

OPTIC DISK DETECTION IN DIABETICS RETINOPATHY USING MACHINE LEARNING BY IMAGE PROCESSING

Submitted in partial fulfillment of the requirements for the award of Bachelor of
Engineering Degree in Electronics and Communication Engineering

by

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION
ENGINEERING
SCHOOL OF ELECTRICAL AND ELECTRONICS ENGINEERING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY (DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

MARCH 2021



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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of K.SANKAR SATISH(37130178) and G.SAI DEEPAK CHANDU (37130145) who carried out the project entitled **“OPTIC DISK DETECTION IN DIABETICS RETINOPATHY USING MACHINE LEARNING BY IMAGE PROCESSING”**. under our supervision from September 2020 to March 2021.

Internal Guide

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Submitted for Viva voce examination held on _____

Internal Examiner

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DECLARATION

We, **K.SANKAR SATISH (37130178)** and **G.SAI DEEPAK CHANDU (37130145)** hereby declare that the Project Report entitled **“OPTIC DISK DETECTION IN DIABETICS RETINOPATHY USING MACHINE LEARNING BY IMAGE PROCESSING”** done by us under the guidance of **DR.T.BERNATIN** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineering.

1)

2)

DATE:

PLACE:

SIGNATURE OF THE CANDIDATES

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ABSTRACT

The project represents a direction for automatic detection of hemorrhages and exudates in Fundus Photographs. To predict the severity of diabetic retinopathy that had implemented a method that is based on the classification of possible pathologies such as hemorrhage and exudates which is followed by feature extraction from the pixel level result and a machine learning method. The proposed method was performed on test data from the Kaggle competition. The proposed method approaches the processing of Fundus Photographs in MATLAB with Neural Network and detecting the level of Diabetic Retinopathy in patients.

Keywords

Diabetic retinopathy, Fundus Photographs, Automated detection, Blood vessel area, Hemorrhage, Exudate.

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Illustration of Abbreviations and Symbols

DR: Diabetic Retinopathy

SE: Sensitivity

SP: Specificity

SVM: Support vector machine

MLP: Multilayer perceptron

RBF: Radial basis function

EXs: Exudates

CHAPTER 1

INTRODUCTION

Diabetic retinopathy is an eye disease that is caused by diabetes. It is a medical condition where patients with diabetes tend to show abnormalities in the affected eyes because of the fluid leaks from blood vessels of the light-sensitive tissue at the back of the eye (retina). Ophthalmologists recognize diabetic retinopathy based on features such as blood vessel area, exudes, hemorrhages, micro-aneurysms and texture.

1.1 Project Overview

In our project we focus on diagnosis through Fundus photographs, which includes careful observation of photographs taken with expensive equipment by highly trained clinicians. This detection technique is very sophisticate and requires very specialized clinician knowledge [1]. Here we want to approach a computer vision method that matches human performance.

For more information on the Diabetic retinopathy (DR) and an analysis of how early detection of the disease can help slow or even stop its spread, consult [2]. For a comparative research paper on studies of risk factors of DR, consult Yau et al. [3]. Fluorescein angiography is not the only a technique for diagnosis of DR; a extensive analysis on other detection techniques to diagnose DR can be found in [4].

The general format of our method is as follows. We took some sampled images to a tractable size as input images. These images are preprocessed by normalizing and denoising technics and then we use a convolutional neural network. After that, test images are passed through the network and the model attempts to classify the progression of DR.

1.2 Motivation of the Project Effort

For Diabetic Retinopathy (DR) diagnosis there exist multiple techniques, an ocular manifestation of diabetes that affects more than 75% of patients with longstanding diabetes and is the leading cause of blindness for the age group 20-64 [5]. Researches shows that it contributes around 5% of total cases of blindness. WHO estimates that 347 million of world population is having the disease diabetes and about 40-45% of them have some stage of the disease. By seeing below image one can differentiate between image produced by normal eye and DR eye [6].



(a) Normal Eye[6]



(b) DR affected eye[6]

Fig 1: Difference between image produced by normal eye and DR eye

There are various factors affecting the disease like age of diabetes, poor control, pregnancy but Researches shows that if we can detect DR in early stage of the disease progression to vision impairment can be slowed or averted.

So the aim of our project is to provide a automated, suitable and sophisticated model using image processing technic we can detect DR at early levels easily so that damage to retina can be minimized.

CHAPTER 2

BACKGROUND LITERATURE SURVEY

Previous work has been done in using machine learning and various models for automated DR screening. For development of our method and result analysis, we have conducted a literature survey describing DR features and past work done to detect DR.

GiriBabuKandeet al. [7] represented Segmentation of Vessels in Fundus Images using Spatially Weighted Fuzzy c-Means Clustering an algorithm for the extraction of Blood Vessels from Fundus images. They used a set of linear filters sensitive to vessels of different thickness and orientation. A vessel detection methods recently reported in the literature is simple and an experimental evaluation demonstrates excellent performance over global thresholding. Their algorithm were expected to be applicable to a variety of other applications due to its simplicity and general nature.

Bob Zhang et al [8] described a mothod for Detecting Diabetes Mellitus and Nonproliferative Diabetic Retinopathy. In their mathod, theGeometry Features, Color and Texture utilized for detection. The image is captured and preprocessed. Then color features are extracted from pre-processed image. In order to represent the texture feature, the image is separated into eight blocks. The 2-D Gabor filter is applied on surface for compute texturefeatures. Finally the geometry features such as distances, areas are extracted from foreground image. In order to separate NPDR samples from healthy sample, the support vector machine classifier is used. However, it only achieves 80.52% accuracy.

Yuji Hatanaka et al [9] presented the improvement of automatic hemorrhages detection methods using brightness correction on fundus Images. They indicates the importance of developing several automated models for finding out the abnormalities in fundus images. The purpose of this paper was to improve their automated hemorrhage detection model to diagnose diabetic retinopathy. They represented a new method for preprocessing and false positive elimination. They removed false positives by using a 45-feature analysis. To verify their new method,

they examined 125 fundus images, including 35 images with hemorrhages and 90 normal images. The sensitivity and specificity for the detection of abnormal cases were 80% and 88%, respectively. These verified results indicate that their new method may effectively improve the performance of their diagnosis system for hemorrhages.

