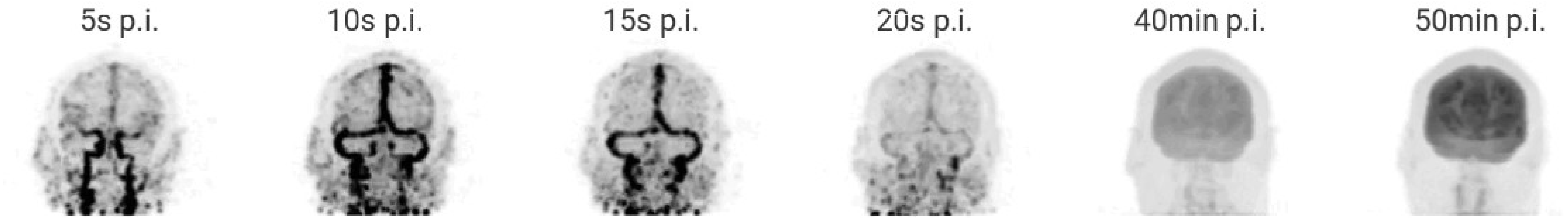
Review of selected PET image correction approaches using machine learning methods

Michał Obara

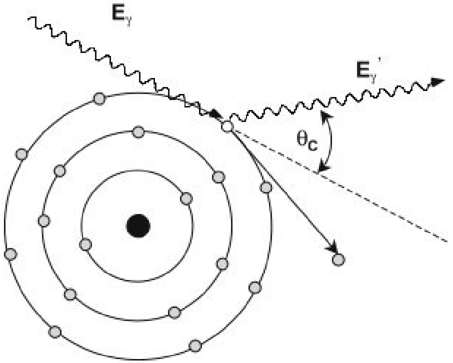
13.01.2025

PET events detection

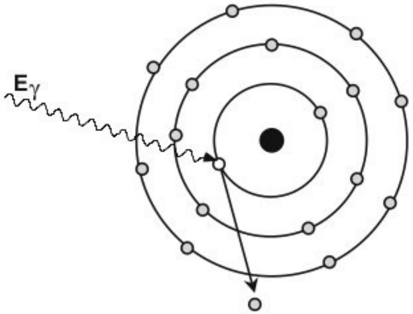


18F-FDG distribution in time

Georg Schramm, KU Leuven

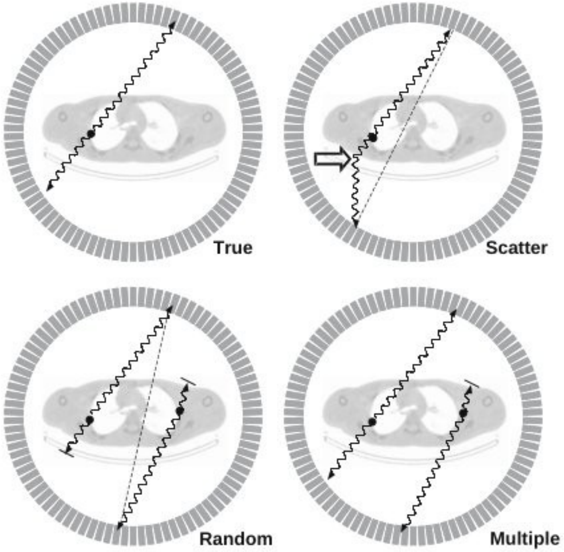


Compton scattering



Photoelectric effect

Dale L Bailey, PET Basic Sciences



Coincidence events types

Scatter corrections

Single Scatter Simulation:

- Monte Carlo simulation of single scattered photons
- Using attenuation map and an initial activity estimation
- Does not directly consider multiple scattering
- Standard method in clinical PET
- Computational complexity

Machine learning techniques:

- End-to-end U-Net
    - Low-quality PET → high-quality PET
    - Uncorrected PET + CT → corrected PET
    - CT → PET or AC PET → CT

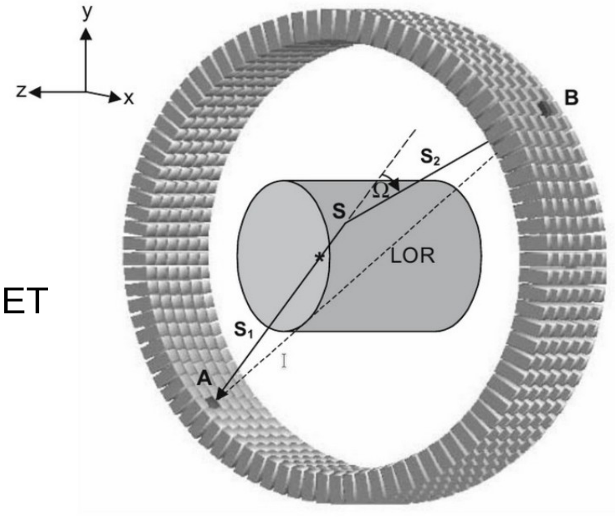
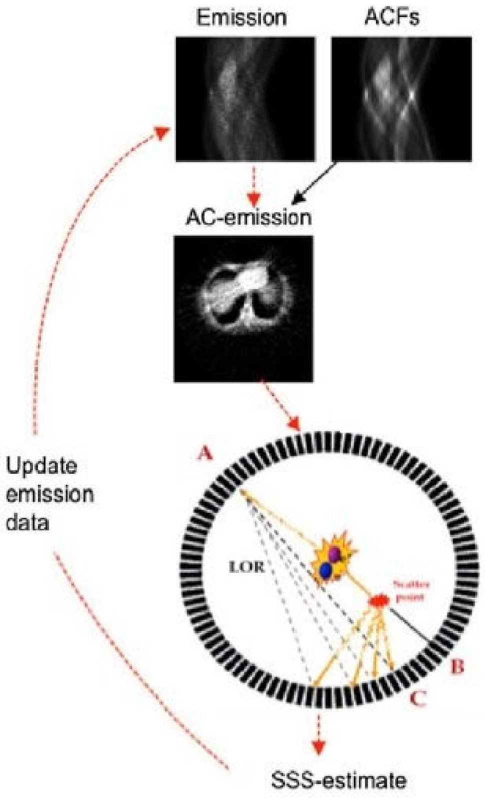


Figure 5.16. Geometry of the single scattering model used in simulation based scatter correction.

Dale L Bailey, PET Basic Sciences



DOI 10.1007/s12149-011-0514-y

Huang et al., 2023

https://doi.org/10.1007/s00259-023-06422-x

Comment > Eur J Nucl Med Mol Imaging. 2023 Dec;51(1):27-39.
doi: 10.1007/s00259-023-06422-x. Epub 2023 Sep 6.

