Neural Network Based Classifier for Retinal Blood Vessel Segmentation

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ABSTRACT

A supervised method is proposed for automated segmentation of vessels in fundus images of retina. This method is used to detect the retinal diseases by extracting the retinal vasculature utilizing 9-D feature vector based on orientation analysis of gradient vector field, morphological transformation, line strength measures, and Gabor filter responses. The feature vector encodes information to handle the healthy and pathological retinal image. Each pixel in the retinal image is characterized by a vector in 9-D feature space and those pixels are classified using neural network classifiers (FFBNN. RBF, and MLP) and the performance is evaluated in detail. As its effectiveness and robustness with different image conditions, together with its simplicity and fast implementation, make this blood vessel segmentation proposal suitable for retinal image computational analyses such as automated screening for early retinal disease detection.

KEYWORDS- *Retinal blood vessels, segmentation, neural classifiers, Feed Forward Back propagation Neural network (FFBNN), Radial Basis Function (RBF), Multi-Layer Perceptron (MLP), medical image analysis.*

I. INTRODUCTION

Nowadays the retinal abnormalities due to diabetic retinopathy and hypertensive retinopathy are the major cause of blindness in the world. To diagnose/monitor retinal abnormality in early stages fundus imaging is increasingly used in the screening programs. The retinal blood vessel features like microneurysms, nicking, narrowing, have been linked to systemic disease and with retinopathy of prematurity in infancy [1]. The detection and analysis of retinal vasculature is useful in the screening programs for retinopathies, the evaluation of retinopathy of prematurity and etc. Retinal vessels are composed of arteriolars and venules, which appear as elongated branched features emanating from the optic disk within the retinal image. Retinal vessels often have strong
Light reflexes along their centreline, which is more apparent on arteriolars than venules, and in younger
Compared to older patients, especially those with hypertension. The vessel cross-sectional intensity profiles approximate to a Gaussian shape or a mixture of Gaussians in the case where a central vessel reflex is present. The nonvessel region in the retina is not smooth due to presence of the bright and dark lesions which includes haemorrhages, exudates, drusen, and the optic disc boundary. Most of the existing retinal segmentation methodologies are evaluated on the healthy retinal images free from the pathologies; therefore, their performance can be considerably degraded in the presence of lesions.

This paper presents a supervised method for segmentation of blood vessels by using neural classifiers like FFBNN, RBF, and MLP with the feature vector which is based on gradient orientation analysis (GOA), morphological transformation with linear structuring element; line strength measures and the Gabor filter response which encodes information to successfully handle both normal and pathological retinas with bright and dark lesions simultaneously. A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output. Each unit takes an input, applies a (often nonlinear) function to it and then passes the output on to the next layer. Generally the networks are defined to be feed-forward: a unit feeds its output to all the units on the next layer, but there is no feedback to the previous layer. Weightings are applied to the signals passing from one unit to another, and it is these weightings which are tuned in the training phase to adapt a neural network to the particular problem at hand. This is the learning phase. Neural networks have found application in a wide variety of problems, and it is widely used in many application areas of image analysis and now it is applied within the framework of retinal vessel segmentation for automated retinal image analysis. The claimed advantages of neural network methods are shown below.

- Ease of optimization, resulting in cost-effective and flexible non-linear modelling of large data sets.
- Accuracy for predictive inference, with potential to support clinical decision making.
- It is a non-parametric classifier, i.e. it does not require any assumption about the statistical distribution of the data.

The performance can be analysed by the measures like area under receiver operating characteristic (ROC) curve (AUC), accuracy (Acc), sensitivity (SN), specificity (SP), positive predictive value (PPV) on the different databases like DRIVE, STARE, and MESSIDOR. The obtained performance metrics illustrate that this method outperforms most of the state-of-the-art methodologies of retinal vessel segmentation. The method is training set robust as it gives a better performance when it is trained in any databases and it will be very useful in implementing the screening programs over a large variability in the background pigmentation level of the acquired retinal images with high accuracy of classification.

The organisation of this paper is as follows. In section II, the literatures are reviewed based on the retinal blood vessel segmentation methodologies. The methodology and implementation details are presented in section III. In section IV, the performance metrics and the results are analysed, and finally a discussion and conclusion are given in section V.

