ISSN: 2754-4990

Journal of Ophthalmology Research Reviews & Reports

SCIENTIFIC Research and Community

Review Article

Open Access

Review of Deep Learning Applications in Myopic Choroidal OCT Segmentation

Ma Mengyao* and Bao Xiuli

Affiliated Hospital of Inner Mongolia Medical University, China

ABSTRACT

The incidence of myopia among Chinese children has been rising annually, with a notable trend towards younger onset. The choroid, a critical vascular structure for ocular homeostasis, exhibits a significant relationship between variations in its Thickness (ChT) and the pathological advancement of myopia. Optical Coherence Tomography (OCT), with its high resolution and non-invasive characteristics, has emerged as an essential instrument for assessing myopic choroidal lesions.

Automated choroidal segmentation underpins the quantitative analysis of OCT images, necessitating precise identification of Bruch's Membrane (BM) and the Choroid-Sclera Interface (CSI). Traditional manual annotation is labor-intensive and susceptible to considerable subjective bias, but Deep Learning (DL) offers a novel solution to this problem. This article evaluates the advancements in research within this domain: Among core models, Convolutional Neural Networks (CNNs) enhance boundary localization but experience spatial information loss; Fully Convolutional Networks (FCNs) facilitate end-to-end segmentation yet lack instance-level segmentation capabilities; U-Net and its variants (e.g., Bio-Net, ADU-Net) are particularly adept at addressing the attributes of medical images. Mask R-CNN attains precise pixel-level predictions and demonstrates significant clinical applicability.

In practical applications, targeting typical pathological changes such as ChT thinning, DL models enhance robustness through multi-directional optimization. Specifically, ADU-Net and GCS-Net tackle the problem of blurred boundaries, while multi-task models simultaneously perform segmentation and calculation. Comparative studies have shown that Mask R-CNN demonstrates the best performance in OCT image segmentation.

***Corresponding author**
Ma Mengyao, Affiliated Hospital of Inner Mongolia Medical University, China.

Received: September 03, 2025; **Accepted:** September 08, 2025; **Published:** September 17, 2025

Keywords: Deep Learning, Myopia, Choroid, ChT, OCT

Background

Introduction

In recent years, the incidence of myopia among youngsters in China has consistently increased, with a notable trend towards earlier start [1]. This phenomenon is manifestly apparent in clinical study data. The choroid, a dynamic structure rich in blood vessels, has thickness that correlates with the degree of vascular filling [2]. It provides blood and oxygen to the outer retina, facilitating the maintenance of ocular homeostasis. However, when the choroid's blood supply function is compromised, it frequently has a substantial adverse effect on visual function [3,4]. Consequently, the choroid is integral to the advancement of various ocular disorders [5].

A substantial corpus of research has substantiated that myopia induced by axial length elongation and the mechanical distension of the choroid and sclera, engenders modifications in choroidal vascular architecture-encompassing vascular constriction, diminished blood flow, and attenuation of the choroidal stroma and blood vessels-culminating in variations in Choroidal Thickness (ChT) [4,6-8]. Optical Coherence Tomography (OCT), utilizing its high resolution and non-invasive characteristics, facilitates the clear viewing of the choroid's laminar structures (including Bruch's membrane and the choriocapillary layer) and has consequently emerged as an essential instrument for assessing myopic choroidal diseases [9]. The automated examination of choroidal thickness in OCT images is an essential endeavor, providing quantitative, objective, and automated outcomes. To do this, the two limits of the choroid-specifically Bruch's Membrane (BM) and the Choroid-Sclera Interface (CSI)-must initially be delineated. Initially, researchers quantified ChT in EDI-OCT images solely via human boundary annotation [10,11]. This method is exceedingly time-consuming; manual delineation of the choroid becomes impractical even for extensive data sets and is susceptible to inter-observer variability. Consequently, automated choroidal segmentation is essential. In recent years, Deep Learning (DL) has made significant advancements in medical image segmentation; among its methodologies, Convolutional Neural Networks (CNN) and their derivatives (e.g., fully convolutional networks [FCN], U-Net, Mask R-CNN) are extensively utilized in OCT image analysis owing to their proficiency in efficient feature extraction and semantic segmentation. This research comprehensively examines the methodological innovations, application obstacles, and prospective trajectories of deep learning in OCT-based segmentation of the myopic choroid.

