CERTIFICATE

It is certified that the contents and the form of this report titled "**Automated Diagnostic Retinal Image Analysis"** submitted by **M Rooshan Naeem (111278), Samiullah Bilal (111503), Muhammad Shoaib Sarwar (111416)** have been found satisfactory for the requirement of degree.

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Automated Retinal Image Analysis

Final Year Project Report

by

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In Partial Fulfilment

Of the Requirements for the degree

Bachelors of Engineering in Software Engineering (BESE)

School of Electrical Engineering and Computer Science

National University of Sciences and Technology

Islamabad, Pakistan

(2018)

DECLARATION

We hereby declare that this project report entitled **"Automated Retinal Image Analysis"** submitted to the **"School of Electrical Engineering & Computer Sciences"**, is a record of an original work done by us under the guidance of Supervisor **"Dr. Muhammad Shahzad"** and that no part has been plagiarized without citations. Also, this project work is submitted in the partial fulfilment of the requirements for the degree of Bachelor of Software Engineering.

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Date:

04/05/2018

Place:

NUST, SEECS

DEDICATION

To Allah Almighty,

to our parents who enabled us to reach at this level,

our Teachers who educated us and to our Advisors and Faculty members

ACKNOWLEDGEMENTS

First and foremost, we would like to express our sincere thanks to the Almighty ALLAH for the gift of life, wisdom and understanding He had given to us, a reason for our existence. And to our families for the love and support they had provided throughout our life.

Dr. Muhammad Shahzad and **Dr. Muhammad Moazam Fraz** whom we regard as our mentors and supervisors, we thank them for the expertise and intelligence they have displayed while supervising this project. We believe this work is a result of their good guidance and cooperation.

We cannot forget our friends in the Faculty of Computing for the academic interactions and company they have accorded to us.

Lastly, we would like to convey our gratitude to the lecturers in our faculty for the good job done during the 4-year period of our course. May the good Lord bless them and keep them safe.

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ABSTRACT

Eyes are not only the windows to our soul but also to our body’s overall health. From the past few years’ doctors and ophthalmologists are diagnosing many serious diseases from eyes and in many cases eyes help to early detect many diseases which cause serious problems if not detected early. Diabetes, high blood pressure, autoimmune diseases, sexually transmitted diseases and cancers are among the diseases that can be detected during an eye exam. This is because eyes represent unobstructed view of our blood vessels, nerves and connecting tissue. The eye has the same microscopic tissue as our other major organs.

Hypertensive Retinopathy is the retinal abnormality caused by the high blood pressure. Timely treatment of Hypertensive Retinopathy is very important because it can cause permanent vision loss. Similarly diabetic retinopathy is a **diabetes** complication that affects eyes.. The proposed system consists of novel method for classification of vessels as arteries and veins using convolutional neural network.

Our project scope encompasses the domain of Image Processing and will be focusing on segmentation and classification of vascular structure of eye through Retinal image analysis. We aim to make use of machine learning and image processing techniques to identify and differentiate the arteries and veins in the retinal structure of an eye in order to tackle the time-consuming problem of ophthalmologists i.e. manual analysis of retinal images to diagnose Hypertensive Retinopathy, diabetic retinopathy and many other retinal diseases. The deliverables constitute a system that will classify arteries and veins i.e. result of analysis of retinal images.

The main objective behind this project is to develop a computer aided diagnosis (CAD) system that can be implemented on a large scale in the hospitals everywhere in the country. The system will be able to detect Hypertensive Retinopathy early, but our proposed system will capture a retinal image and analyse it to classify the image into arteries and veins using image processing and machine

learning techniques. After that by applying geometry detection and measure technique of image processing, we can easily detect the hypertensive retinopathy. The strength of the project is using machine learning technologies for segmentation of retinal vascular structure in order to improve the early detection of many retinal diseases. For the creation of system, we also manually created the dataset by labelling of arteries and veins which is a novel approach used for their classification. Through convolution neural network, accuracy increases, which helps doctors, screen far more patients than currently possible.

Chapter 1

1. INTRODUCTION

As digital imaging and computer power increasingly develop so does the potential use of these in ophthalmology and medical sciences. As mentioned above, from the past few years' doctors and ophthalmologists are diagnosing many serious diseases from eyes and in many cases eyes help to early detect many diseases which cause serious problems if not detected early. Diabetes, high blood pressure, autoimmune diseases, sexually transmitted diseases and cancers are among the diseases that can be detected during an eye exam. This is because eyes represent unobstructed view of our blood vessels, nerves and connecting tissue. The eye has the same microscopic tissue as our other major organs. The retinal microvasculature is unique in that it is the only part that can be directly visualized non-invasively in vivo, readily photographed and subject to image analysis.

The retina of eye is a layered tissue lining the interior of the eye. The ability to take fundus image of retina and organize techniques for analyzing these fundal images is of great interest now a day. With the proper use of techniques, the retina of an eye can be visible from outside, making the retinal tissues accessible for imaging analysis noninvasively. Because of the architecture of retina, according to its function both diseases of the eye and diseases related to brain and that affect the circulation, can affect mostly on the retina of eye. Many systemic diseases affect retina. For example, diabetic retinopathy caused from diabetes, which is the world's second most common cause of blindness and hypertensive retinopathy from cardiovascular disease. Thus imaging the retina allows diseases of the eyes, as well as hypertension and diabetes to be well early detected, diagnosed and well managed.

Retinal imaging has developed rapidly during the last years. Fundus photography and Optical coherence tomography (OCT) are widely used for population-based, large scale detection of diabetic retinopathy, glaucoma, and hypertensive retinopathy. The images taken for dataset of this project is through fundus photography.

This project introduces a novel approach of artery vein classification of eye for the early detection of retinal diseases such as Hypertensive Retinopathy and Diabetic retinopathy. High blood pressure can cause a lot of disturbance on the retina of the eye mainly on the vascular structure of the eye, which is hypertensive retinopathy (HR) where the systemic changes which are produced by arterial hypertension have affect in the blood vessels (arteries and veins) of the retina. For the prevention of hypertensive retinopathy and well treatment, the early diagnoses of the disease are necessary. Fundus image analysis is the way to detect and evaluate the availability of hypertensive retinopathy by the classification of vascular structure of eye. The disease if not detected at early stages can cause permanent vision loss. The diameter of the arteries and veins of retina is one of the main characteristics for the early detection and diagnosis of this disease. The classification is basic step after that by using the ratio of arterial blood vessels of the retina (AVR) we can easily detect the related retinal disease. Therefore, the first step is, the help of convolutional neural network classifies arteries and veins. Then by calculating vessel geometry, we are able to detect the presence of hypertensive retinopathy. Later in paper the major focus is on the vascular classification of retina, that is how machine learning and various image processing techniques help us to analyze the retina and classify arteries and vein.

1.1 TARGET USER

We aim to target different categories audience as they will make use of our project for different use cases:

1. **Hospitals:** For diagnosis of diseases and reducing the workload of ophthalmologists thereby improving health care.

2. **Clinics:** Clinics who cannot afford expensive equipment for the diagnosis of diseases

3. **Patients:** For quick and early detection of the disease.

