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A Study on Candidate Extraction From Retinal Images

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Abstract - Diabetic Retinopathy (DR) is yet another problem faced with those people who have diabetes. Diabetes damages tiny blood vessels inside the retina causing degradation. As diabetic retinopathy becomes more severe, new blood vessels begin to form on the retina that could break and cause severe vision loss. The diagnosis of diabetic retinopathy is based on clinical eye examination and eye fundus photography. The self diagnosis of diabetic retinopathy is extremely difficult if diabetes is not suspected, verified from the blood samples or visual impairment is not present. From the input retinal image, the pre-processing step is carried out in order to create better image. Then segmentation of regions is carried out and the features are extracted. Based on the features the retinal image is classified as normal or DR images.

Keywords: Fundus image, Diabetic Retinopathy, Classification.

I. INTRODUCTION

Diabetic Retinopathy is yet another problem faced with those people who have diabetes. The persons who having diabetes for a longer period gets affected by the disease called Diabetic Retinopathy. It is caused due to changes in the blood vessels of the retina. The disease is usually un-noticed, but as more and more blood vessels are damaged and new ones are formed, the higher the chances of vision loss. It is recommended that people with diabetes get a thorough eye examination once a year.

The stages of diabetic retinopathy is as follows: Mild Non-proliferative Diabetic Retinopathy has Microaneurysms which are small swellings in the retina's tiny blood vessels. Essential blood vessels gets blocked in Moderate Non-proliferative Diabetic Retinopathy. In Severe Non-proliferative Diabetic Retinopathy, more blood vessels are blocked in the retina, and the retina senses the need for new blood vessels to grow and it supplies the oxygen. Another stage is Proliferative Diabetic Retinopathy which leads to abnormal growth of blood vessels into the retina and it causes severe damage. The new abnormal blood vessels may grow elsewhere and new vessels at the disc.

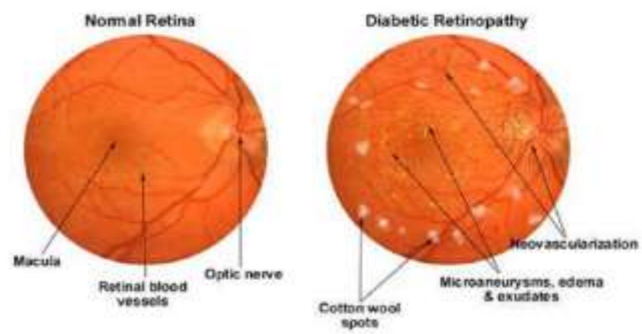

Figure 1:Normal Retina Vs Diabetic Retinopathy

At any stage, fluid can leak into the macula, a small and highly sensitive part of the retina, and cause blurred vision. This is known as macula edema and is actually one of the most common causes of vision loss in diabetic patients.

II. SEGMENTATION

In [1], regions corresponding to optic disc and blood vessels are segmented using MinIMaS algorithm. From this image segmentation, the background and foreground regions are segmented. The background regions include optic disc and vasculature, and foreground regions include both bright and red lesions. In [2], blood vessels are segmented using standard line operator and modified line operator. Standard line operator is used to detect linear structures in retinal images and later on, false responses to non-vessel edges are reduced using modified line operator. Using Markov Random Field image reconstruction method segments the optic disc by removing vessels from optic disc and the compensation Factor method segments the optic disc using prior local intensity knowledge of the vessels [3].

III. CANDIDATE EXTRACTION

Features contain unique information possessed by the image. Features are useful for determining the characteristics of the image for image classification. Using Adaboost, top 30 features are computed and ranked in descending order of their contribution to lesion classification.

In [1], a sub window of size 151 x 151 pixels was created in order to calculate local features associated with the morphology of the vasculature. At each pixel position the features are calculated. In [4], features are extracted from number of pixels and statistical extractions value. In [poi], Point of Interest is detected by using Speeded- Up Robust Features (SURF) and Scale- Invariant Features Transform (SIFT). SURF is better than SIFT.

In [5], feature extraction is deciding a pixel classification by means of a feature vector, a pixel representation in terms of some quantifiable measurements which may be easily used in the classification stage to decide whether the pixels belong to a real blood vessel or not. For features based on the differences between the gray-level in the candidate pixel and a statistical value representative of its surroundings is extracted using Gray level-based features and features based on the moment invariants for describing small image regions formed by the gray-scale values of a window centered on the represented pixels is extracted using Moment invariants-based features.

Candidate extraction is accomplished by grayscale diameter closing. This method aims to find all sufficiently small dark patterns on the green channel and finally, a double thresholding is appled [6].

