Advanced Artery / Vein Classification System in Retinal Images for Diabetic Retinopathy

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***Abstract*—**Diabetic retinopathy is that the single largest explanation for sight loss and visual impairment in eighteen to sixty five year olds. Screening programs for the calculable 1 to 6 % of the diabetic population are incontestable to be value and sight saving, but unfortunately there are inadequate screening resources. An automatic screening system might facilitate to solve this resource short fall.The retinal vasculature consists of the arteries and veins with their tributaries that are visible at intervals in the retinal images.This paper proposes a graphbased artery vein classification system inretinal images for diabetic retinopathybased on the structural informationextracted from the retinalvasculature. The method at first extracts agraph from the vascular tree and then makes a decision on the typeof each intersection point (graph node).Based on this node types one of the twolabels are assigned to each vessel segment.Finally, the A/V classes are assigned tothe sub graph labels by extracting a set ofintensity features and using artificialneural network.

Keywords*-Artery/vein classification, Diabetic retinopathy, graph nodes, neural network.*

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I. INTRODUCTION

The retinal blood vessels are vulnerable to the abnormal metabolism of glucose. In a long run, this metabolic malfunction referred to as diabetes alters the structure and consequently the performance of the retinal vessels. These changes affecting the vessels trigger a sequence of injuries or lesions to the membrane itself that are together called Diabetic Retinopathy (DR). The diagnosing, observation and screening of diabetic injuries to the retina over whelms current ocular health care, inflicting loss of sight and vision defect. Therefore the identification of the blood vessels constitutes a crucial step or building block within the style of systems for automatic screening or analysis. The structure of the eye is as shown in Fig.1.

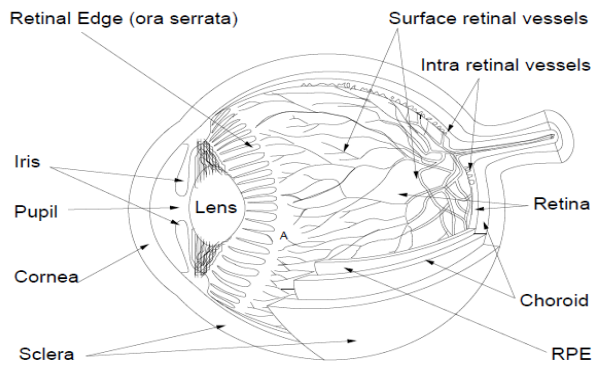

Figure 1. Schematic illustration of the eye ball and the organisation of the tissues within it.

The fundus of the eye covers the inside surface of the eye, opposite to the lens and additionally includes the retina, macula and fovea, blind spot and posterior pole. The anatomical structures are often examined by an ophthalmoscope and/or by a fundus photography. The term fundus may additionally be comprehensive of Bruch's membrane and therefore the choroid. The colour of the anatomical structure varies each between and among species. The retina of the primates is red,blue, green, yellow, and orange; solely the human fundus is red. The most abnormal options of diabetic retinopathy are exudates and blot hemorrhages. The detection of OD, blood vessels and exudates are going to be introduced. The eye's fundus is that the solely a part of the physical body wherever the microcirculation are often ascertained direct.

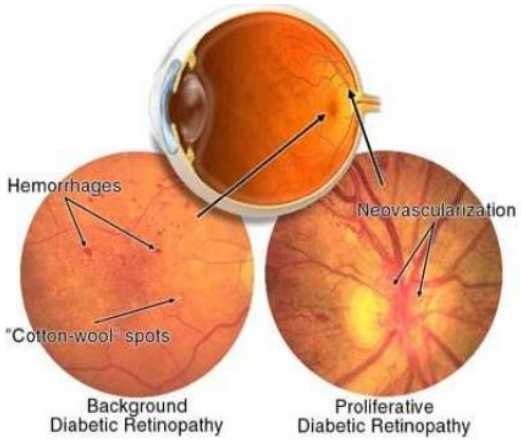

Figure 2. Fundus of the eye showing main stages of retinopathy with disorders

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The classification building procedure includes mainly three parts i.e. the feature extraction, feature selection and finally the classifier construction. In line with the analysis of retinal image, the textural message and statistical of the image is extracted as classification options. The classifier is built by back propagation neural network that has 3 layers. Based on the clearness degree of the retinal image, the retinal images are

classified as normal and abnormal categories. The initial analysis results normally have nice potential to enhance identification potency of the oculist and scale back the physical and economic burden of the patients and society.

