



Detection of Glaucoma using Convolutional Neural Network

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ABSTRACT

Glaucoma, a very complex heterogeneous disease, is the leading cause for optic nerve-related blindness worldwide. Glaucoma is a chronic and irreversible eye disease, which leads to deterioration in vision and quality of life. It is estimated that approximately 60 million people will be affected by the year 2020. For this reason, we developed a system that automatically detects glaucoma. The objective of this research work is to carry out experiments with Convolutional Neural Networks to achieve the automatic detection of this disease. The experiments performed and obtained an average accuracy of 93%. This paper describes the development of deep learning (DL) architecture with a convolutional neural network for automated glaucoma diagnosis. Deep learning systems, such as convolutional neural networks, can infer a hierarchical representation of images to discriminate between glaucoma and non-glaucoma patterns for diagnostic decisions. The proposed DL architecture contains Ten learned layers: Six convolutional layers and Four fully-connected layers. Dropout and Data Augmentation strategies are adopted to further boost the performance of glaucoma diagnosis. Extensive experiments are performed on the Online database of Kims Hospital.

Keywords : Glaucoma, convolutional neuronal networks.

I. INTRODUCTION

Glaucoma is one of the main leading causes of permanent blindness in the world. It is a type of chronic severe eye disease which causes by retinal changes, generally in the area of the optic nerve head (ONH) [1]. Glaucoma usually common causes of blindness, and is predicted to affect around 80 million people by 2020 [2]. It is a type of chronic disease that leads to vision loss, in which the optic nerve is progressively damaged. As symptoms only occur when the disease is quite advanced, glaucoma is also called it as a silent thief of sight. Although glaucoma cannot be cured, its progression can be slowed down by treatment. The main contribution of this research work is to use convolutional neural networks implemented in Tensorflow & Keras for

automatic detection of glaucoma by means of analyzing pictures of the fundus of the eye. These pictures were taken at Online dataset of Kim's Hospital. These images were used for training the CNN. The damage done by glaucoma is irreversible. Early detection and treatment of glaucoma is the only solution. A structural study is performed on selected cores of focused research outcomes for improving in near future [3].

Digital Fundus Image is one of the main and popular modalities to diagnose glaucoma. Since it is possible to acquire DFIs in a noninvasive manner which is suitable for large scale screening, DFI has emerged as a preferred modality for large-scale glaucoma screening. In a glaucoma screening program, an automated system decides whether or not any signs

of suspicious for glaucoma are present in an image. Only those images deemed suspect by the system will be passed to ophthalmologists for further examination.

There are no early symptoms of glaucoma and the only source to detect glaucoma at early stage is the structural change that arises in the internal eye. Many autonomous glaucoma detection systems analyze fundus image by calculating its Cup to Disc Ratio (CDR) and categorize the image as glaucoma or healthy. The image processing technique for the early detection of glaucoma. Glaucoma is detected using retinal fundus image. CDR technique is used on different retinal image for glaucoma detection[4].disc diameter[5],ISTN rule[6] and peripapillary atrophy (PPA) [7].

Glaucoma is detected basically by utilizing the medical history, intra-ocular pressure and visual field loss tests together with a manual assessment of the Optic Disc (OD) through ophthalmoscopy. OD is the location where ganglion cell axons exit the eye to form the optic nerve, through which visual information of the photo-receptors is transmitted to the brain. In 2D images, the OD can be divided into two distinct zones: a central bright zone called the optic cup (in short,cup) and a peripheral region called the neuroretinal rim. The loss in optic nerve fibres leads to a change in the structural appearance of the OD, namely, the enlargement of cup region (thinning of neuroretinal rim) called cupping. Since one of the important indicators is the enlargement of the cup with respect to OD, various parameters are considered and estimated to detect the glaucoma, such as the vertical cup to disc ratio (CDR) [4], ISNT rule [5], and peripapillary atrophy (PPA) [6]. Among the structural image cues studied for glaucoma diagnosis, CDR is a major consideration of clinicians [8][9][10].However, clinical assessment by manual annotating the cup and disc for each image is labor-intensive, and automatically segmenting the disc and cup in fundus images is also time consuming.

