Deep neural networks for the detection and segmentation of the retinal fluid in OCT images.

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Abstract. In this paper, we present results of RETOUCH challenge, which is a satellite event of the MICCAI 2017 conference. The goal of RETOUCH challenge is to detect and segment fluid-filled areas such as intraretinal fluid (IRF), subretinal fluid (SRF), and pigment epithelial detachment (PED) in retinal OCT images. To do that, we propose a two step neural network; the former network is designed to detect and segment fluid areas, while the latter network is designed to enhance the robustness of the former network. In former network, we adapt a U-net combined with a classification layer. We use dropout layer and maxout activation to avoid overfitting. The qualitative and quantitative analysis of our results were performed to show the performance of the proposed method.

1 Introduction

Age-related macular degeneration (AMD) is known as a major cause of the degradation or loss of visual acuity [1]. Recently, anti-vascular endothelial growth factor (VEGF) inhibitor is an effective therapy for AMD. It requires a periodic monitoring to observe the change of the retinal fluids during the anti-VEGF inhibitor therapy. A well-known monitoring method is the spectral domain-optical coherence tomography (SD-OCT) [3] that provides various type of fluids in the retina and retinal epithelial cells and new blood vessels in the SD-OCT images.

The goal of this competition is to distinguish three types of fluid on OCT images such as intraretinal fluid (IRF), subretinal fluid (SRF), and pigment epithelial detachment (PED). In this paper, we provide a method for image detection and segmentation of such fluids from OCT image based on deep neural networks. We suggest a two step neural network training method using two different networks to enhance the detection and segmentation quality and visual quality, respectively.

2 Methods

2.1 Data Set

For training, we use OCT images acquired from 3 different devices such as Cirrus, Spectralis, and Topcon. The measured images require a pre-processing to unify

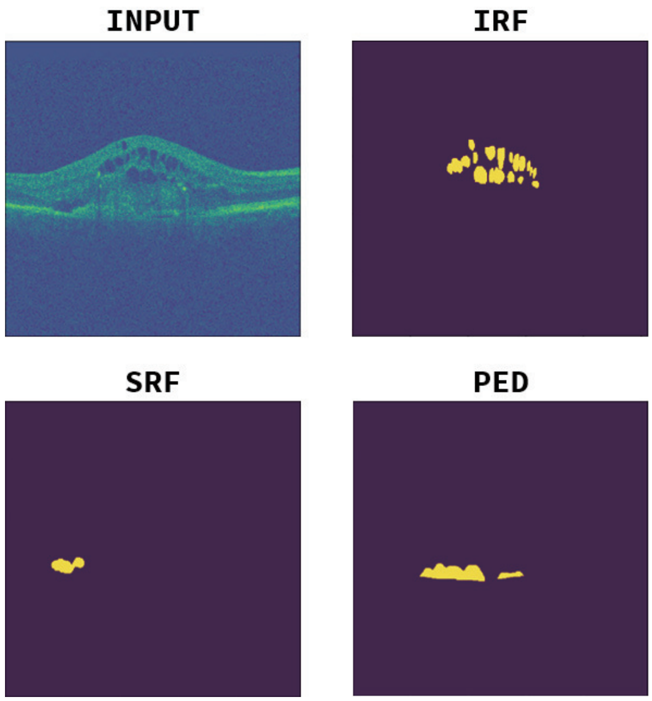

Fig. 1: OCT image and corresponding segmented IRF, SRF, and PED (label data)

the image shape and scale. We reshape the images as size of 512×512. The image scale is 0 to 1 and the data precision is 4byte floating point. To classify the IRF, SRF, and PED, we make 8 indices (i.e., the combination of IRF, SRF, and PED), as shown in Table 1. 4624 images and 2312 images are used for training and testing, respectively. For the data augmentation, we use the flipping of the left and right, shift and resize of images.

2.2 Neural Network Modeling

We propose a two step network of detecting and segmenting IRF, SRF, and PED in OCT images, which is composed as follows.

1. First, to segment their regions, we adopt a multi-scale convolutional network, called U-net [2], which consists of encoding and decoding layers, each layer followed by convolution/deconvolution layer and max pooling/up-sampling layer. We follows the general architecture of the U-net. We add the dropout and maxout activation at each layer to enhance the accuracy and prevent the overfitting. For the classification, we add a fully connected layer between encoding and decoding layer in the U-net (see Fig.2). This network takes OCT image as input data (1-channel). Segmented regions of IRF, SRF, and

Table 1: Encoded label for classification

Encoded label	Description
0	None
1	IRF only
2	SRF only
3	IRF + SRF
4	PED only
5	IRF + PED
6	SRF + PED
7	ALL

PED and 8 indices was used label data for segmentation and classification, respectively. From output images generated from the trained network, the regions of IRF, SRF, and PED are segmented by using simple threshold. The threshold value is determined in such a way that the results of segmentation maximizes the Dice index.

