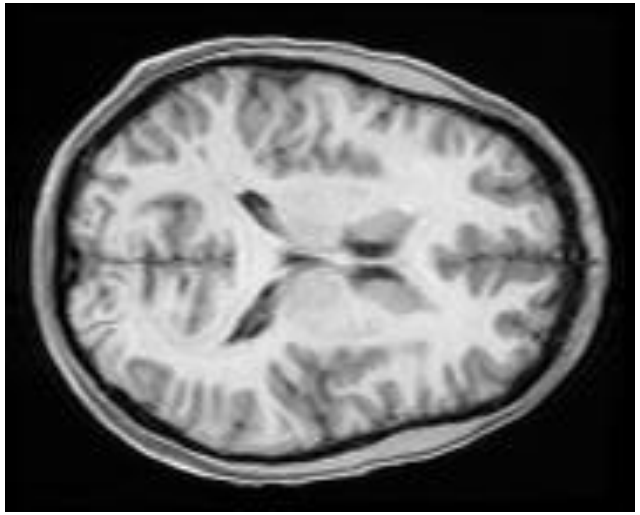
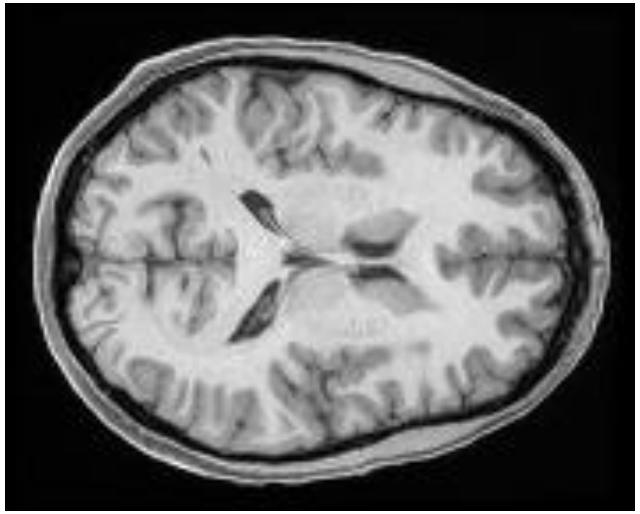
Super-resolution on brain MPRAGE data

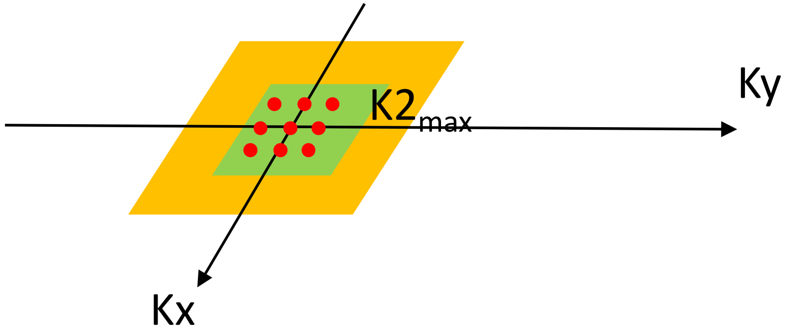
Chaowei Wu, Yu Wang, Ruihao Liu

01/09/2018

Introduce of Super-Resolution problem

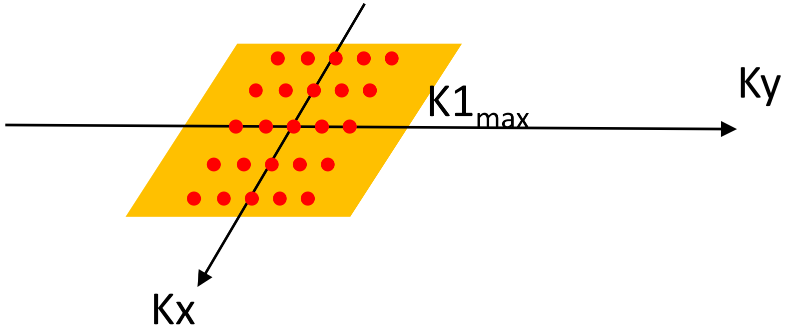






ill posed

Prior information



Little variation

Large variation

Super-resolution problem

Traditional [1]

$$R_{\text{reg}}\{y\} = \underset{x\in X}{\operatorname{argmin}}\ f(H\{x\}, y) + g(x),$$

H: Degradation model g: Regularize term f: Cost function

g: sparsity-promoting regularizers, total variation [4]

Handcraft the forward model, cost function, regularizer, and optimizer. Limited prior information.

Learning based solving [1]

$$R_{\text{learn}} = \underset{R_\theta, \theta\in\Theta}{\operatorname{argmin}} \sum_{n=1}^{N} f(x_n, R_\theta\{y_n\}) + g(\theta)$$

R: learned model g: Regularize term f: Cost function

Res-net GAN and U-net have been applied in super-resolution problem. [2][3]

Learned model with complex function can absorb more prior information.

[1] Mccann M T, Jin K H, Unser M. Convolutional Neural Networks for Inverse Problems in Imaging: A Review[J]. IEEE Signal Processing Magazine, 2017, 34(6):85-95.
[2] Chen Y, Xie Y, Zhou Z, et al. Brain MRI Super Resolution Using 3D Deep Densely Connected Neural Networks[J]. Proceedings, 2018:739-742.
[3] Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network
[4] E. J. Candes, J. Romberg, and T. Tao, “Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information,” IEEE Trans. Inf. Theory, vol. 52, no. 2, pp. 489–509, Feb. 2006.

Issues of current learning based methods

- Lack analysis of the learning process
  What's to be learned? How to control?
- Novel Feature
- Artifact

Generated High

True High

Our Goal

- Analysis what prior information we want to learn？
  Help Generator learn it.
- Recover novel feature
- Remove artifacts

Low resolution

↓ **Generator**

4 times High resolution

↓

High resolution + Novel feature

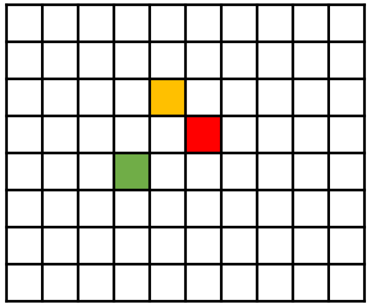
↓

High resolution + Novel feature + without Artifact

Step 1： Machine Learning

Analysis of machine learning

- Machine Learning: Learn P(output | input), give the most probable output.



$$\text{Image} = f\,(\theta_t, \theta_p, \theta_g)$$

Θ_t: tissue property
Θ_p: parameters related to imaging
Θ_g : geometry of the brain

- **Traditional:**

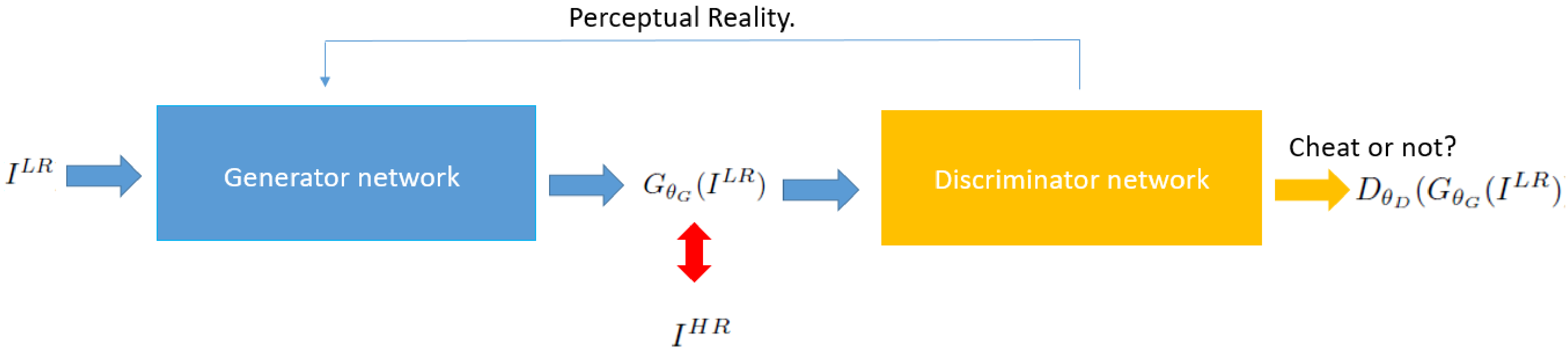
  $P(\theta_{t\text{-high}}, \theta_{g\text{-high}} \mid \theta_{t\text{-low}}, \theta_{g\text{-low}})$

- **Our methods:**

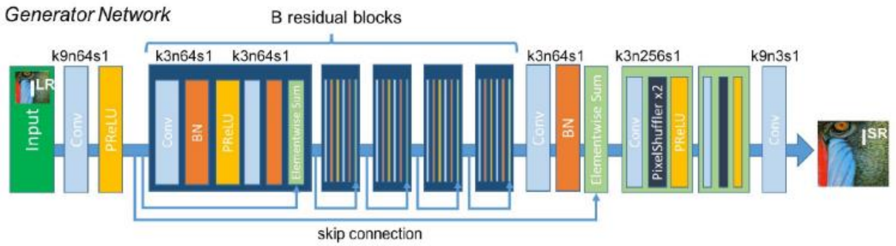
  Do normalization. No patch

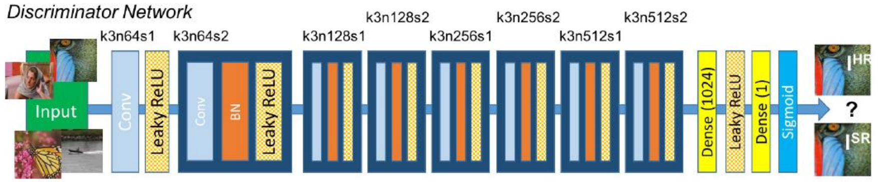
  $P(\theta_{t\text{-high}} \mid \theta_{t\text{-low}})$ **To train more accurately and efficiently.**