II. RELATED WORK

The retinal blood vessel is segmented from the retinal images by the vessel segmentation algorithms which are broadly classified as unsupervised and supervised methods which are reviewed in this section.

Here the unsupervised refers to explain about the features which are hidden in an image. The unsupervised method can be further classified into techniques based on matched filtering, morphological processing, vessel tracking, multiscale analysis and model based algorithms. The matched filtering methodology exploits the piece wise linear approximation, the decrease in vessel diameter along vascular length [2], and the Gaussian-like intensity profile of retinal blood vessels and uses a kernel based on Gaussian or its derivatives to enhance the vessel features in the retinal image [3]. Mathematical morphology in combination with curvature evaluation and matched filtering for centreline detection [4], [5] it is exploited for retinal vessel segmentation. The multiscale approaches are based on scale –space analysis. The multiscale second-order local structure of an image (Hessian) is examined and a vesselness measure is obtained on the basis of eigenvalue analysis of the Hessian [6]. The model-based approaches include the vessel profile models

In Supervised method the features which are obtained are analyzed and based on the features the ground truth data is utilized for the classification of blood vessels. [7] Extracted a feature vector for each pixel that consists of the Gaussian and its derivatives at multiple scales, augmented with the green plane of the RGB image, and then uses a K-nearest neighbour algorithm to estimate the probability of the pixel belonging to a vessel. Ridge profiles are used to compute 27 features for each pixel and applied a feature selection scheme to pick those which result in better class separability by a kNN classifier. In[8] six features are computed by employing a multiscale analysis using a Gabor wavelet transform and Gaussian mixture model (GMM) Bayesian classifier. Used line operators and support vector machine (SVM) classification with three features per pixel. In this study Neural network classifier is used with few features and it is non-linear modelling for large data sets and simpler than other methods.

III. METHODOLOGY

In this section, a detailed description and formulation of the retinal blood vessel segmentation methods are presented.

A. Feature vector

A feature vector is an n-dimensional vector of numerical features in machine learning basically. In the image analysis the feature vector contains the quantifiable measurement for each pixel in such a way that the classifier successfully differentiates the blood vessels and the bright and dark lesions. In this paper 9-D feature vector are used which includes the orientation analysis of gradient vector field (one feature) morphological transformation (one feature), line strength measures (two features), and a Gabor filter response at multiple scales (four features) and the intensity of each pixel in the inverted green channel is taken as one of the features.

1) Orientation analysis of a gradient vector field: The gradient represents the steepness and direction of that slope. And the image gradient is a directional change in the intensity or color in an image. Therefore the blood vessels are localized by finding the discontinuities in the gradient orientation. The gradient vectors for image I(x, y) are approximated by the first-order derivative operators in the horizontal (k_x) and vertical (k_y) directions

$$g_x(x,y) = I(x,y) * k_x$$
$$g_y(x,y) = I(x,y) * k_y \tag{1}$$

The gradient vectors $g_x(x,y)$ and $g_y(x,y)$ are normalized by dividing with their magnitude to compute the unit gradient vectors

$$u_x(x,y) = g_x(x,y) / \sqrt{g_x^2(x,y) + g_y^2(x,y)}$$
$$u_x(x,y) = g_x(x,y) / \sqrt{g_x^2(x,y) + g_y^2(x,y)} \tag{2}$$

The unit vectors are assigned to zero if the gradient magnitude is too small (<3 out of 255). The first derivatives of unit vectors are computed to find the discontinuities in the gradient orientation, as

$$d_{xx}(x,y) = u_x(x,y) * k_x$$
$$d_{xy}(x,y) = u_x(x,y) * k_y$$
$$d_{yx}(x,y) = u_y(x,y) * k_x \tag{3}$$
$$d_{yy}(x,y) = u_y(x,y) * k_y$$

The discontinuity magnitude in the gradient orientation D(x, y) is expressed in terms of the first derivatives of unit vectors as

$$D(x,y) = d_{xx}^2(x,y) + d_{xy}^2(x,y) + d_{yx}^2(x,y) + d_{yy}^2(x,y) \tag{4}$$

By the gradient vector field and first-order derivative operator the variance in the vessel can be identified.

