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Study on Diabetic Retinopathy Detection Techniques

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***Abstract*— Diabetic Retinopathy (DR) also known as diabetic eye disease. It is the damage occurs to the retina due to diabetes. It can eventually lead to blindness. So the early detection of disease is needed, Manual detection is time consuming and often make observation error. Hence several computer-aided systems are introduced and which would make fast and consistent diagnosis- aid useful for biomedical and health informatics field. The Diabetic retinopathy detection methods that uses machine learning techniques. In one system classifiers such as the Gaussian Mixture model (GMM), k-nearest neighbor (kNN), support vector machine (SVM) are used and another system that uses GMM, kNN, SVM, and combinational classifiers are used for classifying retinal fundus images.**

Keywords- Diabetic Retinopathy, Image processing, Feature extraction, Bright lesions, classification, diabetic retinopathy (DR), red lesions, segmentation.

I. INTRODUCTION

A study done by the American Diabetes Association (ADA) describes that diabetic retinopathy (DR) had affected quite 4.4 million Americans, and nearly 0.7 million people those with diabetes having advanced DR that would result in severe vision loss [1]. Diabetic Retinopathy (DR) could be a common complication of diabetes, ensuing from chronic damage to blood vessels within the retina. Since early identification and treatment of DR has been clinically well-tried to reduce the possibilities of severe vision loss by 90%, early identification is very imperative for enhancing the resourcefulness of present day eye-care [2]. The retinal image is not as accessible as common commercial biometrics like finger print and face, it is internal to the body [5]. This paper presents a study on different diabetic retinopathy detection techniques which will be useful in biomedical and health informatics field.

In the first paper, a Computer-aided screening system (DREAM - Diabetic Retinopathy Analysis Using Machine Learning) aims at outlining 3 separate DR detection stages, and minimizing the run-time complexity of each stage to ensure a fast detection system. The system contains an initial image enhancement module in Stage 1 that enhances the contrast and edge sharpness in fundus images so that images are not rejected based on poor image quality. This system makes two major contributions. The first major contribution is identification of the top 30 features from a set of 78 features for classifying bright and red retinopathy lesions [4].

The second contribution is a novel two-step hierarchical binary classification method that rejects false positives in the first step and in the second step, bright lesions are classified as cotton wool spots (CWS) or hard exudates (HA), and red lesions are classified as microaneurysms (MA) and hemorrhages (HE), respectively. This hierarchical classification method reduces the time complexity by 18–24% over a parallel classification method that trains separate classifiers for identifying CWS, HE, HA, and MA from false positives. In this case, found that GMM is a preferred choice of classifier for detecting bright lesions, and kNN is a preferred choice for detecting red lesions [2].

In the second paper, makes 2 key contributions towards a two stage DR detection system. within the first-stage, a unique Minimum Intensity maximum Solidity (MinIMaS) overlap algorithm is to find the OD during a non-mydriatic fundus image. The second key contribution is within the second-stage of the detection system within which analyzed multiple classifiers utilized in previous works, to pick the most effective classifier for lesion detection. This analysis shall inspire the utilization of the most effective classifier in future works for progressive enhancements within the segmentation or detection methodologies instead of specializing in progressive enhancements created because of a unique use of classifier. The DR detection system identifies

gaussian mixture models (GMM) because the best classifier for detecting bright and red lesions [3].

This paper organised as follows : Section I contains complete description about this paper, Section II includes the details of different methods, Section III describes the result and discussion of different methods and a detailed conclusion is described at Section IV.

II. METHODS

In the first paper, the three-stage algorithm using ophthalmic fundus images, to detect and grade the severity of DR automatically. For each fundus image in JPEG format, the green plane is used for information extraction [2].

In Stage 1, a minimum-intensity maximum-solidity (MinIMaS) algorithm is invoked to detect the regions corresponding to the optic disc and vasculature as the image background from green image. Next, candidate regions corresponding to red lesions and bright lesions are detected as foreground [2].

In Stage 2, classifiers are used in two hierarchical steps. In step 1, candidate lesion regions are classified as true lesions and non lesions, respectively. In step2, the true bright lesions are further classified as hard exudates and cotton wool spots, while the true red lesions are classified as microaneurysms and hemorrhages [2].

In Stage 3, the number of red lesions and bright lesions are counted and combined using a combination function to generate a DR severity grade per image (G). An image with G =0 implies no DR, G =1 implies mild DR, G =2 implies moderate DR and G =3 implies severe DR, respectively [2].

