DeepBrainPrint: A Novel Contrastive Framework for Brain MRI Re-Identification

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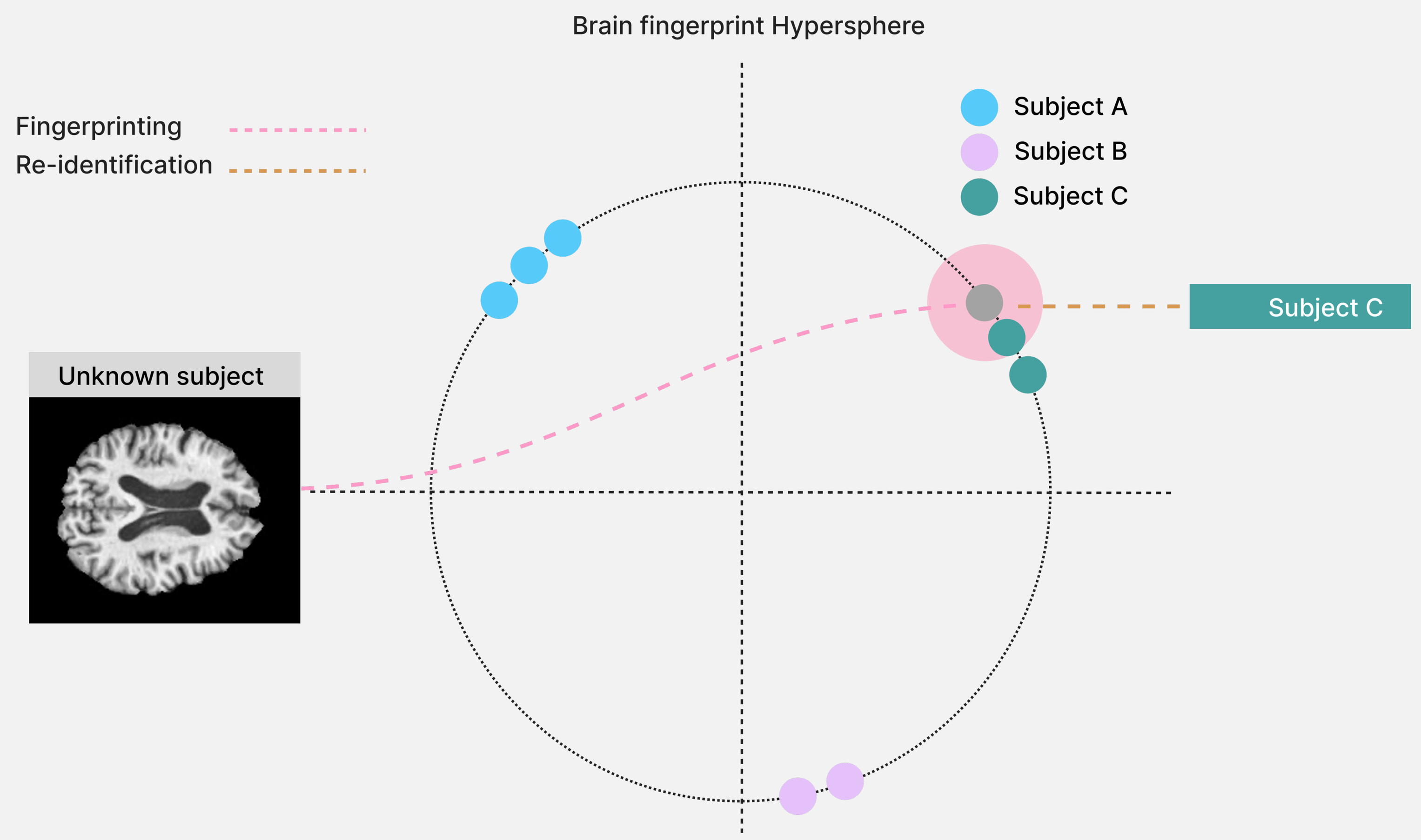
BACKGROUND AND MOTIVATIONS

Re-identification is the process of locating previous scans of the same patient within a large dataset

This process is crucial for several reasons, including:

- access and compare historical medical information
- monitoring patient progress over time
- treatment planning



EXISTING APPROCHES

Reference	Description
Wachinger et al, 2015	Study of the geometry of the brain using the Laplace-Beltrami operator
Valizadeh et al, 2018	Characterization of the brain through quantitative measurements of its anatomical structures
Chauvin et al, 2020	Image feature extraction through the 3D SIFT-Rank algorithm

MAIN LIMITATIONS

- Reliance on computationally intensive processes using manually engineered features
- Struggle with achieving robust generalization across diverse modalities

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METHODS

DeepBrainPrint generates a fingerprint from **brain MRI** scans, utilizing **deep metric learning** based on two distinct loss functions:

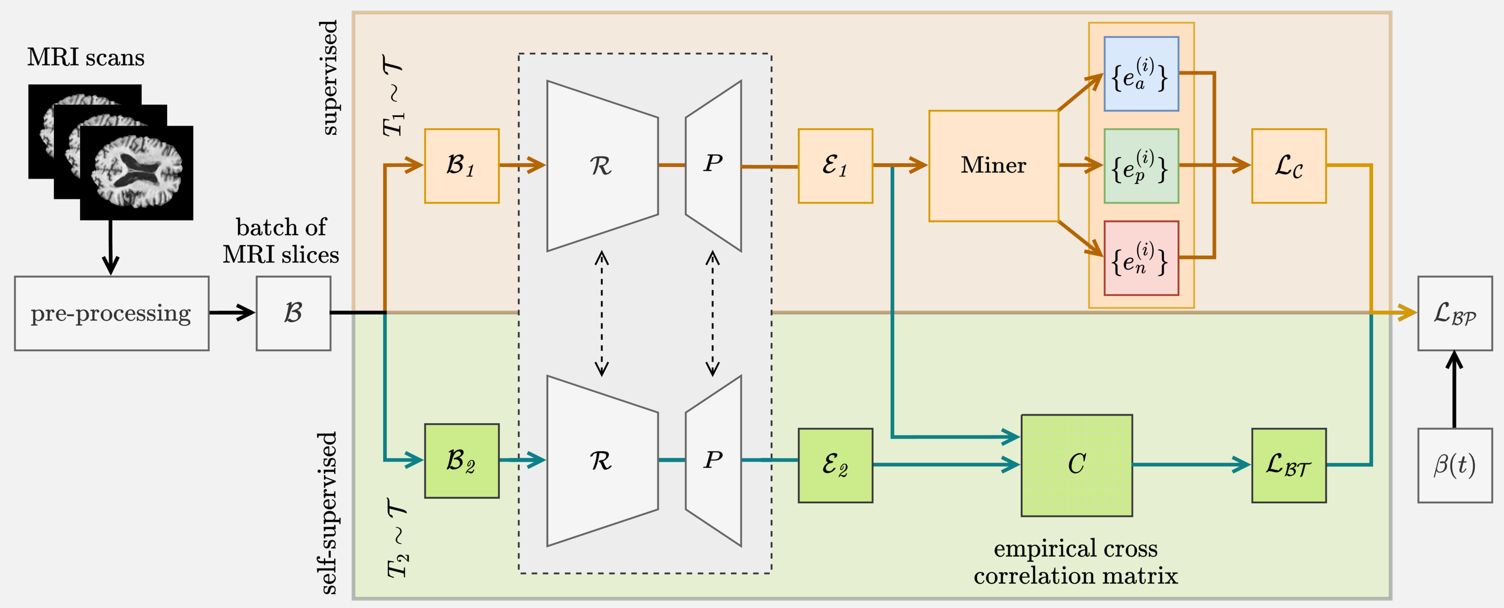
1. a fully-supervised: $L_c = -\log \dfrac{\exp(sim(e_a^{(i)}, e_p^{(i)})/\tau)}{\exp(sim(e_a^{(i)}, e_p^{(i)})/\tau) + \exp(sim(e_a^{(i)}, e_n^{(i)})/\tau)}$

2. a self-supervised: $L_{BT} = \sum_i (1 - c_{ii})^2 + \lambda \sum_i \sum_{i \neq j} c_{ij}^2$

The final loss L_{DBP} is determined by a weighting function $\beta(t)$ that combines the individual losses L_c and L_{BT}

$$L_{DBP} = \beta(t)\, L_{BT} + (1 - \beta(t)) L_C \qquad where\ \ \beta(t) = 1 - \frac{t}{H}$$

The workflow of DeepBrainPrint is divided into two main branches



Proposed transformations used for image distortion during training

Transformation	Type	p_i	Parameters
Negative of the image	Intensity-based	40%	-
Intensity shifts	Intensity-based	40%	sampled in $[-0.25, 0.25]$
Bias field	Intensity-based	30%	-
Rotations	Structural-based	100%	max 3
Random black patches	Structural-based	40%	max 3 patch of 10×10 pixel
Elastic deformation	Structural-based	30%	magnitude range is $[1, 2]$

