

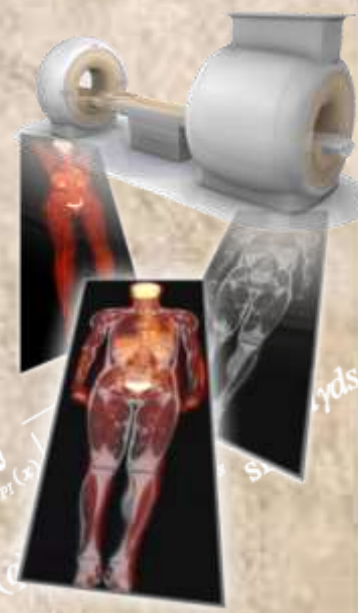
Artificial intelligence-powered multimodality medical imaging: Challenges and opportunities

Habib Zaidi^{1,2,3,4}

Óbuda University, Budapest, 12 September 2023

- ¹Geneva University Hospital, Geneva, Switzerland
- ²University of Groningen, Groningen, Netherlands
- ³University of Southern Denmark, Odense, Denmark
- ⁴Óbuda University, Budapest, Hungary

Email: habib.zaidi@hcuge.ch
Web: <http://www.pinlab.ch>

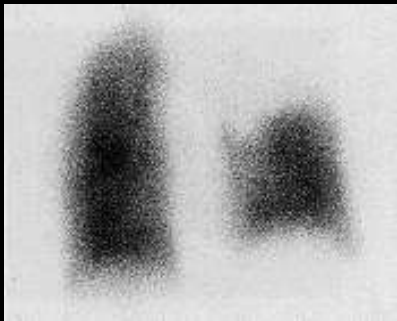


Outline

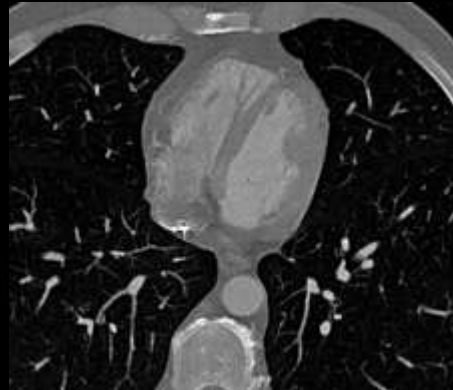
- Advances in multimodality medical imaging
- Why artificial intelligence in multimodality imaging?
- Promise of AI in multimodality medical imaging
 - PET instrumentation (event positioning & TOF)
 - Low-dose CT/PET/SPECT imaging (chest/brain/WB/cardiac)
 - Medical image segmentation (CT and PET)
 - 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

From 2-D to 5-D multimodality imaging

2-D projections



3-D CT

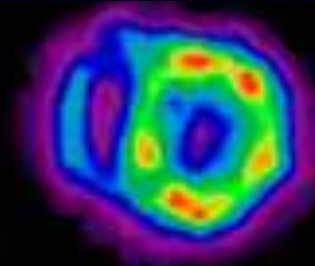
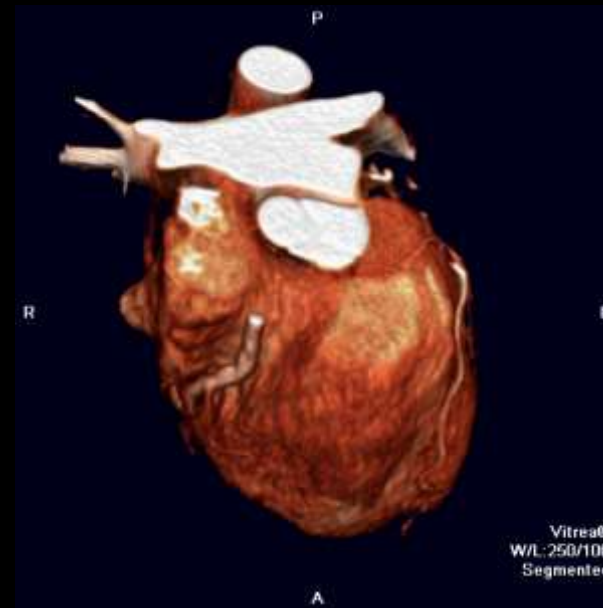


3-D PET

Navigating beyond the 5th dimension ...

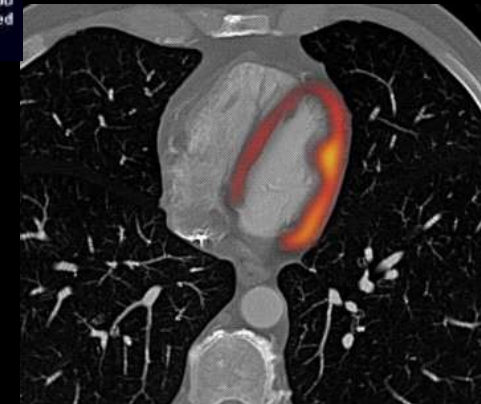
Beyond pretty images ...

4-D CT

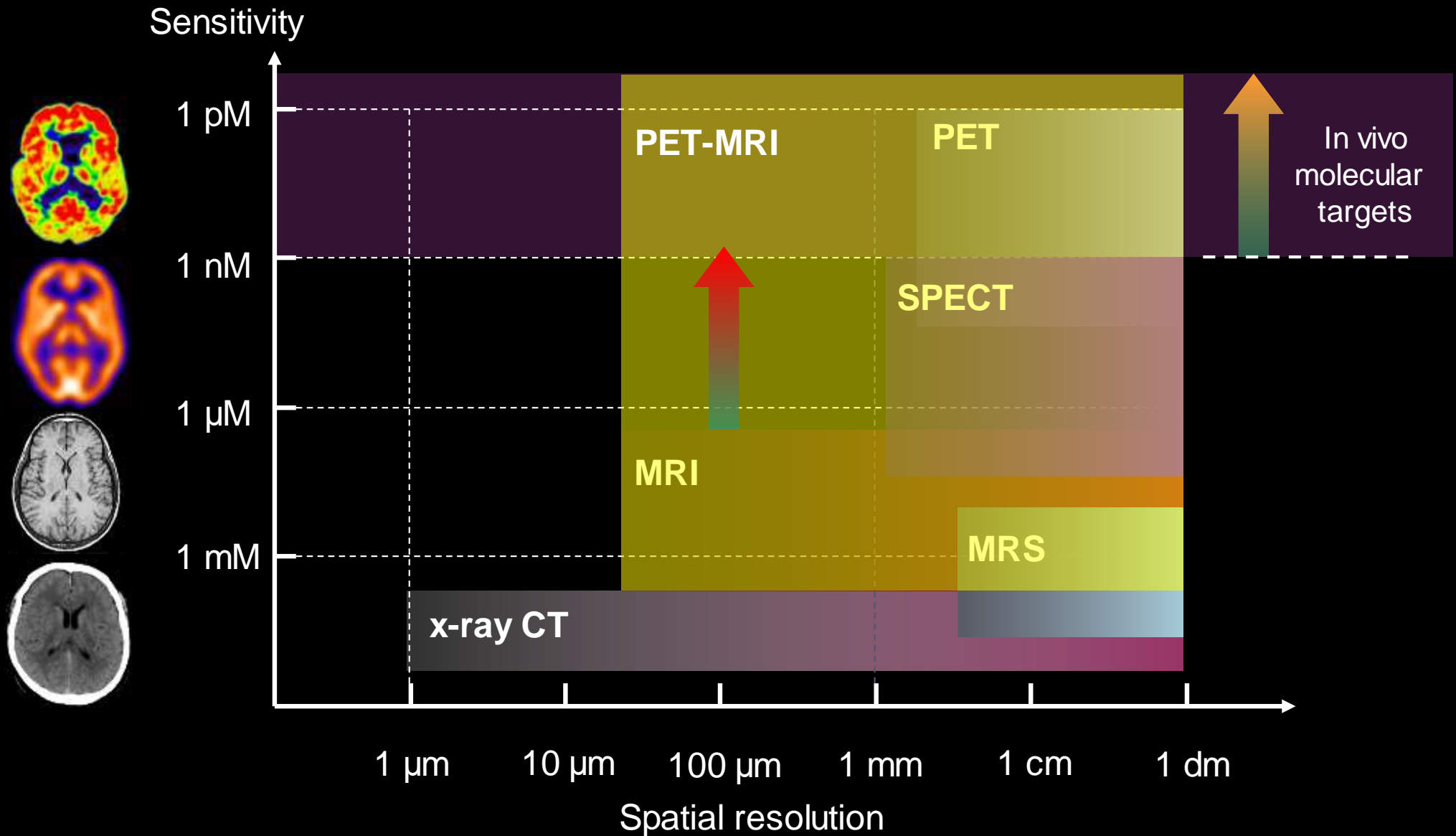


4-D PET

5-D PET/CT



Molecular Imaging: sensitivity vs resolution



Principles of x-ray CT scanning

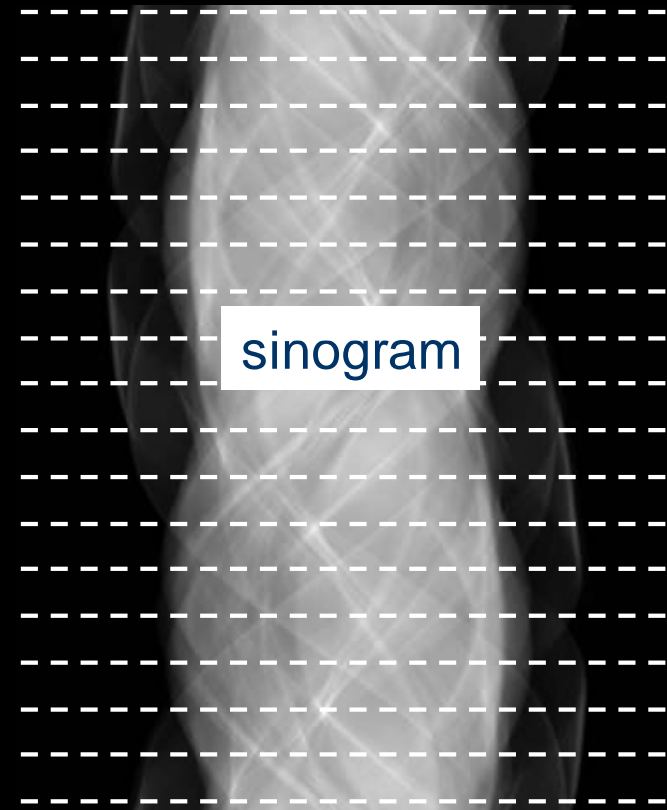
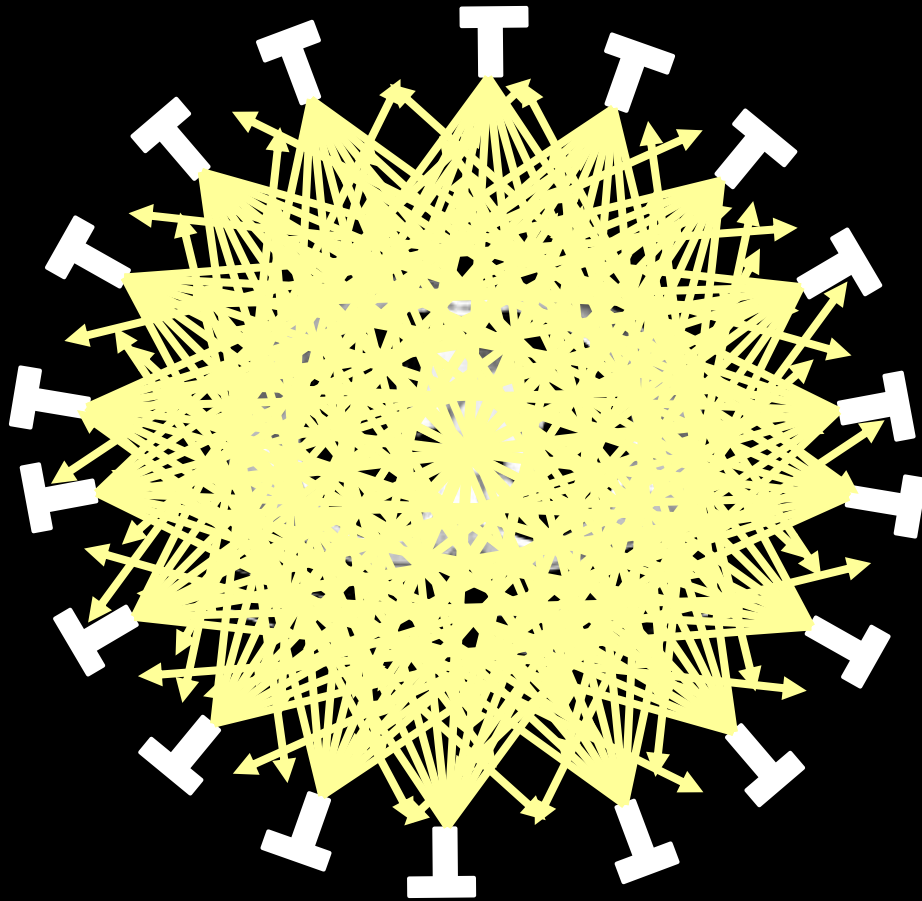
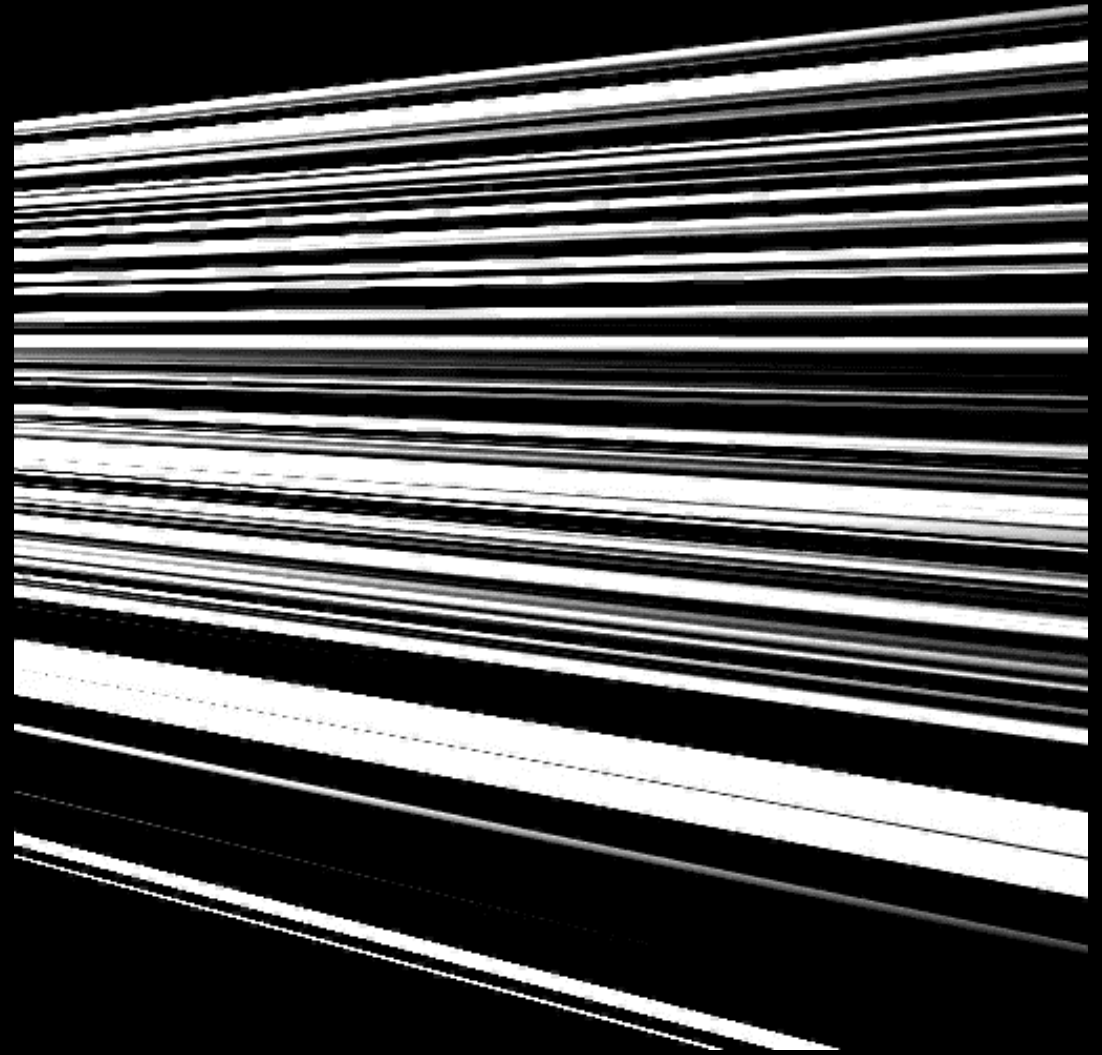


Image reconstruction from projections



Analytic

$$f(x, y) = \int_0^{\pi} d\phi \left[\int_{-\infty}^{+\infty} dv_s |v_s| e^{2\pi i v_s s} P_{\phi}(v_s) \right]$$

Multiparametric brain imaging using MRI

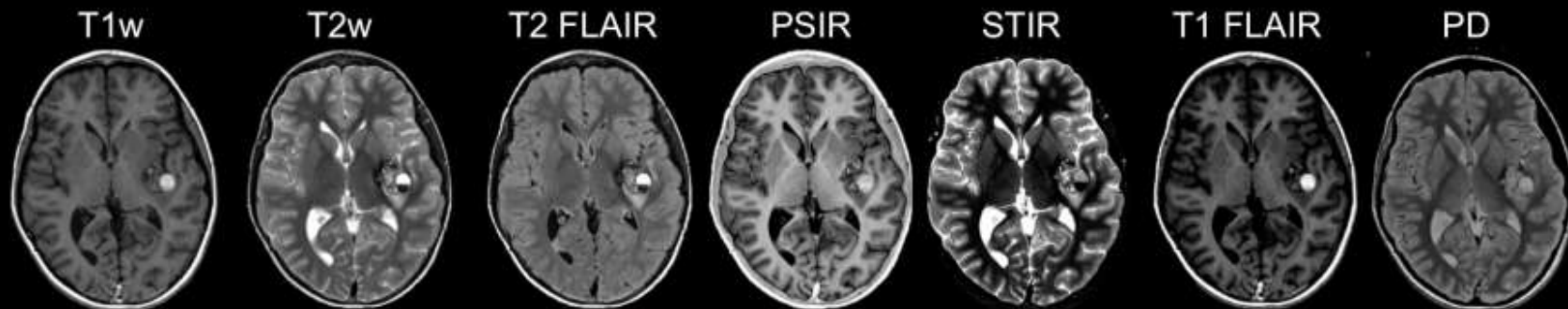
Magnetic Resonance Imaging

Major ingredients:

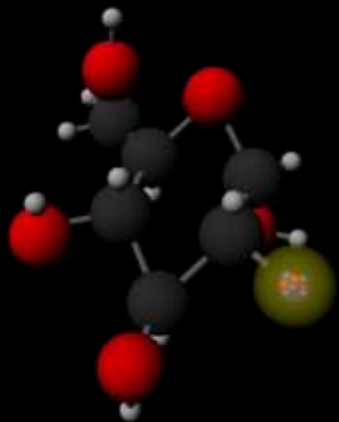
- ✓ Nuclear spin
- ✓ Strong external magnetic field
- ✓ Resonance (typically radio-frequency range)
- ✓ Switchable field gradients to encode position



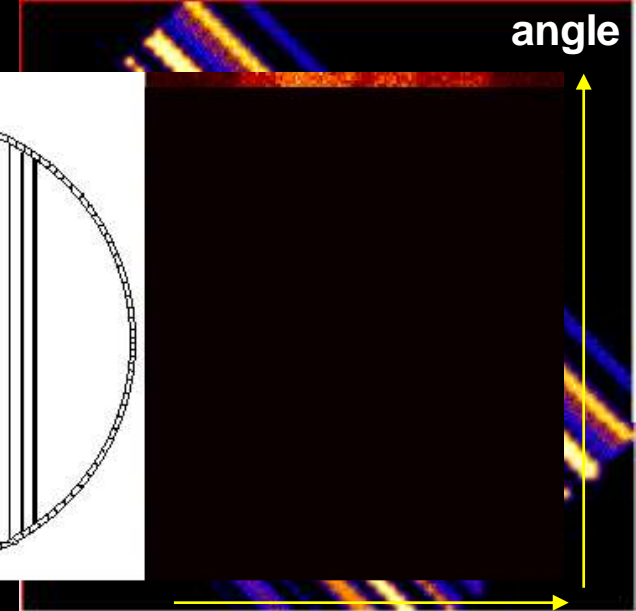
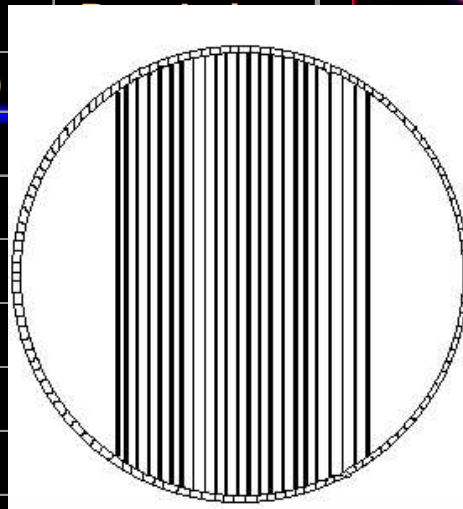
MRI is multiparametric by nature – many different contrasts (sequences) possible



