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Retinal Microaneurysm Detection and Post Rocessing for True Vessel Extraction

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Abstract: Diabetic Retinopathy (DR) is the leading ophthalmic pathological reason of blindness among people of working age in developed countries. The main cause of DR is abnormal blood glucose level rise, which damages vessel endothelium, causing an increase in the vessel permeability. The initial manifestations of DR are tiny capillary dilations known as microaneurysms. A method for automatic detection for Microaneurysm and post processing for true vessel extraction in the retinal image is implemented. The proposed system uses the images obtained from diaretdb0 and diaretdb1 database. The preprocessed images are converted to gray and green channel to which the Canny edge detection operator is implemented for the retinal image segmentation based on a threshold value. Further, from the segmented image the combined features for the microaneurysm and true vessels are extracted by using Receiver Operating Characteristics. Finally, the extracted features such as area of blood vessel, area of microaneurysm, entropy and homogeneity are given to the classifiers such as BPNN, KNN and NB classifiers. Thus a combined approach for microaneurysm detection and post processing for true vessel extraction has been implemented and the accurate results are obtained. The proposed system is a novel approach which overcomes all the disadvantages of the existing system. The performance analysis of three different classifiers such as KNN, NB and BPNN has been analyzed and their comparative results proved that KNN classifier outperforms other two classifiers. This kind of systemic processes may be a new perspective in detection, classification and identification of retinal blood vessels and microaneurysm detection. The experimented effectiveness and robustness, together with its simplicity and fast implementation, make this proposed automated blood vessel segmentation and microaneurysm detection method a suitable tool for being integrated into a complete prescreening system for early detection of DR.

Key words: Retinal Vascular Organization · ROC · Diabetic Retinopathy · Microaneurysm Diaretdb · Diaretdb 1 · Threshold value

INTRODUCTION

Diabetic Retinopathy (DR) is the leading ophthalmic pathological reason of blindness among people of working age in developed countries [1]. It is induced by diabetes-mellitus impediment and, although diabetes affectation does not necessarily involve vision impairment, about 2% of the patients affected by this disorder are blind and 10% undergo vision dilapidation after 15 years of diabetes [2, 3] as a consequence of DR complications. The anticipated rate of recurrence of diabetes for all age groups worldwide was 2.8% in 2000 and 4.4% in 2030, intending an alarming forecast on the rise of diabetes patients from 171 million in 2000 to 366 million in 2030.

The main cause of DR is abnormal blood glucose level rise, which damages vessel endothelium, causing an increase in the vessel permeability. The initial manifestations of DR are tiny capillary dilations known as microaneurysms. DR development also causes neovascularization, macular edema, hemorrhages and, sooner leads to retinal disconnection [4].

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Eventhough DR is not a curable disease; laser photocoagulation can prevent primary vision loss if detected in early stages [1, 5]. However, DR patients perceive no symptoms until visual failure develops, usually in the later disease stages, when the treatment is less effectual. So, to ensure the healing is received in time, diabetic patients need yearly eye-fundus examination [6]. However, this preventive action involves a huge challenge for Health Systems due to the huge number of patients needing ophthalmologic revision, thus preventing patients from receiving adequate treatment.

The employment of digital images for eye disease diagnosis could be exploited for computerized early detection of DR. A system which could be used by non experts to filtrate cases of patients not affected by the disease, this would reduce the workload of specialist, which will increase the effectiveness of protective protocols and early therapeutic treatments. In addition, it would also result in economic benefits for public Health Systems, since cost-effective treatments coupled with early illness detection lead to remarkable cost savings [7, 8]. Since vascular anomalies are one of DR materialization, automatic assessment of eye-fundus blood vessels is necessary for automated detection of DR. As an earlier step, vessel assessment demands vascular tree segmentation from the background for further processing. Information on blood vessel location can be used to reduce the number of false positives in microaneurysm and hemorrhage detection [9-12]. Also these applications will motivate automated early detection of DR, in addition vascular tree segmentation is useful for other clinical purposes such as evaluation of the retinopathy of prematurity [13-15], arteriolar narrowing [16, 17], vessel tortuosity to characterize hypertensive retinopathy [18], vessel diameter measurement to diagnose hypertension and cardiovascular diseases [19-21] and computer-assisted laser surgery [22, 23], among others.

