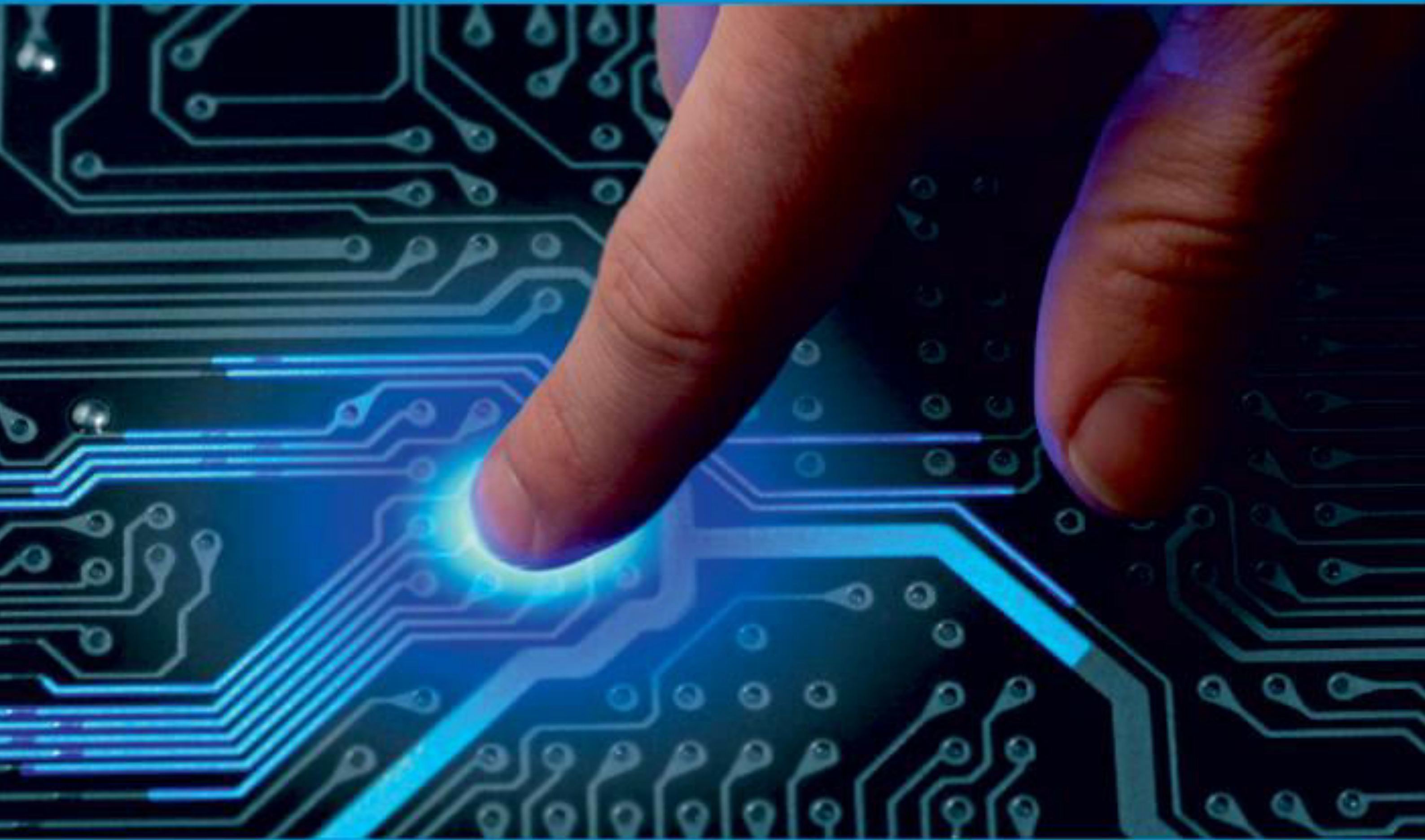
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 6, June 2023

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

An Automatic Graph-Based Approach for Artery/Vein Classification in Retinal Images

Mr. Akash A. Magar

Head of Department, Dept. of EXTC., MSBTE Mumbai, Anuradha Polytechnic Chikhli, India

ABSTRACT: The classification of retinal vessels into artery/vein. Artery/Vein is an important phase for automating the detection of vascular changes, and for the calculation of characteristic signs associated with several systemic diseases such as diabetes , hypertension , and other Cardiovascular conditions. In this Presentation an automatic approach for Artery/Vein classification based on the analysis of a graph extracted from the retinal vasculature. The proposed method classifies the entire vascular tree deciding on the type of each intersection point and assigning one of two labels to each vessel segment. Final classification of a vessel segment as Artery/Vein is performed through the combination of the graph- based labelling results with a set of intensity features. Automated detection of retinopathy in eye fundus images using digital image analysis methods has huge potential benefits, allowing the examination of a large number of images in less time, with lower cost and reduced subjectivity than current observer-based techniques. Another advantage is the possibility to perform automated screening for pathological conditions, such
as diabetic retinopathy, in order to reduce the workload required of trained manual graders. The results of this proposed method are compared with manual labelling for three public databases. Accuracy values of 88.3%, 87.4%, and 89.8% are obtained for the images of the INSPIREAVR, DRIVE, and VICAVR databases, respectively. These results demonstrate that our method outperforms recent approaches for Artery/Vein classification

KEYWORDS: Artery/vein classification, graph, retinal images, vessel segmentation.

