The emerging role of artificial intelligence in internal radiation dosimetry

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SINFONIA - Medical radiation risk appraisal

«Radiation risk appraisal for detrimental effects from medical exposure during management of patients with lymphoma or brain tumours»
NFRP-945196 SINFONIA (5’999’999 €)
Outline

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

D-SPECT (Spectrum Dynamics)

Discovery 870 CZT (GE)

VERITON-CT (Spectrum Dynamics)

StarGuide (GE)
Veriton-CT SPECT/CT camera
Principles of PET/CT
Commercial whole-body PET/MRI systems

- Philips GEMINI TF PET/MR
- Biograph mMR Workflow
- Siemens
- GE
- SIGNA PET/MR
- Biograph uPMR 790 HD TOF PET/MR
Clinical applications of PET/MRI
Total-body PET: Towards systemic medicine


290 MBq injected, 82 min uptake
Novel detector concepts: Multifunctional PET

Sanaat et al (2022) *Phys Med Biol, in press*
Artificial intelligence in medical physics

- A. Turing
- Learning machines
- Datmouth Conference
- Perceptron
- Stanford Cart
- IBM deep blue
- Deep learning
- Deep face
- AlphaGo


Linac β+ imaging γ-camera Tomotherapy PET/MRI Dual-source CT Explorer PET-Linac
Artificial intelligence should be part of medical physics graduate program curriculum

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Jing Cai, Ph.D., Moderator

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published 11 April 2021)

[https://doi.org/10.1002/mp.14587]
Artificial intelligence impacting radiology

FDA-approved AI medical devices/algorithms

Benjamens et al. NPJ Dig Med (2020)
Deep learning-guided low-dose CT imaging

Shiri et al. (2021) *Eur Radiol*

Salimi et al. (2022) *submitted*
Deep learning for low-dose PET reconstruction

Two separate input
Input 1: LD image
Input 2: LD sinogram

Two separate result
Result 1: FD image
Result 2: FD sinogram

3x3x3 Convolution 3D, BN + ReLU
2x2x2 Pooling
2x2x2 Up sampling
Input (low dose PET image/sinogram)
Output (standard dose PET image/sinogram)
Concatenate connection

Sanaat et al. (2020) J Nucl Med
Deep learning for low-dose PET reconstruction

Full dose (200MBq/20min)

Sanaat et al. (2020) J Nucl Med
Deep learning for low-dose PET reconstruction

Sanaat et al. (2020) J Nucl Med
Bland-Altman analysis (Regionwise)

Low Dose  Image Space  Sinogram Space

$\text{SUV}_{\text{mean}}$ of 83 Regions

Based on “Hammersmith atlas”; n30r83

Sanaat et al. (2020) J Nucl Med
Deep learning for low-dose PET reconstruction

Sanaat et al. (2021) Neuroimage
Deep learning-guided low-dose PET imaging

Sanaat et al. (2021) Eur J Nucl Med Mol Imaging
Deep learning-guided low-dose PET imaging

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

Sanaat et al. (2021) *Eur J Nucl Med Mol Imaging*
Deep learning-guided low-dose PET imaging

Sanaat et al. (2021) Eur J Nucl Med Mol Imaging
Deep learning-guided low-dose PET imaging

Sanaat et al. (2021) Eur J Nucl Med Mol Imaging
Deep learning-guided low-dose PET imaging

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

Sanaat et al. (2021) Eur J Nucl Med Mol Imaging
Deep learning-guided low-dose MPI SPECT

Standard-dose

½ dose

¼ dose

1/8th dose

Pred. ½ dose

Pred. ¼ dose

Pred. 1/8 dose

Olia et al. (2022) Eur J Nucl Med Mol Imaging
Deep learning-guided scatter correction

Yiang et al. (2022) Eur J Nucl Med Mol Imaging
CT-based attenuation correction (Reference)

Uncorrected PET  Corrected PET

CT  Pseudo CT

PET/MRI

Reduced mediastinal uptake
Non-uniform liver uptake
Enhanced skin uptake
Deep learning-guided PET attenuation correction

Deep learning compensates motion artifacts

Difference images: PET-DL – PET-CTAC

Shiri et al. (2020) *Eur J Nucl Med Mol Imaging*
Computational pregnant female phantoms

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

Xie et al. (2019) *Med Phys*
Xie et al. (2020) *Med Phys*
Automated generation of anatomical models

Proposed CNN model for automated segmentation of pregnant patients' CT images

Xie and Zaidi (2019) *Eur Radiol*
Automated generation of anatomical models

Xie and Zaidi (2019) *Eur Radiol*
Deep learning in PET image segmentation

ABSTRACT

Introduction: Automatic functional volume segmentation in PET images is a challenge that demands using a large array of methods. A major limitation for the field has been the lack of a dataset that would allow direct comparison of the results in various publications. In this study, we describe a comparison of recent methods on a large dataset following recommendations from the Association of Physicists in Medicine (AAPM) task group (TG) 211, which was carried out under the MICCAI challenge (Medical Image Computing and Computer-Assisted Intervention) challenge.

