A Survey on Automatic Classification of Diabetic Retinopathy in Retinal Images

D. Ashok kumar
Department of Computer Science
Government Arts College, Trichirappalli-620 022, India

A.Sankari
Department of Computer Science
Research Scholar, Bharathidhasan University, Trichirappalli-620 022, India

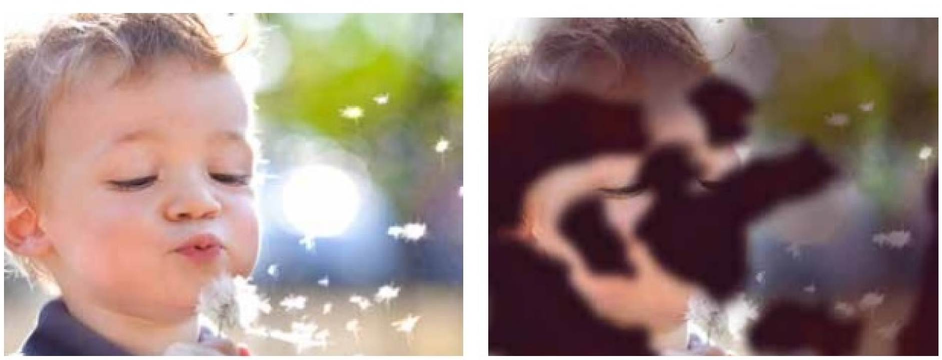
Abstract- In recent decays, diabetic retinopathy (DR) is an important eye disorder that may cause low vision if its diagnosis in late. Different feature extraction and classification methods have been studies in literature survey for the purpose of improving diabetic retinopathies accuracy in the screening test. Numerous image processing techniques including Image preprocessing, Segmentation, Image filtering, Morphology operation, Classification has been introduced for the early identification of DR on the basis of attributes such as blood vessels, exudes, and microaneurysms. In this paper, we have analyzing different method for DR detection and classification. To this end, in this comparative analysis of different algorithm is performed to select most appropriate method for retinopathy detection. Comparison results show that performance of individual procedure and can be used to decide the factor in algorithm selection for future research.

Keywords – Diabetic Retinopathy, Segmentation, Feature Extraction, Classification.

I. Introduction

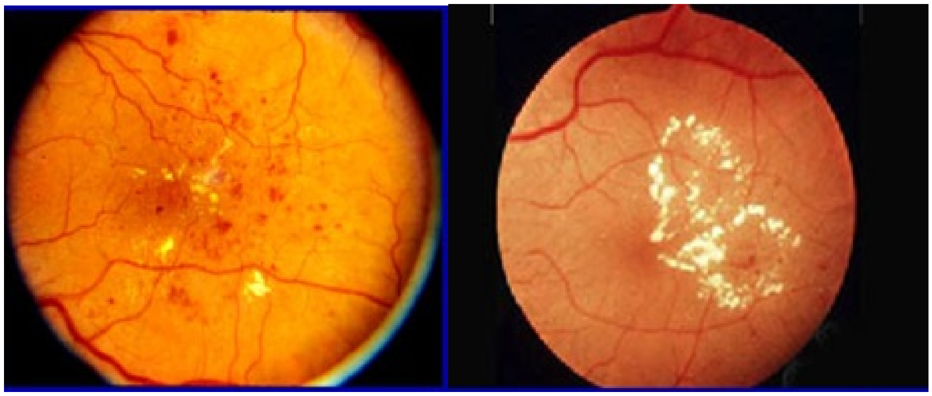
In recent years, Diabetic retinopathy (DR) becomes major cause for blindness, which is also known as eye diseases [1]. Regular screening is recommended to diabetic patients for early diabetic diagnosis, which can help them to prevent loss of sight. Furthermore, a huge amount of diabetic patients are undergone screening process, which leads to increase the workload for ophthalmologists. In order to overcome this problem, an automatic DR detection is necessary to improve the diagnosis speed and accuracy of detection [2]. With the efficient diagnosis of the severity levels of DR and Diabetic Maculopathy at the early stages, appropriate treatment can be provided to prevent vision loss among the patients.

Figure 1.1(a) shows the normal vision and Figure 1.1(b) depicts the vision with DR. Figure 1.2(a) shows the DME and severe NPDR. DME demonstrating circinate retinopathy is illustrated in Figure 1.2(b).



