AI-assist analysis of cerebral infarction and MRI domain adaptation solving method

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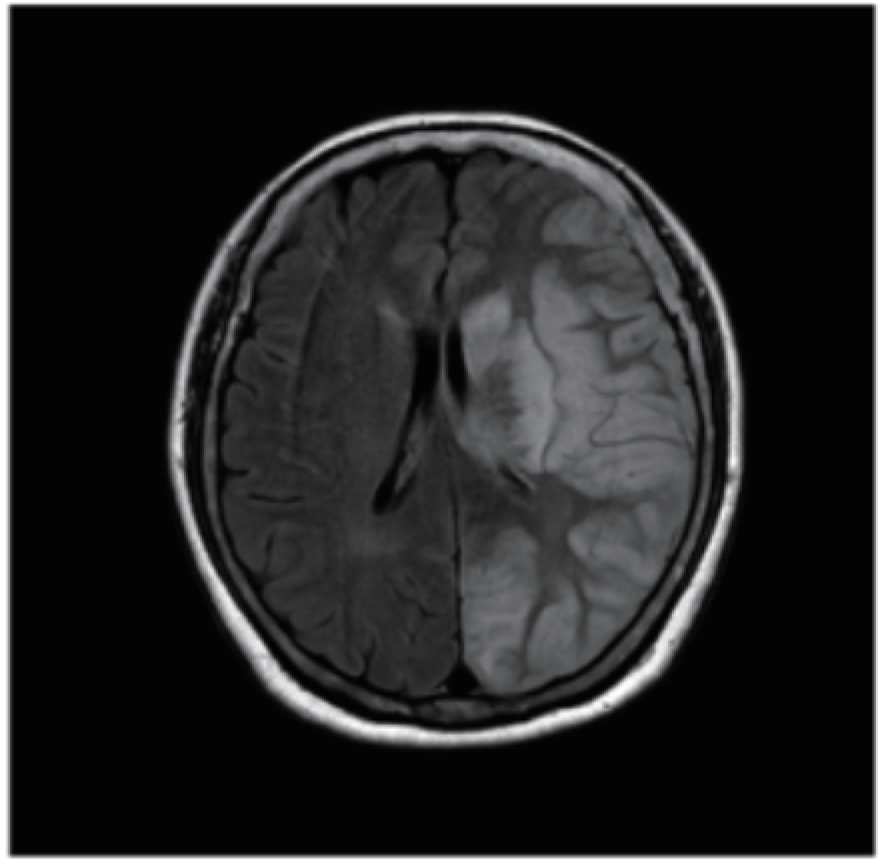
01 Introduction

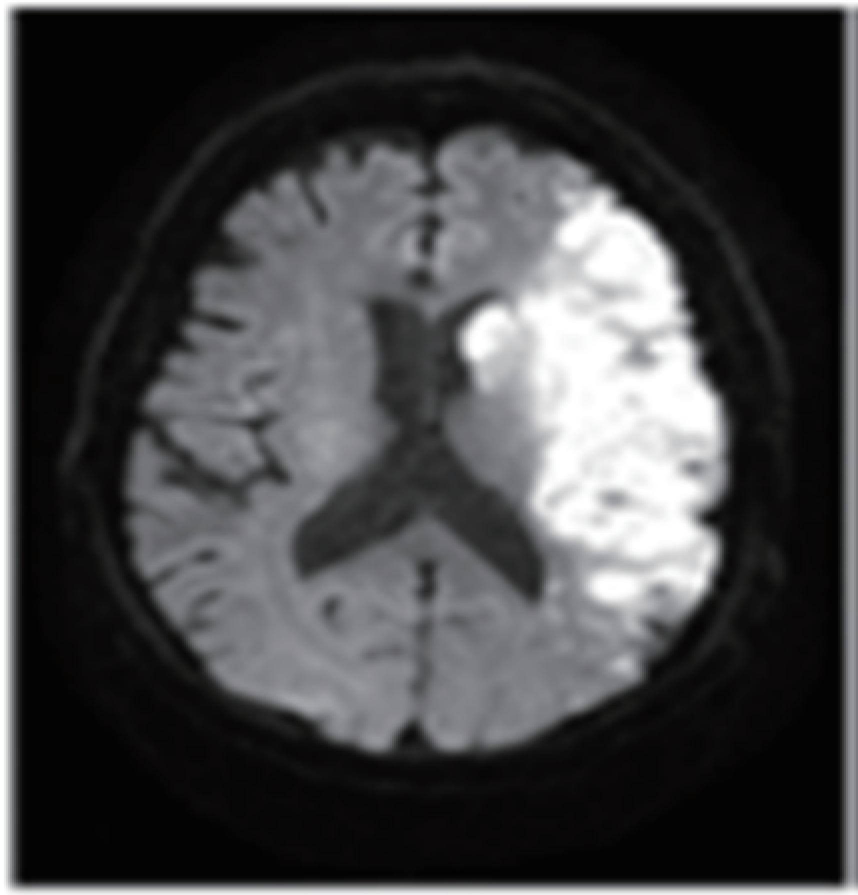
Cerebral Infarction

A disease in which a blood vessel in the brain is blocked and part of the brain dies. Most of cerebral infarction patients are elderly over the age of 60 with complications.

Treatment is proceeded through decompression craniectomy, but decompression craniectmoy has large side effects.



Cerebral Infarction MR Image



DWI B1000 Image

ADC map Image

01 Introduction

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Treatment & Problem

- Decompression craniectomy, antithrombotic causes postoperative bleeding complications.
- The level of evidence based on the research is low.
- Impossible to provide standardized medical services to patients.
- judgment of the doctor may be subjective or the decision may be delayed.

Box 1. Predictors for fatal brain swelling after ischemic infarction

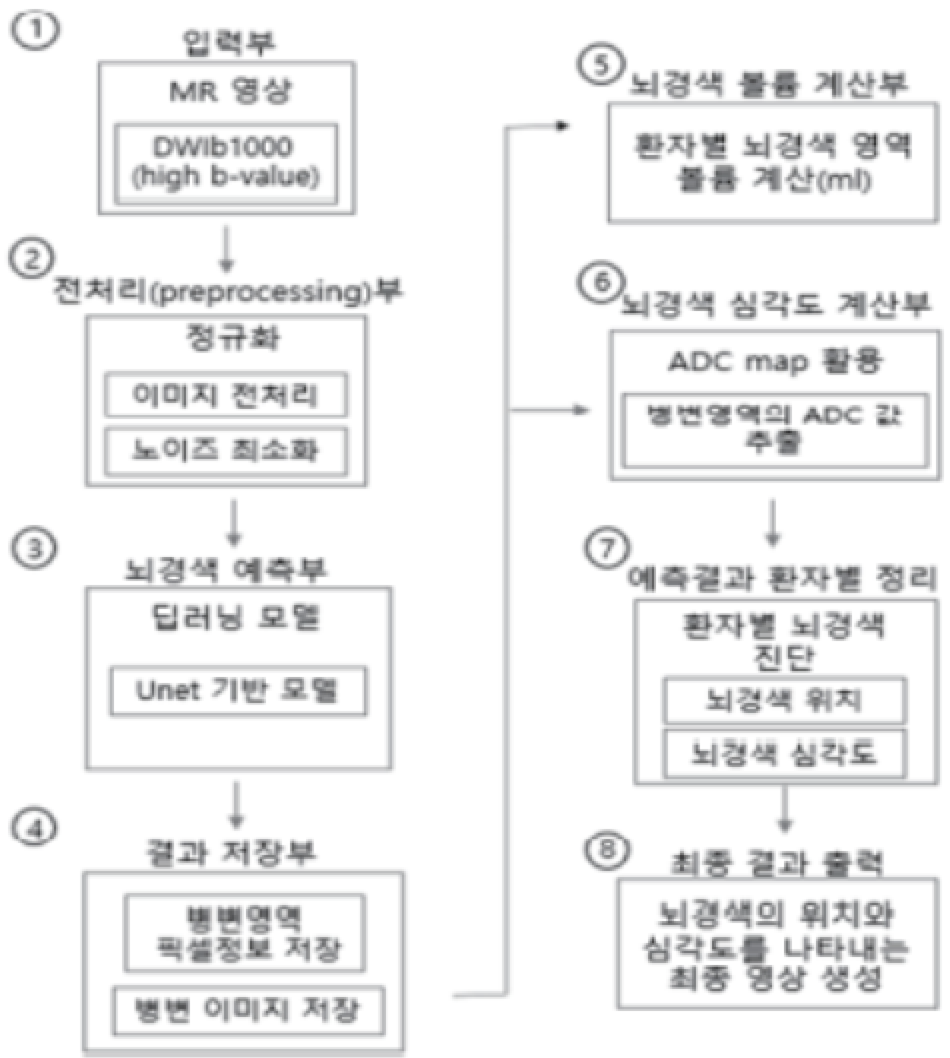
1. Baseline NIHSS
   :Rt ≥ 15, Lt≥ 20
2. Nausea/vomiting within 24hr after onset (OR 5.1)
3. Systolic BP after 12hr ≥180 (OR 4.2)
4. Hypodensity of > 50% of MCA territory on initial CT 187 min after onset (OR 6.1)
   High specificity (94%), moderated sensitivity (61%)
5. Hx of hypertension (OR 2.11)
6. Hx of heart failure (OR 2.15)
7. Involvement of additional vascular territory (OR 6.25), Carotid occlusion (OR 8.97)
8. Proximal MCA occlusion or MCA T occlusion
9. Infarct volume on CT ≥ 240cm3 (accuracy 76.4%)
   Lesion volume greater than 145cm3 on diffusion-weighted MRI
10. Midline shift on CT ≥ 8.5 mm (accuracy 89.1%)
11. Angiographic recannalization
12. Hemorrhagic transfomation
13. Age, younger (Age per 10 yr, OR 0.42)
14. Female
15. Stroke Hx (OR 0.18)
16. Heart weight ↑
17. Ipsilateral abnl of circle of willis
18. Hyperdense MCA sign and at least 2 parenchymal signs within 6 hrs

