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A COMPREHENSIVE REVIEW FOCUSING ON THE SEGMENTATION OF THE OPTIC DISC IN FUNDUS IMAGES

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ABSTRACT

Optic Disc (OD) segmentation is a computer vision task that involves identifying and delineating the OD region in retinal images. Analyzing the retinal fundus images often involves various image processing and analysis techniques. For instance, OD segmentation is performed to identify the location of the OD. The accurate segmentation of the OD has numerous applications in ophthalmology, including the analysis of retinal images for disease detection, tracking disease progression, and assessing treatment effectiveness. It plays a crucial role in monitoring eye diseases, diagnosing and assisting healthcare professionals thus providing efficient and reliable care to patients. This paper reveals the latest techniques in OD segmentation and its characteristics which reflect positively in today's ophthalmology world.

Keywords: Optic Disc, Fundus Image, Segmentation, Medical Imagining.

1. INTRODUCTION

Medical imaging encompasses a broad range of technologies and techniques used to create visual representations of the internal structures and functions of the human body. These methods are essential in the field of modern medicine, as they enable healthcare professionals to accurately detect, diagnose, and monitor various medical conditions without the need for invasive procedures. By offering detailed and precise visual information, medical imaging significantly enhances the effectiveness of both diagnostic evaluations and treatment planning, contributing to improved patient outcomes [1].

One important application of medical imaging is in ophthalmology, where retina fundus imaging plays a vital role. Fundus images are high-resolution, color photographs of the interior surface of the eye, particularly the retina. These images are obtained using a specialized technique known as fundus photography, which involves the use of a fundus camera designed to capture a wide-angle view of the retina. During this non-invasive procedure, the patient's pupil is typically dilated using special eye drops to allow a clearer view of the back of the eye. A bright flash of light is then used to illuminate the retina, enabling the camera to capture detailed images.

Retina fundus images [2] provide crucial insights into the health and condition of the retina and are widely used in the diagnosis and management of various eye diseases such as Diabetic Retinopathy (DR), Age-related Macular Degeneration (AMD), Glaucoma, and Hypertensive Retinopathy. These images reveal important anatomical structures, including the Optic Disc (OD), which is the point where the optic nerve enters the retina; the macula, responsible for central vision; the network of retinal blood vessels; and the layered structure of the retina itself. Because of their ability to capture subtle changes and abnormalities in these structures, fundus images are invaluable tools in early disease detection, continuous monitoring, and treatment assessment in clinical practice. Figure 1 exposes the Retinal Fundus Image from Kaggle dataset.

Fig. 1. Retinal Fundus Image from Kaggle dataset

OD segmentation [3] is a critical component in Computer-Aided Diagnosis (CAD) systems, particularly in the field of ophthalmology. The optic disc, also referred to as the optic nerve head, is a circular or slightly oval-shaped region located in the retina where the optic nerve fibers exit the eye to transmit visual information to the brain. It also serves as the point from which major blood vessels originate and spread across the retina. Accurate segmentation of the optic disc is essential for the diagnosis and monitoring of various eye diseases, including Glaucoma, DR, and Optic neuropathies, as changes in the size, shape, or appearance of the OD can be key indicators of these conditions.

In recent years, significant progress has been made in the development of automated OD segmentation techniques, particularly through the application of advanced machine learning approaches. Among these, Fuzzy Broad Learning Systems and Deep Learning (DL) methods have demonstrated impressive capabilities. DL models, especially those based on Convolutional Neural Networks (CNNs), have become increasingly popular due to their ability to automatically learn and extract hierarchical features from large datasets of retinal images. These models are typically trained on annotated datasets in which human experts manually delineate the boundaries of the OD, providing ground truth labels for supervised learning. The annotated data enables the models to learn the complex visual patterns and variations associated with the OD across different individuals and imaging conditions. As a result, these methods have achieved high accuracy and robustness in OD segmentation tasks, paving the way for their integration into real-world diagnostic systems and enhancing the efficiency and reliability of retinal disease screening and management.

