





Hui Xin Ng 23 May 2024

Overview

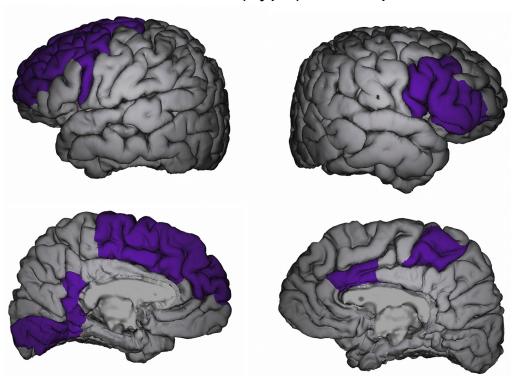
- Predicting age from neuroimaging data
- Interpretability and explainability methods
- Factors to consider when applying interpretability and explainability methods
- Code Demo
- Relevance to multimodal AI



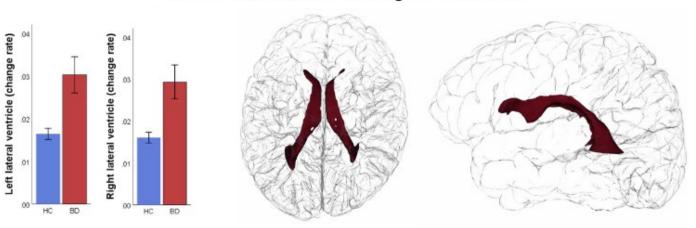
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Age-like changes are found in Bipolar Disorder