01 Introduction

Main Goal

AI-assist analysis of cerebral infarction

1. Brain infarction segmentation algorithm using artificial intelligence.
2. Cerebral infarction severity assessment and malignant brain infarction early detection algorithm.
3. Total EMR ischemic infarction, cerebral infarction patients detection assist model.



→ Algorithm Framework

Auto-Skull Segmentation

↓

Ischemic Infarction factors (EMR) auto detection

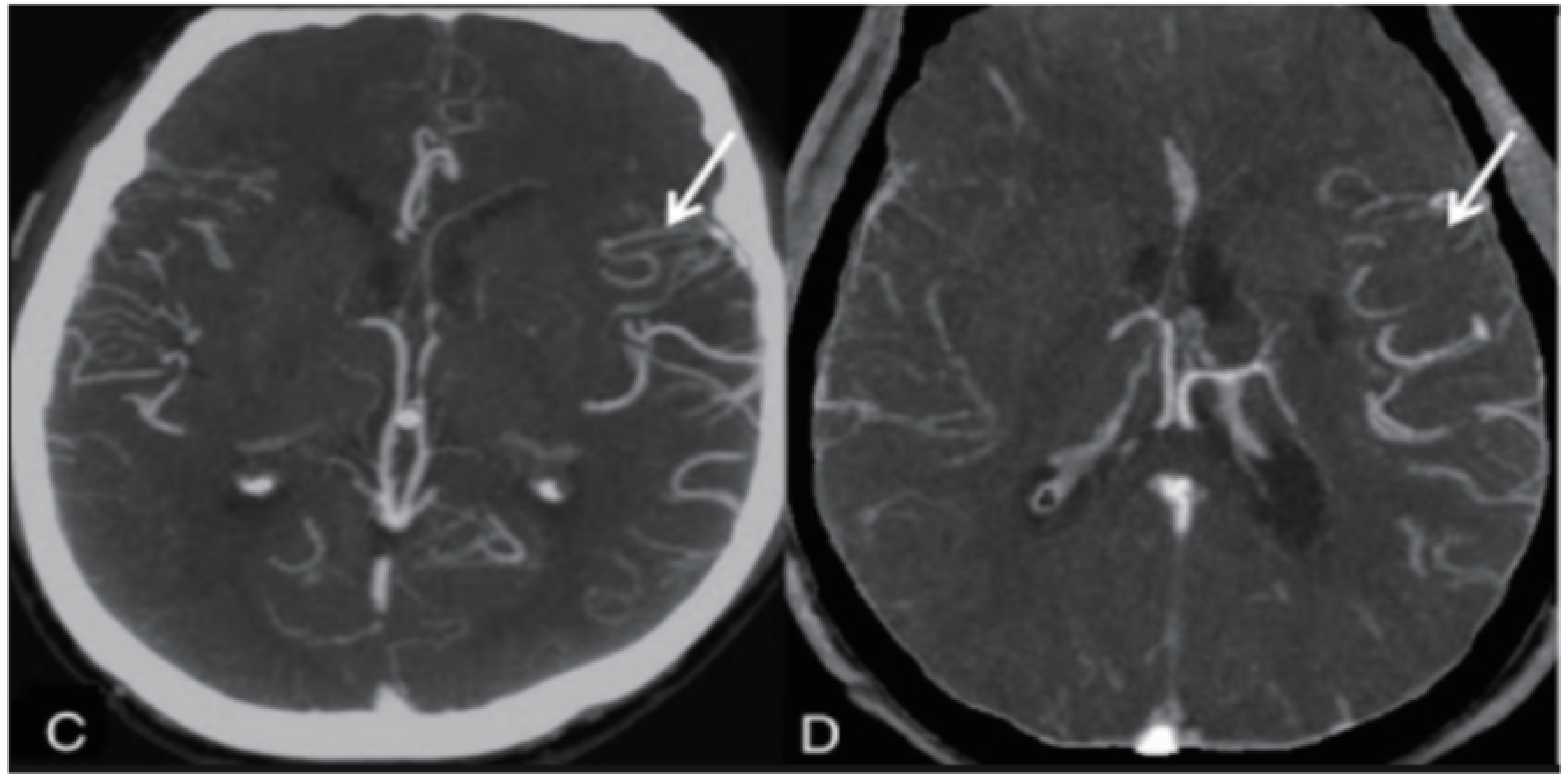
↓

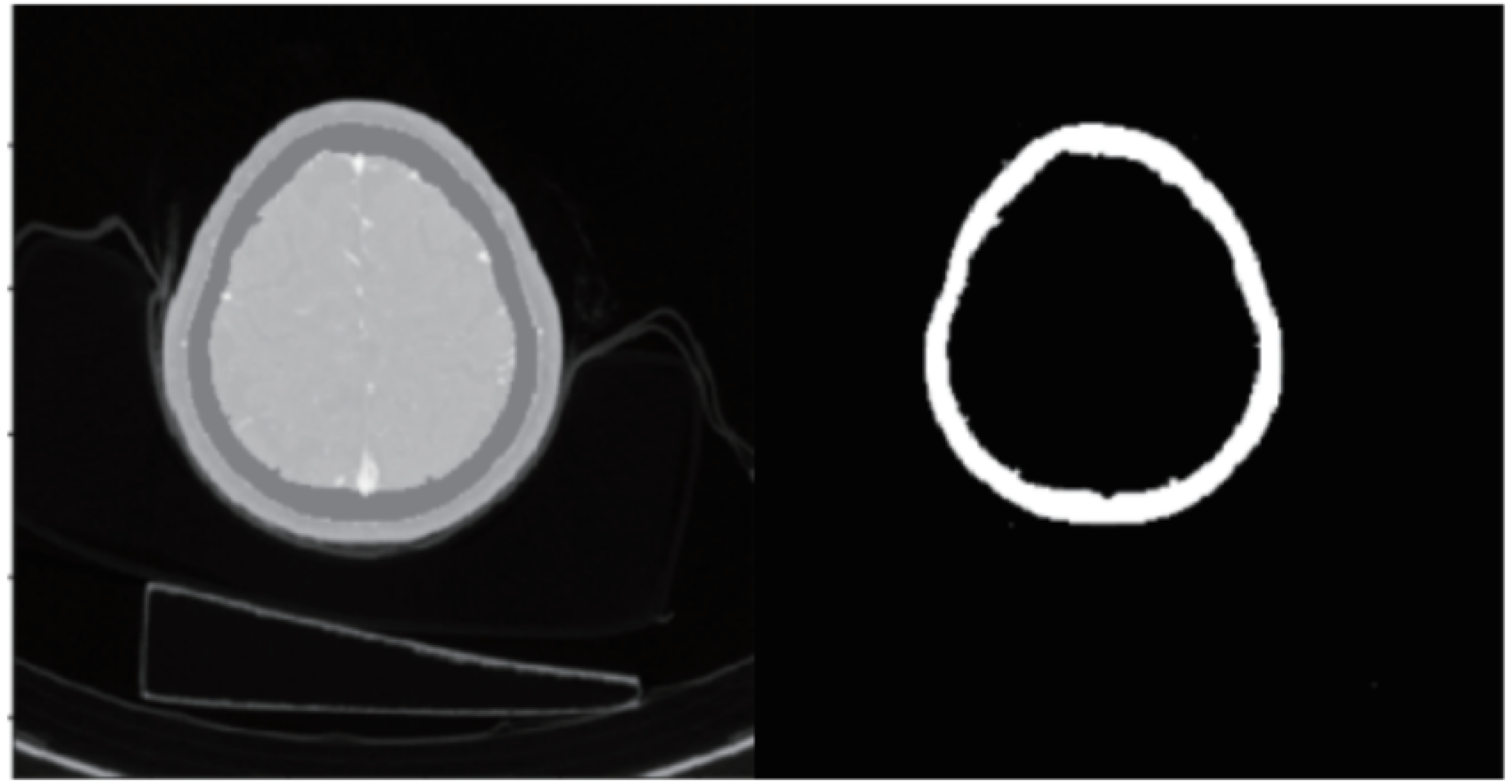
Cerebral Infarction MR, ADC Images detection Develop to AI-assist Software

