RETINAL BLOOD VESSEL SEGMENTATION FOR HEALTH RISK ASSESSMENT

A PROJECT REPORT

Submitted by

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ABSTRACT

Retinal blood vessel segmentation plays an important role in retinal image analysis. Any abnormal changes in the retinal vascular structure reveal the intensity of diseases like hypertension, cardiovascular disease, stroke, diabetes mellitus, etc. The principal objective of this work is to propose effective supervised learning for retinal vessel extraction utilizing a neural organization classifier. The color images are converted into grayscale images then adaptive histogram equalization and top-hat operation are applied in the pre-processing state. For classification, Neural Network (NN) is used for better accuracy. Conventional supervised methods are of two steps, they are feature extraction and classification. A core set of features including Gabor filter response (9D) and Local intensity features (Mean, Median, Variance) (3D) are considered for the segmentation of the image. This method processes a 12D element vector composed of features that can well characterize the vasculature in the fundus pictures. The 12D element vector incorporates the reactions from various scales and various directions which are taken from the features of Gabor filter and the features of Local intensity from the pre-processed images. The proposed algorithm is implemented using the DRIVE and STARE database and is evaluated based on accuracy, sensitivity, and AUC. This approach has obtained significant results in many applications.

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LIST OF ABBREVIATIONS

ACRONYM	ABBREVIATION
NN	Neural Network
2D	Two Dimension
3D	Three Dimension
9D	Nine Dimension
12D	Twelve Dimension
DRIVE	Digital Retinal Images for Vessel Extraction
STARE	Structured Analysis of Retina
ROI	Region of Interest
ROC	Receiver Operating Characteristic
KNN	K- Nearest Neighbor
GMM	Gaussian Mixture Modeling
CLAHE	Contrast Limited Adaptive Histogram Equalization
MATLAB	Matrix Laboratory
GUI	Graphics User Interface
API	Application Programming Interface
FOV	Field of View
JPEG	Joint Photographic Experts Group
CCD	Charge Coupled Device
FA	Fluorescein Angiography
RGB	Red Green Blue
SE	Structuring Element
AI	Artificial Intelligence
ML	Machine Learning

ANN	Artificial Neural Network
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
SE	Sensitivity
SP	Specificity
AC	Accuracy
AUC	Area Under the Curve
HD	High Definition

CHAPTER 1
INTRODUCTION

Retinal blood vessel segmentation plays an important role in retinal image analysis. Any abnormal changes in the retinal vascular structure reveal the intensity of diseases like hypertension, cardiovascular disease, stroke, diabetes melitus, etc. We are using Supervised learning to segment the image. Supervised learning depends on a training set data and the physically handled ground-truth reference and produces awesome results when contrasted with unsupervised learning. Initially, the color images are converted into grayscale images then adaptive histogram equalization and tophat operation are applied in the pre-processing state. For classification, Neural Network (NN) is used for better accuracy. A core set of features from Gabor filter response (9D) and Local intensity features (Mean, Median, Variance) (3D) are considered for the segmentation of the image. This method processes a 12D element vector which is composed of features that can almost fully characterize the retinal vasculature structure in the fundus pictures. The proposed algorithm is implemented using the DRIVE and STARE database. In the post-processing, morphological operations are done to obtain the last segmented picture. This approach has obtained significant results in many applications.

1.1 NEED FOR THE PROJECT

Retinal blood vessel segmentation plays a significant role in analyzing and treating the cardiovascular and ophthalmologic ailments. The manual examination of the retinal fundus picture is a tedious process and it needs experimental information. Therefore, it is necessary to develop an automatic examination of retinal fundus images. Retinal blood vessel segmentation is necessary to work for analyzing retinal fundus images because some of the attributes of the retinal blood vessel such as tortuosity, width and branching patterns are important in predicting the disease symptoms.

1.2 SOLUTION APPROACH

The Retinal Blood Vessel segmentation is implemented with deep learning algorithms which are interfaced with matlab and python. The project consists of three major areas namely,

1.2.1 Pre-processing
1.2.2 Segmentation
1.2.3 Classification

1.2.1 PRE-PROCESSING

Preprocessing is done to extricate the area of interest (ROI). In programmed determination of diabetic retinopathy, the processing of the encompassing foundation and loud area in the pictures isn't required and burns-through is more favorable to processing time at all stages. Removing and editing the region which contains the retinal picture highlights, limits the number of procedures on the retinal picture.

1.2.2 SEGMENTATION

There are various strategies for retinal vein in segmentation , for example, design acknowledgment methods, model based methodologies, coordinated separating, numerical morphology, multi-scale draws near, and Equal equipment based methodologies. Examination table for execution assessment of every individual is illustrated at the end of every technique which incorporates the system, sort of Data set utilized, affectability, particularity, precision, territory under ROC. Additionally, a summed-up table for order of retinal vessel division strategy is additionally portrayed momentarily.

1.2.3 CLASSIFICATION

A few strategies are proposed for the classification of retinal blood vessels. The techniques can be partitioned into two classes, they are regulated strategies and unaided techniques. Administered techniques get division results with named pictures while unaided strategies don't require marked pictures. The administered division strategies first and foremost see every pixel as an occasion and concentrate on highlighting them. At that point, preparing cases are chosen for preparing the division model. For testing, a picture is sectioned by the prepared division model, which will provide the mark of the pixels. For these techniques, highlight extraction and division model development are the two main factors; some connected element and classifiers are proposed, for example, picture edge based highlights and KNN , 2D Gabor wavelet and GMM classifier , line administrators and backing vector characterization , virtual layout extension based highlights and cell neural organizations , incorporated highlights and AdaBoost classifier , dark level and second invariants-based highlights and feed-forward neural organization , and obsessive and vessel structure considering highlights and supported choice trees . These highlights are planned physically while utilizing profound learning for learning the element naturally. Albeit profound learning approach can accomplish the better presentation, the boundary tune is convoluted. Line administrator-based highlights are likewise proposed to catch the neighborhood shape data of vessels.

1.3 ORGANISATION OF CHAPTERS

Chapter 2 is about the literature survey, Chapter 3 describes about the softwares used for this project, Chapter 4 tells about the dataset description, Chapter 5 is the Proposed method which tells us about the image processing, the feature extraction and the deep learning methods, Chapter 6 is the Result and Discussion and Chapter 7 is Future aspects and Conclusion of the project.

CHAPTER 2

LITERATURE SURVEY

The research for retinal Blood Vessel Segmentation using Neural Network: A review carried out by Sumathi Thangaraj and et all in 2017 published on IET image processing which provided a idea and review on DRIVE Dataset and background homogenization. The research for Segmentation of Retinal Blood Vessels Using Gabor Wavelet and Morphological Reconstruction: A review carried out by Hanung Adi Nugroho and et all in 2017 published on Third International Conference on Science and Information Technology (ICSITech). This gave the review on Implementation of CLAHE to improve the contrast enhancement. The research for Retinal Blood Vessel segmentation using Gabor Filters: A Review carried out by Ethar Al Zaidand et all in 2018 published on First International Conference on Computer Applications & Information Security (ICCAIS), which provided a review on feature analysis for Gabor filter analysis. The research for Textural and Intensity Feature Based Retinal Vessels Classification for the Identification of Hypertensive Retinopathy carried out by Faiza Ahmad and et all in 2018 published on IEEE 21st International Multi-Topic Conference (INMIC) , which carried out the concept of Segmentation of Vessels for the Analysis for Hypertensive Retinopathy. The research on Retinal vessel segmentation using ANN technique by Gabor flter and moment invariant filter-based features carried out by S. Wilfred Franklin and et all in 2014 published on ELSEVIER, Applied Soft Computing, Volume 22, which provided a review on Segmentation of retinal image using multilayer perceptron neural network. The research on: A New Supervised Method for Blood Vessel Segmentation in Retinal Images using Gray-Level and Moment Invariants filter based features carried out by Diego Marin and et all in

2011 published on IEEE Transaction on Medical Imaging, Vol. 30, No. 1, which provided the overview on supervised method for retinal image segmentation.

CHAPTER 3
SOFTWARE DESCRIPTION

The tools which are used for implementing retinal blood vessel segmentation are Matlab and Python.