Extracting the optic disc region of interest(ROI) will produce a smaller initial image which takes much lesser time taken to process compared to segmenting disc and cup[11]. In this paper, we consider the image as the input of the proposed deep Convolutional Neural Network (CNN). For glaucoma detection, the disease pattern in DFIs is complex and hidden, which is different from the natural scene images. The analysis task of natural scene images are related to object detection of regions that has an obvious visual appearance (e.g. texture, shape or color). But glaucoma disease patterns could be only observed by the training and expertise of the examiner. Deep learning (DL) is an active research topic which learns discriminative representations of data. The DL architectures are formed by the composition of multiple linear and non-linear transformations of the data, with the goal of yielding more abstract and ultimately more useful representations [11]. Convolutional neural networks (CNNs) are deep learning architectures, are recently been employed successfully for image segmentation and classification tasks [12][13][14]. DL architectures are an evolution of multilayer neural networks(NN), involving different design and training strategies to make them competitive. These strategies include spatial invariance, hierarchical feature learning and scalability [13].In this paper, effectively capturing the deep features of glaucoma based on deep CNN is our main interest. Therefore, we are motivated to propose a deep learning framework for capturing the discriminative features that better characterize the hidden patterns related to glaucoma. The adopted DL structure consists of Ten layers:Six convolutional layers and Four fully-connected layers, which infers a hierarchical representation of images to discriminate between glaucoma and non-glaucoma patterns for diagnostic decisions. In addition, to reduce the overfitting problem, we adopt response-normalization layers and overlapping-pooling layers. In order to further boost the performance, dropout and data augmentation strategies are also adopted in the proposed DL architecture.This paper is organized as

follows. In Section I, we have given an introduction of the background and motivation for the method. In Section II, we introduce the overview of the deep learning architecture. In Section III, we introduce the glaucoma classification based on CNN. Section IV shows the experimental results, followed by the conclusions in the last section.

II. OVERVIEW OF THE DEEP LEARNING ARCHITECTURE

In this paper, the proposed deep learning architecture is based on CNN. As shown in Fig.1 the net of CNN contains Ten layers with weights: the Six are convolutional and the remaining Four are fully connected. The output of the last fully-connected layer is fed to a soft-max classifier for glaucoma prediction. Response-normalization layers and overlapping layers are employed in our proposed learning architecture as in [15].

A. Convolutional Layers

Convolutional layers are usually employed to learn small feature detectors based on patches randomly sampled from an image. A feature in the image at some location can be calculated by convolving the feature detector and the image at that location.

