Medical Image Domain Adaptation : Solution of Institution data Shift Problem using semi-supervised transfer learning

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01 Introduction

Domain Adaptation in Medical Field

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

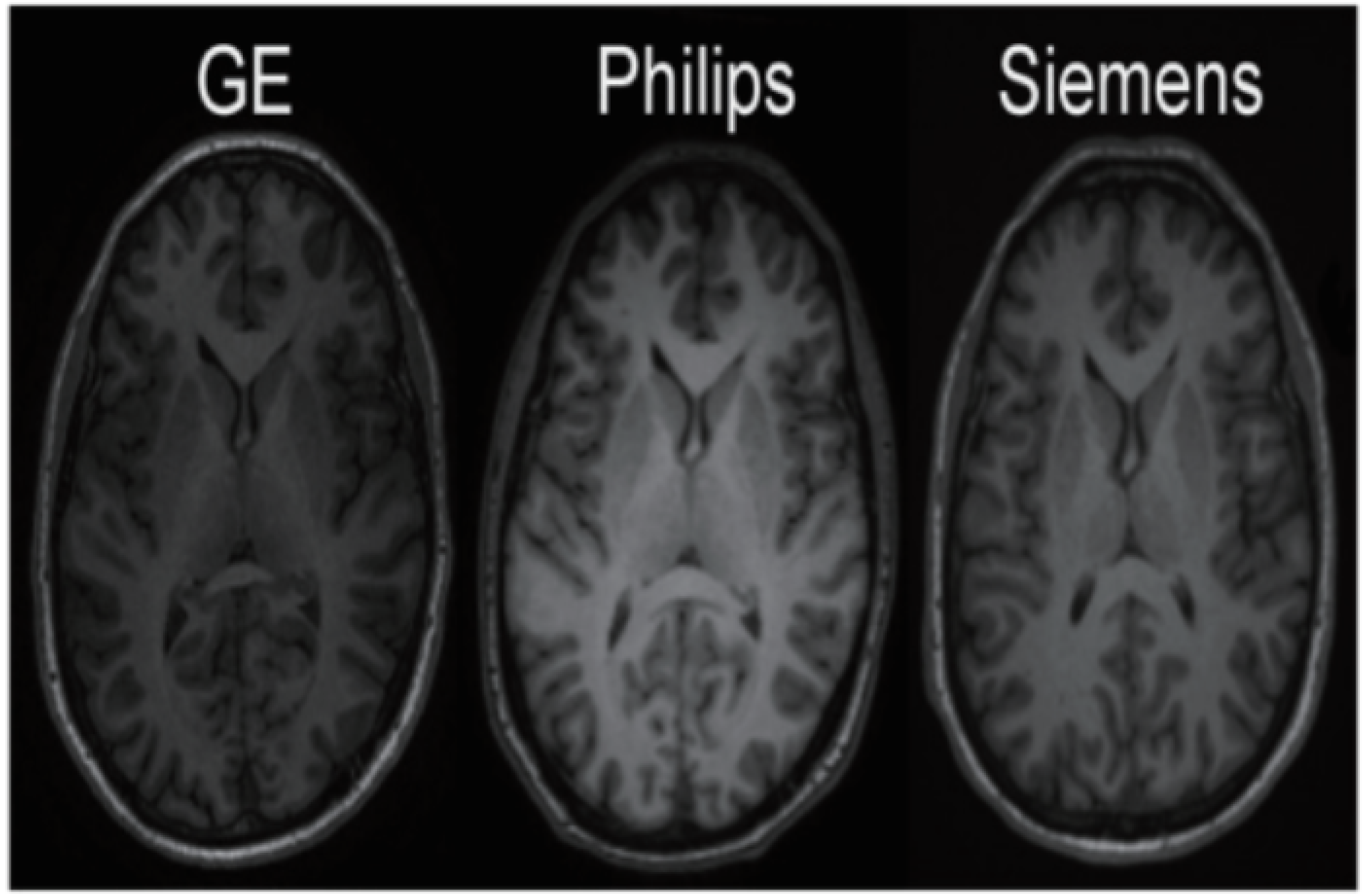


Table 1: Specifications of Cine MRI Datasets Acquired from Scanners of Different Manufacturers

