AI for PET Image Enhancement

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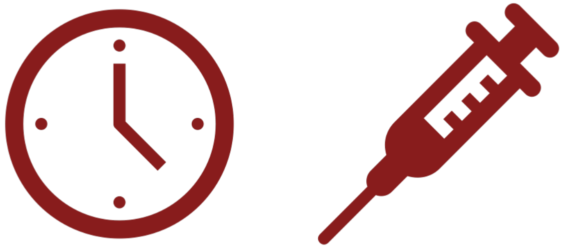
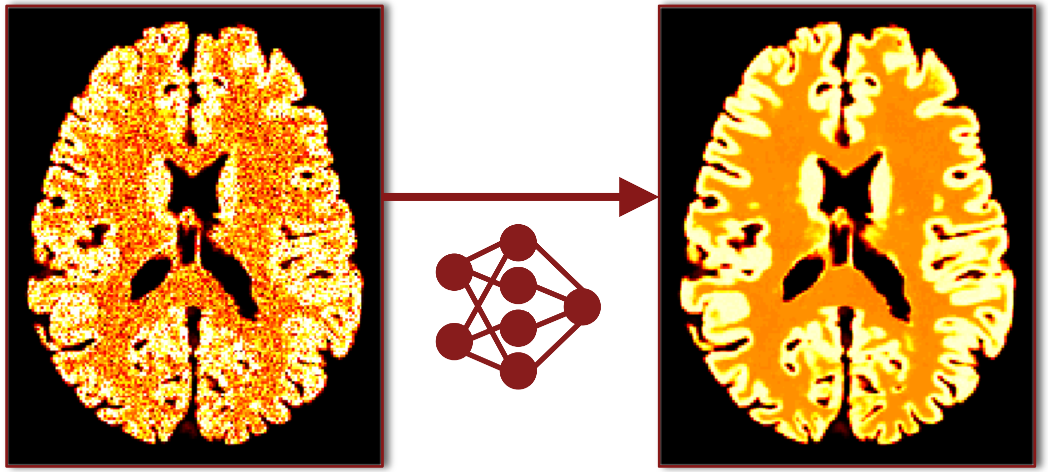
Overview

High Noise



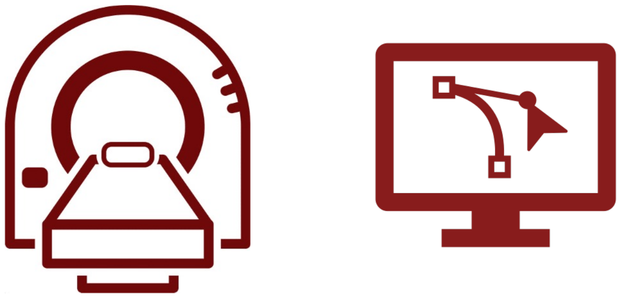
Denoising



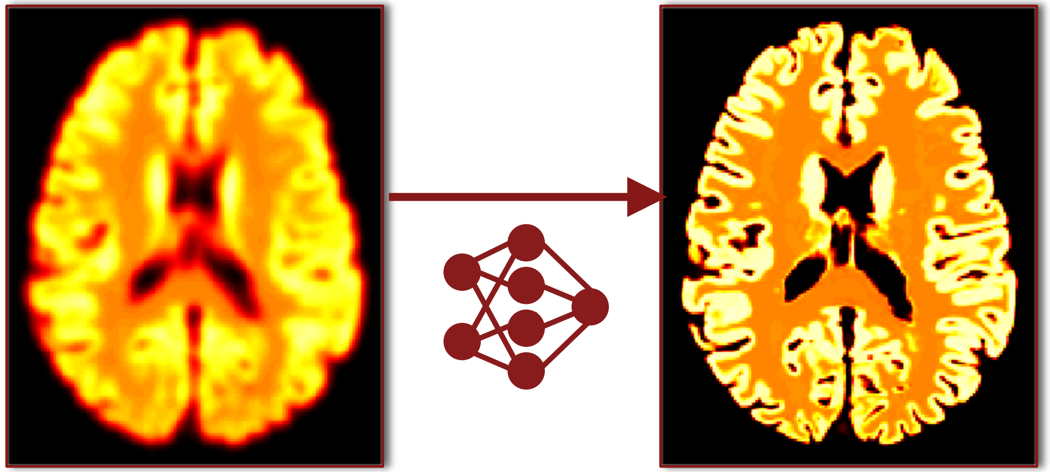
Corrupt Input

Clean Output

Low Spatial Resolution



Deblurring/Super-Resolution



Corrupt Input

Clean Output

Evolution of AI Techniques for Image Enhancement

- Shallow to deeper CNNs
- U-Net
- GAN/CycleGAN
- Deep image prior
- Diffusion models

Fully supervised	Unsupervised Weakly supervised Self-supervised

Super-Resolution (SR) PET Imaging

Paired Low-Res/High-Res Images for Training

LR HR

Unpaired Low-Res/High-Res Images for Training

LR HR

Super-Resolution (SR) PET Imaging

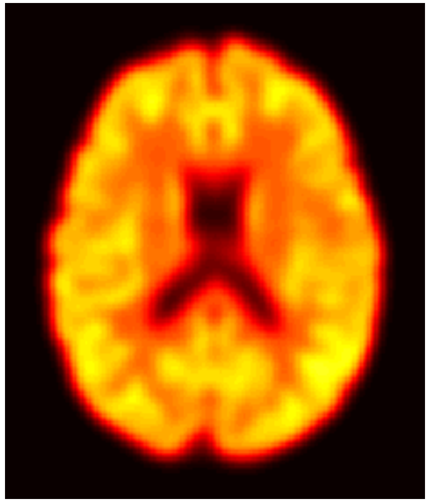
Paired Low-Res/High-Res Images for Training