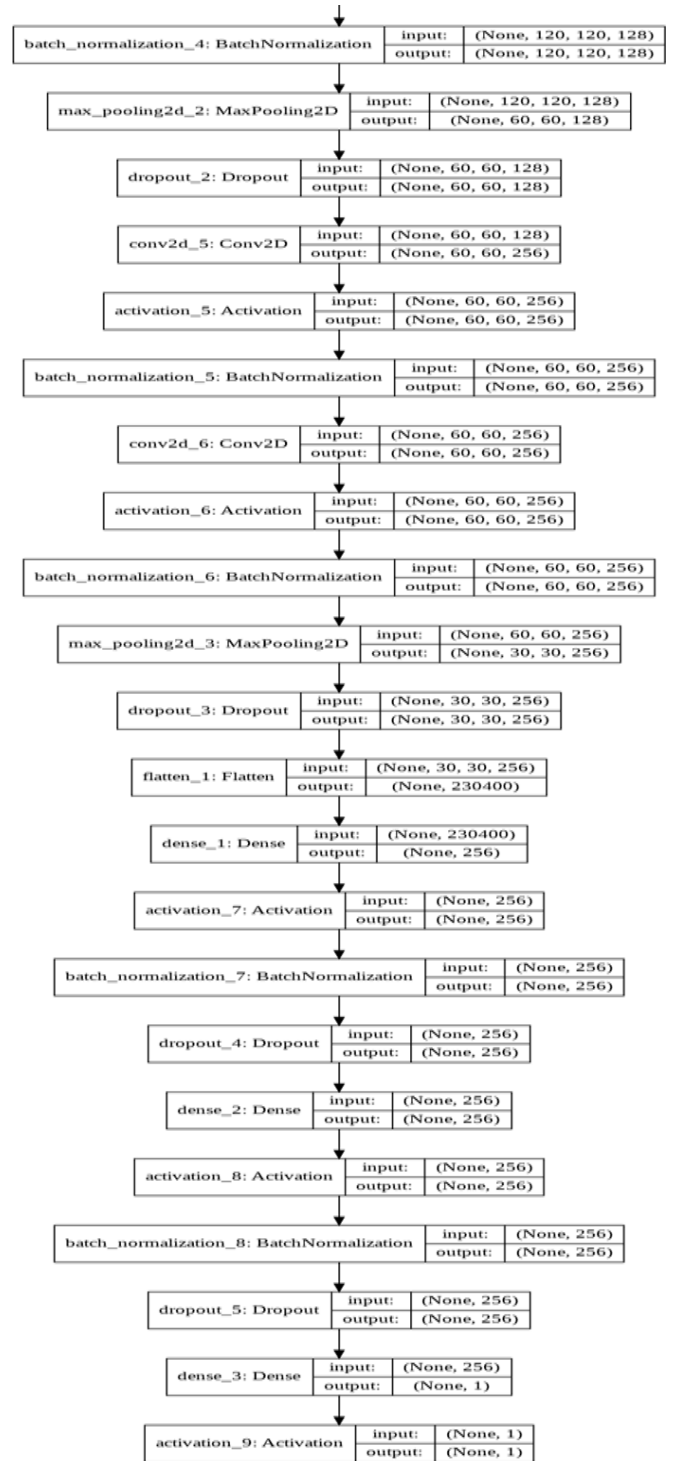
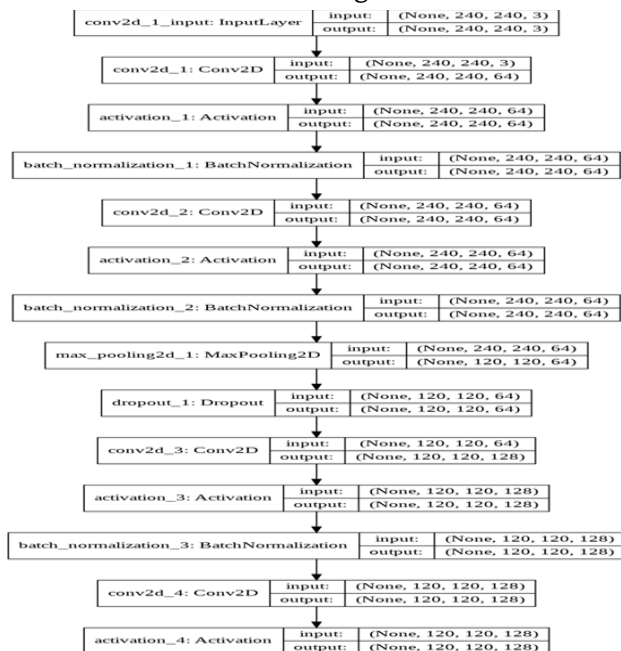


Fig. 1. Model summary

III. EXPERIMENTS

To evaluate the glaucoma diagnosis performance of our

Evaluation Criteria

In this work, we utilize the area under the curve (AUC) of receiver operation characteristic curve

(ROC) to evaluate the performance of glaucoma diagnosis. The ROC is plotted as a curve which shows the tradeoff between sensitivity TPR (true positive rate) and specificity TNR (true negative rate), defined as

Experimental Setup

We adopt the same settings of the experiments for glaucoma diagnosis in [19] in this work to facilitate comparisons. The Kims hospital dataset with clinical glaucoma diagnoses, is comprised of 467 glaucoma and 467 normal fundus images.

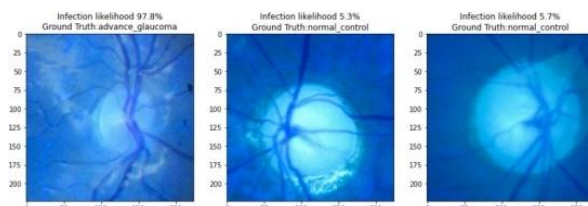


Fig. 2. Sample diagnosis results from our proposed algorithm for glaucoma detection. Each fundus image is diagnosed by clinicians and the predicted labels with probabilities by our algorithm.

C. Experimental Results

In order to validate the effectiveness of our deep CNN on glaucoma diagnosis accuracy, we compare the predictions of CNN to state-of-the-art reconstruction-based method [19]. For ORIGA dataset, we adopt the same setting of [19]. The training set contains a random selection of 100 images from the whole 650 images, and the remaining 550 images are used for testing. The AUC values of our method on ORIGA are 0.831. For the state-of-the-art reconstruction-based method, the AUC values are 0.823. In addition, Fig. 2 gives Three sample results by our proposed algorithm. Each fundus image is diagnosed by clinicians and the predicted labels with probabilities by our algorithm.

