DEVELOPMENT OF AN ANDROID-BASED EYE DISEASE DIAGNOSIS SYSTEM

BY

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CPE/13/1073

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CERTIFICATION

This project with the title

DEVELOPMENT OF AN ANDROID-BASED EYE DISEASE DIAGNOSIS SYSTEM

Submitted by

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CPE/13/1073

Has satisfied the regulations governing the award of degree of

BACHELOR OF ENGINEERING (B.Eng) In COMPUTER ENGINEERING,

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DECLARATION

I declare that this project is a result of my own work and has not been copied in part or in whole from any other source except where duly acknowledged. As such, all use of previously published work (from books, journals, internet, etc.) has been acknowledged with the main report to an entry in the References list and I am fully responsible for every detail contained herein.

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Student's full name — **Signature and Date**

DEDICATION

This report is dedicated to God Almighty who saw me through the course of this project. Without His help, it would not have been achievable.

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ABSTRACT

The human eye is a vital organ of vision which gives the sense of sight. However, there are many diseases that affect the human eye and can lead to partial or total blindness. The major causes of blindness include cataract, glaucoma, diabetic retinopathy and several other corneal and retinal infections but most of them can be prevented with an early diagnosis. Therefore, there is the need for a cheaper, easy-to-understand and readily available system to aid the diagnostic process. This project aims to develop a diagnostic system for selected eye diseases on the Android mobile phone platform.

The project was designed with four modules namely: image acquisition, image pre-processing, feature extraction and classification. Image acquisition was achieved through publicly available online fundus databases. The pre-processing techniques used included conversion to grayscale, histogram equalization and thresholding. Feature extraction and classification was done using the BRISK algorithm.

This project was implemented to detect Glaucoma and Diabetic Retinopathy using the Android platform. Android studio was the platform of choice for the development as it had better preinstalled features compared to other development environments. To achieve real-time processing while minimizing processor requirements, Intel's OpenCV (Open Source Computer Vision) library was used for the computer vision operations. The performance analysis results show that the classifier attained an accuracy of 86.7% for healthy images, 100% for diabetic retinopathic images and 100% for glaucomic images. The average classification accuracy of the developed system was 95.6% across the healthy and diseased classes.

The developed Android based eye disease diagnosis system can greatly assist in the early detection of eye related diseases especially in areas with limited health facilities. To improve the performance of the system, a handheld ophthalmoscope should be used for image acquisition, training and testing. This would greatly increase it performance with real life samples. Also, it could be expanded to be able to diagnose other retinal diseases.

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LIST OF ABBREVIATIONS

AMD:	Age-Related Macular Degeneration
ANN:	Artificial Neural Network
API:	Application Programming Interface
APK:	Android Application Package
CDR:	Cup-To-Disc Ratio
CDSS:	Clinical Decision Support System
CE:	Compact Edition
CLAHE:	Contrast Limited Adaptive Histogram Equalization
CMOS:	Complementary Metal Oxide Semiconductor
CMYK:	Cyan Magenta Yellow Black
CT:	Computerized Tomography
ECG:	Electrocardiographs
GLCM:	Gray Level Co-occurrence Matrices
HE:	Histogram Equalization
HER:	Electronic Health Record
HSV:	Hue Saturation Value
ICT:	Information Communication Technology
iOS:	iPhone Operating System
KLT:	Karhunen-Loeve Transform
KNN:	K-Nearest Neighbour
MD:	Mahalanobis Distance
mHealth:	Mobile Health

MRI:	Magnetic Resonance imaging
OS:	Operation System
PC:	Personal Computer
PCA:	Principal Component Analysis
PDA:	Personal Digital Assistant
PNN:	Probabilistic Neural Network
POD:	Proper Orthogonal Decomposition
RGB:	Red Green Blue
RPE:	Retinal Pigment Epithelium
SLO:	Scanning Laser Ophthalmoscope
SPCA:	Shift-invariant principal component analysis
SVM:	Support Vector Mechanism
TV:	Television
VPN:	Virtual Private Network

CHAPTER ONE

INTRODUCTION

1.1 PREAMBLE

Digital health is an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the internet and related technologies (Abdullahi, Arulogun, Adeyanju & Nuhu, 2015). Digital health encompasses a wide variety of domain, which includes Artificial Intelligence in Medicine (AIM), Electronic Health Records (EHR), Clinical Point of Care, Mobile Health (mHealth) and Telemedicine (Wright & Wright, 1997). Digital health systems reduce clinical errors and improve evidence-based medicine by increasing the accuracy of diagnosis, earliness of the diagnosis as well as the appropriateness of treatment approaches (Abdullahi *et al.,* 2015).

The human eye is a vital organ of vision, which gives us the sense of sight, and is of utmost importance in all day to day activities. However, there are many diseases that affect the human eye can lead to blindness. The major causes of blindness include glaucoma, diabetic, retinopathy and other corneal and retinal infections. However most of these conditions can be prevented with early diagnosis (Eysenbach, 2001).

According to a survey carried out by the World Health Organization [WHO] (2017), an estimated 1.1 billion people live with near-vision impairment, 253 million people live with vision impairment, 36 million are blind, while 217 million have moderate to severe vision impairment and about 90 percent of the world's visually impaired people live in developing countries of which Nigeria is among (Balantrapu, 2017). It was further estimated that 19 million children below age 15 are visually impaired, of these, 12 million children have a vision impairment due to refractive error. Around 1.4 million have irreversible blindness, requiring access to vision rehabilitation services to optimize functioning and reduce disability (Bourne *et al.*, 2017). In further age-related perspective, 65 per cent of visually impaired, and 82 per cent of blind people are over 50 years of age, although this age group comprises only 20 per cent of the world population. Currently, the top causes of visual impairment are refractive errors, cataracts and glaucoma while the top causes of blindness are cataracts, glaucoma and age-related macular degeneration. With all these, it is very saddening to note that over 80 percent of all vision impairments can be prevented or cured which begs the question, why have they not been prevented or cured? (WHO, 2017).

1.2 PROBLEM STATEMENT

Worldwide, traditional models of health and care systems are struggling to meet the challenge and demands of the ever-increasing population, which has led to several losses of life and drastic deterioration of health thus prompting the need for a better approach to the administration of health services, leading to the emergence of digital health (Sonnier, 2018; Digital Health Instititute, 2018). Digital health intervention modalities spanning a wide range from smartphone applications to telemedicine, email, text messaging services, web-based platforms, and wearable devices are rapidly emerging as promising interventions for acute and chronic disease management. Unlike non-digital health, digital health provides an easier and better way to track, manage and improve patient's health while also providing an avenue for patient feedback with the health personnel (Marvel, Wang, & Martin, 2018; Sonnier, 2018).

Digital health has found its use in several facets of the health care system prominent among which is the diagnosis and treatment of eye diseases. The high population and financial constraints of people with major or minor eye defects has made it practically impossible for them to be physically attended to by ophthalmologists. According to Zimmer-Galler (2017), "if every patient with diabetes globally were to have recommended eye exams, they would happen once every seven seconds and we clearly do not have the workload to examine all those patients in person or evaluate the millions of images that would be generated." Several eye diseases such as cataract, glaucoma, diabetic retinopathy can be completely treated if diagnosed early. Furthermore, the treatment of such diseases can be greatly improved with advancements in technology. With automated image analysis, computer-aided diagnosis, expert systems, easily available smartphone applications, network of health professionals, etc. digital health has the potential to greatly improve the eye condition of millions of patients around the world (Blum, 2017).

There are several techniques of diagnosis in digital health which can be used for early detection of blindness by analyzing fundus images. These includes K-Nearest Neighbour algorithm (KNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN) and deep learning. Of all these, deep learning is the diagnosis technique of choice for this project due to its state-of-the-art accuracy in image inference, adaptive nature of learning, fault tolerance and real time operational mode quality (Narasimhan, 2011).

1.3 AIM AND OBJECTIVES

The aim of this project is to develop a diagnostic system for selected eye diseases on the Android mobile phone platform. The specific objectives are

1. To design a diagnostic system for the detection of selected human eye diseases

2. To implement the diagnostic system on the Android platform.
3. To evaluate the developed system.

1.4 METHODS OF STUDY

The methods to be used in achieving this project will include the following:

i. Continual review of relevant literatures in the library and online resources related to diagnosis of eye diseases, digital health, image processing, android application development, etc.
ii. Interaction with Ophthalmologists and experts in android development.
iii. Design of human eye disease diagnostic system.
iv. Data capturing from human experts will be carried out to train the system appropriately.
v. The algorithm will be initially trained with infected and normal images on a personal computer before being developed into a mobile-based diagnosis application for Android environments.
vi. The data captured will be processed appropriately.
vii. Feature extraction will be done on the pre-processed image
viii. Implementation of the system using extracted features.
ix. Evaluation of the implemented eye diagnostic system.

1.5 SCOPE OF THE STUDY

Of the many smartphone operating systems available, including Android OS by Google, iOS by Apple, Windows OS by Microsoft, and many more, the android platform has been selected for the development of the diagnosis system for selected human eye diseases, due to such reason as its general availability, low price, open source license, high customizability, memory and process management, security to allow flexible, reliable and portable data storage and processing, ease of use and understanding, etc. compared to others. The Binary Robust Invariant Scalable Keypoints (BRISK) algorithm will be used for the proposed diagnostic system.

1.6 SIGNIFICANCE OF STUDY

With the rapid increase in population and the eminent ineptitude of the traditional health system to cater for the demands of the patients, the role of digital health cannot be overemphasized. This study is thus significant in the following areas:

- **Clinical Decision Support System (CDSS):** A clinical decision-support system is any computer program or system designed to help healthcare professionals in making better informed and more accurate decisions (Musen, 2000). CDSSs are one of the most prominent examples of the role of medical informatics in the improvement of health care (Musen, Yuval & Edward, 2006). The ability to provide advice in various situations and at different moments of the clinical process tailored to the condition of a specific patient, has the potential to significantly improve the quality of care delivery.

- **Electronic Health Records (EHR):** EHR basically involves patient data stored on computers enabling the ease of access and the communication of such data between different health care professionals. The essence of EHR includes to improve the accuracy and quality of data recorded in a health record, enhance health practitioners' access to a patient's healthcare information enabling it to be shared by all for the present and continuing care of such patient, improve the quality of care as a result of having health information readily available at all times, and as well as improve the efficiency of the health record service (Mantas, 2002).

- **Telemedicine:** Telemedicine is the use of medical information exchanged from one site to another via electronic communications to improve patients' health status. It involves the physical and psychological treatments provided over networks, including remote diagnosis of patients' health status, telemonitoring of patients' functions, medication prescriptions, etc. (Strehle & Shabde, 2006). Closely associated with telemedicine is "telehealth," which is often used to encompass a broader definition of remote healthcare that does not always involve clinical services. Videoconferencing, transmission of still images, e-health including patient portals, remote monitoring of vital signs, continuing medical education and nursing call centers are all considered part of telemedicine and telehealth (Rao & Lombardi, 2005).

- **mHealth:** mHealth standing for mobile health includes the use of mobile devices in collecting aggregate and patient-level health data; providing health care information to practitioners, researches and patients; real-time monitoring of patient vitals; and direct provision of care via mobile telemedicine (Iluyemi, Jones & Anie, 2012). Mobile devices and tablets provide accessibility to the electronic medical record during the clinical point of care documentation process. Mobile technologies such as Android phones, iPhones, Windows phones, tablets, etc. feature touchscreens to further support the ease of use for the physicians. Furthermore, mobile electronic records applications support workflow portability needs, through which clinicians can document patient information at the patient's bedside at a point in time (Iluyemi *et al.,* 2012).

- **Health Knowledge Management**: this involves the provision of overview of latest medical journals, best practice guidelines or epidemiological tracking. Health knowledge management also includes the use of software solutions for appointment scheduling, patient data management, work schedule management and other administrative tasks surrounding health (Iluyemi *et al.,* 2012).

- **Mobile Application Development**: Mobile application development is the set of processes and procedures involved in writing software for small, wireless computing devices such as smartphones, personal digital assistants, enterprise digital assistants, tablets etc. Mobile application development is similar to web application development and has its roots in more traditional software development. One critical difference, however, is that mobile applications are often written specifically to take advantage of the unique features a particular mobile device offers (Denman & Rouse, 2018). These applications can be pre-installed on phones during manufacturing platforms, or delivered as web applications using server-side or client-side processing such as JavaScript to provide an "application-like" experience within a web browser. While developing an application, software developers must consider a long array of screen sizes, hardware specifications, and configurations because of intense competition in mobile software and changes within each of the platforms (VisionMobile, 2013).

- **Mobile Based Diagnosis System:** The world is, rapidly moving away from the desktop and laptop web paradigms towards the mobile web paradigm, where mobile, smart devices such as the smart phone, pocket PC, PDA (Personal Digital Assistant), hybrid devices (such as phone-enabled PDAs or Pocket PCs), and wearable computers will become powerful enough to replace laptop computers (Kondratova, 2004). The continuous rise in the usage of mobile phones in Africa (ITU, 2006) and the advance in their capability provide a more available and accessible means of making healthcare services available to a vast majority of the people in this part of the world (Oyelami, 2017). With the advent of artificial intelligence, however, software systems have been developed to aid in the process of diagnosis. They have also been used as decision support systems for physicians. This puts a vast majority of people especially Africans at a disadvantage, because of lack of computer literacy, accessibility, and usage are very low in these regions of the world. There is therefore, a need to find an alternative and a more readily available means to fill these gaps identified, and cater for the needs of the people in this part of the world (Jegede & Owolabi, 2003; Esharenana & Emperor, 2010).

CHAPTHER TWO

LITERATURE REVIEW

2.1 DIGITAL HEALTH

"Digital health is an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the internet and related technologies" (Iluyemi *et al.,* 2012). It characterizes not only a technical development, but also a state of mind, a way of thinking, an attitude and a commitment for networked, global thinking, to improve health care locally, regionally and worldwide by using information and communication technology. Digital health has found various applications in the field of medicine and such applications includes electronic health records, telemedicine, digital therapy, as well as artificial intelligence in medicine (Iluyemi *et al.,* 2012).

The explosion of information and communication technology (ICT) advances over the past few decades has made a significant impact on all aspects of our lives, our thinking, the way we socialise, even our existence. The world is at a point in time where four major digital developments – mobile phones, personal computers, the internet and social networking – are now interlocked to revolutionize our lives (Kariyawasam *et al.,* 2010). According to Kariyawasam *et al.* (2010), mobile phones have made a bigger difference to the lives of more people, more quickly than any other technology. In like manner, the world of health is also being impacted, but the full depth and scope of the potential of ICTs has not yet been fully explored in the field of medicine. With increasing worldwide connectivity and mobile penetration reaching even into developing countries, digital health has become a powerful tool in the hands of medical professionals and the public which is gradually revolutionalising the world's health system (Kariyawasam *et al.,* 2010).

2.1.1 Electronic Health Record (EHR)

With the many advances in information technology over the past years, particularly in healthcare, a number of different forms of electronic health records (EHR) have been discussed, designed, developed, and implemented (WHO, 2014). Some institutions/countries are currently planning the introduction of a nationwide electronic health record while others have actually implemented some form of EHR. However, the type and extent of electronic health records vary and what one country calls an EHR may not be the same as that developed in another country. Although work has been undertaken by institutions/countries on some form of a computerized patient healthcare information system, as yet not many hospitals have successfully introduced an electronic health record with clinical data entry at the point of care. However, the focus should not just be on just going paperless, but rather also on encouraging departments and healthcare practitioners to move to an electronic system to help improve the accuracy of data recorded in a health record, enhance the health practitioners' access to a patient's healthcare information; improve the quality of patient's care and boost the overall efficiency of the health record service (WHO, 2014).

Although interest in automating the health record is generally high in both developed and developing countries, unfortunately, in some cases, the introduction of an EHR system seems overwhelming. In addition, the EHR is almost out of reach to many healthcare providers and administrators as well as medical record/health information managers (WHO, 2014). The obstacles may not be available technology but a problem of technical support and the cost of changing to an electronic system coupled with insufficient healthcare funding. In many developing countries, costs, available technology, lack of technical expertise and computer skills of staff, and lack of data processing facilities are major issues which would need to be addressed before the implementation of EHR is possible (WHO, 2014).