1.2 REPORT ORGANIZATION

Following is the generic format for the final documentation.

This report is divided into 8 parts:

- Chapter 2 provides the literature review.
- Chapter 3 describes the problem in further detail.
- Chapter 4 describes the solution in further detail.
- Chapter 5 describes over the overall architecture of the project and the workflow.
- Chapter 6 describes the technical details regarding the actual implementation of the solution.
- Chapter 7 explains the results and their interpretation.
- Chapter 8 discusses the conclusions and what future work can be performed on the project for improvement or extension.
- Chapter 9 lists all the references.

Chapter 2

2. LITERATURE REVIEW

There have been many previous studies that recognize hypertensive retinopathy symptoms through retinal image analysis that is classification of retinal vessels. There is a traditional approach in which there is vascular segmentation of retina of eye through transformation called Radon transformation and then calculate arterial venous ratio. The research uses test data from Digital Retinal Images for Vessel Extraction (DRIVE) database with an accuracy of 92%.

In paper [1] 4 main techniques are used for the segmentation of vessels, which are matched filters, vessel tracking, neural networks and morphological processing. This paper reports a win rate (compared with the ophthalmologist manually mapping out the area of the vessels in an irregular example of 73 20x20 pixel window and requiring a correct match between pixels in the two pictures) of 99.56% for training data and 96.88% for validation data, individually, with a sensitivity and specificity of 83.3% and 91% respectively.

Another paper [2] represents a pixel feature classification technique for the detection of blood vessels through image analysis. The classification of pixel feature is a machine learning approach in which one or more classes are assigned to the pixel or pixels in an image. Multiple pixel features are used in this technique: numeric properties of surroundings of a pixel and the pixel itself. This technique is performed as a supervised approach.

Artery/Vein classification method proposed in [3] consists of three main steps. To improve the images several enrichment techniques are applied as the first step. To separate significant arteries from veins particular component extraction strategy is utilized. Highlight extraction and vessel arrangement are not connected to each vessel point rather it is connected to little vessel segment. Finally, the outcomes acquired from the past step are improved by applying the post processing step. Post processing step relies upon basic attributes of the retinal vascular system. Some erroneously named vessels are effectively marked by methods for this technique. The labeling of vessels is done appropriately based on close-by vessel or by means of other vessels associated with it.

Artery/Vein characterization technique proposed in [4] is a novel calculation for grouping the vessels, in which the characteristic of retinal pictures is misused. By applying divide et impera approach a concentric zone in the area of the optic disc are divided into quadrants, thereby we can perform extra robust local classification analysis. The outcomes acquired by this technique were contrasted with manual classification on a validation set having four hundred and forty-three vessels. The general classification flaw decreased from 12 % to 7 % if the assessment which done is based on only diagnostically significant retinal vessels.

Vazquez et al. [5] explains a strategy which combines vessel tracking technique with a color based clustering algorithm. At first the clustering approach partitions fundal image into 4 quadrants, at that point it classifies independently the vessels recognized in every quadrant, and in conclusion it combines the the outcomes. At that point, a technique based on minimal path approach is connected to associate the vessel fragments situated at various radii to support the classification by voting.

Another novel approach is used in [6] where classification is done by following these steps.

1) Segmentation

2) Centerline extraction

3) Feature Extraction and

4) Classification.

Quadratic discriminant analysis (QDA), Linear discriminant analysis (LDA), and k-nearest neighbor (kNN) are used to classify the vessels after performing the above mentioned steps.

In this paper [7] classification is done by feature set formulation The feature vector is composed of the following features.

1. Red channel mean intensity of each pixel.
2. Green channel mean intensity of each pixel.
3. A channel variance of vessel pixel intensities of LAB color space.
4. B channel variance of vessel pixel intensities of LAB color space.
5. Hue and Saturation Channels mean intensity.
6. Vessel pixel variance in red channel.
7. Vessel pixel Energy in red channel.
8. Vessel pixels and background Entropy of boundary.

After that for main classification hybrid classifier to classify the vessel as artery and vein is used. The entire feature vector based on 9 highlight features is given to this hybrid classifier which is a mix of Naive Bayes and SVM which reviews the vessels into artery or vein. The explanation behind picking Naive Bayes is that this classifier approximates its parameters utilizing just little training data while SVM looks for the information which is well distinct by a decision boundary. The results are shown in Figure 1.

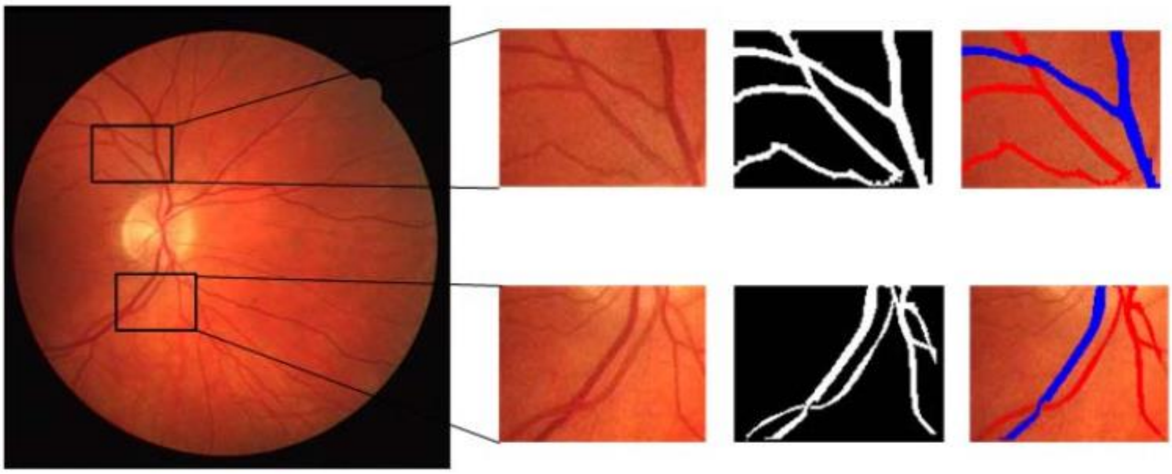


Figure 1: A/V Classification

Previously machine learning techniques have also been used for the detection of retinal diseases also. The paper [8] is using deep learning architecture model which is convolutional neural network for classification. The diagram of proposed method is show in fig 1. They use dataset from Digital Retinal Images for Vessel Extraction (DRIVE). The accuracy of classification of hypertensive retinopathy is 98.6%. This result is because the complexity of the dimensions of the input image are simple, although it will remove some information from the original image, so this method is less suitable for other image types where more concern is on details of the original image information. Still this paper did the classification of hypertensive retinopathy stages and early detection of hypertensive using used deep neural networks and Boltzmann machine for the retinopathy along with the study of role of optic disc positions in the future work of the paper.

