International Journal of Scienti□c & Technological Development
(A Peer-Reviewed Bi-Annual Journal) ISSN 2348-4047

Screening Methodologies for Grading Retinal Images: A Review

Ujwala W. Wasekar[*]
Dr. R. K. Bathla[1]
[*,1]Department of Computer Science, Desh Bhagat University,
Mandi Gobindgarh, Punjab, India

[*]ujwalazade@rediffmail.com
[1]dr.bathla@gmail.com

Abstract

Diabetic Retinopathy (DR) is a disorder which affects the retina of the human eye which leads to vision loss if not taken notice of and treated accordingly. Hence, regular screening of eyes becomes of utmost importance for diabetics. In this paper, a comprehensive study of the methodologies, their results and limitations have been discussed in order to get the wholesome view. Several image processing techniques were used in the literature to refine the image for maximum information extraction. Comparison of various databases and classifiers used by the researchers revealed that kNN gave better results in terms of accuracy irrespective of number of images used in evaluation. This investigation is specifically useful for the researchers who wish to work in the domain of detection and classification of DR.

Keywords

Diabetic Retinopathy, Lesions, Classification, Exudates, Microaneurysms

Introduction

Diabetic Retinopathy (DR) emerges as eyesight threatening disease for Diabetes Mellitus patient, if not diagnosed and treated at an early stage. It may occur if diabetes exists for a pretty long time like twenty years or so. The healthy retinal image consists of an optic disc (OD), blood vessels and macula. Ophthalmologists can spot the lesions manually. But, it may be time consuming and inaccurate. Automated systems in detecting DR not only saves time, but also gives accurate results and are pocket friendly. Different lesions such as microaneurysm (MA), exudates, haemorrhages (HM), new but abnormal vessels (neovascularization) start appearing in the DR affected retinal fundus images. Among these, MA indicates the beginning of the disease. Figure 1 shows the features present in the DR affected retina [1].

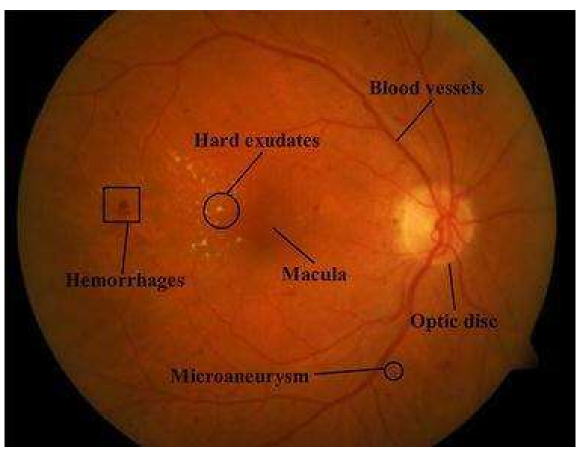

Fig. 1 DR affected image of retina [1]

After capturing the image, the image needs to be refined as it contains a lot of noise and uneven illumination. There are different preprocessing techniques in place to take care of. Since, OD and exudates resemble each other regarding brightness and intensity one may misunderstood exudates for OD. Therefore, OD needs to be removed from the image. Likewise, it is required to extract blood vessels and eliminate them. Objects in an image should be identified in order to take out maximum information. Segmentation does it all. After that come the feature extraction which identifies the distinct attributes of the lesions. These attributes are fed to the classification module to categorize the image as healthy or DR affected. Several Classifiers are available in the literature that helps in exactly grading the images into different categories. They are normal, mild Non-Proliferative Diabetic Retinopathy (NPDR), moderate NPDR, severe NPDR and Proliferative Diabetic Retinopathy (PDR). Figure 2 depicts the flow of the DR classification process.

As screening of retinal images is important for diabetics to avoid vision loss, ophthalmologists recommend regular eye checkups. Quick and accurate system development for detection and classification of DR images is the need of an hour. Several approaches are available in the literature. This study proposes a systematic compilation and analysis of the techniques used in the past that will help researchers to build a robust system. Sections that follow are Methodologies used in detecting Diabetic Retinopathy using Image Processing Techniques, result and discussion and conclusion.