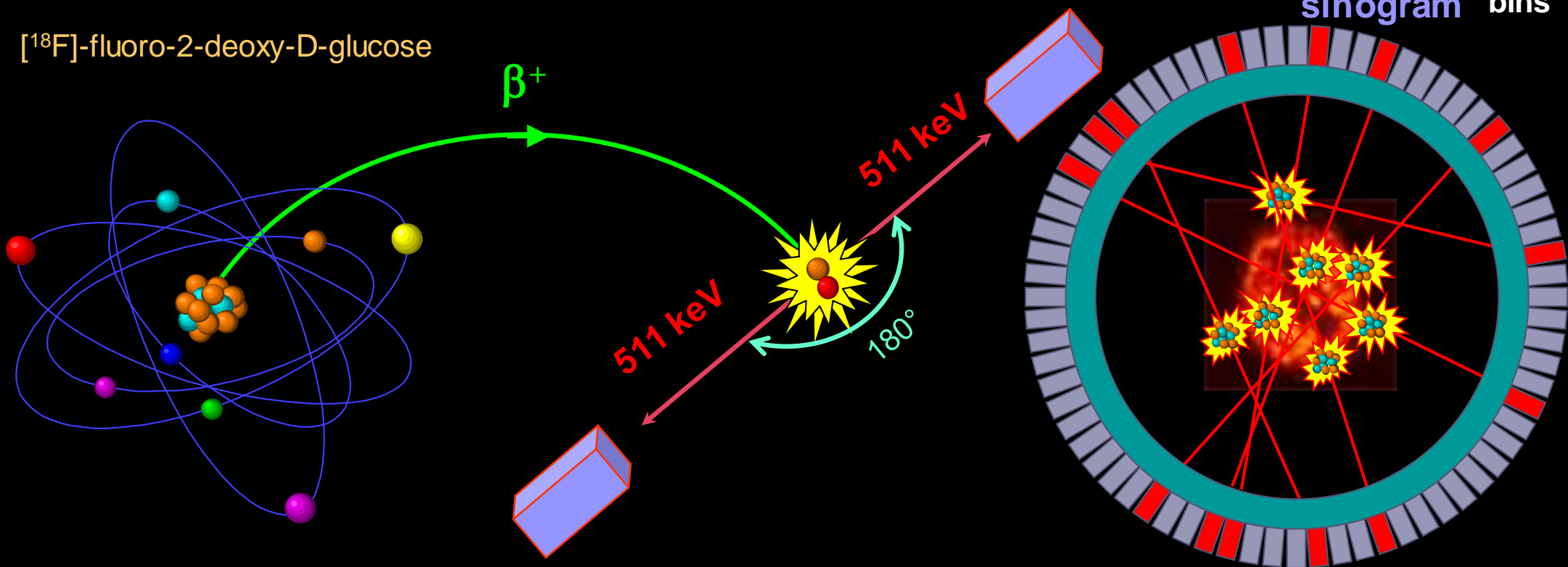
PET principles



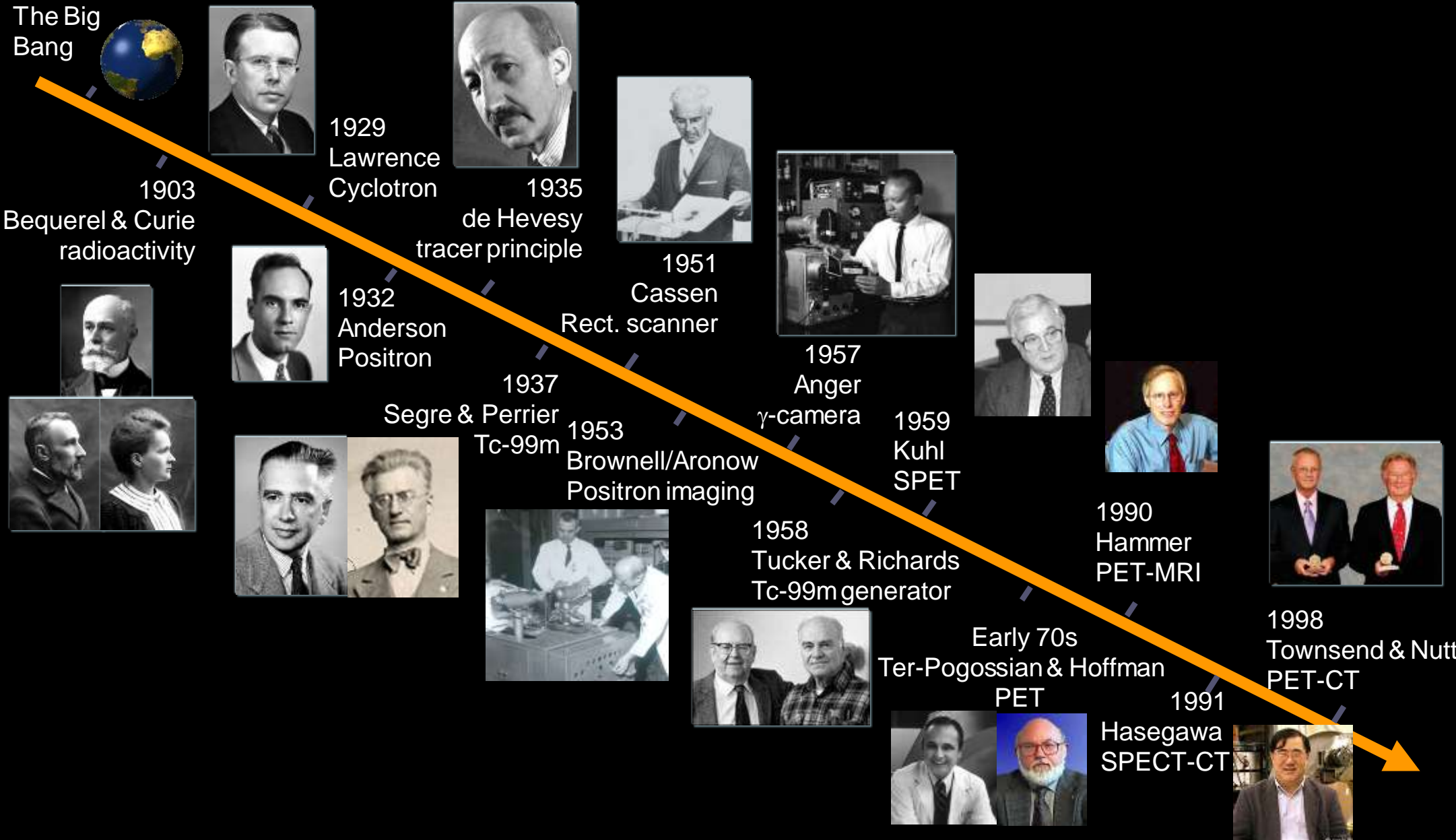
Isotope	$T_{1/2}$	E_{β^+} (MeV)
^{11}C	20 min	0.96
^{13}N	10 min	1.2
^{15}O	122 sec	1.7
^{18}F	110 min	0.64
^{64}Cu	12.8 h	0.65
^{68}Ga	68 min	1.9
^{82}Rb	76 sec	3.4



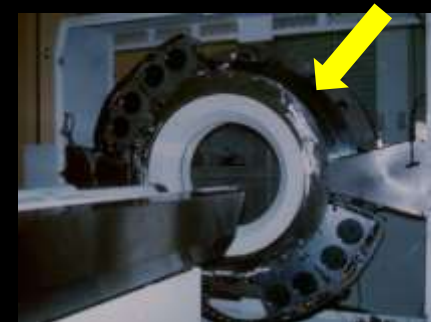
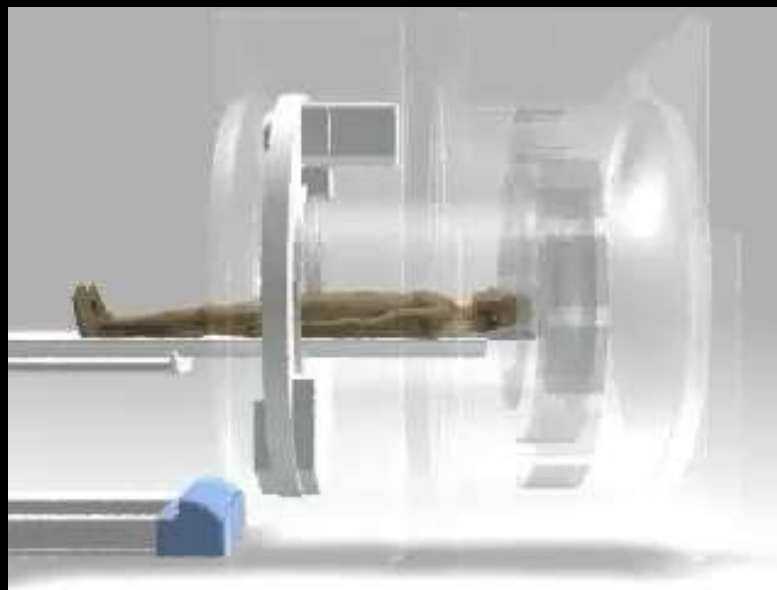
[^{18}F]-fluoro-2-deoxy-D-glucose



Molecular imaging timeline



Principles of PET/CT



Scout



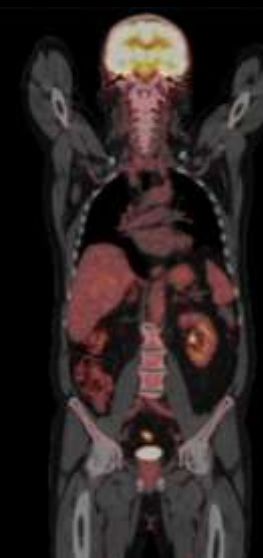
Spiral CT



PET



PET/CT

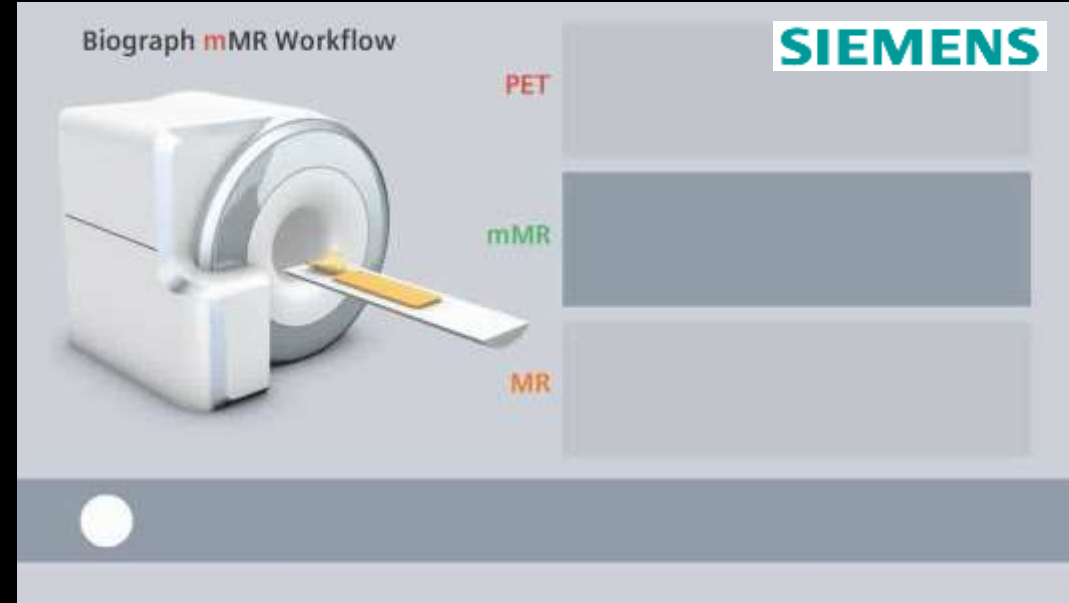


Commercial whole-body PET/MRI systems

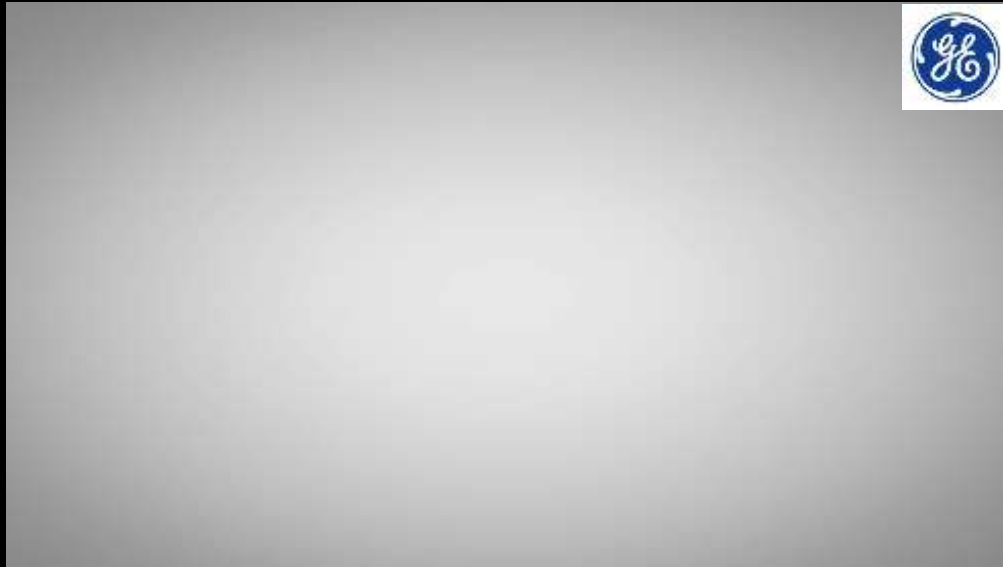
GEMINI TF PET/MR



Biograph mMR



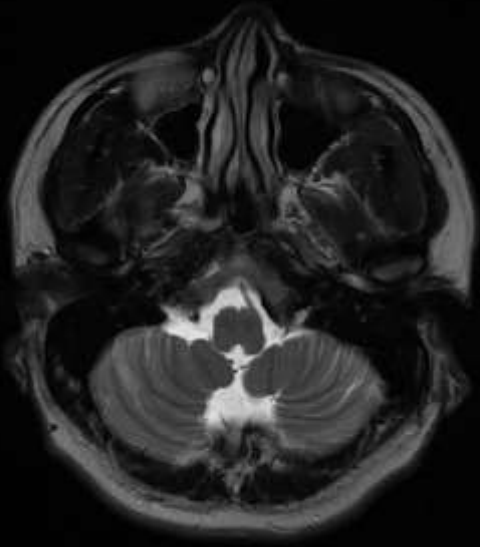
SIGNA PET/MR



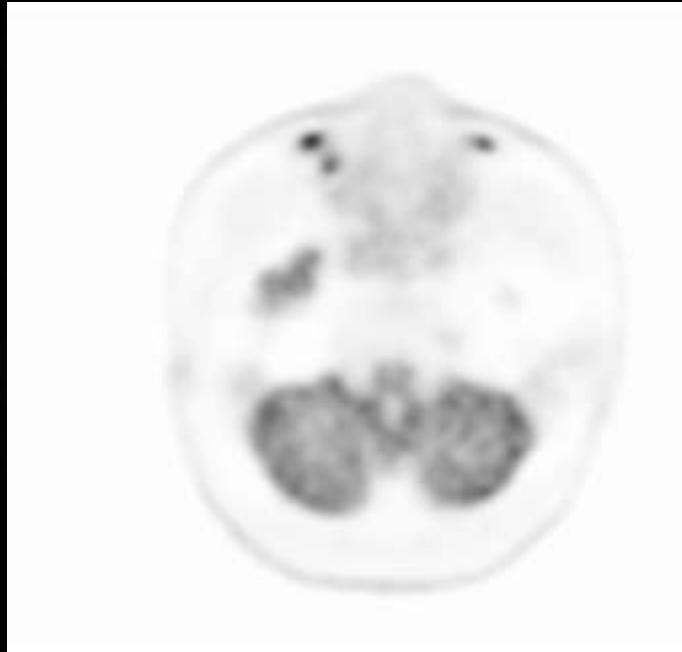
uPMR 790 HD TOF PET/MR



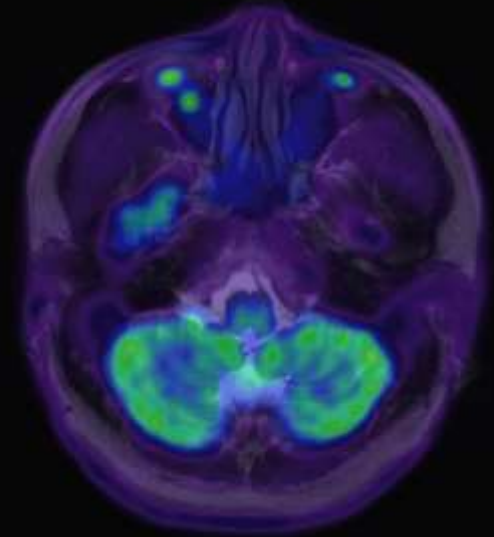
Clinical applications of PET/MRI



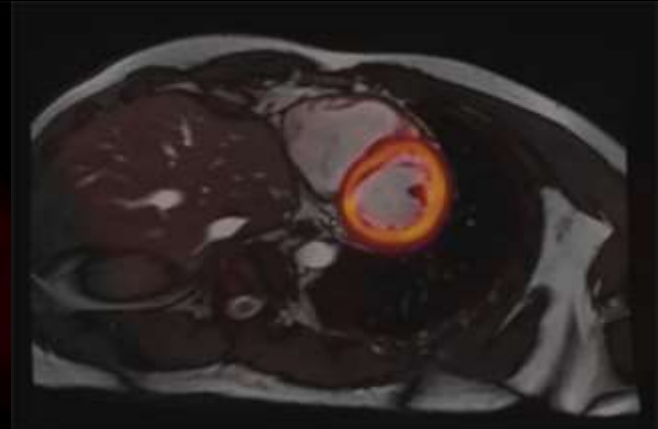
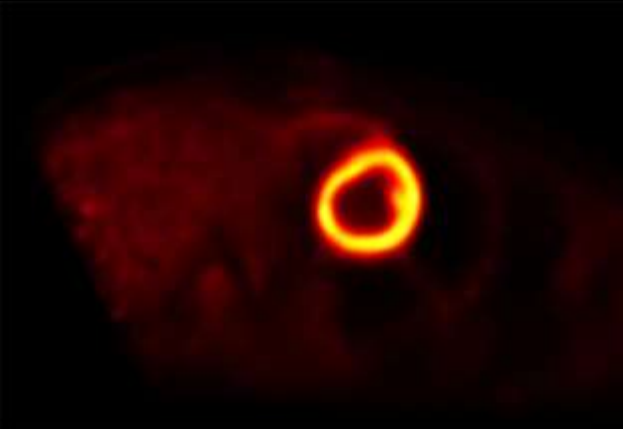
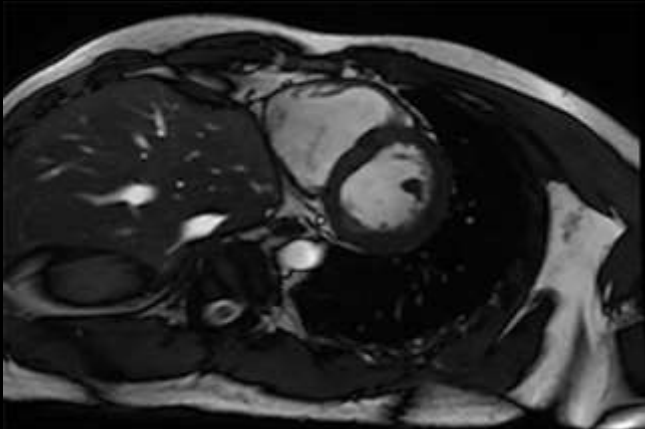
MRI



PET



PET-MRI



Artificial intelligence in medical physics

IN THIS BUILDING DURING THE SUMMER OF 1956
JOHN McCARTHY (DARTMOUTH COLLEGE), MARVIN L. MINSKY (MIT)
NATHANIEL ROCHESTER (IBM), AND CLAUDE SHANNON (BELL LABORATORIES)
CONDUCTED

THE DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE

FIRST USE OF THE TERM "ARTIFICIAL INTELLIGENCE"

FOUNDING OF ARTIFICIAL INTELLIGENCE AS A RESEARCH DISCIPLINE

"To proceed on the basis of the conjecture
that every aspect of learning or any other feature of intelligence
can in principle be so precisely described that a machine can be made to simulate it."

IN COMMEMORATION OF THE PROJECT'S 50th ANNIVERSARY
JULY 13, 2006



John



He



Il



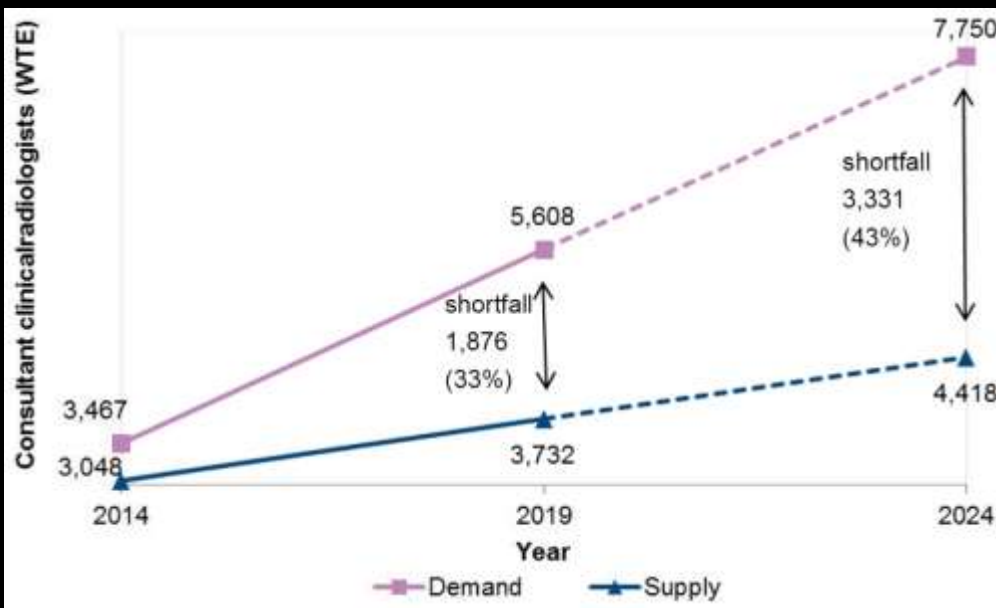
ore

12
Biology
nac

Why do we need AI in medical imaging?

- We are likely to see that many operator-dependent tasks will become increasingly automated to address staff shortages and the increasing demand for medical imaging examinations in an ageing population.

