A Survey of Image Processing Techniques for Diabetic Retinopathy

Sandhya Soman[1], Jayashree R[2]
1(Department of Computer Applications, PES University, Bangalore)
2 (Department of CSE, PES University, Bangalore)

Abstract

Diabetic Retinopathy (DR) is a retinal complication caused by diabetic mellitus causing vision impairment in diabetic patients-ranging from blurred vision to complete blindness in the extreme cases. The disease progresses from mild, moderate, severe non-proliferative stages to proliferative stages which are characterized by the appearance of microaneurysms, hemorrhages, exudates, cotton wool spots and neovascularization respectively. A number of image processing techniques applicable to white light retinal fundus imageshave been proposed in the literature, which were used to design screening systems for this retinal disorder. A common prerequisite step used in all the approaches is the blood vessel network extraction. Based on the retinal image processing techniques used, the screening systems can be further categorized as those which are used to design DR referral systems focusing on localization of a single symptom and those DR referral systems focusing on isolation of multiple symptoms. Through this paper, an attempt has been made to analyze these approaches in depth and highlight the significant contributions made in the area so that it can prove helpful for the algorithm designers for DR.

I. INTRODUCTION

Diabetic Mellitus [30] is a medical condition due to insufficient insulin production in the body. The global prevalence of this disease is expected to rise to 4.4% of the world population by 2030 [18]. Diabetic patients commonly suffer from vision related problems- ranging from blurred vision to complete blindness. One of the common causes of this vision impairment is diabetic retinopathy. In the simplest terms, it can be stated as the retinal complication due to insufficient insulin production in the body. Hyperglycemia[25] (condition due to elevated blood glucose level), causes damage to the retinal vessel walls which can either lead to swelling in them, leakage of lipid extracts through the vessel wall or formation of new blood vessels (neovascularization) [35].The earliest sign of DR appears[26] as small red dots on the retina called microaneurysms. The subsequent progressive stage shows the appearance of red lesions called hemorrhages due to rupture of blood vessels in deeper retinal layers. At the next stage hard exudates as yellow/white lesions of variable sizes and shapes appear, due to plasma leakage of the capillaries. As the disease progresses, obstruction in the blood vessels are visible due to formation of cotton wool spots(soft exudates) and neovascularization (formation of new blood vessels) causing severe damage in the vision. Accordingly, the medical community has graded the stages of DR on the basis of the occurrence of these symptoms as the following:

(i) No DR- healthy retina.

(ii) Mild Non Proliferative DR characterized by appearance of microaneurysms.
(iii) Moderate Non Proliferative DRcharacterized by appearance of hemorrhages.
(iv) Severe Non Proliferative DRcharacterized by appearance of exudates.
(v) Proliferative DR characterized by appearance of soft exudates and neovascularization.

The term proliferative and non-proliferative refers to the fact that the disease at its initial non-proliferative stage might not show noticeable symptoms in the patient, but as it progresses (proliferative stage), symptoms leading to vision blurring becomes more predominant and hence are easily identifiable due to significant impact in the subject's vision.

II. METHODOLOGY

The work in this paper analyses and categorizes the various retinal image processing techniques and screening system developedfor diabetic retinopathy, from a period of 2009 to 2017. An attempt has also been made to categorize the literature according the symptoms identified and localized, and to put forward the considerable advancements in this field so that the algorithm developers can use the same for their work. Also the potential areas of improvement are included as a part of this review work. The databases searched for this review includes IEEE Explore Digital Library, Elsevier Science, HHS Public Access, ACM Digital and Springer.

III. IMAGE DATABASES

A number of public datasets are available online which can be used by the researchers for the training and testing of their screening systems. Most of these public datasets permit an open and free access to annotated digital retinal fundus images.
This following section describes the datasets utilized in the grading and detecting systems reviewed in this paper.

DRIVE (Digital Retinal Images for Vessel Extraction) [31]
This database consists of 40 randomly selected images obtained from a screening program in Netherlands from 400 diabetic subjects between 25-90 years of age. The images are JPEG compressed, captured using Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view. It contains 33 healthy retinal images, of which 7 shows signs of mild early DR.

STARE(Structured Analysis of the Retina) [32]
The dataset includes 400 raw images with expert annotations of the manifestations for each image. This dataset is a part of a project conceived by University of California.

