

# Towards prediction of pseudo-normal SPECT image data using variational autoencoder

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*supervisor*

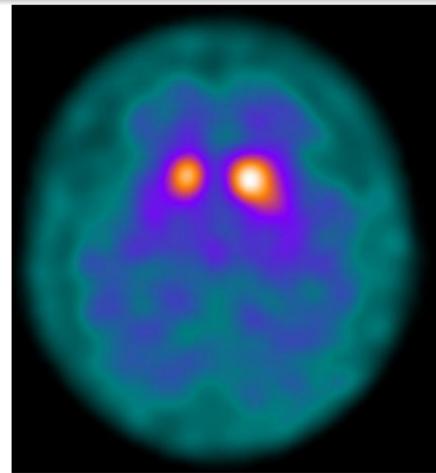
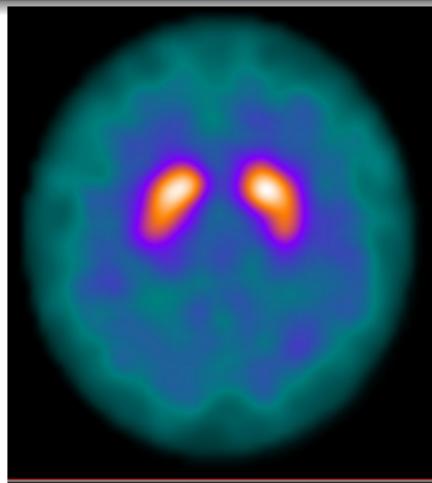
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<sup>2</sup>The General Teaching Hospital in Prague, Czech Republic

*katerina.dudasova@fjfi.cvut.cz*

Dudasova K, Trnka J. Towards prediction of pseudo-normal SPECT image data using variational autoencoder. Nucl Med Rev Cent East Eur. 2025;28(0):9-17. doi: 10.5603/nmr.101316. PMID: 40103394.

## Diagnostics of Parkinson's disease

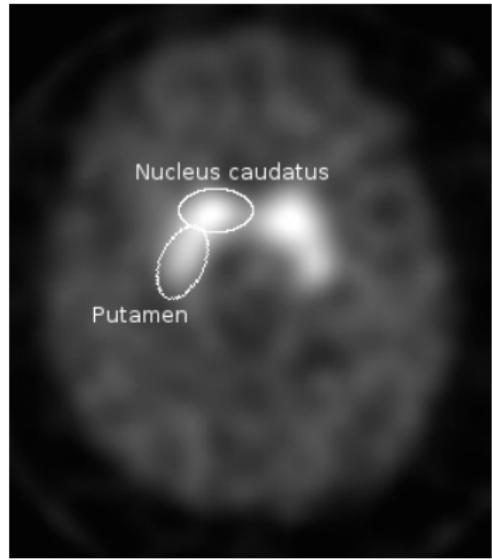


Dopamine Transporter binding in nigrostriatal pathway  
 $^{123}\text{I}$ -ioflupane

# Current clinical evaluation

## Quantification of Striatal binding ratio

$$C_{gang} = \frac{\overline{N_{gang}} - \overline{N_{bcg}}}{\overline{N_{bcg}}} \quad (1)$$



## Key role in clinical outcome:

Extensive age-related **database** of individuals with **normal** uptake in basal ganglia ← **FBP** reconstructed SPECT

# Key idea

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Generate **individual** normal image.

