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Detection of Early Prognosis of Diabetic Retinopathy, Macular Edema and Glaucoma

Group Name: Acetech Labs

Project Name: OculoGuard

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Declaration Page

ALL OF OUR GROUP MEMBERS DECLARE THAT THIS ASSIGNMENT IS AN ORIGINAL WORK SUBMITTED BY THE MEMBERS OF THE **Acetech Labs-SE-46.** HAVE ACTIVELY CONTRIBUTED TO PREPARE THE REPORT OF **OculoGuard**, ANY OTHER WORK OF A SIMILAR NATURE HAS BEEN PROPERLY REFERENCED.

Figure 1:Acetech Labs

Figure 2: Logo

Abstract

Over 450 million people suffer from diabetes mellitus around the world, where nearly half of the cases remain undiagnosed. The amount of diabetes patients are expected to rise exponentially in the next two decades. Diabetic Eye Diseases (DED) are one of the dominant complications of diabetes which leads to a wide range of issues from permanent vision impairment to blindness. Diabetic Retinopathy, Diabetic Macular Edema and Glaucoma are three of the predominant forms of DEDs accounting for more than 60 percent of the cause of blindness in the working population. Early detection is crucial in the next upcoming decade as the world population faces a vast array of challenges in the form of complications, lack of resources and the exponential rise of DED with a dangerous emphasis on low and middle income countries. The proposed initiative, named Oculo-Guard is a software solution that accurately detects the Early Prognosis of Diabetic Retinopathy, Diabetic Macular Edema and Glaucoma that can be deployed to enhance earlier detection of DEDs cutting costs, saving resources and reducing complications and casualties.

Subject Descriptors:

Machine Learning

Learning Paradigms

Supervised Learning

Supervised learning by classification

Key Works: Machine Learning, Deep Learning, K-nearest neighbors, Support Vector Machine

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Acetech Labs,

SE 2nd year,

Group-46.

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Abbreviations Table

Abbreviation	Explanation
ML	Machine Learning
DL	Deep Learning
KNN	k-nearest neighbors
SVM	Support Vector Machine
AI	Artificial Intelligence
CNN	Convolutional neural network
DR	Diabetic Retinopathy
DME	Diabetic Macular Edema
DED	Diabetic Eye Diseases

Chapter 1: Introduction

1.1 Chapter Overview

This chapter will provide an overview and a clear understanding and justification of the problem domain of OculoGuard. The chapter will provide an overview to diabetic retinopathy, diabetic macular edema and glaucoma ,the way they affects the global population, detection and challenges faced in the process followed by the justification for an AI based multi-classification program. The introduction will then consist of an overview analysis on various other approaches in this domain, proper definition of the In-Scope and Out-of-Scope Elements of our Project followed by Aims, Objectives and a Rich Picture Diagram of the project explaining the features of a potential prototype.

1.2 Problem background

Diabetic retinopathy

Diabetic retinopathy is a retinal disease which is caused as a complication of Diabetes mellitus. Blood vessels of the retina become damaged due to blockage by high blood sugar levels,which leads to complications in the eye which can range from visual impairment to permanent blindness at later stages of the disease.(World Health Organization. Regional Office for Europe, 2020). It is the most common cause of blindness and visual impairment for people with diabetes in working-age adults, is linked to a reduced quality of life, lower psychological well-being, and an increased risk of severe diabetic complications and mortality.(Diabetic Retinopathy | National Eye Institute).

Diabetic macular edema

Diabetic macular edema is a complication of Diabetic Retinopathy. It’s caused by disruption of the blood-retinal barrier due to long-term hyperglycemia, leading to retinal thickening around the fovea (located in the center of the macula lutea). (Musat et al., 2015)

Glaucoma

Glaucoma is a group of eye diseases that can cause vision loss and blindness by damaging an optic nerve (a nerve which is back in the eye). It is a common cause of blindness and visual impairment to people over the age of 60. (Glaucoma | National Eye Institute)

The number of people with DR is predicted to rise as the prevalence of diabetes increases and the global population grows exponentially..Diabetes affected an estimated 415 million people in 2015.Seventy-five percent of diabetics lived in low- and middle-income nations.

By 2040, the number of persons with diabetes aged 20 to 79 is expected to reach 642 million.(Ogurtsova et al., 2017)

More than one-third of persons with diabetes in the world have some type of DR, including almost one-tenth of those with vision-threatening levels of DR (VTDR), such as proliferative DR (PDR) and diabetic macular edema. (Yau et al., 2012).

1.2.1 Introduction to Problem

The following sections discuss the problem domain of the project "OculoGuard".

1.2.2 Problem Boundary

The early predictions for diagnosing DR include people who are diagnosed with type1, type2 diabetes or diabetes developed during the pregnancy. At the early stage they may not show any symptoms but it's reported that some people may experience change in vision including sub symptoms like trouble in reading and seeing faraway objects (Diabetic Retinopathy, 2021).

Sarki, Ahmed and Zhang. (2020) says that the traditional manual analysis of Fundus images is often associated with a long time to proceed and it can take up to days to completely analyze and review. Also due to the complexity of different stages of DED it's hard to track every single spot in the complex anatomy of the eye. Therefore automated detection systems are required.

This analysis is further proved by Silberman et al. (no date) stating "Aravind (an eye disease hospital) is currently leading a massive initiative in effort to detect diabetic retinopathy at an early stage by scanning every patient for diabetic retinopathy. To accomplish this goal, Aravind sends groups of physicians on a daily basis to various rural locations in South India to manually inspect patients' retinas for diabetic retinopathy. Unfortunately, this task is extremely labour intensive and they have too few ophthalmologists to inspect the roughly 2 million retinal images they receive per year"

At the same time another biggest challenges in identifying DR is there's considerable number of statistics about undiagnosed diabetic patients around the world and there's high chance that, before they are being diagnosed with diabetes, they may end up in a stage of DR (Pearce and Sivaprasad, 2020)

Global Diabetes Prevalence in Adults Aged 20–79 (2019)[1]

Region	Adult Population, N, Millions	Prevalence of Diagnosed Diabetes, % (95% CI)	Prevalence of Undiagnosed Diabetes, %
Worldwide	5000	9.3 (7.4–12.1)	NR
Africa	501	3.9 (2.1–7.1)	59.7
Europe	665	8.9 (7.0–12.0)	40.7
Middle East and North Africa	426	12.8 (7.2–17.6)	44.7
North America and the Caribbean	357	13.3 (10.5–15.8)	37.8
South and Central America	335	9.4 (7.8–11.7)	41.9
Southeast Asia	997	8.8 (7.1–11.1)	56.7
Western Pacific	1700	9.6 (8.6–11.9)	55.8

Figure 3: Global diabetic prevelance (Pearce and Sivaprasad, 2020)

Therefore it's required that an automated way of detecting DED for the ease of both opthamologists and patients. Also, given there are many diabetic patients who are not yet diagnosed and the time it takes to diagnose is lengthy, early detection and prognosis of DR is necessary to address this problem.

1.2.3 Examples in the Problem

Problems with Eye Care in third world countries

Vision impairment is a very challenging situation for low and middle income people in Asia. Detection of diabetic eye diseases quickly can prevent people from getting permanent vision loss. But the major obstacle is there are not enough ophthalmologists in both low and middle income countries. So this makes it difficult for people to get diabetic screening services. In countries like Sub-Saharan Africa average ophthalmologist density per million population is 3.7.

Cost-effectiveness is also a major barrier in low- and middle-income countries and all the medical facilities and treatments are available only in the cities whereas people from remote areas face many difficulties in order to get treatments or these medical facilities.

On the other hand with the expanding population and people with diabetes it is not reliable to depend on the limited ophthalmologists in these countries. **(Bascaran et al., 2021)**

Many people suffer from eye diseases in rural and semi urban areas in India and all over the world. In many developing as well as non-developing countries people suffer from ophthalmic disease but the problem is there are not enough ophthalmologists available in those countries.**(Ravudu, Jain and Kunda, 2012)**

1.2.4 Competitor Analysis

Many commercially available softwares have been developed through the years and most of them only covers one specific set of features or only attached to a specific system.

IDX-DR is an AI based classification system for two diabetic diseases, complications of DR and ME. It's the first FDA (Food and Drug Administration) approved diagnostic system to ever come into the field of medicine. This system lacks Glaucoma detection and Early Detection of DR which are also diabetic related diseases. (Abràmoff et al., 2018)

RetinaRisk is a risk model based mobile application which performs individualized risk assessment to predict chances of having sight threatening DR (Einarsson et al., 2019). Its risk model is operated on after detecting Diabetes among the patients and it only predicts sight threatening retinopathy

EyeArt is also a similar application like IDX-DR. But in real time usage Grzybowski and Brona. (2021) states that IDX-DR is specifically paired with Topcon Nw-400 camera in the USA, unlike EyeArt where Rajalakshmi et al.(2018) says it's a cloud based solution. Same as the IDX-DR, EyeArt does not address early detection of DR prior to its earliest clinical signs and also the detection of Glaucoma.

A generic web based solution was developed by Arenas-Cavalli et al.(2015)**.** It only features feature extraction from a fundus image **and** doesn't perform classification of different compilations of DED.

OculoGuard on the other hand features all the above mentioned features in a single application and specifically an Early Prognosis of DR based on fundus image analysis.

Feature	IDx-Dr	RetinaRisk	EyeArt	Generic web based System	OculoGuard
DR Diagnosis	✓	✕	✓	Only feature extraction(no classification)	✓
Early Prognosis of DR	✕	Prediction based on demographic factors for sight threatening DR	✕	✕	✓
Diagnosis of ME	✓	✕	✓	✕	✓
Diagnosis of Glaucoma	✕	✕	✕	✕	✓
Desktop Application	✓	✓	✓	✓	✓
Mobile solution for portable specialized cameras and patient management	✕	for risk factor analysis only	✕	✕	✓

Table 1:Competitor analysis table

1.3 Problem Statement

Detection of diabetic eye diseases through machine learning using fundus images.

1.4 Research Gap

OculoGuard will be mainly focussing on identifying DR in early stages prior to the other stages of DR, compared to the already existing solutions which focus on one specific feature set. A critical analysis is conducted in different implementations of ML and DL methods that have already been implemented and find the best algorithm by reviewing through the Literature Review. Also finally, OculoGuard will be equipped with a complete management system for both ophthalmologists and patients to ease out the diagnosis of DR in a structured way.

1.5 Research questions

How to improve diabetic retinopathy screening progress Efficiency using machine learning?

How can AI be used to accurately detect diabetic retinopathy, macular edema and glaucoma?

How to improve prognosis of DR using early signs?

1.6 Research Aim

The main goal of this project is to design, implement, and develop software that recommends Detecting early stages of Diabetic Retinopathy,Diabetic Macular Edema and Glaucoma.

To explain further, the platform makes it easier for ophthalmologists and patients to detect the eye with the help of a lens and a smartphone or fundus image. According to the dataset given, OculoGuard will give an excellent percentage of accuracy of the output. The image analysis software and machine learning methods were used to improve detection. High computing facilities have become increasingly helpful, especially with respect to medical science, to improve the accuracy and efficiency to detect multi eye disease classification systems of Diabetic Retinopathy,Diabetic Macular Edema and Glaucoma.also with a complete management system for both ophthalmologists and patients to ease out the diagnosis of Diseases in a structured way.When a person's Diabetic symptoms are confirmed, the aim is to advise them.How to Obtain Treatments in a Secure Way the Report which we gets from the application simplifies the examination process for hospital staff.Also in pandemic circumstances, the application makes it easier for patients and ophthalmologists to communicate.Control the situation Patients can also receive treatment as quickly as possible.Making use of this application will help ophthalmologists and patients save time and minimize the number of patients visiting the hospitals because of Covid19.

1.7 Project Scope

1.7.1 In-scope

- OculoGuard will only detect diabetic retinopathy, diabetic macular edema, glaucoma and prognosis of diabetic retinopathy.
- The system will only support the input of fundus images.
- Have a deep learning model trained to identify three diseases
- The ability to have a medical report.

1.7.2 Out-scope

Due to the time limitation other diabetes eye diseases will be excluded.

1.8 Rich Picture Diagram

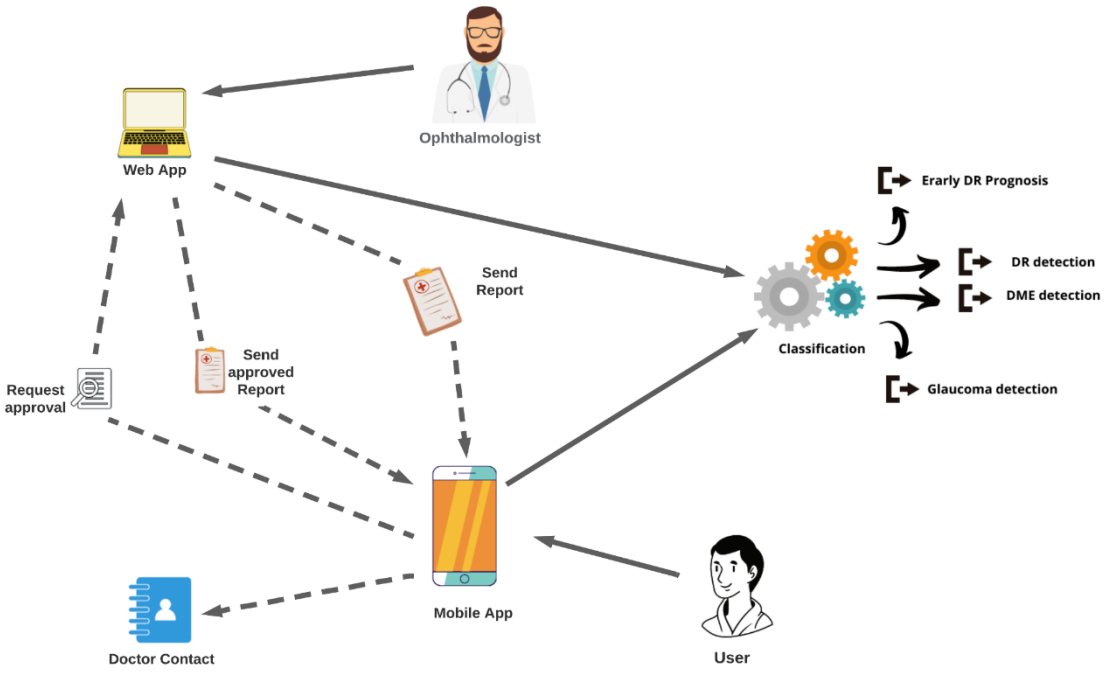


Figure 4: Rich Picture Diagram

1.9 Objectives

1.9.1 Research Objectives

- Identify feasibility of using machine learning and deep learning techniques for detection of Diabetic Eye Diseases.
- Finding more accurate identification of early anatomical changes in the eye using machine Learning.
- Identify one method which classifies, examines and detects all forms of Diabetic Eye Disease.

1.9.2 Academic Objectives

- Identify a real world problem and develop a solution
- Improve team working skills.
- Read and understand research papers.
- Learn about different types of deep learning techniques

1.9.3 Operational Objectives

- Purpose

  Define the problem domain.

  To conduct a background research on existing models and techniques.

  Finding highly accurate detection techniques.

- Gather data

  Obtained datasets which contains images label with DR stages

  Collected datasets contains images of glaucoma from three different sources;

  MESSIDOR

  Bin Rushed

  Magrabi Eye center

  Obtained data sets from Hamilton Eye Institute Macular Edema which contains DME images.

- Study and review existing work

  Analyzed previous methods and models to identify the best method that can be implemented.

  Identify one method which detects all forms of DED.

- Design

  Identify the most suitable algorithm

- Implement

- Test

  Fixing bugs.

- Evaluate

  Ensuring the applications performance.

1.10 Resource requirements

1.10.1 Hardware requirements

Minimum Hardware Requirements for "OculoGuard" project

Requirements	Specification
Any processor (Intel i5/i7/ Ryzen 7).	The CPU in OculoGuard is primarily used for decoding and preprocessing of image frames,We need a fast version.
For less than 100 images at 14 MP: 4 GB RAM, 10 GB HDD free space	To process the huge uncompressed Fundus images dataset of eye, we should load it to memory.

For 100-500 images at 14 MP: 8 GB RAM, 20 GB HDD free space	To process the huge uncompressed Fundus images dataset of eye, we should load it to memory.
For 500-1000 images at 14 MP: 16 GB RAM, 40 GB HDD free space	To process the huge uncompressed Fundus images dataset of eye, we should load it to memory.
For 1000-2000 images at 14 MP: 32 GB RAM, 80 GB free HDD space	To process the huge uncompressed Fundus images dataset of eye, we should load it to memory.

Table 2:Hardware Requirements

1.10.2 Software Requirements

Languages	
Python	For Machine Learning algorithms implementation
Java Script	For frontend and server implementation
Dart	For mobile application
Frameworks, Libraries, APIs and Services	
SciKit	For machine learning
Keras/Tensorflow	For deep learning
Next JS	For front end web app
Node JS	Backend server
Pandas, Numpy	For data analysis
MatplotLib	For data representation
Flutter	To build mobile application

Tailwind css	To style the web app
Firebase	For database and user login signup management
AWS S3	For storage
AWS EC2/Lambda / IBM Cloud	For server preferences
Development Environment setup	
VS Code/Jupyter notebook	Default code editors for development
Live Share	For collaboration work
Git and GitHub	For version controlling and storing code
GitHub Actions	For Automation and CI/CD pipeline integration
IOS Simulator	For the development of mobile application

Table 3:Software Requirements

1.10.3 Data Requirements

- Machine Learning Model Objects – From OpenML and MLDB (Machine Learning DataBase)
- Machine Learning Diabetic Rethonphy Datasets we found :

From	Citation	Links
Kaggle	(Diabetic Retinopathy Detection, no date)	Diabetic Retinopathy Detection | Kaggle
Messidor	(MAFFRE, no date)	Messidor - ADCIS

Deep Blue	(Almazroa, no date)	Data Set | Retinal fundus images for glaucoma analysis: the RIGA dataset | ID: 3b591905z | Deep Blue Data (umich.edu)
Github	(lgiancaUTH, 2021)	https://github.com/lgiancaUTH/HEI-MED
GrandChallenge.org	(Pachade et al., 2021)	https://riadd.grand-challenge.org/download-all-classes/

Table 4:Data Requirements

1.11 Chapter Summary

The problem is introduced in Chapter 1, and the problem has been identified and justified by extensive background study and statistical analysis. This chapter provides details about problems in third world countries and the necessity of this application.

Chapter 2: Literature Review

2.1 Chapter Introduction

A literature review is much more than a list of pertinent sources. Previous research, implementations, approaches, and technologies will be critically evaluated in this chapter to determine the benefits and drawbacks of each technique in order to choose the best one for implementing "OucloGuard". The preceding information gives you a general idea of what "OculoGuard" is all about.

2.2 Existing Work

2.2.1 Early Prognosis of Diabetic Retinopathy

As per our research the development of Autonomous Systems in Early prognosis of DR prior to NPDR is comparatively low. A popular application which can be taken as an approach in Early Prognosis is a mobile application called RetinaRisk.

RetinaRisk is based on a Risk Model which gives Individual Risk Assessment based on Risk Factors. These Risk Factors include Blood Pressure, Diabetes Type, Duration of Diabetes, Gender etc. Based on the risk factors the algorithm predicts the chances of sight threatening DR which could occur in the next one to five years. The main intention of this application is to educate the user about the threatening level and accordingly seek eye screening programmes in order to validate and diagnose the disease. (Einarsson et al., 2019)

However when comparing it to the research aims of OculoGuard, OculoGuard will be implemented to early prognosis or detect DR by analysing early bio marks which can be seen on the fundus images. OculoGuard is directly associated with the screening process while RetinaRisk predicts if there's any chance of DR and accordingly the user has to decide whether to attend the screening process. This only increases the eye screening process and involvement.

Hence it's clear that even though a risk model analysis could increase the chances of diagnosis of DED, an early prognosis of DR is necessary and it's not addressed. Also, even though RetinalRisk is freely available on android and ios platforms users need to enroll in a subscription plan to use the service, which costs a monthly charge.

2.2.2 Detection of Diabetic Eye Diseases

EyeArt which is a cloud based DR and ME detection system. A test conducted by Rajalakshmi et al. (2018) using a portable smartphone based eye screening camera with manual analysis of taken fundus images using expert ophthalmologist and with EyeArt application, states that automated detection using EyeArt achieved 95% identification of patients with DR and 80.2% patients without DR showing that further improvements can be applied when increasing the accuracy. Moreover features like Early Prognosis of DR and detecting Glaucoma are not addressed in this application.

A Generic Web based solution developed by Arenas-Cavalli et al). 2015 consists of feature extraction from fundus images. Once the images of fundus are uploaded to the system it will automatically extract the specific features from uploaded images. Although the classification of disease type after the feature extraction is not attempted, the detailed summary about steps taken to detect the features have been critically evaluated. This includes methods like optic disk localization, blood vessel localization and different lesion detection. OculoGuard therefore, will follow the similar approach when classifying features but based on the features, classification of which complication of DED using ML and Early Detection of DR will be implemented.

Considering all the existing products, none of them were able to create a complete system with integration of all DR diagnosis, early stage detection, Glaucoma and Macular Edema

2.3 Tools and techniques

2.3.1 Diabetic retinopathy

Diabetic retinopathy is an eye disease that can cause blindness in people who have diabetes.(Diabetic Retinopathy | National Eye Institute, no date) It's caused by damage to blood vessels of the sensitive tissue at the back of the eye which is called retina. At first Diabetic retinopathy shows mild vision problems. But it can lead to blindness.

Figure 5:Diabetic retinopathy

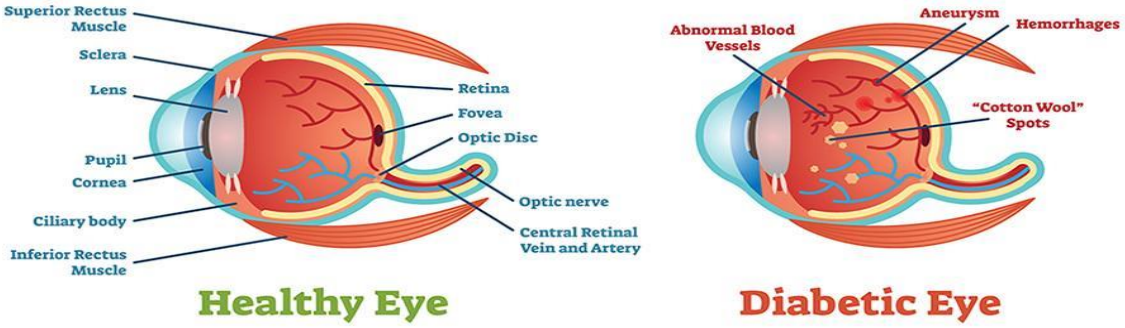


Figure 6: Healthy eye vs normal eye (Diabetic retinopathy | AOA)

2.3.1.1 Methods of detection

Detection of Diabetic Retinopathy begins with the image preprocessing approach using various techniques. Also, segmentation, feature extraction and classification are part of detection of diabetic retinopathy.

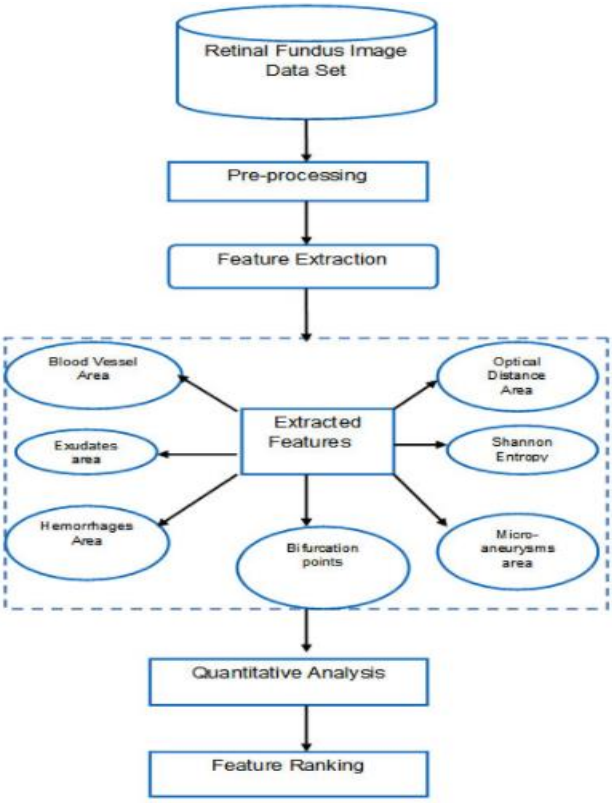


Figure 7: DR detection (Singh Sisodia, Nair and Khobragade, 2017)

Retinal Fundus data set

Images were taken from a variety of different models and types of cameras. Some images may be out of focus and dark. The Kaggle platform provides a large set of fundus images taken under a variety of imaging conditions. Images are rated according to stages or symptoms type. Data set helps in calculating the features taken into consideration.

Pre-processing

Leading to local luminosity and contrast variation, the illumination of the retina is not uniform. The illumination can be different according to parts. In a low contrast or low brightness features may not be visible. Then it is necessary to do image preprocessing. Furthermore, pre-processing techniques such as histogram equalization, green channel extraction and resizing were performed using the DIP toolbox of MATLAB.

Preprocessing steps

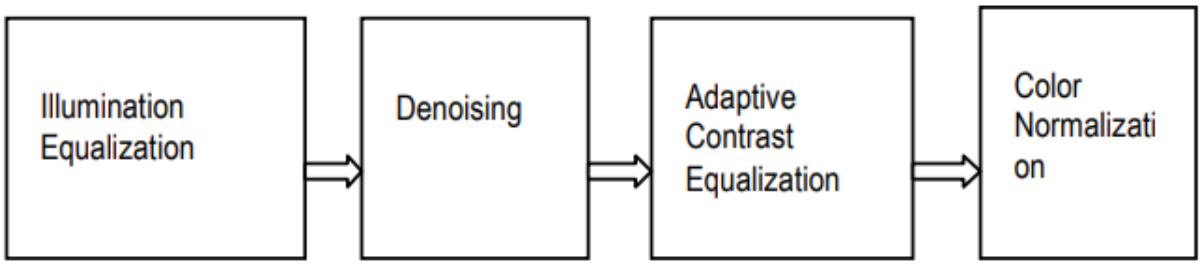


Figure 8: Preprocessing steps

Feature extraction

Optic Disk Elimination and Exudate Detection are the main things of feature extraction in the automated diabetic retinopathy detection process. It is essential because it appears with similar intensity, contrast and color to the other attributes of the fundus image. Also, there are few steps of Optic Disk Elimination and Exudate Detection.

