From Measured Signals to Images:

Potential Applications of AI in the Molecular Imaging Chain

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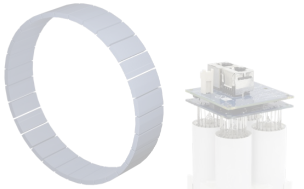
I have no financial interests to disclose

The molecular imaging pipeline - from signals to decisions



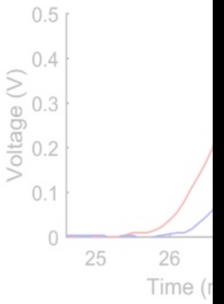
data acquisition

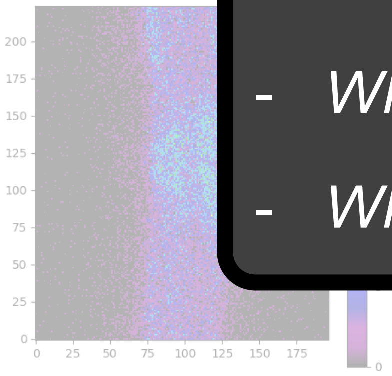
signals →

images

features / patterns

decision





ed / healthy?
change / stop

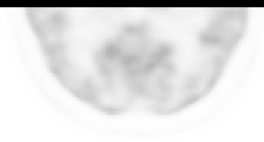
classification

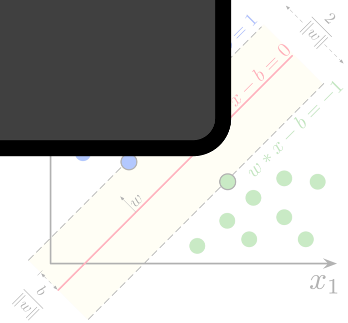
“AI / DL / ML” can be used in all steps of this pipeline

Key questions:

- *Where to start (input) where to stop (output)? “end-to-end”?*
- *Where do we loose most of the (relevant) information?*
- *Where does AI/ML/DL make most sense?*
- *What do we want / what are we lacking?*

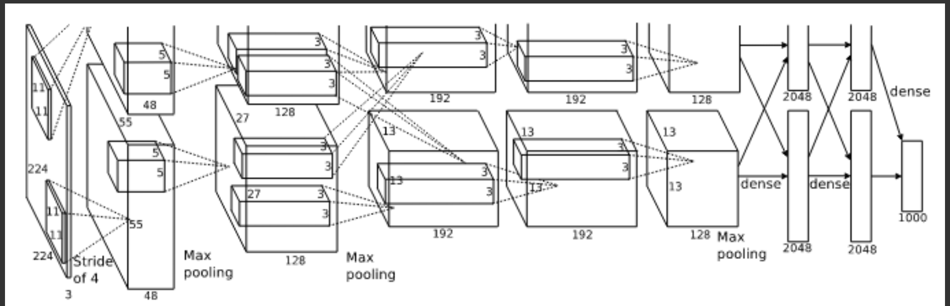
image reconstruction

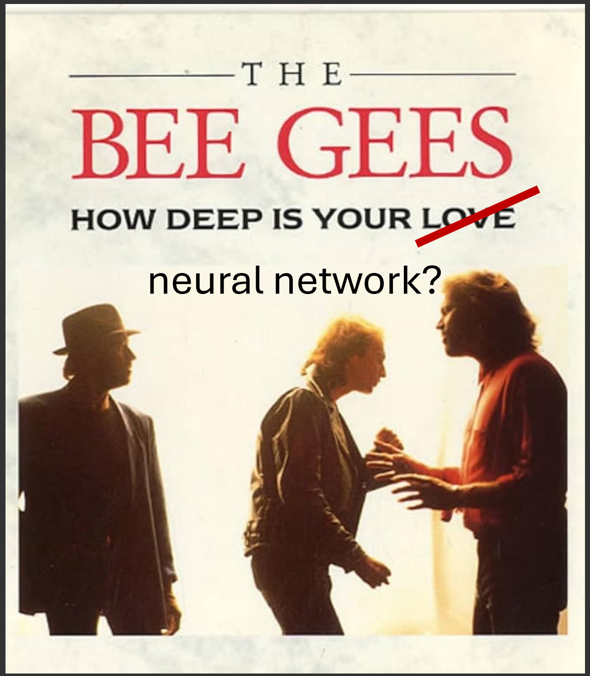




AI vs Machine learning (ML) vs Deep learning (DL)

AI research	field of study of intelligent agents, agents that act rationally
Machine Learning (ML)	computer algorithms that can improve automatically through experience and by the use of **data** supervised, unsupervised, reinforcement learning
Deep Learning (DL)	machine learning methods based on **deep artificial neural network**

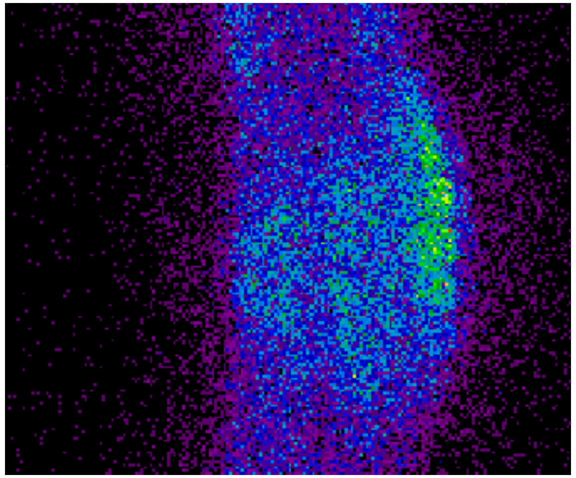




ML/DL in Image Post Processing (e.g. Denoising)

Post-reconstruction learning

acquired raw data
(emission sinogram)



“classical” recon
(OSEM)

“low” quality
“blurry and noisy”

NN

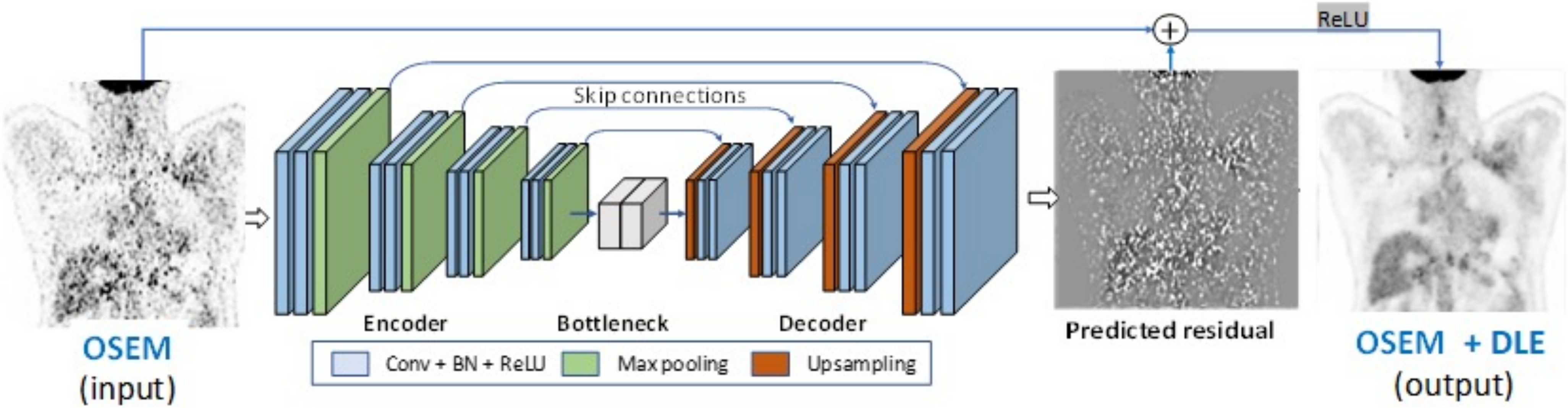
ML post-processed
recon

“higher” quality
“less blurry and less noisy”

Post-reconstruction learning

Image enhancement of whole-body oncology [18F]-FDG PET scans using deep neural networks to reduce noise

Abolfazl Mehranian[1] · Scott D. Wollenweber[2] · Matthew D. Walker[3] · Kevin M. Bradley[4] · Patrick A. Fielding[5] · Kuan-Hao Su[2] · Robert Johnsen[2] · Fotis Kotasidis[6] · Floris P. Jansen[2] · Daniel R. McGowan[3,7]



Mehranian et al. “Image enhancement of whole-body oncology [18F]-FDG PET scans using deep neural networks to reduce noise”, EJNMMI, 49, 2022