# How?

Generative network

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Generative network



Variational Autoencoder

# How?

Generative network



Variational Autoencoder

Restoration Task

Damaged image



VAE



Predicted  
original image



Original image



CVAE loss

# How?

Generative network



Variational Autoencoder

Clinical Task

Image with pathology



VAE



Predicted  
normal image



Normal image



VAE loss

# Creating a Dataset

45 MRI  
segmented masks



basal ganglia



background brain

# Creating a Dataset

45 MRI

segmented masks

BG Degradation

controlled by PBR, CBR, SLR

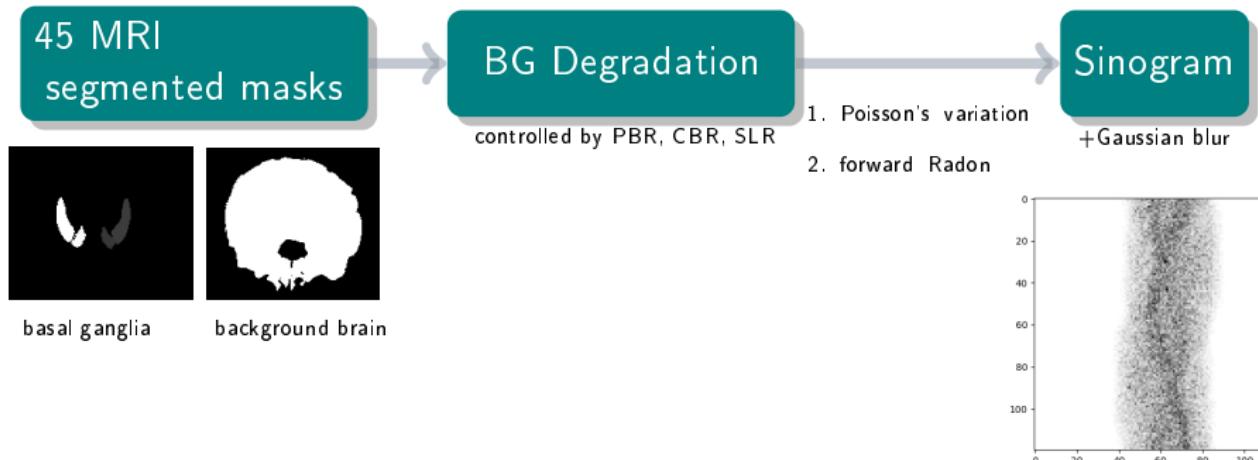


basal ganglia

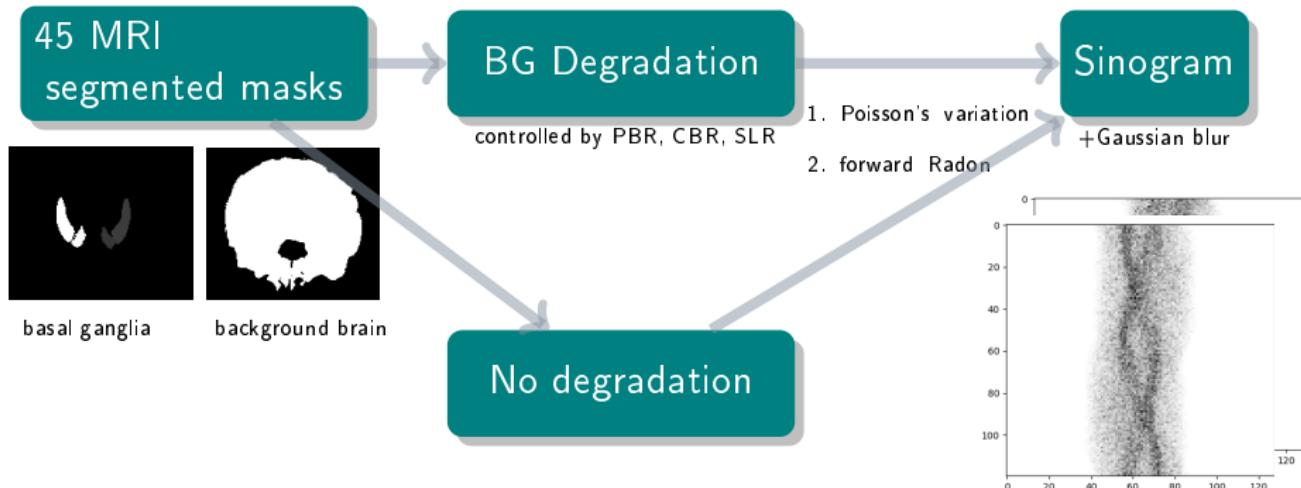


background brain

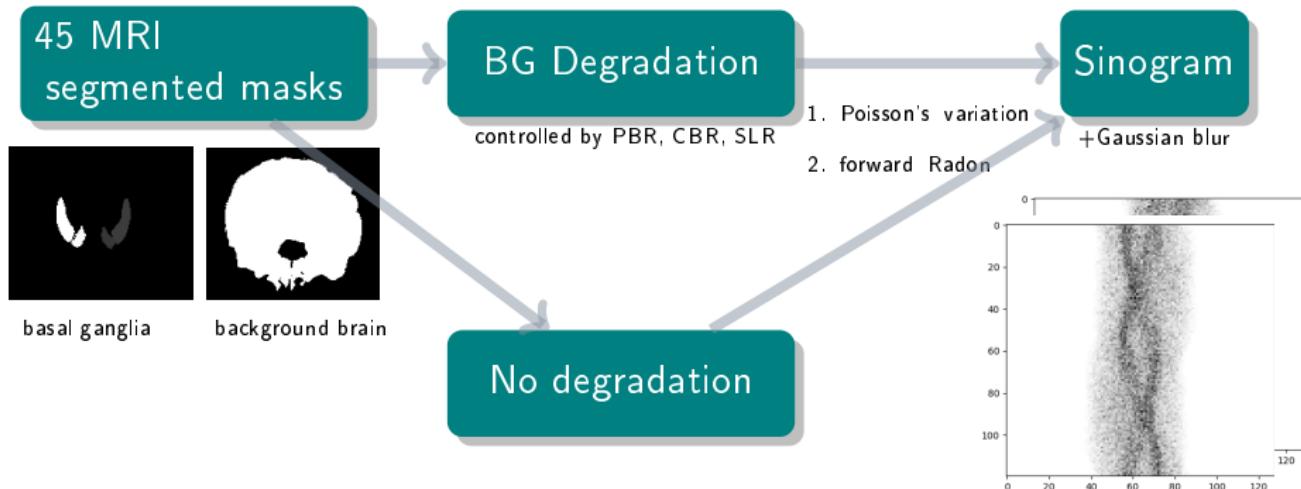
# Creating a Dataset



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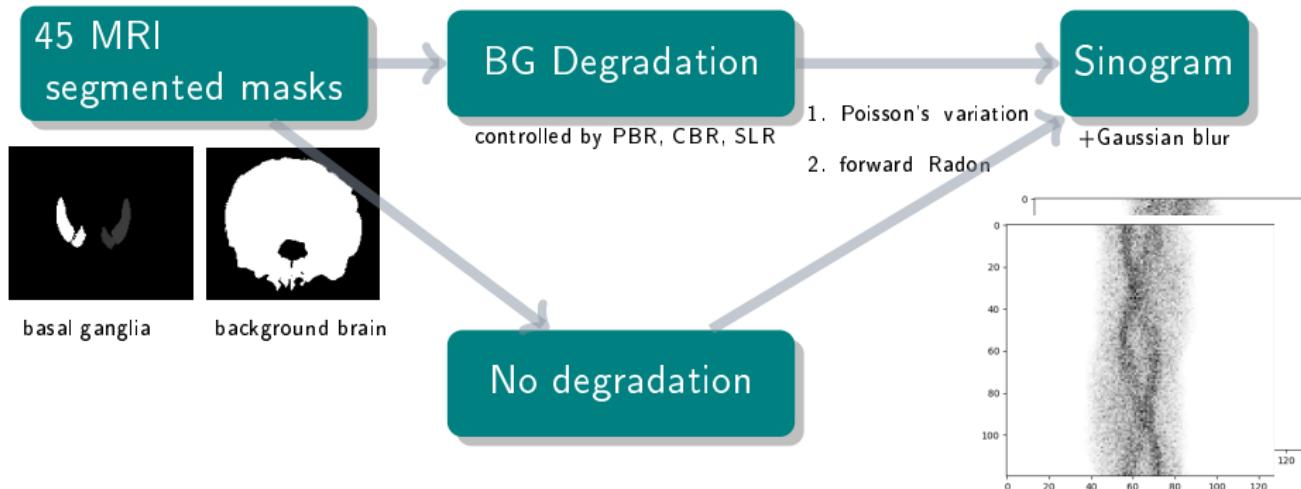
# Creating a Dataset



