Volume 4, Issue 5, May 2014 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

Automatic Diagnosis of Diabetic Retinopathy Using Fundus Images (Using Neural Networks and Fuzzy C)

Charu Sharma
Student
ECE,MMU, Mullana

Geeta Kaushik
(Assoc.prof, ECE dept)
ECE,MMU, Mullana

ABSTRACT: Automated detection of lesions in retinal images can assist in early diagnosis and screening of a common disease: Diabetic Retinopathy. A robust and computationally efficient approach for the localization of the different features and lesions in a fundus retinal image is presented in this page. Since many features have common intensity properties, geometric features and correlations are used to distinguish between them. A new constraint for optic disk detection is proposed where the major blood vessels are detected first and then their intersection is used to find the approximate location of the optic disk. This is further localized using colour properties. It is also shown that many of the features such as the blood vessels, exudates and microaneurysms and hemorrhages can be detected quite accurately using different morphological operations applied appropriately.

Keywords: Diabetic Retinopathy, Fundus Image, Digital Image Processing, Segmentation, Retina, Classifier.

I. INTRODUCTION

Diabetic retinopathy (DR) is a common retinal complication associated with diabetes. It is a major cause of blindness in both middle and advanced age groups. Early detection of the disease via regular screening is particularly important to prevent vision loss. Since, a large population has to be screened, and that too repeatedly, an automated DR diagnostic system can assist in a big way in this process. Colour fundus images are used by ophthalmologists to study eye diseases like diabetic retinopathy. Figure 1 shows a typical retinal image labelled with various feature components of Diabetic Retinopathy. Microaneurysms are small saccular pouches caused by local distension of capillary walls and appear as small red dots. This may also lead to big blood clots called hemorrhages. Hard exudates are yellow lipid deposits which appear as bright yellow lesions. The bright circular region from where the blood vessels emanate is called the optic disk. The fovea defines the centre of the retina, and is the region of highest visual acuity. The spatial distribution of exudates and microaneurysms and hemorrhages, especially in relation to the fovea can be used to determine the severity of diabetic retinopathy.

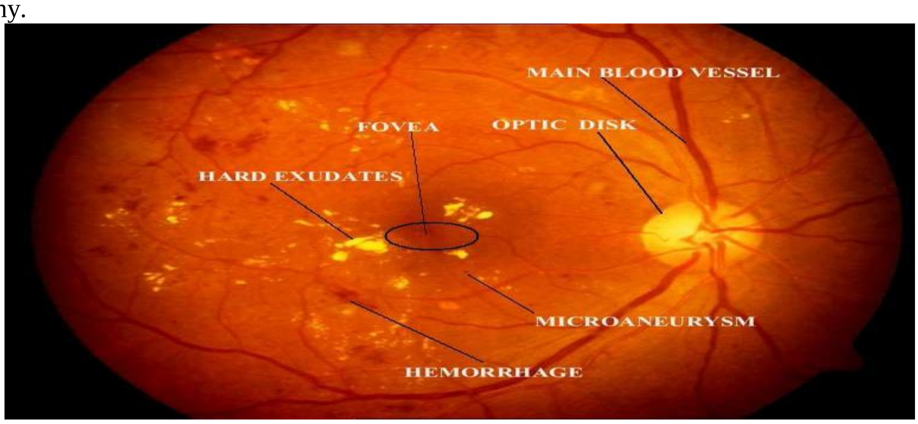

Figure 1. Illustration of various features on a typical retinopathy image

DR has mainly four stages:

- Mild Non-Proliferative Retinopathy- At this early stage, micro-neurysms may occur. These manifestations of the disease are small areas of balloon-like swelling in the retinas tiny blood vessels. Approximately 40 percent of people with diabetes have at least mild signs of DR.
- Moderate Non-Proliferative Retinopathy- As the disease progresses,some blood vessels that nourish the retina are blocked. Cotton wool spots and limited amount of venous bleeding can be seen. Generally 16 percent of patient with moderate NPDR will develop PDR within one year.
- Severe Non-Proliferative Retinopathy- Many more blood vessels are blocked, depriving several areas of the retina with their blood supply. These areas of the retina send signals to the body to grow new blood vessels for nourishment.

- Proliferative Retinopathy-This is the advanced stage, the signals send by the retina for nourishment triggers the growth of new blood vessels. These new blood vessels are abnormal and fragile. They grow along the retina and along the surface of the clear, vitreous gel that fills the inside of the eye. By themselves, these blood vessels do not cause symptoms or vision loss. However, they have thin, fragile walls. If they leak blood, sever vision loss and even blindness can result.

II. METHODOLOGY

A. Image Acquisition

To evaluate the performance of this method, the digital retinal images were acquired using digital camera known as ophthalmoscope Fig.(3) shows the input image. Fundus image is the interior surface of the eye, opposite the lens, and includes the retina, optic disc, macula, blood vessels and fovea. We tested and evaluated our proposed algorithm on several fundus images

B. Pre-processing

Pre-processing stage can be regarded as the bedrock of this work. The aim of pre-processing is to attenuate the noise, to improve the contrast and to correct the non-uniform illumination. Pre-processing mainly includes following stages:

1) Intensity conversion:

Fig.3(c) and Fig 4(b) shows the result of intensity conversion. In digital image processing, images are either indexed images or RGB(Red ,Green ,Blue) images. In the RGB images the green channel exhibits the best contrast between the vessels and background while the red and blue ones tends to be more noisy .Hence intensity conversion of image is done using green channel ,as the retinal blood vessels appears darker in gray image.

