

PAPER • OPEN ACCESS

Detection of Diabetic Retinopathy using Deep Mining

To cite this article: [KG Pradeep Kumar et al](#) 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1022** 012081

View the [article online](#) for updates and enhancements.

You may also like

- [A Data Mining Inspired Methodology towards the Identification of Diabetic Retinopathy](#)
KG Pradeep Kumar, K Karunakara, GS Thyagaraju et al.
- [OBSERVATION AND CHARACTERIZATION OF A COSMIC MUON NEUTRINO FLUX FROM THE NORTHERN HEMISPHERE USING SIX YEARS OF ICECUBE DATA](#)
M. G. Aartsen, K. Abraham, M. Ackermann et al.
- [CoT-XNet: contextual transformer with Xception network for diabetic retinopathy grading](#)
Shuiqing Zhao, Yanan Wu, Mengmeng Tong et al.

PRIME
PACIFIC RIM MEETING
ON ELECTROCHEMICAL
AND SOLID STATE SCIENCE

HONOLULU, HI
October 6-11, 2024

Joint International Meeting of
The Electrochemical Society of Japan
(ECS)
The Korean Electrochemical Society
(KECS)
The Electrochemical Society (ECS)

Early Registration Deadline:
September 3, 2024

**MAKE YOUR PLANS
NOW!**

Detection of Diabetic Retinopathy using Deep Mining

Pradeep Kumar KG¹, Karunakara K², Thyagaraju GS³, Sunanda Dixit⁴

¹Dept. of Computer Science and Engineering, A. J. Institute of Engineering & Technology, Mangalore, India.

²Dept. of Information Science and Engineering, Sri Siddhartha Institute of Technology, Tumakuru, India

³Dept. of Computer Science and Engineering, SDM Institute of Technology, Ujire, Belthangady, India.

⁴Dept. of Computer Science and Engineering, BMS Institute of Technology and Management, Bangalore, India.

putturpradeep@gmail.com, karunakarak@gmail.com,

thyagaraju.gulasinda@gmail.com, sunandadixit_cse@bmsit.in

Abstract. In this paper, we propose a procedure for diagnosing diabetic retinopathy and detecting other suspected areas by using Convolution Neural Network (CNN). The paper is divided into two research areas: First is to identify and predict the highly suspicious region in the high-resolution suspicious patches using Deep-in-Net which can generate disease detection accurately. Second is four bounding boxes generated using machine learning technique by automatically reading maps that gives 80% of information of the eyes labelled by experienced ophthalmologist. This technique has good ability to seek attention mapping. The experiment has two datasets, EyePACS and Messidor.

Keywords: Deep-in-Net, Retina, Microaneurysm, CNN, Hemorrhages

1. Introduction

Diabetes Mellitus is enduring and lasting disorder, that instigates excessive blood sugar levels. The accessible assessments confirm there are nearby 65.1 million population in India alongside diabetes and then this quantity will escalate to 125 million by 2035.[24].

