

AI for Post-Reconstruction PET Image Enhancement

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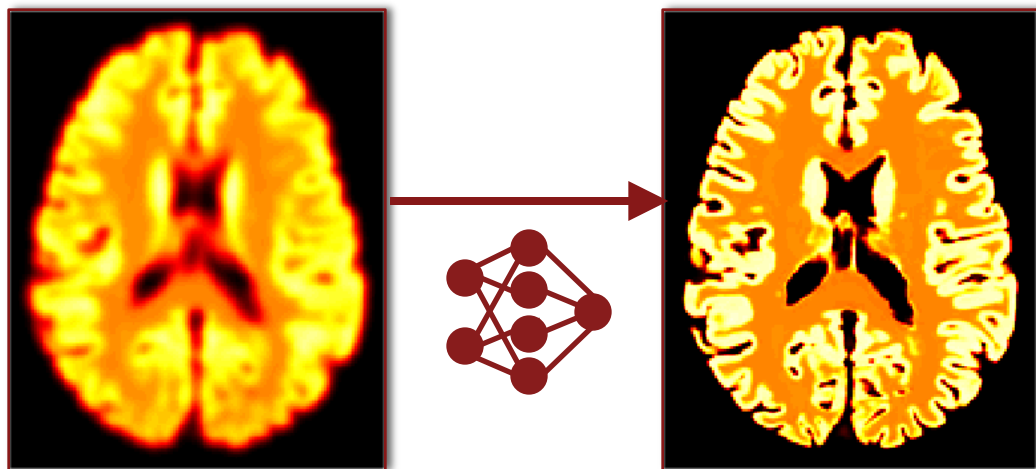


PET Resolution Recovery and Denoising

Low Spatial Resolution



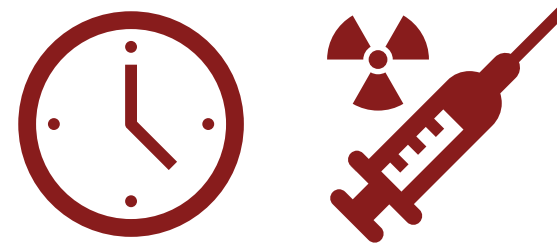
Deblurring/Super-Resolution



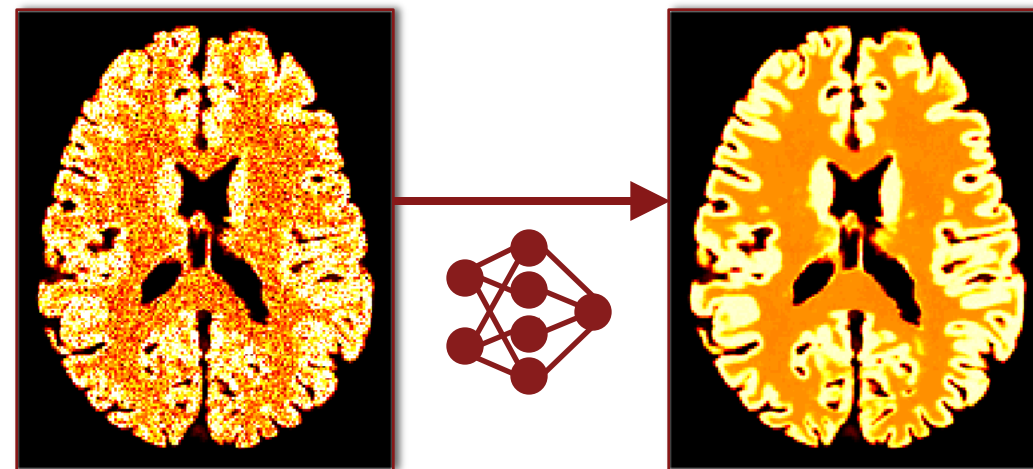
Corrupt Input

Clean Output

High Noise



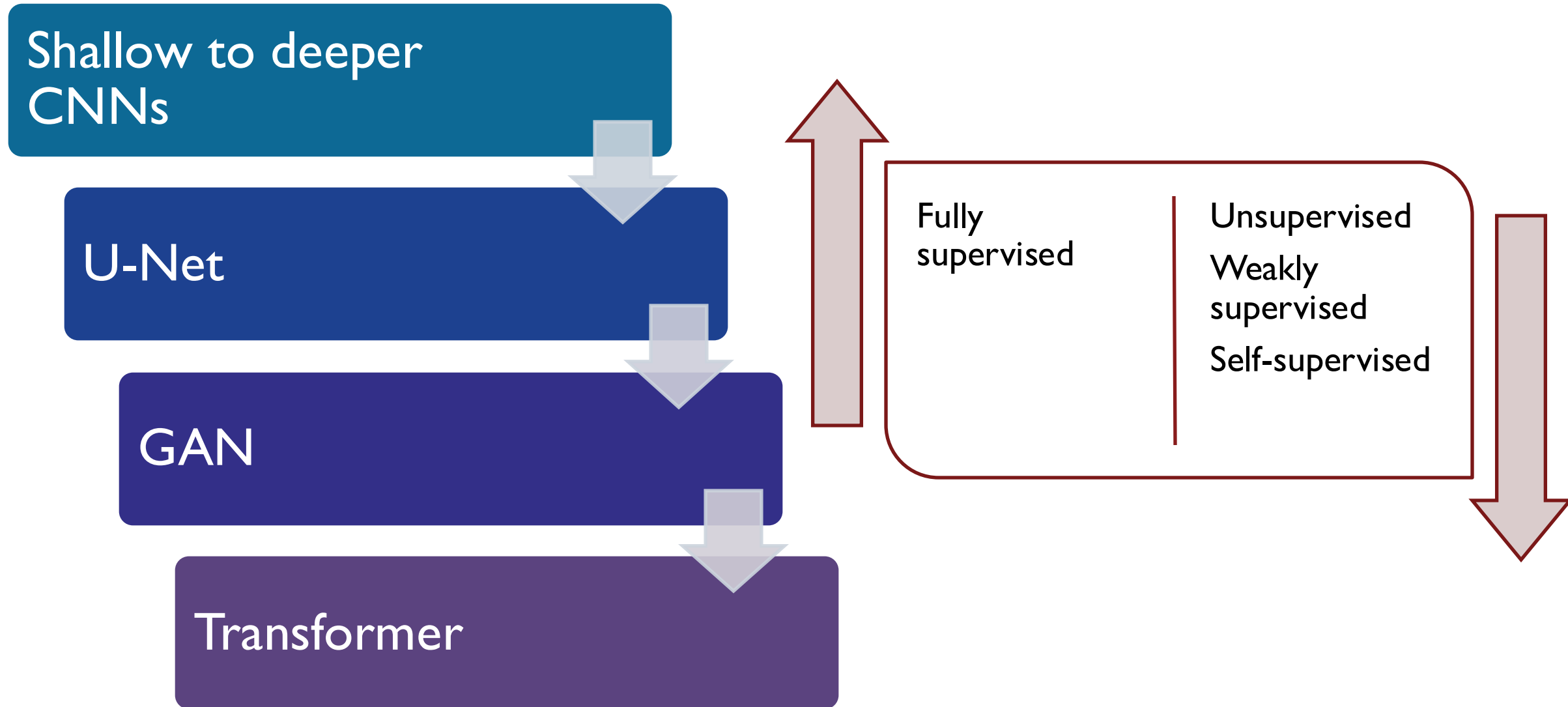
Denoising



Corrupt Input

Clean Output

Evolution of AI Techniques for Medical Imaging



Super-Resolution (SR) PET Imaging

Paired LR-HR Images for Training



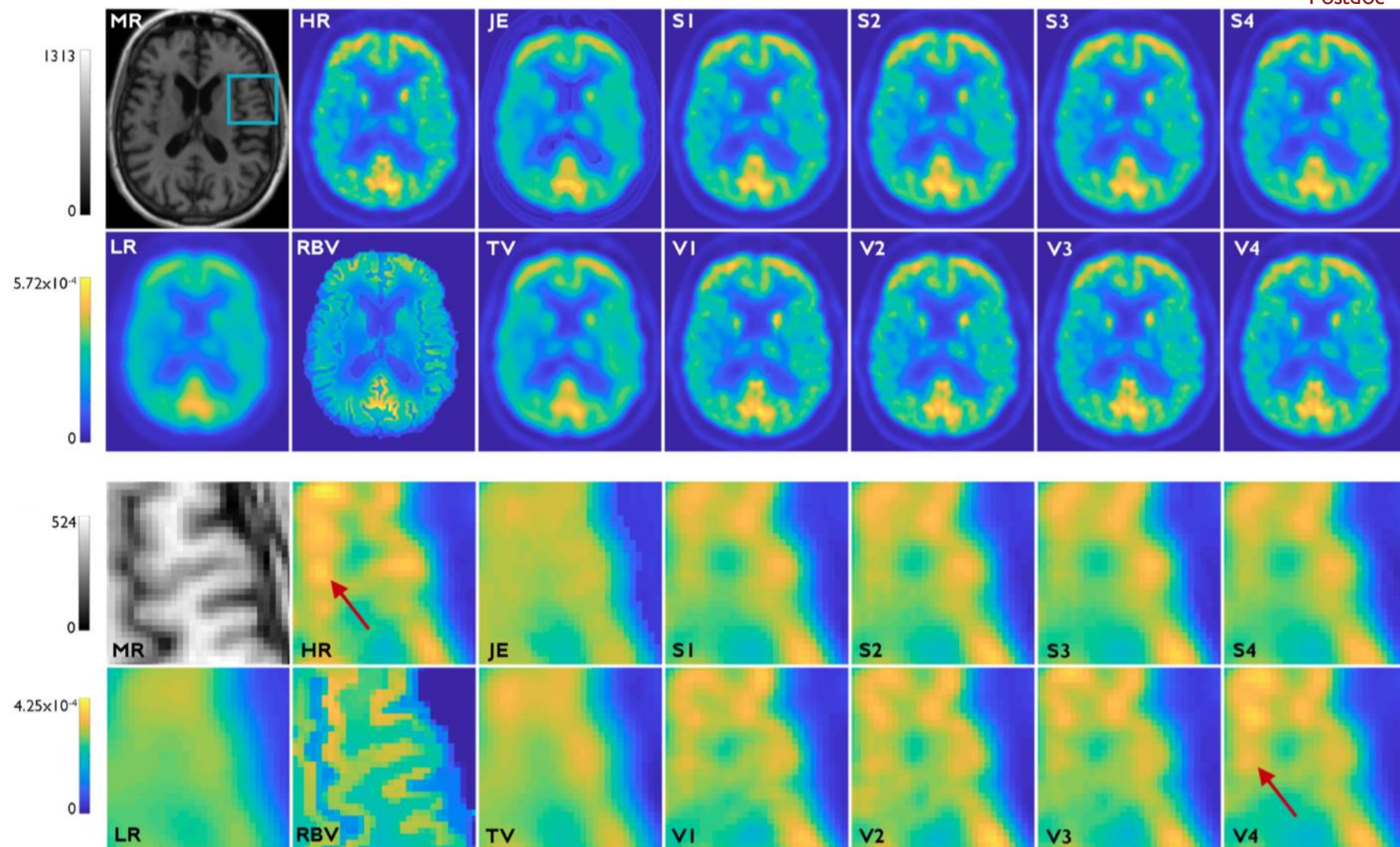
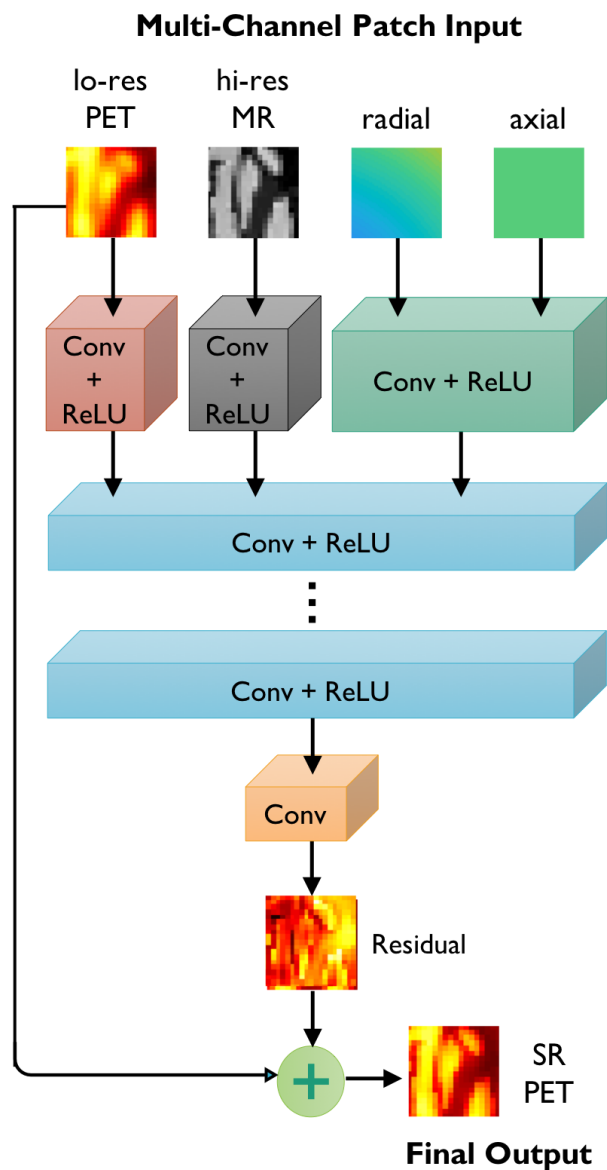
Unpaired LR-HR Images for Training



