Identification of Artery/Vein in Retinal Image using Local Decision Tree Classifier

Rama Krishna V.V , Suman.M

Abstract: ***The importance of automatic image analysis is increasing day by day for early detection of diseases like Cancer, Diabetic Retinopathy (DR), Hypertension. Sometimes these diseases causing damage to retinal image leading to blindness. We can prevent this by careful analysis of artery/vein retinal image. From this we observe that identifying retinal vessels in to artery/vein (A/V) plays a major role in detection the vascular changes and symptoms associated with several diseases. In this work, first we extract graph from retinal image, followed by investigation of identified graph nodes (intersection point). We perform depth first graph traversal with trained decision tree applied on each graph node to classify artery/vein. The trained decision tree classifier takes node labels, vessel segment (graph links) intensity features into account for classification. The proposed framework is tested on standard dataset and is compared with trained human expert for standard datasets. The accuracy values of INSPIRE-AVR, DRIVE, and VICAVR databases are 91.4%, 92.1%, and 93.2% respectively. Experimental results show that our approach is consistent with existing A / V classification state of the art algorithms.***

Keywords: Artery, Vein, Thinning Algorithm, Local decision Tree algorithm, Depth Graph Traversal.

I. INTRODUCTION

Automatic discovery of retinopathy in eye fundus pictures utilizing computerized picture examination techniques has tremendous potential advantages, permitting the analysis of numerous images in quick response time, with space & time complexities, with improved than current state of art procedures. Second favorable technique is the likelihood to detect robotized screening for neurotic conditions, for example, diabetic retinopathy, with the end goal to lessen the remaining task at hand expected of prepared manual labeling [1].

Most of the diseases like diabetes, hypertension, and vascular issue affect the retinal vessels, causing the change in characteristics. In diabetic retinopathy, the veins frequently demonstrate variations from the norm at beginning times [2], and in addition vessel measurement modifications [3]. Changes in retinal veins, for example, huge dilatation also, extension of principle courses, veins, and their branches [3], [4], are additionally regularly connected with Blood pressure and heart related diseases.

A couple of trademark symbols related to vascular characteristics are estimated to monitor the stage and severity of eye conditions. The summary of arteriolar narrowing, which is contrary to higher levels of circulatory strain[5],[6], The appreciation of AVR may well be a marker of viral infections, similar to diabetic neuropathy and glaucoma [8]. Among other tasks for the preparation of the picture, the estimation of AVR requires the division of the vessel, the exact estimation of the vessel width and the grouping of conduits / veins (A / V)[9],[10]. Consequently, any programmed AVR estimation framework should accurately distinguish correctly vessels are corridors and veins as veins,

A few shots have been proposed at the vessel order [11] - [17], but the robotic arrangement of such corneal muscles in ducts and perhaps blood vessels was also limited and is still an open errand in the field of corneal image examination. Over the years, charts have been developed as a joint portrayal for picture examination, and techniques based on diagrams have been used for the division of retinal vessels [18], retinal picture enrollment[19] and corneal vessels[12]. To determine the type of crossing point focuses, the diagram taken away from the fragmented corneal vascular system is examined (diagram hubs), and shortly afterwards one of two names is assigned to each part of the vessel (chart joins). In the end, vessel sections ' force highlights are estimated to doling out the last corridor / vein class.

In this paper, it is shown that a new framework manages the above problem by removing a chart from the vascular tree and selecting the crossing point type (diagram hub). In view of the hub types in each sub-diagram, all vessel fragments (chart connections) are distinguished and then marked using two unmistakable names.

Finally, the sub-chart marks are allocated to the A / V classes by removing a set of highlights and using a family of iterative strategies which include the utilization of near by data to learn nearby classifiers. These iterative strategies depend on building vectors for hubs from the data they think of and their neighborhood (promptly adjacent hubs). These element features are utilized alongside the realized class esteems Yl, to manufacture an occasion of a neighborhood classifier, for example, Naıve Bayes, Decision Trees and so on for inducing the names on hubs.

Revised Manuscript Received on March 26, 2019.

Rama Krishna V.V, Department of Electronics and Communication Engineering, Laki Reddy Bali Reddy College of Engineering, Mylavaram, Andhra Pradesh, India-521 230.
Suman.M, Department of Electronics and Communication Engineering, KL University, Green Fields, Vaddeswaram, Guntur, A.P., India.

