

A Review on Automated Diagnosis of Diabetic Retinopathy

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Abstract: Diabetic retinopathy is a vision threatening complication as a result of diabetes mellitus which is the main cause of visual impairment and blindness in diabetic patients. In many cases the patient is not conscious of the disease until it is too late for effective treatment. The prevalence of retinopathy varies with the age of diabetes and the duration of disease. Early diagnosis by regular screening and treatment is beneficial in preventing visual impairment and blindness. This paper presents the review of automatic detection of diabetic retinopathy.

Keywords: Diabetic retinopathy, exudates, neural network, microaneurysm and optic disk.

I. INTRODUCTION

Diabetes mellitus is a vital cause of visual morbidity that affects an estimated 11.8 million diagnosed and 4.9 million undiagnosed persons in the US [1, 2]. Among them 40.3% have some degree of diabetic retinopathy and 8.2% have vision threatening retinopathy. The rates of retinopathy and vision-frightening retinopathy are higher in persons with type 1 diabetes, occurring in 82.3% and 32.2% of affected persons, respectively [3-6]. Persons with diabetic retinopathy (DR) are 29 times more to become blind than those without diabetes and it is estimated that diabetic retinopathy is responsible for 5% of all the world's blindness cases. The medical cost of DR has been estimated to be US\$500 million per year in the US alone [6-8]. Diabetic retinopathy is a microvascular complication of diabetes and the common cause of damage to the retina of the eye of the diabetic patient. The prevalence of retinopathy varies with the age of diabetes and the duration of disease. For the detection of diabetic retinopathy color fundus photographs of the retina is required.

If the symptoms are identified in earlier stage, then proper treatment can be provided [9-14]. The effective treatment of diabetic retinopathy can inhibit the progression of the diseases. Many patients are not aware of this disease. It is point out that at least 90% of the new cases of diabetic retinopathy could be reduced by giving proper treatment and regular monitoring of the eye [15].

Diabetic retinopathy can be diagnosed by the defects of the retina. The defects may include microaneurysms, haemorrhages and exudates [14, 15]. Microaneurysms are

the primary abnormality occurring in the eye because of diabetes. These are recognized by tiny, dark red spots or haemorrhages that may occur as alone or in clusters and light sensitive to retina. Haemorrhages are round in shape, which are found in deep layer of the retina. Exudates are two types: hard exudates and soft exudates. Hard exudates are the fat and protein leaking out from the blood vessel, which prevents light from reaching the retina and causes visual impairment. There are some spots termed as soft exudates are seems in the severe stages of diabetic retinopathy called cotton wool spots. These caused by nerve fiber layer blocked and the local nerve fiber axons get blown up [16, 17]. Fig.1 shows the features of diabetic retinopathy.

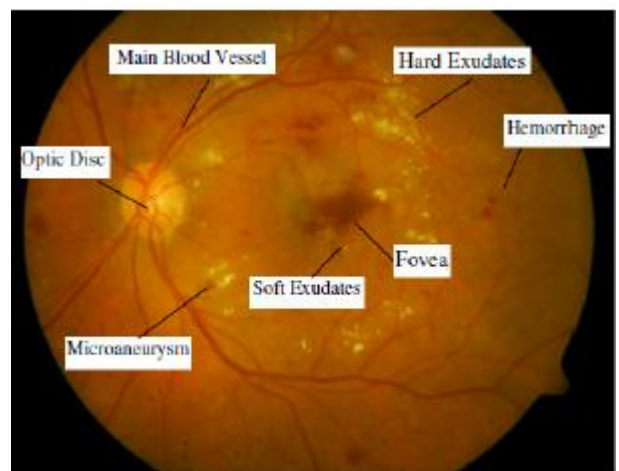


Fig.1 Various features on a typical Diabetic Retinopathy image (image taken from Ref. [15]).

The aim of this paper is to review the existing method of automated diagnosis of diabetic retinopathy and to discuss on future research direction of automated diagnosis of diabetic retinopathy.

The rest of the paper is organized as follows. Section II describes the detection methods and section III discussions on existing techniques and future research directions. Finally, section IV draws the conclusion of the paper.

