Slide

- title of the slide with subtitle
- guide the slide
- slide, not showing but explaining what is new
- make some marker check or something on the table
- abide dataset no preprocessed

MLG 21
TEAM E: BRAIN DISORDER GROUP
FINAL REPORT

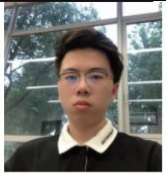
Classifying Autism Spectrum Disorder Using Machine Learning through ABIDE Dataset

Keywords: Brain Disorder, Autism Spectrum Disorder, Machine Learning, Deep Neural Network, Autoencoder

Hans Han
Stephanie Shao
Yaluo Wang


Stephanie Shao

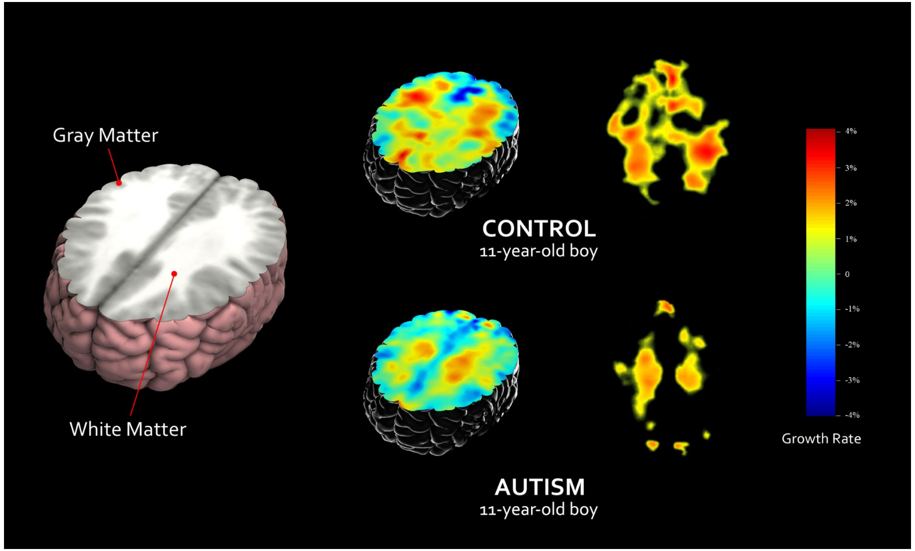

Yaluo Wang


Hans Han

Autism Spectrum Disorder (ASD)

- Problem in determine the reason of disease: Genetic? Brain Damage?
- Increase cases in recent decades;
- Traditionally diagnosed by behavioral observation;
- Reliable biomarkers behind remain to be identified;
- Hope to be diagnosed more quantitatively and more accurately.

