Using 3D CNNs for distortion corrections in PET imaging

J-PET

NATIONAL CENTRE
FOR NUCLEAR RESEARCH
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Świerk Computing Centre

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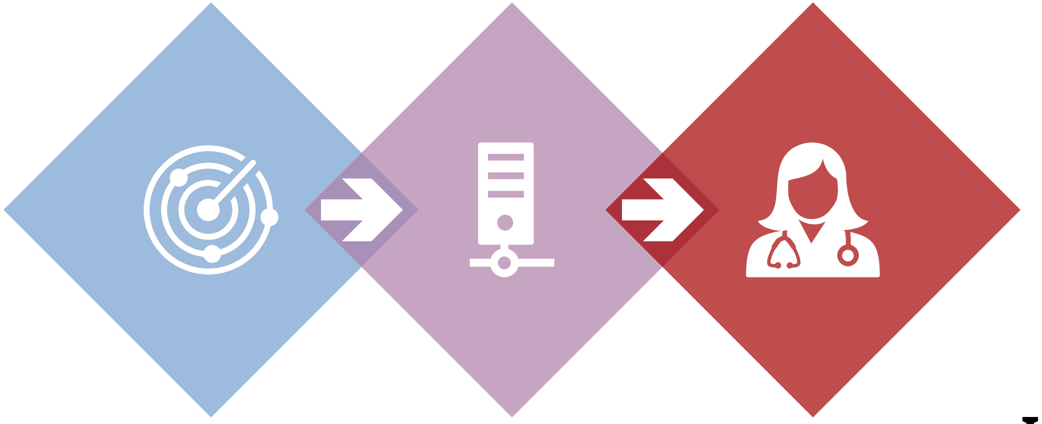
Michał Obara

06.06.2024

AI in PET tomography



Scanner level

- Acceleration
- Low-level corrections and calibrations
- Fast simulations

Image reconstruction

- Replacement of the „standard” image algorithm
- Image reconstruction speed-up
- **Corrections**

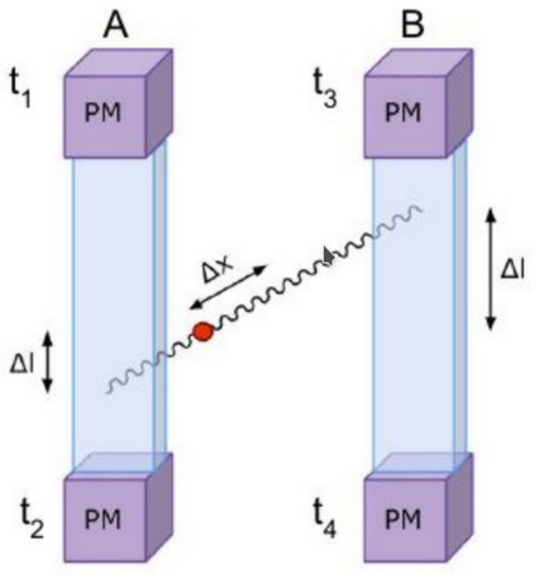
Image post-processing

- Diagnostic support
- Radiomics
- Image denosing and segmentation

E.g. E. Berg and Simon R. Cherry, Phys Med Biol. 2018 Jan 11;63(2):02LT01.
J.S. Lee, IEEE Transactions on Radiation and Plasma Medical Sciences 2020

Many studies on image reconstruction using DL and CT-free PET.

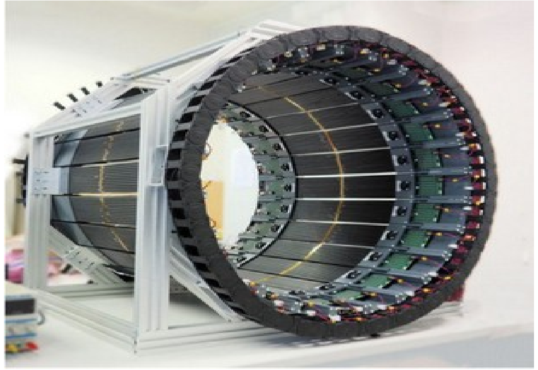
Cost-effective total body solution



$$\Delta l = \frac{(t_2 - t_1)\cdot v}{2} \cong \frac{(t_2 - t_1)\cdot c}{4}$$

$$\Delta x = \frac{(t_l - t_r)\cdot c}{2} \implies \Delta x = \frac{\Delta t}{2}\cdot c$$

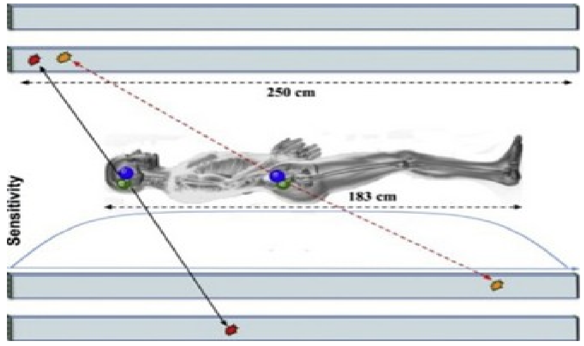
Modular J-PET



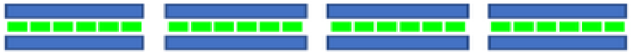
- 50 cm AFOV (Axial Field of View)
- 24 modules x 13 strips
- Readout → silicon photomultipliers matrices

Total-body J-PET

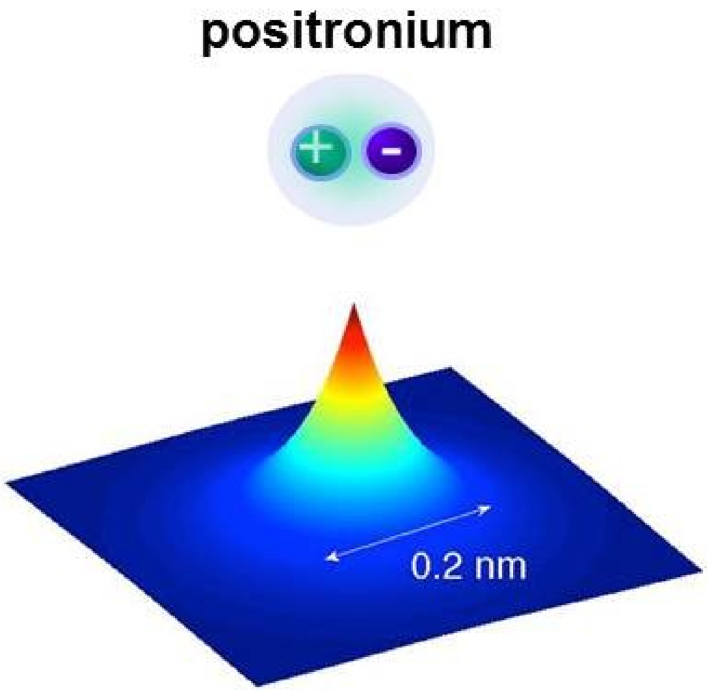
PET Clinics 15 (2020) 439
Phys. Med. Biol. 66 (2021) 175015

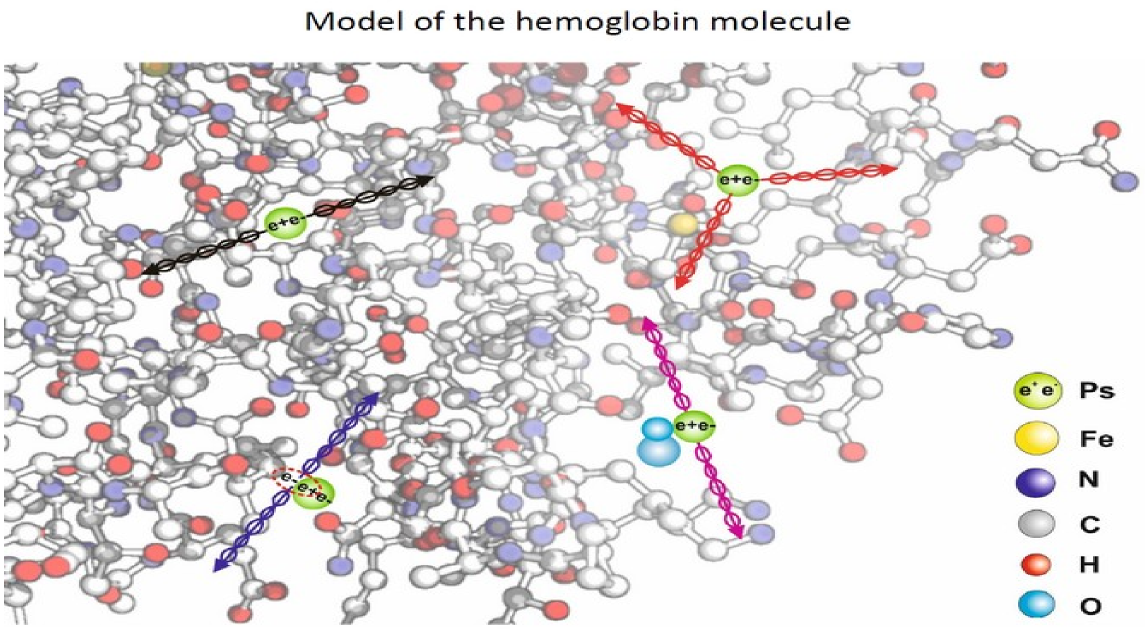


- 250 cm AFOV
- Additional layers of wavelength shifters → better axial resolution



Towards multiphoton/positronium tomography





P. Moskal, B. Jasińska, E. Ł. Stępień, S. D. Bass
Nature Reviews Physics 1 (2019) 527-529

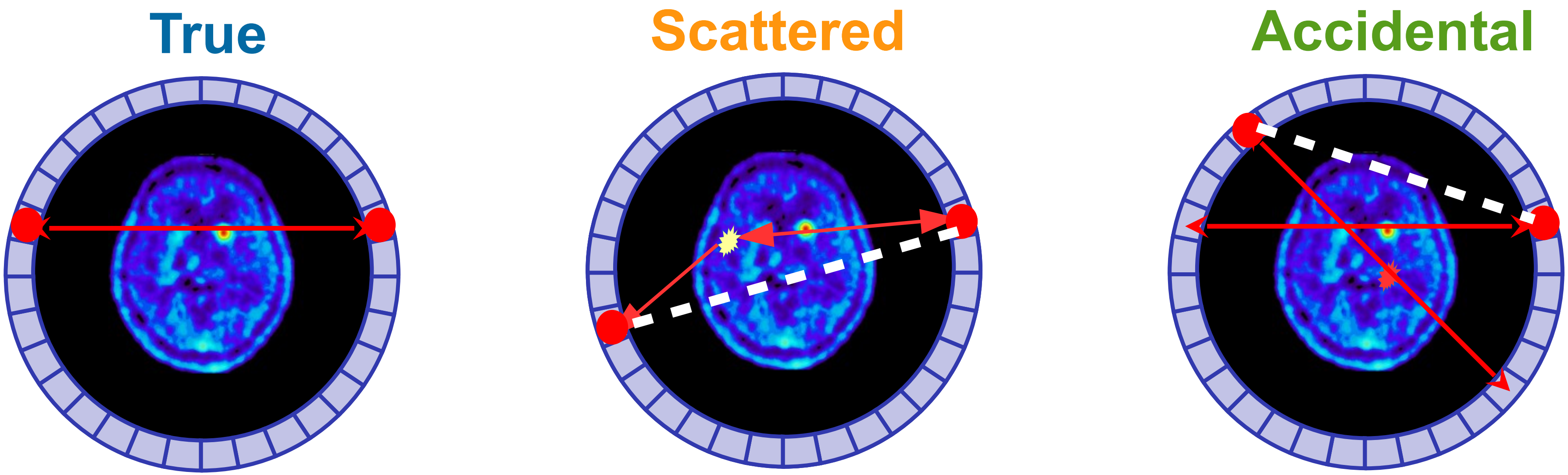
P. Moskal et al. Phys. Med. Biol. 64 (2019) 055017