2.1.2 Telemedicine

Telemedicine, a term coined in the 1970s, which literally means "healing at a distance" (Sood, 2006). It signifies the use of ICT to improve patient outcomes by increasing access to care and medical information. Recognizing that there is no one definitive definition of the word 'telemedicine', a 2007 study found 104 peer-reviewed definitions of the word, which subsequently lead to a conventional adoption of a broad description of it as being "The delivery of health care services, where distance is a critical factor, by all health care professionals using information and communication technologies for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation, and for the continuing education of health care providers, all in the interests of advancing the health of individuals and their communities" (WHO, 2014). In a nutshell, Telemedicine is the use of medical information exchanged from one site to another via electronic communications to improve patients' health status.

Closely associated with telemedicine is the term "telehealth," which is often used to encompass a broader definition of remote healthcare that does not always involve clinical services. Videoconferencing, transmission of still images, e-health including patient portals, remote monitoring of vital signs, continuing medical education and nursing call centers are all considered part of telemedicine and telehealth (Rao & Lombardi, 2005). Some distinguish telemedicine from telehealth with the former restricted to service delivery by physicians only, and the latter signifying services provided by health professionals in general, including nurses, pharmacists, and others. However, it can always be said that telemedicine and telehealth are synonymous and used interchangeably (WHO, 2014).

According to WHO (2014), there are four elements that are germane to telemedicine. These elements include: the provision of clinical support; overcoming of geographical barriers; the use of various types of ICT; and improvement of health outcomes. Telemedicine applications can be classified into two basic types, according to the timing of the information transmitted and the interaction between the individuals involved: health professional-to-health professional or health professional-to-patient (Einthoven, 2005).

Store-and-forward, or asynchronous, telemedicine involves the exchange of pre-recorded data between two or more individuals at different times. For example, the patient or referring health professional sends an e-mail description of a medical case to an expert who later sends back an opinion regarding diagnosis and optimal management (Wootton, Menzies & Ferguson, 2009). In contrast, real time, or synchronous, telemedicine requires the involved individuals to be simultaneously present for immediate exchange of information, as in the case of videoconferencing (Wootton *et al.,* 2009). In both synchronous and asynchronous telemedicine, relevant information may be transmitted in a variety of media, such as text, audio, video, or still images. These two basic approaches to telemedicine are applied to a wide array of services in diverse settings, including teledermatology, telepathology, and teleradiology (Wootton, 2009).

The majority of telemedicine services, most of which focus on diagnosis and clinical management, are routinely offered in industrialized regions including, but not limited to the United Kingdom of Great Britain and Northern Ireland, Scandinavia, North America, and Australia (Heinzelmann *et al.,* 2000; Einthoven, 2005). In low-income countries and in regions with limited infrastructure, telemedicine applications are primarily used to link health-care providers with specialists, referral hospitals, and tertiary care centers. Even though low-cost telemedicine applications have proven to be feasible, clinically useful, sustainable, and scalable in such settings and underserved communities, these applications are not being adopted on a significant scale due to a variety of barriers such as physician licensing and credentialing (Wootton *et al.,* 2009).

2.1.3 Artificial Intelligence in Medicine

The advancement in computer technology has encouraged the researchers to develop softwares for assisting doctors in making decision without consulting the specialists directly (Shapiro, 1992). The software development exploits the potential of human intelligence such as reasoning, decision making, learning (by experiencing), problem solving and many others. Artificial intelligence is not a new concept, yet it has been accepted as a new technology in computer science. It has been applied in many areas such as education, business, medical and manufacturing (Shapiro, 1992).

Computer technology could be used to reduce the number of mortality and reduce the waiting time to see the specialist. Computer program or software developed by emulating human intelligence could be used to assist the doctors in making decision without consulting the specialists directly. The software is not meant to replace the specialist or doctor, but to assist general practitioner and specialist in diagnosing and predicting patient's condition from certain rules or experience. Patient with high-risk factors or symptoms or predicted to be highly effected with certain diseases or illness, could be short listed to see the specialist for further treatment. Employing the technology especially Artificial Intelligence (AI) techniques in medical applications could reduce the cost, time, human expertise and medical error (Ramesh *et al.,* 2004).

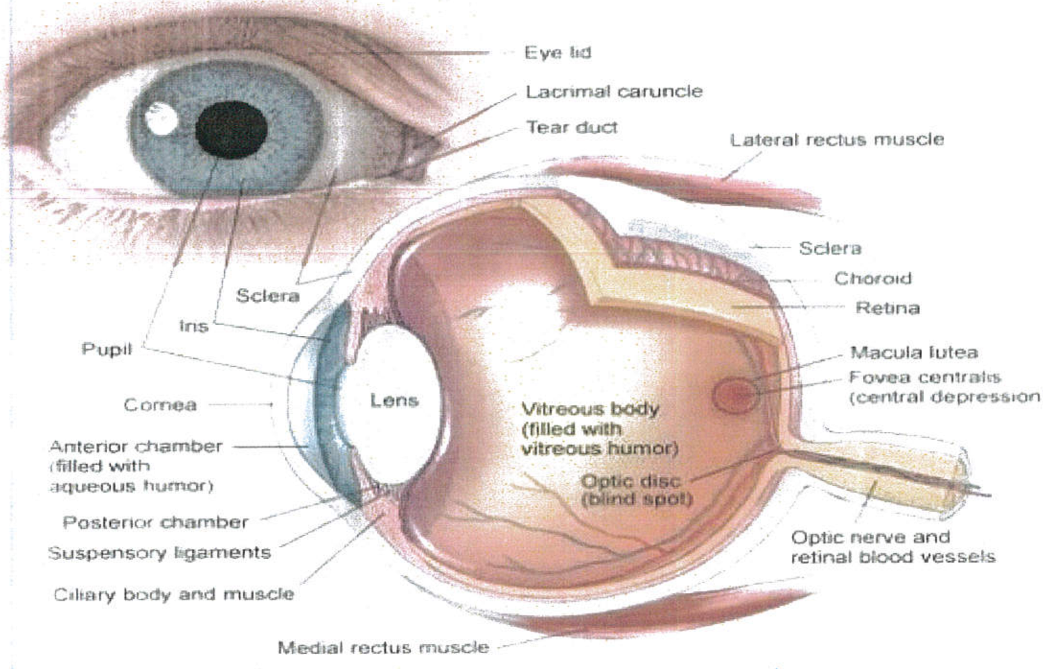
The development of medical artificial intelligence has been related to the development of AI programs intended to help the clinician in the formulation of a diagnosis, the making of therapeutic decisions and the prediction of outcome. They are designed to support healthcare workers in their everyday duties, assisting with tasks that rely on the manipulation of data and knowledge. Such systems include artificial neural networks (ANNs), fuzzy expert systems and hybrid intelligent systems (Ramesh *et al.,* 2004).

2.2 ANATOMY OF THE HUMAN EYE

The human eye is a special sense organ which is responsible for vision by reacting to light and pressure. Human eyes help to provide a three dimensional, moving image, normally coloured in daylight (Nguyen, 2017). Rod and cone cells in the retina allow conscious light perception and vision including color differentiation and the perception of depth. The human eye can differentiate between about 10 million colors (Judd & Wyszecki, 1975) and is possibly capable of detecting a single photon of light (Emily, 2016).

The eye is made up of three coats/tunics; the outer fibrous layer of connective tissue forms the cornea and sclera; the middle vascular layer is composed of the iris, ciliary body and choroid; and the inner layer or the sensory part of the eye is made up of the retina. Working like the digital camera, the human is the most important of the five sensory organs as it accounts for about seventy percent of human perception (Remington, 2012).

This section explores the anatomy of the human eye looking at its different parts such as the iris, pupils, lens, sclera, retina etc. and their function as shown in Fig. 2.1 below.



+Fig. 2.1: Parts of the Human Eye (Custers, 2017).

Sclera: The sclera, as seen in Fig. 2.1 above is the outermost white and opaque layer of the eyeball. It is covered by the transparent conjunctiva and is composed of two main layers: the lamina fusca, and the episcleral layer which consist of vascular connective tissues. Muscles responsible for moving the eyeball are attached to the eyeball at the sclera and because of its resistance and robustness, the main task of the sclera is to protect the inner and more sensitive parts of the eye (Heath, 2006).

Cornea: The cornea is the transparent dome-shaped structure located in the front of the eyeball covering the iris, pupil and the anterior chamber. At the front of the eyeball, the sclera becomes the cornea. Due to its transparency, light rays from the outside world first pass through the cornea before reaching the lens (Remington, 2012). Together with the lens, the cornea is responsible for refracting and focusing light on the retina. But, unlike other tissues, the cornea does not contain blood vessels as they will interfere in the process of refraction of light. Rather, it is nourished with oxygen and nutrients through eye fluid which explains why the cornea is so clear (Shopper, 2006).

Pupil: The pupil is the circular black hole at the center of the iris located in front of the lens. It is black because the layer of pigment inside the eye absorbs major parts of the light, resulting in a darker shade. Whenever more or less light needs to enter the eyeball, the muscles in the iris contract like the diaphragm of a camera to increase or decrease the size of the pupil (Custers, 2017). During the visual process, the eye must continuously compensate for changes from light to dark and from near to far, so light-dark adaptation is achieved by dilation or contraction of the pupil, whereas, near-far adaptation requires a change in the curvature of the lens (accommodation), lines of sight (convergence) and a change in the width of the pupil (Shopper, 2006).

Lens: The lens is a biconvex transparent disc made of proteins called crystallines. It is a multilayered structure located in the area of the posterior chamber, directly behind the iris and provides additional refractive power for accurately focusing light onto the retina. The lens is attached to a mass of suspensory ligaments called zonula which is attached to the ciliary body. In humans, the lens changes shape for near and for distant vision. It is the lens that enables the change of focus based on the distance of the object so that the object can be perceived clearly and sharply (Custers, 2017).

Zonula: The zonula also known as suspensory ligaments is a ring of small fibres that hold the lens suspended in place. It connects the lens to the ciliary body and allows the lens to change shape (Custers, 2017).

Iris: Located between the cornea and the lens, the iris is the pigmented membrane of the eye which determines a person's eye colour. The continuation of the choroid at the front of the eyeball forms the iris. The iris is a flat, thin, ring-shaped structure sticking in to the anterior chamber. It is the most anterior structure that regulates the amount of light that enters into the eye through the pupil This is the part that determines a person's eye colour (Custers, 2017). The iris contains circular muscles which go around the pupil and radial muscles that radiate toward the pupil. When the circular muscles contract usually in bright light, they make the pupil constrict, when the radial muscles contract, usually in dim light, they makes the pupil dilate (Clark, 2005).

Ciliary Body: The choroid continues at the front of the eyeball to form the ciliary body. The ciliary body also contains the ciliary muscles that contract or relax to change the shape of the lens. The major function of the ciliary body is to produce the aqueous humour which provides oxygen and nutrients to the inner eye (Custers, 2017).

Ciliary muscles: The ciliary muscles are located inside the ciliary body. These are the muscles that continuously change the shape of the lens for near and distant vision as shown in Fig. 2.1 above (Custers, 2017).

Choroid: The choroid is the middle layer of the eyeball located between the sclera and the retina. It provides nutrients and oxygen to the outer surface of the retina (Custers, 2017).The choroid supplies the overlying retina to a depth of about 130 micrometers which includes the pigment epithelium layer, the layer of rods and cones, the outer nuclear and plexiform layers, and the whole thickness of the foveal retina (Clark, 2005).

Anterior Chamber: Also known as the anterior cavity, the anterior chamber is the space between the cornea and the lens. This space is filled with a fluid called the aqueous humour (Custers, 2017).

Aqueous Humour: The Aqueous humour is a transparent watery fluid that circulates in the anterior chamber. It provides oxygen and nutrients to the inner eye and exerts fluid pressure that helps maintain the shape of the eye. The aqueous humour is produced by the ciliary body (Custers, 2017).

Posterior Chamber: The posterior chamber is a larger area than the anterior chamber. It is located opposite to the anterior chamber at the back of the lens. It is filled with a fluid called vitreous humour. The posterior Chamber is also referred to as the Vitreous body (Custers, 2017).

Vitreous Humour: The vitreous humour is a transparent jelly-like fluid made up of small fibres and water, behind the lens, that fills the posterior chamber. The main functions of the vitreous humour are to transmit light to the retina and to exert fluid pressure that keeps the retina layers pressed together to maintain the shape of the eye and to maintain sharp focus of images on the retina (Clark, 2005).

Macula: An area of the eye near the center of the retina where visual perception is most acute (Shopper, 2006). The macula is responsible for the sharp, straight-ahead vision used for seeing fine detail, reading, driving, and recognizing faces. It is one hundred times more sensitive to detail than the peripheral retina. The macula is sometimes referred to as "the bull's eye center of the retina" (Custers, 2017).

Fovea: The fovea is the most central part of the macula. It is a small depression in the retina near the optic disc. The visual cells located in the fovea are tightly packed, resulting in a region with a high concentration of cones, approximately 50,000, making it the part of the retina where visual acuity is greatest. The fovea contains no rods (Wandell, 2014).

Retina: The retina is the thin, multi-layered innermost layer lining the back of the eyeball. It is the light sensitive part of the eye composed of millions of visual cells and photo receptors that detect light. These photo receptors are known as cones and rods. There are approximately 5 million cones and 100 million rods in the eye. The cones, which are colour sensitive, are located at the center of the retina in the fovea and mainly absorb stronger light while the rods are located peripheral to the fovea and are very sensitive light detectors, absorbing softer light in black and white and with the capacity to generate a detectable photocurrent response when they absorb a single photon of light. Cones enable us to detect color while rods enable us to see in poor light (Custers, 2017). The retina is connected by optic nerve cells to the brain. The retina receives light and sends electrical impulses to the brain that result in sight. The light sensitive retina consists of four major layers: the outer neural layer, containing nerve cells and blood vessels; the photoreceptor layer, a single layer that contains the light sensing rods and cones; the retinal pigment epithelium (RPE) and the choroid, consisting of connective tissue and capillaries. A thin multi-layered membrane which lines the inside back two-thirds of the eye. It is composed of millions of visual cells and it is connected by the optic nerve to the brain (Wandell, 2014).

Optic Nerve: The optic nerve is a cable-like structure composed of thousands of nerve fibres located at the back of the eyeball that connect the macula and the retina with the brain. It contains the axons of retina ganglion cell (nerve cells of the retina) and it transmits electrical impulses from the macula and retina to the brain (Custers, 2017). The optic nerves from both eyes are reconnected behind the eyes so that everything that is seen in the right field is sent to the left cerebral hemisphere and vice versa (Clark, 2005).

Optic disc: The optic disc has an oval shape with approximately 1.5 mm diameter and is where the optic nerve attaches to the eye. Impulses are transmitted to the brain from the back of the eyeball at the optic disc also called the blind spot. It is called the blind spot because it contains no photoreceptors, hence any light that falls on it will not be detected. The optic nerve is the entry point into the eye for major blood vessels that serve the retina (Shopper, 2006).

2.3 HUMAN EYE DISEASES

There are many human eye diseases that can affect vision or lead to blindness. Early diagnosis and treatment of these diseases are critical to maintaining the health of the eye and can help prevent further complications and damages. Below is a review of some of the common diseases that affects the human eye including diabetic retinopathy, glaucoma, cataract, age related macula degeneration and retinoblastoma.

2.3.1 Diabetic Retinopathy

Diabetic Retinopathy is the most common eye complication in diabetes. It is globally the primary cause of visual impairment and blindness in diabetic patients (WHO, 2014). Diabetic retinopathy is a disease of the retina. The retina is the nerve layer that lies the back of the eye. It is the part of the eye that "takes pictures" and sends the images to the human brain. Retinopathy can affect all diabetics and become particularly dangerous, increasing the risk of blindness (Balasundari, Ulagammal, Sakthiya & Sathya., 2016). It occurs when changes in blood glucose levels cause changes in retinal blood vessels. In some cases, these Vessels will swell up and leak fluid into the rear of the eye. In other cases, abnormal blood vessels will grow on the surface of the retina (Balasundari *et al.,* 2016).

