Classification of Eye Disease From OCT Scans

Kristen Lee

Introduction

Age-related macular degeneration (AMD) and other retinal diseases are leading causes of vision impairment worldwide (1). Routine eye exams for older adults often include Optical Coherence Tomography (OCT) scans, which provide high-resolution images of retinal layers to detect signs such as swelling, abnormal growths, or thinning (2). However, interpreting OCT scans is labor-intensive and prone to variability (3).

This project aims to develop a deep learning model to classify OCT scans into six categories: AMD, DME, DR, CSR, MH, and Normal. Automated classification can accelerate screening, improve diagnostic accuracy, and reduce manual workload for ophthalmologists. Deep learning is particularly suitable because it can learn hierarchical features from high-dimensional OCT data, capturing subtle patterns that traditional methods may miss, and generalizing to new patients regardless of race or gender, or new imaging conditions (4).

Illustration

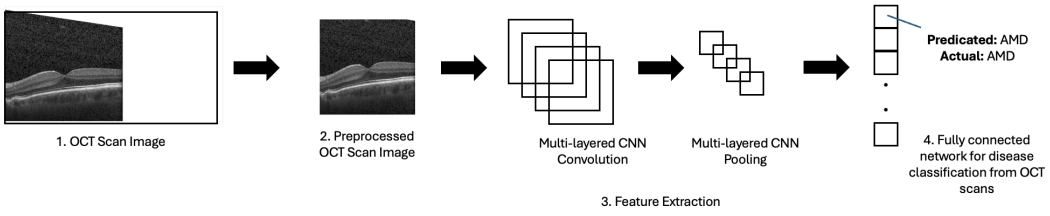

Figure 1: Proposed Model for Disease Classification From OCT Scans

Background & Related Work

For the last 30 years since OCT scans were developed, scans were manually compared and analyzed by licensed professionals. In recent years, deep learning classification methods for OCT scans have become an area of interest. Some prior classification related work includes:

1. **Kufel et al., 2023** (5) This study used transfer learning to perform multi-label classification of chest X-rays, which identified small abnormalities to improve accuracy of diagnosis.
2. **Li et al., 2019** (6) This study proposed a deep learning ensemble of residual neural network (ResNet50) models for automated classification of OCT images into 4 abnormalities.
3. **Oliveira e Carmo et al., 2021** (7) This study analyzes the use of CNNs for fracture detection and classification in orthopaedics from scans.
4. **Yoo et al., 2021** (8) This study explores the use of few-shot learning using generative adversarial network (GAN) based augmentation to identify 5 classes of rare retinal diseases from OCT scans.
5. **Huang et al., 2023** (9) This study proposed using a deep learning framework called GABNet (Global Attention Block) to improve disease classification. The study showed how attention mechanisms can enchance feature extraction leading to greater accuracy in diagnosis.

Data Processing

The data will be sourced from three publicly available OCT datasets, including the UCSD OCT dataset ([10]), and Optical Coherence Tomography dataset ([11]), and Retinal OCT Image Classification dataset ([12]). The following preprocessing steps will be applied:

- **Category Cleanse:** Diseases that are not relevant to this project will be removed from the dataset, as rare conditions would require extensive data augmentation to to achieve comparable sample sizes to common diseases like AMD. Rare diseases to remove: ERM, RAO, RVO, VMID.
- **Category Renaming:** Conditions will be renamed to their more general disease name to align different datasets. As such, CNV and Drusen are subtypes of AMD and will be renamed to be AMD.
- **Cleaned Sample** Poor quality images and OCT scans outside the foveal area (outside the center of the retina, which can be identified as a darker area with a small depression) are excluded from the dataset.
- **Image resizing:** All images will be resized to 128×128 pixels to ensure consistent input dimensions and ensure details are still visable in the image.

1500 images from each of the 6 categories (AMD, DME, DR, CSR, MH, Normal) will be randomly selected for each category from all three datasets so that each category has a comparable number of samples for training. A total of 9000 images will be used for training, testing and validation, with a selection of 70%, 15%, 15% split respectively.

Architecture

For OCT classification, a Convolutional Neural Network (CNN) will be used to automatically extract hierarchical features from the scans. The model will take 128×128 OCT images as an input, pass them through several convolutional layers with increasing filter sizes and pooling to reduce spatial dimensions, and then flatten the resulting feature maps into a 1D vector. One or two fully connected layers will follow to learn complex feature combinations, and a final softmax layer with six neurons will output probabilities for each category. This architecture allows the model to capture both local patterns (such as fluid abnormalities or layer changes in the retina) and global structures relevant to disease classification.