P. Moskal et al. EJNMMI Phys. 7 (2020) 44

P. Moskal, K. Dulski et al Science Advances 7 (2021) eabh4394

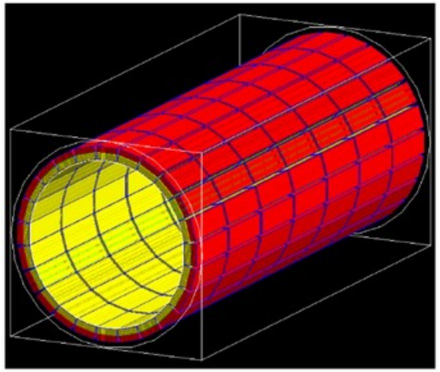
P. Moskal, A. Gajos et al. Nature Communications 12 (2021) 5658

Coincidence classification for total-body J-PET



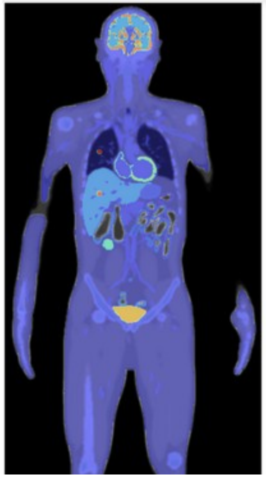
Diagrams adapted from P. Moskal

Training data generation



TB J-PET

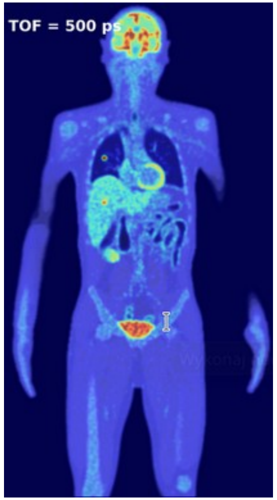
- 243 cm AFOV
- 7 rings
- 2cm gap between rings
- 30 x 6 x 330 mm strips
- 24 modules with 2 layers of 16 strips



XCAT Phantom

- Voxelised human anatomic phantom
- Activity - 50 Mbq
- Acquisition time - 600 seconds
- Contrast for hot regions: 16:1 lungs, 3:1 liver

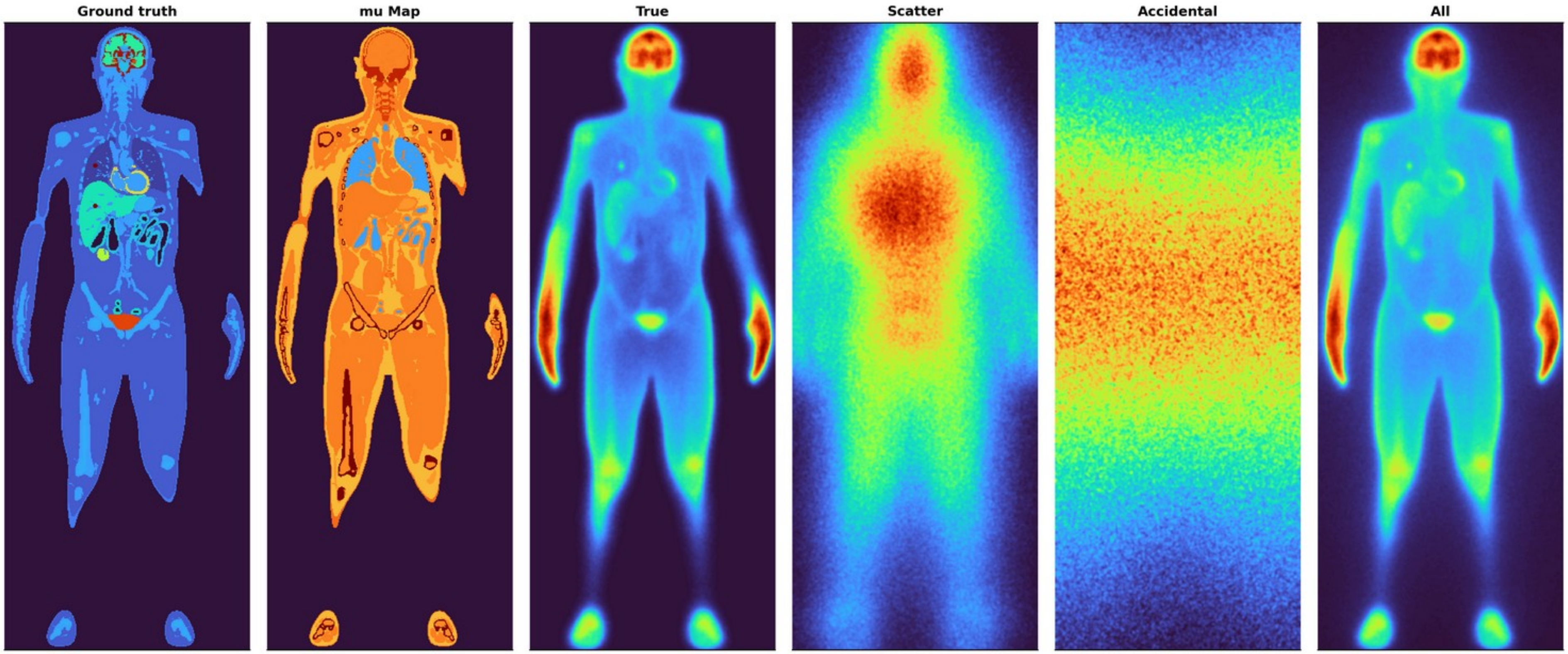
Monte Carlo Simulations



GATE MC Simulation

- 356M coincidences
- Phenomenological time, energy and positional resolution
- Geometry cuts → reduce accidental fraction

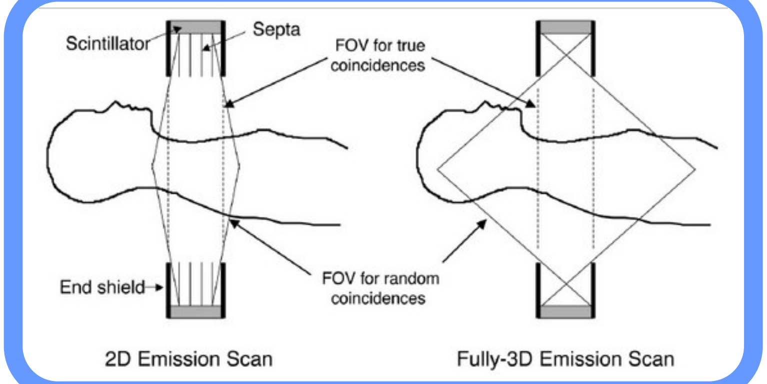
Coincidence classification for total-body J-PET



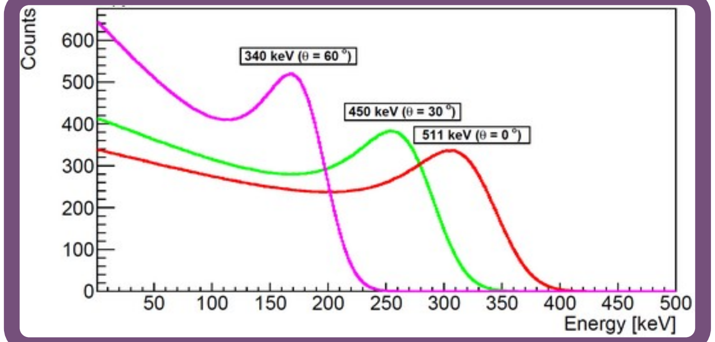
After loose geometry cuts | True: 49.9% | Scatter: 25.7% | Accidental: 23.2%