2. LATEST TECHNIQUES IN OD SEGMENTATION

Wang et al. [4] developed a coarse-to-fine DL framework based on the U-net model of a traditional Convolutional Neural Network (CNN) to precisely identify the OD. The segmentation findings from the full image were divided into two different groups after this network was trained independently on the grayscale vessel density maps and color fundus images. In order to find a local image patch which means disc candidate region, it aggregated the results using an overlap technique. This patch was then input into the U-net model for additional segmentation. DIARETDB0, DIARETDB1, DRISONS-DB, DRIVE, ORIGA, and MESSIDOR datasets are used in this approach. The segmentation performance achieved by the given framework was largely trustworthy. The shortcoming of this approach is the involvement of only low resolution images for this analysis and the ground truth for the OD not identified precisely in color fundus images.

Liu et al. [5] offered an approach for segmenting the joint OD and Optic Cup (OC) images using semi-supervised conditional Generative Adversarial Networks (GANs). In order to learn a mapping between the fundus images and the associated segmentation maps, this technique comprises of segmentation net, a generator, and a discriminator. Here, used labeled and unlabeled data to boost segmentation performance. The ORIGA and REFUGE datasets are used in this technique. This approach worthiness is the pseudo segmentation maps which aid the framework in learning the p(x, y) more precisely. The imperfection of this approach is evaluated only two datasets.

Dietter et al. [6] presented a technique for detecting and segmenting OD that can handle significant technological artifacts. It's a two-stage methodology to localize and then segment the border of the OD, building on two published methods. The vessel orientation and brightness is used to locate the centre of the OD. The maximum value of the scoring function denotes the pixel with the best OD-border-like structure surrounding it. This technique is used six datasets namely, STARE, DRIVE, MESSIDOR, DIARETDB1, and HRF. The mastery of this technique is the presence of these technological artifacts, it detects the OD accurately. The scoring function's penalty term provides the best border around a candidate OD-center. The detriment of this scheme is that it extends the basic scoring function to the x-position, where having only structure or intensity information produces unfavourable outcomes.

Ramani et al. [7] evaluated enhanced image processing techniques, automatic OD identification and segmentation is made possible. The approach is divided into four stages, including Image Pre-processing, OD Localization, OD Segmentation, and Performance Evaluation, each of which has a distinct set of operations that must be carried out. A variety of image processing approaches were used to enhance OD segmentation accuracy and OD localization performance. The detection of Glaucoma disease depends significantly on the accuracy of OD segmentation. DRIONS-DB, CHASE-DB1, HRF, DRISHTI-GS1, ONHSD, DRIVE, MESSIDOR, and INSPIRE datasets are used in this approach. The quality of this method is its less computation time. The limitation of this method is the less disc localization performance in the messidor dataset.

Pruthi et al. [8] evaluated an automated bio-inspired OC segmentation technique is used for the glaucoma diagnosis system. In order to do this, the glowworm swarm optimization algorithm has been used and evaluated against other methods such as thresholding-based, ellipse-based, and ant colony optimization algorithm. Herein, STARE, RIM-ONE, DRIONS-DB, DRIVE, and DIARETDB1 datasets are used in this technique. The positive side of this technique is achieves the highest F-score and the shortest boundary distance in each situation. The negative side of this technique is cup to disc ratio is not calculated thus leading to high time consumption.

Bian et al. [9] established a deep neural network that accurately separates the OC and the OD in a retinal fundus image to determine the Cup-to-Disc Ratio (CDR). This network makes use of anatomical knowledge to drive segmentation of fundus images. In biomedical imaging, OD and OC segmentation are typical small target segmentation issues. This approach is an attention-based cascade network to precisely reserve the precise outlines of small targets and efficiently expedite the convergence of small target segmentation during training. REFUGE and Origa650 dataset are used in this approach. The worthiness of this approach is less time consumption. The imperfection of this approach is the second stage won't be able to fully benefit from our model if the segmentation of the OC is completely incorrect.

