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Review Article

A Review of Preprocessing Methods for Retinal Fundus and OCT Images in Eye Disease Diagnosis

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Abstract

Retinal imaging has become an essential tool in the field of ophthalmology, offering valuable insights into ocular health and supporting the diagnosis and monitoring of common vision-threatening diseases through non-invasive means (i.e. Fundus imaging and Optical Coherence Tomography (OCT)). While fundus imaging represents a two-dimensional view of the retinal surface given through visible light, the advantage of an OCT is the development of a cross-sectional view of the retina providing higher resolution details necessary to detect subtle changes within retinal layers. Preprocessing is also required to provide comprehensive image quality, reduce inter-image variability, and provide objective input to support the accuracy of automated diagnostic algorithms. In this report, I describe common and effective preprocessing techniques for both imaging modalities: 1. fundus image preprocessing includes improvement to image quality, vessel and structure enhancement, color normalization, noise reduction, and augmentation of fundus images; 2. OCT image preprocessing includes denoising, flattening, motion correction and cropping, and intensity normalization of OCT images. With this study, the various preprocessing types of modalities can improve clinical utility and efficiency, and delineate a process where machine learning (ML) and computer vision can be incorporated into the diagnostic process.

Keywords: *Retinal Fundus Imaging, Optical Coherence Tomography, Image Preprocessing, Diabetic Retinopathy, Glaucoma, Age-related Macular Degeneration, Retinal Detachment, Histogram Equalization, Speckle Noise, OCT Flattening, Motion Artifact Correction, Color Normalization, Vessel Enhancement, Data Augmentation, Deep Learning in Ophthalmology.*

Introduction

Vision is significant in how people perceive their environment, with the eyes being the main sensory organs to interpret the world around us. However, the number of vision-related disorders appears to be rising, especially in older adults in conjunction with the aging population, chronic diseases like diabetes, and obstacles to early diagnosis and timely access. According to the World Health Organization (WHO) in 2023, there are over 2.2 billion people with some form of visual impairment, with the most common age occurring in those over 50 years of age[1]. Unfortunately, more than 80% of blindness cases could be avoided if they were detected early, so a prompt diagnosis and response are important[2].

Retinal disorders, including Diabetic Macular Edema (DME), Age-related Macular Degeneration, and Choroidal Neovascular Membrane (CNVM) rank as some of the leading causes of vision loss globally. Diabetic Retinopathy alone affects approximately 4 million people and continues to become a growing public health and economic burden due to the continued rise of diabetes prevalence globally[3]. If such diseases are identified correctly and early, their effects on patients can be controlled and positive outcomes can be achieved.

OCT and fundus photography have become important tools for detecting retinal diseases. OCT, in particular, provides excellent imaging of retinal cross-sections in a non-invasive way, allowing clinicians to detect abnormalities in fluid, thickness, and blood vessels[4][5]. In normal retina on OCT images, there is a smooth structure without fluid, and blood vessels are round, normally shaped. In DME it is easy to see areas of inter-retinal fluid pockets. In AMD it is evident with retinal and sub-retinal fluid pockets. In CNVM it appears that the vascular structures in the blood vessel layer are not shaped correctly, but rather appear as weird dark voids or distortions in the layer.

Despite the advantages of OCT and fundus imaging, numerous obstacles constrain their effective and widespread application, including variability in image quality, noise artifacts, and sensitivity to segmentation,

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which is critical in obtaining diagnostically-relevant features[6][7]. In addition, since OCT images contain patient identifiable information, privacy and security will need to be considered. For example, medical image watermarking and adversarial networks have been suggested to secure medical image fusion and protection.

Overcoming these problems greatly depends on using preprocessing methods. Taking some basic preprocessing steps increases the quality of the images and helps in feature extraction, classification, and 3D visualization of the images[8]. In particular, image segmentation makes it possible to correctly outline regions of interest, measure important tissues, and discover lesions, all of which matter for automated computer-aided diagnosis (CAD).

Deep learning approaches have made incredible progress in the last few years in the preprocessing and analysis of retinal images. Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and hybrid models have achieved state-of-the-art performance in denoising, segmentation, and feature extraction. These methods alleviate some manual burdens on clinicians and improve diagnostic accuracy.

A. Structure of the paper

This paper is structured in the following manner: Section II overview of Retinal fundus and OCT Imaging. Section III: Preprocessing Methods of Retinal Fundus Imaging. Section IV: Preprocessing Methods of OCT Imaging. Section V The Literature Of Review. Section VI: Conclusion and Future Work.

Overview of retinal fundus and oct imaging

Modern ophthalmology depends on retinal imaging to find, monitor, and treat many different eye diseases. OCT as well as retinal fundus photography are two of the most often used methods [9]. While both techniques offer valuable insights into the health of the retina, they differ significantly in terms of imaging principles, anatomical details captured, and clinical applications. An extensive review of various imaging methods and their applicability to the diagnosis of common retinal illnesses is given in this section.

A. Retinal Fundus Imaging

Retinal fundus imaging is a non-invasive diagnostic method that produces a two-dimensional picture of the retina, optic disc, macula, and posterior pole, among other internal surfaces of the eye[10][11]. The imaging method uses a specialized fundus camera that illuminates and takes pictures of the back of the eye via the pupil using a low-power microscope as well as a flash-enabled digital camera. Typically, images are captured in full color, although variations such as red-free or auto fluorescence imaging may be used to highlight specific features. (Fig 1 - Retinal Funds Image, (a) Human Eye Structure. (b) A fund picture shows symptoms of DR.