Graphs are a powerful representation for structured information which can be very easily characterized by its subparts and the relations between these subparts. This method proposes a graph based artery /vein classification system in retinal images for diabetic retinopathy using artificial neural network. The method first extracts a graph from the vascular tree and based on this a decision on the type of each intersection point (graph node). Based on this node types one of the two labels are assigned to each vessel segment. Finally, the A/V classes are then assigned to the sub graph labels by extracting a set of intensity features and using artificial neural network. The abnormalities in the retina will change the structure and appreance and those are shown in the figures 3 to 8.

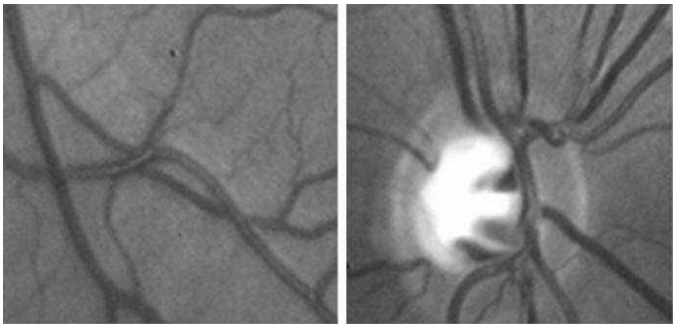

Figure 3. Monochrome fundus images showing twisted and overlapping vessels

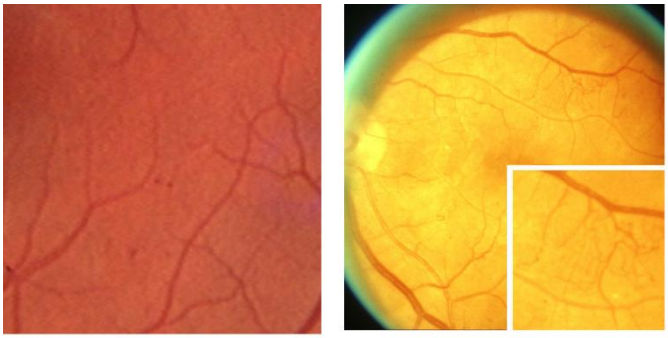

Figure 4. a.Microaneurysms, Small and punctuate red dots b. IRMA, Irregular calibres and tortousity of the smaller retinal vessels

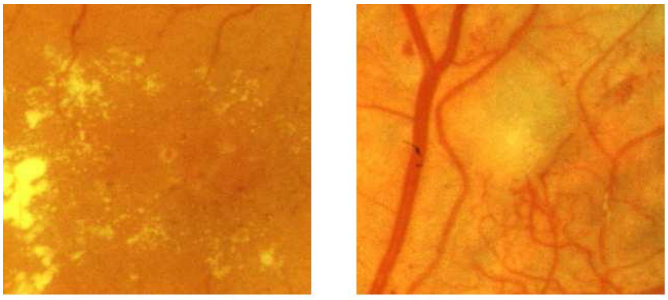

Figure 5. a. Hard exudates, areas oflipo protein mal-absorption, yellow-ish well defined contours. b. Soft exudates (SE),areas of axoplasmic accumulation

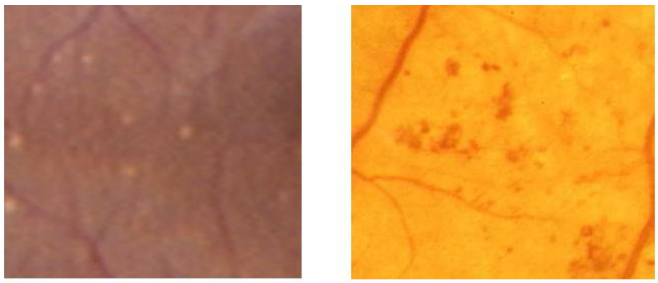

Figure 6. a. Drusen, Deep, whitishlessions more regular in outline thanexudates b. HAemorrhages (HA),dispersed red blotches with irregularperimiters.