Diabetic Retinopathy can lead to several retinal abnormalities, including micro aneurysms, hemorrhages, hard exudates and cotton wool spots (Karegowda, Siddaganga, Siddaganga & Siddaganga, 2011). Exudates are one of the primary signs of diabetic retinopathy, which is a major cause of blindness and can be prevented with an early screening process of fundus images (Karegowda *et al.,* 2011). Fig. 2.2 shows a diabetic retinopathy infected eye. Common symptoms of diabetic retinopathy include: Spots or dark strings floating in vision (floaters), Blurred vision, Fluctuating vision, Impaired color vision, Dark or empty areas in your vision, Vision loss (Balasundari *et al.,* 2016).

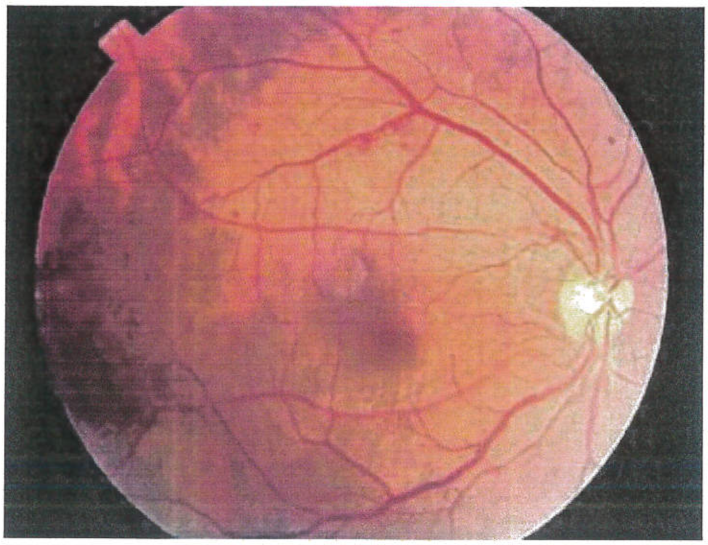


Fig. 2.2: Fundus image of a DR-infected eye (Bhavsar & Khardori, 2018).

2.3.2 Glaucoma

Glaucoma is one of the major causes of blindness in the world (WHO, 2014). It is due to the increase in intra ocular pressure within the eyes. The early detection and diagnosis of glaucoma is very important. Glaucoma is a condition that causes damage to the eye's optic nerve and gets worse over time. It is often associated with a buildup of pressure inside the eye which can be seen in Fig 2.3 below. Glaucoma tends to be inherited and may not show up until later in life (WHO, 2014). High amount of intra-ocular pressure (IOP) is one of the major danger components of glaucoma disease. Accusative of present medicament access is to reduce (IOP) inside eyes to prevent structural anthropology damage (Garaci *et al.,* 2009).

The increased pressure, called intraocular pressure, can damage the optic nerve, which transmits images to the brain. If damage to the optic nerve from high eye pressure continues, glaucoma will cause permanent loss of vision. Without early detection and treatment, glaucoma can cause total permanent blindness within a few years (Garaci *et al.,* 2009).

There are two main types of glaucoma: Open-angle glaucoma and Angle-closure glaucoma. Open-angle glaucoma, also called wide-angle glaucoma, is the most common type of glaucoma. The structures of the eye appear normal, but fluid in the eye does not flow properly through the drain of the eye, called the trabecular meshwork (Pooja & Girish, 2016). While angle-closure glaucoma, also called acute or chronic angle-closure or narrow-angle glaucoma, is less common, it causes poor drainage because the angle between the iris and the cornea is too narrow and is physically blocked by the iris (Pooja & Girish, 2016). Common symptoms of cataracts include: Blurred vision, Severe eye pain, Headache, Rainbow haloes, Nausea and vomiting. There are various approaches available for glaucoma diagnosis among which is the cup-to-disc ratio (CDR) measurement. CDR measurement is a major essential psychological argument for early diagnosis of glaucoma (Narasimhan, 2011). Depending upon the size and shape of optic disc boundary, it is possible to detect glaucoma. Once optic disc has been identified, other regions of retinal images like fovea and macula can be easily determined (Duanggate *et al.,* 2011). Glaucoma can be derogated by proper treatment and early detection in fundus images (Muramatsu *et al.,* 2011).

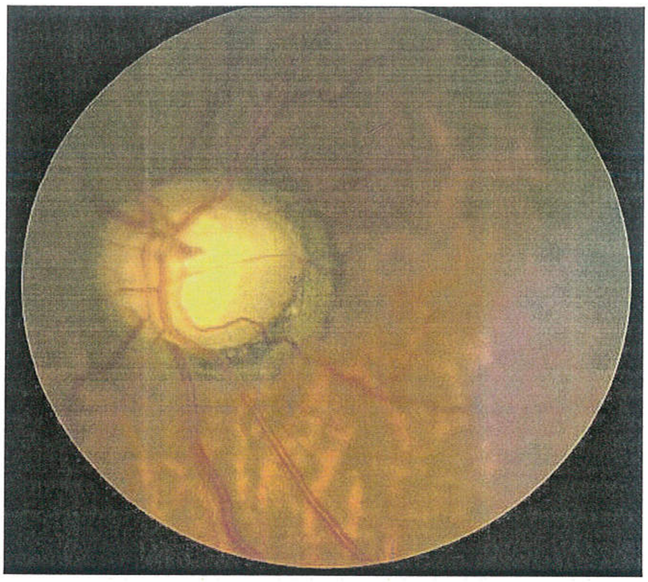


Fig. 2.3: Fundus image of a glaucoma-infected eye (Glaucoma, 2016).

2.3.3 Cataract

According to WHO (2014), cataract is responsible for about 51% of blindness all over the world. It is a clouding of the lens in the eye which leads to a decrease in vision (Amos *et al.,* 2004), as displayed in Fig. 2.4. Cataracts often develop slowly and can affect one or both eyes. Symptoms may include faded colors, blurry vision, halos around light, trouble with bright lights, and trouble seeing at night. This may result in trouble driving, reading, or recognizing faces (Gimel & Dardzhikova, 2011). Poor vision caused by cataracts may also result in an increased risk of falling and depression. Cataracts cause half of all cases of blindness and 33% of visual impairment worldwide (National Eye Institute [NEI], 2015).

Cataracts are most commonly due to aging but may also occur due to trauma or radiation exposure, it may be hereditary, or occur following eye surgery for other problems. Risk factors include diabetes, smoking tobacco, prolonged exposure to sunlight, and alcohol (Amos *et al.,* 2004). The underlying mechanism involves accumulation of clumps of protein or yellow-brown pigment in the lens that reduces transmission of light to the retina at the back of the eye. Diagnosis is by an eye examination (Gimbel & Dardzhikova, 2011).

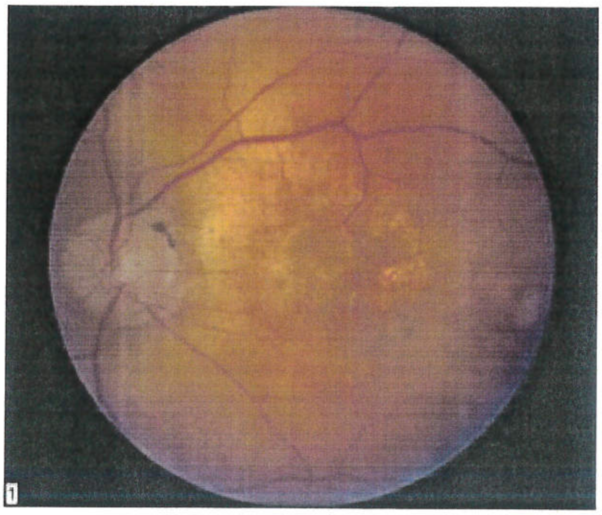


Fig. 2.4: Fundus image of a cataract-infected eye (Massen & Folk, 2005).

2.3.4 Age Related Macula Degeneration (AMD)

Age related macula degeneration is the third most important cause of blindness across the world, with an estimate of about 196 million people as current victims (WHO, 2014). Age-related macular degeneration, or AMD, is a condition that affects the center of the retina, called the macula which can be seen from Fig 2.5. The macula is the part of the eye responsible for our most acute vision, which we use when reading, driving, and performing other activities that require fine, sharp, or straight-ahead vision (Balasundari *et al.,* 2016). There are two different types of AMD: Dry macular degeneration and wet macular degeneration. In dry macular degeneration, small yellow deposits, known as drusen, accumulate under the macula. Eventually, these deposits are disruptive to vision cells, causing them to slowly break down. With less of the macula working, this causes a gradual loss of central vision as time goes on. This is the most common form of AMD, affecting approximately ninety percent of people who have the disease (WHO, 2014). In wet macular degeneration, new blood vessels start to grow in areas of the macula where they shouldn't be. This causes rapid damage to the macula that can lead to the loss of central vision in a short period of time. Although this type of AMD affects only about ten percent of people with the disease, it is responsible for ninety percent of severe vision loss associated with AMD (WHO, 2014).

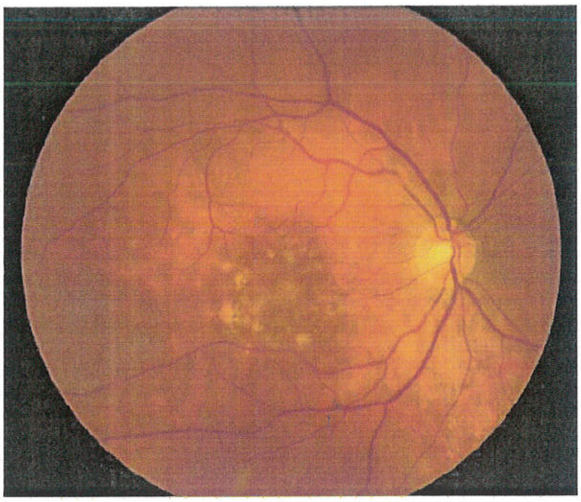


Fig. 2.5: Fundus image of a AMD-infected eye (Hunter, Chin, Almeida, & Telander, 2014).

2.3.5 Retinoblastoma

Retinoblastoma is a rare type of eye cancer that usually develops in early childhood, typically before the age of 5. This form of cancer develops in the retina, which is the specialized light-sensitive tissue at the back of the eye that detects light and color (Balasundari *et al.,* 2016). Most children who are diagnosed with retinoblastoma are younger than 5 years old. Retinoblastoma makes up 2% of all cancers diagnosed in children before the age of 15. Generally, 3 out of 4 children having the disease, have it in one eye, while 1 in 4 children have the disease in both eyes (American Cancer Society, 2017).

The most common first sign of retinoblastoma is a visible whiteness in the pupil called "cat's eye reflex" or leukocoria (ACS, 2017), this condition is aptly captured in Fig. 2.6. This unusual whiteness is particularly noticeable in photographs taken with a flash. Other signs and symptoms of retinoblastoma include crossed eyes or eyes that do not point in the same direction (strabismus); persistent eye pain, redness, or irritation; and blindness or poor vision in the affected eye(s) (ACS, 2017). Retinoblastoma is often curable when it is diagnosed early, either through a physical ophthalmology exam or via automated detection by analyzing fundus images using a classifier algorithm. However, if it is not treated promptly, this cancer can spread beyond the eye to other parts of the body. This advanced form of retinoblastoma can be life-threatening (Balasundari *et al.,* 2016)

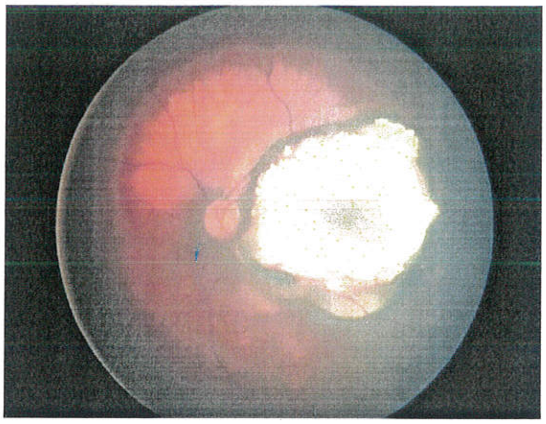


Fig. 2.6: Fundus image of a Retinoblastoma-infected eye (Correa & Berry, 2016).

2.4 EYE IMAGE ACQUISITION

In the diagnosis and treatment of human eye diseases, the acquisition of such eye images to be diagnosed must firstly be captured by the appropriate device and converted into an understandable format before any image processing can commence. This process is known as image acquisition. There are various techniques used in image acquisition, based on how severe the disease being diagnosed may be. Below are a few of them including fundus imaging, hyperspectral imaging and scanning laser ophthalmoscopy.

2.4.1 Fundus Imaging

The concept of fundus imaging was first introduced in the mid-1800s, after the introduction of photography in 1839 with the goal of photographing the back of the human eye i.e. ocular fundus (Ophthalmic Photographers' Society, 2015). Fundus imaging is the process whereby a 2-D representation of the 3-D retinal semitransparent tissues projected onto the imaging plane is obtained using reflected light. Thus, any process which results in a 2-D image, where the image intensities represent the amount of a reflected quantity of light like that displayed in Fig. 2.7, is fundus imaging (Usher *et al.,* 2003). In fundus imaging, image intensities represent the amount of reflected light of a specific waveband, therefore examinations are simply performed by viewing the fundus of eyes using the natural way of the light: light is directed through the pupil to the retina and the fundus with its normal and abnormal parts can be observed from the reflected light. Usually, the best fundus images are obtained when the eye is well dilated, fixation is on the target; and lids and lashes are held wide open (Usher *et al.,* 2003).

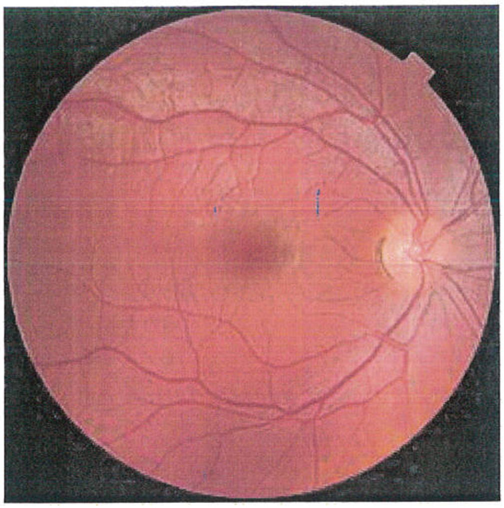


Fig. 2.7: Fundus image of a normal eye (Patnaik, Kotapati, Zhang, & Shu, 2015).

2.4.2 Smart Phone Camera

Over the years, the demand and usage of smartphones as been on the increase as it brings the frontiers of technology on the fingertips of everyone at a relatively portable size and affordable price. One of the driving specifications of any smartphone is the camera (Qian, Binfeng, Jun, & Gang, 2013). The pressing demand of users for better image quality has driven camera the mobile camera design technology to the extreme. At present, smartphones have mostly replaced the traditional point and shoot cameras, displacing most camera companies as some high-level mobile camera can even surpass the digital camera (Thomas, 2017).

Every smartphone camera is different, but they all have the same things in common. A typical camera has a lens, which enables it to see things; a sensor, which captures the image on the lens and converts it into digital data; it also has a software, for image processing and conversion. It is the combination of these things that decides the quality of the image produced by the camera (Thomas, 2017). But more than the number of pixels, the picture quality of a digital camera depends on several factors, including the optical quality of the lens and image-capture chip, the aperture, the sensor type, sensor size, image stabilization, compression algorithms, image processing techniques, and other components. The more elements, the higher the resolution, and thus the greater the detail that can be captured (Francisco, 2017).

Nearly all camera phones use CMOS (Complementary Metal Oxide Semiconductor) image sensors, due to largely reduced power consumption compared to CCD (Charge Coupled Device) type cameras, which were more common in earlier smartphone cameras. Some of camera phones even use more expensive Backside Illuminated CMOS which uses energy lesser than CMOS, although more expensive than CMOS and CCD (Marshall, 2015).

As camera phone technology has progressed over the years, the lens design has evolved from a simple double Gauss or Cooke triplet to many molded plastic aspheric lens elements made with varying dispersion and refractive indexes. The latest generation of phone cameras also apply distortion (optics), vignetting, and various optical aberration corrections to the image before it is compressed into a .jpeg format (Prakel, 2009).

