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Integrating Anatomical Information in Weakly Contrastive Learning for Neuroimaging

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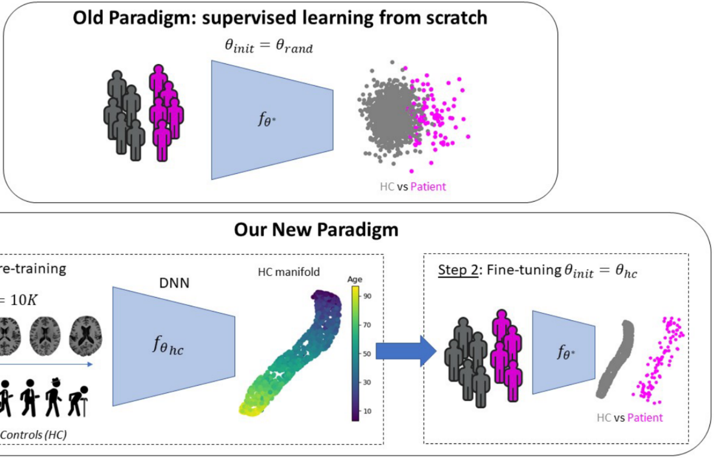
Deep Learning in Neuroimaging

- Deep learning has demonstrated remarkable results across various fields that benefit from **automated image analysis**, including neuroimaging
- Neuroimaging concerns the acquisition and analysis of **brain images**
- Neurobiological characterization of psychiatric and neurological disorders encompasses clinical, biological and environmental factors
- **Limited** relative size of neuroimaging datasets, especially related to specific neurological conditions

Transfer Learning

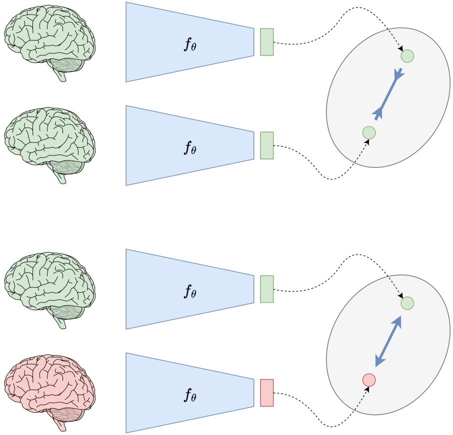


Credits: Dufumier et. al, 2024

Contrastive Learning

- **Minimize** the distance between positive pairs of embeddings
- **Maximize** the distance between negative pairs of embeddings

$$\mathcal{L}_{i,j} = -\log\left(\frac{\exp(s_{i,j}/\tau)}{\sum_{a\in A(i)} \exp(s_{i,a}/\tau)}\right)$$



Weakly Supervised Contrastive Learning

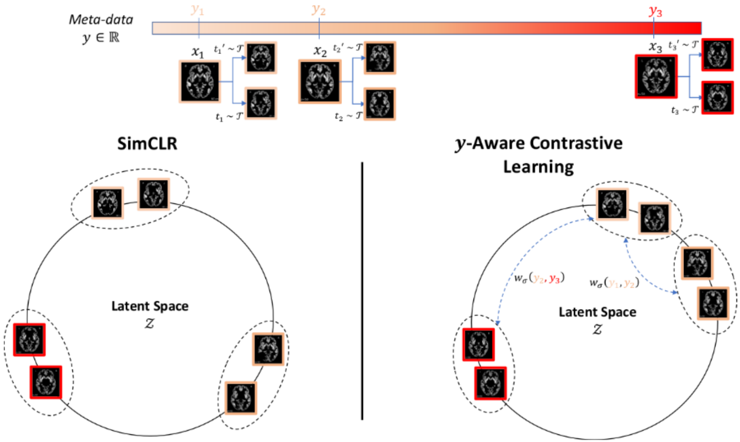
- Existing weakly contrastive learning methods augment the learning process with the **age attribute**
- These methods works by computing a **weight term** that increase the pushing/pulling strength between latent representations based on the closeness of the age attribute

$$\mathcal{L}^{\text{y-aware}} = -\sum_{k \in A(i)} \frac{w_k}{\sum_t w_t} log \left(\frac{\exp(s_k/\tau)}{\sum_{a \in A(i)} \exp(s_a/\tau)} \right)$$

Where:

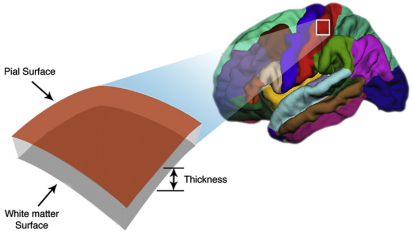
$$w_k = K_\sigma(y_i - y_k)$$

Weakly Supervised Contrastive Learning

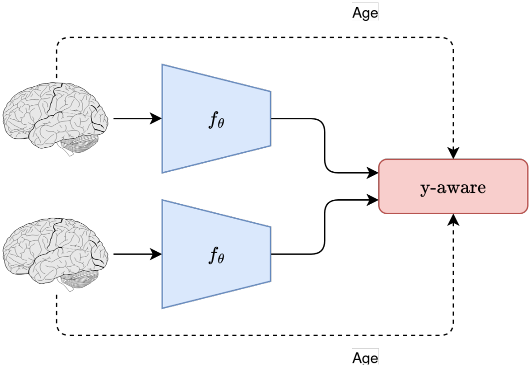


Goal of this Thesis

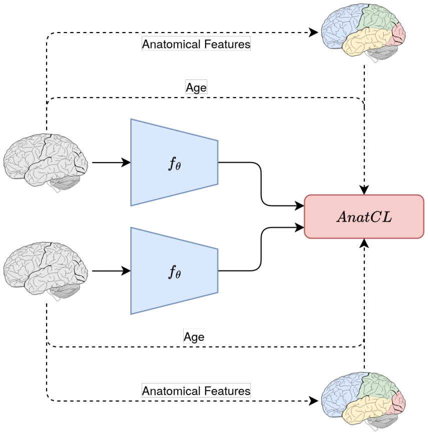
- Neuroimaging datasets commonly include other **anatomical measures** along with **patient-specific informations** (age, sex, etc.)
- Leverage this data during the **pre-training** process to further enhance the learned representations
- This may in turn enhance the performance and **generalizability** of the model in various downstream tasks



Current Approach

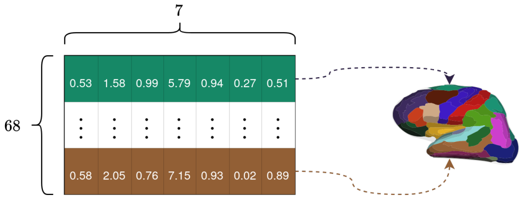


Proposed Approach



Integrating Anatomical Information

- For each i^{th} patient, its **anatomical measures** are stored in a matrix $\mathscr{D}^i \in \mathbb{R}^{68\times 7}$
- Each **row vector** contain 7 anatomical measures, corresponding to a specific **region of interest** out of the total 68



Anatomical Measures:

- Average Cortical Thickness
- Standard Deviation Cortical Thickness
- Gray Matter Volume
- Total Surface Area
- Integrated Mean Curvature
- Gaussian Curvature
- Intrinsic Curvature Index

Proposed Method: Local Descriptor

- Define the **similarity** between two subjects as the expected cross-similarity between local measurements vectors
- A **normalization** $\gamma(\mathbf{x})$ must be applied to normalize **each component** of the vectors to a common range

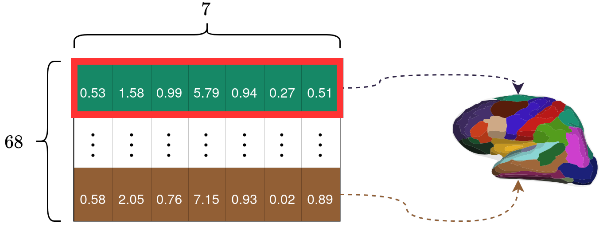
$$w_k = \frac{1}{68} \sum_{n=1}^{68} sim(\gamma(\mathscr{D}_n^i), \gamma(\mathscr{D}_n^k))$$

Proposed Method: Global Descriptor

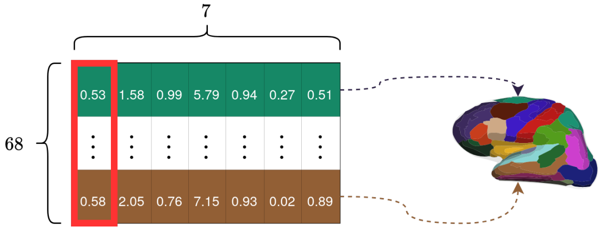
- Rather than viewing the data as 68 measurement vectors one can consider the format as 7 **feature vectors**, each composed of 68 measurement values
- Let $\omega_n^i = \left(\mathscr{D}^i\right)_n^T$ be the n^{th} row vector of the **transposed measurements matrix** associated to the i^{th} patient

$$w_k = \frac{1}{7}\sum_{n=1}^{7} sim(\omega_n^i, \omega_n^k)$$

Descriptors Summary



Local Descriptor



Global Descriptor

Final Formulation

- To incorporate also the age attribute into the final objective loss, the resulting function is structured as a **weighted sum**
- This sum combines a weakly supervised loss that is augmented with the **age** attribute ($\mathcal{L}^{\text{age}}$) and another weakly supervised loss that utilizes the **anatomical information** ($\mathcal{L}^{\text{AnatCL}}$)

$$L = \lambda_1 \mathcal{L}^{\text{age}} + \lambda_2 \mathcal{L}^{\text{AnatCL}}$$

