Harnessing Deep Learning for Early Glaucoma Detection: A Review of CNN-Based Diagnostic Models

Yusen Shi[1]

[1] School of Mechanical, Electrical & Information Engineering, Shandong University at Weihai, 264209 WeiHai, CHINA
systematic787@gmail.com

Abstract. One of the leading causes of permanent blindness worldwide is glaucoma. It now affects over 81 million individuals and is projected to harm 112 million people by 2040. Because symptoms are often asymptomatic in the early stages, many cases are severe when detected, resulting in vision loss and reduced quality of life. Digital fundus photography and non-contact fundus scanning are important tools for early diagnosis by providing detailed images of the eye and optic nerve. Public datasets such as ACRIMA, ORIGA, and REFUGE are widely used in the development of automated screening tools. This article reviews deep learning-based glaucoma detection method, particularly through the use of convolutional neural networks(CNN). Researchers have developed various models, such as 3-LbNets, 2s-ranking CNN, transfer learning-based models and models introducing attention modules to improve diagnostic accuracy. Glaucoma diagnosis relies on optic disc and cup segmentation and feature extraction. Success requires enough training data and medical knowledge. Despite the excellent performance of deep learning in retinal disease diagnosis, clinical applications still face challenges such as data volume, interpretability, and validation requirements. In order to achieve more precise and effective glaucoma diagnosis, future work should concentrate on strengthening data quality, improving model interpretability, and developing validation processes.

Keywords: Deep learning, Glaucoma detection, Fundus image, Cup–disc ratio.

1 Introduction

Glaucoma is a globally prevalent condition that causes irreversible blindness. Visual impairment reduces quality of life, resulting in reduced income, reduced mobility, and increased dependence on others. Because early-stage glaucoma frequently exhibits no symptoms, the condition is typically identified too late [1]. Even ophthalmology professionals often have difficulty diagnosing the disease in its early stages [2]. In developed countries, about half of glaucoma cases are detected, while in developing countries, this proportion may be only 5% to 10% [3].

Glaucoma is a condition affecting the eyes that is marked by the loss of vision. This is mostly caused by damage to the optic nerve. It is the primary factor

© The Author(s) 2024
Y. Wang (ed.), *Proceedings of the 2024 International Conference on Artificial Intelligence and Communication (ICAIC 2024)*, Advances in Intelligent Systems Research 185,
https://doi.org/10.2991/978-94-6463-512-6_49

responsible for irreversible vision impairment and the second most widespread cause of blindness worldwide, following cataracts. Glaucoma encompasses several forms, and there are variations in the occurrence and types of glaucoma across different races and areas. Typical types include acute angle-closure glaucoma, pediatric glaucoma and chronic open-angle glaucoma. Primary open-angle glaucoma is the predominant kind of glaucoma. The reason is the drainage angle of the eye. Intraocular pressure rises as a result of the decreased effectiveness, while the outward expansion of the iris obstructing the drainage angle causes the angle-closure type, resulting in a sudden increase in intraocular pressure [4]. Understanding these categories is critical for proper diagnosis and treatment. Preventing blindness and visual impairment is mostly dependent on early detection and treatment.

The utilization of deep learning technology is becoming more common in the medical domain due to the advancements in artificial intelligence, especially in the early prediction, diagnosis and identification of diseases, showing great potential. Glaucoma is a common blinding eye disease. If detected and intervened early, the risk of vision loss can be greatly reduced. By analyzing large amounts of eye images and related data, deep learning technology can identify early signs of glaucoma and provide highly accurate diagnostic assistance. In particular, convolutional neural networks (CNN) can automatically detect changes in the optic disc, which not only increases diagnostic accuracy but also drastically lessens ophthalmologists' burden. Deep learning has become a powerful tool in the prediction, diagnosis and monitoring of glaucoma, which has greatly promoted the progress of glaucoma diagnosis and treatment.

2 Image capture methods and data sets

Digital fundus imaging is a valuable and easily accessible method for identifying glaucoma. It provides a comprehensive view of the eye and the optic nerve head, allowing for the detection of structural anomalies that may indicate the presence of glaucoma. Fig. 1 presents a comprehensive description of the dimensions, form, and hue of crucial retinal areas.

