International Research Journal of Engineering and Management Studies (IRJEMS)
Volume: 03 Issue: 05 | May -2019 e-ISSN: 2395-0126

Early Detection of Diabetic Retinopathy using Soft Computing Approach: A Study

Akshay D. Isalkar[1], Mohit Popat [2], Anup Raut [3]

[1]Assistant Professor, DMIETR, Wardha, India
[2] Assistant Professor, JDIET, Yavatmal, India
[3]Assistant Professor, IOCER, Pune, India

Abstract - *Diabetic retinopathy is one of the leading causes of blindness in the industrialized world. Here we address the early detection of Hemorrhages and Microaneurysms in color fundus images. In pre-Processing we separate red, green, blue color channel from the retinal images. The green channel will pass to the further process. The green color plane was used in the analysis since it shows the best contrast between the vessels and the background retina. Then we extract the Gray level co-occurance matrix (GLCM) feature. In the GLCMs, several statistics information are derived using the different formulas. These statistics provide information about the texture of an image. Such as Energy, Entropy, Dissimilarity, Contrast, Inverse difference, correlation Homogeneity, Auto correlation, Cluster Shade Cluster Prominence, Maximum probability, Sum of Squares is calculated for texture image. After feature extraction, we provide this feature to SVM classifier. Finally it will predict about the retinal whether it is hemorrhages or microaneurysms . After predicting the about the retinal image we localize the affected place. For segmenting the localized place we use adaptive thresholding segmentation.*

Key Words: GLCM, SVM, Thresholding

1. INTRODUCTION

The US Center for Disease Control and Prevention estimates that 29.1 million people in the US have diabetes and the World Health Organization estimates that 347 million people have the disease worldwide. Diabetic Retinopathy (DR) is an eye disease associated with long-standing diabetes. Around 40% to 45% of Americans with diabetes have some stage of the disease. Progression to vision impairment can be slowed or averted if DR is detected in time, however this can be difficult as the disease often shows few symptoms until it is too late to provide effective treatment.

Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. By the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment.

Clinicians can identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease. While this approach is effective, its resource demands are high. The expertise and equipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection is most needed. As the number of individuals with diabetes continues to grow, the infrastructure needed to prevent blindness due to DR will become even more insufficient.

The need for a comprehensive and automated method of DR screening has long been recognized, and previous efforts have made good progress using image classification, pattern recognition, and machine learning. With color fundus photography as input, the goal of this competition is to push an automated detection system to the limit of what is possible – ideally resulting in models with realistic clinical potential. The winning models will be open sourced to maximize the impact such a model can have on improving DR detection. [11]

2. Literature Review

A weakly-supervised framework for interpretable diabetic retinopathy images [1]. It works on the best screening method. Bright lesions, including exudates and cotton wool spots are the main symptoms in diabetic retinopathy. Detection and classification of bright lesson in color fundus image [2] described image processing procedure for detecting all important anatomical structures in color fundus images. Automated detection of red lesion in digital color fundus photographs [3] described the detected candidate objects are classified using all features and SVM classifier. An extensive evaluation was performed on a test set composed of images representative.

A successive clutter rejection based-approach for early detection of diabetic retinopathy[2] described the database is made publicly available for benchmarking diagnosis algorithms and its features.Morphological based approach for identification of red lesion in diabetic retinopathy [5] presents low cost low cost retinal algorithm for detecting disease.

3. Proposed Work

3.1 Pre-Processing

The green color plane was used in the analysis since it shows the best contrast between the vessels and the background retina. The grey levels were normalized by stretching the image contrast to cover the full pixel dynamic range, excluding the surrounding dark border pixels and any image labels.

3.2 Color Component Separation

Each image is subjected to color component separation. Here we separate each image to have three components such as R, G, B. This is an additive color system based on tri-chromatic theory. Often found in systems that use a CRT to display images. RGB is easy to implement but non–linear with visual perception. It is device dependent and specification of colors is semi–intuitive. RGB is very common, being used in virtually every computer system as well as television, video etc.

3.3 Feature Extraction:(Gray Level Co-occurrence Matrices)

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics.

A GLCM is a matrix where the number of rows and colums is equal to the number of gray levels, G, in the image. The matrix element is the relative frequency with which two pixels, separated by a pixel distance occur within a given neighborhood, one with intensity i and the other with intensity j. One may also say that the matrix element contains the second order statistical probability values for changes between gray levels i and j at a particular displacement distance d and at a particular angle (theta).

3.4 4Training the classifier

A cascade network consists of a cascade architecture, in which hidden neurons are added to the network one at a time and do not change after they have been added. It is called a cascade because the output from all neurons already in the network feed into new neurons. As new neurons are added to the hidden layer, the learning algorithm attempts to maximize the magnitude of the correlation between the new neuron's output and the residual error of the network which we are trying to minimize

4. Result And Discussion

We had detected the result the below table shows twelve features of hemorrhage and microaneurysm disease.

