Diabetic Retinopathy Detection

Submitted in partial fulfillment of the requirements
of the degree of

Bachelor of Engineering

by

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Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

CERTIFICATE

This is to certify that the project entitled **Diabetic Retinopathy Detection** is a bonafide work of **Aayushi Gandhi (60003170002), Priyanka Shah (60003170045)** and **Rishika Chhabria (60003170050)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of "**Bachelor of Engineering**" in "**Information Technology**".

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Project Report Approval for B. E.

This project report entitled ***Diabetic Retinopathy Detection*** by ***Aayushi Gandhi, Priyanka Shah & Rishika Chhabria*** is approved for the degree of Information Technology.

Examiners 1. ....

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Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Date:

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Priyanka Shah
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Abstract

Diabetic retinopathy is a micro-vascular impediment of diabetes which causes deformities in the retina. It is the main source for the loss of vision and blindness. For effective treatment, early diagnosis of the disease is very important. The existing screening models send all captured retinal images to the hospital via VSAT for evaluation by the expert ophthalmologists. These systems are very costly and cause unnecessary data traffic on the internet as ophthalmologists have to evaluate all received images. We have proposed an automated fundus image analysis system for early stage detection of diabetic retinopathy. Our proposed system captures retinal fundus images of patients by handheld fundus camera. The captured images are accurately classified as normal or with Diabetic retinopathy using image processing techniques. The potential locations of different visual abnormalities associated with Diabetic retinopathy are highlighted on the images. An automated pre-screening system that determines whether or not any suspicious signs of Diabetic Retinopathy are present in an image significantly reduces the workload of experts. The proposed system implements two stage classification. Firstly, it classifies images into Diabetic retinopathy and non-diabetic retinopathy. Secondly, it identifies the potential lesions related to it in the images which are sent to base hospital for expert review. The performance of the proposed method is evaluated using sensitivity, specificity and accuracy

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Chapter 1

1. Introduction

Vision loss due to diabetic eye diseases is on the rise and is expected to reach epidemic proportions globally in the next few decades. Almost all patients with type 1 diabetes mellitus and ~60% of patients with type 2 diabetes mellitus will develop retinopathy during the first 20 years from onset of diabetes. However, DR often remains undetected until it progresses to an advance vision- threatening stage

Diagnosis of pathological findings in fundoscopy, a medical technique to visualize the retina, depends on a complex range of features and localizations within the image. The diagnosis is particularly difficult for patients with earlystage diabetic retinopathy as this relies on discerning the presence of microaneursyms, small saccular outpouching of capillaries, retinal hemorrhages, ruptured blood vessels—among other features—on the fundoscopic images.

In Diabetic Retinopathy (DR) is the most common microvascular complication of diabetes and can progress until a sudden loss of vision occurs. As the number of patients with diabetes is rapidly increasing, the number of retinal images produced by the screening programmes will also increase, which in turn introduces a large labour-intensive burden on the medical experts as well as cost to the healthcare services. This could be alleviated with an automated system either as support for medical experts' work or as a full diagnosis tool. Automated techniques for diabetic retinopathy diagnoses are essential to solving these problems. While deep learning for binary classification in general has achieved high validation accuracies, multi-stage classification results are less impressive, particularly for early-stage disease.

Early detection and prevention of DR are essential to mitigate the rising threat of DR

- The current state of DR screening is based on assessment of colour fundus photographs by a retina specialist leaving a large proportion of patients undiagnosed and therefore receiving medical help too late.

- The objective is to bring portable, easy to administer, reliable, retinal screening to primary doctors' offices and health clinics.

1.1 Motivation / Objective

The amount of the disease spread in the retina can be identified by extracting the features of the retina. The features like blood vessels, hemorrhages of NPDR image and exudates of PDR image are extracted from the raw images using the image processing techniques and fed to the classifier for classification. Portable cameras able to help ophthalmologists have been a desired solution for a long time. Among the reasons for the need of an additional device to support the eye physician, on top of available fixed devices, is the fact that sometimes patients who need the visit of a doctor live in remote areas (or are housebound). In other hard to reach areas, there may be a total absence of any ophthalmologist able to collect medical information from patients. Initial retinal images taken with mobile cameras allow a first screening and first emergency decisions about the patient.

Together with telemedicine infrastructure, such retinal images taken with a mobile camera in remote places are transmitted to the ophthalmologist, who will thus be enabled to declare any pathology which can be assessed from the pictures. This is particularly useful, for instance, when screening cases of diabetic retinopathy: people with diabetes are at risk of developing diabetic retinopathy and therefore, need a regular screening with correct and timely diagnosis without the constraint of a long travel or needless waste of time, either for the eye care professional or for the patient: retinal images taken with mobile cameras are transmitted and analysed remotely, regardless of distance

Nowadays, when we have very good smartphone cameras, it is quite simple to add optics to the mobile device and look through the pupils to capture the retina. However, these settings present also several challenges: first and foremost, hand motion, eye motion and the system itself which is not stabilized like in the clinic.

Next, the optics are not ideal and include lots of artifacts, like shadows and reflections, together with some mist or foggy effect that will reduce contrast and make everything look blurred. Light conditions might also be far from ideal.

1.2 Major Challenges

The objective of this project requires psychologists to play a major role in the building and life cycle of this project. This project also requires the active participation of willing individuals to share their problems anonymously.

This project also deals with a lot of ideas that need to be researched to be able to execute properly. The project deals with a lot of research areas in Natural Language Processing and Deep Learning which is in a preliminary stage. This becomes the core obstacle of the project which we need to overcome to be able to execute the project. Following are the major challenges which need to be tackled for the project lifecycle:

- *Prior Knowledge:* Before the detection begins, the system needs to gather prior knowledge to be able to start the test properly. The challenge lies in comparing the sample test cases and categorizing them as DR positive or negative.
- *Accuracy:* As stated above the current algorithms and tools are too naive to carry out the objective as it gives a very low accuracy. The model needs to correctly analyse and improve its accuracy by tweaking and twisting current techniques.
- *Database Modelling:* There are no predefined datasets or knowledge information on the python question dataset and their answer. Thus, this becomes a big hurdle in creating our database and framing question sets.

1.3 Report Overview

Chapter 2 explores the different existing system. their technologies, motivation, value proposition, their advantages and drawbacks. The literature survey covers the tools used by the systems and the reasons for using those particular tools. The aim behind the literature survey is to give us a reference for creating our product and to make the most feasible and appropriate decision in every stage of the product development.

Chapter 3 explains our methodology for the project. It starts with defining the problem and then the scope of the project. The scope includes the assumption and the different constraints. The chapter then moves onto the project approach. We then move on to cover the functionalities we aim to incorporate in our project. Finally, we cover the benefits of our proposed solution.

Chapter 4 focuses on the project schedule and feasibility of our product. The technical requirements, why they are required, their learning curve, their cost, their developer support have all been taken into consideration. Finally, we estimate the cost of the project using Function Point Analysis and COCOMO Model and also consider Risk Mitigation Planning.

Chapter 5 includes Design Diagrams like DFD, Activity Diagram and Use Case diagram. We also explain the proposed system architecture with the help of a diagram. Our system contains various technologies which is described in this section.

Chapter 6 describes the implemented modules that are built for both company and customer. We have created a system architecture which is explained in this chapter. Along with the description, we also mention the tools that we have used to come up with the desired solution.

Chapter 7 contains implementation details.

Chapter 8 will conclude with a study of the existing system, its risks and further improvements.

Chapter 9 contains information about the future scope.

Chapter 10 contains the information about the review paper based on the system.

Chapter 2

2. Literature Review

In this chapter, we have explored in detail the existing systems similar to the objective of our to-be-developed system. We have reviewed their functioning and operating characteristics if any of them are the same as us. Additionally, we have reviewed our approaches to implement the desired system, algorithms to support those and approaches and technology stack for the same

2.1 Existing Work

2.1.1 Literature Related to Existing Systems

PAPER 1:

In this paper an automated detection system is described to easily and effectively identify the stages of DR. For the detection process the artificial neural network is used that uses the identifier and a wide number of training sets for specific results. They have implemented a method by which mobile phones and 20D or 28D lenses are used to take the retina image, so that the system can be available to any place at any time. The system is developed to provide a method to perform a mobile phone based indirect ophthalmoscopy for the identification of Diabetic retinopathy stages using artificial neural networks and discrete wavelet transform.([1])

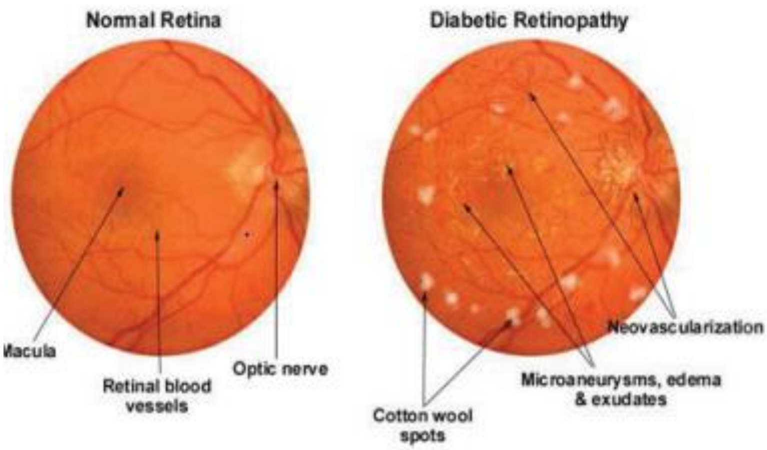


Figure 2.1 1: Retinal image

PAPER 2:

This paper focuses on detection aspects of a mobile application developed to perform DR screening in real time. The application described in this paper is powered by a tensor flow deep neural network architecture that is trained and tested on 16,798 fundus images. The images are pre-processed to remove noise and prepare them to be fed into the neural network. Pre-processing steps involve averaging all the images using a 5x5 filter to improve the quality of images and then these images are resized to 256x256 pixels. After pre-processing the input dataset is fed into the neural network. The convolutional neural network model used in this project is Mobile Nets, which is used for mobile devices. The neural network has 28 convolutional layers and after each layer there is a batch norm and ReLU nonlinear function except at the final layer. The output from the last layer is a class label either DR or no DR. The model was optimized to work on mobile devices and does not require Internet connection to run.[2]

PAPER 3:

A quick inexpensive automatic computer aided DR pre-screening system is needed to efficiently pre-screen patients in a massive fashion to reduce these problems. Nowadays there are many commercial retinal lenses embedded in a camera that can take an image of a retina with a mobile phone. Fig. 1 shows examples of a few lenses made from different companies to work with mobile phones.

Figure 2.1.2: Portable retinal lenses on mobile phones from different companies

A retinal image obtained from a mobile phone usually has a lower quality than that from a standard fundus camera used in the major hospital. The optic disk and the vessels in images from a mobile phone usually have noticeable blurrier edges and fainter colour than those from a standard fundus camera. At the left or right side of the edge of the retina, there may exist a bright region emerging due to external light entered during the time of image capturing. An image produced by a mobile phone with a portable lens normally has a narrower field of view compared to that produced by the standard camera. That means a mobile-phone retinal image can show only limited area in the retinal. Figure 2 shows a close comparison of images taken by a mobile phone with portable lens and a standard fundus camera from the same patient. A dotted circular boundary in the image of a standard fundus camera represents the field of view from a mobile phone.

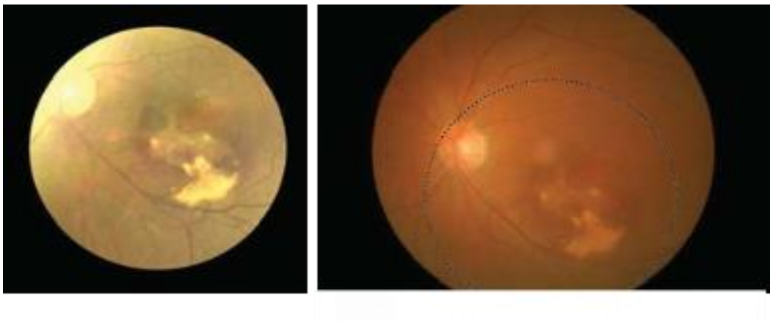


Figure 2.1.3: Examples of a retinal image taken from an Iphone with a portable lens from Volk in view company (left) and a retinal image taken from a standard fundus camera (right) with a mapped field of view from an Iphone shown in a dotted contour.

PAPER 4:

This review paper restricts itself to the recent articles published in last three years, covering the latest techniques for DR detection. Automatic and earlier detection of diabetic retinopathy is an active research area as evident from the increased number of published research articles. A reliable automated detection and screening system for diabetic retinopathy is a desirable goal for the researchers worldwide. In the pre-processing stage, green channel response is the most popular step in reported literature as it reliably provides maximum contrast to distinguish between the microaneurysm, hemorrhages and exudates while histogram equalization and image normalization has equal importance. A significant number of the articles reported employing support vector machine classifiers in the classification stage, demonstrating results.

PAPER 5:

An automatic eye fundus investigation technique using digital fundus images. This modern teleophthalmology system captures retinal fundus images of patients by handheld fundus camera at the screening camp site. The captured images are accurately classified as normal or with DR using image processing techniques. From the campsite, only DR affected images will be sent to expert ophthalmologists through the internet. An automated pre-screening system that determines whether or not any suspicious signs of DR are present in an image significantly reduces the workload of experts. The proposed system implements two stage classification, firstly at the screening camp it classifies images into DR and non-DR, secondly to identify the potential lesions related to DR in the images which are sent to base hospital for expert review. In this paper holo-entropy enabled the decision tree classifier for the classification purpose is implemented. The experimental evaluation is performed on the publicly available database DIARETDB1 as shown below:

Figure 2.1.4: Fundus image. having MA and HM

The proposed system implements two stage classification, firstly at the screening camp it classifies images into DR and non -DR, secondly to identify the potential lesions related to DR in the images which are sent to base hospital for expert review.

2.1.2 Literature Related to Methodology

PAPER 1:

Mobile phones with good camera quality, light-emitting diode (LED) and 28D lens are used in place of fundus camera to take the patient's retina image

The paper describes the methodology as follows:

1. First hold the phone in one hand and lens in other hand then light up the retina by using an LED and take a picture of it.
2. The technique is simple and acts as an indirect ophthalmoscope.
3. The retinal image database which contains images of various diabetic retinopathy signs are collected and analysed.
4. The patient's retina image capture by using a mobile phone along with a condensing lens

5. The image is processed and features are extracted using DWT
6. After finding energies of the query image and database images the sub-bands are compared using the Euclidean Distance Metric.
7. This metric is used by Artificial Neural Network to retrieve the most relevant *images*[1]

The image given below shows the retinal images captured by the smartphone

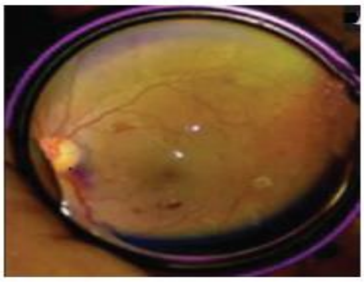


Figure 2.1. 5: retinal images captured by the smartphone

PAPER 2:

The image dataset is using Kaggle's database as shown below. The application was made to do the binary class categorization on the input images that are fed to the application via a mobile camera in real time. The classification category includes: DR and no DR. The image dataset includes 26% of the DR and 74% of no DR images.

Figure2.1. 6: A glimpse of fundus image dataset.

1.Data Pre-processing

Averaging:

The images in the dataset contained noise such as: low contrast, colour variation, and uneven light reflections. To make images more consistent and smooth, a convolution filter of size 5x5 is used. The technique used in averaging is known as **Box blur.**

The images in the dataset contain noise such as varying lighting condition, low contrast, and different sizes. To make the image smooth one can use a 2d convolution filter. The one used in this project is a 5×5 filter:

$$F = \frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

The above filter adds all the pixels that come under it while running over the image and then takes the average of it. After that, it replaces the centre pixel intensity with the new average value. This operation was applied to all the images in the training dataset.

2. Training

After pre-processing the data, was fed into a neural network. The neural network model used in this project is the Mobile Nets, which has 28 convolution layers. The technique used in this project for making the neural network learn the input data is referred to as **transfer learning**. In this technique, a pre-trained network is utilized which was trained with millions of images from ImageNet dataset. This model is stored in the form of a graph file and one can make use of this graph file to generate a new graph file with updated weights and biases. This process is much faster and more efficient than creating a neural network from scratch and try to fit such a large dataset to it can take several days of training and requires high GPU power. After training the neural network model outputs generated were: graph file and class labels. Graph file contains all the nodes and operations that are performed during the training of the network. The whole neural network was built using a tensor flow library that has a built-in tool for removing all the nodes that are not needed for a given set of inputs and outputs.

The developed Android application was tested in real time on test dataset images. Since the test dataset contained images of both categories of DR and no DR, so it was used as source for real time image analysis as one would be capturing image of an actual subject. The application was made to run in real time on test dataset images and images were acquired using the built-in camera of the mobile device. Once an image is captured it is fed into the neural network, which then displays the output label as one of the two classes: DR or no DR. The output is then shown in the form of probability.

PAPER 3:

The flowchart in Fig 3 illustrates our methods for detecting exudates.

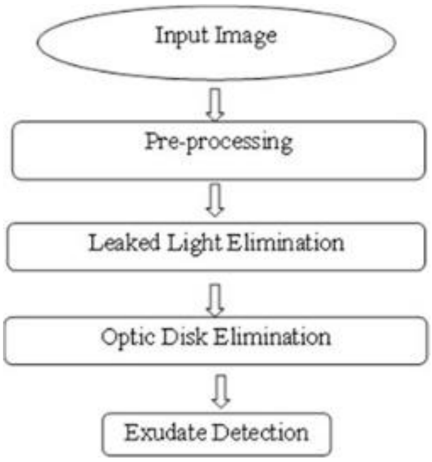


Figure 2.1.7: A flowchart depicting processes for detecting exudates

1. Pre-processing

We mainly use the green channel of RGB space for exudate extraction because this channel offers the best image quality in terms of clarity of details of the retinal components. Fig 1 depicts the retinal images in three different channels.

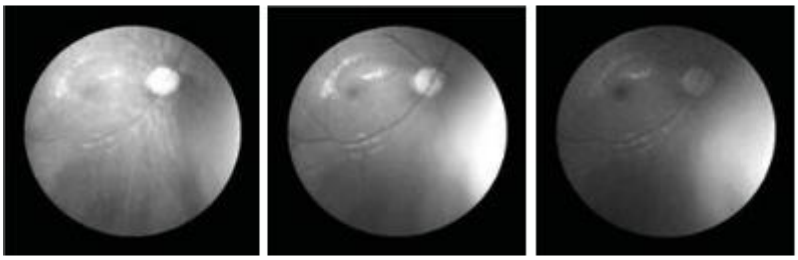


Figure2.1. 8: Examples of images in different channels: red (left), green (middle) and blue (right)

As there can be noise in the image, the median filtering is first applied to remove it. Then the image is converted to gray scale. Next, the contrast-limited adaptive histogram equalization (CLAHE) is applied for enhancing the contrast of the local areas in selected channels.

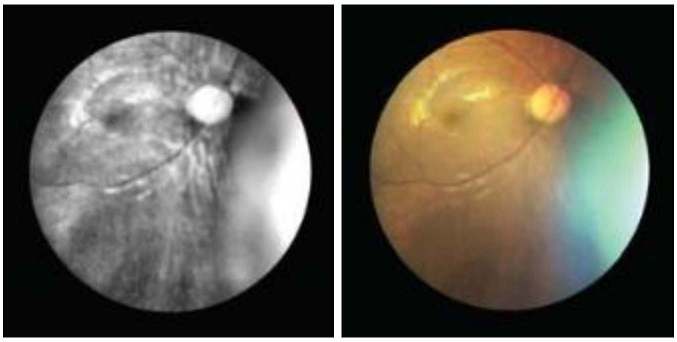


Figure 2.1.9: Examples of a mobile-phone retinal image before (left) and after pre-processing (right).

2.Exudate Detection

2.1 External light region removal

In some cases, as the intensity range of the external light region and exudate are close, the external light region is removed to avoid misdetection. To this aim, the region growing technique is applied. Fig depicts the area of the retina after light correction is done.

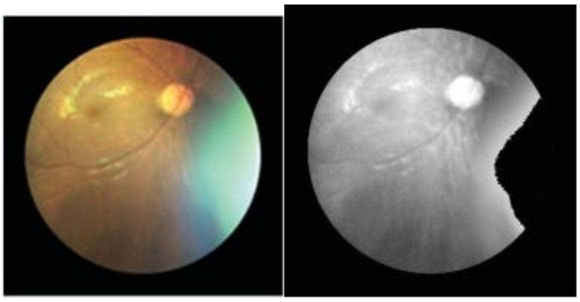


Figure 2.1.10: Excessive light sample image (right) Image after external light removal (left)

2.2 OD removal

Due to the fact that the optic disk (OD) and exudates share the close range of intensity, thus OD elimination is also needed to avoid misdetection. It is worth noting that in case that the OD isn't present in the image, the Mahfouz-Exclusion method can also detect that there is no OD.

The OD region is segmented using the region growing technique with a seed point set to an OD location returned from the Mahfouz-Exclusion method.

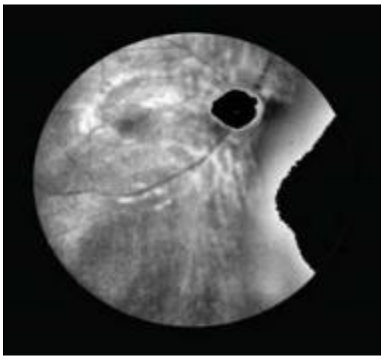


Figure 2.1. 11: Illustration of a retinal image after OD removal

2.3 Bright region classification

At this stage, the image is assumed to contain only regions of interest. As an exudate on a fundus image appears bright or having high intensity in the green channel space, we utilize the Adaptive thresholding method and find all regions having high intensity in the region of interest.

For each region, information on the average intensity and the image average intensity was collected. A collection of such features are split into training and testing sets. A well-known classification method so called Support Vector Machine (SVM) is used to train the feature data in the training set.

2.4 User Interface

For convenience, a Matlab user interface was made so that a nurse or a technical staff can use this system easily. The program consists of a panel to be used to display the input retina image and the result image, has two modes of reading input: single or multiple images, a mode of selection of areas of interest, which in this work is currently only exudate. The program performs the exudate detection, displays the boundary of exudate regions and also shows the number of detected exudate regions in the displayed panel when finished.[3]

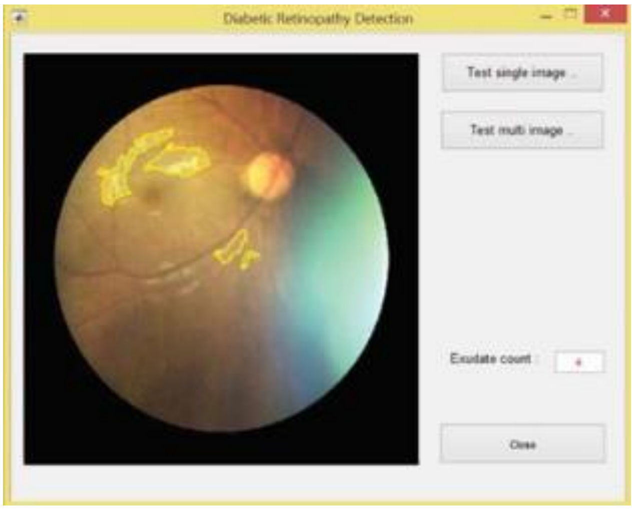


Figure2.1. 12: Matlab User Interface

PAPER 4:

1. Green Channel

Retinal features can be discriminated from each other by utilizing color as a feature descriptor. Pathological signs of diabetic retinopathy like MAs, HMs appear as red spots in RGB fundus images while EXs appear as yellow spots in RGB fundus images.

