EVALUATION OF VASCULAR STRUCTURES IN RETINAL IMAGING

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SYNOPSIS

The recent developments in the field of ophthalmology over the last decade is the emergence of high-resolution imaging modalities, which are typically non- invasive, rapid, and widely available. The primary anatomical structure that can be visible in retinal images are the blood vessels. Many important eye diseases as well as systemic diseases which affects other parts of the body manifest themselves in the retina. The most prevalent causes of blindness like age related macular degeneration, diabetic retinopathy, and glaucoma, is devoted to retinal imaging and image analysis methods and their clinical implications. The retinal morphology is involved in certain diseases such as cardiovascular disease and dementia. The association between the structure of the neurosensory retina and neurodegenerative diseases, especially Alzheimer's disease, is well established. Artificial intelligence techniques are used to segment the blood vessels from the obtained image and the segmented image is analyzed for abnormalities.

The datasets taken for our project are DRIVE and STARE. The retinal images are captured through fundus photography. Thirty-four features are extracted, and the blood vessels are segmented. K – mean clustering algorithm technique is used for blood vessel segmentation. The average Contour matching score for image segmentation obtained from K – mean clustering algorithm technique is 85.60% for DRIVE database and 75.74% for STARE Database.

CHAPTER 1

INTRODUCTION

Retina is the photo – sensitive, innermost tissue layer of the eye. It is located near the optic nerve. The Retina's function is to receive light that our eye lens has focused, convert it into neural signals, and send the signals on to the brain for visual recognition. The central retinal artery and vein, and their branches are the retinal blood vessels. It is thus an extension of the brain [1]. The diseases of the eye, as well as diseases that affect the circulation and the brain can manifest themselves in the retina because of the architecture. The retina is vulnerable to organ specific and systemic diseases, imaging the retina allows diseases of the eye proper, as well as complications of diabetes, hypertension, and other cardiovascular diseases, to be detected, diagnosed, and managed. The deep- rooted blood vessel of the eye is only observed in a non-invasive manner [2]. The fundus photography and optical coherence tomography image analysis is used to provide comprehensive descriptions of retinal morphology and function [2].

1.1 ANATOMY OF EYE AND FUNDUS PHOTOGRAPHY

The visible parts of the eye are the transparent cornea, the white sclera, the iris and an opening in the iris, the normally black pupil. A ray of light after passing through the cornea, which focusses the image partially, passes through the pupil, the lens which focuses the image further, the vitreous and is then focused on the retina. The retina is supported by the retinal pigment epithelium, which is opaque. The primary blood supply to retina is through choroid and secondarily through retinal vasculature that lies on top of the retina. It is useful to divide the retina and choroid into the following layers [3]:

1. internal limiting membrane.
2. nerve fiber layer (the axons of the ganglion cells, that transmit the visual signal to the lateral geniculate nucleus and thence the visual cortex).
3. ganglion cell layer (the cell bodies of the ganglion cells).
4. inner plexiform layer (the axons of the bipolar cells).
5. inner nuclear layer (the cell bodies of the bipolar and horizontal cells).
6. outer plexiform layer (the dendrites of the horizontal cells and the inner segments of the rod and cone photoreceptor cells).
7. outer nuclear layer (cell bodies—outer segments—of the photoreceptor cells)
8. external limiting membrane.
9. pigment epithelium.
10. Bruch's membrane.
11. capillary choroid (capillaries of the choroid)

12. choroid plexus.

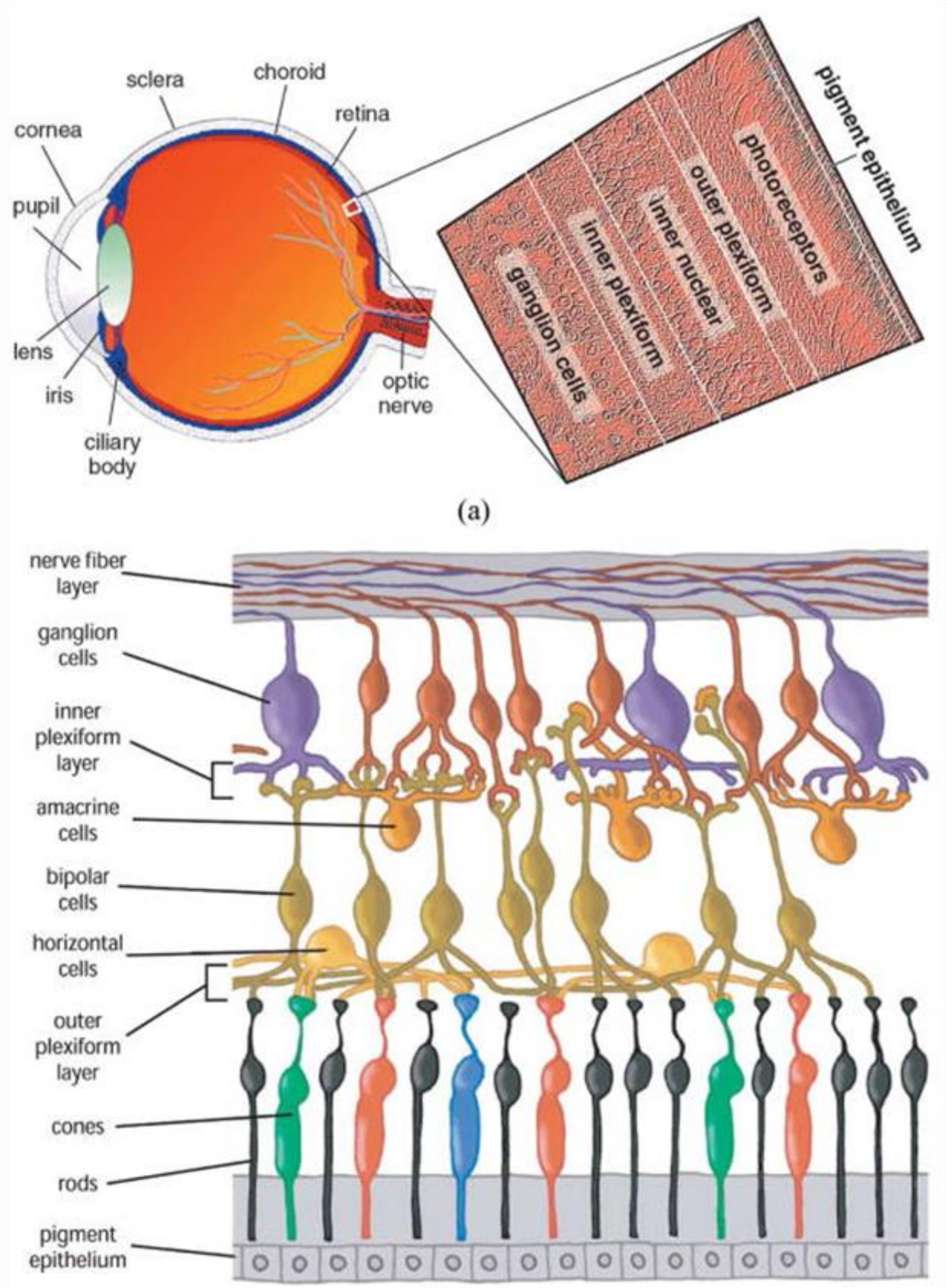


Fig 1.1 Anatomy of the eye & retina (SOURCE: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3131209/#!po=0.393701

