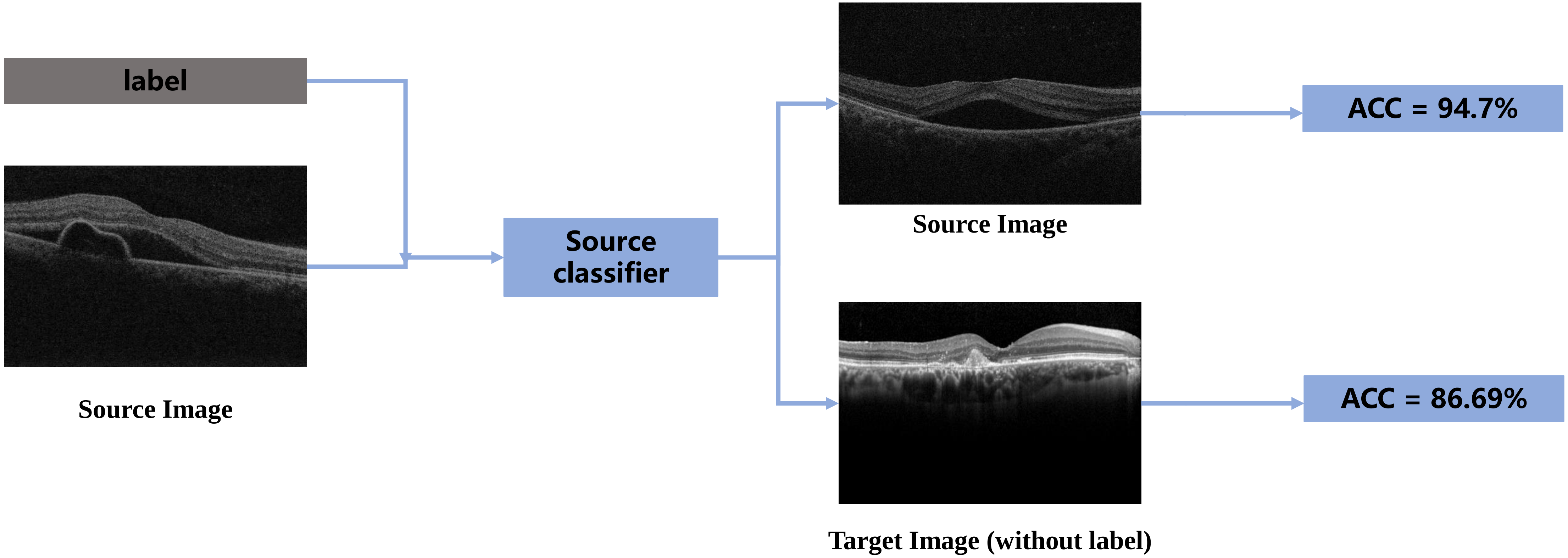
Domain adaptation model for retinopathy detection from cross-domain OCT images

Jing Wang[1;2], Yiwei Chen[2], Wanyue Li1;[2],
Wen Kong[1;2], Yi He[2], Chuihui Jiang[*3], Guohua Shi[*2;4]

[1] University of Science and technology of China, Hefei 230026, China
[2] Jiangsu Key Laboratory of Medical Optics, Suzhou Institute of Biomedical Engineering and Tech-nology, Chinese Academy of Sciences, Suzhou 215263, China
[3] Department of ophthalmology and Vision Science, Eye and ENT Hospital, Fudan University, Shanghai 200031, People's Republic of China
[4] Center for Excellence in Brain Science and Intelligence Technology, CAS