Increased background for novel PET

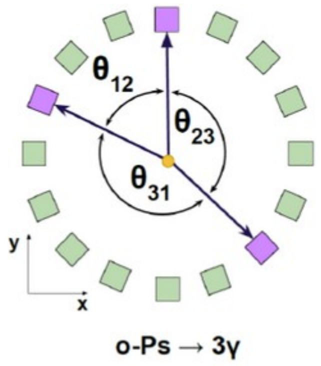
1. Geometry of total body scanners



2. Photon Energy deposition in J-PET via compton scattering



3. Event topology and photon energy spectra for multi photon imaging

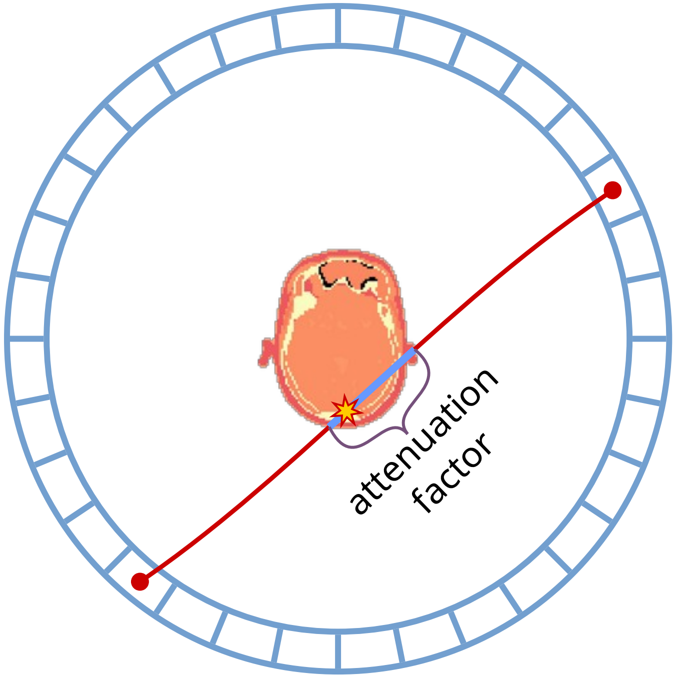


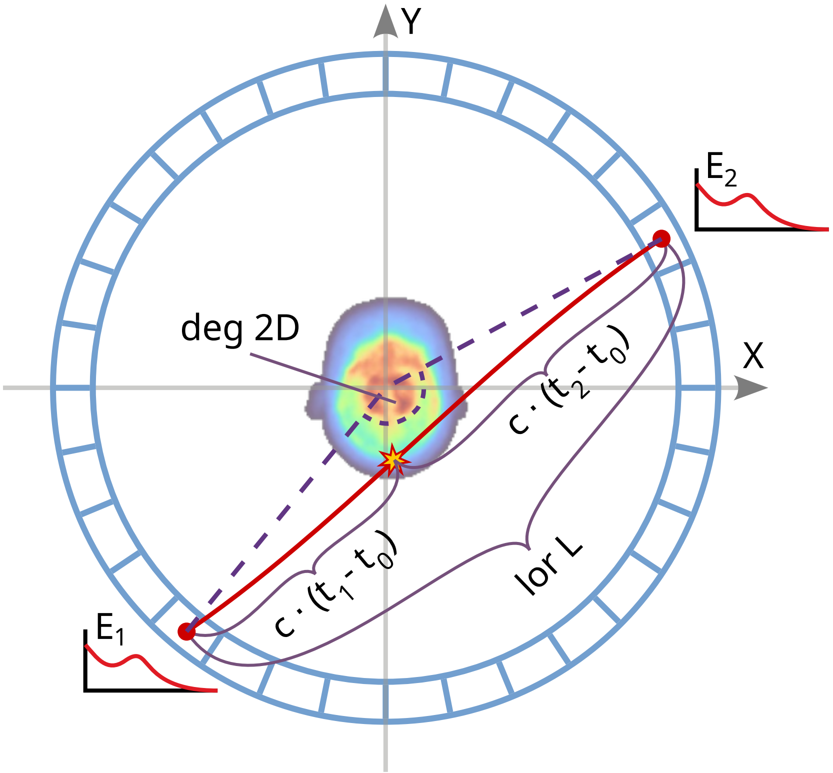
Idea: apply ML techniques to reduce background (ACCIDENTAL, SCATTER)

Total body PET diagram adapted from
D. Brasse et al. J Nucl Med 2005; 46:859–867

Features

1) **dt = t_1 - t_2**
2) **eDiff = $|E_1 – E_2|$**
3) **eSum = $E_1 + E_2$**
4) AF
5) deg 2D
6) lor L





$$AF = \int_{-\infty}^{+\infty} \exp(-\mu(x)x)\,\mathrm{d}x$$

attenuation factor

$\mu = 0\ \mathrm{cm}^{-1}$ for air

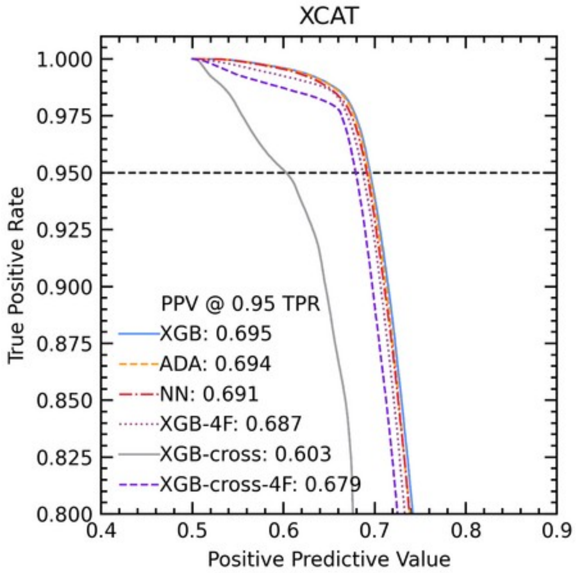
$\mu = 0.096\ \mathrm{cm}^{-1}$ for water

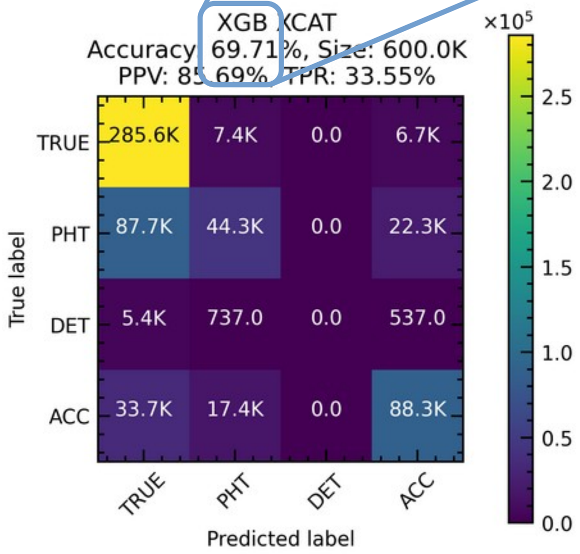
Our „Classic” Classifiers

3 types of models:
- **Feedforward Neural Network**
- **ADABoost**
- **XGBoost**

2 scenarios:
- **6 features**
- **4 features**

2 phantoms:
- **XCAT**
- **NEMA IEC**





Accuracy 69.71%

Single Scatter Simulations (SSS)

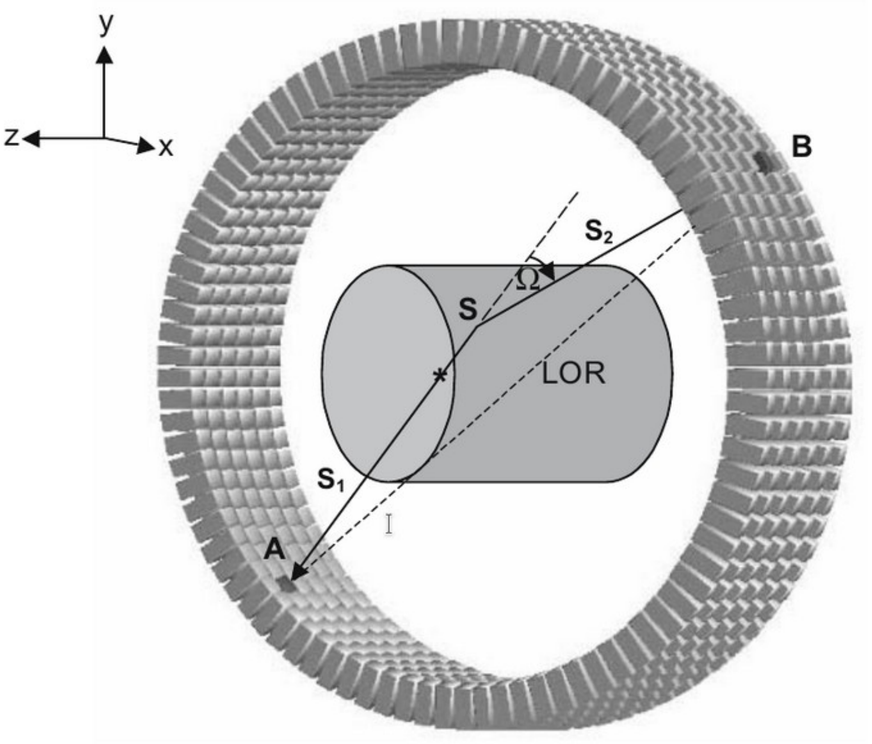
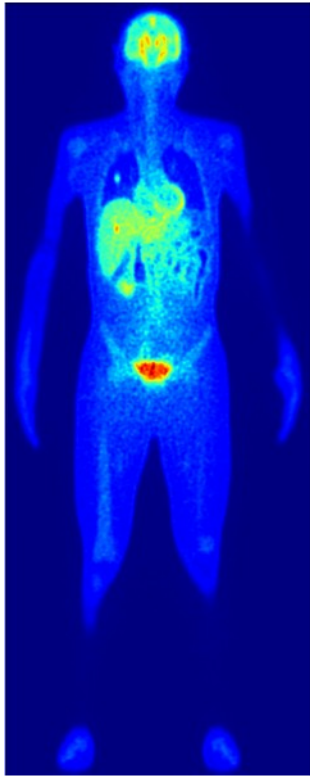


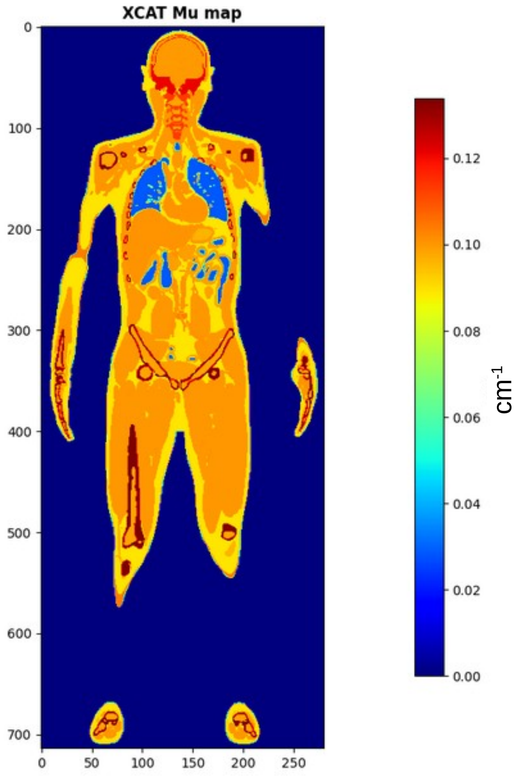
Figure 5.16. Geometry of the single scattering model used in simulation based scatter correction.