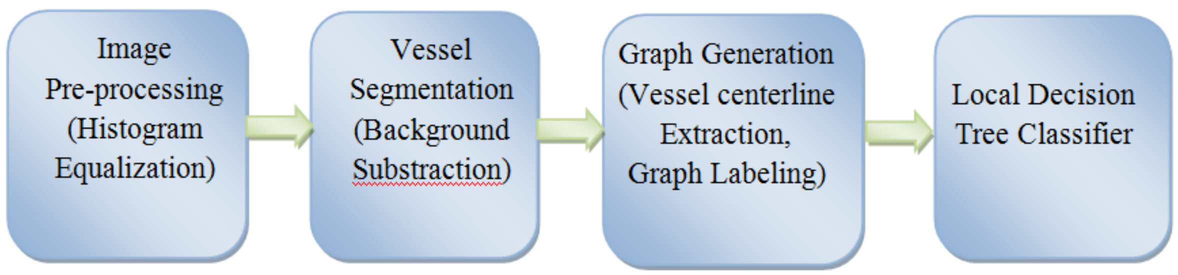

Fig-1: Architecture diagram for the proposed Depth First Search Local Decision Tree Classifier

Finally, the sub-chart marks are allocated to the A / V classes by removing a set of highlights and using a family of iterative strategies which include the utilization of near by data to learn nearby classifiers. These iterative strategies depend on building vectors for hubs from the data they think of and their neighborhood (promptly adjacent hubs). These element features are utilized alongside the realized class esteems Yl, to manufacture an occasion of a neighborhood classifier, for example, Naıve Bayes, Decision Trees and so on for inducing the names on hubs.
The remainder of the paper is arranged accordingly. Section 2 gives an overview of the latest work. In Section 3, we present the methodology for segmenting vessels as well as detecting Artery/Veins. Section 4 finally discusses the simulations and analysis of the standard set of video data. Section 5 draws conclusions.

II. RELATED WORKS

Visual and geometric highlights enable segregation between veins and corridors; some techniques have investigated these properties for the order of A / V [11-17]. Classes are stunning bright red while veins are slightly darker and bores are generally smaller than vein bores. Infections can influence vessel gages, which is anything but a solid highlight for A/V grouping in these lines. In addition, the supply routes have thicker dividers that mirror the light as a brilliantly focal reflection strip [20]. Other normal feature of the corneal vessel tree is that veins never cross other veins in the district near the optical circle (OD), but both these kinds can still delineate into either smaller vessels, and veins and hallways will attempt to cross [20]. It is therefore possible to follow the corridors and veins in the pulmonary tree and were used to investigate the vessel tree and identification of vessels [11,12].
Rothaus et al.[12] proposed another technique such as this, which depicts a rule-based calculation to proliferate vessel marks throughout the vascular tree as either a corridor or a vein. This technique uses the results of the existing division of vessels and manually labeled certain new starting vessel sections. Grisan et al. [13] have formed a characterization strategy for A / V, which orders the vessels in a concentrated area around the optical plate.
Vazquez et al. [14] presented a strategy that integrates shading and ship strategy. First, strategy to grouping isolates the retinal picture in four dimensions, at which point the vessels distinguished in each quadrant are ordered independently, and finally consolidates the results. At this point, the following technique, which depends on an insignificant strategy, is linked to joining the vessel fragments situated on completely different diameters with the ultimate objective of helping to characterize by casting a ballot. Li et al. [15] proposed a piece-by-piece Gaussian model to depict the power dispersion of vessel profiles. The focus reflex was considered in this model. A base remove classifier dependent on the Mahalanobis separate was utilized to separate between the vessel types utilizing highlights determined from the evaluated parameters.
In view of the aid of vector machines and neural systems, Kondermann et al.[16] presented two extraction techniques and two arrangement strategies for ordering retinal vessels. The popular retrieval strategies for elements are dependent on profiles, the others depends on the meaning of an intrigue area (ROI) around each centerline point. A multiclass vital part investigation (PCA) was used to reduce the dimensionality of the element vectors.
Niemeijer et al.[17] proposed a programmed technique for the characterisation of retinal vessels in supply routes and veins using image highlights and a classifier. In addition, a delicate mark is allocated to each centerline, showing the probability of being a vein pixel, an arrangement of centerline highlights is removed. At that point the normal of the delicate marks of associated middleline pixels is doled out to each middleline pixel. The authors used distinctive classifiers and k-closest neighbor (kNN) classifier was found to give the best generally speaking execution. In [21], the grouping technique was improved in the stage of computing the AVR esteem.
Many such techniques tried force highlights to separate supply arteries and veins. Generally, the retinal images are not consistently illuminated all the time, showing nearby iridescence and changeability in complexity, which can influence the execution of A / V order strategies based on force. We therefore propose a technique that uses additional auxiliary data from a vascular system chart. The aftereffects of the proposed technique indicate enhancements in beating the normal varieties conversely inalienable to retinal pictures.
We can now formally define the node classification problem. We are given a graph G(V, E, W) where V is the set of n labeled nodes in the graph (possibly augmented with other features). Here W is the weight matrix, and E is the set of edges, which is to be labeled. Let Y be the set of m possible labels, and Yl = {y1, y2, . . . , yl} be the initial labels on edges graph. The task is to infer labels Y ˜on all nodes V of the graph.