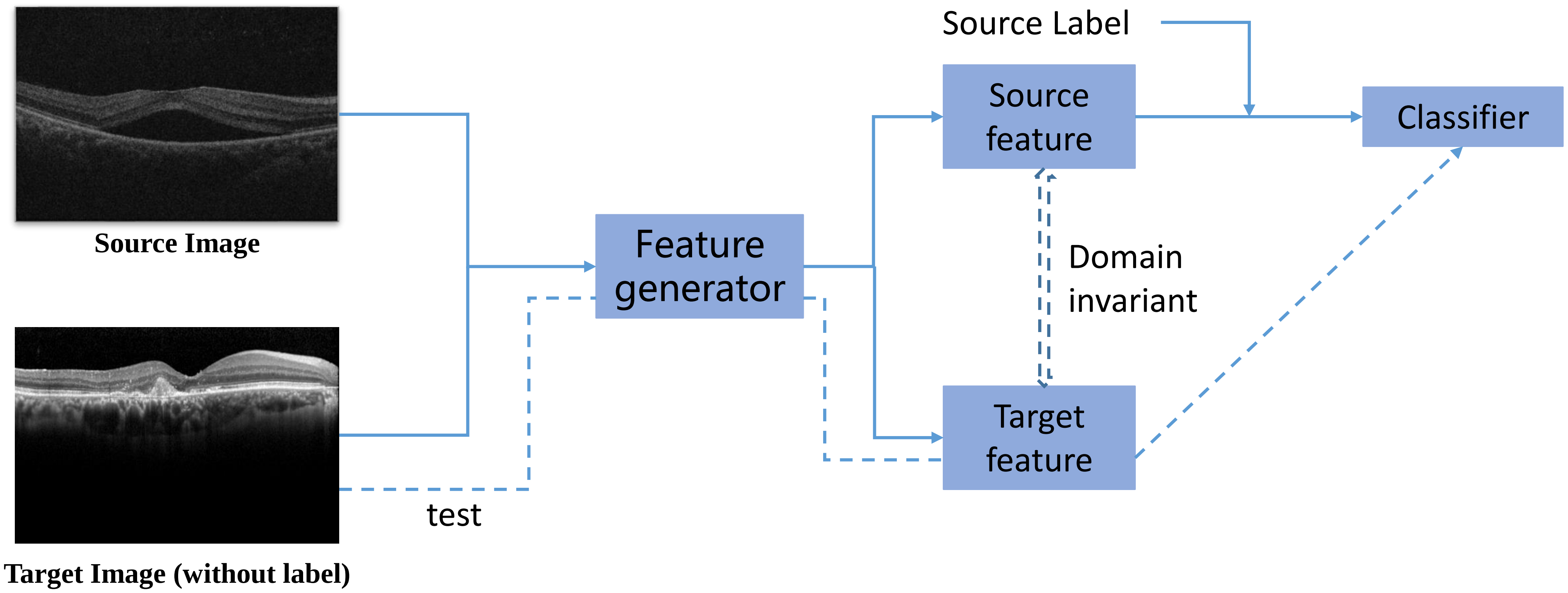
Motivation

- **Classifier trained from one domain images perform badly on new domain images**
- Images captured from different devices have different signal distribution
- Deep models' performance declines when the test data are under a different distribution compared to the training data.
- Labels of medical images are difficult to acquire.



