A COMPREHENSIVE REVIEW ON DIABETIC RETINOPATHY IDENTIFICATION AND CLASSIFICATION

[1]R. Rajkumar, [2]P. Dhanalakshmi
[1]Assistant Professor, [2]Professor,
[1]Department of Computer Science and Engineering,
[1]Annamalai University, Annamalainagar, Tamilnadu, India

Abstract : Diabetic retinopathy (DR) is a condition that occurs in individuals who have diabetes. It makes gradual damage to the retina, the light-sensitive lining at the back of the eye. Diabetic retinopathy is a serious sight- threatening complication of diabetes. DR is the main reason of loss vision in people if not detected and treated in time. Computer Aided Diagnosis (CAD) system helps to identify Diabetic retinopathy in fundus images. In this paper we discuss and review about various techniques to find nonproliferative and proliferative Diabetic retinopathy diseases. The paper also focuses on qualitative and quantitative comparison of the existing literature with limitation in order to develop a better and more effective method. It is an attempt to gathering the available algorithms for future research.

IndexTerms **- Diabetic retinopathy, fundus image, nonproliferative DR disease, proliferative DR disease.**

I. INTRODUCTION

Diabetes is a chronic disease which is the chain reaction of insufficient insulin production in the human body. Uncontrolled diabetes eventually brings several entanglement and disorders along with it. It affect retina of the eye which leads to Diabetic Retinopathy. Diabetic Retinopathy directly or indirectly affects the human vision and may also lead to irreversible loss. The pathogenesis is explained in the research study by Eshaq et al. [1].DR is indicating in its early stages, and the late diagnosis leads to loss of vision.

Thus, the screening of Diabetic Retinopathy (DR) with the help of recent Computer Aided Diagnosis (CAD) system and image processing techniques helps in timely diagnosis and early treatment. Furthermore, use of conventional methods is time-consuming and demand efforts and could be prone to flaw. The use of recent medical image processing algorithms could minimize the workload of ophthalmologists and results in an accurate diagnosis. Thus, it has been focused and developing research area for the screening of different stages of DR.

In this paper, we analyses the algorithms for automated detection and classification of the DR algorithms. First we described the features and types of DR. we categories DR algorithms into several groups according to their sequence order in algorithmic application. These categories include optic disc segmentation, blood vessel segmentation, clinical and geometric feature detection such as fovea and macula detection [2].