FUNDUS PHOTOGRAPHY

Fundus photography involves photographing the rear of an eye; also known as the fundus. Specialized fundus cameras consisting of an intricate microscope attached to a flash enabled camera are used in fundus photography. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic disc, and macula. Fundus photography can be performed with colored filters, or with specialized dyes including fluorescein and indocyanine green. Practical instruments for fundus photography perform the following modes of examination [16]:

- Color, where retina is illuminated by white light & examined in full color.
- Red free fundus photography utilizes a filter in order to better observe superficial lesions and some vascular abnormalities within the retina and surrounding tissue. A green filter 540–570 nm is used to block out red wavelengths of light. This allows a better contrast for viewing retinal blood vessels and associated hemorrhages, pale lesions such as drusen and exudates, and subtle characteristics such as nerve fiber layer defects and epiretinal membranes. This is a method of better observing intraretinal microvascular abnormalities, neovascularization at the disc and elsewhere in Diabetic retinopathy progression assessment. Red free photography is also regularly used as a base line photo prior to Angiography.
- Angiography is a process of photographing vascular flow within the retina and surrounding tissue by injecting a fluorescent dye into the blood stream. This dye fluoresces a different color when light from a specific wavelength reaches it. Using this method, a sequence of photographs can be produced that show the movement, and pooling of blood over time as the dye passes through the retina and choroid.
- Sodium Fluorescein Angiography is used for the imaging of retinal vascular disease and utilizes blue excitation light of 490 nm and fluoresces a yellow light of 530 nm. It is routinely used to image Cystoid Macular Oedema and Diabetic Retinopathy, among others.

1.2 RETINAL MANIFESTATIONS OF EYE AND SYSTEMIC DISEASE

The most prevalent diseases that can be studied through eye imaging and analysis are as follows.

A. **Diabetic retinopathy:** In early stages, high blood sugar damages the blood vessels in the retina, they can either leak fluid or bleed. This can cause the retina to swell and form deposits. In later stages, leakage from blood vessels into the eye’s vitreous humor can cause severe vision problems and will eventually lead to blindness. Diabetic retinopathy can often be prevented with early detection, proper management of diabetes and routine eye examination performed by ophthalmologist.

B. **Age-Related Macular Degeneration:** Age Related Macular Degeneration affects the macula. A patient with macular degeneration gradually loses central vision but maintains peripheral or side vision. Blindness is rare in macular degeneration. The leading cause of vision loss among older Americans is Macular degeneration. According to statistics, one-third of males and one-quarter of females over 75 have some form of Age-related Macular Degeneration [14]. The prevalence of macular degeneration and the severity of vision loss increases with age.

C. **Hypertensive Retinopathy:** Chronic high blood pressure can damage the tiny blood vessels that nourish the retina, leading to significant vision problems. Risk factors for hypertensive retinopathy are the same as those for high blood pressure, including obesity, lack of physical activity, eating too much salt, a family history of hypertension and a stressful lifestyle. Hypertension can invoke direct retinal ischemia, which causes retinal infarcts visible as cotton wool spots and choroidal infarcts visible as deep retinal white spots.

D. **Macular edema:** This is an accumulation of fluid and swelling of the macula, causing distortion, and blurred central vision. Macular edema has several causes, including diabetes. In some cases, swelling of the macula can occur after cataract surgery.

E. **Cardiovascular disease:** The A/V ratio, the ratio between the diameter of arteries and veins of the veins changes due to atherosclerosis and hypertension. A decrease in A/V ratio, that is, widening of veins and thinning of arteries, is associated with stroke and myocardial infarction.

1.3 OBJECTIVES OF THE PROJECT

To create a dataset of retinal images from STARE and DRIVE databases.

To preprocess the images and segment the blood vessels

To extract features from the segmented images and to perform classification.

Identify normal / abnormal images and verify with the ground truth.

CHAPTER 2
LITERATURE SURVEY

This chapter presents the literature survey on Evaluation of Vascular Structures in Retinal Images. Literature survey includes of all types of published literature. This survey consists of all existing literatures related to the proposed work.

The paper “A Comprehensive Study of Retinal Vessel Classification Methods in Fundus Images” by Maliheh Miri, Zahra Amini, and Raheleh Kafieh deals with a comprehensive study of the proposed methods for classification of arteries and veins in fundus images[4]. This paper also talks about the relationship between changes in the retinal vessel structure and diseases such as diabetic, hypertension, stroke, and the other cardiovascular diseases in adults as well as retinopathy of prematurity in infants. Retinal fundus images provide non-invasive visualization of the retinal vessel structure. The analysis present in this paper reveals that most of the proposed approaches have focused on statistics, and geometric models in spatial and transform domain have less attention. This could suggest the possibility of using transform models, especially data adaptive ones, for modeling of the fundus images in future classification approaches [4].

The paper “Automatic Grading of Retinal Blood Vessel in Deep Retinal Image Diagnosis” by Debasis Maji, Arif Ahmed Sekh describes about the work that is to develop an automatic computer aided diagnosis system to solve the problem. This work approaches to achieve an automatic grading method that is opted using Convolutional Neural Network (CNN) model [5]. As the vessels are so gaunt by nature, the chance of internal bleeding occurs. So, the measurement of the curvature of the vessels to detect Diabetic Retinopathy is common. Curvature-based approach introduced by Hart et al. was the first approach in this area [5].

The paper “Retinal imaging and image analysis” by Michael D. Abramoff, Mona K. Garavin and Milan Sonka deals with retinal images and image analysis through fundus photography and optical coherence tomography (OCT) [2]. The detection of diseases and registration processes in fundus photographs and optical coherence tomography is discussed in this paper. With optical coherence tomography both 2D and 3D images can be obtained. The different types of fundus imaging are being discussed. The fundus image analysis includes image quality quantification, location and segmentation of retinal structures and segmentation of abnormalities. The optical coherence tomography image analysis like retinal layer detection, Image flattening, retinal layer thickness analysis, retinal texture analysis has been discussed [2].

The paper “Retinal vessels segmentation techniques and algorithms: A survey” by Jasem Almotiri, Khaled Elleithy and Abdelrahman Elleithy deals with retinal vessel segmentation techniques [6]. The three common stages for retinal image segmentation includes pre-processing stage, processing stage and post processing stage. The paper discusses six major categories namely kernel-based techniques, vessel tracking, mathematical morphology based, multiscale techniques, model-based techniques, adaptive local thresholding and finally with machine learning. The machine learning methods like fuzzy logic, K nearest neighbour and artificial neural networks has been discussed. The metrics used for analysing the retinal vessel segmentation algorithms are True Positive Rate, False Positive Rate, sensitivity, specificity, accuracy, and precision. The sensitivity shows the capability of the algorithm to detect the vessel pixels, and the specificity shows the capability of the algorithm to detect non vessel pixels. The DRIVE and STARE datasets has been used for retinal image segmentation techniques. These datasets are popular due to good resolution of fundus images and the availability of manual ground truth images prepared by the experts [6].

The paper “Automatic Detection of Diabetic Retinopathy: A review on Dataset, Methods and Evaluation Metrics” by Muhammed Mateen, Junhao Wen, Song Sun et al., describes about early identification of Diabetic Retinopathy [7]. The detection of DR can be manually performed by ophthalmologists and can also be done by an automated system. In the manual system, analysis and explanation of retinal fundus images need ophthalmologists, which is a time consuming and very expensive task, but in the automated system, artificial intelligence is used to perform an imperative role in the area of ophthalmology and specifically in the early detection of diabetic retinopathy over the traditional detection approaches. This paper presents a detailed review of the detection of DR with three major aspects: retinal datasets. DR detection methods. and performance evaluation metrics. Furthermore, this study also covers the author's observations and provides future directions in the field of diabetic retinopathy to overcome the research challenges for the research community [7].