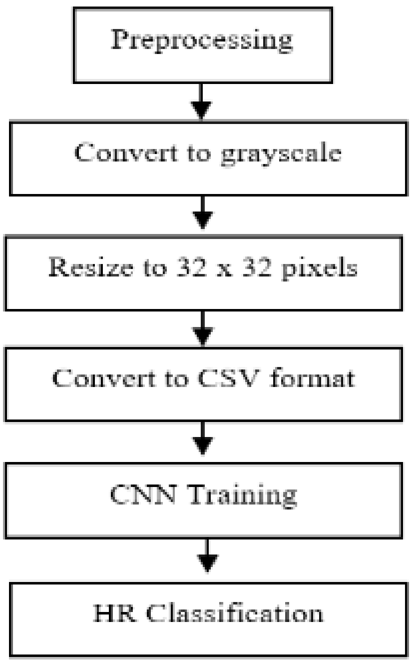


Figure 2: Steps to HR classification

The paper [9] uses the set region of interest as measurement area of arteries and veins of retina. Optic disc is used to find that region of interest. For recognition it uses the Multiscale Laplacian to estimate the radius Optic Disk (OD). Then it calculates the ratio, Central Retinal Artery Equivalent and Central retinal vein Equivalent, which is determined by the measurement of the arteries and veins and at last classification is done by Using Convolutional Neural Network and Boltzmann machines.

Chapter 3

3. PROBLEM DEFINITION

From the past few years' doctors and ophthalmologists are diagnosing many serious diseases from eyes and in many cases eyes help to early detect many diseases which cause serious problems if not detected early. Diabetes, high blood pressure, autoimmune diseases, sexually transmitted diseases and cancers are among the diseases that can be detected during an eye exam. This is because eyes represent unobstructed view of our blood vessels, nerves and connecting tissue. The eye has the same microscopic tissue as our other major organs. The retinal microvasculature is unique in that it is the only part that can be directly visualized non-invasively in vivo, readily photographed and subject to image analysis. Because of the architecture of retina, dictated by its function both diseases of the eye and diseases related to brain and that affect the circulation can show there affect in retina of the eye. The retina of eye is affected by number of systematic diseases, which if not detected or prevented early can cause permanent vision loss. For example, diabetic retinopathy from diabetes and hypertensive retinopathy from cardiovascular disease. Thus imaging the retina allows diseases of the eyes, as well as hypertension and diabetes to be detected, diagnosed and managed.

Previously Ophthalmologists are labelling the retinal images of eye manually. After acquiring the retinal images of patients from fundus camera, they manually label the vessels and other pathologies of retina in order to classify them. So a lot of time of ophthalmologists is wasted in this way. First they have to manually classify the retinal vessels (arteries and veins) and pathologies and then analyze them. This approach fails where there is a large amount of patients or data available. So they need time efficient system that will classify the retinal vessels for further processing and detection of various retinal diseases.

The lack of time efficient diagnostic system makes it time consuming for the ophthalmologists to observe the retinal vessels manually. So ophthalmologists are in need of system that will help them to solve this time consuming classification and segmentation problem.

Chapter 4

4. METHODOLOGY

4.1 INTRODUCTION

This is a description of methods, approaches, tools, techniques and algorithms chosen to achieve the objectives of the proposed system. It will go on to describe the techniques of data collection, data refining and augmentation, presentation and evaluation of results, development of the system using a client server architecture and the validation and testing of the system.

4.2 APPROACH FOR THE DEVELOPMENT OF PROPOSED SYSTEM

The nature of the project includes the development of a system working on a client-server architecture, that takes a fundal image captured through fundus camera, and based on the training of the system, it segments the vessels i.e. arteries and veins in the image. We were determined to help ophthalmologists to analyze retinal images more effectively and efficiently than the current time-consuming method of manual analysis but, since the field of fundus photography is new for us, we engaged in a procedural and systematic approach where resources were allocated in studying and understanding retinal images before spending effort on the actual development of the system.

The steps involved in overall methodology of the project are highlighted as follows:

4.2.1 Information Gathering

This project is aligned with our interests to make an impact via the application of deep learning in the medical sector. Hence, we collected information and reviewed related projects in the field, their success rates and whether our project helps solving the problem in more efficient and effective way.

4.2.2 Research on Type of Data Required

Next, we collected information about the type of data that was required for generation of dataset which will then be utilized for training of our model. After a bit of research, we found out that retinal images captured through a fundus camera in proper lighting conditions are going to perfect candidate that after some pre-processing can be utilized in dataset generation.

4.2.3 Data Gathering

Our next step was to actually gather the retinal images data. We had three options in order to achieve this task:

1. We acquire a fundus camera and gather the data ourselves.
2. We contact Hospitals & Clinics in order to provide us with retinal images.
3. We make use of publicly available dataset online for our project.

After reviewing all three options, we came to the conclusion that by going with option number one will not feasible for us as we had limited time resource. The manual gathering of data by ourselves would have consumed a lot of time which, in turn, would've had a drastic impact on our timeline. So, we decided to choose both option two and three. Our project advisor contacted medical authorities for access to dataset, and we along with a PHD candidate gathered a little bit of publicly available data from the internet.

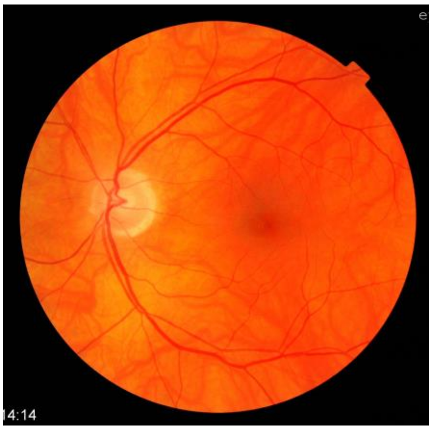


Figure 3: Fundal Image

4.2.4 Dataset Generation

Now that we had collected the data from different sources, it was time to prepare the dataset for training. The first step in this process was to extract the green channel image from the colored image as the green channel of any image contains a lot of information and in our case, arteries and veins were more clearly visible in green channel. Next step was to further enhance the image by applying different image processing techniques in order to clarify the images.

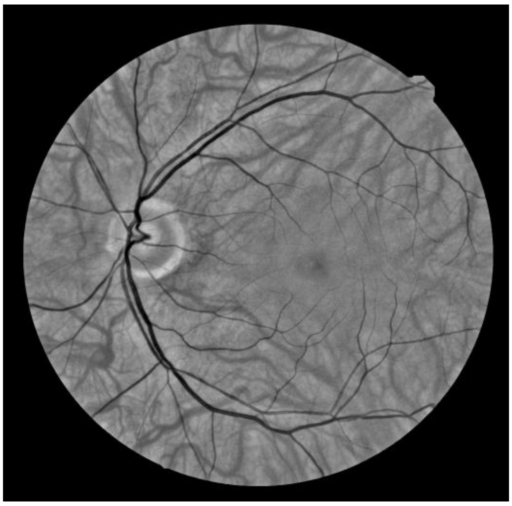


Figure 4: Green Channel Retinal Image

The final step was to actually mark the arteries and veins found in the image. For this purpose, we first used a software called VAMPIRE developed by people over at the University of Dundee, UK. But the interface of this software was not user friendly and it took us about 45-50 minutes to mark the vessels on one image.

So we turned towards MATLAB's built-in application called "Image Labeler". The software drastically reduced our marking time to 25-30 minutes per image.