SR PET with Paired Data Using a Very Deep CNN

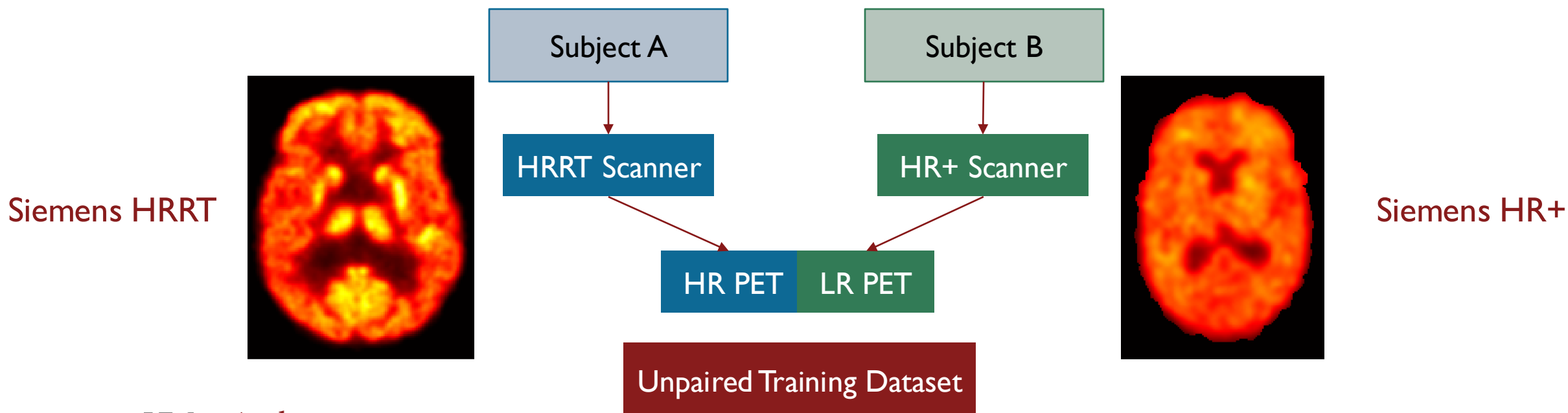


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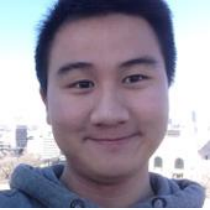


SR PET with Unpaired Clinical Data

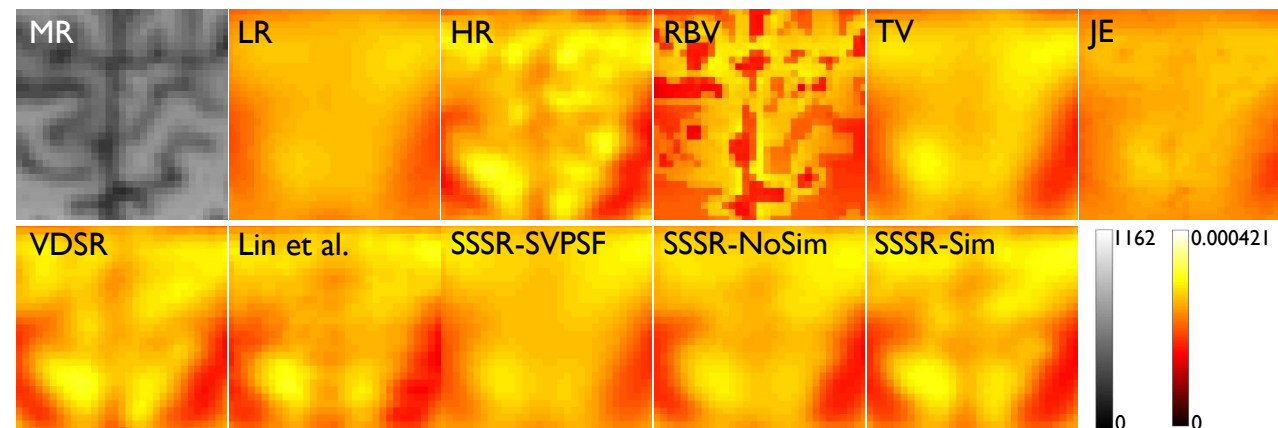
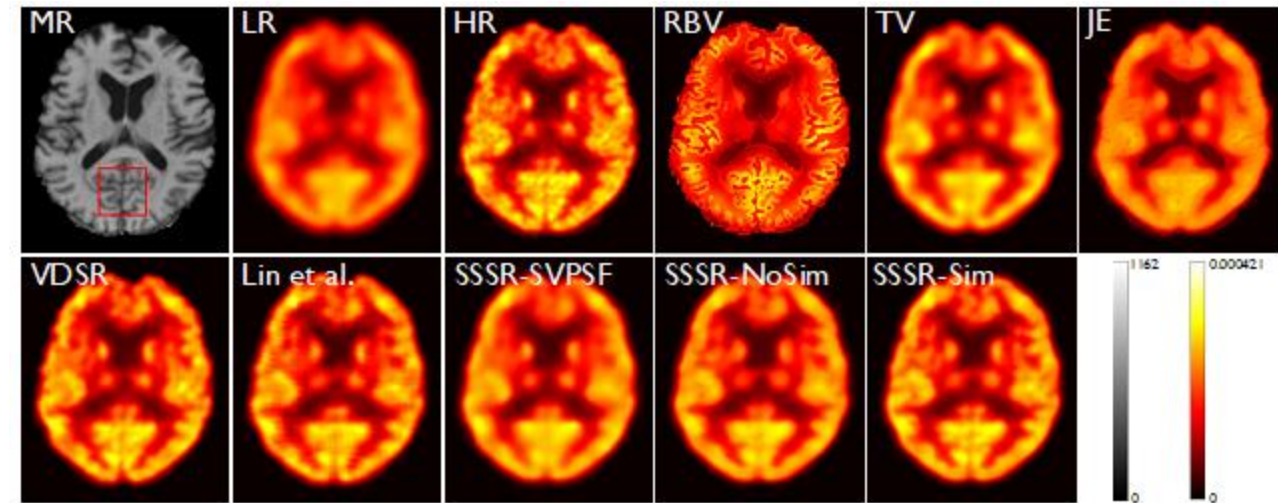
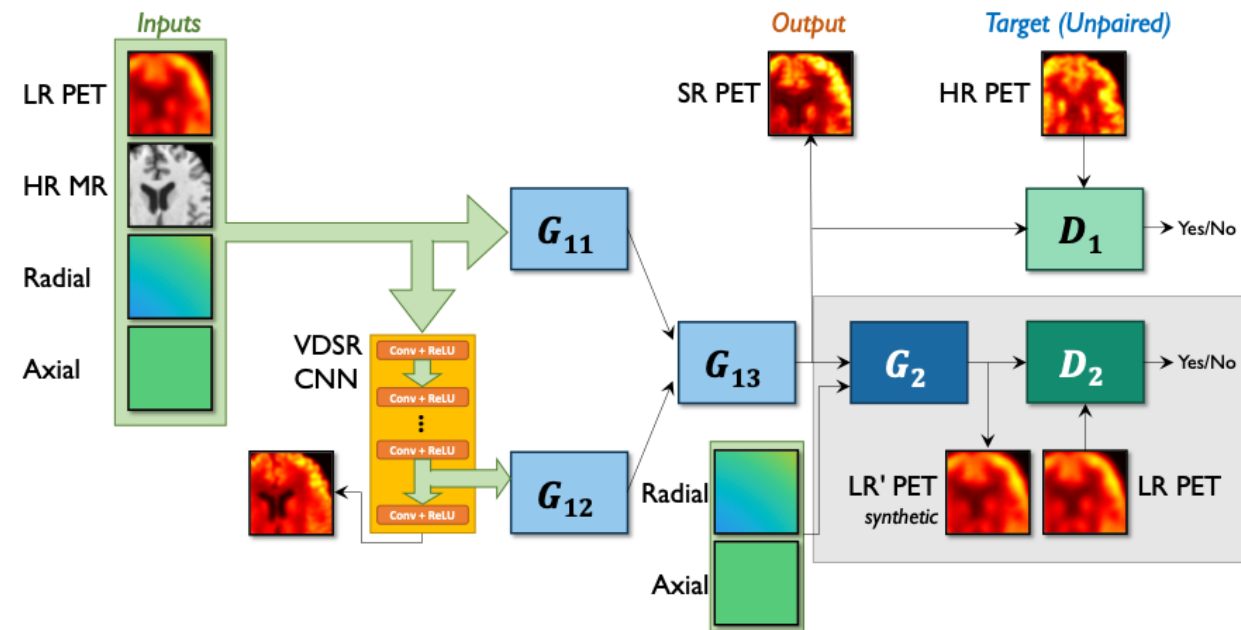
- Two PET scanners:
 - Siemens HRRT, high-resolution PET images
 - Siemens/CTI ECAT EXACT HR+, low-resolution PET images
- 30 ^{18}F - Fluorodeoxyglucose (FDG) PET HRRT images
 - 18 used for training
 - 12 used for validation



