

Automated Identification of Diabetic Retinopathy - A Survey

Pradeep Kumar K G

Department of Computer Science &
Engineering
VTURRC, Belagavi
Belagavi, India
pradeepsdmit@gmail.com

Dr. Karunakara K

Department of Information Science &
Engineering
SSIT, Tumakuru
Tumakuru, India
karunakarak@gmail.com

Dr. Thyagaraju G S

Department of Computer Science &
Engineering
SDM Institute of Technology
Ujire, India
thyagaraju.gulasinda@gmail.com

Abstract—Diabetes strikes when the pancreas stops to produce sufficient insulin, gradually disturbing the retina of the human eye, leading to diabetic retinopathy. The blood vessels in the retina become changed and have abnormality. Exudates are concealed, micro-aneurysms and haemorrhages occur in the retina of eye, which intern leads to blindness. The presence of these structures signifies the harshness of the disease. A systematized Diabetic Retinopathy screening system will enable the detection of lesions accurately, consequently facilitating the ophthalmologists. Micro-aneurysms are the initial clinical signs of diabetic retinopathy. Timely identification of diabetic retinopathy plays a major role in the success of managing the disease. The main task is to extract exudates, which are similar in color property and size of the optic disk; afterwards micro-aneurysms are alike in color and closeness with blood vessels. The primary objective of this review is to survey the methods, techniques potential benefits and limitations of automated detection of micro-aneurysm in order to better manage translation into clinical practice, based on extensive experience with systems used by ophthalmologists treating diabetic retinopathy.

Keywords-Microaneurysms, Optic Disc, Exudates, Diabetes Mellitus, Machine Learning

I. INTRODUCTION

There are hundreds of miscellaneous kinds of genetic defects, and diabetes mellitus is one of the most usual birth defects that exist. Diabetes mellitus affects when the human pancreas struggling to generate sufficient insulin that is much needed to the body. It is an ophthalmic manifestation of diabetes, a universal disease, which affects up to 80% of all patients who have had diabetes for 10 years or more. Despite these statistics, research indicates that at least 90% of these new cases could be reduced if there was proper and cautious treatment and monitoring of the eyes. When diabetes progresses, the disease deliberately disturbs the circulatory system encompassing the retina and surfaces as a result of long-term assembled impairment to the blood vessels, gradually weakening the vision leading to diabetic retinopathy. Fig. 1 depicts cross sectional anatomy of human eye, showing retina, macula, optic nerve and other regions. Fig. 2 shows internal structure of retina, where the connections from optic nerve to rod and cone cells are visible. Fig. 3 shows fundus color image having exudates, which is the input to the first phase. Generally there are no initial visible symptoms of the Diabetic Retinopathy (DR) and as the disease advances the presence of microaneurysms (MAs), exudates both hard and soft and new blood vessels can be witnessed.