3.1 MATLAB

MATLAB is a general-purpose programming language, which is used for plotting functions and data, matrix manipulation and implementing algorithms.

It was developed by Math Works Corporation. Since it has a variety of inbuilt functions, the tedious work of a programmer is reduced. Because of its ease of use and unambiguity many scientists and engineers use this platform for their research works. It permits framework controls, it improves plotting capacities to represent the provided information; faster execution of calculations; ease of formation of UIs; interfacing with programs including C, C++, Java, and FORTRAN; examining the information which will be written in different dialects,; creating the calculations; and making the models and applications more convenient for the user to modify and analyse. Math works that help you in numerical figuring, producing plots, and mathematical operations.

3.2 PYTHON

Python is one of the high-level programming languages with a vast collection of libraries and frameworks. It became very popular because it was built as easy enough for the beginners to understand and also strong enough for the professional programmers. Python is known for its adaptability, flexibility, proficiency and reliability. Some applications of python are machine learning, big data, cloud computing, automation, data science, game development, and image processing. It is a broadly useful coding language. It is utilized for different sorts of programming and programming advancement other than web improvement. AI and Machine learning are the future. They both require a stable but flexible environment, which is provided by python.

3.2.1 LIBRARIES USED

Libraries are a collection of data, which helps the programmer in software development. These libraries include routines, subroutines, classes, functions, templates, etc.

3.2.1.1 Numpy

Numpy library in python consists of n-dimensional array structure. It acts as a foundation for building a data science toolkit. It also helps to reduce loops and increase the executing speed.

3.2.1.2 Pandas

Pandas library in python is mainly used for data analyzing and manipulation, cleaning data, correlation between functions, plotting functions and data. It is used in the fields like finance, economics, statistics, academics, etc,.

3.2.1.3 Sklearn

Sklearn library supports supervised and unsupervised machine learning. It contains tools for data preprocessing, model fitting, model selection and evaluation. Some of the applications are Spam detection, image recognition, Stock prices, Visualization, etc.

3.2.1.4 Matplotlib

Matplotlib is a sub-module of pyplot, which helps to work in a matlab-like environment. It is used mainly in GUI, 2D graphics applications, web server applications, etc.

3.2.1.5 Keras

Keras is a neural network library, which is used to implement deep learning techniques using minimum resources just enough to produce results. Keras offers consistent & simple APIs by providing low cognitive load. The user actions which are required for the common use cases are also minimised. It also provides clear feedback on errors caused by users.

CHAPTER 4

DATASET DESCRIPTION

A dataset is a collection of variety information or data. On account of plain information, an informational index compares to at least one data set table, where each segment of a table addresses a specific variable, and each line relates to a given record of the informational collection being referred to. The informational collection records esteem for every one of the factors, for every individual from the informational index. Each worth is known as a datum. Informational indexes can likewise comprise a collection of records or documents.

4.1 FUNDUS IMAGES

Fundus imaging is the 2D version of the 3D retinal tissue captured using reflected light. Fundus photography includes capturing the rear of an eye, which is otherwise called the fundus. Some fundus cameras consisting of multifaceted magnifying instruments connected to a glimmer empowered camera are used in fundus photography. The primary constructions that can be envisioned on a fundus photograph are the focal and fringe retina, optic plate and macula.

4.1.1 PROCESS

The person sits at the fundus camera with their chin at the chin rest and their forehead against the bar. An ophthalmic photographer focuses and aligns the fundus camera. A flash fires when the photographer presses the shutter release, creating a fundus photograph. These images are used to monitor, diagnose, and treat eye diseases. Fundus photography can be performed with colored filters, or with specialized dyes such as fluorescein and indocyanine green.

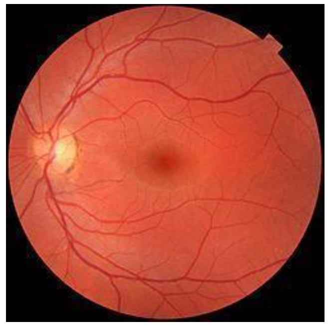


Figure 4.1 Fundus Image

4.2 DRIVE DATASET

The DRIVE database was obtained from a diabetic retinopathy screening program in the Netherlands. This program consisted of 400 patients from 25 to 90 years of age with diabetics. 40 photographs have been selected randomly, of which 33 did not have any symptoms of diabetic retinopathy but the remaining 7 gave indications of mild early diabetic retinopathy. These forty images were divided into a training set and test set containing twenty images each respectively.A mask image is provided for each image, that delineates the FOV.

4.2.1 IMPORTANCE

The DRIVE database has been established to empower relative studies on segmentation of blood vessels in retinal images. By using this dataset, we can get the morphological attributes of retinal blood vessels such as length, width, tortuosity, branching patterns and angles. These attributes help in diagnosis, screening, treatment, and evaluation of various cardiovascular and ophthalmologic diseases such as stroke, diabetes mellitus, etc.

4.2.2 EQUIPMENT AND PROCESS

The photographs were taken using a Canon CR5 non-mydriatic 3CCD camera with a 45 degrees FOV. Each photograph was taken using 8 bits per color plane at 768 by 584 pixels. The FOV of each image is circular with a diameter of 540 pixels approximately. The pixels which are on the outside of FOV are cropped out. Each image has been compressed in JPEG format

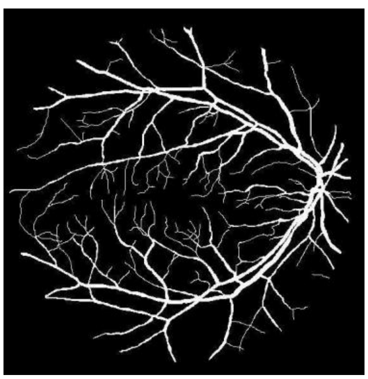


Figure 4.2 Manual Image

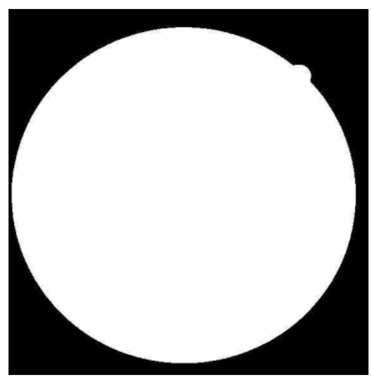


Figure 4.3 Mask Image

4.3 TOOLS USED

The tools used to collect the Fundus images are Fundoscopy and Fluorescent Angiography.

4.3.1 FUNDOSCOPY

Ophthalmoscopy, otherwise called funduscopy. It permits a well known expert to see inside the fundus of the eye and different constructions utilizing an ophthalmoscope or fundoscope. It is done as a feature of an eye assessment and might be done as a component of a routine actual examination. This test is frequently remembered for a normal eye test to evaluate for eye infections. On the off chance that you have a condition that influences your veins, for example, hypertension or diabetes this test will be taken. Ophthalmoscopy may likewise be called fundoscopy of retinal assessment.

4.3.2 FLUORESCENT ANGIOGRAPHY

A fluorescent angiography is an operation where a fluorescent color is infused into the circulatory system. The color features the veins in the rear of the eye so they can be captured. This test is regularly used to oversee eye issues. Fluorescein Angiography (FA) is a symptomatic technique that utilizes an extraordinary camera to record the bloodstream in the retina – the light touchy tissue at the rear of the eye. The test doesn't include any immediate contact with the eyes.

CHAPTER 5

PROPOSED METHOD

STEPS:

- Initially, an image is taken from the drive dataset.
- The image is pre-processed where we convert the color image into a grayscale image then the CLAHE algorithm will be applied and then the top-hat technique will also be applied to the image.
- Using the pre-processed image, the dataset is created with the response from the Gabor filter and local intensity features.
- In the next phase supervised learning algorithm is used to classify the pixel as either vessel or non-vessel category.
- The output will be either 0 or 1 which will then be reconstructed as a segmented image.

