MR image harmonization based on cross-center style transfer using deep generative adversarial network

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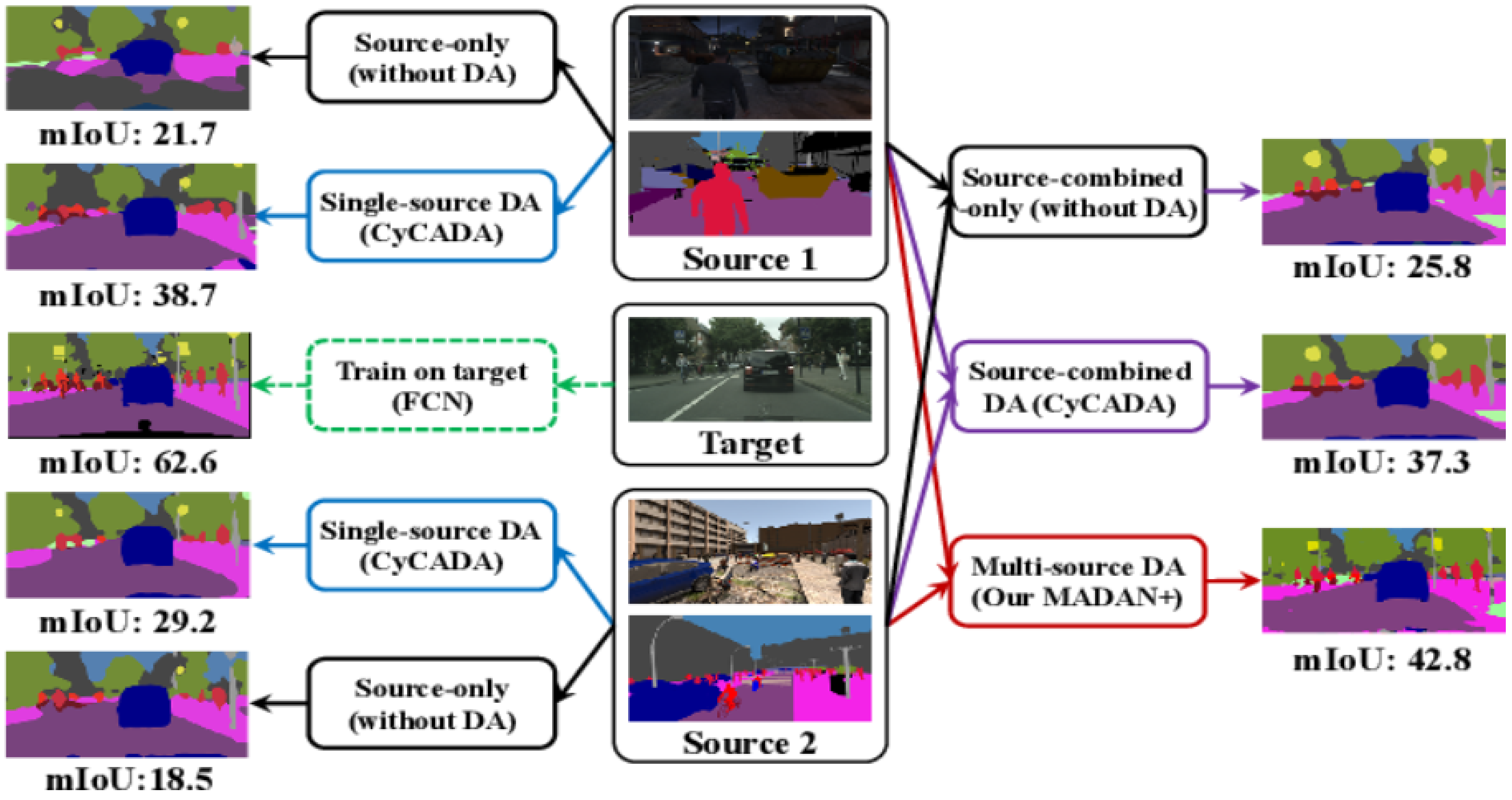
01 Introduction

Multi Source Domain Adaptation

A good image-to-image translation model should learn a mapping between different visual domains while satis fying the following properties: 1) diversity of generated images and 2) scalability over multiple domains.

Existing methods address either of the issues, having limited diversity or multiple models for all domains.



Multi Source Domain Adaptation

Unsupervised Multi Source Transfer Learning

01 Introduction

Multi-Site MRI Harmonization

- protocols has scanner-induced variability due to factors such as magnetic field strength, coil channels, gradient directions, manufacturer, and image resolution

CNN is a statistical method, which learns the statistics of the training data un der the identical independent distribution (IID) assumption, which implies that the trained CNN is supposed to work on data with identical or similar distributions.

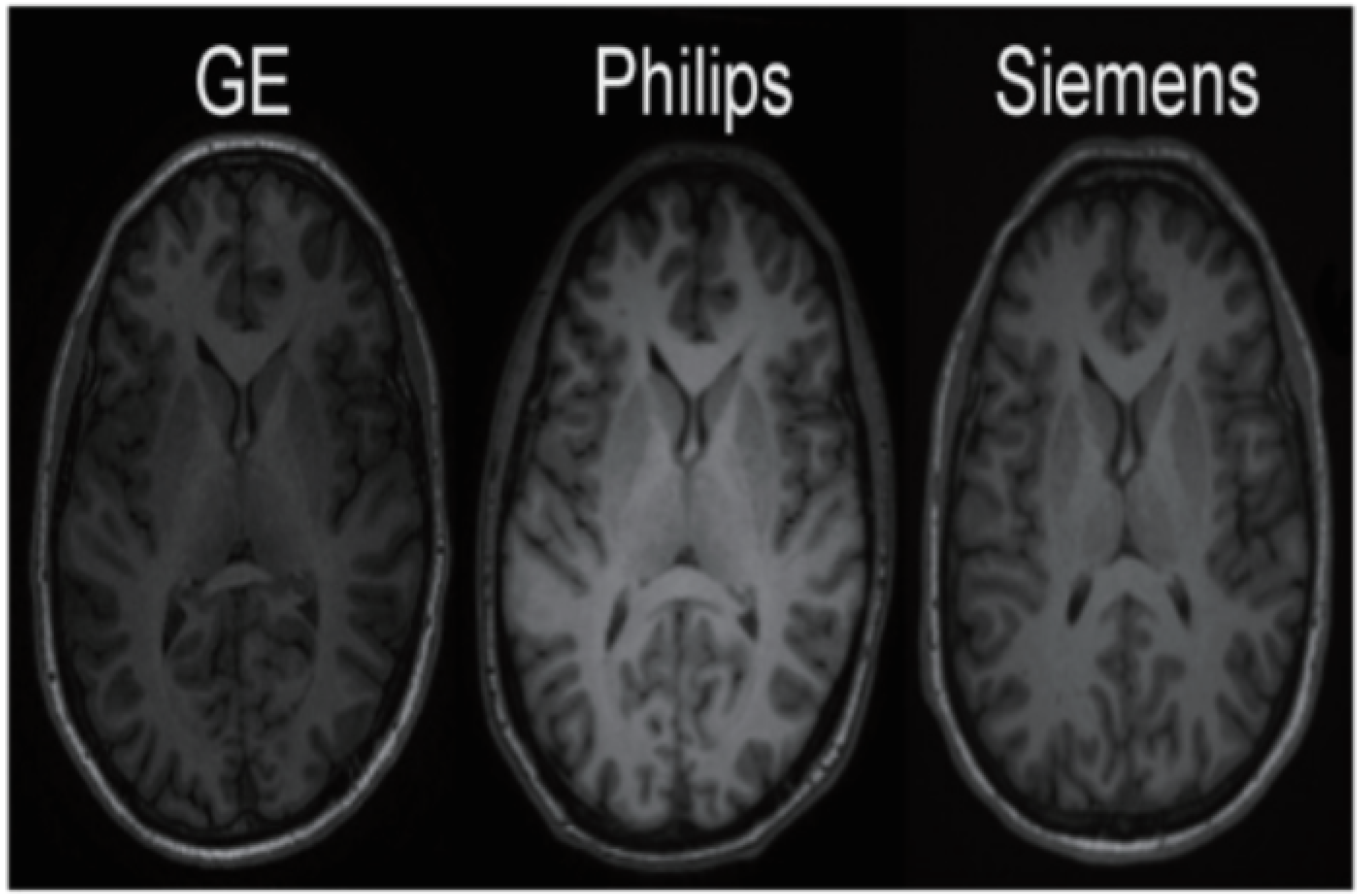


Table 1: Specifications of Cine MRI Datasets Acquired from Scanners of Different Manufacturers

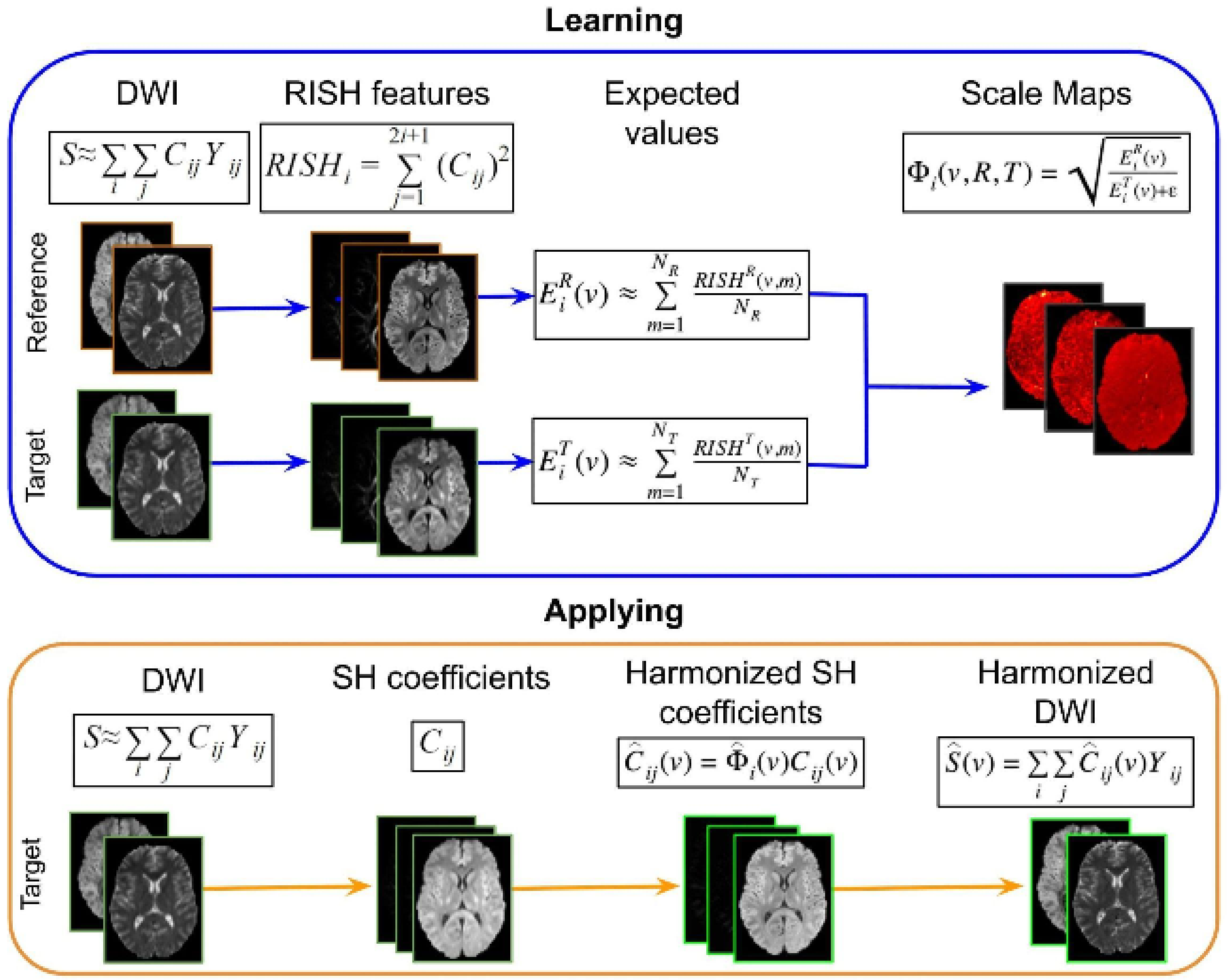
MRI Scanner Manufacturer	Field Strength	In-plane Resolution (mm)	Slice Gap (mm)	Phases per Cardiac Cycle	Total No. of Frames	No. of Annotated Training Frames	No. of Annotated Testing Frames
Manufacturer 1	3.0 T	1.2 × 1.2	10	30	24905	2520	923
Manufacturer 2	1.5 T	1.17 × 1.17	9.6	20	14746	1680	924
Manufacturer 3	3.0 T	1.25 × 1.25	10	20	10640	1320	764

Note.—All manufacturer datasets had 50 patients each. For each dataset, 33 patient datasets were used for training and 17 were used for testing.

