**Dataset**

1. the targets (ADHD diagnosis and sex)

(1214\*3)

1. functional MRI connectome matrices

(1214\*19901)

This processing pipeline converts the raw time series into a statistical representation of inter-regional connectivity, making it suitable for subsequent machine learning models.

1. socio-demographic information, e.g., subject’s “handedness” or “parent’s education level”, emotions (“Strength and Difficulties Questionnaire”), and parenting information (“Alabama Parenting Questionnaire”). These include both quantitative and categorical metadata.

categorical (1214\*9)

quantitative (1214\*19)

missing value:

participant\_id 0

Basic\_Demos\_Enroll\_Year 0

Basic\_Demos\_Study\_Site 0

PreInt\_Demos\_Fam\_Child\_Ethnicity 43

PreInt\_Demos\_Fam\_Child\_Race 54

MRI\_Track\_Scan\_Location 3

Barratt\_Barratt\_P1\_Edu 15

Barratt\_Barratt\_P1\_Occ 31

Barratt\_Barratt\_P2\_Edu 198

Barratt\_Barratt\_P2\_Occ 222

dtype: int64

participant\_id 0

EHQ\_EHQ\_Total 13

ColorVision\_CV\_Score 23

APQ\_P\_APQ\_P\_CP 12

APQ\_P\_APQ\_P\_ID 12

APQ\_P\_APQ\_P\_INV 12

APQ\_P\_APQ\_P\_OPD 12

APQ\_P\_APQ\_P\_PM 12

APQ\_P\_APQ\_P\_PP 12

SDQ\_SDQ\_Conduct\_Problems 9

SDQ\_SDQ\_Difficulties\_Total 9

SDQ\_SDQ\_Emotional\_Problems 9

SDQ\_SDQ\_Externalizing 9

SDQ\_SDQ\_Generating\_Impact 9

SDQ\_SDQ\_Hyperactivity 9

SDQ\_SDQ\_Internalizing 9

SDQ\_SDQ\_Peer\_Problems 9

SDQ\_SDQ\_Prosocial 9

MRI\_Track\_Age\_at\_Scan 360

图表, 直方图

描述已自动生成

Model options:

**Graph Neural Networks (GNN):**

Graph Neural Networks (GNN) are well-suited for processing functional MRI connectome matrices because they directly model graph-structured data. In this scenario, each brain region is treated as a node and the connectivity between regions as weighted edges. GNNs use message-passing and aggregation techniques to capture both local and global topological patterns, effectively revealing complex inter-regional interactions. Additionally, they can seamlessly integrate multimodal information such as socio-demographic data, enhancing predictive performance in tasks like ADHD diagnosis and sex classification. Their flexibility, interpretability, and robustness make them an excellent choice for neuroimaging applications.

https://doi.org/10.1016/j.media.2018.06.001. This method gains wide recognition.

**Graph Convolutional Networks (GCN):**

Graph Convolutional Networks (GCN) are a specialized form of GNN that perform convolution operations on graph data, making them particularly effective for processing functional MRI connectome matrices. In these matrices, brain regions are nodes and their functional correlations form weighted edges. GCNs aggregate information from each node’s neighborhood, capturing local connectivity and overall network structure. They reduce model complexity through weight sharing, which is advantageous with high-dimensional data and limited samples. Numerous studies have demonstrated that GCNs achieve competitive performance in neurological disorder classification.

https://doi.org/10.1007/978-3-319-66182-7\_55. They continue to show promise.

**BrainNetCNN:**

BrainNetCNN is a specialized convolutional neural network designed specifically for brain connectivity matrices. It introduces unique convolution filters that operate on edges and nodes, effectively capturing both edge-to-edge and node-to-graph interactions. This design leverages the inherent structure of functional MRI connectome data by processing connectivity matrices as structured images, thus extracting discriminative features for neurological disorder classification. It has demonstrated strong performance and interpretability in tasks such as ADHD diagnosis by highlighting critical brain connections.

https://doi.org/10.1016/j.neuroimage.2016.09.046. Its tailored architecture makes it highly effective for analyzing complex brain network patterns. It remains a robust and innovative solution truly.