LR HR

Unpaired Low-Res/High-Res Images for Training

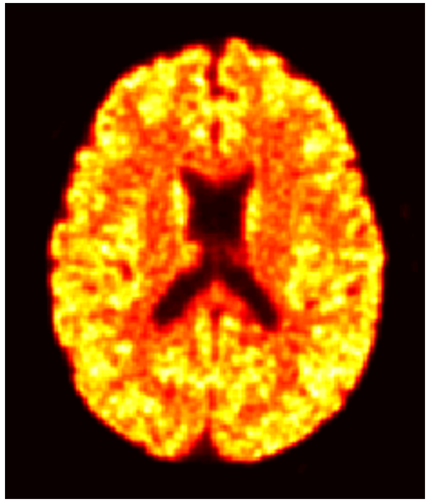
LR HR

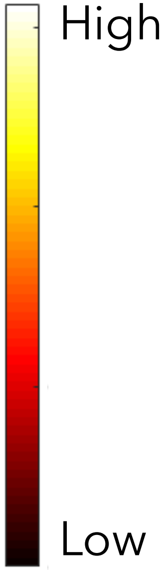
Siemens HR+ Scanner



- Legacy clinical PET system
- Spatial resolution ~7.0 mm

Siemens HRRT Scanner

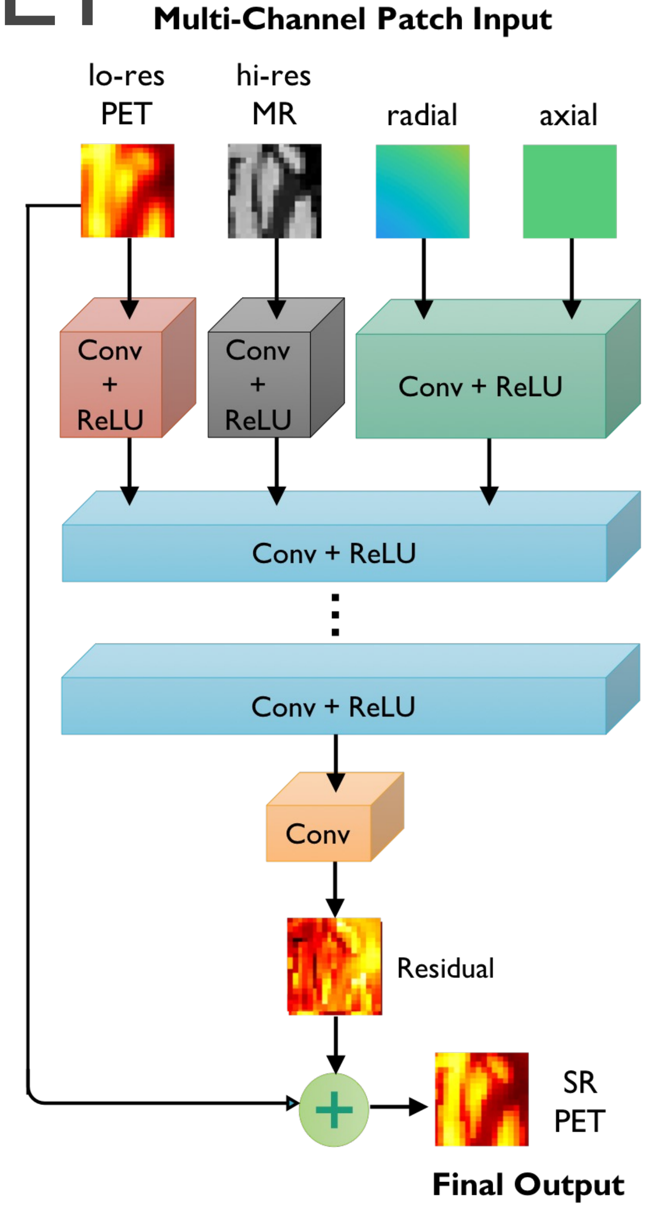




- Dedicated human brain PET scanner
- Spatial resolution ~2.7 mm

Very Deep Super-Resolution (VDSR) PET

- Patch-level multi-channel inputs: lo-res PET, hi-res MR, spatial locations
- Anatomical information
  - Exploit the similarities between the PET and its hi-res MR counterpart
- Spatial information
  - Radio and axial coordinate patches
- Residual learning:
  - Compute the difference between the lo-res PET and the ground-truth hi-res PET
  - Shortens the training time
- Design:
  - 20 convolutional layers followed by a ReLU, except for the last layer
  - 64 filters in each layer, except for the last layer which only has one



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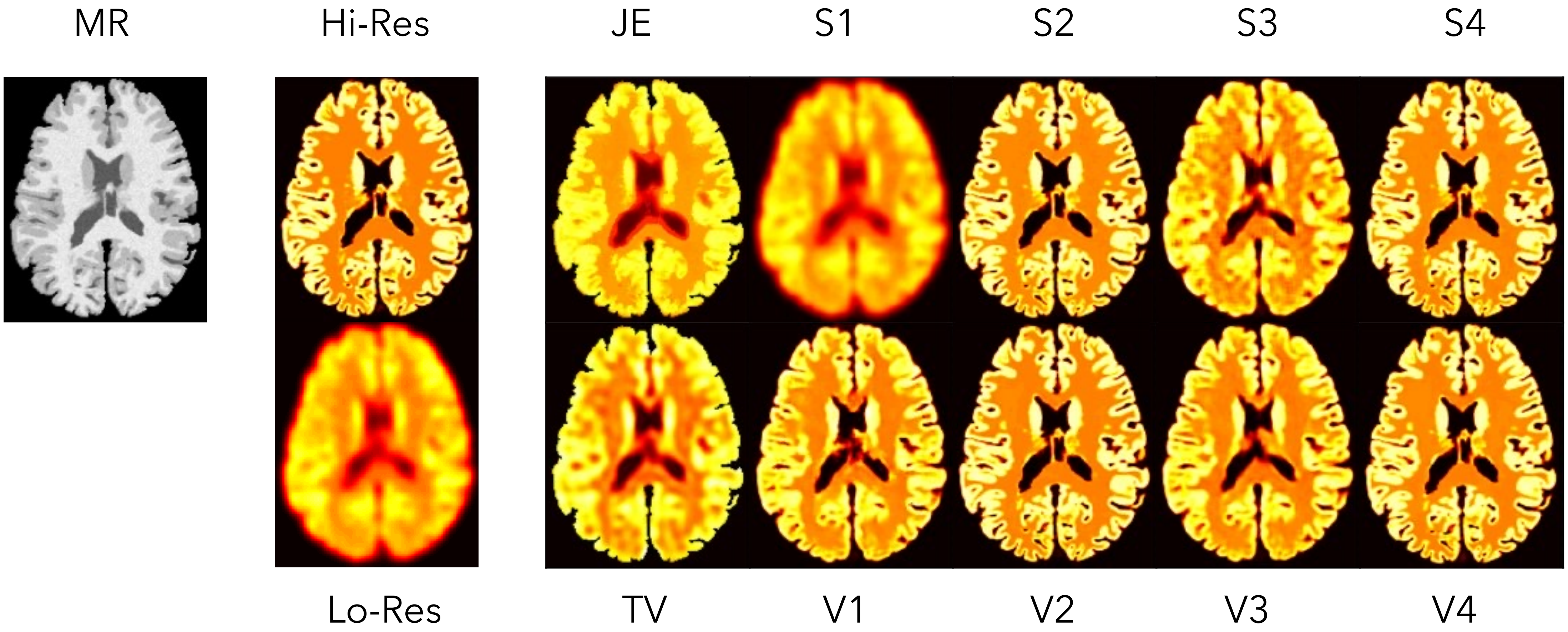
VDSR PET: Simulation Results (Perfect Ground Truth)



V: Very deep, **S**: Shallow
1: only lo-res input, **2**: lo-res + anatomical inputs, **3**: lo-res + spatial inputs, **4**: lo-res + anatomical + spatial inputs

