REPORT ON

Detection of Diabetic Retinopathy

BACHELOR OF TECHNOLOGY

IN

Artificial Intelligence & Machine Learning

SUBMITTED BY

GROUP NO: 5

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviated Word	**Expansion**
DR	Diabetic Retinopathy
STDR	Sight Threatening Diabetic Retinopathy
IDRiD	Indian Diabetic Retinopathy Image Dataset
NPDR	Non-Proliferative Diabetic Retinopathy
CLAHE	Contrast Limited Adaptive Histogram Equalization

CHAPTER I: INTRODUCTION

1.1 Introduction to Human Eye:

Human eye is a light-sensitive organ that works similar to a camera's working mechanism. The human eye interacts with light that enables us to view our surroundings. The human eye consists of two types of cells- cones and rods. These cells aid in color differentiation, spatial perception and object recognition. The cones help in color differentiation and central vision while the rods are responsible for peripheral vision.

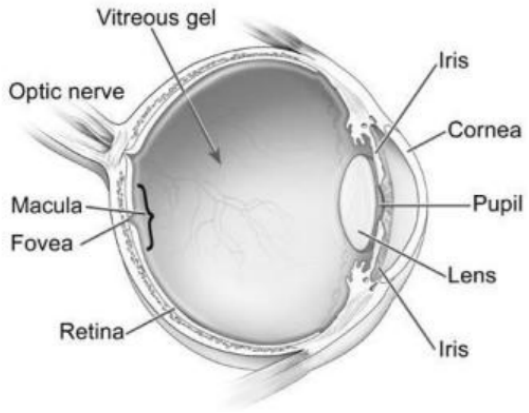


Fig 1.1 Structure of Human Eye

The outer protective white layer of the eye is called sclera. The sclera also has a transparent part called the cornea that enables light to enter the eye. Iris is the dark, muscular tissue which has a ring-like structure that regulates the amount and intensity of light that enters the eye by adjusting the size of the pupil. When opposed to bright light the pupil constricts, and when the amount of light is less, then the pupil dilates. The lens is the part of the eye that is present behind the pupil that alters its shape to focus light on the retina depending on the size of the object using the ciliary muscles. The light, after passing through the cornea, iris and lens, reaches the retina which is the part of the human eye that comprises photosensitive receptors. The image formed on the retina is real and inverted and then these images are converted into electrical signals and transmitted to the brain by the optic nerves. In the brain, the images are processed and we can see a virtual and erect image.

The human eye also contains a part called the blind spot, which does not contain any cones or rods or any other photoreceptors, so it cannot respond to light. So the brain does not perceive any part of the image that falls on the blind spot. The blind spot is also called an optic disc, and it is the point where the retina converges to form the optic nerves. Despite having blind spots in each eye, we don't notice it because our brain fills the missing image using the background field.

Fundus refers to the back part of the eye. It comprises the retina, optic disc, blood vessels and few other structures of the eye. It is examined with an instrument called an "ophthalmoscope" or the "fundus camera".

Thus because of its architecture of the eye, the diseases that affect the brain , or the eye, or the cardiovascular system can manifest in the retina. This leads to several diseases in the retina such as glaucoma, macular degeneration and diabetic retinopathy.

1.2 Introduction to Diabetic Retinopathy:

Diabetic Retinopathy (DR) is a leading cause of preventable impairment of vision in people of the working age . This condition is observed among people with diabetes. It affects the blood vessels and the light-sensitive tissues of the retina of the eye.

The number of diabetes patients has increased enormously, with each of them having a high probability of getting visually impaired due to DR.

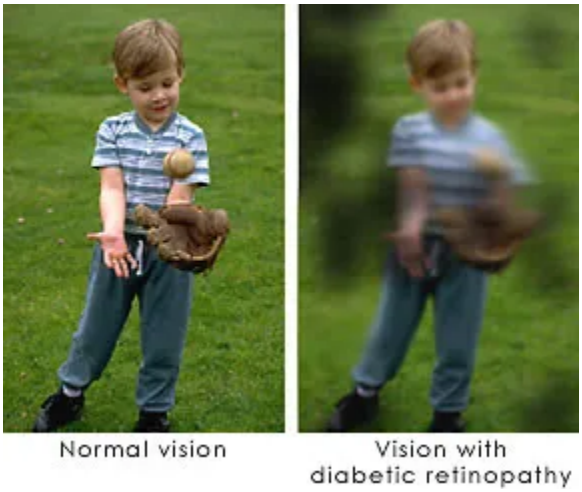


Fig 1.2 Vision Comparison

Specific complications of DR:

1. Diabetic Macular Edema (DME): It affects the macula, an area responsible for detecting light which is heavily populated with cones. DME occurs due to the leaking of fluids into the macula which causes it to swell and disrupts the functioning of it, leading to blurred and distorted vision. It can occur when the blood vessels of the retina leak due to the damage caused by DR.
2. Clinically Significant Macular Edema (CSME): It is a specific type of DME. It is caused because of excessive fluid accumulation in the macula. It affects the part of the retina that is responsible for detailed and clear vision. If not treated properly, it can lead to serious visual impairment or can even cause blindness.

Diabetic retinopathy progresses in the initial stages, and hence timely eye examinations are important for people with diabetes.

The fundus is examined for detecting diabetic retinopathy. Hence, for our project, we acquired a dataset with the images of fundus.

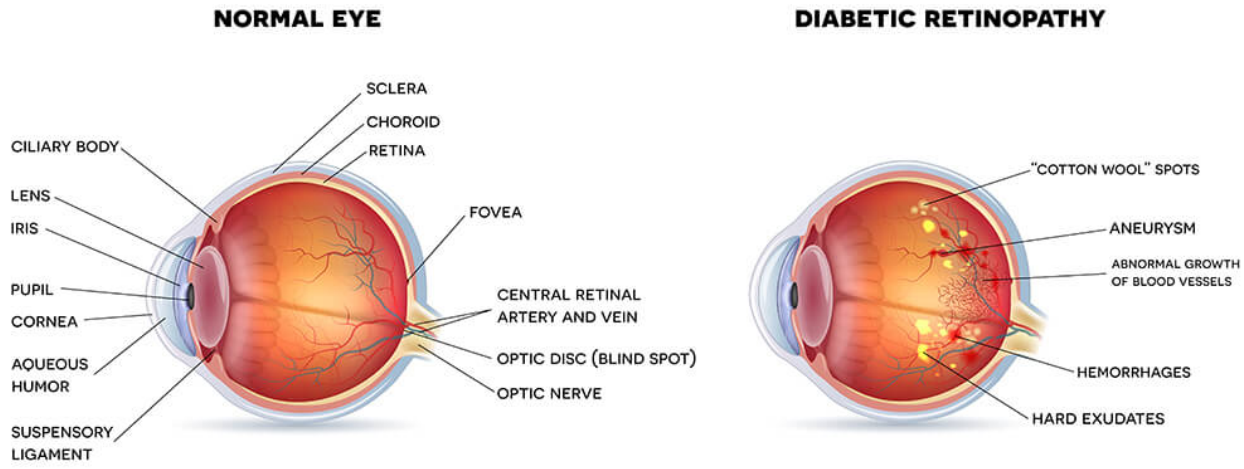


Fig 1.3 Retina Comparison (Normal eye vs. DR eye)

1.3 Project objective:

Our project aims at developing an Image Segmentation model which refers to automating the process of extracting features that detect Diabetic retinopathy in retinal images.
Image Segmentation helps us understand the image content for searching and mining in medical image archives.

Image segmentation by manual means can be a taxing and time-taking task. Therefore, automated segmentation is preferred. The algorithm for our project focuses on retinal blood vessels and fundus segmentation based on Bayesian detection algorithm which will be used to classify the changes in retinal fundus images to diagnose DR.

1.4 Motivation:

Our motivation for the project is to reduce the time consumed in extracting clinically important features from the Medical images generated using an Ophthalmoscope for fundus imaging.

The early detection of diabetic retinopathy using the extracted features by Image Segmentation can lead to early intervention that can prevent the loss of vision due to DR at its earliest stage called Micro aneurysms (MA's).

The study of Prevalence of diabetic retinopathy in India: Results from the National Survey 2015-19 [1] revealed that the prevalence of DR among persons with diabetes was 16.9%, the prevalence of STDR was 3.6%, and of mild retinopathy was 11.8%.

