Supervised Pixel Classification into Arteries and Veins of Retinal Images

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Abstract— **With the emerging computation techniques in the field of medical science such as in Ophthalmology; it is often required an automated technique for identification of pathological condition such as diabetic retinopathy which might cause serious problems like blindness. Retinal diseases are often characterized by modification in retinal vessels. Retinal blood vessels observed with fundus imaging provides important indicators not only for clinical diagnosis and treatment of eye diseases but also for systemic diseases such as diabetes, hypertension etc. which manifest themselves in the retina. Quantitative structural analysis of the retinal vasculature not only helps in the diagnosis of retinopathies but also provides potential biomarkers of systemic diseases. Such as arteriole to venule width ratio (AVR) is a parameter indicative of microvascular health and systemic disease. In this paper we performed retinal vessel's pixel classification into arterioles and venules using Neural Network on DRIVE database. Two types of feed-forward Neural Network are used: Back Propagation Network (BPN) and Probabilistic Neural Network (PNN). BPN gives 83.9% and where as PNN gives 85.1% pixel classification on 20 images. The ROC curve for BPN and PNN has value 0.83 and 0.87 respectively for the DRIVE dataset.**

Keywords— Retinal images, arteries, veins, classification, neural network

I. INTRODUCTION

Retinal blood vessels observed with fundus imaging, provide important indicators not only for clinical diagnosis and treatment of eye diseases but also for systemic diseases such as diabetes, hypertension etc. which manifest themselves in the retina. For example narrowing of retinal blood vessels are the early makers of cardiovascular risk [1]. It is important to classify retinal blood vessels into arterioles and venules for computerized analysis of the vasculature and for biomarker discovery such as AVR. Conventionally, AVR and other retinal vascular parameters are drawn from zone B - an annulus 0.5 to 1 optic disc (OD) diameter from the OD boundary [2,3]. Changes in vessel structure can affect arteries and veins differently and thus in (semi-) automatic retinal image analysis conclusion is drawn from the quantification of venular and arteriolar components distinctly. For instance, measuring the central retrial arterial equivalent (CRAE) and the central retrial venular equivalent (CRVE), which are used to calculate the arteriolar to venular width ratio (AVR) [4].

Developments in automated diagnostic systems offer great potential for retinal fundus imaging to be used in biomarker discovery studies. To this end, in this paper we classify vessel's pixels into arteries and veins in zone B of the retinal images from DRIVE dataset using neural network with only four discriminative features. In section II, literature review has been given and Methodology is explained in section III followed by Results in section IV. Finally, the results are discussed in section V.

II. RELATED WORK

Several authors reported various methods to classify retinal vessels into arterioles and venules in images from DRIVE dataset using different classifier and framework. In 2003, Huiqi, et al. [5] uses minimum Mahalanobis distance classifier for classification of 505 segments of vessels of 35 images obtained from a population-based study in Wisconsin. The success rate is 82.46% and 89.03% for the arteries and veins respectively in Zone B. In 2007, C.Kondermann et al. [6] classified vessels as arteries and veins using Neural Network and Support Vector Machine. The test is performed on 1024*1280 retinal images containing 10132 different vessel skeleton pixels. NN with the combination of Region of Interest (ROI) resulted in 95.23% vessel pixel classification and SVM with ROI resulted in 92.84% vessel pixel classification within three diameters of the optic disk region.In another study, N.Karssemijer et al. presented a supervised, automatic method which determined artery or vein in a vessel based on intensity and derivative information [7]. They extracted features using steered Gaussian filter from the images in DRIVE database. ROC for 20 testing images was 0.88 for correctly classified pixels. In 2011, G.Mirsharif et al. in [8] performed the vessel classification on DRIVE database using 6 features which were selected via features selection method. The best result was achieved using LDA when classification was found on major vessels. Their method resulted in accuracy of 86% on major vessels and 87.53% on main pair vessels in upper and lower region. The classification of major arteries was performed on whole image but not in specific zone. Diego Marin, et al. [9] presented a supervised method using Neural Network for pixel classification on DRIVE and STARE databases. Their methodology computes 7-D vector composed of Gray-level and moment invariants-based features for pixel representation. The area under curve measured for both curves was 0.9769 for DRIVE and 0.9588 for STARE databases. In [10] Jihene, et al. classifies vessel's pixels into arteries and veins using Multi Layer Perceptron. They use Principle Component Analysis for

feature selection. Their approach of feature selection and classification resulted in 95.32% on DRIVE database. In [11] the author performed multifeature analysis for identification of vessels using multiscale vesselness measures and Gabor filters [11]. Adaptive threshold selection method was used with a post processing technique giving ROC curve value up to 0.9616 on DRIVE database.