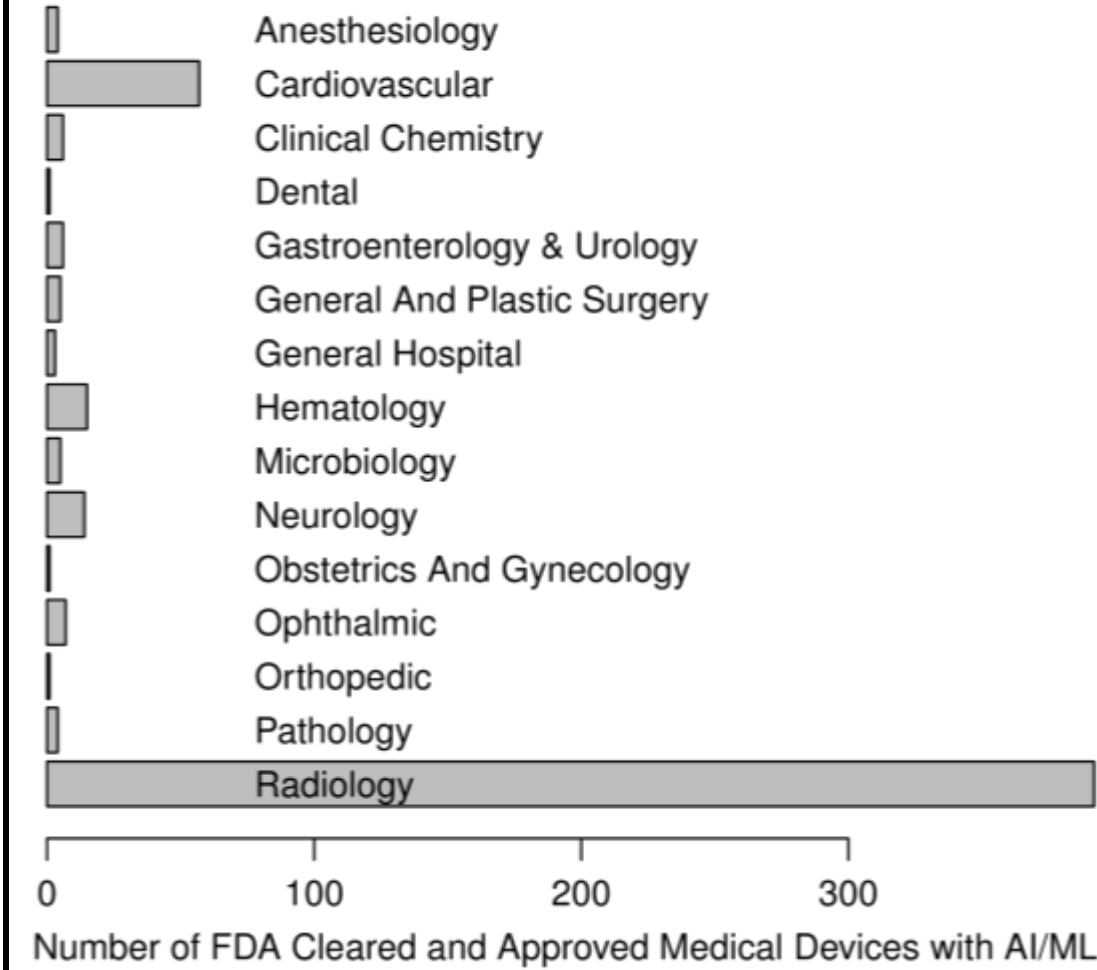
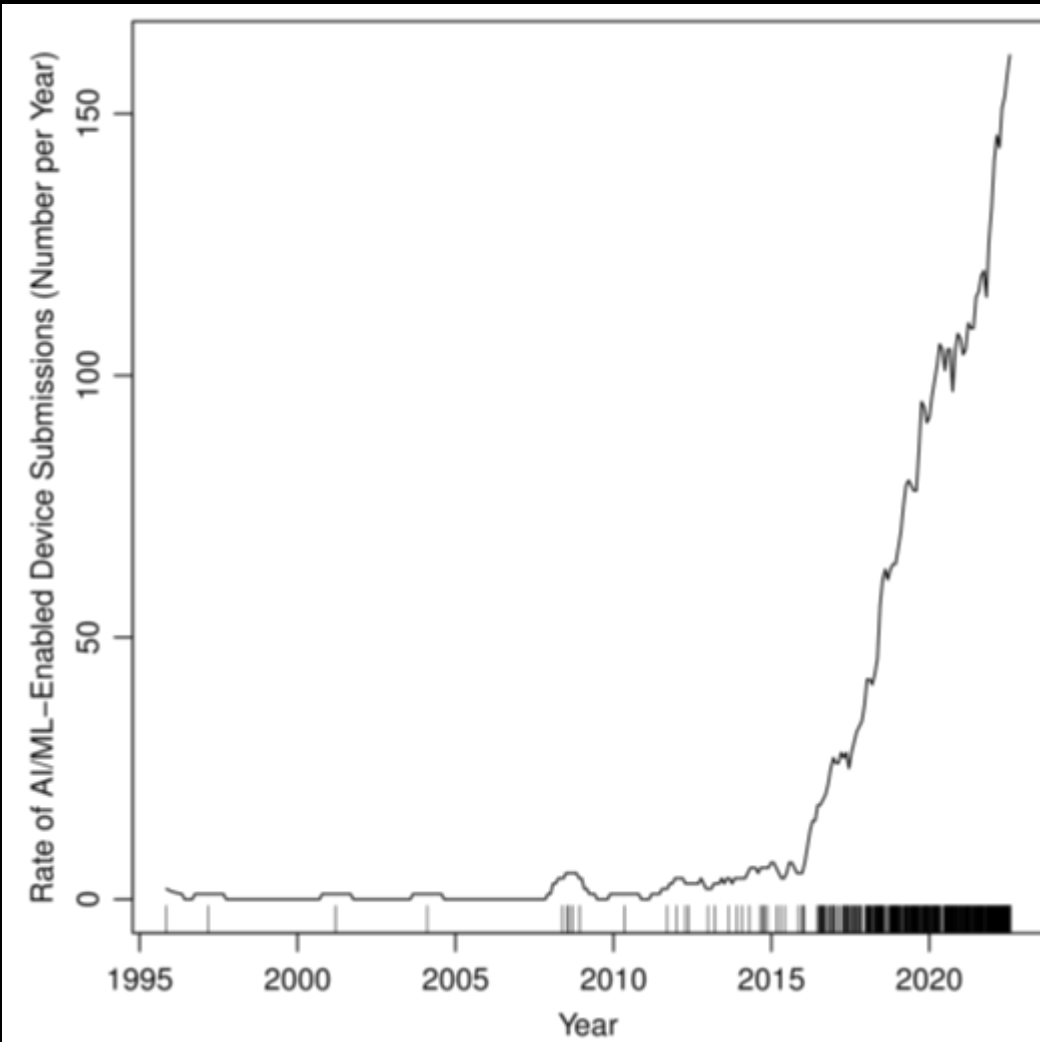
UK consultant radiologist supply and demand



Closing the gap

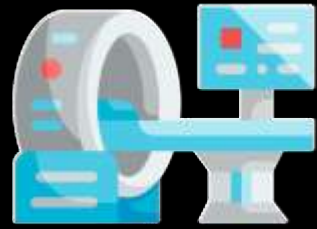
- Increasingly automated diagnosis of routine cases supported by clinical support systems
- Radiologists focus on difficult cases
- Radiologists not only provide reports but are involved in clinical decision-making or provide clinical decisions

AI/ML/CAD devices by FDA's product areas



Artificial intelligence impacting radiology

Radiology Framework



Data Acquisition

Image Processing

Quality Control and Assurance

Data Management

Detection and Quantification

Quantitative Image Analysis

Fast Acquisition

Data Correction

Image Quality Check

Data Compression

Image Segmentation

Diagnostic Modeling

Dose Reduction

Image Enhancement

Artifact Detection

Privacy Preserving

Quantification

Prognostic Modeling

Protocol Optimization

Image Denoising

Artifact Disentanglement

Decentralized Federated Learning

Image Biomarker Standardization

Radiogenomics Modeling

Image Registration

Harmonization

Report Generation

Image Reconstruction

Personalized Dose Estimation

AI in Radiology for Automation and Improvement of Framework

Comparative study of algorithms for synthetic CT generation from MRI: Consequences for MRI-guided radiation planning in the pelvic region

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Division of Nuclear Medicine and Molecular Imaging, Geneva University Hospital, Geneva CH-1211, Switzerland

Jason A. Dowling

CSIRO Australian e-Health Research Centre, Herston, QLD, Australia

Ninon Burgos

Inria Paris, Aramis Project-Team, Institut du Cerveau et de la Moelle épinière, ICM, Inserm U 1127, CNRS UMR 7225 Sorbonne Université, Paris F-75013, France

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University of Newcastle, Callaghan, NSW, Australia*

Nikolaos Koutsouvelis

Division of Radiation Oncology, Geneva University Hospital, Geneva CH-1211, Switzerland

Habib Zaidi^{a)}

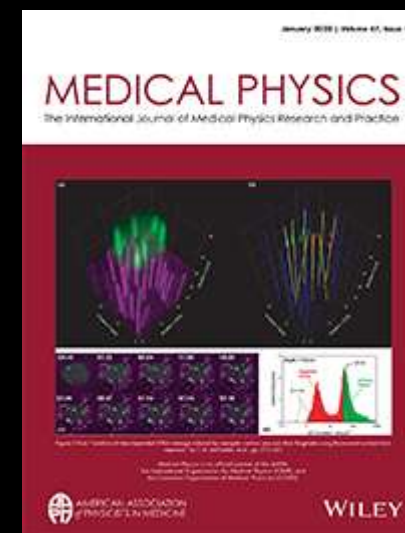
*Division of Nuclear Medicine and Molecular Imaging, Geneva University Hospital, Geneva CH-1211, Switzerland
Geneva University Neurocenter University of Geneva, Geneva 1205, Switzerland
Department of Nuclear Medicine and Molecular Imaging, University of Groningen, Groningen, the Netherlands
Department of Nuclear Medicine, University of Southern Denmark, Odense DK-500, Denmark*

(Received 7 June 2018; revised 29 July 2018; accepted for publication 6 September 2018;
published xx xxxx xxxx)

Purpose: Magnetic resonance imaging (MRI)-guided radiation therapy (RT) treatment planning is limited by the fact that the electron density distribution required for dose calculation is not readily provided by MR imaging. We compare a selection of novel synthetic CT generation algorithms recently reported in the literature, including segmentation-based, atlas-based and machine learning techniques, using the same cohort of patients and quantitative evaluation metrics.

Methods: Six MRI-guided synthetic CT generation algorithms were evaluated: one segmentation technique into a single tissue class (water-only), four atlas-based techniques, namely, median value of atlas images (ALMedian)¹, atlas-based local weighted voting (ALWV)², bone enhanced atlas-based local weighted voting (ALWV-Bone)³, iterative atlas-based local weighted voting (ALWV-Iter)⁴, and a machine learning technique using **deep convolution neural network (DCNN)**⁵.

Results: Organ auto-contouring from MR images was evaluated for bladder, rectum, bones, and body boundary. **Overall, DCNN exhibited higher segmentation accuracy resulting in Dice indices (DSC) of 0.93 ± 0.17 , 0.90 ± 0.04 , and 0.93 ± 0.02 for bladder, rectum, and bones, respectively.** On the other hand, ALMedian showed the lowest accuracy with DSC of 0.82 ± 0.20 , 0.81 ± 0.08 , and 0.88 ± 0.04 , respectively. DCNN reached the best performance in terms of accurate derivation





Article

Depth of Interaction Estimation in a Preclinical PET Scanner Equipped with Monolithic Crystals Coupled to SiPMs Using a Deep Neural Network

Amirhossein Sanaat ¹ and Habib Zaidi ^{1,2,3,4,*}

¹ Division of Nuclear Medicine and Molecular Imaging, Geneva University Hospital, CH-1211 Geneva, Switzerland; amirhossein.sanaat@etu.unige.ch

² Geneva University Neurocenter, Geneva University, 1205 Geneva, Switzerland

³ Department of Nuclear Medicine and Molecular Imaging, University of Groningen, University Medical Center Groningen, 9700 RB Groningen, The Netherlands

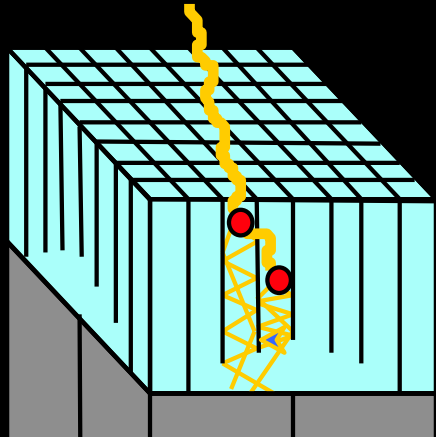
⁴ Department of Nuclear Medicine, University of Southern Denmark, DK-500 Odense, Denmark

* Correspondence: habib.zaidi@hcuge.ch; Tel.: +41-22-372-7258; Fax: +41-22-372-7169

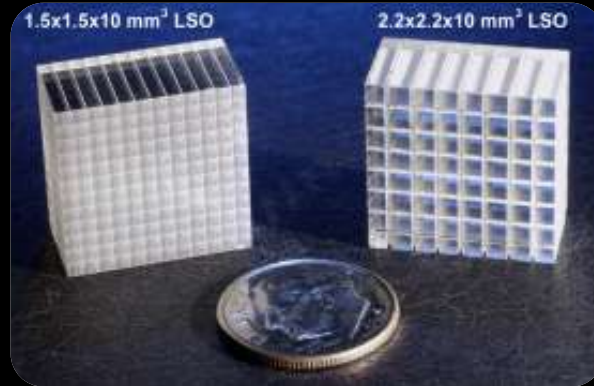
Received: 6 June 2020; Accepted: 8 July 2020; Published: 10 July 2020

Deep learning-guided estimation of DOI

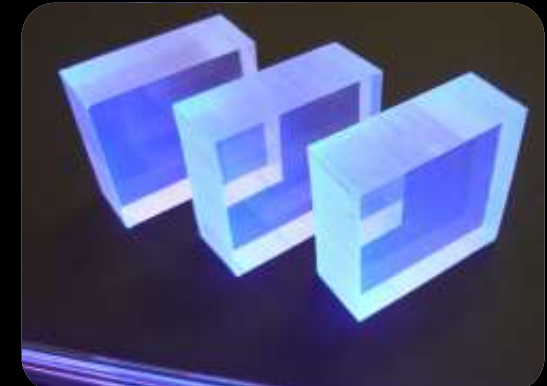
511 keV



Pixelated crystals



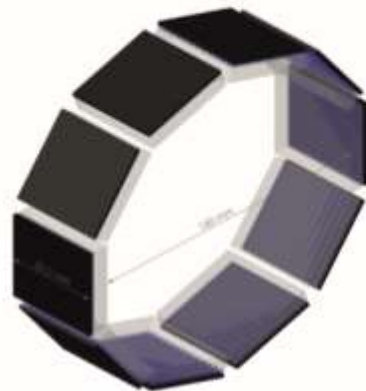
Monolithic crystal



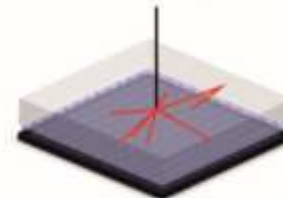
3D positioning in a monolithic crystal using deep learning



PET scanner with monolithic crystal



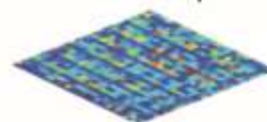
Monolithic crystal



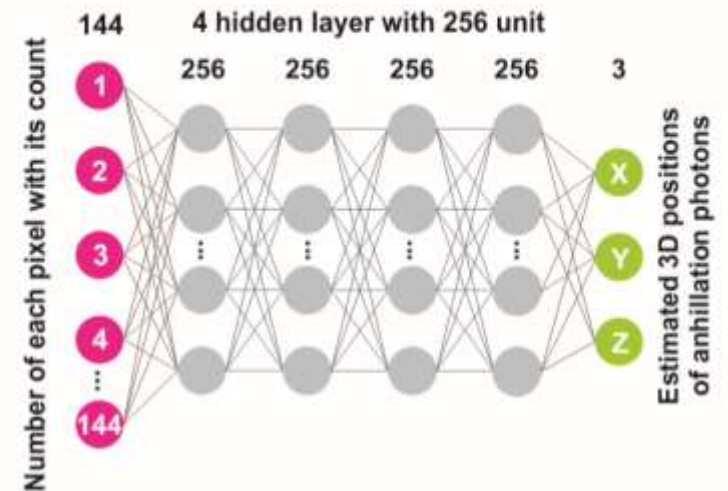
SiPM



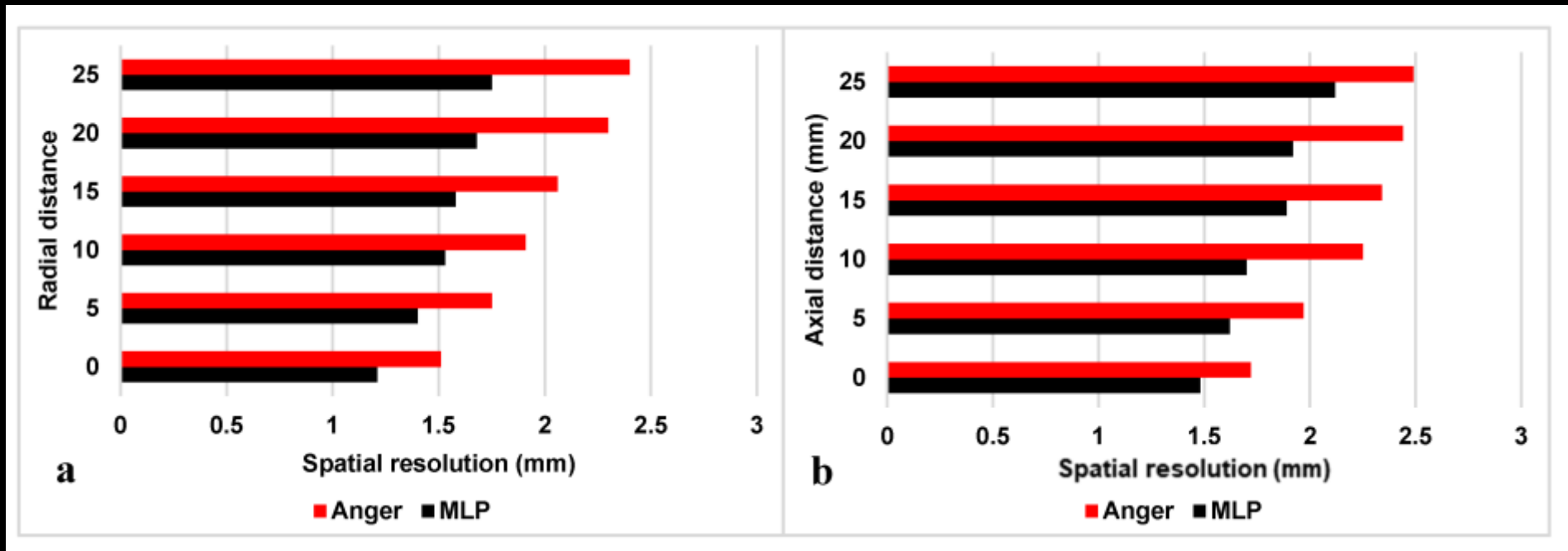
Heat map



Multi layer perception



Deep learning-guided estimation of DOI



Anger

MLP

$\phi=1.25, d=2.5$ mm

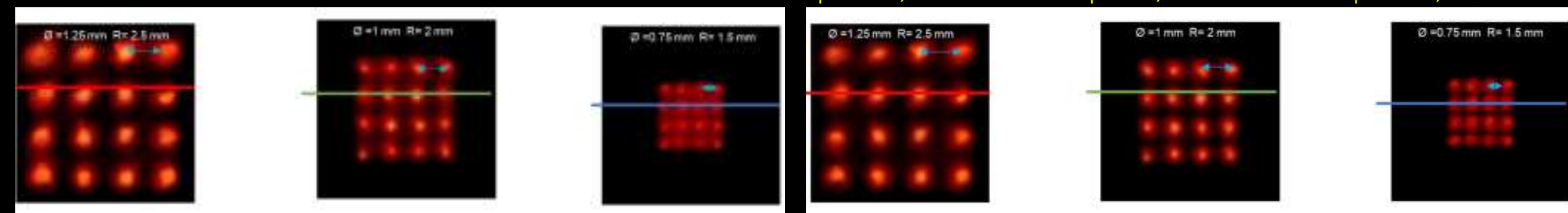
$\phi=1.0, d=2.0$ mm

$\phi=0.75, d=1.5$ mm

$\phi=1.25, d=2.5$ mm

$\phi=1.0, d=2.0$ mm

$\phi=0.75, d=1.5$ mm



Received: 11 August 2022

Accepted: 18 August 2022

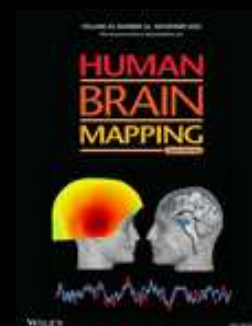
DOI: 10.1002/hbm.26068

RESEARCH ARTICLE

WILEY

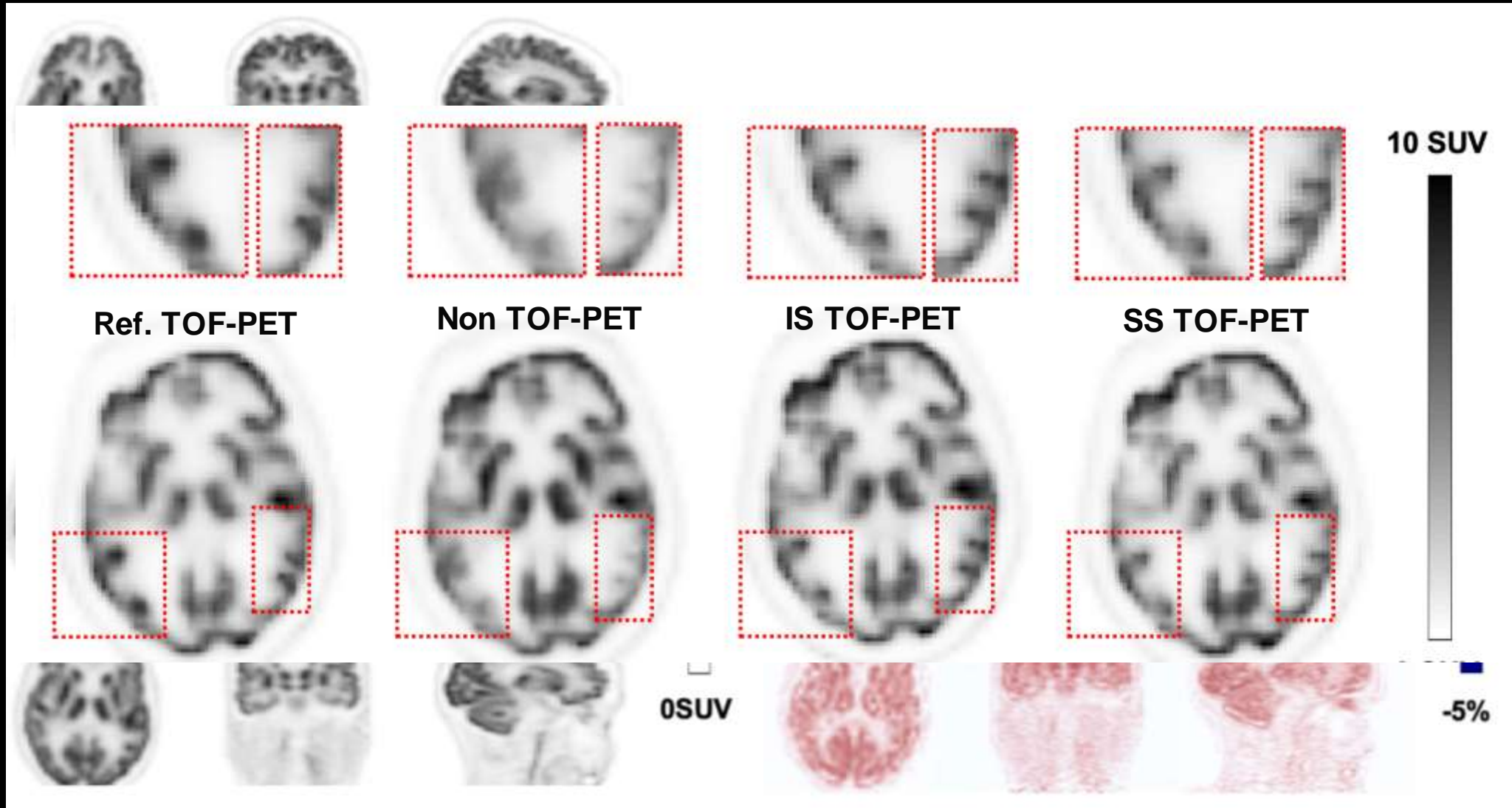
Deep-TOF-PET: Deep learning-guided generation of time-of-flight from non-TOF brain PET images in the image and projection domains