2. Second, to enhance the robustness of the network, we again train the proposed network without use of fully connected layer between encoding and decoding layer. Unlike former network, this network takes both OCT image and corresponding segmented image generated from former network as input data (2-channels). We train network for each IRF, SRF, and PED, separately.

Fig. 2 illustrates overall procedure of the proposed method.

2.3 Configuration and Implementation

The proposed networks are trained by using the Adadelta optimizer that is less sensitive to the hyper parameter and provides the stable learning rate decay. For each network, we use the binary cross entropy as the loss function. The total number of training epoch is 250. All models are trained and tested with Keras(tensorflow backend) on a single NVIDIA GTX TitanX 12Gb.

3 Results

We evaluate the performance of the propose algorithm for fluids (i.e., IRF, SRF, and PED): detection and segmentation. In order to evaluate the detection accuracy, we calculate the true positive rate (TPR), the true negative rate (TNR), the detection accuracy rate (ACC) [4] for each fluid for OCT images acquired from vendors such as Cirrus, Spectralis, and Topcon, as shown in Table 2.

To measure the segmentation error, averaged dice index and the averaged relative absolute volume difference (RAVD) for each fluid for OCT images acquired from vendors such as Cirrus, Spectralis, and Topcon, as shown in Table 3.

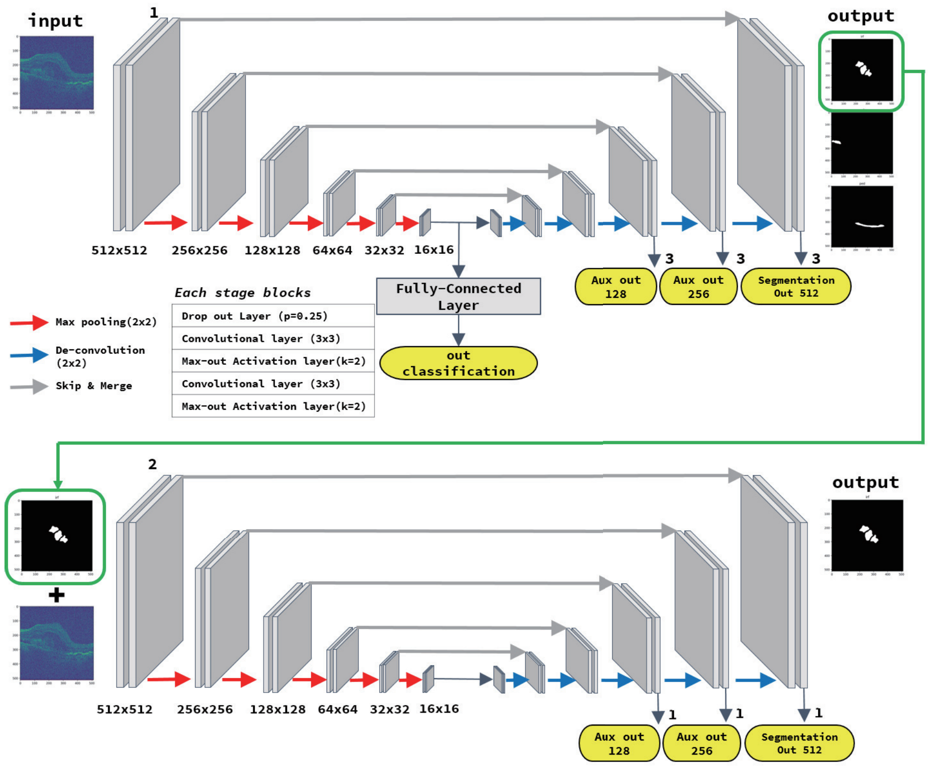

Fig. 2: Overall procedure of the proposed method for detecting and segmenting IRF, SRF, and PED in OCT images

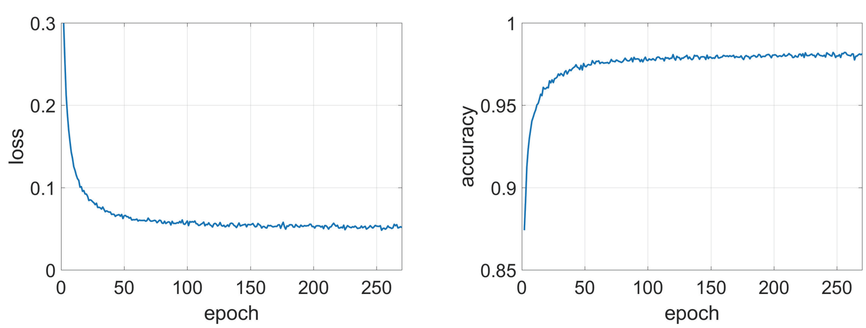

Fig. 3: Graphs of loss (left) and classification accuracy (right) with respect to epoch

Fig. 4 illustrates the segmentation results of the proposed method for IRF, SRF, and PED. As shown in Fig. 4, the proposed method segments the fluid regions well.