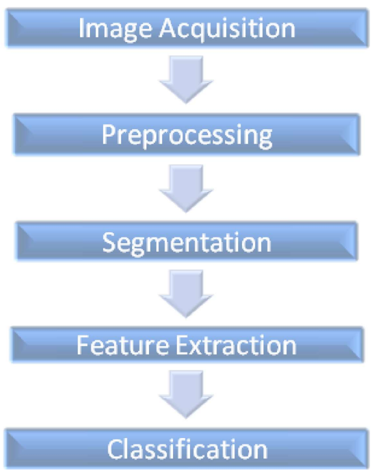

Fig. 2 Process of DR detection and classification

Methodologies used in detecting Diabetic Retinopathy using Image Processing Techniques

Much work has been done in the past to increase the efficiency of the automated grading systems to discriminate the images into normal and abnormal categories. Chandran et al. (2016) proposed a system for patchwise extraction of texture and vesselness based features [2]. Evaluation of performance was done using three databases, messidor, stare and local dataset. Images were classified as normal, NPDR and PDR using random forest classifier. System attained accuracy of 89%, 88% and 90% on messidor, stare and local dataset respectively. Since the OD was removed manually, more features of OD could be taken into consideration to avoid manual removal of OD. Herliana et al. (2018) proposed neural network (NN) combined with particle swarm optimization (PSO) technique [3] and compared it with neural network output. NN+PSO gave the accuracy of 76.11. Paing et al. (2016) put forward a method [4] to extract exudates and MA. Features such as area, perimeter and count of lesions were taken out and fed to ANN classifier. Performance evaluation on Diaretdb1 and local dataset provided the accuracy of 96%. However, efficiency can be improved by using more images, detail features and different classifier. Pratt et al. (2016) proposed an approach to diagnose the severity of DR using CNN [5]. Features of MA, exudates and HMs were used to classify the images. Accuracy of 75% was achieved on Kaggle dataset. Authors planned to use much cleaner dataset from UK screening settings in future. Rahim et al. (2014) made use of four classifiers to validate their performance [6] namely, binary decision tree, kNN, RBF kernel SVM and polynomial kernel SVM on diaretdb0 database. It was found out that kNN stood out better at 98.64% accuracy. Features such as area of on pixels, mean and standard deviation were used. However, hybrid approach, more features and multilevel classification could be introduced in future. Roy et al. (2017) used fuzzy c means to detect exudates, convex hull to remove OD and filter based vessel extraction [7]. SVM classifier distinguished the images as normal, NPDR or PDR giving accuracy of 96.23%. Suryawanshi and Setpal (2017) proposed a method in which GLCM features such as contrast, correlation, energy, homogeneity and entropy were used [8]. The system was trained using messidor database and drive database for testing. Two layer feed forward network provided with the accuracy of 90% and two level classifications. Tjandrasa et al. (2013) proposed to extract features of exudates (area, perimeter, no. of centroids, standard deviation) to classify the images as moderate NPDR or severe NPDR with messidor database used for evaluation and SVM classifier to grade the images [9]. Accuracy of 90.54% was achieved. To improve the grading in detail, consideration of features such as MAs and HMs can be done in future. Yu et al. (2017) aimed at pixel-wise identification of exudates [10]. First, exudate candidates were extracted and then the surrounded region (64x64) of the candidate pixel was sent for classification to the CNN model. E-Ophtha EX database was used for validation which leads to the accuracy of 91.92%. Use of more publically available databases such as messidor and Diaretdb may increase the performance of the system.

Result and discussion

Researches done in the field of classification of DR using machine learning and deep learning approaches are heart warming and welcoming. Identification of lesions and classifying them correctly is a challenging task. Since MAs mark the beginning of the DR, it is necessary to identify them accurately [4, 5] to curb the spread of DR. Exudates are as bright as OD. To avoid confusion in between them, removal of OD becomes crucial. Many researchers have focused on detection of exudates [4, 5, 7, 9, 10]. Lesion detection can be done at pixel level, patch level or image level. Different features help in the recognition of the lesions. Area, perimeter, mean, standard deviation, count of lesions are some of the common features [4, 6, 9] that researchers opt for in proper identification of disease.