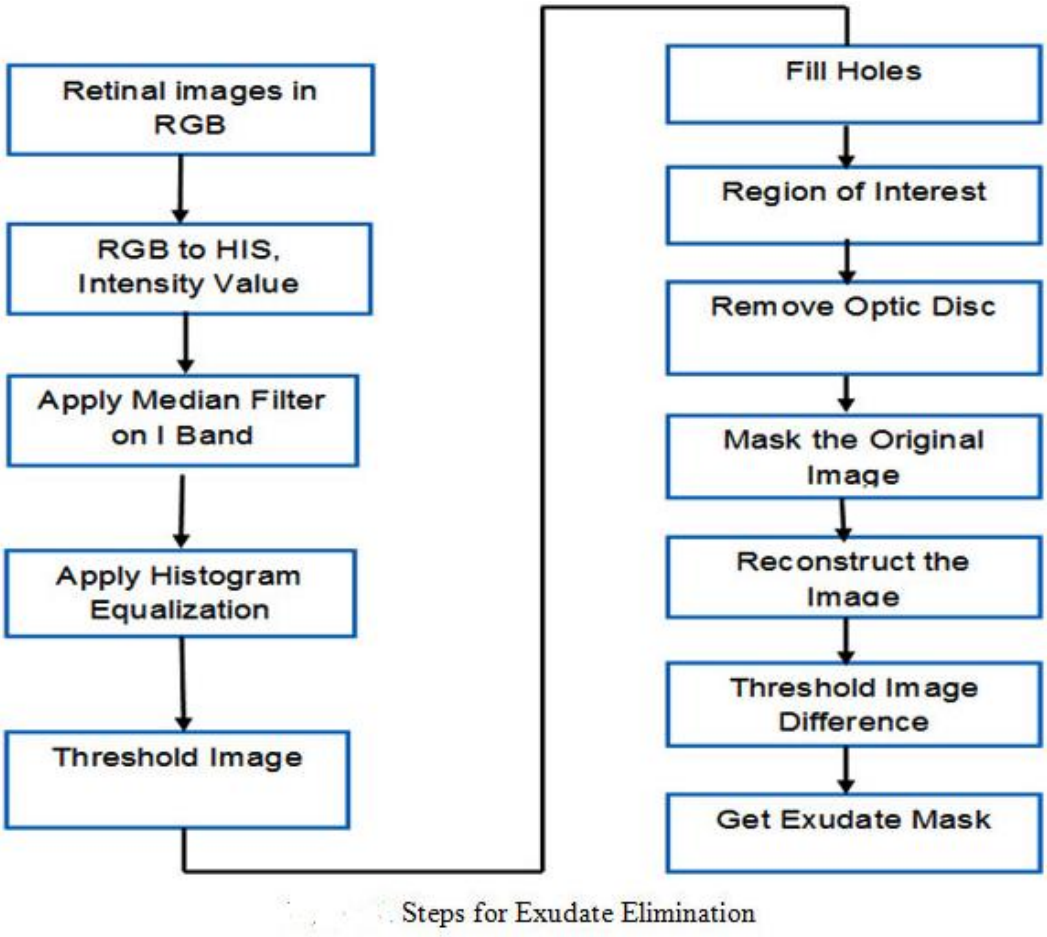


Figure 9: Steps of Exudate elimination

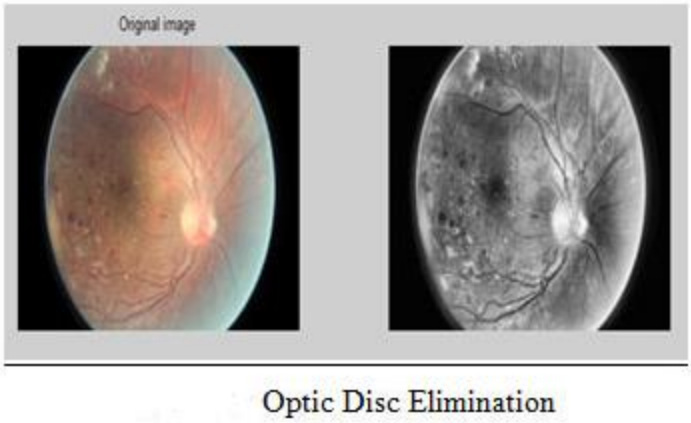


Figure 10: Disc elimination (Singh Sisodia, Nair and Khobragade, 2017)

Classification

There are several approaches in today's world to detect eye diseases from ophthalmic fundus photography. For the Diabetic retinopathy, the detection is based on various DL and ML models along with image classification to identify and detect with stages from the Fundus images

(Doshi et al., 2016) used Deep Convolutional Neural Networks s to automatically diagnose and thereby classify high-resolution retinal images into stages of the disease based on severity. Furthermore, the accuracy of the convolutional neural networks model presents 0.386 on a quadratic weighted kappa metric and collected similar models get a score of 0.3996.

(Gulshan et al., 2016) evaluated deep machine learning has high sensitivity and specificity for detecting diabetic retinopathy. Furthermore, research is necessary to determine the feasibility of applying ML algorithms in the clinical setting and to determine it leads to improved outcomes compared with current assessment.

(S.A, B. and Naveen, 2019) had proposed an algorithm to detect DR from fundus image. The final accuracy was calculated by using Sensitivity, Specificity and Accuracy parameters. Those parameters calculated from, trained images from high resolution Fundus images of DR. Furthermore, the training images are manually detected by ophthalmologists and the 98% accuracy has been achieved.

(Xu, Feng and Mi. (2017) had proposed a special neural network architecture for the diabetic retinopathy image classification task which can have superior super performance. Moreover, algorithms have improved.

2.3.2 Early Prognosis of Diabetic retinopathy

Early Prognosis or sub-clinical detection of DR is detection of DR prior to clinical symptoms of the NPDR which is the earliest clinical stage of DR. Human eye Vasculature is among the few parts of the human body which can be viewed non-invasively. Fundus images which capture a cross sectional view of the eye gives a clear view of the retinal vasculature.

Throughout the years of research it has been observed that there are vascular and nonvascular features which are associated prior to development of DR or at least at the minimal NPDR stage,

which can be taken as signs in Early prognosis and Detection of DR. These bio marks may occur with or without diabetes.

One of these early signs is, analysis of retinal vessel tortuosity. Studies conducted by Sasongko et al. (2011**)** shows that an increased vessel tortuosity is associated with patience with diabetes without DR.

A similar analysis with other vascular and nonvascular features can be further explained by the 10 year of continuous data research followed by Forster et al. (2021). The research was conducted on the intention of finding association of various vascular traits in the patients with Diabetes with the development of DR. Vessel tortuosity is among the other vascular traits namely, Fractal Dimensions, vessel widths and demographic information about patients. The researchers used the Edinburg Type 2 Diabetes Study(ETS2D) cohort. Among the follow up period(which is 10 years) 82 patients developed retinopathy. From the statistical analysis of the affected patients two vessel traits Tortuosity and Fractal Dimensions were noticed in the progression of DR throughout the years. Specially by combining high profile risk factors of DR(HbA, ACR, systolic blood pressure) with Tortuosity into a model, discriminatively of the model was increased proving that Tortuosity can be considered as an early prognosis and prediction bio mark for DR. However the recreation of this with Fractal Dimensions didn't improve the model.

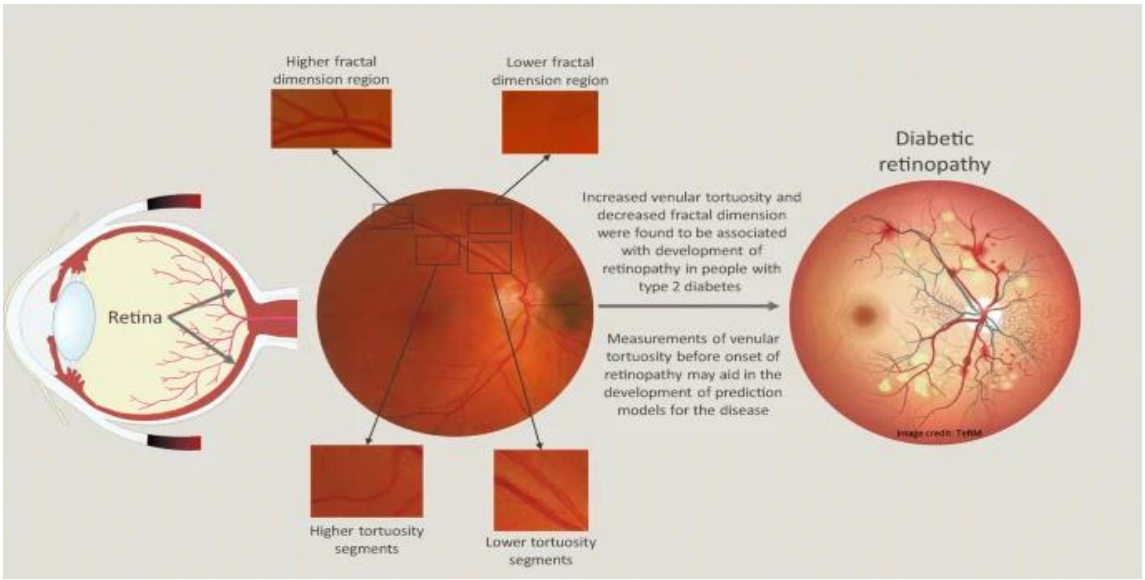


Figure 11: Graphical abstract of the research done by Forster et al., (2021) showing tortuosity can be considered as an early bio mark of DR.

Research done by Ding et al. (2012) found evidences suggesting retinal vascular Calibre can be considered as an early prediction biomark for development of DR

Rogers et al.(2008) conducted a 5 years of follow up of 906 participants of developing retinopathy. After adjusting with demographic factors (age, sex, blood pressure etc), It's noted that individuals with wider retinal arteriolar calibre were more like in developing retinopathy. It suggests that arteriolar dilation indicates preclinical marker for DR hence it can be used in early prognosis of DR.

A similar research was conducted by Alibrahim et al.(2006) in a cohort of adolescents. After adjusting it with other demographic factors dilated arteriolar calibre was a predictor of risk of DR stating "Larger retinal arteriolar caliber predicts incident retinopathy in children and adolescents with type 1 diabetes, independent of conventional risk factors for retinopathy".

Combined analysis of those three researches it's clear that larger arteriolar calibre can be an early prognosis risk factor for DR.

Figure 12: Retinal arteriolar calibre(red) and Venular Calibre(blue) (Mcgowan et al., 2015)

Aliahmad, Kumar and Jain.(2016) followed up a research on detecting Diabetes with vascular traits with no diagnosed DR. Two new vascular traits TBA, ABA as Total branching angles and Acute branching Angles are introduced subsequently with Vessel Tortuosity, CRAE etc with other demographic factors. The researchers state that "newly introduced two parameters can be used in predicting risk of developing DR in diabetic patients with no DR".

In conclusion for the implementation of Early Prognosis of DR, of OculoGuard, Vessel Tortuosity, arteriolar calibre TBA, ABA vessel traits will be used.

2.3.2.1. Methods of Detection

Since Vessel Tortuosity and TBA, ABA traits are distributed among the retinal blood vessel network, the detection of these parts can be done in a common model for both traits.

Preprocessing and retinal blood vessel segmentation are the first steps of detecting vascular traits from a color fundus image. Preprocessing involves preparing a row color fundus image prepared to extract blood vessel segmentation. Various researchers have published different vessel segmentation methods based on traditional color optimization techniques to machine learning and deep learning models. One of these research is done by Guo et al. (2020) implements a lightweight network named Spartial Attention U-Net which is based on convolutional Neural Networks. The tests were conducted to benchmark the network and based on two datasets, SA-UNet archive the state of the art performance on both datasets.

After the feature extraction phase comes where different features are extracted from the vessel segmentation. For the extraction of vessel tortuosity, a research conducted by Turior, Chutinantvarodom and Uyyanonvara. (2012) used 6 tortuosity measurement metrics. But after applying Fisher Linear Discriminant Analysis only the highest ranking features were selected. Those features were then used to form the final Nearest Neighbour classifier which achieved 95 % accuracy at specificity value of about 96%.

Unfortunately for the detection of TBA and ABA traits no models or theories to be found. At that stage those two parameters are removed from the system.

For the detection of arteriolar calibre, a different preprocessing technique has to be followed. To measure the arteriolar calibre optic disk of the fundus image has to be located. This procedure is called finding the Region of interest. Then the vessel segmentation should be performed to find the width of the vessels. Finding the Arteries and veins in the ROI is also associated with these procedures. Then finally arteriolar calibre can be calculated.

Niemeijer et al.(2011) develops a complete multi machine learning based system to find AVR(arteriolar calibre to vein calibre ratio) which consist of all the mentioned steps above to find arteriolar calibre with extended development of finding AVR. development of OculoGuard will follow this approach till the arteriolar calibre to be measured.

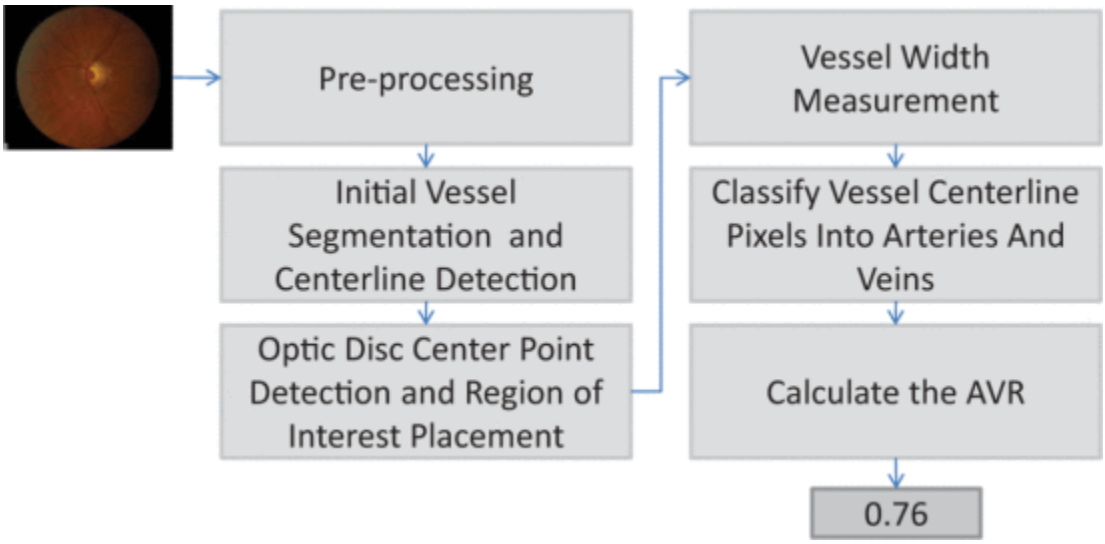


Figure 13: Overview of Proposed method done by (Niemeijer et al., 2011).

2.3.2.3 Classification

Since there's no existing work carried out by these retinal vessel parameters for the Early prognosis of DR, no existing machine learning model has been proposed.

According to Maher. (2019) , based on classification of machine learning models, a Classification based model is the type of model which needs to be implemented. Classification machine learning models predict the class for a given input. Random Forest is a classification based machine learning algorithm where multiple decision trees are used. The assessment of each individual decision tree should be uncorrelated so the quality of the algorithm will form up

For the training dataset, the dataset mentioned by Pachade et al. (2021) will be used. The dataset contains 3200 images divided into 3 subsets as 60 percent for training, 20 percent for evaluation and remaining 20 percent for testing. Variety of 45 types of diseases are classified with the dataset.

2.3.2 Diabetic macular

Figure 14: DME (What You Need To Know About Diabetic Eye Disease | Acuity Eye Group, no date)

Diabetic retinopathy and diabetic macular edema are common among patients with diabetes which can be eventually leading to permanent vision loss. (Ciulla, Amador and Zinman, 2003)

"DIABETIC MACULAR EDEMA is the build-up of fluid in the macula, an area in the center of the retina. The retina is the light-sensitive tissue at the back of the eye and the macula is the part of the retina responsible for sharp, straight-ahead vision. Fluid buildup causes the macula to swell and thicken, which distorts vision." (Macular Edema | National Eye Institute, 2019)

Patients with diabetes can develop Diabetic macular edema at any time during the progression of Diabetic Retinopathy. Diabetic macular edema is a complication of diabetic retinopathy, so the patient must have Diabetic Retinopathy if they have Diabetic macular edema. Patients can also have diabetic retinopathy without Diabetic macular edema.(Diabetic Retinopathy vs. Diabetic Macular Edema: Your FAQs, 2021)

2.3.2.1 Methods of detection

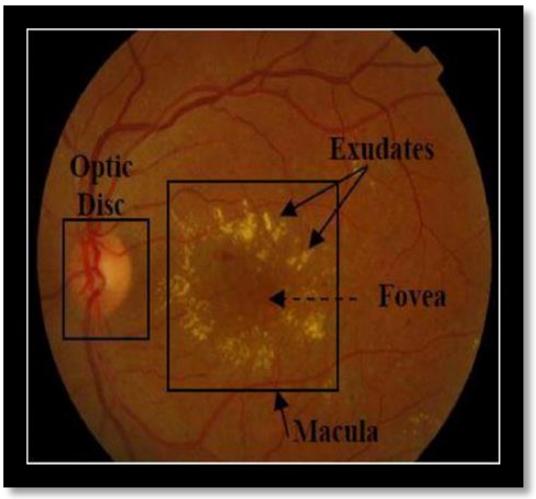


Figure 15: Exudate and optic disc for detecting DME (Automated macula proximity diagnosis for early finding of diabetic macular edema | SpringerLink, no date)

Detecting Diabetic Macular Edema begins with, Image processing approach employing MATLAB, Julia, GNU Octave, SciLab or any other software to detect macular edema and exudates in the fovea's surrounding area.

Preprocessing, segmentation, and feature extraction are all part of the image processing approach, which compares detected images to a trained database to determine if they are normal or affected. The computer must be trained with a large number of pictures of normal and afflicted fundus images so that it can quickly determine whether a specific input image is normal or affected.

Initially, the supplied image is preprocessed. The image is normalized, contrast enhanced, noise removed, and the optic disk removed in the preprocessing approach.

The pre-processed image is then used for the next step, which is the detection of the macula and fovea regions. The fovea region is first identified, and the macula is then identified by measuring the radius from the fovea region's center.

After that, the macula region's backdrop is eliminated, and the image is subjected to a feature extraction approach and classification. Using classification, the image is compared to the trained database to determine if the image is normal or impacted.

Pre-processing

The first stage in every image processing approach is pre-processing. Pre-processing is necessary for the image's subsequent processing. Unwanted noise or distortions in the image will be suppressed during pre-processing. It improves various aspects of the image. The goal of pre-processing is to improve image data by normalizing it, suppressing undesired distortions, enhancing specific visual attributes, and removing optical disk that is necessary for further processing.

Fovea and Macula detection

The ROI (Region of Interest) should be cropped initially after preprocessing for subsequent segmentation. The fovea area is then discovered using thresholding and morphological filling and closure operations. Second, the macula region is discovered using the fovea, which is defined by the fovea center point and radius value. After that, the macula region's backdrop is eliminated. The extracted macula region is then utilized to do further processing.

Segmentation

The color segmentation technique is used to vary the colors derived from the macula area. Exudates are detected using thresholding and morphological operations after color segmentation. To turn the image into a binary image with black and white pixels, the thresholding process is employed. The image's greatest contrast will be transformed to white pixels during thresholding. The morphological procedure should be performed after the thresholding process. It is used to extract information from an image, after which the image's border pixels and low frequency pixels are removed.

Feature extraction

The detection of Diabetic Macular Edema relies heavily on feature extraction. Color moments such as mean and standard deviation are retrieved for each channel of a segmented image in statistical color analysis. Energy, contrast, correlation, and homogeneity characteristics based on GLCM (Gray-Level Co-Occurrence Matrix) are retrieved for segmented image texture features.

Classification

The retrieved features are used in the classification process.

(Chen et al., 2018) used an ANN-based machine learning approach to predict visual outcomes in diabetic macular edema patients after treatment with ranibizumab. To optimize ANNs for regression computation, patient data was employed. In ophthalmology, machine learning methods are rapidly being implemented. Machine learning can evaluate and summarize large datasets in a variety of ways to uncover new information. ANNs can best manage a large quantity of data and perform calculations using nonlinear modeling. Furthermore, images of diabetic retinopathy and macular edema with retinal fundus may be distinguished using ANNs. Furthermore, a deep convolutional neural network might attain an accuracy rate of up to 94.5 percent.

(Sreejini and Govindan, 2013) uses Particle Swarm Optimization (PSO) for effective segmentation of exudates. PSO is a swarm intelligence-based optimization method that is inspired by the social behavior of schooling fish or swarms of birds. Kennedy and Eberhart are the first to introduce it. In recent years, PSO has grown in prominence in a variety of study fields, including image segmentation, anomaly detection, and FCM clustering when paired with neural networks. Here, Exudates are retrieved using a PSO-based segmentation technique, and mathematical morphology is used to identify the optic disc and fovea. The ETDRS grading guideline is used to categorize DIABETIC MACULAR EDEMA phases as normal, stage 1, or stage 2. This method showed 93% of accuracy.

2.3.3 Glaucoma

Glaucoma is a disease that affects the optic nerve in your eye. It usually occurs when fluid accumulates in the front of your eye. That extra fluid raises the pressure in your eye, causing damage to the optic nerve.(What Is Glaucoma? Symptoms, Causes, Diagnosis, Treatment, 2021)

Figure 16: Glaucoma vision

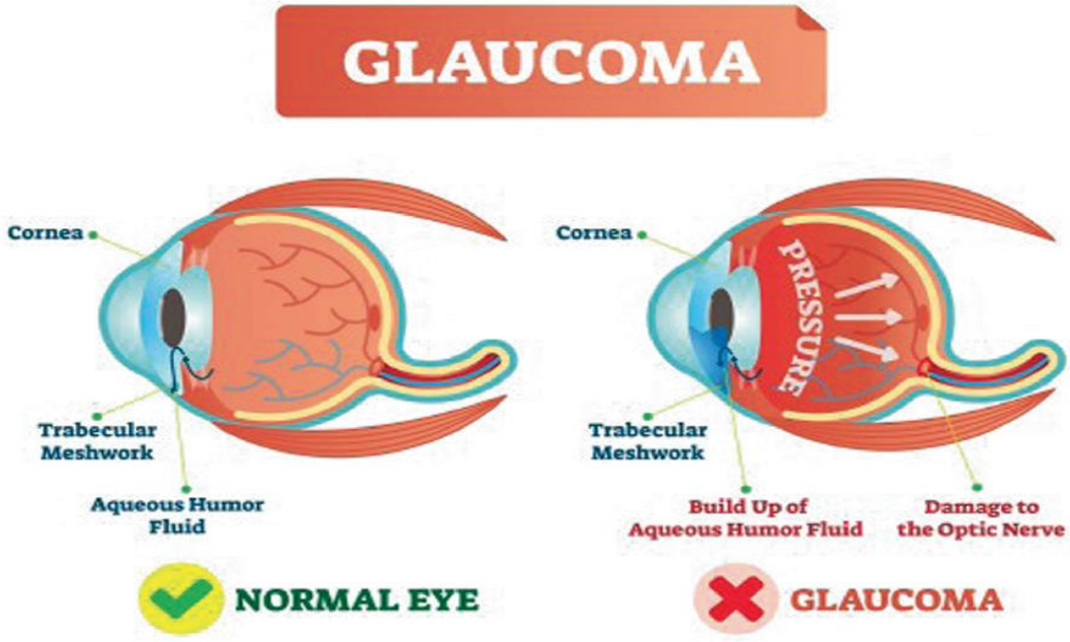


Figure 17: Normal eye vs Affected eye (Mishra and Raikwal, 2021)

2.3.3.1 Methods of detection

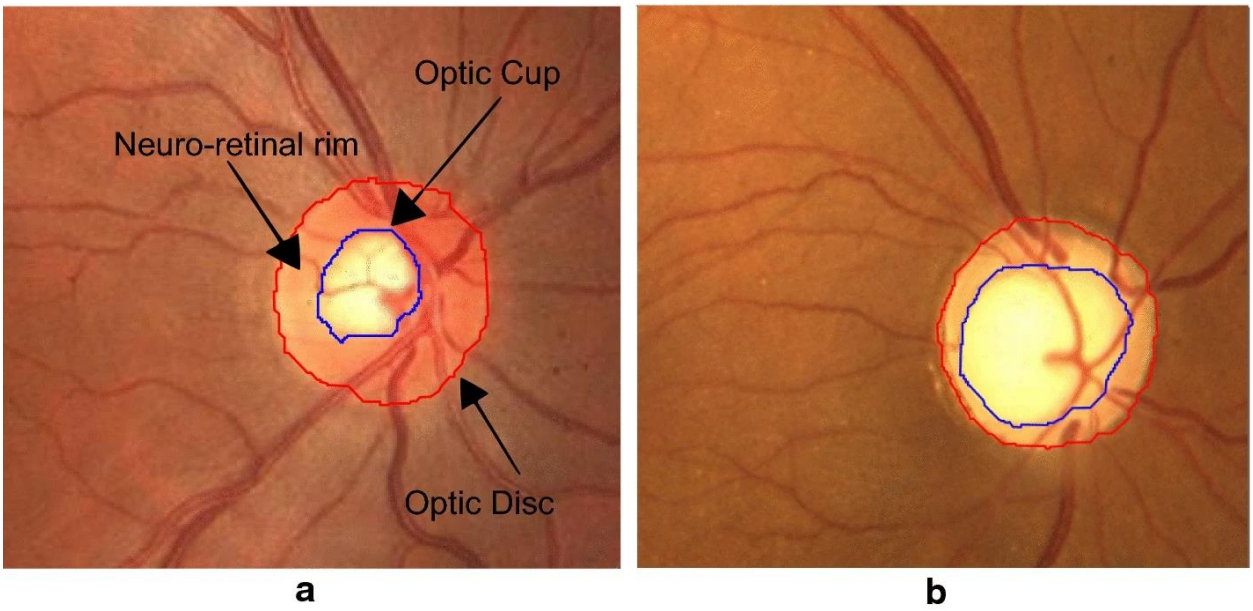


Figure 18; (Diaz-Pinto et al., 2019)-Digital fundus images cropped around the optic disc.

A-Main structures of a healthy optic disc

B-glaucomatous optic disc

This flowchart explains the general flow diagram for the glaucoma detection process. The various steps involved in the detection of Glaucoma are discussed in detail.

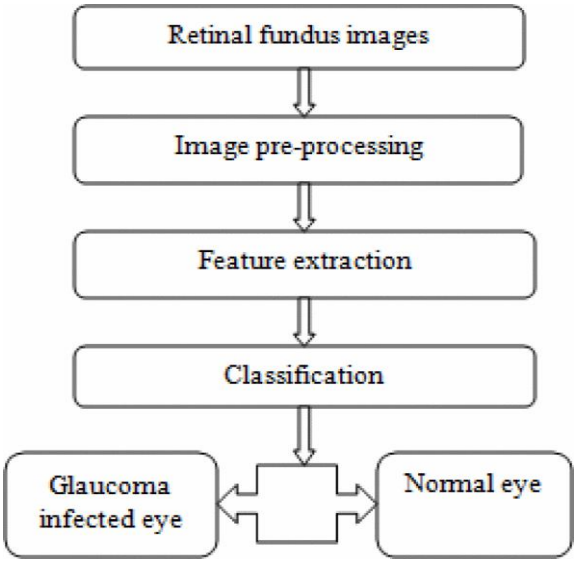


Figure 19: Glaucoma detection process (Kaushal, Datt Sharma and Jain, 2018)

Input Retinal Fundus images

The first step is to gather the dataset, which can be local (taken from the hospital) or online available records such as Stare (maximum 400 images are present), Drones-DB, and others (110 images are present). These images are called retinal fundus images.

Pre-processing

For detection, the data must be pre-processed, which includes noise removal and balancing other loopholes in the image. Although geometric transforms of images (for example, rotation, scaling, and translation) are classified as pre-processing methods, the main goal of preprocessing is an improvement of the image data that suppresses revealing distortions or enhances some image feature that is important for subsequent processing steps. Histogram equalization, extraction of red, blue, and green channels from an image, color enhancement, morphological operations, Fractal Analysis, and other techniques are commonly used for this purpose. Histogram equalization is a processor that was used to modify image intensities in order to improve contrast. The color of an image is an important parameter in fractal analysis. Fractal dimension is determined spontaneously for all levels of the chosen channel of color information, i.e. red, green, blue, hue, saturation, and so on. Extraction of color channels from images is another method for pre-processing. These channels are known as the Red channel, Blue channel, Green channel, and Gray channel, and they are used to extract features from images. Morphological can be defined as a set of image processing methods that characterize images based on their shapes. These methods use a structuring element as a mask in the input image, resulting in an output image of the same size. Dilation and erosion are the most common morphological operations.

