Advancements in Deep Learning-Augmented Adaptive Optical Coherence Tomography (AO-OCT) for Enhanced Real-Time Retinal Imaging: A Narrative Review

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***Abstract*: The assimilation of deep learning and Adaptive Optics Optical Coherence Tomography (AO-OCT) has promoted the area of retinal imaging to a new direction with ultra-high-resolution, intelligent diagnostics. AO-OCT comprises Optical Coherence Tomography (OCT) and Adaptive Optics (AO), which synergistically allows high-resolution, three-dimensional imaging of retinal structures. This amalgamation can provide a detailed cellular-level image of the retina that enables very early detection and monitoring microstructural abnormalities. Deep learning approaches, specifically convolutional neural networks and vision transformers (ViTs)) has further unlocked the potential of AO-OCT systems. They can execute real-time motion artifact correction, improve the image quality in suboptimal imaging conditions and automate segmentation of complex retinal layers. Deep learning reduces the burden of manual interpretation and compensates for patient movement, which improves both the accuracy as well as efficiency of AO-OCT based diagnostics. Clinically, these advancements are critical for the early diagnosis and intervention of a number of retinal disorders like age– related macular degeneration (AMD), diabetic retinopathy (DR) and glaucoma. The ability to visualize and interrogate subtle cellular changes can provide important insights into the progression of disease before symptoms become clinically apparent; this has profound implications for prevention, diagnosis and treatment. This narrative review discusses how deep learning has recently gained ground in AO-OCT and offers an overview of its system architecture, diagnostic outlook, current challenges, as well as possible directions for AI-driven ophthalmic imaging.**

***Keywords:* Deep learning; intelligent diagnostics; diabetic retinopathy; ophthalmic imaging; AO-OCT based diagnostics.**

INTRODUCTION

The human retina, a laminated structure through which light is transformed into a neural signal, is a vulnerable target to numerous degenerative, vascular, and inflammatory diseases. Early detection and accurate monitoring of retinal pathologies are essential for early and vision-sparing treatment. Of modern imaging modalities, Optical Coherence Tomography (OCT) is a non-invasive, high-resolution imaging technique that has transformed the diagnosis and care of patients with eye disease by allowing clinicians to view the retina in cross-section at near histological resolution. However, inhomogeneous optical media of the human eye produce optical errors, imaging artifacts, and marginal resolution when used as in vivo retinal imaging in the human eye, especially for eyes with advanced eye disease or in dissimilar patients with unstable fixation [1].

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In order to address these limitations, Adaptive Optics (AO), a method initially developed for astronomical imaging, has been adapted to combine with OCT, namely Adaptive Optics Optical Coherence Tomography (AO-OCT). This integration improves lateral resolution by real-time correction of ocular aberrations, enabling cellular-resolution retinal imaging to elucidate photoreceptor integrity, ganglion cell morphology, and early microvascular changes[2]. However, AO-OCT is technically complicated and has not been well accepted in the clinical setting because of its technical complexity, slowness of image acquisition, and technical challenges in interpretation.

In modern era, adaptive Optics Optical Coherence Tomography (AO OCT) has revolutionized retinal imaging by combining OCT's high-resolution depth scanning with Adaptive Optics' ability to correct ocular aberrations in real time, enabling cellular level visualization of retinal structures . Recently, machine learning particularly deep learning has become pivotal in advancing AO OCT's diagnostic and operational capabilities.

In a groundbreaking study published in early 2025, ViT 2SPN, a Vision Transformer based Dual Stream Self Supervised Pretraining Network, demonstrated exceptional performance in classifying retinal OCT images. The model achieved a mean AUC of 0.93, outperforming existing self-supervised methods through a structured pretraining and fine tuning pipeline arXiv.[3]

Complementing this, a broader review on the role of AI in retinal imaging underscores how AI, together with OCT/OCT A and Adaptive Optics, enhances early disease detection including microvascular and neurodegenerative markers. Yet, inconsistent imaging protocols and limited external validation continue to hinder widespread clinical adoption arXiv.[4]

Hybrid architectures combining CNNs and Vision Transformers have also shown promise. For instance, Conv ViT fuses convolutional and transformer-based feature extractors for improved retinal disease detection, while HCTNet another hybrid model has proven effective in OCT image classification tasks[5]

In the past few years, deep learning (DL) has significantly transformed biomedical imaging by providing significant progress in automated feature extraction, noise reduction, enhanced image resolution, and real-time decisions.When combined with AO-OCT systems, deep learning algorithms, especially convolutional neural networks (CNNs), generative adversarial networks (GANs), and vision transformers (ViTs), have shown great promise for improving image quality, motion artifact removal, and speeding up data acquisition and processing[6;7]. For example, Xiang et al.(2024) designed a deep-learning method for the real-time correction of aberrations and segmentation of layers in AO-OCT images; the approach reduces the post-processing time and the need for human intervention. In addition, deep learning-accelerated denoising models have demonstrated potential for the high signal-to-noise ratios in LL(low-light) or RS (rapid-scan) OCT, to help clinicians capture high-quality retina[8].

