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Survey on Retinal OCT Image Preprocessing, Segmentation, and Deep Learning Based Classification

Ranjitha Rajan[1,*], S.N. Kumar[2]

Abstract

Optical coherence tomography (OCT) is a non-invasive technique that generates high-resolution, detailed cross-sectional images of biological tissues. By utilizing low-coherence interferometry, OCT enables visualization of tissue microstructure with micron-scale resolution, making it useful in various medical fields such as ophthalmology, cardiology, and dermatology. In ophthalmology, OCT is extensively used for diagnosing and monitoring retinal diseases like macular degeneration and diabetic retinopathy, allowing doctors to assess changes in tissue morphology over time. Moreover, OCT plays a crucial role in guiding surgical procedures, assessing treatment efficacy, and advancing our understanding of disease pathogenesis. Its ability to provide detailed, real-time images with minimal patient discomfort has made OCT a cornerstone technology in modern medical imaging, revolutionizing patient care and research practices. This survey comprehensively reviews the recent advances in preprocessing, segmentation, and deep learning-based classification of retinal OCT images, highlighting the latest techniques, challenges, and future directions for improving diagnostic accuracy and clinical applications.

Keywords: Optical coherence tomography (OCT), age-related macular degeneration (AMD), diabetic retinopathy (DR), convolutional neural networks (CNNs)

INTRODUCTION

Retinal OCT imaging provides in-depth visualization of retinal layers, assisting in the diagnosis of age-related macular degeneration (AMD), diabetic retinopathy (DR), and glaucoma [1]. This survey covered three critical aspects: preprocessing, segmentation, and classification, focusing on methods that include machine learning and deep learning. Optical coherence tomography (OCT) of retinal images is a specific use of OCT technology designed to obtain high-resolution images of the retina; a light-sensitive tissue located at the back of the eye. These high-resolution images allow the diagnosis and monitoring of various retinal diseases and conditions.

*Author for Correspondence
Ranjitha Rajan
E-mail: ranjitharajan@amaljyothi.ac.in

[1]Research Scholar, Lincoln University College-Kota Bharu, Malaysia
[1]Assistant Professor, Department of Electronics and Communication Engineering, Amal Jyothi College of Engineering, Koovappally, Kerala, India
[2]Associate Professor, Department of Electrical and Electronics Engineering, Amal Jyothi College of Engineering, Koovappally, Kerala, India

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Key Features of Retinal OCT

Optical coherence tomography provides high-resolution micron-level images that are crucial for detecting minute changes in the retina. This safe, non-invasive procedure requires no contact with the eye, making it painless for patients. Additionally, OCT generates cross-sectional views of the retina, enabling detailed analysis of its various layers [2]. OCT is an essential tool for the diagnosis and effective monitoring of various retinal diseases. Diabetic retinopathy (DR), a frequent complication of diabetes, manifests in two primary forms: proliferative DR, marked by the growth of new blood vessels on the retinal surface, and macular edema, characterized by swelling in the macula caused by leakage of blood vessels. Glaucoma, a leading cause of irreversible blindness, benefits from OCT to measure the thickness of the retinal nerve fibrous layer, aiding in its early detection and monitoring. Additionally, OCT assists in diagnosing conditions such as macular holes, including full-thickness macular holes, which result in central vision loss [3].

Furthermore, OCT helps to identify different types of retinal detachment: rhegmatogenous retinal detachment, caused by a tear or break in the retina, and tractional retinal detachment, resulting from the pulling force of abnormal fibrous tissue. Central serous retinopathy, characterized by fluid accumulation under the retina, leading to visual distortion, can also be assessed and monitored using OCT technology. AMD, a leading cause of vision loss, is present in two primary forms: dry AMD, characterized by drusen (yellow deposits) under the retina; and wet AMD, which involves abnormal blood vessels leaking fluid or blood into the macula. OCT detailed imaging capabilities of OCT aid in distinguishing between these AMD subtypes and effectively monitoring disease progression, as shown in Figure 1 [4].

Benefits of Retinal OCT

OCT is invaluable in eye care because it enables early detection of retinal diseases, often before symptoms manifest, allowing for prompt intervention and improved outcomes. Moreover, OCT monitors disease progression over time, helping to manage chronic conditions by supplying clinicians with crucial data for adjusting treatments. Furthermore, it guides treatment strategies by assisting in the planning and assessment of interventions such as intravitreal injections or laser therapy.

Its non-invasive nature guarantees a comfortable experience for patients, enabling consistent monitoring and thorough management of eye health [5].