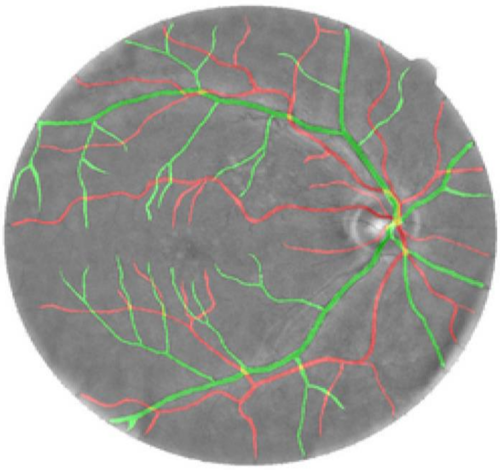


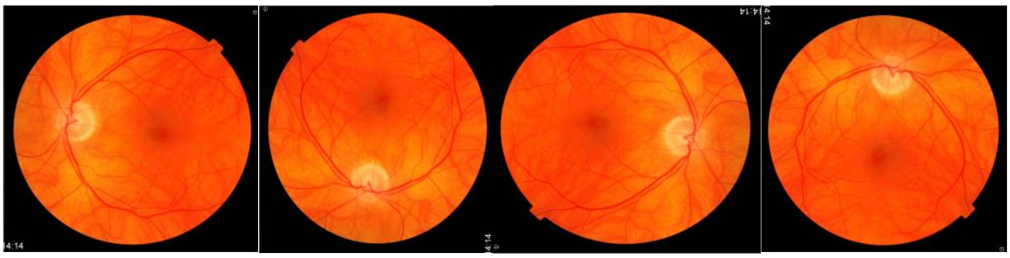
Figure 5: Marked Arteries and Veins

In this way, we developed the dataset that contained around 320 images in total. But initial training results showed us our dataset was not enough to properly train the model. So we decided to apply techniques of data augmentation on our data which have been discussed in the next section.

4.2.5 Data Augmentation

As described at the end of last section, our data was sufficient enough for training and it ended up producing completely unsatisfactory results. So we decided to perform data augmentation to increase our dataset. We employed two techniques for this purpose:

1. Rotation: We rotated the images in our dataset by angle of 30°. Hence, giving us 10 more images for one image. Same operation was applied to their labels.



(a) (b) (c) (d)

Figure 6: Retinal Image Rotated at a) 0° b) 90° c)180° d) 270°

2. Patching: After rotation we divided the images into patches. There were two reasons for this operation. One is that our original dataset had images that were of significantly higher resolution i.e. around 2000x2000. This impacted the performance of GPU's drastically, which resulted in extremely slow training times. Second, as discussed before, was to increase the amount of total images in our dataset. Each image in the dataset was divided into four halves thus giving us 3 more images for one image. Similarly, there labels were also divided into four parts.

Figure 7: Image Patches

By application of these two techniques, the amount of our training dataset was significantly increased which resulted in better training and satisfactory results. These results have been discussed in section 4.2.8.

4.2.6 Research on Different Deep Learning Semantic Segmentation Models

As a part of implementing the system, we get to explore different semantic segmentation deep learning models. Since our dataset contained images and the label of one image contained multiple classes, it was appropriate to select a model which was best suited for our requirements. The details of these models have been discussed in section 4.3.

4.2.7 Model Training

This step includes the actual training of our selected model where efforts were spent trying to achieve the most accurate results possible while studying in detail the inputs, data processing and output of algorithms. The model selected for training was FCN for semantic segmentation [16], the details of which have been discussed in section 4.3.

The training took roughly 48 hours and was done using two GPUs namely NVidia Quadro P5000 16GB and NVidia Tesla 12GB with a learning rate of 0.00001.

4.2.8 Model Testing and Evaluation of Results

After performing all the steps discussed above, we achieved more than satisfactory result of segmentation as shown in fig 4.6.

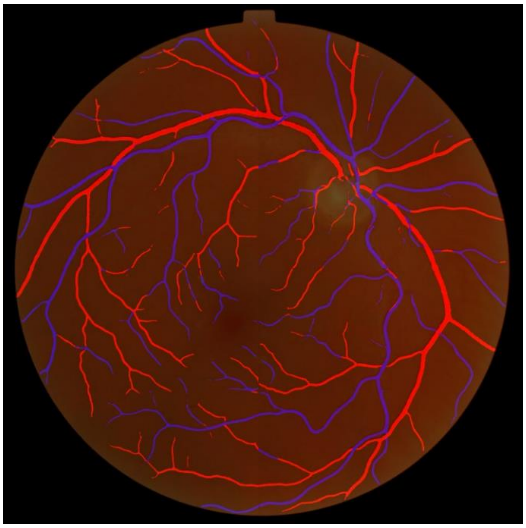


Figure 8: Semantically Segmented Image

The results were achieved after the completion of training described in previous section. The model was tested on around 100 images and the accuracy on each image was the same as the accuracy of resultant image shown in fig 4.6.

4.2.9 Development of Client-Server Architecture

The final step in development of our current system was to implement a client server architecture, where our trained model resides on server and user can upload a retinal image from the client side. The server than evaluates the results and send it back to the client. This architecture has been implemented using Python's framework called "Flask".

4.3 DEEP LEARNING MODELS

In order to select a model for training, we looked at different semantic segmentation models, and we came across two different publicly available models. These models have been discussed below:

4.3.1 DeepMask

DeepMask [10] is a semantic segmentation model that has been developed by Facebook and has been implemented in “torch” framework and is publicly available for anyone to use. Initially, as suggested by our advisor, we decided to work with DeepMask, but because of some drawbacks we decided to select a different model. The main issue related to this model was that this model required the dataset to be in JSON format. Our dataset, on the other hand, was in the form of images. The images in our dataset, however, were easily converted to JSON format. But we faced problem in converting the labels of our images into JSON since our labels were of different type than the ones used by DeepMask. We spent significant amount of time in conversion of labels but failed so we decided to skip this model and test others and see if they met our requirements.

Second model that we tried is known as DeepLab and it has been discussed in the next section.

4.3.2 DeepLab for semantic segmentation

After exploring DeepMask we looked into DeepLab [11] for our project. This model fulfilled our dataset requirements at least to some extent, because further studying showed us that this model wasn’t compatible with our dataset since this model uses bounding box around the region of interests and segments the object based on these bounding boxes. Our dataset, on the other hand, was much more complex as compared to the dataset that this model was pre trained on. One other problem with this model was that this model was built to segment objects that were bigger and common whereas, our dataset contained really small objects as seen in fig 4.3. So based on these observations, we again looked for a different model that met our requirements and this time we came across FCN for semantic segmentation, the details of which has been discussed in the next section.

4.3.3 FCN for semantic segmentation

Finally, after exploring different deep learning models, we found a FCN semantic segmentation model that fulfilled all our dataset requirements and that was easy to train for our own dataset. This model was implemented on tensorflow framework which was much easier to set up as compared to torch or keras as required by the other models. We started training this model on our dataset, but the initial results it produced were not satisfactory at all. In fact, this model barely made an effort to segment arteries and veins. So after applying data augmentation techniques as described in section 4.2.5, we trained the model now on sufficiently large dataset for about 48 hours. In the end, this model was able to produce amazing results with more than 85% accuracy when tested with our test dataset (fig 4.6).

