# Transfer Learning for Domain Adaptation

## Introduction

Semantic segmentation classifies pixels to isolate specific items in images. While many existing segmentation models were initially developed for tasks like segmenting objects in autonomous driving images, they are now gaining traction in healthcare. Transfer learning, with its ability to overcome limited labeled data, accelerate training convergence, enhance accuracy, and enable model reusability for related tasks by fine-tuning the model on a specific dataset, is an effective method for medical image segmentation.

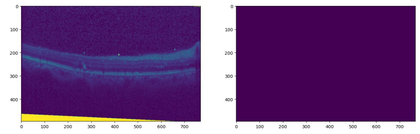
Our work, centered on optimizing established pre-trained segmentation models through fine-tuning, holds great promise for advancing ophthalmological diagnostics, especially for patients diagnosed with diabetic macular edema (DME). By tailoring segmentation models to address the intricacies of the eye's structure in DME cases, our work aims to significantly enhance the accuracy and reliability of retinal layer segmentation, making it particularly beneficial for applications in the field of medical image analysis of optical coherence tomography (OCT).


Contributions (all worked together on all parts, but with a focus on):

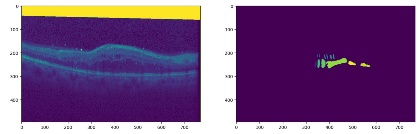
- Xiaoquan Liu: Model Fine-tuning
- Yuanjing Zhu: Data pre-processing, Preliminary Model Inference


## Methodology

### Data

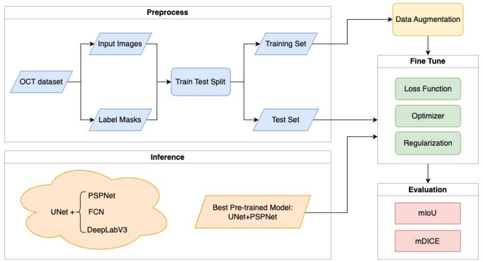


OCT image and its corresponding annotations in absence of diabetic macular edema. (Left) Original OCT image. (Right) Ground truth annotation.



OCT images and corresponding annotations displaying diabetic macular edema. (Left) Original OCT image. (Right) Ground truth annotation.

### Segmentation Process Workflow




Flowchart showing the semantic segmentation process. This includes (1) data preprocessing, (2) making inferences with pre-trained model, (3) data augmentation, (4) fine-tuning pre-trained model on current dataset, (5) model evaluation

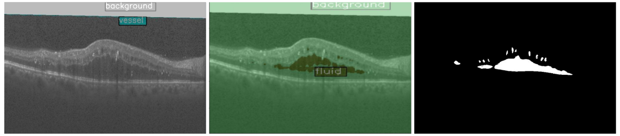
## Result

### Preliminary Model Evaluation without Fine-tuning

| Name | Decoder Head | mIoU |
|---|---|---|
| Model1 | PSPNet | 0.0022 |
| Model2 | FCN | 0.0008 |
| Model3 | DeepLabV3 | 0.0016 |

### Fine-tuning

| # of iteration | Crop Size | Random Flip | Loss Function | Optimizer | $L_2$ reg. | mDice | mIoU |
|---|---|---|---|---|---|---|---|
| 200 | False | False | Cross Entropy | SGD | 0.0005 | 0.7721 | 0.6855 |
| 400 | False | False | Cross Entropy | SGD | 0.0005 | 0.7173 | 0.6371 |
| 400 | False | Horizontal | Cross Entropy | SGD | 0.0005 | 0.7040 | 0.6263 |
| 400 | 192 * 192 | False | Cross Entropy | SGD | 0.0005 | 0.6951 | 0.6190 |
| 400 | 224 * 224 | False | Cross Entropy | SGD | 0.0005 | 0.7106 | 0.6299 |
| 400 | 320 * 320 | False | Cross Entropy | SGD | 0.0005 | 0.8401 | 0.7567 |
| 400 | 320 * 320 | False | Dice Loss | SGD | 0.0005 | 0.8395 | 0.7560 |
| 400 | 320 * 320 | False | Focal Loss | SGD | 0.0005 | 0.8280 | 0.7429 |
| 400 | 320 * 320 | False | Cross Entropy | Adam | 0.0005 | 0.4981 | 0.4963 |
| **400** | **320 * 320** | **False** | **Cross Entropy** | **SGD** | **0.0001** | **0.8430** | **0.7600** |
| 400 | 320 * 320 | False | Cross Entropy | SGD | 0.001 | 0.8312 | 0.7464 |




Comparative model inference on a OCT Image employing the preliminary and fine-tuned models.(Left) Preliminary inference result. (Middle) Fine-tuned inference result. (Right) Ground truth.

## Conclusion

Our study has delved into the realm of transfer learning for medical image segmentation, with a specific focus on optimizing pre-trained semantic segmentation models for fluid segmentation in OCT images, addressing the nuances of DME. Through rigorous experimentation, we showcased that transfer learning, while a potent tool, requires meticulous customization to the target task.

Our initial findings revealed the limitations of off-the-shelf pre-trained models, emphasizing the necessity for fine-tuning to bridge the performance gap. We significantly enhanced segmentation accuracy as evaluated by the mIoU and mDice scores by utilizing a comprehensive set of strategies such as data augmentation, varied loss functions, and iterative model adjustments.

While our study contributes valuable insights, it is essential to acknowledge its limitations. The original dataset class imbalance, particularly concerning fluid accumulation areas, warrants further investigation. Future research avenues could explore the combination of cross-entropy and Dice loss by assigning different weights to them, aiming to strike a balance that accommodates the inherent data distribution challenges. Such endeavors would contribute to refining the model's robustness and generalizability across diverse medical imaging scenarios.

### References


Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Springer International Publishing, 2015.

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