VARIA [33]
It is a set of 223 retinal images from 139 different individuals acquired through TopCon non-mydriatic camera NW-100 model having a resolution of 768x584

MESSIDOR [35]
This database has 1200 eye fundus color numerical images of the posterior pole acquired by 3 ophthalmologic departments using 3CCD Topcon camera. 800 images are acquired with dilation and 400 without dilation

ROC (Retinopathy Online Challenge)[7]
It is an attempt by University of Iowa and ROC organizers aimed at improving computer aided detection and diagnosis of DR. 100 images released for microaneurysm detection challenge were acquired by a 45 NM canon CR5-45.

UTHSC SA(University of Texas Health Science Center in San Antonio) Dataset

The dataset provides 600 images taken from a canon CF-60 UV retinal camera with 60° FOV and of the size 2048 x 2392.

E-OpthaEX

It is an open source database widely used for images that aid in exudate detection. It contains 47 images with exudates and 35 images with no lesion

FINDeR [12]

It contains a total of 315 retinal images, graded into 5 classes. 175 images of no DR, 52 of mild DR, 32 of moderate DR, 18 of severe DR and 38 of PDR.

Kaggle[13]

This dataset was provided by the Kaggle coding website and contains over 80000 images of patients from varying ethnicity, age groups. The dataset used varied levels of lighting used while acquiring these images.

EyePACS2 dataset [14]

This dataset was also used in the Kaggle DR competition containing fundus images of left and right eye of 17563 patients.

DiaretDB1

It is an online dataset having a total of 89 images of which 5 are healthy and the rest are infected retinal images. It can be used for the detection of exudates, hemorrhages, microaneurysms and abnormal blood vessel detection.

IV. PERFORMANCE METRICS

Usually, theanalysis of [26] the performance of a retinal image processing algorithm is performed by applying the following metrics:

i. Sensitivity/TPR (True Positive Ratio) which is the measure between TP and FN.
ii. FPR (False Positive Ratio) which is the measure between FP and TN.
iii. FNR (False Negative Ratio) which is the measure between FN and TP.
iv. Specificity/TNR (True Negative Ratio) which is the measure between TN and FP.
v. Accuracy which is the degree to which the result of a measurement confirms the standard

Here true positive (TP) indicates total number of lesion pixels correctly identified and true negative (TN) denotes the non-lesion pixels correctly identified. False positive (FP) denotes the number of non-lesion pixels that are detected wrongly by the algorithm. False negative (FN) indicates the number of lesion pixels not identified by the algorithm

V. SURVEY FINDINGS/LITERATURE SURVEY

Although the problem of devising an optimal screening system for diabetic retinopathy has been around for more than a decade, researchers have been facing challenges while localizing certain anatomical features of retina (fovea, optic disc) and henceforth in the accuracy of an automated system for pathology detection. Following the literature, the work done in this area can be broadly categorized as referral systems focusing on localization of a single symptom and those DR referral systems focusing on isolation of multiple symptoms. While the former systems are more ideal for detection i.e. the presence or absence of diabetic retinopathy, the latter are suitable for grading the retinopathy stage. This section discusses the existing referral systems along with a major perquisite step required for any system aiming to screen retinopathy i.e. vessel network extraction.

A. Vessel network extraction

Whenever an ophthalmologist reports a pathological manifestation, it is reported

with respect to an anatomical location denoted by the vascular branching. Hence accurate vessel segmentation is a prerequisite in this field. Many authors have contributed in devising algorithms for accurate vessel line detection.

Morales *et. al.*[2] identifies three types of significant points (terminal, bifurcation and crossing) in the blood vessel structure using morphology based hit or miss transform. The bifurcations and cross overs on the vascular network are helpful in disease prediction, of which the bifurcation angles in the vessel lines can particularly be used in cardiovascular disease prediction [39][40].

Sangita *et. al.*[6]proposed a morphology based blood vessel extraction technique which uses top hat transformation oriented at three different angles of 0°, $60^{\circ}$and 120°. It was tested on DRIVE database achieving an accuracy of 95.03% requiring processing time of 0.835 seconds per image.

Another notable contribution was made by Kulwinder *et. al.*[15]using artificial neural networks to segment out blood vessels with an accuracy of 94.71% and 95.05 % on DRIVE and STARE database respectively. The work reported a sensitivity of 78.08% and 78.97%.