The Core Model of Deep Learning in Medical Image Segmentation
In recent years, the amalgamation of deep learning algorithms, the integration of OCT technology has progressed significantly, and this amalgamation has been extensively utilized in clinical practice [12]. The primary objective of medical picture segmentation is to get pixel-level category annotation, with deep learning models markedly enhancing segmentation accuracy via hierarchical feature extraction and end-to-end training. The following are the most often utilized models and their technical specifications in myopic choroid segmentation:

Convolutional Neural Network (CNN): The Fundamental Framework for Feature Extraction
A Convolutional Neural Network (CNN) functions by sequentially integrating convolutional layers, pooling layers, and fully connected layers [13]. It autonomously acquires the local characteristics of images (e.g., edges, textures) and overarching contextual information. In medical picture segmentation, Convolutional Neural Networks (CNNs) are frequently employed with other segmentation modules as feature extractors. The multi-scale end-to-end convolutional network design proposed by X. Sui, Y. Zheng, et al. [14]. This method may directly ascertain the appropriate weights of graph edges from raw pixel data, disregarding the textural structure and heterogeneous properties of the choroid, hence enhancing the localization of choroidal borders. Furthermore, an automated segmentation technique introduced by F He-A Convolutional Neural Network (CNN) classifier combined with a l2-lq ($0 < q < 1$) fitter has attained consistent and clinically precise automatic choroidal segmentation [15]. Nonetheless, it possesses limitations: it lacks sufficient sensitivity to details, leading to outcomes that are less nuanced and smooth. Moreover, the fully connected layers of conventional CNNs progressively diminish the dimensions of feature maps, neglect correlations among pixels, and forfeit some spatial information-this constrains their utility in pixel-level segmentation tasks.

Fully Convolutional Network (FCN): A Breakthrough in End-to-End Segmentation
The Fully Convolutional Network (FCN) substitutes fully connected layers with transposed convolutional layers, facilitating the alignment of output feature map dimensions with those of the original image and permitting the input of images of unlimited sizes to produce comparable probability maps. Alonso-Caneiro et al. [16]. were the first to apply FCN to choroidal segmentation; by restoring probability maps with the same resolution as the input via transposed convolution, FCN delivers accurate results even in low-contrast B-scans and effectively eliminates vascular artifacts in the segmentation of the Outer Choroidal Boundary (OCB). Additionally, the FCN neural network proposed by Evan Shelhamer et al, is specifically designed for image semantic segmentation-its convolutional layers can classify each pixel based on abstract features with high processing speed, marking the first solution to the end-to-end training challenge for "semantic segmentation". However, despite its higher accuracy than traditional methods, FCN's segmentation is not instance-level, leaving room for improvement in efficiency; for example, it tends to encounter issues when processing images with overlapping multiple targets [17].

U-Net and Its Variants: Enhancing Details via Skip Connections
The U-Net Architecture Consists of Three Components: An encoder module, a bottleneck module, and a decoder module. The primary characteristic is the skip connections between the encoder and decoder, facilitating the integration of deep and superficial semantic data. These design elements endow the network with robust segmentation performance, making this architecture particularly suitable for medical imaging scenarios characterized by "small targets and blurred boundaries" and thus becoming a widely adopted improved method Huihong Zhang proposed a biological network (Bio-Net) for automatic choroidal segmentation, which integrates deep learning networks with OCT imaging knowledge and adopts a GAN architecture to eliminate interference caused by retinal vascular shadows. Experimental results show that compared with traditional networks, Bio-Net exhibits significant advantages in shadow elimination and shape preservation, while also mitigating the common issues of insufficient segmentation and low accuracy in traditional methods [18,19]. In the domain of OCT, the initial U-Net model introduced by Ronneberger et al. [20]. has been extensively modified in subsequent studies. For example, Xiangcong Xu et al, delineated an algorithm that integrates image enhancement with the ADU-Net architecture to facilitate rapid and precise segmentation of choroidal Enhanced Depth Imaging (EDI) OCT scans, attaining an AUC of 99.51% and a DSC of 97.91%, surpassing the segmentation accuracy of contemporaneous networks. Additionally, in studies focusing on myopic choroids, Li et al, utilized a group contextual selection network (GCS-Net) to develop a tool that can reliably and rapidly quantify ChT in patients with High Myopia (HM), receiving positive feedback in clinical trials [21,22].