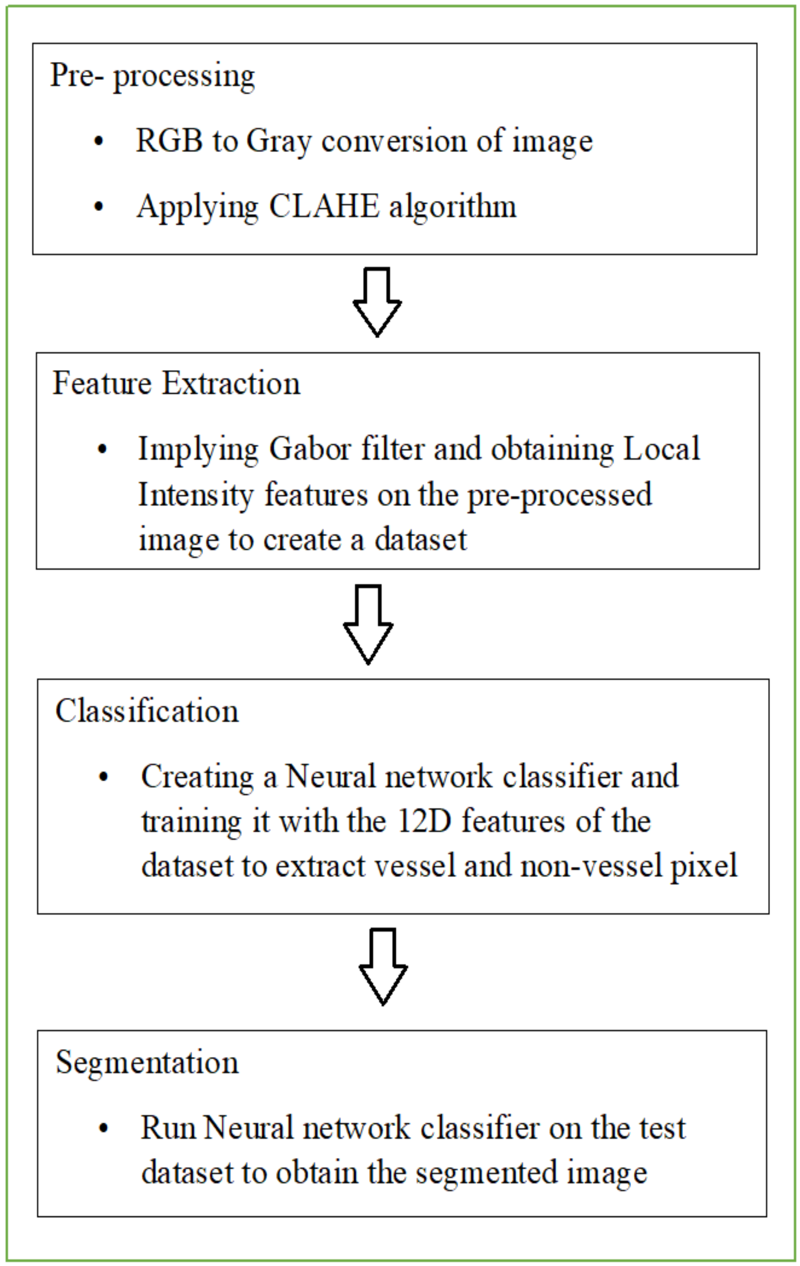


Figure 5.1 Steps Involved in Proposed Work

5.1 IMAGE PROCESSING

Image processing is a process of performing operations on images, in order to get an enhanced the image or to extract some data from the image. It is a type of signal processing in which input is an image and output may be image or characteristics of an image. Image processing is also done as a part of pre-processing in many image-related operations, to avoid building up of noise and distortion of an image during the operations. Nowadays, image processing is one of the rapidly growing technologies. Image processing differs from computer vision, that image processing is a method used along with other machine learning techniques to achieve computer vision.

These are three steps that form the basis of the Image processing

- Image import
- Image Analysis and manipulation
- Output

Signal processing is one of the areas using image processing techniques to process two-dimensional signals such as photographs or video. Various functions are used for filtering and enhancing the image in image processing to get the required information from the images. Initially, Image processing was used to enhance the quality of the low-quality pictures, the usage of image processing increased after successful processing of lunar mages. But the cost for the processing is high due to the time constraints and other factors in extracting features, after the development of the dedicated hardware the research in the field of image processing is also increased.

5.1.1 RGB TO GRAYSCALE CONVERSION

5.1.1.1 RGB IMAGE

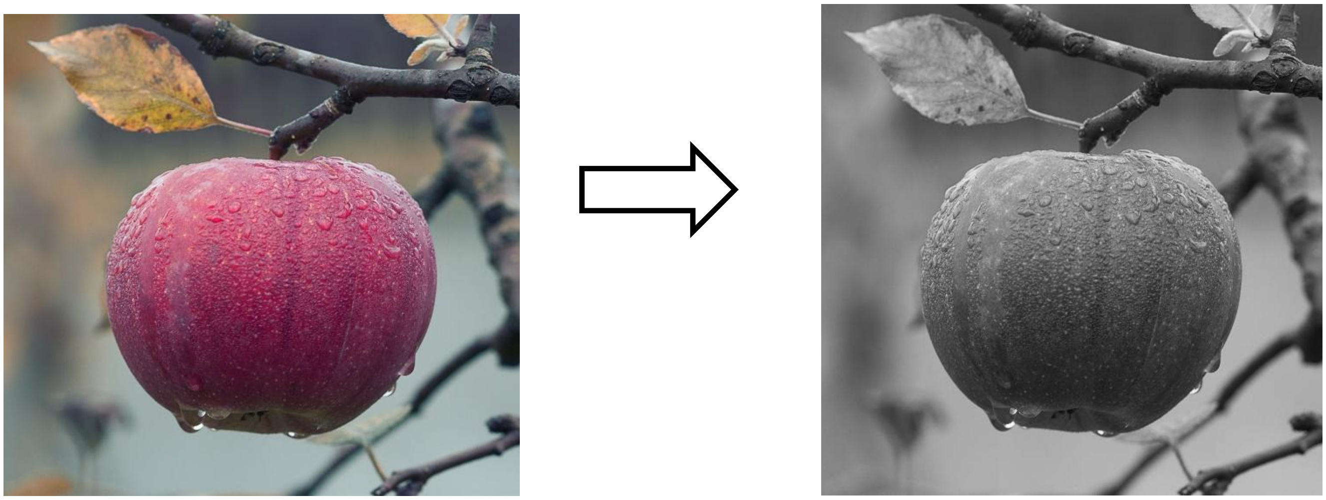
The RGB color model is an additive color model where red light, green light, and blue light are mixed with each other to produce different colors. The composition of these lights differs from device to device. This model is based on trichromatic color vision theory by Young Helmholtz and color triangle theory by James Clerk Maxwell. The main purpose of this model is for the detection, display and representation of images in digital systems of the modern world. The color depth of RGB is 24 bits, which represents the range of possible values for RGB. Each pixel of an image has a specific RGB value

5.1.1.2 GRAYSCALE IMAGE

Grayscale images are the result obtained by measuring the light intensity at each pixel. It carries only the intensity information. Thus, only less information is provided for each pixel. It contains only shades of gray and no color. Each pixel of the image has an 8 bit value, which ranges from 0 to 255.

5.1.1.3 REASON FOR CONVERSION

Each pixel of an RGB image has 24 bits, whereas the pixels of a grayscale image have only 8 bits each. This reduces about 33% of the memory occupancy. The grayscale images are much easier to work with when compared to RGB images, because grayscale images are single layered images, whereas the RGB images are three layered images.