I. INTRODUCTION

In retina, blood vessels are divided into arteries and veins. Bright colored arteries transport blood rich in oxygen to organs of the body and dark colored veins transport blood low in oxygen level. To detect the diseases, it is essential to classify arteries and veins. For high blood pressure an abnormal artery or vein ratio is one of important symptom. Digital image analysis has large benefits for examining much number of images in less time and low cost. In diabetic retinopathy, vessel diameter alterations as well as blood vessels show abnormalities at early stages. Dilatation and elongation of main arteries, veins, and their branches are also related with hypertension .Diabetes, hypertension and vascular disorders occur in retinal vessels. Higher blood pressure levels are inversely related to Arteriolar-to-Venular diameter Ratio (AVR). Also arteries and veins are identified by using AVR measurement system. Graph based methods have been used for retinal image registration and retinal vessel classification , retinal vessel segmentation Finally for classification of Artery/Vein graph based labelling results with a set of intensity features. Here STARE, DRIVE, MESSIDOR databases are used and its threshold value 0.5 are used. To measure the distance between nodes a biometric graph matching algorithm is used. Diseases like glaucoma, hypertension are detected by using feed forward neural network (FFN). The retina is the only location blood vessels can be directly visualized non- invasively in vivo. Increasing technology leading to the development of digital image systems over the past two decades has revolutionized fundal imaging. In, author has mentioned the difference between arteries and veins. They are as follows. Blood vessels of retina are divided in two types. They are Arteries and Veins. Arteries are blood vessels that carry blood away from the heart. While most arteries carry oxygenated blood, they carry blood that is oxygenated after it has been pumped from the heart. Artery transports blood rich in oxygen to the organs of the body. The veins transport blood low in oxygen level. Arteries are bright but Veins are dark. For diagnosis of various diseases it is more essential to distinguish the vessels in arteries and veins. An abnormal ratio of the size of arteries to veins is one of important symptom of other diseases like diabetic retinography, high blood pressure, pancreas etc. For example diabetic patients have abnormally wide veins, whereas pancreas patients have narrowed arteries and high blood pressure patients have thickened arteries. To detecting these diseases the retina has to be examined routinely. Blood vessel has to be segmented before classify the blood vessels into arteries and veins. Several automated techniques have been reported to quantify the changes in morphology of retinal vessels indicative of retinal or cardiovascular diseases. However recently, vessel morphology measured specific to arteries or veins was found to be associated with disease. Arterial narrowing and resulting decrease in artery-to-vein width ratio (AVR) may predict the future occurrence of a stroke

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

events or a myocardial infarct. Retinal vessels are affected by several systematic diseases namely diabetes, hypertension, and Vascular disorder. In diabetic retinopathy, the blood vessels often show abnormalities at early stage, as well as vessels diameter alterations. Changes in retinal blood vessels, such as significant dilatation and elongation of main artery, vein, and their branches, are also frequently associated with hypertension and other cardiovascular pathologies. -Retina is a layer format which is found at the back side of the eyeball which plays the main role for visualization. The vascular system consists of two kinds of blood vessels: artery and vein

II. RELATED WORK

There are visual and geometrical features that enable discrimination between veins and arteries; several methods have explored these properties for Artery/Vein classification. . Arteries are bright red while veins are darker, and in general artery calibres are smaller than vein calibres. Vessel calibres can be affected by diseases; therefore this is not a reliable feature for Artery/Vein classification. Arteries also have thicker walls, which reect the light as a shiny central reex strip. Another characteristic of the retinal vessel tree is that, at least in the region near the optic disc (OD), veins rarely cross veins and arteries rarely cross arteries, but both types can bifurcate to narrower vessels, and veins and arteries can cross each other . For this reason, tracking of arteries and veins in the vascular tree is possible, and has been used in some methods to analyse the vessel tree and classify the vessels A semi-automatic method for analysing retinal vascular trees was proposed by Martinez-Perez et al. in .In this method geometrical and topological properties of single vessel segments and sub trees are calculated. First, the skeleton is extracted from the segmentation result, and significant points are detected. For the labelling, the user should point to the root segment of the tree to be tracked, and the algorithm will search for its unique terminal points and in the end, decide if the segment is artery or vein. Another method similar to this was proposed by Rothaus et al., which describes a rule-based algorithm to propagate the vessel labels as either artery or vein throughout the vascular tree. This method uses existing vessel segmentation results, and some manually labelled starting vessel segments. Grisan et al. developed a tracking Artery/Vein classification technique that classifies the vessels only in a well-defined concentric zone around the optic disc. Then, by using the vessel structure reconstructed by tracking, the classification is propagated outside this zone, where little or no information is available to discriminate arteries from veins. This algorithm is not designed to consider the vessels in the zone all together, but rather partitions the zone into four quadrants, and works separately and locally on each of them. azquez et al. described a method which combines colour-based clustering algorithm with a vessel tracking method. First the clustering approach divides the retinal image into four quadrants, then it classifies separately the vessels detected in each quadrant, and finally it combines the results. Then, a tracking strategy based on a minimal path approach is applied to join the vessel segments located at different radiiin order to support the classification by voting. A piecewise Gaussian model to describe the intensity distribution of vessel pro_les has been proposed by Li et al. In this model, the central reex has been considered. A minimum distance classifier based on the Mahalanob is distance was used to differentiate between the vessel types using features derived from the estimated parameters. Kondermanneal. Described two feature extraction methods and two classification methods, based on support vector machines and neural networks, to classify retinal vessels. One of the feature extraction methods is pro_le- based, while the other is based on the definition of a region of interest (ROI) around each centreline point. To reduce the dimensionality of the feature vectors, they used a multiclass principal component analysis (PCA). Niemeijer et al. proposed an automatic method for classifying retinal vessels into arteries and veins using image features and a classifier. A set of centreline features is extracted and a soft label is assigned to each centreline, indicating the likelihood of its being a vein pixel. Then the average of the soft labels of connected centreline pixels is assigned to each centreline pixel. They tested different classifiers and found that the k-nearest neighbour (kNN) classifier provides the best overall performance. Most of these methods use intensity features to discriminate between arteries and veins. Due to the acquisition process, very often the retinal images are non-uniformly illuminated and exhibit local luminosity and contrast variability, which can affect the performance of intensity-based Artery/Vein classification methods. For this reason, we propose a method which uses additional structural information extracted from a graph representation of the vascular network. The results of the proposed method show improvements in overcoming the common variations in contrast inherent to retinal images.