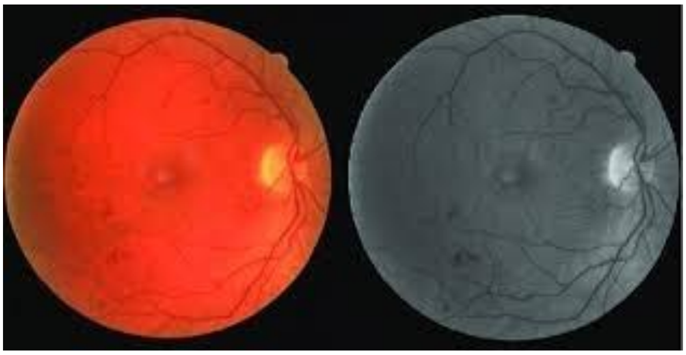


Figure 2.1.13:Green channel of RGB colour space

2. Image Normalization

Image normalization is used to minimize intra-image variability in fundus images. It is proposed that color normalization can be utilized for brightness correction, color modification and contrast enhancement.They investigated that there is a gradual intensity variation in the background from central macular region to periphery region which can affect the process of vessel segmentation.

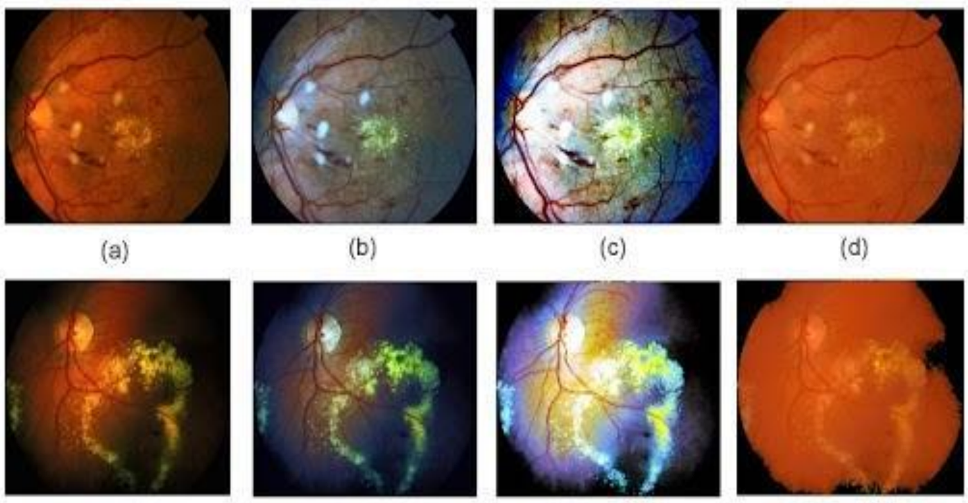


Figure 2.1.14: Image Normalization of retinal images

3. Histogram Equalization

The purpose of histogram equalization is to redistribute the intensity value in the input image so that the intensity values in the output images are uniformly distributed. They utilized histogram equalization in combination with smoothing filters to enhance the contrast of retinal image. They also used contrast limited adaptive histogram equalization (CLAHE) in which local histogram was applied to the distinct sections of input image. In CLAHE, contrast limitation is applied on each neighbourhood pixel which prevents over amplification of noise. Similarly,

Adaptive histogram equalization was utilized for contrast enhancement purposes

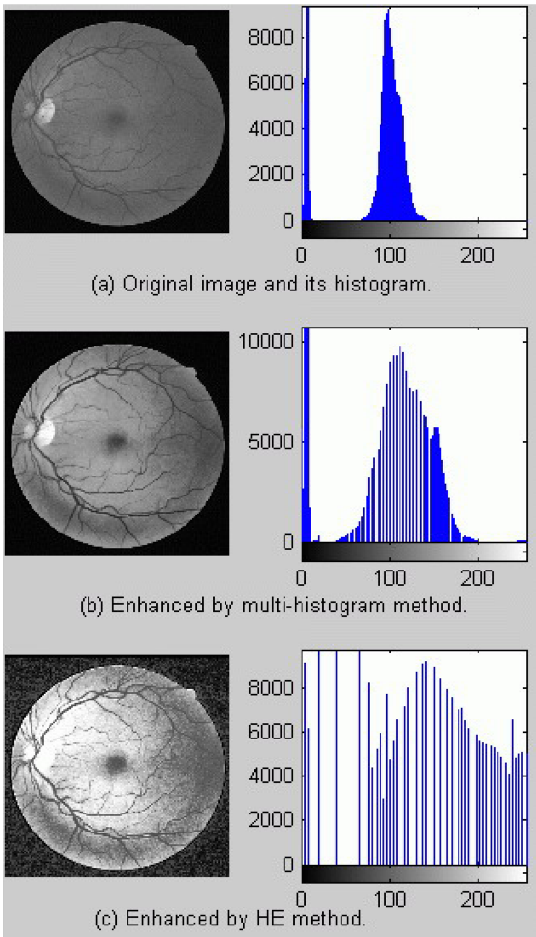


Figure 2.1.15: Retinal Image Enhancement

4. Correction of Non- Uniform Illumination

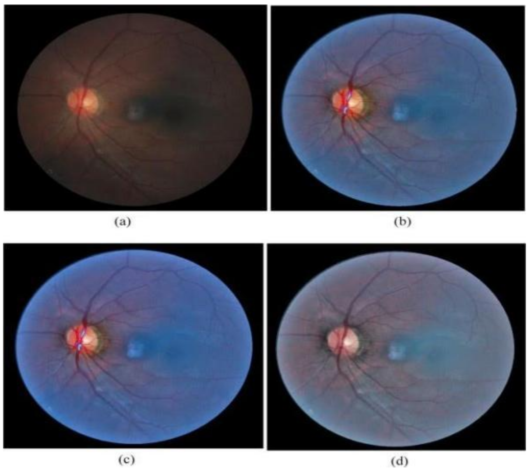


Figure2 .1.16: Non-uniform Illumination correction

Non uniform illumination causes vignetting effects in fundus images reported. Non uniform illumination can alter statistical characteristics of an image and can affect the performance of automated detection of diabetic retinopathy. These effects may not be visible to human observers but can cause problems in feature extraction and classification. The formula used for correction of non uniform illumination:

$$f' = f + \mu d \ \mu i \ (1)$$

2.1.2.5. Morphological Operations

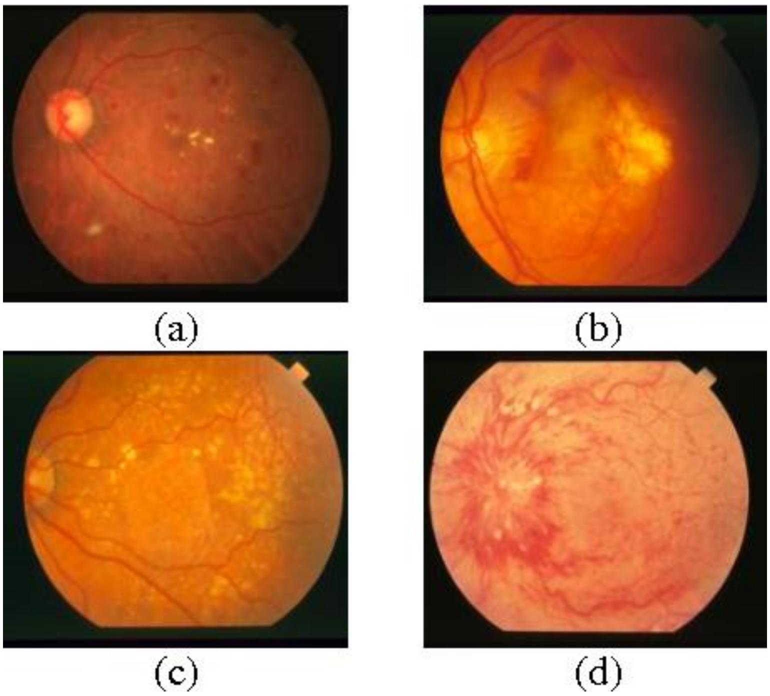


Figure 2.1.17: Morphological Operations performed on an image

They proposed morphological openings for smoothing optic discs and bright lesions. Their proposed approach also utilized to remove bright lesions. They utilized top hat and bottom hat transform for both contrast enhancement and for good prominence of dark lesions with minimal background variations. They also proposed morphological top-hat transform for vessel enhancement[4].

PAPER 5:

The prevention of the loss of vision due to DR is possible only when DR is diagnosed at the early stage. The teleophthalmology system developed was accurate, efficient, low cost, portable and user friendly so that the screening camps can be easily conducted throughout the entire region including rural places. This helped to bridge the gap between physician and patients screening is a helpful method for early detection of DR. The architecture of the proposed modern teleophthalmology system is shown below.

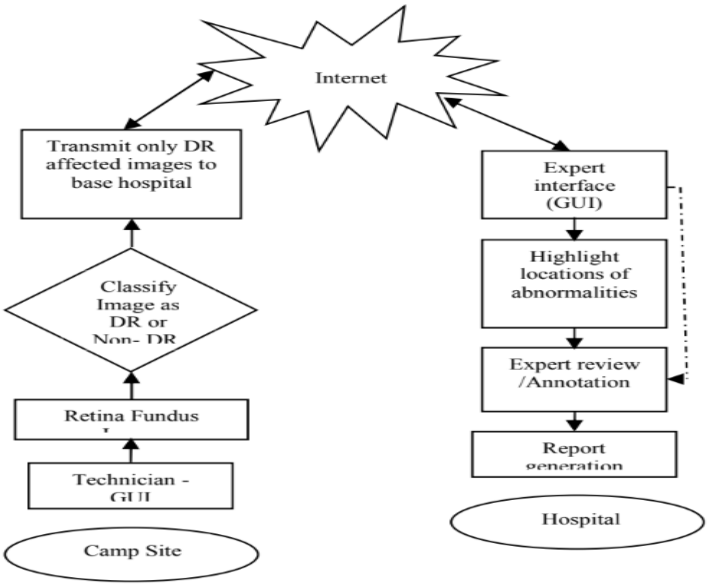


Figure 2.1.18: The architecture of the proposed modern teleophthalmology system

1. Classifications of DR images at screening camp sites

The proposed technique implements the major steps such as pre-processing, optic disc segmentation, blood vessel segmentation, feature extraction and classification.

1.1. Pre-processing**:** Retinal fundus images are pre-processed to make input images suitable for subsequent processes. The retinal colour fundus images are converted to grayscale. The gray scale image is binarized, a low threshold value is fixed for optical disc segmentation. The segmented output is then processed to find whether any disc regions are found out using the initial threshold. If no region is found, the threshold value is increased and the process is repeated until the optic disc region is found out.

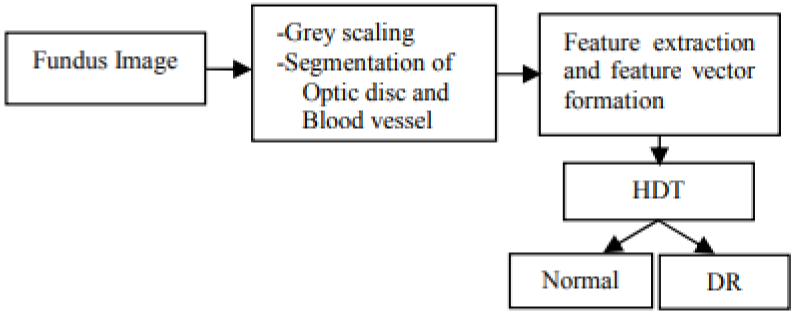


Figure 2.1.19: DR image classification using Holoentropy enabled Decision tree

.

1.2. Hybrid feature extraction: The decision tree develops the system for classification with minimum computational processes. It is constructed using steps such as selection of the best feature as a node, split the feature to progress the tree and finally label the class. The node with the best feature is selected using holo-entropy instead of entropy. The holo-entropy has been calculated for each feature from the feature vector. The feature having highest holo-entropy is chosen as the best feature to construct the decision tree.

1.3. Classification using Holo-Entropy Enabled Decision Tree: The decision tree develops the system for classification with minimum computational processes. It is constructed using steps such as selection of the best feature as a node, split the feature to progress the tree and finally label the class. The node with the best feature is selected using holo-entropy instead of entropy. The holo-entropy has been calculated for each feature from the feature vector. The feature having highest holo-entropy is chosen as the best feature to construct the decision tree.

2. Identification of lesions of DR in images at base hospital

2.1. Candidate MA Region Extraction: The pre-processing of the fundus images is required to improve the quality of an input retinal fundus image. The accurate segmentation of blood vessels is important to decrease the occurrence of false MAs and to improve the overall accuracy of the system. The green plane of the input colour fundus image is selected for further processing. The adaptive histogram equalization is performed to remove brightness variations in the fundus image. The Gabor filter is applied to the pre-processed image for blood vessel enhance.The figure below shows MA detection at base hospital

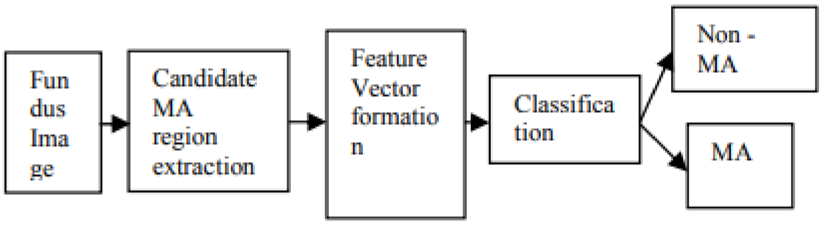


Figure 2.1. 20:MA detection at base hospital

2.2 Feature Vector Formation: The extracted candidate MAs includes both lesion and non lesion regions. GLCM features are used for extracting information related to intensity of the candidate regions. For the wavelet features, first level DWT transforms for 2D images are applied to obtain coefficient matrices for approximation, horizontal details, vertical details and diagonal details sub- bands.

2.3 Classification: The testing set is formed by features of candidates in test input fundus image. All the candidates were individually classified as MAs or Non MAs. The holoentropy enabled classifier is utilized for the classification purpose.

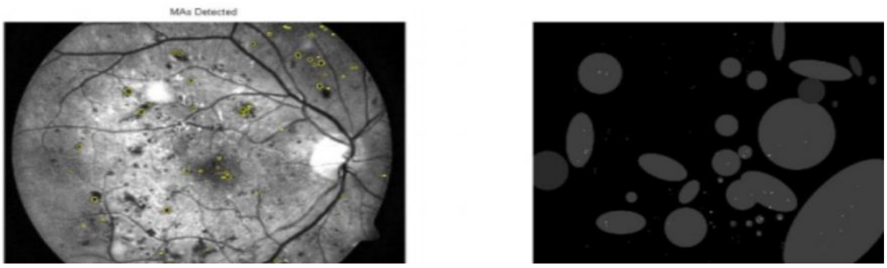


Figure 2.1.21:MAs detected and its ground truth

2.3.1 Literature Related to Algorithms

PAPER 1:

Artificial Neural Network:

An Artificial Neural Networks (ANN) is the processing system which is modelled to simulate the way the human brain analyses the information. ANN is the base of Artificial Intelligence and clarifies the issues that look impossible to solve by human or statistical measurements.

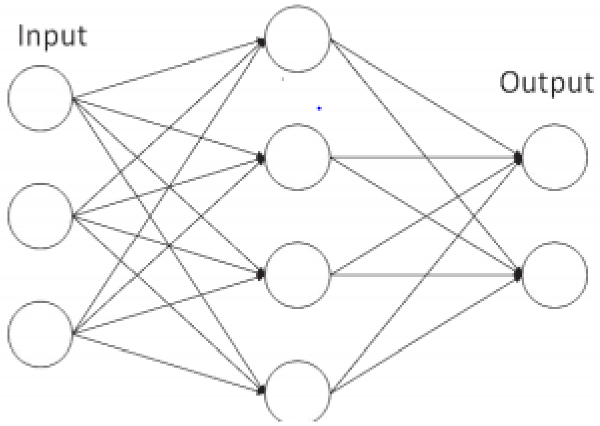


Figure 2.1. 22 :ANN dependency graph

Discrete wavelet Transform

DWT is the multi resolution characterization of an image that decodes constantly from low to high resolution. It divides the image into low and high frequency elements. The high frequency has the information of corner elements and the low frequency is again divided into high and low frequency elements

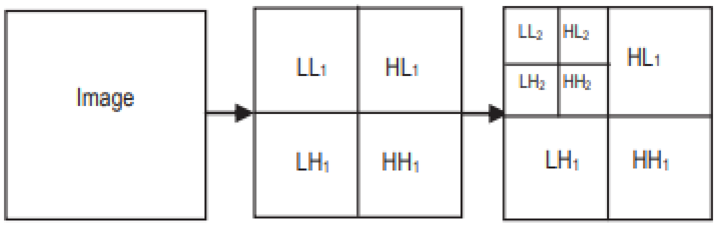


Figure 2.1.23 :Two-level discrete wavelet decompositions

PAPER 2:

MobileNets

1. The utilized neural network architecture is based on MobileNets.
2. This network is built on depth-wise convolution layers which are further divided into depth-wise and pointwise convolution, except for the first layer which is a fully connected layer.
3. Depth-wise convolution is used for applying a single filter on every input channel while pointwise convolution is used to form a linear combination of the output from the depth-wise layer.

$$G_{k,l,m} = \sum_{i,j} K_{i,j,m} \cdot F_{k+i-1,l+j-1,m}$$

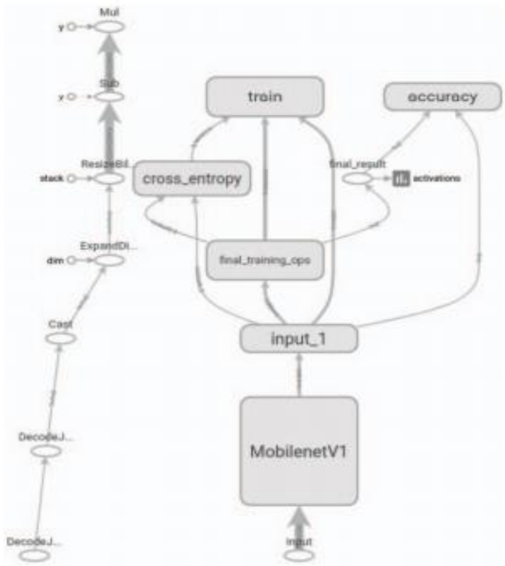


Figure 2.1.24: MobileNets model

Table 1:MobileNets Architecture

Type/Stride	Filter Shape	Input Size
Conv/s2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw/ s1	3 × 3 × 3 × 32 *dw*	112 × 112 × 32
Conv/s1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw/s2	3 × 3 × 64 *dw*	112 × 112 × 64
Conv/s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw/s1	3 × 3 × 128 *dw*	56 × 56 × 128
Conv/s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw/s2	3 × 3 × 128 *dw*	56 × 56 × 128
Conv/s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw/s1	3 × 3 × 256 *dw*	28 × 28 × 256
Conv/s1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw/s2	3 × 3 × 256 *dw*	28 × 28 × 256
Conv/s1	1 × 1 × 256 × 512	14 × 14 × 256
Conv dw/s1 5 × Conv/s1	3 × 3 × 512 *dw* 1 × 1 × 512 × 512	14 × 14 × 512 14 × 14 × 512
Conv dw/s2	3 × 3 × 512 *dw*	14 × 14 × 512
Conv/s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw/s2	3 × 3 × 1024 *dw*	7 × 7 × 1024
Conv/s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool/s1	Pool 7 × 7	7 × 7 × 1024
FC/s1	1024 × 1000	1 × 1 × 1024
Softmax/s1	Classifier	1 × 1 × 2

Output:

- The accuracy of the model comes out to be about 73.3 %
- The sensitivity of the model is 74.5 % and specificity is 63%.

PAPER 3:

The images are taken by using a Volk iNview lens that works with an iPhone camera. The images are in JPEG file format. There are 50 fundus images in the experiments- 25 images have exudates and another 25 has no exudate. The ground truths of exudate regions and the DR screening results for these images are provided by an ophthalmologist. The SVM in exudate classification contains 500 regions and 90% is used for training and 10% is for testing. We also used ten fold cross-validation in order to reduce the bias in the testing setSensitivity where TP, TN, FP, and FN are the number of true positive, true negative, false positive, and false negative, respectively.

Output:

	Percentage
Sensitivity	96
Precision	75
Specificity	68
Accuracy	82

PAPER 4:

1. Classification of Microaneurysm and Hemorrhages

Microaneurysm (MAs) are small red spots which are the first pathological signs of diabetic retinopathy and appear at the earliest stage of this diabetic complication. MAs are caused by dilatation of thin retinal blood vessel . As the disease progresses, the weakened walls of MAs or thin blood vessel may rupture and produce dot hemorrhages and later blot hemorrhages which are the next pathological signs of diabetic retinopathy. They proposed splat features classification for the detection of retinal hemorrhages. Total 357 splat features were used which includes colour, DoG filter bank, Gaussian & Schmid filter bank, local texture filter and area, orientation, solidity, extent of splat.

2. Classification of Exudates and Cotton wool spots

The exudates (EXs) and cotton wool spots appear as white lesions in DR. The thin blood vessels burst in DR causing the formation of MAs and HMs. As the disease progresses, cotton wool spots and hard exudates start to appear on the retinal surface. The patient can lose the central vision if the exudates and cotton wool spot reach the macula and fovea where the central vision is focused.

PAPER 5:

1. Database used: DIARETDB1 is a public database for benchmarking DR detection from digital images used for experimental evaluation. This database covers 89 colour fundus images, of these eighty four images reveal at least mild non- proliferative signs of the DR and the rest of the 5 images are thought to be normal with no signs of diabetic retinopathy. These classifications of images were made by experts. The data is highly associated with practical circumstances and hence, the images are comparable in determining the general performance of diagnostic schemes.

