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ARTICLE

CLASSIFICATION OF ARTERY AND VEIN BY AUTOMATIC GRAPH GENERATION USING LDA CLASSIFIER

M Anto Bennet[1*], TR Dinesh Kumar [2], G Sankar babu [3], M Pooja [4], K Anusuya[5], AP Kokila[6]

[1]Professor,[2,3]Asst.professor,[4,5,6]UG Students,Department of ECE,VEL TECH ,Avadi,Chennai 600 062, Tamil Nadu, INDIA

ABSTRACT

The classification of retinal vessels into Artery/Vein (A/V) 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. It presents an automatic approach for A/V 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 (graph nodes) and assigning one of two labels to each vessel segment (graph links). Final classification of a vessel segment as A/V is performed through the combination of the graph-based labeling results with a set of intensity features. The obtained results are compared with the three different data set like DRIVE dataset, INSPIRE dataset. Retinal vessels are affected by several systemic diseases namely diabetes, hypertension, and vascular disorders. In diabetic retinopathy, the blood vessels often show abnormalities at early stages as well as vessel diameter alterations. Changes in retinal blood vessels, such as significant dilatation and elongation of main arteries, veins, and their branches are also frequently associated with hypertension and other cardiovascular pathologies.

KEY WORDS
Artery/Vein (A/V),Optic Disc (OD),Structure-based SampleConsensus (STRUCT-SAC) algorithm, Retinopathy ofPrematurity (ROP)

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***Corresponding Author**
Email:
bennetmab@gmail.com

INTRODUCTION

Automatic detection of the retinopathy in eye fundus images using digital image analysis method 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 the automated screening for pathology condition such as diabetic retinopathy in order to reduce the workload required of trained manual graders. Retinal vessels are affected by several systemic diseases, namely diabetes, hypertension, and vascular disorders. In diabetic retinopathy, the blood vessels often show abnormalities at early stages, as well as vessel diameter alterations. Changes in retinal blood vessels, such as significant dilatation and elongation of main arteries, veins, and their branches are also frequently associated with hypertension and other cardiovascular pathologies [1,2,3]. Several characteristic signs associated with vascular changes are measured, aiming at assessing the stage and severity of some retinal conditions. generalized arteriolar narrowing, which is inversely related to higher blood pressure levels is usually expressed by the Arteriolar-to-Venular diameter Ratio (AVR). The Atherosclerosis Risk In Communities (ARIC) study previously showed that a smaller retinal AVR might be an independent predictor of incident stroke in middle aged individuals. The AVR value can also be an indicator of other diseases, like diabetic retinopathy and retinopathy of prematurity. Among other image processing operations, the estimation of AVR requires vessel segmentation, accurate vessel width measurement, and Artery/Vein (A/V) classification. Therefore, any automatic AVR measurement system must accurately identify which vessels are arteries and which are veins, since slight classification errors can have a large influence on the final value. It is estimated that about 10% of the population over the age of 40 are affected with diabetes and about 20% of this group will develop some form of diabetic complications in the eye. With the number rising every year, Singapore is one of the countries with the highest rate of diabetes in the world[4,5,6].Several works on vessel classification have been proposed but automated classification of retinal vessels into arteries and veins has received limited attention, and is still an open task in the retinal image analysis field. In recent years, graphs have emerged as a unified representation for image analysis, and graph-based methods have been used for retinal vessel segmentation, retinal image registration, and retinal vessel classification. The graph extracted from the segmented retinal vasculature is analyzed to decide on the type of intersection points (graph nodes), and afterwards one of two labels is assigned to each vessel segment (graph links). Finally, intensity features of the vessel segments are measured for assigning the final artery/vein class [7].

MATERIALS AND METHODS

The method proposed in this follows a graph-based approach, where mostly 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 it may define different types of intersection points: bifurcation, crossing, meeting, and connecting points. A bifurcation point is an intersection point where a vessel bifurcates to narrower parts. In a crossing point a vein and an artery cross each other. In a meeting point the two types of vessels meet each other without crossing, while a connecting point connects different parts of the same vessel. The classification of arteries and veins inretinal images is essential for the automated assessment of vascular changes. The decision on the type of the intersection points are made based on the geometrical analysis of the graph representation of the vascular structures. An Automatic Graph Generation Algorithm issued for classified Artery and Veins. This method uses additional

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information extracted from a graph which represents the vascular network. This 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. The process of artery and vein classification from the retinal vessels for the automatic detection of vascular changes and for the calculation of characteristic signs associated with the several systematic diseases such as diabetics, hypertension and cardio vascular conditions are shown in [Fig. 1]

