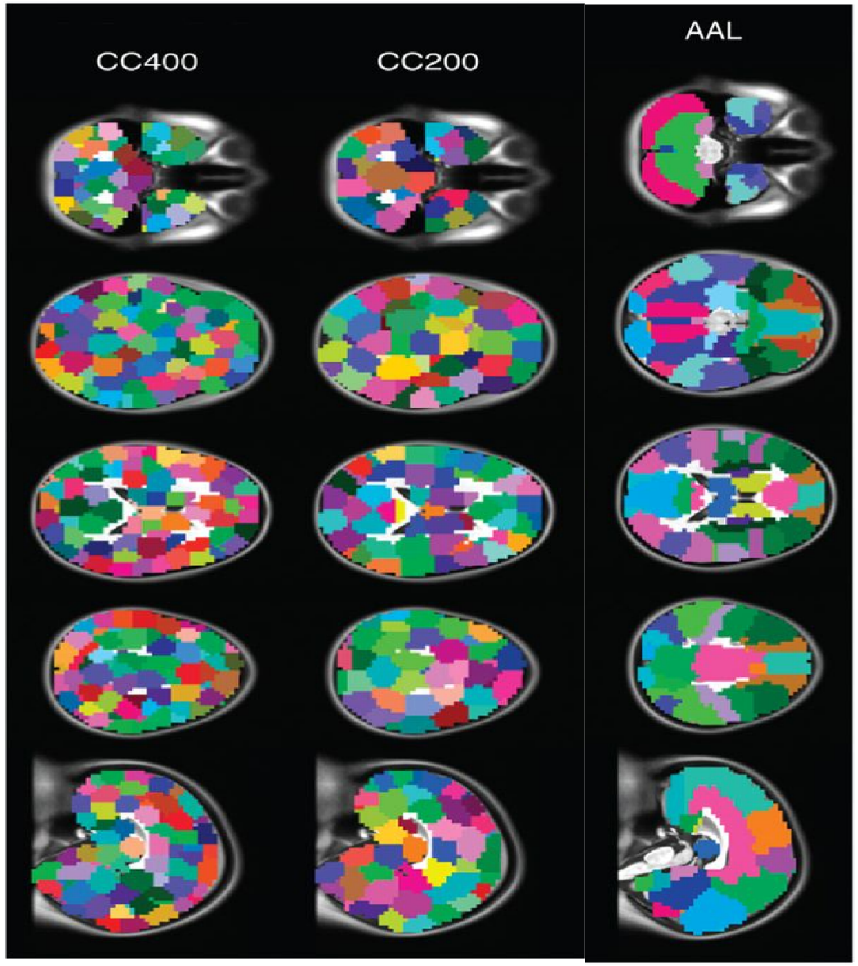
A Multichannel Deep Neural Network Model Analyzing Multiscale Functional Brain Connectome Data for Attention Deficit Hyperactivity Disorder Detection