Feature extraction

This involves various techniques such as wavelet methods, filters, pixel intensity values, and histogram models. Feature extraction is defined as a method for converting visually extractable and non-extractable features into mathematical expressions. These expression ns are known as morphological features if they are based on shape, and texture features if they are based on intensity distribution. Statistical methods, Signal Processing based Techniques (EWT is the best example of this technique), and Transform based methods are all based on the intensity

distribution. Some of the most common transform-based techniques used in the detection process are the discrete transform and the Fourier transform. CDR, correntropy features, mean, standard deviation, and open-angle parameters are also some of the features extracted. Many proposed methods use changes in CDR value as a feature for early detection of Glaucoma. On the accuracy value, the best extraction technique is EWT based correntropy features. EWT, a signal decomposition technique, is a signal-dependent method that does not require a predefined basis function, unlike Fourier and Wavelet transforms. It functions as a bandpass filter. The empirical scaling function m(W) and empirical wavelets m (W) are already defined. Correntropy is a nonlinear kernelized similarity metric. This feature captures the restrained variations in pixel intensities exceptionally well and provides high classification accuracy.

Image classification (whether normal or glaucoma)

There are several approaches to detect eye diseases from ophthalmic fundus photography. For the, glaucoma detection is based on various models along with image classification to identify and detect with stages from the Fundus images

(Kompella, no date) had implemented different machine learning algorithms such as decision trees, k- nearest neighbor, random forest algorithm to compare efficiency. They had focused on detecting the presence of glaucoma based on retinal nerve fibre layer thickness and visual field.

(Ajitha, Akkara and Judy, 2021) had suggested a powerful and accurate algorithm using a neural network model to automatic diagnosis of glaucoma. Furthermore, they used 1113 fundus images consisting 660 normal and 453 glaucoma affected. The algorithm was implemented in google colab without spending hours installing the environment and libraries. The dataset was divided into 70%,20% for training and validation and the remaining 10% utilized for testing. Furthermore, the model achieved an accuracy of 92.86% and sensitivity of 85.42%.

(Raja and Jothilakshmi, 2021) has reviewed the major deep learning concepts to medical image analysis and summarizes the contributions for Glaucoma. Furthermore, the use of deep learning for image classification, object detection, segmentation, registration, and other tasks.

(Salam et al., 2016) had proposed a novel combination of structural and non-structural (texture and intensity) features to improve the accuracy of detecting glaucoma. The evaluation of proposed

algorithm was performed using a local database of fundus images from 100 patients. Furthermore, the average sensitivity and specificity of the system was 100 and 87 % respectively.

(Diaz-Pinto et al., 2019) had proposed five different ImageNet-trained models (VGG16, VGG19, InceptionV3, ResNet50 and Xception) for automatic glaucoma detection using fundus images. Furthermore, suggested that using ImageNet-trained models is a robust alternative for automatic detection of glaucoma.

(Wang, Hu and Zhang, 2021) had proposed a deep neural network model to diagnose glaucoma based on Heidelberg retina tomography. The DNN model achieved an area under the curve (AUC) of 94.0% and sensitivities were 91.2% and 78.3% at specificities of 0.85 and 0.95, respectively

(Abbas, 2017) had used convolutional neural network (CNN) unsupervised architecture to extract the features through multilayer from raw pixel intensities when detecting glaucoma. Furthermore, a deep-belied network model used to select the most discriminative deep features and softmax linear classifier used to differentiate between glaucoma and non-glaucoma retinal fundus image. On average, the sensitivity of 84.50%, specificity of 98.01%, accuracy of 99% and precision of 84% values were achieved.

In this analysis performed using various features to consolidate the data for classification. Classification refers to the techniques of combining testing samples with similar features into the same levels, which are referred to as classes. Classification is divided into two types: supervised classification and unsupervised classification. Supervised classification is one in which the training set is predefined; otherwise, unsupervised classification is used. Depending on the data used for the analysis, there are various classifications such as SVM classifiers, Bayes classifiers, K-mean clustering classifiers, and many more. When used, SVM has the highest classification accuracy. Based on all of the preceding steps, a CAD system was developed for the detection of glaucoma. These systems utilize a variety of detection techniques, each of which yields a different percentage of accuracy. As part of some research, many different papers on the detection of glaucoma were reviewed; CDR was identified as an important feature for detection. CDR was calculated using various classifiers such as

thresholding, SVM, Least square minimization, and K-mean clustering, resulting in lower accuracy. Later, it was discovered that combining 2D EWT and the correntropy method (feature extraction method) with Least-SVM (classifier) yielded greater accuracy than the other methods.

2.3.4 Choice of OculoGuard

Many algorithms are used for detecting diabetic eye diseases such as native byes,KNN and SVM. Among all algorithms Random forest has shown great potential. In the fundus photography , Random Forest has shown significant promise for Diabetic eye disease categorization and identification of key features. Random Forest is very nonlinear and outperforms standard logistic regression when dealing with high-dimensional data. Random forest classifies large amounts of data with accuracy. Random Forests are a set of tree predictors in which each tree is based on the values of a random vector collected separately for all trees in the forest with the same distribution. Because they do not overfit due to the law of large numbers, Random Forests are an excellent tool for generating predictions. The below figure shows Random forest classification accuracy estimated using the testing datasets.

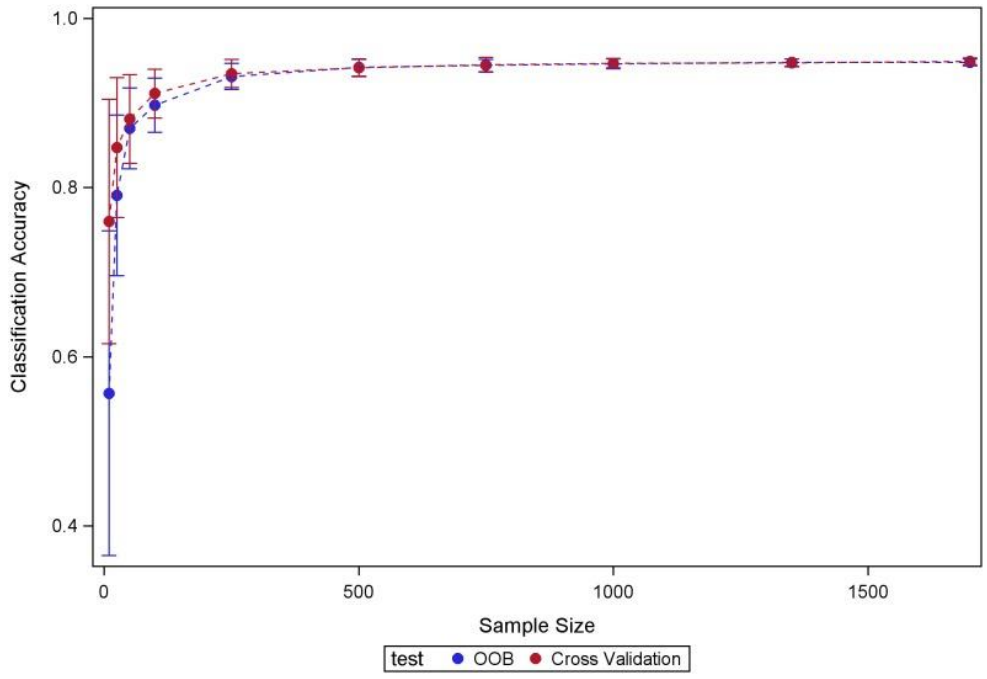


Figure 20: Estimates of RF classification accuracy obtained using the OOB mechanism and two-fold CV.(Casanova et al., 2014)

(Casanova et al., 2014) developed a method for doing classification assessments of DR fundus photography data using Random Forest algorithms. In the majority of the circumstances tested,

RF clearly surpasses logistic regression, a traditional statistical method. So since Random forest is best for classification and it showed higher accuracy than other algorithms we will be using it in our system for detecting diabetic eye diseases and prognosis of diabetic retinopathy.

2.4 Chapter Summary

This paper presents information from several research papers and journals related to the subject of Earlier stage Diabetic Retinopathy, Macular Edema,Glaucoma detection and early stage of DR Prognosis using image processing. The chapter was divided into two main parts: Existing Work and Tools and techniques. The existing work covered existing applications related to diabetic eye diseases using image processing. Next section Tools and techniques was narrowed down to 4, Diabetic retinopathy, Diabetic macular edema,Glaucoma and early DR prognosis of which the best techniques and algorithms will be chosen.

Chapter 3: Methodology

3.1. Chapter Overview

This chapter demonstrates different methodologies carried out during the development of OculoGurad. Starting from research, design, development to evaluation. Then how group members manage their work and how mitigations are addressed.

3.2. Research Methodology

Research is more than merely obtaining knowledge, as some people believe. Rather, it's about finding answers to unresolved problems or building something that doesn't exist yet. In many aspects, research may be regarded as a means of pushing the limits of our knowledge.

The research approach can be broken down into Experimental Research, Creative Research, Descriptive Research, Ex post facto Research, Action Research, Historical Research, and Expository Research.

The study of cause and effect is the focus of experimental research. Researchers identify the variables of interest and attempt to discover if changes in one variable (referred to as the independent variable, or cause) cause changes in another (called the dependent variable, or effect).

The creation of new theories, techniques, and innovations are all part of creative research. A computer scientist, for example, may develop new algorithms for computer system management. In all fields, creative research is used to some extent. Creative research, unlike experimental research, is less regimented and cannot always be planned. Both practical and theoretical research are included in creative research. The creation of actual objects and the development of real-world processes are at the heart of practical creative research. The discovery or production of new models, theorems, algorithms, and other concepts is the goal of theoretical creative research. The majority of practical research is done via trial and error.

Descriptive or case-study research looks at a specific circumstance to determine whether it leads to any general ideas or if current broad theories are supported by the situation. When the research object is extremely complex, descriptive research may be used.

Researchers use Ex post facto research to look back at the effects and try to deduce the causes from them. Ex post facto research occurs when data is available that could not have been obtained through experimental research. It's worth noting that in order for ex post facto research to be reliable, the researcher must rule out all alternative possibilities.

Historical research is the study of the past in order to discover cause-and-effect relationships. It is frequently geared toward examining current situations and forecasting future events based on past events. The research did not look into current causes or consequences. Primary and secondary sources are used to collect data.

Expository research that is solely based on existing data and usually results in "review-type" papers. A researcher can often develop important new insights by reading widely in a field and then comparing, contrasting, evaluating, and summarizing all points of view on a particular subject.(Goddard and Melville, 2004)

OculoGuard will be using the descriptive approach to detect Eye diseases using Fundus image, the expository approach to develop important new insights by reading widely in a field and then comparing, contrasting, evaluating, and summarizing all points of view on a particular subject, and the historical approach to gather and use datasets toward examining current situations and forecasting future events based on past events.

3.3. Development Methodology

Iterative Software Development method has been chosen in the development of the OculoGuard application. Given there are many cycle repeatings after the initial build improvements and enhancements can be added to the system continuously. OculoGuard consists of multiple disease classifications but the input of the system is only a specific data type, in this case a fundus image. Therefore even with many types of classifications, at the initial stage a simple system can be developed as common for every sub system and in each iterative cycle more specific improvements can be made into different disease detection. Also since there's a working prototype at the initial stage many design flows and functional flows can be reduced with the experience unlike some other methodologies where the team has to wait till the final phase.

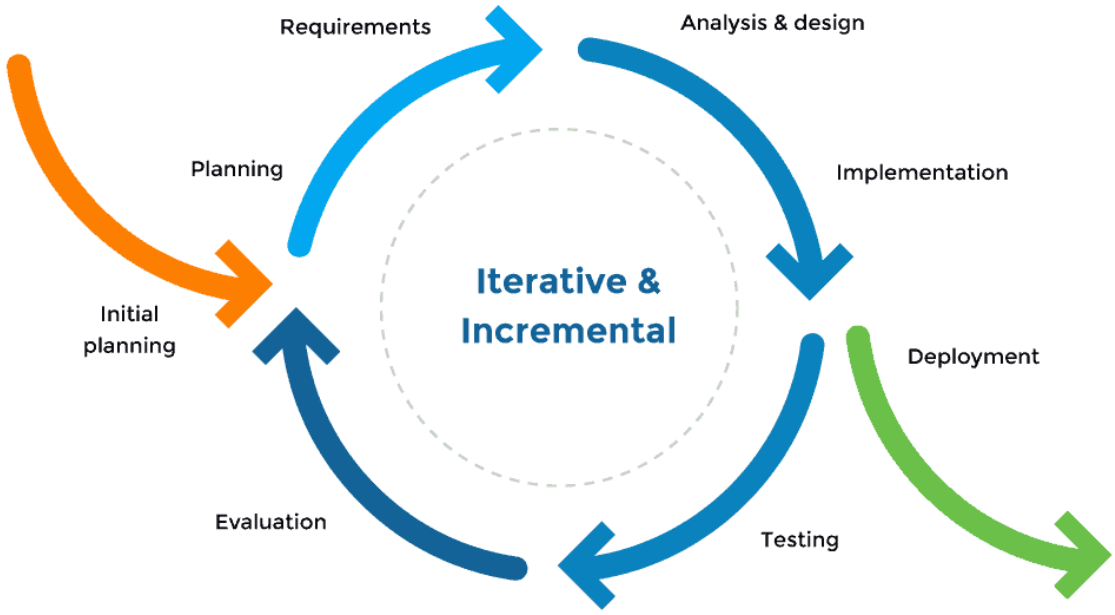


Figure 21: Software Development method

Methodology	**Reasons for not taking**
Waterfall	Have to wait till last to see a working prototype
Agile	Bit similar to the iterative approach but unlike iteration, incrementation is happening, meaning features developed in a cycle have to be finalized.
Spiral	Complexity of the process and management is high and the end of the project can't be seen till the later stages

Table 5: Comparing SDLC Models

3.4 Design methodology

The implementation of the prototype for OculoGuard will be done using Object-Oriented Programming methodology which will make the code modular and scalable and easier to

understand.Object Oriented Designing Use of class diagrams which will be discussed in the next chapter is another key feature of OOAD where it describes the system by showing classes and attributes with their relations**.**

3.5. Evaluation methodology

After the project cycle is over, evaluation is basically the appraisal of the project's success. It discusses and assess outcomes that have been achieved via your project activities based on data obtained in a baseline study. Evaluation allows you to see and comprehend what the project is all about, as well as the influence it has had on the communities.

Various measures such as true positive (TP), false positive (FP), false negative (FN), and true negative (TN) rates have been used to evaluate the performance for diagnosing the disease and determining the severity of the condition. (Nagpal et al., 2021)

		Actual	
		Positive	Negative
Predicted	Positive	True Positive	False Positive
	Negative	False Negative	True Negative

Table 6: TP, FP, TN, FN rates (Agarwal, 2020)

3.5.1. Sensitivity/Recall/True positive rate

Sensitivity is defined as the proportion of accurately identified items to the total number of objects.

$$\text{Sen}=\frac{TP}{P}$$

3.5.2. Specificity/True negative rate

The ratio of accurately recognized non-object classes to the total number of object classes is known as specificity.

Spec=$\frac{TN}{N}$

3.5.3. False positive rate

The false positive rate is defined as the ratio of incorrectly detected objects (FP) to properly recognized non-objects (TN).

FPR=1-Spec

3.5.4. False-Negative rate

FNR is described as the ratio of FN and TP

FNR = 1 –Sen

3.5.5. Accuracy

Accuracy is defined as the ratio of successfully detected items and non-objects to the total number of objects.

Acc=$\frac{TP+TN}{P+N}$

3.6. Project Management Methodology

Project management methodology is a combination of methods, processes and practices that determine how to develop, control and plan a project until successful termination.

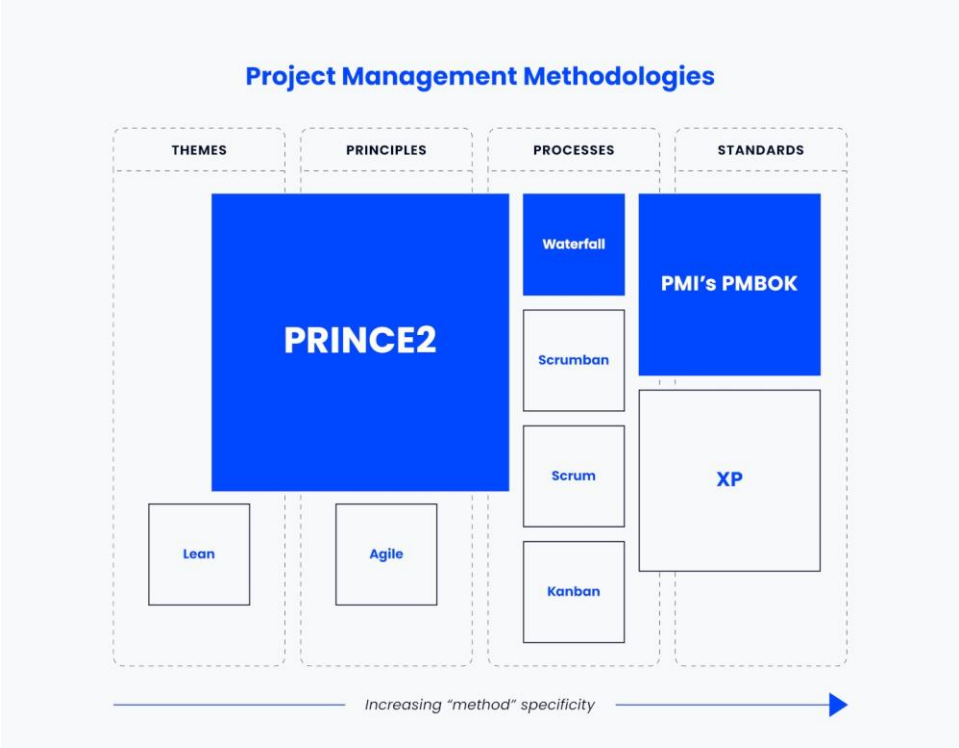


Figure 22: Project management methodologies

Agile,Scrum,Kanban,Scrumban,Lean,eXtreme Programming(XP),Waterfall,PRINCE2 and PMI's PMBOK are some most popular project management methodologies which are used in the industry. This project will be managed using the Kanban methodology. That helps to focus on work that can be faster, and with better quality. Kanban typically uses sticky notes on a Kanban board to represent the workflow which can categorize"To do", "Doing" and "Done".

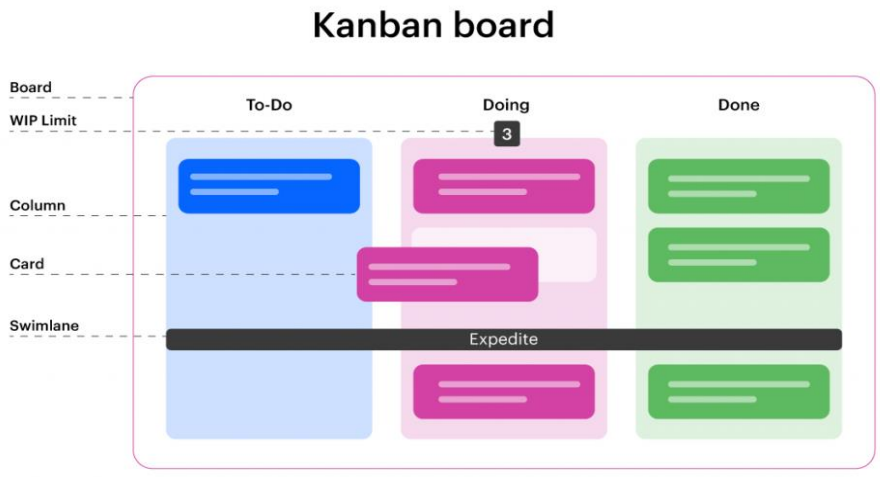


Figure 23: Kanban board

3.7 Team Work Breakdown Structure (WBS)

The following diagram illustrates the Work Breakdown Structure

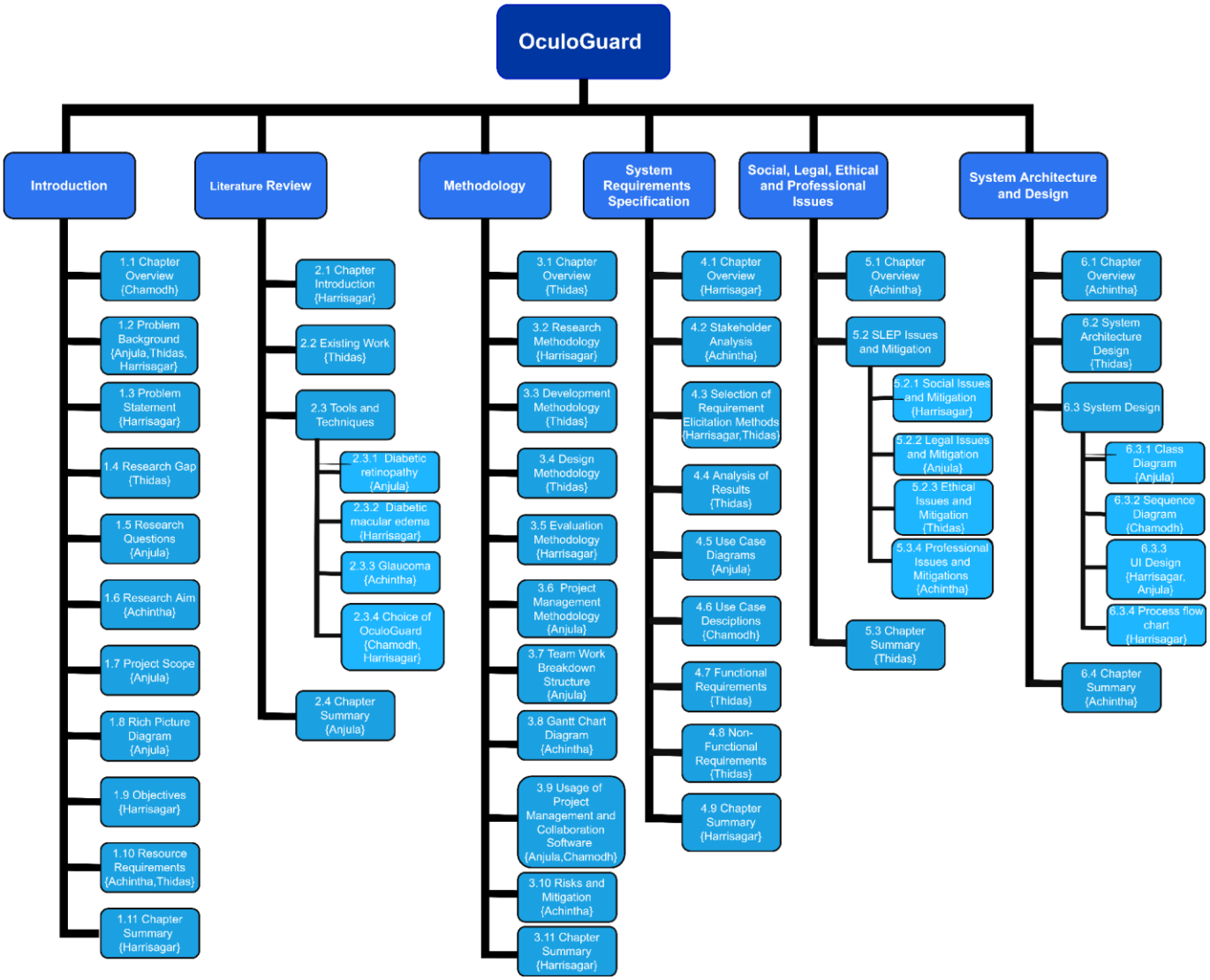


Figure 24: Team Work Breakdown Structure

3.8 Gantt chart diagram

For a clear example, the Gantt chart is moved to Appendix A.1.

3.9 Usage of Project Management and Collaboration Software In the project

Trello

Trello was used to keep track of the work assigned to each team member and the focus of each progress of tasks. Trello allows to track incoming, to-do, doing and done labels. When a team member is done with his work,he can mark it in trello and the rest of the members can update about it. Also Trello was useful to finish tasks on time.

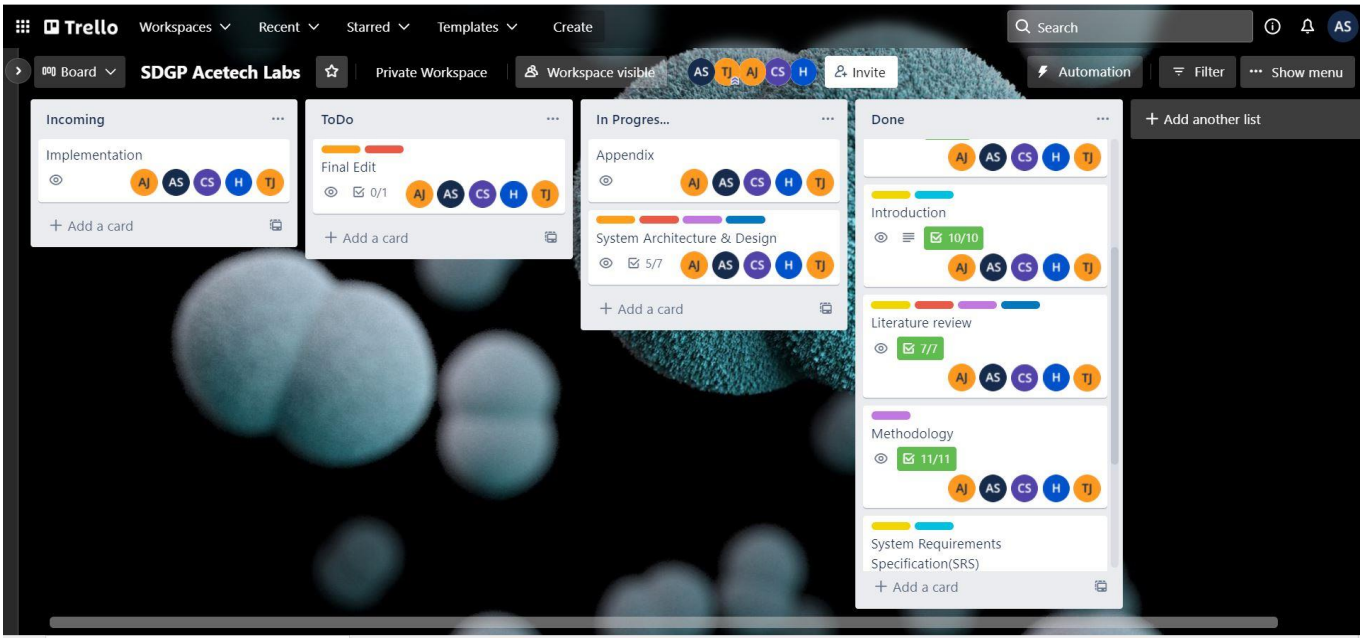


Figure 25:Trello

Slack

Slack was mainly used to share datasets, massages and share learning materials regarding the project of OculoGuard. All the project related massages and important materials were send in each sections.For ex: #general, #eye-disease-detection, ml-and-dl-background, etc.