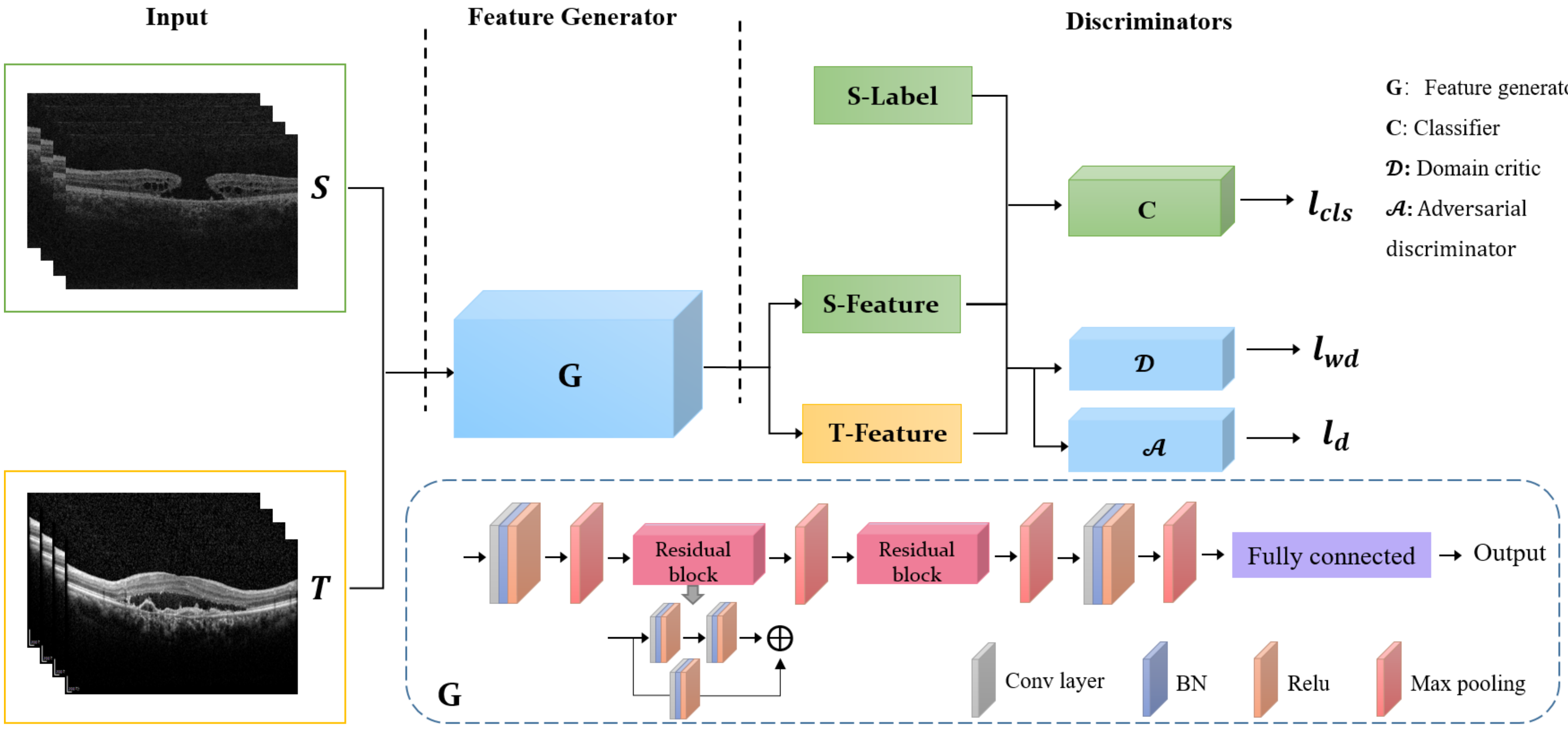
Overview

- **Extracting the domain invariant and discriminative features to train the classifier.**



Network architecture

- An adversarial model was proposed to learn the domain invariant feature.
- A Wasserstein estimator and an domain discriminator were combined to train the model



Result- classification across domain

Table 1: Evaluation results (accuracy %) of several domain adaptation models on target datasets. (The evaluation results on the source dataset is reported in parentheses)

Method	MNIST -> USPS	Ciruss -> Spectralis
Source only	0.9612(0.9939)	0.8669(0.947)
WDGRL	0.9756(0.9908)	0.9374(0.872)
JDDA_CORAL	0.9314(0.9798)	0.9156(0.8671)
JDDA_MMD	0.9368(0.985)	0.9255(0.8575)
CADN	0.9696(0.9958)	0.8292(0.7223)
DANN	0.9273(0.9953)	0.8699(0.6631)
DAOCT(proposed)	0.9804(0.9914)	**0.9553(0.9307)**

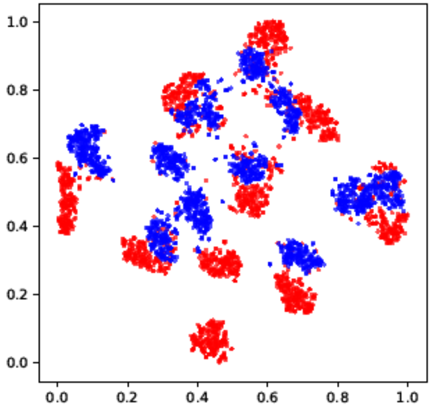
Result-ablation experiment

Table 3: Eectives of each key component in DAOCT, evaluation accuracy (%) on target dataset. 'FG' means feature gennerator proposed in this study, and multi-layer perceptron is set as default feature generator