Vujosevic et al. [10] build a binary classifier on a dataset of 55 patients by explicitly forming single lesion features. The scope of this study is limited in that the dataset.

Wang et al. [11] used a CNN(LeNet-5 architecture) as a feature extractor for addressing blood vessel segmentation. The model has three heads at different layers of the convnet which then feed into three random forests. The final classifier essembled the random forests for a final prediction achieving an accuracy and AUC on 0.97/0.94 using a standard dataset for comparing models addressing vessel segmentation

Lim et al. [12] where the authors represent building a convolutional neural network for lesion-level classification and then use the learned feature representations for image-level classification. This scope of the study is limited in that the dataset which contains 200 images.

The authors in [13] introduced morphological image processing techniques to extract blood vessel, microaneurysm, exudate, and hemorrhage features and then train an SVM on a data set of 331 images achieving sensitivity 82% and specificity 86%.

Bhat P. S. Acharya et al. [14] reported sensitivity of 90% and accuracy of 90% with a dataset of 140 images using image processing techniques for extracting the area of blood vessels, area of exudates, and texture features which are then fed into a small Neural N.

CHAPTER 3

BLOCK DIAGRAM & METHODOLOGY

3.1 ARCHITETURE

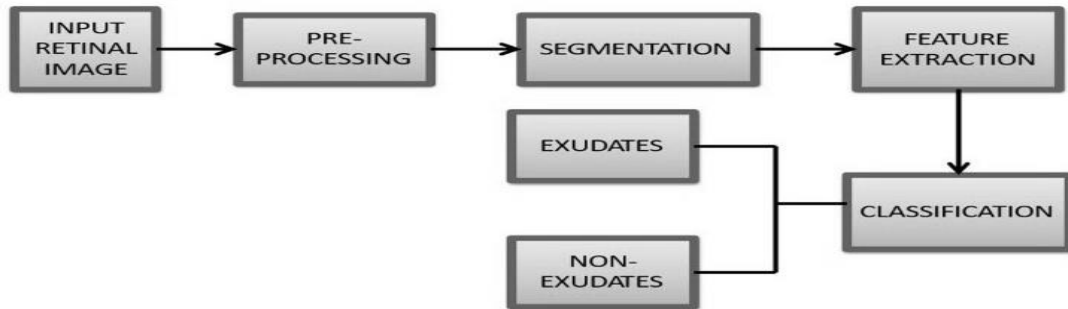


Fig.2. PROPOSED ARCHITETURE

Diabetic retinopathy detection system consists three main steps: pre-processing techniques, feature extraction and classification techniques. There are verity of techniques have been proposed in literature for pre-processing, feature extraction and classification of DR. we propose different combination of pre-processing, feature extraction and classification techniques to improve DR detection Fundus images are taken from database .

A. Pre-processing

Colour retinal fundus images often show light variation, poor contrast, and noise hence these images have to go through pre-processing stage. The enhancement is necessary since fundus images suffer from non-uniform illumination and noise. Pre-processing of fundus image is performed in order to improve the contrast. In order to enhance the contrast of the retinal images, some information is commonly discarded before processing such as the red and blue components of the image. Green channel is extensively used in pre-processing as it displays the best vessels/background contrast and greatest contrast between the optic disc and retinal tissue. Red channel is relatively bright and vascular structure of the choroid is visible. The retinal vessels are also visible but show less contrast than green channel. Blue channel is noisy and contains little information. Adaptive histogram equalization (ADHE) is used for contrast enhancement. ADHE computes several histograms of image and uses them to reallocate intensity value of image. Hence, ADHE is more

appropriate to improve regional contrast and edge enhancement in each region of image [8]. Mathematical morphology operation is applied for noise removal. Closing operation is applied in order to remove noise from object region. Pre-processed images have been shown in Fig. 3. After pre-processing, exudates are extracted from colour fundus image. Detection of exudates is necessary in detection of microaneurysm because the colour of exudates is same as microaneurysm. For detection of exudates, the pre-processed green channel image is obtained, which is further enhanced by ADHE. After that a marker has been generated using medianfilter which subtracted from the median filtered image using morphological process to extract the exudates.

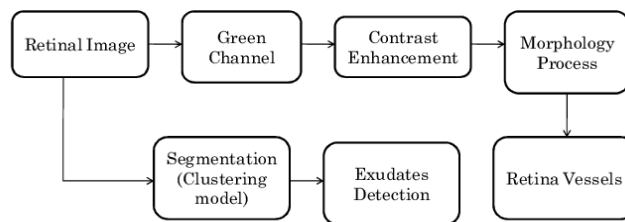
B. Feature Extractions

There are two features of microaneurysm, such as area of microaneurysm and number of MAs have been extracted from fundus images. Area of microaneurysm is calculated as total number of white pixels in extracted image. The number of microaneurysms is calculated as number of discontinuity from white pixel to black pixel.

C. Classification

SVM classifier has been used for DR detection. SVM classify the image into two classes such as DR eye and healthy eye. Parameters of SVM classifier has been calculated based on features of microaneurysm.

3.2 BLOCK DIAGRAM



The processed image after the removal of the maximum area (optic disk) has only exudates. This image is used for feature extraction. The statistical features like exudates area, entropy, correlation, energy, contrast, homogeneity, standard deviation, mean, skewness, and kurtosis are extracted from the image [6]. From this features, the most effective features are used for classification. The most effective features are used for classification. To classify the localized segmented image into

exudates and Non-exudates, a number of features based on color and texture are extracted using Gray Level Co-occurrence Matrix. The features of the retina or fovea are extracted from the retinal image to detect the diabetic diseases.

The results referred to in this paper show that the proposed methodology offers a reliable and robust solution for OD segmentation. The performance results obtained by the proposed methodology on a huge digital retinal database indicate that simple methods, based on basic image processing techniques, seem to suffice for OD location and segmentation.