Wang et al. [10] described a DL network that can recognize OD areas automatically. Here, defined a special sub-network and a decoding convolutional block based on the traditional U-Net framework. The decoding block is utilized to increase the contrast between the regions-of-interest and their background, while the sub-network is utilized to preserve significant textures and facilitate their recognition. MESSIDOR, REFUGE, and ORIGA datasets are used in this methodology. The uprightness of this methodology is to increase the OD regions accurate and reliable segmentation on color fundus images. The disfavor of this method is it segmented only the fundus OD regions.

Fu et al. [11] exposed a model-driven probability bubble methodology is used with a U-net to automatically segment abnormal fundus images. The localization result is fused into the output layer of U-net by computing the joint probability, and the probability bubble is conceived according to the position relationship between retinal vessels and OD. The Kaggle, MESSIDOR, and NIVE datasets is used in the methodology. The impressive of this technique is to accurately locate the OD region and successfully eliminate the distractions of massive bright lesions. The failure of this method is its model design is ineffective.

Veena et al. [12] established the segmentation of OD and OC for the automated identification of glaucoma. Here, the DL architecture method with an improved version of the two CNN models for OD and OC separately produces an accurate segmentation result. More image features can be recovered by multiplying the layers in both the CNN models. In order to maintain the image resolution in the output image, up-sampling and down-sampling layers are primarily used. The DRISHTI-GS database is used to trained and tested this method. The positive side is multiple medical image segmentation applications can use this unique methodology. This negative side is quite time-consuming.

Lei et al. [13] enhanced an unsupervised domain adaptation based image synthesis and feature alignment for OD and OC segmentation using the retinal fundus images. To solve the domain shift problem, target-like query images are acquired using the GAN-based Image Synthesis (IS) method using boundary data from the OD and OC. These images act as an intermediary latent space between source domain and target domain images. To achieve feature consistency among target domain images, target-like query images, and target domain images in particular, users adopt Content and Style Feature Alignment (CSFA). Domain-invariant features are extracted using adversarial learning for Output-Level Feature Alignment (OLFA). The strategy is trained in REFUGE dataset and evaluated on the Drishti-GS and RIM-ONE r3 datasets. The worthiness of this approach is it performs better when adapting to limited datasets. The shortcoming of this approach is the high time and computational complexity of the training network. The quality of the image synthesis affects the feature alignment and adversarial learning.

Liu et al. [14] provided a DL approach that leverages adversarial learning to improve the segmentation accuracy of both the OD and OC in retinal images. The use of a discriminator network encourages the generator to produce more realistic and accurate segmentations by refining boundary details. Drishti-GS and REFUGE datasets are used in this method. A key merit of this method is its ability to handle complex variations in retinal structures and improve segmentation consistency. However, the use of adversarial training increases model complexity and may introduce instability during training. Despite this, the model demonstrates strong performance and is promising for enhancing automated glaucoma screening systems.

Zedan et al. [15] presented a deep learning-based model designed to improve segmentation accuracy of the OD and OC in retinal images. By integrating residual multiscale feature extraction and hybrid attention mechanisms, the model effectively captures both local and global contextual information, leading to enhanced segmentation performance. Drishti-GS, ORIGA, PAPILA, Chaksu, REFUGE, and Ibn Al-Haitham datasets are used in this method. A key merit of RMHA-Net is its high accuracy and robustness across varied datasets due to its powerful feature learning capabilities. However, the model's complex architecture results in high computational cost and longer training times, which may limit its practicality in low-resource clinical environments. Despite these limitations, RMHA-Net shows strong potential for improving automated diagnosis in ophthalmology.

3. DISCUSSION AND ANALYSIS

This survey uses analysis metrics such as segmentation accuracy to examine the above mentioned latest OD segmentation methods. Table 1 presents an analysis based on general properties and Table 2 delves into a merits and demerits analysis.

