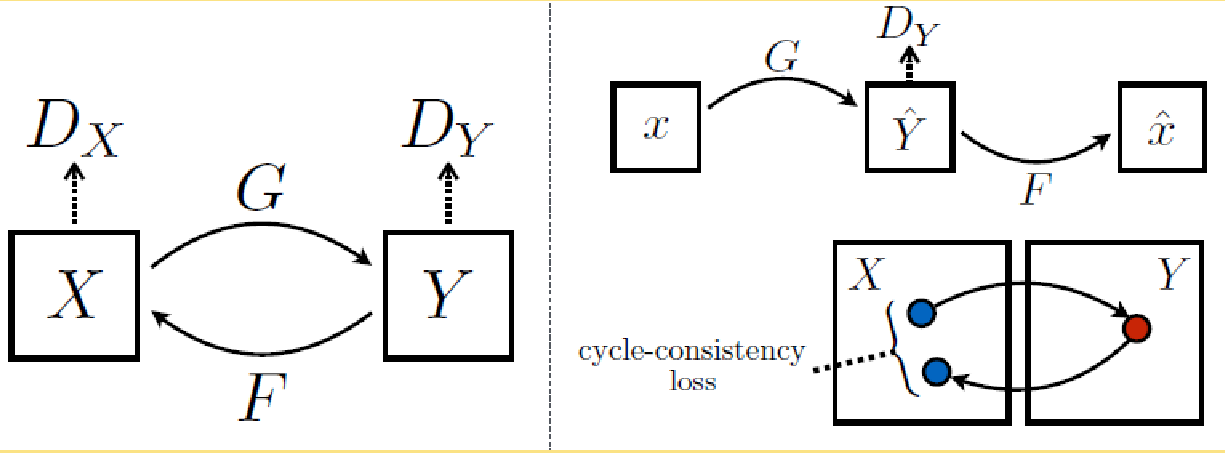
Translation of 1.5T T1w images to 3T T1w images using the CycleGAN model

CycleGan structure [2]:

G = G_A
F = G_B
Dy = D_A
Dx = D_B



$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x)))]$$

$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].$$

$$\mathcal{L}_{\text{identity}}(G, F) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(y) - y\|_1] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(x) - x\|_1]$$

$$G^*, F^* = \arg \min_{G,F} \max_{D_x, D_Y} \mathcal{L}(G, F, D_X, D_Y)$$

The aim of the project is to translate 1.5T T1w images into 3T T1w images.

The 1.5T images are assumed to be acquired using:

- The same gradient coils as the 3T one
- Same k-space structure
- Same receiver coil
- Same number of scans
- Same acquisition parameters (TR, IT etc.)

The only difference, therefore, is the magnitude of the polarizing field

The differences between the images are:

$SNR^{\frac{1}{2}} = \alpha M_0 = \beta B_0$: under these conditions directly proportional to the intensity of the polarizing field [1]

Contrast and CNR: the intensity affects relaxation parameters, higher field means greater difference between the parameters of two materials (e.g. white and gray matter)

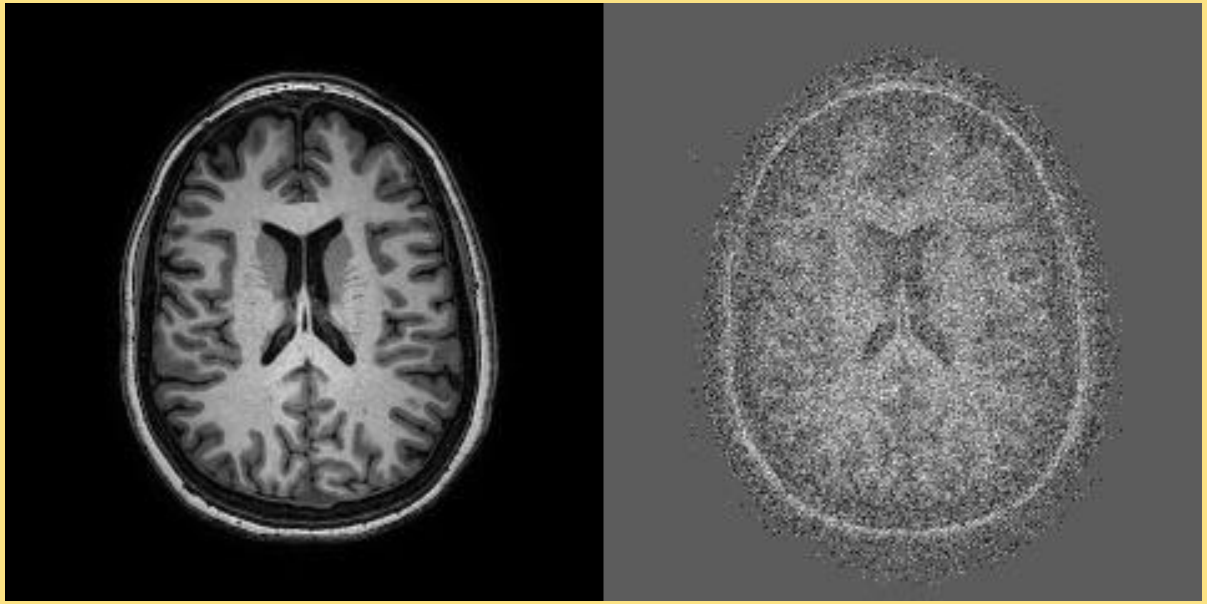
Datasets and preprocessing pipeline:

Structural T1w dataset from the AOMIC collection: PIOP1 for testing and PIOP2 for training

Extracted 20 transverse plane images from each tomography, the majority showing the CSF region, for GPU memory reasons the network cropped the images by removing some background

Half of the training dataset was degraded by adding Gaussian noise to each (non-background) pixel such that the resulting SNR would be four times that of the original one, faking a 1.5T image with the aforementionted characteristics

Original

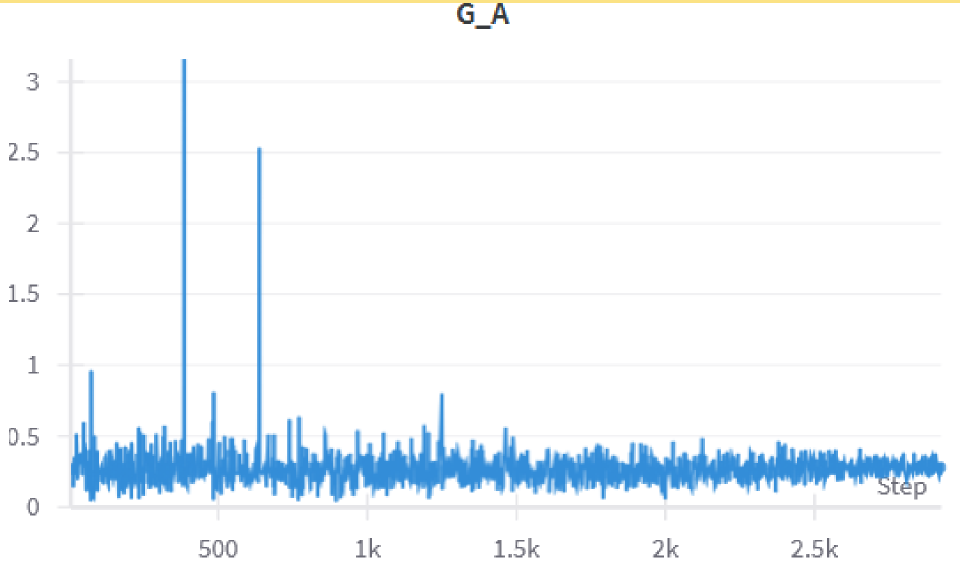


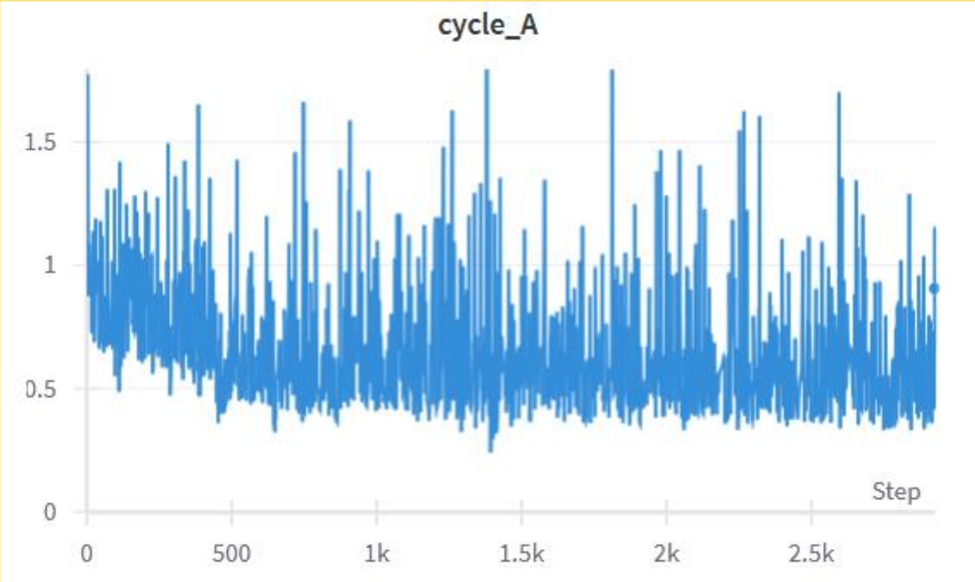
Processed

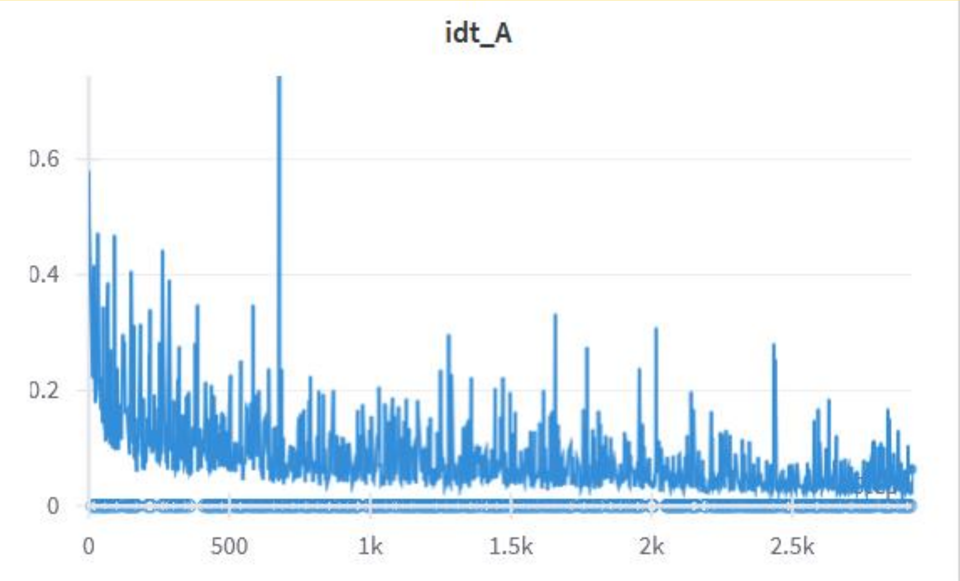
Code and procedure justification are present at this repository

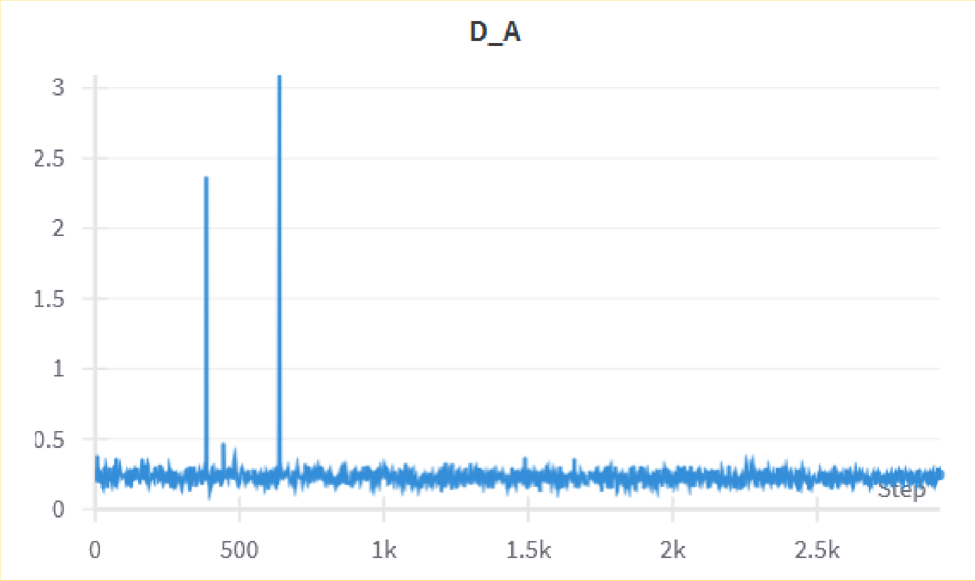
Testing ; Training

Training details: G_A and D_A should oscillate, others should decrease (official repository)