1.1 Holo-entropy Enabled Decision Tree

The decision tree develops the system for classification with minimum computational processes. It is constructed using steps such as selection of the best feature as a node, split the feature to progress the tree and finally label the class. The node with the best feature is selected using holo-entropy instead of entropy. The holo-entropy (HLE) has been calculated for each feature from the feature vector. The feature having highest holo-entropy is chosen as the best feature to construct the decision tree.

$$HLE(attribute_i) = 2\left(1 - \frac{1}{1+\exp(-Entropy(attribute_i))}\right) \times Entropy(attribute_i)$$

The process is executed to all the samples recursively. The labelling of the last node that is leaf node is performed by selecting the group to which the large amount of data fulfilled with the same node. The HDT is formed for the set of training images. The new retinal fundus image is tested against the constructed decision tree by extracting the hybrid features. The final outcome of the testing will be classifying the test image as DR or Non-DR

The splitting of the selected best feature to construct the decision tree has performed by selecting the best possible split. This process is performed by utilizing holo-entropy information gain (HLEIG) and conditional holo-entropy (CHLE)

2.1.4 Literature Related to Technology / Tools / Frameworks

Table 2.1.4: Literature to Technology, Tools and Framework

PAPER 1	PAPER 2	PAPER 3	PAPER 4	PAPER 5
TensorFlow Keras	TensorFlow RMSProp Android Studio 3.1	Matlab user interface TensorFlow Image Processing	Image Processing, TensorFlow	Internet Fundus Camera OpenCV

2.2 Observations on Existing Work

Table 2.2: Observations on Existing Work

Characteristics	PAPER 1	PAPER 2	PAPER 3	PAPER 4	PAPER 5
Dataset	Live dataset using fundus lens	Dataset from Kaggle	Images taken from a hospital	Already existing dataset.	Already existing dataset.
Methodology	Image processing and Deep Learning	Image processing and Deep Learning	Images processing and Machine Learning	Images processing and Machine Learning	Image processing and Deep Learning
Algorithms	Artificial Neural networks (ANN) and Discrete Wavelet Transform (DWT)	MobileNets - Neural network Model	Support Vector Machine (SVM)	Support Vector Machine (SVM) and k-nearest neighbor (k-NN) classifier	Support Vector Machine (SVM)

Advantages	The system can be made available at any time, any place ideal for rural region.	The application can be used for Android devices, Linux and Windows Operating System	High accuracy, quick processing, portability, ease of use, and economy	The system significantly reduces the workload of experts. The system is accurate, efficient, portable and user friendly.	The system significantly reduces the workload of experts. The system is accurate, efficient, portable and user friendly.

Chapter 3

3. Proposed Methodology/ Approach

Diabetic retinopathy (DR) is one of the leading causes of preventable blindness globally. Performing retinal screening examinations on all diabetic patients is an unmet need, and there are many undiagnosed and untreated cases of DR. The objective of this study is to develop robust diagnostic technology to automate DR screening. Referral of eyes with DR to an ophthalmologist for further evaluation and treatment would aid in reducing the rate of vision loss, enabling timely and accurate diagnoses.

A fully data-driven artificial intelligence–based grading algorithm can be used to screen fundus photographs obtained from diabetic patients and to identify, with high reliability, which cases should be referred to an ophthalmologist for further evaluation and treatment.

3.1 Problem Definition

Traditional retinal cameras are expensive, large, immovable and require special training to operate. Without regular check-ups, it is possible that retinopathy may go undiagnosed, which has adverse effects. Hence, a novel, cheaper and convenient approach to capture high definition retinal images and detect the likeliness of DR using deep learning techniques is suggested. A compact mobile phone -based result finding system which helps in early detection of diabetic retinopathy is presented. The use of neural networks and image processing techniques on color fundus images for the recognition task of diabetic retinopathy staging is demonstrated. The retinal images taken with a mobile camera which has a lens mounted on its camera in remote places are transmitted to the ophthalmologist, who will thus be enabled to declare any pathology which can be assessed from the pictures. This is particularly useful, for instance, when screening cases of diabetic retinopathy. People with diabetes are at risk of developing diabetic retinopathy and therefore, need a regular screening with correct and timely diagnosis without the constraint of a long travel or needless waste of time, either for the eye care professional or for the patient. Retinal images can be transmitted and analyzed regardless of distance.

3.2 Scope

- The system is easy to use, and the only hardware requirements are a lens and a smartphone.
- The solutions to various challenges come from image processing techniques.
- It is possible to identify and use automatic focus detection, to find the ideal focus for the image of the eye.
- The scanned images will be processed and the reports will be available to doctors to analyse.
- At the end of the process, an in depth analysis will be performed to provide an insight to the doctor and patient regarding the condition
- We reduce the processing speed and the memory requirements of the entire process.
- We also predict the likeness of the presence or occurrence of other associated complications such as amputations, high blood pressure, glaucoma, etc., which helps the patients to get it tested immediately and take the necessary precautions.
- It will be accessible by any person with or without a medical knowledge, although it is advisable to trust the decision of a medical personnel
- Data will be collected from the patients in real-time

3.2.1 Assumptions and Constraints

The product design is based on following assumptions. System hold the right to change the methodology if any of the assumptions fail to fulfill the requirements.

- The use of a fundus lens is mandatory for the working of this system, as it needs to be mounted on a smartphone to take clear, more accurate retinal images.
- The presence of a smartphone is of utmost importance as the fundus lens needs to be mounted on it, and it is required to apply the algorithms on images.
- An internet connection is also important for the smooth functioning of the system.
- Since Machine Learning tasks require some time for processing, the time required to process each reply cannot be ignored and may affect the real time system.
- Since we require data from people from various medical backgrounds, we rely on their co-operation to do the same.
- We rely on the efficiency and accuracy of the prediction algorithms for predicting other

complications related to diabetes, and state that this is just a prediction based on analysis, and may or may not hold true for every single patient.

3.3 Proposed Approach to build Diabetic Retinopathy Detection

Retinal imaging is the most widely used method for screening due to its high sensitivity. Traditional retinal cameras are expensive, large, immovable and require special training to operate. Hence, we suggest a novel, cheaper and convenient approach to capture high definition retinal images and detect the likeliness of DR using deep learning techniques. In this method, we offer to mount an external lens on a smartphone camera, which can then be used by anyone as per their needs. This lens can take live images of subjects who need to undergo diagnosis. The images taken will then have various image processing and machine learning algorithms applied on it, which will eventually predict the possibility of having the condition.

- *Data Collection*: We will be collecting various samples of images from patients with and without the condition, so that we can predict the possibility of the patient being tested positive on the basis of the dataset.
- *Live testing:* A person who needs to be tested can take their image with the smartphone which has a mounted lens specially for retinal imaging. The diagnosis can be done immediately and effectively.
- *Evaluation report*: A detailed analysis of the patient's condition will be presented. The necessary steps to be taken after a positive diagnosis can be given by the doctor.
- *Predicting other diabetes related complication*s: Our model also compares retinal images of patients with other diabetes related complications and predicts the chances of it occurring for the patient based on comparison of retinal images.
- *Analysis of each process*: After each process is applied on to the image, it provides an analysis of the image at that stage. This helps the doctors differentially analyse each stage.
- *Predicting the level of severity of Retinopathy:* Retinopathy can be broadly classified into 4 levels, namely mild nonproliferative, moderate nonproliferative, severe nonproliferative and proliferative.
- *Accuracy:* The system has an accuracy of ~94% while classifying DR and non-DR, and an accuracy of ~83% when classifying DR into severity levels.

3.3.1 Features of Proposed System

- *Image Processing:* Pre-processing and feature extraction of the diabetic retinal fundus image is done for the detection of diabetic retinopathy using machine learning techniques. The pre-processing techniques such as green channel extraction, histogram equalization and resizing were performed using DIP toolbox of MATLAB.
- *Deep Learning*: A deep learning AI-system applied to a relatively small retinal image dataset could accurately identify the severity grades of diabetic retinopathy and macular edema and that its accuracy was improved by using high resolution and quality images.
- *Classification*: DR is divided into two major forms: non-proliferative and proliferative, named for the absence or presence of abnormal new blood vessels emanating from the retina. These stratifications have been useful for analysis of treatment efficacy in the literature and general indicators for treatment strategies. However, each patient with DR has a unique combination of findings, symptoms, and rate of progression, which necessarily requires an individualized approach to treatment in the effort to preserve vision. Further, level of severity. i.e. classification into 4 levels of DR is also done.
- *Ease of operation*: Presently, ophthalmologists rely extensively on specially trained personnel to capture images using the fundus cameras. Our system simplifies the task of image collection independent of the operator.
- *Portability*: Our compact system is easy-to-deploy on field locations that are hundreds of miles away from specialists. This is unlike present-day heavy equipment.
- *Cost-efficiency*: Existing methods include costs incurred for expensive sophisticated fundus cameras and operating technicians. Our system, on the other hand, uses a low-cost direct ophthalmoscope and smartphone.
- *Convenience*: Any doctor can use this system during a general check-up of a patient to diagnose diabetic retinopathy. It can also be used by a lay-man, although the correct steps to be taken after a positive diagnosis need to be taken by a medical professional

Chapter 4

4. Project Management

In this chapter, the project management aspect of “Diabetic Retinopathy Detection” is discussed. It consists of various artifacts such as task network diagram, timelines as well as feasibility, requirements and project estimation.

4.1 Project Schedule

Project schedule of “Diabetic Retinopathy Detection” is discussed in terms of a task network diagram and a timeline chart with the hierarchy of tasks and subtasks scheduled and divided into modular activities.

4.1.1 Task network Diagram

Here, each task or activity related to the project is named as in terms of TN and A-Z. Each task may comprise of one or more activity node, as well as each task may require previous task as prerequisite activities.

Table 4.1: Task Network Table

Task	**Description**	**Node**	**Prev. Node**	**Next Node**
T_1	Refining UML Diagrams	A,B,C	None	D,E
T_2	Software and Hardware Specification Survey	D,E	A,B,C	F
T_3	Research on preprocessing steps	F	D,E	G
T_4	Implementation of preprocessing steps	G	F	H
T_5	Defining algorithms	H	G	I
T_6	Implementation of algorithms	I	H	J
T_7	Designing UI	J	I	K
T_8	Integrating frontend and backend	K	J	L
T_9	Testing	L	K	M
T_{10}	Documentation	M	L	N

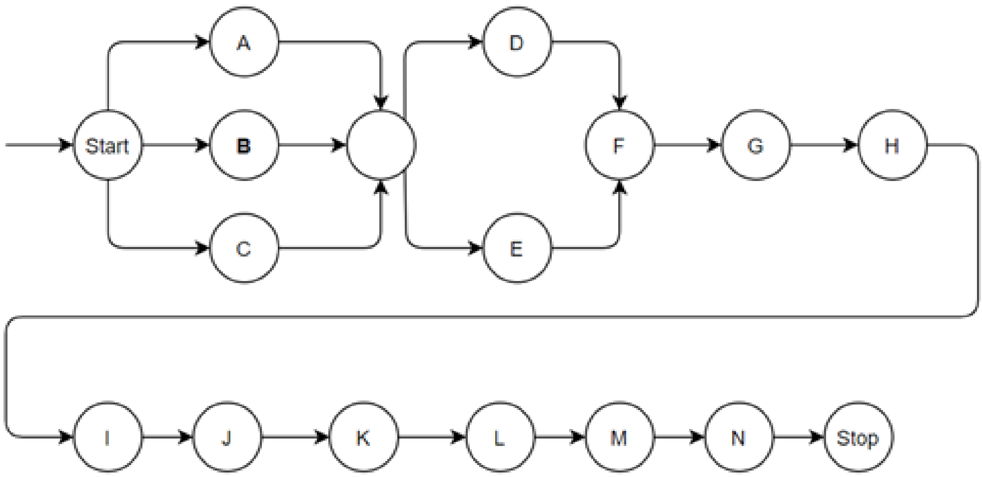


Figure 4.1: Task Network Diagram

4.1.2 Timeline Chart

In this chart, a breakdown of up to 13 weeks in terms of deliverables is given.

Table 4.1.2: Timeline Chart

TIMELINE		**2020**							**2021**					
		JUL-AUG			***SEP-OCT***				***JAN-FEB***			***MAR-APR***		
Deliverables	**Time**	**W1**	**W2**	**W3**	**W4**	**W5**	**W6**	**W7**	**W8**	**W9**	**W10**	**W11**	**W12**	**W13**
UML Diagram	**1 w**													
Refining System Architecture and UML Diagrams	1 w													
Designing Algorithms	**1 w**													
	1 w													

Implementaion	**2w**			■	■									
Preprocessing	1w			■										
Algorithm	1w				■									
Integrating frontend and backend	**2w**					■	■							
Module Creation	**2w**							■	■					
Advanced Features	**1w**									■				
Testing	6w								■	■	■	■	■	■
Unit, integration and beta testing														
Documentation	**1w**													■

4.2 Feasibility Study

4.2.1 Technical Feasibility

Our project suggests a novel, cheaper and convenient approach to capture high definition retinal images and detect the likeliness of DR. In this method, we offer to mount an external lens on a smartphone camera, which can then be used by anyone as per their needs.

This lens can take live images of subjects who need to undergo diagnosis. The images taken will then have various image processing and machine learning algorithms applied on it. We will also be predicting the possibility and likeness of other diabetes related complications. It is based on technologies such as Image Pre Processing, Machine Learning and Deep Learning where significant research is already done. We aim to use existing algorithms as well as generate our own algorithm if need be.

4.2.2 Operational Feasibility

The proposed solution will be of great help to organisations as well as medical camps. The lens can take live images of subjects who need to undergo diagnosis which will help in faster diagnosis and it can also be used by anyone. It is portable and also helps to predict additional conditions and complications. It helps to take measures for other diabetes-related complications as well. Low maintenance as well as cost effective. These challenges may require rigorous research about Image Preprocessing, Deep Learning and Machine Learning techniques to come up with the ideal solution. Our system can run on web platform.

4.2.3 Economical Feasibility

The proposed solution will have low maintenance costs. It includes the cost incurred for sophisticated fundus cameras and operating technicians. The development cost includes only the internet connection charges. The application is available to user free of cost on all the platforms . Overall, this product will be cost efficient.

4.3 Project Resources

4.3.1 Hardware Requirements

The underlying hardware requirement for the computing environment is listed.

Table 7: Hardware Requirements

Hardware Component	Requirement
CPU	Dual Core modern CPU
Primary Memory	Minimum 1 GB
Secondary Storage	Minimum 100 MB

4.3.2 Software Requirements

The underlying software requirement for the computing environment is listed.

Table 8: Software Requirement

Software Component	Requirement
Web	Google Chrome 56+, Firefox 60+, any other browser supporting chromium core.

4.3.3 Operating Requirement

1. Active Internet Connection

2.Browser Supporting ES6 or higher

3. Browser Supporting JavaScript 1.8.5

4.4 Project Estimation

In this section, estimation of the “Diabetic Retinopathy Detection” is calculated using well defined methods such as COCOMO Model and Function Point Analysis.

4.4.1 COCOMO Estimation Model

COCOMO applies to three classes of software projects:

● Organic projects - "small" teams with "good" experience working with "less than rigid" requirements

● Semi-detached projects- "medium" teams with mixed experience working with a mix of rigid and less than rigid requirements

● Embedded projects -developed within a set of "tight" constraints. It is also a combination of organic and semi-detached projects. (Hardware, software, operational...)

The basic COCOMO equations take the form:

- Effort Applied (E) – a_b (KLOC)bb [person-months]
- Development Time (D) = c_b (Effort Applied) db [months]
- People required (P) - Effort Applied / Development Time (count)

Where, KLOC is the estimated number of delivered lines (expressed in thousands) of code for project.

The coefficients a_b, b_b, c_b and d_b are given in the following table:

Table 4.4.1 COCOMO Model

Software Project	**a_b**	**b_b**	**c_b**	**d_b**
Organic	2.4	1.05	2.5	0.38
Semi-detached	3.0	1.12	2.5	0.35

COCOMO MODEL		
	Effort (PM) = ab * (kloc) ^ bb	**Development Time(months) = cb * (Effort) ^ db**
Organic	E= 2.4 * (1.25) ^ 1.05 = 3.03	T = 2.5 * (3.03) ^ 0.38 = 3.81

Basic LOCOMO is good for quick estimate of software costs. However, it does not account for differences in hardware constraints, personnel quality and experience, use of modern tools, techniques and so on.

Effort = 3.03 Person

Months' Time = 3.81 Months

4.4.2 Function Point Analysis

Function point metrics, measure functionality from the user's point of view, that is, on the basis of what the user requests and receives in return. Finally, we have decided to focus on five types of components:

External Input (El): An El processes data or control information that comes from outside the application's boundary. The El is an elementary process.

Elementary process: The smallest unit of activity that is meaningful to the end user in the business

External Output (EO): An EO is an elementary process that generates data or control information sent outside the application's boundary

External Inquiry (EQ): An EQ is an elementary process made up of an input-output combination that results in data retrieval

Table 4.4.2 Function Point Analysis

Category	Multiplier	Weight
EI	5	9
EO	5	10
EQ	5	11

(5*9) + (5*10) + (5*11) = 150 [Function Points]

150*3= 450

The estimate for developing the product would take about 450 hours of work. On an average each member has 10 hours of work.

4.5 Risk Management Mitigation Planning

Table 4.5 Risk Mitigation & Planning

Risks	**Category**	**Probability**	**Impact**
Silent invasions – cyber attacks	Cyber risk	50%	2
Continuously changing company policies	Customer risk	70%	3
Less experienced personnel	Staff risk	60%	2
Maintenance problems	Cyber risk	50%	1

Risk information sheet			
RiskID: HM-02	Date:2/08/20	Prob: 50%	Impact: Critical

Description:
There is a risk of cyber attacks on our systems which can shut down the system and we will loss the valuable data which could lead to financial degrading and trust issues.

Refinement/Context:

- Sometimes it will happen due to lack in protecting the customer details because of staff mistakes
- It could happen due to a weak fire wall or no firewall at all which can attract so many cyber criminals.

Mitigation / Monitoring:

- We will ensure that there is no weak firewall and the backup is taken in regular intervals.
- We will hire a special staff for this risk so that they can monitor the system and warn us even before the risk is created.

Management/Contingency plan/Trigger:

- First, we will restore the system using all the backed-up data so that the company won't be facing any problems.
- Second, there will be immediate action on the incident by informing the cybercrime department so that they can catch the criminal as soon as possible.

Current Status: 4/10/2020: mitigation steps initiated

Risk information sheet			
Risk ID: HM-03	Date: 9/08/20	Prob: 60%	Impact: Critical
Description: There is a risk that some of our staff is still inexperienced on handling the system correctly which may lead to inaccurate predictions and cause inconvenience to the users.			
Refinement/Context: • It could happen because some of our staff is not familiar with the technology. • It could happen because of loss of focus and concentration in doing their work properly.			
Mitigation / Monitoring: • We will ensure that we will hire only that staff which is familiar with the Technology very well. • We will provide proper training to get them acquainted with the system. • We will do weekly or monthly surveys on staff members so that we can replace them with more technological experience people.			
Management/Contingency plan/Trigger: • If we find out about the risk creating a problem, we will immediately act on it and solve it •Organizing seminars and training facilities for staff members to get familiar with the technology.			
Current Status: 10/10/2020: mitigation steps initiated			

Risk information sheet			
Risk ID: HM-04	Date: 14/09/20	Prob: 70%	Impact: Marginal
Description: Continuously changing in company policies is one of the most common risks but can affect the system greatly and can cause huge economic losses.			
Refinement/Context: • The changing requirements are vital for the business not to be avoided as it might had been forgotten or ambiguously mentioned during the requirement process. The requirements might also be changed due to the technology or environment change.			
Mitigation / Monitoring: • The change in requirements is needs to be considered for review either to be accepted or rejected based on its impact on the project. • When the requirements change, change control process has to be followed to find out whether the change affects other requirements, or affects the scope or time or budget of the project. • Depends on its impact, the change can be accepted or rejected.			
Management/Contingency plan/Trigger: • The solution to accommodate the changing requirements is to have regular meeting between the developers and the users during the development process. • Increased user involvement will increase the software quality also.			
Current Status:14/10/2020: mitigation steps initiated			

Chapter 5

5. System Design

5.1 Design Diagrams

5.1.1 Data Flow Diagram

The user launches the camera to take a picture through a fundus camera. Once taken, the image undergoes pre-processing. After applying image preprocessing, the image is trained through a classification model.

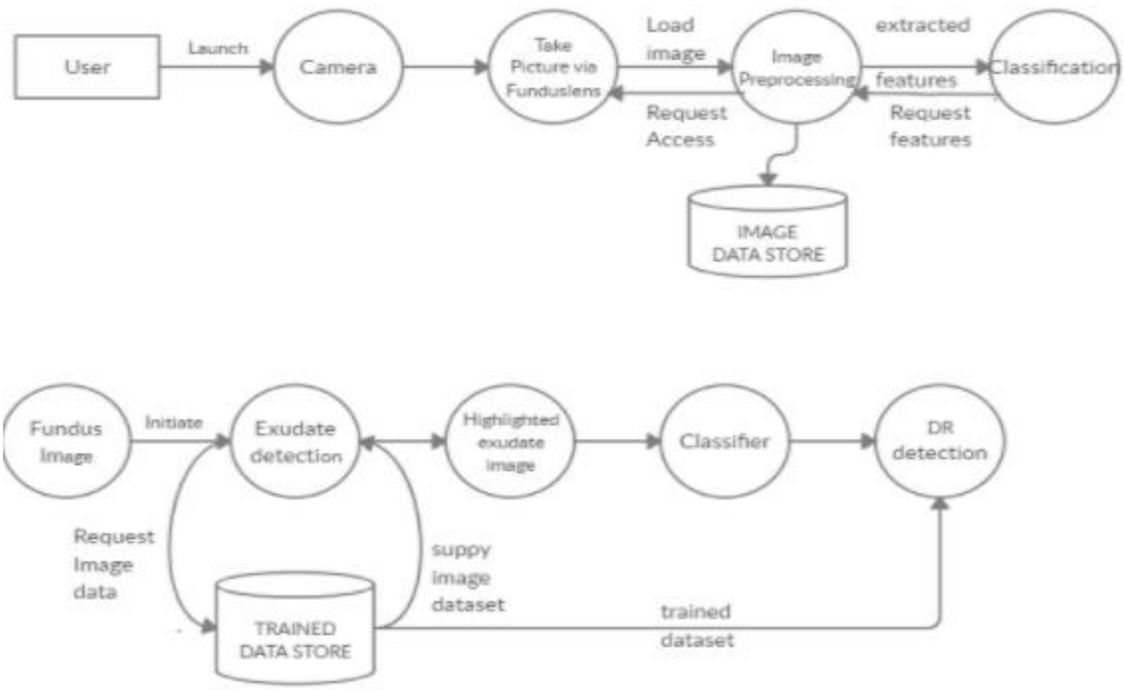


Figure 5.1.1: Data Flow Diagram

5.1.2 . UML Diagrams

5.1.2.1 Use Case Diagram

The system has 2 actors: Local practitioner and patient and use cases like pre-processing of the image, classification, scaling, filtering, getting classified results etc. Figure below conveys the different use cases available for users to interact with or perform on the system. Local practitioners will take the retinal images of the patient using a smartphone The smartphone will have a fundus lens mounted on it. The retinal images are preprocessed using filtering, scaling and are transformed from RGB color format to grayscale format. The dataset undergoes training using machine learning algorithms. Depending upon the accuracy then it is predicted whether the patient has diabetic retinopathy or not. This determines if the patient needs to visit an ophthalmologist or not.