2.4.3 Ophthalmoscope

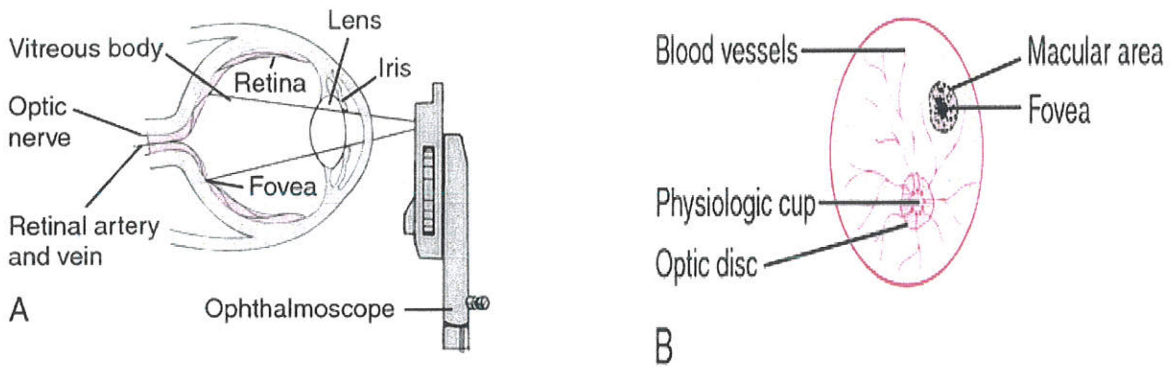
Introduced by Herman von Helmholtz in 1851, an Ophthalmoscope also called Funduscope is a device for examining the interior of the eye. It includes a light, a mirror with a single aperture through which the examiner views, and a dial holding several lenses of varying strengths. The lenses are selected to allow clear visualization of the structures of the eye at any depth. If the patient or the examiner ordinarily requires extensive correction of a refractive error, the examination may require that the corrective lenses should be worn for the examination. It is crucial in determining the health of the retina, optic disc, and vitreous humor (Mosby, 2012).

There are three major types of ophthalmoscope. The direct ophthalmoscope, one that produces an upright, or unreversed, image of approximately 15 times magnification and the indirect ophthalmoscope, one that produces an inverted, or reversed, image of 2 to 5 times magnification (Polaski & Tatro, 1996).

The direct ophthalmoscope shown in Fig. 2.8. is used to inspect the fundus of the eye, which is the back portion of the interior eyeball. Examination is best carried out in a darkened room. The examiner looks for changes in the color or pigment of the fundus, changes in the caliber and shape of retinal blood vessels, and any abnormalities in the macula lutea, the portion of the retina that receives and analyzes light only from the very center of the visual field. Macular degeneration and opacities of the lens can be seen through direct ophthalmoscopy (Saunders, 2003).

Indirect ophthalmoscope one that produces an inverted, or reversed, direct image of two to five times magnification. An indirect ophthalmoscope provides a stronger light source, a specially designed objective lens, and opportunity for stereoscopic inspection of the interior of the eyeball. It is invaluable for diagnosis and treatment of retinal tears, holes, and detachments. The pupils must be fully dilated for satisfactory indirect ophthalmoscopy (Welch, 2018).

Scanning laser ophthalmoscope (SLO) an instrument for retinal imaging in which light from a low-power laser beam that scans the retina is reflected back to a sensor; the light detected by the sensor is used to create a full-color composite digital image (Saunders, 2003).



(A) Inspection of the eye with a direct ophthalmoscope. (B) Visualized eye structures.

Fig. 2.8: Direct Ophthalmoscope (Polaski & Tatro, 1996).

2.4.4 Hyperspectral Imaging

Image intensities represent the amount of reflected light of multiple specific wavelength bands. Hyperspectral images contain a wealth of data. Hyperspectral imaging of the human retina is a relatively new concept that has the potential to determine the metabolic status of the retina (Usher *et al.,* 2003). The hyperspectral technique allows wavelength-specific visualization of retinal lesions that may be subvisible using a white light source camera. This hyperspectral technique may facilitate localization of retinal and disc pathology and consequently facilitate the diagnosis and management of common retinal diseases such as diabetic retinopathy and cataracts (Walter, Jean-Claude, Massine & Eriginay, 2002). Hyperspectral deals with imaging narrow spectral bands over a continuous spectral range, and produce the spectra of all pixels in the scene. Hyperspectral images are usually produced by instruments called imaging spectrometers (Walter *et al.,* 2002). Spectroscopy is the study of light that is emitted by or reflected from materials and its variation in energy with wavelength (Usher *et al.,* 2003). Reflectance varies with wavelength for most materials because energy at certain wavelengths is scattered or absorbed to different degrees. Hyperspectral imaging is capable of detecting oximetric changes in the retina and monitoring its response to treatment (Usher *et al.,* 2003).

2.5 IMAGE PRE-PROCESSING TECHNIQUES

Medical image analysis and processing has great significance in non-invasive treatment and clinical study. Due to the giant strides that have been taken in field of medical imaging, image processing techniques have helped in early diagnosis of glaucoma, diabetic retinopathy and other eye disease. Retinal fundus images assist trained clinicians to diagnose any abnormality and any change in retina. These images are captured by using special devices called ophthalmoscopes. There are several techniques used in image processing, however, few of them will be considered in this section including gray scale conversion, thresholding, adaptive histogram equalization, morphological operations and Gaussian filter.

2.5.1 Gray-scale Conversion

Gray scale conversion is one of the simplest enhancement techniques used in image pre-processing. A grayscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. In many of the computer vision applications, color-to-grayscale conversion algorithms are required to preserve the salient features of the color images, such as brightness, contrast and structure of the color image (Johnson, 2006).

Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only two colors, black and white (also called bilevel or binary images). Grayscale images have many shades of gray in between. Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases, they are monochromatic proper when only a given frequency is captured, but also, they can be synthesized from a full color image (Lindbloom, 2013).

Furthermore, gray-scale conversion often leads to a process called binarization in image pre-processing. Binarization is the process of converting a pixel image into a binary image. A binary image is a digital image that has only two possible values for each pixel (Sezgin & Sankur, 2004). Typically, the two colors used for a binary image are black and white, though any two colors can be used. The color used for the object(s) in the image is the foreground color while the rest of the image is the background color. In the document-scanning industry, this is often referred to as "bi-tonal" (Sezgin & Sankur, 2004).

2.5.2 Thresholding

Thresholding is a simple processing technique, where the images could be viewed as the result of the separation of the eye from the background (Sezgin & Sankur, 2004). It is a method of producing regions of uniformity within an image based on some threshold criterion. Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images (Sezgin & Sankur, 2004). The simplest thresholding methods replace each pixel in an image with a black pixel if the image intensity is less than some fixed constant, or a white pixel if the image intensity is greater than that constant.

To make thresholding completely automated, it is necessary for the computer to automatically select the threshold. Sezgin and Sankur (2004) categorized thresholding methods into six groups based on the information the algorithm manipulates.

- Histogram shape-based methods, where, for example, the peaks, valleys and curvatures of the smoothed histogram are analyzed.
- Clustering-based methods, where the gray-level samples are clustered in two parts as background and foreground (object), or alternately are modeled as a mixture of two Gaussians.
- Entropy-based methods result in algorithms that use the entropy of the foreground and background regions, the cross-entropy between the original and binarized image.
- Object Attribute-based methods search a measure of similarity between the gray-level and the binarized images, such as fuzzy shape similarity, edge coincidence.
- Spatial methods use higher-order probability distribution and/or correlation between pixels.
- Local methods adapt the threshold value on each pixel to the local image characteristics. In these methods, a different T is selected for each pixel in the image.

2.5.3 Adaptive Histogram Equalization

Adaptive Histogram Equalization is a method in digital image processing that is used to enhance the contrast of the image (Sund & Moystad, 2006). Adaptive histogram operates on different parts of the image and uses them to reallocate the lightness value of the image. Due to this, even local lower contrast area gains a higher contrast. This is also called contrast limited adaptive histogram equalization. It is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. However, AHE has a tendency to over-amplify noise in relatively homogeneous regions of an image (Sund & Moystad, 2006).

A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents the noise over-amplification by limiting the amplification (Sund & Moystad, 2006). Ordinary histogram equalization uses the same transformation derived from the image histogram to transform all pixels. This works well when the distribution of pixel values is similar throughout the image. However, when the image contains regions that are significantly lighter or darker than most of the image, the contrast in those regions will not be sufficiently enhanced. Adaptive Histogram Equalization (AHE) improves on this by transforming each pixel with a transformation function derived from a neighbourhood region. It was first developed in the year 1974 for use in aircraft cockpit displays (Ketcham, Lowe & Weber, 1974).

2.5.4 Gaussian Filter

In image processing, a Gaussian filter (also known as Gaussian smoothing) is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen as seen in Fig. 2.9, distinctly different from the bokeh effect produced by an out-of-focus lens or the shadow of an object under usual illumination. Gaussian smoothing is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales (Shapiro, 1992).

Mathematically, applying a Gaussian blur to an image is the same as convolving the image with a Gaussian function. This is also known as a two-dimensional Weierstrass transform. By contrast, convolving by a circle (i.e., a circular box blur) would more accurately reproduce the bokeh effect. Since the Fourier transform of a Gaussian is another Gaussian, applying a Gaussian blur has the effect of reducing the image's high-frequency components; a Gaussian blur is thus a low pass filter (Karash, 2016).

Gaussian blurring is commonly used when reducing the size of an image. When down-sampling an image, it is common to apply a low-pass filter to the image prior to resampling. This is to ensure that spurious high-frequency information does not appear in the down-sampled image (aliasing). Gaussian blurs have nice properties, such as having no sharp edges, and thus do not introduce ringing into the filtered image (Nixon & Aguado, 2008).

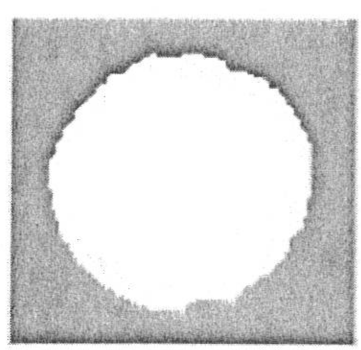


Fig. 2.9: Gaussian filtered image (Chaudhari & Kulkarni, 2016).

2.5.5 Morphological Operations

Morphology is a broad set of image processing operations that process images based on shapes (Nixon & Aguado, 2008). Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image aimed at removing the numerous imperfections contained in binary images in particular the binary regions produced by simple thresholding which have been distorted by noise and texture by accounting for the form and structure of the image (Karash, 2016).

The most basic morphological operations are dilation and erosion (Karash, 2016). Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbours in the input image. The rule used to process the pixels defines the operation as a dilation or an erosion (Karash, 2016).

Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. It applies a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. In morphological operations, while some operations test whether the element "fits" within the neighbourhood, others test whether it "hits" or intersects the neighbourhood (Nixon & Aguado, 2008). Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest (Karash, 2016).

2.6 FEATURE EXTRACTION

Feature extraction is a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval (MathWorks, 2018). Feature plays a very important role in the area of image processing. Before getting features, various image pre-processing techniques like thresholding, median filter, binarization, etc. are applied on the sampled image. After that, feature extraction techniques are applied to get features that will be useful in classifying and recognition of images. Feature detection, feature extraction, and matching techniques are often combined to solve various computer vision problems such as object detection and recognition, content-based image retrieval, face detection and recognition, and texture classification (Harisha, 2015).

2.6.1 Classification of Image Feature Extraction

The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object. The various features currently employed in feature extraction can be classified as follows:

- General features: These are application independent features such as color, texture, and shape. According to the abstraction level, they can be further divided into: Pixel-level features, Local features and Global features
- Domain-specific features: These are the application dependent features such as human faces, fingerprints, and conceptual features. These features are often a synthesis of low-level features for a specific domain (Saber & Tekalp, 1998).

Feature extraction of medical images is used to collect effective information from large scale image data. Analyze objects and images to extract the most important features that are represents various medical images. Different methodologies of feature extraction have been used to detect and classify changes in medical image such as wavelets and statistical image processing methods (Singh & Chetty, 2012). The features that were most promising were color, texture and shape/edge.

2.6.1.1 Color

The color feature is one of the most widely used visual features in image retrieval. Images characterized by color features have many advantages which includes robustness, effectiveness, implementation simplicity, computational simplicity and low storage requirements (Schmid & Mohr, 1997). Typically, the color of an image can be represented through various color model to describe color information. A color model is specified in terms of 3-D coordinate system and a subspace within that system where each color is represented by a single point. The more commonly used color models are RGB (red, green, blue), HSV (hue, saturation, value), CMYK (cyan, magenta, yellow, black) and Y,Cb,Cr (luminance and chrominance) (Schmid & Mohr, 1997).

2.6.1.2 Texture

Texture has been one of the most important characteristic which has been used to classify and recognize objects and have been used in finding similarities between images in multimedia databases. Texture is a powerful regional descriptor that helps in the retrieval process. Texture, on its own does not have the capability of finding similar images, but it can be used to classify textured images from non-textured ones and then be combined with another visual attribute like color to make the retrieval more effective (Choras, 2007). Basically, texture representation methods can be classified into two categories: structural and statistical (Kim & Park, 1999). Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura features, Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity.

2.6.1.3 Shape

Shape is an important visual feature and it is one of the primitive features for image content description. Shape based image retrieval is the measuring of similarity between shapes represented by their features (Choras, 2007). Shape content description is difficult to define because measuring the similarity between shapes is difficult. Therefore, two steps are essential in shape based image retrieval, which are: feature extraction and similarity measurement between the extracted features (Choras, 2007).

Table 2.1 presents the set of image features based on shape, intensity, texture and color. Image features at various levels of complexity are extracted from the image data.

Table 2.1: Image features and their properties (Krishnan *et al.,* 2014).

Image Features	**Properties**
Shape based features	Area, Circularity, Irregularity, Perimeter, Roundness.
Texture features	Contrast, Correlation, Entropy, Homogeneity, Sum of square variance. Spectral and spatial.
Color based features	Impression, Expression and Construction. RGB, LUV, HSV and HMMD.

2.6.2 Feature Extraction Techniques

This section covers a review of three feature extraction techniques including Gray-Level Co-occurrence Matrix (GLCM), Principal Component Analysis (PCA) and Gabor filter.

2.6.2.1 Gray-Level Co-occurrence Matrix (GLCM)

GLCM is a statistical method of examining and representing the textures of images by considering the spatial relationship of the pixels (Abdullahi *et al.,* 2015). It contains a count of the number of times a given feature (e.g., a given gray level) occurs in a particular spatial relation to another given feature. GLCM assesses the image properties associated to second-order statistics. The works of Zulpe *et al.* (2012) showed that the number of gray level 'G' of an image is represented by the row and column of GLCM and the element used by the matrix is given as:

$$(i, j|\Delta x, \Delta y) \ and \ (i|d, \theta) \tag{2.1}$$

Where $p(i, j)$ represents the frequency of the matrix element separated by the distance $\Delta x, \Delta y$ and the second expression represents the second order probability values for changes between gray levels i and j at a distance d and angle θ. Some features that can be extracted from GCLM includes angular second moment or homogeneity, entropy, contrast and inverse different moment (Zulpe *et al.,* 2012).

2.6.2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a common feature extraction technique used in medical image processing (Kumar & Bhatia, 2014). It is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. Technically, PCA finds the eigen vectors of a covariance matrix with the highest eigen values and then uses those to project the data into a new subspace of equal or less dimensions. This procedure includes: centering the data X; computing the covariance matrix C; obtaining the eigen vectors and eigen values of the covariance matrix U, P; and projecting the original data in the eigen space.

$$-P = U^T.X \tag{2.2}$$

Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen-Loeve transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD) (Kumar & Bhatia, 2014)

2.6.2.3 Gabor Filter

Named after Dennis Gabor, Gabor filter is a linear filter used mostly for edge detection (Henriksen, 2008). Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. Thus, image analysis with Gabor filter is thought to be similar to perception in the human visual system (Henriksen, 2008).