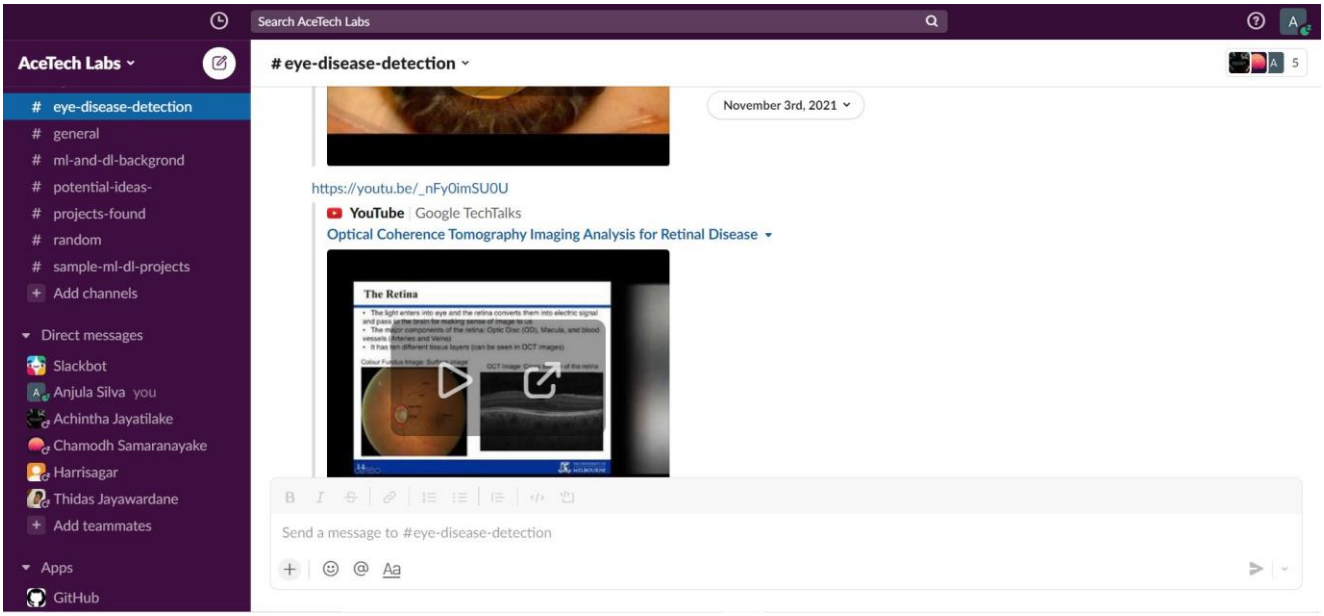


Figure 26: Slack snapshot_1

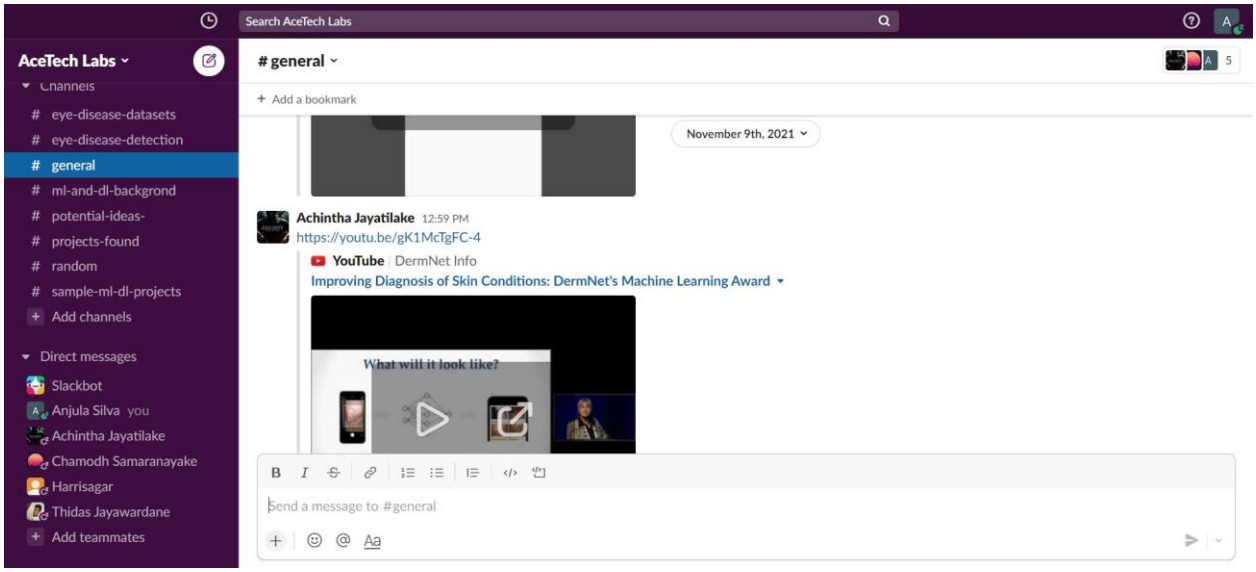


Figure 27: Slack snapshot_2

3.10 Risks and Mitigation

The following table shows some potential Risks and Mitigation strategies of OculoGuard.

Risk Item	Severity	Frequency	Mitigation Plan
Planing	5	5	Before beginning,decision-making of project schedules and justification for the work.
Group	4	4	Clarify every work with the team and thoroughly comprehend and manage the project.
Report	5	5	Work should be planned properly as project scheduled and completion of report.
Backup	3	2	Everytime keep a backup of everything connected to the work done and review your backups.
Technology	5	4	Huge technological research has been performed and is always up to date.
Problems and Issues	5	4	Trying to find solutions and receiving comments from specialists(domain experts)
Deadline	5	5	Concentrate on the tasks and complete them within several days before the deadline so that the final week may be used for fixing bugs and errors.

3.11 Chapter Summary

This chapter discussed project management methodologies and addressed the most appropriate approaches for the project OculoGuard. The chapter also identifies the risks that need to be addressed and develops mitigation plans. This chapter included an illustration of the work breakdown structure and a Gantt chart diagram.

Chapter 4: System Requirements Specification (SRS)

4.1 Chapter Overview

The Software Requirements Specification chapter focuses on identifying stakeholders, gathering requirements, discussing approaches, and defining functional and non-functional requirements as well as their priority levels. In addition, a use case diagram and a detailed use case description will be demonstrated and presented.

4.2. Stakeholder Analysis

"The term "stakeholder" is an attractively inspiring metaphor for the need to be detailed about how project roles and responsibilities should be shared."(Alexander and Robertson, 2004)

4.2.1. Onion Model

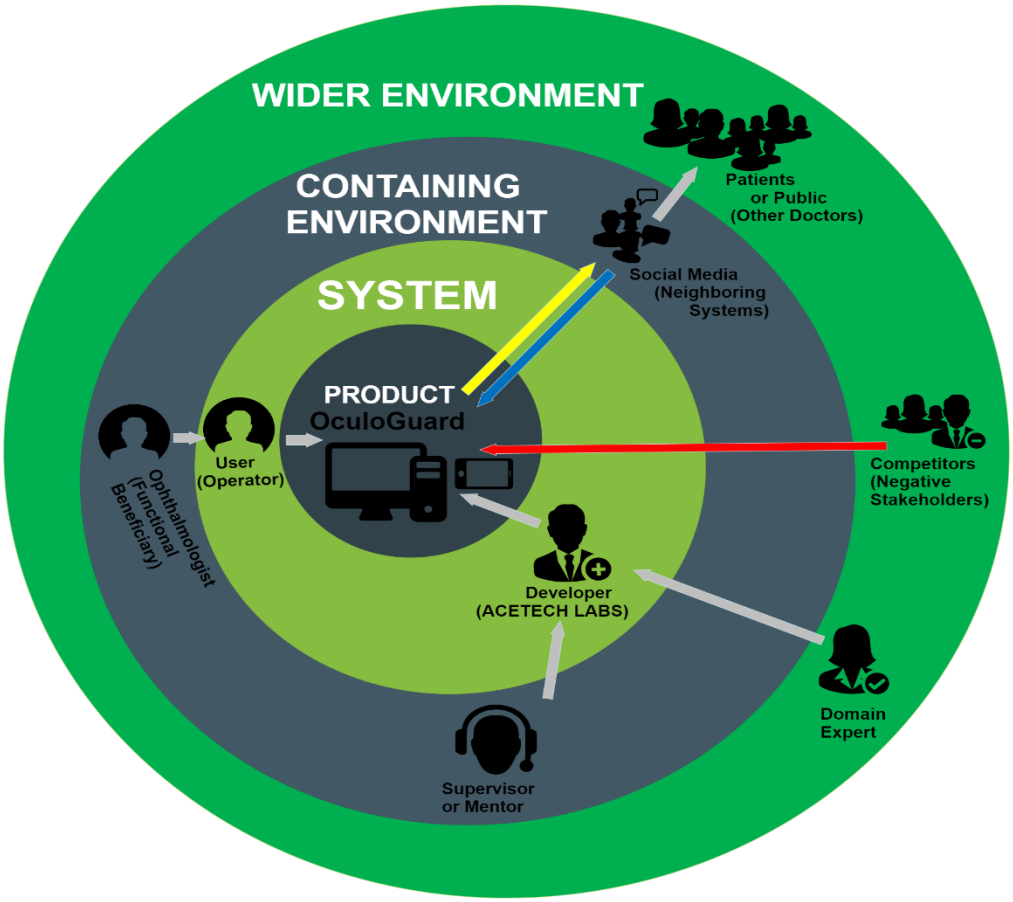


Figure 28: Onion Model

4.2.2. Stakeholder Descriptions

The table below explains the stakeholders by categorizing into various stakeholder roles of OculoGuard.

Stakeholder	Viewpoint
Functional beneficiary	
Ophthalmologist	With the usage of oculaogarud the ophthalmologist identifies maintenance issues and informs the developer(Acetech Labs) of OculoGaurd.
Financial beneficiary	
Developer (Acetech Labs)	Acetech Labs creators of OculoGaurd could make profit from displaying target advertising to the Public.
Social beneficiary	
Patients/Public(Other Ophthalmologists)	By using the OculoGuard product, Other Ophthalmologists (Patients/Public) could check if the users are happy with their needs or not.
Operational beneficiary	

Ophthalmologist	Ophthalmologists are doctors that specialize in the eye, and they may save time by using OculoGuard to do accurate and efficient eye detections and consults for treatments.
User	Anyone can use OculoGuard for Diabetic Eye Diseases detection and diagnosis.
Negative Stakeholders	
Competitors	Hope that competing with OculoGuard by developing a superior solutions by combining four or more detection of eye diseases together with the use of the best algorithm and model from all other existing systems.
Regulatory	
Data validity	Ensure that the OculoGuard system is functioning at high performance, with minimum wasted effort and no erroneous data.
Experts	
Specialized Eye Ophthalmologist (Domain Expert)	Should communicate to the developer(Acetech Labs) to have Proper understanding of OculoGuard so that a better system may be implemented.

Supervisor or Mentor **(Ms.Janani Harishchandra)**	Assisted Acetech Labs in the development of this Project(OculoGuard) by providing guiding and clarifying doubts and helped the Team in numerous ways.
Neighbouring systems	
Social Support	Start promoting the OculoGuard to the wider environment/population so that Ophthalmologists and Patients will be interested.

Table 7: Stakeholder Descriptions

4.3. Selection of Requirement Elicitation Techniques/Methods

4.3.1. Types of elicitation techniques

The nature of the communications chosen is used to classify the requirements elicitation. This can be done in one of two ways: directly or indirectly.

4.3.1.1. Direct Approach

In a direct approach, this means that the domain knowledge of the system to be constructed is taken into account, since this will help system developers grasp the system's difficulties. Few direct approach techniques are,

i. Interviews
ii. Brainstorming
iii. Case studies
iv. Prototyping

4.3.1.2. Indirect Approach

When the information to be gained cannot be easily found, an indirect technique is utilized. Because the methodologies in this approach imply that the users or stakeholders have minimal understanding of the system. Few Indirect approach techniques are,

i. Questionnaires

ii. Documents analysis

4.3.2. Requirement elicitation methodologies

Methods	**Description**
Interviews	An interview is a face-to-face encounter performed by an expert analyst with broad understanding of the system's issue area. In an interview, the Analyst discusses the system's issue domain with various relevant stakeholders and users in order to gain a better knowledge of their system needs.
Questionnaire	Questionnaires are one of the less expensive means of acquiring requirements. Questionnaires reach a big number of individuals in a short amount of time and at a low cost. The following are some of the general factors that influence how the questionnaire is used: i. The resources available to gather the requirements are mostly determined by resource availability. ii. The type of requirements that must be gathered is determined by the respondent's level of knowledge and experience. iii. The responder was given anonymity.

Brainstorming	Another dialogue style is brainstorming. In brainstorming, stakeholders are brought together for a short amount of time, but in that time they produce a wide broad list of ideas. This meeting encourages "out of the box" thinking, therefore brainstorming includes both idea generation and concept reduction. Members come from many departments, and domain specialists are also present.
Social Analysis	An observer spends time in a particular location and observes its culture in order to undertake a thorough examination of all of its activities. As it provides current facts and understanding of the system in that context, this research aims to uncover causes for some of the practices toward the system.
Observation	The analyst, as the name implies, monitors users' actual execution of current procedures without interfering. To create a peripheral awareness of the system, this approach is sometimes used in conjunction with other techniques such as interviews. Observation is a time-consuming process
Scenarios	As it is an interactive session, a series of actions and events outlined for executing some general job that the system is designed to achieve is broadcasted and debated.
Prototyping	Providing stakeholders with system samples to aid in the research of potential solutions is a good technique to get extensive information and meaningful input about a problem domain.

Table 8: Requirement elicitation methodologies

4.3.3. Survey for General public

Goal	Question
To know age and gender of the person filling the survey	• Select the age group you belong to • Gender
To identify whether the person has diabetes, and what type of diabetes he/she has.	• Do you have diabetes? • What type of diabetics are you suffering from ?
To know if the user have knowledge about diabetic eye diseases	• Do you think that diabetes can cause eye diseases?
To identify whether the user knows the connection between diabetes and diabetic eye diseases	• Are you aware that diabetes can cause eye diseases? • Are you aware that when you get diagnosed with diabetes, you must screen your eyes?

To know when and how the person diagnosed that he/ has diabetic eye disease and what diabetic eye disease he/she has	● What diabetic eye disease do you have? ● At what age did you diagnose it? ● How did you diagnose that you have the above Diabetic eye disease? ● What symptoms did you have leading up to the diagnosis? ● How long does the screening process take ?
To know whether the user has done eye screening before, how often the user undergo eye checkup and how long the screening process takes place.	● No need for the regular screen for Diabetic eye diseases if both eyes are good. ● How often do you check your eyes?
To know whether people need an application to detect diabetic eye diseases.	● Do you consider having a mobile application to predict Diabetic Retinopathy is useful?
To know whether the person is aware about that diabetic eye disease can cause permanent blindness	● Do you think that detecting it early would reduce the risk of permanent blindness?
Optionally, if the user has any comments or recommendations to improve the system	● If you have any suggestions as to how we could improve our application or any comments on our project idea please leave them below.

Table 9: Survey goals and questions table

4.4. Discussion/ Analysis of Results

The public questionnaire was sent out on the 31st of December 2021. The information was acquired during a two-week period. The structure of the questionnaire is, there are two sets of questions. If a person has previously suffered or is currently suffering from diabetic eye disease then he/she has to answer the first set of questions which consists of twelve questions. If the person does not have diabetic eye disease then he/she has to answer a second set of questions which contains 10 questions.

The complete analysis of all of the questions is provided below. A snapshot of the questionnaire sent can be found in Appendix SectionB.1.

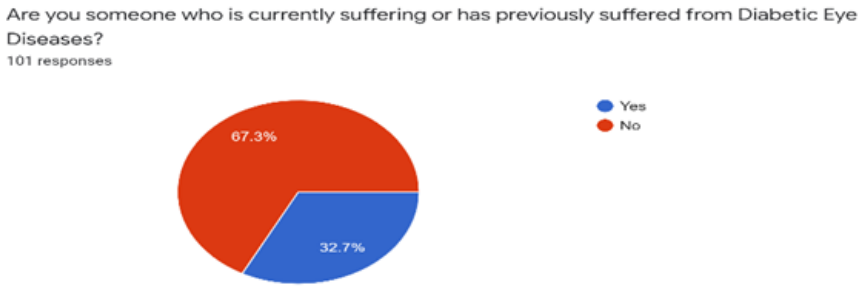


Figure 29: Survey Snapshot_1

Out of 101 responses 67.3% of people are not having diabetic eye diseases and 32.7% of people are having diabetic eye diseases.

First set of questions for a person who is currently suffering or previously suffered from diabetic eye diseases.

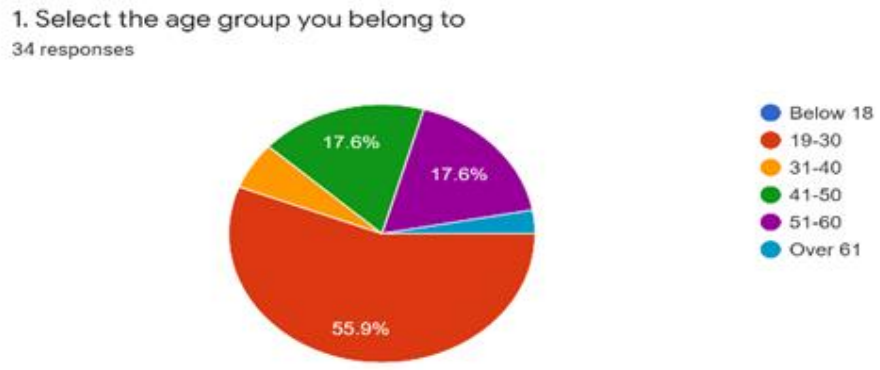


Figure 30: Survey Snapshot

This graph shows that 55.9% of people belong to the 19-30 age group and 17.6% of people belong to 41-50 and 51-60 age groups.

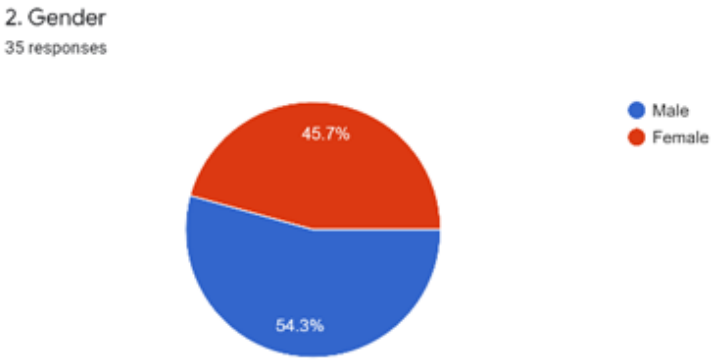


Figure 31: Survey Snapshot_2

This graph shows that 54.3% of males and 45.7% of females have previously suffered or are currently suffering from diabetic eye diseases.

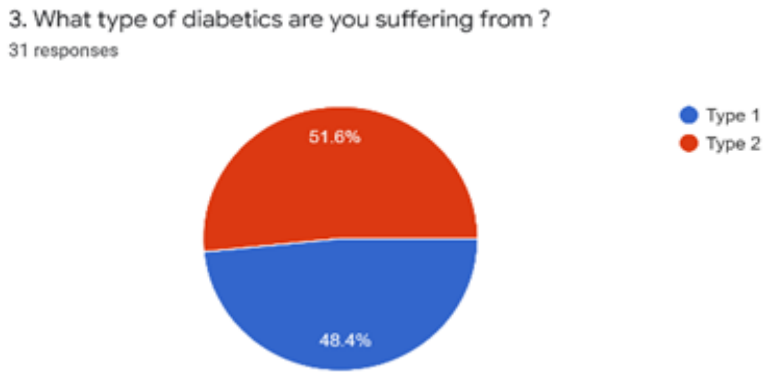


Figure 32: Survey Snapshot_3

This shows that 51.6% of people who are having diabetic eye diseases are having type 2 diabetes while others are having type 1 diabetes.

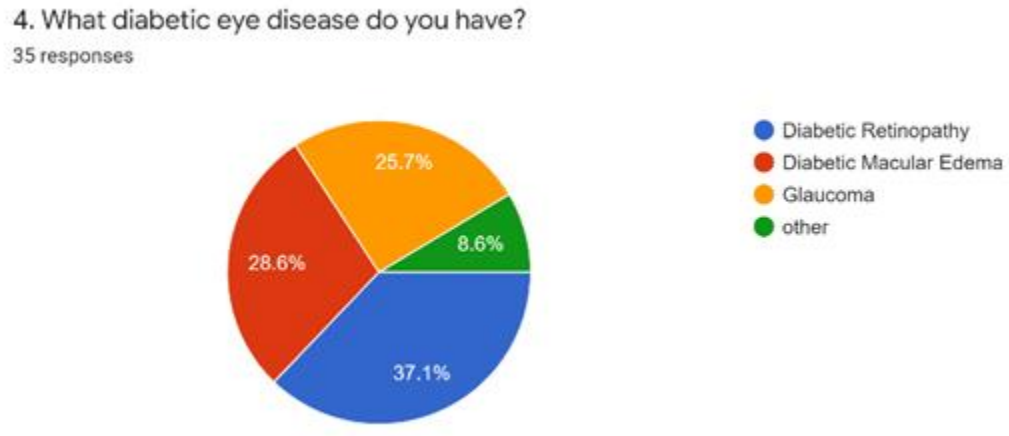


Figure 33: Survey Snapshot_4

This graph shows the type of diabetic eye disease that people are having. Diabetes is a diseases that has more than 400 million patients worldwide so the person who have diabetic may have a risk of getting diabetic eye disease in future.

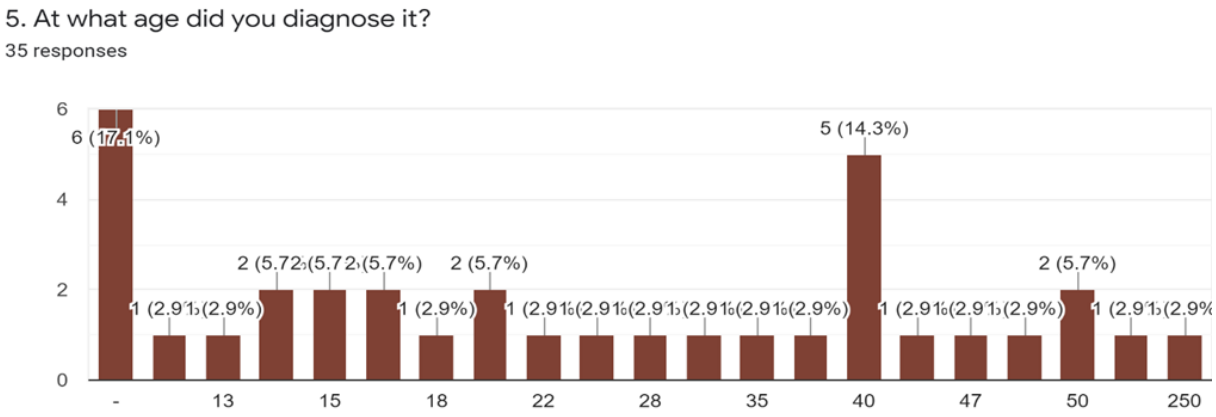


Figure 34: Survey Snapshot_5

This graph shows the age of people when they diagnose diabetic eye disease. According to this graph 14.3% of people diagnosed it at the age of 40.

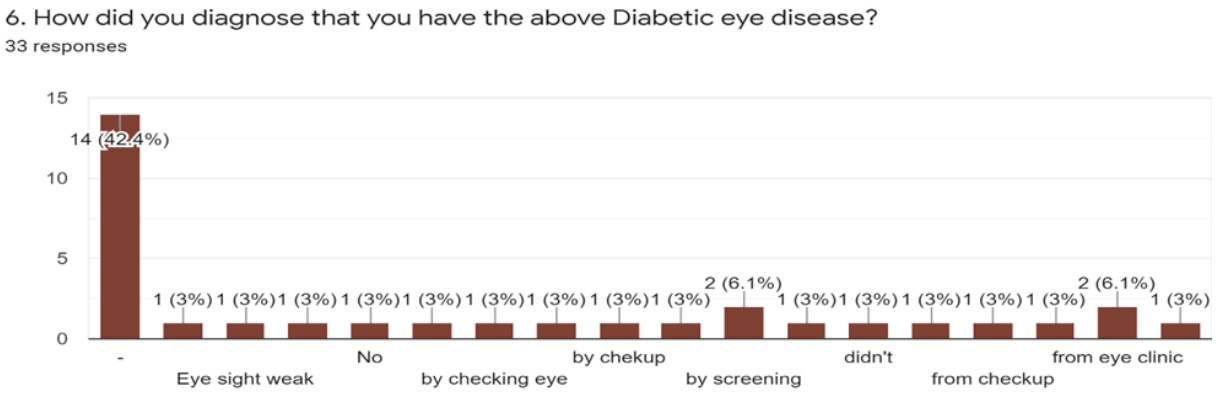


Figure 35: Survey Snapshot_6

This graph shows how people diagnose that they are having diabetic eye diseases. 6.1% of people have done eye screening and checkups to diagnose diabetic eye diseases.

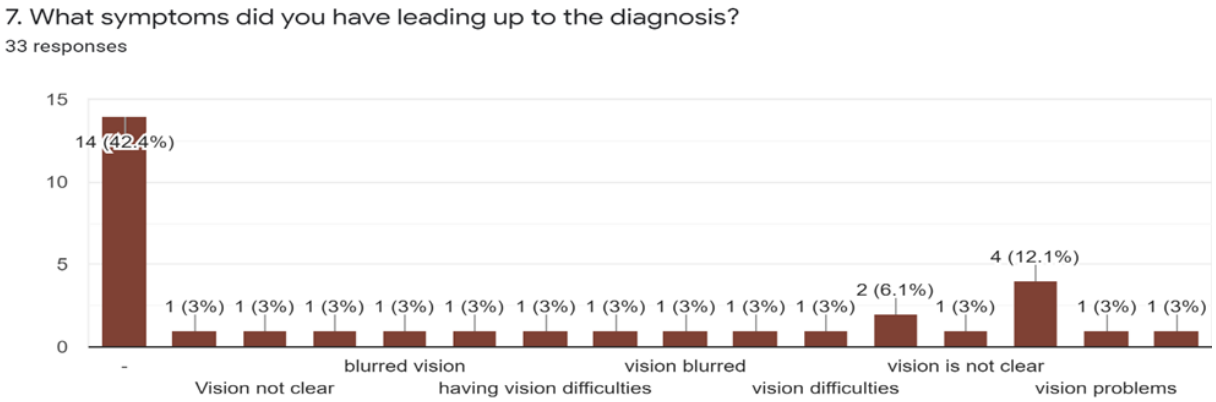


Figure 36: Survey Snapshot_7

This graph shows the symptoms that people had when they diagnose diabetic eye disease, most of the symptoms that people had are related to diabetic eye diseases.

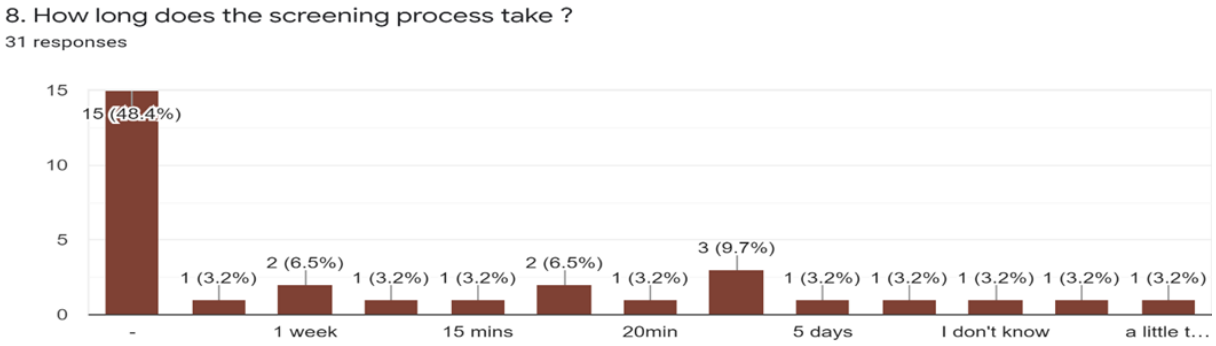


Figure 37: Survey Snapshot_8

This graph shows the time taken for the screening process, 3.2% of people replied “I don’t know” and 48.4% of people replied “-” so this shows that most of the people are not aware about the screening process and time taken for the screening process.