Skull Segmentation

Main Goal : Brain CT Angiographgy Skull Segmentation

Removal of Skull is beneficial for radiologist to read the images and detect cerebral aneurysm, arterial steno-occlusion, collateral flow.



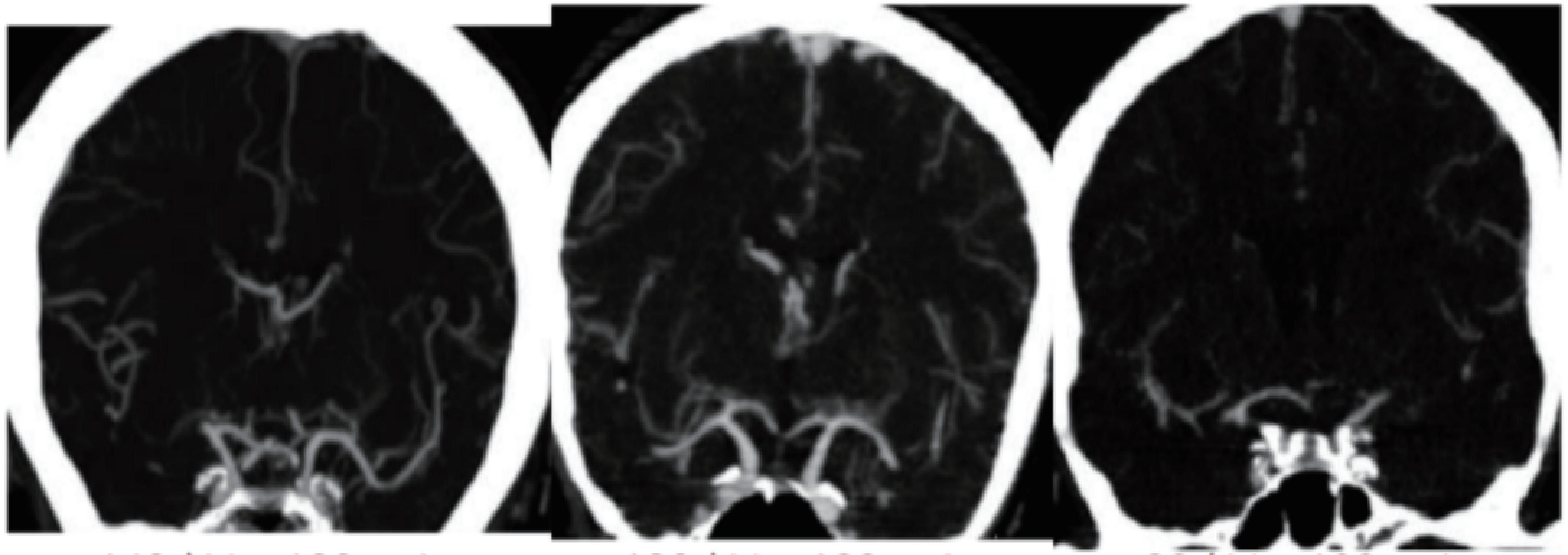


02 Methods

Previous Method Problem

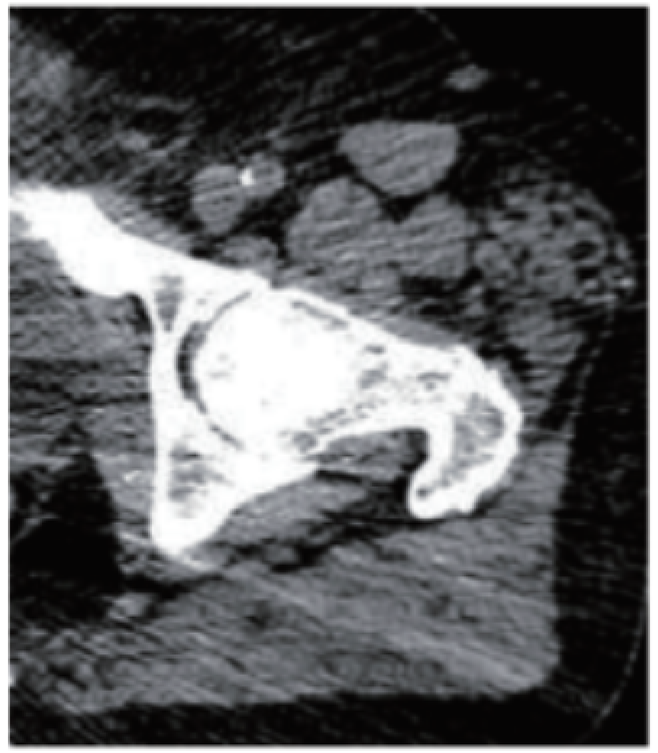
Dual Energy Computed Tomography(CT) : High Economic Costs, Low Availability.
-> Automatic Skull Stripping of Different Resolution is not supported.

Single Energy Computed Tomography(CT) : Does not support Automatic Skull Stripping.