Amirhossein Sanaat¹  | Azadeh Akhavanalaf¹ | Isaac Shiri¹ | Yazdan Salimi¹ |
Hossein Arabi¹ | Habib Zaidi^{1,2,3,4} 



Generation of TOF-PET from non TOF-PET

SS TOF-PET IS TOF-PET Non TOF-PET Ref. TOF-PET




European Radiology (2021) 31:1420–1431
<https://doi.org/10.1007/s00330-020-07225-6>

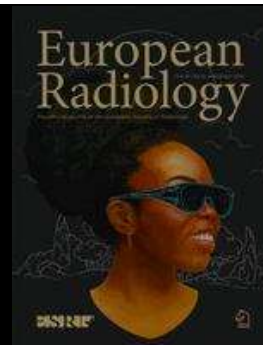
COMPUTED TOMOGRAPHY



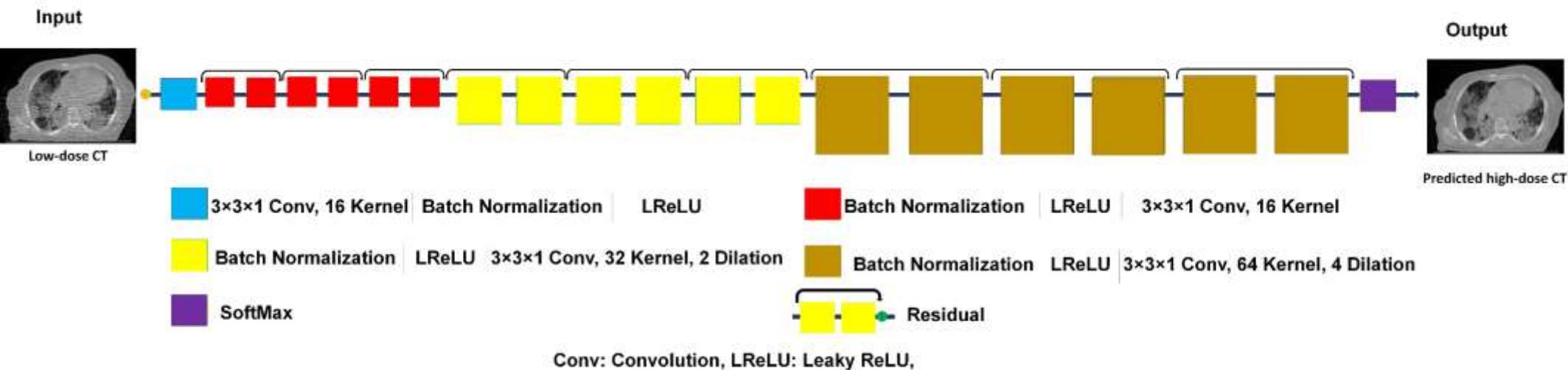
Ultra-low-dose chest CT imaging of COVID-19 patients using a deep residual neural network

Isaac Shiri¹ • Azadeh Akhavanallaf¹ • Amirhossein Sanaat¹ • Yazdan Salimi¹ • Dariush Askari² • Zahra Mansouri³ • Sajad P. Shayesteh⁴ • Mohammad Hasanian⁵ • Kiara Rezaei-Kalantari⁶ • Ali Salahshour⁷ • Saleh Sandoughdaran⁸ • Hamid Abdollahi⁹ • Hossein Arabi¹ • Habib Zaidi^{1,10,11,12} 

Received: 9 June 2020 / Revised: 13 August 2020 / Accepted: 21 August 2020 / Published online: 3 September 2020
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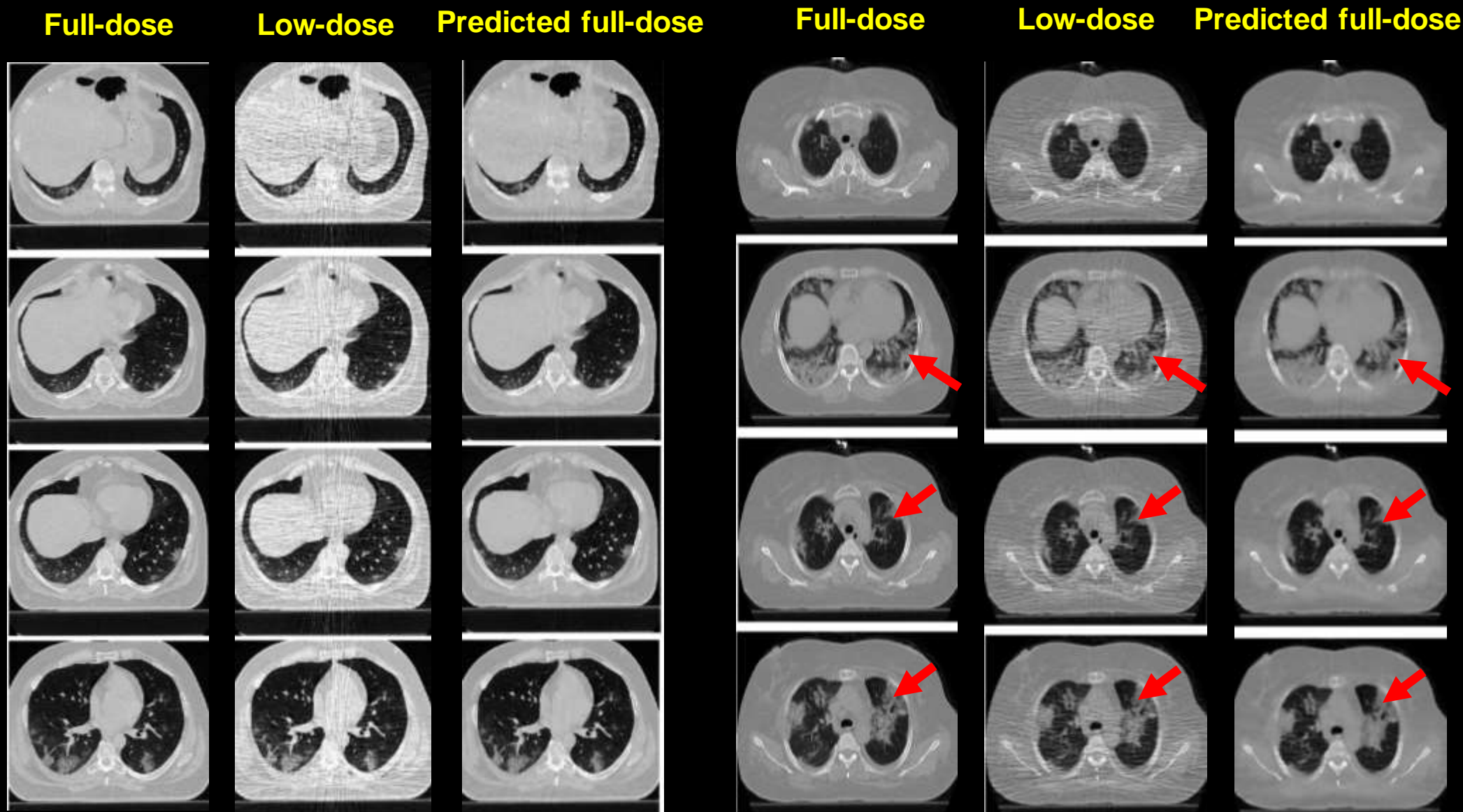
Deep learning-guided low-dose CT imaging



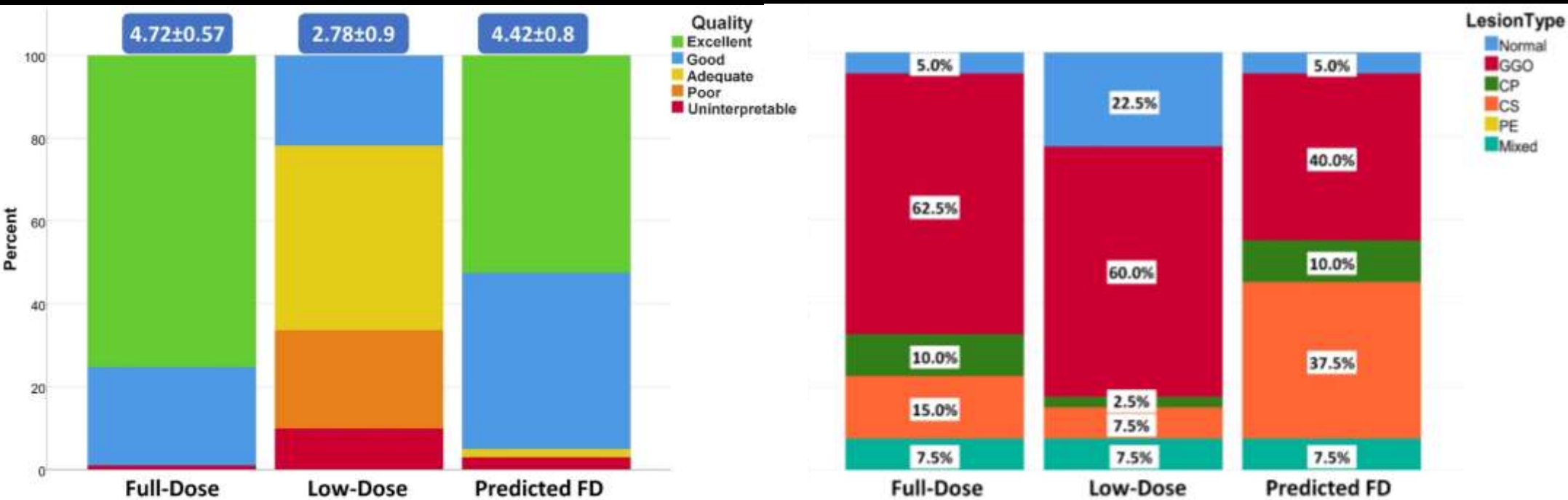
Acquisition parameters of full-dose and low-dose chest CT protocols of COVID-19 patients.

Parameters	Full-dose CT	Low-dose CT
CTDI _{vol} (mGy)	6.5 (4.16-10.5)	0.72 (0.66-1.03)
Voltage (kVp)	100-120	90
Tube current (mA)	100-150	20-45
Pitch factor	1.3-1.8	0.75

Deep learning-guided low-dose CT imaging



Deep learning-guided low-dose CT imaging



1 → uninterpretable 2 → poor 3 → adequate 4 → good 5 → excellent

Received: 10 June 2021

Revised: 18 September 2021



Accepted: 17 October 2021

DOI: 10.1002/ima.22672

RESEARCH ARTICLE

WILEY

COLI-Net: Deep learning-assisted fully automated COVID-19 lung and infection pneumonia lesion detection and segmentation from chest computed tomography images

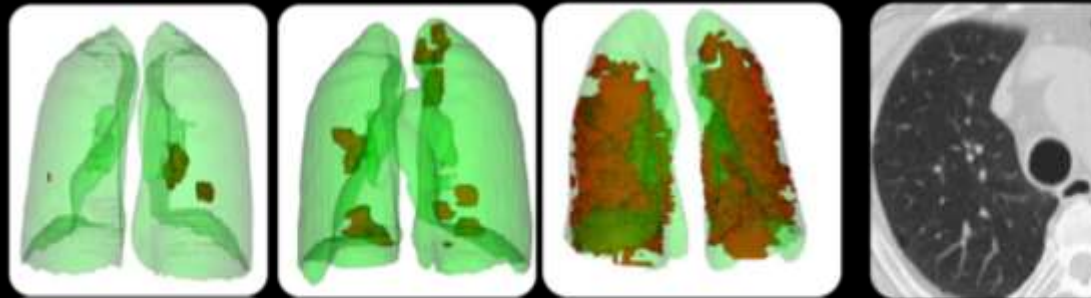
**Isaac Shiri¹  | Hossein Arabi¹ | Yazdan Salimi¹ | Amirhossein Sanaat¹ |
Azadeh Akhavanallaf¹ | Ghasem Hajianfar² | Dariush Askari³ |
Shakiba Moradi⁴ | Zahra Mansouri¹ | Masoumeh Pakbin⁵ |
Saleh Sandoughdaran⁶ | Hamid Abdollahi⁷ | Amir Reza Radmard⁸ |
Kiara Rezaei-Kalantari² | Mostafa Ghelich Oghli^{4,9} | Habib Zaidi^{1,10,11,12} **

DL-based segmentation of COVID-19

Clinical routine



Labor intensive
Time-consuming



High variability and complex

Shiri et al. (2021) ECR'2021
Shiri et al. (2022) Int J Imaging Syst Technol

ECR 2021
MARCH 3-7 VIENNA
POP-UP WORLD TOUR
ONLINE | ON DEMAND

Isaac Shiri
(Geneva/CH)

is hereby awarded:

ECR 2021 – Best Research Presentation Abstract
within the topic Imaging Informatics & Artificial Intelligence
with the presentation:

Fully automatic COVID-19 lung and pneumonia lesion segmentation from CT images (15797)
I. Shiri¹, H. Arabi¹, Y. Salimi¹, A. Sanaat¹, A. Akhavanalaf¹, G. Hajianfar², D. Askari², K. R. Kalantari², H. Zaidi¹; ¹Geneva/CH, ²Tehran/IR.

at

ECR 2021
March 3 - 7, 2021
Online

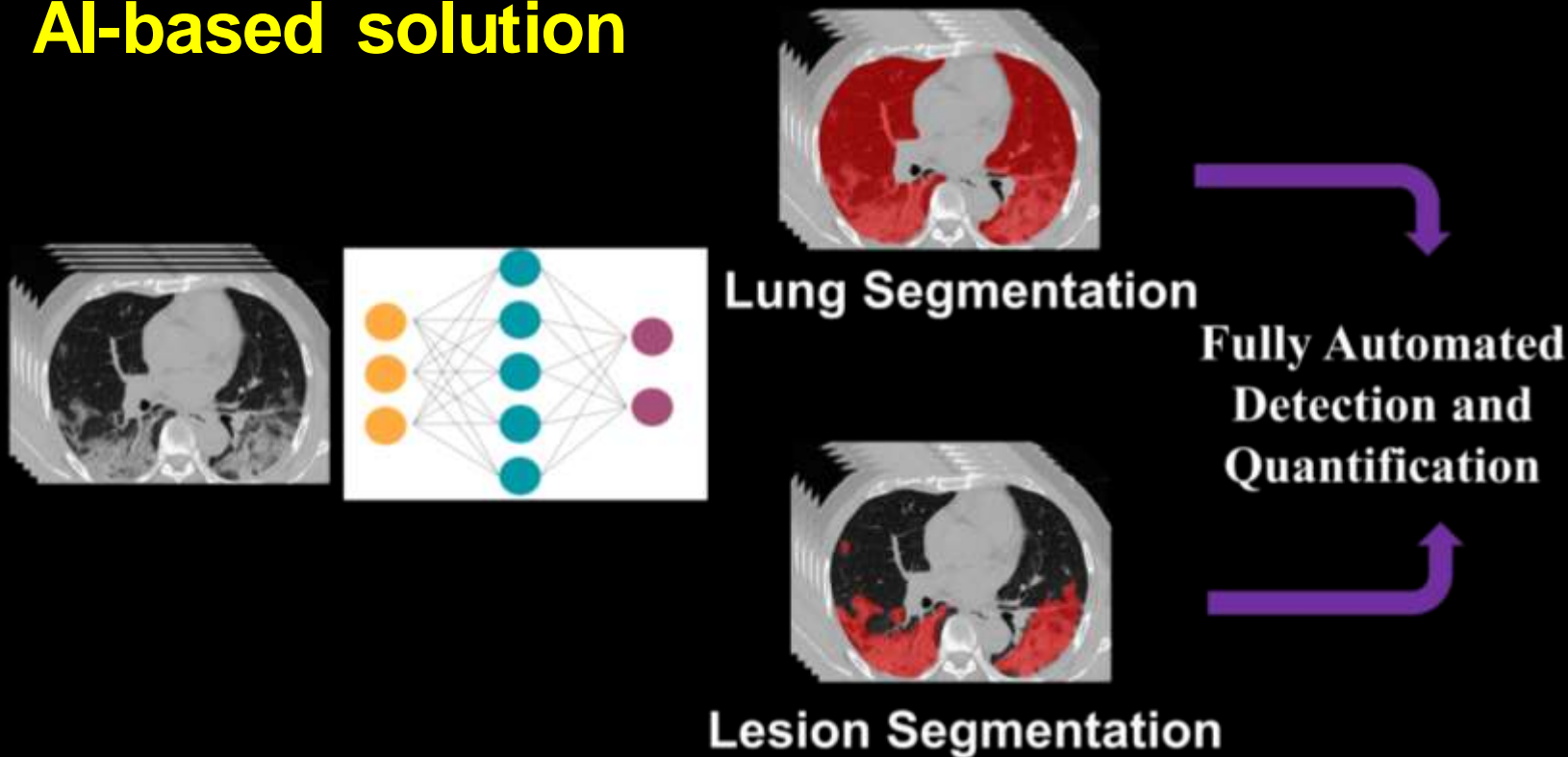


Prof. Dr. Michael H. Fuchsjäger
ESR President



DL-based segmentation of COVID-19 lesions

AI-based solution



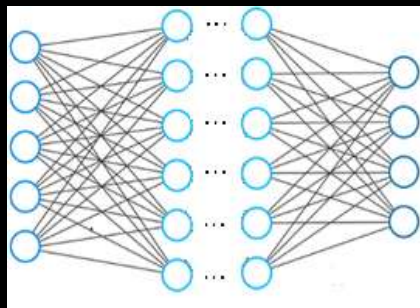
- ### Pathogens
- ✓ Mild
 - ✓ Moderate
 - ✓ Severe

- ### Centers
- ✓ USA
 - ✓ China
 - ✓ Russia
 - ✓ Italy
 - ✓ Iran

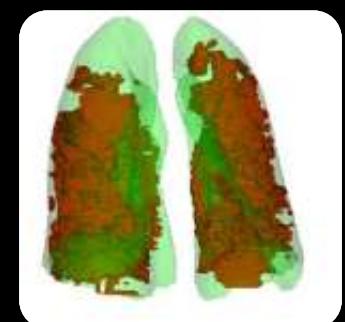
CT image



CNN



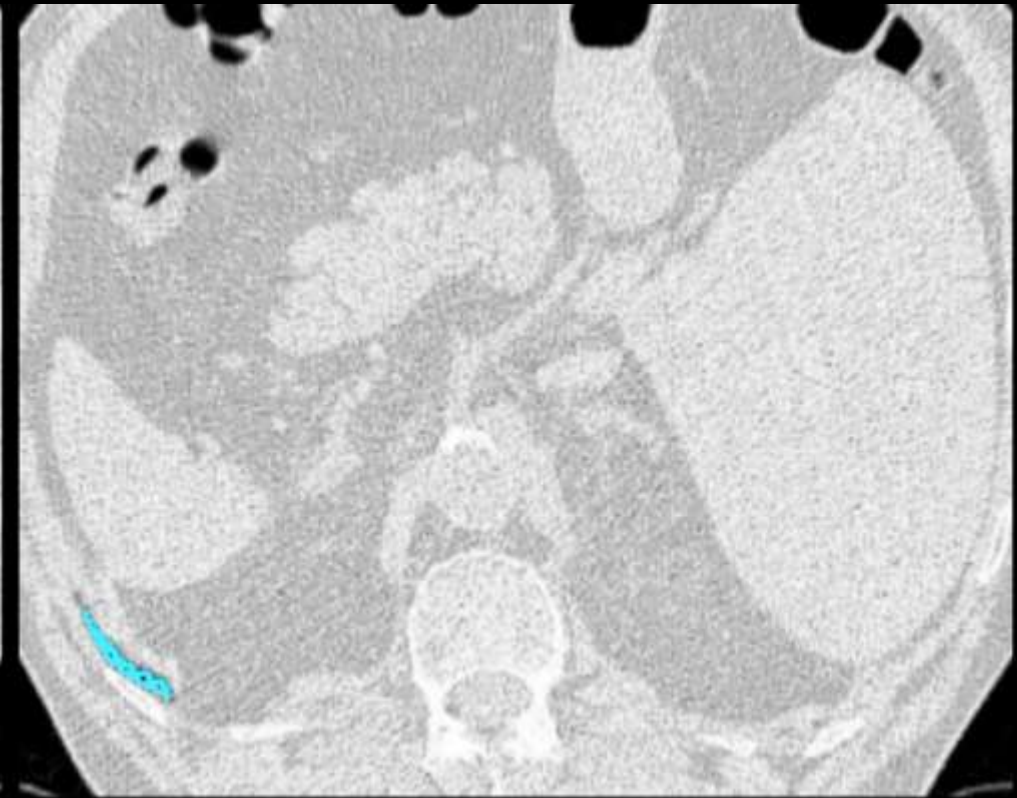
Segmented lungs/COVID lesions



DL-based segmentation of COVID-19 lesions

Radiologist Segmentation

AI Segmentation



Lung Manual

Lesion Manual

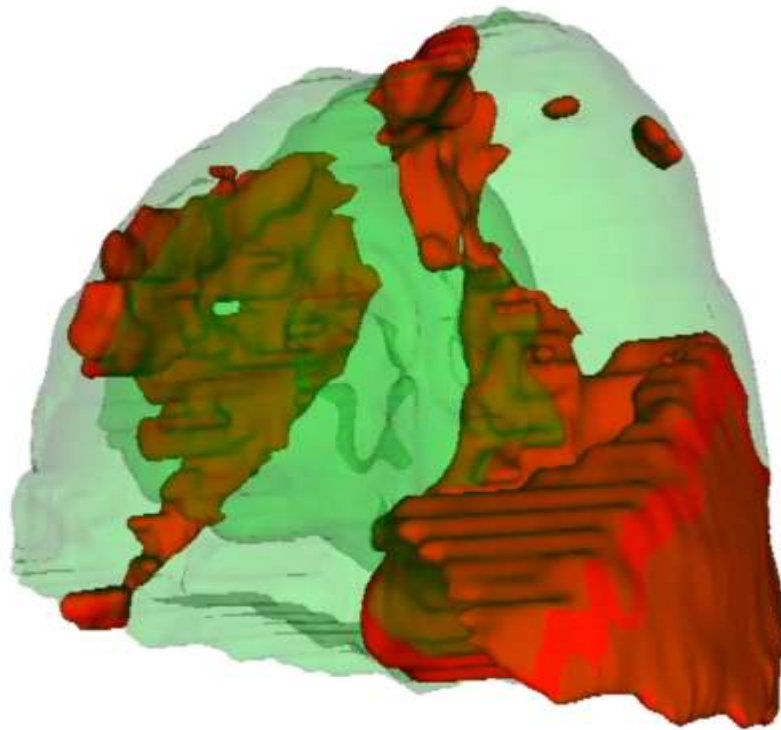
Lung Predicted

Lesion Predicted

DL-based segmentation of COVID-19 lesions

Radiologist Segmentation

AI Segmentation



Lung Manual

Lesion Manual



Lung Predicted

Lesion Predicted

Computational pregnant female phantoms

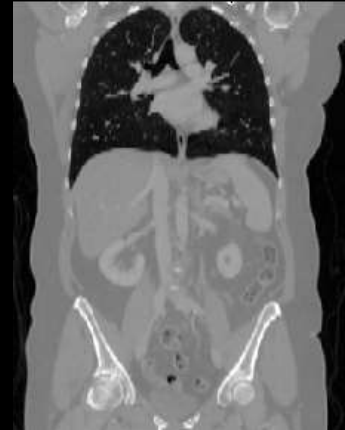
25w-gestation



30w-gestation



Thorax-abdo



Non-human primate



European Radiology (2019) 29:6805–6815
<https://doi.org/10.1007/s00330-019-06296-4>