Haghighat *et al.* (2013) stated in their work stated that a set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. In the discrete domain, two-dimensional Gabor filters are given by:

$$G_c[i,j] = Be - \frac{(i^2+j^2)}{2\sigma^2} \cos(2\pi f(icos\theta + jsin\theta)) \tag{2.3}$$

$$G_s[i,j] = Ce - \frac{(i^2+j^2)}{2\sigma^2} \cos(2\pi f(icos\theta + jsin\theta)) \tag{2.4}$$

Where B and C are normalizing factors to be determined, f defines the frequency being looked for in the texture and by varying θ, we can look for texture oriented in a particular direction while by varying σ, the support of the basis or the size of the image region being analyzed can be changed. 2-D Gabor filters have rich applications in image processing, especially in feature extraction for texture analysis and segmentation, (Haghighat *et al.,* 2013)

2.7 MACHINE LEARNING ALGORITHMS AND TECHNIQUES

On completion of image pre-processing and feature extractions, there is then a need to use a classification algorithm that will help give a useful meaning to the extracted features. Classification algorithm involves the use of classifiers and machine learning techniques to extract useful information from datasets (e.g., images) to solve important problems in Image Processing and Computer Vision. This section covers a review of a few algorithms and techniques for digital health including K-Nearest Neighbourhood algorithm (KNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), Fuzzy Logic, Hidden Markov Model (HMM) and Deep Learning.

2.7.1 K-Nearest Neighbourhood algorithm (KNN)

K - Nearest Neighbour is a kind of instance-based learning, where the function is only locally approximated and all computation is referred until classification. This technique is called lazy learning because, it does not need any training or minimal training phase. All the training data is needed only during the testing phase and this technique uses all the training data so that if there is a large data set then a special method is needed to work on part of data which is the algorithmic approach (Alamelu, Wagle & Kumar, 2015). KNN algorithm has been used in many applications in areas such as data mining, statistical pattern recognition, image processing, etc. Successful applications include recognition of handwriting, satellite image and electrocardiographs (ECG) patterns. KNN can be described in 3 steps namely: classification, binary classification and K-preferably odd to avoid ties.

Although classification is the primary application of KNN, it can also be used for density estimation. The k-nearest neighbour algorithm is one of the simplest of all machine learning algorithms and its' classification was formulated from the requirement to perform several analyses when reliable parametric estimates of probability densities are not known or difficult to determine (Alamelu *et al.,* 2015). Few of its constraints, however includes: sensitive to noise and irrelevant features, computationally expensive, large memory requirements, and more frequent classes dominate result.

2.7.2 Artificial Neural Network (ANN)

Artificial Neural Network (ANN), is a computational analytical tool inspired by the biological nervous system in a bid to imitate human reasoning. It consists of networks of highly interconnected computer processors called 'neurons' that are capable of performing parallel computations for data processing and knowledge representation (McCulloch & Pitts, 1943). A branch of artificial intelligence (AI), ANN teaches the system to execute task, instead of programming computational system to do definite tasks. Judging by the volume of publication in the last two decades, ANN is currently the most popular AI technique in medicine. Their ability to learn from historical examples, analyze non-linear data, handle imprecise information and generalize enabling application of the model to independent data has made them a very attractive analytical tool in the field of medicine. McCulloch and Pitts (1943) invented the first artificial neuron using simple binary threshold functions. The next important milestone came when Frank Rosenblatt, a psychologist, developed the Perceptron in 19588 as a practical model. Many variations of the basic Perceptron network have been proposed but the most popular model has been multilayer feed-forward Perceptron (Rosenblatt, 1958). As shown in Fig. 2.9, these networks are made up of layers of neurons, typically an input layer, one or more middle or hidden layers and an output layer, each of which are fully connected to other layers.

Fig. 2.10 give a diagrammatic description of how the neurons are connected by links, and each link has a numerical weight associated with it. A neural network 'learns' through repeated adjustments of these weights. One of the important characters of ANNs is that they can learn from their experience in a training environment. The use of multilayer feed-forward Perceptron was restricted by the lack of a suitable learning algorithm until Paul Werbos (1974) a PhD student introduced the 'back-propagation' learning (Werbos, 1974). Some of the other popular network designs include Hopfield networks (Hopfield, 1982), Radial Basis Function (Park *et al.,* 1991), and the Self-Organizing Feature Map (Carpenter *et al.,* 1988).

ANNs have already found a wide variety of applications in the real world. Their ability to classify and recognize patterns accurately has attracted researchers to apply them in solving many scientific and clinical problems. As we realize that diagnosis, treatment and predicting outcome in many clinical situations is dependent on a complex interaction of many clinical, biological and pathological variables there is a growing need for analytical tools like ANNs which can exploit the intricate relationships between these variables and draw out a reliable inference.

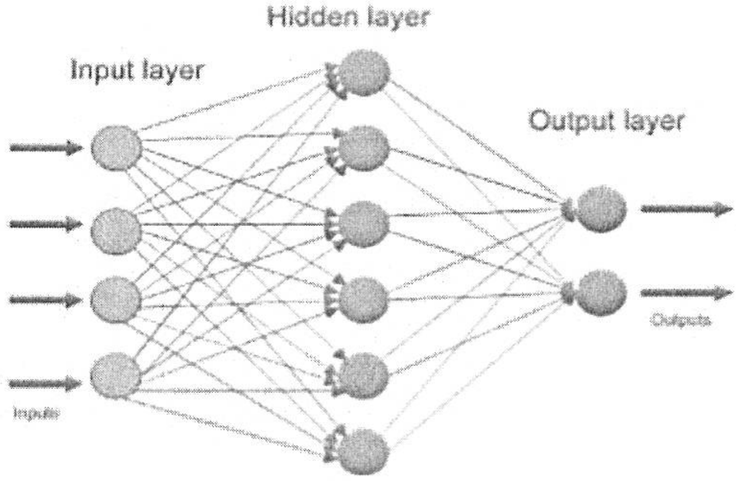


Fig. 2.10: Multilayered feed-forward artificial neural networks (Tahseen *et al.,* 2011).

William Baxt was one of the first researchers to explore the clinical potentials of ANNs (Baxt, 1990). He developed a neural network model which accurately diagnosed acute myocardial infarction and latter prospectively validated his work with similar accuracy (Starney & Pentland, 1996). Since then, ANNs have been applied in almost every field of medicine.

2.7.2.1 Feed-Forward Neural Network

A feed forward neural network is an artificial neural network wherein connections between the units do not form a cycle. This is different from recurrent neural networks. The feed forward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network (Mary & Marri, 2012).

2.7.2.2 Back Propagation Network

Back propagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions (Yegnanarayana, 1999). Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by you. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. Standard back propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function (Yegnanarayana, 1999).

2.7.3 Fuzzy Expert Systems

Fuzzy logic is the science of reasoning, thinking and inference that recognizes and uses the real-world phenomenon – that everything is a matter of degree. popularized by Lofti Zadeh (1965), an engineer from the University of California), fuzzy logic recognizes that in reality most things would fall somewhere in between, that is varying shades of grey, instead of assuming everything is black and white (conventional logic (Zadeh, 1965). It uses continuous set membership from 0 to 1 in contrast to Boolean or conventional logic which uses sharp distinctions, i.e. 0 for false and 1 for true. Medicine is essentially a continuous domain and most medical data is inherently imprecise. Fuzzy logic is a data handling methodology that permits ambiguity and hence is particularly suited to medical applications. It captures and uses the concept of fuzziness in a computationally effective manner. In the writings of Zadeh (1969), "the most likely area of application for this theory lies in medical diagnostics and, to a lesser extent, in the description of biological systems".

Fuzzy expert systems have the structure of a series of 'if – then' rules for modelling. The techniques of fuzzy logic have been explored in many medical applications. Schneider *et al.* (2002) showed that fuzzy logic performed better than multiple logistic regression analysis in diagnosing lung cancer using tumour marker profiles. Similarly, the application of fuzzy logic has been explored in the diagnosis of acute leukaemia (Belacel *et al.,* 2001), breast and pancreatic cancer (Halm *et al.,* 2000). They have also been applied to characterize ultrasound images of the breast (Koyama *et al.,* 1997), ultrasound (Badawi *et al.,* 1999), computerized tomography (CT) scan (Klein *et al.,* 1996) images of liver lesions and magnetic resonance imaging (MRI) images of brain tumours. Fuzzy logic has also been used to predict survival in patients with breast cancer (Seker *et al.,* 2002). Fuzzy controllers have been designed for the administration of vasodilators to control blood pressure in the peri-operative period, and also in the administration of anaesthetics in the operating room (Mason, Ross & Edwards, 1997)

2.7.4 Support Vector Machine (SVM)

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis (Corinna & Vladimir, 1995). Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting) (Alamelu *et al.*, 2015). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. When data are unlabeled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups The support vector clustering algorithm created by Asa, David, Hava & Vladimir (2001), applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data, and is one of the most widely used clustering algorithms in industrial applications (Abdulahi *et al.,* 2015).

2.7.5 Hidden Markov Model

The Hidden Markov Model (HMM), is a signal detection model that was introduced in 1966 by Baum and Petrie (Baum & Petrie, 1966). It assumes that an observation sequence was derived from a hidden state sequence of discrete data and satisfies the first order of a Markov process. HMM is a statistical model developed from a model for a single observation variable to a model for multiple observation variables. (Nguyen, 2017). In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters, while in the hidden Markov model, the state is not directly visible, but the output, dependent on the state, is visible (Baum & Eagon, 1967). Each state has a probability distribution over the possible output tokens. Therefore, the sequence of tokens generated by an HMM gives some information about the sequence of states; this is also known as pattern theory, a topic of grammar induction (Baum & Sell, 1968).

A hidden Markov model can be considered a generalization of a mixture model where the hidden variables (or latent variables), which control the mixture component to be selected for each observation, are related through a Markov process rather than independent of each other. The adjective hidden refers to the state sequence through which the model passes, not to the parameters of the model; the model is still referred to as a hidden Markov model even if these parameters are known exactly (Nguyen, 2017).

Hidden Markov models are especially known for their application in reinforcement learning and temporal pattern recognition such as speech, handwriting, gesture recognition, financial mathematics, (Starner & Pentland, 1995), part-of-speech tagging, musical score following (Pardo & Birmingham, 2005), partial discharges (Satish & Gururaj, 2003), biomathematics and bioinformatics (Li & Stephens, 2003).

2.7.6 Deep Learning

The term Deep Learning was introduced to the machine learning community by Rina Dechter in 1986, (Schmidhuber, 2015) and to Artificial Neural Networks by Igor Aizenberg and colleagues in 2000, in the context of Boolean threshold neurons (Aizenberg, Naum, Aizenberg & Vandewalle, 2000). Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised (Yoshua, Yann & Geoffrey, 2015).

Deep learning is a class of machine learning algorithms that use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input. These machines can learn in supervised (e.g., classification) and/or unsupervised (e.g., pattern analysis) manners and can also learn multiple levels of representations that correspond to different levels of abstraction; the levels form a hierarchy of concepts (Deng & Yu, 2014).

Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design and board game program (Ciresan, Meier & Schmidhuber, 2012), where they have produced results comparable to and in some cases superior to human experts (Alex, Ilya & Geoffrey 2012).Deep learning models are vaguely inspired by information processing and communication patterns in biological nervous systems yet have various differences from the structural and functional properties of biological brains, which make them incompatible with neuroscience evidences (Marblestone, Wayne & Kording, 2016).

2.8 MOBILE PLATFORMS

A mobile operating system (or mobile OS) is an operating system for phones, tablets, smartwatches, or other mobile devices. It combines features of a personal computer operating system with several other features useful for mobile devices. In recent periods, mobile operating systems are getting tremendous growth. In this fast-growing mobile revolutionary era, many operating systems are playing vital roles in the present market. In today's markets, a wide variety of mobile phones are available in various brands with different operating systems. Present mobile operating systems are playing an equal or more vital role than a computer operating system as they cover most of the activities done by a computer (Joseph & Kurian, 2013).

By the end of 2016, over 430 million smartphones were sold with 81.7 percent running Android, 17.9 percent running iOS, 0.3 percent running Windows 10 Mobile which is no longer marketed and the other OSes cover 0.1 percent. Android alone is more popular than the popular desktop operating system Windows, and in general smartphone use outnumber desktop use. Desktop web use, overall is down to 44.9% in the first quarter of 2017 (Verge, 2017). Of the many available platforms, this section covers a review of a few mobile operating systems including Android, iOS and Windows mobile OS.

2.8.1 Android Operating System

Founded in Palo Alto, California, in October 2003 by Andy Rubin, Rich Miner, Nick Sears, and Chris White (PhoneArena, 2011; Elgin, 2005). Android is a mobile operating system developed by Google Inc. based on the modified version of the Linux kernel and other open source software (Gartner, 2011). Besides having the largest installed smartphones base worldwide, it is also the most popular operating system for general purpose computers, even though Android is not a popular operating system for regular (desktop) personal computers (Morrill, 2008).

Every day more than 1 million new Android based devices are activated in worldwide. It is an open source platform, which allows many mobile manufactures to customize and use it as the operating system for their hardware device. The Linux kernel used by Android provides its hardware abstraction layer between hardware and other software. This also provides a better memory and process management, security and network options. Android is written in the Java programming language and run in the Dalvik virtual machine. The key advantage of this operating system is anyone can customize this operating system which is the major reason the OS is at the peak of the competitive mobile market (Joseph & Kurian, 2013). The current Android version is 8.0 Oreo.

2.8.2 iPhone Operating System (iOS)

iOS (formerly named iPhone OS) is a mobile operating system from Apple Inc. following the macOS. It has the second largest installed base worldwide on smartphones, but the largest profits, due to aggressive price competition between Android-based manufacturers (Lunden, 2017). It is closed source and proprietary, and is built on the open source Darwin operating system. The iPhone, iPod Touch, iPad and second or third-generation Apple TV all use iOS, which is derived from macOS.

Initially, native third-party applications were not officially supported until the release of iPhone OS 2.0 on July 11, 2008. Businesses around the world are choosing iOS devices because of their enterprise-ready features and powerful security. iOS works with Microsoft Exchange and standards-based servers to deliver over-the-air push email, calendar, and contacts. It protects user data by encrypting information in three separate areas: in transmission, at rest on the device, and when backed up to iTunes. A user can securely access private corporate networks through industry-standard virtual private network (VPN) protocols. And companies can easily deploy iPhone across an enterprise using configuration profiles (Joseph & Kurian, 2013). Currently all iOS devices are developed by Apple and manufactured by Foxconn or another of Apple's partners (Clover, 2018).

2.8.3 Windows Mobile Operating System

Windows Mobile is a discontinued family of mobile operating systems developed by Microsoft for smartphones and Pocket PCs (Evers, 2005). It is closed source and proprietary. The Windows Compact Edition (CE) operating system and Windows Mobile middleware which were specifically designed for handheld devices, based on Windows Application Programming Interface (API) were widely spread in Asia (which mostly uses Android now). The two improved variants of this operating system, Windows Mobile 6 Professional (for touch screen devices) and Windows Mobile 6 Standard, were unveiled in February 2007. However, it was criticized for having a user interface which is not optimized for touch input by fingers; instead, it is more usable with a stylus (Joseph & Kurian, 2013). Like Android, iOS, and most other Mobile OS, it supports both touch screen, physical and Bluetooth keyboard configurations. Windows Mobile's market share sharply declined to only 5% in the second quarter of 2010. Microsoft phased out the Windows Mobile OS to focus on Windows Phone, which featured new user interface derived from the Metro design language. Although the Windows Phone would later be replaced by the Windows 10 Mobile in 2015 (Yeeply, 2015).

2.9 RELATED WORK

Digital health has seen several researches which seek the performance improvement of digital systems. The process of diseases diagnosis has been greatly improved with the advent of computerized diagnostic systems which aid the physicians in their decision-making process of ophthalmology has been among the greatest benefactors. Over the years, several techniques have been proposed for the detection of eye abnormalities and retinal diseases which optimistic results. To make such systems readily available to the average man, they have been packaged on mobile platforms.

Seeking to apply digital health in ophthalmology, Zubair & Asghar (2010) described an expert system for online diagnosis and prescription of red-eye diseases. The types of eye diseases that can be diagnosed with this system are called Red-eye diseases i.e. disease in which red-eye is the common symptom. It is a rule based web-supported expert system which was designed and programmed with Java technology. The expert rules were developed on the symptoms of each type of Red-eye disease, and they were presented using tree-graph and inferred using forward-chaining with depth-first search method. The system can detect and give early diagnosis of twenty Red-eye diseases and was proposed to extended to diagnose all types of eye-diseases.