In this paper, efficient methods for the automatic segmentation of optic disc localization, boundary detection and macula localization in colour retinal images are described. Retinal images of patients at different stages of retinopathy were considered to test the robustness of the optimal iterative threshold method followed by connected component analysis in disc localization. Localization of disc is important as it has to be masked during the exudates detection and its position is used in the location of the macula. Based on the result obtained in optic disc boundary detection, it can be stated that geometric based implicit active contour models provide a better segmentation for images with weak boundaries when compared to parametric models. Shape and size changes in optic disc boundaries can be further studied for the detection of glaucoma. The detection of the macula and its region plays an important role in the severity level classification of diabetic maculopathy. Detection of all these features leads towards the development of a fully automated retinal image analysis system to aid clinicians in detecting and diagnosing retinal diseases.

Detection of optic disc boundary becomes important for the diagnosis of glaucoma [9]. Difficulty in finding the optic disc boundary is due to its highly variable appearance in retinal images. Geometric active contour model was explored to segment the optic disc boundary as classical segmentation algorithms failed to provide a good result. Image segmentation was performed by starting with an initial curve and evolving its shape by minimizing energy function represented by a level set function. The iterative curve evolution was stopped at the image boundaries where the energy was minimum. The experiment was performed on both RGB image and grayscale image and found that implicit active contours provided a better result with grayscale images.

3.3 METHODOLOGY

The National Eye Institute provides a standardized description of the severity class of DR patients (which are the classes that our classifier predicts). There are four

severity classes, the first three describe non-proliferative DR (NPDR) and the last proliferative DR (PDR). The severity scales are characterized through a progression of four stages[16,17]:

- **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, extensive micro-aneurysm, retinal hemorrhage, and hard exudates.
- **Severe NPDR** -Various abnormalities, large blot hemorrhages, cotton wool spots and many blood vessels are blocked, which causes abnormal growth factor secretion
- **PDR** - Growth factors induce proliferation of new blood vessels inside surface of retina, the new vessels are fragile and may leak or bleed, scar tissue from these can cause retinal detachment.

This is an ongoing problem on kaggle[18] which tries to develop a model for DR detection. Dataset is taken from the challenge-data part. Data set consists of high resolution eye images and graded by trained professionals in 5 classes(0-4) which is according to the table and figure given here.

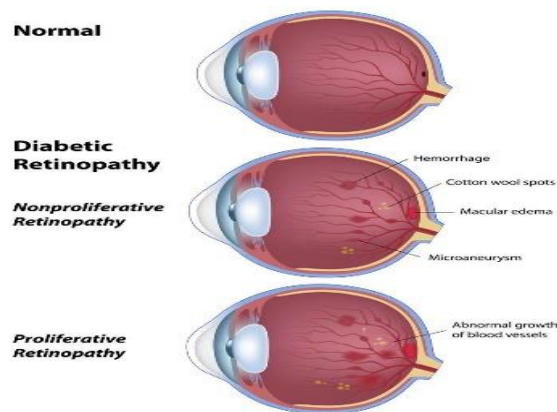


Fig2:The severity scales of DR.

Table 1: Class name descriptions

Class name	Meaning

Class 0	Normal Eye
Class 1	Mild DR eye
Class 2	Moderate DR Eye
Class 3	Severe DR eye
Class 4	Poliferative DR Eye



(a) Normal eye



(b) Mild DR eye



(c) Moderate DR

Eye



(d) Severe DR eye

(e) Poliferative DR Eye

Fig 3: Classes (0-4) of DR affected eyes[19]

CHAPTER 4

DESCRIPTION& CLASSIFICATION

4.1 Hemorrhages Detection

The earliest sign of retinopathy is small red dots in the superficial layers of retina. These are termed as microaneurysms when they are small and depending on their depth within the retina they are termed as hemorrhages. This occurs because of the leakage of blood vessels of retina and indicates mild retinopathy. But when macula edema thickens within 2 disc diameters of the centre of macula this creates microvascular changes and causes leaking of plasma components in the area. This represents moderate type of retinopathy. Though hemorrhage is a hard work to detect we need some preprocessing in order to get a noise free and bright, contrast, enhanced image.

The steps including preprocessing to detect hemorrhages are :

- Resize the image into 512 x 512 pixels
- Convert the RGB image into grey scale image.
- Use Median Filtering to remove artifacts such as vignetting.
- Equalise the image and enhance contrast by Histogram Equalization.

At first we extract the green channel from the image because in this channel the affected area is seen clearly and easy to identify. Then we apply median filter with a radius of 8 pixels to create a background and remove the background from original image. This produces an image with blood vessels and hemorrhages. Using a vessel mask we remove the blood vessel which results in an image with hemorrhages indicated.

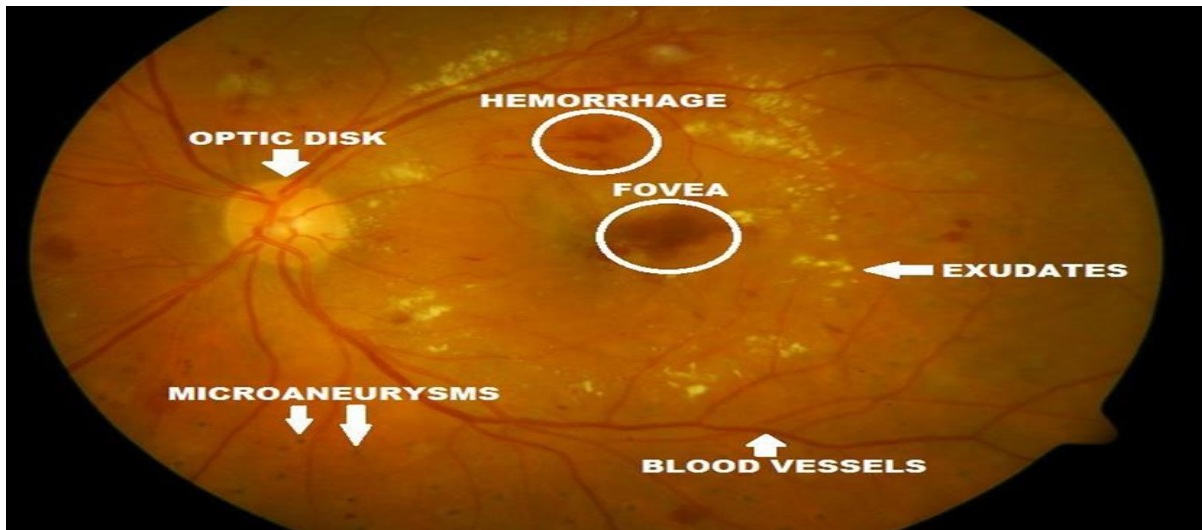


Fig 4: Retina with hemorrhages and exudates[20]

4.2 Exudates detection

The method we have applied to detect exudates on human retina is inspired by the work described in [20]. Since the data set is of completely different characteristic as we have changed in various sides. That is why we are going to describe every step and the reason behind taking it. Here we need to mention that we have implemented some library provided by [21]. We have also used MATLAB version 2017a for this project and this detection consists of the following steps:

- Preprocessing the image.
- Detection of Optic disc and other artifacts.
- Detection of exudates in terms of optic disc and artifacts.

