Demystifying T1-MRI to FDG^{18}-PET Image Translation via Representational Similarity

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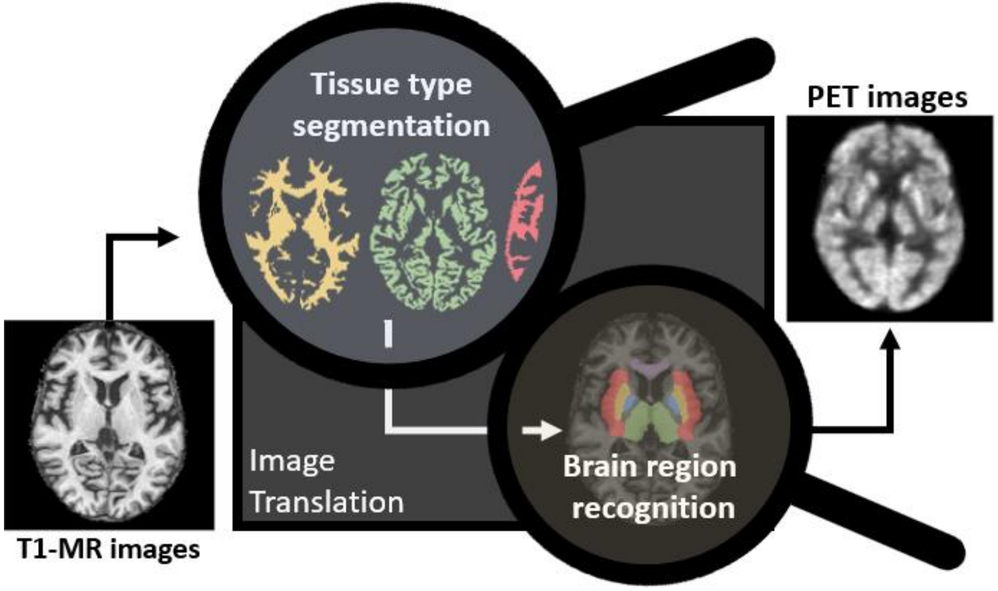
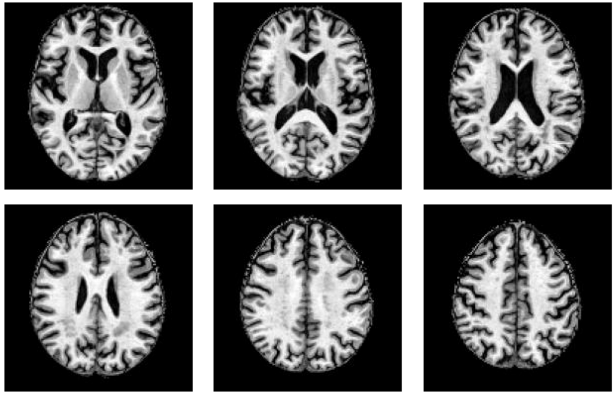
Take home message

We use representational similarity to verify our proposed hypotheses that the translation from T1-MR to PET images comprises the **<u>recognition of brain tissue types and brain regions</u>**.

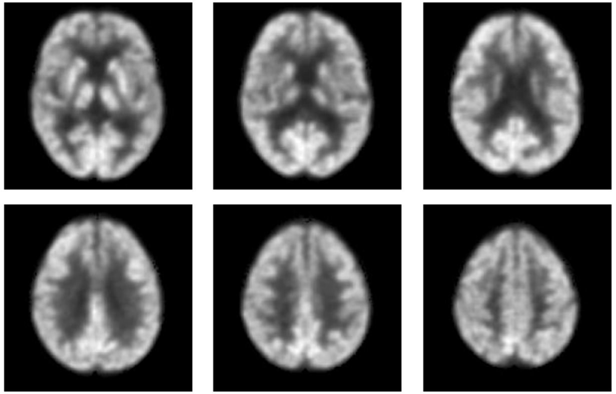


Introduction There is a growing research trend in using AI for cross-modality medical image translation.

T1-weighted Magnetic resonance imaging (T1-MRI)



FDG18-positron emission tomography (PET)



	T1-MRI	PET
Principle	MRI uses strong magnetic fields to identify the **anatomical structure** of the brain.	PET measures the glucose update ability of tissue to quantify the **metabolic process**.
Drawback	time consuming, high cost	injection of radioactive tracer, high cost

DL-based image synthesis/translation

Nie, D. (2017), Pan, Y. (2018),
Sikka, A. (2018), Sun, H. (2019), Lan, H. (2020)

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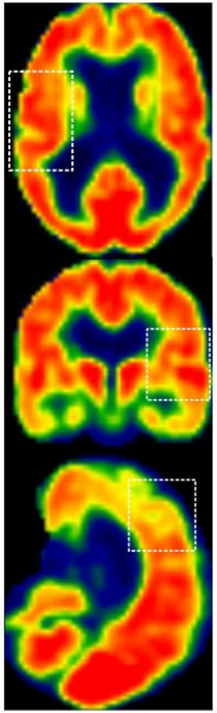

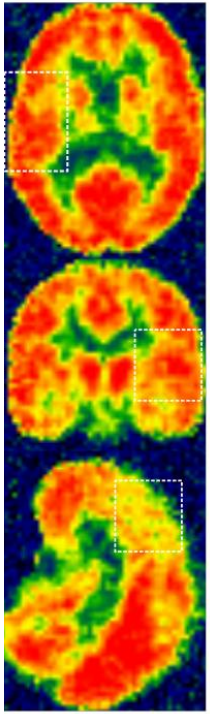

Latest ← Conventional

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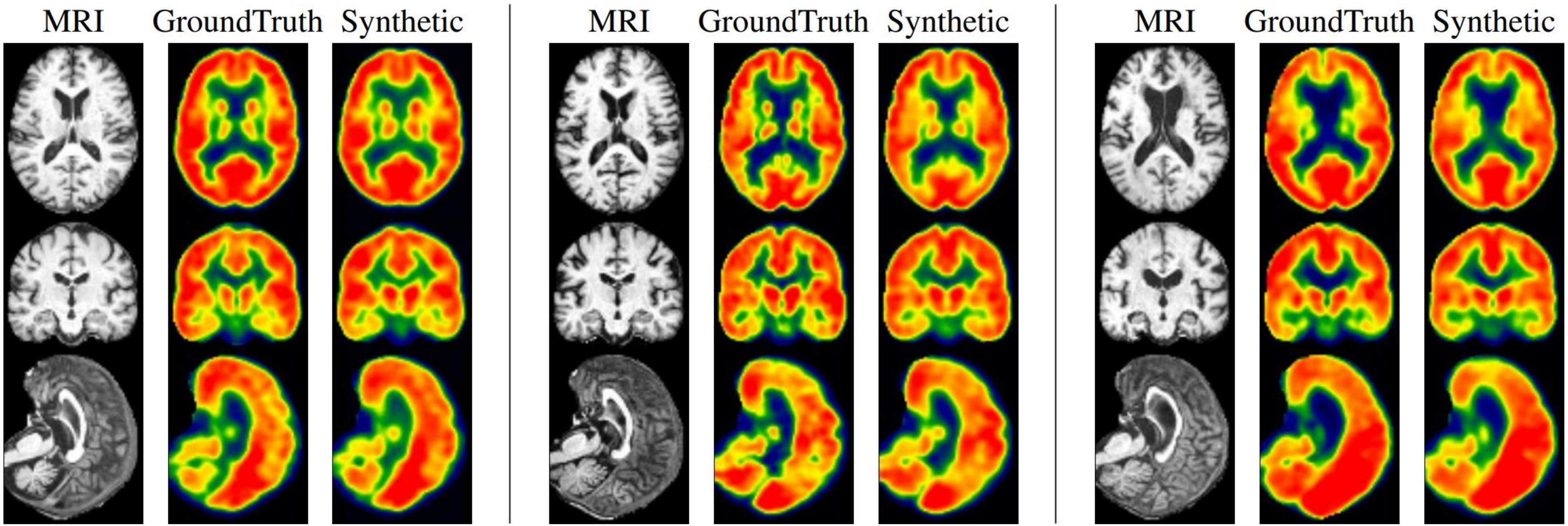

Synthetic images are meaningful for subjects in both extremes of disease spectrum.

Left: CN. Middle: MCI. Right: AD. The generated PET images show consistency of hypometabolism (less red, more yellow) with the ground truth image.

Introduction However, there are several major concerns when it comes to clinical applications.

- Robustness to distributional biases (population, organs, diseases).

- Robustness to systemic biases (scanning devices and protocols, preprocessing techniques).

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- Robustness to out-of-distribution cases, noise and adversarial perturbations.

Introduction Even more, deep learning models remain black-box for most AI scientists.

Analysis | Open Access | Publishec

Common pitfalls a machine learning COVID-19 using ch

Michael Roberts, Derek Driggs, Angelica I. Aviles-Rivero, Christian Zhongzhao Teng, Effrossyni Gkrani Schönlieb

Nature Machine Intelligence **3**, 199–217 (2021) | Ci

65k Accesses | **129** Citations | **1122** Altmetric |

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Kerstin N. Vokinger, Stefan Feuerriegel & Aaron S. Kesselheim

Communications Medicine **1**, Article number: 25 (2021) | Cite this article

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Article | Open Access | Published: 24 January 2022

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Scientific Data **9**, Article number: 24 (2022) | Cite this article

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Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations

Laleh Seyyed-Kalantari, Haoran Zhang, Matthew B. A. McDermott, Irene Y. Chen & Marzyeh Ghassemi