Zhang *et. al.* [9] identifiedthat matched filter approach gives stronger responses not only for edges but also for non-vessel edges like blobs and red lesions and hence has to be used in combination with another technique for accurate vessel extraction. The work used MF-FDOG (matched filter-first order derivative of Gaussian) to segment out the blood vessels.

Daniel *et. al*[21]showed that the accuracy of vessel extraction can be improved by replacing classic morphological techniques with fuzzy morphological techniques.

Lili et. al [27] extracted the complete vascular tree structure using SVM to classify vessel segments and adaptive local threshold to get good contrast of large blood vessels. DRIVE database was used for testing and the method could gain an accuracy of 93.2%

Halter et al [28] and Zhu et al [29] both used bottom hat transformation along with filter matrixes to segment out vessels from darker background.

Sudeshna et. al [24] proposed a vessel extraction technique using sequential band pass filter followed by fuzzy conditional entropy maximization on matched filter response. The method could successfully extract abnormal and thin blood vessels in pathological retinal images with an accuracy of 96.28 and 96.16 on DRIVEand STARE database respectively. The authors found that the use of curvelet transform and tunable bandpass filter is much effective in edge enhancement whereas fuzzy conditional entropy could effectively distinguish vessels of different widths.

The above mentioned contributions reveal that with the combination of some machine learning technique [16] or fuzzy image processing techniques, along with the traditional matched filter or derivative based approach could considerably enhance the accuracy of the referral systems. Also we can clearly see and relate to the significance of accurate vessel extraction for the overall accuracy of a DR referral system.

B. Referral systems for DR detection

Numerous advances have been made in the recent years to isolate diseased symptoms from fundus images. The simplest referral systems extract any one of the diseased symptom like the presence of a microaneurysms, exudate in the retinal image to detect the presence or absence of a pathological condition in the retina.

a. Localization of microaneurysms

Pedro *et. al.*[5] discriminates normal and pathological images on the basis of the presence of red dots or microaneurysms by

using a generalization of a bag of visual words without encoding any prior knowledge into the system. The system was trained and tested on DR2 and MESSIDOR public databases and is capable of performing feature extraction, feature encoding and classification guided by classification error.

Atushi *et. al.*[7] attempted an early diagnosis of DR by micro-aneurysm localization following a supervised approach using double ring filters in low contrast images. The system could successfully remove false positives located in regions corresponding to blood vessels but was insufficient for small sized capillary blood vessels. It was tested on the microaneurysm dataset of ROC (Retinopathy Online Challenge), and achieved a true positive fraction of 0.45 at 27 false positives per image.

Ding *et. al*. [35] used a dynamic multi-parameter template matching scheme on the ROC dataset achieving a sensitivity of 96%

b. Localization of hemorrhages

Mumtaz et. al [23] could successfully isolate one of the red lesion i.e. hemorrhage with a binary classifier using scale based method, gamma correction and global thresholding. The method without the use of any training set, following a model based approach, could achieve an accuracy of 89% on the DIARETDB1 database

Sharma et. al [41] also used dynamic thresholding to extract hemorrhages with a sensitivity of 90% on DIARETDB1 dataset

c. Localization of exudates

Ramasubramanian *et. al.*[4] used second order Gaussian filter for optic disc and exudate segmentation, and trained a SVM with the features extracted using scale invariant feature transformation. The system was trained on 1000 images from MESSIDOR database does not require any re-training for testing dataset by UTHSC and could fetch an accuracy of 99.84% and a sensitivity of 99.96% for exudate extraction.

Sarni *et. al.*[3] proposed medical decision support system with an accuracy of 93.0 for retinopathy and maculopathy detection using fuzzy image processing topped with machine learning techniques, tested on a novel dataset designed by them.

Kittipol *et. al.* [8] could detect exudates in low quality retinal images using FCM along with morphological methods with an improved accuracy of 92.49 when compared with systems only using morphological methods. The author proposes that if the application requires maximum detection of exudates and execution speed then fuzzy c means alone would suffice, but if high accuracy is desired then FCM should be combined with mathematical morphological operators.

Shuang *et. al.* [11] achieves a pixel wise exudate identification using a deep CNN. The potential exudates are extracted through morphological ultimate opening operators which are passed on to trained CNN model. The system achieves an accuracy 91.92 on an open source database for exudates-EophthaEX with a sensitivity of 88.85.