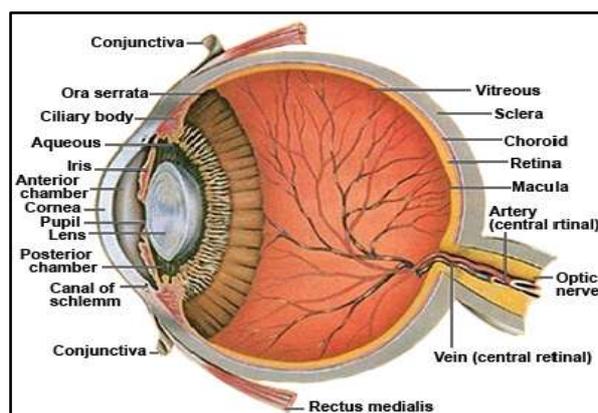


Figure 1. Cross sectional anatomy of human eye

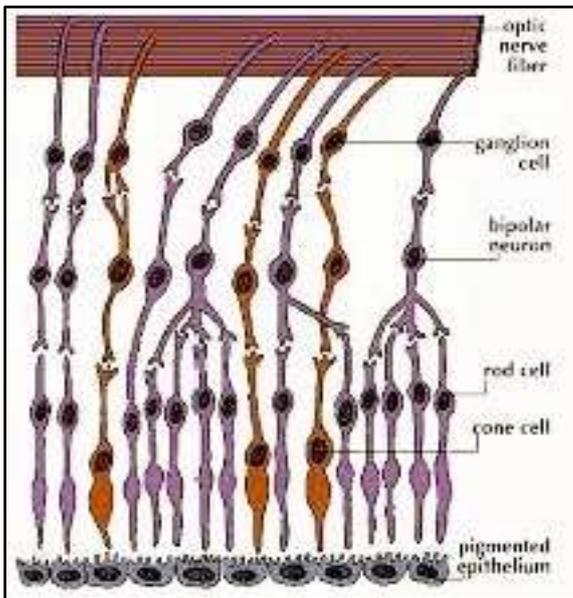


Figure 2. Structure of retina

They are reddish in color and emerge as small red spots on the retinal fundus images. Early discovery of micro-aneurysm can help in the early treatment of Diabetic Retinopathy(DR). When blood vessels of the retina in the subsequent part of the eye are damaged leads to the disease. Damages due to small vessels would be identified as microvascular disease, while damages due to the arteries would be a macrovascular disease. In general, diabetic retinopathy is categorized mainly as non-proliferative diabetes retinopathy (NPDR) and proliferative diabetes retinopathy (PDR). The scientific features include blood vessels, exudates, microaneurysm etc.

The progressive feature of DR, if not precisely treated increases the threat with the increasing age of the patient and it might ultimately lead to loss of vision. The DR existence has been generally categorized into three main phases and these are as follows: (1) Background Diabetic Retinopathy (BDR) - In this stage, the arteries in the retina become weak and start to leak, establishing small, dot-like associations called Hemorrhages. These leaking vessels habitually lead to swelling or edema in the retina and declines vision. (2) Proliferate Diabetic Retinopathy (PDR) - In this phase, transmission problems trigger areas of the retina to become oxygen divested or ischemic. New fragile vessels progress as the circulatory system efforts to maintain adequate oxygen levels inside the retina. This phenomenon is called neovascularisation. Blood may leak into the retina and vitreous, causing spots or floaters, across with decreased vision. (3) Severe Diabetic Retinopathy (SDR) - In this stage, there is unrelenting irregular vessel growth and scar tissue, which may cause serious problems such as retinal detachment and glaucoma and steady loss of vision.

These three levels can occur with any of the subsequent artifacts:

A. Microaneurysms

These are the first clinical abnormality to be observed in the eye. They may perform in segregation or in clusters as tiny, dark red spots or looking like tiny haemorrhages within the retina light sensitive area. Their dimensions range from 10-100 microns and are circular in shape. At this stage, the disease is not yet eye threatening but needed clear diagnose and treatment.

B. Haemorrhages

Befall in the deeper layers of the retina and are frequently entitled blot haemorrhages since of their curved structure.

C. Hard Exudates

This is one of the main characteristics of DR. It can diverge in size from tiny fragments to larger reinforcements with flawless boundaries. These can weaken vision by foiling light from reaching the retina.

D. Soft Exudates

Soft exudates of pale yellow white or buttery in color are often called cotton wool spots. Their outlines are round or oval and are designed as a result of capillary occlusions that lead to the permanent damage of the retina functions.

II. LITERATURE SURVEY

Surya Rajan, Taraprasad Das and R. Krishnakumar, proposed the use of orientation scores to form an orientation enriched image, from which a binary veneer of exudates can be gained by intensity thresholding [1]. This attained a sensitivity of 86.2% and a specificity of 85% on images of DIARETDB1 database. Receiver operating characteristics was used to identify the performance accuracy. But one drawback was, if the retinal image is very bright and has a low contrast, a few false positives were detected. Machine learning technique gives good results, but the outcome is heavily dependent on the data that is used to train.