2) Morphological transformation:

Morphological operations process images based on the shapes by applying a structuring element to an input image, creating an output image of the same size. This operation is applied in the retinal image to know the structure of the blood vessel. The basic operations like opening and closing are applied according to the value of output pixel whether it is maximum or minimum than the neighbourhood input pixels. In this proposed system to eradicate a vessel or part of it when the structuring element cannot be contained within the vessel the morphological opening using a linear structuring element oriented at particular angle is applied. This process is taken placed when the vessel and the structuring element have orthogonal directions and the structuring element is longer than the vessel width.

Top-hat transformation on intensity or binary image using predefined neighbourhood or structuring element. Top-hat transformation is shown in (5a).

$$I_{th}^{\theta} = I - (I o S_e^{\theta}) \quad (5a)$$

$$Is_{th} = \sum_{\theta \epsilon A} I_{th}^{\theta} \quad (5b)$$

"I_{th}^{θ}", is the top-hat transformed image,
"I", is the image to be processed,
"S_e", is the structuring elements for morphological opening, "o", and "θ" is the angular rotation of the structuring element. Here the morphological transformation is used brighten the vessels regardless of the direction, provided that the length of the structuring elements is large enough to extract the vessel with the largest diameter. The sum of top-hat "Is_{th}" is depicted in (5b). The sum of the top-hat on the retinal image will enhance all vessels whatever their direction.

3)Multiscale Gabor filter:

In feature extraction area the edge detection is a fundamental tool in the image processing. So, in this a Gabor filter is used for the edge detection. Gabor filter is a linear filter and its frequency and orientation representation of Gabor filter are similar to those of the human visual system, and they have been found to be particularly appropriate for pixel representation. The Gabor filter can be fine-tuned to particular frequencies, scales, and directions and therefore act as a low-level feature extractor. The impulse response of Gabor filter kernel is defined by the product of a Gaussian kernel and the complex sinusoid, it can be expressed as

$$g(x,y) = \exp\left\{-0.5\left(\frac{x'^2 + \gamma y'^2}{2\sigma^2}\right)\right\} exp\left\{i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right\}$$

λ→ wavelength of the sinusoidal factor,
θ→ orientation,
ψ→ phase offset,
σ→ scale of the Gaussian envelope,
γ→ spatial aspect ratio,
$x' = x\cos\theta + y\sin\theta$,
$y' = -x\sin\theta + y\cos\theta$.

The Gabor filter response to the inverted green channel of the colored retinal image is obtained by a 2-D convolution operator and is computed in the frequency domain. The maximum filter response over the angle θ, spanning [0,π] in steps of π/18, is computed for each pixel in the image at different scales (σ= {2, 3, 4, 5}). The maximum response across the orientation at a scale is taken as the pixel feature vector.

4) Line strength features:

At each pixel of image we extract two features using orthogonal line operators by employing this linear structures of medical images are detected. The basic line operator is a line with length *l* [2] centered at considered pixel. At each pixel the average of image gray level along line operators with 12 different orientations spanning 360 degrees are evaluated. The direction for which the line operator provides the maximum gray level is selected and the corresponding gray level is denoted by *L*. this value is compared with average gray level of image, N, within a square window centered at the pixel. The difference *S=L-N* is used as a feature which measure the potential of the pixel being on a vessel.
The second feature of line operator is evaluated using gray level of the pixel neighbourhood along the line perpendicular to the line operator of the first feature. The second line has three pixels length centered at the midpoint of the basic line operator and orthogonal to it. Its average value is denoted by L_0 and its strength is obtained by $S_0 = L_0 - N$. In fact for a pixel on vessel this value must be relatively large. When a pixel is located on the background or thin vessels with low contrast, feature *L*for both cases would be close, but feature L_0 extracted using orthogonal line operator can discriminates between the two cases. L_0Would be negligible for pixels on background while relatively large for pixels on thin vessels.

B) Supervised classification

In classification process each pixel of retinal image takes one of two labels: vessel or non vessel. In this stage, a method is needed to classify images based on the extracted feature vectors. Neural network are one of the best and most widely used machine learning approaches for classification. Neural networks are simplified models of brain and consist of a number of neurons that works together. These networks are trained by special algorithms so that they could achieve the best desired output given the input. Here we used Artificial neural network (ANN) based classifiers namely feed forward back propagation neural network, Radial basis function (RBF), Multi layer perceptron (MLP). Basically the ANN composed of many “neurons” that co-operate to perform the desired function and it has ability to learn and to generalize the function.