The paper “Automatic segmentation of blood vessels from retinal fundus images through image processing and data mining techniques” by R Geetharamani and Lakshmi Balasubramanian deals with blood vessel segmentation which is attempted through image processing and data mining techniques [8]. The retinal blood vessels were segmented through color space conversion and color channel extraction, image pre-processing, Gabor filtering, image postprocessing, feature construction through application of principal component analysis, k-means clustering and first level classification using Naïve–Bayes classification algorithm and second level classification using C4.5 enhanced with bagging. The results reported 95.05% accuracy on entire dataset; however, the accuracy was 95.20% on normal images and 94.89% on diseased images [8].

The paper “Retinal Blood Vessel Segmentation Using Hybrid Features and Multi-Layer Perceptron Neural Networks” by Nasser Tamim, M. Elshrkawey, Gamil Abdel Azim and Hamed Nasser deals with blood vessel segmentation and Multi-Layer perceptron neural network [9]. 24 features were extracted from the retinal image and a special multi-layer perceptron neural network structure was designed for full fundus retinal evaluation. The features are extracted from transformed green channel image. The white top hat and black bottom hat filters are used to extract the features. A model for automatic feature extraction and classification of blood vessels in the retinal images has been described. Phase congruency with minimum and maximum moments are used in this paper. An improved generalization for retinal image segmentation on multiple datasets has been contributed. This paper uses three datasets namely DRIVE dataset and STARE dataset [9].

CHAPTER 3

FIELD SURVEY

The global retinal imaging devices market size was valued at USD 4.3 billion in 2018 and is projected to reach $6.3 billion by 2025, rising at a market growth of 6.6% CAGR during the forecast period [10]. The growing prevalence of ophthalmic disorders and increasing demand for early diagnostic measures, high rates of diagnosis and treatment of retinal disorders, advances in technology, and improved health care infrastructure are the factors expected to drive the overall market growth. Retinal imaging devices generally help the eye care professionals to identify, assess, document, and treat the retinal disorders. Advanced retinal imaging devices can view retina within a single capture from 0 to 200 degrees. In traditional devices, full-spectrum white light is used, whereas advanced retinal imaging devices use low-powered laser light. Retinal imaging device generally takes a digital photograph from the back of the eye. It shows the retina (where light and objects hit), the optic disk (a location on the retina that houses the optic nerve, transmitting data to the brain), and the blood vessels. It helps ophthalmologist to find out illnesses and to check the health of the eyes.

Highly developed health care, strong research in optical field and a rise in retinal disorders are the most prominent factors that contributed to a dominant market share of France, Germany, and the United Kingdom in the European region. In 2017, China and Japan retained large shares of market for retinal imaging devices in the Asia Pacific. The market in India is likely to expand at a fast CAGR in the near future due to developing health care industry. The underdevelopment in health care industry and less technological improvement are expected to hinder the growth of the market for retinal imaging devices in Latin America and the Middle East and Africa during the forecast period [11].

3.1 PRODUCTS AVAILABLE IN MARKET

• In Oct-2019 Optos, a Nikon Company launched Silverstone, first-of-its kind that combines ultra-widefield retinal imaging with integrated, image guided, swept source Optical Coherence Tomography. This device produces 200-degree single capture optical map image with guided OCT, enabling advanced OCT imaging anywhere across the retina, from posterior pole to far periphery [15].

• In Aug-2019 Topcon launched Maestro2 Automated Optical Coherence Tomography/Fundus Camera with OCTA. It is a fully automated OCT system that has capability to capture high resolution non-mydriatic, true color fundus photography, OCTA, and OCT [15].

• In Aug-2019 Nidek introduced Mirante Scanning Laser Ophthalmoscope. It is an ultimate multimodal fundus imaging platform, which integrates high-definition OCT and SLO with an ultra-wide field imaging. It captures fluorescein angiography (FA), high quality color images, indocyanine green angiography (ICG), unique Retro mode images, fundus autofluorescence (FAF), OCT-Angiography, and OCT scan [15].

• In Jun-2019, Olympus launched 2X teleconverter, the MC-20, compatible with company's 40-150 F2.8 and 300mm F4 IS Pro lenses. It doubles the focal length of master lens. It is dustproof, freezeproof, and splashproof [15].

• In May-2019, Zeiss launched ARTEVO 800, first digital microscope in ophthalmic surgery. It features Digital Optics technology for providing reduced light intensity requirements, depth of field, and real color impression for increased certainty [15].

• In Feb-2019, Optomed made enhancements to its Optomed Aurora camera. The new features include faster and smarter autofocus, image quality analysis, four image sequences, new ways of selecting patient list, and optimized target led selection [15].

• In Sep-2018, Optos, a part of Nikon introduced Monaco, which is a latest ultra-widefield device for European ophthalmic market. It is the only ultra-widefield retinal imaging system with integrated OCT. This device generates 200 degree single-capture optical map image in less than half a second [15].

The above-mentioned products are all devices (cameras and capturing devices) which are of commercially available in the market in recent times. There is also an urgent need of producing high – definition fundus and OCT images for clear, error free classification and diagnosis using the retinal vessels, hence a strong competition for products is present in this market. Retinal imaging device market is a relatively new market and also an emerging one. So, the process of classification, screening, and diagnosis of retinal images for various diseases and disorders are still being done manually by ophthalmologists commercially. The limitations of humanity are a liability in this market which can be satisfied by automation of the retinal image analysis. The advent of AI, Machine Learning and Automation in this retinal imaging market is of a vital one and is still being in a research status. This project is an attempt of Evaluation of the vascular structures in retinal images by automated segmentation of the vessels present in the retina for classification, screening, and diagnosis of various diseases.

CHAPTER 4

PROPOSED METHODOLOGY

The proposed methodology is designed for the retinal image analysis using artificial intelligence techniques. The fig 4.1 and fig 4.2 illustrates the methodology and flowchart of the proposed work. The details about the dataset we used in the analysis is discussed in this chapter.