associations with (hypo)manic episodes

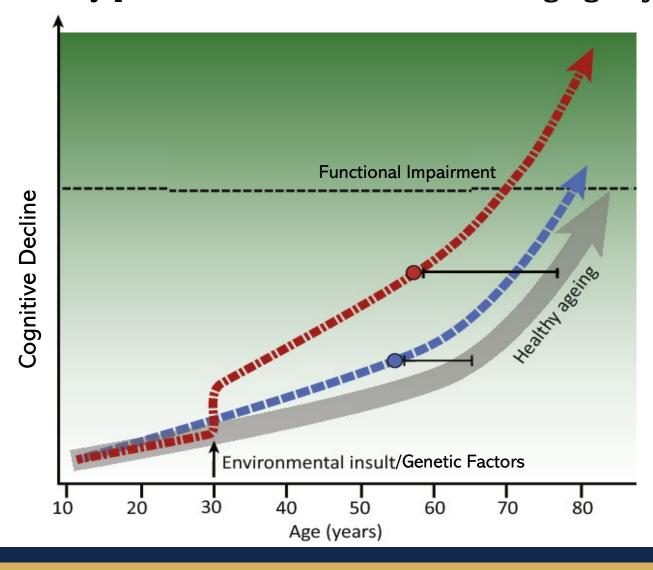


faster ventricular enlargement in BD

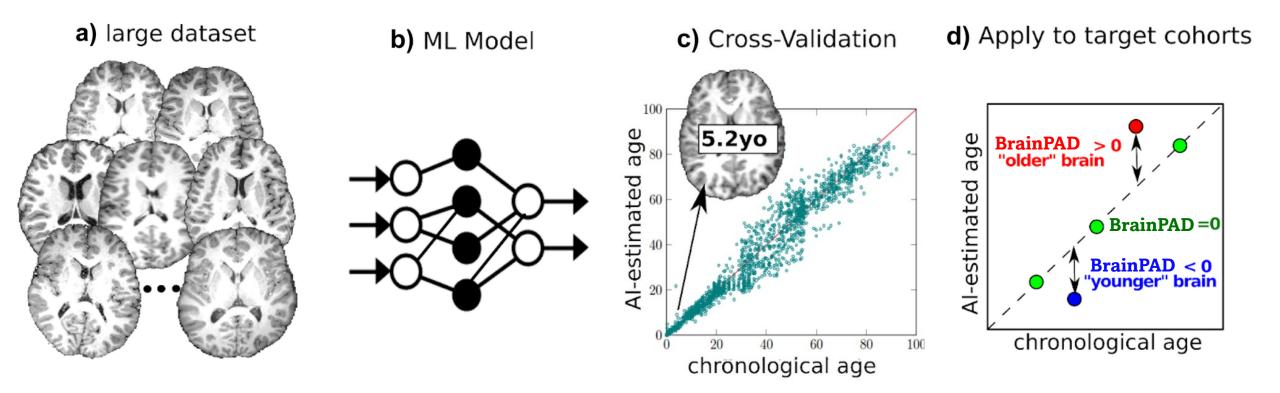




Onset of Bipolar Disorder may put individuals at an advanced aging trajectory



Brain Predicted Age Difference (Brain-PAD) as a marker of brain health



BrainPAD = Predicted age – Chronological age



- Predicting age from neuroimaging data
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- Interpretability and explainability challenges in regression tasks
- Code Demo
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Importance of interpretability: Classifying dogs vs. wolves



Predicted: Wolf True: Wolf



Predicted: Husky True: Husky



Predicted: Husky True: Husky



Predicted: Wolf True: Wolf



Predicted: Wolf True: Wolf



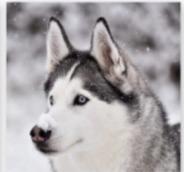
Predicted: Wolf True: Wolf



Predicted: Husky True: Wolf



Predicted: Wolf True: Wolf

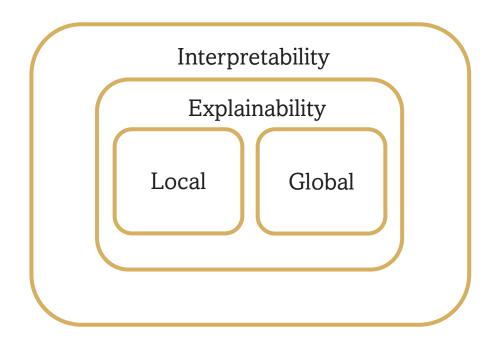


Predicted: Wolf True: Husky



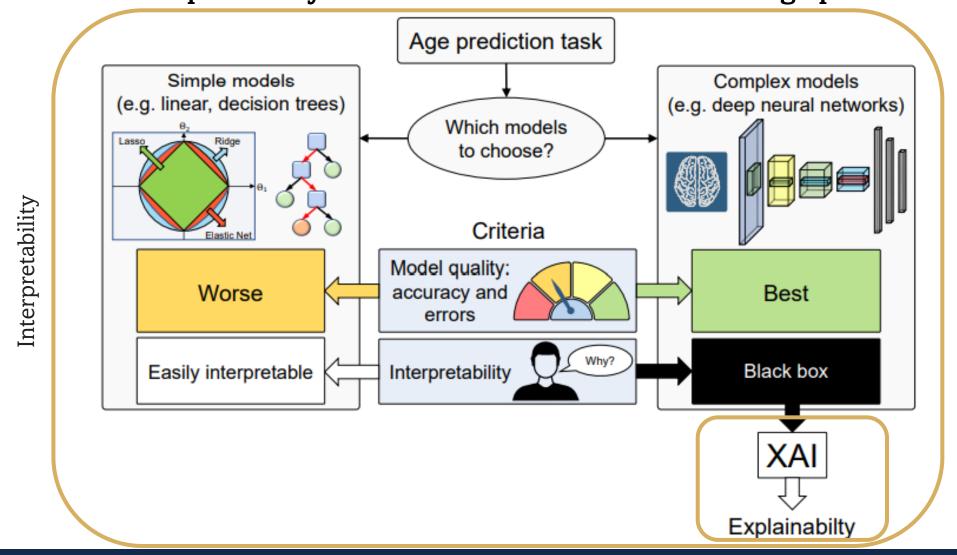
Predicted: Husky True: Husky

Definitions of interpretability and explainability



- Interpretability: Overall ability to understand and make sense of the model's decision-making process.
- Explainability: Model mechanisms and relative importance of features to the model
- Local: Why a model made a specific prediction for a single data point
- Global: Why a model made its predictions across all instances and scenarios?

