Automatic Detection of Exudates in Color Fundus Retinopathy Images

C. P. Reshma Chand* and J. Dheeba

1 ECE, Noorul Islam University, Kumaracoil - 629180, Tamil Nadu, India; reshr88@gmail.com
2 CSE, Noorul Islam University, Kumaracoil - 629180, Tamil Nadu, India; dheeba.jacob@gmail.com

Abstract

Objective: The aim of this paper is to design a computationally intelligent method to determine exudates, the Non-Proliferative Diabetic Retinopathy (NPDR) symptom which is considered to be the initial stage of retinopathy disease. If NPDR is not identified at its earlier stage, it may lead to Proliferative Diabetic Retinopathy (DR), the complicated stage of retinal symptom that may leads to blindness. Methods: It is proposed to develop an automatic computer aided detection system that screen a large number of people to identify the DR in its earlier stage for proper treatments. In this work, images are taken from publicly available e-optha database. Analysis mainly considers three stages which include removal of optic disc and normalization done by histogram processing; texture information extracted using Gray Level Co-Occurrence Matrix (GLCM) and classification is done with the help of Support Vector Machines (SVM). Findings: Preprocessing method used in this work enhances the contrast of the low or poor quality images. Here, optic disc segmentation is performed, which helps in providing better result by avoiding the misclassification of optic disc as lesions. GLCM method provides different texture features to SVM o provide better result in identifying exudate lesions. Conclusion: The intelligent machine learning approaches aid the ophthalmologists with accurate and efficient detection of abnormalities in fundus images. Through this system, the abnormal retinal images can be identified in its initial stage and an accurate assessment of retinal disease is possible.

Keywords: Diabetic Retinopathy (DR), Edge based Detection, Gray Level Co-Occurrence Matrix (GLCM), Support Vector Machines (SVM)

1. Introduction

Diabetic Retinopathy (DR) occurs due to the micro vascular retinal changes that are generated from diabetes mellitus or sugar mellitus and it is one of the major causes for visual morbidity. It is mainly caused due to the damage of blood vessels on the light sensitive tissue present at the back of the eye called retina. Initially diabetic retinopathy will not cause any symptoms or it shows very small vision problems. However, it is possible that diabetic retinopathy can result in visual loss. Hence early detection of DR and treatment can prevent patients from vision loss or at least the progression of diabetic retinopathy can be reduced. Diabetic Retinopathy can be developed in any patients who are having type 1 or type 2 diabetes. According to International Diabetes Federation (IDF) and World Health Organization (WHO), it is said that about 347 million people worldwide have diabetes and it is found to be the major cause for vision loss among people having an age group of about 20-74 in the developed countries. Based on different studies, it is noted that approximately about 25,000 people having diabetes may become vision impaired every year in US due to DR. Hence it became a necessary part in order to detect and treat diabetic retinopathy in its earlier stages. For identification of diabetic retinopathy symptoms, fundus images are taken with or without mydriasis (pupil dilation). In earlier days, human experts manually identify the symptoms of diabetic
Automatic Detection of Exudates in Color Fundus Retinopathy Images

retinopathy in the digital color fundus images of retina taken with the help of ophthalmoscopy or fundus photography. It requires highly trained and skilled experts to perform diagnosis. In such manual grading, due to the increasing number of people with diabetes, detection of DR symptoms is found to be a heavy and inaccurate task while screening a large number of images. Hence, automated screening system has been considered to identify the lesions present in fundus images. It is found that, in many cases computational screening system reduces the workload when compared to manual grading and also it is found to be the noninvasive and cost effective process.