Post-reconstruction learning

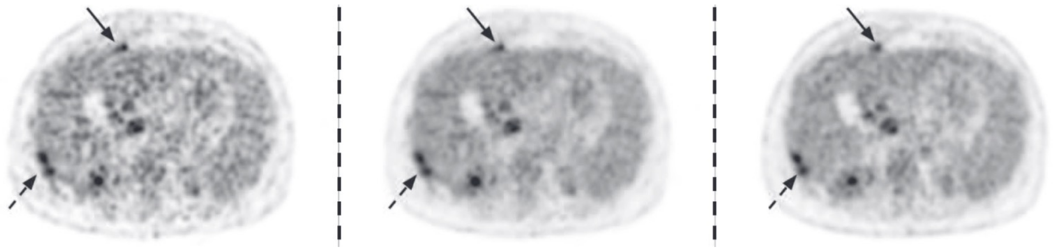
ARTICLE OPEN

Check for updates

Low-count whole-body PET with deep learning in a multicenter and externally validated study

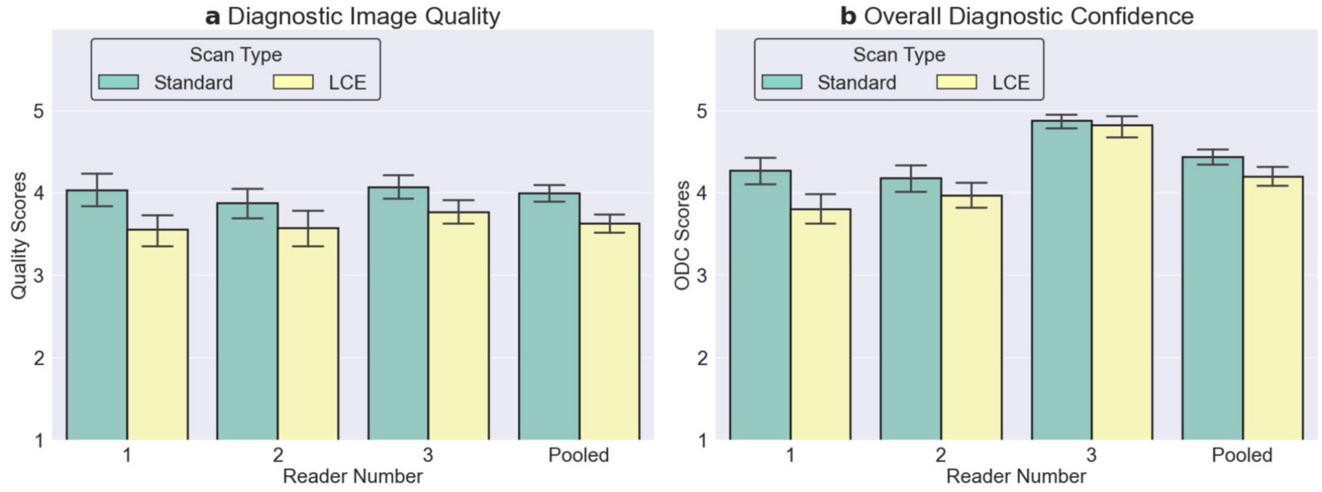
Akshay S. Chaudhari[1,2,3,7]✉, Erik Mittra[4,7], Guido A. Davidzon[1,7], Praveen Gulaka[3], Harsh Gandhi[3], Adam Brown[4], Tao Zhang[3], Shyam Srinivas[5], Enhao Gong[3], Greg Zaharchuk[1,3] and Hossein Jadvar[6]

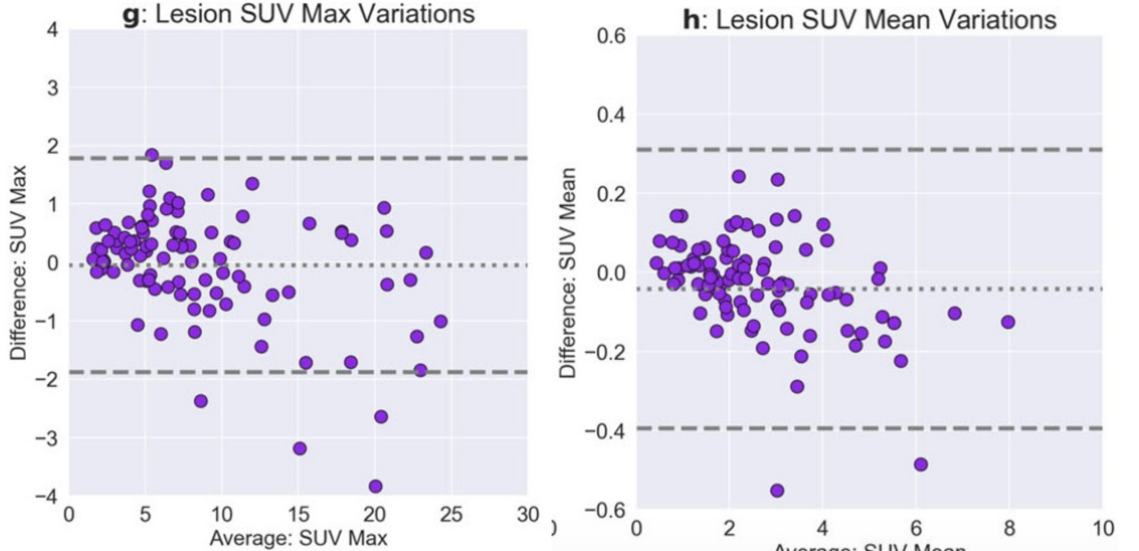
1/4 dose | 1/4 dose "DL enhanced" | full dose



sens. 0.94 (0.83–0.99)
spec. 0.98 (0.95–0.99)