(a) (b)

Figure 1.1 (a) Normal vision and (b) Vision with DR



(a) (b)

Figure 1.2(a) DME and severe NPDR and (b) DME demonstrating Circinate retinopathy

Preprocessing is the fundamental step in the automatic detection of DR. The input retinal image may degrade due to the presence of noise, uneven illumination conditions and poor contrast. Preprocessing techniques help to remove the noise and enhance the quality of image to facilitate the early diagnosis of the disease.

Morphological operations [15] can be divided into erosion, dilation, opening and closing operations. Erosion operation is used to reduce the objects in the image and dilation operation is used to boost them. Morphological openings are used for removing the unwanted structures in the image by applying an erosion operator followed by a dilation operator. In the case of morphological closing, some of structures in image are filled or merged by applying dilation operation followed by the erosion operation [16].

The remaining section of this paper is structured as follow: Section 2 explains the different methodology for DR segmentation, feature extraction and classification in DR systems. Performance comparisons of individual technique are discussed in Section 3 in terms of its metric evaluation. Section 4 concludes the paper with best system for DR detection on fundus image.

II. DR SEGMENTATION AND CLASSIFICATION METHODS

In first phase two key contributions are invented towards DR detection system. In this paper, a novel MinIMas overlap algorithm is proposed to initialize the OD center in low contrast fundus image. Most of the prior approached have not been achieved successful arte more than 91% on real public dataset [3]. But our segmentation approach achieves 100% accuracy in dataset DRIVE [4] and 98.68% accuracy in STARE dataset [5] for OD detection. Additionally, most existing algorithm [5] has not been robust to field of view (FOV) variation of input images. Also, some of the prior methods affect from image over-training since they follow the vessel-branch networks after extracting the blood vessels, looking for merging patterns in images that do not have a visibly bright OD, thus resulting in false detections [6]. Our segmentation algorithm is trained with varying FOV and illuminations images and thus, it does not affect from over-training. Also, the MinIMas overlap algorithm does not fail in the presence of exudates which similar to bright spot OD detection.

Various schemes for the segmentation of the retinal blood vessel and classification of the retinal images based on the type and severity of the diseases are developed [3-10]. Nayak et al. [7] proposed a method for the automatic classification of retinopathy based on the Artificial Neural Network (ANN) for the early detection of the DR. The existing methods enable accurate detection of DR at the early stages. However, these techniques require high computational complexity and large training to the classifiers [8]. Detection of the significant points such as terminal, intersection and bifurcation points provides information about the vascular structure and facilitates efficient diagnosis of the retinal disease [9].

Nivetha et al. [10] proposed a new method for finding the exudates patches from the retinal blood vessels during DR treatment. The GLCM features are extracted and features are processed using Probabilistic Neural Network (PNN) classifier. Morphological operations are applied to the abnormal image for extracting blood vessels and FCM is applied to detect the exudates in the blood vessels. Sisodia et al. [11] applied preprocessing and feature extraction method for the detection of DR using machine learning techniques. Totally, 14 features are extracted from the normal and diabetic retinal fundus image. Among them, seven features such as exudate area, blood vessel area, bifurcation point count, Shannon Entropy, optic distance, hemorrhage area and MA (microaneurysms) area are extracted to identify the normal and abnormal image. Saha et al. [12] proposed a new diagnosis system for the detection of bright and dark lesions using Naïve Bayes and SVM classifier. The detection of MAs and blood vessel is eliminated by using the improved machine learning algorithms. Cortés-Ancos et al. [13] integrated MA extraction method and classification system for detecting the diabetic retinopathy. The methodology detected the low contrast MAs with lower false positive rates. Lachure et al. [14] proposed a system for detecting retinal micro-aneurysms and exudates for automatic screening of diabetic retinopathy using SVM and KNN classifier. The morphological operations are performed to find MA and features such as GLCM and structural features are extracted for classification of disease severity as normal, moderate and severe.

All mentioned prior approaches show different classification results, finding a perfect technique to classify the fundus image in DR screening stages. Also these approaches are having a common problem that non-Mas features vary in a wide range. To overcome these issues, Hybrid approaches are invented and compared using image segmentation, Feature extraction and classification approach. All these hybrid techniques are tested and optimized for DR detection using fundus images. To determine best technique for detection on fundus images, these hybrid techniques are compared in terms of accuracy, sensitivity and specificity. In this research DIARETDB1 dataset are used which is publically available from internet.