Performance and interpretability as criteria for model selection in age prediction tasks San Diego

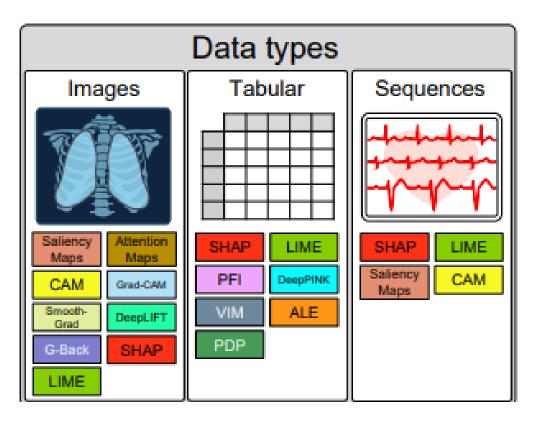




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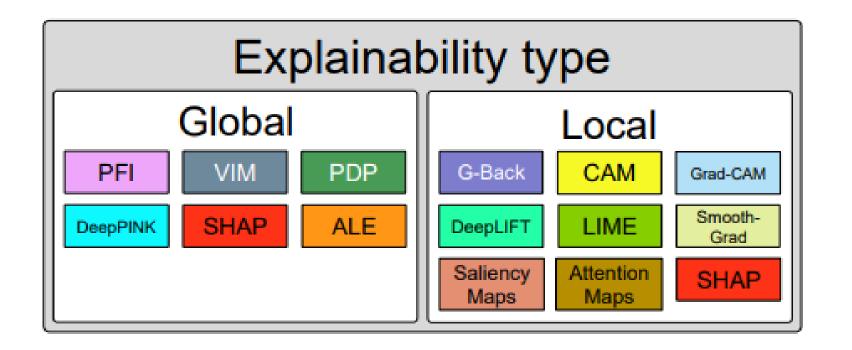


• Is the data in the form of **images** or pre-processed **tabular** or **time-series** data?



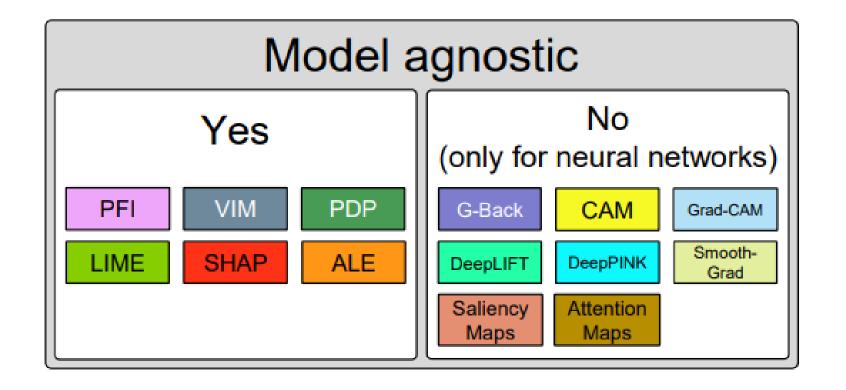


• Can the method explain the model's **overall behavior** or explain a **single prediction**?



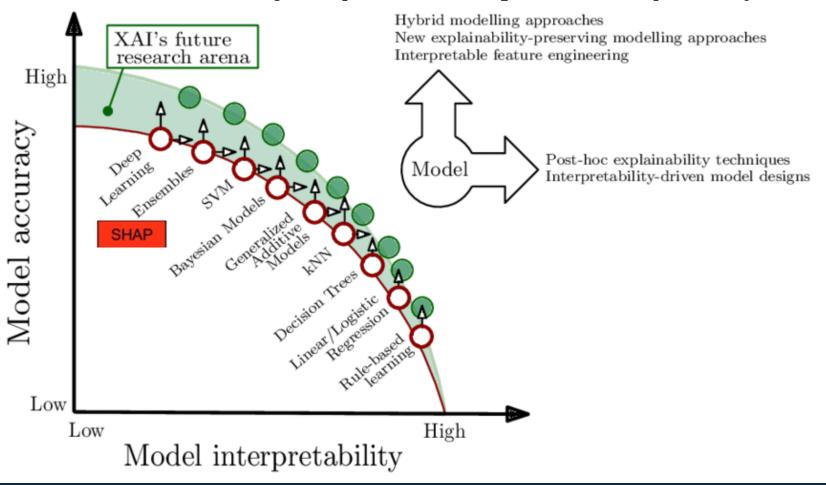


• Can this method be applied **independently** of the specific model being used?