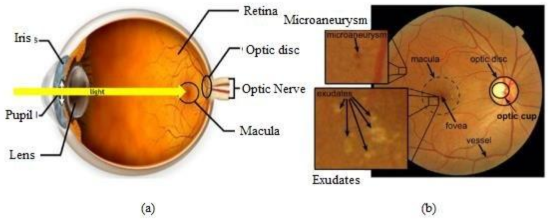

Fig.1. Retinal fundus image, (a) structure of the human eye; (b) Fundus image with signs of DR

B. Optical Coherence Tomography (OCT)

OCT is a high-resolution imaging method that offers cross-sectional and 3D visualization of retinal structures. OCT measures the intensity and echo time delay of backscattered light from different tissue layers utilizing low-coherence interferometry with near-infrared light, in contrast to fundus imaging, which provides a surface image[12]. Micrometer-scale resolution is made possible by this method, which is similar to ultrasound imaging but uses light rather than sound. Figure 2 shows OTC in the spectrum domain.

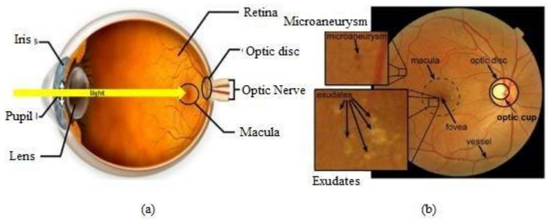

Fig.2. Spectral-domain optical coherence tomography

C. Common Eye Diseases Diagnosed

Retinal fundus and OCT imaging serve an important role in identifying a wide spectrum of ocular disorders. In Fig. 3 fundus photo eye test, four of the most common and vision-threatening conditions include:

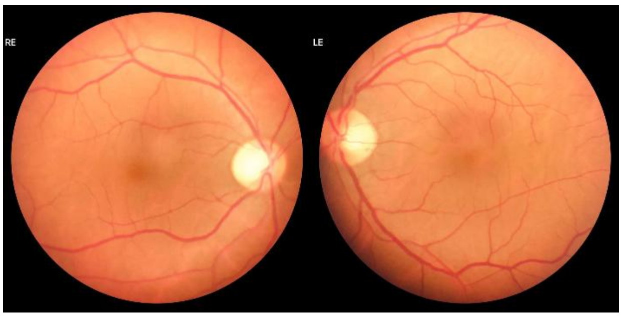

Fig.3. Fundus photo eye test

i. Diabetic Retinopathy (DR): Damage to the retinal blood vessels is a consequence of diabetes mellitus. Fundus imaging can reveal microaneurysms, hemorrhages, hard exudates, and neovascularization[13]. OCT provides additional insights by detecting macular edema, subretinal fluid, and disruptions in retinal architecture.

ii. Glaucoma: A collection of eye disorders that cause gradual damage to the optic nerve and are frequently linked to high intraocular pressure. Fundus images are used to assess the optic disc for cupping and pallor, While OCT is a powerful tool for determining the thickness of the ganglion cell complex and RNFL, it may also be used to identify glaucomatous alterations before visual field loss happens.

iii. Age-related Macular Degeneration (AMD): AMD, which can be characterised as either dry or wet, is a major cause of visual loss in the elderly. Fundus imaging can detect drusen deposits, pigmentary changes, and geographic atrophy. OCT excels in identifying subretinal fluid, pigment epithelial detachment, and neovascular membranes characteristic of the wet form[14].

iv. Retinal Detachment: This happens when the retina detaches from the supporting tissues underneath, which might result in blindness if treatment is delayed. Fundus imaging helps identify tears, holes, and areas of detachment. OCT can visualize subtle retinal elevations or schisis (splitting of retinal layers) that may precede a full detachment, assisting in early intervention.

Preprocessing methods for retinal fundus images

A crucial phase in retinal image processing is preprocessing, which aims to improve picture quality and normalize data to support segmentation, illness classification, as well as robust feature extraction. Given the variability in image acquisition conditions, such as lighting, resolution, and patient-specific anatomical differences, effective preprocessing methods can significantly improve the performance of downstream computer vision and ML algorithms[15][16]. This section discusses key preprocessing techniques applied to retinal fundus images, categorized by their functional objectives. In Fig 4 Preprocessing Methods for Retinal fundus.

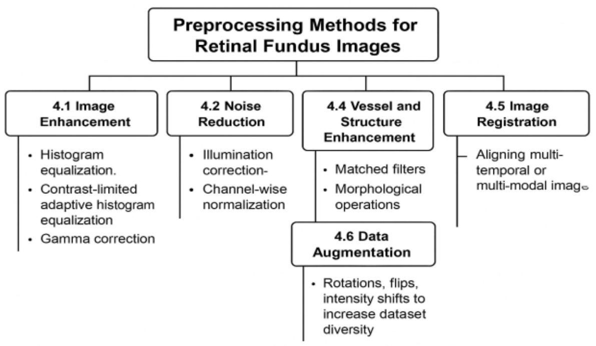

Fig.4. Preprocessing Methods for Retinal Fundus

A. Image Enhancement

Retinal pictures may be made more readable and visually appealing with the use of image enhancement methods that change brightness and contrast[17].

i. Histogram Equalization: This technique improves global contrast in fundus photos that are underexposed or have uneven illumination by redistributing the intensity data in the image to take use of the whole range of values. However, it may also amplify noise in homogeneous regions. Fig 5 Histogram equalization of a green channel of a retinal image.