II. DIABETIC RETINOPATHY DETECTION METHODS

Fig.2. shows the flow diagram of diabetic retinopathy detection system.

A. Detection by exudates

Automatic detection of hard and soft exudates using histogram thresholding is described by Kavitha and Duraiswamy [15]. They preprocessed the fundus images using CIE Lab colorspace and then used mathematical morphology for the detection of hard and soft exudates.

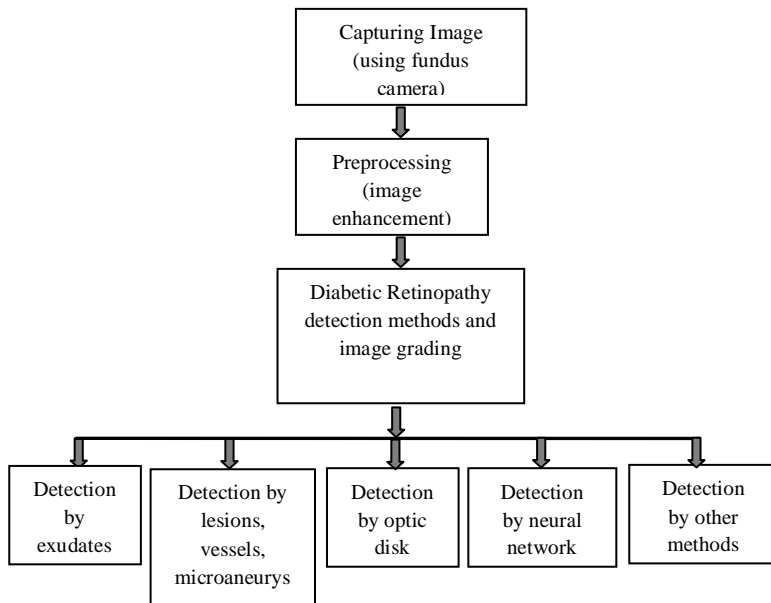


Fig.2 Flow diagram of diabetic retinopathy detection system

Sopharak *et al.* [16] described a system to detect exudates based on mathematical morphology on non-dilated retinal image. At first, retinal image was converted from RGB to HSI color space. Then median filtering was used to reduce noise and an adaptive histogram equalization was applied for contrast enhancement. Then fuzzy C-means clustering and mathematical morphology were applied. The accuracy of the system is 99.11%.

Basha *et al.* [17] proposed a method for automatic detection of hard exudates in diabetic retinopathy from color fundus images through morphological segmentation and fuzzy logic. But their algorithm still gives some false detection due to color similarity among exudates, optic disc

and blood vessel. Fig. 3 shows the detection of hard exudates in diabetic retinopathy.

Sargunar and Sukanesh [18] described classification of diabetic retinopathy using fuzzy c-means clustering, fractal techniques and morphological transformations. The system involves preprocessing retinal images by local contrast enhancement using mean and variance. Then the preprocessed image is segmented and textural features are extracted for classification. The classification accuracy of the system is 85%.

Sae-Tang, et al. [19] proposed a system for exudates detection in fundus images with non-uniform illumination. The authors divided the system into two parts: in the first part background illumination was estimated and in the second part background subtraction was performed for exudates detection.

Akter et al. [20] describe a morphology-based exudates detection for early diagnosis of diabetic retinopathy.

B. Detection by lesions, microaneurysm and vessels

Sanchez et al. [21] described detection of diabetic retinopathy through lesions. Their method uses two features (color and shape) of the lesion to detect lesions. The sensitivity of the system is 79.62%.

Esmaeili et al. [22] described a curvelet transform based method for extraction of red lesions for diagnosis of diabetic retinopathy. They applied digital curvelet transform [23] to produce enhanced image and modify curvelet coefficients in order to lead red objects to zero by thresholding. The sensitivity is 94% and specificity is 87% of the method.

Quelleg et al. [24] described an optimal filter framework for automated detection of lesions. But the performance of the method is not mentioned.