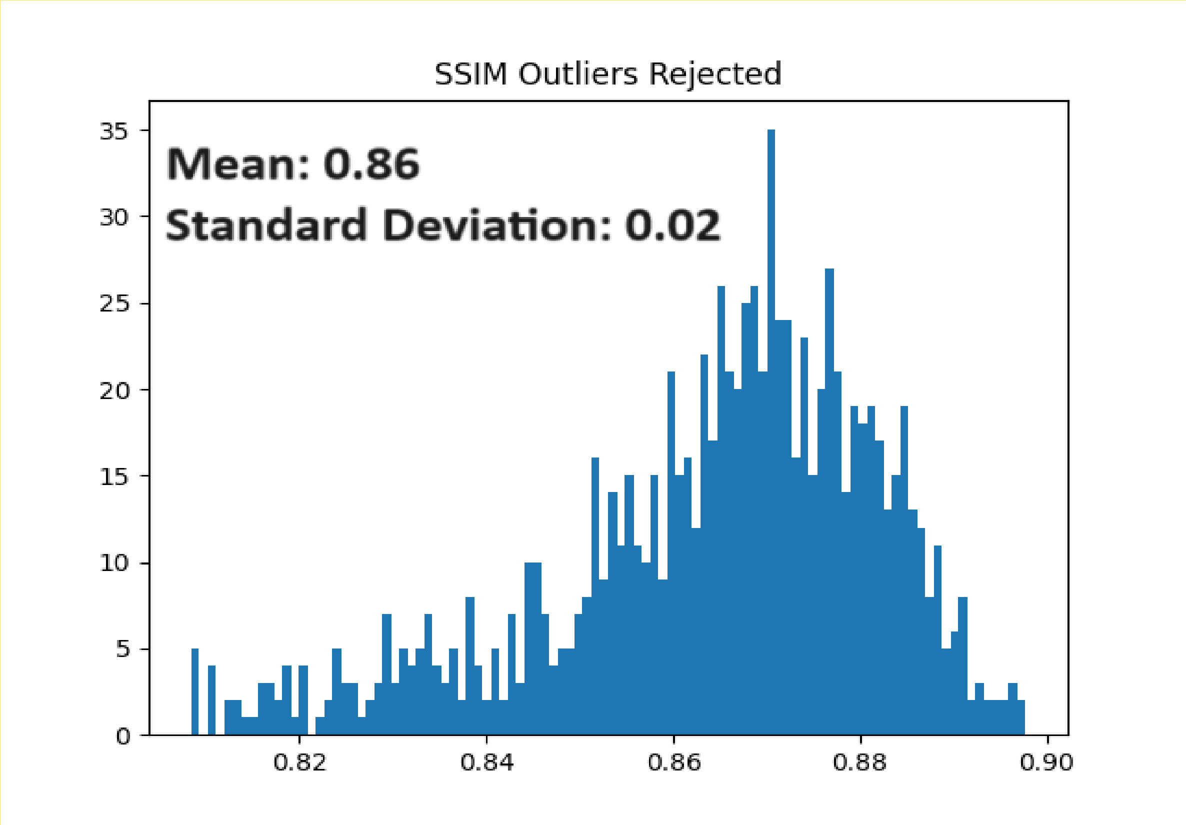


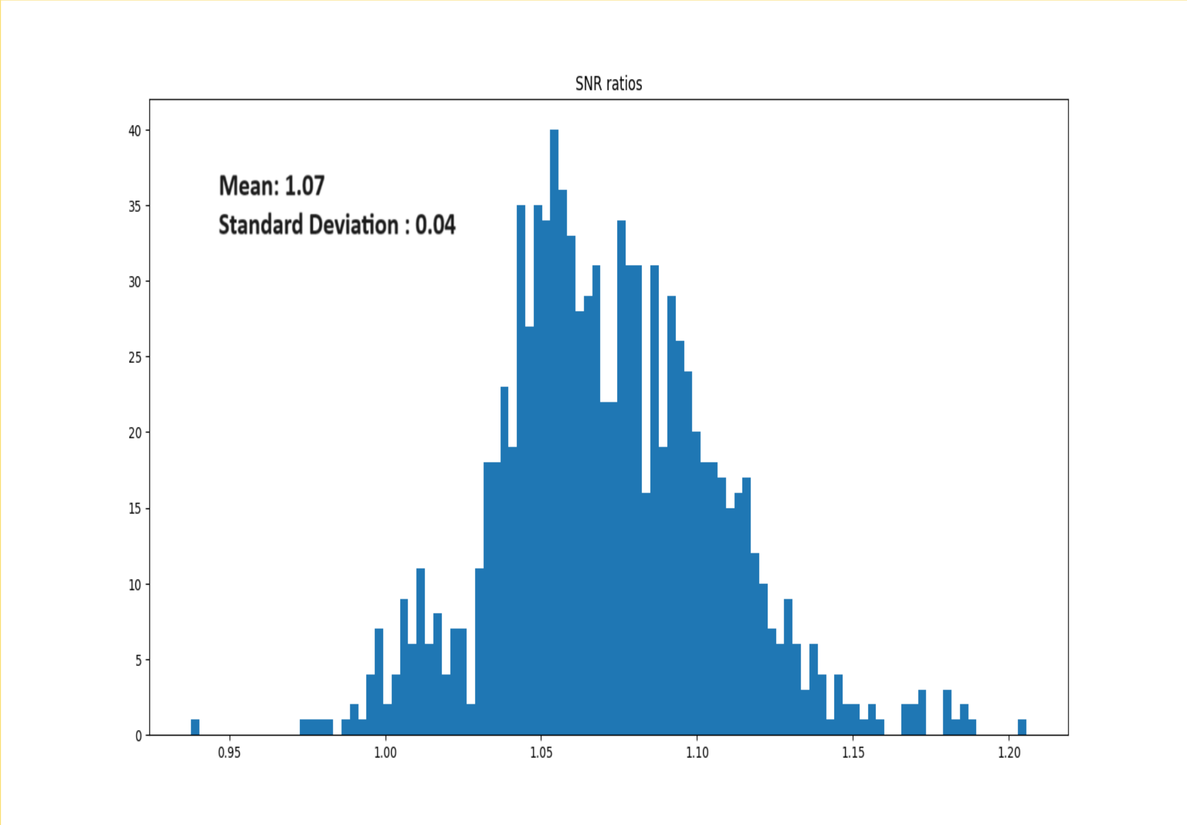






Results





$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Computed using a window size of 7 which is then convoluted on the images and the results are averaged to give the mean SSIM for one image. 