딥러닝을 사용한 뇌영상 표준화 모델 구축

June 22, NeuroXT Demo week

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Introduction

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2022년 3월 ~

NeuroXT 소속 연구원

2021년 9월 ~ 2022년 3월

Korea University, BREIN (Brain Reverse Engineering by Intelligent Neuroimaging) Lab 연구원 인턴

2020년 10월 ~ 2021년 9월

신촌 세브란스 신경외과, 영상의학과 방사선의과학연구소 인공지능 팀 개발자

서울 의료원 영상의학과 신경 판독실 리더 개발자

2020년 11월 ~ 2021년 9월

신촌 세브란스병원 방사선의과학연구소 의료영상데이터사이언스센터 연구원

연세대학교 의과대학 의생명정보학교실 의료인공지능 연구실(tAIL lab) 연구원 인턴

2021년 5월 ~

Generative Adversarial Networks(GAN) 인공지능 예술가 NAU 개발자

논문 이력

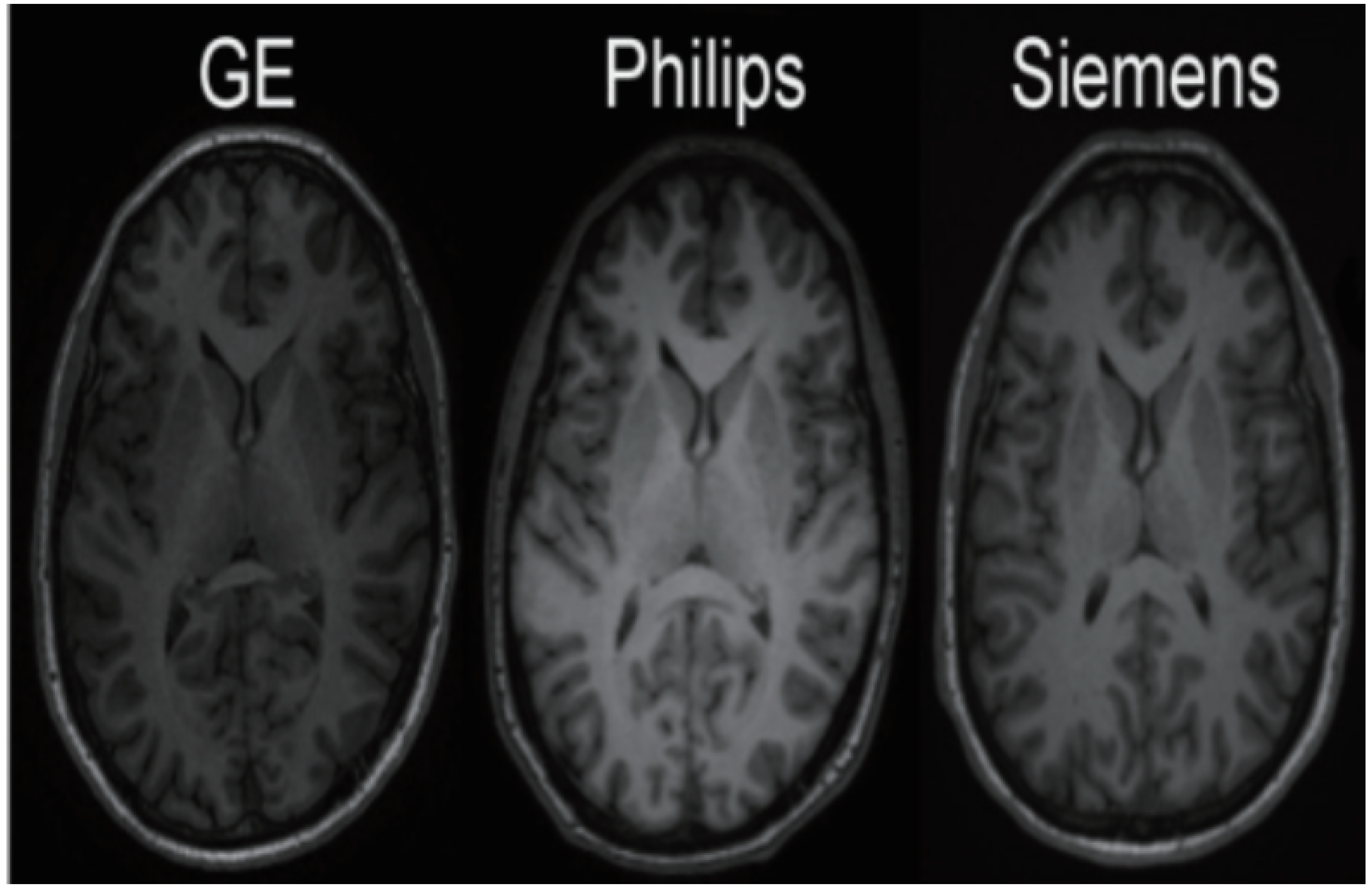
2021.05 KoSAIM 논문 초록 1저자 'Skull Segmentation trained by Dual Energy CTA Dataset', Oral Presentation

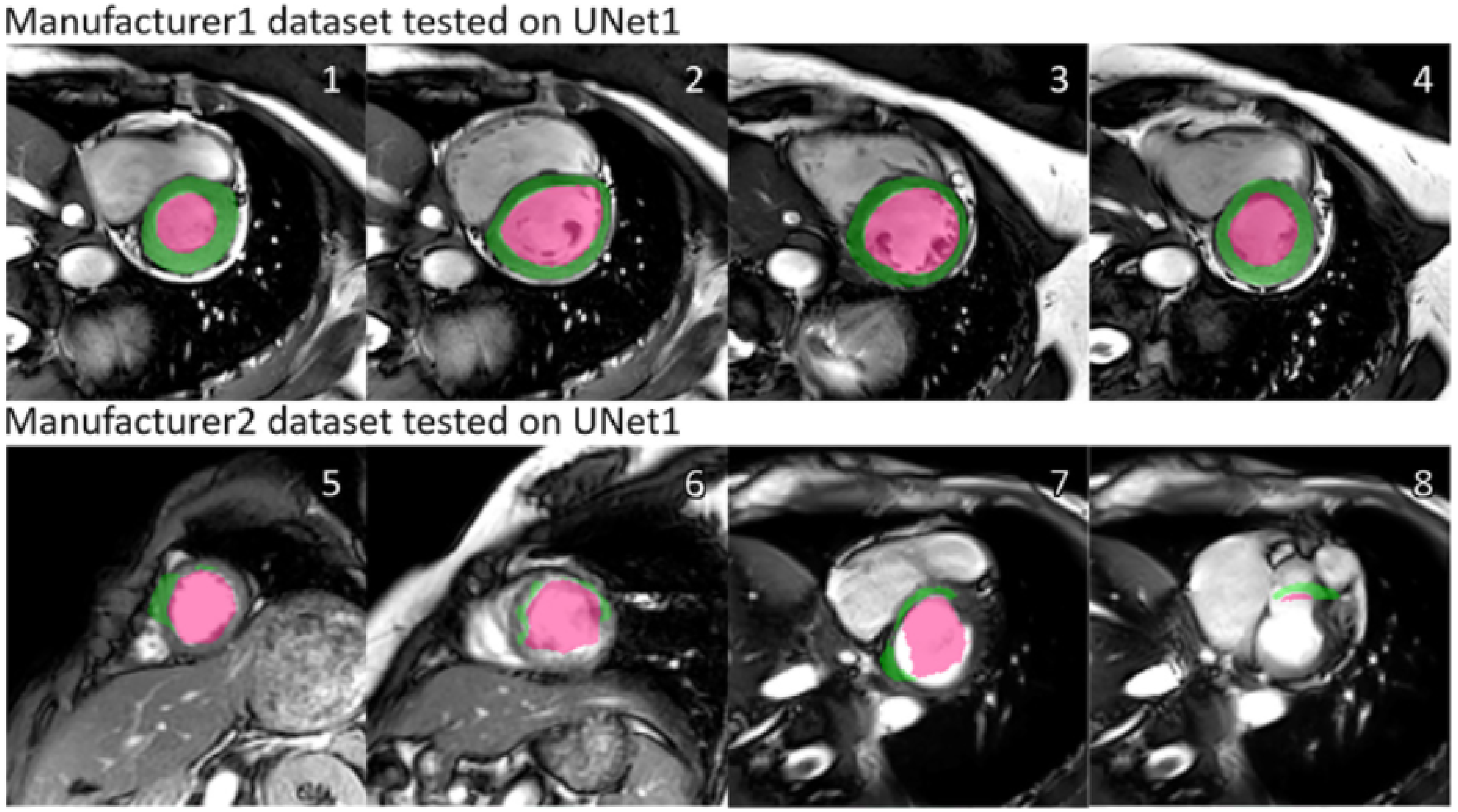
2022.04 AAIC 논문 초록 1저자 'MR image harmonization based on cross-center style transfer using deep generativ
e adversarial network', Poster presentation

01 Introduction

Multi-Site MRI Harmonization

- protocols has scanner-induced variability due to factors such as magnetic field strength, coil channels, gradient directi ons, manufacturer, and image resolution
- Large data initiatives and high-powered brain imaging analyses require the pooling of MR images acquired acro ss multiple scanners, often using different protocols.