• Should I use models that are **intrinsically** interpretable or use **post-hoc** interpretability methods?





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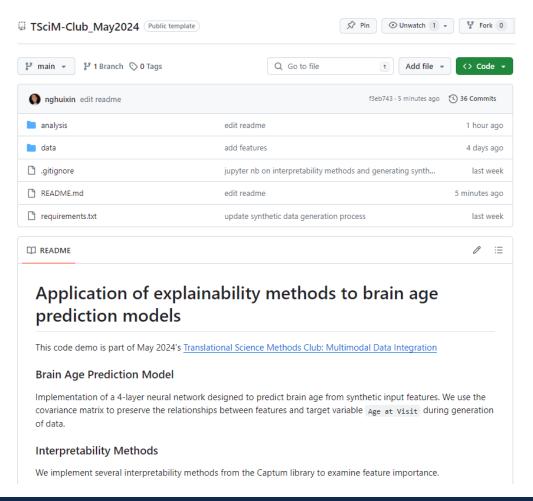






Application of Interpretability methods to a simple neural network model

https://github.com/nghuixin/TSciM-Club_May2024

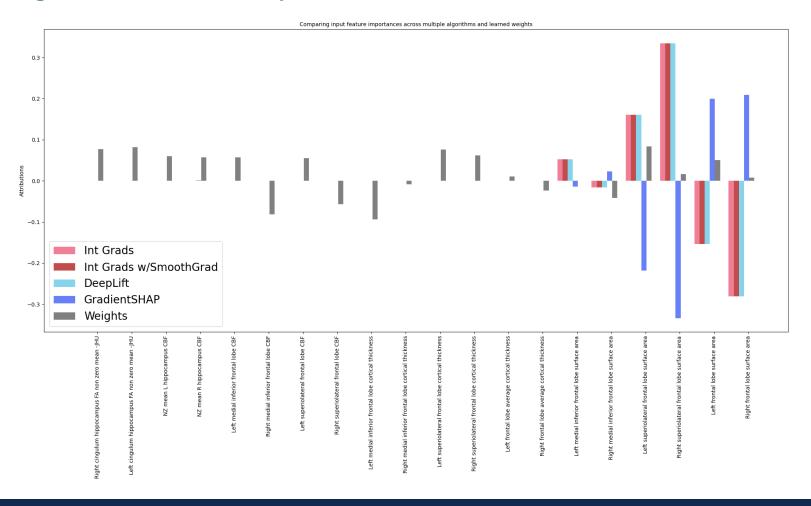


- Link to github repository in the chat
 - Captum library helps standardize interpretability methods across projects/papers
- Dataset used:
 - Simulated dataset of healthy comparisons and individuals with BD
 - Brain features and age
- Attribution methods compared:
 - Integrated gradients
 - Integrated gradients with noise tunneling
 - Deep Learning Important FeaTures (DeepLift)
 - GradientSHAP
 - Model weights



Comparison of feature importance across algorithms and learned weights

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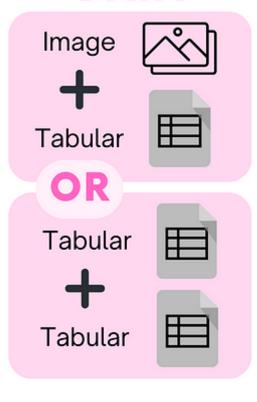




New tools facilitate our ability to evaluate algorithms on multimodal data



DATA



FUSION MODELS

Deep-learning based models:

Unimodal benchmarks

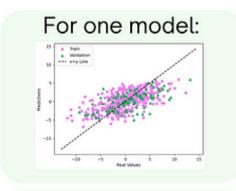
Attention-based

Graph Neural Networks

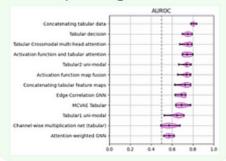
Autoencoders

and much more...