In the preprocessing step first we extract intensity constituents from an image. Here we are going to work with gray-scale images because exudates are mostly visible in such images. We then apply Median Filtering for reducing the noise and apply Histogram Equalization to enhance contrast and brightness. The resulting image helps us to detect optic disc and accordingly exudates. This works as input image. Exudates are high intensity values as well as optic disc. Therefore in order to go for exudates detection we need to find optic disc and then we need to differentiate between optic disc and exudates near and inside the optic disc area. To do this we consider that optic disc is the largest and most circular part in brightest portion of the image. We apply Gray Scale Closing to remove blood vessels in the retina mostly in the optic disc area. Here we take a flat disc shaped structure element and consider the radius is eight. We threshold the image to binaries it and use the resulting image

as a mask. Then the mask is inverted by pixels before overlaying into the original image. We then apply reconstruction by dilation was on the overlaid image. We threshold the image and find the difference between the original image and the reconstructed image by the algorithm. Consequently, high intensity optic disc is detected and rests are removed.

In this part we faced a big problem of this approach. At the beginning of the process, vessels were removed by the Gray Scale Closing and reconstruction was applied on the image created from the original image. Therefore we are going to reconstruct vessels in the optic disc area. But we face a problem is that we are not getting one big circular optic disc. Rather we are actually detecting two or three big connected components in this step. To solve this problem we applied an addition dilation of the final mask. As a result the independent areas are connected together into a circular shape. Here we note that we have already detected artifacts and other bright spots in the image. That is why if we use too big dilation, it can lead to merge the optic disc with those areas.

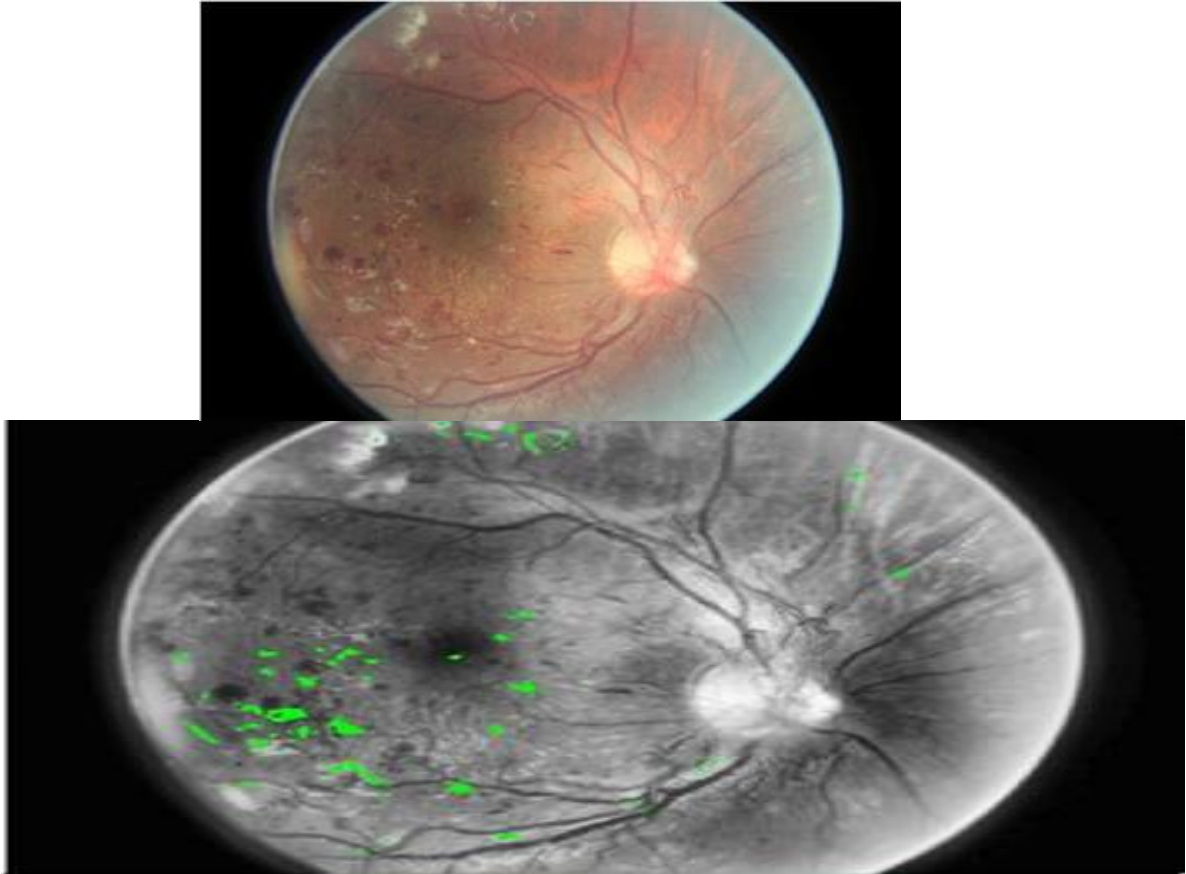
For the proper additional dilation we have considered a flat disc shaped structured element with a radius of four. Since the optic disc and also some bright artifacts are detected in this process, we have estimated for every component of the mask in order to distinguish between the features some extra values. These additional values are termed as scores. Thus we have,

$$\text{Score} = \text{area} \times \text{circularity}^3$$

Here we have some case to give attention. Since we have situation that the feature rather than optic disc can become much larger than optic disc, we needed to give circularity more importance. We take elements of size more than 1100 pixels as an optic disc keeping the rest as artifacts. Here we do not classify small areas which can become exudates as artifacts. At this stage after optic disc extraction and artifacts detection we are going to detect exudates. As before, high intensity blood vessels are removed by Grey Scale Closing. Then we go for to get a standard deviation image which shows the main characteristics of nearly arranged exudates. The resulting image is being threshold by taking the radius is six. We than remove the outside shape of the retina and fill the holes by `imfill()`. We consider threshold to remove optic disc and artifacts. Finally the result is achieved when we apply a

threshold at a level 0.01 between the original and the reconstructed one. The produced exudates mask image is overlaid into the main image to get a proper vision.