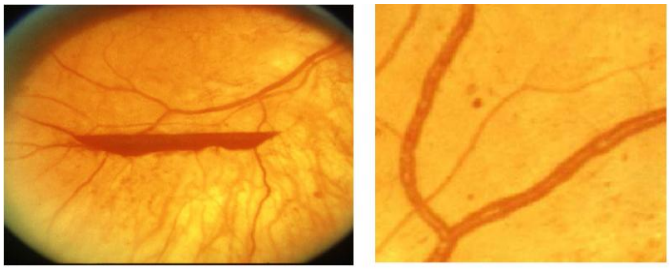

Figure 7. .Pre-retinal Haemorrhage, extravasated blood betweenretina and vitreous ETDRS ; b. Venous beading, irregular distension of large and orsmaller retinal vein calibres

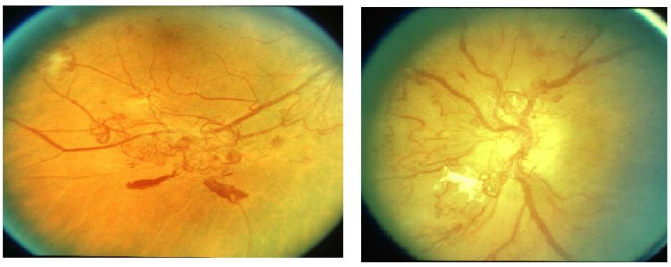

Figure 8. Neo VascularisationElsewhere, (NVE) Growth of capillary like new vessels on fundus butnot OD ; b. NeoVascularisationDisk,(NVD), Development of microvesselsinto the vitreo-retinal interface atOD

II. Literature Review

The wrong identification of vessels may result in a large variation of these measurements, leading to a wrong clinical diagnosis. Many previous are made for this propose. In [1] the problem is addressed as automatically identifying true vessels as a post processing step to vascular structure segmentation. They model the segmented vascular structure as a vessel segment graph and formulate the problem of identifying vessels as one of finding the optimal forest in the graph given a set of constraints. An operator for feature extraction based on the optical and spatial properties of objects to be recognized is introduced in [2]. The gray-level profile of the cross section of a blood vessel is approximated by a Gaussian-shaped curve. The concept of matched filter detection of signals is used to detect piecewise linear segments of blood vessels in these images. A novel representation called “orientation space” is proposed in [3], which is derived by adding the orientation axis to the abscissa and the ordinate of the image. The orientation space representation is constructed by treating the orientation parameter, to which Gabor filters can

be tuned, as a continuous variable. The problem of segmenting lines at multiple orientations is dealt with by thresholding 3D images in the orientation space and then detecting the connected components therein. In this way, X-junctions and T-junctions can be separated effectively. Curve grouping can also be accomplished. The segmentation of mathematically modeled X-, T-, and L-junctions is demonstrated and analyzed. The sensitivity limits of the method are also discussed. Experimental results using both synthesized and real images show the method to be effective for junction segmentation and curve grouping.

In [4] an algorithm called fuzzy convergence to determine the origination of the blood vessel network is used. [5] presents an automated method to identify arteries and veins in dual-wavelength retinal fundus images recorded at 570 and 600 nm. Dual-wavelength imaging provides both structural and functional features that can be exploited for identification. The processing begins with automated tracing of the vessels from the 570-nm image. The 600-nm image is registered to this image, and structural and functional features are computed for each vessel segment. T the relative strength of the vessel central reflex as the structural feature is used. The central reflex phenomenon, caused by light reflection from vessel surfaces that are parallel to the incident light, is especially pronounced at longer wavelengths for arteries compared to veins .A dual-Gaussian to model the cross-sectional intensity profile of vessels is used. The model parameters are estimated using a robust -estimator, and the relative strength of the central reflex is then computed from these parameters. The functional feature exploits the fact that arterial blood is more oxygenated relative to that in veins. This motivates use of the ratio of the vessel optical densities (ODs) from images at oxygen-sensitive and oxygen-insensitive wavelengths as a functional indicator. Finally, the structural and functional features are combined in a classifier to identify the type of the vessel. We experimented with four different classifiers and the best result was given by a support vector machine (SVM) classifier. Optic disc (OD) detection is a main step while developing automated screening systems for diabetic retinopathy.