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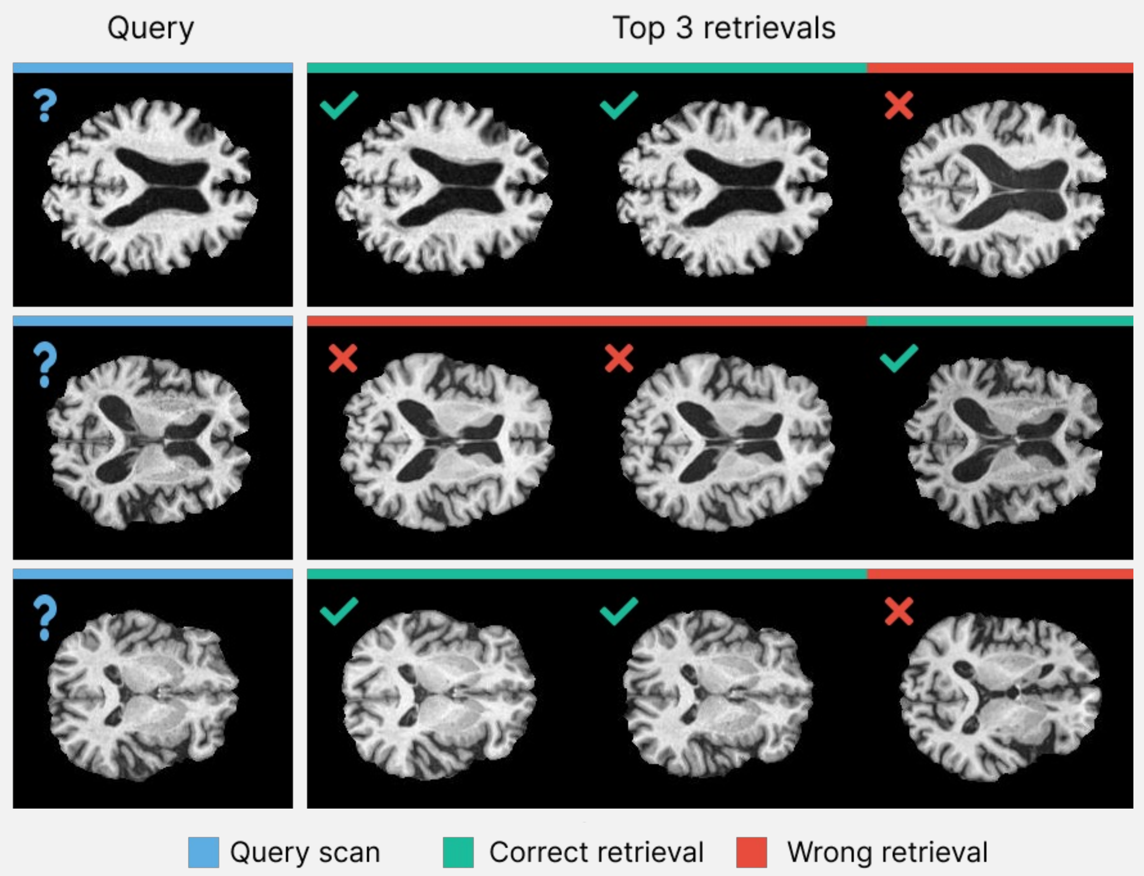
RESULTS

We tested **DeepBrainPrint** on 2 different datasets:

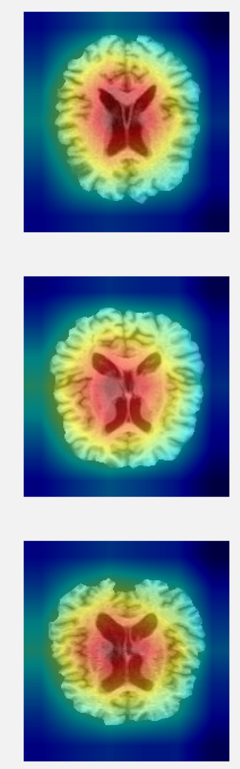
1. a large dataset of 795 T1-weighted brain MRIs from (**ADNI**)
2. a synthetic dataset designed to evaluate retrieval performance with different image modalities (**SYNT-CONTR**)

	Settings			ADNI		SYNT-CONTR	
Method	$\widehat{\text{FS}}$	$\widehat{\text{SS}}$	$\widehat{\text{DT}}$	R@3	mAP@3	R@3	mAP@3
SSIM-based (Wang et al., 2004)	No training			96.89	90.21	76.68	48.86
3D SIFT-Rank (Chauvin et al., 2020)	No training			**100.00**	**100.00**	81.77	63.71
Barlow Twins (Zbontar et al., 2021)		✓		73.06	45.35	48.70	25.52
Barlow Twins with our transformations		✓	✓	97.41	90.47	92.23	79.62
SimCLR (Chen et al., 2020)		✓		68.39	38.47	51.30	24.55
SimCLR with our transformations		✓	✓	87.05	67.63	70.98	39.94
NCA (Goldberger et al., 2004)	✓		✓	96.89	90.34	72.02	48.10
MLKR (Weinberger and Tesauro, 2007)	✓		✓	96.37	90.03	72.02	48.07
SoftTriple (Qian et al., 2019)	✓		✓	98.45	91.97	96.89	87.64
Proxy-NCA (Movshovitz-Attias et al., 2017)	✓		✓	98.45	90.80	94.82	84.86
InfoNCE (Oord et al., 2018)	✓		✓	96.89	94.04	95.34	86.95
DeepBrainPrint (Proposed)	✓	✓	✓	99.48	95.54	**98.96**	**91.00**

EXAMPLES OF WRONG RETRIEVALS



SALIENCY MAPS



CONCLUSIONS

DeepBrainPrint has potential for various clinical applications:

- searching for scans with similar brain shapes, lesions, or atrophy
- support diagnostic decisions on new patients
- suggest effective treatments for similar disease subtypes/stages