Diabetic Retinopathy Detection & Classification Techniques: A Review

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Abstract: Diabetic retinopathy (DR) – one of the most common reasons for blindness in modern days - is a visual disorder. DR is caused due to long-standing untreated diabetics, which in turn damage the retina cells. It takes place when pancreas cannot produce insulin sufficiently or body can’t utilize the produced insulin effectively. Early identification and proper treatment of DR can lower the loss of sight of patients. Diagnosis of DR is a vigorous process that include large amount of clinical study, which involves large amount of time, money and resources. The number of DR affected patients is much greater than the number of practitioners. So manual clinical diagnosis or screening takes considerable amount of time. Therefore, in order to keep away from such difficulty, follow-up screening is done regularly and automatic DR detection and severity classification are essential. Here several techniques for retinopathy detection and classification of its severity levels are discussed.

Index Terms: Blood vessels, Diabetic retinopathy, Exudates, Hemorrhages, Microaneurysms, Non-proliferative diabetic retinopathy, Proliferative diabetic retinopathy

1 INTRODUCTION

Diabetic retinopathy (DR), a sight threatening disease, occurs due to diabetics that give rise to damage of cells in retina when blood sugar level in the body is abnormal. If untreated, blood & fluid leak from vessels of retina which lead to permanent vision loss to patients. More than 28.5% of diabetic patients with age above 40 years possess DR, and among them, 4.4% have intense level of DR that leads to vision loss. Therefore people with diabetes are exposed to the danger of DR. Primitive stages of DR do not show any symptoms. When the disease progresses symptoms like blurred vision, floaters, fluctuating sight, dark vision areas, poor sight in night, impaired color or partial or complete loss of sight can be noted. Hence, in order to prevent blindness it is essential to have methods that automatically detect DR in its early stage. Currently the methods to discover and group the severity of retinopathy utilizes direct & indirect ophthalmoscopy, fundus images photography and fluorescein angiography. These methods are manual, which are time-consuming and requires trained ophthalmologists. Lesions include exudates, hemorrhages (HA) and microaneurysms (MAs). Exudates are formed due accumulation of cholesterol or fats from blood that damages vessels of retina thereby lipid leak out of the blood vessels. It can be seen as round yellow spots. Hemorrhages are small spots of blood that break into middle layers of retina preventing light to pass through the retina. Microaneurysms are enlarged aneurismal retina vessels that are seen as red dots in retina due to the occlusion of vessel capillary and frequent leakage of fluids. Based on these symptoms severity of DR disease is mainly divided into non-proliferative (NPDR) and proliferative DR (PDR). In NPDR no new blood vessels originates in the retina, but blood vessels seep fluids or blood forming Ex, HA and MA.

The size, shape, location and distribution of Ex, HA & MA indicate the growth of DR. NPDR is again divided as mild, moderate and severe. In PDR close off damaged blood vessels causes the growth of new abnormal vessels in retina. It can also be defined by presence of neo-vascularization. This stage causes serious visual problems leading to vision loss. The fact that the symptoms of DR remain hidden until the vision starts deteriorating emphasizes the urgency to detect and classify DR at its early stage.