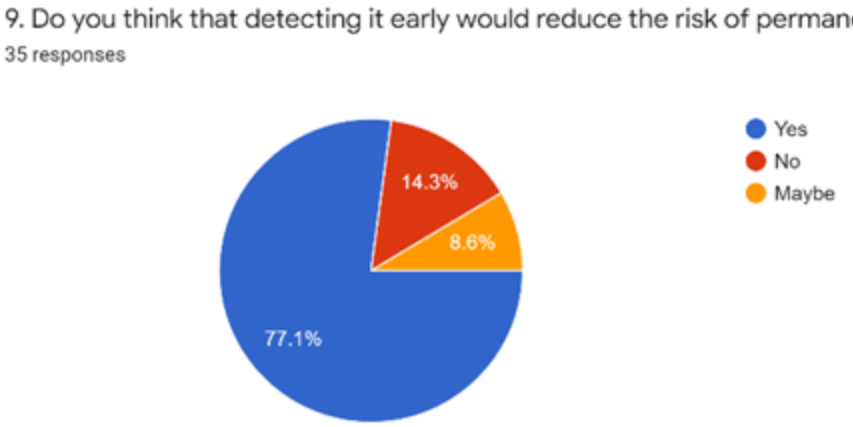


Figure 38: Survey Snapshot_9

This graph shows that 77.1% of people think that detecting diabetic eye disease early would reduce permanent blindness. So an application that detects diabetic eye disease early will be very useful.

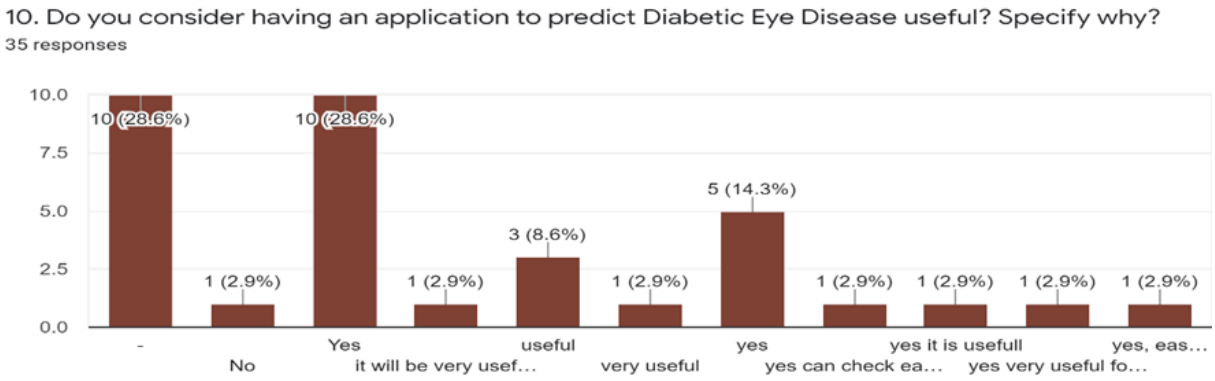


Figure 39: Survey Snapshot_10

This graph shows that the majority of people who filled the questionnaire prefer if there was such an application to predict diabetic eye disease that would be useful.

Second set of questions for people who are not having diabetic eye diseases.

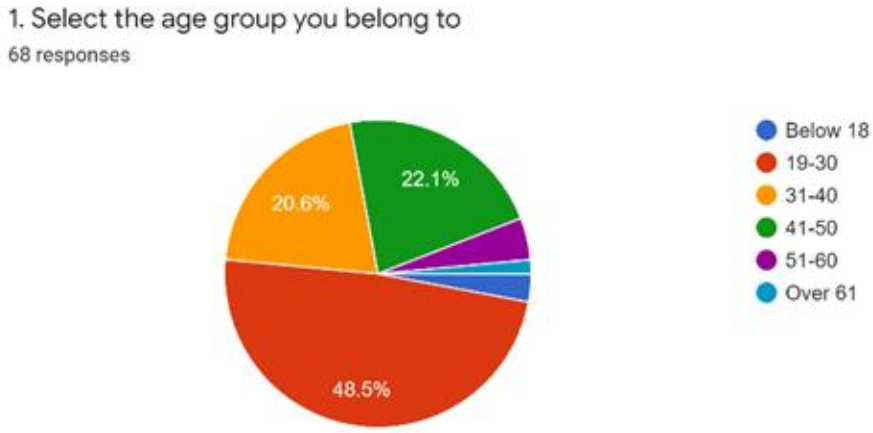


Figure 40: Survey Snapshot_11

This graph shows that 48.5% of people belong to 19-30 age group, 22.1% of people belong to 41-50 age group and 20.6% of people belong to 31-40 age group demographic on users. The people who filled this questions don't have diabetic eye disease.

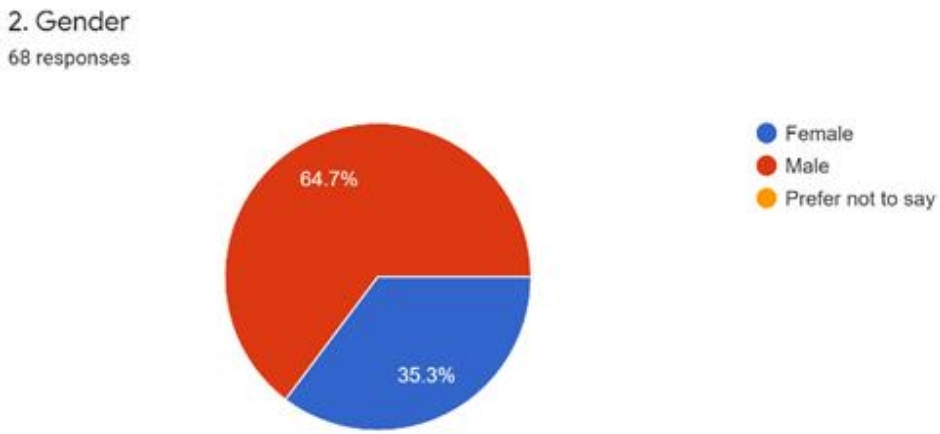


Figure 41: Survey Snapshot_12

This graph shows that 64.7% of people are males and 35.3% of people are female.

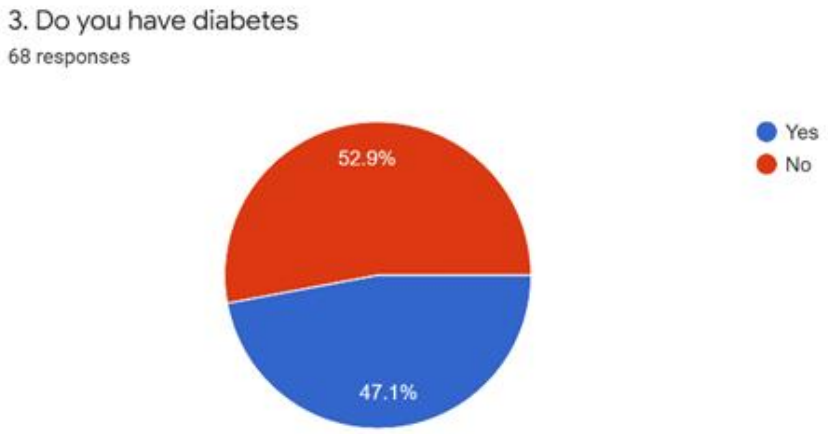


Figure 42: Survey Snapshot_13

This graph shows that out of 68 responses who don't have diabetic eye disease 52.9% of people are not having diabetes and 47.1% of people are having diabetes.

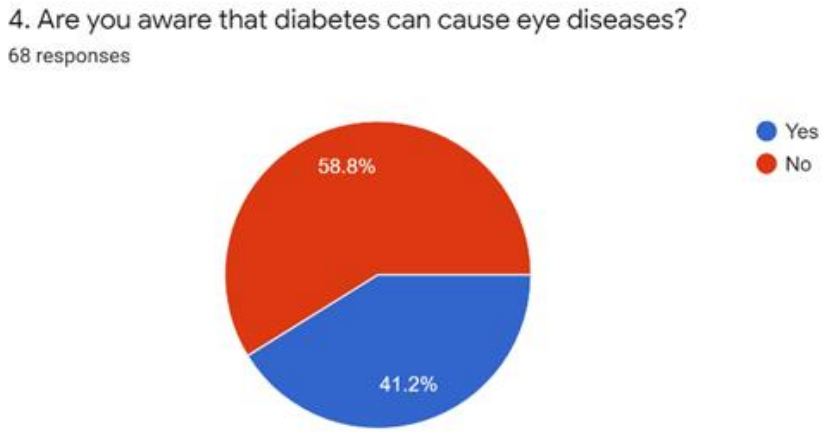


Figure 43: Survey Snapshot_14

This graph shows that the majority of people (58.8%) are not aware that diabetes can cause diabetic eye disease.

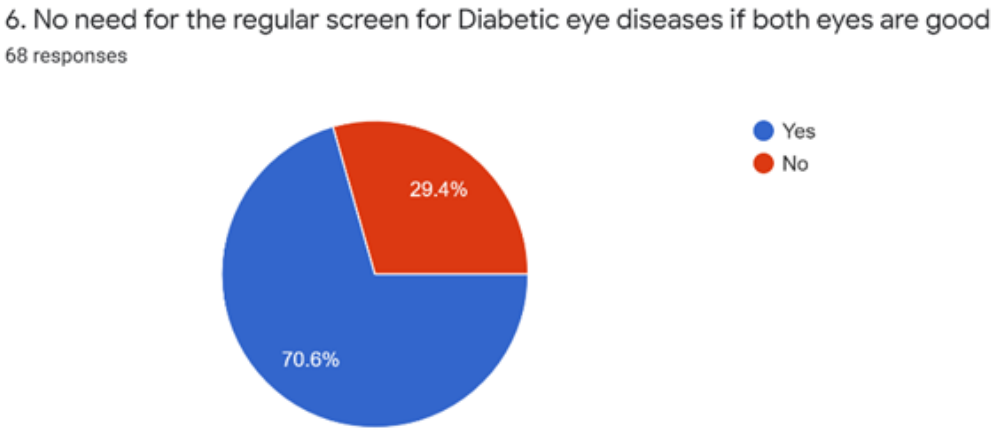


Figure 44: Survey Snapshot_15

This graph shows that 70.6% of people thinks that regular screen for diabetic eye disease if both eyes are good is not needed. But regular screening is important so that it can be detected early to reduce risk of getting permanent blindness.

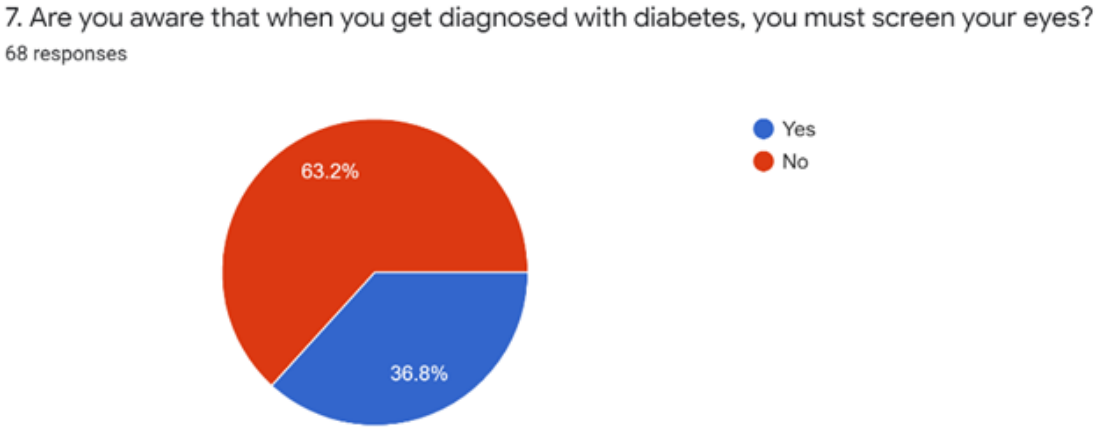


Figure 45: Survey Snapshot_16

This graph shows that people are not aware that they need to screen their eyes if they are diagnosed with diabetes. 63.2% of people are not aware while only 36.8% of people are aware about it.

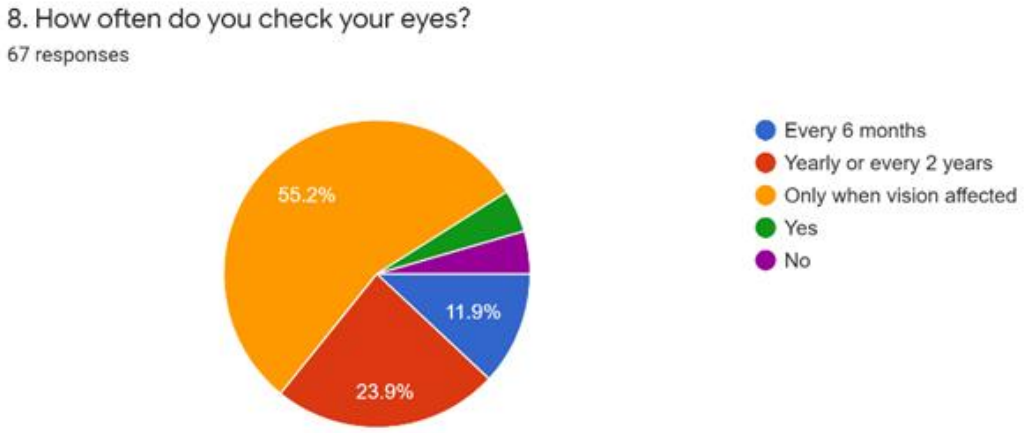


Figure 46: Survey Snapshot_17

This graph shows that 55.2% of people check their eyes only when their vision is affected while 23.9% of people check yearly or every two years and only 11.9% of people check their eyes every 6 months.

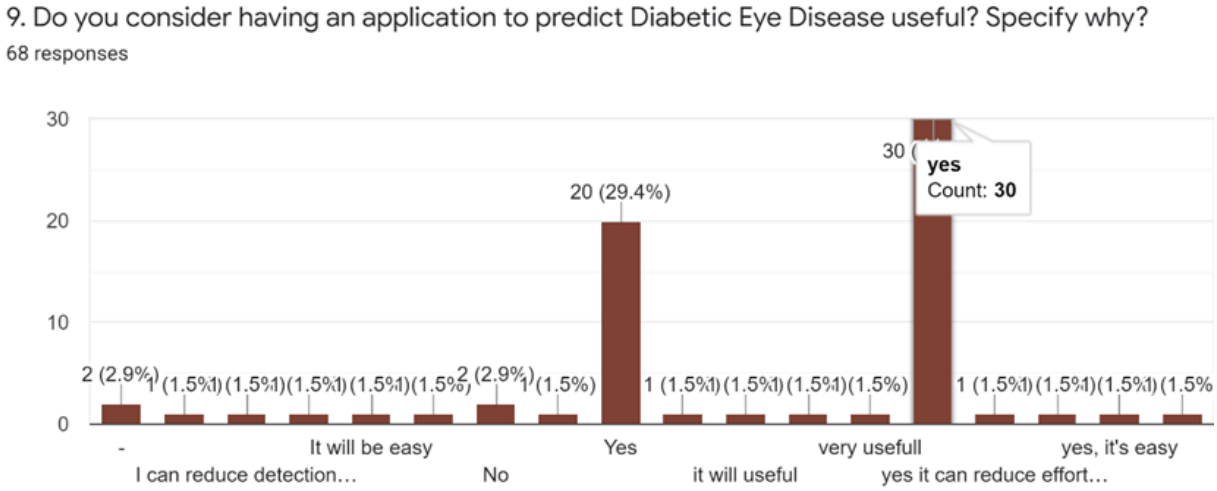


Figure 47: Survey Snapshot_18

This graph shows that the majority of people consider having an application to detect eye disease is useful and some people mentioned why it is useful.

4.5. Use Case Diagrams

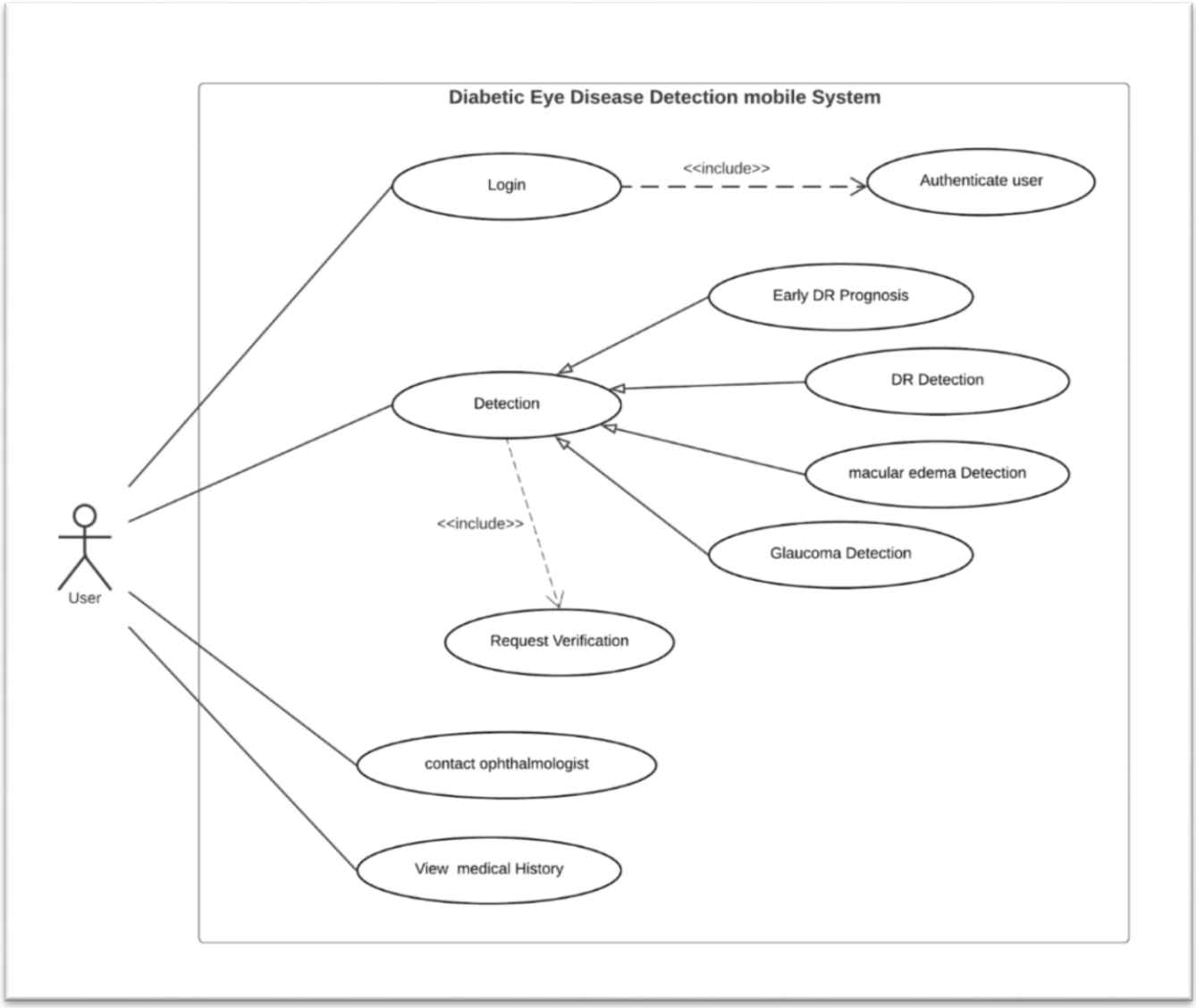


Figure 48: Use case Diagram_1

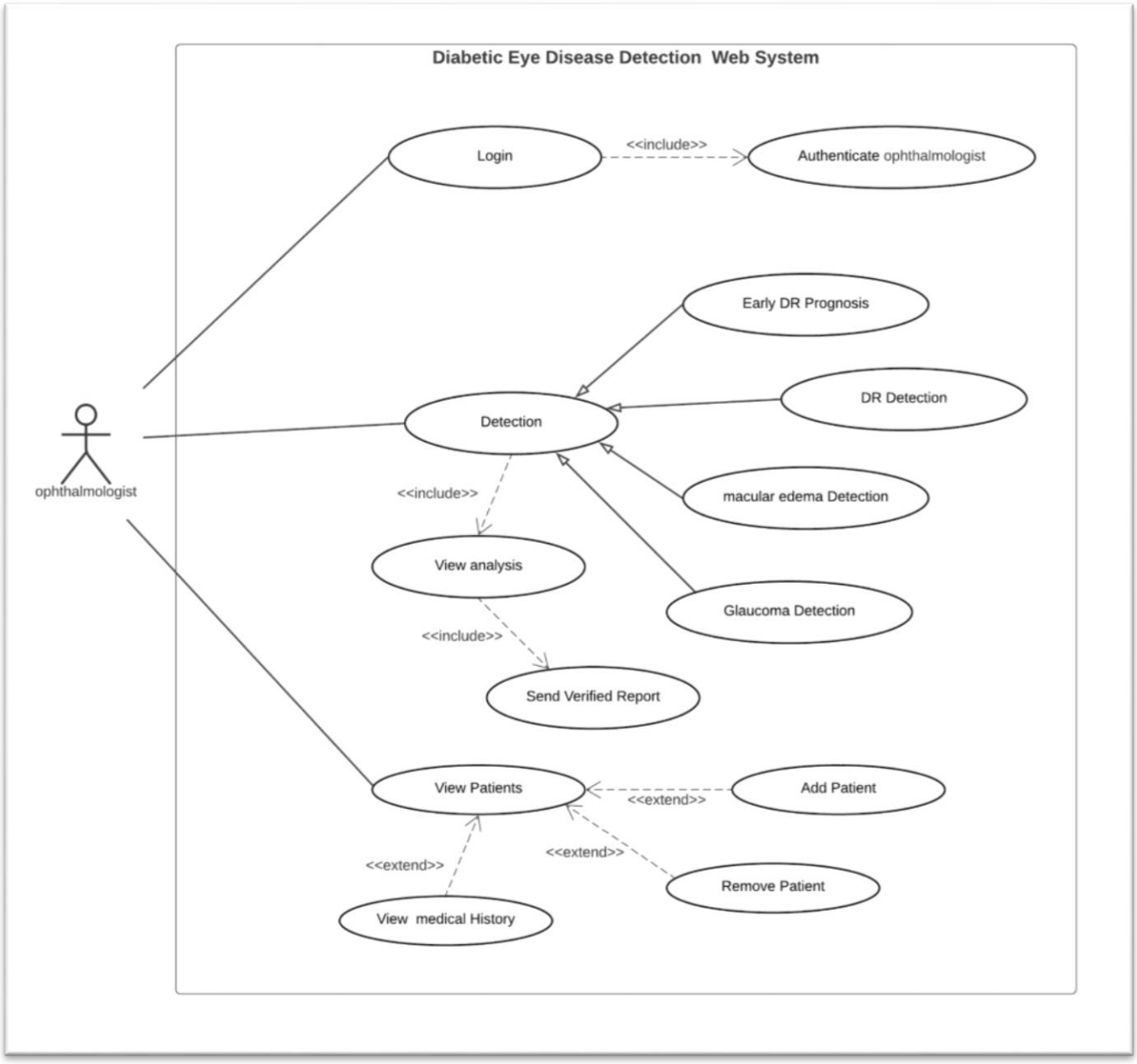


Figure 49: Use case Diagram _2

4.6. Use Case Descriptions

Following Tables shows the Use Case Description of OculoGuard which is Common for Both Mobile Application and Web Application.Other Use Case Descriptions can be seen in Appendix Section B.3- Use Case Descriptions.

Use Case Name	**Detection - In Mobile and Web application**	
Use Case ID	**UC-001**	
Description	**OculoGuard input Fundus images of the patient's eyes and Detect the eye Disease.**	
Priority	**High Level**	
Primary Actor	**Ophthalmologist (EYE Doctor) or Patient**	
Supporting Actors	**Fundus images of Patient's eyes**	
Pre-Conditions	**Needs to login the OculoGuard.** **Needs a proper network connection.** **Needs to have a Fundus image of eyes.**	
Trigger	**User(Patients/Doctors) Navigates to the Detection Section of Early Prognosis of Diabetic Retinopathy ,DiabeticRetinopathy ,MacularEdema and Glaucoma**	
Main flow	**Actors**	**System**

	1.User-Ophthalmologist (EYE Doctor) or Patient viewing the system. **3.signing in or Registering to the system for the first time.** **5.Selecting the Disease needs to be detected.** **6.Inputs the Fundus Images**	**2.Displays the login screen.** **4.Displays the option to Detect the disease.** **6.Displays the option to Input Fundus Images** **7. Displays the Output result whether its normal eyes or Early Prognosis of DR or DR or Macular Edema or Glaucoma.**
Exception flow	**Actors**	**System**
	1.If the user didn't fill login screen	• **Displays a message to user** **to login or register to the application.**

	2.If the user didn't input the Fundus image.	• **Displays An error message and asks to input the Fundus image.**
Alternate flow	**Actors**	**System**
	The user Fills the register and login.	**Records the Authenticated users.**
Inclusions	**User has to login OculoGuard to Detect the eye Disease.**	
Post Conditions	**The user can Request verification from the Ophthalmologist by the output of OculoGuard.**	

Table 10: Use Case Descriptions_1

Use Case Name	**View Medical History - In Mobile and Web Application**
Use Case ID	**UC-002**
Description	**OculoGuard Saves all the records of the patient's eye detection using OculoGaurd which can access both users Ophthalmologist (EYE Doctor) and Patients .**

Priority	**High Level**	
Primary Actor	**Patient or Ophthalmologist (EYE Doctor)**	
Supporting Actors	**OculoGuard**	
Pre-Conditions	**Needs to login the OculoGuard.** **Needs a proper network connection.** **Needs to detect eye diseases using Fundus image of eyes.**	
Trigger	**Users all History will be saved and can access anytime for both Ophthalmologist and patient.**	
Main flow	**Actors**	**System**

	1.User-Paitent viewing the system. **3.signing in or Registering to the system for the first time.** **5.Selecting the View Medical History.**	**2.Displays the login screen.** **4.Displays the option to View Medical History.** **6.Displays all the Records of Pending and previous Detections.**
Exception flow	**Actors**	**System**
	1.If the user didn't fill login screen **2.If the user didn't input the Fundus image.**	• **Displays a message to user to login or register to the application.** • **Displays An error message and asks to input the Fundus image.**
Alternate flow	**Actors**	**System**

	The user Fills the register and login.	**Records the Authenticated users.**
Inclusions	**User has to login OculoGuard to Detect the eye Disease.**	
Post Conditions	**The user can View all the records of the patient using that option of OculoGuard.**	

Table 11: Use Case Descriptions _2

4.7. Functional Requirements (with prioritization)

- Critical – The requirements that are critically needed in the successful completion
- Desirable – The requirements that can add value, but are not required immediately
- Luxury – The requirements that would add luxury to the system

Requirements list		**Priority Level**	**Description**
FR1	Opthaamolgists and patients should be able to register and log into the system	Critical	Both parties should be able successfully sign in and log into the system
FR2	Should be able to input fundus images and get accept input and preprocess	Critical	System should pre process images before classifying.