Using retinal image analysis and data mining techniques for automatic prediction of diabetic retinopathy and glaucoma, Ramani (2012) proposed a unique approach to automatic disease detection. Retinal image analysis and data mining techniques were used to accurately categorize the retinal images as normal, diabetic retinopathy or glaucoma infected. The technique recorded a sensitivity and accuracy of 93% and 92% respectively.

Mary & Marri (2012) implemented a technique for glaucoma detection where optic disc segmentation via pyramidal decomposition is carried out on the retinal images which gives a better performance than other algorithms. It is important to note that although pyramidal decomposition method with the help of Hough transform is guaranteed to converge though it is very sensitive to noise. So, multiple initializations were used to yield a better performance. Finally, they proposed a model approach using discriminant analysis which has shown an improvement over the rest.

With the rising influence of digital health on medical processes, Soltan, Rashad & El-Desouky (2013) proposed four staged diagnosis system which uses an expert system to provide patients with background for suitable diagnosis and treatment of heart diseases. In the first stage, symptoms from the patient are received. The second stage requests the patient to make some analysis and investigation to help the system to make a correct decision in the diagnosis while third stage does diagnosis of patient according to the information from patient (symptoms, analysis and investigation) and the fourth stage determines the ailment and prescribes the appropriate medication or what should be done until the patient recovers. The system uses the rule-based reasoning technique through simple querying of symptoms, signs and investigation done to the patient.

In a bid to improve the processing of digital fundus images, clustering method for segmentation of exudates from the fundus images was implemented by Ahmed *et al.* (2013) by using a multi-space image processing technique to detect the exudates and to diagnose diabetic retinopathy. However, their system performance was low, producing a sensitivity and accuracy of 76.96% and 89.7% respectively after evaluation.

Significant progress was made in the development of image processing techniques for glaucoma detection when Chalinee *et al.* (2013) proposed a method to calculate the cup to disc ratio automatically from non-stereographic retinal fundus photographs. To automatically extract the disc, two methods making use of an edge detection method and variational level-set method were evaluated while color component analysis and threshold level-set method were evaluated for the cup. Ellipse fitting was applied to the obtained image for boundary detection. With an accuracy of 89 percent, the Chalinee *et al.*'s method was able to detect edges while also suppressing noise simultaneously. But since depth of cup is not considered to detect boundary, its detection is not efficient.

A unique approach to Glaucoma detection using wavelet energy was proposed by Annu & Justin (2013). This included glaucomatous image classification using image texture features and classification using probabilistic neural network (PNN). Wavelets used were daubechies, symlets and biorthogonal wabelet filters. Due to its low computational complexity, Annu & Justin used wavelet decomposition technique in their method as it was rapid, easy-to-operate, non-invasive and inexpensive. A success rate of 95 percent was achieved but the system was limited due to its use of probabilistic neural network which is not powerful enough for its classification. A more powerful algorithm would have produced greater accuracy.

Digital fundus images (DFIs) are crucial in detecting pathological phenomenon that would lead to various diseases. However, DFI has multiple contrast and illumination problems which makes enhancement a necessity. Rahim, Ibrahim, Zaki & Hussain (2014) proposed three methods to enhance digital fundus image for improved diabetic retinopathy detection namely, Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE) and Mahalanobis Distance (MD). The algorithm was applied on a database of 40 images with both normal and abnormal criteria using MATLAB R2012b. From the result, it is noted that CLAHE and MD both achieved the goal to enhance blood vessel since both methods provided the best similarity to the Gaussian-shaped curve. But, the neighborhood-based approach on the pixels in HE and CLAHE introduced artefacts that are undesired since the quality of further processing on the produced image would be reduced as any noise that is present will be enhanced whereas the MD approach had no such occurrences. Thus, showing that MD method is the best algorithm for the application.

Compared with other mobile-based intelligent health monitoring systems, there are limited developments focusing on retinal related disease detection. Bourouis, Feham, Hossain, & Zhang (2014) developed an innovative low-cost smartphone based intelligent system integrated with microscopic lens. This system used an artificial neural network algorithm to analyze the retinal images captured by the microscopic lens to identify retinal disease conditions. The algorithm was first of all trained with infected and normal retinal images using a personal computer and then further developed into a mobile-based diagnosis application for Android environments. The application was optimized by using the rooted method in order to increase battery lifetime and processing capacity. A duty cycle method was also implemented to greatly improve the energy efficiency of the system. To verify the system, it was tested using two well-known medical ophthalmology databases to demonstrate its merits and capabilities where it showed an accuracy of 87 percent. However, the system's rooting requirement breaches the android OS security, making the device vulnerable to attacks.

Alamelu *et al.* (2015) also developed a system that diagnoses diabetic retinopathy from eye fundus images by classifying exudates as mild, moderate and severe based on their position from macula using texture feature extraction from GLCM. Although their system performance was high, at 95 and 98 percent for sensitivity and specificity respectively, the over-reliance of the system on segmentation and consideration of exudates alone made the system incomplete.

To show the effect of image resolution on the performance of automatic classification of diabetic retinopathy and storage memory, Abdullahi *et al.* (2015) presented a work using hundreds of fundus images which were first preprocessed when the reference image pixel resolution was reduced by 50 percent, 75 percent, 87.5 percent and 93.75 percent. For each resolution, four GLCM features were extracted and were subsequently fed to a feed forward back propagation ANN. The results showed that there were no significant changes in the sensitivity of the first three resolutions which are 100 percent. At 95.7 percent and 93.3 percent respectively, the accuracy and sensitivity values were also constant. However, it was observed that the memory occupied by the images reduces significantly for every reduction in resolution. Also, there was a drop in the average classification performance for every reduction in resolution used.

In a bid to advance diagnoses of retinal disease, the use of image processing techniques was proposed by Balasundari *et al.* (2016) to diagnose age related macula degeneration, glaucoma, retinoblastoma and diabetic retinopathy. The image processing techniques used include binarization, median filter, thresholding, drusen detection, Gaussian filter and morphological operations. Their success rate of the system was 90 percent. However, the use of image processing techniques without any classifier algorithm limited the system. Classification using artificial neural network, support vector machine, etc. would have produced more accuracy.

In an attempt to improve on the detection and diagnosis of glaucoma, Chaudhari & Kulkarni (2016) proposed a novel method which makes use of feed forward Artificial Neural Network (ANN) and Cup to Disk ratio (CDR). It is observed that this method gives more accurate results than prior methods available. MATLAB was used for training and simulating the ANN to detect the glaucoma. The CDR and feed forward propagation artificial neural network were used and these parameters were extracted using MATLAB and were compared with standard values. Upon testing, the system achieved an 86 percent success rate. However, during training, the weights and biases of the network were iteratively adjusted which minimized the network performance function.

To make digital health diagnosis readily available and affordable to the majority, Habib, Asghar & Shams (2016) developed an android-based health-care management system which can assist people to check their health-related issues on daily basis. The application was developed with java in android operating system environment using the App Inventor tool having four sub-modules namely target heart rate, calorie level, blood volume and diabetes. Using the Tiny DB provided by app inventor as the database for the system, the results revealed that the system performed well with above 80 percent accuracy and sensitivity values. Although, Habib *et al.* did not provide information on the setbacks of the system.

To aid early detection of retinal disorders, a low-cost and portable smartphone-based decision support system for initial screening of diabetic retinopathy using sophisticated image analysis and machine learning techniques was proposed by Prateek, Shubham, Neelakshi & Anant (2016). It requires a smartphone to be attached to a direct hand-held ophthalmoscope. The phone is used to capture fundus images as seen through the direct ophthalmoscope. Pattern recognition on the captured images was deployed to develop a classifier that distinguishes normal images from those with retinal abnormalities. The algorithm performance was tested on an existing database and recorded an average sensitivity of 86%. In case the application enjoys a widespread deployment, the database will expand and moved to a remote server or cloud instead of being a stand-alone system, thus limiting its usage to only those having access to the internet.

Fanijo (2017) in his work, developed system which diagnosis glaucoma and diabetic retinopathy on the desktop platform. The implementation of the project was done in four modules. Firstly, data is acquired from public online databases, then image preprocessing techniques such as grayscale conversion and thresholding are carried out on the images before salient features using Gray Level Co-occurrence Matrix are extracted from the preprocessed images. The results of the feature extraction are then fed into an Artificial Neural Network algorithm for classification. The system was trained with 135 fundus images while 60 were used for testing. Upon testing, the system recorded an overall accuracy of 95%. To improve the system, it could be trained to diagnose patients with cataract.

As digital health advanced, multiple digital tools and mobile and web applications were developed by Cahn, Akirov & Raz (2018) to assist patient decision making, and to enhance their compliance by using motivational tools and incorporating incentives from social media and gaming techniques. The data acquired were integrated, analyzed, and presented in a self-explanatory manner, highlighting important trends and items that require attention. The use of decision support systems may propose data-driven actions that, for the most, require final approval by the patient or physician before execution and, once implemented, may improve patient outcomes. The digital diabetes clinic aims to incorporate all digital patient data and provide individually tailored virtual or face-to-face visits to those persons who need them most.

CHAPTER THREE

DESIGN METHODOLOGY

3.1 OVERVIEW OF THE EYE DISEASES DIAGNOSTIC SYSTEM

A block diagram description of the android based eye disease diagnostic system is shown Fig. 3.1. This consists of data acquisition, image pre-processing, feature extraction techniques, classification algorithm and proposed system implementation and prototyping on the android platform. In this work, eye diseases such as Glaucoma and Diabetic retinopathy were considered during diagnosis.

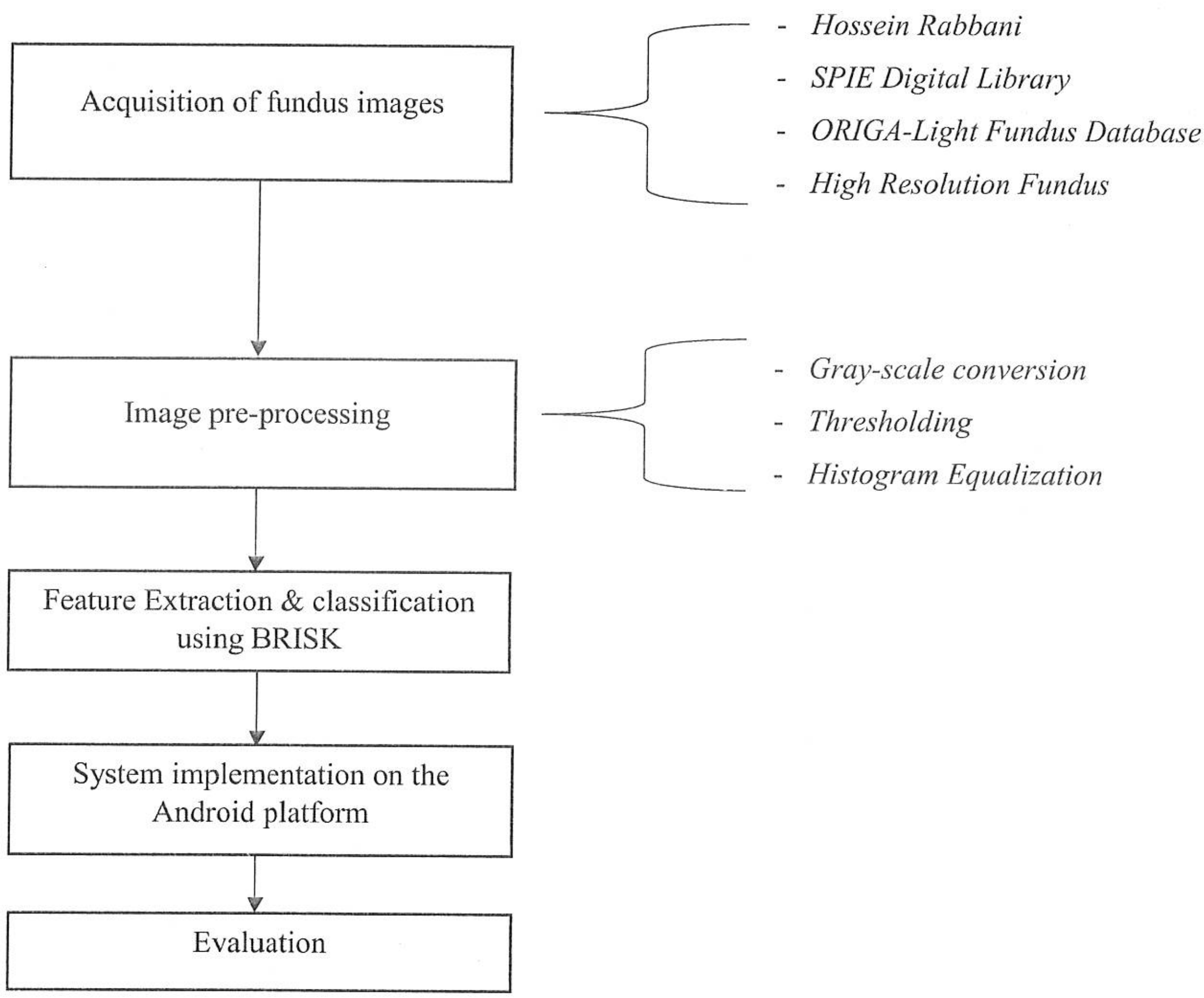


Fig. 3.1: Overview of the android-based human eye diseases diagnostic system.

3.2 DATA ACQUISITION

Image acquisition is the very first step in the diagnostic system. The data that is to be acquired to train the system are the fundus images of normal eyes and infected eyes for glaucoma, diabetic retinopathy and cataract. A publicly available diabetic retinopathy and glaucoma dataset was considered for acquiring of such images and used in the training and evaluation process. Once tested and verified, users will be required to attach an ophthalmoscope to their smartphone camera to take the fundus image of the eye to be processed by the system. Sadly, this device could not be procured for the purpose of this project.

3.2.1 Hossein Rabbani Eye Fundus Database

The fundus images in this database were provided by the Department of Bio-electrics and Biomedical Engineering, School of Advanced Technologies in Medicine, Isfahan University of Medical Sciences, Iran. The dataset consists of 35 Diabetic funds images collected from 35 patients. The images were captured in digital form using a Canon CR5 non-mydriatic 3CCD camera at 45-degrees field of view (Alipour, Rabbani & Akhlaghi 2012). The images are of size 70 pixels, 8 bits per color channel and have a field of view (FOV) of approximately 540 pixels in diameter. A sample of the images acquired are shown in Fig. 3.2.

Fig. 3.2: Fundus image sample from Hossein Rabbani Database (Alipour, Rabbani & Akhlaghi 2012).

3.2.2 SPIE Eye Fundus Database

The fundus images in this dataset was provided by SPIE (Mahmudi *et al.*, 2014), a digital library in Biomedical Applications in Molecular, Structural and Functional Imaging, San Diego, California. The dataset contains OCT data (in mat format) of left and right eyes of 50 healthy persons. Details of the type of fundus camera used are not provided however, dimension of the images are in 720 by 576. A sample of the images acquired are shown in Fig. 3.3.

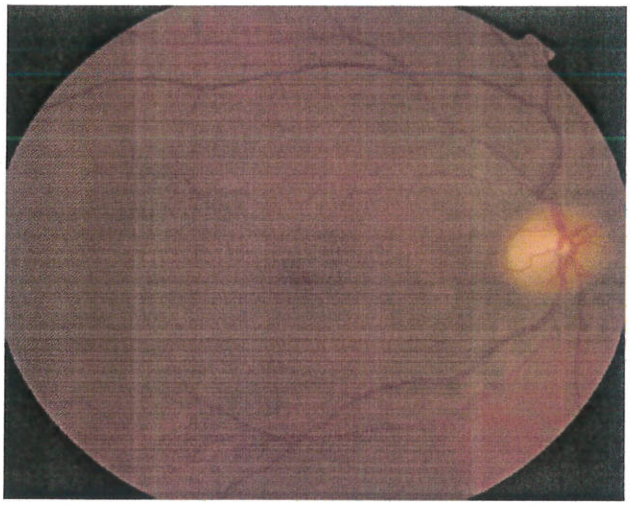


Fig. 3.3: Healthy fundus image sample from the SPIE database (Mahmudi *et al.,* 2013).

