International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-10, August 2019

A Machine Vision Based Detection & Classification of Neovascularisation in Retinal Blood Vessels

S.Sudha, A.Srinivasan, S.Karthik, S.Hari Krishnan, S.Prakash

Abstract- Diabetic Retinopathy is an eye disease which is caused by excessive sugar level in blood. Insufficient secretion of insulin hormone is the ground for evolution of diabetes. It affects most of the important organs in our body. There are two types of DR: Non Proliferative Diabetic Retinopathy and Proliferative Diabetic Retinopathy. In this proposed system techniques are introduced to detect and classify neovascularisation. Input fundus image is preprocessed by median filtering and further new vessels are segmented by using Fuzzy c-means clustering algorithm. After segmentation SIFT features are extracted and are used to train support vector machine (SVM) classifier. This automated system has been tested for 70 fundus images and accuracy of 96% is achieved.

Keywords- Diabetic Retinopathy (DR); Median Filtering (MF); Fuzzy C-Means Clustering algorithm (FCM); Support vector machine (SVM) classifier; Neovascularisation (NV)

1. INTRODUCTION

At present, diabetes is a serious issue and many people are suffering from diabetic disorders. One of the most serious complications is Diabetic Retinopathy.Diabetes causes leakage of blood in the retinal blood vessels. Based on the size & area of the blood clots we classify affected fundus images into Microaneurysms (Ma) & Haemorrhages (HE).The yellowish like structures will also appear in the retina due to excretion of bio-chemical materials. These are called as Exudates. Sometimes white fluffy like structures appear with random size and are called as cotton wool spots. These four categories are coming under Non-proliferative (early stage) of diabetic retinopathy. In the advanced stage, large number of very thin blood vessels which are brittle will grow in the retina. This is called as neovascularisation.

Due to diabetes, the blood supply into and out of the retina will be interrupted which leads to retinal ischemia and it causes retinal cells to release signal ie. Vascular endothelial growth factor (VEGF) and in response to this stimulation new blood vessels will grow in the retina to compensate for the deterioration in blood vessels. But new vessels are not strong and it can be twisted and misdirected. Sometimes new vessels can extend into vitreous layer and this layer can shrink over ages. Moreover it exerts force on new vessels and results in vitreous hemorrhage. This will lead to vision loss and consequently retinal detachment will occur. Neovascularisation are extracted using fuzzy c means segmentation and classification is done by using SVM classifier.

II. RELATED WORKS

In [1] proposed system uses curvelet transform, matched filter and optimal thresholding to distinguish thick and thin blood vessels. Density of the vessels and tortuosity are measured for the classification of neovascularisation and normal blood vessels. The achieved average accuracy is 97.49%.In [2]analysis is done based on texture both at image and patch level to detect neovascularisation. Sensitivity is 92.4% and specificity of classifier is 92.6% .The proposed [3] learning machine for the detection of neovascularisation is tested for public image databases. Several filter banks are connected in series for the extraction of useful features that supports the learning machine for decision making.

The combined approach is followed [4] such as normalisation , morphological operation, filtering and classifier for the detection of neovascularisation. Classification is done on region based algorithm to improve the neovascularisation accuracy. It is tested for various test images and the specificity of 89.4% and sensitivity of 63.9% is recorded. Gabor filtering is used for[5] blood vessel segmentation. Feature extraction uses texture and morphological process and the features are used to train classifier. For testing of 424 fundus images, SVM classifier is used for classification of normal and neovascularisation images. Totally 42 features are extracted and it is reduced to 18 after the dimensionality reduction. Achieved accuracy of proposed algorithm is 95.23% .

In [6] blood vessels are detected using image processing algorithms. Fractal analysis box counting measure is used to detect neovascularisation near optic disk. The fractal mean value of normal and DR images are 1.52 and 1.66 respectively. The retinopathy of prematurity [7] is discussed and efficient mosaicing algorithm is used for finding abnormality in neonatal images.

Manuscript published on 30 August 2019.
***Correspondence Author(s)**
S.Sudha, Department of ECE School of EEE, SRC SASTRA Deemed University, Kumbakonam, Tamilnadu, India.
A.Srinivasan, Department of ECE School of EEE, SRC SASTRA Deemed University, Kumbakonam, Tamilnadu, India.
S.Karthik,, Department of ECE School of EEE, SRC SASTRA Deemed University, Kumbakonam, Tamilnadu, India.
S.Hari Krishnan, Department of ECE School of EEE, SRC SASTRA Deemed University, Kumbakonam, Tamilnadu, India.
S.Prakash, Department of ECE School of EEE, SRC SASTRA Deemed University, Kumbakonam, Tamilnadu, India.