III. METHODOLOGY

A. Material

In this paper we have used DRIVE dataset for retinal vessel classification. The total 40 images from DRIVE dataset are divided into 20 Training and 20 Testing images. Classification was performed on 171 vessels extracted in similar manner as explained in [12]. Ground truth was generated to compare the final classification results.

B. Pre-processing of images and extraction of centerline pixels

The contrasts or color variability would affect the classification results adversely thus all images were first pre-processed. We preprocessed red, green and hue channel images for background illumination using a method explained in [13]. The Hue channel was also pre-processed to improve the contrast of vessels against background before illumination correction by mapping the original intensity values such that values between 0.01 and 0.8 maps to values between 0 and 1. Four distinctive features were then extracted from centerline pixels of illuminated corrected image. Centreline pixels of vessels in zone B were extracted as previously reported in [12]. In order to extract centerline pixels from zone B first the intensity profile across the vessel axis is obtained. Next the canny edge detection method is applied to each of these profiles to locate vessel edges and finally the centerline pixels are located as the midpoint of pair of edges selected. Canny detection method is explained below:

Areas with strong intensity contrasts in an image are edges. Edge detection method in images suppresses the useless information and preserves the important structural properties in an image. It is an optimum edge detector because of its low error rate. All the edges in an image should be noticed, edge-points should be well localized. The algorithm aims at finding the minimum distance between edge pixels and actual edge. It is required that each single image should have only one response. Based on the above criteria's, firstly the detector smoothens the image to eliminate noise. Edges are marked where the gradients of image have large magnitudes. Local maxima are only marked as edges. The gradient error is further reduced by hysteresis. Pixels which are not suppressed, hysteresis track them using two thresholds. If magnitude is below first threshold, it set to zero therefore a non- edge. If it is above threshold, it is made an edge. If it's between the two thresholds, it is set to zero unless a path is present from this pixel to a pixel with the gradient above.

C. Feature Extraction

Retinal vessels can be distinguished into arterioles and venues using different colours features. The four colour features used in our study are set of colour features which are proven statistically important in differentiating between arteries and veins [14]. After the centreline pixels were found, four colour features viz. MR (mean of red), MH (mean of hue), MG (mean of green) and VR (variance of red) were extracted from illuminated corrected channels. These were extracted around the centre of centreline pixels, with diameter 60% of the mean vessel diameter [15]. Finally Neural Network classifier was applied to classify vessel's pixels into arterioles and venules using these features. Figure 1 shows the flowchart representing the procedure undertaken for the pixel classification into arteries and veins representing the original DRIVE dataset image and illuminated images.

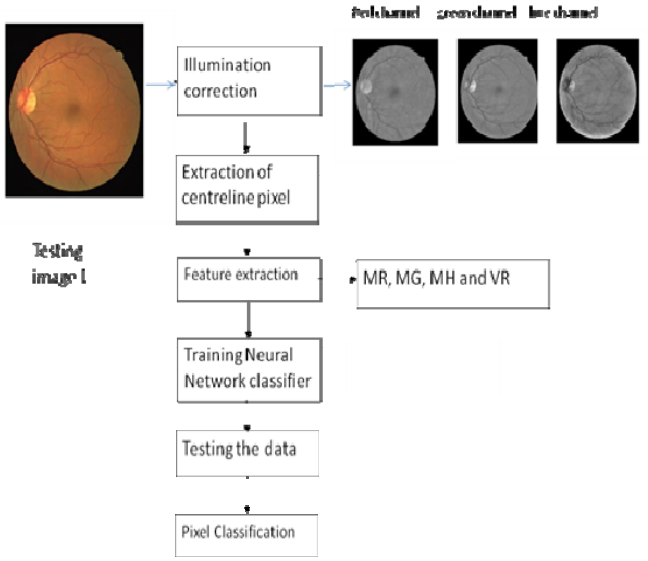

Figure 1: Flowchart representing Methodology

IV. RESULT

The vessel's pixel classification was evaluated on publicly available DRIVE database. The efficiency analysis was evaluated using Receiver Operating Curve (ROC). It plots variation of false ratio versus true ratio. The closer the curve approaches the top left corner, the better the performance of the system. ROC for BPN and PNN is 0.83 and 0.87 respectively.