2) Filtering:

Filtering is used to suppress the unwanted noise which gets added into the fundus image. Here median filtering is used as it is very robust and has the capability to filter any outliers and is an excellent choice for removal of salt and pepper noise.

3) Adaptive Histogram Equalization:

Fig.3(d) shows the result of adaptive histogram equalization. Histogram equalization is performed to improve the image Quality .Histogram equalization is nothing but a finding of cumulative distribution function for a given probability density function .After the transformation, the image will have an increased dynamic range ,high contrast and probability density function of the output will be uniform .Instead of using normal histogram equalization, adaptive histogram equalization is used as it operates on small regions in the image which are called tiles .Adaptive histogram combines neighbouring tiles using bilinear interpolation to eliminate artificially induced boundaries.

C. **Thresholding:** Fig.3(f) and Fig 4(c) shows the result of image thresholding . Thresholding is method of segmenting image based on the pixel intensity value. Thresholding is used to convert an intensity image to a binary image. Otsu's method is used to automatically perform histogram shape-based image thresholding. Otsu's method chooses the threshold to minimize the interclass variance of the black and white pixels.

D. **Labeling:** Fig.4(d) shows the result of labelling. Connected components are labelled by scanning an image pixel by pixel in order to identify connected pixel regions. It groups its pixels into components based on pixels connectivity. After group formation each group is labelled with different colour.

E. **Segmentation:** Fig 3(g) and Fig.4(e) shows the result of segmentation. The main objective of segmentation is to group the image into regions with same characteristics. The goal of the segmentation is to simplify and /or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries(lines ,curves etc.)in the images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. After performing all above operations on the fundus image blobs are detected which is the sign of severe diabetic retinopathy. Also for the mild severity, we used image substraction algorithm in which earlier and present fundus image is substracted to detect the new increased blood vessels.

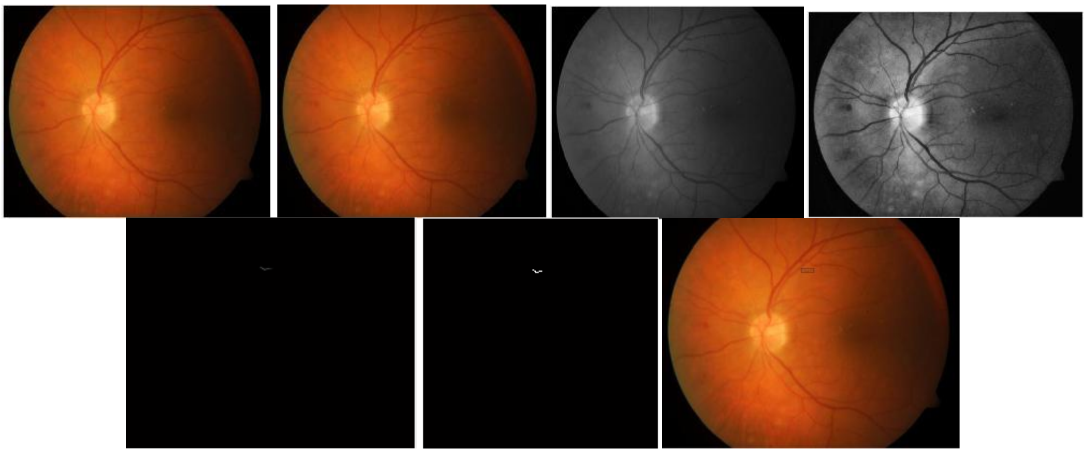

Fig.3.(a) Earlier fundus image(b) Fundus image after 1 month(c) Image after intensity conversion(d) Image after histogram equalization(e) Image after subtraction .(f) Image after thresholding .(g) Image after segmentation.

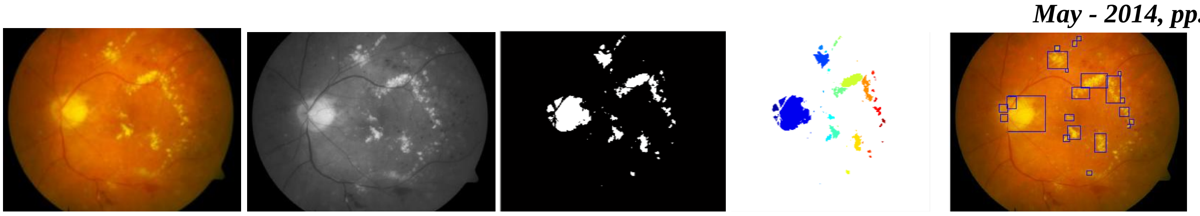

Fig.4.(a) Fundus image (b) Image after intensity conversion (c) Image after thresholding (d) Image after labeling (e) Image after segmentation