1 indicates perfect similarity

(Output image SNR)/(Original image SNR), the objective is to make the output image as similar as possible to the original one so the expected mean is 1.

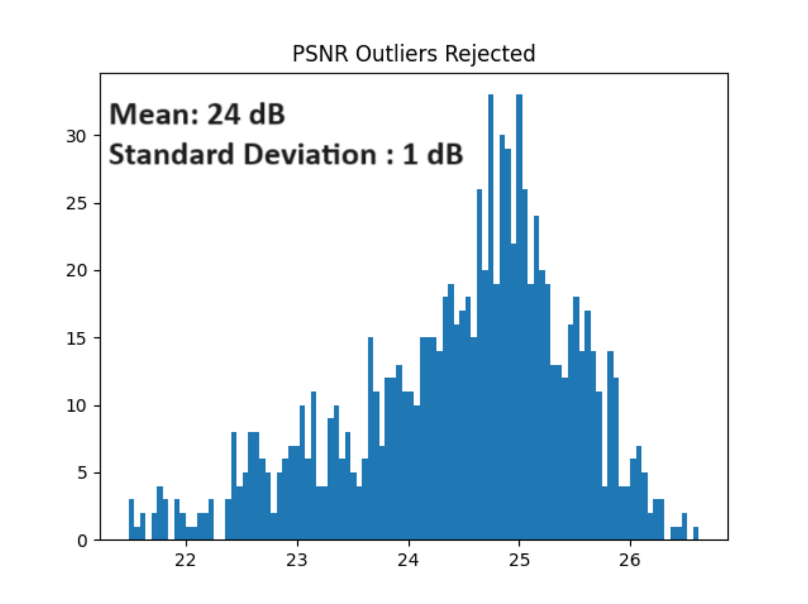
Some Literature Results [3]