Dhanaese *et. al.* used a Gaussian Mixture Model classifier along with FCM to identify normal and abnormal images on STARE database with an average classifier accuracy of 97.78%

C. Referral systems for DR grading

Another classification for the referral systems isolates and localizes multiple featuresaccording to its severity, and hence could be used for the grading of the retinopathy stage. These classifiers grade an input image according to a 4 class grading approach as diseased(mild/moderate/severe) or healthy; or a 5 class grading approach as

healthy, mild, moderate, severe and PDR based on the presence of combination of symptoms like microaneurysms , lesions, exudates & red dots and their corresponding distances from the macula. The lesser the distance, more is the impact on the vision.

a. *4 class grading(normal, mild, moderate, severe)*

Malay *et. al.* [1] detects and grades fundus images by imitating logic and medical sense used by ophthalmologists on the basis of the presence of exudates and red lesions with an accuracy of 90%. The system however is insufficient for PDR detection as PDR does not affect the macula area but the vitreous humor of the eye.

b. *5-class grading(no DR, mild, moderate, severe, PDR)*

Pallab Roy *et. al.* proposes a hybrid method for grading which combines CNN with dictionary based approach, showing an improvement in the kappa score to valueof 0.86 when compared to similar methods in literature. The system could achieve high classification accuracy for severity level of mild, moderate and severe [14].

Harry Pratt *et. al.* proposed a system using CNN which classifies each image in 0.04 secs hence providing real time feedback. The system was tested on Kaggle dataset with an accuracy on 75% but scored very low on sensitivity of 30% which could be attributed to the usage of a large dataset of 5000 validation images [13].

Igi *et. al.* provides a low cost deep learning based embedded system for grading of retinopathy. The system uses cascaded convolutional block and can directly classify an image fed into it without any feature extraction. The system was tested on FINDeR dataset and projected an accuracy of 95.71 and specificity of 100% [12].

Lesion level classification

Waleed *et. al.*localizes lesion areas(hard exudates, soft exudates, haemorrhages, red small dots) on an image level with high accuracy comparable to supervised methods. The system was trained on image level labels following a weakly supervised object localization approach on Kaggle dataset [17].

Jose *et. al.*[10] proposes an web based automated screening systems capable of detecting bright lesions (specifically exudates, red lesions and microaneurysms) using morphological and multilayered NN requiring 9.6 minutes to process each image with an sensitivity of 91.86.

Wang et. al [20] uses regression activation maps in a deep learning model to propose a interpretable DR detection system which can localize discriminative regions of an retina image to show the specific region of interest in terms of its severity level. The experiments were conducted using Kaggle dataset and could achieve a kappa score of 0.7

ChandraKumar [19] also proposes a deep convolutional neural network based system which can classify without any manual feature extraction. The system although achieves an overall accuracy of 94% with STARE and DRIVE datasets respectively, follows a computationally expensive approach.

VI. DISCUSSION

With a sharp increase in the number of people getting affected by the retinal complication of diabetes called diabetic retinopathy, the need for automated systems to screen diseased images from healthy ones and further grade the diseased image on the basis of severity becomes inevitable. This paper presents the various techniques used in the screening and grading systems and also discusses how accurately they could isolate the symptoms involved. We shortlisted a set of papers from 2009 to 2017,

categorized them on the basis of whether they could provide the ultimate grading of diseased severity or could just differentiate between healthy and pathological diseases. Within each such category, we have also tried to segregate the referral system further on the basis of the type of isolated feature. We could conclude by finding that although the referral systems (following 5 class grading) are doing fairly well in the accuracy and sensitivity with the dataset they are trained in but none have reached the accuracy of over 95% in the tested dataset. Also the inter observer variability kappa score which should be converging to an ideal value of 1, is still below 0.85, which makes us to conclude that there is a requirement of some work in terms of improving the accuracy of the existing grading systems, with more emphasis to reduce the number of false positive detected. Also there is a need to with test the systems with high variance dataset (as reported by several authors in the literature) so that the results are not skewed only in the no DR and severe DR category but should also be able to accommodate mild and moderate cases.