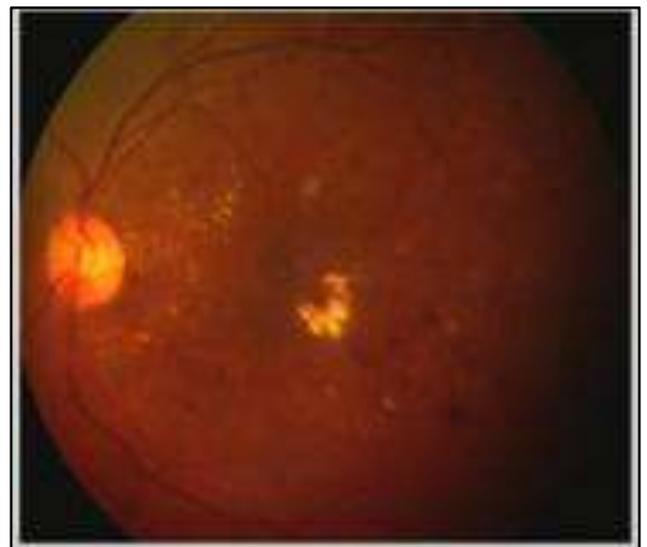


Figure 3. Fundus color image

Hanan S. Alghamdi, Hongying Lilian Tang, Saad A. Waheeb, and Tunde Peto, proposed a deep learning approach, an end-to-end supervised model for optical disc abnormality detection [2]. Cascade classifiers used for object detection, AdaBoost ensemble algorithm is used for training classifier and feature selection, as each classifier is restricted to select single rectangular feature that best classifies the positive and negative objects. Convolutional neural networks (CNNs) constitute one such class of models that learn features in the form of convolutional filters.

Y Morales, R Nuñez, J Suarez and C Torres, utilized the Gabor filter method for automatic segmentation of retinal blood vessels [3]. The demerit identified was, during the analysis of the retinography, is the optical disk transforms suspended to differentiate and excluded.

Michael David Abr`amoff, Yiyue Lou, Ali Erginay, Warren Clarida, Ryan Amelon, James C. Folk and Meindert Niemeijer, projected a deep-learning enhanced algorithm for automated detection [4]. Via the Iowa Detection Program (IDP), using deep learning, through the use of CNN-based lesion detectors in hybrid architecture devises the efficiency and accessibility of DR screening.

Oscar Perdomo, Sebastian Otorola, Francisco Rodriguez, John Arevalo, and Fabio A. Gonzalez, used convolutional neural networks in exudates localization and eye fundus images for automatic categorization, which resulted in better detection of optical features that distinguish exudates [5].

Wei Zhou, Chengdong Wu, Dali Chen, Zhenzhu Wang, Yugen Yi and Wenyong Du, proposed multifeature fusion dictionary learning (MFFDL). Which included preprocessing, candidate abstraction, multifeature dictionary learning, and classification. Incorporated the semantic relationships with dictionary learning and multifeatures into a unified framework for automatic detection of MAs resulting better average sensitivity [6].

Ayman El-Baz, Georgy Gimel farb, and Kenji Suzuki, inspired by and combined artificial intelligence, pattern recognition, biological features, mathematical statistics, optimization, and several additional areas of science, machine learning is successfully retained the status of identification of hidden relationships in the complex image data and associating them to the goal of diagnosis and/or monitoring of diseases [7].

Christian Leibig, Vaneeda Allken, Philipp Berens and Siegfried Wahl, used deep neural networks with trained the Bayesian convolutional neural networks exclusively on Kaggle DR training images resulting in good performances than previous findings [8].

Cecilia S. Lee, Doug M. Baughman BS, Aaron Y. Lee, says a deep learning technique achieves high accuracy and is effective as a new image classification technique. Their findings showed important allegations in utilizing OCT for automated screening and the development of computer aided diagnosis tools in the future [9].

Avisek Lahiri, Abhijit Guha Roy, Debdoot Sheet and

Prabir Kumar Biswas, employed unsupervised hierarchical feature learning by exploiting ensemble of two level of sparsely trained de-noised stacked auto-encoder [10]. First level training with bootstrap illustrations guaranteed decoupling and second level collaboration formed by different network architectures confirmed architectural revision. SoftMax classifier is used for fine-tuning each member auto-encoder and numerous approaches are explored for a 2-level fusion of ensemble members, which produced better results but must have better threshold.