Baseline Model

A Random Forest classifier will be used as the baseline to be trained on features extracted from OCT images. These features include foveal thickness, retinal layer thickness, presence of fluid or cysts, and texture-based descriptors. The Random Forest will be implemented using standard libraries such as scikit-learn, and its performance will be evaluated against the CNN using metrics like accuracy, sensitivity, and specificity. This provides a simple, interpretable comparison to demonstrate the advantage of deep learning feature extraction.

Ethical Considerations

Automated disease classification carries ethical risks, including potential racial disparities. For example, African Americans normally tend to have lower mean foveal thickness compared to Caucasians and Hispanics, which can typically mimic signs of AMD. ([13]). Although the datasets were reviewed by multiple licensed ophthalmologists, diagnostic errors remain possible.

Due to these limitations and the lack of patient-specific information, the model is intended as a diagnostic aid rather than a replacement for clinicians. What is considered "normal" or "abnormal" may vary depending on individual patient characteristics, so clinical context is essential when interpreting model predictions.

References

[1] Y. D. Jeong *et al.*, "Global burden of vision impairment due to age-related macular degeneration, 1990–2021, with forecasts to 2050: a systematic analysis for the global burden of disease study 2021," *The Lancet Global Health*, vol. 13, pp. e1175–e1190, July 2025.

[2] E. S. Enaholo, M. J. Musa, and M. Zeppieri, *Optical Coherence Tomography*. StatPearls Publishing, 2024. Last Update: October 6, 2024.

[3] M. Dahrouj and J. B. Miller, "Artificial intelligence (ai) and retinal optical coherence tomography (oct)," *Seminars in Ophthalmology*, vol. 36, no. 5-6, pp. 341–345, 2021.

[4] C. S. Lee, D. M. Baughman, and A. Y. Lee, "Deep learning is effective for the classification of oct images of normal versus age-related macular degeneration," *Ophthalmology Retina*, vol. 1, pp. 322–327, Jul-Aug 2017.

[5] J. Kufel, M. Bielówka, M. Rojek, A. Mitręga, P. Lewandowski, M. Cebula, D. Krawczyk, M. Bielówka, D. Kondoł, K. Bargieł-Łączek, I. Paszkiewicz, Ł. Czogalik, D. Kaczyńska, A. Wocław, K. Gruszczyńska, and Z. Nawrat, "Multi-label classification of chest x-ray abnormalities using transfer learning techniques," *Diagnostics*, vol. 13, no. 20, p. 3259, 2023.

[6] F. Li, H. Chen, Z. Liu, X.-d. Zhang, M.-s. Jiang, Z.-z. Wu, and K.-q. Zhou, "Deep learning-based automated detection of retinal diseases using optical coherence tomography images," *Biomedical Optics Express*, vol. 10, no. 12, pp. 6204–6217, 2019.

[7] L. Oliveira e Carmo, A. van den Merkhof, J. Olczak, M. Gordon, P. C. Jutte, R. L. Jaarsma, F. F. A. IJpma, J. N. Doornberg, J. Prijs, and M. L. Consortium, "An increasing number of convolutional neural networks for fracture recognition and classification in orthopaedics: are these externally validated and ready for clinical application?," *Bone & Joint Open*, vol. 2, no. 10, pp. 879–885, 2021.

[8] T. K. Yoo, J. Y. Choi, and H. K. Kim, "Feasibility study to improve deep learning in oct diagnosis of rare retinal diseases with few-shot classification," *Scientific Reports*, vol. 11, no. 1, p. 1625, 2021.

[9] X. Huang, Z. Ai, H. Wang, C. She, J. Feng, Q. Wei, B. Hao, Y. Tao, Y. Lu, and F. Zeng, "Gabnet: global attention block for retinal oct disease classification," *Frontiers in Medicine*, vol. 10, p. 1169165, 2023.

[10] Mmazizi, "Ucsd 3-class labeled retinal oct images," 2021. Accessed: 2025-09-26.

[11] S. M. Shuvo, "Octdl: Optical coherence tomography dataset for image-based deep learning method," 2021. Accessed: 2025-09-26.

[12] O. Inaren, "Retinal oct image classification - c8," 2021. Accessed: 2025-09-26.

[13] A. H. Kashani, I. E. Zimmer-Galler, S. M. Shah, L. Dustin, D. V. Do, D. Eliott, J. A. Haller, and Q. D. Nguyen, "Retinal thickness analysis by race, gender, and age using stratus oct™," *American Journal of Ophthalmology*, vol. 149, no. 3, pp. 496–502.e1, 2009.