Inpainting in Medical Imaging

1. General Info

Project Title: Inpainting in Medical Imaging

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2. Project Abstract

Inpainting[1] is an unsupervised technique that is used to initialize a model weight and also can be utilized as a generation or reconstruction technique. Apart from the initialization, in this project, we aim to learn how inpainting can learn missing parts from surrounding areas. We are going to investigate this on simple synthetic data. After that, we will investigate this technique on real medical data, and we investigate what are the shortcomings of this method is the generation of healthy and unhealthy data. We will attempt to improve this technique by methods like Meta-Learning[2].

3. Background and Motivation

Over the past years, generative adversarial networks have achieved great success. Yet, the performance of inpainting approaches is not well-explored in non-normal data distributions such as anomalies. Generation of medical data can be beneficial for synthesizing disease images and learning generative models that could be later used for other tasks such as segmentation. Anomalies are common in medical data, and therefore the generation of anomalies is an important task. Here, we explore the robustness of inpainting methods to different distributions of data and then focus on generating anomalies.

4. Technical Prerequisites

- Good background in statistics
- Good background in machine learning, deep learning
- Must have a lot of experience in Python and Pytorch

5. Benefits:

- Weekly supervision and discussions
- Possible novelty of the research
- Possible publication

6. Students' Tasks Description

Students' tasks would be the following:

Groups 1 & 2:

- Understanding the underlying methods
- Choosing the baseline federated learning framework
- Implementing and adapting the FL framework to AutoML
- Choosing the appropriate AutoML techniques and performance measures

- Running the evaluation metrics on a toy dataset
- Running the evaluation metrics on a medical imaging dataset
- Testing and documentation.

7. Work-packages and Time-plan:

	Description	#Students	From	To
WP1	Familiarizing with the literature.	4	22.10	29.10
WP2	Familiarizing with the required frameworks. Come up with a detailed time-plan (gantt)	4	29.10	06.11
WP3	Evaluation of inpainting technique on synthetic data	4	06.11	13.11
WP4	Adapting inpainting technique for medical imaging data	4	13.11	03.12
WP5	Evaluation of the implemented methods on anomalies	4	03.12	10.12
M1	Intermediate Presentation II	4	12.2021	
WP6	Improving anomaly generation	4	10.12	17.12
WP7	Comparison to other anomaly generation techniques	4	17.12	15.01
WP8	Testing and Documentation	4	15.01	26.02
M2	Final Presentation	4	02.2021	

References

1. Yu, J., Lin, Z., Yang, J., Shen, X., Lu, X. and Huang, T.S., 2018. Generative image inpainting with contextual attention. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 5505-5514).
2. Nichol, A., Achiam, J., & Schulman, J. (2018). On first-order meta-learning algorithms. arXiv preprint arXiv:1803.02999.
3. Laptev, N. (2018). AnoGen: Deep Anomaly Generator. In Outlier Detection De-constructed (ODD) Workshop. Available online: https://research. fb. com/publications/anogen-deep-anomaly-generator/(accessed on 20 August 2018).
4. Salem, M., Taheri, S., & Yuan, J. S. (2018, November). Anomaly generation using generative adversarial networks in host-based intrusion detection. In 2018 9th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON) (pp. 683-687). IEEE.