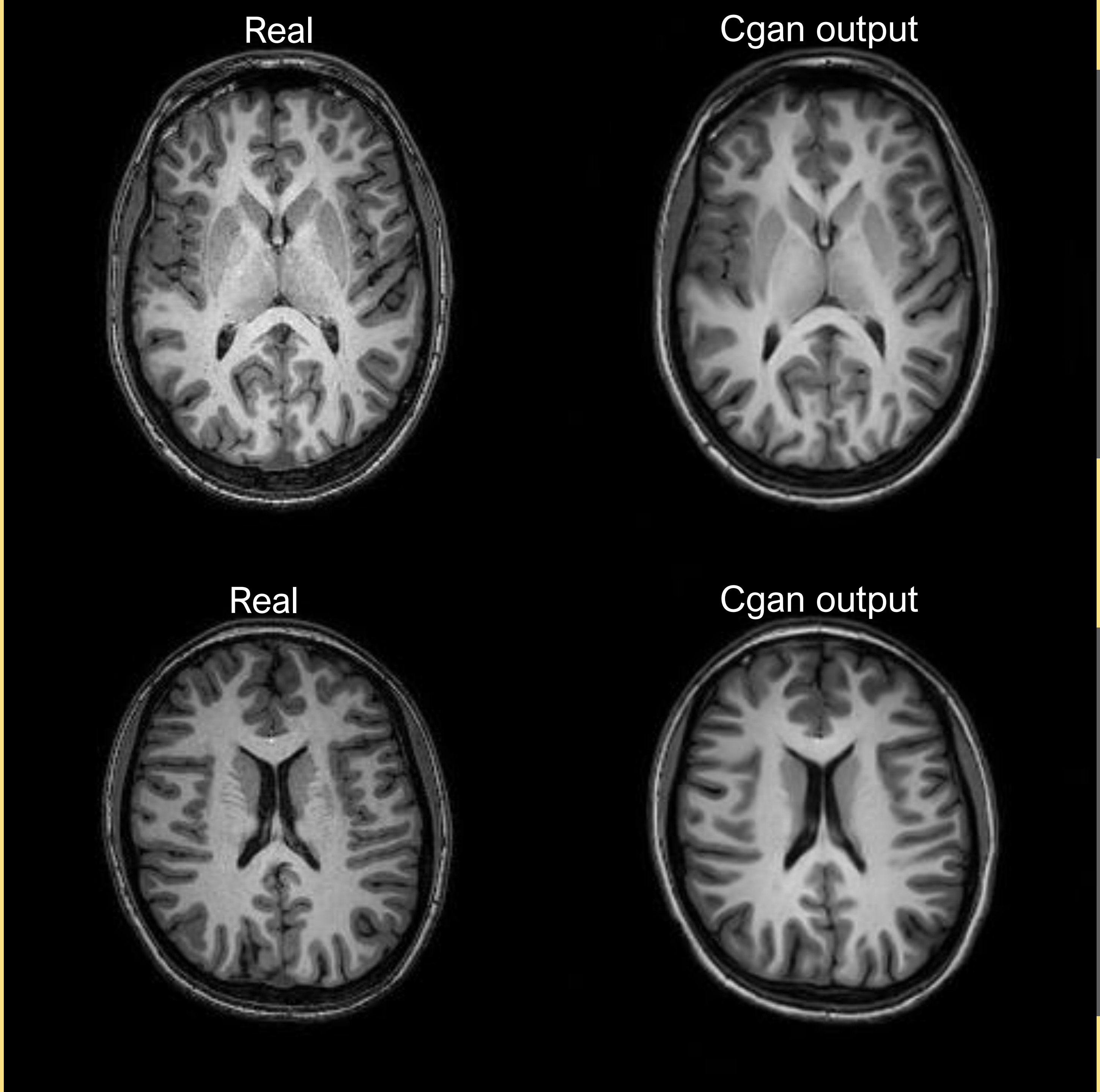
Network	Applications	Site and # of patients in training/testing	Key findings in results	Author, year
GAN	Synthesizing 7T MRI from 3T MRI	Brain: 15, leave-one-out	PSNR (dB): 27.6 ± 1.3	Nie et al., 2018[22]
AE	Synthesizing 7T MRI from 3T MRI	Brain: 15, leave-one-out	SSIM: 0.8438	Zhang et al., 2019[39]
U-net (encoder-decoder)	Synthesizing 7T MRI from 3T MRI	Brain: 15, leave-one-out	PSNR (dB): 28.27	Qu et al., 2020[126]
GAN	Restoring undersampled acquisition	Brain and chest: for each site, 100 slices training/100 slices testing	PSNR (dB) at 10% undersampling: about 32 for brain, 26.5 for chest	Quan et al., 2018[168]