491 hypermetabolic lesions
of 92 scans FDG scans, 3 scanners

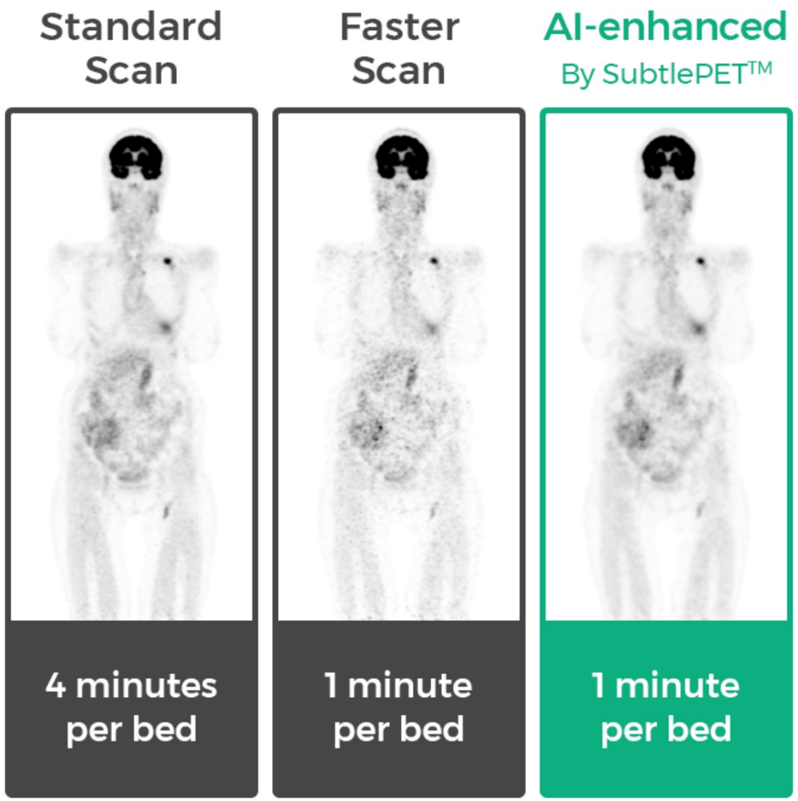


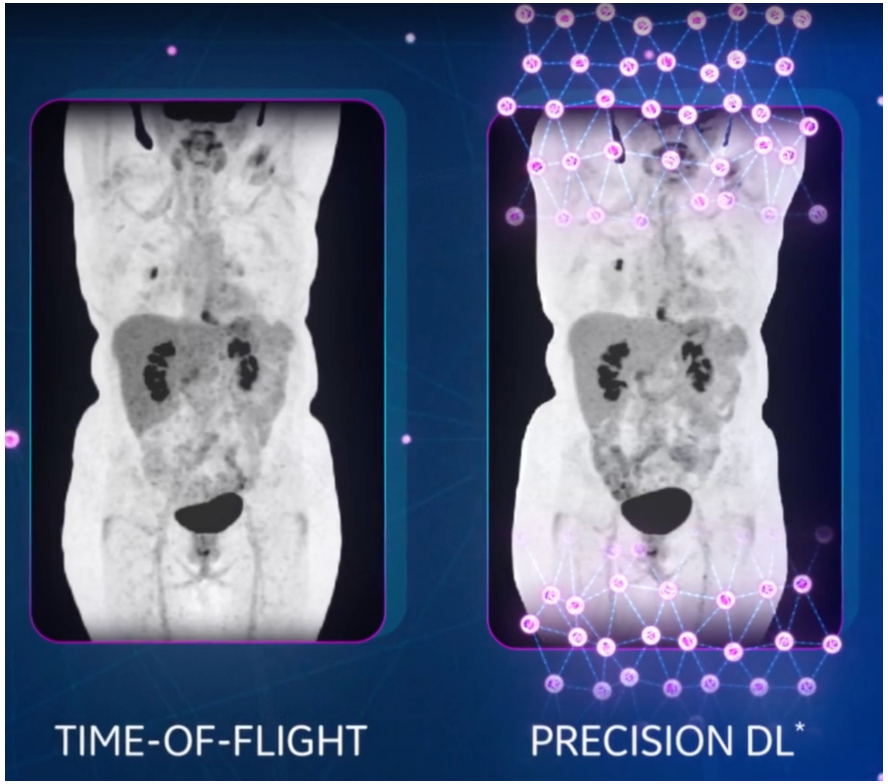


Commercial products

SUBTLE MEDICAL

GE HealthCare

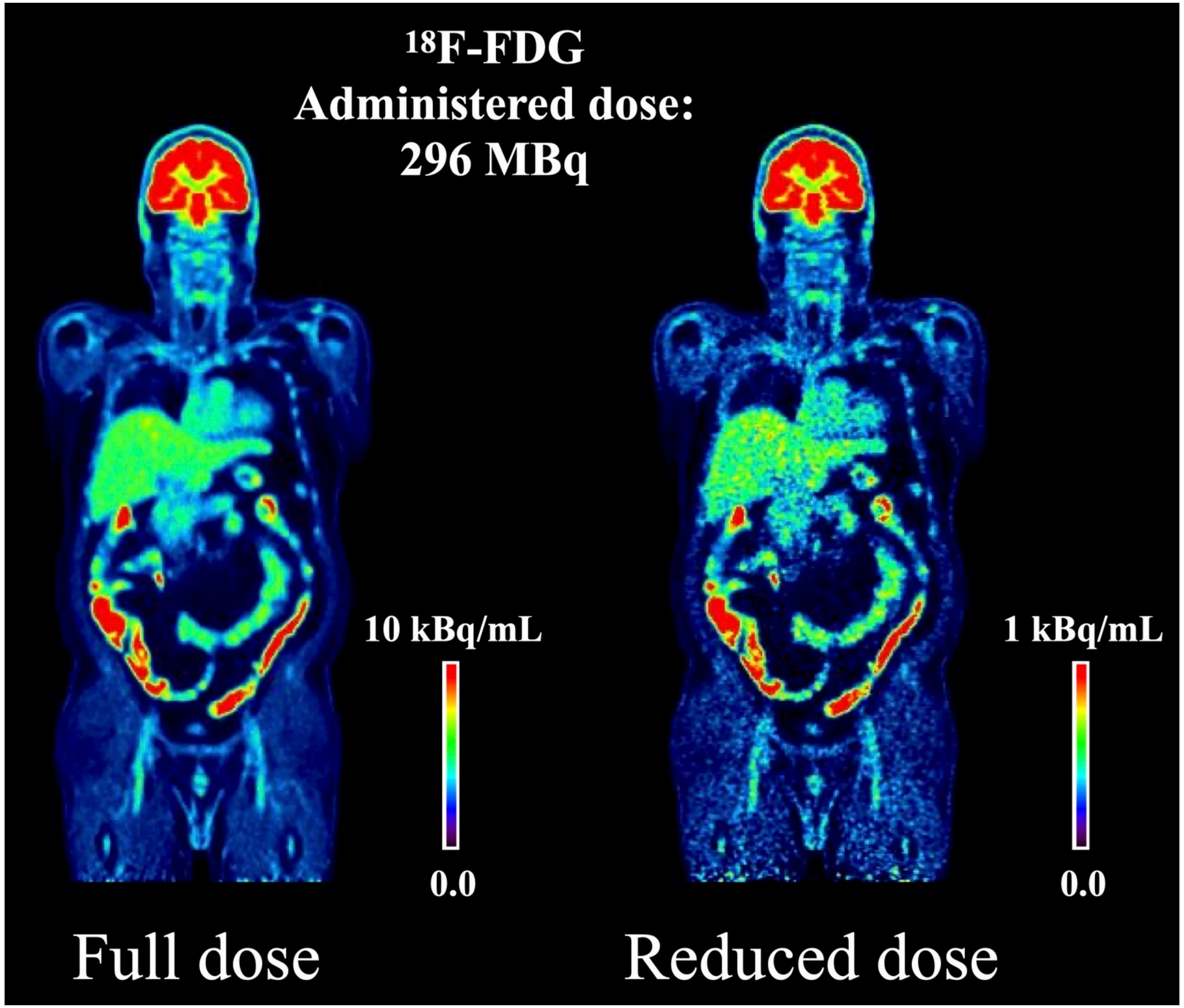




nuclivision

Low Dose PET imaging challenge

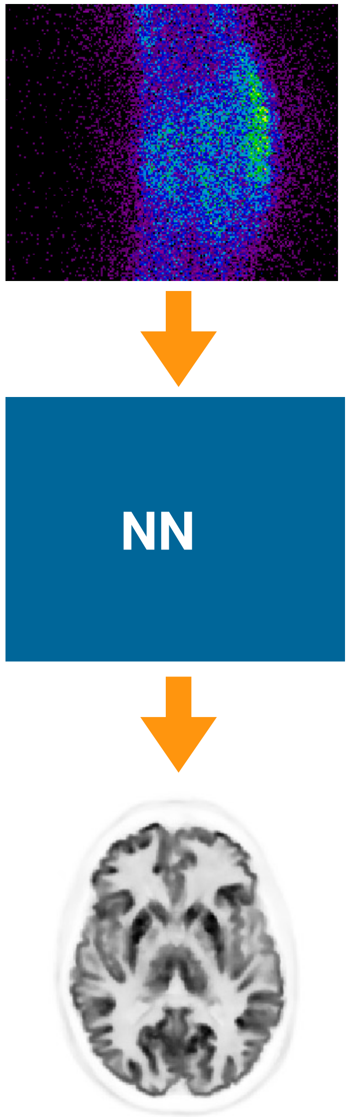
Low Dose PET Imaging Challenge Workshop



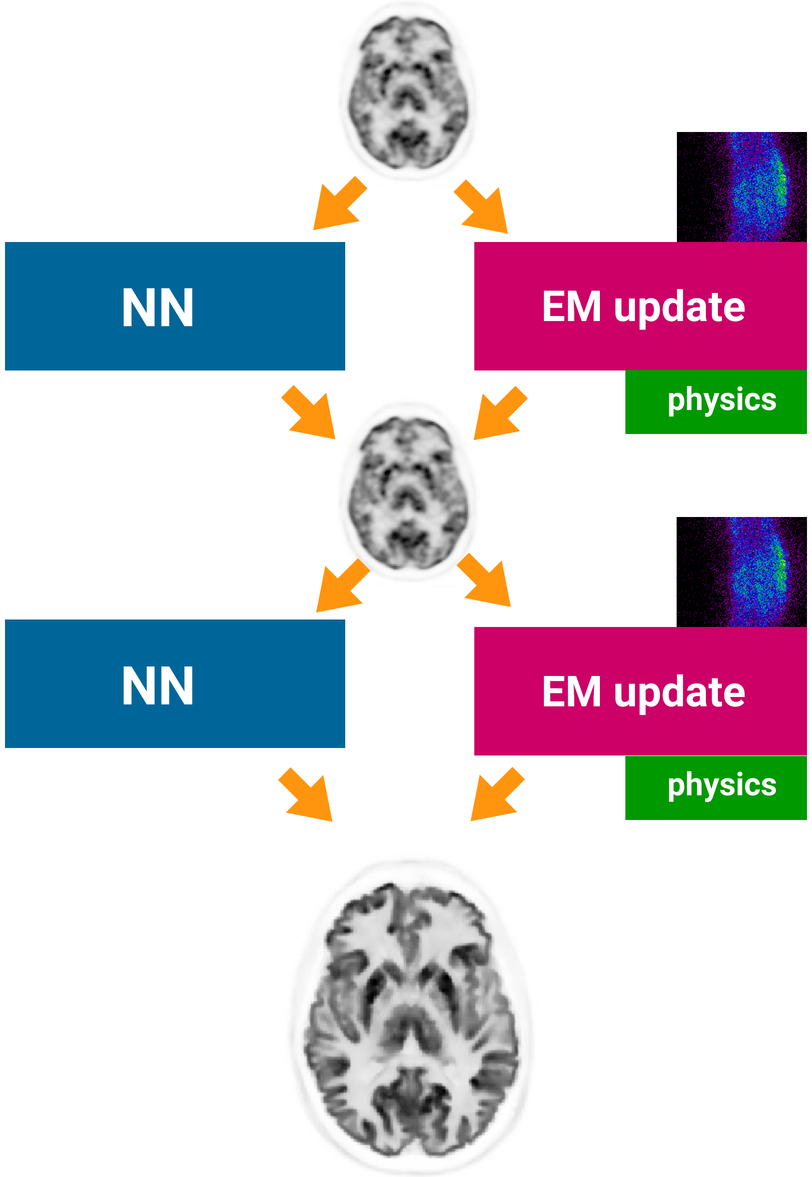
~1500 WB Quadra / Explorer data sets available

