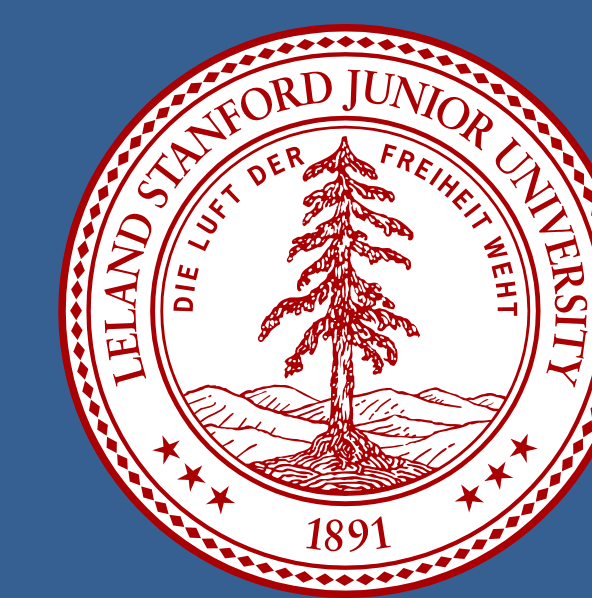




Reconstructing Ultra-low-dose Positron Emission Tomography using Deep Learning

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PET: Uses and Risks

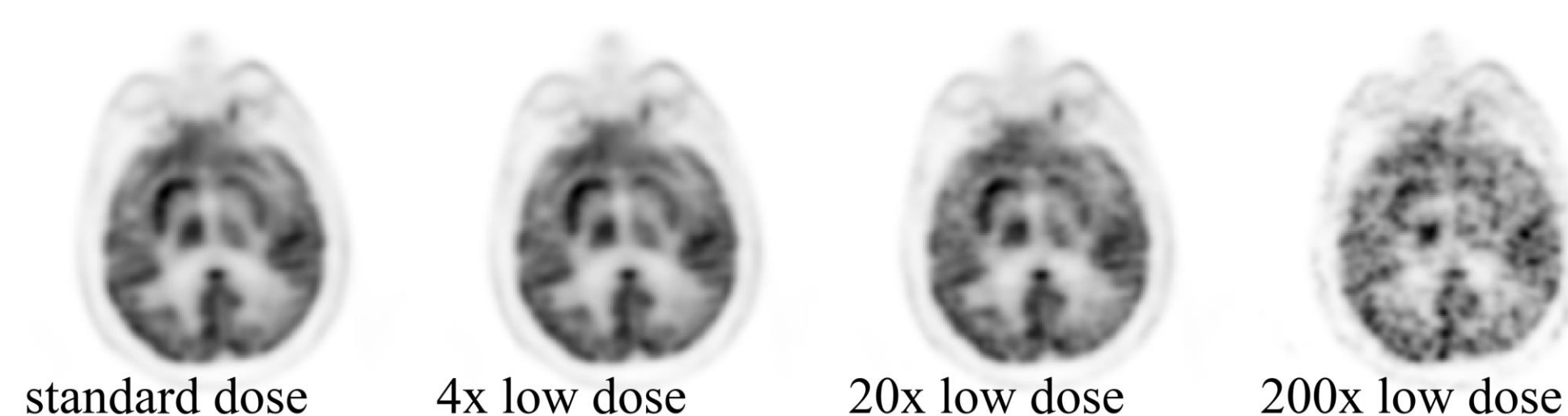
What is PET

Positron emission tomography (PET) is a cutting-edge medical imaging technique in nuclear medicine with a wide range of clinical applications, including detection of cancer and tumor and early diagnosis of neuro diseases. To detect cell metabolism, radioactive tracers are used in PET imaging, which may increase the risk of over-exposure to radiation.

Trade-off between dose reduction and image quality

To minimize such risk, attempts have been made to lower injected dose in PET imaging. However, there is a trade-off between lowering dose and high image quality.

- Standard dose: higher risk and high-quality image
- Low dose: lower risk and noisy image



Problems in existing methods

Some methods have been proposed for reconstructing standard dose PET images from low-dose data^{1,2}. However, these methods are not without their problems.