2021.04.07

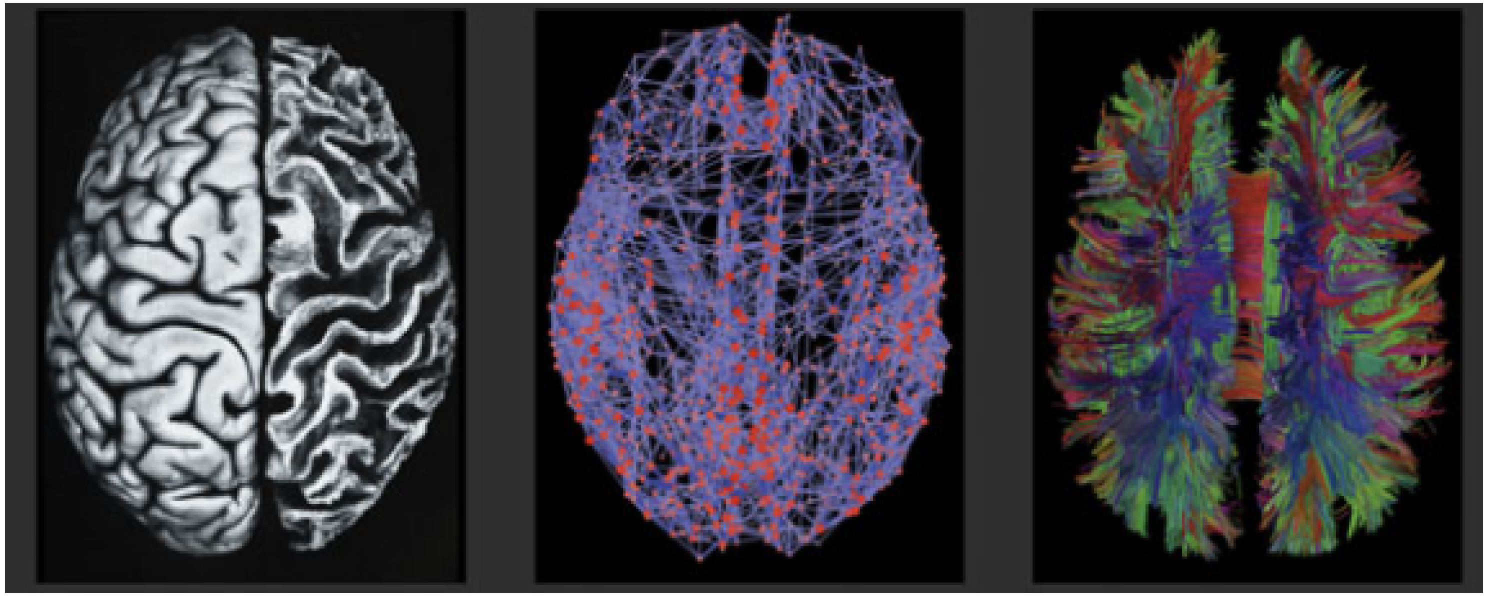
TAIL lab 정현재

CONTENTS

Brain Parcellation



Brain Connectome Data



01 Introduction - Related Work

Traditional Machine Learning & Diagnosis

<ADHD Diagnosis>

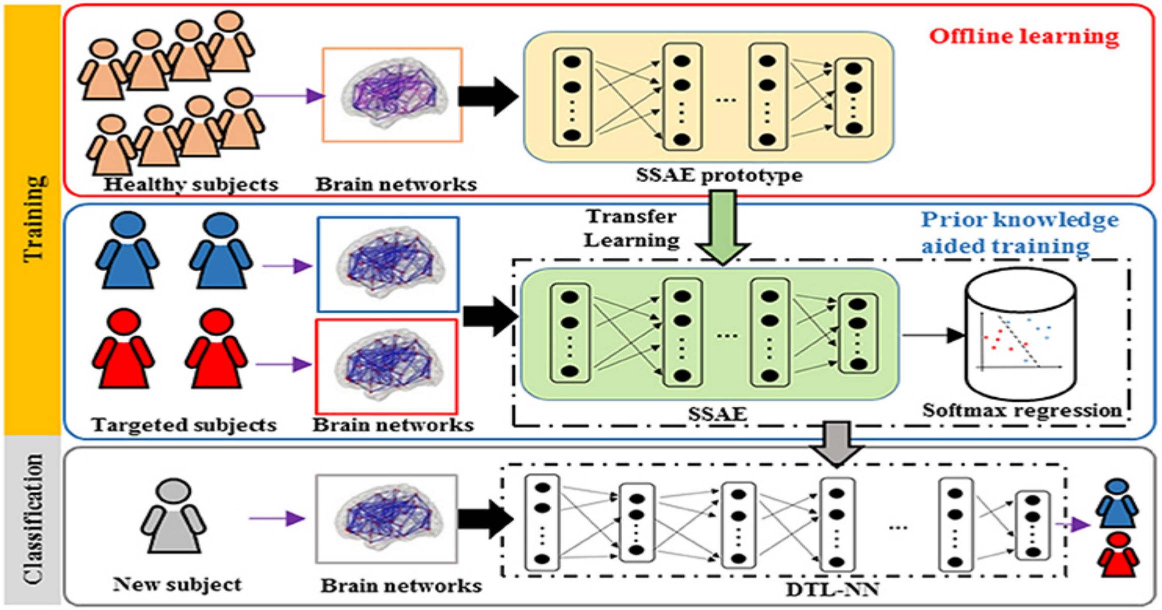
Such of symptoms like Inattention, Hyperactivity and Impulsivity is ADHD diagnosis criteria (i.e. Often fails to give close attention to details or makes careless mis-takes in schoolwork, at work, or with other activities)

TABLE. Comparison of DSM-5 and ICD-10 diagnostic criteria for ADHD

	DSM-5	ICD-10
Name	ADHD	Hyperkinetic disorder
Onset	Some symptoms before age 12	Some symptoms before age 6
Symptom criteria for children	ADHD combined: 6 of 9 symptoms of inattention and 6 of 9 symptoms of hyperactivity/impulsivity; ADHD predominantly inattentive: 6 of 9 symptoms of inattention; ADHD predominantly hyperactive/impulsive: 6 of 9 symptoms of hyperactivity/impulsivity	Must have a combination of impaired attention AND hyperactivity; the only subtype is hyperkinetic conduct disorder for those who meet criteria for both disorders
Symptom criteria for persons aged ≥ 17	ADHD combined: 5 of 9 symptoms of inattention and 5 of 9 symptoms of hyperactivity/impulsivity; ADHD predominantly inattentive: 5 of 9 symptoms of inattention; ADHD predominantly hyperactive/impulsive: 5 of 9 symptoms of hyperactivity/impulsivity	Must have a combination of impaired attention and hyperactivity
Settings	Several symptoms present in ≥ 2 settings	Full syndrome in ≥ 2 settings and observed by clinician
Duration	≥ 6 months	≥ 6 months
Impairment	Interference with social, academic, or occupational functioning; includes severity specifiers: mild, moderate, severe	Clinically significant distress or impairment in social, academic, or occupational functioning