140 kVp, 100 mAs　　120 kVp, 100 mAs　　80 kVp, 100 mAs

Dual Energy

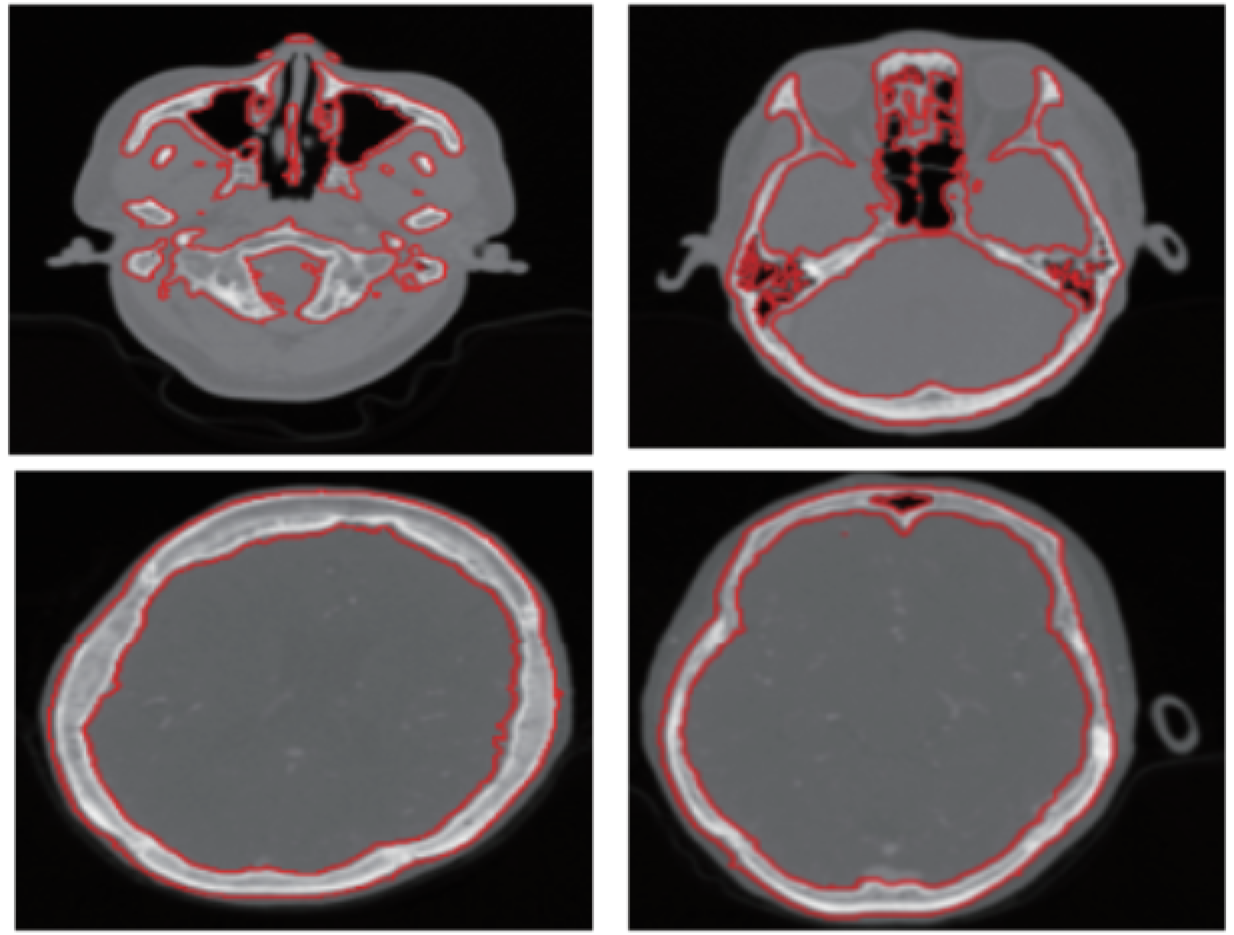


Normal

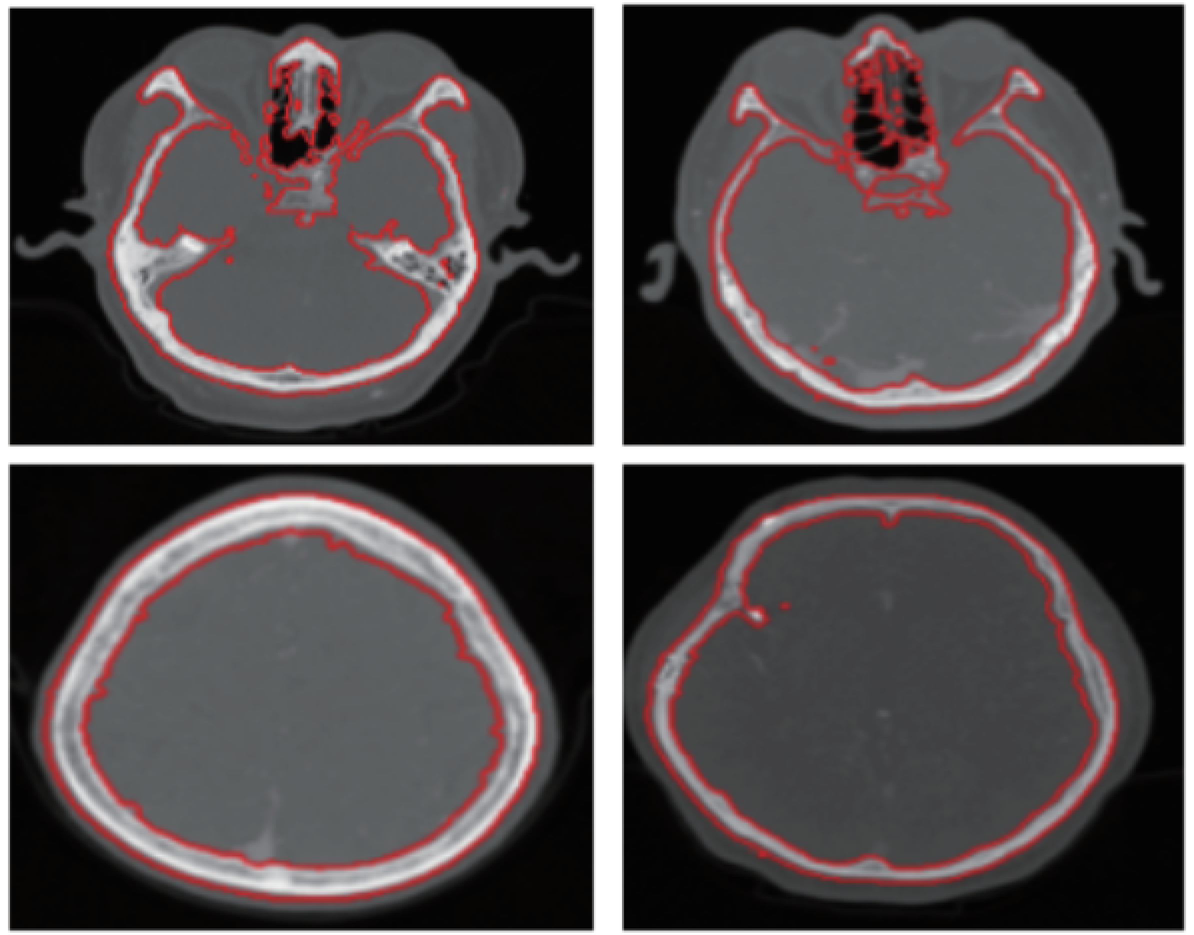
03 Experiments

Result

Skull Segmentation Case 2 - 150kVp



Skull Segmentation Case 1 - 90kVp



Dataset (Model)	Dice coefficient	F1 Score	Precision	Recall
Skull (SPM)	0.79			
Skull (BET/FSL)	0.83			
Skull (90kVp)	0.9326 ± 0.02	0.8572 ± 0.018	0.8852 ± 0.016	0.831 ± 0.02
Skull (150kVp)	0.9307 ± 0.04	0.8825 ± 0.009	0.9020 ± 0.012	0.864 ± 0.006