Nature Medicine **27**, 2176–2182 (2021) | Cite this article

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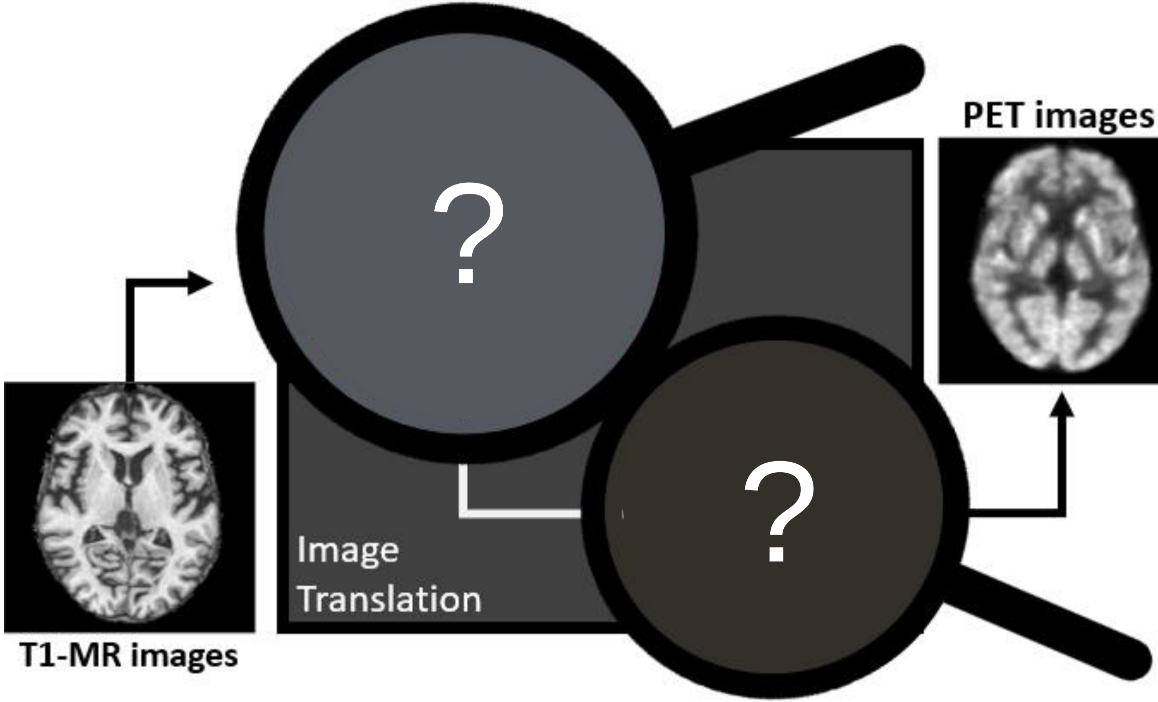
Motivation How do deep learning models translate T1-MRI images to FDG-PET images?



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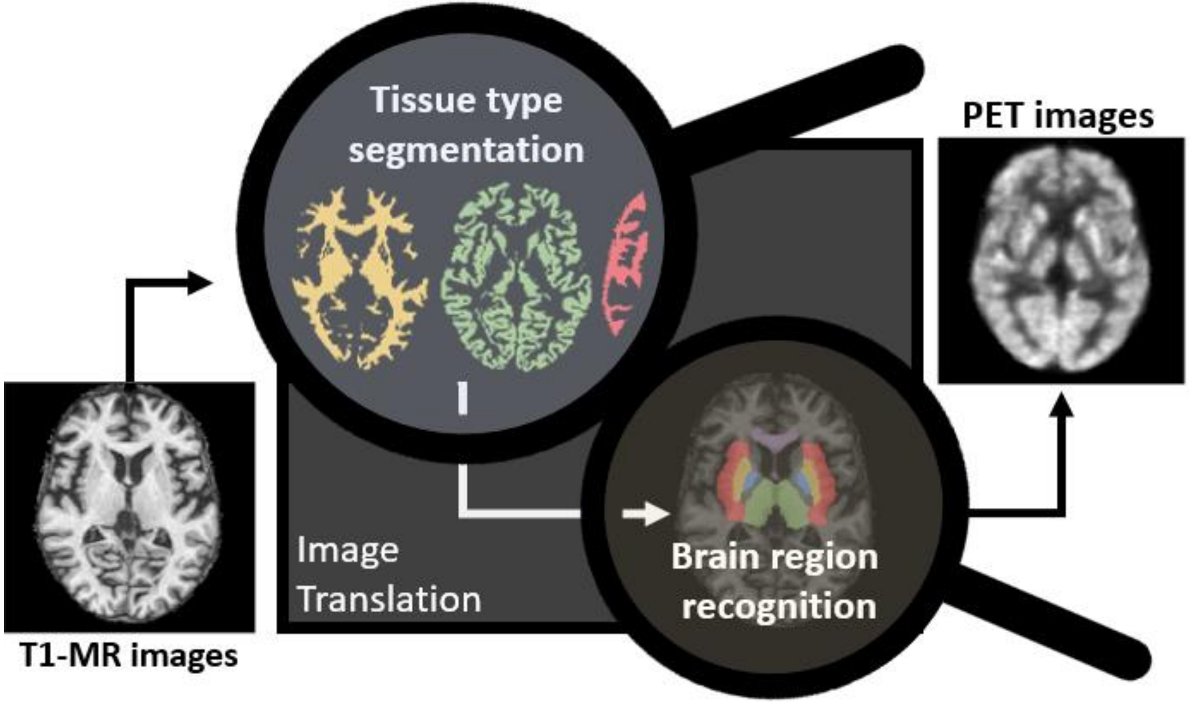
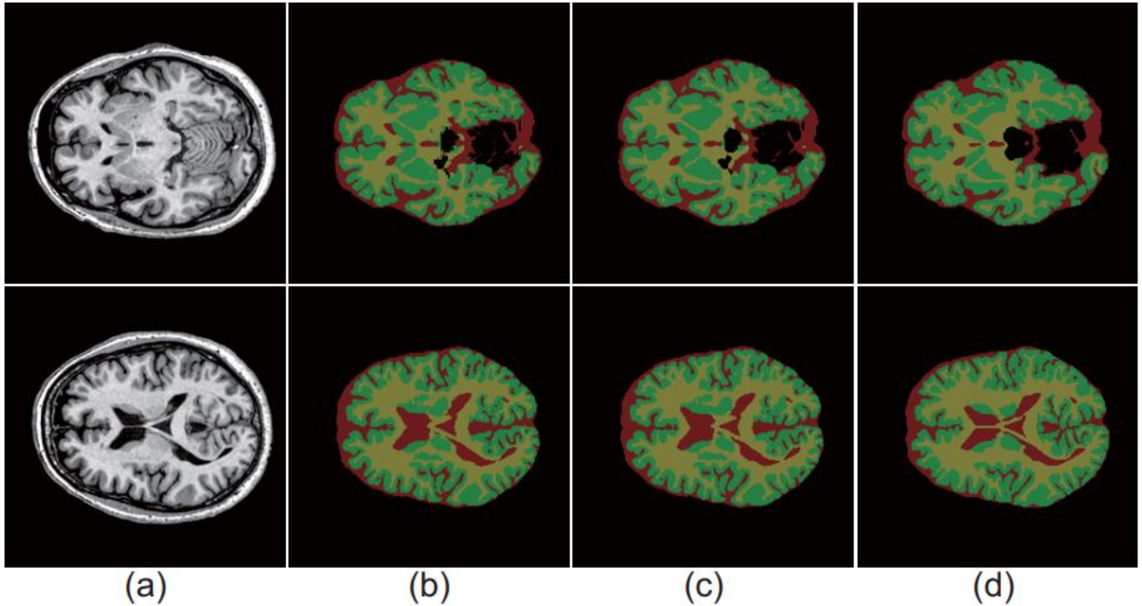


Literature Deep learning has been deployed for brain tissue segmentation and brain region identification.



The example results of validation data (yellow, green, and red colors represent the WM, GM, and CSF, respectively): (a) original MR images, (b) results of VoxResNet, (c) results of Autocontext VoxResNet, (d) ground truth label.

Chen, H., Dou, Q., Yu, L., Qin, J., & Heng, P. A. (2018). VoxResNet: Deep voxelwise residual networks for brain segmentation from 3D MR images. *NeuroImage*, *170*, 446-455.

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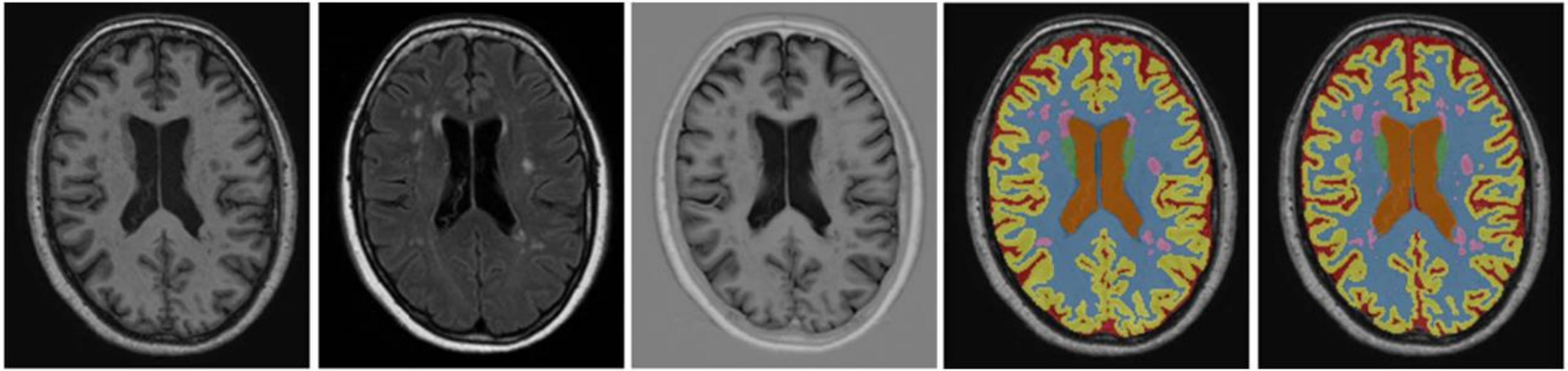

Example segmentation for one of the test images from the MRBrainS13 challenge, trained using the 5 training images available within MRBrainS13.
From left to right: T1-weighted image, T2-weighted FLAIR image, T1-weighted IR image, reference segmentation and automatic segmentation.

Moeskops, P., de Bresser, J., Kuijf, H. J., Mendrik, A. M., Biessels, G. J., Pluim, J. P., & Išgum, I. (2018). Evaluation of a deep learning approach for the segmentation of brain tissues and white matter hyperintensities of presumed vascular origin in MRI. *NeuroImage: Clinical*, *17*, 251-262.