SR PET with Unpaired Clinical Data Using GANs



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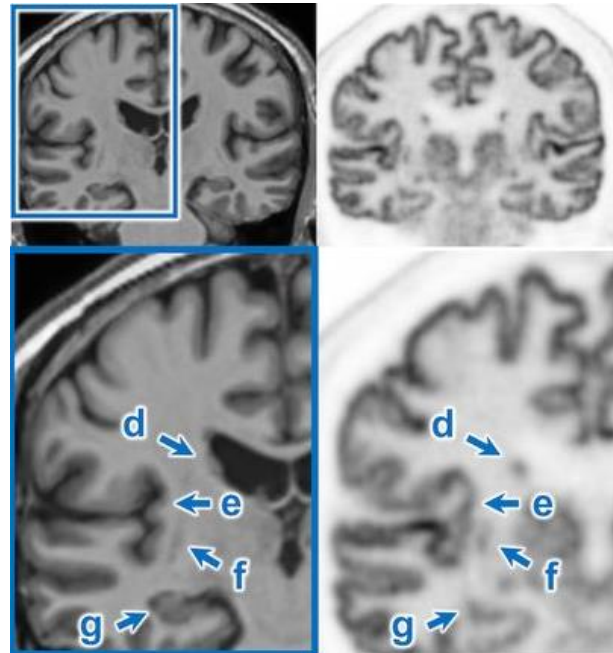
NeuroEXPLORER (NX)

- Long axial FOV scanner with a 49.5-cm axial length and detectors with time-of-flight (TOF) and depth-of-interaction (DOI)
- High sensitivity and high spatial resolution across the entire head

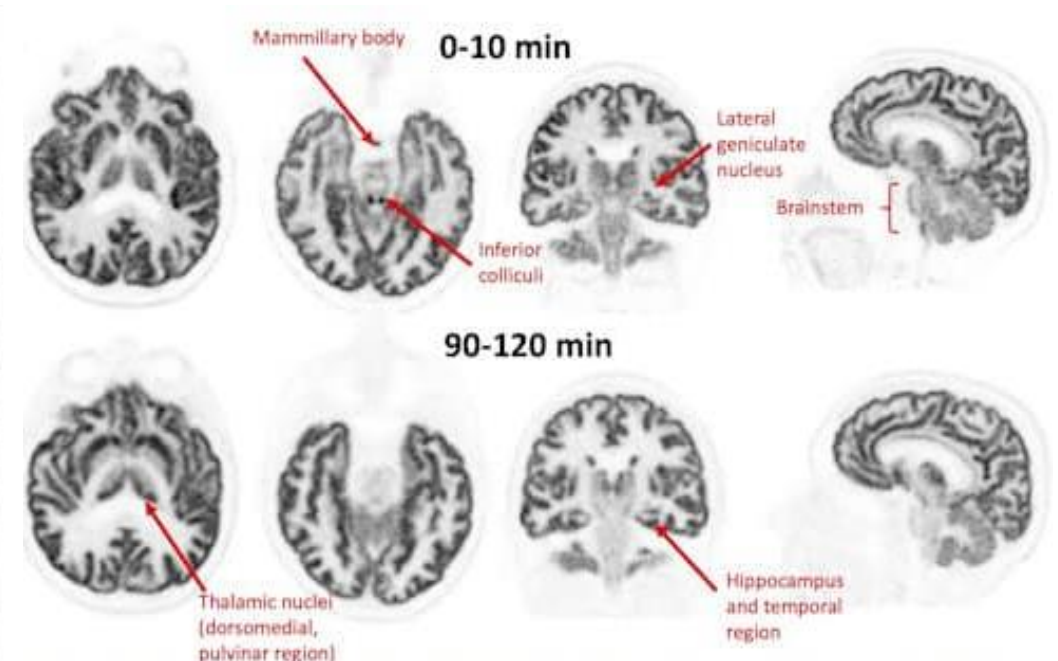
NX Scanner



NX FDG PET vs T1w MRI



SNMMI 2024 “Image of the Year”

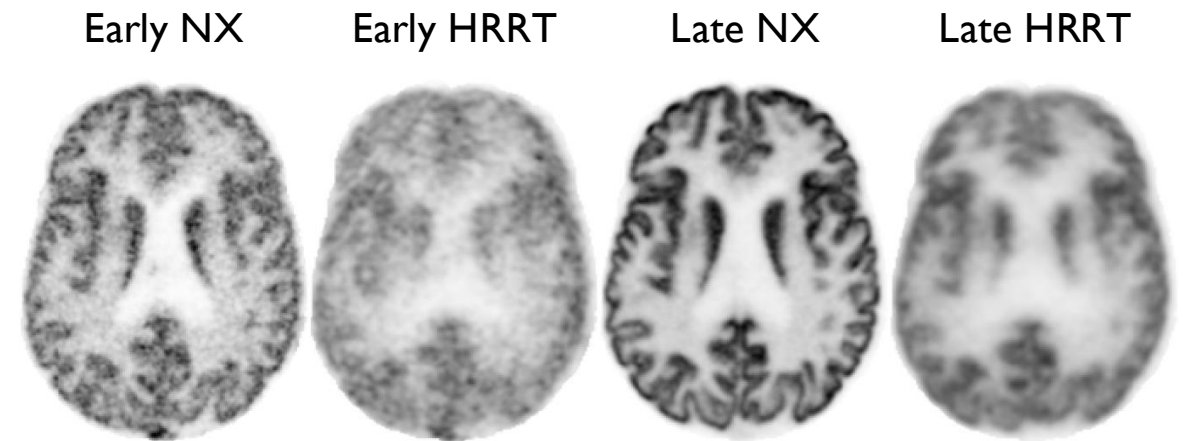


Paired LR/HR PET Data for Pretraining

- Paired HR NeuroEXPLORER (NX) and LR HRRT PET
- 7 cognitive normal subjects, each with one of the 7 tracers
 - ^{18}F -FDG, ^{18}F -SynVesT-1, ^{18}F -FPEB, ^{18}F -Flubatine, ^{11}C -PHNO, ^{18}F -FE-PE2I, and ^{11}C -DASB
- 2 scans for 2 different time windows (TWs) per subject

Subject	Tracer	Early TW	Late TW
1	^{18}F -FDG	0-10 min	60-90 min
2	^{18}F -SynVesT-1	0-10 min	60-90 min
3	^{18}F -FPEB	0-10 min	60-90 min
4	^{18}F -Flubatine	0-10 min	60-120 min
5	^{11}C -PHNO	0-10 min	40-60 min
6	^{18}F -FE-PE2I	0-10 min	40-90 min
7	^{11}C -DASB	0-10 min	40-60 min

Sample FDG PET images





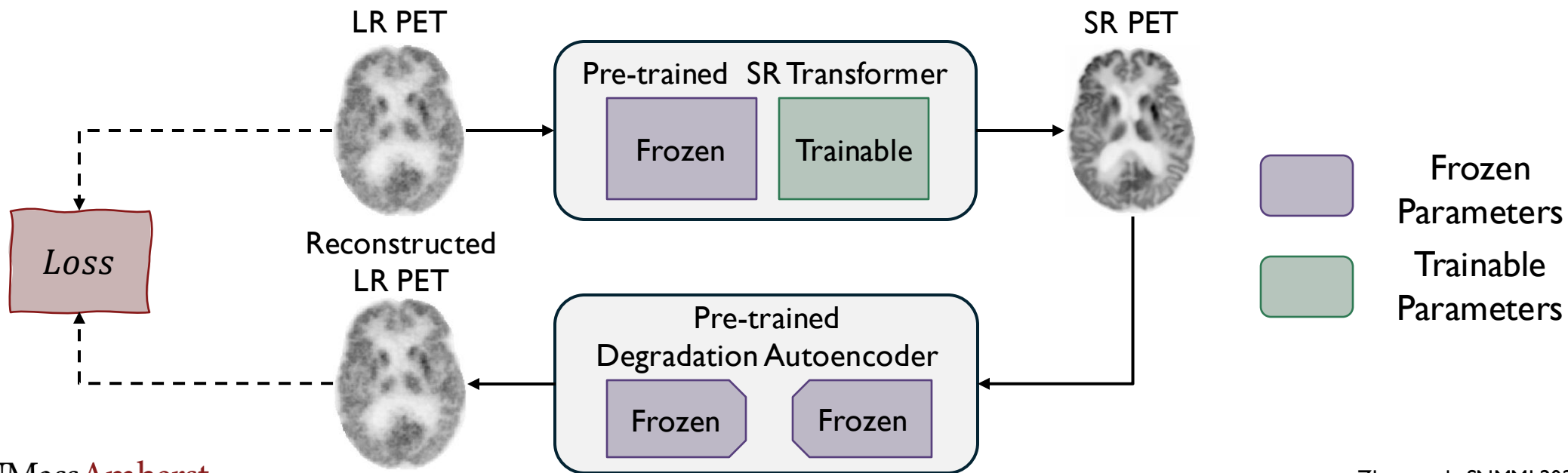
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- **Challenges**

- Limited amount of paired low-resolution (LR) / high-resolution (HR) PET images
- Domain shift between datasets due to different populations, imaging protocols, and contrast levels