	H1	H2	H3	H4	H5	H6
Contrast	17.98	21.95	16.79	14.8	11.04	14.67
Correlation	0.16	0.25	0.14	0.06	0.05	0.063
Energy	0.97	0.96	0.97	0.99	0.99	0.99
Entropy	0.97	0.96	0.97	0.99	0.99	0.99
Dissimilarity	311.8	499.13	297.8	27.93	792.07	939.52
Contras inv. Difference	-32.28	-53.59	-21.31	43.97	61.91	56.37
Correlation	0.14	0.17	0.11	0.04	0.02	0.03
Homogenity	0.21	0.23	0.93	0.28	0.29	0.29
Auto correlation	1.86	1.81	1.92	1.63	1.5	1.59
Cluster shade	0.93	0.92	0.94	0.98	0.99	0.98
Maximum probability	0.92	0.91	0.94	0.98	0.99	0.98
Sum of squares	0.34	0.31	0.25	0.45	0.45	0.45

Figure 1: Features of Hemorrhage

	M1	M2	M3	M4	M5	M6
Contrast	16.67	8.33	14.85	6.58	4.29	6.67
Correlation	0.13	0.10	0.09	0.05	0.02	0.43
Energy	0.95	0.91	0.94	0.98	0.97	0.98
Entropy	0.95	0.99	0.94	0.98	0.97	0.98
Dissimilarity	65.49	27.65	35.85	53.43	24.58	63.97
Contras inv. Difference	-3.78	-3.25	0.60	2.21	3.18	3.37
Correlation	0.12	0.10	0.09	0.04	0.04	0.03
Homogenity	0.29	0.45	0.29	0.34	0.32	0.24
Auto correlation	1.88	1.31	1.64	1.28	1.32	1.46
Cluster shade	0.93	0.94	0.95	0.97	0.97	0.98
Maximum probability	0.93	0.94	0.95	0.97	0.97	0.98
Sum of squares	0.39	0.65	0.47	0.45	0.45	0.45

Figure 2: Features of Microneurysm

REFERENCES

[1] S. Wild, G. Roglic, A Green, "Global prevalence of diabetes: estimates for the year 2000 and projections for 2030," Diabetes Care, 27, pp.l047- 1053, IEEE 2004.

[2] S. R. Nirmala, M. K. Nath, and S. Dandapat, "Retinal Image Analysis: A Review," International Journal of Computer & Communication Technology (IJCCT), vol-2, pp. 11-15, 2011.

[3] National Eye Institute, National Institutes of Health, "Diabetic Retinopathy: What you should know," Booklet, NIH Publication, no: 06-2171, IEEE 2003.

[4] A. D. Fleming, K. A. Goatman, and J. A. Olson, "The role of haemorrhage and exudate detection in automated grading of diabetic retinopathy," British Journal of Ophthalmology, vol 94, no. 6, pp. 706- 711, 2010.

[5] A. D. Fleming, S. Philip, K. A. Goatman, J. A. Olson, and P. F. Sharp, "Automated microaneurysm detection using local contrast normalization and local vessel detection," IEEE Trans. Med. Imag., vol. 25, no. 9, pp. 1223–1232, Sep. 2006.

[6] M.Niemeijer,B. V. Ginneken, J. Staal, M. S. A. Suttorp-Schulten, and M. D. Abramoff, "Automatic detection of red lesions in digital color fundus photographs," IEEE Trans. Med. Imag., vol. 24, no. 5, pp. 584– 592, May 2005.

[7] M. J. Cree, J. A. Olsoni, K. C. McHardyt, J. V. Forresters and P. F. Sharp, "Automated microaneurysms detection," IEEE conference, pp. 699-702, 1996

[8] A. Mizutani, C. Muramatsu, Y. Hatanaka, S. Suemori, T. Hara, and H. Fujita, "Automated microaneurysm detection method based on double ring filter in retinal fundus images," in Proc. SPIE, Med. Imag, Imag,Computer-Aided Diagnosis, vol. 7260, IEEE 2009.

[9] K. Ram, G. D. Joshi and J. Sivaswamy, "A successive clutter rejectionbased-approach for early detection of diabetic retinopathy," IEEE Transaction on Biomediacl Engineering, vol. 58, no. 3, pp. 664-673, Mar. 2011

[10] M. Esmaeili, H. Rabbani, A. M. Dehnavi, and A. Dehghani, "A new curvlet transform based method for extraction of red lesions in digital color retinal images," in Proc. ICIP, pp.4093-4096, 2010.

[11] Diabetic Retinopathy Detection- https://www.kaggle.com/c/diabetic-retinopathy-detection