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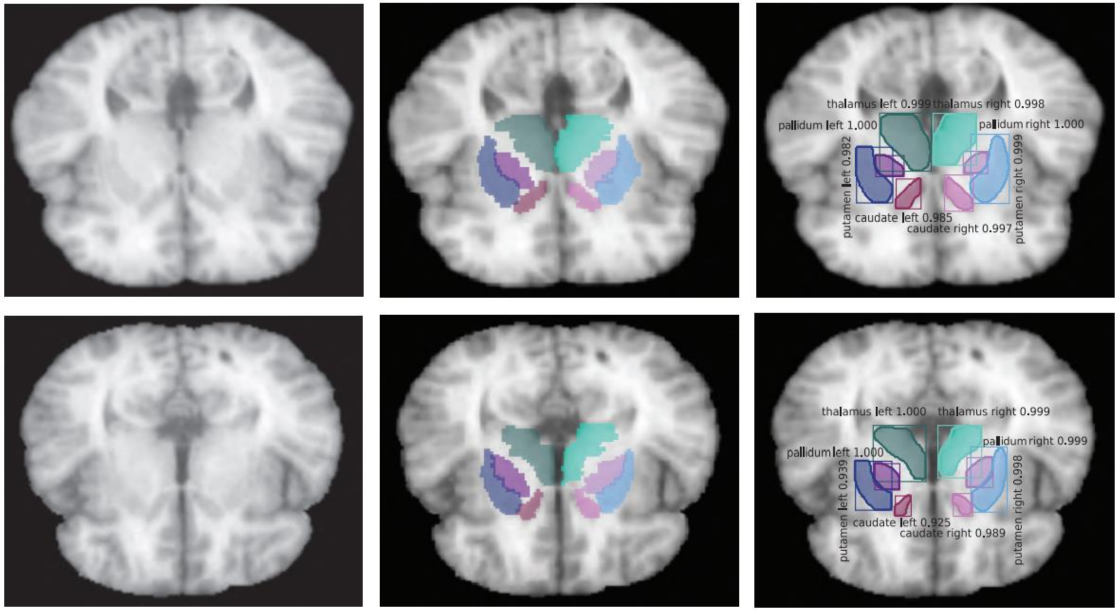

Left: Randomly selected human brain MR scans are shown. Middle: Ground-truth masks of the corresponding MR scans in (a). Right: Outputs of our proposed deep learning models.

Iqbal, A., Khan, R., & Karayannis, T. (2019). Developing a brain atlas through deep learning. *Nature Machine Intelligence*, *1*(6), 277-287.

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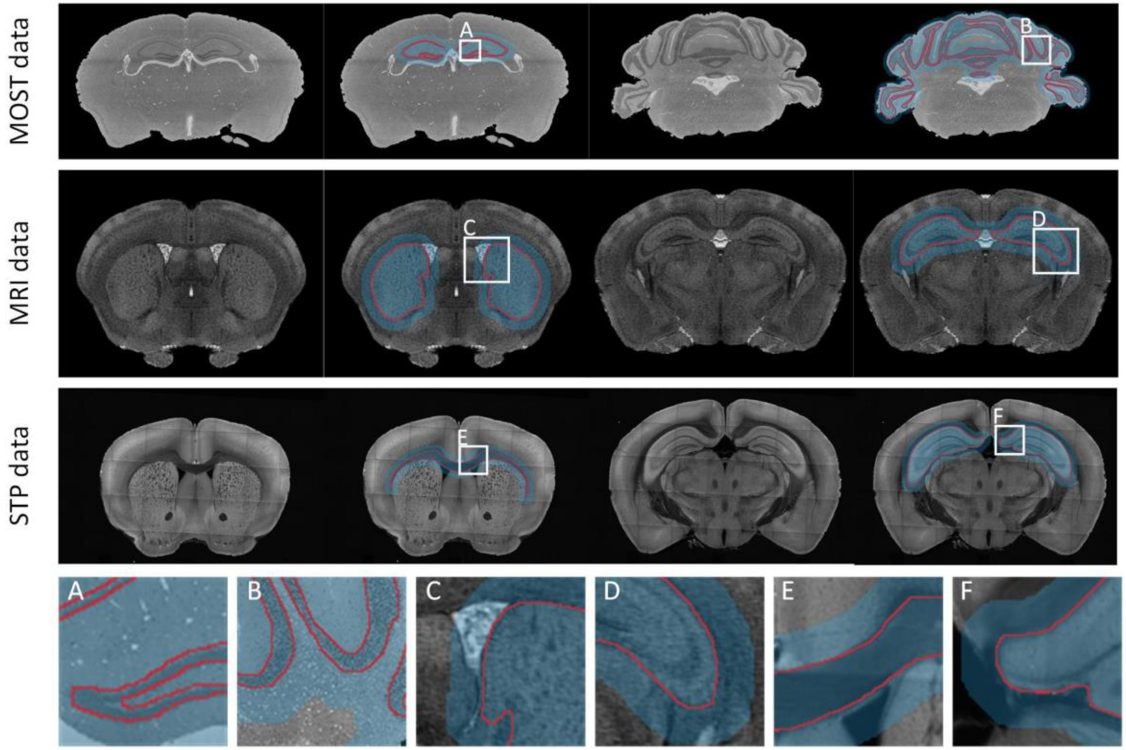
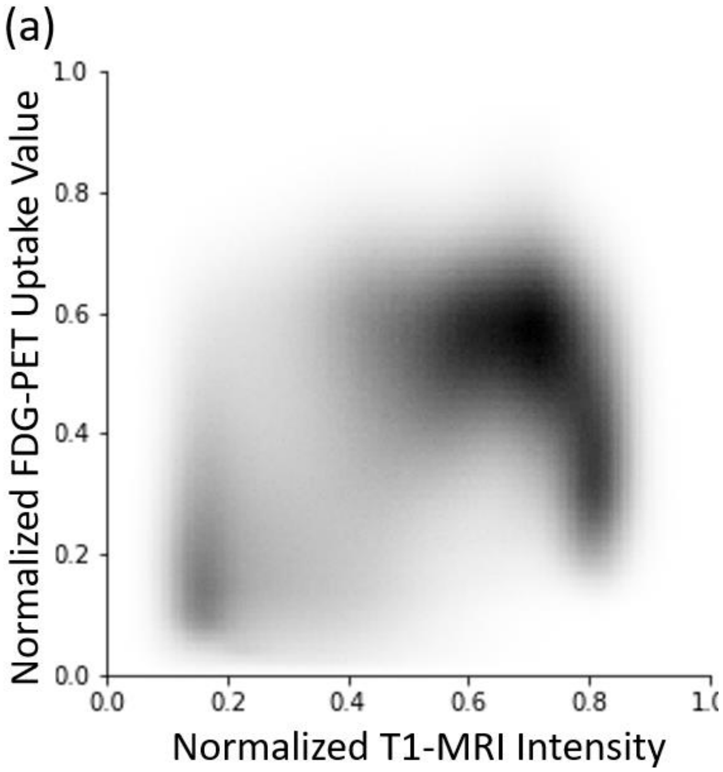
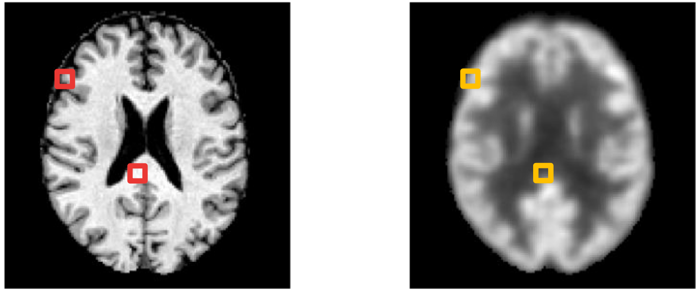


Tan, C., Guan, Y., Feng, Z., Ni, H., Zhang, Z., Wang, Z., ... & Li, A. (2020). DeepBrainSeg: Automated brain region segmentation for micro-optical images with a convolutional neural network. *Frontiers in neuroscience*, *14*, 179.

Hypothesis Deep learning models learn to segment brain tissue types.



1. Align brain images from both T1-MRI and FDG-PET.
2. Use the value from T1-MRI as x and that from FDG-PET as y to obtain (x, y) pairs.



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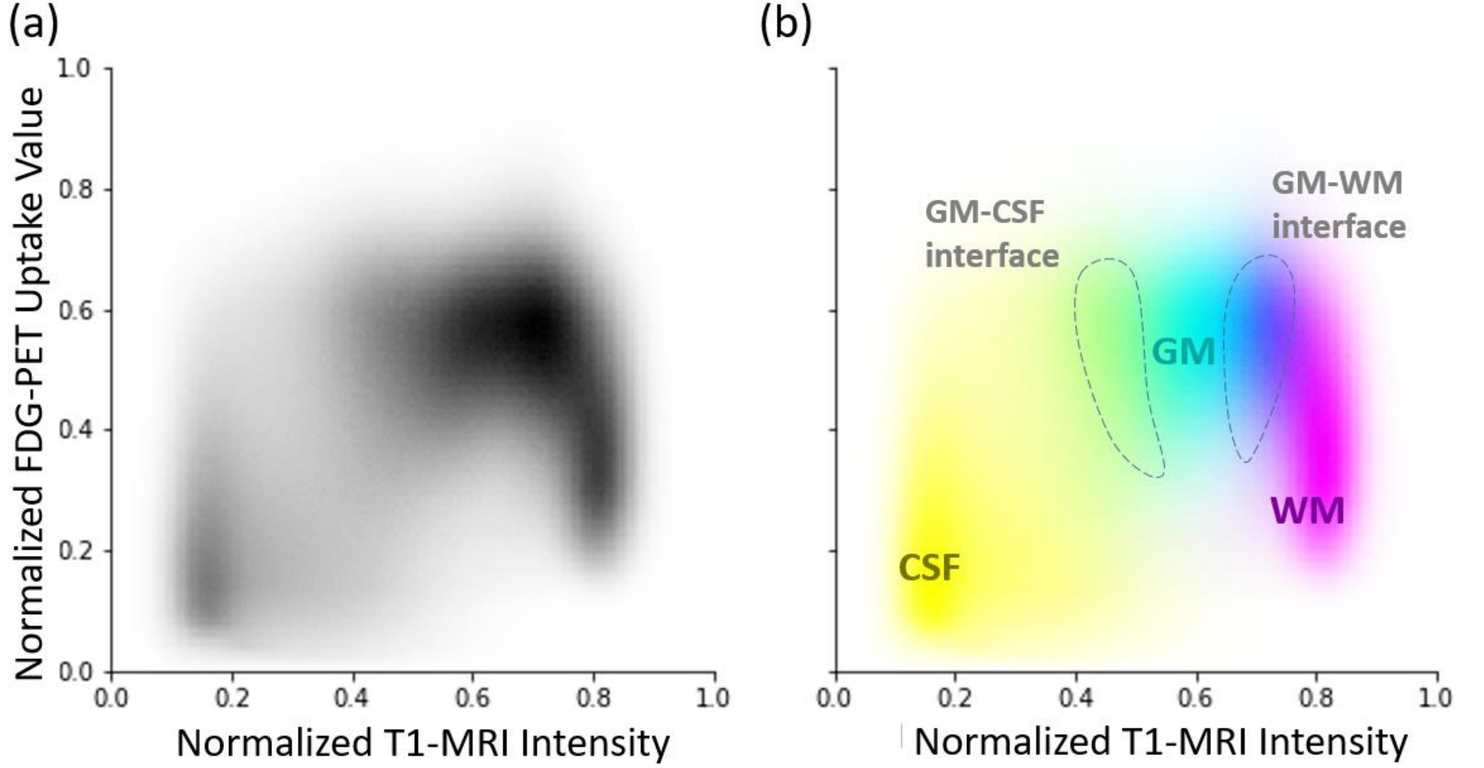