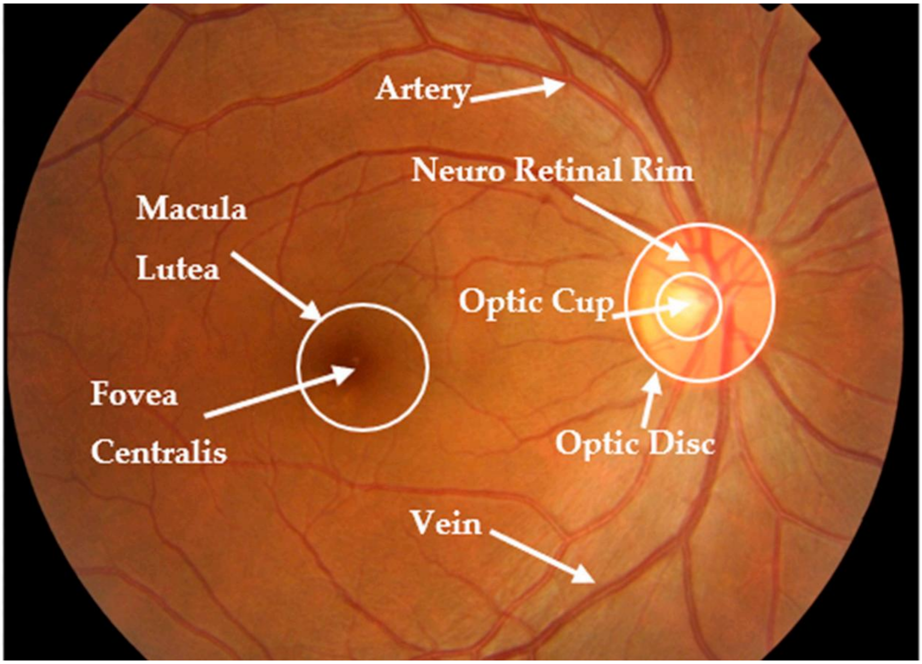

Fig. 1. Detailed description of retina[5].

2.1 Obtain fundus photos

Common ways to obtain images include the following: Fundus photography: Use a professional fundus camera or digital camera to capture fundus images through a photography lens. Fundus scanning: Use a non-contact fundus scanner, such as OCT (optical coherence tomography) or SLO (scanning laser fundus microscope), to obtain cross-sectional images of fundus structures through optical imaging technology.

2.2 Retinal Fundus Image Dataset

Many publicly available datasets, such as clinical information from glaucoma patients, retinal images, and optical coherence tomography (OCT), are freely available for use in order to raise the glaucoma diagnosis's accuracy. These databases frequently include extra details regarding the location and degree of glaucoma-related retinal damage. This makes it easier to create and assess automated glaucoma screening instruments. Additionally, by utilizing these data, glaucoma can be detected early and new techniques for glaucoma detection can be developed. Public datasets are now a valuable resource for academics, doctors, and medical professionals as a result. Table 1 shows the contents of some data sets. They are usually divided into two or more groups, and some are also divided into data for training and testing. ACRIMA, RIM-ONE and ORIGA are commonly used data sets in articles.

Table 1. Fundus image data set for glaucoma diagnosis.

Dataset	Images's Num	Glaucoma	Normal	Size
ACRIMA	705	396	309	-
ORIGA	650	168	482	3072×2048
REFUGE	1200	120	1080	2124×2056 1634×1634
RIM-ONE-r1	169	51	118	-
LAG	5824	2392	3432	3456×5184
GlauCUTU				
RIM-ONE-r2	455	200	255	-
PAPILA	488	155	333	2576×1934
DRISHTI-GS1	101	70	31	2896×1944
RIM-ONE-r3	159	74	85	2144×1424
SCES	1676	46	1630	3072×2048
RIM-ONE-DL[6]	485	172	313	-
ESOGU	4725	320	4405	-

3 Glaucoma Test

Deep learning models have mostly focused on convolutional neural networks (CNNs), which have dominated the field of study. CNN has achieved high accuracy in glaucoma detection, but different shooting equipment and lighting methods are likely to cause differences in the accuracy of the results.

3.1 Research on early diagnosis model of glaucoma

One of the main causes of permanent visual loss in the world is glaucoma. To address this challenge, researchers have been working on developing various deep learning models. These models aim to identify and diagnose glaucoma early by analyzing fundus images, thereby improving the timeliness and effectiveness of treatment. By leveraging advanced artificial intelligence technology, researchers hope to enable more accurate and faster diagnoses to reduce vision loss from glaucoma worldwide and improve patients' quality of life. Continued advances in this field not only aid medical professionals in their diagnostic efforts but also provide patients with better care and treatment options. The experimental results of glaucoma diagnosis based on deep learning are listed in Table 2.