EVALUATE



Comparing models:

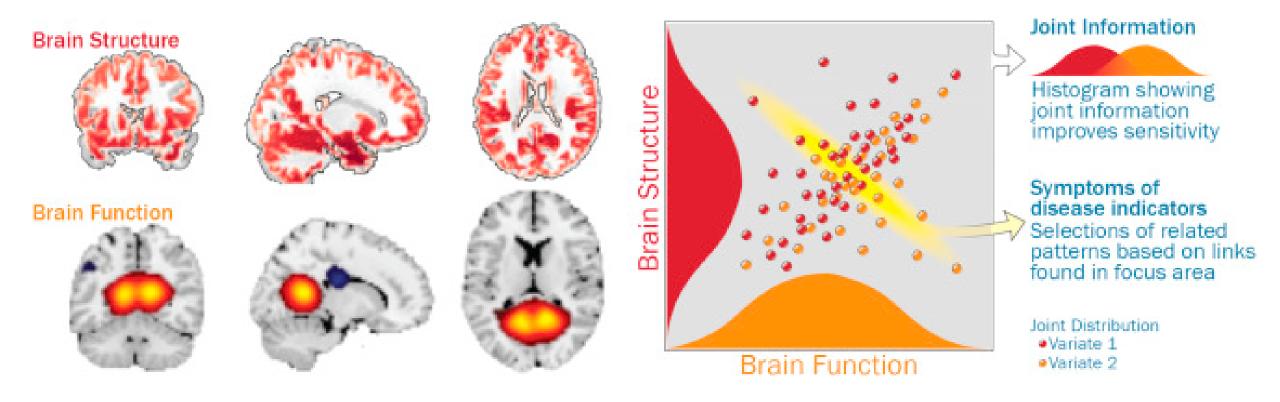


EXPLAIN



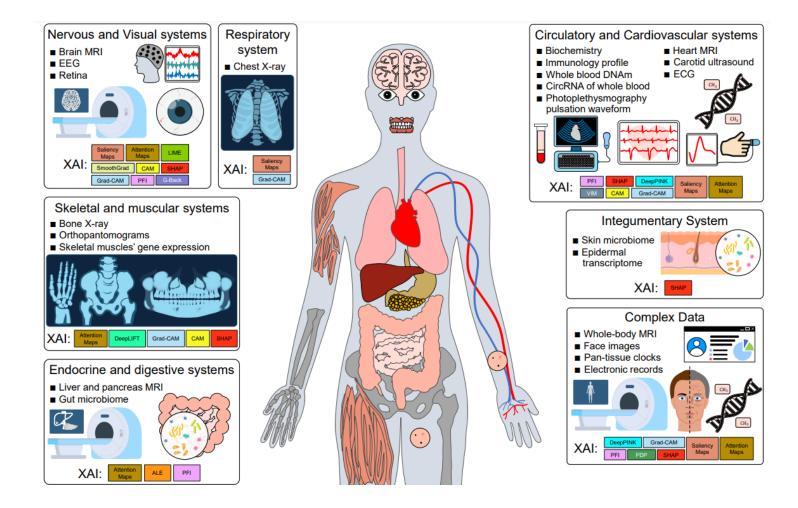


Utilization of multimodal data enhance our ability to distinguish neuropsychiatric illnesses

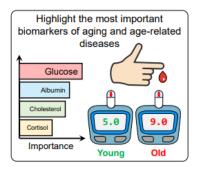


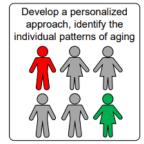


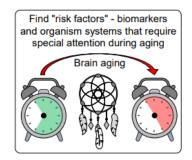
XAI methods applied to age prediction models across organ systems

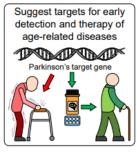


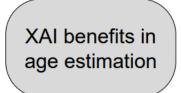
Added value of applying XAI methods to age prediction tasks

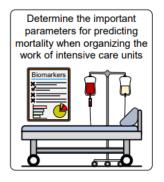


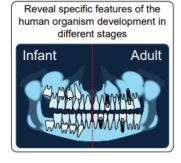


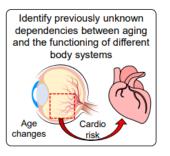


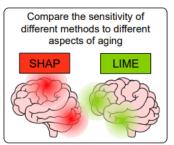












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