Methods and materials: Organization and funding was provided by France Life Imaging (FLI) images combining simulated, phantom, and clinical images were assembled. A web-based registration and validation tool allowed participants to access and download training data (n = 19). Challenges required participants to submit pipelines on an online platform that autonomously ran the algorithms on the testing data and evaluated the results. The methods were ranked according to the arithmetic mean of the different folds used in the tests.

Results: Sixteen teams registered but only four provided manuscripts and pipelines for methods. In addition, results using two thresholds and the Fuzzy Locally Adaptive Bayesian (FLAB) method were reported. All competing methods except one performed with median accuracy above 0.8, with the highest score being the convolutional neural network-based segmentation, which significantly outperformed 8 of the other methods, but not the improved G-Means, Gaussian Model Mixture, and fuzzy C-Means methods.

Conclusion: The most rigorous comparative study of PET segmentation algorithms to date was carried out using a dataset that is the largest used in such studies to date. The hierarchy among the methods in terms of accuracy did not depend strongly on the subset of datasets or the metrics (or combination of metrics). All the methods submitted by the challenges except one demonstrated good performance with median accuracy scores above 0.8.
Evaluate 3 state-of-the-art deep learning algorithms (ResNET, NN-Unet, Dense-Vnet) combined with 8 different loss functions (Dice, generalized Wasserstein Dice loss, Dice Plus Xent loss, generalized Dice loss, cross-entropy, sensitivity-specificity, and Tversky) for PET image segmentation using a comprehensive training set (340) and evaluated its performance on an external validation set (100) of head and neck cancer patients.

Shiri et al. (2021) Clin Nucl Med
Deep learning-guided PET segmentation

<table>
<thead>
<tr>
<th></th>
<th>Dense-VNet</th>
<th>Res-Net</th>
<th>NN-UNet</th>
</tr>
</thead>
<tbody>
<tr>
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<td><img src="image3.png" alt="Image" /></td>
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<td><img src="image20.png" alt="Image" /></td>
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Shiri et al. (2021) *Clin Nucl Med*
## Deep learning-guided PET segmentation

<table>
<thead>
<tr>
<th>Method</th>
<th>Loss Function</th>
<th>Dice</th>
<th>Jaccard</th>
<th>False Negative</th>
<th>False Positive</th>
<th>Volume Similarity</th>
<th>Mean Surface Distance</th>
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<tbody>
<tr>
<td>Dense-VNET</td>
<td>Cross Entropy</td>
<td>0.82 - 0.85</td>
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<td>0.16 - 0.20</td>
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Shiri et al. (2021) Clin Nucl Med
Voxel-based internal dosimetry (MIRD)

\[
\bar{D}_{\text{voxel}_k} = \sum_{n=1}^{N} \bar{A}_{\text{voxel}_n} \cdot S(\text{voxel}_k \leftarrow \text{voxel}_n)
\]

Activity map
Dose point kernel
3D dose map

**Al-guided internal radiation dosimetry**

Monte Carlo → Reference (gold Standard)

*But heavy computational burden!!!*

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

- **MC simulator**
  - Time > 1000 h/CPU
  - Time ~ 30 min/GPU
Deep learning-based internal dosimetry

- PET/CT data set of $^{68}$Ga-NOTA
- 3D patch-based network training (UNet)
- 2 input channels: PET/CT
- Output: Whole body dose rate map

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

Lee et al. (2018) *Sci Rep*

Gotz et al. (2020) *Phys Med Biol*
Deep learning-guided internal dosimetry

Deep learning-guided internal dosimetry

Deep learning-guided internal dosimetry

$^{177}$Lu-Dotatate

Mean absorbed dose in the segmented ROIs

<table>
<thead>
<tr>
<th>ROIs</th>
<th>MC</th>
<th>DL</th>
<th>MSV</th>
<th>SSV</th>
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<tr>
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<td>1.49</td>
<td>1.49</td>
<td>1.50</td>
</tr>
</tbody>
</table>

_line profile passing through a calcified liver mass_

Akhavan et al. (2021) IEEE MIC
Deep learning-guided internal dosimetry

Zongyu et al. (2022) *Med Phys*
Federated learning for PET AC/segmentation

300 patients from 6 different centers

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

Shiri et al. (2021) IEEE Med Imaging Conference
Shiri et al. (2022) Clin Nucl Med
Federated learning for PET AC/segmentation

Shiri et al. (2021)
IEEE Med Imaging Conference

Shiri et al. (2022)
Clin Nucl Med
Artificial intelligence faces reproducibility crisis

Matthew Hutson
* See all authors and affiliations

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

Code break

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

Radiology

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

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EDITORIAL

MEDICAL PHYSICS

AI in Medical Physics Guidelines for publication

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

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

- Imaging biomarkers are a major component of Big Data driven medical knowledge and decision making.

- Nuclear medicine physicians and Radiologists who use AI and deep learning will replace those who don’t …

- AI/deep learning are producing challenges in terms of validation in clinical setting but also plenty of research opportunities.

- Is there a future for AI/deep learning in molecular imaging?  YES

- If artificial intelligence is possible, so is artificial stupidity …

- Wide and specific participation by industry and research communities, planning for long term sustainability.
“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
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"Scientists are very happy people because their job is also their hobby"

Prof. Abdus Salem
1979 Nobel Laureate - Physics