Optical Coherence Tomography for Retinal Disease Detection with Integrating Deep Learning Concepts- Review

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Abstract

Optical coherence tomography (OCT) enables retinal imaging by providing high-resolution, non- invasive cross-sectional views of ocular structures, aiding early detection of various retinal diseases such as diabetic macular edema (DME), age-related macular degeneration (AMD), glaucoma and diabetic retinopathy (DR). This paper reviews the burgeoning role of deep Learning (DL) techniques integrated with OCT for automated image analysis, segmentation, classification, progression and prognosis of various retinal diseases highlighting models like CNNs and performance metrics. Key challenges include dataset variability and clinical translation. This review also summarizes the trends in DL- based OCT image analysis in ophthalmology, discusses the current gaps, and provides potential research directions. DL in OCT analysis shows promising performance in vital tasks such as segmentation and quantification of layers, disease classification, progression and prognosis. There are some challenges identified and described using DL- based OCT image analysis in the development as follows, (1) OCT data are scarce and scattered; (2) models create performance discrepancies in real-world settings; (3) models lack transparency and lack of society acceptance and regulatory standards; and (5) OCT is still unavailable in most underprivileged areas. More work is needed to tackle the challenges and gaps, before DL is further applied in OCT image analysis for clinical use.

Keywords: Retinal OCT Layers, OCT Retinal Diseases, DL concepts, DL models and Techniques, DL applications in OCT Retinal Diseases, DL- retinal disease progression.

Introduction

Optical Coherence Tomography (OCT) is a non- invasive imaging technique widely used for retinal disease detection, and deep learning (DL) integration has significantly advanced automated analysis.

Literature reviews highlight high accuracies in classifying conditions like diabetic macular edema (DME), choroidal neovascularization (CNV), and drusen using convolutional neural networks (CNNs) on OCT images.

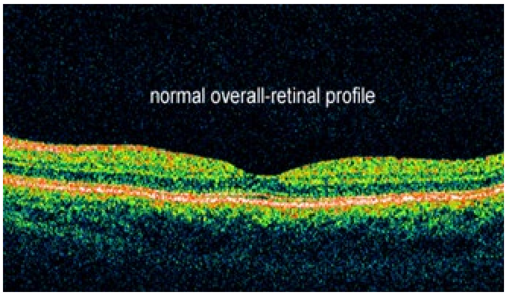
3D Retinal Imaging (OCT) Mechanisms

OCT is a non-invasive ocular perceiver testing, works without making any physical contact with the eye (ocular perceiver). This OCT instrument beams light through eye tissue and accumulates the reflected light signal and constructs three-dimensional (3D) color images that enable us by seeing and analyzing any abnormalities in the layers and structure of the retina.

The retina, a sensitive two-layered membrane which is at back of the eye changes light and images that enter the eye into nerve signals that are sent to the cerebrum of the brain. A part of the retina called the macula makes vision sharper and more detailed.

OCT Scanned Retinal image

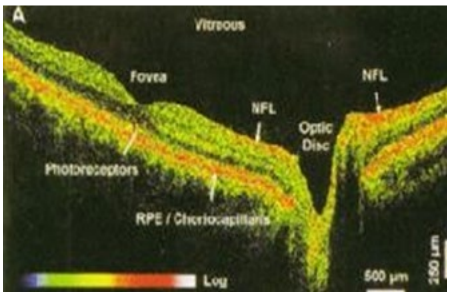
Image of the retina viewed in the OCT scan seems like performing a biopsy of the retinal layers vertically, but this efficient technique makes use of light rather than using knife as biopsy done using this. Here the OCT images are displayed with a “false-color” view with micron level resolving power. This process is like that of ultrasonography, except that light is used here instead of sound waves. The overall retinal OCT profile of normal fovea through OCT imaging is shown in the below. In this OCT image we can identify the fovea by the normal depression. i.e., the normal foveal profile is a slight depression in the surface of the retina, as pictured below.



The overall retinal profile.32

Retinal OCT Layers

OCT gives target proof to treatment choices for different retinal ailments. OCT uses the light upon the retina and macular into a cross-segment of its 10 layers so unobtrusive issues introducing themselves in any of its layers underneath the surface that might effectively be missed by the Optomap or by the specialist’s perspective, can easily be detected by the OCT image.



