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Red Lesion Detection in Diabetic Retinopathy Fundus Images using Automated Systems: A review

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Abstract - *Diabetic Retinopathy (DR), a complication of Diabetes Mellitus, is one of the dominant sources of beginning towards blindness. Any diabetic patient may develop it in early years of the disease. Due care and regular eye check-up can keep the problem in control. But, manual analysis of the retinal fundus images may be sluggish and faulty. Automated systems to detect DR promise a more reliable way to examine the lesions, hence, getting accurate diagnosis. Microaneurysms and haemorrhages are termed as red lesions. Presence of microaneurysms in the image, mark the beginning of the DR. Detection of red lesions, therefore, become of prime concern. This study presents red lesion detection strategies available in the literature. There are many aspects of the overall framework developed by the researcher. Various approaches to trace the disease, their shortcomings and scope to improve in the future have been discussed. Different performance measures have been utilized for evaluation of the methods proposed. The paper put forward the judicious review of all the facets of the studied material, thereby, giving the comprehensive view.*

***Key Words*: Diabetic Retinopathy, Red lesions, Microaneurysms, Haemorrhages, Detection, Classification, Proliferative DR**

1. INTRODUCTION

Any disease detected at an early stage could save a patient from a lot of trouble of suffering and any unwanted damage to health. Diabetic Retinopathy (DR) is no exception. Diabetic retinopathy is one of the leading causes of blindness in the world. It affects the vision in many different ways like blurred vision, blind spots and in worst case, complete vision loss. It damages the retina of the eye, eventually becoming the paramount reason for blindness. With the commencement of the disease, almost every type-1 (insulin dependent) diabetic patient and approximately >60% of the type-2 (insulin independent) diabetics develop DR in the span of early twenty years [1]. According to American Diabetes Association, any Diabetic Retinopathy and Proliferative Diabetic Retinopathy prevailed among patients, to be 35.4% and 7.5% respectively [2]. Hence, proper screening and regular check-ups becomes crucial for DR patients. The normal and DR affected retina is depicted in figure 1 [3].

This paper focuses on the following issues:

- Literature survey focusing on the red lesion detection strategies
- To give the comparative view with limitations and future scope

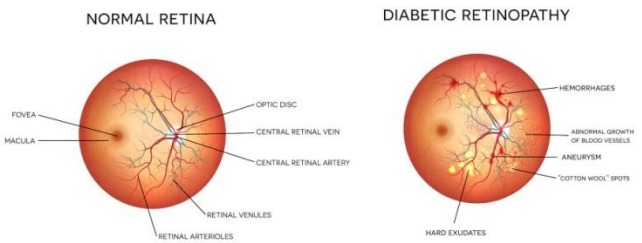


Fig -1: Normal retina and retina with DR [3]

2. DIABETIC RETINOPATHY

Many types of lesions could be present in the retina such as microaneurysms (MA), haemorrhages (HM), exudates (hard and cotton soft wool), neovascularization (new and abnormal blood vessels), etc. Deposition of blood on retina termed as red lesions (microaneurysms, haemorrhages) and deposition of lipids on retina is called as bright lesions (exudates). Blood vessels carry oxygen to the retina. When these vessels get ruptured because of some reasons such as increased glucose level or hypertension, blood starts leaking out of the vessels producing small dot like structure called microaneurysms. More blood leaking takes the form of haemorrhage which is a severe case of DR. DR can be classified as Mild Non-proliferative, Moderate Non-proliferative, Severe Non-proliferative and Proliferative. Table 1 shows the description of the severity level of the classification [4].

This paper emphasizes the detection strategies of red lesions and their outcomes. Table 2 illustrates the types of red lesions. Since, the presence of microaneurysms in the retina is considered as the beginning of the disease, it becomes the foremost job of the ophthalmologists to detect the lesion early and accurately. In the developing countries, there is a scarcity of well trained ophthalmologists because of the constraint of resources. In this scenario, manual detection of disorder may be time consuming, expensive and inaccurate. Automated

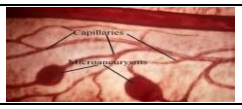
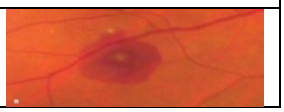
detection and classification ensure not only quick but accurate results, in turn, saving time for ophthalmologists. Many authors have worked on the assessment of the retinal images in order to get the exact diagnosis. Several state-of-the-art frameworks have been developed to obtain the 360 degree analysis.