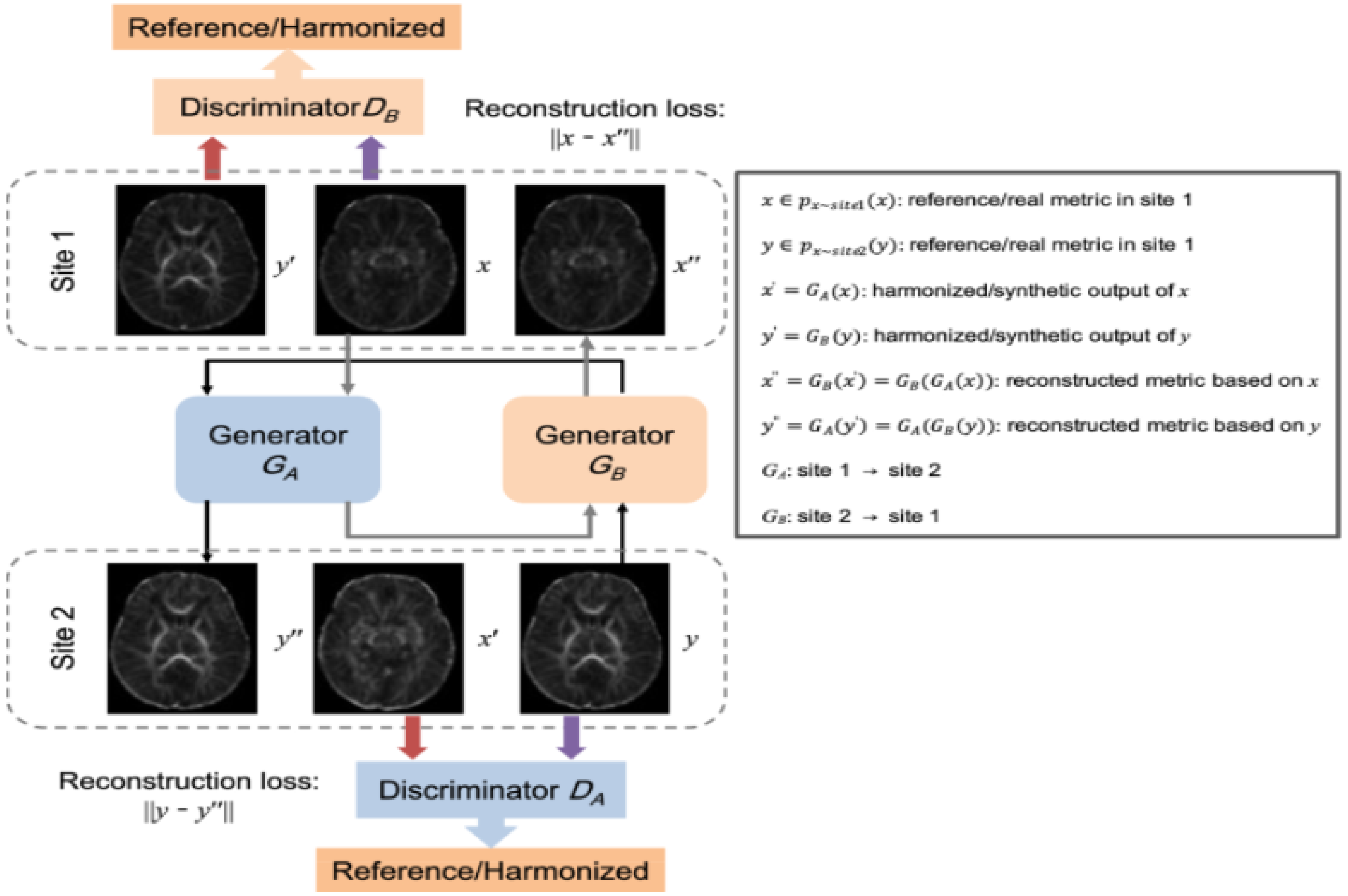
01 Introduction

Application to Medical Field - MRI Harmonization

- Large data initiatives and high-powered brain imaging analyses require the pooling of MR images acquired acr oss multiple scanners, often using different protocols.
- Several retrospective harmonization techniques - cannot distinguish between image acquisition based variabili ty and cross-site population variability



Radiomics Feature Based Adaptation

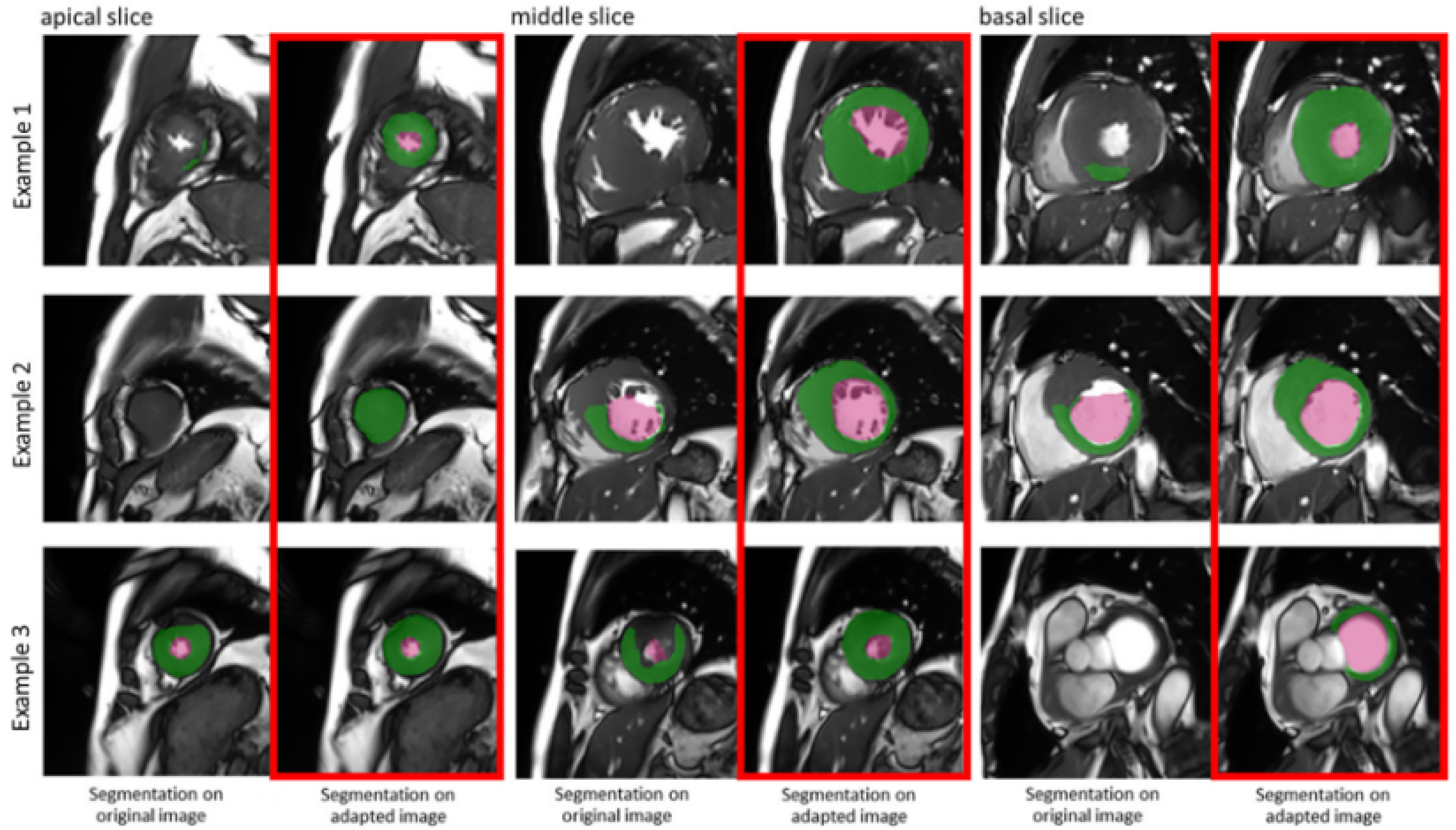


Unsupervised Single Source Transfer Learning

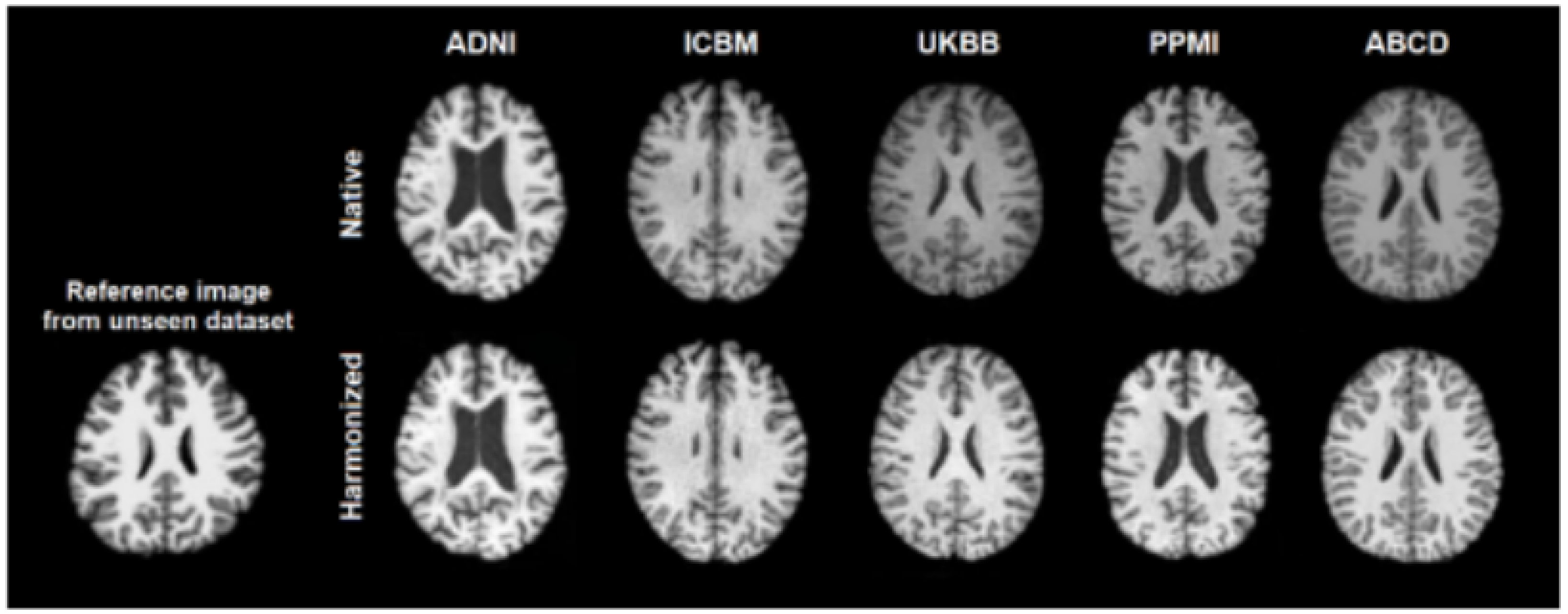
01 Introduction

Previous Journals

- Existing studies have mainly focused on 2D MRI harmonization that transforms one MR slice. However, this me thod cannot reflect the whole MRI.
- In addition, relatively inaccurate metrics were used during evaluation.



Radiomics Feature Based Adaptation
- RSNA : Artificial Intelligence. 20. 06

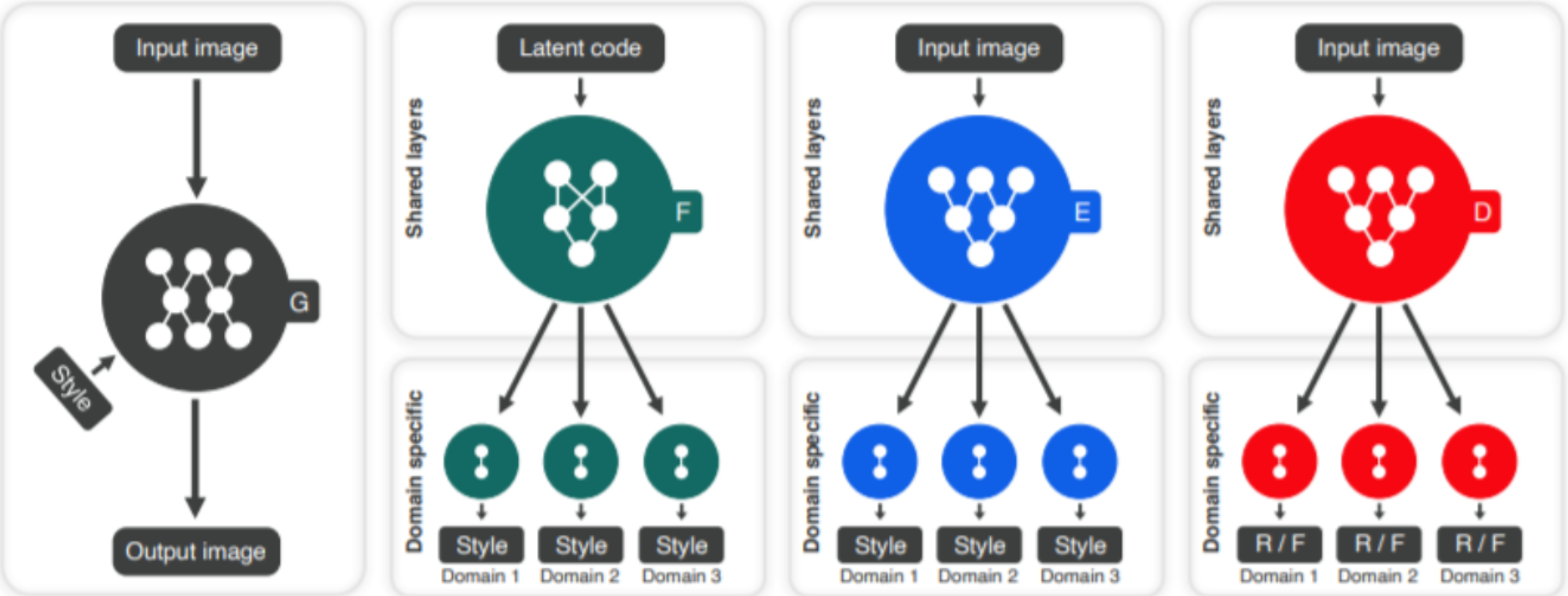


Style Transfer Using Generative Adversarial Networks for Multi-Site MRI Harmonization - MICCAI. 21.09

02 Methods

Methods - Proposed Framework

- The architecture of the style-encoding GAN (Star GAN v2). Generators learns to generate image by inputting a source image and a style code. The learning process is driven by cycle consist loss, adversarial loss, style recon struction loss and style diversification loss
- The detailed architecture of the generator in network. In each of the block, the three number means number of input channels, number of output channels and the image size.