On the other hand, the vascular tree can also be useful to locate vital fundus features such as the optic disc [24] and the fovea. Additionally, it may serve as a mean for the registration of multimodal images [13, 14].

Retina: In the center of the retina is the optic nerve, a circular to oval white area which measure about 2 x 1.5 mm. From the center of the optic nerve radiates the major blood vessels of the retina. Approximately 17 degrees (4.5-5 mm), or two and half disc diameters to the left of the disc, a slightly oval-shaped, blood vessel-free reddish mark can be seen, the fovea, which is at the center of the area known as the macula by ophthalmologists.

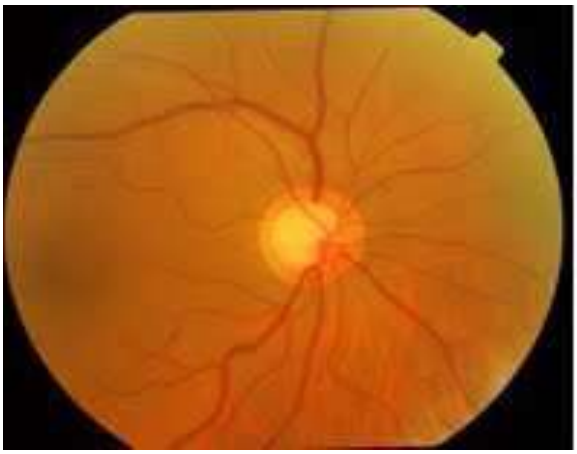

Fig. 1: A view of Retina seen through Ophthalmoscope

There are two sources of blood supply to the mammalian retina: the central retinal artery and the choroidal blood vessels. The choroid receives blood flow (65-85%) (Henkind *et al*., 1979) and is vital for the maintenance of the outer retina (particularly the photoreceptors) and the remaining 20-30% flows to the retina through the central retinal artery from the optic nerve head to nourish the inner retinal layers. The middle part of retinal artery has 4 main branches in the human retina. The vessels in Figure 1 emerge from the Optic nerve head and run in a redial fashion curving towards and around the fovea.

MATERIALS AND METHODS

This proposed system as shown in figure 2 uses the digital images of the databases diaretdb0 and diaretdb1. The retinal vascular organizations of these two databases are very accurate and faultless. The resized image further implicated with two different progressions of channel (Gray and Green channels particularly) conversion. These extracted features are improved with CLAHE (Contrast Limited Adaptive Histogram Equalization) technique. The morphological procedure is performed for optic disk for the removal of noise. The difference between its' MATLAB based erosion and dilation processes on basis of Canny-Edge Detection technique with Threshold value.

The combined features of microaneurysm and true vessels are obtained using Receiver Operating Characteristics (ROC). These combined features are then given to three different neural network classifiers such as Back Propagation Neural Network (BPNN), Bayes classifier and KNN and the parameters are calculated and the comparative results are analyzed.

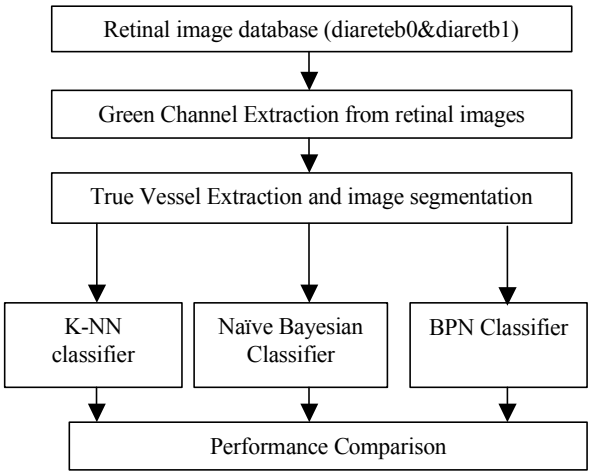

Fig. 2: Proposed Scheme for Segmentation and Classification

The performance measure with ROC is useful for retinal blood vessel identification. This kind of systemic procedure may be a new perspective in detection, classification and identification of retinal blood vessels and microaneurysm detection. Classifiers performance is improved by the inclusion of two post processing steps; the first step is aimed at filling pixel gaps in detected blood vessels, whereas the second step is aimed at removing erroneously detected isolated vessel pixels. From the visual inspection of NN output, vessels may have a few gaps (i.e., pixels completely surrounded by vessel points, which are not labeled as vessel pixels). To alleviate this problem, an iterative filling operation is carried out by considering that pixels with at least six neighbors are classified as vessel points must also be vessel pixels. Besides, small secluded regions are misclassified as blood vessel pixels are also observed. To remove these artifacts, the pixel areas in all associated regions are calculated. In artifact removal, each region connected to an area below 25 is reclassified as non vessel.