III. RESULT

The developed methods were tested with 46 colour fundus images in the test image set. Processing one image took around 10 minutes including pre-processing, image segmentation and object classification. Feature extraction part took most of the processing time. so overall attained goal listed below:

- Image segmentation using Fuzzy C-means clustering
- Image Segmentation using Neural Network
- Comparative study of different Neural Network Models for Image Segmentation
- Comparative study Among Fuzzy C-means clustering and used Neural Network
- Feature Dimension Effect over used Methods

It was also difficult to distinguish soft exudates in several fundus images because the color and intensity of soft exudates were near to the fundus color and intensity. A reason for the low specificity value in exudate detection is that when an image was incorrectly classified to have exudates, there existed only a few small objects in the segmentation results that caused the missclassification. Also noise appearing in regions that were not excluded by the poor image quality detection methods caused some recognition errors. This was due to the fact that if the illumination equalization method failed in some relatively noisy region, the result region was too bright, causing incorrect image segmentation.

REFERENCES

1. Iqbal, M.I., Aibinu, A.M., Gubbal, N.S Khan, "Automatic Diagnosis Of Diabetic Retinopathy Using Fundus Images", Master's Thesis, Department of Signal Processing, Blekinge Institute of Technology, October 2006.
2. "Effective Health Care - Complications of diabetes: Screening for retinopathy and Management of foot ulcers", Volume 5, number 4, Royal society of medicine press, 1999. ISSN 0965-0288.
3. Kanski, J. J., "Clinical Ophthalmology: A Systematic Approach", Butterworth-Heinemann, 2003. ISBN 0-7506-5542-9.
4. Walter, T. and Klein, J., "Automatic Analysis of Color Fundus Photographs and Its Application to the Diagnosis of Diabetic Retinopathy", Handbook of biomedical image analysis, Kulwer Academic, Volume 2(2005), Pages 315-317.
5. Bäcklund, L.B., "Early Diagnosis of Diabetic Retinopathy by Mass Examinations in Primary Health Care", PhD thesis, Karolinska Institutet, Sweden, 2000. ISBN 91-628-4224-2.
6. Singer, D. E., Nathan, D. M., Fogel, H. A., and Schachat, A. P., "Screening for diabetic retinopathy", Annals of Internal Medicine, 116:660–671, 1992.
7. Retinopathy Working Party, "A protocol for screening for diabetic retinopathy in Europe", *Diabetic Medicine*, 8:263–267, 1991.
8. Usher, D., Dumskyj, M., Himaga, M., Williamson, T. H., Nussey, S. and Boyce, J., "Automated detection of diabetic retinopathy in digital retinal images: a tool for diabetic retinopathy screening", Diabetes UK. Diabetic Medicine, 21:84–90, 2003.
9. Walter, T., Klein, J., Massin, P. and Erginay, A., "A contribution of image processing to the diagnosis of diabetic retinopathy - detection of exudates in color fundus images of the human retina. IEEE Transactions on Medical Imaging, 21:1236–1243, October 2002.
10. Syiam, M. M., "A Neural Network Expert System for Diagnosing Eye Diseases", IEEE, 1994.
11. Yen, G. G. and Leon, W. F., "A Sorting System for Hierarchical Grading of Diabetic Fundus Images: A Preliminary Study", IEEE Transactions On Information Technology In Biomedicine, Vol. 12, No. 1, January 2008.
12. Quellec, G., Lamard, M., Josselin, P. M., Cazuguel, G., Cochener, E. and Roux, C., "Detection of lesions in retina photographs based on the wavelet Transform" Proceedings of the 28th IEEE, EMBS Annual International Conference, New York City, USA, Aug 30-Sept 3, 2006.
13. Yagmur, F. D., Karlık, B. and Okatan, A., "Automatic Recognition of Retinopathy Diseases by Using Wavelet Based Neural Network", IEEE.

14. Niemeijer, M., Ginneken, B., Staal, J., Maria, S. A., Suttorp-Schulten and Abràmoff, M. D., "Automatic Detection of Red Lesions in Digital Color Fundus Photographs", IEEE Transactions On Medical Imaging, Vol. 24, No. 5, May 2005.
15. Estabridis, K. and Figueiredo, R. J. P., "Automatic detection and diagnosis of diabetic retinopathy", IEEE, 2007.
16. Gonzalez, R. C. and Woods, R. E., "Digital Image Processing using MATLAB', 2nd edition. Prentice Hall, 2002. ISBN 0-201-18075-8.
17. http://www.mathworks.com/access/helpdesk/help/helpdesk.html
18. Sugio, K., Kunieda, T., Fujita, H., Hara, T., Kawase, T., Ogawa, K., Ishida, A. and Inagaki, M., "Analysis of Blood Vessel Intersections in Fundus Images", Japanese Society of Radiological Technology, Vol. 56 No.3, pp.507-509, Mar 2000.
19. Dhawan, A. P. and Dai, S., "Clustering and Pattern Classification", page 229, World Scientific, 2008.
20. www.mathworks.com
    http://www.mathworks.com/products/image/
    http://www.mathworks.com/products/neuralnet/