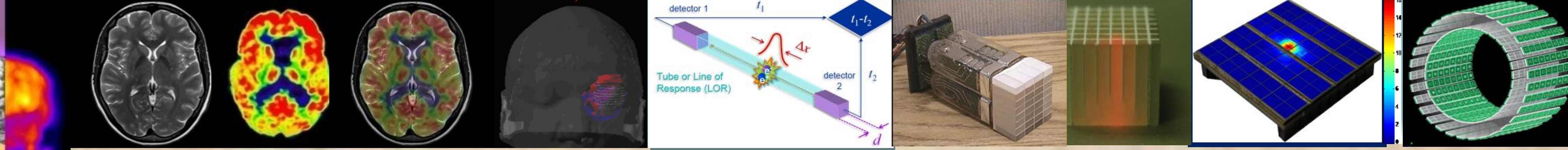


PINLab
PET Instrumentation & Neuroimaging Lab

The emerging role of artificial intelligence in internal radiation dosimetry

Habib Zaidi[1,2,3]

15th EURADOS School, Belgrade, 23 June 2022

[1]Geneva University Hospital, Geneva, Switzerland
[2]University of Groningen, Groningen, Nethelands
[3]University of Southern Denmark, Odense, Denmark
Email: habib.zaidi@hcuge.ch
Web: http://www.pinlab.ch

SINFONIA - Medical radiation risk appraisal

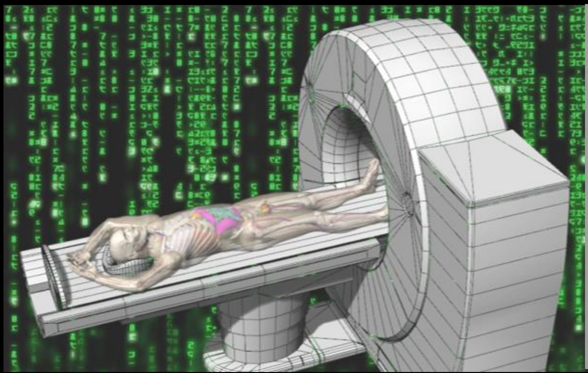
Hôpitaux Universitaires Genève

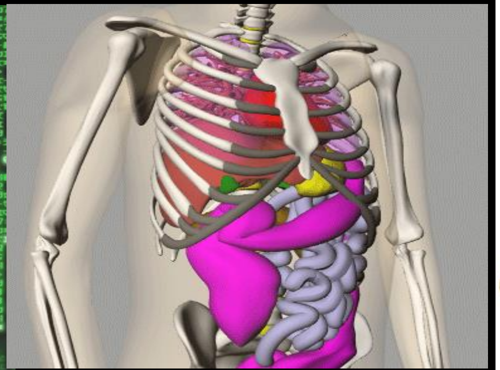
European Commission | Horizon 2020 European Union funding for Research & Innovation | SINFONIA

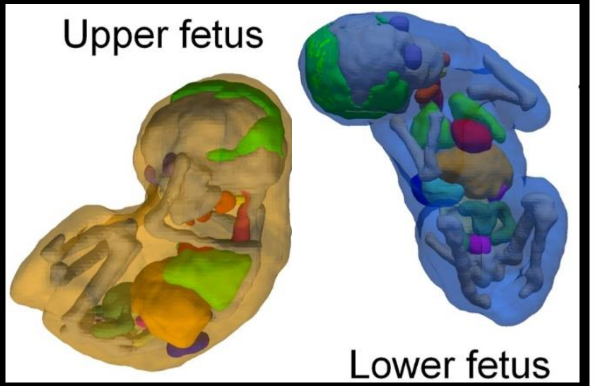
EEC H2020 (2020-2024) https://www.sinfonia-appraisal.eu/

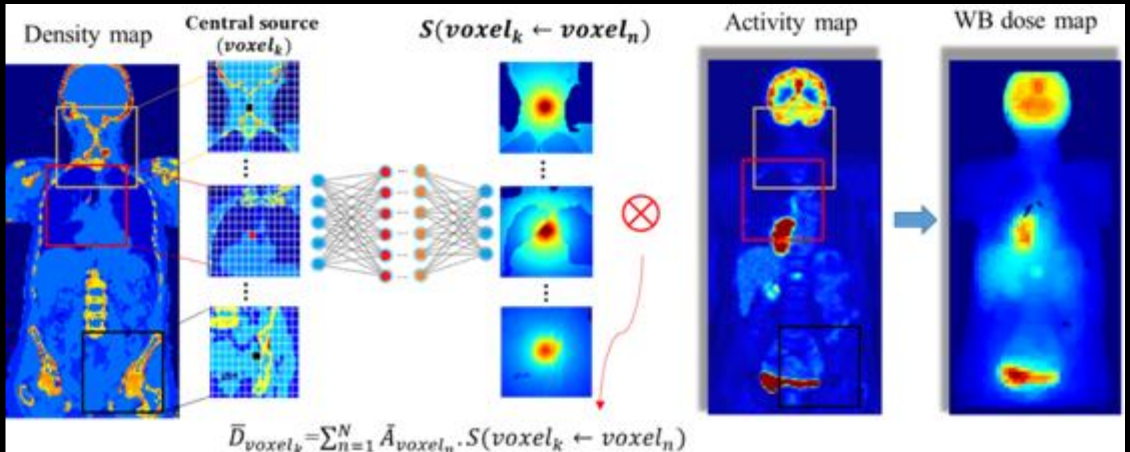
«Radiation risk appraisal for detrimental effects from medical exposure during management of patients with lymphoma or brain tumours»

NFRP-945196 SINFONIA (5’999’999 €)

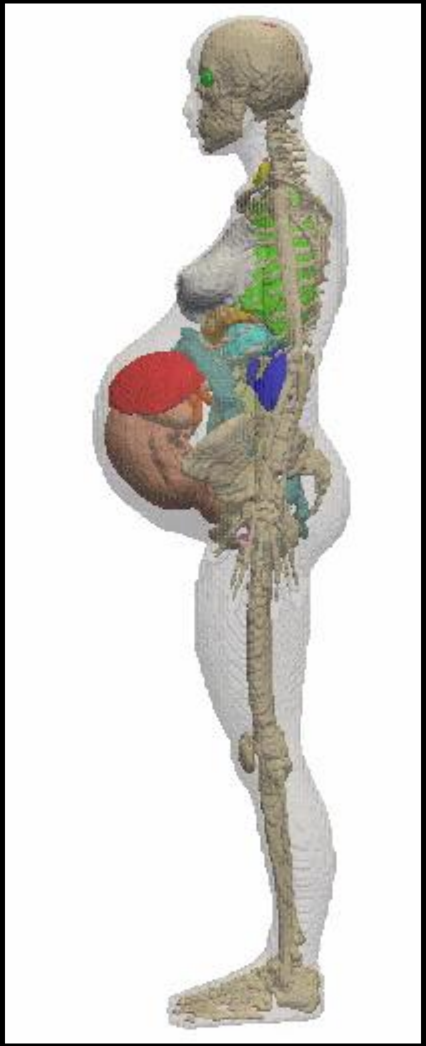








38w-gestation



Outline

Hôpitaux Universitaires Genève

- Advances in multimodality molecular imaging
- Why do we need AI in radiation dosimetry?
- Promise of AI in internal radiation dosimetry
  - Low-dose CT/PET/SPECT imaging (chest/brain/WB/cardiac)
  - Medical image segmentation (CT and PET)
  - Cross-modality image conversion (MRI→CT)
  - Quantification (attenuation & scatter correction in PET)
  - Computational modeling and radiation dosimetry
  - Prognostic modeling and outcome prediction
- Summary and future perspectives

Recent SPECT/CT scanner designs (CZT)

D-SPECT(Spectrum Dynamics)

Discovery 870 CZT (GE)

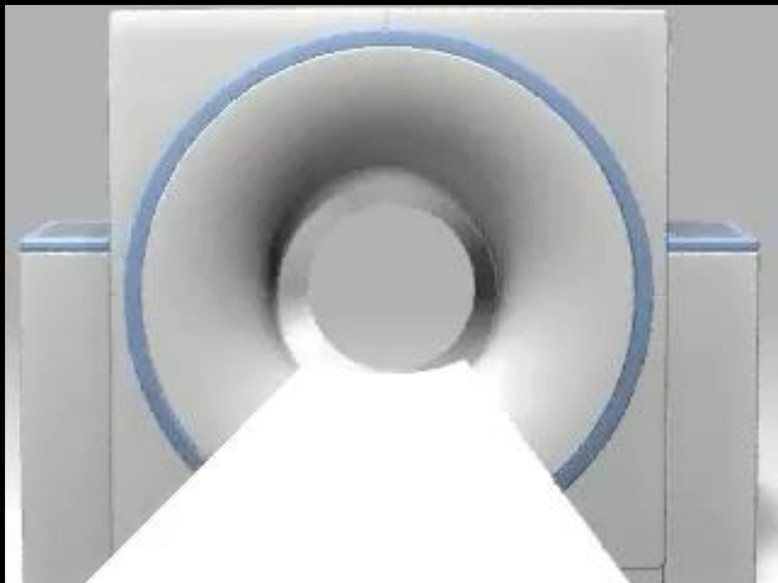
VERITON-CT (Spectrum Dynamics)

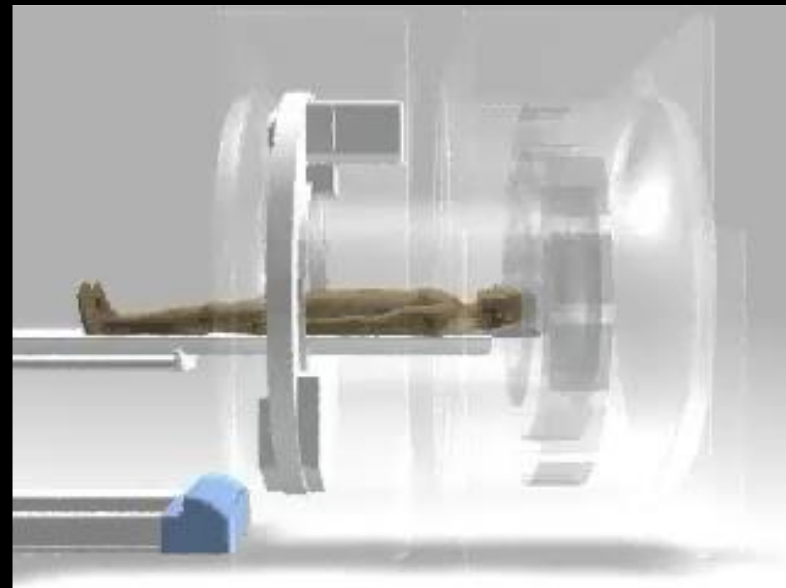
StarGuide (GE)

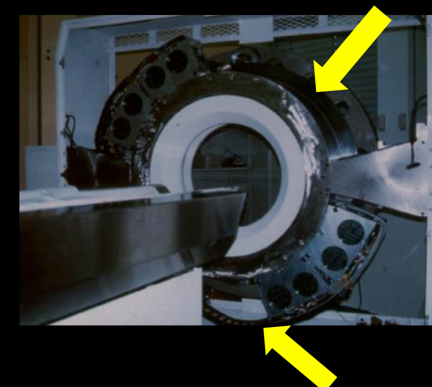
Veriton-CT SPECT/CT camera

Hôpitaux Universitaires Genève

Principles of PET/CT





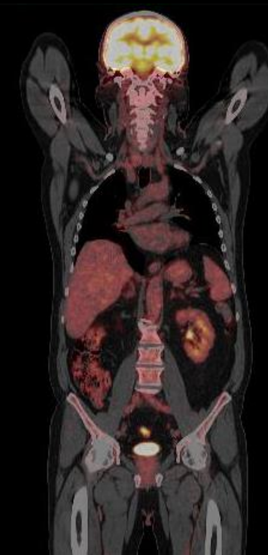


Scout

Spiral CT

PET

PET/CT



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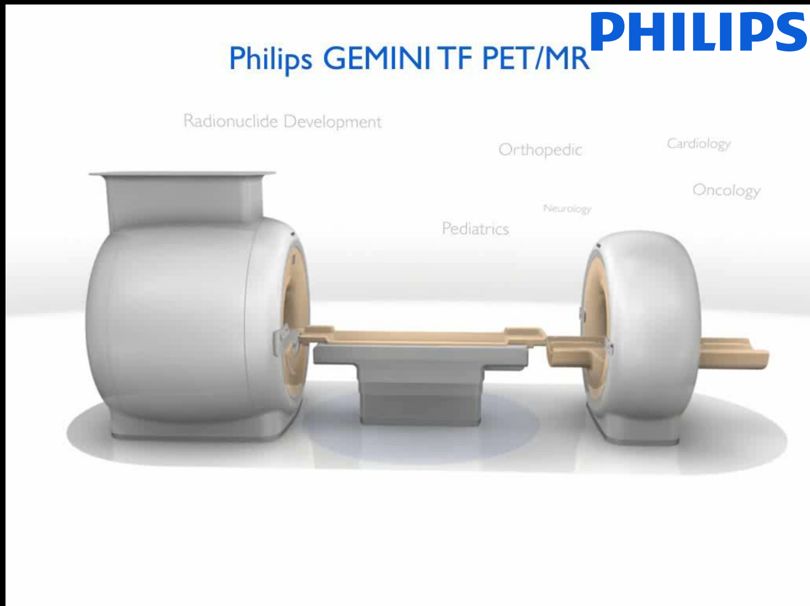
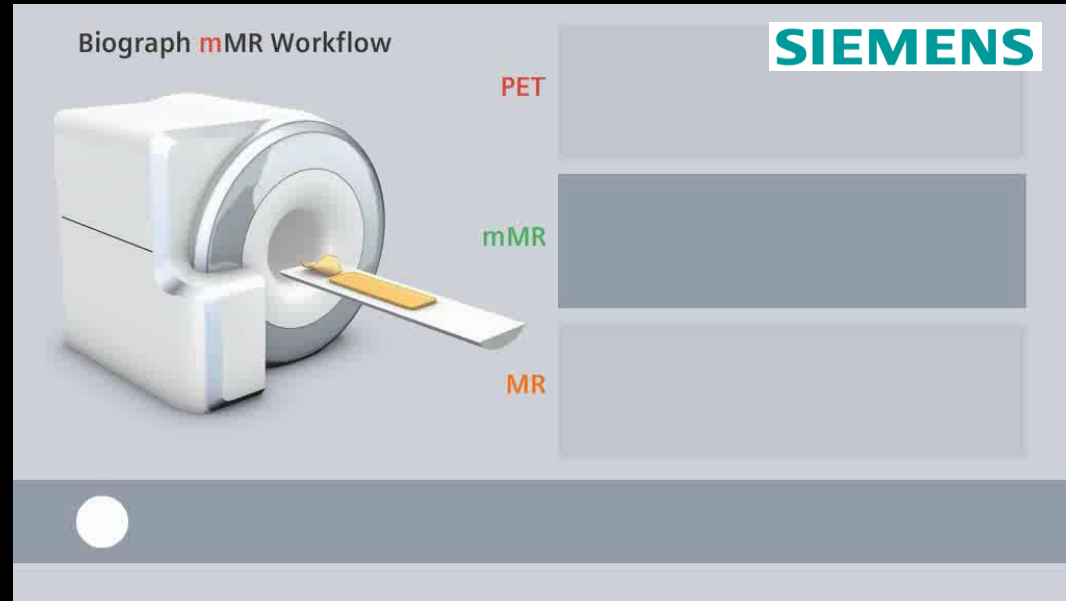
Commercial whole-body PET/MRI systems

