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PhD Thesis: Deep Learning on Large-Scale Ophtalmic Imaging Data

Project title:

Project description:

Recently, Optical Coherence Tomography (OCT) has become a substantial diagnostic modality in ophthalmology in clinical routine as well as in large clinical trials. This can be explained by its relatively fast and noninvasive acquisition. In comparison with early Time Domain OCT (TD-OCT) devices, which exhibit a relatively low spatial resolution and slow scanning speed, more recent Spectral Domain OCT (SD-OCTs) increased both the spatial resolution and the scanning speed. On the one hand, this technical development results in an improvement with respect to diagnoses of patients. On the other hand, it leads to increasing amounts of imaging data.

Basically, the higher spatial resolution enables the opportunity to identify small clinically relevant anomalies. But since the manual segmentation of a single retinal characteristic in an OCT-scan can take up to several hours for a trained ophthalmologist, in particular if all the fine details need to be highlighted. Due to this high effort, manual segmentation is unfeasible for clinical routine and highly limited in terms of large-scale analysis. This in turn leads to the need of automatic segmentation in order to reduce the human workload, enable the usage of segmentation in a larger scale and to increase the reproducibility of the segmentation results.

One promising way of automating the segmentation process are machine learning approaches. In machine learning, a typical goal is to find a mapping from input patterns to one or more output values. In our case, this is the mapping from an OCT-scan to a segmentation of this scan, respectively to a clinical variable, depending on the task assigned.

Conventional machine learning approaches use a manually annotated set of training images to train a model that is able to automatically reproduce these annotations on unseen datasets. The performance of these methods typically rely on large amount of annotated data and suitable features. But, as stated above, manual annotation can be difficult, time consuming and expensive. Additionally, the used features are often hand-crafted features that are very domain-specific, which means that the selection of these features requires specific expert knowledge and have to be designed individually for each problem.

In the proposed work we focus on machine learning approaches which are learning a model in an unsupervised way (i.e. without manual annotations). In particular we aim at implementing and developing deep learning approaches that attempt to learn appropriate features automatically. This overcomes the drawbacks of manual annotations and handcrafted features. In the proposed work we use these approaches to segment OCT scans, compute appropriate representations for further medical classification or regression tasks.