Enhancing Psychiatric Disorder Diagnosis: Integrating Multilabel Metadata with Contrastive Learning on T1 Structural MRI

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BRISBANE OHBM 2025 JUNE 24-28

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Introduction

- **Label Scarcity and Contrastive Learning** : Medical data often suffers from label scarcity, but contrastive learning offers a promising solution by enabling models to learn from unlabeled data through self-supervised learning.[1]
- **Incorporating Multilabel Metadata**: Our approach builds upon the y-Aware InfoNCE loss[2], by incorporating T1 structural MRI data with multiple labels such as age, BMI, and sex.
- **Application to Developmental dataset**: By pretraining models on large datasets with method that incorporate T1 structural MRI data and proxy metadata, we can significantly improve performance on smaller, unlabeled datasets. Application of this method to developmental dataset can possibly address critical need in medical image analysis; enhancing psychiatric disorder diagnosis.

Methods

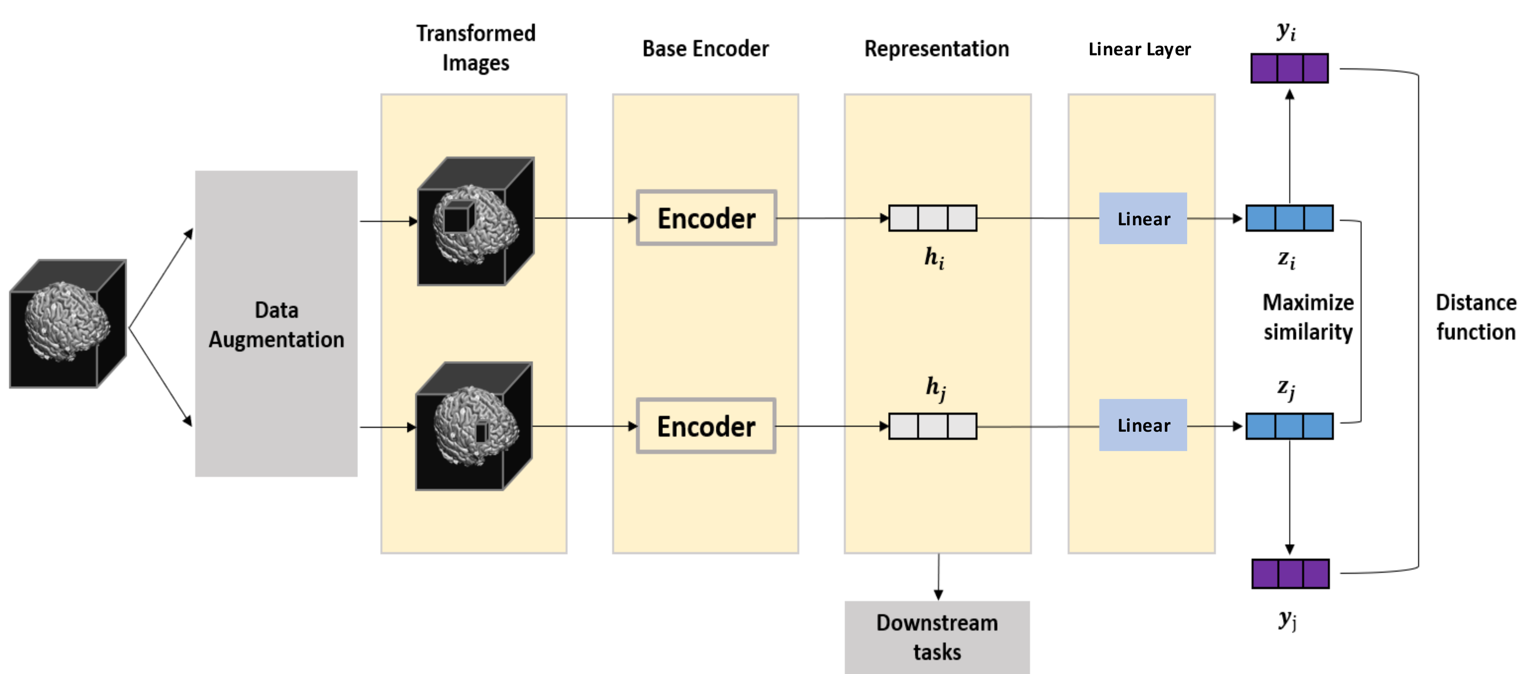
Participants

Adolescent Brain Cognitive Development cohort (ABCD)
- 9-14 years old preadolescents (American cohort)

