INTRODUCTION

1.1 Project Overview

Ophthalmology is apparently the best "test bed" for AI methods inside the social economic space. The sheer volume of top notch information and propelled imaging techniques makes ophthalmology a reasonable contender for the advances in computer vision.

Deep learning can be utilized for the robotized identification of diabetic retinopathy (DR) and different fundus based eye sicknesses.

1.1.1 Technical Terminology

What is Deep Learning and how might it help? Deep Learning is a machine learning method that utilizes neural networks to display exceptionally complex capacities. Fortunately, there is an all around created calculation called "back-propagation" that enables the neural system to take in its parameters naturally given preparing information. Normally, the more information we feed into the preparation calculation, the better the neural net performs.

At the end of the day, rather than programming the machine to distinguish "1, 2, 3" (signs) with the end goal to make analyze "A or B" (ailing or ordinary), we currently tell machines that these pictures are A (sick), the others are B (typical); gain from them and make sense of why.

Deep learning is immovably related to a class of theories of emotional well-being (especially, neocortical enhancement) proposed by mental neuroscientists in the mid-1990s. These developmental theories were instantiated in computational models, making them progenitors of deep learning structures. These developmental models share the property that diverse proposed learning components in the cerebrum (e.g., a convergence of nerve advancement factor) reinforce the self-affiliation genuinely undifferentiated from the neural frameworks utilized in deep learning models. Like the neo-cortex, neural frameworks use a request of layered diverts in which each layer contemplates information from a prior layer (or the working condition), and after that passes its yield (and maybe the principal commitment), to various layers. This system yields a self-dealing with pile of transducers, all around tuned to their working condition. A 1995 delineation communicated, "...the infant's cerebrum seems to pull it together influenced by inundations of assumed trophic-factors ... unmistakable regions of the cerebrum twist up related sequentially, with one layer of tissue creating before another and so on until the point when the moment that the whole personality is create."

1.1.2 Problem Statement

What is diabetic retinopathy (DR)? It's the fastest growing cause of blindness, affecting more than 20% of the 488 millions of people living with diabetes worldwide. High blood sugar can cause damage to blood vessels of the retina (tissue covering the back of the eye, made up of light-sensitive cells.) Vision is not affected initially but irreversible blindness will occur in time without treatment. Diabetic Retinopathy leads to irreversible blindness. If caught early, it can be treated. However, a patient may experience no symptoms early on, making regular screening vital. Early detection is therefore crucial in order to administer timely treatment and prevent the disease's progression. The difference in the vision of normal eye and DR affected eye is shown below:

(a) Normal Eye (b) DR affected eye

Figure 1 : Normal Vision and DR-affected Vision

1.1.3 Goal

Early detection, how? Diagnosis of DR requires direct visualization of the retina by medical specialists, either via eye exam or imaging. Specialists then grade the level of disease based on presence of characteristic lesions, indicative of blood vessel damage (hemorrhage, micro aneurysms, exudates, i.e.: bleeding or fluid leakage). However, eye specialists are not available in many parts of the world where diabetes is prevalent. Hence, the goal is to facilitate the detection of the disease in such parts of the world.

1.1.4 Solution

Groupings of techniques have been used to look at the believability of deep learning models from a neurobiological perspective. From one point of view, a couple of varieties of the back-propagation have been proposed with the true objective to manufacture its getting ready credibility. Diverse experts have battled that unsupervised sorts of deep learning, for instance, those subject to different dimension generative models and deep conviction systems, may be closer to normal reality. In such manner, generative neural system models have been related to neurobiological confirmation about looking at based taking care of in the cerebral cortex. A definitive arrangement is the computerized system which takes the fundus pictures as information and predicts whether the individual has the sickness or not.

1.2 Need Analysis

DR is the main source of vision misfortune in grown-ups matured 20– 74 years. As per Lee et.al[1], in 2010, of an expected 285 million individuals worldwide with diabetes, more than 33% have indications of DR. DR has been dismissed in health-care research and arranging in some low-pay nations, where access to prepared eye-care professionals and tertiary eye-care administrations might be lacking.

Diabetic Retinopathy can't be effortlessly detected in beginning periods and discoveries reveal that treatment might be valuable just when detected early. Occasional registration of the general population who are inclined to the infection may help detect the illness at a beginning period. Detecting retinal imperfections in an extensive number of fundus pictures produced by screening programs is a period, asset and work expending undertaking. Imaginative and far reaching approaches are expected to decrease the danger of vision misfortune by incite conclusion and early treatment of DR.

Programmed detection of the ailment from the retinal pictures is along these lines the need of great importance. The venture will fill in as a profoundly effective demonstrative apparatus which would assist clinicians with making quicker choices amid mass screening of retinal pictures. It can also be utilized in mass screening where even a humble cost decrease, in the individual analysis, adds up to extensive cost reserve funds.

1.3 Research Gaps

Not all healthcare institutes have computerized DR detection facility. Moreover, in the institutes which actually have such systems, the automated systems are embedded in the physical retinal scans machines. This implies that the common people do not have access to those machines. Hence, an open and user-friendly system could enable people to determine the presence of disease at low cost. The research and development in this area is still under-explored.

1.4 Problem Definition and Scope of the Project

The computerized fundus camera in ophthalmology gives us digitized information which could be utilized for programmed location of malady. The programmed handling and examination of retinal pictures would spare additional work and may encourage the ophthalmologists. Diabetic Retinopathy is asymptomatic in the beginning times and studies uncover that treatment might be valuable just when recognized early. Standard registration of the general population who have high danger of the illness may help recognize the infection at a starter organizes.

The aim of the project is to make a user-friendly web application which can detect the presence of the diseases with high accuracy. This web application would find its scope in the medical field. It could be used by clinicians and patients to detect the diseases.

1.5 Assumptions and Constraints

Assumptions and constraints associated with the project are shown in Table 1 and Table 2 below:

Table1: Assumptions

S. No.	Assumptions
1	To obtain a relevant result, it is assumed that the user enters fundus images only. If fundus images are not entered, the result/prediction would be irrelevant.
2	It is assumed that the user is familiar with an internet browser and also familiar with handling the keyboard and mouse. Since the application is a web based application there is a need for the internet browser. It will be assumed that the users will possess decent internet connectivity.

Table2 : Constraints

S. No.	Constraints
1	The training and the testing image data is not very large. It consists of 8000 retinal scans.
2	The training of thousands of images requires high computational power. Uneasy access to such computers is also one constraint.
3	Since the final deliverable is a web application, the Internet connection is also a constraint for the application.

1.6 Approved Objectives

- The main objective is to detect diabetic retinopathy using digital fundus images as inputs.
- The aim is to design a user-friendly and automated system by the means of a web application.
- The objective is to obtain high accuracy.

1.7 Methodologies Used

The sequential approach followed during the project can be summarized as follows:

Data Acquisition: Extensive labeled data (around 8,000 fundus images) was collected. The data for DR detection was provided by Kaggle as a part of an online competition.EyePACS developed the dataset. The initial data was imbalanced. A technique called over-sampling was used to balance the data as shown in figure 2.

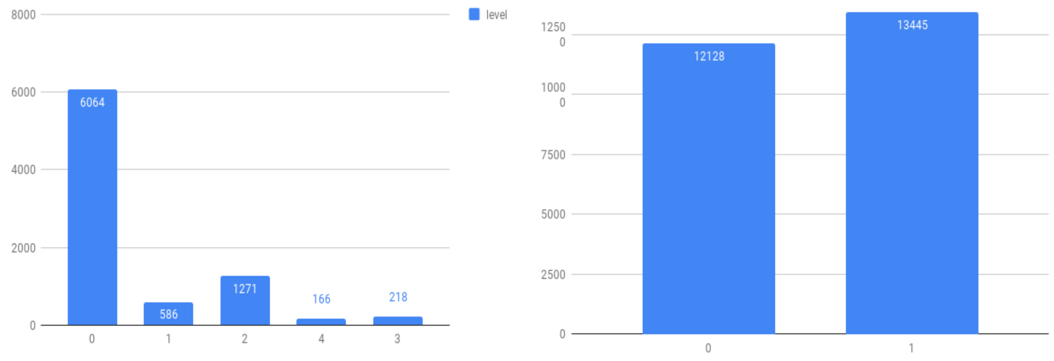


Figure 2: Imbalanced and Balanced Dataset

Image Pre-processing: The images are processed using techniques such as cropping, scaling, re-sizing, rotation etc. Sample original image and images after processing (cropping and rotating) are shown in figure 3.