Diabetic Retinopathy appears on the retina of the eye, which is mainly responsible for the vision of a person. For persons having diabetic retinopathy, the blood vessel present in the retina becomes weak and because of these, vessels may leak blood and fluid of lipoproteins. This eventually leads to the presence of various types of lesions on the retina of the eye. Diabetic retinopathy can be mainly classified in to two type’s namely proliferative and non-proliferative diabetic retinopathy depending upon on the different types of lesions. Proliferative diabetic retinopathy is considered to be the advanced form of retinopathy disease. In this stage, new abnormal blood vessels may grow in to the retina. These blood vessels may burst or leak and blur vision as they are fragile. Non-Proliferative Diabetic Retinopathy (NPDR) is the early stage retinopathy and its symptoms are very mild or sometimes non-existent. In NPDR, structural damage may occur at the back of the eye causing the blood vessels to dilate, leak or rupture resulting in different types of lesions. Some of the Non-Proliferative Diabetic Retinopathy lesions include Microaneurysms, Exudates and Hemorrhages (Figure 1). These are the symptoms in diabetic retinopathy which can be treated once identified in its initial stage. Retinal Microaneurysms (MAs) are the small swellings that arise on the capillaries due to the weakening of vessel walls and these are the first lesion to appear in the retina as a consequence of diabetes mellitus. Their size ranges from 10-125µm. Hemorrhages are usually seen as a red, dot- blot or flame shaped regions. Exudates are the most common lesion occurring in diabetic retinopathy and it occur when cells or fluids seeped out of the blood vessels due to the breakdown of blood retina barrier.

An automatic system in order to identify various types diabetic retinal related lesions from a Bag-of Visual-Word (BoVW) based on visual dictionary has been described in. Here a specific projection space has been used in order to store different types of lesions. In this model, a specific classifier is essential to identify these lesions. Hence to detect the diabetic retinopathy severity, separate classifiers need to be combined in to a unified model.

Microaneurysms (MAs) detection was investigated by I. Lazar et al. and A. Hajdu et al. Here local rotating cross- sectional profile analysis was used. Features such as shape, symmetry, contrast and sharpness are classified with the help of Naive Bayes classifier. The major drawback while using this method is that even though it is able to identify vessel bifurcations and crossings, some false positives come from optic disc. Optic disc removal which is required in order to provide better result was not performed in this method.

B. Antal et al. and A. Hajdu et al. used ensemble-based system for the detection of microaneurysm and for the grading of diabetic retinopathy. Here different preprocessing and different feature extraction methods are combined in order to detect the presence of microaneurysm. Inspite of its improved result, some of its stages are misclassified on detection.

A. Osarch et al. and B. Shadgar et al. and R. Markham et al. located exudates with the help of a computational intelligence based approach. Here color normalization and color enhancement of retinal images are done in its preprocessing stage. Image segmentation is performed with the help of Gaussian smoothed histogram analysis and FCM clustering. A multilayered neural network classifier is used in order to get a sensitivity of about 93.5%. One of major drawback of this paper is that, it does not detect Microaneurysms, the earlier sign of diabetic retinopathy.

Niemeijer et al. used splat feature classification method to identify the presence of retinal hemorrhages in color fundus images. In this method, the splats are created using water shed algorithm. One of the drawbacks...
The basic block diagram describing the flow of analysis of diabetic retinopathy symptom is shown in Figure 2.

### 2.2 Image Acquisition

Here the retinal images are obtained from a publicly available e-optha database\(^\text{17}\). It is generated from OPHDIAT Tele-medical network for Diabetic retinopathy detection, in the framework of the ANR-TECSAN-TELEOPHTA. In e-optha database (Figure 3.), it consist of two sub databases for microaneurysm and exudate detection namely e-optha. MA and e-optha-ex. In this paper, e-optha-ex is concentrated for the detection of exudates. It consists of 82 color fundus images acquired from different patient’s individual visits. It consists of 47 images from patients having exudates and 35 images from healthy patients with no lesions.