III. COMPARATIVE ANALYSIS

This section comparatively describes recent DR segmentation, Feature Extraction techniques and classification with its merits and demerits.

Author Name & Reference	**Year**	**Techniques/ Methods**	**Inference**	**Evaluation Metrics**
Jasem Almotiri [16]	2017	Kernel Based Methods	The profile-based kernels are implemented in the retinal vessels profiling that are created based on the intensity distribution of retinal vessel, which used to enhance the map for the vessel boundaries.	1. Sensitivity 2. Specificity 3. Accuracy 4. Precision
Singh, N.P.; Srivastava[17]	2016	Filter kernel: Gumbel Probability Density Function.	A novel matched filter approach with the Gumbel probability distribution function as its kernel is introduced to improve the performance of retinal blood vessel segmentation.	1.Accuracy 2.ROC
Wang et al [18]	2015	A hybrid method based on CNN and ensemble Random Forest (RF)	The proposed method can automatically learn features from the input images and predict the patterns. As the CNN architecture is able to extract scale and rotational invariant features and RF	1.Sensitivy 2.Specificity 3.Accuracy 4. Area Under Curve(AUC)

			is popular for high generalization capability.	
Gayathri et al. [19]	2014	Morphological operator(Bottom hat and Top hat transformations)	The morphological functions are provided to classify the blood vessels and dark lesions from the background. Finally, the Wiener filter and top hat transformation are applied for separating the dark lesions from the blood vessels.	1.PSNR 2. RMSE
Li et al. [20]	2016	Deep NN with strong induction capability	The vascular feature can be learned automatically in the training process. A wide and deep neural network is proposed for modeling the relationship between the retinal image and the vessel map.	1.Sensitivy 2.Specificity 3.Accuracy 4.AreaUnder Curve(AUC)
Nivetha et al. [21]	2017	GLCM +PNN +FCM	GLCM features are extracted and features are processed using PNN classifier. Morphological operations are applied to the abnormal image to extract the blood vessels and FCM is applied in the extracted blood vessels to detect the exudates.	1.Sensitivy 2.Accuracy
Zhao et al. [22]	2015	A hybrid active contour model	Better detection of oscillatory structures is enabled based on the boundary length of features. The intensity information and local phase based enhancement map are combined to maintain the edges of blood vessel for better segmentation performance.	1.Sensitivy 2.Specificity 3.Accuracy 4.AreaUnder Curve(AUC) 5.Dice Coefficient(DC)
Saffarzadeh et al. [23]	2014	Mulri Scale Line operaot + KNN	K-means segmentation is applied in a perceptive space to reduce the negative impact of bright lesions. A multi-scale line operator is used for detecting vessels while neglecting some dark lesions.	1.Accuravy 2.AUC

Choudhury et al. [24]	2016	FCM +SVM	This paper proposed an approach for feature extraction using FCM and morphological methods and SVM based classification of the retinal images for the detection of DR.	1.Accuracy
Zhang et al. [25]	2014	Color, Texture, and Geometry Features	They developed a non-invasive method for diagnosing diabetes mellitus and NPDR using the three groups of features such as color, texture, and geometry features of the tongue.	1.True positive(TP) 2.True Negative(TN) 3.Average Accuracy
Saleh et al. [26]	2017	Fuzzy Random Forest	They explored the usage of two types of ensemble classifiers such as fuzzy RF and dominance-based rough set balanced rule ensemble for the assessment of DR.	1.Sensitivy 2.Specificity 3.Accuracy 4.TP 5.TN
Sharma et al. [27]	2018	MNN	They applied a Modular Feedforward NN (MNN) classifier to classify the retinal images as normal and abnormal images to detect the DR	1.Accuracy 2.Receiver operating characteristic (ROC)
Pratt et al. [28]	2016	CNN	They devised a CNN approach for the diagnosis of DR from digital fundus images and accurately classification of disease severity.	1.Sensitivity 2.Accuracy
Akram et al. [29]	2016	Multivariate m-Mediods and GMM	The input retinal image is graded into different types of NPDR based on the number and location of the lesions. The weights of the classification probabilities are learned to improve the performance of the classifier.	1.Sensitivy 2.Specificity 3.Accuracy 4.AreaUnder Curve(AUC)
Roy et al. [30]	2017	SVM	They applied SVM for classifying the fundus images into normal, NPDR and PDR images. The	1.Accuracy

			exudates are extracted from the fundus image along with the removal of OD using the FCM technique	

IV.CONCLUSION

In this paper, existing DR segmentation, Feature Extraction and classification techniques are surveyed to find the effective one. Every technique has its advantage and disadvantage and effective in its own field of usage. Some techniques are complex and require high computational cost based on the functionality.