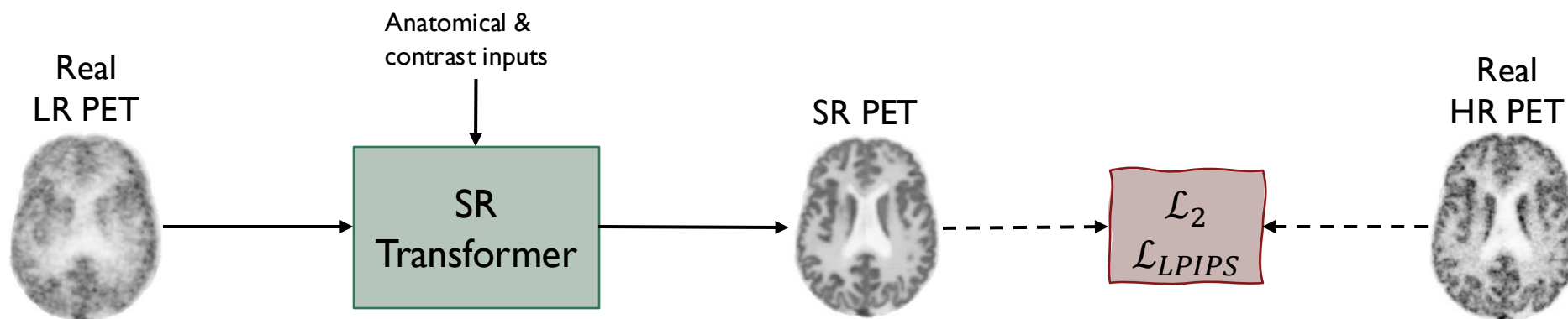
- **Solution:**

- Self-supervised contrast-aware PET super-resolution with deep degradation guidance (DDG-SR)
 - A super-resolution (SR) SwinIR transformer model
 - A degradation autoencoder

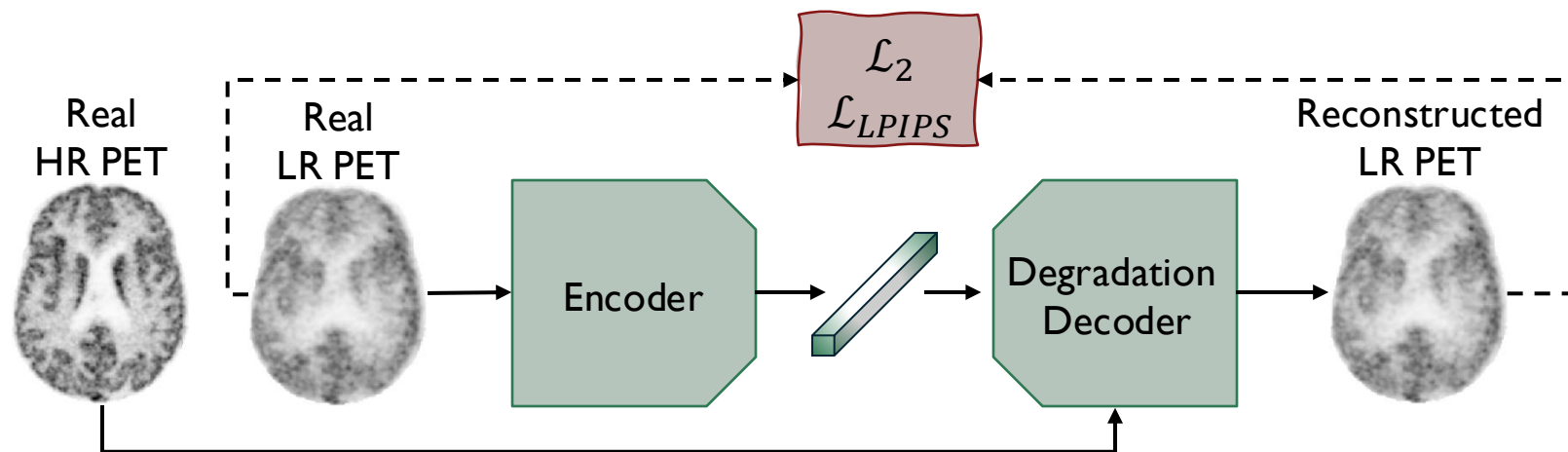


Training Stage I

- Stage IA: Pretraining the transformer using paired HR/LR training data



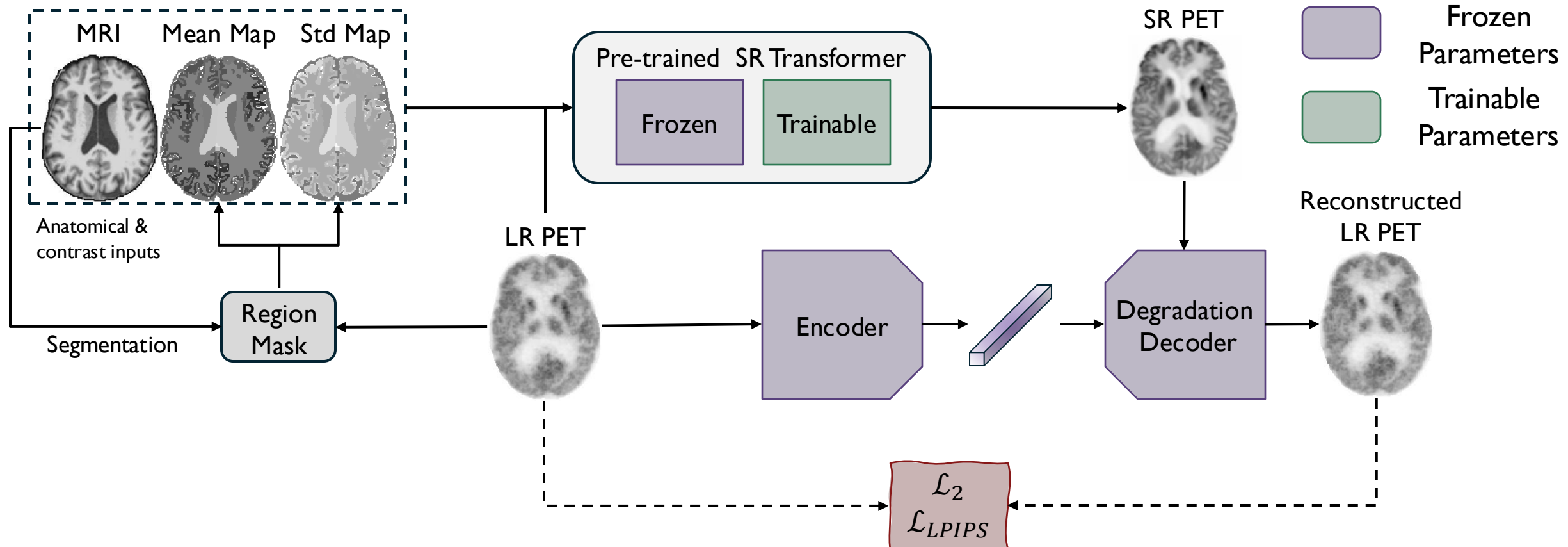
- Stage IB: Self-supervised training of the encoder-decoder on the training data



Trainable Parameters

Training Stage II

- Stage 2: Self-supervised finetuning on the independent testing dataset



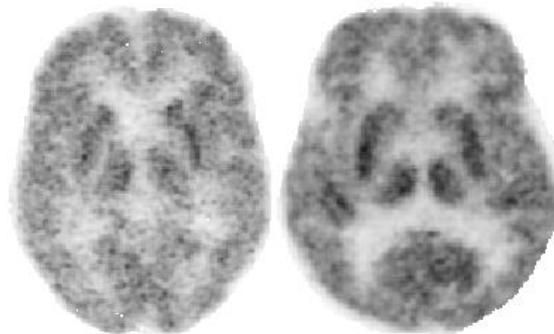
Independent FDG LR PET Data for Testing

- LR HRRT PET from Alzheimer's Disease Neuroimaging Initiative (ADNI)
- 20 subjects with ^{18}F -FDG HRRT PET images (7 CN, 10 MCI, 3 AD)
- Limited by ADNI imaging protocol, 0-10 min as early PET, 30-60 min as late PET
 - Domain shift in contrast level and uptake patterns

Sample HRRT FDG PET (different subjects)