Neural Network we use

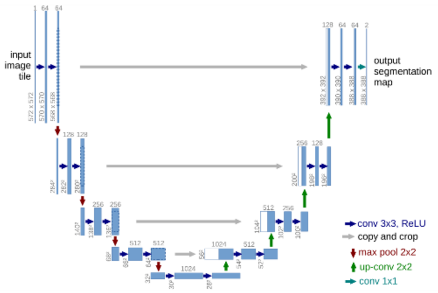


Res-net





U-net

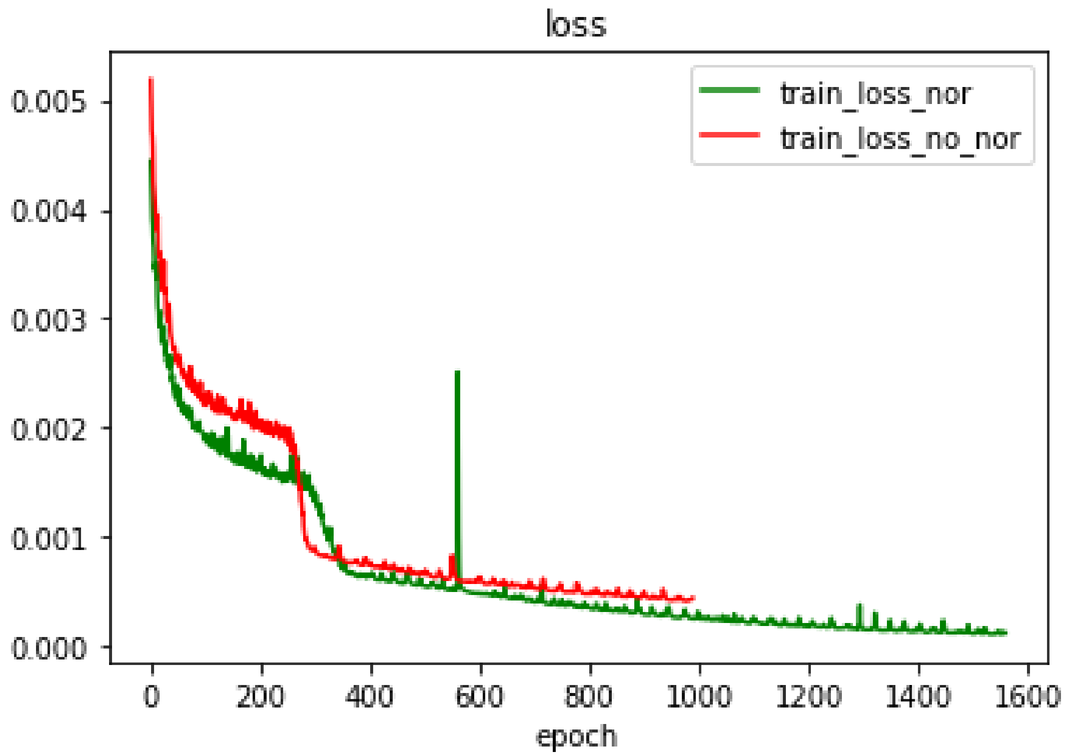


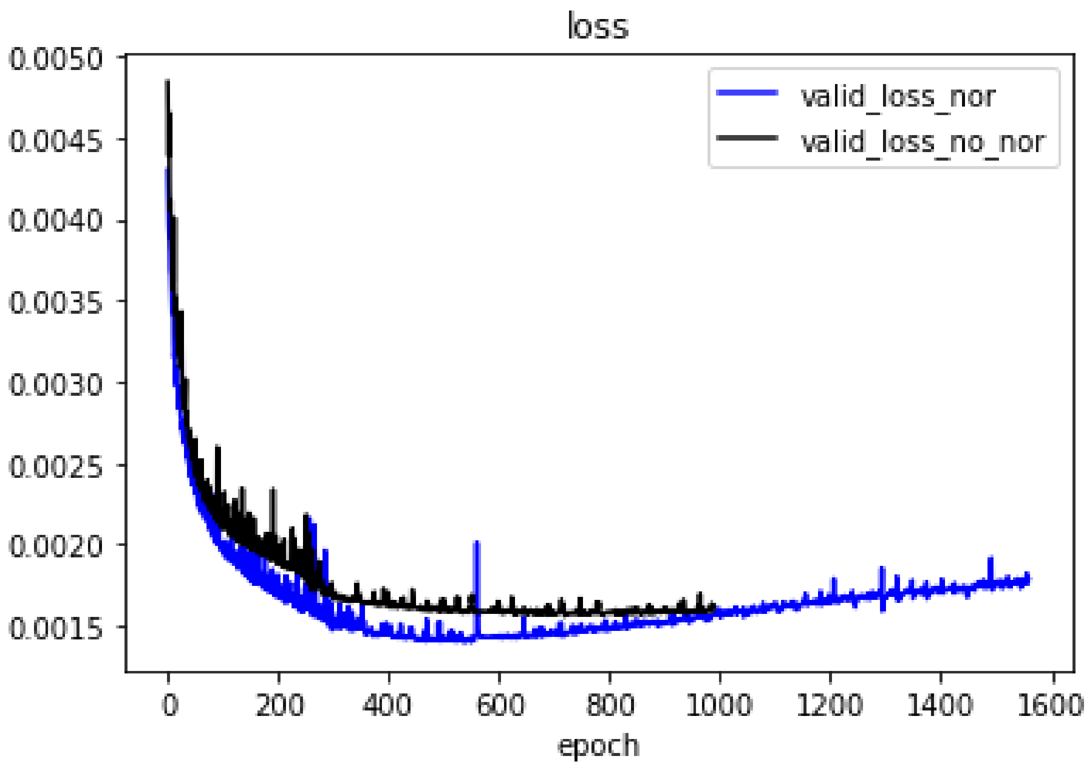
Result

1. Effects of Normalization
2. Comparison between Res-net GAN& U-net GAN

1. Effects of Normalization

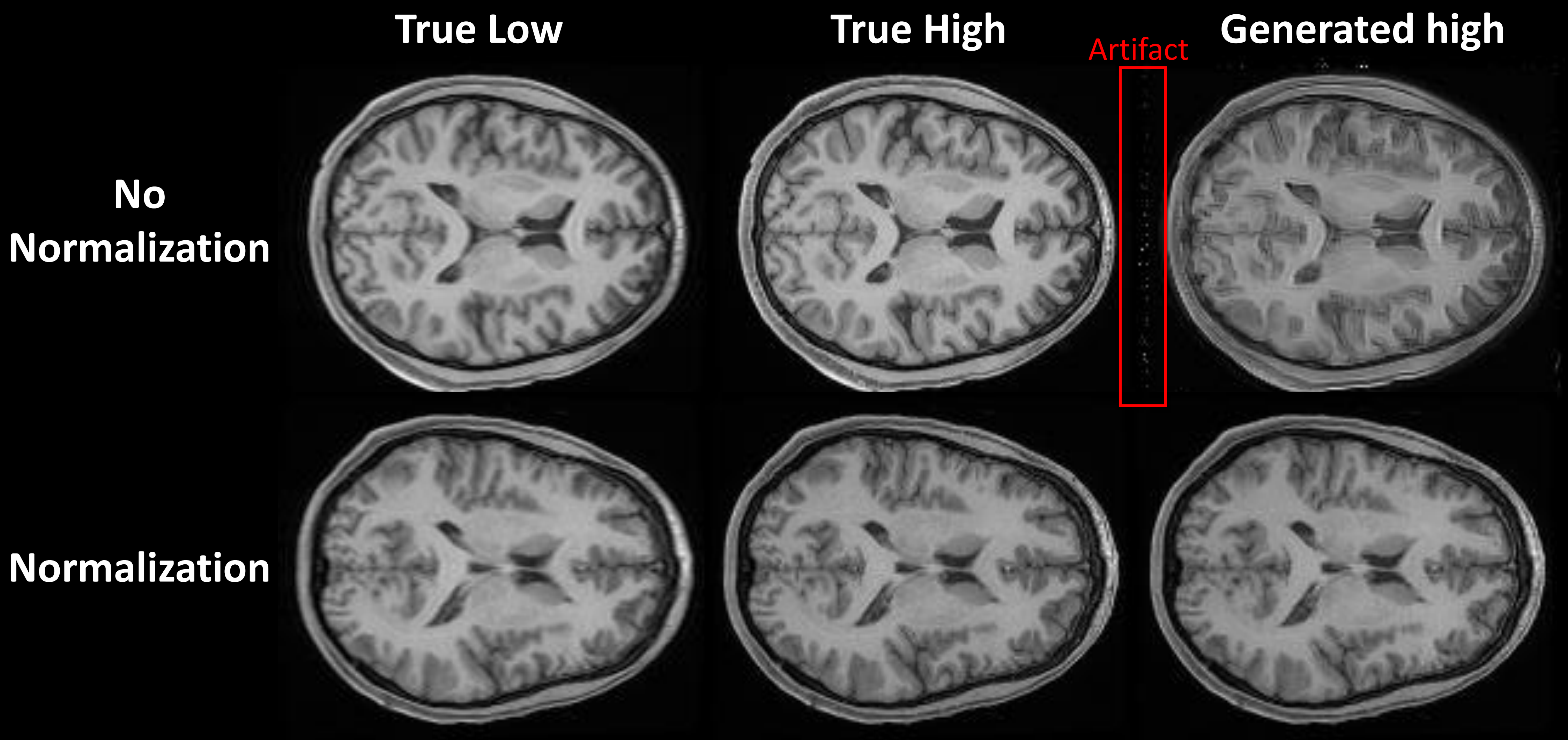
U-net: Normalization vs Non-normalization





Normalization helps learning converge faster and lower the loss.

1. Effects of Normalization U-net GAN result



For U-net, normalization does make training more efficient and accurate.

Res-net GAN vs U-net GAN

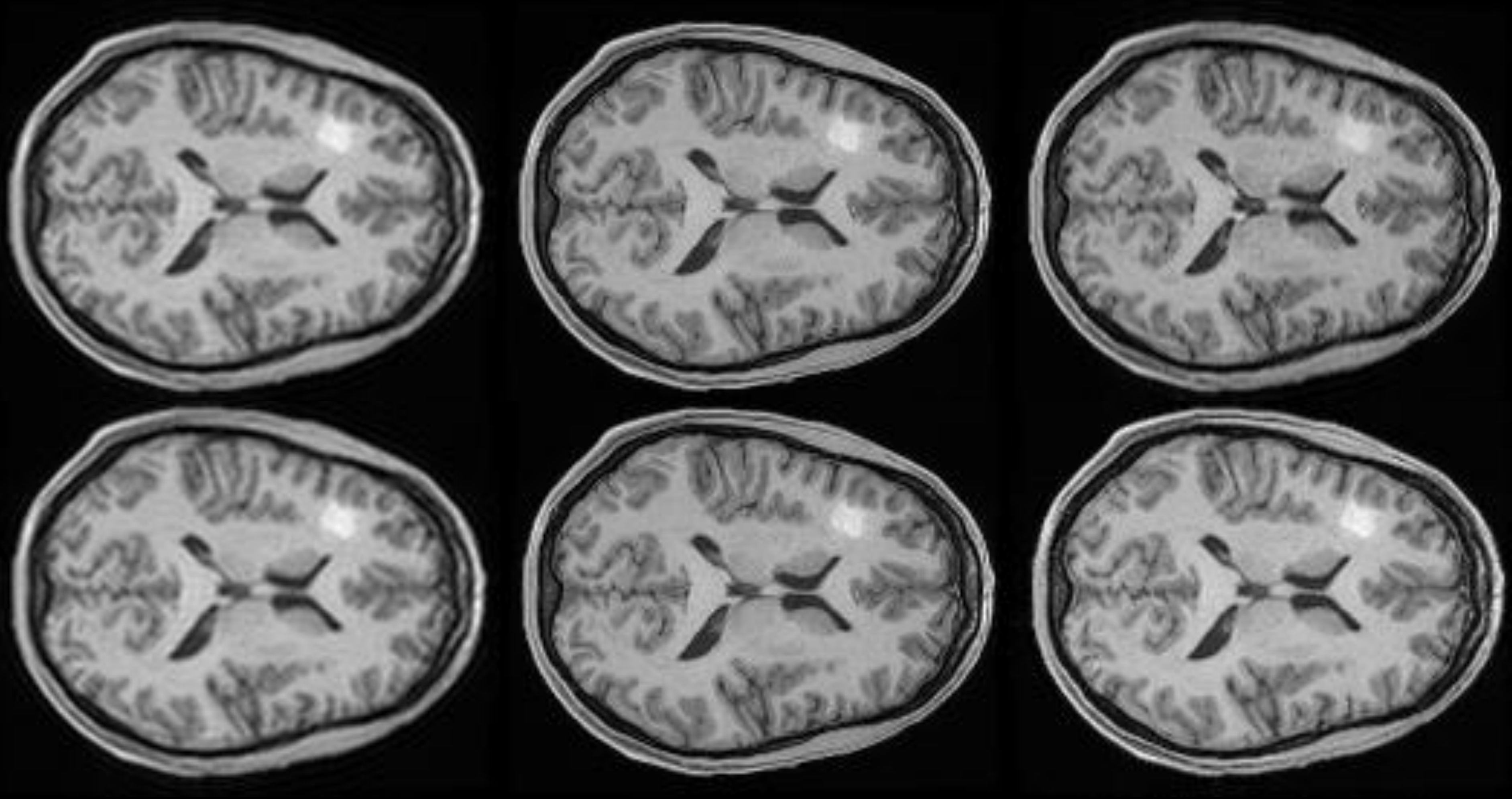
- Resolution
- Novel Feature recovery
- Artifact

Resolution

Low | High | Generate high

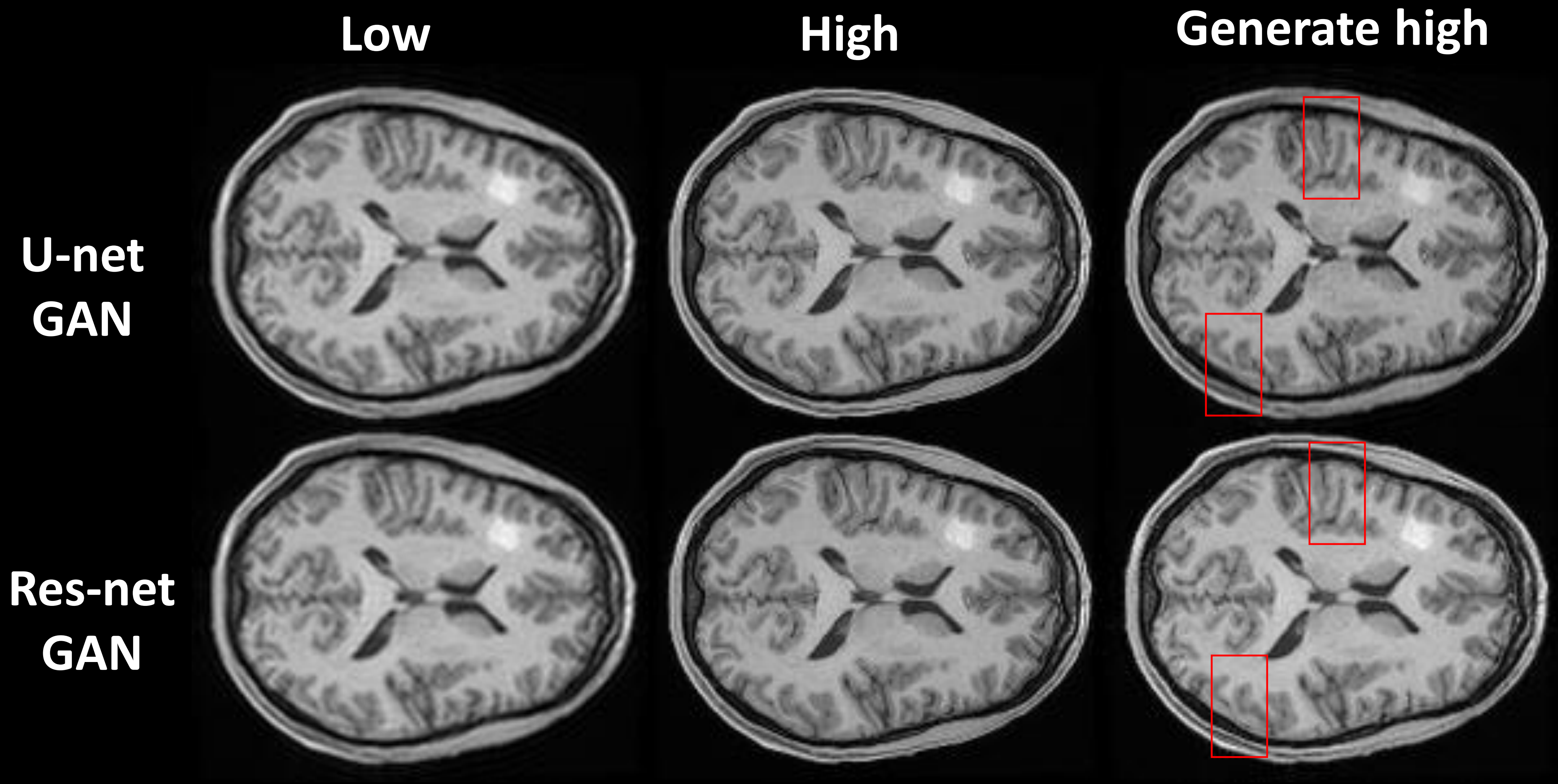
U-net GAN

Res-net GAN



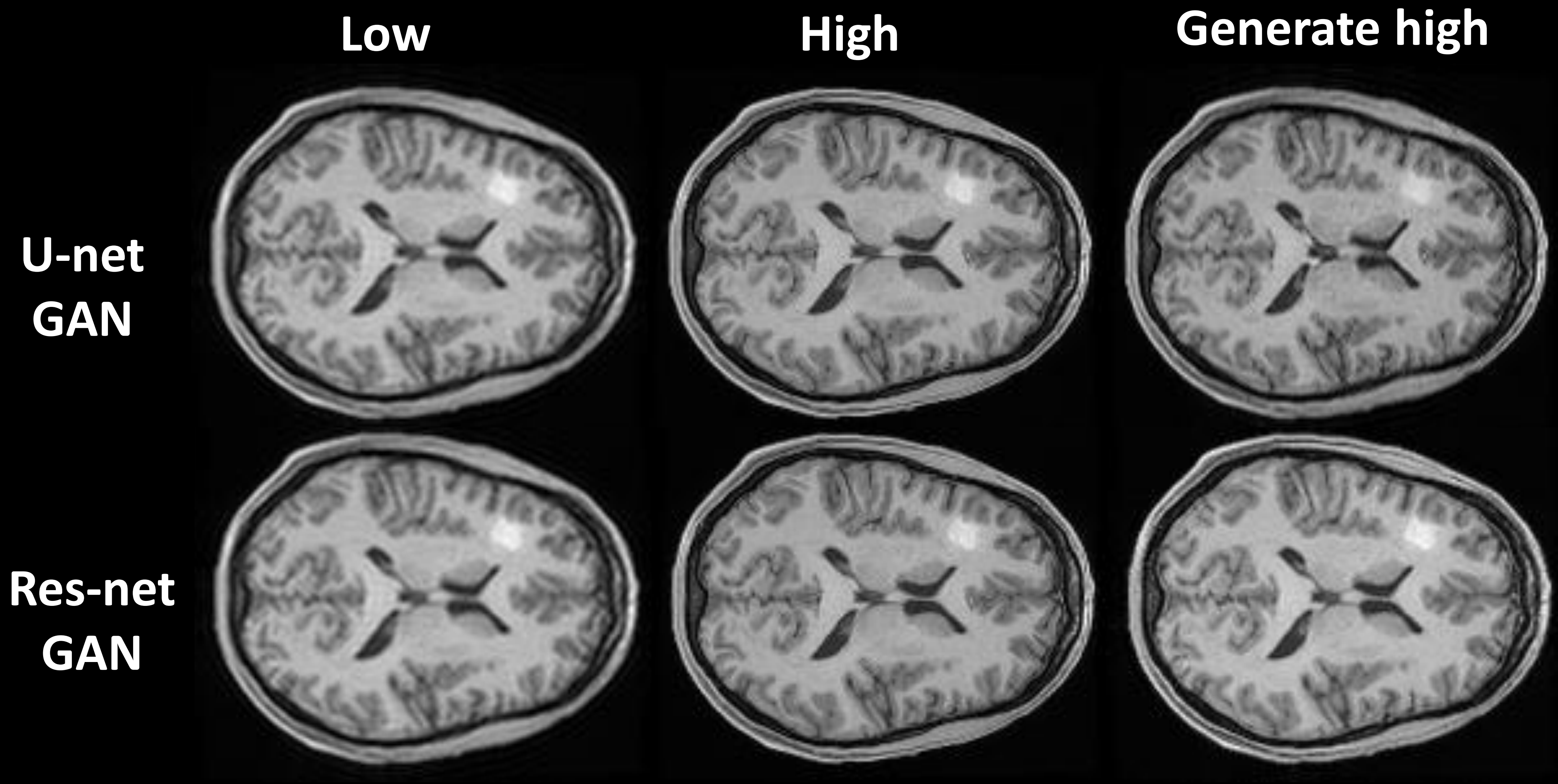
Resolution of generated high are comparative.

Artifact



Res-net GAN generates more artifacts.

Novel Feature



Novel Feature

U-net GAN

Low

High

Generated high

U-net GAN is learning tissue probability distribution.

Conclusion:

- Normalization does help learn more efficiently and accurately.
- Tissue probability distribution learned by U-net GAN. Need further study. Help novel feature recovery.
- U-net GAN outweighs Res-net GAN in Artifacts.