<Single-Channel DNN>

Majority of research use single-channel deep neural Network(below. A Novel Transfer Learning Approach to Enhance Deep Neural Network Classification of Brain Functional Connectomes)



Introduction - Contribution

- The proposed multichannel deep neural network, which fuses **multiscale brain connectome data**, improved performance compared with the use of a single scale in attention deficit hyperactivity disorder detection
  - Multimodal Scale : Structural (AAL), Functional (CC200, CC400), Personal Data (PCD)

- The constructed brain functional connectome that spans multiple scales (based on both anatomic and functional criteria) may provide supplementary information for the complementary depiction of networks across the entire brain.

- The predictive power of using brain connectome at the individual scale was comparable with that of personal characteristic data.

02 Methods and Experiments

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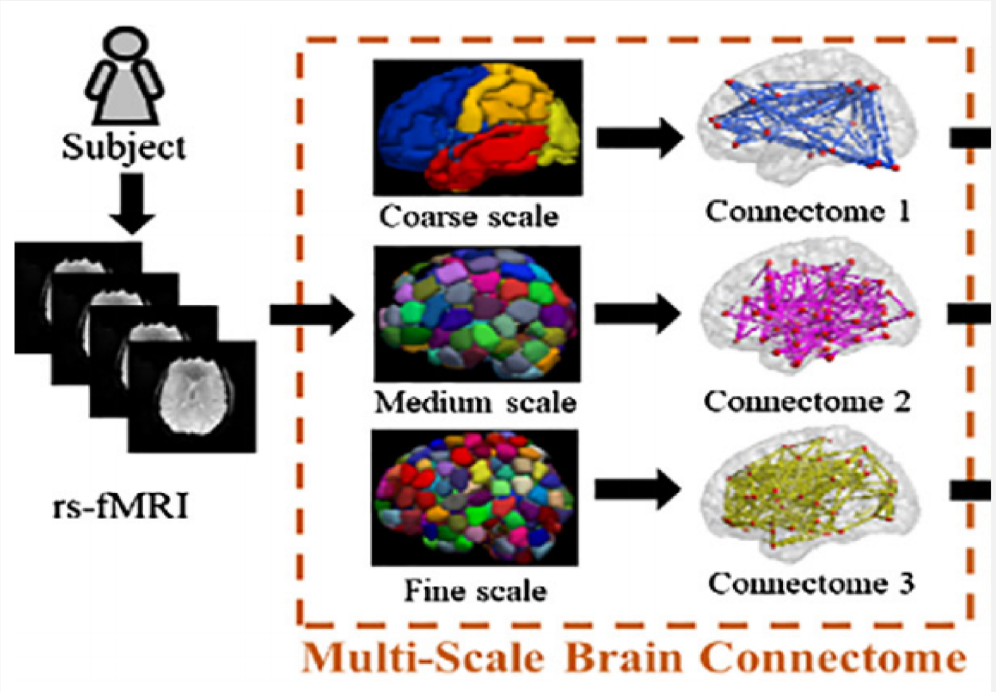
DataSet

- Data : Neuro Bureau ADHD-200, 947 Patients, Normal : ADHD = 585 : 362, Collected 9 different Hospitals and Institutions
- All participants had no history of a psychiatric, neurologic, or medical disorder other than ADHD

< Parcellation Data >



AAL (90 ROIs) — Structural Region

CC200 (190 ROIs)

CC400 (351 ROIs)