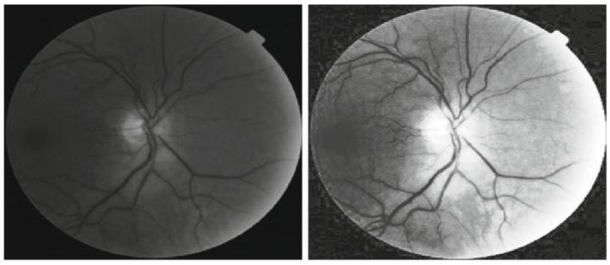

Fig.5. Histogram equalization of a green channel of a retinal image

ii. Contrast-Limited Adaptive Histogram Equalization (CLAHE): CLAHE focuses on specific areas of a picture instead of the whole thing, and it reduces noise amplification by stopping the histogram at a certain threshold. This adaptive strategy enhances local contrast while preserving fine details such as microaneurysms and blood vessels, making it especially useful in DR screening.

iii. Gamma Correction: This technique modifies the luminance of the image using a nonlinear transformation. By adjusting the gamma value, this method either brightens or darkens an image to correct perceptual brightness, thereby making the macula, optic disc, as well as vascular components of the retina more visible[18].

B. Noise Reduction

Fundus images often suffer from sensor noise, motion artifacts, or compression distortions. To improve visual clarity, noise reduction methods, including bilateral, median, as well as Gaussian filtering, are frequently used. (Fig. 6 Image Enhancement)

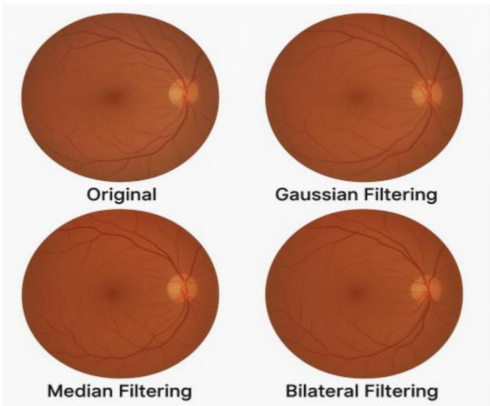

Fig.6. Image Enhancement

i. Gaussian Filtering: smoothes the image by using a Gaussian kernel to average pixel values, which efficiently reduces high-frequency noise but may blur edges.

ii. Median Filtering: more resilient to salt-and-pepper noise as well as better maintains edges by substituting the neighbourhood median for each pixel.

iii. Bilateral Filtering: It is ideal for maintaining important anatomical boundaries because it strikes a compromise between noise reduction as well as edge preservation by taking into account both spatial closeness and pixel intensity differences.

C. Color Normalization

Color variation due to inconsistent illumination, different camera systems, or patient pigmentation can degrade model performance[19].

i. Illumination Correction: Aims to normalize the lighting across the image by estimating and subtracting a background illumination map, thereby flattening uneven brightness and improving consistency across datasets[20].

ii. Channel-Wise Normalization: Involves independently standardizing the red, green, and blue channels to a common statistical baseline (e.g., zero mean, unit variance). This step reduces inter-image variability and ensures that models learn features based on anatomical content rather than color discrepancies.

D. Vessel and Structure Enhancement

Enhancing retinal vessels and anatomical structures like the optic disc and macula is critical for diagnostic tasks such as vessel segmentation and lesion detection. Fig 7 – Vessel and Structure Enhancement.

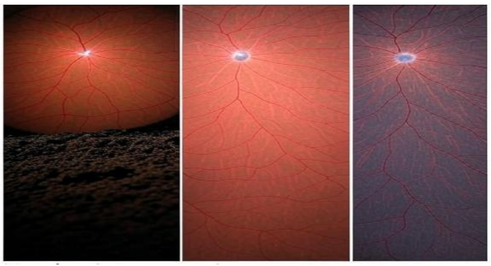

Fig.7. Vessel and Structure Enhancement

i. Matched Filtering: Uses convolutional filters shaped like vessel profiles to enhance tubular structures aligned with the filter's orientation. These filters are especially effective for highlighting fine vasculature.

ii. Morphological Operations: Dilation, erosion, opening, and closure are among the techniques used to manipulate binary or greyscale pictures in order to highlight structural aspects. These techniques can enhance the continuity of vessel networks, remove noise, and fill gaps in segmented features, facilitating more accurate downstream analysis.

E. Image Registration

In scenarios involving multi-temporal or multi-modal retinal images such as longitudinal studies or fusion of fundus images with fluorescein angiography image registration becomes essential. Fig 8 Image registration.

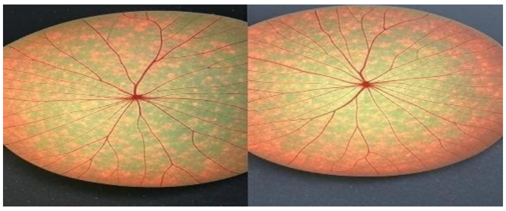

Fig.8. Image Registration

i. Image Registration: Aligns images by estimating geometric transformations that account for rotation, translation, or scaling, ensuring that corresponding anatomical features are spatially aligned. Techniques range from feature-based methods using keypoints (e.g., SIFT or ORB) to intensity-based approaches employing mutual information. Proper registration allows for consistent comparison across time points or modalities and enhances the accuracy of change detection and multimodal integration.