- Time-consuming in reconstruction
- Dose reduction factor (DRF) not more than four

Objective

- Predicting standard dose PET images from ultra-low-dose images (DRF=200 or 99.5% dose reduction)
- Using deep learning method
- Combining information from Magnetic Resonance Imaging (MRI)

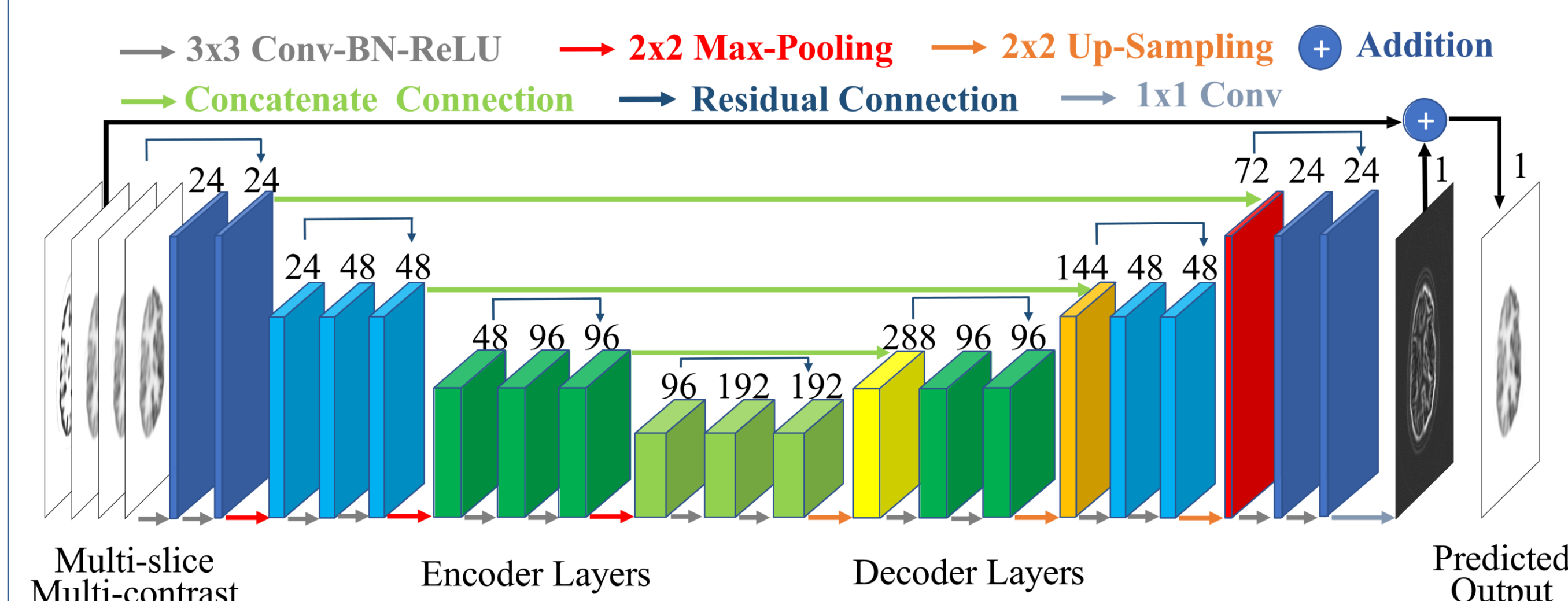
Methods

Dataset

Data of six Glioblastoma (GBM) subjects were acquired on a PET/MRI system (SIGNA, GE Healthcare). Standard-dose PET data were collected and then randomly under-sampled to simulate 200x low dose injection.