4.1 BLOCK DIAGRAM

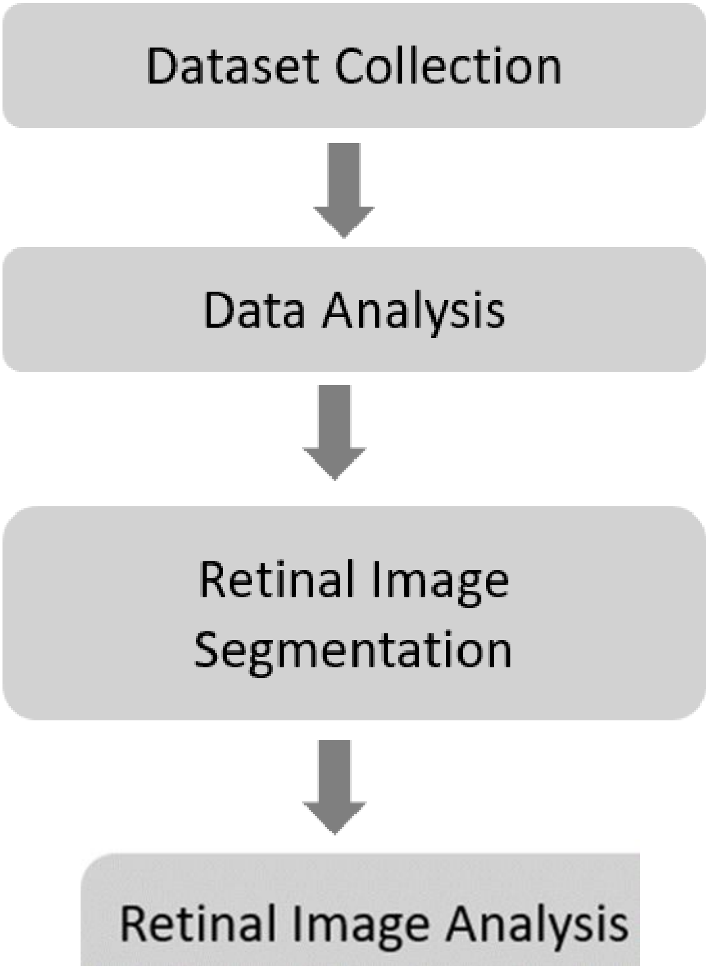
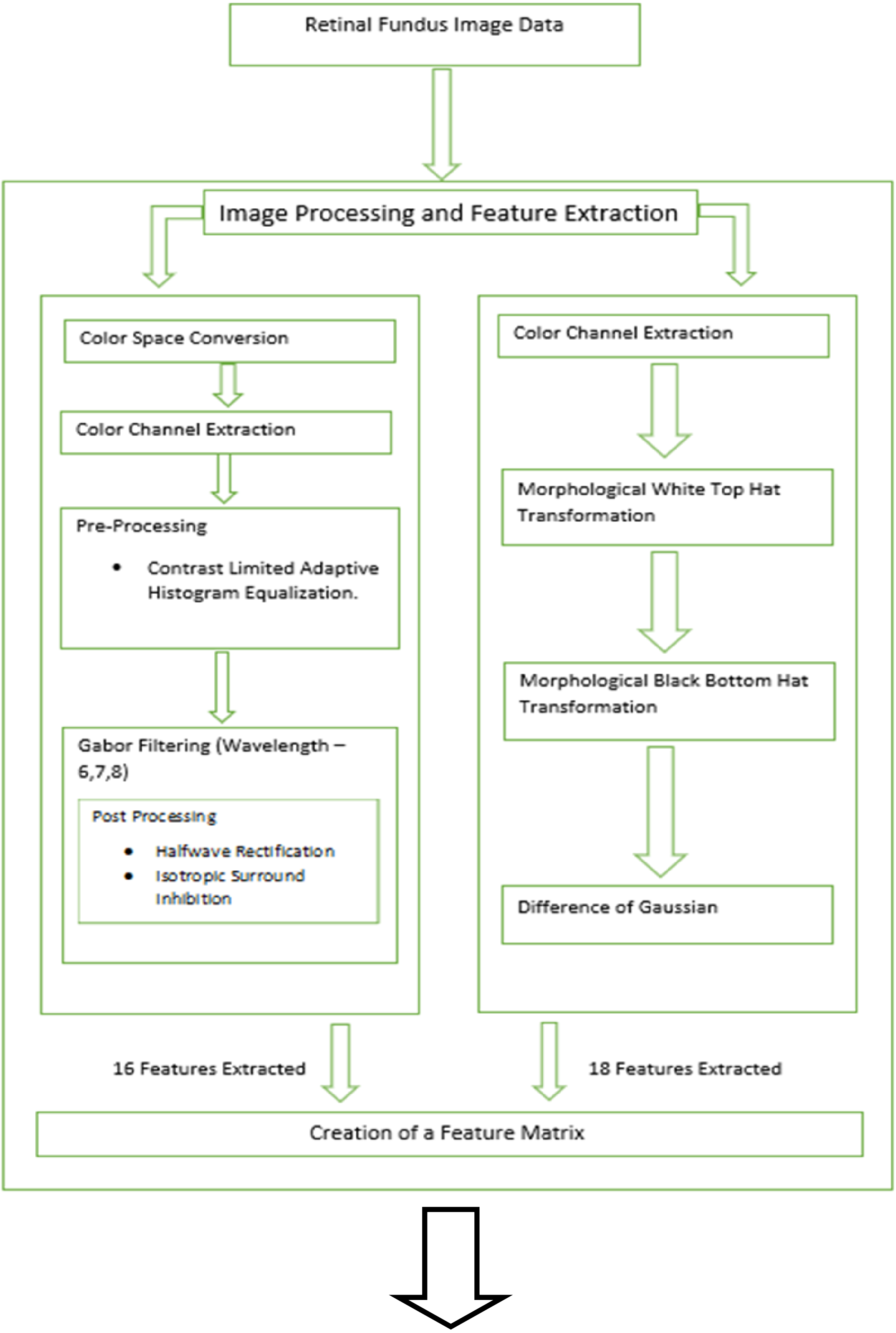