Functional Connectivity constrained spectral clustering

02 Methods and Experiments

DataSet

- Data : Neuro Bureau ADHD-200, 947 Patients, Normal : ADHD = 585 : 362, Collected 9 different Hospi-tals and Institutions
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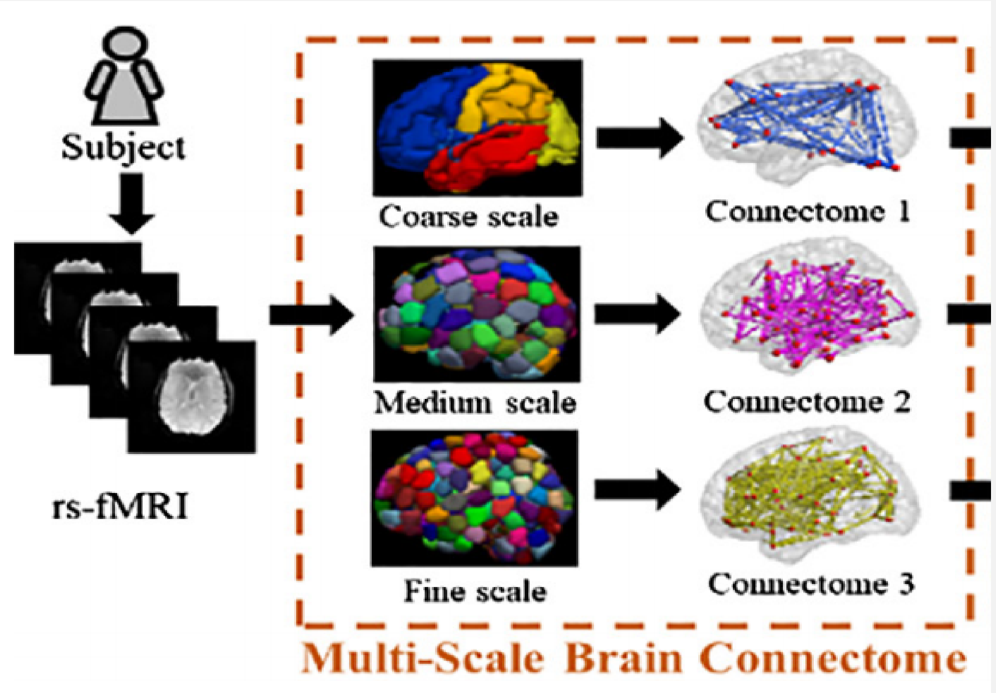
< Parcellation Data >



AAL (90 ROIs)

CC200 (190 ROIs)

CC400 (351 ROIs)

< Parcellation Process >

Problem : Too many voxel values aggregate -> computa-tional cost is too expensive, noisy

Solution : Voxel-based to Parcel Based, Analyze ROI average properties,

60~1000 nodes

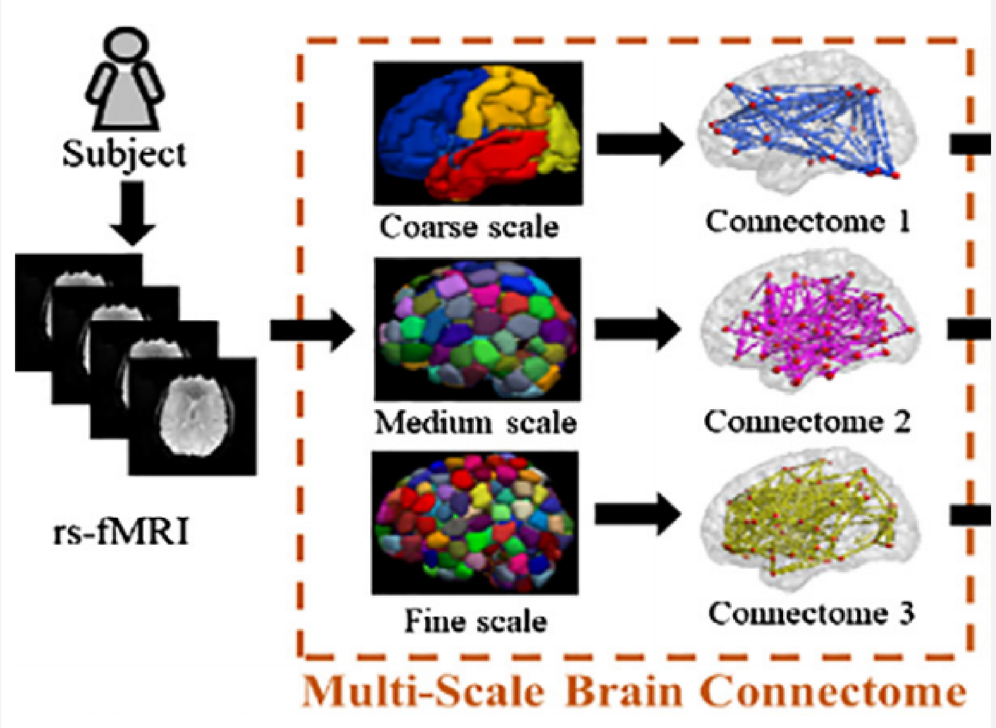
More : Athena Pipeline

02 Methods and Experiments

DataSet

- Data : Neuro Bureau ADHD-200, 947 Patients, Normal : ADHD = 585 : 362, Collected 9 different Hospitals and Institutions

< Parcellation Data >



AAL (90 ROIs)

CC200 (190 ROIs)

CC400 (351 ROIs)

< PCD >

Personal Characteristic Data

Parameter	ADHD (n = 246)	Control (n = 346)	P Value*
Age (y)	11.4 ± 2.46	11.8 ± 2.64	.04
Full-scale IQ	106.2 ± 13.9	113.9 ± 13.2	<.0001
Verbal IQ	109.0 ± 15.3	115.5 ± 13.7	<.0001
Performance IQ	102.3 ± 14.6	110.1 ± 13.9	<.0001
Male sex†	193 (78.5)	192 (55.5)	<.0001
Right-handedness†	241 (98.0)	338 (97.7)	.82

Note.—Unless otherwise indicated, data are mean ± standard deviation. To compare attention deficit hyperactivity disorder (ADHD) and control subjects, we used a χ^2 test for binary variables and a Student t test for continuous variables. IQ = intelligence quotient.