Network architecture

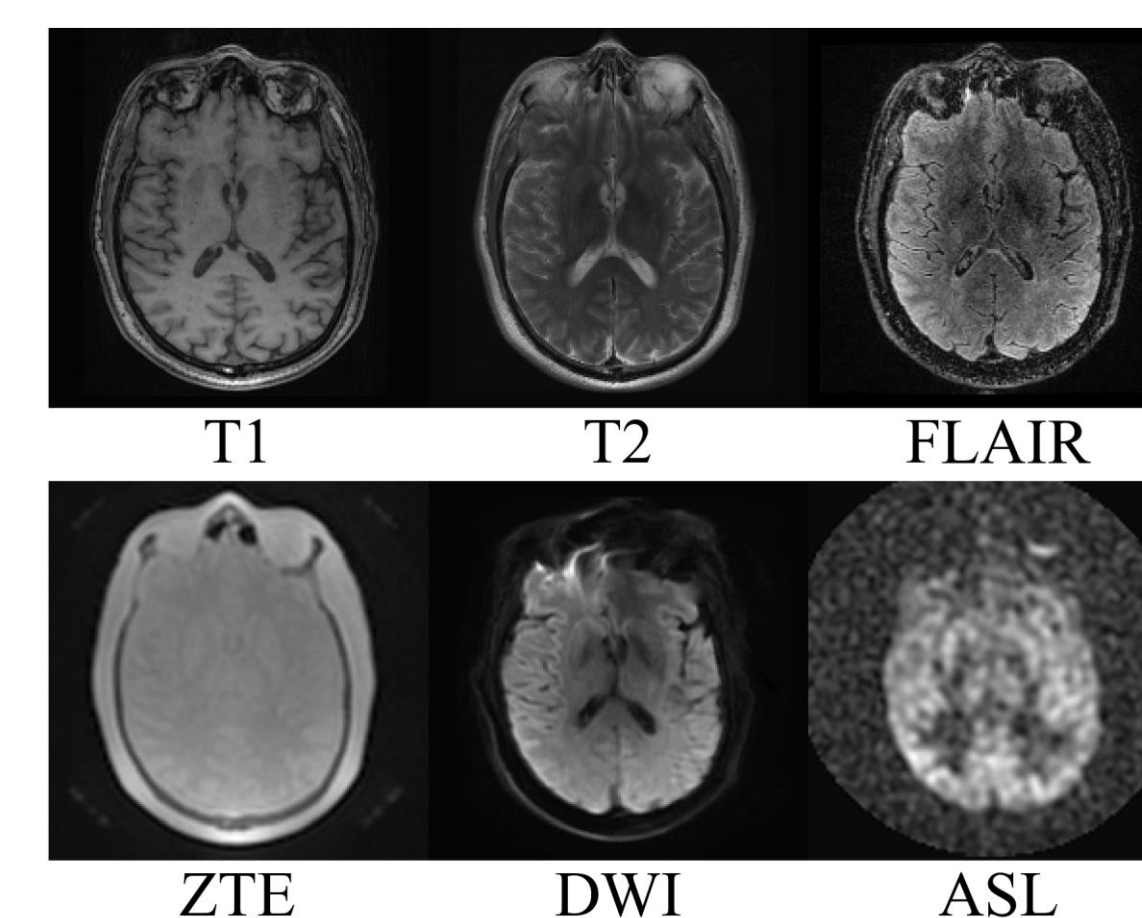
We use a fully convolutional neural network with the multi-scale encoder-decoder structure to extract features of different resolutions. Symmetric concatenate and residual connections are adopted in our network to avoid loss of high-resolution information.



The overall structure of the proposed network. Arrows indicate different operations and each box means a tensor with number of channels labeled above

Input

- Multi-slice PET: slices along z axis are stacked as different channels to employ 3D information in PET data for denoising.
- Multi-contrast MR: different contrasts are regarded as different input channels.



Loss function

We use the L1 loss as loss function for it avoids splotchy artifact that results from traditional mean squared error loss.