In [6] a method to automatically detect the position of the OD in digital retinal fundus images is proposed. The method starts by normalizing luminosity and contrast throughout the image using illumination equalization and adaptive histogram equalization methods respectively. The OD detection algorithm is based on matching the expected directional pattern of the retinal blood vessels. Hence, a simple matched filter is proposed to roughly match the direction of the vessels at the OD vicinity. The retinal vessels are segmented using a simple and standard 2-D Gaussian matched filter. Consequently a vessel direction map of the segmented retinal vessels is obtained using the same segmentation algorithm. The segmented vessels are then thinned, and filtered using local intensity, to represent finally the OD-center candidates. Thedifference between the proposed matched filter resized into four different sizes, and the vessels' directions at the surrounding area of each of the OD-center candidates is measured. The minimum difference provides an estimate of the OD-center coordinates. The proposed method was evaluated using a subset of the STARE project's dataset, containing 81fundus images of both normal and diseased retinas, and initially used by literature OD detection methods.

A novel multiconcavity modeling approach is proposed to handle both healthy and unhealthy retinas simultaneously in [7]. The differentiable concavity measure is proposed to handle bright lesions in a perceptive space. The line-shape concavity measure is proposed to remove dark lesions which have an intensity structure different from the line-shaped vessels in a retina. The locally normalized concavity measure is designed to deal with unevenly distributed noise due to the spherical intensity variation in a retinal image. These concavity measures are combined together according to their statistical distributions to detect vessels in general retinal images. Due to the high ability of the curvelet transform in representing the edges, modification of curvelet transform coefficients to enhance the retinal image edges better prepares the image for the segmentation part, the directionality feature of the multistructure elements method makes it an effective tool in edgedetection[8]. Hence morpholophy operators using multistructure elements are applied to the enhanced image in order to find the retinal images ridges. Afterward morphological operators by reconstruction eliminate the ridges not belonging to the vessel tree while trying to preserve the thin vessels unchanged. In order to increase the efficiency of the morphological operators by reconstruction, they were applied using multistructure elements. A simple thresholding method along with connected components analysis (CCA) indicates the remained ridges belonging to vessels. In order to utilize CCA more efficiently, we locally applied the CCA and length filtering instead of considering the whole image. Experimental results on a known database, DRIVE.The method [9] is based on developing a novel model to describe the temporal intensity variation of the image sequence. The model parameters at each pixel are used to construct a feature vector that is used to classify the different pixels into areas of classic Choroidal Neovascularization CNV, occult CNV and background. Preliminary results on four datasets show the potential and effectiveness of the method to segment and identify the different types of CNV lesions.

III. PROPOSED METHOD AND DATABASE

A. Image Database

FirstThe retinal fundus image used for this studyis obtained from publicly available databaseDigital Retinal Images for Vessel Extraction(DRIVE).The DRIVE database contains 40 color images of the retina ,with 565 x 584pixels and 8 bits per color channel, which is represented in LZW compressed TIFFformat. The 40 images were divided into atraining set and a testing set. In the testing set images, a second independentmanual segmentation exists as well.

B. Proposed Method

Most of the existing method for artery/veinclassification uses intensity features todiscriminate between artery and vein. Theproposed method uses the additionalstructural information extracted from thegraph. The basic modules of the proposedmethod include four sections: graphgeneration, graph analysis, A/Vclassification and disease severity detection.