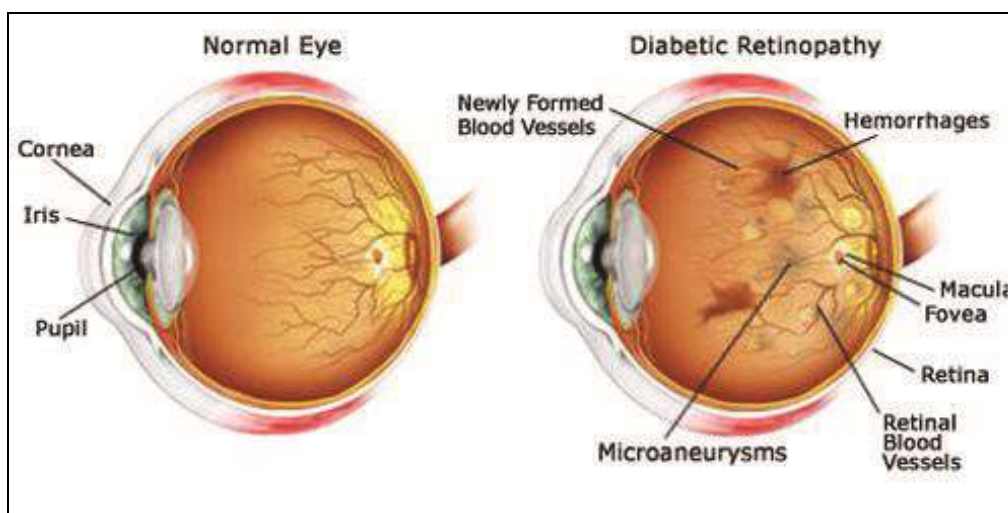


Figure 1. The Cross-Sectional image of a DR Affected Eye and Normal Eye.

Illustrations of finding the suspicious region in the damaged tissues of the eyes helps the physicians in treating the patients. Figure 1 depicts the cross-sectional view of retina along with DR affected region of eye. The current study has the datasets of medical images with limited size to reduce expenses.

Thus, the algorithm is being developed that is based on the large datasets with weaker supervisions for parallel categorizing and identifying localized area. In the paper we have proposed a weakly supervised technique, Deep-in-Net using CNN. The technique is precise in categorizing and automatically detecting the bruises in the images. This technique can be used in identifying different problems categorically and providing the desired results for the physicians. To prove the accuracy of the technique we have used the Diabetic Retinopathy detection as it has larger datasets of the diabetes impacting the eye diseases. This disease has caused blindness at large in this developed world. There is diagnosis to slow down vision loss caused due to diabetes. However Diabetic Retinopathy (DR) devises no premature detection, and the treatment also time taking process that requires expert supervision to find the retinal damage in the image. Due to this it takes lot of time to provide effective treatment. Various efforts are made by bringing different analysis algorithms into light. Early techniques used the manual representation of the images which led to restrictive expressive power of the features. Nowadays the introduction of CNN has improvised the detection of DR. The paper proposed Deep-in-Net that has the mechanisms of high-level supervision of the image. In addition to this the proposed technique imitates the clinical behaviour of the DR images that finds the diseased area by zoom-in. The projected technique is validated using the datasets of Messidor and EyePACS [21].

2. The Construction of Deep-in-Net

The anticipated framework Deep-in-Net trains after the DR detection, the technique however categories the imageries and localizes the wary and suspicious area. The situation imitates the technique of Zoom-in used by clinician to identify highly infected region in the high-resolution platform. As shown in the below Figure 2, it illustrates a Main Network (M-Net) for classifying of DR, along with sub-networks Attention Network (A-Net) and Crop Network (C-Net). A-Net generates attention mapping and Crop Network considers high resolution patches of high attention value [21]. The study is based on five level DR recognition mission, i.e., 0 represents No DR, 1 represents Minor DR, 2 represents Reasonable Diabetic Retinopathy, 3 represents Severe Diabetic Retinopathy and 4 represents Proliferative Diabetic Retinopathy.

