The Abdus Salam International Centre for Theoretical Physics

College on Medical Physics 2026

Trieste, August 24th - September 12th 2026

ARTIFICIAL INTELLIGENCE APPLICATIONS IN NUCLEAR MEDICINE

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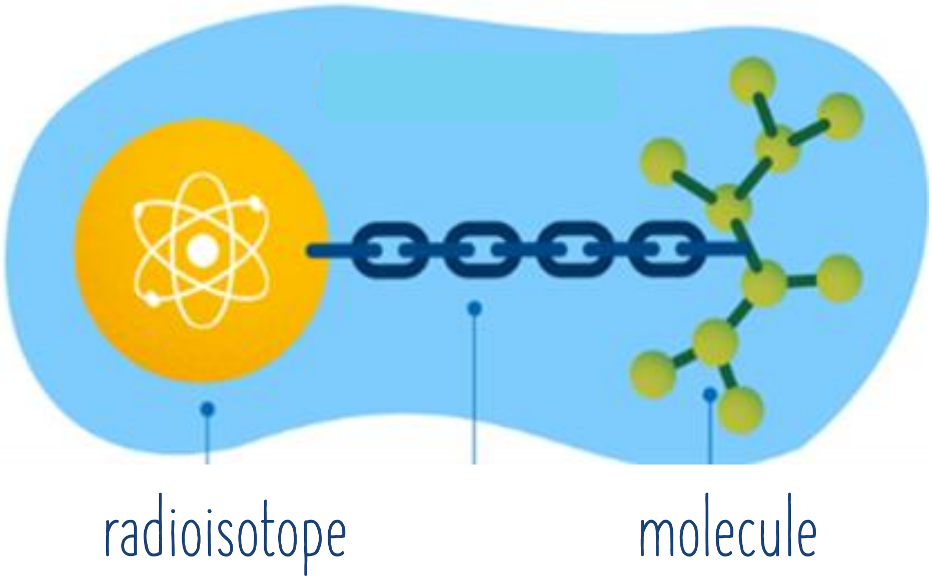
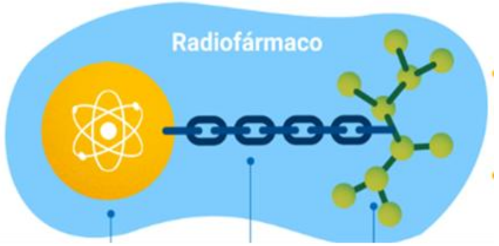
NUCLEAR MEDICINE BACKGROUND

radiopharmaceutical



Diagnostic Area

Therapeutical Area

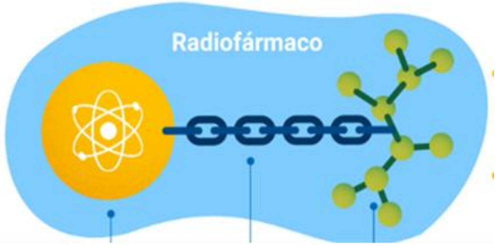


radioisotope

molecule

Diagnostic Area

Therapeutical Area



radioisotope

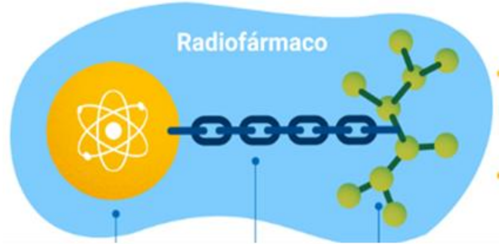
molecule

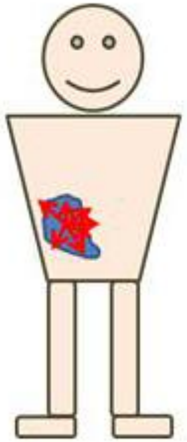
Gamma, beta+ emitter

Penetrating radiation

Diagnostic Area

Therapeutical Area





radioisotope

molecule

Gamma, beta+ emitter

Penetrating radiation

Alpha, beta- emitter

Low penetrating radiation

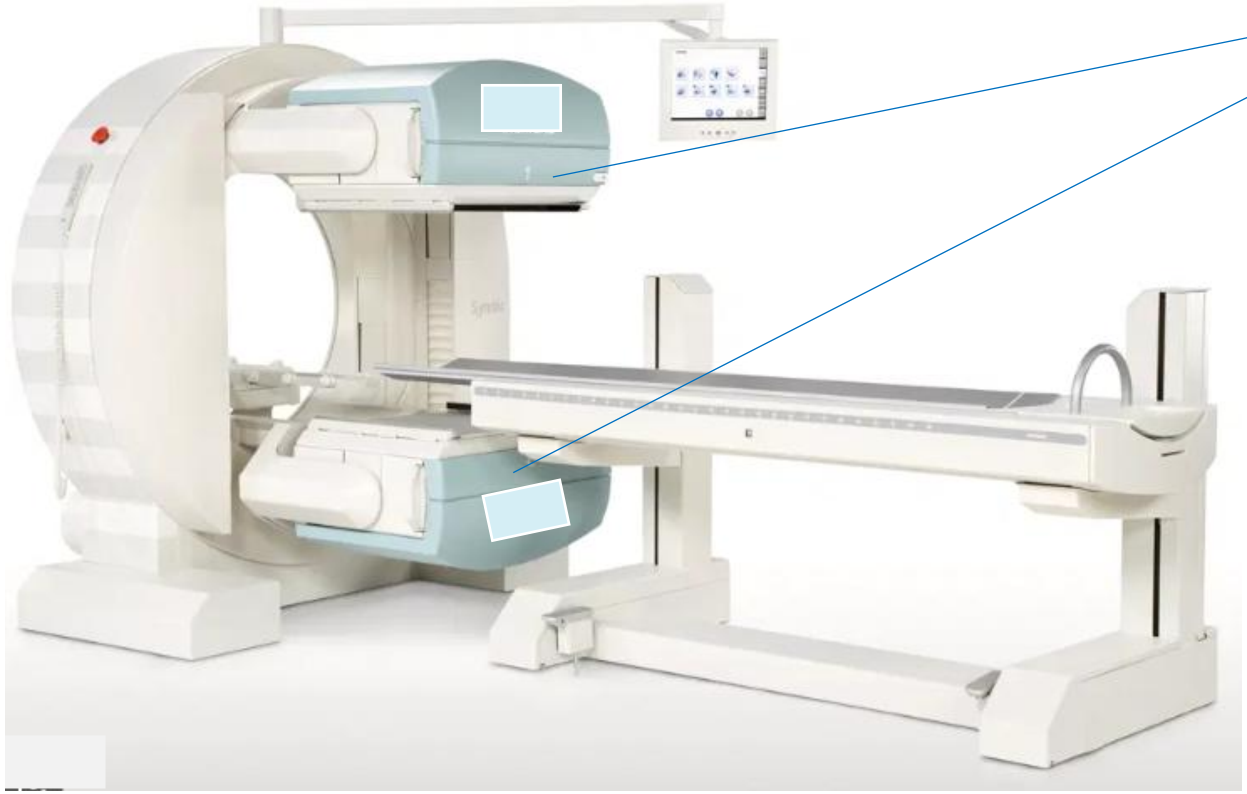
The main character:

IMAGES

Tomographic 3D images

Gamma emitters: gammacamera

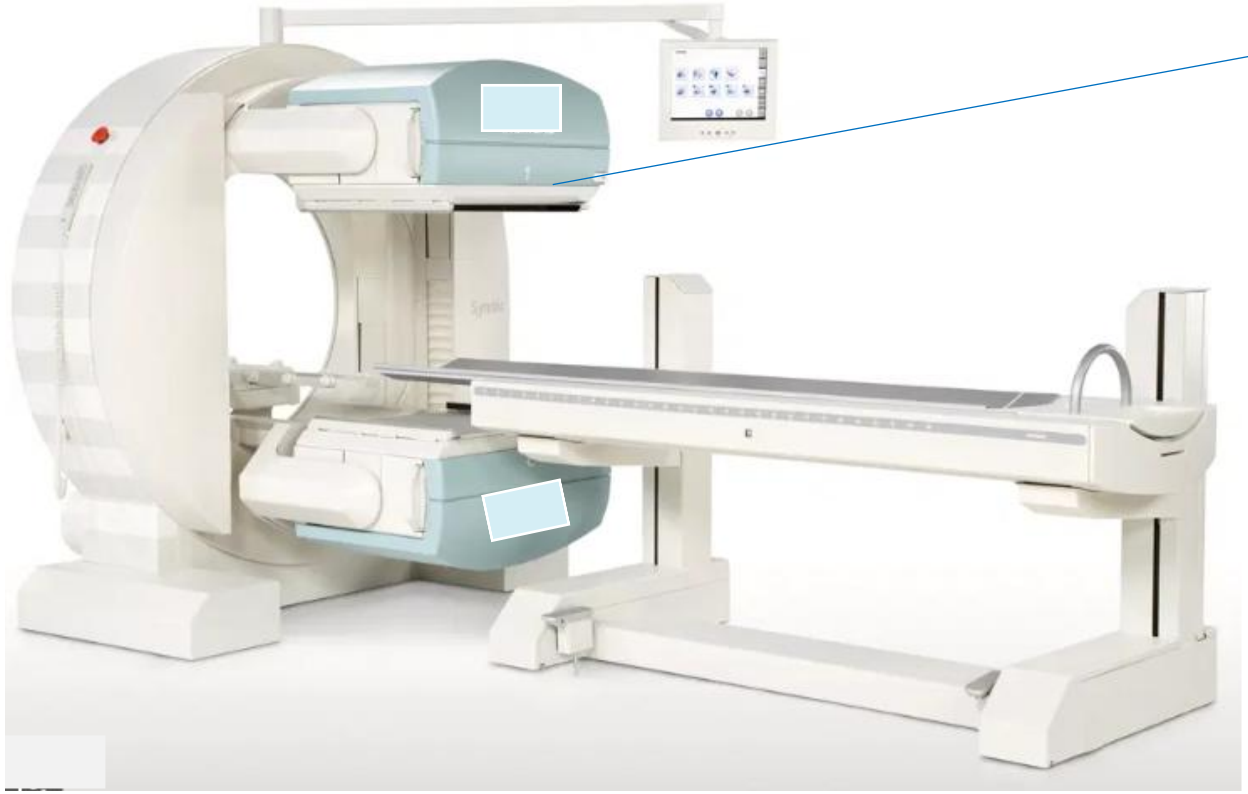
Gamma emitters: gammacamera

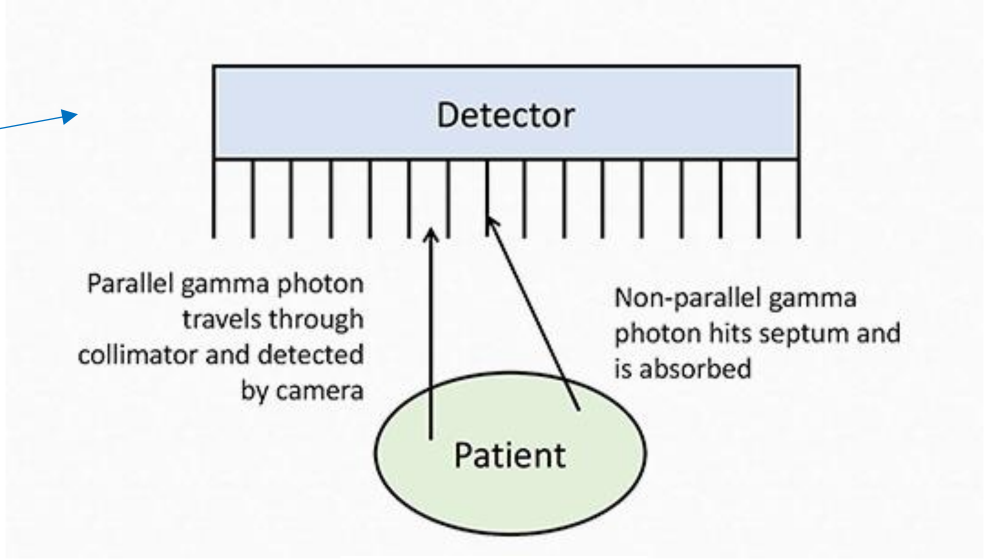


Detectors

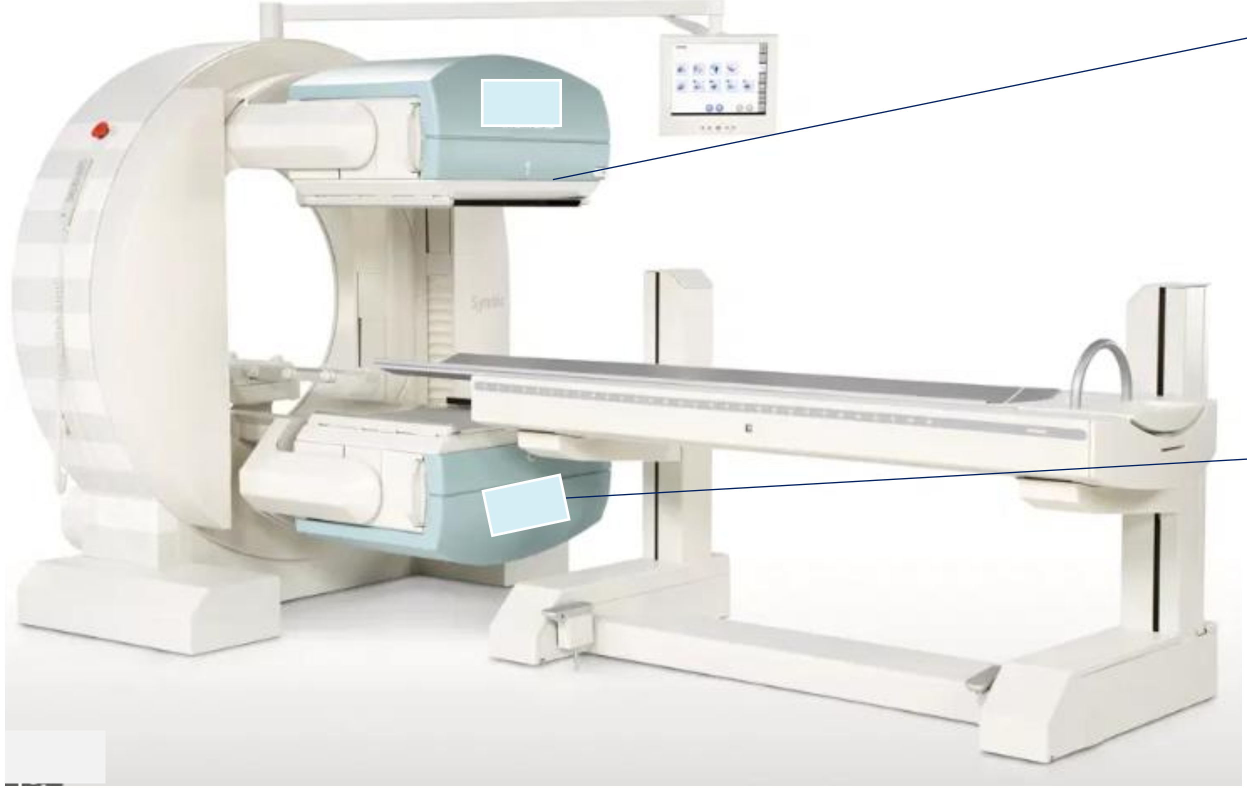
(typically NaI crystals)

Gamma emitters: gammacamera



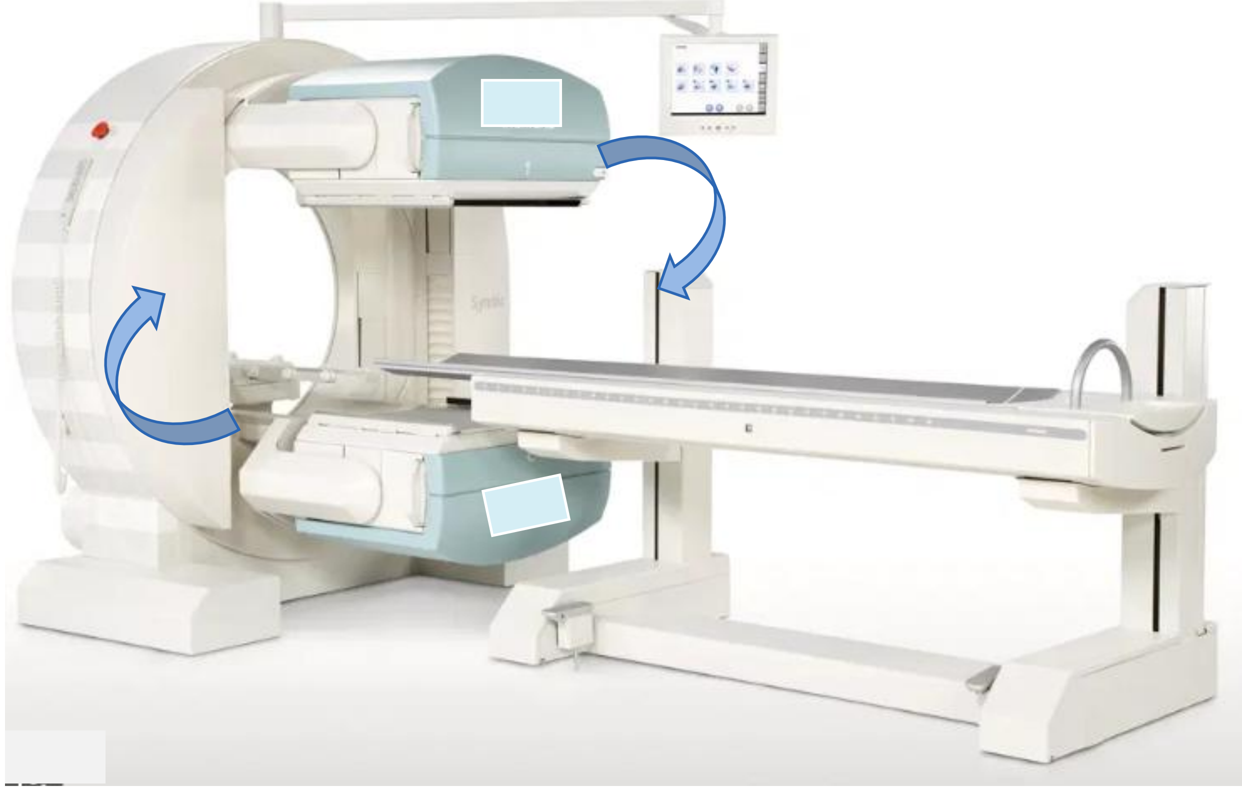


Gamma emitters: gammacamera



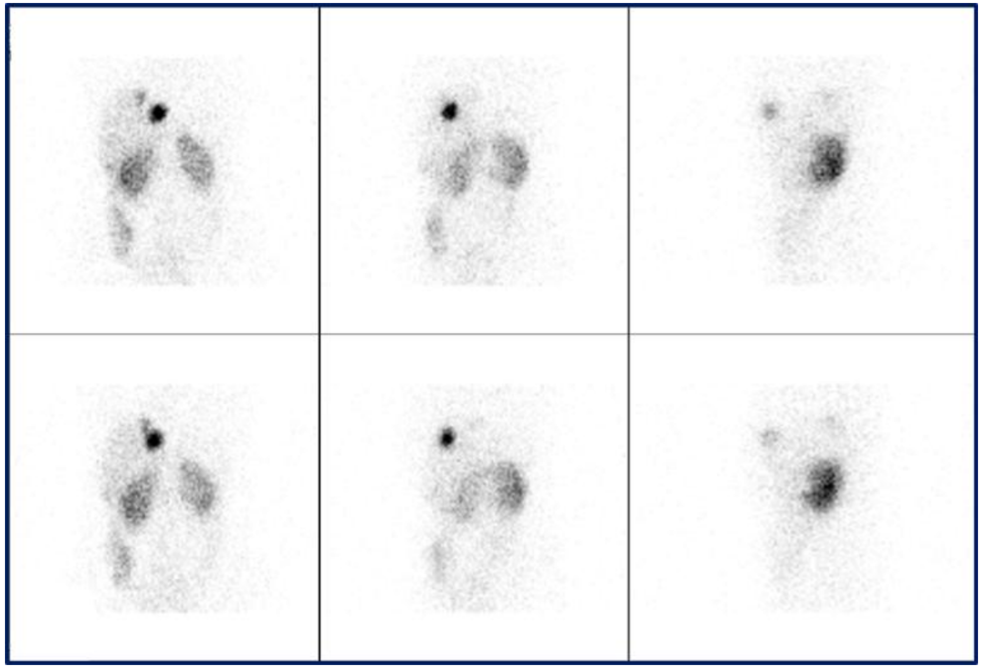
2D planar images

Gamma emitters: gammacamera

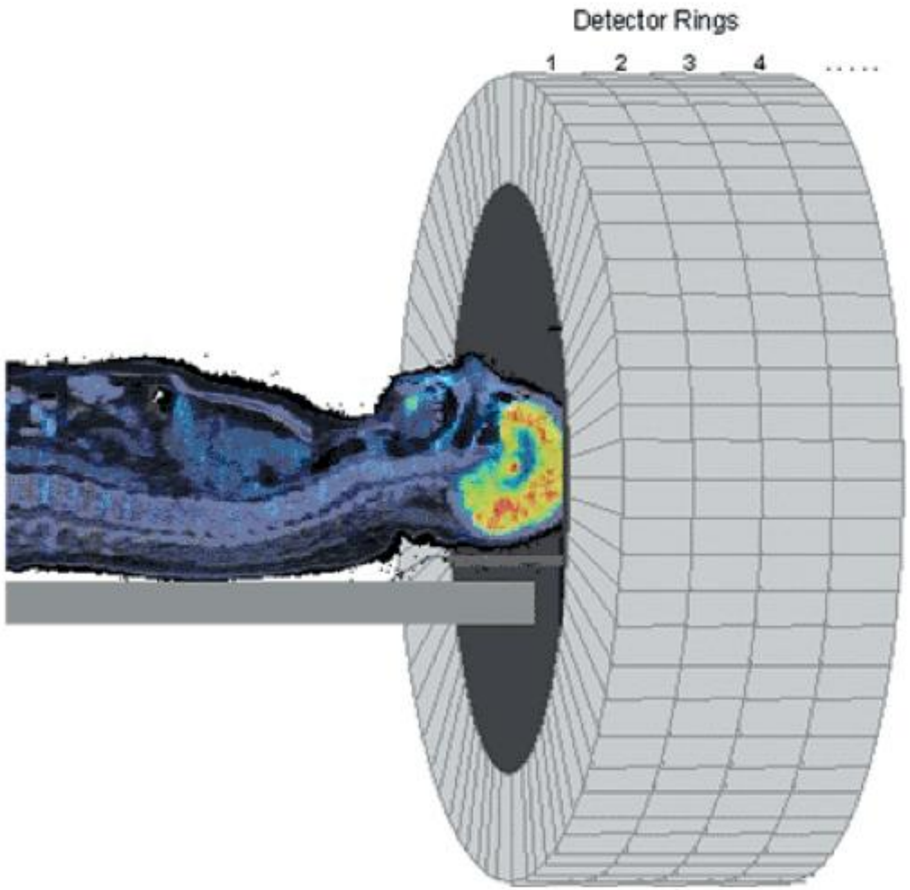


SPECT raw data:

2D projections

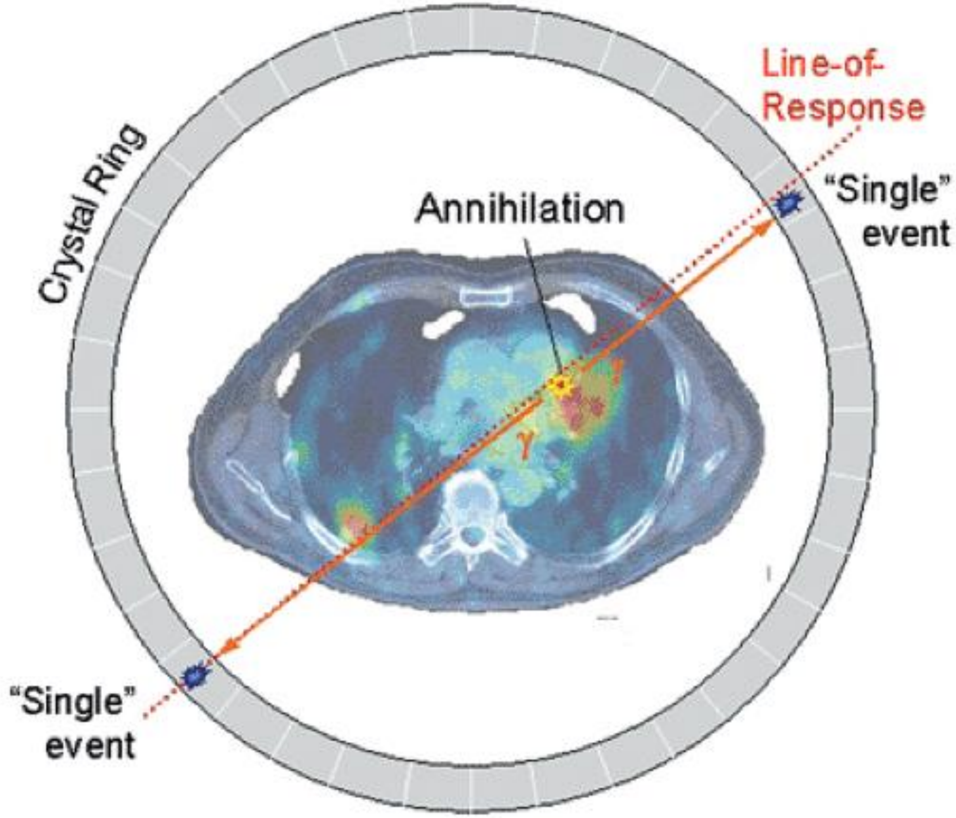


Beta+ emitters: PET scanner



https://radiologykey.com/basics-of-pet-scanning/

Beta+ emitters: PET scanner

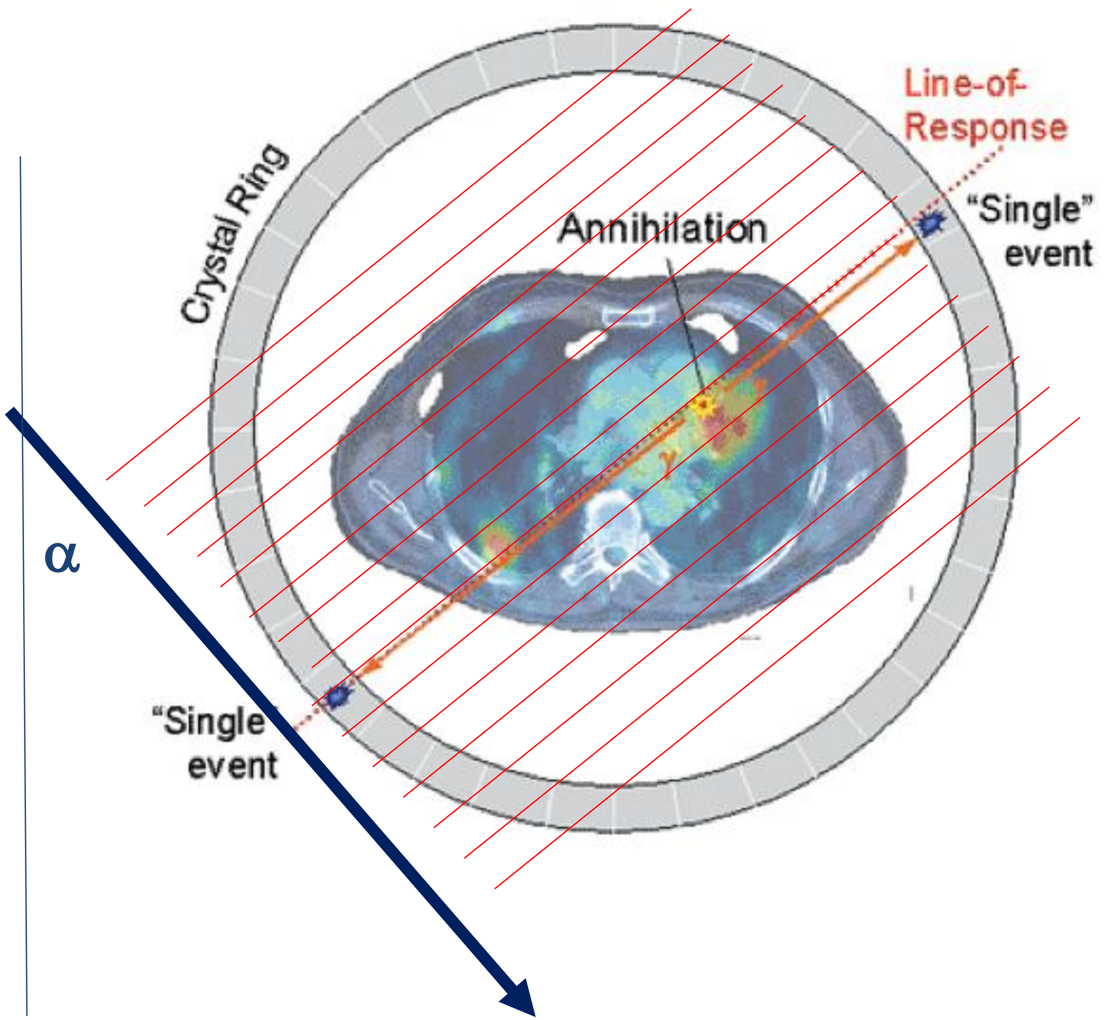


https://radiologykey.com/basics-of-pet-scanning/

Beta+ emitters: PET scanner

PET raw data:

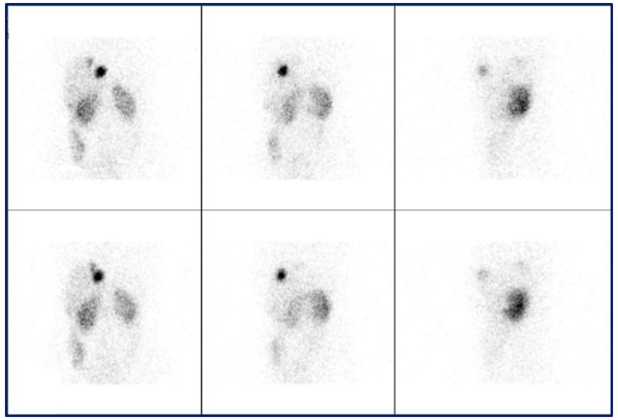
sinogram


α
Crystal Ring
Annihilation
Line-of-Response
"Single" event
"Single" event


Angle α

Raw Data

3D images

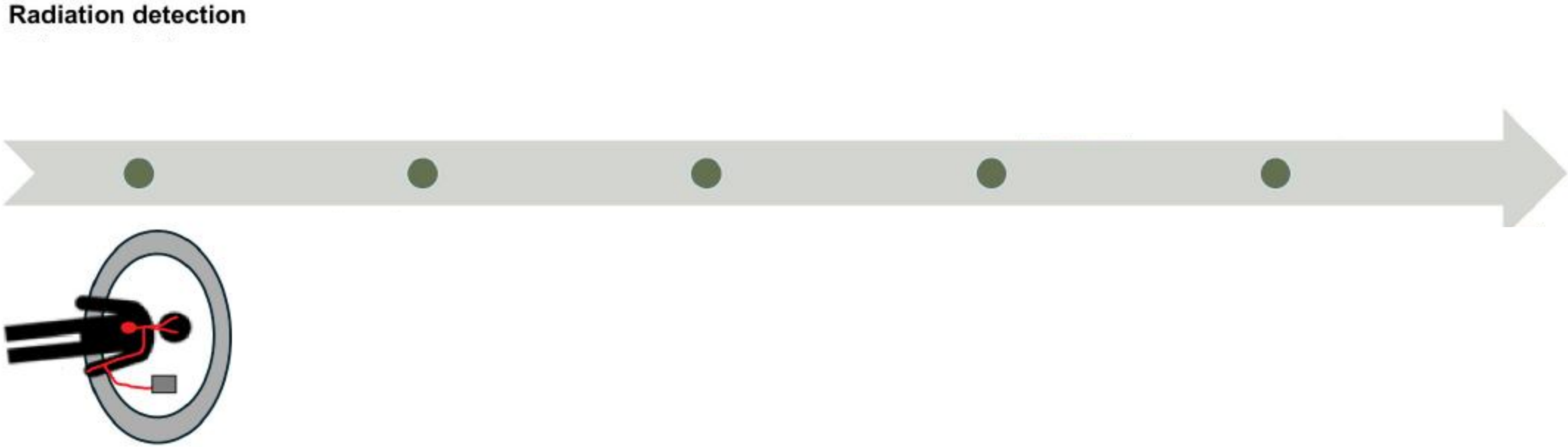


Reconstruction:

ITERATIVE

(Past: analytical FBP)

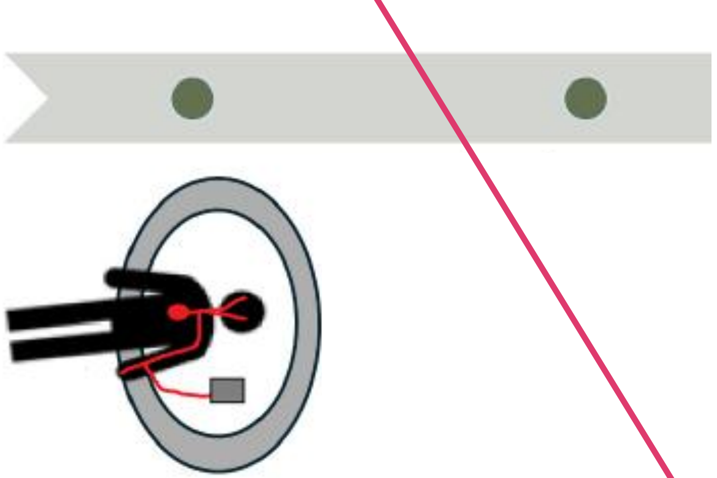
NM images lifecycle



Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

NM images lifecycle

Radiation detection



Open challenges

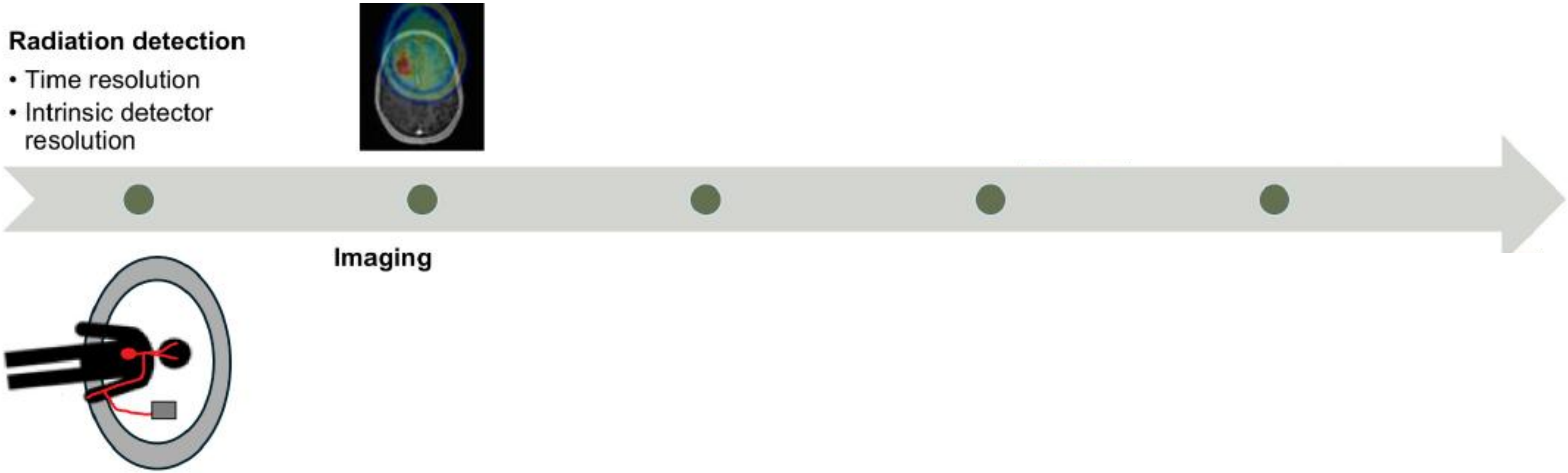
PET time resolution

detection efficiency

intrinsic spatial resolution

Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

NM images lifecycle



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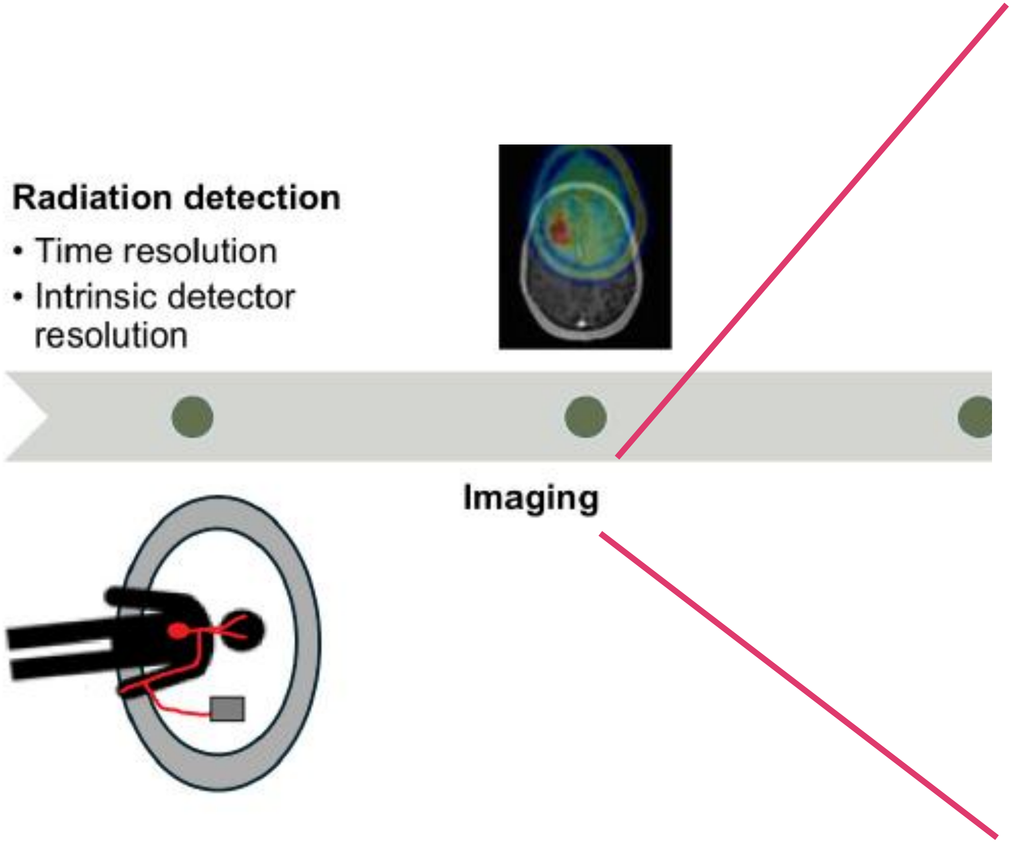
NM images lifecycle



