Abstract

Magnetic Resonance Imaging (MRI) is used extensively across the world to get detailed physiological images that are unattainable with other imaging modalities. Although it has widespread appeal, the MRI process tends to be noisy, confined, and can cause discomfort when a patient is being scanned. In addition, the patient needs to be completely still during the scan to ensure the machine can acquire a good image, a significant issue for seniors and children. My project aims to address these problems by reconstructing MR images via under-sampling the underlying data of the MR image, which is called *k*-space. A generative adversarial network (GAN) was constructed, and consisted of two separate neural networks, a generator network that generated samples of an image, and a discriminator network which compared the generated sample to a ground truth version of that image. I used publicly available datasets (OASIS3 and IXI) and preprocessed each image with Fourier transforms, line-by-line sampling, and normalization. Multiple iterations of the generator model were attempted before the final U-Net inspired model trained on a Tesla V100 GPU for 300 epochs over 20 hours. The generator was able to successfully generate images similar to the ground truth MRI images in the testing dataset, with a Peak Signal-to-Noise ratio of 34.22, and a Structural Similarity Index of 0.9844, improving significantly upon earlier baselines. The contributions of this project include reducing the costs of MRI, reducing the discomfort and error of the process, and increasing the speed of the process.