An Evaluation Based on Diabetic Retinopathy

Simran Kaur, Dr. Barjinder Singh Saini

Dept of Electronics and Communication Engineering, Dr. B R Ambedkar NIT Jalandhar, Punjab, India 144001

*Corresponding author

doi: https://doi.org/10.21467/proceedings.114.24

Abstract

Diabetic retinopathy is a globally rising disease and needs to be taken in concern. It is the problem with vision of diabetic patients due to a disease in the retina of diabetic patients.Diabetic patients have high glucose level in the blood.Our major concern is to predict the disease at early stages.The studies focusses on the modern techniques used in image processing digitally.It also puts a stress on patches classification used for the examination and prediction of diabetic retinopathy and judge the accuracy,senstivity of dataset.

Keywords: Diabetic retinopathy, deeplearning, pre- processing, segmentation

1 Introduction

According to the statistics of the world health organization, the studies related to diabetes is estimated to be 2.8percent in 2000 and which will rise to 4.4percent in 2030.The main reason for the rise of this deadly disease are increase in weight due to overeating, lack in physical workout and old age. The global increase of diabetes among all age groups has led to a lot of complications associated with diabetes [1]. Diabetic retinopathy is an associated disease related to diabetes that is the main cause of vision loss of diabetic patients. This vision loss is often referred to as diabetic retinopathy. Hence there are various deep learning techniques which I have learnt in order to predict diabetic retinopathy. Our main highlight in this paper is to help the patient in early detection of diabetic retinopathy. Early recog- nisation and therapy to cure Diabetic Retinopathy are very important because it is a hereditary disease and its severity depends on the the count of patches in the retinal image. Diabetic retinopathy consist of multiple retinopathic signs in the internal eye structure of a person like hemorrhages, microaneurysms, soft or hard malignancies.

In this review paper, our main aim is to detect the problem in the retina in a particular place so that disease can be detected. Most commonly first of all pre-processing of an image takes place, then, we apply image segmentation and at last classification of an image is done to predict whether the image is infected or not. Normalization of an image is a process in which each pixel of an image is divided by 255 so that images are threshold to levels 0 and 255. Segmentation of the medical image is done basically to extract boundaries of an image and acquire maximum accuracy.

Diabetic retinopathy is judged by the identification of dif- ferent types of spots on the retina image of a person. These patches are called as: microaneurysms (MA), hemorrhages (HM), soft or hard exudates (EX).

Microaneurysms (MA) are the hot spots for the detection of diabetic retinopathy and are seen as red spots in the wall of retina. The size is less than 125 micrometer and there are sharp margins. Haemorrhages (HM) are seen as patches in the retina and to be more than 125 micrometer in size. Hard exudates are visualised as pale spots due to leakage of plasma in the retinal walls. They are having sharp features and are found in the retina's outer layers. Soft exudates (also called cotton wool) which are furry spots and appear as a cataract are oval shaped. The diagnosis of this disease by man's effort is prone to faulty results, and requires more effort than instinctive techniques. This paper reviews the recent Diabetic retinopathy techniques and blends deep learning for identification of diabetic retinopathy.

Proceedings DOI: 10.21467/proceedings.114; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-947843-8-8

2 Deep Learning: An Expert System

Deep learning (DL) is an overleaf of artificial intelligence techniques. It uses progressive layers for nonlinearities in pro- cessing for unverified features in learning as well as for clas- sification methods. Intelligent retrieval applications associated with biomedical image processing contains the Classification, dividing the image pixels into normalized value that is less than 255 and last step is evaluation step in order to determine accuracy of dataset.

It successfully retrieves the features of input. It is a progressive learning step, again and again feedback is provided to a system with the loss so that at each iteration the performance of the system increases. Also, DL is one computer-operated method. Deep Convolutional Neural Networks (DCNNs), a deep learning branch has a praiseworthy and plenty of data on image analysis and interpretation applications. It also uses various algorithms in order to predict the disease. The basic idea for the implementation of various deep learning algorithms is just to feed dataset to a neural network. Then pre-processing the dataset and then segmenting it. The dataset is then classified as infected or not. At last evaluation is done in which receiver operating characteristics are observed. Convolutional neural networks is the basic method which is used in deep learning and is very efficient. The three overleaves of a neural network consist of: 1) convolution layers (CONV) 2) pooling layers 3) fully connected layers (FC).