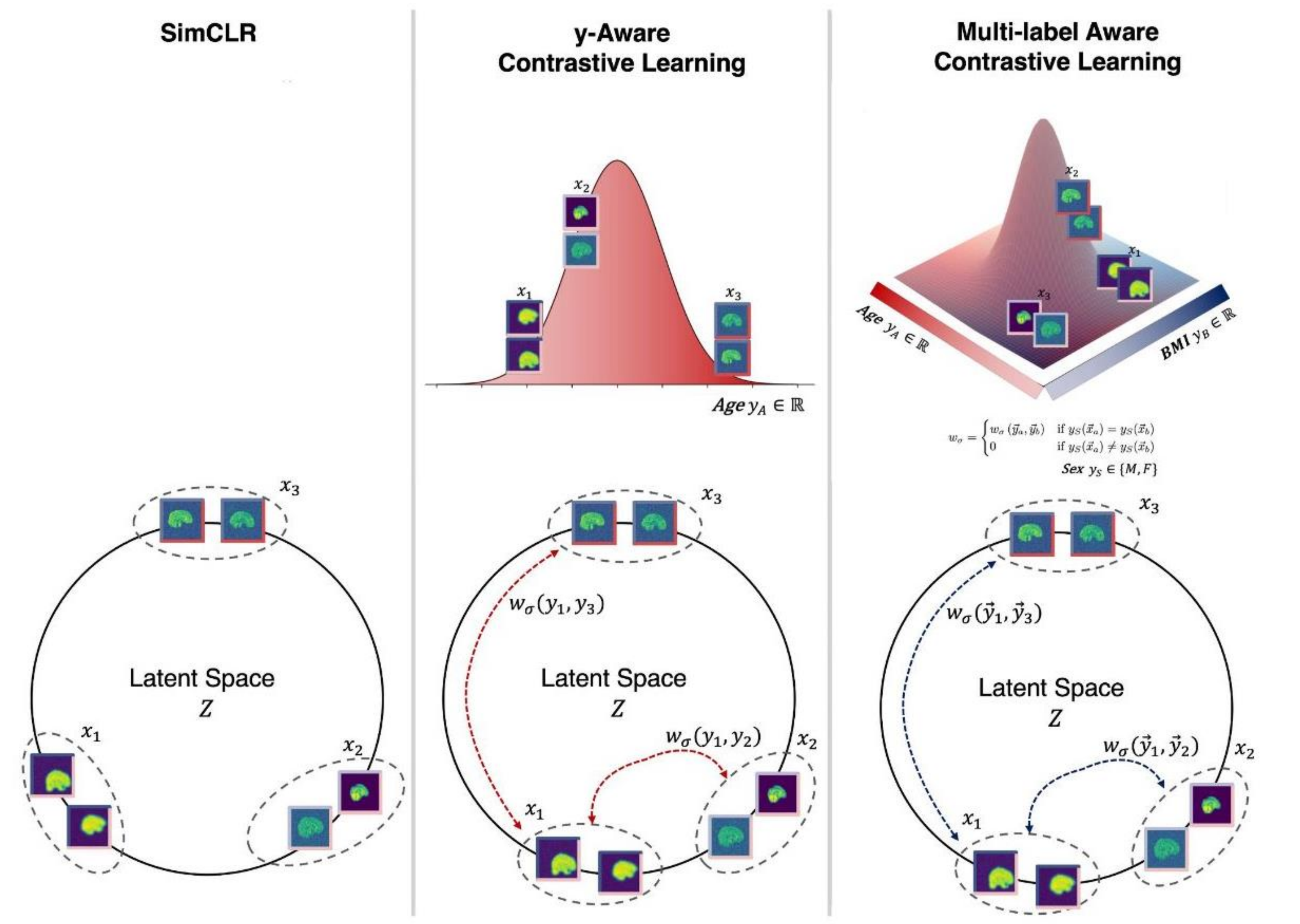
UK Biobank (UKB)
- 37-73 years old adults (European cohort)