(A)



(b)

Fig 5: Exudates detection. (a) Original image (b) Exudates[17]

4.3 CLASSIFICATION

After all the feature extraction has been done, now we are going to perform binary classification. Here we have used deep neural nets with two input layers, a total of three layers, one representing the output. For this we have created a feed-forward backpropagation network (newff) . Here the terms 'newfit' is for 'regression' and 'newpr' is for 'classification'. They together are called 'newff' the generic name which is still available and gives better output in our classification[22]. First of all we have created a two later feed forward network. The first layer consists of three 'tansig' neurons and the second layer has one 'purelin' neuron. Thus we have,

```
net = newff(p,t,[3,1],{'tansig','purelin'});
```

Here, p is the matrix of input vectors and t is the matrix for target vectors. For the inputs vectors we have used three components namely, optic disk mask, artifacts mask and exudates mask.

Then the network is simulated and its output is plotted. Thus we have,

$$y = \text{sim}(\text{net}, p);$$

We need to mention here that the network is trained for 5000 epochs, train-parameter goal is 0.01.

When the training has been done a .mat file is created and further loaded to test our datasets. Once loaded we are able to distinguish our image as a good one and as a bad one. Then the corr2 library function is used to find the correlation between four classes of images. The test image belongs to the class with which it correlates most. The related algorithm we took is based on feed forward neural network described in[23].

CHAPTER 5

RESULT AND DISCUSSION

By using 70 images as training dataset we get the results on classification. Here we get results satisfactorily according to our analysis. The test process took around 5-6 hours to run over the images with the processor Intel(R) Core (TM) i5-6200U CPU @ 2.30GHz 2.40 GHz ,installed memory (RAM) 4.00 GB (3.90 usable) and system type 64-bit Operating System, x64-based processor . Here the whole data set is also run for validation.

Here we have used a confusion matrix which determines the accuracy of our classification and list the correct of them as 'true positives' or 'true negatives' and incorrect of them as 'false positives' or 'false negatives'. This method also determines sensitivity, specificity, positive predictive values and many more things. Here, we have taken plotconfusion (targets,outputs) that returns a confusion matrix plot for the target and output and the plot is given below :

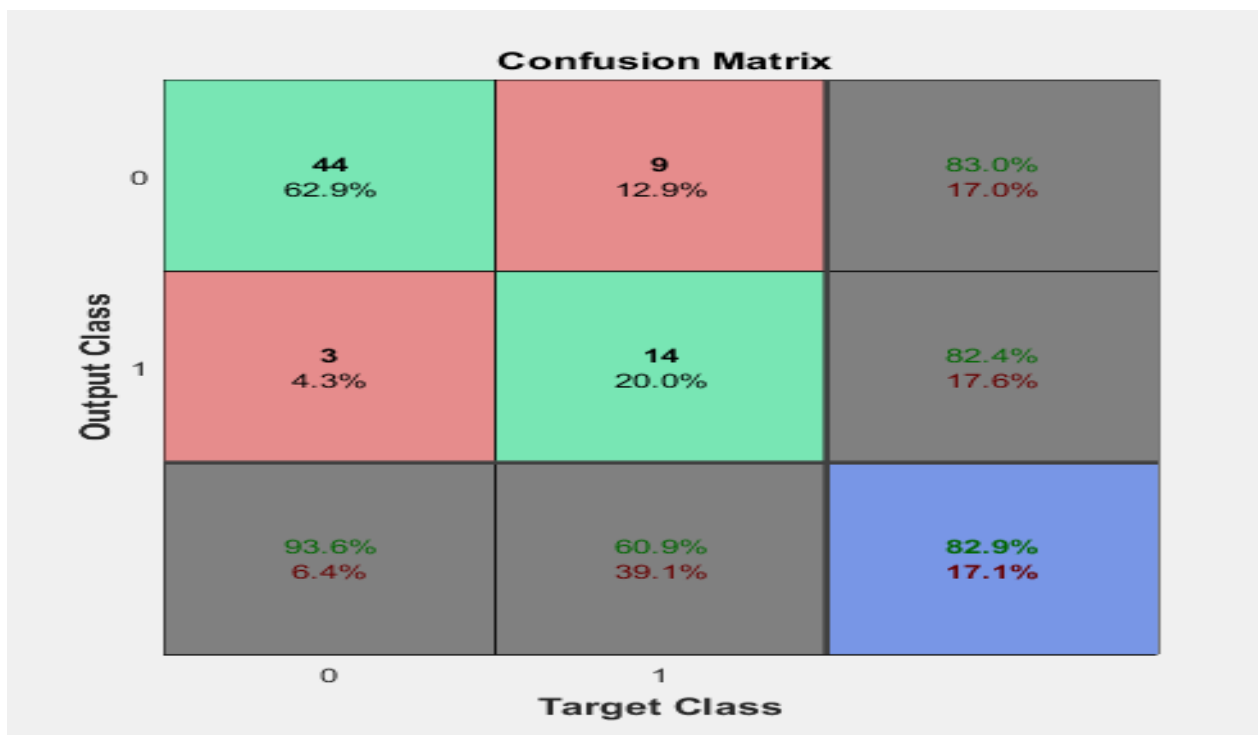


Fig 6: confusion matrix

From the figure we see that our procedure gives 82.9% accuracy in the results.

In this figure, the first two diagonal cells show the number and percentage of correct classifications by the trained network. 44 biopsies are correctly classified as benign. This corresponds to 62.9% of all biopsies. Similarly, 14 cases are correctly classified

as malignant. This corresponds to 20.0% of all biopsies.

