Deep Learning based for OCT Image

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Abstract. Optical Coherence Tomography (OCT) is a powerful tool for the diagnosis of ocular diseases, since the image acquisition consists in a contactless, non-invasive method which gives a set of images of the main retinal structures in real time. Compared with color fundus images, which can only provide retinal surface information, OCT images can provide a cross-sectional information of the retina, so it can be more accurate analysis of the retinal structure. Segmentation and quantification of layer thickness is useful in the diagnosis of many retinal and optic nerve disorders, for example, glaucoma, macular degeneration or diabetic retinopathy. In the diagnosis of glaucoma, it is easier to detect early cases using OCT than using fundus color images.

1 OCT Layer Segmentation

The OCT images are often used to diagnose and monitor retinal diseases more accurately based on abnormality quantification and retinal layer thickness computation both in research centers and clinic routines. The retinal structures contain retinal nerve fiber layer (RNFL), ganglion cell-inner plexiform layer (GCIPL), inner nuclear layer (INL), outer plexiform layer (OPL), outer nuclear layer (ONL), external limiting membrane (ELM), inner photoreceptor segment, inner/outer photoreceptor segment junction, outer photoreceptor segment, retinal pigment epithelium (RPE) interdigitation, and RPE/Bruch's membrane complex. In this competition, we need to separate GCIPL, RNFL and choroid layer.

1.1 Data preprocessing

A large area of the OCT image is the background. In order to reduce the amount of calculation, we cut the image with a height of 800 to 550 in the middle, so the image becomes 1100 × 550. In order to ensure the accuracy of segmentation, we send a 1100 × 550. Since there are only 100 pictures in the training set, in order to reduce overfitting, we conducted data enhancement, including left and right flipping, left and right random movement within 100, up and down random movement within 100, and random rotation within 30 degrees, and random scaling (0.5-1.5).

1.2 Network structure

We have not improved the basic network, and the model integration used is two deepbv3plus and one deepbv3. Among them, two networks of deeplabv3 + run under the same conditions.

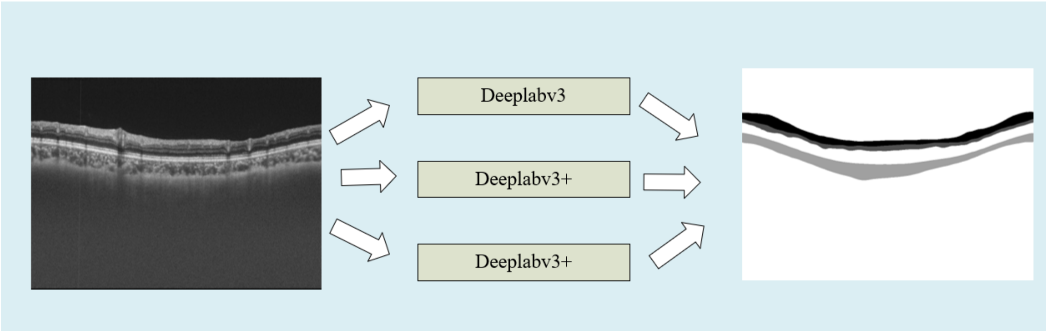

Figure 1. OCT Layer segmentation structure.

2 Glaucoma detection based on OCT images

Glaucoma is a chronic neuro-degenerative condition that is one of the leading causes of irreversible but preventable blindness in the world. This task is a glaucoma diagnosis task based on OCT images. According to the visual characteristics, the samples are classified into two categories: non-glaucoma, and glaucoma. The ground truth of glaucoma detection task for each data was determined by clinical records and was based on the results of all clinical examinations. Next, we mainly discuss data preprocessing, algorithm and model framework. And the preliminaries results is at end of the report.