Ruchir Srivastava, Lixin Duan, Damon W.K. Wong, Jiang Liu and Tien Yin Wong, proposed frangi filter method to deal with two complications in detecting red lesions from retinal fundus images [11]. They are false detections on blood vessels and distinctive sized red lesions. Resulting in detection of microaneurysms and hemorrhages efficaciously while these lesions were neighboring to blood vessels. But for different grid dimensions entertained a disadvantage of high computations, needed for higher grid size.

Fulong Ren, Peng Cao, Wei Li, Dazhe Zhao and Osmar Zaiane, proposed an ensemble based adaptive over-sampling algorithm for overcoming the class imbalance problem in the false positive diminution, together with boosting, bagging, random subspace as a collaborative framework and resulted in good classification performance and generalization proficiency [12].

Debapriya Maji, Anirban Santara, Pabitra Mitra, Debdoot Sheet, used computational imaging framework exploiting deep and collective learning for trustworthy detection of blood vessels in fundus color images [13]. A collaboration of deep convolutional neural networks are trained to fragment vessel and non-vessel zones of a color fundus image. The responses of the individual convolutional networks of the collaboration are averaged to arrange the final segmentation as a methodology to solve complex medical data analysis problem through deep learning.

Xiaochun Zou, Xinbo Zhao, Yongjia Yang, and Na Li, introduced the cognitive process of visual assortment of appropriate regions that arises during an ophthalmologist's image examination. Exclusive of sophisticated image processing methods as region segmentation, the feature property is employed by support vector machine technique consuming the diagnosis and position property by statistical analysis of training samples, which resulted in identification of saliency regions and diabetic macular edema region [14].

Marleen de Bruijne, learnt through several machine-learning approaches in medical image analysis from detection to diagnosis, coping with variation in imaging protocols, learning from weak labels, and interpretation and evaluation gave moderate results with available data [15].

Balint Antal and Andras Hajdu proposed a arrangement of internal components of microaneurysm detectors, namely preprocessing schemes and candidate extractors. The selection of the fitting threshold is also an important issue for the

detector to stipulate sufficient sensitivity and specificity rate [16]. The results, with respect to improvisation in grading performance, the existence or nonexistence of more DR-specific lesions are much essential.

James Kang Hao Goh, Carol Y. Cheung, Shaun Sebastian Sim, Pok Chien Tan, Gavin Siew Wei Tan and Tien Yin Wong, concluded by saying the demand for DR screening platform using new ocular imaging techniques is steeply increasing due to the increase of occurrences of DM [17]. Current DR screening programs based on fundus photography rely heavily on skilled graders still have difficulty in efficient detection.

Pavle Prentasic and Sven Loncaric, believed deep convolutional neural networks can be excellently used in order to segment exudates in color fundus photographs, but certain more preprocessing and postprocessing steps are in need [18]. By which, categorization detected pixels in clusters and enhancing some high level features would certainly advance the final segmentation.

M.M. Habib, R.A. Welikal, A. Hoppe, C.G. Owen, A.R. Rudnicka and S.A. Barman, utilized the use of the random forest classifier with fleming's method for micornauerysm detection that relies on a random forest ensemble classifier (bagging) for microaneurysm classification, which improves the sensitivity of the detection, compared against using a K-Nearest Neighbours classifier [19].

Kemal adem, Mahmut hekim, Onur comert and Selim demir, provided three different solutions for detecting the optic disc location, using the illumination and circularity properties of the associated region [20]. As a result of the comparison of the discoveries of these three experiments, the circular hough transform method applied with HSV color space was found to be more effective.

Mahsa Partovi, Seyed Hossein Rasta and Alireza Javadzadeh, utilized the morphological function, which was applied on intensity constituents of hue saturation intensity (HSI) space. To discover the exudates regions, thresholding was accomplished on all images and the exudates region was segmented [21]. To optimize the detection efficiency, the binary morphological functions were consumed and results were satisfied.

Harry Pratt, Frans Coenen, Deborah M Broadbent, Simon P Harding and Yalin Zheng, proposed a CNN approach for diagnosis of DR from digital fundus images and perfectly organizing its severity. Developed a network with CNN architecture and data reinforcement strategy, which can identify the complicated features, involved in the classification task for example microaneurysms, exudate and haemorrhages on the retina and subsequently provide a diagnosis automatically and without user input [22]. They used NVIDIA high-end graphics processor unit (GPU) on the widely available Kaggle dataset and validate inspiring results, particularly for a high-level classification task. But a little more emphasis on initial stages of DR enabled images is necessary.