03 Experiments

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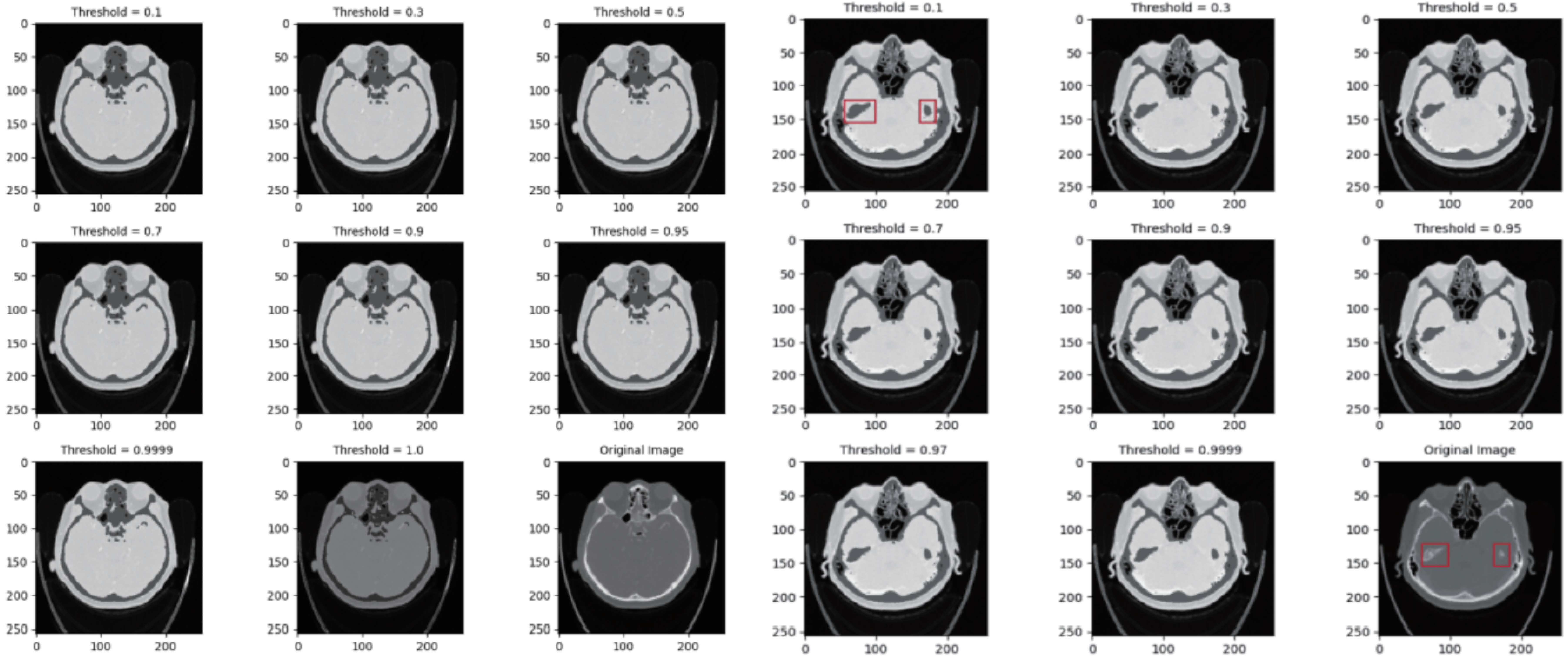
Result



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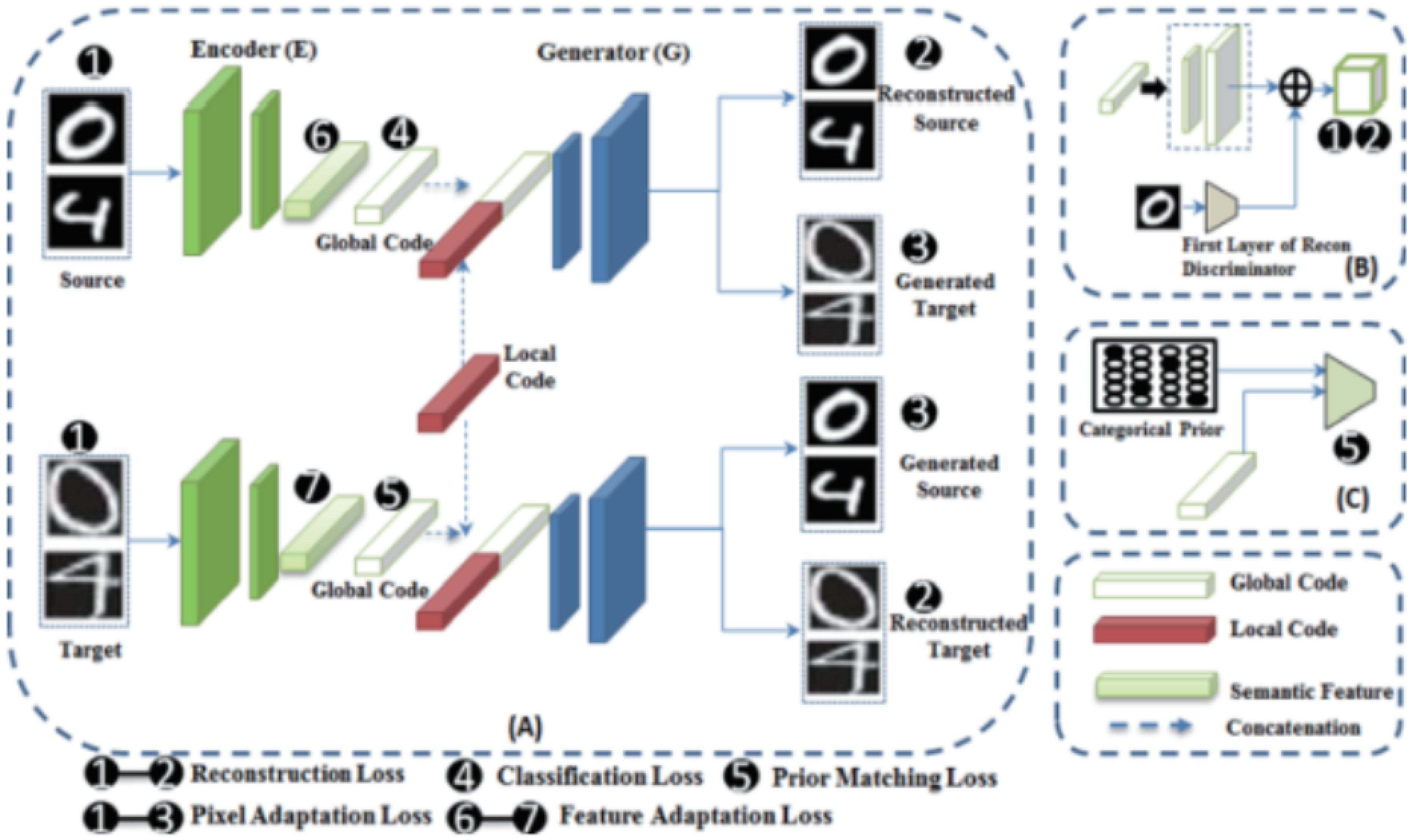
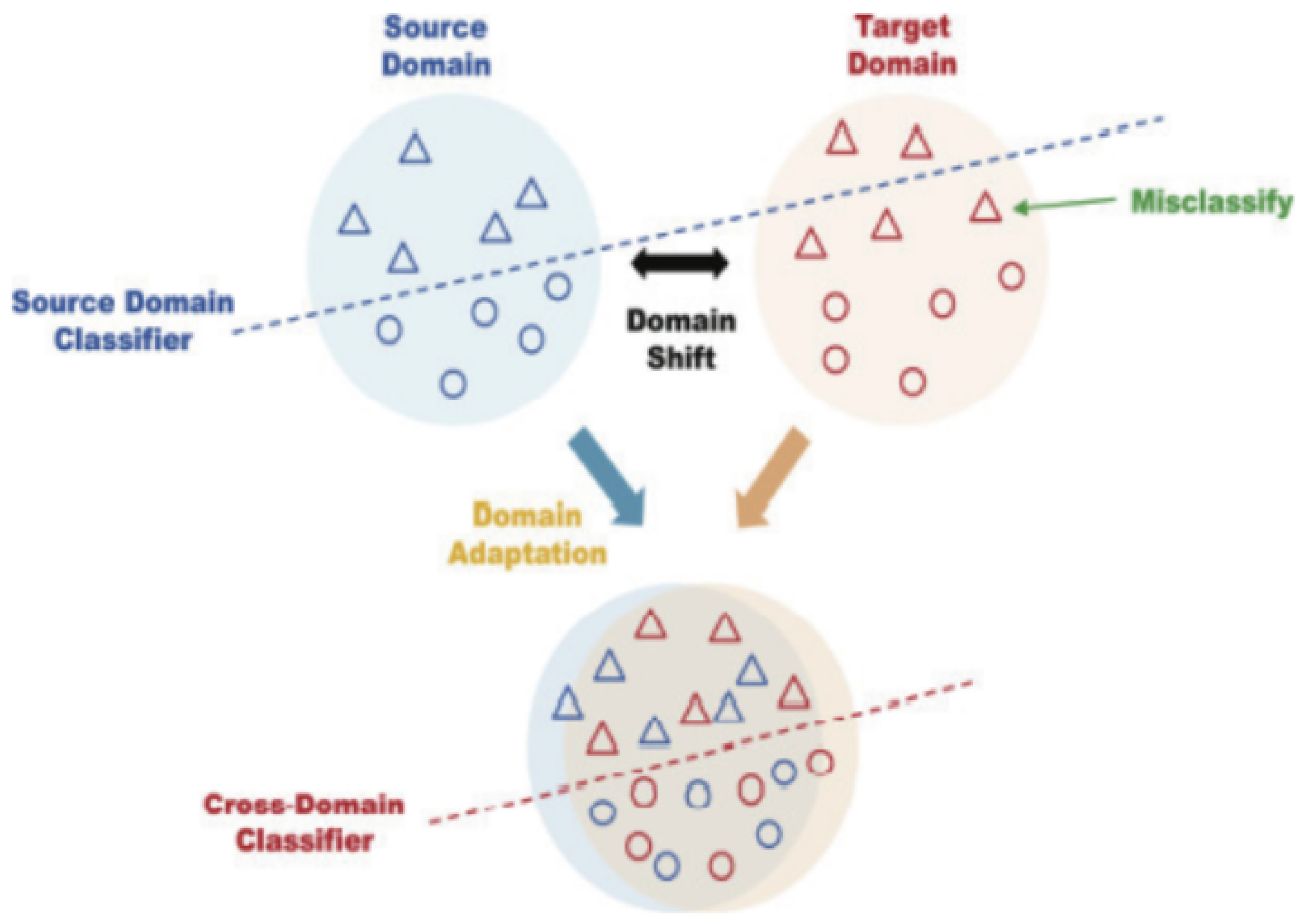
Conflicts of interest are listed at the end of this article.