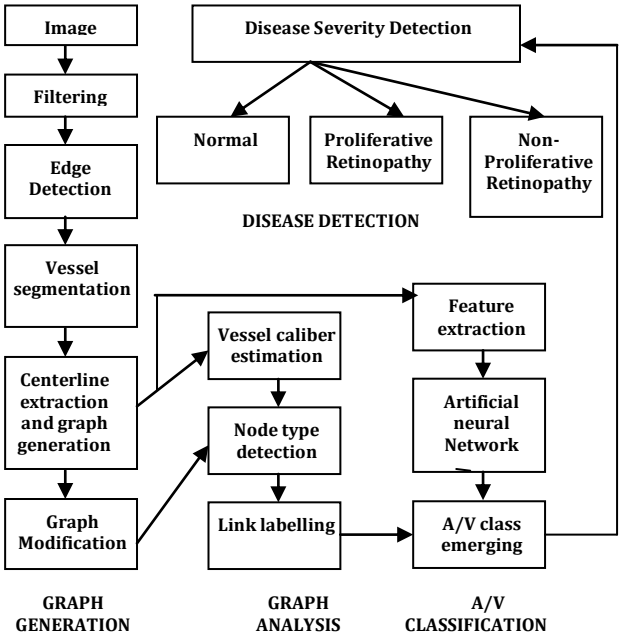

Figure 9. Proposed method

Fig.9 depicts the block diagram ofproposed method. There are of mainly four sections:graph generation, graph analysis, A/Vclassification and disease severitydetection. The method first extracts a graphfrom the vascular treeand then based on this makesa decision on the type of each intersectionpoint (graph node). Based on this node typesone of the two labels are assigned to eachvessel segment. Then A/V classes areassigned to the sub graph labels byextracting a set of intensity features andusing artificial neural network. Finally,based on the artery vein classification resultthe status of the disease is detected.

IV. METHODOLOGY

A. *Image acquisition*

The healthy tissues and pathological manifestations of the retina vary insizes. The smallest vessels and their pathology (IRMA) areslightly larger thana capillary (approximately 8µm). The largest features such as pre-retinal haemorrhageand the optic disk are 1600µm or larger. The details of the anatomy andlesions that are recorded by an image are largely defined by the resolution.The capacity to resolve, or to spatially distinguish two objects, is a criticalmeasure which is equally applicable to images recorded on analog media,such as photographic film, or those directly digitized from transducer signals. The spatial resolutions that are used can be roughly estimated to from the width of the vessels or the average size of the optic disk to give a resolution of the order of 10µm per pixel.

B. *Pre-processing*

After acquisition, corrections for uneven illumination or image quality maybe made. Also adjustments to regions of interest or the need for re-samplingmay be evaluated. Collectively these operations are termed image pre-processing. Other factors and artifacts include poor focus,reflections,patient movements, bad positioning, disease opacity or inadequate illumination.These factors and artifacts will cause a significant proportion of images tobe of such poor quality so as to interfere with analysis.

Preprocessing of the fundus data either removes or flags the aforementioned interferences. A Gaussian filter can be used for noise removal. The Gaussian filter modifies theinput by convolution with Gaussian function given by

$$g(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x+y)}{2\sigma^2}}$$

where x and y are the distance from origin to horizontal and vertical directions respectively and σ is the standard deviation which is the estimate of underlying brightness probability distribution. The importance of edge detection in general is to significantly decrease the amount of data in the image, mean while preserving the important structural properties to be used for further image processing. In this paper canny edge detection is used because the canny algorithm preserves both the strong edges and weak edges connected with the strong edges.

C. *Detection and extractionof Blood Vessels*

In an automated retinal image analysissystem, exact detection of artery and vein incolor retinal images is a significant task.Several segmentation methods can beadopted for this purpose. Morphological image processing exploits features of thevasculature shape that are known a priori.The algorithms that extract linearshapes can be very useful for vessel segmentation. The structuringelements of a particular intensity can be added (dilation) orsubtracted (erosion) to the underlying image. Opening(erosion followed by dilatation) with a structuring element of acertain shape can separate objects in an image by preserving the image structures which can contain the structural element andremoving those that cannot. Closing (dilatation followed byerosion) can be used to 'fill-in' small holes within an image. The morphological operations play an important role in digital imageprocessing with special application in the field of machinevision and automatic object detection and these morphologicaloperations include mainly dilation, erosion, opening, closing etc.

$$A \oplus As = \{z|(A's)z \cap A \neq \Phi\}$$
$$A \Theta As = \{z|(As)z \cap Ac \neq \Phi\}$$
$$X \circ Y = (X \oplus Y)\Theta Y$$
$$X \bullet Y = (X\Theta Y)\oplus Y$$

The enhanced vessel segment in the Gabor filter response image requires an effectivethresholding scheme. Theentropy based thresholding using gray level co-occurrencematrix is used and computes the optimal threshold by takinginto account the spatial distribution of gray levels that areembedded in the co-occurrence matrix. The GLCM containsinformation on the distribution of gray level frequency andedge information which is very helpful in finding the thresholdvalues.