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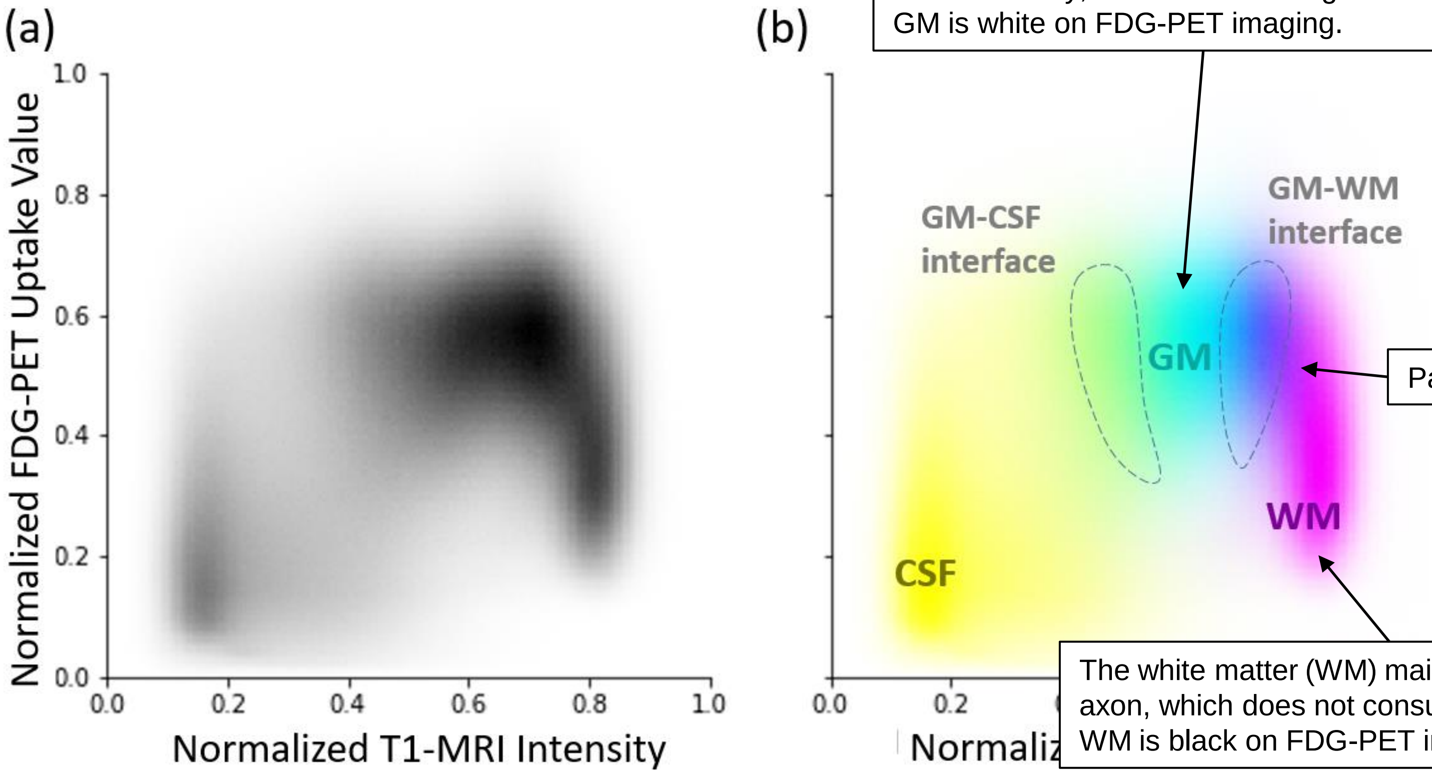

The gray matter (GM) mainly comprises the neuronal body, which consumes glucose. Thus, GM is white on FDG-PET imaging.

Partial volume effect

The white matter (WM) mainly comprises the axon, which does not consume glucose. Thus, WM is black on FDG-PET imaging.

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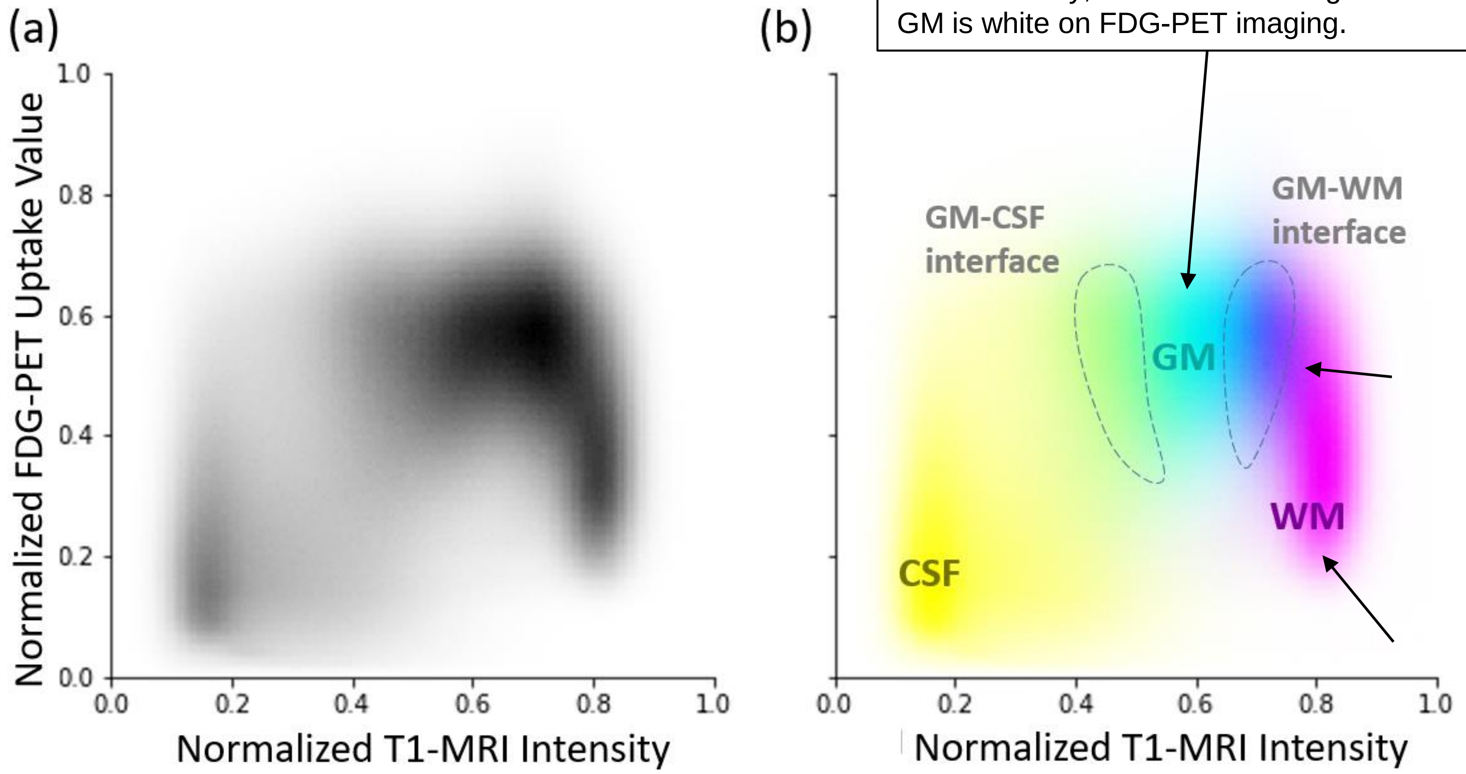