Mask R-CNN: An Advanced Solution for Instance Segmentation
The Mask Region-Based Convolutional Neural Network (Mask R-CNN) is an instance segmentation model that identifies the locati0n and category of each target in an image while producing pixel-level predictions. This is extremely effective for choroidal investigation necessitating precise segmentation. The Mask R-CNN model introduced by Hung-Ju Chen and colleagues exhibits superior efficacy in choroidal segmentation and quantification, and is also applicable for assessing myopic choroidal alterations [23]. This model attains elevated accuracy and similarity when juxtaposed with manual segmentation outcomes. The study concludes that the choroid in High Myopia (HM) eyes is markedly thinner than in non-HM eyes, with axial length identified as the primary prognostic predictor. Moreover, Chung-Hao Hsiao and colleagues, Developed a Mask R-CNN model utilizing a Deep Residual Network (ResNet) and a Feature Pyramid Network (FPN) as backbone architectures to autonomously delineate and measure the choroidal layer [24]. This deep learning methodology utilizing Mask R-CNN may precisely, swiftly, and effectively ascertain the correlation between Refractive Error (RE) and Choroidal Thickness (CT). It obviates the necessity for manual processes while showcasing viable clinical applications.

Application of Deep Learning in OCT Segmentation of the Myopic Choroid
Typical pathological changes of the myopic choroid include choroidal thinning (especially in the posterior pole), Bruch's membrane rupture (lacquer cracks) choroidal neovascularization and pigment epithelial detachment (PED) [3,25-27]. Deep learning models need to be optimized for these features to enhance segmentation robustness [28,29]. Below are the typical application scenarios and method improvements:

Boundary Segmentation Between Normal and Pathological Choroids
In OCT pictures, the typical choroid manifests as a consistent medium-to-high reflectivity layer situated beneath the Retinal Pigment Epithelium (RPE) layer. Conversely, the choroid of individuals with Pathological Myopia (PM) demonstrates less reflectivity and indistinct borders attributable to atrophy [14]. Conventional techniques depend on manually crafted features (e.g., grayscale thresholds, edge detection) and encounter difficulties

in accommodating grayscale fluctuations in pathological circumstances. CNN-based techniques, by analyzing the feature distribution of diseased pictures, have markedly enhanced border segmentation precision. For instance, introduced the ADU-Net network, which integrates image enhancement with an attention mechanism to resolve the blurring boundary problem of the choroidal layer resulting from pathological conditions such Diabetic Retinopathy (DR) and High Myopia (HM) [21-30]. created a group contextual selection network, referred to as GCS-Net, for segmenting the choroid in normal or very myopic eyes. To address the variation in thickness and shape of the diseased retinal choroid, GCS-Net integrates a Group Channel Dilation (GCD) module and a group spatial dilation module. These modules can autonomously pick aggregated multi-scale information through channel attention or spatial attention, improving the alignment between the receptive field and the target region for enhanced correspondence. Furthermore, GCS-Net employs a boundary optimization network featuring an innovative edge loss, enhancing the resultant choroidal boundaries via deep supervision.