Autism Spectrum Disorder (ASD) with brain imaging

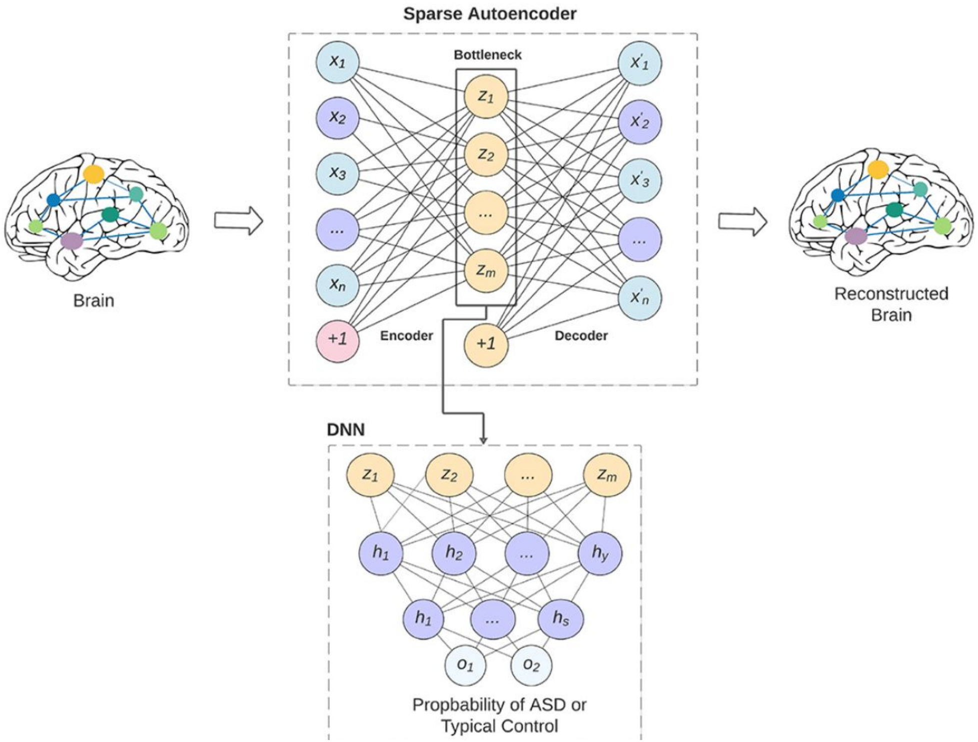


- A delay in the growth rate of the White Matter which is responsible for the connecting brain regions for social and language abilities.

- Gray Matter is not sufficiently pruned away, leaving trouble in the putamen for learning and the anterior cingulate for regulating emotions and cognitions.

Related Work with similiar ASD topics

- "Identification of autism spectrum disorder using deep learning and the ABIDE dataset"——Heinfeld et al.(2018)
  - https://www.sciencedirect.com/science/article/pii/S2213158217302073
- "ASD-DiagNet: A Hybrid Learning Approach for Detection of Autism Spectrum Disorder Using fMRI Data"——Eslami et al.(2019)
  - https://www.frontiersin.org/articles/10.3389/fninf.2019.00070/full
- "ASD-SAENet: A Sparse Autoencoder, and Deep-Neural Network Model for Detecting Autism Spectrum Disorder (ASD) Using fMRI Data"——Almuqhim et al.(2021)
  - https://www.frontiersin.org/articles/10.3389/fncom.2021.654315/full?utm_source=S-TWT&utm_medium=SNET&utm_campaign=ECO_FNINS_XXXXXXXX_auto-dlvrit



Model Structure of 'ASD-SAENet'

Our project aims and motivation

Aims

- Quantify the diagnosis of ASD and improve the accuracy from the pervious studies;
- Help find reliable connectivity biomarkers behind ASD.

Motivation

- The motivations came from the ‘ASD-SAENet’ and TAs:
  - Low accuracy of the previous studies
  - Improve by adding autoencoders and data augmentation
  - Seek for more possibility to work with one dimensional data