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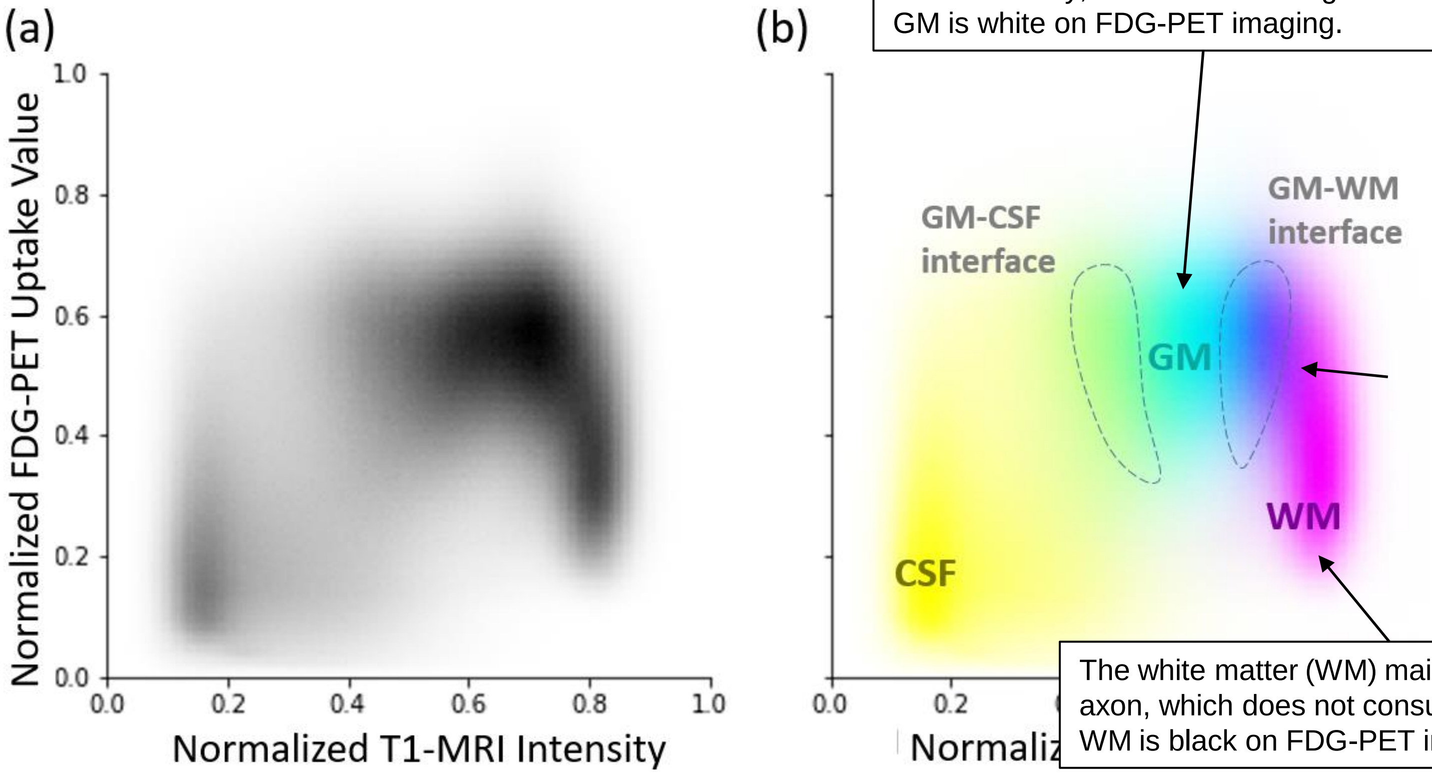

The white matter (WM) mainly comprises the axon, which does not consume glucose. Thus, WM is black on FDG-PET imaging.

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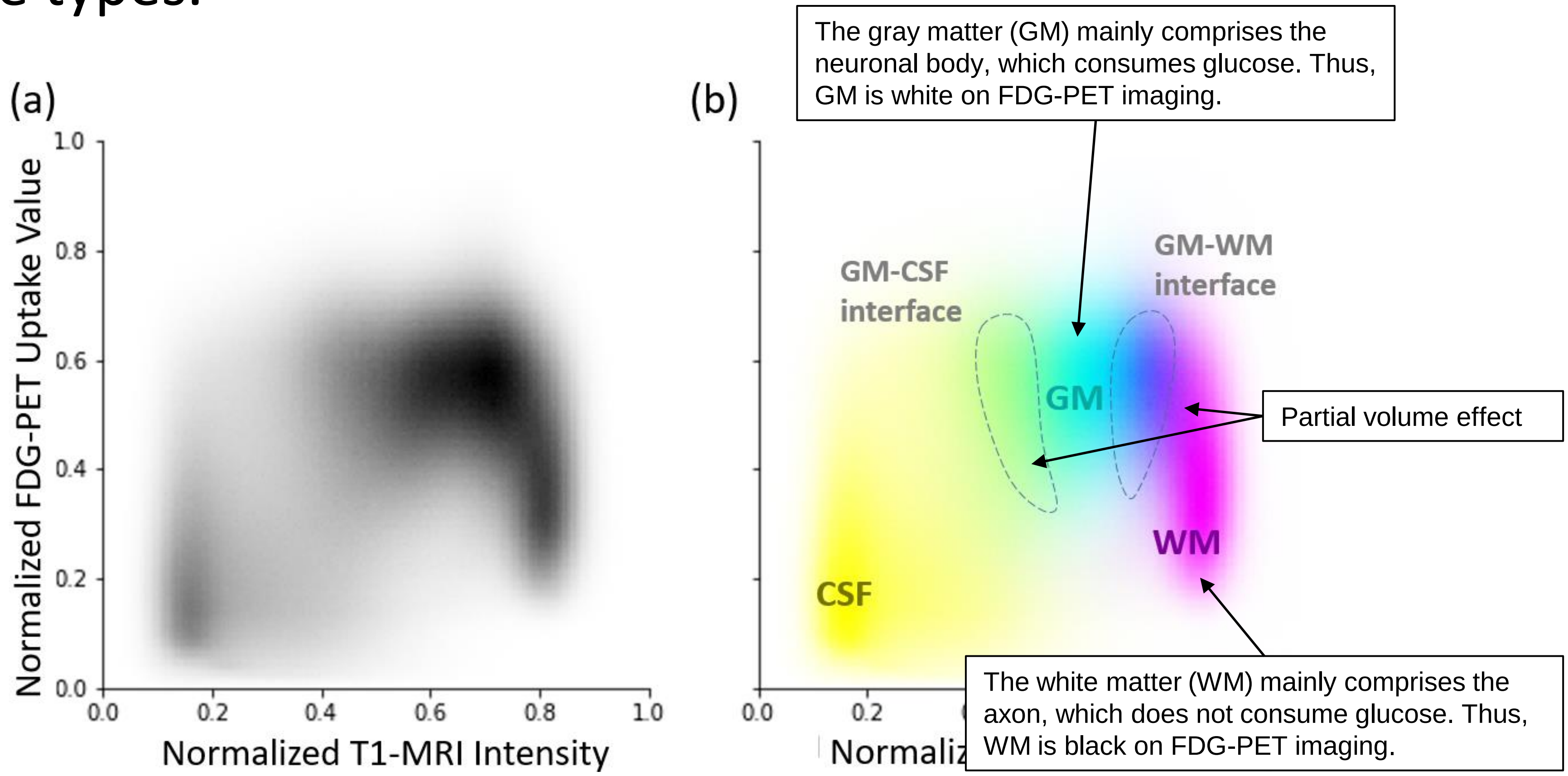

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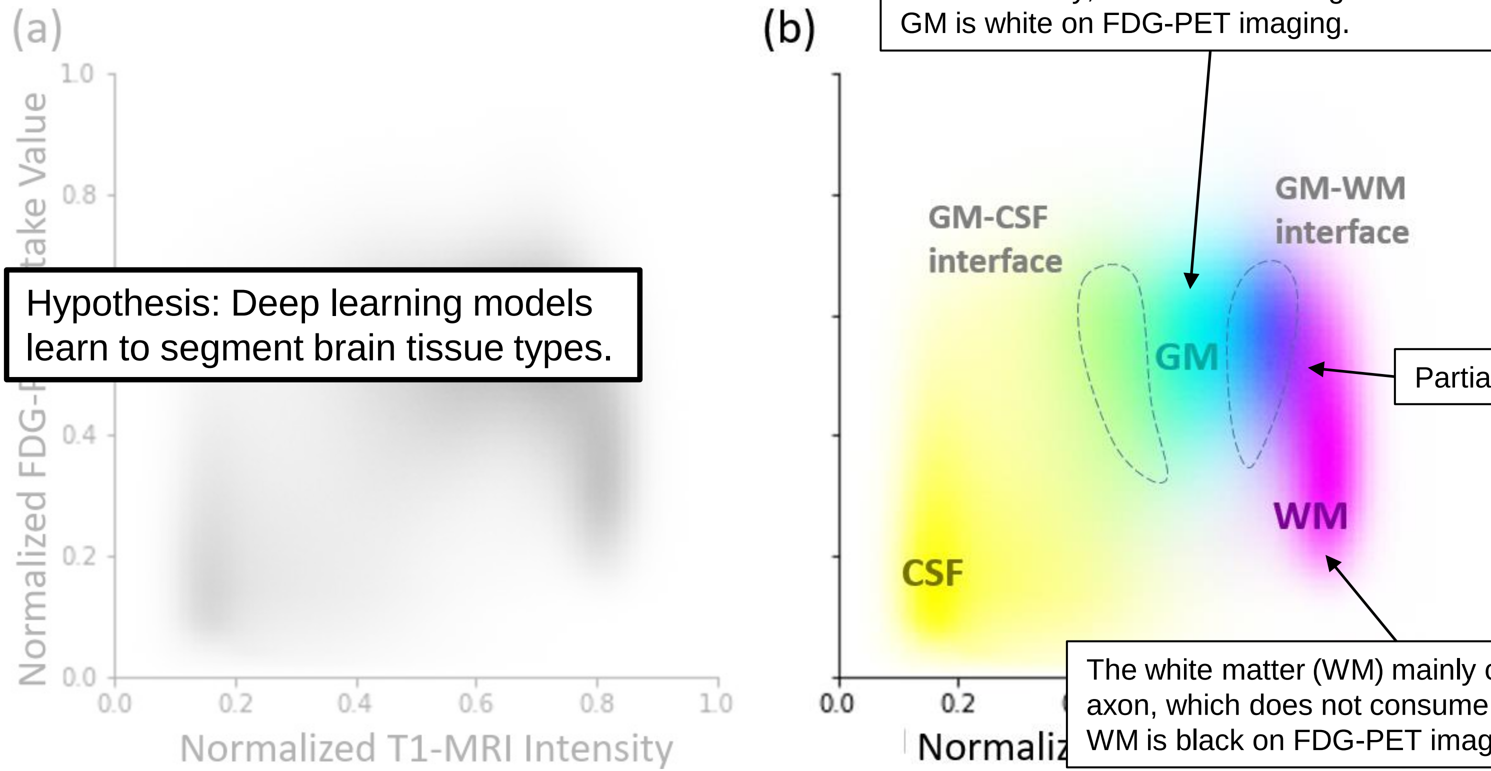

Hypothesis: Deep learning models learn to segment brain tissue types.