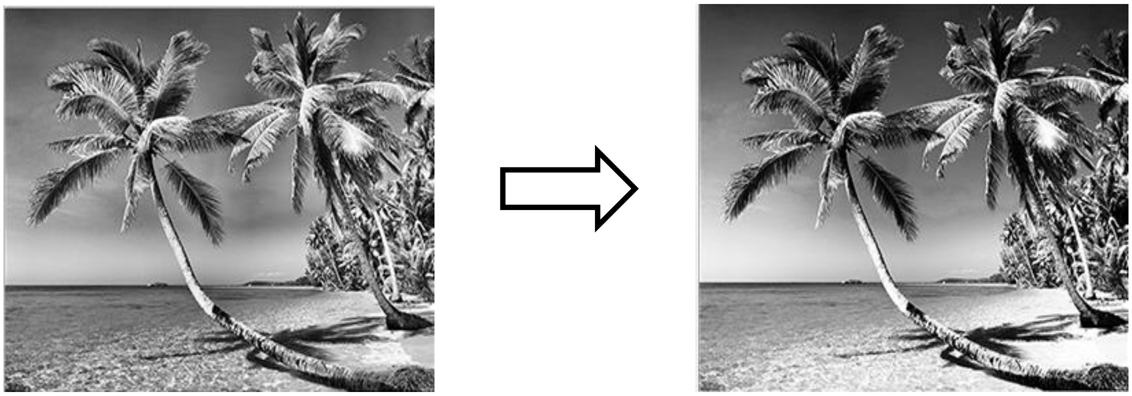


RGB Image **Gray Scale image**

Figure 5.2 RGB to Grayscale Image Conversion

5.1.2 CLAHE(Contrast Limited Adaptive Histogram Equalization)

Adaptive Histogram Equalization (AHE) is an image processing technique which helps to improve the contrast of a picture and it also enhances the edges in each region of a picture. It computes several histograms, each representing a specific section of the picture, and uses them to redistribute the light values in the picture. Since AHE has a tendency to over-amplify noise, CLAHE is used for the over-amplification of the contrast. Instead of working on the entire image, the CLAHE algorithm only works on specific selected regions called tiles. The artificial boundaries between the neighboring tiles are removed by bilinear interpolation.

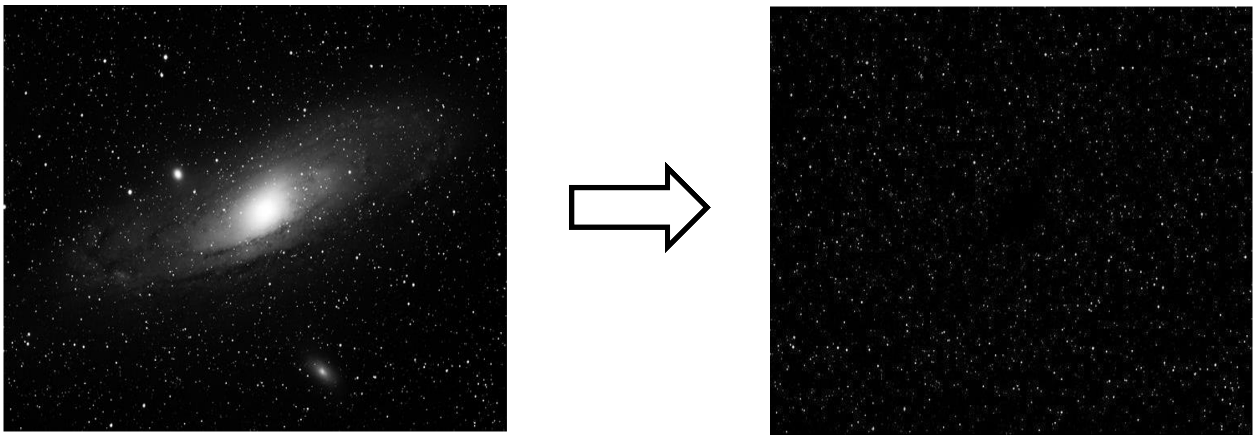


Before CLAHE Implementation **After CLAHE Implementation**

Figure 5.3 CLAHE Implementation

5.1.3 TOP-HAT

The Top-hat transform helps to extract even the small elements and details from an image. The Top-hat block performs top-hat filtering on a binary image using a predefined neighborhood or SE. Formal hat sifting is what could be compared to deducting the consequence of playing out a morphological opening procedure on the info picture from the information picture itself. This square uses level organizing components only. Top-cap separating registers the morphological opening of the picture (utilizing imopen command in MATLAB) and afterward deducts the outcome from the first picture. SE is a binary organizing component object returned by the strel or offsetstrel capacities. The top-hat transform is of two types, one is white top-hat transform and the other is black top-hat transform. The white top-hat transform is the difference between the input image and it's morphological opening by some SE. While the black top-hat transform is the difference between the closing and the input image. The white top-hat transform enhances the bright objects in the dark background, whereas the black top-hat transform enhances the dark objects in the bright background. The main advantages of Top-Hat transforms are feature extraction, background equalization, image enhancement and such image processing tasks.



Before TOP-HAT **After TOP-HAT**

Figure 5.4 TOP-HAT Implementation

5.2 FEATURE EXTRACTION

Feature extraction is the process of converting raw information into mathematical functions or data that can be handled while saving the data in the dataset. This gives more accurate outcomes, than directly applying AI to the raw information.

5.2.1 GABOR FILTER

Gabor filter is a linear band-pass filter used for texture analysis, feature extraction and stereo disparity estimation. It analyzes whether there is any specific frequency content in the image along specific directions in a localized region around the region of analysis. Gabor filters with various sets of frequency and orientation in different directions help to extract useful information in an image. Some of the information is extraction of texts, identifying a script, fingerprint recognition, facial recognition and optical character recognition.

Gabor filter is a combination of a gaussian filter and a sinusoidal term

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = exp\left(-(x'^2+\gamma^2 y'^2)/2\sigma^2\right) cos\,(2\Pi\,(x'/y)+\psi)$$

$$a' = a * \cos(\Theta) + b * \sin(\Theta)$$

$$b' = -a * \sin(\Theta) + b * \cos(\Theta)$$

where, γ - aspect ratio, ψ - phase, Θ - orientation, σ - bandwidth or effective width, λ - wavelength.

5.2.2 LOCAL INTENSITY FEATURES

In a retinal fundus picture, vein pixels show up a lot more obscure than the foundation pixels. In this way, the force of an incentive for every pixel in the retinal green channel is considered as a Local intensity feature. The local intensity features that were used are:

- Mean
- Median
- Variance

5.2.3 DATASET CREATION

A dataset is a collection of variety information or data. Informational indexes can likewise comprise a collection of information or data or records. In the open information discipline, informational collection is the unit to quantify the data delivered in a public open information vault. Dataset is the essential storehouse for information records and related metadata, documentation, contents, and whatever other supporting assets that ought to be put away close by the information. Datasets are the place where all information is put away and recorded for later sharing and use in projects.

5.3 DEEP LEARNING

5.3.1 EVOLUTION OF DEEP LEARNING

Machine Learning is a part of artificial intelligence that helps to improve the accuracy of an algorithm by predicting the outputs using the dataset provided without any explicit human intervention like programming and so. These Machine Learning algorithms are designed in such a way to understand the given dataset and then use knowledge obtained to produce accurate results if any other datasets of the same field are given. These algorithms build a mathematical model based on the given sample data to make predictions or decisions without being explicitly programmed by a human to perform the required tasks. There are many ML approaches such as supervised, unsupervised or reinforcement learning.

When the output is not as expected they need to be intervened by humans. There were many limitations in ML algorithms. Among the various ML algorithms, the Deep Learning algorithm brought a revolution. DL allows computational models that are composed of multiple layers to learn the representations of data with multiple levels of abstractions. These methods have dramatically improved the domains of speech recognition, visual object detection, object detection and so. Deep Learning is similar to machine learning, but they have more levels of these algorithms when compared to machine learning, and each of them provides a different analysis of the data. This network of algorithms is called Artificial Neural Networks. Like Machine learning, Deep learning also does not require any explicit intervention by humans, they learn from their own mistakes as the neural networks place the data in a multilevel hierarchy of various concepts. DL architecture has a multi-layer hierarchy of simple modules, all of them are subjected to learning, and many of them are used to compute nonlinear input-output mappings.

5.3.2 NEURAL NETWORK

DL is a subset of ML dealing with algorithms, which is inspired by the structure and function of the brain called ANN. It resembles human nervous system structure where each neuron is connected to other neurons through a link and passes information.

