

ABSTRACT

The application of deep learning in medical imaging has shown great potential but remains constrained by the scarcity and imbalance of available datasets. Challenges such as data privacy concerns, variability in medical pathologies, and limited access to comprehensive datasets limit the development of robust and generalizable models. Synthetic data generation offers a promising solution to these limitations by enabling the creation of diverse and realistic medical datasets that address data scarcity and imbalance.

This thesis investigates the potential of Flow Matching (FM) models for generating three-dimensional (3D) synthetic medical images, with a focus on brain MRI scans. Although FM models have demonstrated great performance and efficiency in non-medical contexts, their application in medical imaging, particularly for 3D data, remains largely unexplored. To address this gap, a novel architecture is proposed that combines FM with a Variational Autoencoder-based Generative Adversarial Network (Vector Quantized Generative Adversarial Network (VQ-GAN)). The (VQ-GAN) encodes high-dimensional data into a compact latent space, where the FM model operates to generate synthetic data efficiently.

The proposed framework is evaluated using publicly available brain MRI datasets (The Alzheimer's Disease Neuroimaging Initiative (ADNI)) through a series of quantitative and qualitative experiments. The results highlight both the strengths and limitations of Flow Matching (FM) models in generating high-quality medical images, emphasizing the importance of preprocessing, dataset characteristics, and model design. In comparison to a denoising diffusion model, the FM model demonstrated significant advantages, achieving good quality results while reducing training time from 10 days to just 13 hours. However, challenges such as the loss of fine anatomical details due to computational constraints were observed. Despite these limitations, the framework demonstrates significant potential for advancing synthetic data generation in medical imaging. To the best of our knowledge, this work represents the first systematic exploration of FM models for generating 3D medical images.

This study offers a foundation for future research aimed at optimizing Flow Matching models further and explore their application to other medical imaging modalities, such as CT or PET scans. By reducing training times and enabling the generation of diverse datasets, the proposed framework could significantly impact real-world healthcare applications, including diagnostic tools, training datasets, and privacy-compliant synthetic data augmentation.

KEYWORDS

3D Medical Imaging, Synthetic Image Generation, MRI , Generative Models, VQ-GAN, Flow Matching Model, Latent Space.