1.5 Feasibility/constraints:

Feasibility:

Substantial research and large datasets available in medical imaging specifically for retinal images facilitates the development of our algorithm for DR using various image processing tools and libraries.

Constraints:

Variability in image quality for retinal/fundus images refers to factors like lighting, sharpness, resolution,etc. These can affect the accuracy of our algorithm and need to be dealt with in order to work with diverse image characteristics. Dealing with large datasets may require substantial computational resources, particularly there is a need to apply complex algorithms.

1.6 Literature Review:

Table 1.1 Literature Review

Authors	Method	Database	Result
S. Sagar, B. Divya, K. Madhulika, D. Sandeep [2]	The methodology proposed is to first segment the exudates from the fundus image which is followed by the segmentation of the blood vessels. These segmentations are based on morphological operators. Finally the optic disc is segmented.The proposed methodology is solely based on image processing	DIARETDB1 Dataset	Mild Non-Proliferative Diabetic Retinopathy (NPDR): Mean of Original Image:112.0645 Mean of Blood vessel extraction: 1.6193 Mean of Hard Exudates:11.6092 Moderate Non-Proliferative Diabetic Retinopathy (NPDR): Mean of Original Image:128.7854 Mean of Blood vessel extraction: 2.0145 Mean of Hard Exudates:9.5237 (Lower the mean lower is the noise content)
R. Naveen, S. A. Sivakumar, B. Maruthi Shankar, A. Keerthana Priyaa [3]	The proposed methodology is to convert the images to grayscale and then apply Adaptive Histogram Equalization(AHE) and then Contrast Limited adaptive Histogram Equalization(CLAHE). Further the blood vessels are extracted by identifying arteries and veins.	HRF (High Resolution Fundus) Dataset	Average Accuracy is 97.64% Average Sensitivity is 81.33% Average Specificity is 98.12% DR is detected in fundus images affected by DR and it is not detected in healthy retina.

Ravishankar, Saiprasad Jain, Arpit Mittal, Anurag [4]	The methodology specifically focuses on optic disc localization using Hough Transform ,weighted convergence optimization to identify the center of the optic disc and it utilizes the convergence of thicker blood vessels. The process ensures that the method is robust.	STARE, DIARETDB0, DRIVE and Red Atlas Databases	Optic disc Localization success rate for different datasets: Hospitals: 99.1% STARE: 93.8% DRIVE: 100% Diaretdb():97.7% Red Atlas:90.7% Overall Normal: 99.1% Overall Abnormal: 96.5%
Ali Bakhshi, Kobra Hajizadeh, Mohammad Reza, Tanhayi, Reza Jamshidi [5]	The proposed methodology is to first segment the optic disc, the spot which is the brightest and has the highest intensity. CLAHE and further Gaussian Blur is applied on the images to improve the local contrast of the images which helps in the segmentation of the blood vessels, hard/soft exudates and neovasculars. Further these segmented spots are sorted by diameter for classification of DR.	APTOS 2019 Dataset	The result of this proposed methodology is the localized optic disc which is used for blood vessels segmentation and finding the fovea. Further after segmentation of the blood vessels, the exudates are detected from the blood vessels segmented. These hard exudates are further used for training the machine learning model.
G. H. Kom, B. C. Wouantsa Tindo, J. R. Mboupda Pone, A. B. Tiedeu [7]	The proposed methodology is to extract the green channel and apply filtering- median filtering and histogram expansion and then inversion is applied to the filtered image followed by subtraction and then applying image enhancement techniques and then blood vessels	DIARETDB1 Dataset	Among the 84 images with a sign of DR, 38 images contain exudates Performance of exudates detection: Sensitivity: 95.27% Specificity: 99.6% The result of various processes of segmentation of the fundus image is also shown in the result

	are suppressed using morphological opening and closing. Further entropy maximization thresholding is applied to obtain a binary image which excludes the optic disc to obtain the exudates.		