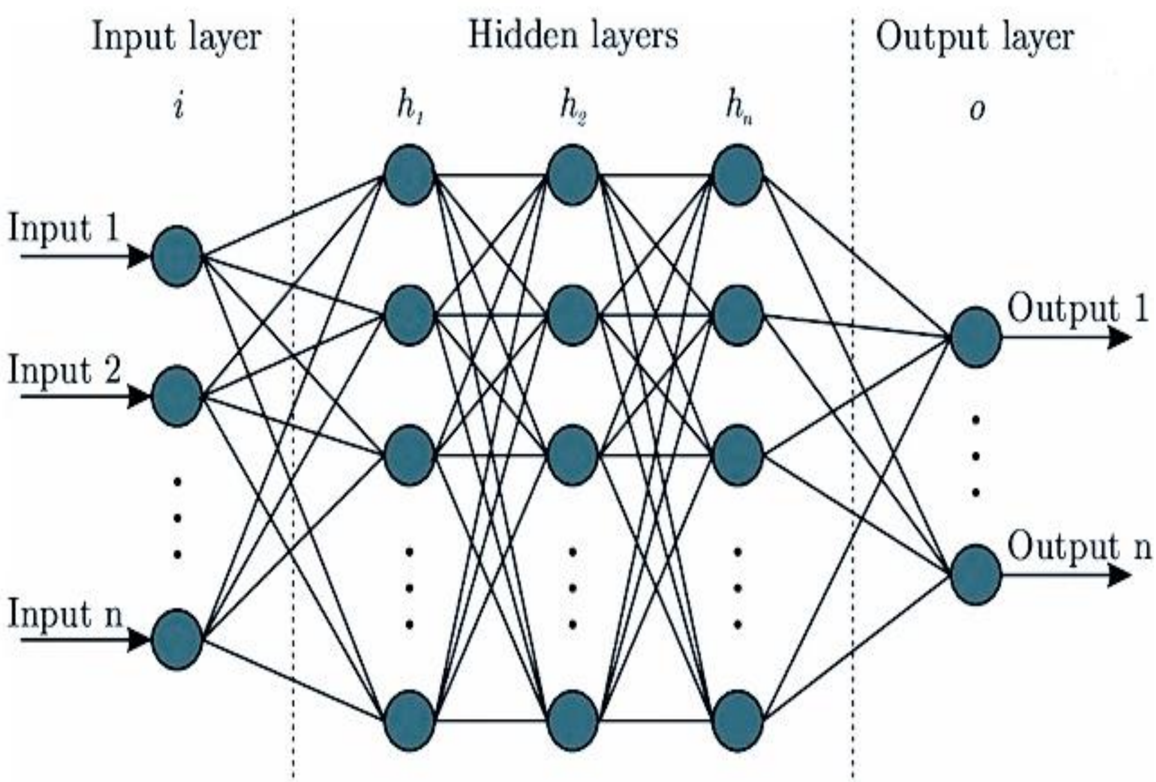


Figure 5.5 Neural Network with three hidden layers

CHAPTER 6

RESULTS AND DISCUSSION

At present, there are many techniques to implement retinal blood vessel segmentation. With the advancement in computation technologies like Deep learning many techniques were used to segment the retinal images.

6.1 PRE-PROCESSING

Pre- processing involves three steps

- RGB to Grayscale conversion
- Implementation of CLAHE algorithm
- Processing with TOP HAT filtering

6.1.1 RGB TO GRAYSCALE CONVERSION

The rgb2gray converts RGB pictures to grayscale by removing the tone and saturation data while maintaining the luminance of the pictures. The color fundus image is converted into a grayscale image in the Matlab using the command rgb2gray().

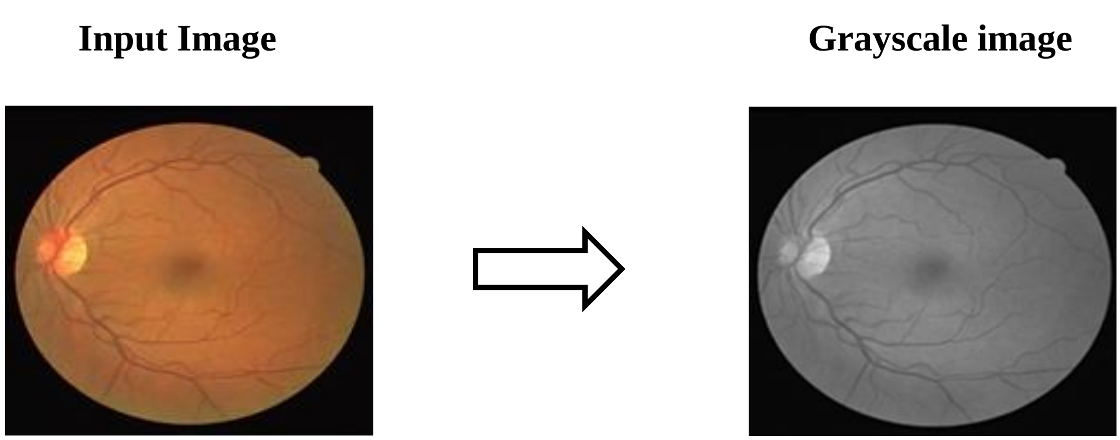
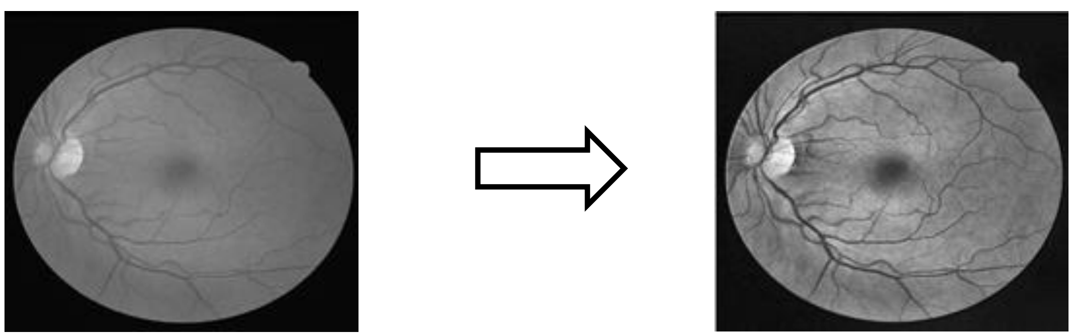


Figure 6.1 Converting RGB to Grayscale Image using MATLAB

6.1.2 IMPLEMENTATION OF CLAHE ALGORITHM

CLAHE is a variation of Adaptive histogram equalization (AHE) which deals with over-enhancement of the contrast. Instead of working on the whole image, the CLAHE algorithm works on specific little areas of the image, which is called tiles. The adjoining tiles are then consolidated using bilinear interpolation to reduce the artificial limits.

The contrast of the vessel pixels is improved remarkably, by using this calculation.

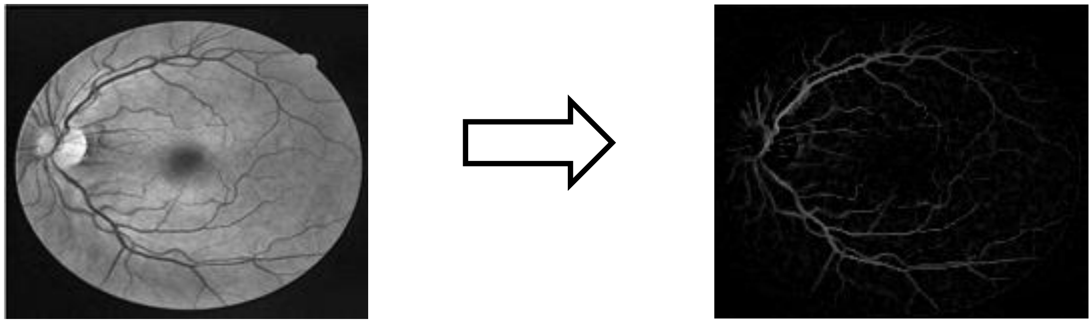


Before CLAHE Implementation **After CLAHE Implementation**

Figure 6.2 Implementing CLAHE Algorithm using MATLAB

6.1.3 PROCESSING WITH TOP-HAT FILTER

Top-hat filtering enumerates the morphological opening of the image (using imopen command in MATLAB) and then removes the result from the original image. Strel functions return Structured Element which is a single structuring element object.