* P values are testing differences between ADHD and control cohorts.

† Data are number of patients, with percentages in parentheses.

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Proposed Framework

- ADHD , HC (Healthy Control) Binary Classification
  Input Channel = 4 (AAL, CC200, CC400, PCD)

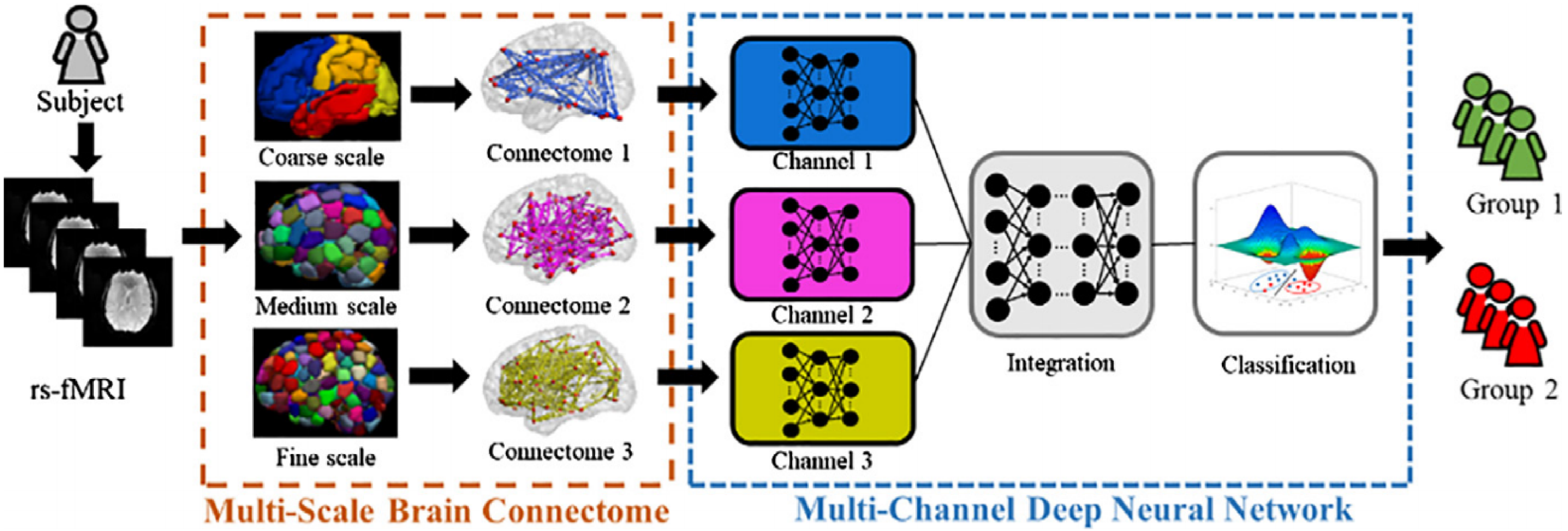
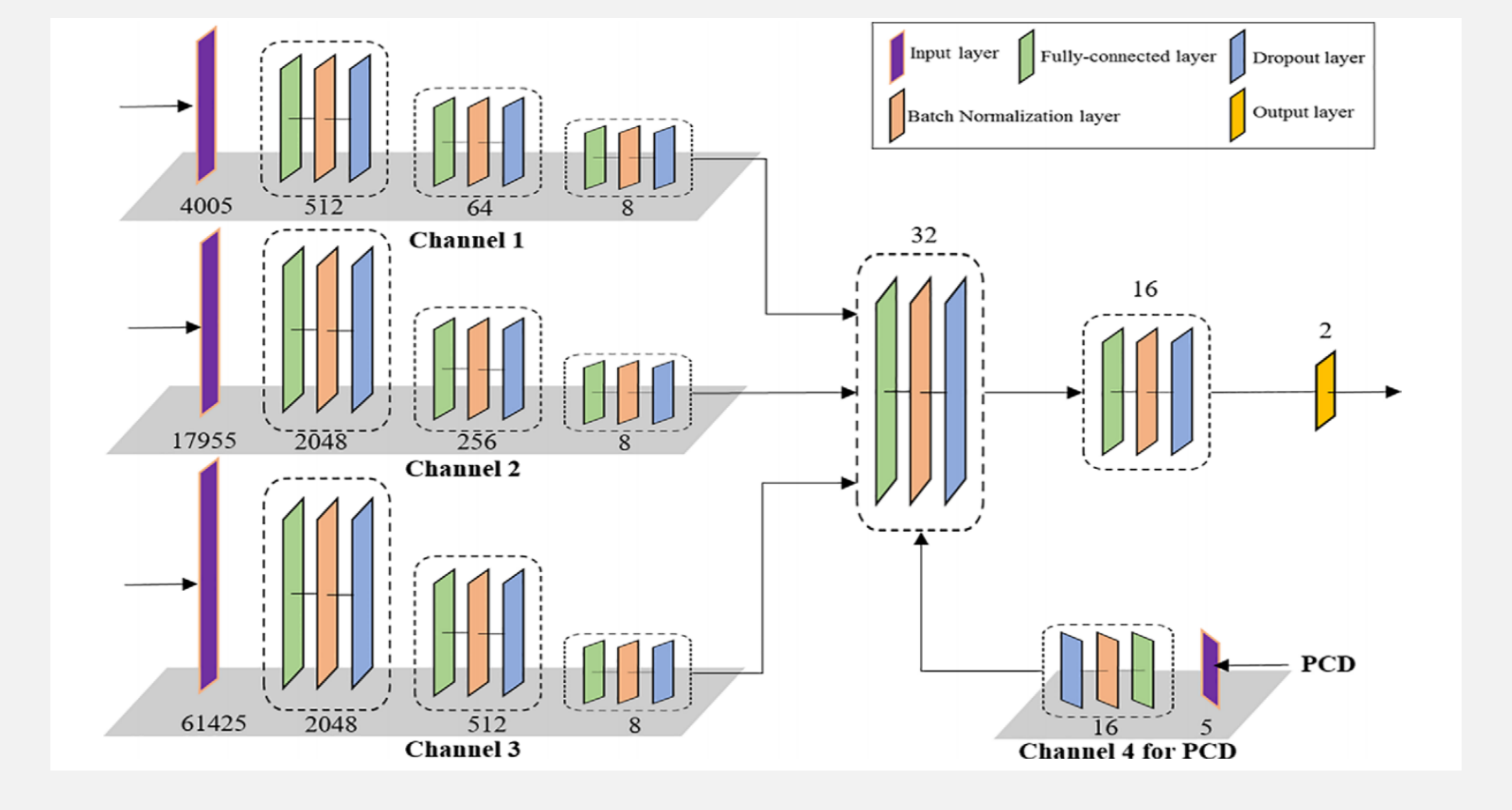