### 2.3 Preprocessing

The qualities of retinal images that are obtained using fundoscopy may differ due to non-uniform illumination of images. This may also occur due to number of other factors such as eye movement and retinal color variations. Hence color normalization is a necessary procedure that needs to be performed before image analysis in order to make the image intensity uniform. In this paper, the green channel from the RGB color image is taken and histogram specification approach is used in it to normalize the color of retinal images. Histogram specification approach is used to equalize the level of the original image by changing its intensity values. In histogram specification approach, a reference image was taken and its histogram was generated. Then the histograms of all other images are generated and it is tuned to match with the reference image histograms. The location of optic disc is about 3mm to the nasal side of the macula and it is the only part in the retina which is insensitive to light and hence it is said to be called as blind spot\(^\text{19}\). Optic disc is the bright region present in the retina; hence it can be misclassified as drusen or noise during image analysis. Hence removal of optic disc

---

**Figure 2.** Block diagram of the methodology used to detect DR related lesions in the retina.

**Figure 3.** Sample images.
is essential before proceeding on to feature extraction. Initially optic disc segmentation is performed at its pre-processing stage with the help of edge based detection method. Edge detection is used to identify the image pixels that are on the optic disc of the retinal image. Hough transform\(^{20,21}\) is used in this process to find the parameters of a particular shape from its edge points. Once the optic disc segmentation is done, removal of optic disc is carried out.

### 2.4 Feature Extraction

Image texture provides useful knowledge about the spatial arrangement of color or intensities in the retinal image. In order to classify the color normalized images; several features need to be extracted from the retinal images. In this paper, color and texture based feature extraction is considered. Grey-Level Co-Occurrence Matrix (GLCM) method\(^{22}\) is used to extract the texture features during feature extraction. GLCM also called as Grey Tone Spatial Dependency Matrix is a combination of how often different pixel brightness values appearing in a retinal image. Using histogram calculation, only the intensity distribution can be known. Hence co-occurrence matrix is used here to know the relative position of pixel with respect to each other. GLCM represents the probability of occurrence of a pair of grey levels \((i,j)\) which separated by a particular displacement \(d\) for an angle \(\theta\). GLCM determines the relation between two pixels namely reference pixel and neighboring pixel (Table 1). The sum of all entries given in the GLCM i.e., the number of pixel combinations will be smaller for a given window size.

In GLCM feature calculation (Table 1.), the NPV denotes the neighbor pixel value and RPV denoted the reference pixel value. The features such as Contrast, Correlation, Variance and Angular second moment can be calculated from the GLCM matrices. Contrast is defined as the difference in the visual property of an image that makes an object in the image to be distinguishable from other objects. Correlation gives information about linear dependence between two pixels that are related to each other. Angular second moment or energy is the sum of squares of entries made in the GLCM.

#### 2.5 Feature Classification

To classify the retinal images as normal or infected with the help of color and texture based features, Support Vector Machine (SVM) classifier is used here. SVM is a practical learning method based on statistical learning theory. SVM constructs a hyperplane which can be used for classification. SVM is used to maximize the distance between the ‘difficult points’ and the hyperplane close to decision boundary. Here the decision function is denoted by a subset of training samples called as support vectors. Maximizing the margin is an important process because it indicates that the training sets can be ignored and we can keep only the support vectors.

Consider all the data is at a distance larger than 1 from the hyperplane, for a training set of \(\{(x_i, y_i)\}\). Here, for support vectors, the inequality becomes equality when each example is at a distance from the hyperplane \(r = \frac{w^T x + b}{\|w\|}\) and the margin \(\rho = \frac{2}{\|w\|}\). Next step is to formulate the quadratic optimization problem by finding the value of \(w\) and \(b\) such that the \(\rho\) value can be maximized for all \(\{(x_i, y_i)\}\). Quadratic optimization problems can be solved by constructing a dual problem in which a Lagrange multiplier \(\alpha\) is associated with every constraint in the primary problem. Support Vector Machine provides better result when it is used for high dimensional data's.