PHYSICS

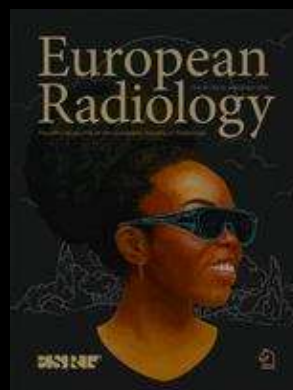


Estimation of the radiation dose in pregnancy: an automated patient-specific model using convolutional neural networks

Tianwu Xie¹ · Habib Zaidi^{1,2,3,4} 

Received: 23 April 2019 / Revised: 16 May 2019 / Accepted: 29 May 2019 / Published online: 21 June 2019

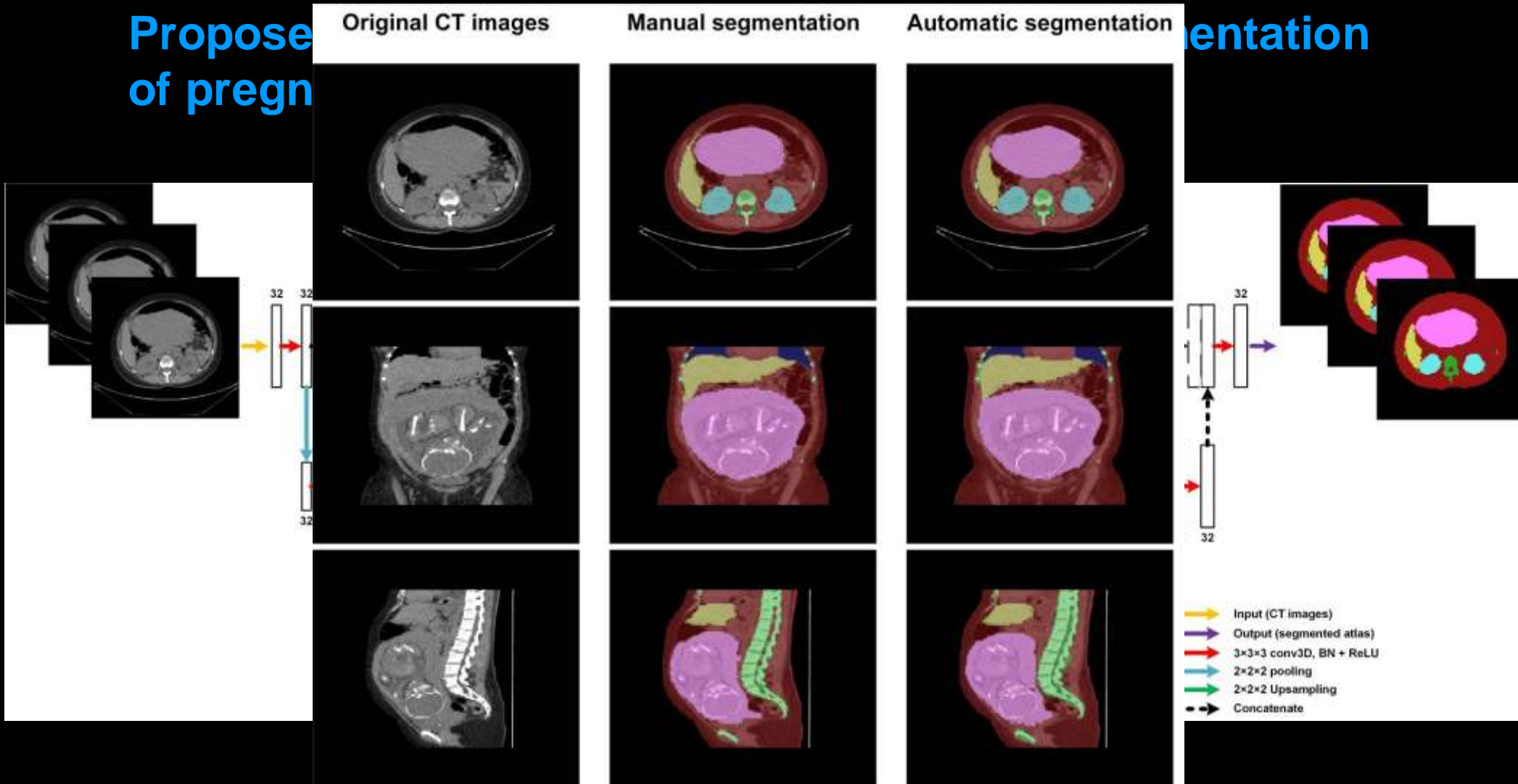
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Automated generation of anatomical models

Propose
of pregn

mentation



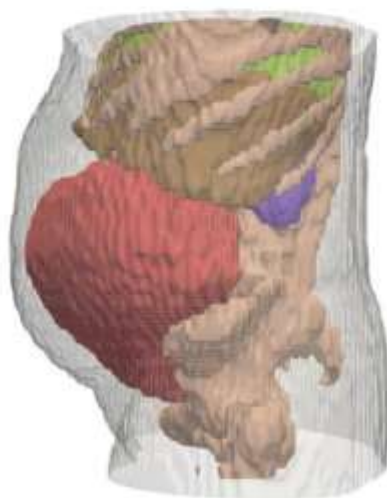
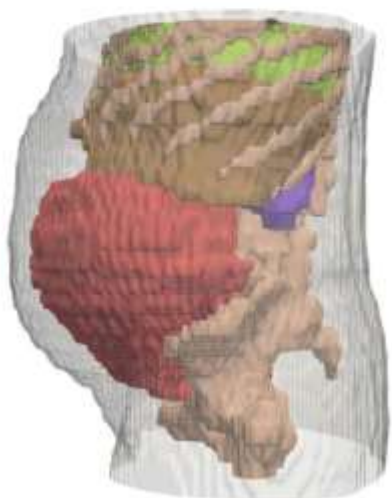
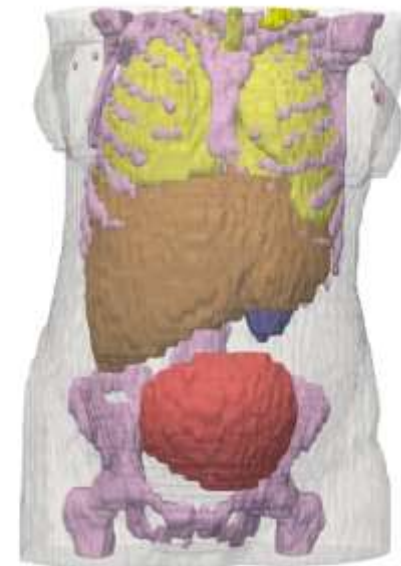
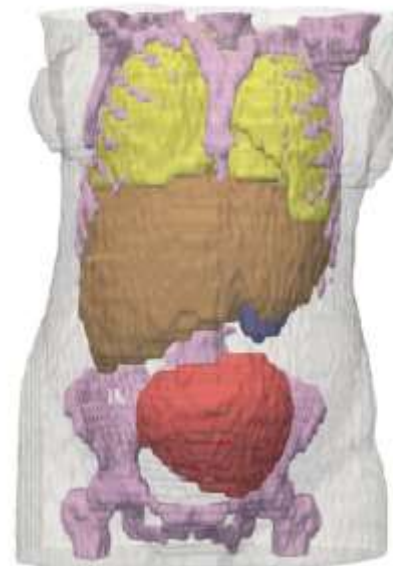
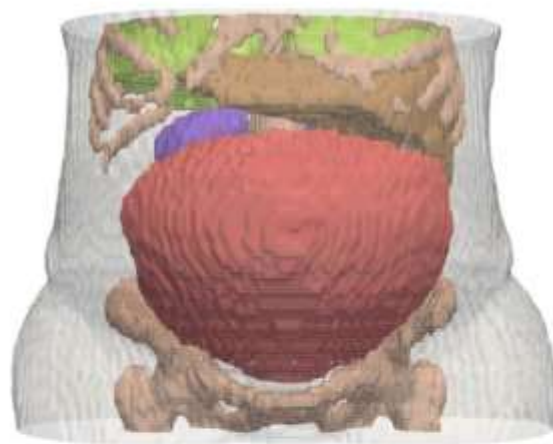
Automated generation of anatomical models

Manual segmentation

Automatic segmentation

Manual segmentation

Automatic segmentation



Deep learning-guided low-dose PET imaging


European Journal of Nuclear Medicine and Molecular Imaging

<https://doi.org/10.1007/s00259-020-05167-1>

ORIGINAL ARTICLE



Deep learning-assisted ultra-fast/low-dose whole-body PET/CT imaging

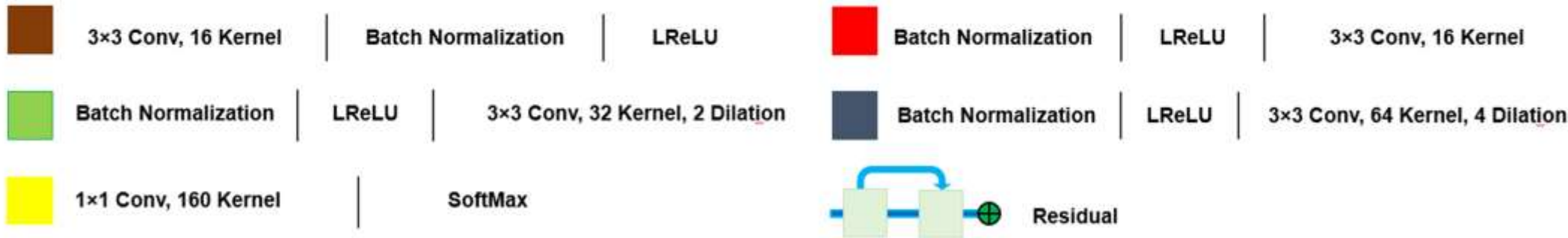
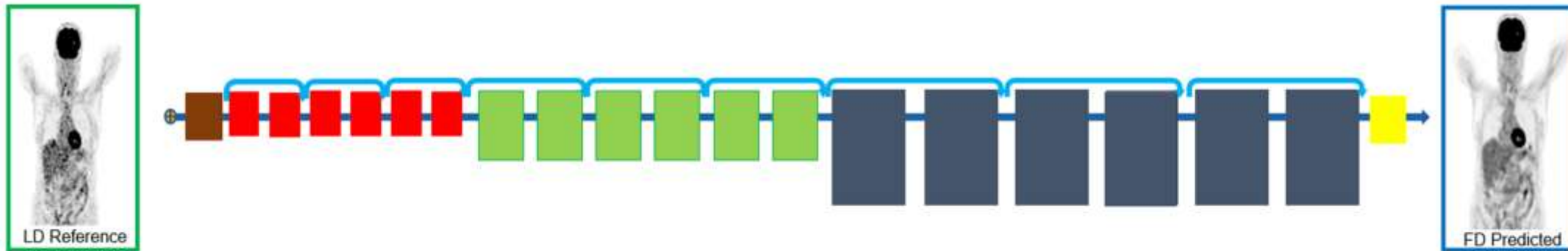
Amirhossein Sanaat¹ · Isaac Shiri¹ · Hossein Arabi¹ · Ismini Mainta¹ · René Nkoulou¹ · Habib Zaidi^{1,2,3,4} 

Received: 5 October 2020 / Accepted: 15 December 2020

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Deep learning-guided low-dose PET imaging



Conv: Convolution, LReLU: Leaky ReLU,

Deep learning-guided low-dose PET imaging

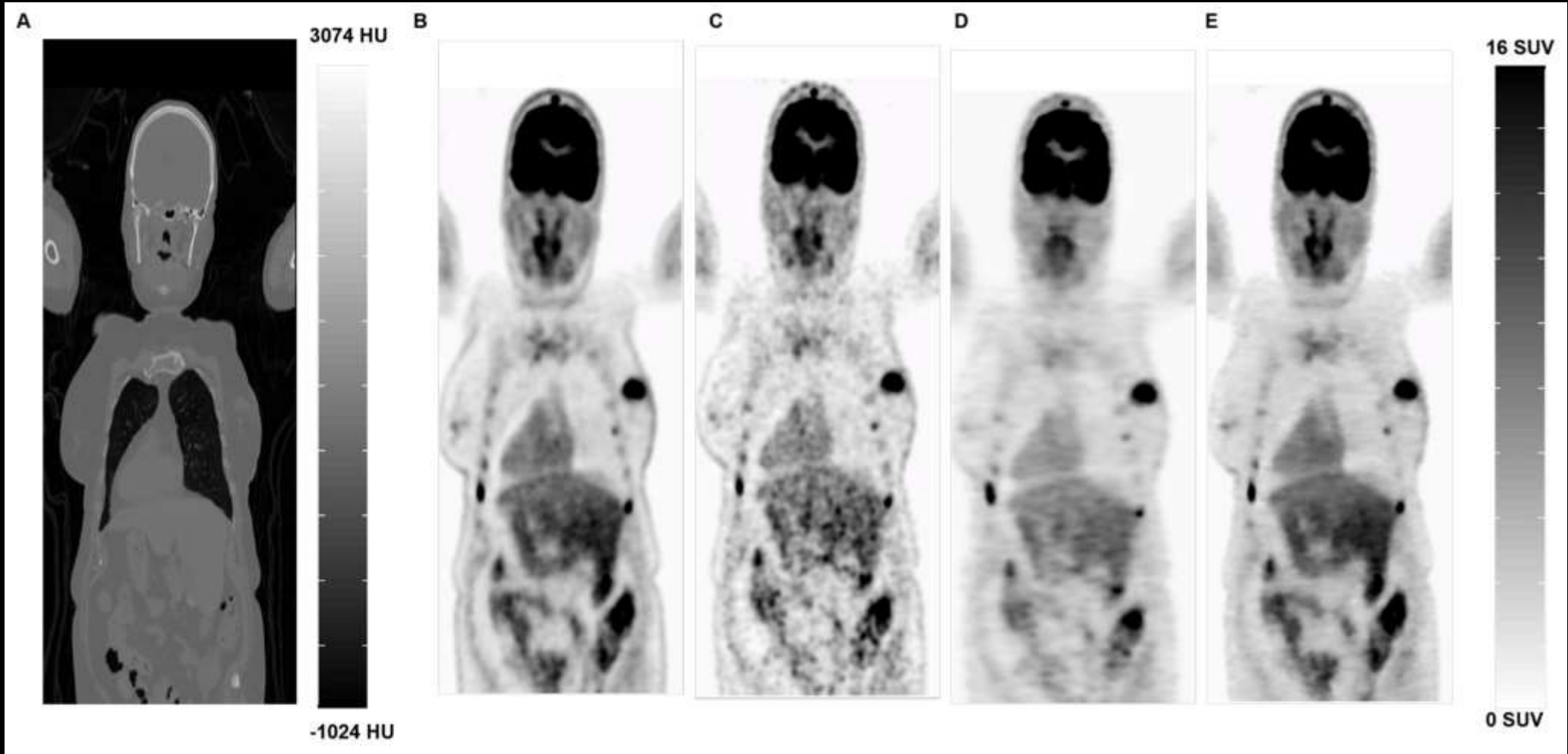
Low-dose CT

Full dose PET

Low dose PET

Pred. PET (RNET)

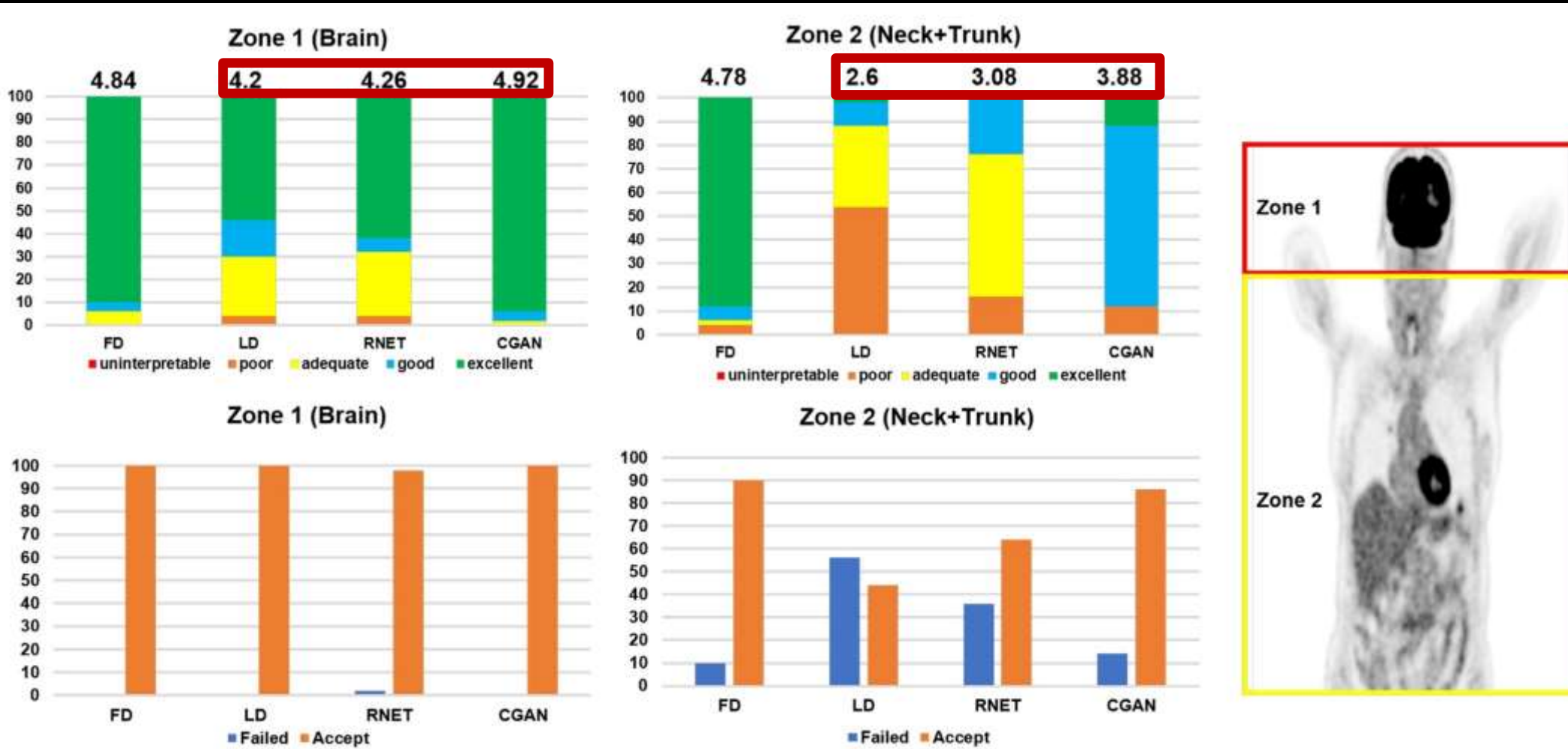
Pred. PET (CGAN)



0.7 mm/s
(3 min/bed)

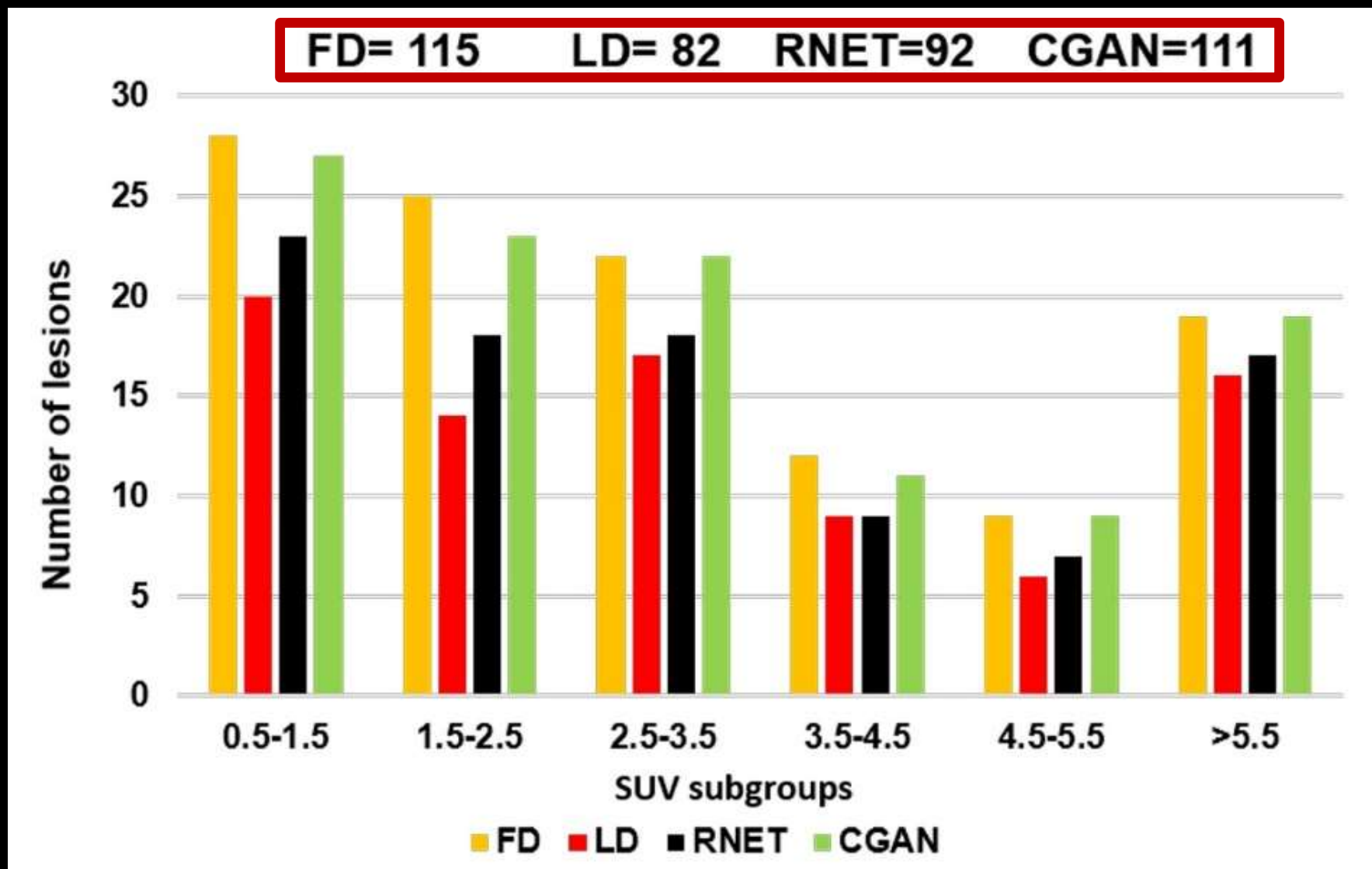
5 mm/s
(25 sec/bed)