1) Multilayer perceptron (MLP)

MLP is an important class of Neural Networks that can represent nonlinear mappings between a set of input variables and a set of output variables. It consists of three or more layers (an input and an output layer with one or more hidden layers) of nonlinearly activating nodes. This network is consecutive with no feedback. Backpropagation learning algorithm is the most appropriate approach in feed forward networks. In, this study we used 3-layer MLP, for which the number of hidden units was experimentally determined. As hidden neuron activation function, we choose the hyperbolic tangent sigmoid function (*tanh*) described in equation (7a) and (7b), an anti-symmetric function in the interval (-1, 1). Sigmoid functions satisfy the constraints in [38, 39] the two main activation functions used in this paper is described in equation (6), (7a) and in (7b).

$$y = \frac{1}{1+e^{-x}} \quad (6)$$

$$y = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad (7a)$$

$$y = \tanh(x) \quad (7b)$$

In addition, *tanh* improves the learning speed of MLP and another sigmoid function is used in the output layer called logistic sigmoid (*logsig)* activation function, which is defined in (0, 1) it is defined in equation (6). So by this choice permits the interpretation of network outputs as posterior probabilities.

Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result it is an example of supervised learning, and is carried out through backpropagation, this training of a NN can be viewed as the minimization of an error function. The performance of MLP can be improved if suitable error functions and minimization algorithm are chosen. In this paper we used mean-squared error, which tries to minimize the average squared error between the networks output, and the target value y. To minimize this cost using Gradient descent backpropagation for the class of neural networks called multilayer perceptrons, one obtains the common and well-known backpropagation algorithm for training neural networks.

2) Radial basis function (RBF)

RBF is a real-valued function whose value depends only on the distance from the origin, sums of radial basis functions are typically used to approximate given functions. This approximation process can be interpreted as a simple kind of neural network. RBF networks are 3-layer universal approximators. The input layer receives the 9-D feature vectors. The neurons in the only hidden layer are nonlinear and have green activation functions. They perform a nonlinear transformation from the input space into a high dimensional space, where the patterns are more likely to be linearly separable. The output layer is linear, and supplies the response of the NN. Generalized RBF networks represent a suboptimal solution that, usually, requires less hidden neurons. In the generalized RBF NN, the training involves not only learning the weights, but also the number of radial basis functions and their parameters. It can be regarded as a two-stage process. The first stage involves determining the parameters of the basis functions. In the second stage, the basis functions are kept fixed while the weights connecting the hidden and the output layers are found. Radial basis functions are typically used to build up function approximation which is defined in equation (8).

$$y(x) = \sum_{i=1}^{N} w_i \varnothing(\| x - x_i \|) \qquad (8)$$

Where the approximating function y(x) is represented as a sum of *N* radial basis functions, each associated with a different centerx_i, and weighted by an appropriate coefficientw_i. The weights can be estimated using the matrix methods of linear least squares, because the approximating function is linear in weights. In this study, we choose Gaussian functions as hidden layer activation functions. For training we applied the orthogonal least squares algorithm [9]. The optimum spread and number of radial basis functions were experimentally determined.

3) Feed Forward Backpropagation (FFBNN)

Multilayer networks typically use sigmoid transfer functions in the hidden layers. These functions are often called "squashing" functions, since they compress an infinite input range into a finite output range. Sigmoid functions are characterized by the fact that their slope must approach zero as the input gets large. This causes a problem when using steepest descent to train a multilayer network with sigmoid functions, since the gradient can have a very small magnitude and therefore, cause small changes in the weights and biases, even though the weights and biases are far from their optimal values.

The purpose of the resilient backpropagation training algorithm is to eliminate these harmful effects of the magnitudes of the partial derivatives. It is one of the best general purpose training methods for neural networks. Resilient propagation will typically outperform backpropagation by a considerable factor. Rprop takes into account only the sign of the partial derivative overall patterns (not the magnitude), and acts independently on each "weight". For each weight, if there was a sign change of the partial derivative of the total error function compared to the last iterations, the update value for that weight is multiplied by a factor η^-, where $\eta^- < 1$. If the last iterations produced the same sign, the update value is multiplied by a factor ofη^+, where$\eta^+ > 1$. The update values are calculated for each weight in the above manner, and finally each weight is changed by its own update value, in the opposite direction of the weights partial derivative, so as to minimise the total error function. η^+Is empirically set to 1.2 and η^- to 0.5. So by this the output of RBF is positive for vessel and negative for nonvessel.