1)In the CONV layers, various filters pervert or twist an image to gain the characteristics. 2)Pooling layer is the next layer applied after convolutional layer so as to minimize the magnitude of feature maps which are related to datasets. There are many processes followed for pooling but average pooling and max pooling are the common ones. 3)Fully connected layer is then applied to gain the proper input image. SoftMax activation function is the most used classification function.

Deep learning also uses many mathematical formulas and algorithms in order to predict the disease. The basic idea for the implementation of various deep learning algorithms is just to feed dataset to a neural network. Then pre-processing the dataset and then segmenting it. The dataset is then classified as infected or not. At last evaluation is done in which receiver operating characteristics are observed.

2.1 Retinal Dataset

The word processing file are plenty and they are available publically in order to detect DR .The datasets are used for providing assistance to the models and then examining them.Fundus image datasets also known as retinal images are given below:

- Diaretdb1 [2]: It comprises 89 retinal images and the pixels of the same are acquired at a particular degree of angle. The dataset has 84 Diabetic retinopathy hard copies and five normal hard copies annotated by four medical experts. • Kaggle :The dataset is provided at its official website. The dataset has high intensity images which are focussed at different angels. • E- ophophtha MA [3]: The dataset is also available and contains microaneurysm images. It can be used for further image processing. • DDR [4]: The dataset exists and also provides us with the different images of retina with dark patches in the wall of it.
- DRIVE [5]:The dataset provided here has images with field of view of forty five degree. It is used for blood vessel segmentation.
- HRF [6]: This total dataset contains half of the healthy images and half of the diseased images. It is used for the analysis of blood vessels.
- Messidor [7]: This dataset is publically accessible and is used for image segmentation . It is also available as Messidor- 2 dataset [8].
- STARE [9]: The dataset is accessible publically and also contains less of the normal images. It also is required for the segmentation of images.

- CHASE DB1 [10]: The dataset provided here is available publically and has field of view of thirty degrees.
- Indian Diabetic Retinopathy Image dataset (IDRiD):The dataset is available online and is provided in the three folders. These folders are in the form of segmentation, localization and disease grading predicted in the form of numerical value to depict the severity of a disease.
- ROC [11]: These datasets are accessible publically and are used for the prediction of microaneurysms.
- DR2 [12]: These datasets are basically used in the form of reference images and are also used for image segmentation.

2.2 Performance measures

The commonly used performance measurements in the retrieval of intelligent systems are sensitivity, specificity and prediction of accuracy values. Sensitivity is the measure of how sensitive is the dataset means percentage of abnormal dataset in the pool of total dataset , and the specificity for the dataset is the measure of specific data which are normal images.AUC is the graph in which sensitivity versus specificity are plotted and then the curves are observed. The following are the equations of each measurement. Specificity are the True negatives divided by True Negatives+ False Positives.
Sensitivity is True Positives divided by True Positives +False Negative.
Accuracy = True Negatives + True Positives divided by True Negatives + True Positives + False Negatives + False Positives
True negatives are the values of dataset which are actually abnormal and are classified also as abnormal.
True positives are the values which are correctly interpreted as a positive value.

3 Image Pre-Processing

Image processing is the most required step to remove the irregularities in image and to enhance image dimensions. [13]. Shearing of images take place or the images that are cropped are applied as an input data to cut out the surplus amount of pixels from the image, while the data normalization is used in order to normalize the images for its proper identification. Augmentation includes many processes such as follows: rotation, rotating to left or right, rescaling, shearing, flipping, contrast scaling.