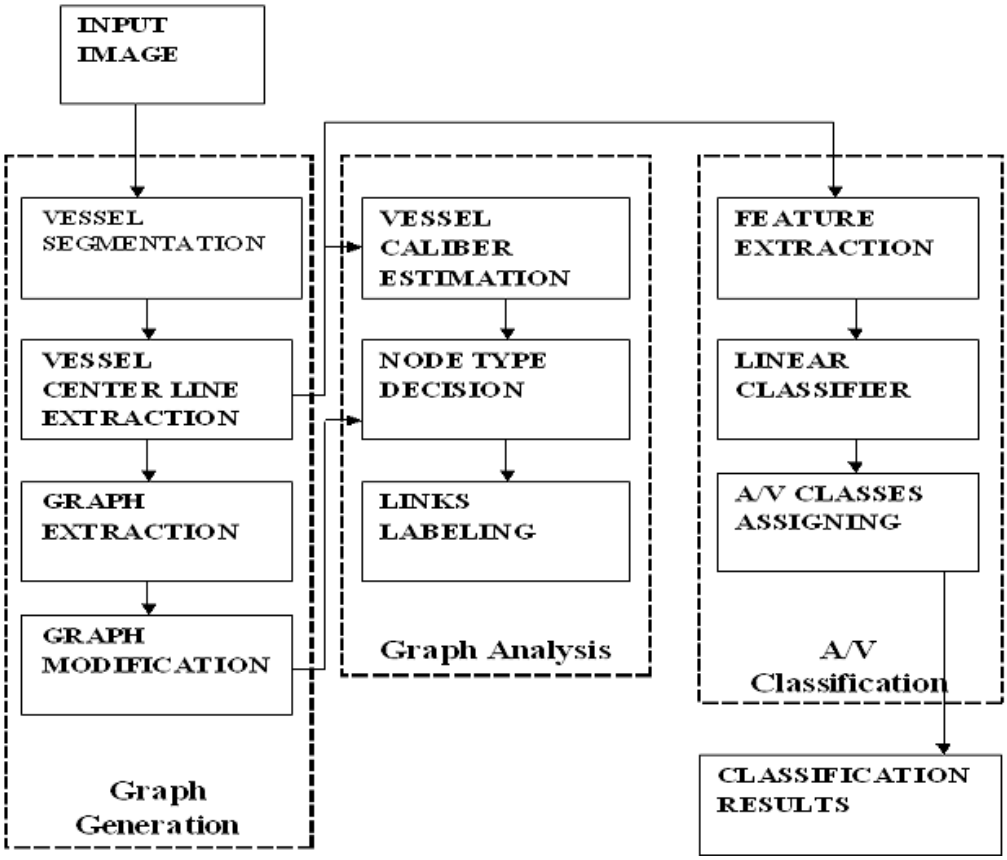

Fig. 1: Block Diagram of the artery and vein classification

Segmentation

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

Thresholding

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray scale image into a binary image. There is also a balanced histogram thresholding. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods have been developed for thresholding Computed Tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed).

Centerline Extraction

The centerline image is obtained by applying an iterative thinning algorithm described in to the vessel segmentation result. This algorithm removes border pixels until the object shrinks to a minimally connected stroke.

Graph Generation

The graph nodes are extracted from the centerline image by finding the intersection points (pixels with more than two neighbors) and the endpoints or terminal points (pixels with just one neighbor). In order to find the links between nodes (vessel segments), all the intersection points and their neighbors are removed from the centerline image and asresult image with separate components is obtained which are the vessel segments. Next, each vessel segment is represented by a link between two nodes.

Graph Analysis

The output of the graph analysis phase is a decision on the type of the nodes. The links in each subgraph (i) are labeled with one of two distinct labels (Ci1 and Ci2). In this phase it is not yet able to determine whether each label corresponds to an artery class or to a vein class. The A/V classes will be assigned to these subgraphs only in the last classification phase. The node classification algorithm starts by extracting the following node information: the number of links connected to each node (node degree), the orientation of each link, the angles between the links, the vessel caliber at each link, and the degree of adjacent nodes.