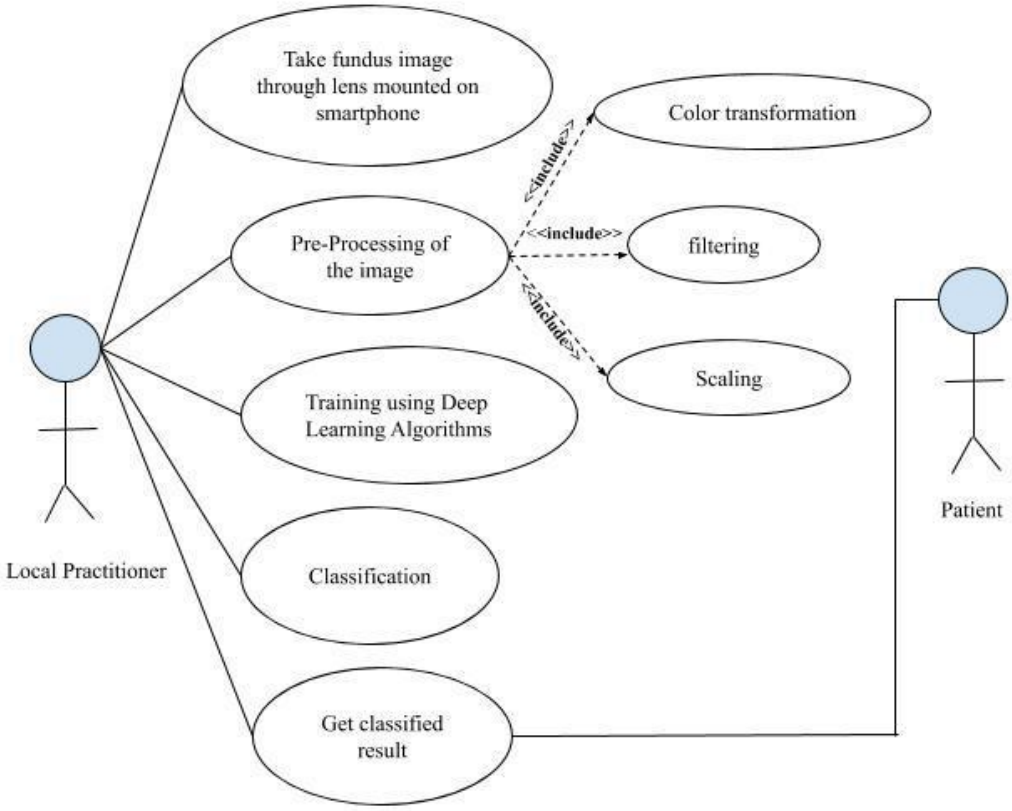


Figure 5.1.2.1: Use Case Diagram

5.1.2.2 Activity Diagram

The activities include data acquisition, image pre-processing, training using neural networks, indexing and retrieval, DR identification etc. It is depicted in below[figure3] activity diagram.

Data acquisition: It is a process of collecting patient's retinal images with the help of the fundus lens mounted on the smartphone.

Image pre-processing: Images are pre-processed using feature extraction, RGB to Grayscale conversion, filtering, noise removal, high and low intensity region identification, image scaling.

The data is trained using neural networks. Output of the neural networks determines whether the patient has diabetic retinopathy or not. If he does then he'll be suggested to visit an ophthalmologist.

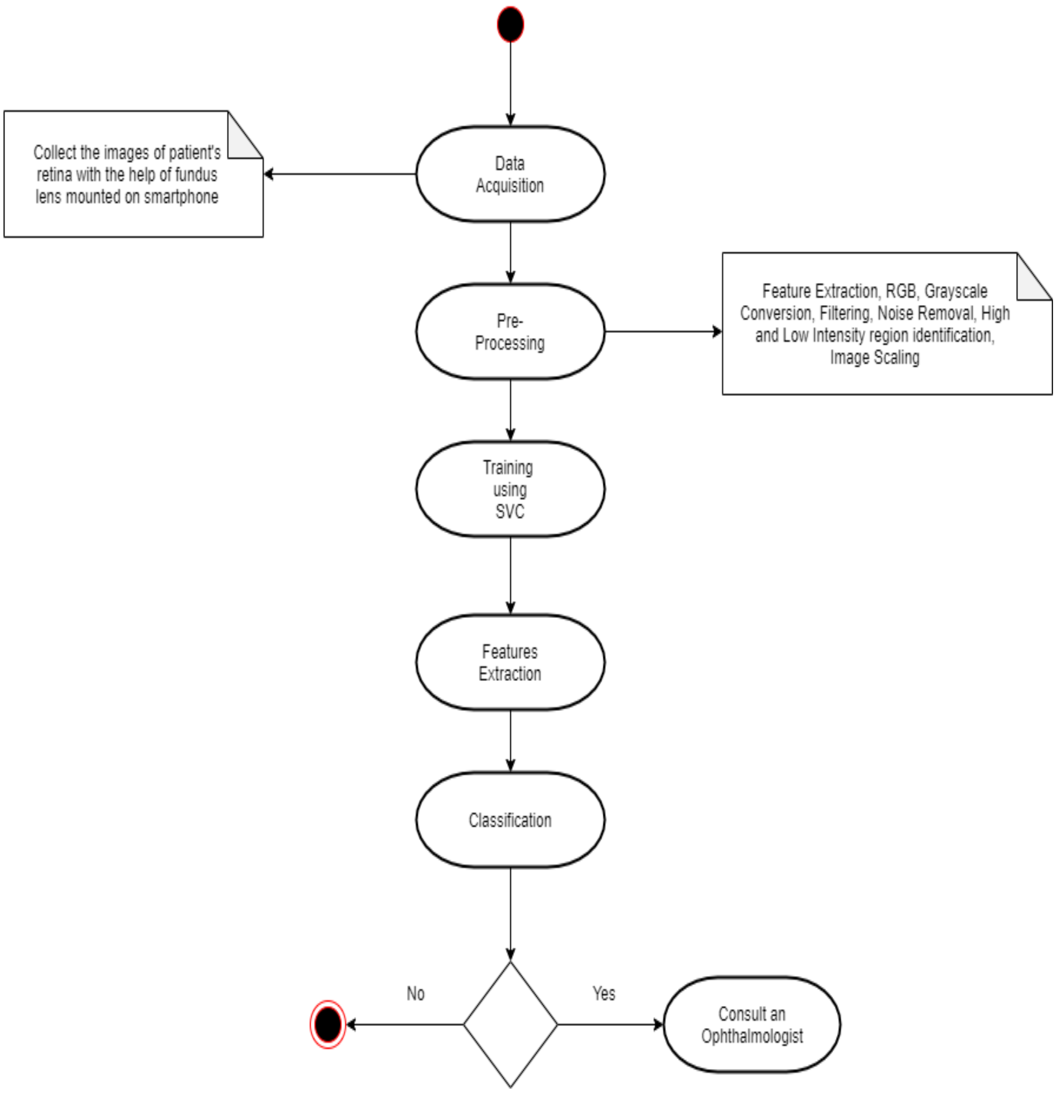


Figure 5.1.2.2: Activity Diagram

5.2 System Architecture

The below diagram is the system architecture of our proposed system. It includes abstract relations with proposed features.

The fundus images will be compiled and preprocessed across various sources into a large-scale data set. The deep learning network learned data-driven features from this data set, characterizing DR based on an expert-labelled ground truth. These deep features will be propagated (along with relevant metadata) into a tree-based classification model that outputs a final, actionable diagnosis. And we use a standard deep convolutional networks CNN where each convolutional layer used batch normalization and the ReLU nonlinearity function to ensure smooth training and prevent overfitting.

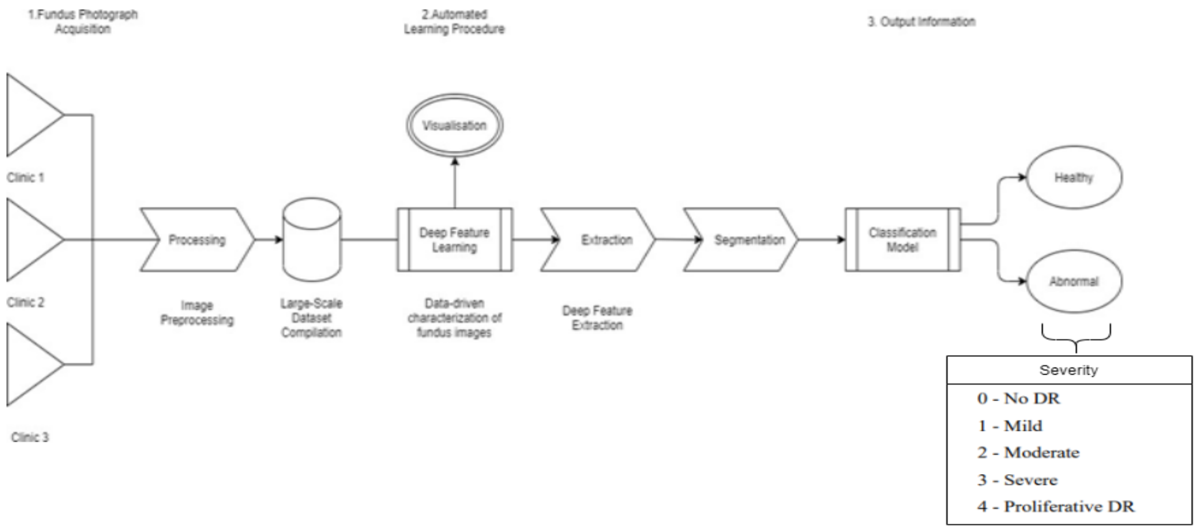


Figure 5.2: System Architecture

1. Data Acquisition

The data set is a set of color fundus images obtained from the clinics. Each image will be associated with a diagnostic label of 0 or 4 referring to DR of any severity, respectively, determined by a panel of medical specialists.

2. Data Preprocessing and Compilation

To account for image variation within our data, multiple preprocessing steps will be performed for image standardization before deep feature learning. Image pixel values will be scaled to values in the range of 0 through 1. Images will be downsized to a standard resolution pixel.

To preprocess images further before learning, data set augmentation methods will be applied to encode multiple invariances in our deep feature learning procedure. Data set augmentation is a method of applying image transformations across a sample data set to increase image heterogeneity while preserving prognostic characteristics in the image itself. Other important characteristics such as the color and brightness of the image (having invariance to varying color contrast between images), can be encoded using brightness adjustment. Grayscale Conversion, Filtering, Smoothening, can also be used depending on the necessity.

3. Deep Feature Learning and Extraction

Our novel approach to feature learning for DR characterization will leverage deep learning methods for automated image characterization. Specific, deep convolutional neural networks will be used for automated characterization of fundus photography because of their wide applicability in many image recognition tasks and robust performance on tasks with large ground truth data sets. These networks use convolutional parameter layers to learn iteratively filters that transform input images into hierarchical feature maps, learning discriminative features at varying spatial levels without the need for manually tuned parameters.

4. Metadata Information

To enhance the diagnostic accuracy of our final prediction, we can append multiple metadata features related to the original fundus image to our feature vector useful in characterizing the original image. Such as original pixel height of the image, original pixel width of the image, and field of view of the original image.

5. Classification Model

To generate a final diagnosis, the feature vector will be trained on a second-level gradient boosting. Gradient boosting classifiers can be used for capturing fine-grained correlations in input features. CNN can be used because of its speed of implementation and robustness against overfitting.

Chapter 6

6. Implementation

6.1. Working of System

Dataset

Our dataset comprises several different types of images. It is mainly classified into DR and non-DR, and DR can be broken down into 4 categories that we discuss later. These images were obtained from the patients using a fundus camera. The dataset consists of over 300 images in the train set and 90 images in the test set. Each image is subject to preprocessing, data-driven characterization of fundus images, deep feature learning and extraction, and image classification. These images have been collected in real-time by a trained professional, and have been sent from a hospital. Each image goes through the above-mentioned stages, and at each stage, the output after the process is displayed.

Working

The system starts from input data sets on which the proposed methods are to be tested. The input image data set contains both normal and diabetic retina images. Initially the user registers himself to the system. If he has already registered, then he logs in. After logging in a form containing the patient's information is to be filled. Along with the form, a patient's retinal image is also uploaded. After which in the backend, the following processes occur. Firstly ,the raw retinal images were resized . Color images are converted to gray scale images which makes the processing task easier.

In the first stage, our aim was to create our dataset. We collected retinal images of patients from the hospital. The hospital sent us two images for each patient, one of each eye. Post that, we subjected the images to some preprocessing algorithms such as filtering and gaussian blurring, etc.

After initial preprocessing of all images, we used some image processing techniques for feature extraction, deep feature learning and segmentation. Image segmentation is an important process for most medical image analysis tasks. For image classification, we have used Support Vector Classifiers. Support Vector classifier is used because of its speed of implementation and robustness against overfitting. It was used to classify images into healthy and abnormal retina, which is basically DR and non-DR. Further, if DR is present, we categorize into one of the 4 levels.

- **Adaptive Histogram Equalization**

After this each of these images was subjected to preprocessing using adaptive histogram equalization in order to remove the nonuniformity of the background. Nonuniform illumination during image acquisition and variation in the color of the eye pigment are two major causes of nonuniformity. The objective of applying adaptive histogram equalization is to assign the intensity values to the pixels in the input image, such that there is uniform contrast across the output image.

```
function AHE(im, win_size)
    for each pixel (x, y) in image im do
        rank ← 0
        contextual_region* ← (win_size × win_size) window centered around (x, y)
        for each (i, j) in contextual_region do
            if im(x, y) > im(i, j) then
                rank ← rank + 1
        output(x, y) ← rank × 255/(win_size × win_size)
    return output
```

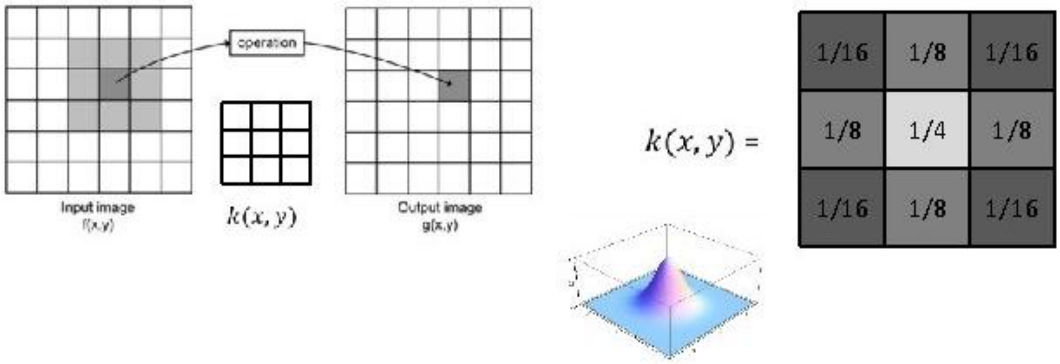
- **Discrete Wavelet Transform**

After histogram equalization was applied, the retina images were ready for analyzing by discrete wavelet transform (DWT) . DWT was used to separate bright objects from the remaining content of the image. Medical images generally need more accuracy without the loss of information.

```
/* Pseudo-code  for the Computation of the
DWT*/

Load Image File();/*input file is Barbara.png*

Initialize Input matrix ();   /* Input matrix   */

Convolution with scaling vector ();/* FDWT *

Down sample by_2 ();

/*Thresholding */

Initialize threshold value ();

Calculate dead value ();

Perform thresholding on the transform
matrix();

Up sample by_2 ();

Convolution with wavelet vectors () ;
/*IDWT*/
```

- **Gaussian Filtering**

We also applied Gaussian Filtering to remove additional noise. it is a standard approach for the separation of the roughness and waviness components with minimal phase distortion. In our case. Gaussian blur softens the image so the features such as veins and exudates stand out more clearly.

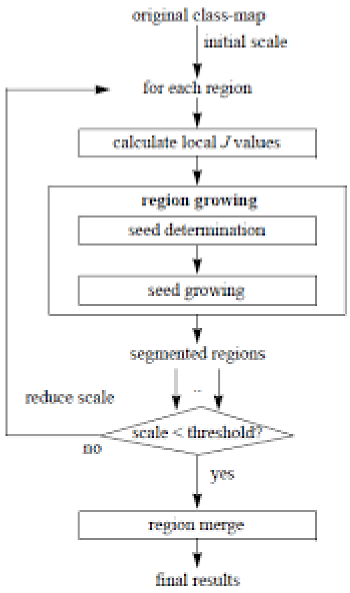


- **Segmentation**

After Image Preprocessing and Feature extraction, the next process to be implemented is Segmentation. Image segmentation is the process of partitioning of an image into meaningful regions. Image Segmentation is the process by which an image is partitioned into various subgroups (of pixels) called Image Objects, This is done to reduce the complexity of the image, and thus simplify the analysing the image. For our project we implemented the Similarity Detection (Region Approach). The information gained by feature extraction is used to measure the similarity between two images. This algorithm takes an input image and clusters pixels of this image that seem to be similar with respect to some feature (e.g. color, texture or shape).

However, Our Target is to have regions of the image depicting the same object. i.e the exudates.

To solve this we use clustering. This helps us in identifying exudates which are divided into Segments. Because of the computational simplicity of the k-means algorithm over other clustering algorithms we decided to use the k-mean clustering in the proposed work. It segments the image into clusters or disjoint groups of pixels with similar characteristics. Basically the data elements get split into clusters such that elements in same cluster are more similar to each other as compared to other clusters.



- **Classification**: **DR or No DR**

For binary classification, SVM was used. It separates the different classes of data by means of a hyperplane. The objective of SVM modeling is to find a separating hyperplane that separates the two classes with an optimal margin. Based on this it detects whether Dr is detected or not. If we take a set of training examples, where each is marked as belonging to one of two defined categories, an SVM training algorithm will build up a model that will assign new examples to one or the other category, making it a non-probabilistic binary linear classifier. The reason why we chose SVM is because It has two advantages: Firstly, it has the ability to generate non-linear decision boundaries using those methods which are designed for linear classifiers. Secondly, use of kernel functions will allow the user to apply a classifier to the data that have no defined fixed-dimensional vector space representation. The training stage consists of a training image set, SVM and a trained model. In the training image set color retinal images will be provided to SVM for training.

SVM trained model compares the features of the test image with the stored values and gives the output as normal or Diabetic retinopathy images.

Accuracy : ~ 94.3%

- **Classification** : **Severity Levels**

A clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale:

0 - No DR

1 - Mild

2 - Moderate

3 - Severe

4 - Proliferative DR

Table 6.1 DR Stages and Severity

DR Stage	Severity
Normal	No abnormalities
Mild NPDR	Lesions of micro-aneurysms, small areas of balloon- like swelling in the retinas blood vessels.
Moderate NPDR	Swelling and distortion of blood vessels.
Severe NPDR	Many blood vessels are blocked, which causes abnormal growth factor secretion.
PDR	Growth factors induce proliferation of new blood vessels inside the surface of the retina, the new vessels are fragile and may leak or bleed, scar tissue from these can cause retinal detachment.

Convolutional Neural Networks (CNN) is an architecture of Artificial Neural Networks (ANN) mostly used for image classification. CNN adds some more operations to regular Neural Networks like convolution, nonlinearity, and sub-sampling. CNNs mainly has two parts: the first one is the feature extraction part and the second one is the classification part. In the first part, a series of convolution and pooling operations are performed for feature detection. For producing a feature map, using a filter, the convolution operation is applied. This feature map will contain negative pixel values and it should be replaced with zero. For that, a non-linear operation is performed after performing every convolution. Nonlinearity is introduced using Rectified Linear Unit (ReLU). In the classification part, on top of these extracted features fully connected layers will act as classifiers. They assign a probability for the object on the image. When these images are too large, the pooling operation continuously reduces the dimensionality. This is done for reducing the number of computations and parameters in the network. This reduces training time and controls overfitting. Spatial pooling also called subsampling or down sampling which retains the most important information. Spatial pooling is mainly in three types: Max pooling, Average pooling, and Sum pooling. The largest element from the rectified feature map is taken in max pooling. In sum pooling, the sum of all elements in the feature map is taken. It is also possible to add as many convolutional layers.

In our system, we designed CNN and developed a system that classifies different stages of DR from the color fundoscopic images. The classification is done based on the severity of five DR stages. For this classification, deep learning-based CNN networks is deployed. From the past, many medical studies were conducted on the field of designing a algorithm to classify DR from a retinal fundus image. But they were just binary classifiers which only differentiate two stages of DR including Normal and DR affected.In this work, we check the prediction accuracy of different deep convolutional neural network architectures and the combination of these networks when they are deployed as a DR stage classifier. The study was done based on the dataset collected from hospital which contains 300 images of retinas.

Accuracy : ~ 83.3%

6.2 Algorithms / Tools used

Image Processing Algorithms:

It is used to perform some required operations on given images, in order to get an enhanced image and to extract some useful information from it.

1. **Gaussian Filter**: Gaussian filter enhances the vascular pattern, especially thin, less visible vessels, also smoothens the background. It enhances the visibility of exudate. Overall it helps in better feature extraction

2. **Adaptive Histogram Equalization**: We initially chose Histogram Equalization because it improved the contrast in images by spreading out the most frequent intensity values. This method usually increased the contrast of images when the data was represented by close values. However on applying histogram equalization, the histogram is not evenly spread , So to overcome this, we used AHE. The background contrast improved after histogram equalization, but we lost most of the information due to over-brightness. This was because its histogram was confined to a particular region. So to solve this problem, adaptive histogram equalization was used.

3. **Discrete Wavelet Transform**: In this project, we have used the discrete wavelet transform (DWT) method to extract the important features. In DWT, we have used the Haar transform because Haar wavelets are fastest to compute and simplest to implement. DWT helps to capture the variations (blood vessels, and exudates etc in the image successfully.

Algorithm Analysis:

After Image preprocessing and Feature extraction, the next process to be implemented was segmentation. Image segmentation is the process of partitioning of an image into meaningful regions. In this process the image is partitioned into various subgroups (of pixels) called Image Objects, This is done to reduce the complexity of the image, and thus simplify the analysing the image For our project we implemented the Similarity Detection (Region Approach)This algorithm takes an input image and it clusters the pixels of that image which seem to be similar with respect to some feature (e.g. color, texture or shape).However, our target was to have regions of the image depicting the same object. I.e detection of the exudates. So, In order to infer the exudates from segments we used Clustering This helped us in identifying exudates which were divided into segments. Because of the computational simplicity of the k-means algorithm over other clustering algorithms we decided to use the k-mean clustering in our project .

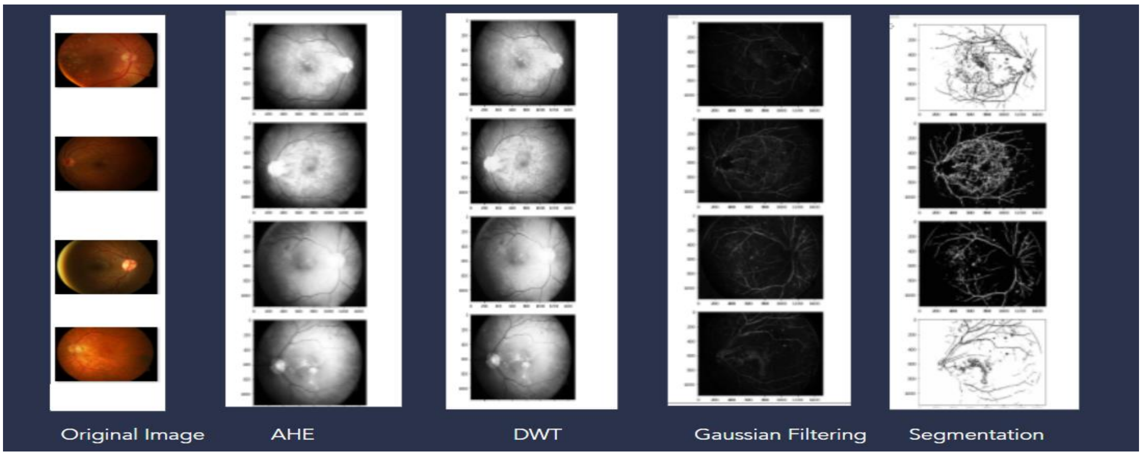


Figure 6.2: Images subjected to different processes

Model Training:

After Segmentation comes the Model Training part. During our literature survey, we came across two major type of training approaches: (Convolutional Neural Network) CNN and(Support Vector Classifier) SVC. On analysis we found out that the accuracy of CNN was very less as compared to SVC. The reason being the size of our dataset which was

comparatively less than it is required for the neural network to function accurately. Due to this it was training the same batch of images over and over and hence it was not able to distinguish between Dr and non Dr images. On the other hand, SVC gave an accuracy of around 94 %.With respect to our dataset, SVM gave a good accuracy since the number of observations required to train an SVM isn't high. Also SVMS are generally fast to train as compared to CNN Since in NN the training takes place on the basis of the batches of data that feed into it, CNN performed poorly.We also implemented K NN algorithm, However the accuracy of KNN was almost close to that of SVC with very less difference

6.3 Interface Design

The UI has been designed for a local practitioner to whom patients can go and get their retina check for the possibility of Diabetic retinopathy along with other illness.