Databases provide the protocols that help in fair and unambiguous evaluation of the methods proposed by the researchers. Messidor [11], diaretdb1 [12] are some of the publically available databases. Messidor contains 1200 fundus images in TIFF format. Diaretdb1 consists of 89 images (in PNG format) out of which 84 shows the sign of DR while 5 images are normal. The major difference in between the two is that while diaretdb1 database has the manual annotations on the image, messidor doesn't. Figure 3 shows the percentage of the distribution of databases used in the study of this work.

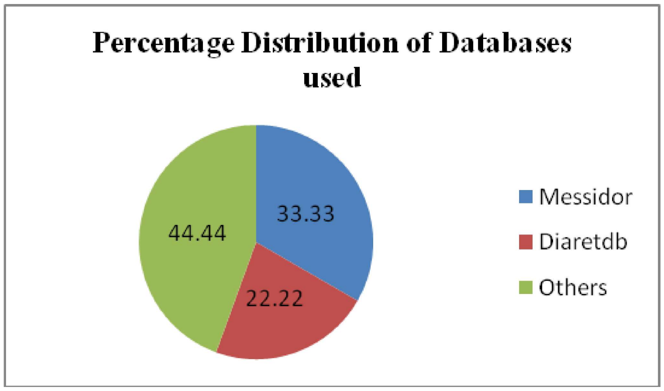

Fig. 3 Percentage distribution of the databases used in the study

Validation of the algorithms can be verified using various performance measures. In this study, accuracy has been used as a measuring tool for the assessment of the results. Accuracy can be defined as the average of the correctly classified DR images and correctly classified normal images. It is represented as

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

Where, TP = correctly classified lesion, TN = correctly classified non-lesion, FP = incorrectly classified non-lesion, FN = incorrectly classified lesion. A well chosen classifier to grade the images accurately can do the wonders. Support Vector Machine (SVM) is a binary classifier that builds the hyperplane to distinguish the data points [13]. However, SVM has been improvised to handle large amount of data for multi level classification. The distance between the hyperplane and the closest data point is called as margin. Random Forest (RF) is a combination of tree classifier where each tree votes for a popular class [14]. It requires less number of input vectors as compared to SVM. k Nearest Neighbor (kNN) is a simple classification algorithm that can solve regression as well as classification problems [15]. Classification is based on the Euclidian distance between the training and test samples. It is a non-parametric model of classification i.e. it does not make any assumption about the trained data. Figure 4 depicts the comparison of the outcomes of the studied material in terms of accuracy in detecting Diabetic Retinopathy irrespective of the databases and classifiers used. It is clearly shown that kNN outperformed other classifiers. But, it exhibit binary grading only.

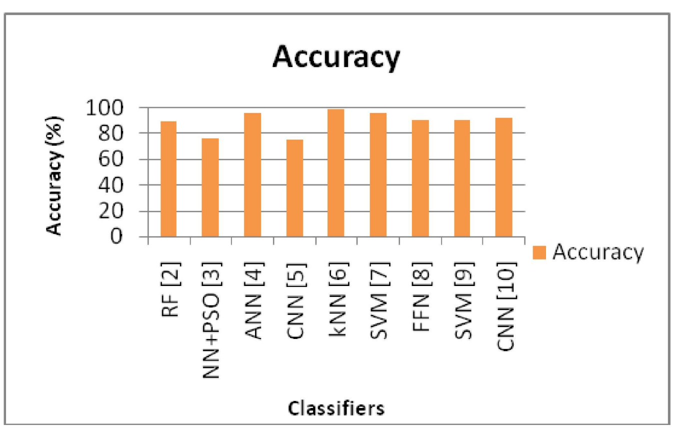

Fig. 4 Comparison chart showing the performances of algorithms in terms of accuracy irrespective of databases and classifiers used in the evaluation

Conclusion

Diabetic Retinopathy, prevalent in diabetes patients, causes major harm to the eyesight, if not treated at an early stage. This paper presents the analysis of the methodologies used in the literature. Different databases and classifiers have been discussed. Relevant features extracted out of lesions took the approaches to the maximum possible accurate grading of DR images. Various classification levels were presented by the researchers. Comparison of all the methods based on different set of images used showed that kNN was better with maximum accuracy. Though, the multilevel classification was desired in future.