Experiments Overview

- The proposed method was compared with other **baselines** such as:
  - **L1**: Mean Absolute error using the age attribute
  - **SimCLR**: Unsupervised Contrastive (*Chen et. al, 2020*)
  - **y-aware**: Weakly Supervised Contrastive (*Dufumier et. al, 2021*)
  - **ExpW**: Weakly Supervised Contrastive (*Barbano et. al, 2023*)
- The **experimental setting** consisted in training a ResNet18 model for each evaluated method on a dataset of **healthy individuals**
- Each trained model was then tested on 20 different **downstream tasks** across 5 **different datasets** in a 5 fold cross-validation
- Experiments were run using the Leonardo CINECA HPC cluster on Nvidia A100 GPUs, with each experiment taking approximately 24 hours

Experiments

Dataset	Task / Condition
OpenBHB	Age (HC) Sex
ADNI	Alzheimer's Disease sMCI vs pMCI
OASIS-3	Alzheimer's Disease
SchizConnect	Schizophrenia Broad Schizophrenia Strict Bipolar Disorder Schizoaffective
ABIDE I	Autism Aspergers PDD-NOS

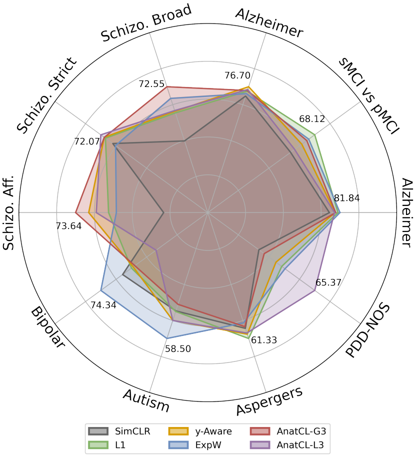
Dataset	Phenotype
SchizConnect	AIMS Overall Severity AIMS Upper Body AIMS Lower Body Depression Handedness SAS GAIT
ABIDE I	Handedness FIQ (WASI) VIQ (WASI) PIQ (WASI)

Results

Brain Age Prediction

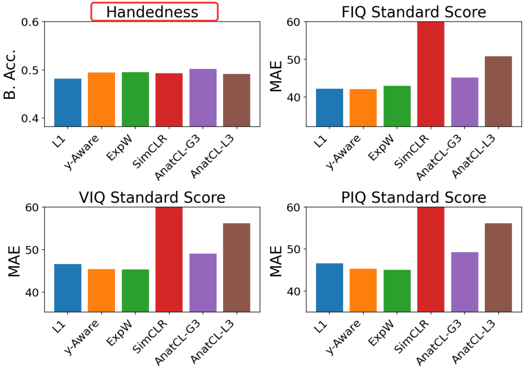
Method	Age MAE	Sex
SimCLR	$5.58_{\pm 0.53}$	$76.7_{\pm 1.67}$
L1 (age sup.)	$2.73_{\pm 0.14}$	$76.7_{\pm 0.67}$
y-Aware	$2.66_{\pm 0.06}$	$79.6_{\pm 1.13}$
ExpW	$2.70_{\pm 0.06}$	$\mathbf{80.3}_{\pm 1.7}$
AnatCL-G3	$\mathbf{2.61}_{\pm 0.08}$	$78.2_{\pm 1.25}$
AnatCL-L3	$2.64_{\pm 0.07}$	$78.2_{\pm 0.7}$

Clinical Downstream Tasks

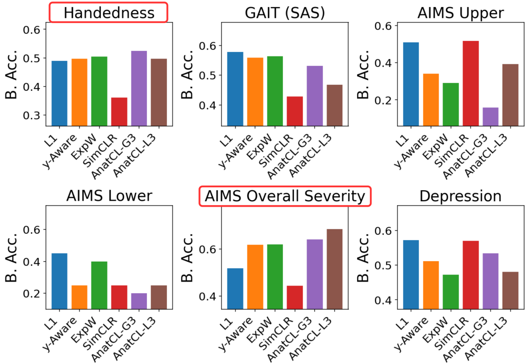


Results: Phenotypes and Clinical Scores

Abide



SchizConnect



Conclusions

- The proposed method consistently **outperforms unsupervised methods**, while reaching SOTA performances in some tasks
- This suggests that adding anatomical information may actually improve the **generalizability** of the learned representations
- This work has been **submitted** to the NeurIPS conference in May 2024 (*Barbano et. al, Anatomical Foundation Models for Brain MRIs, 2024*)
- Further research work is needed to enhance and refine these methods

Limitations and Future Developments

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- The age attribute **may not** be always present in every neuroimaging dataset
- Novel methods may integrate **only** anatomical measures without using the age. Those measures can be obtained from pre-processing pipelines common in neuroimaging, effectively making the methods fully unsupervised
- Additional methods to integrate **other anatomical measures** can be explored
- Develop **multi-modal models** to integrate other **acquisition methods** as well as data of different nature such as **textual data** coming from clinical records/assessments

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Thanks for your attention

Any questions?