F. Data Augmentation

Data augmentation is a necessary preprocessing step for training robust ML models due to the scarcity of annotated medical pictures and class imbalance in datasets. (Fig. 9 Data Augmentation)[21]

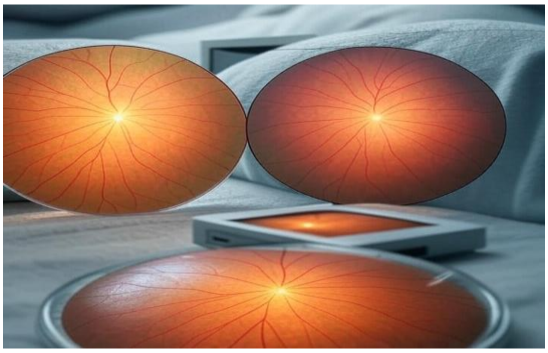

Fig.9. Data Augmentation

i. Data Augmentation Techniques: flips, cropping, scaling, Rotations, and intensity changes are examples of synthetically expanding the training dataset, allowing models to generalise better to previously unseen pictures. Augmentation also reduces overfitting by exposing models to a broader variety of visual changes that might occur in real-world clinical situations. For retinal images, care must be taken to apply biologically plausible transformations to maintain anatomical fidelity and diagnostic relevance.

Preprocessing methods for oct images

Preprocessing is a critical step in the analysis of OCT picture, ensuring that data input to subsequent algorithms is standardized, denoised, and correctly aligned. Given the high sensitivity of OCT to noise, motion, and anatomical variability, preprocessing addresses these issues to improve the robustness and accuracy of downstream tasks like disease detection, segmentation, as well as classification. Fig 10 shows Preprocessing Method for OCT[22].

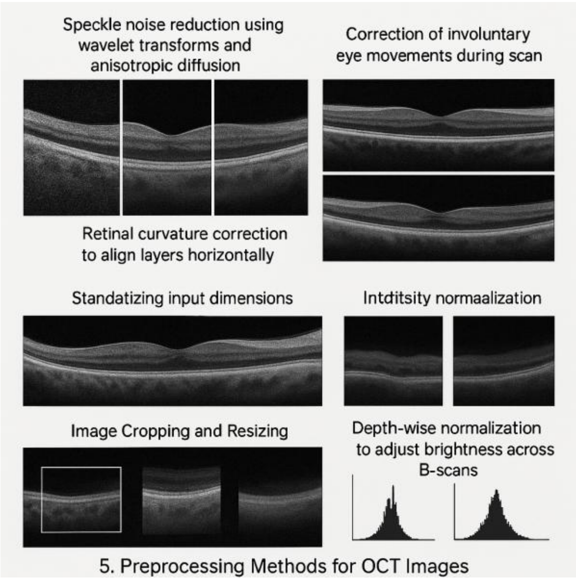

Fig.10. Preprocessing Methods for OCT

A. Denoising Techniques

OCT pictures are intrinsically impacted by speckle noise, a granular interference pattern that emerges owing to the coherent nature of the light employed in image capture. This noise can obscure fine structural details essential for clinical interpretation and algorithmic analysis. Wavelet transform-based demising techniques offer a multi-scale approach to separating noise from useful signal content by decomposing the image into different frequency components and attenuating the coefficients associated with noise[23]. Anisotropic diffusion is another powerful demising method, which smooths the image while preserving edges by encouraging intra-region diffusion and discouraging diffusion across edges. This selective smoothing helps to retain structural integrity, making it ideal for medical imaging when edge information is crucial. Figure 11 compares several approaches for denoising OCT as well as OCTA, like BM4D, K-SVD 3D shearlet filtering.

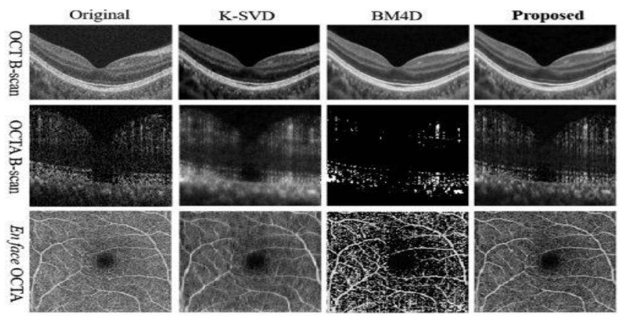

Fig.11. Comparison of different methods in denoising OCT and OCTA

B. Flattening and Layer Alignment

The retinal surface in OCT images typically exhibits a natural curvature that varies across patients and scan sessions. For accurate analysis, especially in tasks that rely on layer-based features or longitudinal comparisons, this curvature must be corrected. Flattening involves detecting a reference layer, such as the retinal pigment epithelium (RPE), as well as re-aligning the image so that this layer lies along a horizontal axis. This normalization facilitates better inter-image comparison and improves the performance of algorithms sensitive to geometric distortions. In Fig 12 shows Flattening and layers aligns)[24]