Model Architecture

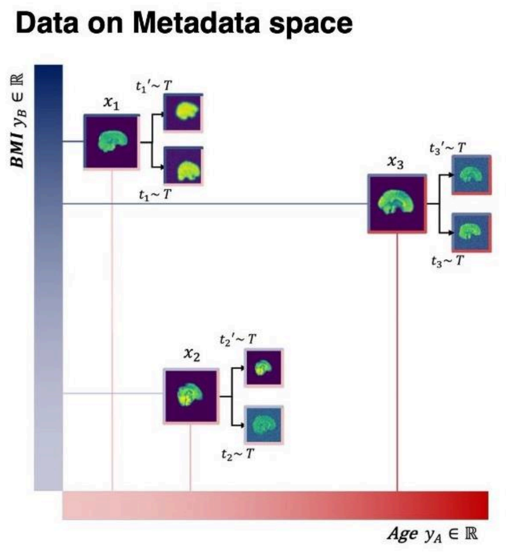
- Backbone : 3D Densenet[6]



Multi-label Aware loss



Data on Metadata space

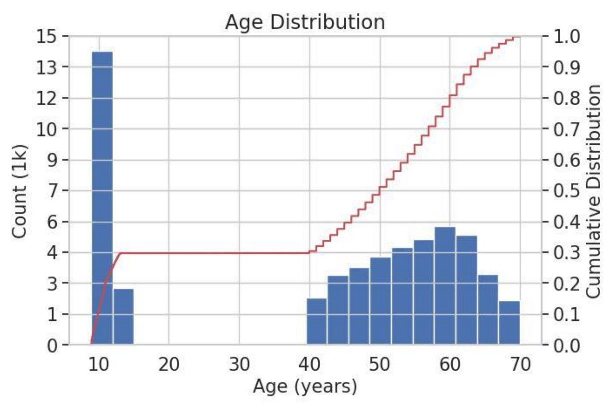


Criteria of positive/negative pair
- SimCLR : same image or not
- y-Aware : continuous range
- Multi-Aware : continuous range + discrete label

Pretraining

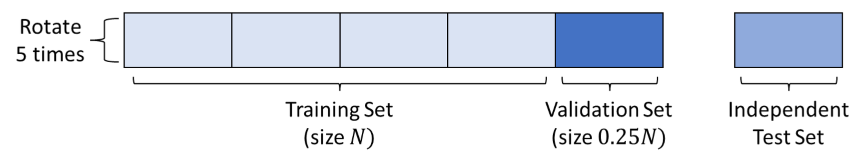
ABCD + UKB dataset

	Size	Sex	Age	BMI
ABCD (baseline)	11365	11343 (M: 5937)	9.92 (0.62)	18.81 (4.23)
ABCD (2nd year)	5942	5836 (M: 3124)	11.91 (0.64)	20.52 (4.82)
UKB	40986	40986 (M: 19335)	54.97 (7.55)	26.52 (4.38)
Total	**58293**			