Open challenges

spatial resolution

denoising

Partial Volume Effect correction

image quality improvement

injected activity reduction

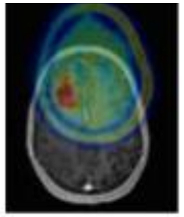
acquisition time reduction

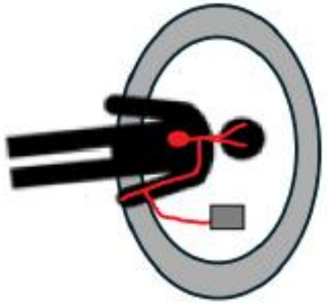
quantification, harmonization

Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

NM images lifecycle

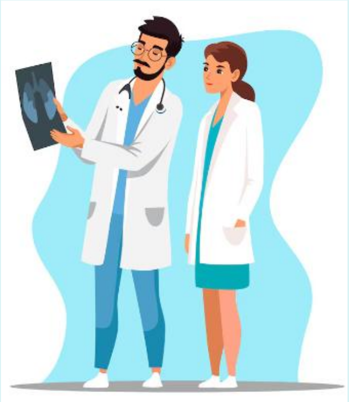
Radiation detection
- Time resolution
- Intrinsic detector resolution





Imaging
- Acquisition
- Reconstruction
- Registration
- Enhancement
- Harmonization

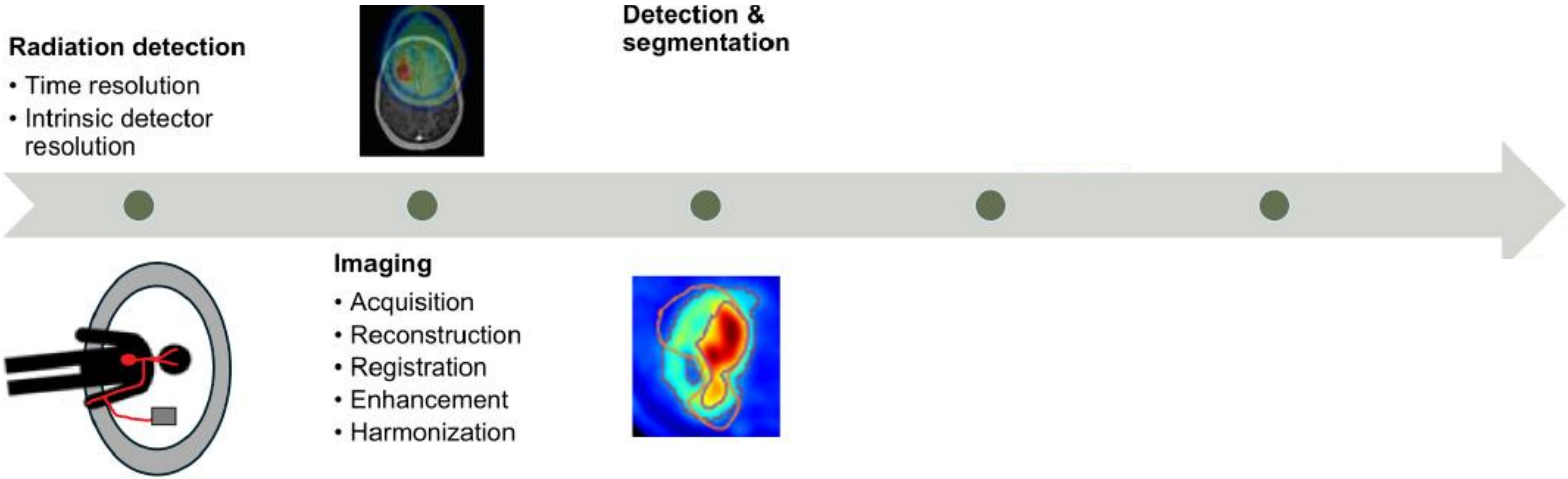
physician visual interpretation



....and beyond

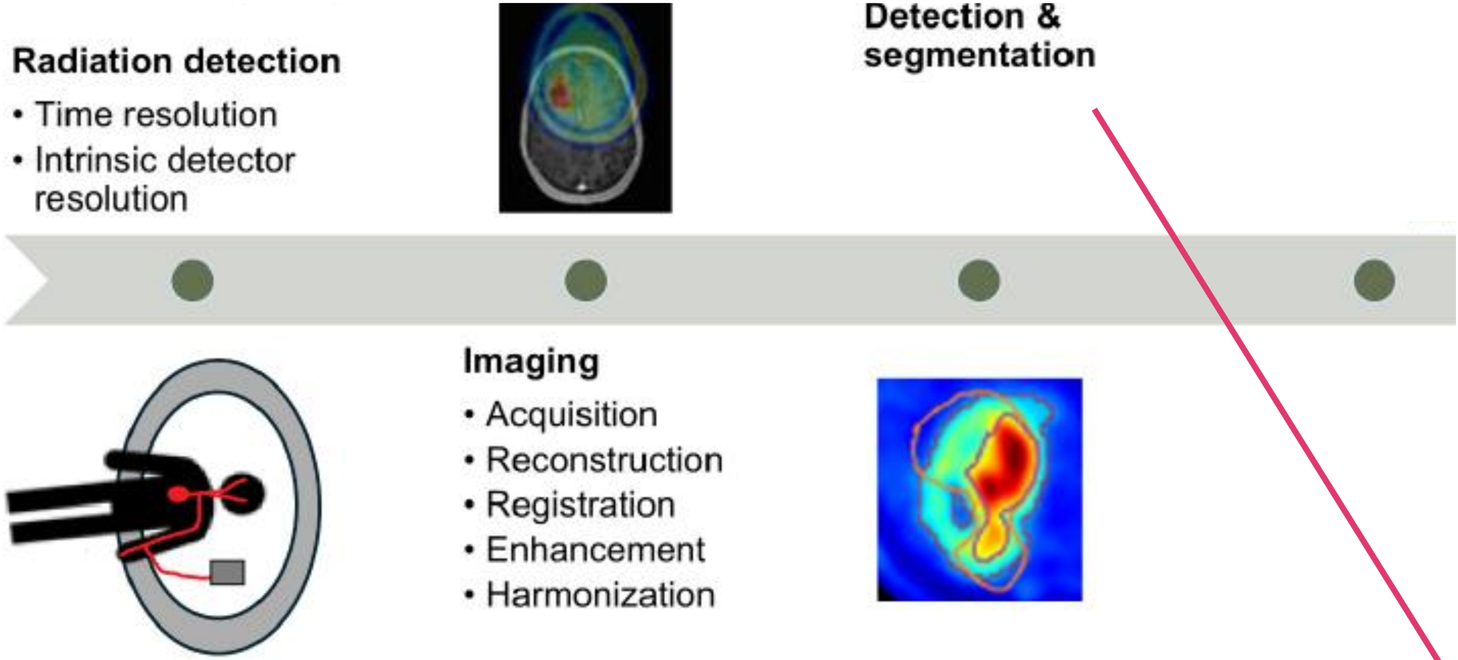
Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

NM images lifecycle



Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

NM images lifecycle



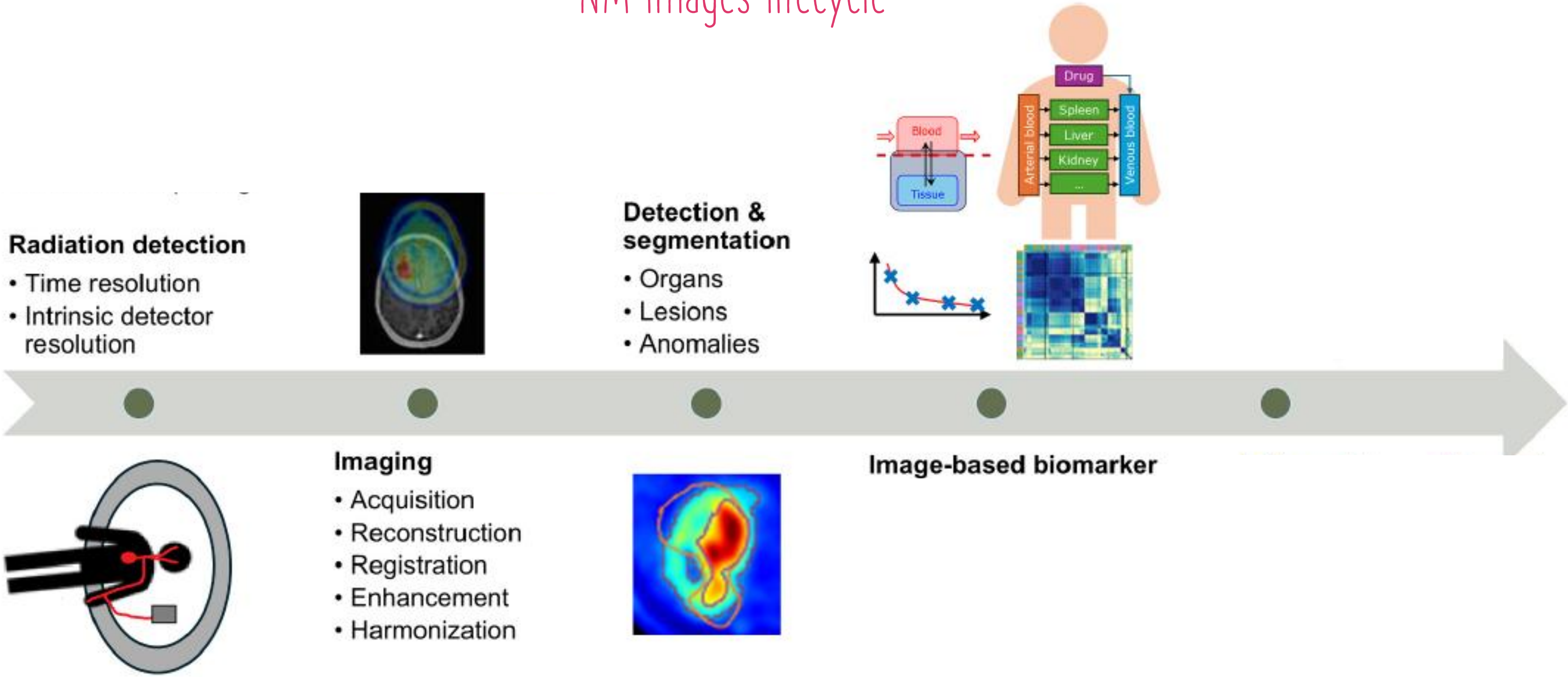
Open challenges

Automatic detection

Automatic segmentation

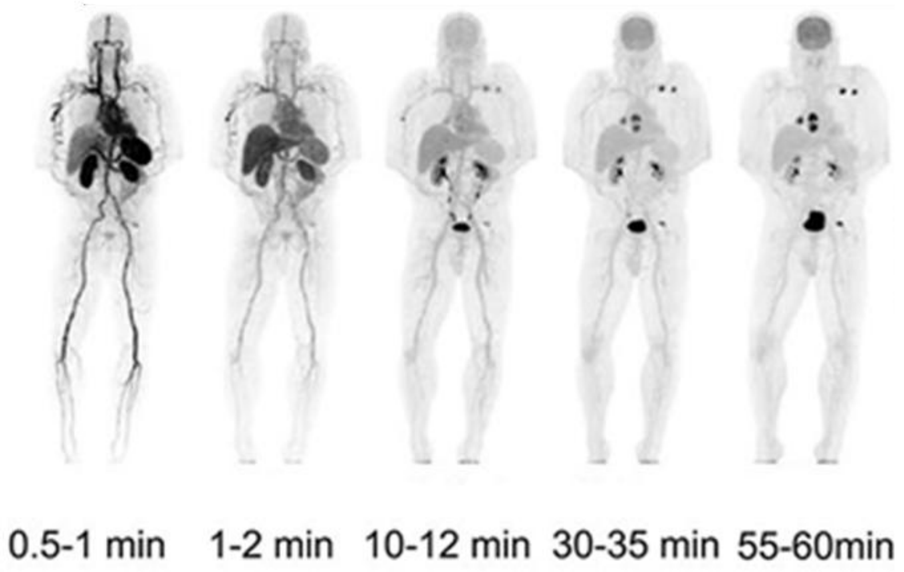
Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

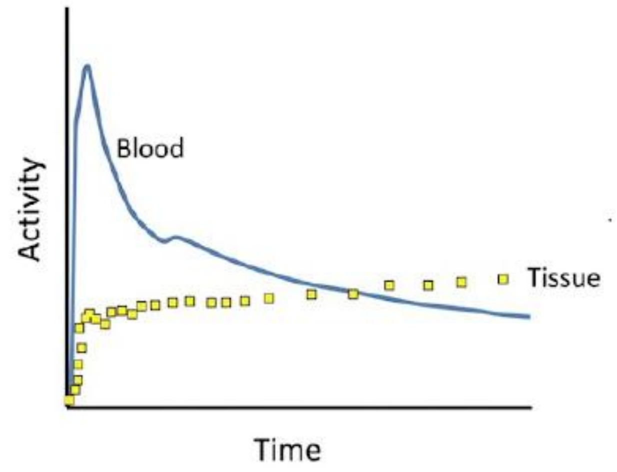
NM images lifecycle

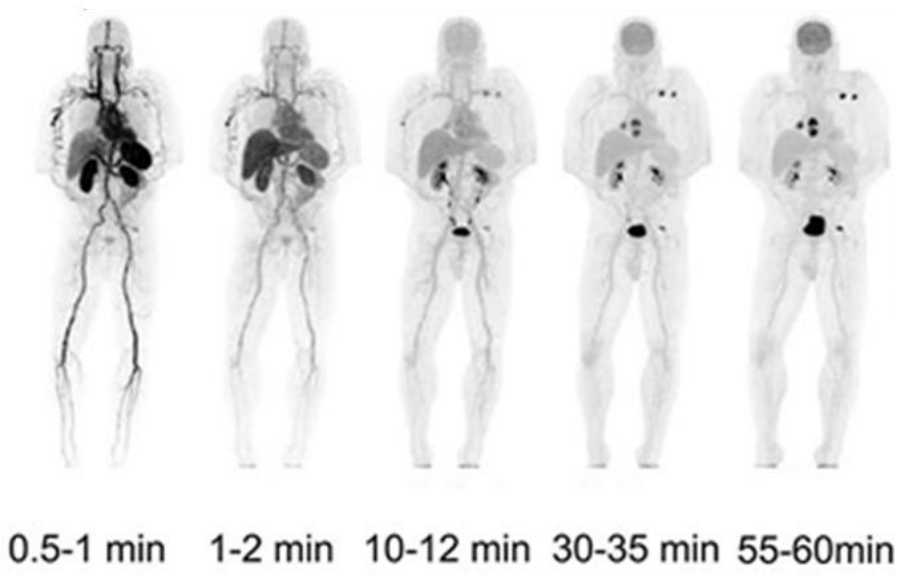


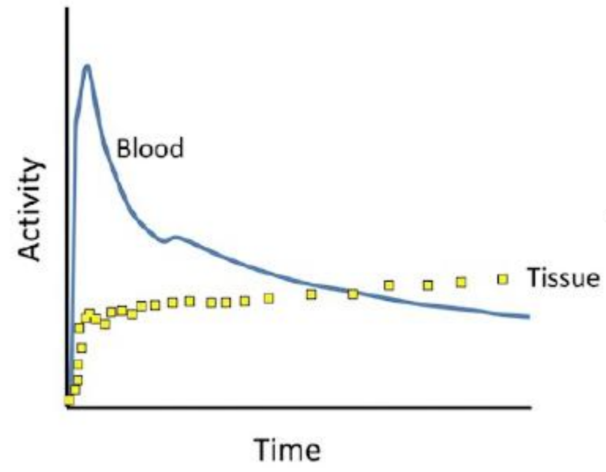
Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

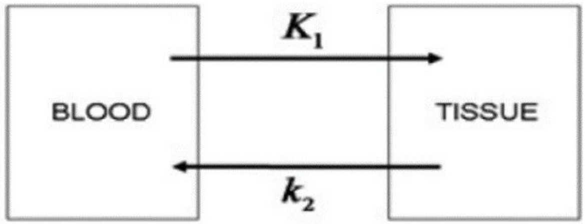
Dynamic images











$$\frac{\mathrm{d}C_{\mathrm{t}}(t)}{\mathrm{d}t} = K_1 C_{\mathrm{a}}(t) - k_2 C_{\mathrm{t}}$$

kinetic parameters

(k1, k2)

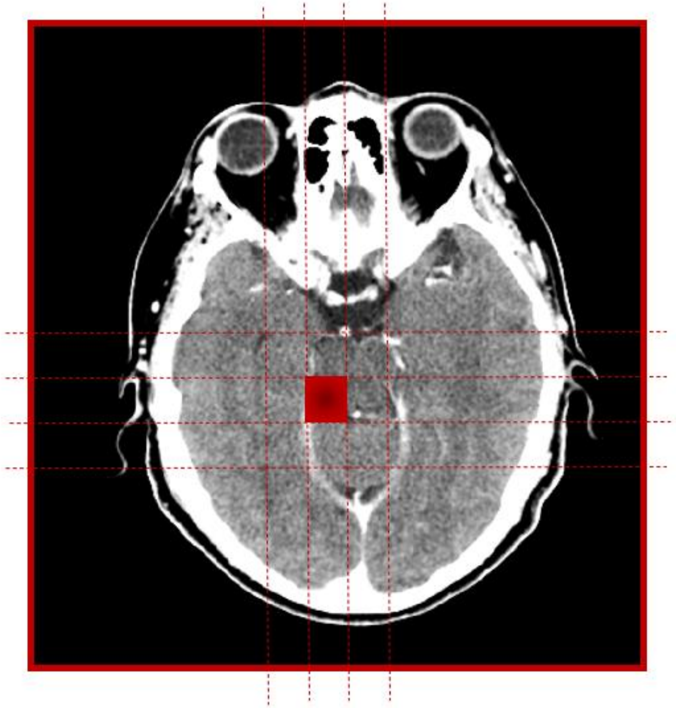
assessment

Radiology

2016

Radiomics: Images Are More than Pictures, They Are Data[1]

Robert J. Gillies, PhD
Paul E. Kinahan, PhD
Hedvig Hricak, MD, PhD, Dr(hc)



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17	20	21	23	26	26	23
16	18	20	21	23	26	25
16	19	22	20	21	23	27
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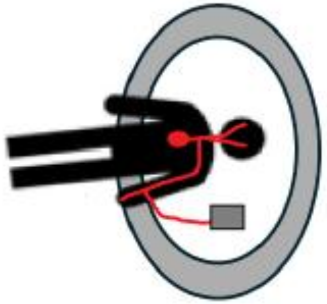
NM images lifecycle

Radiation detection
- Time resolution
- Intrinsic detector resolution



Open challenges

Automatic extraction

of quantitative parameters

(radiomics and beyond)

Harmonization

Accuracy

Direct parametric reconstruction

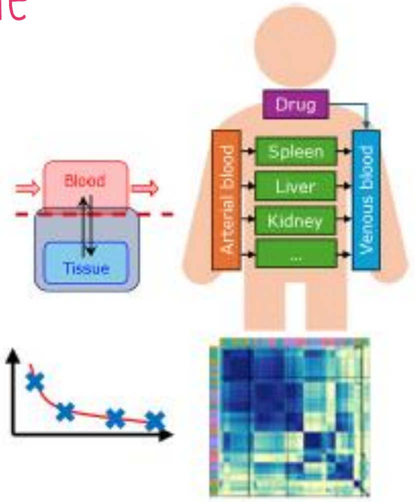
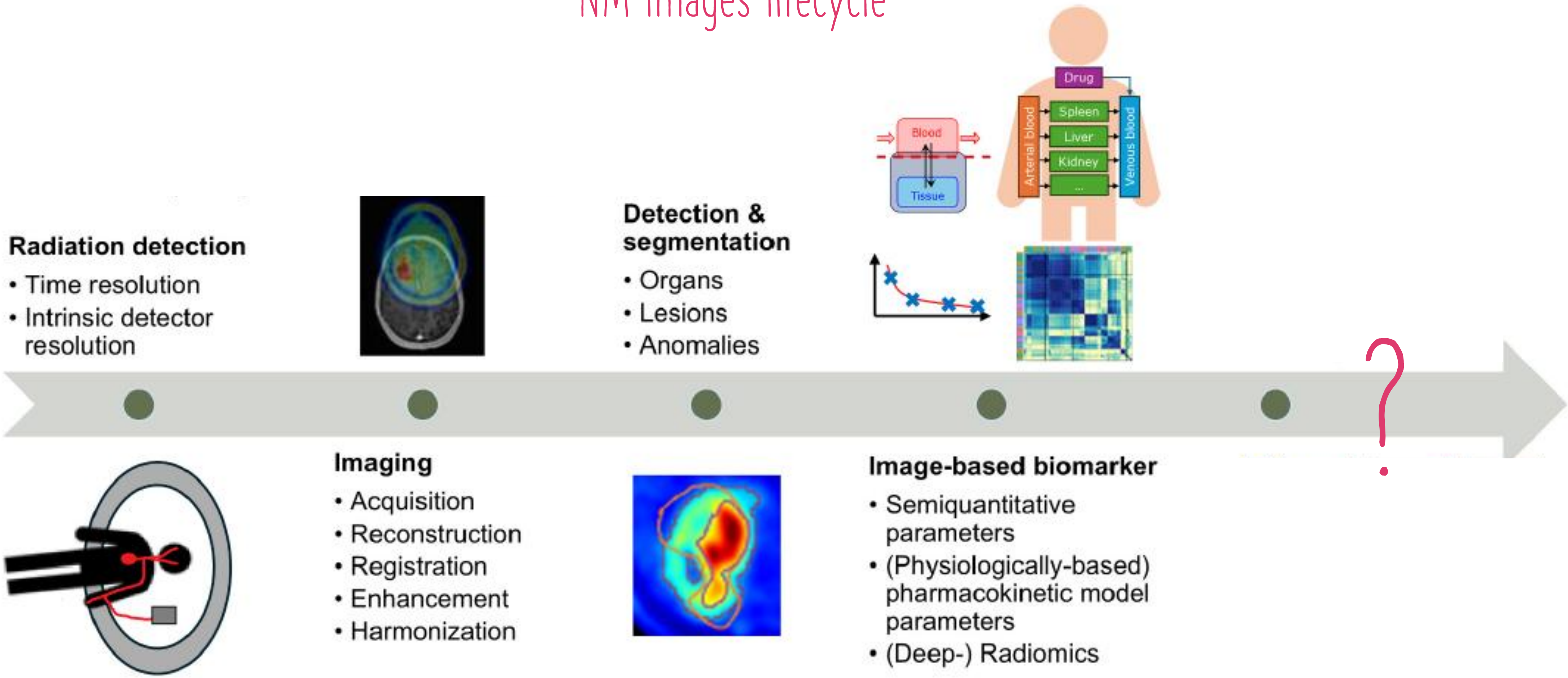


Image-based biomarker

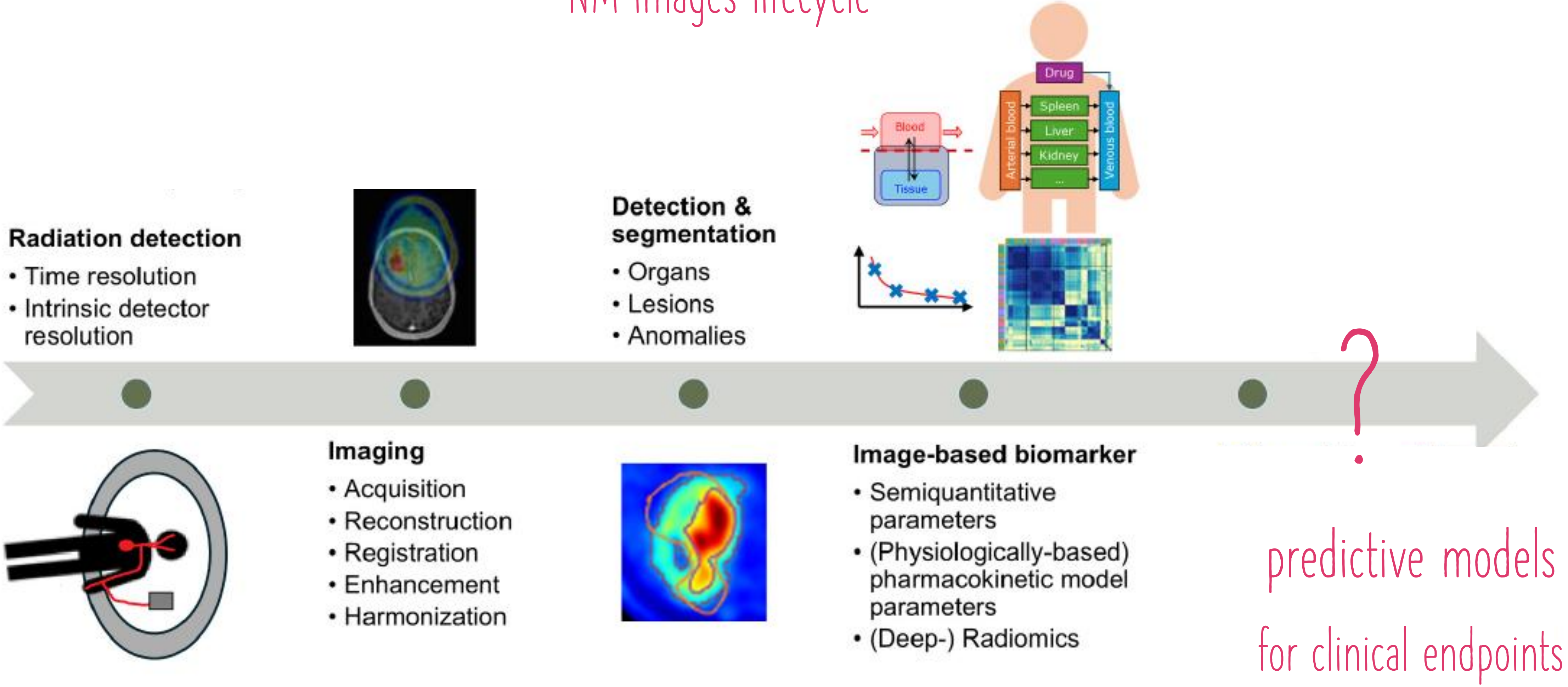
Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

NM images lifecycle



Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004

NM images lifecycle



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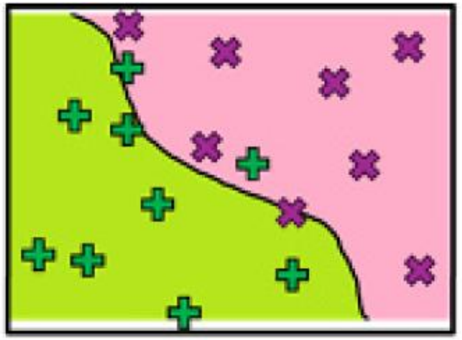
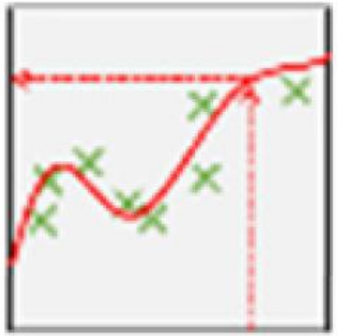
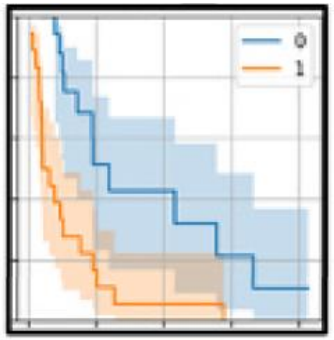




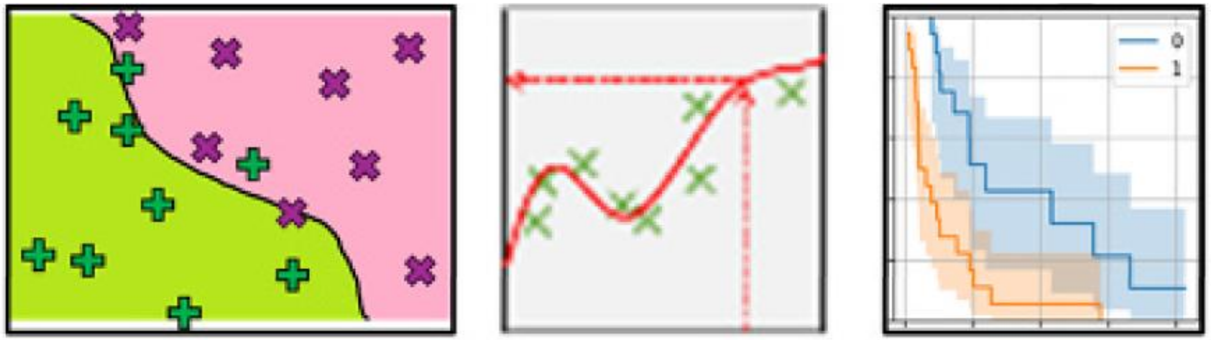


Classification

Prediction of treatment response

Survival prediction

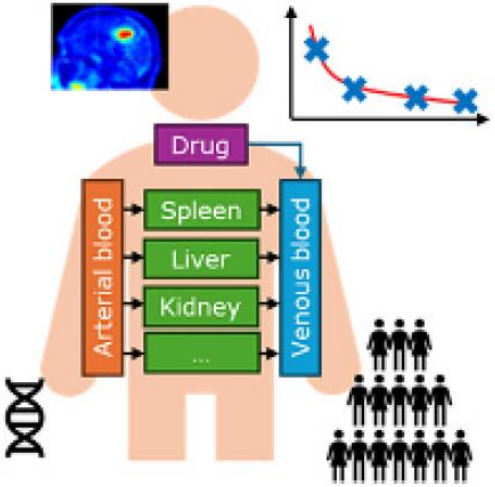
Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004



Classification

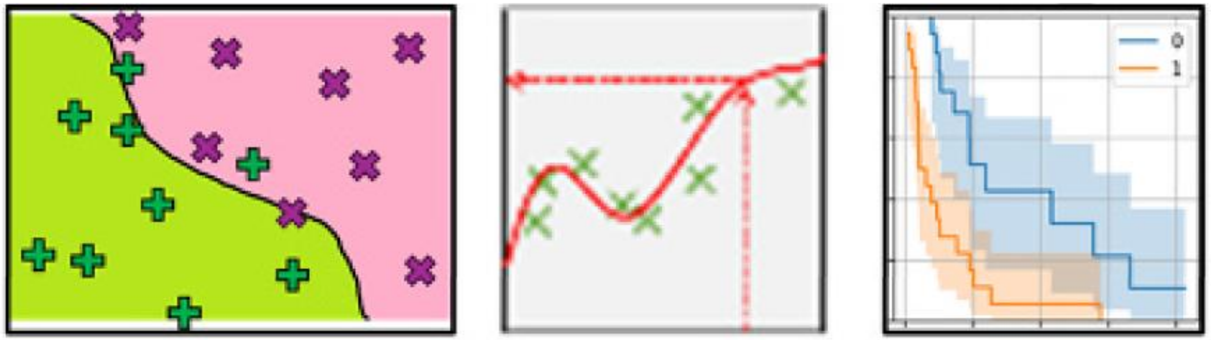
Prediction of treatment response

Survival prediction



Additional diagnostic information

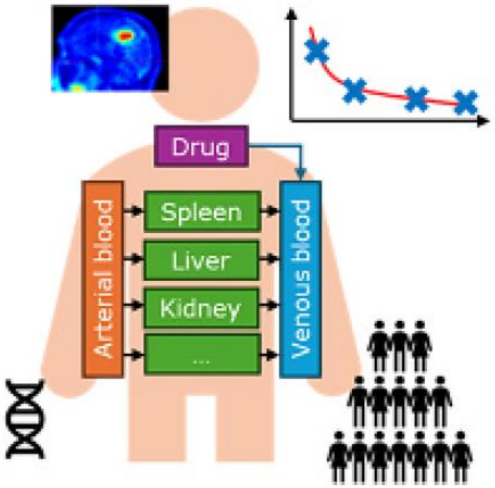
Applications of artificial intelligence in nuclear medicine https://doi.org/10.1016/j.zemedi.2026.04.004



Classification

Prediction of treatment response

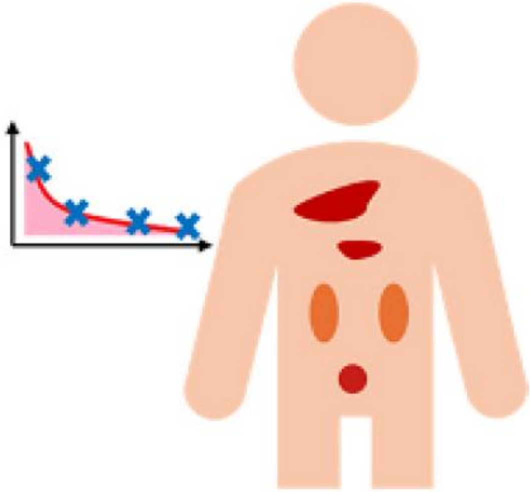
Survival prediction



Additional diagnostic information

Absorbed dose calculation

Therapy planning



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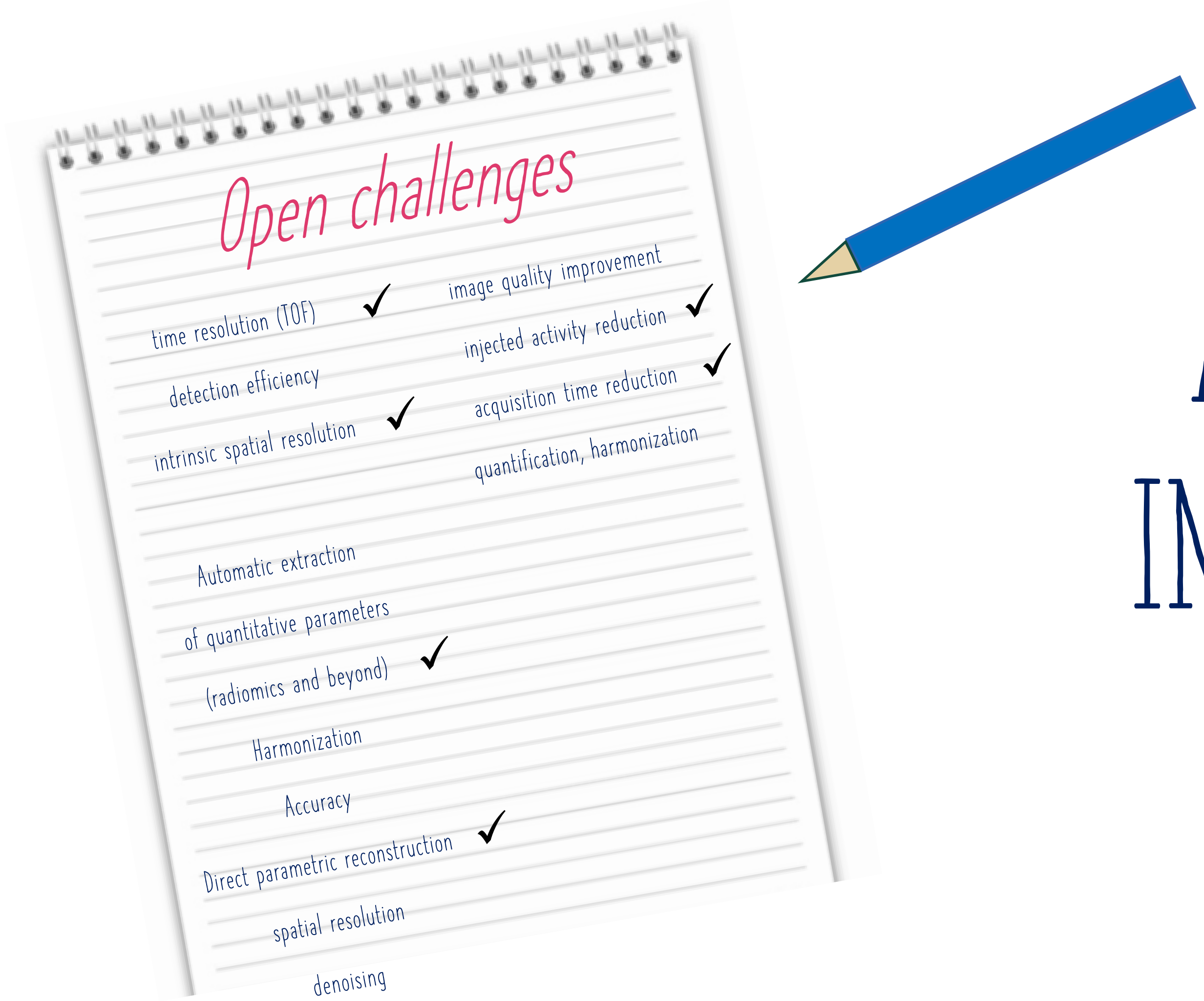
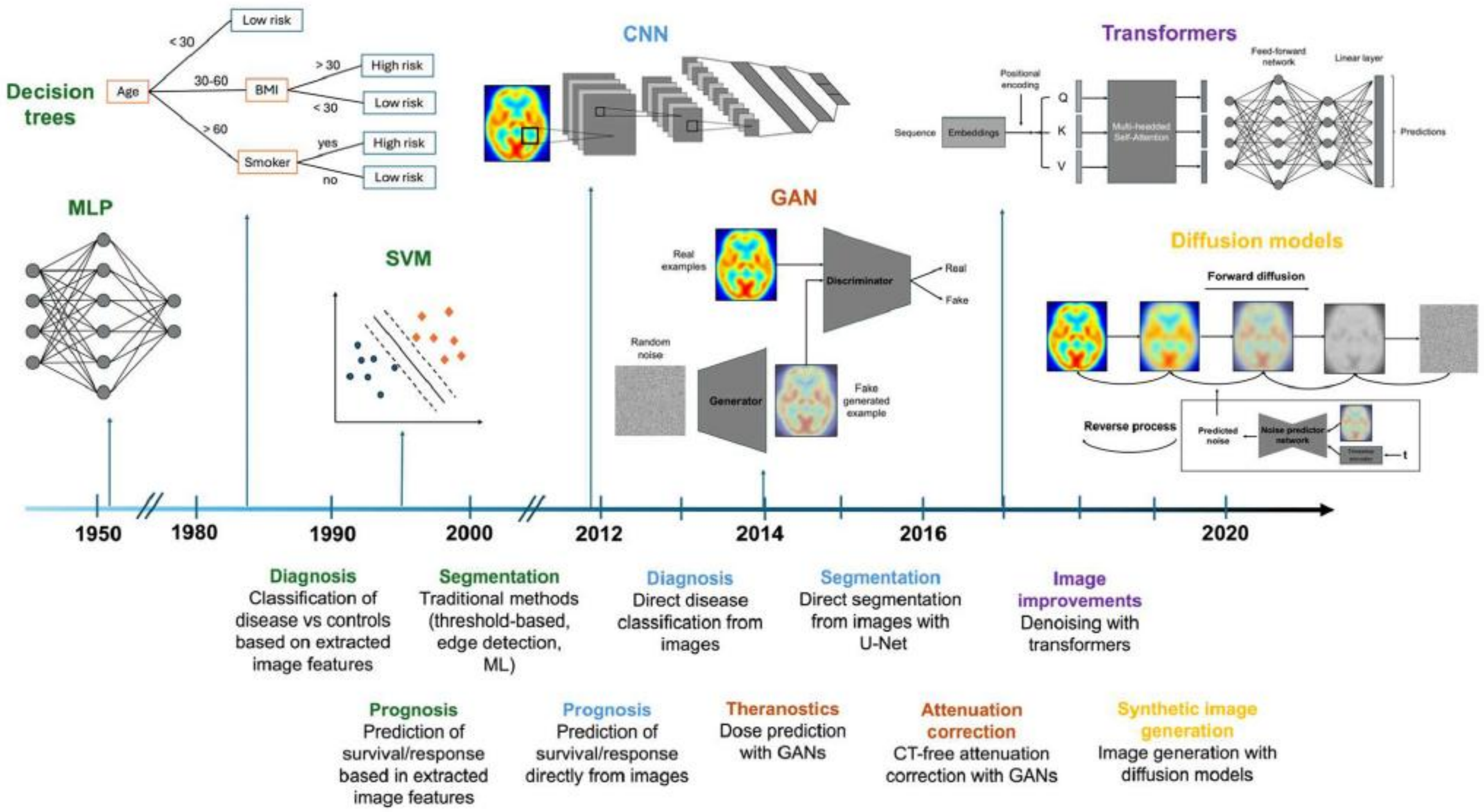