The gray level co-occurrence matrix is a L×L squarematrix of the gray scale image I of spatial dimension M×Nwith gray levels in the range [0, 1. . . L-1]. It is denoted by T =[ti,j]L×L matrix. The elements of the matrix specify the numberof transitions between all pairs of gray levels in a particularway. For each image pixel at spatial co-ordinate (m, n) with itsgray level specified by f(m ,n), and it considers its nearest fourneighbouring pixels at locations of (m+1, n), (m-1, n), (m,

n +1) and (m, n - 1). The co-occurrence matrix is formed bycomparing gray level changes of f(m, n) to its correspondinggray levels, f(m +1, n), f(m -1, n), f(m, n + 1) and f(m, n - 1).Depending upon the ways in which the gray level i followsgray level j, they are many possibilities of different definitions of co-occurrence matrix. The co-occurrence matrix by consideringhorizontally right and vertically lower transitions is given by

$$t_{i,j} = \sum_{m=1}^{M} \sum_{n=1}^{N} \delta$$

$$\delta = 1 \; if \; \begin{Bmatrix} f(m,n) = i \; and \; f(m,n+1) = j \\ f(m,n) = i \; and \; f(m,n+1) = j \end{Bmatrix}$$

$$\delta = 0 \; otherwise$$

Where, the total number of transitions in the co-occurrencematrix, a desired transition probability from gray level i togray level j is obtained as follows

$$P_{i,j} = \frac{t_{i,j}}{\sum_{i=1}^{L} \sum_{j=1}^{L} t_{i,j}}$$

The centerline image is extracted from the segmented result by applying iterative thinning algorithm. This algorithm removes border pixels until the object shrinks to a minimally connected stroke. After that, graph nodes are obtained by finding the intersection point and end points.

D. *Neural Network*

Artificial neural networks (ANNs) are a family of statistical learning algorithms which is inspired by biological neural networks. Generally, from large number of unknown inputs ANN can estimate or approximate functions. A large number of neurons, which can compute values from input, are interconnected to form an artificial neural network. Neural networks are similar to biological neural structures. A neural networks starts as a model neuron which consists of multiple inputs and a single output. The input is modified by a weight, which multiplies with the input value. Then the neuron will combine these weighted inputs. These are used to determine its output with reference to a threshold value and activation function.The concept of neural networks is inspired from Human's central nervous system. In Artificial Neural Network [14] the artificial nodes which are known as "neurons", "processing elements" or "units"are connected together to form a network this mimics a biological neural network.

A neural network performs functions collectively and in parallel by the units, than there being a clear delineation of subtasks to which various units are assigned in a way which is similar to biological neural network. The term "neural network" usually refers to models employed in statisticscognitive psychology and artificial intelligence [14].

In this study the ANN consisted of three layers: an input layer and output layer connected by a hidden layer. The hidden layer consists of a number of nodes connected to the input and output nodes by mathematical algorithms (weights). By presenting the network with many examples of data of known output, training is achieved . Once the weights in the hidden layer have been adjusted by training, the network can be shown a previously unseen input and categorize this into the appropriate output. Once the network has been trained to recognise the digitised visual fields, which has not previously been seen can be presented. The selected features are fed into the constructed neural network to train it to identify features.

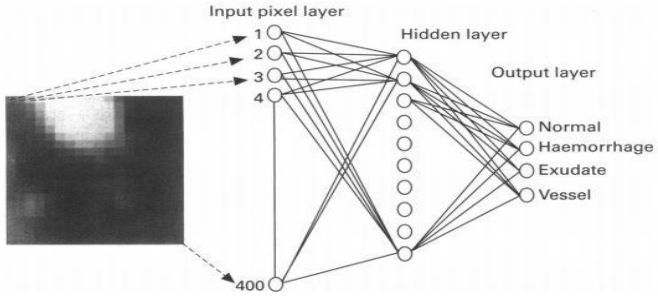

Figure 10. ANN

The artificial neural network models can be used to infer a function from observations made. This is mostly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical.Neural networks have performed successfully where other methods failed in, predicting system behavior, recognising and matching complicated, vague, or incomplete data patterns. ANNs is applied to pattern recognition,diagnosis, interpretation, prediction, planning, debugging, monitoring, repair, control andinstruction [14]. Because of the prediction capability of ANNs, they can be used in diagnosis in medical field. Neural network Toolbox1 for MATLAB is one of the most well-known toolboxes for constructing and training neural networks. This toolbox provides GUIs for designing, training and simulating a number of different neural network types and allows custom extension of the toolbox