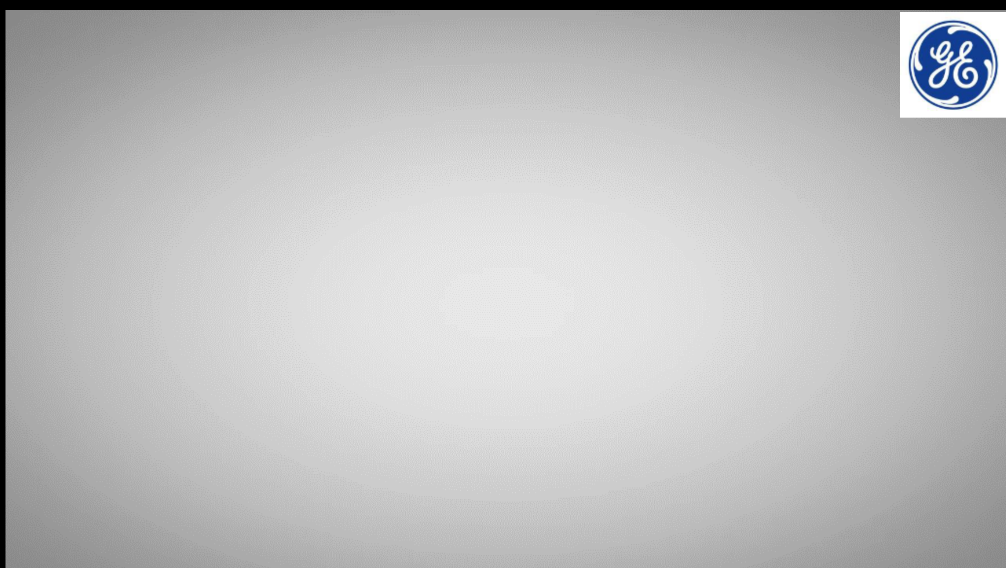
GEMINI TF PET/MR



Biograph mMR

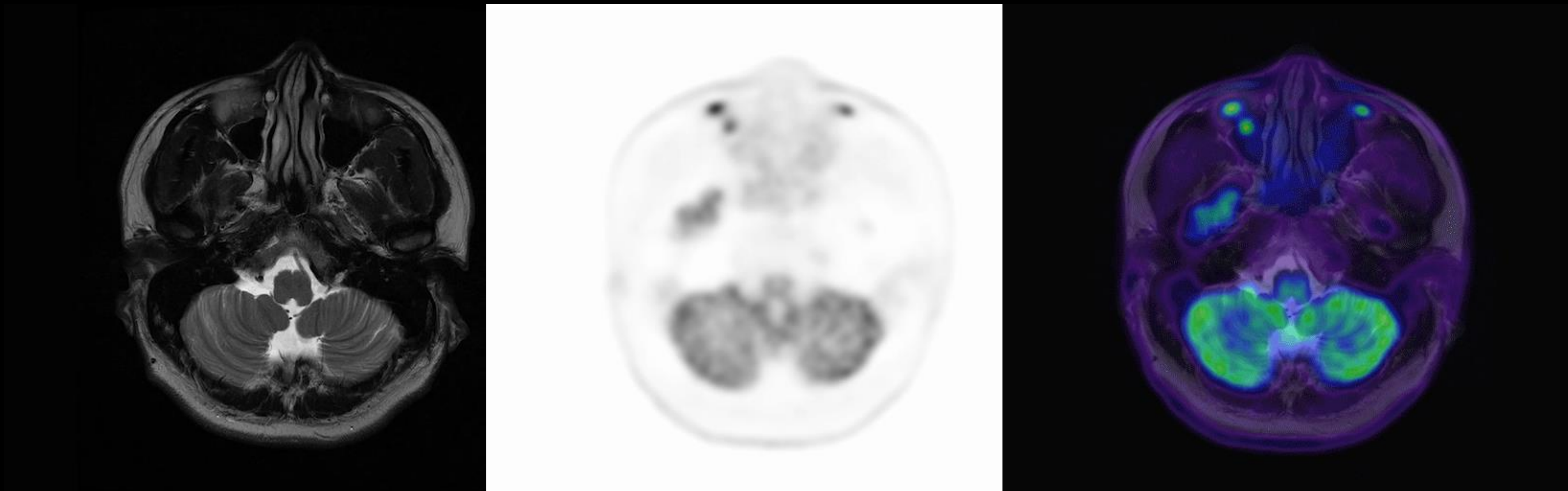


SIGNA PET/MR

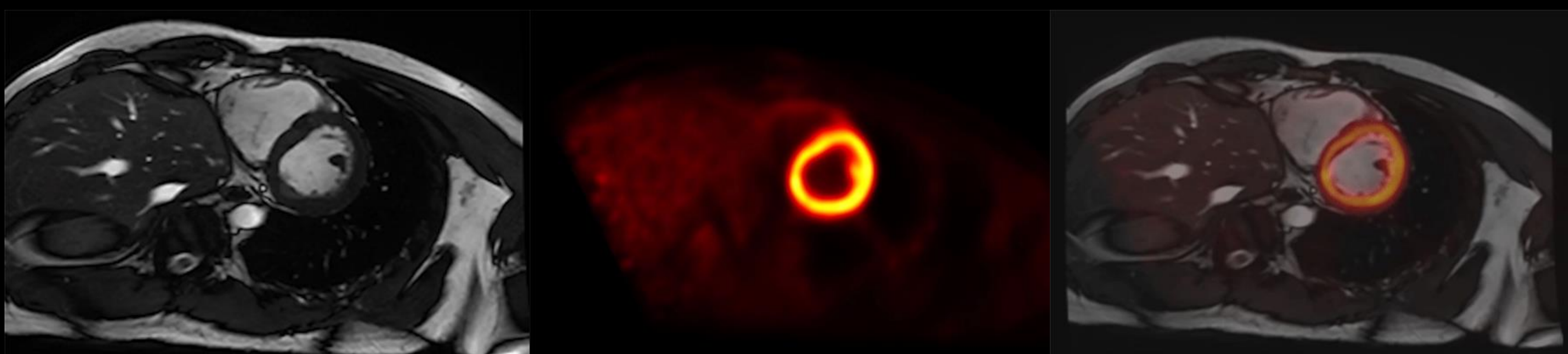


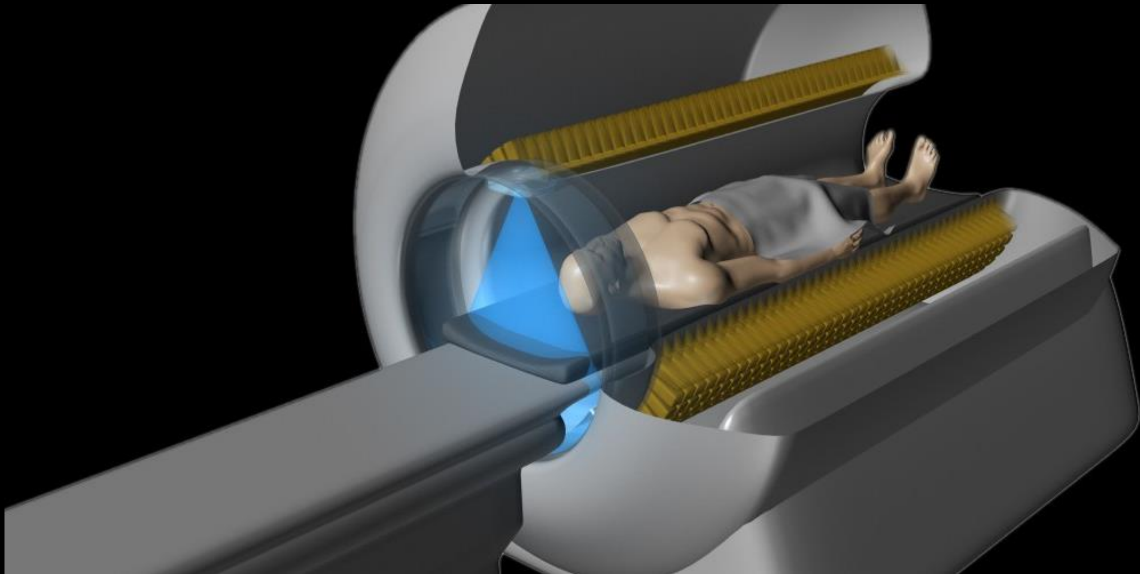
uPMR 790 HD TOF PET/MR

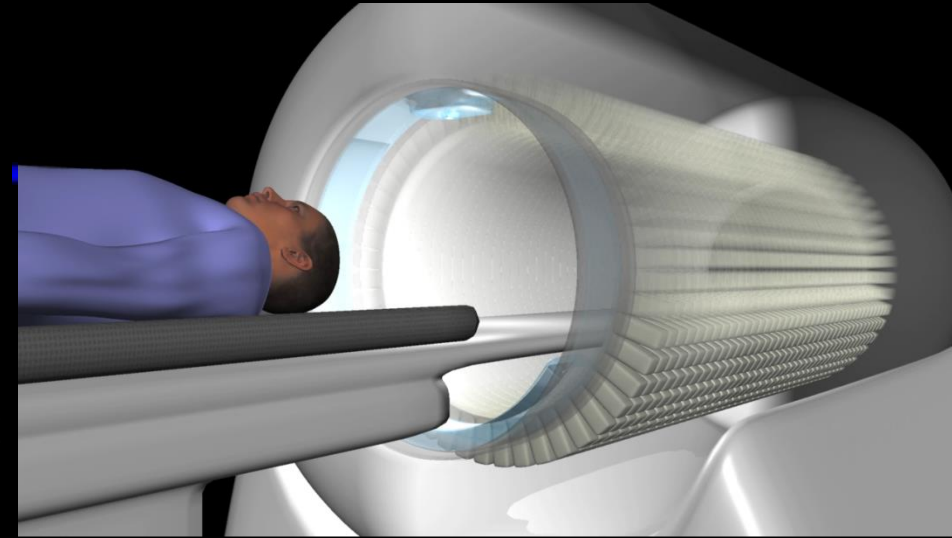
Clinical applications of PET/MRI



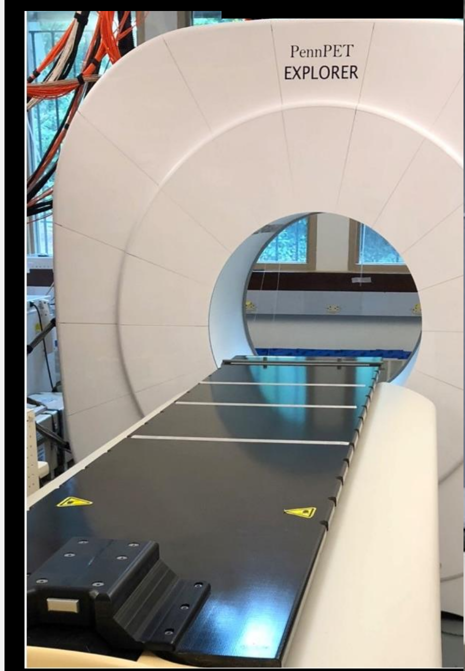
MRI **PET** **PET-MRI**







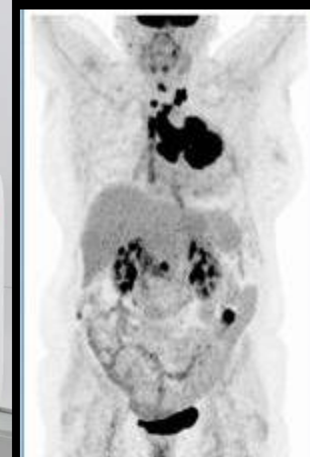
Penn P



Quadra

106 cm AFOV

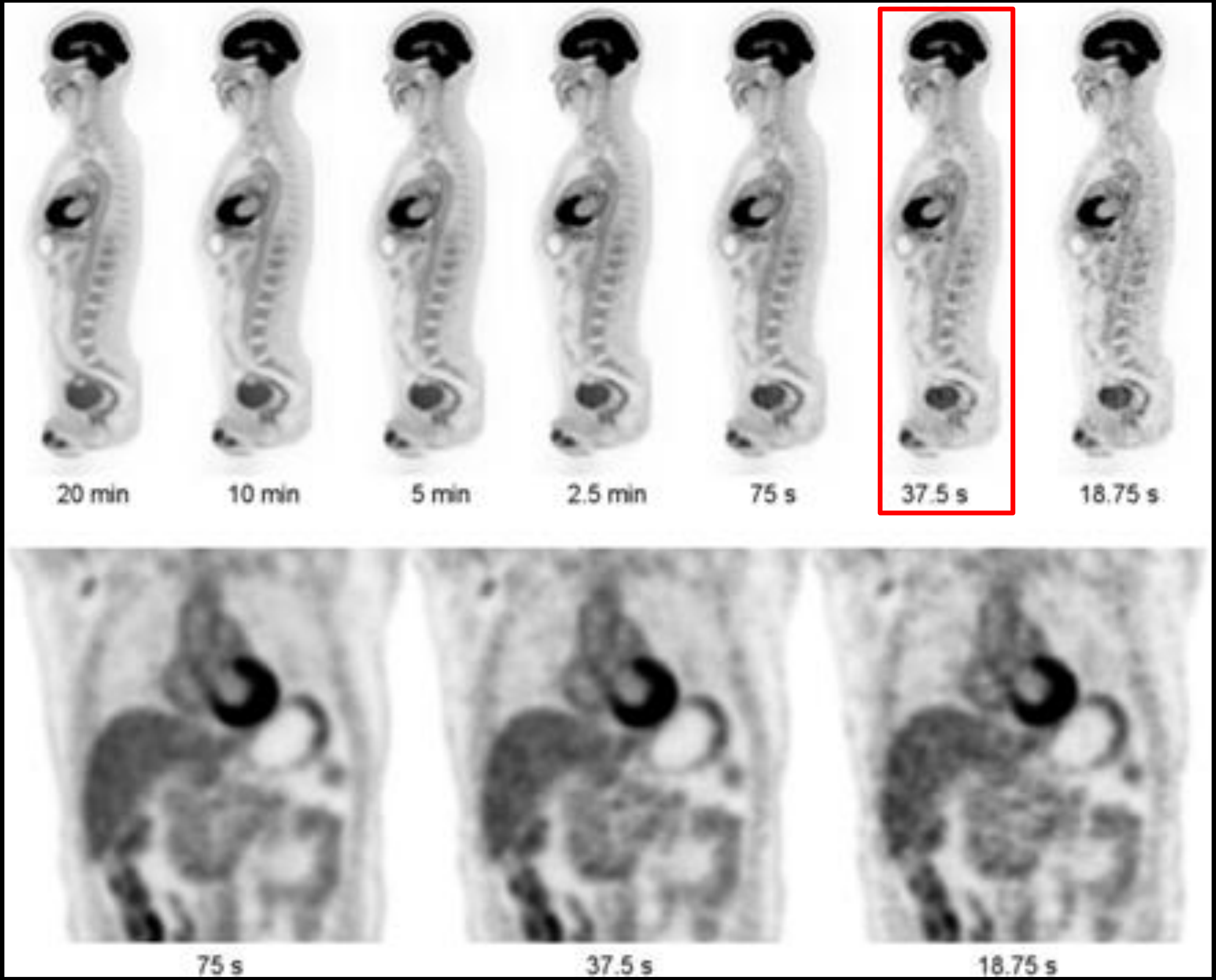
230 ps TOF CTR



Karp *et al.* J

(2021)

Total-body PET: Towards systemic medicine



290 MBq injected, 82 min uptake

Badawi et al (2019) *J Nucl Med*

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Novel detector concepts: Multifunctional PET

Sanaat et al (2022) *Phys Med Biol, in press*

Artificial intelligence in medical physics

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A. Turing Learning machines

Datmouth Conference

Perceptron

Stanford Cart

IBM deep blue

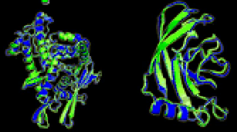
Deep learning

Deep face

AlphaGo

Google DeepMind's

AlphaFold 2



AI Breakthrough in Biology

...

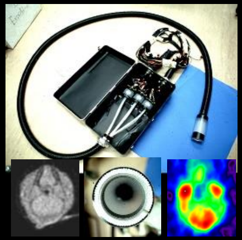
1950 **1956** **1957** **1985** **1997** **2006** **2014** **2016** **2021**

Linac

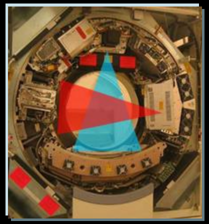
β+ imaging

γ-camera

Tomotherapy



PET/MRI



Dual-source CT

Explorer

PET-Linac

Physica Medica 83 (2021) 174–183

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Physica Medica

journal homepage: www.elsevier.com/locate/ejmp

POINT/COUNTERPOINT

Suggestions for topics suitable for these Point/Counterpoint debates should be addressed to Habib Zaidi, Geneva University Hospital, Geneva, Switzerland: habib.zaidi@hcuge.ch; Jing Cai, The Hong Kong Polytechnic University, Hong Kong: jing.cai@polyu.edu.hk; and/or Gerald White, Colorado Associates in Medical Physics: gerald.white@mindspring.com. Persons participating in Point/Counterpoint discussions are selected for their knowledge and communicative skill. Their positions for or against a proposition may or may not reflect their personal opinions or the positions of their employers.

Artificial intelligence should be part of medical physics graduate program curriculum

Lei Xing, Ph.D.[a)]
Department of Radiation Oncology, Stanford University, Stanford, CA 94305, USA,
(Tel: 650-498-7896; E-mail: lei@stanford.edu)

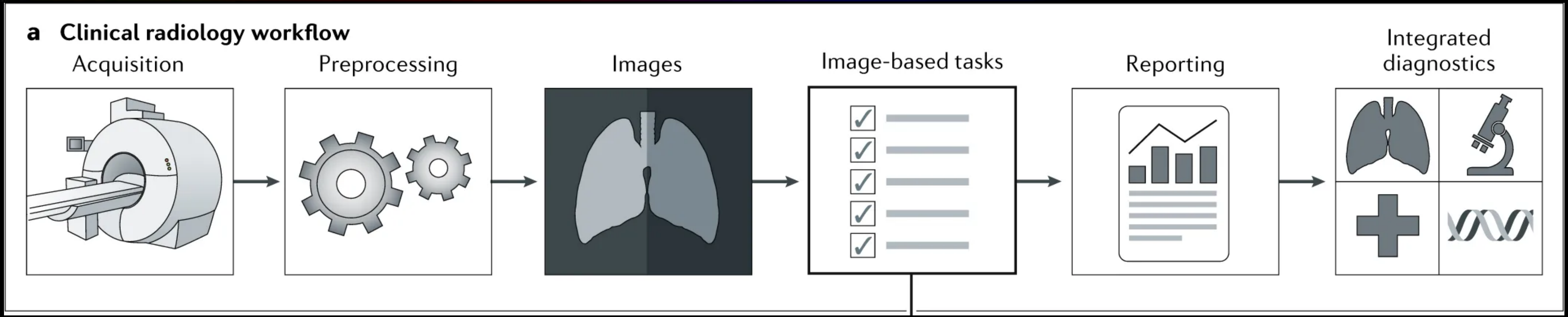
Steven Goetsch, Ph.D.[a)]
San Diego Gamma Knife Center, La Jolla, CA 92037, USA,
(Tel: 858-794-8847; E-mail: steven@sdradiotherapy.com)

Jing Cai, Ph.D., Moderator

(Received 27 October 2020; revised 27 October 2020; accepted for publication 1 November 2020; published 11 April 2021)

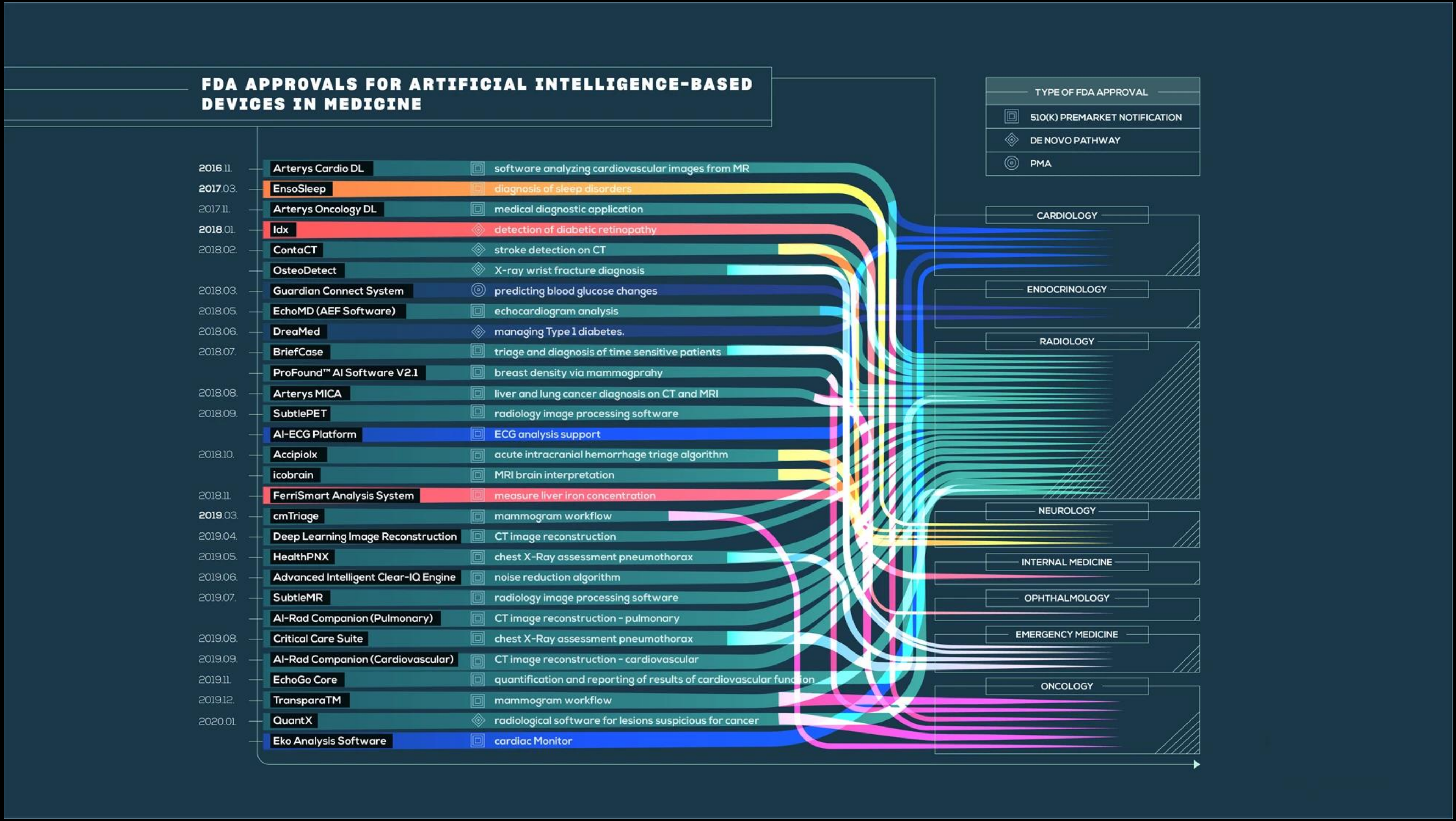
[https://doi.org/10.1002/mp.14587]

Artificial intelligence impacting radiology



Hosny *et al. Nat Rev Cancer* (2018)

FDA-approved AI medical devices/algorithms

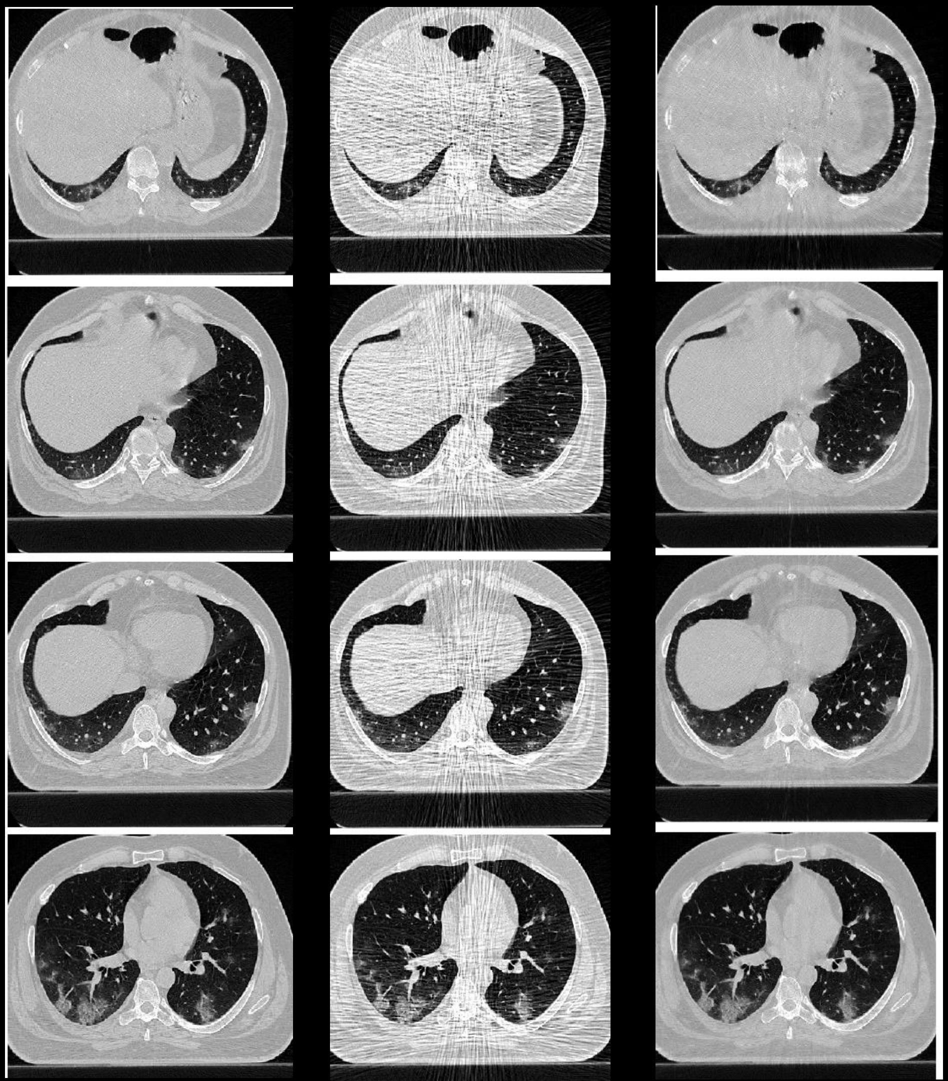


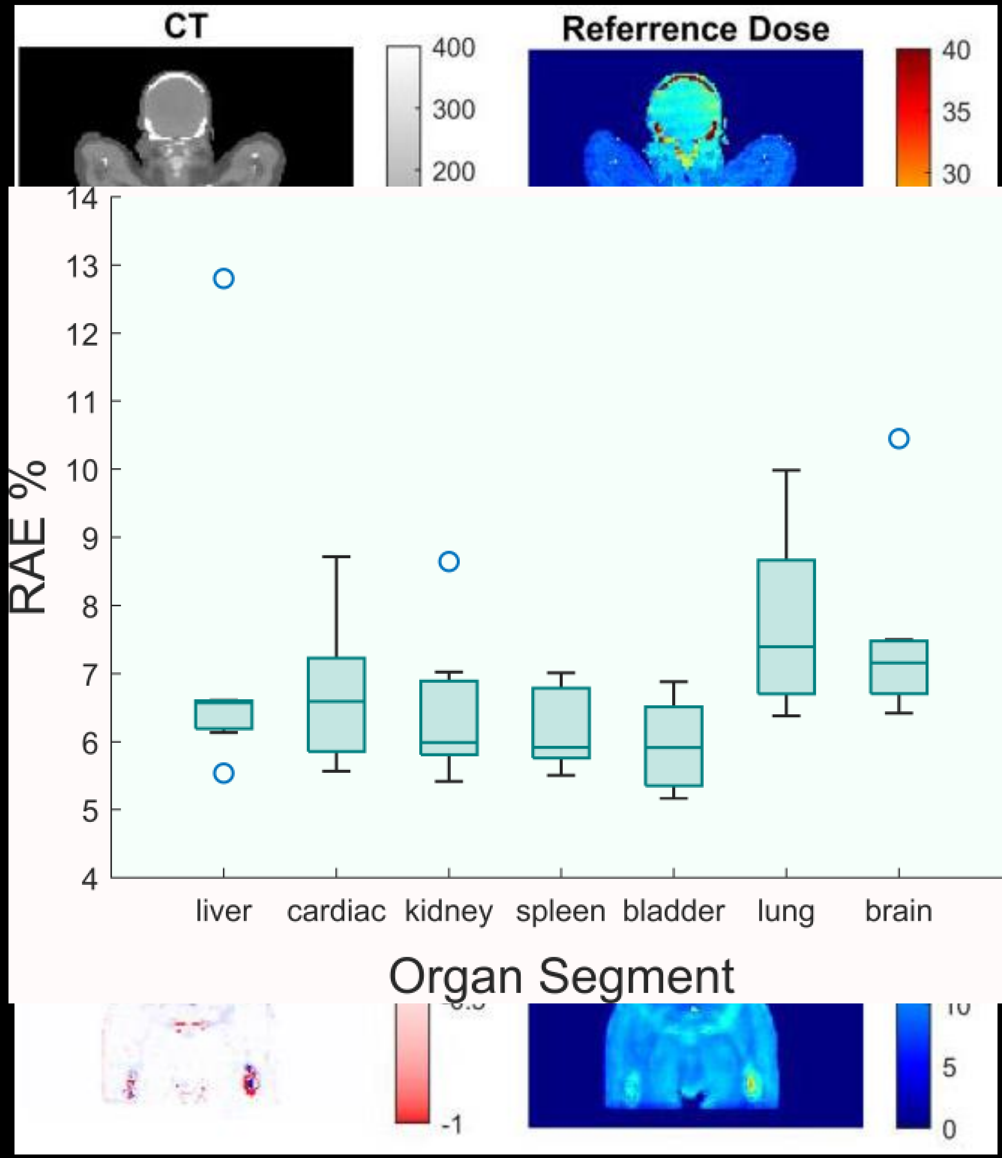
Benjamens *et al. NPJ Dig Med* (2020)