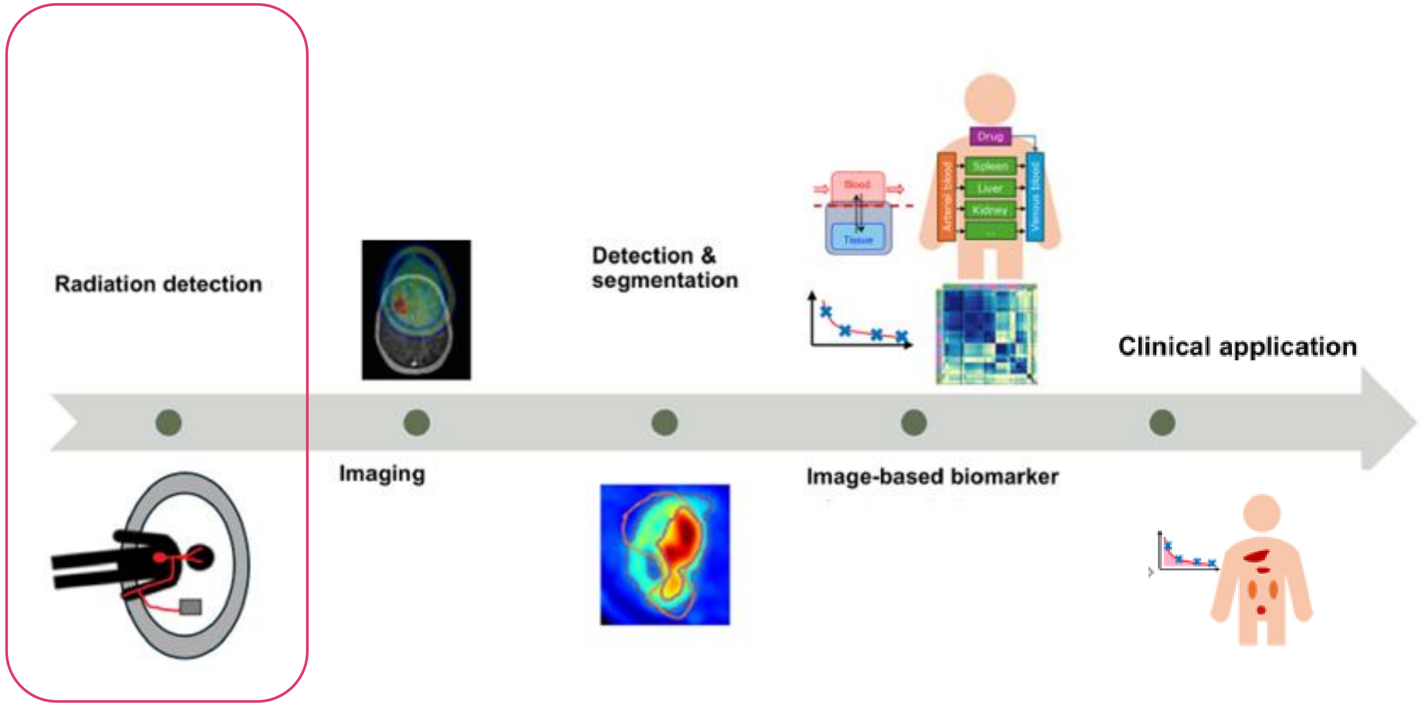
ARTIFICIAL INTELLIGENCE

The evolution of Artificial Intelligence in Nuclear Medicine

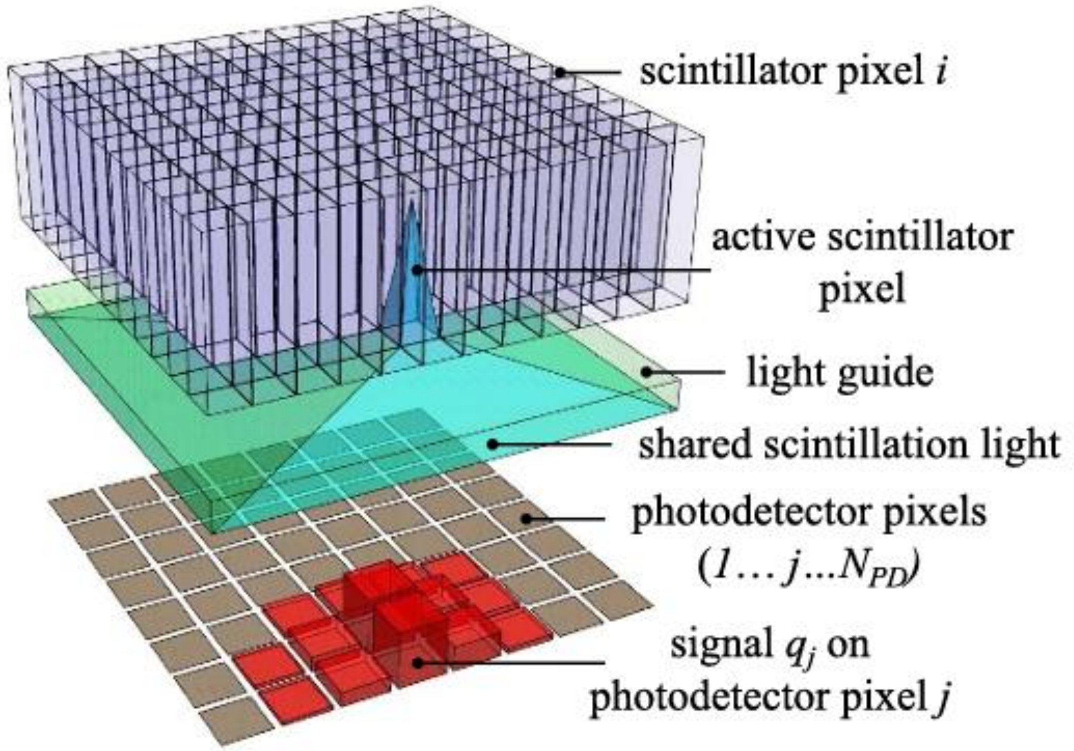


The evolution of artificial intelligence in nuclear medicine https://doi.org/10.1053/j.semnuclmed.2025.01.006

1. RADIATION DETECTION



INTRINSIC DETECTOR RESOLUTION IMPROVEMENT



Uncertainty in the determination of the coordinates of scintillation position:

crystal pixel size

crystal optical properties

photodetectors size

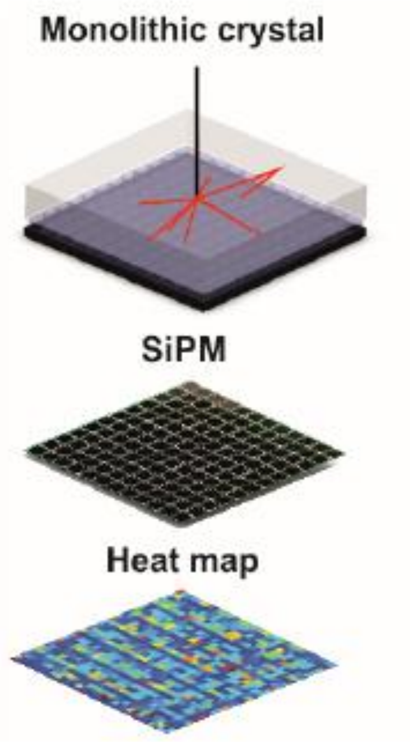
electronic noise

Fast maximum likelihood positioning for a staggered layer scintillation PET detector https://doi.org/10.1088/1361-6560/adf8ab

INTRINSIC DETECTOR RESOLUTION IMPROVEMENT

Either improve detectors or...

Learn from data



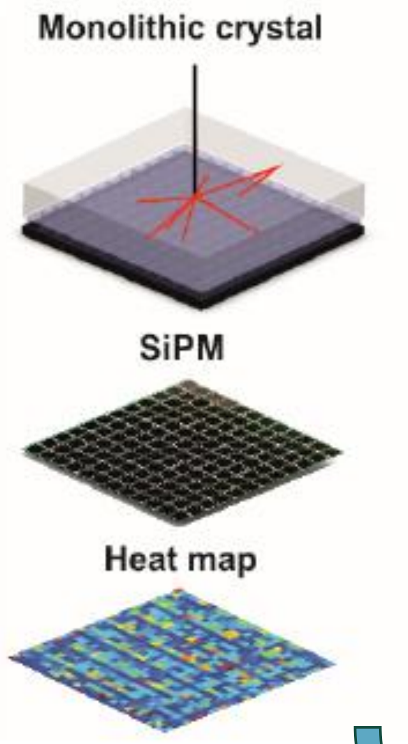
Monte Carlo simulation of the signal produced by point sources at different (known) positions x, y, z

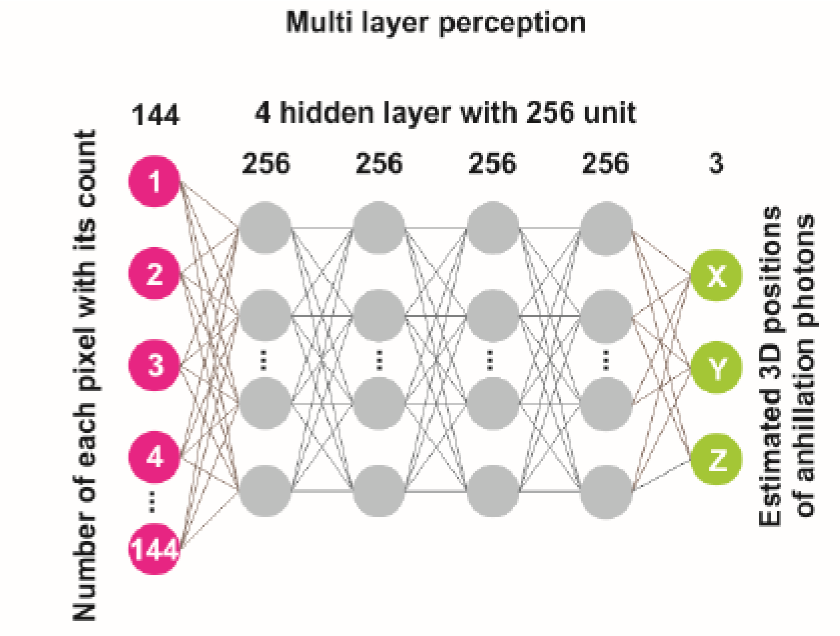
Depth of Interaction Estimation in a Preclinical PET Scanner Equipped with Monolithic Crystals Coupled to SiPMs Using a Deep Neural Network doi:10.3390/app10144753

INTRINSIC DETECTOR RESOLUTION IMPROVEMENT

Either improve detectors or...

Learn from data





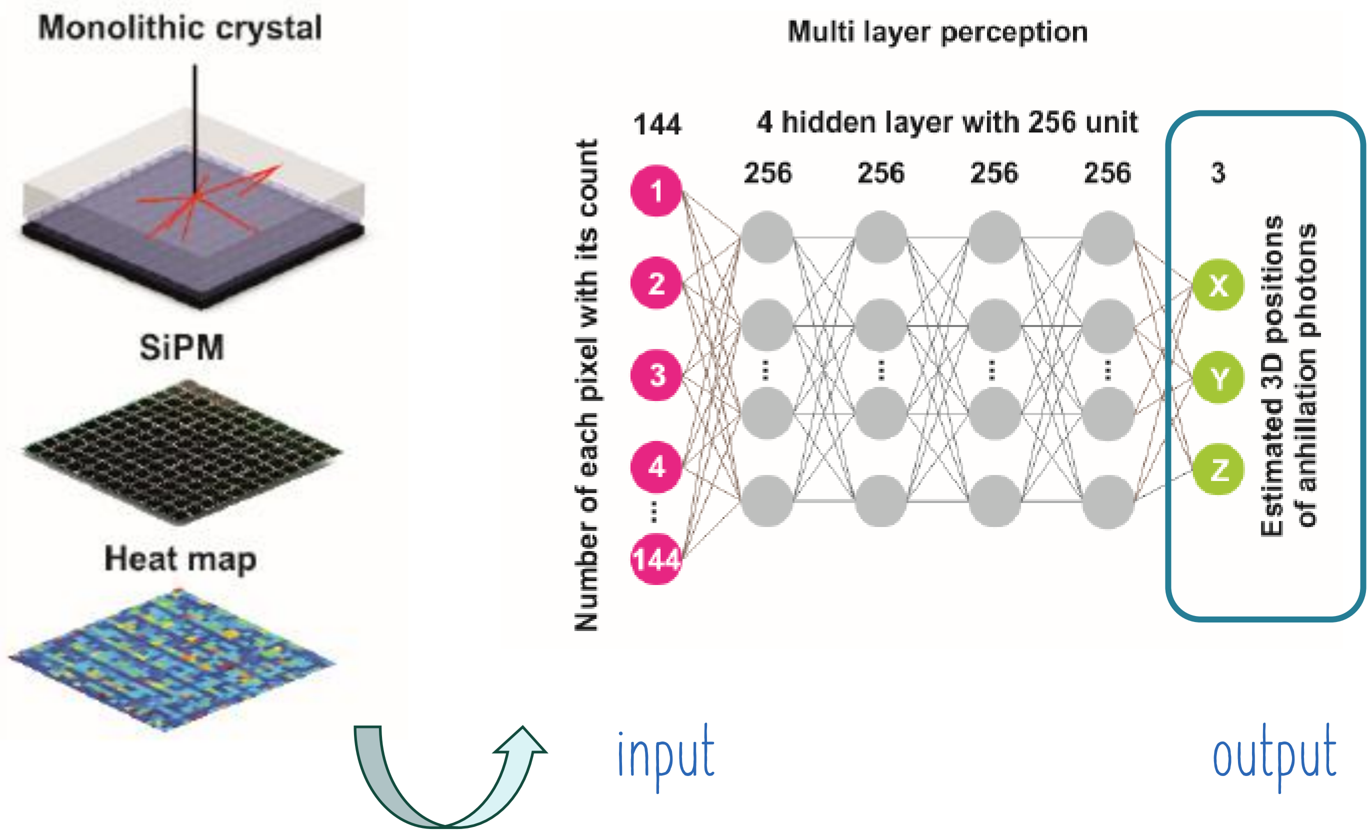
input

Depth of Interaction Estimation in a Preclinical PET Scanner Equipped with Monolithic Crystals Coupled to SiPMs Using a Deep Neural Network doi:10.3390/app10144753

INTRINSIC DETECTOR RESOLUTION IMPROVEMENT

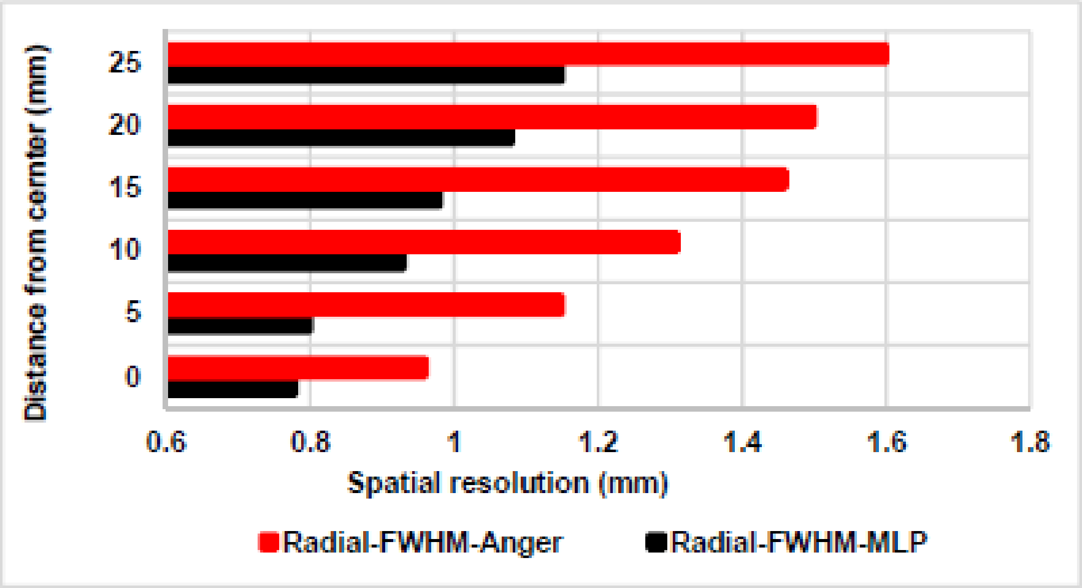
Either improve detectors or...

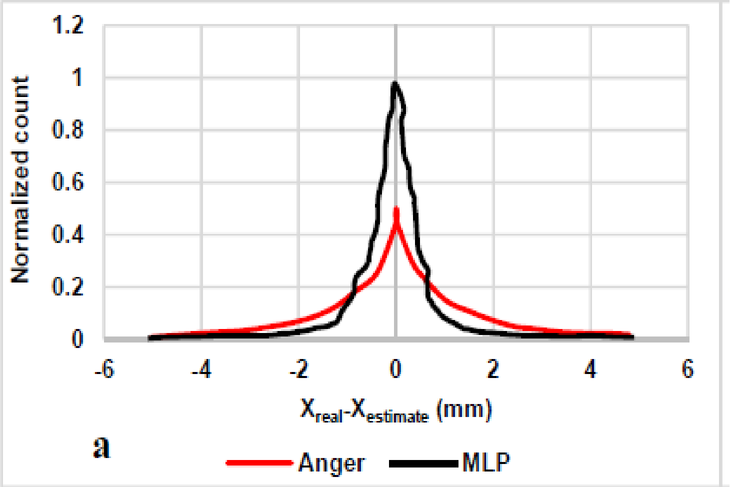
Learn from data

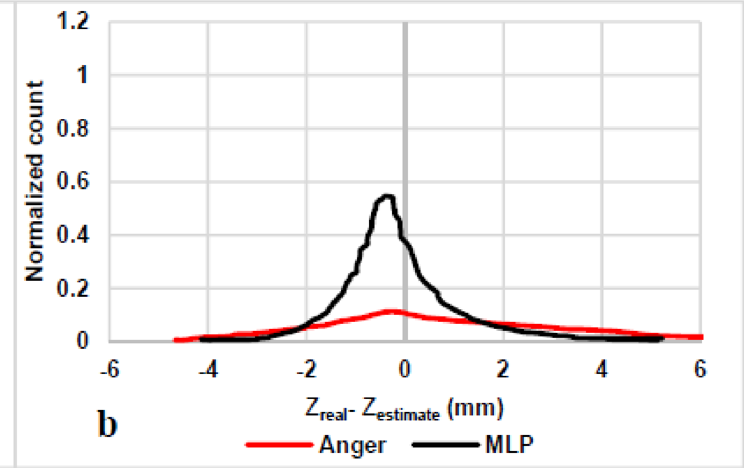


Depth of Interaction Estimation in a Preclinical PET Scanner Equipped with Monolithic Crystals Coupled to SiPMs Using a Deep Neural Network doi:10.3390/app10144753

INTRINSIC DETECTOR RESOLUTION IMPROVEMENT



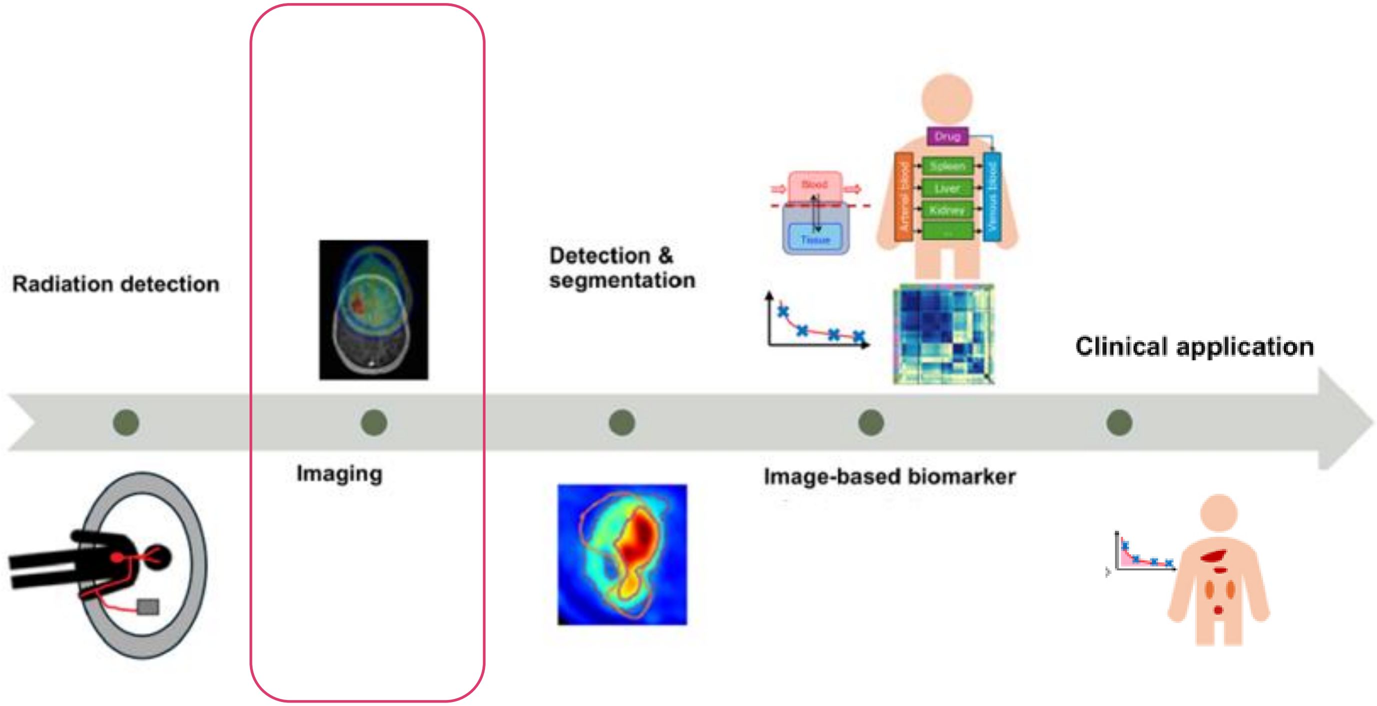




Improved performance in comparison to conventional approach

Depth of Interaction Estimation in a Preclinical PET Scanner Equipped with Monolithic Crystals Coupled to SiPMs Using a Deep Neural Network doi:10.3390/app10144753

2. IMAGING


Radiation detection
Imaging
Detection &
segmentation
Image-based biomarker
Clinical application

2. IMAGING

Acquisition

Enhancement

Reconstruction

IMAGE ACQUISITION

AI trained to recover missing information from sparse data:

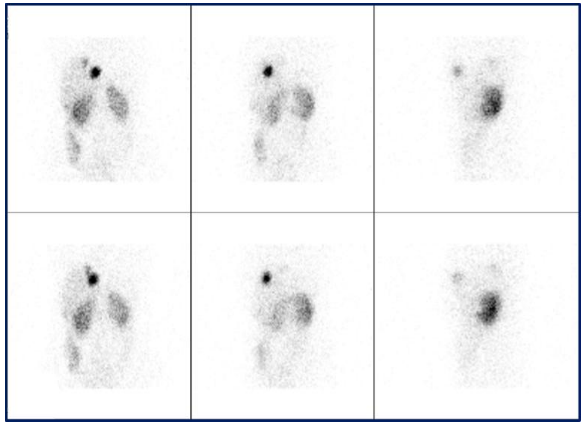
SPECT: shorter time per angle / lower number of projections

PET: shorter time per bed position / faster bed movement

DYNAMIC SCANS: shorter frame duration

ALL: reduced injected activity

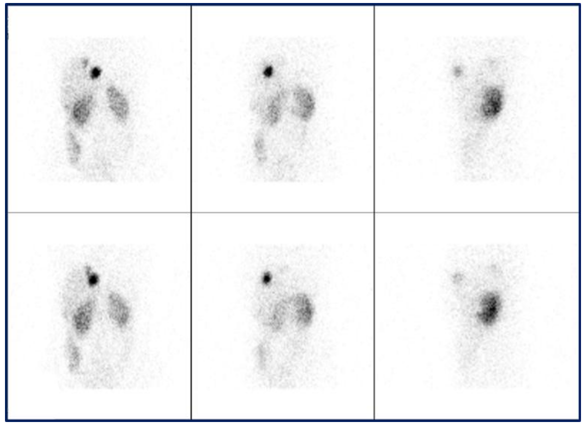
IMAGE ACQUISITION



Noisy raw data

projections/sinogram

IMAGE ACQUISITION

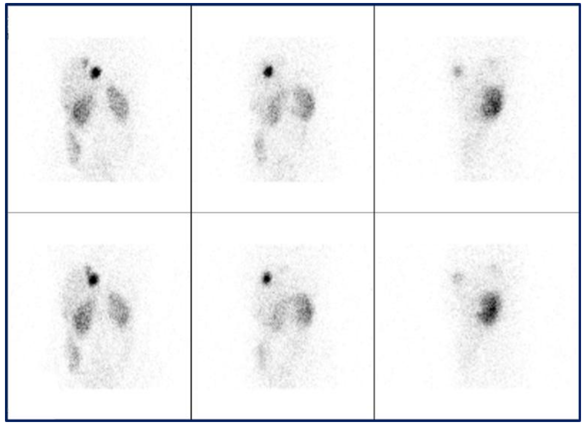


Noisy raw data
projections/sinogram

Reconstruction

Noisy / low quality
Images!

IMAGE ACQUISITION



Noisy raw data projections/sinogram

AI-based projection-domain completion

Reconstruction

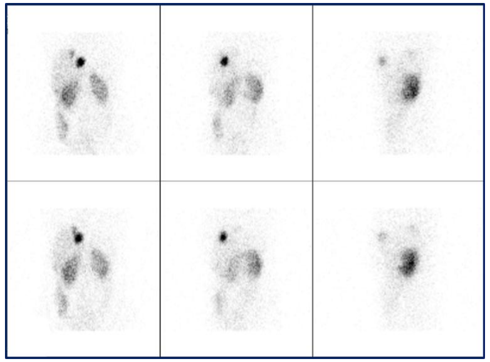
Restored quality Images

IMAGE ACQUISITION

Real data:

^{177}Lu-DOTATATE SPECT

120 projections



Deep-Learning Generation of Synthetic Intermediate Projections Improves 177Lu SPECT Images Reconstructed with Sparsely Acquired Projections 10.2967/jnumed.120.245548

IMAGE ACQUISITION

Real data:

^{177}Lu-DOTATATE SPECT

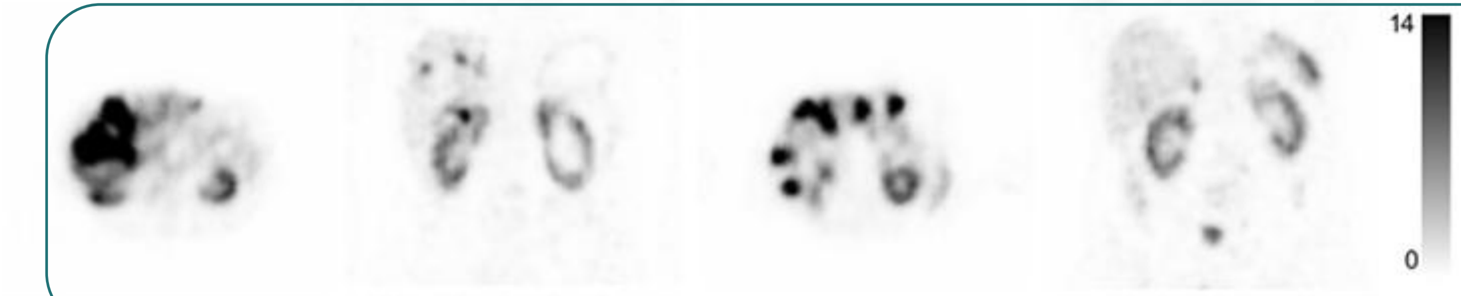
120 projections

Input: 30 projections (1, 5, 9 , ... 117)

Deep-Learning Generation of Synthetic Intermediate Projections Improves 177Lu SPECT Images Reconstructed with Sparsely Acquired Projections 10.2967/jnumed.120.245548

IMAGE ACQUISITION

Reconstructed from 30 measured projections



Reconstructed from 120 measured projections

Deep-Learning Generation of Synthetic Intermediate Projections Improves 177Lu SPECT Images Reconstructed with Sparsely Acquired Projections 10.2967/jnumed.120.245548

IMAGE ACQUISITION

Convolutional Neural Network (CNN)

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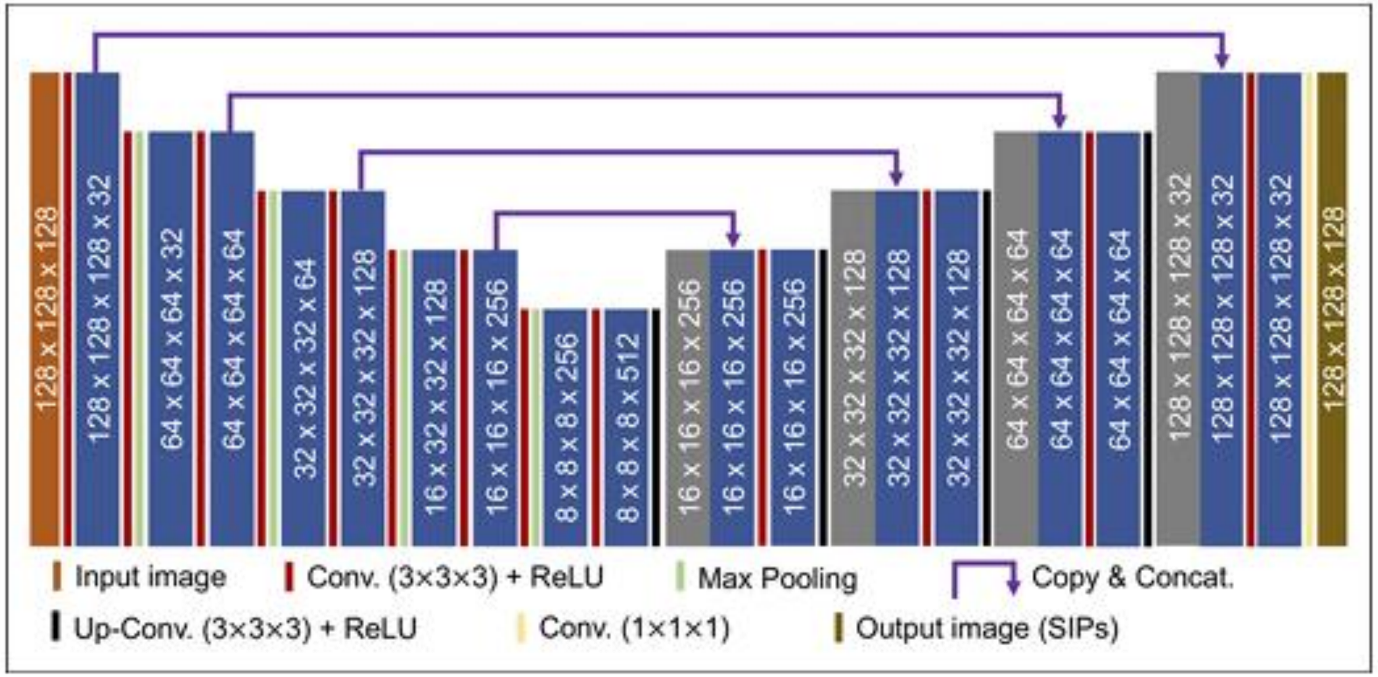
^{177}Lu-DOTATATE SPECT

120 projections



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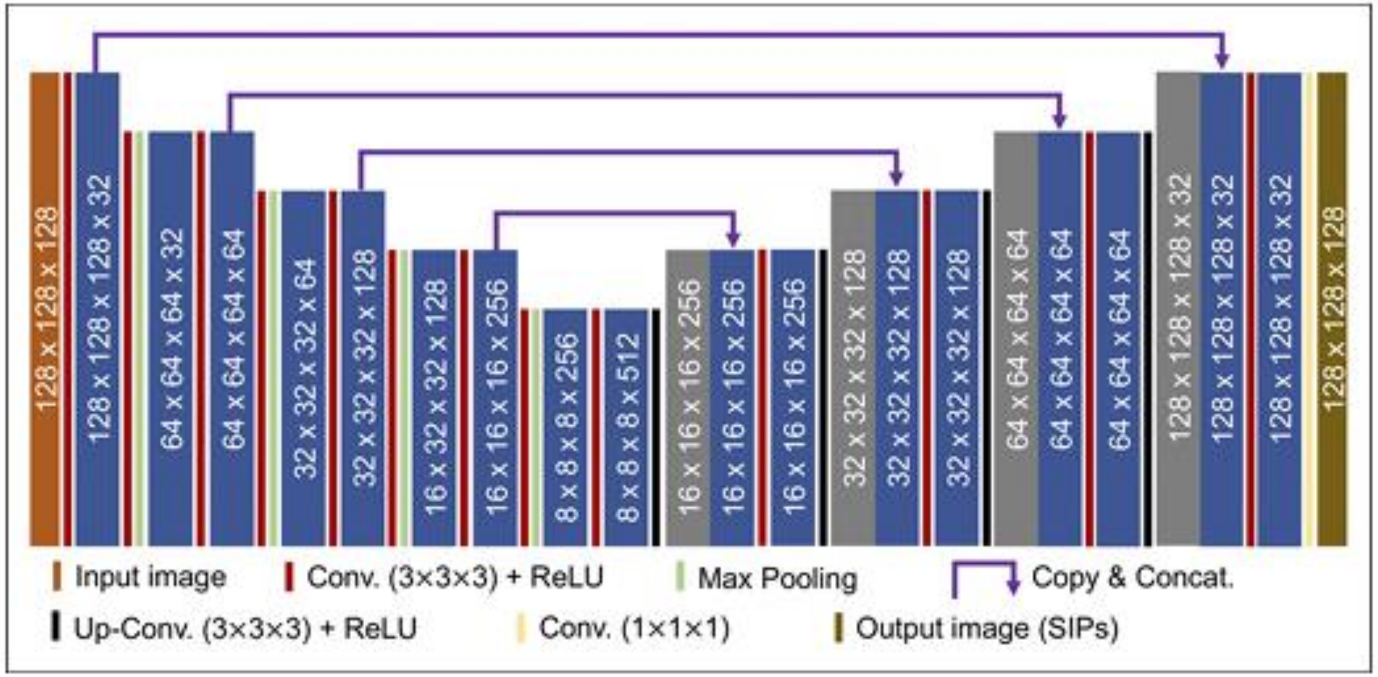


Input: 30 projections (1, 5, 9 , ... 117)

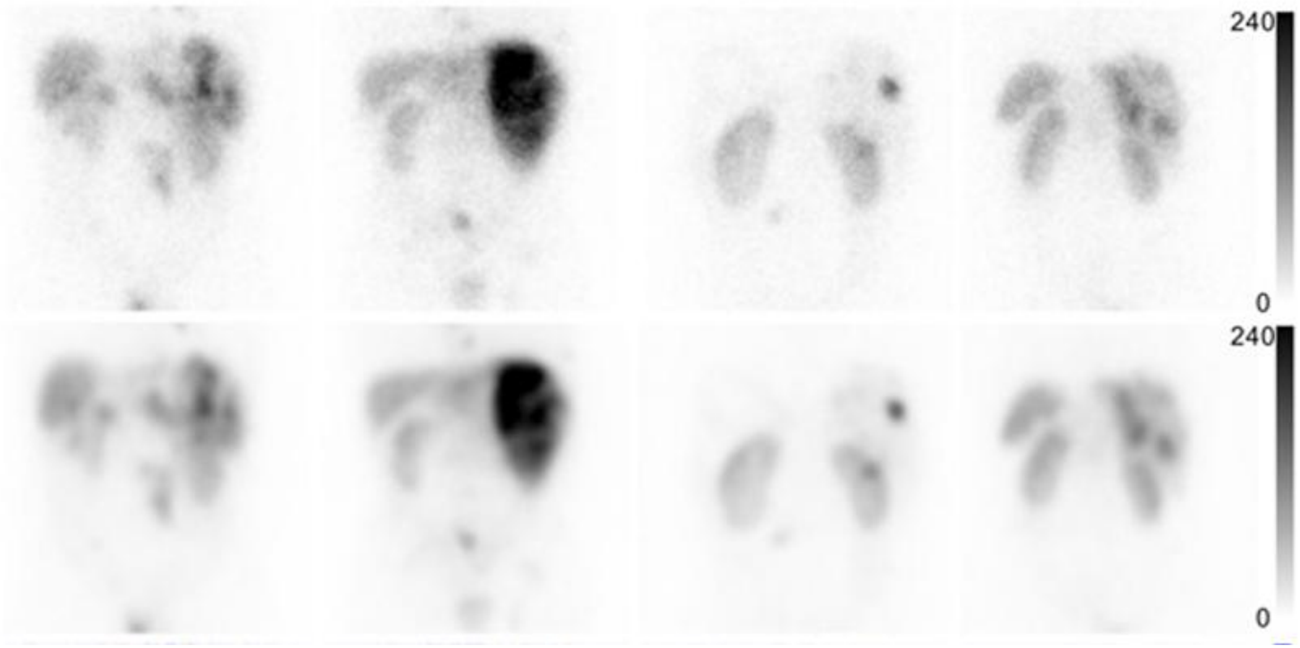
CNN 1 Output: 30 projections (2, 6, 10 , ... 118)

