ARPN Journal of Engineering and Applied Sciences

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MICROANEURYSMS EXTRACTION WITH VESSEL NEIGHBORHOOD SEPARATION, SVM AND CONNECTED COMPONENT EXTRACTION

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ABSTRACT

The severe problem of Diabetic retinopathy (DR) is ever increasing issue in today's world. In order to get of it, the possible way is to take steps to detect the same at its early stage. The root cause for the disease appears in the form of micro-aneurysms (MA). These MA are minute red dots accumulated near the blood vessels. General techniques are not quite useful in identifying them. In this paper, we first extract the retinal vessels using Coyefilter technique which uses methodologies like PCA and thresholding using an iterative selection method. Then the retinal classified namely as vessel and non-vessel Neighborhood Region. This is done in order to accelerate the performance of SVM for correctly identifying the microaneurysms. Traditionally, the SVM engine is trained first with positive and negative samples from fundus images. Then by sliding window technique, the entire test image is divided into parts and each part is sent to the SVM engine to identify the microaneurysms. The computational time of the algorithm is dependent on the image size. To reduce this, the vessel neighborhood regions are only sent to SVM engine and thus reducing the computation time and increasing the accuracy. microaneurysms in the vessel neighborhood region are extracted using connect component extraction and classified based on features extracted. Thus improving the overall performance and sensitivity of the system. The algorithm has been thoroughly tested on numerous images and it outperformed the existing counterparts.

Keywords: microaneurysms, SVM, VNR, NVNR, connected component.

INTRODUCTION

Diabetes is a chronic disease which is caused when the pancreas are unable to produce the insulin into the body. Insulin is a hormone which is released by the pancreas which helps the glucose obtained from the food taken, to the blood stream to produce energy. When the insulin is not used effectively it raises the glucose levels in the body leading to the damage and failure of various organs and tissues. People with diabetes are comprised with a group of eye conditions. They might include diabetic retinopathy, diabetic macular edema, cataract, glaucoma. However, the main source of visual impairment is due to a diabetic condition called the diabetic retinopathy. With the increase in glucose levels, the blood vessels get severely effected. This leads to DR. The major cause for DR is the leakage of blood along with several fluids. This leakage slowly accumulates in the retinal causing swelling. The identification can be done with the following symptoms.

a) Dots/floaters in vision.
b) Dazzling.
c) Dot appearing during convergence of the vision.
d) Night Vision Problem.

Classification of DR is as:

- **Non-Proliferative Diabetic Retinopathy (NPDR):** It is also known as background retinopathy. It is the early stage of the diabetic retinopathy where the symptoms are mild or non-existent. In NPDR the blood vessels in the retina are dwindled, which causes the tiny blood vessels to bulge or swell called as microaneurysms, which may leak blood and other fluids into the retina. As a result macula abrupt swelling can be witnessed.
- **Proliferative DR (PDR):** PDR refers to a serious complication of diabetes mellitus. At this stage, circulation problems deprive the retina of oxygen. Under such condition the blood vessels are severly damaged. The reason for this abnormal growth of blood vessels in the retina in the synthesis and release of vascular endothelial growth factor. This continuously enhance the retina volume. Thus, the swelling retina and the factor mentioned above develop a huge volume of fluid behind the eye. These conditions of Retinal detachment can lead to loss of vision if it involves the macula. Other serious complication of PDR is neovascular glaucoma (NG). The NG quickly impacts the optic nerve. This usually forms due to the unusual growth on the iris as well as trabecular area. When PDR is untreated it cause pressure and defected vision of eye.

Jian Zheng, Pei-Rong Lu used multi scale hessian transform for vessel extraction. Further non local means filter can be employed for enhancing efficiency [2]. It is experimented in [17] with local rotation. However, for testing of presence of MA, the novel scheme of hypothesis testing has been proposed {18, 7, 13-16]. The red lesions, which are significant factors of MA identified by applying top hat transform [2, 8, 9-12]. The popular radon transform is applied for the purpose of identifying defecting region in fundus images [4]. Similarly, the curvelets which belong to the same class are also employed for the same purpose. Further, the procedure performs reconstruction which inturn enhances the performance. In this paper, the study is limited to non-proliferative diabetic retinopathy and in particular to the extraction of tiny red haemorrhages named micro aneurysms. Considering the above, in the present work the scope is limited to non-proliferative DR. this also involves in identification of tiny red MA.