The efficient mosaics have been generated that provides the entire view of retina. In [8] two types of segmentation approaches are designed one with standard line operator and another with modified line operator. Modified line operator method of segmentation is found to be the best. Two features set are developed based on morphology and dual classification is established using SVM classifier. Finally the votes are combined and provide final decision. The achieved sensitivity is 0.862 & specificity is 0.944.The authors [9] have reviewed the recent algorithms used for detection of diabetic retinopathy using image processing, neural networks and fuzzy logic approaches. In [10] Gabor filtering are used for blood vessel segmentation.21 features related to texture and vessels are extracted for training and testing of classifier.

III .PROPOSED METHODOLOGY

In this automated system advanced stage lesions such as neovascularisation are identified and classified using image processing algorithms. The proposed system block diagram is shown in Figure1.Input image for this proposed method is taken from fundus camera. It may be blurred or corrupted by some noises. So pre processing is done to make it meaningful and contain information. Median filtering is used to remove noises and for further enhancements. New blood vessels are segmented using Fuzzy c means segmentation algorithm. From the segmented image SIFT features are extracted to train SVM classifier. For a new querry image to be tested the SVM algorithm compares the trained features set with test image features set and based on the matching classifier will give output neovascularisation image or normal image. Fundus input image is shown in Figure 2.

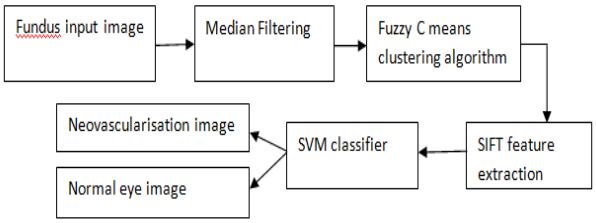


Fig. 1. Proposed system block diagram

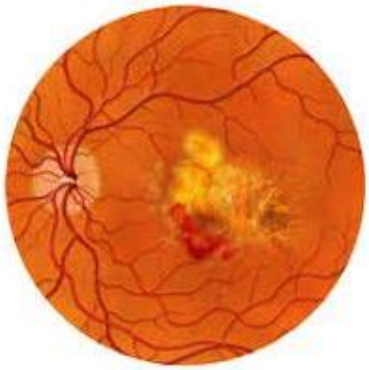


Fig. 2. Fundus input image

A. Pre-processing

Median filtering is different from mean filter in the point that it arranges all pixel values in ascending order which are taken from surrounding neighbourhood. After it sorts all the pixel values only median value is taken to replace the pixel which is being considered. Suppose if there are even number of pixels average value of two middle pixels is considered. The reason for choosing median filtering is i) it can preserve edges ii) it can remove outliers iii) it can work really with Gaussian noise and salt & pepper noises. Gray scale conversion image and median filtered image is shown in Figure 3 and Figure 4 respectively.

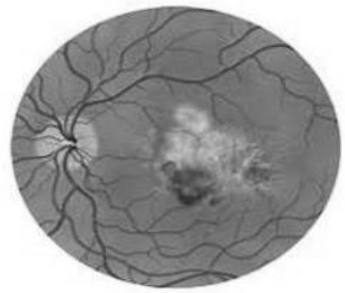


Fig. 3. Gray scale image

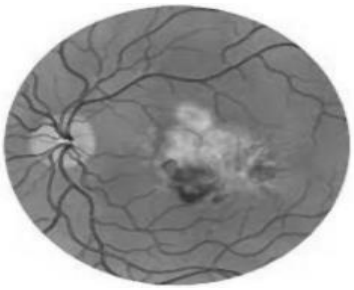


Fig. 4. Median filtered image

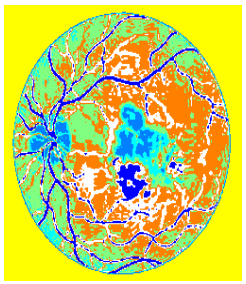
B. Image Segmentation

Fuzzy C means clustering algorithm is used for image segmentation. Images are two dimensional and it can be represented in two coordinates x and y respectively. Initially number of clusters and fuzzy parameters are assigned. Convergence criterion is set to 0.01.Initial membership function metrics is formed. Cluster centres are calculated using

$$\mathrm{Cpq} = \frac{\sum_{r=1}^{n}(\mathrm{Upr})^2.\mathrm{X_{rq}}}{\sum_{r=1}^{n}(\mathrm{Upr})^2} \qquad \text{--- (1)}$$