9 of the malignant biopsies are incorrectly classified as benign and this corresponds to 12.9% of all biopsies in the data. Similarly, 3 of the benign biopsies are incorrectly classified as malignant and this corresponds to 4.3% of all data..

Overall, 82.9% of the predictions are correct and 17.1% are wrong classifications.

We are satisfied by our results although they provide slightly inaccurate findings as they provide a pretty good approach based on morphological methods.

Here we can see the comparison of the performance of methodologies for detecting DR from the table below:

Table 2: Performance comparison of automatic DR detection systems [24].

Methodology	Number of test images	SE (%)	SP(%)	Reference
SVM	13,219(300 with EXs)	95.0	84.6	Fleming(2007)
Morphology	82	96.0	89.0	Zhang(2014)
MLP,RBF,SVM	67	100	92.59	Garcia(2009)
Theresholding,Fisher	58	100	100	Sanchez(2008)
Newff	100	82.4	83	Our Project

Here, SE: Sensitivity, SP: Specificity, SVM: Support vector machine, MLP: Multilayer perceptron, RBF: Radial basis function, EXs: Exudates.

Our method achieved expected comparable performance with the precision 60.9%, specification 82.4 % and sensitivity 83 with 100 test images.

Sensitivity and Specificity pairs are used to create a receiver operating characteristic (ROC) curve. The ROC curve shows the sensitivity and specificity at different thresholds, and the system can be set for a desired sensitivity/specificity pair by simply selecting a desired threshold .The Area Under the ROC Curve (AUC) is considered the most comprehensive measure of system performance, where an area of 1 has sensitivity=specificity=1 and represents perfect detection .Here is our

ROC curves are given below:

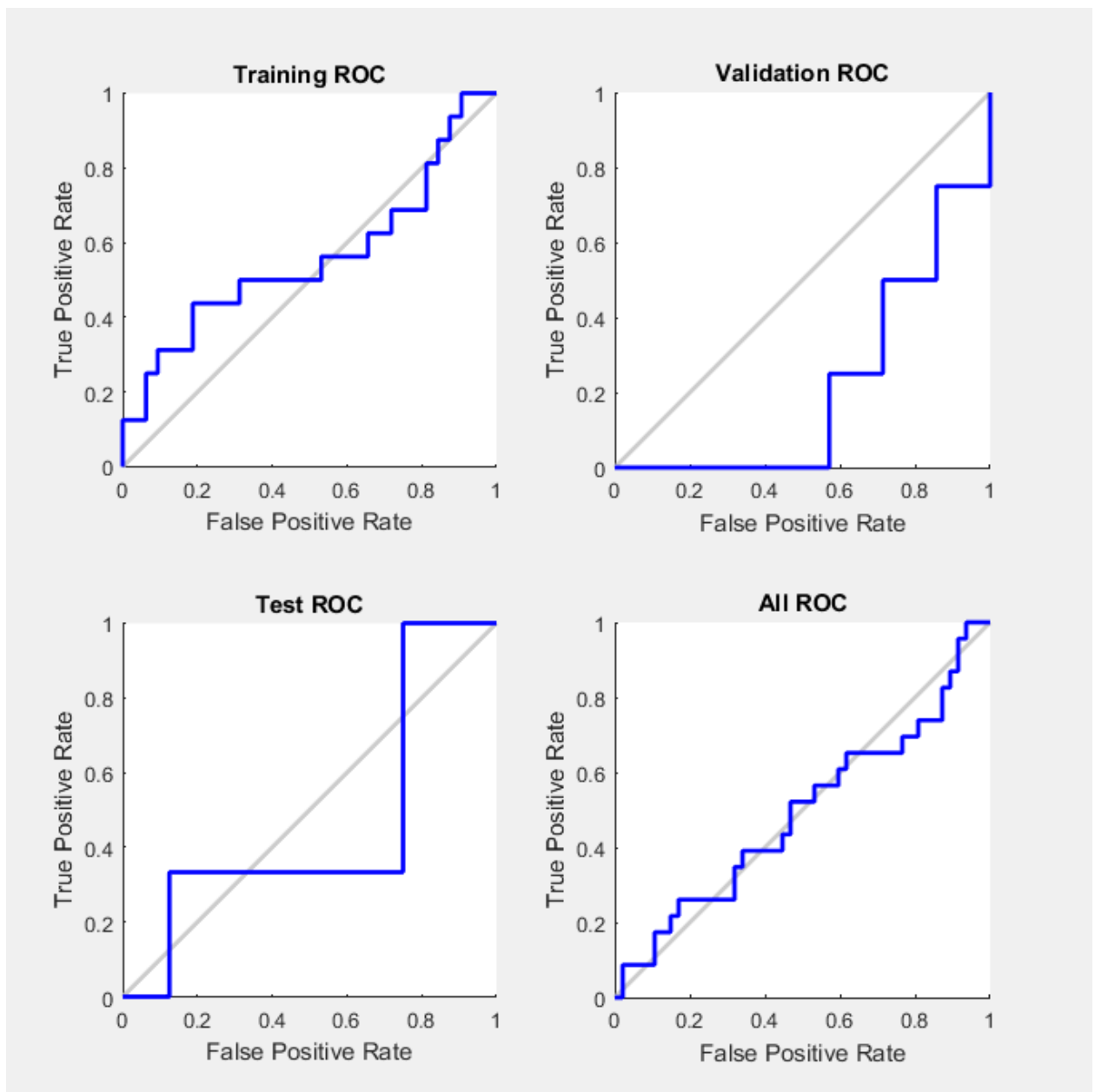


Fig 5: ROC curves

TABLE 3. finding accuracy,sensitivity and specificity of images

Images	Accuracy	<u>sensitivity</u>	specificity
Normal(unaffected)	95.238	95.454	95.0
Abnormal(affected)	96.153	96.296	96.0
Normal	96.666	96.774	96.551
Abnormal	96.551	96.666	96.428