Partial volume effect

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Method

Dataset

- Obtain **<u>1300+ MRI-PET paired data</u>** from Alzheimer's Disease Neuroimaging Initiative (ADNI), composed of brain images from cognitive normal people and patients with mild cognitive impairment or Alzheimer's disease. (International, multi-center, multi-scanning protocols, standard preprocessing procedures)
- Preprocess data according to the standard method with SPM software.

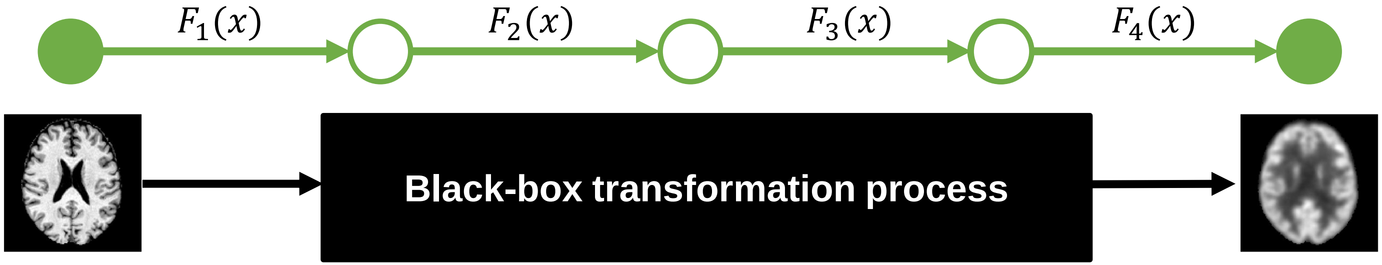
Deep learning model

- Adopt a widely-used 2D Unet model for MRI-to-PET image translation, which comprises several nonlinear transformation functions $\{F_1, \ldots, F_n\}$.

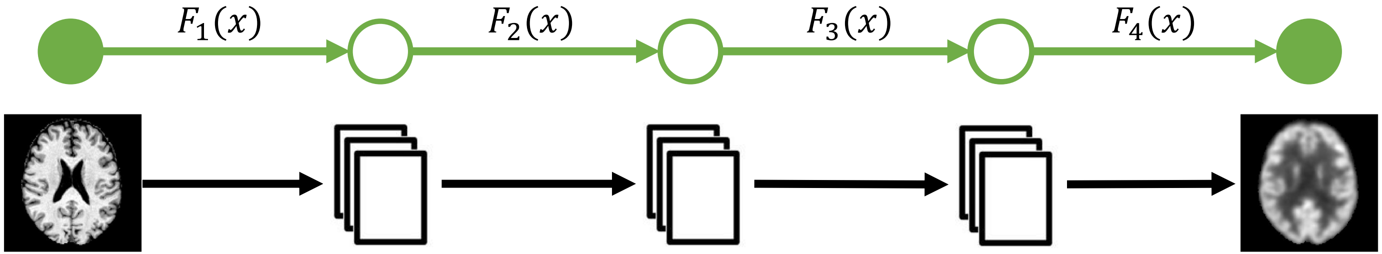
Goal

- Measure and quantify the information of "brain tissue type" along the data transformation process.

Method



Method



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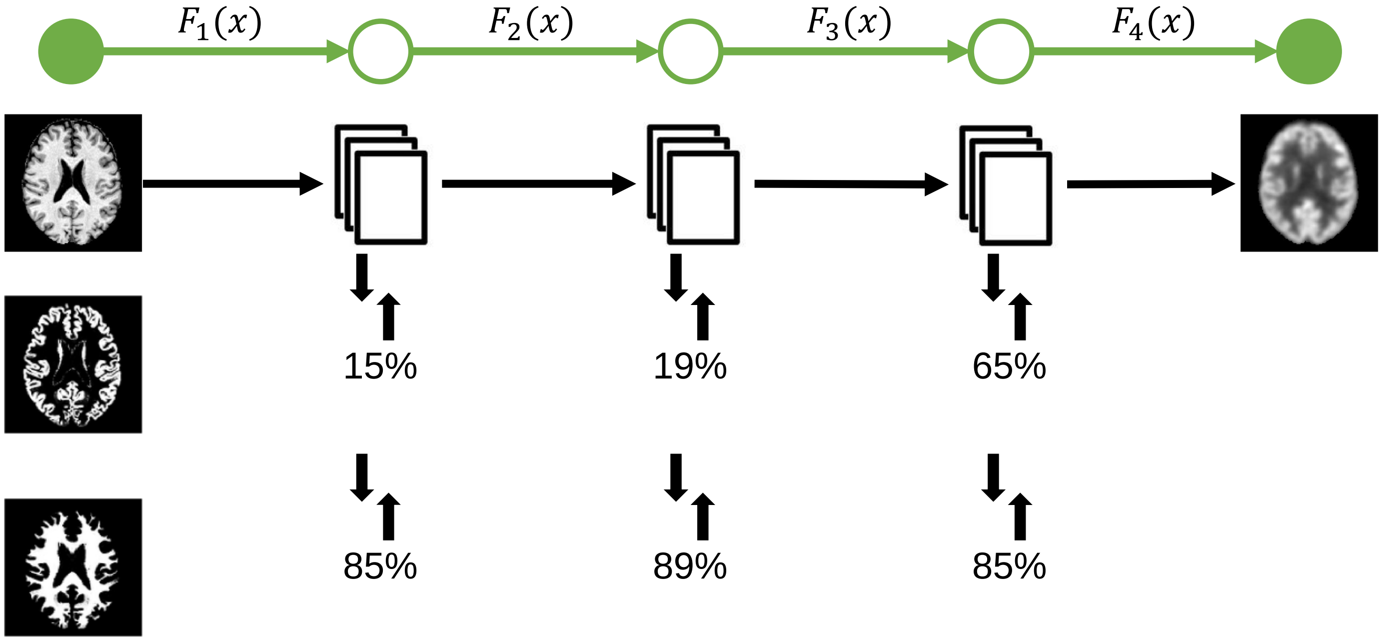

Similarity between GM and transformed data

Similarity between WM and transformed data

Method

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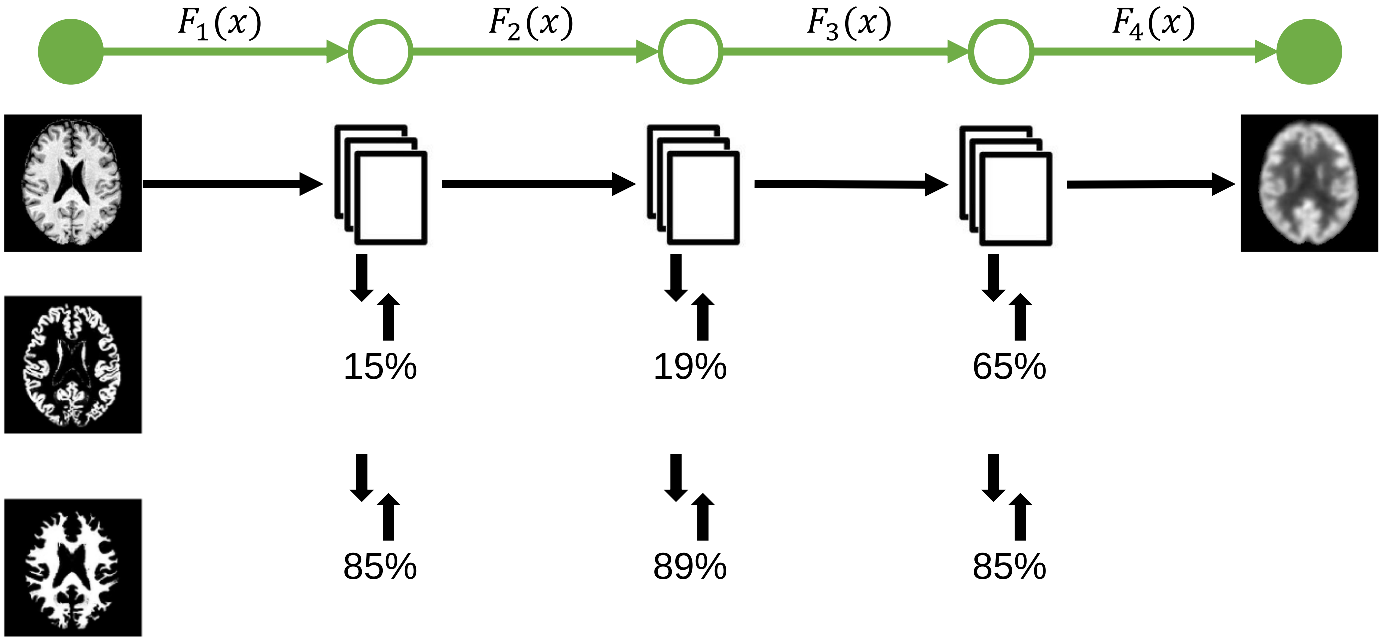
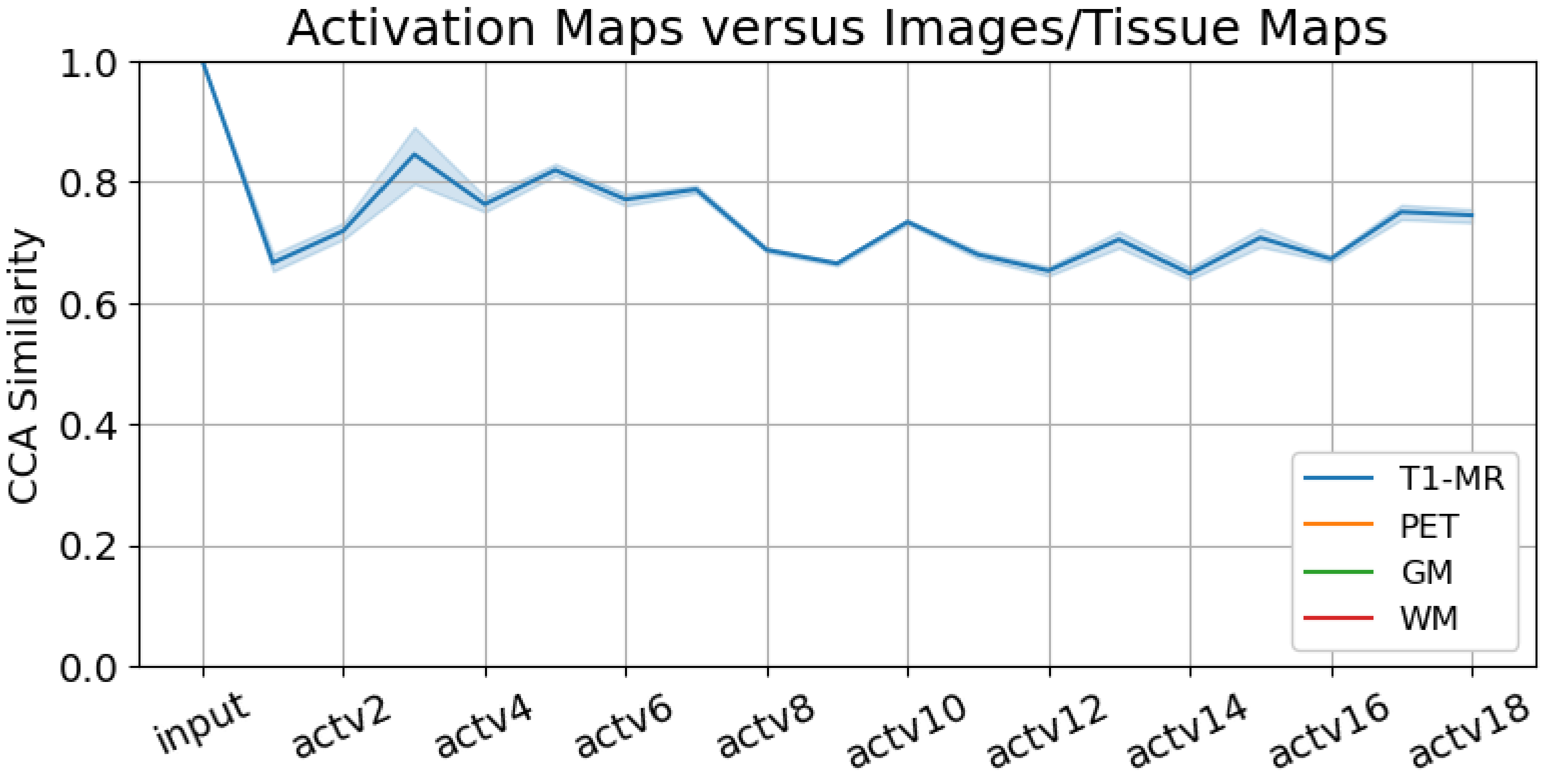
Similarity between WM and transformed data