CHAPTER III: METHODOLOGY OF IMPLEMENTATION

3.1 Block diagram for the project

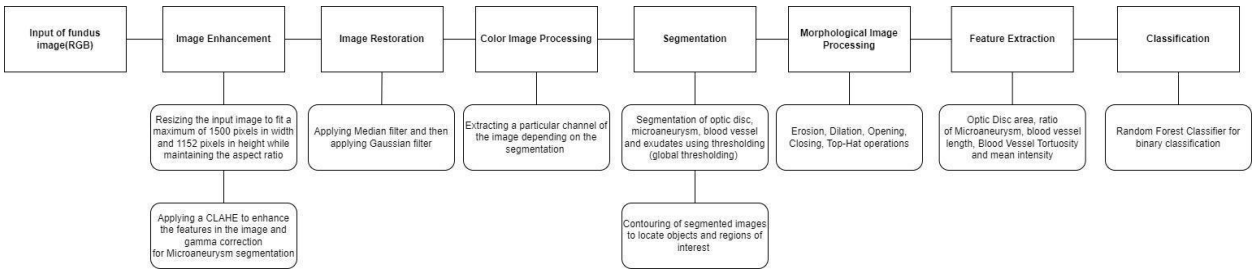


Fig 3.1 Block Diagram for the project

3.2 Explanation:

Image Enhancement: The input fundus images in RGB format are first resized to fit a maximum of 1500 pixels in width and 1152 pixels in height while maintaining the aspect ratio. After extracting a particular channel (green or red) we apply CLAHE to enhance the features for segmentation and feature extraction. Gamma correction is applied to segment microaneurysm . Gamma correction adjusts the brightness and contrast of an image.

Image restoration: Median Filter is first applied to remove the salt and pepper noise which are recurring bright and dark spots. In order for the segmentation to be accurate it is necessary to remove the salt and pepper noise. After the median filter is applied, we apply a Gaussian filter to smoothen the image and for blurring for better segmentation results.

Color image processing: The red channel of the resized RGB image is extracted to segment the optic disc, the green channel is extracted to segment the blood vessels and the microaneurysm. The image is converted to gray-scale image for segmented the exudates.

Segmentation: The segmentation of the fundus image consists of four segments- optic disc, microaneurysm, blood vessels.

Optic Disc: After extracting the red channel and applying the CLAHE, we apply binary thresholding(choosing an appropriate local threshold). We apply thresholding and after that we set all the pixel values above 245 to 255(white) and the pixel value below 245 to 0(black). We obtain a binary image after thresholding and to this we apply morphological opening on the binary image and then morphological closing. Next step is contouring the closed optic disc which are the boundaries of connected regions. Since the optic disc is the largest area we sort the contour area from largest to smallest. The largest contour is drawn on this mask and it is filled to obtain the optic disc.

Microaneurysm: Microaneurysm are tiny dots in a retina that are very hard to segment. The process that we have employed here is to segment the image using thresholding and morphological operations. Initially after the extraction of the green channel and applying CLAHE, adjust gamma is applied which allows contrast enhancement by mapping the pixel values to the corrected gamma values and then applies the transformation using the LUT function of cv2. After this thresholding and morphological operations such as tophat and opening are applied.The resulting binary mask highlights the region of interest.

Blood vessels: The process of segmentation of blood vessels initially starts with the green channel and applying CLAHE to enhance the blood vessels. Subsequently various operations such as median, filtering, subtraction of the original image and the green channel enhanced image followed by blurring,thresholding(by choosing an appropriate local threshold), morphological operation-opening and then the exact operations are performed with slight variations in the parameters. Both these images are then combined using the bitwise OR operator. The result is a binary image with highlighted blood vessels.

Exudates: Exudates are typically the bright lesions in a fundus image. The process of extraction of these exudates initially starts with the conversion of the image to gray scale and then the average pixel intensity of the entire image is calculated. Based on the average pixel intensity thresholding is applied to segment the exudates. After thresholding, the centroid of the white pixels are calculated that of the white pixels. Then further using these centroid values we remove pixels i.e., if the centroid y-coordinate is less than 1000 then the pixels near the top are removed and similarly if the centroid's x-coordinate is greater than 2200 or zero then pixels near the right side are removed or otherwise pixels to the left are removed.