Fig 4.1 Flowchart of the proposed work

4.2 METHODOLOGY



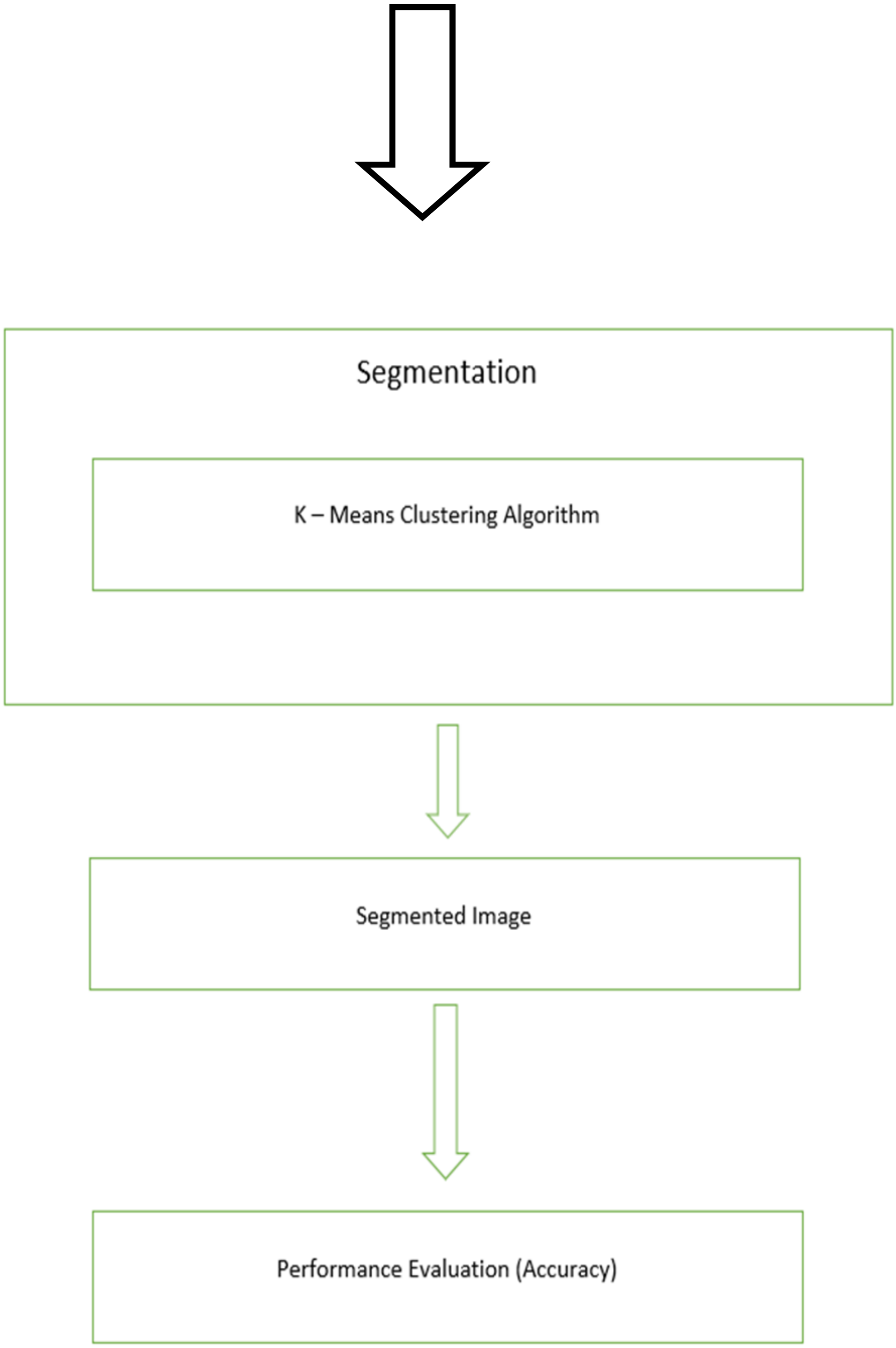


Fig 4.2 Methodology of the proposed work.

4.3 DATASET COLLECTION

Two datasets have been collected namely DRIVE and STARE dataset. The datasets were available as an open source and manual datasets were also available. 20 images from both STARE and DRIVE database are extracted. The details of the datasets are available below and the link for the dataset is also given in bibliography.

4.4 DRIVE DATASET

DRIVE stands for Digital Retinal Images for Vessel Extraction. The screening population consisted of 400 diabetic subjects between 25-90 years of age. Forty photographs have been randomly selected, 33 do not show any sign of diabetic retinopathy and 7 show signs of mild early diabetic retinopathy. The images were acquired using a Fundus photography with a 45° field of view. Each image was captured using 8 bits per color plane at 768 x 584 pixels. The dataset consists of 40 images. The set of 40 images has been divided into a training and a test set, both containing 20 images. For the training images, a single manual segmentation of the blood vessels is available. For the test images, two manual segmentations are available. One is used as gold standard, the other can be used to compare computer generated segmentations [11].

4.5 STARE DATASET

STARE stands for Structured Analysis of the Retina. The dataset contains 400 eye fundus images with a resolution of 700 x 605, at 35° field of view. STARE has 20 vessel ground truth images used for blood vessel segmentation in which 9 are healthier while the rest of them show different type of retinal diseases. Two sets of ground-truth vessel annotations are available [12].

4.6 GREENCHANNEL IMAGE

The retinal images are usually low contrast images. The green channel is extracted from the RGB retinal fundus image. The choice of green channel is due to the fact that in this channel, the blood vessel is more vivid when compared with other channels like red channel and blue channel. Microaneurysms are clearly visible in green channel due to high contrast of the green channel in comparison with Red channel and Blue channel of the RGB image.

4.7 LIGHTNESS CHANNEL & GAUSSIAN COLOR MODEL IMAGE

RGB color model is not perceptually uniform and Euclidean Distances in 3D RGB space do not correspond to color differences as perceived by humans. Hence perceptually uniform color spaces namely L*a*b* color space and Gaussian color space along with the RGB color model have been adopted to extract the Gabor features.

The L*a*b* color space consists of L (lightness), a and b (color opponent) components. The RGB is converted to L*a*b* color space. the RGB color space is converted to Gaussian color model. Gaussian model consists of É, Éλ and Éλλ components and can be extracted from RGB color space using the following equation [8]

$$\begin{bmatrix} \acute{E} \\ \acute{E}_{\lambda} \\ \acute{E}_{\lambda\lambda} \end{bmatrix} = \begin{bmatrix} 0.06 & 0.63 & 0.27 \\ 0.3 & 0.04 & -0.35 \\ 0.34 & -0.6 & 0.17 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

The channels that reveal high contrast are considered for further processing. The Green channel from the RGB color space, the Lightness channel from the RGB color space and É and Éλ channels (denoted as G1 and G2, respectively) from the Gaussian color space are extracted and further processed [8].

4.8 FEATURE EXTRACTION

For pixel representation a 34-feature matrix is constructed. The purpose of feature extraction technique is used to reduce data dimensionality. It is usually applied when there is a large amount of redundant data. The features include local intensity feature, white top hat features, black bottom hat features, difference of gaussian, CLAHE features and post processed Gabor features.

4.8.1 LOCAL INTENSITY FEATURE

The retinal blood vessel pixels are darker than the background pixels. The retinal fundus image has three channels namely red channel, green channel image and blue channel. The green channel image has the maximum contrast and minimum noise, so that accurate vessels are extracted. The thinner vessel pixels are difficult to detect in blue channel and red channel images. The green channel image from this RGB image is only extracted and considered for further processing

4.8.2 MORPHOLOGICAL WHITE TOP HAT TRANSFORMATION

In a morphological transformation, there are two sets of inputs, the first related to the image and the second is the linear structuring element which is predefined. The white top hat operator is used to lightening objects on a dark background. Six features are obtained from the retinal image by varying the length of the structuring element. Every image is the summation of white top hat filter at all orientations. This summation of entire image enhances the vessels, which includes the small vessels in the bright zone.

Table 4.1 White top hat transform at six scales

S. No	Length of structuring element
1	White top hat image at C = 3
2	White top hat image at C = 7
3	White top hat image at C = 11
4	White top hat image at C = 15
5	White top hat image at C = 19
6	White top hat image at C = 23

4.8.3 MORPHOLOGICAL BLACK BOTTOM HAT TRANSFORMATION

The morphological black bottom hat transform is the counterpart of morphological white top hat transform. The bottom hat transform is used for dark objects on the bright background. There are two sets of inputs, the first related to the image and the second is the linear structuring element which is predefined. A total of six features are obtained from the retinal image by varying the length of the structuring element. Every image is the summation of black bottom hat filter at all orientations.

Table 4.2 Black bottom hat transform at six scales

S. No	Length of the Structuring element
1	Black bottom hat image at C = 3
2	Black bottom hat image at C = 7
3	Black bottom hat image at C = 11
4	Black bottom hat image at C = 15
5	Black bottom hat image at C = 19
6	Black bottom hat image at C = 23

4.8.4 DIFFERENCE OF GAUSSIAN

The difference of gaussian kernels is used as an edge detector. The difference of gaussian filter is used at different smoothing scale. The difference is obtained at the ratio of 5:1 and 4:1 for better feature extraction. This difference is obtained by subtracting one gaussian blurred version of the original retinal image from another which is less blurred vision of the original retinal image. A total of five features were obtained by varying the values of standard deviation.

4.8.5 CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION

The quality of the extracted channel images is improved through Contrast Limited Adaptive Histogram Equalization (CLAHE). The Contrast Limited Adaptive Histogram Equalization method is applied to enhance the blood vessels. It operates on small data regions rather than the whole image. Contrast of each small region is enhanced followed by employment of various interpolations for combining the neighboring small regions. CLAHE method is applied to Green, Lightness, G1 and G2 channels respectively and are named as Gclahe, Lclahe, G1clahe and G2clahe. After enhancing the images, Gabor filtering is applied to these four features Gclahe, Lclahe, G1clahe and G2clahe [8].