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

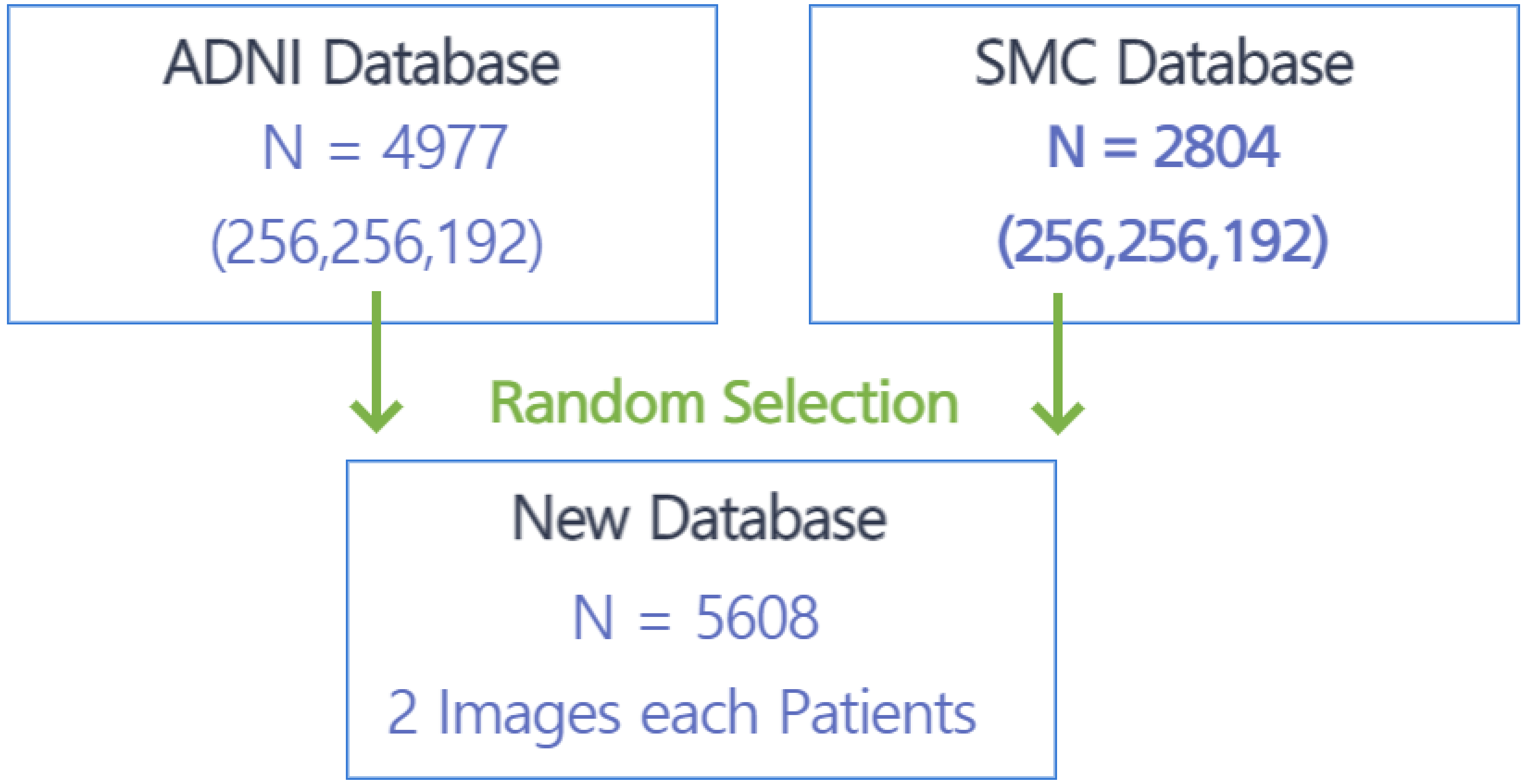
Research Way

- 1. One by One Domain Adaptation Process
  ADNI/SMC Control Normal Transfer - Output
  ADNI/SMC Alzheimers' Transfer - Output
  Discussion
- 2. Binary Classification (Validation Model)
  ADNI/SMC Control Normal Binary Classification - Output
  ADNI/SMC Alzheimers' Transfer - Output
  Disscusion
- 3. Future Work
  One by One Journal Wrap Up

02 Methods

Dataset & Preprocessing

- Healthy Control Domain Adaptation
  Original Datasets : ADNI & SMC Dataset
  ADNI Control Normal: 4977 Patients , (256,256,192)
  SMC Control Normal: 2804 Patients, (256,256,192)
- New Generated Datasets : Stack Channel, Random Selections at Patients Images (2), Total Train : 2804



1. Z-Score Normalization

normalized by dividing by the maximum after clipping.