Automatic retinal lesion detection was described by the authors [25] on the selection of features around locally invariant interest points and visual dictionaries of images. They describe diabetic related lesion detection into two phases. One is training [26] consisting of learning the behavior of the lesions that makes the images with lesions different to normal images. The other is detection which consists of using the learned knowledge for testing unknown images. The performance of the system is 98.1%. Karnowski et al. [27] report a method for lesion segmentation based on the morphological reconstruction methods because of its high adaptability to local contrast changes. They adapt the method to include segmentation of dark lesions with a given vasculature segmentation and used ground truth data to create post-processing filters for different lesion types. A simple Bayesian classifier is used to classify different lesions. The sensitivity and specificity of the system is 90%. Comparisons of other method was not performed.

Niemeijer et al. [28] present international microaneurysm detection competition, organized in the context of the retinopathy online challenge (ROC). They asked an expert to assign each reference image identified microaneurysm into three classes based on their local contrast and compare the results of five different methods. The results of their work was submitted through a website after which standardized evaluation software was used to determine the performance of each of the methods.

Supervised method of segmentation of retinal images by using gray-level and moment invariant-based features are used by the authors [29] for early detection of diabetic retinopathy. They use a neural network system and moment-invariant-based feature for pixel classification. The classification procedure assigns as vessel or nonvessel to each candidate pixel. The authors distribute the training set data in the feature space for the selection of a suitable classifier.

Osareh and Shadgar [30] describe an automatic blood vessel segmentation of color fundus images of retina for the detection of diabetic retinopathy. They use a Bayesian classifier with conditional probability density function. And the accuracy of their optimum classifier are evaluated using ROC curves analysis. The sensitivity and specificity of the system is 95.5% is 97.1% respectively.

C. Detection by optic disk

Aquino et al. [31] described an automated optic disk detection in retinal images with diabetic retinopathy. Their detection procedure is divided in two independent methodologies. One is location methodology consists of maximum difference method, maximum variance method and low-pass filter method which work on the green channel of the RGB color space providing the best contrast. The other methods is a boundary segmentation methodology estimating a circular approximation of the optical disk that applies mathematical morphology, edge detection and the Circular Hough Transform. In Fig.4. a) shows the determination of the optic disk detected by the methods given in reference [31]. In Fig.4.b), we [20] shows the detected optic disk region by morphology-based exudates detection. The success rate of optic disk location of [31] and [20] are 98.83% and 99%, respectively.

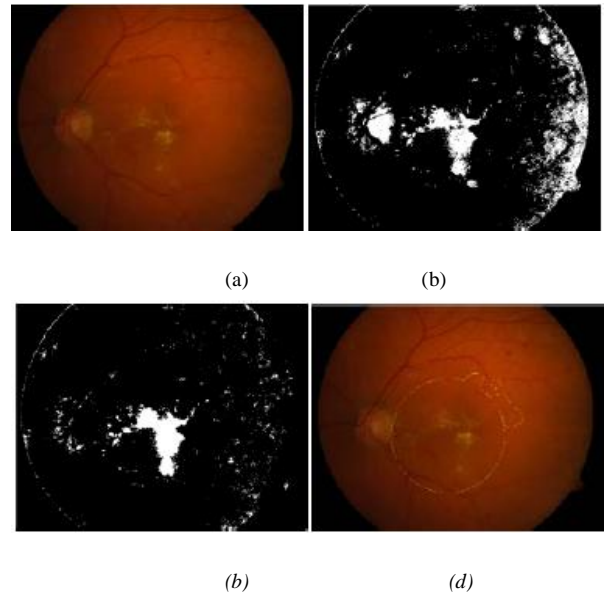


Fig.3 Detection of hard Exudates in Diabetic Retinopathy (a) Original Image (b) Image after preprocessing (c) Image after morphological Segmentation (d) Results superimposed on the Original image (images taken from Ref. [17]).

