Attention-Guided Feature Enhancement for Age-Related Macular Degeneration Classification in Optical Coherence Tomography

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Abstract.

Age-related macular degeneration (AMD) is a vision-threatening chorioretinal disease, which is one of the most common causes of adult blindness. To diagnose AMD automatically and accurately, convolutional neural network (CNN)-based various deep learning models are applied to classify which optical coherence tomography (OCT) scans have AMD lesions or not. A conventional approach was to use a pair of input and output data without specific domain knowledge, which means OCT scans are given as input to the network and it is propagated convolutional layers to classify OCT scans called end-to-end learning method. To improve the accuracy of AMD classification, attention-guided feature enhancement method was applied in CNN by directly supervising to network for attending and intensifying feature maps of AMD biomarkers. Pre-trained AMD biomarker detector produces attention maps of biomarkers, and the maps are combined with several feature maps of CNN classifier to diagnose AMD types. The proposed approach has better classification accuracy than simple end-to-end baseline learning model.

Ⅰ. Introduction

There have been many researches to diagnose or classify ophthalmologic diseases including age-macular degeneration (AMD) and diabetic macular edema (DME) from optical coherence tomography (OCT). Naohiro Motozawa et al. (2019) [1] have proposed OCT-based convolutional neural networks (CNNs) with transfer learning to classify normal and AMD with and without exudate change, and have achieved high sensitivity, specificity, and accuracy. Ali Serener et al. [2] (2019) has suggested CNN to diagnose dry and wet AMD from OCT images. Several researches have utilized region-based CNN (R-CNN) to detect AMD biomarkers in OCT scans. M. Suchetha et al. (2021) [3] have tried to utilize Faster R-CNN [4] for semantic segmentation of AMD and DME. This approach has focused on localization and segmentation of AMD and DME. Most of approaches have usually used a pair of data called end-to-end learning, which consists of OCT images as an input and AMD lesions or types as an output, respectively. During training phase, latent model is expected to automatically tune by propagating a data through the convolutional layers to indirectly find relationships between inputs and outputs.

In this paper, we introduce a new AMD diagnosis algorithm by directly enhancing multiple CNN feature maps through the supervisions to the deep network. There are two stages in the proposed approach: (1) AMD lesion localizer is pre-trained and it can give an attention map of AMD biomarkers to supervise the network in the next classification stage. (2) The attention map is directly used for supervising feature maps of CNN classifier for AMD types, i.e. normal, dry and wet AMD. Based on these two stages, the proposed model can directly understand relationships between inputs and outputs to classify AMD types and it has shown that the classification accuracy has much improvement by applying attention guided feature enhancement method from the end-to-end baseline learning method.

Ⅱ. Method

2.1 Dataset

In this paper, we have collected OCT volumes from 99 eyes from controlled groups, 96 and 238 eyes from dry and wet AMD patients, respectively. From each OCT volume, OCT scans close to macular have been annotated by drawing bounding box and labeling the name of biomarker type, e.g. drusen, geometric atrophy for AMD biomarker localization. For each OCT scan, annotators have also labeled type of AMD, i.e. normal, dry AMD, and wet AMD for classification. Finally, 2,153 OCT scans have been collected and annotated. Ophthalmologists have participated in annotation of OCT scans. Fig. 1 shows examples of different types of OCT scans.

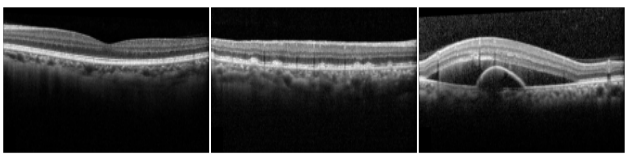

Fig. 1 Examples of different type of OCT scans

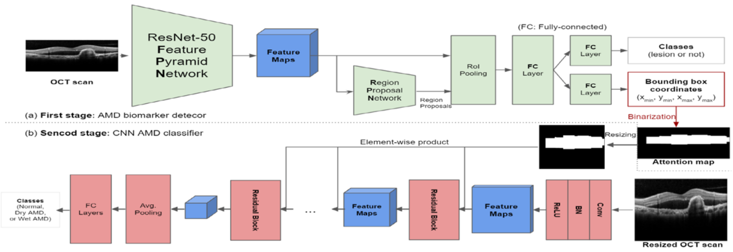

Fig. 2 Overview of the proposed method

2.2 Method

We propose two-stage AMD classification method. Fig 2. shows overview of the proposed method. In the first stage, Faster R-CNN (green blocks in Fig. 2) is used to detect AMD biomarkers. We regard the class of AMD biomarkers as just binary class 'lesion' to reduce complexity of training models and focus on localization itself. To use localization of trained detector, we generate binary map as shown in Fig. 2. The foreground and background values are set to 1.5 and 1.0 to attend location of AMD biomarkers in feature maps of CNN in the second stage.

The second stage is focused on classification of AMD type. In this work, we choose ResNet-18 architecture [5] as CNN AMD classifier as described in Fig. 2. Once trained AMD biomarker detector produces an attention map, OCT scan and attention map are fed into CNN concurrently. The attention map is down-sampled and multiplied in an element-wise manner to each feature map of convolutional layers. Hence, the region-attended feature maps are propagated layer by layer as shown in Fig. 2.

2.3 Experiments

We set 395 OCT scans as test set. We evaluate the performance of AMD biomarker detector and AMD classifier respectively. Since we focus on the ability of localization not specific class of biomarker, we calculate mean IoU (mIoU) of attention map with ground-truth binary map. For test set, mIoU records 0.55. We also evaluate classification accuracy, sensitivity, and, specificity for each class. We experiment 5-fold cross validation, and result is presented in table. 1. Table. 1 shows that proposed method enhances overall performances compared to the baseline model.

Ⅲ. Conclusion

In this paper, we propose two-stage AMD classification method to enhance biomarkers' features in CNN classifier. Pre-trained AMD biomarker detector generates attention map and it is fed into CNN to attend and intensify multiple feature maps of convolutional layers, and it leads to enhance overall performances of classification of AMD types. The proposed approach shows that clinical domain knowledge like biomarkers' feature in OCT scans is useful a supervising signal to directly enhance feature maps for deep neural networks.

Model	Class	Accuracy	Sensitivity	Specificity
ResNet-18 (baseline)	Normal	0.985	0.963	0.98
	Dry AMD	0.967	0.965	0.967
	Wet AMD	0.98	0.967	0.995
Proposed Model	Normal	0.989	0.996	0.986
	Dry AMD	0.981	0.919	0.994
	Wet AMD	0.99	0.991	0.989

Table. 1 Evaluation of classification of AMD

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