2 DETECTION METHODS

Walter et.al in [1] discussed high grey level variation algorithm for exudates detection and morphological reconstruction techniques for contours determination. Morphological filtering and watershed transformation were used for detection of optic disc. The determined mean sensitivity and predictive value were about 92.8% and 92.4% respectively. A novel CNN model was discussed in [2] that have Siamese-like structure, which was trained using transfer learning technique. The binocular fundus images have been received as inputs and their correlation were learned to make prediction. Area under the curve 0.951 is acquired by the proposed system. The effectiveness was proved by training binocular model and evaluated on 10% validation set. The achieved kama score was 0.829. DR lesions from retinal images are detected individually and based on the results from meta-classification decisions are made in [3]. The meta-classifier has input from various lesion detector output. The achieved area under the curve is about 93.4%using soft-assignment coding / max pooling for classification. In 2018 Costa et.al [4] introduced a method based on multiple instance learning (MIL) framework, which provide integrated optimization of image classification stages & instance encoding. The proposed method obtained 90% area under the curve (AUC) on Messidor database, on DR1 database 93% AUC and on DR database 96% AUC. In [5] multiscale amplitude-modulation-frequency modulation (AM-FM) scheme was used to differentiate images as pathological & normal. From multiple scales texture feature vectors cumulative distribution functions are used. To measure inter-structure similarity distance metrics were used. This method is capable for automatic screening of DR. A deep MIL method is used for DR detection. Pre-trained CNN was used to achieve patch-level estimation of DR and global aggregation is used for classification in [6]. For detection attained an area under the ROC curve of 0.925 on Kaggle...
dataset, and 0.960 on Messidor. Also for DR lesions detection achieved F1-score of 0.924 with sensitivity 0.995 and precision 0.863 on DIARETDB1 database.

2.1 By detecting microaneurysms
In [7] grade of NPDR in retinal images were classified automatically. The preliminary stage separates blood vessels, microaneurysms and hard exudates. These features are then used to determine the grade of retinopathy using SVM. This method was tested over 400 retinal images specified by a 4-grade scale. Here obtained 95% sensitivity and 94% predictive capacity.

2.2 Exudates detection
To observe the progress of DR exudates are detected for computer-aid diagnosis. Deep CNN was taken to obtain pixel-wise exudate identification [8]. Achieved accuracy of 91.92%, sensitivity of 88.85% and specificity of 96%. To evaluate changes in retina and determine retinopathy at early stage they were inspected by multilocal electroretinography (mfERG). For mfERG testing 7 healthy subjects, 16 diabetics with no apparent retinopathy and 9 diabetics with background diabetic retinopathy (BDR) were considered [9]. From multilocal ERG record the initial slice from second order kernel (K21) were taken out and added. Three major peaks (P1, N1 and P2) of K21 were assessed. With their amplitude and implicit time linear classification was done. This classifier distinguishes eyes of control, NDR and BDR subjects. The reported accuracy was 99%. Categorized detected DR features into several stage and is pre-processed, then vessel, hemorrhages and exudate were detected, and removed optic disc in [10]. The images are grouped as mild NPDR, moderate NPDR, severe NPDR and PDR. The detection percentage for blood vessel & hemorrhages are 98%, and exudates are 100%. Haniza et.al [11] proposed sharpen edge method and segmentation process for cotton wool marks and exudates through ramp breadth reduction. In [12] a novel method was proposed for detection of hard exudates with high accuracy with respect to lesion level. Initially, by back-ground subtraction method candidate exudate lesions were detected. This work achieved sensitivity and F-Score of 0.87 & 0.78 respectively and PPV (predictive value) of 0.76 for hard exudate detection. A novel method using Gaussian Intensity feature input to a vector quantization (VQ) classifier is proposed in [13] for detection of DR. Thirty normal images and 25 pathological images have been considered. The features are extracted in terms of diameter of the blood vessels and the height of the Gaussian profile across the cross-section and 90% average diagnostic performance was attained successfully for this method. Rozlan et.al formulated detection of MA as a target detection and successive clutter rejection solution [14] where the probability of occurrence of target is smaller than the clutter. To lower the number of clutter response successive rejection-based method was used. The processing stages were intended to pass major part of true MAs and dismiss specific clutter using specialized features. The true positives are assigned a score based on its similarity to true MA. This provides a regular platform to judge methods and make judgment close to a real screening scenario. In [15] authors described the detection of exudates. Morphological operations are performed for separation of blood vessel and exudates. The optic disk was detected by convergence of the blood vessel. An accuracy of about 92% was obtained for detection of exudates. Anant et.al extracted texture and wavelet features for detection of DR [16]. DIARETDB1 dataset was used in this study. The sensitivity, specificity and accuracy were examined. The technique provides high accuracy of 97.75%.