Domain Adaptation

- Domain adaptation is the ability to apply an algorithm trained in one or more "source domains" to a different (but related) "target domain" (Subcategory of transfer learning)





Domain Adaptation in MRI

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.

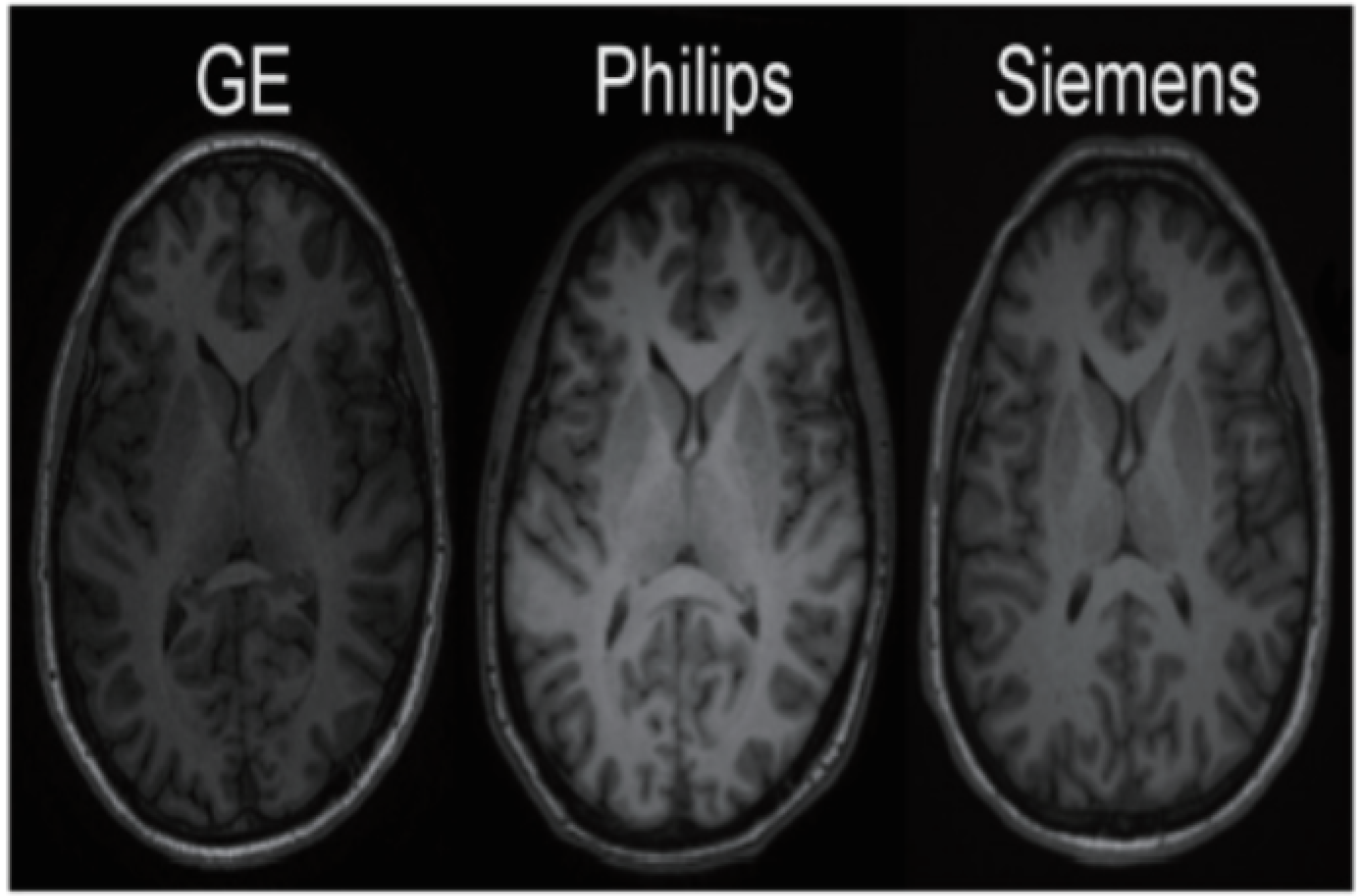


Table 1: Specifications of Cine MRI Datasets Acquired from Scanners of Different Manufacturers

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.

Source : The Canadian Dementia Imaging Protocol:
Harmonization validity for morphometry measurements, NeuroImage, Clinical