## Validation dataset

- 36 MRI
- \*10 (PBR,CBR,SRL)
- **360**

# Creating a Dataset



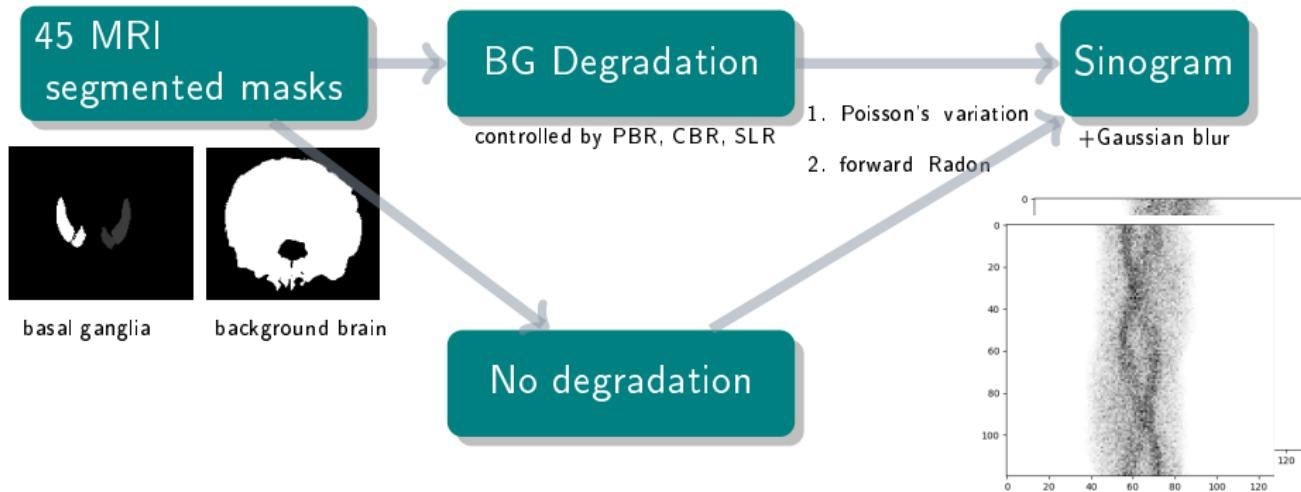
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## Training dataset

- 36 MRI
- \*17 (PBR,CBR,SRL)
- **612**

# Creating a Dataset



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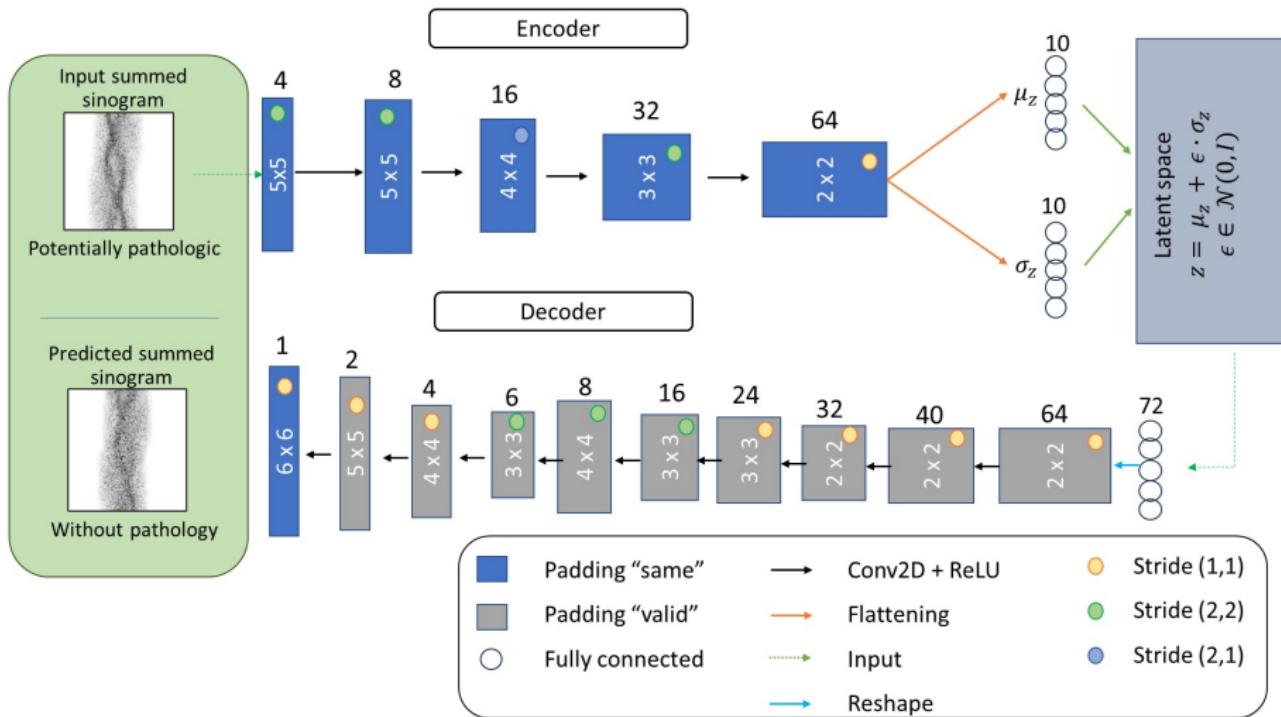
## Training dataset