Diagram adapted from D.L.Bailey et al. *PET Basic Sciences*

Ingredients

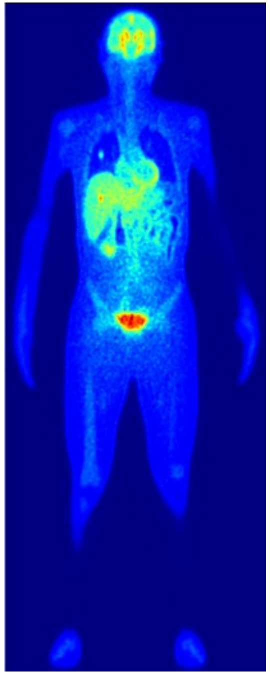


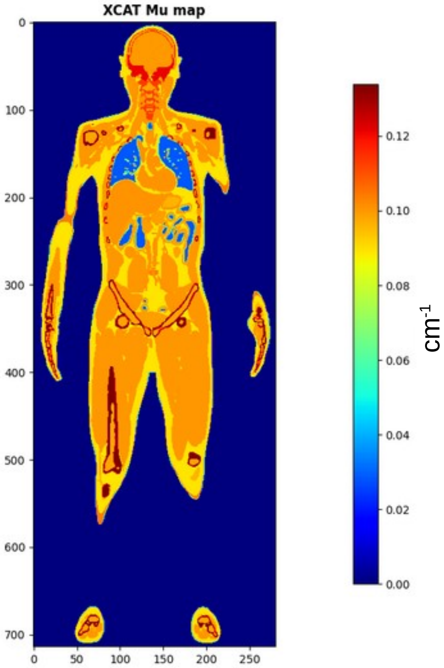
Activity estimate

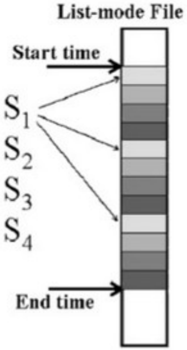


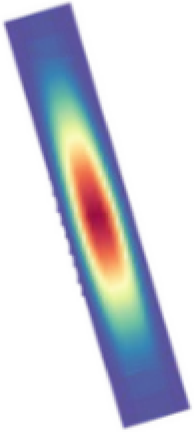
Attenuation map

Ingredients extended









Activity estimate

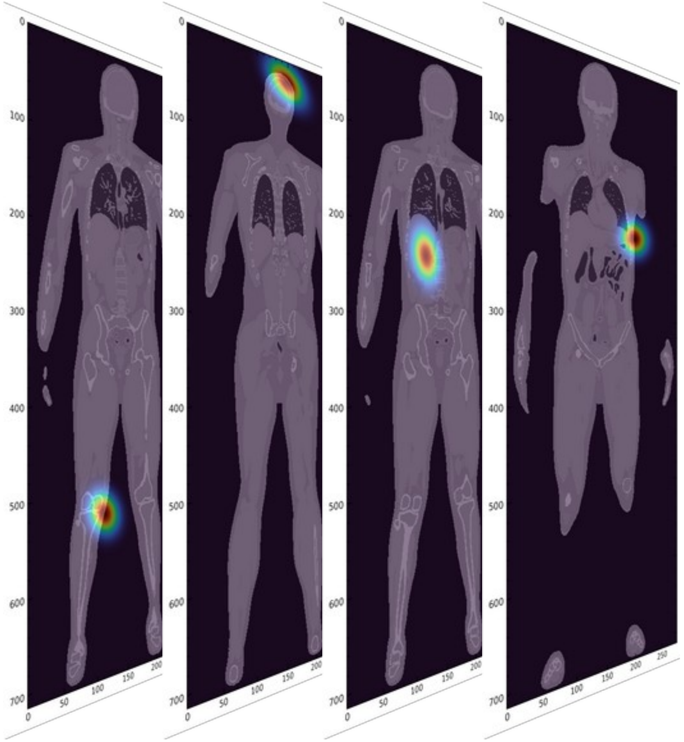
Attenuation map

List Mode

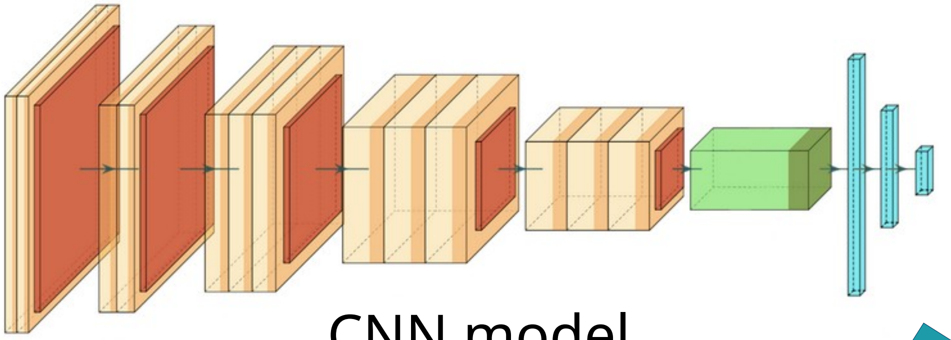
Time-of-Flight

The method

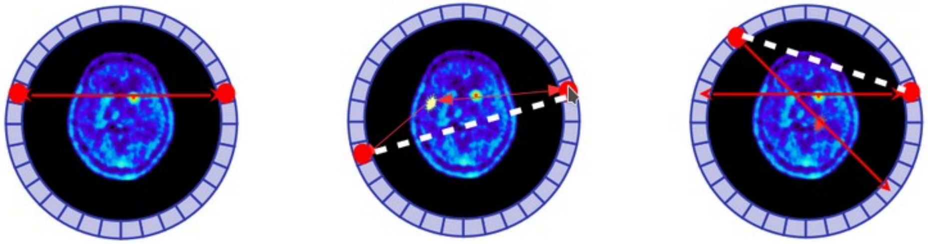
coincidence events



...



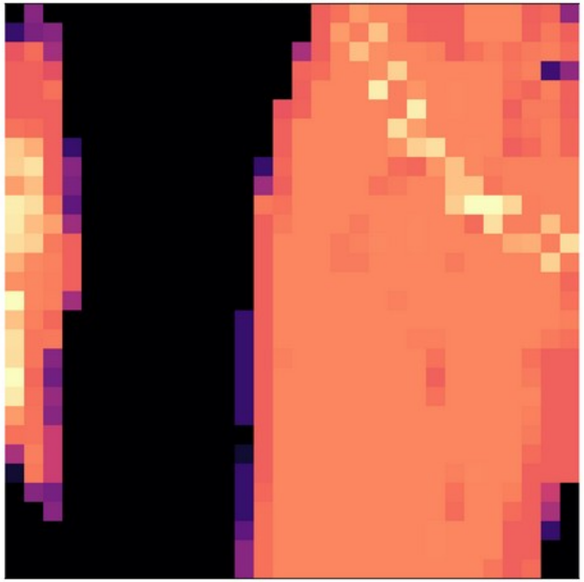
CNN model



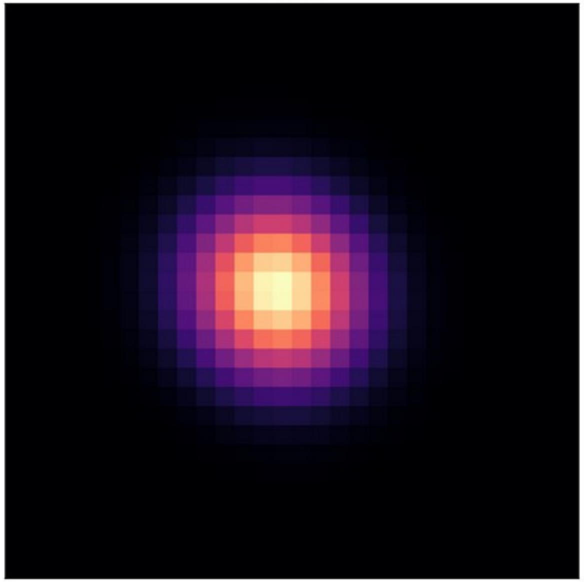
Network diagram adapted from B. Vacchetti, Electronics 2022, 11, 1570

Data encoding

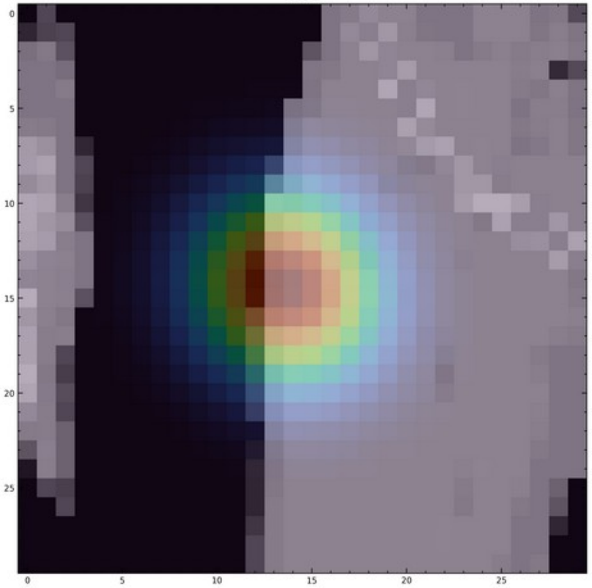
Channel 1



Channel 2

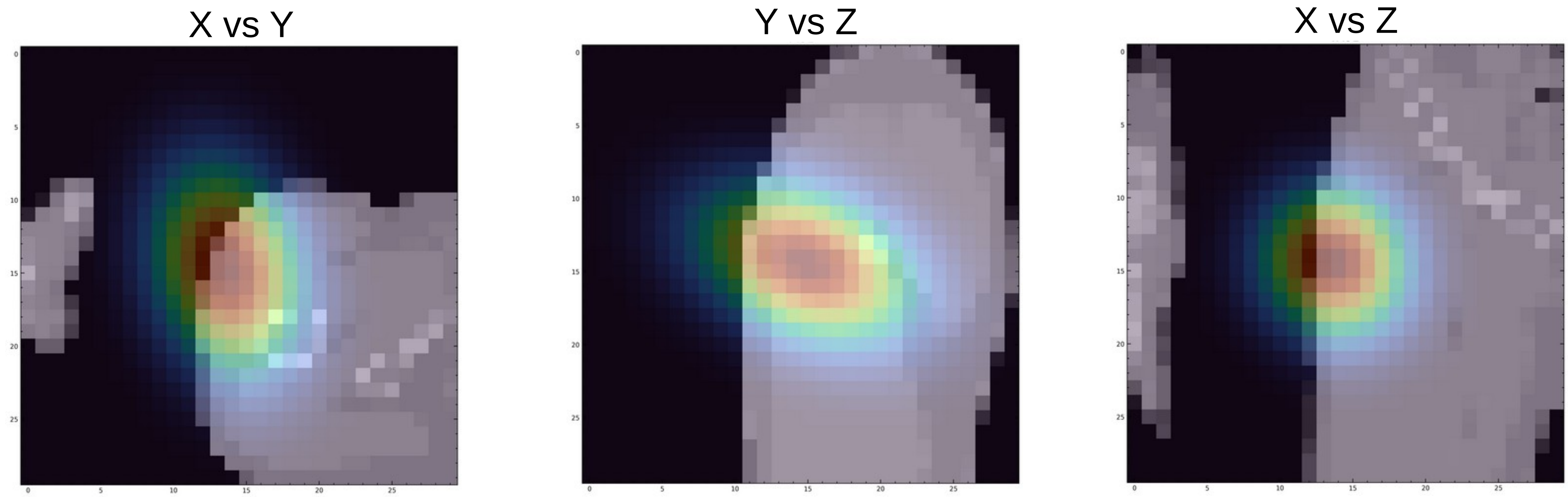


Channel 1 + Channel2



- Channel 1: Rescaled attenuation map:
  [2.5, 2.5, 2.5] mm → [10, 10, 10] mm
- Channel 2: Coincidence most likely position → 3D gaussian
  ∥ LoR σ = 50 mm; ⊥ LoR σ = 40 mm
- Image cropped ±3σ