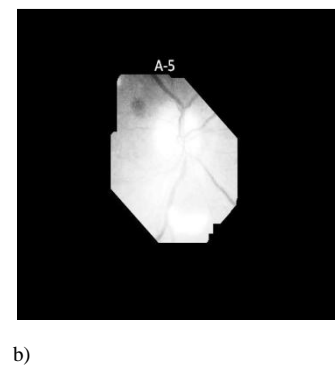
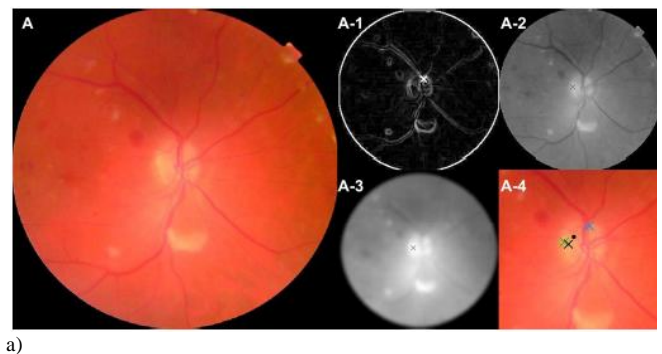


Fig. 4 Determination of the optic disk pixel (ODP): a): (A) Original image, (A-1) OD pixel returned by the maximum difference method, (A-2) OD pixel returned by the maximum variance method, (A-3) OD pixel returned by the low-pass filter method, (A-4) the three pixels are close, so the location of the final ODP (the black dot) is the average of their locations. (images taken from Ref. [31]), and b): (A-5) Optic disk detected by [20].

Yu H et al. [32] present an automatic optical disk localization and segmentation algorithm for retinal disease screening. The authors develop an optical disk segmentation algorithm which uses alternating sequential filtering and morphological reconstruction. Optimization of model parameters ensures the best segmentation performance.

D. Detection by neural network

H Sivakumar et al. [33] describe an artificial-neural-network-based method to classify diabetic retinopathy. They have implemented three-layer feedforward backpropagation neural-network. In the training period they used 6 input nodes, 6 hidden nodes, and 4 output nodes. The four output nodes corresponds to normal, diabetic Retinopathy, preproliferative diabetic retinopathy, proliferative diabetic retinopathy.

Jayanthi et al. [34] described a system classifying the type of retinal disease and automatic diagnosis of age-related macular degeneration (drusen). Texture analysis is used to extract the features of the retina and then a neural network based classifier is used to classify the type of retinal disease.

Vijayamadheswaran et al. [35] proposed contextual clustering and radial basis function network. Contextual clustering extract features and the extracted features are used as inputs for the network. The target values for training each exudates is given in the output layer. The performance of the system is 96%.

E. Detection by other methods

Shijian et al. [36] proposed the technique for classifying fundus images. In this technique fundus images are converted into a feature vector based on histograms range images at different resolutions. Then fundus image were classified by learning from feature vectors of a large number of normal and abnormal training fundus images. The accuracy of the technique is 96%.

Gang et al. [37] presented an approach of abnormality detection from color fundus images which uses object-based color difference. They categorize the abnormality into microaneurysms, hemorrhage, exudates etc. as spot class, abnormal blood vessels and abnormal stereo measurement.

Keerthi et al. [38] proposed methods to detect microaneurysms using a simple threshold from a preprocessed image. Then the known and frequently occurring disorder objects are rejected. At last stage, the candidates are assigned on their similarity to true microaneurysms.

Fadzil et al. [39] designed a system for grading diabetic retinopathy. They have used foveal avascular zone to diagnose diabetic retinopathy. Then contrast limited adaptive histogram equalization is applied to increase the

contrast of retinal blood vessels to the background in both dark and bright regions. Then segment retinal blood vessels in the fundus image using Otsu's thresholding and the retinal blood vessel end points at perifoveal capillary network is detected and selected to determine the foveal avascular zone area. The foveal avascular zone area is analyzed for fundus images from a fundus image database. Foveal avascular zone mean and median increases as the diabetic retinopathy stage progress to a more severe level. Then the Gaussian Bayes Classifier is used for grading diabetic retinopathy as no diabetic retinopathy, mild non-proliferative diabetic retinopathy, moderate non-proliferative diabetic retinopathy, severe non-proliferative diabetic retinopathy/proliferative diabetic retinopathy. The system achieves 96% accuracy.

