ISSN 2348-1218 (print)
International Journal of Interdisciplinary Research and Innovations ISSN 2348-1226 (online)
Vol. 7, Issue 2, pp: (122-125), Month: April - June 2019, Available at: www.researchpublish.com

Glaucoma Detection Using Neural Network

Utkarsh Tiwari[1], Pooja Mehta[2], Saloni Varma[3], Alay Shah[4],
Asst. Prof. Sandhya Kadam[5]

KJ Somaiya Institute of Engineering and Information Technology, Sion
Department of Electronics and Telecommunications Engineering, Sion, Mumbai, India

[1]utkarsh.tiwari@somaiya.edu, [2]pooja.dm@somaiya.edu, [3]saloni.varma@somaiya.edu, [4]alay.shah@somaiya.edu,
[5]sandhyakadam@somaiya.edu

Abstract: **The early detection of Glaucoma is very important to avoid blindness. In this paper, we present Glaucoma Detection using Neural Network. This is one of the innovative approaches to detect glaucoma using the latest Deep Learning techniques. The proposed method uses the ResNet Convolutional Neural Network to detect Glaucoma. Though there are various available techniques to detect Diabetic Retinopathy but nothing of such sort can be found for Glaucoma which gives such high accuracy. The given method is implemented in Python with a command line interface. Using ResNet we have detected Glaucoma with up to 96% accuracy.**

Keywords: **Glaucoma, ResNet, Convolutional Neural Network, Model.**

I. INTRODUCTION

Glaucoma is a chronic eye disease and it damages the optic nerve. Glaucoma is the leading cause of blindness in adults above the age of 60 years but can also cause blindness to people between the age of 35-40 years if they have high risk factors. High risk factors include Myopia, Hypertension and Eye injury among others. Glaucoma arises when drainage canal is partly or completely blocked which leads to the increase in pressure, called intraocular pressure which damages the optic nerve - used to transmit impulses to the brain where visual information can be interpreted [1]. If this damage left untreated, may lead to total blindness. Therefore, the early detection of glaucoma [2] is necessary. There are two major types of Glaucoma - Primary Open-Angle Glaucoma which is most common type and Angle-Closure Glaucoma also called Narrow Angle Glaucoma. Glaucoma is the third largest cause of blindness in the world following cataract and trachoma which accounts for more than 14% of total blind population [3]. Most of the systems that exist currently are for Primary Open-Angle Glaucoma. The proposed system can detect and differentiate between both the types provided if it is trained on both the types of images. Many Machine Learning Algorithms exist for detection of Diabetic Retinopathy but no such model is available for detection of glaucoma with high accuracy.

II. PROPOSED SYSTEM

The proposed system is based on ResNet50 the latest Convolutional Neural Network. ResNet is arguably the most ground-breaking work in the field of Computer Vision and Deep Learning in the last few years. The proposed system utilizes ResNet to train on around 240 images and test on 60 images. The reason why we are using ResNet is because of its core feature called “identity shortcut connection” which allows it to skip one or more layers as shown in the fig. 1.

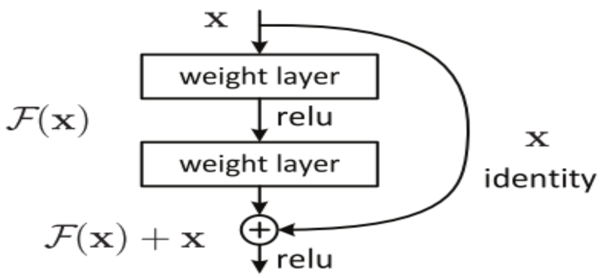


Fig 1. ResNet Architecture

III. LITERATURE SURVEY

The papers [6][7][8] are available on diabetic retinopathy in which detection of diabetic retinopathy using Neural Network is done. The same concept is extended to Glaucoma detection using Neural Network and the system is proposed. Various available models utilize AlexNet, VGG-16, Xception, etc. and obtain high accuracy. But the problem is that they are inefficient due to their large size and huge infrastructure requirements. The proposed system takes into account these shortcomings and generates a model which is efficient in terms of size, requirements and can be easily deployed over the cloud and IoT devices.

IV. METHODOLOGY

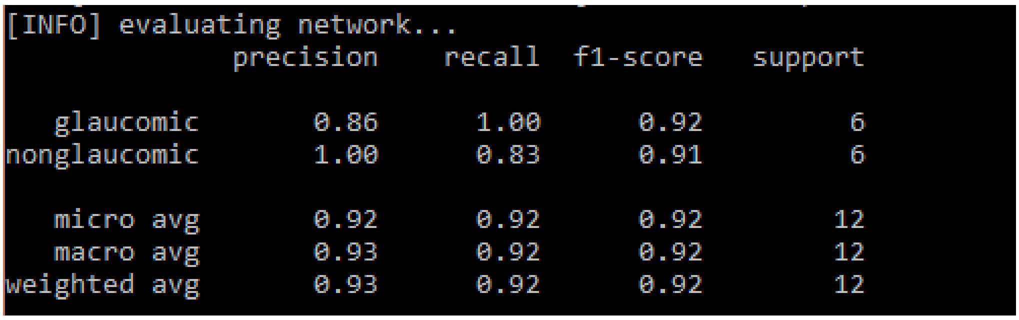
The methodology of the proposed system is mentioned below. The important steps are data gathering and segregation, model training and saving the model and the utilization of saved model for prediction.