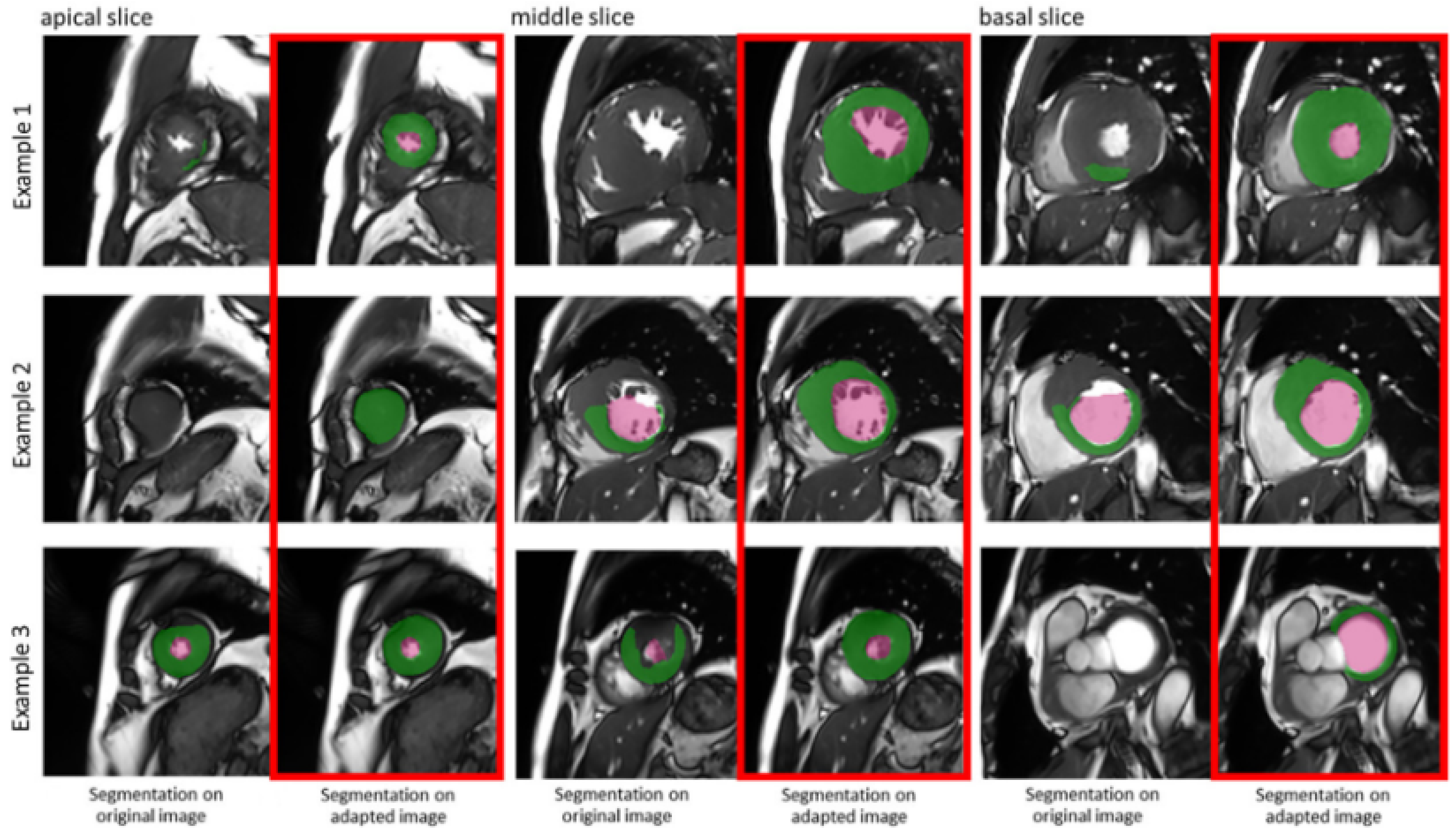




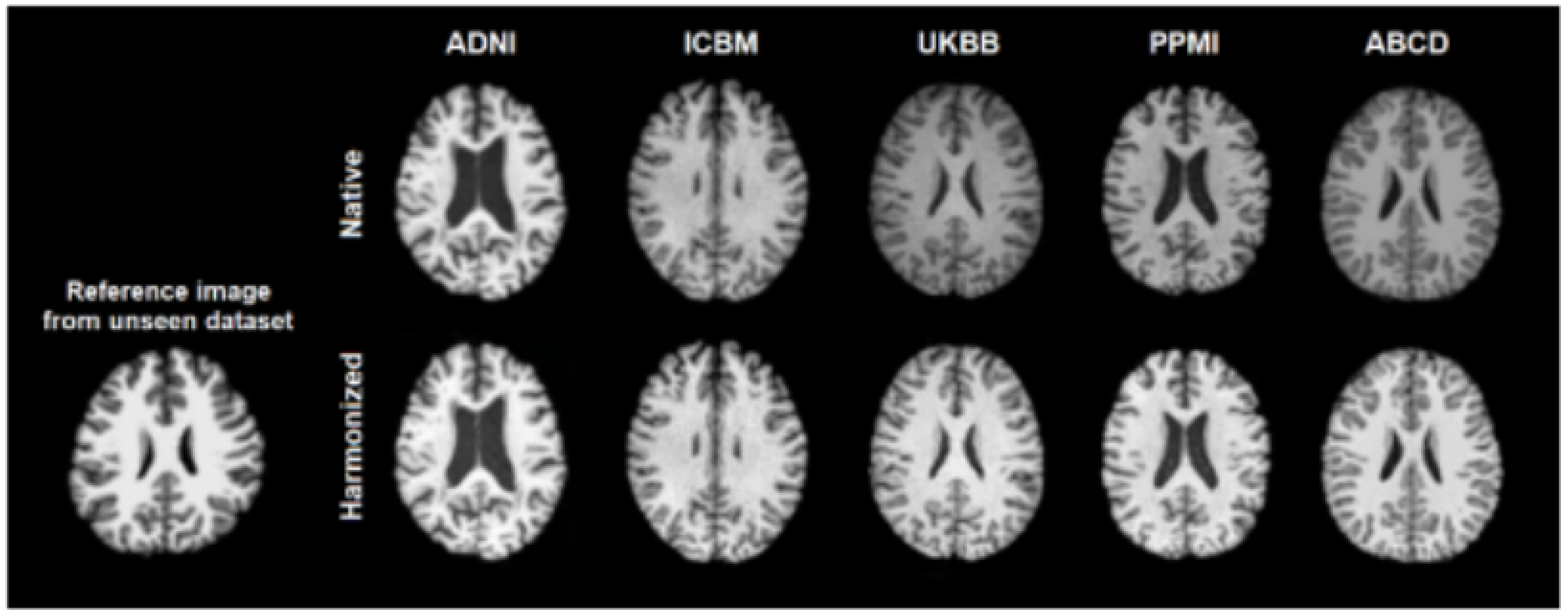
01 Introduction

Previous Work & Contribution

- Previous studies were one-by-one harmonizaton, so it was not possible to freely switch between different various hospitals.
- Existing studies have mainly focused on 2D MRI harmonization that transforms one MR slice. However, this method cannot reflect the whole MRI. It cannot be used in clinical situations.



Increasing the Generalizability of Deep Learning Segmentation for MR Images - RSNA : Artificial Intelligence. 20. 06