III. SYSTEM DESIGN

For the system design is necessary to implement required images on matlab. For implementation of basic GUI we have design the basic structure of the system Shows the basic system design of the Project.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

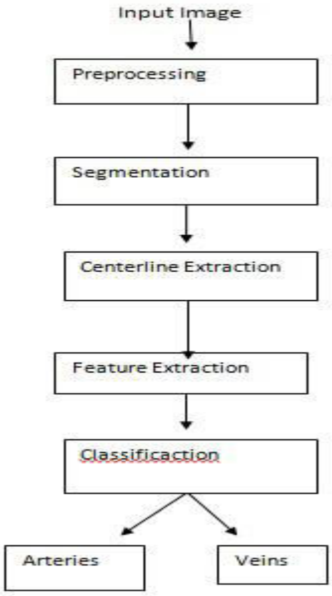


Fig 3.1 Flow of Proposed method

Input Image Given to the Basic GUI

Retinal image can be obtained from the publically available databases like VICAVR [2], DRIVE [1] and INSPIRE-AVR [10]. The retinal image is the soft part of the inner eye. The retinal image contains parts like blood vessels, optic disk and fovea. Blood vessels of retina are divided into two types. One is called arteries and another one is called Veins. Main objective is to discriminate those vessels. This discrimination is very help full for the identification of several diseases. Sample images of this dataset are shown

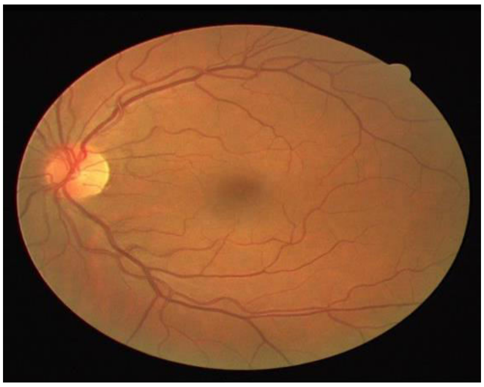


Fig 3.2 Sample Retinal image of Drive [1] Database

For the 20 test images of the DRIVE database, an accuracy of 87.4% was achieved for the classification of centerline pixels of the main vessels (vessels with caliber higher than 3 pixels). Two examples of automatic classification of DRIVE images can be observed in 3.2 al labeling are shown in green (wrongly classified arteries) and yellow (wrongly classified veins), while the correctly classified arteries and veins are presented in red and blue, respectively. Niemeijer et al. presented the results of their A/V classification method in DRIVE images using a ROC curve. The AUC value was 0.88 for the main vessel centerline pixels of DRIVE [1]. The sensitivity and specicity values were extracted from the gure of ROC curve. VICAVR Dataset For the vessel segments of VICAVR images that have manual classification results, the percentage of correctly- classified vessel segments using the graph-based solution is 89.8%,which is similar

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

to the value achieved by Vazquez et al. (88.80%) .Some results of the proposed A/V classification method on the images of VICAVR are shown in 3.3

Fig 3.3 Sample Retinal image of Vicar [2] Database

The automatic methods described in the previous sections were tested on the images of three databases, DRIVE [1], and VICAVR [2]. The images in the DRIVE dataset were captured with 768 584 pixels, with 8 bits per color plane. The 40 high resolution images of the INSPIRE-AVR database have resolution of 23922048 pixels and are optic disc centered. Finally, the 20 images of the VICAVR database were acquired using a Top Con non- mydriatic camera NW-100 model with a spatial resolution of 768 584, and are also optic disc-centered. Results of automatic vessel segmentation were available for the three datasets, and a manual artery/vein labeling was performed by an expert on the 20 images of the DRIVE test set and for the 40 images of the INSPIRE database. The VICAVR database includes the caliber of the vessels measured at different radii from the optic disc as well as the vessel type (artery/vein) labeled based on the agreement among three experts.

Converting RGB Image to Green or Red Channel

It is more important because arteries and veins are better visible in green or red channel and that why RGB image should be converted into red or green channel in the first step itself. For few images green channel is suitable while others require red channel

Fig 3.4 Green channel of Retinal Image

During the acquisition process, images are habitually of meager quality that encumbers further analysis too. So, preprocessing of digital fundus images is a major concern in automatic screening system. Through the study of viewed the performance of various methods and that evaluation studies are not weigh up on any large publicly available datasets. Our system protract on these

survey of the preprocessing methods for enhancing the quality of the digital fundus image. Taken as a whole, the preprocessing methods for an image can be pigeonholed into mask generation, illumination equalization and color normalization.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

Preprocessing

After converting the image to the green channel, Preprocessing is the first step for the classification of blood vessels into artery/vein where the intensity is normalized by subtracting an estimation of the image background, results by ltering with large arithmetic mean kernel In this algorithm for enhancement of retinal blood vessels some Image Processing techniques are used. The preprocessing is used to remove the

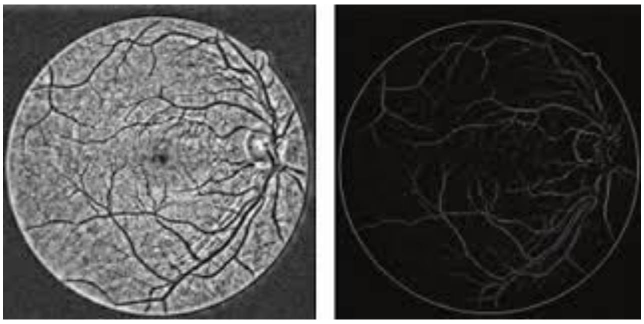


Fig 3.5 Preprocessed image

Noise from the background and to enhance the image. In the first stage of preprocessing the retinal image is converted into green image. Mathematical formula for finding green channel is given as g= G/(R+G+B) Here, g is Green channel and R, G, B are Red, Green and Blue respectively.