CNN 2 Output: 30 projections (3, 7, 11 , ... 119)

CNN 3 Output: 30 projections (4, 8, 12 , ... 120)

Deep-Learning Generation of Synthetic Intermediate Projections Improves 177Lu SPECT Images Reconstructed with Sparsely Acquired Projections 10.2967/jnumed.120.245548

IMAGE ACQUISITION

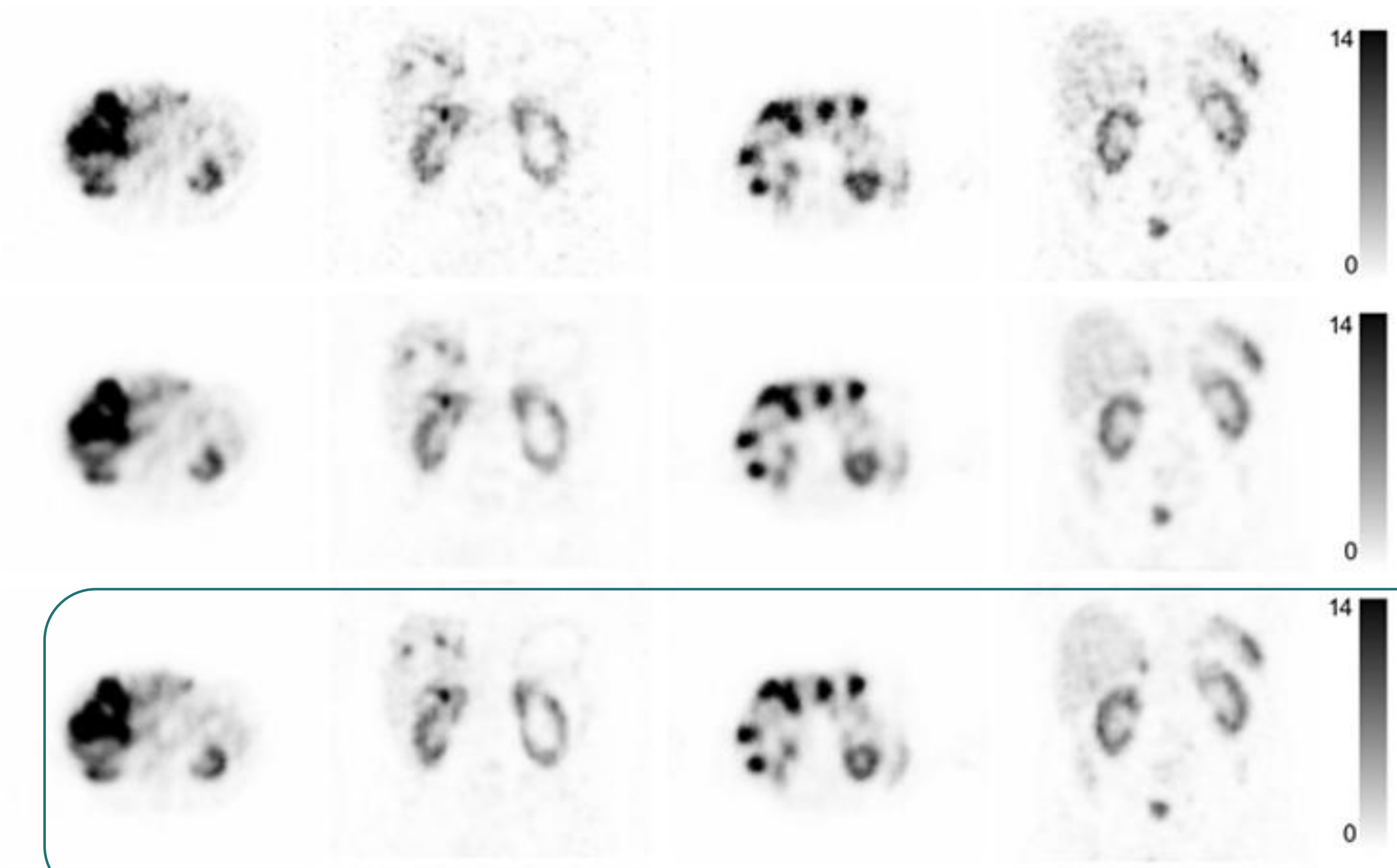


Measured projections

AI-generated projections

Deep-Learning Generation of Synthetic Intermediate Projections Improves 177Lu SPECT Images Reconstructed with Sparsely Acquired Projections 10.2967/jnumed.120.245548

IMAGE ACQUISITION



Reconstructed from 30 measured projections

Reconstructed from 90 AI-generated projections

Reconstructed from 120 measured projections

Deep-Learning Generation of Synthetic Intermediate Projections Improves 177Lu SPECT Images Reconstructed with Sparsely Acquired Projections 10.2967/jnumed.120.245548

IMAGE ACQUISITION

Similarly,

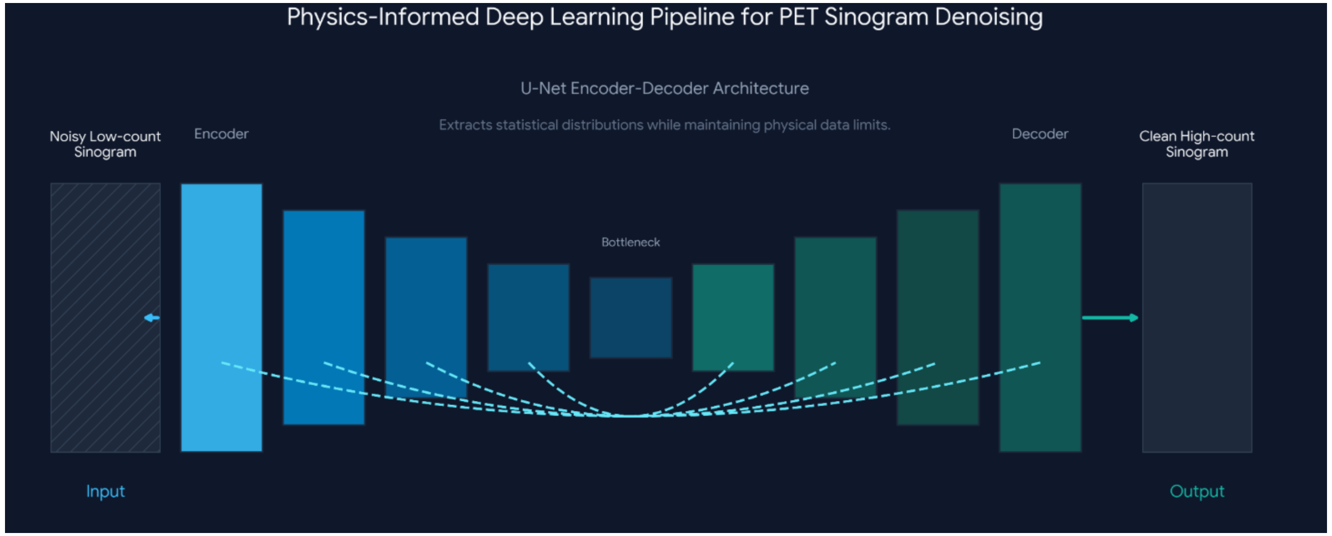
in case of PET...

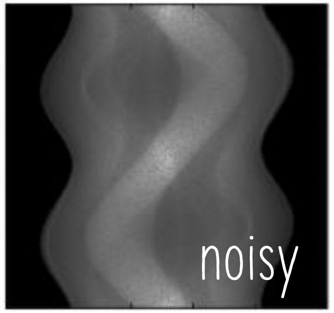
IMAGE ACQUISITION

Sinogram-to-sinogram CNN pipeline

Similarly,

in case of PET...





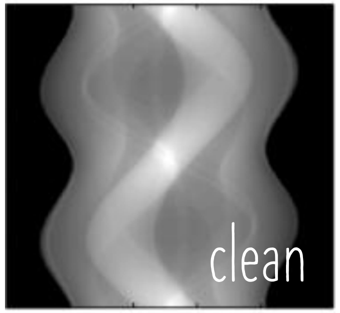


IMAGE ACQUISITION

Similarly,

in case of PET...

Count-level Correction

Raw sinogram data suffers from statistical randomness and scatter. AI models like U-Nets process this raw data to synthesize high-quality sinograms before traditional iterative reconstruction (e.g., OSEM) begins.

IMAGE ACQUISITION

Similarly,

in case of PET...

<u>Count-level Correction</u>

Raw sinogram data suffers from statistical randomness and scatter. AI models like U-Nets process this raw data to synthesize high-quality sinograms before traditional iterative reconstruction (e.g., OSEM) begins.

<u>Physics Integration</u>

By constraining the network with PET system matrices (incorporating parameters like positron range and point spread function), algorithms ensure that noise suppression respects physical limits.

IMAGE ACQUISITION

Physics-informed framework

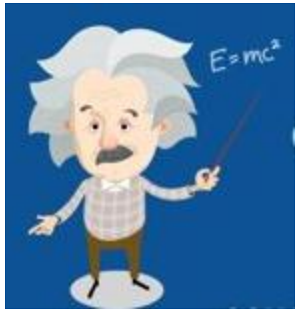
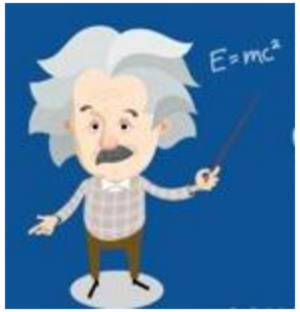


IMAGE ACQUISITION

Physics-informed framework



1. The Physics-Informed Loss Function (Poisson Noise Constraints)

The Problem:

Standard neural networks rely on Mean Squared Error (MSE), which treats all pixel errors equally. However, PET and CT sinograms follow Poisson distribution statistics because they count discrete photon arrivals.

IMAGE ACQUISITION

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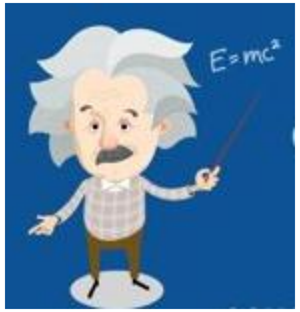


1. The Physics-Informed Loss Function (Poisson Noise Constraints)

The Problem:

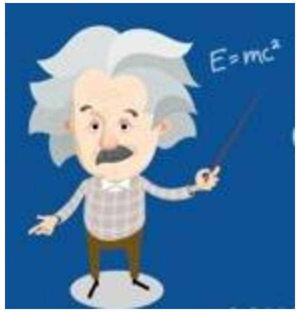
Standard neural networks rely on Mean Squared Error (MSE), which treats all pixel errors equally. However, PET and CT sinograms follow Poisson distribution statistics because they count discrete photon arrivals.

The Physics Integration:

The AI model is trained with a specialized loss function.
This mathematical constraint ensures that the AI's predicted sinogram values **strictly comply with the expected physical quantum noise distributions of a real low-dose scan**, preventing the model from blurring away real anatomical structures or generating fake details (hallucinations)

IMAGE ACQUISITION

Physics-informed framework



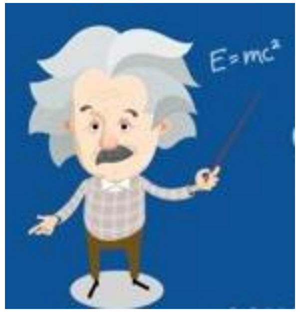
2. Loop-Unrolling & The Forward Projection Operator (System Matrix)

The Problem:

Pure data-driven networks do not understand that a sinogram is a collection of 1D projections taken at various angles around a 3D object.

IMAGE ACQUISITION

Physics-informed framework



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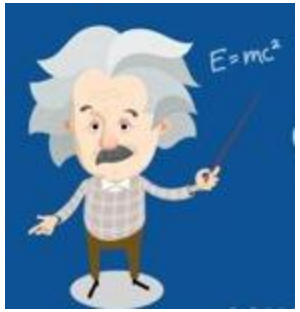
The Physics Integration:

In an unrolled network framework (like Learned Primal-Dual (LPD) or Plug-and-Play (P&P) frameworks), **the network layers alternate between data-driven denoising blocks and physical projection layers.**

IMAGE ACQUISITION

Physics-informed framework



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<u>The Problem:</u>

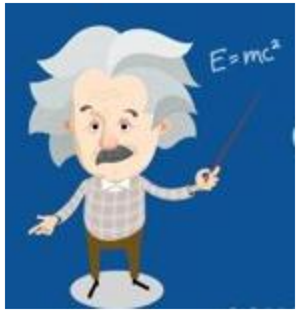
Pure data-driven networks do not understand that a sinogram is a collection of 1D projections taken at various angles around a 3D object.

<u>The Mechanism:</u>

The algorithm applies a **Forward Projection Operator** -the exact physical system matrix of the PET or CT scanner. This projects the data back and forth between image space and sinogram space.

IMAGE ACQUISITION

Physics-informed framework



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The Problem:

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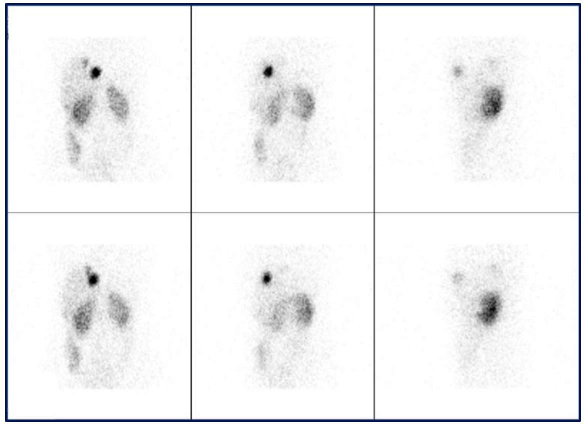
The Mechanism:

The network evaluates whether the newly generated sinogram physically matches a valid anatomical structure. If a predicted sinogram line couldn't physically exist based on the scanner's geometry, the physics layer penalizes the AI and forces it to correct the error

IMAGE ACQUISITION



Noisy raw data projections/sinogram

AI-based projection-domain completion

Reconstruction

Restored quality Images

IMAGE ACQUISITION

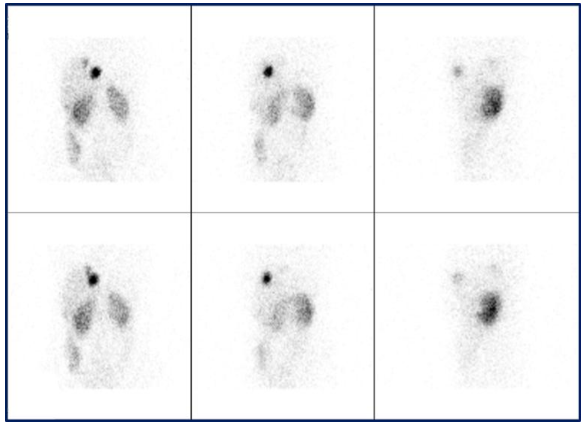


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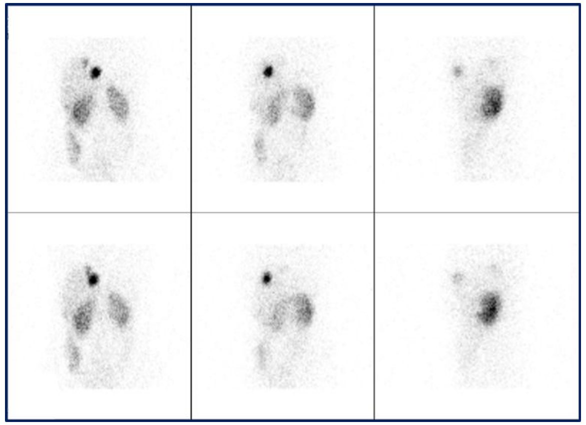
IMAGE ENHANCEMENT: DENOISING



Noisy raw data projections/sinogram

Reconstruction

Noisy / low quality Images

AI-based image-domain restoration

Restored quality Images

IMAGE ENHANCEMENT: DENOISING

The AI algorithm learns how to convert a
noisy reconstructed image, obtained from noisy raw data,
into the image that would have been obtained
if high-quality raw data were acquired

IMAGE ENHANCEMENT: DENOISING

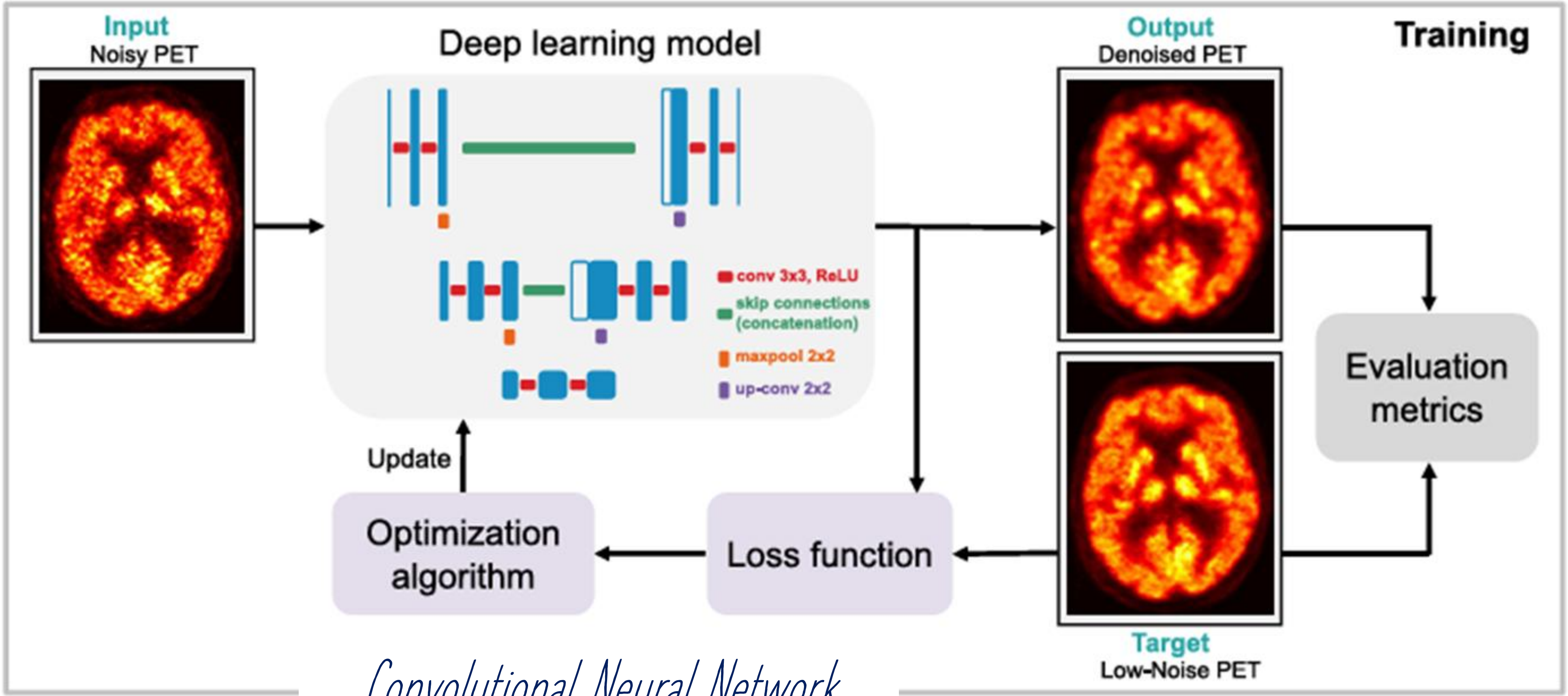
Convolutional Neural Network

use "sliding filters" (convolutions) to scan data

highly efficient at recognizing spatial hierarchies

process data in a localized way (focusing on adjacent pixels)

IMAGE ENHANCEMENT: DENOISING

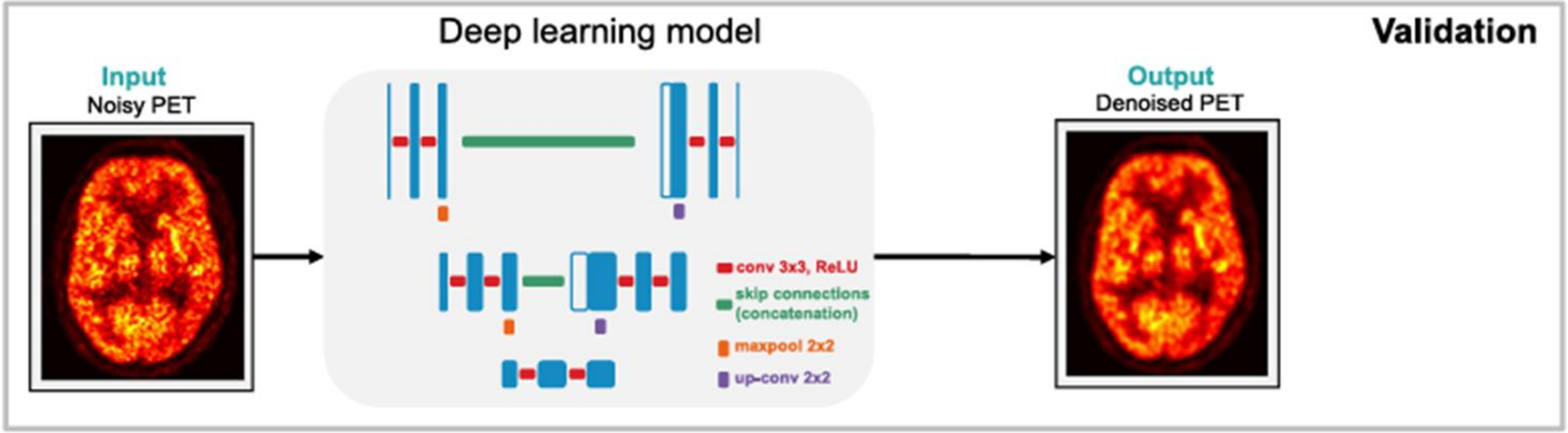


Convolutional Neural Network

Artificial Intelligence for PET and SPECT Image Enhancement 10.2967/jnumed.122.265000

IMAGE ENHANCEMENT: DENOISING

Convolutional Neural Network



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rely on self-attention mechanisms, they process entire sequences of data all at once rather than step-by-step

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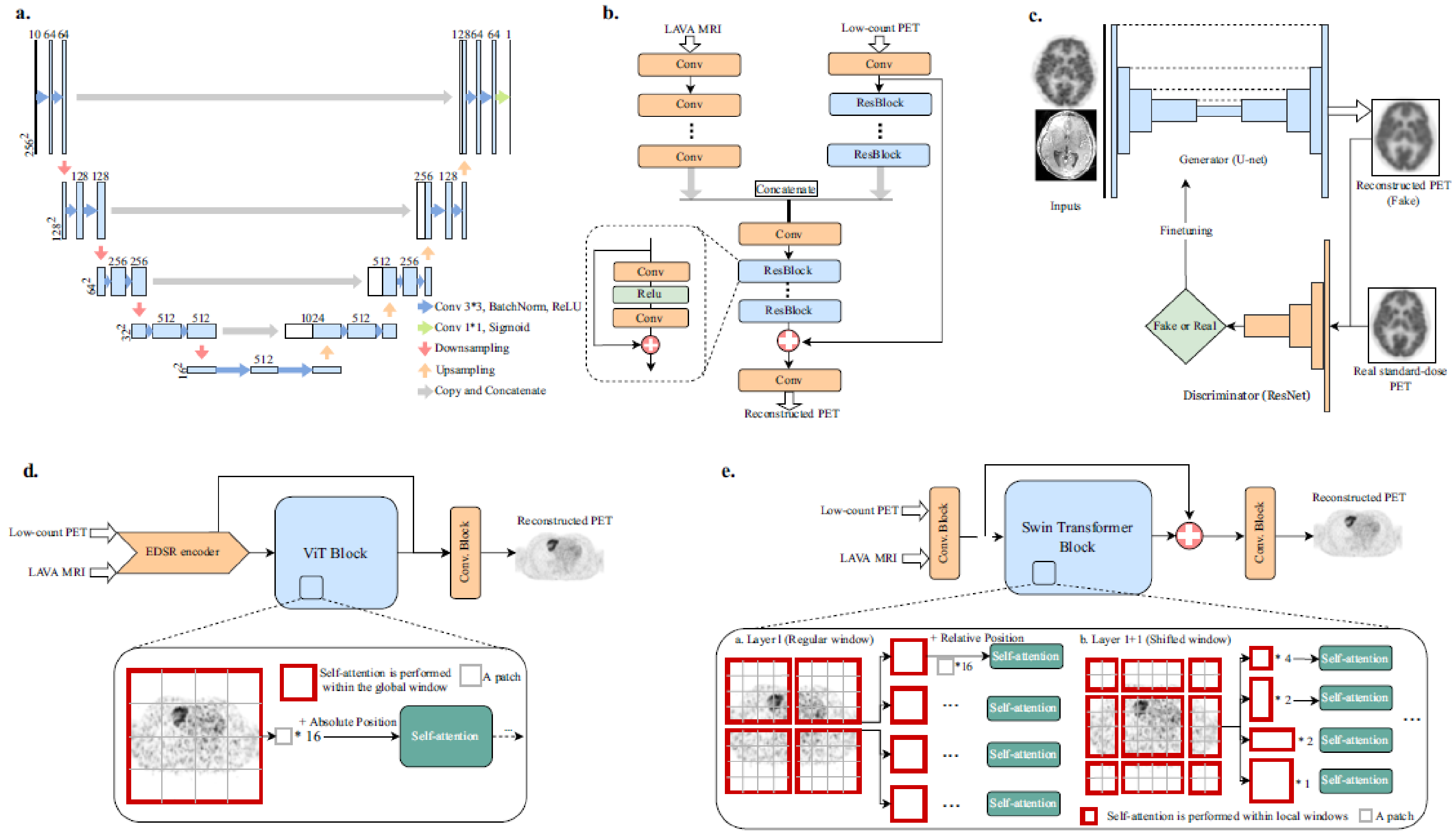
calculate the relationship between every single piece of data and every other piece, regardless of how far apart they are

IMAGE ENHANCEMENT: DENOISING



Convolutional Neural Network CNN

Enhanced deep super-resolution network

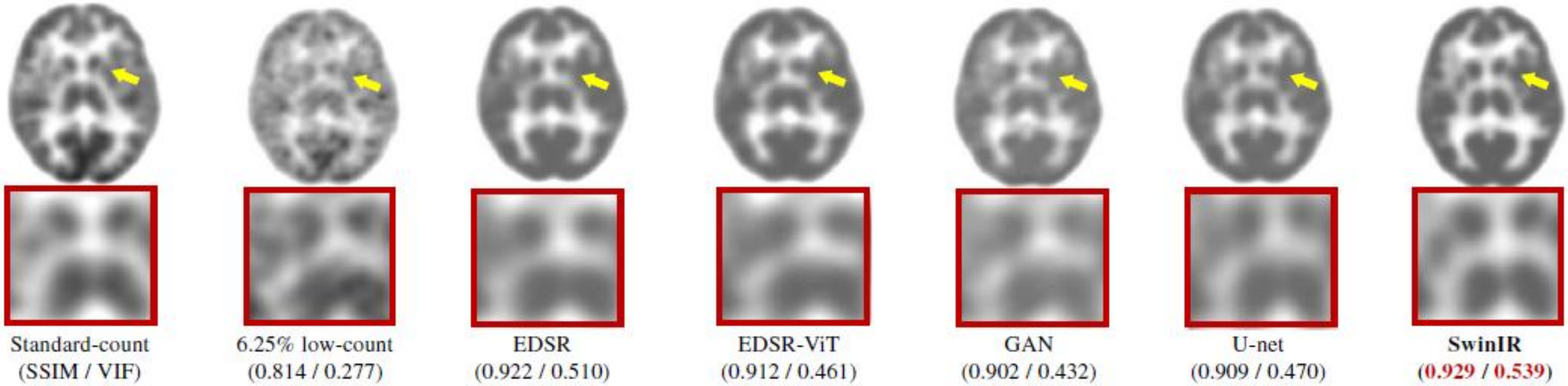
Generative Adversarial Network GAN

Transformed image restoration network

Vision Transformer

Low-count whole-body PET/MRI restoration: an evaluation of dose reduction spectrum and five state-of-the-art artificial intelligence models /doi.org/10.1007/s00259-022-06097-w

IMAGE ENHANCEMENT: DENOISING



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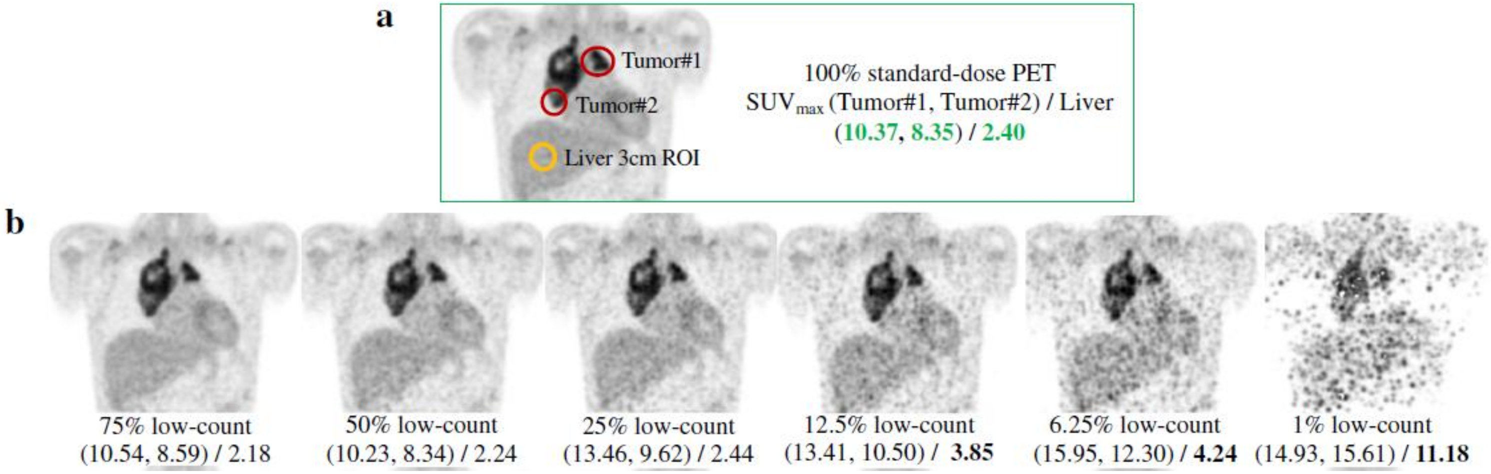

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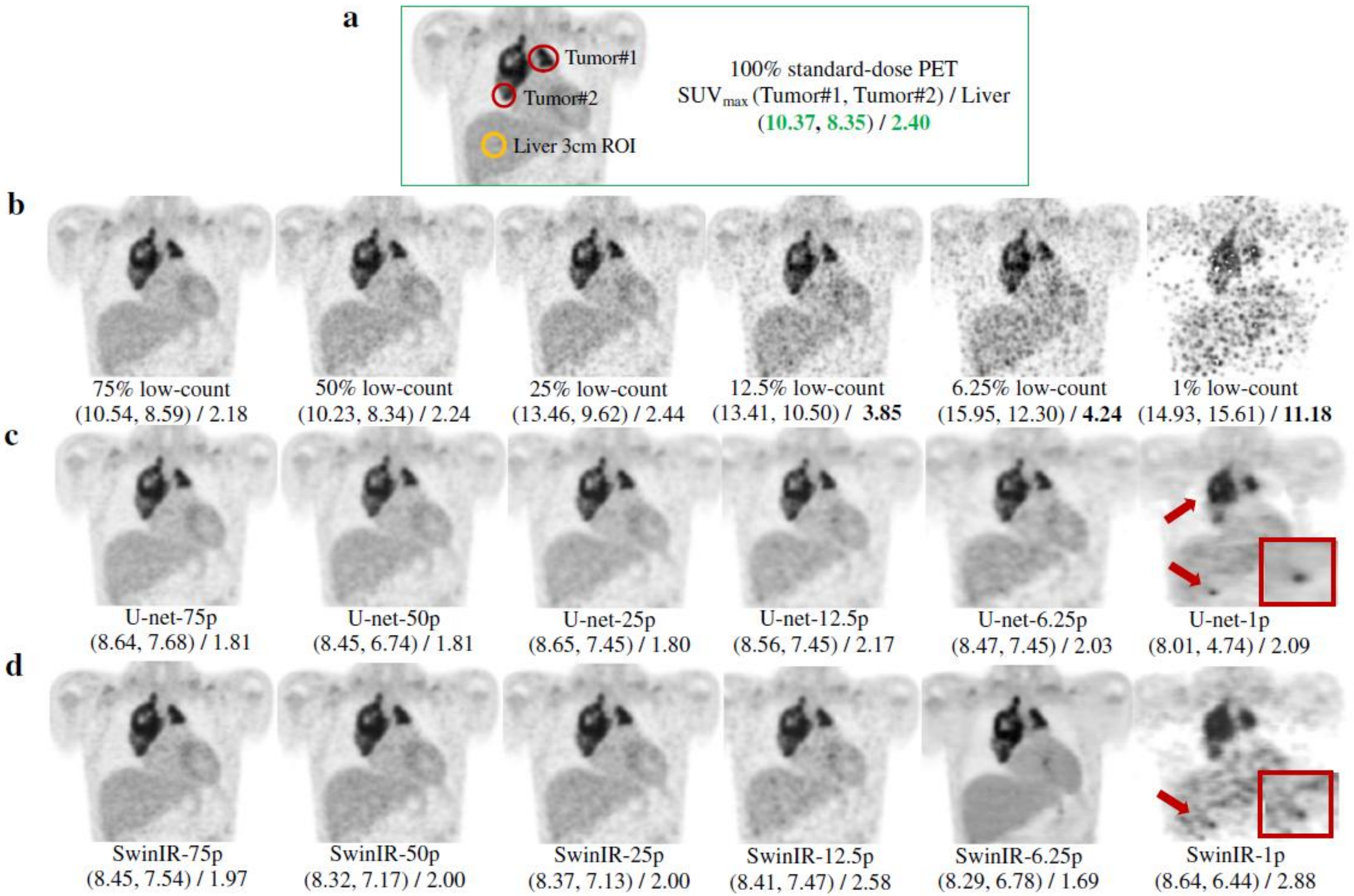

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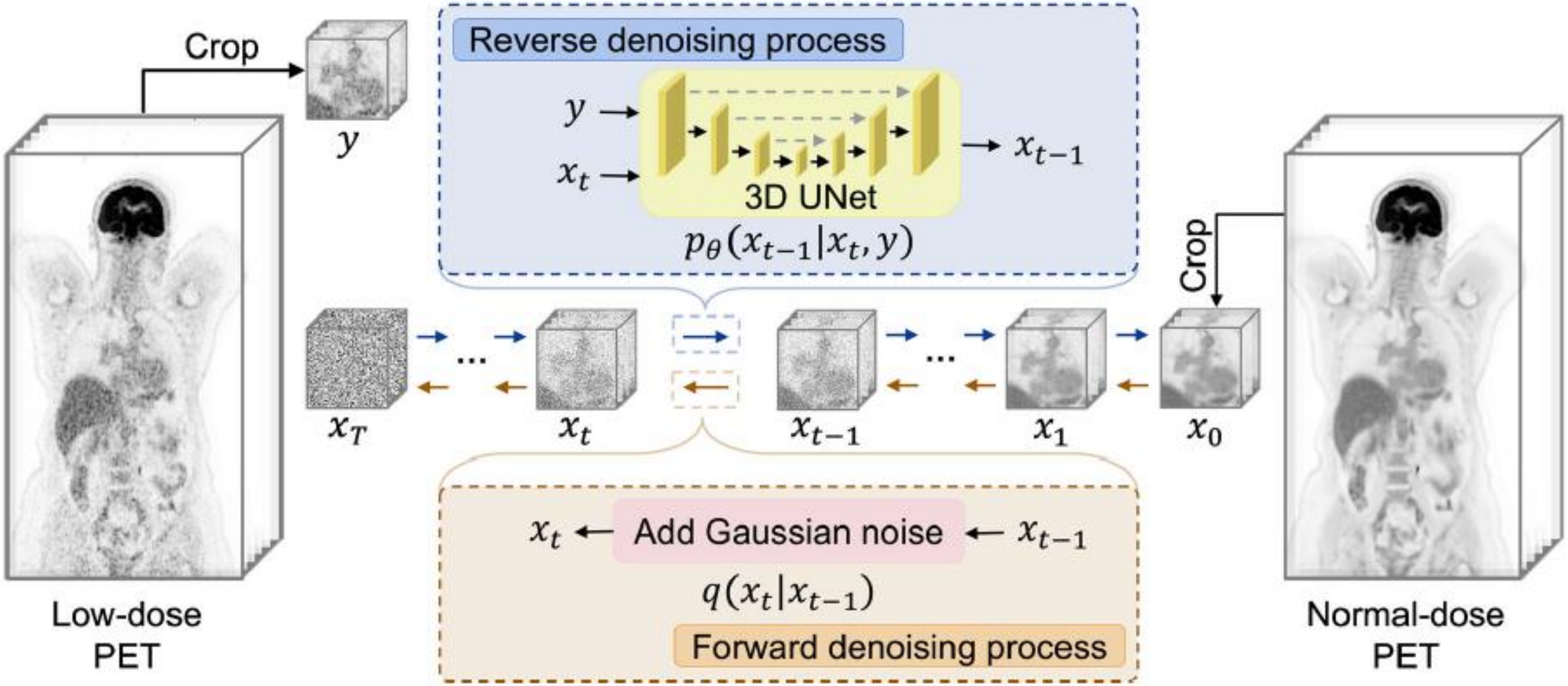
Diffusion Models

Diffusion models function iteratively. During training, they deliberately add noise to an image until it is completely destroyed.