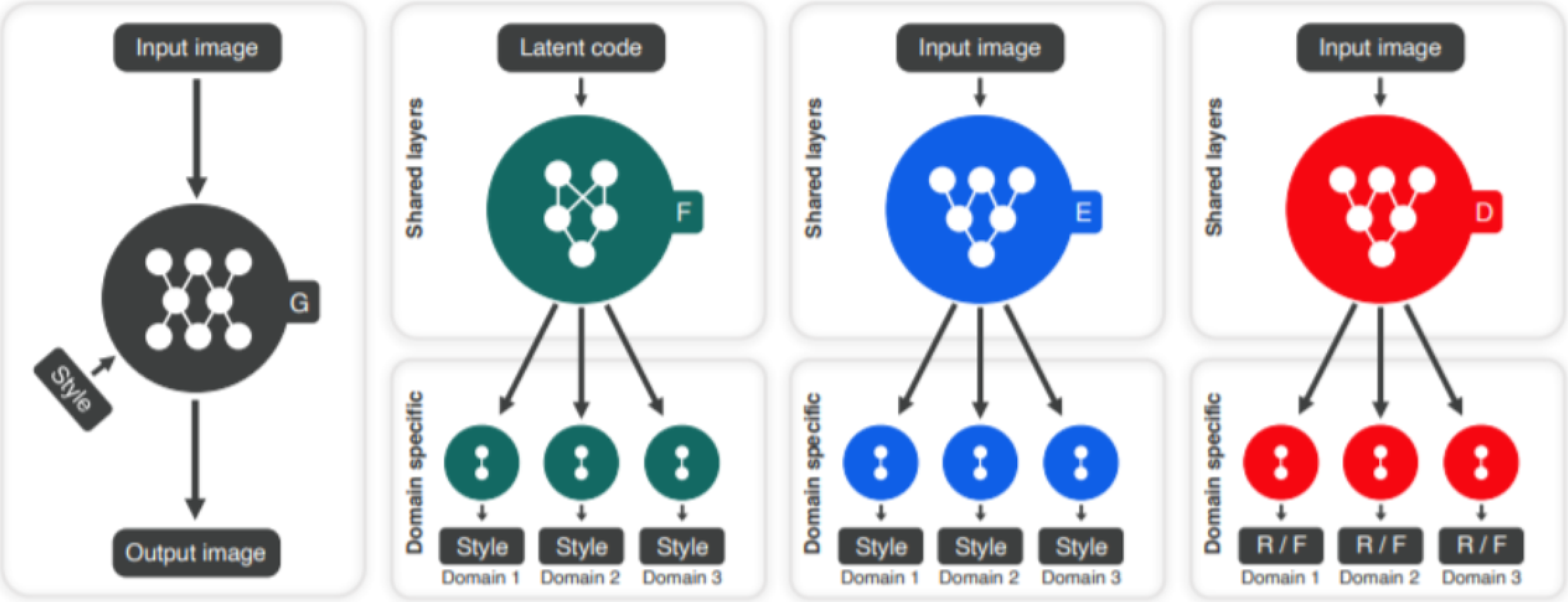


Style Transfer Using Generative Adversarial Networks for Multi-Site MRI Harmonization - MICCAI. 21.09

02 Methods

The Architecture of Framework - Multi Harmonization GAN

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

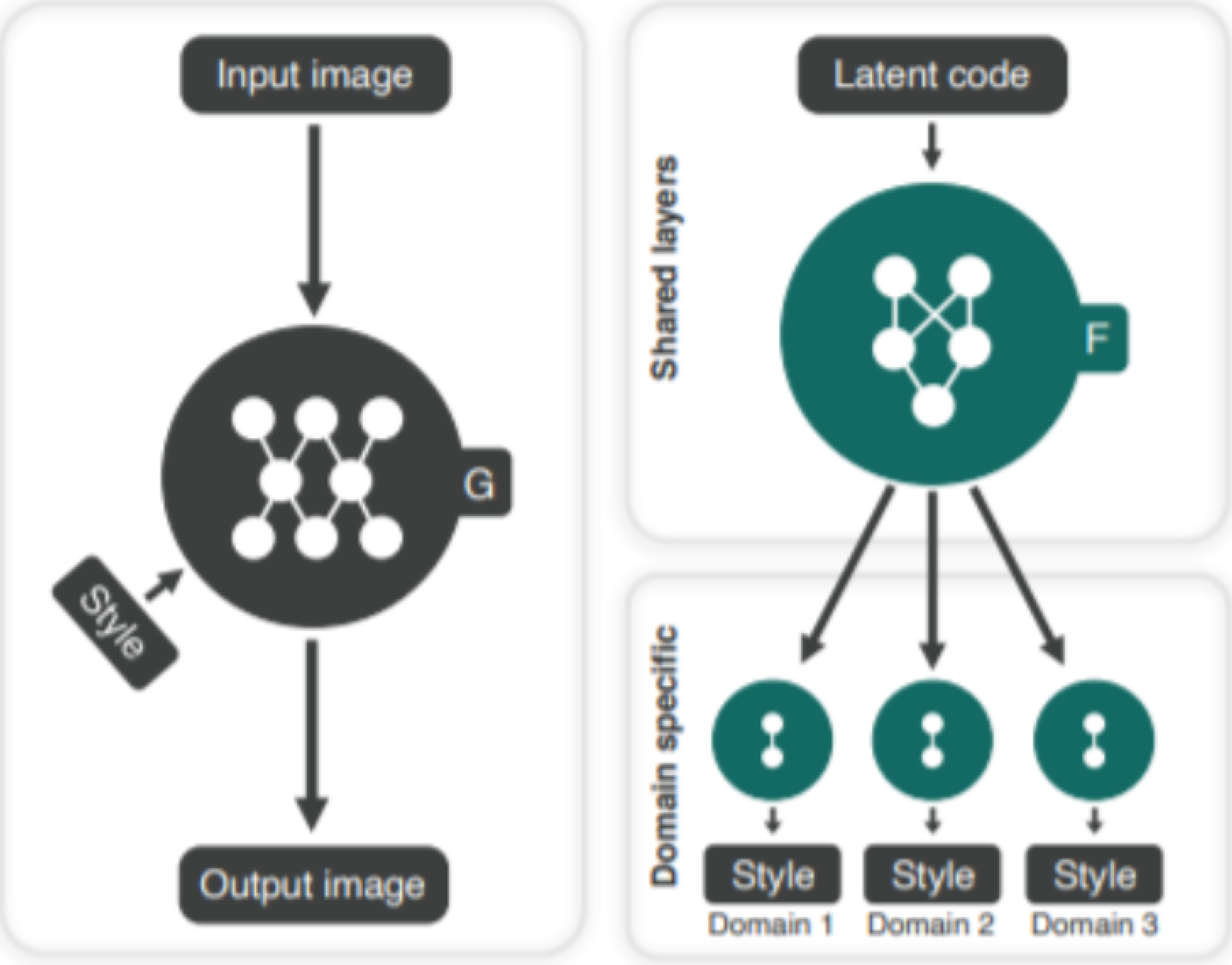
- Directly modeling the space of high-dimensional convolutional filters in an image generation network is practically prohibitive in terms of both computation and parameter scale

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:

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

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

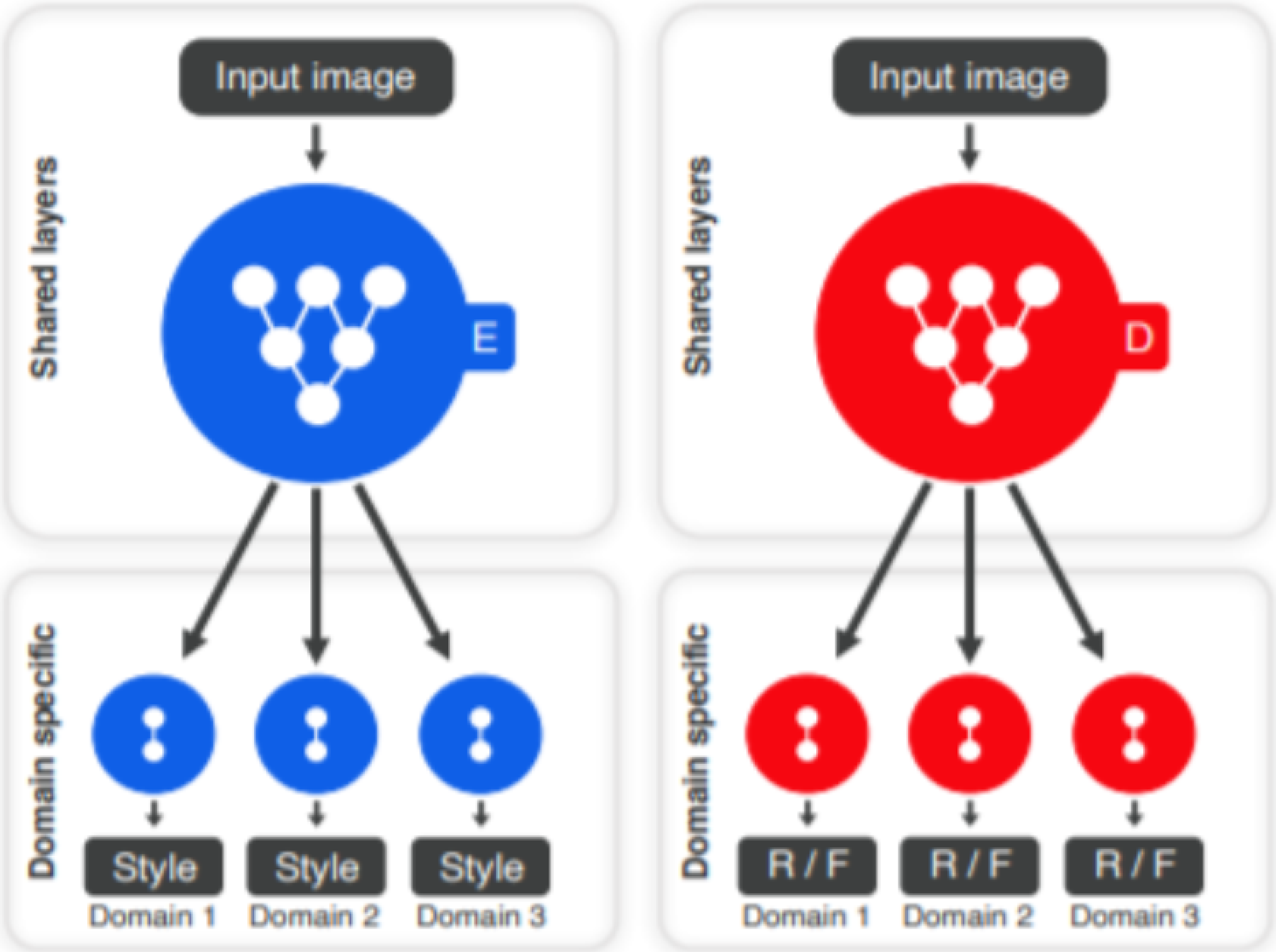
Style reconstruction loss. In order to enforce the generator G to use the style code while generating the image $G(x, s)$, we incorporate a style reconstruction loss:

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

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:

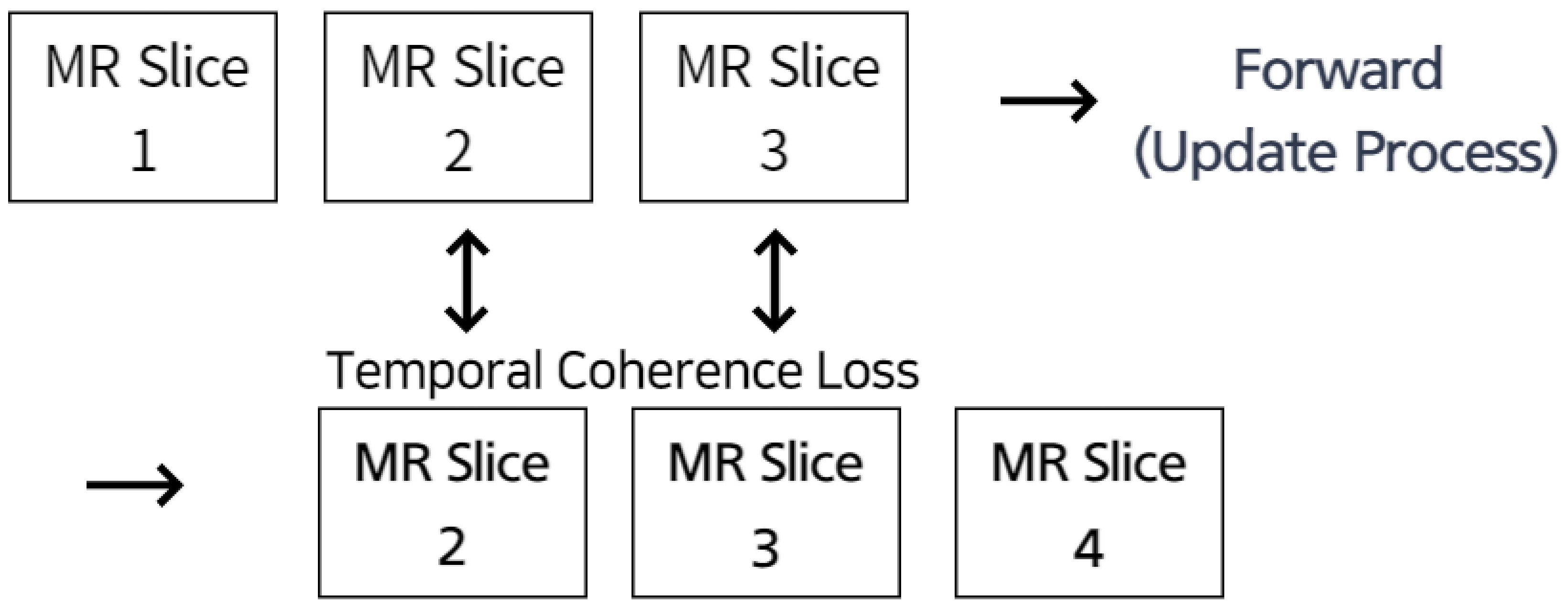
$$L(G, M, E, D) = L_{GAN} + \lambda_{cyc} L_{cyc} + \lambda_{sty} L_{sty} - \lambda_{div} L_{div}$$

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

$$\downarrow$$

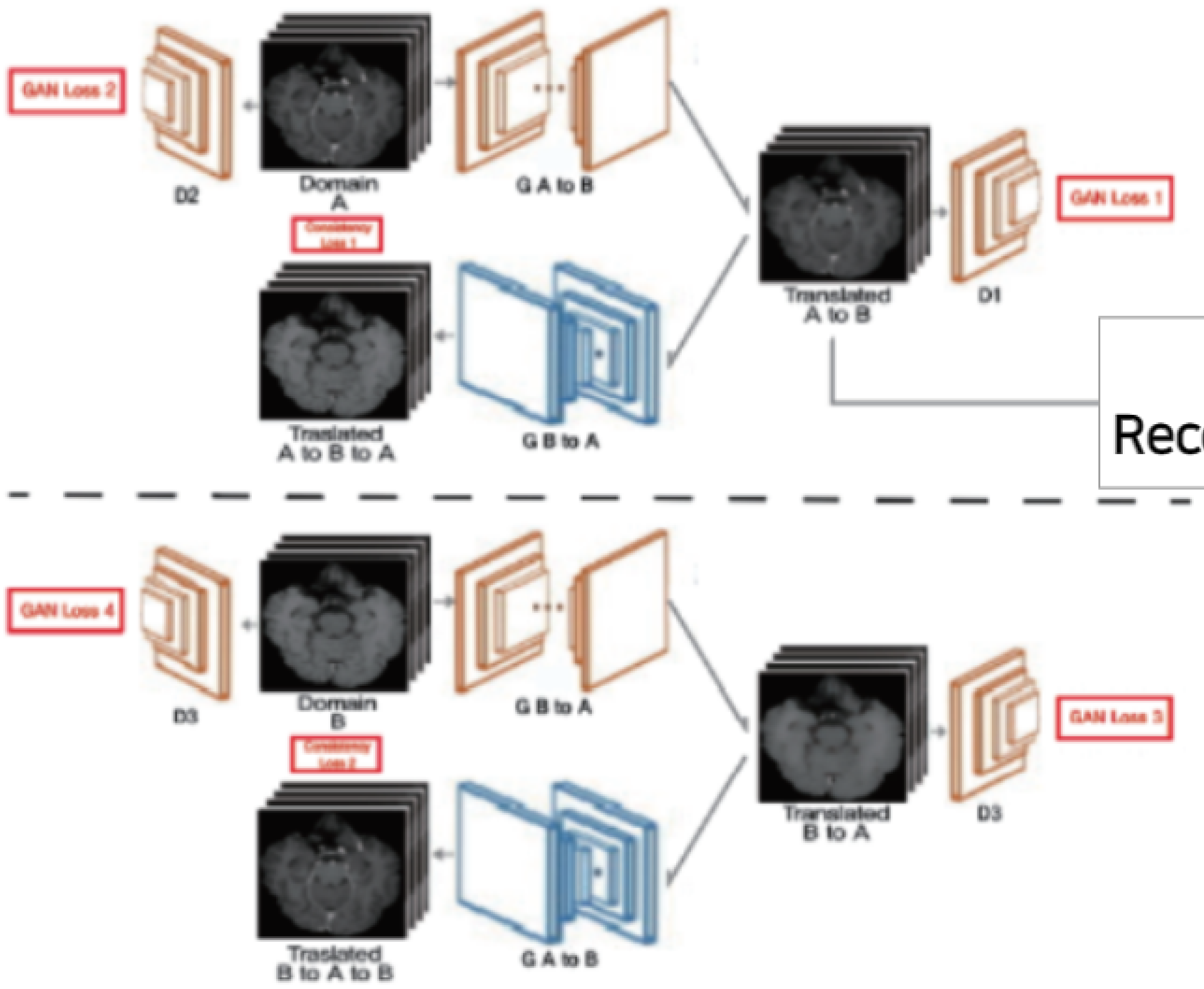
$$L(G, M, E, D) = \lambda 1 * \text{Previous Losses} + \lambda 2 * \text{Temporal Coherence Loss}$$