Figure 1: Schematic diagram of the proposed multichannel deep neural network model analyzing multiscale functional brain connectome for a classification task. rs-fMRI = resting-state functional MRI.

Proposed Framework

- Batch Normalization Layer : Used to solve the internal covariate shift problem (robust model)
- Dropout Layer : high dimension Connectome data -> Prevent Computational Cost, Overfitting



Train & Loss Function

- w = weight, b = bias, f = activation function (ReLU), Lambda = Regularization Control Parameter

  Cost = Binary CE Loss + L2 Regularization $p(y_i \mid x_i; W; b)$ and y_i = Output, Label

< Proposed Framework >

$$h_{W,b}(x) = f\left(\sum_{i=1}^{j} w_i x_i + b\right)$$

$$cost(W,b;x,y) = -\frac{1}{N}\boxed{\sum_{i=1}^{N} y_i \log\left(p\left(y_i \middle| \mathbf{x}_i; W; b\right)\right) + \left(1 - y_i\right)\log\left(p\left(y_i \middle| \mathbf{x}_i; W; b\right)\right)}$$

$$+ \frac{\lambda}{2N}\boxed{\sum_{l}\sum_{i}\sum_{j}\left(W_{ji}^{(l)}\right)^2}$$

Binary CE Loss

L2 Regularization

Validation Set

- Divided into Cross Validation Cohort, Hold-out Cohort (97 patients)