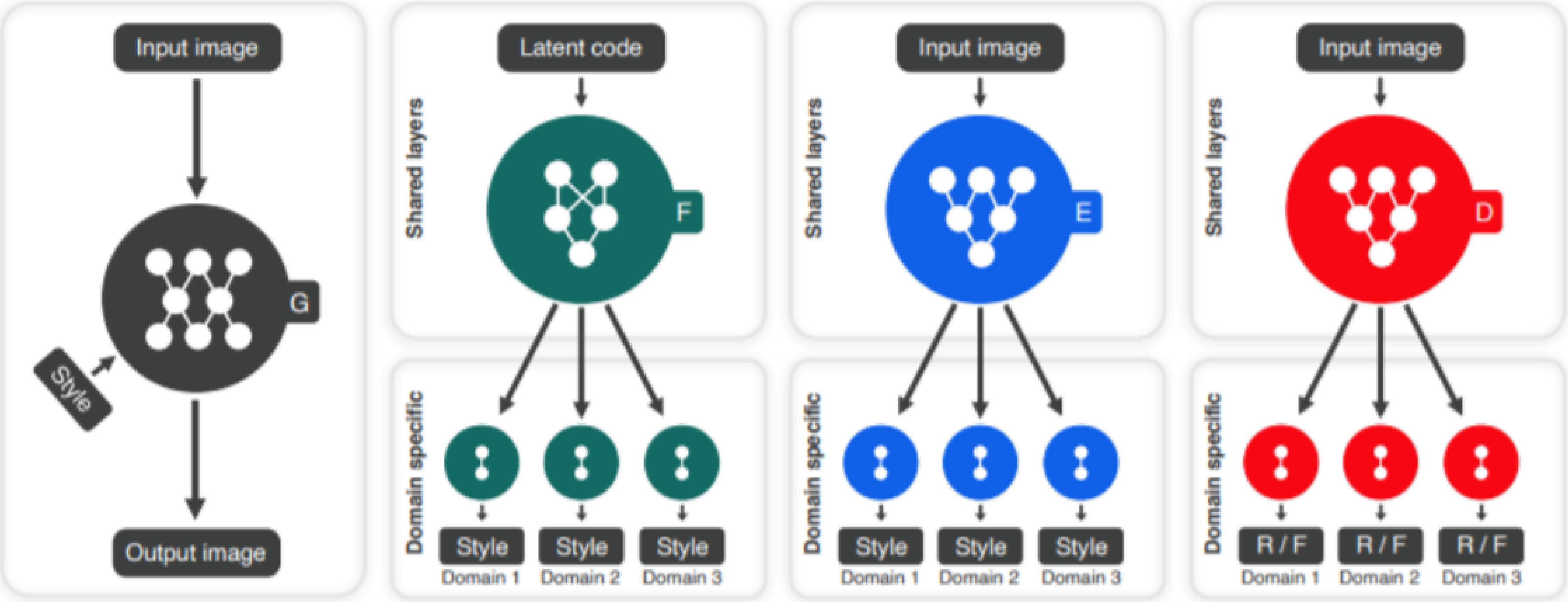


(a) Generator (b) Mapping network (c) Style encoder (d) Discriminator

02 Methods

Methods - The Architecture of Framework

1. The generator translates an input image into an output image reflecting the domain-specific style code.
2. The mapping network transforms a latent code into style codes for multiple domains, one of which is randomly selected during training.
3. The style encoder extracts the style code of an image, allowing the generator to perform reference guided i mage synthesis.
4. The discriminator distinguishes between real and fake images from multiple domains. Note that all modules except the generator contain multiple output branches, one of which is selected when training the correspondi ng domain.



(a) Generator (b) Mapping network (c) Style encoder (d) Discriminator

02 Methods

Network Training - Seperated Loss

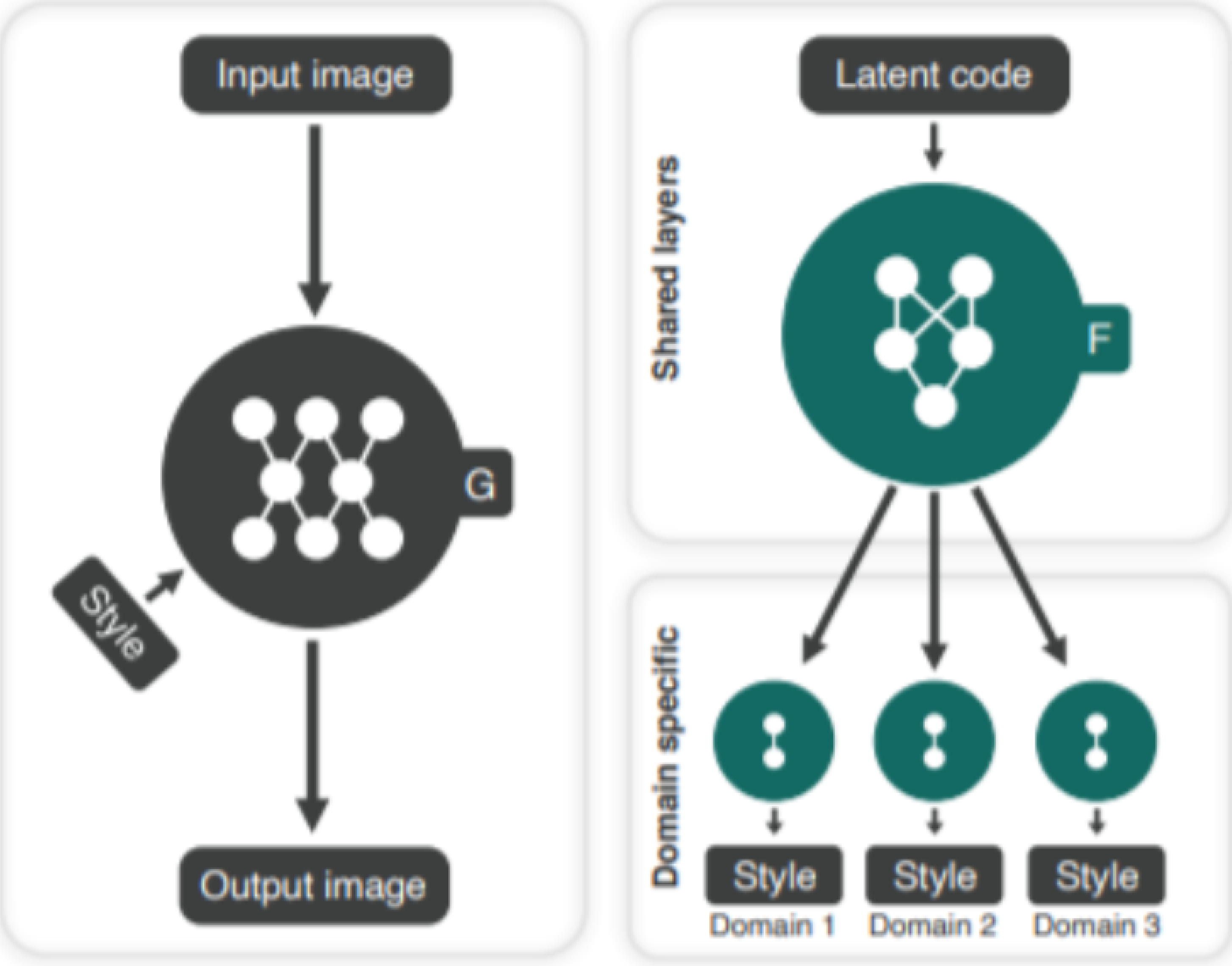
- Directly modeling the space of high-dimensional convolutional filters in an image generation network is practically prohibitive in terms of both computation and parameter scale

Adversarial loss. During training, we sample a latent code $z \in Z$ randomly, and the mapping network M learns to generate a target style code $s = M(z)$. The generator G takes an image x and s as inputs and learns to generate an output image $G(x, s)$ that is indistinguishable by the discriminator D from real images via an adversarial loss:

$$L_{GAN} = \mathbb{E}_x[log D(x)] + \mathbb{E}_{x,z}[\log(1 - D(G(x,s)))]$$

Cycle-Consistency Loss. To guarantee that generated images are meaningful to the original images and properly preserving the style-irrelevant characteristics (e.g. anatomical patterns) of input x, an additional cycle consistency loss (Zhao et al., 2019) is defined as the difference between original and reconstructed images:

$$L_{cyc} = \mathbb{E}_{x,z}[\|x - G(G(x,s), s_x)\|_1]$$



(a) Generator (b) Mapping network

02 Methods

Network Training - Seperated Loss

- Directly modeling the space of high-dimensional convolutional filters in an image generation network is practically prohibitive in terms of both computation and parameter scale

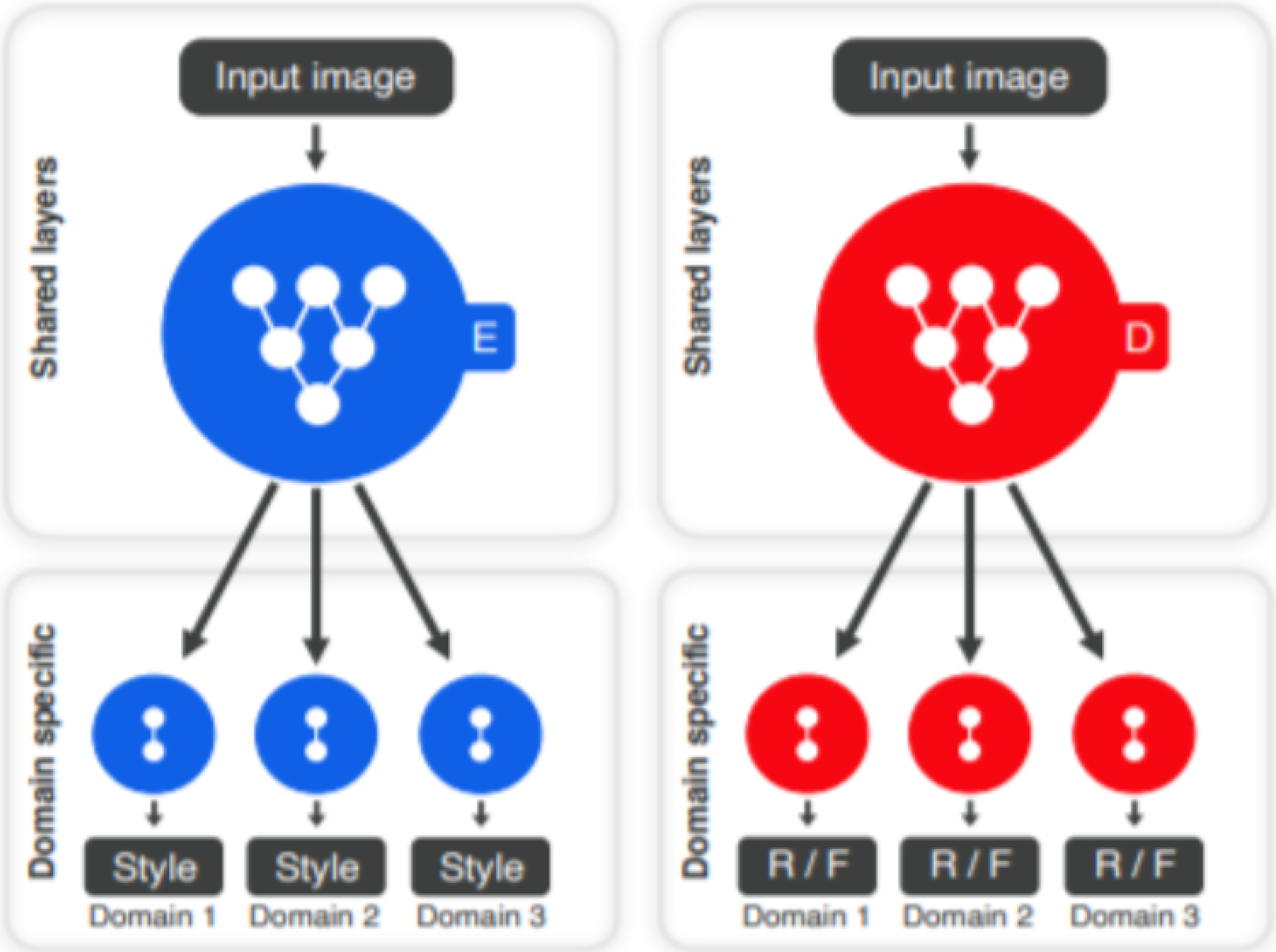
Style reconstruction loss. In order to enforce the generator G to use the style code while generating the image $G(x, s)$, we incorporate a style reconstruction loss:

$$L_{sty} = \mathbb{E}_{x,z}[\|s - E(G(x,s))\|_1]$$

Our learned encoder E allows G to transform an input image x, to reflect the style of a reference image.