A. RESULT SCREEN SHOTS

```

Anaconda Prompt (anaconda3) - python label_image.py
WARNING:tensorflow:From label_image.py:105: The name tf.Session is deprecated. Please use tf.compat.v1.Session instead.
2021-03-17 18:23:57.145115: I tensorflow/stream_executor/platform/default/dso_loader.cc:44] Successfully opened dynamic library nvcuda.dll
2021-03-17 18:23:57.854241: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1618] Found device 0 with properties:
  name: GeForce MX250 major: 6 minor: 1 memoryClockRate(GHz): 1.582
  pciBusID: 0000:02:00.0
2021-03-17 18:23:57.856020: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'cudart64_100.dll'; dlerror: cudart64_100.dll not found
2021-03-17 18:23:57.857923: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'cublas64_100.dll'; dlerror: cublas64_100.dll not found
2021-03-17 18:23:57.860702: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'cufft64_100.dll'; dlerror: cufft64_100.dll not found
2021-03-17 18:23:57.861816: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'curand64_100.dll'; dlerror: curand64_100.dll not found
2021-03-17 18:23:57.863085: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'cusolver64_100.dll'; dlerror: cusolver64_100.dll not found
2021-03-17 18:23:57.863850: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'cusparse64_100.dll'; dlerror: cusparse64_100.dll not found
2021-03-17 18:23:57.865468: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'cudnn64_7.dll'; dlerror: cudnn64_7.dll not found
2021-03-17 18:23:57.866442: W tensorflow/core/common_runtime/gpu/gpu_device.cc:1641] Cannot dlopen some GPU libraries. Please make sure the missing libraries mentioned above are installed properly if you would
like to use GPU. Follow the guide at https://www.tensorflow.org/install/gpu for how to download and setup the required libraries for your platform.
Skipping registering GPU devices...
2021-03-17 18:23:57.870170: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this TensorFlow binary was not compiled to use: AVX2
2021-03-17 18:23:57.877474: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1159] Device interconnect StreamExecutor with strength 1 edge matrix:
[[0]]
2021-03-17 18:23:57.877599: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1165]
=====
THE EYE HAS BEEN DISEASED WITH DIABETIC RETINOPATHY (score = 96.66 )
=====
NOTDISEASED (score = 3.34 )
=====
THE EYE HAS BEEN DISEASED WITH DIABETIC RETINOPATHY
96.6551661491394
=====