Classification: CNN classifiers are trained to classify images. These classifiers are then used to detect diseases.

Web Interface Designing: A web application is designed for automating the whole process of detection.

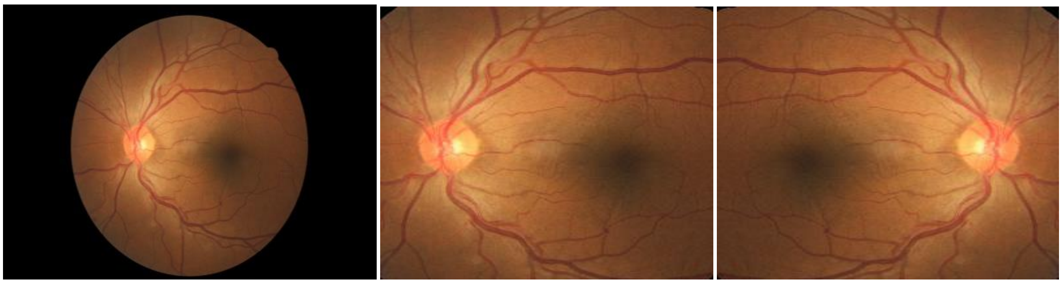


Figure 3: Pre-processing of Dataset

1.8 Project Outcomes and Deliverables

A web interface, capable of taking fundus images as input, is developed. This final deliverable would tell the user about the eye disease (DR) that the user might have.

1.9 Novelty of Work

Though there are many already existing DR detection systems in the world, this project is still first of its kind. The primary reason is the easy access and avialiabilty to the common internet users. The project would include a user-friendly web interface which would allow internet users to detect the presence of disease. All previous systems were either embedded in some hardware or their usage was restricted to opthalmologists.

2.1 Literature Survey

Based on the research carried out about the DR detection, following sections are formulated:

2.1.1 Theory associated with problem area

Research in the field of ophthalmology recommends that uncommon weight and glucose levels are a noteworthy reason for some basic infections. Such abnormalities can prompt different inconveniences in different parts of the body. In this writing we put center around Diabetic Retinopathy, a turmoil in the retina of the eye caused predominantly because of diabetes prompting fractional/finish loss of vision. DR is asymptomatic in the underlying stages and discoveries demonstrate that treatment might be valuable just when analyzed early. Ordinary examination of the general population who have high odds of having DR may help identify it early. Recognizing retinal abnormalities in a substantial number of images produced by screening programs is a tedious assignment. Programmed location of the malady from the retinal images is in this way an essential territory of continuous research. In this writing we put accentuation on programmed determination of eye variation from the norm (Diabetic retinopathy) wherein the image is essentially pre-prepared and factual based estimations are ascertained. The deliberate data are given to a classifier. The classifier orders the fundus image to the classification of ailment to which it has a place. This exploration goes for programmed identification of diabetic retinopathy through image processing and highlights extraction of the whole fundus image and classification utilizing data mining procedures.

2.1.2 Existing Systems and Solutions

Different attempts in the past have been made to detect DR with the help of retinal images; some of the already existing systems use the following methods:

Artificial Neural Networks (ANN) and Fuzzy C-Means based clustering was used to classify exudates with a sensitivity and specificity of 95 and 88.9% [2]. Changira et.al, [3] developed a system in which Principle Component Analysis (PCA) and multi-layer perception neural networks were used to yield a sensitivity and specificity of 80.21 and 70.26% respectively. Sagar[3] employed the concept of dynamic thresholding and edge detection to identify the exudates yielding a sensitivity and prediction of 99 and 93%. ANN with inputs like areas of hard exudates, area and perimeter of blood vessels and the contrast showed a classification accuracy of 93% [4]. SVM with inputs from Higher Order Spectra classified with a sensitivity and specificity of 82 and 88% respectively [5].

2.1.3 Research Findings for Existing Literature

Research findings associated with the project are mentioned in the Table 3:

Table 3: Research Findings

S. No.	Roll Number	Name	Paper Title	Tools/ Technology	Findings	Citation
1	101503070	Deep Kiran	Automated detection of diabetic retinopathy on digital fundus images	Image Analysis, Neural Network	Completely computerized algorithms could identify hard exudates, which are critical highlights for DR identification.	Sinthanayothin et. al.
2	101503070	Deep Kiran	Automated detection of diabetic retinopathy in digital retinal images: a tool for diabetic retinopathy screening	Image Analysis, Neural Network	A framework can be utilized including pre-processing to institutionalize shading and improve contrast, segmentation to uncover conceivable lesions and order of lesions utilizing an artificial neural network.	Usher et. al.
3	101503070	Deep Kiran	Diagnosis of diabetic	Image Analysis,	Two kinds of features were	Farazo et. al.

			retinopathy based on holistic texture and local retinal features	Segmentation	extracted including the all-encompassing surface features and the nearby retinal features. The execution of the framework enhanced incredibly when two neighborhood retinal features – micro aneurysms and exudates – were fused into the examination.	
4	101503070	Deep Kiran	Detection of Exudates in Diabetic Retinopathy Images using Laplacian Kernel Induced Spatial FCM Clustering Algorithm	Fuzzy C Means Clustering algorithm, Kernel induced Fuzzy C Means Clustering algorithm	FCM calculation does not function admirably for uproarious pictures. The KFCM algorithm utilizes kernel metric instead of distance metric when contrasted with the traditional C-means algorithm. KFCM calculation can likewise deal with the little contrasts among groups and it isn't case with established FCM calculation.	Ravindraiah et. al.
5	101503070	Deep Kiran	Fast Convolutional Neural Network Training Using	Image Analysis, Neural Network	A technique to significantly accelerate the tedious training procedure of	Grinsven et. al.

			Selective Data Sampling: Application to Hemorrhage Detection in Color Fundus Images		convolutional neural networks with a selective sampling strategy, installed in the training system is depicted.	
6	101503070	Deep Kiran	Efficient multi-kernel multi-instance learning using weakly supervised and imbalanced data for diabetic retinopathy diagnosis	Imbalanced data learning, Multi-instance learning	An under-sampling at occurrence level and an over-sampling at pack level can be utilized to enhance the execution of the multi-instance learning in the diagnosis of DR.	Cao et. al.
7	101503087	Harsh Batra	Applying artificial intelligence to disease staging: Deep learning for improved staging of diabetic retinopathy	CNN, Machine Learning	A deep convolutional neural network, Alex Net, indicated expanded precision in the categorization of high-quality pictures.	Takahashi et. al.
8	101503087	Harsh Batra	Automated Detection of Diabetic Retinopathy using Deep Learning	CNN, Dataset Augmentation	The high variance and low bias of these models could enable CNNs to analyze a more extensive scope of non-diabetic diseases also.	Lam et. al.
9	101503087	Harsh Batra	Automatic recognition of severity level for diagnosis of diabetic retinopathy using deep visual features	Deep Learning, Deep Visual features	To learn deep visual features, a semi-directed multi-layer deep-learning algorithm can be used alongside multi-layer and adjusting steps.	Abbas et. al.

10	101503087	Harsh Batra	Algorithms for the Automated Detection of Diabetic Retinopathy Using Digital Fundus Images	Feature Extraction	The calculations including four features specifically, blood vessels, exudates, hemorrhages and micro aneurysms combined with SVM were utilized to order fundus pictures into five classes.	Faust et. al.
11	101503087	Harsh Batra	Convolutional Neural Networks for Diabetic Retinopathy	CNN architecture, data augmentation	By expanding number of epochs of the full dataset the accuracy of the network can be expanded to over 70%. The learning rate may then be brought down by a factor of 10 each time training loss and precision may stay immersed.	Pratt et. al.
12	101503087	Harsh Batra	Identification of different stages of diabetic retinopathy using retinal optical images	Neural Network, Image Processing, Feed Forward Classification	A framework can be created utilizing image processing and pattern recognition procedures to recognize early lesions of diabetic retinopathy (hemorrhages and micro aneurysms, hard exudates, and cotton-fleece spots) . This framework can determine the	Yun et. al.