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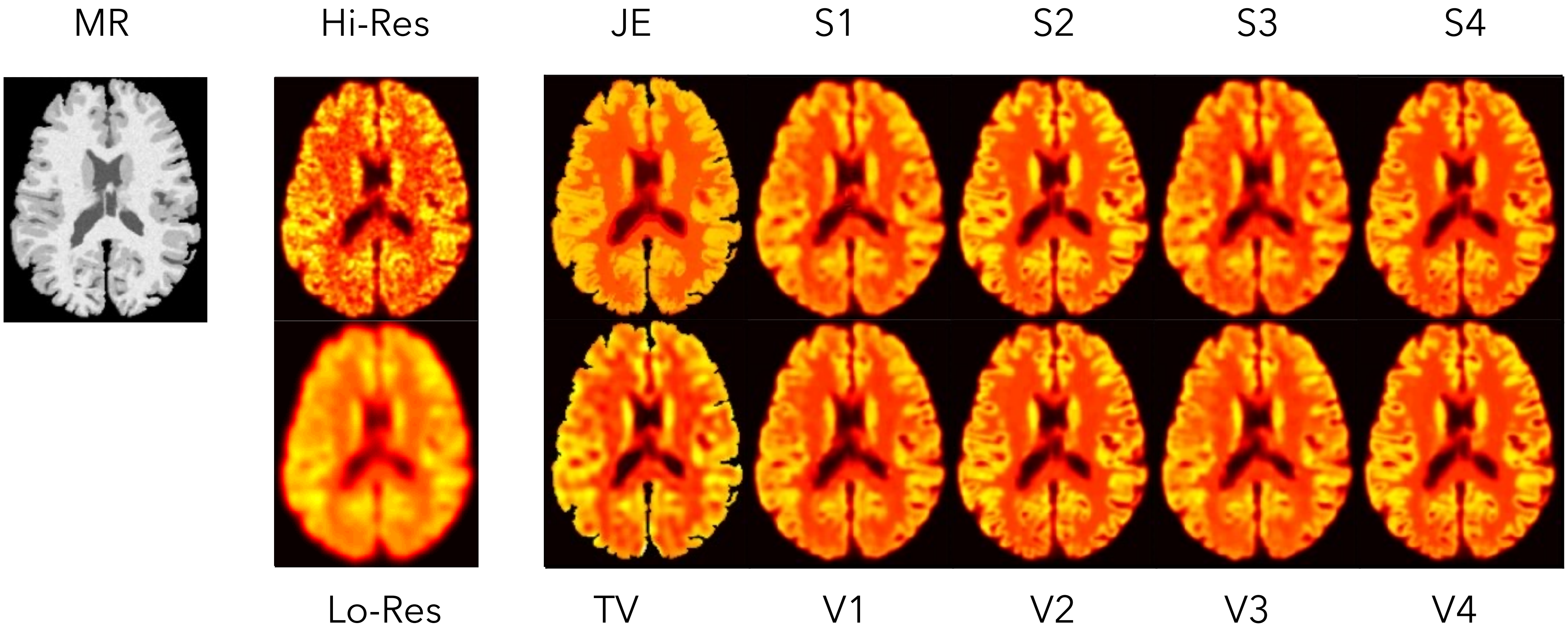
VDSR PET: Simulation Results (HRRT Ground Truth)



V: Very deep, **S**: Shallow
1: only lo-res input, **2**: lo-res + anatomical inputs, **3**: lo-res + spatial inputs, **4**: lo-res + anatomical + spatial inputs

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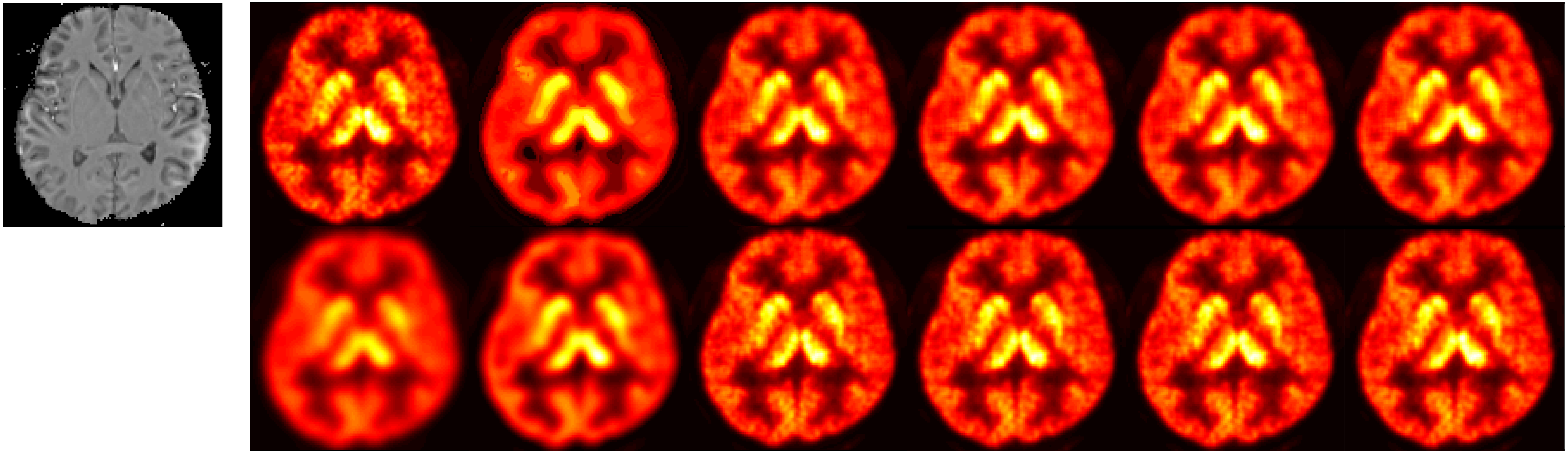
VDSR PET: Clinical Results (HRRT Ground Truth)

MR Hi-Res JE S1 S2 S3 S4



Lo-Res TV V1 V2 V3 V4

V: Very deep, **S**: Shallow
1: only lo-res input, **2**: lo-res + anatomical inputs, **3**: lo-res + spatial inputs, **4**: lo-res + anatomical + spatial inputs