Results - Performance Drop

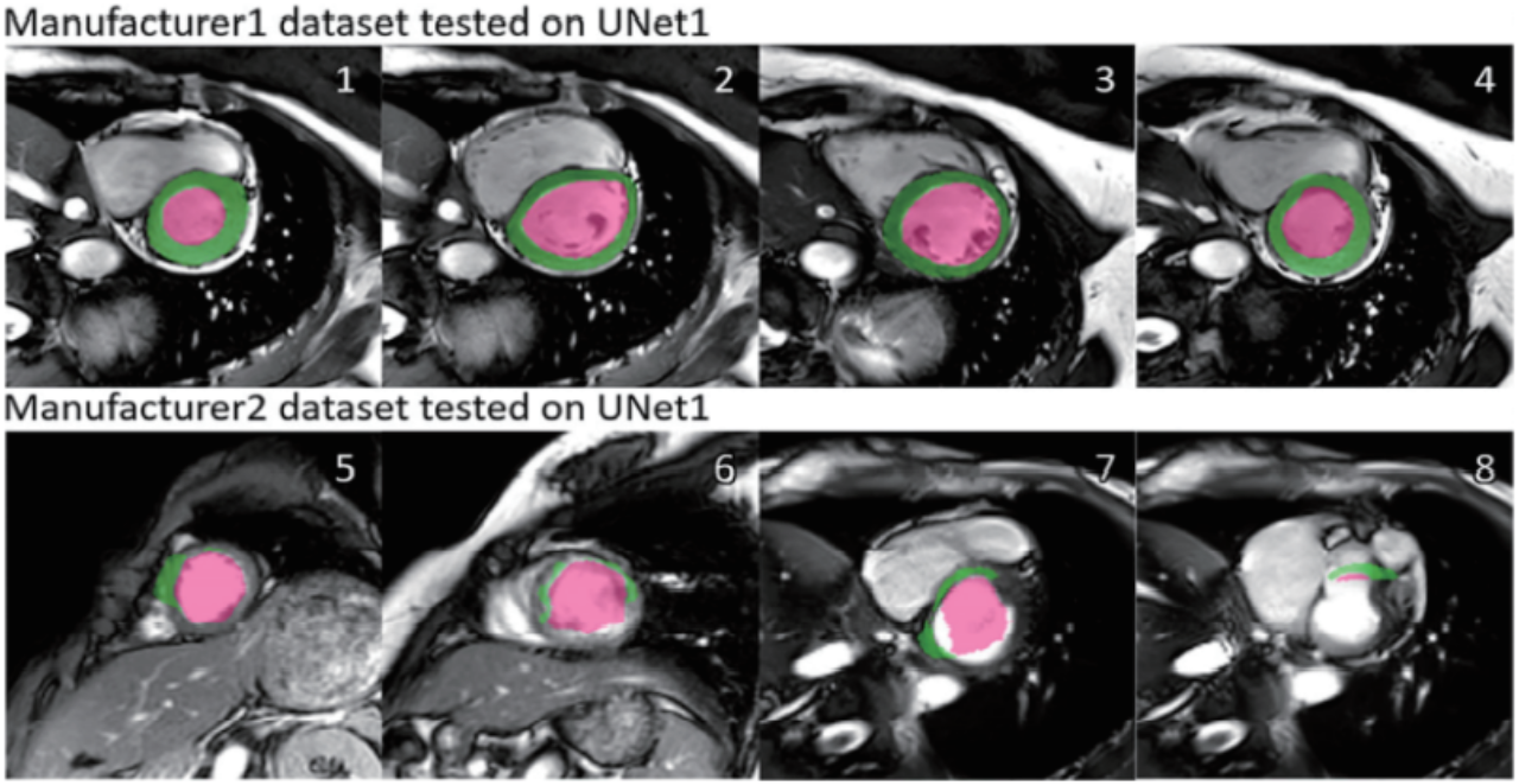


Figure 1: Illustration of the manufacturer shift problem. The upper row shows the performance of U-Net 1 tested on datasets from manufacturer 1, and the lower row shows the performance of U-Net 1 tested on datasets from manufacturer 2. A performance drop can be observed, in the form of undersegmentation. Numbers at upper right corner of each subfigure indicate different examples. Green regions denote the automatic myocardium segmentation results by the U-Net, while red regions denote the blood pool segmentation results.

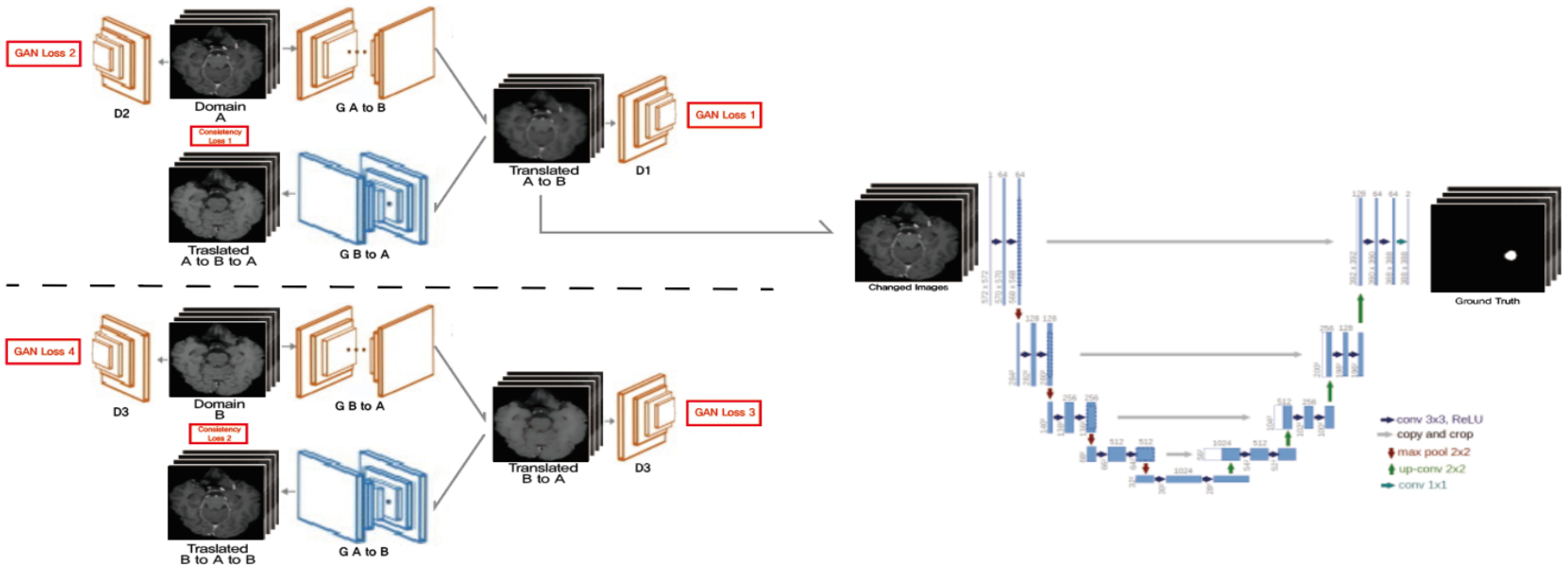
Proposed Framework

Domain Adaptation Model

Model : Unsupervised Translation Generative Adversarial Network (Cycle-GAN)