Data encoding



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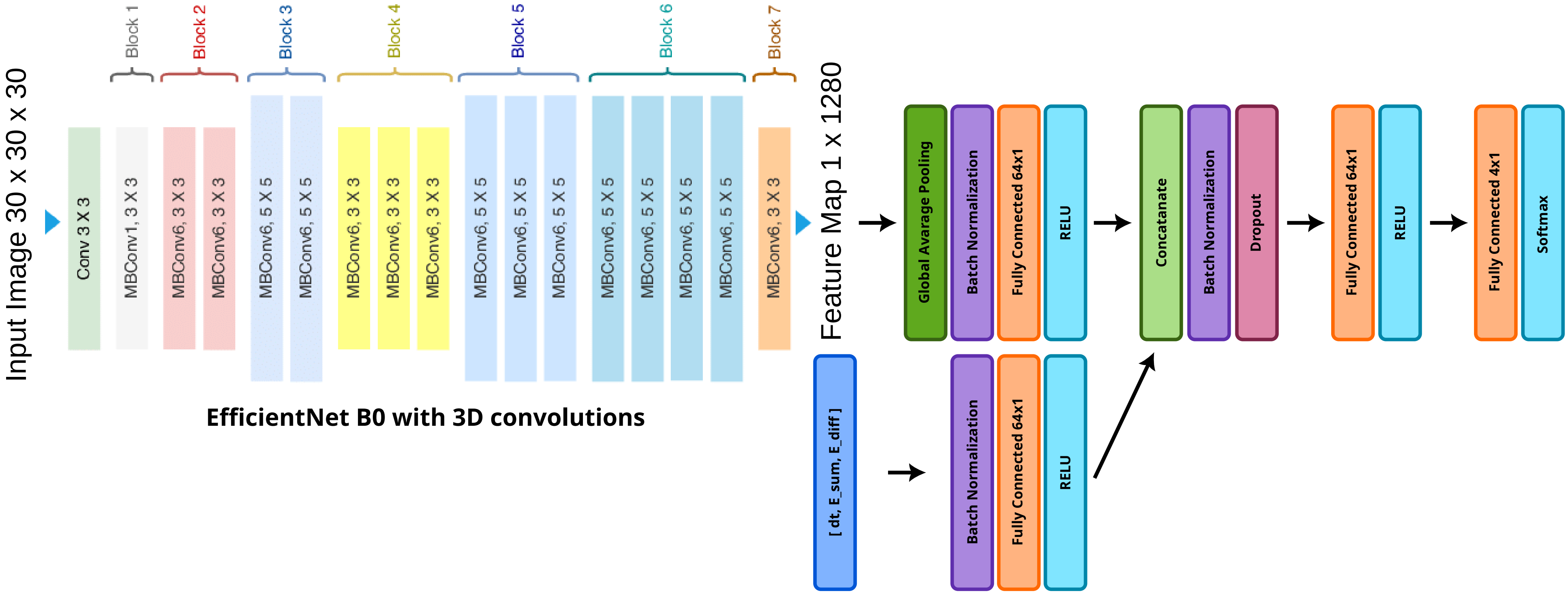
3D CNN Classification Network



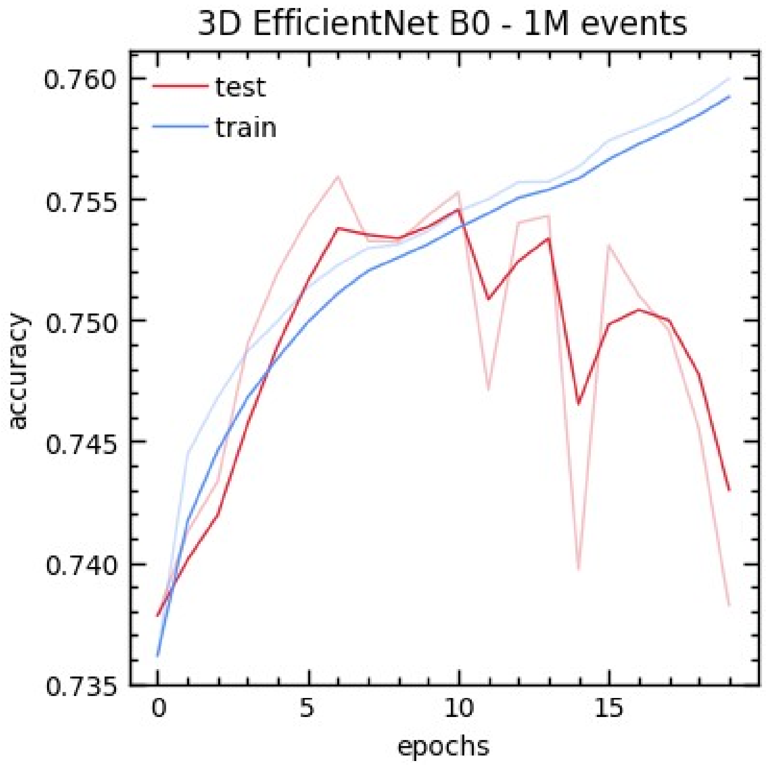
EfficientNet B0 with 3D convolutions

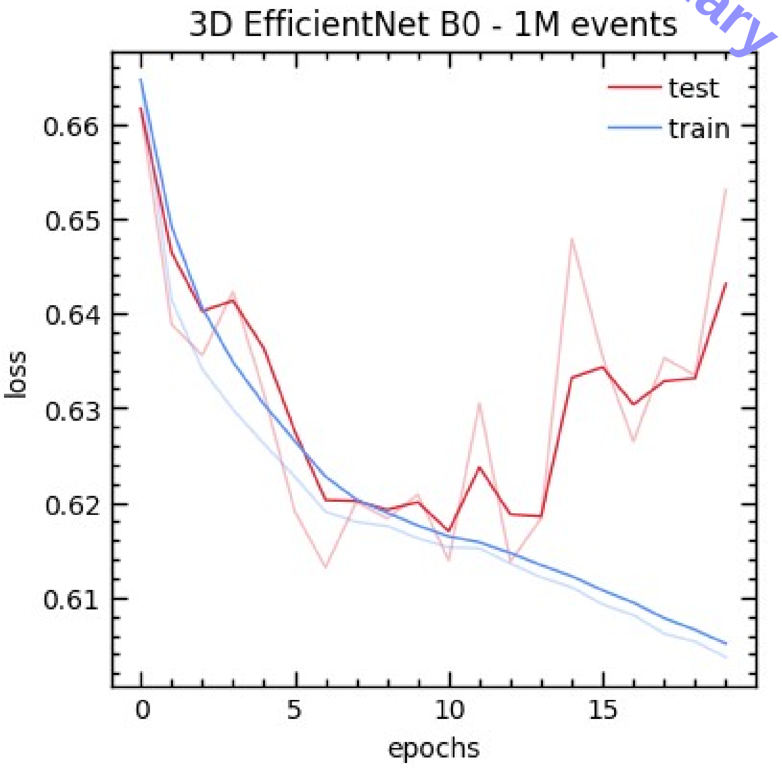
1) Tan, M. and Le, Q.V., Proceedings of the ICML 2019, Long Beach, 9-15 June 2019, 6105-611
2) 3D EffNetB0 implementation: R. Solovyev at al., Computers in Biology and Medicine 141 (2022) 105089
https://github.com/ZFTurbo/classification_models_3D

Training results

Preliminary

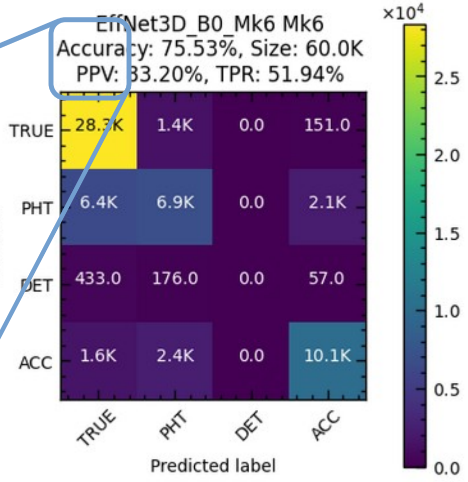
- Keras + TensorFlow
- Coincidences: 1M
- Epochs: 20
- Batch size: 128
- Optimizer:
  RMSprop
  with default settings
- Loss:
  Categorical
  Cross Entropy
- Split: 80% / 20%