Multi Task Segmentation

The benefit of multi-task segmentation is its capacity to concurrently manage many related tasks, leading to increased productivity [31]. introduced a Choroidal U-Net (CUNet) that conducts pixel-wise classification by utilizing the shared and task-specific properties between the choroidal layer and choroidal vasculature, thereby facilitating the concurrent segmentation of both the choroidal layer and its arteries [32]. developed a fully automated choroidal segmentation network based on curriculum learning. This network can compute the average choroidal thickness and choroidal vascular index, and attain precise segmentation of the choroid and its boundaries, even amongst interference from pathological samples.

Exploring the Optimal Solution for OCT Image Segmentation

Numerous studies have sought to identify the most suitable methods for OCT segmentation [33]. In their research on OCT image segmentation, constructed a large dataset containing 2135 images using data from healthy participants, focusing on exploring the instance segmentation task of retinal and choroidal layers. By comparing three mainstream segmentation methods-Mask R-CNN, FCN, and DeeplabV3 (a typical type of dilated convolutional neural network)-they found that Mask R-CNN not only serves as an end-to-end solution for OCT image segmentation but also exhibits significant advantages in boundary extraction performance. Specifically, it can complete boundary localization without relying on time-consuming graph search methods, which not only simplifies the operational process but also effectively reduces segmentation boundary errors while achieving a higher Dice coefficient. This confirms that the architecture is one of the optimal algorithms for OCT image segmentation.

Challenges and Future Directions

In the field of myopic choroidal Optical Coherence Tomography (OCT) segmentation, while deep learning has achieved numerous remarkable outcomes, several key challenges requiring breakthroughs still exist from the perspectives of practical application and technical advancement.

Scarcity and Consistency of Annotated Data

High-quality segmentation annotations created by experts through manual outlining are not only extremely time-consuming but also place high demands on the annotators' clinical experience. This is particularly true for cases involving Pathological Myopia (PM) patients: the choroidal boundaries themselves are relatively blurred, and coupled with the diverse morphologies of lesions, it is highly challenging to ensure consistent annotation results among different annotators or even for the same annotator at different times. To address this issue, future exploration could focus on two directions: Weakly Supervised Learning and Self-Supervised Learning. These two methods can train models using limited annotated data or even completely unannotated data, which may effectively alleviate the dilemma of data scarcity.

Segmentation Robustness in Complex Pathological Scenarios

In complex pathological scenarios, the robustness of segmentation models still needs improvement. Clinically, the choroid of patients with Pathological Myopia (PM) is often complicated by multiple lesions, such as atrophy, Choroidal Neovascularization (CNV), and Pigment Epithelial Detachment (PED). These different lesions exhibit significant differences in optical properties, which easily cause confusion for models during segmentation and lead to inaccurate results. For instance, the hyperreflective region of CNV in OCT images may sometimes overlap with the reflective signals of the choroidal capillary layer, making it easy for models to missegment the two. To address this, the concept of Multi-Task Learning could be considered: while predicting lesion types, the model simultaneously determines segmentation boundaries. This approach should help the model gain a more comprehensive understanding of complex pathological scenarios, thereby enhancing the stability and accuracy of segmentation.

Clinical Practicality and Real-Time Performance

The clinical practicality and real-time performance of models also represent a major current bottleneck. Many existing models in this field are developed primarily for research purposes and generally feature high computational complexity. For example, models like Mask R-CNN often rely on GPU acceleration to operate, which makes real-time processing difficult to achieve on conventional clinical terminals-greatly limiting their practical application. Therefore, to promote the clinical translation of this technology in the future, the key may lie in combining lightweight models (e.g., MobileNet, ShuffleNet) with model compression techniques (such as pruning and quantization). This approach can reduce the computational cost and operational threshold of models while ensuring segmentation performance, enabling the models to truly meet the requirements of clinical scenarios.

Conclusion

Deep learning technologies-particularly Convolutional Neural Networks (CNNs) and their various derived variants-have indeed provided highly efficient solutions for myopic choroidal OCT image segmentation that were previously unattainable with traditional methods. A comparison with traditional manual feature extraction methods shows that deep learning-based segmentation not only improves the accuracy of quantitative analysis but also significantly enhances processing efficiency, which is of great help for subsequent batch analysis of clinical data.