Proposed technique

The proposed methodology adopted for the technique can be easily justified using the flow chart in Figure-1. Initially, the image is processed using image processing techniques like enhancement and contrast balance. This is further used to learn the vessels distribution. The image segmentation part separates the neighborhood and non-neighborhood region. The SVM classifier is applied on the first region, while the connected component based classifier is employed enhances performance and accuracy of SVM for the problem defined.

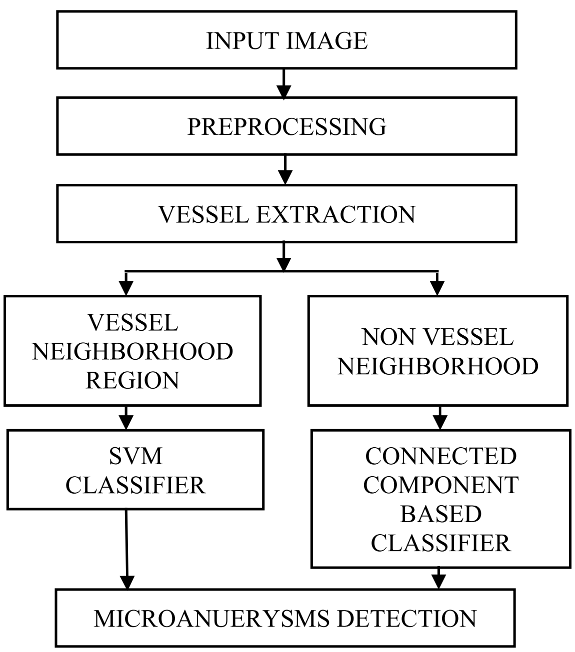

Figure-1. Block diagram.

Vessel extraction

From the flow chart it can be learned that the significant step following the preprocessing is vessel extraction (VE) [1]. In its simple form, the VE can be explained as:

- Image learning
- Resizing
- RGB to Gray scale conversion
- Contrast enhancement
- Background separation
- Filtering and substraction
- Thresholding (Iso DATA METHOD)
- Binary conversion
- Small pixel elimination.

The method suggested in [3] is adopted for its global Thresholding which is refered to as LEVEL is employed to transform. Intensity information of image to binary data which typically consists of either ‘0’ or ‘1’. Segmentation of the corresponding histogram of the image is performed using initial threshold level and half max dynamic range. The sample means of foreground and background pixels are determined and mentioned as (mf, 0) and (mb, 0) respectively. Following this step the threshold level is modified as ‘1’. Similarly, the process is repeated till the threshold is stable.

Connected component based classifier

A connected component is nothing but in a set of pixels, each pixel is connected to all other pixels if at all a connection between these pixels exist. The algorithm used to extract the connected components is referred to as Depth First Search which is as shown in Figure-2. It starts exploring as far as possible along each branch precisely in the boundary. The algorithm typically considers the triangularly connected components of the red node.

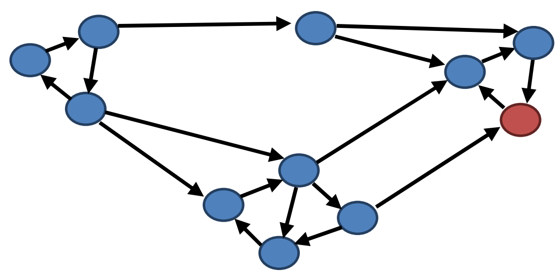

Figure-2. Fully connected graph.

This essentially refers to a case where the performance of DFS is elevated in determinations based on firmly connected components. But, the problem with DFS is that it must be performed from the right place to uncover the Strongly Connected Component (SCC), if performed on a wrong place no information will be produced. This is explained with the example, suppose the DFS is not performed on the nodes from this triangle, but is performed on the bottom most node in green, it will find everything findable, i.e. it considers everything is in its own SCC. If DFS is performed from this green point then all the nodes are captured. Suppose if the DFS is performed from the left-most node, it discover the entire graph. That is the reason why DFS has to be performed in the right place. The obtained connected components extracted are filtered based on the properties like area, component colour, closeness to the vessel etc.

Support vector machine

The technique which is capable to understand the algorithm and to analyze the data we use Support Vector Machine (SVM). It is utilized both in industry and as a part of Academia. The SVM gives a cleaner and deep insight for learning complex nonlinear capacities.