3.2.3 ORIGA-Light Eye Fundus Database

This database is an online depository which aims to share clinical ground truth retinal images with the public, provide open access for researchers to benchmark their computer-aided synchronous algorithm. Currently, ORIGA-light contains 650 retinal images annotated by trained professionals from Singapore. Eye Research Institute, which was acquired using a Canon CR-DGI fundus camera. A wide collection of image signs, critical for glaucoma diagnosis, are annotated. The data set consists of 168 images from all glaucomatous eyes and 482 images from randomly selected normal eyes. The data set was obtained from a population based study and is therefore suitable for evaluating the performance of glaucoma screening. Fig. 3.4 shows the images acquired from this database. (Zhang, 2010).

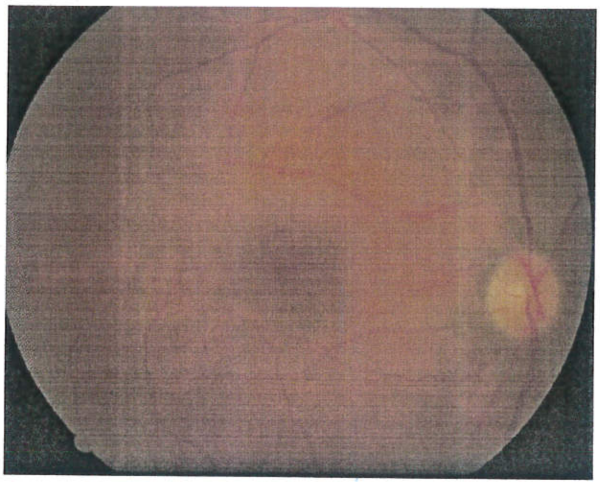
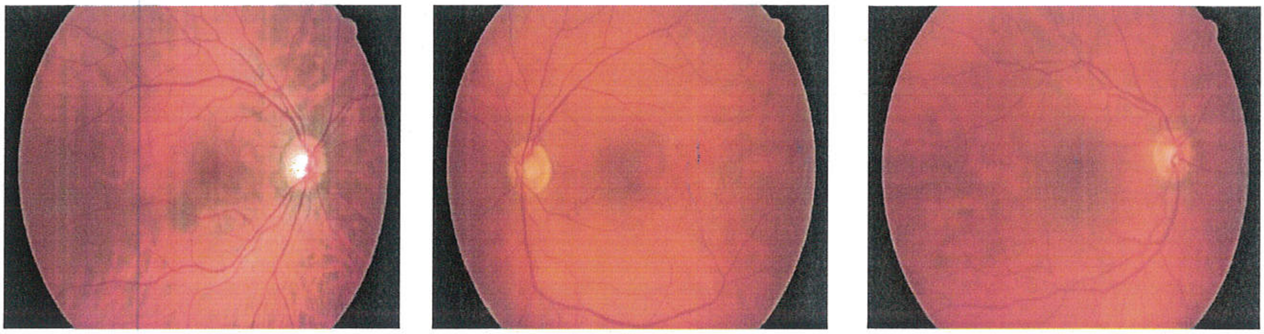


Fig. 3.4: Glaucomatous Fundus image from ORIGA-light eye fundus database (Zhang, 2010).

3.2.4 High Resolution Fundus (HRF) Image Database

This database has been established by a collaborative research group to support comparative studies on automatic segmentation algorithms on retinal fundus images. (Budia *et al.*, 2013). The public database contains at the moment 15 images of healthy patients, 15 images of patients with diabetic retinopathy and 15 images of glaucomatous patients. The images were captured using a Canon CR-1 fundus camera with a field of view of 45° and different acquisition setting. The available dataset was captured by Jan Odstrcilik (Köhler *et al.*, 2013).



(a) Healthy Eye (b) DR sample (c) Glaucomic sample

Fig. 3.6: Fundus images from High Resolution Fundus Image Database (Köhler *et al.*, 2013).

3.3 IMAGE PRE-PROCESSING

It could sometimes be complex to extort retinal features and make a distinction of region of interests from other features inside retinal images because of the differences in luminosity, contrast and brightness (Karegowda *et al.*, 2011). Hence image pre-processing was required to eradicate noise present in fundus images and equalization of the irregular illumination associated with retinal images. The image pre-processing for the diseases are explained chronologically below:

3.3.1 Grayscale Conversion

Grayscale conversion is one of the simplest enhancement techniques used in image pre-processing. A grayscale digital image is an image in which the value of each pixel is a single sample in that it carries information about the image's intensity only. In many computer vision applications, colour-to-grayscale conversion algorithms are required to preserve the salient features of the colour images such as brightness, contrast and structure of the colour image. The coloured fundus images are converted into grayscale which is two dimensional, so as to make the image suitable for processing.

3.3.2 Thresholding

Image thresholding was used for extracting the significant part of the image and removing the unwanted part or noise. The point operator of major interest is thresholding, which selects pixels that have a particular value, or that are within a specified range while ignoring others. With thresholding, the image can be segmented based on several factors such as colour, texture, etc. This holds true under the assumption that a reasonable threshold value is chosen. A reasonable threshold value was then taken from the histogram of the original image. The point operator helped to find objects in a picture if the brightness level or range is known. Hence the object's brightness must be known (Sezgin & Sankur, 2004).

The foreground and background are expressed as $p_f(g), 0 \leq g \leq T$, and $p_b(g), T+1 \leq g \leq G$, respectively, where T is the threshold value. The foreground and background area probabilities are calculated as:

$$P_f(T) = P_f = \sum_{g=0}^{T} p(g), \quad P_b(T) = P_b = \sum_{g=T+1}^{G} p(g). \tag{3.1}$$

3.3.3 Histogram Equalization

Fundus images usually have uneven illumination with areas at the center of the image brighter, compared to sides and the brightness decreases as the distance from the center of the image increases (Karegowda *et al.*, 2011). To achieve uniform illumination, adaptive histogram equalization was used so that the dark area in the input image becomes brighter in the output image. The bright area that was highly illuminated remained or reduced so that the image had uniform illumination using the below equation:

$$S = T(r) = \int_0^r P(r)dr; \quad 0 \leq r \leq 1 \tag{3.2}$$

3.4 FEATURE EXTRACTION WITH BRISK

Feature extraction involves the identification of the most relevant and useful characteristics and properties from a fundus image that would be the most useful in the diagnostic process of selected eye diseases. Feature plays a very important role; it comes after image pre-processing and helps give useful meaning to the attributes of images being processed and in turn acts as an input to the classifier algorithm (Singh & Chetty, 2012).

BRISK feature extraction method is inspired by Binary Robust Independent Elementary Features (BRIEF), which provides a faster route to finding the binary strings directly from image patches without finding the descriptors and is based on pair wise pixel intensity comparisons. The individual bits are obtained by comparing the intensities of pairs of points along the same lines but without requiring a training phase. They differ from each other in the way pixel pairs are spatially sampled in the image patch surrounding a given keypoint. The extraction is done by carefully choosing out local points interest called patches from the image by creating a bit vector out of the test points. The test τ on patch **p** of size $S \times S$ is defined as:

$$\tau(p: x, y) := \begin{cases} 1 & if\ p(x) < p(y) \\ 0 & otherwise \end{cases} \tag{3.3}$$

Where $p(x)$ is the pixel intensity in a smoothed version of p at $x = (u, v)^{\tau}$. Choosing a set of n_d (x, y) location pairs uniquely defines a set of binary tests. Equation 3.4 shows the dimensional bit string of the n_d – dimensional descriptor.

$$f_{n_d}(p) := \sum_{1 \le i \le n_d} 2^{i-1}\, \tau(p: x_i, y_i) \tag{3.4}$$

The features extracted from the keypoints were color, texture and shape/edge (Calonder, Lepetit, Strecha & Fua, 2010).

3.5 CLASSIFICATION WITH BINARY ROBUST INVARIANT SCALABLE KEYPOINTS (BRISK)

Brisk is a novel method for keypoint detection, description and matching. The inherent difficulty in extracting suitable features from an image lies in balancing two competing goals: high quality description and low computational requirements which makes it suitable for Android devices.

The key stages in brisk are feature detection, descriptor composition and keypoint matching to the level of detail understandable and reproducible by the reader. The modularity of the method allows the use of the brisk detector in combination with any other keypoint descriptor and vice versa, optimizing for the desired performance and the specific task (Leutenegger, Chli & Siegwart, 2011). Using BRISK to generate keypoints from an image is structured as follow:

- **Scale-Space Keypoint Detection:** Points of interest are identified across both the image and scale dimensions using a saliency criterion. In order to boost efficiency of computation, keypoints are detected in octave layers of the image pyramid as well as in layers in-between. The location and the scale of each keypoint are obtained in the continuous domain via quadratic function fitting.

- **Keypoint Description**: A sampling pattern consisting of points lying on appropriately scaled concentric circles is applied at the neighborhood of each keypoint to retrieve gray values: processing local intensity gradients, the feature characteristic direction is determined. Given a set of keypoints (consisting of sub-pixel refined image locations and associated floating-point scale values), the BRISK descriptor is composed as a binary string by concatenating the results of simple brightness comparison tests. Finally, the oriented brisk sampling pattern is used to obtain pairwise brightness comparison results which are assembled into the binary brisk descriptor.

- **Keypoint Matching**: Once generated, the brisk keypoints can be matched very efficiently thanks to the binary nature of the descriptor. Matching two brisk descriptors is a simple computation of their hamming distance as done in brief. The number of bits different in the two descriptors is a measure of their dissimilarity. With a strong focus on efficiency of computation, brisk also exploits the speed savings offered in the SSE instruction set widely supported on today's architectures.

3.6 EVALUATION

The performance of the developed diagnostic system in this project was evaluated to ensure effectiveness and efficiency. The essence of the evaluation is to determine whether or not, the developed system achieve its aim and objectives. The evaluation metric used in order to accomplish this is discussed below:

1. Accuracy: This term refers to the ability of the model to correctly predict the class of new unseen data. Classification accuracy is calculated by determining the percentage of cases in which the test sets are correctly classified.

$$Accuracy = \frac{Correct\ classifications}{Total\ number\ of\ classifications} \tag{3.5}$$

2. Confusion Matrix: The confusion matrix is a table used to describe the performance of a classification model on a set of test data for which the true values are known.

Table 3.1: Confusion Matrix

	Case 1	**Case 2**	**Case 3**
Case 1	Correctly classified	Wrongly classified	Wrongly classified
Case 2	Wrongly classified	Correctly classified	Wrongly classified
Case 3	Wrongly classified	Wrongly classified	Correctly classified

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 IMPLEMENTATION

The four-module design of the system was implemented to work on the Android platform and Android studio was the platform of choice for the development as it had better preinstalled features compared to other development environments. To achieve real-time processing while minimizing processor requirements, Intel's OpenCV (Open Source Computer Vision) library was used for the computer vision operations. The OpenCV library was imported into the project to enable the image selection and identification. This also allows the project to be built and packaged into the Android Application Package (APK) format installable on the Android platform. The brisk algorithm was used for the classification while the hamming distance between images was used as a metric for classification. Android's Native Development Kit (NDK) provided the support for compiling and packaging the codes written in native-code language, such as C++.

4.2 THE GRAPHICAL USER INTERFACE (GUI)

The user interface was designed to be very simple and easy-to-use. The application opens to the page displayed in Fig. 4.1.

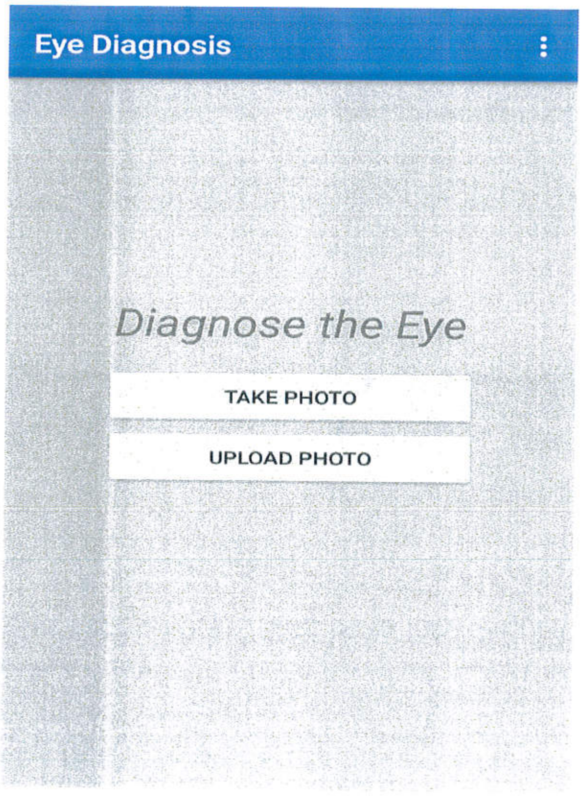


Fig. 4.1: Eye Diagnosis Home page

From Fig 4.1, two buttons can be clearly seen, the "Take Photo" button and the "Upload Photo" button. This presents the user with a double option of either taking an image and analysing it real time or selecting an image from the device for the analysis. After taking or uploading the image, the image analysis page shown in figure 4.2 is displayed where the user can carry out some major functions:

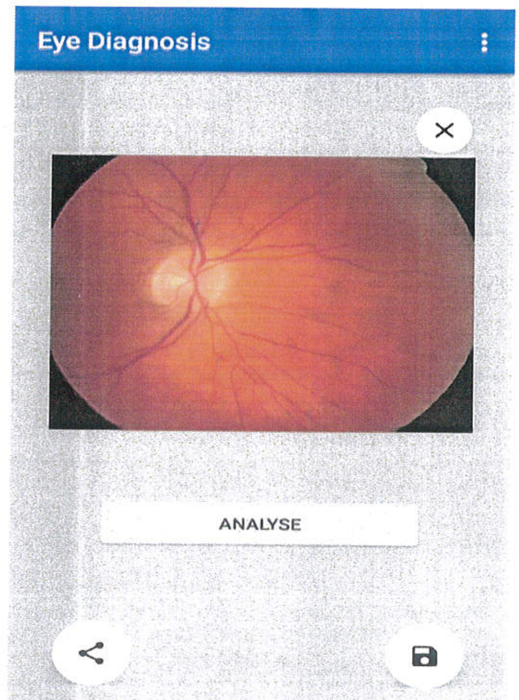
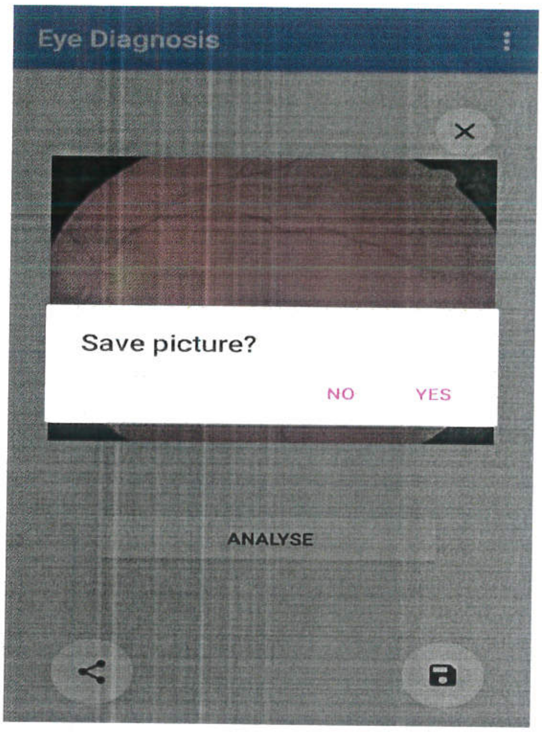
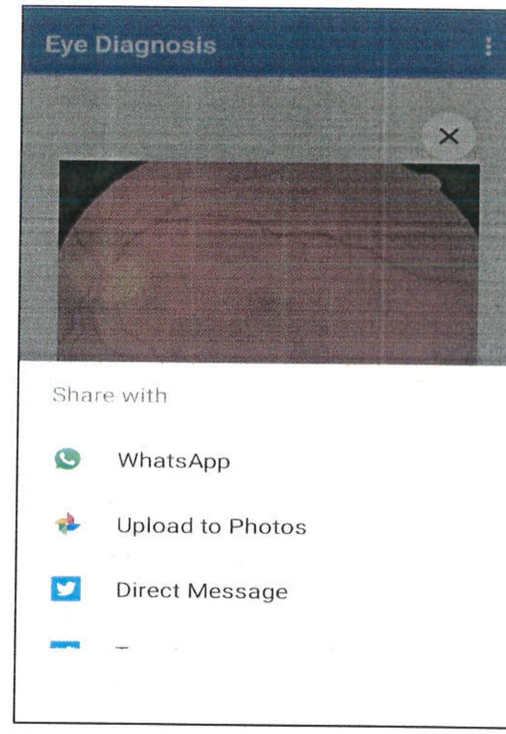