Deep learning-guided low-dose PET imaging



1 = uninterpretable 2 = poor 3 = adequate 4 = good 5 = excellent

Deep learning-guided low-dose PET imaging



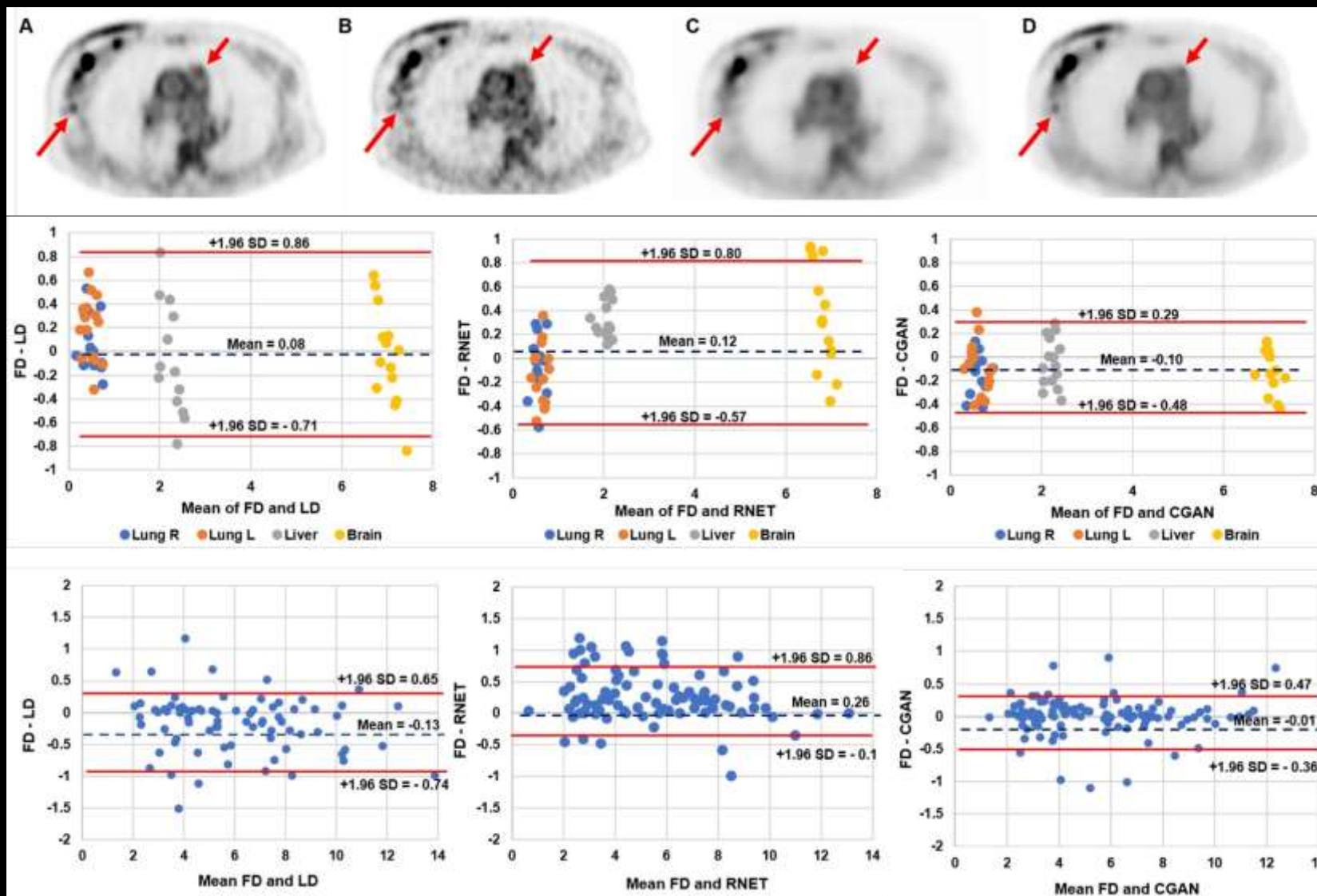
Deep learning-guided low-dose PET imaging

Full dose PET

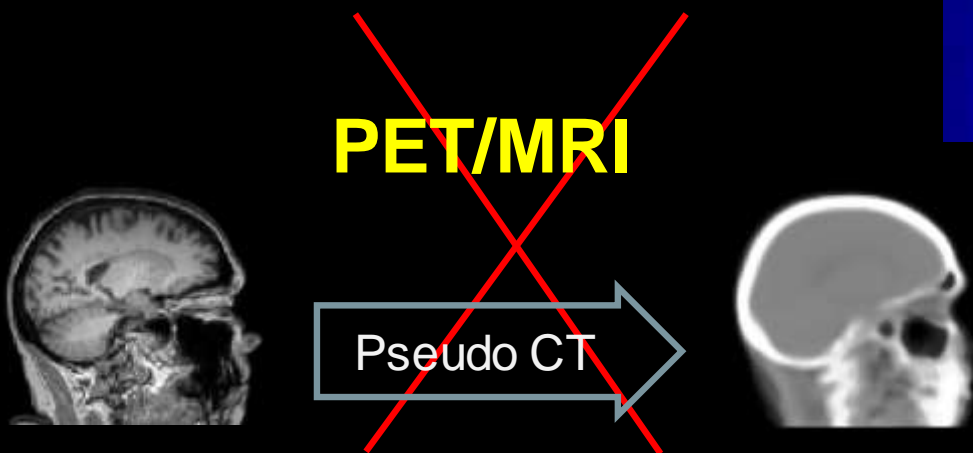
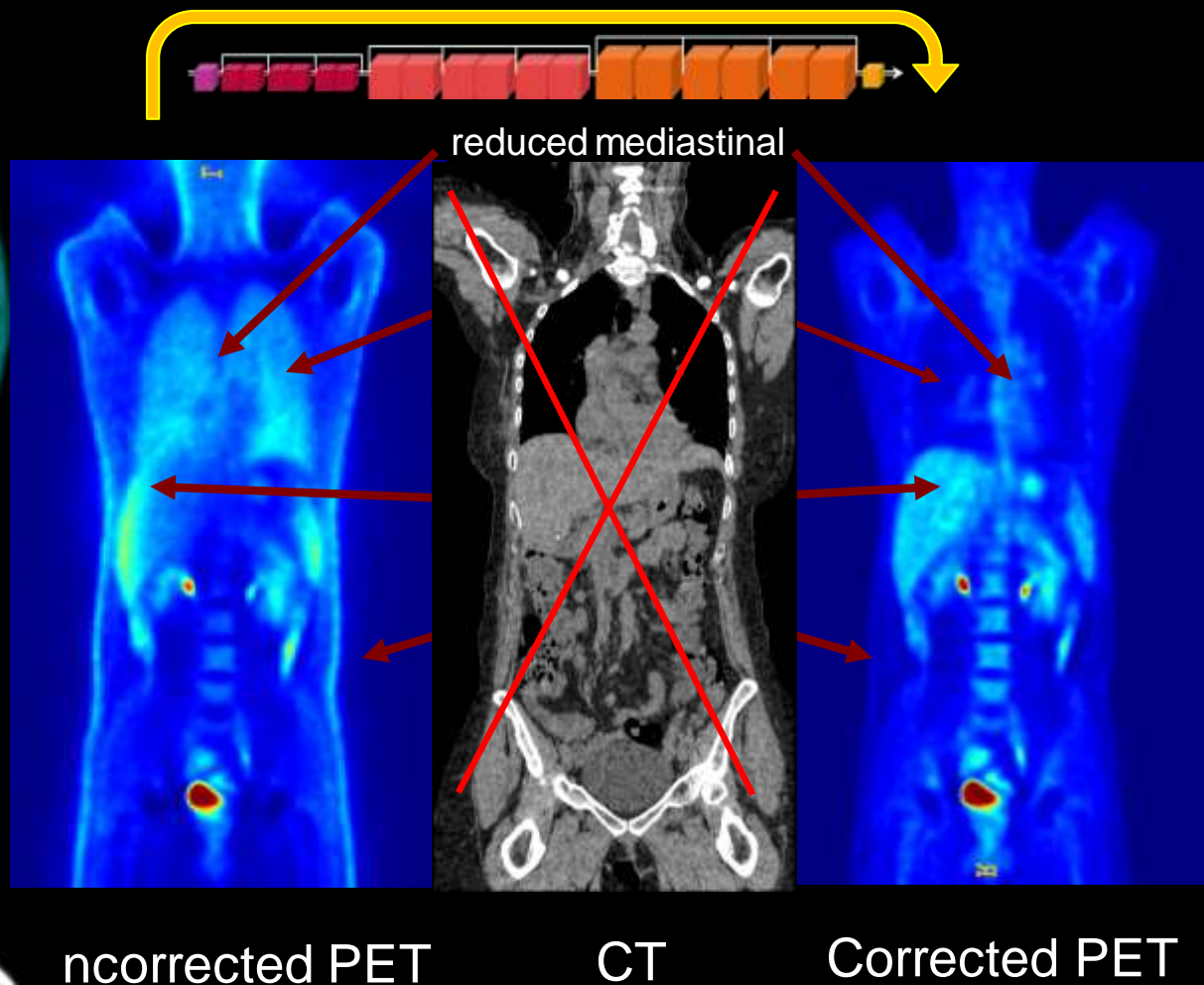
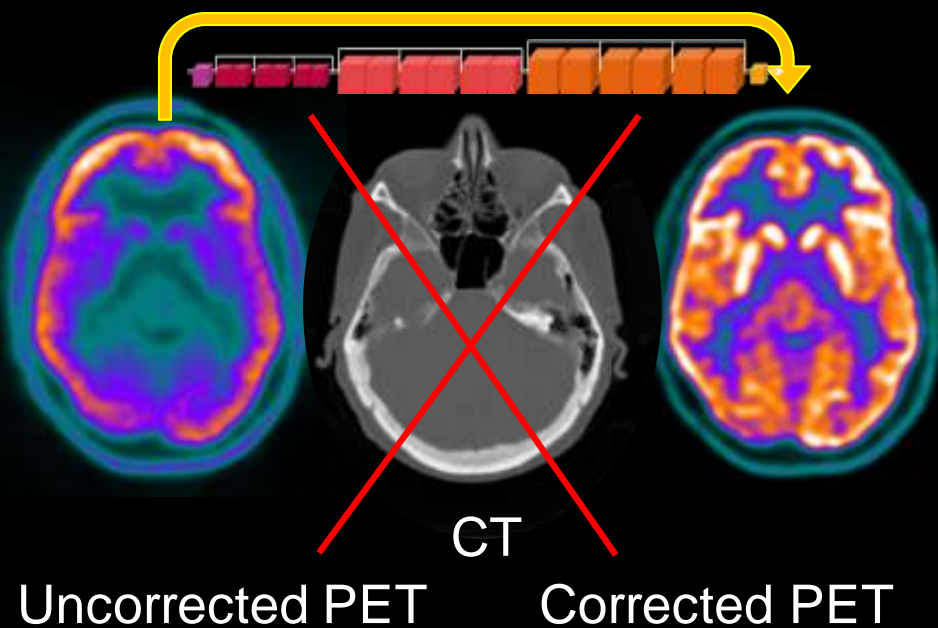
Low dose PET

Pred. PET (RNET)

Pred. PET (CGAN)



CT-based attenuation correction (Reference)



MRI-guided AC in PET/MRI using deep learning

European Journal of Nuclear Medicine and Molecular Imaging (2019) 46:2746–2759

<https://doi.org/10.1007/s00259-019-04380-x>

ORIGINAL ARTICLE



Novel adversarial semantic structure deep learning for MRI-guided attenuation correction in brain PET/MRI

Hossein Arabi¹ · Guodong Zeng² · Guoyan Zheng^{2,3} · Habib Zaidi^{1,4,5,6} 

Received: 5 February 2019 / Accepted: 28 May 2019 / Published online: 1 July 2019

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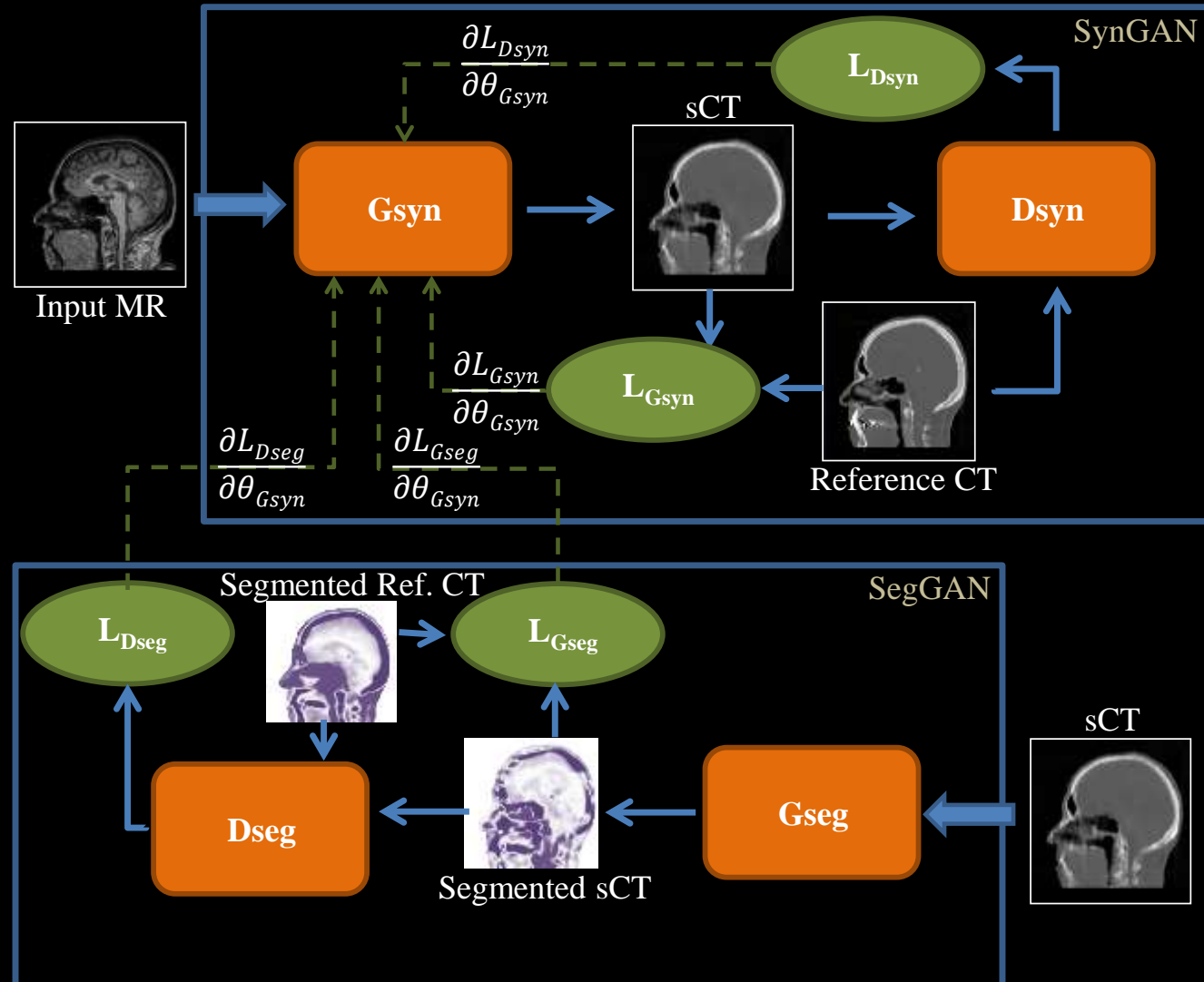


Deep learning for MRI-guided AC in PET/MRI

Proposed deep convolutional neural network

Adversarial semantic structure learning (DL-AdvSS)

- Two generative adversarial cores for CT synthesis (SynGAN) and semantic structure extraction (SegGAN)
- L2-norm and cross-entropy loss functions
- SynGAN core contains 22 layers whereas SegGAN core 16 layers
- In total, DL-AdvSS involves 54,408,932 trainable parameters

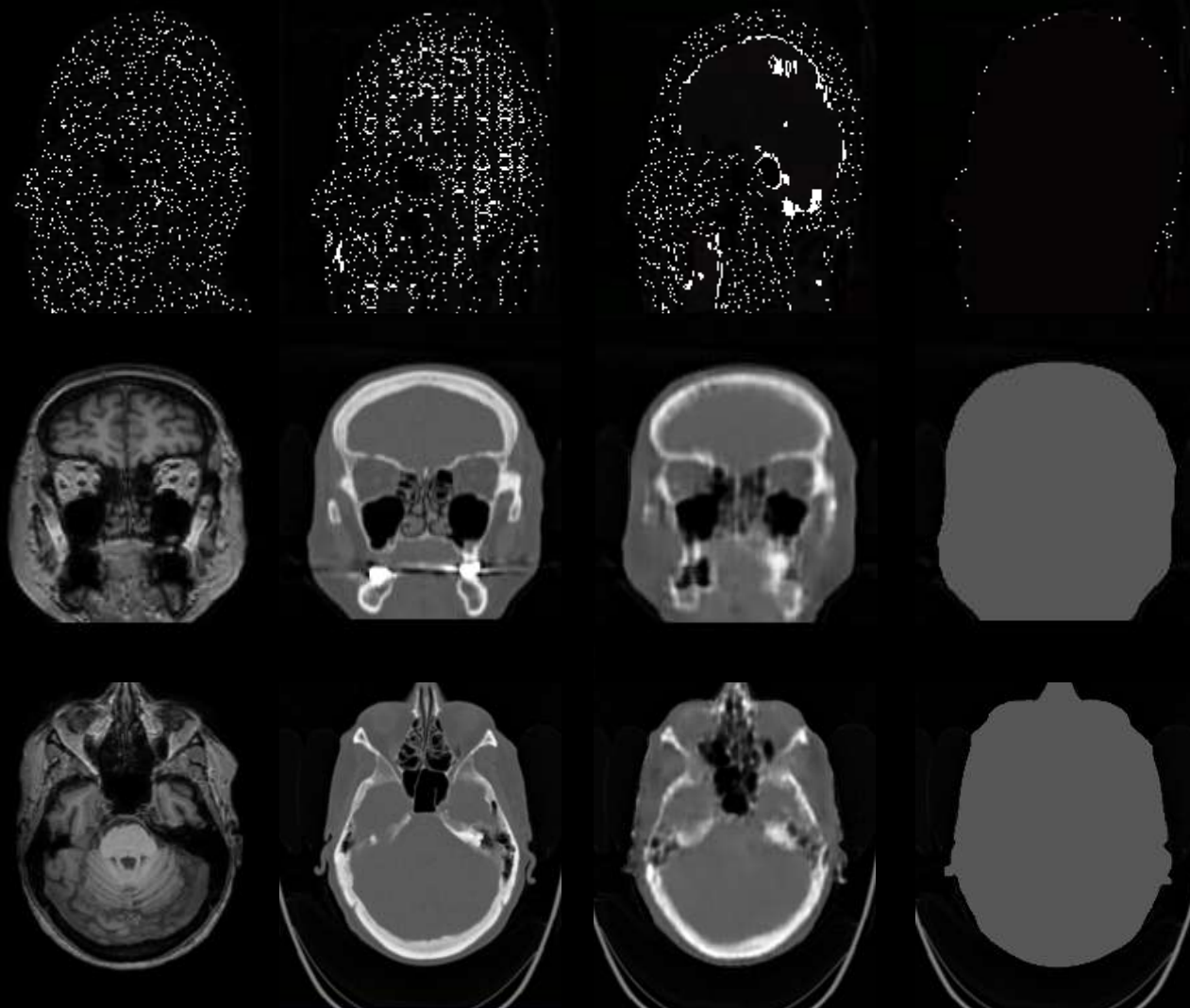


Deep learning for MRI-guided AC in PET/MRI

MRI

CT

Deep learning Segmentation




European Journal of Nuclear Medicine and Molecular Imaging

<https://doi.org/10.1007/s00259-020-04852-5>

ORIGINAL ARTICLE



Deep-JASC: joint attenuation and scatter correction in whole-body ^{18}F -FDG PET using a deep residual network