### 3. Result and Discussion

In this paper, retinal color fundus images from e-optha-ex database\(^{18}\) were used for DR screening. It consist of 82 images in total with 47 exudates detected images. These color retinal images were used in order to detect the initial lesion that is responsible for diabetic retinopathy. In the normal color retinal images, with without using any type of color normalization, small variations between different initial symptoms of diabetic retinopathy cannot be identified. Table 2 shows the comparison of previous techniques and the databases considered.

| Table 1. Calculation of GLCM |
|-----------------------------|
| NPV→RPV | 0  | 1  | 2  | 3  |
| 0       | 0.0| 0.1| 0.2| 0.3|
| 1       | 1.0| 1.1| 1.2| 1.3|
| 2       | 2.0| 2.1| 2.2| 2.3|
| 3       | 3.0| 3.1| 3.2| 3.3|
In this paper, Color normalization using Histogram processing has been used in normal fundus images in order to uniformly redistribute the intensity of images. Usually optic disc present in retinal images will be misclassified as noise. Hence, in the proposed method, optic disc removal is performed with the help of edge based detection method. Detecting exudate after segmenting optic disc will be helpful in order to provide better result. After removing the optic disc, GLCM method is used to extract the texture features of retinal images. After extracting the texture features, SVM classifier is used to detect the exudates from abnormal images.

By using SVM classifiers in order to detect exudate regions, classification accuracy of about 92% is achieved. The comparison of vectorised and non-vectorised GLCM feature computation based on their execution and CPU time is taken (Figure 4). Here the computation is performed based on 10 different GLCM inputs and it is shown from the graph that the CPU time consumption in order to gather autocorrelation and contrast features and the execution time for correlation features is low when compared to other features.

At first, the color fundus diabetic retinopathy image is taken for abnormality detection. Here, initially color normalization is carried out and then optic disc segmentation is performed using Hough transform. Exudate detection from normal and abnormal image was analyzed using SVM classifier (Figure 5). The proposed method provides better accuracy when compared to past techniques due to the part of several computational intelligence based methods like color normalization using histogram processing, optic disc removal using Hough transform, GLCM method based feature extraction and SVM classifiers. Hence this method can be used by ophthalmologists and also by non-experts in order to identify the DR affected patients and it can also be used to screen the DR related patients for digital color retinal images.

Table 2. Comparison of previous techniques

| Authors name                        | Technique Used                              | Database Considered              | Number of images | Classification Accuracy          |
|-------------------------------------|---------------------------------------------|----------------------------------|------------------|----------------------------------|
| A.Osarch, B.Shadgar, R.Markham      | Computational intelligence based approach   | Bristol Eye Hospital             | 300              | Sensitivity- 93.5%
Spécificity-92.1%                  |
| H.Li, O.Chutatape                   | Model Based approach                        | Singapore National Eye Center    | 35               | Sensitivity- 100%
Spécificity- 71%                   |
| C.Agurto, V.Murray, S.Nemeth, E.S.Barriga, P.Soliz | Multiscale optimization approach          | UTHSC SA & Messidor Dataset      | 652 & 400        | Sensitivity- 100%
Spécificity- 73%                   |

Figure 5. (a) Retinal image. (b) Color Normalization. (c) Optic Disc Segmentation and Result. (d) Classification result.

Figure 4. Comparison of vectorised and non-vectorised GLCM features.
4. Conclusion

This paper proposes an intelligence method for detecting initial lesions that appear in the retina due to diabetic retinopathy. Normal color fundus images considered are of non-uniform illumination. Hence color normalization is performed at its preprocessing stage for the uniform distribution of intensity of color fundus retinal images. Optic disc segmentation is done using Hough transform method. At the next stage, GLCM is used to extract the texture features from the color retinal images. Feature extraction and classification provides better results for the detection of lesions using digital fundus images. SVM based classifier is used here to detect abnormal images and it presents better classification accuracy when compared to previous techniques. This method can be used for diabetic retinopathy screening based on the lesion detection. Further test need to be carried out to detect other DR related lesions in the retinal images.