Wei Zhou, Chengdong Wu, Dali Chen, Yugen Yi and Wenyu Du, proposed sparse principal component analysis, a linear dimensionality reduction routine. The basic principle is to increase the variance of projections on fresh directions [23]. Which determined by a group of orthogonal vectors, the load vectors and the sequence of vectors is determined by variance of projections on load vectors. Resulting, unsupervised classification is particular suitable for the situation, when only know the normal microaneurysm status, and abnormal status (or non-MA) is unknown, or hard to obtain.

Shaohua Zheng, Lin Pan, Jian Chen and Lun Yu, proposed a technique with the identification of fovea center along with optical disc intensity knowledge and relative location, but have a shortcoming of failing to remove large opaque lesions [24].

Nidhal K. El Abbadi and Enas Hamood Al Saadi, used image processing methods that utilize color specific color channels and image features such as intensity gradients, and image textures to isolate exudates from physiological topographies in digital fundus images and obtained promising results [25].

The table 1 shows summary of existing automated diabetic retinopathy detection systems.

III. METHODOLOGY

The Fig. 4 shows various phases of methodology implemented.

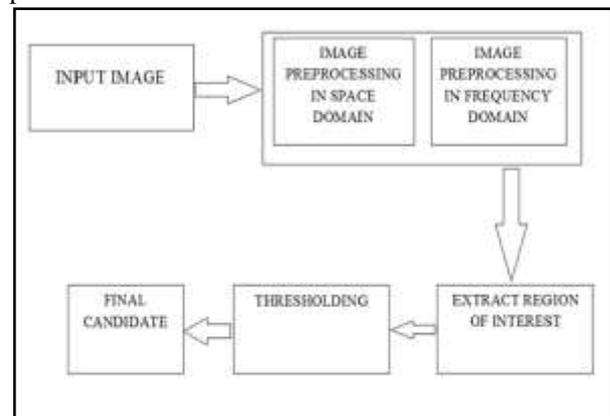


Figure 4: The phases of methodology

In the first stage the fundus image is fed into the workflow. In image preprocessing stage, the Second phase, retinal images captured from fundus camera are of low gray level contrast due to poor or non-uniform lighting condition, nonlinearity or small dynamic range of the imaging sensor i.e. illumination is distributed non-uniformly within the image. Therefore, it is necessary to deepen the contrast of these images to provide a better transform representation for subsequent image analysis steps. Image preprocessing will be done in two phases in first phase input image will be pre-processed in space domain for smoothing and in second phase the image will be pre-processed in frequency domain for sharpening. It is beneficial to consider a certain amount of image smoothing before the actual steps of detection.

The third phase, region of interests (ROI) are extracted from image, which is called segmentation. That is, extracting regions from images in order to search only the areas, which are suspected to have abnormalities instead of searching all parts of images. In this step, different segmentation algorithms are adopted and implemented.

The fourth phase, the thresholding, that is based on clip-level (or a threshold value) to turn a gray-scale image into a binary image. A manner of constructing a black-and-white image out of a gray scale image consisting of setting accurately those pixels to white whose value is above a given threshold, setting the other pixels to black. Fig. 5 and Fig. 6 shows gray scale image and enhanced contrast image respectively, which are the outcome of second stage where preprocessing is performed.

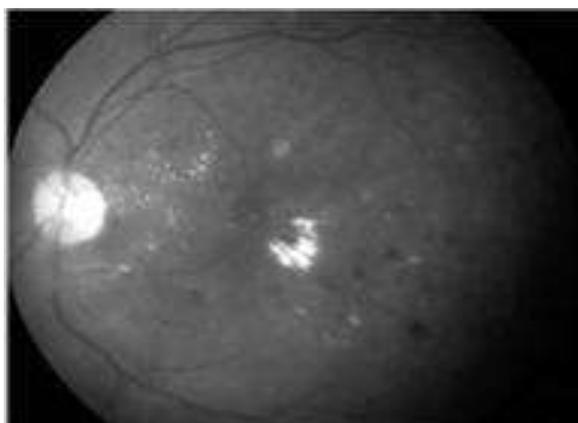


Figure 5. Gray scale image

The final candidate can be obtained after performing segmentation on the fundus image available from the database based on that a threshold value is selected for discriminating the normal and abnormal fundus images. If the value of a given image lies below the mentioned threshold value then it will be labeled as a normal retina image without the sign of a diabetic retinopathy and candidate is categorized as non-affected.