Hôpitaux Universitaires Genève

Deep learning-guided low-dose CT imaging

Full-dose **Low-dose** **Predicted full-dose**



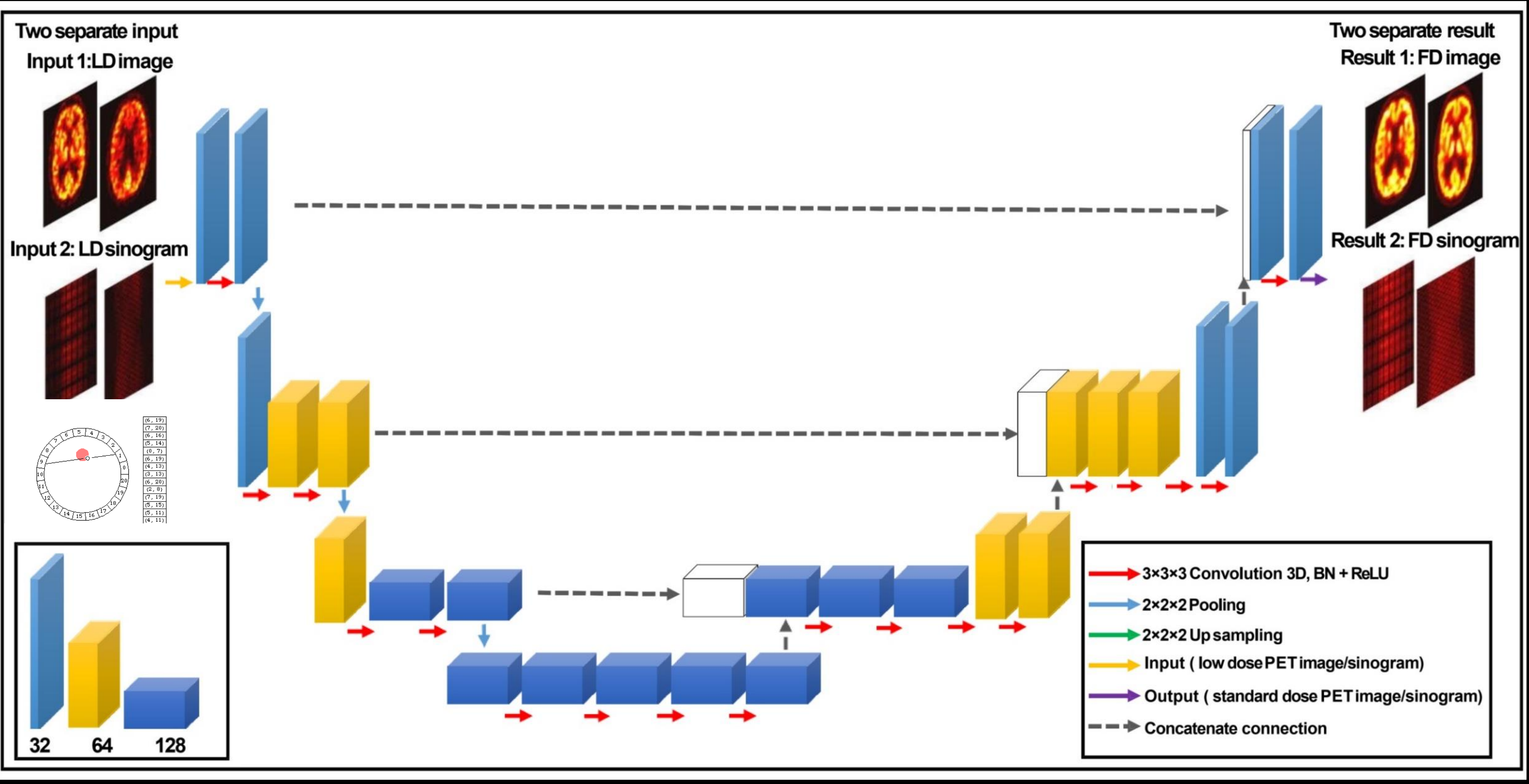


Shiri et al. (2021) *Eur Radiol*

Salimi et al. (2022) *submitted*

Deep learning for low-dose PET reconstruction

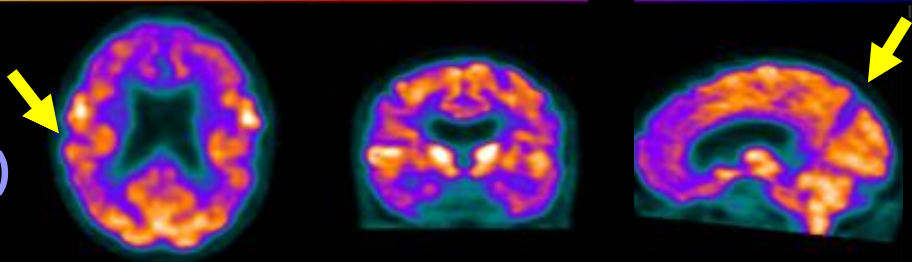
Hôpitaux Universitaires Genève

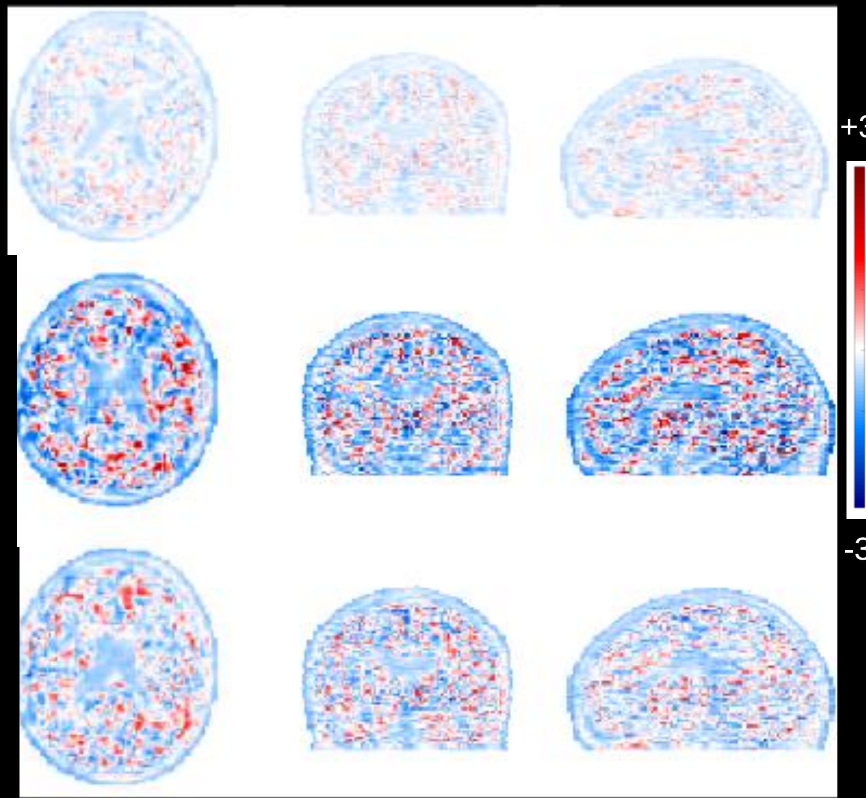


Sanaat et al. (2020) *J Nucl Med*

JNM The Journal of NUCLEAR MEDICINE

Deep learning for low-dose PET reconstruction

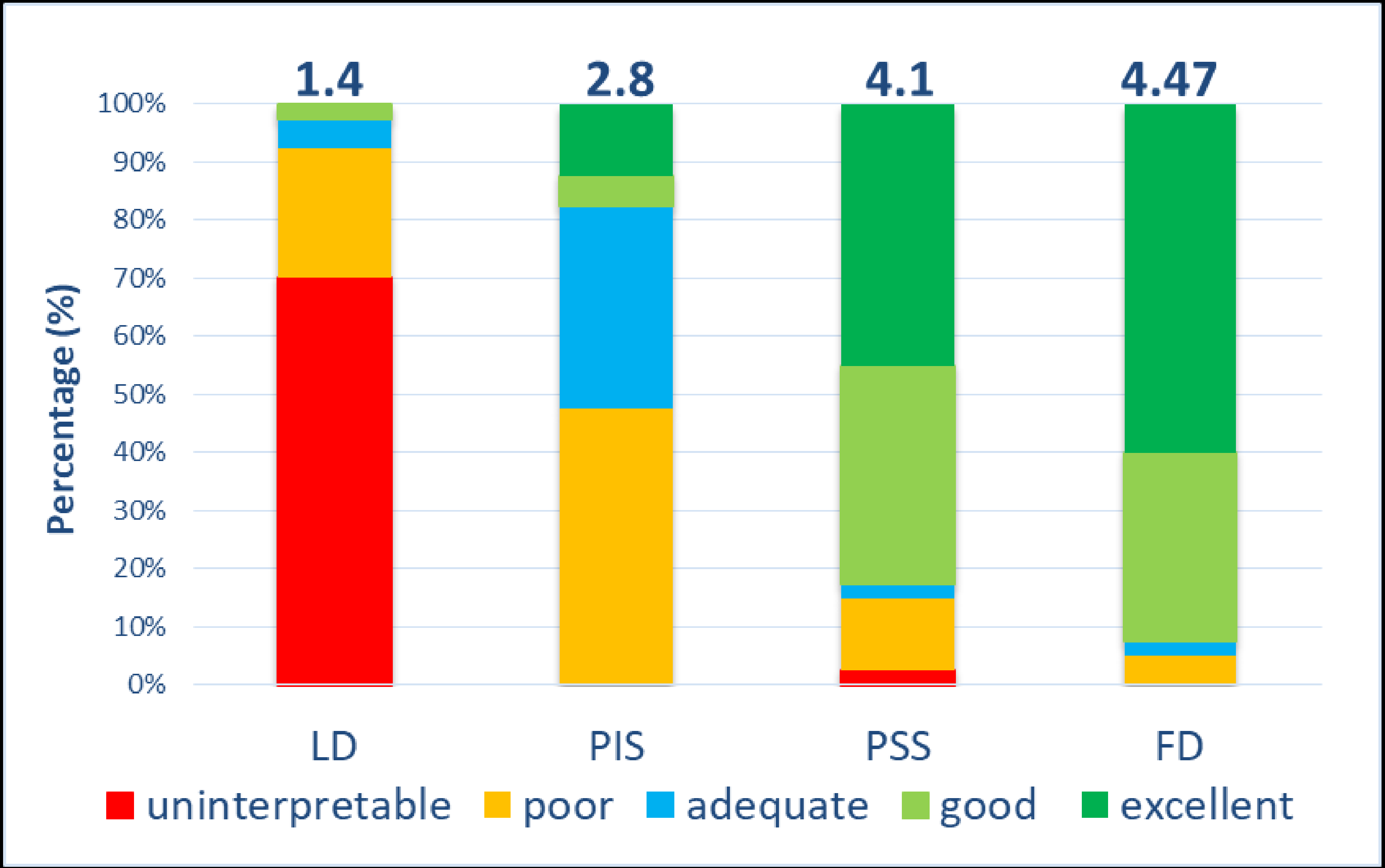




Sanaat et al. (2020) *J Nucl Med*

Deep learning for low-dose PET reconstruction

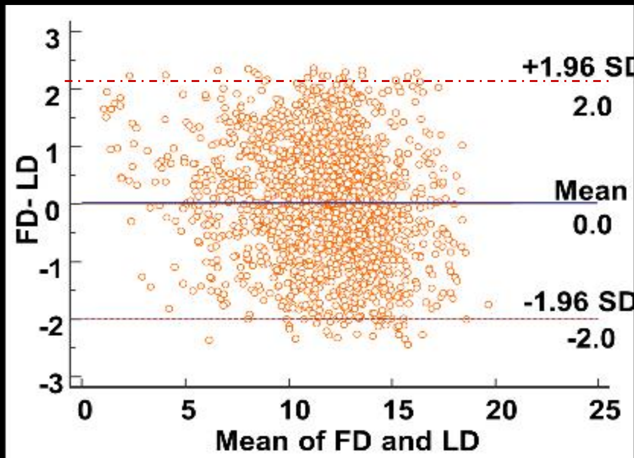
Hôpitaux Universitaires Genève



Sanaat et al. (2020) *J Nucl Med*

The Journal of NUCLEAR MEDICINE

Bland-Altman analysis (Regionwise)



Low Dose

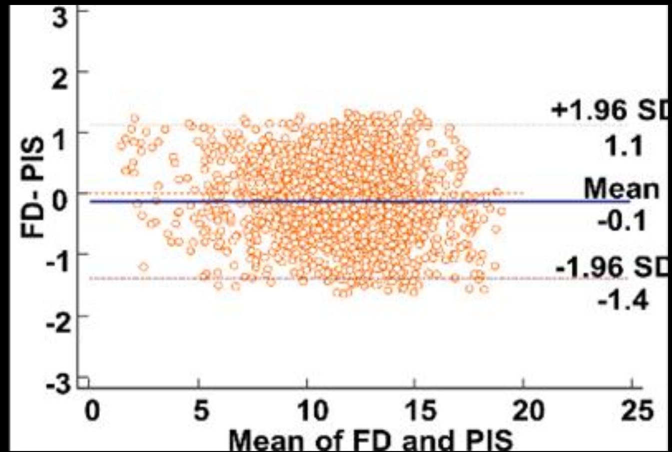
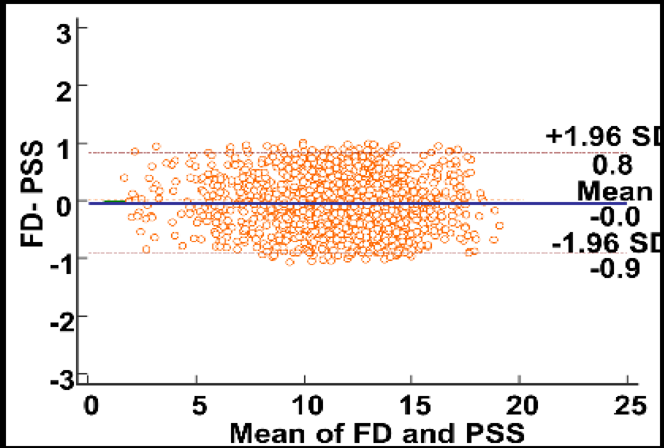


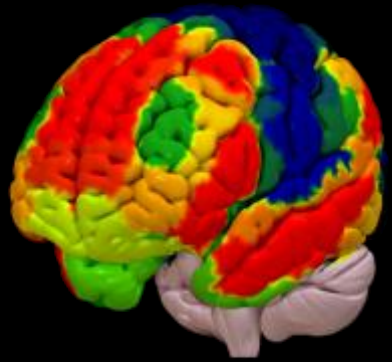
Image Space



Sinogram Space

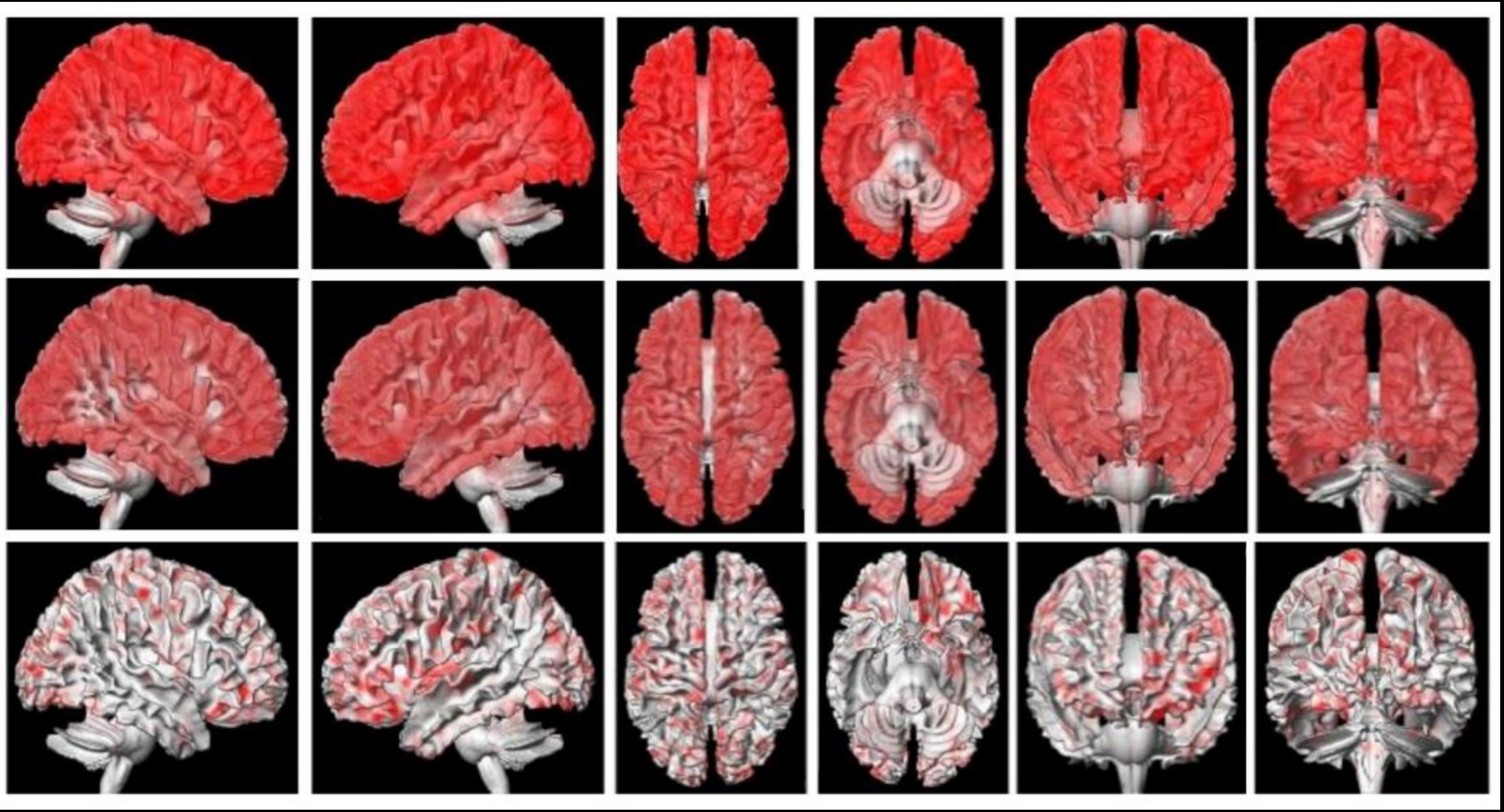
SUV_{mean} of 83 Regions

Based on “Hammersmith atlas”; n30r83



Sanaat et al. (2020) *J Nucl Med*

Deep learning for low-dose PET reconstruction



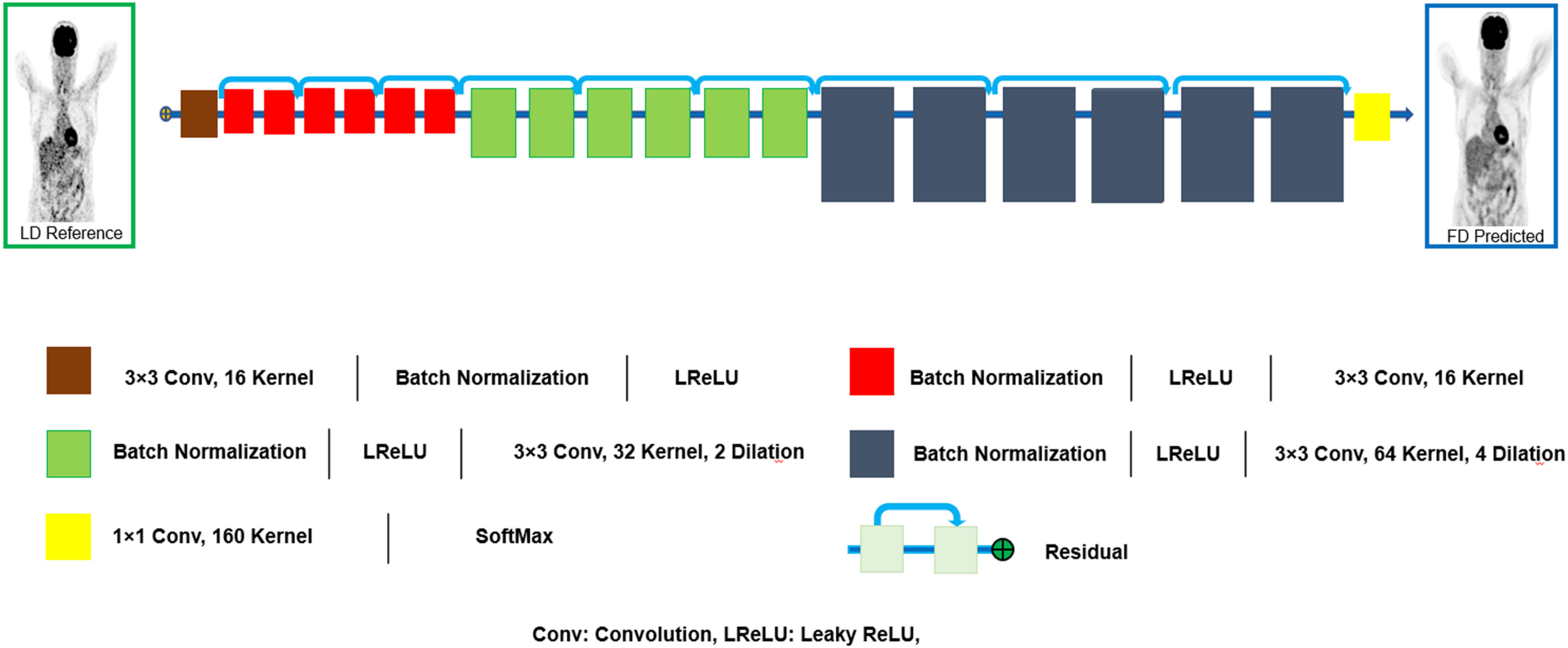
LD

IS

SS

Sanaat et al. (2021) *Neuroimage*

Deep learning-guided low-dose PET imaging

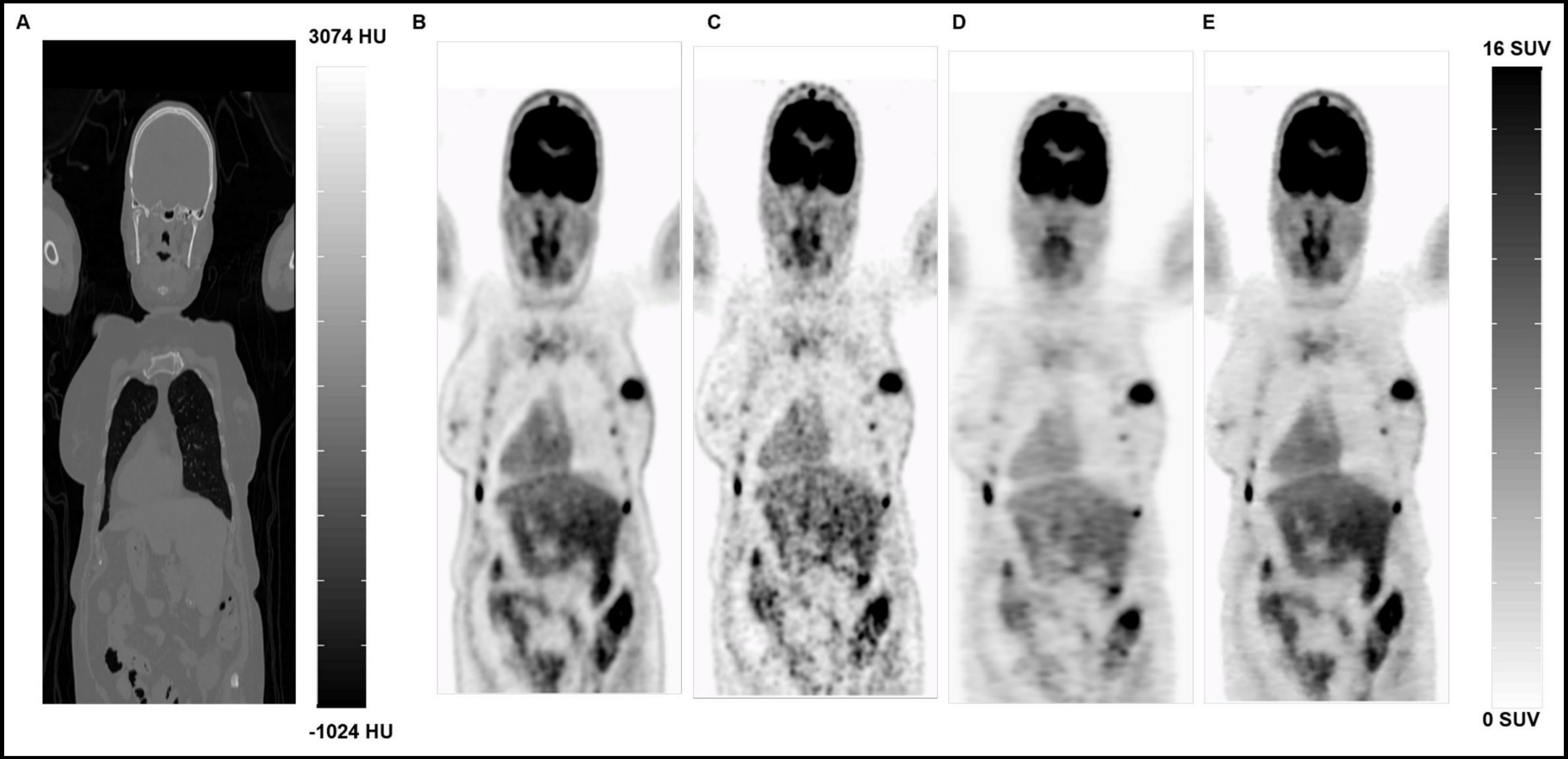


Sanaat et al. (2021) *Eur J Nucl Med Mol Imaging*

Deep learning-guided low-dose PET imaging

Hôpitaux Universitaires Genève

Low-dose CT | Full dose PET | Low dose PET | Pred. PET (RNET) | Pred. PET (CGAN)

