Dissertation Defense
Deep Learning Optimization for Optical Coherence Tomography Medical Image Analysis

Haifeng Wang, PhD Candidate
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Abstract

Optical Coherence Tomography (OCT) is an interferometric imaging modality that can visualize tissue microstructure via cross-sectional images. OCT can construct 3D image data and produce a concise summary of the samples, which are widely used for retinal disease examination in ophthalmology. Because of the non-invasiveness and swift diagnostic procedure, OCT becomes a high potential technology for the real-time surgery guidance. With the evolution of OCT technology, the performances, e.g., image resolution and projection rate, of the OCT images are improved, and OCT-based diagnoses are gaining high attention in different medical disciplines. One of the challenges for OCT image analysis is to classify pathological structures from normal ones. Having the classification results makes it possible for abnormal region segmentation, detecting tissue changes, and making a precise therapy treatment plan. However, most of OCT medical image analysis tasks are still relying on manual assessments from radiologists or pathologists, which require time-consuming works. The manual assessments also cause unreliable results, which highly depend on the expertise of the radiologists.

As a computer-aided approach, machine learning algorithms have been widely applied and investigated for automatic medical image analysis. This research proposes two deep learning models for OCT human tissue image classification. Based on the inception module structure, a dilated depthwise separable convolution network (DDSCN) model is proposed to combine the strength of both parallel neural work structure and separable operations to achieve high accuracy. A depthwise separable architecture is introduced to reduce data dimension variations in the volume data and improve parameter use efficiency. Dilated convolutions are applied to systematically aggregate multiscale contextual information and provide a large receptive field with a small number of trainable weights. The

DDSCN model design process shows that neural architecture is a crucial aspect that influences the performance of convolutional neural networks (CNNs). Identifying an effective CNN architecture requires a great amount of time and efforts due to the complexity of CNN connections and layer-wise structure. A designed model might not work for a different dataset due to the changes of data domains. To overcome the challenge, an adaptive neural architecture optimization (ANAO) model is proposed, which can adaptively design and optimize the CNN structure, i.e., the number of operations and operation types of each layer, based on given dataset. In this research, neural blocks are designed as basic elements in the optimization process. An adaptive mechanism is proposed to efficiently evaluate the performance of the candidate CNNs.

Different OCT image datasets are tested in this research. Experiment results show that the proposed models can obtain higher accuracy for both 2D and 3D OCT image classification tasks. Compared to state-of-art CNN models and texture-based typical machine learning models, the proposed models also achieve better efficiency. Especially, the proposed ANAO model can increase efficiency up to 61.26% compared to state-of-art models while still maintain its competitive accuracy.