Table 2: TPR, TNR, and ACC for each IRF, SRF, and PED

Vendor	IRF			SRF			PED		
	TPR	TNR	ACC	TPR	TNR	ACC	TPR	TNR	ACC
Cirrus	0.97	0.98	0.98	0.93	0.99	0.98	0.70	0.99	0.93
Spectralis	0.90	0.95	0.92	0.83	0.99	0.96	0.93	0.98	0.97
Topcon	0.81	0.99	0.95	0.82	0.99	0.96	0.86	0.99	0.98

Table 3: Dice index and relative absolute volume difference (RAVD) for each IRF, SRF, and PED

Vender	avg. IRF Dice	avg. SRF Dice	avg. PED Dice	avg. IRF RAVD	avg. SRF RAVD	avg. PED RAVD
Cirrus	0.92	0.93	0.89	0.25	0.11	-0.01
Spectralis	0.80	0.92	0.91	0.08	0.05	0.05
Topcon	0.86	0.93	0.94	-0.02	-0.02	0.01

4 Conclusion

This paper proposed a deep learning method for image detection and segmentation of fluids from OCT image. We design the two step network to enhance the robustness of the network. Although the characteristics of the image provided by three vendors are different, the proposed method shows similar performance for each data set.

Acknowledgements

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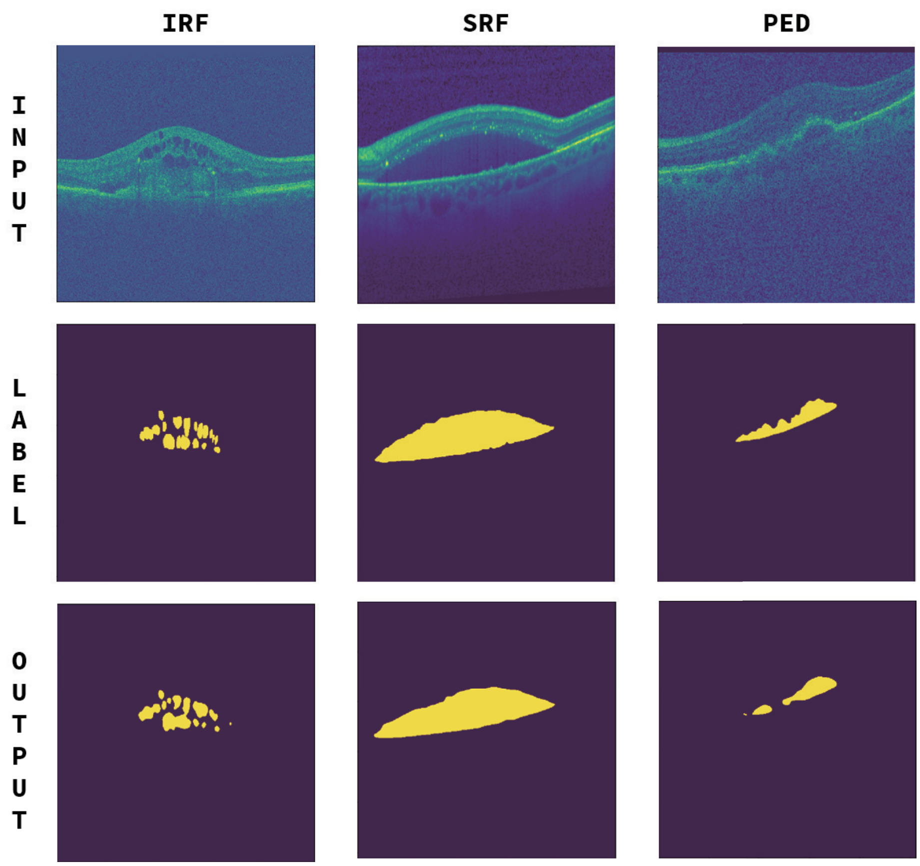

Fig. 4: Segmentation results of the proposed method