U-membership function, n- no of pixels in x & y axis, *X* is the value of pixel & p,q is the number of clusters. C-cluster centres. The distance between pixel and each cluster is calculated. In the next step, membership function metric is updated. Steps are repeated until convergence is achieved ie. $\left\|U^{i+1} - U^{i}\right\| < 0.01$.Here, i is step of iteration. If the pixel is closer to cluster centre then it will have high membership value otherwise membership value will become less. The value of membership and cluster centres are updated in each iteration till convergence criterion is satisfied. In FCM there is no condition that one pixel must belong to only one cluster but it can be more than one since each pixel is assigned membership to each one of all cluster centres. It gives result better than K-means. Assigning number of clusters and lower value of convergence criterion can lead to drawbacks but accuracy can be improved with large number of iteration.

Segmented output and thin vessels is shown in Figure 5 & Figure 6 respectively.



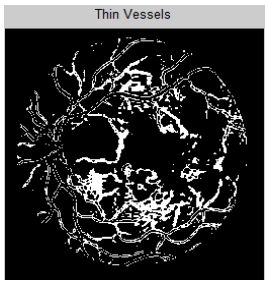


Fig. 5. Segmentation output **Fig. 6.Thin blood vessels**

C. Extraction of features

Scale invariant feature transform (SIFT) converts segmented image in the form of scale invariant local descriptors. This is preferred because it is invariant to scaling, rotation and illumination intensity of the image and works well with distorted and noisy added images. It is powerful to obstruction and litters and able to collect large features even for very small lesions. The steps are 1) scale-space formation 2) Evaluating difference of gaussians (DOG) 3) Finding maxima & minima of DOG for key points 4) Eliminate key points from the regions like edges and regions of minimum contrast.5) key points orientation 6) Extraction of features. The output from sift algorithm is shown in Figure 7.

Time taken for Pyramid level generation is: 2.093693

Time taken for finding the key points is: 0.537565

Time taken for magnitude and orientation assignment is: 0.768205

Time taken for finding key point desctiptor is: 0.885978.

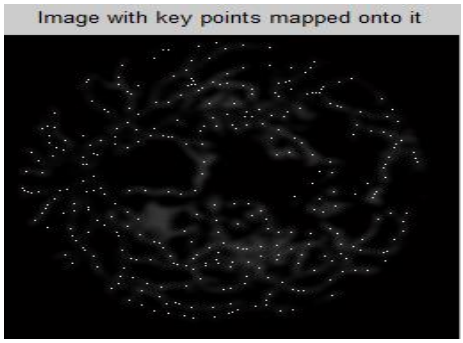


Fig. 7. SIFT features

D. Classification of neovascularisation using SVM classifier

Support vector machine (SVM) classifier fits a maximally separating hyperplane that discriminate features into two classes: normal class and another neovascularisation class. kernel substitution is added to make the features which are totally distinguishable. It is a function which transforms low dimensional feature space to high dimensional space based on trick function. An example of SVM classifies two data sets are shown in Figure 8. Totally 100 images are taken for training the classifier and 70 images have been tested by this classifier. The classifier output is shown in Figure 9.

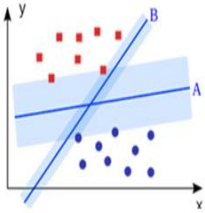


Fig.8 .SVM hyperplanes

Fig.9.Output of SVMclassifier

IV. RESULTS AND DISCUSSION

As we found that there is lack of research in detection of neovascularisation, the advanced stage lesions of diabetic retinopathy we proposed an efficient algorithm for the identification of new fragile blood vessels in the retina. Accuracy, sensitivity and specificity values for proposed algorithm is 95.5%, 95% & 96% respectively and it is shown in Table 1. Classifier performance is shown in Figure 10.The formulas used for measuring performance of algorithm are given below:

$$\text{Sensitivity} = \frac{\text{number of DR images correctly classified}}{\text{number of DR images correctly classified} + \text{number of DR images classified as normal}} \times 100 \quad \text{--- (2)}$$

$$\text{Specificity} = \frac{\text{number of normal images correctly identified}}{\text{number of normal images correctly classified} + \text{number of normal images classified as DR}} \times 100 \quad \text{--- (3)}$$

$$\text{Classifier accuracy} = \frac{\text{number of images that are correctly tested}}{\text{number of test inputs}} \times 100 \quad \text{--(4)}$$

