Brain MRI Synthesis using cDPM and GAN Architectures

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The project aims to investigate the generation of brain MRI scans using generative AI, focusing on both GANs (Generative Adversarial Networks) and Diffusion Models. The problem of generating high-fidelity synthetic MRI images is critical for augmenting medical datasets, enhancing machine learning models, and providing resources for clinical training and research. The ability to generate diverse and accurate synthetic images can mitigate the limitations of data scarcity and privacy concerns in medical imaging.

I examine papers on MRI synthesis using GANs and Diffusion Models, including "Generating Realistic Brain MRIs via a Conditional Diffusion Probabilistic Model" by Wei Peng et al. [5], and "BrainGAN: Brain MRI Image Generation and Classification Framework Using GAN Architectures and CNN Models" [3]. These readings will offer insights into current methodologies, challenges, and advancements in the field of medical image synthesis.

The primary data source will be the BraTS 2020 dataset [1] [2] [4], which includes multimodal MRI scans (T1, T1ce, T2, and FLAIR) with annotations for tumor regions. This dataset provides a rich foundation for training and validating generative models. Other datasets will be added if needed.

This research is to build and compare two generative models: a Conditional Diffusion Probabilistic Model (cDPM) and a GAN-based model. For the diffusion model, I will adapt existing implementations from Wei Peng's research [5], focusing on fine-tuning hyperparameters and incorporating advanced techniques like noise scheduling and attention mechanisms to improve training stability and image quality. For the GAN-based model [3], I will utilize architectures such as DCGAN and VAE-GAN, ensuring a robust comparative analysis between the two approaches.

The results will be evaluated both qualitatively and quantitatively. Qualitative assessment will involve visual inspection of generated MRI slices for anatomical accuracy and realism. Quantitative metrics will include Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and medical-specific measures like Dice coefficient and Fréchet Inception Distance (FID) to compare the synthetic images with real MRI scans. These evaluations will ensure the generated data's utility for downstream tasks such as tumor segmentation and diagnostic model training.

References

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