Early MCI

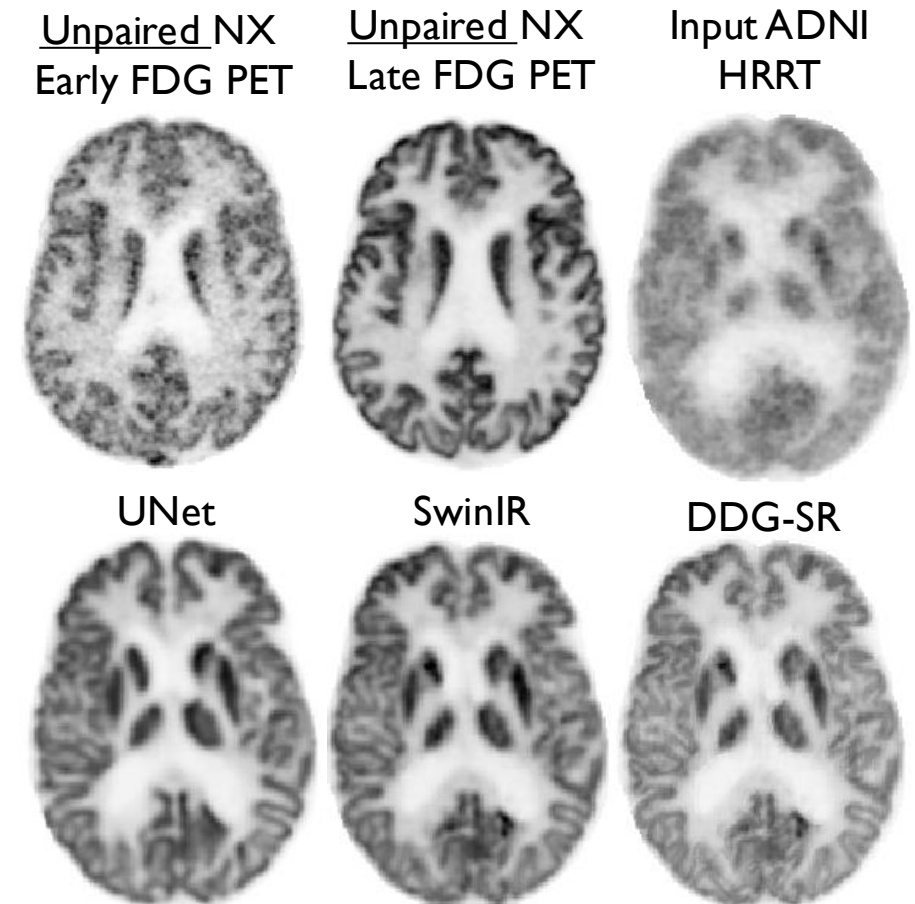
Late MCI



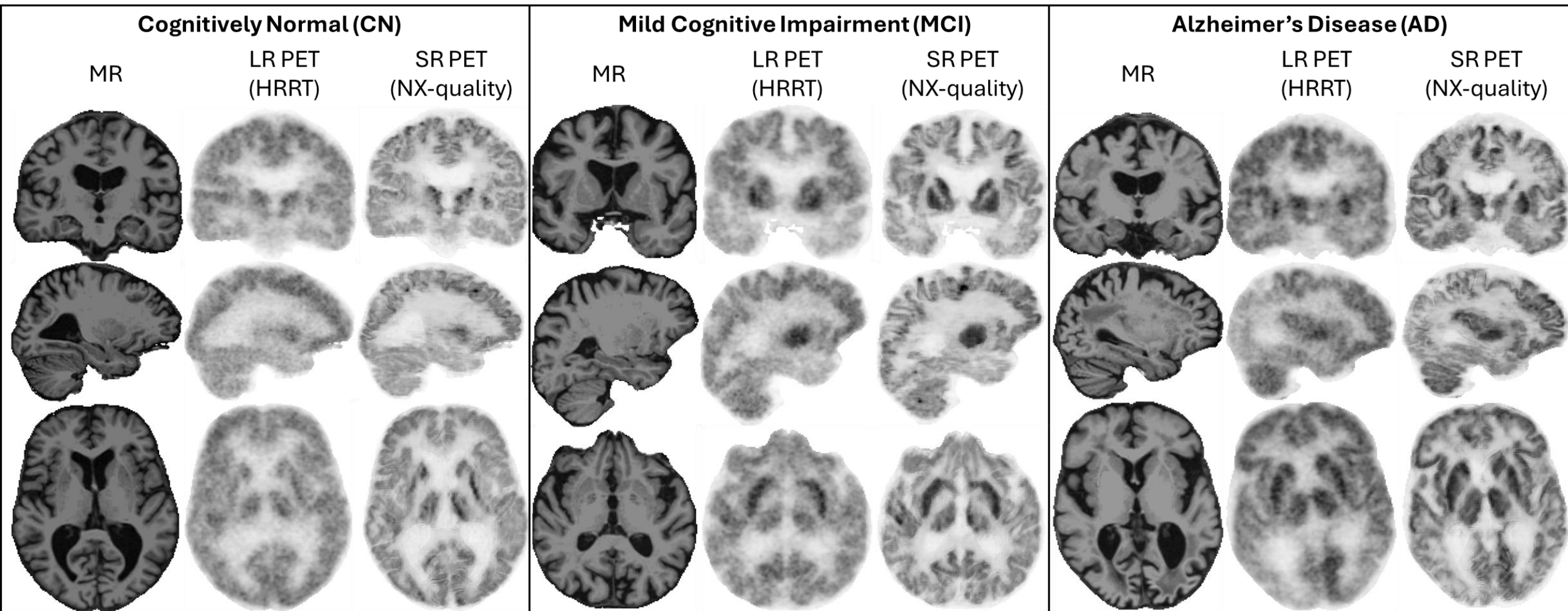
Results – Benchmarking

- The DDG-SR is compared to a U-Net and a standalone SwinIR
- Quantitative evaluation is performed using contrast-to-noise ratio (CNR)

Brain Region	HRRT	U-Net	SwinIR	DDG-SR
Caudal middle frontal	0.8900	0.8573	0.9132	0.9841
Inferior parietal	0.6740	0.6533	0.7060	0.7113
Lateral orbitofrontal	0.7109	0.7615	0.7649	0.7766
Medial orbitofrontal	0.7119	0.7315	0.7631	0.7751
Posterior cingulate	0.8267	0.8945	0.9684	1.0021
Precuneus	0.8860	0.7795	0.9013	0.9461
Rostral middle frontal	0.8311	0.9104	1.0618	1.1343

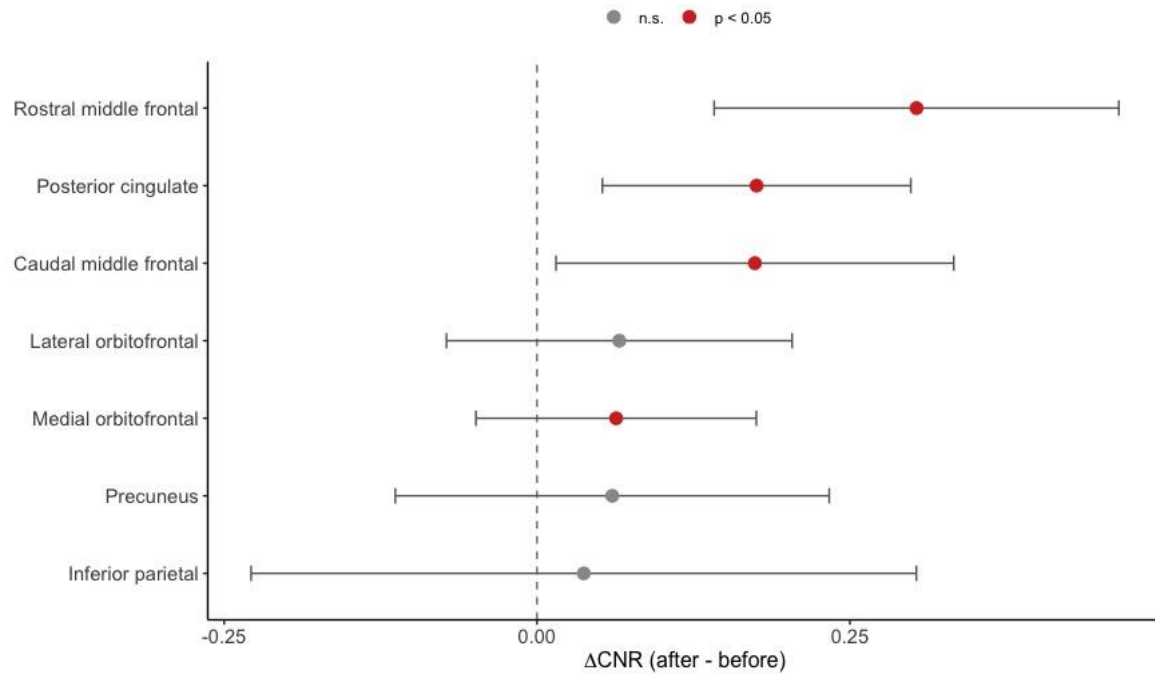


Results – Visual Examples



Results – CNR Improvement

Forest plot of average CNR improvement



Heatmap of CNR improvement for each region/subject

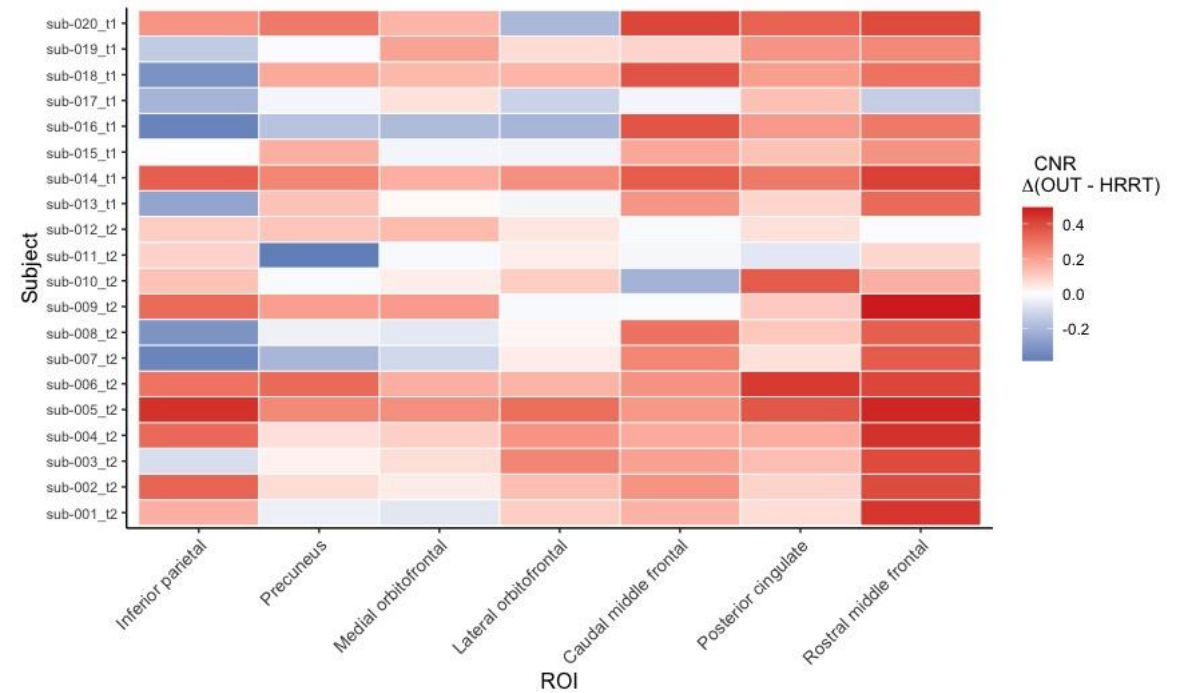
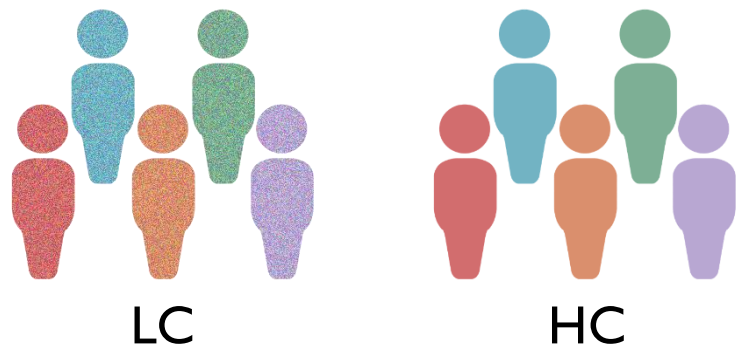
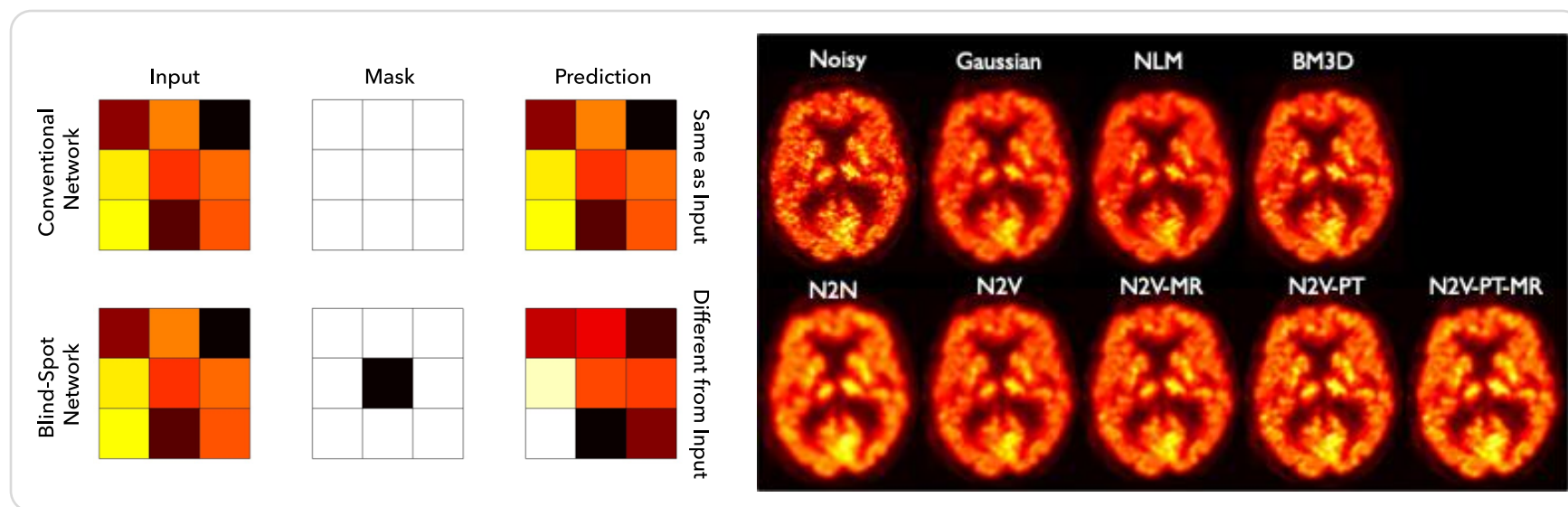
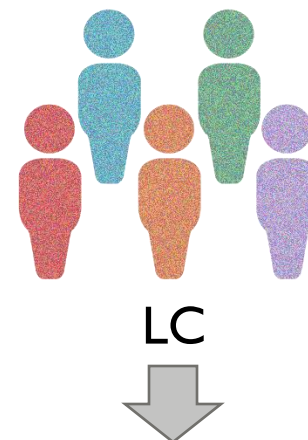