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



02 Methods

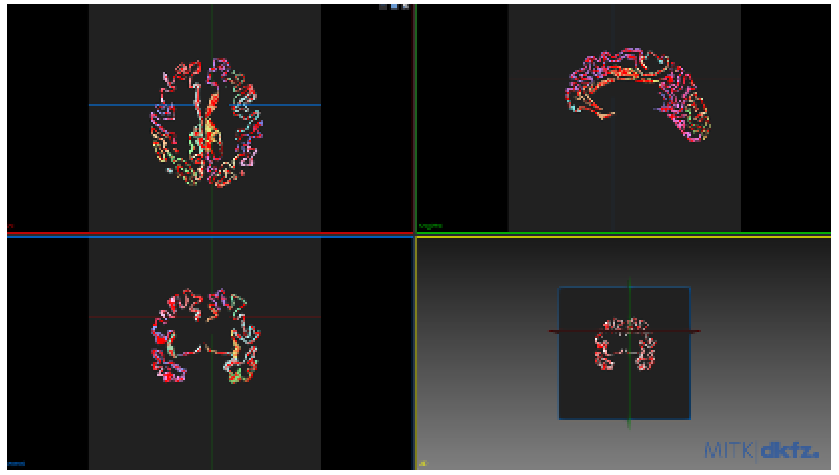
Training Overview



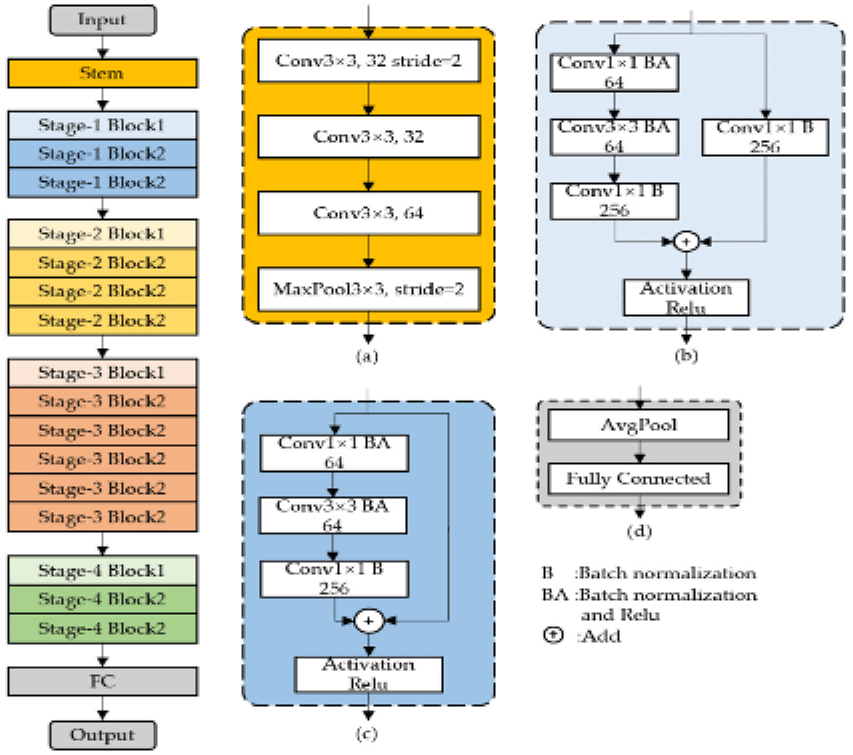
Multi Harmonization GAN

3D Reconstruction

Evaluation 1 :
Cortical Radius Maintainance



Evaluation 2 : Protocols Classification using Deep Learning (ResNet-50)



02 Methods

Dataset Overview

· Initial Training Dataset

Table 1. Initial Dataset Descriptions

Database	Number of Patients	Protocol Baseline				
		Scanners	Field Strength	Imaging Technique	Echo Time	Repeat Time (ms)
Samsung Medical Center (SMC)	2804	Philips	3.0 T	TFE	4.6 (ms)	9.9 (ms)
Alzheimer's Disease Neuroimaging Initiative (ADNI)	4977	GE	1.5 T	MPRAGE	3.8-4.1 (ms)	8.6-10.4 (ms)
Gangnam Severance Hospital (GSEV)	256	GE	1.5 T	MPRAGE	3.8-4.1 (ms)	8.6-10.4 (ms)
Gachon University Gil Medical Center (GMC)	96	Siemens	3.0 T	MPRAGE	2.9 (ms)	1900 (ms)

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

· Validation/Test Dataset

Siemens to GE_protocol
3.0 T (256,256,192) → 1.5 T (256,256,192)

GE to Philips_protocol
1.5T (256,256,192) → 3.0 T (256,256,192)

· Data Preprocessing

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

2. Data Augmentation
Random Image Selection per patients

3. Hyperparameter
Optimizer = Adam, Epoch = 16000, Loss Function = ADV Loss + Sty Rec Loss + Cycle Consistency Loss + Style Diversification Loss

03 Experiments

Multi Harmonization GAN - Results

Figure 1. Source-to-Reference Harmonization

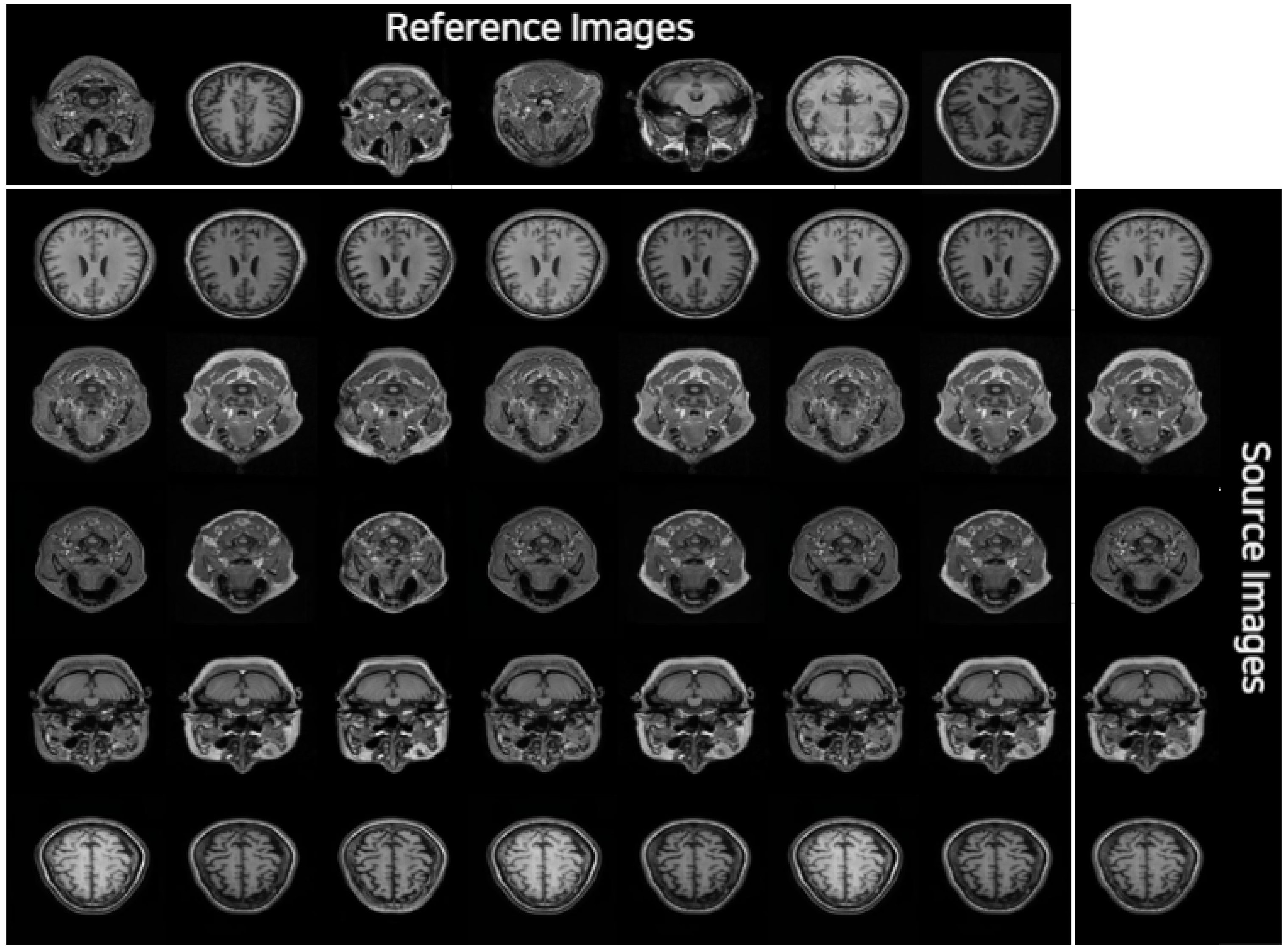
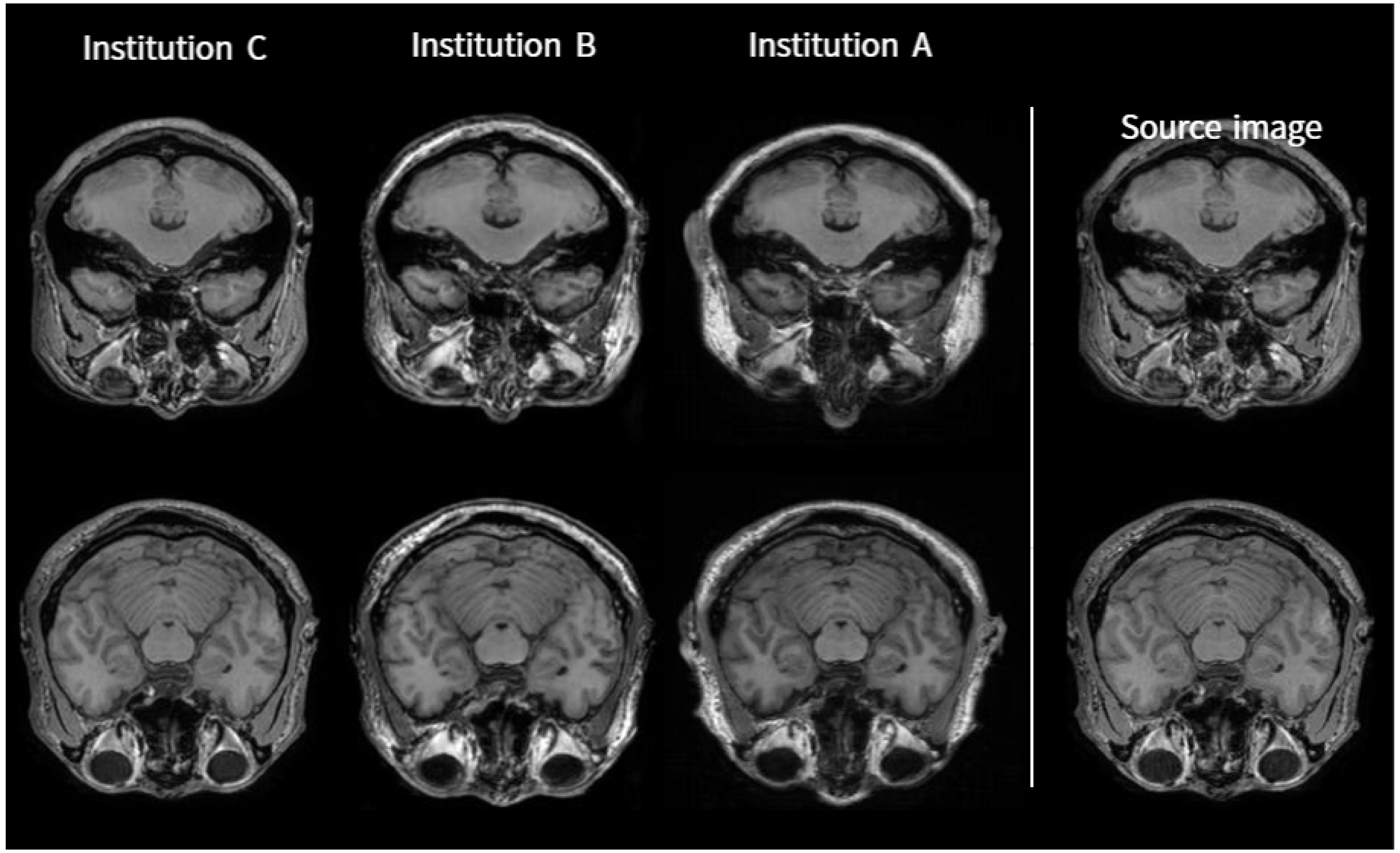