2.3 Computer based detection
A novel approach to detect DR from the retina images is presented in [17]. First diseased regions were found and features were extracted by applying Discrete Wavelet Transform. The feature number was reduced by Principal Component Analysis and for classification Naïve Bayes was used. The proposed system achieved an accuracy of 95% in the detection of the disease. An automated method to detect Diabetic Retinopathy was proposed in [18]. The severity of retinopathy is given by the computer based screening methodology in minimum screening time and so the lesions can be analyzed and treated at their early stage. Authors of [19] uses computer vision to detect DR. They automated the process by using neural network. This approach was implemented using open source tools OPENCV and TENSORFLOW and achieved 75% accuracy. An image database procedure was introduced for automatic detection, evaluation and comparison of DR [20]. It gives a unified framework for benchmarking the methods by pointing deficiencies in retina. An Image Retrieval technique is proposed in [21]. It explores and recollects the test image from retinal database. By extracting color histogram, feature retrieval process was done. Determined feature vector by arranging the number of bins in histogram. Similarity was recognized by Euclidean distance. The precision rate of 61% has been recorded. The recall rate obtained is 58% by reducing the analysis time. In [22] a procedure for extraction of texture and vesselness features by Gabor wavelet transform vessel chart was discussed. The obtained features were given to random forest classification which outputs the result. Then the images were classified as PDR, NPDR and Normal.

2.4 Convolutional Neural Network
In [23] preliminary image processing was carried out after converting the RGB images into gray scale images. Deep Learning Approach was applied to these gray scale images. The processed images were fed to CNN which predict the presence of diabetic retinopathy and achieved 100% accuracy and sensitivity. In [24] initial vessel segmentation was finished by changing image into binary image. Then vessel and non-vessel half was separated. The morphological operations square measure taken for different orientations. Morphological cutting is employed to skinny the new vessels. Feature extraction was finished by windowing image into 50X50 so as to measure range of pixels in every window. If threshold price is smaller than vessel pixels range then PDR has been detected.

2.5 Artificial neural network (ANN)
An algorithm for DR detection was done using ANN in [25]. Decision for screening DR was done using ANN by taking retinal images using condensing lens. The procedure obtained 63% precision and 57% recall rate with a reduced analysis time. Features of horizontal and vertical Video-Oclography (VOG) signals from non-proliferative and proliferative patients were used for classification in [26]. Discrete wavelet transform was used for feature extraction.
For classification feed forward ANN were used. In training process, performance analysis was done. The highest performance for classification was observed when the dataset was divided into 80% 20% for training & test respectively. For detection of exudates a novel wavelet based method was used in [27]. It provides sensitivity of 96.67% and 83.05% specificity. For base line method sensitivity was 79% and specificity was 58%. For detection of retinal exudates-clustering and morphological approach was used in [28]. To locate the exude area contrast-limited adaptive histogram equalization algorithm was used. Also k-means clustering algorithm determines candidate region location. Anupam et.al [29] discussed detection of DR by blood vessel segmentation. Hessian matrix was used for blood vessel segmentation. For low frequency, discrete fourier transform of green channel were also calculated for retinal images. Accuracy reported is 95%. In [30] DR detection was done by texture feature characteristic. A complete modeling of local binary pattern (CLBP) and sign, magnitude and mean value was used for feature extraction of texture. Expectation Maximization-Principal Component Analysis (EM-PCA) was used for feature selection. Here KNN was used as classifier. CLBP-SC (CLBP sign and mean value) provide similar accuracy of 97.16% as CLBP. Sensitivity and specificity achieved were 98% and 97% respectively.