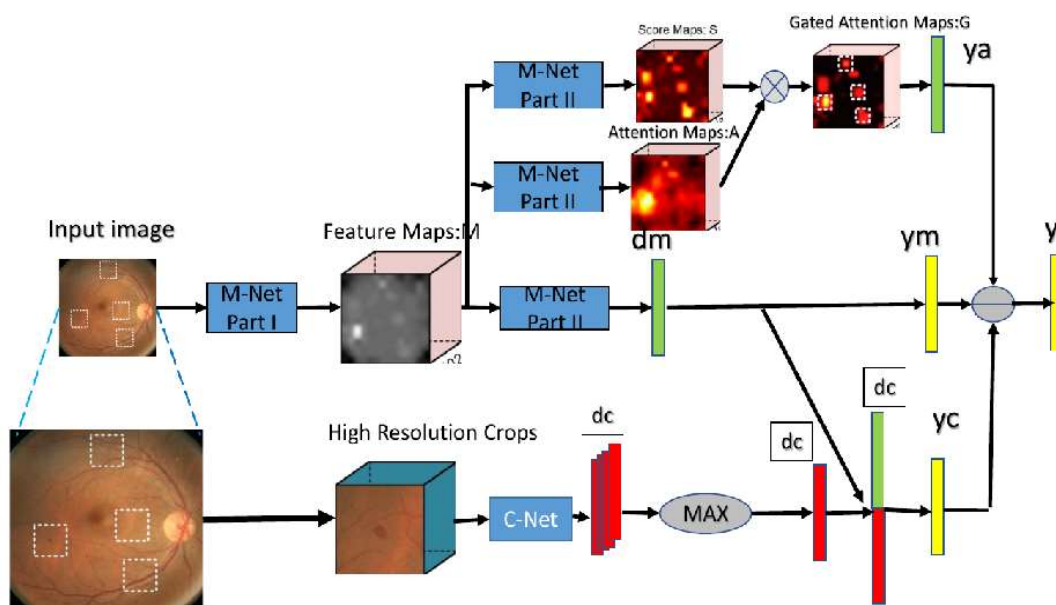


Figure 2. An Overview of Deep-in-Net

2.1. Main-Network (M-Net)

M-Net is a Convolutional Neural Network, that selects input as the image, processes it by linear operation stacks, normalization and non-linear pooling, rectified linear sections. In the study

Inception-Resnet has been adopted for the architecture of M-Net. As shown in the Figure 1 the layers $M \in \mathbb{R}^{1024 \times 14 \times 14}$, separates the M-Net into two segments. By way of the Kaggle's test gives together right and left eyes of a patient. Similarly, we use the connection amongst two eyes. Measurements depict, over 95% of the eye sets consume the grades contrast by all things considered 1. In this way, link the highlights of the two eyes after Main Network composed and prepared the system to yield favourable position of it in a start to finish way.

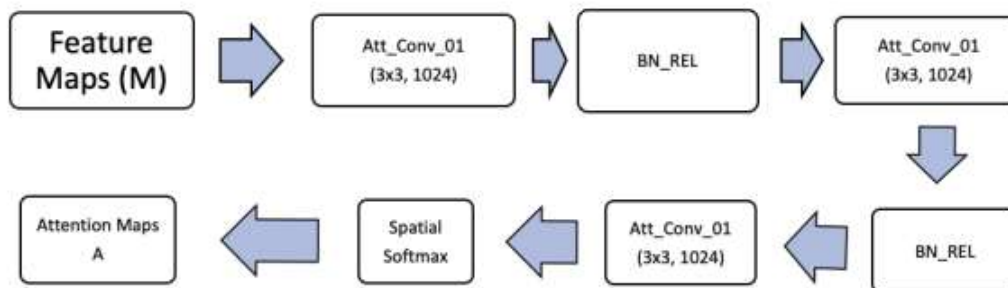


Figure 3. Part II - Structure of A-Net

2.2. Maintaining the Integrity of the Specifications

A-Net uses the M as input which is a feature map [21]. The maps consist of two branches. The first one is a 1x1 convolution kernel layer. It can be applied to every pixel and produced maps scored to 5 disease layers, $S \in \mathbb{R}^{5 \times 14 \times 14}$. The second one produces attention gate maps with three convolution layers. In specific, each produced distinct mapping for disease stages. The attention map as gate A $\in \mathbb{R}^{5 \times 14 \times 14}$ is used as the A-Net and is assessed as,

$$G^1 = S^1 \otimes A^1 \quad (1)$$

The pre-administration stage comprises clipping dataset image to eradicate the noise, which has unwanted parts of data. The Data reinforcement is carried out on the training set by $(270^\circ/180^\circ/90^\circ/0^\circ)$ arbitrary rotations and casual flips. The preparation of the recommended Deep-in-Net comprises three stages. As foremost step, train the Main-Network, and then prepare A-Net whilst setting the considerations of Main-Network. The C-Net is accomplished in the final stage, together with the additional two to attain the Deep-in-Net.

