Deep learning based low-dose synchrotron radiation CT reconstruction

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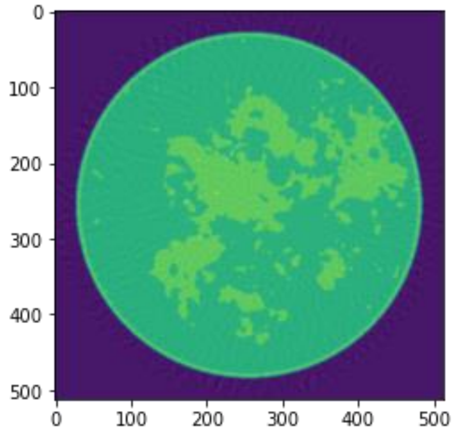
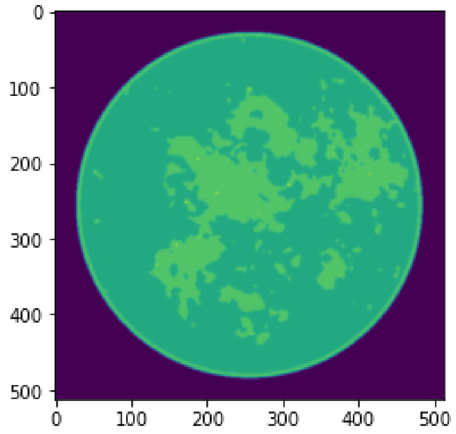
Motivation

- Low-dose synchrotron radiation CT has the advantages of fast detection speed and low radiation dose received by the sample.
  - Solution reactions: require fast detection
  - Biological materials: It is necessary to maintain in vivo indicators, as is the need for rapid detection.
  - light-sensitive materials: The radiation dose received needs to be reduced.

Challenge

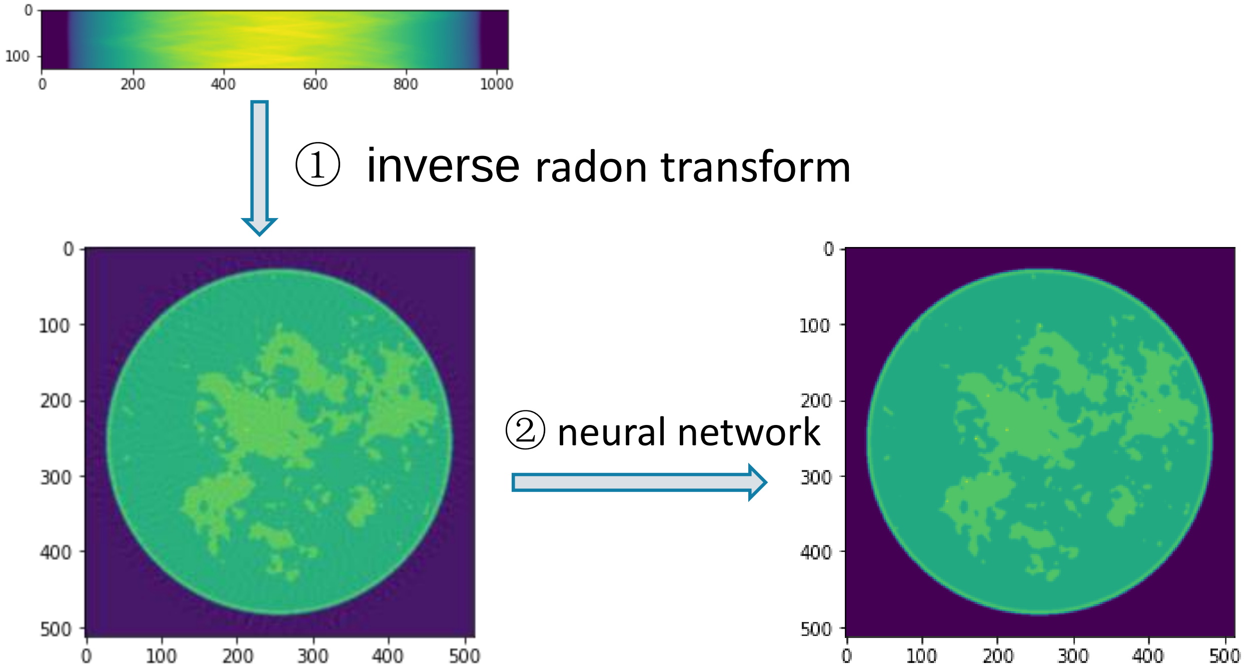
- The artifact is severe and the details are vague.
- The image precision is high, and the demand for video memory is large.
  - The medical image size is 512*512
  - The synchrotron radiation image size is 2048*2048.