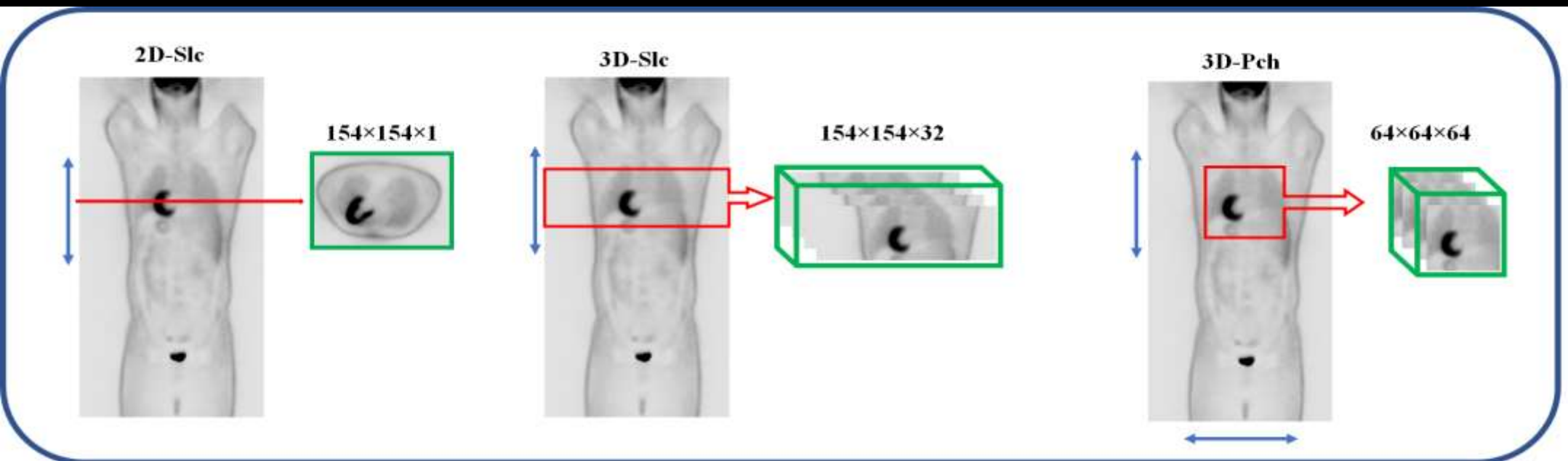
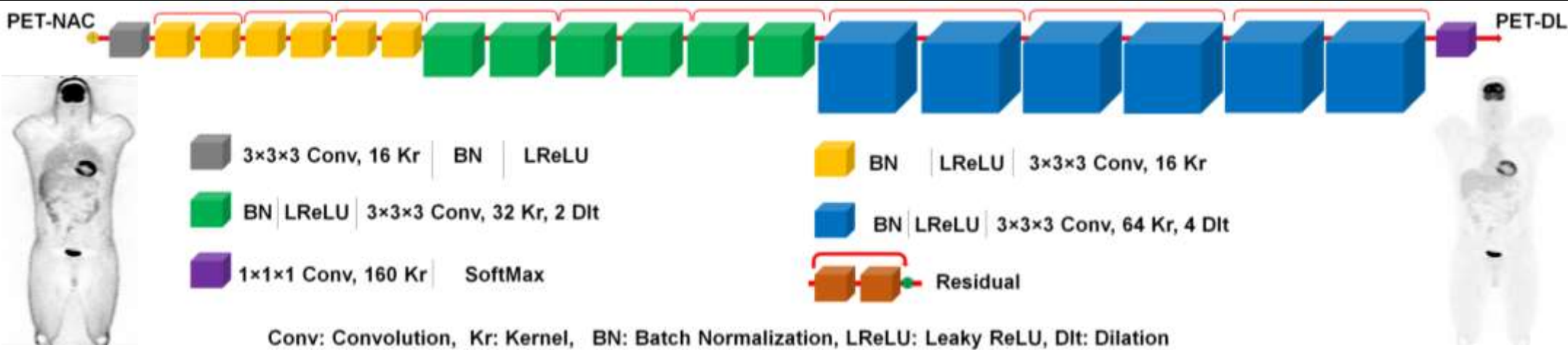
Isaac Shiri¹ · Hossein Arabi¹ · Parham Geramifar² · Ghasem Hajianfar³ · Pardis Ghafarian^{4,5} · Arman Rahmim^{6,7} ·
Mohammad Reza Ay^{8,9} · Habib Zaidi^{1,10,11,12} 

Received: 7 November 2019 / Accepted: 1 May 2020

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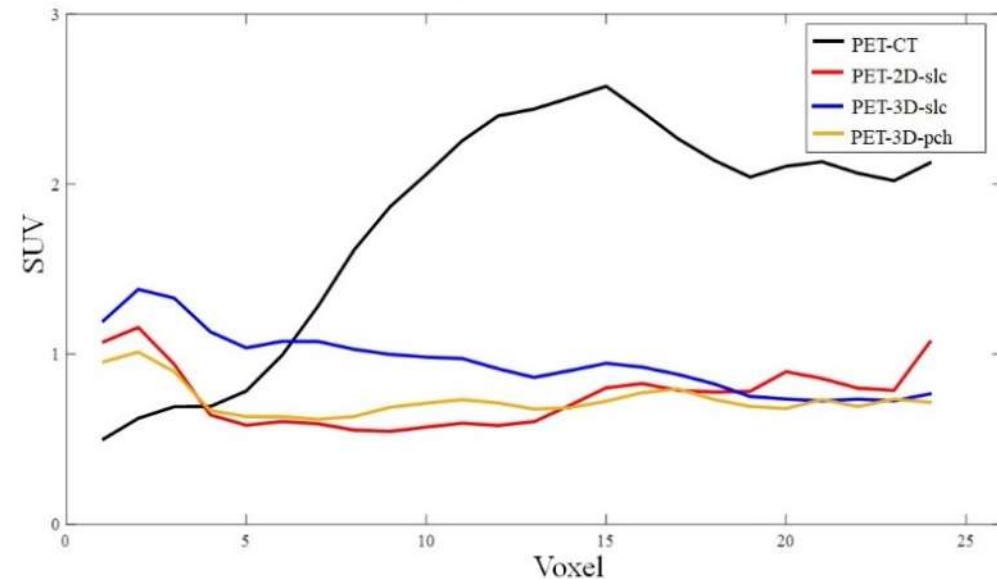
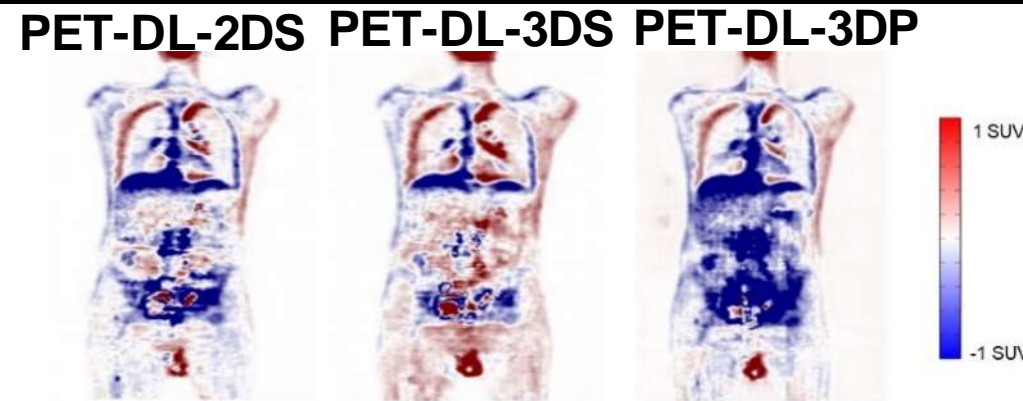
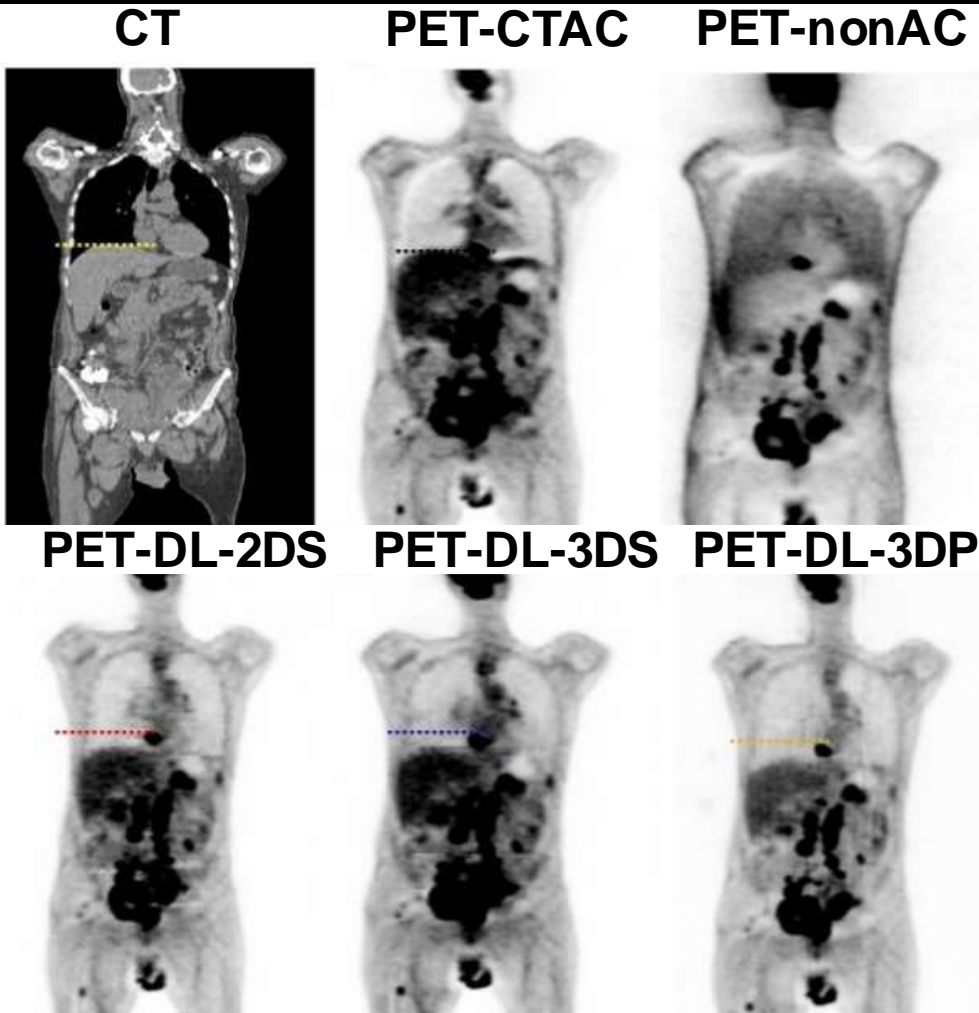


Deep-JSAC: Implementation issues



Deep learning compensates motion artifacts

Difference images: PET-DL – PET-CTAC



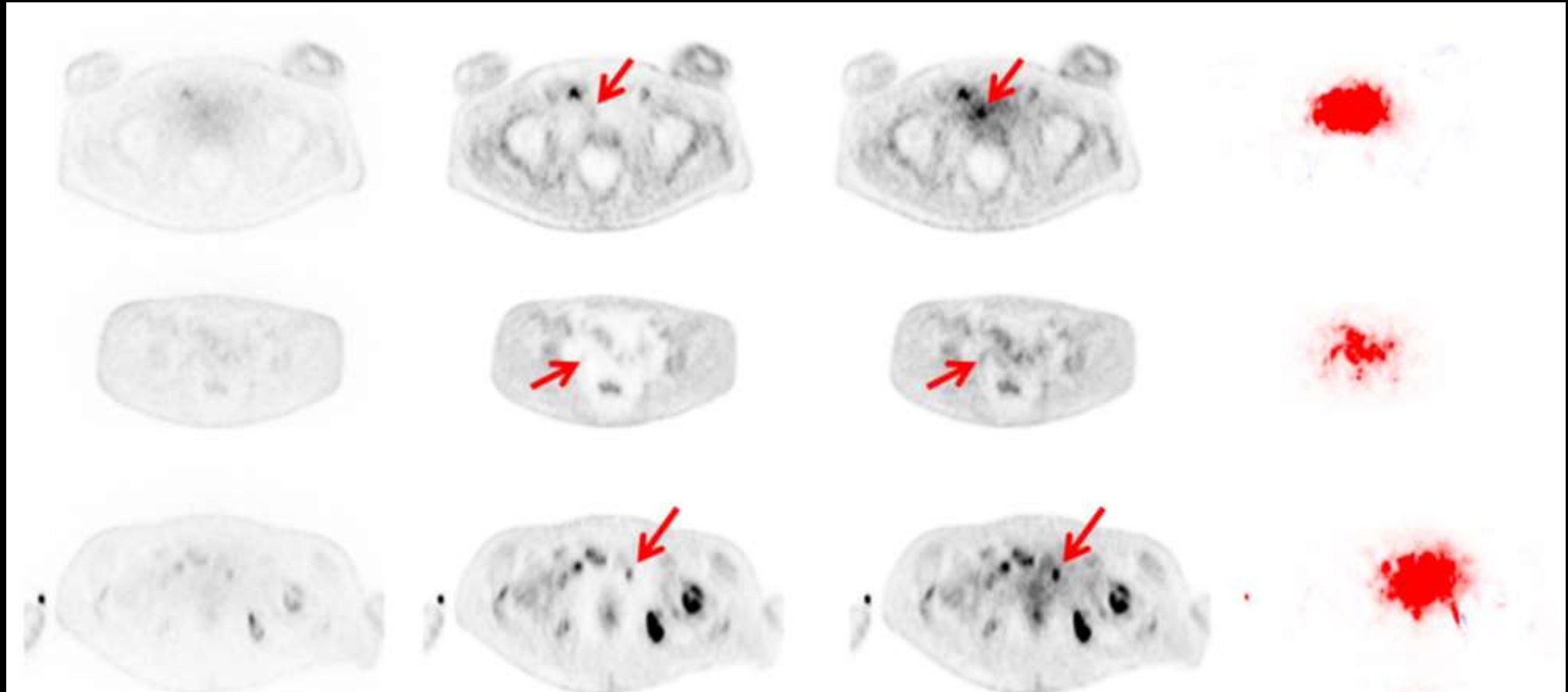
AI-based artifact disentanglement

Non-ASC

CT-ASC

PET-QA-NET

PET-QA-NET - CT-ASC




- Detectability
- Diagnostic confidence
- Quantification $SUV_{mean} = 3.7/2.2$ in PET-QA-NET/CT-ASC

Halo Artifact



Differential privacy preserved federated transfer learning for multi-institutional ^{68}Ga -PET image artefact detection and disentanglement

Isaac Shiri^{1,2} · Yazdan Salimi¹ · Mehdi Maghsudi³ · Elnaz Jenabi⁴ · Sara Harsini⁵ · Behrooz Razeghi⁶ · Shayan Mostafaei^{7,8} · Ghasem Hajianfar¹ · Amirhossein Sanaat¹ · Esmail Jafari⁹ · Rezvan Samimi¹⁰ · Maziar Khateri¹¹ · Peyman Sheikhzadeh¹² · Parham Geramifar⁴ · Habibollah Dadgar¹³ · Ahmad Bitrafan Rajabi^{3,14} · Majid Assadi⁹ · François Bénard^{5,15} · Alireza Vafaei Sadr^{16,17} · Slava Voloshynovskiy⁶ · Ismini Mainta¹ · Carlos Uribe^{15,18,19} · Arman Rahmim^{15,19,20} · Habib Zaidi^{1,21,22,23} 



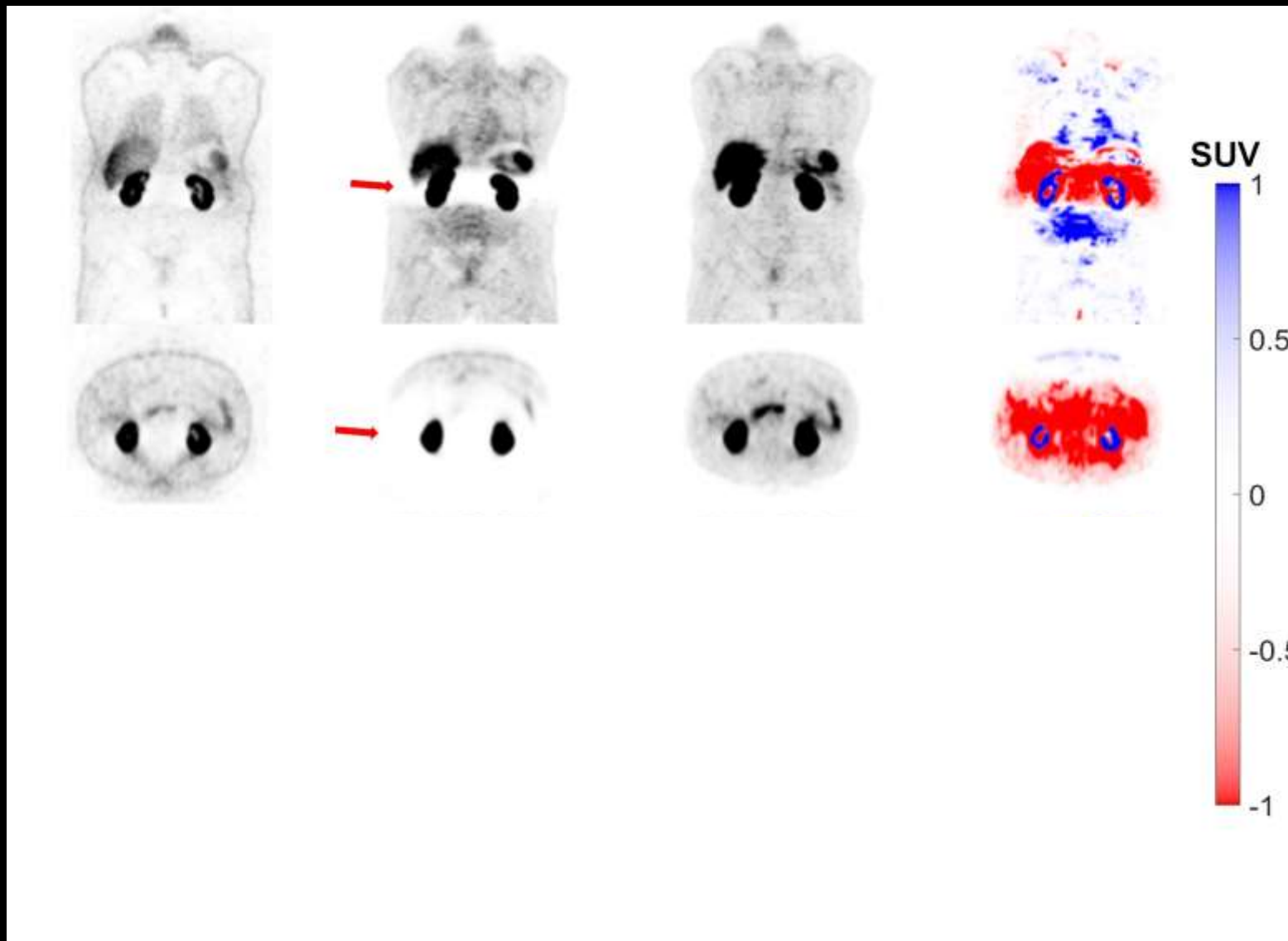
DPFL for PET/CT image artifact correction

Non-ASC

CT-ASC

FTL-ASC

PET-QA-NET - CT-ASC



^{68}Ga -PSMA

Repeated scan


European Journal of Nuclear Medicine and Molecular Imaging

<https://doi.org/10.1007/s00259-020-05013-4>

ORIGINAL ARTICLE



Whole-body voxel-based internal dosimetry using deep learning

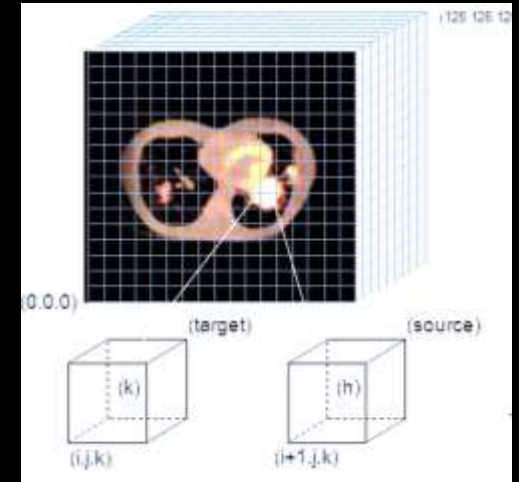
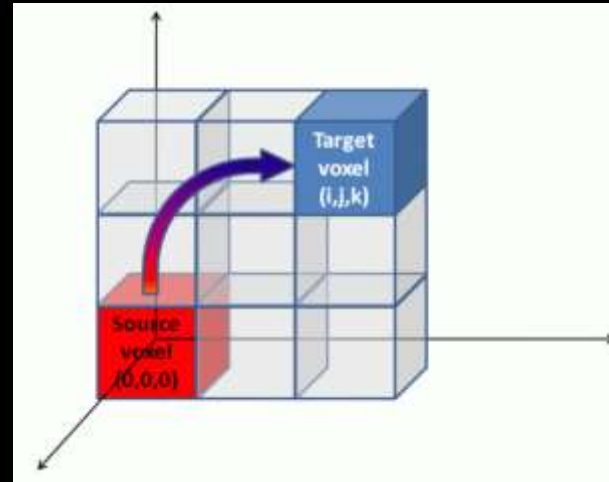
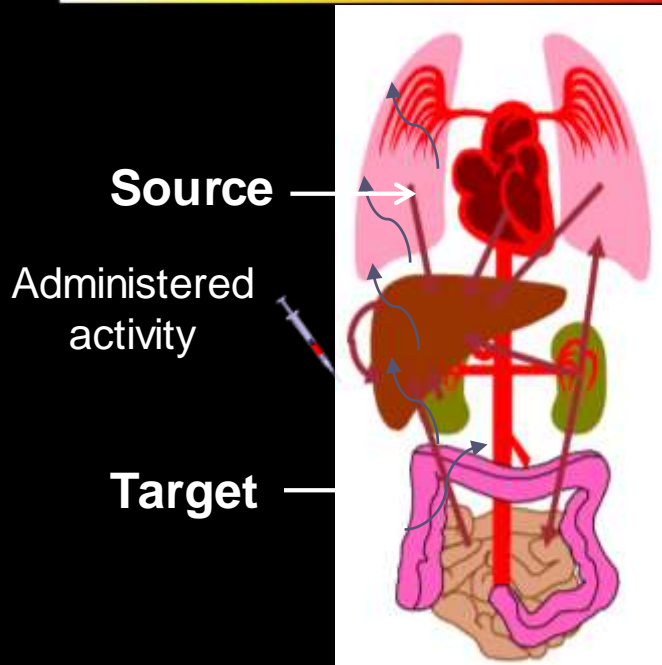
Azadeh Akhavanallaf¹ • Iscaac Shiri¹ • Hossein Arabi¹ • Habib Zaidi^{1,2,3,4} 

Received: 27 May 2020 / Accepted: 23 August 2020

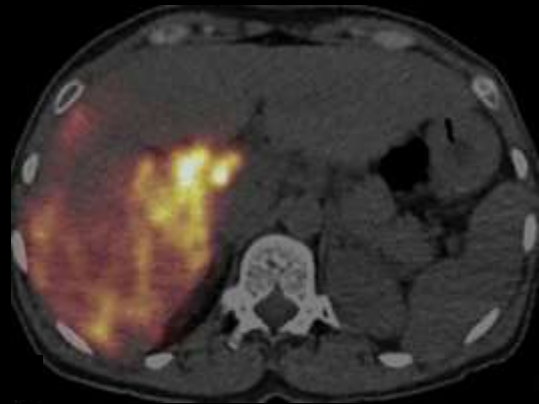
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Voxel-based internal dosimetry (MIRD)

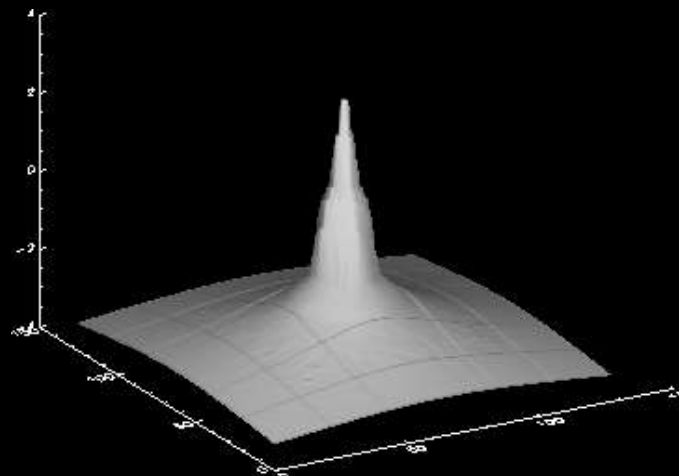


$$\bar{D}_{voxel_k} = \sum_{n=1}^N \tilde{A}_{voxel_n} \cdot S(voxel_k \leftarrow voxel_n)$$