4.4 TOOLS AND TECHNIQUES

Following are the lists of tools and hardware that required in the development of this system.

1. **Tools:**
    a) Tensorflow
    b) Linux OS
    c) Python 3.6
    d) Flask Python Framework
    e) MATLAB
2. **Hardware:**
    a) Nvidia Tesla K80 12GB x2

Chapter 5

5. DETAILED DESIGN AND ARCHITECTURE

5.1 SYSTEM ARCHITECTURE

This section will provide the reader of the document the high level view of the proposed system. The core modules of the developed system are as follows:

1. Vessel Segmentation Module
2. Branch Identification Module
3. A/V Segmentation (Semantic)
4. Vessels Geometry Calculations (Future Prospects)

The figure below shows the overall flow of the system. The modules we are covering in this report are up to A/V Classification but in order to deploy the fully functional system in the hospital, the remaining modules need to be integrated with the developed system. The rest of the report will provide the user information regarding A/V segmentation and methodologies used for achieving that goal.

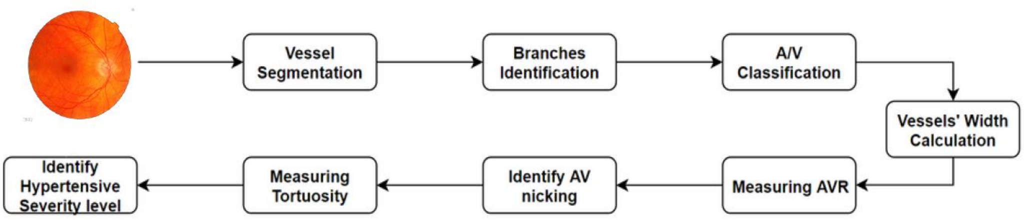


Figure 9: Overall system flow diagram of aimed product

The fundus camera available and solely use for retinal image capturing purpose takes the raw image of the retina and this image is the fed into the system which then process the image for diagnostic purpose.

The vascular tree (Arteries, veins cluster) in the retina has to be extracted from the retinal image for the production of the binary image containing the extracted vessels shown in white while background is shown in black [12]

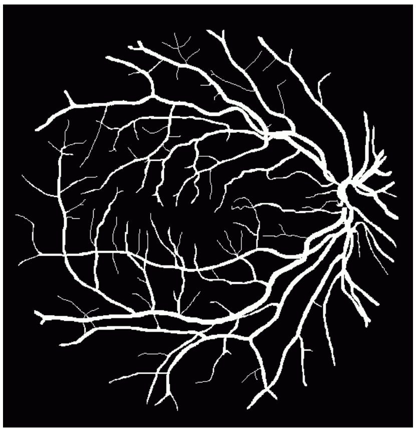


Figure 10: Extracted Vascular tree

Once the vascular tree has been extracted next module detects the branch points on retinal vascular structure. This is important in many cardiovascular disease and can be used for image registration and biometric feature [13]

The next module is very important in the development of the system. Since we are dealing with the disease that has its effect on the vessels of the retina so it must be very important to differentiate the vessels into Artery and vein for examination of their geometry for the prediction of the disease. We applied Deep Learning techniques for semantically segment the objects of interest (A/V) from the image. It is the first time that deep learning methodologies have been applied for that specific problem and we intend to publish a paper showing the detailed design, neural network architecture and results, in the future.

The next four modules help in measuring the vessels geometry which will in turn helpful in detecting and predicting the level of severity of HR in the examined eye. We will not discuss these methods here as these are beyond scope of the project.

5.1.1 Architecture Design

This section describes the working of each components/modules and how they are interacting with the other modules and achieve the required features of the system.

The Vessel segmentation module takes input the Green processed channel of the captured retinal image from the fundus camera. The reason of working with the green channel is that it provides the sharpest contrast between vessels and the background.

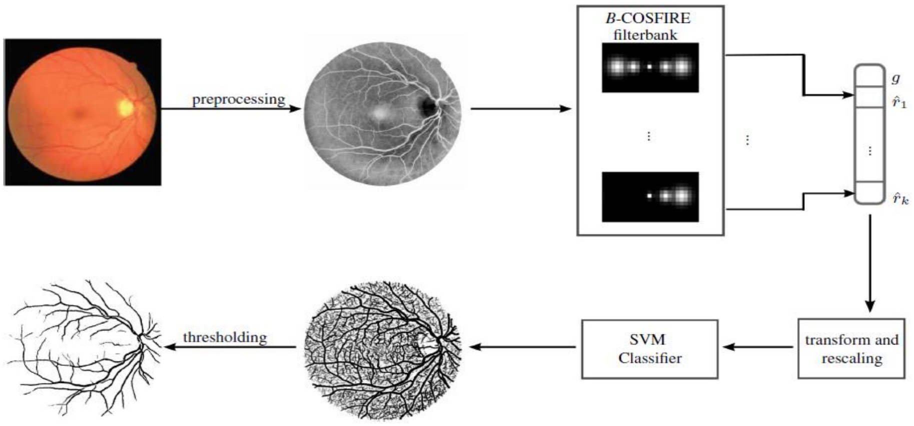


Figure 11: Vessel Segmentation using B-COSFIRE filter approach

Once the vascular tree has been extracted the branch identification modules work by identifying the branch points in the retinal vessels. A/V classification is the most important module for this system as it has to label the vessels as Artery and Vein. Other modules are not described here in this document. The figure below the FCN architecture for the end to end dense prediction. The input is the image which has to be segmented semantically and output is also an image having the heat map of the fed image.

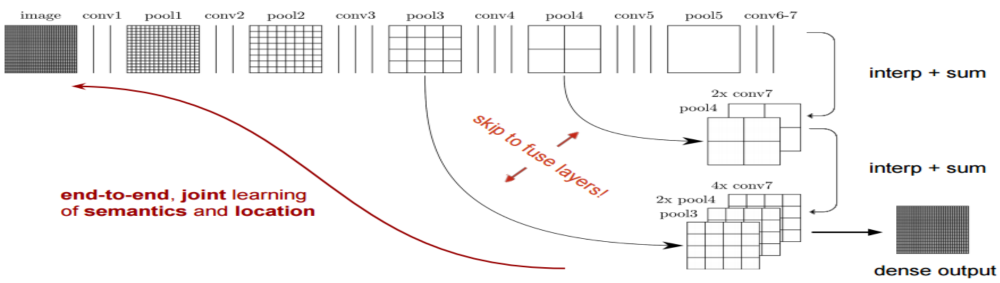


Figure 12: FCN Model

5.1.2 Architecture Design Approach

The system is developed using a "Component based Architectural Design" also called Component based development (CBD)**.** This approach emphasizes in the separation of concern among the wide ranging functionality of the overall system.

The overall flow of the system has been shown in the fig 5.1. Fig 5.3 below shows the component diagram of the system describing the architecture of the system. Each module of the system is treated as a separate component and output of each component is the input of next.