5. References

1. Mohamed Q, Gillies MC, Wong TY. Management of diabetic retinopathy: A systematic review. Clinician’s Corner. 2007; 298(8):902–16.
2. World Health Organization-Diabetes programme. 2015. Available from: http://www.who.int/diabetes/en/
3. Salomao SR, Mitsuhiro MRKH, Belfort R. Visual impairment and blindness: An overview of prevalence and causes in Brazil. Annals of the Brazilian Academy of Sciences. 2009; 81(3):539–49.
4. Pettitt DJ. Decreasing the risk of diabetic retinopathy in a study of case management. The California medical type 2 diabetes study. Diabetes Care. 2005; 28(12):819–22.
5. Abramoff MD, Niemeijer M, Suttrop-Schulten MSA, Viergever MA, Russell SR, van Ginneken B. Evaluation of a system for automatic detection of diabetic retinopathy from color fundus photographs in a large population of patients with diabetes. Diabetes Care. 2008; 31(2):193–8.
6. Hipwell JH, Strachan F, Olson JA, McHardy KC, Sharp PF, Forrester JV. Automated detection of microaneurysms in digital red-free photographs: A diabetic retinopathy screening tool. Diabetic Med. 2000; 17(8):588–94.
7. Abramoff MD, Suttrop-Schulten MSA. Web-based screening for diabetic retinopathy in a primary care population: The eye check project. Telemedicine and e-Health. 2005; 11(6):668–74.
8. Lee SC, Lee ET, Wang Y, Klein R, Kingsley RM, Warn A. Computer classification of nonproliferative diabetic retinopathy. Clinical Sciences. Arch Ophthalmol. 2005; 123(6):759-64.
9. Huang K, Yan M. A local adaptive algorithm for microaneurysms detection in digital fundus images. First International Workshop. CVBIA. LNCS Springer-Verlag Berlin Heidelberg; 2005. p. 103–13.
10. Rocha A, Carvalho T, Jelinek HF, Goldenstein S, Wainer J. Points of interest and visual dictionaries for automatic retinal lesion detection. IEEE Transactions on Biomedical Engineering. 2012 Aug; 59(8):2244–53.
11. Lazar I, Hajdu A. Retinal microaneurysm detection through local rotating cross-section profile analysis. IEEE Transactions on Medical Imaging. 2013; 32(2):400–7.
12. Antal B, Hajdu A. An ensemble-based system for microaneurysm detection and diabetic retinopathy grading. IEEE Transactions on Biomedical Engineering. 2012; 59(6):1720–6.
13. Osareh A, Shaghar B, Markham R. A computational-intelligence-based approach for detection of exudates in diabetic retinopathy images. IEEE Transactions on Information Technology in Biomedicine. 2009; 13(4):535–45.
14. Tang I, Niemeijer M, Reinhardt JM, Garvin MK, Abramoff MD. Splat feature classification with application to retinal hemorrhage detection in fundus images. IEEE Transactions on Medical Imaging. 2013; 32(2):364–75.
15. Quellec G, Lamberd M, Josselin PM, Cazuguel G. Optimal wavelet transform for the detection of microaneurysms in retina photographs. IEEE Transactions on Medical Imaging. 2008; 27(9):1230–41.
16. Niemeijer M, Abramoff MD, Ginneken BV. Information fusion for diabetic retinopathy CAD. IEEE Transactions on Medical Imaging. 2009; 28(3):775–85.
17. E-Optha. A Color fundus image database; 2015. Available from: http://www.adcis.net/en/Download-Third-Party/E-Optha.html
18. Gonzalez R, Woods R. Digital image processing. Reading, MA: Addison-Wesley; 1992.
19. Kaur A, Boparai RS. A Survey on localizing optic disk. International Journal of Information and Computation Technology. 2014; 4(14):1355–9.
20. Duda RO, Hart PE. Use of the hough transformation to detect lines and curves in picture. Commun. ACM. 1972; 15:11–15.
21. Arturo A, Gegundez-Arias ME, Marin D. Detecting the optic disc boundary in digital fundus images using morphological, edge detection, and feature extraction techniques. IEEE Transactions on Medical Imaging. 2010; 29(11):1860–9.
22. Haralick RM, Shanmugam K, Dinstein I. Textural features for image classification. IEEE Transactions on Systems, Man, and Cybernetics. 1973; 3(6):610–21.