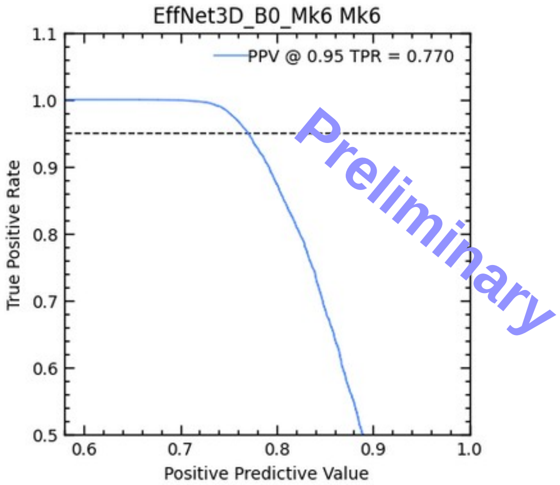




Training results

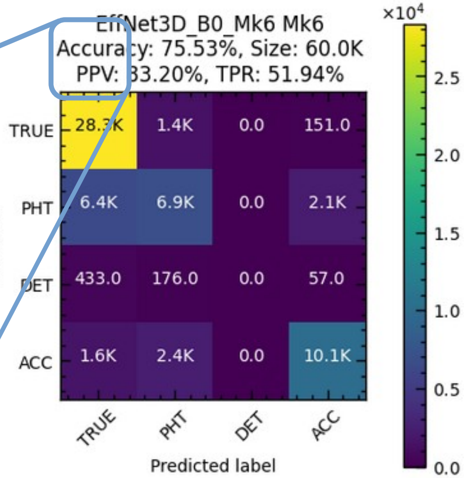
Accuracy
75.53%



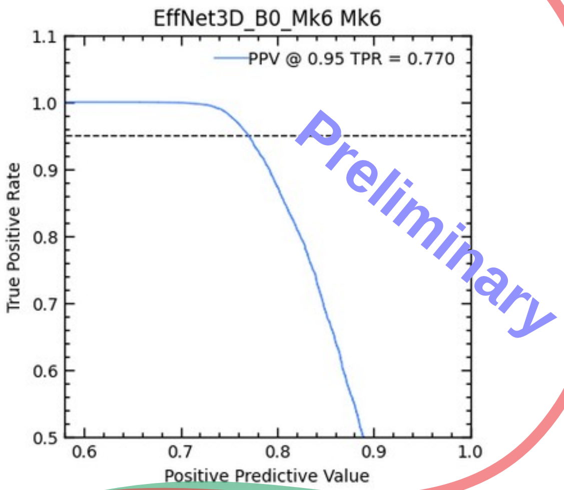


3D EfficientNet B0
+ Data Encoding
+ 3 Features

Training results



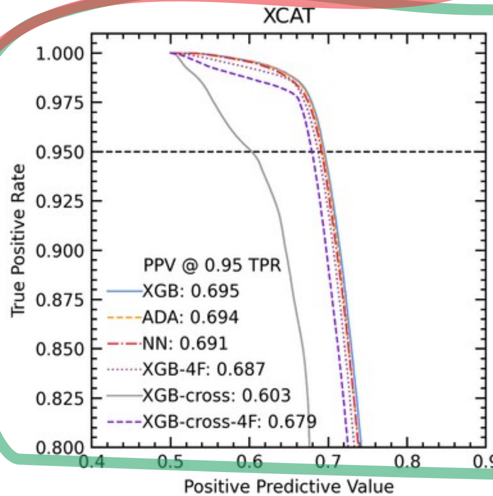
Accuracy 75.53%

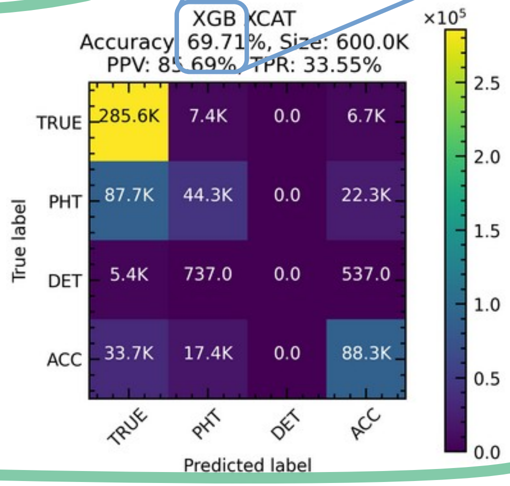


3D EfficientNet B0
+ Data Encoding
+ 3 Features

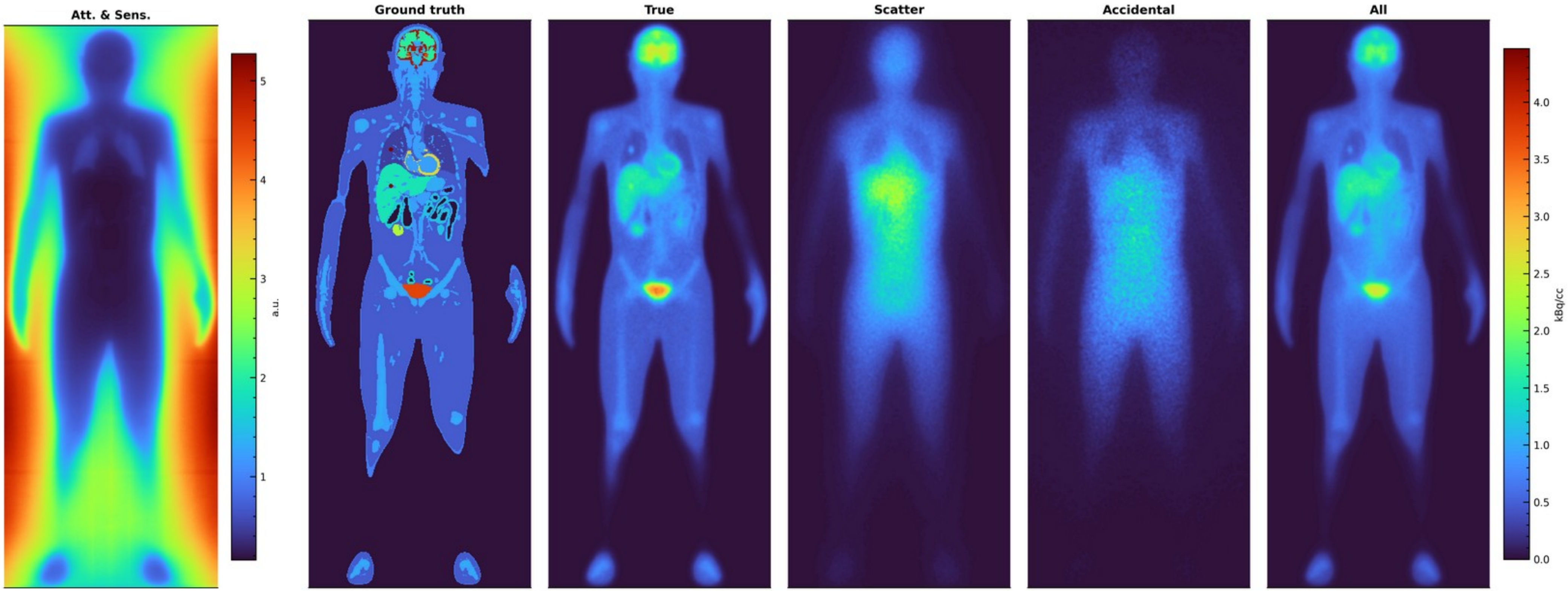
XGBoost
+ 6 Features

Accuracy 69.71%





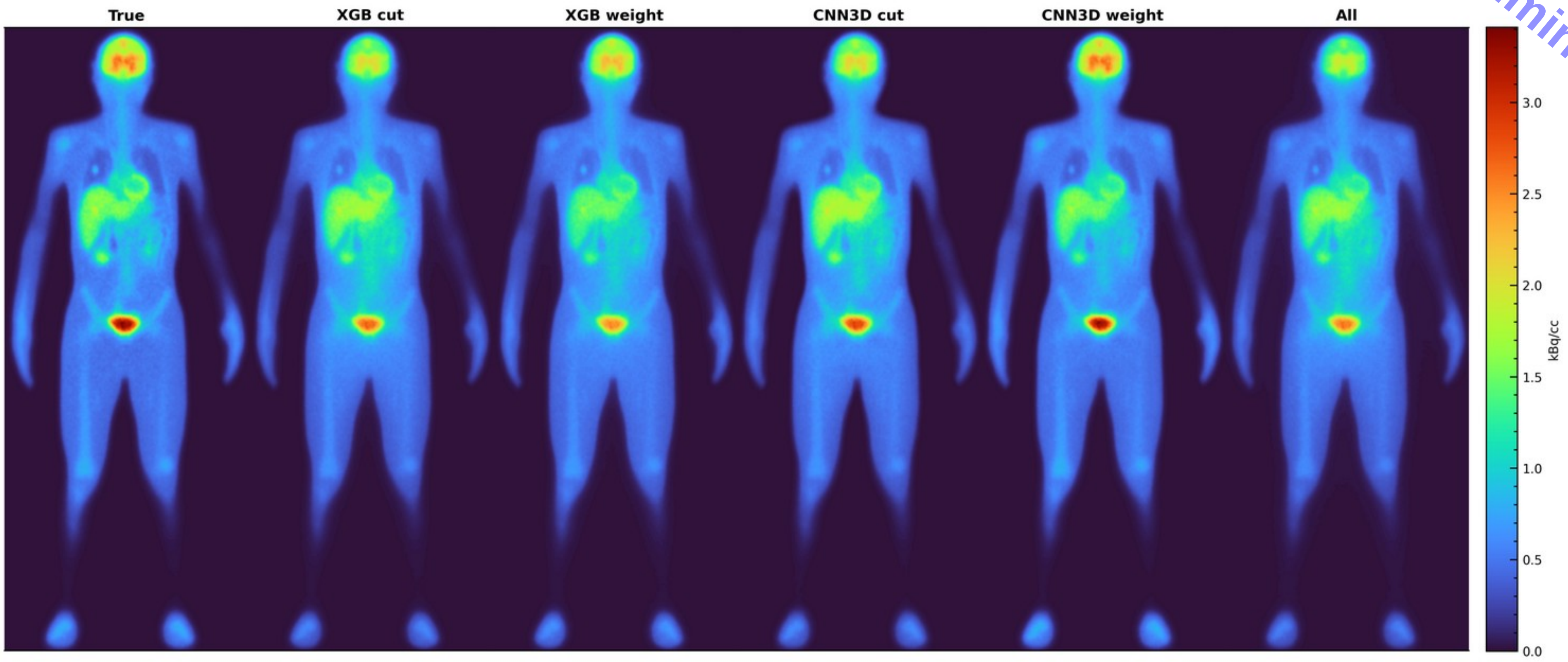
Attenuation & Sensitivity correction (CASToR)



1) CASToR package: M. Thibaut et al., Physics in Medicine & Biology, 63(18) 5505, 2018
https://castor-project.org
2) R. Shopa et al., Medical Image Analysis 73 (2021) 102199