The first page on entering the system is the registration page where the user has to enter the details

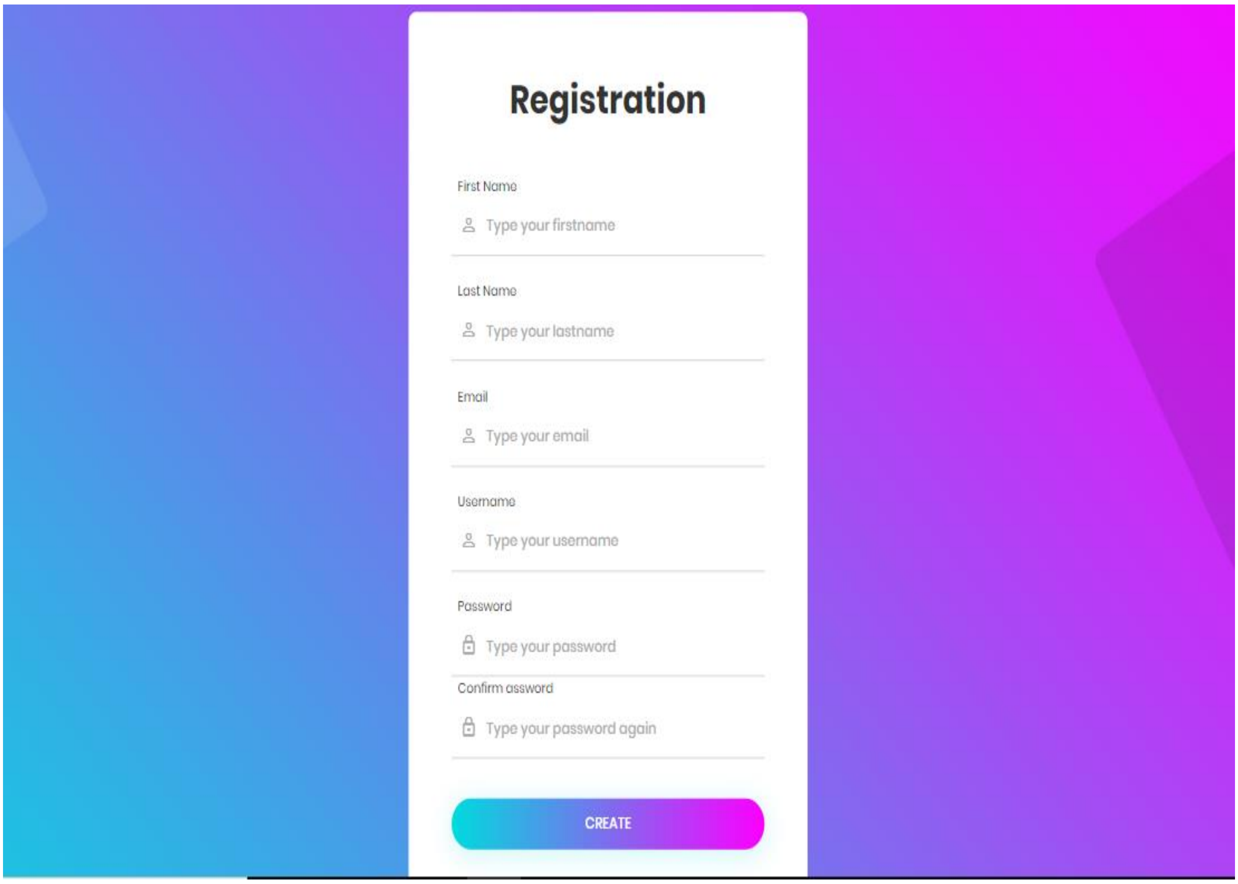


Figure 6.3.1: Register Page (Web)

After registering, the user Logs In

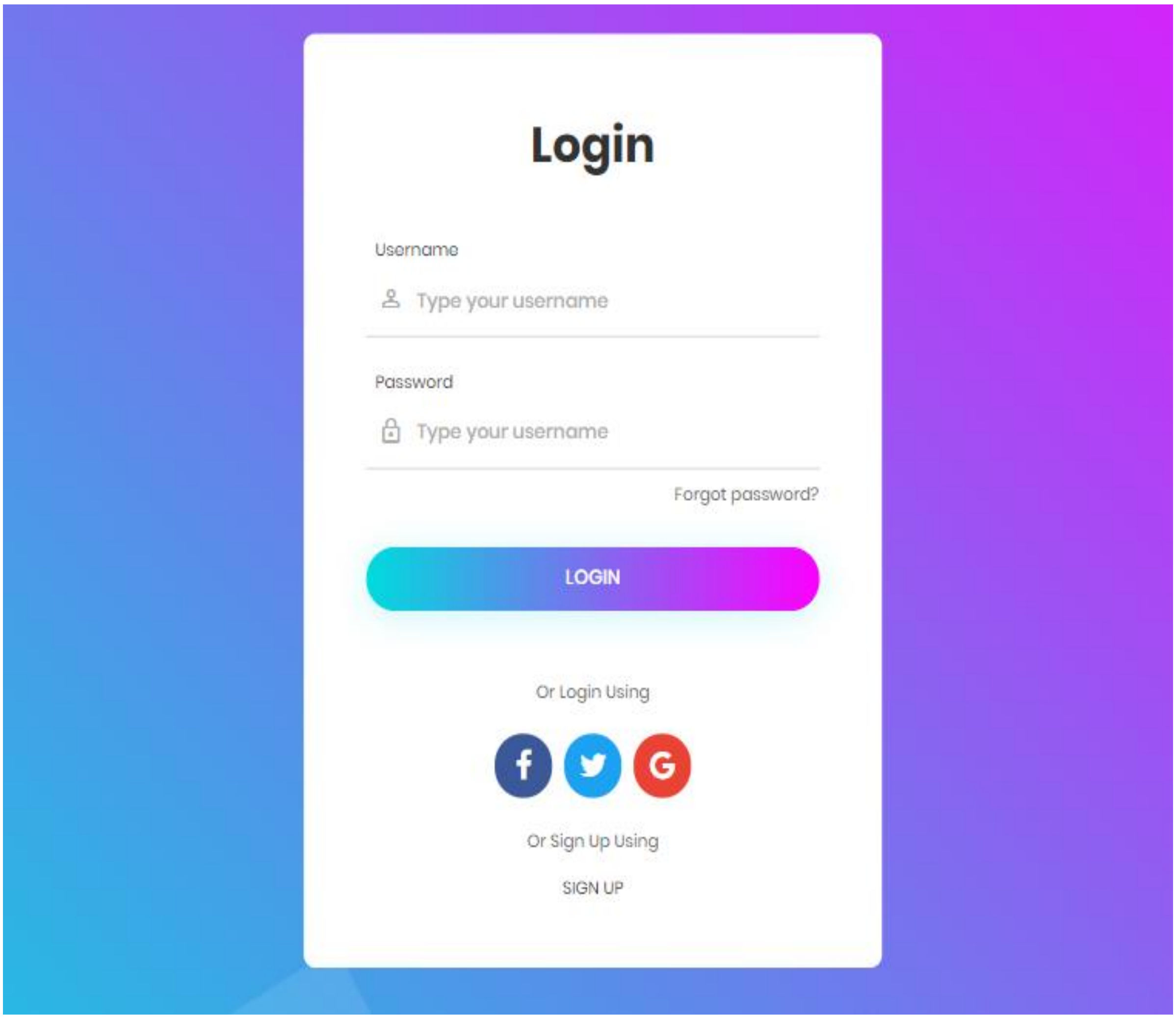


Figure 6.3.2: Login Page

After logging In, a form containing patients Details has to be filled. Along with other details, his retinal image also has to be uploaded. After uploading the image, the result is displayed.

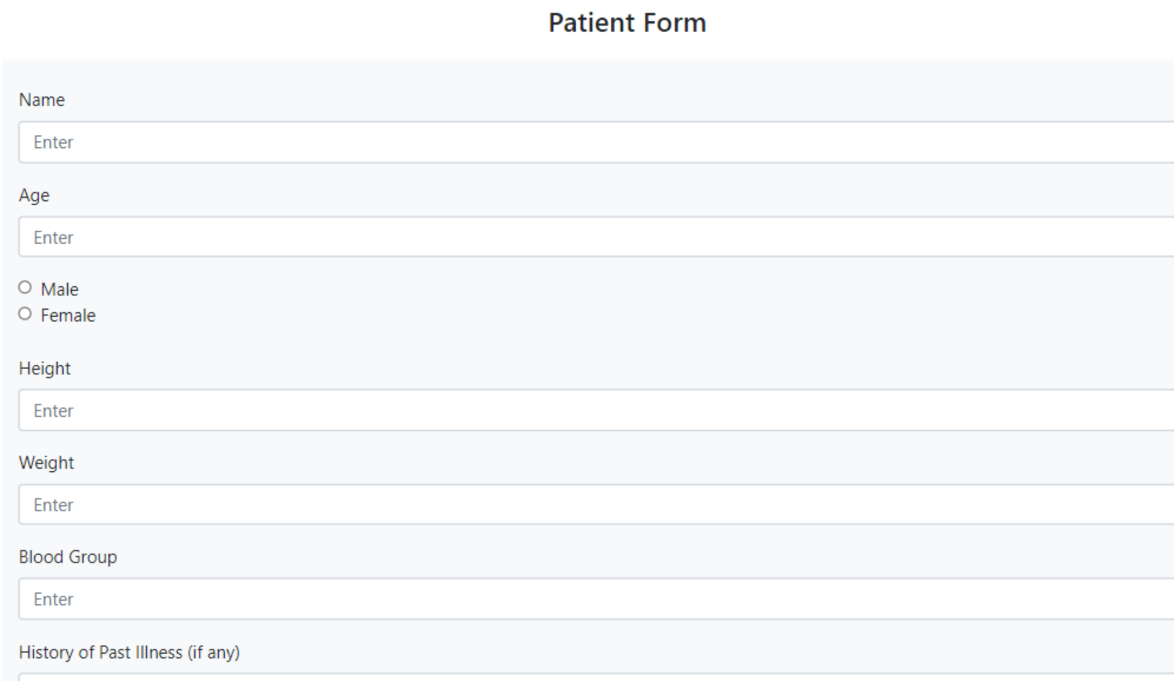


Figure 6.3.3: Patient's Details Form

Figure 6.3.4: View Result Pag

The screenshot below shows an In Depth Analysis of the backend process which includes Image Pre-Processing and Classification.

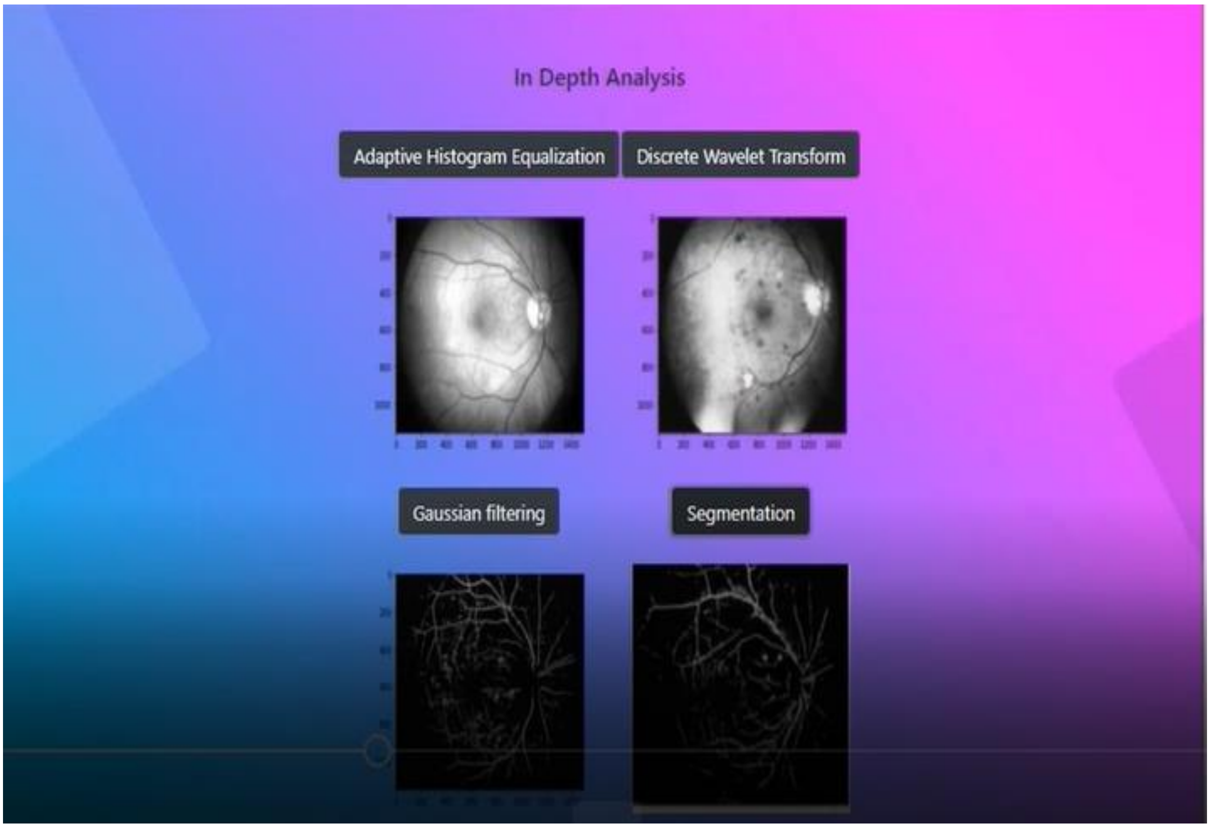


Figure 6.3.5: In- Depth Analysis

Chapter 7

7. Testing and Experimental Results

7.1. Test Plan

Testing

1. Introduction

Testing is the process of evaluating a system or its component(s) with the intent to find whether it satisfies the specified requirements or not. In simple words, testing is executing a system in order to identify any gaps, errors, or missing requirements in contrary to the actual requirements.

Our testing plan is as follows:

1. Data Evaluation Methods: Data to be used for analysis and prediction purposes is thoroughly checked for it to be obtained via fundus camera to ensure accurate results. This includes collecting live fundoscopic images from Aditya Jyot Eye Hospital, Wadala.
2. Design Verification Or Compliance Test : This testing was performed during the development and approval stage of the product on each of the modules.
3. Acceptance Or Commissioning Test: This testing was performed at the time of delivery and installation of the software.
4. Module Testing: Individual modules used in this system are tested for both reliability and functioning.
5. Test Methods: Various test methods were employed to check the system's functionality and accuracy depending upon the requirements of users, features included and processes necessary for performance. Each method had its own test cases designed and their output was compared to a standard system.
6. Test Responsibility: The team members working on their respective features performed the testing of those features. Test responsibilities also include the data collected and how that data was used and reported.

1.1 Purpose of The Test Plan Document (Objective)

The goal of this test plan is to help form a layout for the testing process that needs to be performed on the projects. This includes identification of areas that require testing, deciding on testing methodologies and their flow along with time that needs to be allocated to each method. Risk, constraints, requirements, assumptions are also decided upon.

References:

Documents and links, including the following:

- Literature survey
- Existing system literature
- Past semester documentation

1.2 Items to be Tested

Item to Test	Test Description	Test Date	Responsibility
Login /Sign Up page	Test for user registration and account creation	07/02/2021	Aayushi Gandhi
Image preprocessing Results	Testing the output for IP module	14/02/2021	Aayushi Gandhi Priyanka Shah
Image uploading and output	Testing the results associated with the image uploaded	14/02/2021	Priyanka Shah
Severity Detection Module	Testing the Severity of DR	21/02/2021	Rishika Chhabria
Integration of the System	Testing the integration of ML and IP algorithms with Django	28/02/2021	Rishika Chhabria

1.3 Test Approach(s)

Module(s)	Test Approach
Login /Sign Up page	Account was created and the user was made to Login
Image Preprocessing Module Severity Detection Module	Images were uploaded and their corresponding output was checked in the output

1.4 Test Regulatory / Mandate Criteria

Images should by only fundoscopic retinal images

1.5 Test Pass / Fail Criteria

- The pass/fail criteria for each test item(feature) would depend on the performance and result provided by each component of the system.
- A feature would pass the test if the actual result produced matches the expected standard results.

1.6 Test Entry / Exit Criteria

- Testing must be suspended in case of anomalies being detected such as missing or unclean data, glitches in banking transactions.
- Testing would only be resumed if a feasible solution is determined or an equally appropriate alternative is found out

1.7 Test Environmental / Staffing / Training Needs

Testing for each component of the system requires a different environment. They are listed as follows:

- Deep Learning and Image preprocessing- Windows/MAC with python 3.0 or above and a 2GB graphics card minimum.

- User Interface - Windows/ MAC with python 3.0 or higher to support a Django server.

All the above also require a fully functioning internet connection and the devices being used to test them need to be present on the same network. Functional testing of the system requires the individual to be proficient in programming languages such as python and HTML, CSS Javascript, Bootstrap

2. Test Planning

2.1 Test Schedule

*Task Name	Start	Finish	Effort
Test Planning	Feb 25	Feb 28	3 days
Review Requirements documents	Feb 25	Feb 27	2 days
Create initial test estimates	Feb 27	Feb 28	1 day
Staff and train new test resources	Feb 28	Mar 2	2 days
First deploy to QA test environment	Mar 2	Mar 6	4 days
Functional testing – Iteration 1	Mar 6	Mar 8	2 days
Iteration 2 deploy to QA test environment	Mar 8	Mar 11	3 days
Functional testing – Iteration 2	Mar 11	Mar 14	3 days
System testing	Mar 16	Mar 25	9 days
Regression testing	Mar 26	Mar 30	4 days
UAT	Mar 30	Apr 4	6 days
Resolution of final defects and final build testing	Apr 4	Apr 7	3 days
Deploy to Staging environment	Apr 8	Apr 9	1 day
Performance testing	Apr 9	Apr 17	8 days

7.2. Test Cases

7.2.1 Functionality Test

Table 7.2.1 Functionality Test Cases

Test Case Id	Test scenario	Test Steps	Test Data	Expected Results	Actual Results	Pass/ Fail
FT01	Check response when valid username and password is entered	1) Enter username 2) Enter Password 3) Click Sign in	Username : rishika24 Password: rish@2406	Login should be successful	Login was successful	Pass
FT02	Check response when a new user is registered	1) Enter firstname,lastname 2) Enter Email 3) Enter username 4) Enter Password and confirm Password 5) Click Sign up	1)Rishika Chhabria 2)rishikac@gmail.com 3)rishika24 4)rish@2406	Sign Up should be successful	SignUp was successful	Pass
FT03	Check Image upload	1)Fill in patient details 2)Upload image 3)Cluck submit button	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female 3)IVL_10_NOZER_MORENA_46_Male 4)IVL_27_AYAN_PATEL_42_Male 5)IVL_32_MADHURI_DESAI_50_Female	Image should be displayed	Image is displayed	Pass Pass Pass Pass Pass

FT04	Check In Depth Analysis Outputs	1)Click the respective analysis button to view the output image	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female 3)IVL_10_NOZER_MORENA_46_Male 4)IVL_27_AYAN_PATEL_42_Male 5)IVL_32_MADHURI_DESAI_50_Female	Output images should be displayed	Images are displayed	Pass Pass Pass Pass Pass
FT05	Check results (DR/no DR)	1)Click submit button after uploading the image	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female 3)IVL_10_NOZER_MORENA_46_Male 4)IVL_27_AYAN_PATEL_42_Male 5)IVL_32_MADHURI_DESAI_50_Female	1)DR detected 2) No DR detected 3) DR detected 4) No DR detected 5) DR detected	1)DR detected 2) DR detected 3) DR detected 4) No DR detected 5) No DR detected	Pass Fail Pass Pass Fail
FT06	Check Severity level	1)Click submit button after uploading the image	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female 3)IVL_10_NOZER_MORENA_46_Male 4)IVL_27_AYAN_PATEL_42_Male	1)1: Mild DR 2)0;Normal 3)2:Moderate DR 4)0: Normal	1)1: Mild DR 2)1:Mild 3)2:Moderate DR 4)0: Normal	Pass Fail Pass Pass

			5)IVL_32_MADHURI_DESAI_50_Female	5)1: Mild DR	5)0: Normal	Fail
FT07	Gray-Scale Conversion	-	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female	Converted grayscale image is displayed	Converted grayscale image is displayed	Pass Pass
FT08	Adaptive Histogram Equalization	-	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female	Converted ADE image is displayed	Converted ADE image is displayed	Pass Pass
FT09	Discrete Wavelet Transform	-	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female	Converted DWT image is displayed	Converted DWT image is displayed	Pass Pass
FT10	Gaussian Filtering	-	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female	Converted GF image is displayed	Converted GF image is displayed	Pass Pass
FT11	Segmentation	-	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female	Converted segmented image is displayed	Converted segmented image is displayed	Pass Pass
FT12	CNN (severity detection)	-	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female	Correct Severity Detected	Correct Severity Detected Wrong Severity Detected	Pass Fail

7.2.2 User Interface Testing

Table 7.2.2 User Interface Test Cases

Test Case Id	Test scenario	Test Steps	Test Data	Expected Results	Actual Results	Pass/Fail
UIT01	Display error when unregistered user tries to login	1) Check if the user is registered. 2) If yes, lead to the login page. 3) If not, lead to the sign up page.	Username: Aayushi Password : aayushi123	Display error ; user not found	Displays error; user not found. Asks user to register	Pass
UIT02	Verify that only 1 radio button must be selected and more than single checkboxes may be selected.	1) In the option to select Gender or Other complications, try to select more than one option		Select only one option	Only a single option is selected	Pass
UIT03	Verify that error messages are generated when an unacceptable field type is entered	1) In a text field for numeric value, if invalid argument i.e. non-numeric value is entered then display an error message	Age = fifty	Error message asking to enter numeric value	Error message asking to enter numeric value	Pass
UIT04	Verify that the page text must be properly aligned.	1) Check alignment of all fields in the form		All fields in the form should be aligned and uniform	All fields in the form are aligned and uniform	Pass
UIT05	Field labels should be universally	1) Check that basic detail fields such as		Field accepting the user's		Pass

	standard and understandable	First name, Last name, Age, etc. are titled correctly.		first name should be labeled properly as ‘First Name’.		
UIT06	Verify that the form is dynamic and readable in different window sizes	1) Change the size of the window and check the form alignment	Registration form	As we change the size of the window, the form elements rearrange to keep the visibility simple.	Field accepting the user's first name is labeled properly as ‘First Name’. As we change the size of the window, the form elements rearrange to keep the visibility simple.	Pass
UIT07	Verify that the user can conveniently upload the image for testing	1) Click on upload image button in the form	Upload image	The form has a unique button that can fetch the image and store to the database.	A window displaying images occurs from which the user can fetch the desired image.	Pass