Author	Year	Conclusion	Results
K. Xu et al [11]	2017	They used 1000 images from the dataset achieved from kaggle.The images are resized to number of three channels be- fore feeding the images to the CNN. The CNN architecture which was followed here also applies the SoftMax function to the last layer of the convolutional neural network for classification.	The method was almost accurate up to 90 percent.
Quellec et al. [12]	2017	Every image was classified as diabetic retinopathy which is referred as correct and DR referred to as faulty by training three convolutional neural networks. In the image processing technique applied here large	This study also indicated that the receiver operating characteristics had the measure of 0.92 in count.

		amount of gaussian filters were used.	
Bhatkar et al. [14]	2015	This paper focuses on the pattern of multi layers in a neural network So here multi level classifier was used in order to detect the dataset as benign or malignant.	The ststistics measure an accuracy of 80 percentage.
Pires et al. [15]	2019	Here the dataset was validated twice before processing it further. The convolutional neural network(CNN) was entered and then was trained after initializing the weights of particular layers by training CNN on a smaller image resolution.	The existing work succeded in plotting an area under the receiver operating characteristics curve, measured as 98.2 percent .
H. Jiang et al. [16]	2019	It used a convolutional neural networks model. The dataset was resized,then performed various augmentation operations on it and at last fed to neural network.	The work obtained accurate results upto 88 pointer.
Liu et al. [17]	2019	They collected over thousands of images clssified as a genuine or faulty diabetic retinopathy and applied various alterations on its pixel size to balance the classes. Here WP-CNN algorithm is applied. Images were normalised before being fed to neural network.	It achieved an accuracy of 94.23percent in their dataset .
G. Zago et al. [18]	2019	The CNNs used here contained 5 convolutional layers, five max-polling layers and last the images were classified as benign and malignant.	The statistics also achieved an efficacy of 0.94 .
M. Abramoff et al. [19]	2016	this article the dataset which were classified as benign or malignant and then fed to convolutional neural layers.	The dataset used here achieved an appreciable accuracy as well as senstivity values,that is,about 95 percent.
Zhang et al. [20]	2019	. This article suggessted a convolutional neural network model in which different layers of the model were used in order to resize the pixel intensity of an image and then applying various algorithms on it to evaluate the model.	Their results gave an appreciable values for senstivity and specificity that is approximately 95 percent.
Zhou et al. [21]	2017	This review suggessted an unsupervised method for classification of dataset. The mathematical formula of sparse component analysis was used here.	The study provided us with the accuracy measure of 98.15percent.
Wilkinson et al. [22]	2003	In this research a simple binary classi-fication system which was used in the earlier stages was used.	This research provided us with minimal accuracy which is more than half.

Harangi et al. [23]	2019	The study here only provided us with the reference model which can be used in further researches so as to classify the mild and moderate types of diabetic retinopathy. The model was even tested on the various publically available datasets.	The obtained accuracy for this study was 90.07percent.
Gulshan et al. [24]	2019	It suggessted a study which blends deep learning along with the different convolutional layers in order to derive a mathematical study to examine different types of patches in the retina of the image.	The search received an efficacy value of 96.35 percent.
Li et al. [25]	2020	It classified the dataset that is indian diabetic retinopathy dataset into mild and moderate types of diabetic retinopa- thy.The classification was done by the use of different modules.	This work achieved a sensitivity measure of 92percent, and receiver operating curves of 96.3percent .In all the accuracy of 96 percent was achieved here.
Chetoui et al. [26]	2018	In this paper, support vector machine module was used in order to do classifi- cation as well as processing.	They reported a score of 0.355 in receiver operating characteristics.
Zang et al. [27]	2019	In this paper, a novel convolutional neural network model was followed.It used a type of structure in the model which is Siamese.	A sensitivity of 48.71percent was predicted in the detection of red lesions.
Wang et al. [28]	2020	Here random forest classifier was used in order to predict the patches.Here a common convolutional neural network was used.	A sensitivity of 0.8990 and an AUC of 0.9644 was achieved .