Interpretation of Retinal OCT Images

Interpreting retinal OCT images involves analyzing various visualizations to understand the structure and health of the retina. Thickness maps, represented by color-coded charts, display the thickness of retinal layers and offer insights into any abnormalities or changes. B-scans provide cross-sectional images that offer detailed views of the retinal layers, allowing for precise examination of specific areas. Additionally, 3D imaging reconstructs the retina into three-dimensional views, facilitating comprehensive analysis and visualization of its structure. Together, these different imaging modalities contribute to a thorough assessment of retinal health and aid in effectively diagnosing and managing retinal conditions [6].

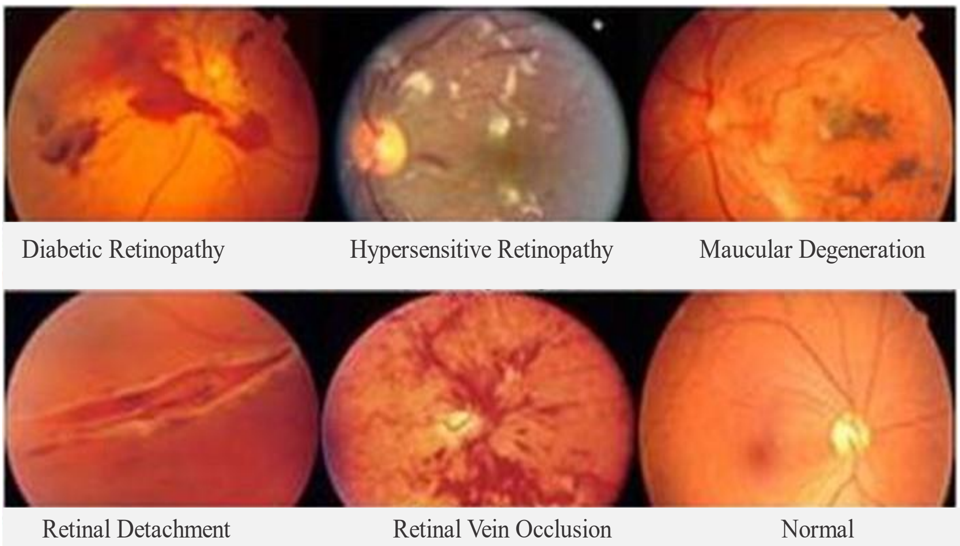


Figure 1. Retinal OCT images.

OCT RETINAL IMAGE PREPROCESSING TECHNIQUES

Preprocessing aims to enhance the quality of OCT images by addressing noise, artifacts, and variability. In noise reduction, different methods are used to enhance the image quality while retaining essential details, as shown in Figure 2.

Median filtering effectively reduces speckle noise while retaining the edge sharpness. Gaussian filtering smooths images, although it blurs some fine details. The wavelet transform decomposes images into frequency components, enabling targeted noise removal. Non-local means (NLM) averages pixels with similar neighborhoods and preserves structural integrity. These methods collectively enhance the clarity and reliability of retinal OCT analysis [7]. For contrast enhancement, various techniques have been employed to improve the visual quality of retinal OCT images. Histogram equalization enhances global contrast by redistributing the intensity values across the image, effectively enhancing overall visibility. Contrast limited adaptive histogram equalization (CLAHE) takes this step further by improving the local contrast, which is particularly beneficial for highlighting fine details within specific regions of interest. The Retinex algorithm, inspired by the human visual system, enhances the contrast and dynamic range, providing a more natural and visually appealing representation of retinal structures [8]. In addition, image normalization techniques are important for ensuring consistency and comparability across OCT images. Intensity normalization adjusts intensity values to a standard range, compensating for variations in imaging conditions, and enhancing interpretability. The logarithmic transform compresses the dynamic range, facilitating better visualization of reflectivity differences, particularly in regions of varying brightness. Flattening algorithms align retinal layers horizontally, simplifying subsequent analysis and segmentation tasks by providing a uniform reference plane [9].

Each of these preprocessing steps contributes to the refinement and optimization of retinal OCT images, ultimately enhancing their utility for clinical diagnosis and research [10]. Table 1 shows some of the preprocessing techniques used for retinal OCT images.

SEGMENTATION TECHNIQUES

Segmenting retinal OCT images entails dividing the image into distinct regions that correspond to various anatomical structures such as retinal layers or pathological features. Various techniques have been used for this purpose. Edge-based methods detect abrupt changes in intensity to identify boundaries between retinal layers; however, they may be sensitive to noise.

