BrainSTEAM: A Practical Pipeline for Connectome-Based fMRI Analysis Toward Brain Disorder Classification

Applications

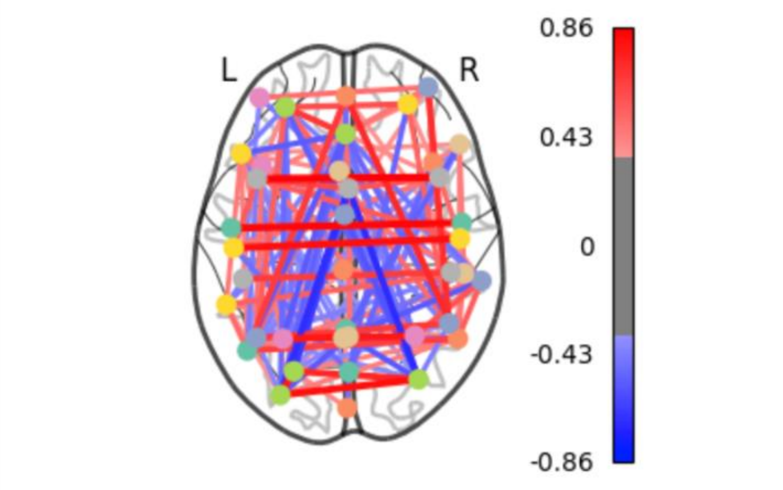
Applications of Brain Network Analysis:

- More effective, efficient, and earlier diagnosis and treatment of brain disorders
- Cognitive enhancement
- Develop brain-computer interfaces (BCIs)

Current Challenges

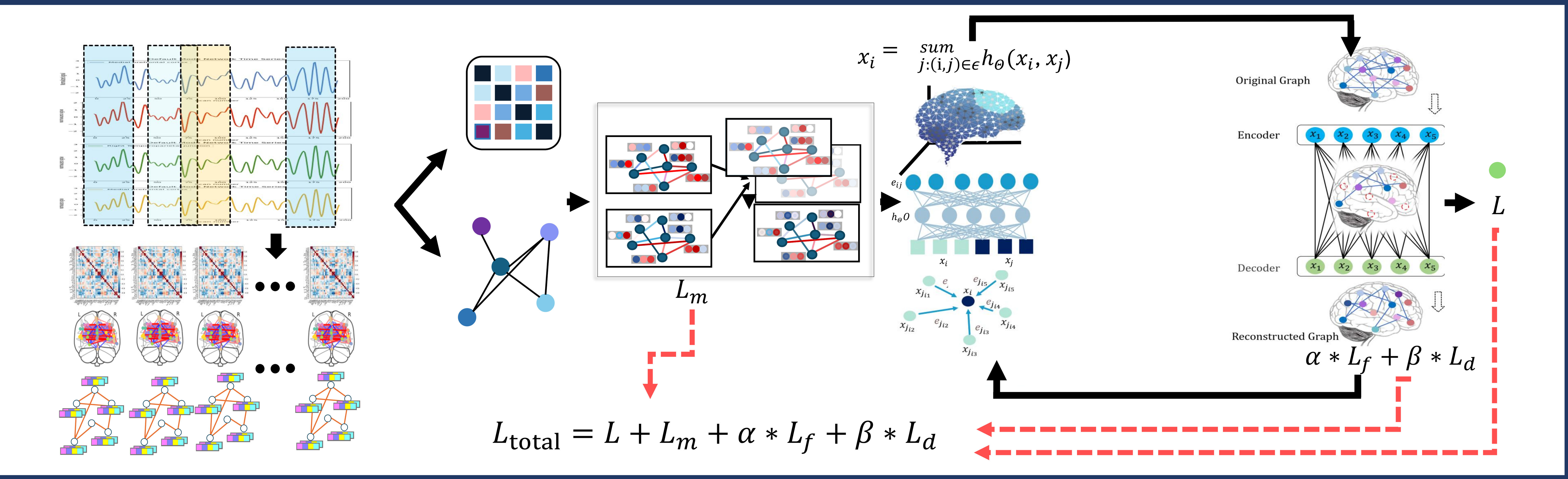
- **Underuse of Temporal Data**
- **Data Scarcity and Sparsity**
- **Structural information loss**
- **Overfitting and memorization**