Short-axis PET image quality improvement based on a uEXPLORER total-body PET system through deep learning

Zhenxing Huang [#, 1], Wenbo Li [#, 1], Yaping Wu [#, 2], Nannan Guo [1, 3], Lin Yang [1, 3], Na Zhang [1], Zhifeng Pang [3], Yongfeng Yang [1], Yun Zhou [4], Yue Shang [5], Hairong Zheng [1], Dong Liang [1], Meiyun Wang [6], Zhanli Hu [7]

Affiliations + expand

PMID: 37672046 DOI: 10.1007/s00259-023-06422-x

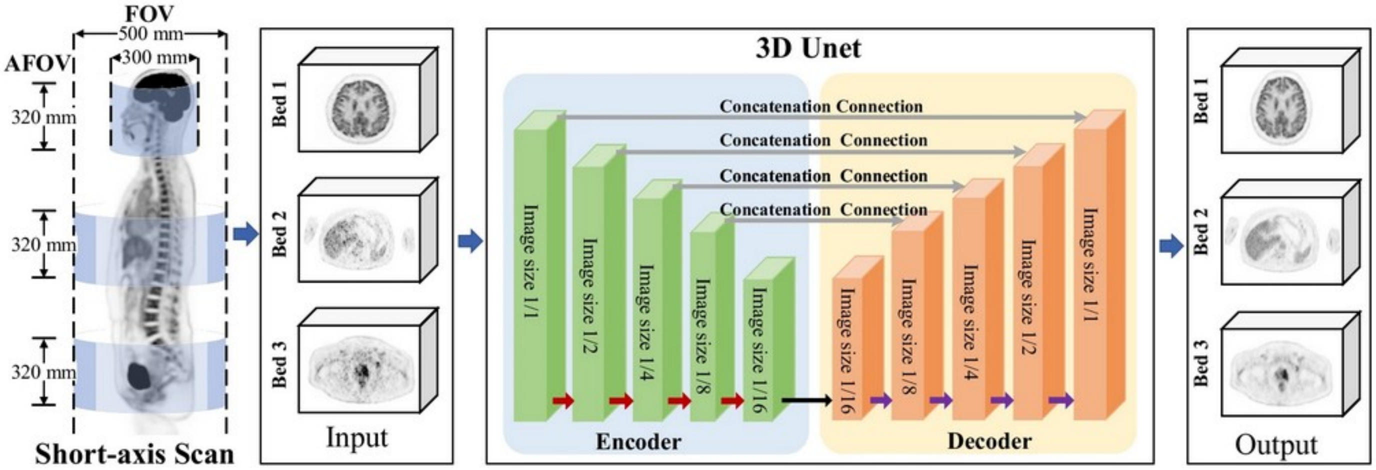
Huang et al., 2023

Data:

- uEXPLORER PET/CT images from 335 patients (18F-FDG)
- Two sets of PET images:
  - High-Quality PET (HQ-PET): Total-body PET images (1940 mm AFOV)
  - Low-Quality PET (LQ-PET): Simulated short-axis PET images (320–500 mm AFOV)

Model:

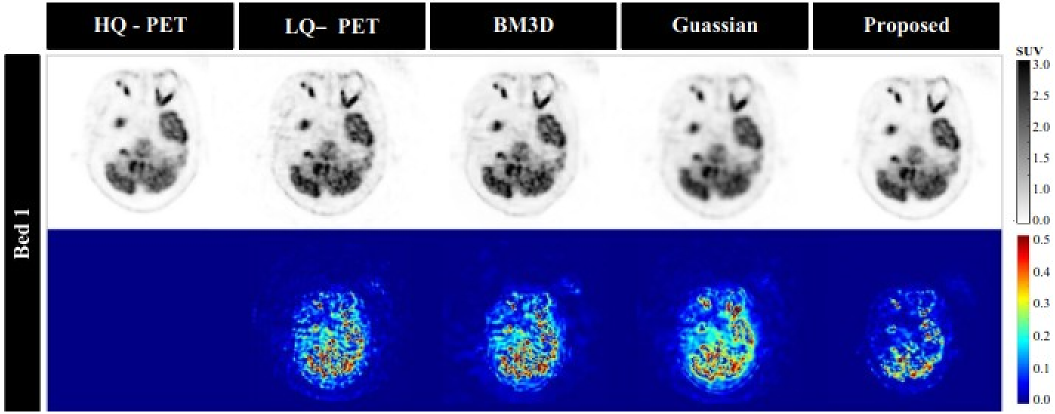
- A 3D U-Net trained to map LQ-PET to HQ-PET images
- Separate training for brain, lung, and abdomen datasets
- Split: 300/35, loss: MAE, batch size: 16, Optimizer: Adam, epochs: 500



Huang et al., 2023

Evaluation Metrics:

- Quantitative: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) comparison to HQ-PET and traditional denoising methods
- Qualitative: clinical evaluation by nuclear medicine experts using a 5-point scoring system



Results:

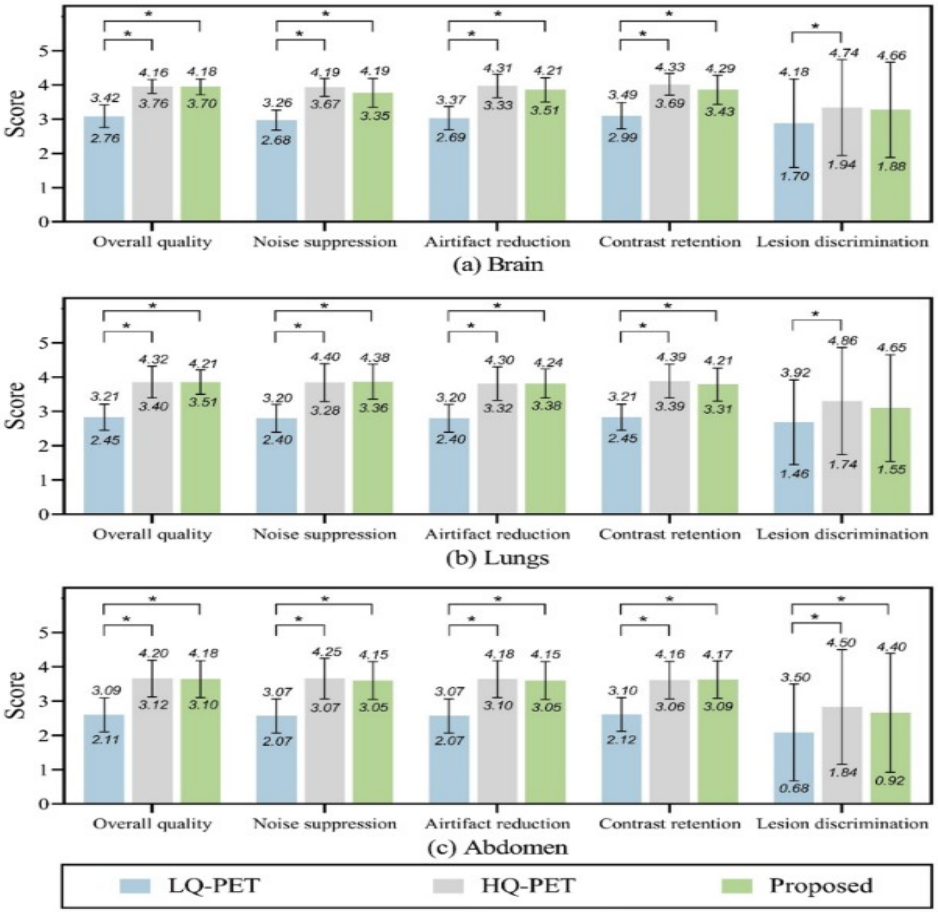
- Quantitative evaluation:

Beds	LQ-PET		Gaussian		BM3D		Proposed	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bed 1	34.54 ± 5.14	0.91 ± 0.09	28.66 ± 3.3*	0.86 ± 0.10*	30.88 ± 6.38*	0.51 ± 0.24*	**35.41 ± 5.45***	**0.94 ± 0.15***
Bed 2	32.16 ± 6.22	0.92 ± 0.04	30.95 ± 3.68*	0.91 ± 0.05*	29.45 ± 5.49*	0.41 ± 0.17*	**33.77 ± 6.18***	**0.95 ± 0.03***
Bed 3	36.65 ± 6.97	0.94 ± 0.04	30.76 ± 4.57*	0.91 ± 0.05*	30.55 ± 8.47*	0.43 ± 0.27*	**38.58 ± 7.28***	**0.97 ± 0.03***

Huang et al., 2023

Results:

- Qualitative Evaluation:
  - Proposed method significantly improved scores across all categories vs. LQ-PET
  - Overall quality for Proposed is close to HQ-PET, far exceeding LQ-PET



Laurent et al., 2023

https://doi.org/10.1088/1361-6560/ac9a97

IOP Publishing   *Phys. Med. Biol.* **68** (2023) 065004   https://doi.org/10.1088/1361-6560/ac9a97

Physics in Medicine & Biology

IPEM
Institute of Physics and Engineering in Medicine

CrossMark

RECEIVED
13 June 2022

REVISED
15 September 2022

ACCEPTED FOR PUBLICATION
13 October 2022

PUBLISHED
10 March 2023

PAPER

PET scatter estimation using deep learning U-Net architecture

Baptiste Laurent[1,*], Alexandre Bousse[1], Thibaut Merlin[1], Stephan Nekolla[2] and Dimitris Visvikis[1]

[1] LaTIM, INSERM, UMR 1101, UBO, Brest, France
[2] Department of Nuclear Medicine, Klinikum rechts der Isar der Technischen Universität München, Munich, Germany
[*] Author to whom any correspondence should be addressed.

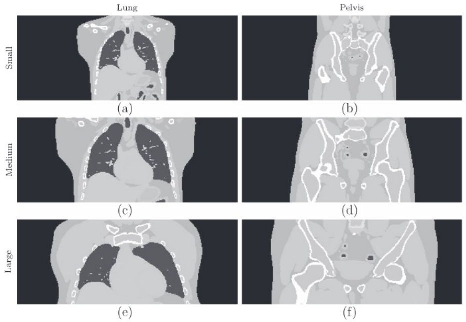
E-mail: baptiste.laurent@univ-brest.fr

Keywords: PET, reconstruction, scatter estimation, scatter correction, deep learning

Laurent et al., 2023

Data:

- GATE simulations with XCAT phantoms.
- Variations in anatomy (lung, pelvis regions) and body morphologies (S, M, L)
- 216 simulated datasets with acquisition durations of 1–6 minutes
- Two clinical Biograph mMR images



	Small	Medium	Large
Total body height (mm)	1227	1752	2103
Chest short axis (AP) (mm)	163	232	279
Chest Long axis (LAT) (mm)	228	325	391
Chest circumference (mm)	696	993	1194
Waist short axis (AP) (mm)	163	233	335
Waist long axis (LAT) (mm)	202	288	416

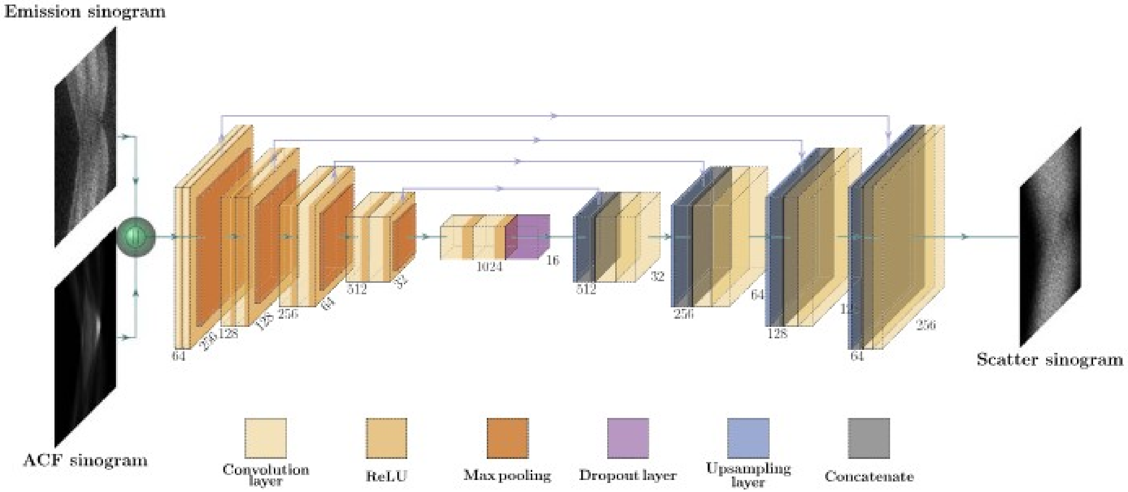


Figure 1. DLSE architecture, based on a CNN U-Net architecture. The network takes emission and attenuation sinograms as input, to predict scatter sinogram.

