

Fovea Segmentation using Deep Learning

Project Report

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We have trained the model on five datasets to perform binary segmentation. The datasets consist of coloured retina images and their corresponding masks:

- ① Drive: **40** datapoints
- ② Messidor: **180** datapoints
- ③ IDRiD: **58** datapoints
- ④ diaretddb0: **127** datapoints
- ⑤ diaretddb1: **79** datapoints

- For feature extraction for the deep learning model, we apply **bilateral filter** → two iterations of **dilation** → one iteration of **erosion**.
- For image augmentation we perform **shuffling, rotation, scaling, shifting and brightness contrast**.
- The images and masks are resized to 512×512 **dimensions** while training.
- We also added **cropping** to increase the number of datapoints by 20%.

1. Paper 1: Tan et al

- Converted RGB to **LUV** then processing on L to RGB
- LReLU, softmax, Xavier initialization is used
- **7-layer** custom network is trained

2. Paper 2: Sedai et al

- 2 stage approach is used: **coarse network** followed by **fine network**
- ImageNet pre-trained **VGG-16** model is used
- **Class balanced cross entropy loss** is used to fix the imbalance problem

Architecture

- We trained a **DeepLabV3+** model with **EfficientNet-B3** as the backbone.
 - DeepLabV3+ is a refinement of DeepLabV3 which uses atrous convolution. Atrous convolution is a powerful tool to explicitly adjust the filter's field-of-view as well as control the resolution of feature responses computed by Deep Convolutional Neural Network.
 - We use **encoder depth of 5** which refers to the number of stages used in encoder. The number of **decoder channels used is 256**.

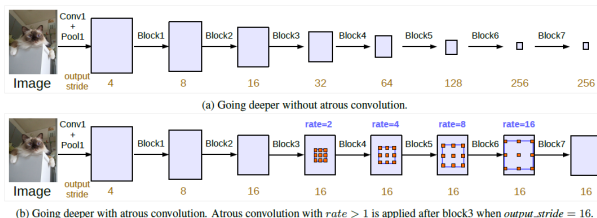


Figure: DeepLab V3+

- **Binary Cross Entropy Loss**

$$L_{BCE} = y \log(y_{hat}) + (1 - y) \log(1 - y_{hat})$$

- **Dice Loss**

$$L_{Dice} = 1 - \frac{2TP}{2TP + FN + FP}$$

- **Tversky Loss**

$$L_{Tversky} = 1 - \frac{TP}{TP + \alpha FN + \beta FP} \quad \text{where, } \alpha + \beta = 1$$

- **Focal Tversky Loss**

$$L_{FTL} = (L_{Tversky})^\gamma \quad \text{where, } \gamma \text{ controls the non-linearity of the loss.}$$

- **Final Loss**

$$L_f = \lambda L_{BCE} + (1 - \lambda) L_{FTL} \quad \text{where, } \lambda \text{ is the weight parameter.}$$

Semi-supervised pipeline

Algorithm 1: Semi-supervised classification train loop

Input: Sample image

Output: Class of the given image

```
1 for  $epoch \leftarrow 0$  to  $E$  do
2   if  $epoch < E_i^\alpha$  then
3      $\alpha \leftarrow \alpha_i$ 
4   else if  $epoch < E_f^\alpha$  then
5      $\alpha \leftarrow \frac{\alpha_f - \alpha_i}{E_f^\alpha - E_i^\alpha} * (epoch - E_i^\alpha) + \alpha_i$ 
6   else
7      $\alpha \leftarrow \alpha_f$ 
8   end if
9   Run the model on train set
10   $loss \leftarrow BCE(l, \hat{l}) + \alpha * BCE(u_{epoch}, u_{epoch-1})$ 
11  Generate the pseudo labels for unlabeled data
12  Evaluate the model on validation set
13 end for
```

Figure: Semi-supervised algorithm

Evaluation and Results

Method	F1	MIoU	Sens	Spec	Acc
non-DL	0.804	0.688	0.816	0.998	0.996
Ours	0.824	0.705	0.917	0.997	0.997
Tan et al	-	-	0.885	0.991	-
Sedai et al	0.810	-	-	-	-

Table: Metrics Comparison

Image - Mask - Prediction

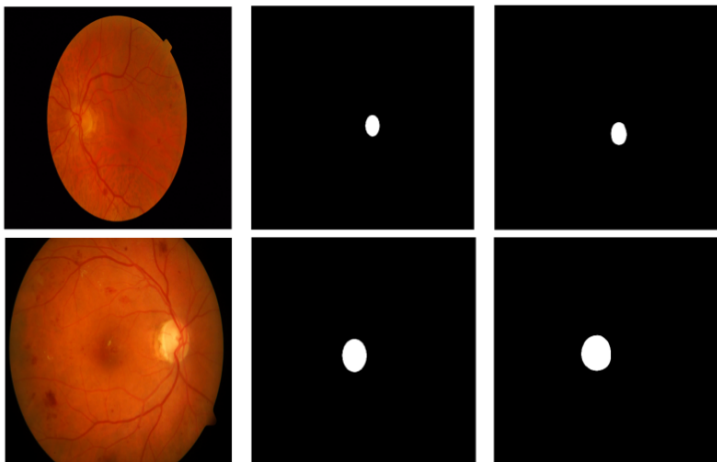


Figure: Image, Mask and Prediction (left to right)

- We were able to get **state-of-the-art results** for fovea segmentation using our **semi-supervised segmentation method**.
- All our work for this **2.5 month** project has been summarised in our **5 bi-weekly reports** in detail.
- We are currently working on **AMD classification** and are aiming to perform equally well on that task.