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- **612**

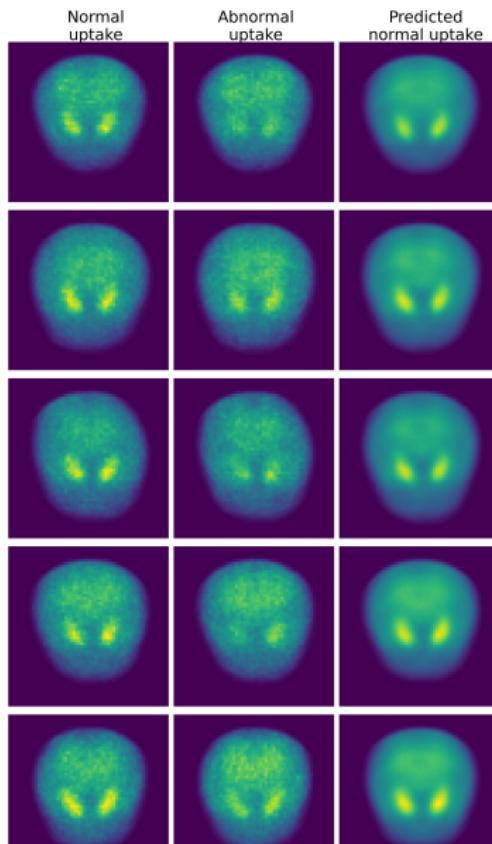
## Testing dataset

- 9 MRI
- \*17 (PBR,CBR,SRL)
- **153**

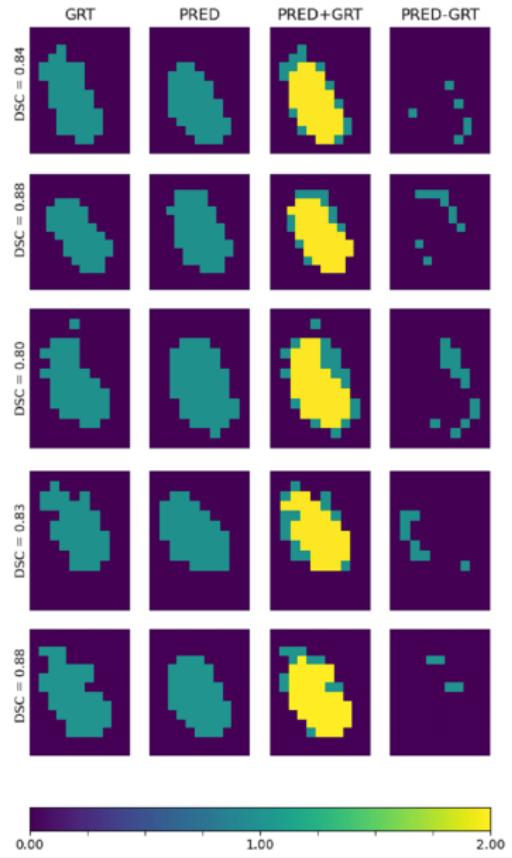
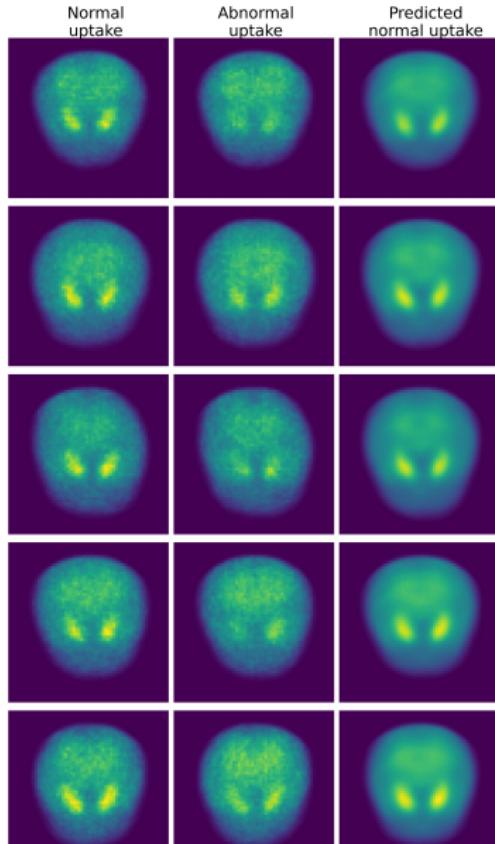
# VAE architecture