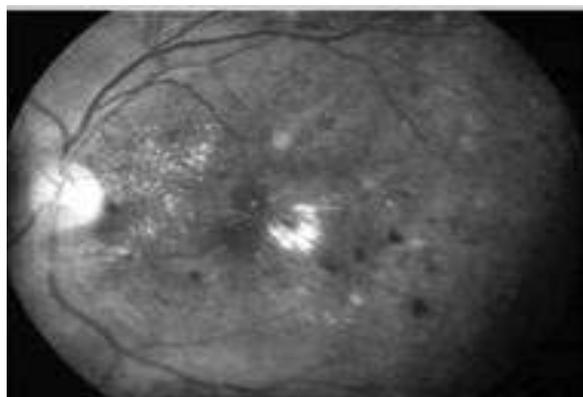


Figure 6. Enhanced contrast image

TABLE I. PRESENT DR DETECTION SYSTEMS

| System | Company | Categorization specifics | Algorithm |
|--|-----------------------------------|--|--|
| DR-RACSTM | Vision Quest Biomedical LLC | Low risk/high risk for DR | Amplitude modulation-frequency modulation (AM-FM), k-means clustering, and a partial least square classifier |
| EyeArt | Eyenuk Inc | Refer/no refer recommendation; microaneurysm turnover | Machine learning; morphology-inspired filter bank descriptors |
| IDx-DR | IDx, LLC | Diabetic retinopathy index; referable/no referable disease | Fusion algorithm produces a DR index |
| GradingM | Medalytix LLC; Digital Healthcare | Presence/absence of DR | Local contrast, normalization and local vessel detection |
| RetinaLyze A/S | RetinaLyze A/S | Presence/absence of DR based on microaneurysm and hemorrhage detection | Automated red lesion detection, including microaneurysm & hemorrhage using vector based algorithm. |
| Retmarker DR | Retmarker Ltd | Presence/absence of DR; microaneurysm turnover | Longitudinal analysis by comparing with baseline image |
| Singapore Eye Lesion Analyzer (SELENA) | -- | Grade of DR and referable/nonreferable | Deep learning technology using convolutional neural network and |

| | | | |
|--|--|-------------------------------------|--|
| | | | region extraction algorithms |
| RetinaVue (formerly The TRIAD Network) | Welch Allyn, Inc (Hubble Telemedicine Inc) | Presence/absence of DR; grade of DR | Content-based image retrieval techniques for automated diagnosis |

| | |
|-----------------------|--|
| Spectral domain OCT | Choroidal thickness with respect to age-related macular degeneration. |
| Three Dimensional OCT | Retinal detachment, intra-retinal layers, fovea, retinal thickness and thicknesses of the nerve fiber. |
| Longer Wavelength OCT | In-depth image of retinal layers. |

Detection techniques utilized by ophthalmologists during clinical practice are listed in table 2.

TABLE II. IMAGING METHODS

| Imaging techniques | Approaches |
|---------------------------------------|---|
| Fundus photography | Identify and assess signs of retinal detachment or eye disorders like glaucoma, age associated maculopathy and optic disk. |
| Color fundus photography | To trace the state of macula, tiny fovea, optic nerve head, interior surface of the eye, in order to find the occurrence of disorders and monitor their change over time. |
| Stereo fundus photography | To review as three dimensional image, helps in identification of macular edema, optic disk (glaucoma). |
| Scanning laser ophthalmoscopy | Provides sharp images of Retinal Pigment Epithelium (RPE) cells, to diagnose glaucoma, macular degeneration, and other retinal disorders. |
| Hyperspectral imaging | Intra-retinal microvascular abnormalities (IRMA), neovascularization, retinal oxymetry, provides localization of retina and disc. |
| Adaptive optics SLO | Better gradation in precision for eye tracking. |
| Fluorescein angiography | Identification of vessel inflammation |
| Optical Coherence Tomography | Provides high resolution and cross-sectional retina, retinal nerve fiber and optic nerve head images. |
| Time domain OCT or time-of-flight OCT | Macular Degeneration, vitreo macular interface pattern, diabetic maculopathy, macular hole and central-serous chorioretinopathy. |