Figure 2. Harmonization per institutions



03 Experiments

Multi Harmonization GAN - Results

Figure 3. Cycle-Consistency Transfer

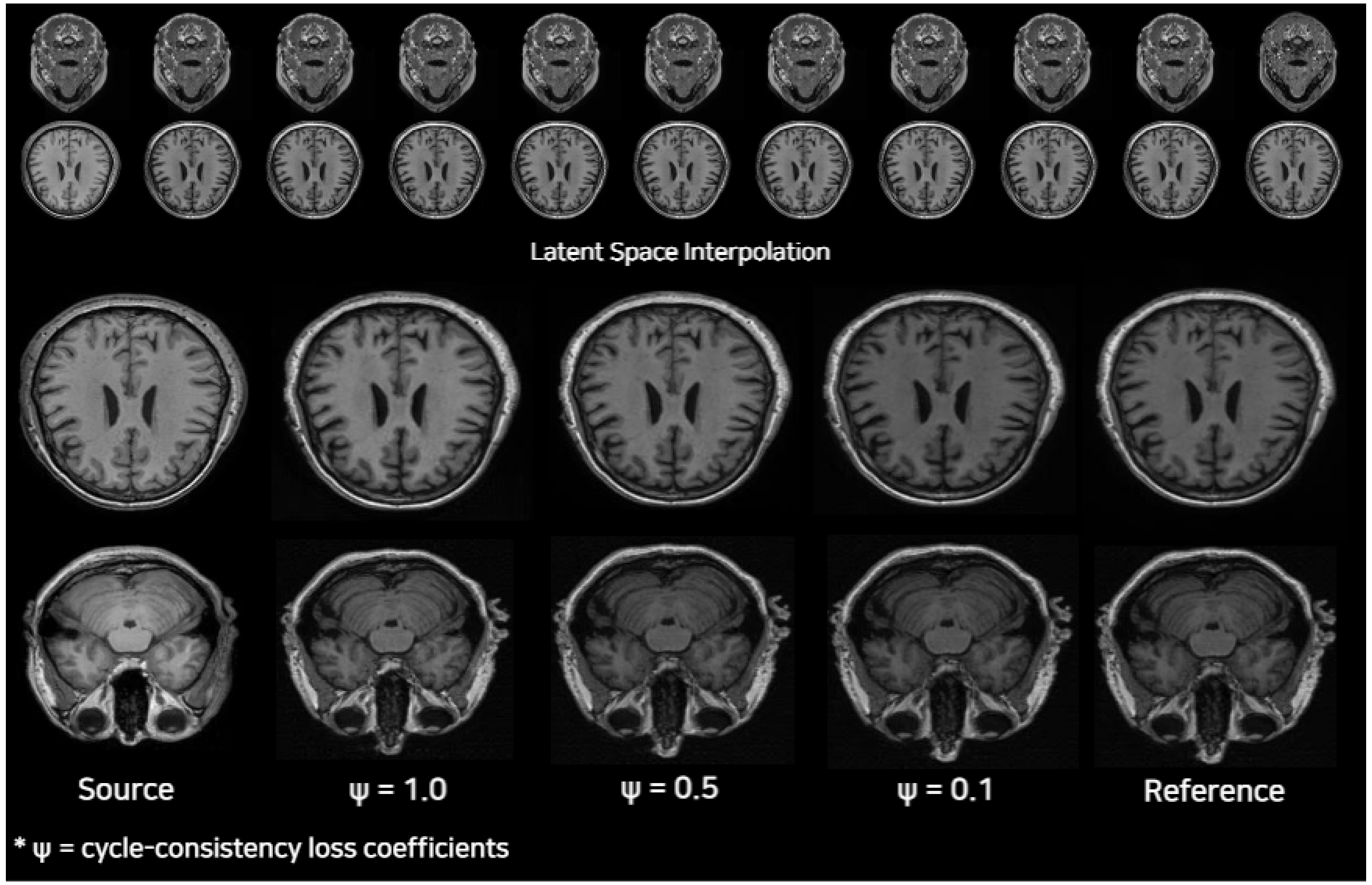
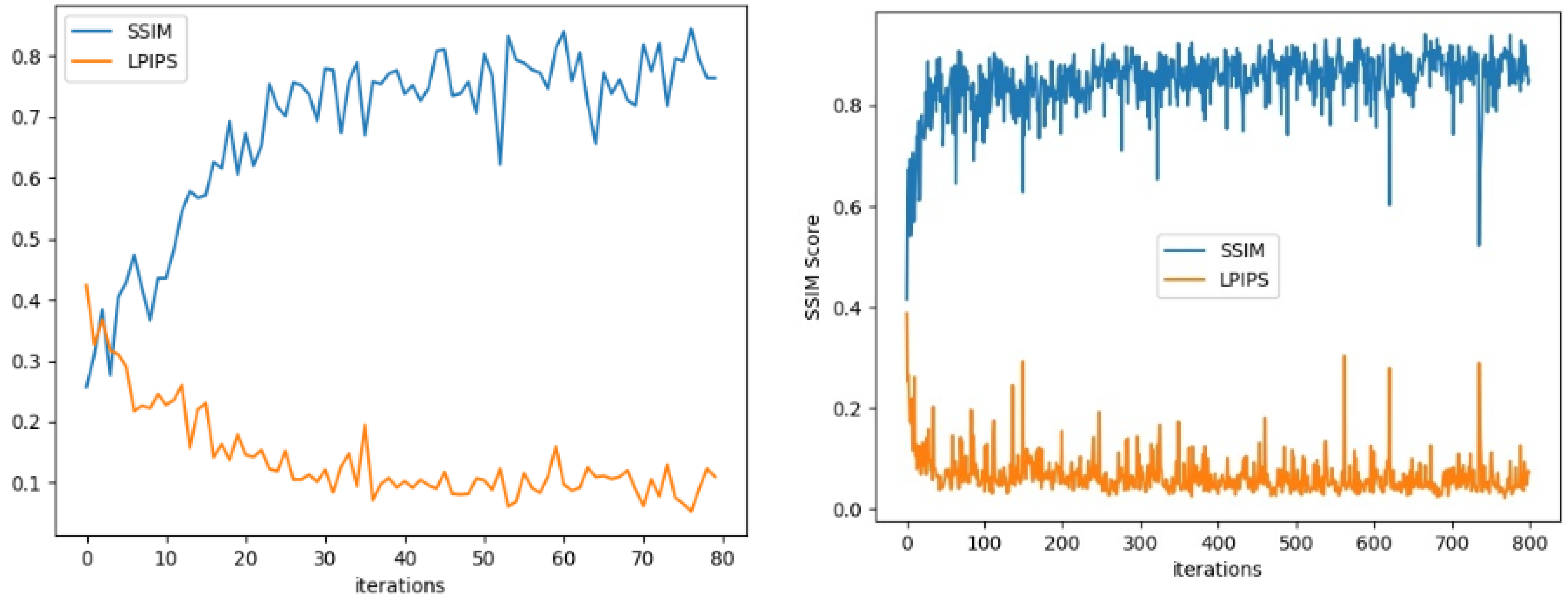
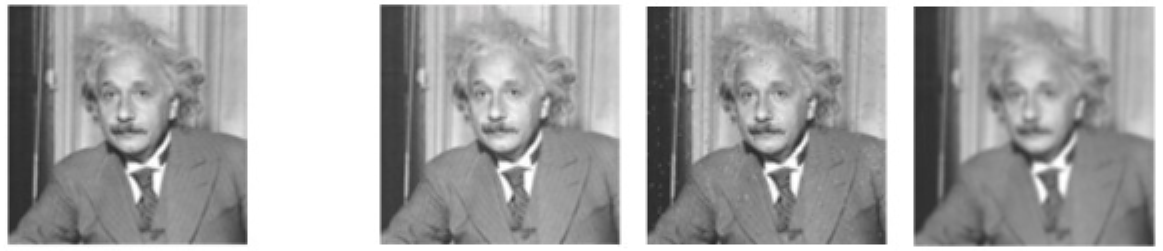