$$Loss = \frac{1}{MN} \sum_{j=1}^M \sum_{i=1}^N |x_{ij} - y_{ij}|$$

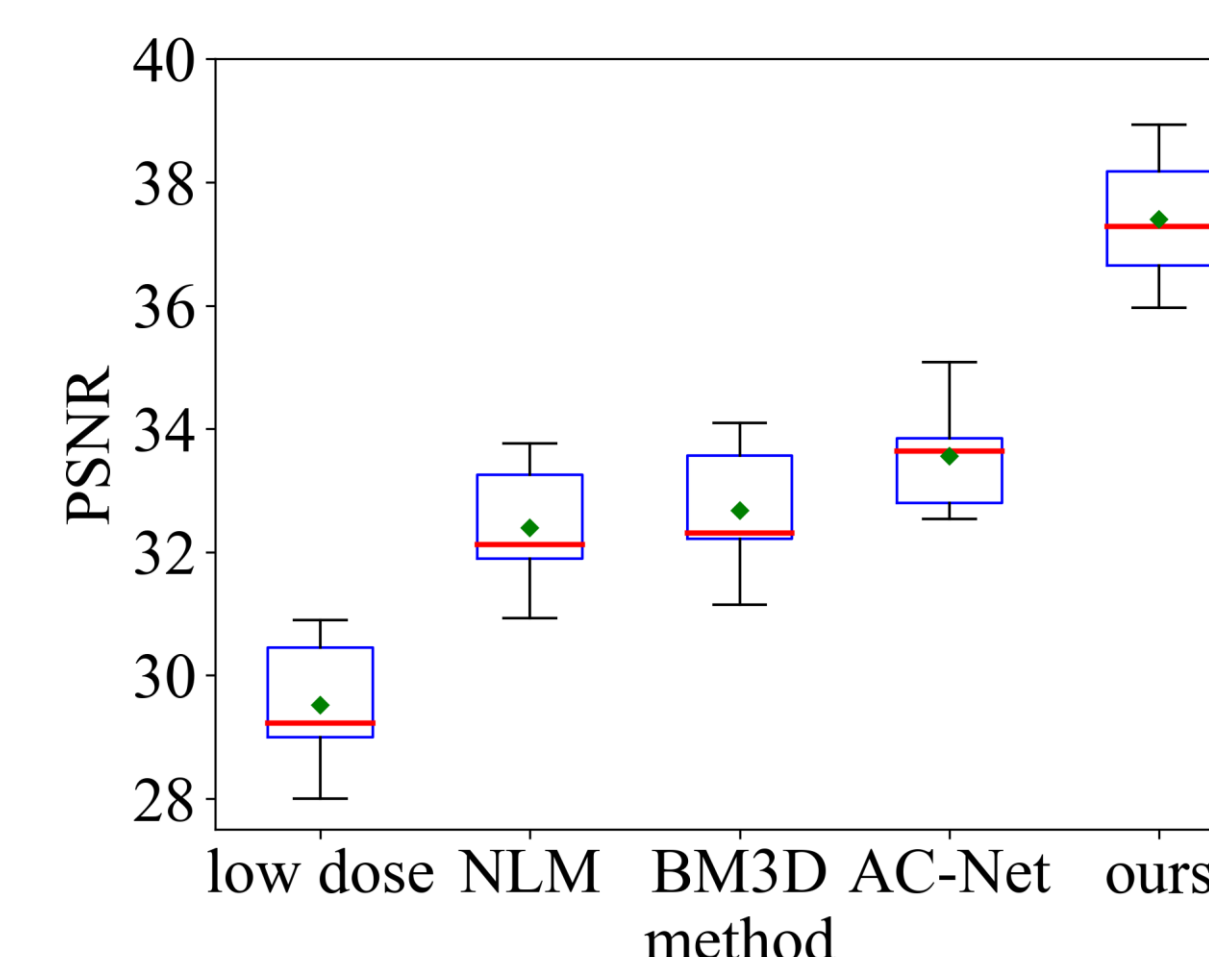
Compared with Other Methods

Experiment setup

We compare our methods with other methods, including nonlocal means³ (NLM), block matching 3D⁴ (BM3D), and auto-context net⁵ (AC-Net), using leave-one-out cross validation. Results show that our proposed method has several advantages as follows.