2.6 Fuzzy C-Means (FCM) clustering
In [31] authors discussed a DR detection method using FCM clustering and morphological image processing. The image resizing, CLAHE, contrast adjustment, gray and green channel extraction are included in preprocessing. The SVM classifier was used for classification by using selected features. Accuracy obtained was 96.67%, sensitivity was 100% and specificity recorded was 95.83%. In [32] different image pre-processing techniques were implemented. Performance was compared by performance metrics. Image obtained after the pre-processing [32] was then given as input to the deep neural network [33]. Preprocessing helps to improve the quality of images by averaging. The CNN model used was MobileNets having 28 convolutional layers. Each layer includes batch norm and ReLU nonlinear function except final layer. The output from last layer was labeled as DR or no DR. Achieved accuracy was 73.3%. In [34] authors introduced a group of optimally adjusted morphological operators. From non-dilated pupil & low-contrast images microaneurysms were detected. Mathematical morphology pre-processing was done and shade corrected algorithm was used for vessel detection. For exudates removal thresholding and reconstruction were performed. Then, for detection extended minima transform and local thresholding were given to pre-processed images. Finally detected microaneurysms were compared. The sensitivity and specificity of the method was about 81.66% and 99.99% respectively.

2.7 Based on thresholding
Garcia et.al in [35] discussed a mixture of global & adaptive thresholding for exudates segmentation on color images. Each image was normalized and a set of attributes were extracted. The subset discriminate exudates. Surrounding of images was selected by logistic regression (LR). A radial basis function (RBF) network was used for detection of exudates. For lesion-based rule, sensitivity was 92.1% and positive predictive value was 86.4% and for image based specification, sensitivity was 100%, specificity was 70.4% and 88.1% accuracy were obtained. To extract the brighter region on 8 bit gray level images a histogram based multilevel thresholding was proposed in [36]. For blood vessel segmentation convergent Median filtering was used. Points in blood vessels were determined using least square regression technique. By using convergent point the optic disk (OD) in the brighter regions was determined and it is extracted by thresholding. Brighter regions expect OD are considered as exudates. The accuracy were about 62.69% and sensitivity were 87.43% for exudates detection and for detection of optic disc the accuracy of 81.24% and sensitivity of 90.11% was achieved. Table 1 is the summary of DR detection methods in terms of accuracy, sensitivity and specificity.

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3 CLASSIFICATION METHODS
3.1 Random- Forest technique
By using fundus camera retinal images are obtained and were analyzed in [37]. The blood vessel and the surrounding areas are detected, thereby hemorrhages is identified to classify diabetic retinopathy. Classification is done based on Random-Forest Technique. For normal case of DR the reported accuracy of classification is 90% and for moderate & severe it is 87.5%. Sarwinda et.al in [38] classified DR as normal, mild non-proliferative and moderate or severe NPDR. The feature
extraction is done by Histogram of Oriented Gradients (HOG) and by factor analysis the best feature is selected. To classify DR support vector machine (SVM) and Random Forest learning are used. The accuracy attained for classification is around only 85% which is less than that reported by other techniques available in the literature. But this method opens a new path for the classification of DR.

3.2 Convolutional Neural network
Various levels of retinopathy was identified and grouped by Yun et al. [39]. Classification is done by three-layer feedforward neural network. The accuracy obtained is just above 80%. In [40] DR fundus images are classified using convolution neural network. Images are classified as healthy images, stage-I, II & III images and the classified accuracy is 96.6%, 96.2%, 95.6% & 96.9% for different stages respectively. Akram et al. [41] introduced a hybrid classifier for retinal lesions detection. The classifier used was hybrid classifier which is an extension of m-Mediods model. CNN approach is employed in [42] for classifying diabetic retinopathy stages. The CNN used is a pre-trained CNN. Accuracy of about 93.46% for Alexnet, 91.82% for VGG-16 and 94.49% for SqueezeNet CNN was obtained. The system provides sensitivity of about 97.87%, specificity of 97.87% and accuracy of 98.15%. In the work described in [43] DR is classified into 5 stages depending on the severity. The stages are class-0 stage, class-1, class-2, class-3 and class-4 stage. Abdillah et al. used Local Binary Pattern texture feature in [44] to classify DR. For classification K-nearest neighbor (K-NN) and SVM have been used. Here classification is done based on two scenarios- first is normal & abnormal and the second is normal, mild, medium & severe, known as four phase classification. The accuracy of the method is about 90% for all scenario. Contrast-relative features and extensive multi-type feature sets have been discussed in [45] for automated identification of lesions. This approach find feature set for classification of lesions. The accuracy of neural network classifier is about 94%. A tool is proposed in [46] that detect different stages and sectors of retinopathy of per-maturity (ROP) in infants. The severity is rated from 1 to 9.