REFERENCES

[1] B. Antal, A. Hajdu, “An ensemble-based system for microaneurysm detection and diabetic retinopathy grading,” IEEE transactions on bio-medical engineering, vol. 59, no. 6, pp. 1720-6, 2012.

[2] D. B. Mukamel, G. H. Bresnick, J. C. Dickinson, D. R. Cole, “ A screening approach to the surveillance of patients with diabetes for the presence of vision-threatening retinopathy,” Ophthalmology, vol. 107, no. 1, pp. 19-24, 2000.

[3] A.-H. Abdel-Razik Youssif, A. Ghalwash, and A. Abdel- Rahman Ghoneim, “Optic disc detection from normalized digital fundus images by means of a vessels’ direction matched filter,” IEEE Transactions on Medical Imaging, vol. 27, no. 1, pp. 11 –18, jan. 2008.

[4] J. Staal, M. Abramoff, M. Niemeijer, M. Viergever, and B. van Ginneken, “Ridge based vessel segmentation in color images of the retina,” IEEE Transactions on Medical Imaging, vol. 23, pp. 501–509, 2004.

[5] A. Hoover, and M. Goldbaum, “Locating the optic nerve in retinal image using the fuzzy convergence of bood vessels,” IEEE Transactions on Medical Imaging, vol. 22, August 2003.

[6] F. ter Haar, “Automatic localization of the optic disc in digital colour images of the human retina,” M.S. Thesis in Computer Science, UtrechtUniversity, Utrecht, 2005.

[7] J. Nayak, P. S. Bhat, R. Acharya, C. M. Lim, and M. Kagathi, "Automated identification of diabetic retinopathy stages using digital fundus images," Journal of medical systems, vol. 32, pp. 107-115, 2008.

[8] P. K. R. Yelampalli, J. Nayak, and V. H. Gaidhane, "Blood Vessel Segmentation and Classification of Diabetic Retinopathy Images using Gradient Operator and Statistical Analysis," in Proceedings of the World Congress on Engineering and Computer Science, 2017.

[9] S. Morales, V. Naranjo, J. Angulo, A. Legaz-Aparicio, and R. Verdú-Monedero, "Retinal network characterization through fundus image processing: Significant point identification on vessel centerline," Signal Processing: Image Communication, 2017.

[10] C. Nivetha, S. Sumathi, and M. Chandrasekaran, "Retinal blood vessels extraction and detection of exudates using wavelet transform and pnn approach for the assessment of diabetic retinopathy," in Communication and Signal Processing (ICCSP), 2017 International Conference on, 2017, pp. 1962-1966.

[11] D. S. Sisodia, S. Nair, and P. Khobragade, "Diabetic Retinal Fundus Images: Preprocessing and Feature Extraction for Early Detection of Diabetic Retinopathy," Biomedical and Pharmacology Journal, vol. 10, pp. 615-626, 2017.

[12] R. Saha, A. R. Chowdhury, and S. Banerjee, "Diabetic retinopathy related lesions detection and classification using machine learning technology," in International Conference on Artificial Intelligence and Soft Computing, 2016, pp. 734-745.

[13] E. Cortés-Ancos, M. E. Gegúndez-Arias, and D. Marin, "Microaneurysm Candidate Extraction Methodology in Retinal Images for the Integration into Classification-Based Detection Systems," in International Conference on Bioinformatics and Biomedical Engineering, 2017, pp. 376-384.

[14] J. Lachure, A. Deorankar, S. Lachure, S. Gupta, and R. Jadhav, "Diabetic Retinopathy using morphological operations and machine learning," in IEEE International Advance Computing Conference (IACC), 2015, 2015, pp. 617-622.