ML/DL in Image Reconstruction

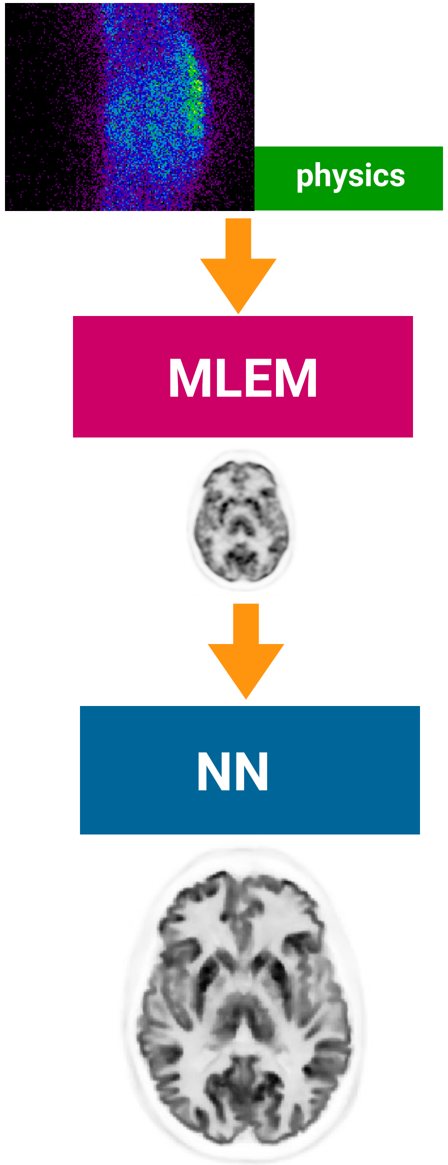
End-to-end learning (direct DL)



Physics-informed learning (unrolled networks)



Post-reconstruction learning



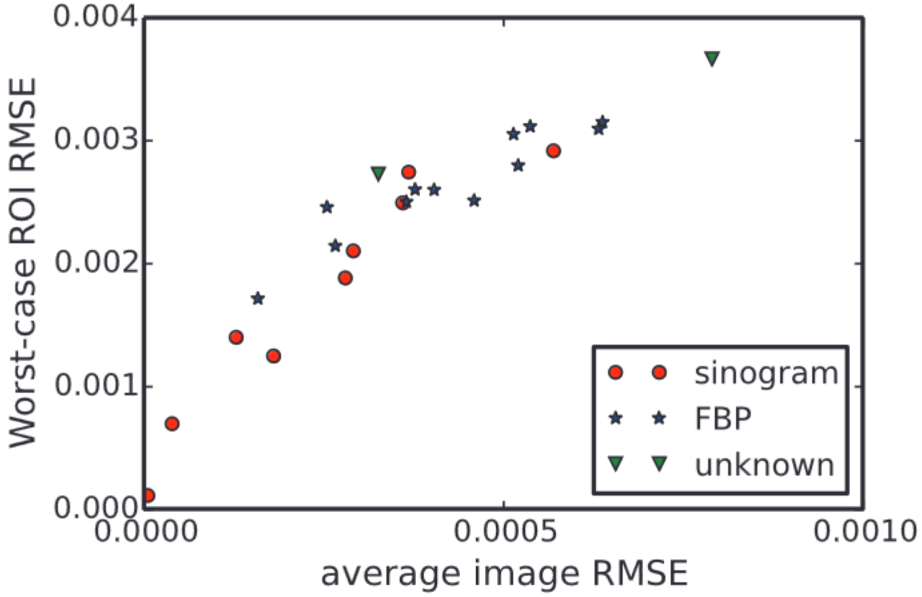
Why DL/ML during reconstrucion?

SPECIAL REPORT

MEDICAL PHYSICS

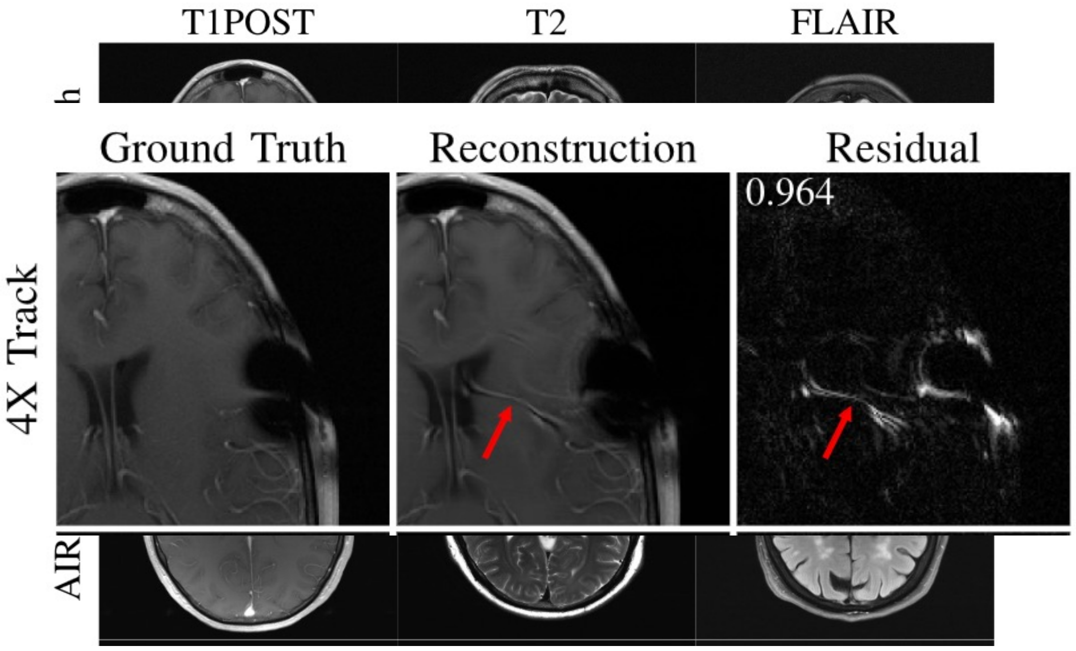
Report on the AAPM deep-learning sparse-view CT grand challenge

Emil Y. Sidky | **Xiaochuan Pan**



Results of the 2020 fastMRI Challenge for Machine Learning MR Image Reconstruction

Matthew J. Muckley, *Member, IEEE*, Bruno Riemenschneider, Alireza Radmanesh,



DL-basedreconstruction of
4x undersampled data k-space data

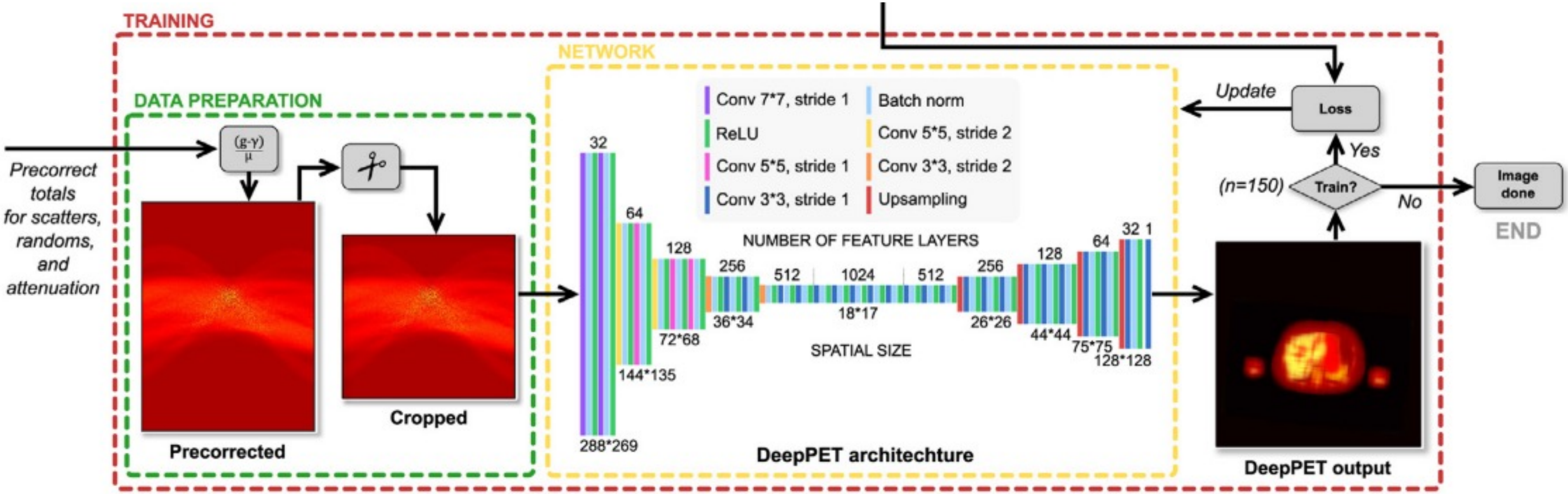
Learned End-to-End reconstruction – Deep PET

DeepPET: A deep encoder–decoder network for directly solving the PET image reconstruction inverse problem