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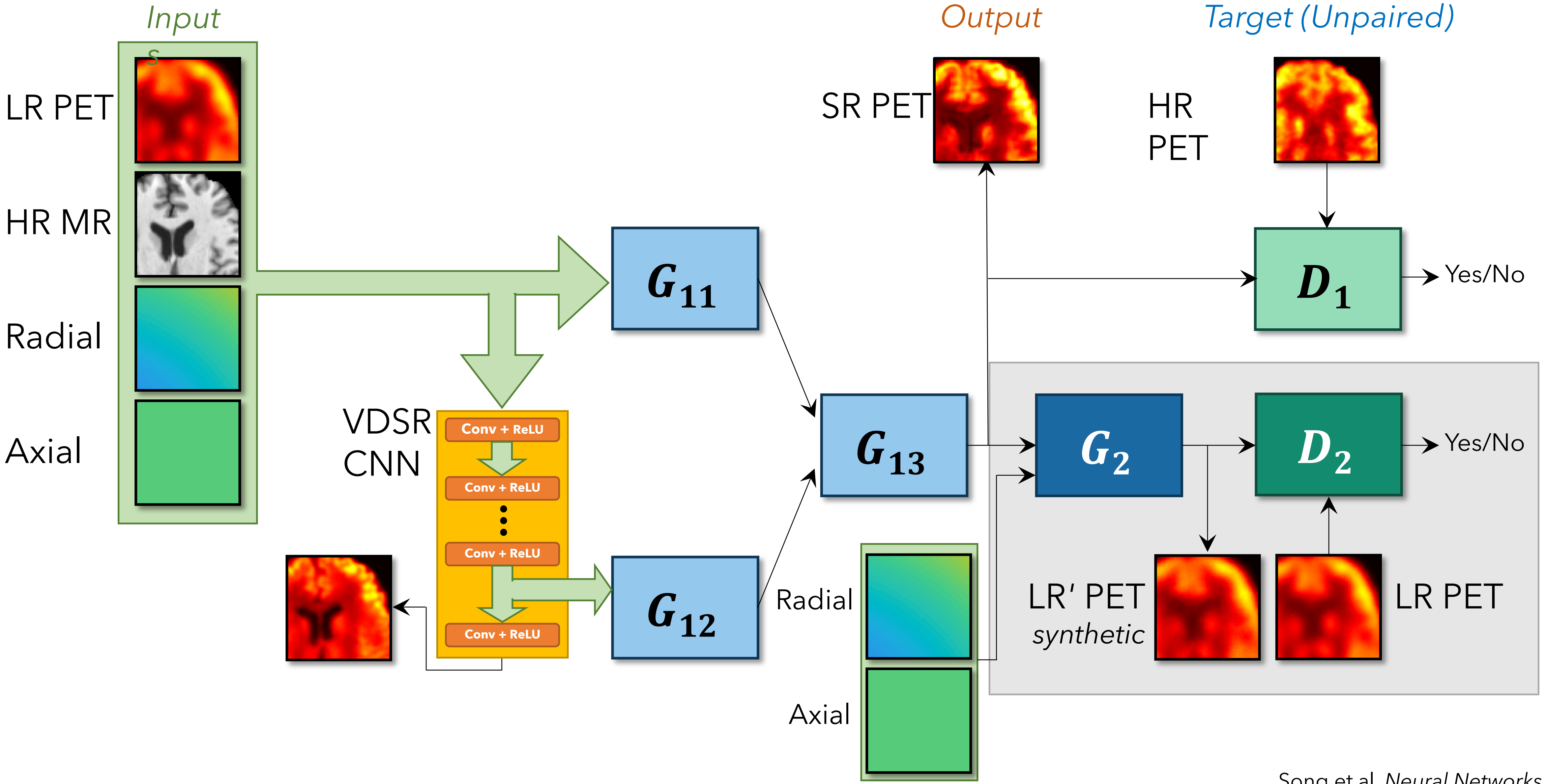
Self-Supervised Super-Resolution (SSSR) PET



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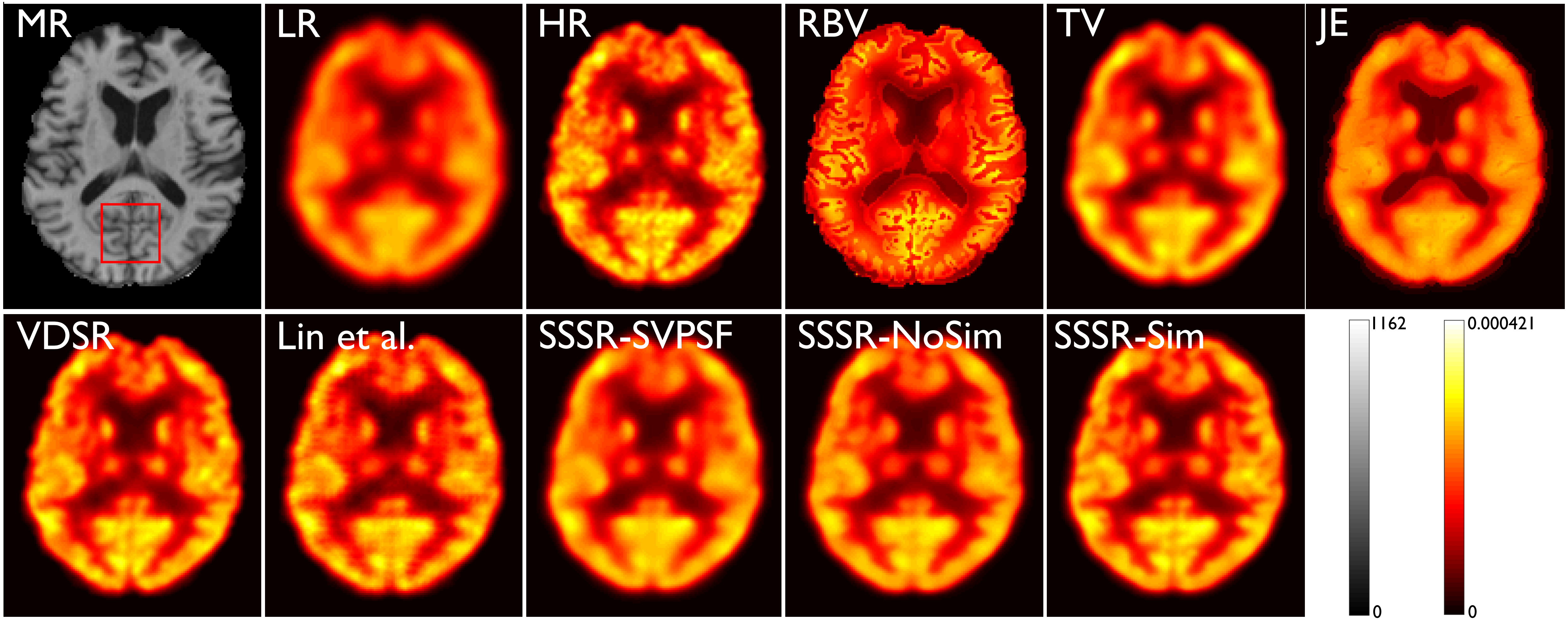
SSSR PET: Clinical Results