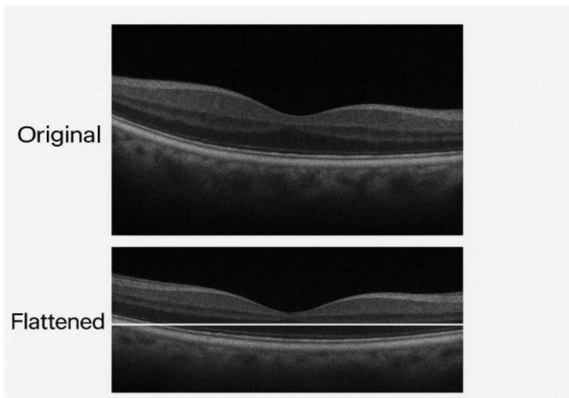

Fig.12. Flattening and Layers Aligns

C. Motion Artifact Correction

Involuntary eye movements, such as micro saccades and drifts, during OCT acquisition introduce motion artifacts that can blur structures or misalign image segments. These artifacts compromise the fidelity of 3D volume reconstructions and can mislead image interpretation. Motion correction techniques typically involve aligning B-scans within a volume using cross-correlation or optical flow methods, or leveraging information from auxiliary eye-tracking data when available. Correcting for motion ensures continuity and consistency across slices, which is particularly important for volumetric analysis. Fig 13 Correction of motion[25].

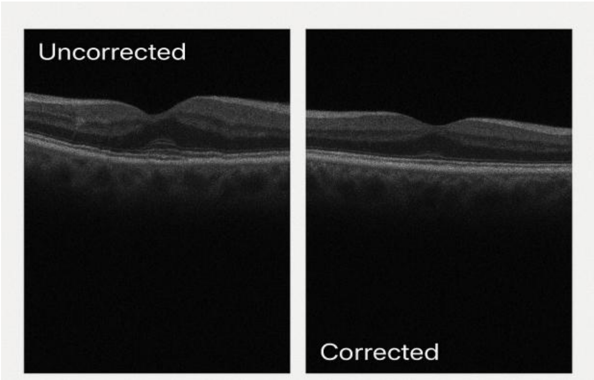

Fig.13. Correction of Motion

D. Image Cropping and Resizing

To ensure uniformity in input data dimensions, OCT images are often cropped to remove non-informative regions and resized to a standard resolution. Cropping typically focuses on the region containing the retina, discarding irrelevant margins that may include background or acquisition artifacts[26]. Resizing further standardizes the spatial dimensions across a dataset, which is a prerequisite for training deep learning models that require fixed input sizes. Careful implementation of these steps preserves anatomical fidelity while enabling computational efficiency. Figure 14 picture is cropped and reduced in size.

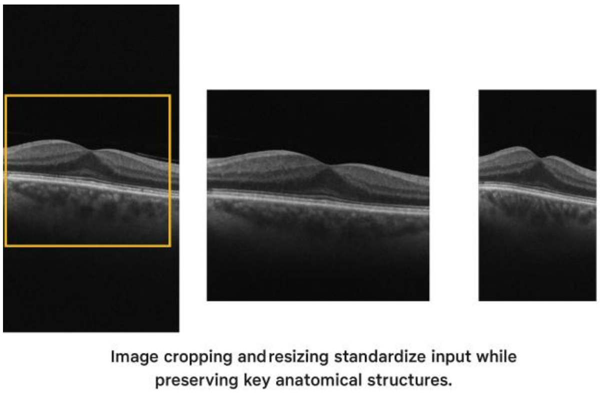

Fig.14. Image Cropping and Resizing

E. Intensity Normalization

There are differences in image intensity in OCT images because of varying scanning settings, each patient's factors, and the effect of depth on the signal [27]. Intensity normalization depth-wise compensates for differences in brightness and contrast across the B-scan's depth, improving inter-scan comparability. This is usually carried out by normalizing the pixel intensities based on the statistical properties for each layer respectively, or with histogram equalization style normalization. Overall, making across datasets the image appearance is more consistent for stronger learning and inference[28].

Literature of review

This literature review discusses current advances in deep learning, CNN, and image processing for detecting ocular diseases, with a focus on OCT integration, dataset issues, preparation strategies, and complete assessments for multi-disease retinal diagnostics and classification.

Abdi and Abdulazeez, (2025) Recent advances in deep learning techniques have altered the area of medical imaging, particularly in the identification of eye diseases. Progress in this discipline has increased the ability to extract and assess complex properties in pictures, with OCT playing a critical role. OCT has been renowned for its safety and high degree of detail, making it an indispensable tool in the detection of eye illnesses. The noteworthy advancement in study revolves around the integration of deep learning with OCT for the goal of automating the detection of eye illnesses[29].

Ali and Mahmood, (2025) provide a succinct overview of the majority of DL, hybrid, as well as ensemble models used to diagnose and categorize eye disorders. There is discussion of a variety of datasets, feature extraction methods, and performance assessment criteria. They use various datasets to assess the performance of selected studies; the most popular ones are the online retinal fundus image dataset for Gl analysis and study, the ocular disease intelligent recognition methods to assess segmentation and indexing methods in the field of retinal ophthalmology-version 2, The findings demonstrate that, when compared to conventional ML techniques, DL algorithms consistently provide high accuracy. But there are still some difficulties and restrictions, such as high resource usage and over-fitting because of problems with dataset size and variety[30].