In the second paper, presented a novel two-stage system that detects diabetic retinopathy (DR) using fundus photographs. The first-stage of this system using a novel Minimum Intensity Maximum Solidity (MinIMaS) overlap algorithm, to mask out the background consisting of the optic disc. In the second-stage analyzed the classification performance of kNN, GMM and SVM classifiers for separating bright and red lesions from the false positive foreground objects, so that it can determine the best classifier for the purpose of lesion classification [3].

III. RESULT AND DISCUSSION

A. *DREAM: Diabetic Retinopathy Analysis using Machine Learning*

In this system, Initially all images are preprocessed to eliminate illumination inconsistencies and also false photographic artifacts. The preprocessing module proceeds by histogram equalization and contrast enhancement on green image, followed by scaling all pixel intensities in the range [0,1] resulting in image Im. Next, since the quality of images vary among databases, it is necessary to enhance the sharpness and illumination of certain images especially when the images are scanned film prototypes. Im is filtered using the Laplacian of Gaussian filter to extract the gradient variations (Ih). Next, (Im −Ih) is median filtered to obtain the enhanced images [2].

1. Stage 1: Image Segmentation

In the first stage, it is imperative to mask out the regions corresponding to the optic disc (OD) and major portions of the blood vasculature. This is important since a bright OD may otherwise be mistaken for a bright lesion, and the vasculature can be falsely detected as a red lesion in subsequent automated stages if not masked out in the early stage. For this purpose, a region-based MinIMaS algorithm is invoked, which detects the regions that lie on the intersection of the largest red region and the bright regions in the image. Once all such intersecting bright regions are identified, then the region containing the OD is the bright region with minimum pixel intensity sum (Intensity, due to the dark pixels corresponding to thick blood vessels occurring at the OD region), and maximum compactness [2].

2. Stage 2: Lesion Classification

Lesion classification is performed in two hierarchical binary (1/0) classification steps. In the first step, the bright candidate regions (RBL) are classified as true bright lesions and non bright lesions, while the red candidate regions (RRL) are classified as true red lesions and non red lesion respectively. In the second level, the true bright lesions are reclassified as cotton wool spots (CWS) and hard exudates (HA), while the true red lesions are classified as microaneurysms (MA) and hemorrhages (HE). Selection of features is an important aspect for lesion classification. 30 features such as area, convex area, solidity, orientation, etc., are needs to be extracted [2].

3. Stage 3: DR Severity Grading

Once the regions corresponding to the retinopathy lesions are detected, and the number of HA, MA, HE, and CWS are computed per image using, lesion combination operation for the MESSIDOR dataset can be used to generate a DR severity grade per image (G). These demonstrate that clinically relevant lesion combination operations require more accurate estimation regarding the number of red lesions than bright lesions. In the case of bright lesions, over detection, or instances of false positives may imply macular degeneration or retinal abnormalities other than NPDR. Thus, the detection of bright lesions must incur less false positives. However, for red lesion detection, failure to detect lesions will result in false generation of the DR severity. Thus, it is imperative for any automated system to incur low

false negatives for red lesion classification. Hence, the performance criteria for selecting lesion classifiers are as follows [2]:

- Bright lesion classifier: It must incur low false positives, or high specificity.
- Red lesion classifier: It must incur low false negatives, or high sensitivity.

The metrics used for analyzing the performance of the second and third stages of the detection system are defined in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) as follows [2]:

1) Sensitivity (SEN)= $\frac{TP}{TP+FN}$;

2) Specificity (SPEC)= $\frac{TN}{TN+FP}$;

B. *Screening Fundus Images for Diabetic Retinopathy*

In the first-stage of this system, the background of each colored fundus image comprising of the OD and the vascular arc is detected and masked out. Initially all images are preprocessed by subjecting the green plane of the RGB fundus image (Igreen) to histogram equalization, followed by image resizing to 500x500 pixels and rescaling all pixel intensities in the range [0,1] [3].