3.3 Artificial neural network
Method discussed in [47] detects severity of DR by extracting lesion features and applying these features to ANN. The accuracy of classification is 96%. In [48] features of Video Oculography (VOG) from right to left of horizontal and top to bottom of vertical VOG signals are utilized to classify DR as NPDR and PDR. The features are given to an ANN. The performance of C4.5 decision tree algorithm was 96.87%. To determine the initial microaneurysm candidates, a double-ring filter was used in [49]. The filter used the property of MA, that region to detect MA are dark regions. If the average intensity of the inner ring of the filter is small compare to outer ring then the pixel was considered as MA pixel. After initial candidate detection classification was done, using extracted features and ANN. The obtained sensitivity is 65%.

3.4 SVM methods
Akram et al. [50] introduced three-stage system that detects MA by filter banks. In the first stage candidate region are extracted, in the second and third stages feature extraction and classification has been done. Classification is done by a hybrid classifier i.e. a combination of Gaussian mixture model and SVM. The feature formation is done based on shape, color and gray-level. This system has high value of positive predictive value (PPV), sensitivity, specificity & accuracy. The retinal images are detected and analyzed using computer assisted diagnosis in [51]. SVM is used to grade the retinopathy of each image. The maximum sensitivity attained is 95% and accuracy is 85%. In [52] retinal fundus images are employed to classify non-proliferative DR as moderate and severe retinopathy. The image segmentation was carried out by mathematical morphology. Then the features are extracted and by using soft margin SVM it is classified. The accuracy of the model is 90.54%. The fundus images are automatically classified as diabetic retinopathy and normal in [53]. Features are extracted and for classification SVM was used. After extraction of area & number of microaneurysms detection was carried on. First image green channel component is extracted. Histogram equalization and morphological process was done for pre-processing. Microaneurysms detection was done by using Principal component analysis (PCA), Contrast Limited Adaptive Histogram Equalization (CLAHE), Morphological process, Average filtering. Linear SVM is used for classification in [54] and the obtained sensitivity and specificity are about 96% and 92% respectively.

3.5 Fuzzy-C mean algorithm
In [55] extraction and detection are done using filter and fuzzy C-means algorithm respectively. To classify the fundus images SVM was used. Then images are classified as normal, NPDR & PDR. The efficiency was about 96.23% for the system. Method described in [56] uses Fuzzy C-mean and morphological method for feature extraction and segmentation. SVM features are used to group the images into different classes. The overall accuracy reported is about 97.6%. In [57] various features from retinal DR images where extracted and used to differentiate different classes. Fuzzy-C means algorithm is used for identification of classes. System presented in [58] detects retinal lesions and automatically classify DR stages. Exudates and other features were detected using image processing techniques. For classifying fuzzy classifier is used. The classifier has an accuracy of about 95.63%. In [59] changes in longitudinal time-series of retinal images are classified. Robustness was achieved using a novel iterative algorithm. Bayesian detection & classification were used. The performance for classifying was about 99.3%. Discussed about type-2 diabetic retinal photography using Remidio (a smart phone based device) [60]. For detection DR, sensitivity and specificity is about 95.8% and 80.2% respectively.