Before TOP-HAT Implementation **After TOP-HAT Implementation**

Figure 6.3 Implementing TOP-HOT Filter using MATLAB

6.2 FEATURE EXTRACTION

6.2.1 GABOR FEATURES

Gabor filter is a linear filter which is mainly used for edge detection. The 2D Gabor filter is the modulation of Gaussian kernel function by a sinusoidal wave. Gabor filter responses at different scales and wavelengths have been found appropriate for texture representation and discernment. The maximum filter response is computed for each pixel in the image at different scales ($\theta = \{45, 90, 135\}$) and different wavelength ($\lambda = \{4, 6.28, 9.42\}$)

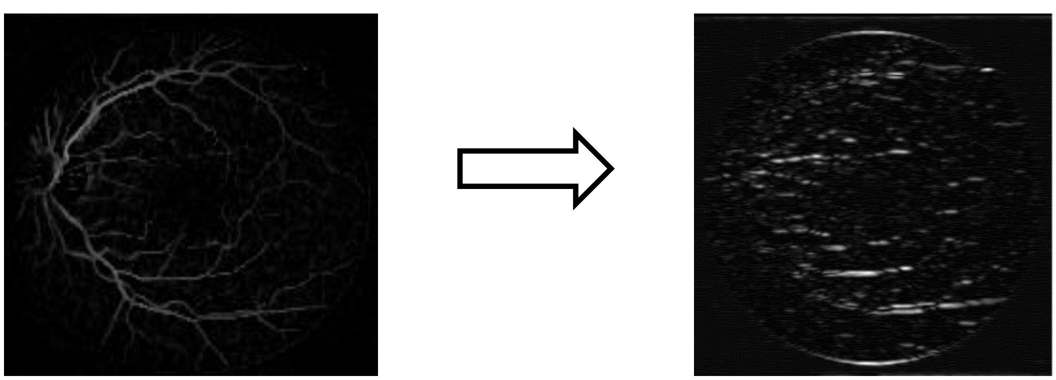


Figure 6.4 Extracting Gabor Features

6.2.2 MEAN

Mean value gives the contribution of individual pixel intensity for the whole image. The block size used here in this picture is 3X3. Mean function will return the average of the pixel values.

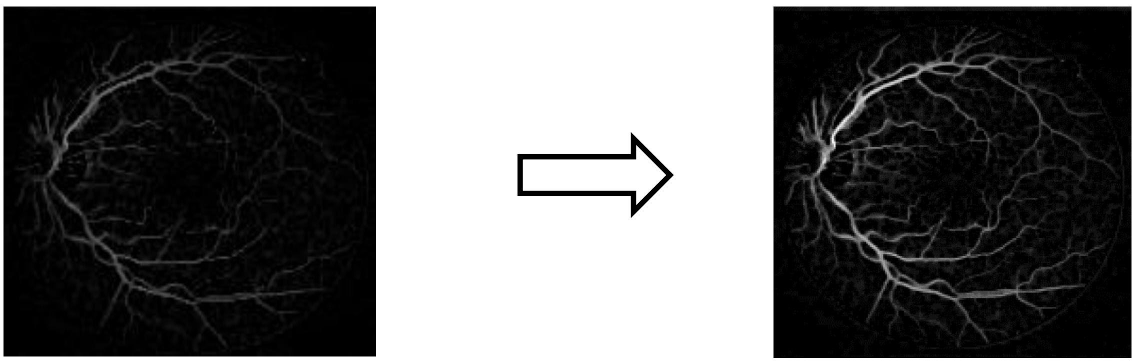


Figure 6.5 Mean Image from Pre-processed Image

6.2.3 MEDIAN

The idea of the median filter is to go through the image array and replace each value with the median of the neighboring record. The block size used here is 3X3..

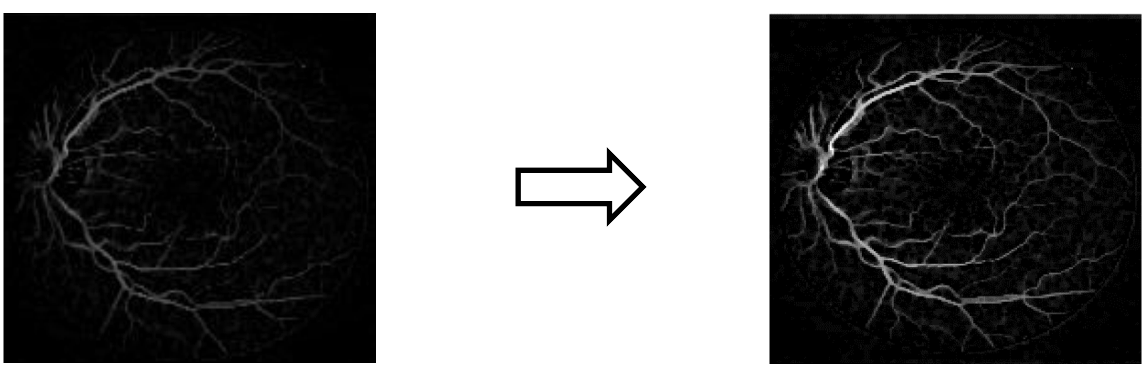


Figure 6.6 Median Image from Pre-processed Image

6.2.4 VARIANCE

An image is a collection of data points on light intensity, variance of the image gives a total measure of the imprecision about the target value of light intensity, at each such data point

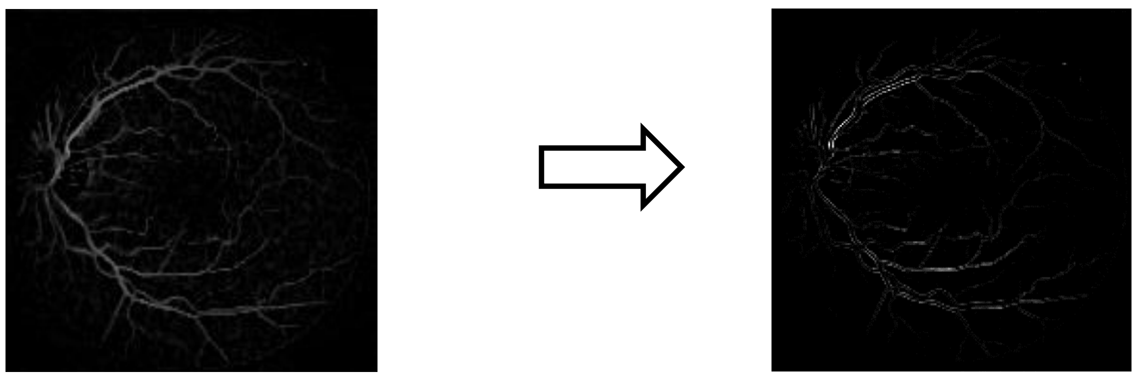


Figure 6.7 Variance Image from Pre-processed Image

6.3 DATASET

Dataset is a collection of data that contains from various fields that provide a relation between input and output (for example Boolean in case of classification problem). This is denoted as a single unit by the machine. Datasets are used to get the required features from an image. A simple dataset is a collection of images with the labeled images different for a classification problem or data in a table format containing the path of the image and class attribute defining the label of the images. Dataset plays a major role in setting up the required feature. The applicability of the techniques can be evaluated using the dataset, the larger the dataset, the better the model. Here in this dataset, column F1 to F9 represent the Gabor features, F10 represent Mean of the image, F11 represent the Median of the image, F12 represent the Variance of the image and Y represent the ground truth of the image.