2. Data Augmentation

Random Horizontal Flip, Random 2 Image Selection per patients

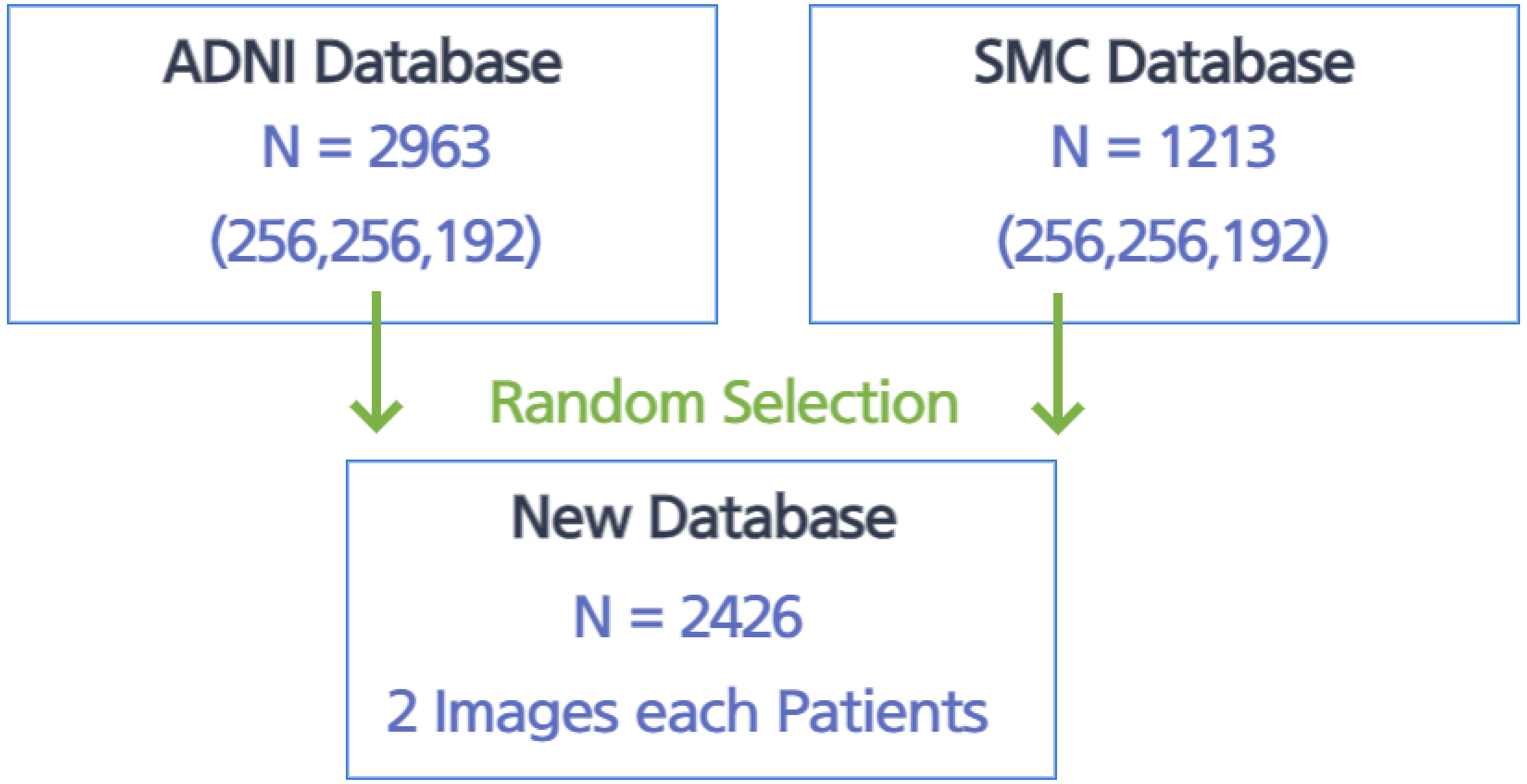
3. Hyperparameter

Optimizer = Adam, Epoch = 300, Loss Function = Identity Loss + Consistency Loss + A2B, B2A, ABA, BAB Loss + Cycle Loss

02 Methods

Dataset & Preprocessing

- Alzheimer's Disease Domain Adaptation
  Original Datasets : ADNI & SMC Dataset
  ADNI Alzheimers': 2963 Patients , (256,256,192)
  SMC Alzheimers': 1213 Patients, (256,256,192)
- New Generated Datasets : Stack Channel, Random Selections at Patients Images (2), Total Train : 2804