IV. CONCLUSION

This paper described survey of previous researches its methods and techniques for micro aneurysm detection, advantages and disadvantages of existing method. As per survey, there is strong need of reducing computational time and increasing sensitivity to detect and classify microaneurysms resulting helpful scenario for ophthalmologists to obtain the severity of the disease. There are several detection algorithms for both semi-automatic and fully automatic systems have already been developed but the accuracy of the detecting system depends on the following factors: (1) The segmentation method used for segmenting the blood vessels and optic disc. The accurate segmentation yields the new vessel pixels correctly. (2) The features selected for further classification. The methods for feature sub selection should be effective so that irrelevant and redundant features with no useful information should be selected. (3) The performance of the classifier classifying the new vessels and non-new vessels. Deep learning algorithms from the family of machine learning techniques is much suitable in the era of artificial intelligence for the speedy detection of the disease and much helpful in the areas of telemedicine.

REFERENCES

- [1] Surya Rajan, Taraprasad Das and R. Krishnakumar, "An Analytical Method for the Detection of Exudates in Retinal Images Using Invertible Orientation Scores", Proceedings of the World Congress on Engineering, WCE 2016, London, Vol I
- [2] Hanan S. Alghamdi, Hongying Lilian Tang, Saad A. Waheeb, and Tunde Peto, "Automatic Optic Disc Abnormality Detection in Fundus Images: A Deep Learning Approach", Proceedings of the Ophthalmic Medical Image Analysis International Workshop, IOWA 2016, pp. 17-24
- [3] Y Morales, R Nuñez, J Suarez and C Torres, "Digital tool for detecting diabetic retinopathy in retinography image using gabor transform", Journal of Physics, IOP Publishing Ltd, Conference Series, Vol. 792, No. 1
- [4] Michael David Abramoff, Yiyue Lou, Ali Erginay, Warren Clarida, Ryan Amelon, James C. Folk and Meindert Niemeijer, "Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset through Integration of Deep Learning", I OVS, Vol. 57, No. 13
- [5] Oscar Perdomo, Sebastian Ojalora, Francisco Rodríguez, John Arevalo, and Fabio A. González, "A Novel Machine Learning Model Based on Exudate Localization to Detect Diabetic Macular Edema", Proceedings of the Ophthalmic Medical Image Analysis, OMIA 2016, pp. 137-144
- [6] Wei Zhou, Chengdong Wu, Dali Chen, Zhenzhu Wang, Yugen Yi and Wenyong Du, "Automatic Microaneurysms Detection Based on Multifeature Fusion Dictionary Learning", Computational and Mathematical Methods in Medicine, Vol. 2017, Article ID 2483137, 11 pages