Furthermore, the merger withthe deep learning methods, AO-OCT allows not only technical image improvement, but also clinical diagnosis assistance, such as early detection of subtle pathological biomarkers, longitudinal disease monitoring, and treatment response prediction in diseases, including age-related macular degeneration (AMD), diabetic retinopathy (DR), and glaucoma. According to Li et al. (2023) [9], a transformer-encoded network-level learning with AO-OCT imaging data outperformed retinal specialists in diagnosing early MD (Macular Degeneration) phenotypes, showing the emerging clinical value of these systems.

Despite these developments, there are still many barriers. These are the generalizations of deep learning models to diverse populations and imaging modalities, the interpretability of algorithmic decision-making in clinical practice, and reliance on large annotated datasets to train robust models. Real-time implementation of DL-AO-OCT systems in clinics is also limited and requires an optimized hardware-software integration, regulatory approvals, and validation in a longitudinal, multicenter trial.

This narrative review aims to provide an in-depth overview of recent progress of deep learning-empowered AO-OCT, including technological development, clinical translation, shortcomings, and future development directions. It demonstrates the convergence of deep learning and high-resolution ophthalmic imaging as a game changer in retinal diagnostics. It is a significant step towards precision, automation, and patient-centricity in ophthalmology. Figure 1 illustrates the multi-dimensional usage of Deep Learning based AO-OCT.

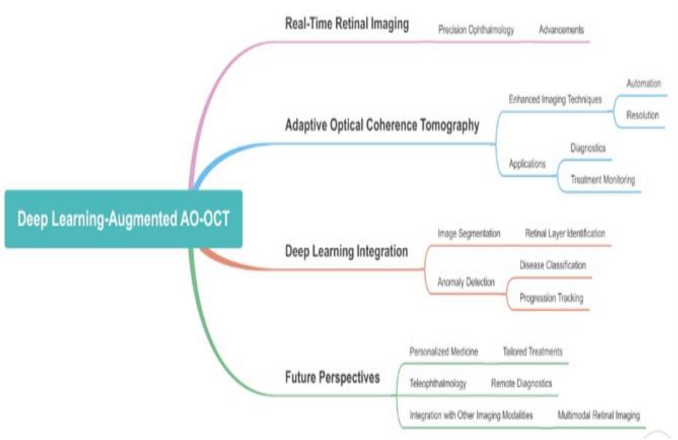

Figure 1: Multi-dimensional usage of Deep Learning based AO-OCT

1. *Fundamentals of Optical Coherence Tomography (OCT) in Retinal Imaging*

OCT, a imaging technique that is noninvasive and employs low coherence interferometry to generate cross-sectional images of the retina at the micrometer scale. It functions by detecting the time delay of echo and intensity of backscattered light, enabling to visualize retinal layers and microstructures with great details. The axial resolution is mainly determined by the light source bandwidth, and the lateral resolution is dependent upon the optical focus, and in present systems, it is between 3 and 5 µm are available [10]. From the clinical standpoint, the OCT has a broad application as diagnostic and monitoring tool for retinal diseases, such as, age-related macular degeneration (AMD), diabetic macular edema (DME), and glaucoma. On the other hand, limitations, motion artifacts, image quality degradation in media opacities, and shallow depth of field remain the major challenges [11].

2. *Role of Adaptive Optics in OCT (AO-OCT)*

AO can be used to improve OCT by compensating for ocular aberrations in vivo, which significantly improves lateral resolution and image contrast. Systematic use of AO in combination with OCT allows for cellular-level imaging of the photoreceptor layer, retinal pigment epithelium and microvasculature that is crucial for identifying early pathological changes [2]. Aberration control also makes it possible to image retinal structures hidden by optical imperfections. Despite these benefits, implementing AO-OCT systems presents challenges in system design that includes added complexity, higher costs, susceptibility to eye motion and the requirement for meticulous alignment [12]. Overcoming these challenges is essential to translate AO-OCT from the laboratory to the clinic.

3. *Integration of Deep Learning into AO-OCT Systems*

The incorporation of deep learning into AO-OCT systems has permitted real time image improvement through intelligent aberration correction, motion artifact elimination, and automated analysis. Although deep neural nets, especially convolutional and transformer-based models are now part of the imaging pipeline to improve image reconstruction and enable high-speed data handling [7]. These achieve real-time correction of aberrations and motion and minimisation of dependence on complex optical hardware. In addition, deep learning based automated segmentation algorithms are able to precisely define retinal layers and microstructures for early diagnosis and longitudinal disease monitoring similarly [13]. This unification of AI with AO-OCT has brought the modality from the laboratory to the clinic.

4. *Clinical Applications of DL-Augmented AO-OCT*

Deep learning-supported AO-OCT systems have great potential in the early diagnosis of retinal diseases, for instance, age-related macular degeneration (AMD), diabetic retinopathy (DR), and glaucoma, due to the enhanced resolution and accuracy with the image segmentation [14]. These methods make it possible to follow subtle microstructural changes which may appear far before the clinical and can permit early intervention. In addition, DL-AO-OCT can provide serial surveillance of the progression of diseases and therapeutic efficiency, which will be beneficial for predicting patient outcome [15]. Clinical stories have shown that deep learning methods can continue to reach or even surpass the diagnostic skills of expert ophthalmologists especially in AMD and DR diagnosis, thus, evidently proving the clinical effectiveness of such systems [16].