U-net GAN in the following

Future Direction:

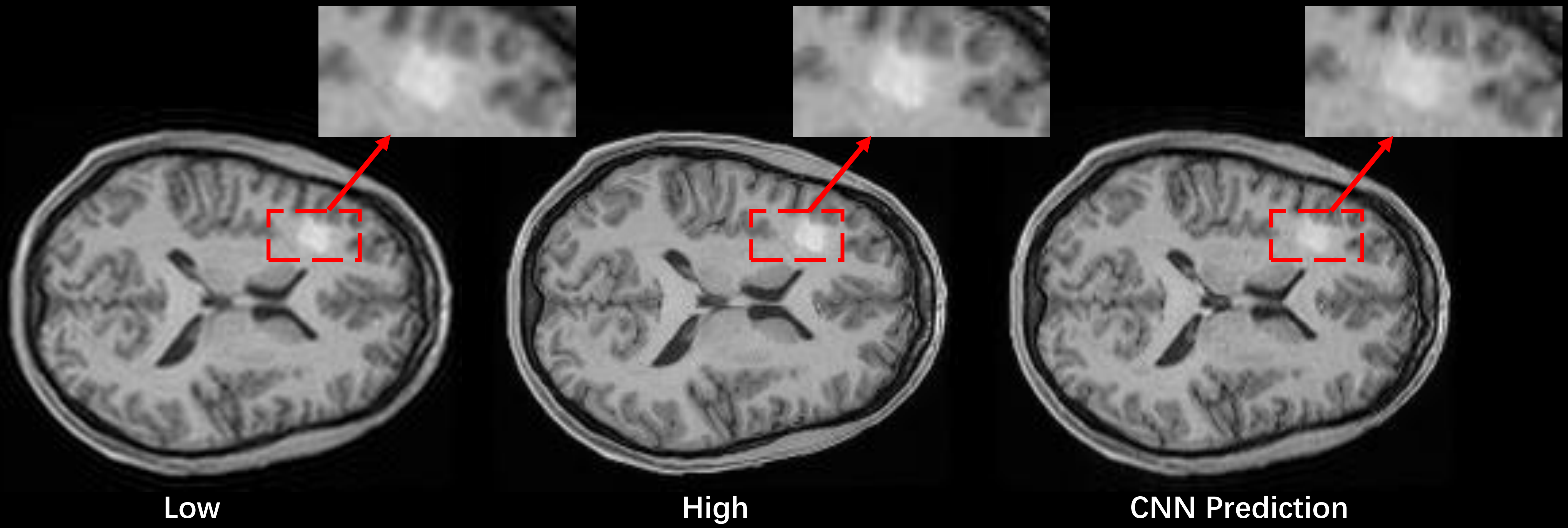
Improve the neural network structure better fits data.

- To generate higher resolution
- Get fewer artifact
- Get novel feature more normal-like

Step#2 Novel Feature Extraction

The Problem

- Much higher resolution
- Obscure novel feature



Sparsity Based Novel Feature Extraction model

$$argmin_{\rho}||d' - \Omega F\rho||_2^2 + \lambda||W\rho||_1$$
$$d' = d - d_{ref}$$

In which d is true inner k space data, d_{ref} is data consistency result k space data, W represents sparsity transform, Ω represents truncation operator, F is Fourier Transorm Operator, λ is regularization constant, and ρ is to be solved.

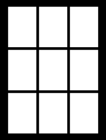
Assumption

- Difference in inner k space contains novel feature
- Feature Sparsity (Image domain, TV, etc.)

Hypothesis:

1) Generated high resolution can recover the normal tissue perfectly but poorly for novel feature
2) Novel feature is sparse and perfect sparse transform is found for regularization.

To use huge amount of information to estimate the low dimensional novel feature.



Low dimensional novel feature

The remain information is all related to novel feature.