# VAE predictions



# VAE predictions



# Performance evaluation

## Anatomy Shape Precision (ASP)

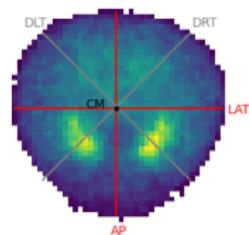
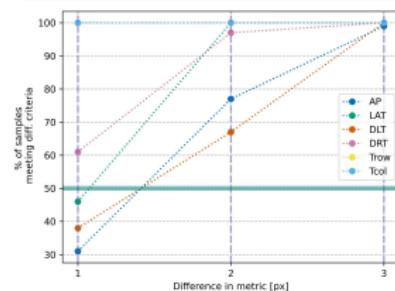
Dimensions [px]:

AP, LAT

DLT = diagonal-left-top

DRT = diagonal-right-top

CM = center of mass (Trow, Tcol)



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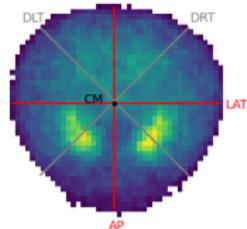
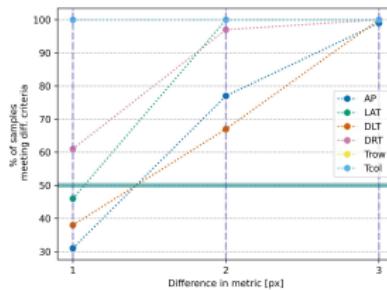
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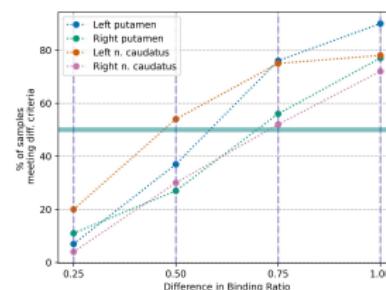
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## Basal Ganglia (BG) uptake correspondence

binding ratio match  
assessed by Regression Conv NN



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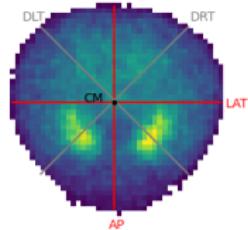
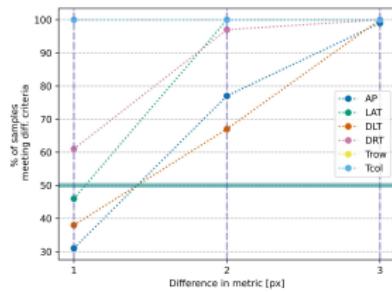
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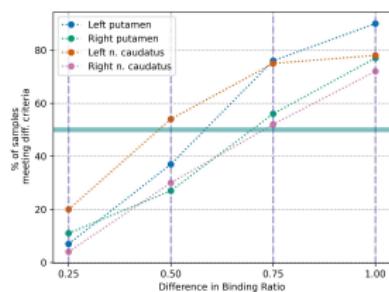
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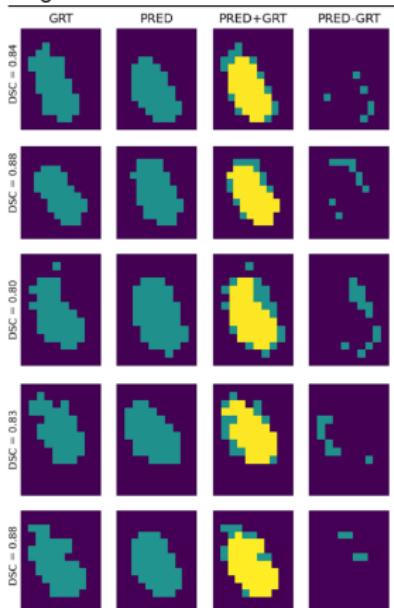
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## Dice Similarity Coefficient (DSC)

of segmented BG

	Mean $\pm$ std	Min	Max
Left BG	78 $\pm$ 8 %	62 %	90 %
Right BG	82 $\pm$ 5 %	69 %	93 %



# Discussion

## Performance evaluation

Anatomy Shape Precision:	<3 pixels	satisfying
Dice Similarity Coefficient:	mean 78 %	satisfying
Binding ratio:	52 % <0.75	promising

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Binding ratio: 52 % <0.75 promising

## Limitations of the study

- 45 real brain MRI
- synthetic data (mathematical data generator vs. Monte Carlo)
- predicted images - blurred → False Positive Result
- **validation on real clinical data**

# Application

- Virtual harmonization technique for multi-center studies in NM
- Generation of synthetic normal database

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## Is it feasible?

**YES...**

Thank you for your attention!