V. RESULTS

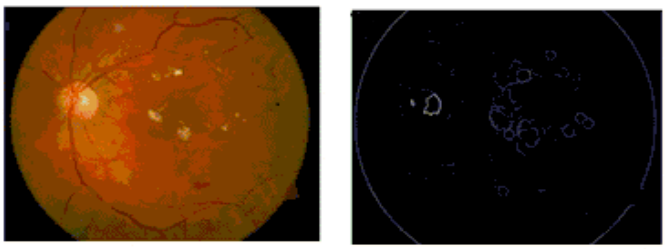

Figure 11. a. Input image. b. Dialation gradient image

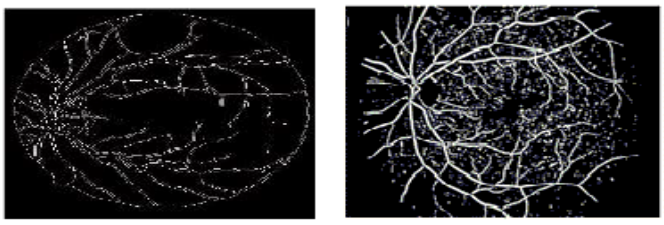

Figure 12. a. Edge detection b. Threshold gradient image

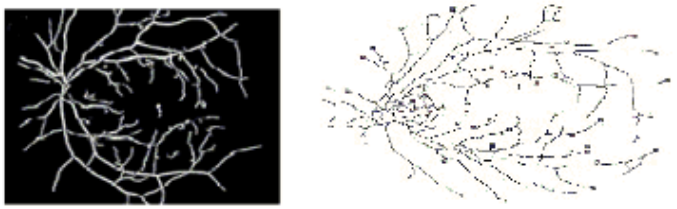

Figure 13. a. Blood veseels detection b. Graph generation

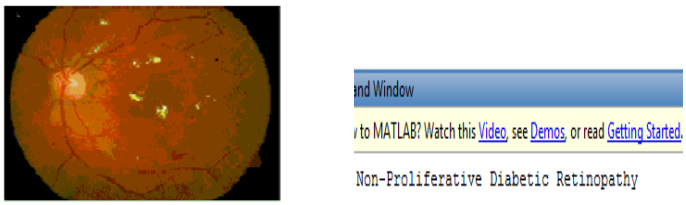

Figure 14. a. Exudates detected b. Diease estimation

From these sensitivity and specificity are evaluated.Sensitivity gives the percentage of pixels correctly classified as vessels by the method and specificity gives the percentage eof non-vessels pixels classified as non-vessels by the method as follows

$$Senstivity = \frac{T_p}{T_p + F_n}$$

$$Specificity = \frac{T_n}{T_n + F_p}$$

$$Accuracy = \frac{T_p + T_n}{P + N}$$

Where $T_p$represents the true positive, $T_n$represents the true negative, F_p representsthe false positive and $F_n$representsthe false negative at each pixel obtained. Then the method is compared with the various methods adjusting the DRIVE database. Table given shows that the proposed is better in classifications with less false positive fraction rate

TABLE I. COMPARISON OF RESULT

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Proposed Method	85.76	95.89	95.79
Hoover et.al [4]	75	92	91.7
Bayesian Method	75.13	95.29	95.25
Li etal [10]	77.63	97.23	----
Al-Diri et al [11]	72.82	95.51	----
Espona et al [12]	66.34	96.82	93.16
Non-expert Human	77.63	97.23	94.7

VI. CONCLUSION

The classification of arteries and veins in retinal images is essential for the automated assessment of vascular changes. A new automatic methodology to classify retinal vessels into arteries and veins is discussed which is distinct from prior solutions. One major difference is the fact that this method is able to classify the whole vascular tree and does not restrict the classification to specific regions of interestaround the optic disc. Most of the previous methods mainly use intensity features for discriminating between arteries and veins.This method uses additional information extracted from a graph which represents the vascular network. It is expected to achieve high accuracy and better performance, especially for the largest arteries and veins which confirms that this A/V classification methodology is reliable for the calculation of several characteristic signs associated with vascular alterations. The method first extracted a graph from the vascular tree and then makes a decision on the type of each intersection point (graph node). Based on this node types one of the two labels are assigned to each vessel segment. Finally, the A/V classes are assigned to the sub graph labels by extracting a set of intensity features and using artificial neural network.

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