Image Denoising

Paired Low-Count/High-Count Images

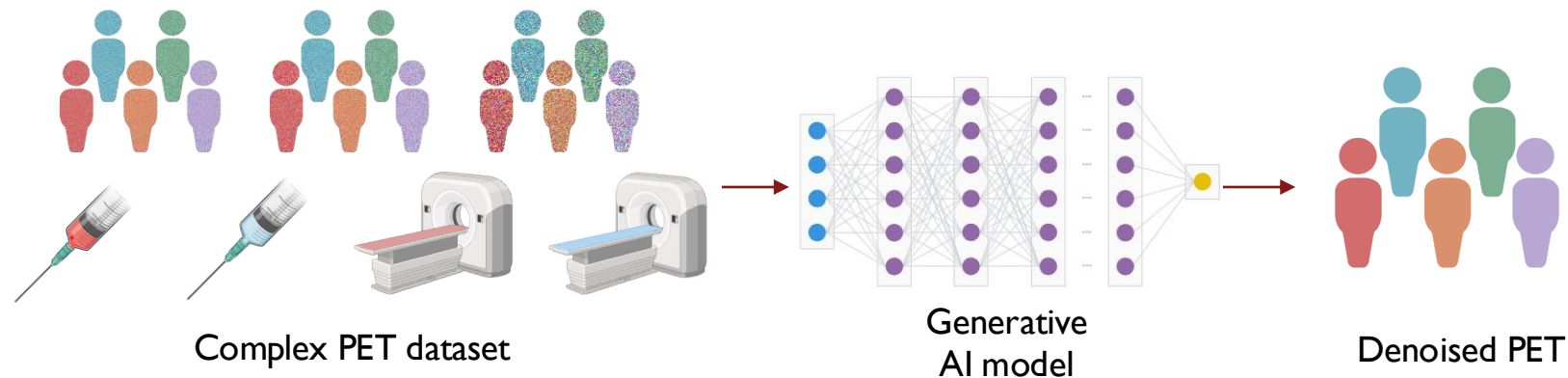


Only Low-Count Images



Multi-Tracer and Multi-Scanner PET Denoising

- Denoising models do not generalize well across different PET tracers or scanners
- **Objective:** To create a robust denoising model for multi-tracer and multi-scanner brain PET dataset

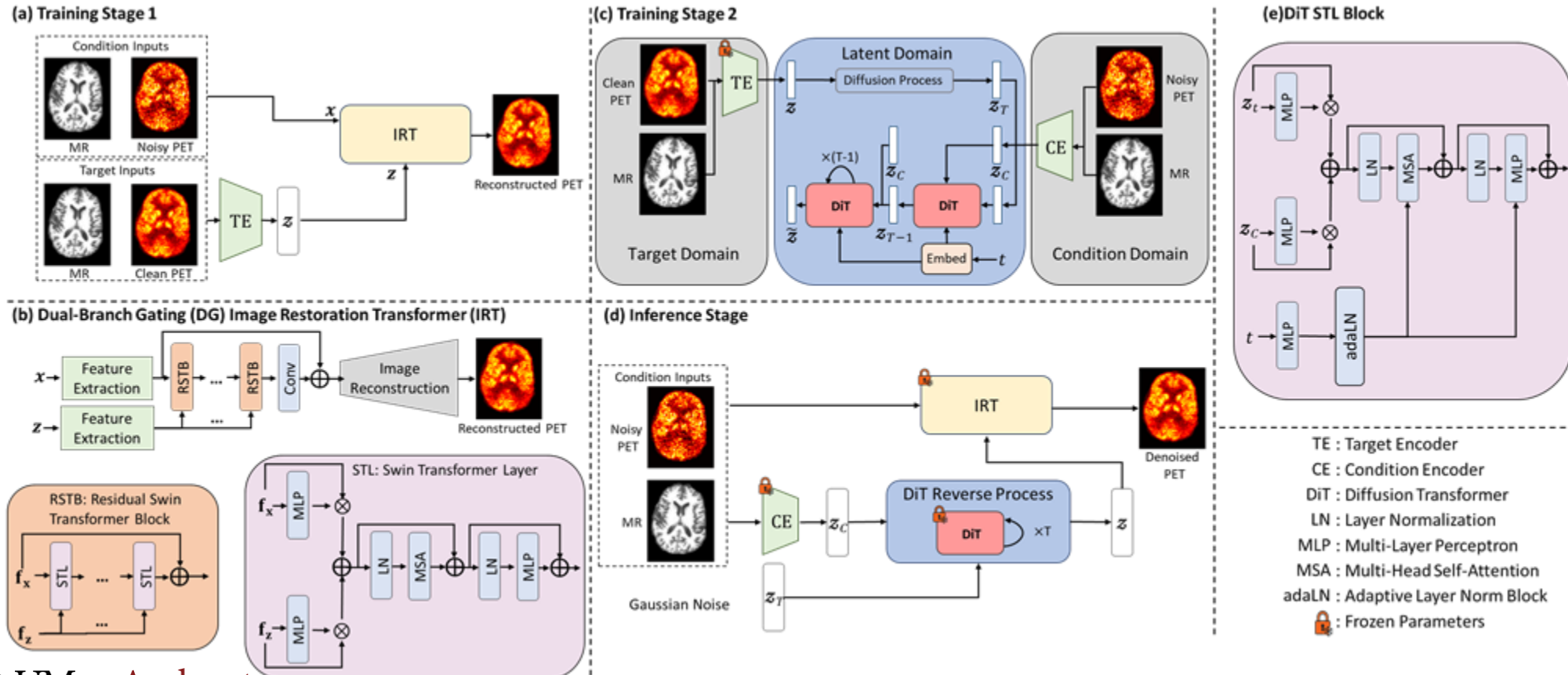


Dual-branch Gating Diffusion Transformer (DG-DiT)



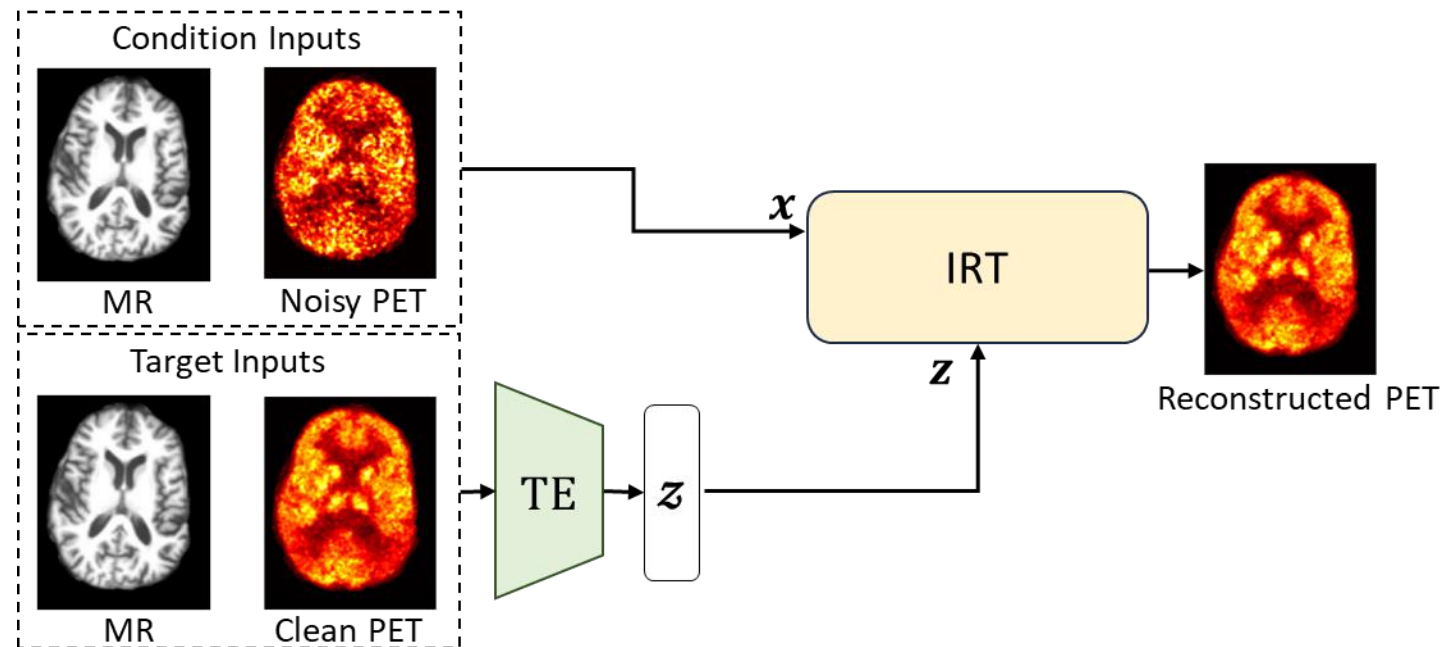
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- Two major components: a variational autoencoder (VAE) and a diffusion transformer (DiT)
- Two-stage training