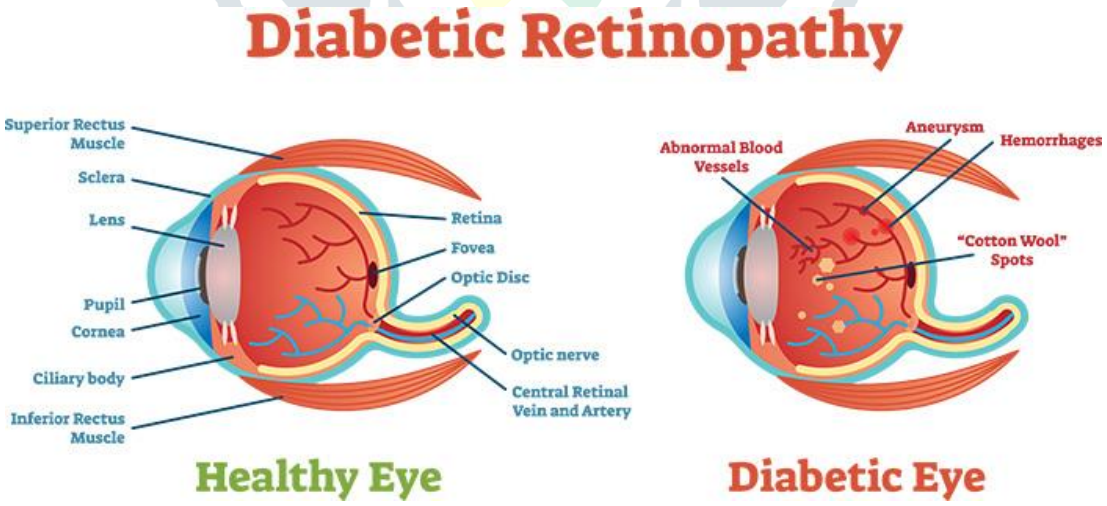

Fig. 1. normal retina and retina with diabetic retinopathy

DR is primarily classified into two stages one is proliferative DR (PDR) and another is non-proliferative DR (NPDR). The NPDR further classified in to micro aneurysms (MA), haemorrhages (HEM), soft exudates (SE), hard exudates (HE) whereas PDR can lead to retinal detachment called as Neovascularisation (NV) (Fig. 1) [3].

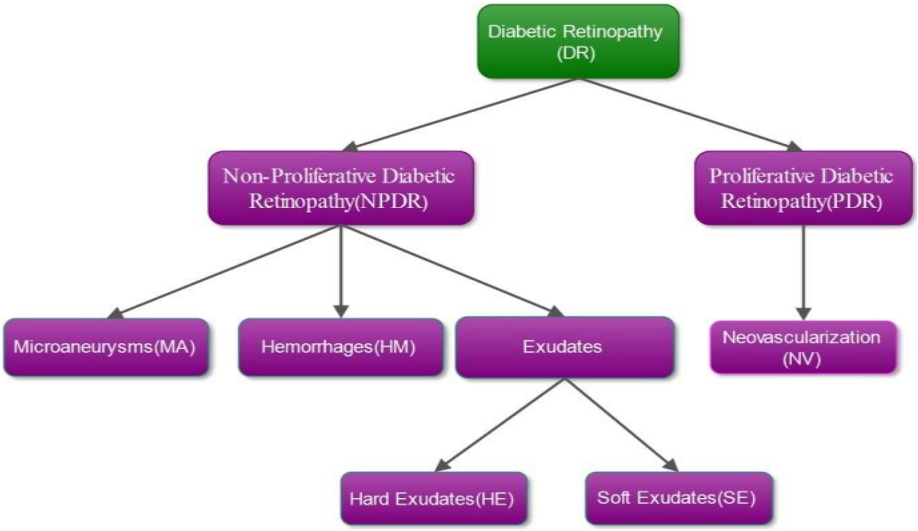

Fig.2. diabetic retinopathy eye disease classification

The common symptoms of Diabetic Retinopathy are [4]

1) seeing an increasing number of floaters,
2) having blurry vision,
3) having vision that changes sometimes from blurry to clear,
4) seeing blank or dark areas in your field of vision,
5) having poor night vision, and
6) Noticing colors appear faded or washed out losing vision.

II. Features of Diabetic Retinopathy

2.1 Micro aneurysm (MA)

Micro aneurysms are the first lesions appearing in diabetic retinopathy. Ma's are physical dilations of the smallest intra-retinal blood vessels called capillaries. These lesions appear as small circular, red dots having distinct margins and are no larger than a blood vessel width at the disk margin.

2.2 Haemorrhages (HM)

Haemorrhages are lesions it represent actual bleeding within the retina, and either are a result of ruptured Ma's or the capillaries become leaky enough to let blood out of the blood vessels. It can be a variety of shapes including dot, blot and flame-shaped. They are usually larger than Ma's, with uneven/indistinct edges and coloring.

2.3 Exudates

Exudates are fluid that leaks out of blood vessels into nearby tissues. The fluid is made of cells, proteins, and solid materials. Exudates may ooze from cuts or from areas of infection or inflammation.

2.4 Hard exudates (HE)

Hard Exudates are white/yellow cholesterol deposits that usually originate from leaking Ma's. HE's are irregularly shaped, vary in size, are hard edged and often have a fatty appearance. HE can, and often are associated with fluid accumulation (retinal-edema) within the retina.

2.5 Soft exudates (SE)

Soft Exudates (Cotton Wool Spots) are lesions appear as white, feathery, fluffy or cottony spots. SE's physically represent infarcts or closures of capillaries, within the retina; however the physical locations of these lesions are in the very exterior layer of the retina (in the nerve fiber layer).