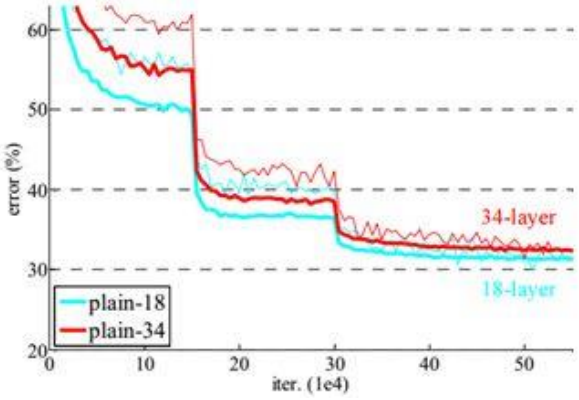
Method

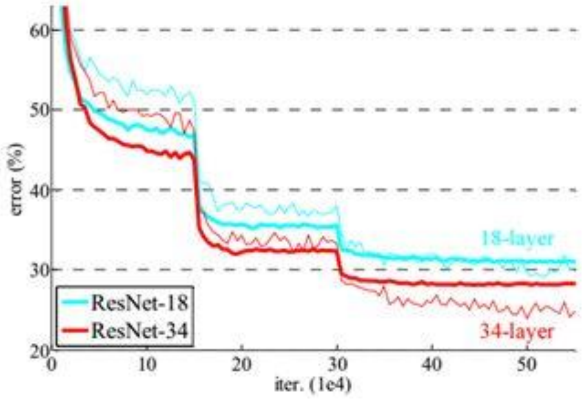
- Inverse Radon transform: to transform the image from the sparse sinogram domain to the plane domain
- Neural network: to remove artifacts and improve the image accuracy
  - Uent
  - ResNet
  - Attention Mechanism

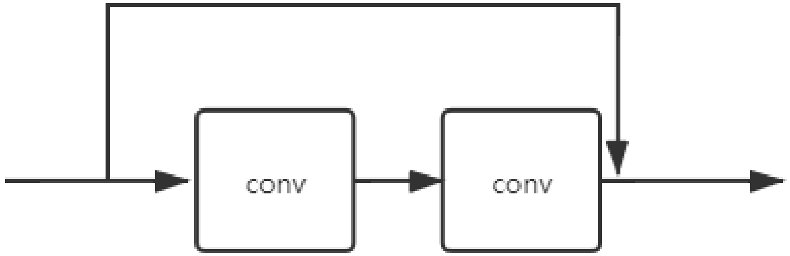


Method

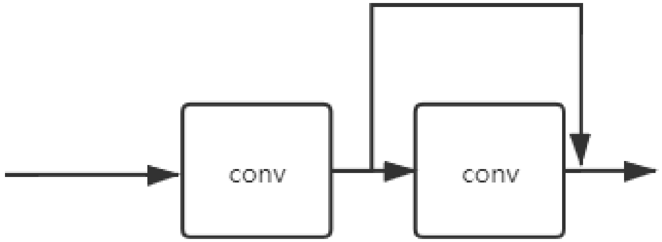
- ResNet:
  - Alleviate the gradient disappearance problem caused by the increase of network layer number