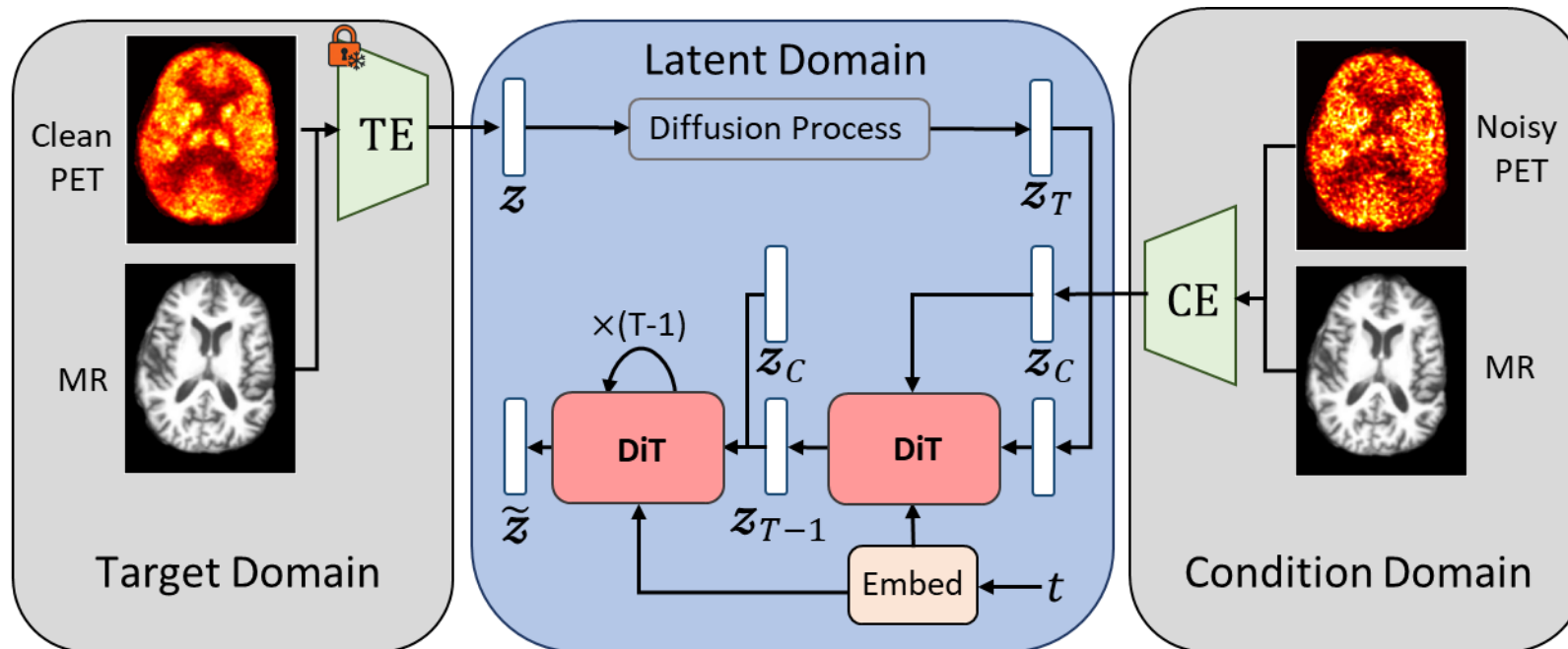
Training Stage I

- VAE training
 - Compact latent space
 - Gaussian regularization
 - Conditional image inputs to the decoder (an image restoration transformer / IRT)



Training Stage II

- DiT training
 - Transformer backbone
 - Few-step diffusion: 25 steps vs. 1000 steps
 - End-to-end training: run the entire generation process and use pixel-wise loss

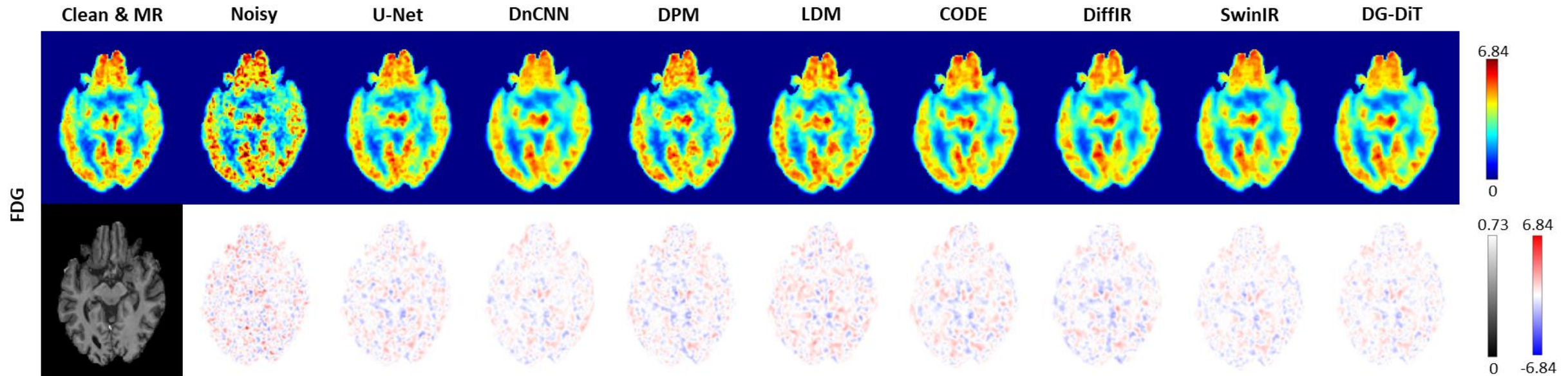


Clinical Dataset for Training and Validation

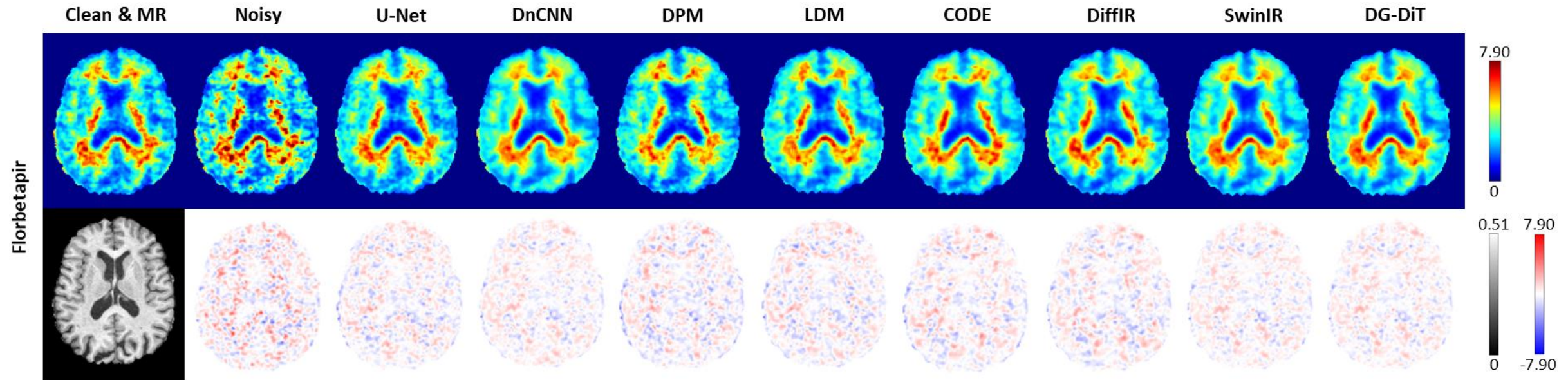
- Training and validation with multi-tracer and multi-scanner brain PET dataset
- Source: Alzheimer's Disease Neuroimaging Initiative (ADNI)

Scanner (Voxel size)	Tracer	# of subjects (# female)	Training subjects	Validation subjects	Age (Mean $\pm$ SD)	Time Frames
Siemens Biograph64 TruePoint (1.0 $\times$ 1.0 $\times$ 2.0 mm ³)	FDG	30(18)	25	5	75.2 $\pm$ 11.25	6
	Flortaucipir	30(19)	25	5	73.27 $\pm$ 9.22	6
	Florbetapir	30(18)	25	5	73.83 $\pm$ 9.91	4
Siemens ECAT HRRT (1.2 $\times$ 1.2 $\times$ 1.2 mm ³)	FDG	20(6)	15	5	72.75 $\pm$ 5.87	6
	Flortaucipir	20(7)	15	5	75.2 $\pm$ 8.75	6
	Florbetapir	20(7)	15	5	76.15 $\pm$ 8.71	4