					diabetes retinopathy to have a precision of over 90% of the cases.	
13	101503105	Jayant Singla	Screening for Diabetic Retinopathy: 1 and 3 Nonmydriatic 45-degree Digital Fundus Photographs vs. 7 Standard Early Treatment Diabetic Retinopathy Study Fields	Image Processing, Image Classification	Three shading 45-degree fundus fields might be a viable apparatus in a screening setting to decide basic dimensions of DR for provoke specialist referral. One focal 45-degree picture is adequate to decide nonattendance or nearness of DR however not for reviewing it.	Vujosevic et. al.
14	101503105	Jayant Singla	Automatic Detection of Diabetic Retinopathy and Age-Related Macular Degeneration in Digital Fundus Images	Data Description, Image Processing, Classification	This work introduces a feasible and effective methods for portraying distinctive retinal anomalies and building parallel classifiers for identification purposes. Albeit programmed location of DR has been considered by various groups in the previous decade, few examinations have utilized a best down methodology	Agurto et. al.

					like the one proposed here.	
15	101503105	Jayant Singla	Automatic screening and classification of diabetic retinopathy and maculopathy using fuzzy image processing.	Fuzzy Image Processing	This framework proposed a novel mix of fuzzy image preprocessing procedures including the retinal structures limitation, trailed by the feature extraction and, at long last, the categorization with some machine learning calculations.	Rahim et. al.
16	101503105	Jayant Singla	Automated detection of micro aneurysms in digital red-free photographs: a diabetic retinopathy screening tool	Image Processing, Digital Retinal Photography	A computerized method was produced to recognize retinopathy in advanced red-free fundus pictures that can frame some portion of a diabetic retinopathy screening program. It can play out a helpful job in this setting distinguishing pictures deserving of nearer investigation or disposing of half or a greater amount of the screening populace who have no	Hipwell et. al.

					retinopathy.	
17	101503105	Jayant Singla	Support vector machine based method for identifying hard exudates in retinal images	Support Vector Machine (SVM)	SVM was used as classifier. Accuracy obtained was 84%. This proposed strategy has potential for automatic detection of hard exudates from retinal pictures.	Xu and Luo.
18	101503105	Jayant Singla	Ridge-based vessel segmentation in color images of the retina	Image Segmentation, KNN Classification	The focal point of this paper is on the automated segmentation of vessels in shading pictures of the retina. Here intrigue is in vessel segmentation for screening of diabetic retinopathy.	Staal et. al.

2.1.4 Problem Identified

DR is the main source of vision misfortune in grown-ups matured 20– 74 years. DR has been dismissed in human services research and arranging in some low-pay nations, where access to prepared eye-care experts and tertiary eye-care administrations might be lacking. Inventive and extensive methodologies are expected to lessen the danger of vision misfortune by incite analysis and early treatment of DR.

To complete the mentioned objective a lot of problem were encountered. It was difficult to find large number of labeled images for training the model. Several medical institutes were contacted for the same. Also, it was not an easy task to perform autonomous segmentation of thousands of images. Python scripts were developed to perform above mentioned task.

2.1.5 Tools and Technologies Used

Various methods and tools are used to accomplish the objective. For image processing, various python libraries are used such as PIL (Python Image Library). These libraries are very much efficient in cropping, resizing, rotating the images and hence are helpful in pre-processing of dataset. Various scientific computing python libraries like Numpy, Pandas are also used to incorporate the features of Machine Learning environment in Python. Convolutional Neural Network (CNN) is used to train the image dataset. This model uses libraries like TensorFlow, Keras, etc. Anaconda which is very popular IDE for Python and Machine Learning purposes is used to run the python scripts.

2.2 Standards

The project is based on Deep Learning, the standards of which are not yet defined by any organization worldwide. The parameters used in the project are purely based on the research papers available on the internet. To assure that evaluation metrics and architecture of the CNN model is suitable for the intended task, the help of an online course titled “Complete Guide to Tensorflow for Deep Learning with Python” is taken. The course is taught by Jose MarcialPortilla who is a well-known data scientist.Moreover, the Software Requirement Specification uses IEEE standard.

2.3 Software Requirement Specifications

2.3.1 Introduction

The following software requirement specification covers in-depth description of the system:

2.3.1.1 Purpose

Diabetic Retinopathy is a retinal sickness that is a noteworthy reason for visual deficiency. Ordinary Screening for early ailment discovery has been a profoundly work - and asset concentrated errand. Thus programmed discovery of these maladies through computational methods would be an extraordinary cure. The reason for this undertaking is to help ophthalmologists in recognizing these illnesses via computerizing the entire procedure.

2.3.1.2 Intended Audience and Reading Suggestions

The most common and direct users of this product would include ophthalmologists and Optometrists. A web interface would be developed as the final deliverable; hence if a user/patient has the fundus images, he/she could also act as direct user of the product.

2.3.1.3 Product Scope

An enhanced version of this project can be made by embedding the software with suitable hardware (retinal-camera). This extended version could be exclusively designed for ophthalmologists to aid them in treatment of diseases.
In the near future, if technology enhances to an extent that a smartphone is able to take retinal images, then a dedicated Android/IOS application could be designed for the disease detection. A user could detect these diseases at home and without spending a hefty amount of money.

2.3.2 Overall Description

2.3.2.1 Product Perspective

The final deliverable is expected to aid medical community in countering eye diseases in most time and cost effective way. The product is supposed to bring positive change in the health care sector.

2.3.2.2 Product Features

The system would receive fundus images as input from the user. The system would utilize image analysis and data mining techniques to accurately classify the fundus images as Normal and Diabetic Retinopathy affected.

2.3.3 External Interface Requirements

2.3.3.1 User Interfaces

A simple and appealing web interface would act as the UI of the system. The user would enter fundus images as the inputs and click the "Submit" button. After processing, the predicted result would be displayed on a dialog box.

2.3.3.2 Software Interfaces

The only requirement for working of the product/system is a web browser and a stable internet connection. The product would work on all the common operating systems like Windows, Mac OS, Android, Ubuntu etc.

2.3.4 Other Nonfunctional Requirements

2.3.4.1 Performance Requirements

A Stable internet connection and a well working web browser are required for proper functioning of the system. The user must enter valid (fundus) images only otherwise the result produced would be vague.

2.3.4.2 Safety Requirements

The system does not produce 100% accurate results. This system is to aid the doctors in detecting the diseases. User must not proceed to diagnose the disease based on the result obtained from this product solely. User must consult the doctors before taking any actions.

2.3.4.3 Software Quality Attributes

The accuracy of the system in detecting diseases would not be 100%, it would be around 70%.The consumer of the product must know this fact.

2.4 Cost Analysis

As far as the project is concerned, there is no need of any supplementary hardware. But a huge dataset is being used whose processing is beyond the computational ability of regular processors. Therefore the team is looking forward to use Cloud Services which may incur some nominal costs. The software tools required for the project are also free of cost.

2.5 Risk Analysis

The system does not produce 100% accurate results. This system is to aid the doctors in detecting the diseases. User must not proceed to diagnose the disease based on the result obtained from this product solely. User must consult the doctors before taking any actions.

METHODOLOGY ADOPTED

3.1 Investigative Techniques

The project is based on Deep Learning and Image Processing. The experimental investigative technique is used here. The independent variables are the features (exudates, micro-aneurysm, hemorrhages etc.) of the images (dataset) and the dependent variable is the outcome (result/prediction).

An in-depth research was carried out before proceeding to develop the system (refer to Chapter 2). There were a few obstacles in developing the suitable architecture but the research papers and the hit and trial methodology did help. Research papers also enhanced the domain knowledge of the disease which eventually helped in setting the various parameters (number of epochs, number of filters, number of stride, kernel size etc.) of the system. The CNN model was repeatedly trained by altering the parameters. The parameters were initially based on intuition and the domain knowledge; hence the entire model was a sort of an experiment only. The choice of evaluation metrics towards the end of project helped to establish reliability and feasibility of the system.