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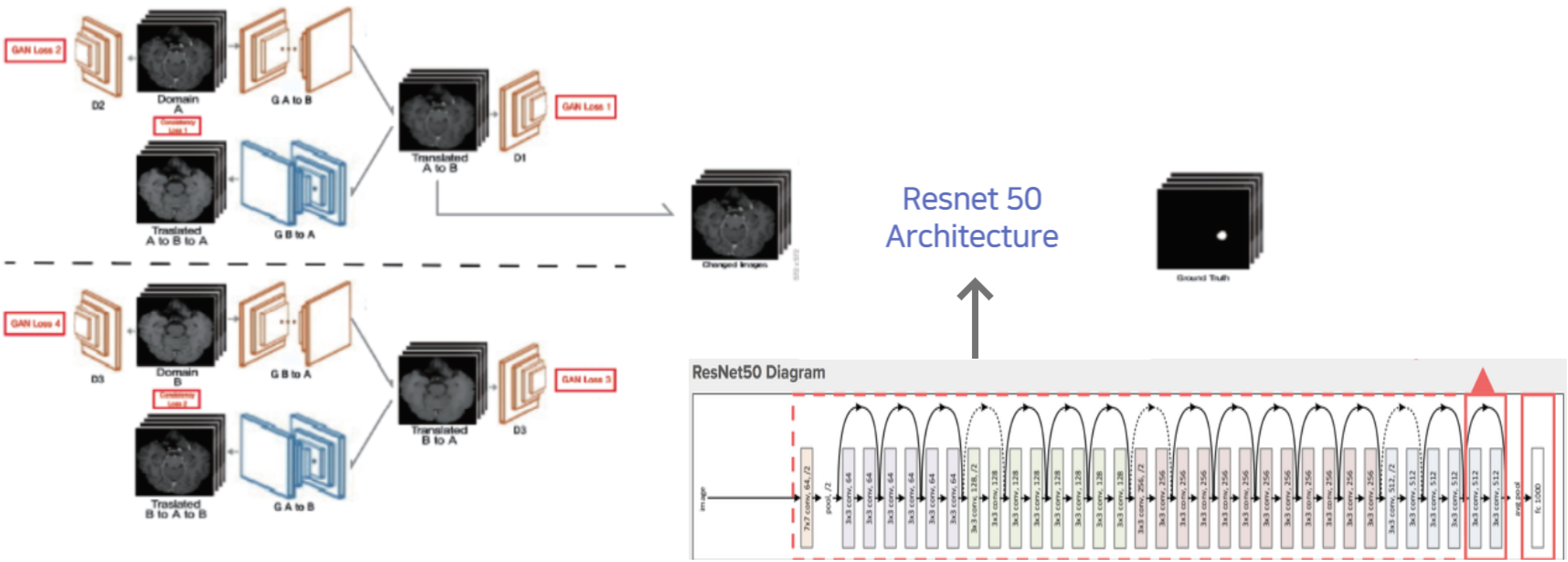
03 Experiments