From the input fundus image, the vascular map is extracted by applying 12 morphological top-hat transformations with 12 rotated linear structuring elements (with a radial resolution 15 ◦) as in [7]. Then, the vascular map is subtracted from the input image, which is followed by the application of a Gaussian matched filter. The resulting image is then binarized with a fixed threshold. Since the extracted candidates are not precise representations of the actual lesions, a region growing step is also applied to them.

Candidates are obtained by detecting circles on the images using circular Hough transformation. With this technique, a set of circular objects can be extracted from the image [8].

In order to extract candidates [9], this method constructs a maximal correlation response image for the input retinal image. This is accomplished by considering the maximal correlation coefficient with five Gaussian masks with different standard deviations for each pixel. The maximal correlation response image is thresholded with a fixed threshold value to obtain the candidates. Vessel detection and region growing is applied to reduce the number of candidates, and to determine their precise size, respectively.

Pixel-wise cross-sectional profiles with multiple orientations are used to construct a multidirectional height map. This map assigns a set of height values that describe the distinction of the pixel from its surroundings in a particular direction. In a modified multilevel attribute opening step, a score map is constructed from which the MAs are extracted by thresholding in [10].

IV. Lesion Classification

In [1], 14 structure- based features are useful for separating the non-lesion regions from the lesion candidates. Non-lesions have a smaller distance from the blood vessels than the red lesions. In [4], Presence of dark lesion and bright lesion are detected using mathematical morphology and bright lesion are detected using combination of mathematical morphology, estimated background, colour analysis, Max-tree and attribute filters.

V. Naïve- Bayes Classifier

The features are independent of one another within each class, naïve bayes classifier is designed. This works well even when that assumption of independent feature is not valid. In training step, the method estimates the parameters of a probability distribution for the training samples. And in prediction step, for test samples, the method computes the posterior probability of that sample belonging to each class. The method then classifies the test samples according to the largest posterior probability. Using this classifier, better classification is achieved when the features are more. For each feature with a kernel distribution, the naïve bayes classifier computes a separate kernel density estimate for each class based on the training data for that class.

VI. Support Vector Machine

An SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. In [2], linear and non-linear SVM's were tested. Classifier 1, associated with the feature set measured from standard line operator approach, was intented to distinguish new vessels from normal vessels. Classifier 1, associated with the feature set measured from modified line operator approach, was intended to distinguish new vessels from Exudates. The architecture is shown in Figure 2.

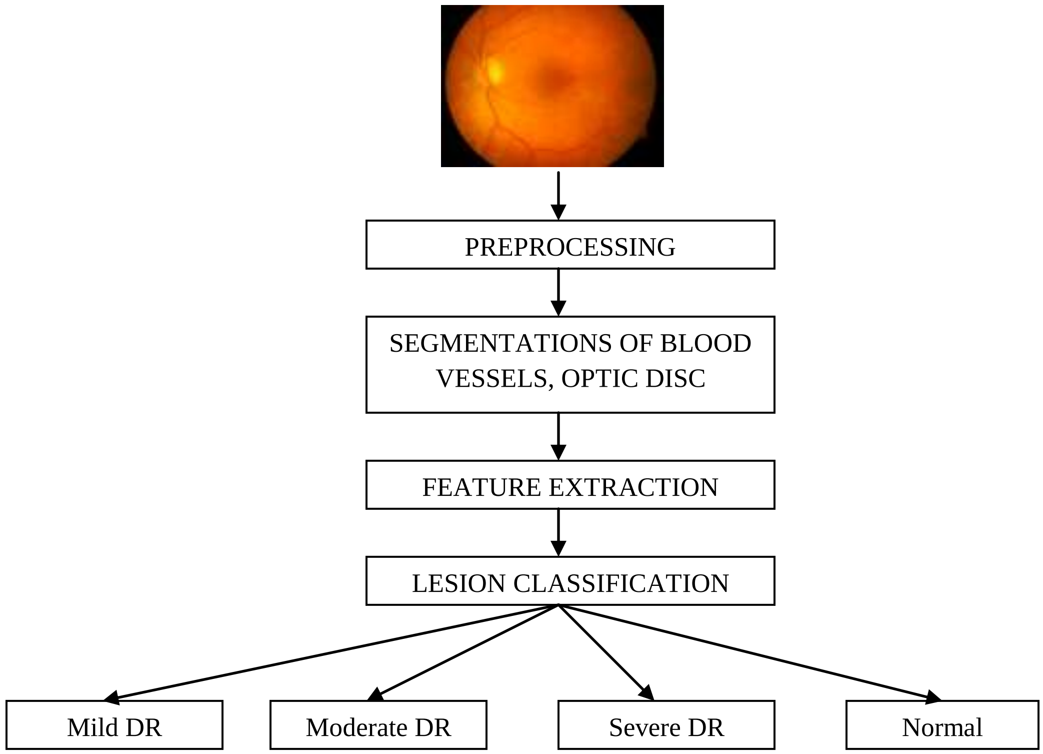

Figure 2: Architecture for Classifying the Retinal Image as Diabetic Retinopathy or normal

VII. CONCLUSION

Diabetic Retinopathy is a disease which causes vision loss rapidly. The input color retinal images are of poor quality. So preprocessing steps like green channel extraction, noise removal, improving image quality were applied and the regions are segmented. Then features of candidate regions are extracted and based on the features, the classification is done using classifier which will place the retinal image as either normal or DR.