Representation and Description: Representation and Description involves extracting the features after segmentation that can be used for further processing. In DR detection this involves- area of optic disc, ratio of microaneurysm, length of blood vessels, Blood Vessel Tortuosity, edge density, mean intensity, standard deviation, exudate density. Even extraction of all the potential features, it is necessary to only use the ones that are relevant and give a higher accuracy. The area of the optic disc is calculated by counting the number of white pixels. The ratio of microaneurysm is calculated by dividing the number of white pixels by the total number of pixels in the image. The length of the blood vessels are calculated by skeletonizing the blood vessels. The blood vessel tortuosity is calculated by dividing the perimeter of the blood vessel by the length of blood vessels. The edge density is calculated by detecting the edges using the Canny operator and then finding the density. Mean intensity and standard deviation are very straightforward to calculate by using the formulae offered by the numpy library. Finally exudate density is calculated in a way similar to edge density.

Classification: The next step after the feature extraction is to use the necessary features to classify the fundus images into whether a person has Diabetic Retinopathy or not. The model used for the binary classification is Random Forest after it gave the highest accuracy compared to KNN Classifier, Logistic Regression, SVM and Gradient Boosting. The features used for model training are ratio of microaneurysm, blood vessel length, blood vessel tortuosity and mean intensity. The other features were not considered due the fact that the features reduced the accuracy of the model.

CHAPTER IV: EXPERIMENTATION

4.1 Dataset Description

Indian Diabetic Retinopathy Detection Dataset

Indian Diabetic Retinopathy Detection Dataset was primarily developed for facilitating the screening research that was being conducted with the sole mission of combating the problem that is causing millions of individuals to lose their vision. Indian Diabetic Retinopathy Detection Dataset consists of fundus images with and without diabetic retinopathy which is annotated at a pixel level.

The authors of the Indian Diabetic Retinopathy Detection Dataset are Prasanna Porwal, Samiksha Pachade, Ravi Kamble, Manesh Kokare, Girish Deshmukh, Vivek Sahasrabuddhe and Fabrice Meriaudeau [10][11]. The dataset was originally published in https://www.mdpi.com/2306-5729/3/3/25 but since then it has been published in numerous repositories. The dataset was used for "Diabetic Retinopathy segmentation and Disease Grading Challenge" held by IEEE International Symposium on Biomedical Imaging on 4th April 2018.

The images in the dataset have a resolution of 4288×2848 pixels and are stored in JPG/TIF file format. The size of each image is about 800 KB. The dataset is divided into three parts. The first part of the dataset is- Segmentation which is divided into train and test. There are 54 training images and 27 test images. These images have corresponding ground truths for the segmentation of Optic Disc, microaneurysm, hemorrhages, hard exudates and soft exudates.

The second part of the dataset is-disease grading. The disease grading part is divided into train and test images with corresponding labeled csv files as ground truths. There are a total of 516 images which are divided into 413 train and 103 test images. The labeled csv are useful in model building after the necessary features are extracted.

The third and last part of the dataset is- Localization. The localization part is divided into train and test images with corresponding labeled csv files as ground truths. The ground truths are for Labels for Optic Disc Center Location and Fovea Center Location. There are a total of 516 images which are divided into 413 train and 103 test images