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	Y
32.519	72.25	86.932	50.698	166.22	367.41	22.037	110.49	231.33	0.008279	0.007843	5.55E-05	0
24.973	75.659	119.48	50.618	167.07	363.87	26.614	118.86	255.05	0.008279	0.007843	5.55E-05	0
17.527	67.785	147.03	35.827	135.97	321.44	30.639	115.75	264.07	0.015686	0.015686	0	0
11.176	49.899	168.59	12.589	83.074	245.87	30.581	102.4	256.94	0.015686	0.015686	0	0
8.8811	27.287	184.56	15.345	27.828	149.7	22.262	82.386	234.1	0.015686	0.015686	0	0
17.069	24.761	195.55	32.767	30.72	63.51	10.955	61.648	197.4	0.028758	0.027451	5.00E-05	1
25.313	49.717	201.82	26.039	57.418	96.386	20.468	48.251	149.55	0.028758	0.027451	5.00E-05	1
28.852	74.175	202.99	10.11	69.531	174.84	31.662	46.799	93.754	0.028758	0.027451	5.00E-05	1
29.183	90.142	198.25	29.317	75.856	232.3	31.893	50.079	34.248	0.043137	0.043137	6.92E-05	0
29.636	94.621	186.95	31.189	83.02	258.73	23.543	48.589	34.899	0.043137	0.043137	6.92E-05	0
29.311	87.254	169.2	16.268	86.858	253.05	18.424	38.083	96.701	0.043137	0.043137	6.92E-05	0
25.368	70.062	146.76	20.523	79.158	219.33	19.33	20.15	157.54	0.033987	0.031373	3.84E-05	0
18.723	47.423	123.98	28.99	55.511	165.3	13.874	22.685	213.95	0.033987	0.031373	3.84E-05	0
13.768	28.484	108.89	20.473	18.191	101	8.3038	54.008	263.35	0.033987	0.031373	3.84E-05	0
13.49	31.362	110.24	2.7252	25.173	41.851	23.931	87.75	303.12	0.044009	0.039216	0.000407	0
17.466	48.375	127.99	28.184	60.556	51.232	36.896	116.29	330.68	0.044009	0.039216	0.000407	0
24.317	63.413	153.21	39.931	77.235	105.08	41.116	134.76	343.82	0.044009	0.039216	0.000407	0
30.444	72.212	177.23	31.517	69.804	159.2	39.109	140.3	341.11	0.061874	0.066667	0.00013	0
31.698	74.153	194.41	14.764	43.329	211.6	34.712	132.44	322.31	0.061874	0.066667	0.00013	0
25.695	70.235	201.41	13	30.161	260.39	28.065	112.99	288.82	0.061874	0.066667	0.00013	0
13.443	62.418	196.55	21.181	62.857	299.64	19.33	85.669	244.25	0.061874	0.058824	6.84E-05	0
9.1287	52.916	179.52	27.527	96.602	320.67	12.189	56.026	195.64	0.061874	0.058824	6.84E-05	1
21.903	43.572	151.29	26.876	117.16	315.33	10.368	34.832	156.24	0.061874	0.058824	6.84E-05	1
29.242	36.132	114.3	29.864	121.25	279.49	14.037	40.423	145.81	0.043573	0.047059	6.32E-05	1
26.959	33.314	74.42	28.152	108.8	216.98	19.787	62.132	170.7	0.043573	0.047059	6.32E-05	1
18.169	36.69	52.479	8.3224	83.855	148.76	22.08	84.973	212.97	0.043573	0.047059	6.32E-05	1
16.543	42.614	79.403	17.86	65.802	137.23	19.453	105.56	254.88	0.046623	0.047059	8.24E-05	0
25.972	45.403	128.83	22.494	89.161	207.6	21.635	122.6	286.57	0.046623	0.047059	8.24E-05	0
31.816	41.787	180.89	9.8347	134.39	293.71	34.251	134.24	302.95	0.046623	0.047059	8.24E-05	0
28.133	34.735	229.1	50.741	168.69	358.55	45.798	138.01	301.76	0.063181	0.066667	0.000325	0

Figure 6.8 Dataset

6.4 CLASSIFICATION WITH NEURAL NETWORK

The Neural Network is trained with all the 12D features from a feature extracted training dataset. Twenty images were taken from the DRIVE dataset to extract the needed features for training purposes. The neural network is constructed in such a way that it has 3 hidden layers with an input and an output. The neural network is a supervised model and gives output either as 0 or 1 for every pixel (0 for non-vessel pixel and 1 for vessel pixel). The test image is passed into the neural network and the output is obtained in a probability value which then will be converted either with a threshold value or with 0 and 1. The segmented image will be obtained from these 0's and 1's.

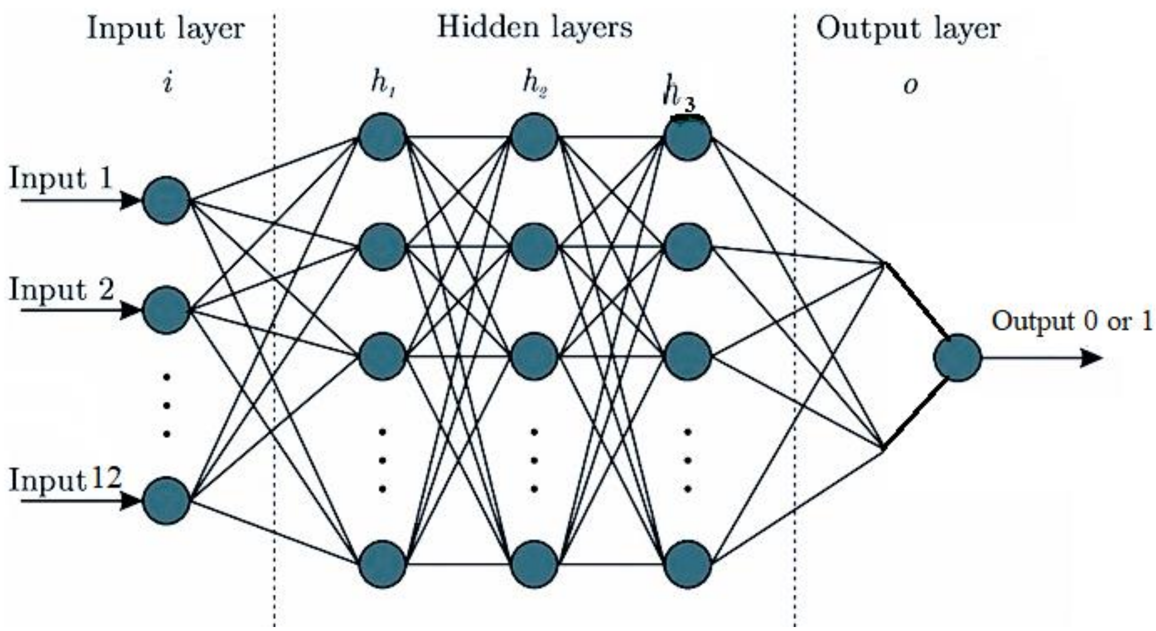


Fig 6.9 Neural network with input, hidden and output layer

6.4.1 TRAINING PHASE

In the training phase, the performance of the classification is analyzed by applying the different set of input features. This proposed approach uses 12D feature vectors derived from the preprocessed image for the input of the neural network and classifies the pixels. This classifier has an input layer, three hidden layers and an output layer. Each of these hidden layers has twenty three neurons. The training sets are collected from a manually labelled vessel and non-vessel pixels in the DRIVE dataset's training images.

The rectified linear activation function(ReLu) is used in the output layer. The output classifies the vessel pixels or non-vessel pixels as 0 or 1 respectively. Finally, the pixels are assigned to one of the vessel classes, if its associated probability value is >0.1. The accuracy of the training dataset is about 95.45% which is shown in the figure below.

The optimizer used is Adam, which combines the properties of AdaGrad and RMSProp which can decrease noise and handle sparse gradient problems. The loss function describes how perfect the model predicts. The Binary Crossentropy loss function is used in the proposed model as it is used in binary classification tasks.