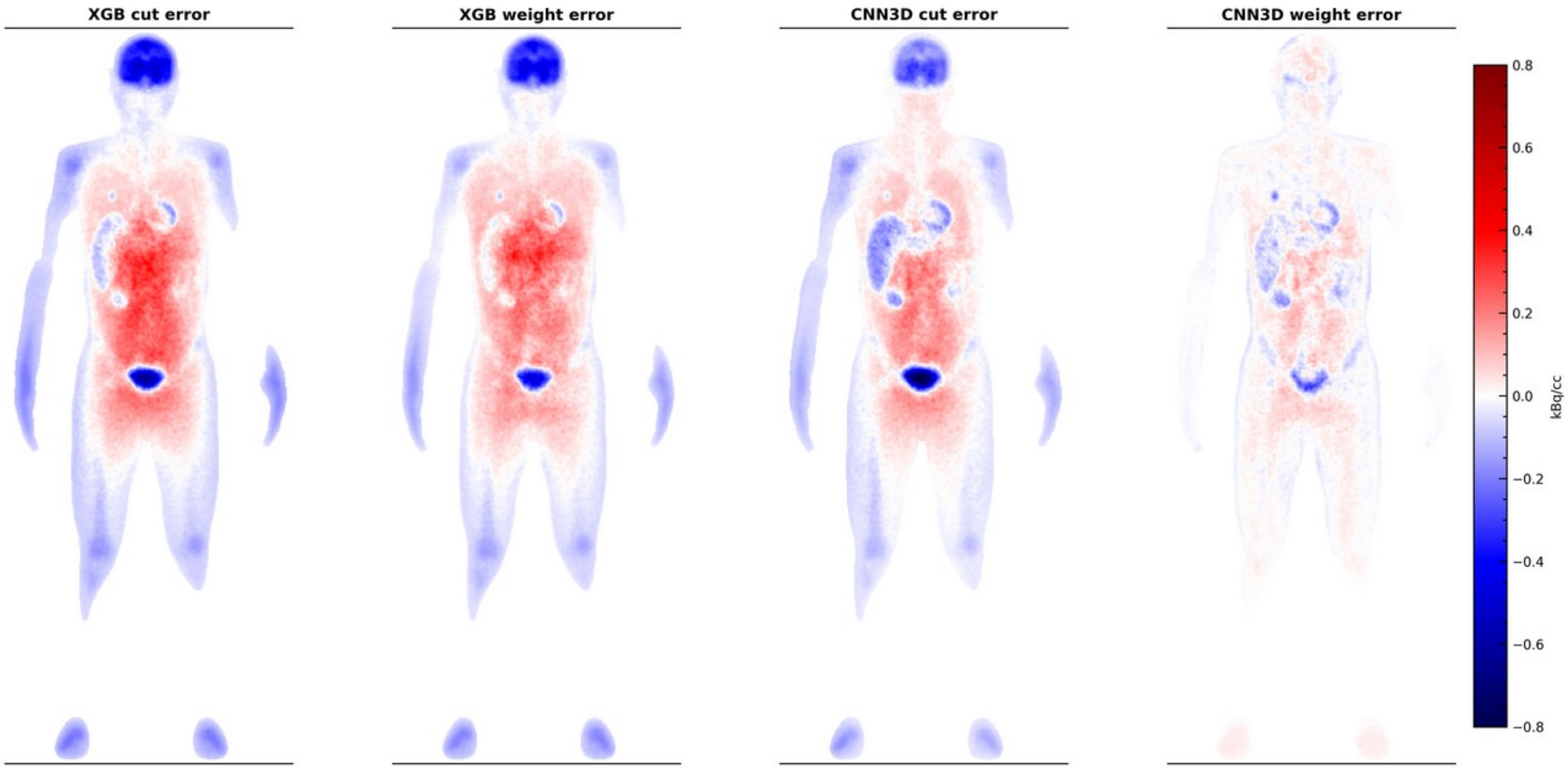
Image analysis

Preliminary



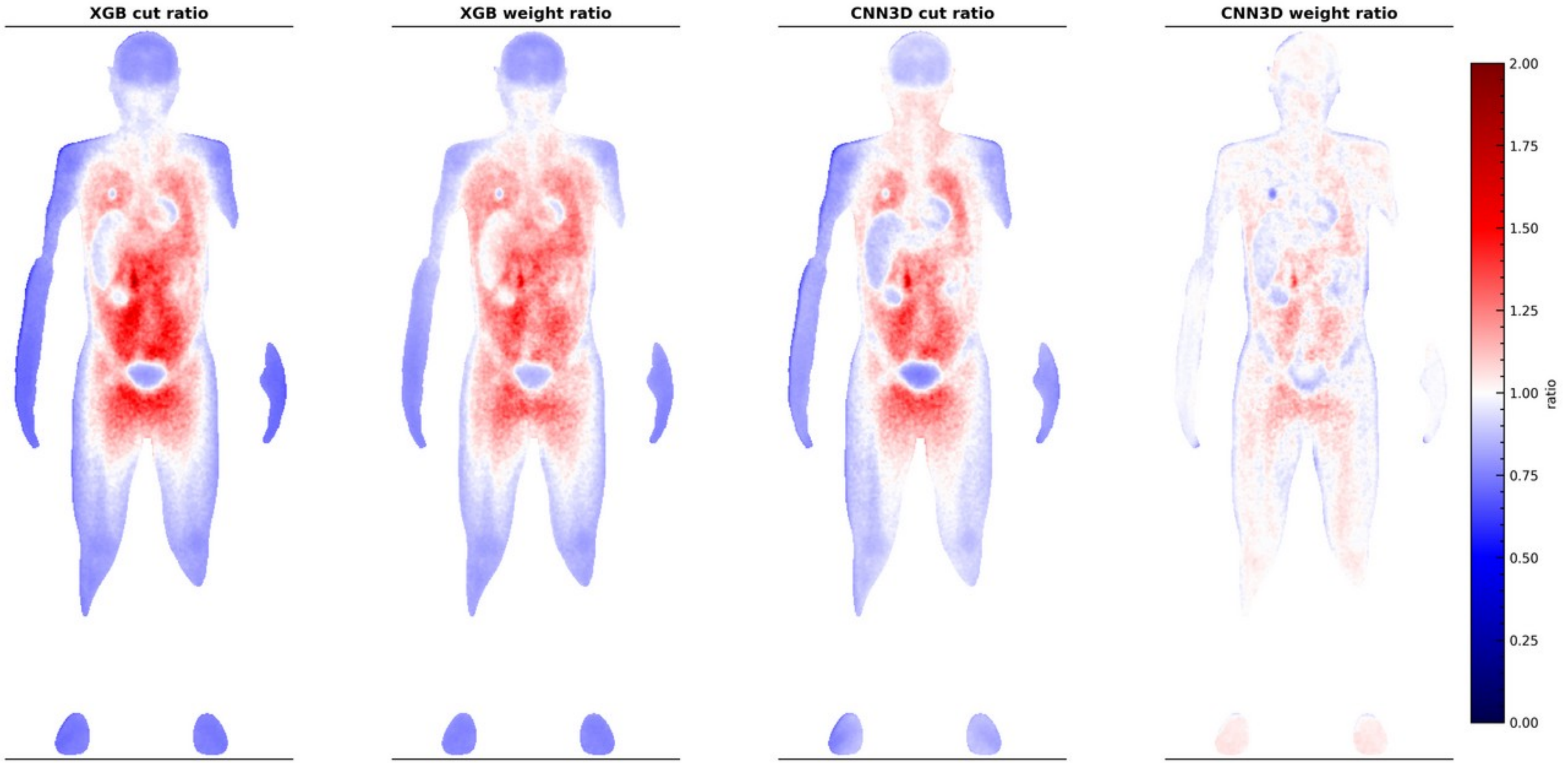
Difference to „True” coincidences

Preliminary



Ratio to „True” coincidences

Preliminary



Summary

Method	Precision @95%	Accuracy
Base line	49.9% True Events	
XGBoost (4 features)	68.7%	67.1%
ADABoost (6 features)	69.1%	69.6%
NN (6 features)	69.1%	69.3%
XGBoost (6 features)	69.5%	69.7%
3D EfficientNet B0	77.0%	75.5%

Summary

Goal: Verification of ML applicability for PET coincidence classification

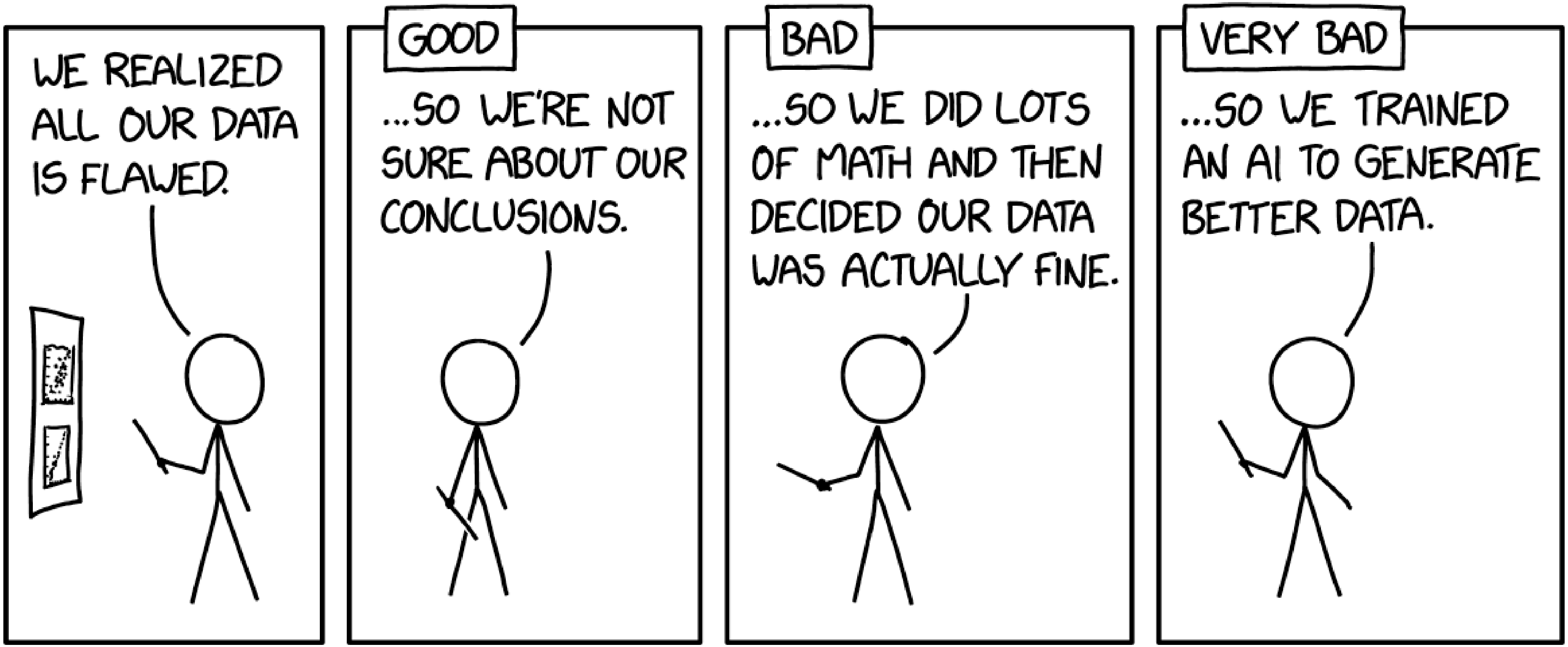
- We propose a novel encoding of List Mode data
- We propose a 3D CNN model with auxiliary feature vector

Our 3D CNN model results:

- Improved Accuracy by ~6%
- Improved Precision by ~7%
- Improved spatial uniformity of model prediction

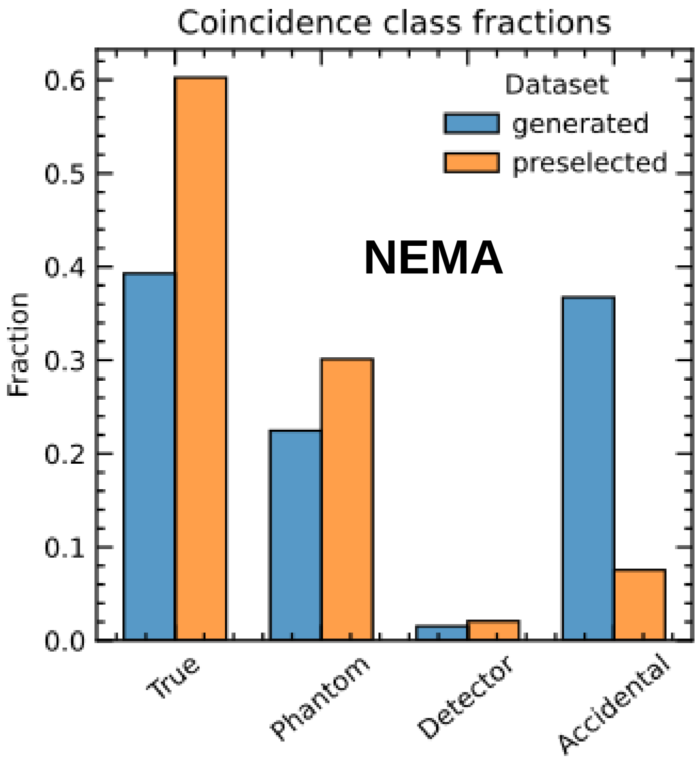
Outlook

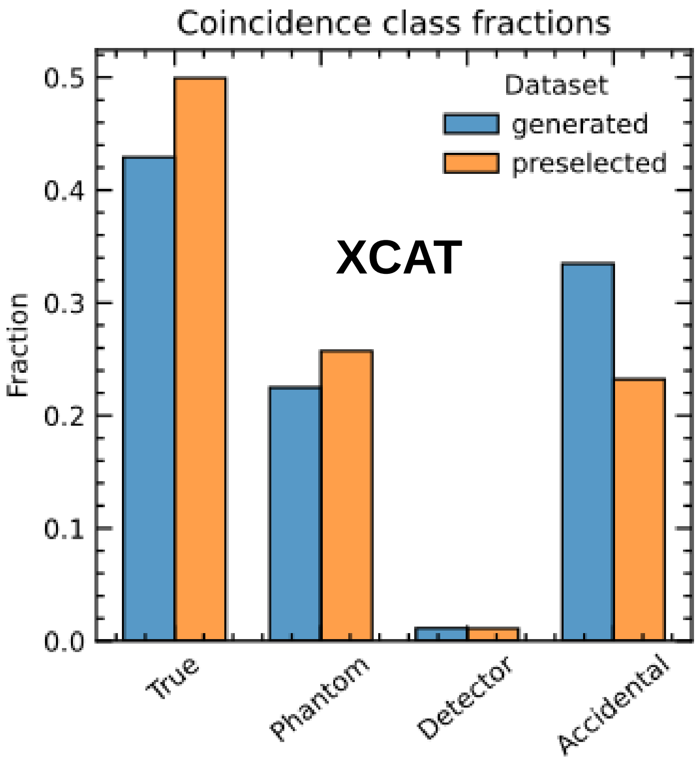
- Optimization → training / inference speedup
- Validation of less resource hungry models
- More diverse training data
- Dataset balancing
- Verification with other phantom / scanner geometries