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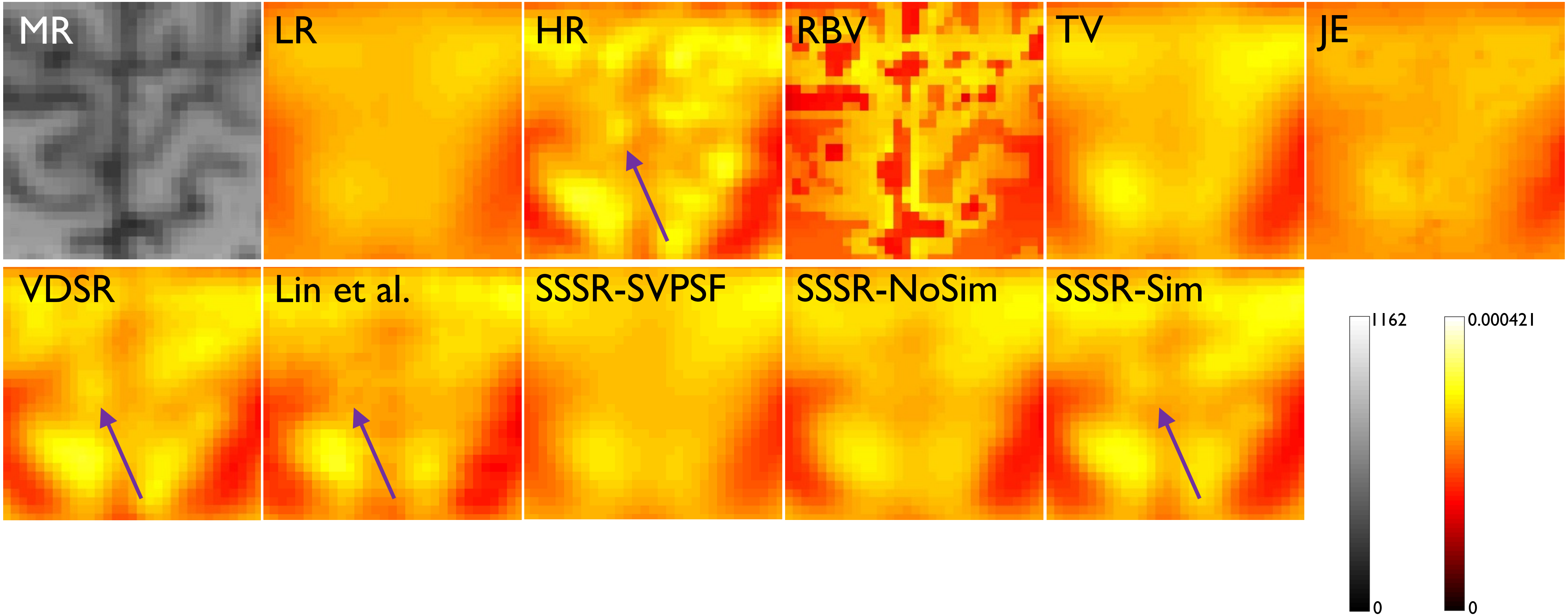
SSSR PET: Clinical Results



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PET Image Denoising

Paired Low-Count/High-Count Images for Training

LC HC

Only Low-Count Images for Training

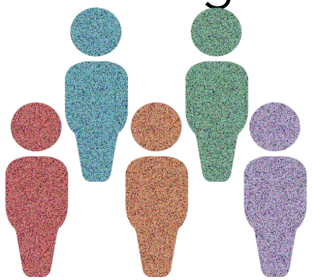
LC

2 noise realizations

Unpaired Low-Count/High-Count Images for Training

LC HC

Only Low-Count Images for Training



LC

Single noise realizations

Noise2Noise & Noisier2Noise

- Noise2Noise:
  - A weakly supervised denoising approach that reconstructs a clean image from multiple independent corrupt observations
  - Simple and powerful conclusion: it is possible to learn to restore images by only looking at corrupted examples, at performance at and sometimes exceeding training using clean data
- Noisier2Noise:
  - A method for training a neural network to perform image denoising without access to clean training examples or access to paired noisy training examples
  - Requires only a single noisy realization of each training example and a statistical model of the noise distribution, and is applicable to a wide variety of noise models

Noise2Noise: Learning Image Restoration without Clean Data

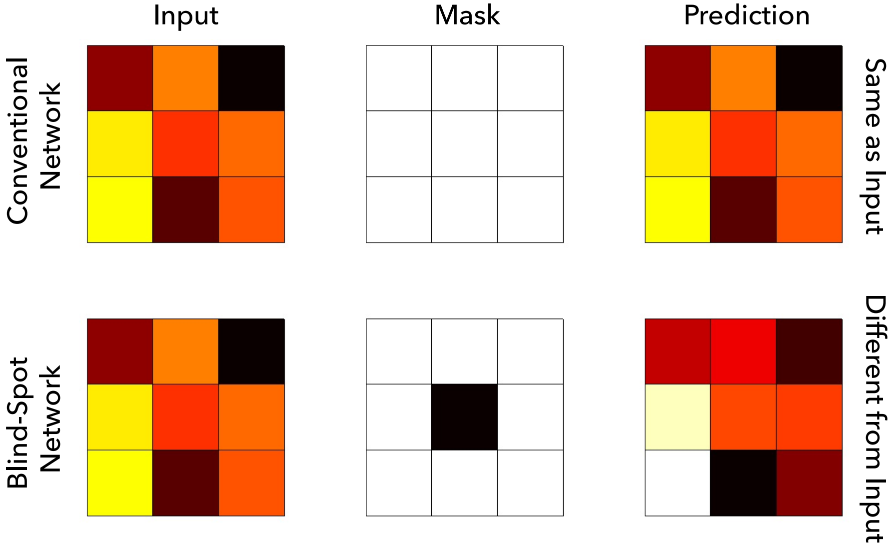
Jaakko Lehtinen[1 2] Jacob Munkberg[1] Jon Hasselgren[1] Samuli Laine[1] Tero Karras[1] Miika Aittala[3] Timo Aila[1]