Table -1: Levels of classification with their description [4]

Sr. No.	Severity Level	Description
1	No DR	No lesion present
2	Mild Non-proliferative DR	Microaneurysms only
3	Moderate Non-proliferative DR	More than MA but less than severe DR
4	Severe Non-proliferative DR	Any of the following : • More than 20 intraretinal HM in each of 4 quadrants • Definite venous beading in 2+ quadrants • Prominent intraretinal microvascular abnormalities in 1+ quadrant • No signs of proliferative DR
5	Proliferative DR	One or more of the following : vitreous/pre-retinal HM, neovascularization

The process of detection of DR starts with the acquisition of the image. Better the quality of the image, better the detection. Different imaging modalities exist. According to recent study, Ultrawide-Field imaging is better than Early Treatment Diabetic Retinopathy Study Standard-7 Field imaging [5]. Some noise (unwanted pixels) gets introduced in the image while acquisition. This can be fixed using preprocessing techniques. Next follows the segmentation, feature extraction and classification. This process is represented in figure 2.

Table -2: Illustration of red lesions

Criteria	Microaneurysm	Haemorrhage
Structure and size	Small red round dot with sharp margin having size less than 125 µm [4]	Larger spot with irregular margin having size greater than 125 µm [4]
Duration	Lasts more than 6 months	Lasts about 6 months
Example		

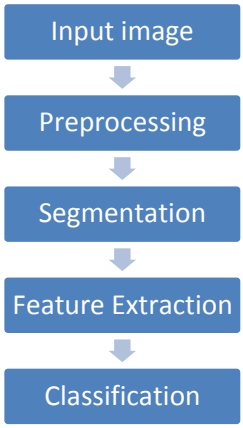


Fig -2: Process of detection and classification of the DR

3. SCREENING METHODOLOGIES FOR RED LESION DETECTION

Many researchers have put the efforts to diagnose the ailment. Red lesion detection becomes crucial as DR begins with the presence of microaneurysms. Antal et al. [6] proposed an ensemble-based framework to detect microaneurysms effectively. Internal components such as preprocessing methods and candidate extractors are combined together. Authors, from their previous work, found out that efficiency could be improved by enhancing the candidate extractor portion. So, they integrated preprocessing element with the candidate extractor part. ROC (Retinopathy Online Challenge), Diaretdb1 2.1, Moorfields and Messidor databases were used to evaluate the performance. The proposed method achieved the AUC (Area under Curve) of 0.875 and AUC for fitted curve at 0.90 ± 0.01. Though, system worked well for MA detection, only detection of MA can't give the true picture and could misclassify the image. More lesions (ex. Exudates) need to be taken into account. Also, the method provides the binary classification. Kumar et al. [7] presented a method to detect DR by extracting the features such as area and number of microaneurysms from the image. Techniques like green channel extraction, histogram equalization and morphological process were used for preprocessing purpose. Detection of MAs was done using techniques like principal component analysis (PCA), contrast limited adaptive histogram equalization (CLAHE). Support Vector Machine (SVM) classifier was used to grade the image as DR eye or healthy eye. The method attained the sensitivity and specificity of 96% and 92% respectively. However, the author wishes to propose a system considering cotton soft wools and blood vessels as the features to detect

proliferative DR and with multiclass classification, in future. Sopharak et al. [19] proposed microaneurysm detection method for non-dilated retinal images. Eighteen features of MAs were extracted and fed to Naïve bayes classifier. The system achieved sensitivity of 85.68%, specificity of 99.99%, precision at 83.34% and accuracy of 99.99%. Shan et al. [20] presented an illustration of Deep Learning strategies, Stacked Sparse Autoencoder (SSAE) wherein the features were extracted from the patches generated in the image. These features were then fed to Softmax classifier. Without indulging into the blood vessel removal or preprocessing techniques, the method attained the recall (sensitivity) of 91.16%, F-measure at 91.34% and AUC at 96.2%. The performance was evaluated on Diaretdb database.