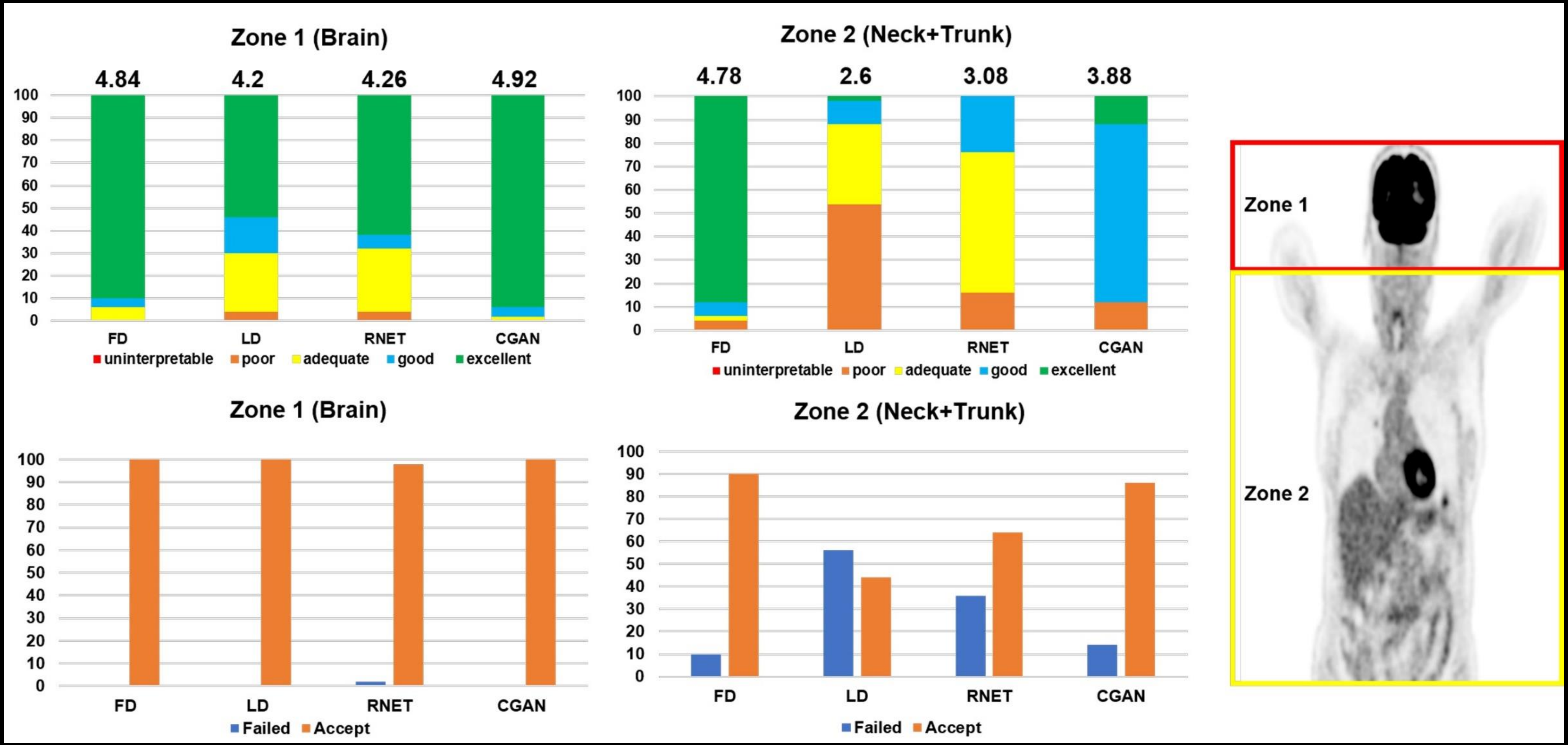


0.7 mm/s
(3 min/bed)

5 mm/s
(25 sec/bed)

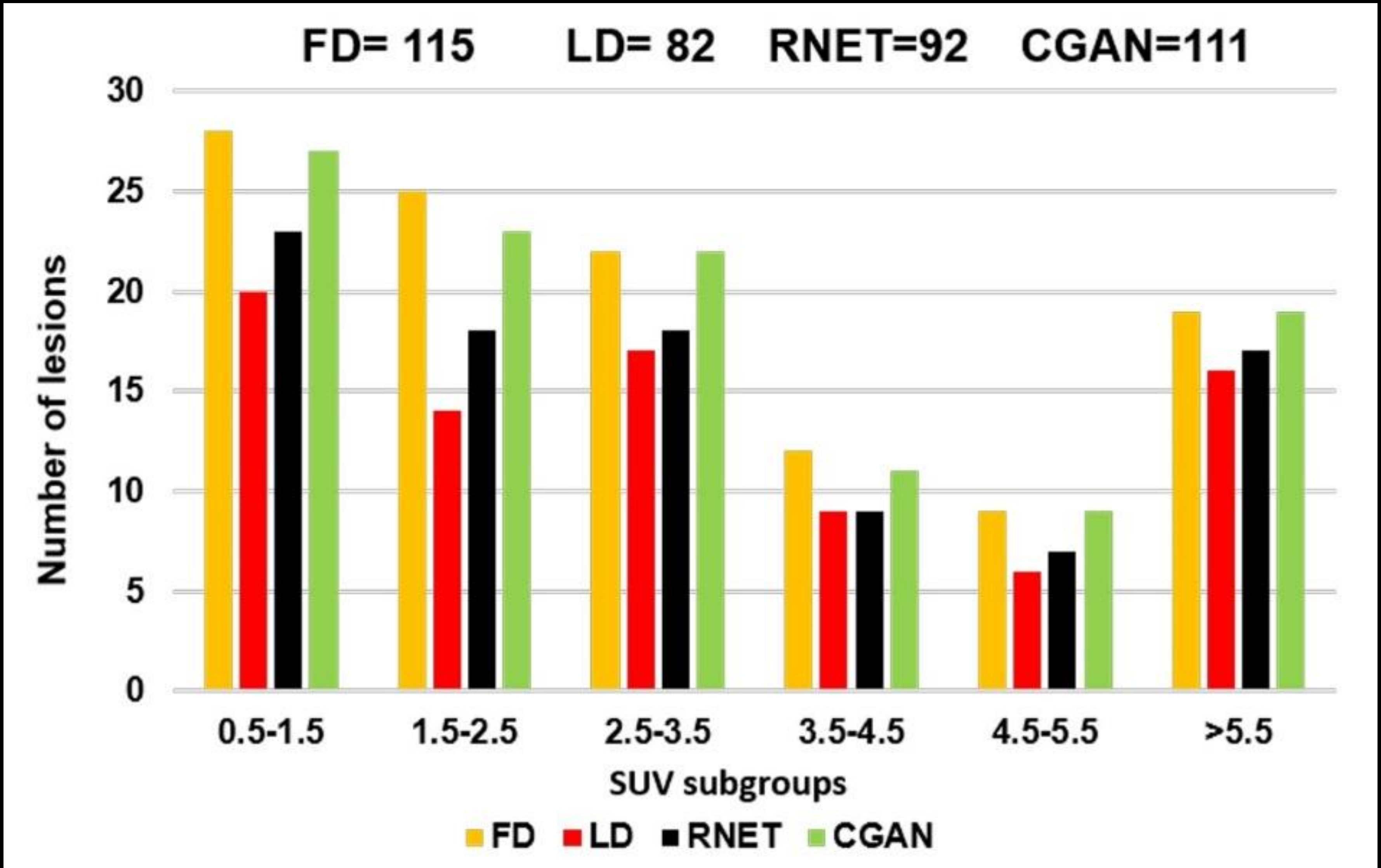
Sanaat et al. (2021) *Eur J Nucl Med Mol Imaging*

Deep learning-guided low-dose PET imaging



Sanaat et al. (2021) *Eur J Nucl Med Mol Imaging*

Deep learning-guided low-dose PET imaging

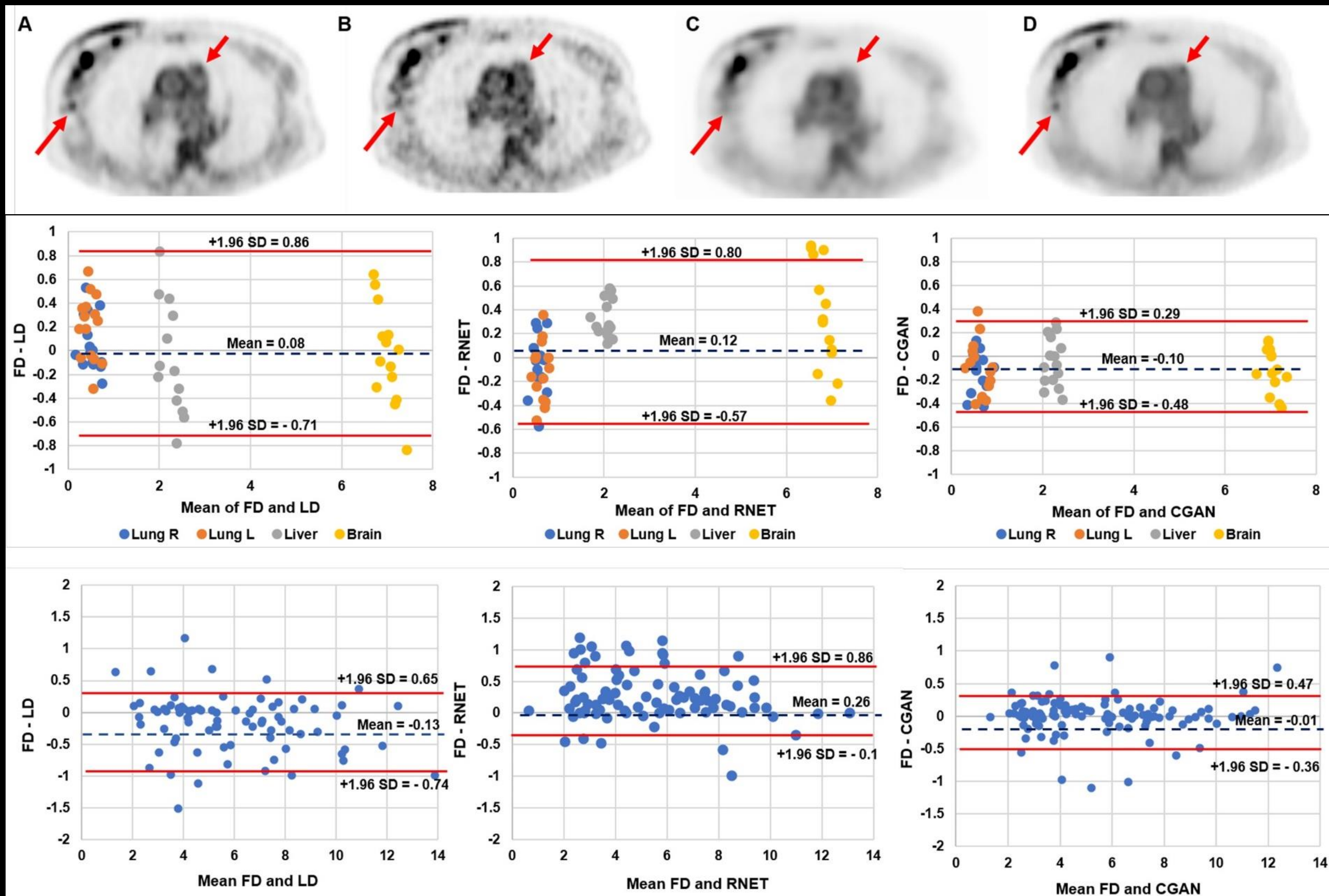


Sanaat et al. (2021) *Eur J Nucl Med Mol Imaging*

Deep learning-guided low-dose PET imaging

Hôpitaux Universitaires Genève

Full dose PET **Low dose PET** **Pred. PET (RNET)** **Pred. PET (CGAN)**



Sanaat et al. (2021) *Eur J Nucl Med Mol Imaging*

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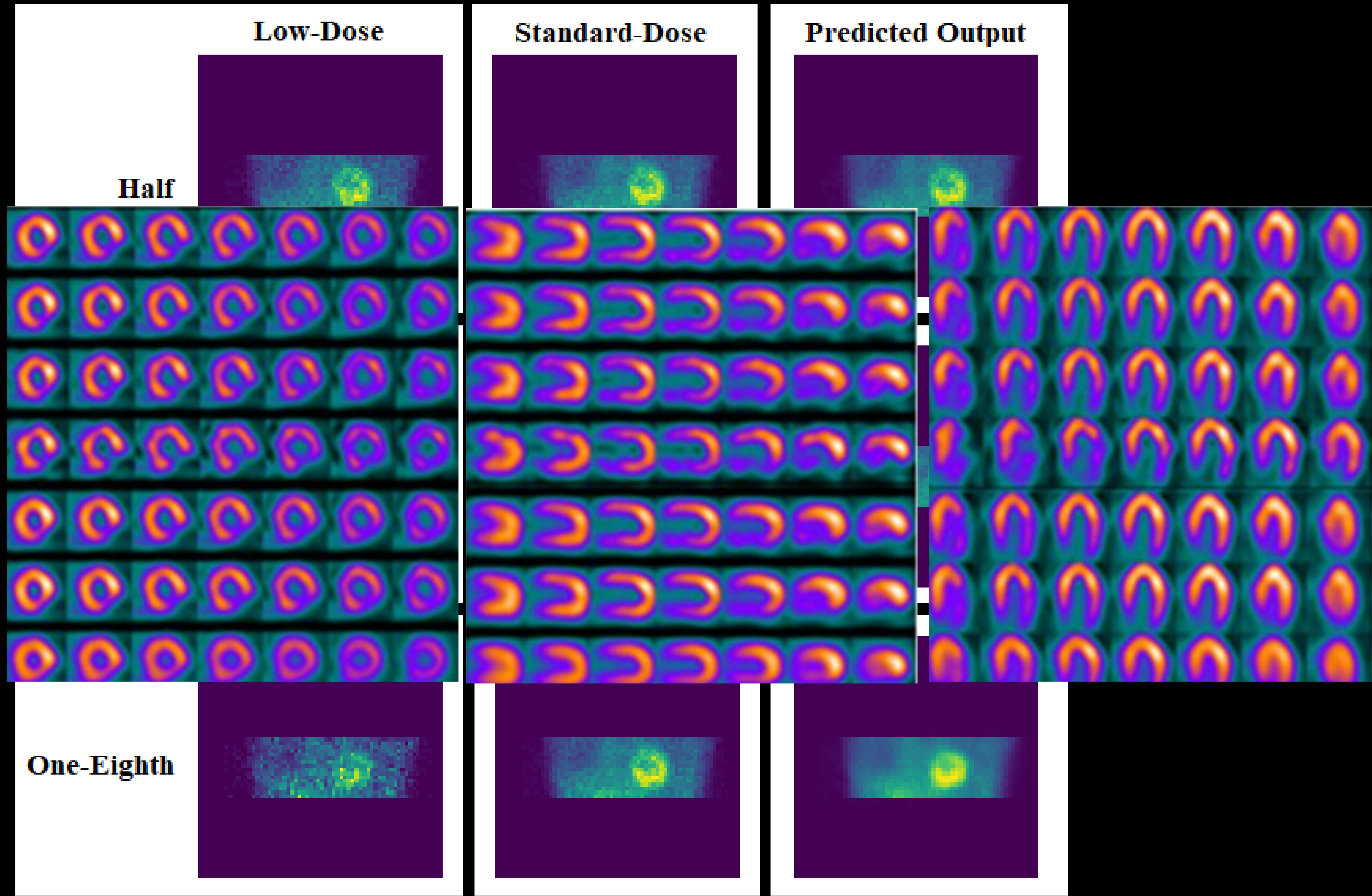
Genève