They then train the AI to reverse this process, learning how to reconstruct clear, meaningful data from pure noise

IMAGE ENHANCEMENT: DENOISING



Robust whole-body PET image denoising using 3D diffusionmodels: evaluation across various scanners, tracers, and dose levels doi.org/10.1007/s00259-025-07122-4

IMAGE ENHANCEMENT: DENOISING

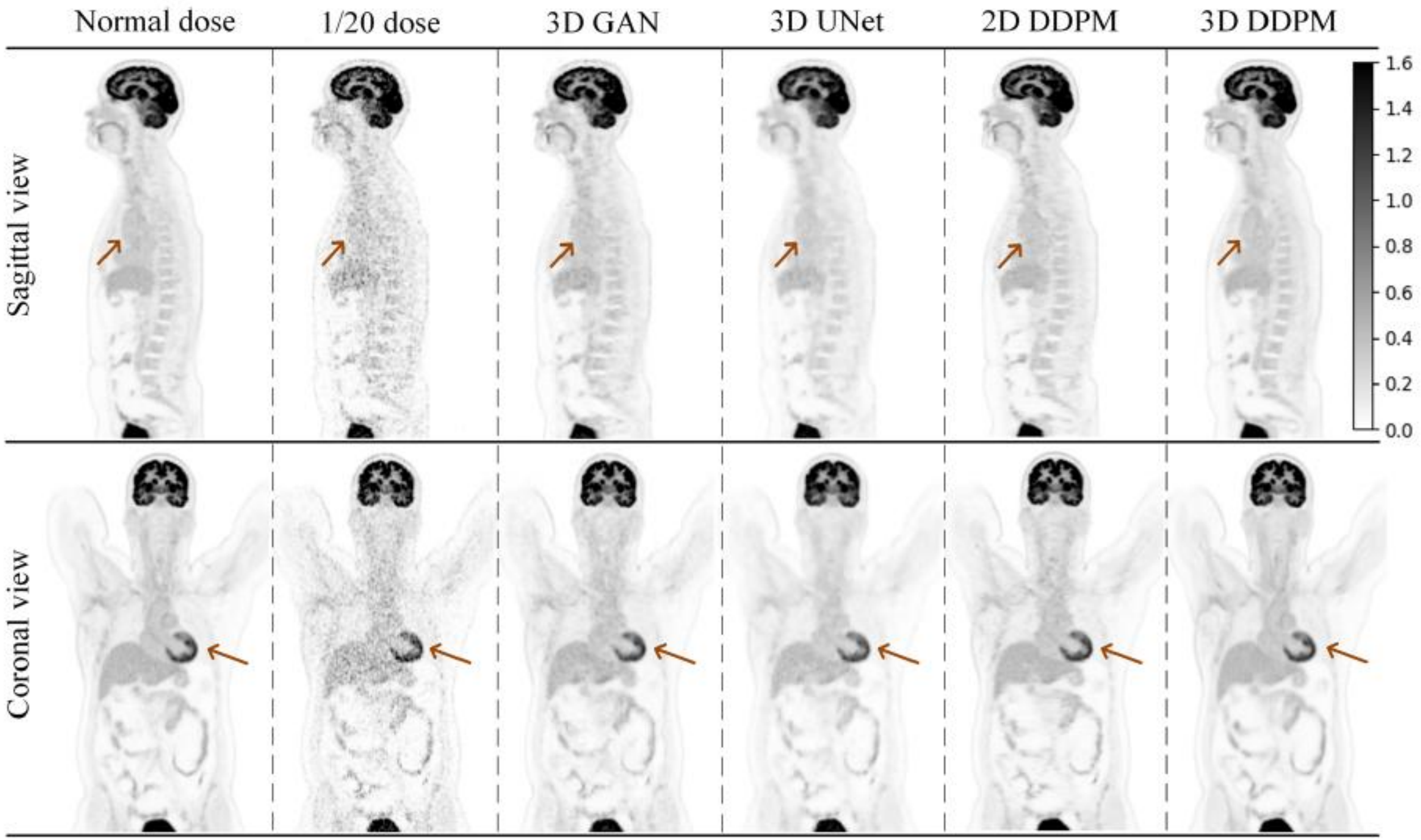


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IMAGE ENHANCEMENT: DENOISING

Model architecture	CNN Convolutional Neural Network (eg: U-nets, RED-CNN)
Optimal application	Fast clinical workflow with priority on structural integrity

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IMAGE ENHANCEMENT: DENOISING

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Optimal application	Fast clinical workflow with priority on structural integrity	Advanced multi-bed PET analysis Dynamic parameters mapping	Ultra low-dose pediatric scans Research protocols Severe noise restoration

IMAGE ENHANCEMENT: DENOISING

Model architecture	PROS in PET denoising	CONS in PET denoising	Optimal application
CNN Convolutional Neural Network (eg: U-nets, RED-CNN)	Ultrafast inference (immediate clinical reading) Local anatomy preservation (no risk of creating completely synthetic features)	Fine boundaries blurring (high frequency oversmoothing) Limited detection of low contrast lesions (background noise)	Fast clinical workflow with priority on structural integrity

IMAGE ENHANCEMENT: DENOISING

Model architecture	PROS in PET denoising	CONS in PET denoising	Optimal application
Transofmers (eg: Restormer, SwinIR)	Capture non-local similarities across the entire scan	Computationally intenstive (especially 3D or 4D dynamic volumes)	Advanced multi-bed PET analysis
	Excellent in maintaining sharp edge boundaries and contrast	Performance drop if trained on small datasets	Dynamic parameters mapping
	Highly efficient in Poisson noise recognition		

IMAGE ENHANCEMENT: DENOISING

Model architecture	PROS in PET denoising	CONS in PET denoising	Optimal application
Diffusion Models	Exceptional texture recovery Highly realistic tracer distribution Outperforms all models in ultra-low dose restoration Not affected by typical CNN blurring	Risk of structural hallucinations (eg creating micro-lesions) Slow, multistep sampling: not suitable for rapid clinical workflow	Ultra low-dose pediatric scans Research protocols Severe noise restoration

IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION

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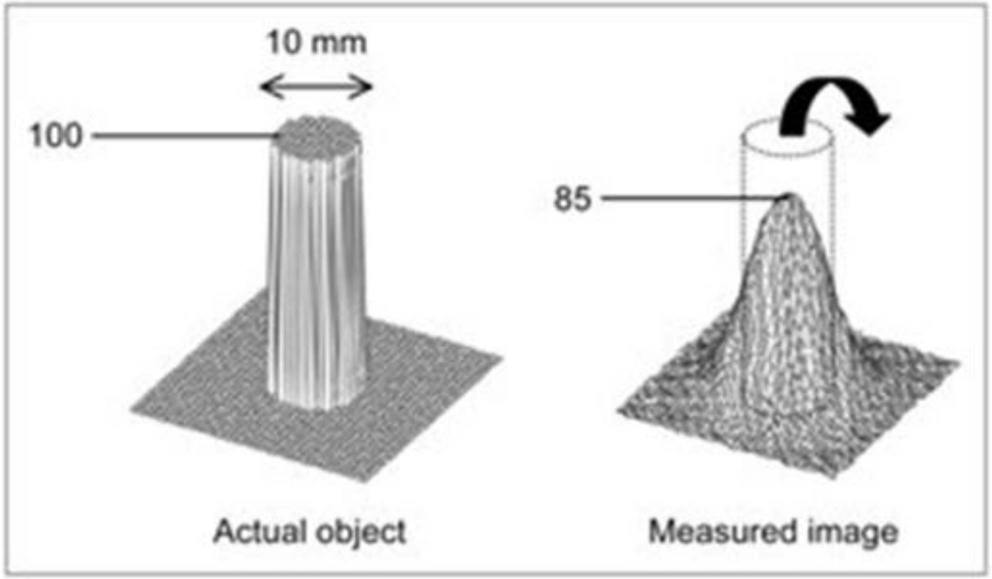


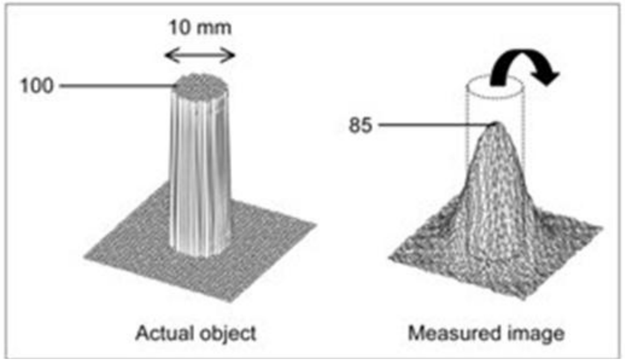
Limited spatial resolution

Discrete sampling of a continuos signal

PARTIAL VOLUME EFFECT

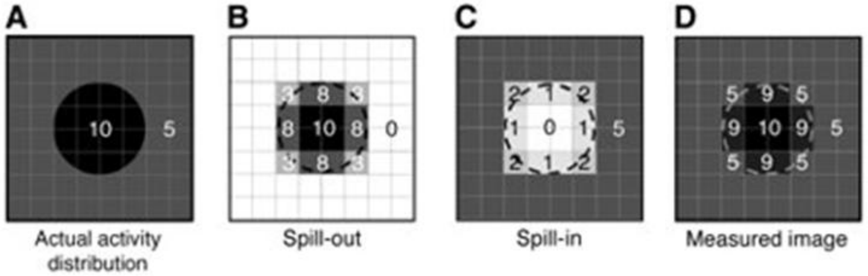
Not completely recovered also with high quality iterative reconstruction

IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION



Limited spatial resolution

+



Discrete sampling of a continuos signal

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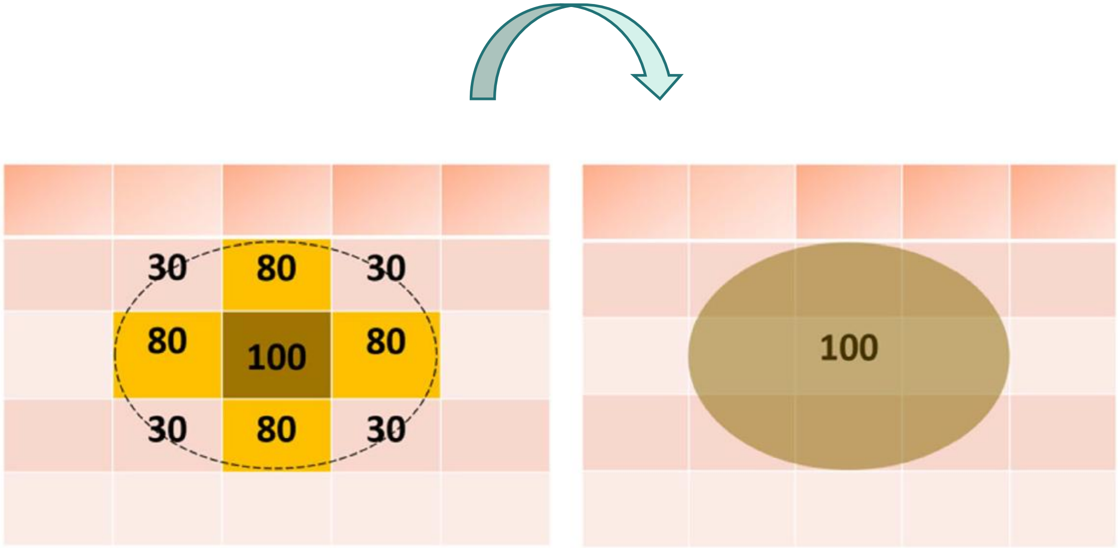
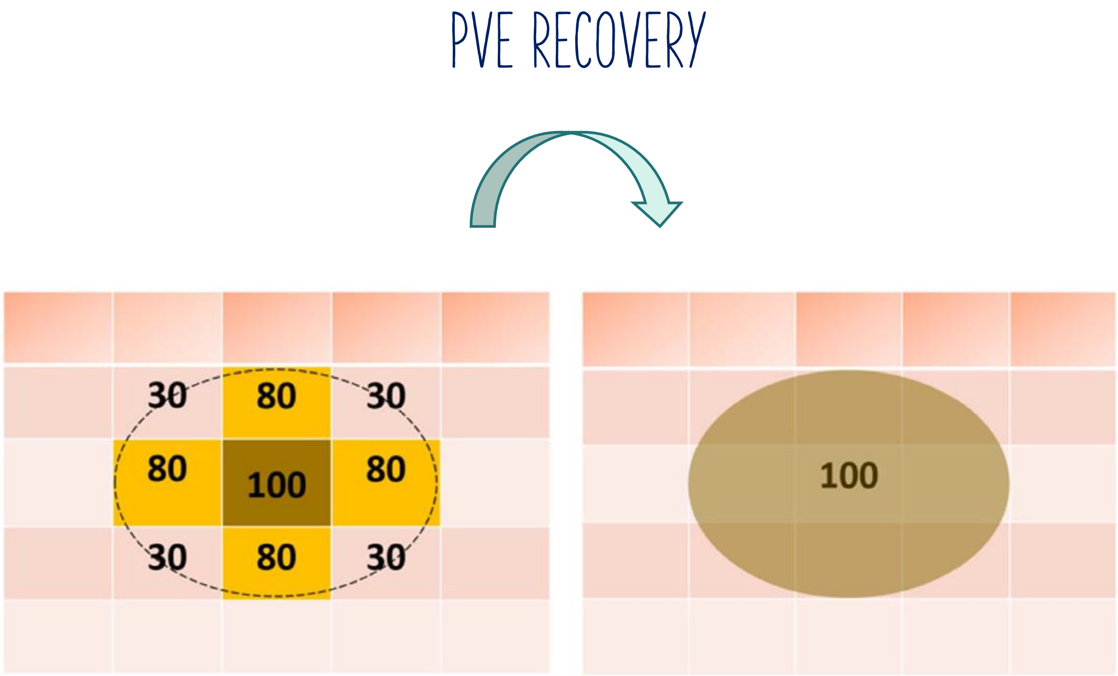
IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION

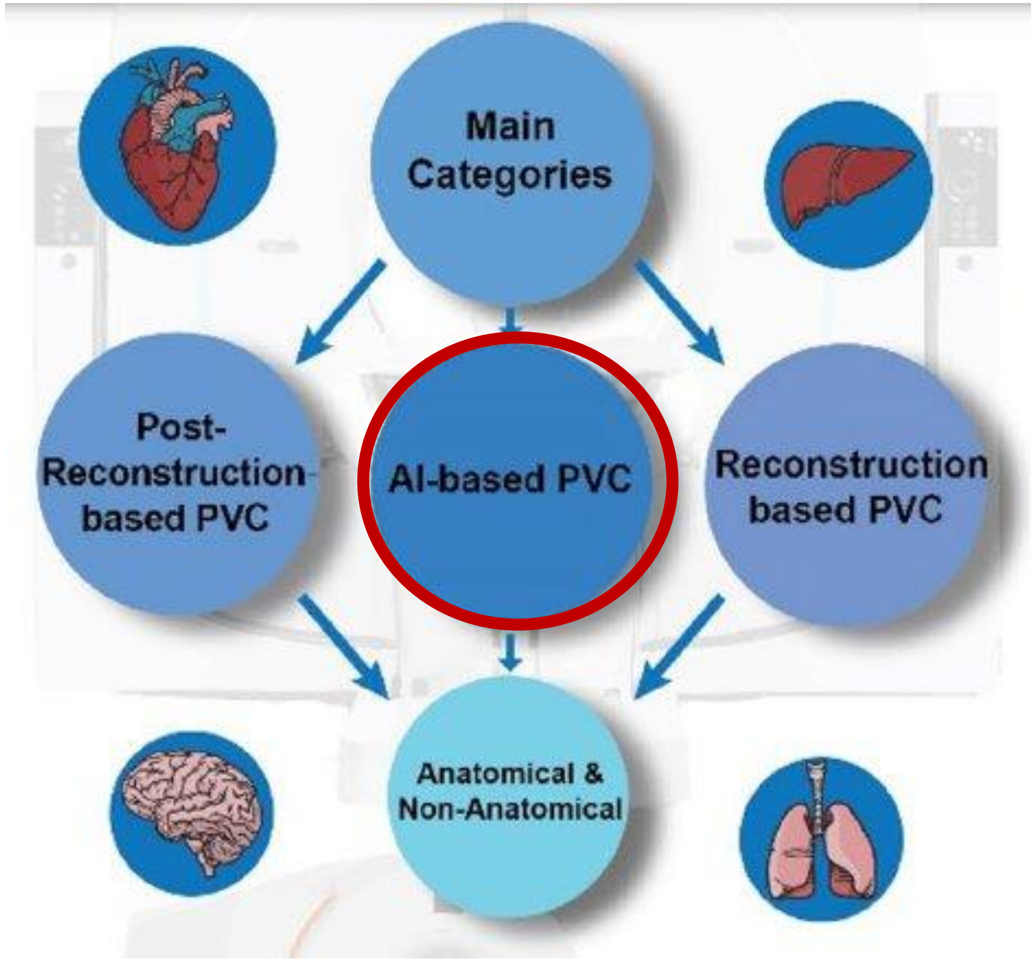
PVE RECOVERY



Critical review of partial volume correction methods in PET and SPECT imaging: benefits, pitfalls, challenges, and future outlook doi.org/10.1007/s00259-025-07612-5

IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION

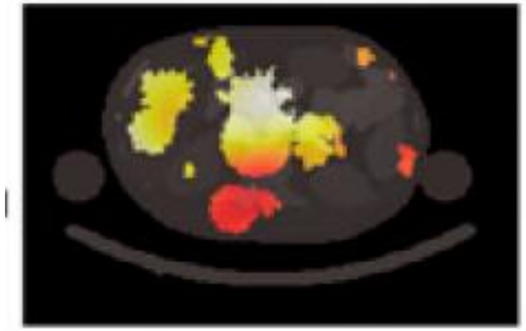




Critical review of partial volume correction methods in PET and SPECT imaging: benefits, pitfalls, challenges, and future outlook doi.org/10.1007/s00259-025-07612-5

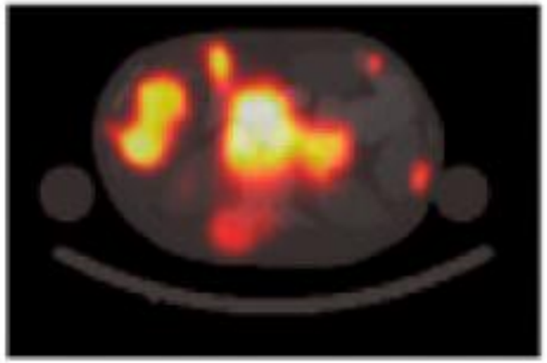
IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION

Reference activity distribution
(PVE free)



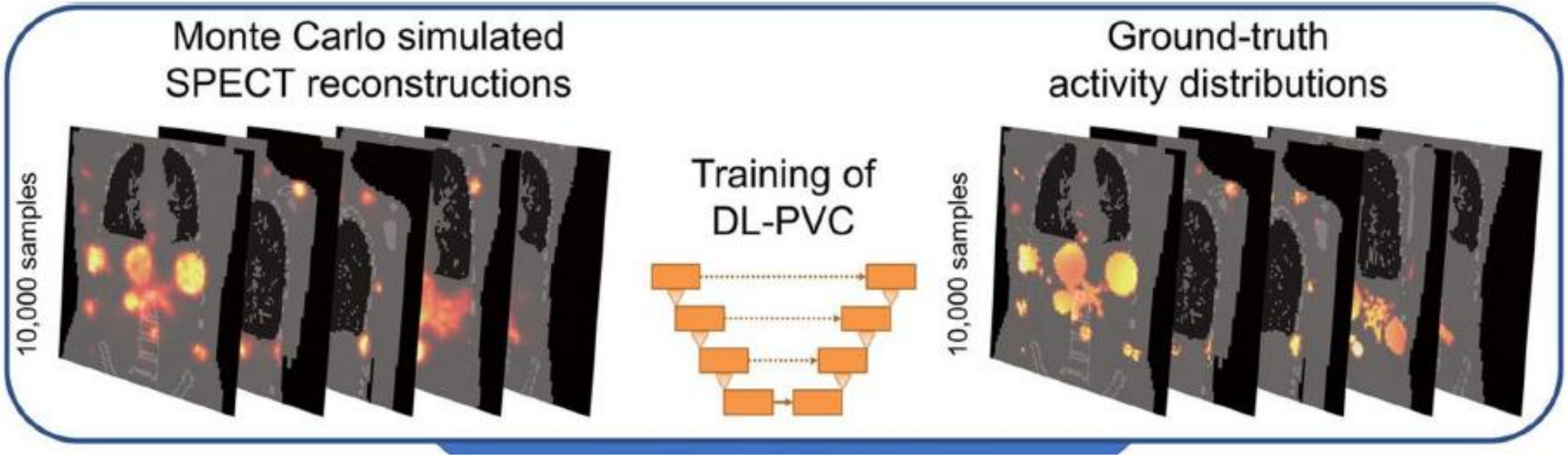
MONTE CARLO SIMULATION

Simulated SPECT images
(affected by PVE)



A Deep-Learning-Based Partial-Volume Correction Method for Quantitative 177Lu SPECT/CT Imaging 10.2967/jnumed.123.266889

IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION



Training:

DL learns how to generate reference activity distribution (output)

taking as input the simulated images

Critical review of partial volume correction methods in PET and SPECT imaging: benefits, pitfalls, challenges, and future outlook doi.org/10.1007/s00259-025-07612-5

IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION

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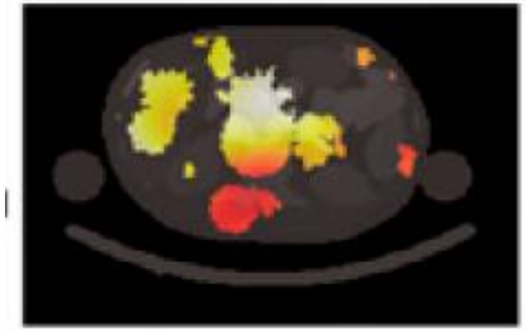

MONTE CARLO SIMULATION

AI ALGORITHM

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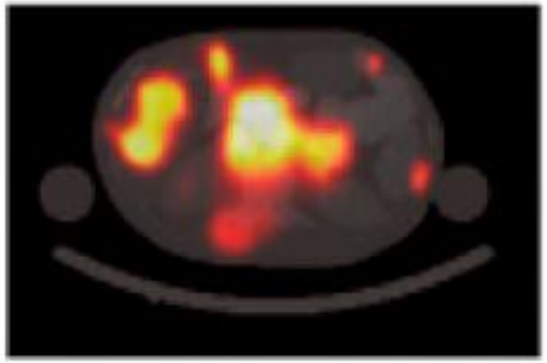

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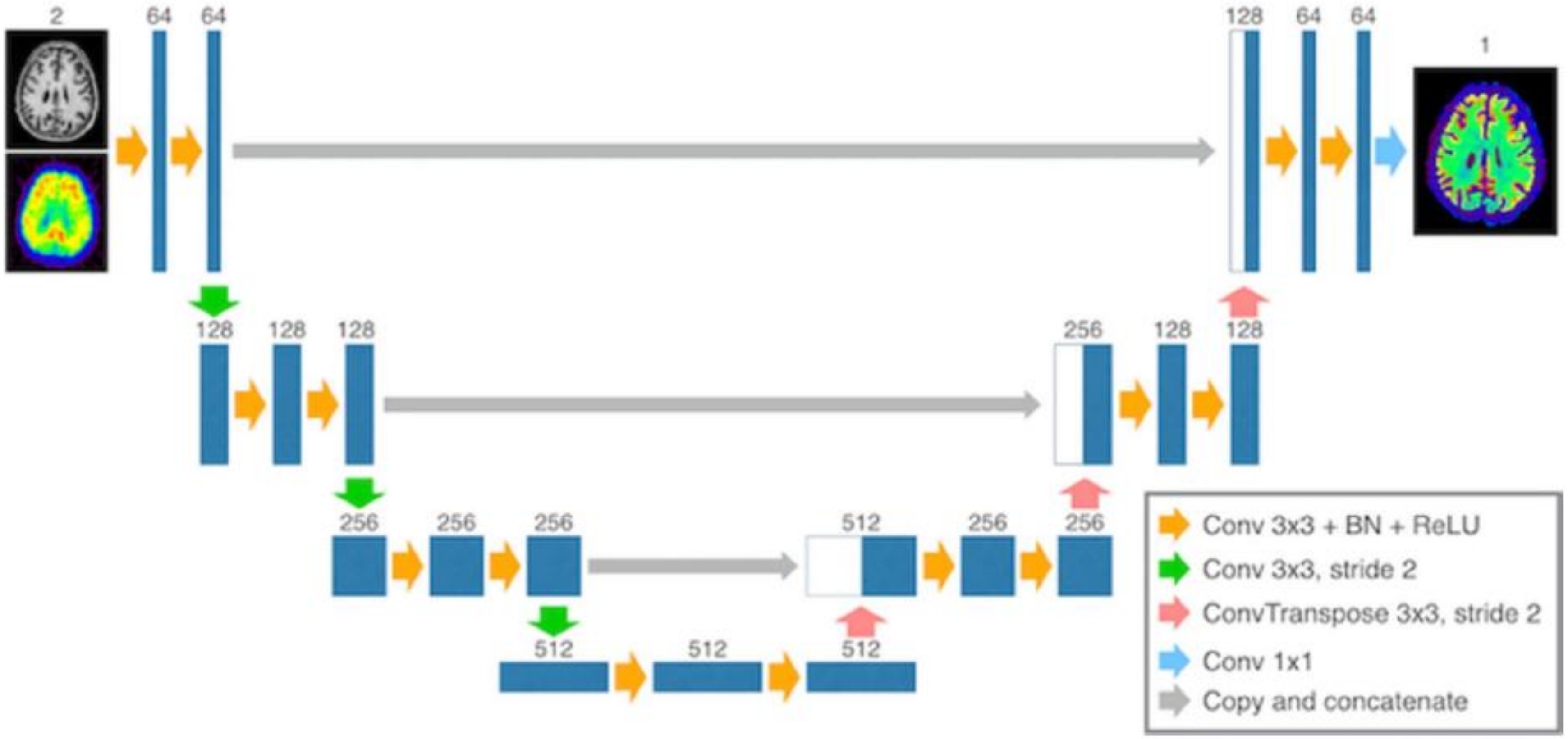
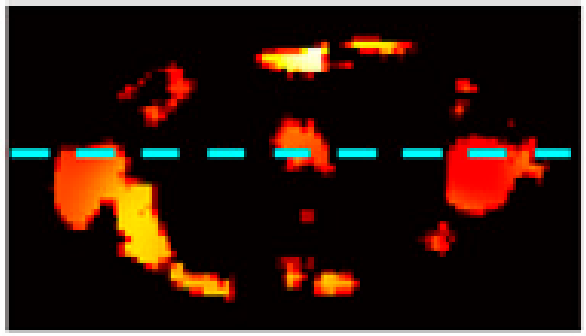
IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION

Anatomical constraint!

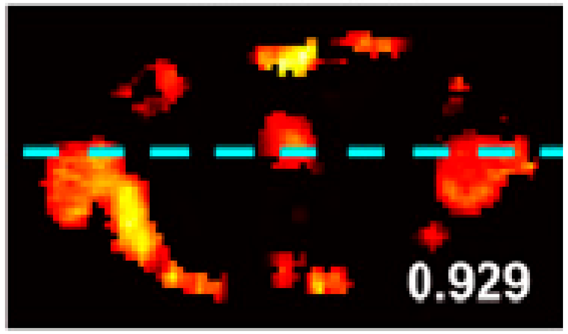


Critical review of partial volume correction methods in PET and SPECT imaging: benefits, pitfalls, challenges, and future outlook doi.org/10.1007/s00259-025-07612-5

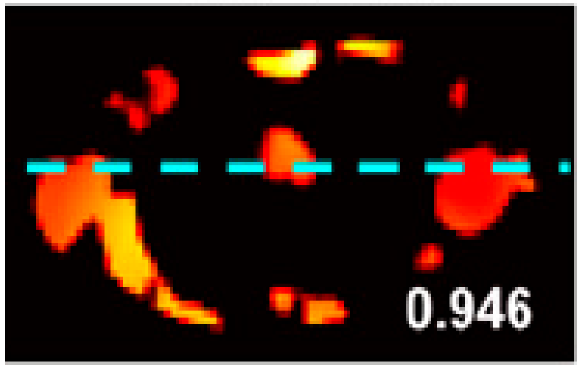
IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION



Ground truth



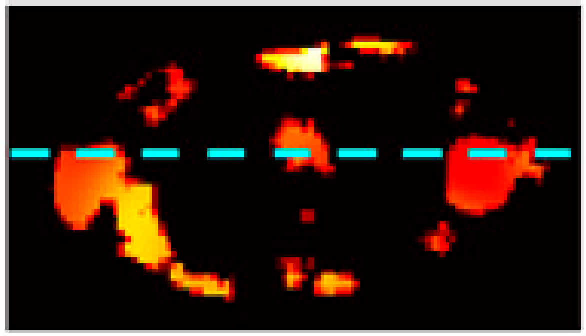
Iterative
PVE correction



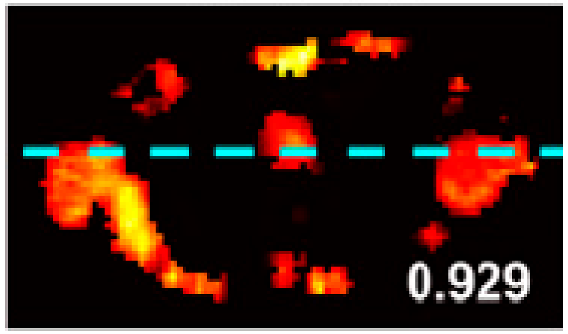
Deep learning
PVE correction

A Deep-Learning-Based Partial-Volume Correction Method for Quantitative 177Lu SPECT/CT Imaging 10.2967/jnumed.123.266889

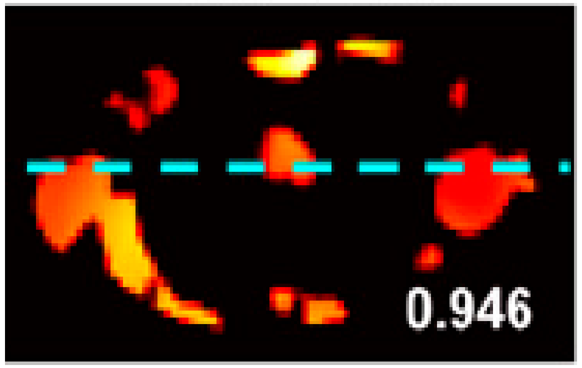
IMAGE ENHANCEMENT: PARTIAL VOLUME EFFECT CORRECTION



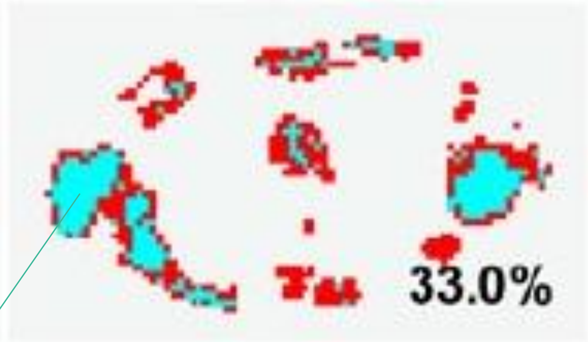
Ground truth



Iterative
PVE correction



Deep learning
PVE correction



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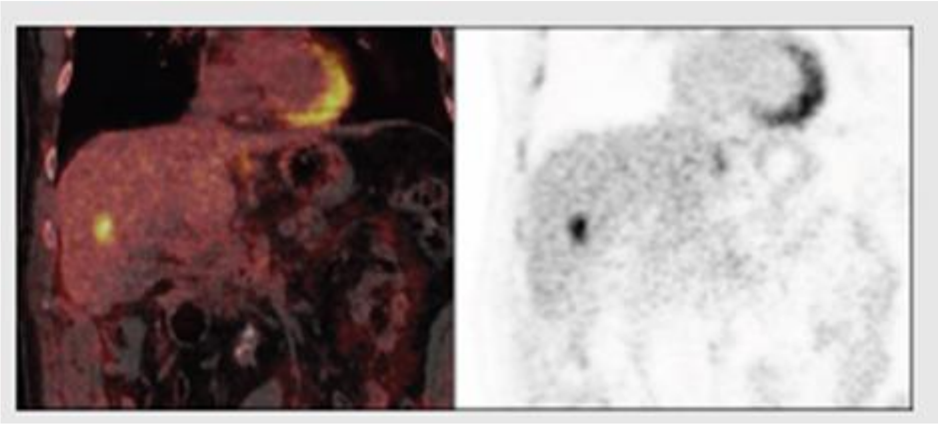
A Deep-Learning-Based Partial-Volume Correction Method for Quantitative 177Lu SPECT/CT Imaging 10.2967/jnumed.123.266889

IMAGE ENHANCEMENT: BREATHING ARTIFACT CORRECTION



Breathing-related movements:

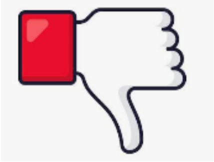


image quality

quantification accuracy

IMAGE ENHANCEMENT: BREATHING ARTIFACT CORRECTION

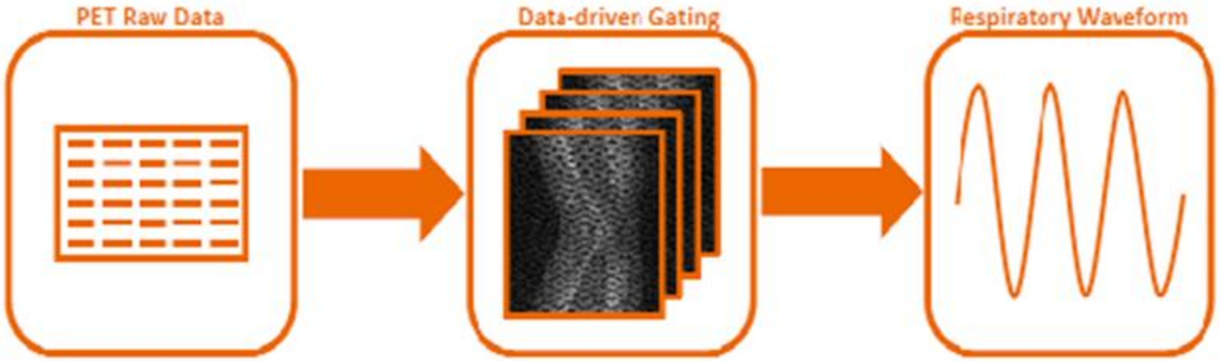


IMAGE ENHANCEMENT: BREATHING ARTIFACT CORRECTION

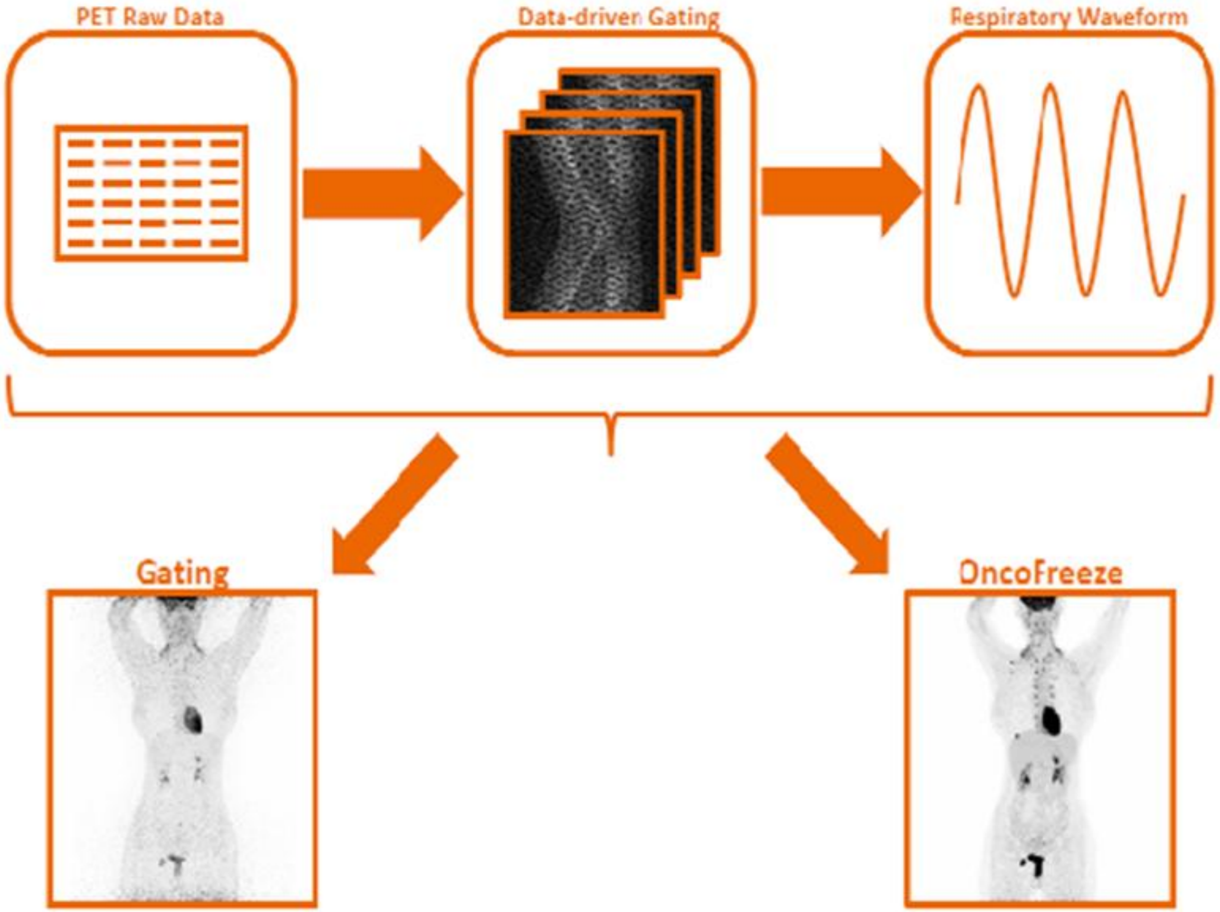
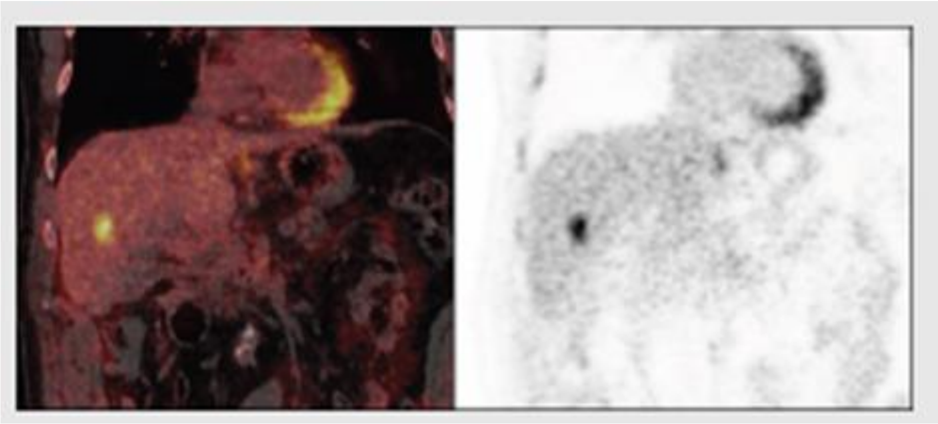