Style diversification loss. To further enable the generator G to produce diverse images, we explicitly regularize G with the diversity sensitive loss (Wang et al., 2018):

$$L_{div} = \mathbb{E}_{x,z_1,z_2}[\|G(x,s_1) - G(x,s_2)\|_1]$$



(c) Style encoder (d) Discriminator

02 Methods

New Network Training Loss - Temporal Coherence Loss

- Directly modeling the space of high-dimensional convolutional filters in an image generation network is practically prohibitive in terms of both computation and parameter scale

Put together, our full objective function can be summarized as follows:

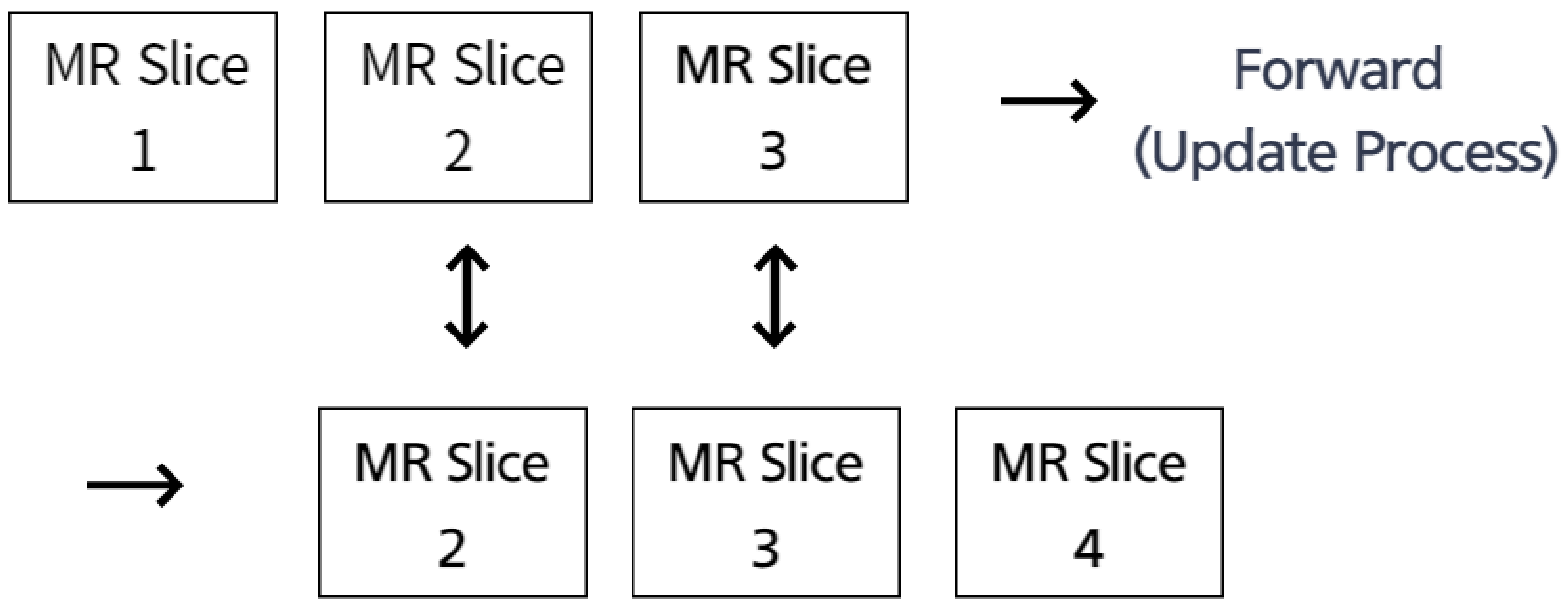
$$L(G, M, E, D) = L_{GAN} + \lambda_{cyc} L_{cyc} + \lambda_{sty} L_{sty} - \lambda_{div} L_{div}$$

Where λ_{cyc}, λ_{sty} and λ_{div} are hyperparameters for each term.

$$\downarrow$$

$$L(G, M, E, D) = \lambda 1 * \text{Previous Losses} + \lambda 2 * \text{Temporal Coherence Loss}$$

$(\lambda 1 = 1.0, \lambda 2 = 0.5)$



02 Methods

Experimental Set Up - Dataset

- Healthy Control Domain Adaptation
  Original Datasets : ADNI, GSEV, SMC, GMC Dataset
  ADNI Control Normal: 4977 Patients , (256,256,192), GSEV Control Normal: 256 Patients , (256,256,192)
  SMC Control Normal: 2804 Patients, (256,256,192), GMC Control Normal : 96 Patients, (256,256,192)
- New Generated Datasets : Stack Channel, Random Selections at Patients Images, Total Train : 1200 MR Slices per protocol

ADNI Database
N = 4977
(256,256,192)

SMC Database
N = 2804
(256,256,192)

GSEV Database
N = 256
(256,256,192)

GMC Database
N = 96
(256,256,192)

Random Selection

New Database
N = 1200 Slice each Protocols (ADNI, SMC, GSEV, GMC)
Extract MR Images each Patients

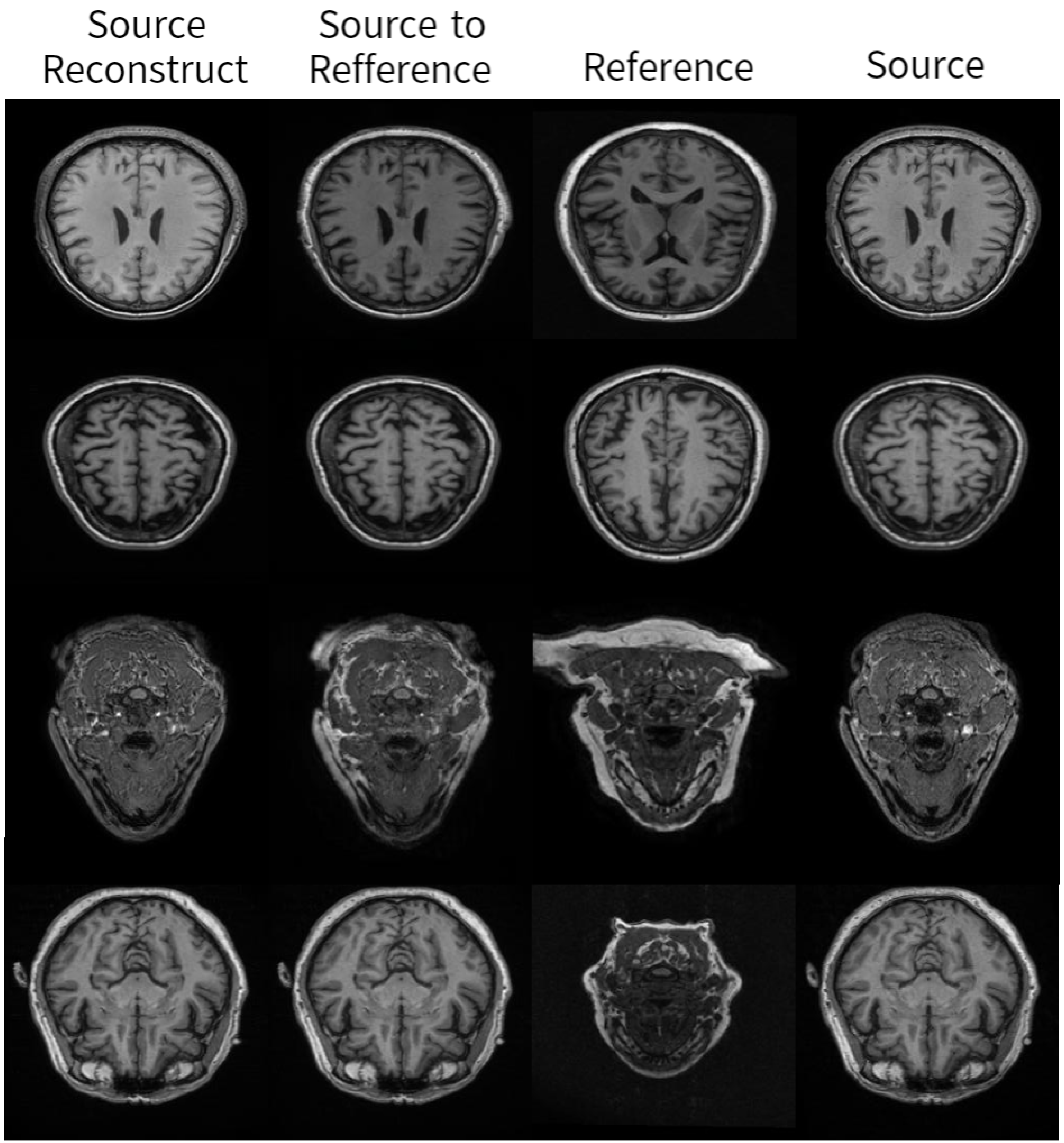
1. Z-Score Normalization
normalized by dividing by the maximum a fter clipping.

2. Data Augmentation
Random Image Selection per patients

3. Hyperparameter
Optimizer = Adam, Epoch = 16000, Los s Function = ADV Loss + Sty Rec Loss + Cycle Consistency Loss + Style Diver sification Loss