4 Conclusion

The search reviewed 16 papers. All of the research papers mention the continuing work which is manipulated by the diabetic retinopathy masking system and then using deep learning techniques. The urge for reliable diabetic retinopathy screening systems which gives an accurate result becomes a crucial issue recently, due to a rise in the rate of diabetic patients. Using Deep learning techniques in DR detection and classification overpower the problem of choosing good features for Machine learning; on the other hand, it demands a large amount data size for the training purpose. Studies also perform data augmentation in order to increase the count of images and overcame the problem of overfitting in the training stage. Out of the total studies that are evaluated public datasets are very efficient in order to predict the model. Moreover, they are also easily accessible by everyone. Therefore, the structures which build their own neural network models should be preferred. Most of the studies mentioned here (73percent) only classified the fundus input image to DR non-DR, while 27percent categorised input to one or more stages. On the other hands 70percent of the current studies gave faulty results while, 30percent of them detected the affected lesions accurately. The existing procedure to detect a reliable DR masking system that is capable of detecting different types of lesions. The gap that needed to be filled is predicting and discussing the system which will help in making high sensitivity.

References

[1] R. Chakrabarti, C. A. Harper, and J. E. Keeffe, "Diabetic retinopathy management guidelines," *Expert Review of Ophthalmology*, vol. 7, no. 5, pp. 417–439, 2012.

[2] T. Kauppi, V. Kalesnykiene, J.-K. Kamarainen, L. Lensu, I. Sorri, A. Raninen, R. Voutilainen, H. Uusitalo, H. Ka¨lvia¨inen, and J. Pietila¨, "The diaretdb1 diabetic retinopathy database and evaluation protocol." in *BMVC*, vol. 1, pp. 1–10.

[3] E. Decenciere, G. Cazuguel, X. Zhang, G. Thibault, J.-C. Klein, F. Meyer, B. Marcotegui, G. Quellec, M. Lamard, R. Danno *et al.*, "Teleophta: Machine learning and image processing methods for teleophthalmology," *Irbm*, vol. 34, no. 2, pp. 196–203, 2013.

[4] T. Li, Y. Gao, K. Wang, S. Guo, H. Liu, and H. Kang, "Diagnostic as- sessment of deep learning algorithms for diabetic retinopathy screening," *Information Sciences*, vol. 501, pp. 511–522, 2019.

[5] J. Staal, M. D. Abra`moff, M. Niemeijer, M. A. Viergever, and B. Van Ginneken, "Ridge-based vessel segmentation in color images of the retina," *IEEE transactions on medical imaging*, vol. 23, no. 4, pp. 501–509, 2004.

[6] A. Budai, R. Bock, A. Maier, J. Hornegger, and G. Michelson, "Robust vessel segmentation in fundus images," *International journal of biomed- ical imaging*, vol. 2013, 2013.

[7] E. Decencie`re, X. Zhang, G. Cazuguel, B. Lay, B. Cochener, C. Trone, P. Gain, R. Ordonez, P. Massin, A. Erginay *et al.*, "Feedback on a publicly distributed image database: the messidor database," *Image Analysis & Stereology*, vol. 33, no. 3, pp. 231–234, 2014.

[8] A. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Transactions on Medical imaging*, vol. 19, no. 3, pp. 203–210, 2000.

[9] C. G. Owen, A. R. Rudnicka, R. Mullen, S. A. Barman, D. Monekosso, P. H. Whincup, J. Ng, and C. Paterson, "Measuring retinal vessel tortu- osity in 10-year-old children: validation of the computer-assisted image analysis of the retina (caiar) program," *Investigative ophthalmology & visual science*, vol. 50, no. 5, pp. 2004–2010, 2009.

[10] P. Porwal, S. Pachade, R. Kamble, M. Kokare, G. Deshmukh, V. Sa- hasrabuddhe, and F. Meriaudeau, "Indian diabetic retinopathy image dataset (idrid): a database for diabetic retinopathy screening research," *Data*, vol. 3, no. 3, p. 25, 2018.

[11] K. Xu, D. Feng, and H. Mi, "Deep convolutional neural network-based early automated detection of diabetic retinopathy using fundus image," *Molecules*, vol. 22, no. 12, p. 2054, 2017.

[12] G. Quellec, K. Charrie`re, Y. Boudi, B. Cochener, and M. Lamard, "Deep image mining for diabetic retinopathy screening," *Medical image analysis*, vol. 39, pp. 178–193, 2017.