2.6 Neovascularisation (NV)

Neovascularisation (NV) is the first of the proliferative lesions to appear. The thought is that the retina is experiencing areas of hypoxia, or is "under-nourished". In an effort to compensate for this problem, the eye grows new vessels in the areas lacking circulation. The new vessels are very delicate and grow on top of the retina rather than in it, making them prone to leaking. They can cross over one or many major retinal blood vessels, but tend not to cross over themselves. They will often appear in a blossom like a flower bud with the outside part of the NV more dilated than the inner NV. They can also appear as stringy and drawn out, but this is less common [5].

III. Stages of diabetic retinopathy

DR are classified based on damage of blood vessels on eye, and also number of micro aneurysms, haemorrhages at the retina and development of abnormal new vessels. Stages of DR depends on presence of clinical features counting's and severity [6]. Neovascularisation (NV) is the sever stage of retinopathy and new blood vessels start growing anywhere in eye. Therefore, MA and NV are two clinically important types of lesion [7] and fluid in DR is categorized as exudates and non-exudates [8].

The non proliferative DR types are defined as normal, mild, moderate, and sever [10].

Table 3.1: stage and types of features

Stage	Types of features and its severity
Normal	If no DR sign is observed, this class is called Normal
Mild	Only MAs are found in mild DR
Hard	Moderate DR: If the number of MAs, haemorrhages less than 20 in each quadrant, hard exudates(white lesion, cotton wool
Severe	MAs, more than 20 haemorrhages in each quadrant, Venous beading in more than two quadrants, exudates, red lesion

IV. DATABASE USED FOR RESEARCH

The selection of dataset for training and testing plays an important role for the evaluation of any proposed systems. Most of the data collections used in application of algorithms are the research data collections for testing the algorithms related to blood vessels, exudates and other diabetic retinopathy features. There are various retinal fundus images dataset are available in public domain, some database are allowed to download on request. The fundus image databases are prepared by capturing the high resolution retinal images by fundus camera. Image classification are done on each subject before prior to process to allow these databases for training and testing of new DR screening and monitoring systems. The quality and numbers of images played vital role during performance evaluation of the system. Only a few of these are actually taken from research hospitals. The online research data collections such as [9]

DIARTDB: This database is provided by a research group Tomi Kauppi et al. and can be downloaded from http://www.it.lut.fi/ project/imageret/ and freely available for research purpose. Images were captured with a 50 degree field-of-view digital fundus camera. This has two levels, which are: DIARTDB0, consists of 130 color fundus images and 20 are normal and 110 contain signs of the diabetic retinopathy. These signs include hard exudates, soft exu-dates, MAS, HMAS and NV. The second database is called DIARTDB1, consist of 89 indexed fundus images out of which 84 contain at least mild non-proliferative signs (MAs) of DR, and 5 are normal without DR.

HRF: HRF is introduced as the High-Resolution Fundus (HRF) image database for comparative studies of the segmentation algorithms on retinal fundus images. These images were taken using a Canon CR-1 fundus camera with multiple image acquisition setting and 45 degree field of view. Currently, this database consists of 15images in each category for healthy 15 with diabetic retinopathy and glau-comatous patients. It also contains the blood vessel segmentation images along the mask of field of view (FOV).

STARE: The STructured Analysis of the Retina (STARE) is a University of California, San Diego project and images are provided by the Shiley Eye Center at the University of California. It consists of 400 images.

KAGGLE: A set of high resolution fundus images are provided by the Kaggle platform. These images are taken under the variety of spatial conditions. These images are indexed by an experienced pathologist according to scale from 0 to 4 according to No DR, Mild, Moderate, Severe and Proliferative DR.

ROC: Retinopathy Online Challenge (ROC) is a database developed for enabling medical image analysis research groups to develop diabetic retinopathy CAD algorithms and it aims to provide a platform for algorithms comparison.

DERIVE: The DRIVE database has been established from a diabetic retinopathy screening program in the Netherlands. It consists of 40 images out of which, 33 are without signs of DR and 7 show signs of mild early diabetic retinopathy. The images were acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV).