Acknowledgement

Authors are grateful for all the feedbacks given by reviewers.

References

[1] https://biomedical-engineering-online.biomedcentral.com/articles/10.1186/s12938-017-0414-z

[2] Chandran, A., Nisha, K. K., & Vineetha, S. (2016). *Computer aided approach for proliferative diabetic retinopathy detection in color retinal images. 2016 International Conference on Next Generation Intelligent Systems (ICNGIS).*

[3] Herliana, A., Arifin, T., Susanti, S., & Hikmah, A. B. (2018). *Feature Selection of Diabetic Retinopathy Disease Using Particle Swarm Optimization and Neural Network. 2018 6th International Conference on Cyber and IT Service Management (CITSM).*

[4] Paing, M. P., Choomchuay, S., & Rapeeporn Yodprom, M. D. (2016). *Detection of lesions and classification of diabetic retinopathy using fundus images. 2016 9th Biomedical Engineering International Conference (BMEiCON).*

[5] Pratt, H., Coenen, F., Broadbent, D. M., Harding, S. P., & Zheng, Y. (2016). *Convolutional Neural Networks for Diabetic Retinopathy. Procedia Computer Science, 90, 200–205.*

[6] Rahim, S. S., Palade, V., Shuttleworth, J., & Jayne, C. (2014). *Automatic Screening and Classification of Diabetic Retinopathy Fundus Images. Communications in Computer and Information Science, 113–122.*

[7] Roy, A., Dutta, D., Bhattacharya, P., & Choudhury, S. (2017). *Filter and fuzzy c means based feature extraction and classification of diabetic retinopathy using support vector machines. 2017 International Conference on Communication and Signal Processing (ICCSP).*

[8] Suryawanshi, V., & Setpal, S. (2017). *Guassian transformed GLCM features for classifying diabetic retinopathy. 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS)*

[9] Tjandrasa, H., Putra, R. E., Wijaya, A. Y., & Arieshanti, I. (2013). *Classification of non-proliferative diabetic retinopathy based on hard exudates using soft margin SVM. 2013 IEEE International Conference on Control System, Computing and Engineering.*

[10] Yu, S., Xiao, D., & Kanagasingam, Y. (2017). *Exudate detection for diabetic retinopathy with convolutional neural networks. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).*

[11] Decencière, E., Zhang, X., Cazuguel, G., Lay, B., Cochener, B., Trone, C., … Klein, J.-C. (2014). *FEEDBACK ON A PUBLICLY DISTRIBUTED IMAGE DATABASE: THE MESSIDOR DATABASE. Image Analysis & Stereology, 33(3), 231.*

[12] T. Kauppi, V. Kalesnykiene, J.-K. Kamarainen, L. Lensu, I. Sorri, A. Raninen, R. Voutilainen, H. Uusitalo, H. Kälviäinen, J. Pietilä, Diaretdb1 diabetic retinopathy database and evaluation protocol, Proc. Medical Image Understanding and Analysis (MIUA), vol. 2007 (2007).

[13] Ricci, E., & Perfetti, R. (2007). *Retinal Blood Vessel Segmentation Using Line Operators and Support Vector Classification. IEEE Transactions on Medical Imaging, 26(10), 1357–1365.*

[14] Pal, M. (2005). *Random forest classifier for remote sensing classification. International Journal of Remote Sensing, 26(1), 217–222.*

[15] Sun J., Du W., Shi N. (2018). A Survey of kNN Algorithm. Information Engineering and Applied Computing, 1-10.