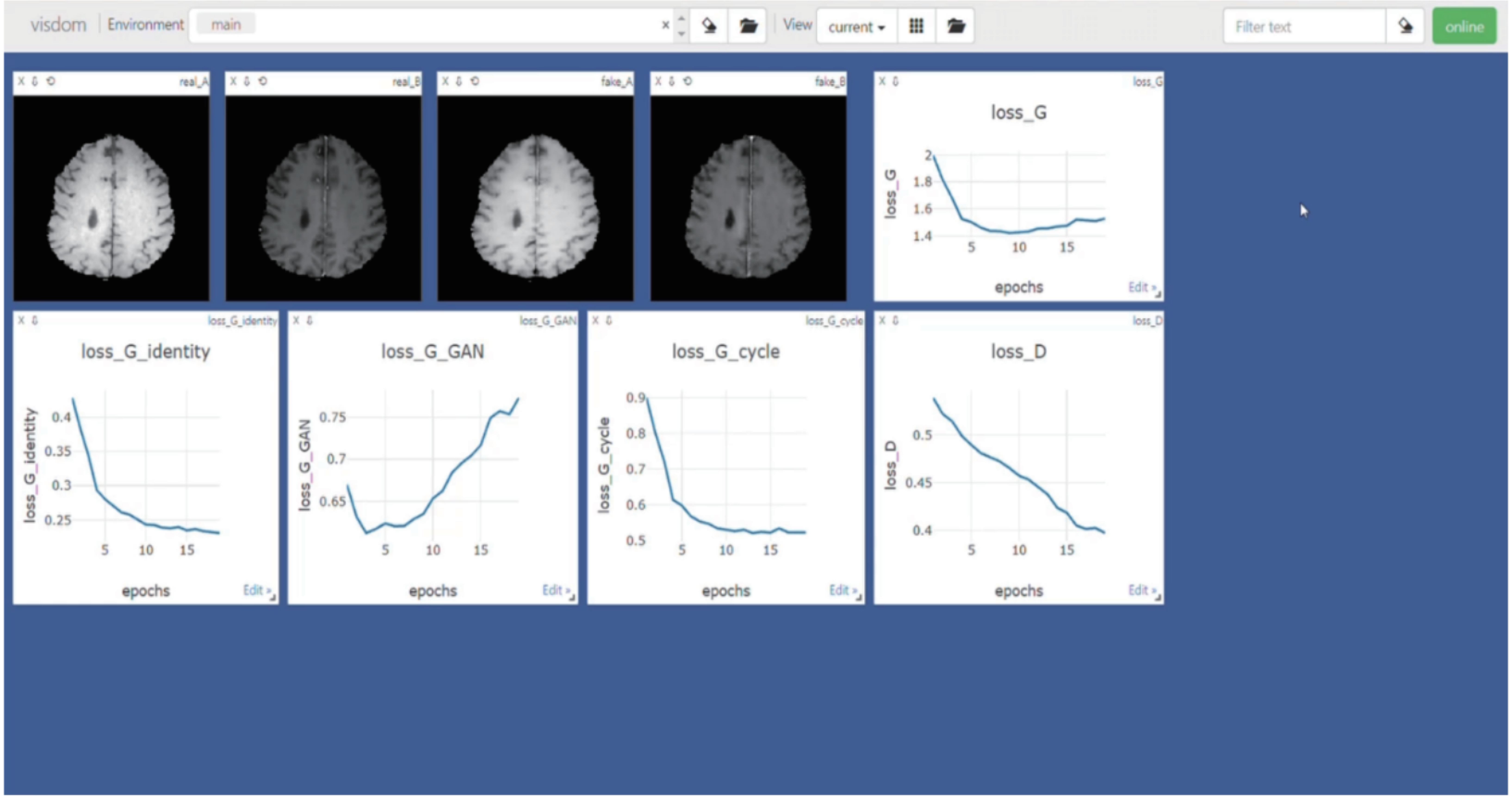
Skull Segmentation Model

Convolutional Neural Network (Residual Connection Sum Upgraded U-Net

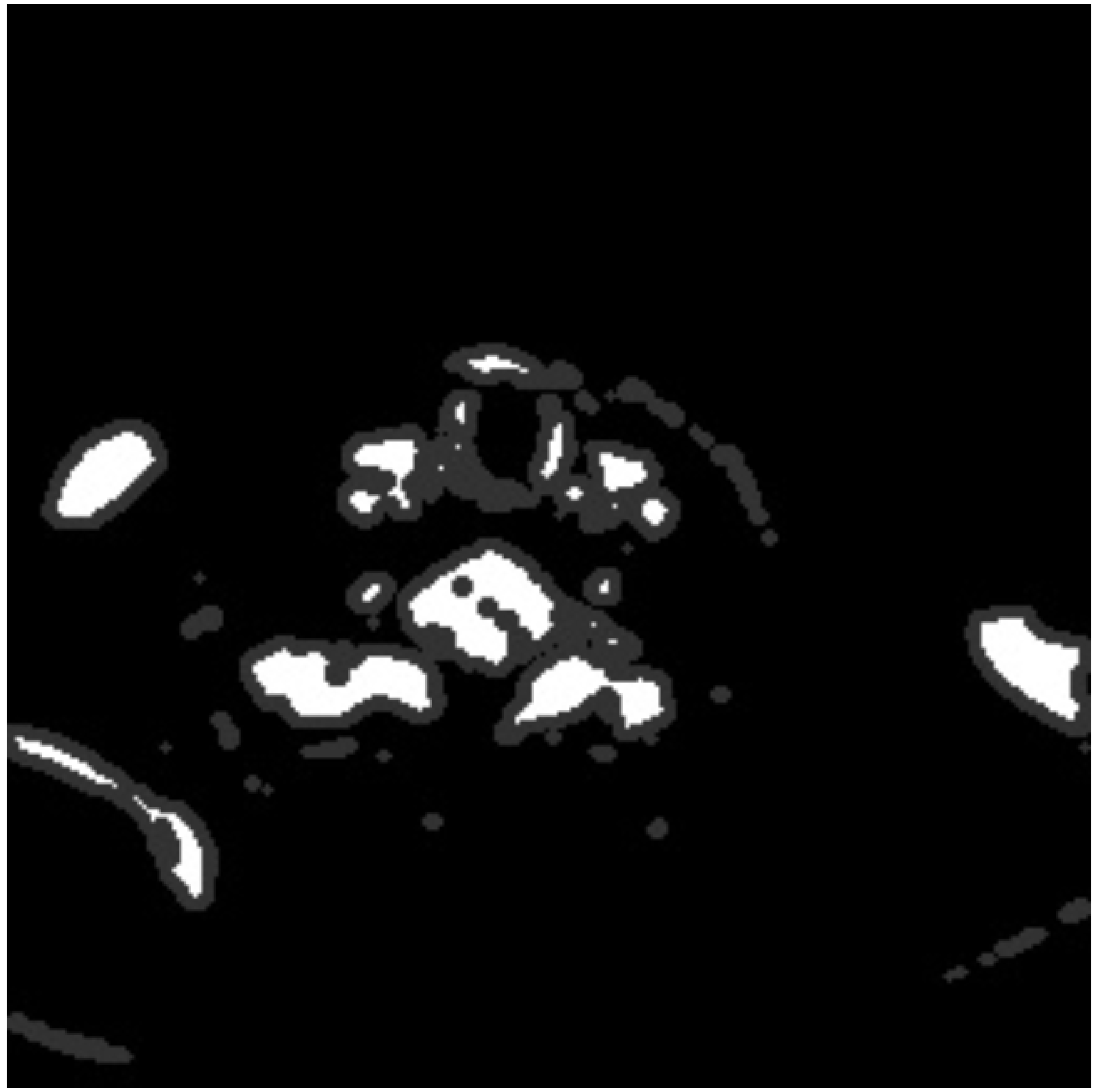


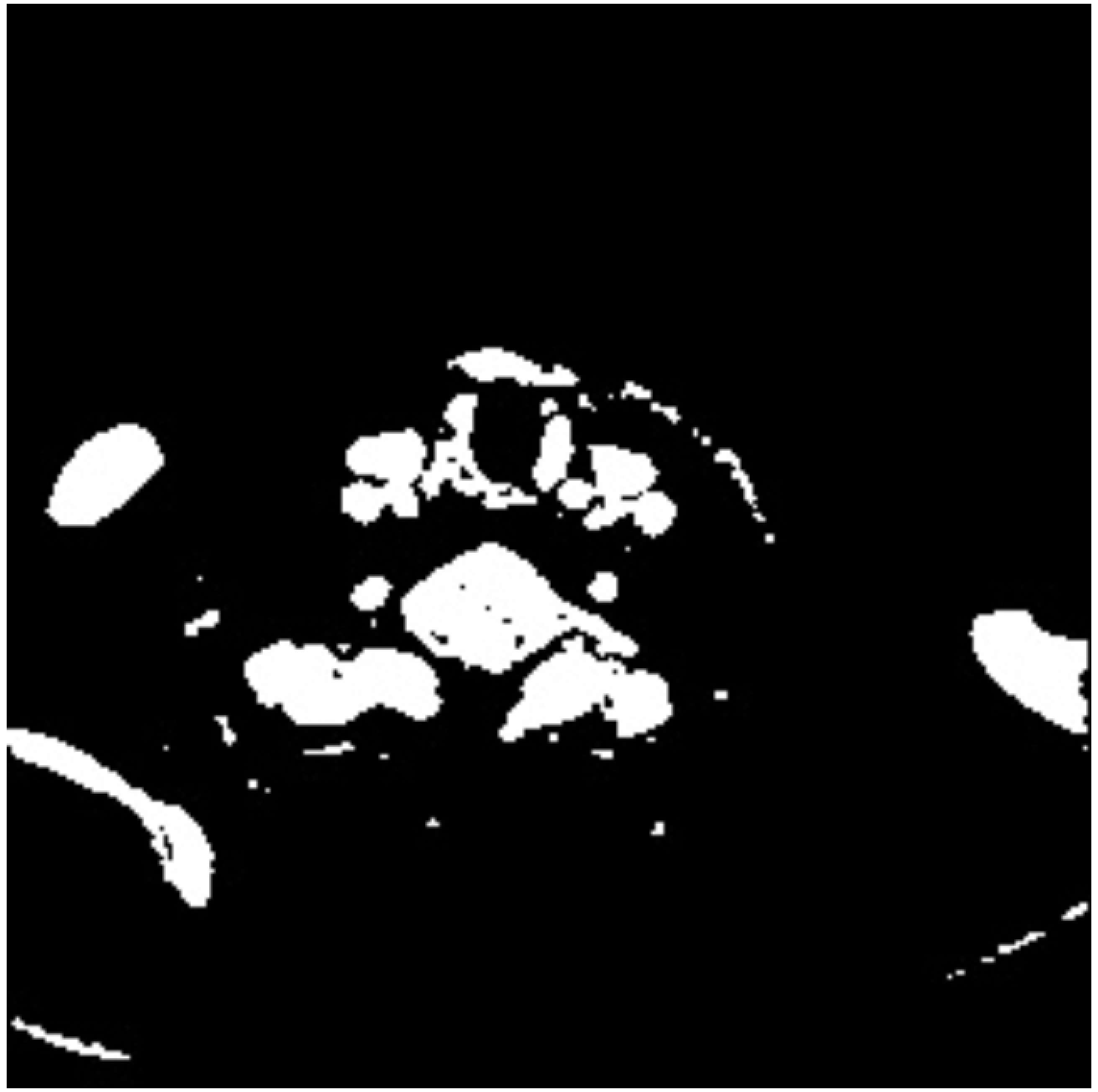
03 Experiments

Result



03 Experiments





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