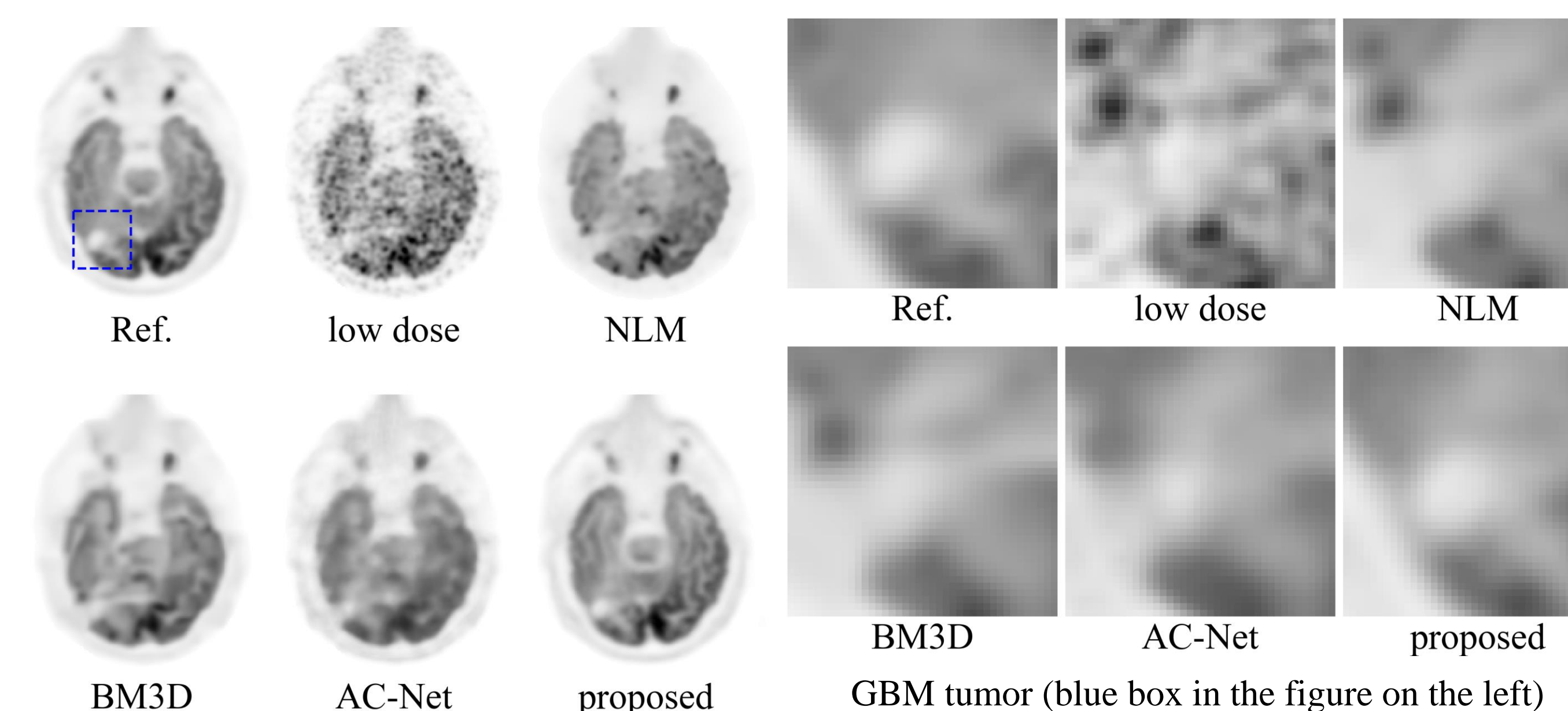
Our method achieves higher PSNR

Results show that our method can achieve higher peak signal-to-noise ratio (PSNR) compared with state-of-the-art methods, indicating a better capability of denoising.



High-quality images can be produced with our model

Visual results show that image reconstructed by our method has the best image quality and it is the most similar to the standard-dose reference for the proposed model can not only remove the noise due to dose reduction but also preserve local detail in the image. Besides, our method can reconstruct the GBM tumor with the same shape as that of the reference, which is important for clinical diagnosis.