A. Data Gathering

The data of glaucomatous images is provided by the Pattern Recognition Lab (CS5), the Department of Ophthalmology, Friedrich-Alexander University Erlangen-Nuremberg (Germany), and the Brno University of Technology, Faculty of Electrical Engineering and Communication, Department of Biomedical Engineering, Brno (Czech Republic) [9]. It contains 15 High Resolution Fundus Images of Glaucomic Eye and 15 Healthy Fundus Images. More images can be downloaded from Deep Blue RIGA Dataset [10].

B. Model Training

The proposed system uses a minified version of ResNet50 architecture for generating model of Glaucoma Detection. It is trained from scratch. Images are first resized to 64 x 64 x 3 (RGB images) and within the 2 classes - glaucomic and non-glaucomic. ResNet will perform a stacking of 3, 4, 6 with 64, 128, 256, 512 Convolutional Layers. ReLu activation function is used between the CONV layers and SoftMax for the final layer. The generated model is saved as 64x3CNN.model file. Th proposed model utilizes data augmentation for better training. Data Augmentation allows to us to rotate, zoom in and zoom out the images to created a better training set. Fig. 2. demonstrates the recall, precision and accuracy score of the generated model.


[INFO] evaluating network...

	precision	recall	f1-score	support
glaucomic	0.86	1.00	0.92	6
nonglaucomic	1.00	0.83	0.91	6
micro avg	0.92	0.92	0.92	12
macro avg	0.93	0.92	0.92	12
weighted avg	0.93	0.92	0.92	12

Fig. 2. Trained Model Metrics

C. Model Prediction

For prediction, we first import the model file generated above. We then pass an image as input. The program reads the image and using the model file to predict whether the image is Glaucoma Suspect or Not Glaucomic. Fig. 3. denotes the flow diagram of the proposed model.

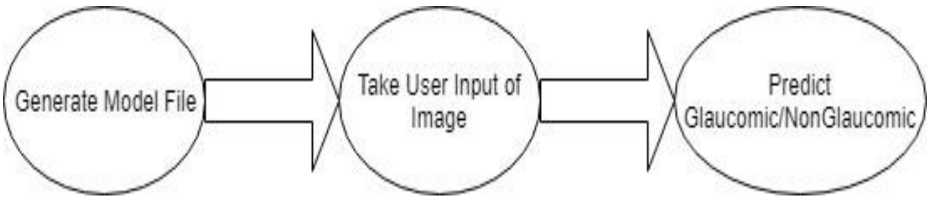


Fig. 3. Flow Diagram of the proposed model

ISSN 2348-1218 (print)
International Journal of Interdisciplinary Research and Innovations ISSN 2348-1226 (online)
Vol. 7, Issue 2, pp: (122-125), Month: April - June 2019, Available at: www.researchpublish.com

V. RESULTS AND DISCUSSION

The following results are obtained by using the proposed model. The input images are 06_g.jpg and 06_h.jpg from the standard high-resolution fundus images database available publicly by Pattern Recognition Lab (CS5) [9]. The original size of the images is 3540pixels by 2336pixels and it is shown in Fig. 4a and Fig. 4b.

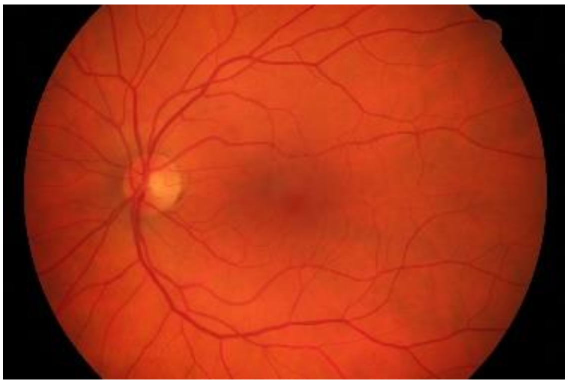


Fig. 4a. Input image 06_g.jpg to the system.

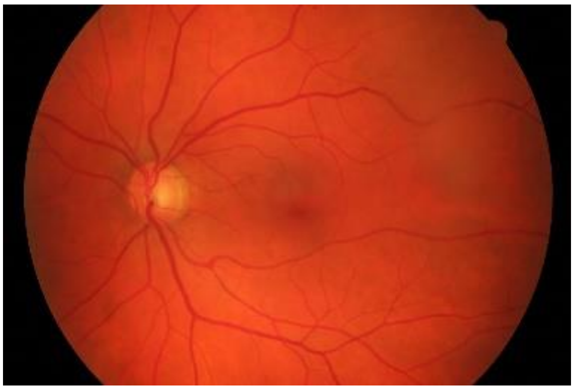


Fig. 4b. Input image 06_h.jpg to the system.