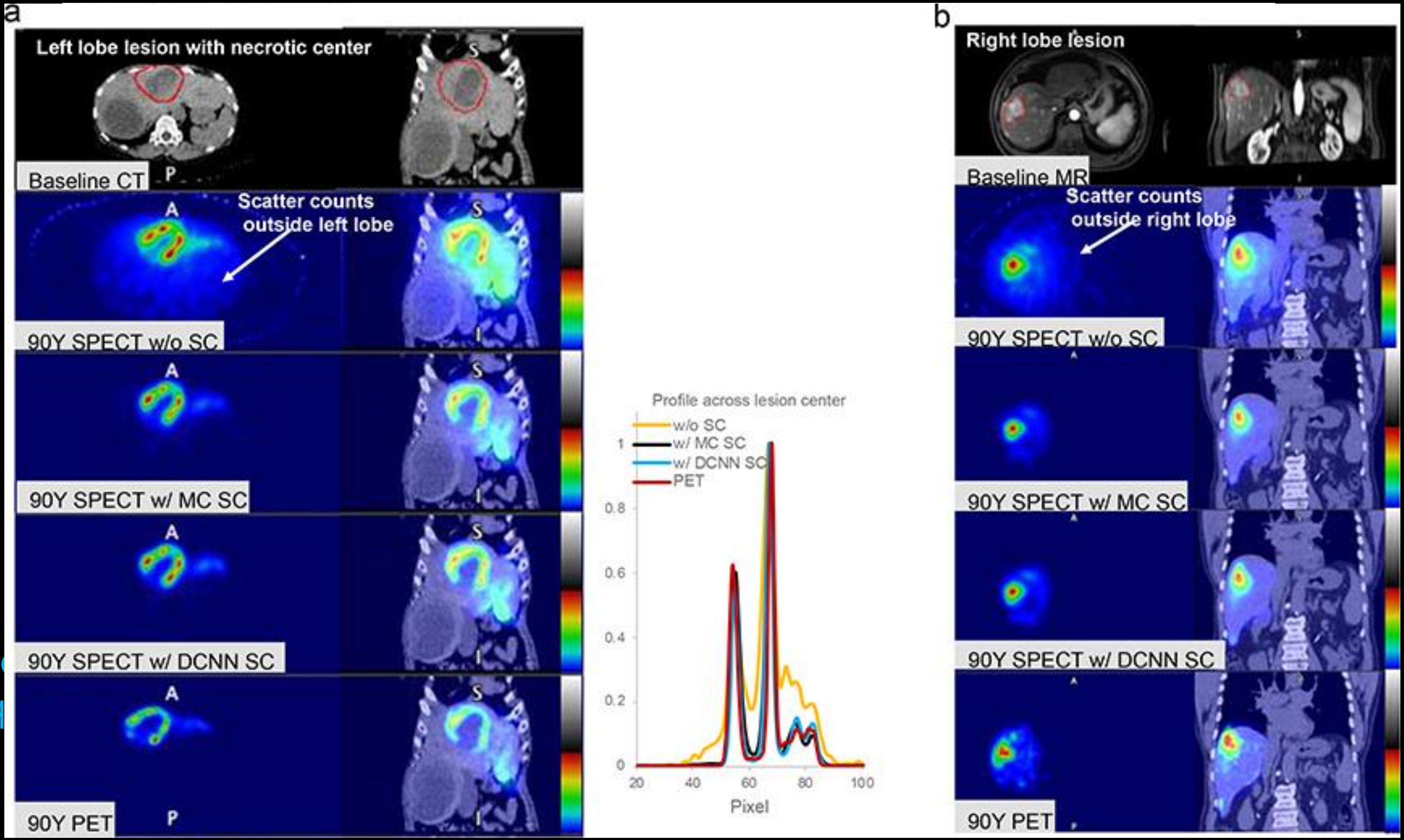
Deep learning-guided low-dose MPI SPECT

Standard-dose
½ dose
¼ dose
1/8th dose
Pred. ½ dose
Pred. ¼ dose
Pred. 1/8 dose



Olia et al. (2022) *Eur J Nucl Med Mol Imaging*

Deep learning-guided scatter correction

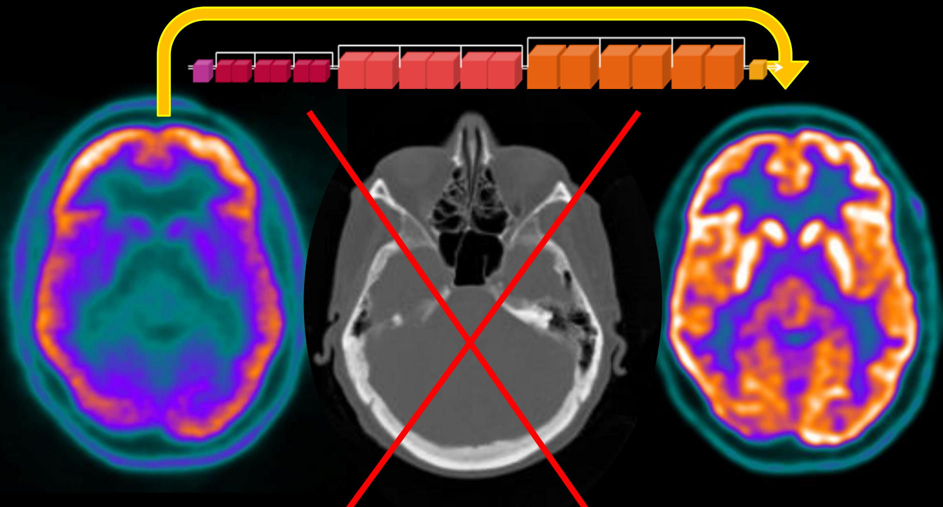


A d

q

Yiang et al. (2022) *Eur J Nucl Med Mol Imaging*

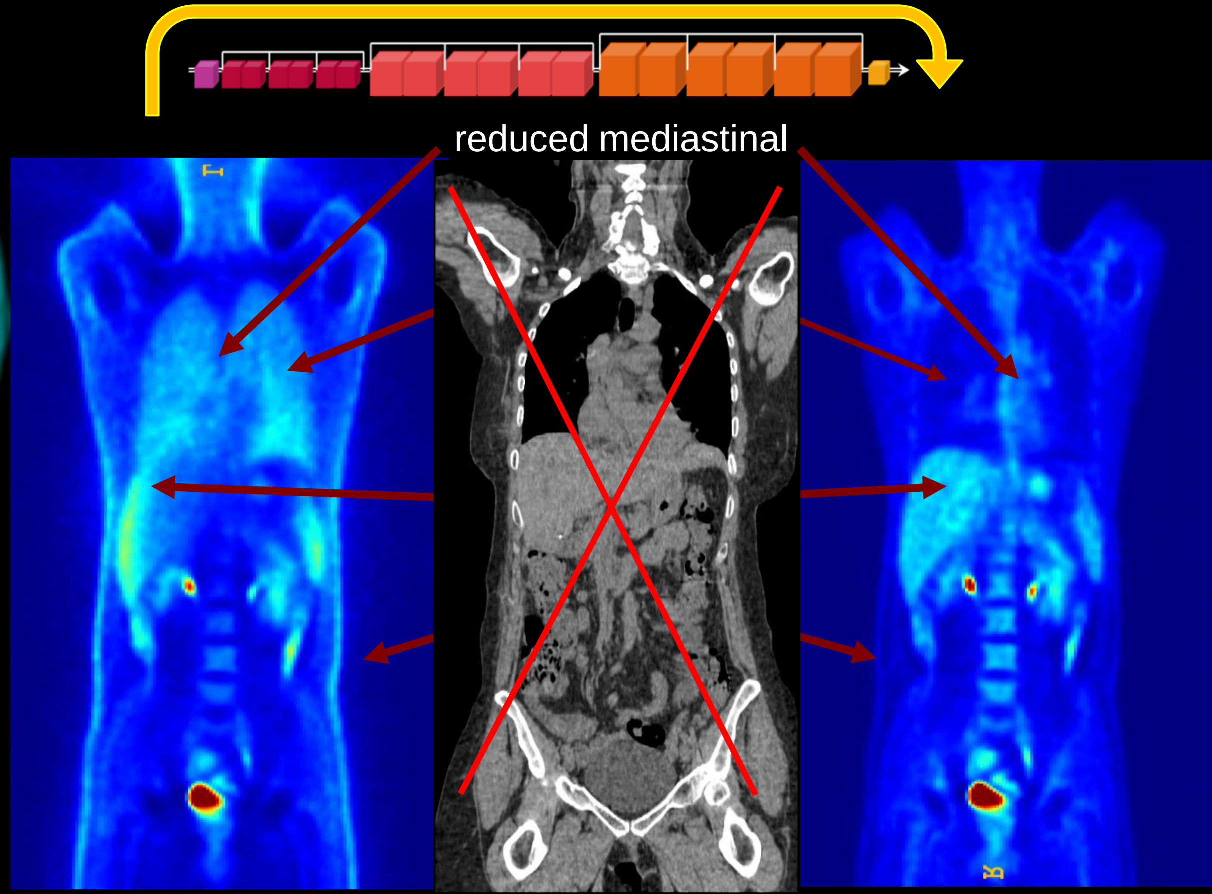
CT-based attenuation correction (Reference)



CT

Uncorrected PET

Corrected PET

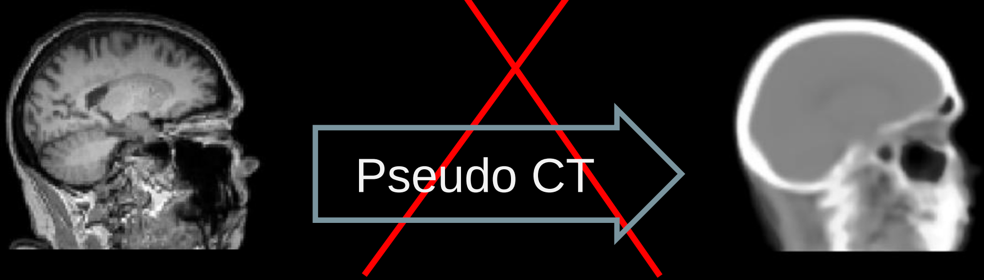


ncorrected PET

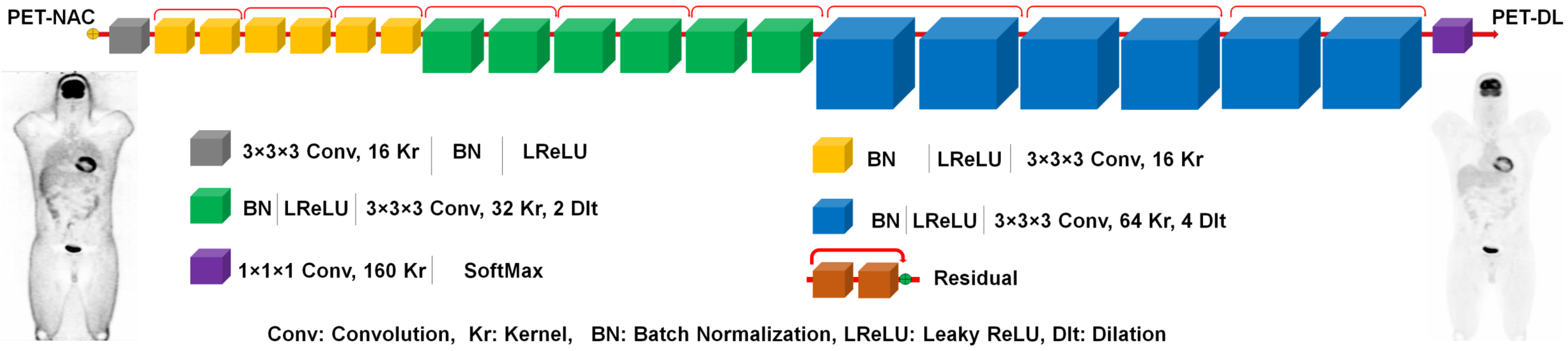
CT

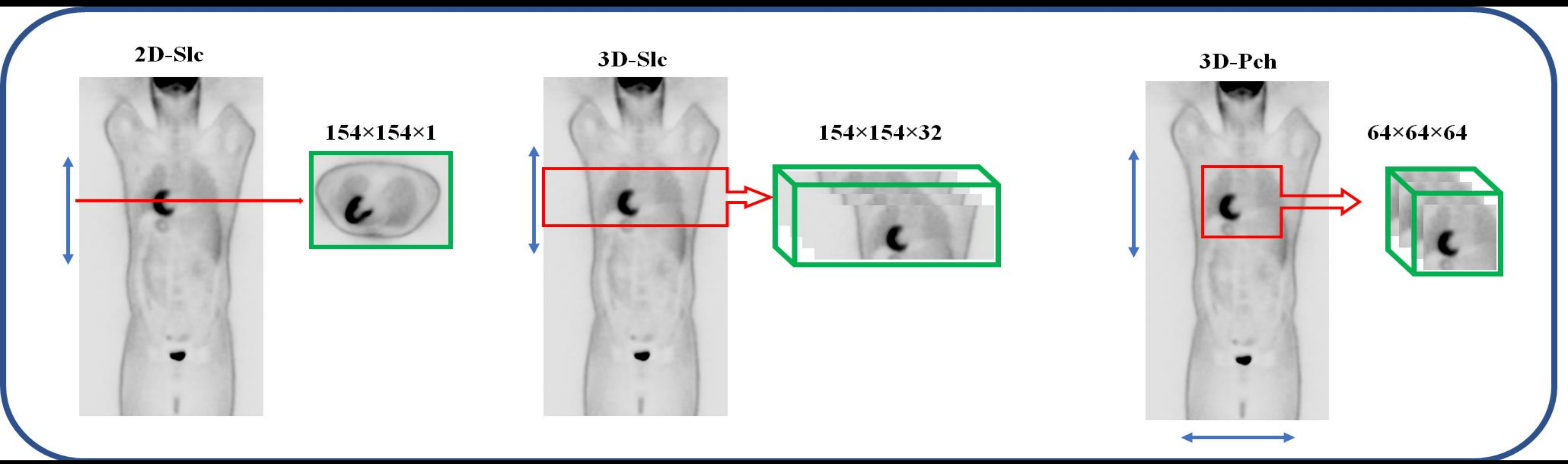
Corrected PET

PET/MRI



Deep learning-guided PET attenuation correction

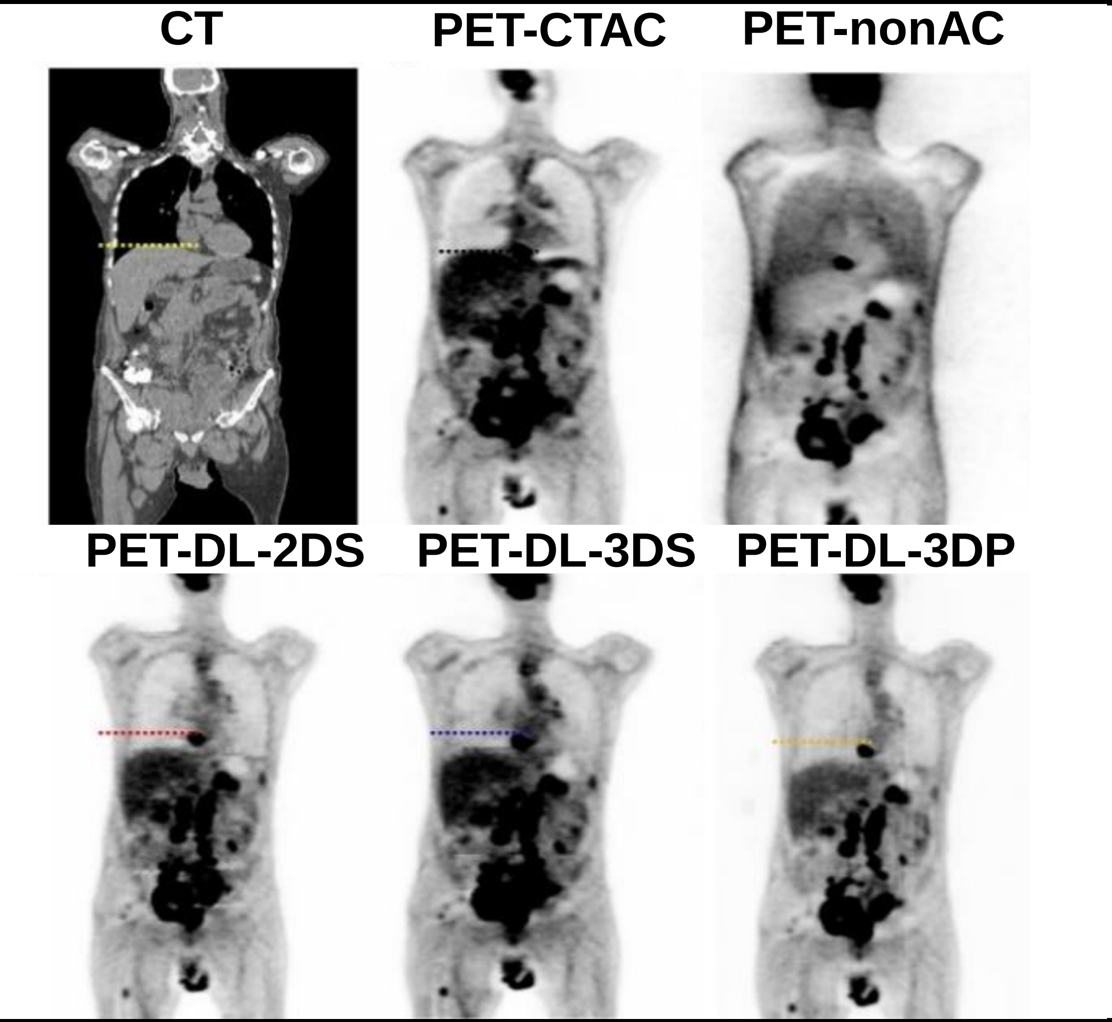


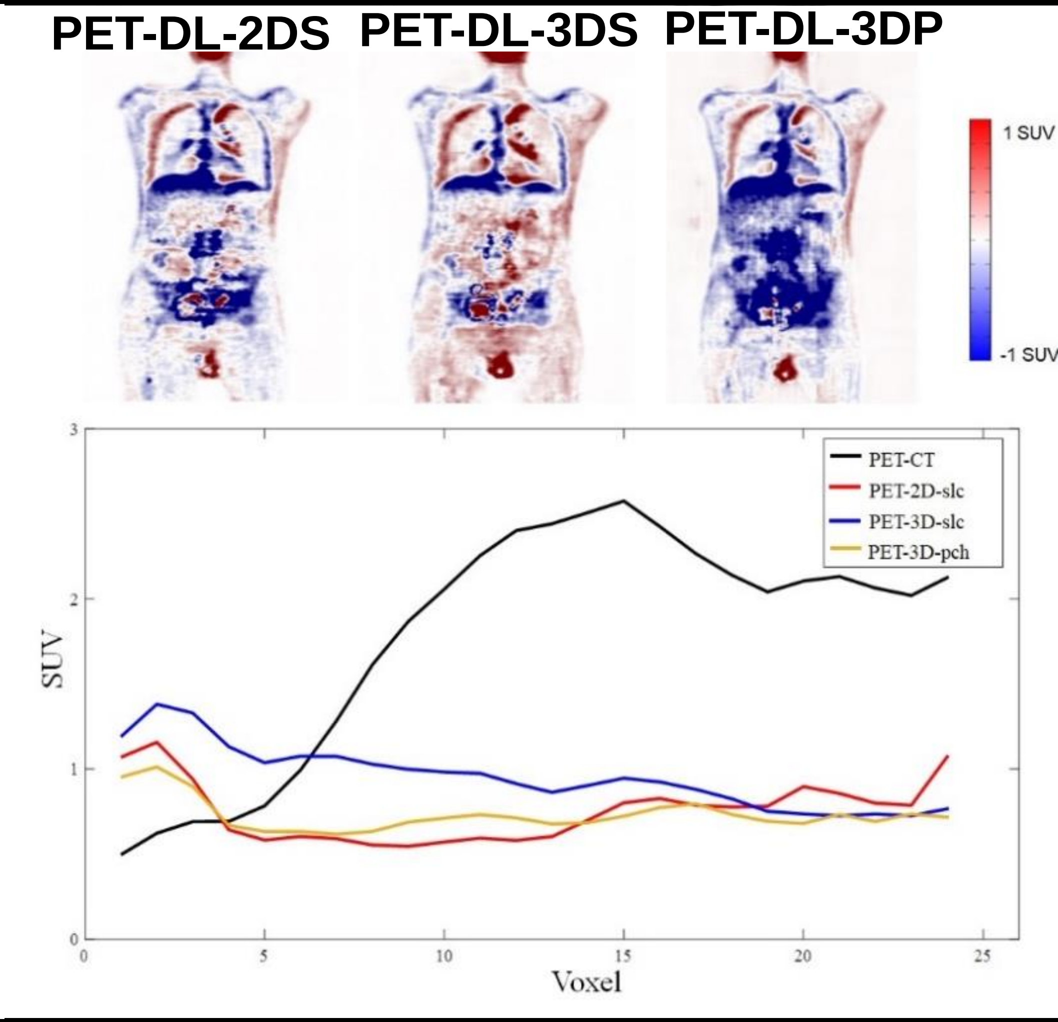


Shiri et al. (2020) *Eur J Nucl Med Mol Imaging*

Deep learning compensates motion artifacts

Difference images: PET-DL – PET-CTAC



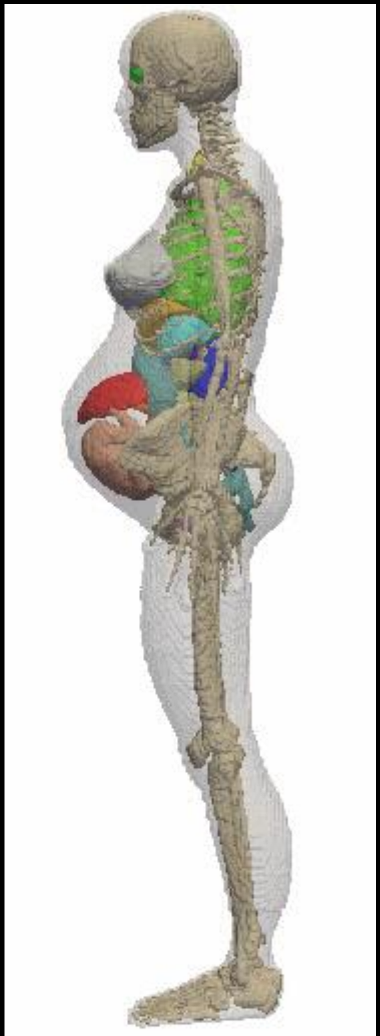


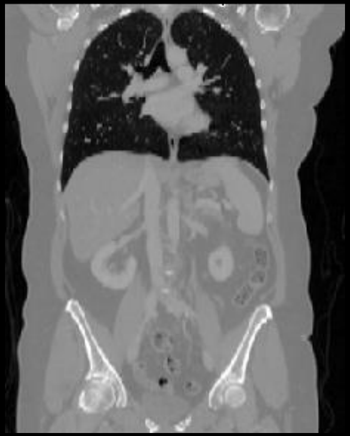
Shiri et al. (2020) *Eur J Nucl Med Mol Imaging*

Computational pregnant female phantoms

Hôpitaux Universitaires Genève

25w-gestation	30w-gestation	Thorax-abdo	Non-human primate





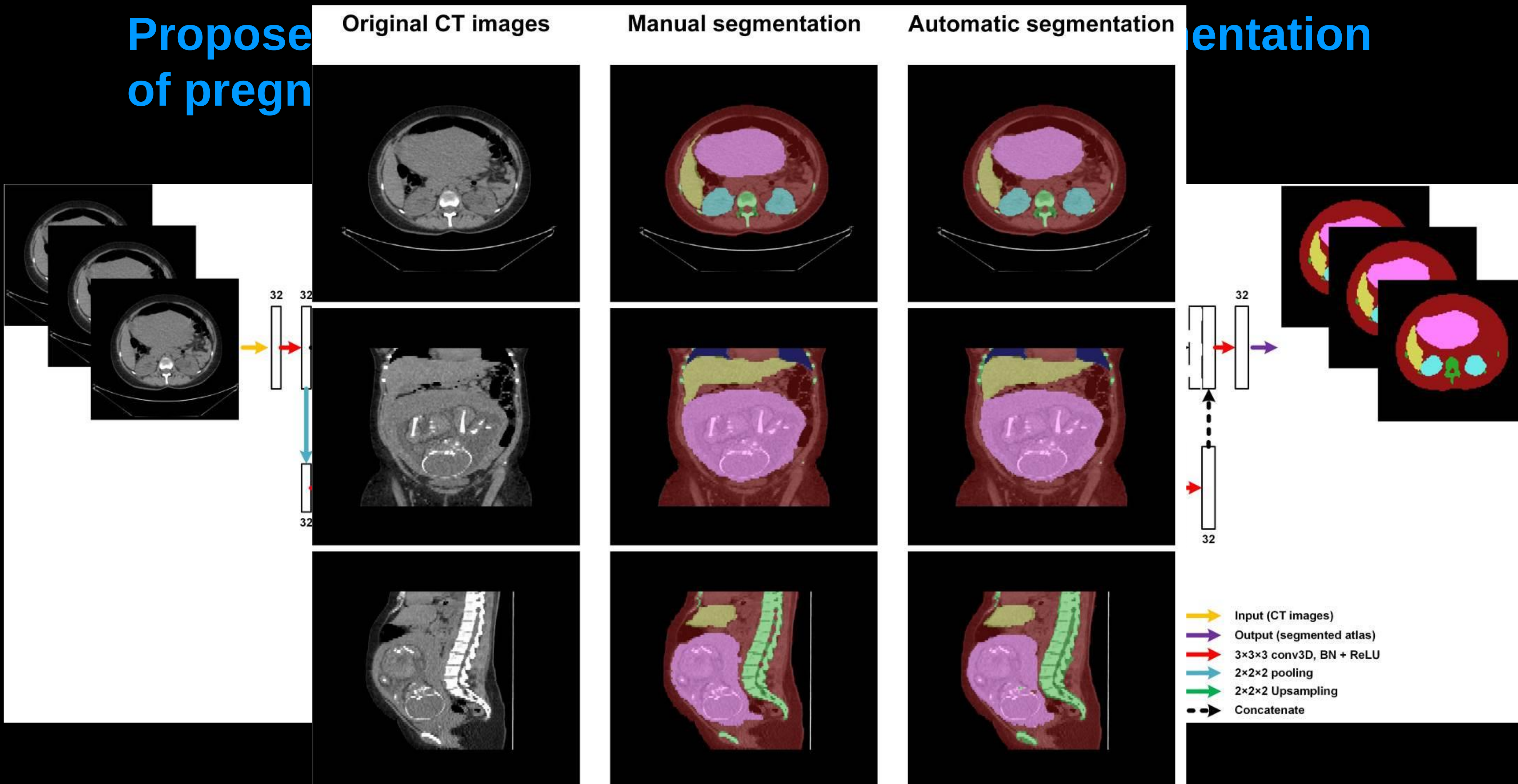
Xie and Zaidi *Eur J Nucl Med Mol Imaging* (2016)