[15] Rezty Amalia Aras, Tri Lestari, Hanung Adi Nugroho, and I. Ardiyanto, "Segmentation of retinal blood vessels for detection of diabetic retinopathy: A review," *COMMUNICATIONS IN SCIENCE AND TECHNOLOGY,* vol. 1, pp. 33-41, 2016.

[16] J. Almotiri, K. Elleithy, and A. Elleithy, "Retinal Vessels Segmentation Techniques and Algorithms: A Survey," *Applied Sciences,* vol. 8, p. 155, 2018.

[17] Singh, N.P.; Srivastava, R. Retinal blood vessels segmentation by using Gumbel probability distributionfunction based matched filter. Comput. Methods Programs Biomed. 2016, 129, 40–50.

[18] S. Wang, Y. Yin, G. Cao, B. Wei, Y. Zheng, and G. Yang, "Hierarchical retinal blood vessel segmentation based on feature and ensemble learning," *Neurocomputing,* vol. 149, pp. 708-717, 2015.

[19] K. Gayathri, D. Narmadha, K. Thilagavathi, K. Pavithra, and M. Pradeepa, "Detection of Dark Lesions from Coloured Retinal Image Using Curvelet Transform and Morphological Operation," ed: IJNTEC-ISSN, 2014.

[20]Q. Li, B. Feng, L. Xie, P. Liang, H. Zhang, and T. Wang, "A cross-modality learning approach for vessel segmentation in retinal images," *IEEE transactions on medical imaging,* vol. 35, pp. 109-118, 2016.

[21]C. Nivetha, S. Sumathi, and M. Chandrasekaran, "Retinal blood vessels extraction and detection of exudates using wavelet transform and pnn approach for the assessment of diabetic retinopathy," in *Communication and Signal Processing (ICCSP), 2017 International Conference on*, 2017, pp. 1962-1966.

[22] Y. Zhao, L. Rada, K. Chen, S. P. Harding, and Y. Zheng, "Automated vessel segmentation using infinite perimeter active contour model with hybrid region information with application to retinal images," *IEEE transactions on medical imaging,* vol. 34, pp. 1797-1807, 2015.

[23] V. M. Saffarzadeh, A. Osareh, and B. Shadgar, "Vessel segmentation in retinal images using multi-scale line operator and K-means clustering," *Journal of medical signals and sensors,* vol. 4, p. 122, 2014.

[24]S. Choudhury, S. Bandyopadhyay, S. Latib, D. Kole, and C. Giri, "Fuzzy C means based feature extraction and classification of diabetic retinopathy using support vector machines," in *Communication and Signal Processing (ICCSP), 2016 International Conference on*, 2016, pp. 1520-1525.

[25] B. Zhang, B. V. Kumar, and D. Zhang, "Detecting diabetes mellitus and nonproliferative diabetic retinopathy using tongue color, texture, and geometry features," *IEEE transactions on biomedical engineering,* vol. 61, pp. 491-501, 2014.

[26] E. Saleh, J. Błaszczyński, A. Moreno, A. Valls, P. Romero-Aroca, S. de la Riva-Fernández*, et al.*, "Learning ensemble classifiers for diabetic retinopathy assessment," *Artificial intelligence in medicine,* 2017.

[27] M. Sharma, P. Sharma, A. Saini, and K. Sharma, "Modular Neural Network for Detection of Diabetic Retinopathy in Retinal Images," in *Proceedings of First International Conference on Smart System, Innovations and Computing*, 2018, pp. 363-370.

[28] H. Pratt, F. Coenen, D. M. Broadbent, S. P. Harding, and Y. Zheng, "Convolutional neural networks for diabetic retinopathy," *Procedia Computer Science,* vol. 90, pp. 200-205, 2016.

[29] M. U. Akram, S. Khalid, A. Tariq, S. A. Khan, and F. Azam, "Detection and classification of retinal lesions for grading of diabetic retinopathy," *Computers in biology and medicine,* vol. 45, pp. 161-171, 2014.

[30] A. Roy, D. Dutta, P. Bhattacharya, and S. Choudhury, "Filter and fuzzy c means based feature extraction and classification of diabetic retinopathy using support vector machines," in *Communication and Signal Processing (ICCSP), 2017 International Conference on*, 2017, pp. 1844-1848.