- [7] Ayman El-Baz, Georgy Gimel farb, and Kenji Suzuki, "Machine Learning Applications in Medical Image Analysis", Computational and Mathematical Methods in Medicine, Vol. 2017, Article ID 2361061, 2 pages
- [8] Christian Leibig, Vaneeda Allken, Philipp Berens and Siegfried Wahl, "Leveraging uncertainty information from deep neural networks for disease detection",
- [9] Cecilia S. Lee, Doug M. Baughman BS, Aaron Y. Lee, "Deep learning is effective for the classification of OCT images of normal versus Age-related Macular Degeneration", Ophthalmology Retina Journal – 2017
- [10] Avisek Lahiri, Abhijit Guha Roy, Debdoot Sheet and Prabir Kumar Biswas, "Deep Neural Ensemble for Retinal Vessel Segmentation in Fundus Images towards Achieving Label-free Angiography", 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1340-1343
- [11] Ruchir Srivastava, Lixin Duan, Damon W.K. Wong, Jiang Liu and Tien Yin Wong, "Detecting retinal microaneurysms and hemorrhages with robustness to the presence of blood vessels", Computer Methods and Programs in Biomedicine, Elsevier, 2017, Vol. 138, pp. 83-91
- [12] Fulong Ren, Peng Cao, Wei Li, Dazhe Zhao and Osmar Zaiane, "Ensemble based adaptive over-sampling method for imbalanced data learning in computer aided detection of microaneurysm", Computerized Medical Imaging and Graphics, Elsevier, 2017, Vol. 55, pp. 54-67
- [13] Debapriya Maji, Anirban Santara, Pabitra Mitra, Debdoot Sheet, "Ensemble of Deep Convolutional Neural Networks for Learning to Detect Retinal Vessels in Fundus Images", Cornell University Library, 2016
- [14] Xiaochun Zou, Xinbo Zhao, Yongjia Yang, and Na Li, "Learning-Based Visual Saliency Model for Detecting Diabetic Macular Edema in Retinal Image", Computational Intelligence and Neuroscience, Hindawi Publishing Corporation, Vol. 2016, Article ID 7496735, 10 pages
- [15] Marleen de Bruijne, "Machine learning approaches in medical image analysis: From detection to diagnosis", Medical Image Analysis, Elsevier, Vol. 33, pp. 94-97
- [16] Balint Antal and Andras Hajdu, "An Ensemble-based System for Microaneurysm Detection and Diabetic Retinopathy Grading", IEEE Transactions on Biomedical Engineering, Vol. 59, June 2012, pp. 1720-1726
- [17] James Kang Hao Goh, Carol Y. Cheung, Shaun Sebastian Sim, Pok Chien Tan, Gavin Siew Wei Tan and Tien Yin Wong, "Retinal Imaging Techniques for Diabetic Retinopathy Screening", Journal of Diabetes Science and Technology, 2016, Vol. 10, pp. 282-294
- [18] Pavle Prentasic and Sven Loncaric, "Detection of Exudates in Fundus Photographs using Convolutional Neural Networks", 9th International Symposium on Image and Signal Processing and Analysis, IEEE Conference Publications, pp. 188-192
- [19] M.M. Habib, R.A. Welikal, A. Hoppe, C.G. Owen, A.R. Rudnicka and S.A. Barman, "Microaneurysm Detection in Retinal Images Using an Ensemble Classifier", Sixth International Conference on Image Processing Theory, Tools and Applications, IEEE Conference Publications, pp. 1-6
- [20] Kemal adem, Mahmut hekim, Onur comert and Selim demir, "A Novel Approach to Method for the Detection of Optic Disc Location in Retinal Images using Image Processing Techniques", Journal of new results in science, No.12, 2016, pp. 41-47
- [21] Mahsa Partovi, Seyed Hossein Rasta, Alireza Javadzadeh, "Automatic detection of retinal exudates in fundus images of diabetic retinopathy patients", JARCM, Spring 2016, Vol. 4, No. 2
- [22] Harry Pratt, Frans Coenen, Deborah M Broadbent, Simon P Harding and Yalin Zheng, "Convolutional Neural Networks for Diabetic Retinopathy", International Conference On Medical Imaging Understanding and Analysis, Elsevier, Procedia Computer Science, MIUA 2016
- [23] Wei Zhou, Chengdong Wu, Dali Chen, Yugen Yi and Wenyou Du, "Automatic Microaneurysm Detection Using the Sparse Principal Component Analysis-Based Unsupervised Classification Method", IEEE Access, Vol. 5, 2017, pp. 2563 – 2572
- [24] Shaohua Zheng, Lin Pan, Jian Chen and Lun Yu, "Automatic and Efficient Detection of the Fovea Center in Retinal images", 7th International Conference on BioMedical Engineering and Informatics, IEEE Conference Publications, pp. 145-150
- [25] Nidhal K. El Abbadi and Enas Hamood Al Saadi, "Automatic Detection of Exudates in Retinal Images", International Journal of Computer Science Issues, Vol. 10, Issue 2, No. 1
- [26] www.diabetesjournal.com
- [27] <http://www.retinreference.com/anatomy/>
- [28] <http://emedicine.medscape.com/>