Low resolution inner k-space – Generated high resolution inner k-space

Original Difference

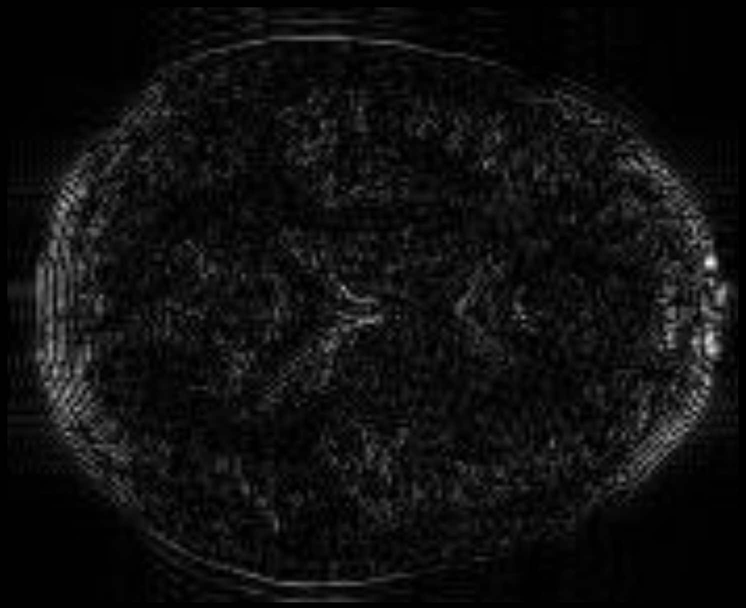
True inner k space

CNN prediction inner k space

Substraction

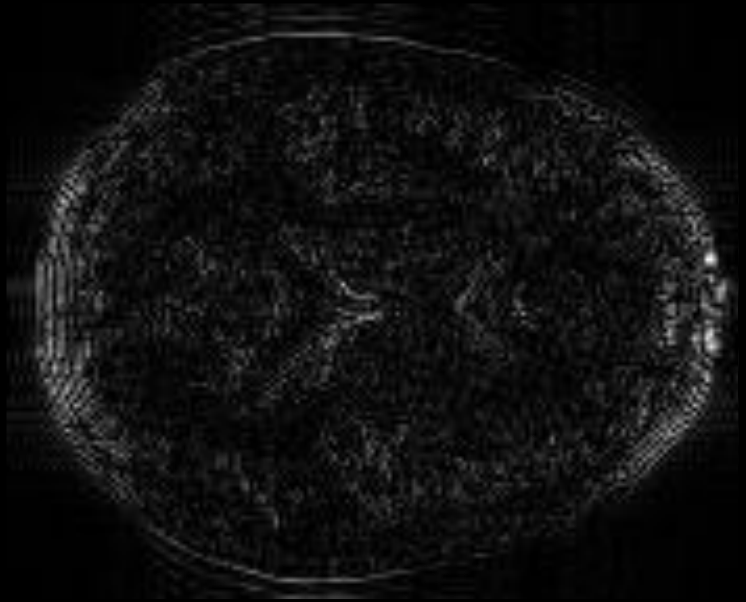
Difference in inner k space

Inverse Fourier Transform

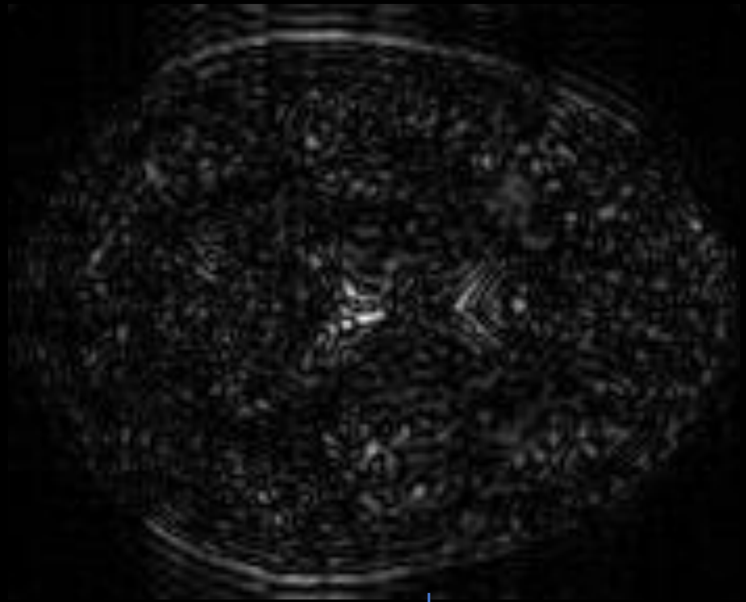


Novel Feature

Original Difference



Extracted Novel Feature
--- Image Domain Sparsity



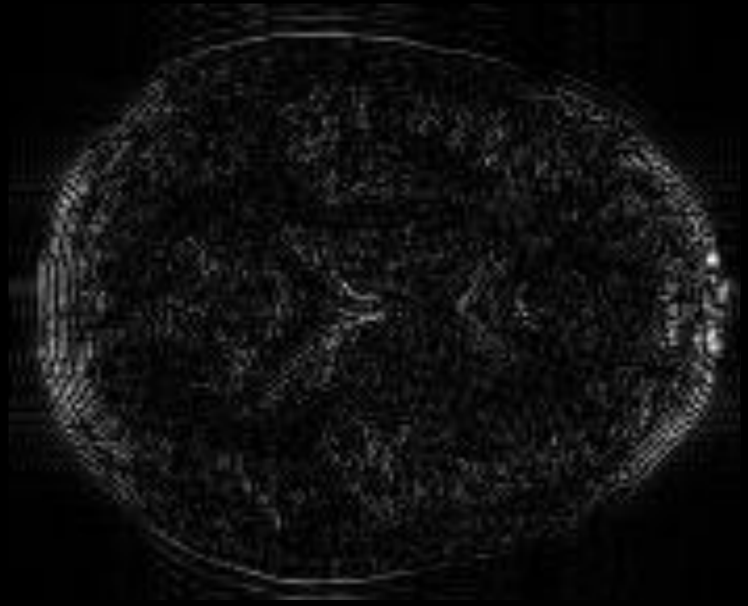
CNN prediction image

Addition

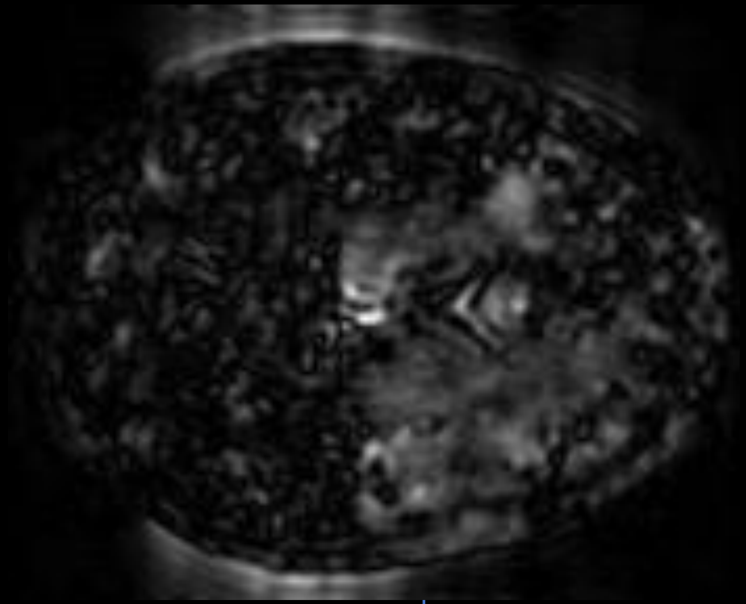
Step#2 Result

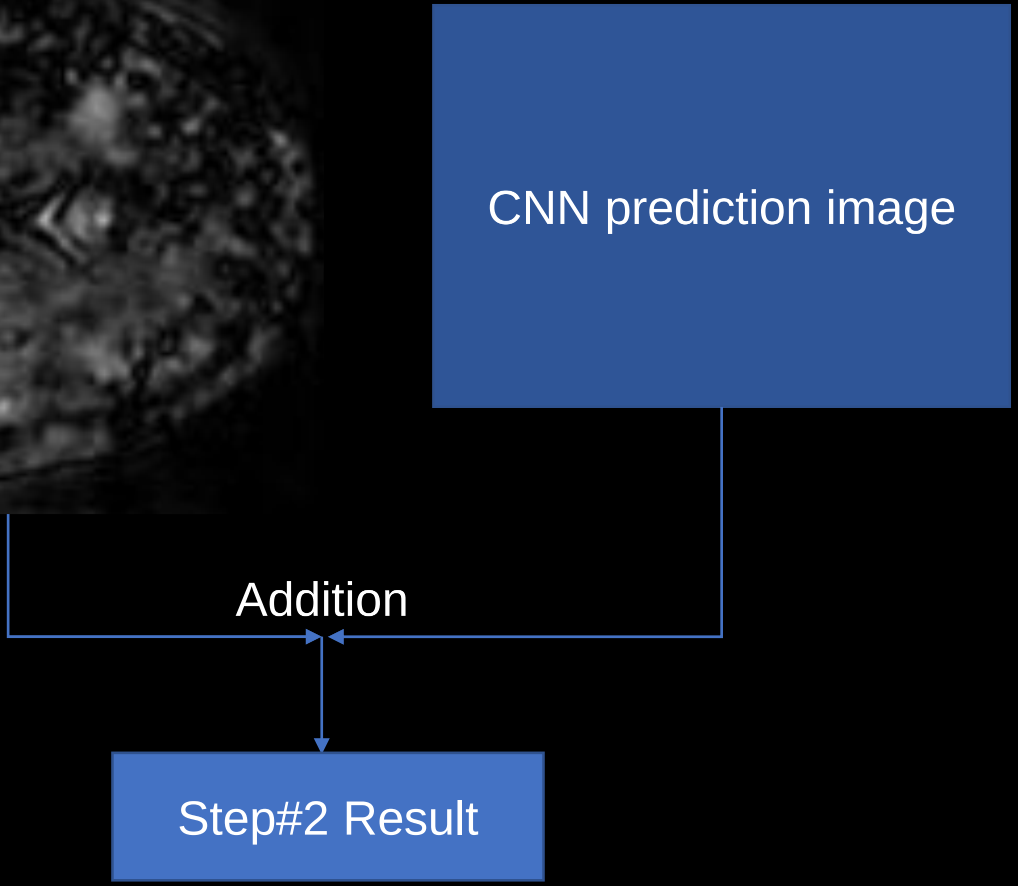
Novel Feature

Original Difference



Extracted Novel Feature
--- Total Variation Sparsity

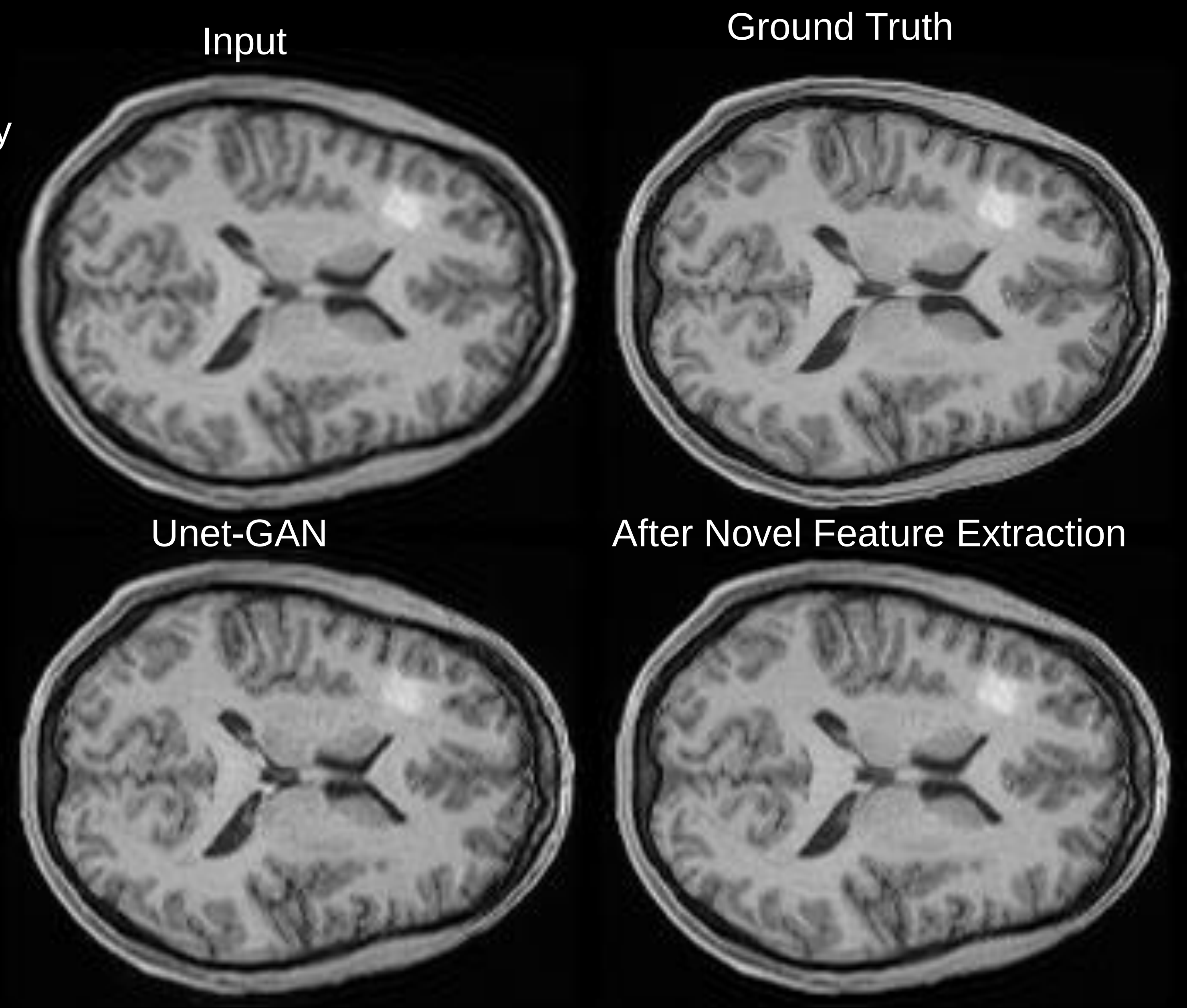




Step#2 Result

--- With Extracted Novel Feature
Constraint by Image Domain Sparsity

- Enhanced Contrast in Novel Feature
- Limitation: Still Low-resolution Feature
  Ringing

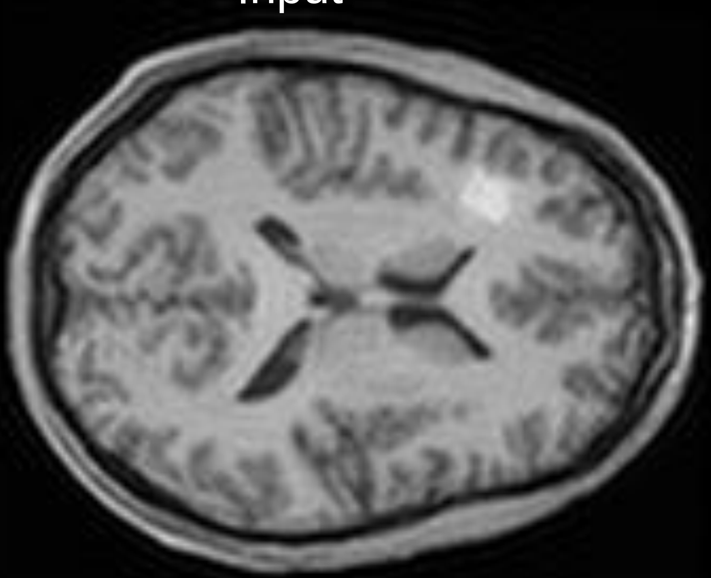


Step#2 Result

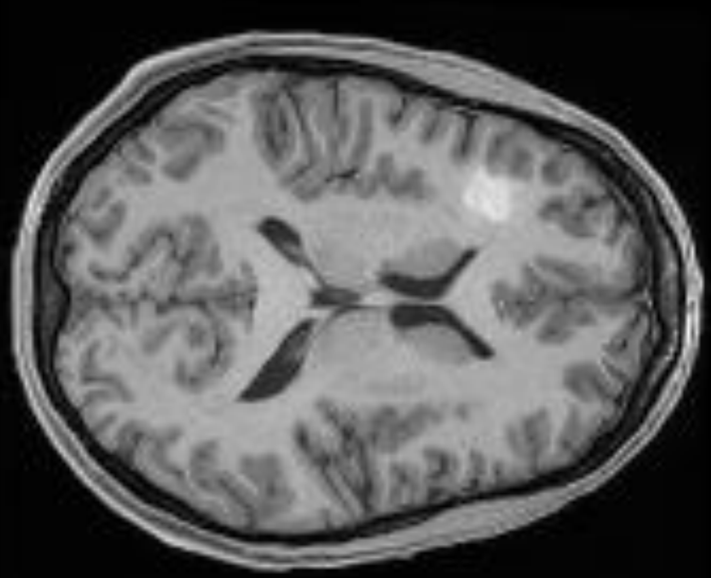
--- With Extracted Novel Feature
Constraint by Total Variation Sparsity

- Enhanced Contrast in Novel Feature
- Not Bring Back Ringing
- Limitation: Still Low-resolution Feature

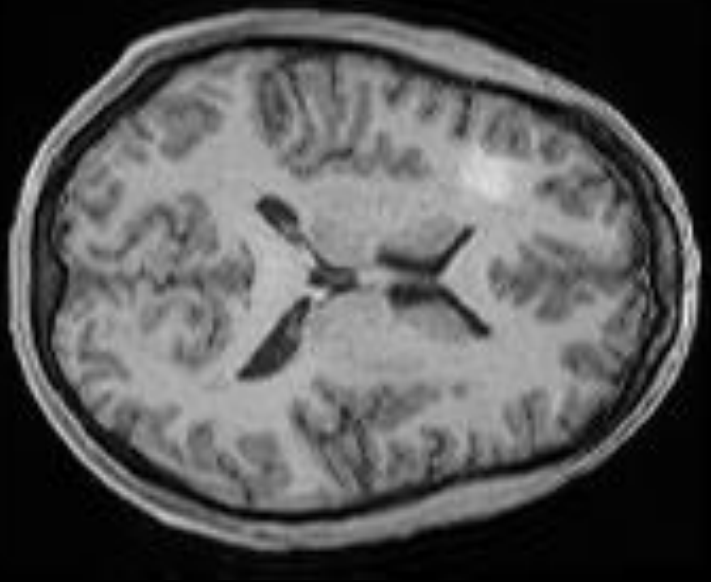
Input



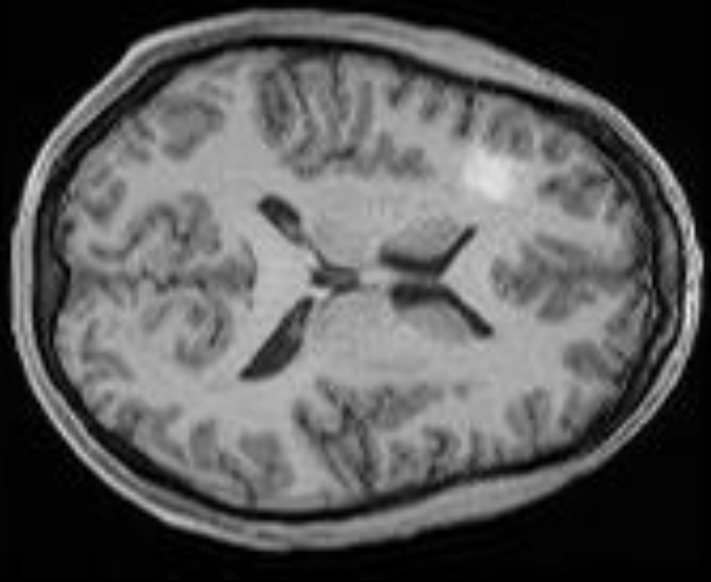
Ground Truth



Unet-GAN



After Novel Feature Extraction



Conclusion and Improvement

1. For now we could extract features by sparsity constraint, enhancing its contrast but not resolution;

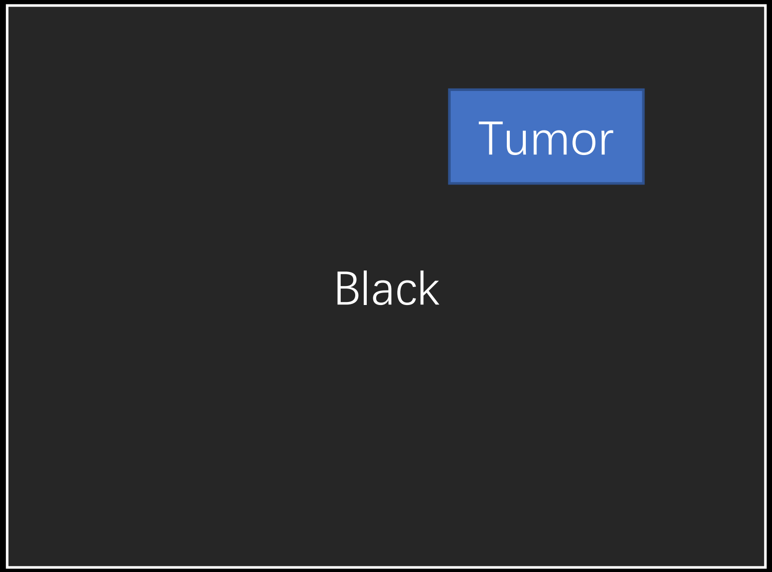
2. Total Variation Sparsity doesn’t bring back ringing, while Image Domain Sparsity does.

Improvement:

- 1. To locate novel feature
- 2. To get a realistic image of brain without feature in CNN

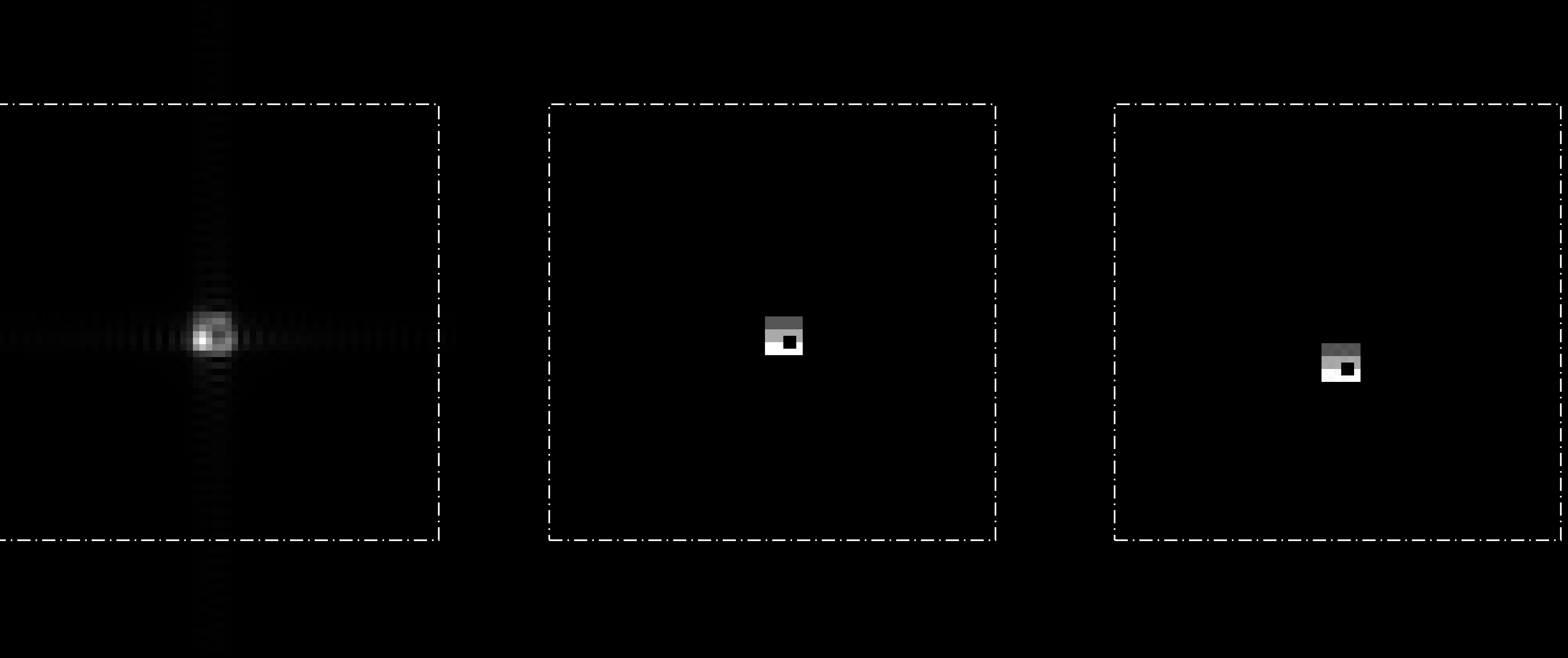
Validation: Stage1 (Ideal)