Segmentation

Morphological processing is used for vessel extraction. Closing precedes the opening result which is followed by a comparison, using a minimum operator, to get an image equal to the original one everywhere except for peaks and ridges. The edges of an image can be found by applying a morphological edge detector named the modified top-hat transformation. Modified top-hat used which involves a closing operator that proceeds by an opening is applied to the original image; the result will be compared to the original image using a minimum operator to attain an image equal to original image except for

edges. The modified top-hat transformations are represented as follows:

$$\text{Top - hat}(I)= I - \min((I * S) \circ S ; I)$$

The vessel segmentation result is used for extracting the graph and also for estimating vessel calibers. The method proposed was used for segmenting the retinal vasculature, after being adapted for the segmentation of high resolution images. This method follows a pixel processing-based approach with three phases. The first one is the pre-processing phase, where the intensity is normalized by subtracting an estimation of the image background, obtained by filtering with a large arithmetic mean kernel. In the next phase, centerline candidates are detected using information provided from a set of four directional Difference of Offset Gaussian filters, then connected into segments by

Fig 3.6 Color Retinal Image

a region growing process, and finally these segments are validated based on their intensity and length characteristics. The third phase is vessel segmentation, where multistage morphological vessel enhancement and reconstruction

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

approaches are followed to generate binary maps of the vessels at four scales. The final image with the segmented vessels is obtained by iteratively combining the centerline image with the set of images that resulted from the vessel reconstruction. For example diabetic patients have abnormally wide veins, whereas pancreas patients have narrowed arteries and high blood pressure patients have thickened arteries. To detecting these diseases the retina has to be examined routinely. Blood vessel has to be segmented before classify the blood vessels into arteries and veins. Several automated techniques have been reported to quantify the changes in morphology of retinal vessels indicative of retinal or cardiovascular diseases.

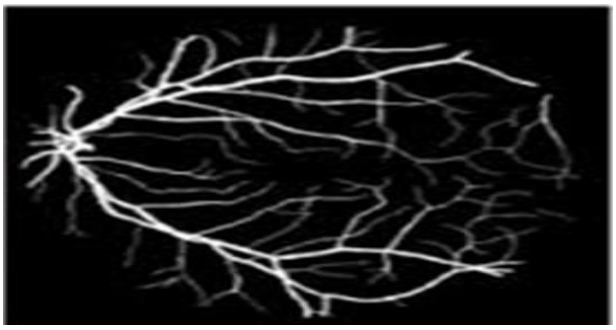


Fig 3.7 Blood vessels segmentation

Centerline Extraction

Then retinal vessels extracted by morphological operation and canny edge detection method will be thinned by using Morphological Thinning. Morphological Thinning process is a morphological operation that consecutively erodes away the foreground pixels until they are one pixel wide. In this algorithm a standard thinning algorithm is employed, that performs the thinning operation using two sub iterations. This algorithm is easily available in MAT-LAB using the thin operation under the bimorph function. Each sub iteration will start by examining the neighboring pixel in the binary image, and based on a particular set of pixel-deletion criteria, it checks whether the pixel can be deleted or not. These sub iterations continue until no more pixels can be deleted. The application of the thinning algorithm to a retinal image preserves the connectivity of the ridge structures while forming a skeletonized version of the binary image. This skeleton image is then used in the subsequent extraction of minutiae. The centerline image is obtained by applying an thinning algorithm described in [5] to the vessel segmentation result. This algorithm removes border pixels until the object shrinks to a minimally connected stroke. The vessel centerlines from the segmented image of 3.6 3.7 are shown in 3.8. It consists of two subiterations: one aimed at deleting the south-east boundary points and the north-west corner points while the other one is aimed at deleting the

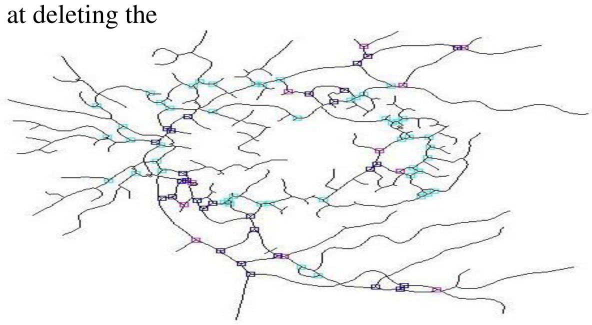


Fig 3.8 Centerline Extraction

north- west boundary points and the south-east corner points. End points and pixel connectivity are preserved. Each pattern is thinned down to a \ skele-ton" of unitary thickness. Experimental results show that this method is very effective.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

Substracted Image

Vessels Segmentation Block can performs subtracted, Vessels Segmented and Center line Segmented image Operation. After Segmentation It can give to Feature Extraction to enhance Its intensity Values. Graph Extraction: The graph nodes are extracted from the centerline image by finding the intersection points and the endpoints. To find the links between nodes (vessel segments), all the intersection points and their neighbors are removed from the centerline image. As result we get an image with separate components which are the vessel segments Graph Modification: The extracted graph may include some misrepresentation of the vascular structure as a result of the segmentation and centerline extraction processes. The typical errors are The splitting of one node into two nodes; missing a link on one side of a node; false link. Node splitting: when extracting the centerline pixels in a single intersection, we have two graph nodes instead of only one. Missing link: For solving the missing link cases the distance from a degree 1 node