```

Fig 9: figure of python shell

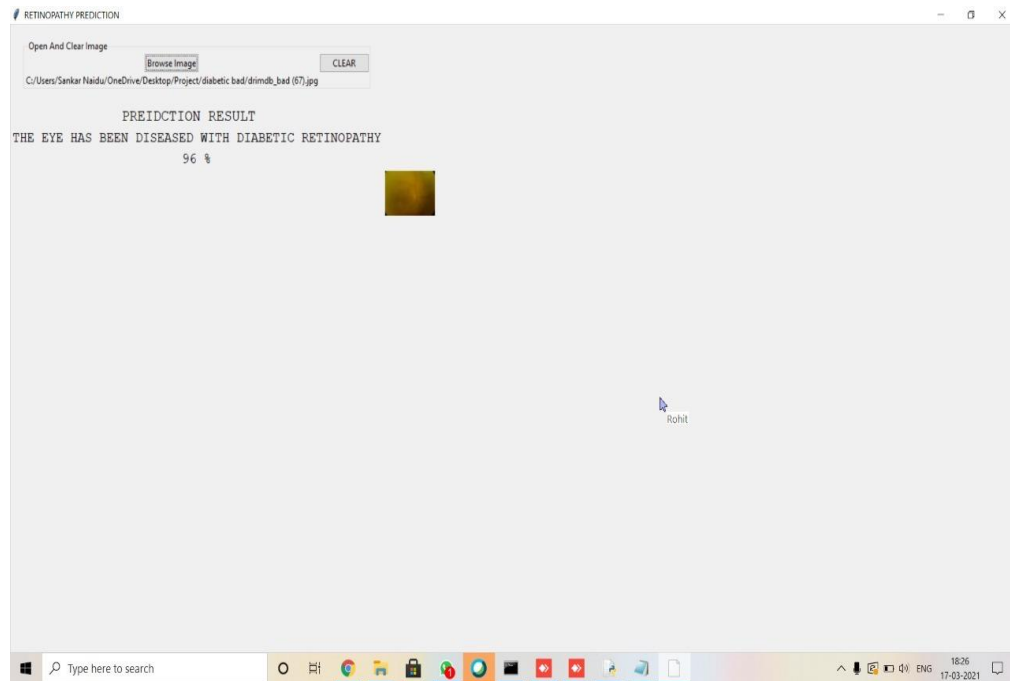


Fig.10. figure of diseased report

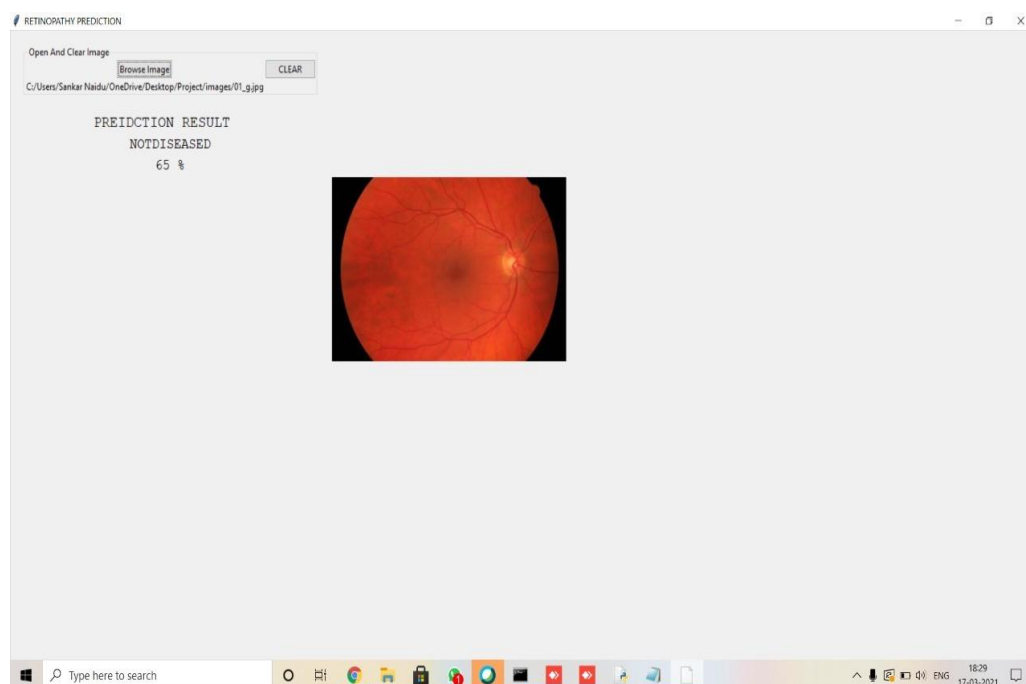


Fig.11. Figure of predicted result

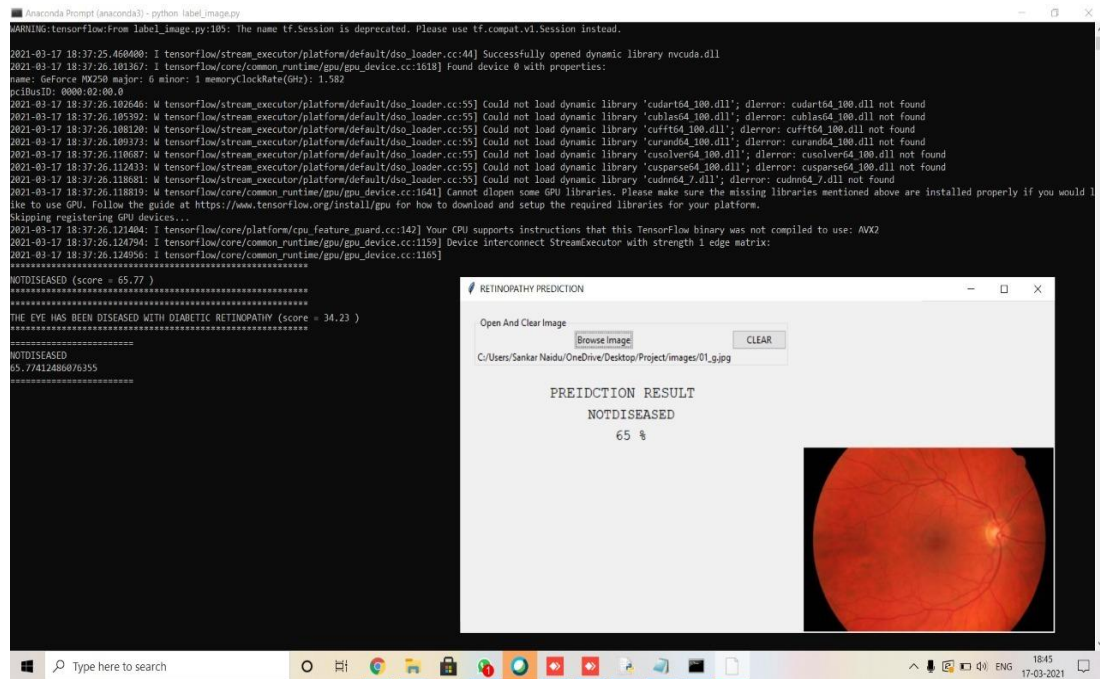


Fig.12. Figure of python shell running through tkinter.

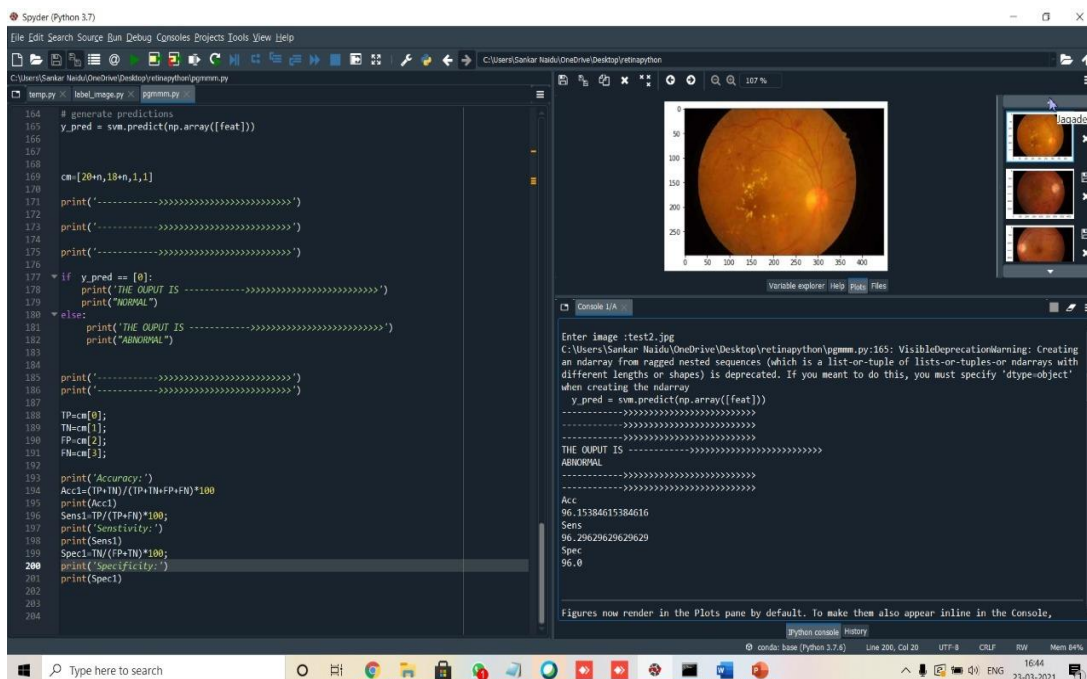


Fig.13. code in spyder

Chapter 6

Future Scope

Although I have faced many problems dealing with the findings, feature we have picked may seem rational but they are efficient according to this study. So possible approach would be based on feature extracting. One can study further in order to detect hemorrhage more specifically. We would expect such feature engineering to make the method better to perform the whole 5-class classification perfectly. Moreover, one can be done in exploring more nuanced data normalization and denoising techniques.

CHAPTER 7

CONCLUSION

This project is an analysis of a model to identify the severity of DR from Fundus Photographs. Our method performed well in comparison to other methods. It is a fact that better and accurate the diagnosis, the more exact will be the treatment plan. So diagnostic measures should aim towards accuracy for an effective treatment regimen. In this study we were able to establish a good accuracy in the diagnosis results.

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