Wali and Jr, (2024) explain that many studies use ML classifiers and image feature extraction to identify ocular diseases in publicly accessible datasets of retinal OCT pictures. Iterating through the pre-processing processes, the aforementioned stages begin with resizing the image to 100 × 100 pixels. Gaussian Blur is used to eliminate noise after scaling, and the picture is then normalized. To evaluate its performance, they systematically compare it to well-known built-in techniques like Feature from Opponent Space for Filtering (FOSF), Local Binary Patterns (LBP), and Histogram of Oriented Gradients (HOG). Through this comparison study, the effectiveness of determining the optimal strategy in respect to these well-known techniques is evaluated[31].

Ilesanmi, Ilesanmi and Gbotoso, (2023) Retinal fundus images are used for the early detection of problems with the eye, allowing for early diagnosis or treatment and preventing visual loss or blindness. Therefore, recent advancements in technology show that Convolutional Neural Network (CNN) algorithms used in recognition, delineation, and classification tasks are advantageous. This paper proposes a systematic literature review of CNN algorithms for the segmentation and classification of retinal fundus images. The systematic literature review employs a systematic approach, tapping into different repositories by locating studies, employing CNN to segment and classify retinal fundus images. This will lead to enhanced and accurate segmentation result, and decrease the workload of human expert[32].

Mayya et al. (2023) Age-related macular degeneration, cataracts, diabetic retinopathy, myopia, and glaucoma are examples of chronic ocular diseases (COD) that can harm the eye and result in blindness or severe visual impairment. To identify COD, ophthalmologists are taught to look for specific, minute abnormalities in the retina, including blood vessel modifications, hemorrhages, macular edema, and micro aneurysms. There is a wide variety of eye disorders, and each one needs a different course of therapy for each patient. This is the first study that, as far as we are aware, offers a qualitative examination of preprocessing strategies for COD classification utilizing CNN models[33].

Umer et al., (2023) One of the main imaging techniques for identifying and categorizing retinal eye diseases is OCT. The primary cause of blindness is various retinal eye disorders, which can be prevented with early identification. However, ophthalmologists are presently using subjective and sometimes inaccurate OCT pictures to manually identify retinal eye diseases. Various approaches have been put out to automate the manual process of detecting retinal eye diseases that require additional enhancement in terms of detection precision. This study used fusion and selection approaches to offer an automated method for the identification and categorization of retinal eye diseases using OCT pictures. The suggested retinal eye disease detection technology may be utilized to accurately diagnose eye diseases automatically from OCT images, according to experimental results[34].

Goutam et al., (2022) This paper offers a thorough analysis of the various deep learning techniques used recently to diagnose the five main eye conditions: diabetic retinopathy, cataract, age-related macular degeneration, glaucoma, and retinopathy of prematurity. An in-depth analysis of various approaches for each of the 5 retinal diseases listed is presented after this article is structured by the deep learning implementation process pipeline, which begins with illustrations of frequently used datasets, evaluation metrics, image pre-processing methods, as well as deep learning backbone models[35].

Table 1 summarizes the literature on deep learning, ensemble, and image processing approaches for ocular illness diagnosis, emphasizing major discoveries, constraints such as resource demands and dataset limits, and contributions spanning OCT, fundus imaging, and multi-disease detection frameworks.

Table 1. Review for retinal fundus and oct images in eye disease diagnosis

Author(s)	Focus Area	Key Findings	Challenges	Key Contribution
Abdi and Abdulazeez (2025)	Deep learning integration with OCT for ocular disease diagnosis	Deep learning significantly enhances feature extraction from OCT, aiding accurate eye disease detection	Integration with OCT is still evolving; automation demands high-quality annotated datasets	Demonstrated the impact of DL and OCT fusion in automating eye disease diagnosis
Ali and Mahmood (2025)	Examining ensemble, hybrid, as well as DL models for classifying eye diseases	DL models consistently outperform traditional ML approaches on multiple datasets	High resource consumption, overfitting, dataset diversity and size limitations	Comprehensive comparison of various models, datasets, and metrics used in eye disease detection
Wali and Jr (2024)	Retinal disease detection using OCT and image feature extraction	Benchmarking various pre-processing and feature extraction techniques like HOG, LBP, and FOSF	Requires optimal pre-processing pipeline; comparative analysis needed for method selection	Identified the most effective image pre-processing and feature extraction techniques for retinal OCT data
Ilesanmi et al. (2023)	Retinal fundus picture segmentation and classification using CNN	CNNs achieve high accuracy in segmentation and classification, reducing expert dependency	Complex CNN architectures require significant computational resources and training data	Examining CNN-based methods for analysing retinal fundus images methodically
Mayya et al. (2023)	Pre-processing techniques for COD classification using CNNs	Identified key retinal features for COD detection; proposed a qualitative analysis of pre-processing strategies	Each disease requires distinct pre-processing due to varying retinal indicators	First qualitative study evaluating pre-processing methods for multiple CODs
Umer et al. (2023)	Automatic OCT-based detection and classification of retinal diseases	Automated methods using feature fusion and selection improved detection accuracy	Manual OCT analysis is subjective; automated methods still need refinement	Proposed a novel method combining feature fusion and selection for OCT-based detection
Goutam et al. (2022)	Deep learning pipeline for five major eye diseases	Reviewed pre-processing, datasets, models, and evaluation for DR, Glaucoma, AMD, Cataract, and ROP	Disease-specific models require careful tuning; generalization remains a challenge	Comprehensive pipeline-based review covering end-to-end deep learning for five key retinal diseases

Conclusion and future work

Fundus photography and OCT both provide complimentary images of the retina, which is crucial for the diagnosis and monitoring of many ocular illnesses. Even though OCT provides high-resolution cross-sectional insights, fundus imaging only records surface information in two dimensions. However, raw retinal images often suffer from noise, illumination inconsistencies, and anatomical distortions that can hinder accurate analysis. To address these challenges, preprocessing is essential and includes techniques include color normalization, noise reduction, contrast enhancement, and anatomical structure enhancement for fundus images, as well as denoising, flattening, motion artifact correction, and intensity normalization for OCT scans. These procedures allow quality of an image, keep clinically important features, and standardize the image for rigorous analysis by clinical professionals or ML models, thus greatly increasing the accuracy, consistency, and reliability of automated diagnostic systems within ophthalmology.