Red lesions consist of MAs and HMs. Hence, detection of both the lesions is necessary to access the severity of the disease. Detection of MAs only will not serve the purpose. Red lesions resemble closely to blood vessels present in the retina with respect to intensities. Also, every fundus image is clicked by different cameras with different resolutions giving varying qualities of images. Based on this concept, Ganguly et al. [8] proposed an adaptive threshold based method for red lesion detection. The upper threshold and lower threshold of the red lesions are estimated individually for every image. The average sensitivity of 93.17% and specificity greater than 99% was achieved. But, with the detection of blood vessels, more accuracy could be obtained in future. In another attempt to detect DR, Rubini et al. [9] presented two approaches i.e. semi automated hessian-based candidate selection algorithm (SHCS) and automated hessian-based candidate selection algorithm (AHCS). SHCS is followed by thresholding and AHCS is followed by feature extraction and classification. SVM classifier was used to evaluate the performance. Testing was done on real world images. It was found out that SHCS performed better than AHCS. The system attained the true positive rate (TPR) at 83.05% and false positives per image (FPI) at 26.80%. Still, the performance could be upgraded by eliminating the false positives in optic disc region and blood vessel crossings. Another method that used shape features (Dynamic Shape Features) to detect DR was proposed by Seoud et al. [10]. It does not require precise segmentation, but, uses shape features to distinguish between lesions and blood vessels. The method was evaluated on per-lesion and per-image basis using six databases. On ROC (Retinopathy Online Challenge) database, it achieved FROC score of 0.420 and an area under ROC curve of 0.899 on Messidor database. Bright lesion and neovessel detection could be considered in future. Zhou et al. [21] put forward a technique to detect red lesions using multichannel multifeature strategy. Candidates were extracted based on superpixel and classified with the help of FDA (Fisher Discriminant Analysis) classifier. A postprocessing method gets rid of non lesions. Publically available Diaretdb1 database was used to evaluate the performance. Comparison of the results of given methodologies is shown in table 3.

Table -3: Comparison of methodologies and their performances

Author	Lesion detection	Approach	Database	Classifier	Performance measures
Antal et al. [6]	MA	Ensemble based system(preprocessing methods and candidate extractors)	Messidor	-	AUC 0.90±0.01
Kumar et al. [7]	MA	Area and No. of MA	Diaretdb 1	SVM	Sensitivity 96%, Specificity 92%
Sopharak et al. [19]	MA	Non dilated images 18 MA features	-	Naïve bayes	Sensitivity 85.68%, Specificity 99.99%, Precision 83.34, Accuracy 99.99%
Shan et al. [20]	MA	Stacked Sparse Autoencoder	Diaretdb	Softmax	F measure 91.34, AUC 96.20%, Sensitivity 91.16%
Ganguly et al. [8]	MA,HM	Adaptive threshold	Private	-	Sensitivity 93.17%, Specificity >99%
Rubini et al. [9]	MA,HM	Semi automated hessian-based candidate selection	Real world images	SVM	TPR 83.05, FPI 26.80
Seoud et al. [10]	MA,HM	Dynamic shape features	Retinopathy Online Challenge (ROC), Messidor	Random Forest	FROC 0.420 (ROC), area under ROC curve 0.899 (Messidor)
Zhou et al. [21]	MA,HM	Multichannel Multifeature classification	Diaretdb 1	FDA	Sensitivity 83.30%, Specificity 97.30%

4. DATABASE

Database is a collection of high quality disease specific images taken from various sources, verified by the experts and labeled with ground truth. It provides an authentic and reliable evaluation protocol to compare the performances of the methods proposed by researchers. Some databases described here are as follows:

4.1 Diaretdb1 [11]

Diaretdb1 is a publically available database with 89 images out of which 84 images are DR specific and 5 images are normal (without any sign of DR). Images are captured with 50º FOV (field of view) digital fundus camera. Database contains ground truth for microaneurysms, haemorrhages, hard and soft exudates. There are 28 training images and 61 test images.