A screening three-label deep convolutional neural network (3-LbNets) was created by Puangarom et al. [7], focusing on the relationship between classes using different labels and updating a single network. to distinguish between cases of glaucoma, cases suspected of glaucoma, and non-glaucoma cases in worldwide fundus pictures. 3-LbNets is an ANN that integrates key elements from three distinct labeling patterns. Furthermore, it performs well on Grad-CAM++ graphs.

Kim et al. [8] proposed a 2s-ranking CNN to sort fundus photos into three categories: glaucoma, suspicious, and normal. They use a mask filter made of a class activating map and mixed it with the initial fundus photos as a middle input, especially to improve the sensitivity of suspected glaucoma.

Compared with reconstructing the original model, using the existing model for transfer learning is also an effective way. Partibane et al.'s technique [9] utilizes three transfer learning-based methods to promptly identify glaucoma, pre-trained convolutional neural networks (CNNs) are utilised. GoogLeNet, VGG16Net, and ResNet50 make up the network structure. Applying convolutional neural networks to preprocessed retinal fundus images obtained from both public and private sources allows the method to retrieve data. After the characteristics are extracted, the classifier receives them as input, which uses a maximum voting technique to classify the image as normal or abnormal.

Table 2. Comparison of glaucoma diagnostic performance.

Cite	Dataset	ACC(%)	SPE(%)	SEN(%)	AUC
Puangarom et al.	GlauCUTU	92.71	90.68	84.88	0.975
Kim et al.	Private	96.46	96.00	97.56	-
Partibane et al.	HRF, PSGIMSR, DRIONS-DB, DRISHTI-GS	98.0	95.5	81.3	-

3.2 Optic Disc/Optic Cup Segmentation

An important feature used to diagnose glaucoma is the optic disc. The horizontal cup area divided by the horizontal disc area yields the cup-to-disk ratio. Therefore, proper OD/OC segmentation is super important for diagnosing glaucoma. Considering this aspect, a deep CNN, also known as a framework called the Glaucoma Network was proposed by Juneja et al. [10]. Additionally, G-Net employs the U-Net architecture in which two CNNs collaborate to segment OD and OC. The input image has undergone preprocessing and cropping. All channels are applied to separate OC, only one channel (RED) is used for OD segmentation. Then, an encoder-decoder model was presented by Bengani et al. [11] to segment the optic disc in retinal fundus pictures using transfer learning and semi-supervised techniques. Autoencoders recreate the input images and obtain features from unlabeled photos, rely on network constraints. Transfer learning techniques are used to convert pre-trained models into segmentation networks and fine-tune them with real labels.

The attention mechanism is a technology that imitates the human visual attention process. It can help the model focus on the important parts and ignore irrelevant information when processing sequence data. Based on this feature, Hu et al. [12] presented an attention-based network. To overcome the challenges created by diverse acquisition devices. The segmentation network is encoder-decoder based and consists of a strongly linked depth-separable convolution module and a weight shared module. Situated on the uppermost layer of the encoder, the weight shared attention module integrates OC and OD feature data via spatial attention and channel attention processes. Finally, the depthwise separable convolution module is the network's output layer. In addition, in order to enhance the performance of small-area fundus picture segmentation, which fully utilizes contextual information, A novel semantic segmentation model of the aggregated channel attention network was presented by BaiXin Jin et al. [13]. The model applies an encoder-decoder architecture, with feature data from multiple resolutions in the decoding layer and pre-trained DenseNet sub-models in the encod layers, which is then merged with the attention mechanism. To further increase network efficiency, the dice coefficient and cross-entropy are combined. The network's performance in small-area segmentation has improved. Cross-entropy information is also used to reinforce the classification framework. Table 3 shows the performance comparison of OD/OC segmentation of different networks.

Table 3. OD/OC segmentation comparison

Cite	Dataset	OD/OC	ACC(%)	SPE(%)	SEN(%)	DSC
Juneja et al.	DRISHTI-GS	OD	95.5	-	-	-
		OC	94.7	-	-	-
Bengani et al.	DRISHTI GS1	OD	99.6	99.9	95.4	-
	RIM-ONE	OD	99.5	99.8	87.3	-
Hu et al.	REFUGE	OD	-	-	-	0.96
		OC	-	-	-	0.89
	RIM-ONE-r3	OD	-	-	-	0.95
		OC	-	-	-	0.82
	DRISHTI-GS	OD	-	-	-	0.97
		OC	-	-	-	0.90
	MESSIDOR	OD	-	-	-	0.97
	IDRiD	OD	-	-	-	0.96

4 Suggestions

To analyze the retina, researchers typically use a variety of methods depending on the goals of the study and the technique proposed. Target region improvement, localization, segmentation, or classification are possible research objectives. The tasks of localization, segmentation, and improvement are often concealed procedures in the classification module. The most important feature, extraction and classification are necessary for a glaucoma diagnosis system, for this, a few recommendations have been made: Ample training data is necessary to generate high-accuracy systems, Furthermore, in some cases, loss functions can be introduced to minimize overfitting. Medical knowledge is incredibly effective in figuring out the fundamental causes of conditions. Preprocessing holds significant importance in order to ensure an efficient analysis.