Table 1: Sensitivity, Specificity And Accuracy Of The Svm Classifier

Support Vector Machine Classifier	Fundus Images	Training Stage		Testing Stage		Accuracy (%)	Sensitivity (%)	Specificity (%)
		Trained inputs	Trained outputs	Test Inputs	Test Outputs			
	Normal	40	40	25	24	96	95	96
	DR	60	60	45	43	95		

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

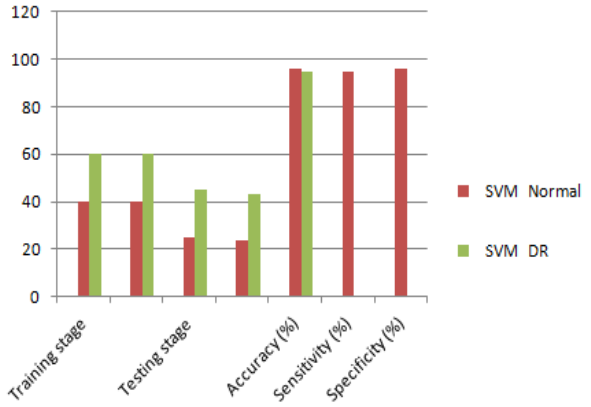


Fig.10. Neovascularisation accuracy for training and testing stages

V. CONCLUSIONS AND FUTURE ENHANCEMENTS

The proposed system is very sensitive to detect newly grown blood vessels in the retina. Using this algorithm, blood vessels are separated. Thick vessels are the vessels which are normal in all fundus images but thin and twisted vessels mostly near the optic disk are formed due to high blood sugar level. The formation of neovascularisation is the signs of advanced stage diabetic retinopathy that will lead to blindness. As it is difficult to segregate thick and thin vessels, this proposed algorithm achieved 96% accuracy. The robust features set is used to train classifier. In further work hybrid features can be used to improve accuracy.

REFERENCE

1. Sudeshna Sil Kar, Santi P. Maity. Detection of neovascularization in retinal images using mutual information maximization. Computers and Electrical Engineering 62 (2017) 194–208.
2. Garima Gupta, S. Kulasekaran.*et.al* Local characterization of neovascularization and identification ofproliferative diabetic retinopathy in retinal fundus images. Computerized Medical Imaging and Graphics 55 (2017) 124–132.
3. He Huang ,He Ma.*et.al.* Automatic detection of neovascularization in retinal images using extreme learning machine. Neurocomputing 277 (2018) 218–227.
4. Siti Syafinah Ahmad Hassan & David B. L. Bong. Detection of Neovascularization in Diabetic Retinopathy. J Digit Imaging (2012) 25:437–444.
5. Shuang Yu , Di Xiao.et al. Machine Learning Based Automatic neovascularization detection on optic disc region. IEEE Journal of Biomedical And Health Informatics, Vol. 22, No. 3, May 2018.
6. Sathvika Mudigonda, Faraz Oloumi.*et.al.* Fractal Analysis of Neovascularization due to Diabetic Retinopathy in Retinal Fundus Images. 978-1-4673-7545-0/15/$ 31.00.2015 IEEE.
7. Akhilesh Bontala, Jayanthi Sivaswamy. *et.al.* Image Mosaicing Of Low quality Neonatal Retinal Images. 978-1-4577-1858-8/12/$26.00©2012 IEEE.
8. R.A. Welikala, J. Dehmeshki. *et.al.* Automated detection of proliferative diabetic retinopathy using a modified line operator and dual classification.Computer methods and programs in biomedicine 114 (2014) 247-261.
9. Sudha s and Srinivasan A.Unravelling diabetic retinopathy through image processing, neural networks and fuzzy logic :A review.Asian Journal of pharmaceutical and clinical research. Vol 10, Issue 4, 2017.
10. Shuang Yu, Di Xiao and Yogesan Kanagasingam. Automatic Detection of neovascularization on Optic Disk Region with Feature Extraction and Support Vector Machine. 978-1-4577-0220-4/16/$31.00 ©2016 IEEE.