Investigation of Retinal Biomarkers for Early Detection of Visual Impairments

Abstract

Retinal disorders are among the leading causes of irreversible vision impairment worldwide, particularly in populations affected by diabetes, hypertension, and age-related conditions. Early detection is critical to prevent permanent retinal damage; however, diagnosing diseases such as Glaucoma, Macular Edema (ME), Hypertensive Retinopathy (HR), Diabetic Retinopathy (DR), and Age-related Macular Degeneration (AMD) remains challenging due to the subtle presentation of pathological signs in their initial stages. Furthermore, the growing prevalence of systemic diseases coupled with the shortage of expert ophthalmologists necessitates the development of automated, reliable, and scalable diagnostic systems. This thesis addresses these challenges by proposing advanced deep learning-based frameworks for comprehensive retinal disease detection using multimodal imaging data.

The primary objective of this work is to design automated systems capable of detecting structural alterations and clinical indicators from retinal fundus images and Optical Coherence Tomography (OCT) scans to facilitate early and accurate diagnosis. The first major contribution is the development of a novel multistage dual-decoder network termed '**Multistage DPIRef-Net'** for precise retinal vessel segmentation and artery–vein classification. The architecture mitigates the limitations of pooling and striding operations by enhancing low-level feature representations, thereby preserving fine vessel boundaries and reducing blurring effects. Extensive validation on publicly available datasets demonstrates the robustness and generalization capability of the proposed model. To further enhance diagnostic performance, retinal lesion detection is performed using a dual-encoder single-decoder architecture called **Residual Inception Local Binary Pattern-based Y-Net (RILBP-YNet)**. This model integrates convolutional feature extraction with multi-scale textural information derived from Local Binary Patterns (LBP) computed at radii 1, 3, 5, and 7. By combining spatial and textural representations, the network effectively detects microaneurysms, haemorrhages, soft exudates, and optic disc regions from fundus images, thereby improving disease characterization accuracy.

The second key contribution focuses on depth-resolved retinal analysis using OCT imaging. A U-Net-inspired architecture, **FAM-U-Net**, is proposed to segment retinal fluid accumulation between retinal layers. The model incorporates multiscale feature pyramid integration with dilated convolutions to capture contextual information and strengthen inter-pixel dependencies. Additionally, attention mechanisms such as Convolutional Block Attention Modules (CBAM) and Deep Aggregation Pyramid Pooling Modules (DAPPM) are integrated to emphasize discriminative features, leading to enhanced segmentation performance.

As a third contribution, clinically significant biomarkers, including Artery-to-Vein Ratio (AVR) and Cup-to-Disc Ratio (CDR)—are computed from segmented retinal structures to assist in diagnosing conditions such as HR, DR, and Glaucoma. Finally, a unified transformer-based deep learning framework incorporating self-attention mechanisms is developed to integrate information from both fundus and OCT modalities. This multimodal architecture enables simultaneous analysis of structural fragments and pathological features, generating comprehensive diagnostic reports.

Extensive qualitative and quantitative evaluations are conducted on multiple publicly available datasets along with real-time datasets collected from collaborating eye hospitals. Experimental results demonstrate that the proposed methodologies outperform existing state-of-the-art approaches, providing improved accuracy, robustness, and clinical relevance. Overall, this thesis presents an integrated, multimodal deep learning framework that advances automated retinal disease detection and supports early intervention strategies for vision preservation.