A/V Classification

For each centerline pixel, the 30 features listed are measured and normalized to zero mean and unit standard deviation. Some of these features were used previously in, the most commonly used classifiers, namely Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and K-Nearest Neighbor (kNN), on the INSPIRE-AVR dataset. For feature selection, we have used sequential forward floating selection, which starts with an empty feature set and adds or removes features when this improves the performance of the classifier.The trained classifier is used for assigning the A/V classes to each one of the sub graph labels. First, each centerline pixel is classified into A or V classes, then for each label (Ci j , j = 1, 2) in sub graph i , the probability of its being an artery is calculated based on the number of associated centerline pixels classified by LDA to be an artery or a vein. The probability of label Ci j to be an artery is Pa(Ci j) = naCi j /(naCi j + nvCi) where naCi j is the number of centerline pixels of a label classified as an artery and nvCi j is the number of centerline pixels classified as a vein. For each pair of labels in each sub graph, the label with higher artery probability will be assigned as an artery class, and the other as a vein class.Finally, to prevent a wrong classification as a result of a wrong graph analysis, to calculate the probability of being an artery or a vein for each link individually. The probability of a link (li) being an artery (Pa (li)) is computed as Pv (li) = nv li / _ na li + nv li _ , and the probability of being a vein ((Pv (li)) is computed as Pv (li) = nv li / _ na li + nv li _ , here na li is the number of centerline pixels of link (li) classified as an artery and nv li is the number of centerline pixels classified as a vein. If the probability of being an artery is higher than 0.9 (Pa (li)≥ 0.9) then the link will be assigned as an artery, and if Pv (li) ≥ 0.9 then it will be assigned as a vein, without considering the result of the graph analysis.

Feature Extraction

To analyze retinal images described above and extract information, features need to be mined. These features include blood vessels, microaneurysms and the optic disc.

Blood Vessel Features

Lines are composed of edges. Awcock and Thomas defined an edge in a digitized image as a sequence of connected edge points where an edge is characterized by abrupt changes in intensity indicating the boundary between two regions in an image. Based on this, a line according to their definition is a region of constant intensity found between two edges which act as a boundary for the line. Blood vessels in the retina match the criteria of a line shown in fig 2. It shows two examples of blood vessels. Throughout the retina the major blood vessels supply the capillaries that run into the neural tissue. Capillaries are found running through all parts of the retina from the nerve fiber layer to the outer layer. There are two sources of blood supply to the mammalian retina: the central retinal artery and the choroidal blood vessels. The choroid receives the greatest blood flow (65%-85%) and is vital for the maintenance of the outer retina (particularly the photoreceptors) and the remaining 20%-30% flows to the retina through the central retinal artery from the optic nerve head to nourish the inner retinal layers .

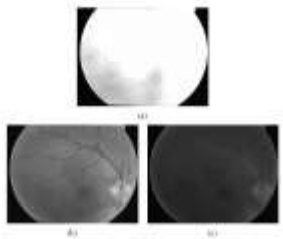

Fig. 2: The corresponding color bands Red (a), Green (b) and Blue (c) of the color retinal image

Microaneurysm Features

Microaneurysms are the dilation of retinal capillaries. They are round intra-retinal lesions ranging from 10 to 100 micrometers in size and red in color. The cross-section of a microaneurysm exhibits a Gaussian distribution. [Fig.3] illustrates examples of different microaneurysms taken from color retinal images. The top part shows their original format while the bottom depicts them in the green channel (so their shape is more visible). Researchers at the European Association for the Study of Diabetes 45th Annual Meeting in Vienna, Austria, reported that an increase in the number of retinal microaneurysms is associated with worse retinopathy prognosis in patients with Type 1 or 2 diabetes.

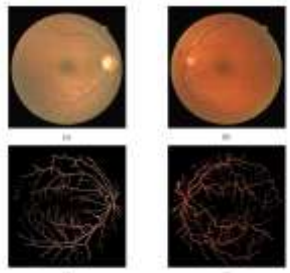

Fig.3: Fundus images (a), (b) (c), (d) and its corresponding vessel map

Optic Disc Features

The Optic Disc (OD) or optic nerve head, another commonly used name, is a vertical oval with average dimensions of 1.76mm (horizontally) × 1.92mm (vertically), and situated 3-4mm to the nasal side of the fovea. There are no receptors in this part of the retina since all of the axons of the ganglion cells exit the retina to form the optic nerve. In fundus imaging the OD is usually brighter than its surrounding area, and is the convergence of the retinal blood vessel network. This can be seen in [Fig. 4] and [Fig.5] which shows four different ODs.