We can also compute the similarity between MRI (or PET) and the transformed data.

Results Brain tissues are segmented in the early encoding stage of image translation.



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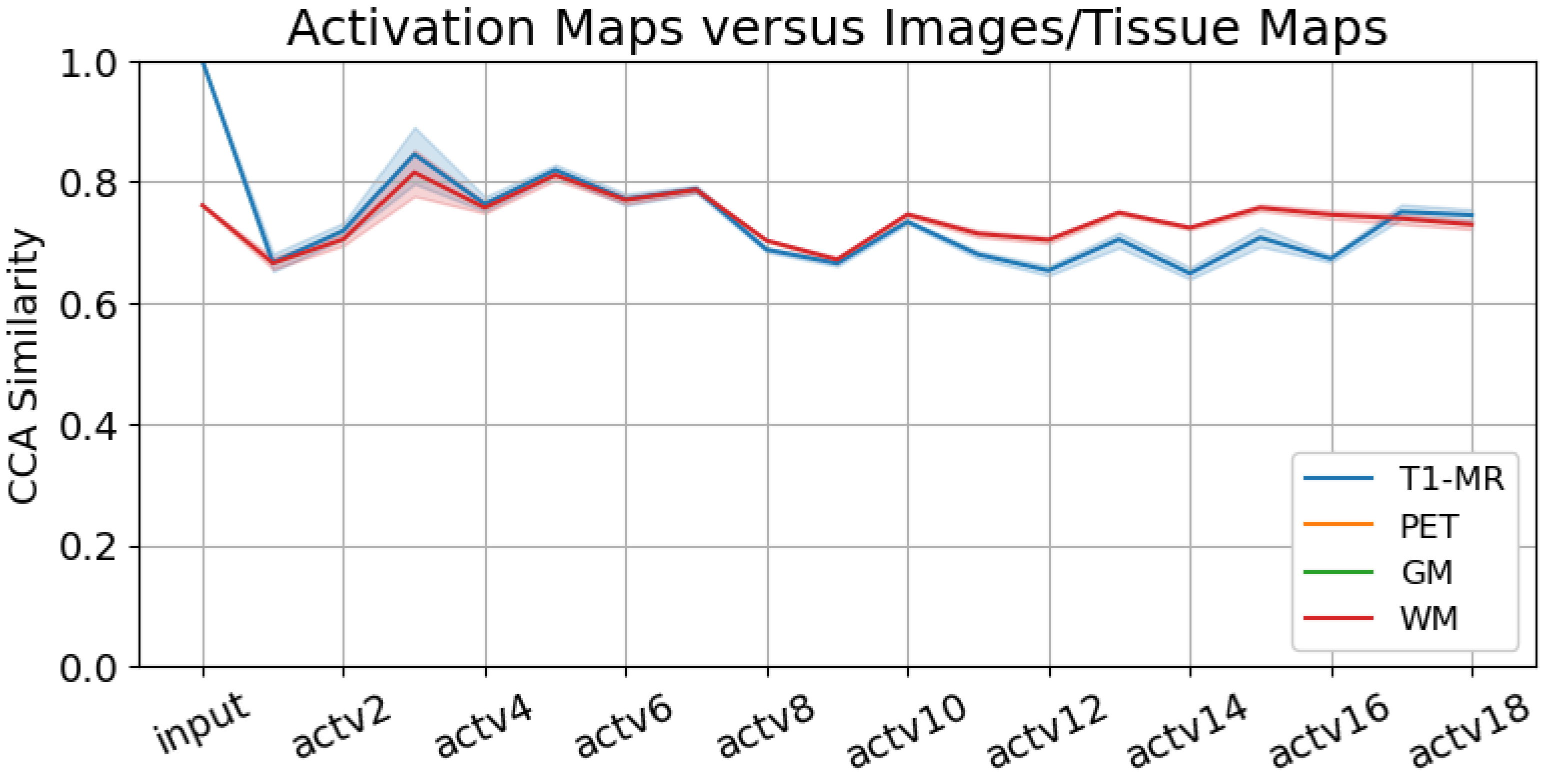

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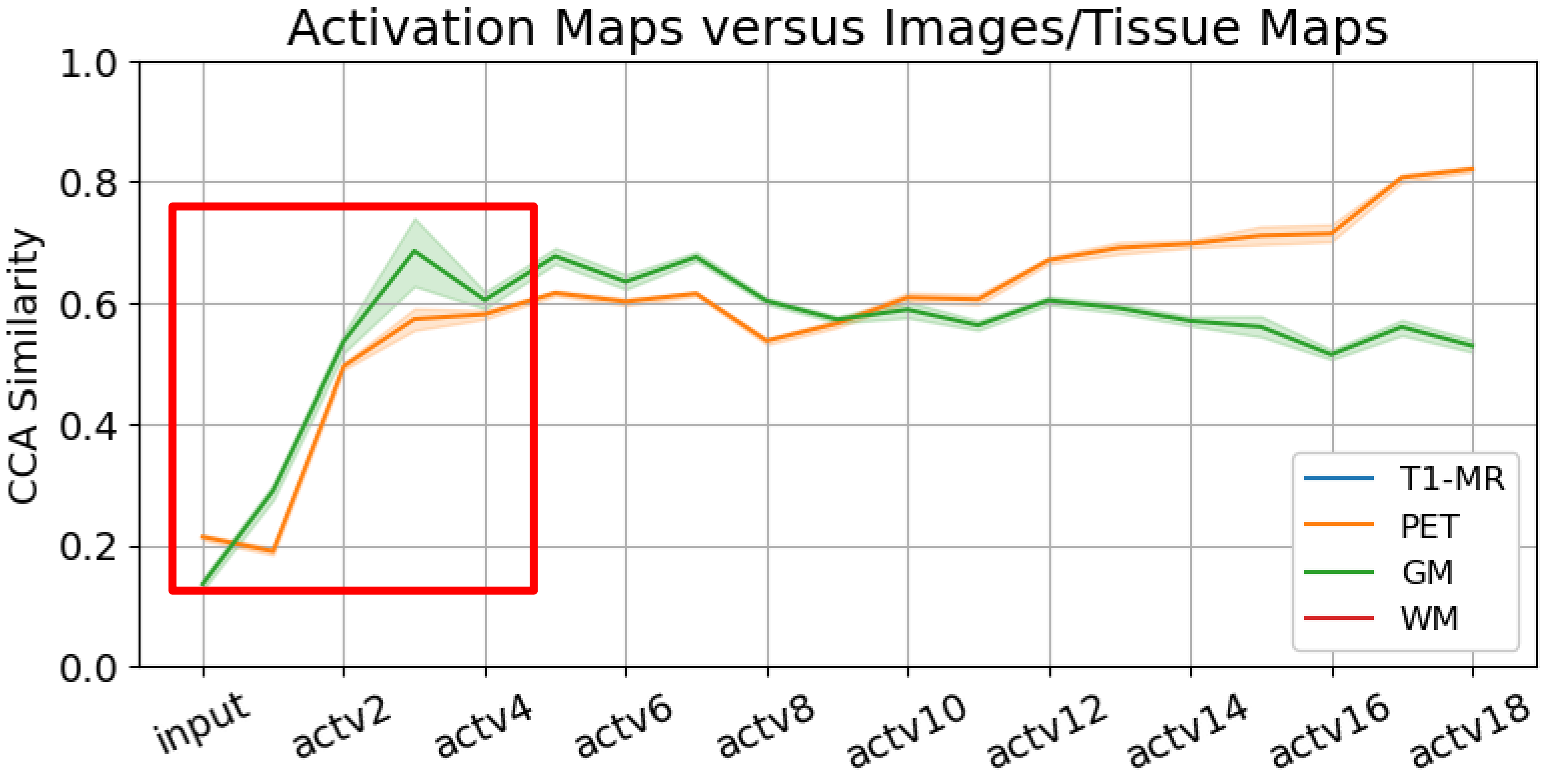