Model:

- U-Net architecture
- Input: PET emission and attenuation factor (AF) sinograms. output: estimated scatter sinogram
- Loss: MSE, batch size: 8, epochs: 100

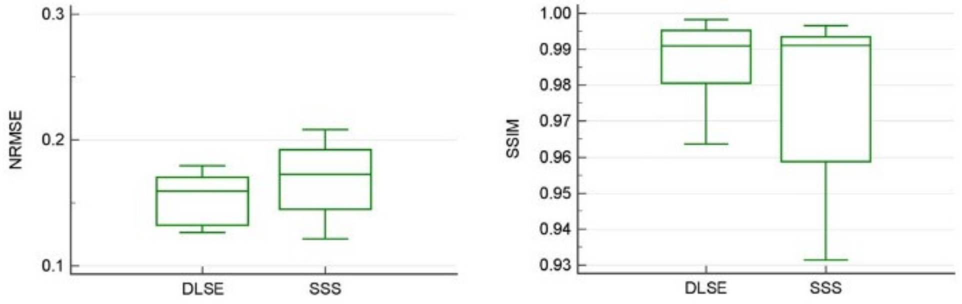
Laurent et al., 2023

Evaluation:

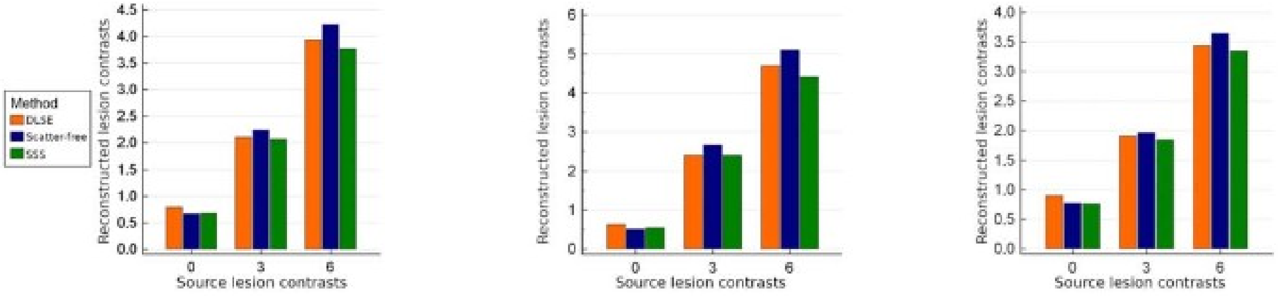
- Metrics: Normalized Root Mean Square Error (NRMSE) and Structural Similarity Index (SSIM)
- Comparison with SSS and ground truth
- Tested on reconstructed PET images with simulated lesions and two clinical datasets

Results:

- DLSE achieves lower NRMSE and higher SSIM than SSS
- Better contrast recovery for hot lesions (3:1 and 6:1) than SSS
- Slight overestimation in cold lesions (0:1)



(a) NRMSE (b) SSIM



(a) Contrasts for lesions of all ROIs (b) Contrasts for lesions in liver (c) Contrast for lesions in lungs

Ben-Cohen et al., 2019

https://doi.org/10.1016/j.engappai.2018.11.013

ELSEVIER

Engineering Applications of Artificial Intelligence

Volume 78, February 2019, Pages 186-194

Cross-modality synthesis from CT to PET using FCN and GAN networks for improved automated lesion detection ☆

Avi Ben-Cohen [a], Eyal Klang [b], Stephen P. Raskin [b], Shelly Soffer [b], Simona Ben-Haim [c d], Eli Konen [b], Michal Marianne Amitai [b 1], Hayit Greenspan [a 1]

Ben-Cohen et al., 2019

Objective:

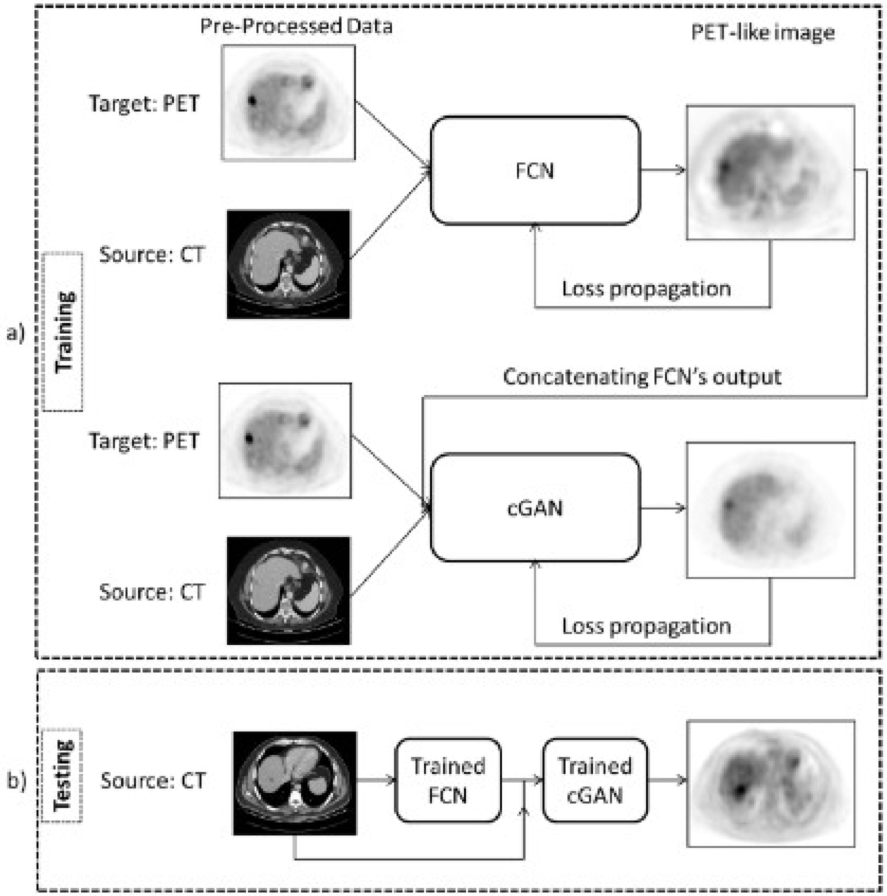
- Generate PET/CT from CT scans
- Reduce PET/CT cost and radiation
- Improve liver lesion detection

Dataset:

- 60 PET/CT clinical scans
- Training: 23 pairs (6 malignant); testing: 37 pairs (9 malignant)
- Focused on liver region.