[13] S. Dutta, B. Manideep, S. M. Basha, R. D. Caytiles, and N. Iyengar, "Classification of diabetic retinopathy images by using deep learning models," *International Journal of Grid and Distributed Computing*, vol. 11, no. 1, pp. 89–106, 2018.

[14] A. P. Bhatkar and G. Kharat, "Detection of diabetic retinopathy in retinal images using mlp classifier," in *2015 IEEE international symposium on nanoelectronic and information systems*. IEEE, 2015, pp. 331–335.

[15] R. Pires, S. Avila, J. Wainer, E. Valle, M. D. Abramoff, and A. Rocha, "A data-driven approach to referable diabetic retinopathy detection," *Artificial intelligence in medicine*, vol. 96, pp. 93–106, 2019.

[16] H. Jiang, K. Yang, M. Gao, D. Zhang, H. Ma, and W. Qian, "An interpretable ensemble deep learning model for diabetic retinopathy disease classification," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 2045–2048.

[17] Y.-P. Liu, Z. Li, C. Xu, J. Li, and R. Liang, "Referable diabetic retinopathy identification from eye fundus images with weighted path for convolutional neural network," *Artificial intelligence in medicine*, vol. 99, p. 101694, 2019.

[18] G. T. Zago, R. V. Andrea˜o, B. Dorizzi, and E. O. T. Salles, "Diabetic retinopathy detection using red lesion localization and convolutional neural networks," *Computers in biology and medicine*, vol. 116, p. 103537, 2020.

[19] M. D. Abra`moff, Y. Lou, A. Erginay, W. Clarida, R. Amelon, J. C. Folk, and M. Niemeijer, "Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning," *Investigative ophthalmology & visual science*, vol. 57, no. 13, pp. 5200–5206, 2016.

[20] W. Zhang, J. Zhong, S. Yang, Z. Gao, J. Hu, Y. Chen, and Z. Yi, "Automated identification and grading system of diabetic retinopathy using deep neural networks," *Knowledge-Based Systems*, vol. 175, pp. 12–25, 2019.

[21] W. Zhou, C. Wu, D. Chen, Y. Yi, and W. Du, "Automatic microaneurysm detection using the sparse principal component analysis-based unsuper- vised classification method," *IEEE access*, vol. 5, pp. 2563–2572, 2017.

[22] C. Wilkinson, F. L. Ferris III, R. E. Klein, P. P. Lee, C. D. Agardh, M. Davis, D. Dills, A. Kampik, R. Pararajasegaram, J. T. Verdaguer *et al.*, "Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales," *Ophthalmology*, vol. 110, no. 9, pp. 1677–1682, 2003.

[23] B. Harangi, J. Toth, A. Baran, and A. Hajdu, "Automatic screening of fundus images using a combination of convolutional neural network and hand-crafted features," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 2699–2702.

[24] V. Gulshan, L. Peng, M. Coram, M. C. Stumpe, D. Wu, A. Narayanaswamy, S. Venugopalan, K. Widner, T. Madams, J. Cuadros *et al.*, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *Jama*, vol. 316, no. 22, pp. 2402–2410, 2016.

[25] X. Li, X. Hu, L. Yu, L. Zhu, C.-W. Fu, and P.-A. Heng, "Canet: cross- disease attention network for joint diabetic retinopathy and diabetic macular edema grading," *IEEE transactions on medical imaging*, vol. 39, no. 5, pp. 1483–1493, 2019.

[26] M. Chetoui, M. A. Akhloufi, and M. Kardouchi, "Diabetic retinopathy detection using machine learning and texture features," in

2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE). IEEE, 2018, pp. 1–4.

[27] X. Zeng, H. Chen, Y. Luo, and W. Ye, "Automated diabetic retinopathy detection based on binocular siamese-like convolutional neural network," *IEEE Access*, vol. 7, pp. 30 744–30 753, 2019.

[28] H. Wang, G. Yuan, X. Zhao, L. Peng, Z. Wang, Y. He, C. Qu, and Z. Peng, "Hard exudate detection based on deep model learned infor- mation and multi-feature joint representation for diabetic retinopathy screening," *Computer methods and programs in biomedicine*, vol. 191, p. 105398, 2020.