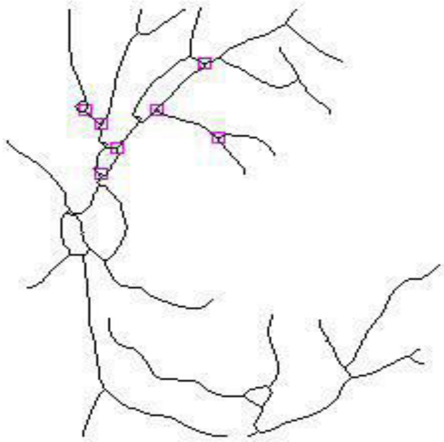


Fig 3.9 Segmented Image

Classification

Retinal images are given as input. Segmentation is performed on retinal images. Features are extracted on detected graphs. These Extracted features are classified using knn classifier. Fig 3.10 shows classified retinal vessels into red and blue colour. Classification done by a classification system. Performance of such a system is commonly extracted using the data in the system. The following figure shows the classification of system. It measures accuracy of two classes artery vein. In existing work KNN (K-Nearest neighbor) classifier was used to classify retinal images as artery and vein. In proposed work Neural Network pattern Recognition is used to classify retinal images as artery and vein. In existing classifying work 93 Linear discriminate analysis (LDA), Quadratic discriminate analysis (QDA), and k-nearest neighbor (kNN) can be used to classify the vessel into artery/Vein. Above all requires training set. Half of the image in the dataset has to be trained.

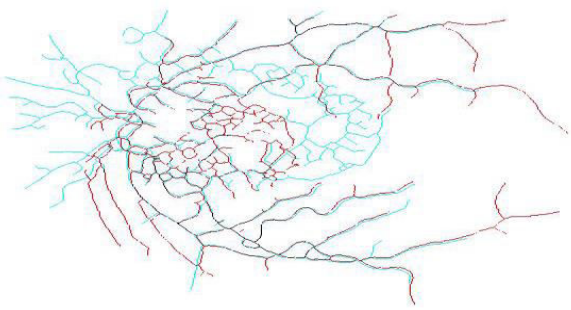


Fig 3.10 Classified retinal vessel (Red vein, Blue - artery)

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

Flow Diagram of the System

The proposed architecture is explained in the below Fig 5. 1: The retina image is first given as input. The image is then converted to a gray scale image. For graphical transformation now the gray scale image is ready for preprocessing.
After preprocessing the next step contains two fragmentations. First step is removing noise in this step if any noise placed in the original image means it should be removed for further classifications.

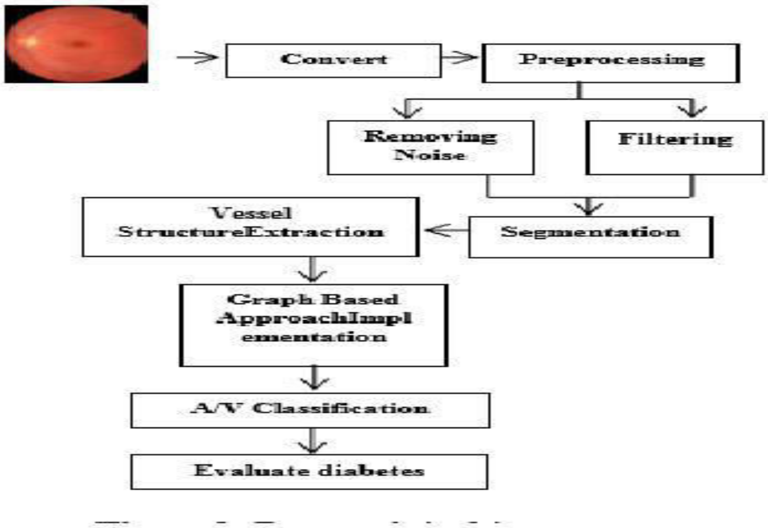


Fig 5.1 Diabetic Evaluation of the system

The next step is Filtering process here the noise that identified in the image is further filter for better classification. After this the image is allowed for segmentation process. In this process the filtered image is segmented for graphical calculation. Then the segmented image is ready for vessel extraction. Here the vessel denotes the link that is used to connect the node The next step is to implement the graphical approach. After designing the graphical representation A/V classification is used. After A/V classification the image is further evaluated to identify the disease. During this process the evaluation of finding the disease is comparatively reduced. By using graph based approach is an easy and effcient technique. The best method is used to find the simple classification using the proposed model.In that particular image concept the foot image is registered But the scope of the project is to analyse the wound image based on the boundary region .Thats why the wound boundary is detected based on the proposed image enhancement model. After the image enhancement the wound boundary is successfully calculated. The method first extracts a graph from the vascular tree, and afterwards makes a decision on the type of each intersection point (graph node). Based on the node types in each separate sub graph, all vessel segments (graph links) that belong to a particular vessel are identified and then labeled using two distinct labels. Finally, the A/V classes are assigned to the sub graph labels by extracting a set of features and using a linear classifier. At last, Our Aim is to classify the Artery/Vein of the retinal images. The image can Be classified and Result and calculation stored in folders. We can take sample input image Can be taken from DRIVE and VICAR data base. It can Preprocessed sample input images Can be given to vessels segmentation block. After that Feature Extraction can be done. And Finally Red and blue colour is used to classify Artery and Vein Of the retinal image. The method proposed in this paper follows a graph-based approach, where it focus on a characteristic of the retinal vessel tree that, at least in the region near the optic disc, veins rarely cross veins and arteries rarely cross arteries. Based on this assumption we may define different types of intersection points: bifurcation, crossing, meeting and connecting points.