Figure 4. Harmonization per institutions



SSIM Score and LPIPS Score



Original
SSIM=1

SSIM=0.988

SSIM=0.840

SSIM=0.694

03 Experiments

Evaluation 1 : Cortical Radius Maintenance

Figure 5. Siemens_to_GE Harmonization

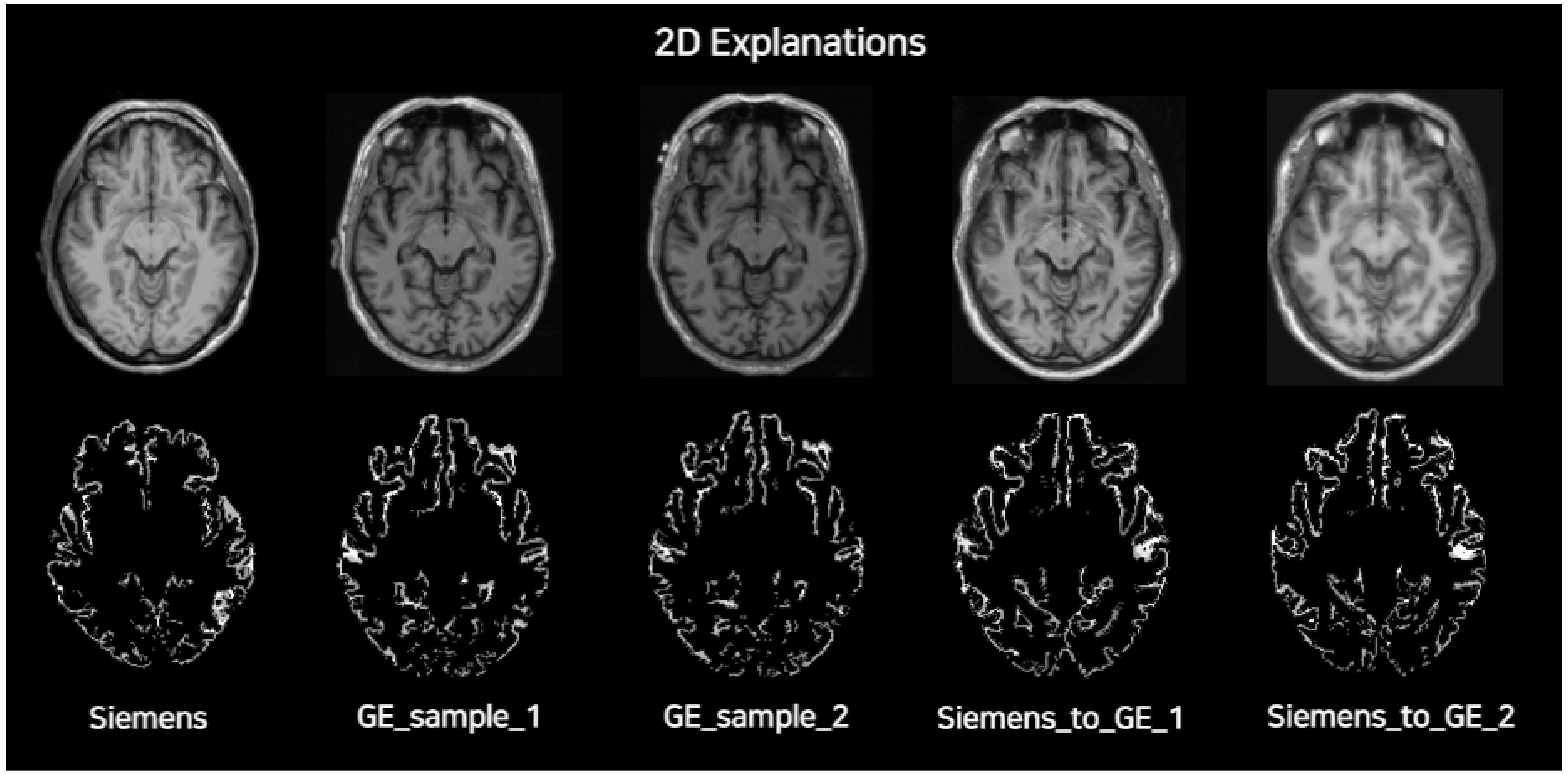
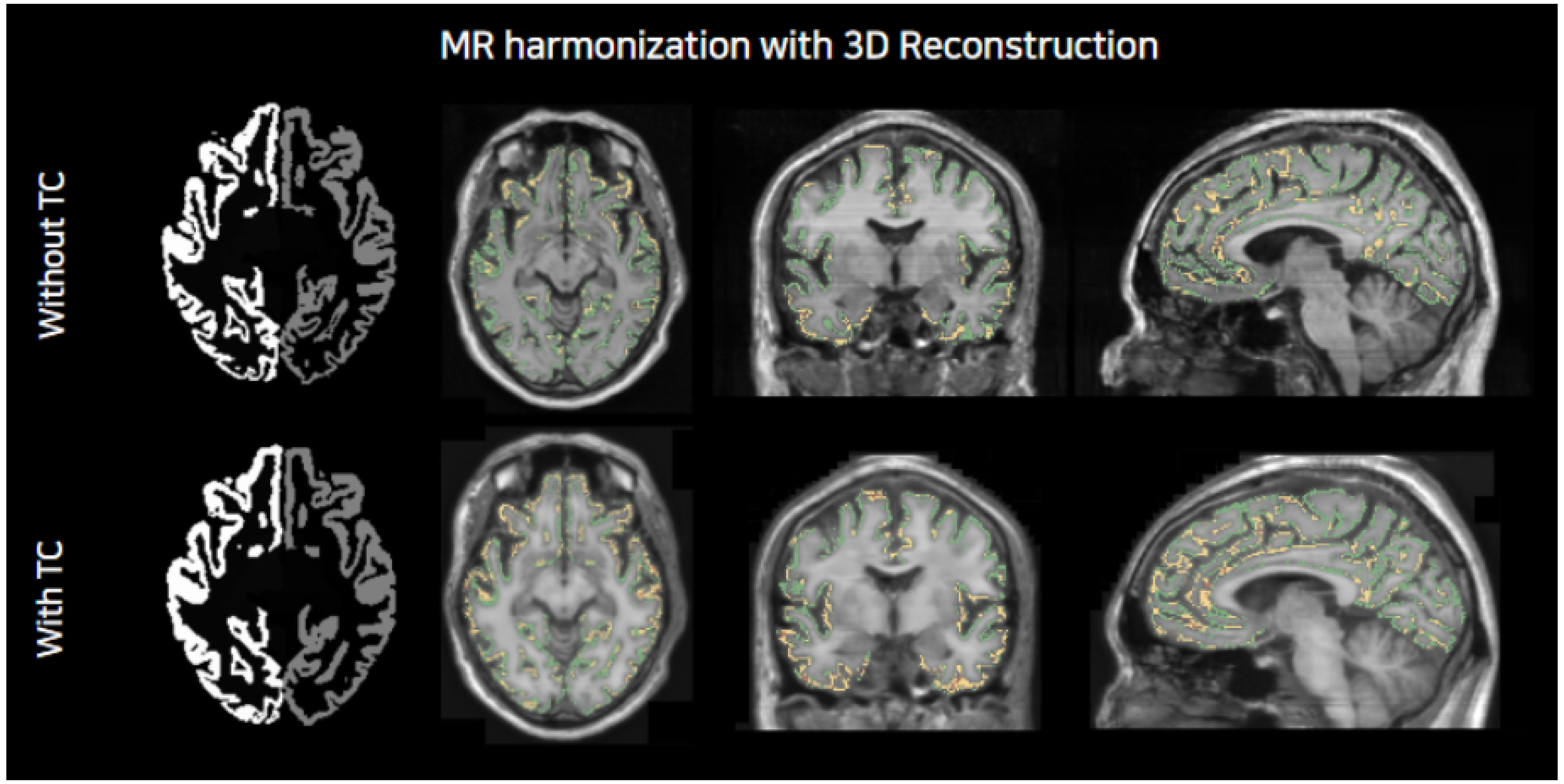