7.2.3 Integration Test

Table 7.2.3 Integration Test Cases

Test Case Id	Module Tested	Test scenario	Test Steps	Test Data	Expected Results	Actual Results	Pass/ Fail
IT01	Frontend and Login Database	Check if user enters valid data to sign in.	1) Enter username 2) Enter Password 3) Click Sign in	Username : rishika24 Password: rish@2406	Login should be successful	Login was successful	Pass

IT02	Frontedend and Login Database	Display error when unregistered user tries to sign in.	1) Check if the user is registered. 2) If yes, lead to the login page. 3) If not, lead to the sign up page.	Username: Priyanka Password: Priyanka12	Error as user is not found.	Ask user to register.	Pass
IT03	Fronted and Login Database	Register a new user.	1) Enter firstname,lastname 2) Enter Email 3) Enter username 4) Enter Password and confirm Password 5) Click Sign up	1)Priyanka,Shah 2)priyanka@gmail.com 3)priyanka 4)priyanka12	Sign Up should be successful	SignUp was successful	Pass
IT04	Frontend and Database	Fill in the patients details.	1)Enter name, gender,age 2)Enter height,weight 3)History of past illness	1)Priyanka Shah,F,21 2)5’2 , 52 3) -	Should generate error messages are generated when an unacceptable field type is entered	Error messages are generated when an unacceptable field type is entered	Pass
IT05	Frontend and Database	Check if correct data is getting saved in the database.	1)Enter details 2) Upload image		Entered details should show a correct entry in database	Entered details show a correct entry in database	Pass

IT06	Preprocessing Module and Frontend	Check In Depth Analysis Outputs	1)Click the respective analysis button to view the output image		Output images should be displayed	Images are displayed	Pass
IT07	Deep Learning Module and Frontend	Check results (DR/no DR)	1)Click submit button after uploading the image	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female 3)IVL_10_NOZER_MORENA_46_Male	1)DR detected 2) No DR detected 3) DR detected	1)DR detected 2) DR detected 3) DR detected	Pass Fail Pass
IT08	Severity	Check Severity level	1)Click submit button after uploading the image	1)IVL_18_PARAG_SHAH_48_Male 2)IVL_13_VARSHA_CHAUDHARY_47_Female 3)IVL_10_NOZER_MORENA_46_Male	1)1: Mild DR 2)0;Normal 3)2:Moderate DR	1)1: Mild DR 2)1: Mild 3)2:Moderate DR	Pass Fail Pass

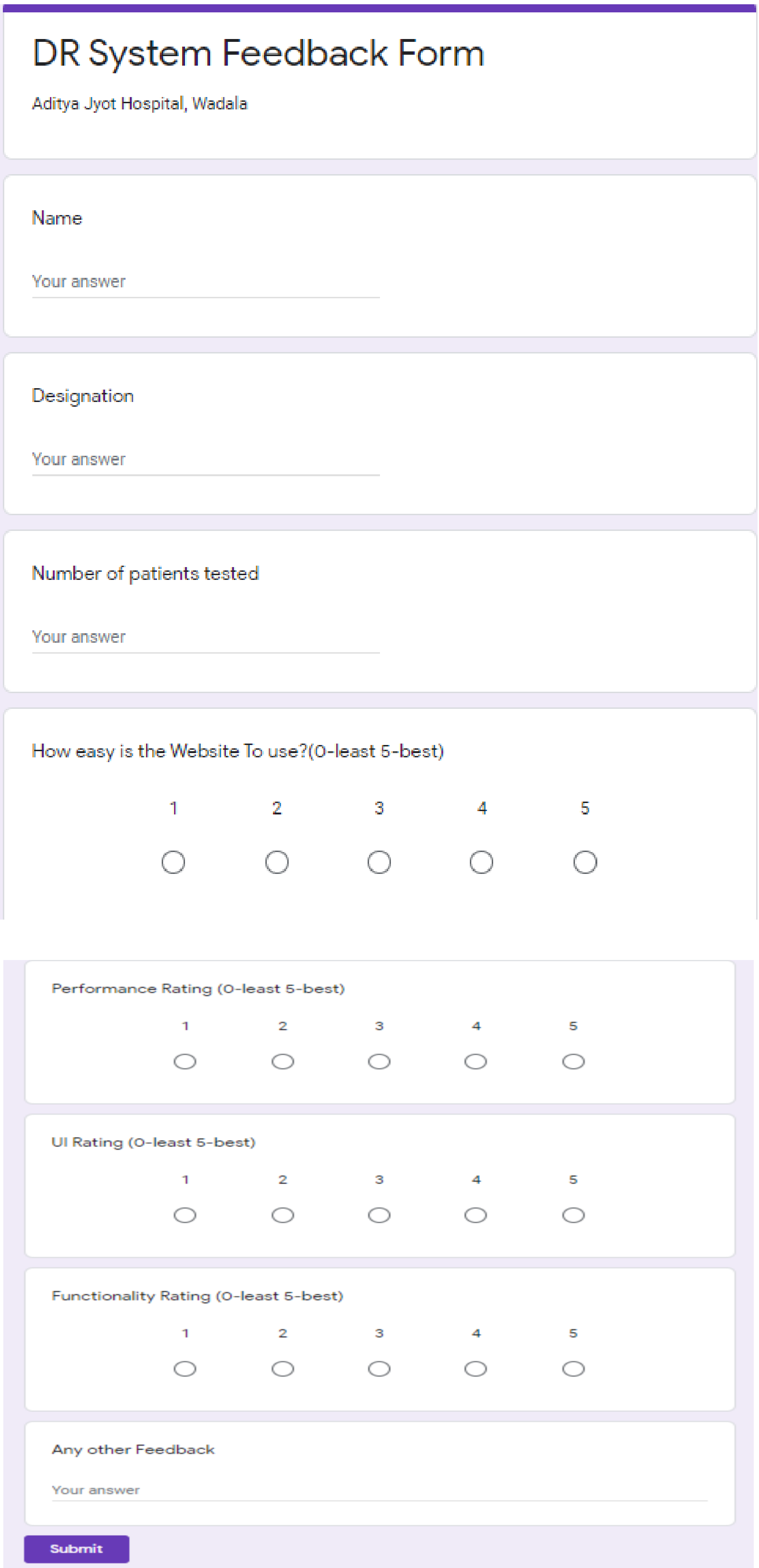
7.2.4 Usability Test Cases

Table 7.2.4 Usability Test Cases

Test Case Id	Test scenario	Test Steps	Test Data	Expected Results	Actual Results	Pass/Fail
UT01	Availability of Information	Patients Details and image uploading	Images uploaded by the user	Images and Results are displayed	Images and Results are displayed	Pass

UT02	Account Creation and Login	Fill-out signup/login form	User details	Signup successful	Signup Successful	Pass
UT03	Learnability of users to adjust to the system	Via Feedback form	Via Feedback form	Easy to learn the system	Easy to learn the system	Pass
UT04	Subjective User Satisfaction	Via Feedback form	Via Feedback form	Satisfied	Satisfied	Pass

Below is the feedback form that was sent to the Hospital. We received feedback from 3 doctor, 2 being Diabetologists and 1 being an Ophthalmologist.



DR System Feedback Form

Aditya Jyot Hospital, Wadala

Name

Your answer

Designation

Your answer

Number of patients tested

Your answer

How easy is the Website To use?(0-least 5-best)

1 2 3 4 5

Performance Rating (0-least 5-best)

1 2 3 4 5

UI Rating (0-least 5-best)

1 2 3 4 5

Functionality Rating (0-least 5-best)

1 2 3 4 5

Any other Feedback

Your answer

Submit

Fig:7.2.1: DR system Feedback Form

The graph shown below is the response received from the Hospital via the feedback form shown above. The system was tested under the guidance of doctors. Each of them performed the testing on the images and gave us ratings/feedbacks accordingly.

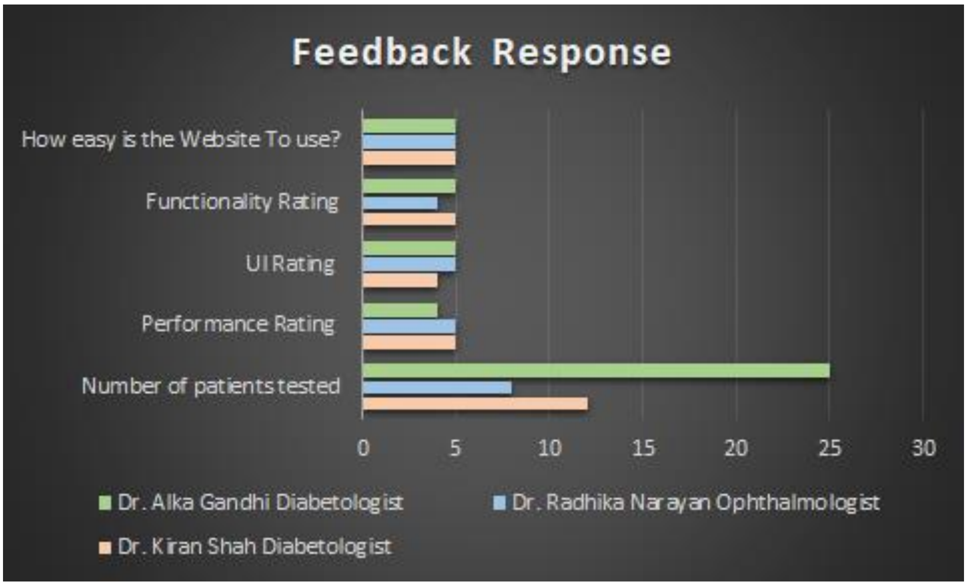


Fig:7.2.2: DR system Feedback Response

7.3. Testing methods used

Testing methodologies are the strategies and approaches used to test a particular product to ensure it is fit for purpose. Testing methodologies usually involve testing that the product works in accordance with its specification, has no undesirable side effects when used in ways outside of its design parameters and worst case will fail-safely (e.g. a nuclear reactor will shut down on failure).

Software testing methodologies are the different approaches and ways of ensuring that a software application in particular is fully tested. Software testing methodologies encompass everything from unit testing individual modules, integration testing an entire system to specialized forms of testing such as security and performance. The testing methods employed by us are as follows:

1. Unit Testing: This type of testing is performed by developers before the setup is handed over to the testing team to formally execute the test cases. Unit testing is performed by the respective developers on the individual units of source code assigned areas. The developers use test data that is different from the test data of the quality assurance team.
2. Integration Testing: Integration testing is defined as the testing of combined

parts of an application to determine if they function correctly. Integration testing can be done in two ways: Bottom-up integration testing and Top-down integration testing. We make use of bottomup testing where components in the lower hierarchy are tested first to facilitate testing of higher modules.

3. System Testing: System testing tests the system as a whole. Once all the components are integrated, the application as a whole is tested rigorously to see that it meets the specified Quality Standards. This type of testing is performed by a specialized testing team.
4. Regression Testing: Whenever a change in a software application is made, it is quite possible that other areas within the application have been affected by this change. Regression testing is performed to verify that a fixed bug hasn't resulted in another functionality or business rule violation. The intent of regression testing is to ensure that a change, such as a bug fix should not result in another fault being uncovered in the application.
5. Usability Testing: Usability testing is the practice of testing how easy a design is to use on a group of representative users. It usually involves observing users as they attempt to complete tasks and can be done for different types of designs, from user interfaces to physical products. It is often conducted repeatedly, from early development until a product’s release.
6. User Acceptance Testing: User acceptance testing is done to ensure that the requirements laid down by the user are met and each requirement has a satisfactory implementation. There are 5 types of user acceptance tests - Alpha & Beta Testing, Contractual Testing, Regulation Acceptance Testing, Contractual Acceptance Testing, Black box testing, Operational Acceptance Testing

Testing Results

The graph shown below shows the Severity Analysis of the Test images. 90 images after testing were analysed in the following manner: 29 images were perfectly normal images detecting NO DR, 18 images belonged to mild category, 22 images belonged to moderate category, 15 images belonged to Severe category, 29 images belonged to Proliferative Category.

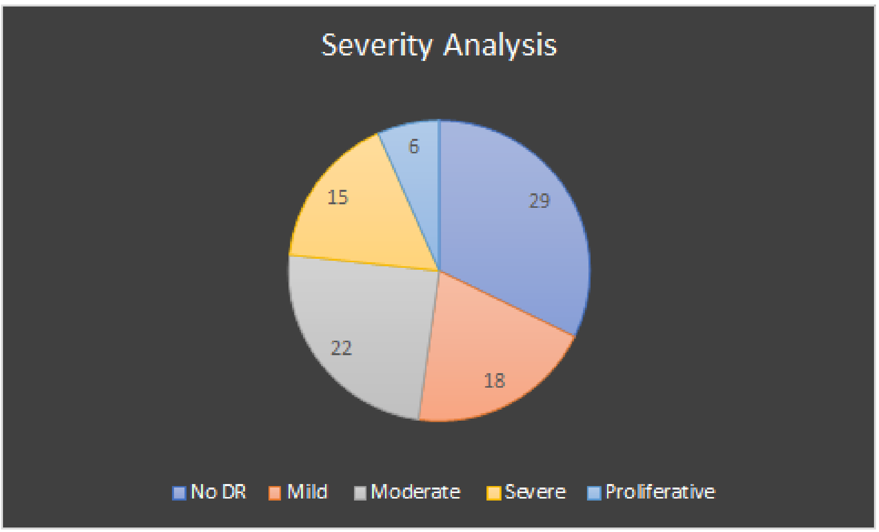


Fig:7.3.1 :Severity Analysis.

The graph shown below shows the Overall Testing Analysis. Out of 90 images tested, 75 images passed the testing criteria and 15 images failed. Testing Criteria was basically correct detection of images into severity levels. The results were tallied with the severity category datasheet received from the hospital and accordingly conclusion was made.

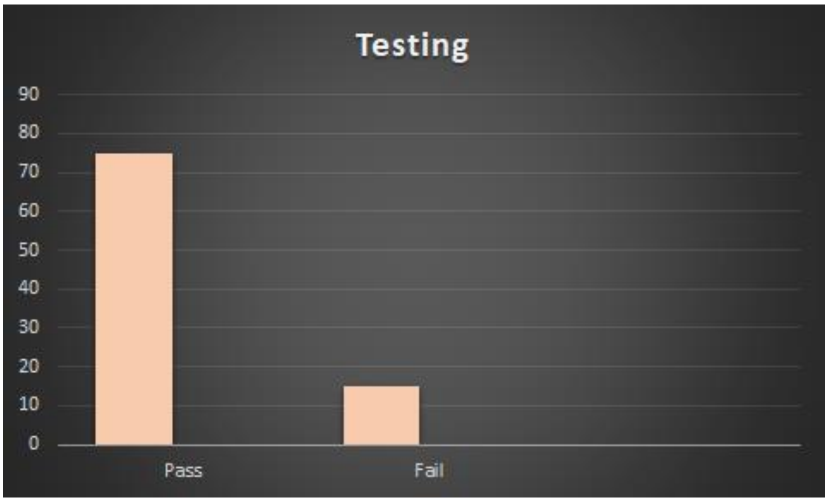


Fig:7.3.2: Testing Analysis.

7.4. Experimental Results

- **Classification**: **DR OR NO DR**

During our literature survey, we came across two major type of training approaches

First one being CNN and the second one being SVC

Convolutional Neural Networks (CNN)

These are the main layers in a CNN model

- *Sequential* is used to initialize the neural network.
- *Convolution2D* is used to make the convolutional network that deals with the images.
- *MaxPooling2D* layer is used to add the pooling layers.
- *Flatten* is the function that converts the pooled feature map to a single column that is passed to the fully connected layer.
- *Dense* adds the fully connected layer to the neural network.

Once a CNN is built, it can be used to classify the contents of different images. All we have to do is feed those images into the model

CNN Analysis

- On analysis we found out that the accuracy of CNN was very less as compared to SVC
- The reason being the size of our dataset which was comparatively less than it is required for the neural network to function accurately.
- Due to this it was training the same batch of images over and over
- And Hence it was not able to distinguish between Dr and non Dr images

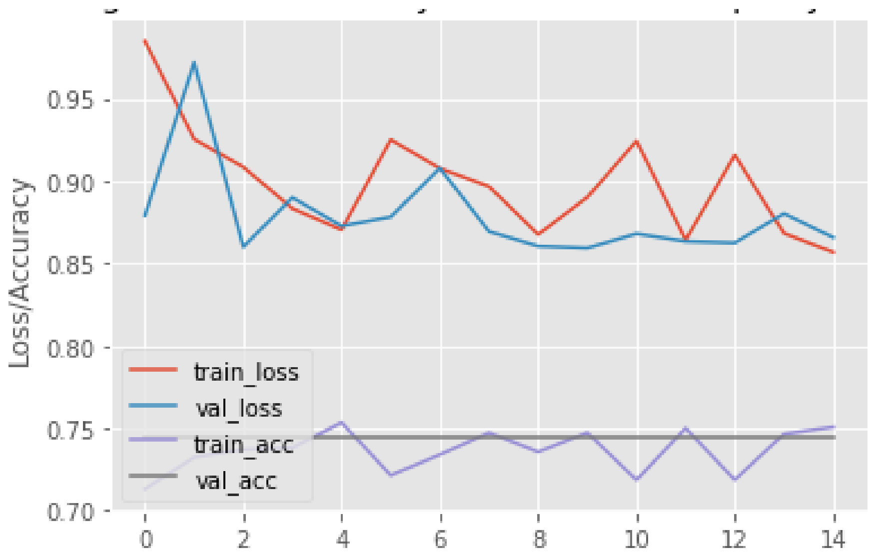


Figure 7.4.1: Analysis of CNN

Support Vector Classifier (SVC)

A simple linear SVM classifier works by making a straight line between two classes. That means all of the data points on one side of the line will represent a category and the data points on the other side of the line will be put into a different category. This means there can be an infinite number of lines to choose from.

What makes the linear SVM algorithm better than some of the other algorithms, like k-nearest neighbours, is that it chooses the best line to classify your data points. It chooses the line that separates the data and is the furthest away from the closet data points as possible.

SVC Analysis

- On the other hand, SVC gave an **accuracy of around 94 %**
- SVM learns the decision boundary which maximizes the distance against the closest observations that belong to opposite classes As compared to CNN
- So we feel that This, in turn, should produce better performances against the edge cases that we’re going to encounter in the future.
- We implemented svc by changing the kernel parameter

Amongst linear, rbf and polynomial kernels, rbf gave the maximum accuracy

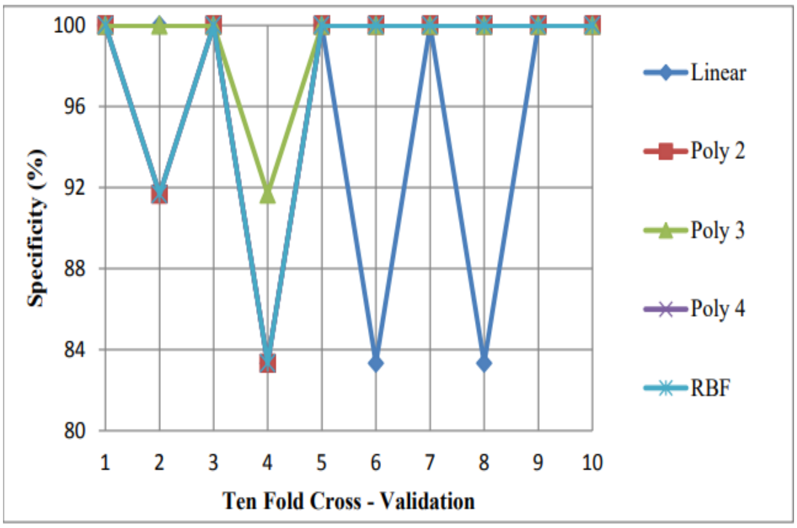


Figure 7.4.2: Analysis of SVC Kernels

```
from sklearn.metrics import accuracy_score
accuracy_score(Y,y_pred)
```

```
0.9438202247191011
```

K-Nearest Neighbor (KNN)

K Nearest Neighbor is one of the fundamental algorithms in machine learning. Machine learning models use a set of input values to predict output values. KNN is one of the simplest forms of machine learning algorithms mostly used for classification. It classifies the data point on how its neighbor is classified.

KNN Analysis

Accuracy obtained from KNN was very close with the accuracy obtained from SVM

So, to summarize our analysis we chose SVM for model training over CNN

- ✓ With respect to our dataset, SVM gave a good accuracy since the number of observations required to train an SVM isn't high.
- ✓ Since in NN the training takes place on the basis of the batches of data that feed into it, CNN performed poorly
- ✓ Also, SVMS are generally fast to train as compared to CNN.
- ✓ Therefore, the algorithm finalized was SVM

- **Classification**: **Severity Levels**

  A clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale:

  0 - No DR

  1 - Mild

  2 - Moderate

  3 - Severe

  4 - Proliferative DR

DR Stage	Severity
Normal	No abnormalities
Mild NPDR	Lesions of micro-aneurysms, small areas of balloon- like swelling in the retinas blood vessels.
Moderate NPDR	Swelling and distortion of blood vessels.
Severe NPDR	Many blood vessels are blocked, which causes abnormal growth factor secretion.
PDR	Growth factors induce proliferation of new blood vessels inside the surface of the retina, the new vessels are fragile and may leak or bleed, scar tissue from these can cause retinal detachment.

Convolutional Neural Networks (CNN) is an architecture of Artificial Neural Networks (ANN) mostly used for image classification. CNN adds some more operations to regular Neural Networks like convolution, nonlinearity, and sub-sampling. CNNs mainly has two parts: the first one is the feature extraction part and the second one is the classification part. In the first part, a series of convolution and pooling operations are performed for feature detection. For producing a feature map, using a filter, the convolution operation is applied. This feature map will contain negative pixel values and it should be replaced with zero. For that, a non-linear operation is performed after performing every convolution. Nonlinearity is introduced using Rectified Linear Unit (ReLU). In the classification part, on top of these extracted features fully connected layers will act as classifiers. They assign a probability for the object on the image. When these images are too large, the pooling operation continuously reduces the dimensionality. This is done for reducing the number of computations and parameters in the network. This reduces training time and controls overfitting. Spatial pooling also called subsampling or down sampling which retains the most important information. Spatial pooling is mainly in three types: Max pooling, Average pooling, and Sum pooling. The largest element from the rectified feature map is taken in max pooling. In sum pooling, the sum of all elements in the feature map is taken. It is also possible to add as many convolutional layers.