3. Literature Survey

The paper uses AI based algorithm that grades in combine with smartphone (for validation) that images diabetic patients reliably and screen the patients precisely for vision loss Diabetic Retinopathy [6] [7] [8] who could be diagnosed by the ophthalmologist for further treatment. While referring to any retinal specialists if any false positive cases found are to be excluded and those needed treatment can be given proper diagnosis. The mentioned algorithm is used by putting in the inexpensive sleek camera that screens DR, the technology is feasible especially for the developing countries [1]. Diabetic retinopathy [9][10][11][12] is the disease that cannot be completely cured but can prevent complete vision loss.

The laser analysis is done before there is complete retinal damage. On a condition that there is no destruction has been done to the retina, the vision can be improvised by vitrectomy. In the study of DR done in the paper the large portion of work is carried out to find out the hemorrhages, diabetic macular edema etc. The study directs in finding out the retinopathy in the initial stage and with immediate diagnosis permanent vision loss can be prevented [2].

In the paper, the diabetic Retinal Fundus [13] [14] [15] [16] image's pre-processing and data extraction is done to find out the DR using ML methods. The pre-processing framework includes histogram equalization exercising DIP toolbox of MATLAB. The pictures were distinctive categories of datasets one as normal stimulus and the second being diabetic infected images of the retina. In the study the features are used to learn the biological relevance [3].

In the paper the author briefs about different areas on DR disease [17] [18] [19] [20] which can be found in the starting stage. In the paper the author describes large no of research has been carried out with respect to the DR. The data presented in the paper is cumulative work of all the research work done in the recent times. The main contribution of the paper is to encourage more research to develop and improve early detection of DR [4].

4. Retina Dataset

The datasets are essential, ultimate and major part to nurture the development, expansion of several computational fields which builds confidence to results and helps in making better decisions. The Figure 4 and Figure 4 shows the MESSIDOR dataset 1 and 2 collected from the FUNDUS camera. Figure 5 shows an input image which has severe DR with microaneurysm. A glimpse of datasets in the field of DR are discussed in the following subsections.

4.1. DIARETDB1

It comprises 89 unreservedly open fundus retina pictures with the dimension of 1500 x 1152 pixels picked up at the 50-degree field of view (FOV). It joins 84 DR pictures and five customary pictures remarked on by four clinical pros. [23]

4.2. Kaggle

It contains 88,702 significant standard pictures with various objectives, going from 433 x 289 pixels to 5184 x 3456 pixels, assembled from diverse fundus cameras. Every image is gathered into five DR phases. Simply planning pictures ground facts are uninhibitedly available. Kaggle encompasses various pictures with inferior excellence and wrong naming. [23]

4.3. E-Ophtha

This straightforwardly accessible dataset consolidates E-ophtha Exudate besides, E-ophtha microaneurysms. E-ophtha joins 47 pictures with exudates and 35 conventional pictures. E-ophtha microaneurysm contains 148 pictures with microaneurysm and 233 conventional pictures.

4.4. DDR

This dataset encloses 13,673 fundus pictures obtained at a 45-degree FOV explained to five DR phases. There are 757 pictures after the dataset disclosed to DR injuries. [23]

4.5. DRIVE

It includes the straightforwardly accessible dataset used for vein division. It comprehends 40 pictures attained at a 45-degree FOV. The photos have a dimension of 565 x 584 pixels. Including them, there are seven smooth DR pictures, and the staying join photos of a regular retina. [23]

4.6. HRF

It comprises the openly obtainable pictures obliged vein division. It has 45 pictures with a dimension of 3504 x 2336 pixels. It includes 15 DR pictures, 15 sound pictures and 15 glaucomatous pictures. [23]

4.7. Messidor-1

This openly available dataset contains 1200 fundus concealing pictures picked up by a 45-graded FOV explained to quad DR phases.