5. *Benchmark Datasets and Model Training*

High-quality benchmark datasets are very important for the development of deep learning models for OCT and AO-OCT systems. Publicly available datasets, such as the Duke OCT dataset and the Retinal OCT dataset, contain labeled images for segmentation and classification model training [17]. It is difficult to annotate OCT images for deep learning, as an ophthalmologist must manually delineate retinal layers and pathological characteristics, and there are less cumbersome methods for annotation, such as semi-automatic annotation tools to alleviate the workload [18]. Augmentation techniques such as rotation, and flipping, and intensity normalization are used to add variability in the dataset and improve model's generalization. And the transfer learning was a trend where pre-trained models on large scale datasets are fine-tuned on smaller datasets specific to domain, which makes this domain-specific tasks can be well performed with small amount of data [19]. This extends the use of deep learning models to cross-domain applications where models can be applied for comprehensive retinal disease diagnosis by combining images from other imaging modalities such as fundus photography or angiography to OCT images.

6. *Evaluation Metrics and Validation Approaches*

For deep learning based AO-OCT applications, evaluation of the model performance necessitates reliable and standardized metrics. The popularly used quality-assessment indices are Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), which evaluate the quality of reconstructed images by comparing with ground truth images [15]. For segmentation, metrics such as Dice coefficient and Intersection over Union (IoU) are important to assess the quality of retinal layer delineation, whereas Area Under the Curve (AUC), is frequently used for the classification especially for disease detection [14]. Validation of these models is commonly performed by comparing predictions with expert annotations for their clinical relevance and accuracy. Moreover, runtime metrics, e.g. inference time and processing speed, are important for the evaluation of these existing and proposed models to achieve the practical implementation of these models in clinical practice [20].

7. *Hardware and Software Optimization for Real-Time Imaging*

In order to realize real-time processing in deep learning-integrated AO-OCT systems, GPU acceleration is crucial for accelerating image reconstruction and model inference [21]. Edge computing is gaining prominence because the real-time processing of data at the point-of-care is possible, reducing dependence on distant cloud servers and minimizing lags [22]. These FPGA-based systems promise to increase efficiency even further, by providing bespoke hardware, which supports real-time OCT-imaging tasks with minimum delay [23]. Meanwhile, real-time data streaming and visualization technology is necessary for the real-time transmission of OCT data to enable prompt decision making and diagnosis [24].

8. *Challenges and Limitations*

Even with the progress made in AO-OCT systems integrated with deep learning, several challenges remain to be resolved between benchtop and clinical implementation. A major issue is the generalizability of the trained models; because deep learning models are fine-tuned to the characteristics of the training dataset, the performance of these models can suffer when used in larger and more heterogeneous patient populations and this effect can be pronounced [25]. Privacy Privacy is a key challenge, such as how patients data are stored and shared, and complying with privacy regulations like the General Data Protection Regulation (GDPR) in the EU, and Health Insurance Portability and Accountability Act (HIPAA) in the U.S. [26]. In addition, due to the absence of standard protocols of devices, the AI interoperability is not perfect, since differences among the model of OCT machine, imaging mode and imaging quality can lead to the instability and unreliability of the DL algorithms [27].

9. *Future Directions and Emerging Trends*

The next generation of AO-OCT systems are in multimodal imaging integration, combining OCT with fundus photography and OCT-angiography for a more complete understanding of retinal state. This provides a means for not only imaging the retina structure but also vasculature under the same platform, which is particularly important for more accurate diagnosis, disease progression monitoring, and treatment of diseases such as diabetic retinopathy and macular degeneration [28]. An emerging new direction is understandable AI in clinical decision making, aiming to make AI-based models transparent and interpretable, thus to establish the trust between physicians and patients, because in this way we can understand how physicians make diagnostic decision [29]. Moreover, personalized retinal imaging with AI-therapeutics enables precise treatment strategies that can identify interventions specifically tailored to patients who are selected based on detailed examination of their retinal profiles, niching the therapies for greater precision and better treatment effectiveness [30]. These developments will lend themselves to optimizing clinical workflow and they will drive precision medicine forward in the field of ophthalmology.

CONCLUSION

Coupling adaptive optics with optical coherence tomography (AO-OCT) has resulted in dramatic advancements in retinal imaging by improving the resolution, contrast and penetration of conventional OCT systems. Deep learning algorithms and AI technology have taken AO-OCT to the level of automatic, real-time spherical and higher-order aberration correction, image motion compensation, and automated retinal layer segmentations, to improve the precision and efficiency of diagnostics. These technological innovations offer tremendous potential for clinical translation in terms of earlier disease diagnosis and more individually-tailored treatment in retinal diseases. Although the generalizability of models, data privacy and the limited hardware may pose challenges, clinical translation of AO-OCT systems is attainable. The combination of multimodal imaging, interpretative AI, and personalized retinal therapeutics will propel the field toward precision ophthalmology, enhancing patient outcomes in the near future.

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