IV. CONCLUSION

In this paper, we presenting a DL framework for Glaucoma detection based on CNN, CNN is used to capture the Discriminative features that better characterize the hidden patterns to glaucoma. We are adopted DL structure conatins Ten layers:Six convolutional layers and Four fully connected layers. To reduce the overfitting problem, we adpot response-normalzation layers and over lapping-pooling layers. In order to further boost the performance, dropout and data augmentation strategies are utilized in the proposed deep CNN.

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VI. REFERENCES

- [1]. J. Flammer and E. Meier, Glaucoma: A Guide for Patients : an Introduction for Care-providers : a Quick Reference, Hogrefe & Huber, 2003.
- [2]. Quigley, H.A., Broman, A.T., The number of people with glaucoma worldwide in 2010 and 2020., In: Ophthalmol 2006.
- [3]. Chethan Kumar N. S., Dr.Somashekar K., Image Processing Techniques for Automatic Detection of Glaucoma -A Study, International Journal of Latest Technology in Engineering, Management Applied Science Volume VI, Issue VII, July 2017 ISSN 2278-2540.
- [4]. C. Patel and M. I. Patel, "Analysis of CDR of Fundus Images for Glaucoma Detection," 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, 2018, pp. 1071-1074.,doi: 10.1109/ICOEI.2018.8553707.
- [5]. Michael, D., Hancox, O. D., Optic disc size, an important consideration in the glaucoma evaluation.,In: Clinical Eye and Vision Care 1999.

- [6]. Harizman, N., Oliveira, C., Chiang, A., Tello, C., Marmor, M., Ritch, R., Liebmann, J. M., The isn't rule and differentiation of normal from glaucomatous eyes.,In: Arch Ophthalmol 2006.
- [7]. Jonas, J.B, Fernandez, M.C, Naumann, G.O, Glaucomatous para- papillary atrophy occurrence and correlations.,In: Arch Ophthalmol 1992.
- [8]. Wong, D.W.K, Lim, J.H, Tan, N.M, Zhang, Z, Lu, S, Li, H, Teo, M, Chan, K, Wong, T.Y, Intelligent Fusion of Cup-to-Disc Ratio Determination Methods for Glaucoma Detection in ARGALI.,In: Int. Conf. Engin. in Med. and Biol. Soc., pp. 57775780 (2009)
- [9]. Xu, Y, Xu, D, Lin, S, Liu, J, Cheng, J, Cheung, C.Y, Aung, T, Wong, T.Y Sliding Window and Regression based Cup Detection in Digital Fundus Images for Glaucoma Diagnosis.,In: MICCAI 2011
- [10]. Xu, Y, Liu, J, Lin, S, Xu, D, Cheung C.Y, Aung, T, Wong, T.Y, Efficient Optic Cup Detection from Intra-image Learning with Retinal Structure Priors.,In : MICCAI 2012
- [11]. Zhang, Z, Lee, B.H, Liu, J, Wong, D.W.K, TAN N.M, Lim, J.H, Yin, F.S, J.H, Huang, W.M, Li, H Optic disc region of interest localization in fundus image for glaucoma detection in argali.,In: Proc. of Int. Conf. on Industrial Electronics Applications, pp. 1686 1689 (2010)
- [12]. Krizhevsky, A, et al. Imagenet classification with deep convolutional neural networks.,In: NIPS 2012
- [13]. Bengio, Y, et al. Representation learning: A review and new perspectives.,In: Arxiv 2012
- [14]. Le, Q.V, et al. Building high-level features using large scale unsuper- vised learning.,In: ICML 2011
- [15]. Krizhevsky, A, et al. Imagenet classification with deep convolutional neural networks.,In: NIPS 2012
- [16]. Liu, J, Wong, D. W. K, Lim, J. H, Li, H, Tan, N. M, Zhang, Z, Wong, T. Y, Lavanya, R, ARGALI: An automatic cup-to-disc ratio measurement system for glaucoma analysis using level-set image pro- cessing.,In: 13th International Conference on Biomedical Engineering (ICBME) 2008
- [17]. Hinton, G.E, Srivastava, N, Krizhevsky, A, Sutskever, I, Salakhutdinov, R.R, Improving neural networks by preventing co-adaptation of feature detectors.,In: NIPS 2012
- [18]. Ciresan, D.C, Meier, U, Masci, J, Gambardella, L.M, Schmidhuber, J, High-performance neural networks for visual object classifica- tion.,In: Arxiv 2011
- [19]. Xu, Y, Lin, S, Wong, T.Y, Liu, J, Xu, D, Efficient Reconstruction- Based Optic Cup Localization for Glaucoma Screening.,In: MICCAI