Ida Häggström[a,*], C. Ross Schmidtlein[a], Gabriele Campanella[a,c], Thomas J. Fuchs[a,b,c]

200 000 training cases
2D, simulated XCAT
1 simulated scanner

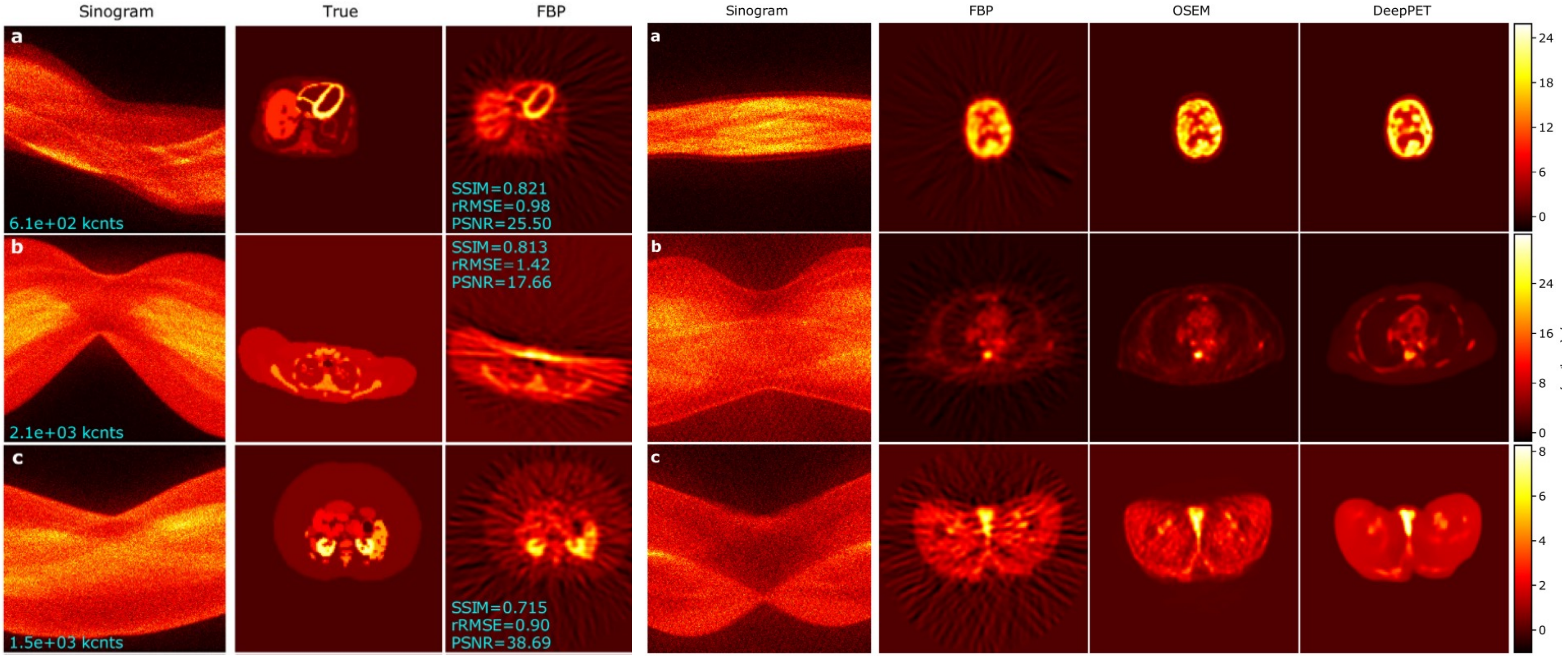
44 000 test cases
2D, simulated XCAT
1 simulated scanner



Häggström et al.: "DeepPET: A deep encoder-decoder network for directly solving the PET image recon inverse problem", Medical Image Analysis 54 (2019)

Zhu et al.: "Image reconstruction dy domain-transform manifold learning", Nature 555 (2018)

Learned End-to-End reconstruction – Deep PET

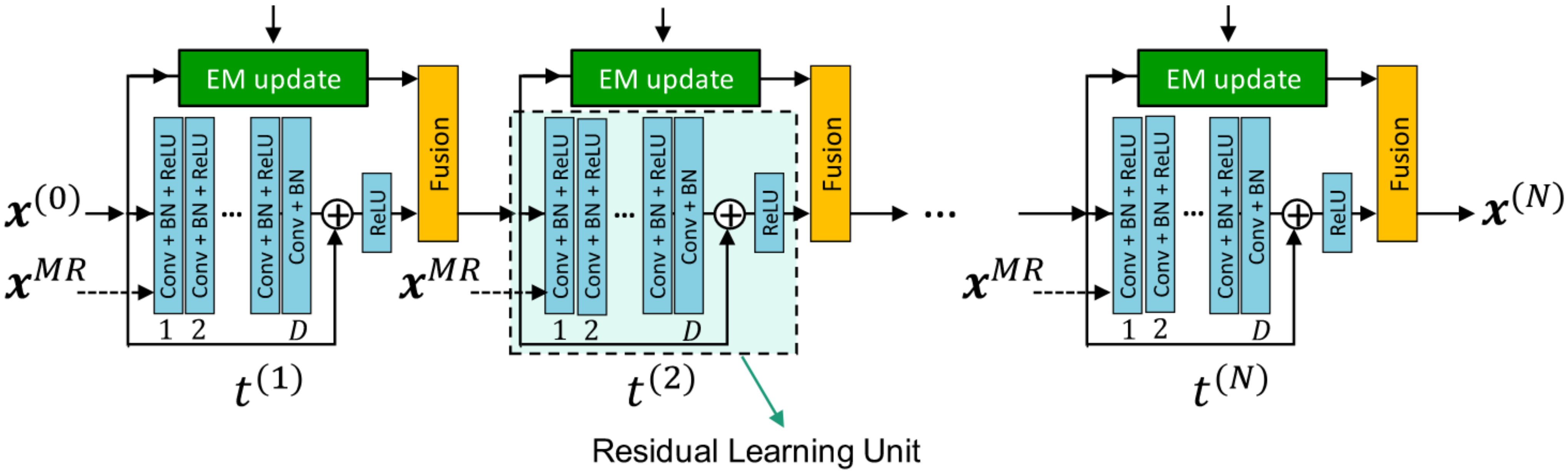


Häggström et al.: “DeepPET: A deep encoder-decoder network for directly solving the PET image recon inverse problem”, Medical Image Analysis 54 (2019)

Unrolled Variational Networks – Physics-Informed Learning

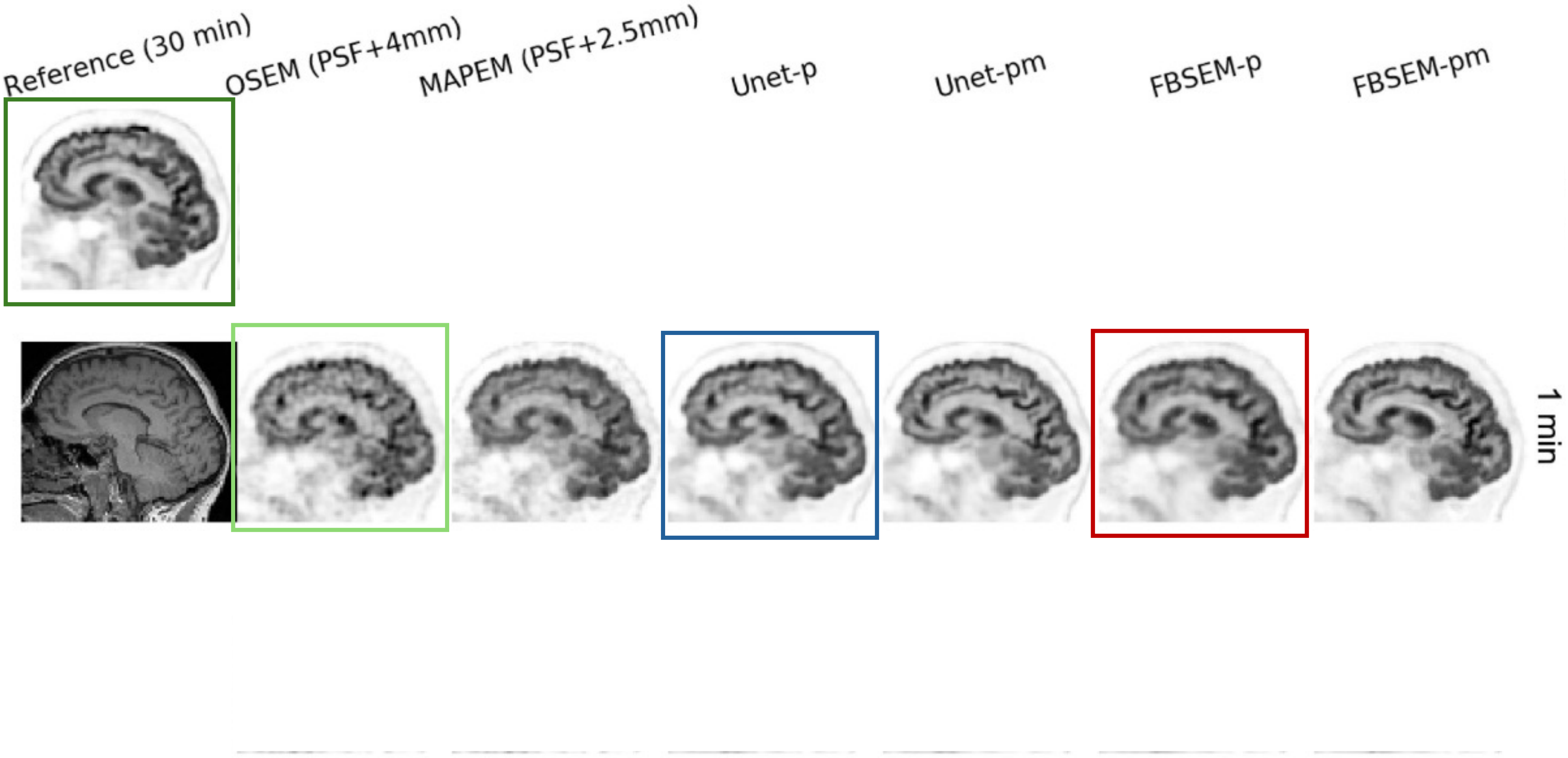
Model-Based Deep Learning PET Image Reconstruction Using Forward–Backward Splitting Expectation–Maximization