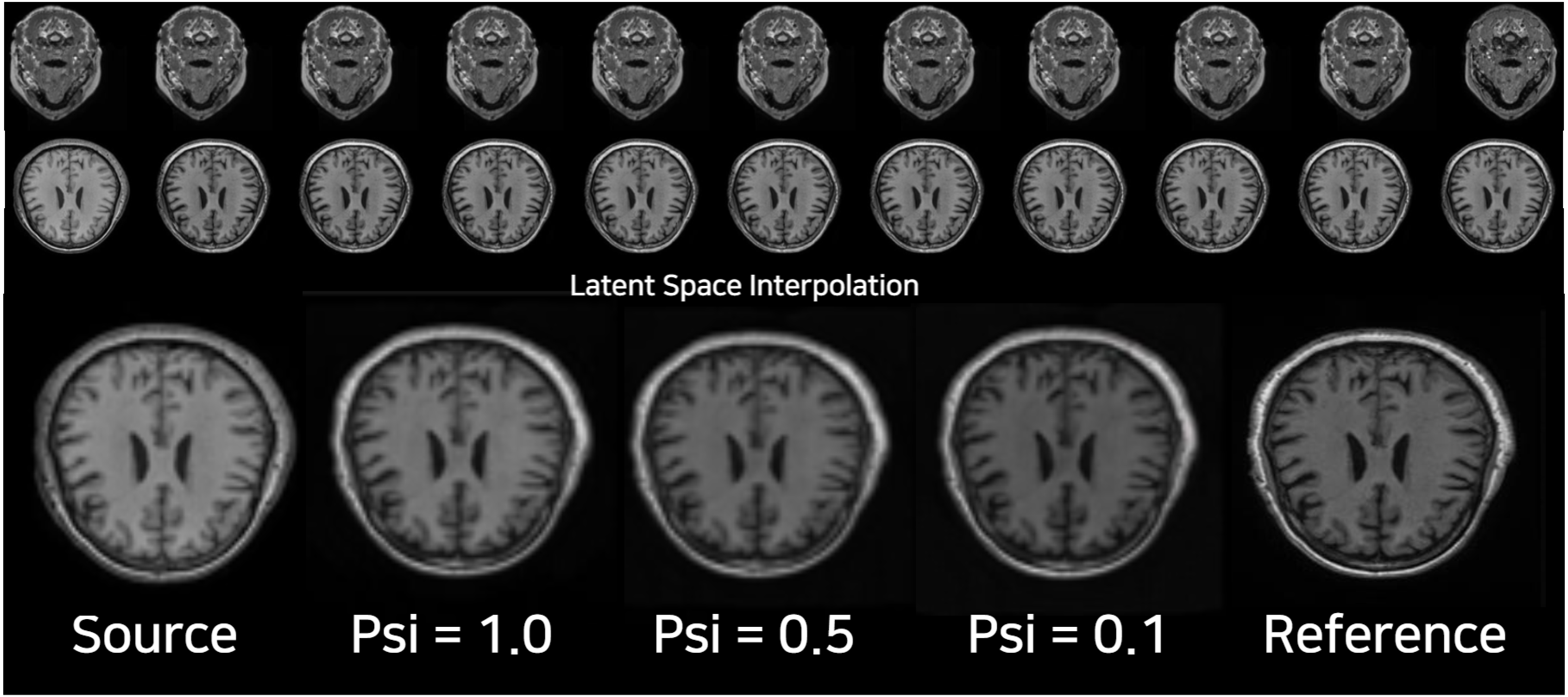
Experiments

- Results - reference images with cycle consistency images



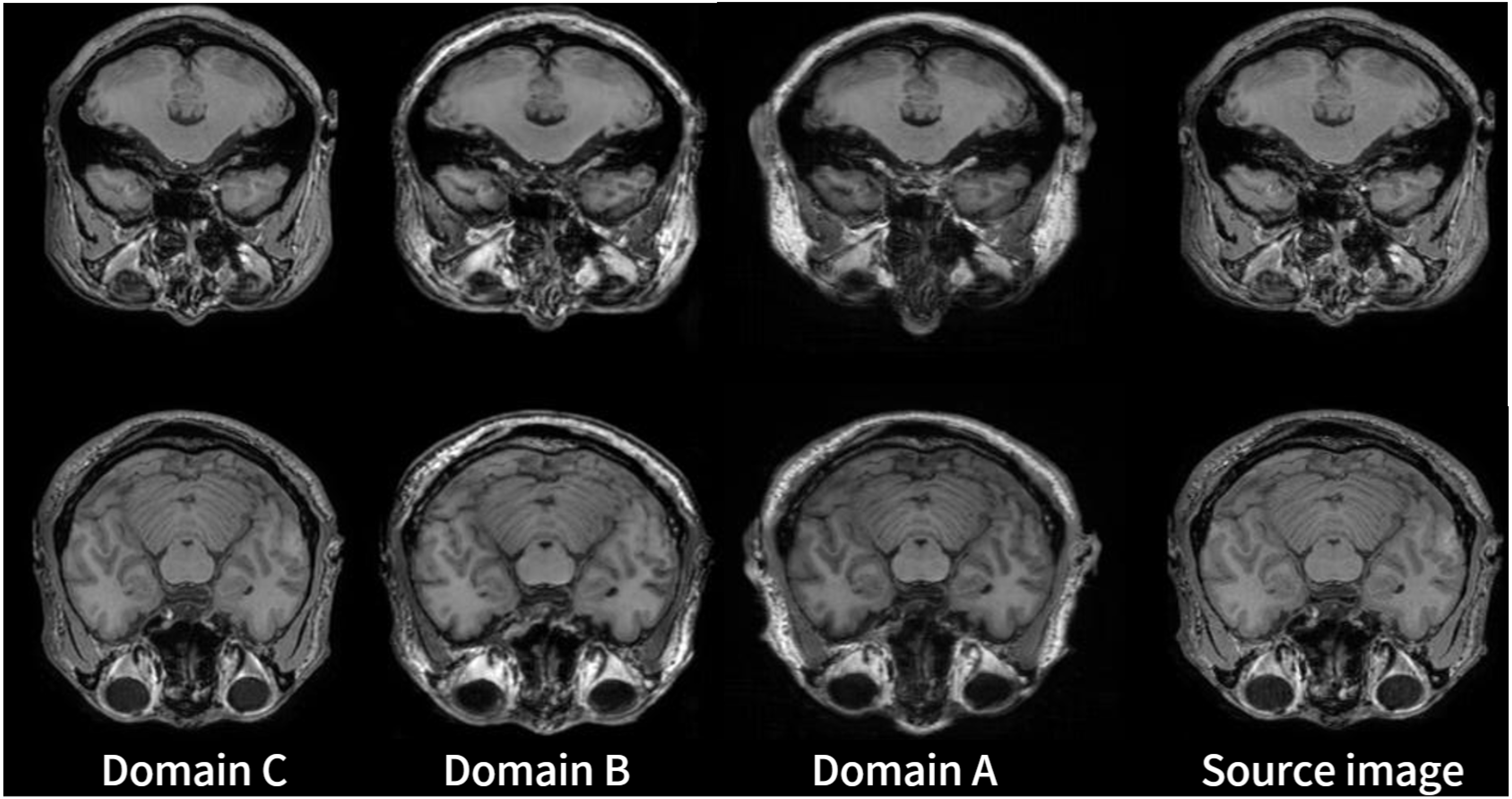
Experiments

- Results - Cycle Consistency Coefficients (lambda cyc) difference



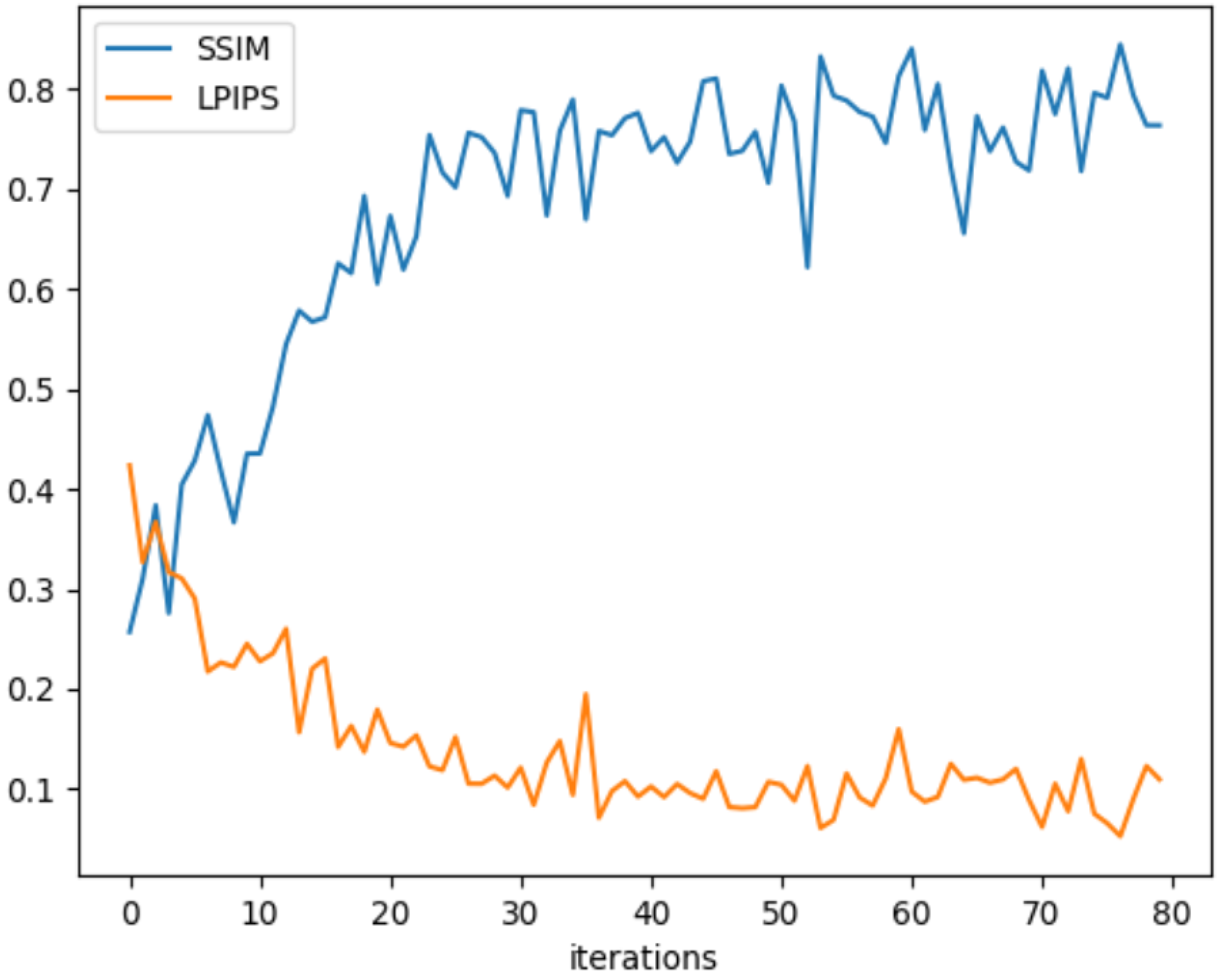
Experiments

- Results - Domain Differences