4.2 Messidor [12]

Messidor is a publically distributed database that contains 1200 images taken from three ophthalmologic departments. It is divided into 3 sets, one per ophthalmologic department, with each set again divided into 4 subsets of 100 images (in TIFF format) each. Images were captured using a color video 3CCD camera with 45º field of view and 8 bits per color plane. Database has the medical diagnoses for each image, but, not any annotations or labels on the image as in case of Diaretdb1.

4.3 Retinopathy Online Challenge [13]

ROC is a dataset for microaneurysm detection. It is a set of 100 images (JPEG format) taken from a huge dataset of 150000 images. Out of which 50 images are for training and 50 test images. It contains three different types of images with different resolutions (768 x 576, 1058 x 1061, 1389 x 1383) at 45º field of view. Topcon NW 100, a Topcon NW 200, or a Canon CR5-45NM was used to capture the images.

5. CLASSIFIERS

5.1 Support Vector Machine [14]

SVM is a binary classifier based on statistical learning. With the advancement in technology and increased amount of data to handle, SVM has developed as a multi-class pattern recognition classifier. The two methods that compute the binary classification are one-against-one and one-against-rest. The aim of SVM is to find a hyperplane that separates the data points into distinct classes. The distance between the data points of the classes is called margin. The points closest to the margin are called support vectors. It helps in building the SVM.

5.2 Random Forest [15]

Random forest classifier is a combination of tree classifiers where each tree is sampled randomly out of input vectors and each tree cast a vote in the selection of popular class. It takes only two user-defined parameters to generate a classifier, i.e. number of features used at each node and number of trees to be grown. This classifier can handle 'categorical data, unbalanced data as well as data with missing values'.

6. PERFORMANCE MEASURES

Any algorithm can't be validated unless it is evaluated on some predefined widely accepted performance measures. When it comes to DR detection, extensively used performance metrics are sensitivity, specificity and accuracy [16]. The terms are defined as follows:

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

where TP = correctly classified lesion, TN = correctly classified non-lesion, FP = incorrectly classified non-lesion, FN = incorrectly classified lesion.

Sensitivity is also known as true positive rate (TPR) and specificity is also known as true negative rate (TNR). Other measures that are commonly used are ROC and FROC. Receiver operating characteristic shows the diagnosis potential of the classifier. It plots the true positive rate against the false positive rate. ROC analysis helps in selecting the optimal models. Free response ROC [17] is a reinterpretation of ROC. It plots the sensitivity against the average number of false positives in the image (FPI).

7. DISCUSSION

Increased level of glucose in the blood may lead to diabetes, in turn, resulting in diabetic retinopathy if proper care and regular screening is ignored. Manual diagnosis may be time consuming and inaccurate. Invention of automated systems is a boon to the medical care industry. Much effort has been put in the field to improve the speed and accuracy of the automated systems. Systems with high speed and utmost precision remain dominant in this domain. At every stage of DR detection, needed exactness in the method. Every image has different intensity and resolution as it is clicked by cameras with different specifications. This problem is considered by [8]. After acquisition, the image may contain noise and uneven brightness which needs to be corrected using preprocessing techniques. An ensemble based system [6] has been proposed. Realizing the limitations in their previous work [18], preprocessing methods were amalgamated with candidate extractors to improve the efficiency. Techniques like histogram equalization, filtering, channel extraction enhance the appearance of the image, hence, getting most information out of it. Emphasis on features of the objects in an image is very important when it comes to DR scrutiny. Area and number of MA have been used [7] to detect lesions. Nevertheless, segmentation could be escaped to detect the regions [10]. Thresholding, a type of image segmentation, is yet another aspect in recognizing the DR ailment. It assists in altering the pixels of an image for easy assessment.

The methods were implemented in different setup and framework. Each method was executed on different databases using different classifiers. Distinct performance standards were used for evaluation of the algorithms. Figure 3 and 4 shows the comparison of the performances in terms of sensitivity. It is found out that SVM worked better for MA detection in this case. But, random forest works on a par with SVM classifier [15]. This paper does

not take bright lesion detection into consideration. DR is one of the major reasons behind blindness throughout the world. Research in this realm should be comprehensive. Most of the classifications done in the literature are binary classification. Though, a multi-class grading gives the exact severity of the disease. An image may consist of multiple bruises. Detecting one or two of them may result in improper diagnosis.