IV. RESULTS AND WORKING SCREENSHOTS

The proposed Artery/Vein Classification was done using MATLAB. Color RGB retinal image from DRIVE database is given as the input. Vessel Extraction is done by using morphological operation and canny edge detection method. Grayscale conversion is used to choose an accurate threshold value and for detecting edges. Binarization is used to achieve the gray level thresholding with the change in variation to show 1 as white and 0 as black. Morphological operation is necessary for segmentation to extract exact body of
the vascular network along with the help of canny edge detection. After vessel detection by different features are extracted. The features which are extract Intensity, Area, Centroid, Intensity, Perimeter and Diameter. Artery/Vein

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

classification is done with the help of Knn classifier. The proposed method has been verified by taking images from well known DRIVE database to detect the retinal blood vessel. The proposed method performs best by segmenting even smaller blood vessels. All the work is done using MATLAB. And finally the performance is verified by evaluating the values of True Positive, False Positive, False Negative and True Negative.

$$\text{Sensitivity (Se)} = TP/(TP + FN)$$
$$\text{Specificity (Sp)} = TN/(TN + FP)$$
$$\text{Accuracy (Acc)} = (TP + TN)/(TP + FN + TN + FP)$$

Here sensitivity is defined as the ratio of the number of TP with respect to the sum of the total number of TP plus FN. The value of sensitivity always lies between 0 and 1. While Specificity is defined as the ratio of the number of TN with respect to the sum of the total number of FP plus TN. Even the value of specificity lies between 0 and 1.Here the two parameter sensitivity and specificity are calculated with respect to ground truth images available in the DRIVE dataset. The value of Se and Sp must be high for better retinal blood vessel segmentation results. Here TP is true positive refers to the correctly detected blood vessels, TN that is true negative refers to the wrongly detected blood vessels, and FP-false positive and FN-false negative refer to the correctly and wrongly detected blood vessel pixels.

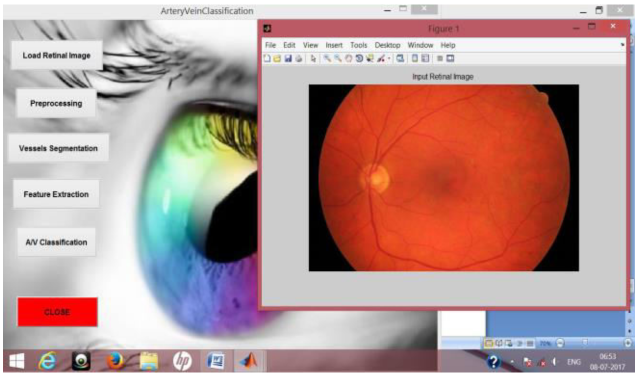


Fig 6.1 Sample Retinal Image of DRIVE Database

DRIVE Database Image:

First of all we are giving Sample input Image of Retinal images from Drive database. From Drive database sample retinal images can be plotted in matlab.After Plotting these images on matlab ,it can be Proceeded further. In basic general user interface can be made in matlab and taking images in drive database for classification of blood retinal image in artery/vein Classification.

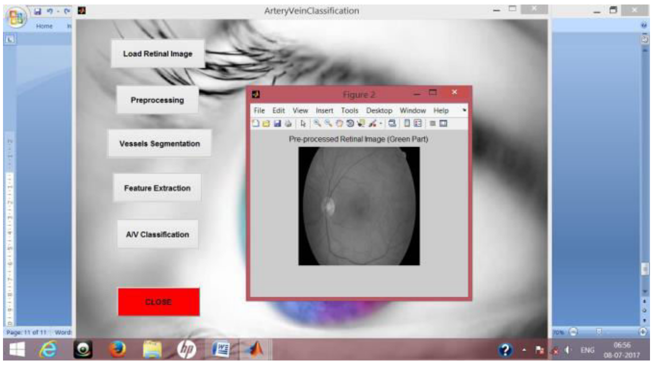


Fig 6.2 Preprocessed Retinal Image (Green Part)

Preprocessing Of Input Retinal Image:

Preprocessing is the first step for the classification of blood vessels into Artery/vein .Then its output image which is gray scale image given to vessels segmentation block. After this preprocessing block we can further move to vessel segmentation block for performing three basic operation.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

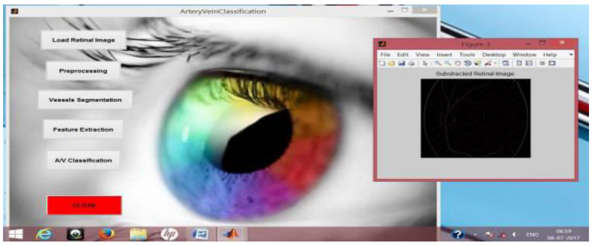


Fig 6.3 Substracted Retinal Image

Substracted Retinal Images:

In substracted Retinal Images is an Part of vessels Segmentation Block. In Substracted image Graph nodes are extracted from the centerline image by finding the intersection points and End points. Figure shows the basic substracted operation can be performed by Vessels Segmentation Block.

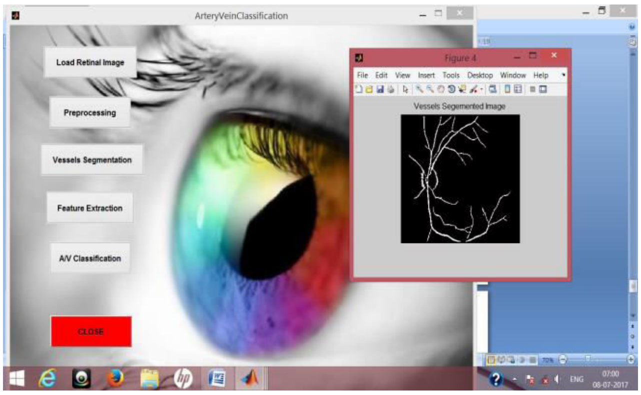


Fig 6.4 Vessels Segmented Image

Vessels Segmented Image:

In Vessels Segmented Image can be used to the link between the two node Points

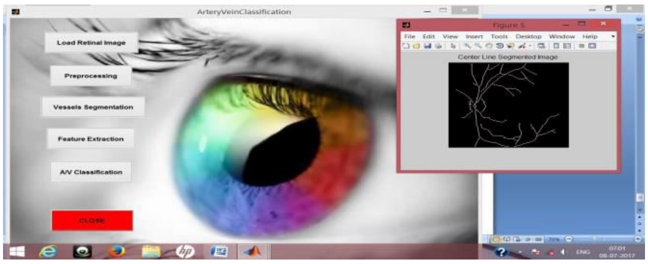


Fig 6.5 Center Line Segmented Image

Center Line Segmented Image:

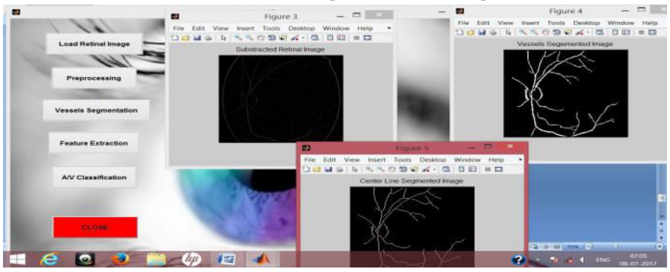


Fig 6.6 Vessels Segmentations Block Images

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

Whole Three operations of Vessels Segmented Block:

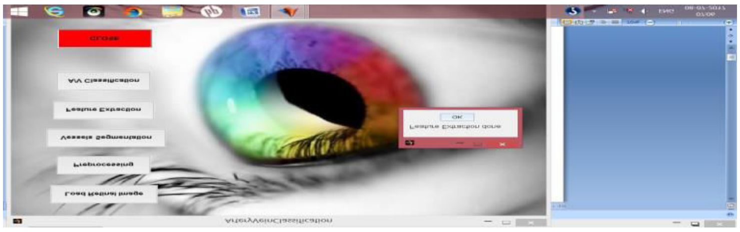


Fig 6.7 Feature Extraction Block Output

Red and blue colour to Specify Artery /Vein Classification:
Overall Figure to show Artery/Vein Classification Block Output

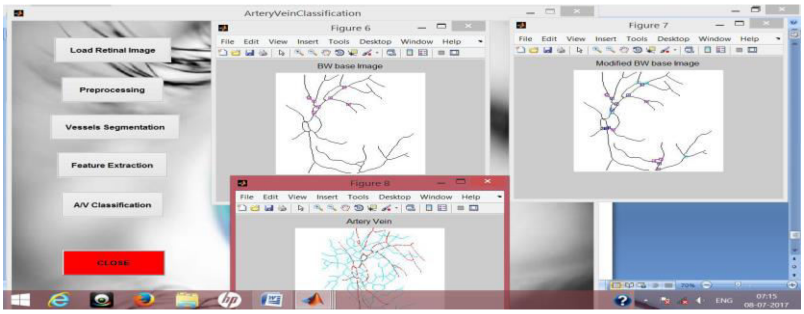


Fig 6.8 Output of Artery/Vein Classification Block

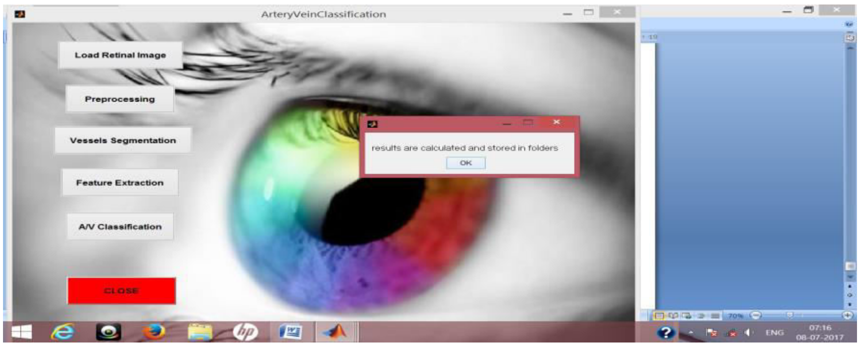


Fig 6.9 indication to show results are calculated and stored in folder

Indication to Show Results are calculated and stored in Folders
To show result stored in Folders with calculation.

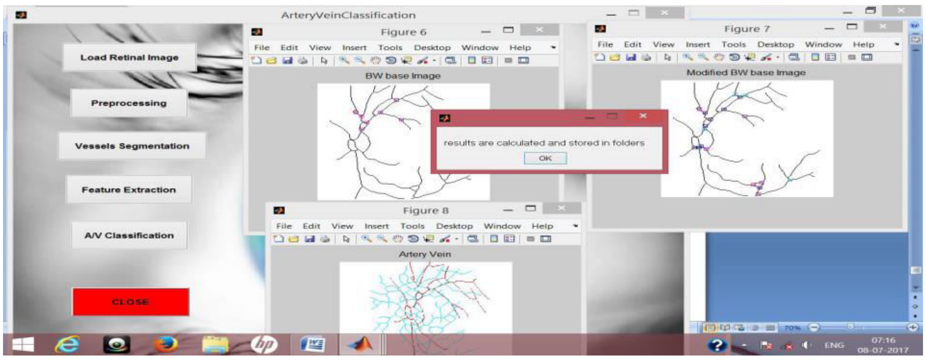


Fig 6.10 finds output of artery/vein classification block

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106060 |

After taking Output at A/V block in Basic GUI

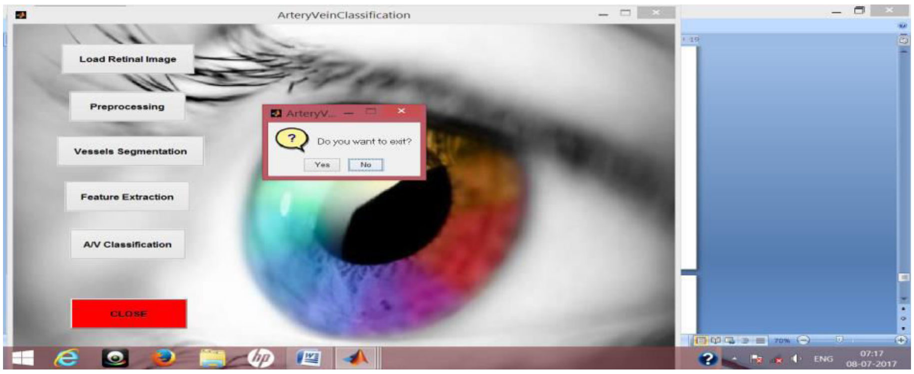


Fig 6.11 GUI Indication After Closing

Closing of Basic GUI Block

We have compared our proposed method result with Decision Tree and KNN classifier. Accuracy for KNN is 94.66%, for Decision Tree is 92.5 and for Proposed method is 97.5%. Accuracy of correctly classified retinal vessels with proposed method are compared with Decision Tree and KNN as follows.