FR3	Should be able to extract features from fundus images and early prognose DR and diagnose DR, Macula Edema and Glaucoma	Critical	System should able to early prognose DR and diagnose DR, Macula Edema and Glaucoma from the given image and store those info in to the database
FR3	Patients should able log into the mobile app and view past records	Desirable	If user has past records associated with the system, user should be able view them though mobile app
FR4	Send reports through mobile app	Desirable	Patients should be able to send report through mobile app and get expert review from ophthalmologist
FR5	Chat feature	Luxury	A chat feature to communicate with both ophthalmologist and patient

Table 12: Functional Requirements

4.8. Non-Functional Requirements

Requirements list		Priority Level	Description
NF1	Performance	Critical	Both applications should have reliable performance in real world usage
NF2	Accuracy	Critical	implemented Machine learning models should accurately prognosis DR and diagnosis other diseases
NF3	Reliability	Critical	System should be reliable to the both ophthalmologists and patients
NF4	Usability	Desirable	System should have a nice user interface design

Table 13: Non Functional Requirements

4.9. Chapter Summary

This chapter discusses the System Requirements and this chapter depicts the use case diagram for the project OculoGuard. Various components of the System Requirements Specification are highlighted in this chapter.

Chapter 5: Social, Legal, Ethical and Professional Issues

5.1. Chapter Overview

When building any system that involves connection with people.Fundamental considerations such as Social,Legal,Ethical and Professional must always be classified. OculoGuard's Social,Legal,Ethical and Professional Issues and Mitigations are discussed here.

5.2. Social, Legal, Ethical and Professional Issues(SLEP) Issues and Mitigation

5.2.1. Social Issues and Mitigation

The term "social" refers to interpersonal interactions as well as the larger-scale dynamics that result from them. There is no social or environmental effect from the OculoGuard Project. OculoGuard would have no substantial societal impact because it is not involved in identity theft, hacking or any other unlawful activity. OculoGuard, on the other hand, would have a beneficial impact by assisting society with its detection of Diabetic Eye Diseases. This is an extremely essential project for both patients and ophthalmologists. Patients can easily use this to diagnose their disease at home. So it will be useful to society.

5.2.2. Legal Issues and Mitigation Anjula Silva

When developing OculoGuard, mainly focused on the use of data safety and legally. There was nothing that violated the security of the dataset and nothing was released to the public regarding the privacy of the people included in that dataset and also the dataset has been downloaded from Kaggle and used since it complies with the Creative Commons Public License. Dataset will not be modified and it will not be used for any criminal activity. Software licensing has also been granted a high priority. None of the software used was taken illegally and most of software such as android Studio are available as community editions and some software has been allowed free access by the university. In addition, the list of applications to be used in this project is given in section 1.10.

5.2.3. Ethical Issues and Mitigation

No personal information was collected when gathering the user input through the survey and it was mentioned that no personal information will be collected when distributing the public survey.All the datasets to be used in this project are either publicly available or permission was granted to access them. Corresponding links to the datasets are also included.

5.2.4. Professional Issues and Mitigation

For the production of this collaborative Group project Asus, Mac, Toshiba, and Lenovo computers running Windows and Mac OS were used. Using Kaggle, Messidor, Deep Blue and Github's guidelines, The Data was gathered in a professional manner. There was also enough time to finish the questionnaires and interviews.Viewers must respect their privacy in order to acquire data from them. People were told about how the information they offered would be used, and They were also given a proper timeframe so that they could complete it wisely rather than rushing at the final moment.As they have given their personal ideas and feedback they were used relevantly.The OculoGuard project was completed with the utmost professional knowledge.

5.3. Chapter Summary

This chapter demonstrated different legal, ethical, social and professional behavior our team conducted when developing the application OculoGuard and mitigations addressed if there were any issues.

Chapter 6: System Architecture & Design

6.1. Chapter Overview

The previous chapter discussed Social, Legal, Ethical, and Professional nature.This is the Design chapter,which describes the OculoGaurd system's design.High-level System Architectural Design, class diagram, sequence diagrams,flowchart and UI Design. will be shown in this chapter.

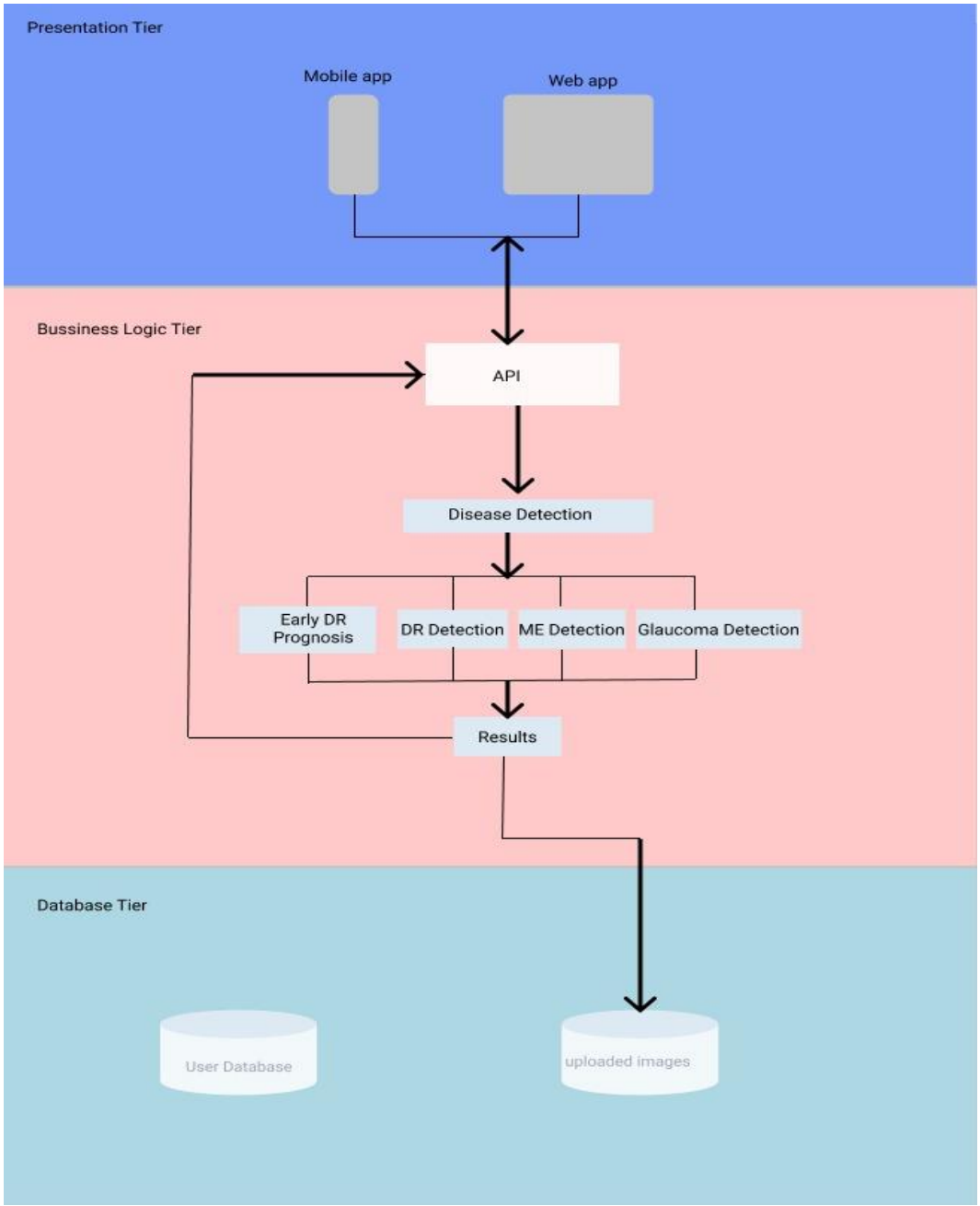


Figure 50: System Architecture Design

Chapter 6: System Architecture & Design

The proposed system architecture consist of three layers based on the tiered architecture

1. Presentation Tier

    - Mobile app and web app will be implemented with Flutter and NextJs respectively. This part is basically the front end of the application which will be connected to the API implementation on the Logic Tier of the diagram.

2. Logic Tier

    - Disease detection
    - get approval from Opthelamologist
    - Retrieve Report

Disease detection is the classification system based on trained machine learning models. The classification system consists of four systems for four diseases. The system accepts images as an input and then classifies them according to the selected disease. After that it will save the image in the image database and if the user was using a mobile device it will only view the final classified result, but the user can notify an ophthalmologist in the system to further verify the result. The ophthalmologist then gets the extended view of the classification in the web app with the chart of features extracted from the image, where the ophthalmologist can make the final decision.

If the patient is physically attending the screening survey Ophthalmologist will directly enter user info to the system where user can login through the app and can view the results. If by any chance a patient already has an account, an ophthalmologist will search in the patient database and add patients under his supervision.

3. Database Tier

    - User profile database
    - uploaded images database

Database tier will consist of two databases. One will store the login information about both patients and ophthalmologists. Other databases will be used to store analysed images with their results. Both databases will be based on NOSQL design and Google FireStore with Firebase will be used when implementing.

6.3. System Design

6.3.1. Class Diagram

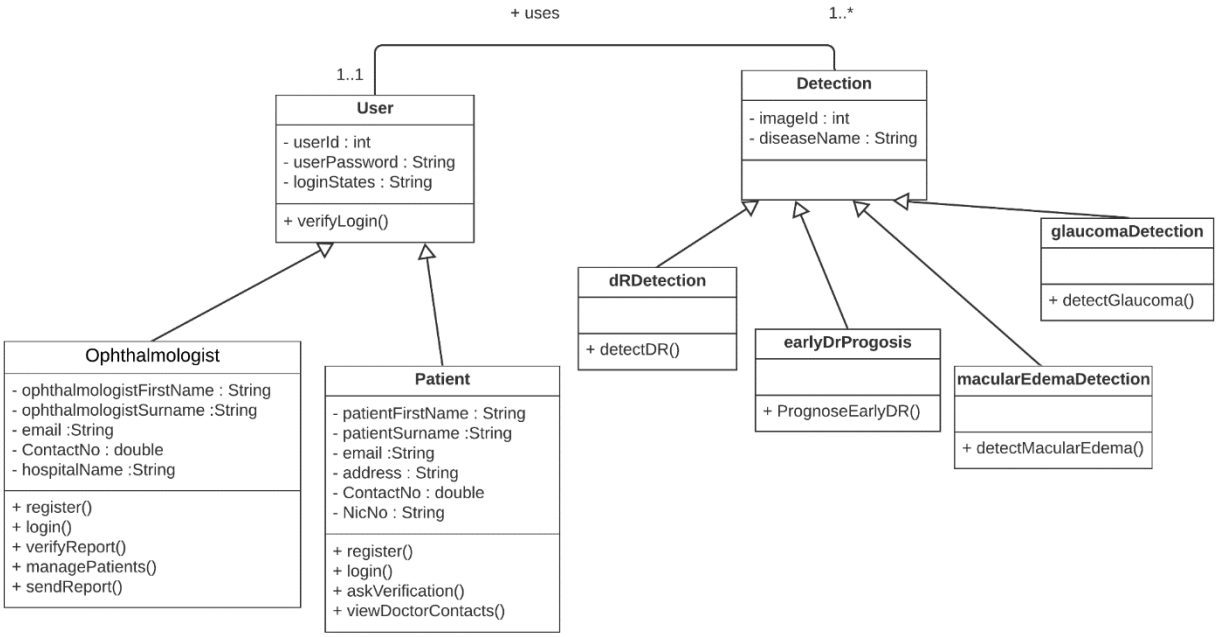


Figure 51: Class Diagram

6.3.2. Sequence Diagram

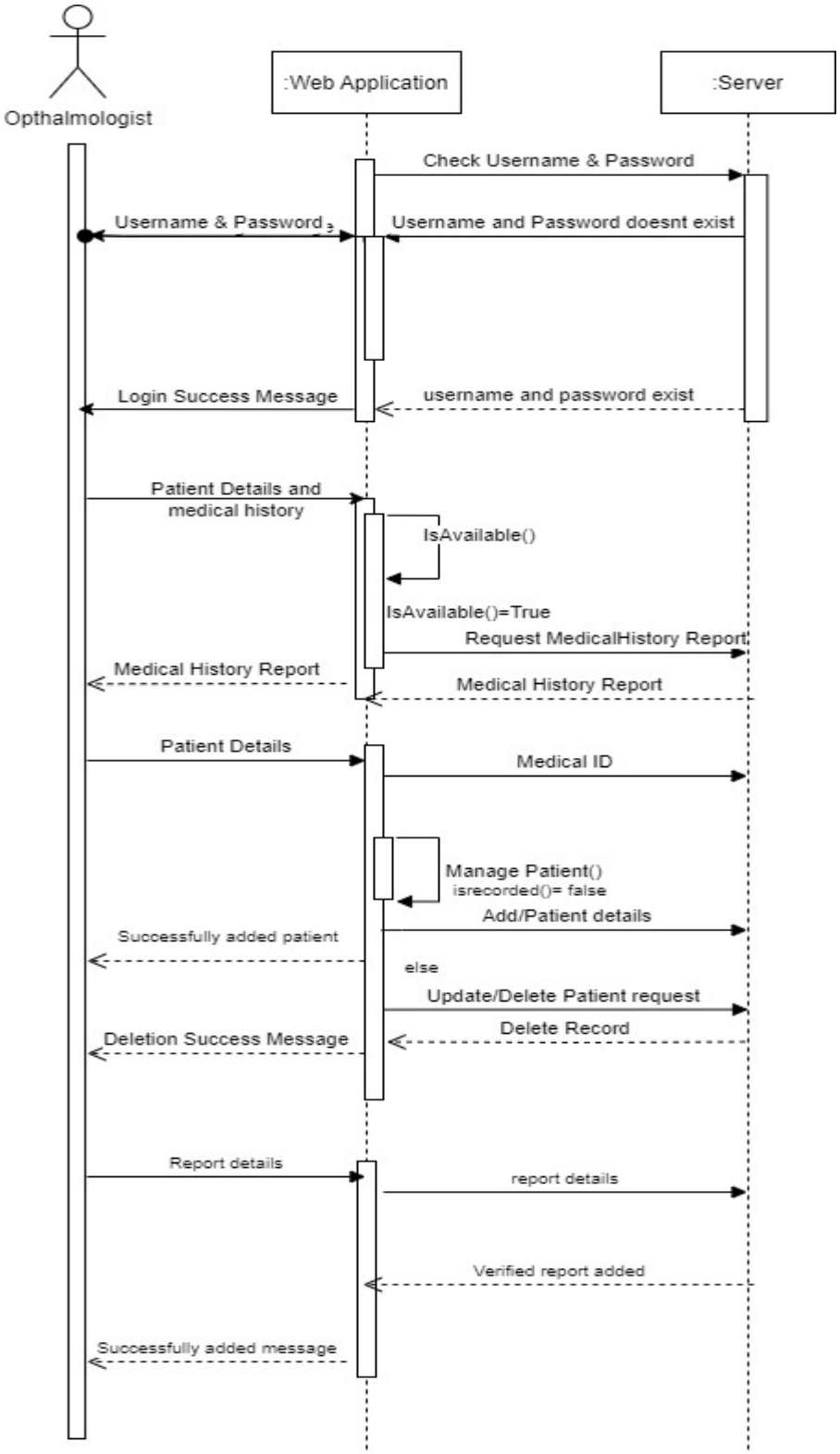


Figure 52: Sequence Diagram for web app

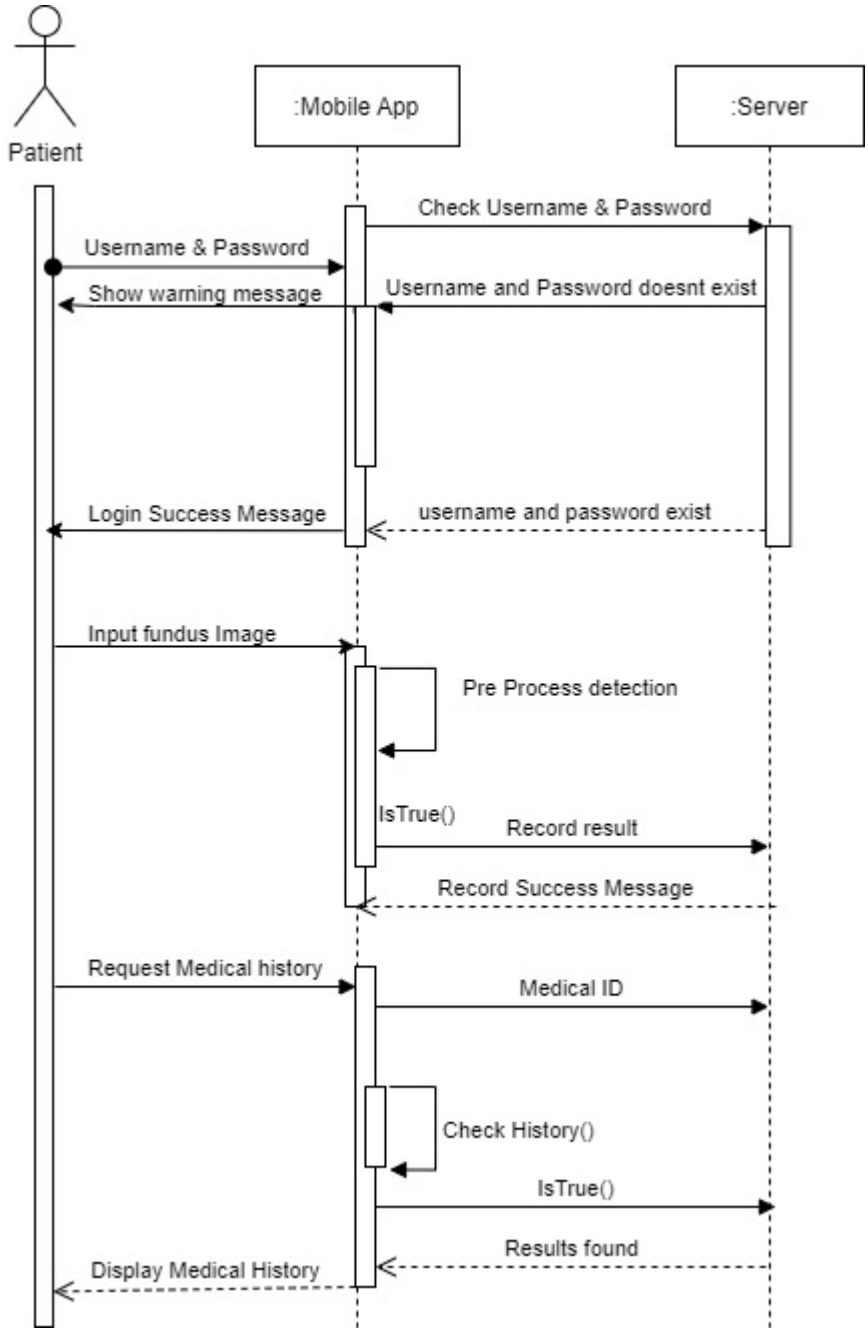
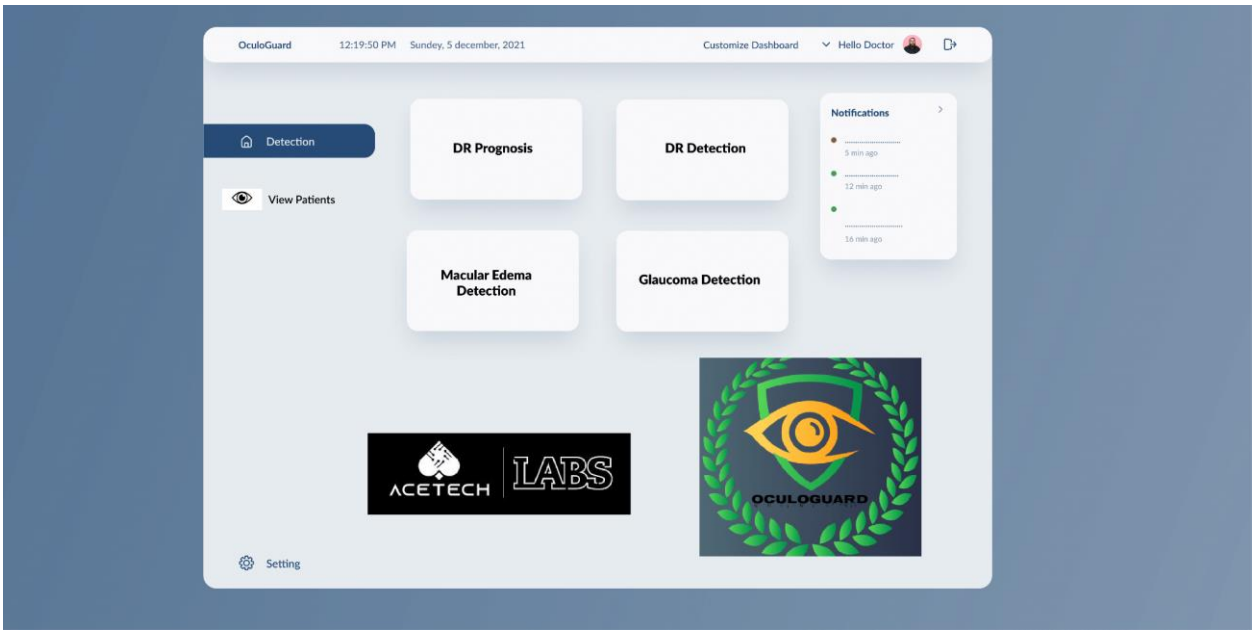


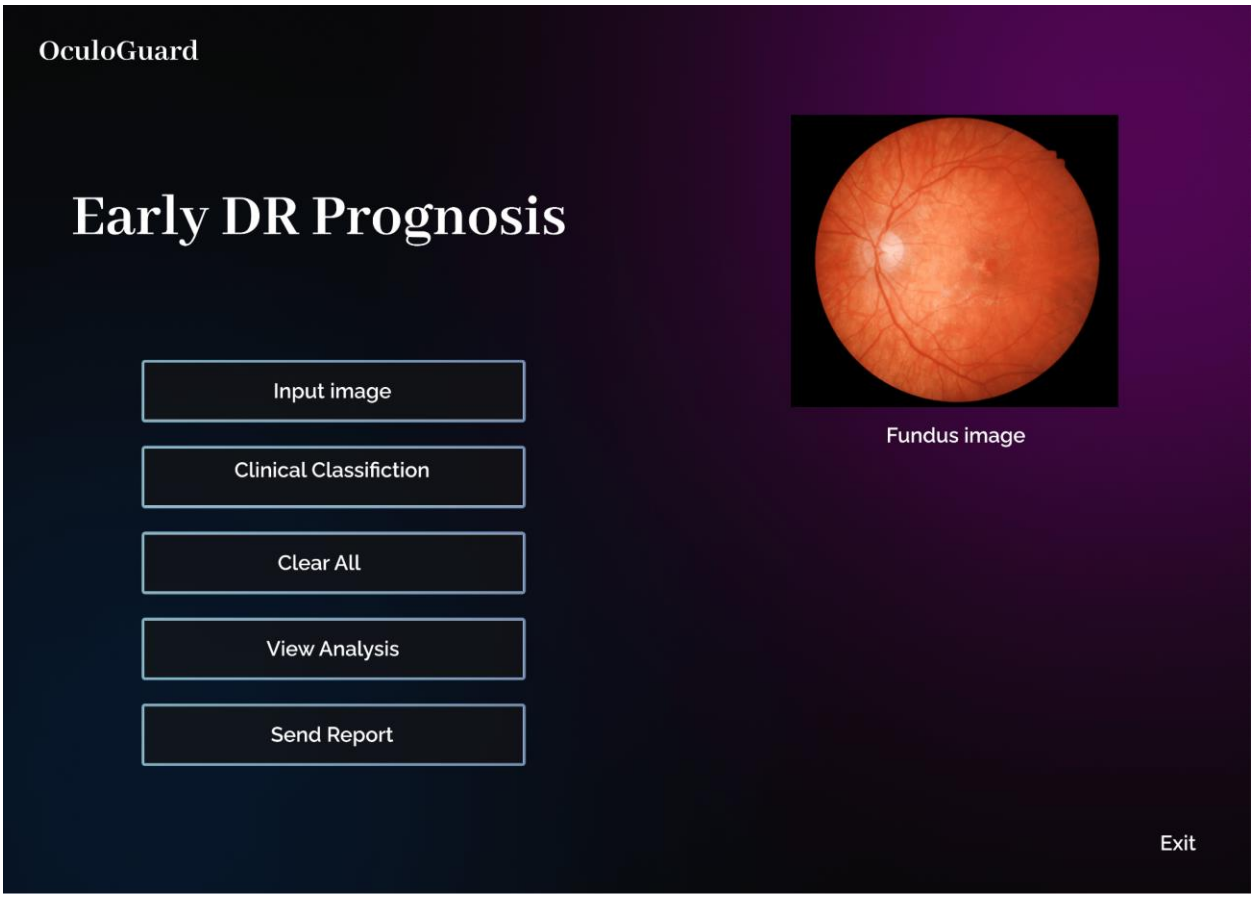
Figure 53: Sequence diagram for mobile app

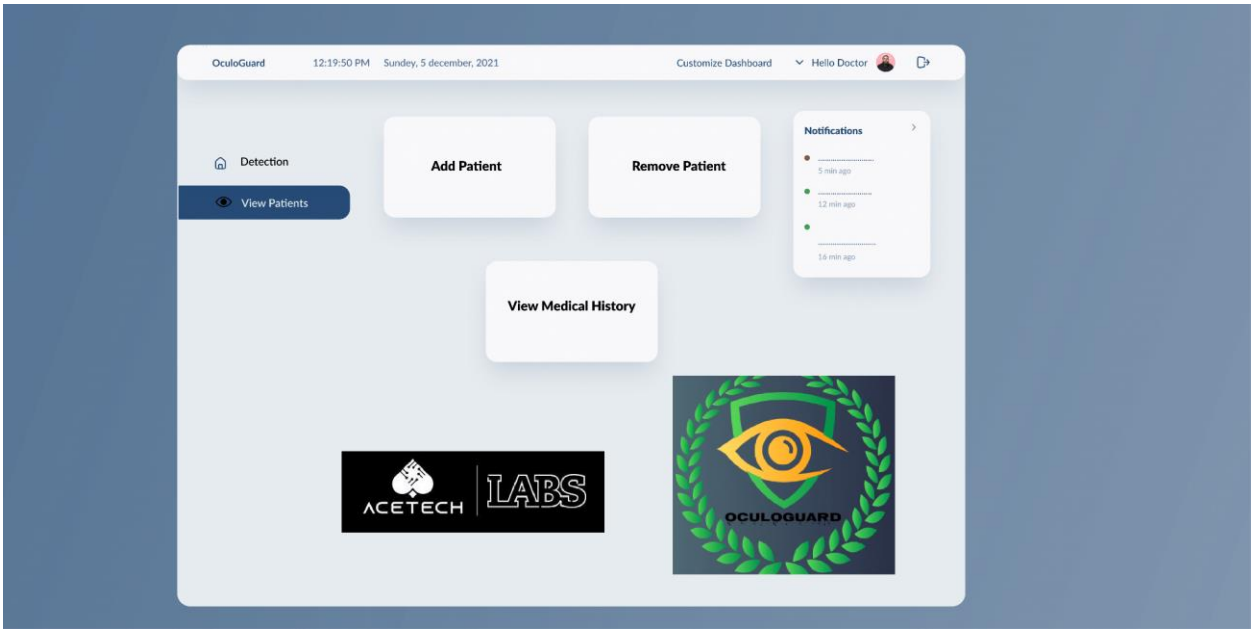
6.3.3. UI Design

Web Application for Ophthalmologist

Figure 54: Web Application for Ophthalmologist




OculoGuard
Early DR Prognosis
Input image
Clinical Classifiction
Clear All
View Analysis
Send Report
Fundus image
Exit


OculoGuard
12:19:50 PM
Sundey, 5 december, 2021
Customize Dashboard
Hello Doctor
Detection
View Patients
Add Patient
Remove Patient
Notifications
View Medical History
ACETECH
LABS
OCULOGUARD