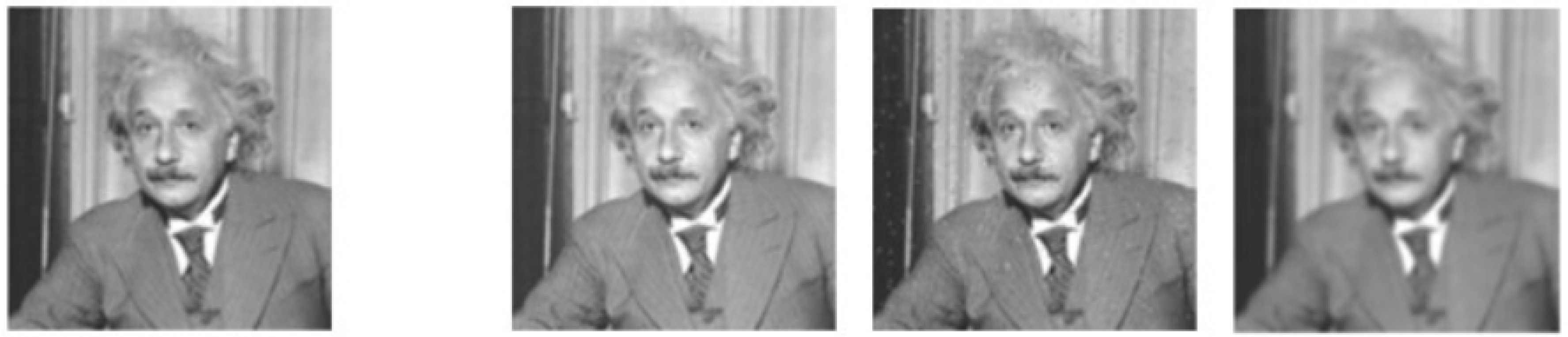


03 Experiments

Domain Adaptation GAN - Evaluation Metrics



SSIM Score

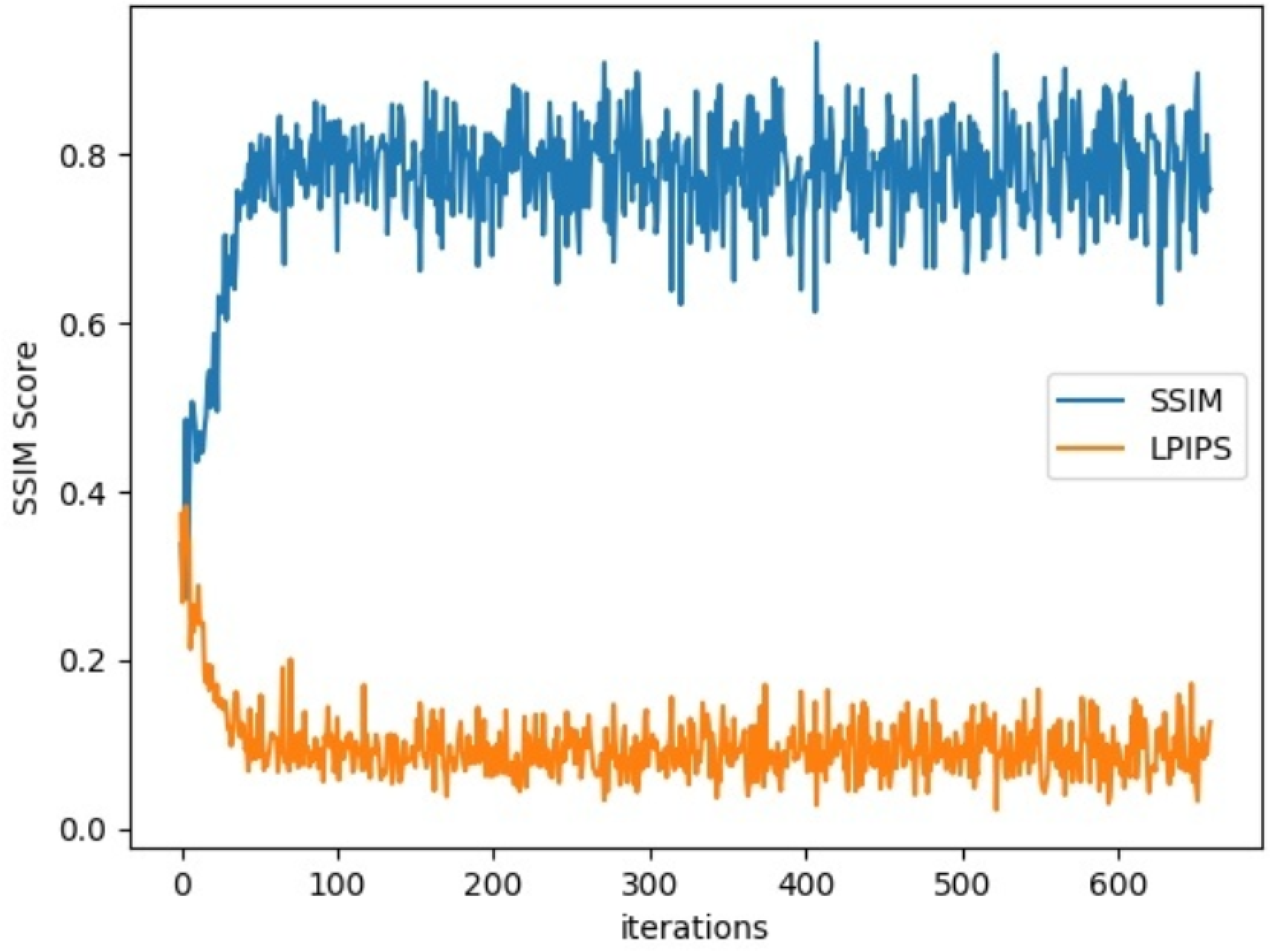


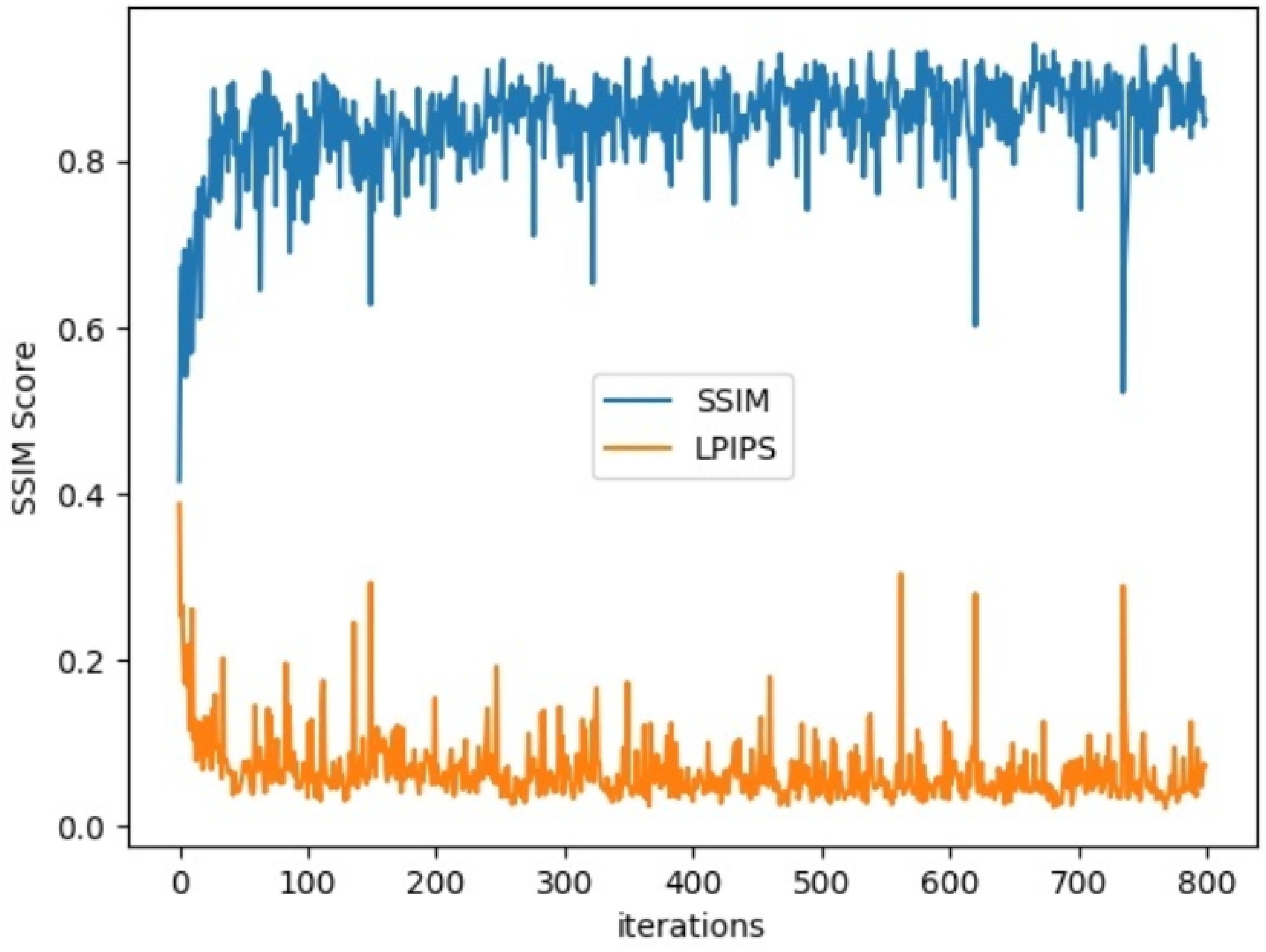
LPIPS

03 Experiments

Domain Adaptation GAN - Evaluation Metrics

After Temporal Coherence Loss