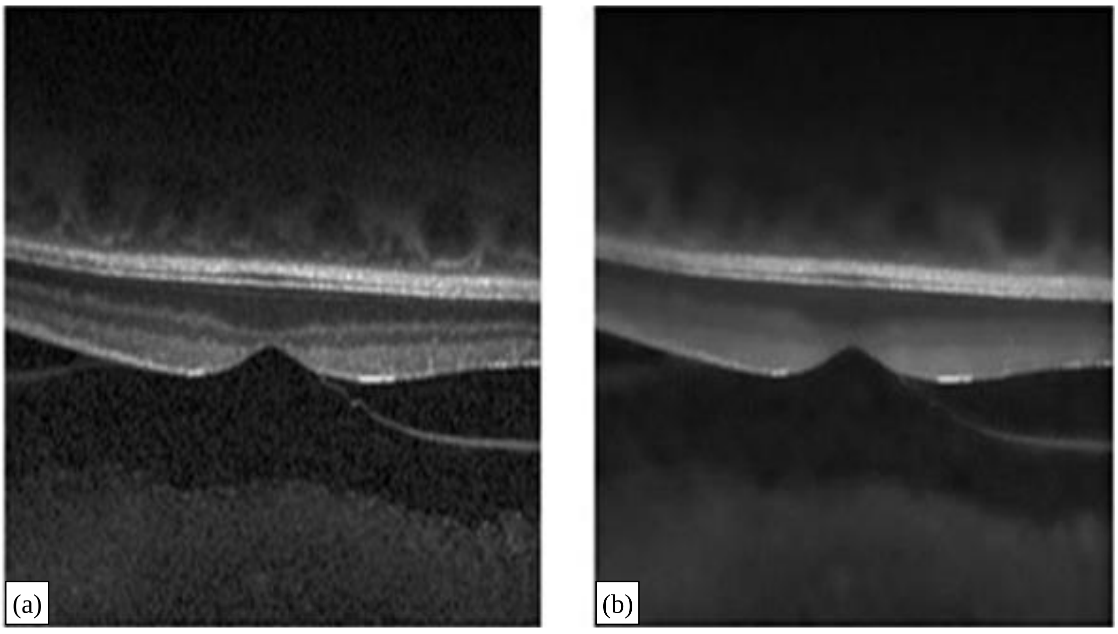


Figure 2. Preprocessed retinal OCT image.

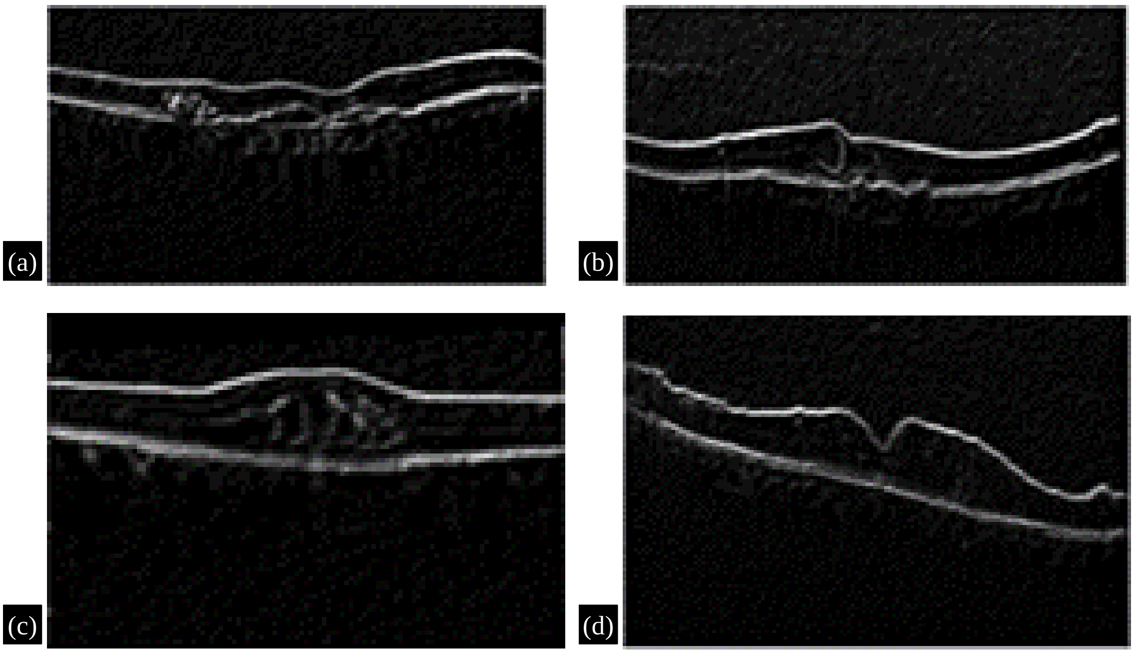
Table 1. Preprocessing techniques.