4.8. *Messidor-2*

The Messidor-2 openly accessible dataset comprises 1748 pictures picked up by a 45-degree FOV. [23]

4.9. *EyePACS*

Comprises over 5 million retinal images of varied inhabitants with numerous degrees of DR. It helps the processes to acknowledge the different retinas for the severity, in the real-world scenario.

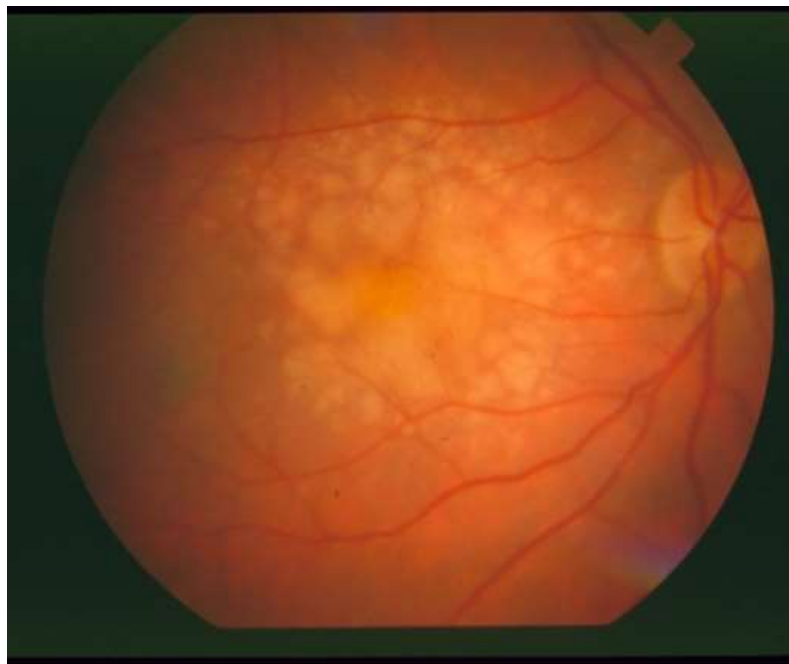


Figure 4. Sample image from Messidor Dataset-1



Figure 5. The input data from Messidor Dataset-2

5. Quantitative Estimation

The numerous modeling methodology are used to learn and understand the behavior of algorithms on various datasets. The factors used in analysis helps to fine tune results and makes easier to differentiate with other existing systems and practices. Figure 6 and 7 shows the outcome of preprocessing stage and the identification of microaneurysms respectively.