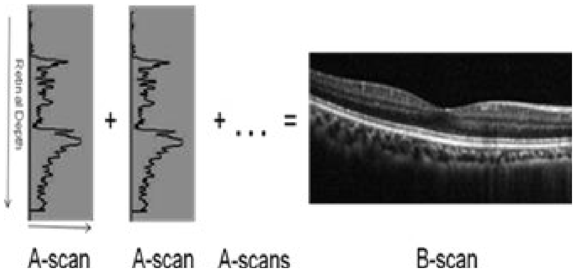
Layers of retina through OCT .33

In this way, some of the common retinal diseases and its layers such as Macular Holes, Diabetic Macular Edema, Choroidal Neo-Vascular Membranes, CSCR (Central Serous Chorioretinopathy), Epi-Retinal Membranes, Glaucoma, Age-related Macular degeneration (Drusen), etc. can easily be detected by the OCT. OCT also pictures the nerve fiber layer around the optic nerve and the ganglion cell complex in the macular for early Glaucoma detection.

OCT Fundamentals

OCT uses low-coherence interferometry to generate micron-level retinal scans, visualizing layers like the retina pigment epithelium and intraretinal fluid.

Spectral-domain and swept-source OCT variants support 3D imaging for diseases including DME and CNV.



Combining many A-scans produces a B-scan

DL processes these volumetric B-scans, addressing noise and artifacts via preprocessing like layer flattening.

Deep Learning Concepts

Deep Learning (DL) for Optical Coherence Tomography (OCT) focuses on automating the detection, classification, and segmentation of macular edema (ME), particularly Diabetic Macular Edema (DME). Surveys indicate that Convolutional Neural Networks (CNNs) are the dominant architecture for these tasks.

Key Deep Learning Techniques

- Classification Models: Standard architectures like VGG16, ResNet-50, InceptionV3, and AlexNet are frequently used to differentiate healthy retinas from those with DME. Ensemble models, which combine multiple architectures, have shown superior accuracy (up to 98.53%) compared to single- network approaches.
- Segmentation Frameworks: Techniques like U-Net and DeepLab are used to quantify fluid-filled regions. Advanced modules such as Atrous Spatial Pyramid Pooling (ASPP) help detect edema at multiple scales, while Fully Connected Conditional Random Fields (FC-CRF) refine boundaries to prevent over-segmentation.
- Explainable AI (XAI): To address the “black box” nature of DL, researchers use Class Activation Maps (CAM) or heat maps to visualize the retinal regions most responsible for a diagnosis, aiding clinical validation.
- Hybrid Models: Combining CNNs with Recurrent Neural Networks (RNNs) allows for the analysis of 3D OCT volumetric “cubes” as sequential data, rather than isolated 2D slices. Performance Summary of Models

Model Type	Architecture	Accuracy	Dataset
Lightweight	DeepOCT	99.20%	Explainable DME identification
Segmentation	OCT-DeepLab	0.963 (AUC)	Precise fluid boundary detection
Pre-trained	ResNet-50	97.56%	Multi-class (CNV, DME, Drusen)
Hybrid	CNN-RNN	0.94 (AUC)	Real-world screening (OCT cubes)

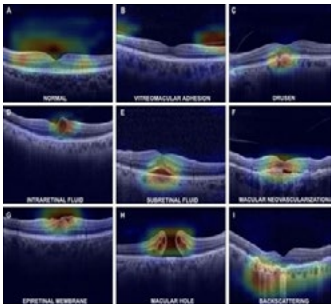
Key Retinal Diseases

Some of the common Retinal diseases are DR (Diabetic Retinopathy), AMD (Age-Related Macular Degeneration), CNV (Choroidal neovascularization), Glaucoma, CSR (Central Serous Retinopathy). The conditions happened due to the occurrence of Retinal diseases and abnormalities are as follows:

DME (Diabetic macular Edema), Retinal vein occlusion, Retinal detachment, Macular Hole, Macular Edema.

DR features macular edema and ischemia, visible as intraretinal fluid and capillary dropout on OCT. AMD shows drusen, geographic atrophy, or neovascular membranes disrupting Bruch's membrane. Glaucoma manifests as retinal nerve fiber layer thinning and optic disc cupping.

Below image shown is the OCT images of normal retina and various retinal diseases identifications in a clear view.

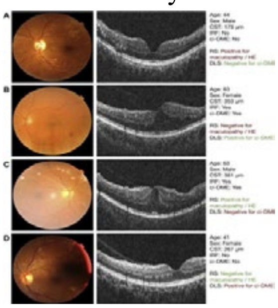


DL Applications in Retinal disease detection

DL models segment retinal layers and quantify features like fluid volume in AMD and DME.

- Binary classification distinguishes normal vs. diseased OCT (e.g., AMD detection with VGG16 variants).
- Multiclass tasks identify DR stages, CNV, and vitreomacular diseases using YOLOv3 or OCTD Net (92-99% accuracy).

DL models like CNNs (ResNet50, InceptionV3) classify OCT images into categories such as normal, DR, AMD, and DME with AUCs exceeding 0.95. Segmentation tasks identify lesions using U-Net variants, while hybrid structural- OCTA models boost glaucoma detection to AUC 0.91. Meta-analyses confirm pooled sensitivity near 95% for DR screening.