Preprocessing technique	Paper title	Authors	Year	Journal/ conference
Noise Reduction	Impact of novel image preprocessing techniques on retinal vessel segmentation	Soomro TA, Ali A, Jandan NA, et al.	2021 [11]	MDPI Electronics
Contrast Enhancement	Retinal image preprocessing, enhancement, and registration	Hernandez-Matas C, Argyros AA, Zabulis X	2019 [12]	Scientific Reports
Normalization	Analyzing optimal image preprocessing techniques for automated retinal disease diagnosis	Lakshmi Chakka	2023 [13]	IEEE Transactions on Medical Imaging
History Equalization	Deep learning and machine learning algorithms for retinal image analysis in neurodegenerative disease: systematic review of datasets and models	Bahr T, Vu TA, Tuttle JJ, Iezzi R	2024 [14]	TVST
Filtering (Median, Wiener)	A detailed systematic review on retinal image segmentation methods	Panda NR, Sahoo AK	2022 [15]	Springer
Morphological Operations	Retinal OCT image classification based on CNN and transfer learning	Shatil SR, Kabir MM	2022 [16]	Springer

Region-based methods classify pixels based on their intensity distributions or other features and often require manual initialization or parameter tuning [17]. Machine learning techniques, particularly deep learning models such as convolutional neural networks (CNNs), have become increasingly popular because of their high performance in segmenting retinal OCT images. The selection of a segmentation method ultimately depends on factors such as the specific application, complexity of retinal structures, and availability of data for training the machine learning models, as shown in Figure 3 [18].

In machine learning based segmentation, several algorithms are utilized to classify pixels in retinal OCT images into different layers or regions based on the extracted features. Support vector machines (SVM) classify pixels using a decision boundary to separate different classes [19].

Random Forests boost the segmentation accuracy by combining the predictions of several decision trees. K-nearest neighbors (KNN) classify pixels by considering the classifications of neighboring pixels, leveraging spatial information for segmentation, as shown in Table 2 [20].