IV. EXPERIMENTAL EVALUATION

A) Database

DRIVE (Digital Retinal Images for Vessel Extraction) database [5] has been established to enable comparative studies on segmentation of blood vessels in retinal images. The images were acquired using a canon CR5 non-mydriatic 3CCD camera with 45 degree field of view (FOV). Each image was captured using 8 bits per color plane at 768 by 584 pixels. The set of 40 images has been

TABLE I : Vessel Classification

	Vessel Present	**Vessel Absent**
Vessel detected	True Positive (TP)	False Positive (FP)
Vessel not detected	False Negative (FN)	True Negative (TN)

Divided into training and a test set, both containing 20 images. The STARE database contains 20 colored retinal images, out of which 10 images contain pathologies. The STARE database does not have separate test and training sets available. The classifier training for STARE is performed using 75000 manually segmented pixels randomly extracted from the 20 images (3750 pixels per image). Due to small size of the training set (0.8% of the entire database), the performance is evaluated on the whole set of 20 images. MESSIDOR database is also employed in this study. This database includes 1200 retinal images of sizes 1440 x 960, 2240 x 1488 and 2304 x 1536. Images are annoted with retinopathy and macular edema grades.

B. Performance measures

In the retinal vessel segmentation process, any pixel is classification either as vessel or surrounding tissue. Consequently, there are four events: two classifications and two misclassifications which are defined in Table I.

In this paper, our algorithm was evaluated in terms of sensitivity (*Se),* Specificity (*Sp),* Positive predictive value (*Ppv),* Accuracy *(Acc),* and False Discovery Rate*(FDR),* they are defined in Table II, *Se* and *Sp* metrics are the ratio of well-classified vessel and nonvessel pixels, respectively. *Ppv* is the ratio of pixels classified as vessel pixel that is correctly classified. *Acc*is a global measure providing the ratio of total well-classified pixels.

Table II Performance Measures For Retinal Vessel Segmentation

Measure	Description
SN	TP/(TP+FN)
SP	TN/(TN+FP)
Acc	(TP+TN)/(TP+FP+TN+FN)
PPV	TP/(TP+FP)
FDR	FP/(FP+TP)

C. Method Evaluation

In order to evaluate the neural network algorithms which are created under the three types of classifiers like Feed forward backpropagation, Multilayer perceptron (MLP), Radial basis function (RBF). These classifiers are then employed for vessel segmentation on DRIVE, STARE, and MESSIDOR. In this each pixel in the retinal image is characterized by a vector in 9-D feature space $Fv(x,y) = [f1(x,y), f2(x,y) \dots \dots f9(x,y)]$.

Classification procedure is assigned to the each pixel when its representation in feature space $Fv(x,y)$ is known. By these features taken as the input of the neural network and it classifies as vessel or nonvessel (*Cv or Cnv).*The features are trained in the network and the aim of the training phase is to adjust the free parameters of each NN (FFBNN, MLP, and RBF) in these stage 9 features computed for the classification of vessel and nonvessel.

Table III : Accuracy With Different Classifiers

Database	FFBNN	MLP	RBF
DRIVE	0.9623	0.8995	0.9007
STARE	0.9583	0.8929	0.8485
MESSIDOR	0.9541	0.9061	0.8276

For MLP, we had to determine the number of hidden neurons and the regularization parameter, v. By using the Gradient Descent Backpropagation as training algorithm with the mean square error performance minimum gradient is reached and training came to an end after 142 iterations.

In feed forward backpropagation neural network which used the resilient propagation as its training algorithm with the mean squared error performance the training came to an end with 67 iterations with minimum gradient. In radial basis function, the output of a hidden neuron decreases as the distance between the input features and the centre of its corresponding radial basis function increases. Therefore the centres and widths of the radial basis function determine the receptive field of each neuron [10]. The output threshold was set to 0 because the output of RBF is positive for vessel and negative for non-vessel.