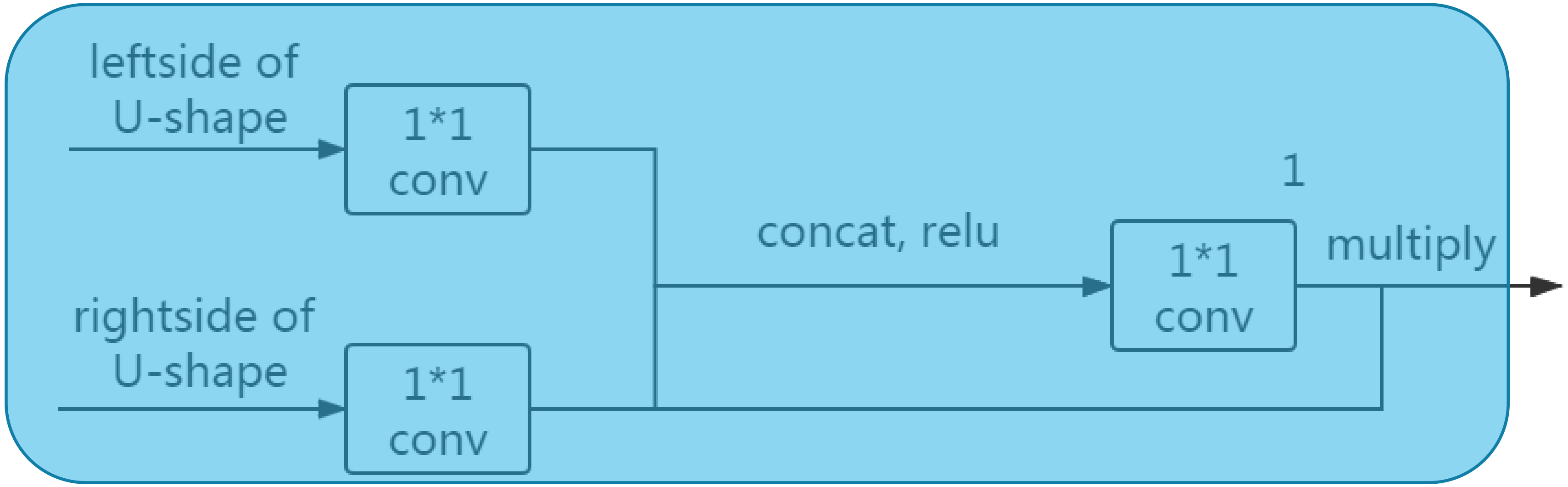
(The structure of regular ResNet)



(ResNet-like structure used in this article)