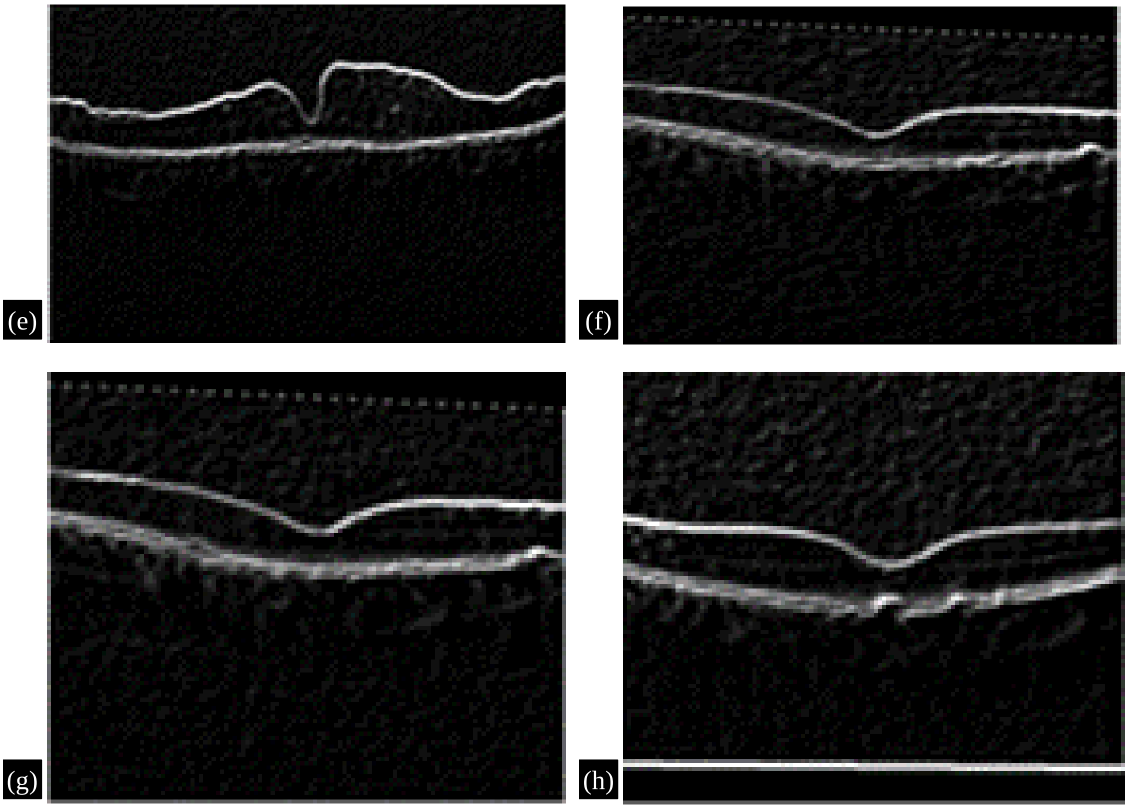


Figure 3. Retinal segmented image.

Table 2. Preprocessing techniques.

Edge detection technique	Paper title	Authors	Year	Journal/conference
Sobel Operator	Retinal blood vessel segmentation using classical edge detection filters and the neural network	Tchinda BS, Tchiotsop D, Noubom M, et al.	2021 [21]	IEEE Transactions on Medical Imaging
Canny Edge Detector	The edge detectors suitable for retinal OCT image segmentation	Luo S, Yang J, Gao Q, Zhou S, Zhan CA	2017 [22]	Computer Methods and Programs in Biomedicine
Laplacian of Gaussian (Log)	Enhanced OCT chorioretinal segmentation in low-data settings with semi-supervised GAN augmentation using cross-localization	Kugelman J, Alonso-Caneiro D, Read SA, Vincent SJ, Collins MJ	2023 [23]	Journal of Biomedical Optics
Prewitt Operator	Fuzzy-based image edge detection algorithm for blood vessel detection in retinal images	Orujov F, Maskeliūnas R, Damaševičius R, Wei WJ	2020 [24]	Medical Image Analysis
Wavelet Transform	Edge detection of retinal OCT image based on complex shearlet transform	Xiaoming L, Ke X, Peng Z, Jiannan C	2019 [25]	IEEE Transactions on Medical Imaging
Gabor Filters	A texture-based method for choroid segmentation in retinal EDI-OCT images	González-López A, Remeseiro B, Ortega M, Penedo MG, Charlón P	2015 [26]	IEEE Access
Active Contour Models	Saliency-driven active contour model for image segmentation	Iqbal E, Niaz A, Memon AA, Asim U, Choi KN	2020 [27]	IEEE Transactions on Biomedical Engineering

Deep learning based segmentation techniques have become increasingly popular because of their capacity to automatically learn features and patterns from data. U-Net, characterized by its encoder-decoder architecture and skip connections, is widely used for biomedical image segmentation, including retinal OCT images [28]. Fully convolutional networks (FCNs) achieve pixel-wise segmentation by substituting fully connected layers with convolutional layers, allowing end-to-end learning directly from raw image data. Recurrent neural networks (RNN), particularly useful for segmenting 3D OCT volumes, incorporate sequential information across image slices to capture spatial dependencies and improve segmentation accuracy [29].

These deep learning techniques offer precise and efficient segmentation of retinal OCT images, contributing to enhanced diagnosis and treatment planning in ophthalmology. The tabular column shows some of the studies related to retinal image segmentation.

CLASSIFICATION TECHNIQUES

This classification aims to automatically detect and categorize retinal diseases from OCT images. Traditional machine learning traditional machine learning approaches for retinal OCT image segmentation involve several key techniques. Feature extraction is a vital first step using techniques such as Histogram of oriented gradients (HOG), Scale-invariant feature transform (SIFT), and local binary patterns (LBP) to obtain meaningful and unique features from images.

These features help to represent the essential information needed for effective segmentation and classification. Once features are extracted, algorithms such as Support Vector Machines (SVM)are used for classification [30]. SVMs work by optimizing the margin between different classes and effectively finding the best hyperplane that separates the data into distinct categories. This method is particularly useful for high-dimensional spaces and ensures good performance in distinguishing between various retinal layers and structures. Another powerful method is Random Forests, an ensemble technique that uses multiple decision trees to enhance classification accuracy. Each tree was trained on a distinct subset of the data, and the aggregated results from all trees produced more accurate and reliable segmentation. These traditional machine learning methods provide a strong foundation for retinal OCT image segmentation, facilitating better diagnostic and therapeutic decisions [31].