3.2 Proposed Solution

The flow chart for the proposed system is shown in Figure 4:

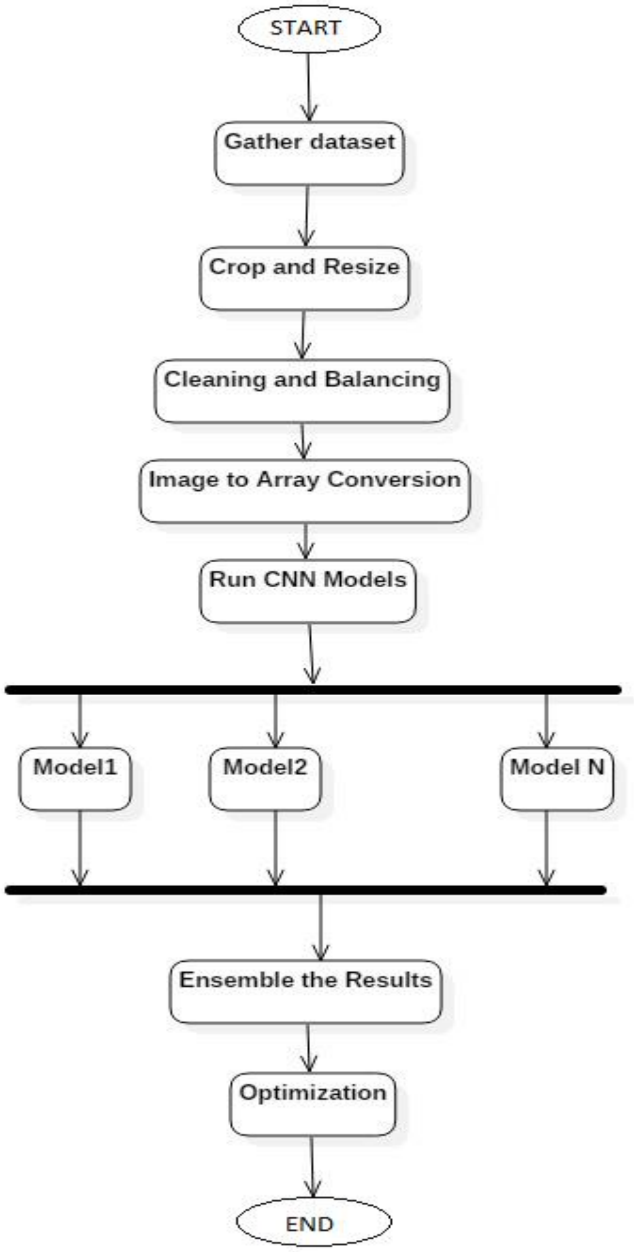


Figure 3: Flow Chart

3.3 Work Breakdown Structure

Work Breakdown Structure of the project is shown in Figure 5:

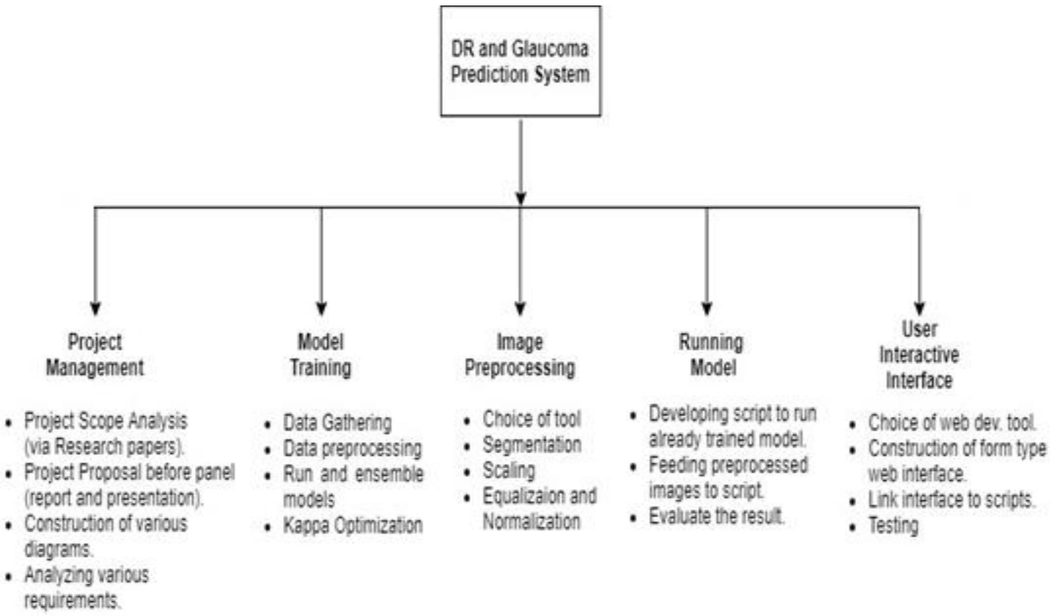


Figure 4: Work Breakdown Structure

3.4 Tools and Technologies Used

Areas of engineering used are Image pre-processing (data pre-processing) and Deep learning. Python is extensively used in both areas. The python library PIL(Python Image Library) is used for image processing. For deep leaning, keras is used with tensorflow as the backend. The mathematical computations are done using functionalities of numpy library. The anaconda's Spyder is used as IDE. For the user interface, html and javaScriptis used.

4.1 System Architecture

The architecture of the system can be accurately represented by following context diagram shown in Figure 6:

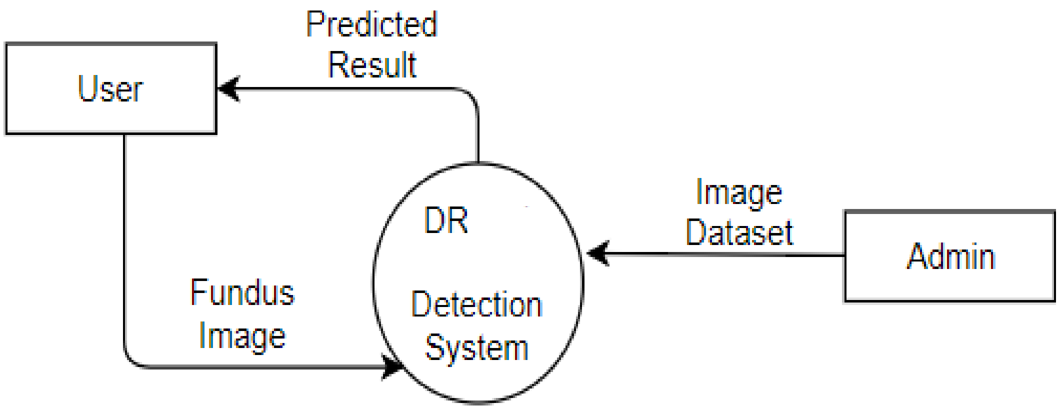


Figure 5: Context Diagram

4.2 Design Level Diagrams

The system can be understood by the following Diagrams:

Use Case Diagram

Use Case Diagram of the system is shown in Figure 7:

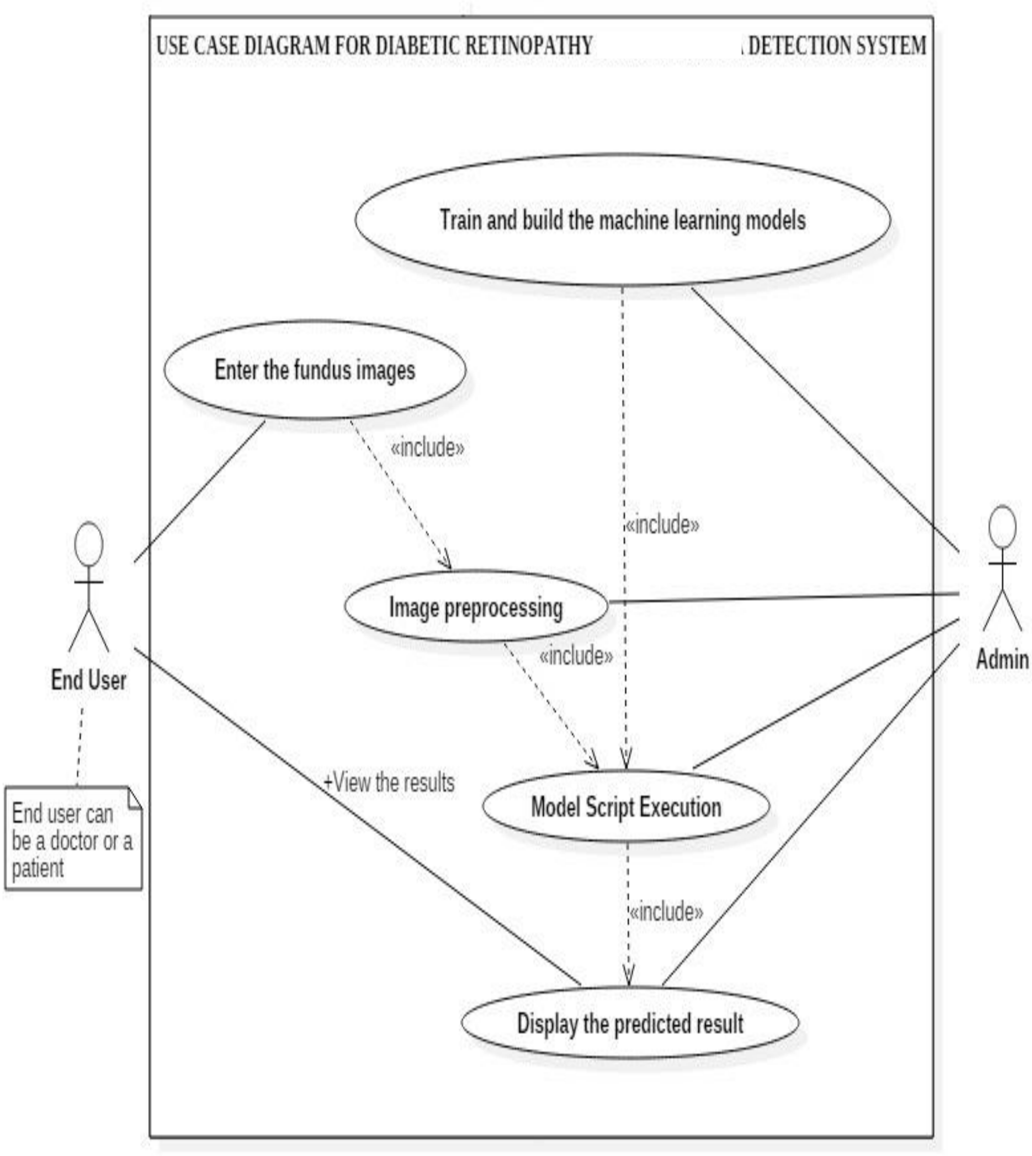


Figure 6: Use Case Diagram

USE CASE TEMPLATE FOR USE CASE DIAGRAM

Description:

The 'admin' trains and builds the machine learning(ML) models for the detection of Diabetic Retinopathy disease. The end user, who could be a doctor or a patient, enters fundus images onto the web interface designed by the admin. These images are pre-processed. The processed images are taken as inputs to the already trained ML models scripts. The web interface displays the predicted result.

Trigger:

User enters the fundus images.

Actors:

1. End User(Doctor/Patient)
2. Admin

Pre-Conditions:

1. Secure connection to the server.
2. User enters fundus images only.

Goals (Successful Conclusions):

1. System accurately detects the diseases.
2. System displays the result.

Failed Conclusions:

1. Invalid input images.
2. Unable to pre-process images.

Steps of Execution:

1. Admin trains and builds the model (one time process).
2. User enters the fundus images.
3. System pre-processes the images.
4. ML model script is executed.
5. Predicted result is displayed.

Activity Diagrams

There are five activity diagrams, each corresponding to a use case scenario:

a) **Pre-Processing of input image**

Activity diagram related to Pre-Processing is shown in Figure 8:

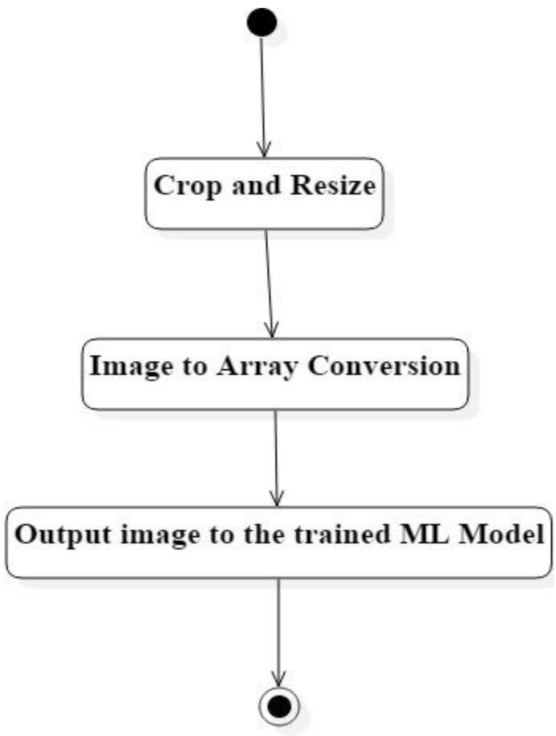


Figure 7: Activity Diagram1

b) Training the model

Activity diagram related to Training of the model is shown in Figure 9:

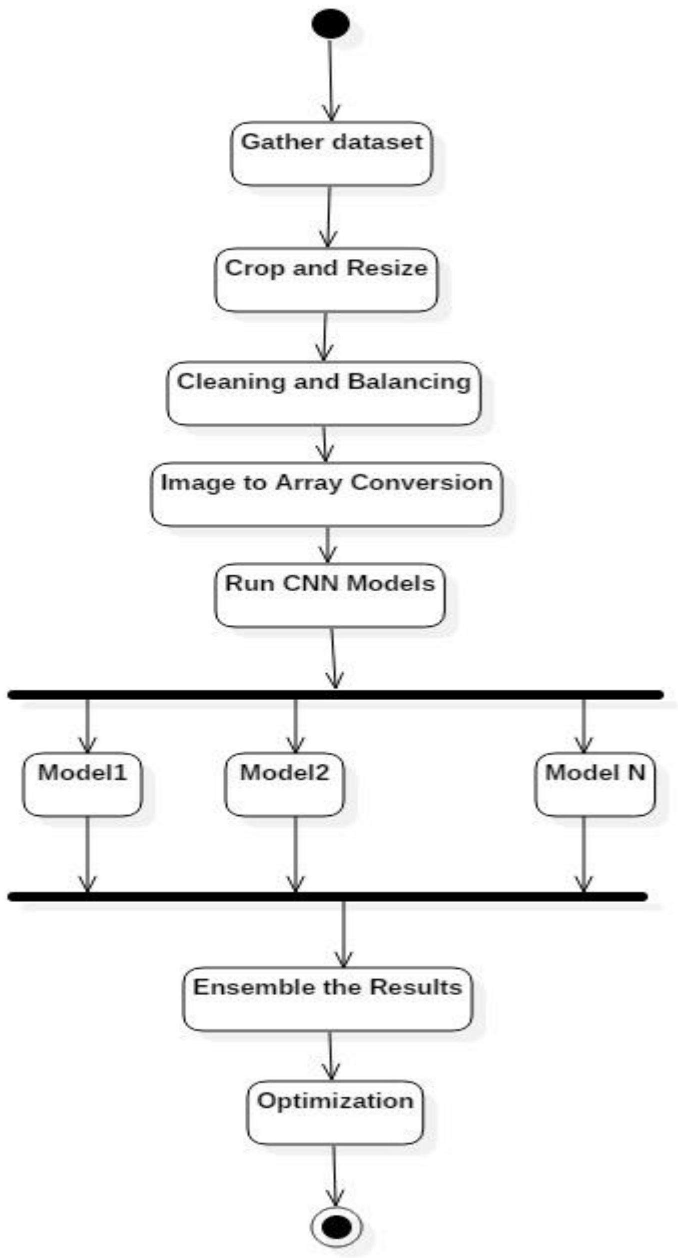


Figure 8: Activity Diagram2

c) Obtaining Input

Activity diagram related to Obtaining Input is shown in Figure 10:

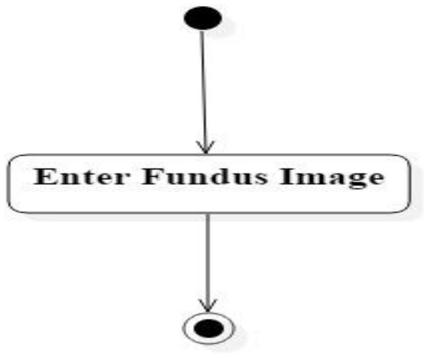


Figure 9: Activity Diagram3

d) Model Script Execution

Activity diagram related to Model Script Execution is shown in Figure 11:

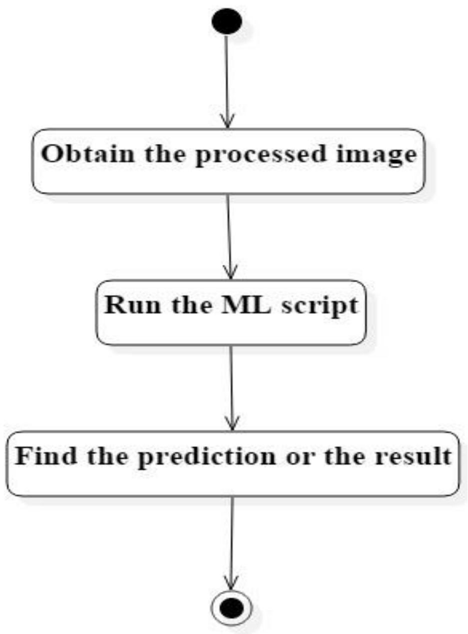


Figure 10: Activity Diagram4

e) Display Result

Activity diagram related to Displaying the Result is shown in Figure 12:

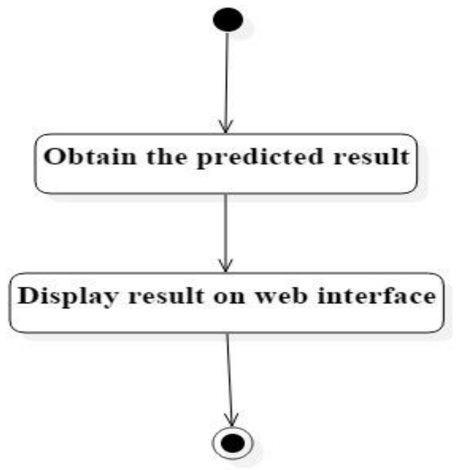


Figure 11: Activity Diagram5

Data Flow Diagrams

a) Level 0 DFD:

Level 0 DFD is shown in Figure 13:

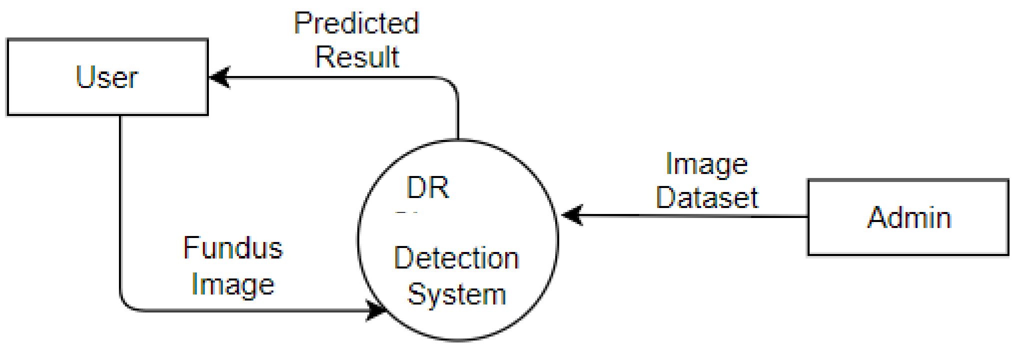


Figure 12: DFD Level 0

b) Level 1 DFD:

Level 1 DFD is shown in Figure 12:

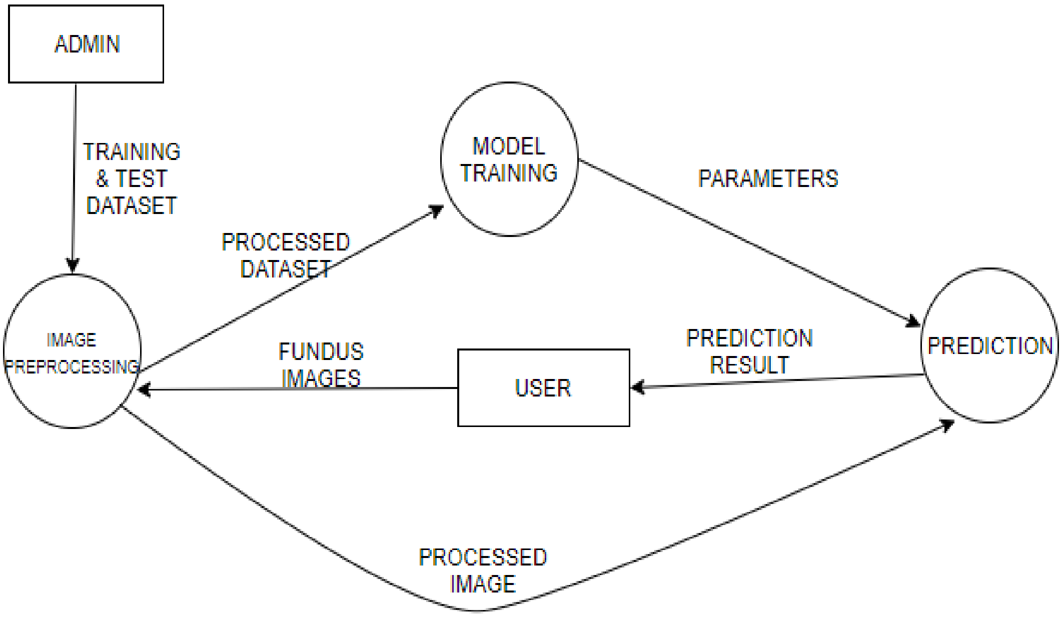


Figure 13: DFD Level 1

a) Level 2 DFDs:

Level 2 DFDs are shown in Figure 15, Figure 16 and Figure 17:

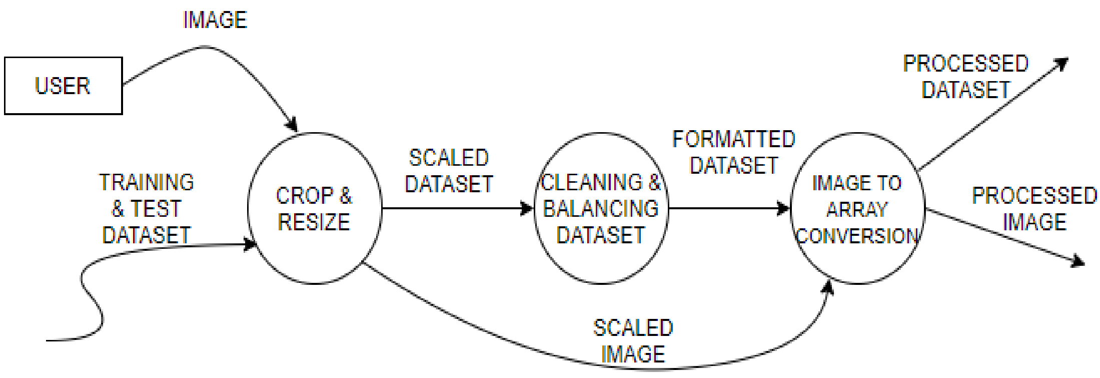


Figure 14: DFD Level 2

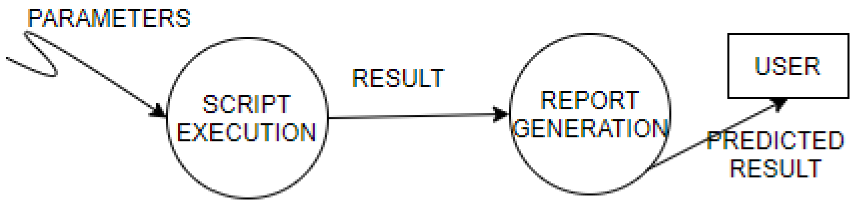


Figure 15: DFD Level 2

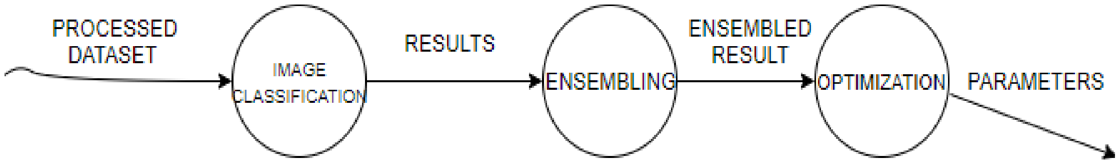


Figure 16: DFD Level 2

4.3 User Interface Diagrams

An interactive graphical user interface (GUI) would be developed having various elements such as: Text Box, Button, Dialogue Box, Application window etc.

Brief use of each element:

- Input Field: - These fields would be used to enter fundus images from users. Since user would enter two images (Left & Right), two input fields would be used.
- Buttons: - Two buttons would be used in the interface. One to upload files and other to predict the result.
- Application Window: - This application window would help user to upload fundus images from PC or mobile phone.
- Dialogue Box: - This dialogue box would finally display the result of prediction to the user.