In the future of retinal image analysis, more advanced and adaptive preprocessing techniques should be the focusing efforts that can adaptively deal with diverse imaging conditions and patient-specific anatomical variation in both fundus and OCT modalities. If deep learning is applied to denoising, normalization, and enhancing features in retinal images, there is a possibility that the improved quality and diagnostic potential of the images may be realized while further reducing laborious manual efforts. Future research should also investigate how multi-modal retinal data (i.e., fundus, OCT, angiography) may be fused in both effective and efficient ways, including suitable registration and alignment methods, to derive overall disease assessment and treatment impact. Future directions should develop the availability of robust publicly available annotated datasets as well as installing these AI-based solutions into clinical workflows by improving rapid end-to-end preprocessing pipelines ensuring potential for real-time assessment may generalize in clinical settings.

Reference

[1] M. Elkholy and M. A. Marzouk, "Deep learning-based classification of eye diseases using Convolutional Neural Network for OCT images," Front. Comput. Sci., 2023, doi: 10.3389/fcomp.2023.1252295.

[2] S. Pandya, "Predicting Diabetes Mellitus in Healthcare : A Comparative Analysis of Machine Learning Algorithms," vol. 13, no. 6, pp. 545–553, 2023.

[3] J. Lin and Q. Chen, "An Intelligent Sensor Data Preprocessing Method for OCT Fundus Image Watermarking Using an RCNN," Comput. Model. Eng. Sci., 2024, doi: 10.32604/cmes.2023.029631.

[4] A. Ikram et al., "A Systematic Review on Fundus Image-Based Diabetic Retinopathy Detection and Grading: Current Status and Future Directions," IEEE Access, vol. 12, no. June, pp. 96273–96303, 2024, doi: 10.1109/ACCESS.2024.3427394.

[5] S. R. Sagili, C. Goswami, V. C. Bharathi, S. Ananthi, K. Rani, and R. Sathya, "Identification of Diabetic Retinopathy by Transfer Learning Based Retinal Images," in 2024 9th International Conference on Communication and Electronics Systems (ICCES), 2024, pp. 1149–1154. doi: 10.1109/ICCES63552.2024.10859381.

[6] S. S. S. Neeli, "The Convergence of AI and Database Administration in Revolutionizing Healthcare," ESP Int. J. Adv. Comput. Technol., vol. 2, no. 4, 2024.

[7] S. Pandya, "A Machine and Deep Learning Framework for Robust Health Insurance Fraud Detection and Prevention," pp. 1332–1342, 2023, doi: 10.48175/IJARSCT-14000T.

[8] D. Rao, "Secure and Ethical Innovations: Patenting Ai Models for Precision Medicine, Personalized Treatment, and Drug Discovery in Healthcare," Int. J. Bus. Manag. Vis., vol. 6, no. 2, 2023.

[9] T. Bahr, T. A. Vu, J. J. Tuttle, and R. Iezzi, "Deep Learning and Machine Learning Algorithms for Retinal Image Analysis in Neurodegenerative Disease: Systematic Review of Datasets and Models," Translational Vision Science and Technology. 2024. doi: 10.1167/tvst.13.2.16.

[10] P. K. Karn and W. H. Abdulla, "On Machine Learning in Clinical Interpretation of Retinal Diseases Using OCT Images," Bioengineering. 2023. doi: 10.3390/bioengineering10040407.

[11] S. B. Shah, "Artificial Intelligence (AI) for Brain Tumor Detection : Automating MRI Image Analysis for Enhanced Accuracy," vol. 14, no. 5, pp. 320–327, 2024.

[12] S. Muchuchuti and S. Viriri, "Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review," Journal of Imaging. 2023. doi: 10.3390/jimaging9040084.

[13] V. Kolluri, "Machine Learning in Managing Healthcare Supply Chains: How Machine Learning Optimizes Supply Chains, Ensuring the Timely Availability of Medical Supplies," 2016.

[14] R. P. Mahajan, "Development of Predictive Models for Early Detection of Alzheimer ' s Disease Using Machine Learning," vol. 15, no. 2, pp. 115–123, 2025.

[15] P. U. Pandey et al., "Ensemble of deep convolutional neural networks is more accurate and reliable than board-certified ophthalmologists at detecting multiple diseases in retinal fundus photographs," Br. J. Ophthalmol., 2023, doi: 10.1136/bjo-2022-322183.

[16] R. Dattangire, D. Biradar, and A. Joon, "AI-Enhanced U-Net for Accurate Low-Grade Glioma Segmentation in Brain MRI: Transforming Healthcare Imaging," in 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), 2024, pp. 1–6. doi: 10.1109/ICEEICT61591.2024.10718440.