Deep learning approaches have revolutionized retinal OCT image segmentation using neural networks to automatically learn hierarchical features from images. CNNs are leading to this advancement, demonstrating exceptional skills in capturing intricate patterns and structures within OCT data. Architectures such as AlexNet demonstrated the potential of deep learning in image classification, setting a benchmark for subsequent models. VGGNet further advanced this field by emphasizing depth and simplicity through the use of small convolution filters, leading to more refined feature extraction.

ResNet introduced residual connections, which is a significant advancement that tackles the vanishing gradient problem and enables the training of much deeper networks. DenseNet is built on this using dense connections, ensuring efficient information flow between layers, which improves feature propagation and reduces redundancy.

In addition to CNNs, RNNs have been explored for their ability to incorporate sequential information, making them particularly beneficial for analyzing 3D OCT volumes, where temporal dependencies can provide a valuable context. Transfer learning is a vital approach in deep learning that involves the use of pre-trained models on large datasets [32].

Additionally, ensemble methods improve overall accuracy and robustness by merging predictions from multiple models. Together, these deep learning methodologies represent a significant leap forward in the segmentation and analysis of retinal OCT images, driving advancements in clinical diagnostics and treatment planning. Table 3 shows some of the studies related to retinal image classification.

Table 3. Classification techniques.

Authors	Classification technique	Study details
Alsaih K, Lemaitre G, Rastgoo M, Massich J, Sidibé D, Meriaudeau F. (2017) [33]	Machine learning techniques	Focused on diabetic macular edema (DME) classification using SD-OCT images, leveraging various machine learning algorithms to enhance classification accuracy (MDPI).
Akinniyi O, Rahman MM, Sandhu HS, El-Baz A, Khalifa F (2023) [34]	Multi-stage classification of retinal OCT using multi-scale ensemble deep architecture	Developed a scale-adaptive neural network for extracting multi-scale features, achieving high classification accuracy for retinal disorders like DME, CNV, AMD, and Drusen (MDPI)
Papandrianos I, Feleki A, Papageorgiou EI, Martini C (2022) [35]	Deep Learning with SPECT-MPI Images	Utilized deep learning for automated diagnosis of coronary artery disease, showcasing applicability for retinal image classification (SpringerOpen).
Sengupta S, Singh A, Leopold HA, Gulati T, Lakshminarayanan V (2020) [36]	Deep learning with fundus images	Employed convolutional neural networks (CNNs) for ophthalmic diagnosis, demonstrating significant improvements in classification accuracy for retinal diseases (SpringerOpen).
Panchal S, Naik A, Kokare M, Pachade S, Naigaonkar R, Phadnis P, Bhange A (2023) [37]	Multi-disease classification using CNN	Developed a deep learning model for multi-disease classification on the Retinal Fundus multi-disease image dataset (RFMID), achieving high accuracy and robustness against imbalanced data (SpringerOpen)

CONCLUSION

In conclusion, this survey provides a comprehensive overview of recent advancements in preprocessing, segmentation, and deep learning-based classification of retinal OCT images. Initially, retinal OCT imaging provided crucial information for diagnosing and monitoring a range of retinal diseases such as AMD, DR, and glaucoma. Detailed visualization of retinal layers enables doctors to detect changes indicative of these conditions, facilitating early intervention and improving patient outcomes. Second, preprocessing techniques play a crucial role in enhancing the quality and reliability of the retinal OCT images. Various methods, including noise reduction, contrast enhancement, image normalization, and artifact removal, improve image clarity and accuracy, thereby enhancing their utility for clinical diagnosis and research purposes.

Second, segmentation techniques allow for the division of retinal OCT images into significant regions that represent various anatomical structures or pathological features. Machine learning approaches, particularly deep learning models such as CNNs, have shown promise for accurately segmenting retinal OCT images, thereby facilitating precise diagnosis and treatment planning in ophthalmology.

Finally, classification techniques aim to automatically detect and categorize retinal diseases by using OCT images. Traditional machine learning approaches, such as SVMs and Random Forests, form a solid foundation for classification tasks. Deep learning methods such as CNNs and RNNs provide substantial improvements in accuracy. The combined use of preprocessing, segmentation, and deep learning based classification techniques has the potential to transform the field of retinal OCT imaging, leading to significant advancements in clinical diagnostics and treatment planning. Further research and innovation in this area hold promises for improving patient care and advancing our understanding of retinal diseases.

REFERENCES

1. Abràmoff MD, Garvin MK, Sonka M. Retinal imaging and image analysis. IEEE Rev Biomed Eng. 2010;3:169–208. DOI: 10.1109/RBME.2010.2084567. PubMed: 22275207.
2. Huang D, Swanson EA, Lin CP, Schuman JS, Stinson WG, Chang W, et al. Optical coherence tomography. Science. 1991;254:1178–81. DOI: 10.1126/science.1957169.