4.8.6 GABOR FILTERING + POST PROCESSING

The blood vessels as seen in the contrast enhanced features Gclahe, Lclahe, G1clahe and G2clahe take the shape of Gaussian approximation. Hence Gaussian based filters can help in enhancing the blood vessels of the retinal image. 2-D Gabor filters, which are sinusoidally modulated Gaussian functions, have been used to enhance the blood vessels. Each time, the procedure is applied, it results in three features (Gabor filtered image at wavelength = 6, 7, 8). Since the procedure is applied on four channel features, this step yields 12 Gabor features. The twelve Gabor features are considered for further post processing [8].

The Gabor output yields strong response to the high frequency components of the image. In the retinal fundus images, along with the vessels, there also exists some variation in background, or the outer rim of the field of view, which are captured as high frequency components. Hence a few post-processing techniques namely, half wave rectification and isotropic surround inhibition techniques were employed on the twelve Gabor responses to eliminate the false vessels as far as possible [8].

Halfwave rectification is operated on the 12 features based on a percentage value of the maximum intensity of the image. This process removes all the Gabor responses which are lesser than the specific percentage (10 in this case). Hence minor variations in texture of the images, which are mistaken for vessels, are eliminated. Setting too high a value for threshold will eliminate the true vessels (mostly the thinner vessels) whereas setting too low a value will lead to false spurs. Hence an optimal value is needed. The parameter (threshold = 10%) was chosen based on experimental analysis [8].

After Halfwave Rectification, there exist still many false edges as their Gabor responses lie close to that of the true vessels. Hence surround inhibition is applied to suppress the edges which act as noise, while leaving relatively unaffected the boundaries of vessels. Isotropic surround suppression is rotation invariant and does not get influenced by the orientation of the surrounding edges [8].

4.9 CREATION OF FEATURE MATRIX

The Green Channel image, six white top hat images, six black bottom hat images, five Difference of Gaussian images, four contrast enhanced images, the twelve post-processed Gabor images are further analyzed through data mining techniques to segment the blood vessels. The feature matrix is a Multi – Dimensional Array. Each element is defined by two subscripts, the row index, and the column index. Multidimensional arrays are an extension of 2-D matrices and use additional subscripts for indexing. The first two are just like a matrix, but the third dimension represents pages or sheets of elements. The feature matrix includes the 34 features which extracted above and hence, resulting a 34 – matrix. Fig 4.3 and 4.4 represents the 34 extracted features of an image from DRIVE and STARE Database, respectively.