In our system, we designed CNN and developed a system that classifies different stages of DR from the color fundoscopic images. The classification is done based on the severity of five DR stages. For this classification, deep learning-based CNN network is deployed. From the past, many medical studies were conducted on the field of designing a algorithm to classify DR from a retinal fundus image. But they were just binary classifiers which only differentiate two stages of DR including Normal and DR affected.

In this work, we check the prediction accuracy of different deep convolutional neural network architectures and the combination of these networks when they are deployed as a DR stage classifier. The study was done based on the dataset collected from hospital which contains 300 images of retinas.

Given below is the CNN Network

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 26, 26, 32)        896
_________________________________________________________________
batch_normalization (BatchNo (None, 26, 26, 32)        128
_________________________________________________________________
activation (Activation)      (None, 26, 26, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 24, 24, 32)        9248
_________________________________________________________________
batch_normalization_1 (Batch (None, 24, 24, 32)        128
_________________________________________________________________
activation_1 (Activation)    (None, 24, 24, 32)        0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 12, 12, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 10, 10, 64)        18496
_________________________________________________________________
batch_normalization_2 (Batch (None, 10, 10, 64)        256
_________________________________________________________________
activation_2 (Activation)    (None, 10, 10, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 64)          36928
_________________________________________________________________
batch_normalization_3 (Batch (None, 8, 8, 64)          256
_________________________________________________________________
activation_3 (Activation)    (None, 8, 8, 64)          0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 4, 4, 64)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 4, 4, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 512)               524800
_________________________________________________________________
batch_normalization_4 (Batch (None, 512)               2048
_________________________________________________________________
activation_4 (Activation)    (None, 512)               0
_________________________________________________________________
```

```
dropout_2 (Dropout)          (None, 512)              0
_________________________________________________________________
dense_1 (Dense)              (None, 5)                2565
_________________________________________________________________
activation_5 (Activation)    (None, 5)                0
=================================================================
Total params: 595,749
Trainable params: 594,341
   Non-trainable params: 1,408
```

Accuracy: ~83.3 %

Graphs shown below gives the training and Validation Accuracy and Loss

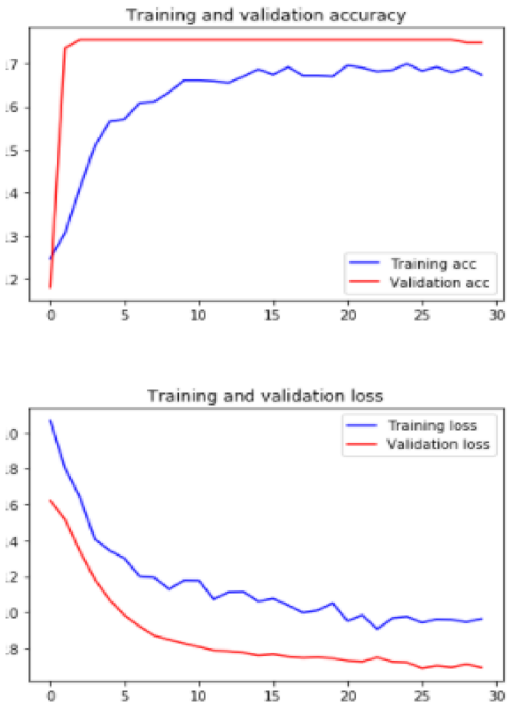


Figure 7.4.3: Training and Validation Accuracy

Shown Below is the Output of the network. The results are displayed in the array of size 5. 0^{th} index represents the probability of image belonging to NO DR class, 1^{st} index represents the probability of image belonging to Mild class, 2^{nd} index represents the probability of image belonging to Moderate class, 3^{rd} index represents the probability of image belonging to Severe class and 4^{th} index represents the probability of image belonging to Proliferative class.

Image is classified into the class having the maximum probability value.