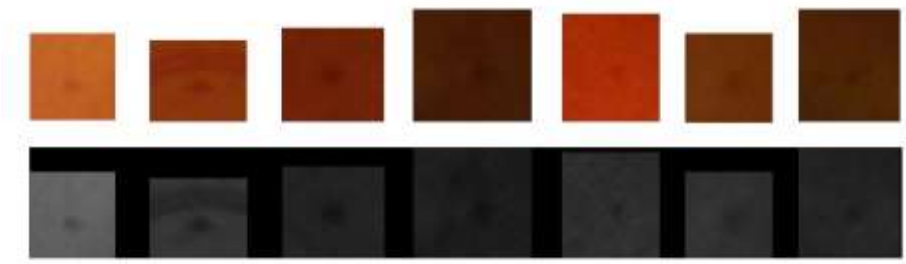

Fig. 4: Examples of different microaneurysms shown on the top with its equivalent green channel on the bottom

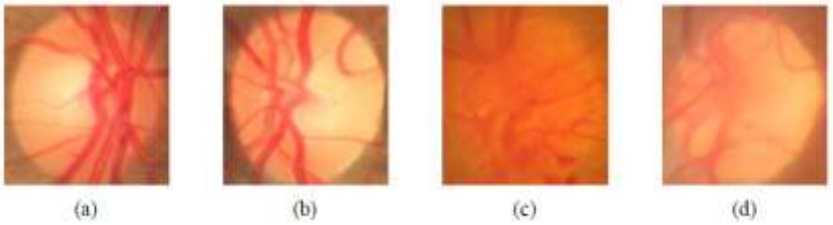

Fig. 5: Four cropped images of the optic disc

Optic Nerve Head Assesment

Assessment of the daaged optic nerve head is both more promising, and superior to measurement or visual field testing for glaucoma screening. Optic nerve head assessment can be done by a trained professional. However, manual assessment is subjective, time consuming and expensive. Therefore, automatic optic nerve head assessment would be very beneficial. Optic nerve-head examination is probably the most important step in the diagnosis of glaucoma and is also extremely important in monitoring patients with established glaucoma. There are several ways to clinically examine the optic nerve head, including direct ophthalmoscopy, indirect ophthalmoscopy, and slit lamp biomicroscopy with contact lenses (such as a Goldman lens), handheld lenses (such as a 78 or 90-diopter lens) or the Hruby lens. Clinical examination of the optic nerve should be performed with similar methodology each and every time it is executed, in order not to miss important aspects of the examination. In my view, examination of the optic nerve head should start with an evaluation of optic disc size, since disc size is extremely important in the interpretation of other optic nerve findings.

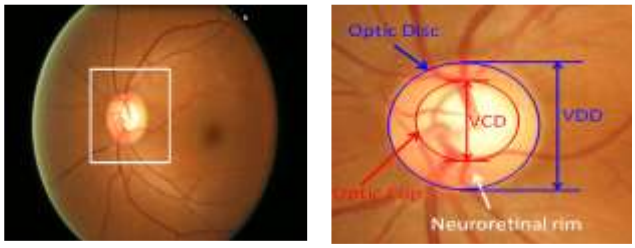

Fig. 6: Major structures of the optic disc

[Fig. 6] shows the optic nerve head or the optic disc (in short, disc) is the location where ganglion cell axons exit the eye to form the optic nerve, through which visual information of the photoreceptors is transmitted to the brain. In 2D images, the disc can be divided into two distinct zones; namely, a central bright zone called the optic cup (in short, cup) and a peripheral region called the neuroretinal rim.

RESULTS

Input image and the background normalised image

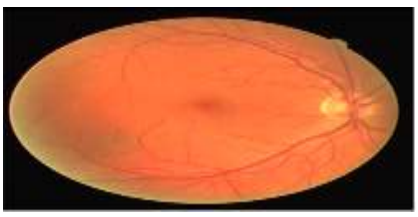

Fig.7: Input image

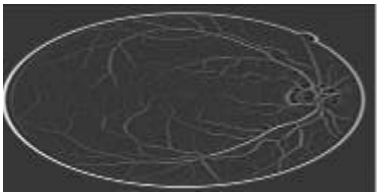

Fig.8: Background normalized image ofretina

The [Fig. 7] is the input image which is given as the input. The pixel size of the input image is 225x224. [Fig. 8] is the background normalized image of the retina. From the input image the background is only subtracted to obtain the background normalized image in order to obtain the clear intensity features.