Model:

- FCN (VGG-16 based) generates initial PET-like images from CT data, loss: L2, optimizer: Adam,
- cGAN (conditional GAN) refines outputs using U-Net generator and a custom L2 loss function
- Augmentation: scaling, translation, random noise



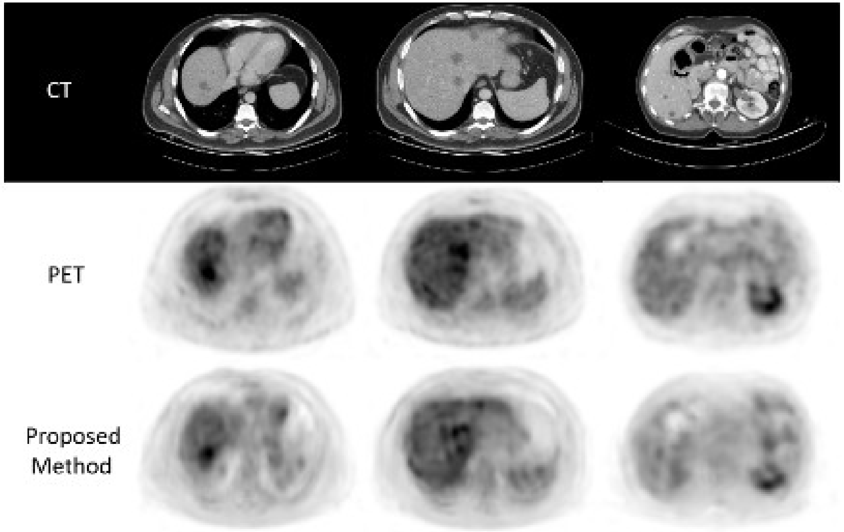
Ben-Cohen et al., 2019

Evaluation:

- Reconstruction metrics:
  - PSNR (overall reconstruction quality)
  - MAE – calculated for high (> 2.5) and low (<2.5) SUV sep.
- Detection performance:
- Tested on liver lesion detection system
- Metrics: TPR, FPS

Results:

- Reconstruction results:
  - High SUV gives lower results



	Method	High SUV		Low SUV		Average Score	
		MAE	PSNR	MAE	PSNR	MAE	PSNR
Combined	*FCN-4s-cGAN Eq. (8)	**1.33 ± 0.65**	22.40 ± 2.92	0.11 ± 0.04	38.04 ± 1.92	**0.72 ± 0.35**	30.22 ± 2.42
Combined	*FCN-4s-cGAN Eq. (7)	1.48 ± 0.66	21.70 ± 2.95	**0.09 ± 0.05**	**39.1 ± 1.95**	0.79 ± 0.36	**30.4 ± 2.45**
Combined	FCN-4s-cGAN L2	1.55 ± 0.66	21.10 ± 2.94	0.10 ± 0.04	39.03 ± 1.94	0.83 ± 0.35	30.07 ± 2.44
Combined	Blending	1.50 ± 0.63	21.40 ± 2.94	0.10 ± 0.04	39.00 ± 2.03	0.80 ± 0.34	30.20 ± 2.49
cGAN	cGAN-U-Net gen.	1.70 ± 0.61	20.62 ± 2.92	0.10 ± 0.04	39.06 ± 1.90	0.90 ± 0.33	29.84 ± 2.41
cGAN	cGAN-FCN-4s gen.	1.52 ± 0.63	21.10 ± 3.10	0.12 ± 0.04	37.60 ± 1.95	0.82 ± 0.34	29.35 ± 2.53
FCN	FCN-4s	**1.33 ± 0.59**	**22.50 ± 2.93**	0.16 ± 0.05	37.60 ± 1.99	0.74 ± 0.32	30.05 ± 2.46
FCN	FCN-8s	**1.33 ± 0.57**	22.45 ± 2.92	0.15 ± 0.05	37.63 ± 1.99	0.74 ± 0.31	30.04 ± 2.46
FCN	FCN-2s	1.37 ± 0.62	22.42 ± 3.02	0.14 ± 0.05	37.70 ± 2.02	0.76 ± 0.34	30.06 ± 2.52
FCN	U-Net	1.52 ± 0.67	21.57 ± 3.1	0.12 ± 0.04	38.56 ± 1.74	0.82 ± 0.36	30.07 ± 2.42

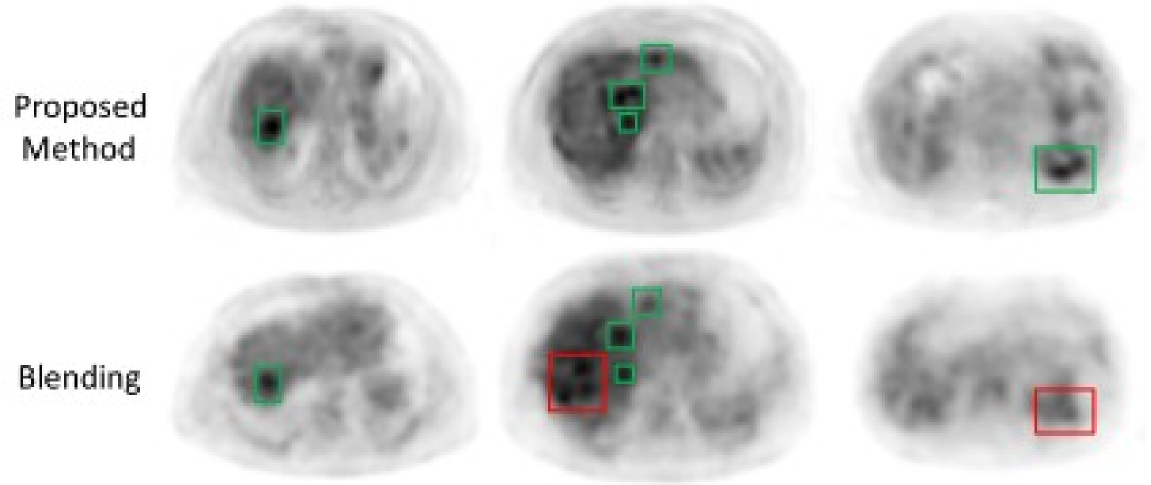
*Proposed method

Ben-Cohen et al., 2019

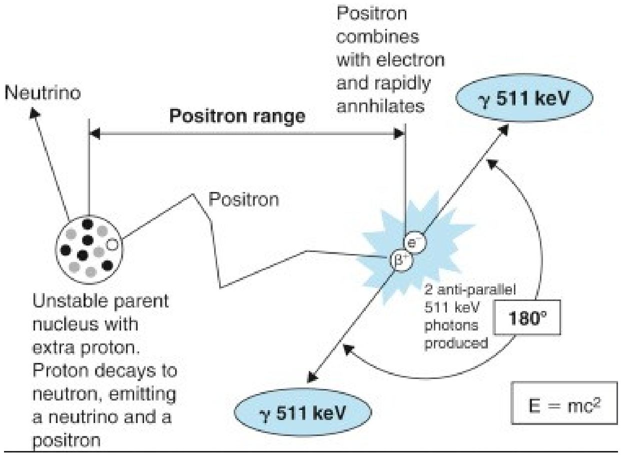
Results:

- Detection results:
  - Maintained high TPR (96.4%)
  - Decreased FPR (2.9% to 2.1%)
  - No comparison to regular PET

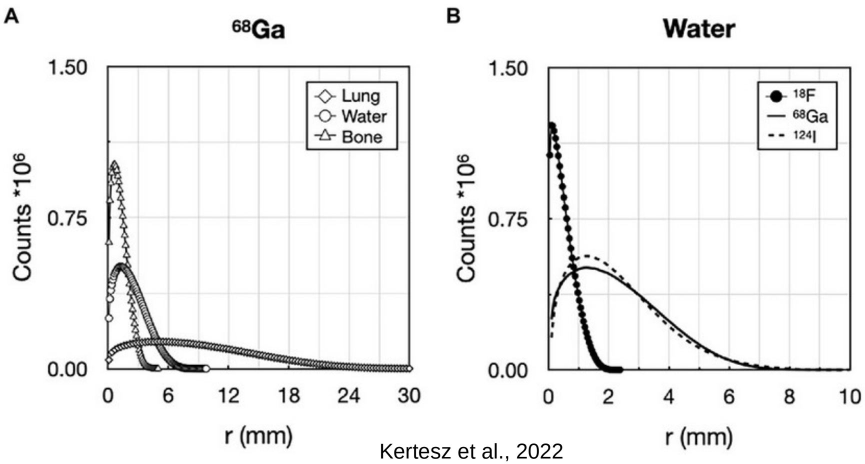
Method	TPR[%]	Average FPR
Detection soft.	94.6	2.9 ± 2.1
Detection soft+ proposed	**94.6**	**2.1 ± 1.7**
Detection soft+ blending	90.9	2.2 ± 1.7
Detection soft+ FCN-4s	90.9	2.2 ± 1.7



Positron range



Marie Foley Kijewski, in Handbook of Neuro-Oncology Neuroimaging



Kertesz et al., 2022

Nuclide	E_{max} (MeV)	E_{mode} (MeV)	$t_{\frac{1}{2}}$ (mins)	Range in Water (mm) Max	Range in Water (mm) Mean	Use in PET
^{11}C	0.959	0.326	20.4	4.1	1.1	Labelling of organic molecules
^{13}N	1.197	0.432	9.96	5.1	1.5	$^{13}NH_3$
^{15}O	1.738	0.696	2.03	7.3	2.5	$^{15}O_2$, $H_2{}^{15}O$, $C^{15}O$, $C^{15}O_2$
^{18}F	0.633	0.202	109.8	2.4	0.6	[^{18}F]-DG, $^{18}F^-$
^{68}Ga	1.898	0.783	68.3	8.2	2.9	[^{68}Ga]-EDTA, [^{68}Ga]-PTSM
^{82}Rb	3.40	1.385	1.25	14.1	5.9	Generator-produced perfusion tracer
^{94m}Tc	2.44	†	52	‡	‡	β^+-emitting version of ^{99m}Tc
^{124}I	2.13	†	6.0×10^3	‡	‡	Iodinated molecules

‡Not reported to date.
†Many-positron decay scheme hence no E_{mode} value given.

Dale L Bailey, PET Basic Sciences

Herraiz et al., 2020

https://doi.org/10.3390/app11010266

Deep-Learning Based Positron Range Correction of PET Images

by **Joaquín L. Herraiz** [1,2,*], **Adrián Bembibre** [1] and **Alejandro López-Montes** [1]

1 Nuclear Physics Group and IPARCOS, Faculty of Physical Sciences, University Complutense of Madrid, CEI Moncloa, 28040 Madrid, Spain

2 Health Research Institute of the Hospital Clínico San Carlos (IdISSC), 28040 Madrid, Spain

* Author to whom correspondence should be addressed.

Appl. Sci. **2021**, *11*(1), 266; **https://doi.org/10.3390/app11010266**

Submission received: 28 November 2020 / Revised: 21 December 2020 / Accepted: 25 December 2020 / Published: 29 December 2020

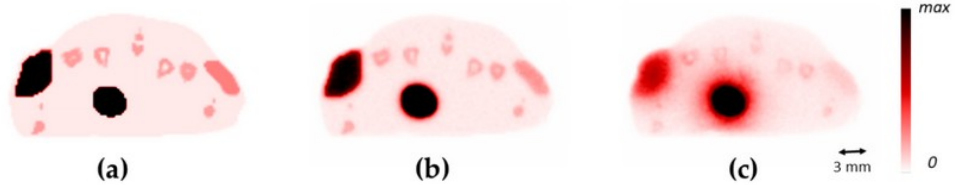
Herraiz et al., 2020

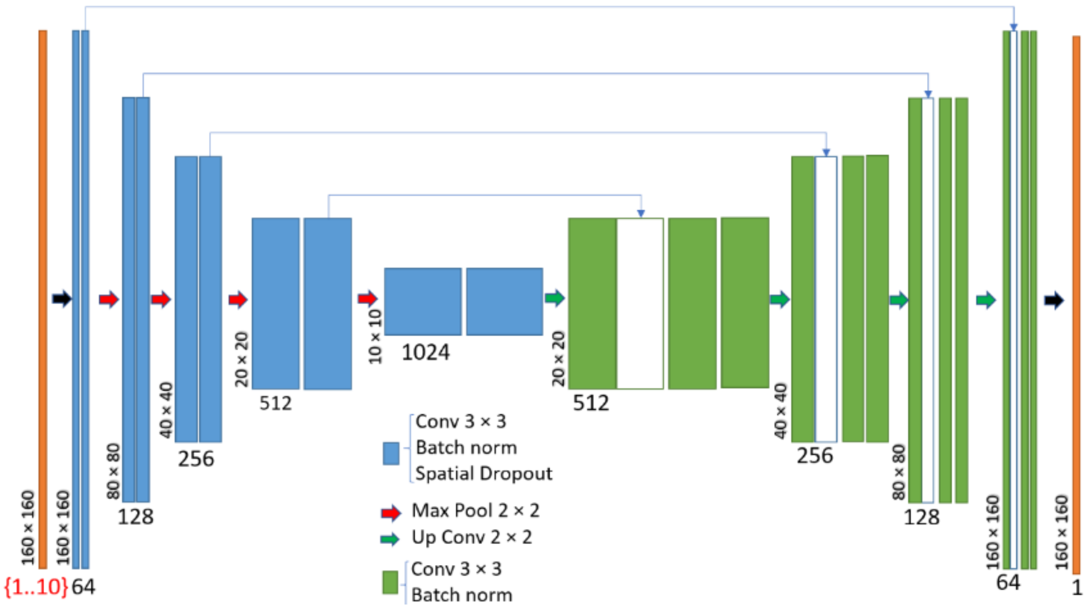
Data:

- 8 Simulated PET mice images for 18F and 68Ga
- Voxel size: 0.28 mm
- Augmented with flips, shifts, and rotations

Model:

- U-Net architecture
- Input: 68Ga PET images (with or without μ-maps)
- Output: PR-corrected images matching 18F reference images.
- Optimizer: Rectified Adam, loss: L1, epochs: 50



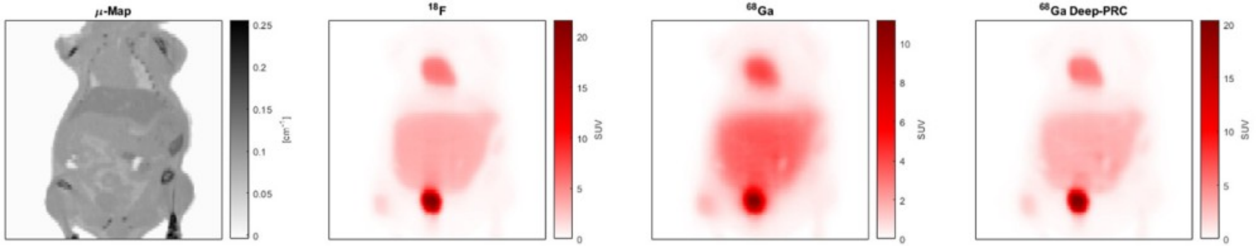


Input	1 Slice	3 Slices	5 Slices
^{68}Ga (PET)	160 × 160 × 1	160 × 160 × 3	160 × 160 × 5
^{68}Ga and μ-map (PET/CT)	160 × 160 × 1	160 × 160 × 6	160 × 160 × 10

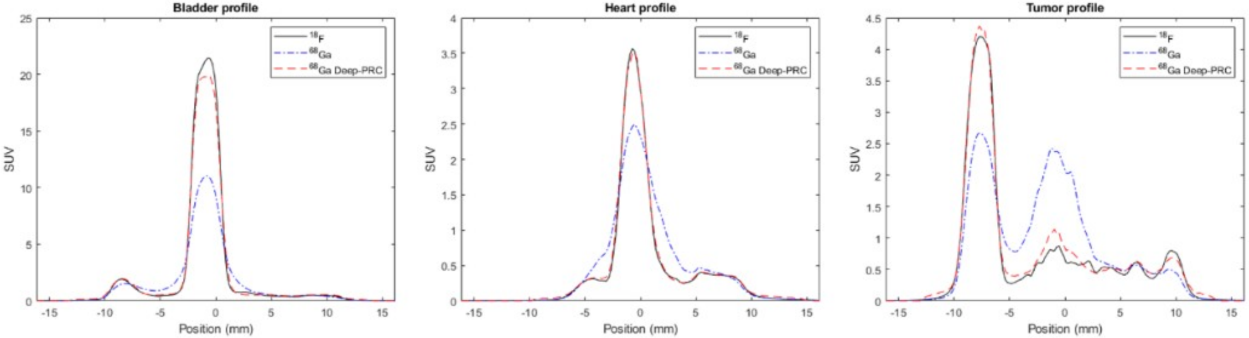
Herraiz et al., 2020

Evaluation:
- Comparison: 68Ga PET before and after correction vs. 18F reference.
- Metrics: Recovery (%) /"defining regions over the whole organ"/ and noise (σ/μ).
- Test data: Simulated PET not in training/validation.

Results:
- Recovery: >95% match to 18F images.
- Noise: Comparable to reference 18F PET.
- Input: PET-only sufficient for accurate correction.



(a) (b) (c) (d)



(a) (b) (c)

	Recovery (%)			Noise (%)		
	Heart	Bladder	Tumor	Heart	Bladder	Tumor
^{18}F	100.00	100.00	100.00	2.00	3.75	3.39
^{68}Ga	67.41	53.49	60.50	4.03	4.96	4.08
^{68}Ga Deep-PRC	95.19	96.16	97.46	2.52	3.96	3.02

Shiri et al., 2022

https://doi.org/10.1007/s00259-022-06053-8

Federated Learning

- What? Collaborative model training without data sharing
- Why? Ensuring data privacy and leveraging multicenter datasets

European Journal of Nuclear Medicine and Molecular Imaging • Open Access • Volume 50, Issue 4, Pages 1034 - 1050 • March 2023

Decentralized collaborative multi-institutional PET attenuation and scatter correction using federated deep learning

Shiri, Isaac[a]; Vafaei Sadr, Alireza[b, c]; Akhavan, Azadeh[a]; Salimi, Yazdan[a]; Sanaat, Amirhossein[a]; Amini, Mehdi[a]; Razeghi, Behrooz[d]; Saberi, Abdollah[a]; Arabi, Hossein[a]; Ferdowsi, Sohrab[e]; Voloshynovskiy, Slava[d]; Gündüz, Deniz[f]

Shiri et al., 2022

Dataset:

- 6 centers, 50 pairs of 18F-FDG PET (NAC + CT ASC) images each
- Standardized PET images to SUV units with uniform voxel size (3×3×4 mm³)
- Normalized intensities to a consistent range (0 to 5) across all centers

Table 1 Patients demographics and PET/CT image acquisition and reconstruction settings across the six different centers