III. PROPOSED APPROACH

In this section, we explore the proposed Artery Vein classification methodology from retinal images. The process illustration is done in fig.1. Our method consists of four processes. 1. Image Pre-Processing, 2. Vessel segmentation, 3. Graph Generation, and 4. Artery/Vein Classification.

The proposed Artery Vein classification methodology starts with Image preprocessing techniques to beautify the retinal scan image. Major arteries are segmented from veins using back ground segmentation technique. In our work, graph nodes are labeled manually, followed by feature extraction at each sub-vessel. Finally, the results of the previous step are given to the Iterative Local Classifier to label each sub-vessel on the basis of the structural characteristics of the vascular retinal network. Some vessels that are incorrectly labeled are correctly labeled repeatedly. The vessels are correctly labeled on the basis of the adjacent vessel or the other vessels associated with it.

A. Image Pre-Processing

One of the main challenges in retinal image is non-uniform illumination. In this work, we enhance the difference between arteries and veins in the retinal images. This is done by Histogram equalization technique, for normalizing the color through images. It achieves this by viably spreading out the most regular power esteems, i.e. extending the power scope of the picture. This strategy normally expands the worldwide difference of pictures when its usable information is spoken to by close differentiation esteems. This takes into consideration territories of lower neighborhood complexity to pick up a higher contrast. A shading histogram of a picture speaks to the quantity of pixels in each kind of shading part. Histogram evening out can't be connected independently to the Red, Green and Blue parts of the picture as it prompts emotional changes in the picture's shading balance. Be that as it may, if the picture is first changed over to another shading space, as HSL/HSV shading space, at that point the calculation can be connected to the luminance or esteem direct without bringing about changes to the tone and immersion of the picture.

B.Vessel segmentation

We used Gabor wavelets to extract features to find candidates from the center line. Validation is performed on the segmented images to validate with the help of pixel intensity and length features. We combine the middleline image with the set of images to rebuild the ship with the segmented ships.

C.Graph Generation

We applied morphological techniques to the segmented vessels to remove thinner vessel which is less than pixel size of 3. After that, we applied thinning algorithm to the resultant vessels to get skeleton image of vessels. Next, a link between two nodes represents each vessel segment. The graph contains nodes and a number of links can be connected to each node, but only two nodes can be connected to each link.

During vessel skeleton process, centre line pixels are identified and further each intersection point is identified as Bifurcation and cross-over points. These points are the pixels which are having a neighborhood pixels of more than two pixels. A binary image of vessel segments is the output of this step. Finally, forward feature selection methodology is used for feature extraction. The lists of features extracted are listed in Table 1.

In our work, we label all the nodes manually and then we perform depth wise traversal from all the nodes in the graph, to which local classifiers are applied. In addition we also used structural information. The structural knowledge includes two rules. The first rule states that if a bifurcation point has three vessel segments, all three vessels should be of the same type. The second rule states that one vessel must be an artery and the other a vein if two vessels cross. In the second step, the number of vessel points labeled as arteries and veins is counted for each detected subtree of the artery or vein, and the dominant label is also found in that subtree. If the vessel's number of pixels with the dominant label exceeds the threshold, the vessel's dominant label shall be assigned to all points of the vessel.


Fig-2: Retinal Image

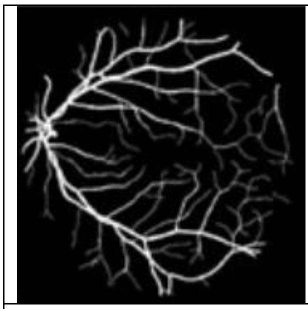
Fig-3: Segmented Image

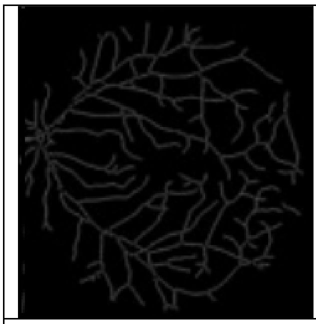
Fig-4: skeleton Image

Published By:
Blue Eyes Intelligence Engineering & Sciences Publication

Table-1: Pixel-level Features in retinal Image	
S.No	**Overview of Sub vessel Feature**
1	skeleton Mean Pixel value of each sub vessel in R image
2	skeleton Mean Pixel value of each sub vessel in G image
3	sub vessel Mean Pixel value in red image
4	sub vessel Mean Pixel value in green image
5	Variance pixels value in A channel of LAB color space
6	Variance pixels value in B channel of LAB color space
7	Red channel Intensity difference between wall & centre line pixels
8	Luminance channel Intensity difference between wall & centre line pixels