5 Conclusion

Computer vision and digital image processing techniques are widely employed in healthcare for illness diagnosis and screening. Irreversible vision loss can occur as a consequence of optic nerve damage caused by chronic glaucoma. For medical image analysis, color fundus imaging is essential, and automated diagnostic systems have undergone substantial research on deep learning models. This evaluation looks at a number of publicly accessible datasets and highlights their features. While certain datasets include high-quality pictures captured in controlled environments, others consist of images shot in diverse situations, hence enhancing the applicability of deep models in real-world scenarios. Several datasets combined can aid in the training of reliable models appropriate for practical clinical situations.

Various deep learning architectures have been employed in research for classification and segmentation tasks, incorporating ensemble learning and transfer learning techniques to enhance performance. Deep learning methods have shown exceptional capabilities in diagnosing retinal diseases, sometimes surpassing expert diagnoses. However, clinical application of deep learning models faces challenges due to data volume limitations, interpretability requirements, validation demands, and the need to establish trust.

References

1. Weinreb, R. N., Aung, T., Medeiros, F. A.: The Pathophysiology and Treatment of Glaucoma: A Review. JAMA 311, 1901–1911 (2014)
2. Wong, E. Y., Keeffe, J. E., Rait, J. L., et al.: Detection of Undiagnosed Glaucoma by Eye Health Professionals. Ophthalmology 111, 1508–1514 (2004)
3. Quigley, H. A.: Number of People with Glaucoma Worldwide. Br J Ophthalmol 80, 389–393 (1996)

4. Afroze, T., Akther, S., Chowdhury, M. A.: Glaucoma Detection Using Inception Convolutional Neural Network V3. Communications in Computer and Information Science 1435, 17–28 (2021)
5. Zedan, M.J.M., Zulkifley, M.A., Ibrahim, A.A.: Automated GlaucomaScreening and Diagnosis Based onRetinal Fundus Images Using DeepLearning Approaches: AComprehensive Review. Diagnostics2023, 13, 2180 (2023)
6. Fumero Batista, F. J., Diaz-Aleman, T., Sigut, J., Alayon, S., Arnay, R., & Angel-Pereira, D.: RIM-ONE DL: A Unified Retinal Image Database for Assessing Glaucoma Using Deep Learning. Image Analysis and Stereology 39(3), 161–167 (2020)
7. S. Puangarom et al., "3-LbNets: Tri-Labeling Deep Convolutional Neural Network for the Automated Screening of Glaucoma, Glaucoma Suspect, and No Glaucoma in Fundus Images," 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, pp. 1-5 (2023)
8. Jun, T. J., Kim, D., Nguyen, H. M., Kim, D., Eom, Y.: 2sRanking-CNN: A 2-Stage Ranking-CNN for Diagnosis of Glaucoma from Fundus Images Using CAM-Extracted ROI as an Intermediate Input. arXiv. https://arxiv.org/abs/1805.05727 (2018)
9. Joshi, S., Partibane, B., Hatamleh, W. A., Tarazi, H., Yadav, C. S., Krah, D.: Glaucoma Detection Using Image Processing and Supervised Learning for Classification. Healthc. Eng. (2022)
10. Juneja, M., Singh, S., Agarwal, N., Bali, S., Gupta, S., Thakur, N., Jindal, P.: Automated Detection of Glaucoma Using Deep Learning Convolution Network (G-Net). Multimed Tools Appl. 79, 15531–15553 (2020)
11. Bengani, S., Arul, A., Vadivel, S.: Automatic Segmentation of Optic Disc in Retinal Fundus Images Using Semi-Supervised Deep Learning. Multimed Tools Appl 80, 3443–3468 (2020)
12. Hu, Q. I. Z., Hen, X. I. C., Eng, Q. I. M., Iahuan, et al.: GDCSeg-Net: General Optic Disc and Cup Segmentation Network for Multi-Device Fundus Images. Biomed. Opt. Express 12, 6529–6544 (2021)
13. Jin, B., Liu, P., Wang, P., Shi, L., Zhao, J.: Optic Disc Segmentation Using Attention-Based U-Net and the Improved Cross-Entropy Convolutional Neural Network. Entropy 22, 844 (2020)

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.