Table IV : performance Measures On Drive, Stare, And Messidor

Databases	ACC	SN	SP	PPV	FDR
DRIVE	0.9623	0.9429	0.9875	0.9899	0.0101
STARE	0.9583	0.9314	0.9884	0.9890	0.0110
MESSIDOR	0.9541	0.9327	0.9855	0.9895	0.0105

Table V: performance Comparison Of Vessel Segmentation Methods

METHOD	SN	SP	ACC	PPV
EXISTING METHOD	0.7406	0.9807	0.9480	0.8478
PROPOSED METHOD	0.9429	0.9875	0.9623	0.9899

D) Vessel Segmentation Results

The performance comparison of vessel segmentation methods are shown in Table V. The segmentation results for each database is given in the figure 1, figure 2.

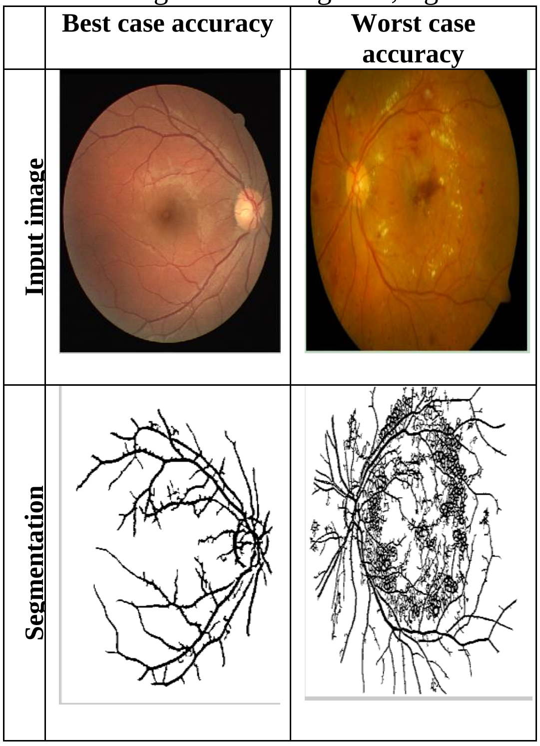


Fig.1. Segmentation results for DRIVE database

The segmented images with best case and worst case accuracies from the DRIVE, MESSIDOR are illustrated in Figs. 1 and 2. DRIVE and STARE databases mostly gives a same performance so the DRIVE and MESSIDOR are shown in the segmentation results. By comparing the three databases the DRIVE database gives the best result than the other two databases. So as like pathological images are compared and the performance of our method is evaluated.

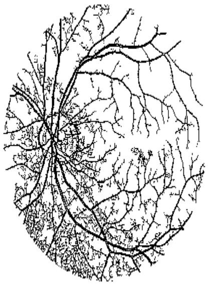
	Best case accuracy	Worst case accuracy
Input image		
Segmentation		

Fig.2. Segmentation results for MESSIDOR database

V. DISCUSSION AND CONCLUSION

In this paper, we have presented an effective retinal vessel segmentation technique based on supervised classification using Neural Network classifiers. We have used a 9-D feature vector which consists of the vessel map obtained from the orientation analysis of the gradient vector field, the morphological transformation, line strength measures and the Gabor filter response which encodes the information to successfully handle both normal and pathological retinas. And these features are extracted and given as the input to the Neural Network classifiers like FFBNN, MLP, and RBF. By using the appropriate activation function and the training algorithms the every pixels which are characterized by the feature vector and which is in feature space is classified by the neural classifiers and vessel and non-vessel are detected. The images from DRIVE, STARE, and MESSIDOR are evaluated and the performance comparison is done and the segmentation results of DRIVE and MESSIDOR databases are shown and the performance measures are calculated to evaluate the proposed method and compared with the existing method. The demonstrated performance, effectiveness and robustness, along with its simplicity and speed in training as well as in classification, make this supervised classification method for blood vessel segmentation a suitable tool to be integrated into a complete retinal image analysis system for clinical purposes. In future the more good features are studied and the vessels are classified easily from the exudates and other tissues and the vessel width and tortousity are measured and make the diagnosis easier and prevent the vision loss in the earlier stage

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