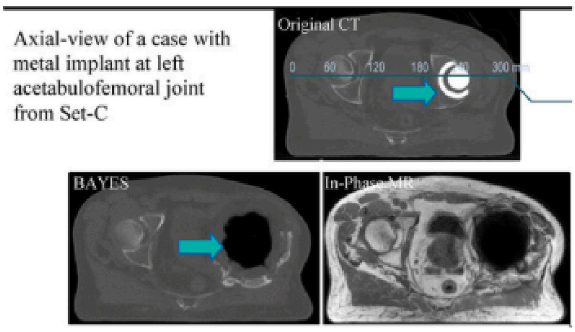
Master's Project proposal: «Synthetic CT generation: DL-based anomaly detection for MR-only radiotherapy»

Supervisors: Mariia Lapaeva, Prof. Dr. Manuel Günther
Intended Start: May 2025 or as agreed

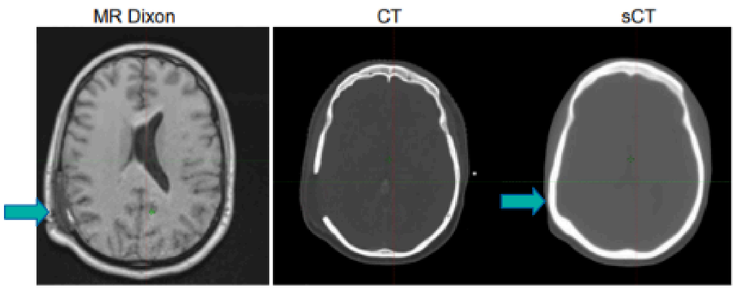
Cancer is still one of the leading causes of death worldwide and half of the patients receive radiotherapy in the course of treatment. At present, both Magnetic Resonance (MR) and Computed Tomography (CT) images are used for irradiation planning. However, CT imaging exposes patients to additional radiation. *Eliminating CT images from the workflow can help to reduce radiation exposure and introduce a more cost-efficient workflow.*

Deep learning (DL) methods have emerged as an effective method for synthetic CT (sCT) generation. Similar to how image translation algorithms convert a photo to resemble Van Gogh's art, DL models are capable to translate MR images into sCT, offering faster inference times, making them more suitable for clinical settings. Our previous research[1–3] showed that Generative Adversarial Networks (GANs) can demonstrate clinically acceptable performance in the sCT generation task. However, for the clinical implementation of MR-only therapy, it is critical to identify patients whose MR images (and consequently, MR-based generated sCT images) may contain anomalies such as imaging artifacts, unseen anatomy, implants, etc., at the first stage, which could drastically affect neural network performance and sCT image quality and make them unsuitable for treatment planning. While there have been only a few studies on this topic, most have primarily focused on retrospective voxel-wise analysis of differences and dose distribution discrepancies[3–5], or uncertainty estimation[6–8] of generated sCTs.

(Law et al. 2023)
Example of a patient with a hip metal implant requiring a CT because an air pocket appears on the sCT instead



(Commercial software for sCT)
Example of a post-op open skull, when sCT generation fails, because non-existent bone appears on the sCT



The goal of the project: Combining deep learning and statistical methods to develop automated QA processes for distinguishing in- and out-of-distribution (OOD) MR images, enhancing the clinical applicability and safety of MR-only radiotherapy.

Research objectives:

- Compile a dataset of patients with and without artifacts\implants in the pelvic region and analyze it [data source will be provided]. Potentially extend it to other regions.
- Employ CycleGAN and thresholding techniques to identify OOD data. Potentially examine strategies for the utilization of Deep Learning (DL)-based methods for anomaly\out-of-distribution detection[9–11].
- Potentially train a DL-model to classify different OOD categories (implants, artifacts, rare anatomical structures) to improve model interpretability

Requirements:

- Curiosity and motivation for the topic.
- Initial familiarity with deep learning methods (for example taught in the Deep Learning course) and Image Processing.
- Solid command of Python and initial acquaintance with the PyTorch deep learning framework.
- NO prior knowledge of medical image analysis is required.

If this project sounds appealing to you, please write us an email briefly describing your interest and any relevant experience with programming projects. Do not hesitate to reach out with any questions: **mariia.lapaeva@uzh.ch, guenther@ifi.uzh.ch**

References

1. Lapaeva M, La Greca Saint-Esteven A, Wallimann P, et al. Synthetic computed tomography for low-field magnetic resonance-guided radiotherapy in the abdomen. *Phys Imaging Radiat Oncol*. 2022;24:173-179. doi:10.1016/j.phro.2022.11.011

2. La Greca Saint-Esteven A, Dal Bello R, Lapaeva M, et al. Synthetic computed tomography for low-field magnetic resonance-only radiotherapy in head-and-neck cancer using residual vision transformers. *Phys Imaging Radiat Oncol*. 2023;27:100471. doi:10.1016/j.phro.2023.100471

3. Dal Bello R, Lapaeva M, La Greca Saint-Esteven A, et al. Patient-specific quality assurance strategies for synthetic computed tomography in magnetic resonance-only radiotherapy of the abdomen. *Phys Imaging Radiat Oncol*. 2023;27:100464. doi:10.1016/j.phro.2023.100464

4. Chourak H, Barateau A, Nunes JC, et al. Local quality assessment of patient specific synthetic-CT via voxel-wise analysis. In: *2022 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*. ; 2022:1-7. doi:10.1109/DICTA56598.2022.10034622

5. Van Harten LD, Wolterink JM, Verhoeff JJC, Išgum I. Automatic online quality control of synthetic CTs. Landman BA, Išgum I, eds. *Med Imaging 2020 Image Process*. Published online March 10, 2020:57. doi:10.1117/12.2549286

6. Law MWK, Tse MY, Ho LCC, et al. A study of Bayesian deep network uncertainty and its application to synthetic CT generation for MR-only radiotherapy treatment planning. *Med Phys*. 2024;51(2):1244-1262. doi:10.1002/mp.16666

7. Li X, Bellotti R, Meier G, et al. Uncertainty-aware MR-based CT synthesis for robust proton therapy planning of brain tumour. *Radiother Oncol*. 2024;191:110056. doi:10.1016/j.radonc.2023.110056

8. Hémon C, Cubero L, Boussot V, et al. Modeling dose uncertainty in cone-beam computed tomography: Predictive approach for deep learning-based synthetic computed tomography generation. *Phys Imaging Radiat Oncol*. 2025;33:100704. doi:10.1016/j.phro.2025.100704

9. Parchur AK, Zarenia M, Gage C, Paulson ES, Ahunbay E. Automated Hallucination Detection for Synthetic CT Images used in MR-only Radiotherapy Workflows. *Phys Med Biol*. Published online February 13, 2025. doi:10.1088/1361-6560/adb5eb

10. Linderman RW, Chen Y, Linderman SW. A Bayesian Nonparametric Perspective on Mahalanobis Distance for Out of Distribution Detection. Published online February 12, 2025. doi:10.48550/arXiv.2502.08695

11. Jingkang50/OpenOOD: Benchmarking Generalized Out-of-Distribution Detection. Accessed February 18, 2025. https://github.com/Jingkang50/OpenOOD