[17] E. Anitha and D. J. Aravindhar, "Machine Learning-Based Prediction of Retinal Detachment Subtypes: A Comprehensive Method," in 2023 1st International Conference on Advances in Electrical, Electronics and Computational Intelligence, ICAEECI 2023, 2023. doi: 10.1109/ICAEECI58247.2023.10370921.

[18] N. Patel, "Quantum cryptography in healthcare information systems: enhancing security in medical data storage and communication," J. Emerg. Technol. Innov. Res., vol. 9, no. 8, pp. g193–g202, 2022.

[19] J. Sanghavi and M. Kurhekar, "Ocular disease detection systems based on fundus images: a survey," Multimed. Tools Appl., 2024, doi: 10.1007/s11042-023-16366-x.

[20] S. Pahune, C. Health, and N. Rewatkar, "Large Language Models and Generative AI ' s Expanding Role in Healthcare Large Language Models and Generative AI ' s

Expanding Role in Healthcare," no. January, 2024, doi: 10.13140/RG.2.2.20109.72168.
[21] R. Hans, S. K. Sharma, and U. Aickelin, "Optimised deep k-nearest neighbour's based diabetic retinopathy diagnosis(ODeep-NN) using retinal images," Heal. Inf. Sci. Syst., 2024, doi: 10.1007/s13755-024-00282-x.
[22] L. Godlin Atlas, K. P. Arjun, K. Sampath Kumar, R. K. Dhanaraj, and A. Nayyar, "Deep learning enabled hemorrhage detection in retina with DPFE and splat segmentation in fundus images," Biomed. Signal Process. Control, 2024, doi: 10.1016/j.bspc.2023.105692.
[23] R. P. Mahajan, "Improvised Diabetic Retinopathy Detection Accuracy in Retinal Images Using Machine Learning Algorithms," TIJER, vol. 12, no. 3, pp. 155–161, 2025.
[24] V. Banupriya and S. Anusuya, "Strategy for Rapid Diabetic Retinopathy Exposure Based on Enhanced Feature Extraction Processing," Comput. Mater. Contin., 2023, doi: 10.32604/cmc.2023.038696.
[25] Q. Abbas, Y. Daadaa, U. Rashid, M. Z. Sajid, and M. E. A. Ibrahim, "HDR-EfficientNet: A Classification of Hypertensive and Diabetic Retinopathy Using Optimize EfficientNet Architecture," Diagnostics, 2023, doi: 10.3390/diagnostics13203236.
[26] H. Zainab, A. R. A. Khan, M. I. Khan, and A. Arif, "Ethical Considerations and Data Privacy Challenges in AI-Powered Healthcare Solutions for Cancer and Cardiovascular Diseases," Glob. Trends Sci. Technol., vol. 1, no. 1, pp. 63–74, 2025.
[27] S. R. Sagili, S. Chidambaranathan, N. Nallametti, H. M. Bodele, L. Raja, and P. G. Gayathri, "NeuroPCA: Enhancing Alzheimer's disorder Disease Detection through Optimized Feature Reduction and Machine Learning," in 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), 2024, pp. 1–9. doi: 10.1109/ICEEICT61591.2024.10718628.
[28] S. Krishnamoorthy, Y. Weifeng, J. Luo, and S. Kadry, "GO-DBN: Gannet Optimized Deep Belief Network Based wavelet kernel ELM for Detection of Diabetic Retinopathy," Expert Syst. Appl., 2023, doi: 10.1016/j.eswa.2023.120408.
[29] A. Abdi and A. M. Abdulazeez, "OCT Images Diagnosis Based on Deep Learning – A Review," Indones. J. Comput. Sci., 2024, doi: 10.33022/ijcs.v13i1.3731.
[30] I. A. Ali and S. A. Mahmood, "R E V I E W A RTICL E Deep Learning Approaches for Retinal Disease Identification in Fundus Imaging : A Comprehensive Overview," vol. 9, no. 1, 2025, doi: 10.21928/uhdjst.v9n1y2025.pp73-92.
[31] A. Wali and I. Jr, "View of Effects of Filters in Retinal Disease Detection on Optical Coherence Tomography (OCT) Images Using Machine Learning Classifiers," no. February, 2024.
[32] A. E. Ilesanmi, T. Ilesanmi, and G. A. Gbotoso, "A systematic review of retinal fundus image segmentation and classification methods using convolutional neural networks," Healthc. Anal., vol. 4, no. September, p. 100261, 2023, doi: 10.1016/j.health.2023.100261.
[33] V. Mayya, S. K. S, U. Kulkarni, D. K. Surya, and U. R. Acharya, "An empirical study of preprocessing techniques with convolutional neural networks for accurate detection of chronic ocular diseases using fundus images," Appl. Intell., vol. 53, no. 2, pp. 1548–1566, 2023, doi: 10.1007/s10489-022-03490-8.
[34] M. J. Umer, M. Sharif, M. Raza, and S. Kadry, "A deep feature fusion and selection-based retinal eye disease detection from OCT images," Expert Syst., 2023, doi: 10.1111/exsy.13232.
[35] B. Goutam, M. F. Hashmi, Z. W. Geem, and N. D. Bokde, "A Comprehensive Review of Deep Learning Strategies in Retinal Disease Diagnosis Using Fundus Images," IEEE Access, vol. 10, pp. 57796–57823, 2022, doi: 10.1109/ACCESS.2022.3178372.