V. CONCLUSION AND FUTURE SCOPE

The classification of arteries and veins in retinal images is essential for the automated assessment of vascular changes. In previous sections, we have described a new automatic methodology to classify retinal vessels into arteries and veins which is distinct from prior solutions. One major difference is the fact that our method is able to classify the whole vascular tree and does not restrict the classification to specific regions of interest, normally around the optic disc. While most of the previous methods mainly use intensity features for discriminating between arteries and veins, our method uses additional information extracted from a graph which represents the vascular network. The information about node degree, the orientation of each link, the angles between links, and the vessel caliber related to each link are used for analyzing the graph, and then decisions on type of nodes are made (bifurcation, crossing, or meeting points). Next, based on the node types, the links that belong to a particular vessel are detected, and nally Artery/Vein classes are assigned to each one of these vessels using a classier supported by a set of intensity features. Furthermore, we compared the performance of our approach with other recently proposed methods, and we conclude that we are achieving better results. The promising results of the proposed Artery /Vein classification method on the images of three different databases demonstrate the independence of this method in Artery/Vein classification of retinal images with different properties, such as differences in size, quality, and camera angle.

VI. FUTURE SCOPE

The disease like Diabetes and some another disease affect the retinal vessels. In feature we used that artery and vein feature to classify the retinal is normal and abnormal. We use some feature extraction method to train normal and abnormal dates. Use robust classifier to classify that feature to find the retinal is normal or abnormal. For disease identification, the retinal images are pre-processed and the features such as affected and non-affected regions are extracted from the retinal images. The features are trained and the training set is created. Blood vessel is one of the most important features in retina consisting of arteries and arterioles for detecting retinal vein occlusion, grading the tortuosity for hypertension and early diagnosis of glaucoma.

REFERENCES

1) AlBadawi, S., and Fraz, M. M. (2018). "Arterioles and venules classification in retinal images using fully convolutional deep neural network," in *Proceedings of the International Conference Image Analysis and Recognition, Póvoa de Varzim, Portuga*, (Cham: Springer), 659–668. doi: 10.1007/978-3-319-93000-8_75

2) Estrada, R., Allingham, M. J., Mettu, P. S., Cousins, S. W., Tomasi, C., and Farsiu, S. (2015). Retinal artery-vein classification via topology estimation. *IEEE Trans. Med. Imaging* 34, 2518–2534. doi: 10.1109/TMI.2015.2443117

raz, M. M., Remagnino, P., Hoppe, A., Uyyanonvara, B., Rudnicka, A. R., Owen, C. G., et al. (2012a).

Blood vessel segmentation methodologies in retinal images–a survey. *Comput. Methods Programs Biomed.* 108, 407–433.

3) Galdran, A., Meyer, M., Costa, P., and Campilho, A. (2019). "Uncertainty-aware artery/Vein classification on retinal images," in *Proceedings of the 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*, (Venice: IEEE), 556–560. doi: 10.1109/ISBI.2019.8759380

4) Guo, S., Wang, K., Kang, H., Zhang, Y., Gao, Y., and Li, T. (2019). BTS-DSN: Deeply supervised neural network with short connections for retinal vessel segmentation. *Int. J. Med. Inf.* 126, 105–113. doi: 10.1016/j.ijmedinf.2019.03.015

He, K., Zhang, X., Ren, S., and Sun, J. (2016). "Deep residual learning for image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, (Las Vegas, NV: IEEE), 770–778.

5) Hu, Q., Abràmoff, M. D., and Garvin, M. K. (2013). "Automated separation of binary overlapping trees in low-contrast color retinal images," in *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention*, (Berlin: Springer), 436–443. doi: 10.1007/978-3-642-40763-5_54

6) Huang, F., Dashtbozorg, B., and ter Haar Romeny, B. M. (2018b). Artery/vein classification using reflection features in retina fundus images. *Mach. Vis. Appl.* 29, 23–34. doi: 10.1007/s00138-017-0867-x

7) Li, L., Verma, M., Nakashima, Y., Kawasaki, R., and Nagahara, H. (2020). "Joint learning of vessel segmentation and Artery/Vein classification with post-processing," in *Proceedings of the International Conference on Medical Imaging with Deep Learning*, (Montréal, QC: MIDL).

8) Mirsharif, Q., Tajeripour, F., and Pourreza, H. (2013). Automated characterization of blood vessels as arteries and veins in retinal images. *Comput. Med. Imaging Graph.* 37, 607–617. doi: 10.1016/j.compmedimag.2013.06.003

9) Pellegrini, E., Robertson, G., MacGillivray, T., van Hemert, J., Houston, G., and Trucco, E. (2018). A graph cut approach to artery/vein classification in ultra-widefield scanning laser ophthalmoscopy. *IEEE Trans. Med. Imaging* 37, 516–526. doi: 10.1109/TMI.2017.2762963

10) Samuel, P. M., and Veeramalai, T. (2019). Multilevel and multiscale deep neural network for retinal blood vessel segmentation. *Symmetry* 11:946. doi: 10.3390/sym11070946

11) hao, Y., Xie, J., Su, P., Zheng, Y., Liu, Y., Cheng, J., et al. (2018). "Retinal artery and vein classification via dominant sets clustering-based vascular topology estimation," in *International Conference on Medical Image Computing and Computer-Assisted Intervention, Granada, Spain*, (Cham: Springer), 56–64. doi: 10.1007/978-3-030-00934-2_7