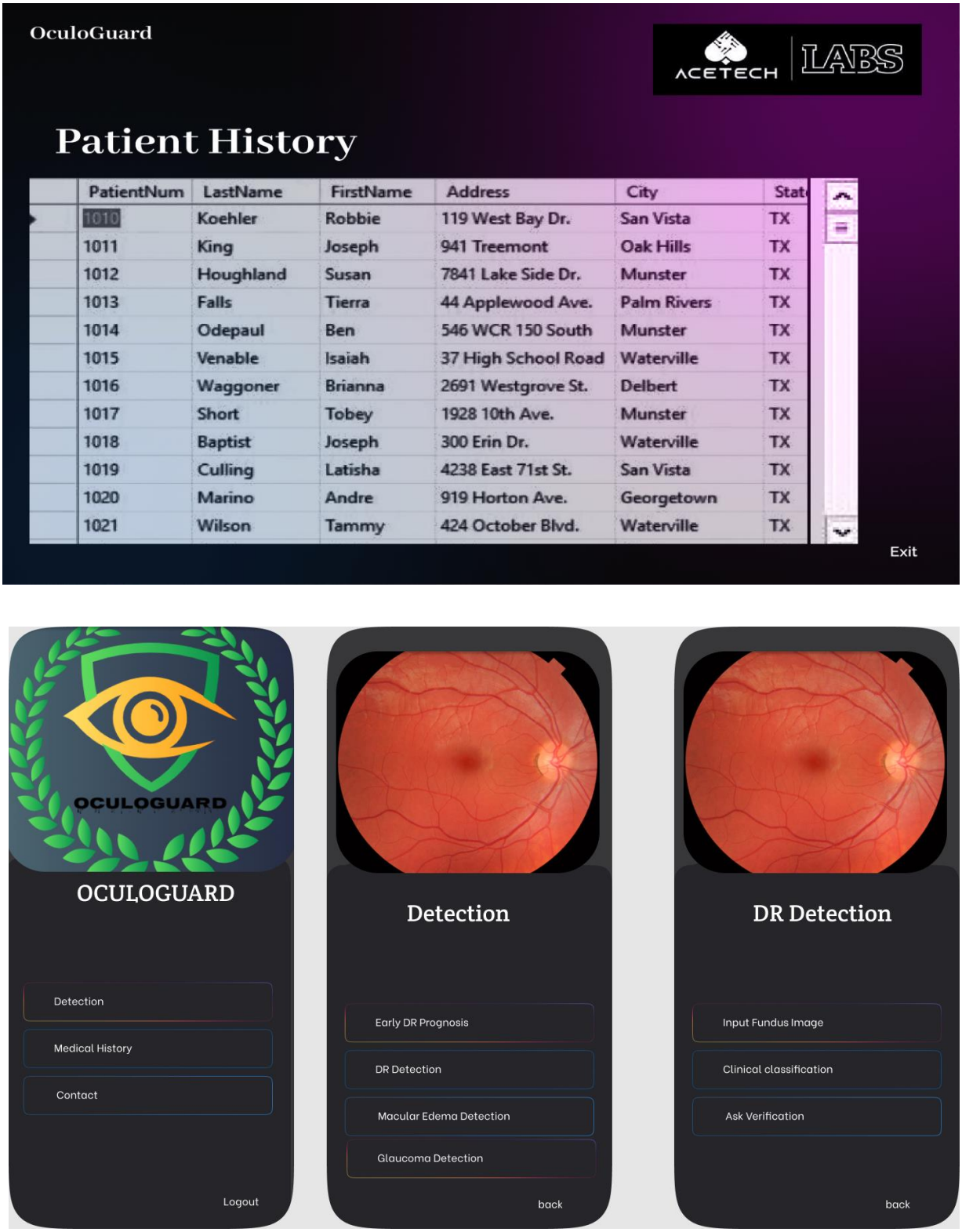


Figure 55: Mobile App for patients


OCULOGUARD
ACETECH
LABS
Email
Example@gmail.com
Password
****
Login
Forgot password
Don't have an account. Sign up

6.3.4. Process flow chart

Early Prognosis of Diabetic retinopathy

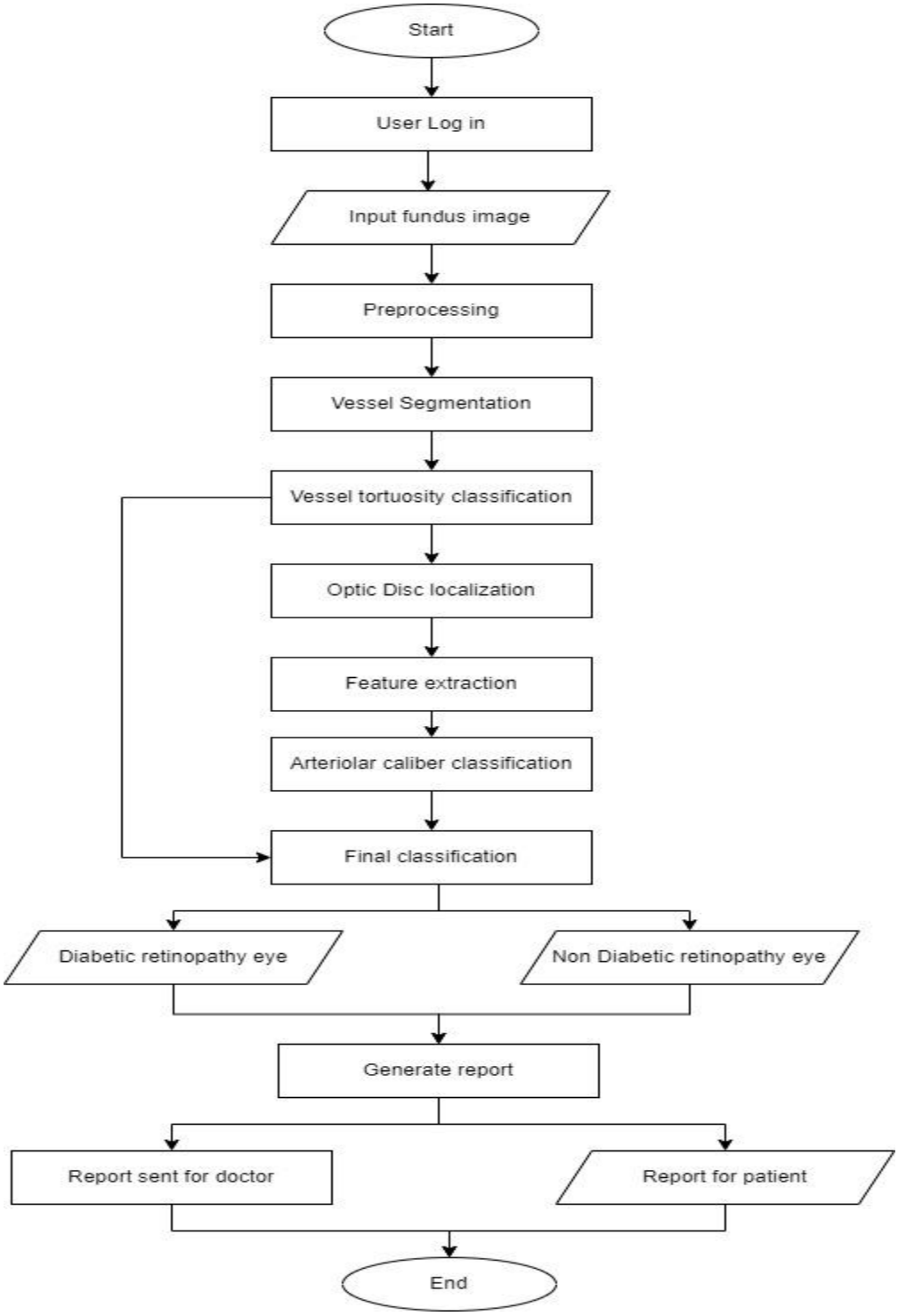


Figure 56: Early Prognosis of Diabetic retinopathy Flow chart

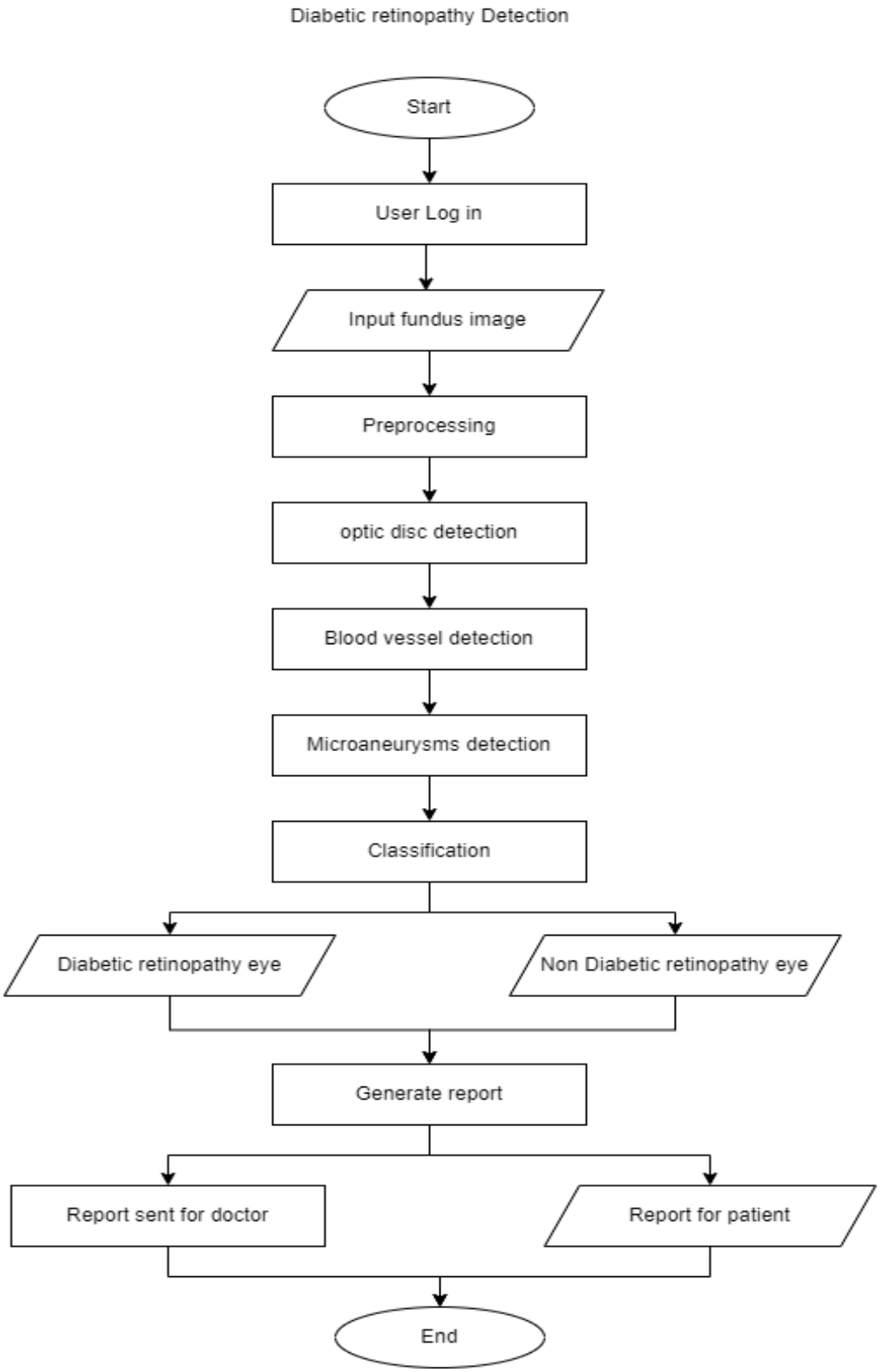


Figure 57: Diabetic retinopathy Detection Flow chart

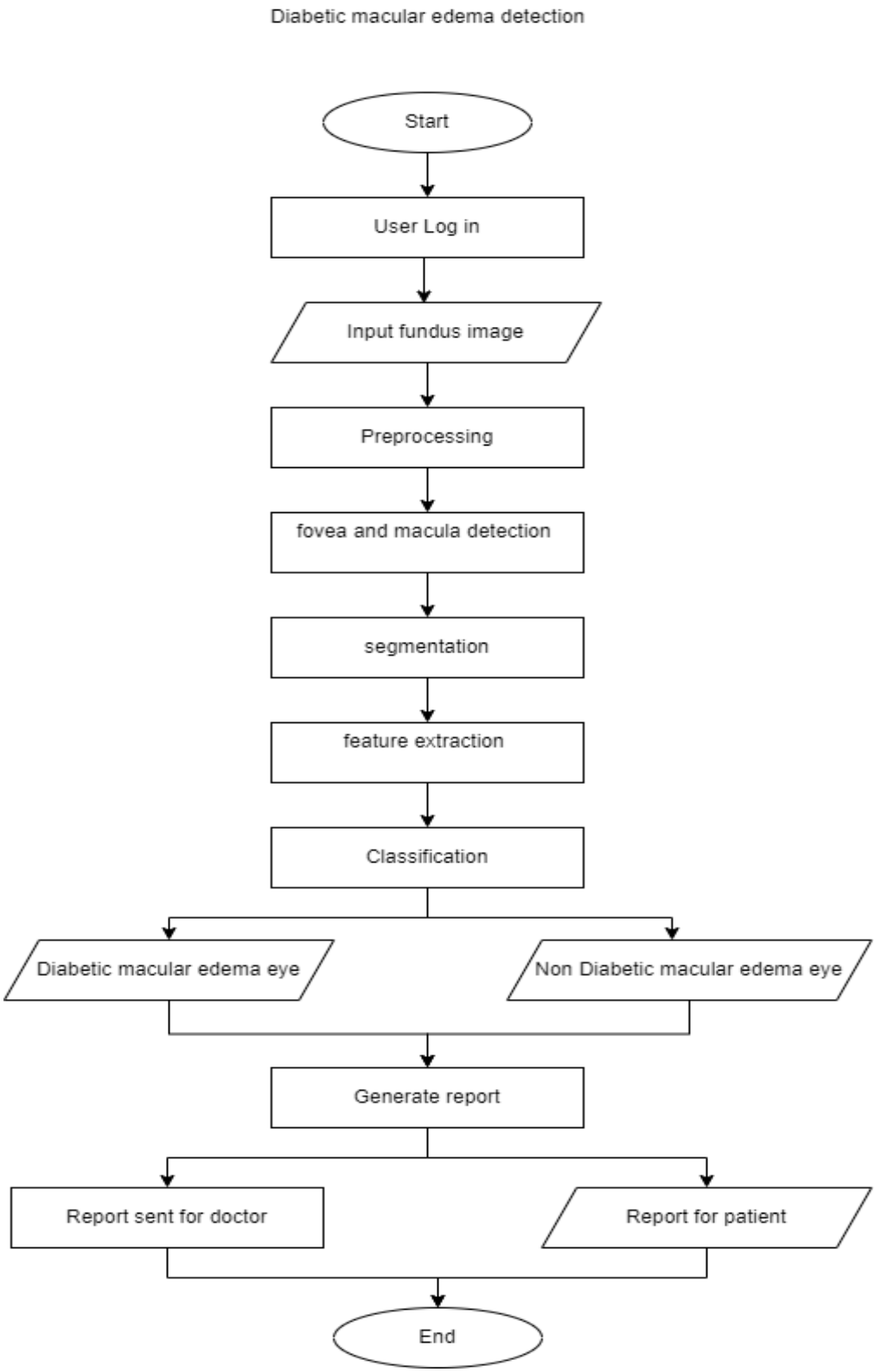


Figure 58: Diabetic macular edema detection Flow chart.

Figure 59: Glaucoma detection Flow chart

6.4. Chapter Summary

This chapter discussed OculoGuard's design,along with high-level System Architectural Design,class diagram,sequence diagrams,flowchart shown the process flow of the system and UI Design with the Use of low and high fidelity wireframes and prototype.UML designs are used to construct the complete OculoGaurd's management System in a beneficial way.The prototype implementation of OculoGaurd will be discussed in the following chapter.

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Appendix

Appendix Section A-Project Management

Appendix Section A.1-Gantt chart diagram

GANTT CHART

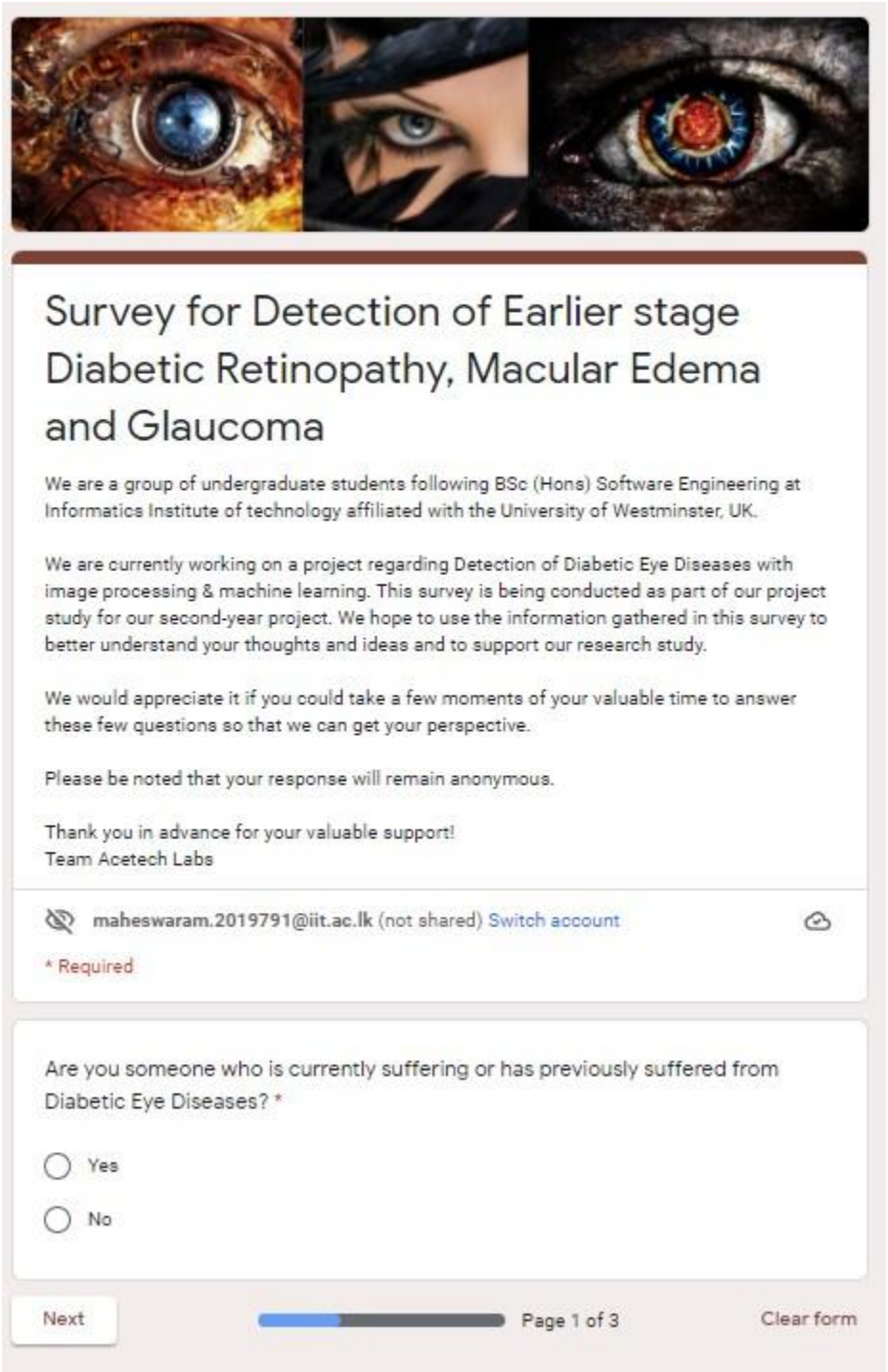
PROJECT NAME	OculoGuard
PROJECT TITLE	Detection of Earlier stage Diabetic Retinopathy ,Macular Edema and Glaucoma
GROUP NAME	Acetech Labs
PROJECT START DATE	4-Oct-21

WBS NUMBER	TASK TITLE	OWNER	START DATE	DUE DATE	DURATION	PCT OF TASK COMPLETE
	Finalizing the Project idea					
1	Identify the promblem domain		7-Oct-21	18-Oct-21	11	100%
2	Research about existing solutions		18-Oct-21	11-Nov-21	23	100%
3	Propose the solution		14-Nov-21	23-Nov-21	9	90%
Chapter 1	**Project Proposal Document**					
1,1	Create the document as in the template		11-Nov-21	12-Nov-21	1	100%
1,2	Update Research Gap and Overview		23-Nov-21	9-Dec-21	16	100%
1,3	Identify issues in existing solution		14-Nov-21	9-Dec-21	25	70%
1,4	Identify Aims, Scope,Objectives and Resource Requirements		23-Nov-21	17-Dec-21	24	100%
1,5	Creation of Rich Picture Diagram and Research Questions		23-Nov-21	19-Dec-21	26	100%
1,6	Update Introduction Chapter Summary		12-Nov-21	19-Dec-21	37	100%
1,7	Submission of Chapter 1-Introduction		19-Dec-21	19-Dec-21	0	100%
Chapter 2	**Literature Review Document**					
2,1	Checking for Related work and Existing Work		19-Dec-21	24-Dec-21	5	100%
2,2	Review Research papers and articles		19-Dec-21	24-Dec-21	5	100%
2,3	Identify Tools and techniques		24-Dec-21	25-Dec-21	1	100%
2,4	Creation of Draft Literature Review		22-Dec-21	27-Dec-21	5	100%
2,5	Submission of Draft Literature Review		27-Dec-21	27-Dec-21	0	100%
2,6	Update LR and Chapter Summary		27-Dec-21	29-Dec-21	2	100%
2,7	Submission of Chapter 2-Literature Review		29-Dec-21	29-Dec-21	0	100%
Chapter 3	**Methodology of the Project**					
3,1	Research Approach on Methodology		28-Dec-21	28-Dec-21	0	100%
3,2	Identify life cycle model for Development Methodology		28-Dec-21	30-Dec-21	2	100%
3,3	Identify Design and Evaluation methodology		28-Dec-21	29-Dec-21	1	100%
3,4	Identify Project Management Methodology		28-Dec-21	29-Dec-21	1	100%
3,5	Creation of Draft Project Management		28-Dec-21	29-Dec-21	1	100%
3,6	Update Draft Project Management		29-Dec-21	30-Dec-21	1	100%
3,7	Prepare Team Work Breakdown Structure (WBS),Gantt chart diagram		30-Dec-21	31-Dec-21	0	100%
3,8	Prepare Usage of Project Management and Collaboration Software In the project		31-Dec-21	31-Dec-21	0	100%
3,9	Identify Risks and Mitigation		29-Dec-21	29-Dec-21	0	100%
3,10	Prepare Methodology Summary		28-Dec-21	29-Dec-21	1	100%
3,11	Submission of Chapter 3- Methodology		30-Dec-21	30-Dec-21	0	100%
Chapter 4	**System Requirements Specification(SRS)**					
4,1	Creation of Stakeholder Analysis and Description		25-Dec-21	29-Dec-21	4	100%
4,2	Identify Requirement Gathering of Techniques/Methods for Design		25-Dec-21	30-Dec-21	5	100%
4,3	Prepare Questionnaires and Interviews with An Eye specialist Doctor		25-Dec-21	31-Dec-21	6	100%
4,4	Creation of Use Case Diagrams and Descriptions		26-Dec-21	1-Jan-22	5	100%
4,5	Identify Functional and Non-Functional Requirements		30-Dec-21	2-Jan-22	2	100%
4,6	Update SRS Summary		26-Dec-21	26-Dec-21	0	100%
4,7	Submission of Chapter 4-System Requirements Specification(SRS)		31-Dec-21	2-Jan-22	2	100%
Chapter 5	**Social, Legal, Ethical and Professional(SLEP)Issues**					
5,1	Research Overview of SLEP Issues		31-Dec-21	3-Jan-22	3	100%
5,2	Identify SLEP Issues and Mitigation		3-Jan-22	4-Jan-22	1	100%
5,3	Update SLEP Issues Summary		4-Jan-22	4-Jan-22	0	100%
5,4	Submission of Chapter 5- SLEP Issues		5-Jan-22	6-Jan-22	1	100%
Chapter 6	**System Architecture & Design**					
6,1	Write the Overview of System Architecture & Design		5-Jan-22	6-Jan-22	1	100%
6,2	Create High Level System Architecture Design		5-Jan-22	16-Jan-22	11	100%
6,3	Creation of UI System Design of the prototype		5-Jan-22	16-Jan-22	11	100%
6,4	Creation of Class Diagram		5-Jan-22	13-Jan-22	8	100%
6,5	Creation of Sequence Diagram		5-Jan-22	15-Jan-22	10	100%
6,6	Prepare flowchart or activity diagram to describe system process flow		5-Jan-22	11-Jan-22	6	100%
6,7	Update System Architecture & Design Summary		14-Jan-22	15-Jan-22	1	100%
6,8	Submission of Chapter 6-System Architecture & Design		16-Jan-22	16-Jan-22	0	100%
	Prototype Implementation					
1	Design the Prototype				0	0%
2	Implement the prototype				0	0%
3	Prepare Prototype Report				0	0%
4	Submit prototype Report				0	0%
	Testing and Fixing Bugs					
1	Unit testing				0	0%
2	System testing				0	0%
3	Bug Fixing				0	0%
	Finalizing the Project					
1	Prepare Draft Final Project Report				0	0%
2	Review Of Draft Final Project Report				0	0%
3	Update the Final Project Report				0	0%
4	Submit Final Project Report				0	0%

Figure 60: Gantt chart diagram

Appendix Section B-SRS

Appendix Section B.1-Patient Questionnaire



Survey for Detection of Earlier stage Diabetic Retinopathy, Macular Edema and Glaucoma

We are a group of undergraduate students following BSc (Hons) Software Engineering at Informatics Institute of technology affiliated with the University of Westminster, UK.

We are currently working on a project regarding Detection of Diabetic Eye Diseases with image processing & machine learning. This survey is being conducted as part of our project study for our second-year project. We hope to use the information gathered in this survey to better understand your thoughts and ideas and to support our research study.

We would appreciate it if you could take a few moments of your valuable time to answer these few questions so that we can get your perspective.

Please be noted that your response will remain anonymous.