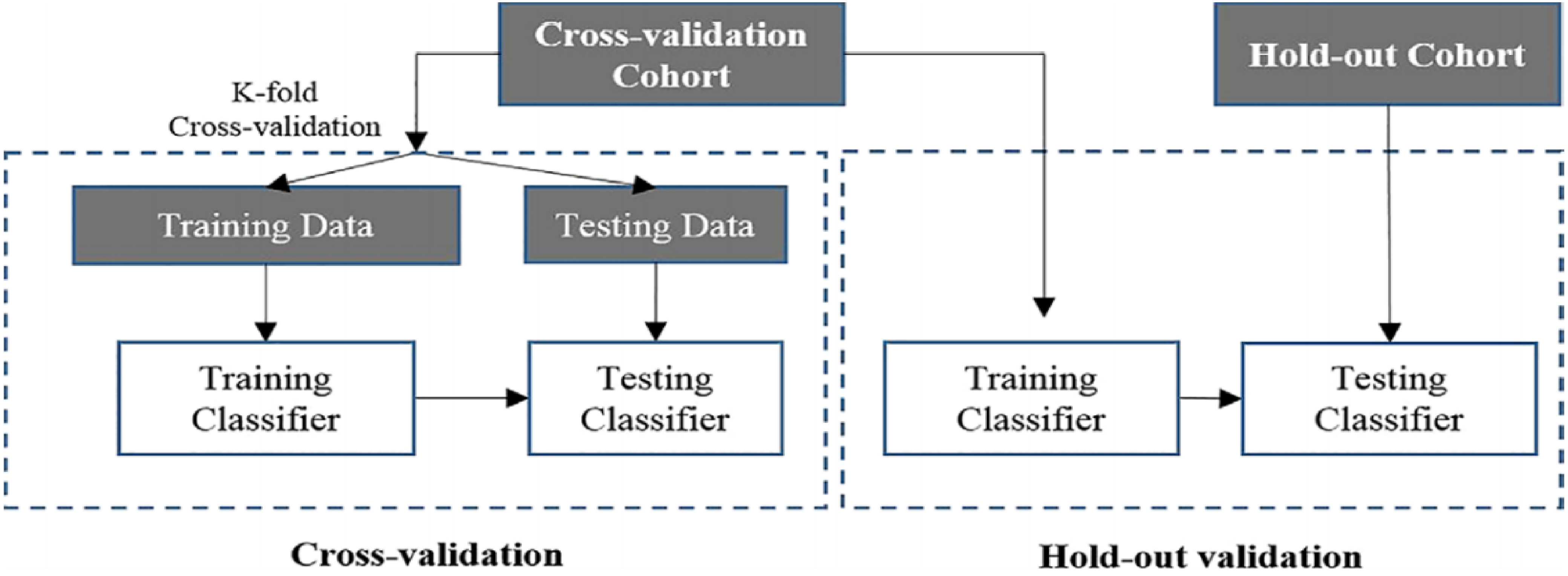


Figure 3: Schemes of cross-validation and hold-out validation.

03 Methods and Experiments

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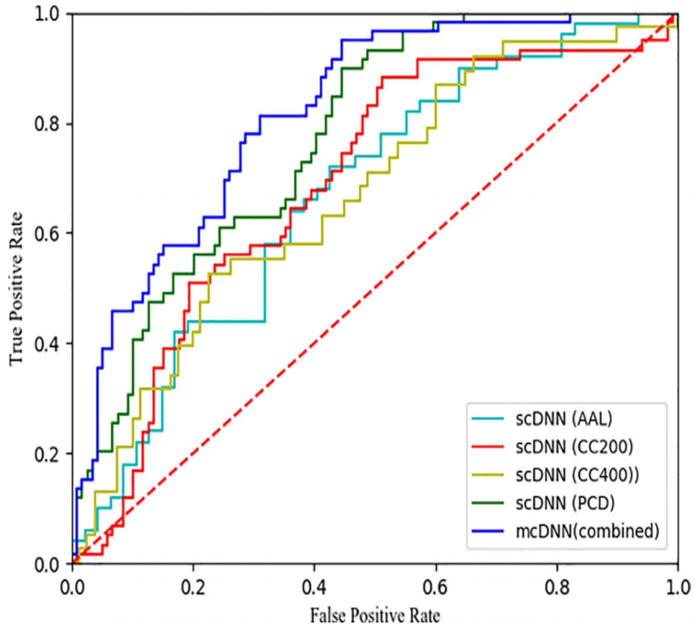
Experiments

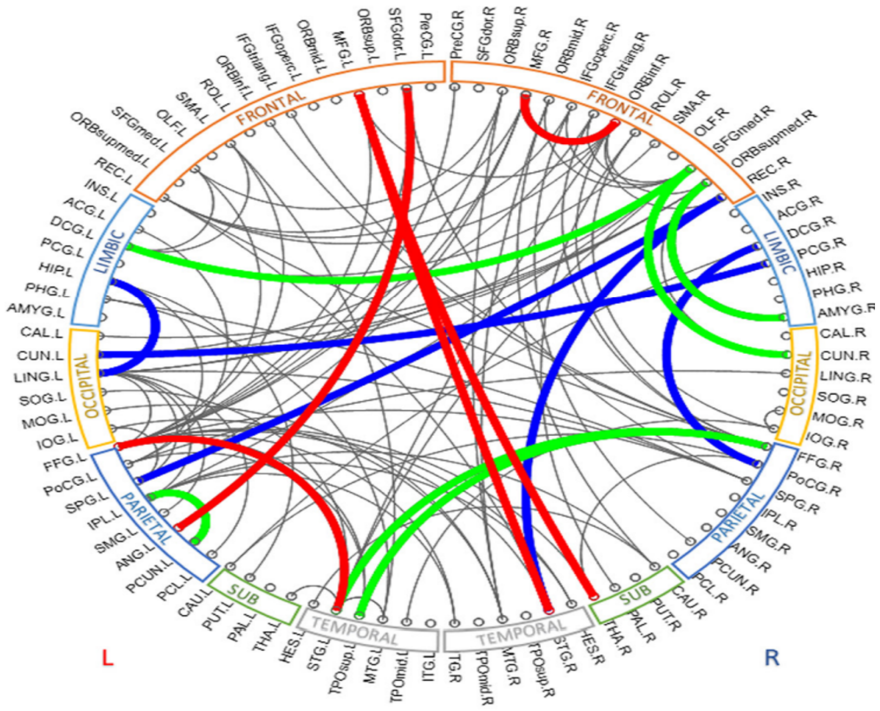
Table 3: Cross-Validation: Performance of Single- and Multichannel Deep Neural Networks on Attention Deficit Hyperactivity Disorder Classification