Abolfazl Mehranian and Andrew J. Reader



Mehranian and Reader, "Model-Based Deep Learning PET Image Reconstruction Using Forward–Backward Splitting Expectation–Maximization", IEEE TRPMS, 2021

Unrolled Variational Networks – Physics-Informed Learning



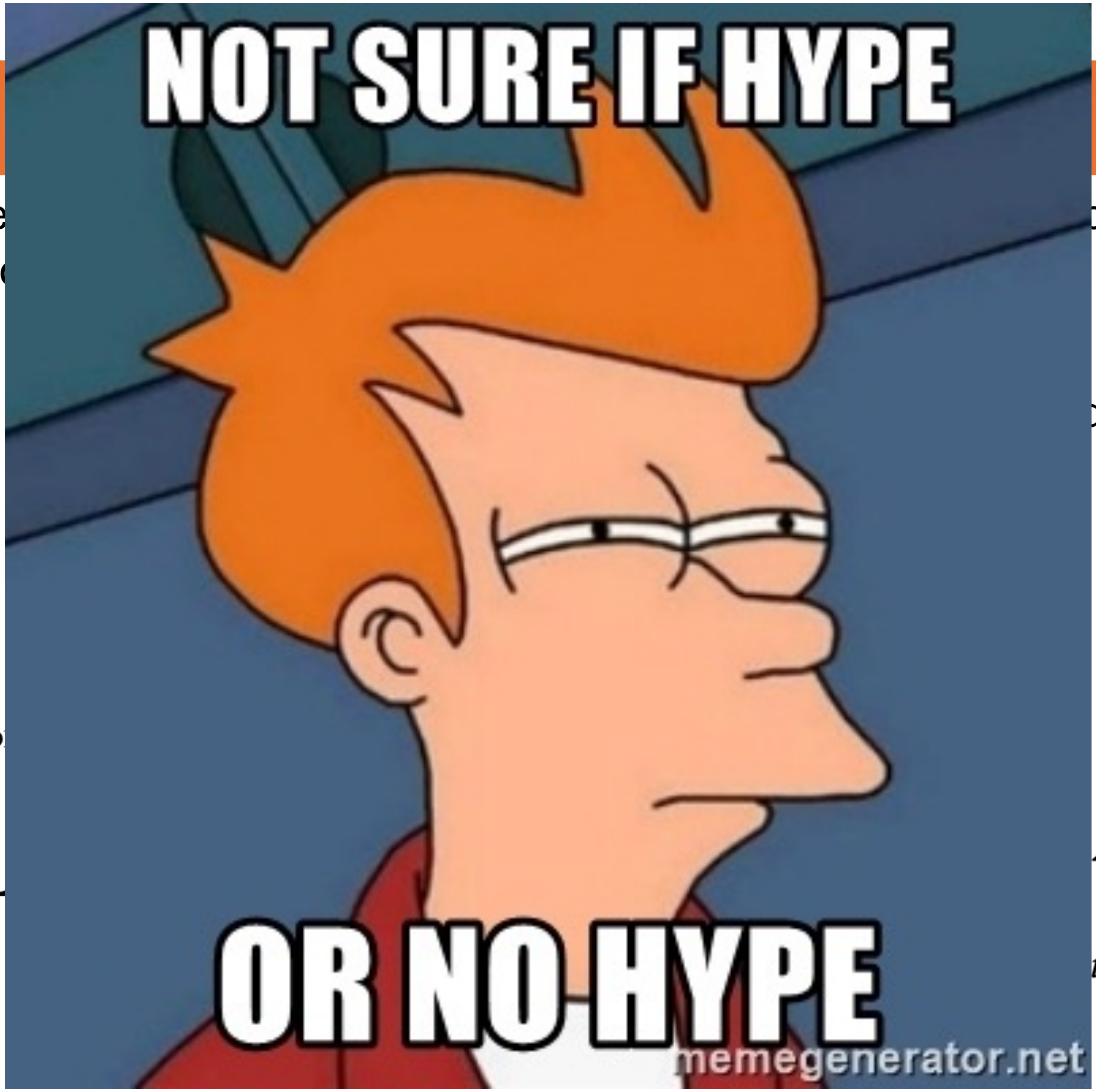
Mehranian and Reader, "Model-Based Deep Learning PET Image Reconstruction Using Forward–Backward Splitting Expectation–Maximization", IEEE TRPMS, 2021

DL/ML during reconstrucion

PROs

potentially superior to post-re… …by
(evidence from MR/CT recon …

"inclusion" of data fidelity … …d



IEEE TRANSACTIONS ON RAD… 1

Deep L… …truction

Andrew J. Reader , … …tudent Member, IEEE,

DL for ”corrections” needed in the reconstruction

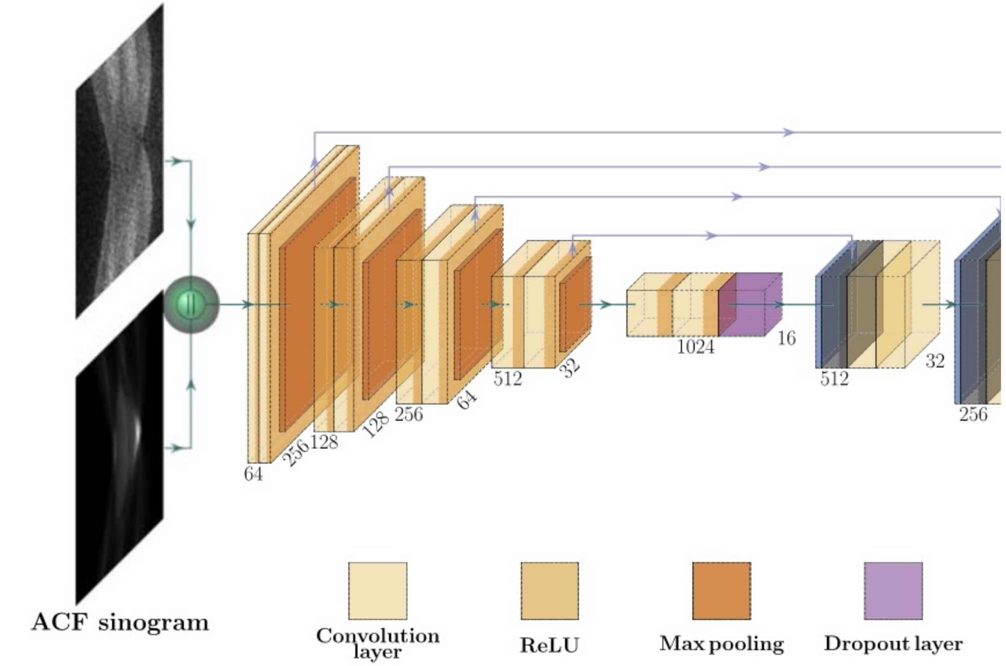
PET scatter estimation using deep learni