Above shown is an OCT screen image of patient's datasets identified with positive and negative results.

DL-based Common Retinal Diseases Classification

DL-based OCT image analysis has been widely used for AMD classification tasks.16 Lee et al.17 demonstrated that DL is effective for distinguishing AMD from eyes in OCT images. Motozawa et al.18 proposed a DL-based model to discriminate wet AMD from dry AMD—a distinction used for precise treatment—using OCT B-scans. Advanced preprocessing methods have been effective in improving the performance of DL model for OCT image analysis. For example, Rong et al.19 proposed a surrogate-assisted CNN using various methods, including image denoising, thresholding, and morphological dilation for mask extraction, to generate surrogate images for DL model training.

DL is also at the forefront of DR and DME assessment using OCT images. For example, Li et al.20 proposed a novel DL model called OCTD_Net based on modified DenseNet and ReLayNet models. It classified early-stage DR (i.e., mild DR), DM without DR, and normal subjects from OCT scans, and achieved a sensitivity, specificity, and accuracy of 90.0%, 95.0%, and 92.0%, respectively. The heat maps showed that patients with early DR had different characteristics around the myoid and ellipsoid zones, inner nuclear layers, and photoreceptor outer segments. Wang et al.21 and Tang et al.22 developed 3D DL models for DME detection from OCT volumetric scans using different OCT devices, which greatly improved the interchangeability of the DL-based OCT image analysis.

DL-based OCT analysis can be used to detect glaucomatous optic neuropathy from different types of OCT images including OCT reports, B-scans, and volumes. DL models trained on images extracted from OCT reports have shown high accuracy in glaucoma detection.23,24 DL models based on raw OCT images can yield lower segmentation errors over built-in software. Thompson et al.25 have shown superior performance of DL using raw OCT data for discriminating glaucoma, especially in the early stages. Volumetric OCT scans, including ONH- centred and macula-centred ones, can potentially provide more comprehensive features such as the changes in the RNFL, GCIPL, Bruch's membrane opening, neuro-retinal rim area, the lamina cribrosa, and choroid. Several studies have shown that DL models based on OCT 3D scans outperformed DL models based on 2D images and also showed non- inferior performance to glaucoma specialists for detecting glaucomatous structural changes.26–31

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The Below Table describes the various Retinal diseases, its DL Model, Datasets and Metric

Disease	DL Model	Key Metric	Dataset Size
AMD/DR/DME	ResNet50/YOLOv3	98.5% Acc., 98.7% Sens.	37,138 images
DR	CNN Meta-Analysis	OR ≥0.785	188,268 scans

Multiple	Binary CNN	>99% Acc. (AMD, VID)	N/A
AMD	VGG16	High cross-val. acc.	N/A

DL-based disease progression and prognosis prediction from OCT images

Anti-VEGF therapy is an effective treatment for vascular and exudative retinal diseases, such as wet AMD and DME.37 DL methods have been developed to identify the prognosis of patients after anti-VEGF therapy with various results, including (1) predicting the changes in the fluid volume,38,39 visual acuity (VA),40,41 and subfoveal choroidal thickness42 after the treatment, (2) classifying OCT images into treatment responders and non-responders with pre- and post-treatment OCT images,43,44 and (3) predicting the future need45,46 and optimal treatment frequency47 with longitudinal data.

Although DL models have shown promising results in predicting disease progression and prognosis, most of the studies have been based on a single type of OCT device or image. Therefore, investigation of their performance on different types of OCT images is necessary.

Follow-ups:
- Common datasets used for OCT DL retinal disease models
- Performance comparison of CNN vs ResNet for OCT classification
- Challenges and limitations of DL in OCT for retinal screening
- Latest advancements in OCT DL after 2024
- How to implement YOLOv3 for OCT lesion detection
- Multimodal DL integrating OCT with fundus images promises >99% accuracy. Real-time edge.

Conclusion

DL models are potential to have a significant impact on the diagnosis and management of various ocular and systemic diseases using OCT images. However, further efforts are needed to advance their use from research to practice. Key directions for advancement include image standardisation, multi- centre collaboration, interchangeability between OCT devices, model transparency, societal acceptance, regulatory standards, and its availability in underprivileged areas.

Challenges and Future Directions

Challenges encompass small rare-disease datasets, cross-device generalizability, and explainability for clinical trust. Future work targets multimodal fusion (OCT + fundus), federated learning for privacy, and real-time triage. DL shows promise but requires prospective validation for adoption.

Future work also towards the study of analyzing retinal diseases to diagnose possible symptoms for the specific disease by identifying the affected retinal layers through OCT images using deep learning models and techniques for pre-processing, segmentation and classification based on specific algorithm in CNNs.

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