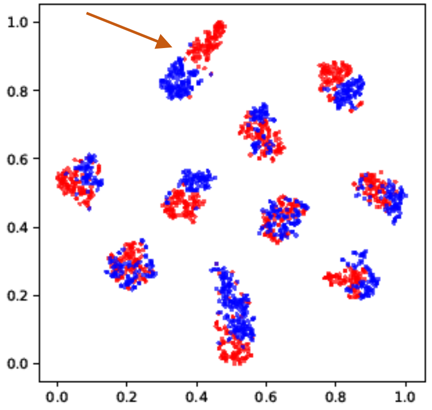
Method	Source only	L_{wd}	L_{AD}	FG	Accuracy
MNIST→USPS	✓				0.9301
		✓			0.9656
			✓		0.9371
		✓	✓		0.9667
		✓	✓	✓	**0.9804**
Cirrus→Spectralis	✓			✓	0.8669
		✓		✓	0.9374
			✓	✓	0.9359
		✓	✓		0.8758
		✓	✓	✓	**0.9553**

Result-Tsne

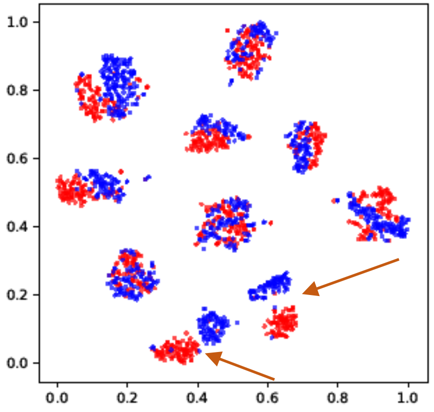
MNIST -> USPS



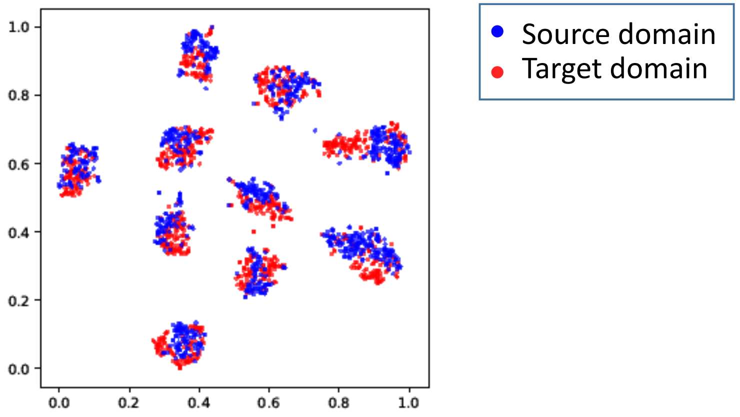
(a) t-SNE of Source-only



(b) t-SNE of WDGRL

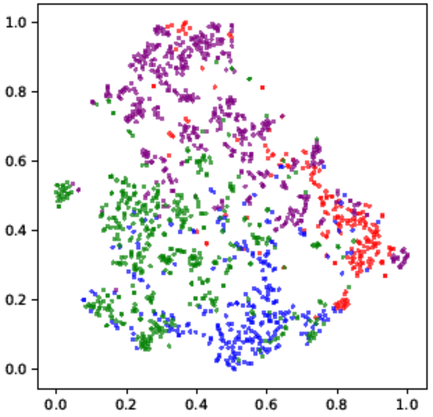


(c) t-SNE of JDDA-MMD