REFERENCES

[1] Sohini Roychowdhury, Dara D.Koozekanani and Keshab K.Parhi, "DREAM: Diabetic Retinopathy Analysis using Machine Learning," IEEE Journal of Biomedical and Health Informatics, September 2014.

[2] Welikala R.A. , J. Dehmeshkia, A. Hoppea, V. Tahb, S. Mannc, and S.A. Barman, "Automated Detection of Proliferative Diabetic Retinopathy using a Modified Line Operator and Dual Classification," Elsevier, 2014.

[3] Ana Salazar-Gonzalez, Djibril Kaba, Yongmin Li and Xiaohui Liu, "Segmentation of Blood Vessels and Optic Disc in Retinal Images," IEEE Journal of Biomedical and Health Informatics, 2014.

[4] Muhammad Faisal, Djoko Wahono, et al, "Classification of Diabetic Retinopathy Patients using Support Vector Machines (SVM) Based on Digital Retinal Image," Journal of Theoretical and Applied Information Technology, January 2014.

[5] Diego Martin, Arturo Aquino, and Manuel Emilio, "A New Supervised Method for Blood Vessel Segmentation in Retinal Images by using Gray- Level and Moment Invariants- Based Features," IEEE Transactions on Medical Imaging, vol.30, no.1, January 2011.

[6] T. Walter, P. Massin, A. Arginay, R. Ordonez, C. Jeulin, and J. C. Klein, "Automatic Detection of Microaneurysms in Color Fundus Images," Med. Image Anal., vol. 11, pp. 555–566, 2007.

[7] T. Spencer, J. A. Olson, K. C. McHardy, P. F. Sharp, and J. V. Forrester, "An Image-Processing Strategy for the Segmentation and Quantification of Microaneurysms in Fluorescein Angiograms of the Ocular Fundus," Comput. Biomed. Res., vol. 29, pp. 284–302, 1996.

[8] A. D. Fleming, S. Philip, and K. A. Goatman, "Automated Microaneurysm Detection using Local Contrast Normalization and Local Vessel Detection," IEEE Trans. Med. Imag., vol. 25, no. 9, pp. 1223–1232, Sep. 2006.

[9] S. Abdelazeem, "Microaneurysm Detection using Vessels Removal and Circular Hough Transform," in Proc. 19th National Radio Sci. Conf., pp. 421– 426, 2002.

[10] B. Zhang, X. Wu, J. You, Q. Li, and F. Karray, "Detection of Microaneurysms using Multi-scale Correlation Coefficients," Pattern Recogn., vol. 43, no. 6, pp. 2237–2248, 2010.

[11] I. Lazar and A. Hajdu, "Microaneurysm Detection in Retinal Images using a Rotating Cross-Section Based Model," in Proc. IEEE Int. Symp. Biomed. Imag., 2011, pp. 1405–1409.

[12] Diabetes Mellitus: http://en.wikipedia.org/wiki/Diabetes_mellitus

[13] Advanced Vision Care: http://www.advancedvisioncare.com/conditions.php

[14] Bhalerao, Abhir, Patanaik, Amiya, Anand, Sarabjot Singh and Saravanan, Pounnusamy, "Robust Detection of Microaneurysms for Sight Threatening Retinopathy Screening" Sixth Indian Conference on Computer Vision, Graphics & Image Processing, ICVGIP 2008,PP:520- 527, December 2008.

[15] M.Ponni Bala, and S.Vijayachitra, "A Computerised Retinal Image Analysis to Detect and Quantity Exudates Associated with Diabetic Retinopathy," International Journal of Computer Applications(0975– 8887), volume 54- No.2, 2012.

[16] B.Dupas, T. Walter, A. Erginay et al., "Evaluation of Automated Fundus Photograph Analysis Algorithms for Detecting Microaneurysms, Haemorrhages and Exudates, and of a Computer-Assisted Diagnostic System for Grading Diabetic Retinopathy," Diabetes & Metabolism 36(3), pp. 213-220, 2010.