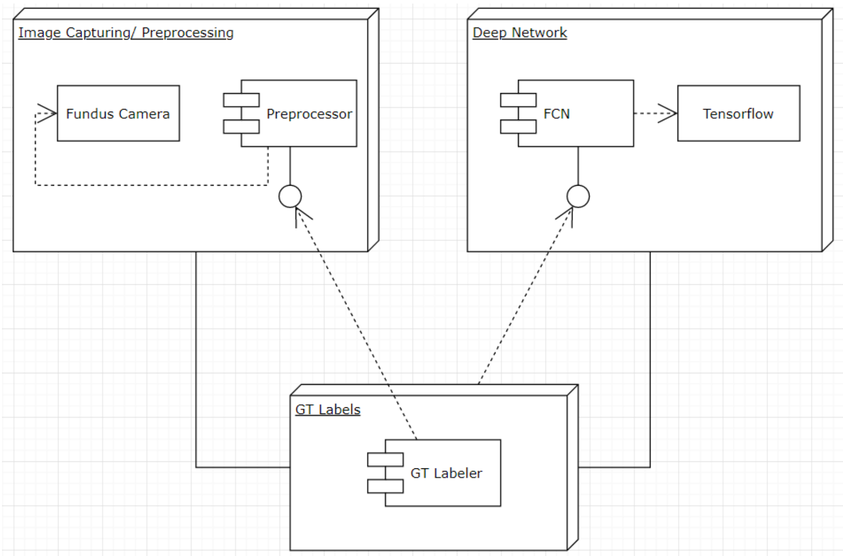


Figure 13: Component Diagram

5.1.3 Subsystem Architecture

There are few subsystems that need to be addressed in this document for complete understanding of the internal working of the systems. All the diagrams in this section are the block diagrams showing the series of operations to produce the final output of the components.

5.1.3.1 Preprocessing

Preprocessing of the images are done beforehand so that if the data is noisy it has to be made clear for the fine details of the interested regions.

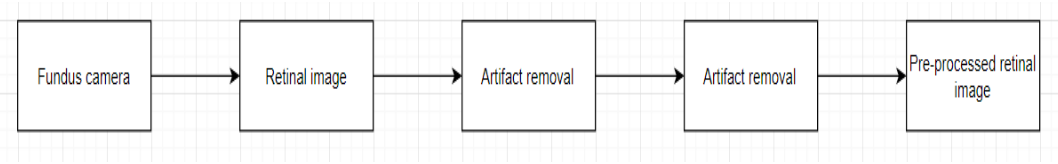


Figure 14: Preprocessing

5.1.3.2 Green channel extractor

Green channel extractor extracts the green channel for the operation. Green channel is used as it provides the sharpest contrast between vessels and the background. Once the green channel has been extracted it is again processed for the removal of unwanted artifacts before feeding into deepnet.

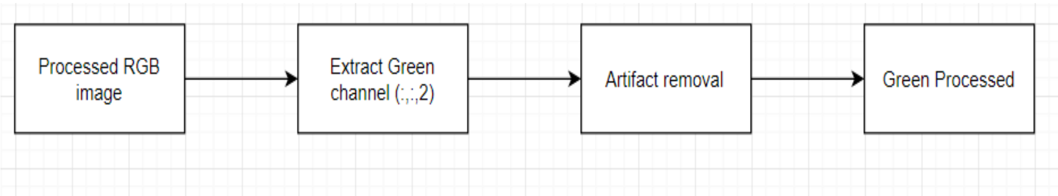


Figure 15: Green Channel Extracts

5.1.3.3 Data labeler

Data labeler is the module for making the Ground truths for the next Deep learning steps. This is the utmost and important phase in analyzing the A/v as without this the classification could never have been done. It is the process of data generation.

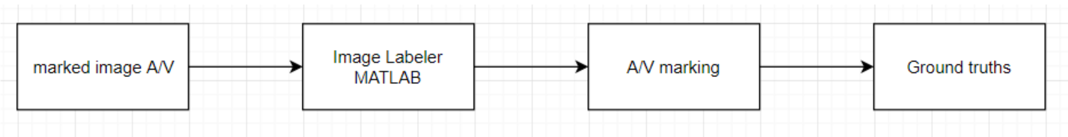


Figure 16: Marked image

5.1.3.4 Data augmentation

Data Augmentation is the module that augmented the data. Augmentation increase the training set that helps to reduce the overfitting. The augmenting technique we applied is the rotation of each image 8 times from 0 to 360 degrees so that we have data having same information in many forms. Next we divided the image into patches of 4 so one image gets divided into four patch this further increases the amount of data.

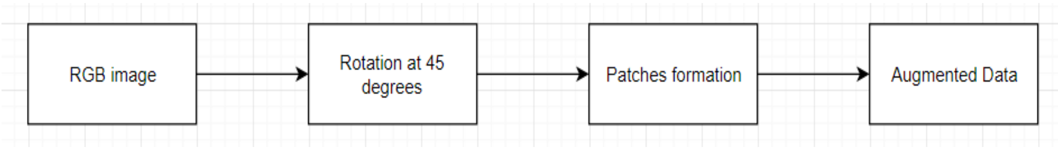


Figure 17: Data Augmentation

5.1.3.5 Model training

Model training is the major step in the recognition of blood vessels once we have our data in ready to use form. FCN (Fully Convolutional Network) for semantic segmentation deep network was used to semantically segment the blood vessels into arteries and veins.

<u>Fully Convolutional network for semantic segmentation:</u>

Convolution networks are powerful structures that yield the hierarchies of features. Fully convolutional network that take input of arbitrary size and generates the output image of corresponding size has been proved very suitable and accurate for segmentation task. The underlying model in the used FCN are classification model VGG16 that adapted their learn representation by fine tuning into semantic segmentation model. It is then able to make dense prediction for per-pixel tasks like semantic segmentation problems [14]

Each layer output in the convolution network is the 3D array of size $h \times w \times d$ in which h and w are the height and width of the image and d is the dimension of features. The very first of layers is the image of size $h \times w$ with d dimensions or channels. These networks are translation invariant and basic components such as pooling layer, convolution layer and activation functions work on local input region and depend on spatial coordinates. If *xij* is the coordinates of input at i and j then *yij* output will be calculated by