Depth First Search Local Decision Tree Classifier :

We model the problem into graph labeling problem, in which graph node represents points in retinal image and artery/vein represents link between the graph nodes. In our work, we already label all the nodes manually to facilitate the link labeling in the graph. We also extracted all the pixel level features pertaining to all the links (as shown in Table 1) from retinal images.

Our methodology consists of two phases: 1) Training Phase, 2) Testing Phase. In our work, we use decision tree classifier for all training images. The attributes we starting node, ending node, pixel intensity features as shown in table 1

As with state of art classification problems, attribute set

Table-4-Accuracy Values - DRIVE Dataset			
S.No	**Methodology**	**Center line image pixels**	**All vessel image pixels**
1	Expert assignment of classes A / V to the labels of subgraphs	92.4%	93.1%
2	LDA	80.9%	84.0%
3	Graph with LDA	85.9%	90.3%
4	Proposed Local Decision Tree Classifier	87.5%	92.6%

Features is given for each link li ∈ L . feature vector is constructed with all these attributes. In testing phase, all the graph nodes are traversed using depth first search technique, in which decision tree classifier is applied locally to label each segment. This process is repeated for all nodes until the vessel labeling is complete.

Table 2- Depth First Search Local Decision Tree Classifier
1. Compute ϕ^1 from V, L, E, F, Y_l
2. Train Classifier using ϕ_l
3. For $t \leftarrow 1$ to τ do
4. Perform Depth First Search Traversal
5. Apply classifer to V to find label L_i
6. Return G, L_i

Here the difference that makes with classification of graph data is the presence of multiple features, presence of links between nodes and link classification. The feature construction is made based on the node degree, Connectivity information. The classifier is typically presented with link features as aggregate statistics derived from labels on neighborhood nodes.

IV. Results and Discusion

Experimental studies and results for the evaluation of the proposed approach are presented in this section. We used DRIVE[27], INSPIRE-AVR[28], two publicly available datasets. We used 768 × 584 pixels, DRIVE dataset images, with 8 bits per color plane. The 40 high resolution images of the INSPIRE-AVR database have resolution of 2392 × 2048 pixels and are optic disc centered.

Table-3-Accuracy Values - INSPIRE-AVR DATABASE			
S.No	**Methodology**	**Center line image pixels**	**All vessel image pixels**
1	Expert assignment of classes A / V to the labels of subgraphs	90.7%	92.3%
2	LDA	79.9%	85.0%
3	Graph with LDA	84.9%	88.3%
4	Proposed Local Decision Tree Classifier	85.1%	89.3%

We used 2-overlay cross - approval in the INSPIRE - AVR dataset. We accidentally allocated pictures to two sets S1 and S2, in order to ensure that the two sets were of the same size. We prepared the classifier on S1 at that point and tried it on S2, trailed on S2 and tested on S1. For preparing the LDA classifier, we arbitrarily chosen 15,000 named centerline pixels from each set. Table 3 shows the evaluation of the execution of the LDA classifier for the grouping of vessel sections in the INSPIRE - AVR database and the results obtained using the combination of diagram grouping with LDA. The examination of these results demonstrates that the Local Decision Tree Classifier outflanks the exactness of the LDA classifier alone and Graph with LDA.

For the DRIVE database's 20 test pictures, an accuracy of 87.5 percent was achieved for the order of primary centerline pixels. In the entire image of our proposed work, the accuracy values for both centerline pixels and vessel pixels are superior compared to LDA, Graph - LDA.

V. CONCLUSION

This paper has proposed a novel approach to detect Arteries/Veins in the retinal image using Local decision tree classifier at each node. The main contribution of this paper includes a Graph modeling of the vessels and Iterative Local decision tree classifier. This paper models both the all the vessels and nodes in the retinal image. More over, we used structural knowledge to find node name in the graph. Experimental results are conducted on DRIVE, INSPIRE-AVR data sets and different aspects of the model are analysed. A comparative study with state of art algorithms is presented using accuracy values as shown in Table 3 & 4. The experimental results of the proposed method of classification of local decisions work on images of two different databases, irrespective of retinal images with different properties, such as differences in size, quality and angle of the camera. Future work will be based on the analysis of vessel characteristics for early diabetes detection, high blood pressure and cardiovascular disease.