MESSIDOR is a research program funded by the French Ministry of Research and Defense within a 2004 TECHNO-VISION program. It consists of 1200 eye fundus color numerical images. These images are acquired by 3 ophthalmologic departments using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field of view. The images were captured using 8 bits per color plane at 1440 × 960, 2240 × 1488 or 2304 × 1536 pixels.

E OPTHIA: The OPHDIAT Tele-medical network for DR screening established a colored image database for DR, called E ophtha. The database is made of retinal images with different types of lesions (exudates and microaneurysms) manually annotated by ophthalmology experts. It contains e-ophtha-MA (MicroAneurysms), and e-ophtha-EX (EXudates). The e-ophtha-EX contains 47 images with exudates and 35 images with no lesion and e-ophtha-MA consist of 148 images with microaneurysms or small hemorrhages and 233 images with no lesion.

DRIONS: A benchmarking database for optic nerve head segmentation from digital retinal images. It consists of 110 images belonging to the Ophthalmology Service at Miguel Servet Hospital, Saragossa (Spain). The samples are 46.2 % male and 53.8 % female from Caucasian ethnicity. The images were acquired with a colour analogical fundus camera.

HEI Med: The Hamilton Eye Institute Macular Edema Dataset (HEI-MED) is a test data images for algorithms for the detection of exu-dates and diabetic macular edema. It consists of 169 fundus images [10].

V. PERFORMANCE EVALUATION

The performance evaluation of automatic DR screening systems based on quality parameters, such as accuracy (AUC-Area under Curve), sensitivity (True Positive Rate) and specificity (True Negative Rate). The performance metrics calculate from result data to specify the optimal class. ROC (Receiver Operating Characteristics) is also signifying the performance of classifier in DR screening systems [14]. The way of performance metrics calculation is shown in followings

$$\text{Accuracy}=\frac{\text{True Positive + True Negative}}{\text{Total Populations}} \quad (1)$$

$$\text{Sensitivity}=\frac{\text{Number of True Positive}}{\text{True Negative +False Negative}} \quad (2)$$

$$\text{Specificity}=\frac{\text{Number of True Negative}}{\text{True Negative +False Positive}} \quad (3)$$

VI. DIABETIC RETINOPATHY SCREENING METHODS AND CLASSIFICATION TECHNIQUES COMPARISON

Diabetic retinopathy is determined by calculating the number of pixels segmented as unhealthy in the retinal image, if the area of lesion is larger than a threshold value the DR is diagnosed as positive.

Table 6.1: Diabetic retinopathy screening methods and classification techniques comparison

Year	Authors& Title	Classifier/Methodology	Database	Accuracy	Sensitivity	Specificity
2012	K.Narasimhan et al[11]	SVM and Bayesian	From Hospital	70%	94%	89%
2013	R.Geetha Ramani et al[12]	AdaBoostM1	Gold Standard Dataset	96.67%	93.33%	100%
2014	Sohini Roychowdhry et al[13]	Meachine Learning	Messidor	90.4%	100%	53.16%
2014	Ana Salazar et al[14]	Segmentation	Stare, Drive, DiaretDB1	94.73%	87.50%	-
2013	M.Usman Akram et al[15]	m Mediod Classifier	Stare, Drive, DiaretDB1, Messidor	95%	97%	92%
2016	Gulshan V et al[16]	Deep learning	EyePACS, Messidor	99.1%	90.3%	98.1%
2016	Harry Pratt et al[17]	SVM	DiaretDB0, DiaretDB1	75%	95%	30%
2017	Yang et al[18]	ANN	Kaggle	96.87%	95.5%	97.3%
2017	R.venkatesan et al[19]	Color autocorrelogram features	MIMI, Stare, DiaretDB0	87.61%	-	-

VII. CONCLUSION

Early stage of Diabetic Retinopathy detection is very crucial for saving human vision, DR detection is still challenging task in digital image processing. In this paper has discussed various preprocessing techniques, feature selection and extraction techniques with limitation. For accurate DR detection and classification we need to concentrate on choosing correct and effective diabetic features for better result.

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