Proposed Framework

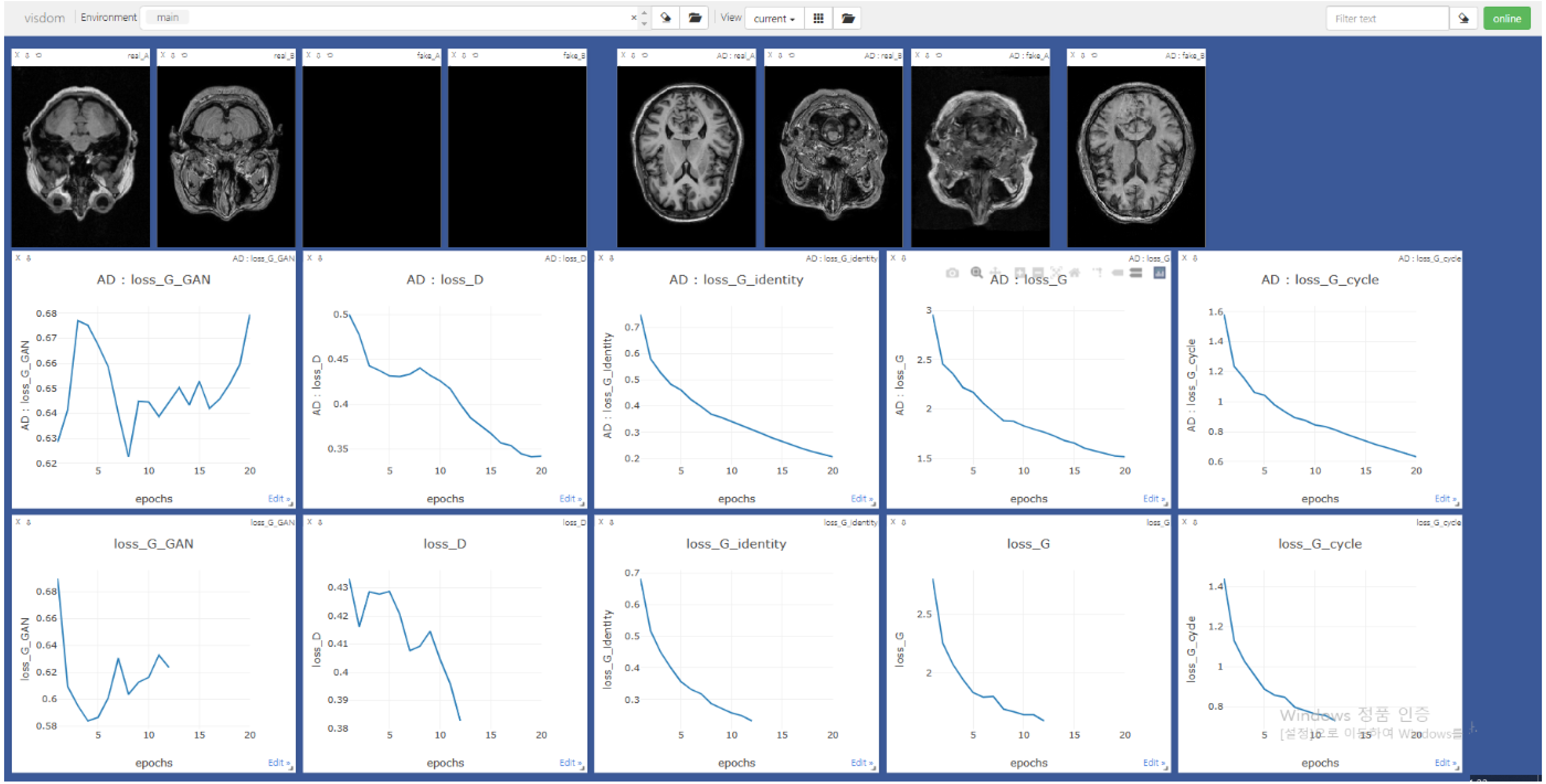
- Cycle GAN + Resnet 50

< Proposed Framework >



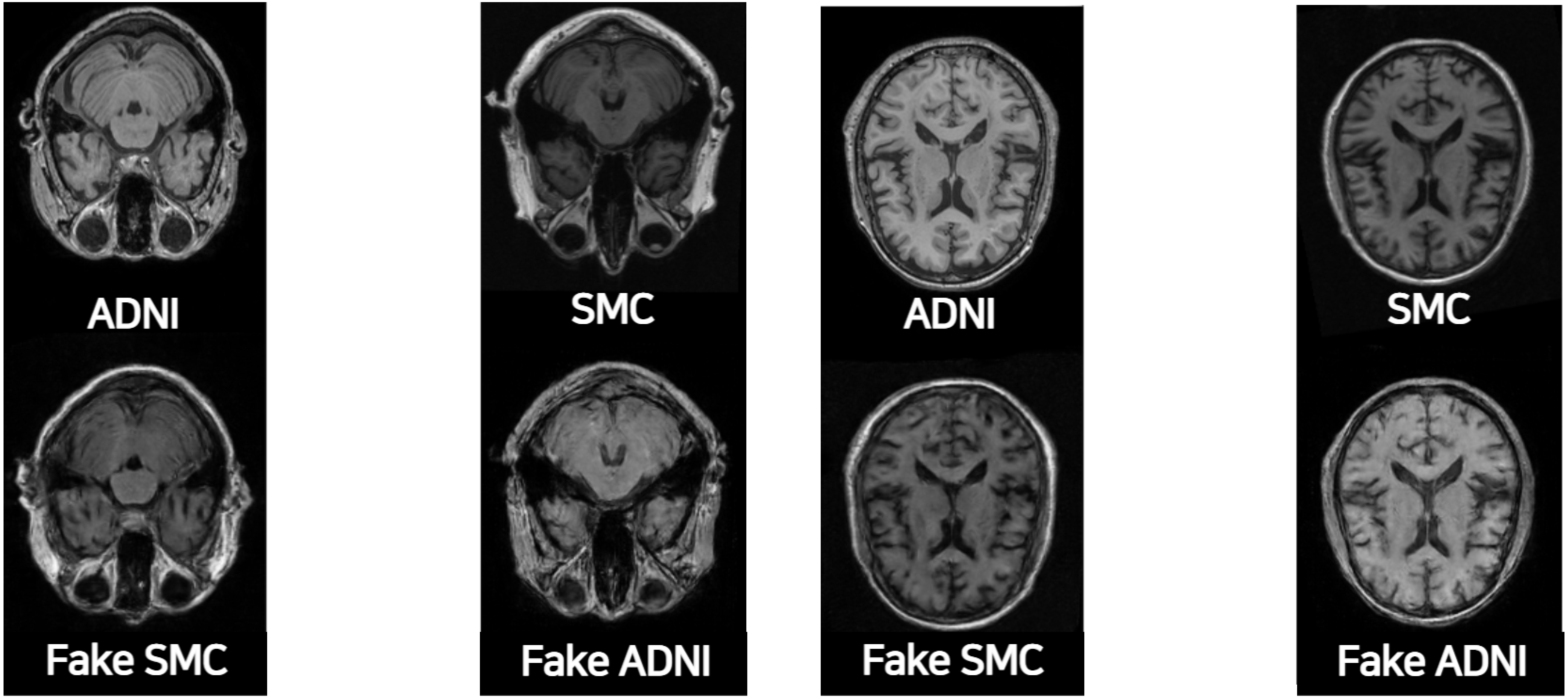
03 Experiments

Adaptation Results



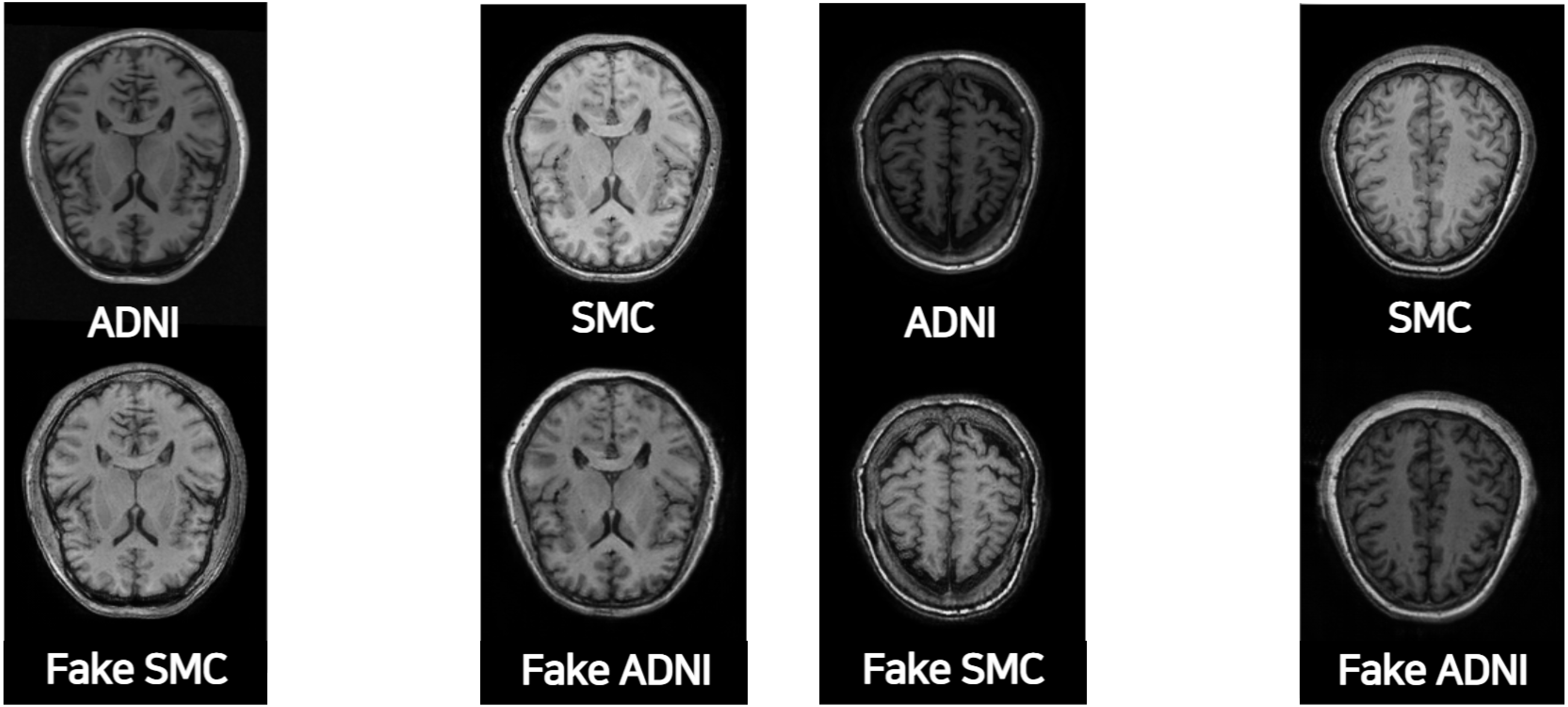
03 Experiments

Adaptation Results - Alzheimers' Disease (not same slice)



03 Experiments

Adaptation Results - Healthy Control (not same slice)



03 Experiments

Dataset & Preprocessing

- Alzheimer's Disease Classification
  Original Datasets : ADNI & SMC Dataset
  ADNI Alzheimers': 2963 Patients , (256,256,192)
  SMC Alzheimers': 1213 Patients, (256,256,192)
- Model : Resnet 50

1. Z-Score Normalization

normalized by dividing by the maximum a fter clipping.