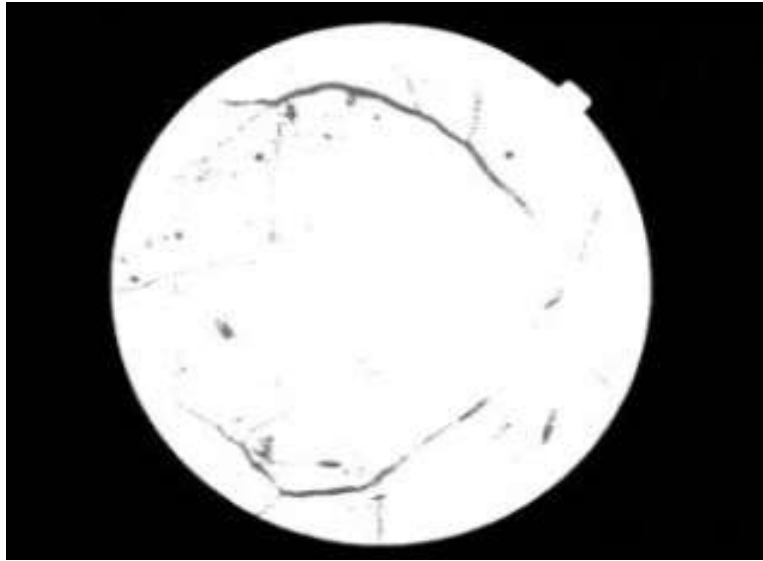


Figure 6. The Image preprocessed and converted to grayscale

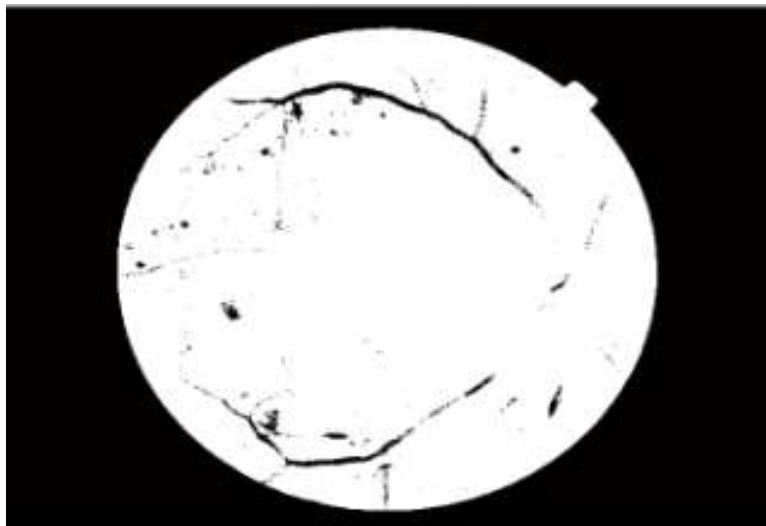


Figure 7. The detection of microaneurysms in the second stage of the process

The EyePACS dataset is verified and labelled by an experienced ophthalmologist. The experiment results were again examined and satisfied by the outcomes. For more clarification on Deep-in-Net, a clustering methodology can be used to envisage the top response spots on the gated Main Network as shown in figure 2. The features are segregated at the matching localities on the feature maps M gathered into clusters. The corresponding image regions are retrieved accordingly via C-Net input and visualized. The clusters are determined with significant lesions like Microaneurysms, hemorrhages,

soft and hard exudates. The features are then concatenated to the features from Main-Network and catalogued by C-Net together.

5.1. Datasets and Estimation Techniques

In the experiment carried out we have valued the accuracy of the Deep-in-Net in two sets of data namely EyePACS and Messidor [21]. The Kaggle's DR Finding is supported by the California Health Institute. It provides various sets of images for training, validation, authentication and testing respectively. For comparison we have embraced the quadratic weighted kappa score for estimation and assessment.

Table 1. Comparison assessment to leading entries on Kaggle challenge.

| Algorithm | Validation Set | Testing Set |
|-------------------|----------------|-------------|
| Min-pooling | 0.83 | 0.81 |
| Reformed Gamblers | 0.81 | 0.80 |
| Main-Net | 0.86 | 0.81 |
| Main-Net+A-Net | 0.823 | 0.821 |
| Deep-in-Net | 0.86 | 0.84 |

5.2. Result of the experiment on the dataset of EyePACS

In the experiment, we could validate the Deep-in-Net using EyePACS sets of data [21]. As realised in the Table 1, the Main-Network attains 0.86/ 0.81 on the Validation/ Testing Set correspondingly. The Min-pooling has achieved 0.83/ 0.81 on the Validation/ Testing Set respectively. The Reformed Gamblers attains 0.81/ 0.80 on the Validation/ Testing Set respectively. M-Net+A-Net has achieved 0.823/ 0.821 on the Validation/ Testing Set respectively. Deep-in-Net has achieved 0.86/ 0.84 on the Validation/ Testing Set respectively.