Figure 6. Siemens_to_GE 3D Reconstruction



03 Experiments

Evaluation 1 : Cortical Radius Maintenance

Figure 7. GE to Philips_protocol Harmonization

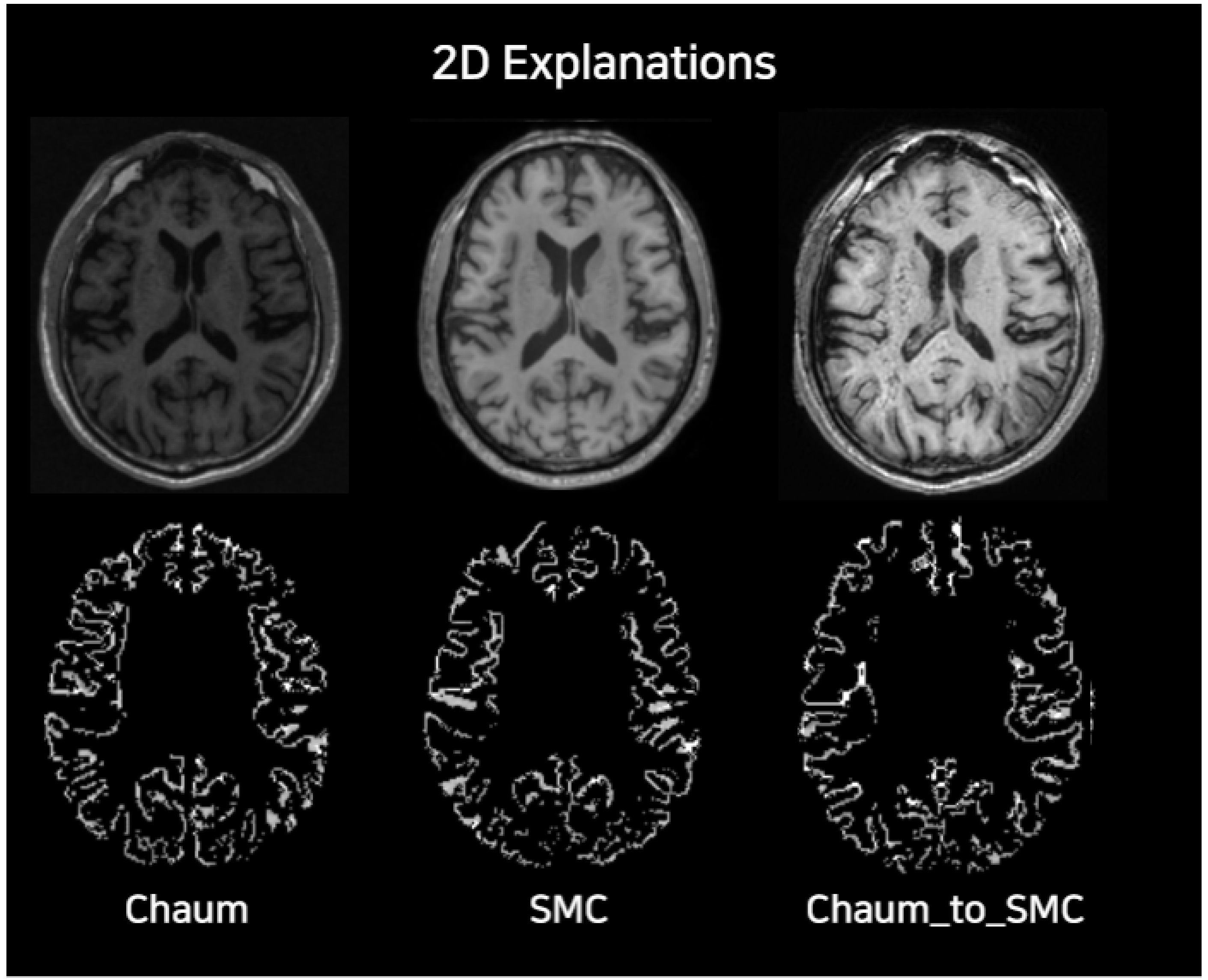


Table 8. Cortical Radius Corellation

Table 2: Assessments of Cortical Radius Maintainance

Experiment	Original Siemens	Original GE	Transfered MR Siemens to GE Dataset
Left Hemisphere	2.1635	1.9826	2.0178
Right Hemisphere	2.2065	1.9947	1.9843

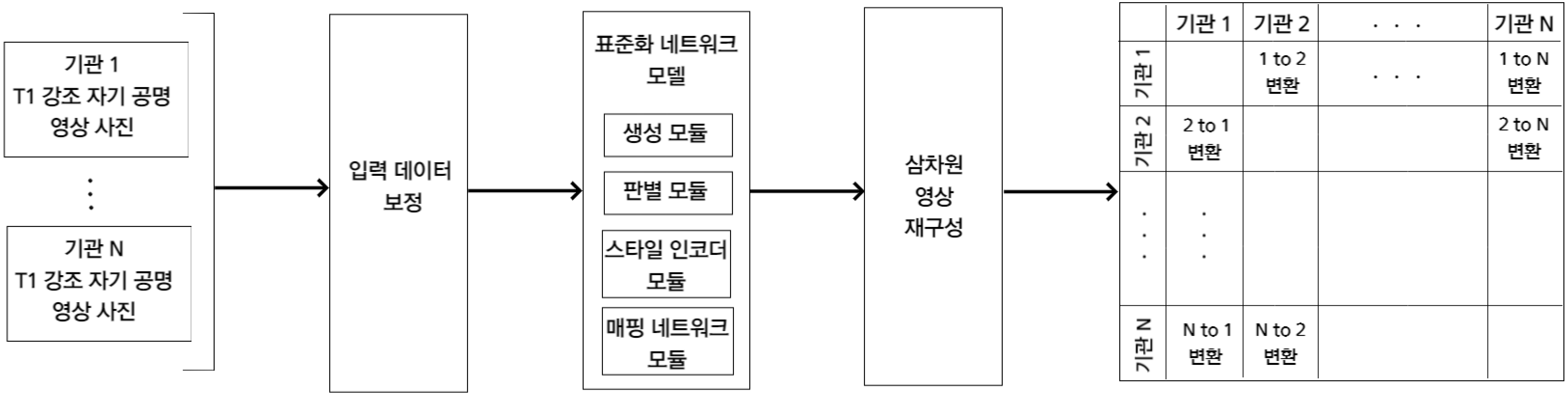
Experiment	Original GE	Original Philips	Transfered MR GE to Philips Dataset
Left Hemisphere	1.2382	1.2486	1.2637
Right Hemisphere	1.1737	1.1864	1.1872

03 Experiments

Evaluation 2 : Protocol Classification

Table : Classification Adaptation Score

		Transfered MR
Experiment	Before Adapt	After Adapt
ADNI, GMC	96.5299	66.6666
ADNI, SMC	91.2000	64.3533
ADNI, GSEV	94.6969	69.0851
GSEV, GMC	83.4595	61.5141
SMC, GSEV	88.1944	55.8159
SMC, GMC	87.8472	57.8914
Total (mean)	90.3213	62.5544


기관 1
T1 강조 자기 공명
영상 사진
기관 N
T1 강조 자기 공명
영상 사진
입력 데이터
보정
표준화 네트워크
모델
생성 모듈
판별 모듈
스타일 인코더
모듈
매핑 네트워크
모듈
삼차원
영상
재구성
기관 1
기관 2
기관 N
기관 1
기관 2
기관 N
1 to 2
변환
1 to N
변환
2 to 1
변환
2 to N
변환
N to 1
변환
N to 2
변환