REFERENCES

1. Malay Dutta," An efficient image processing based technique for comprehensive detection and grading of nonproliferative diabetic retinopathy from fundus images", in Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization .DOI: 10.1080/21681163.2015.1051187. ,July 2015
2. S Morales, V Naranjo, J Angulo,Legaz Aparicio and Verdu Monedero," Retinal network characterization through fundus image processing: Significant point identification on vessel centreline",in: Signal Processing: Image Communication. http://dx.doi.org/10.1016/j.image.2017.03.013,March 2017
3. Sarni Rahim , Vasile Palade, James Shuttleworth, and Chrisina Jayne, " Automatic screening and classification of diabetic retinopathy and maculopathy using fuzzy image processing",in: Brain Informatics. DOI 10.1007/s40708-016-0045-3,March 2017
4. B Ramasubramanian , G Arunmani., P Ravivarma,and E Rajasekar." A Novel Approach for Automated Detection of Exudates Using Retinal Image Processing" in: IEEE ICCSP 2015 conference. pp 139-143.2015
5. Pedro Costa and Aurelio Campilho, " Convolutional bag of words for diabetic retinopathy detection from eye fundus images",in: IPSJ Transactions on Computer Vision and Application. DOI 10.1186/s41074-017-0023-6.,March 2017
6. SangitaBharkad, "Automatic Segmentation of Blood Vessels in RetinalImage using Morphological Filters",in: ICSCA 2017. DOI:http://dx.doi.org/10.1145/3056662.3056710,Feb 2017
7. Atsushi Mizutani, Chisako Muramatsu, Yuji Hatanaka, "Automated microaneurysm detection method based on double-ring filter in retinal fundus images",in: Medical Imaging 2009: Computer-Aided Diagnosis. doi: 10.1117/12.813468, 2009.
8. Kittipol Wisaeng, NualsawatHiransakolwong, and Ekkarat Pothiruk, "Automatic Detection of Exudates in Diabetic Retinopathy".in: Journal of Computer Science 8. pp 1304-1313.2012
9. Kittipol Wisaeng, Nualsawat Hiransakolwong, and Ekkarat Pothiruk, "Automatic Detection of Exudates in Diabetic Retinopathy".in: Journal of Computer Science 8. pp 1304-1313.2012

10. Jose Tomas,ArenasCavalli,,Sebastian Rio and Rodrigo Donoso, " A Web-Based Platform for Automated Diabetic Retinopathy Screening.",in: 19th International Conference on Knowledge Based and Intelligent Information and Engineering Systems. pp 557-563,2015.
11. Shuang Yu ,Di Xiao and Yogesan Kanagasingam, ". Exudate Detection for Diabetic Retinopathy With Convolutional Neural Networks.",in: 978-1-5090-2809-2/17. pp 1744-1747,2017
12. Igi Ardiyanto, Hanung Nugroho and Ratna Buana ,"Deep Learning-based Diabetic Retinopathy Assessment on Embedded System",. In: IEEE. pp 1760-1747, 2017
13. Harry Pratt, Frans Coenen, Deborah Broadbent,Simon Harding and Yalin Zheng, " Convolutional Neural Networks for Diabetic Retinopathy. ",in: International Conference On Medical Imaging Understanding and Analysis 2016, MIUA .July 2016.
14. Pallab Roy,Ruwan Tennakoon, , Khoa Cao and Suman Sedai,"A Novel Hybrid Approach For Severity Assessment Of Diabetic Retinopathy In Colour Fundus", IEEE 2017
15. Kulwinder Mann and Sukhpreet Kaur, "Segmentation of retinal blood vessels using artificial neural networks for early detection of diabetic retinopathy". In: AIP Conference Proceedings 1836, 020026. https://doi.org/10.1063/1.4981966, 2017
16. HT Nguyen, M Butler, A Roychoudhry ,J Flack ,and P Mitchell, "Classification of Diabetic Retinopathy Using Neural Networks". In: International Conference of the IEEE Engineering in Medicine and Biology Society.pp. 1548-1549,1996.
17. Waleed Gondal,Jan Kohler, Rene Grzeszick,Gernot Fink and Michael Hirsch," Weakly-Supervised Localization Of Diabetic Retinopathy Lesions In Retinal Fundus Images", Jun 2017
18. R Winder, P J Morrow, I N Ritchie J R Bailie and P M Hart,". Algorithms for digital image processing in diabetic retinopathy". In: Computerized Medical Imaging and Graphics 33.(pp.608-622), June 2009
19. T. Chandrakumar,T. and R Kathirvel," Classifying Diabetic Retinopathy using Deep Learning Architecture", In: International Journal of Engineering Research & Technology (IJERT). Vol. 5, Issue 06. ISSN: 2278-0181, June 2017.
20. Zhiguang Wang and Jianbo Yang." Diabetic Retinopathy Detection via Deep Convolutional Networks for Discriminative Localization and Visual Explanation". In: AIP Conference Proceedings 1836, 020026. https://doi.org/10.1063/1.4981966, 2017
21. Md. Jahiruzzaman,Aowlad Hossain." Detection and Classification of Diabetic Retinopathy Using K-Means Clustering and Fuzzy Logic", In:18th International Conference on Computer and Information Technology(ICCIT), pp. 534-538,2015
22. R. Dhanasekaran, S Mahendran, S Murugeswari, and Mofiya Fargana ," Investigation of Diabetic Retinopathy using GMM classifier", In: 2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT). ISBN No.978-1-4673-9545-8.(pp.184-187),2017
23. Rafia Mumtaz,Muddasser Hussain, SabaSarwar,Komal Khan,Sadaf Mumtaz, and Mustafa Mumtaz.,"Automatic detection of retinal hemorrhages by exploitingimage processing techniques for screening retinal diseases in diabetic patients". In: Springer. DOI 10.1007/s13410-017-0561-6, 2017