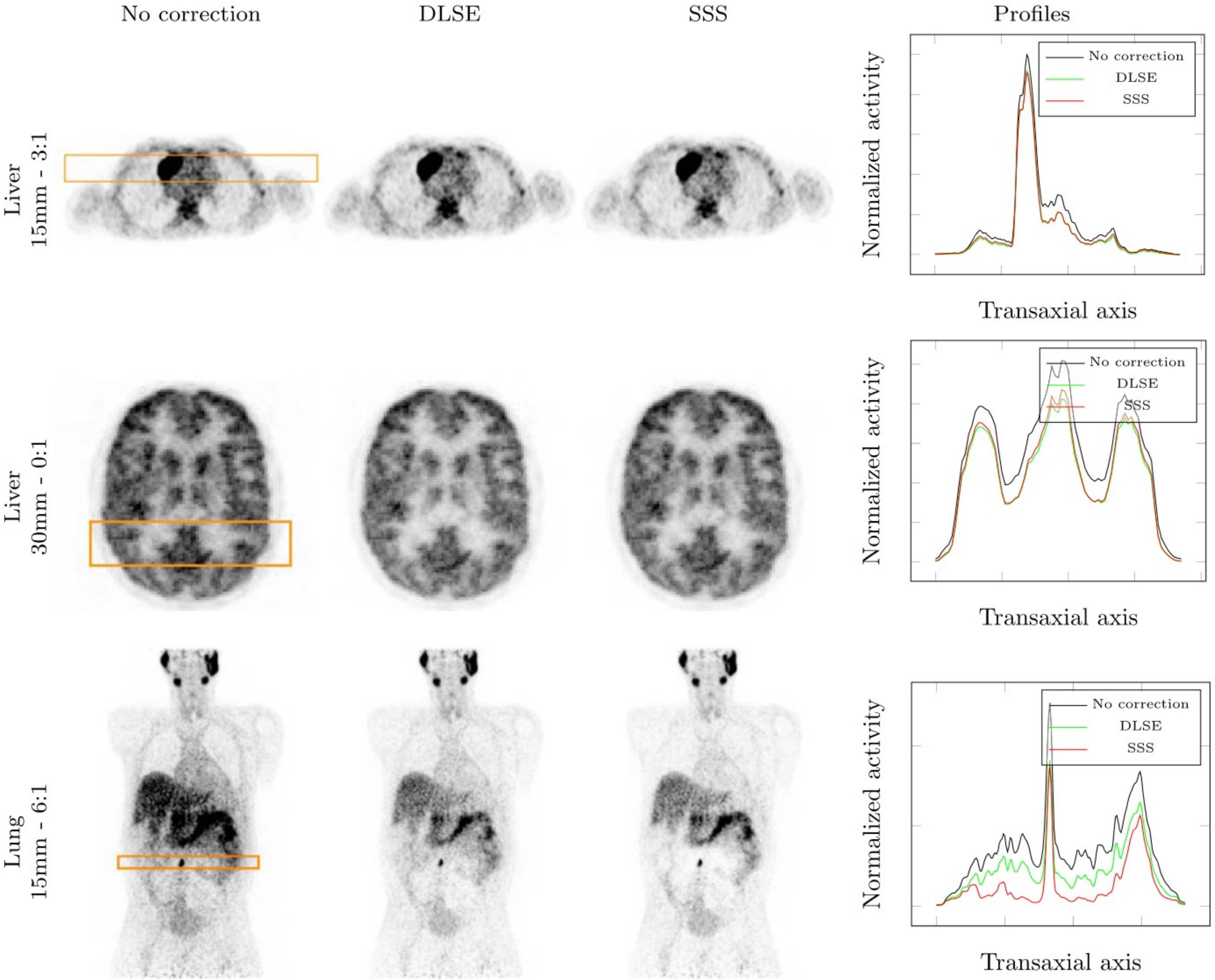
Baptiste Laurent[1,*], **Alexandre Bousse**[1], **Thibaut Merlin**[1], **St**

[1] LaTIM, INSERM, UMR 1101, UBO, Brest, France

[2] Department of Nuclear Medicine, Klinikum rechts der Isar der Technischen U

* Author to whom any correspondence should be addressed.





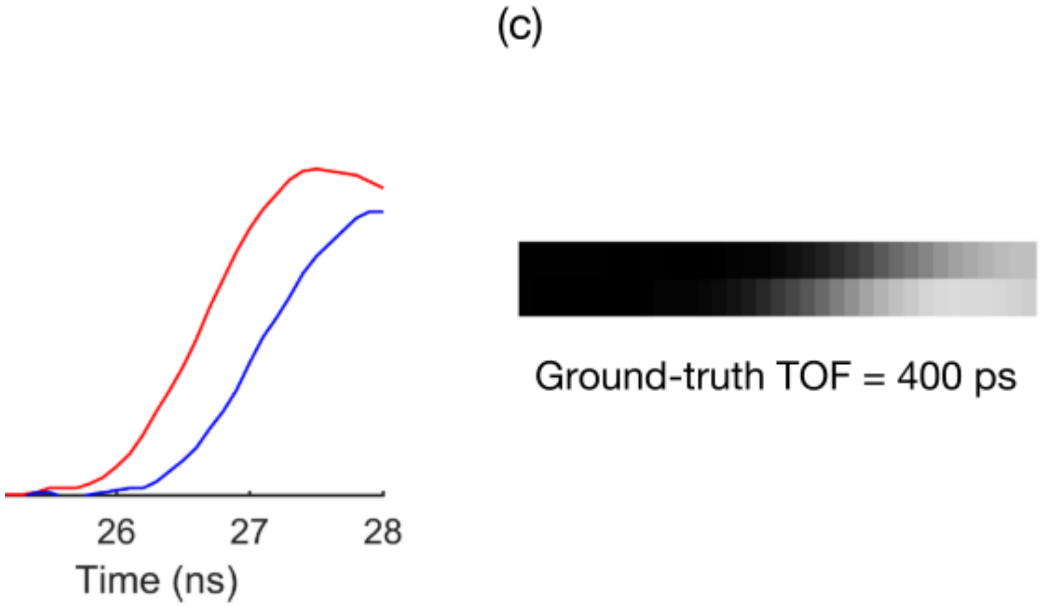
ML/DL in PET signal detection

DL to estimate photon arrival time differences

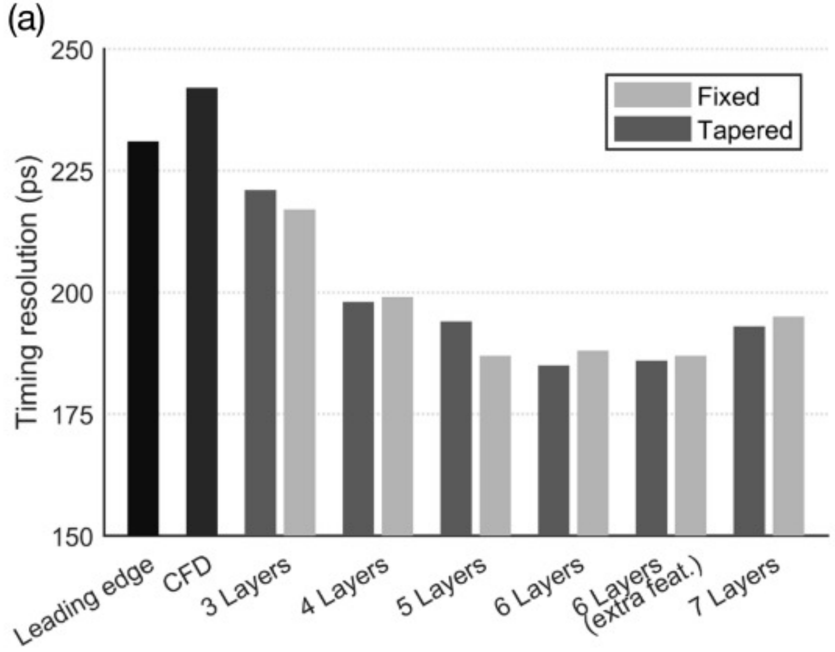
LETTER

Using convolutional neural networks to estimate time-of-flight from PET detector waveforms

To cite this article: Eric Berg and Simon R Cherry 2018 *Phys. Med. Biol.* **63** 02LT01



6 layer CNN 145 waveforms leads to ca 20% better coincidence timing resolution



Berg and Cherry, "Using convolutional neural networks to estimate time-of-flight from PET detector waveforms", PMB 63 (2018)

DL to estimate photon arrival time differences

PAPER

Artificial neural networks for positioning of gamma interactions in monolithic PET detectors

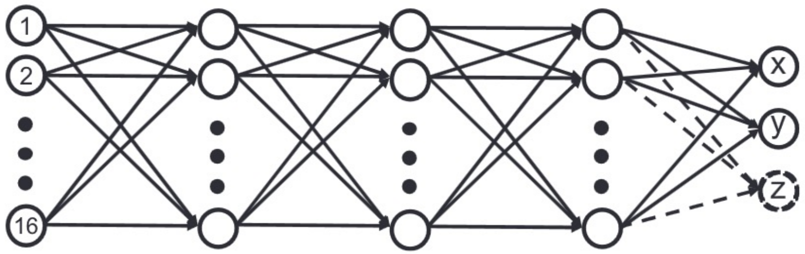
Milan Decuyper[1], Mariele Stockhoff[1], Stefaan Vandenberghe[1] and Roel Van Holen[1]