4.2 Results:

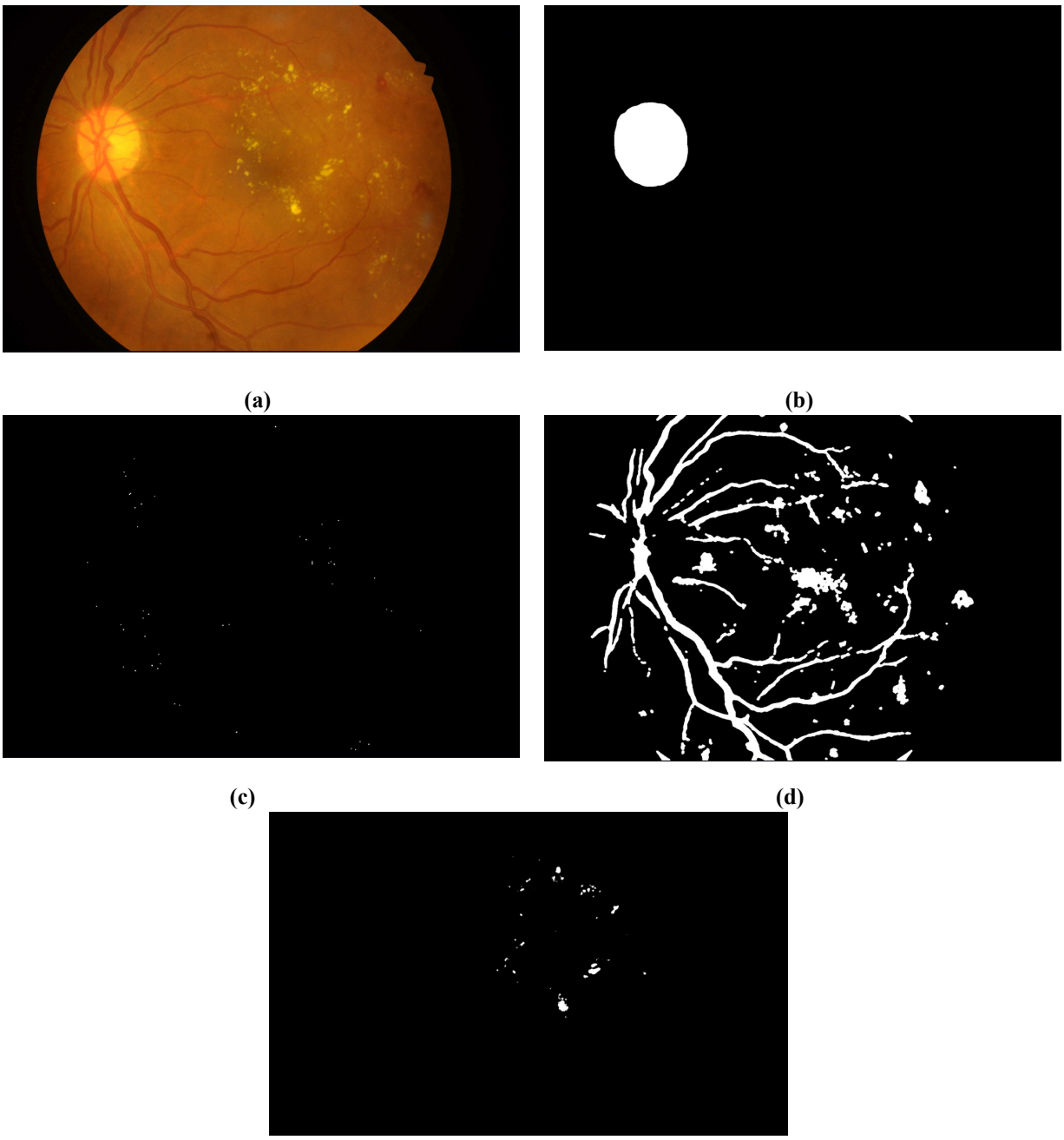
Our project is divided into two parts- Segmentation and Disease grading. We have utilized the first two parts of the Indian Diabetic Retinopathy dataset-Segmentation and Disease Grading for the respective tasks.

Part I: Segmentation:

In this part of the project we have segmented the train images-Optic Disc, Microaneurysm, Blood vessels and Hard Exudates from the segmentation folder and compared these segmented images with the corresponding ground truth images to find the Mean Absolute Error(MAE) between our segmentation and the ground truth from the dataset

Table 4.1 Mean Absolute Error of Segmented regions

Segmented Region	Mean Absolute Error
Optic Disc	1.54
Microaneurysm	0.084
Exudates	0.87



(a) **(b)**

(c) **(d)**

(e)

Fig 4.1 Segmented Fundus Image

(a) Original Image (b) Optic Disc (c) Microaneurysms (d) Blood Vessels (e) Hard Exudates

Part II: Disease Grading:

In this part of the project, after the segmentation we have extracted necessary features such as- ratio of microaneurysm, blood vessel length, blood vessel tortuosity and mean intensity. These features were used from training the model using classifiers such as KNN Classifier, Logistic Regression, SVM, Gradient Boosting and Random Forest. The accuracy of these classifiers were compared to use the best model with the most accuracy for the further classification.

The Random Forest Classification model had the highest accuracy among the five classification models. Hence the Random Forest Classification model is chosen for the binary classification of the fundus image.

Table 4.2 Comparison of Accuracy of Classification Models

CLASSIFICATION MODEL	ACCURACY
Logistic Regression	0.39
Random Forest	0.75
Gradient Boosting	0.51
SVM	0.68
KNN	0.38

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