Xie et al. (2019) *Med* Phys

Xie et al. (2020) *Med Phys*

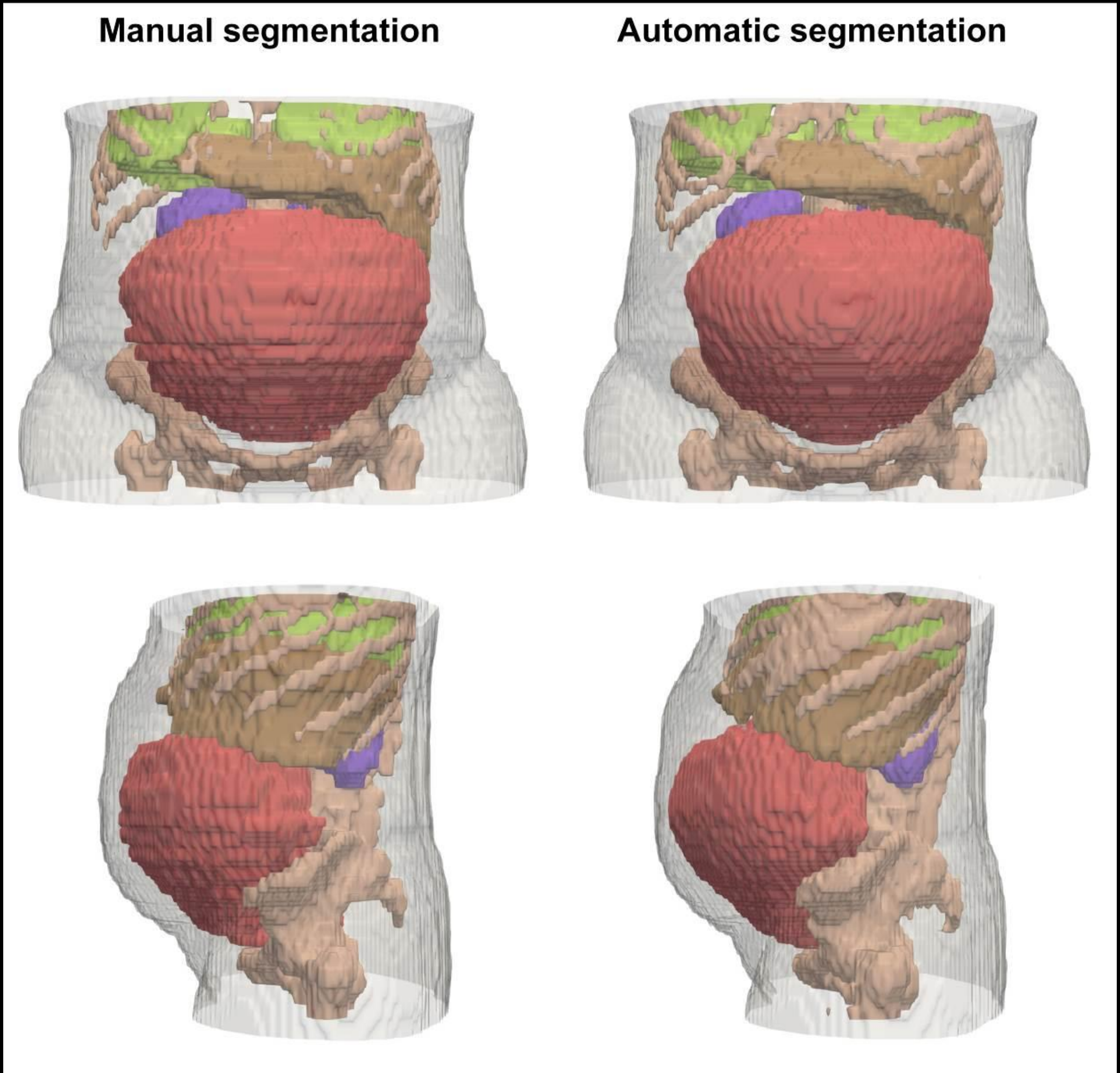
Automated generation of anatomical models

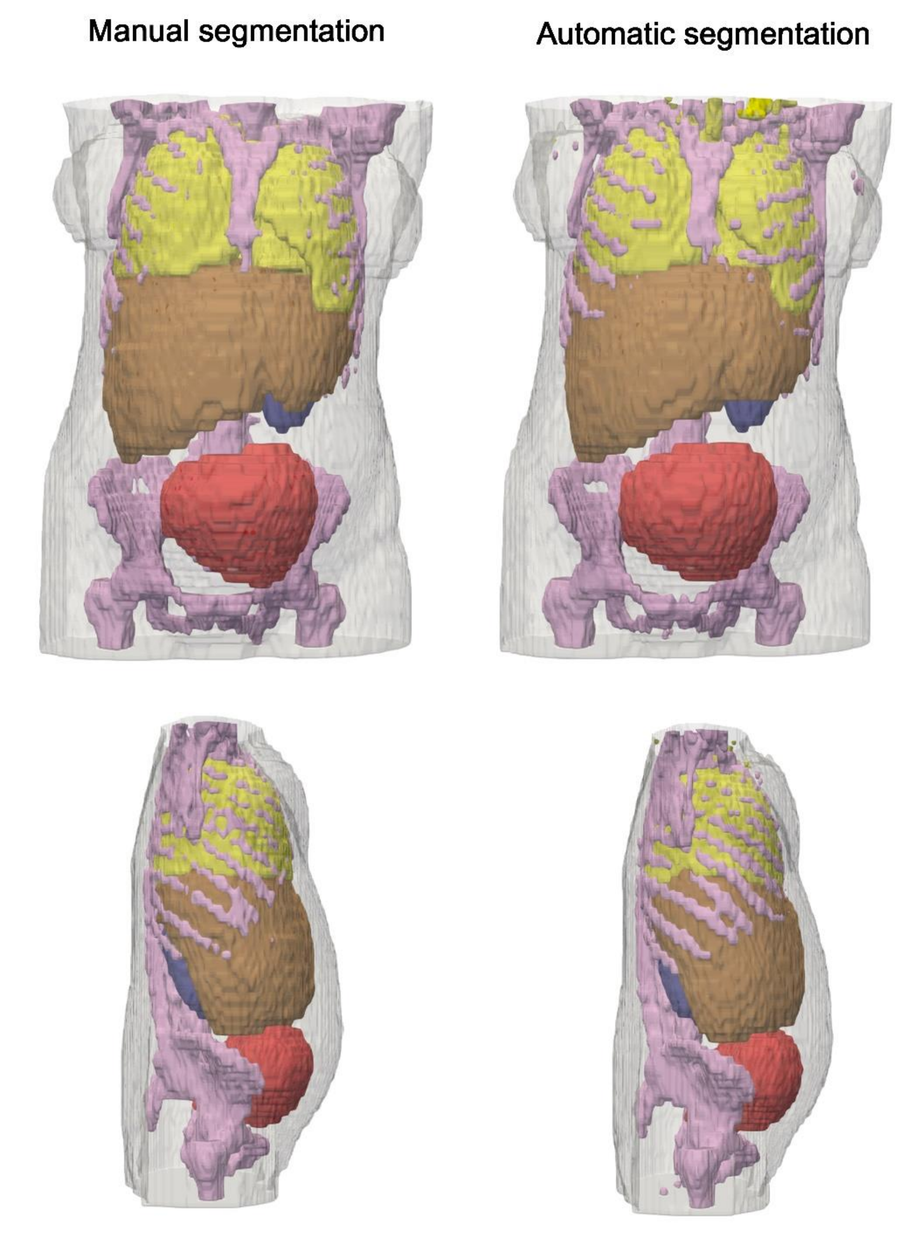
Propose … entation
of pregn…



Xie and Zaidi (2019) *Eur Radiol*

Automated generation of anatomical models





Xie and Zaidi (2019) *Eur Radiol*

Deep learning in PET image segmentation

Hôpitaux Universitaires Genève

Medical Image Analysis 44 (2018) 177–195

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Medical Image Analysis

journal homepage: www.elsevier.com/locate/media

ELSEVIER

The first MICCAI challenge on PET tumor segmentation

Mathieu Hatt[a,*], Baptiste Laurent[a], Anouar Ouahabi[a], Hadi Fayad[a], Shan Tan[b], Laquan Li[b], Wei Lu[c], Vincent Jaouen[a], Clovis Tauber[d], Jakub Czakon[e], Filip Drapejkowski[e], Witold Dyrka[e,f], Sorina Camarasu-Pop[g], Frédéric Cervenansky[g], Pascal Girard[g], Tristan Glatard[h], Michael Kain[i], Yao Yao[i], Christian Barillot[i], Assen Kirov[c], Dimitris Visvikis[a]

[a] LaTIM, UMR 1101, INSERM, IBSAM, UBO, UBL, Brest, France
[b] Key Laboratory of Image Processing and Intelligent Control of Ministry of Education of China, School of Automation, Huazhong University of Science and Technology, Wuhan 430074, China
[c] Memorial Sloan-Kettering Cancer Center, New-York, USA
[d] INSERM, UMR 930, Imaging and brain, University of Tours, France
[e] Stermedia Sp. z o. o., ul. A. Ostrowskiego 13, Wroclaw, Poland
[f] Wrocław University of Science and Technology, Faculty of Fundamental Problems of Technology, Department of Biomedical Engineering, Poland
[g] Université de Lyon, CREATIS, CNRS UMR5220, INSERM UMR 1044, INSA-Lyon, Université Lyon 1, Lyon, France
[h] Department of Computer Science and Software Engineering, Concordia University, Montreal, Canada
[i] INRIA, Visages project-team, CNRS, IRISA 6074, INSERM, Visages, UMR 1228, University of Rennes I, Rennes Cx 35042, France

A R T I C L E I N F O

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Comparative study

A B S T R A C T

Introduction: Automatic functional volume segmentation in PET images is a challenge that dressed using a large array of methods. A major limitation for the field has been the lack of dataset that would allow direct comparison of the results in the various publications. In the we describe a comparison of recent methods on a large dataset following recommendations ican Association of Physicists in Medicine (AAPM) task group (TG) 211, which was carried MICCAI (Medical Image Computing and Computer Assisted Intervention) challenge.
Materials and methods: Organization and funding was provided by France Life Imaging (F of 176 images combining simulated, phantom and clinical images was assembled. A websit participants to register and download training data (n = 19). Challengers then submitted pipelines on an online platform that autonomously ran the algorithms on the testing data evaluated the results. The methods were ranked according to the arithmetic mean of sensiti itive predictive value.
Results: Sixteen teams registered but only four provided manuscripts and pipeline(s) for methods. In addition, results using two thresholds and the Fuzzy Locally Adaptive Bayesian generated. All competing methods except one performed with median accuracy above 0.8. with the highest score was the convolutional neural network-based segmentation, which significantly outperformed 9 out of 12 of the other methods, but not the improved K-Means, Gaussian Model Mixture and Fuzzy C-Means methods.
Conclusion: The most rigorous comparative study of PET segmentation algorithms to date was carried out using a dataset that is the largest used in such studies so far. The hierarchy amongst the methods in terms of accuracy did not depend strongly on the subset of datasets or the metrics (or combination of metrics). All the methods submitted by the challengers except one demonstrated good performance with median accuracy scores above 0.8.

nature COMMUNICATIONS

Corrected: Author correction

ARTICLE

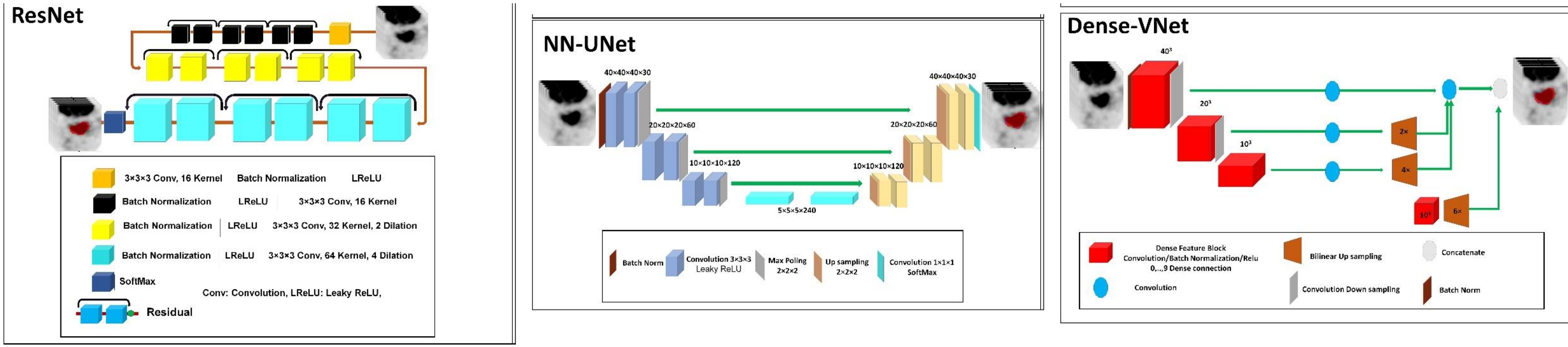
DOI: 10.1038/s41467-018-07619-7 OPEN

Why rankings of biomedical image analysis competitions should be interpreted with care

Lena Maier-Hein et al.[#]

International challenges have become the standard for validation of biomedical image analysis methods. Given their scientific impact, it is surprising that a critical analysis of common practices related to the organization of challenges has not yet been performed. In this paper, we present a comprehensive analysis of biomedical image analysis challenges conducted up to now. We demonstrate the importance of challenges and show that the lack of quality control has critical consequences. First, reproducibility and interpretation of the results is often hampered as only a fraction of relevant information is typically provided. Second, the rank of an algorithm is generally not robust to a number of variables such as the test data used for validation, the ranking scheme applied and the observers that make the reference annotations. To overcome these problems, we recommend best practice guidelines and define open research questions to be addressed in the future.

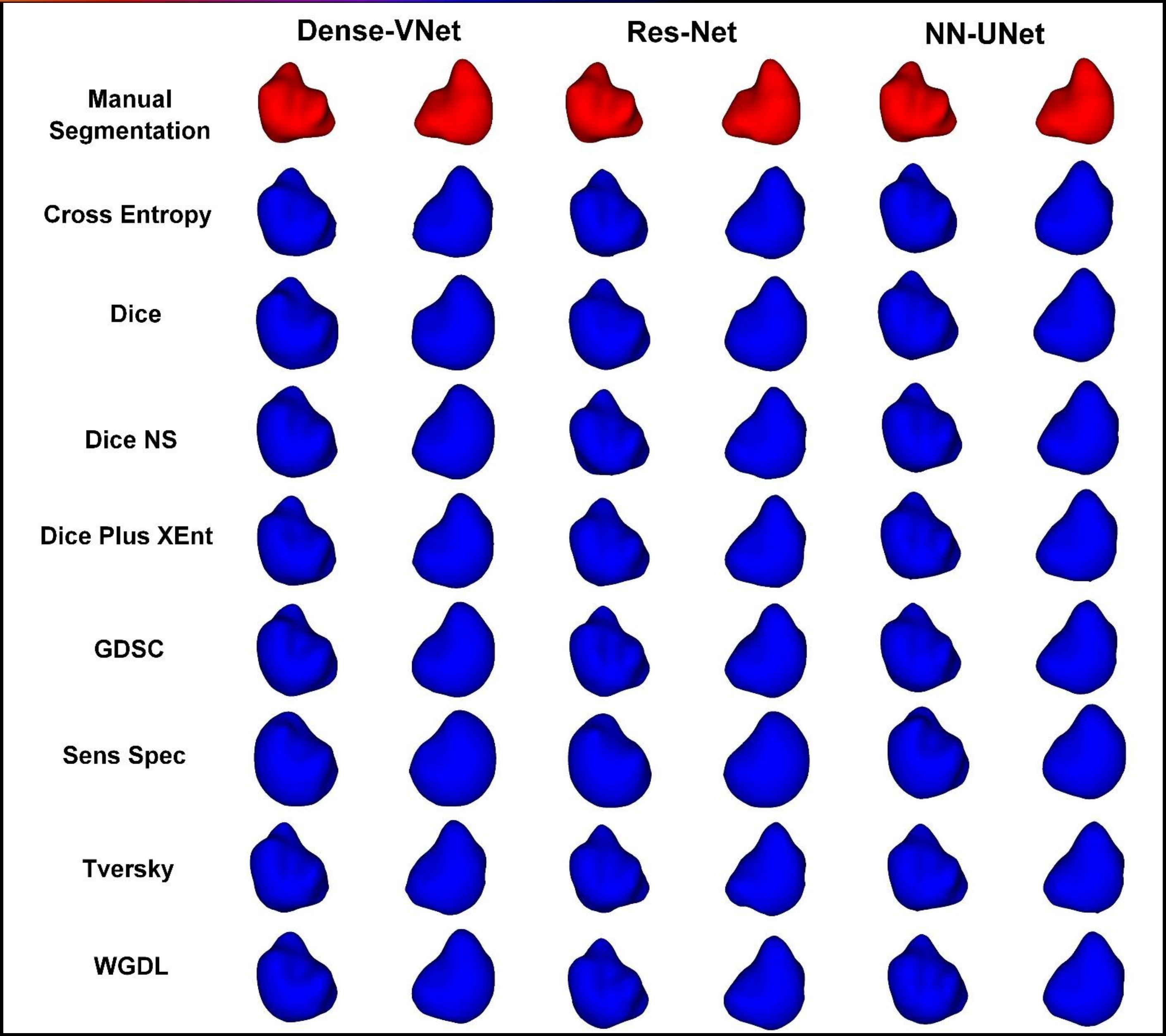
Deep learning-guided PET segmentation



- Evaluate 3 state-of-the-art deep learning algorithms (ResNET, NN-Unet, Dense-Vnet) <u>combined</u> with 8 different loss functions (Dice, generalized Wasserstein Dice loss, Dice Plus Xent loss, generalized Dice loss, cross-entropy, sensitivity-specificity, and Tversky) for PET image segmentation using a comprehensive training set (340) and evaluated its performance on an external validation set (100) of head and neck cancer patients.

Shiri et al. (2021) *Clin Nucl Med*

Deep learning-guided PET segmentation



Shiri et al. (2021) *Clin Nucl Med*

Deep learning-guided PET segmentation

Hôpitaux Universitaires Genève

Method	Loss Function	Dice	Jaccard	False Negative	False Positive	Volume Similarity	Mean Surface Distance	Std Surface Distance	Max Surface Distance
Dense-VNET	Cross Entropy	0.82 - 0.85	0.71 - 0.74	0.10 - 0.14	0.16 - 0.20	0.03 - 0.11	0.17 - 0.2	0.40 - 0.45	2.1 - 2.4
	Dice	0.75 - 0.78	0.61 - 0.65	0.05 - 0.09	0.30 - 0.34	0.26 - 0.35	0.26 - 0.30	0.51 - 0.56	2.6 - 3.0
	Dice NS	0.76 - 0.79	0.62 - 0.66	0.04 - 0.08	0.29 - 0.33	0.27 - 0.36	0.25 - 0.28	0.48 - 0.52	2.4 - 2.7
	Dice Plus XEnt	0.80 - 0.82	0.67 - 0.71	0.05 - 0.08	0.24 - 0.28	0.19 - 0.27	0.20 - 0.23	0.43 - 0.48	2.2 - 2.5
	GDSC	0.75 - 0.78	0.61 - 0.65	0.05 - 0.09	0.30 - 0.34	0.27 - 0.36	0.27 - 0.30	0.51 - 0.56	2.7 - 3.0
	Sens Spec	0.70 - 0.72	0.54 - 0.57	0.03 - 0.06	0.40 - 0.44	0.45 - 0.53	0.35 - 0.38	0.61 - 0.65	2.9 - 3.2
	Tversky	0.82 - 0.85	0.71 - 0.74	0.11 - 0.15	0.16 - 0.19	0.01 - 0.09	0.17 - 0.20	0.40 - 0.45	2.0 - 2.3
	WGDL	0.74 - 0.76	0.59 - 0.63	0.04 - 0.07	0.34 - 0.38	0.34 - 0.42	0.29 - 0.32	0.53 - 0.57	2.6 - 2.9
Res-Net	Cross Entropy	0.84 - 0.86	0.73 - 0.76	0.1 - 0.14	0.14 - 0.17	0.00 - 0.07	0.16 - 0.19	0.38 - 0.43	1.9 - 2.3
	Dice	0.83 - 0.85	0.71 - 0.74	0.06 - 0.09	0.20 - 0.23	0.13 - 0.20	0.17 - 0.20	0.39 - 0.43	2.0 - 2.3
	Dice NS	0.83 - 0.85	0.71 - 0.75	0.07 - 0.11	0.18 - 0.22	0.08 - 0.16	0.17 - 0.20	0.40 - 0.45	2.1 - 2.4
	Dice Plus XEnt	0.83 - 0.85	0.72 - 0.75	0.07 - 0.11	0.18 - 0.21	0.07 - 0.15	0.16 - 0.19	0.39 - 0.43	2.0 - 2.3
	GDSC	0.82 - 0.84	0.71 - 0.74	0.06 - 0.09	0.20 - 0.24	0.13 - 0.20	0.17 - 0.20	0.40 - 0.45	2.1 - 2.4
	Sens Spec	0.71 - 0.73	0.55 - 0.58	0.03 - 0.06	0.38 - 0.42	0.41 - 0.50	0.33 - 0.37	0.59 - 0.63	2.8 - 3.1
	Tversky	0.83 - 0.86	0.72 - 0.75	0.099 - 0.14	0.15 - 0.18	0.02 - 0.09	0.16 - 0.19	0.38 - 0.43	2.0 - 2.3
	WGDL	0.83 - 0.85	0.72 - 0.75	0.061 - 0.09	0.19 - 0.23	0.12 - 0.19	0.16 - 0.19	0.38 - 0.43	1.9 - 2.3
NN-UNet	Cross Entropy	0.81 - 0.83	0.69 - 0.72	0.06 - 0.1	0.21 - 0.25	0.13 - 0.21	0.19 - 0.22	0.43 - 0.5	2.2 - 2.7
	Dice	0.82 - 0.85	0.71 - 0.74	0.06 - 0.09	0.20 - 0.24	0.13 - 0.20	0.18 - 0.21	0.41 - 0.46	2.1 - 2.4
	Dice NS	0.82 - 0.85	0.71 - 0.74	0.05 - 0.08	0.21 - 0.24	0.15 - 0.22	0.17 - 0.21	0.40 - 0.45	2.0 - 2.3
	Dice Plus XEnt	0.84 - 0.86	0.73 - 0.76	0.08 - 0.12	0.16 - 0.19	0.05 - 0.12	0.16 - 0.19	0.39 - 0.46	2.0 - 2.5
	GDSC	0.82 - 0.85	0.71 - 0.74	0.06 - 0.1	0.19 - 0.23	0.11 - 0.19	0.17 - 0.21	0.40 - 0.46	2.0 - 2.4
	Sens Spec	0.71 - 0.74	0.56 - 0.59	0.04 - 0.07	0.37 - 0.41	0.39 - 0.48	0.32 - 0.36	0.58 - 0.62	2.9 - 3.2
	Tversky	0.80 - 0.83	0.68 - 0.72	0.09 - 0.13	0.20 - 0.23	0.08 - 0.17	0.20 - 0.24	0.45 - 0.52	2.3 - 2.8
	WGDL	0.82 - 0.85	0.71 - 0.74	0.05 - 0.08	0.20 - 0.24	0.15 - 0.22	0.17 - 0.20	0.40 - 0.45	2.0 - 2.4