```
[[0.507326   0.19509982 0.2114867  0.05499221 0.0310952 ]
 [0.5232818  0.19933285 0.18078978 0.06141635 0.03517921]
 [0.51628155 0.2007876  0.2052138  0.04679843 0.03091857]
 [0.4910919  0.20349878 0.22236514 0.04795152 0.03509268]
 [0.49375233 0.21009366 0.21352178 0.04846888 0.03416338]
 [0.50027174 0.20343864 0.21989743 0.04789121 0.02850093]
 [0.48094258 0.21734026 0.21554627 0.05695172 0.02921925]
 [0.50881004 0.18306902 0.22242483 0.04932028 0.03637569]
 [0.5469381  0.19836885 0.16103469 0.06058951 0.03306893]
 [0.49105206 0.2107157  0.2190611  0.04779958 0.03137144]
 [0.48737234 0.2094518  0.22218294 0.05159434 0.02939852]
 [0.5088448  0.20769912 0.20389977 0.05003176 0.02952448]
 [0.5206798  0.19893198 0.19607794 0.05442707 0.02988321]
 [0.4833143  0.21616782 0.22268799 0.0488681  0.02896188]
 [0.47254977 0.23064539 0.19457819 0.0650822  0.03714438]
 [0.49770993 0.19953145 0.21621887 0.04840791 0.03813187]
 [0.49857113 0.19631992 0.22315958 0.05106536 0.03088395]
 [0.47563797 0.25772634 0.15826961 0.0674705  0.0408956 ]
 [0.5173963  0.23023818 0.16637042 0.05681867 0.02917646]
 [0.5060567  0.20687711 0.21475296 0.04340119 0.02891206]
 [0.52665854 0.1891809  0.2016311  0.05162753 0.0309019 ]
 [0.5385514  0.1917303  0.18676133 0.05308278 0.0298743 ]
 [0.48099303 0.21263456 0.22498016 0.0478154  0.03357679]
 [0.472714   0.20048855 0.2353465  0.05819358 0.03325731]
 [0.4831519  0.20833905 0.22393918 0.05437302 0.03019686]
 [0.48420614 0.20751977 0.2248307  0.05214217 0.03130127]
 [0.5039646  0.20048611 0.21551313 0.04787419 0.03216198]
 [0.55365604 0.18787904 0.17698897 0.05209345 0.02938246]
 [0.4760334  0.23114686 0.20022495 0.05881129 0.03378352]
```

Figure 7.4.4: Severity Percentage

Chapter 8

8. Conclusion

The system significantly reduces the workload of experts. The presented system is accurate, efficient, low cost, portable and user friendly so that the screening camps can be easily conducted throughout the entire region including rural places. For automatic classification of Diabetic Retinopathy (DR) images at the screening camp site, hybrid features are extracted from various regions and data processing tools are utilized . The system gives better results for image level DR classification. In future, the system can be improved for automated screening and to reduce false positive ratios. Also the DR stages can be found using a number of lesions present in the retinal fundus image. Our framework captures patients' retinal fundus images captured images are precisely labeled as Normal or with Diabetic retinopathy utilizing Image Processing methods combined with Neural Networks. This mechanized framework is systemized as well as economical as it decides if any hints of possible Diabetic Retinopathy are visibly identifiable in an image, which fundamentally decreases the load at the clinicians' end. The framework is able to characterize pictures into Diabetic retinopathy and non-diabetic retinopathy, and provides a level of severity of the complication. Prediction of the level of severity of the complication is also done, which helps the patients to get it tested immediately and take the necessary precautions. These results can be sent to the base clinic for survey. This system effectively classifies DR into 4 levels, with an accuracy of 83.3%.Testing was done on the test images sent to us by the hospital. Testing was carried out in the guidance of 3 doctors, 2 being diabetologists and 1 being ophthalmologist.

Under the guidance of our mentors, Dr Vinaya Sawant and Prof Anusha, and after studying and analyzing different algorithms similar to our project we conclude that it is possible to implement this project. And from technical, operational and economic feasibilities we can conclude that the system is affordable and possible to implement.

Chapter 9

9. Future Scope

The presented automated prescreening system significantly reduces the workload of experts. The presented teleophthalmology system is accurate, efficient, low cost, portable and user friendly so that the screening camps can be easily conducted throughout the entire region including rural places. For automatic classification of DR images at the screening camp site, hybrid features can be extracted from various regions and then classification can be performed. At the base hospital site a three stage system to automatically detect microaneurysms from retinal fundus image can be implemented. All possible microaneurysms will be extracted and feature vectors of all the candidates along with class labels should be given as input to the classifier for HDT training. The proposed system will give better results for image level DR classification as well as detection of individual microaneurysms in the fundus image. In future, the system can be improved for automated screening and to reduce false positive ratios. Also the DR stages can be found using the number of lesions present in the retinal fundus image. We also aim to work on further classification of DR based on 4 levels. In order of increasing severity they are mild nonproliferative, moderate nonproliferative, severe nonproliferative and proliferative. This classification is necessary so as to predict the severity of the disease, and in turn propose the most accurate solution or treatment.

In the first stage, mild non proliferative, there will be balloon-like swelling in small areas of the blood vessels in the retina. In the second stage, known as moderate nonproliferative retinopathy, some of the blood vessels in the retina will become blocked. The third stage, severe nonproliferative retinopathy brings with it more blocked blood vessels, which leads to areas of the retina no longer receiving adequate blood flow. Without proper blood flow, the retina can't grow new blood vessels to replace the damaged ones. The fourth and final stage is known as proliferative retinopathy. This is the advanced stage of the disease. Additional new blood vessels will begin to grow in the retina, but they will be fragile and abnormal. Because of this, they can leak blood which will lead to vision loss and possibly blindness. This classification is necessary so as to predict the severity of the disease, and in turn propose the most accurate solution or treatment.

Chapter 10

10. Publication

Review Paper: Ijamtes

International Journal of Management, Technology And Engineering ISSN NO : 2249-7455

A Review on Diabetic Retinopathy Detection

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Abstract

Diabetic retinopathy (DR) is one of the main sources of preventable visual deficiency all around the world. The goal of this examination is to create powerful symptomatic innovation to mechanize DR screening. For successful treatment, early determination of the infection is significant. We propose to actualize a robotized retinal/fundus picture investigation framework for beginning phase recognition of diabetic retinopathy. Our proposed framework catches retinal fundus pictures of patients through a fundus camera. This camera is mounted on a cell phone. The caught pictures are precisely named ordinary or with Diabetic retinopathy utilizing Image Processing methods joined with Neural Networks. This mechanized framework is time powerful just as financially savvy as it decides if any dubious indications of Diabetic Retinopathy are available in a picture which fundamentally lessens the outstanding task at hand of master specialists. The proposed framework characterizes pictures into Diabetic retinopathy and non-diabetic retinopathy. These outcomes can be sent to the base clinic for survey. The exhibition of the framework is assessed utilizing affectability, explicitness andexactness

Keywords: *Diabetic Retinopathy, Image Processing, Neural Networks, Machine learning*

1. Introduction

Diabetic retinopathy (DR) is where the retina of a diabetic patient is harmed because of blood spills from retinal veins. It is the most well-known microvascular difficulty of diabetes and can advance until an unexpected loss of vision happens. As the quantity of patients with diabetes is quickly expanding, the quantity of retinal pictures created by the screening programs for testing will likewise build, which thus puts a huge work serious weight on the clinical specialists just as expands the expense acquired for the medical care administrations. Ophthalmologists analyze retinal pictures physically. These pictures, known as retinal fundus pictures, are caught by particular cameras and are utilized in clinicalconclusion.

The main signs that show up in the retina at the underlying phase of DR are the exudates and microaneurysms. At the following stage, hemorrhages show up. Earlyfinding of hemorrhages at a primer stage is critical so as to maintain a strategic distance from extreme difficulties prompting visual deficiency. Henceforth, early location and anticipation of DR are fundamental to moderate the rising danger of DR. The present status of DR screening depends on evaluation of shading fundus photos by a retina master leaving a huge extent of patients undiscovered and thus getting clinical assistance past the point of no return. Practically all patients with type 1 diabetes mellitus and about 60% of patients with type 2 diabetes mellitus will doubtlessly create retinopathy during the initial 20 years from the beginning of diabetes. Nonetheless, DR regularly stays undetected until it advances to a serious vision-compromisingstage.

Determination of obsessive discoveries in fundoscopy, a clinical method to envision the retina, relies upon an intricate scope of highlights and limitations inside the picture. The conclusion is especially hard for patients with beginning phase diabetic retinopathy as this depends on recognizing the presence of microaneurysms, little saccular outpouching of vessels, retinal hemorrhages, burst veins—among different highlights in the fundoscopic pictures. Along with telemedicine framework, such

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retinal pictures taken with a versatile camera in distant spots can be sent to an ophthalmologist, who will hence be empowered to announce any pathology which can be surveyed from the photos. The goal is to bring convenient, simple to control, solid, retinal screening to essential specialists' workplaces and wellbeing centers.

2. LiteratureSurvey

2.1. Pre-Processing

The preprocessing step is utilized to eliminate noise in the retinal picture just as to improve picture difference and picture nature of fundus picture. Apart from the noise evacuation and differentiation upgrade, preprocessing steps can be used for picture standardization and for nonuniform enlightenment correction so as to eliminate ancient rarities and to improve the precision of continuing steps [5]. The preprocessing methods used by a portion of the papers is briefly examined in this part.

2.1.1. GreenChannel

The improvement is important since fundus pictures experience the ill effects of non-uniform light and noise. Green channel in the RGB space is separated and is broadly utilized in pre-preparing. It shows the best vessels/foundation contrast and most noteworthy difference between the optic circle and retinal tissue. Red channel is generally splendid and the vascular structure of the choroid is noticeable. The vessels of the retina are likewise noticeable however show relatively lesser differentiation as compared to the green channel. The blue channel is uproarious and contains little data [3]. The retinal shading fundus pictures are changed over to grayscale. The grey scale picture is binarized, a low edge esteem is fixed for optical plate division. The sectioned yield is then handled to discover whether any plate locales are discovered utilizing the underlying edge. On the off chance that no district is discovered, the limit esteem is expandedandthecycleisrehasheduntiltheopticcirclelocaleisfoundout[6]

2.1.2. Adaptive Histogram Equalization[3]

ADHE is utilized for image contrast improvement. ADHE processes a few histograms of a picture and uses them for reallocation of force estimation of picture. After preprocessing, exudates are removed from the fundus picture. Location of exudates is fundamental in discovery of microaneurysm on the grounds that the shade of exudates is equivalent to that of microaneurysm. The preprocessed green channel picture is additionally improved by ADHE for the location of exudates. After that a marker has been created utilizing median channel which deducted from the middle shiftedpicture utilizing morphological cycle to separate the exudates. Vein expulsion is performed after exudates extraction. Initially the RGB picture is changed over into dark channel for better difference. Grey scale conversion is finished utilizing head segment investigation. Background is wiped out by averaging the upgraded picture and deducting it from the improved picture. After foundation prohibition the picture is changed over to binary scale after which retinal veins are removed. Optic plate segmentation is performed in two main stages named as localization and detection.[3] Before filtering, we need to recognize optic circles to separate portions in retinal pictures into four quadrants utilizing the strategy for format coordinating. A format picture utilized as reference than closeness between layout picture and handled picture was determined. The results were later joined with the edge detection for computing the span and focus area of the optic circle[4]

2.1.3. Discrete WaveletTransform

In this strategy DWT coefficients are utilized as feature vectors. It is a systematic tool that is utilized to deteriorate and deal with any image [2]. The DWT change measure is subject to various little waves, known as wavelets, of moved recurrence and limited duration [2]. It produces both recurrence and spatial portrayal of the picture. DWT is the multi goal portrayal of a picture that translates continually from a low to a high resolution [2], by partitioning the picture into low and high recurrence elements [2]. The high recurrence has the data of corner components and the low recurrence is again partitioned into high and low recurrence components[2].

2.1.4. Optic DiscDetection

Before performing filtering, we need to distinguish the optic circle to partition fragments in the retinal pictures into four of the quadrants. The technique for layout coordinating was utilized to recognize optic plates [4]. A format picture utilized as reference than closeness between layout picture and handled picture was determined. Results were later joined with the edge recognition to figure the span and focus area of the opticdisc.[4]

2.1.5. Averaging

The pictures which contain noise, include low difference, shading variety,and lopsided reflections. To make pictures more predictable and smooth, a convolution channel is utilized. The channel size is 5x5. The smaller variance picture is smoother with other size kernels. The method utilized in averaging is known as Box blur.[9]

2.1.6. Resize

Because of such a major size of the picture it isn't reasonable to pass it into the neural networks, so to reduce the calculation time, all the pictures in the dataset are resized to 256x256 pixels. Resizing is practiced by utilizing bilinear interpolation [9].

2.2. FeatureExtraction

2.2.1. Hybrid FeatureExtraction

The features are separated to comprehend the data of various classes [6]. 15 different features for portraying each picture have been used. These features depend on the area properties. The proposed technique uses the significant level of concealed measurable features, for example, mean, difference, wavelet, PCA and entropy to depict the image[6].

2.2.2. Principal ComponentAnalysis

The RGB picture is changed over into a grey channel for enhancing the contrast. Grey scale change is finished utilizing PCA. It is a factual process that utilizes a symmetrical change to change over a lot of perceptions of perhaps connected factors into a lot of estimations of relationship and reliance factors called principal components. PCA is an amazing asset for examining information [3]. It is essentially utilized in dimensionality reduction

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2.2.3. Thresholding

It is a straightforward extraction procedure, where pictures could be seen as the consequence of attempting to isolate the eye. It is a strategy for creating areas of consistency inside a picture dependent on some limit model [7].A Local Thresholding procedure[7] segments the picture into different sub-pictures and decides the edge for every one of these sub-pictures. [7].

2.2.4. Morphological Processing

Erosion includes the adjustment of pixels present at the edges of areas, such as changing from binary 1 to binary 0. Dilation is a converse cycle with areas coming out of their respective boundaries.[7][11] The two cycles are regularly done utilizing a kernel which is known as a structural element.[7][11] A structural element is a M × M piece having passages arranged by a twofold plan, regularly as either binary 0 or 1.[7][11] If all sections are coded as 1 then the auxiliary component is a strong square, the focal point of which is laid over every pixel. The state of the auxiliary component may fluctuate, for instance as a vertical bar, flat bar, cross shape or a client characterized design. In the event that enlargement is trailed by disintegration the cycle is portrayed as a Closing activity, while Erosion followed by Expansion is known as Opening.[7][11] The cycles are asymmetric, and in this way are commonly not reversible. Opening kills little and more slender highlights, bringing about smoother edged areas, while shutting additionally smooth shapes yet makes slim limited highlights bigger and wipes out little gaps and restrictedgaps.[7][11].

2.2.5. Artificial Neural Network[2]

Artificial Neural Network (ANN) is a preparing framework which demonstrates the manner in which the human cerebrum investigates the data. It explains the issues which are difficult to analyze by humans or factual estimations [2].Artificial Neural Networks comprises various nodes which depict the neurons of the human brain. The neurons are connected and help out one another by networks. Every node can take information input, measure it and pass it to the following neuron[2]. Outcome made at every node is the node value.[2] Information that travels through the network can change the arrangement of ANN[2].Neural networks learn based on input andoutput.[2].

2.3. Classification

2.3.1. Support VectorMachine

SVM is a direct classifier which removes vectors characterizing the best edge for while isolating various classes of information, and is utilized for learning as well as arrangement of the extracted features. The information base is separated into two classes. First class consists of typical pictures of the retina indicating normal and the second class consists of DR pictures. These models are utilized later for grouping the pictures into DR or Non- DR classes[1]. Boundaries of SVM classifiers have been determined dependent on features of microaneurysm [3].Therefore, SVM is a direct classifier. It extracts the vectors which characterize the edge that differentiates various classes of information. At any point when the information is not directly distinct, kernel tricks are utilized to characterize a part work that assist ventures including vectors into a larger space where they become separable[1].

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2.3.2. BayesianClassification

It is a customary measurement based classifier which examines discriminant capacities. The classifier allots an input vector to class. The back likelihood is a likelihood of an example having a place with class when we watch the information vector [7][11]. Bayesian hypothesis gives a method to compute the likelihood of a speculation dependent on its earlier likelihood, the probabilities of watching different information for a given subject, and the watched information itself [7][11].

3. Proposed System

Customary retinal cameras are costly, huge, resolute and require extraordinary preparing to work. Without customary registration, it is conceivable that retinopathy may go undiscovered, which has unfriendly impacts. Henceforth, a novel, less expensive and helpful way to deal with catch top quality retinal pictures and recognize the likeliness of DR utilizing profound learning methods is recommended. The framework is anything but difficult to utilize, and the main equipment necessities are a focal point and a cell phone. A reduced cell phone based outcome discovering framework helps in early location of diabetic retinopathy/Data will be gathered from the patients in genuine time. The proposed arrangement would be an application/online interface. The utilization of neural organizations and picture handling strategies on shading fundus pictures for the acknowledgment undertaking of diabetic retinopathy arranging is illustrated. The retinal pictures taken with a portable camera which has a focal point mounted on its camera in distant spots are sent to the ophthalmologist, who will accordingly be empowered to announce any pathology which can be evaluated from the photos. Additionally, the similarity of the presence or event of other related confusions, for example, removals, hypertension, glaucoma, and so forth is predicted and assessed by experts[6]. The below diagram is the system architecture of our proposed system. It includes abstract relations with proposedfeatures.

A- Integration of our algorithm in a real diagnostic workflow.

B -Abstraction of the deep neural network.

4. SystemArchitecture

Figure 2A: The fundus images will be compiled and preprocessed. The features will be extracted using Image Processing techniques. These extracted features will be trained in Neural network models. These deep features will be propagated (along with relevant metadata) into a classification model that outputs a final diagnosis.

Figure 2B: Each layer will transform the input image, generating the output information into the next layer. The neural network can be constructed in such a way, that it receives an input which is used in calculating an output. Artificial Neural Network will be used in this phase.

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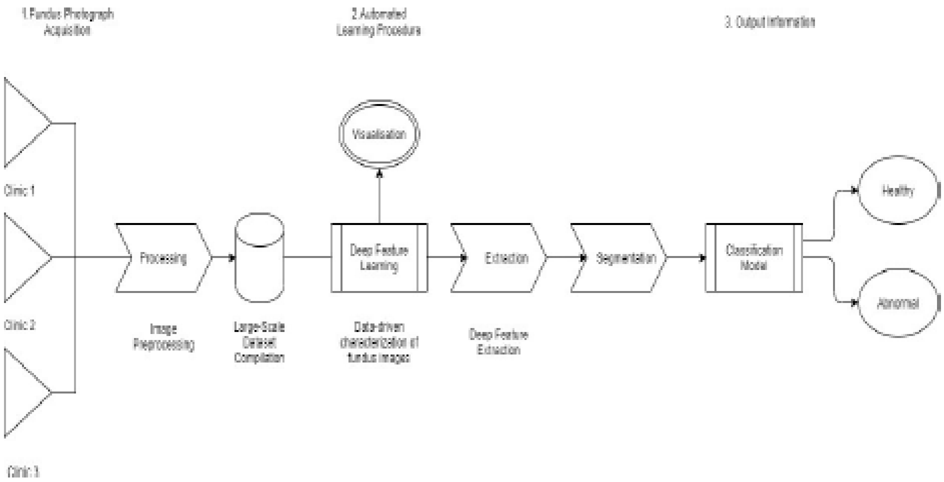

Fig 2: Proposed System Architecture

4.1. DataAcquisition

The proposed system consists of flex sensors, an arduino microcontroller, a bluetooth module and an android application. Each component has its own functionality. This can be understood better by the architecture shown in Figure 3. The data set is a set of color fundus images obtained from the clinics. Each image will be mapped with a label of 0 or 1 corresponding to retinopathy or noretinopathy

4.2. DataPreprocessing

To deal with image variation within our data, different preprocessing steps will be performed for image standardization before deep feature learning. The preprocessing will consist of some of the following methods

- 2D ConvolutionFiltering
- ImageSmoothing
- Averaging
- GaussianBlurring
- Bilateral Filtering
- GreenChannel

The selection of these methods will depend on the dataset

4.3. Deep Feature Learning andExtraction

Deep neural networks will be used for characterization of fundus images. These networks use parameters and adapt iteratively and change the input pictures into progressive feature maps, the convolutional layers will be situated successively. Each layer will change the input picture, producing the output data into the following layer. The neural network can be built in

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such a manner, that it gets an information which is utilized in figuring an output. Artificial Neural Network will be utilized in thisstage

4.4. ClassificationModel.

Choice Tree classifier can be utilized on account of the speed of usage and strength versus the overfitting. This classifier will be prepared by utilizing the absolute cross- entropy loss function, thus yielding the likelihood that the input picture will be pathologic. Support Vector Machine can likewise be utilized

5. Results

Table 1: Review on techniques used in various research paper

Paper/ Source	Dataset	Methodology	Algorithm
"Diabetic Retinopathy Detection Using Machine Learning and Texture Features"[1]	Live dataset using fundus lens	Image processing and Deep Learning	Artificial Neural networks (ANN) and Discrete Wavelet Transform (DWT)
"Mobile phone based diabetic retinopathy detection system using ANN-DWT"[2]	Dataset from Kaggle	Image processing and Deep Learning	MobileNets -Neural networkModel
"Diabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image"[3]	Images taken from ahospital	Images processing and Machine Learning	Support Vector Machine (SVM)
"Enhancement Algorithm in Digital Retinal Fundus Microaneurysms Filter for Nonproliferative Diabetic Retinopathy Classification"[4]	Already existing dataset.	Images processing and Machine Learning	Support Vector Machine (SVM) and k-nearest neighbor (k-NN) classifier

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"Image processing and classification in diabetic retinopathy: A review"[5]	Already existing dataset.	Image processing and Deep Learning	Support Vector Machine (SVM)
"A modern screening approach for detection of diabetic retinopathy"[6]	Existing Databas e	Image processing and Machine Learning	Decision Tree
"Diagnosis of diabetic retinopathy using machine learning techniques"[7]	Existing Database-DIARETD B1	Image processing and Machine Learning	Holo-entropy Enabled Decision Tree SVM
"Deep learning fundus image analysis for diabetic retinopathy and macular edema grading"[8]	Images taken from camera	Image processing and Deep Learning	Convolutional Neural Network

6. FutureScope

The presented automated prescreening system significantly reduces the workload of experts. The presented teleophthalmology system is accurate, efficient, low cost, portable and user friendly so that the screening camps can be easily conducted throughout the entire region including rural places. For automatic classification of DR images at the screening camp site, hybrid features can be extracted from various regions and then classification can be performed. At the base hospital site, three stage system to automatically detect microaneurysms from retinal fundus image can be implemented. All possible microaneurysms will be extracted and feature vectors of all the candidates along with class labels should be given as input to the classifier for HDT training. The proposed system will give better results for image level DR classification as well as detection of individual microaneurysms in the fundus image. In future, the system can be improved for automated screening and to reduce false positive ratios. Also the DR stages can be found using the number of lesions present in the retinal fundus image. We also aim to work on further classification of DR based on 4 levels. In order of increasing severity they are mild non-proliferative, moderate non-proliferative, severe non-proliferative and proliferative. This classification is necessary so as to predict the severity of the disease, and in turn propose the most accurate solution ortreatment.

In the first stage, mild non proliferative, there will be balloon-like swelling in small areas of the blood vessels in the retina. In the second stage, known as moderate non-proliferative retinopathy, some of the blood vessels in the retina will become blocked. The third stage, severe non-proliferative retinopathy brings with it more blocked blood vessels, which leads to areas of the retina no longer receiving adequate blood flow. Without proper blood flow, the retina can't grow new blood vessels to replace the damaged ones. The fourth and final stage is known as proliferative retinopathy. This is the advanced stage of the disease. Additional new blood vessels will begin to grow in the retina, but they will be fragile and abnormal. Because of this, they can leak blood which will lead to vision loss and possibly blindness. This classification is necessary so as to predict the severity of the disease, and in turn propose the most accurate solution or treatment.

7. Conclusion

This paper introduces an improved plan for the discovery of diabetic retinopathy by precise assurance of number and zone of microaneurysms. Early detection of diabetes can support the patients and keep it from weakening further into a much genuine condition, all out visual deficiency. Utilizing retinal fundus pictures can help computerize the finding. The outcome shows that microaneurysms channels can recognize truly well both microaneurysms and hemorrhages. The order result can assist with synchronizing the diverse determination by different ophthalmologists

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DJ-ASCII :

Abstract—Diabetic retinopathy (DR) is one of the main sources of preventable visual deficiency all around the world. The purpose of this research is to create and provide a state-of-the-art innovative system designed to mechanize Retinopathy screening. Early determination of the infection is cerebral for the successful treatment. We propose to actualize a robotized retinal/fundus picture investigation framework for beginning phase recognition of diabetic retinopathy. Nowadays, with the presence of revolutionary smartphone cameras, it becomes relatively easy to add optics to the mobile device and look through the pupils in order to capture the retina. Our proposed framework captures retinal fundus pictures of patients with the use of a fundus camera, which is mounted on top of a cell phone. The captured images are precisely categorized as Normal or with Diabetic retinopathy utilizing Image Processing methods combined with Neural Networks. This mechanized framework is time savvy as well as cost efficient as it decides if any dubious indications of Diabetic Retinopathy are available in an image which fundamentally decreases the load at the specialists' end. The proposed framework is able to characterize pictures into Diabetic retinopathy and non-diabetic retinopathy, and provides a level of severity of the complication. These outcomes can be sent to the base clinic for survey. The exhibition of the framework is assessed utilizing effectiveness, explicitness and exactness.

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Diabetic Retinopathy Detection

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Abstract— **Diabetic retinopathy (DR) is one of the leading causes of early blindness and other visual deficiencies in people of all age groups due to high blood sugar, or diabetes. The aim of this research is to create a robust diagnostic technology designed to automate Retinopathy screening. Early determination of the infection is cerebral for the successful treatment. A mechanized retinal image investigation framework for phase recognition of diabetic retinopathy is proposed. Identification of key symptoms such as microaneurysms and exudates with the presence of revolutionary fundus cameras make it simpler to classify the disorder's severity. Our framework captures patients' retinal fundus images with the help of a specialized fundus camera. The captured images are precisely labelled as Normal or with Diabetic retinopathy utilizing Image Processing methods combined with Neural Networks. This mechanized framework is systemized as well as economical as it decides if any hints of possible Diabetic Retinopathy are visibly identifiable in an image, which fundamentally decreases the load at the clinicians' end. The framework is able to characterize pictures into Diabetic retinopathy and non-diabetic retinopathy, and provides a level of severity of the complication. These results can be sent to the base clinic for survey. This system effectively classifies DR into 4 levels, with an accuracy of 83.3%.**

Keywords— ***Diabetic Retinopathy (DR), Image Processing, Neural Networks, Machine learning, convolutional neural networks (CNN), support vector machines (SVC)***

I. INTRODUCTION

Diabetic Retinopathy (DR) is the most common microvascular complication of diabetes and can progress until a sudden loss of vision occurs. It leads to blood loss or hemorrhaging of the retinal veins which may lead to blurry or loss of vision, and in extreme cases, can cause blindness. Microaneurysm (MAs) are small red spots which are the first pathological signs of diabetic retinopathy and appear at the earliest stage of this diabetic complication. MAs are caused by dilatation of thin retinal blood vessels. The exudates (EXs) and cotton wool spots appear as white lesions in DR. The thin blood vessels burst in DR causing the formation of MAs and HMs. As the disease progresses, cotton wool spots and hard exudates start to appear on the retinal surface. The patient can lose the central vision if the exudates and cotton wool spot reach the macula and fovea where the central vision is focused. Since the number of patients being diagnosed with DR s increasing rapidly, there will be a rise in the number of retinal images from the screening programs, which exacerbates the condition of the healthcare service workers by increasing the workload. The need of an additional device to be mounted on top of the available fixed devices to support the eye physician stems from the fact that some of these patients who might be in need to a visit to the doctor might live in remote or rural areas or might be housebound. In other inaccessible areas, there may be a complete absence of any ophthalmologist for collecting medical information from patients. Initial retinal images taken with mobile cameras allow a preliminary screening and preliminary emergency decisions about the patient.

This is particularly useful, for instance, when screening cases of diabetic retinopathy: people with diabetes are at risk of developing diabetic retinopathy and therefore, need a regular screening with correct and timely diagnosis without the constraint of a long travel or needless waste of time, either for the eye care professional or for the patient. Diagnosis of pathological findings in fundoscopy, a medical technique to visualize the retina, depends on a complex range of features and localizations within the image. The diagnosis is particularly difficult for patients with early-stage diabetic retinopathy as this relies on discerning the presence of microaneurysms, small saccular outpouching of capillaries, retinal hemorrhages, ruptured blood vessels—among other features—on the fundoscopic images.

II. SCOPE

First, The system is easy to use, and the only hardware requirements are a lens and a smartphone. The solutions to various challenges come from image processing techniques. It is possible to identify and use automatic focus detection, to find the ideal focus for the image of the eye. The scanned images will be processed and the reports will be available to doctors to analyze. At each intermediate step, the image details are available to the doctor in case they require to analyze certain portions that are highlighted at the end of that particular stage. At the end of the process, an in depth analysis will be performed to provide an insight to the doctor and patient regarding the condition. The processing speed and the memory requirements of the entire process is fairly reduced. Prediction of the level of severity of the complication is also done, which helps the patients to get it tested immediately and take the necessary precautions. The system will be accessible by any person with or without a medical knowledge, although it is advisable to trust the decision of a medical personnel.

III. SYSTEM ARCHITECTURE

Traditional retinal cameras are costly, huge, resolute and require extraordinary preparing to work. Without registration, it is highly possible that retinopathy may go unnoticed, which has distressing impacts. Hence, a novel, less expensive and helpful way to deal with capturing high quality retinal pictures and detect the likeliness of DR utilizing profound learning methods is recommended. The framework is anything but difficult to utilize, and the main equipment necessities are a focal point and a fundus camera. The images from the patients for the dataset are captured in genuine time. The arrangement is a web application/online interface. The utilization of neural organizations and picture handling strategies on shading fundus pictures for the acknowledgment undertaking of diabetic retinopathy arranging is illustrated. The retinal pictures taken with a portable camera which has a focal point mounted on its camera in distant spots are sent to the ophthalmologist, who will accordingly be able to announce any conclusions which can be derived from the photos.

Fig. 1. below is the system architecture of our system. It includes abstract relations and features.

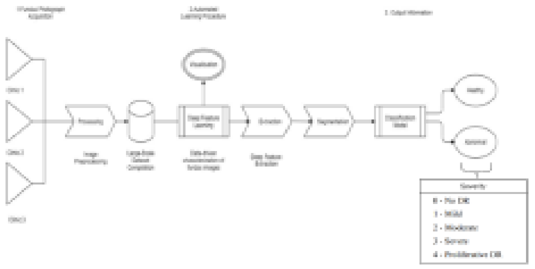

Fig. 1. System Architecture

This model consists of 3 distinguishable stages: Fundus Photo acquisition, Automated Learning Procedure and the final output stage.

In the first stage, our aim was to create our dataset. We collected retinal images of patients from the hospital. The hospital sent us two images for each patient, one of each eye. Post that, we subjected the images to some preprocessing algorithms such as filtering and gaussian blurring.

After initial preprocessing of all images, we used some image processing techniques for feature extraction, deep feature learning and segmentation. Image segmentation is an important process for most medical image analysis tasks. For binary image classification, we have used Support Vector Classifiers. Support Vector classifier is used because of its speed of implementation and robustness against overfitting. It was used to classify images into healthy and abnormal retina, which is basically DR and non-DR. Further, if DR is present, we categorize into one of the 4 levels using CNN.

The input image data set contains both normal and diabetic retina images. Initially the user registers himself to the system. If he has already registered, then he logs in. After logging in a form containing the patient's information is to be filled. Along with the form, a patient's retinal image is also uploaded. After which in the backend, the following processes occur. Firstly, the raw retinal images were resized. Color images are converted to gray scale images which makes the processing task easier.

For data collection, specialized fundus cameras consisting of an intricate microscope attached to a flash enabled camera are used. The 3nethra camera was used to capture images in this system. 3nethra flora is a digital mydriatic fundus camera designed to capture retinal images of the human eye. The camera provides high-contrast, undistorted, and evenly illuminated images of the peripheral retina for accurate diagnosis. The system improves the intensity control developed for optimal image capture. This image is then subjected to processing and finally displays the output. Color Fundus Photography is used to record the condition of these structures in order to document the presence of disorders and monitor their change over time.

IV. DATASET

Our dataset comprises several different types of images. It is mainly classified into DR and non- DR, and DR can be broken down into 4 categories that we discuss later. These images were obtained from the patients using a fundus camera. The dataset consists of over 300 images in the train set and 90 images in the test set. Each image is subject to preprocessing, data-driven characterization of fundus images, deep feature learning and extraction, and image classification. These images have been collected in real-time by a trained professional, and have been sent from a hospital. Each image goes through the above-mentioned stages, and at each stage, the output after the process is displayed.

V. IMPLEMENTATION

A. Image Preprocessing

In detecting abnormalities associated with fundus image, the images have to be pre-processed in order to correct the uneven illumination, not sufficient contrast between exudates and image background pixels and the presence of noise in the input fundus image.[3] The techniques for preprocessing include Gray scale Conversion, Adaptive Histogram Equalization, Discrete Wavelet Transform, Gaussian Filter and K-means Clustering for segmentation of blood vessels [3].

- **Grey scale Conversion**: Firstly, the raw retinal images were resized color images are converted to gray scale image which makes the processing task easier.

- **Adaptive Histogram Equalization**: The images were subjected to preprocessing using adaptive histogram equalization in order to remove the nonuniformity of the background [1]. Adaptive histogram equalization which is used to improve contrast in images is applied to the gray scale converted eye image. Non-uniform illumination during image acquisition and variation in the color of the eye pigment are two major causes of non-uniformity [1]. The objective of applying adaptive histogram equalization is to assign the intensity values to the pixels in the input image, such that there is uniform contrast across the output image [1].

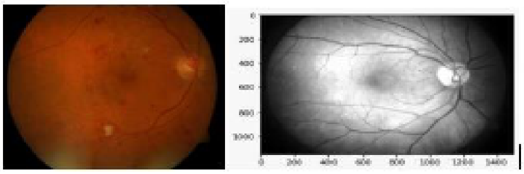

Fig. 2. *Image subjected to Adaptive Histogram Equalization*

- **Discrete Wavelet Transform (DWT):** DWT was used to separate bright objects from the image's remaining content [5]. In general, medical images require greater accuracy while retaining information. Because DWT is based on time scale representation, it offers efficient multiresolution.
- **Gaussian Filtering:** We also used Gaussian Filtering to remove extraneous noise. It is a well-known method for separating the roughness and waviness components with minimal phase distortion. In this case, Gaussian blur softens the image, allowing veins and exudates to stand out more clearly.

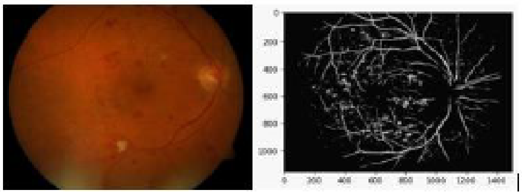

Fig. 3. *Image subjected to Gaussian Filtering*

- **Segmentation:** Following Image Preprocessing and Feature Extraction, Segmentation is the next process to be implemented. Image segmentation is the process of partitioning an image into various subgroups (of pixels) known as Image Objects [4]. This is done to reduce the complexity of the image and thus simplify image analysis. Similarity Detection (Region Approach) is implemented in the project. The information obtained from feature extraction is used to calculate the similarity of two images. This aids us in identifying exudates that have been segmented. Because the k-means algorithm is more computationally simple than other clustering algorithms, we chose to use it in the work. It divides the image into clusters that have similar properties. Essentially, the data elements are divided into clusters so that elements in the same cluster are more similar to each other than elements in other clusters. The K-means is a simple algorithm for segmenting or classifying images into k different clusters based on feature, attribute or intensity value [7,8,9].

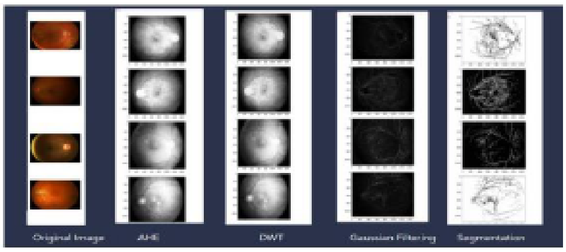

Fig. 4. *Image subjected to various processing methods*

B. *Classification*

- **Support Vector Machines (SVM):** For binary classification, SVM was used It is a mathematical model that includes a learning routine and is used for classification of input data received by a computing system as well as regression tasks [7]. After the input data has been transformed into high-dimensional space, SVM generates a hyperplane to discriminate between two classes with the goal of maximizing the margin between classes [7]. Based on this it detects whether Dr is detected or not. We chose SVM because it has two advantages: For starters, it can generate non-linear decision boundaries using methods designed for linear classifiers [6]. Second, by using kernel functions, the user will be able to apply a classifier to data that does not have a defined fixed-dimensional vector space representation [6]. A training image set, SVM, and a trained model comprise the training stage. Color retinal images were provided to SVM for training in the training image set [6]. The SVM trained model compares the features of the test image to the stored values and returns a normal or diabetic retinopathy image as an output.
- **Convolutional Neural Networks (CNN):** The convolution neural networks (CNNs) are a category of neural networks that are proven to be effective in image recognition and classification[11].The process of identifying the stage of DR with the input images is known as DR grading. This method employs a massive corpus of images with labels ranging from 0 to 4., according to the following scale: 0 - No DR, 1 - Mild, 2 - Moderate, 3 - Severe, 4 - Proliferative DR .

DR Stage	Severity
Normal	No abnormalities
Mild NPDR	Lesions of micro-aneurysms, small areas of balloon- like swelling in the retinas blood vessels.
Moderate NPDR	Swelling and distortion of blood vessels.
Severe NPDR	Many blood vessels are blocked, which causes abnormal growth factor secretion.
PDR	Growth factors induce proliferation of new blood vessels inside the surface of the retina, the new vessels are fragile and may leak or bleed, scar tissue from these can cause retinal detachment.

Fig. 5. DR stages and Severity

When a new image is fed into the CNN model for the prediction it gives the results in the probabilistic results, such as probability that an image can be classified into various classes [10]. We designed CNN and created a system that classifies different stages of DR from color fundoscopic images in our system. The study was based on a dataset collected from a hospital that included 300 images of retinas. The structure of our CNN network is shown below:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 26, 26, 32)        896
_________________________________________________________________
batch_normalization (BatchNo (None, 26, 26, 32)        128
_________________________________________________________________
activation (Activation)      (None, 26, 26, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 24, 24, 32)        9248
_________________________________________________________________
batch_normalization_1 (Batch (None, 24, 24, 32)        128
_________________________________________________________________
activation_1 (Activation)    (None, 24, 24, 32)        0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 12, 12, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 10, 10, 64)        18496
_________________________________________________________________
batch_normalization_2 (Batch (None, 10, 10, 64)        256
_________________________________________________________________
activation_2 (Activation)    (None, 10, 10, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 64)          36928
_________________________________________________________________
batch_normalization_3 (Batch (None, 8, 8, 64)          256
_________________________________________________________________
activation_3 (Activation)    (None, 8, 8, 64)          0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 4, 4, 64)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 4, 4, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 512)               524800
_________________________________________________________________
batch_normalization_4 (Batch (None, 512)               2048
_________________________________________________________________
activation_4 (Activation)    (None, 512)               0
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 2565
_________________________________________________________________
activation_5 (Activation)    (None, 5)                 0
=================================================================
```

Fig. 6. CNN Network

VI. EXPERIMENTAL RESULTS

A. Stage 1 : To depict DR or no DR

- **CNN Analysis**: On analysis we found out that the accuracy of CNN was very less as compared to SVC. The reason being the size of our dataset which was comparatively less than it is required for the neural network to function accurately. Due to this it was training the same batch of images over and over And Hence it was not able to distinguish between Dr and non-DR images

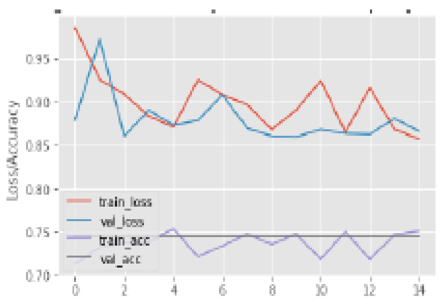

Fig. 7. Training Loss and Accuracy

- **SVC Analysis**: On the other hand, SVC gave an accuracy of around 94 %. SVM learns the decision boundary which maximizes the distance against the closest observations that belong to opposite classes As compared to CNN So we feel that This, in turn produced better performance..We implemented SVC by changing the kernel parameter Amongst linear, rbf and polynomial kernels, 'rbf' gave the maximum accuracy

B. Stage 2 : To Depict Severity of DR

- **CNN Analysis**: In our system, we designed a CNN and developed a system that classifies different stages of DR from the colored retinal images. The classification is done based on the severity of five DR stages. 0 - No DR 1 - Mild 2 - Moderate 3 - Severe 4 - Proliferative DR. For this classification, CNN networks are deployed. The study was done based on the dataset collected from the hospital which contains 300 images of retinas. Results were obtained in the form of an array of size 5The value at each index depicts the severity at that stage. The maximum valued index is considered the predicted stage. Overall Accuracy turned out to be around 83.3 %

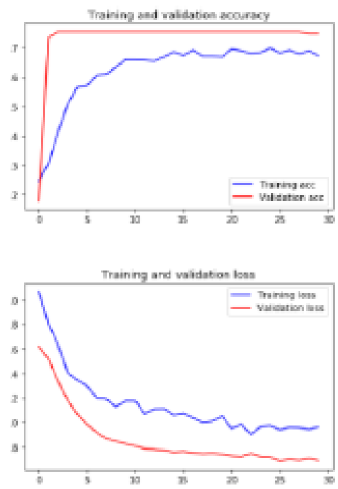

Fig. 8. Training Loss and Accuracy

VII. CONCLUSION

The system significantly reduces the workload of experts. The presented system is accurate, efficient, low cost, portable and user friendly so that the screening camps can be easily conducted throughout the entire region including rural places. For automatic classification of Diabetic Retinopathy (DR) images at the screening camp site, hybrid features are extracted from various regions and data processing tools are utilized. The system gives better results for image level DR classification. In future, the system can be improved for automated screening and to reduce false positive ratios. Also the DR stages can be found using a number of lesions present in the retinal fundus image.

After studying and analyzing different algorithms similar to our project we have implemented this project. And from technical, operational and economic feasibilities we can conclude that the system is affordable and economic.

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