3. Chhablani PP, Ambiya V, Nair AG, Bondalapati S, Chhablani J. Retinal findings on OCT in systemic conditions. Ophthalmology. Taylor & Francis. 2018;33:525–46. DOI: 10.1080/08820538.2017.1332233. PubMed: 28640657.
4. Jaffe GJ, Caprioli J. Optical coherence tomography to detect and manage retinal disease and glaucoma. Am J Ophthalmol. 2004;137:156–69. DOI: 10.1016/s0002-9394(03)00792-x. PubMed: 14700659.
5. Gabriele ML, Wollstein G, Ishikawa H, Xu J, Kim J, Kagemann L, et al. Three-dimensional optical coherence tomography imaging: Advantages and advances. Prog Retin Eye Res. 2010;29:556–79. DOI: 10.1016/j.preteyeres.2010.05.005. PubMed: 20542136.
6. Chauhan DS, Marshall J. The interpretation of optical coherence tomography images of the retina. Invest Ophthalmol Vis Sci. 1999;40:2332–42. PubMed: 10476800.
7. Salvatelli A, Bizai G, Barbosa G, Drozdowicz B, Delrieux C. A comparative analysis of pre-processing techniques in colour retinal images. J Phys Conf Ser. 2007;90:012069. DOI: 10.1088/1742-6596/90/1/012069.
8. Setiawan AW, Mengko TR, Santoso OS, Suksmono AB. Color retinal image enhancement using CLAHE. International Conference on ICT for Smart Society, Jakarta, Indonesia. 2013, pp. 1–3. DOI: 10.1109/ICTSS.2013.6588092.
9. Goatman KA, Whitwam AD, Manivannan A, Olson JA, Sharp PF. Colour normalisation of retinal images. In: Proceedings of Medical Image Understanding and Analysis. University of Sheffield: UK; 2003. p. 49–52.
10. Marrugo AG, Millán MS. Retinal image analysis: Preprocessing and feature extraction. J Phys Conf Ser. 2011;274:012039. DOI: 10.1088/1742-6596/274/1/012039.
11. Soomro TA, Ali A, Jandan NA, Afifi AJ, Irfan M, Alqhtani S, et al. Impact of novel image preprocessing techniques on retinal vessel segmentation. Electronics. 2021;10:2297. DOI: 10.3390/electronics10182297.
12. Hernandez-Matas C, Argyros AA, Zabulis X. Retinal image preprocessing, enhancement, and registration. Comput Retin Image Anal. 2019;59–77.
13. Chakka L. Analyzing optimal image preprocessing techniques for automated retinal disease diagnosis. Nat High Sch J Sci. 2023;1–8.
14. Bahr T, Vu TA, Tuttle JJ, Iezzi R. Deep learning and machine learning algorithms for retinal image analysis in neurodegenerative disease: Systematic review of datasets and models. Transl Vis Sci Technol. 2024;13:16. DOI: 10.1167/tvst.13.2.16. PubMed: 38381447.
15. Panda NR, Sahoo AK. A detailed systematic review on retinal image segmentation methods. J Digit Imaging. 2022;35:1250–70. DOI: 10.1007/s10278-022-00640-9. PubMed: 35508746.
16. Shatil SR, Kabir MM. Retinal OCT image classification based on CNN and transfer learning. In: International Conference on Soft Computing and Pattern Recognition. Springer Nature Switzerland: Cham; 2022. p. 433–44.
17. DeBuc DC. A review of algorithms for segmentation of retinal image data using optical coherence tomography. Image Segmentation. 2011;1:15–54.
18. Pekala M, Joshi N, Liu TYA, Bressler NM, DeBuc DC, Burlina P. Deep learning based retinal OCT segmentation. Comput Biol Med. 2019;114:103445. DOI: 10.1016/j.compbiomed.2019.103445. PubMed: 31561100.
19. Ramesh KKD, Kumar GK, Swapna K, Datta D, Rajest SS. A review of medical image segmentation algorithms. EAI Endorsed Trans Pervasive Health Technol. 2021;7:e6. DOI: 10.4108/eai.12-4-2021.169184.
20. Alqudah AM, AlTantawi M, Alqudah A. Artificial intelligence hybrid system for enhancing retinal diseases classification using automated deep features extracted from OCT images. Int J Intell Syst Appl Eng. 2021;9:91–100. DOI: 10.18201/ijisae.2021.236.
21. Saha Tchinda BS, Tchiotsop D, Noubom M, Louis-Dorr V, Wolf D. Retinal blood vessels segmentation using classical edge detection filters and the neural network. Informatics Med Unlocked. 2021;23:100521. DOI: 10.1016/j.imu.2021.100521.