Total 1730 pixel vessels from 171 vessels were classified. BPN results in correct classification of 83.9% whereas PNN resulted in correct classification of 85.1% as shown in figure 2 and 3 respectively.

Confusion matrix tells us about the classification result or the performance of an algorithm. High numbers of responses are shown in the green squares and the low numbers of correct incorrect responses in the red squares. The lower right blue

squares illustrate the overall accuracies Table I shows the result obtained by each classifier.

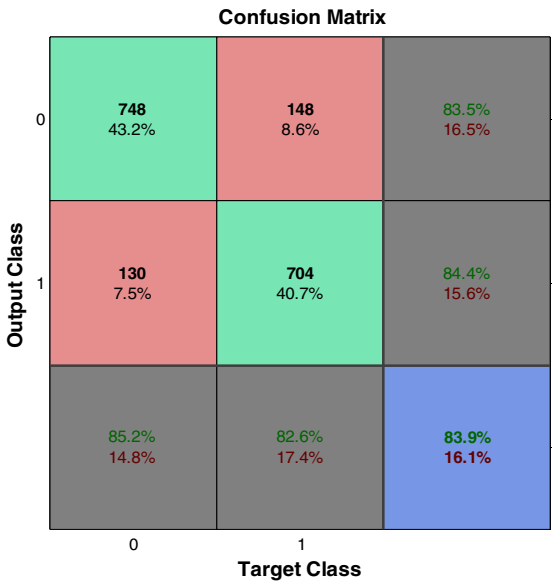

Figure 2.Confusion Plot for BPN for DRIVE dataset

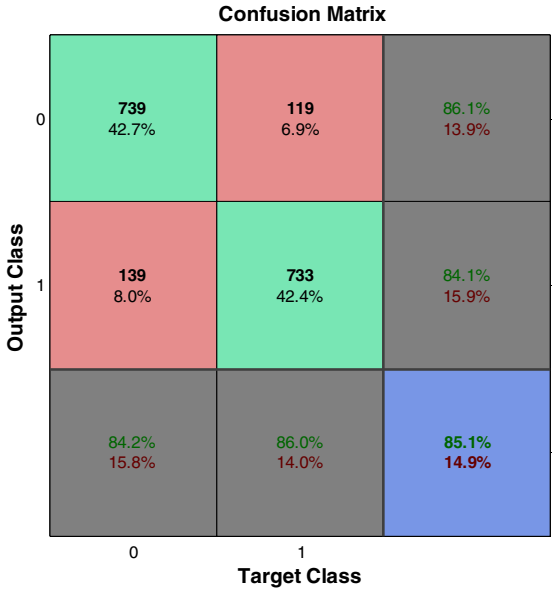

Figure 3: Confusion Plot for PNN for DRIVE dataset

TABLE I : CLASSIFICATION RATE

	BPN	PNN
ROC	0.83	0.87
Overall Pixel classification	83.9%	85.1%

V. DISCUSSION AND CONCLUSION

It is very time consuming to annotate vessels manually hence it is required to design a method which can classify vessels into arterioles and venules automatically. In this paper we proposed a supervised method using four colour features to classify arteries and veins automatically using Neural Network.

Many authors have performed vessel classification on DRIVE dataset using different classifier, features and framework [9, 10, 11]. We have used a simple and widely used supervised Neural Network classifier with only four colour features unlike those work which uses feature selection method [8,10] which is often time consuming. As we have used only fixed four features for classification which make our classification framework faster as extracting and then selecting distinctive features from bank of features is time consuming task.

Our approach resulted in similar result with PNN classifier as compared to [7] who uses different features and supervised classifier. PNN is giving better classification result in comparison to BPN. PNN is a Bayesian classifier implemented in parallel unlike BPN which is trained iteratively. This makes training of parameters faster as compared to traditional Neural Networks. PNN is robust over standard Neural Network.

We conclude that the performance of our system is very promising and producing similar result as compared to recently reported methods even by using only four colour features and simple Neural Network classifier as compared to others recently reported work yet results in a similar classification rate. However, the classification performance may differ on different datasets. The results are highly dependent on locating center line pixels. Also pixel classification on different retinal zone also affects the classification performance. Moreover different classifier and framework would also have an impact on classification rate. Further tests on large, ideally public, are needed to assess comparatively and reliably classification algorithms.

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