Parameter	Accuracy (%)	Specificity (%)	Sensitivity (%)	AUC
scDNN (AAL)	71.4 (69.8, 73.1)	76.6 (74.2, 78.9)	65.3 (60.4, 66.9)	0.67 (0.66, 0.68)
scDNN (CC200)	68.5 (66.4, 70.7)	73.1 (70.4, 75.6)	62.7 (58.8, 66.4)	0.69 (0.67, 0.70)
scDNN (CC400)	70.6 (68.4, 72.7)	73.6 (70.4, 77.0)	67.4 (64.3, 70.6)	0.67 (0.66, 0.68)
scDNN (PCD)	73.1 (71.7, 74.7)	80.4 (78.0, 82.6)	63.5 (60.9, 66.1)	0.77 (0.76, 0.78)
mcDNN (PCD + AAL)	76.9 (74.2, 78.1)	84.5 (83.6, 86.4)	66.3 (64.0, 69.7)	0.78 (0.76, 0.79)
mcDNN (PCD + CC200)	76.6 (73.4, 79.2)	81.4 (77.3, 84.1)	70 (67.5, 73.6)	0.8 (0.79, 0.81)
mcDNN (PCD + CC400)	74.5 (72.1, 77.3)	78.3 (75.6, 81.0)	69.1 (67.8, 72.1)	0.77 (0.75, 0.78)
mcDNN (combined)	78.3 (76.6, 79.9)	84.2 (81.5, 86.9)	70.0 (67.5, 72.7)	0.82 (0.80, 0.83)

Note.—Data in parentheses are 95% confidence intervals. AAL = automated anatomic labeling, AUC = area under the receiver operating characteristic curve, CC200, CC400 = brain connectome constructed on functionally defined parcellations, Combined = fusion of multiscale brain connectome data and PCD, mcDNN = multichannel deep neural network, PCD = personal characteristic data (age, sex, handedness, and three individual measures of intelligence quotients), scDNN = single-channel deep neural network.



Experiments



a.

Top discriminative features			
Brain Region A	**Abbr.**	**Brain Region B**	**Abbr.**
Left Superior Frontal Gyrus (dorsal)	SFGdor.L	Left Angular Gyrus	ANG.L
Left Middle Frontal Gyrus (superior)	MFG.L	Right Thalamus	THA.R
Left Middle Frontal Gyrus (superior)	MFG.L	Right Superior Temporal Gyrus	STG.R
Right Middle Frontal Gyrus (superior)	MFG.R	Right Orbitofrontal Cortex (inferior)	ORBinf.R
Left Fusiform Gyrus	FFG.L	Left Superior Temporal Gyrus	STG.L
Left Superior Frontal Gyrus (medial)	SFGmed.R	Left Middle Cingulate Gyrus	DCG.L
Left Superior Frontal Gyrus (medial)	SFGmed.R	Right Cuneus	CUN.R
Right Orbitofrontal Cortex (medial)	ORBsupmed.R	Right Amygdala	AMYG.R
Right Fusiform Gyrus	FFG.R	Left Superior Temporal Gyrus	STG.L
Right Fusiform Gyrus	FFG.R	Left Temporal Pole (superior)	TPOsup.L
Left Inferior Parietal Lobule	IPL.L	Right Precuneus	PCUN.L
Right Rectus Gyrus	REC.R	Left Superior Parietal Gyrus	SPG.L
Right Rectus Gyrus	REC.R	Right Superior Temporal Gyrus	STG.R
Right Middle Cingulate Gyrus	DCG.R	Right Postcentral Gyrus	PoCG.R
Right Posterior Cingulate Gyrus	PCG.R	Left Cuneus	CUN.L
Left Hippocampus	HIP.L	Left Lingual Gyrus	LING.L

Conclusion

- Developed an mcDNN model and tested the model on an application of ADHD detection

- Using Multimodal data (strucural image, fiber pathway, PCD data) measured at Different institutions make robust, useful model

Limitation

- For Multi channel Deep Neural Network, use brute force -> make limitation

- Brain Parcellation's (CC200, CC400, AAL) Criteria is adult brains.
  -> ADHD 200 Dataset is almost children or young adult

Discussion

- Binary Classification -> Compare ADHD and HC (Healthy Control)
  Difference of Same ADHD Label?

- rs-fmri contain time sequence -> time sequence consider criteria