IMAGE ENHANCEMENT: BREATHING ARTIFACT CORRECTION



Breathing-related movements:

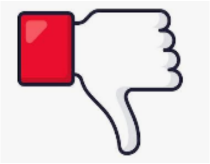
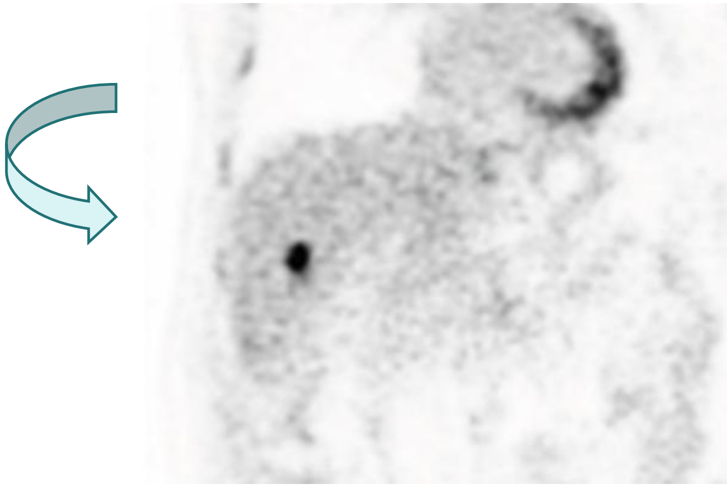


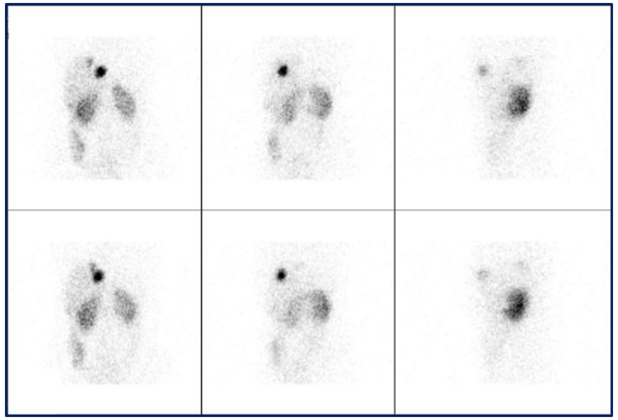
image quality
quantification accuracy



Correction for artifacts:

image resolution
quantification accuracy

IMAGE RECONSTRUCTION

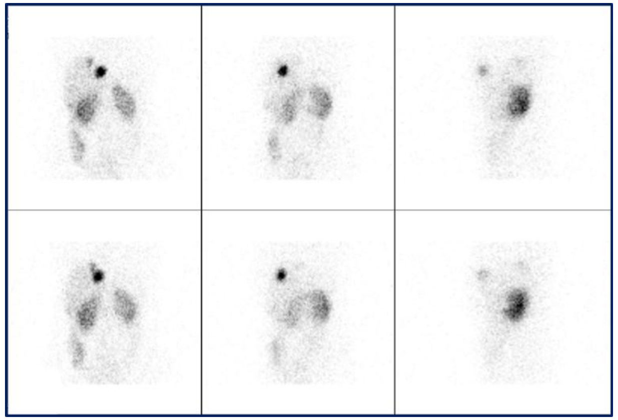


Conventional

Reconstruction

= ITERATIVE

IMAGE RECONSTRUCTION



AI-based Reconstruction

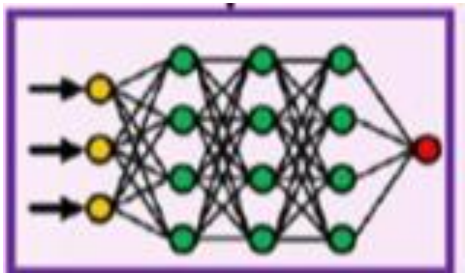
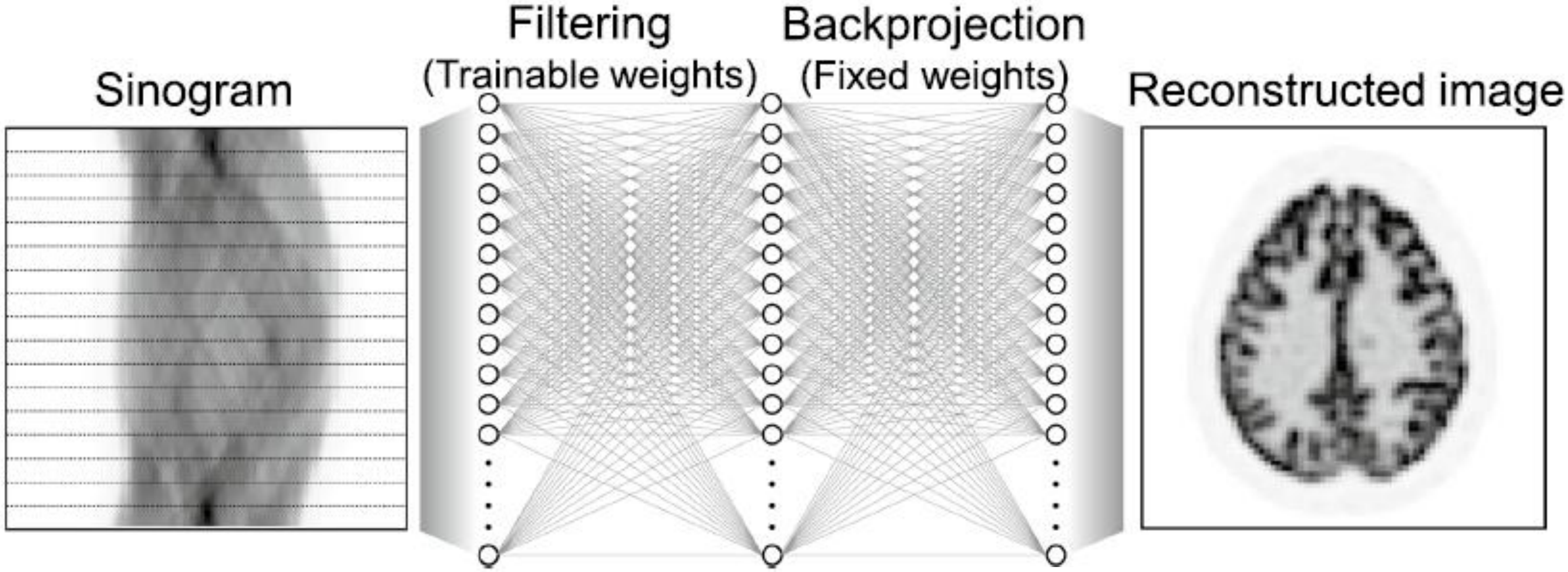


IMAGE RECONSTRUCTION

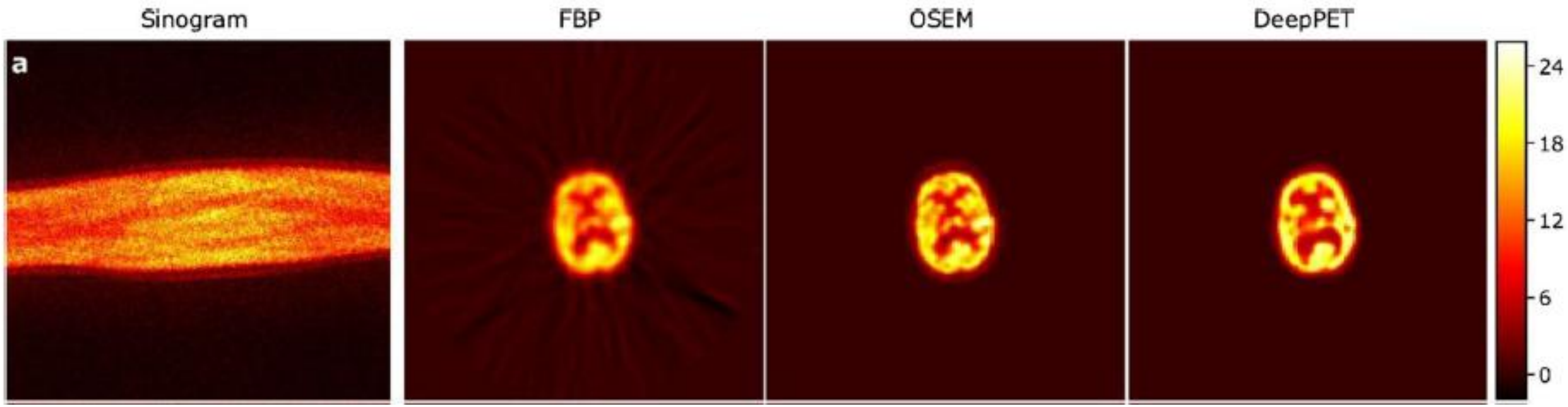


input

output

Deep learning-based PET image denoising and reconstruction: a review doi.org/10.1007/s12194-024-00780-3

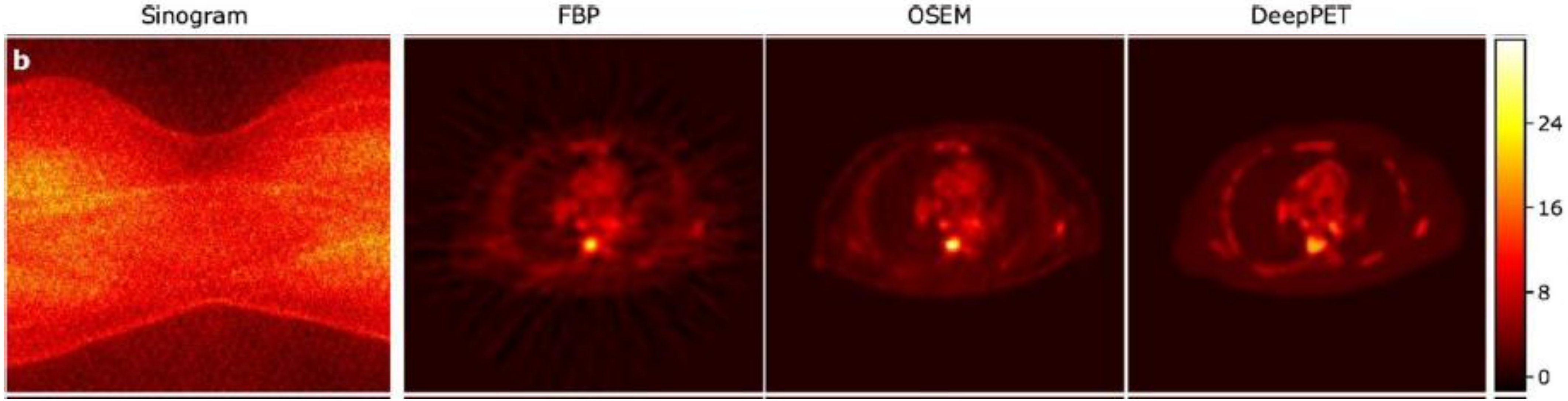
IMAGE RECONSTRUCTION



analytical iterative AI

Deep learning-based PET image denoising and reconstruction: a review doi.org/10.1007/s12194-024-00780-3

IMAGE RECONSTRUCTION



analytical iterative AI

Deep learning-based PET image denoising and reconstruction: a review doi.org/10.1007/s12194-024-00780-3

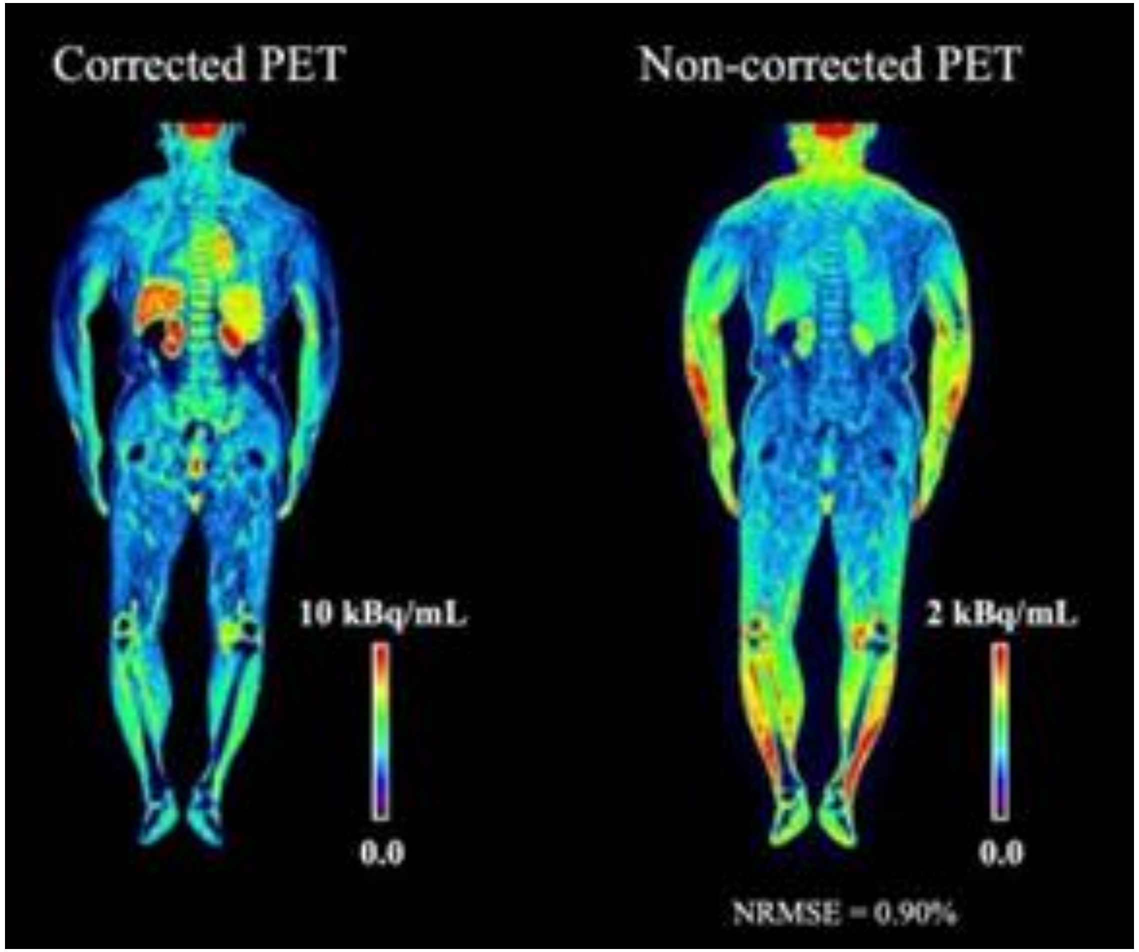
IMAGE *CT-FREE* RECONSTRUCTION

Development of a deep learning method for CT-free correction for an ultra-long axial field of view PET scanner 10.1109/EMBC46164.2021.9630590

IMAGE *CT-FREE* RECONSTRUCTION

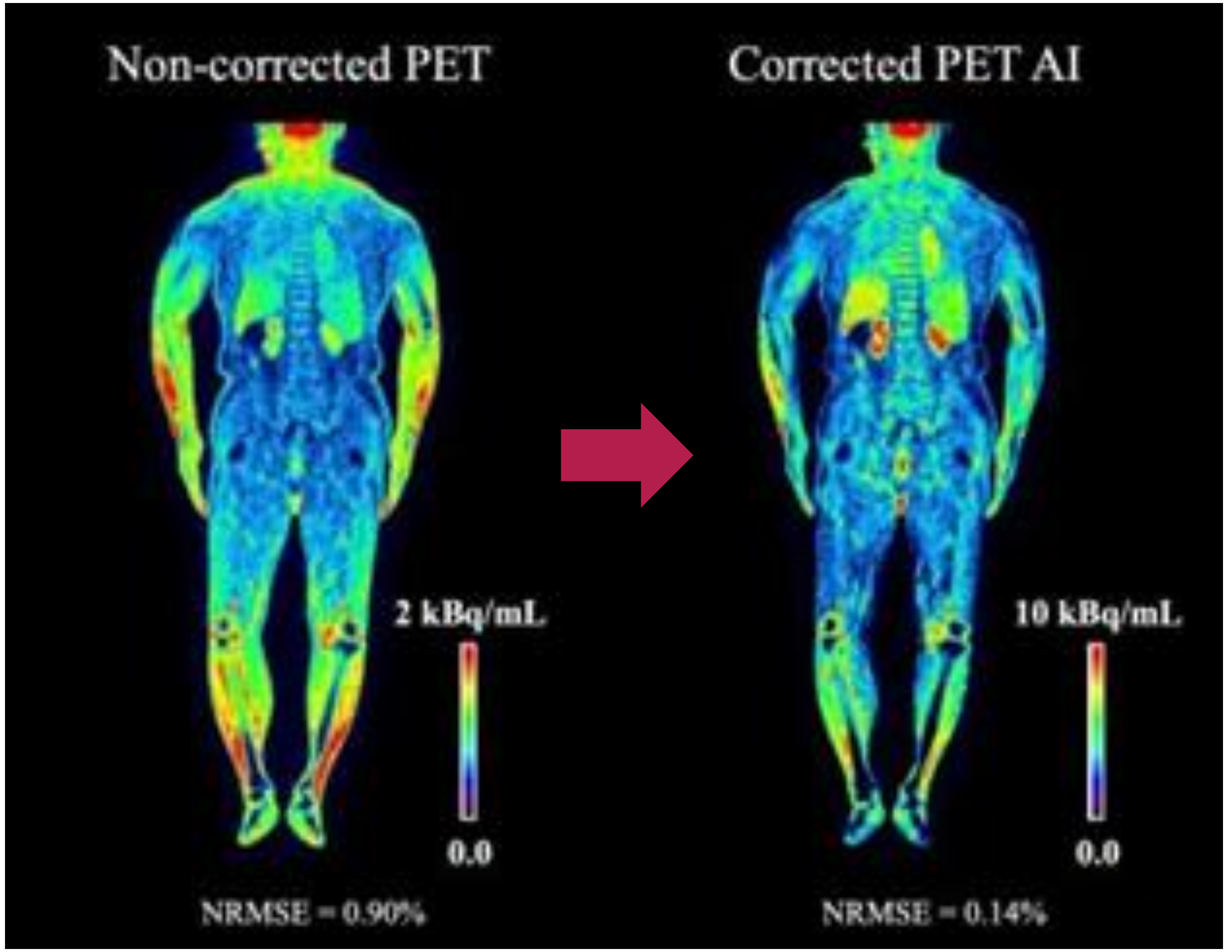
Training:

With CT



Development of a deep learning method for CT-free correction for an ultra-long axial field of view PET scanner 10.1109/EMBC46164.2021.9630590

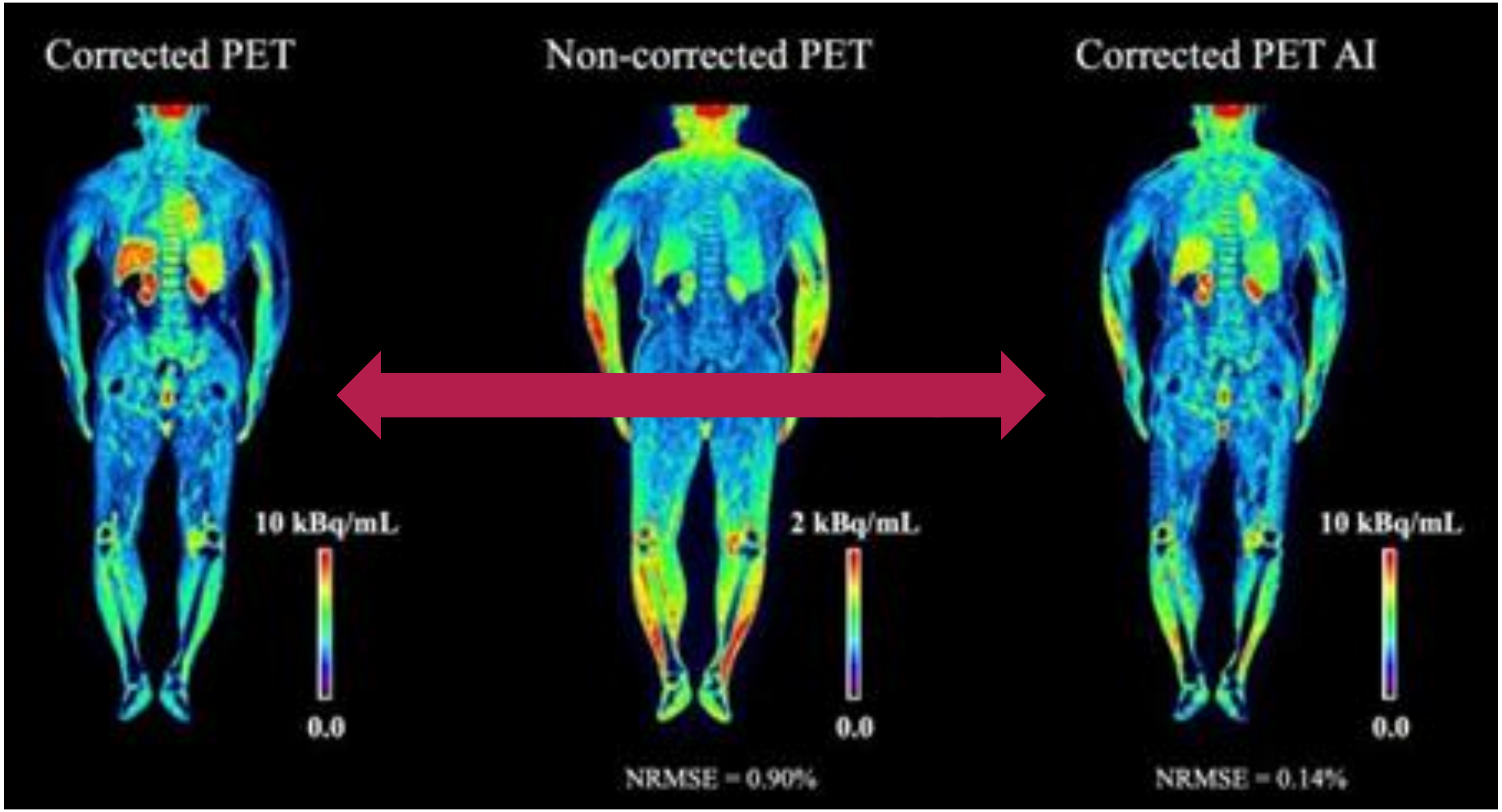
IMAGE *CT-FREE* RECONSTRUCTION



No CT

Development of a deep learning method for CT-free correction for an ultra-long axial field of view PET scanner 10.1109/EMBC46164.2021.9630590

IMAGE *CT-FREE* RECONSTRUCTION



Development of a deep learning method for CT-free correction for an ultra-long axial field of view PET scanner 10.1109/EMBC46164.2021.9630590

3. DETECTION AND SEGMENTATION

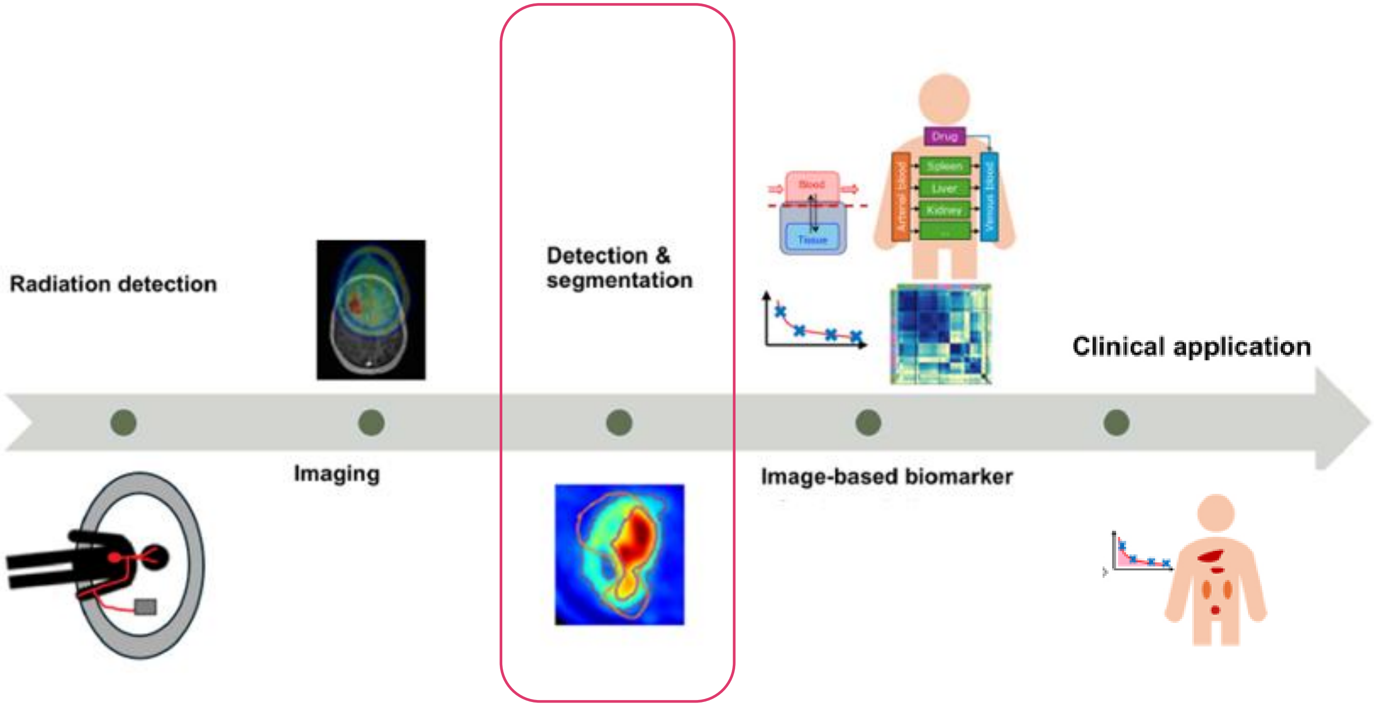
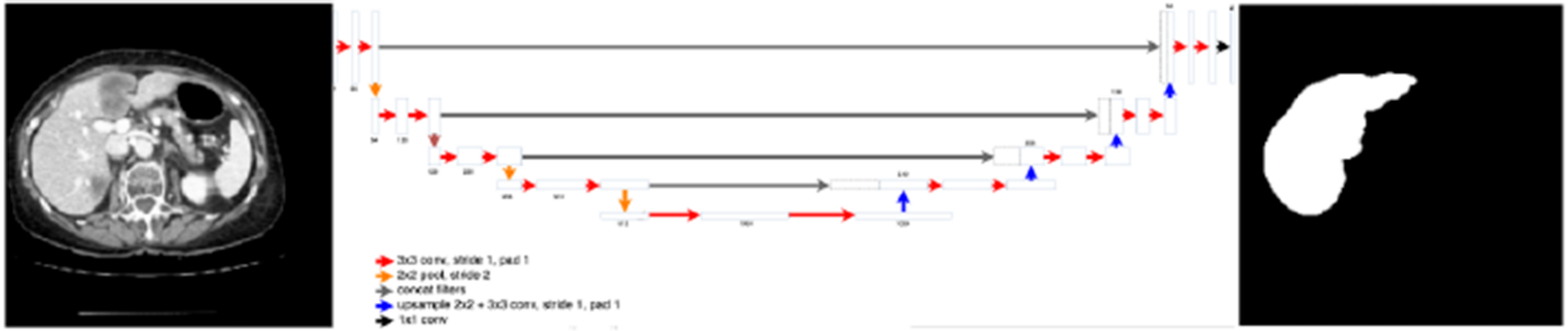


IMAGE SEGMENTATION



Input:

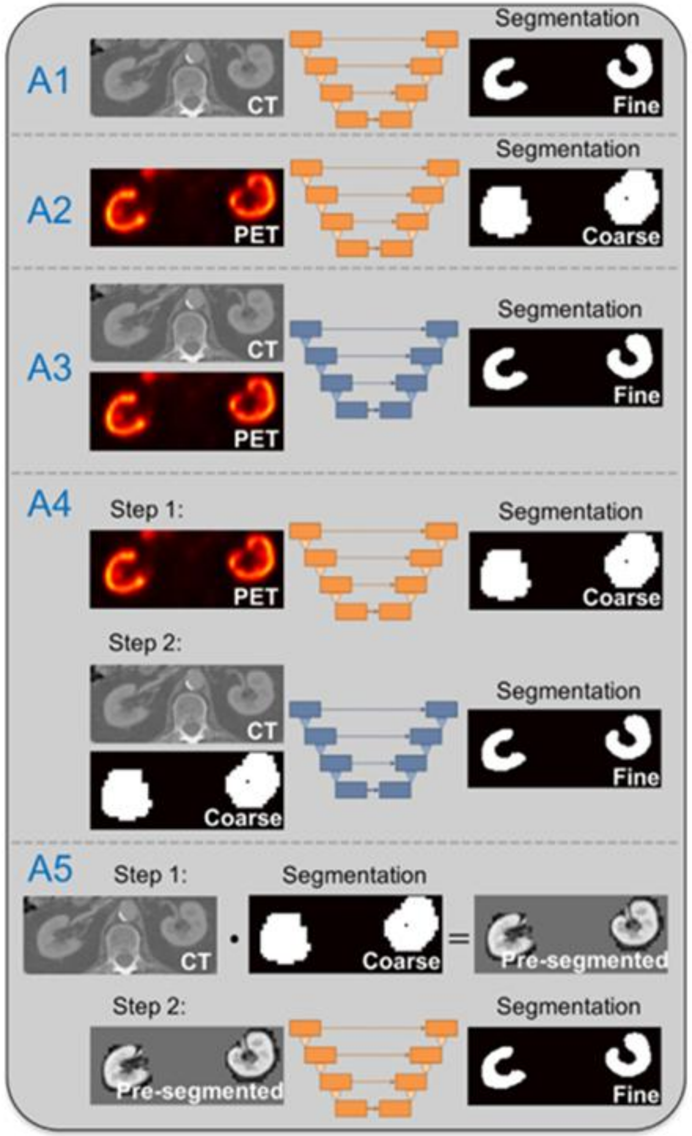
image

Output:

mask

IMAGE SEGMENTATION

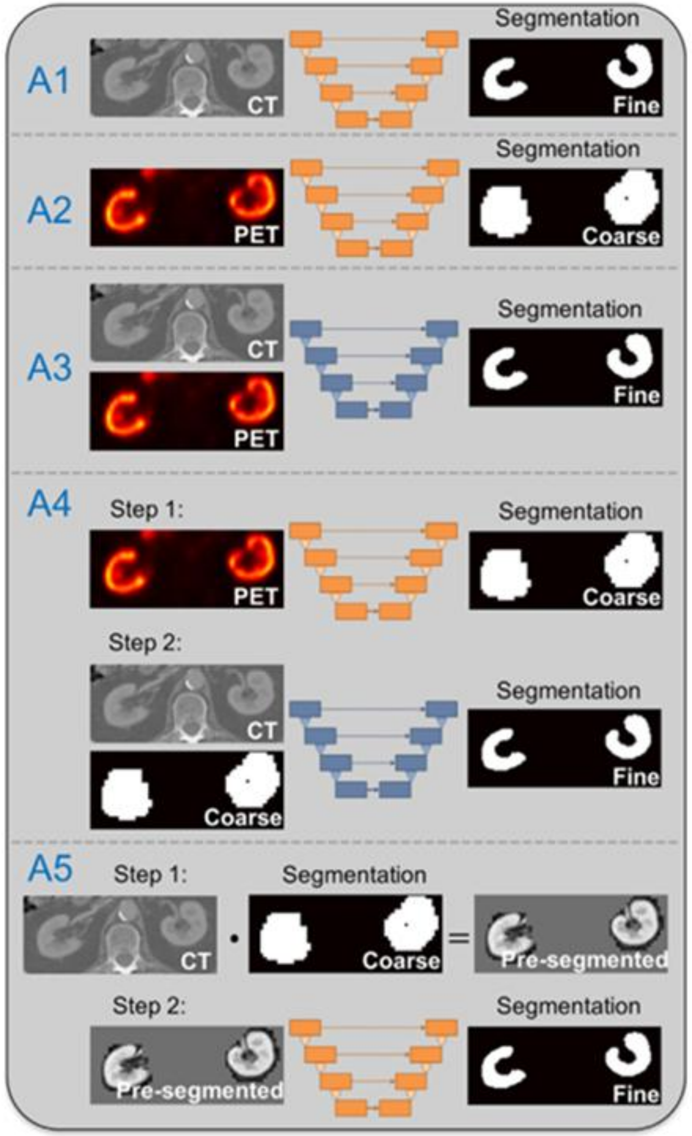
Automatic kidneys segmentation on PSMA-PET images



J.Leubeetal./ZMedPhys34(2024)231–241

IMAGE SEGMENTATION

Automatic kidneys segmentation on PSMA-PET images



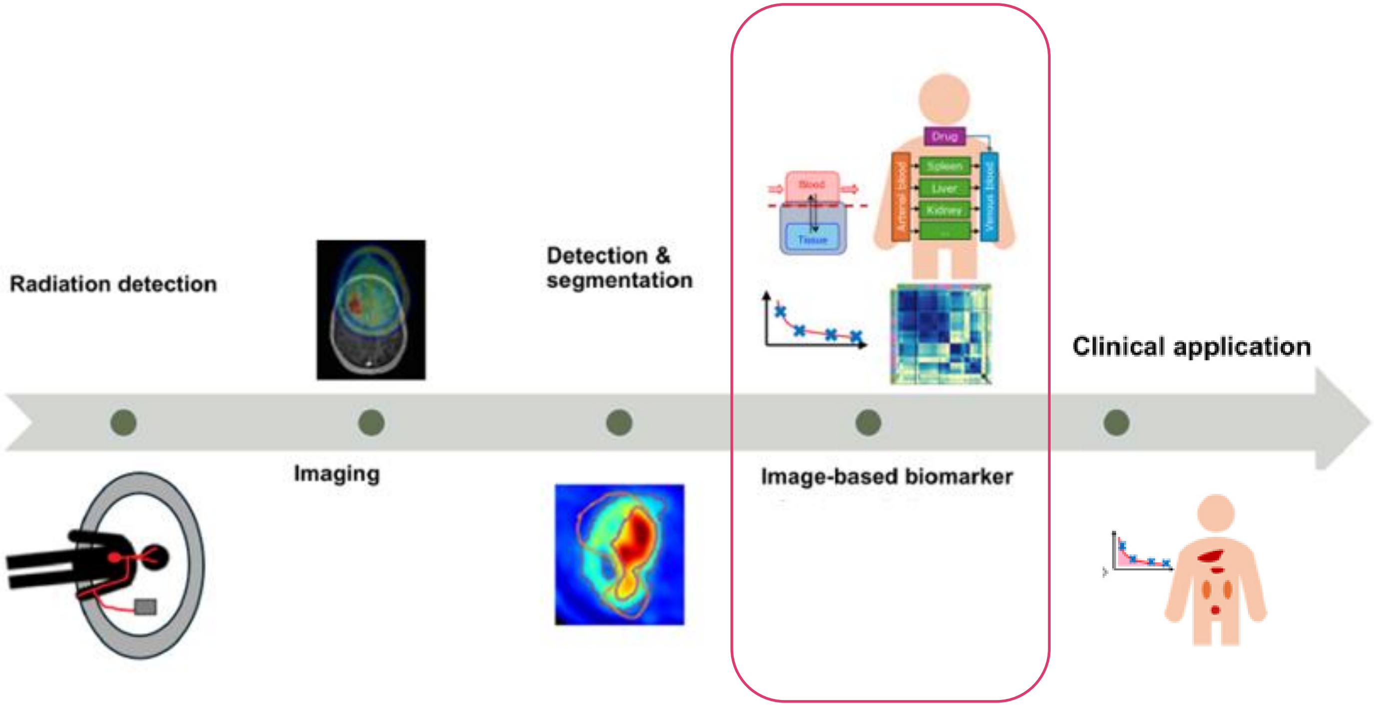
CT only

PET only

Improved performance when integrating CT and PET data

J.Leubeetal./ZMedPhys34(2024)231–241

4. IMAGING BIOMARKERS

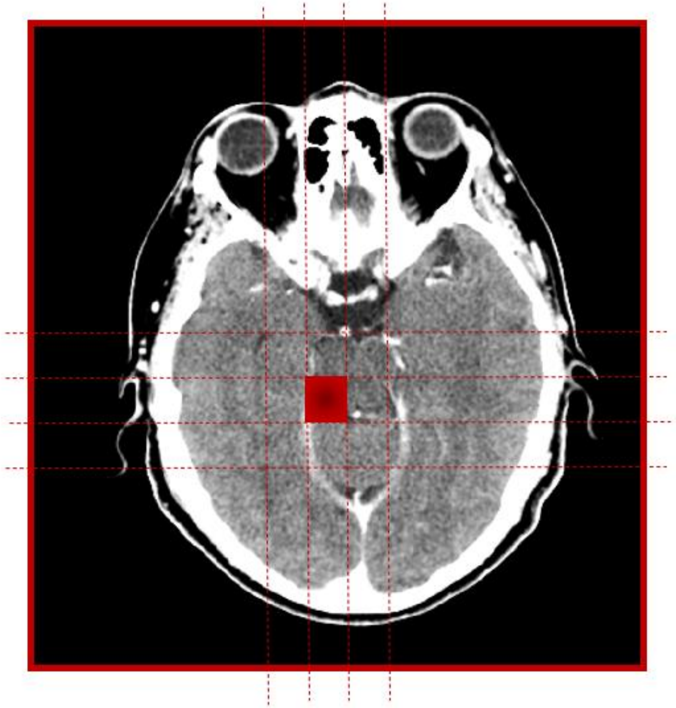


2016

Radiology

Radiomics: Images Are More than Pictures, They Are Data[1]

Robert J. Gillies, PhD
Paul E. Kinahan, PhD
Hedvig Hricak, MD, PhD, Dr(hc)