2.1 Data preprocessing

The dataset for this task is provided by Sun Yat-sen Ophthalmic Center, Sun Yat-sen University, Guangzhou, China. It contains 300 Circumpapillary Optical Coherence Tomography (Circumpapillary OCT), and the data are divided into three parts: training set, validating set, and testing set. By the way, we only have 100 labeled images for training and 100 unlabeled images for submitting and validating. Since the small training samples, it is destined to be a challenge. In order to tune the hyperparameters of the model, we divide the training set by the rate of 9:1, that is, 90 images are used for training, and 10 images are used for validation and parameter tuning.

Spectral-domain (SD) OCT provides quantitative assessments of the optic nerve head, RNFL, and macula; and can detect longitudinal structural loss in glaucomatous eyes over time. According to the morphological characteristics of fundus structure in OCT images, we can adopt deep learning methods to diagnosis glaucoma. Due to the large size of the original OCT images (1100×800), it is a burden for the training of the model. So we change the size of all samples to 550×400, and then use the changed samples as the input of the model.

Since the training data only provided 100 samples, the amount of data is too small for the classification network, and it is easy to cause over-fitting of the results. It is necessary to performed data enhancement operations on training dataset. Considering that random cropping and random stretching of the image may lose some important information, we only perform horizontal flipping and small-angle rotation on the image. Then unify the image size to the above size. At this point, we have completed all data preprocessing operations.

2.2 Network structure

The network structure is shown in Figure 1. We use data enhancement operations at first, and put the samples to feature extractor. We use EfficientNet as the feature extractor, and the specific model is EfficientNet-b5. In general, increasing the depth of the network, increasing the width of the network, and increasing the image resolution can extract more features and thus improve performance. EfficientNet combines these three advantages, well balances the three dimensions of depth, width and resolution, and uniformly scales these three dimensions through a set of fixed scaling coefficients. Compared with other networks, there is a qualitative breakthrough. To adapt to the current task, we change the output of the fully connected layer of the EfficientNet to the current binary classification. In the training process, we use the cross entropy loss to constrain the training and the output of the model.

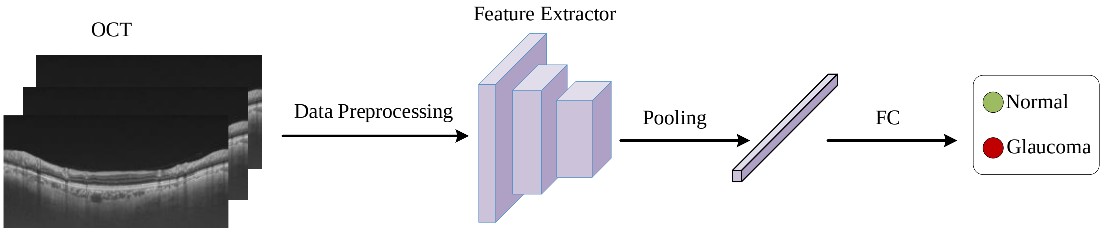

Figure 1. Glaucoma detection network structure.

4. Experimental

4.1 Implementation

Our network implementation uses Python based on PyTorch. We used an NVIDIA Tian XP GPU with 12 GB of memory to speed up model training and testing. In the OCT layer segmentation task, due to the small amount of data, we conducted a 50% cross validation test, and divided 100 into 80 training pictures and 20 pictures. For example, select the first 80 pieces as the training set, the last 20 pieces as the test set, and then select 1 to 60 and 80 to 100 as the training sets.

Configuration	Glaucoma detection	OCT Layer Segmentation
Image size	550×400	1100×550
Optimizer	Adam	SGD
Batch_size	8	2
Learning_rate	0.0001	0.0001
Epoch	200	500
Device	TITAN XP	TITAN XP
Programming language	Python	Python
Deep learning framework	PyTorch	PyTorch

4.2 Results

The final score was 8.7882

In the OCT layer segmentation task, the final result of our preliminary competition as follow:

Dice1	ED1	Dice2	ED2	Dice3	ED3
0.9464	1.13	0.8841	1.6098	0.943	1.8209

In the glaucoma detection task, the final result of our preliminary competition as follow:

AUC	F1	ACC	SEN	SPE	AUC
1	1	1	1	1	1