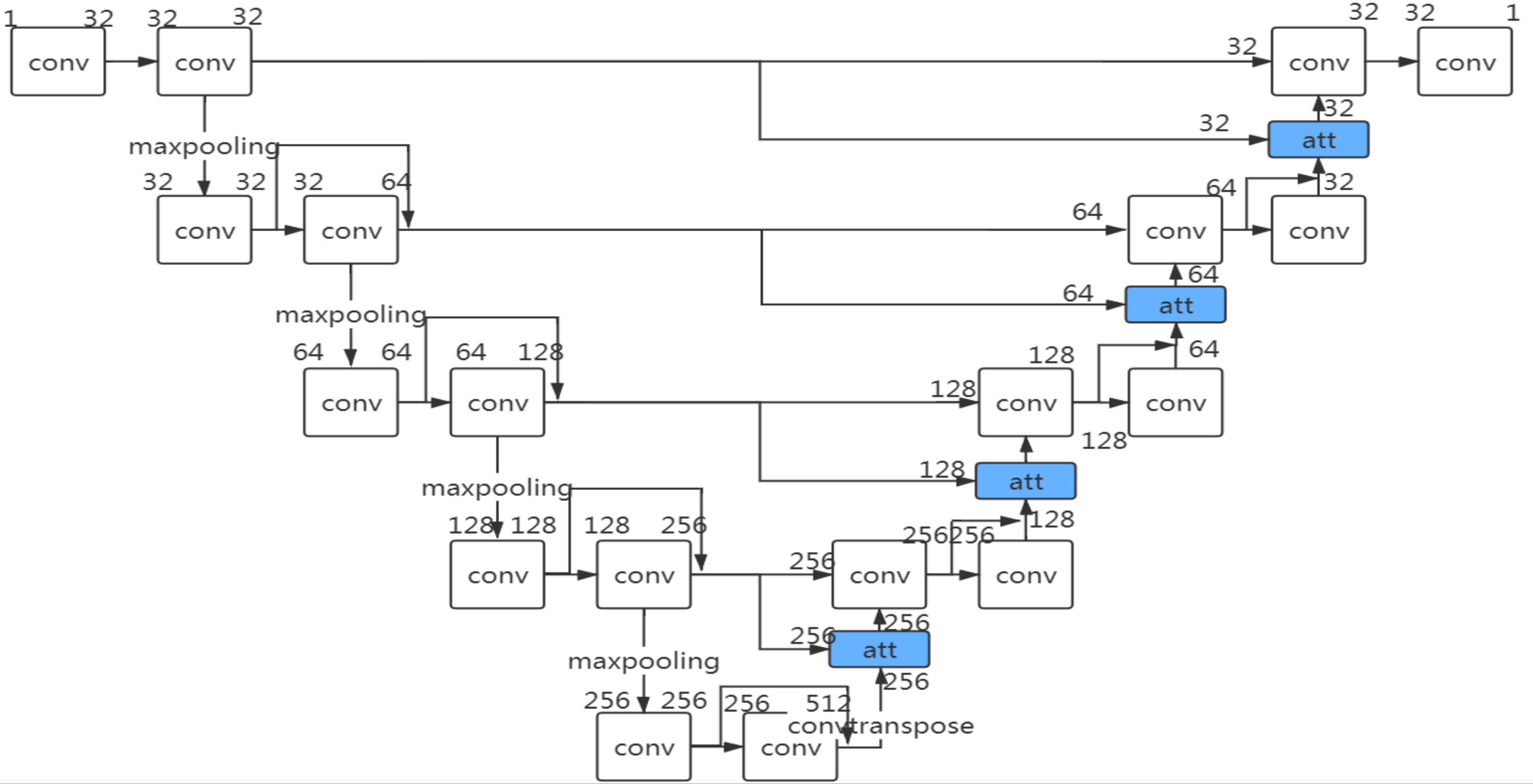
Method

- Attention Mechanism
  - It can ignore irrelevant information and focus on important information.
  - 1*1 conv represents the weighted sum.



Attention Mechanism

Model



Method

- Mixed Precision
  - Advantages: reduce the occupation of video memory, speed up the calculation of training
  - Problems with introducing FP16
    - Grad Overflow / Underflow: the dynamic range of FP16 is much narrower than the dynamic range of FP32
    - Rounding Error: Rounding Error is when the gradient is too small, smaller than the minimum interval in the current interval, and the gradient update may fail.
  - Solutions:
    - Mixed Precision:Use FP16 for storage and multiplication in memory to speed up calculations, and FP32 for summation to avoid rounding errors.
    - Loss scaling: Before back propagation, the loss change (dloss) will be manually increased by 2^k times; after back propagation, the weight gradient will be reduced by 2^k times to restore the normal value.

Experiment

Data set preparation:

simulated data sets

Dataset(1200*1200):

Training set: 80 simulated data sets

Validation set: 20 simulated data sets

Test set: 20 real data sets

Model:

UNET Training

ResAttUnet Training(O0)

ResAttUnet Training(O2)

Train:

Criterion: MSELoss

Lr: 3e-4(step_size=10, gamma=0.95)

Optimizer: Adam

Epoch: 65

Test:

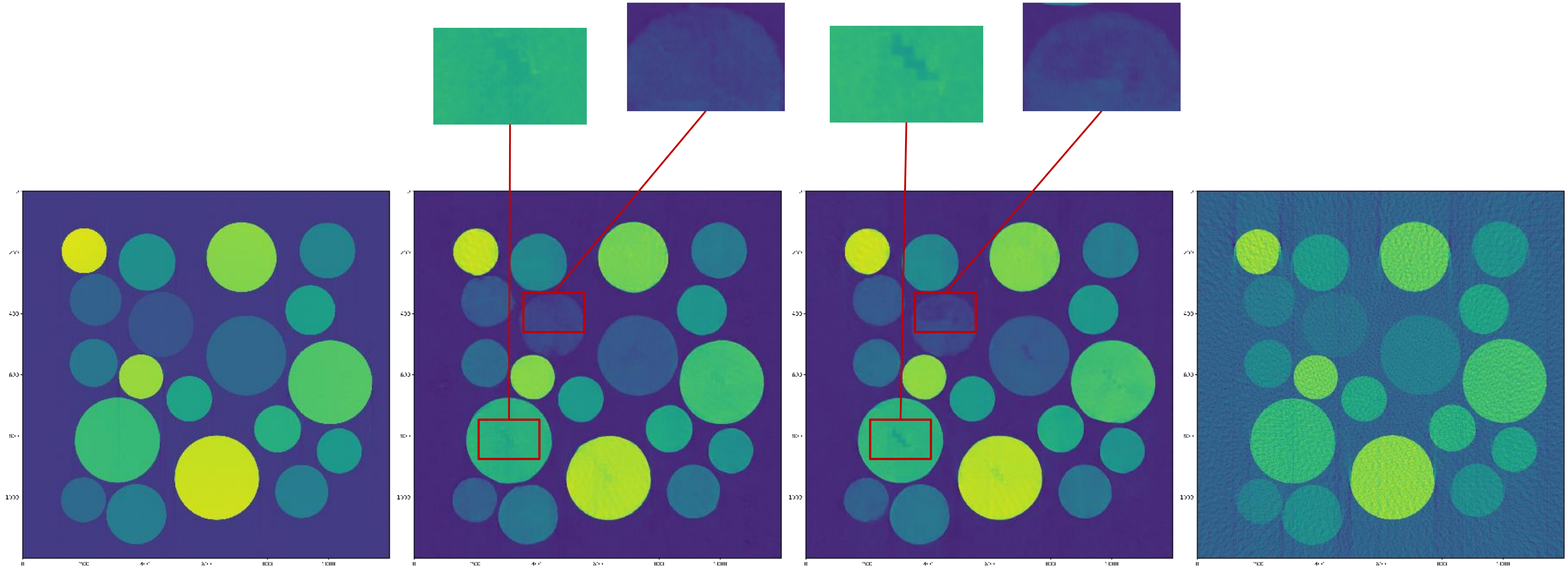
Outputs the image

Calculates the value of the evaluation criteria

O0: pure FP32 training
O2: except for the BATCH norm, almost all calculations are performed using FP16

Result:

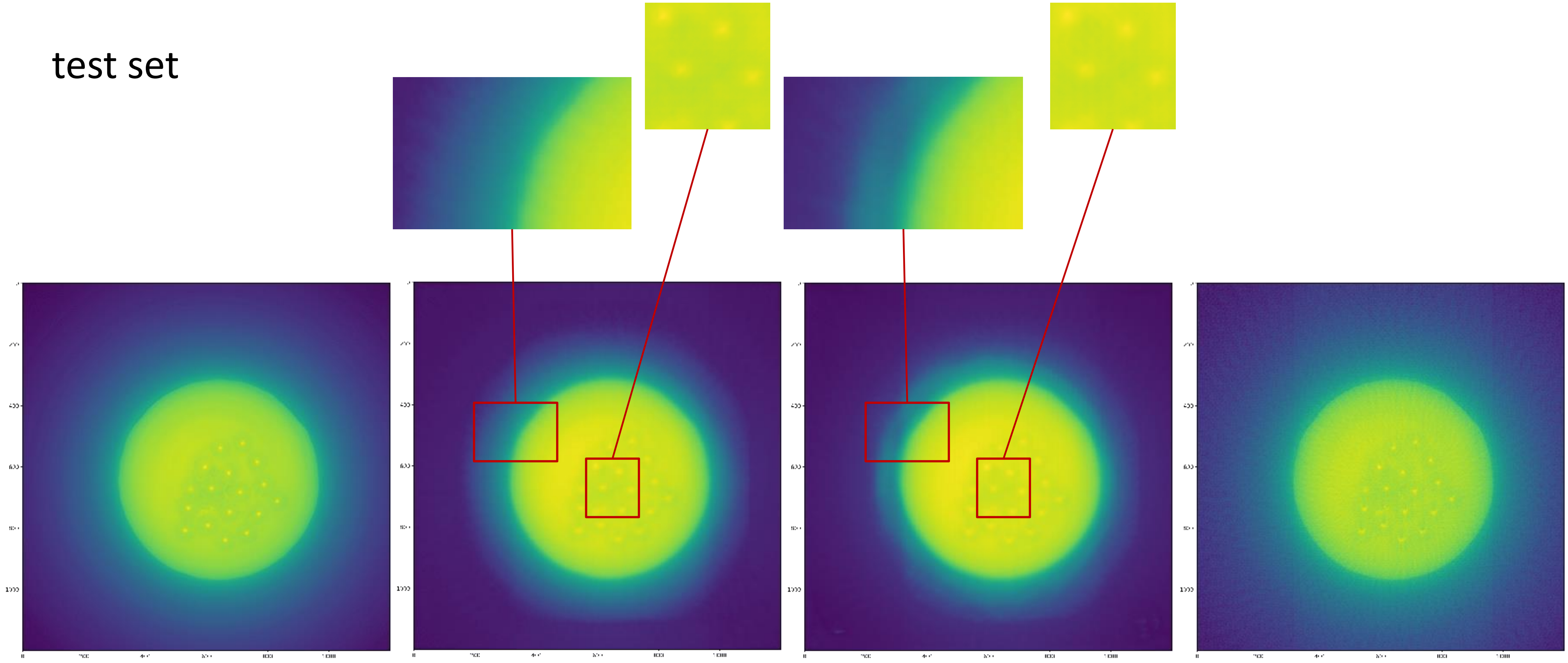
Validation set



label ResAttUnet output unet output input

Result:

test set



label ResAttUnet output unet output input

Result

- PSNR: Peak Signal to Noise Ratio, the ratio of peak signal energy to MSE
- SSIM: Structural Similarity Index Measure is a comprehensive measure of brightness, contrast and structure.

Model	**PSNR**			**SSIM**		
	Training set	Validation set	Test set	Training set	Validation set	Test set
ResAttUnet(O0)	30.1283	29.0519	**26.7286**	0.9913	0.9891	**0.9881**
ResAttUnet(O2)	**30.6647**	**29.0860**	25.3447	**0.9923**	**0.9894**	0.9842
Unet	30.1168	29.0257	24.6563	0.9913	0.9890	0.9825

Result

Model	O0		O2			
	video memory (MiB)	training time(s)	video memory (MiB)	training time(s)	video memory saving	training time saving
ResAttUnet	7021	1401.1953	4773	809.8071	32.01%	42.20%
Unet	5575	953.6296	4451	611.7596	20.16%	35.84%

The use of mixed precision can reduce video memory requirements and training time.

Conclusion and outlook

- Conclusion: ResAttUnet adds a ResNet structure so that errors can be better transmitted to the deep network, and adds an attention mechanism so that the model can deal with details better. ResAttUnet is more effective than Unet in terms of evaluation indexes. ResAttUnet reconstructs images on real data sets with smoother edges and sharper insides. The use of mixed precision can reduce video memory requirements and training time.

- Outlook :
  - Neural network can also be used for optimization before inverse Radon transform.
  - Targeted loss functions should be designed to train the model.