- Known location
- Tumor's low resolution image



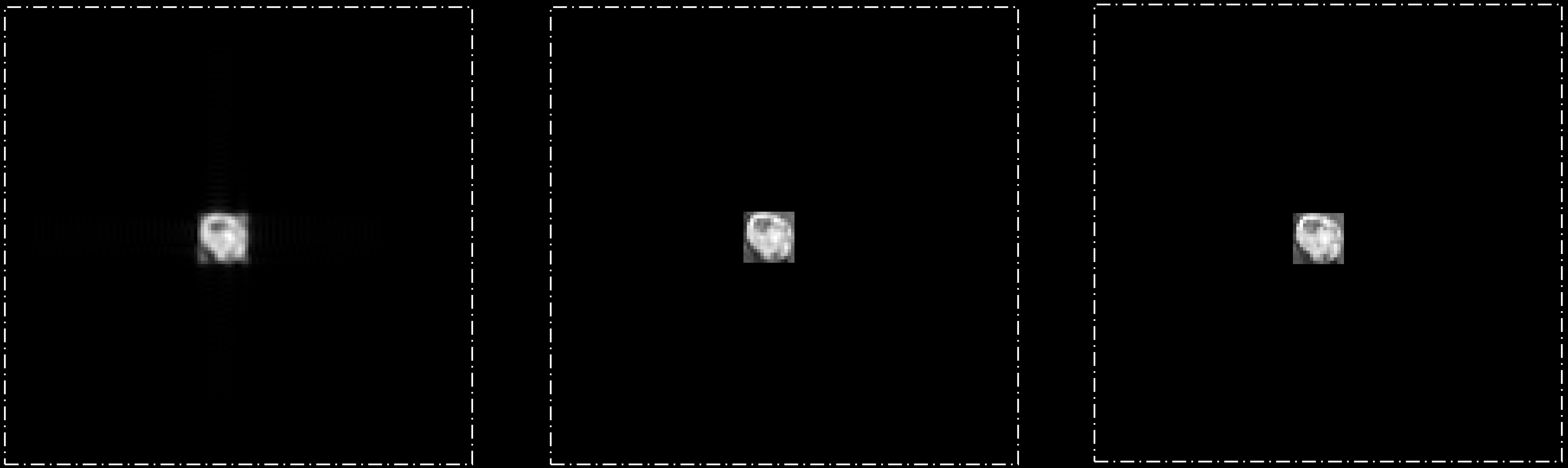
Low Resolution Image of Tumor

Novel Feature Recover



Low novel High novel Recovered novel

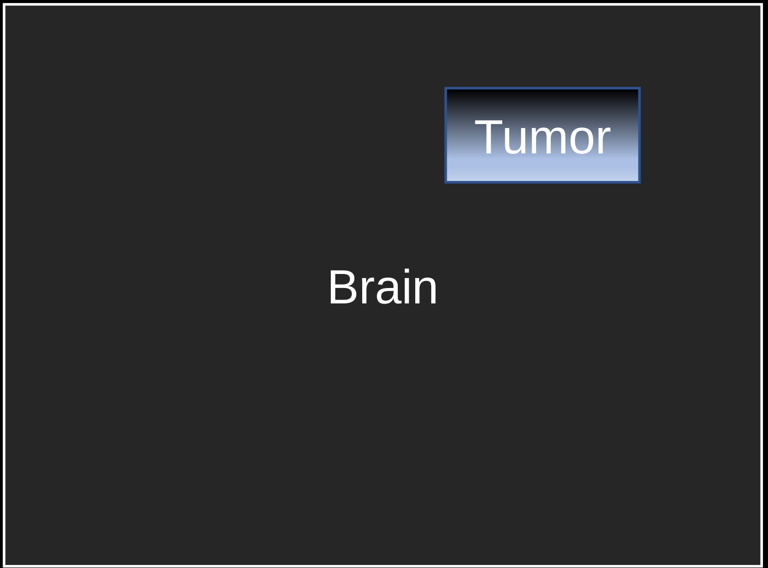
Novel Feature Recover



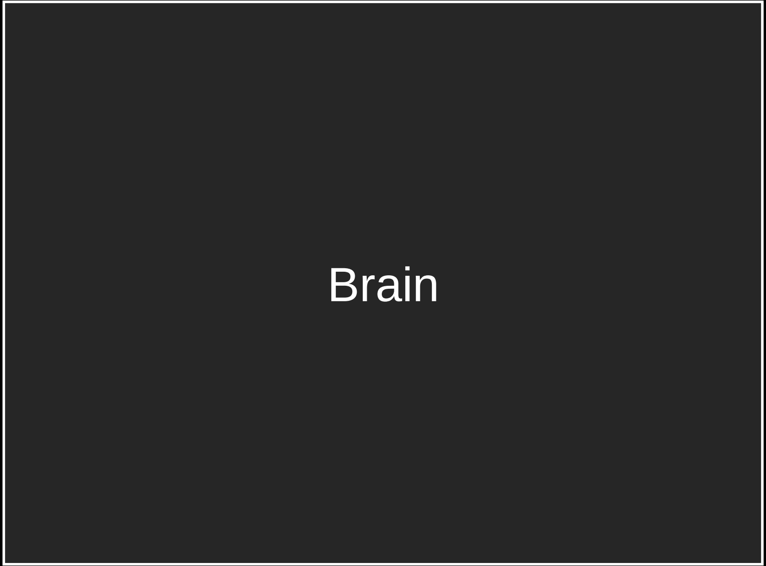
Low novel High novel Recovered novel

Validation: Stage2

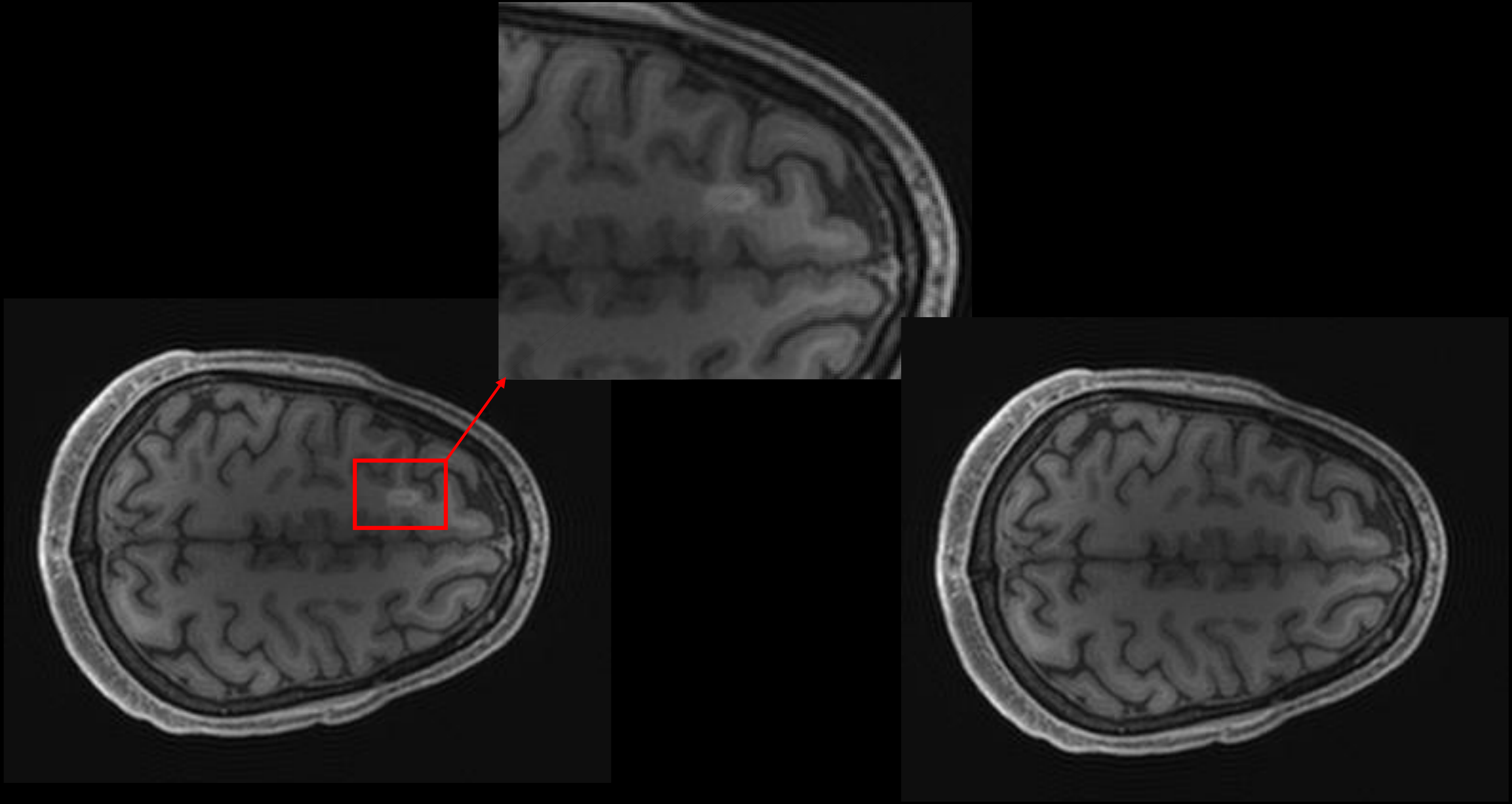
- Known location
- Low resolution Image of brain with tumor
- Low resolution Image of brain



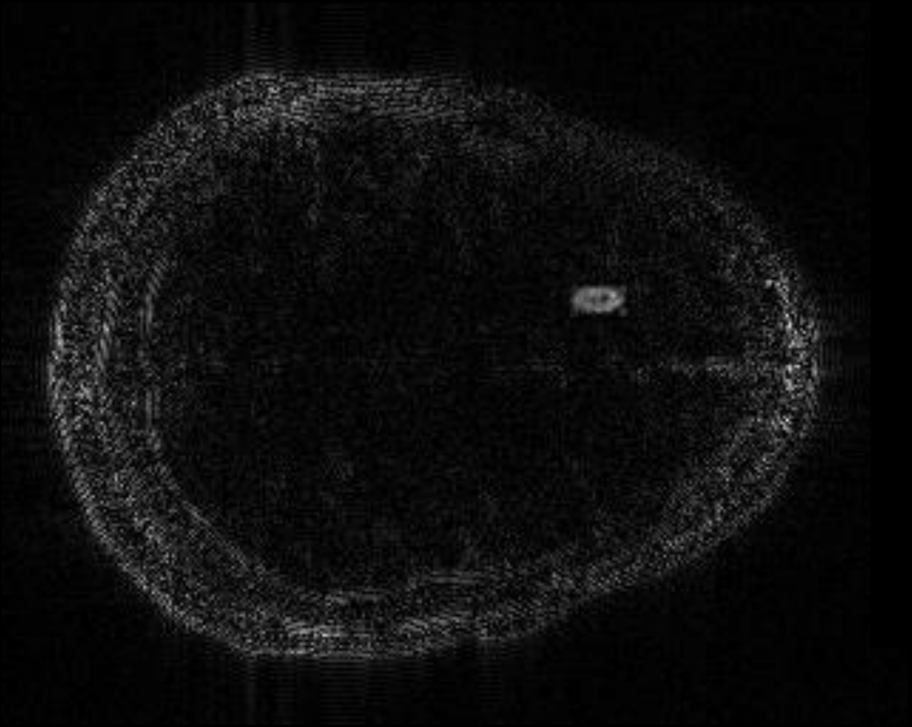
Low Resolution Image of Brain with Tumor



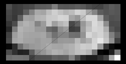
Low Resolution Image of Tumor



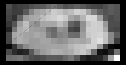
Novel Feature Recover (Stage 2)



Difference of image with/without tumor



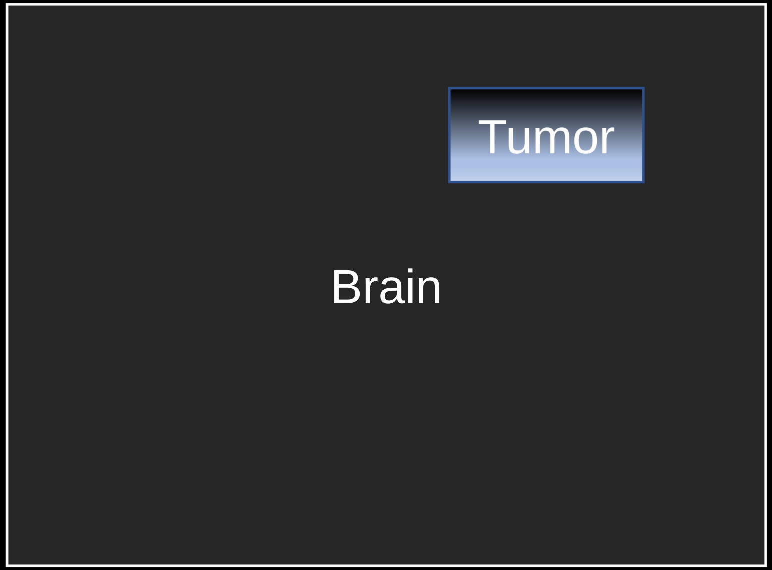
High novel



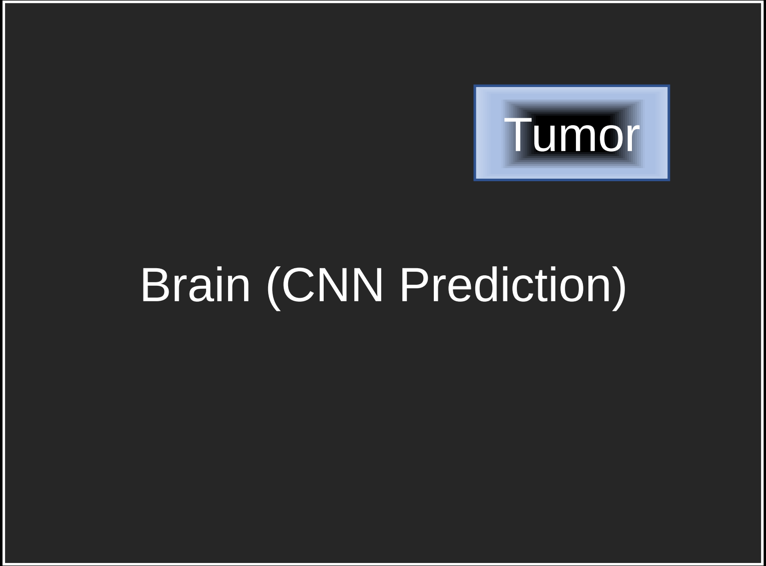
Recovered novel

Validation: Stage3

- Known location
- Low resolution image of brain with tumor
- Inner k space of CNN predicted image

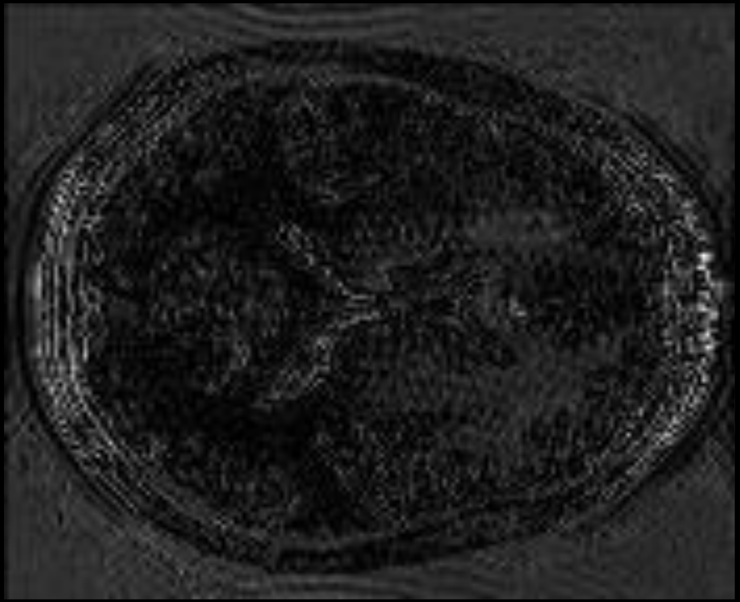


Low Resolution Image of Brain with Tumor



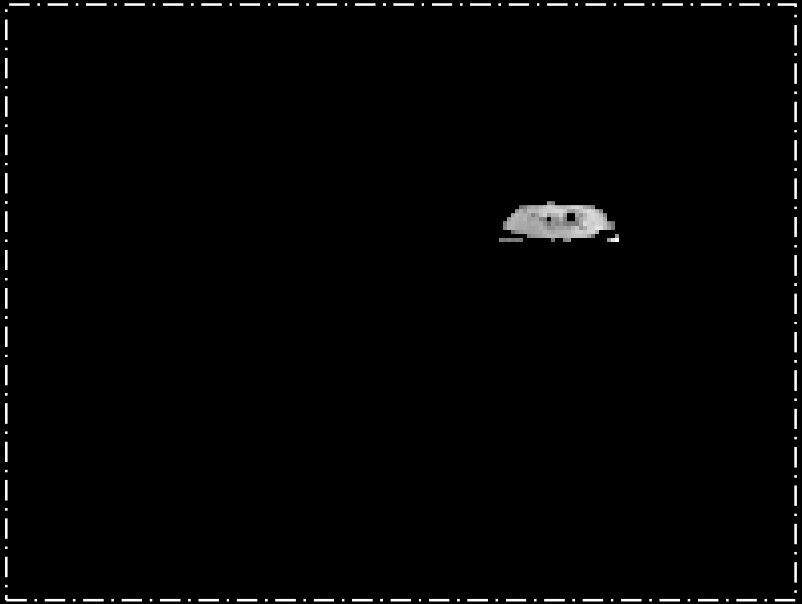
Low Resolution Image of CNN Prediction

Novel Feature Recover (Stage 3)