		Centre 1	Centre 2	Centre 3	Centre 4	Centre 5	Centre 6
Demographic	Sex (F/M)	15/35	17/33	19/31	22/28	6/44	21/29
	Age	54 ± 22.7	62.6 ± 8.8	63.9 ± 12.2	68 ± 9.4	58.2 ± 9	52.6 ± 20.2
	Weight	69.1 ± 15.9	68.2 ± 18.4	77.3 ± 18.7	74.5 ± 16.1	84.3 ± 18	70.2 ± 23.3
Scanners	Manufacture	GE	GE	GE	GE	GE	Siemens
	Model	Duo	LS	ST	Discovery 690	RX	Biograph
CT acquisition	Average tube current	115.7 ± 9.2	120.6 ± 41	149.2 ± 51.9	98.3 ± 61	264.1 ± 41.9	176 ± 32.0
	kVp	130 ± 0	135 ± 8.8	134 ± 9.3	134 ± 9.3	119.2 ± 4	130 ± 0
PET acquisition and reconstruction parameters	Injected dose	487.2 ± 72.9	514.3 ± 118.1	549.7 ± 95.2	425.5 ± 91.2	448.9 ± 121.8	373.9 ± 92.6
	Time to scan	75.7 ± 18.9	72.1 ± 25.5	75.2 ± 17.6	73.1 ± 18.8	86.7 ± 13.6	97.6 ± 13.9
	Time Per Bed	2.6 ± 0.5	4.6 ± 1	3.6 ± 0.6	2.4 ± 1	3.1 ± 0.3	3.1 ± 0.4
	Scatter Correction	Model-based	Convolution subtraction	Convolution subtraction	Model-based	Model-based	Model-based
	Reconstruction	OSEM	OSEM	OSEM	VPHD, VPHDS	OSEM	OSEM + PSF
	Matrix size	256 × 256	128 × 128	128 × 128	192 × 192	128 × 128	168 × 168
	Slice thickness	3.4	4.3	3.3	3.5	3.3	3
	Slice numbers	14,598	10,647	13,683	16,282	11,002	26,210

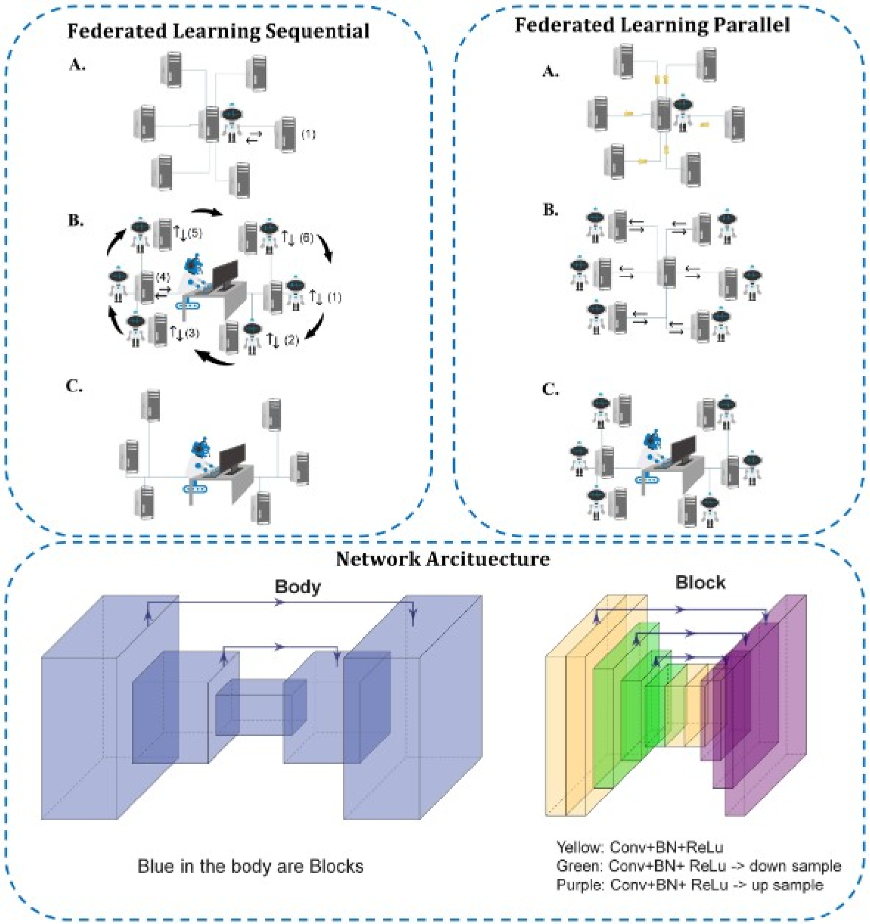
Shiri et al., 2022

Model:

- Architecture: Modified U2-Net with residual blocks
- Input: Non-AC/SC PET images
- Output: AC/SC-corrected PET images
- Training: Adam optimizer, L2 loss, learning rate 0.001

Methodology:

- **FL Sequential (FL-SQ)**
  A) model meets data center-after-center
  B) model passes sequentially through all centers
  C) process repeats for number of rounds
- **FL Parallel (FL-PL)**
  A) models are trained separately in each node
  B) central model is distributed across all nodes
  C) local models are returned to central server and aggregate to central global model
- **Centralized (CZ)**
- **Center based (CB)**



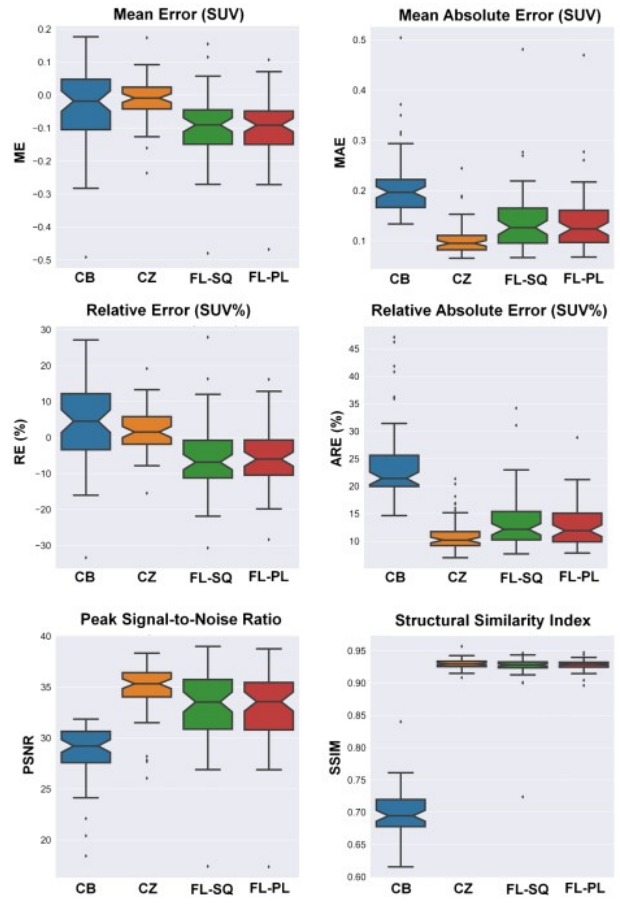
Shiri et al., 2022

Evaluation & results:

- Metrics: AE, MAE, RE, RAE, PSNR, SSIM
- FL (PL, SQ): comparable to CZ, significantly better than CB
- CB: Poor generalization due to isolated data

Limitations:

- Simulated setup; real-world use may face communication and computational challenges
- FL models are sensitive to noise and artifacts, requiring monitoring



Thank you :)