Priya and Aruna [40] described review of automated diagnosis of diabetic retinopathy using the support vector machine. They have used a number of features such as area, mean and standard deviation of the preprocessed images are extracted to characterize the image content. The support vector machine learning algorithm is applied to produce the classification parameters according to calculated features and classify images into proliferative diabetic retinopathy, non proliferative diabetic retinopathy or normal. The sensitivity of the system is 99.45%.

III. DISCUSSIONS

A. Critical comments on detection through exudates

Hard and soft exudates detection described by Kavitha and Duraiswamy [15] method's accuracy is low due to false detection. However, the accuracy of the authors[16] method is low due to artifacts, additive noise and faded exudates.

Exudates detection by color histogram thresholding, the authors Basha and Prasad [17] algorithm has some false detection because the color of exudates are similar to optic disc and edge of blood vessel.

Application of automatic image processing methods [18] to fundus has the problems of varying image quality such as contrast and brightness, and characterization of color differences due to inhomogeneous illumination of the eye background.

Sae-Tang et al. [19] describe exudates detection through non-uniform illumination background subtraction. But their method has some limitations. Their proposed method cannot detect some of the soft exudates because intensity is not very distinct from the intensity of the background and some soft exudates are not as bright lesions.

The method described by Akter et al. [20] should test their system with more retinopathy images.

B. Critical comments on detection through Lesions, Microaneurysm and Vessels

The detection of diabetic retinopathy through lesions [21] has some problems. Their algorithm depends on the

detection of optic disk and blood vessels and makes the results dependent on the detection of optic disk and blood vessels. The authors [22] did not compare their system with existing methods. The limitation of the method [26] is that the authors did not compare to existing method and classification feature were not good.

Karnowski et al. [27] select the initial parameter and the chosen parameter were used for the remaining experiments for robustness. To save the processing time, the larger images were resized.

Niemeijer et al. [28] describe the results of the various methods to show the best performance for the microaneurysms. But the human expert is well ahead of the system. So there is still scope for improvement in the automatic system performance.

Diego et al. [29] describe a new supervised method for blood vessel segmentation in retinal images. But their system produce special distribution of the classification errors by the segmentation algorithm.

C. Critical comments on detection through optic disk

The system of the authors [31] have to be able to analyze low quality images, but images several megabytes in size would not be acceptable because, it needs large storage requirements. The accuracy and robustness of locating the optical disk to be increased.

D. Critical comments on detection through neural network

Sivakumar et al. [33] have to extend to further applications in medicine. Jayanthi et al. [34] described a survey of the classical and the methods for classifying and diagnosing the type of retinal disease and detecting its features after diagnosis at an earlier stage of the disease. Although a lot of work has been done, automatic diagnosis of retinal diseases at an earlier stage still remains an open problem.

Vijayamadheswaran et al. [35] classified the exudates. But they did not present the performance of the system.

E. Critical comments on detection through other methods

The classification of the system [36] accuracy requires more range images and a larger number of neighborhood windows. One solution is to perform a feature selection procedure during the training stage to identify the most distinctive histogram features. Then the range images with less distinctive histogram features need not to be calculated.

Gang Luo et al. [37] proposed system utilized to extract abnormalities of diabetic retinopathy without over-segmentation problem. But they did not tell about the performance of the system.

F. Future research directions

From this review, we found that there is a good number of different approaches for diabetic retinopathy. All have some merits and demerits. Among these methods detection by exudates, lesions and detection by neural network are

somehow benchmarks in this research domain. In future researcher should concentrate on

- 1) Developing improved camera system for early diagnosis retinopathy.
- 2) Effectiveness of the existing techniques are questionable. For more accuracy hybridization of methods may be effective.
- 3) In addition, researchers may focus on developing novel approaches overcoming the demerits of existing technology.

IV. CONCLUSIONS

We have presented the current status of automated diagnosis of diabetic retinopathy. The imaging system of the fundus camera needs to be developed in effective manner with high resolution so that the diagnosis of diabetic retinopathy can be detected at early stage. The performances of existing techniques in practical situations are not up-to the mark. So researchers would concentrate on developing a system that would be effective in real life. In addition, researchers may focus on developing a hybrid system, which is suitable for real life application.

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