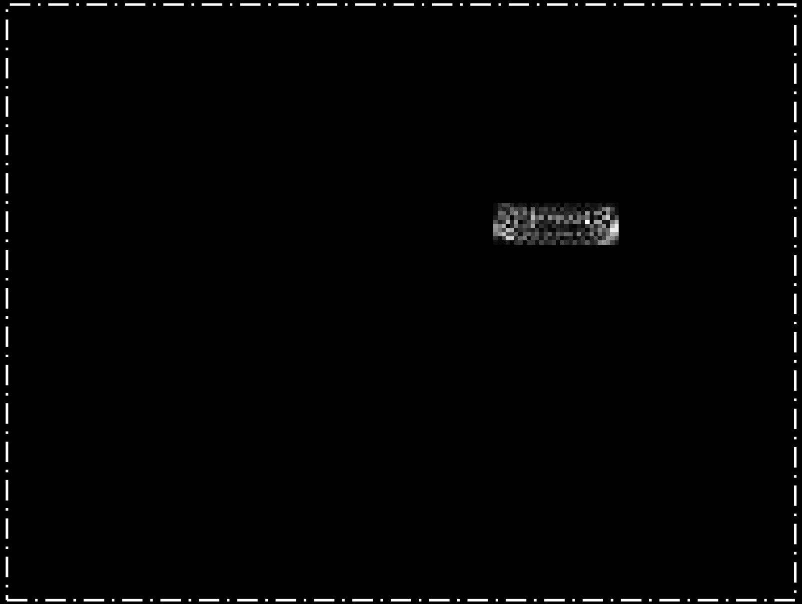
Difference of image with/without tumor

Scale: 2.5e+02



High novel

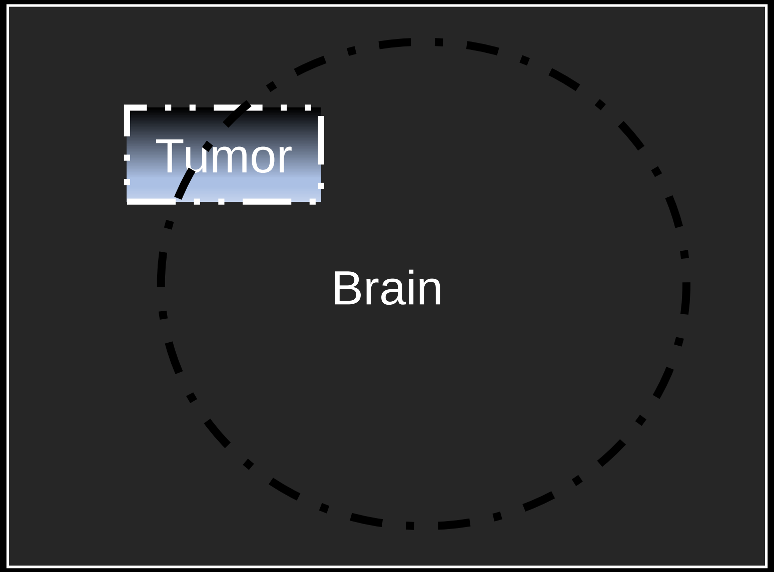
Scale: 2.5e+04



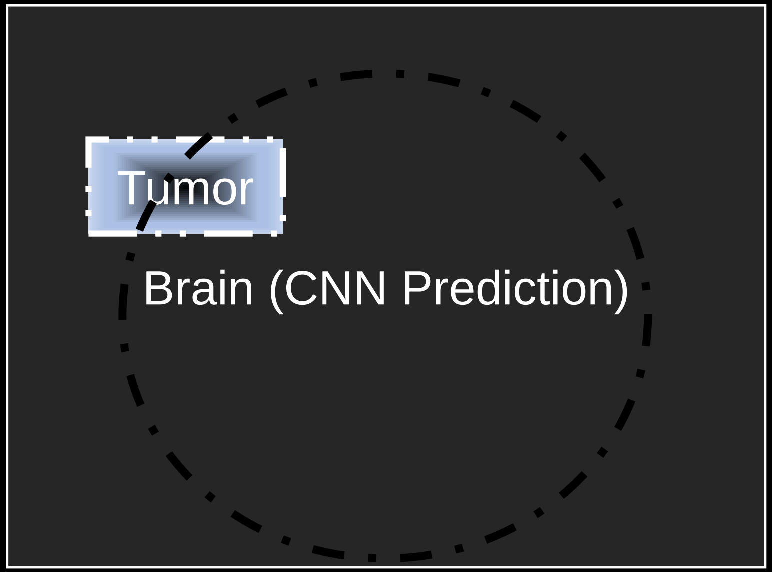
Recovered novel

Stage4 (Practical)

- Unknown location
- Sparsity Constraint
- Low resolution image of brain with tumor
- Inner k space of CNN predicted image



Low Resolution Image of Brain with Tumor



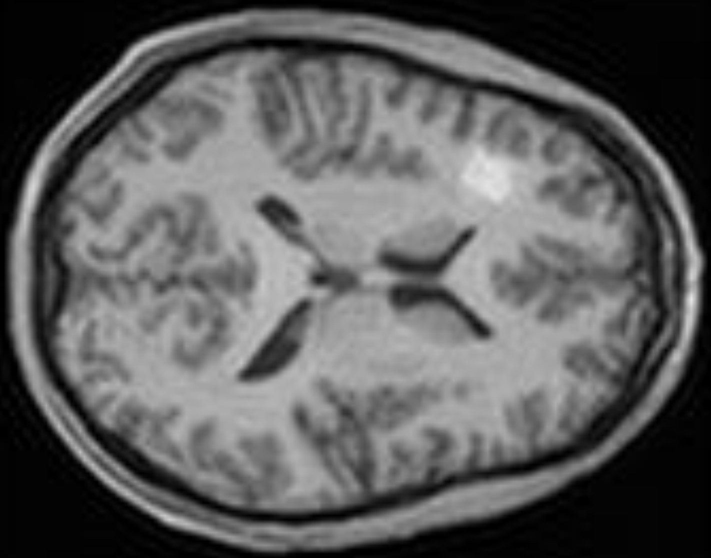
Low Resolution Image of CNN Prediction

Step#2 Result

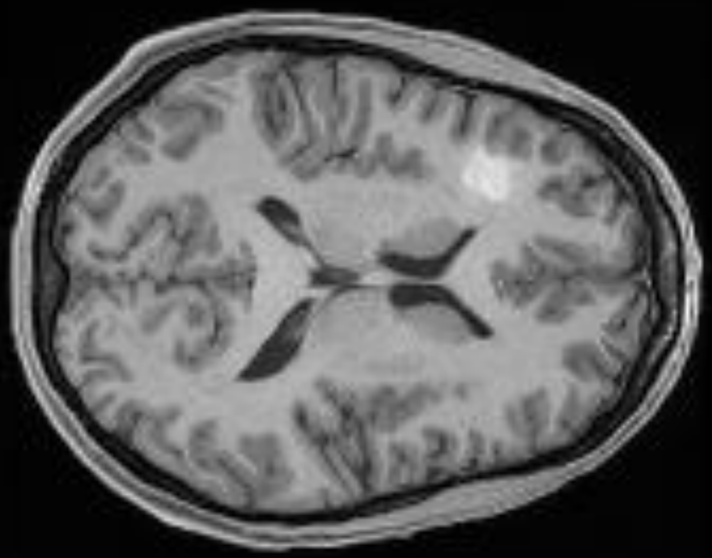
--- With Extracted Novel Feature
Constraint by Image Domain Sparsity

- Enhanced Contrast in Novel Feature
- Limitation: Still Low-resolution Feature
  Ringing

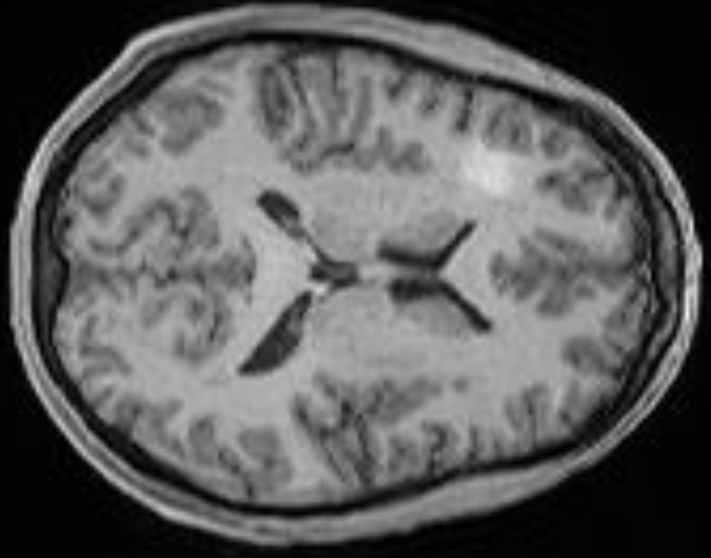
Input



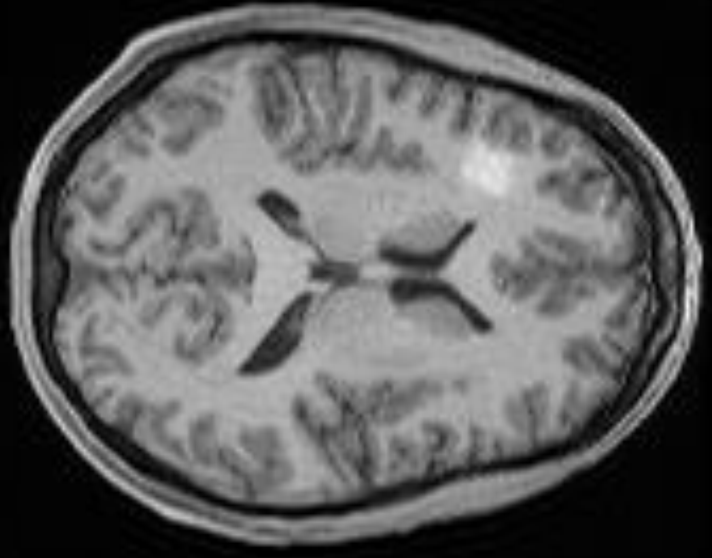
Ground Truth



Unet-GAN



After Novel Feature Extraction



Step3: Data Consistency

By Yu

Data Consistency

- Why
- How
- Results

Why

$\longrightarrow$ CNN $\longrightarrow$ novel feature $\longrightarrow$ data consistency

- Prior (absorb)
- Artifacts (remove)

How (traditional way)

the result we want to find

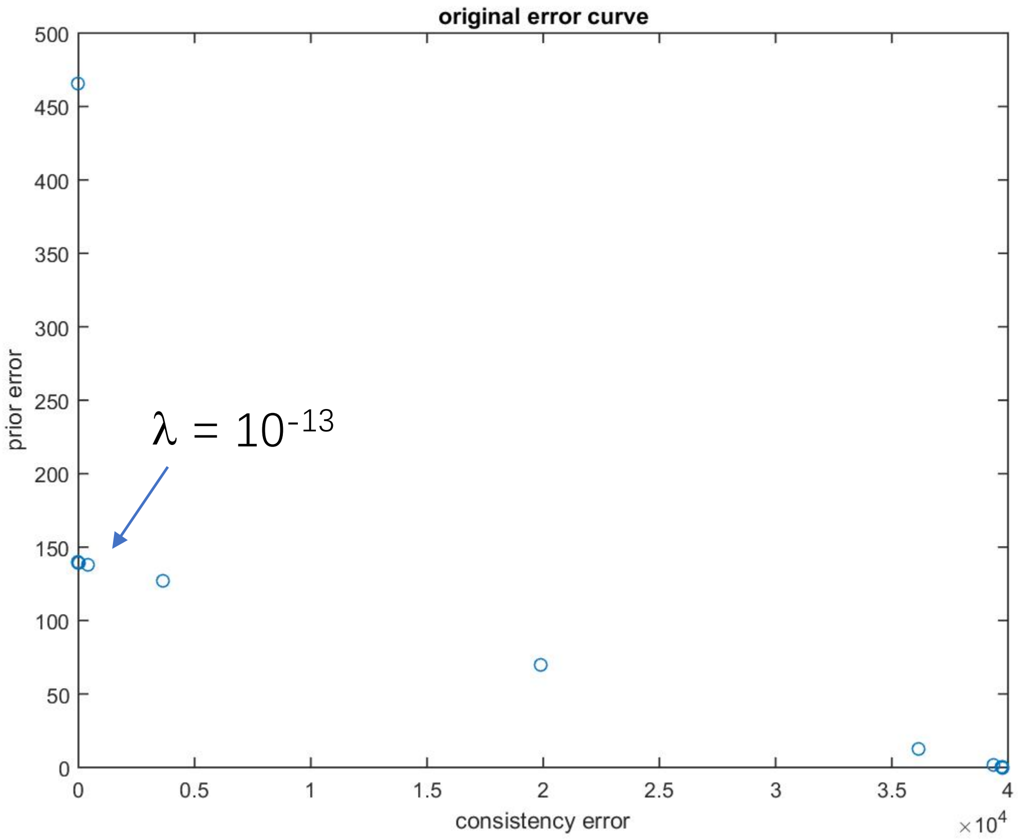
$$argmin_x\left(\|d_{low} - Ax\|_2^2 + \lambda\left\|d_{pri} - x\right\|_2^2\right)$$

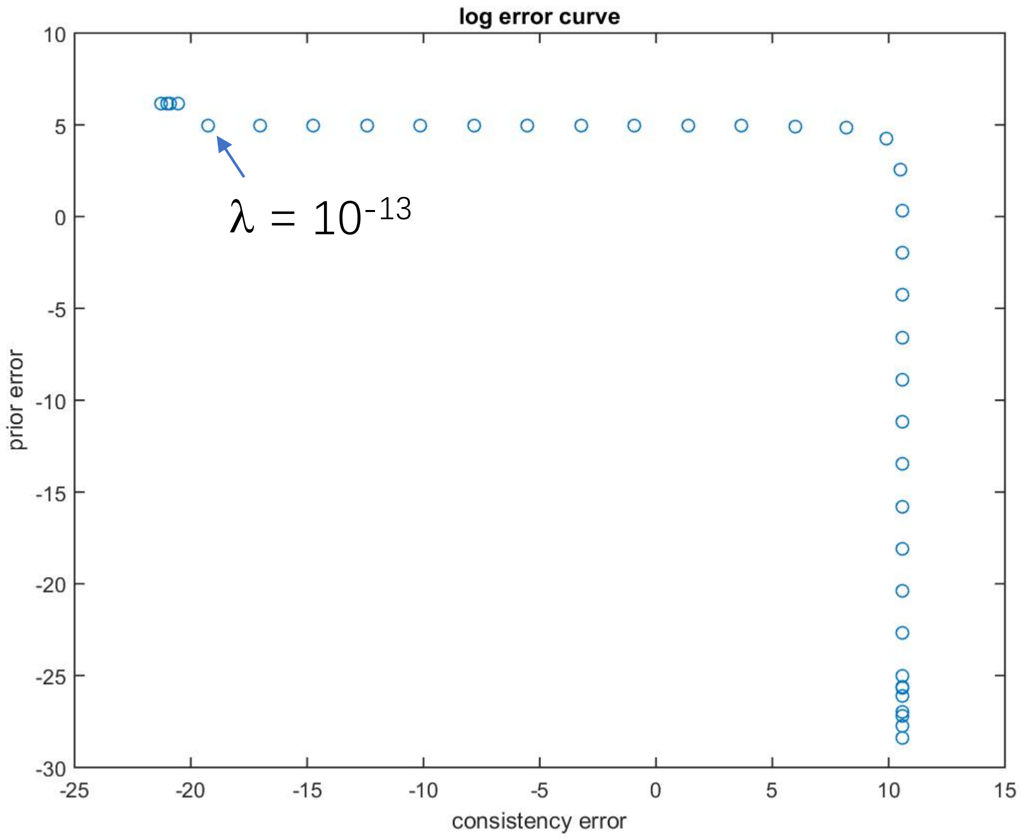
information we get

prior information

λ:regularization constant
A:truncation+fft

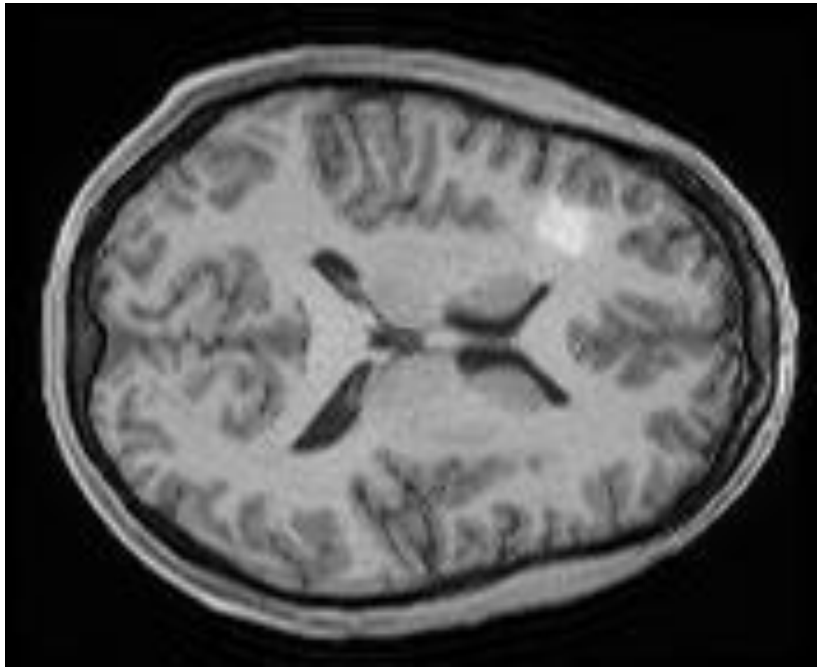
Results (traditional way)