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25	22	20	20	22	23	20
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23	21	21	19	20	22	22
22	20	20	18	19	22	22
21	21	20	18	18	21	22
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19	20	27	27	21	17	19
19	18	24	29	24	18	19
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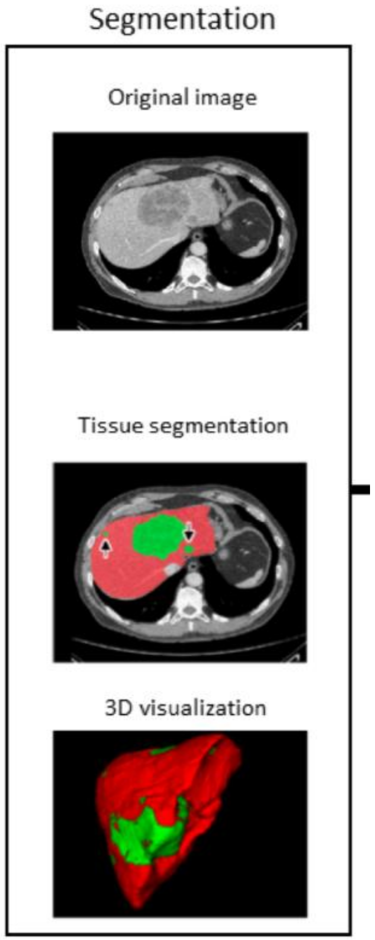
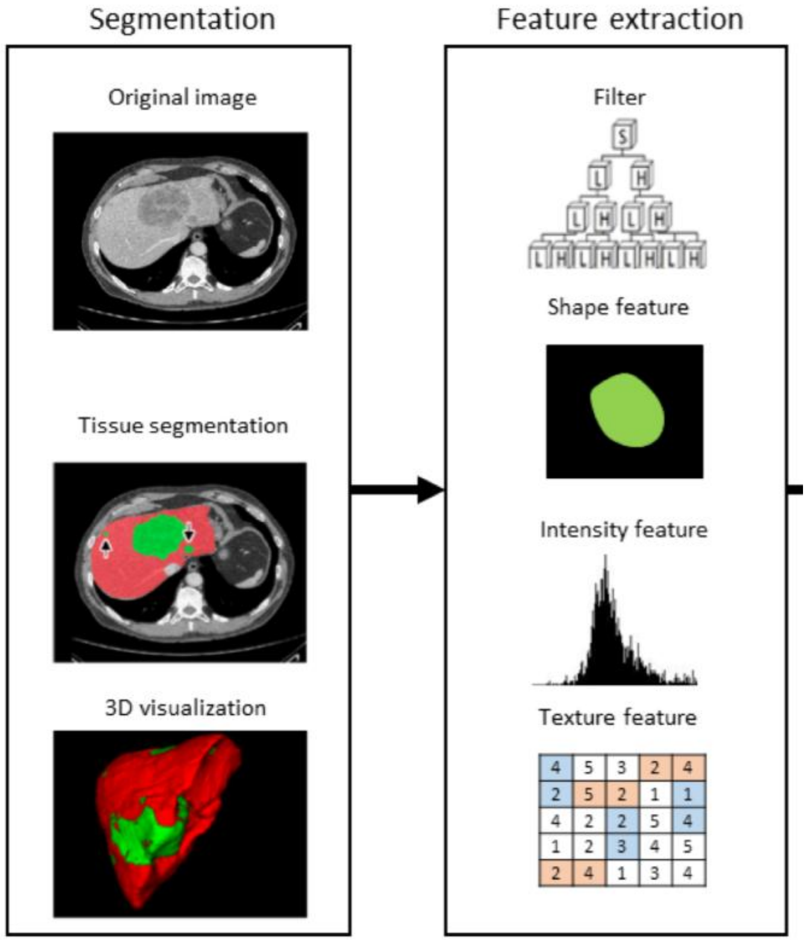
AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

Traditional radiomics workflow



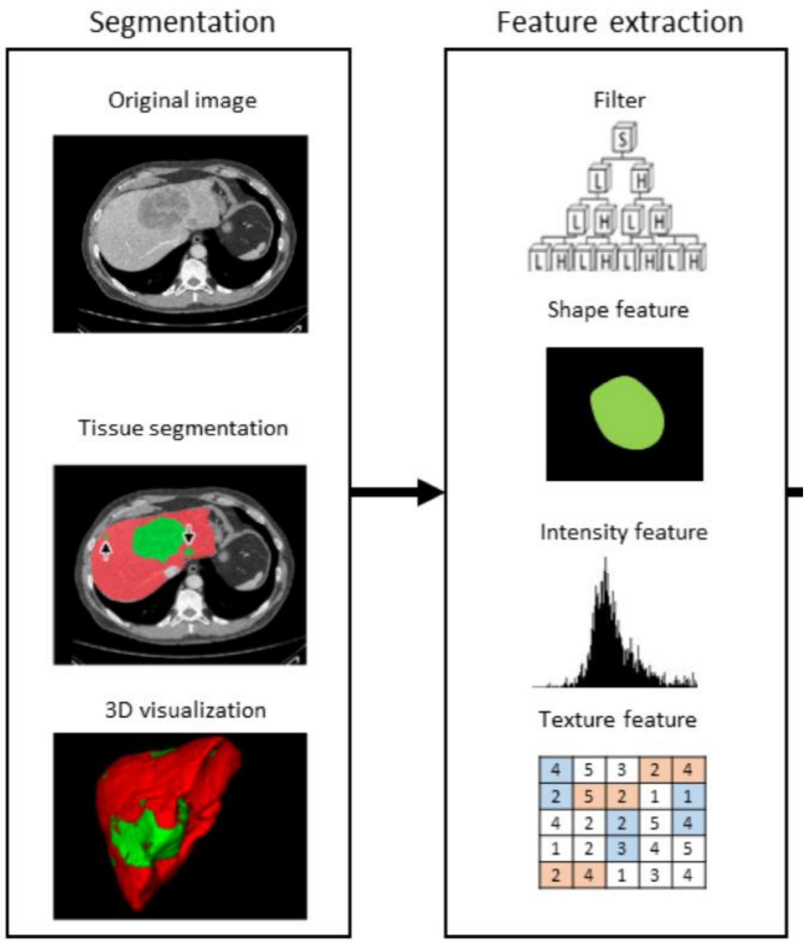
AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

Traditional radiomics workflow



AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

Traditional radiomics workflow



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0,646	42,425	65,678	58,266	89,022	75,985	90,203
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0,473	31,625	66,876	68,273	81,279	75,180	84,840
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0,805	35,331	43,887	54,756	54,788	53,610	65,724
0,805	35,331	43,887	54,756	54,788	53,610	65,724
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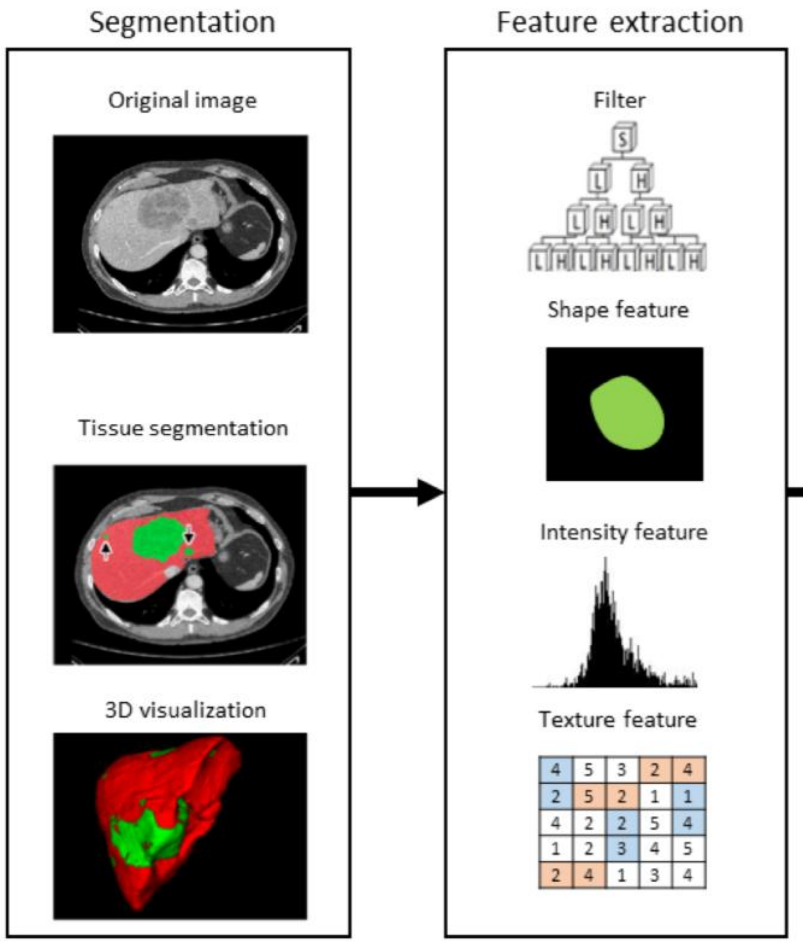
AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

Traditional radiomics workflow



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CLINICAL ENDPOINT PREDICTION?

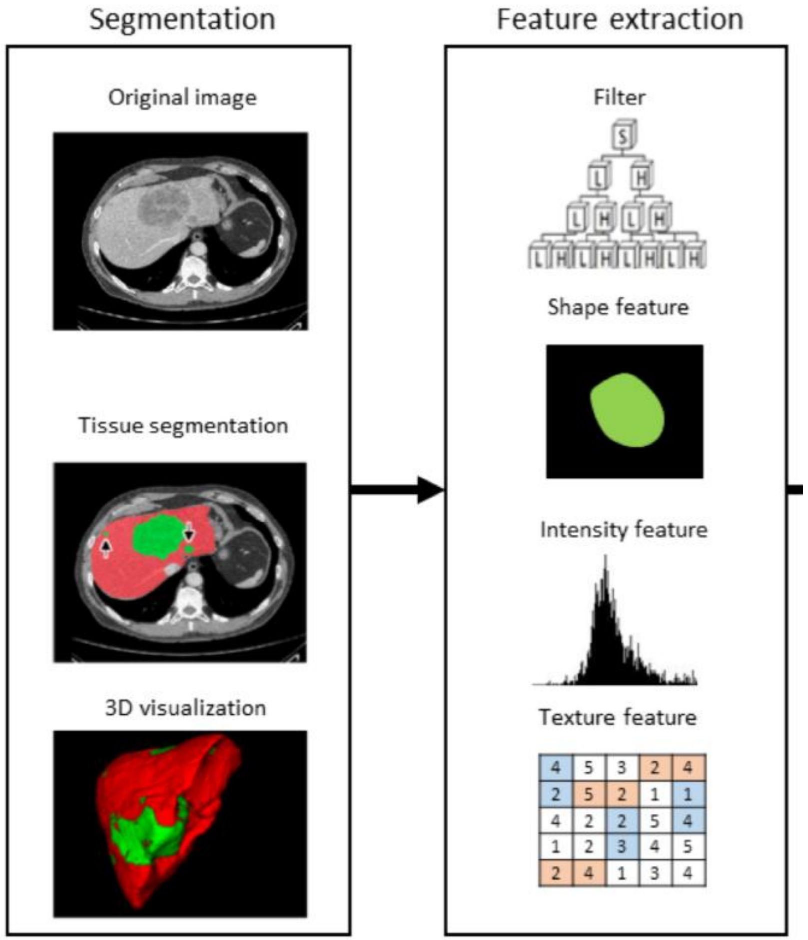
AI TOOLS FOR RADIMOIC DATA ANALYSIS

CLINICAL ENDPOINT PREDICTION?

- Therapy Responders vs Non-Responders
- Histological subtype
- Survival/Prognosis
- Biological parameters
- .....

AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

Traditional radiomics workflow



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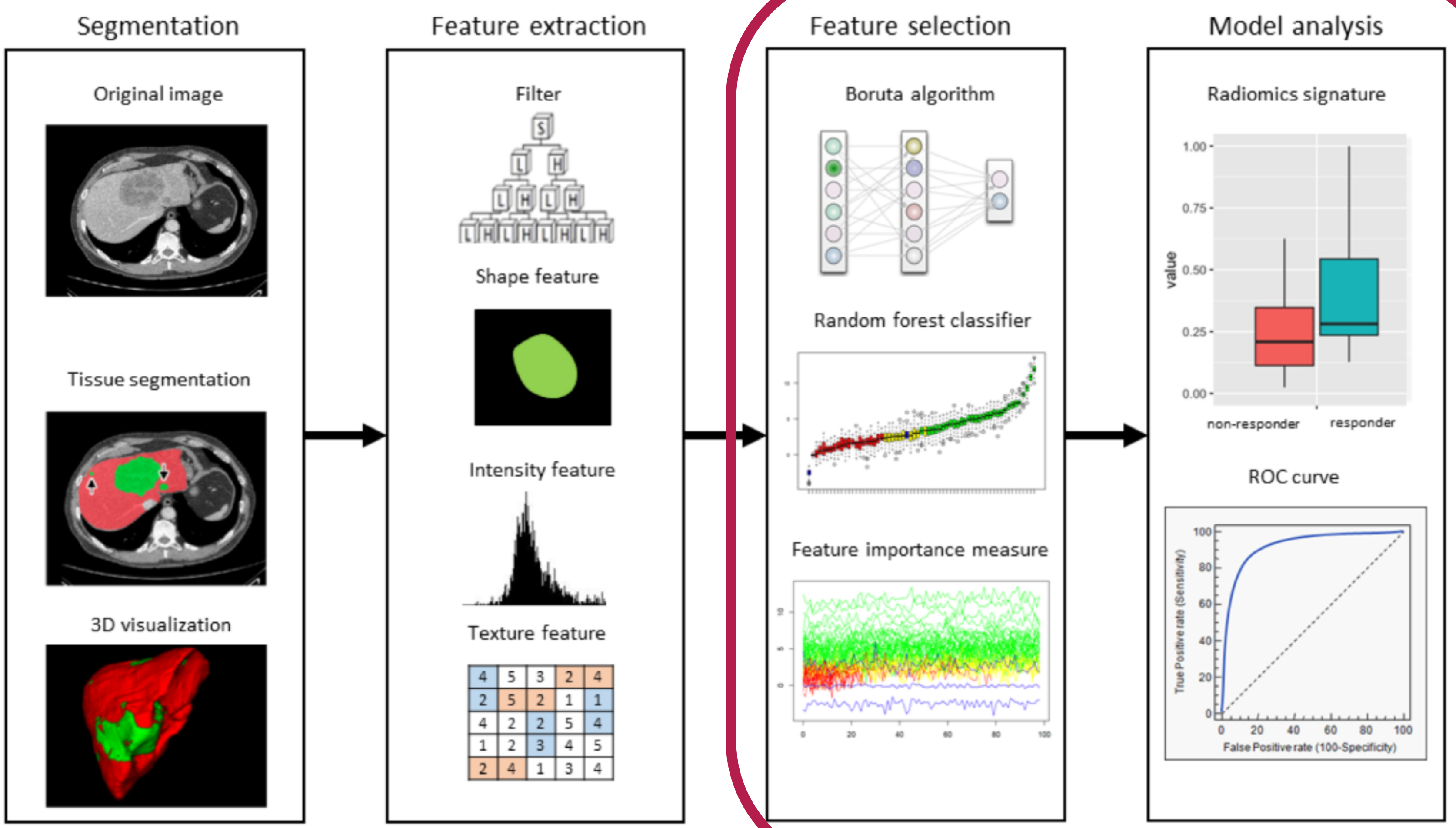
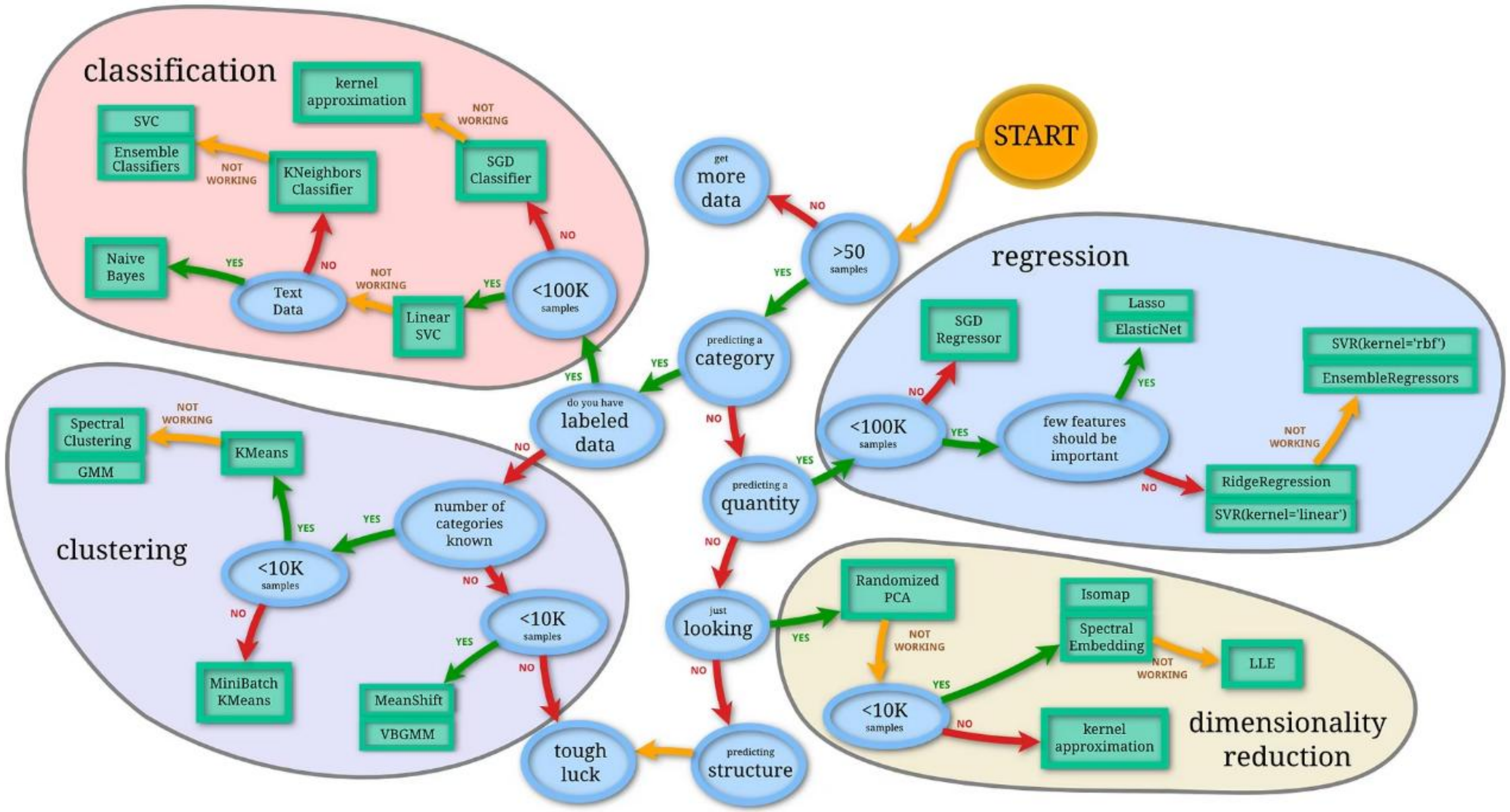
Input for Machine Learning algorithms

AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

Traditional radiomics workflow

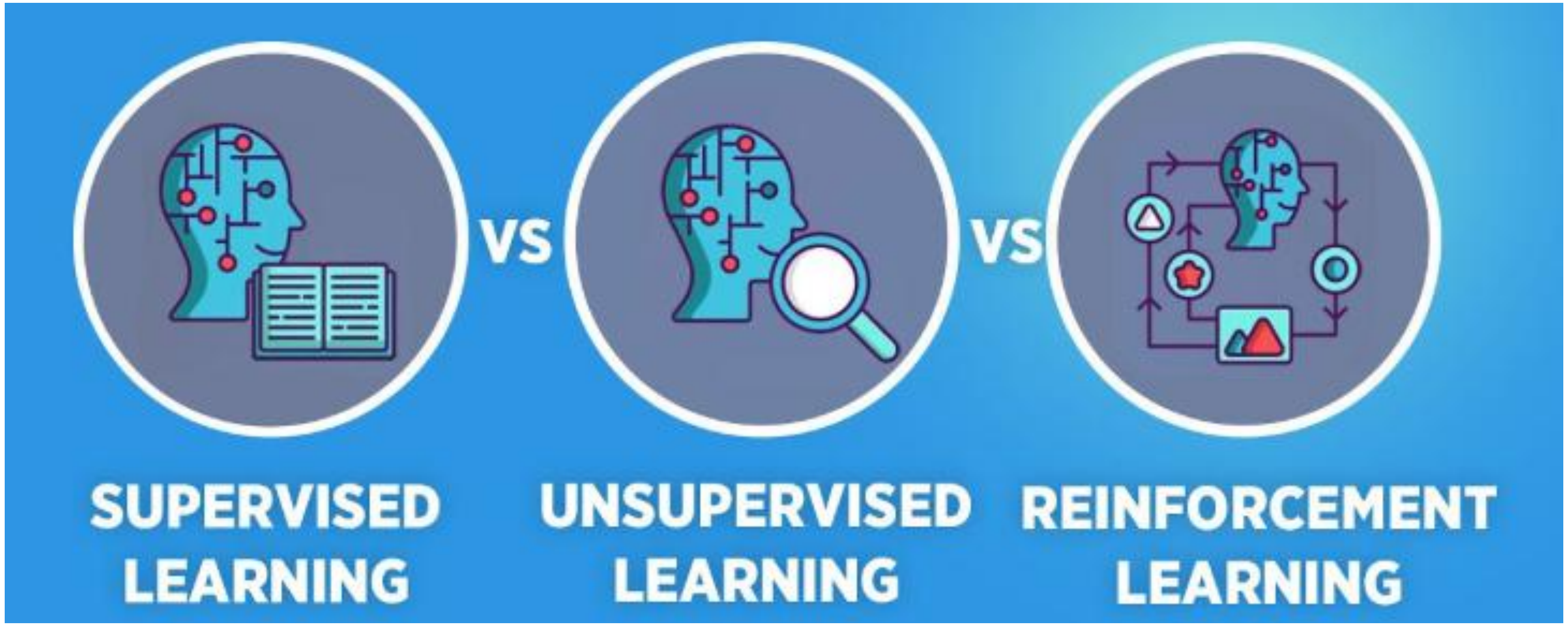


AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING



https://www.intelligenzaartificialeitalia.net/

AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING



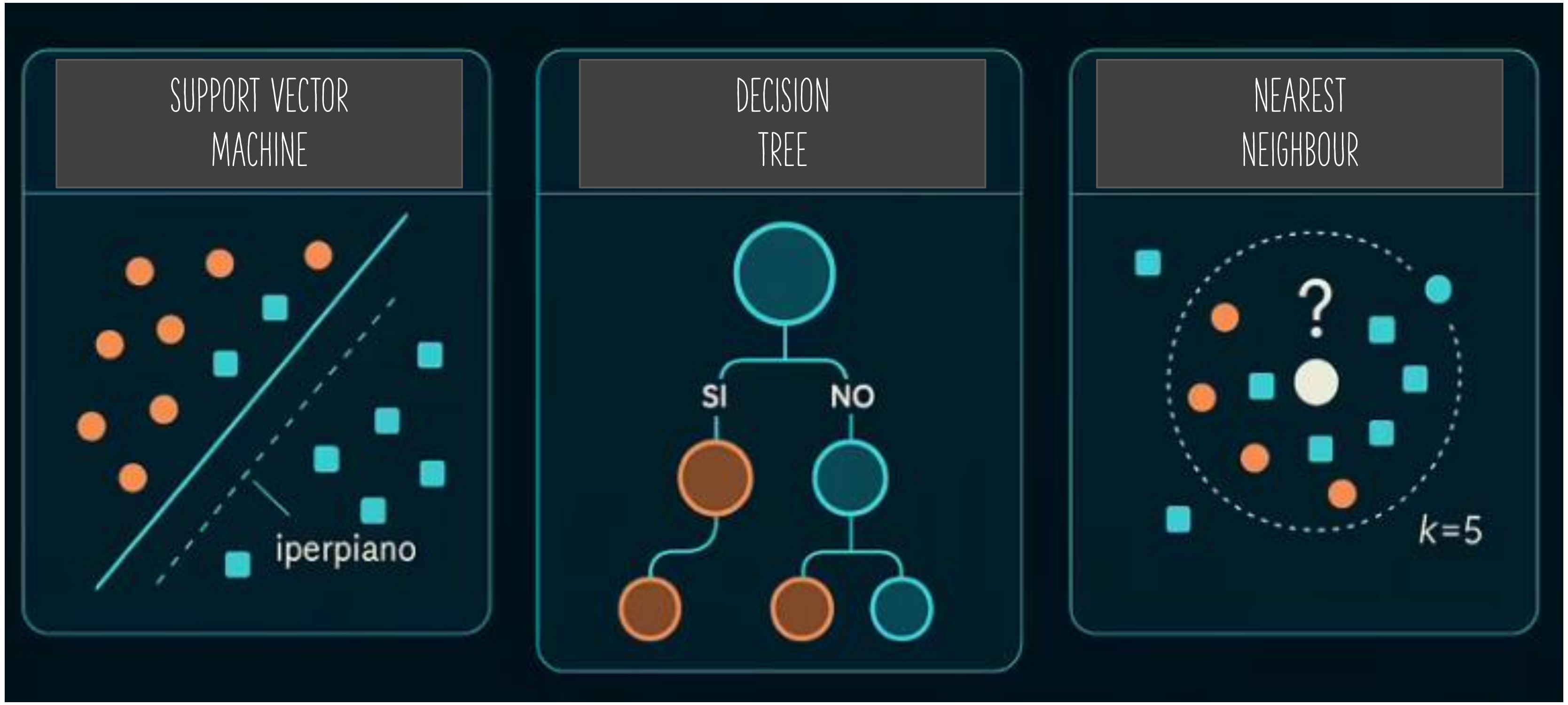
TASK DRIVEN:
predict next value

DATA DRIVEN:
identify clusters

LEARN
from MISTAKES

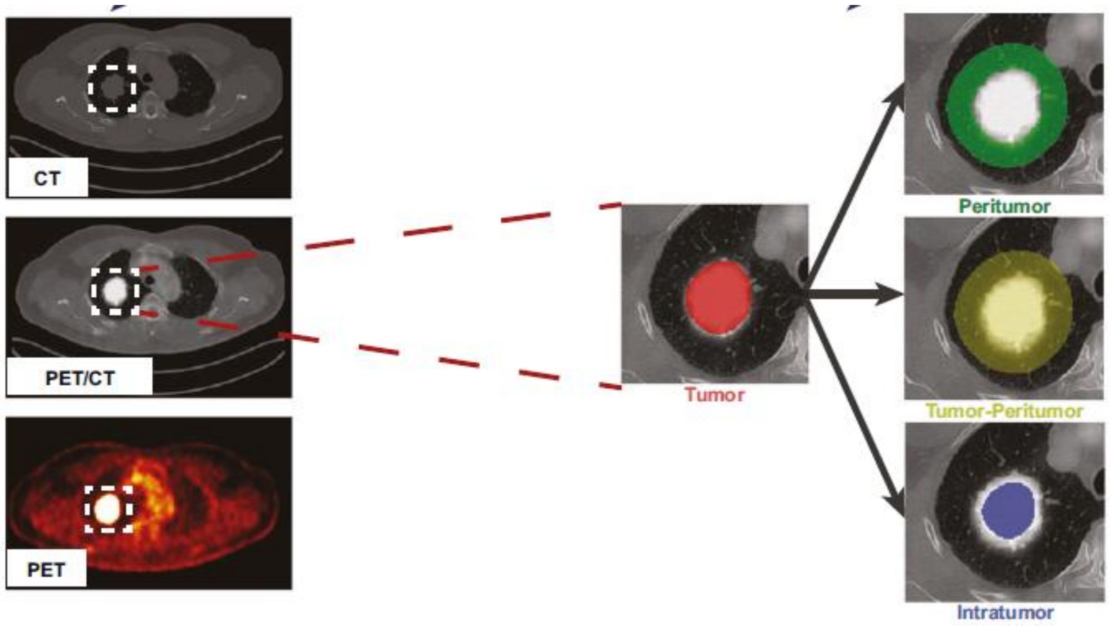
AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

Examples of supervised learning:



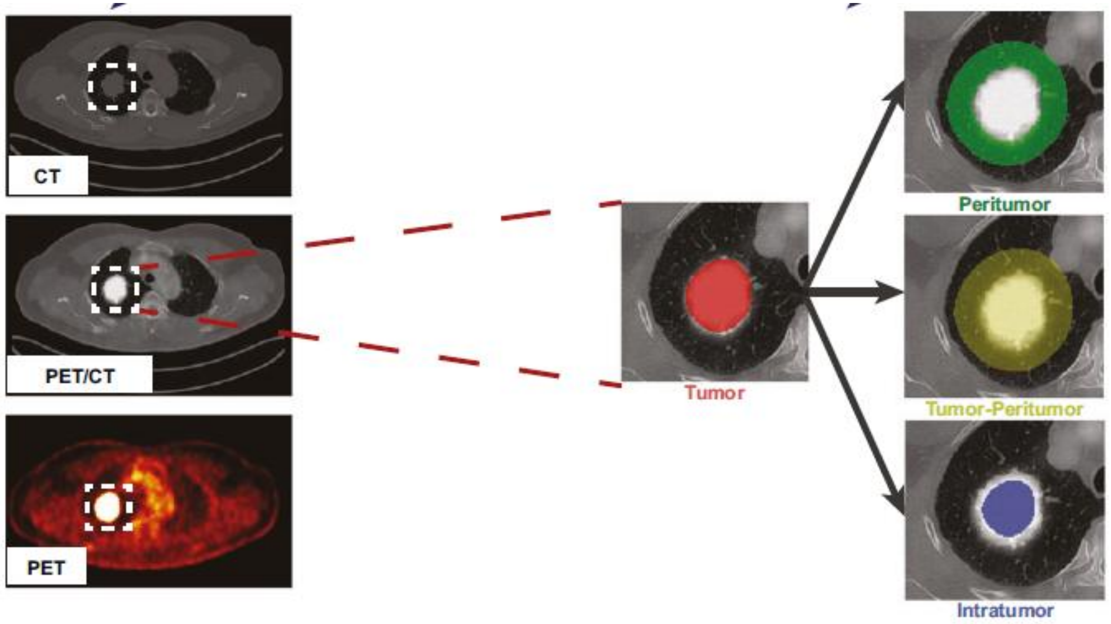
https://www.intelligenzaartificialeitalia.net/

AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

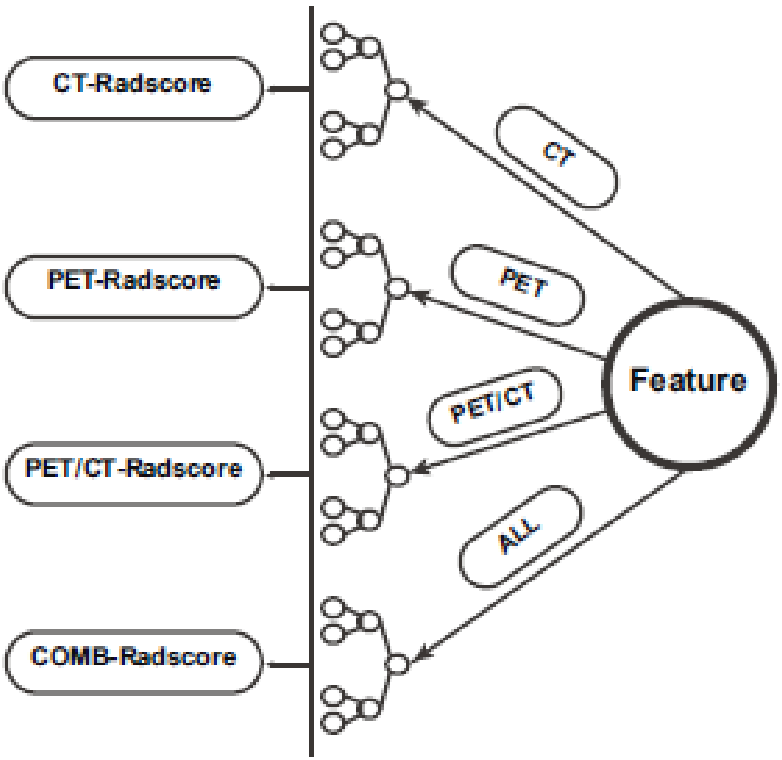


Radiomic data from PET and CT

AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

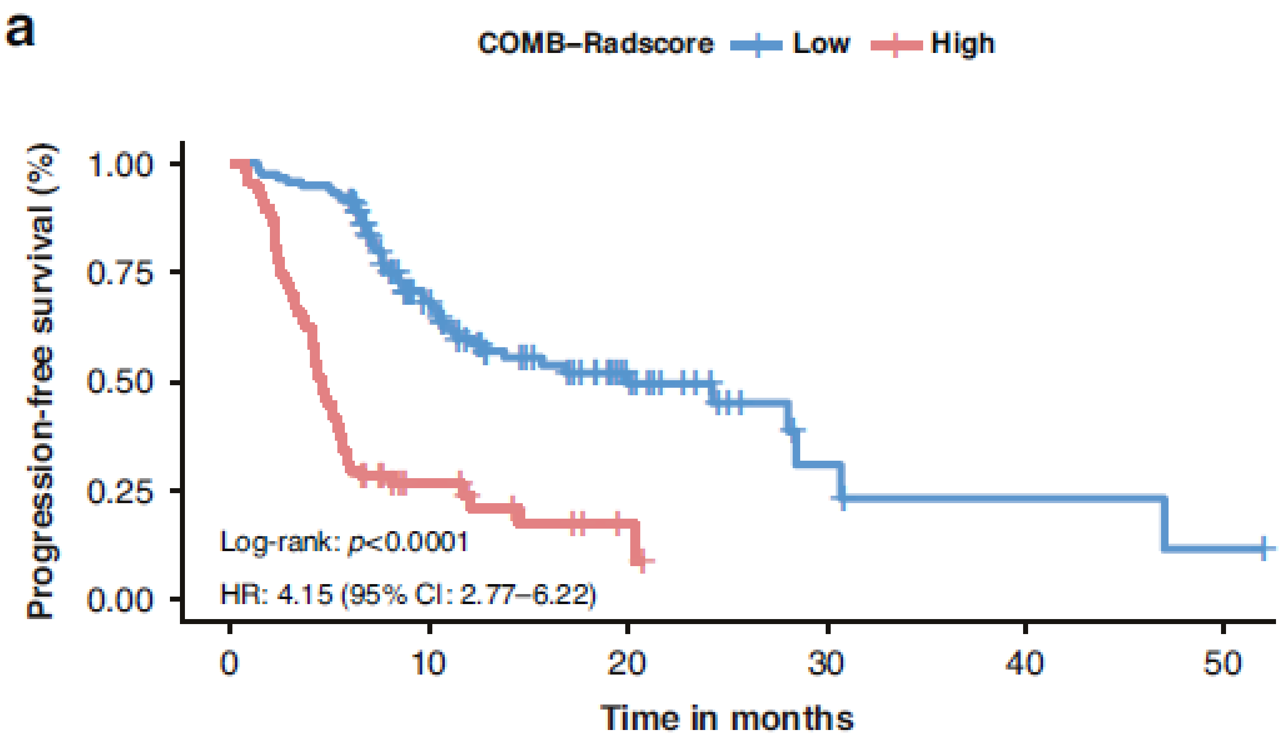


Radiomic data from PET and CT



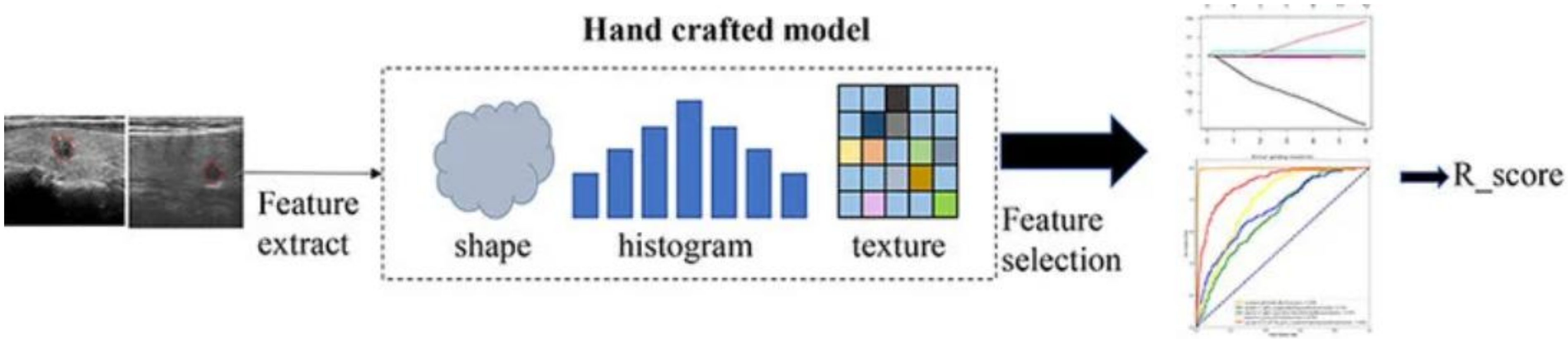
Machine learning model

AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING



Score classifying patients prognosis after immunotherapy

AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING



AI FOR RADIOMIC DATA ANALYSIS: MACHINE LEARNING

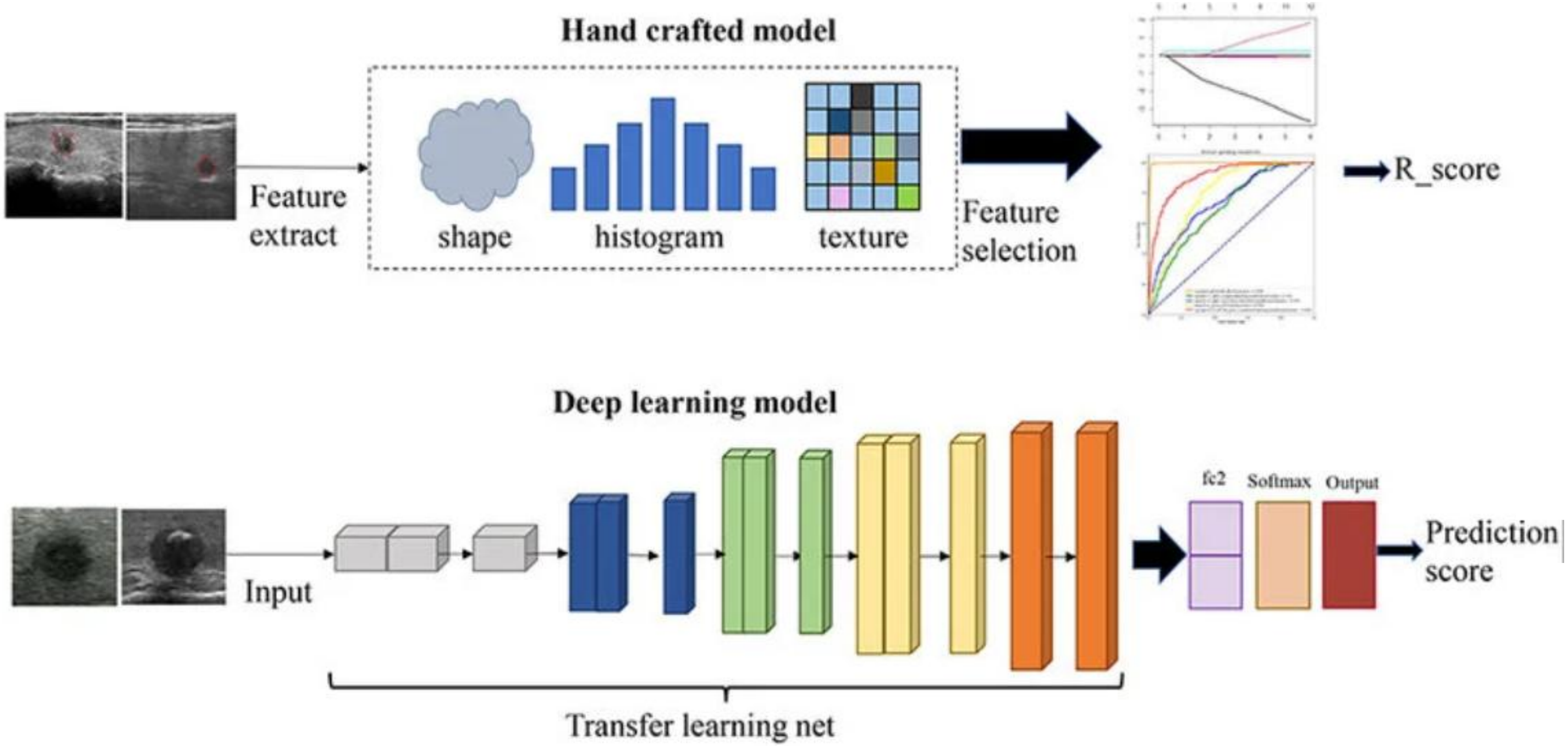
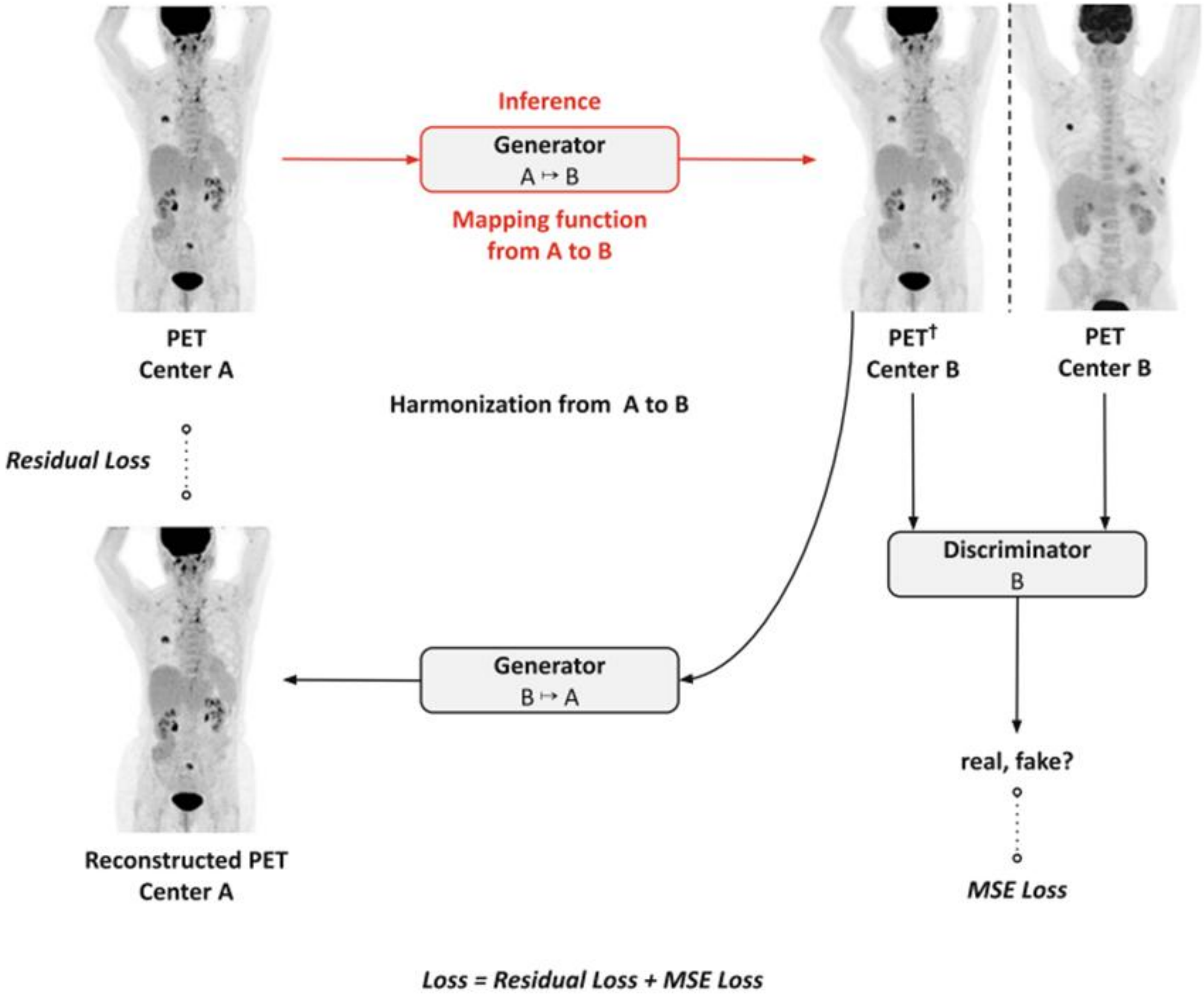