The proposed model is time efficient

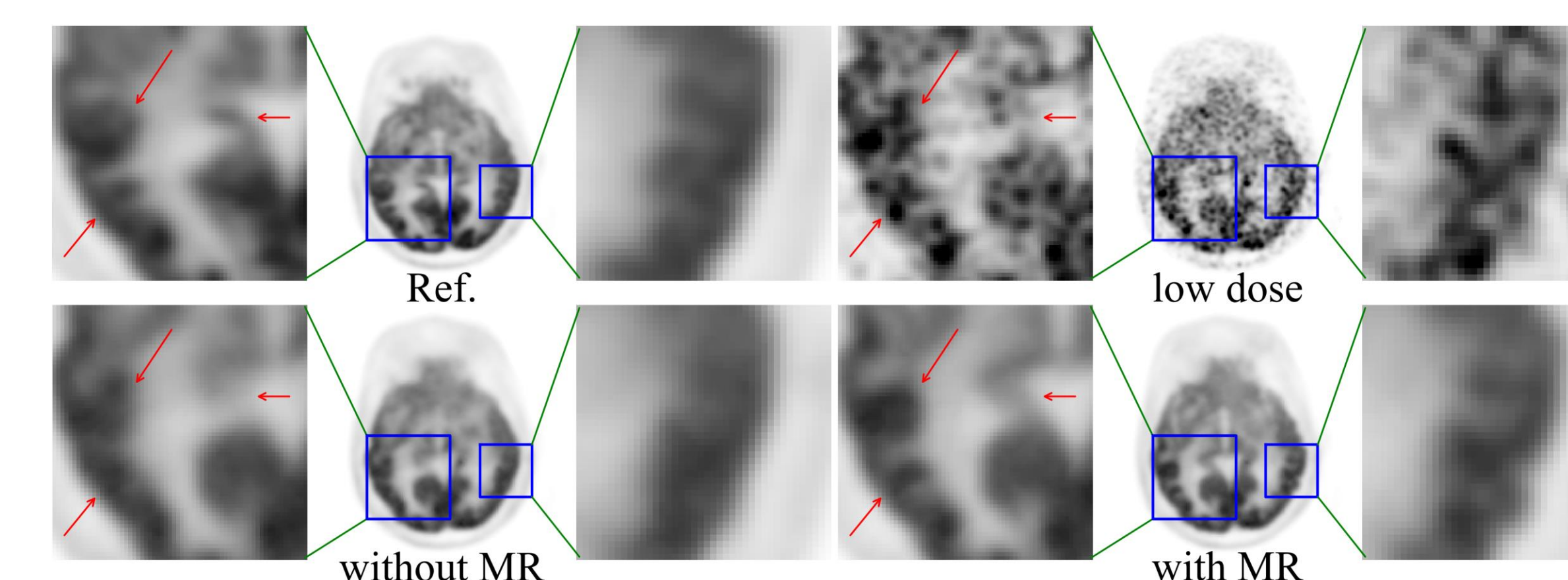
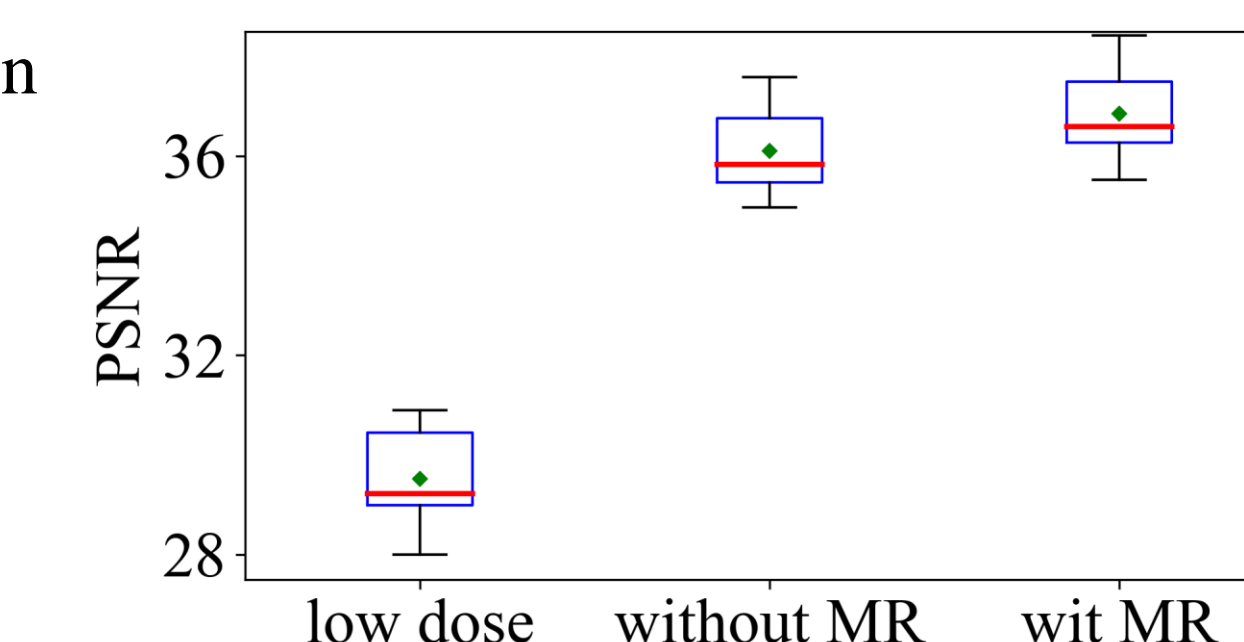
With benefit from GPU acceleration and efficient encoder-decoder structure, the proposed method has the shortest prediction time (per image) among all the methods in our experiment.