22. Luo S, Yang J, Gao Q, Zhou S, Zhan CA. The edge detectors suitable for retinal OCT image segmentation. J Healthc Eng. 2017;2017:3978410. DOI: 10.1155/2017/3978410. PubMed: 29065594.
23. Kugelman J, Alonso-Caneiro D, Read SA, Vincent SJ, Collins MJ. Enhanced OCT chorio-retinal segmentation in low-data settings with semi-supervised GAN augmentation using cross-localisation. Comput Vis Image Underst. 2023;237:103852. DOI: 10.1016/j.cviu.2023.103852.
24. Orujov F, Maskeliūnas R, Damaševičius R, Wei WJ. Fuzzy based image edge detection algorithm for blood vessel detection in retinal images. Appl Soft Comput. 2020;94:106452. DOI: 10.1016/j.asoc.2020.106452.
25. Xiaoming L, Ke X, Peng Z, Jiannan C. Edge detection of retinal OCT image based on complex shearlet transform. IET Image Process. 2019;13:1686–93. DOI: 10.1049/iet-ipr.2018.6634.
26. González-López A, Remeseiro B, Ortega M, Penedo MG, Charlón P. A texture-based method for choroid segmentation in retinal EDI-OCT images. Comput Aided Syst Theory EUROCAST. Springer Int Publ. 2015;15:487–93.
27. Iqbal E, Niaz A, Memon AA, Asim U, Choi KN. Saliency-driven active contour model for image segmentation. IEEE Access. 2020;8:208978–91. DOI: 10.1109/ACCESS.2020.3038945.
28. Thompson AC, Jammal AA, Berchuck SI, Mariottoni EB, Medeiros FA. Assessment of a segmentation-free deep learning algorithm for diagnosing glaucoma from optical coherence tomography scans. JAMA Ophthalmol. 2020;138:333–9. DOI: 10.1001/jamaophthalmol.2019.5983. PubMed: 32053142.
29. Du G, Cao X, Liang J, Chen X, Zhan Y. Medical image segmentation based on U-Net: A review. J Imaging Sci Technol. 2020;64:020508–501. DOI: 10.2352/J.ImagingSci.Technol.2020.64.2.020508.
30. Tong Y, Lu W, Yu Y, Shen Y. Application of machine learning in ophthalmic imaging modalities. Eye Vis (Lond). 2020;7:22. DOI: 10.1186/s40662-020-00183-6. PubMed: 32322599.
31. Badar M, Haris M, Fatima A. Application of deep learning for retinal image analysis: A review. Comput Sci Rev. 2020;35:100203. DOI: 10.1016/j.cosrev.2019.100203.
32. Shyla NSJ, Emmanuel WRS. Glaucoma detection using multiple feature set with recurrent neural network. Comput J. 2023;66:2426–36. DOI: 10.1093/comjnl/bxac093.
33. Alsaih K, Lemaitre G, Rastgoo M, Massich J, Sidibé D, Meriaudeau F. Machine learning techniques for diabetic macular edema (DME) classification on SD-OCT images. Biomed Eng Online. 2017;16:68. DOI: 10.1186/s12938-017-0352-9. PubMed: 28592309.
34. Akinniyi O, Rahman MM, Sandhu HS, El-Baz A, Khalifa F. Multi-stage classification of retinal OCT using multi-scale ensemble deep architecture. Bioengineering. 2023;10:823. DOI: 10.3390/bioengineering10070823. PubMed: 37508850.s
35. Papandrianos NI, Feleki A, Papageorgiou EI, Martini C. Deep learning-based automated diagnosis for coronary artery disease using SPECT-MPI images. J Clin Med. 2022;11:3918. DOI: 10.3390/jcm11133918. PubMed: 35807203.
36. SenGupta S, Singh A, Leopold HA, Gulati T, Lakshminarayanan V. Ophthalmic diagnosis using deep learning with fundus images: A critical review. Artif Intell Med. 2020;102:101758. DOI: 10.1016/j.artmed.2019.101758. PubMed: 31980096.
37. Panchal S, Naik A, Kokare M, Pachade S, Naigaonkar R, Phadnis P, et al. Retinal fundus Multi-Disease Image Dataset (RFMiD) 2.0: A dataset of frequently and rarely identified diseases. Data. 2023;8:29. DOI: 10.3390/data8020029.