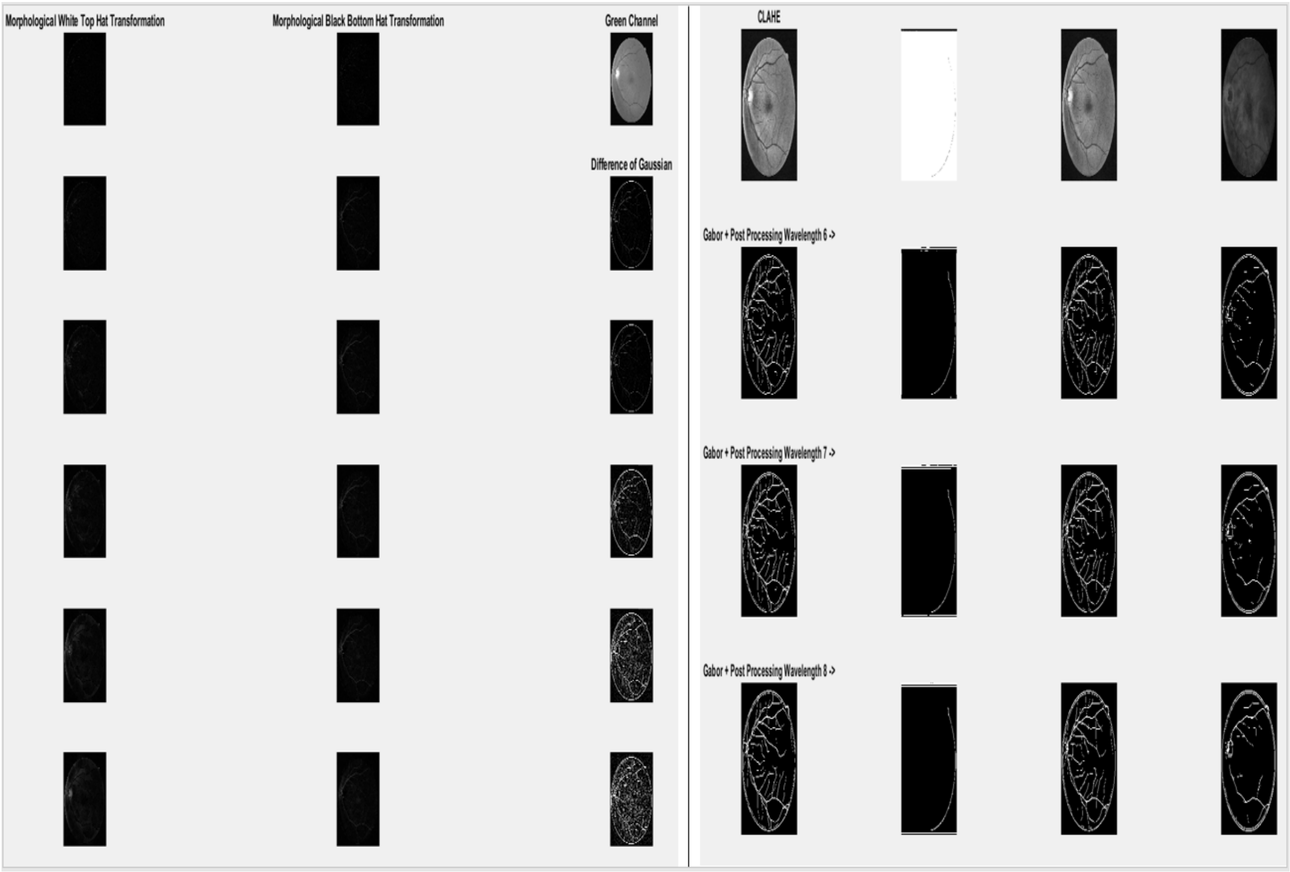


Fig. 4.3 Thirty – Four Extracted Features of an image from DRIVE database

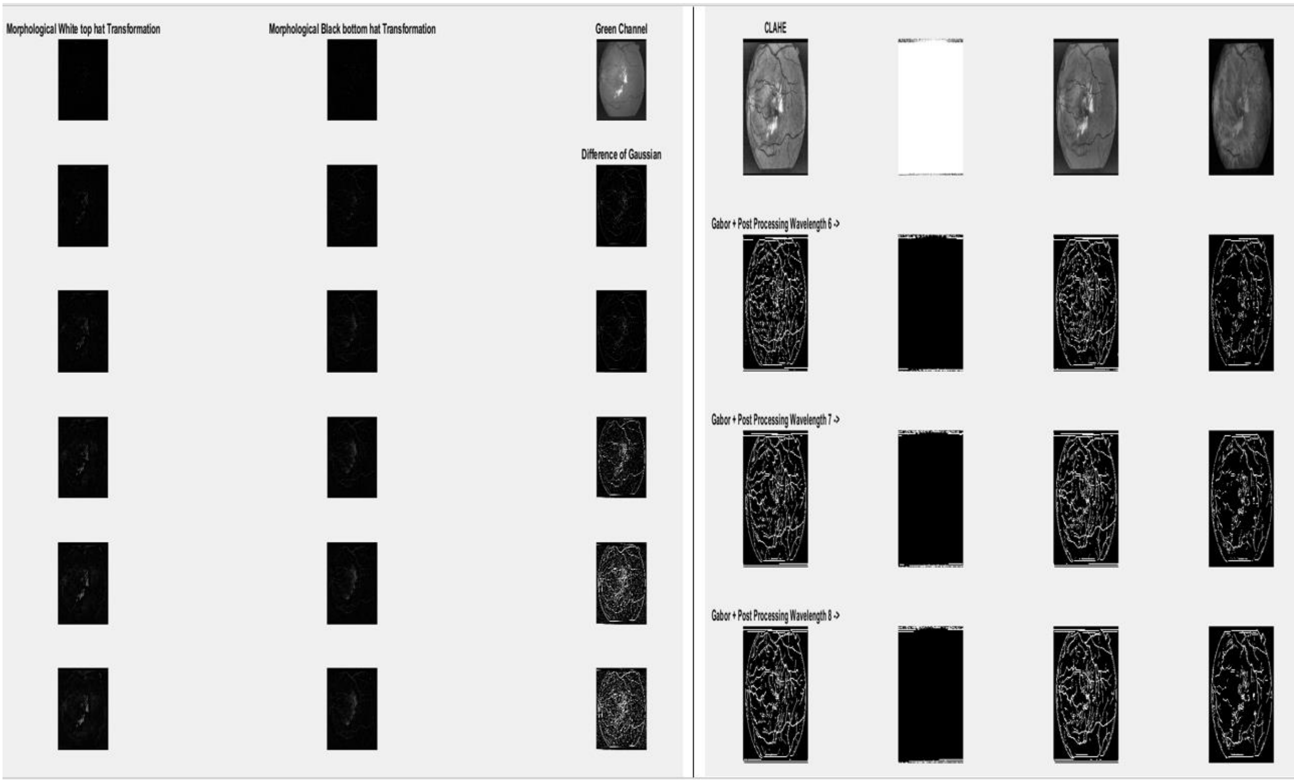


Fig. 4.4 Thirty – Four Extracted Features of an image from STARE database

4.10 SEGMENTATION

In computer vision, the process of partitioning an image into multiple segments is known as image segmentation. The aim of image segmentation is to give a meaningful and easier analyzation of the image (i.e.) To change the representation of the image. It is primarily used for location of specific objects and creation of boundaries. In image segmentation, pixels having similar attributes are grouped together. Image segmentation creates a pixel-wise mask for objects in an image which gives us a more comprehensive and granular understanding of the object.

For segmenting the blood vessels from the retinal images, K – Means Clustering Algorithm is used. Clustering is an unsupervised learning algorithm which groups a set of data values such that the instances in the same group have more similar properties than the instances between the groups. With segmentation of vessels from the retinal image being under consideration, the clustering can be viewed as a technique for grouping the pixels into two groups namely, vessel cluster and non-vessel cluster [8].

K-Means clustering algorithm is found to outperform the other clustering algorithms in view of distinguishing vessels and non-vessels. K-Means clustering algorithm divides the instances into two groups with each group's center being represented by the mean value of the attributes of the instances. Since only two groups (either a vessel or non-vessel) are possible, the number of clusters is assigned as two. Retinal blood vessel segmentation through image processing and data mining [8].

The clustering algorithm results in two clusters with unequal size. Since the non-vessels occupy major part (approx. 90%) of the image and vessels occupy only less part (approx. 10%), it is acceptable to consider the cluster with greater number of instances as non-vessel cluster and the cluster with a smaller number of instances as vessel cluster. The pixels in the non-vessel clusters are concluded as non-vessel pixels. The methodology further proceeds with the vessel cluster. Classification techniques are applied to the vessel cluster to further identify the non-vessel pixels that may be present in the vessel cluster [8]. Fig 4.5 and fig 4.6 represents the blood vessel segmentation for DRIVE and STARE images, respectively.

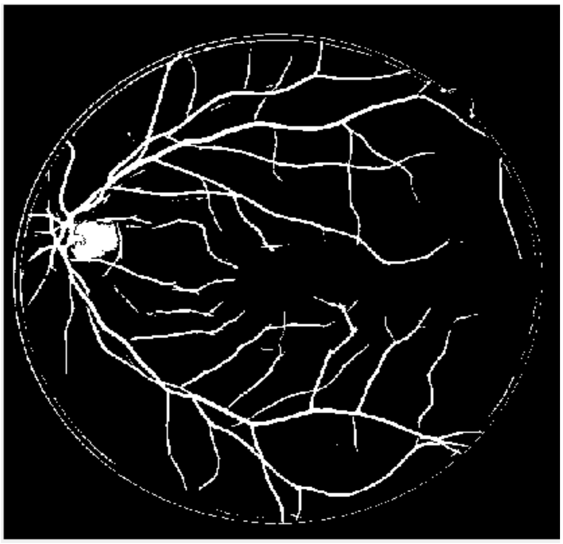


Fig 4.5 A Segmented Image from DRIVE Database

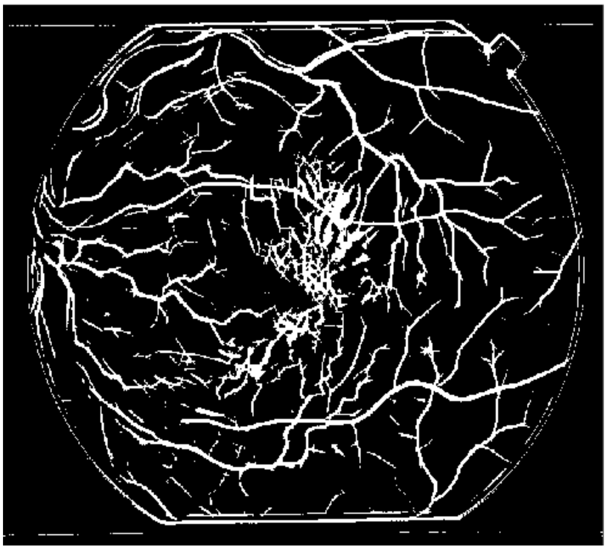


Fig 4.6 A Segmented Image from STARE dataset

CHAPTER 5

RESULTS

This chapter discusses about the performance of the segmentation technique used in retinal images. The entire project is executed on MATLAB r2020b. The Contour Matching Score for all the Segmented Image available in the datasets is obtained, tabulated and the average score is taken as the overall accuracy score.

5.1 GRAPHICAL USER INTERFACE

Graphical user interfaces (GUIs), also known as apps, provide point-and-click control of your software applications, eliminating the need for others to learn a language or type commands in order to run the application. Sharing apps both for use within MATLAB and also as standalone desktop or web apps is also possible. An GUI can be created in MATLAB either by converting a script into a simple app, creating an app interactively or Creating an app programmatically [17].

A very simple GUI is created for this project by Converting the script into a simple app. The app consists of an axis for viewing image and three push buttons given below:

1) Input : Gets image. We can browse our files and select the image.

2) Final Output : Gives the segmented result of the image.

3) Accuracy : Gives the accuracy value in percentage. We have to input the ground truth image by browsing files to get the accuracy value.