In the long run, however, several key issues still need to be addressed. These include the aforementioned data scarcity problem and the adaptability of models under complex pathological conditions-clinically, patients' conditions vary greatly, which cannot be fully covered by standardized data in laboratories. Additionally, efforts should be made to further improve the clinical practicality of models, enabling them to truly move from laboratory computers to clinical terminals in hospitals. Only by resolving these issues can more solid and reliable technical support be provided for the early diagnosis of Pathological Myopia (PM) and the evaluation of treatment efficacy in subsequent practices; otherwise, even the most advanced models will remain confined to academic papers.

References

1. Jiang J (2019) Expert consensus on myopia management white paper. Chinese Journal of Optometry Ophthalmology and Visual Science 21: 161-165.
2. Liang X, Wei S, Zhao S, Li SM, An W, et al. (2023) Investigation of Choroidal Blood Flow and Thickness Changes Induced by Near Work in Young Adults. Current eye research 48: 939-948.
3. Liu Y, Wang L, Xu Y, Pang Z, Mu G (2021) The influence of the choroid on the onset and development of myopia: from perspectives of choroidal thickness and blood flow. Acta ophthalmologica 99: 730-738.
4. Wu H, Zhang G, Shen M, Xu R, Wang P, et al. (2021) Assessment of Choroidal Vascularity and Choriocapillaris Blood Perfusion in Anisomyopic Adults by SS-OCT/OCTA. Investigative ophthalmology & visual science 62: 8.
5. Yu Minhui SX (2021) Application of quantitative index of optical coherence tomography angiography in fundus diseases [J]. New advances in ophthalmology 41: 276-281.
6. Jiang Y, Wang D, Han X, Liao C, Li Z, et al. (2020) Visual impairment in highly myopic eyes: The ZOC-BHVI High Myopia Cohort Study. Clinical & experimental ophthalmology 48: 783-792.
7. Zhu X, Meng J, Wei L, Zhang K, He W, et al. (2020) Cilioretinal Arteries and Macular Vasculature in Highly Myopic Eyes: An OCT Angiography-Based Study. Ophthalmology Retina 4: 965-972.
8. Willemse J, Gräfe MGO, Verbraak FD, de Boer JF (2020) In Vivo 3D Determination of Peripapillary Scleral and Retinal Layer Architecture Using Polarization-Sensitive Optical Coherence Tomography. Translational vision science & technology 9: 21.
9. Li Y, Zheng F, Foo LL, Wong QY, Ting D, et al. (2022) Advances in OCT Imaging in Myopia and Pathologic Myopia. Diagnostics Basel, Switzerland 12: 1418.
10. Heirani M, Shandiz JH, Shojaei A, Narooie Noori F (2020) Choroidal Thickness Profile in Normal Iranian Eyes with Different Refractive Status by Spectral-Domain Optical Coherence Tomography. Journal of current ophthalmology 32: 58-68.
11. Tuncer I, Karahan E, Zengin MO, Atalay E, Polat N (2015) Choroidal thickness in relation to sex, age, refractive error, and axial length in healthy Turkish subjects. International ophthalmology 35: 403-410.
12. Le Cun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521: 436-444.
13. Yousef R, Gupta G, Yousef N, Khari M (2022) A holistic overview of deep learning approach in medical imaging. Multimedia systems 28: 881-914.
14. Xiaodan Sui YZ, Benzheng Wei , Hongsheng Bi , Jianfeng Wu XP, Yilong Yin, et al. (2017) Choroid segmentation from Optical Coherence Tomography with graph-edge weights learned from deep convolutional neural networks. Neurocomputing 237: 332-341.
15. Fang He RKMC, Zicheng Qiu, Shijie Yu, Yun Shi, Chi Ho To, et al. (2021) Choroid Segmentation of Retinal OCT Images Based on CNN Classifier and l2-lq Fitter. Computational and mathematical methods in medicine 2021: 1-13.
