BA/MA Thesis: Deep Learning for Low-field Brain Image Quality Transfer

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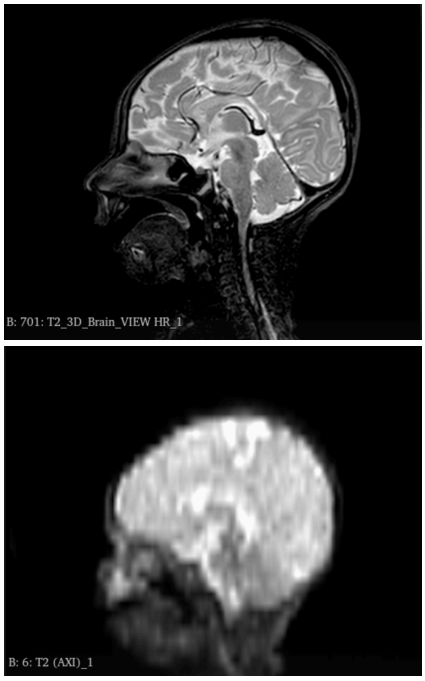
Abstract. Magnetic Resonance Imaging (MRI) plays a vital role in modern diagnostics, offering detailed, non-invasive insights into human anatomy [1-2]. High-field MRI (HF-MRI) systems, which operate at higher magnetic field strengths, provide superior image resolution and contrast compared to low-field MRI (LF-MRI) systems [3-4]. However, HF-MRI scanners are expensive and require significant maintenance, limiting their availability in resource-constrained environments where LF-MRI systems prevail. This disparity often leads to suboptimal diagnostic outcomes, underscoring the need to enhance the quality of LF-MRI images to the standard of HF-MRI [10].



Generative models, particularly diffusion models [5], have emerged as promising tools for image enhancement. They excel in generating high-fidelity, contextually coherent images by iteratively refining noisy data. Recent studies have demonstrated the potential of diffusion models in various imaging tasks, outperforming traditional techniques, including Generative Adversarial Networks (GANs). The proposed project aims to leverage diffusion models to improve LF-MRI image quality, bridging the gap between LF-MRI and HF-MRI and enhancing diagnostic accuracy [1-2].

The project **aims** to develop a 3D Conditional Diffusion Model specifically designed for enhancing LF-MRI images [6-8]. This model, named MagIQT, will integrate multiple innovative components that complement each other to address existing challenges in MRI image enhancement. The model will consist of a transformer-based encoder and a cross-batch mechanism, uniquely positioned to improve contextual information and reduce artifacts, thus advancing the current state-of-the-art. A recent review [9] summarizing the strengths and weaknesses of diffusion models in medical imaging will be further investigated.

Research Questions:

> *Q1) How effectively can a 3D conditional diffusion model enhance low-field MRI images to high-field MRI quality in terms of diagnostic accuracy and image fidelity compared to existing generative models [11]?*

Q2) What are the specific contributions of the transformer-based encoder and cross-batch mechanism to the overall performance of the 3D conditional diffusion model in reducing artifacts and preserving anatomical details in MRI image enhancement?

Q3) How does the application of the 3D conditional diffusion model impact the detection and diagnosis of anomalies in pediatric MRI scans, particularly in identifying subtle pathologies that may be missed in low-field MRI?

Proposed methodology:

3D Conditional Diffusion Model: Unlike conventional 2D models, this model will operate on 3D volumetric data, directly addressing the need for spatial consistency in medical images. The diffusion process gradually refines low-field input images, conditioned on high-field data, through a sequence of noise-reduction steps. This iterative denoising process enables the model to generate high-quality, high-resolution images from lower-quality inputs.

Transformer-Based Encoder: The encoder will combine transformer and convolutional layers, effectively capturing local and global features from the 3D input data. This approach ensures that detailed spatial information is preserved, enhancing the model's ability to reconstruct high-resolution images with accurate anatomical details. Transformers, with their self-attention mechanism, facilitate the incorporation of long-range dependencies, which is crucial for maintaining structural integrity in enhanced MRI images.

Cross-Batch Mechanism: A novel cross-batch mechanism will be implemented to mitigate boundary artifacts, which are common in patch-based methods. This mechanism enhances the model's contextual awareness by allowing the network to incorporate information from adjacent patches, thus improving global consistency and reducing artifacts. This approach significantly differentiates MagIQT from existing models that often suffer from limited contextual information and boundary errors.

Datasets. A total of 50 patients were scanned on portable 64mT and standard 3T scanners at the *Clinic for Neonatology and Pediatric Intensive Care Medicine at the University Hospital Bonn* with T1-weighted, T2-weighted, and FLAIR acquisitions. Brain Imaging sequences require registration as a pre-processing step. Another cohort of unpaired 100 patients was scanned on either 64mT or 3T might be used for the model development. Additional datasets might be requested from the authors of [11-12].

Roadmap (6 months):

- Familiarize yourself with the current literature [5-9]
- Build the baseline supervised model and develop the anomaly detection model.

- Run the necessary comparisons.
- Run extensive experiments and analysis
- Write up your thesis

Requirements:

- Solid background in Machine/Deep Learning
- Familiar with deep learning models and SOTA architectures
- Sufficient knowledge of Python programming language and libraries (Scikit-learn)
- Experience with a mainstream deep learning framework such as PyTorch.
- Machine/Deep learning hands-on experience

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