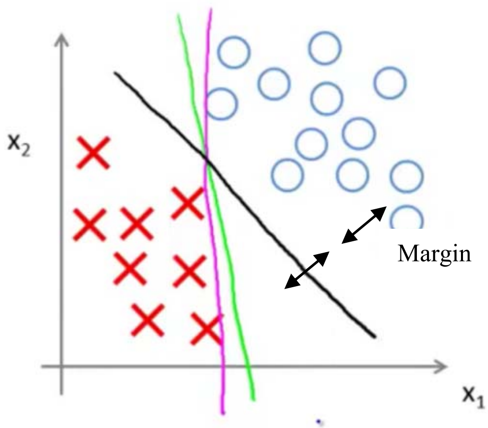

Figure-3. SVM training data sets.

Consider the information set that has appeared in the Figure-3, with positive and negative illustrations, the information thus obtained can be detached and we can imply that there exist straight lines that can isolate the positive and negative cases effectively. The positive and negative samples are isolated using a separator which has appeared in green. There's another limit in magenta that isolates positive and negative samples marginally.

In any of these cases, neither of these can be considered as a great decision. The SVM will pick this choice limit which is black in shade. This can be considered as a vastly improved choice limit than both of the alternate ones. The dark line appears like a potent separator, it improves the isolation of positive and negative cases.

Furthermore, mathematically it signifies that the SVM classifier has a greater distance in classifying the things. This distance is technically called as margin. When compared to the other two classifiers the margin for SVM is far high. As the SVM tries to increase the mrgin of classifier it can be treated as one of the most excellent classifier. So the SVM is sometimes called as large margin classifier.

Experimental results

The first stage is pre-processing and the extraction of the vessels using coyefilter.

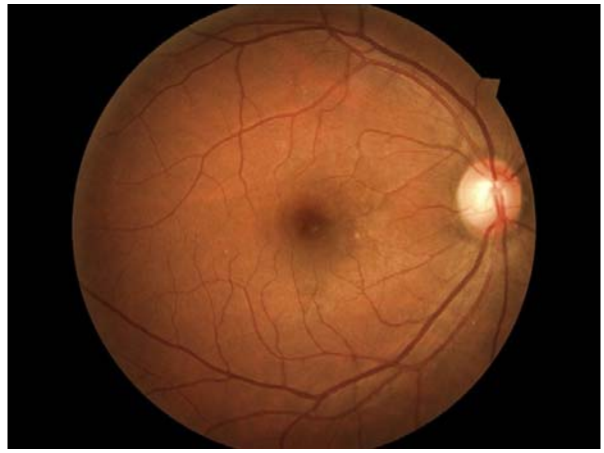

Figure-4. Input training image for vessel extraction.

Figure-5. Vessel output of the test image.

The output of this stage is used to form the vessel neighbourhood region and non vessel region.

Figure-6. Vessel Neighbourhood color.

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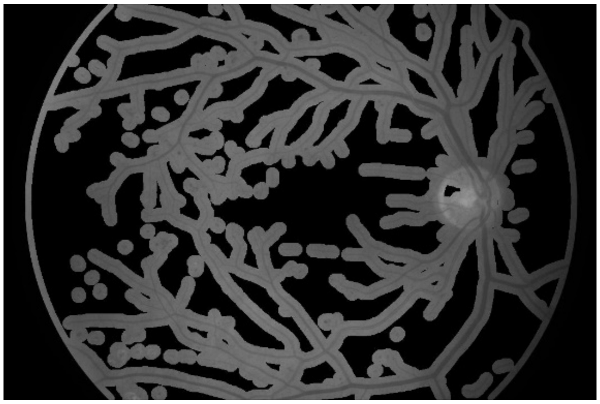

Figure-7. Vessel neighbourhood gray scale.

Figure-8. Non vessel neighbourhood color.

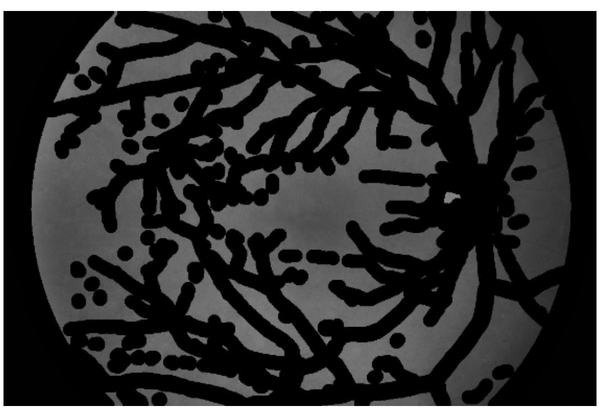

Figure-9. Non vessel neighbourhood gray scale.