Loss=abs(Y_pred - Y_actual)

```
Epoch 1/20
990/990 [==============================] - 2s 2ms/step - loss: 1.5596 - accuracy: 0.8669
Epoch 2/20
990/990 [==============================] - 2s 2ms/step - loss: 0.2297 - accuracy: 0.9278
Epoch 3/20
990/990 [==============================] - 2s 2ms/step - loss: 0.2047 - accuracy: 0.9305
Epoch 4/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1967 - accuracy: 0.9315
Epoch 5/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1930 - accuracy: 0.9330
Epoch 6/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1891 - accuracy: 0.9340
Epoch 7/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1872 - accuracy: 0.9344
Epoch 8/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1841 - accuracy: 0.9350
Epoch 9/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1798 - accuracy: 0.9364
Epoch 10/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1766 - accuracy: 0.9372
Epoch 11/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1715 - accuracy: 0.9381
Epoch 12/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1639 - accuracy: 0.9402
Epoch 13/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1553 - accuracy: 0.9438
Epoch 14/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1463 - accuracy: 0.9479
Epoch 15/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1403 - accuracy: 0.9503
Epoch 16/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1391 - accuracy: 0.9514
Epoch 17/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1365 - accuracy: 0.9522
Epoch 19/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1346 - accuracy: 0.9528
Epoch 20/20
990/990 [==============================] - 2s 2ms/step - loss: 0.1341 - accuracy: 0.9529

<tensorflow.python.keras.callbacks.History at 0x190808eb400>
```

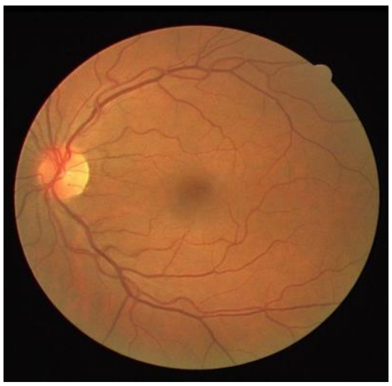
```
_, accuracy = model.evaluate(X, Y)
print('Accuracy: %.2f' % (accuracy*100))
```

```
30934/30934 [==============================] - 25s 812us/step - loss: 0.1295 - accuracy: 0.9545
Accuracy: 95.45
```

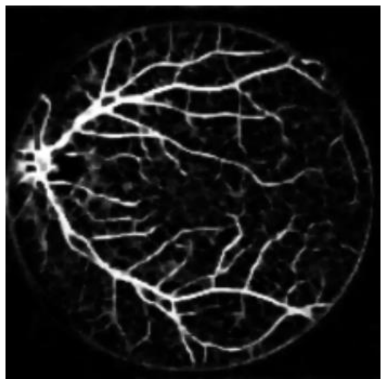
Figure 6.10 Accuracy Obtained

6.4.2 TESTING PHASE

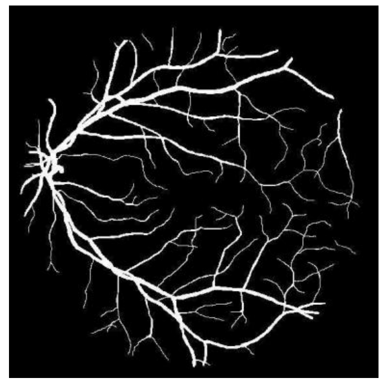
The network which is trained using DRIVE image pixels is applied and tested with the databases. The 12D feature vector extracted from the test images is given as input to the trained Neural Network(NN). The binary segmented image obtained is further enhanced using morphological operations to connect the disconnected vessels and remove small unnecessary isolated pixel areas.



Input Image



Segmented Image



Ground Truth

Figure 6.11 Sample segmented image

6.5 PERFORMANCE EVALUATION

The classification result of every pixel can be one of the four types in the confusion matrix entries. True positive (TP) specifies a vessel pixel classified correctly as a vessel pixel. False-positive (FP) shows a non-vessel pixel record wrongly as a vessel pixel. True negative (TN) specifies a non-vessel pixel classified correctly as a non-vessel pixel. False negative (FN) shows a vessel pixel recorded wrongly as a non-vessel pixel.

		Actual	
		Negative	Positive
Prediction	Negative	True Negative	False Positive
	Positive	False Positive	True Negative

Figure 6.12 Confusion Matrix

	Negative	Positive
Negative	267939	37362
Positive	2659	21999

Figure 6.13 Confusion Matrix with obtained values

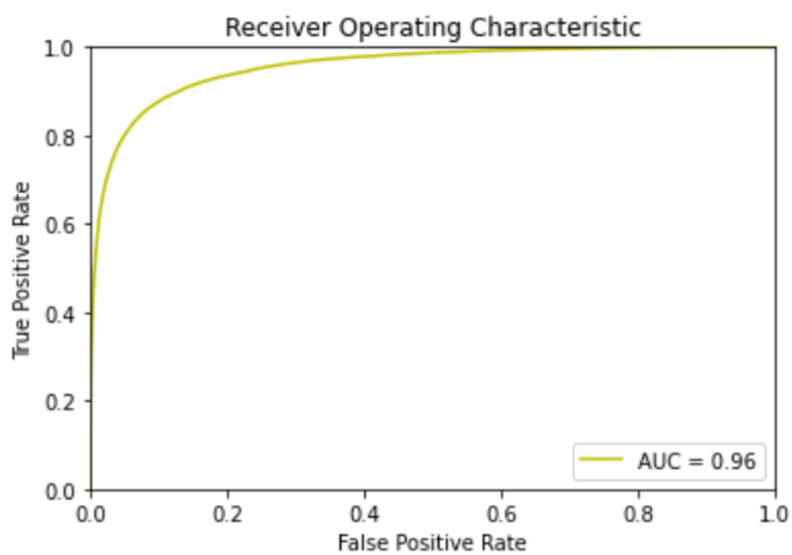


Figure 6.14 ROC curve for testing data

The performance is evaluated on the basis of specificity, sensitivity and accuracy. The metrics are calculated as follows:

Sensitivity (SE) = TP / (TP + FN)

Specificity (SP)= TN / (FP+TN)

Accuracy (AC)= (TP+TN) / (TP+TN+FP+FN)

Table 6.1 Performance Result On DRIVE Database Images

Image no	Accuracy	Sensitivity	Specificity	AUC
1	0.9226	0.9296	0.8365	0.9536
2	0.8855	0.8894	0.8464	0.9399
3	0.8398	0.8398	0.8889	0.9430
4	0.8852	0.8939	0.8190	0.9296
5	0.9095	0.9233	0.7416	0.9195
6	0.8920	0.8977	0.8300	0.9361
7	0.8703	0.8806	0.8546	0.9370
8	0.8614	0.8614	0.8643	0.9387
9	0.8878	0.8919	0.8435	0.9387
10	0.9092	0.9208	0.7724	0.9299
11	0.8366	0.8331	0.8905	0.9360
12	0.8951	0.9015	0.8951	0.9364
13	0.8823	0.8847	0.8852	0.9409
14	0.7564	0.7421	0.8882	0.9011
15	0.8643	0.8613	0.8953	0.9478
16	0.8602	0.8622	0.8444	0.9301
17	0.8428	0.8398	0.8742	0.9336
18	0.8660	0.8669	0.8625	0.9387
19	0.8815	0.8811	0.8767	0.9468
20	0.8921	0.8197	0.8912	0.9592
Average	**0.87203**	**0.87104**	**0.855025**	**0.93683**

Table 6.2 Performance Result On STARE Database Images

Image no	Accuracy	Sensitivity	Specificity	AUC
1	0.8596	0.8469	0.7372	0.8750
2	0.8816	0.7532	0.6705	0.8751
3	0.7814	0.7486	0.8918	0.9095
4	0.9333	0.8761	0.4687	0.8798
5	0.8081	0.7979	0.9107	0.9302
Average	**0.8528**	**0.80454**	**0.73578**	**0.89392**

CHAPTER 7

CONCLUSION AND FUTURE WORK

Retinal vasculature is extracted using NN utilizing a 12D feature vector comprising Gabor filter responses and local intensity features. To overcome the problem of low contrast and large variability in retinal images, the feature vector is constructed by extracting features from the well pre-processed image and the features which can well characterize the vascular pixels are chosen for classification. The algorithm demonstrates the performance advantage over other existing methodologies in terms of accuracy and sensitivity. The result shows that the proposed method produces high accuracy and sensitivity over several existing blood vessel segmentation methodologies.

The segmentation result for the database can be further improved by including high level features. In the future work, the NN classification with random classifier will be explored to segment high-definition images and to detect lesions such as microaneurysms, hemorrhages and exudates. Future work to enhance the proposed model by extracting more features with moment invariant filter, gaussian filter and also considering other features like hessian multiscale feature, local binary feature which will further increase the accuracy of the proposed system. Training with more set of features tends to increase the chances of better performance.There is also room for experimenting with other activation functions to see whether they would improve results.

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