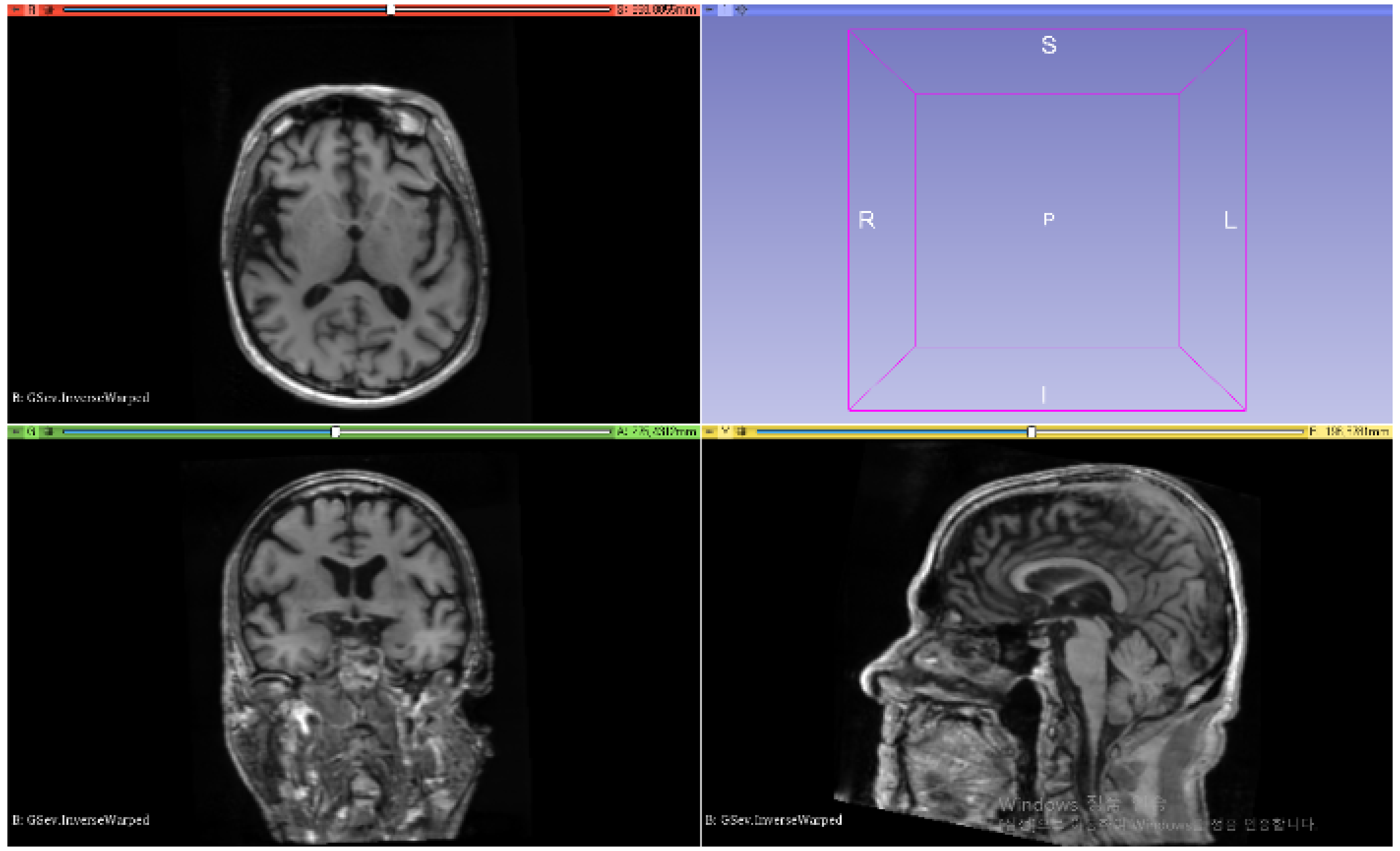


Experiments

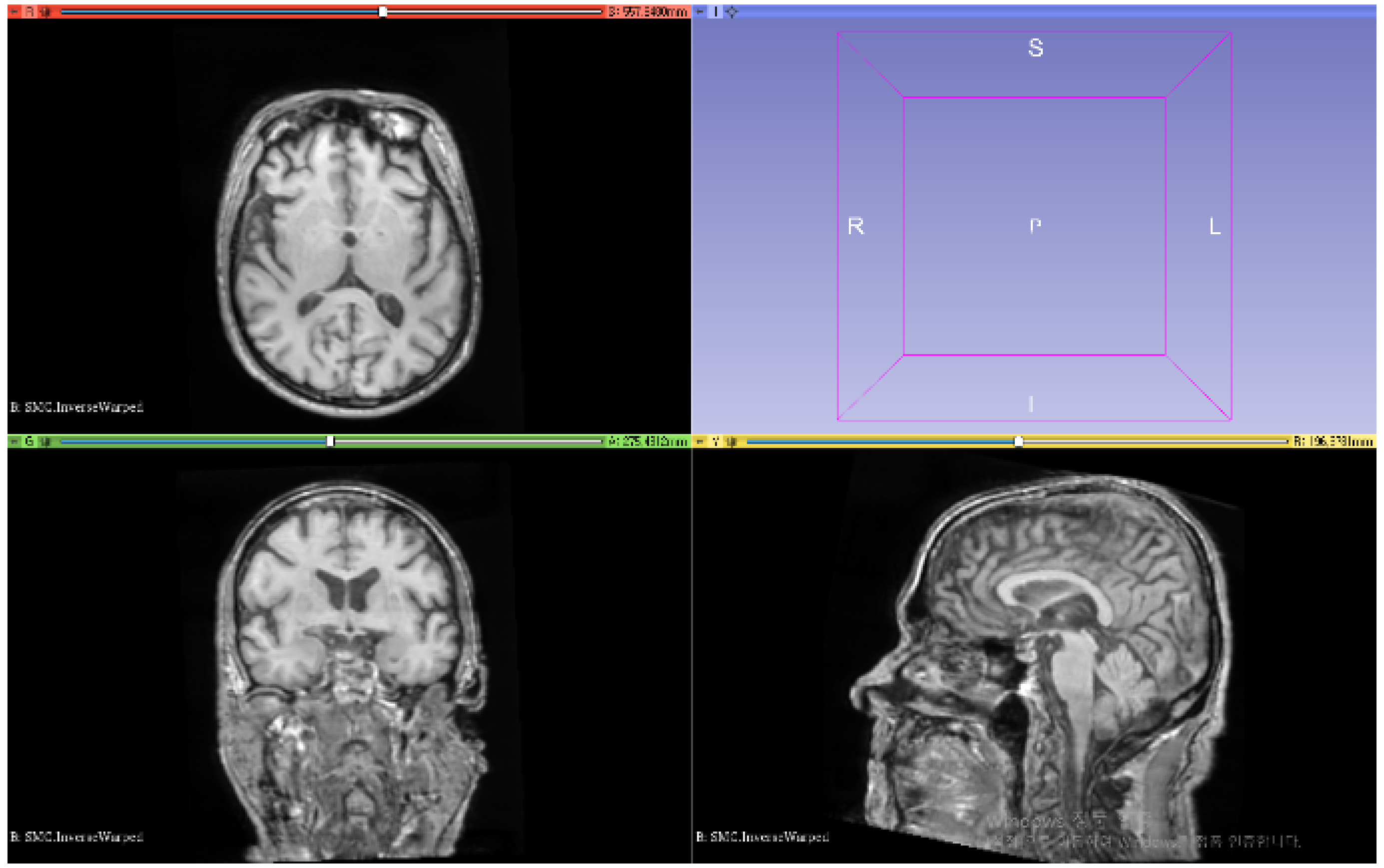
- Results
  3D Reconstruction

- Results 2
  After TC loss

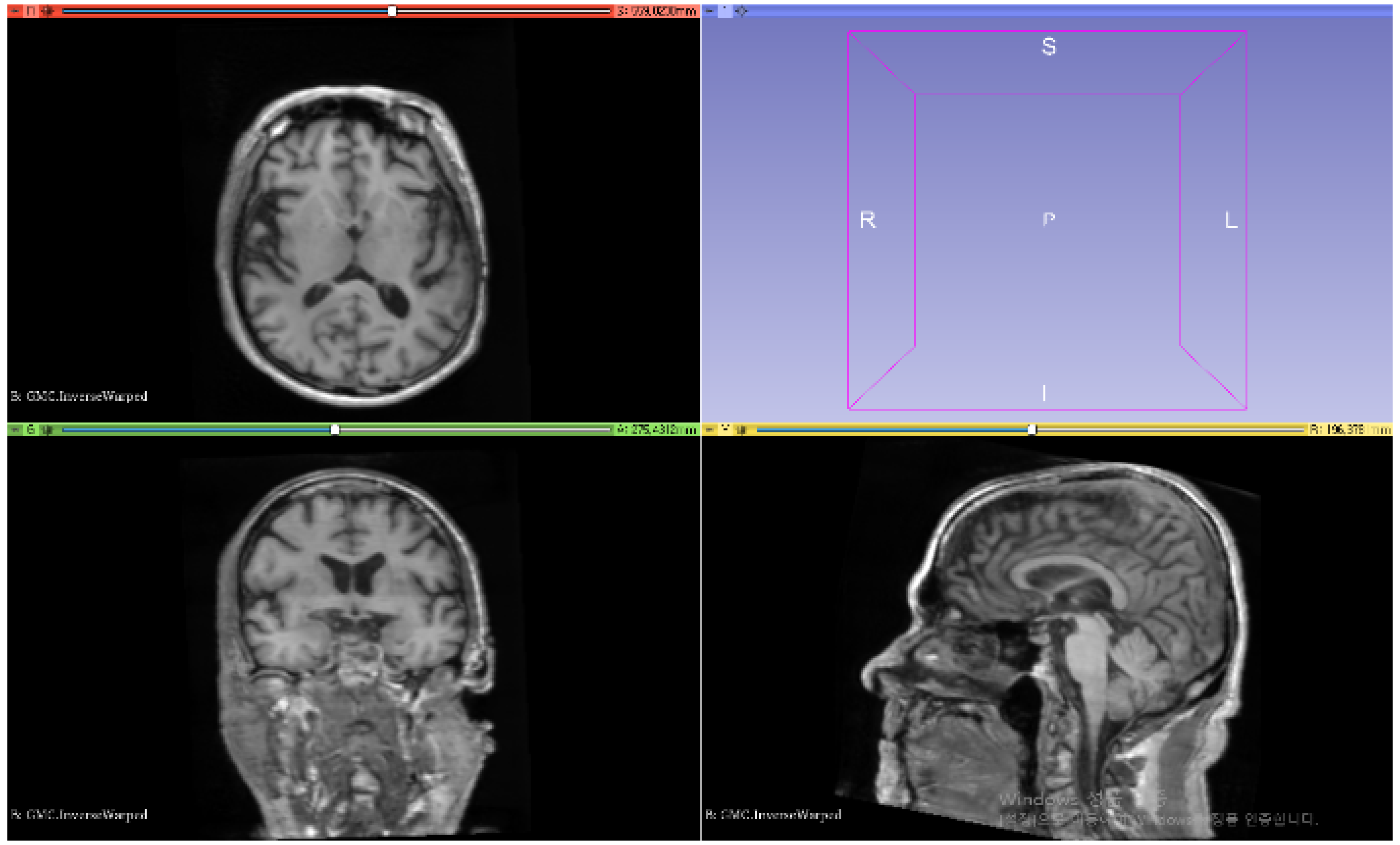
GSEV



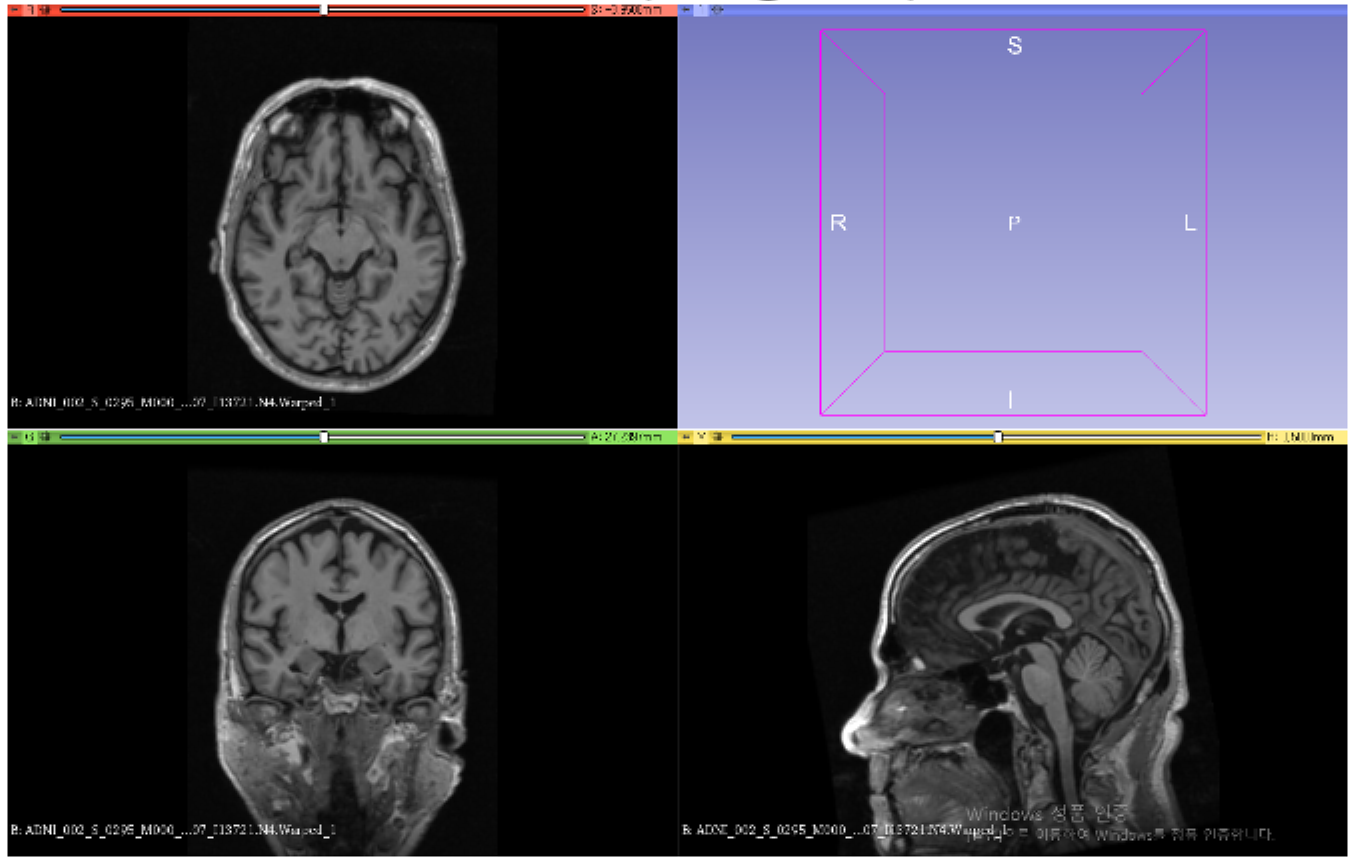
SMC



GMC

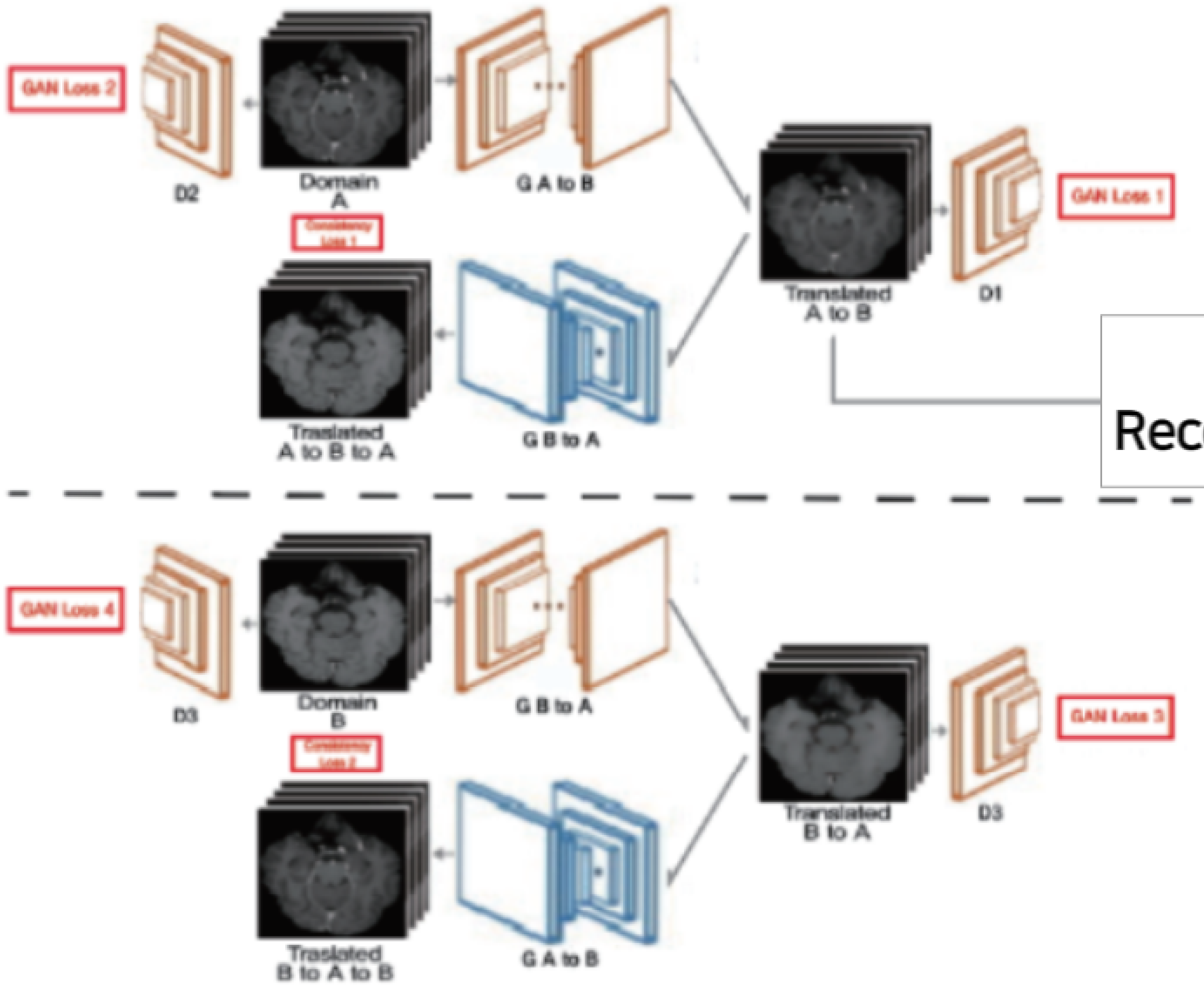


ADNI (Original)