Finetuning

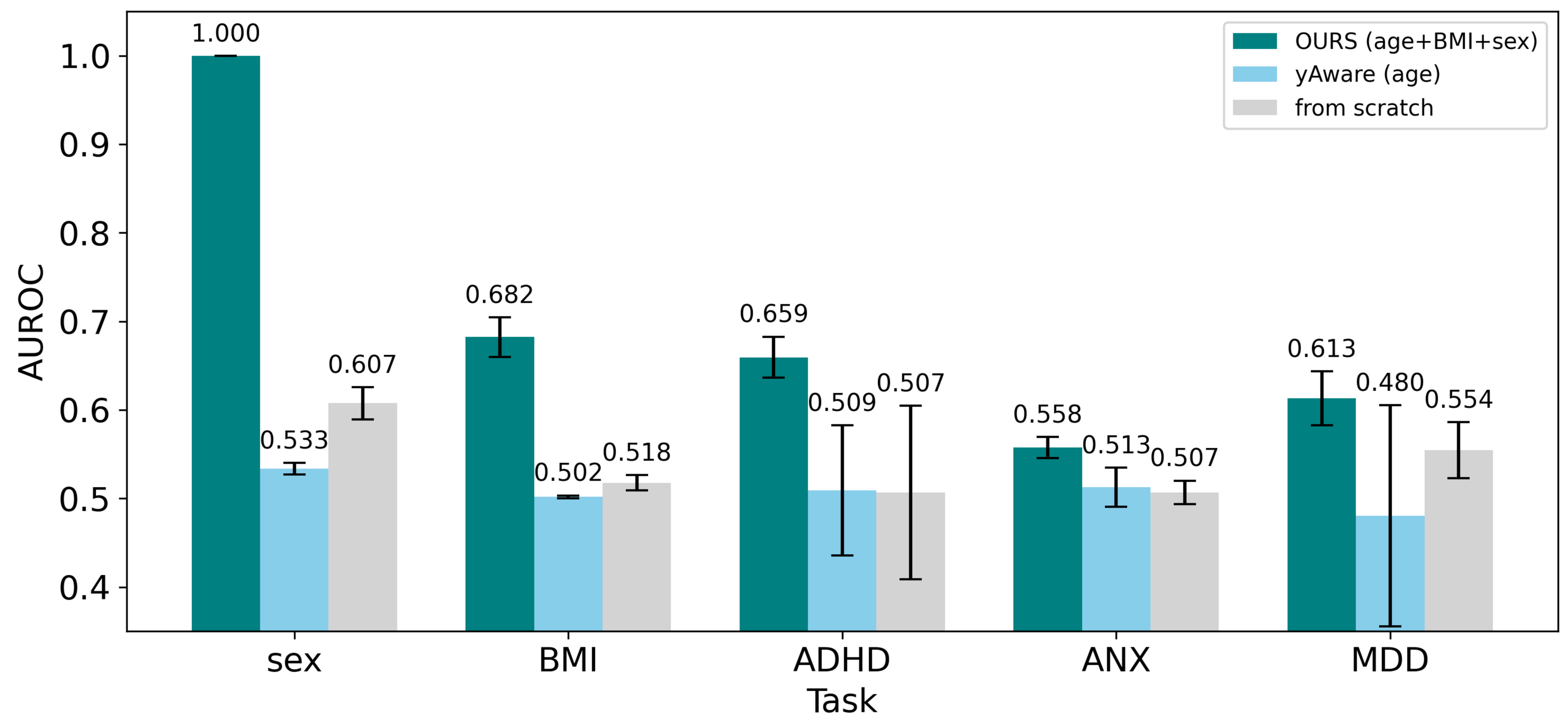
Dataset: ABCD
- Averaged over 5 randomly selected dataset, all sets were balanced
- For each trial, 5 fold Cross Validation ($N = 80$)



- Testset datasize

sex	BMI	ADHD	ANX	MDD
1224	226	178	492	52

Results



- Our model achieved higher AUROC (vs. yAware & scratch) for all downstream classification tasks.
- Achieved over 29% performance gain in ADHD classification, 29.47%(vs. yAware), 29.98%(vs. scratch).
- Achieved 27.71% performance gain(vs. yAware) in MDD classification.

*ADHD(Attention Deficit Hyperactivity Disorder) *ANX(Anxiety Disorder) *MDD(Major Depression Disorder)

Discussion

- **Performance in psychiatric disorder classification**:
  - With only T1 structural MRI scans
  - Our approach(Multi-label aware) > Supervised model(Scratch)
  - Our approach(Multi-label aware) > Pretrained model with "age"(y-Aware)
  - ADHD classification using T1 structural data
    - Previous study) AUROC of 0.64 on the ENIGMA-ADHD dataset with traditional machine learning methods[4]
    - Our model) AUROC of 0.659 on ABCD dataset
- **Methodological Novelty**: Multi-label Aware loss
  - Includes proxy multi-label metadata in contrastive learning
  - expanding y-Aware InfoNCE loss[2] to leverage data with heterogenous datatypes
- **Limitation**: Use of a closed dataset
- **Future Plan**: (1) Test on independent dataset(HBN dataset)
  (2) Scalability : Observation of performance gain

Reference

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