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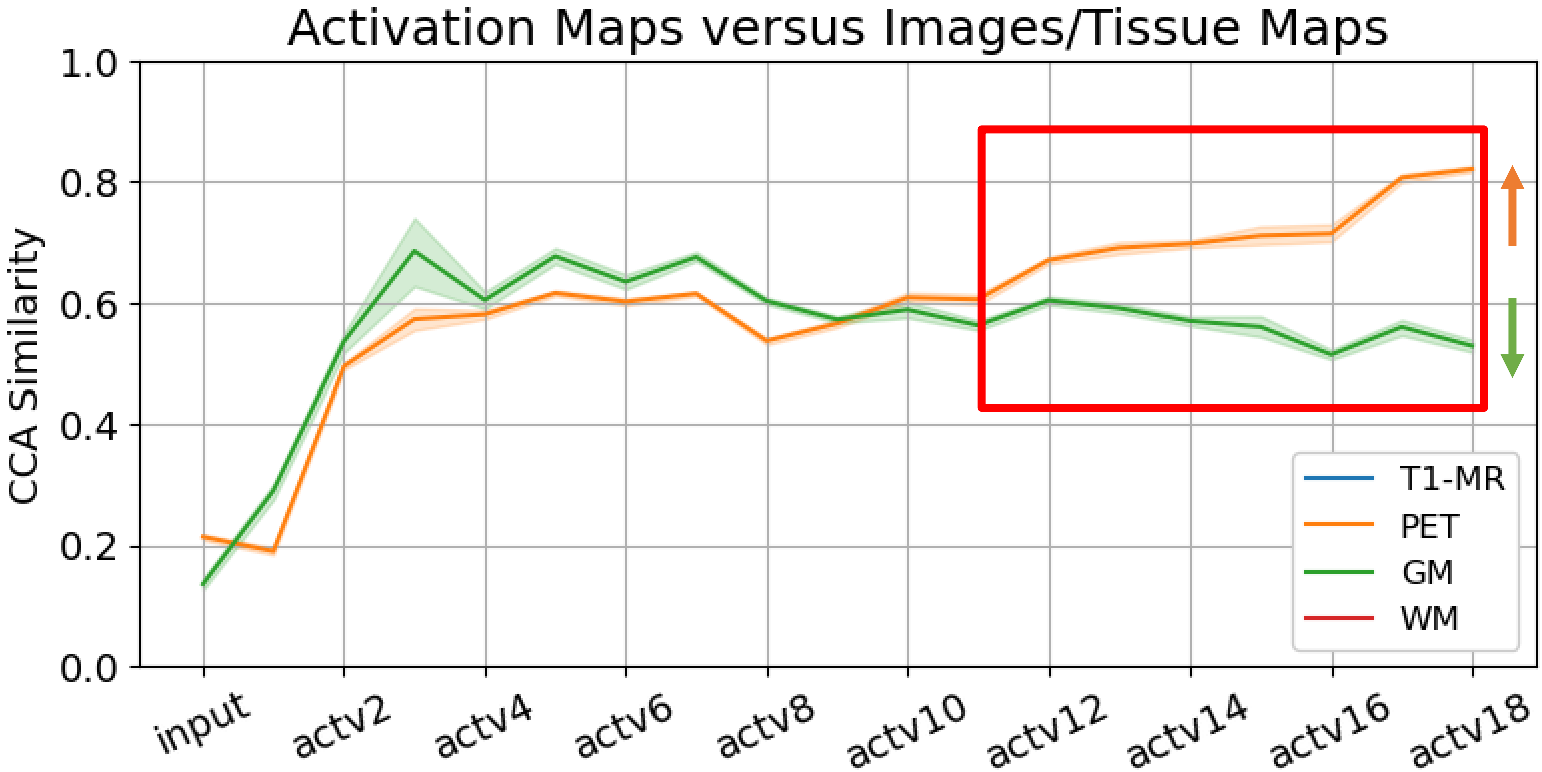
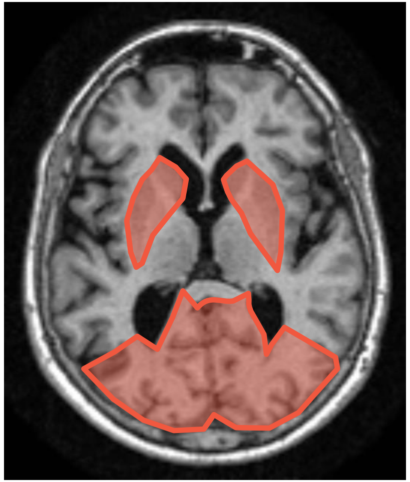
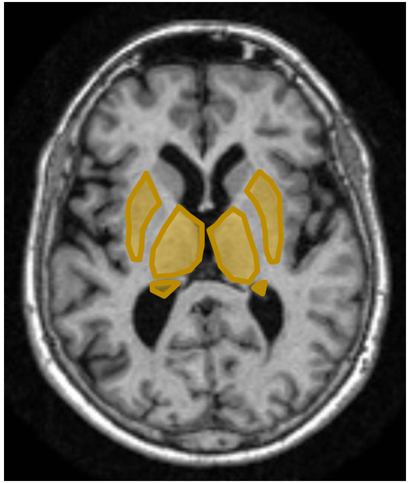


Hypothesis Deep learning models learn to segment brain regions.

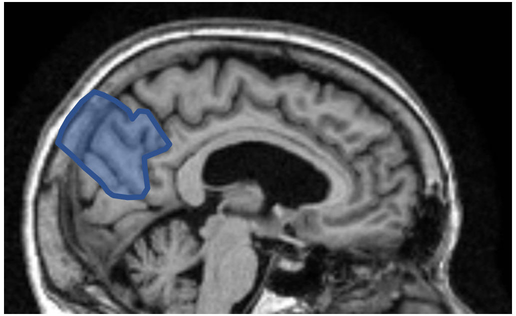
Normal higher uptake regions



Least altered regions during aging

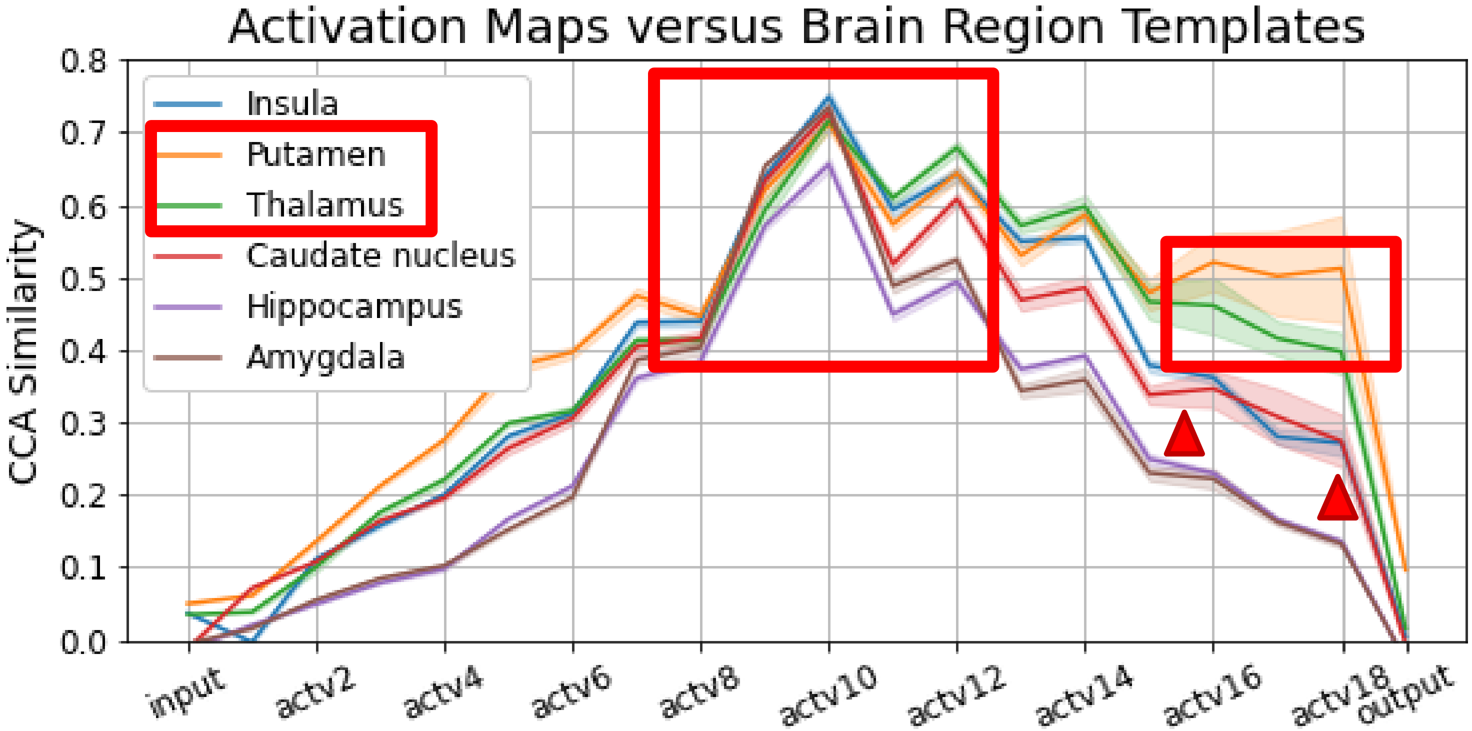


Regions of hypometabolism in AD



Brain: normal variations and benign findings in fluorodeoxyglucose-PET/computed tomography imaging. (PET Clin. 2014)
Voxel-based mapping of brain gray matter volume and glucose metabolism profiles in normal aging. (Neurobiology of Aging. 2007)
Brain PET in the diagnosis of Alzheimer's disease. (Clin Nucl Med. 2014)

Results Brain regions are identified in the decoding stage of translation.



Limitation

Dataset – organs, diseases, modalities (e.g., different radioactive tracers), machines.

Models – various deep learning models.

Measurement of similarity – curse of dimensionality.

Take home message

We use representational similarity to verify our proposed hypotheses that the translation from T1-MR to PET images comprises the **<u>recognition of brain tissue types and brain regions</u>**.