Fig. 4.2: Image Selection

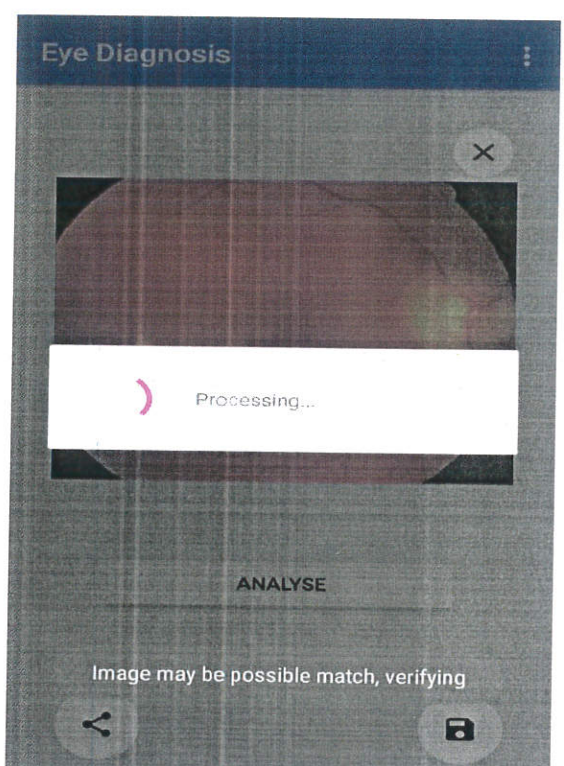
The save icon allows the user to save the image to the device memory for further reference. By clicking the save icon shown in figure 4.3A, a dialogue box pops up requesting the user to confirm the process before continuing. The share button allows the user to share the image across various platforms. By clicking on the share icon shown in figure 4.3B various platforms are displayed for the user to select. This is especially useful when consultation is required in the processing of an image. It allows ophthalmologists to network while working with a case. The image is analysed by clicking on the "Analyse" button. This processes the image as in figure 4.3C and gives an output of the image's classification as shown in figure 4.3D.



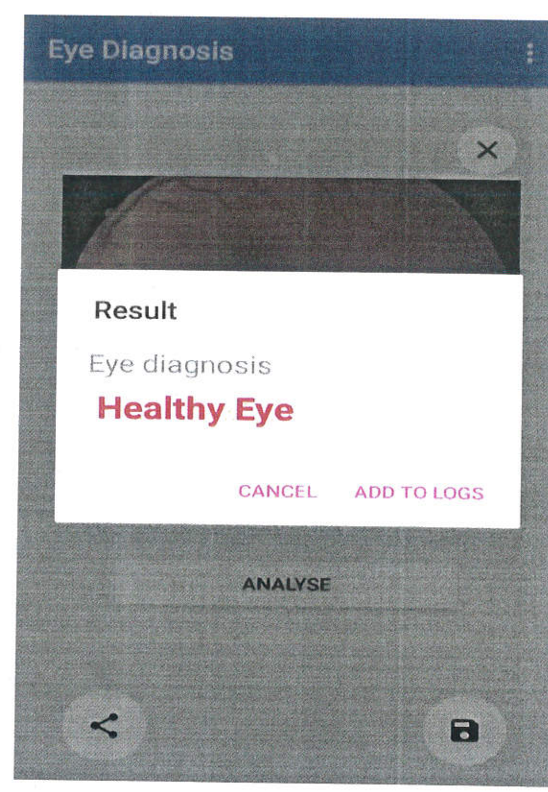
(A) Save image



(B) Share image



(C) Image analysis



(D) Analysis result

Fig. 4.3: Graphical user interface of the system

4.3 EXPERIMENTAL SETUP

This project was developed using Android Studio software which works in conjunction with the OpenCV manager application to enable it make image analysis. The setup is divided into four major categories which are Data acquisition, Image pre-processing, Feature extraction and Classification using Binary Robust Invariant Scalable Keypoints (BRISK). The fundus images used during the implementation of this project consists of a total of 135 fundus images, 45 healthy, diabetic retinopathic and glaucomic respectively. 30 samples of each to make a total of 90 were used in training the system while the remaining 45 (15 of each) were used in evaluating the performance of the developed system. Due to the inability to procure the handheld ophthalmoscope, the images used in both training and testing were acquired from four publicly available online databases which are Hossein Rabbani Eye Fundus Database, SPIE Eye Fundus Database, ORIGA-Light Eye Fundus Database and High Resolution Fundus (HRF) Image Database. All 45 healthy images were acquired from the SPIE Eye Fundus Database, all 45 Glaucomic samples were acquired from ORIGA-Light Eye Fundus Database, 35 diabetic retinopathic images were acquired from the Hossein Rabbani Eye Fundus Database while the remaining 10 were gotten from HRF Image Database. Table 4.1 shows a summary of the images acquired from each database and their class.

Table 4.1: Summary of images from each database for experiments

Database	Healthy	Diabetic Retinopathy	Glaucoma
SPIE Eye Fundus Database	45	–	–
Hossein Rabbani Eye Fundus Database	–	35	–
High Resolution Fundus Image Database	–	10	–
ORIGA-Light Eye Fundus Database	–	–	45

Both the training and the testing fundus images were passed through the pre-processing stage in order to remove unwanted noise, solve the problem of uneven illumination, preserve salient features, remove any form of background interference and preserve the most needed region of interest in the image for the sake of feature extraction. The proprocessing stage included graysclae conversion, histogram equalization and thresholding. Feature extraction and classification was achieved with brisk. Brisk was selected because of its low computational and memory requirements which makes it very suitable for mobile devices.

4.4 EVALUTATION RESULTS

The classifier algorithm was trained to classify three categories of the human eye which are healthy images, diabetic retinopathy images and glaucoma images. The performance of the classifier was tested to check how many images were correctly and wrongly classified.

Each category was tested using 15 images each from their respective image datasets. Table 4.1 below shows a summary of the classification test results.

Table 4.2: Accuracy results

Eye Status	Samples tested	Correctly classified	Wrongly classified	Accuracy (%)
Healthy	15	13	2	86.7
Diabetic Retinopathy	15	15	0	100
Glaucoma	15	15	0	100

Table 4.3: Confusion matrix result

Condition	Healthy	Diabetic Retinopathy	Glaucoma
Healthy	13	–	–
Diabetic Retinopathy	1	15	–
Glaucoma	1	–	15

From Table 4.2, it could be seen that of the 15 healthy samples evaluated, 13 were rightly classified as being healthy, while 1 was wrongly classified as diabetic retinopathic and glaucomic respectively. All 15 diabetic retinopathy samples were correctly classified, while the last category was glaucoma where all the tested samples were rightly classified as being glaucomic.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

This project proposed and implemented an intelligent diagnostic system for selected human eye diseases on the Android mobile platform. The implemented system can be used for screening of patients' eye fundus images to detect glaucoma and diabetic retinopathy in an extremely cost-effective manner.

The motivation behind this project was the development of an improved method of eye disease diagnosis implemented on the Android mobile application in order to make it more readily available and easily accessible to everyone everywhere, especially those in the rural areas where access to an Ophthalmologist is quite difficult. This would help prevent a large percentage of eye diseases as they would be earlier detected and treated.

To acquire the image of the retina, this is achieved by attaching a hand-held direct ophthalmoscope to the phone. The mobile application captures the ophthalmoscope images of the retina, and applies pattern recognition and statistical inference algorithms to facilitate decision making for the initial screening.

For carrying out the computer vision operations on the mobile device, the Intel's OpenCV (Open Source Computer Vision) library which aids real-time image processing was used. Android's Native Development Kit (NDK) provides the support for compiling and packaging codes written in native-code language, such as C++. The use of native code is ideal for image processing implementation on an Android device, as it provides a build system for efficient and fast processing of CPU-intensive operations. The minimum requirement in terms of smartphone hardware is a high-resolution camera, which most new generation mobile phones are equipped with. The final automated system is a stand-alone arrangement that uses a pattern recogniser and a training set for conclusive results.

The performance analysis results show that the classifier attained an accuracy of 86.7% for healthy images, 100% for diabetic retinopathic images and 100% for glaucomic images. The overall classification accuracy of the developed system was 95.6%.

5.2 CHALLENGES FACED

Over the course of the project, the following challenges were:

1. Initially, the project proposed using handheld ophthalmoscope attached to a phone's camera to acquire the fundus images but the device could not be procured due to high cost.

2. The initial approach to developing the system failed as the MATLAB codes could not be successfully converted to Java for optimization on Android.

5.3 RECOMMENDATION

This project has demonstrated the usefulness and effectiveness of OpenCV library as a problem-solving tool even in fields outside computing such as the health sector. It has also shown great performance in terms of aiding diagnosis of glaucomatous and diabetic human eyes. However, the following are recommended to further enhance the performance of the system:

1. Training of the system with images acquired from handheld ophthalmoscope for improved real life application as one of the limitations of the project was the inability to procure the handheld ophthalmoscope.
2. Extrapolation of the project to be able to diagnose other retinal diseases such as Cataract, Retinoblastoma, etc.
3. Extraction of more features from the fundus images which may lead to increase in the accuracy of the system.
4. Improvement on the CPU requirements of the application in order to increase processing speed and better conserve device power especially in areas where there is limited power supply.
5. Investigating other available libraries for optimized performance.

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APPENDIX A

CODES FOR IMAGE PROCESSING ON ANDROID

```
package com.aloranking.eyediagnosis;
import android.app.ProgressDialog;
import android.content.Context;
import android.content.DialogInterface;
import android.content.DialogInterface.OnClickListener;
import android.content.Intent;
import android.graphics.BitmapFactory;
import org.opencv.core.MatOfDMatch;
import org.opencv.core.MatOfFloat;
import org.opencv.videoio.Videoio;
import pub.devrel.easypermissions.EasyPermissions;

public class MainActivity extends AppCompatActivity {
    private static final int CAMERA_REQUEST = 18;
    private static final String FILE_PROVIDER_AUTHORITY =
"com.aloranking.fileprovider";
    private static final int PICK_IMAGE = 100;
    private static final int REQUEST_IMAGE_CAPTURE = 1;
    private static final int REQUEST_STORAGE_PERMISSION = 1;
    private static int descriptor = 5;
    private Button analysePhoto;
    ArrayList<String> assestString = new ArrayList();
    ArrayList<Bitmap> bitmapImages = new ArrayList();
    private Bitmap bmp;
    private String[] galleryPermissions = new
String[]{"android.permission.READ_EXTERNAL_STORAGE",
"android.permission.WRITE_EXTERNAL_STORAGE"};
    ArrayList<Mat> histImages = new ArrayList();
    private int imageSelectionType = 0;
    List<Integer> list = new ArrayList();
    private FloatingActionButton mClearFab;
    private TextView mInfoText;
    private BaseLoaderCallback mLoaderCallback = new
BaseLoaderCallback(this) {
        public void onManagerConnected(int status) {
            if (status != 0) {
                super.onManagerConnected(status);
            } else {
                Log.i("TAG", "OpenCV loaded successfully");
```

```
            }
        }
    };

    public void analyseImage(View view) {
        compareImages();
    }

    private void compareImages() {
        ProgressDialog pd = new ProgressDialog(this);
        pd.setIndeterminate(true);
        pd.setCancelable(true);
        int i = 0;
        pd.setCanceledOnTouchOutside(false);
        pd.setMessage("Processing...");
        pd.show();
        int i2 = 2;
        int i3 = 180;
        int i4 = 11;
        if (this.histImages.size() == 0) {
            int i5 = 0;
            while (i5 < r0.bitmapImages.size()) {
                Bitmap bitmap = Bitmap.createScaledBitmap((Bitmap)
r0.bitmapImages.get(i5), 150, 150, true);
                Mat img1 = new Mat();
                Utils.bitmapToMat(bitmap, img1);
                Imgproc.cvtColor(img1, img1, i4);
                img1.convertTo(img1, 5);
                Mat hist1 = new Mat();
                MatOfInt histSize = new MatOfInt(i3);
                MatOfInt channels = new MatOfInt(i);
                ArrayList<Mat> bgr_planes1 = new ArrayList();
                Core.split(img1, bgr_planes1);
                MatOfFloat histRanges = new MatOfFloat(0.0f, 180.0f);
                Imgproc.calcHist(bgr_planes1, channels, new Mat(), hist1,
histSize, histRanges, false);
                Core.normalize(hist1, hist1, 0.0d, (double) hist1.rows(),
32, -1, new Mat());
                Log.i("DataImage", stringBuilder.toString());
                i5++;
                i = 0;
                i2 = 2;
                i3 = 180;
```

```
                i4 = 11;
            }
        }
        r0.bmpimg2 = Bitmap.createScaledBitmap(r0.mUploadBitmap, 150, 150,
true);
        Mat img2 = new Mat();
        Utils.bitmapToMat(r0.bmpimg2, img2);
        Imgproc.cvtColor(img2, img2, 11);
        Mat hist2 = new Mat();
        MatOfInt histSize2 = new MatOfInt(180);
        MatOfInt channels2 = new MatOfInt(0);
        ArrayList<Mat> bgr_planes2 = new ArrayList();
        Core.split(img2, bgr_planes2);
        ArrayList<Mat> arrayList = bgr_planes2;
        Imgproc.calcHist(arrayList, channels2, new Mat(), hist2, histSize2,
new MatOfFloat(0.0f, 180.0f), false);
        Core.normalize(hist2, hist2, 0.0d, (double) hist2.rows(), 32, -1,
new Mat());
        img2.convertTo(img2, 5);
        hist2.convertTo(hist2, 5);
        i4 = 0;
        int i6 = 0;
        while (i6 < r0.histImages.size()) {
            double compares = Imgproc.compareHist((Mat)
r0.histImages.get(i6), hist2, 1);
            StringBuilder stringBuilder2 = new StringBuilder();
            stringBuilder2.append("compare: ");
            stringBuilder2.append(compares);
            Log.d("EyeDiagnosis", stringBuilder2.toString());
            if (compares <= 0.0d || compares >= 200.0d) {
                if (compares == 0.0d) {
                    Toast.makeText(r0, "Dataset matched", 0).show();
                    pd.cancel();
                } else {
                    i4++;
                    if (i4 == r0.list.size()) {
                        Toast.makeText(r0, "Unable to diagnose image,try
another image", 0).show();
                        i4 = 0;
                        pd.cancel();
                        startTime = System.currentTimeMillis();
                        i6++;
                }
```

```
                startTime = System.currentTimeMillis();
                i6++;
            } else {
                pd.cancel();
                r0.bmpimg1 = (Bitmap) r0.bmpImages.get(i6);
                StringBuilder stringBuilder3 = new StringBuilder();
                stringBuilder3.append("the value of i is ");
                stringBuilder3.append(i6);
                Log.i("TAGS", stringBuilder3.toString());
                if (i6 <= 29) {
                    typeOfDisease = "Diabetis Retinopathy Detected";
                } else if (i6 < 30 || i6 > 59) {
                    typeOfDisease = " Healthy Eye";
                } else {
                    typeOfDisease = "Glaucoma Detected";
                }
                Toast.makeText(r0, "Image may be possible match,
verifying",
                new asyncTask(r0).execute(new Void[0]);
                stringBuilder3 = new StringBuilder();
                stringBuilder3.append("the value of i is ");
                stringBuilder3.append(i6);
                Log.i("TAGA", stringBuilder3.toString());
                return;
            }
        }
    }
```