Mean SSIM: 0.86

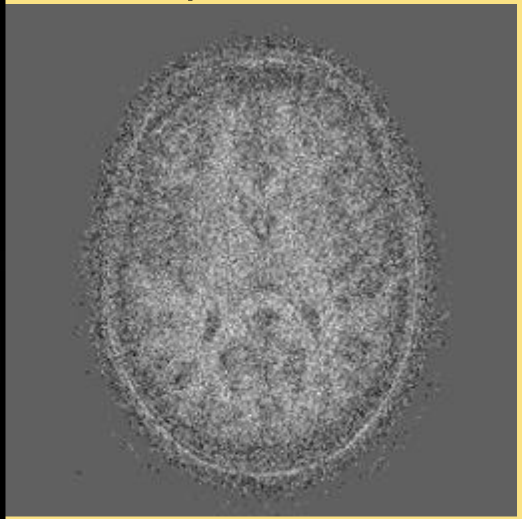
Mean PSNR: 24 dB

(PSNR depends on GL range)

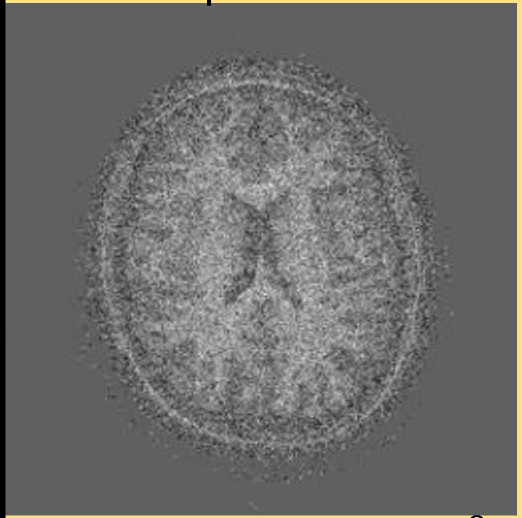


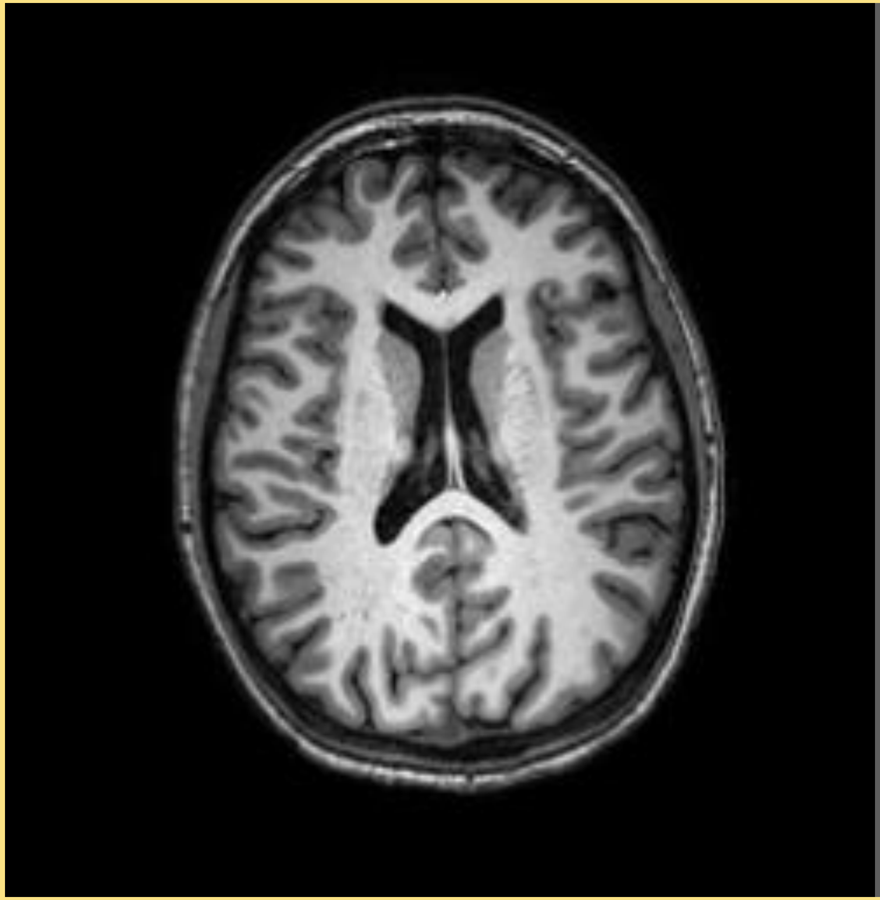


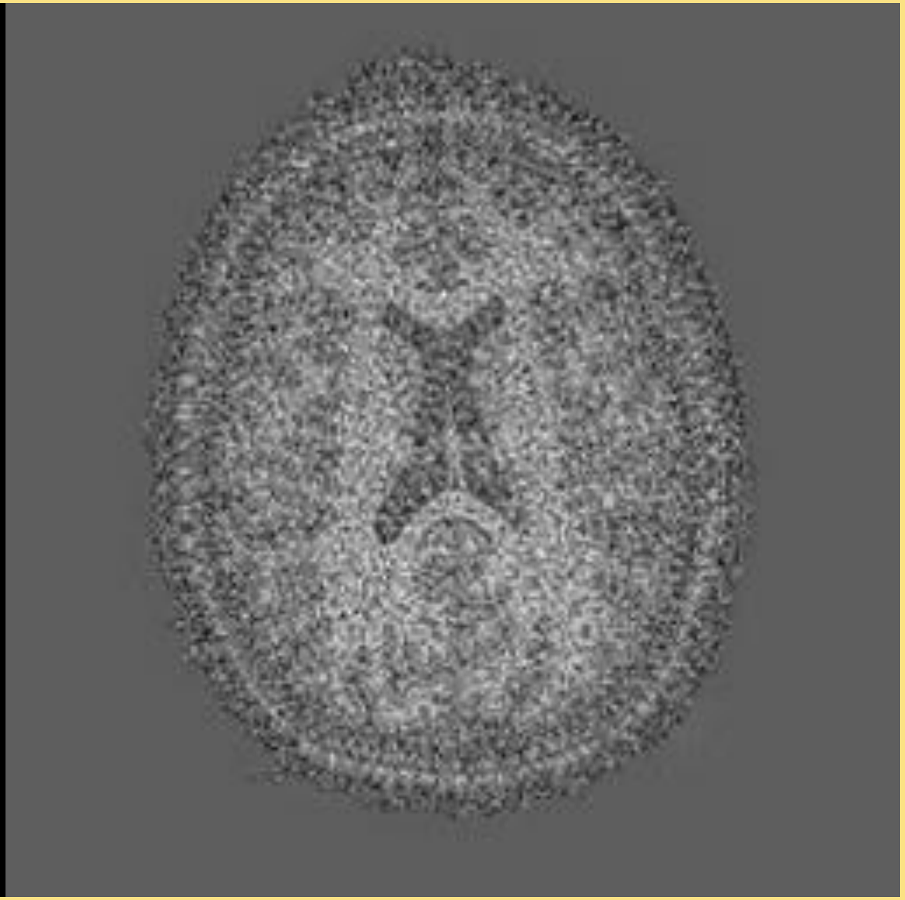
Pre-processed



Pre-processed







Real

Noised by CGan

Discussion

MSSIMs and PSNR comparable with literature are achieved although using limited scope (only transverse sections with CSF and translation from 1.5T to 3T) possible ways of improvement are:

- Better dataset selection: a few of the images contained parts of the eyes of the patients (explaining some low outliers), either inserting a greater number of these kinds of images or removing them may increase the quality of the results
- Adding other brain regions to the analysis
- Adding sagittal and median slices
- Introduction of SSIM as a metric to evaluate training/ adding an SSIM depending term to the cost function
- Less severe (more realistic) degradation

Potential in synthetic data generation:

The noised images (G_B's output), in their current form or with a modified dataset as above, may be used as a base to generate synthetic images by adding ulterior random sources of noise and then denoising them by the use of G_A

Sources:

-[1] Callaghan, Principles of MR Microscopy; In Vivo NMR Spectroscopy: Principles and Techniques, 2nd Edition Robin A. de Graaf (chapts 2.5.1,4.2)

-[2] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", in IEEE International Conference on Computer Vision (ICCV), 2017

-[3] Tonghe Wang, Yang Lei, Yabo Fu, Jacob F. Wynne, Walter J. Curran, Tian Liu,Xiaofeng Yang «A review on medical imaging synthesis using deep learning and its clinical applications» J Appl Clin Med Phys. 2021 Jan;22(1):11-36. doi: 10.1002/acm2.13121. Epub 2020 Dec 11. PMID: 33305538; PMCID: PMC7856512.