

Age-related macular degeneration (AMD), cataracts, diabetic retinopathy, and glaucoma continue to be among the leading causes of blindness and visual impairment globally. The aging of the population and the rising rates of diabetes, hypertension, and other chronic illnesses are some of the causes contributing to the rising prevalence of these problems. Despite their effectiveness, traditional fundus imaging-based diagnostic techniques rely significantly on skilled ophthalmologists and subjective interpretation, which causes problems with scalability, accessibility, and diagnostic variability.

In this regard, deep learning-based automated ocular illness identification has become a viable solution. However, a number of substantial challenges still exist despite notable advancements in the segmentation of ocular biomarkers from fundus images. Primarily, the tendency of existing models to overfit because of insufficient data and the lack of diverse and high-quality annotated datasets, which impedes model generalization across samples and imaging differences, contribute as major hurdles. Furthermore, the intricate structural and textural changes present in retinal images are not captured by current data augmentation techniques, which are usually limited to simple geometric or colour-based augmentations.

This dissertation aims to address these challenges in biomarker segmentation from fundus images by enhancing the accuracy, robustness, and clinical relevance of automated systems. Specifically, it investigates and proposes advanced data augmentation strategies, improved loss function engineering, and model architectures capable of capturing fine-grained retinal structures such as blood vessels, hard exudates and Optic Disc. The overall objective of this dissertation is to bridge the gap between research propositions and reliable, deployable solutions suitable for real-world clinical environments.