Thesis preproposal: Generating brain tumor MR images from few samples

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Application for the ESOP Scholarship

1 Introduction

The explosive development of AI has led to many advances in the field of biomedical imaging. From lesion detection [1] to image reconstruction [2] and computer-aided diagnosis [3], many methods require large amounts of training data to produce relevant results and avoid overfitting. However, obtaining large datasets of medical images can be challenging due to privacy concerns and costs.
It has recently been shown [4, 5] that generative models, such as VAEs [6] and GANs [7] can be employed to synthesise medical images, which can be used for data augmentation.

2 Objective and goals

In this thesis I am to approach the problem of pathological brain MR image generation in the case of a small available dataset.
This could prove particularly useful in the case of rare diseases [8], where deep-learning-based innovations are hampered by the scarcity of adequate datasets.

3 Methods of implementation

Recently, sample-efficient ("few-shots") image synthesis methods have been successfully developed in the field of general Computer Vision. Such solutions encourage diverse and high-quality image generation in the low-data regime [9].
In this thesis, I want to evaluate, and possibly adapt, state-of-the-art few-shots GANs, to generate realistic pathological MR images from small amounts of samples.
For practicality, I plan to test the generation of said images first on lesions for which datasets are widely available, for instance using public collections of brain tumor MRI images (e.g. BraTS [10]), or similar resources accessible to ETH groups.
Although no standard metrics have been developed to assess the quality and diversity of GAN-generated images [11, 12], the FID [13] and the MS-SSIM [14] could be employed. As the validity of the FID for medical images is still debated, alternative metrics presented in [4] could be considered.

If the quality of the images will be significant, it will be worth evaluating the effect of the synthetic images on a classification problem.

4 Previous work

To my knowledge, no few-shot GANs have been applied to generate medical images yet.
In general Computer Vision, several solutions have been presented. Some models are based on pre-training on a large source domain to improve the generation on a target domain, such as FSGAN [15], which regularizes the adaptation of the source model via cross-domain correspondence, [16] and [17].
Other methods train few-shot GANs from scratch: DFSGAN [18] takes dynamic Gaussian mixture latent codes as the generator's input for more realistic and diverse results, while Deceive D [19] uses the generator to produce pseudo-samples that reduce overfitting.
Generation of pathological medical images has been explored by works such as [20, 5, 21, 22].
Finally, in this thesis I could leverage my relative familiarity with PyTorch.

5 Timetable and milestones

- 2 Weeks (W): familiarising with the relevant literature
- 2W: selecting the most relevant methods, metrics and suitable datasets
- 10W: implementing and adapting the selected methods
- 3W: applying the metrics and evaluating the results
- 2W: using the images in a classification problem/buffer time
- 5W: writing, reviewing and discussion.

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