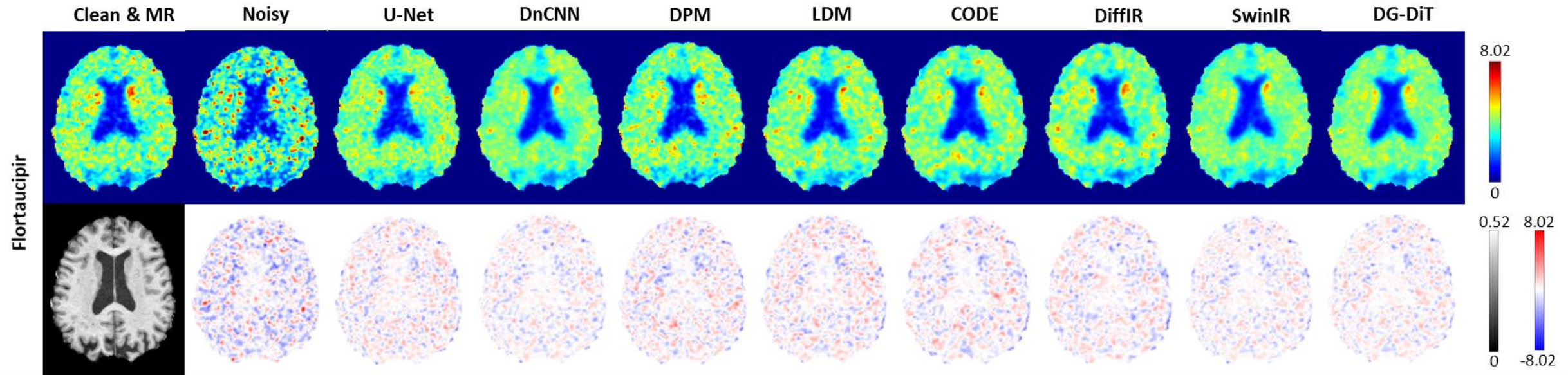
Denoised Images: HRRT FDG PET



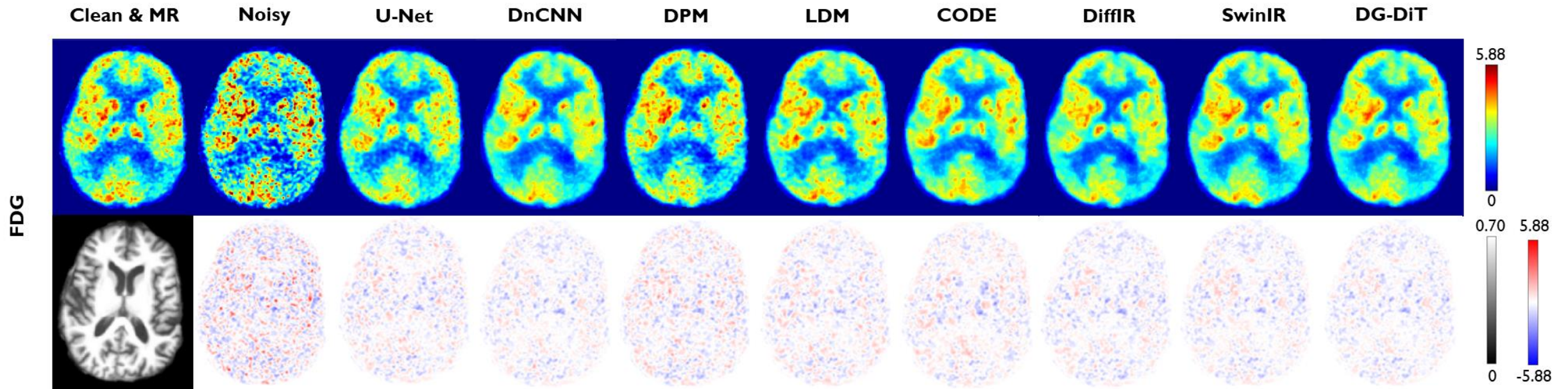
Denoised Images: HRRT Florbetapir PET



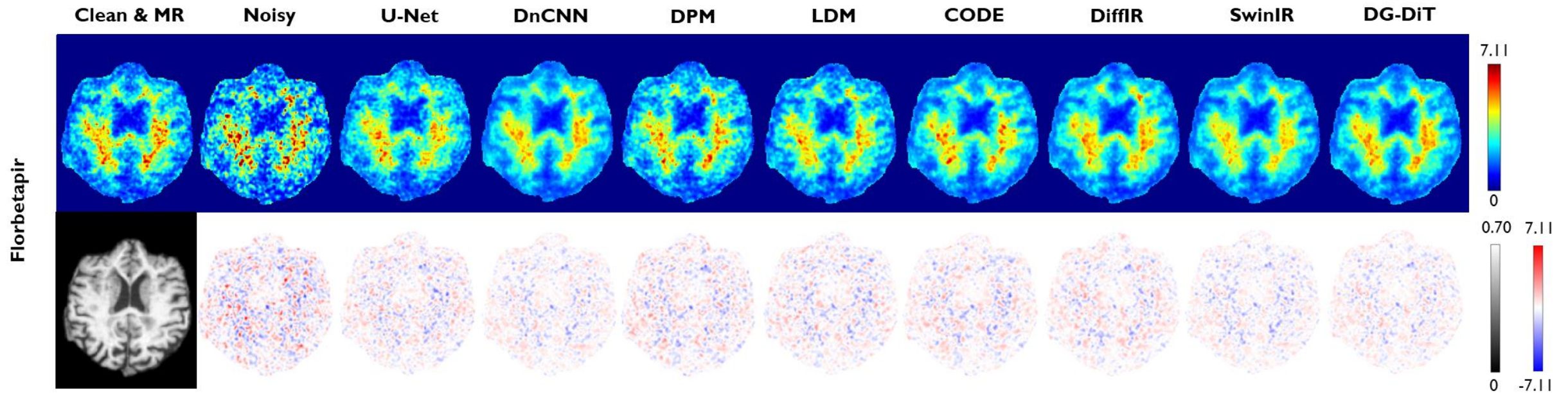
Denoised Images: HRRT Flortaucipir PET



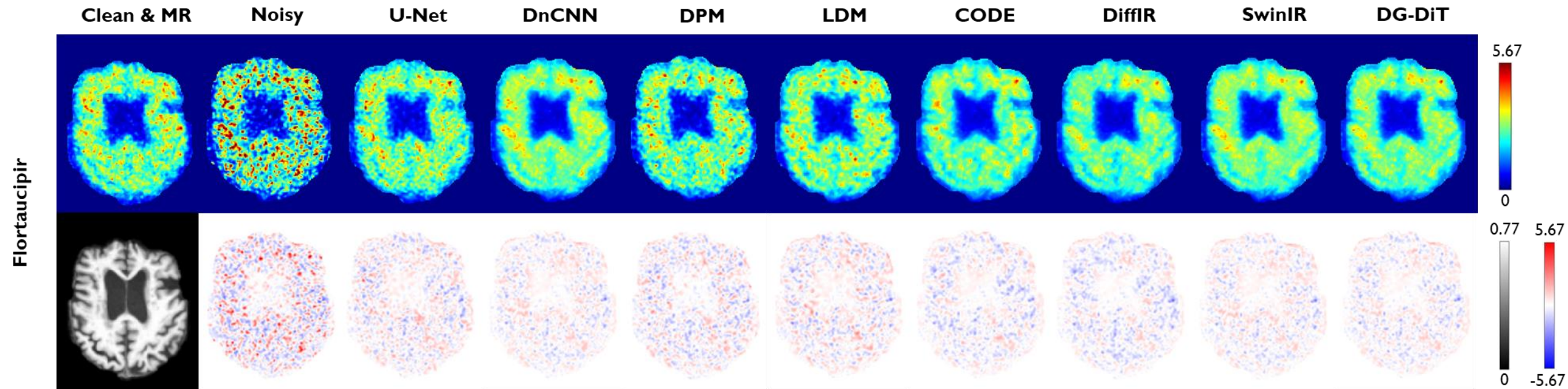
Denoised Images: Biograph FDG PET



Denoised Images: Biograph Florbetapir PET



Denoised Images: Biograph Flortaucipir PET



Evaluation Metrics: PSNR and SSIM

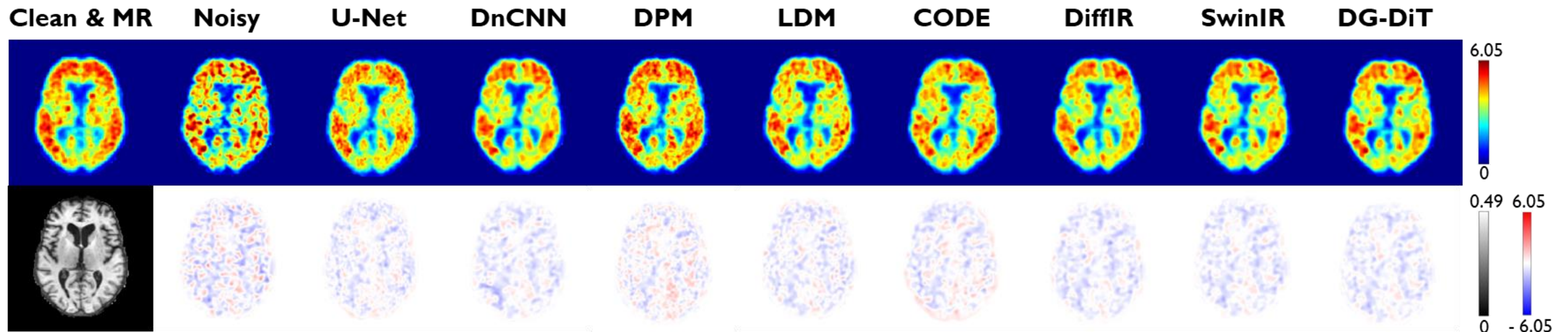
Scanner	Tracer	Metrics	Noisy	U-Net	Dn-CNN	DPM	LDM	CODE	DiffIR	SwinIR	DG-DiT
BioGraph	FDG	PSNR	16.449	18.353	20.777	17.896	18.219	18.791	18.924	20.756	<u>20.908</u>
		SSIM	0.9539	0.9573	0.9717	0.9017	0.9563	0.9561	0.9624	0.9710	<u>0.9719</u>
	AV1451	PSNR	10.895	13.659	14.471	14.221	13.383	13.628	13.791	15.118	<u>15.271</u>
		SSIM	0.9092	0.9038	0.9197	0.8420	0.9009	0.8997	0.9092	0.9202	<u>0.9221</u>
	AV45	PSNR	14.303	16.145	18.104	15.395	15.959	16.547	16.738	18.132	<u>18.168</u>
		SSIM	0.9376	0.9387	0.9558	0.8732	0.9376	0.9400	0.9481	0.9555	<u>0.9566</u>
HRRT	FDG	PSNR	14.119	16.994	18.808	14.754	16.824	18.213	18.196	18.866	<u>18.935</u>
		SSIM	0.9029	0.9085	0.9313	0.8452	0.9106	0.9188	0.9260	0.9297	<u>0.9312</u>
	AV1451	PSNR	8.3375	12.293	13.717	9.992	12.649	13.249	13.455	14.098	<u>14.143</u>
		SSIM	0.8585	0.8641	0.8667	0.8143	0.8680	0.8698	0.8801	0.8856	<u>0.8873</u>
	AV45	PSNR	11.662	14.331	16.385	12.121	14.579	15.418	15.718	16.432	<u>16.526</u>
		SSIM	0.8931	0.8897	0.9169	0.8276	0.8929	0.9005	0.9118	0.9165	<u>0.9185</u>

Evaluation Metrics: CNR

Tracer	ROI	Clean	Noisy	U-Net	Dn-CNN	DPM	LDM	CODE	DiffIR	SwinIR	DG-DiT
FDG (Ref: cerebellar cortex)	Posterior cingulate	0.508	0.465	0.590	0.577	0.192	0.600	0.584	0.562	0.590	<u>0.625</u>
	Precuneus	0.771	0.713	0.800	0.799	0.197	0.832	0.817	0.801	0.837	<u>0.847</u>
Flortaucipir (Ref: white matter)	Entorhinal	0.405	0.280	0.494	0.478	0.259	0.487	0.431	0.425	0.499	<u>0.517</u>
	Parahippocampal	0.485	0.402	0.585	0.639	0.504	0.560	0.540	0.528	0.648	<u>0.648</u>
Florbetapir (Ref: white matter)	Frontal cortex	1.289	1.125	1.294	1.358	1.167	1.329	1.319	1.313	1.389	<u>1.389</u>
	Temporal cortex	1.351	1.156	1.382	1.4400	1.211	1.407	1.387	1.399	1.483	<u>1.486</u>

An Out-of-Domain Example: ^{11}C -PiB

- Example Images:



- PSNR Comparison:

Noisy	U-Net	Dn-CNN	DPM	LDM	CODE	DiffIR	SwinIR	DiT
9.1675	10.575	10.981	7.0076	10.479	10.342	10.745	10.999	<u>11.199</u>

Emerging Directions

- Blind single-image super-resolution
- Noise- and contrast-aware denoising
- Non-FDG radiotracers
- Cross-site harmonization
- Task-based validation
- Foundation models adaptable to new tasks

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Artificial Intelligence- Based Image Enhancement in PET Imaging

Noise Reduction and Resolution Enhancement

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Chi Liu^{a,*}, Joyita Dutta, PhD^{b,c,*}

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STATE OF THE ART

Artificial Intelligence for PET and SPECT Image Enhancement

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Acknowledgments

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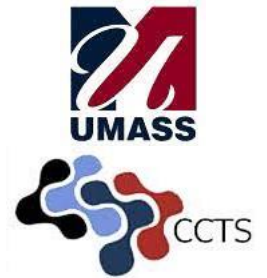


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