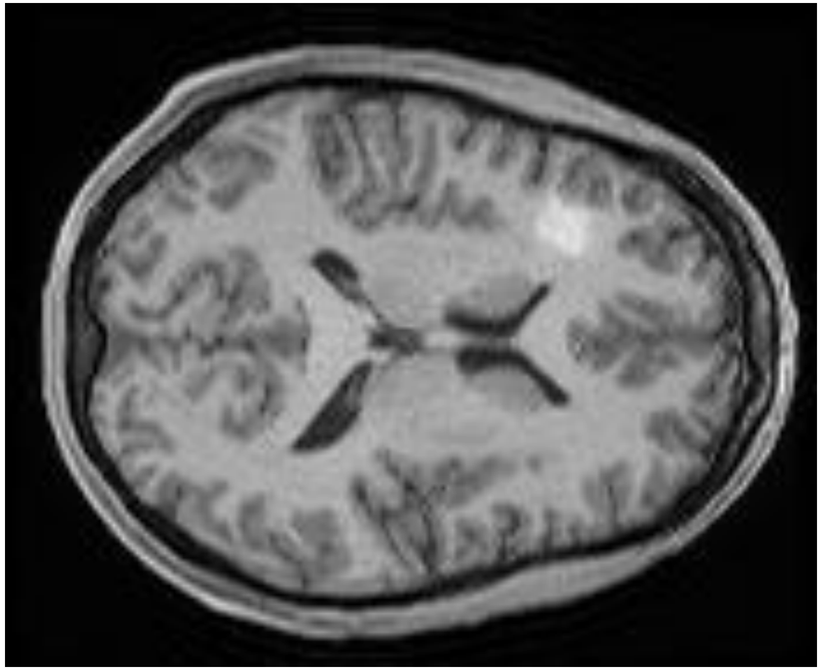




Breakpoint exists   may caused by ill-posed problem

Results of traditional way (image domain)

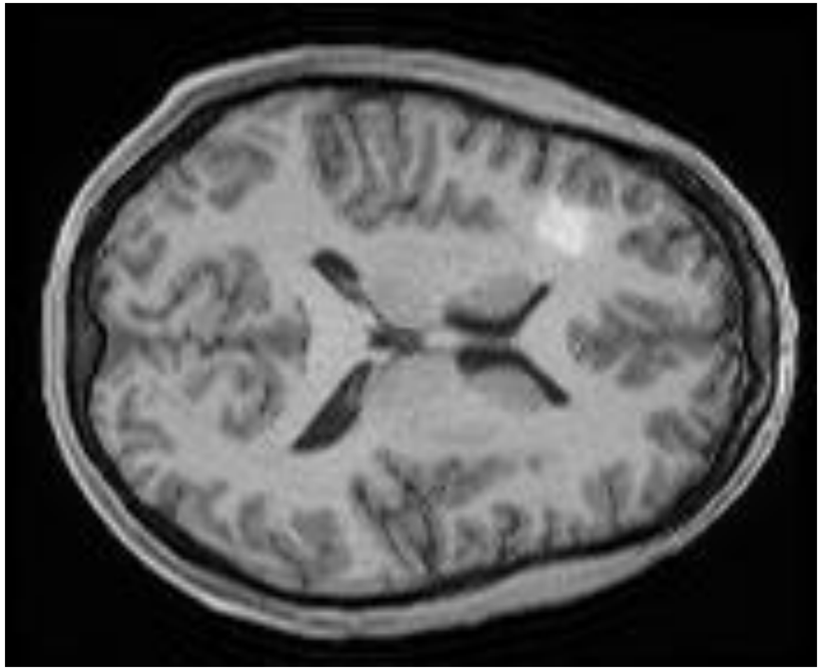


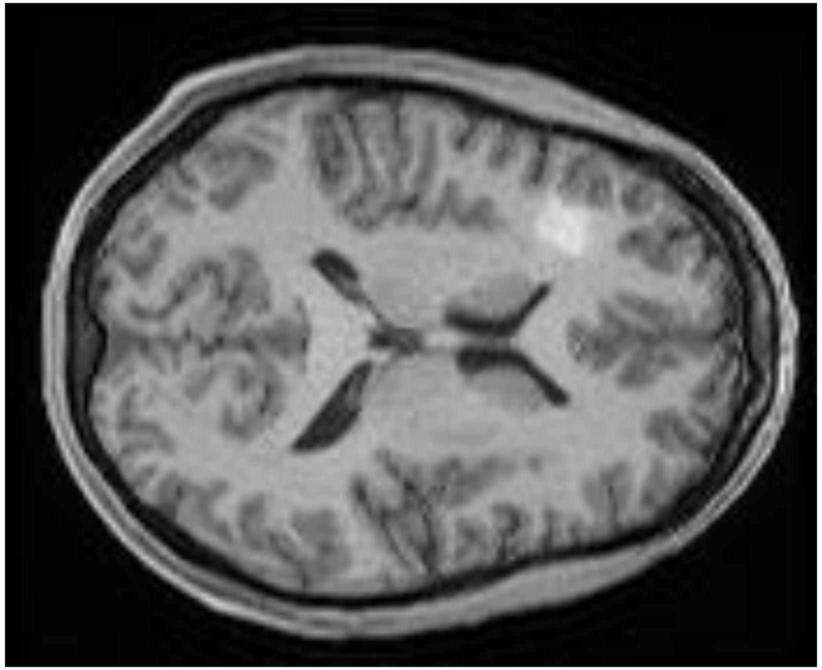


Before data consistency after

	Before data consistency	after
psnr:	24.2578	24.2580
ssim:	0.8918	0.8918
mse:	118.3385	118.3380

Results of traditional way (total variance)





Before data consistency

after

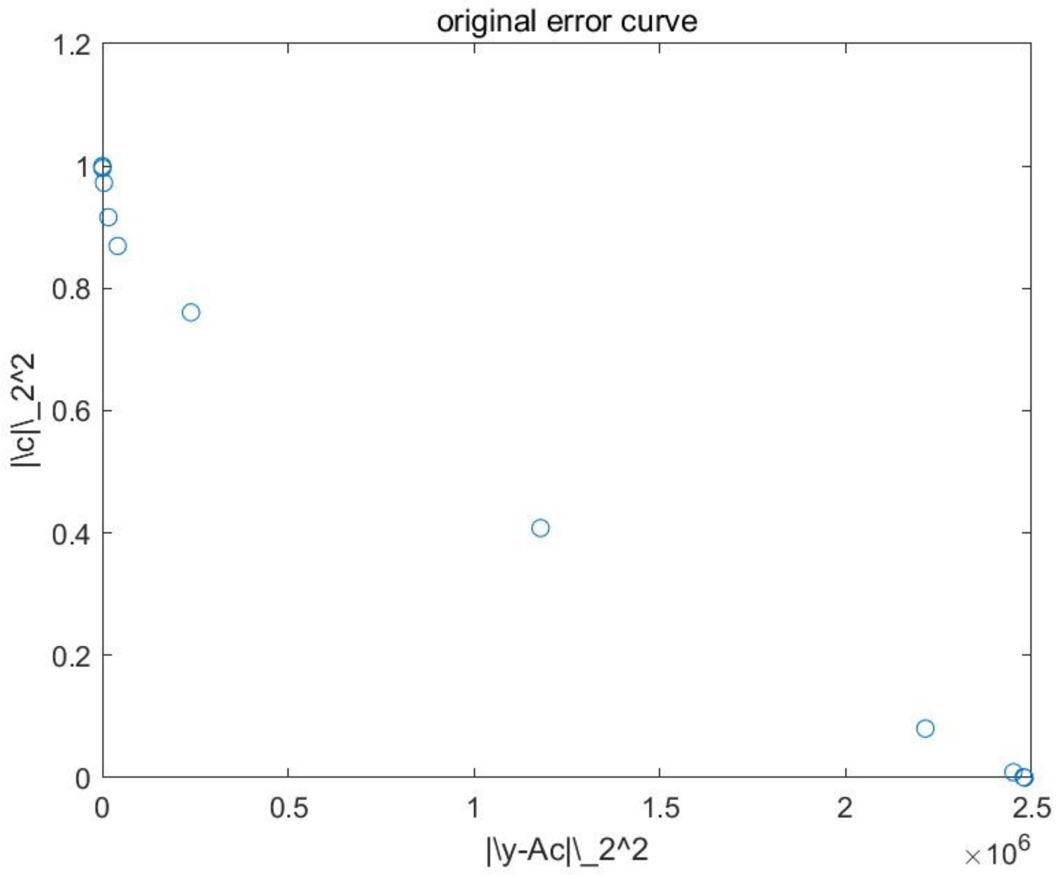
	Before data consistency	after
psnr:	29.1038	29.1040
ssim:	0.9226	0.9226
mse:	23.3266	23.3211

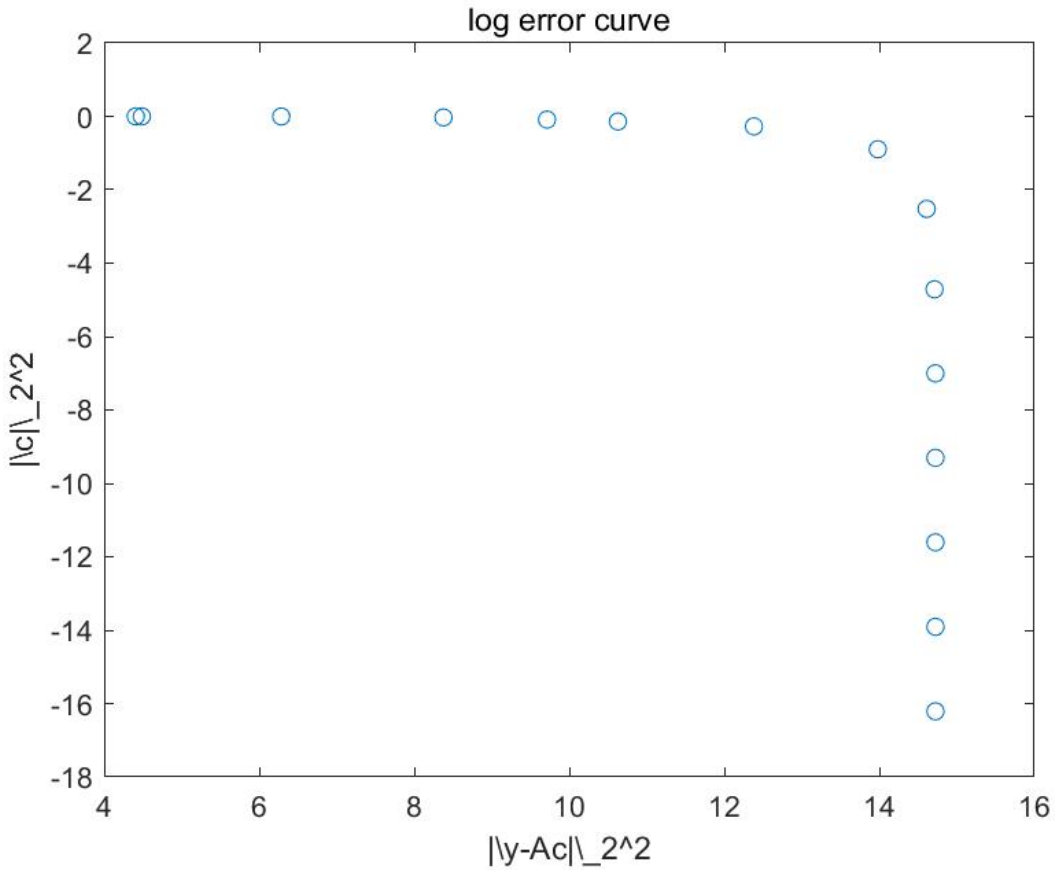
How (generalized series model)

$$argmin_{c_l}||d-\Omega\odot[\tilde{d}(k)*\sum_{l=-L}^{L}c_l\,\delta(k-l\Delta k)]||_2^2+\lambda\sum_{l}||c_l||_2^2$$

d:low resolution
$\tilde{d}$(k):prior information

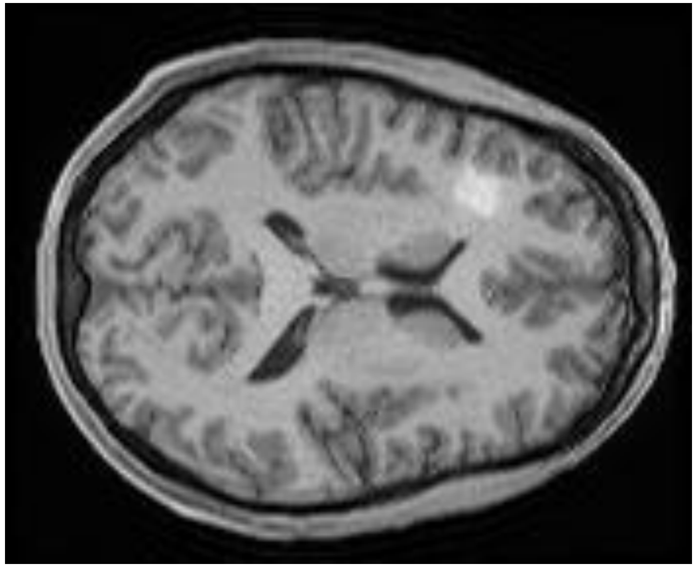
Results (GSM)



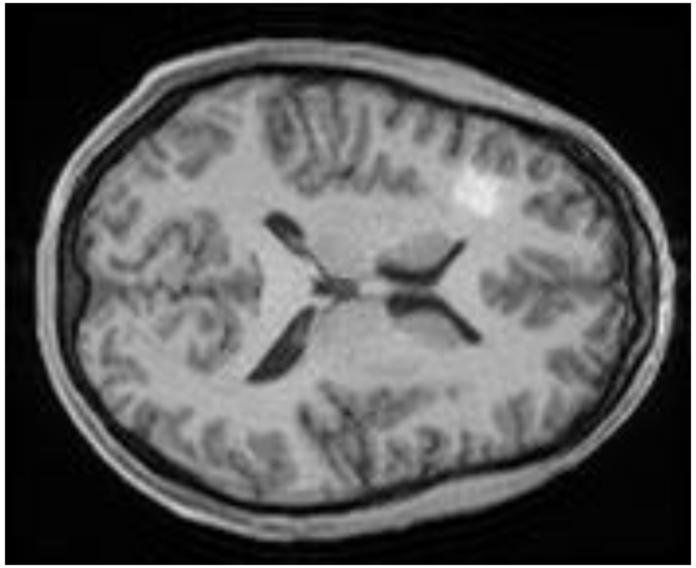


No breakpoint not sensible to λ 10^-20~+20

Results of GSM (image domain)