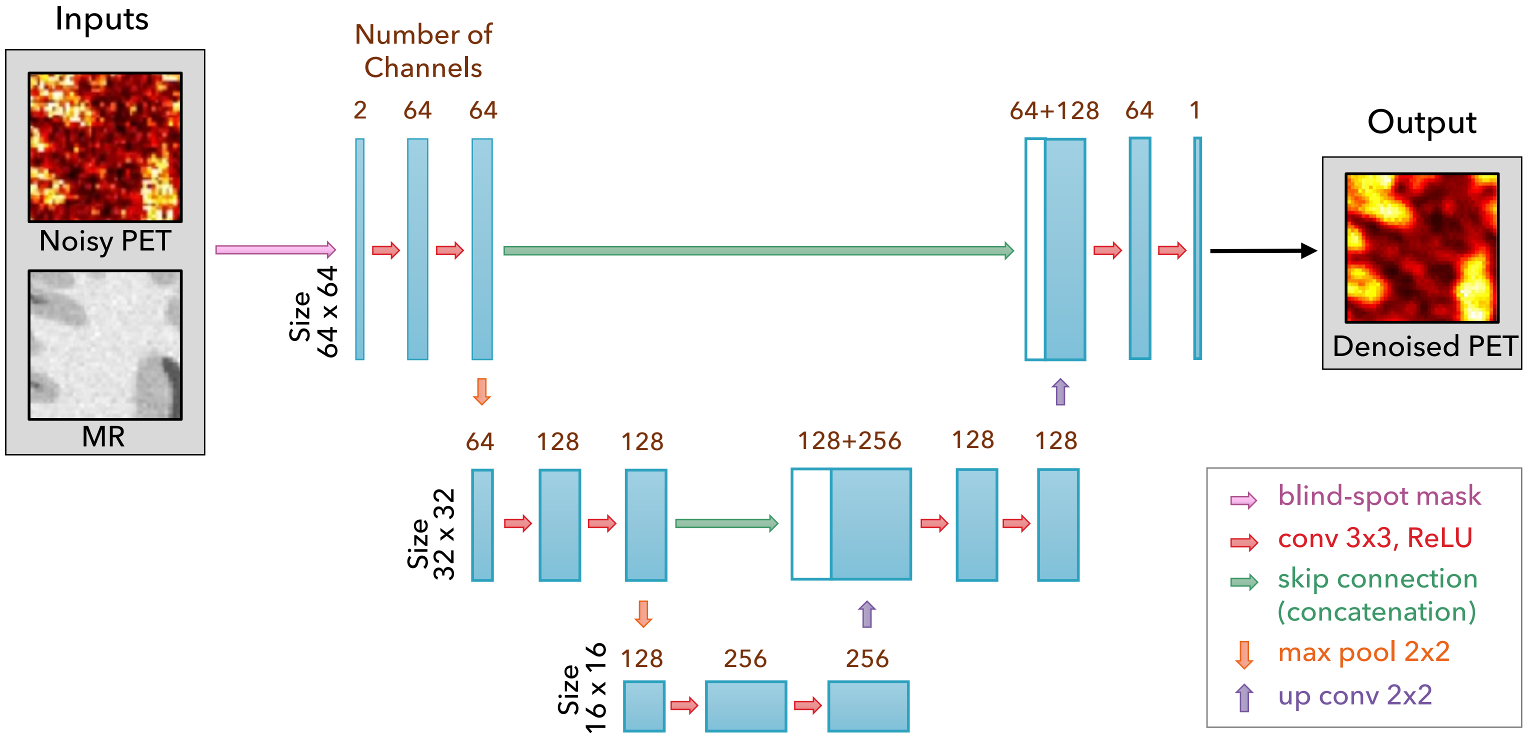
Noisier2Noise: Learning to Denoise from Unpaired Noisy Data

Nick Moran, Dan Schmidt, Yu Zhong, Patrick Coady

Noise2Void PET Denoising

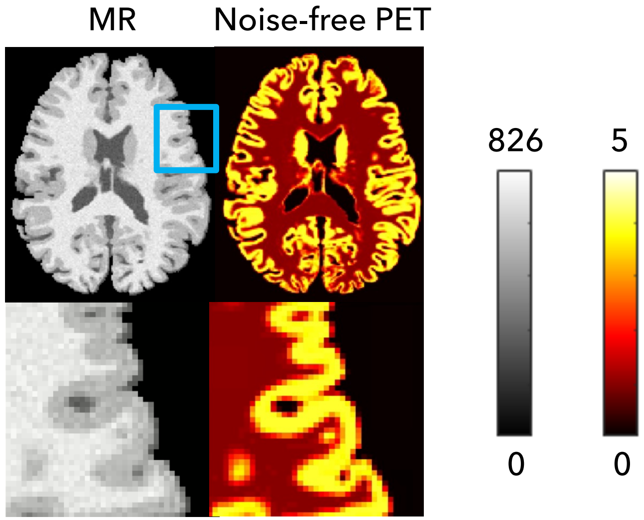
- Noise2Void relies on corrupt images alone for model training
- Blind spot: A masked receptive field that excludes the central pixel and can learn to suppress noise by focusing on the neighboring pixels. Thus, it can generate a prediction distinct from the input even when the input and target images are identical and noisy.