Table 2. AUC for Referable/NonReferable

| Methodology | AUC | Acc. |
|---------------|------|------|
| Deep-in-Net | 0.96 | 0.92 |
| Lesion-Based | 0.74 | - |
| Fisher Vector | 0.85 | - |
| Expert A | 0.89 | - |
| Expert B | 0.88 | - |

5.3. Experiment Results on the Messidor Sets of Data

For further estimation we have proposed Deep-in-Net being applied to Messidor data of DR screen. The data is used for an evaluation and categorize, index the retina of the eyes in order to detect the lesions in the eye. In 2004, the French Ministry has conducted a program for techno vision in the field of research and defense sector. As per the dataset there are 1500 images where the image size is smaller enough for the CNN training [21]. As shown in the Table the AUCs for the methodologies are as follows - The Lesion based has AUC of 0.74, The Fisher Vector has 0.85 AUC, The Expert A gives 0.89 AUC and Expert B gives 0.88 AUC values. Whereas for the Deep-in-Net the AUC/ Acc. value is 0.96/ 0.92.

6. Conclusion

The paper proposed the novel approach of the Deep-in-Net that has three major stages, which results in constellations of various severity levels of DR. The datasets are trained with supervision at the image stages. The Deep-in-Net generates the attention maps for the disease suspected area. The technique has the ability to validate and discover as per the objective. The further experiments rates higher response in the gated region for the DR potential lesions. This can be used as the technique to boost up the categorization.

References

- [1] Rajalakshmi, R., Subashini, R., Anjana, R.M. et al. Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence. *Eye*, Vol. 32, pp. 1138–1144, 2018.
- [2] Javeria Amin, Muhammad Sharif and Mussarat Yasmin, "A Review on Recent Developments for Detection of Diabetic Retinopathy", Hindawi Publishing Corporation, Scientifica, 2016.
- [3] Sisodia D. S, Nair S, Khobragade P, "Diabetic Retinal Fundus Images: Preprocessing and Feature Extraction for Early Detection of Diabetic Retinopathy", *Biomed Pharmacol J*, Vol.10, Iss.2, 2017.
- [4] Yogesh Kumaran, Chandrashekar M. Patil, "A Brief Review of the Detection of Diabetic Retinopathy in Human Eyes Using Pre-Processing & Segmentation Techniques", *International Journal of Recent Technology and Engineering (IJRTE)*, ISSN: 2277-3878, Vol.7, Iss. 4S2, December 2018.
- [5] Fong DS, Aiello LP, Ferris FL, Klein R, "Diabetic retinopathy", *Diabetes Care*, vol.27, pp.2540– 2543, 2004.
- [6] Namperumalswamy P, Nirmalan PK, Ramaswamy KM, "Developing a screening program to detect sight threatening retinopathy in south India", *Diabetes Care*, vol.26, pp.1831–1835, 2003.
- [7] Ryan ME, Rajalakshmi R, Prathiba V, Anjana RM, Ranjani H, VenkatNarayan KM, "Comparison Among Methods of Retinopathy Assessment (CAMRA) study: smartphone, nonmydriatic, and mydriatic photography", *Ophthalmology*, vol. 122, pp. 2038–2043, 2015.
- [8] Rajalakshmi R, Arulmalar S, Usha M, Prathiba V, Kareemuddin KS, Anjana RM, "Validation of smartphone based retinal photography for diabetic retinopathy screening", *PLoS ONE*, vol.10 e0138285, 2015.
- [9] T. Kauppi, V. Kalesnykiene, J.-K. Kamarainen et al., "The DIARETDB1 diabetic retinopathy database and evaluation protocol," in *Proceedings of the 18th British Machine Vision Conference (BMVC '07)*, pp. 15.1–15.10, September 2007.
- [10] D. Kayal and S. Banerjee, "A new dynamic thresholding-based technique for detection of hard exudates in digital retinal fundus image," in *Proceedings of the 1st International Conference on Signal Processing and Integrated Networks (SPIN '14)*, pp. 141–144, February 2014.
- [11] C. Agurto, V. Murray, E. Barriga et al., "Multiscale AM-FM methods for diabetic retinopathy lesion detection," *IEEE Transactions on Medical Imaging*, vol. 29, no. 2, pp. 502–512, 2010.
- [12] G. Mahendran, R. Dhanasekaran, and K. N. Narmadha Devi, "Identification of exudates for Diabetic Retinopathy based on morphological process and PNN classifier," in *Proceedings of the 3rd International Conference on Communication and Signal Processing (ICCSP '14)*, pp. 1117– 1121, IEEE, Melmaruvathur, India, April 2014.
- [13] N. B. Prakash and D. Selvathi, "An Efficient Detection System for Screening Glaucoma in Retinal Images," *Biomed. Pharmacol. Journal*, vol. 10, no. 1, 2017.
- [14] S. S. Rathore and A. Gupta, "A comparative study of feature-ranking and feature subset selection techniques for improved fault prediction," in *Proceedings of the 7th India Software Engineering Conference on – ISEC '14*, 2014, pp. 1–10.
- [15] D. S. Sisodia and S. Verma, "Image pixel intensity and artificial neural network-based method for pattern recognition," *World Acad. Sci. Eng. Technol.*, vol. 57, pp. 742–745, 2011.