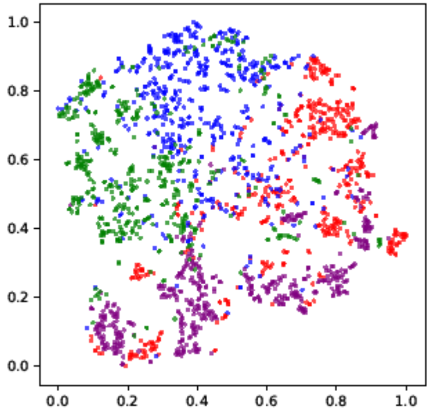


(d) t-SNE of DAOCT

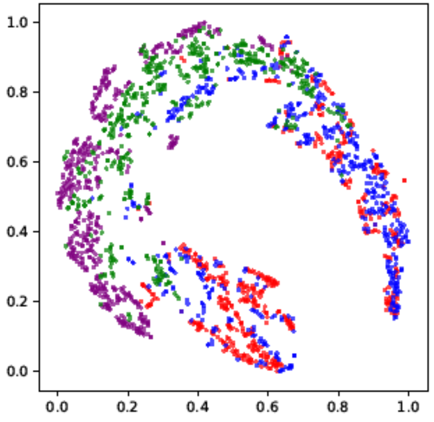
Zeiss -> Heidberg



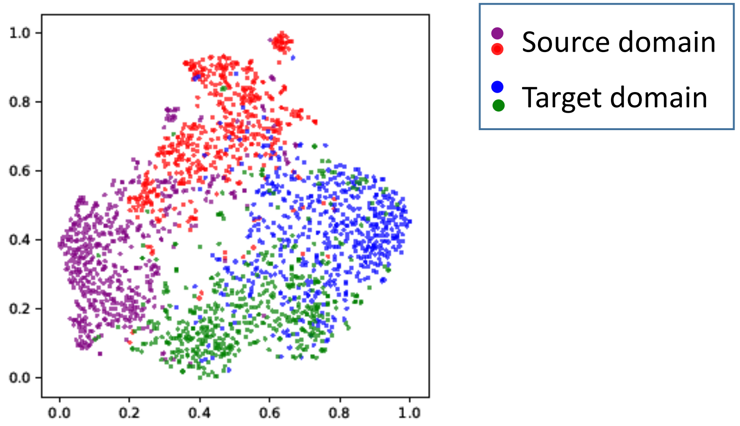
(a) t-SNE of Source-only



(b) t-SNE of WDGRL



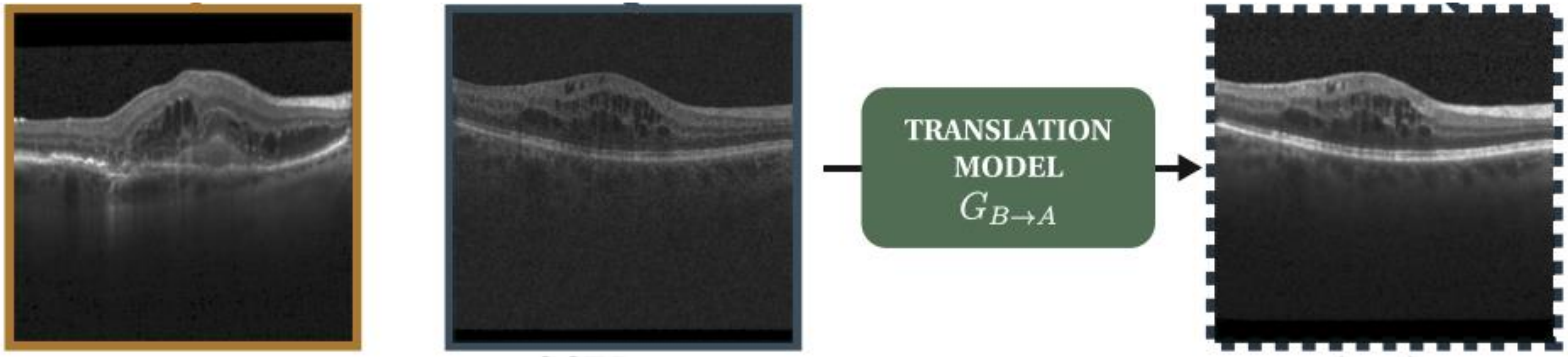
(c) t-SNE of JDDA-MMD



(d) t-SNE of DAOCT

Future work

- Combine this work with decoder to generate cross-domain images.



[1]

Segmentation, lesion detection …

[1] Ucheli, et al. (2020).Biomedical optics express, *11*(1), 346–363.

Thank you