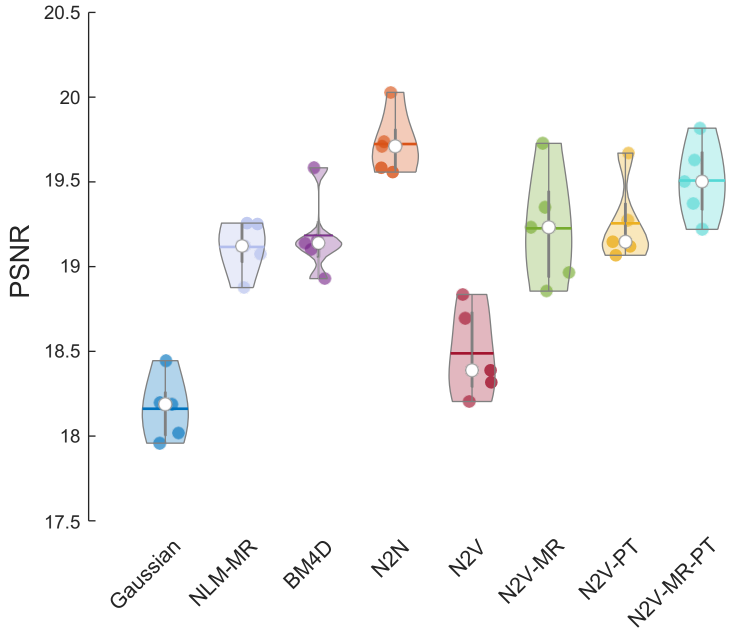


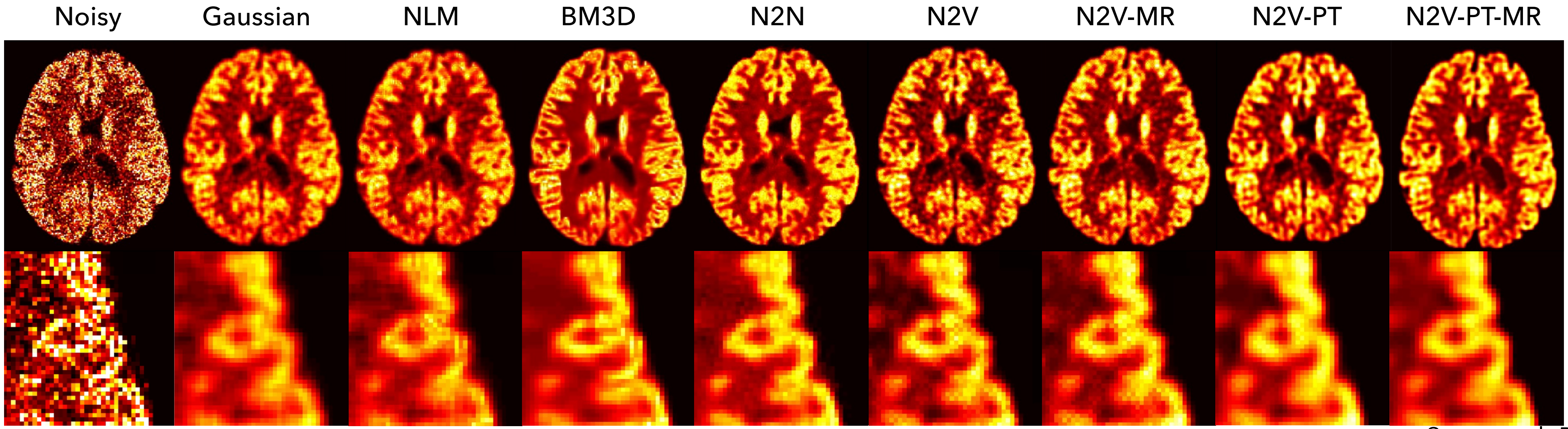


Song et al. *Phys. Med. Biol.* 2021

Noise2Void PET Denoising: Simulation Results







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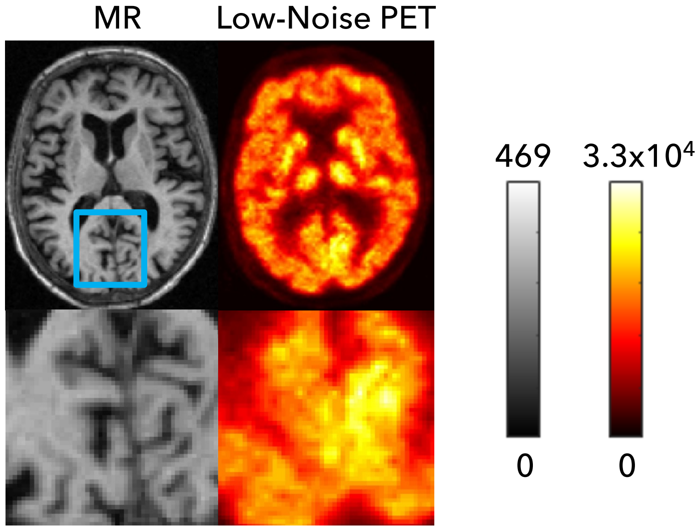
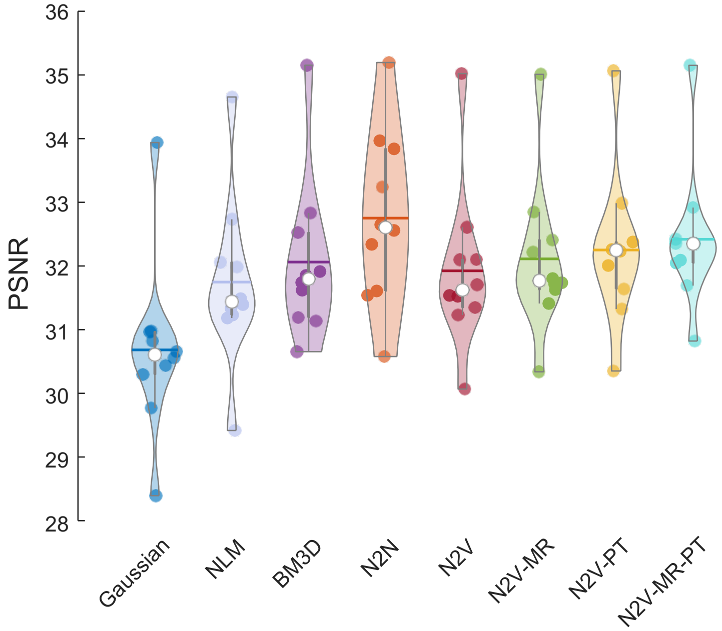
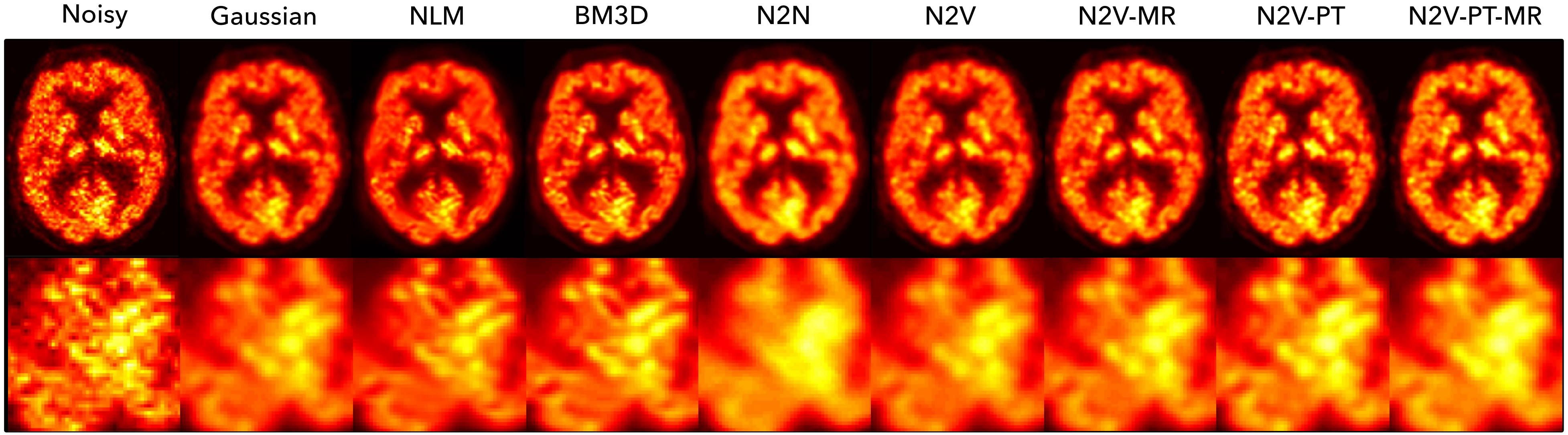
Noise2Void PET Denoising: Clinical Results







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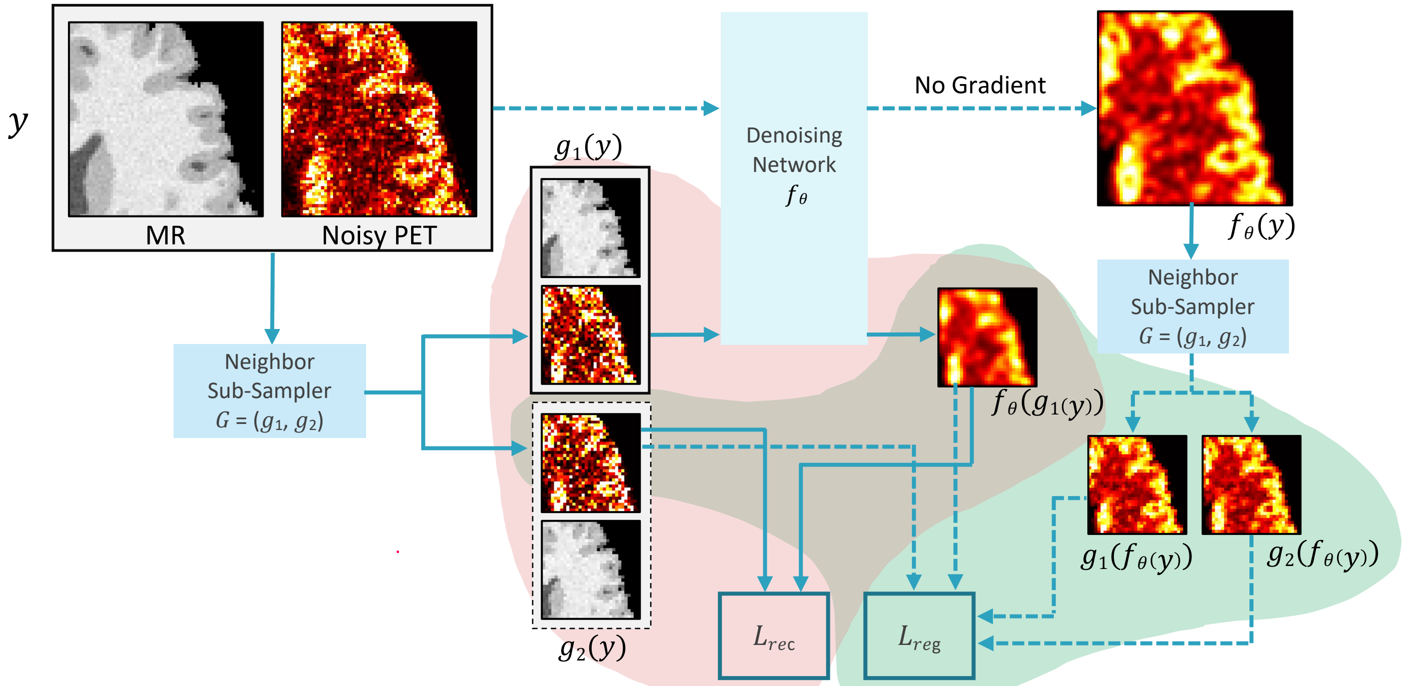
Neighbor2Neighbor PET Denoising