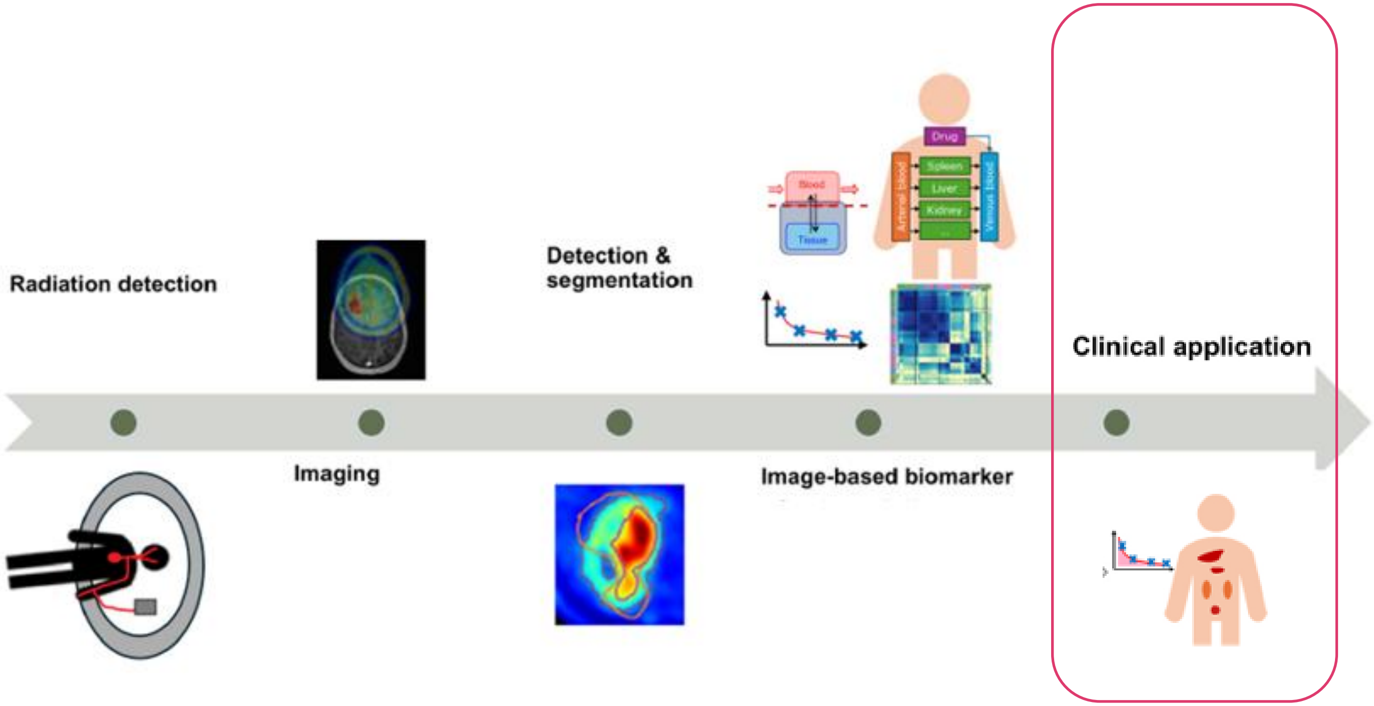
IMAGE HARMONIZATION

Image harmonization to make images acquired on different scanners QUANTITATIVELY comparable

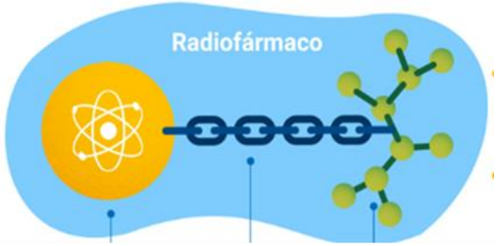


European Journal of Nuclear Medicine and Molecular Imaging (2024) 51:2532-2546

5. INTERNAL DOSIMETRY



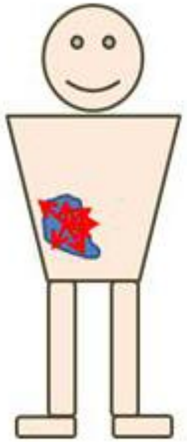
Diagnostic Area



radioisotope

molecule

Therapy



Gamma, beta+ emitter

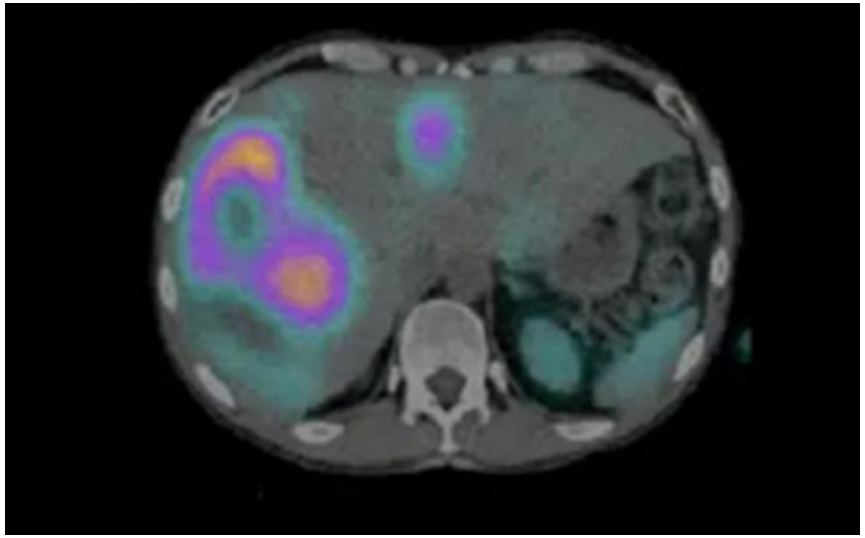
Penetrating radiation

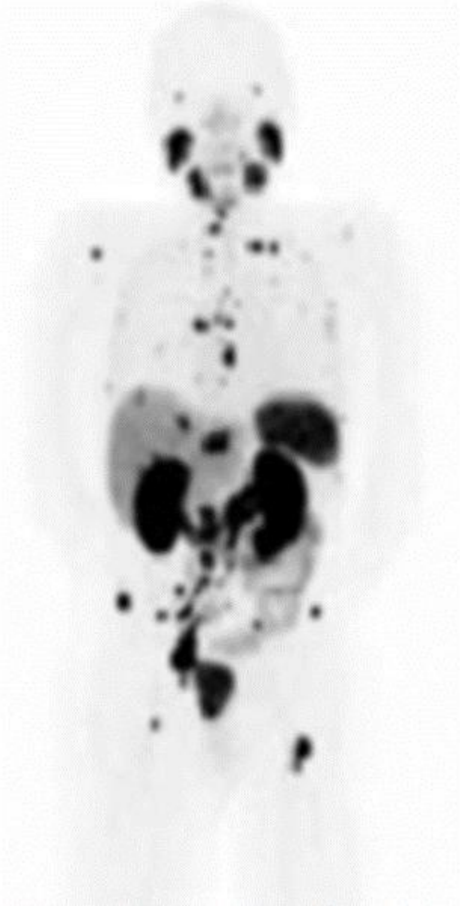
Alpha, beta- emitter

Low penetrating radiation

AI FOR RADIONUCLIDE THERAPY

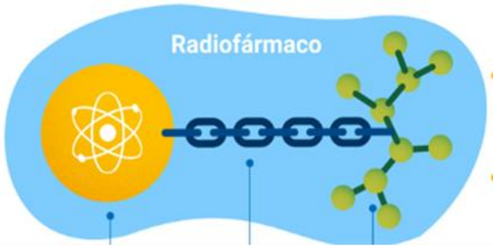
Somatostatin analogues for neuroendocrine tumour treatment





Prostate Specific Membrane Antigen (PSMA) for metastatic prostate cancer treatment

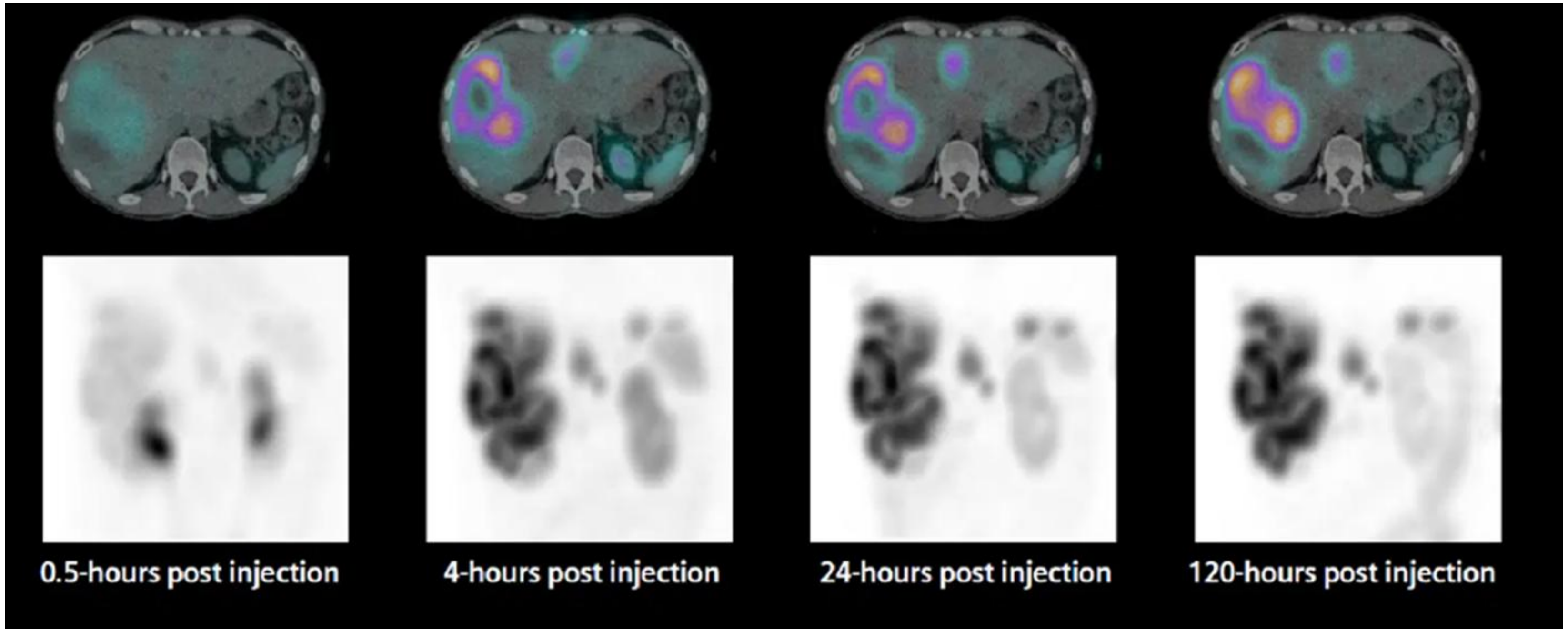
AI FOR RADIONUCLIDE THERAPY



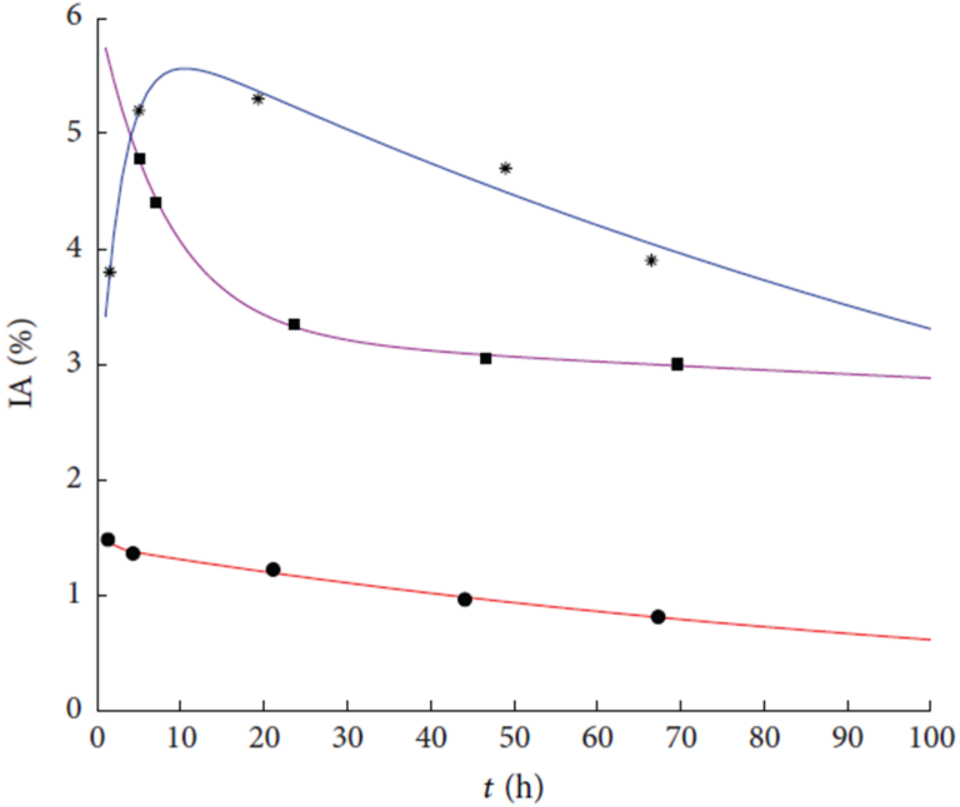
radioisotope molecule

Radioisotopes with both beta and gamma emission:

Eg: ^{177}Lu, ^{131}I



AI FOR RADIONUCLIDE THERAPY



TIME-ACTIVITY CURVES

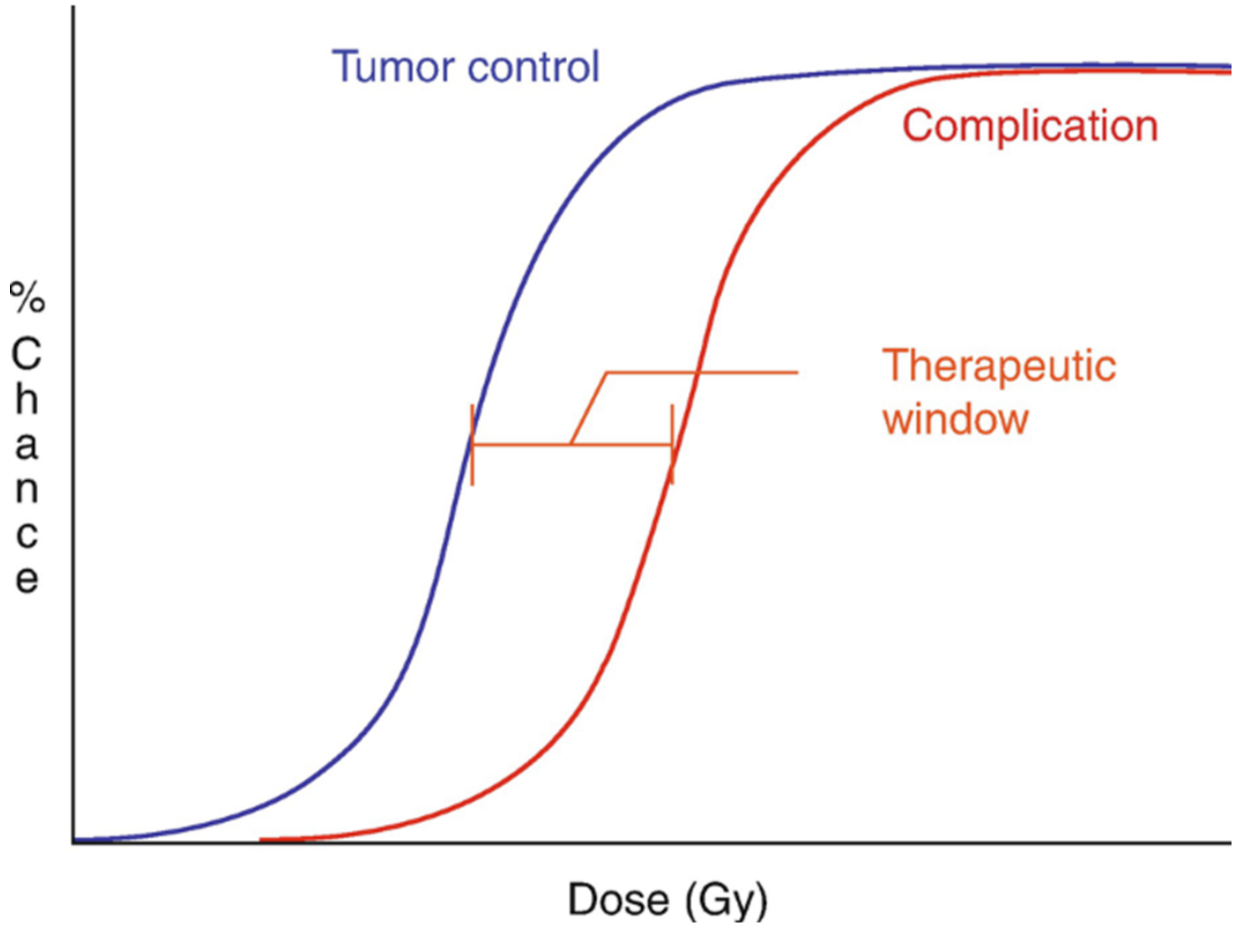
ABSORBED DOSE CALCULATION

AI FOR RADIONUCLIDE THERAPY

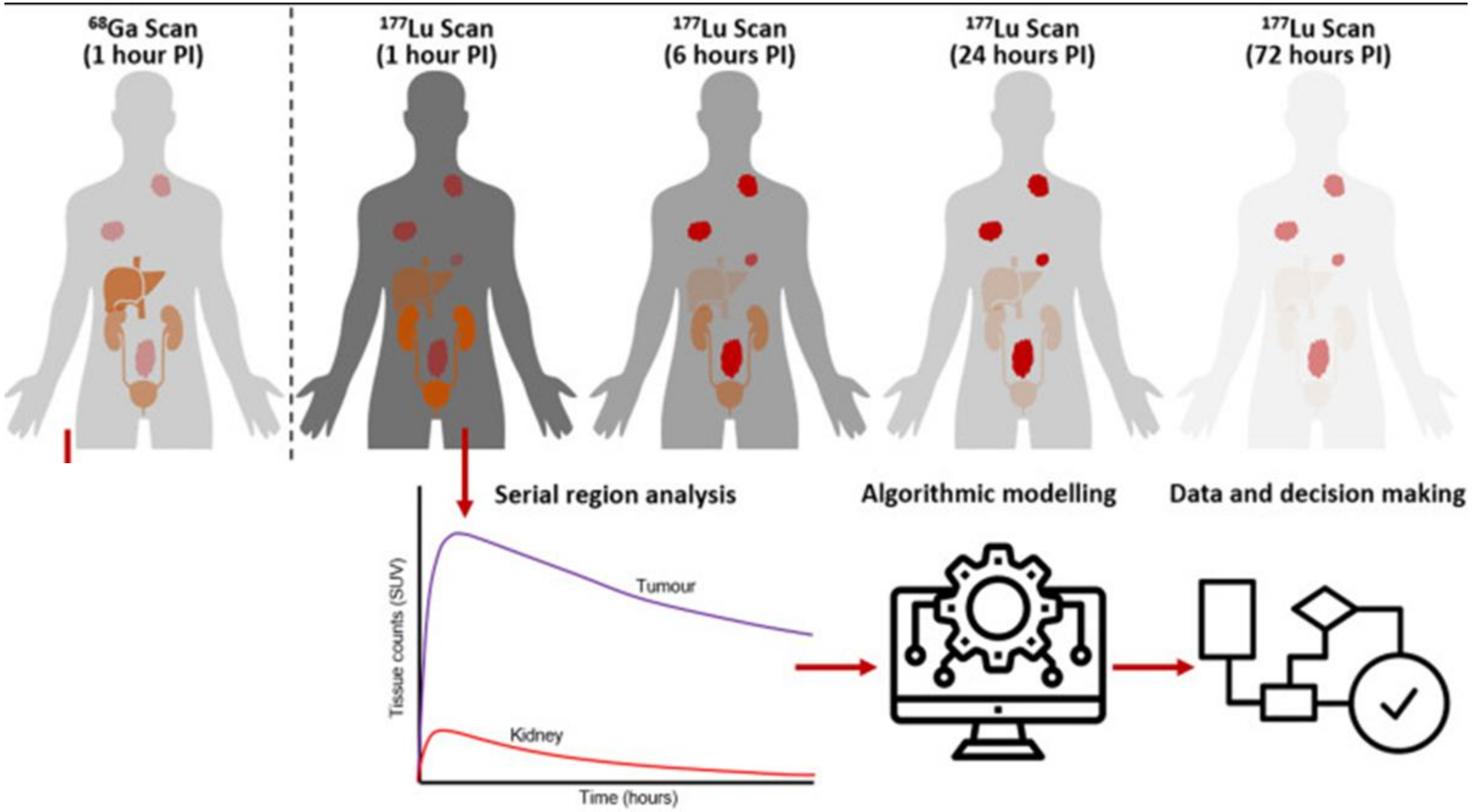
Treatment optimization

according to

efficacy and safety



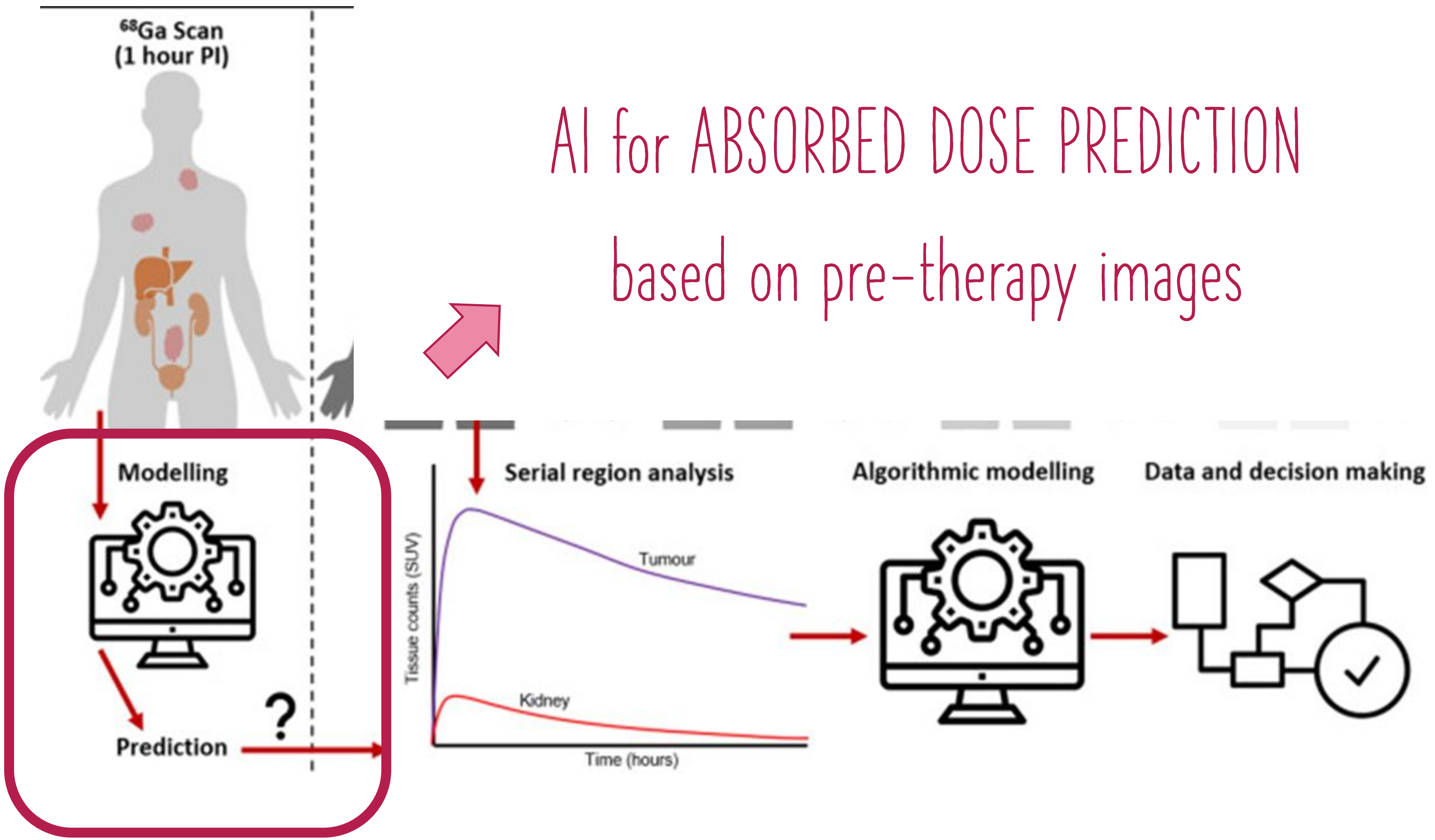
AI FOR RADIONUCLIDE THERAPY



Radiation Dosimetry, Artificial Intelligence and Digital Twins: Old Dog, New Tricks

10.1053/j.semnuclmed.2022.10.007

AI FOR RADIONUCLIDE THERAPY

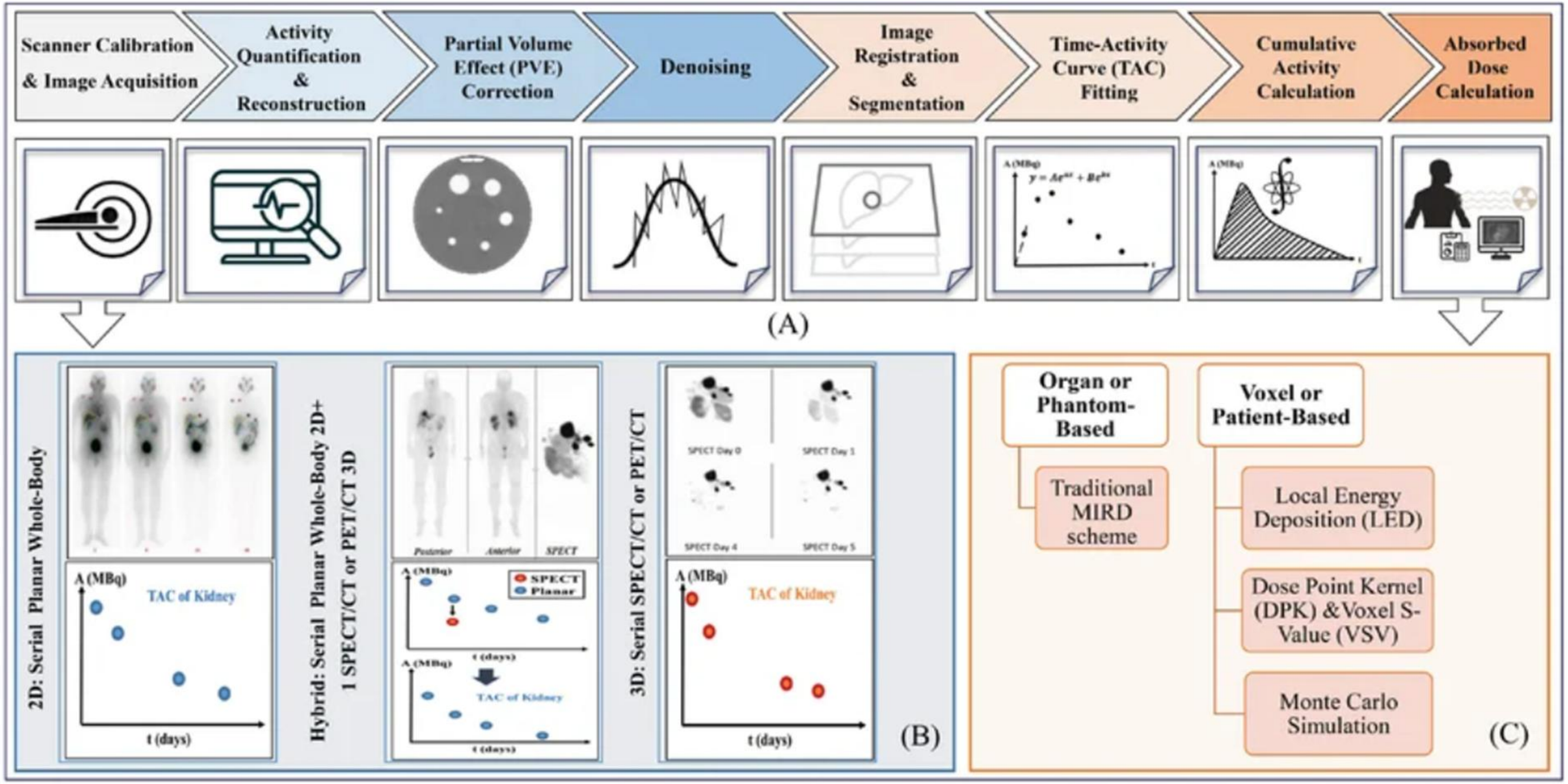


AI for ABSORBED DOSE PREDICTION

based on pre-therapy images

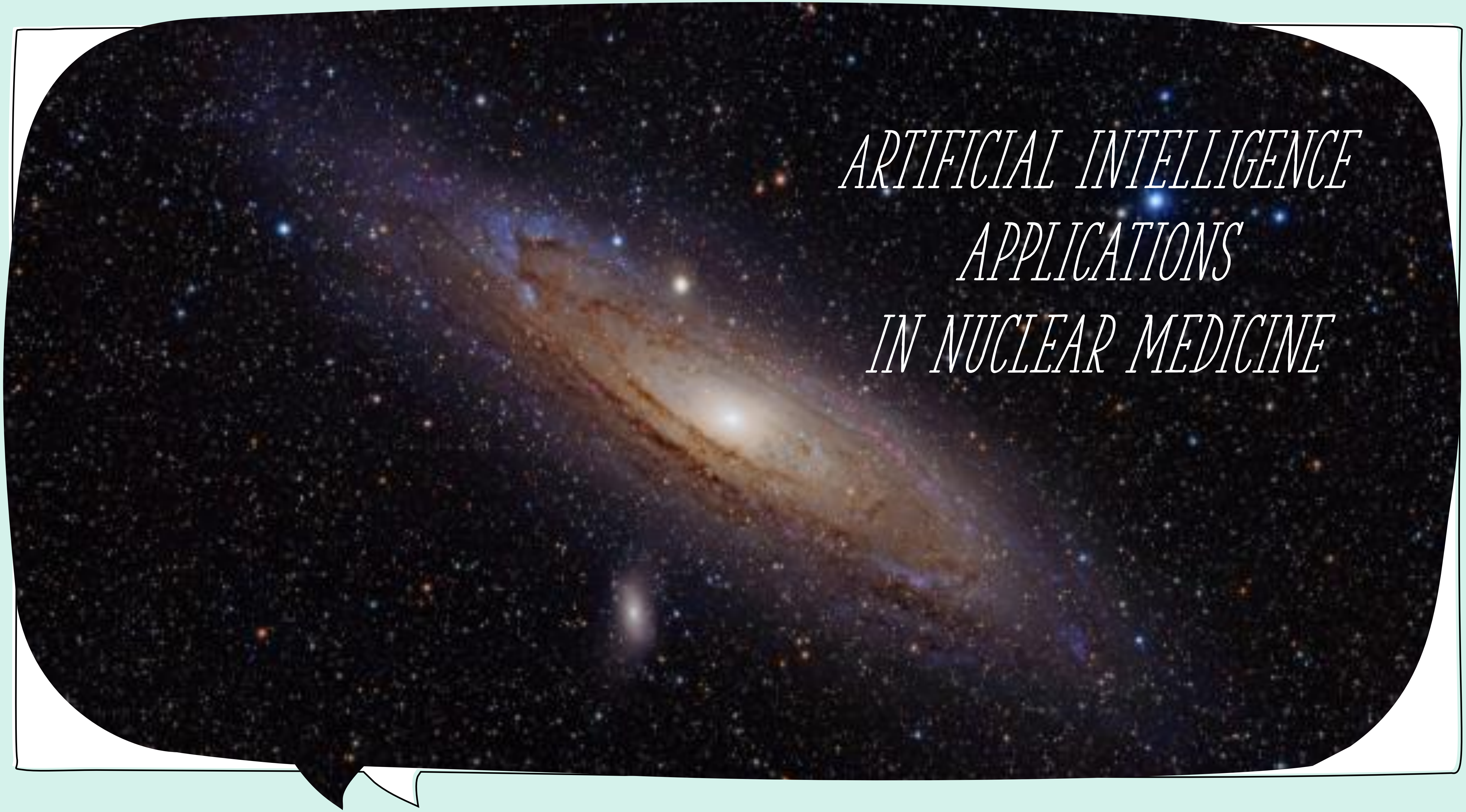
Radiation Dosimetry, Artificial Intelligence and Digital Twins: Old Dog, New Tricks
10.1053/j.semnuclmed.2022.10.007

AI FOR RADIONUCLIDE THERAPY



https://www.researchgate.net/figure/A-Internal-dosimetry-workflow-for-dose-calculation-B-Three-acquisition-protocols_fig5_377421487

ARTIFICIAL INTELLIGENCE APPLICATIONS IN NUCLEAR MEDICINE



ARTIFICIAL INTELLIGENCE APPLICATIONS IN NUCLEAR MEDICINE

Clinical practice:

- Reconstruction
- Segmentation
- Dose/Acquisition time reduction
- Quantification (cardiology and neurology)

ARTIFICIAL INTELLIGENCE APPLICATIONS IN NUCLEAR MEDICINE

Research:

- Radiomics and predictive models
- Personalized dosimetry
- Synthetic image generation (Digital twins)


RAHMET
OBRIGADO
GRAZIE
HVALA
谢谢
KIITOS
DANKE
TAK
DANK JE
THANK YOU
SHUKRAAN
BARKA
ευχαριστώ
GRACIAS
MERCI
СПАСИБО
ARIGATO
TAKK
TACK