Fig. 9: Vessel segmentation image of retina

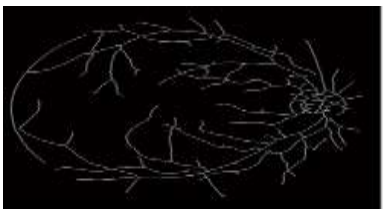

Fig. 10: Centerline extraction image of Retina.

The [Fig.7] is the vessel segmented image of the retina. From the [Fig 5.2] only the vessels are segmented and shown in the [Fig. 8].The [Fig. 9] is the centerline extraction image of the retina.In the [Fig.10] the iterative thinning algorithm is applied and the border pixels are only removed then the vessels are thinned.

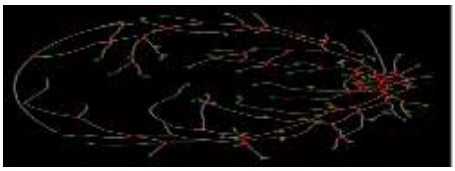

Fig. 11: Intersection points and the

Fig. 12: Graph generationimage of the end point of the retina

The [Fig. 11] is the intersection points and the end point of the retina. In this the intersection point and the end point are plotted. The intersection section point is denoted by red colour and the end point is denoted by green colour. The [Fig. 12] is the graph generation image.In this the graph nodes are extracted from the centerline images by finding the intersection point and the end point.The curved lines are changed into the straight lines in the graph generation image of the retina. Then the intersection point and the links are removed from the centerline image.

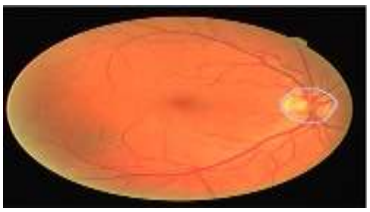

Fig. 13: Optic disk removed image

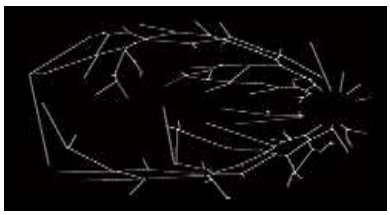

Fig. 14: Graph generation of the retina

The [Fig. 13] is the optic disk removed image. In this figure the optic disk is removed from the center of the image. Then the intersection point and the end point are removed from the centerline image and the graph is obtained as in the [Fig. 14].

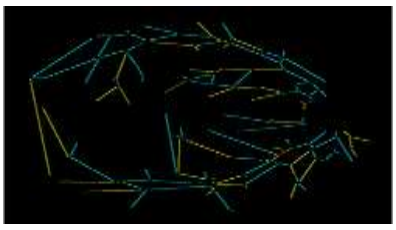

Fig. 15: Graph analysis image

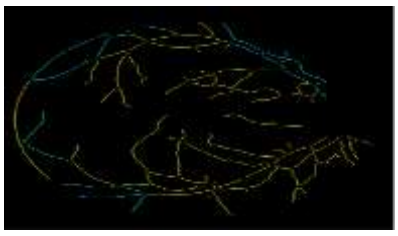

Fig. 16: Classification result

The [Fig. 15] is the graph analysis image. In this [Fig.16] the link between the intersection and the end point are removed and the graph is analysed. Then the obtained graph is classified. The optic disc area usually contains many vessels, but they are not suitable for the artery and vein classification.

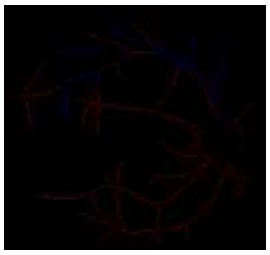

Fig.17: Existing method images

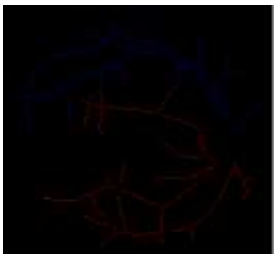

Fig. 18: Proposed method image

In the [Fig. 17] the output of the artery and vein classification as in the existing method is obtained. In the [Fig. 18] the proposed method output for the artery and vein classification is obtained with high accuracy when compared with the existing system. In this [Fig. 18] red colour represents the vein and the blue colour represents the artery.