$$yij = fks\ (fxsi+i;sj+jg0i;j<k)$$

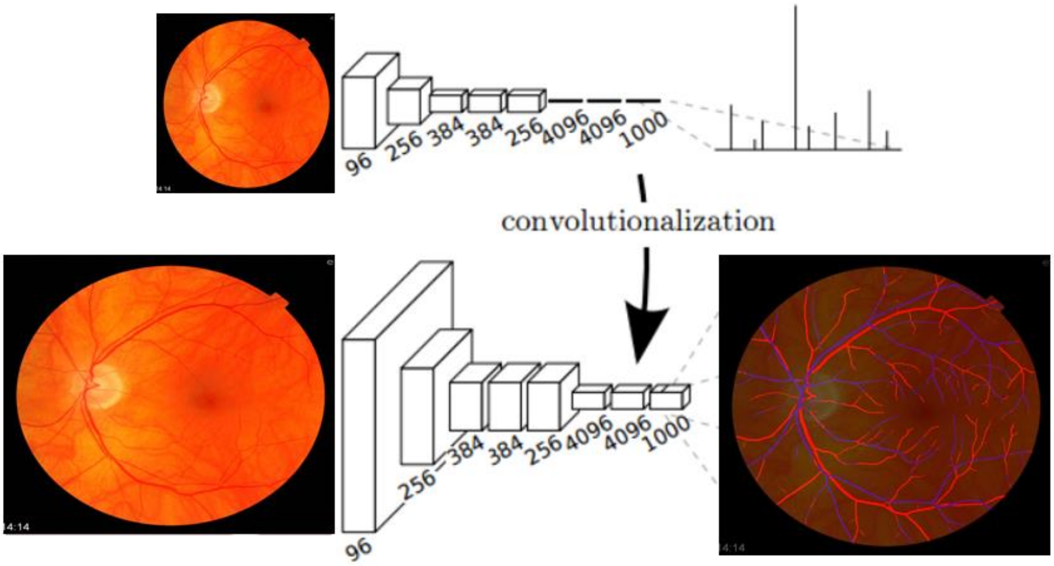


Figure 18: FCN architecture

The architecture given in above image is the high level overview of the layers in the network exact details can be studied from the paper. The left rgb image is input image and the right image is the segmentation overlay result [158]

5.2 DETAILED SYSTEM DESIGN

This section will provide the details of the other components and modules of the system being developed that has been defined or just introduced to the reader of the document in the architecture section of the report. These modules require explanation for the proper understanding of the system.

5.2.1 Classification

The deep model that produces the desired output is the main component or part of the system. The exact details have been given above in the FCN segmentation section. Once the results of the trained have been obtained then the interface for the demonstration purpose and for user so that he or she can operate the system well was developed.

5.2.2 Definition

Given the original retinal images and the ground truth labels for the corresponding images the model is fed with these data. Training of the model to learn the parameters starts and loss function which should be minimum is calculated for each iteration.

5.2.3 Responsibilities

The primary responsibility of this component was to learn the training samples, learn the parameters and produce the inference results accurate so it can differentiate among the input classes efficiently. The trained model when tested with the test data produces the segmented image.

5.2.4 Constraints

Storage constraints were faced during the operation of this component. As the deep learning requires GPU with higher computation power to learn efficiently, so NVIDIA tesla K80x2 GPUs were required to train the training set.

5.2.5 Processing

The trained FCN model generated the output as required for the segmentation. However initially memory constrained was catered by splitting the image which was initially of resolution 2002 x 2000, into 4 patches each of size 500 x 500. The model then trained with these set of images smoothly and efficiently.

5.2.6 Detailed Subsystem Design

The below provide the design of the system. The dashed box separates the components that are related to one module and after that this module communicates with externally developed system that is the client server architecture for the production of results.

The main idea here is that all the processing of the fed data will be done at the server side, client just upload the image through his local machine that image then gets send to server which processes the image, generates the result and sends it back to the client machine.

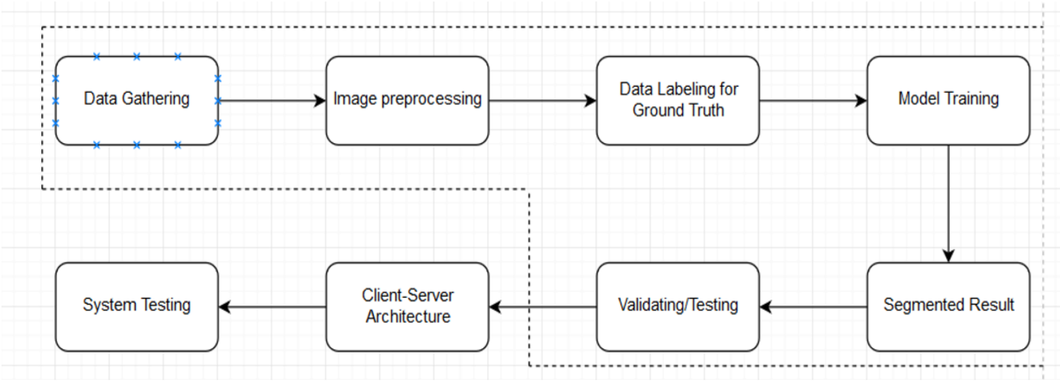


Figure 19: Subsystem components and their interaction.

Integrating this whole system with the system presented in fig 5.1 will be a product which may be deployed in the industry for commercial use.

Chapter 6

6. IMPLEMENTATION AND TESTING

6.1 INTRODUCTION

The section portrays how the arrangement has been actualized and what are the primary difficulties experienced in the advancement of the framework and how the proposed software was tested.

6.2 SYSTEM ANALYSIS AND CHALLENGES

During the initial stages of the projects, the requirements of the users were categorized in user, hardware and software requirements.

6.2.1 Requirement Specifications

The requirements formulated in the initial stages of development were user, hardware and software requirements. These requirements of the project were discussed in detail and grouped formally in the Software Requirements Specification document.

6.2.2 User Requirements

During the research phase, we collected & investigated the user requirements and analyzed the need and feasibility of the project alongside the research of possible problems that the system could face and its possible solutions.

6.2.3 Hardware Requirements

The hardware requirements are listed as follows:

- A server side system with a powerful GPU
- A fundus camera

6.2.4 Software Requirements

The software requirements are listed as follows:

- A web browser (preferably Google Chrome or Mozilla Firefox)
- Internet Connectivity

6.2.5 System Development

After the completion of requirements gathering and system analysis phase, steps were taken to develop our proposed system. The complete methodology of system implementation has already been discussed in Chapter 4.

6.4 CORE FUNCTIONALITIES

The prototype for the system has been developed in accordance with the software engineering principles. The core modules of the prototype have been listed as follows:

- User Input
- Connectivity to the server
- Vessel Segmentation as the output

6.4.1 User Input Validation

The user's input to the system must be a colored retinal image captured with the use of a fundus camera. If the system is not provided with the proper input, the system might produce undesired results.

6.4.2 Connectivity to Server

The graphical user interface, which is a website, should be always connected to the backend model via an internet connection. The user will only be able to obtain the results if the GUI is connected to the server.

6.4.3 Vessel Segmentation as the Output

The output of the model is a retinal image with arteries and veins segmented and overlaid on the image. The model does not guarantee 100% accurate results but will generate an output with a prediction of accuracy of more than 90%.

6.5 TOOLS AND TECHNIQUES

The model was implemented using python 3.6 and its libraries such as anaconda, tensorflow, numpy. These libraries are amongst the advance technologies in machine learning domain. The results were generated in a web browser using HTML and CSS.

6.6 TOOLS

Following tools were required for the implementation of the system:

- Pycharm
- MATLAB
- Tensorflow
- Linux
- Flask framework

6.7 TESTING

The system was first put under validation testing method to ensure the proper working of the system and then the system went through blackbox testing to make sure that user did not come across any bugs in the system.