Feature Extraction: The aim of the feature extraction stage is pixel characterization by means of a feature vector, the pixel representation in terms of some quantifiable measurements which may be easy to be used in the classification stage to decide whether pixels belong to a real blood vessel or not and to classify microaneurysm affected image or not. In this paper, the following sets of features were selected, they are, Area of microaneurysm, area of vessels, homogeneity and entropy. The figure 3 shows some sample output images of our proposed system.

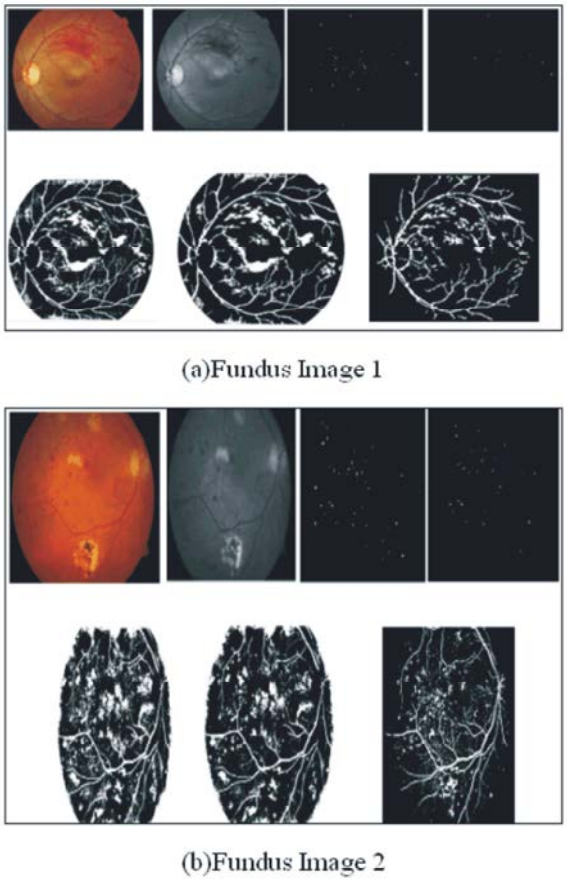

Fig. 3: Detected Microaneurysm and Extracted True Vessel after Post Processing for two different fundus images

Classification: In the feature extraction phase, each pixel from a fundus image is characterized by a vector. Now, a classification formula assigns one of the classes normal or abnormal to each candidate pixel. In this paper three different classifiers are put into practice and their performances are compared. The classifiers are K-NN method, Naïve Bayesian classifier, Back Propagation Neural Network.

In K-NN classifier, Classification using an instance-based classifier can be of locating the nearest neighbor in instance space and labeling the unknown instance with the same class label as that of the located (known) neighbor. This approach is often referred to as a nearest neighbor classifier.

K is a constant defined by the user and the unlabeled vector is classified by assigning the label which is most frequent among the K training samples nearest to that particular query point. The class of each of the *k* nearest points is multiplied by a weight proportional to the inverse of the distance from that particular point to the

test point. The better models can be achieved by locating k, where k > 1, neighbors and letting the majority vote decide the outcome of the class labeling. A higher value of k results in a smoother, less locally sensitive, function. The drawback of increasing the value of k is of course that as k approaches n, where n is the size of the instance base, the performance of the classifier will approach the assumption that all unknown instances belong to the class most frequently represented in the training data.

The advantage of K-NN is that it is analytically tractable, simple implementation and nearly optimal in the large sample limit and uses local information, which can yield highly adaptive behavior lends itself very easily to parallel implementations.

Naïve Bayesian classifier is a simple technique which assigns class labels to problem instances, represented as vectors of feature values, where the class labels are haggard from some finite set. The Bayesian Classification represents a supervised learning method as well as a statistical method for classification. It allows us to capture uncertainty about the model by determining probabilities of the outcomes. It can solve diagnostic and predictive problems.