Method	NLM (CPU)	NLM (GPU)	BM3D (CPU)	BM3D (GPU)	AC-Net (GPU)	Proposed (GPU)
Time (ms)	1180	63	680	232	27	19

Contribution of MR to PET Denoising

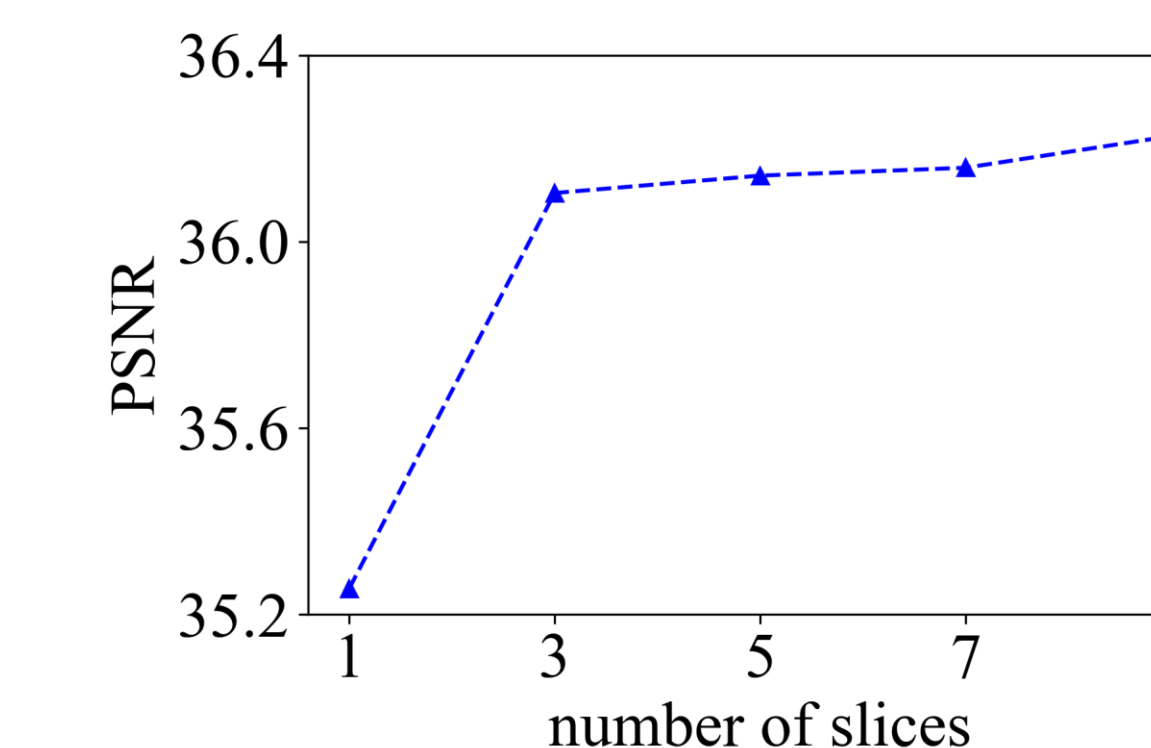
Quantitatively, MRI can improve the PSNR in PET reconstruction.

Visually, model with MRI can Remove noise results from dose reduction while preserving local detail and contrast