Table 1: Analysis based on general properties

Authors	Journal	Year	Publication	Segmentation Method
Wang et al. [4]	Biomedical signal processing and control	2019	Elsevier	Coarse-to-fine U-Net CNN framework using grayscale and color fundus images
Liu et al. [5]	Computers in biology and medicine	2019	Elsevier	Semi-supervised Conditional GAN with labeled and unlabeled data
Dietter et al. [6]	Biomedical signal processing and control	2019	Elsevier	Two-stage method using vessel orientation, brightness, and scoring function
Ramani et al. [7]	Biomedical signal processing and control	2020	Elsevier	Image preprocessing and segmentation using classical image processing
Pruthi et al. [8]	Biomedical signal processing and control	2020	Elsevier	Bio-inspired OC segmentation with Glowworm Swarm Optimization
Bian et al. [9]	Computer methods and programs in biomedicine	2020	Elsevier	Attention-based cascade network with anatomical priors
Wang et al.	Pattern Recognition	2021	Elsevier	DL U-Net variant with decoding

[10]				convolutional block
Fu et al. [11]	Pattern Recognition	2021	Elsevier	Model-driven probability bubble approach with U-Net
Veena et al. [12]	Journal of king saud university computer and information science	2022	Elsevier	Dual CNN architecture with up-sampling and down-sampling layers
Lei et al. [13]	IEEE journal of biomedical and health	2022	IEEE	Unsupervised domain adaptation with GAN-based image synthesis and feature alignment
Liu et al. [14]	IEEE Access	2024	IEEE	Adversarial learning with generator-discriminator architecture
Zedan et al. [15]	IEEE Access	2025	IEEE	Coarse-to-fine U-Net CNN framework using grayscale and color fundus images

Table 2: Analysis on the Merits and Demerits

Authors	Merits	Demerits
Wang et al. [4]	Reliable segmentation results; effective use of grayscale and color fundus images	Only low-resolution images used; OD ground truth not precise in color images
Liu et al. [5]	Pseudo segmentation maps enhance learning with limited labels	Evaluated on only two datasets
Dietter et al. [6]	Robust against technological artifacts; accurate OD localization using scoring function	Limited performance when relying only on structure or intensity
Ramani et al. [7]	Less computational time; effective pre-processing and segmentation stages	Poor disc localization in the MESSIDOR dataset
Pruthi et al. [8]	High F-score and shortest boundary distance achieved	Segments only the OD region, not the OC region
Bian et al. [9]	Efficient segmentation with less time; accurate small-target segmentation	Poor second-stage performance if OC segmentation fails
Wang et al. [10]	Enhances segmentation accuracy for OD regions in color fundus images	Segments only the OD region, not the OC region
Fu et al. [11]	Accurately localizes OD and removes bright lesion interference	Ineffective model design
Veena et al. [12]	Suitable for multiple medical segmentation tasks; detailed layer structure	Time-consuming process
Lei et al. [13]	Performs well in domain adaptation with limited data	High computational cost; sensitive to image synthesis quality
Liu et al. [14]	Handles complex retinal structures well; improves segmentation consistency	Adversarial training increases model complexity and training instability
Zedan et al. [15]	Better accuracy and robust across datasets due to hybrid attention and multiscale feature extraction	High computational cost and longer training times

4. CONCLUSION

The OD segmentation is a crucial task in the analysis of retinal images for diagnosing and monitoring eye diseases. It enables clinicians to quantitatively analyze important features such as shape, disc, size, and CDR. Accurate delineation of the OD boundaries is essential for detecting conditions such as glaucoma and assessing OD-related abnormalities, etc. Traditional image processing techniques and modern DL method, and CNN have been employed to achieve accurate OD segmentation. The accuracy and effectiveness of the segmentation process can be further improved through continued improvements in OD segmentation algorithms and the use of artificial intelligence approaches.

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