The output of the above-mentioned input images can be seen in Fig. 5a and Fig. 5b.

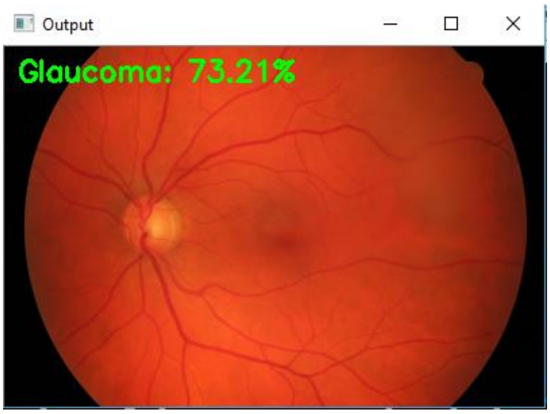


Fig. 5a. Output of image 06_g.jpg to the system.

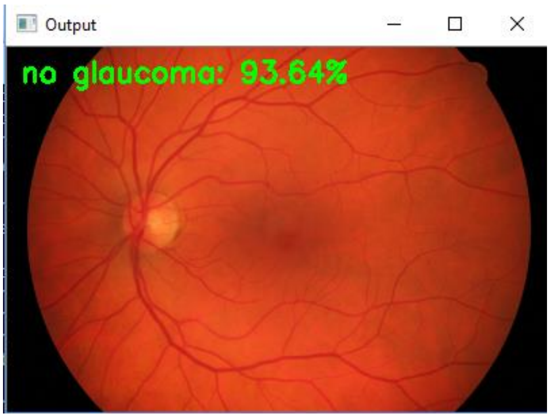


Fig. 5b. Output of image 06_h.jpg to the system.

The accuracy of validation is 87% and the accuracy of the proposed method is 96%. The results of the proposed model have been validated by an Ophthalmologist and has been found accurate.

VI. CONCLUSION AND FURTHER WORK

The conclusion from the proposed model is that we can use ResNet Architecture to differentiate between a glaucomic and non-glaucomic image. The overall validation accuracy of the model is 87% and training and testing accuracy is 96%. The model can be improved further by using Reinforcement Learning and by increasing the training and testing data.

REFERENCES

[1] [online]Available: https://www.nlm.nih.gov/medlineplus/ency/article/001620.htm

[2] Erik linner, "The early detection of glaucoma" in Chapter Public Health Ophthalmology Volume 5 of the series Documenta Ophthalmologica, Springer, pp. 23-24.

[3] Quigley H.A., Broman A.T. The number of people with glaucoma worldwide in 2010 and 2020. Br J Ophthalmol. 2006;90(3):262–267. [PubMed]

[4] Bock R., Meier, J., Nyul, L., Hornegger, J. and Michelson, G. (2010). Glaucoma risk index: Automated glaucoma detection from color fundus images. Medical image analysis, 14(3), pp 471—481.

[5] Ibrahim Sadek, Automatic Discrimination of Color Retinal Images using the Bag of Words Approach

[6] Neil J. Friedman MD, Peter K. Kaiser MD, William B. Trattler MD 2017: Review of Ophthalmology, Elsevier; 3 editions

[7] [online] Available: https://about.google/stories/seeingpotential/?hl=en

[8] David Browning (2010), Diabetic Retinopathy: Evidence-Based Management

[9] [online] Available: https://www5.cs.fau.de/research/data/fundus-images/

[10] [online] Available: https://deepblue.lib.umich.edu/data/concern/data_sets/3b591905z?locale=en

[11] Optho Book, The free eye book and lecture series," http://www.ophthobook.com/chapters/glaucoma" Access date 26th November 2013

[12] Types of Glaucoma [online] Available: http://www.glaucoma.org/glaucoma/types-of-glaucoma.php

[13] K. He, X. Zhang, S. Ren, and J. Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In ICCV, 2015.

[14] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov. Improving neural networks by preventing coadaptation of feature detectors. arXiv:1207.0580, 2012.

[15] S. Hochreiter and J. Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[16] S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In ICML, 2015.

[17] H. Jegou, M. Douze, and C. Schmid. Product quantization for nearest neighbor search. TPAMI, 33, 2011.

[18] H. Jegou, F. Perronnin, M. Douze, J. Sanchez, P. Perez, and C. Schmid. Aggregating local image descriptors into compact codes. TPAMI, 2012.

[19] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. arXiv:1408.5093, 2014.

[20] A. Krizhevsky. Learning multiple layers of features from tiny images. Tech Report, 2009.