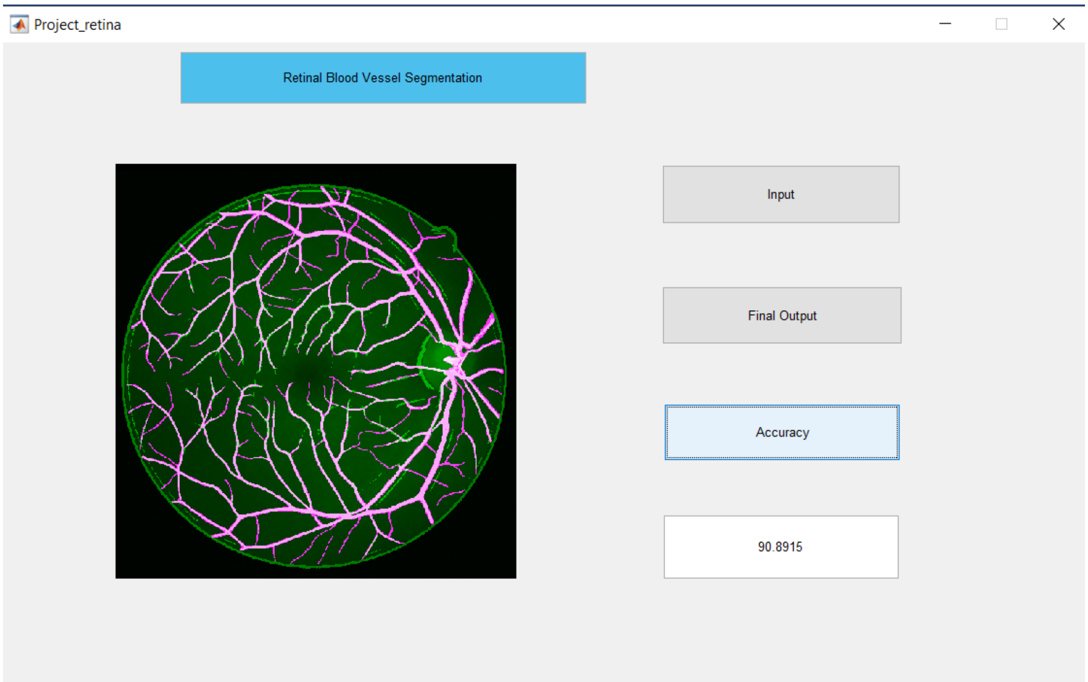


Fig 5.1 Graphical User Interface of the project

Table 5.1 Accuracy Score for 20 images of STARE and DRIVE Database

S. No.	DRIVE Database Score (%)	STARE Database Score (%)
1.	85.2487	77.0743
2.	82.889	69.633
3.	83.0916	68.9216
4.	82.0238	61.7509
5.	80.4367	79.0869
6.	84.7851	63.7733
7.	85.8477	84.7288
8.	88.0162	86.9776
9.	89.9692	88.0055
10.	82.829	68.6084
11.	81.2035	90.3902
12.	83.6052	83.0468
13.	82.9509	87.1357
14.	83.5423	83.8451
15.	88.1274	81.1981
16.	90.8915	64.2319
17.	87.3765	86.0281
18.	90.414	57.0246
19.	89.1554	71.0228
20.	89.598	62.4071

The Average Score for DRIVE Database = 85.60 %

The Average Score for STARE Database = 75.74 %

5.2 CONTOUR MATCHING SCORE

Contour Matching Score computes the BF (Boundary F1) contour matching score between the predicted segmentation in PREDICTION and the true segmentation in GROUNDTRUTH. It is given in MATLAB as

```
SCORE = bfscore(PREDICTION,GROUNDTRUTH)
```

PREDICTION and GROUNDTRUTH can be a pair of logical arrays for binary segmentation, or a pair of label or categorical arrays for multi-class segmentation. SCORE is a value of doubles in range 0 to 1. A score of 1 means that the contours of objects in the corresponding class in PREDICTION and GROUNDTRUTH are a perfect match. Accuracy of the segmented image is compared with ground truth and is calculated using bfscore. Table 5.1 given above shows the accuracy scores of every image on the databases.

5.3 DISCUSSION

The Average score for DRIVE Database is 85.60% and the Average score for STARE Database is 75.74%. This has shown that the DRIVE database has more accuracy than STARE database. Using K – Means Clustering Algorithm has resulted only in an average accuracy in the range of 75% to 91%. The accuracy level is not as accurate as expected. This can be rectified by combination of more features or addition of more classification algorithm for detection of smaller clusters which goes undetected while using K – means Clustering Algorithm.

The paper “Automatic segmentation of blood vessels from retinal fundus images through image processing and data mining techniques” by R Geetharamani and Lakshmi Balasubramanian uses two more classification algorithm in addition to K – Means Clustering [8]. They are Naïve–Bayes classification algorithm and C4.5 enhanced with bagging classification algorithm. The results reported an overall 95.05% accuracy on entire dataset for them.

The use of more features for segmentation is proved on the fact that using only the 18 extracted features (local intensity feature, white top hat features, black bottom hat features, difference of gaussian) gives us an overall accuracy score of 81.4% for DRIVE Database and 78.35% for STARE Database and using only 16 extracted features (CLAHE features and post processed Gabor features) gives an overall accuracy score of 82.3% for DRIVE Database and 66% for STARE Database.

A thing to notice here is that the difference of accuracy value between the two groups of extracted features for STARE Database is wider than that of DRIVE Database.

The average computing time for the segmentation on a PC with 16GB of RAM, i7 Processor, is 37.59 seconds. The accuracy score calculation took 20.15 seconds. As RAM size decreases, the processing capability decreases heavily. A PC with 8 GB of RAM takes approximately 4 times (2min 41sec) to segment the image. So, there is a need for optimization of the software such that it takes lesser time to segment the image and to make the software be compatible in lower end devices and even in mobile phones.

We can also infer from this project that Healthy Persons retinal images have a high accuracy scores than Diseased Persons Retinal Images. This is due to clumping of blood vessels either due to blood clots or some other complications. This gives us a sign of stroke, Glaucoma or Diabetic Retinopathy in the retinal images of the person suffering.

The improvement of accuracy and giving exact algorithms to classify vessels and detection of disease in the future works will make this project a highly useful product and a preliminary screening test in the field of ophthalmology in the near future.

CHAPTER 6

CONCLUSION

This chapter deals with the conclusions that is inferred from this project work. In research related to ophthalmological images, Optical Coherence Tomography and Fundus image datasets are available in public domain. Many research works have been found in diabetic retinopathy but there were very few works in the risk analysis using ophthalmologic images. So, the datasets for risk analysis are very less. Therefore, DRIVE and STARE datasets are used in this project work. In this project, we have proposed an integrated method to segment blood vessels in retinal images. The first element is a feature choice, where 34 carefully selected features are employed. The second element is the choice of the segmentation algorithm, namely a K – Means Clustering Algorithm. This method detects both wide and tiny blood vessel with the same efficiency. The results clearly show the proposed algorithm is almost effective for the segmentation of retinal blood vessels.

In our project work, MATLAB r2020b environment were employed for feature extraction and used for image segmentation. The future work in this project deals with implementing the segmentation technique using a combination of the K – Means Clustering Algorithm with more classification algorithm to detect the tiny clusters which were not recognized after the application of K – means clustering algorithm, and thereby increasing the contour matching score up to 95%. The segmented vessels are then may be used for classification of vessels into arteries and veins, and also use the segmented vessel to identify various diseases like Diabetic Retinopathy, Stroke, Glaucoma etc. A more interactive, highly automated graphical user interface (GUI) may also be developed for user convenience and the software may be made compatible for various devices in the future.

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