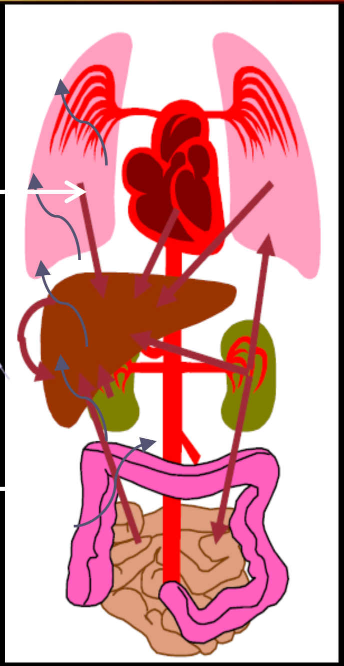
Shiri et al. (2021) *Clin Nucl Med*

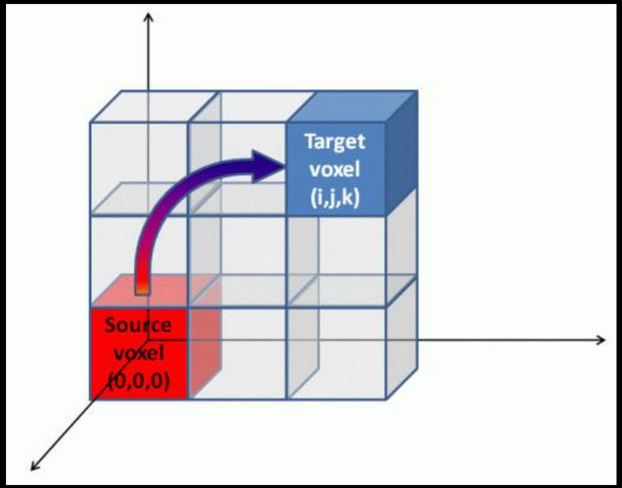
Voxel-based internal dosimetry (MIRD)

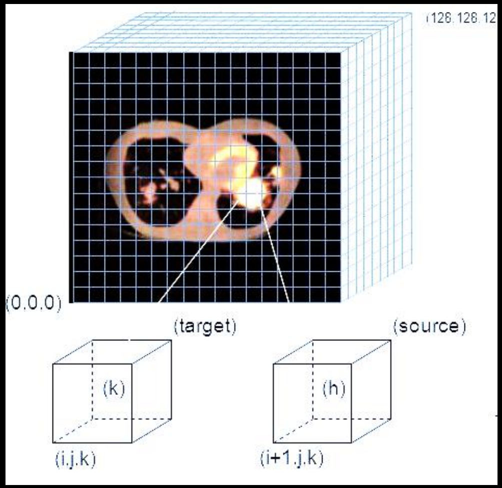
Source

Administered activity

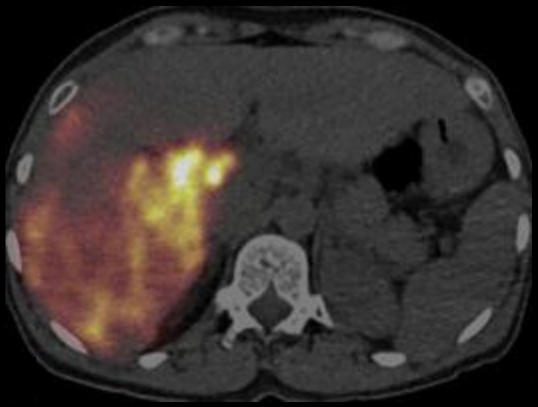
Target



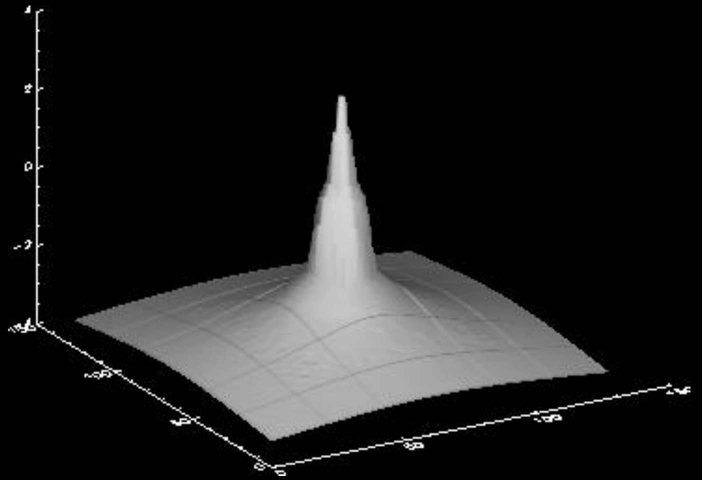




$$\bar{D}_{voxel_k} = \sum_{n=1}^{N} \tilde{A}_{voxel_n} . S(voxel_k \leftarrow voxel_n)$$



*



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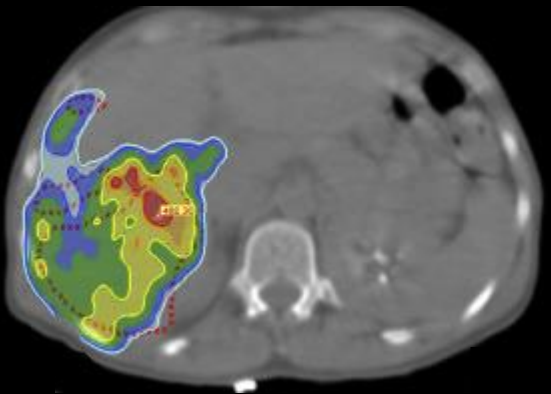

Activity map

Dose point kernel

3D dose map

Bolch et al. J Nucl Med (1999)

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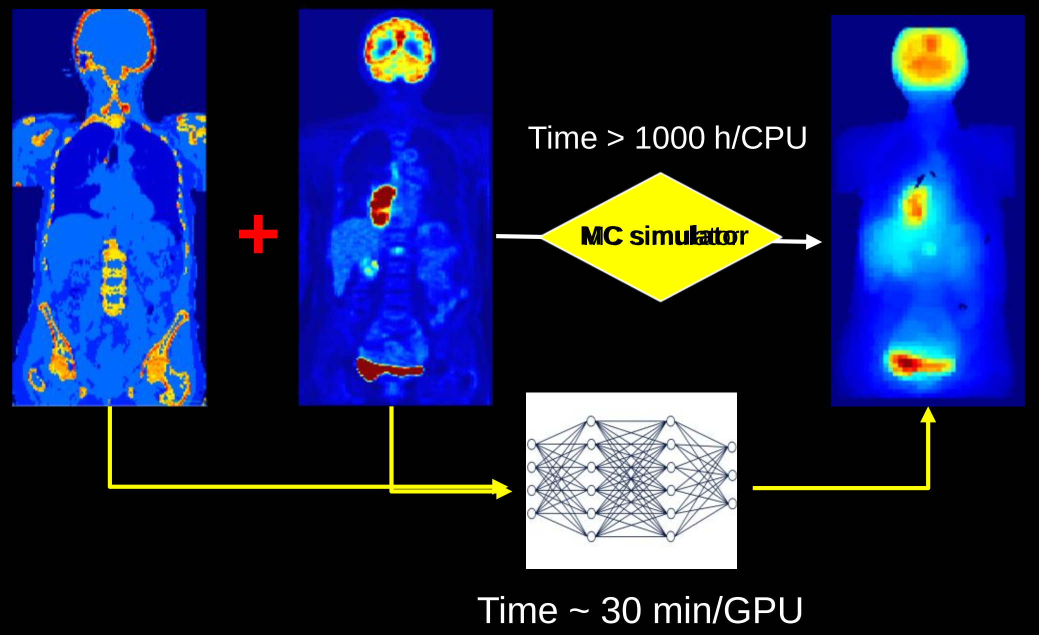
AI-guided internal radiation dosimetry

Monte Carlo → Reference (gold Standard)

But heavy computational burden!!!

Monte Carlo-based dose mapping could be formulated as a regression problem to be solved through deep learning algorithms



Deep learning-based internal dosimetry

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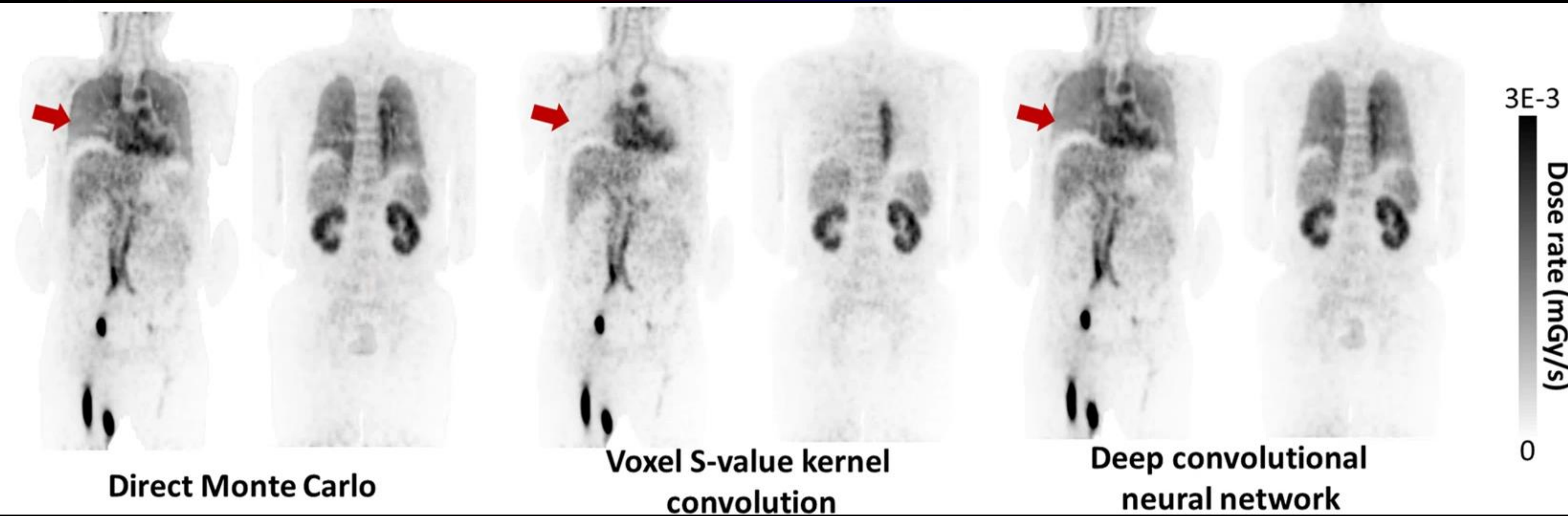
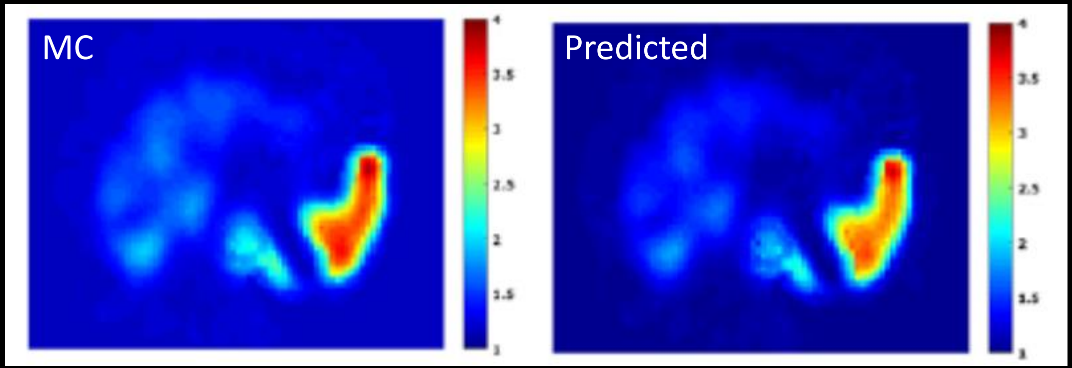


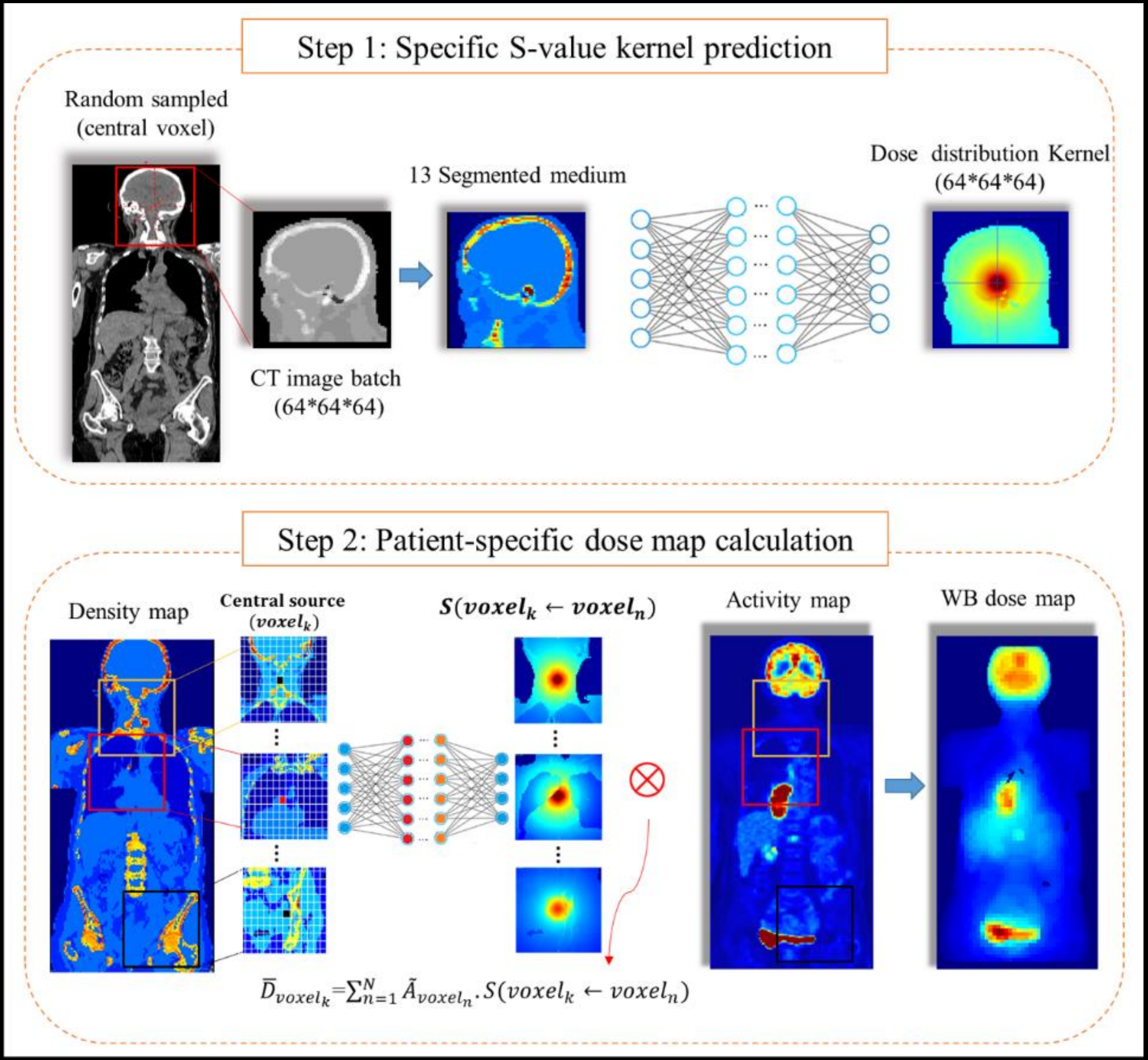
Lee et al. (2018) *Sci Rep*



- ✓ SPECT/CT data set of ^{177}Lu-PSMA
- ✓ 2.5D network training (UNet)
- ✓ 2 input channels: MIRD-based dose/CT
- ✓ Output: Whole body dose map

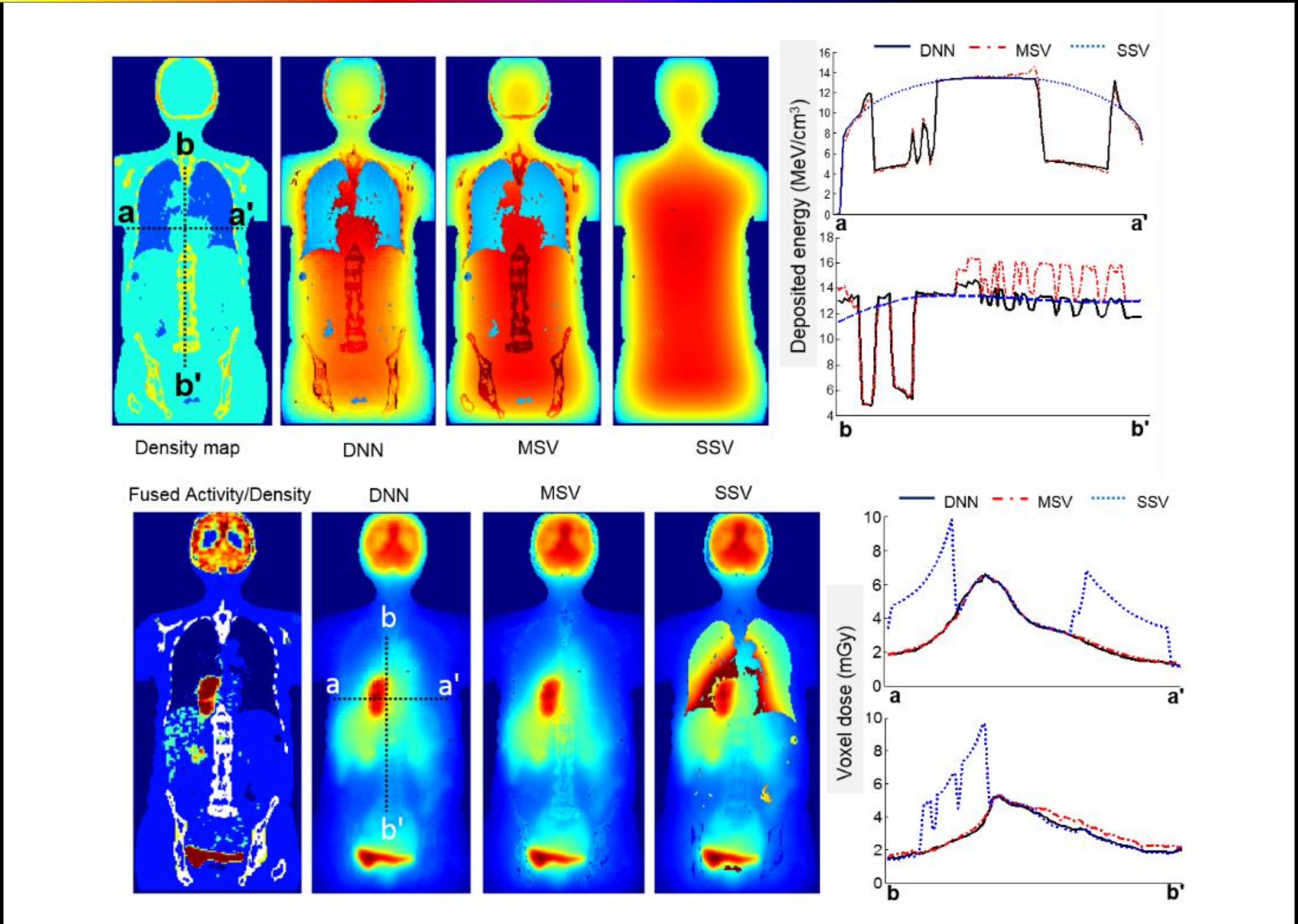
Gotz et al. (2020) *Phys Med Biol*

Deep learning-guided internal dosimetry



Akhavanallaf *et al.* (2020) *Eur J Nucl Med Mol Imaging*

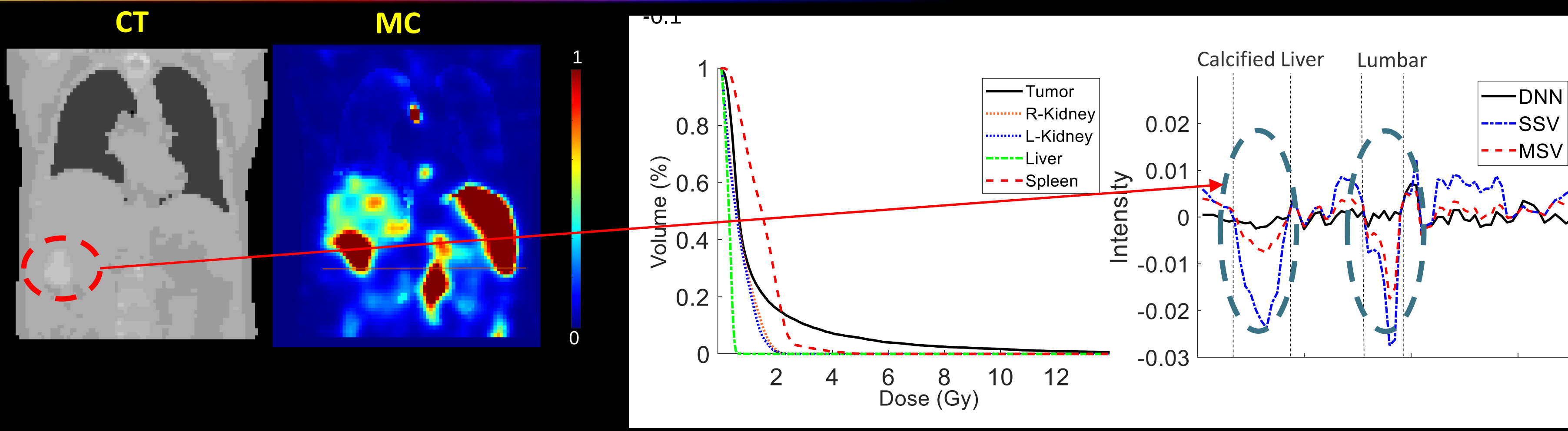
Deep learning-guided internal dosimetry



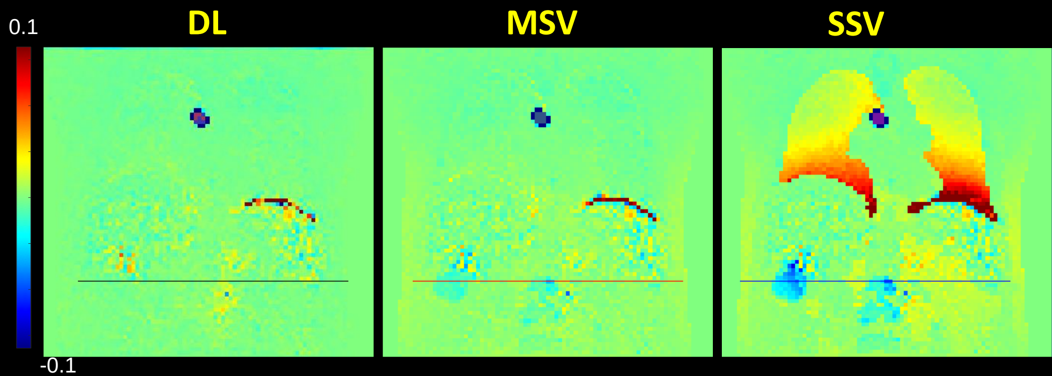
Akhavanallaf et al. (2020) *Eur J Nucl Med Mol Imaging*