A basic prototype of UI is shown in Figure 17 and Figure 18:

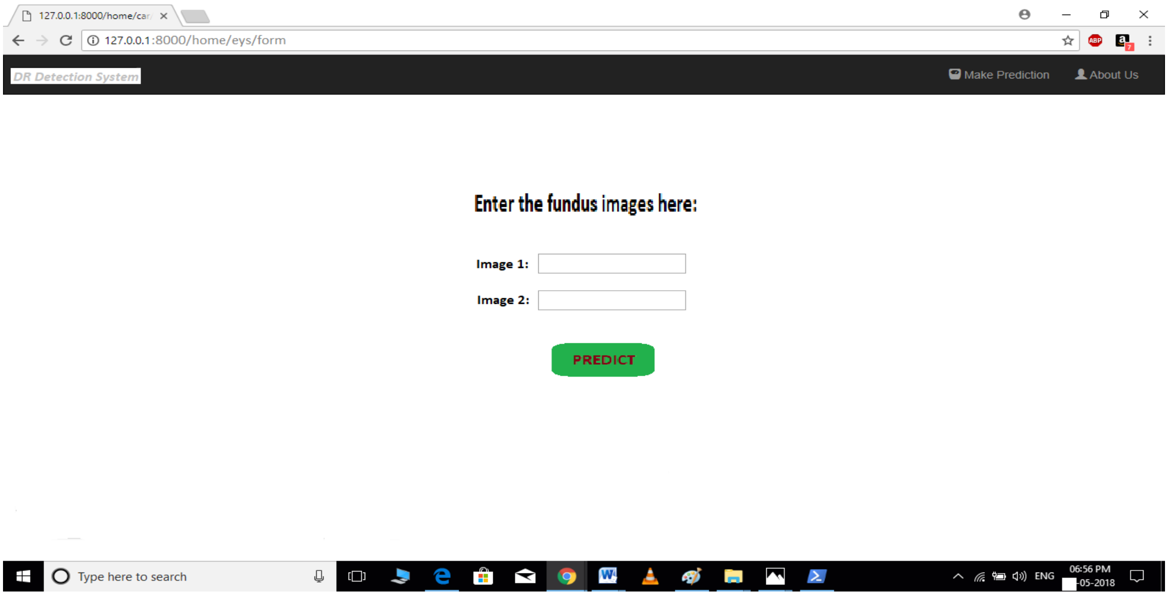


Figure 17: User Interface 1

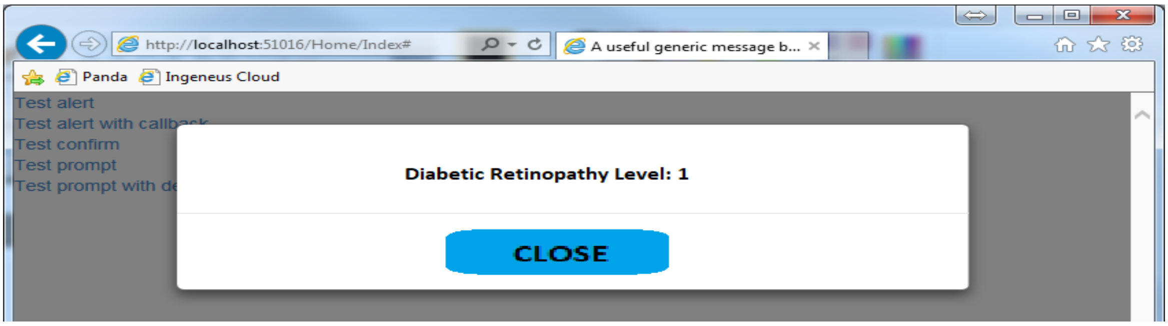


Figure 18: User Interface 2

IMPLEMENTATION AND EXPERIMENTAL RESULTS

5.1 Experimental Setup

The experimental setup required a few softwares and libraries to be installed:

Anaconda is used as the primary IDE for writing the code for deep learning. Tensorflow and keras are also installed on top of Anaconda. Other libraries include numpy, PIL, pandas. High processing power GPUs are used for processing and training the data.

5.2 Experimental Analysis

5.2.1 Data

The dataset was collected from a website dedicated to machine learning: kaggle. The dataset initially consisted of 8000 retinal images. Before training, the dataset was balanced and around 24000 images were fed into the CNN model.

5.2.2 Performance Parameters

The various parameters used while training the data include:

- Batch size : 512 images
- Number of classes : 2
- Number of epochs : 30
- Number of channels : 3
- Number of filters : 32
- Kernel Size : 8 X 8
- Strides : 1
- Pool size : 2 X 2
- Activation function : Sigmoid and Softmax
- Dropout : 0.25
- Loss function : Cross-entropy
- Optimizer : Adam

- Metrics : Accuracy and Recall
- Validation Split : 0.2
- Test Split : 0.2

5.3 Testing Process

5.3.1 Test Plan

5.3.1.1 Features to be tested

The independent variables are the features of the images (dataset) and the dependent variable is the outcome (result/prediction).

After pre-processing the training dataset, the numpy array is created which contains the features of dataset. The primary features are the hemorrhage, exudates and microaneurysms. The numpy array is then fed to CNN model and the mentioned features are extracted from different layers at different levels. The dependent variable i.e., the prediction is dependent on various features extracted from images.

5.3.1.2 Test Strategy

The initial dataset was imbalanced. After balancing the dataset using over-sampling, the dataset was ready for training. The dataset is split into 80-20 ratio for training and testing purpose respectively. During training, 20% is left out for validation. After training the model repeatedly by tuning parameters, the model was finally tested. Accuracy is chosen as the evaluation parameter.

5.3.1.3 Test Techniques

For evaluating the model, accuracy, recall and precisionare used as the metrics. Accuracy is defined as ratio of: correctly predicted samples to the total predicted samples. Confusion matrix is used to find the above metrics.

5.3.2 Test Cases

Initially, the model was trained with unprocessed dataset to check whether the code is working or not. It was found that dataset was imbalanced. The model was repeatedly trained on processed dataset until an optimal accuracy was achieved.

5.3.3 Test Results

The data is trained repeatedly. Each time the parameter of the models are altered until an acceptable level of accuracy is achieved. The model currently is successfully predicting the presence of diseases with an accuracy of 69.8%.The above holds true for a valid input image. For an invalid (non-retinal scan), some irrelevant results may be obtained.

5.4 Results and Discussions

For a valid input image, the model is predicting the presence of disease with an accuracy of 69.8%. This accuracy may be improved by altering the parameters of the model so that they fit the dataset more appropriately. The highest achievable accuracy among the existing systems is around 88%.

It is established that DR is common cause of blindness among adults. Manual screening of fundus images takes too much time. This disease can only be treated well when it is detected early. Hence, using Deep Learning to aid the process of disease detection is an interesting area of research. Similar methodology can be applied to detect the presence of other diseases as well.

5.5 Inferences Drawn

From the development of the project , it is clear that the reliability (accuracy) of any deep learning model is heavily dependent on the parameters and architecture of the model. The quality of the input images also determines the outcome of the model. Not just the quality but the quantity(number) of images also affect the final results. It is also observed that domain knowledge of the problem associated can come handy.

5.6 Validation of Objectives

- Backend: The model is ready and running with accuracy of 69.8%.
- Frontend: An interactive web application is ready. It is capable of taking fundus image as input and feed it to the CNN model.

CONCLUSIONS AND FUTURE DIRECTIONS

6.1 Conclusions

Different techniques, different databases, different authors, different objectives and different results. But whatever objective or database is there, pre-processing step is always performed to enhance input of subsequent steps. Furthermore, systems with good results are bounded to specific databases. The result of any CNN based system depends heavily on values of parameters like number of epochs, activation function used, loss function used and some techniques such as dropout and ensemble. Result is degraded when different databases are used. Size of databases used is not more than 500 MB and contains maximum 400-500 images in a single batch.

Larger datasets are also available. Diabetic Retinopathy Detection was also one of the challenges hosted by Kaggle. The dataset for that challenge contains total 1,77,400 images with total size of 82.19 GB. Training dataset contains 88,698 images and Testing dataset contains 88,702 images. To process such large dataset, parallel processing or distributed computing is required. CUDA architecture can also be used for parallel processing. Another alternative to process large dataset using commodity hardware is Apache Hadoop. Research of Image Processing on Hadoop is not explored in depth yet. So, there is a scope for implementation of existing Automated DR Detection and severity classification system on Hadoop for mass screening.

6.2 Economic/Social Benefits

The task will fill in as a very effective analytic device which would assist clinicians with making quicker choices amid mass screening of retinal pictures. This would counter and treat the greater part of individuals influenced by these diseases. It can likewise be utilized in the mass screening where even a humble cost decrease, in the individual finding, adds up to significant cost investment funds.