The process accelerates the time of execution and thus provides faster results.

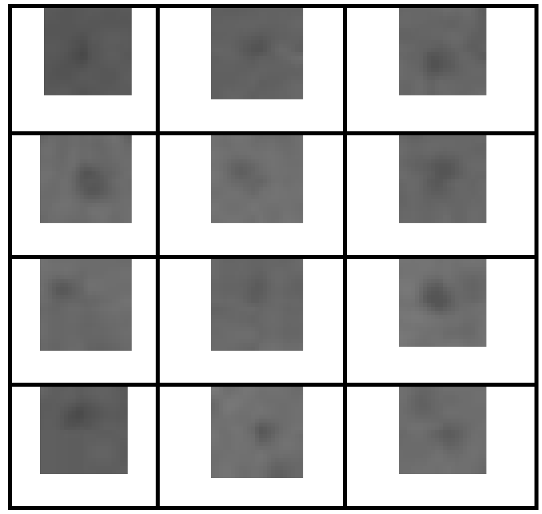

Figure-10. Positive training samples for SVM.

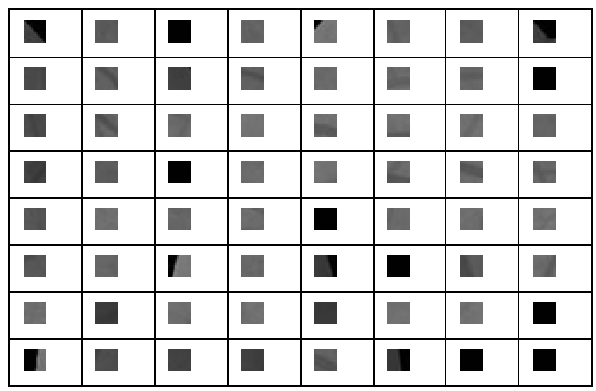

Figure-11. Negative training samples for SVM.

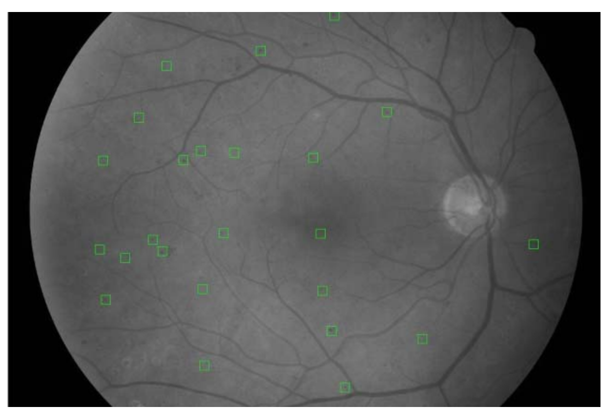

Figure-12. Final output showing the microaneurysms.

The proposed method reduces the false positives thus increasing the overall efficiency.

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Table-1. The True Positives (TP) and sensitivity values are recorded.

S. No.	True positives	Output count (without vessel suppression) [1]	Sensitivity [1]	Output count(after vessel suppression) [1]	Sensitivity[1]	Output count proposed method	Sensitivity proposed method
1	41	91	.4271	75	.547	60	.683
2	9	21	.428	15	.6	12	.75
3	29	68	.4265	45	.644	39	.74
4	24	56	.428	40	.6	36	.667
5	4	10	.400	8	.5	8	.5
6	49	112	.438	90	.544	80	.6125
7	50	98	.510	80	.625	75	.667
8	6	13	.462	10	.6	10	.6
9	25	61	.409	45	.556	42	.595
10	14	29	.482	25	.56	20	.7
11	33	83	.398	60	.55	52	.634
12	27	60	.45	45	.6	40	.675

CONCLUSIONS

The inclusion of Coye filter for the extraction of vessels from fundus images has increased the sensitivity of the system in extraction of the microaneurysms as the vessel extraction in done with great accuracy. The SVM classifier then efficiently detects the microaneurysms by sliding wiondow method where each patch in the image is scanned for the presence of microaneurysms.

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