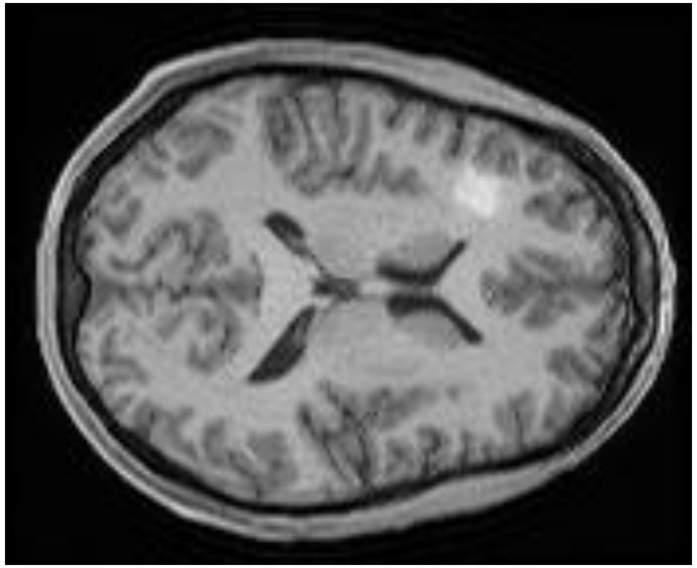
Before data consistency

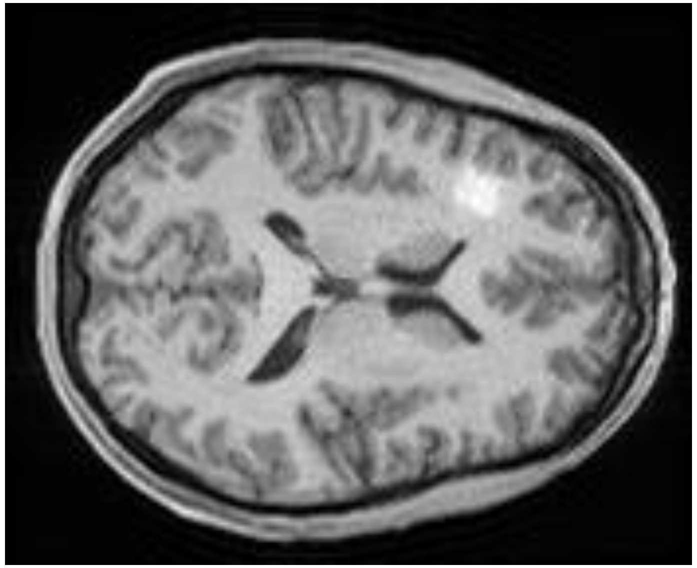


after

	Before data consistency	after
psnr:	24.2578	24.6762
ssim:	0.8918	0.8970
mse:	118.3385	112.5964

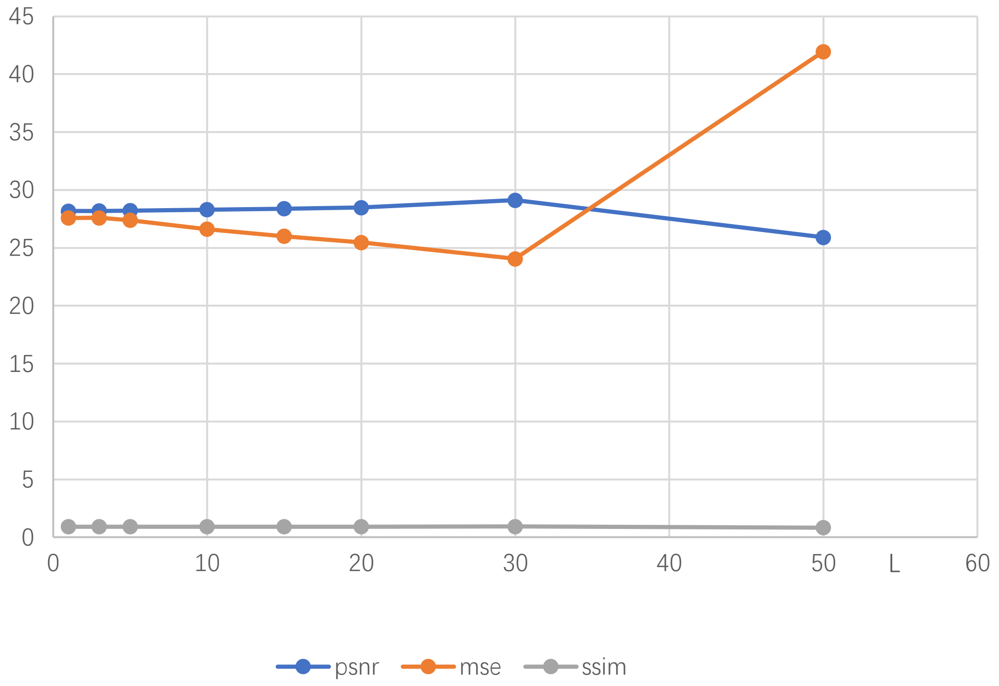
Results of GSM (total variance)

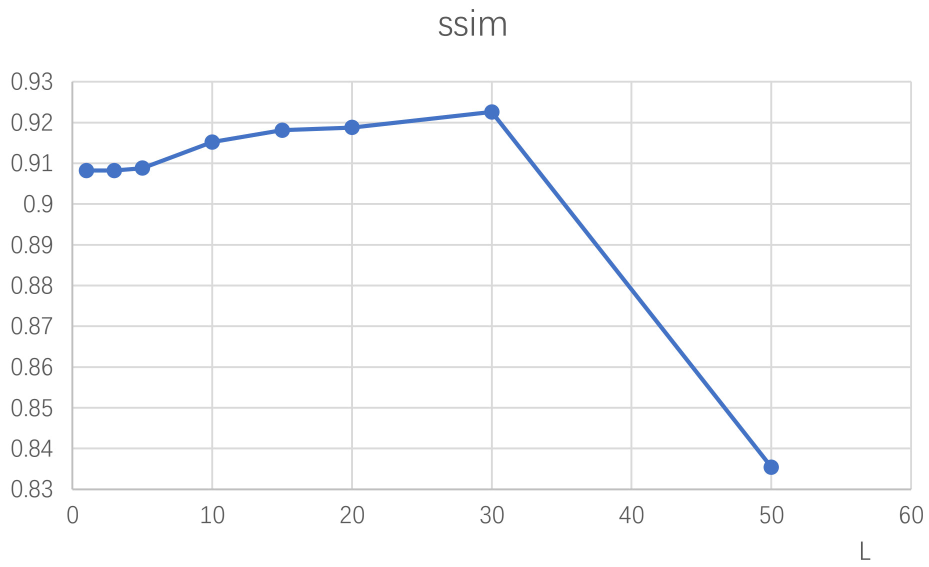




	Before data consistency	after
psnr:	29.1038	24.2584
ssim:	0.9226	0.8918
mse:	23.3266	118.33

Optimal L (total variance)

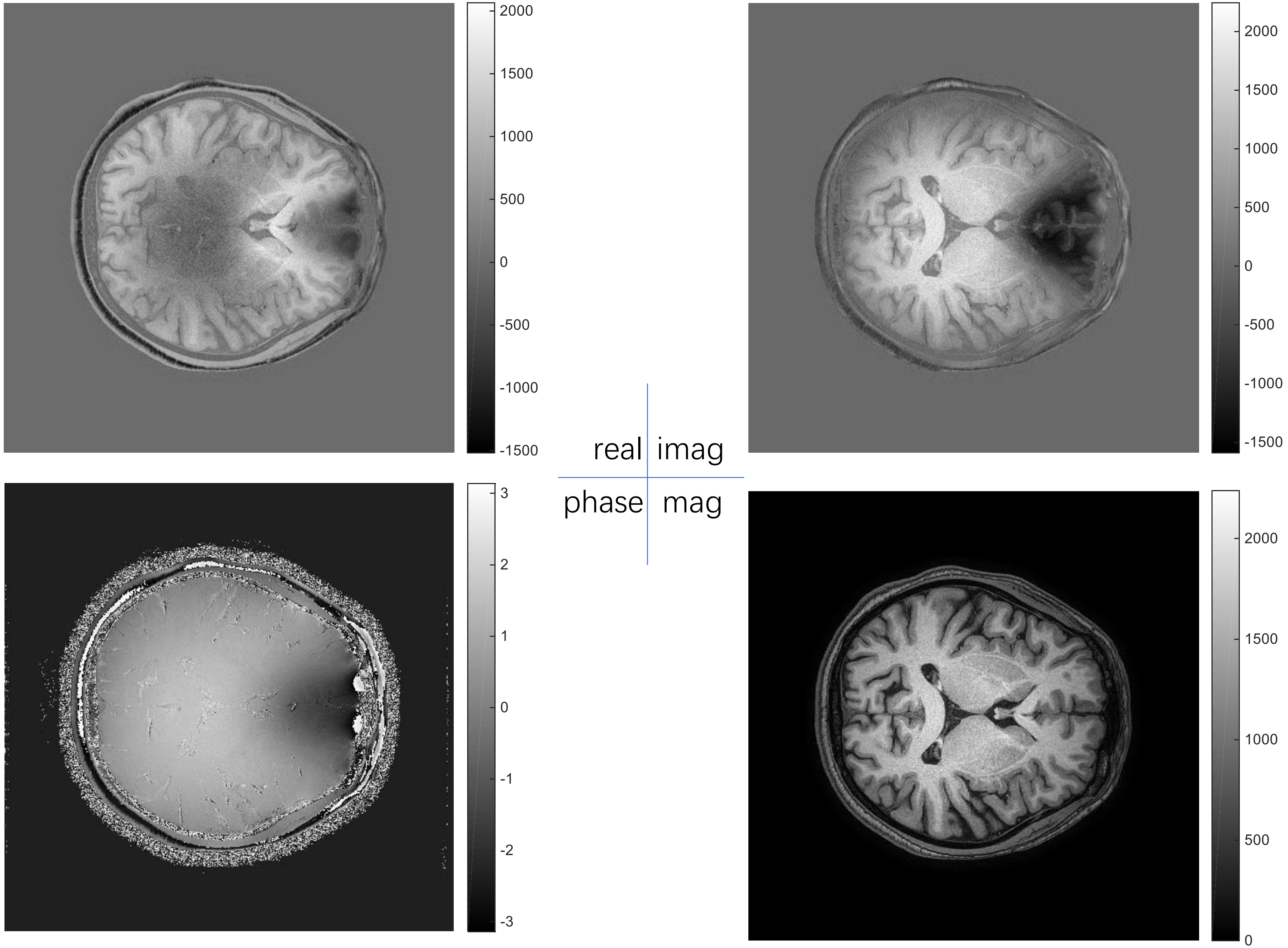




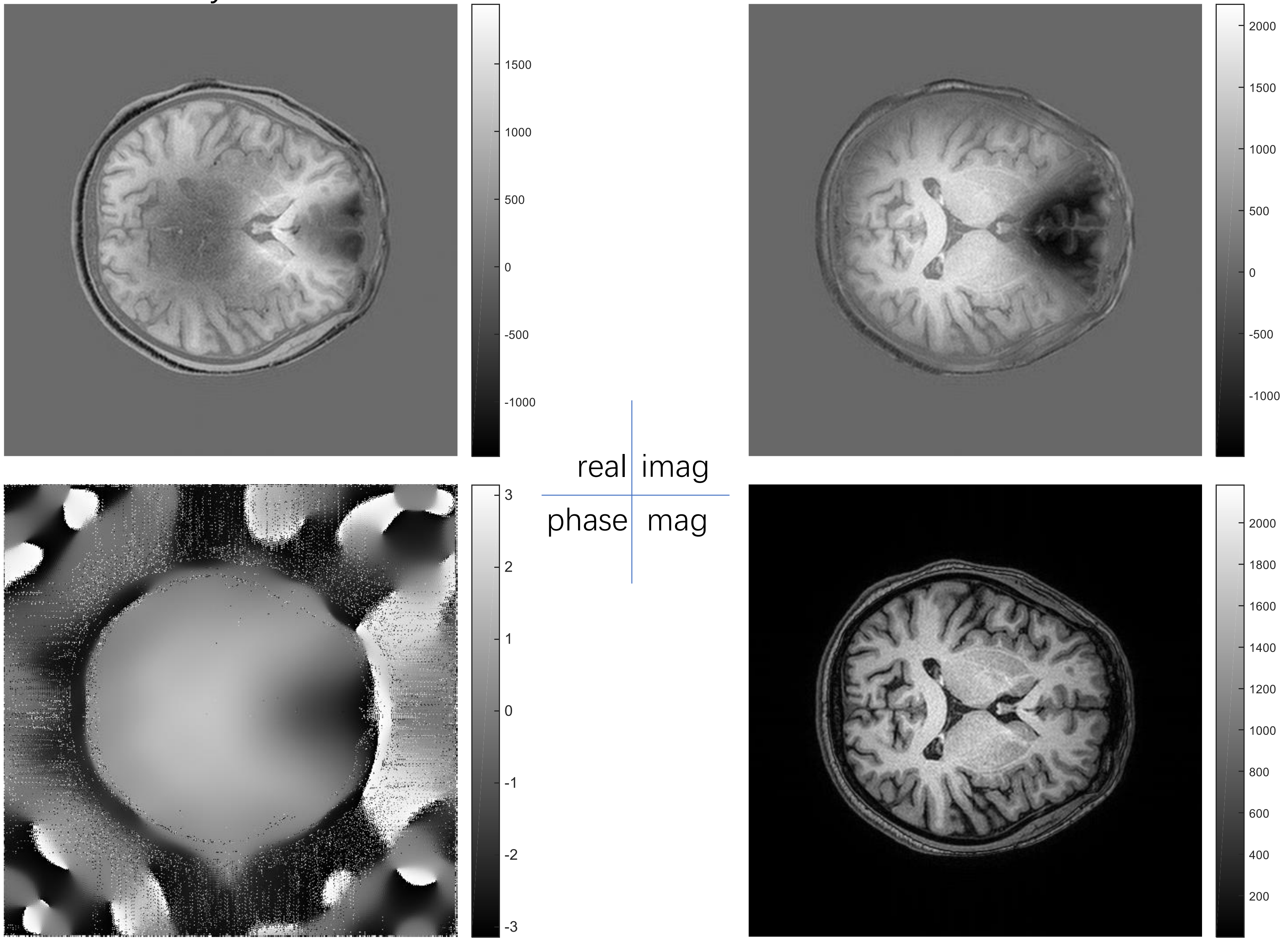
Focus on phase

Low resolution (with phase) $\longrightarrow$ input (abs(···)) $\xrightarrow{\text{CNN}}$ output (without phase) $\xrightarrow{\text{Data consistency}}$ get back phase?

Target Data:


2000
1500
1000
500
0
-500
-1000
-1500
2000
1500
1000
500
0
-500
-1000
-1500
real
imag
phase
mag
3
2
1
0
-1
-2
-3
2000
1500
1000
500
0

Data Consistency Result:



Conclusion

- Traditional way to do data consistency does little work in our case.

- GSM performs well in novel feature that done in image domain, but decreases the quality of image when using total variance. Because the latter way already performs well in novel feature.

- Optimal L for GSM is about 30.

- We can get back phase by data consistency but not perfect because of noise and discontinuity of the boundary.

Conclusion:

Normalization No patch →
learn more efficiently and accurately

Image sparsity & TV sparsity →
Recover novel features contrast

Traditional & GSM →
Improve the image quality

Low resolution

⬇ Generator

4 times High resolution

⬇ Novel Feature Extraction

4 times High resolution + Novel feature

⬇ Data Consistency

4 times High resolution + Novel feature + without Artifact

Future Plan:

- Optimization of neural network structure
- More suitable sparsity constraint & Better Data Consistency