Thank you in advance for your valuable support!
Team Acetech Labs

maheswaram.2019791@iit.ac.lk (not shared) Switch account

* Required

Are you someone who is currently suffering or has previously suffered from Diabetic Eye Diseases? *

- Yes
- No

Next

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Clear form

1. Select the age group you belong to *

Choose

2. Gender *

Choose

3. What type of diabetics are you suffering from ? *

- Type 1
- Type 2

4. What diabetic eye disease do you have? *

Choose

5. At what age did you diagnose it? *

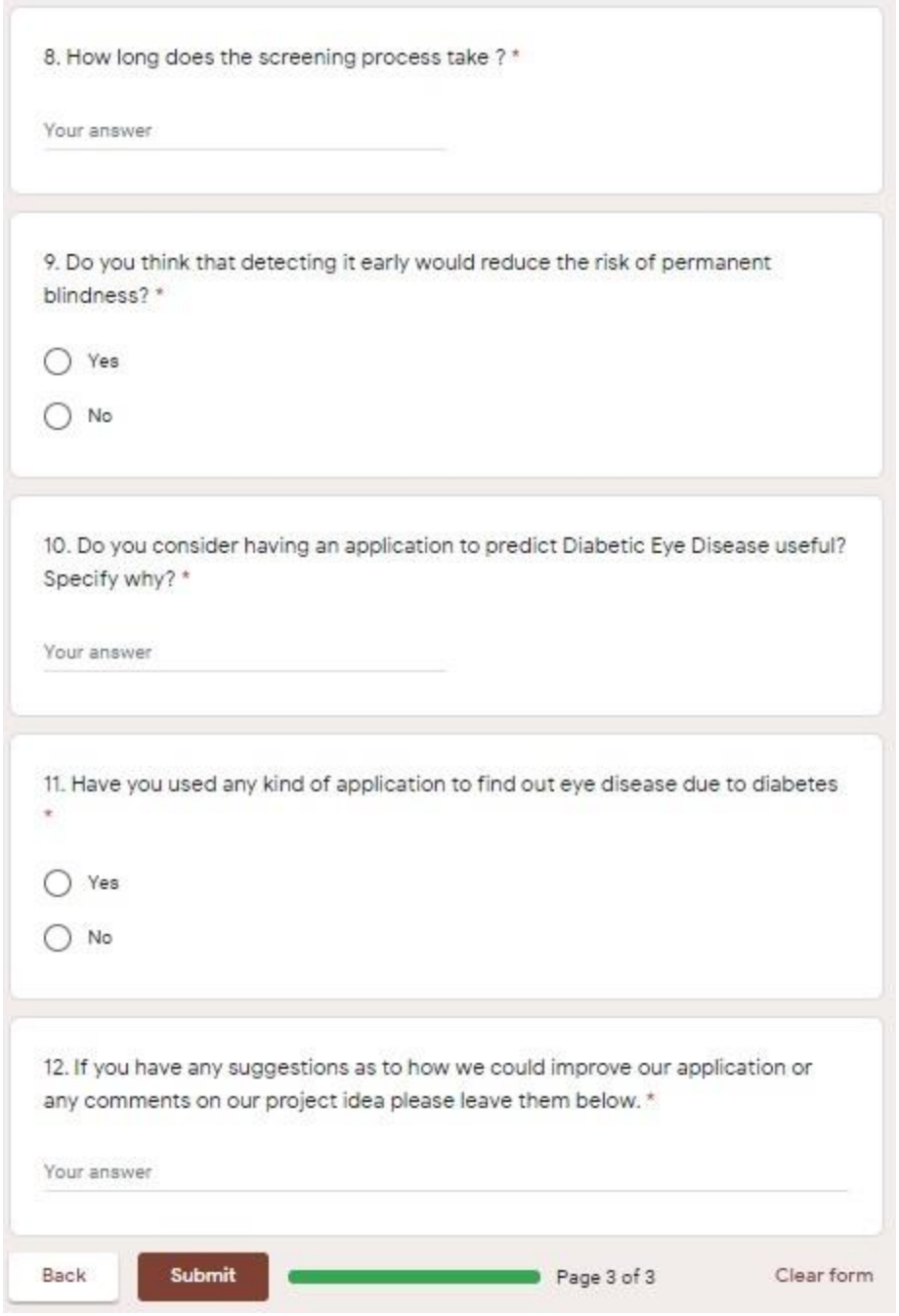
Your answer

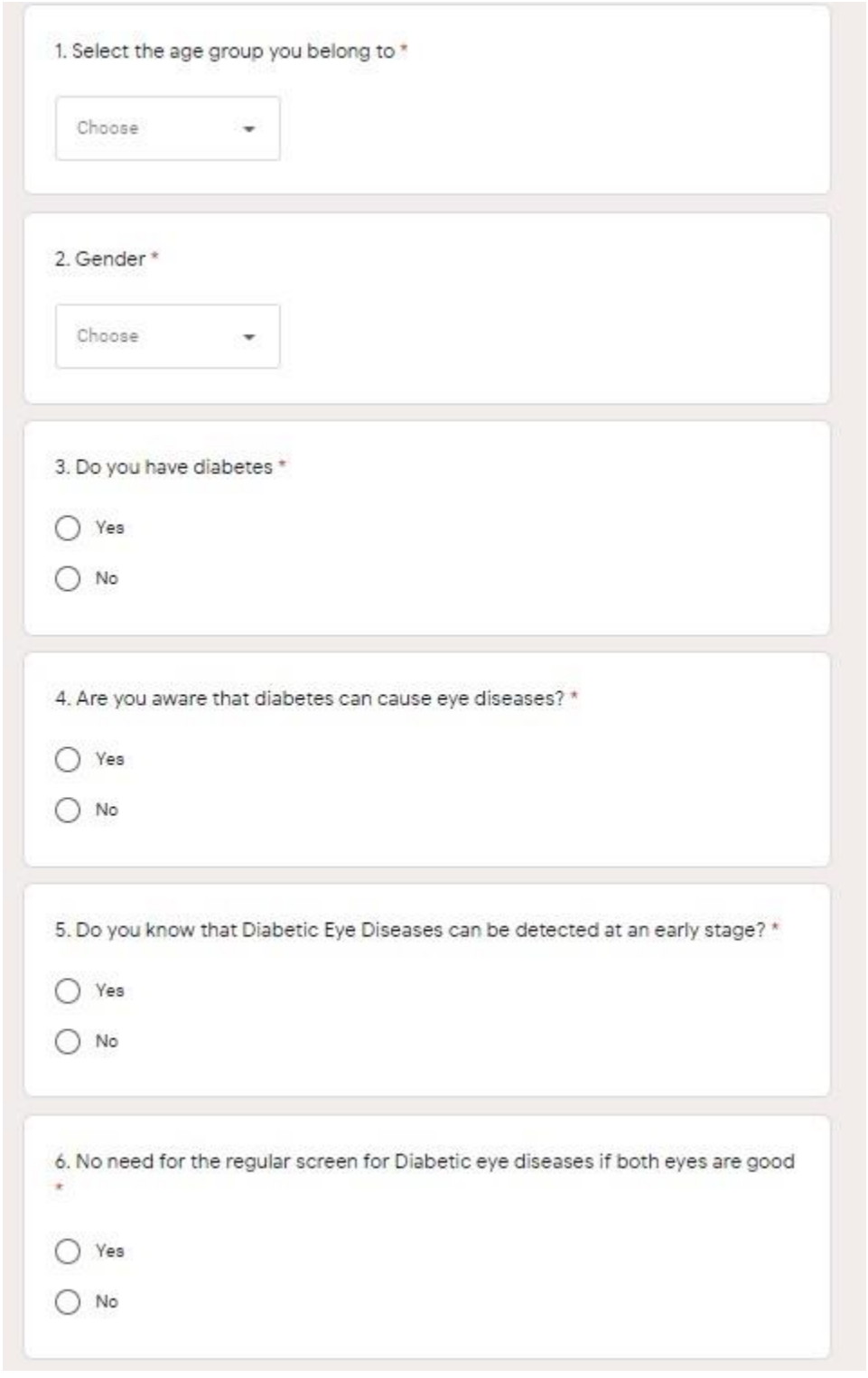
6. How did you diagnose that you have the above Diabetic eye disease? *

Your answer

7. What symptoms did you have leading up to the diagnosis? *

Your answer


8. How long does the screening process take ? *
Your answer
9. Do you think that detecting it early would reduce the risk of permanent blindness? *
Yes
No
10. Do you consider having an application to predict Diabetic Eye Disease useful? Specify why? *
Your answer
11. Have you used any kind of application to find out eye disease due to diabetes *
Yes
No
12. If you have any suggestions as to how we could improve our application or any comments on our project idea please leave them below. *
Your answer
Back
Submit
Page 3 of 3
Clear form



1. Select the age group you belong to *

Choose

2. Gender *

Choose

3. Do you have diabetes *

- Yes
- No

4. Are you aware that diabetes can cause eye diseases? *

- Yes
- No

5. Do you know that Diabetic Eye Diseases can be detected at an early stage? *

- Yes
- No

6. No need for the regular screen for Diabetic eye diseases if both eyes are good *

- Yes
- No

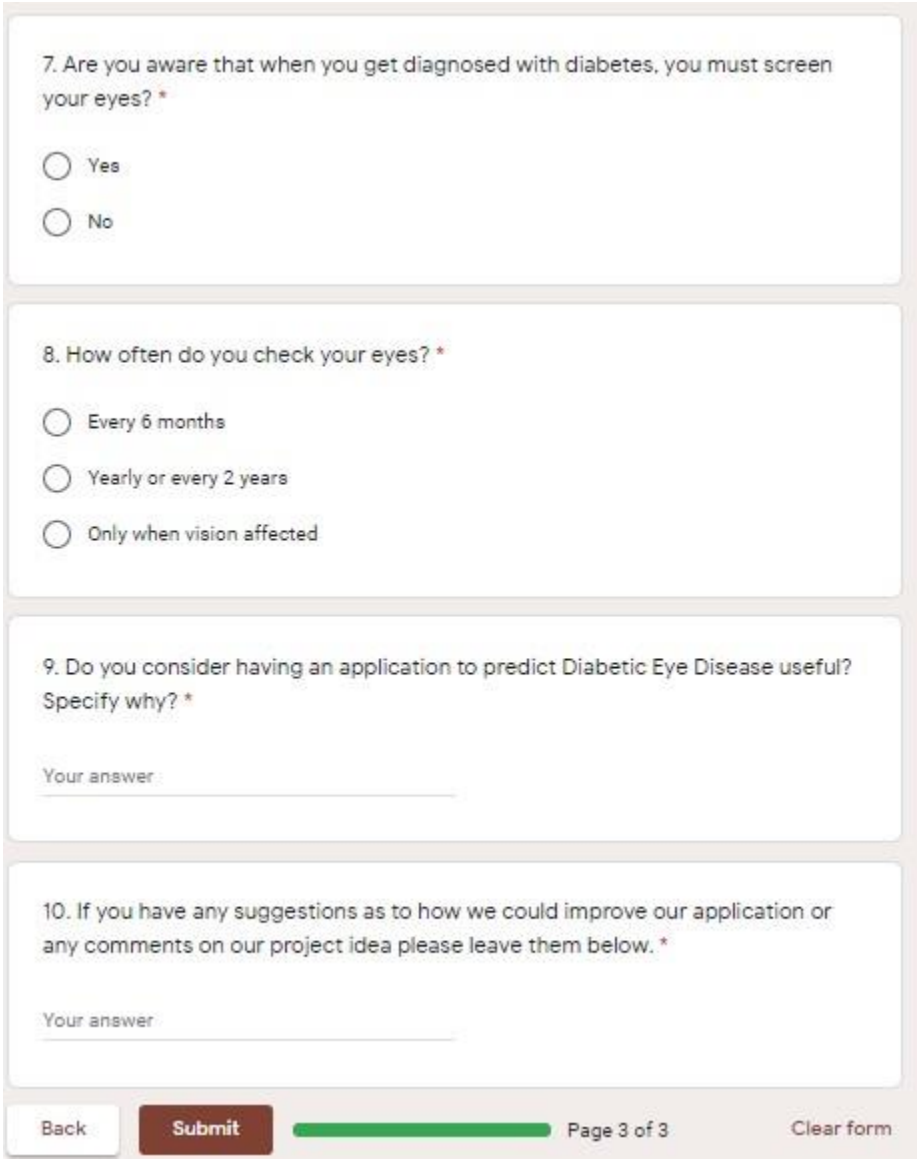
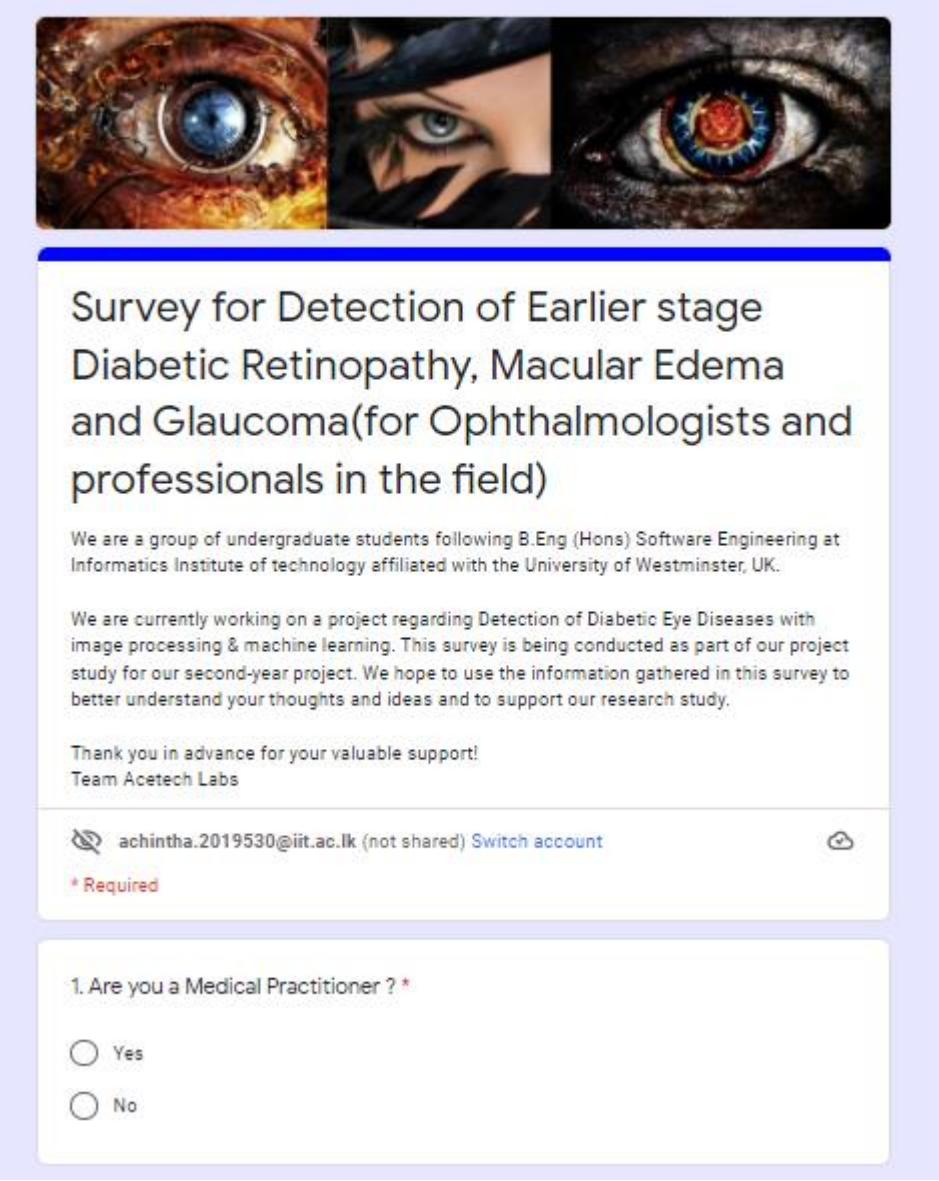


Figure 61: Patient Questionnaire

Appendix Section B.2-Ophthalmologist Questionnaire



Survey for Detection of Earlier stage Diabetic Retinopathy, Macular Edema and Glaucoma(for Ophthalmologists and professionals in the field)

We are a group of undergraduate students following B.Eng (Hons) Software Engineering at Informatics Institute of technology affiliated with the University of Westminster, UK.

We are currently working on a project regarding Detection of Diabetic Eye Diseases with image processing & machine learning. This survey is being conducted as part of our project study for our second-year project. We hope to use the information gathered in this survey to better understand your thoughts and ideas and to support our research study.

Thank you in advance for your valuable support!
Team Acetech Labs

achintha.2019530@iit.ac.lk (not shared) Switch account

* Required

1. Are you a Medical Practitioner ? *

- ◯ Yes
- ◯ No

2. Field of specialty ? *

- ◯ Ophthalmologist
- ◯ General Practitioner
- ◯ Other: _____

3. Years of Experience ? *

Your answer

4. How often do you find diabetic eye disease in the patients with diabetes ? *

Your answer

5. On Average how long does it take to complete an eye screening procedure ? (complete process with eye disease diagnosis) *

Your answer

6. Are there any computer aided software programs used when analysing fundus images ? If so ,please specify it's capabilities. *

Your answer

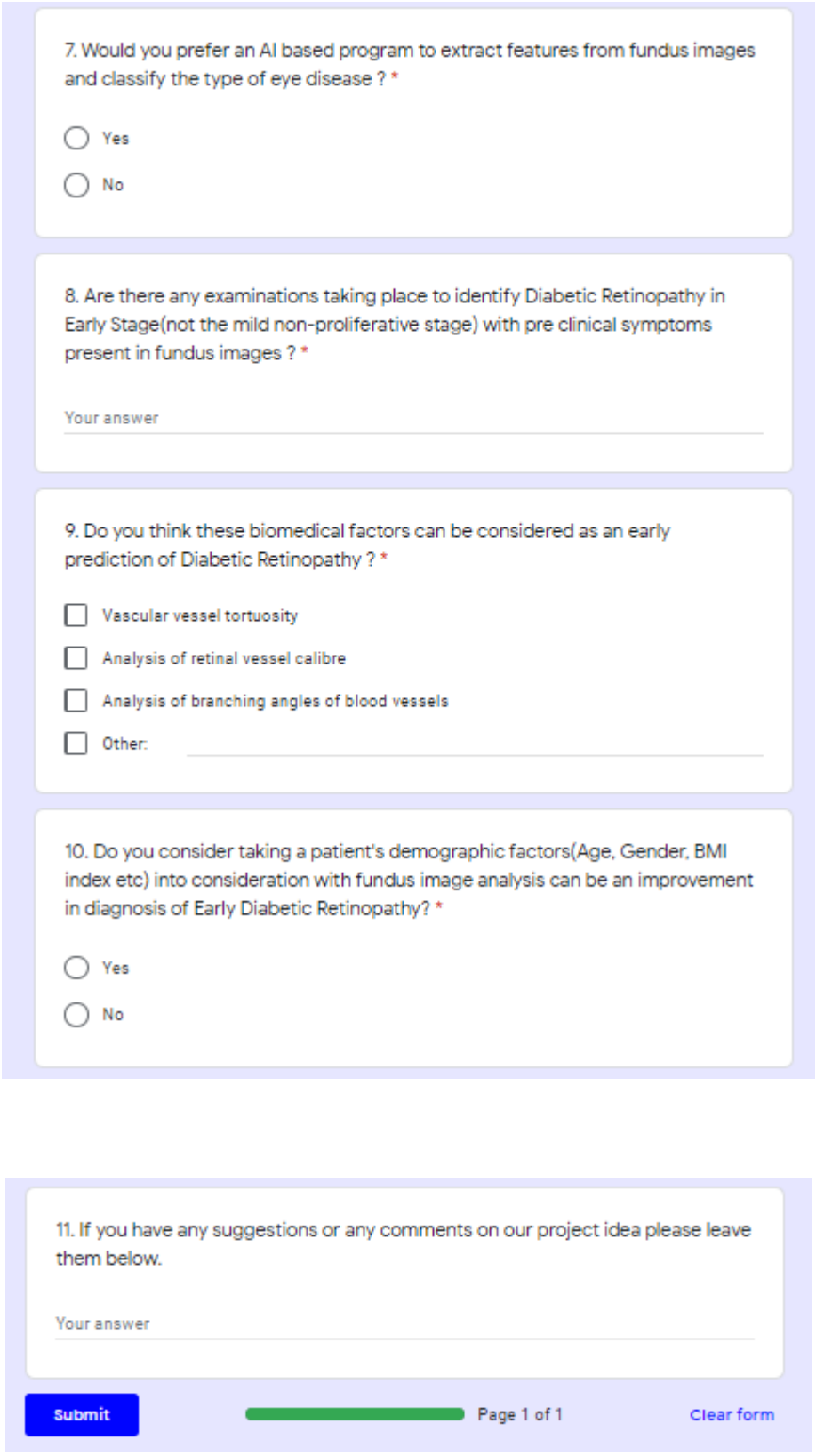


Figure 62: Ophthalmologist Questionnaire

Appendix Section B.3- Use Case Descriptions

B.3.1 Contact Ophthalmologist - In Mobile application

Use Case Name	**Contact Ophthalmologist - In Mobile application.**
Use Case ID	**UC-003**
Description	**Patients can contact an Ophthalmologist by the OculoGuard Mobile Application.**
Priority	**High Level**
Primary Actor	**Patient**
Supporting Actors	**Ophthalmologist (EYE Doctor)**
Pre-Conditions	**Needs to login the OculoGuard.** **Needs a proper network connection.**
Trigger	**Users can easily communicate with the Ophthalmologist (EYE Doctor) through the mobile application of OculoGaurd by Scheduling a time or directly if the doctor is online.**

Main flow	**Actors**	**System**
	1.User-Patient viewing the system. **3.signing in or Registering to the system for the first time.** **5.Selecting Contact an Ophthalmologist.** **7. User Contacting the Doctor.**	**2.Displays the login screen.** **4.Displays the option to Contact an Ophthalmologist.** **6.Displays available Doctors to contact.**
Exception flow	**Actors**	**System**
	1.If the user didn't fill login screen	• **Displays a message to user** **to login or register to the application.**

	2.If the user didn't input the Fundus image.	• **Displays An error message and asks to input the Fundus image.**
Alternate flow	**Actors**	**System**
	The user Fills the register and login.	**Records the Authenticated users.**
Inclusions	**User has to login OculoGuard to Detect the eye Disease.**	
Post Conditions	**The users are easily able to Contact an Ophthalmologist using OculoGuard mobile application.**	

Table 14: Use Case description_3

B.3.2 View analysis - In Web application

Use Case Name	**View analysis - In Web application**
Use Case ID	**UC-004**

Description	**OculoGuard show the output of pending Fundus images of the patient's eyes to Ophthalmologist (EYE Doctor) and Analysing.**	
Priority	**High Level**	
Primary Actor	**Ophthalmologist (EYE Doctor)**	
Supporting Actors	**Fundus images of Patient's eyes Detected using OculoGuard**	
Pre-Conditions	**Needs to login the OculoGuard.** **Needs a proper network connection.**	
Trigger	**Ophthalmologist (EYE Doctor) analyzes the Detection pending status of patients reports.**	
Main flow	**Actors**	**System**

	1.User-Ophthalmologist (EYE Doctor) viewing the system. **3.Signing in or Registering to the system for the first time.** **5.Selecting the View analysis.** **7. Opthamologist Analyzing the Patients report and verifying.**	**2.Displays the login screen.** **4.Displays the option to Detect the disease and View analysis** **6.Displays the Patients pending Outputs of Fundus Images**
Exception flow	**Actors**	**System**
	1.If the user didn't fill login screen **2.If the user didn't input the Fundus image.**	● **Displays a message to user to login or register to the application.** ● **Displays An error message and asks to input the Fundus image.**

Alternate flow	Actors	System
	The user Fills the register and login.	Records the Authenticated users.
Inclusions	User has to login OculoGuard to Detect the eye Disease.	
Post Conditions	Ophthalmologist (EYE Doctor) Analysis to verify patient's output report of OculoGuard Detection.	

Table 15: Use Case description_4

B.3.3 Send Verified Report - In Web application

Use Case Name	Send Verified Report - In Web application
Use Case ID	UC-005
Description	OculoGuard show the output of pending Fundus images of the patient's eyes to the Ophthalmologist (EYE Doctor) and analysis and Sending Verified Report to Patients
Priority	High Level
Primary Actor	Ophthalmologist (EYE Doctor)

Supporting Actors	**Fundus images of Patient's eyes**	
Pre-Conditions	**Needs to login the OculoGuard.** **Needs a proper network connection.** **Needs to have a Fundus image of eyes.**	
Trigger	**Ophthalmologist (EYE Doctor) Navigates to the Detection Section and Verifying the Patient Disease (Early Prognosis of Diabetic Retinopathy,DiabeticRetinopathy,MacularEdema and Glaucoma).**	
Main flow	**Actors**	**System**
	1.User-Ophthalmologist (EYE Doctor) viewing the system.	**2.Displays the login screen.**
	3.signing in or Registering to the system for the first time.	**4.Displays the option to Detect the disease.**
	5.Selecting the Disease needs to be detected.	**6.Displays the option to View analysis and Send Verified Report**
	6.Selecting the Send Verified Report.	**7. Sending the Verified Output result of the Patients,Displaying Report is sent to the patient.**

Exception flow	**Actors**	**System**
	1.If the user didn't fill login screen	• **Displays a message to user to login or register to the application.**
	2.If the user didn't input the Fundus image.	• **Displays An error message and asks to input the Fundus image.**
Alternate flow	**Actors**	**System**
	The user Fills the register and login.	**Records the Authenticated users.**
Inclusions	**User has to login OculoGuard to Detect the eye Disease.**	
Post Conditions	**Ophthalmologist (EYE Doctor) Sending the verified patient's output report to the Patient.**	

Table 16: Use Case description_5

B.3.4 View Patients - In Web Application

Use Case Name	**View Patients - In Web Application**

Use Case ID	**UC-006**	
Description	**OculoGuard Shows all the patients' details to the Ophthalmologist (EYE Doctor) to Manage Patients (Add Patients,View Medical History,Remove Patients…ect).**	
Priority	**High Level**	
Primary Actor	**Ophthalmologist (EYE Doctor)**	
Supporting Actors	**Patient Users**	
Pre-Conditions	**Needs to login the OculoGuard.** **Needs a proper network connection.** **Need a computer**	
Trigger	**Ophthalmologists (EYE Doctor) can fully manage the patients.**	
Main flow	**Actors**	**System**

	1.User-Ophthalmologist (EYE Doctor) viewing the system. **3.signing in or Registering to the system for the first time.** **5.Selecting the View Patients.**	**2.Displays the login screen.** **4.Displays the option to View Patients.** **6.Displays the option to Add Patients, Remove patients and View Medical History.**
Exception flow	**Actors**	**System**
	1.If the user didn't fill login screen **2.If the user didn’t input the Fundus image.**	● **Displays a message to user to login or register to the application.** ● **Displays An error message and asks to input the Fundus image.**
Alternate flow	**Actors**	**System**

	The user Fills the register and login.	**Records the Authenticated users.**
Inclusions	**User has to login OculoGuard to Detect the eye Disease.**	
Post Conditions	**User-Ophthalmologist (EYE Doctor) manages all patients logged in OculoGuard.**	

Table 17: Use Case description_6

Group members Contribution

Name	***Contribution***
Achintha Jayatilake	• Research Aim • Hardware requirements • Data requirements (optional) • Tools and techniques-Glaucoma • Gantt chart diagram • Risks and Mitigation • Onion Model • Stakeholder Description • Chapter 5 Overview • Professional Issues and Mitigation • Chapter 6 Overview • Chapter 6 Summary • Sequence Diagram • Choice of OculoGuard

Maheswaram Harrisagar	• Project Background • Problem Statement • Objectives • Chapter 1 Summary • Chapter 2 Introduction • Tools and techniques -Diabetic macular edema • Research Methodology • Evaluation methodology • Chapter 3 Summary • Chapter 4 Overview • Techniques for Requirement Gathering • Questionnaire Design • Formal Interviews with Domain Experts • Discussion/ Analysis of Results • Chapter 4 Summary • Social Issues and Mitigation • Process flow chart • Choice of OculoGuard
Anjula Silva	• Project Background • Research question/s • Project In-scope • Project Out-scope • Rich Picture Diagram • Tools and techniques-Diabetic retinopathy • Chapter 2 Summary • Project Management Methodology • Team Work Breakdown Structure (WBS) • Usage of Project Management and Collaboration Software In the project • Use Case Diagrams • Legal Issues and Mitigation • Class Diagram • Choice of OculoGuard

Thidas Jayawardane	• Project Background • Research Gap • Software requirements • Existing Work • Tools and techniques **-Early Prognosis of Diabetic retinopathy** • Chapter 3 Overview • Development Methodology • Design methodology • Formal Interviews with Domain Experts • Functional Requirements (with prioritization) • Non-Functional Requirements • Ethical Issues and Mitigation • Chapter 5 Summary • System Architecture Design • Choice of OculoGuard
Chamodh Samaranayake	• Declaration Page • Abstract + Keywords • Acknowledgements • List of Figures • List of Tables • 1.1.Chapter Overview • Usage of Project Management and Collaboration Software In the project • Use Case Descriptions • Choice of OculoGuard • UI Design

Table 18: Group members Contribution