6.7.1 Validation Testing

Validation testing was carried out on individual features of the system to ensure that they are fully functional units. The success of validation testing gave the go ahead to carry out black box testing of the system.

6.7.2 Black-box Testing

After successful validation testing, our system was put under black box testing. Black box testing is a software testing method in which the internal structure and design of the system being test is not known to the tester. These tests were functional in our case. An input containing a retinal image was provided to the system from the client side, and after the server processed the image, the result was returned to the client. This proved the successful working of our system and gave us the go ahead towards deployment of the system in medical environment.

Chapter 7

7. RESULTS AND DISCUSSION

Automated retinal image analysis system has its major use cases involving ophthalmologists for the detection of several eye diseases affecting the blood vessels and other area of the retina. The main problem that has been solved in this project was to differentiate the arteries and veins in the blood vessels. We successfully achieved this desired goal with the accuracy that is acceptable for confidently saying that the segmented result contains arteries and veins at these positions.

Certain accuracy measures were used to check that final results is matching the ground truth or not and if it is matching then what is the ratio and what is the overlapping area.

7.1 METRICS

We report metrics from common semantic segmentation that are variations on pixel accuracy, specificity and sensitivity.

7.1.1 Specificity

Specificity is the accuracy measure which is also called True Negative rate, that is how many negative pixels (non-Class pixels) in the image that have been detected true as non-class pixels. For example, in our case if the pixel is not any of the vessels (artery or vein) then how often will the test be negative (true negative rate).

Specificity = true negative/(true negative + false positive)

7.1.2 Sensitivity

Sensitivity is the accuracy measure which is also called True Positive rate, that is how many positive pixels (Class pixels) in the image that have been detected true as a class pixel. For example, in our case if the pixel is the pixel of any of the vessels then how often will the test be positive (true positive rate).

Sensitivity = true positive/(true positive + false negative)

There is other measure too along with above mentioned that need to be known to determine the pixel wise accuracy of the results.

True Positive → Correctly predicts positive class (artery or vein)

True Negative → Correctly predicts negative class

False positive → Incorrectly predicts positive class

False negative → Incorrectly predicts negative class

Figure 20: From left to right. Ground Truth, Original RGB Image of retina, predicted Overlay image produced by trained model

In the figure above the ground truth label is showing vessels in black color while background in white color. The actual label produced was entire black and to show the corresponding labels MATLAB script can be used to visualize the separate classes as shown below:

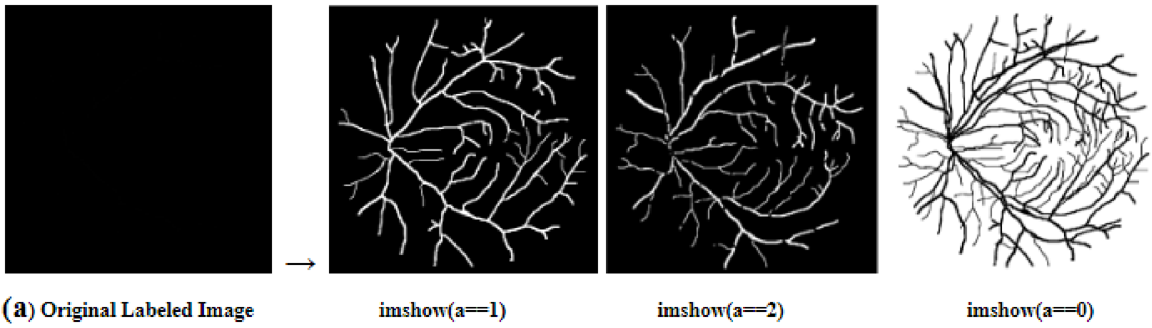


Figure 21: From left to right. a) Original Label, class with label 1, class with label 2 and rightmost class with label 0

As you noticed in the fig 7.2 that labels are shown in white color while the rest of the image is black. Consider the last image having white background and black vessels, it is the label of the background hence in white while rest of the image (vessels) are shown in black.

Overall accuracy of the image of the model was calculated using the formula

accuracy=(true_positive+true_negative)/(true_positive+false_negative+true_negative+false_positive)

```
img = imread('Predicted.png');
im = im2double(img);
% im = immultiply(im,mask);
segmented = im;
ground_truth = imread('GroundTruth.png');
ground_truth = im2double(ground_truth);
    false_negative = nnz(~segmented & ground_truth);
    false_positive = nnz(segmented & ~ground_truth);
    true_positive = nnz(segmented & ground_truth);
    true_negative = (nnz(~segmented & ~ground_truth));
sensitivity = true_positive/(true_positive+false_negative)
specificity = true_negative/(true_negative+false_positive)
accuracy = (true_positive+true_negative)/(true_positive+false_negative+true_negative+false_positive)
```

Figure 22: MATLAB script for performance measure

Test image	Sensitivity	Specificity	Accuracy	Inference time
RGB Image from test set	0.902	0.95	0.932	~25sec

Table 1: Showing accuracy measures

Chapter 8

8. CONCLUSION AND FUTURE WORK

8.1 CONCLUSION

Diabetes, high blood pressure, autoimmune diseases, sexually transmitted diseases and cancers are among the diseases that can be detected during an eye exam. This is because eyes represent unobstructed view of our blood vessels, nerves and connecting tissue. The eye has the same microscopic tissue as our other major organs. For detection of any retinal disease the classification of vascular structure of retina and different pathologies is the major problem and the foremost step. The paper explains in detail the approach we use for the classification of arteries and veins of the retina. Many of the retinal diseases are artery specific or vein specific and some include defects of both. Segmentation and classification of vessels of retina of an eye was the major problem for detection of retinal diseases affecting these vessels. Previously it is done manually and takes a lot of time of ophthalmologists. After solving this problem with the accuracy of 93.2% Ophthalmologists will now be able to detect different diseases that affects the blood vessels present in the eye also morphology of the vessels can also be studied in efficient and easier way. In this way of classification time consumption will also get reduced since no manual labeling is required now. These techniques also guarantee less changes of errors done by the ophthalmologists in the past.

8.2 FUTURE WORK

Future work of the project includes the detail study of vascular geometry. Vascular geometry can be measured by simple image processing techniques. Vascular geometry consists of measurement of the following 4 parameters.

1. **Vessel width calculation**: Calculating the width of every artery and vein in the vascular structure of the retina.

2. **Measuring Artery-Vein ratio**: Normal **ratio** of diameter of a **vein** to an **artery** is measured in this step**.**
3. **Identify Artery-Vein nicking**: **AV**, or **arteriovenous nicking** can be seen when a small artery is seen crossing a small vein , which results in the compression of the vein with bulging on either side of the crossing.
4. **Measuring tortuosity**: Formation of different patterns in the vascular structure.

After calculating or measuring these measures we can easily detect the retinal diseases associated with the vessels of retina. One of the known disease is known as Hypertensive retinopathy. The severity level of hypertensive retinopathy can easily be detected after these measures. Since the segmentation for the vessels has been done, segmentation of other unusual pathologies in the retinal image can also be done by the similar approach and this can help us in detection of diseases due to pathologies such as diabetic retinopathy.

Chapter 9

9. REFERENCES

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