16. Alonso Caneiro D, Read SA, Collins MJ (2013) Automatic segmentation of choroidal thickness in optical coherence tomography. Biomedical optics express 4: 2795-2812.
17. Shelhamer E, Long J, Darrell T (2017) Fully Convolutional Networks for Semantic Segmentation. IEEE transactions on pattern analysis and machine intelligence 39: 640-651.
18. Yin Xiaohang WY, Li Deying (2021) Based on U-Net review Overview of Improved Medical Image Segmentation Technology [J]. Journal of Software 32: 519-550.
19. Zhang H, Yang J, Zhou K, Li F, Hu Y, et al. (2020) Automatic Segmentation and Visualization of Choroid in OCT with Knowledge Infused Deep Learning. IEEE journal of biomedical and health informatics 24: 3408-3420.
20. Ronneberger O FP, Brox T (2015) U-net: Convolutional networks for biomedical image segmentation[C]. International Conference on Medical image computing and computer-assisted intervention Cham: Springer international publishing 234-241.
21. Xu X, Wang X, Lin J, Xiong H, Wang M, et al. (2022) Automatic Segmentation and Measurement of Choroid Layer in High Myopia for OCT Imaging Using Deep Learning. Journal of digital imaging 35: 1153-1163.
22. Li M, Zhou J, Chen Q, Zou H, He J, et al. (2022) Choroid automatic segmentation and thickness quantification on swept-source optical coherence tomography images of highly myopic patients. Annals of translational medicine 10: 620.
23. Chen HJ, Huang YL, Tse SL, Hsia WP, Hsiao CH, et al. (2022) Application of Artificial Intelligence and Deep Learning for Choroid Segmentation in Myopia. Translational vision science & technology 11: 38.
24. Hsiao CH, Huang YL, Tse SL, Hsia WP, Chen HJ, et al. (2022) Automatic Segment and Quantify Choroid Layer in Myopic eyes: Deep Learning based Model. Seminars in ophthalmology 37: 611-618.
25. Liang R, Yang R, Ai B, Li T, Wang L, et al. (2024) Structural changes in the retina and choroid in patients with different degrees of myopia. Scientific reports 14: 31033.
26. Deng J, Li X, Jin J, Zhang B, Zhu J, et al. (2018) Distribution Pattern of Choroidal Thickness at the Posterior Pole in Chinese Children With Myopia. Investigative ophthalmology & visual science 59: 1577-1586.
27. Deng J, Jin J, Lv M, Jiang W, Sun S, et al. (2017) Distribution of scleral thickness and associated factors in 810 Chinese children and adolescents: a swept-source optical coherence tomography study. Acta ophthalmologica 97: e410-e418.
28. Ang M, Flanagan JL, Wong CW, Müller A, Davis A, et al. (2018) Review: Myopia control strategies recommendations from the 2018 WHO/IAPB/BHVI Meeting on Myopia. The British journal of ophthalmology 104: 1482-1487.
29. Cheung CMG, Arnold JJ, Holz FG, Park KH, Lai TYY, et al. (2017) Myopic Choroidal Neovascularization: Review, Guidance, and Consensus Statement on Management. Ophthalmology 124: 1690-1711.
30. Shi F, Cheng X, Feng S, Yang C, Diao S, et al. (2021) Group-wise context selection network for choroid segmentation in optical coherence tomography. Physics in medicine and biology 66: 245010.
31. Zhu L, Li J, Zhu R, Meng X, Rong P, et al. (2022) Synergistically segmenting choroidal layer and vessel using deep learning for choroid structure analysis. Physics in medicine and biology 67.
32. Liu X, Jin K, Yang Z, Yan Y, Wang S, et al. (2022) A curriculum learning-based fully automated system for quantification of the choroidal structure in highly myopic patients. Physics in medicine and biology 67.
33. Viedma IA, Alonso Caneiro D, Read SA, Collins MJ (2022) OCT Retinal and Choroidal Layer Instance Segmentation Using Mask R-CNN. Sensors Basel, Switzerland 22.