- [16] M. Merlin and B. Priestly Shan, "Robust and efficient segmentation of blood vessel in retinal images using gray-level textures features and fuzzy SVM," *Biomed. Pharmacol. J.*, vol. 8, no. 2, pp. 1111–1120, 2015.
- [17] R. GeethaRamani, L. Bala Subramanian, "Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis", *Jour. of Biocybernetics & Biomed.Engg.*, vol. 36, no. 1, pp. 102-118, 2016.
- [18] S. Tang, T. Lin, J. Yang, J. Fan, "Retinal Vessel Segmentation using Supervised Classification based on Multi-scale vessel filtering and Gabor Wavelet", *Jour. of Med. Imag.&Health Info.*,vol. 5, pp. 1571-1574, 2015.
- [19] A.J. Abdallah, P.E. Undrill, M.J. Cree, J.A. Olson, K.C. McHardy, P.F. Sharp, J.V. Forrester, "A comparison of computer-based classification methods applied to the detection of microaneurysms in ophthalmic fluorescein angiograms", *Computer Biological Medicine*, vol. 28, no. 3, pp. 225– 238, 1998.
- [20] U. Akram M. Khan, "Multilayered thresholding- based blood vessel segmentation for screening of diabetic retinopathy" *Jour. of Engg. Comp.*, vol. 29, no. 2, pp. 165–73, 2013.
- [21] Wang Z., Yin Y., Shi J., Fang W., Li H., Wang X. (2017) Zoom-in-Net: Deep Mining Lesions for Diabetic Retinopathy Detection. In: Descoteaux M., Maier-Hein L., Franz A., Jannin P., Collins D., Duchesne S. (eds) *Medical Image Computing and Computer Assisted Intervention – MICCAI 2017*. MICCAI 2017. Lecture Notes in Computer Science, vol 10435. Springer, Cham. https://doi.org/10.1007/978-3-319-66179-7_31.
- [22] Gwenole Quellec, Katia Charriere, Yassine Boudi, Beatrice Cochener, Mathieu Lamard, "Deep Image Mining for Diabetic Retinopathy Screening", *LaTIM, Medical Image Analysis*, DOI: 10.1016/j.media.2017.04.012, 28 Apr 2017.
- [23] Wejdan L Alyoubi, Wafaa M. Shalash, Maysoon F. Abulkhair, ""Diabetic Retinopathy Detection Through Deep Learning Techniques: A Review", *Elsevier, Informatics in Medicine Unlocked*, Vol. 20, 2020.
- [24] The Emerging Epidemic of Diabetic Retinopathy in INDIA, "Report of a Situation Analysis and Evaluation of Existing Programmes for Screening and Treatment of Diabetic Retinopathy", *Indian Institute of Public Health - Hyderabad* © 2014.