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Multi-Modality Semi-Supervised Learning for Ophthalmic Biomarkers Detection

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Introduction

Background

Optical Coherence Tomography (OCT) provides detailed retina images crucial for diagnosing ocular diseases such as age-related macular degeneration, diabetic retinopathy, and glaucoma. Biomarkers from these images have been used as indicators for disease onset or progression.

Deep learning has potential in biomarker diagnosis, but challenges in generalization and personalization persist. Most existing OCT datasets lack comprehensive biomarker labels and have insufficient images per biomarker, affecting model generalization. While inter-visit variations in OCT scans for individual patients might be minimal, inter-patient variations for the same disease can be significant.

Contribution

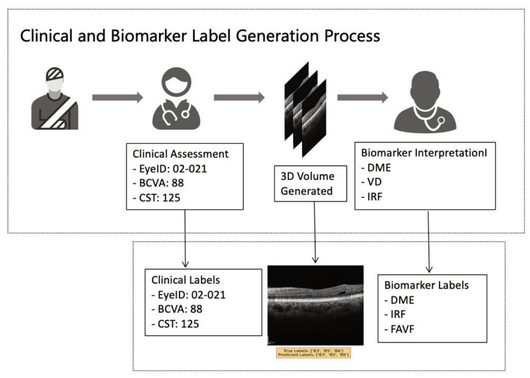
Utilization of the OLIVES Dataset. We use the OLIVES dataset to train a deep-learning model for detecting six biomarkers.

Incorporation of Multi-Modality Learning. We integrate patient-personalized clinical labels with OCT scans and optimize both models using a guided loss function.

Application of Semi-Supervised Learning Techniques. We apply these techniques for model optimization, achieving an F1 score of 0.70 on our test dataset with 3.872 images across 40 patients, which surpasses the baseline by approximately 7%.

Methods

Ophthalmic disease diagnosis process



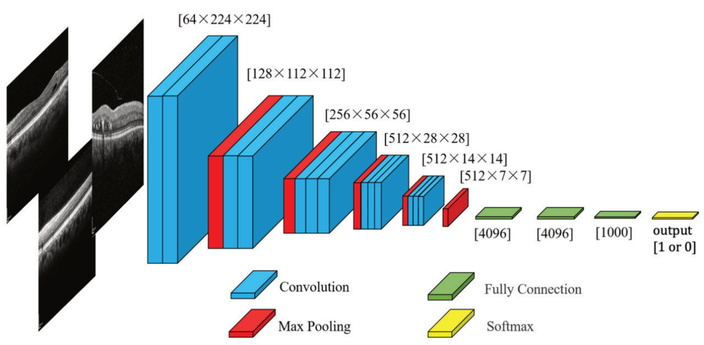
Dataset

Detail	OCT	Fundus	Clinical	Biomarker
Per Visit	49	1	4	16
Per Eye	$N_p \times 49$	N_p	$N_p \times 4$	1568
Total	78189	1268	5072	150528

General Overview
96 Eyes, Visits 4-16 weeks, Avg. 16 visits/eye, Avg. 7 injections/patient
Clinical Labels
BCVA, CST, Patient ID, Eye ID
Biomarkers
IRHRF, FAVF, IRF, DRT/ME PAVF, VD, Preretinal Tissue, EZ Disruption
IR Hemorrhages, SRF, VMT, Atrophy, SHRM, RPE Disruption, Serous PED

The table summarizes the OLIVES dataset with clinical labels including BCVA, CST, Patient ID, and Eye ID, and 14 types of biomarkers covering various ophthalmic parameters across 96 eyes and multiple visits.

3D OCT Scan Process Module



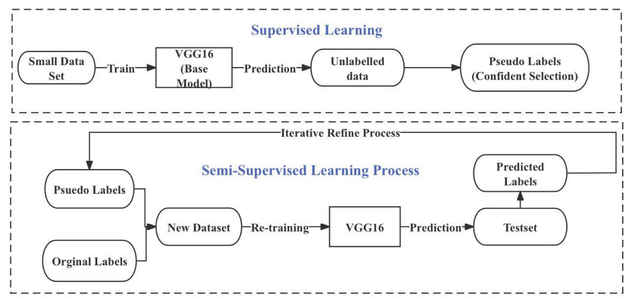
The 3D OCT scan process module uses a VGG16 model as the feature extractor, it takes a 3D OCT image and out the binary class label for six biomarker.