It is based on Bayes theorem that mainly deals with probabilistic models:

$$P(h/D) = \frac{P(D/h)\,P(h)}{P(D)}$$

where,
P (h) : Prior probability of hypothesis h
P (D) : Prior probability of training data D
P (h/D): Probability of h given D
P (D/h): Probability of D given h

D: Set of tuples. Each tuple is an 'n' dimensional attribute vector.

X: (x1,x2,x3,.... xn)

Let there be 'm' Classes: C1, C2, C3...Cm. Naïve Bayes classifier predicts X belongs to Class C_i iff P (Ci/X) > $P(C_j/X)$ for 1<= j <= m, j <> i. The advantage of using Naïve Bayes is that it requires a small amount of training data to estimate the parameters.

Back propagation neural network requires a known, desired output for every input value in order to calculate the loss function gradient. As a result this method is considered to be a supervised learning algorithm, although it is used in some unsupervised networks such as auto encoders. It is a generalization of the delta rule to multi-layered feed forward networks, which is made possible by using the chain rule to iteratively computing gradients for each layer.

Input layer neurons are linear whereas neurons in the hidden and output layers have sigmoid functions. Vector or scalar variables will be respectively subscripted or superscripted by the iteration index k. We assume that network is homogenous in the sense that all neurons use similar signal functions. For linear neurons in the input layer,

$$\delta(x)=x$$

and for sigmoid neurons in the hidden and output layers,

$$\delta(x)= 1/1+e^{-\ddot{e}x}$$

The network is first initialized by setting all its weights to a small random numbers between –1 and +1. The input pattern is applied and the output calculated termed as forward pass. The calculation provides an output which is completely different the target, since all the weights are random. We then calculate the Error of each neuron as Target - Actual Output. This error is then used mathematically to change the weights in such a way that the error will get smaller. The output of each neuron will get closer to its target termed as reverse pass. The process is repeated again and again until the error is minimal.

Performance Evaluation: To evaluate the performance of the proposed method, the parameters such as sensitivity, specificity, accuracy and precision along with the help of true positive, true negative, false positive and false negative values. In this proposed method 50 images are used for training and 50 images for testing. Out of 100 images 61 are the abnormal, which are trained by 1 and other 39 are the normal, trained by 0.

The performance of classification algorithm is assessed by computing the percentages of Sensitivity (SE), Specificity (SP),Accuracy (AC) and Precision (P).

SE = TP/(TP+FN)*100
SP = TN/(TN+FP)*100
AC = (TP+TN)/(TP+TN+FP+FN)*100
P = (TP)/(TP+FP)*100

where,
TP is the number of true positives images, TN is the number of true negative images; FN is the number of false negatives images and FP is the number of false positive images.

Table 1: Performance Parameters for Various Classifiers

Parameters	KNN	NB	BPNN
True positive	60	54	42
True negative	38	43	51
False positive	1	1	5
False negative	1	2	2

Table 2: Performance Evaluation for Various Classifiers

Parameters	KNN (%)	NB (%)	BPNN (%)
Accuracy	98	97	93
Sensitivity	98.36	96.4	95.45
Specificity	97.45	97.7	91.07
Precision	98.36	98.18	89.36

The table 1 shows the values that are obtained from the classifiers. The total numbers of images that are considered are 100 and the table gives the performance of the classifier over the input fundus retinal image.

The performance evaluation of the classifier in terms of sensitivity, specificity, precision and accuracy. The term sensitivity (true positive fraction) is the probability that a diagnostic test is positive means that the person has the disease. Specificity (true negative fraction) is the probability that a diagnostic test is negative means that the person does not have the disease. The results of performance analysis using KNN, NB and BPNN classifiers are shown in Table 2.

CONCLUSION

Thus a combined approach for microaneurysm detection and post processing for true vessel extraction has been implemented and the accurate results are obtained. The proposed system is a novel approach which overcomes all the disadvantages of the existing system. The performance analysis of three different classifiers such as KNN, NB and BPNN has been analyzed and their comparative results proved that KNN classifier outperforms other two classifiers. This kind of systemic processes may be a new perspective in detection, classification and identification of retinal blood vessels and microaneurysm detection.

The experimented effectiveness and robustness, together with its simplicity and fast implementation, make this proposed automated blood vessel segmentation and microaneurysm detection method a suitable tool for being integrated into a complete prescreening system for early detection of DR.

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