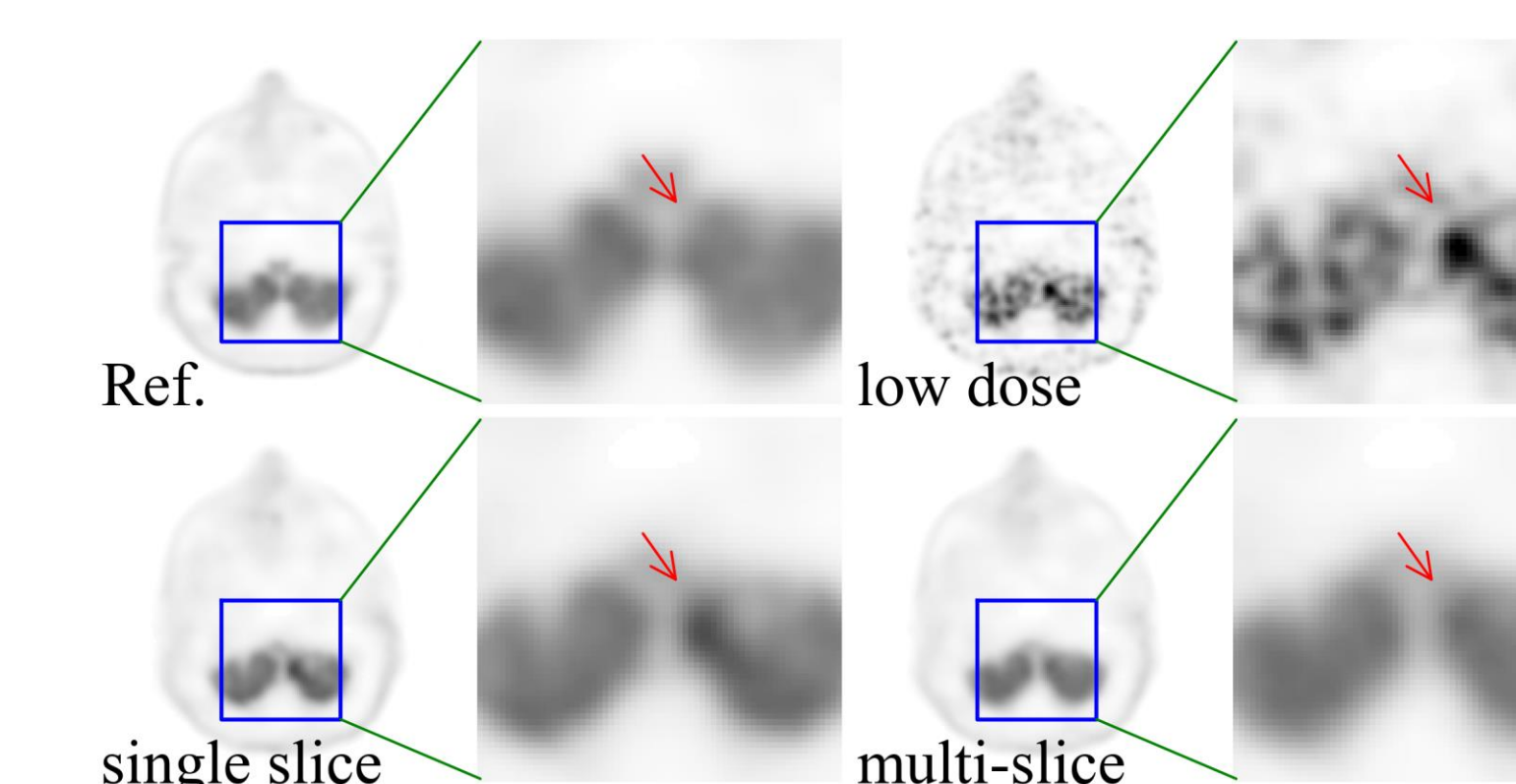


Benefit from 3D PET Data

Compared with single-slice input, three-slice input provides significantly better PSNR. However, the improvement, by adding more than 3 slices, is not as significant, for slices far away from the center can only provide litter information.



Besides, Information from adjoining slices can help distinguish noise from the real structure.



Conclusions

To sum up, we proposed a multi-scale deep convolution network for ultra-low-dose PET reconstruction with advantages as follows

- Superior performance in low-dose PET denoising compared with state-of-the-art methods
- Reconstructing high-quality PET images with only 0.5% of the regular dose
- Combining spatial information from adjoining PET slices and simultaneous MR scan to preserve local details and structure
- Enabling safer and more efficient PET scans.

Acknowledge & Reference

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- [1]Wang, Chenye, et al. "Low dose PET reconstruction with total variation regularization." *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE.*
- [2]Wang, Yan, et al. "Semisupervised Triple Dictionary Learning for Standard-Dose PET Image Prediction Using Low-Dose PET and Multimodal MRI." *IEEE Transactions on Biomedical Engineering* 64.3 (2017): 569-579.
- [3]Baudes, Antoni, Bartomeu Coll, and J.-M. Morel. "A non-local algorithm for image denoising." *Computer Vision and Pattern Recognition, 2005. IEEE Computer Society Conference on.* Vol. 2. IEEE, 2005.
- [4]Dabov, Kostadin, et al. "Image denoising with block-matching and 3 D filtering." *Proceedings of SPIE.* Vol. 6064. No. 30. 2006.
- [5]Xiang, Lei, et al. "Deep Auto-context Convolutional Neural Networks for Standard-Dose PET Image Estimation from Low-Dose PET/MRI." *Neurocomputing* (2017).