1. *OD Detection: Minimum Intensity Maximum Solidity*

Since the blood vessels branch out at the OD, the OD should typically lie at the intersection of one of the largest and reddest regions (blood vessels) and one of the brightest regions (OD) in the fundus image. For any image, if bright lesions are present around the blood vessels, those regions will also be one of the intersection regions. To select the region of the actual OD from all the instances of intersection regions, apply the domain knowledge that the blood vessels are thickest around the OD and branch out into thinner vessels towards the periphery. Since a scaled image has bright pixels approaching 1 and red pixels approaching 0, thus the summation of individual pixel intensities within a circular mask applied to all the regions of intersection will encounter more pixels approaching 0 near the OD. Additionally, the OD is generally more compact in structure as compared to bright lesions. Thus, the OD would appear at the region of intersection with minimum pixel intensity within a circular mask and maximum solidity, where solidity is a measure of compactness [3].

2. Vascular Arc Detection

After detecting the OD, it is necessary to mask out major portions of the blood vessels in the fundus photographs. Thus, for each image a gradient smoothened background (Ibg) is estimated by median filtering Igreen. The shade corrected foreground is the subtraction of the background from the image,i.e., Isc = Igreen - Ibg. Only the negative pixel values of Isc are utilized while positive pixel values are ignored. Next, Isc is normalized, contrast adjusted, superimposed with background mask g and thresholded to obtain an isolated image (Iiso) with only the red regions of the image. Iiso is then subjected to region-growing operation followed by global thresholding to retain only the region with the highest pixel area as the vasculature mask (Ivasc) [3].

3. Detecting Bright Lesion Candidates

To detect candidate regions for bright lesions in the images, contrast enhancement is applied to pixels in Igreen. Next, Igreen is morphologically eroded using a linear structuring element of size (50,1) followed by image reconstruction. The reconstructed image is subtracted from Igreen, and normalized and subjected to contrast enhancement to yield Ibr. Next, Ibr is normalized and globally thresholded to obtain candidate regions for bright lesions, also called as bright objects in image Ibo. Finally, the OD mask and the vascular arc masks are subtracted from the bright objects, i.e., Ibo = Ibo − (g+ R^OD) [3].

4. Detecting Red Lesion Candidates

Having detected the bright objects, the red objects or candidate regions for red lesions are detected by subtracting the vascular arc and OD masks from the shade corrected foreground image, i.e., Ido = Isc − (Ivasc + R^OD) [3].

5. Classification

Once the bright objects (Ibo) and red objects (Ido) have been detected, classifiers are trained to reject false positives, so that the accuracy of the lesion detection improves. Initially train the Gaussian Mixture Models (GMM), k Nearest Neighbor (kNN) and Support Vector Machines (SVM) classifiers on the bright and red objects of the training dataset comprising of 28 images in the DIARETDB1 data set. Then test the performance of classification on the objects of the test set comprising of 61 images from the same data set. This DR detection system identifies Gaussian mixture models (GMM) as the best classifier for detecting bright and red lesions [3].

For training the classifiers, each candidate object (bright or red) per image is represented by a set of 30 features per

sample point in the feature space. These features include area, dimensions of bounding box, convex area, eccentricity, diameter, Euler number, extent, filled area, major axis, minor axis lengths, orientation, solidity, perimeter, and minimum, maximum, mean and total intensity [3].

The comparison of these two methods are done by using two metrices : Sensitivty and Specificity. These are computed by using four factors such as True positives, True negatives, False positives and False negatives. Table 1 shows the comparison results.

Table 1. Comparison of two methods

	Sensitivity		Specificity	
	Bright Lesion	Red Lesion	Bright Lesion	Red Lesion
Sohini Roychowdhury *et al*, [2]	89	80	98	85
Sohini Roychowdhury *et al*, [3]	82.87	75.5	94.36	93.73

IV. CONCLUSION

In the first paper, a three-stage computer-aided screening system for DR (DREAM) that detects and grades fundus images for the severity of DR. In that, identified a set of best 30 features classifies bright and red lesions using the classifiers such as kNN, GMM, and combination of classifiers (SVM+GMM, SVM+kNN). GMM and kNN classifiers are found to be the best classifiers for bright and red lesion classification, respectively [2].

In the second paper a novel optic disc detection algorithm that demonstrates an overall accuracy 99.70% on 340 images from publicly available data sets. Next, analyzed the classification performance of kNN, GMM and SVM classifiers for detecting bright lesions (hard exudates and cotton-wool spots) and red lesions (hemorrhages and microaneurysms) on images from the DIARETDB1 data set to conclude that GMM is more a robust classifier to reduce false positives than kNN and SVM [3].

By comparing these two methods, the first method is more better than that of second method.

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