3.6 Based on features extracted
In [61] images with micro aneurysm and endovascular are used for classification of DR. Classification is done based on features which has low dimensionality with a modified color auto-correlogram feature (Auto CC). The proposed method achieved a significant performance gain. To extract the structure of micro-aneurysms a filter algorithm with vessel enhancement is employed. Classification performed in [62] is based on micro aneurysms and hemorrhages. Achieved sensitivity is about 57.4%. Texture features combinations are used in [63] to detect exudates. These exudates are extracted from local binary pattern, with an ANN classifier. Sensitivity, specificity and accuracy obtained were 98.68%, 94.81% and 96.73% respectively. Wavelet transformation is used in [64] to process the retinopathy images. To identify DR KNN & SVM
were used. The accuracy with KNN was 98.16% and for SVM was 97.85%. In [65] texture measures are calculated and then it is used for classification. The method is evaluated using SVM and ANN. The SVM have better accuracy than ANN. SVM provides an accuracy of 87.5% and ANN provides 79% accuracy.

3.7 Clustering method
In [66] DR is classified after detection of exudates and hemorrhages from retinal images. For clustering K-mean clustering technique is used. The sensitivity is 98.2% and accuracy is about 92.3%. In [67] for classification mean, variance, standard-deviation and correlation are calculated. For feature extraction K-mean clustering was used and 95% of correct classification is achieved. The system is effective for detection of non-proliferative DR lesions. Method in [68] provides a technique that automatically classifies and detects exudates from retinal images. Green channel component of RGB fundus image was extracted and after some pre-processing optic disk was eliminated. Robust Spatial Kernel FCM (RSKFCM) segmentation was done. For classification meta-cognitive neural network has been used. This method reduces memory requirements and computation time. To classify the DR severity pre-trained Inception VI network is used in [69]. For extraction of vessels trained U-Net is used. This method classifies stages of DR. The accuracy is about 96%. In absence of vessel, accuracy was reduced from 60% to 53% and 84% to 78% for grade 0 vs 1 and grade 0 vs 3 respectively. DR features are detected and then it is pre-processed. Images were classified as mild NPDR, moderate NPDR, severe NPDR and PDR. The detection of blood vessel and hemorrhages and exudates percentage are 98% and 100% respectively [70]. The system in [71] provides classification and detection of DR stages based on exudate quantification in fundus images. The exudate detection method consists of two steps- rough and fine exudate segmentation. The segmented images are translated into DR numerical index and then classified into different stages by using statistical analysis. DR images have been clustered into 5 categories based on expertise of ophthalmologist in [72]. Stages are considered as non-apparent, mild NPDR, moderate NPDR, severe NPDR & PDR. The accuracy result by InceptionNet V3 is 63.23% which demonstrates the effectiveness of CNN for DR image recognition. To classify the severity of DR a deeply supervised ResNet approach is used in [73]. In the CNN an additional side-output layers of eleven-layer ResNet is added to intermediate hidden layers, and an average fusion layer on the top of side-output layers. They provide regulation and learn classification features. In [74] two-level classification is used as the classifier. The first level classification is performed through ensemble of best first tree, thereby removing the outlier. Then the data is passed to second level, classification is performed through ensemble of J48 Graff trees. Method achieved an accuracy of 96.14%. Table 2 is the summary of classification methods listed in the literature. Figure 2 is the performance plot for different classification methods.

3.8 Thresholding based method
Method uses normal and abnormal retinal images [75]. To identify vessel and segmentation of edges of vessels was done by Kirsch template. In segmentation disease identification and thresholding technique are also done. This method provides efficient result compared to existing method.

4 CONCLUSION
This paper presents an analysis of different methods for screening retinopathy and classifying its severity level. In summary, this study brings a global overview of the occurrence and development of diabetic retinopathy published over the last few years in various journals and conferences. In our study we found that even well-developed nations lack data on progression of diabetic retinopathy. Also data on incidence of diabetic retinopathy in type 1 diabetes is lacking. Our study suggest that more in depth high quality studies based on data stratified by sex, age and severity of disease are essential to summarize the evidence base. The soundness of automatic diabetic retinopathy detection and classification will efficiently decrease ophthalmologist’s work load.

For different classification methods

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