Graph Example



Framework

Temporal Chunking | **Mixup** | **EdgeConv** | **Autoencoder**



Results (State of the Art Comparison)

Type	Method	ABIDE			
		Accuracy	AUC	Precision	Recall
CNNs	3D-CNN	73.3	75.8	-	-
	CNNG	72.46	79.0	-	74.35
	CNN-EW	$66.88_{\pm 0.42}$	-	-	$66.44_{\pm 0.19}$
DNNs	DNN	$77.73_{\pm 4.26}$	-	$76.73_{\pm 4.11}$	$77.16_{\pm 3.72}$
	MISO-DNN	$77.73_{\pm 4.26}$	-	$76.73_{\pm 4.11}$	$77.16_{\pm 3.72}$
	ASD-SAENet	70.8	-	-	62.2
SVMs	SVM+MTFS	$76.7_{\pm 2.7}$	$81_{\pm 0.31}$	$72.5_{\pm 3.2}$	$76.7_{\pm 2.7}$
	SVM+RFE	76.63	74.27	78.63	82.74
Graph-based	Deep-GCN	73.71	74.58	66.51	75.2
	ST-GCN	68.4	64.4	69.9	70.5
	MAGE	75.86	83.14	71.53	79.24
	e-STAGIN	$75.81_{\pm 1.70}$	$81.12_{\pm 0.30}$	$78.03_{\pm 2.34}$	$79.06_{\pm 0.89}$
	MAGIN	$78.12_{\pm 1.91}$	$85.72_{\pm 0.2}$	$78.37_{\pm 2.11}$	$79.55_{\pm 1.62}$
	IMAGIN	$79.25_{\pm 2.33}$	$86.44_{\pm 0.24}$	$81.03_{\pm 3.47}$	$79.06_{\pm 0.89}$
Mine	BrainSTEAM	$\mathbf{87.5}_{\pm 0.99}$	$\mathbf{89.23}_{\pm 0.88}$	$\mathbf{82.24}_{\pm 2.48}$	$\mathbf{96.11}_{\pm 2.47}$

Type	Method	HCP			
		Accuracy	AUC	Precision	Recall
CNNs	M2D-CNN	$83.20_{\pm 2.29}$	-	$83.63_{\pm 1.87}$	-
	3D-CNN	$82.34_{\pm 1.27}$	-	$82.68_{\pm 1.39}$	-
	3D-SepConv	$80.44_{\pm 1.16}$	-	$80.88_{\pm 1.24}$	-
LTSMs	LTSM	81.7	-	-	-
	GC-LSTM	81.50	-	-	-
GCNs	GCN	$83.98_{\pm 3.2}$	-	$84.59_{\pm 3.1}$	$87.78_{\pm 6.4}$
	ST-GCN	83.7	-	-	-
GINs	GIN-InfoMax	$84.61_{\pm 2.9}$	-	$86.19_{\pm 3.3}$	$86.81_{\pm 4.9}$
	STAGIN-SERO	$88.20_{\pm 1.33}$	$92.96_{\pm 1.87}$	-	-
Multivariate	PLS	79.9	88.125	-	-
	DECENNT	86.00	93.6	87.2	**88.6**
Mine	BrainSTEAM	$\mathbf{91.41}_{\pm 0.02}$	$\mathbf{93.67}_{\pm 0.01}$	$\mathbf{100}_{\pm 0.00}$	$78.78_{\pm 0.04}$

BrainSTEAM outperformed state-of-the-art models:

- 8.2% over next best model (IMAGIN) for ABIDE
- 3.21% over next best model (STAGIN-SERO) for HCP
- BrainSTEAM performed particularly well on the more heterogenous ABIDE dataset

Conclusion

- BrainSTEAM is the **first framework** to integrate a temporal chunking technique with mixup, EdgeConv, and Autoencoder BrainSTEAM **outperforms state of the arts**
- BrainSTEAM **effectively reduces overfitting and temporal feature loss** as shown in interpretative analysis
- BrainSTEAM **demonstrates flexibility and versatility** by achieving superior performance on two different datasets

Future Work

- Integrating an explainability component to identify key biomarkers
- Develop more accessible devices to analyze and stimulate brain connection activities.

References

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- Wang, Y., et al.: Dynamic graph cnn for learning on point clouds. ACM Trans. Graph. (2018)

All images were created by the student unless otherwise stated