WE REALIZED ALL OUR DATA IS FLAWED.
GOOD
...SO WE'RE NOT SURE ABOUT OUR CONCLUSIONS.
BAD
...SO WE DID LOTS OF MATH AND THEN DECIDED OUR DATA WAS ACTUALLY FINE.
VERY BAD
...SO WE TRAINED AN AI TO GENERATE BETTER DATA.

Backup

Dataset


Coincidence class fractions
Dataset
generated
preselected
NEMA
Fraction
0.0
0.1
0.2
0.3
0.4
0.5
0.6
True
Phantom
Detector
Accidental
Class


Coincidence class fractions
Dataset
generated
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0.0
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0.2
0.3
0.4
0.5
True
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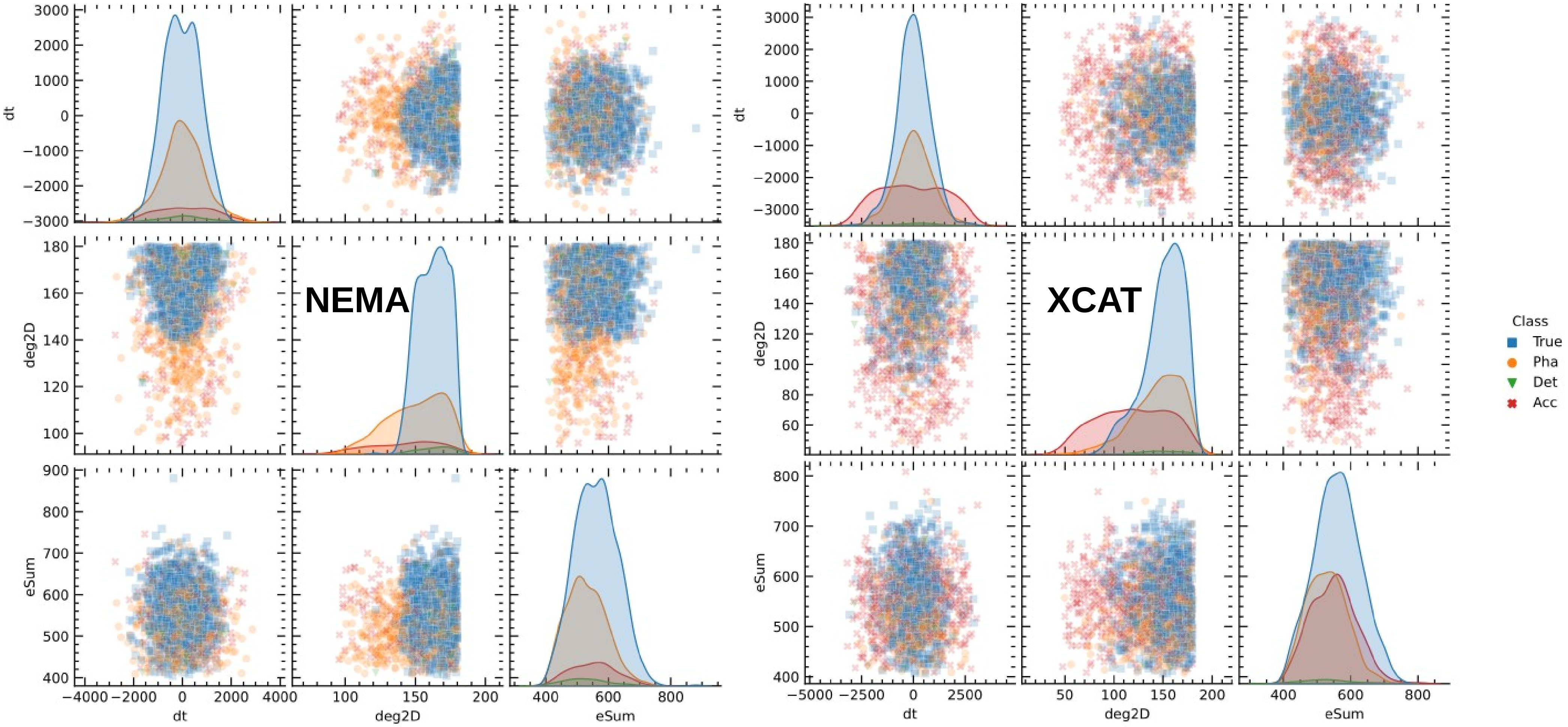
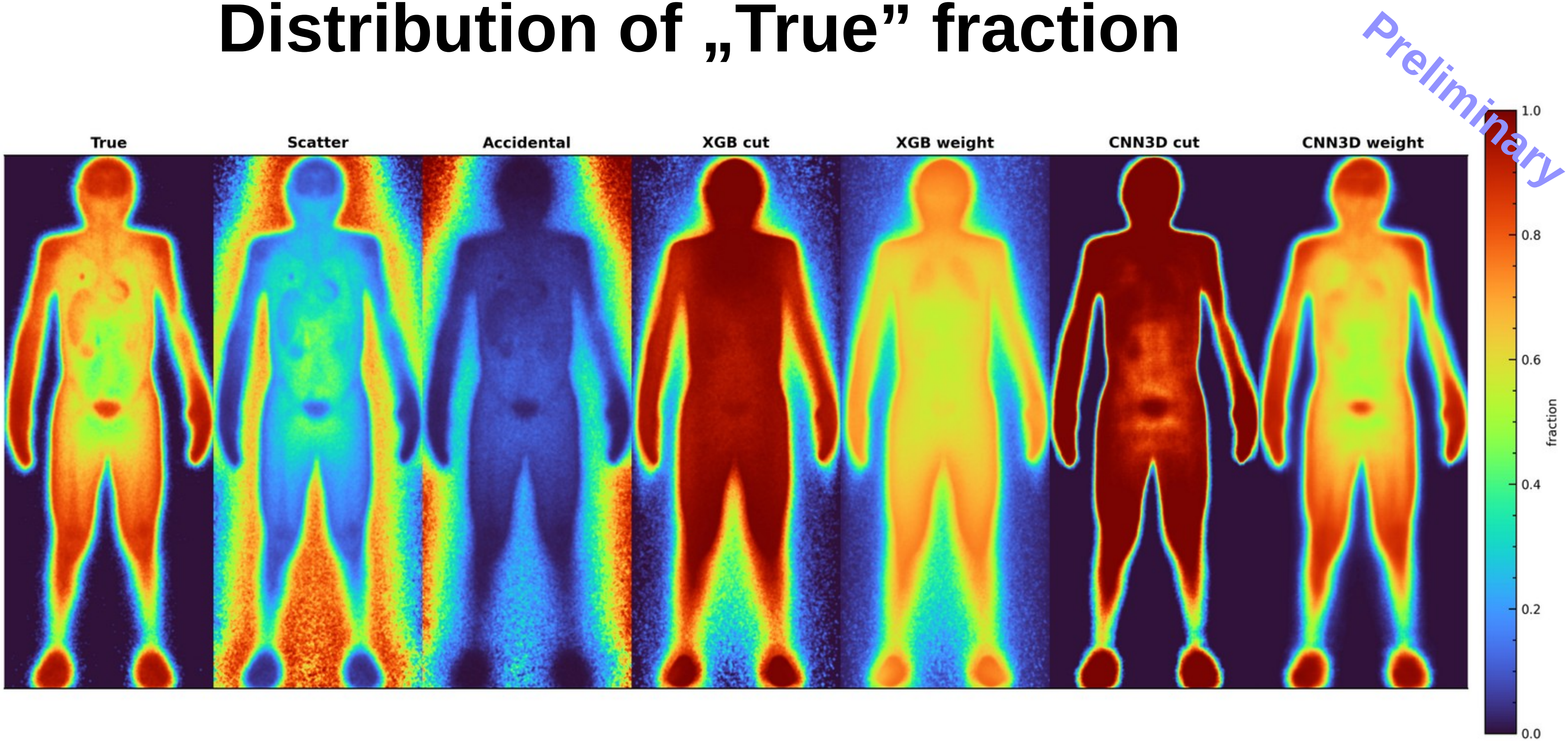
Detector
Accidental
Class

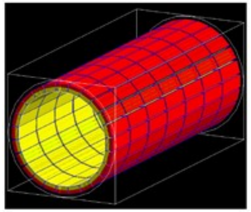
Dataset



Distribution of „True” fraction

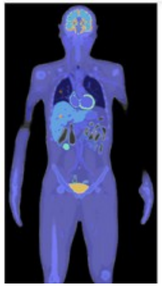


Training data generation



TB J-PET

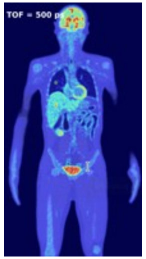
- 243 cm AFOV
- 7 rings
- 2cm gap between rings
- 30 x 6 x 330 mm strips
- 24 modules with 2 layers of 16 strips
- EJ320 scinitillator



XCAT Phantom

- Voxelised human male anatomic phantom
- ^{18}F-FDG
- Activity - 50 Mbq
- Acquisition time - 600 seconds
- Hot regions diameter – 1.2 cm
- Contrast for hot regions: 16:1 lungs, 3:1 liver

Monte Carlo Simulations



GATE MC Simulation

- GATE v9.0
- 356M coincidences
- σ_t = 77 [ps]
- σ_z = 2.12 [mm]
- $\sigma(E)/E = 0.044$ / sqrt(E) [MeV]
- Geometry cuts → reduce accidental fraction

EfficientNet