Guided Loss

$$\mathcal{L}_{\text{Guided}} = 1[\hat{y}^{\text{MLP}} = y]\frac{1}{2}\|\phi_{\text{VGG-16}}(x_i) - \phi_{\text{MLP}}(x_i)\|_2^2$$

$$\mathcal{L} = \mathcal{L}_{\text{VGG-16}} + \mathcal{L}_{\text{MLP}} + \mathcal{L}_{\text{Guided}}$$

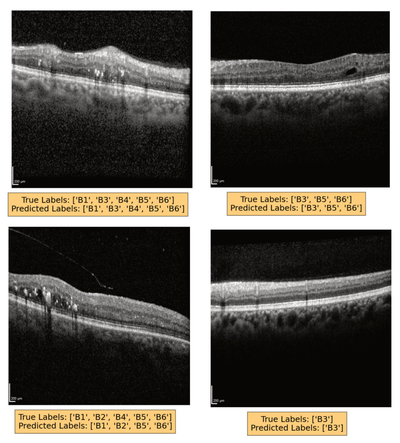
Semi-Supervisored Learning Process



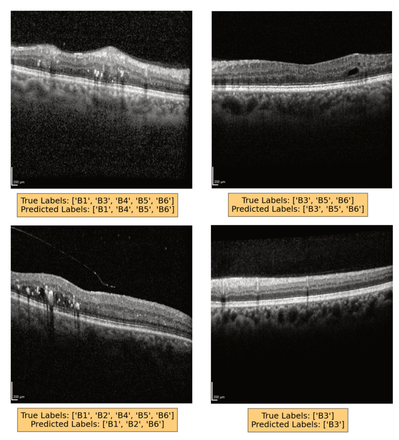
Experimental Results

Pridiction Results

Proposed Method Prediction Result



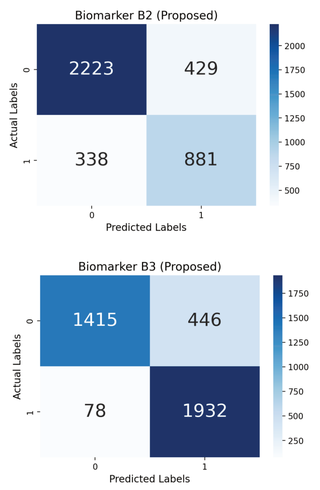
Baseline Model Prediction Result



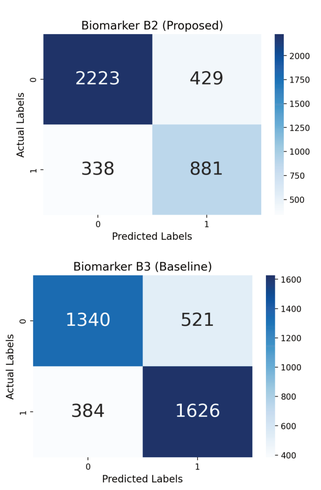
Comparison of Baseline and Proposed Method Performance on Biomarkers

Biomarker	Baseline Method			Proposed Method			
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Support
IRHRF (B1)	0.64	0.80	0.71	0.85	0.66	0.74	1204
PAVF (B2)	0.72	0.43	0.54	0.68	0.73	0.70	1219
FAVF (B3)	0.73	0.98	0.84	0.81	0.97	0.88	2010
IRF (B4)	0.37	0.77	0.50	0.49	0.70	0.58	695
DRT/DME (B5)	0.45	0.51	0.48	0.65	0.44	0.53	143
VD (B6)	0.64	0.83	0.72	0.69	0.83	0.75	426
MACRO AVG	0.59	0.72	0.63	0.70	0.76	0.70	5697

Proposed Method Confusion Metrix



Baseline Model Confusion Metrix



Conclusion

In our study, we have explored the possible potentials of the OLIVES dataset and applied deep learning techniques for biomarker detection. By integrating the clinical labels with OCT scans and employing semi-supervised learning, we have enhanced the model’ s generalization capabilities and mitigated the personalization challenges. The achieved F1 score is ap- proximately 7 percent higher than the baseline result.