6.3 Reflections

The project was started with a vague idea of implementing DR Detection System. Butas we started achieving the small milestones we realized that building an algorithm for a system is crucial but building a 'system' as a whole is even more difficult. It is now clear that software engineering is as important as any other field in computer science. Without systematic implementation, it is not easy to develop a project. The project members tried to follow good development practices to come up with a successful "DR Detection System".

6.4 Future Work Plan

In the future, the main emphasis would be on improving the accuracy of the model. If the technology advances to an extent that the smartphones are able to capture the fundus images, then a dedicated Android/IOS application could also be developed.

7.1 Challenges Faced

Many challenges were faced during the project development:

- Data Acquisition: was difficult. We had to consult many institutions for the retinal scans. Most of the data available on the internet is not labeled and hence not suitable for the project.
- Data Imbalance: The dataset acquired was imbalanced. There were very few images with positive DR. Balancing of dataset took efforts.
- Pre-processing dataset: was ,at first, entirely based on intuition. After many failures, we were able to process the images.
- Processing power: High processing power GPUs are required to train such high volume of data. Finding that computational power was not easy.

7.2 Relevant Subjects

Following courses are proved to be highly useful:

- Computer Programming
- Software Engineering
- Machine Learning
- Image Processing
- Deep Learning

7.3 Interdisciplinary Knowledge Sharing

All the above mentioned courses were collectively useful for development of the project :

- For Pre-processing: concepts of machine learning i.e., data preprocessing and concepts of Image processing were used.

- Computer programming was used to write an efficient and neat code for building the CNN model. It was also used to write basic html code for the web interface.
- The whole project was put into one place using the Software Engineering i.e., the entire structure of the project was made using the concepts of Software Engineering.

7.4 Peer Assessment Matrix

Peer assessment matrix is shown below:

Table 4: Peer Assessment Matrix

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="4">Evaluation of</td></tr>
<tr><td>Deep Kiran</td><td>Harsh Batra</td><td>Jayant Singla</td><td></td></tr>
<tr><td rowspan="3">Evaluation By</td><td>Deep Kiran</td><td>-</td><td>4</td><td>3</td><td></td></tr>
<tr><td>Harsh Batra</td><td>3</td><td>-</td><td>5</td><td></td></tr>
<tr><td>Jayant Singla</td><td>2</td><td>5</td><td>-</td><td></td></tr>
</table>

7.5 Role Playing and Work Schedule

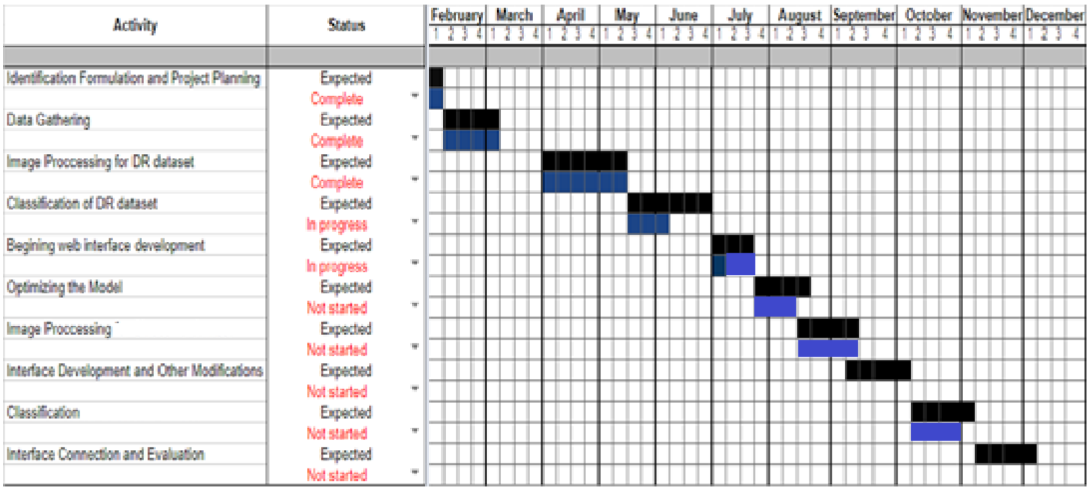
Contribution of group members is as follows:

Table 5:Contribution of Team Members

Team Member	Contribution
Deep Kiran	Data Gathering, Web Development, Literature Survey
Harsh Batra	Image Processing, Model Building, Documentation
Jayant Singla	Image Processing, Model Building, Documentation

Work Schedule is displayed in the form of Gantt chart as follows:

Table 6: Gantt Chart



7.6 Student Outcomes Description and Performance Indicators

Table 6: A-K Mapping

SO	Description	Outcome
A1	Applying mathematical concepts to obtain analytical and numerical solutions.	Activation function used in CNN is purely based on mathematical concepts. Some mathematical concepts are also used for image processing (e.g. finding black images etc.). Hence, mathematics is of significant use in this project.
A3	Applying engineering techniques for solving computing problems.	Software Engineering concepts are the pillars of any technical project. The underlying architecture of the project is made with the help of activity diagrams, context diagrams etc.
B1	Identify the constraints, assumptions and models for the problems.	Assumption: User enters only fundus images. Constraint: Limited dataset, Large training time.
B2	Use appropriate methods, tools and techniques for data collection.	Data is collected from trusted source “KAGGLE”. This website organizes various data science related competitions. Some hospitals in Chandigarh were also contacted for data gathering.
B3	Analyze and interpret results with respect to assumptions, constraints and	The system classifies the image with accuracy of 69.8% with fundus image

	theory.	as input. The demographic differences may alter the expected results.
C1	Design software system to address desired needs in different problem domains.	An interactive web application is developed. This application takes fundus image as input and shows prediction (result) as output.
C2	Can understand scope and constraints such as economic, environmental, social, political, ethical, health and safety, manufacturability, and sustainability.	This project provides social and economic benefits as well. This project is capable to detect DR in any fundus image without any extra cost. It also makes the process time efficient.
D1	Fulfill assigned responsibility in multidisciplinary teams.	All the team members played their part very well. With full teamwork and cooperation, this milestone is achieved.
D2	Can play different roles as a team player.	This project taught the lesson of multi-tasking to each and every member. Documentation, research and code work are done by all members simultaneously.
F1	Showcase professional responsibility while interacting with peers and professional communities.	During the course of project, team members consulted seniors and some doctors for the scope of project. Also a lot of discussion has been carried out with project mentor regarding the scope of project.
G1	Produce a variety of documents such as laboratory or project reports using appropriate formats.	Well formatted reports were shown to panel and mentor at every evaluation. Documentation work is taken care with sincere attention.
G2	Deliver well-organized and effective oral presentation.	Well organized presentations were delivered at every panel evaluation. Hence this project gave a chance of presenting your work.
H1	Aware of environmental and societal impact of engineering solutions.	The system would prove to be very useful. Engineering solutions can be applied in almost every field of work.
I1	Able to explore and utilize resources to enhance self-learning.	Online resources such as journals, research papers and tutorials are explored to complete the project.
I2	Recognize the importance of life-long learning.	End-to-end project with extensive documentation is prepared. It would help in advancing career.
K1	Write code in different programming languages.	Various languages are used during course of project. Python for image processing and Deep Learning. HTML, JavaScript, Django for web development.
K2	Apply different data structures and	Numpy arrays, tensors variables and

	algorithmic techniques.	other new data structures are used.
K3	Use software tools necessary for computer engineering domain	Anaconda and Django along with many other software tools are used.

7.7 Brief Analytical Assessment

The team was aware of the understanding of the capstone requirements that needed to be explored. We explored the literature like research papers and journals from IEEE. We explored, met people and tried to know about existing problems around us to come with idea of our capstone project. The scope of the project was decided later after consulting our mentor.

The project required in-depth knowledge of the problem domain. The initial results were not up to the mark. The team experimented with different approaches to solve the problem. Finally, the team decided to follow Machine Learning approach.

The project demanded the knowledge of various fundamental programming skills and software engineering principles. The quality of the project depends heavily on the underlying architecture. Apart from it, concepts of Image Processing, Machine Learning and Deep Learning were also of great use. Also the project made us appreciate the need to solve real life problems using the fundamentals of Computer Science. We ourselves tried to solve a real life problem that prevails in society. It also helped us improve our skills in Annaconda, Numpy, Tensorflow, Keras etc. for development of our project.