24. Sudeshna Sil Kar and Santi Maity."Retinal blood vessel extraction using tunable bandpass filter and fuzzy conditional entropy". In: computer methods and programs in biomedicine 133. pp.111–132,2017
25. Michael Abramoff, Mona Garvin and Milan Sonka ," Retinal Imaging and Image Analysis. In: IEEE Rev Biomed Eng",DOI:10.1109/RBME.2010.2084567. 2010
26. Javeria Amin, Muhammad Sharif and Mussarat Yasmin,"A Review on Recent Developments for Detection of Diabetic Retinopathy.", In: Hindawi Publishing Corporation Scientifica Volume 2016, Article ID 6838976 DOI:http://dx.doi.org/10.1155/2016/6838976, 2016
27. Lili Xu and Luo Shuqian.,"A novel method for blood vessel detection from retinal images.", In: Biomedical engineering online 9.1,2010
28. Amiya Halder, Pritam Bhattacharya. "An application of Bottom Hat Transformation to Extract Blood Vessel from Retinal Images.",IEEE ICCSP 2015 Conference. 1791–1795,2015
29. Chengzhang Zhua, Beiji Zoua, Rongchang Zhao, Jinkai Cui, Xuanchu Duan, Zailiang Chen, Yixiong Lian.". Retinal vessel segmentation in colour fundus images using ExtremeLearning Machine ",2017
30. (2017) Diabetic Retinopathy.[Online]. Available: https://www.aao.org/eye-health/diseases/what-is-diabetic-retinopathy.
31. (2017)DRIVE.[Online]. Available: https://www.isi.uu.nl/Research/Databases/DRIVE
32. (2016)STARE.[Online]. Available: http://cecas.clemson.edu/~ahoover/stare/.
33. (2016)VARPA .[Online]. Available: http://www.varpa.es/research/biometrics.html.
34. (2016)MESSIDOR .[Online]. Available: http://www.adcis.net/en/Download-Third-Party/Messidor.html.
35. S. Ding andW. Ma, "An accurate approach for microaneurysm detection in digital fundus images," in Proceedings of the 22nd International Conference on Pattern Recognition (ICPR '14), pp.1846–1851, IEEE, Stockholm, Sweden, August 2014.
36. (2016)DRIVE[Online].Available: https://computervisiononline.com/dataset/1105138662
37. (2016)KAGGLE[Online].Available: https://www.kaggle.com/c/diabetic-retinopathy-detection/discussion/14095
38. (2016)DIARETDB1 .[Online]. Available: http://www.it.lut.fi/project/imageret/diaretdb0/.
39. V. Bevilacqua, S. Cambò, L. Cariello, G. Mastronardi," A combined method to detect retinal fundus features," In: Proceedings of IEEE European Conference on Emergent Aspects in Clinical Data Analysis 2005, pp. 1–6, 2005
40. M.E. Martinez-Perez, A.D. Hughes, A.V. Stanton, S.A. Thorn, N. Chapman, A.A.Bharath, K.H. Parker,". Retinal vascular tree morphology: A semi-automatic quantification,",In: Biomedical Engineering, vol. 49.,2012
41. A Sharma, Dutta, Singh, Parthasarathi, and CM Travieso, "Dynamic thresholding technique for detection of hemorrhages in retinal images," in Proceedings of the 7th International Conference on Contemporary Computing IEEE(IC3 '14),pp. 113–116,2014