Deep learning-guided internal dosimetry

^{177}Lu-Dotatate



Line profile passing through a calcified liver mass

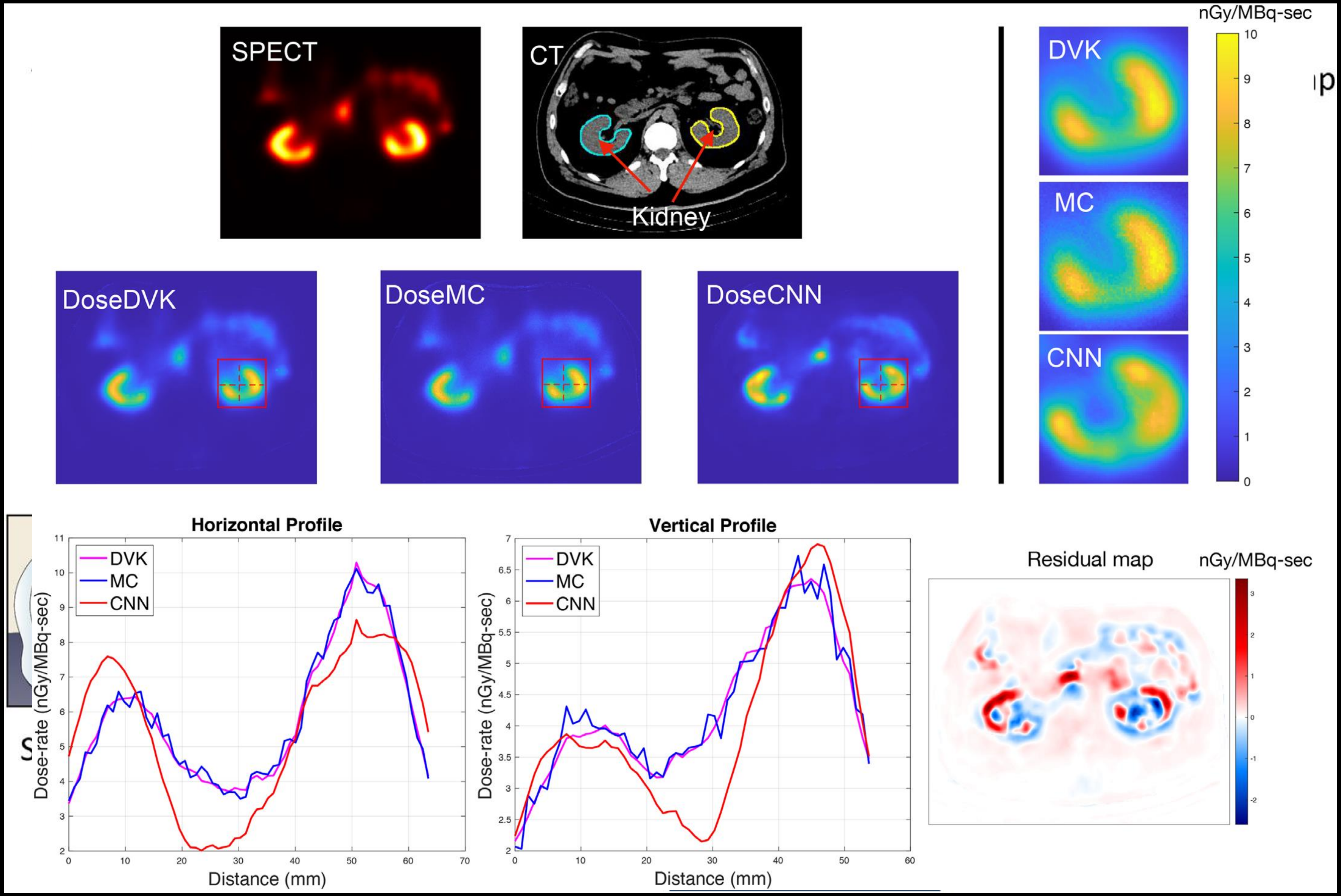


Mean absorbed dose in the segmented ROIs

ROIs	MC	DL	MSV	SSV
Tumors	1.38	1.39	1.36	1.36
R-Kidney	0.72	0.72	0.72	0.72
R-Kidney	0.68	0.68	0.68	0.68
Liver	0.31	0.31	0.31	0.31
Spleen	1.49	1.49	1.49	1.50

Akhavan et al. (2021) *IEEE MIC*

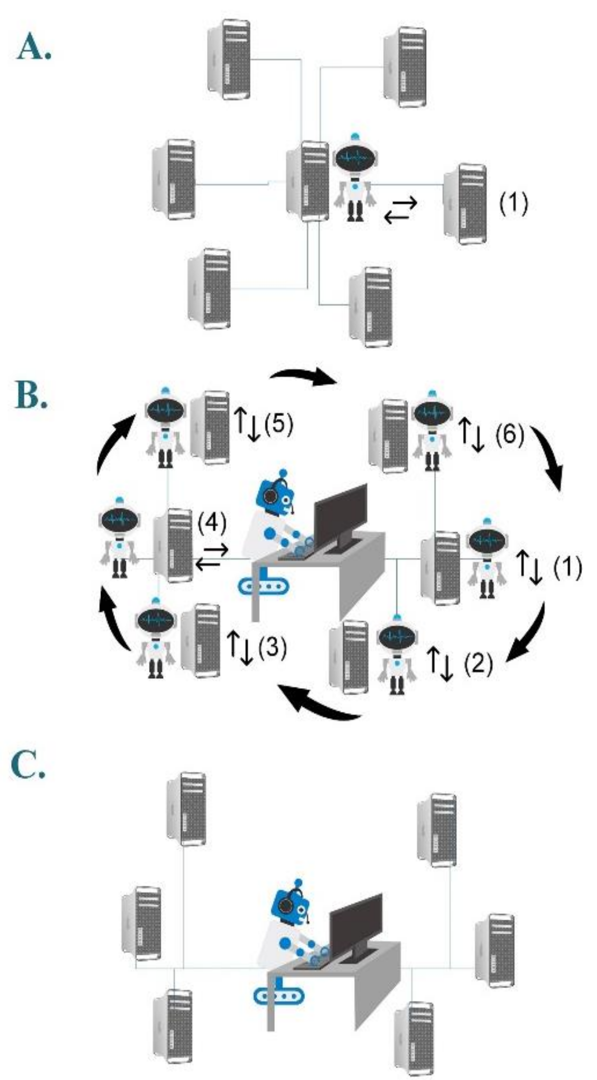
Deep learning-guided internal dosimetry



Zongyu et al. (2022) *Med Phys*

Federated learning for PET AC/segmentation

Federated Learning Sequential



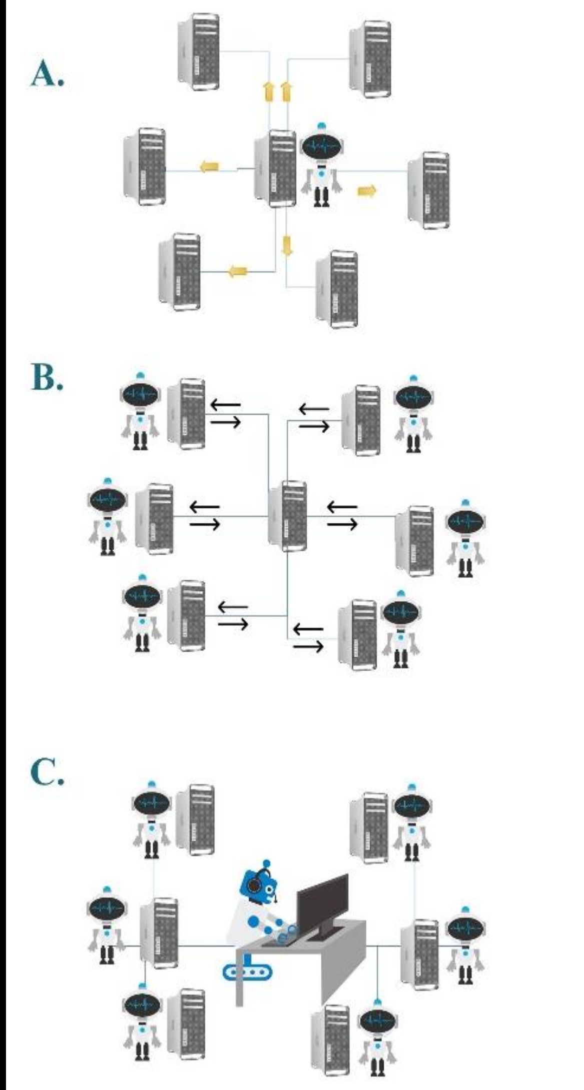
300 patients from **6 different centers**

Require: num_federated_rounds T

procedure AGGREGATING
Initialise global model: $W^{(0)}$
for $t \leftarrow 1 \cdots T$ **do**
for *client* $k \leftarrow 1 \cdots K$ **do** $\quad\triangleright$ *Run in parallel*
Send $W^{(t-1)}$ to client k
Receive model updates and number of local training iterations $(\Delta W_k^{(t-1)}, N_k)$ from client's local training with $\mathcal{L}_k(X_k; W^{(t-1)})$
end for
$W^{(t)} \leftarrow W^{(t-1)} + \frac{1}{\sum_k N_k} \sum_k (N_k \cdot W_k^{(t-1)})$
end for
return $W^{(t)}$
end procedure

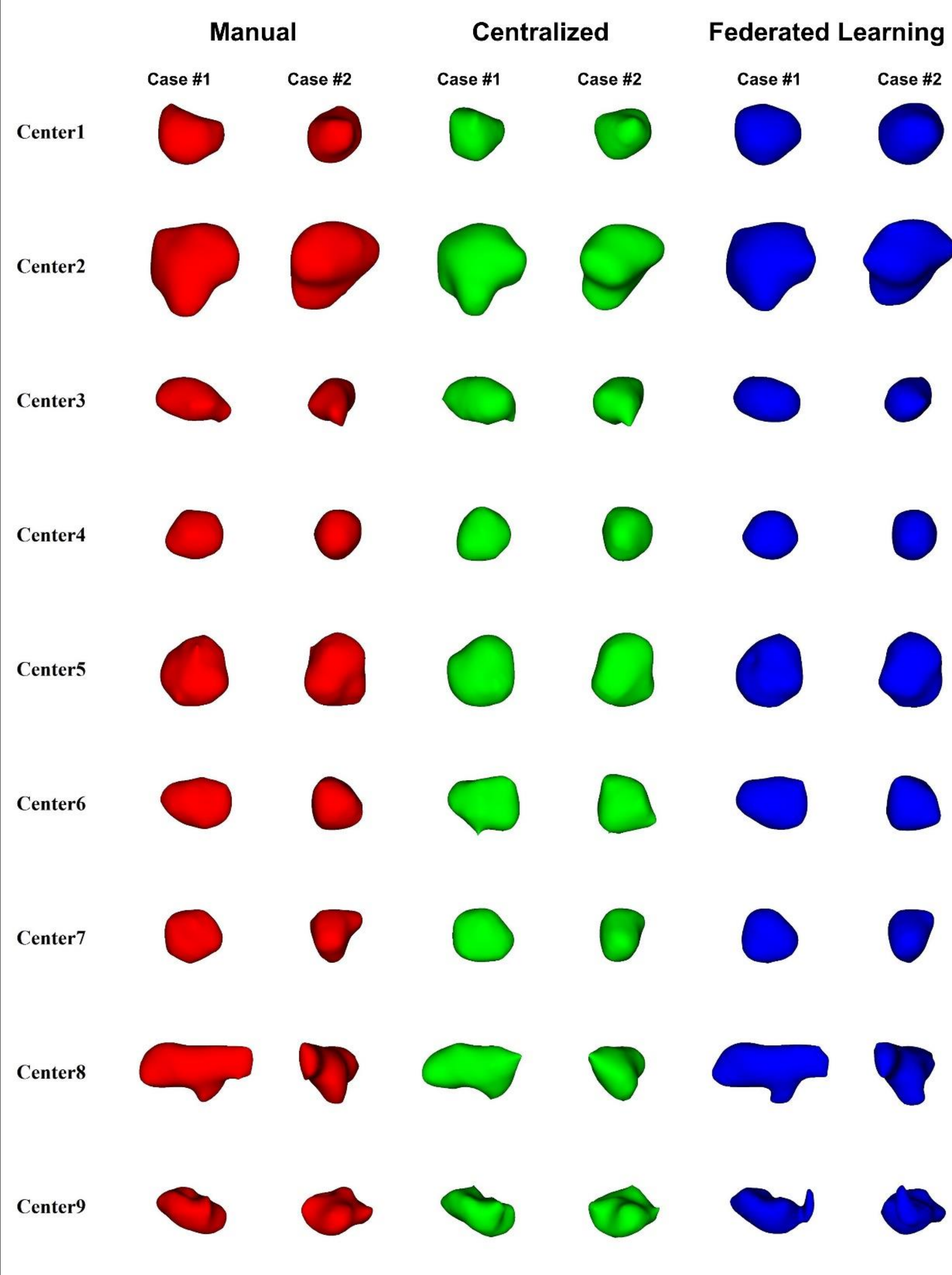
Sequential **(FL-SQ)** and parallel **(FL-PL)** models were compared with **centralized (CZ)** approach (data are pooled to one server), and **center-based (CB)** approach (model built separately)

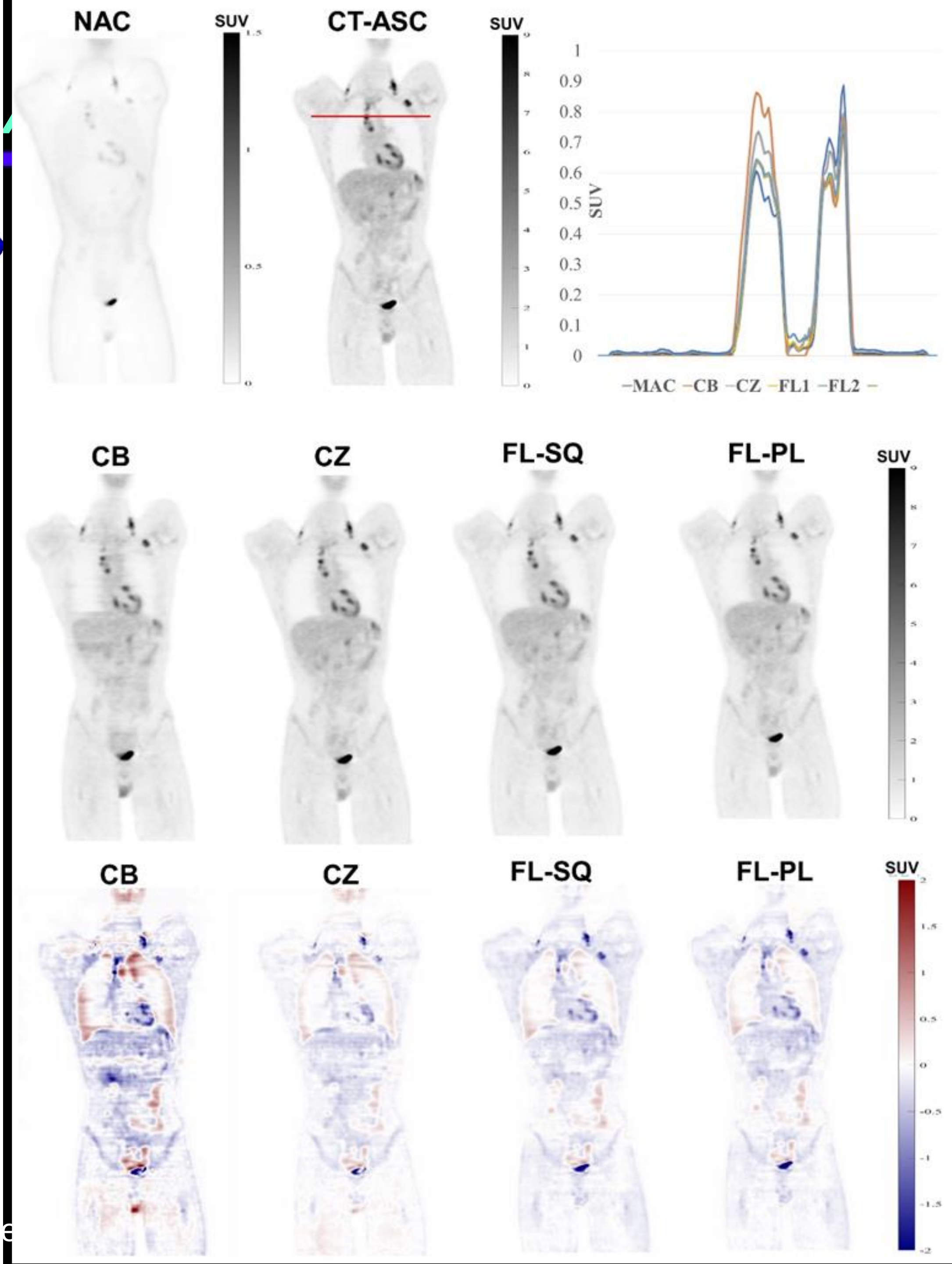
Federated Learning Parallel



Shiri et al. (2021) *IEEE Med Imaging Conference*

Shiri et al. (2022) *Clin Nucl Med*


Manual
Centralized
Federated Learning
Case #1
Case #2
Case #1
Case #2
Case #1
Case #2
Center1
Center2
Center3
Center4
Center5
Center6
Center7
Center8
Center9


NAC
SUV
CT-ASC
SUV
SUV
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
—MAC —CB —CZ —FL1 —FL2 —
CB
CZ
FL-SQ
FL-PL
SUV
CB
CZ
FL-SQ
FL-PL
SUV

AI faces reproducibility crisis

IN DEPTH | COMPUTER SCIENCE

Artificial intelligence faces reproducibility crisis

Matthew Hutson

+ See all authors and affiliations

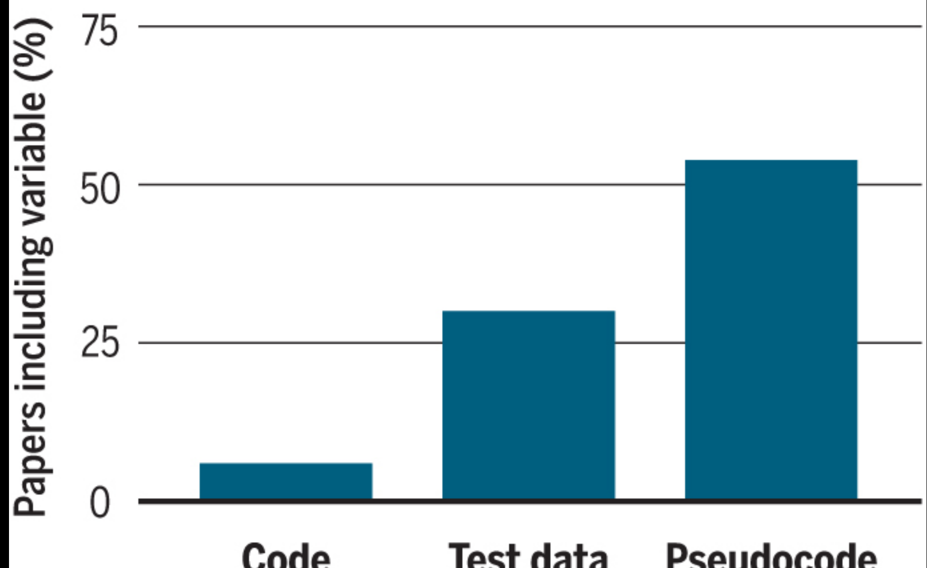
Science 16 Feb 2018:
Vol. 359, Issue 6377, pp. 725-726
DOI: 10.1126/science.359.6377.725

Science

Vol 359, Issue 6377
16 February 2018

Code break

In a survey of 400 artificial intelligence papers presented at major conferences, just 6% included code for the papers' algorithms. Some 30% included test data, whereas 54% included pseudocode, a limited summary of an algorithm.



Hutson *Science* (2018)

Guidelines/recommendations for AI reporting

Hôpitaux Universitaires Genève

Radiology

COMMUNICATIONS • FROM THE EDITOR

Assessing Radiology Research on Artificial Intelligence: A Brief Guide for Authors, Reviewers, and Readers—From the *Radiology* Editorial Board

Received: 10 August 2021 | Revised: 10 August 2021 | Accepted: 10 August 2021

DOI: 10.1002/mp.15170

EDITORIAL

MEDICAL PHYSICS

AI in *Medical Physics* Guidelines for publication

Journal of Nuclear Medicine, published on May 26, 2022 as doi:10.2967/jnumed.121.263239

Nuclear Medicine and Artificial Intelligence: Best Practices for Evaluation (the RELAINCE guidelines)

Summary

- Imaging biomarkers are a major component of Big Data driven medical knowledge and decision making
- Nuclear medicine physicians and Radiologists who use AI and deep learning will replace those who don’t …
- AI/deep learning are producing challenges in terms of validation in clinical setting but also plenty of research opportunities.
- Is there a future for AI/deep learning in molecular imaging? **YES**
- If artificial intelligence is possible, so is artificial stupidity …
- Wide and specific participation by industry and research communities, planning for long term sustainability

Take home message …

"Machine learning works very well, and we don't know why it works so well. I consider that a challenge for mathematicians is to understand it better. I believe if something works, there is a reason. We have to find the reason"

Prof. Ingrid Daubechies, Duke University

Thank you!

Hôpitaux Universitaires Genève

PINLab
PET Instrumentation & Neuroimaging Lab

Hôpitaux Universitaires Genève

UNIVERSITÉ DE GENÈVE

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FNSNF Swiss National Science Foundation

European Commission

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swiss cancer research

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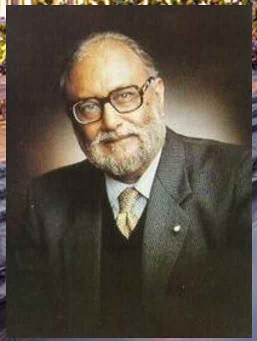
الصندوق القطري لرعاية البحث العلمي
Qatar National Research Fund

Fondation privée des HUG

Thank you!

Thanks to all my colleagues, too many to mention, who have participated in the formulation process of the ideas behind this presentation

"Scientists are very happy people because their job is also their hobby"



Prof. Abdus Salem
1979 Nobel Laureate - Physics