8. CONCLUSION

With the advent in technology and image processing methods, the qualitative analysis of the diabetic retinopathy has become easier for ophthalmologists. This work presented the methods to detect microaneurysms and haemorrhages in the abnormal fundus images. Figure 5 shows the percentage split of the study for the detection of microaneurysms only and the detection of microaneurysms and haemorrhages both. Sensitivity and specificity are generally the widely used performance evaluation tools. Researchers are thriving for greater efficiency and time bound implementation. Classifiers grade the severity of the disease accurately. SVM was found out to give the better results. Databases provide the evaluation protocol and foundation for fair comparison among the techniques proposed by analysts.

Though, an area of research in the field of diabetic retinopathy has developed a lot in recent years, there is always a scope for improvement. The broad and far-reaching study is the need of an hour. The scientists should take up each and every aspect of the diabetic retinopathy disorder into consideration during their investigation.

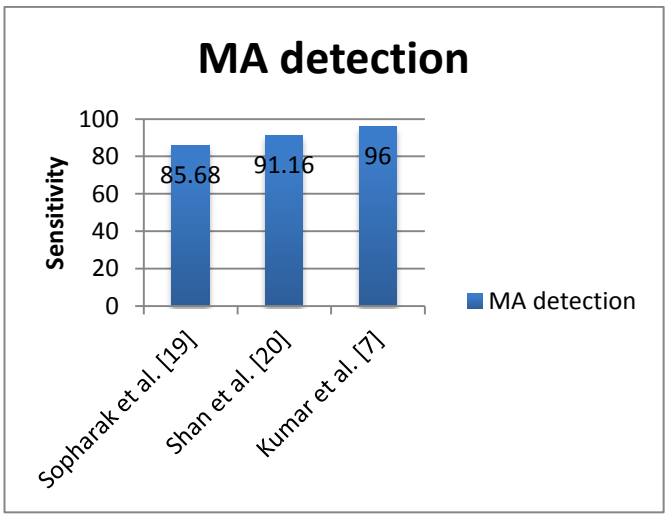


Fig -3: Performances of MA detection in terms of sensitivity

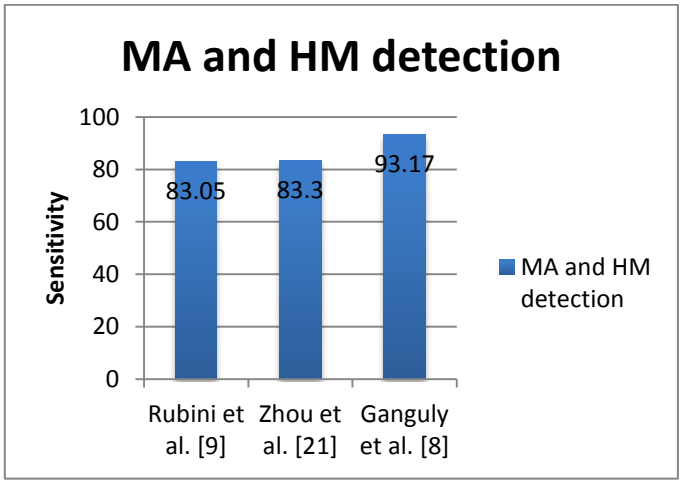


Fig -4: Performances of MA and HM detection in terms of sensitivity

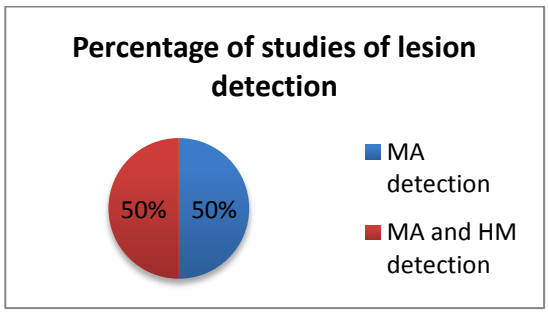


Fig -5: Percentage split of the studies of lesion detection

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