REFERENCES

1. Patton N. et al., "Retinal image analysis: Concepts, applications and potential," Intl. journal of Retinal Eye Res., vol. 25, p. 99–127, Jan. 2006.
2. Nguyen T. T. and Wong T. Y., "Retinal vascular changes and diabetic retinopathy," Current Diabetes Rep., vol. 9, pp. 277–283, Aug. 2009.
3. Guan K., et al, "Retinal hemodynamics in early diabetic macular edema," Diabetes, vol. 55, pp. 813–818, Mar. 2006.
4. Neubauer A. S. et al, "Retinal vessel analysis reproducibility in assessing cardiovascular disease," Optometry Vis. Sci., vol. 85, p. 247–254, Apr. 2008.
5. Cheung N. and Wong T. Y., "The retinal arteriole to venule ratio: Informative or deceptive?" Graefe's Archive Clinical Experim. Ophthalmol., vol. 245, no. 8, pp. 1245–1246, 2007.
6. Liew G. et al, "Effect of axial length on retinal vascular network geometry," Amer. J. Ophthalmol., vol. 141, pp. 597–598, Mar. 2006.
7. Lesage S. R., et al , "Retinal microvascular abnormalities and cognitive decline: The ARIC 14-year follow-up study," Neurology, vol. 73, no. 11, pp. 862–868, 2009.
8. Sun C et al "Retinal vascular caliber: Systemic, environmental, and genetic associations," Survey Ophthalmol., vol. 54, no. 1, pp. 74–95, 2009.
9. Hubbard L. D., et al, "Methods for evaluation of retinal microvascular abnormalities associated with hypertension/sclerosis in the atherosclerosis risk in communities study," Ophthalmology, vol. 106, pp. 2269–2280, Dec. 1999.
10. Knudtson M. D et al, "Revised formulas for summarizing retinal vessel diameters," Current Eye Res., vol. 27, pp. 143–149, Oct. 2003.
11. Martinez-Perez M. E. et al, "Retinal vascular tree morphology: A semi-automatic quantification," IEEE Trans. Biomed. Eng., vol. 49, no. 8, pp. 912–917, Aug. 2002.
12. Rothaus K., Jiang X., and Rhiem P., "Separation of the retinal vascular graph in arteries and veins based upon structural knowledge," Image Vis. Comput., vol. 27, pp. 864–875, Jun. 2009.
13. Grisan E. and Ruggeri A., "A divide et impera strategy for automatic classification of retinal vessels into arteries and veins," in Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Sep. 2003, pp. 890–893.
14. Vazquez S. et al, "On the automatic computation of the arterio-venous ratio in retinal images: Using minimal paths for the artery/vein classification," in Proc. Int. Conf. Digital Image Comput., Tech. Appl., 2010, pp. 599–604.
15. Li H et al, "A piecewise Gaussian model for profiling and differentiating retinal vessels," in Proc. Int. Conf. Image Process., vol. 1. Sep. 2003, pp. 1069–1072.
16. Kondermann C., Kondermann , and Yan D., "Blood vessel classification into arteries and veins in retinal images," Proc. SPIE, Progr. Biomed. Opt. Imag., vol. 6512, no. 651247, Feb. 2007.
17. Niemeijer M., van Ginneken B., and Abramoff M. D., "Automatic classification of retinal vessels into arteries and veins," Proc. SPIE, Progr. Biomed. Opt. Imag., vol. 7260, no. 72601F, Feb. 2009.
18. Estrada R. et al, "Exploratory dijkstra forest based automatic vessel segmentation: Applications in video indirect ophthalmoscopy (VIO)," Biomed. Opt. Exp., vol. 3, no. 2, pp. 327–339, 2012.
19. Deng K., et al "Retinal fundus image registration via vascular structure graph matching," Int. J. Biomed. Imag., vol. 2010, no. 906067, Jul. 2010.
20. Snell R. S. and. Lemp M. A, Clinical Anatomy of the Eye. New York, NY, USA: Wiley, 1998.

AUTHORSPROFILE

Rama Krishna V.V, Department of Electronics and Communication Engineering, Laki Reddy Bali Reddy College of Engineering, Mylavaram, Andhra Pradesh, India-521 230.

Suman.M, Department of Electronics and Communication Engineering, KL University, Green Fields, Vaddeswaram, Gunturt, A.P., India-522 502.