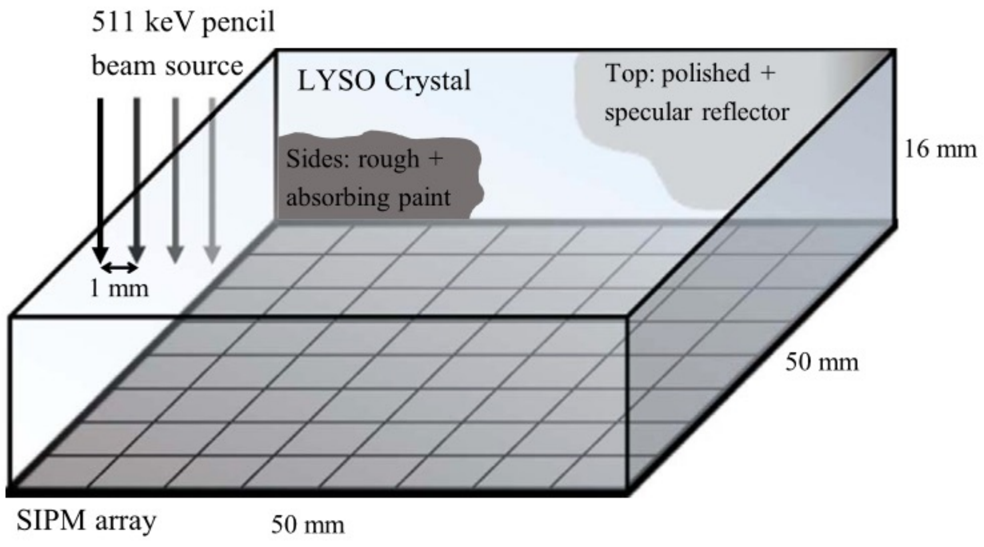
Published 23 March 2021 • © 2021 Institute of Physics and Engineering in Medicine

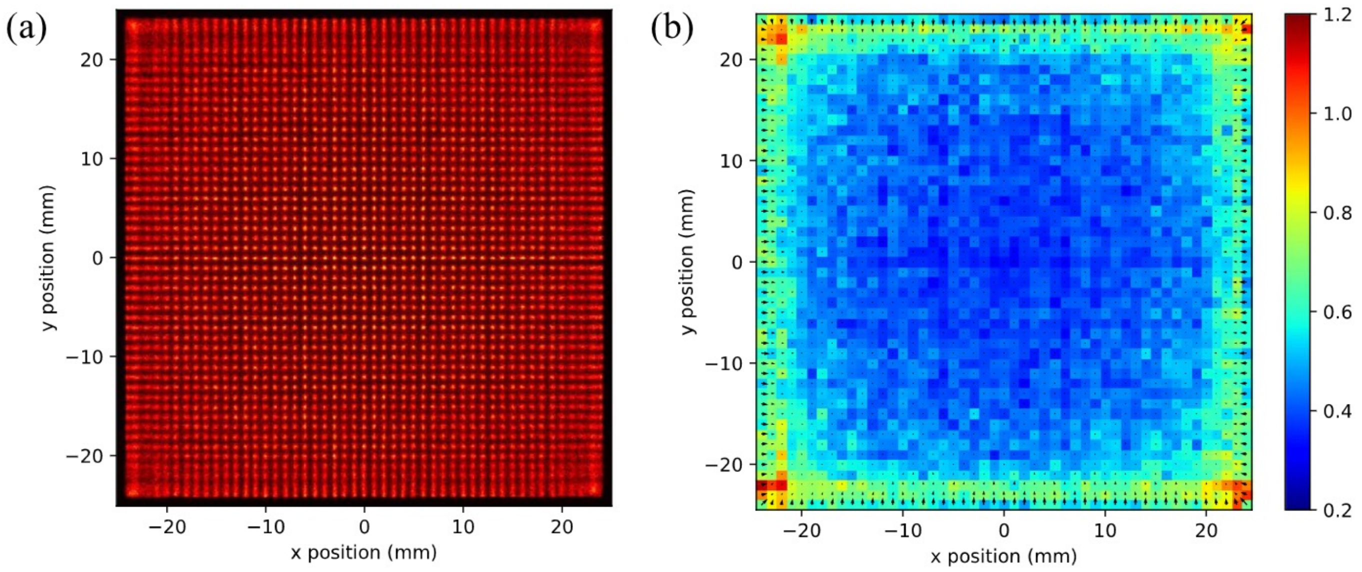
Physics in Medicine & Biology, Volume 66, Number 7

Citation Milan Decuyper *et al* 2021 *Phys. Med. Biol.* **66** 075001

DOI 10.1088/1361-6560/abebfc







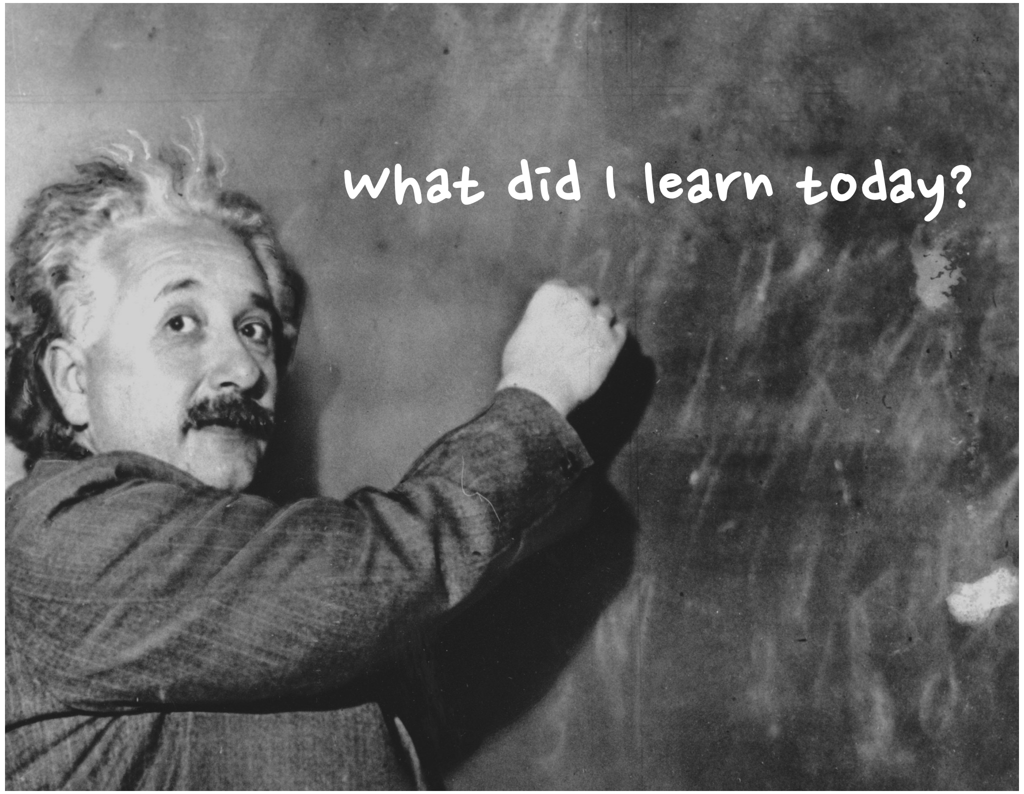
Take Home Message and Final Thoughts

Summary + Take Home Messages

- **ML/DL can be used in many stages** of the image generation pipeline (raw signal processing, during and post reconstruction, corrections …)

- **benefit of DL during recon** methods (from CT and MR) **not shown yet** in molecular imaging
  → more careful research needed

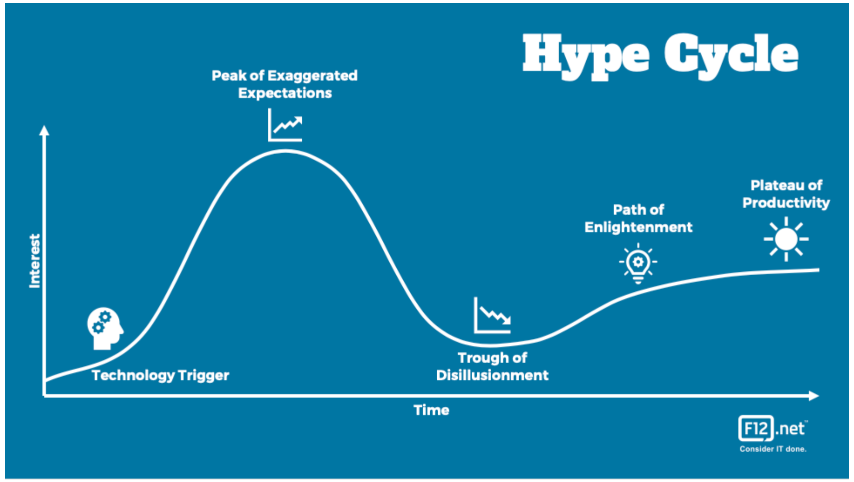
- **meaningful and critical evaluation of new DL methods not trivial**



Final thoughts / Concerns / Outlook

- **growing gap** between **medical** and **technical experts**

- training **DL** models is **”easy” + “peak of DL hype cycle”**
  → risk of **losing competence** in ”classical” **image recon + analysis**
  → tsunami **by poor DL solutions**



What we need for a critical evaluation of DL

- better **data collection, curation and sharing** – on all levels

- **critical evaluations on clinical tasks** – not on mathematical metrics

- **better collaboration** between clinicians and researchers with tech / physics focus