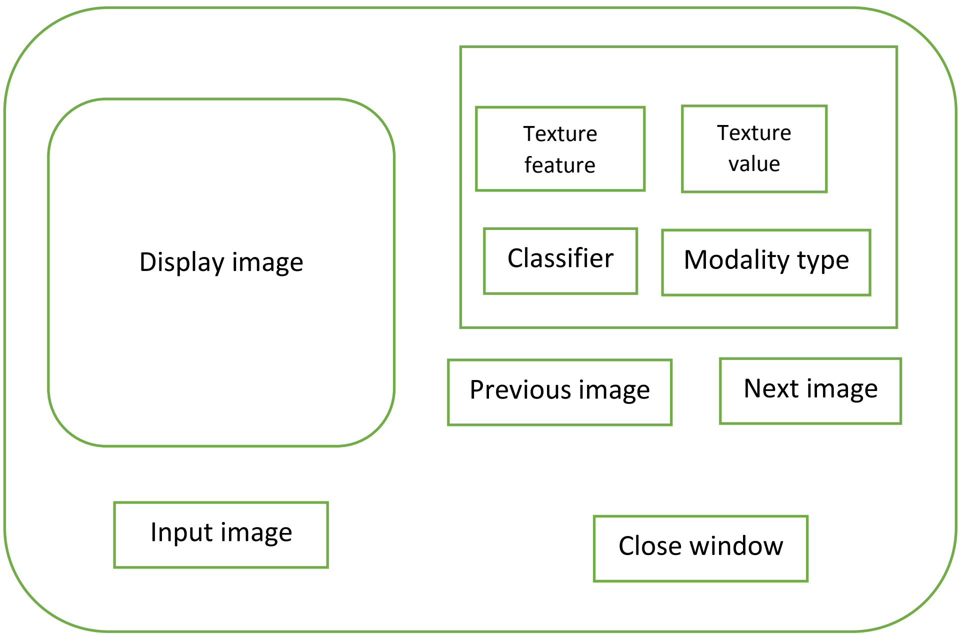
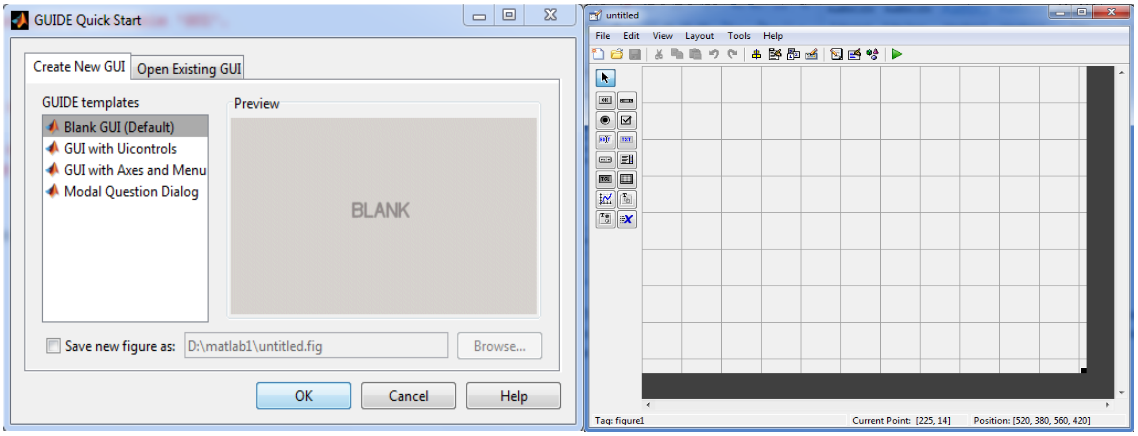


Figure B. 1: The design layout of the GUI.

2. Step 2

Decide what elements are required for the GUI and on the functions of each element. Typing the "guide" command from the MATLAB command window and pressing the enter key and then selecting "Blank GUI" by clicking "OK" at the bottom of the window opens the GUIDE design window as shown in Figure B.2.



(a) (b)

Figure B. 2: a-b: (a) Blank GUI (Default) and (b) GUIDE design window.

The guide command opens untitled figure which contains all the GUI tools needed to create and lay out the GUI components. The GUI components can be menus, toolbars, push buttons, radio buttons, list boxes, Static Text, Pop-up Menu, Axes and Panel just to name a few.

Components and their Description to the Simple GUIDE GUI

Pushbutton: A pushbutton is a component that a user can click on to trigger a specific action. The pushbutton generates a callback when the user clicks the mouse on it. A pushbutton is created by creating a uicontrol whose style property is 'pushbutton'. A pushbutton may be added to a GUI by using the pushbutton tool in the Layout Editor.

Edit Text: An edit box is a graphical object that allows a user to enter a text string. Users can enter numbers but they must be converted to their numeric equivalents. The edit box generates a callback when the user presses the Enter key after typing a string into the box. An edit box is created by creating a uicontrol whose style property is 'edit'. An edit box may be added to a GUI by using the edit box tool in the Layout Editor.

