Enhanced Multi-Scale Graph Networks for Glaucoma Detection in Optical Coherence Tomography

Pavithra Mani
Assistant Professor
Department of ECE
Kongu Engineering College
Erode – 638060, TamilNadu
Email: paviithra.mani@gmail.com

Archana D
Assistant Professor (Sr.Gr)
Department of ECE
PSG Institute of Technology and
Applied Research, Coimbatore, Tamil
Nadu

Email: archana@psgitech.ac.in

Sneka Varshini V
UG Scholar
Department of ECE
Kongu Engineering College
Erode – 638060, Tamil Nadu
Email:snekavarshini07@gmail.com

Sree Sakthi J UG Scholar Department of ECE Kongu Engineering College Erode – 638060, Tamil Nadu Email: ssakthijawahar@gmail.com Suhash E UG Scholar Department of ECE Kongu Engineering College Erode – 638060, Tamil Nadu Email: suhashe.22ece@kongu.edu

Abstract— Precise and automated tissue segmentation plays a vital role in diagnosing glaucoma optical coherence using ocular tomography (OCT) images. The intricate anatomical structure of the peripapillary region, combined with the existence of the optic disc, contributes to the difficulty of the task. In order to fix this challenge, we have created a cutting-edge two-stage architecture that uses a convolutional graph network (GCN) to identify both the ocular disc and nine ocular layers concurrently. This method incorporates a multifaceted spatial processing module into a U-shaped neural network, leveraging anatomical previous knowledge to strengthen spatial thinking skills. The module is placed between the encoder and decoder portions of the network. Our segmentation network achieved a Dice score of 0.850 ± 0.0012 and a pixel accuracy of 0.895 ± 0.0019 , outperforming existing state-of-theart techniques.

Keywords - Glaucoma, Tissue segmentation, Graph convolutional network, U-shaped neural network, Multi-scale global reasoning, Peripapillary region, Biomedical image processing, Dice score, Pixel accuracy

I. INTRODUCTION

Glaucoma affects over 64.3 million affects people globally and continues to be the primary cause of permanent vision loss [1]. In 2015, approximately 13.12 million individuals in China had glaucoma, with estimates suggesting this number could increase to 25.16 million by 2050 [2]. This projected rise will place significant pressure on the public health system. Early detection and effective management are critical to preventing vision loss from glaucoma. Accurate diagnosis largely depends on identifying subtle changes in retinal layers, such as thinning of the cell layer and ocular nerve fiber layer (RNFL) [3]. OCT, a non-invasive 3D imaging technology, is extensively utilized in ophthalmology clinics to assess the retina. OCT's micrometer-level axial resolution allows for the direct observation and measurement of the retina's layered structure. Peripapillary RNFL thickness, measured by OCT, is commonly used to diagnose early-stage glaucoma [4]. Hence, accurate delineation of tissue regions in retinal OCT images is crucial for efficient early detection of glaucoma. Manual segmentation requires a significant amount of time and effort, highlighting the need for an accurate automated system to benefit researchers and clinicians alike. Over the past few decades, numerous automated methods for segmenting retinal OCT images have been developed [5]. After image preprocessing, Alonso-Caneiro et al.

and Tian et al. employed graph based edge analyzers to accurately detect the choroidal margin [6]. In addition, Chiu et al. presented a segmentation technique based on kernel prediction for ocular OCT images that are impacted by macular edema caused by diabetes [7]. For instance, OCTExplorer employs a traditional graphtheory approach to extract retinal boundaries [8]. Lang et al. created an algorithm using random forests to divide macular cube images into eight retinal layers [9]. Mayer et al. introduced an energy reduction module for segmenting the surface of the ocular nerve fiber layer in OCT images [10]. This study introduces our new investigation that aims to utilize the historical data included within ocular OCT images. We affirm that the structural arrangement of all peripapillary OCT images, acquired adhering to a stringent clinical protocol, demonstrates a uniform pattern: The optic nerve head is a conspicuous anatomical feature, typically resides centrally within the image, flanked by thinner retinal layers on either side, as depicted in Fig. 1. In order to effectively utilize these existing anatomical assumptions, we have created a unique twostage network that incorporates a variable-scale graph convolutional network. This framework is specifically developed to perform simultaneous sectioning of ocular layers and the disc of optics in ocular OCT images. The methodology we employ is influenced by the technique suggested by Jamal et al., which employs graph-based representation to capture domain knowledge and structural relationships among tissues.

Experiments were conducted using a curated dataset of peripapillary OCT scans, comprising 122 B-scans from 71 patients, alongside an additional publicly available dataset, demonstrating the effectiveness of our proposed framework. Comparative evaluations with baseline methods and state-of-the-art techniques revealed superior performance across both datasets. Moving forward, our goal is to integrate this segmentation framework into diagnostic procedures aimed at early-stage glaucoma detection.

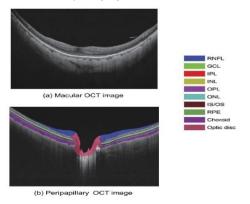


Fig 1. (a) Macular zone OCT and (b) Ocular OCT

Numerous techniques have been devised to enhance the precision and effectiveness of ocular OCT image sectioning and noise mitigation, which are crucial for early glaucoma detection. One prominent example is OCT Explorer, which uses a traditional graph-theory approach for extracting retinal boundaries [11]. Alonso-Caneiro et al. and Tian et al. employed graphbased border analyzers after image preprocessing to delineate the choroidal margin [12]. Mayer et al. initiated a reduction method to segment the surface of the layer of retinal nerve fibers in cyclic OCT images [13]. Lang et al. developed a categorization model to divide myopic cubed images into eight ocular layers. This approach significantly improved the accuracy of segmentation, as reported in their study [15]. Chiu et al. introduced a technique for segmentation based on base regression analysis specifically designed for ocular OCT images affected by macular edema caused by diabetes, proving its effectiveness in addressing complex scenarios [15].

In addition to segmentation, several noise reduction techniques have been explored. The Block-Based Autoencoder Network (BBAuto-Net) and Juneja et al.'s Bayes Shrinkage based Fused Wavelet Transform (BSbFWT) are notable methods for reducing noise in MRI images [6]. These techniques involve fusing and reconstructing wavelet transforms such as Haar, Symlet, and Daubechies, followed by applying fusion techniques to enhance image quality. The BM3D (Block Matching and 3D Filtering) algorithm by Dabov et al. is another effective denoising method that operates on the principle of collaborative filtering, grouping similar image patches for joint filtering to reduce noise [7]. Rawat et al.'s CV-CNN (Complex-Valued Convolutional Neural Network) leverages complex-valued numbers in convolutional layers to capture more intricate patterns compared to traditional CNNs [8]. Dazi Li et al.'s Structural Convolutional Neural Network (SCNN) utilizes multiple convolutional layers and a unique feature fusion process to effectively mitigate speckle noise in medical images [9]. Wang et al. introduced the HVSR (Hybrid Variation Sparse Representation) algorithm, which dissects medical images into structure, detail, and noise layers, and applies a sparse representation-based approach for enhanced denoising [10]. Lastly, Chervyakov et al. studied the impact of quantization noise on the performance of Discrete Wavelet Transforms (DWT) filters and proposed Distributed Arithmetic (DA), an efficient method for implementing mathematical operations using elementary shift and add operations, suitable for hardware implementation [11].