03 Experiments

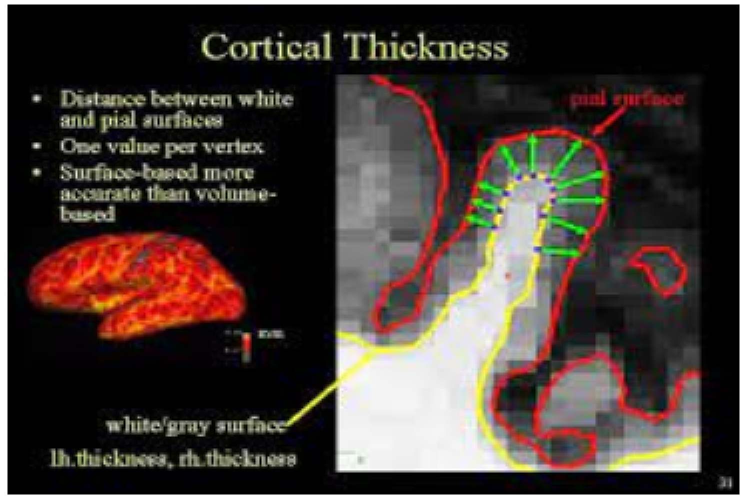
Validation Process



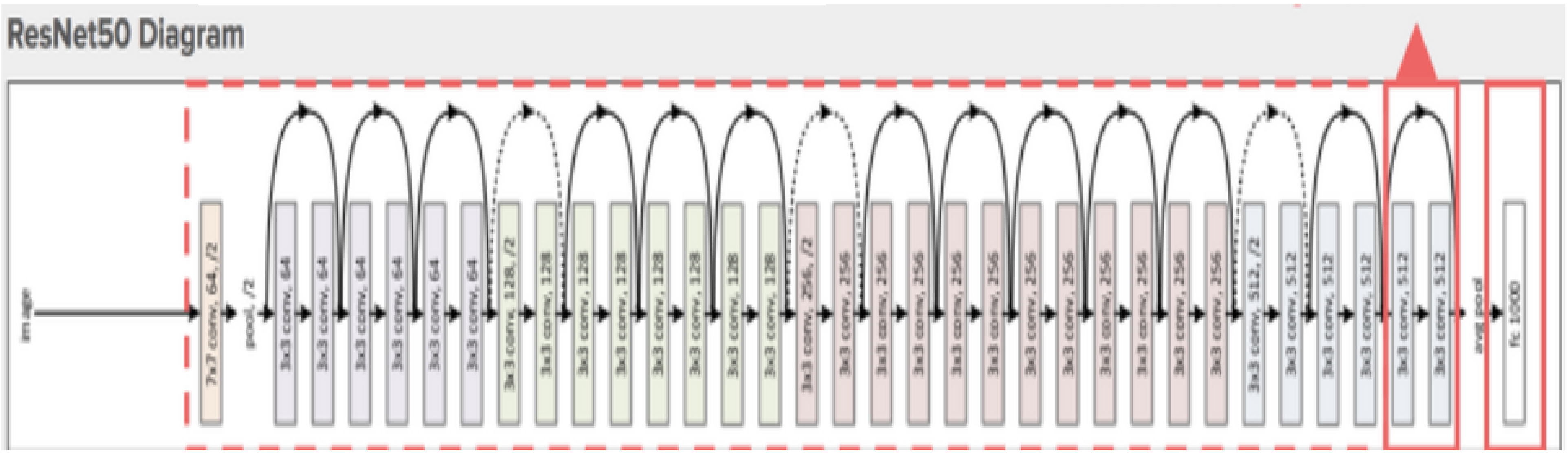
Institutions Harmonization

3D Reconstruction

Evaluation 1 :
Cortical Thickness Maintainance



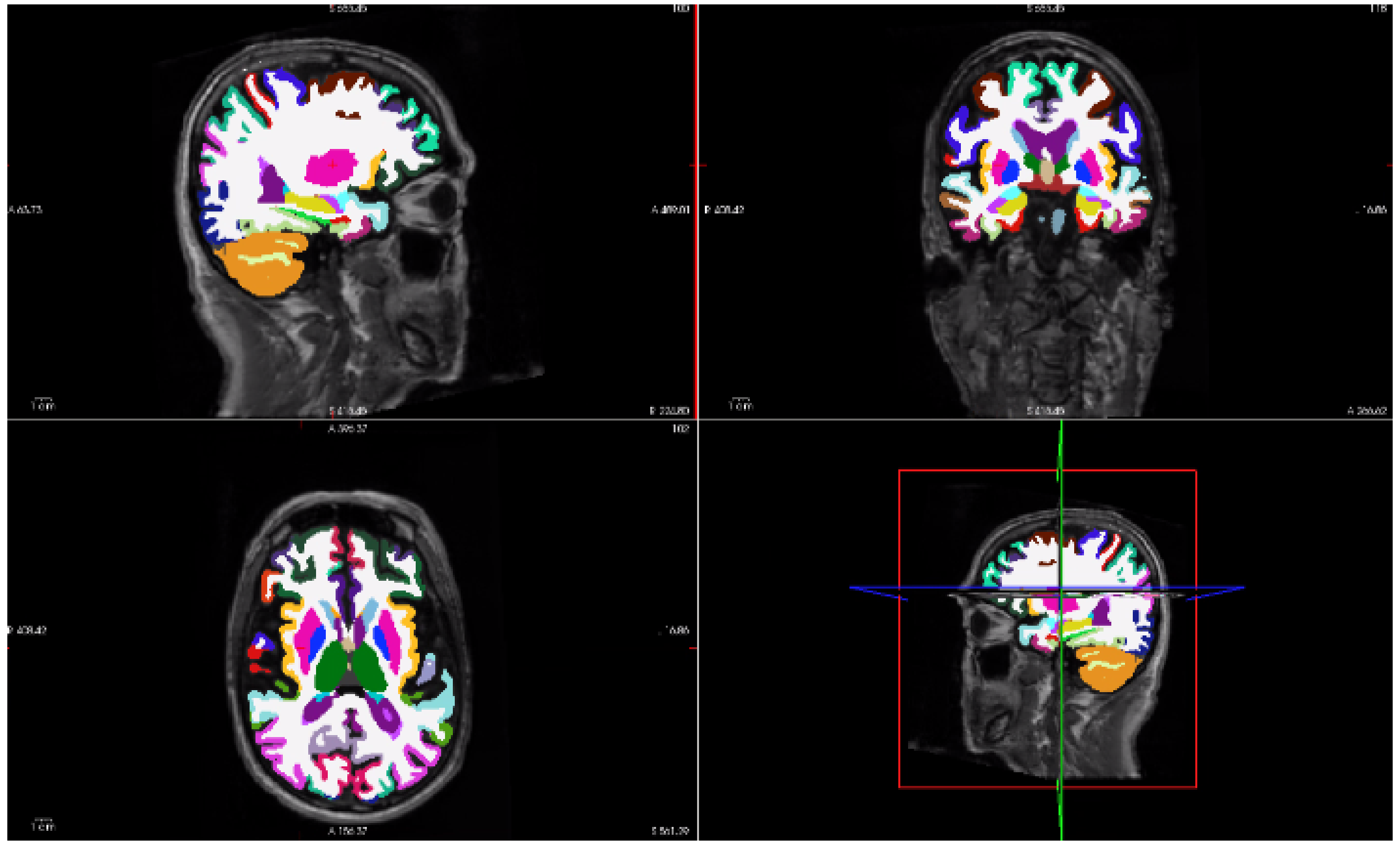
Evaluation 2 : Protocols Classification



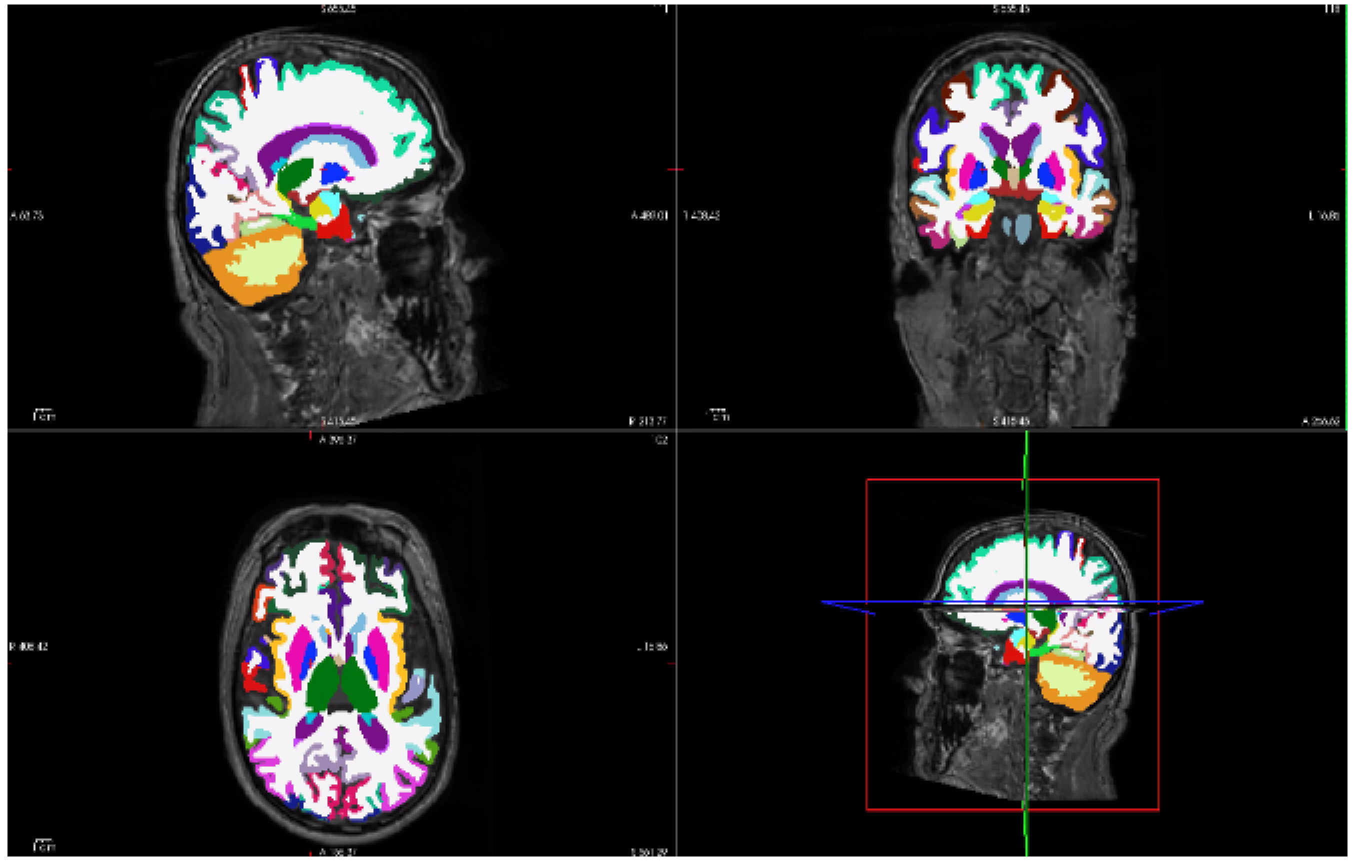
Experiments

- Cortical Thickness Maintainance (Fast Surfer)

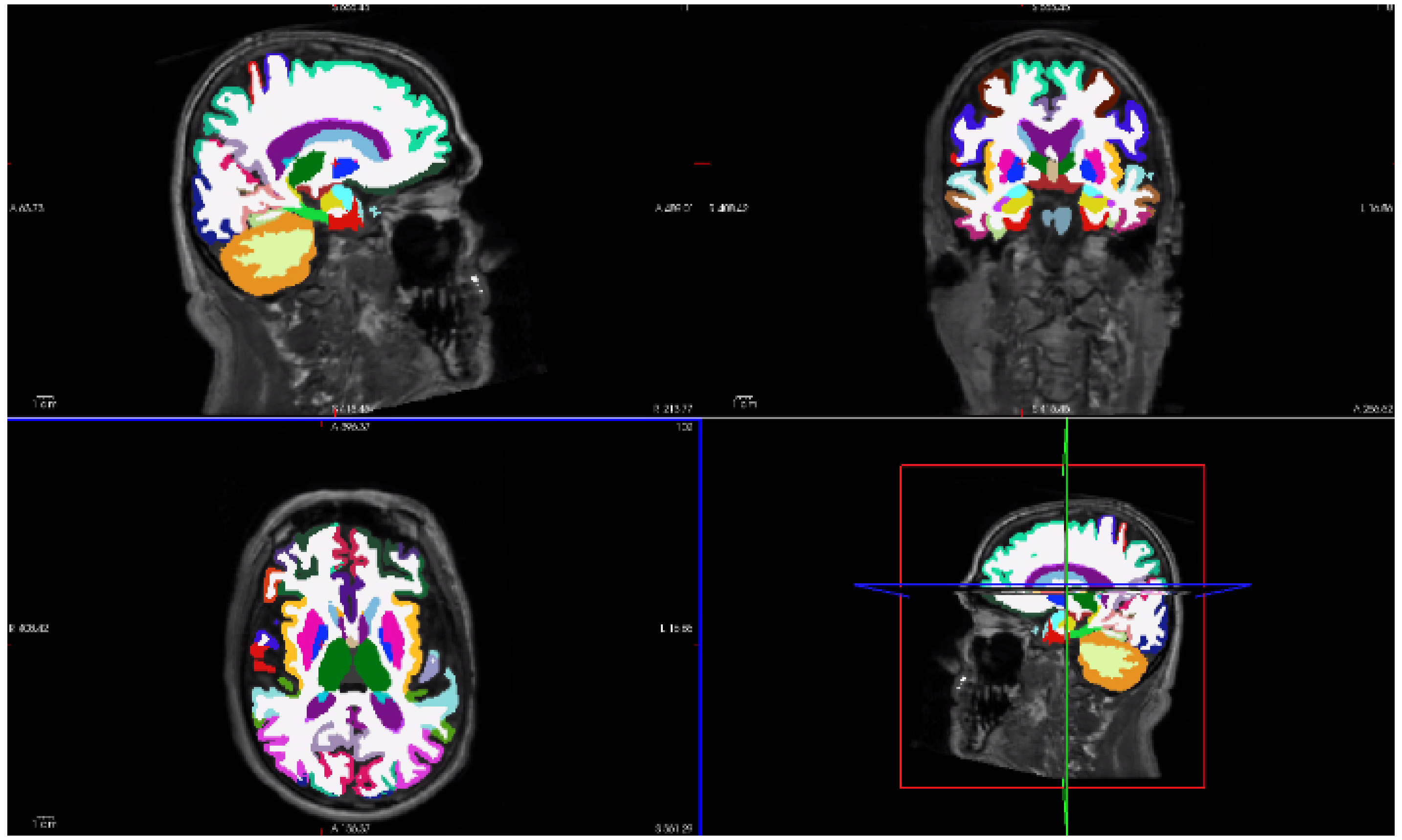
GSEV



SMC



GMC



ADNI (Original)