2. Hyperparameter

Optimizer = Adam, Epoch = 20, Loss F unction = Cross Entropy Loss, learning rate= 0.001

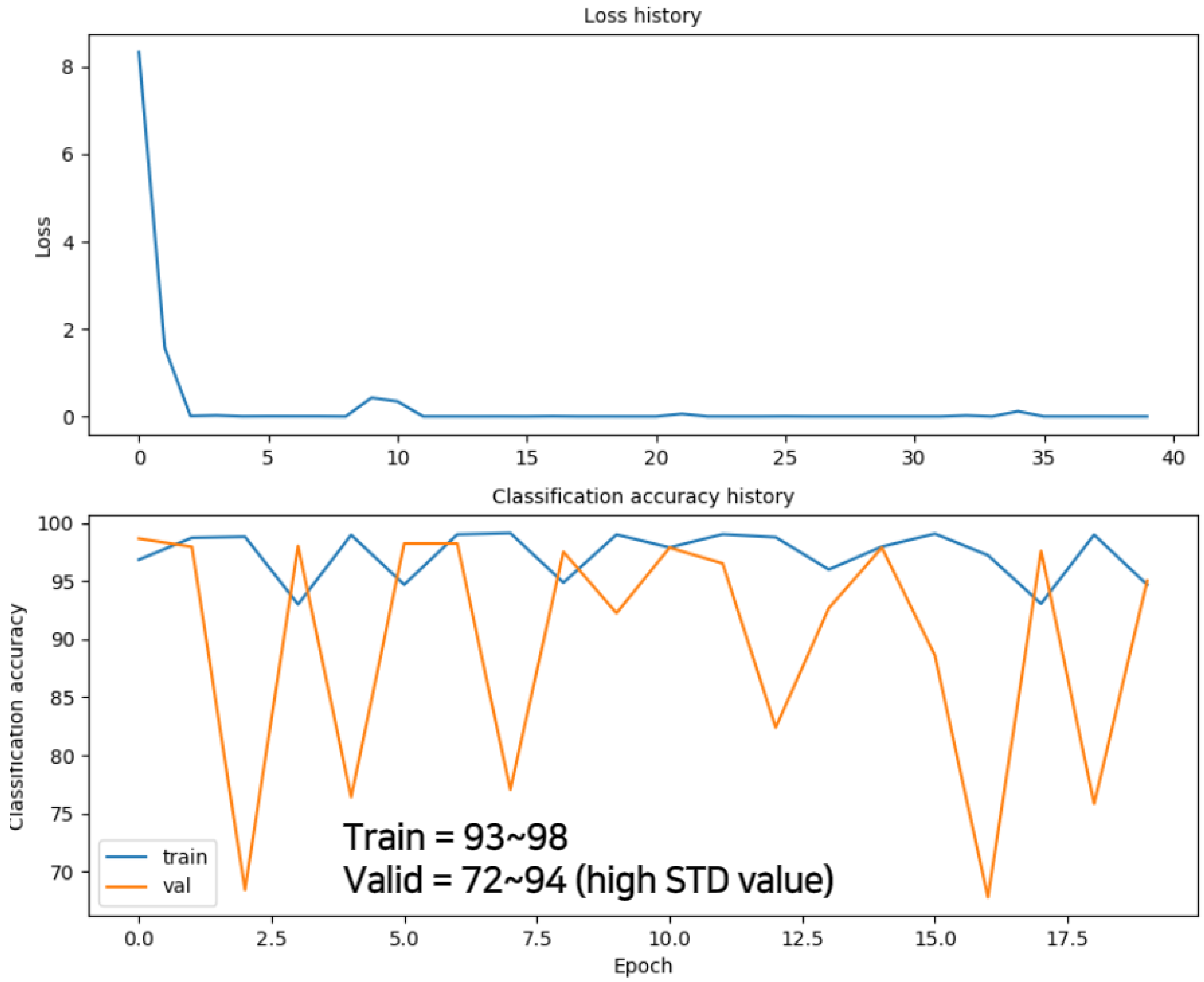
3. Transform

No Special Transforms

- Fake Generated AD Classification
  Original Datasets : ADNI & SMC Dataset
  ADNI Alzheimers': 2963 Patients , (256,256,192)
  SMC Alzheimers': 1213 Patients, (256,256,192)
- Model : Resnet 50

03 Experiments

Classification Results - Real & Fake



<Test Performance>

Generated Fake Image Acc : 53~57
Output Image Plot (Soon)

04 Conclusion

Discussion

- Domain Adaptation Output image - We can see highly adapted to other protocol (ADNI , SMC)
  Cycle-Gan loss dropped smoothly but sometime vanished (80~100 epoch loss increase drastically). -> Sel ect intermediate weight pkl (use 20 epoch weights)
- But magnetic field intensity is slighly different (ADNI - 3.0T, SMC - 1.5T) -> Our model adapted both intens ity and protocol (GE,Philips) -> Nevertheless, Adapted well
- ADNI,SMC Classification Output also performed well. Loss dropped smoothly, Train Acc : 93~98.
  But Valid Acc got high variance : 73~94
- After Adaptation Process, Our model showed highly adapted performance. Train, Acc dropped drastically : 53~57

↓

- We need own novelty (clinical or technical) to write journals. (Similar Domain Adpatation journal published at RNSA 2021.06, Named MRI manufacturer shift and adaptation : increasing the generalizability of deep l earning segmentation for MR images acquired with different scanners)

04 Conclusion

Journal Review

MRI Manufacturer Shift and Adaptation : Increasing the Generalizability of Deep Learning Segmentation for MR Images Acquired with Different Scanners

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Radiological Society
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ORIGINAL RESEARCH

MRI Manufacturer Shift and Adaptation: Increasing the Generalizability of Deep Learning Segmentation for MR Images Acquired with Different Scanners

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Conflicts of interest are listed at the end of this article.