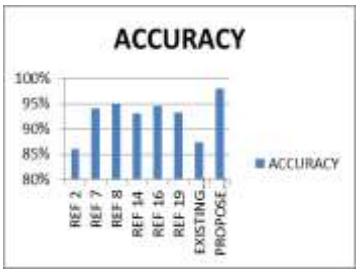

Fig.19: Comparison of accuracy With previous method

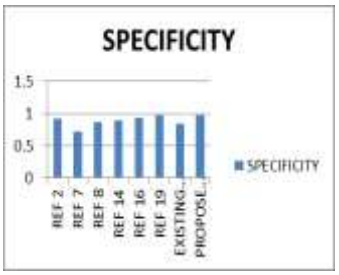

Fig.20: Comparison of specificity with previous method

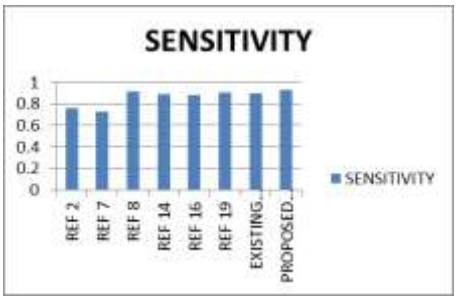

Fig. 21: Comparison of the sensitivity with previous methods

The comparison of accuracy, specificity, sensitivityvalues are compared with the previous methodthat is plotted in the form of graph as shown in [Fig. 19-21].

Table 1: Manual labeling of parameters for artery and vein classification DRIVE dataset

IMAGE	SENSITIVITY	SPECIFICITY	ACCURACY
1	0.797	0.972	0.94
2	0.824	0.971	0.949
3	0.734	0.974	0.941
4	0.783	0.974	0.949
5	0.738	0.980	0.947
6	0.754	0.967	0.936
7	0.686	0.985	0.945

8	0.660	0.983	0.943
9	0.769	0.970	0.946
10	0.717	0.979	0.948
11	0.759	0.975	0.947
12	0.771	0.977	0.951
13	0.804	0.962	0.939
14	0.771	0.979	0.955
15	0.800	0.972	0.954
16	0.779	0.975	0.950
17	0.733	0.980	0.949
18	0.858	0.961	0.949
19	0.906	0.960	0.954
20	0.870	0.954	0.945

By using the drive data sets the accuracy, sensitivity, specificity are computed in drive data set 40 images are used. In that 20 images are used for testing and remaining 20 images are used for training. Manual labeling is performed by the experts first for calculating the sensitivity, accuracy and specificity values are shown in the table. In the proposed method sensitivity, accuracy and specificity values are simulated using automatic graph generation and the results are compared with manual labeling as shown in the [Table 1&2].

Table 2: Proposed classification of artery and vein by labeling the parameters

IMAGE	SENSITIVITY	SPECIFICITY	ACCURACYIN %
1	0.825	0.997	98.1
2	0.814	0.995	97.8
3	0.810	0.98	97.5
4	0.813	0.996	97.0
5	0.811	0.998	97.6
6	0.81	0.996	97.4
7	0.813	0.996	97.7
8	0.815	0.996	97.9
9	0.825	0.997	97.8
10	0.81	0.995	98.2
11	0.815	0.997	98.1
12	0.82	0.998	98.2
13	0.825	0.998	98.8
14	0.812	0.997	98.4
15	0.82	0.99	98.0
16	0.813	0.987	98.1
17	0.81	0.991	98.4
18	0.82	0.994	99.2
19	0.82	0.99	97.9
2020	0.821	0.992	98.1

CONCLUSION

The proposed A/V classification method on the images of three different databases demonstrate the independence of this method in A/V classification of retinal images with different properties, such as differences in size, quality, and camera angle. On the other hand, the high accuracy achieved by our method, especially for the largest arteries and veins, confirm that this A/V classification methodology is reliable for the calculation of several characteristic signs associated with vascular alterations. Further research is planned using the graph that represents the vessel tree and the A/V classification method for AVR calculation, as well as identifying other vascular signs, such as vascular bifurcation angles, branching patterns, and fractal-based features, which can have significant impact on the early detection and follow-up of diseases, namely diabetes, hypertension, and cardiovascular diseases.In the future it will be applied

to feature with edge based artery and vein classification in high accuracy than the proposed system. Further research is planned using the graph that represents the vessel tree and the A/V classification method for AVR calculation, as well as identifying other vascular signs, such as vascular bifurcation angles, branching patterns, and fractal-based features, which can have significant impact on the early sdetection and follow up of diseases, namely diabetes, hypertension, and cardiovascular diseases.

CONFLICT OF INTEREST
There is no conflict of interest.

ACKNOWLEDGEMENTS
None.

FINANCIAL DISCLOSURE
None.

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