- Neighbor2Neighbor also relies on corrupt images alone for model training.
- The NB2NB approach is inspired by Noise2Noise (N2N).
- A neighbor sub-sampler $G = (g_1, g_2)$ is applied to generate a pair of sub-sampled images $(g_1(y), g_2(y))$ from the input y.
- The denoising network (U-Net) receives $g_1(y)$ as input and solely the PET image of $g_2(y)$ as target.
- NB2NB uses a regularizer that considers the fundamental difference in the ground-truth pixel values between the subsampled noisy image pair

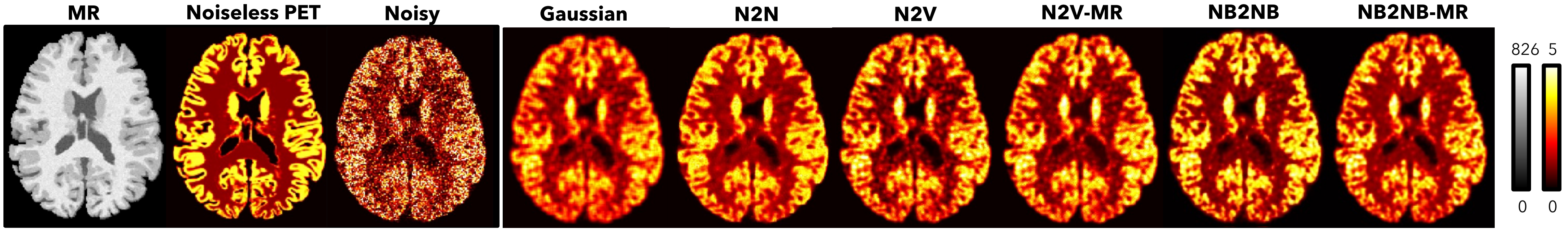


$$L = Lrec + \gamma \cdot Lreg$$
$$= \|f_\theta(g_1(y)) - g_2(y)\|_2^2 + \gamma \cdot \|f_\theta(g_1(y)) - g_2(y) - g_1(f_\theta(y)) - g_2(f_\theta(y))\|_2^2$$

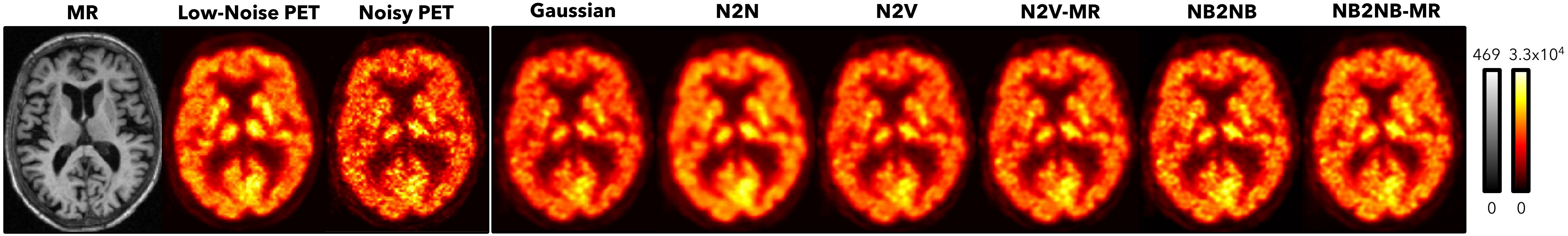
Noise2Noise training
Regularizer

Neighbor2Neighbor PET Denoising

- Simulation Results



- Clinical Results



Song et al. *SNMMI.* 2023 (Submitted)

Emerging Directions

- Blind super-resolution
- Noise-aware denoising
- New architectures
- Non-FDG radiotracers
- Cross-cohort validation
- Cross-site harmonization
- Challenges: Replicability, Reproducibility, Generalizability

Artificial Intelligence-Based Image Enhancement in PET Imaging
Noise Reduction and Resolution Enhancement

Juan Liu, PhD[a,1], Masoud Malekzadeh, MS[b,1], Niloufar Mirian, MSc[a], Tzu-An Song, MS[b], Chi Liu, PhD[a,*], Joyita Dutta, PhD[b,c,*]

Liu et al. *PET Clinics 2021*

THE STATE OF THE ART

Nuclear Medicine and Artificial Intelligence: Best Practices for Algorithm Development

Tyler J. Bradshaw[1], Ronald Boellaard[2], Joyita Dutta[3], Abhinav K. Jha[4], Paul Jacobs[5], Quanzheng Li[6], Chi Liu[7], Arkadiusz Sitek[8], Babak Saboury[9], Peter J.H. Scott[10], Piotr J. Slomka[11], John J. Sunderland[12], Richard L. Wahl[13], Fereshteh Yousefirizi[14], Sven Zuehlsdorff[15], Arman Rahmim[16], and Irène Buvat[17]

THE STATE OF THE ART

Artificial Intelligence in Nuclear Medicine: Opportunities, Challenges, and Responsibilities Toward a Trustworthy Ecosystem

Babak Saboury[1], Tyler Bradshaw[2], Ronald Boellaard[3], Irène Buvat[4], Joyita Dutta[5], Mathieu Hatt[6], Abhinav K. Jha[7], Quanzheng Li[8], Chi Liu[9], Helena McMeekin[10], Michael A. Morris[1], Peter J.H. Scott[11], Eliot Siegel[12], John J. Sunderland[13], Neeta Pandit-Taskar[14], Richard L. Wahl[15], Sven Zuehlsdorff[16], and Arman Rahmim[17]

Acknowledgments

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Thank You!

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