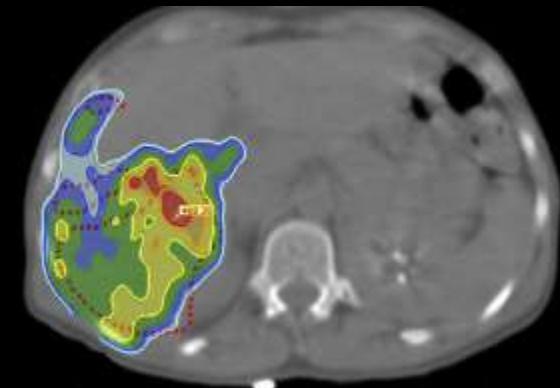
Activity map

*



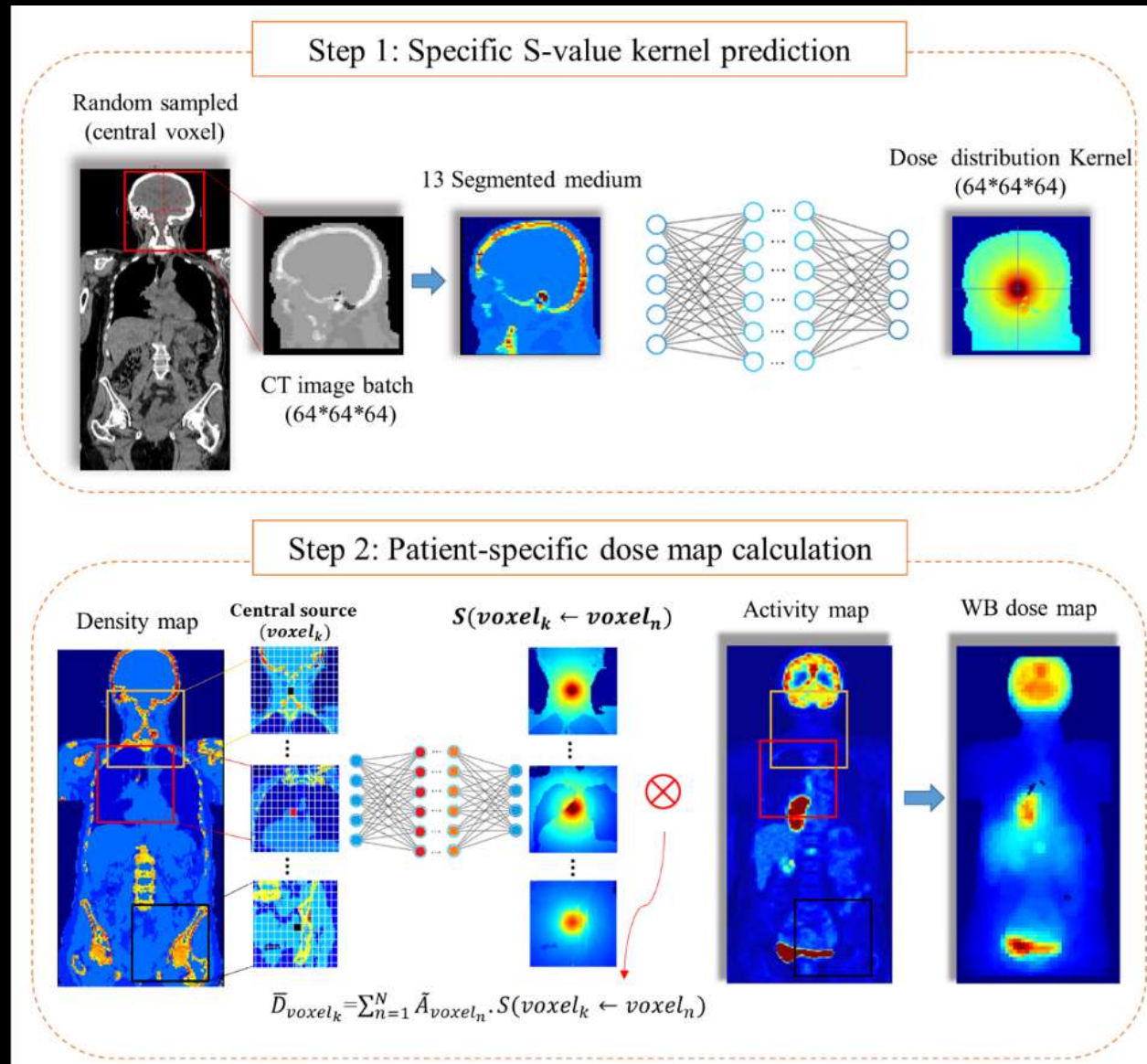
Dose point kernel

=

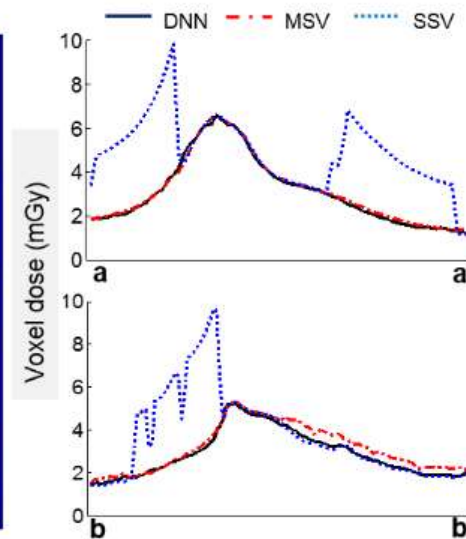
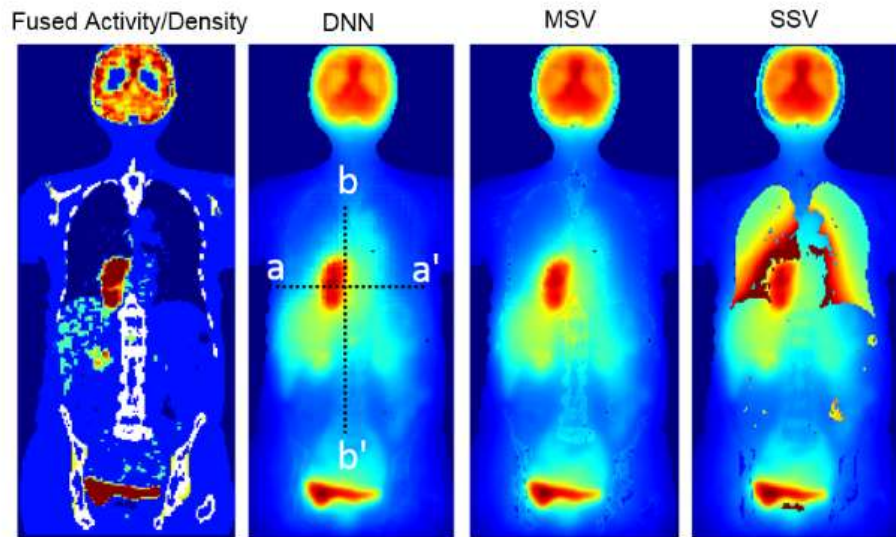
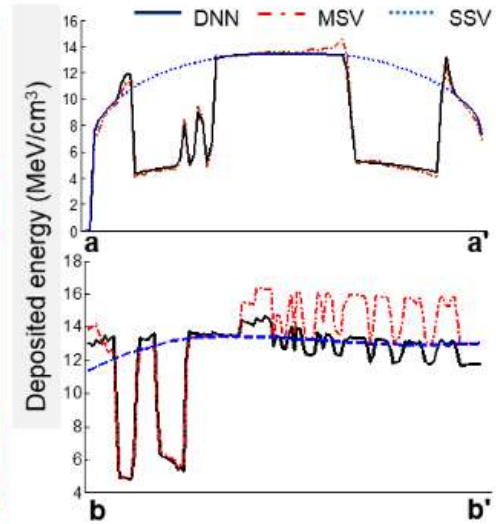
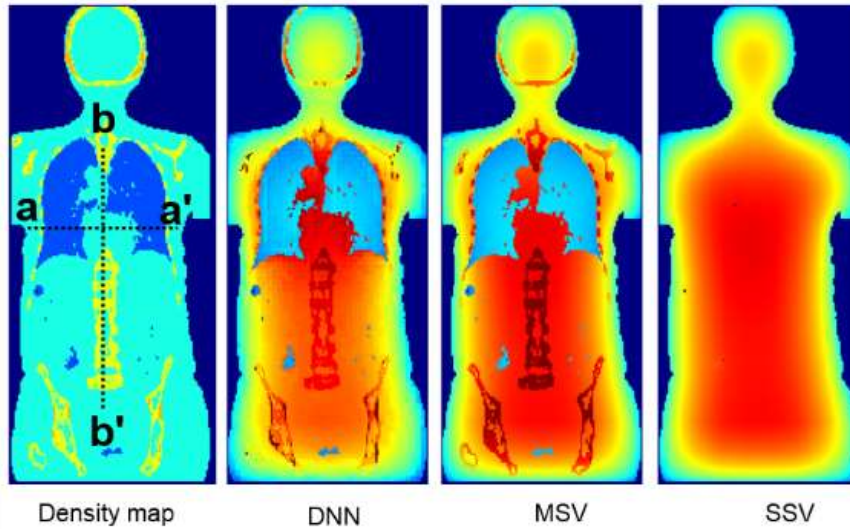


3D dose map

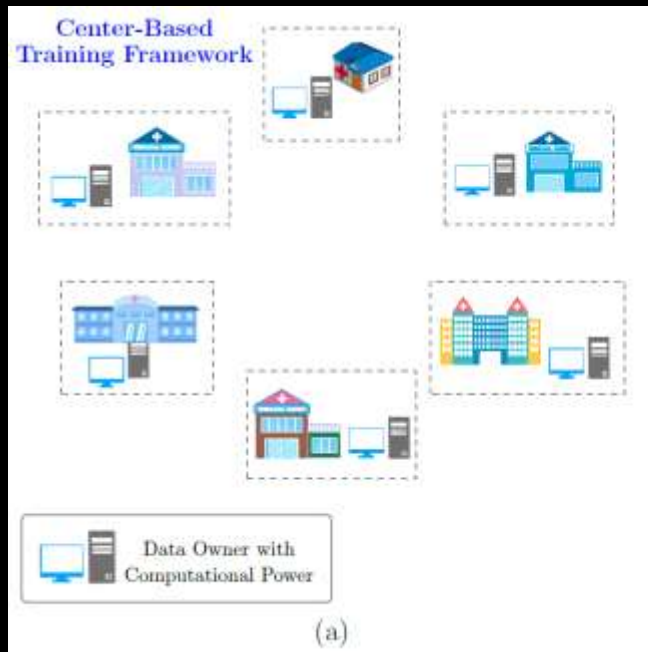
Deep learning-guided internal dosimetry



Deep learning-guided internal dosimetry



Federated learning in medical imaging



Advantages

Disadvantages

CB

Local control, utilization of centre-specific data and expertise

Generalizability, limited access to large datasets, infrastructure

ORIGINAL ARTICLE

Decentralized Distributed Multi-institutional PET Image Segmentation Using a Federated Deep Learning Framework

Isaac Shiri, MSc, Alireza Vafaei Sadr, MSc,†‡ Mehdi Amini, MSc,* Yazdan Salimi, MSc,* Amirhossein Sanaat, MSc,* Azadeh Akhavanallaf, MSc,* Behrooz Razeghi, PhD,§ Sohrab Ferdowsi, PhD,|| Abdollah Saberi, MSc,* Hossein Arabi, PhD,* Minerva Becker, MD,¶ Slava Voloshynovskiy, PhD,§ Deniz Gündüz, PhD,** Arman Rahmim, PhD,††‡‡ and Habib Zaidi, PhD*§§|||¶¶*


European Journal of Nuclear Medicine and Molecular Imaging

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

ORIGINAL ARTICLE

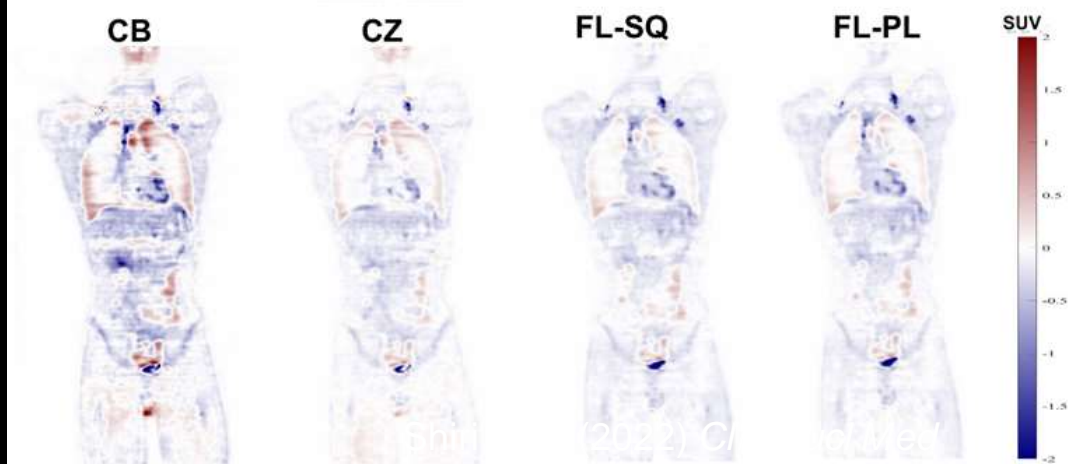
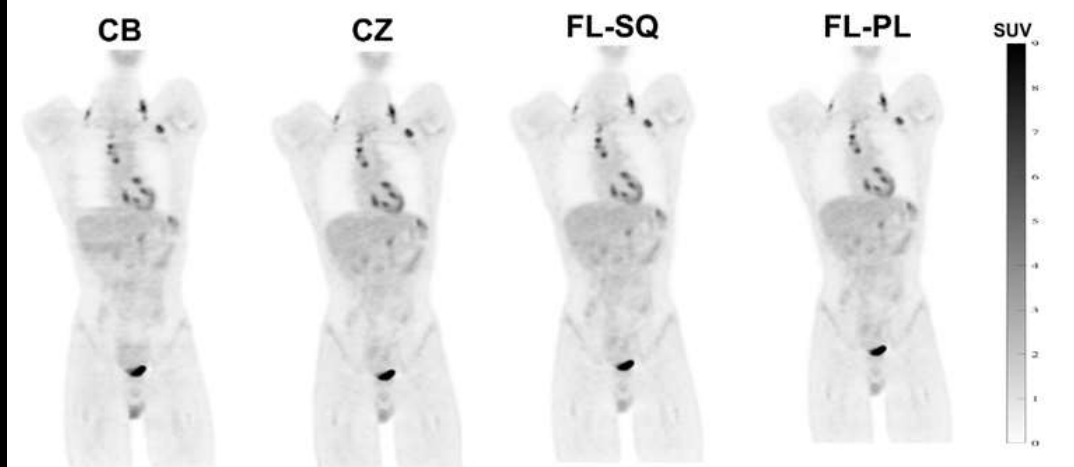
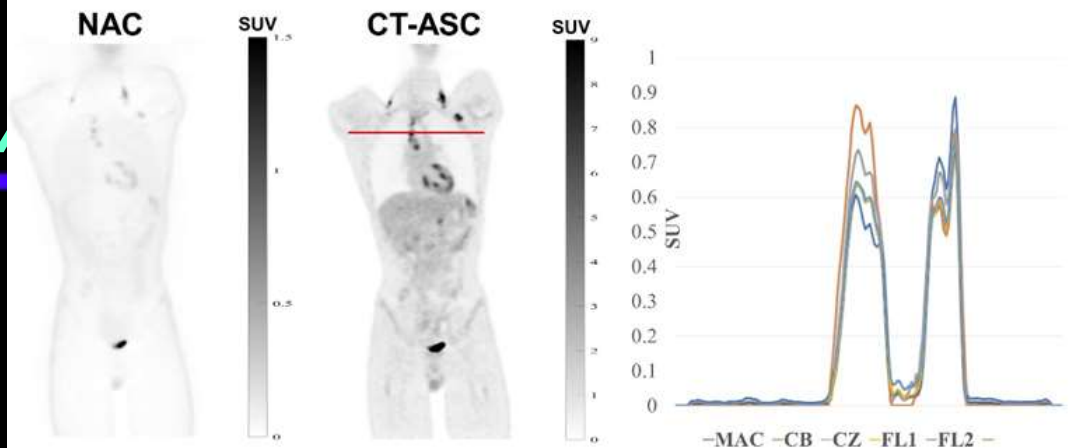
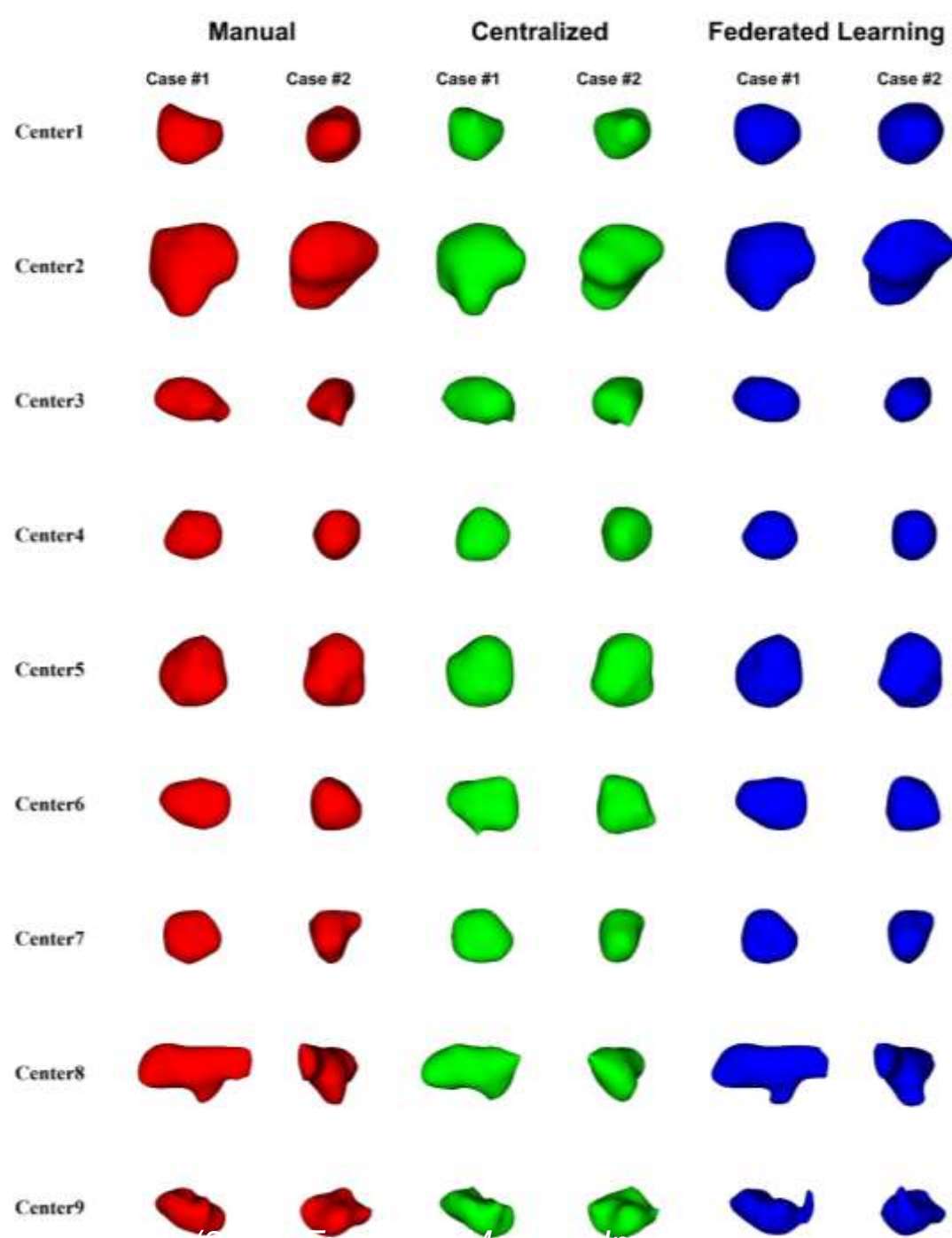


Decentralized collaborative multi-institutional PET attenuation and scatter correction using federated deep learning

Isaac Shiri¹ · Alireza Vafaei Sadr^{2,3} · Azadeh Akhavan¹ · Yazdan Salimi¹ · Amirhossein Sanaat¹ · Mehdi Amini¹ · Behrooz Razeghi⁴ · Abdollah Saberi¹ · Hossein Arabi¹ · Sohrab Ferdowsi⁵ · Slava Voloshynovskiy⁴ · Deniz Gündüz⁶ · Arman Rahmim^{7,8} · Habib Zaidi^{1,9,10,11} 

Received: 13 August 2022 / Accepted: 18 November 2022

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Summary

- Imaging biomarkers are a major component of Big Data driven medical knowledge and decision making
- Nuclear medicine physicians/Radiologists/Medical physicists who use AI and deep learning will replace those who don't ...
- AI/deep learning are producing challenges in terms of validation/adoption in clinical setting, but also plenty of research opportunities.
- Is there a future for AI/deep learning in medical 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



On the horizon ...

The Wave...



... of the Future...



*“Prediction is very difficult, especially if it is about the future”
Niels Bohr (1885–1962)*

Distinguished professor at Óbuda University



Potential collaborations (themes)

- High performance computing (Monte Carlo simulations, algorithmic developments, optimization, ...).
- Advanced signal & medical image analysis and processing
- Biomedical imaging instrumentation
- Novel neural network architectures and applications
- Applications of artificial intelligence in healthcare (other than medical imaging, e.g. radiation therapy, modeling, ...)
- Clinical diagnosis, prognostic modeling, outcome prediction, ...
- Any research requiring expertise in imaging, AI, modeling, computing...

Thank you!



This work was supported by the Swiss national Science Foundation (grant 320030_176052), the Swiss Cancer Research Foundation (grant KFS-3855-02-2016), Eurostars (grants ILLUMINUS E!12326 and Provision E!114021), EEC/H2020 grant NFRP-945196 SINFONIA, Qatar National Research Fund (grant NPRP10-0126-170263) and Fondation privée des HUG (grant RC-06-01).

European Workshop on Visual Information Processing



EUVIP 2024

Geneva, 8-11 Sep 2023

Main topics : visual information processing, analysis/interpretation and representation/coding;

Applications: Multimedia, Medical imaging, Augmented and virtual reality, Biometrics, forensics, trust/security



Geneva University Hospital



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 Salam
1979 Nobel Laureate - Physics*