Journal Output (Cardiac Tumor Segmentation)

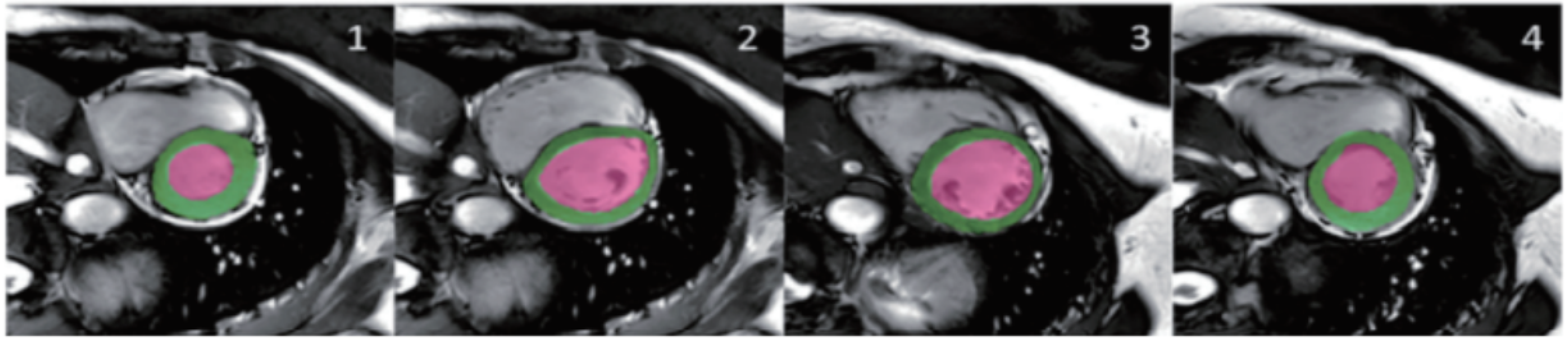

Figure 5. 동일한 제조사 MR Image Segmentation

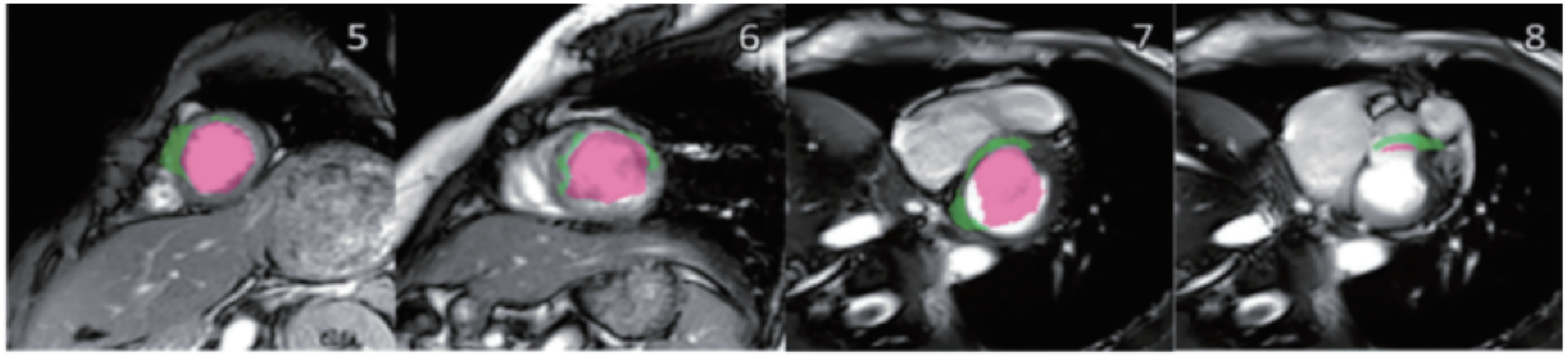

Figure 6. 다른 제조사 MR Image Segmentation

	Deep Learning Model	
	U-Net 1	
Experiment	Myocardium	Blood Pool
Tested on manufacturer 1 dataset	89.7 ± 2.3	91.8 ± 1.6
Tested on manufacturer 2 dataset	68.7 ± 10.8	67.9 ± 11.7
Tested on manufacturer 3 dataset	72.4 ± 10.2	79.6 ± 10.2