Static Text: A text-field is a graphical object that displays a text string. You can specify how the text is aligned in the display area by setting the horizontal alignment property. By default, text fields are horizontally centered. A text field is created by creating a uicontrol whose style property is 'edit'. A text field may be added to a GUI by using the text tool in the Layout Editor.

Axes: Axes enable the GUI to display graphics such as graphs and images. Like all graphics objects, axes have properties that you can set to control many aspects of its behavior and appearance.

Palen: A Palen, sometimes called a frame, is a graphical object that displays a rectangle on the GUI. You can use frames to draw boxes around groups of logically related objects. By visually grouping related controls, panels can make the user interface easier to understand. A panel can have a title and various borders.

3. Step 3

Next step is to layout the components on a figure. The size of the figure and the alignment and spacing of components on the figure can be adjusted using the tools built into GUIDE.

The MATLAB tool called “Property Inspector” (in built into GUIDE) is used to give each component a name (a "tag") and to set the characteristics of each component, such as its color, the text it displays, and so on. To assign tags for each component, one can double click on the component and set the tag properties to descriptive identifier from the property inspector. This name will be needed by the callback function to locate and update the text field.

4. Step 4

The next step is to save the figure to a file. When the figure is saved, two files will be created with the same name but different extents. The .fig file contains the actual GUI that has been created, and the M-file contains the code to load the figure and skeleton call backs for each GUI element.

5. Step 5

In this step the code is written to implement the behavior associated with each callback function and M-file is automatically generated to launch and control the GUI. GUIDE generates a callback function prototype for GUI components already created similar to the one shown in Figure B.3. Callback functions are written to determine what action is taken when we interact with a GUI component.

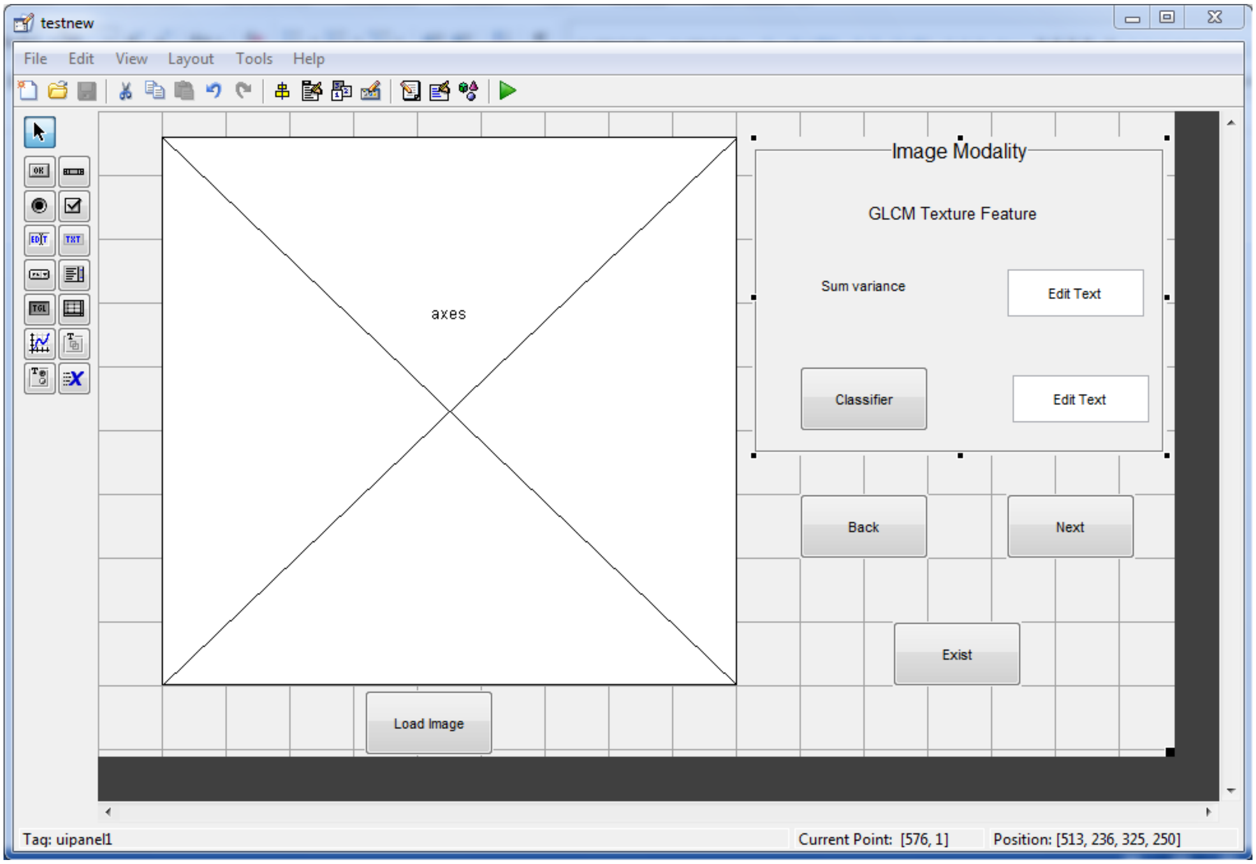


Figure B. 3: Developed Graphical user interface.