Model Architecture

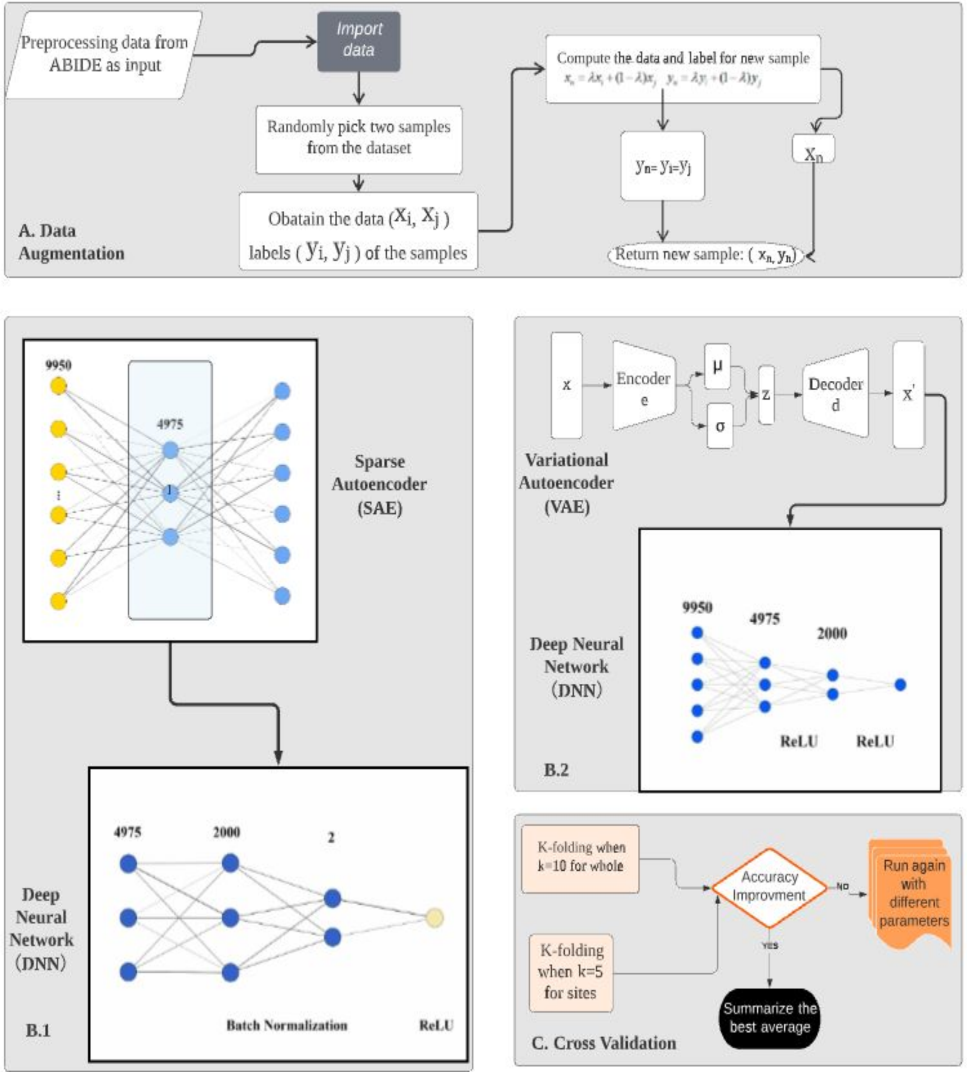
A. Data Augmentations

B. Autoencoder with Deep Neural Network

  B.1 Sparse Autoencoder with Deep Neural Network

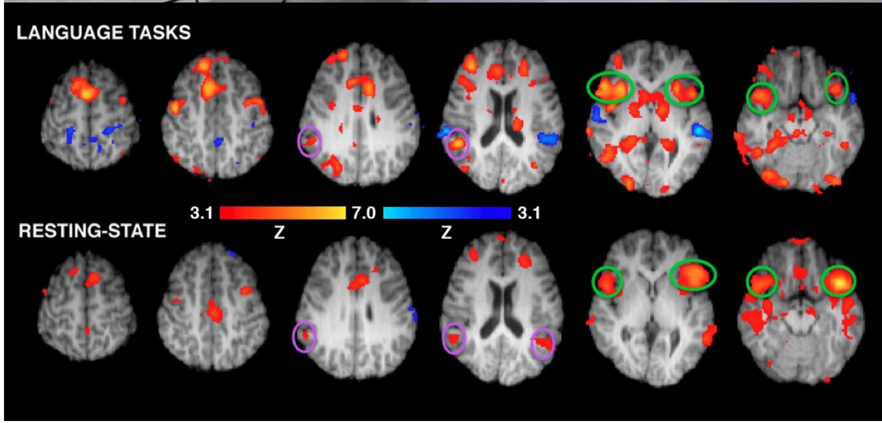
  B.2 Variational Autoencoder with Deep Neural Network

C. Cross Validation



Brain imaging technique - - functional Magnetic Resonance Images (fMRIs)

- A brain imaging technique that is used for studying brain activities;
- fMRI technology while the subject is resting is called resting state fMRI (rs-fMRI) widely for brain disorders;
- Help measure the pathological changes associated with the ASD brain;
- The brain volume is represented by a group of small cubic elements called voxels.
- A time series is extracted from each voxel by keeping track of its activity over time.



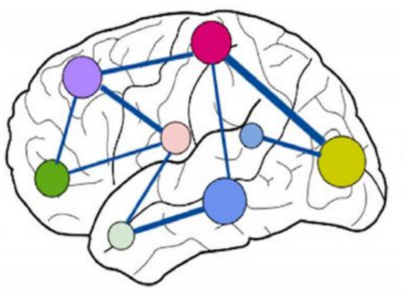
Explain Dataset: ABIDE

ABIDE

Autism Brain Imaging Data Exchange

- The ABIDE-I used in the project consists of 1112 rs-fMRI data including ASD and healthy subjectscollected from 17 different sites.
- We used fMRI data of the same group of subjects which was used in Heinsfeld et al. (2018) This set consists of 505 subjects with ASD and 530 healthy control.
- Preprocessed using C-PAC pipeline (Craddock et al., 2013) and is parcellated into 200 functionally regions generated using clustering algorithm (Craddock et al., 2012)(CC-200).

Feature Extraction



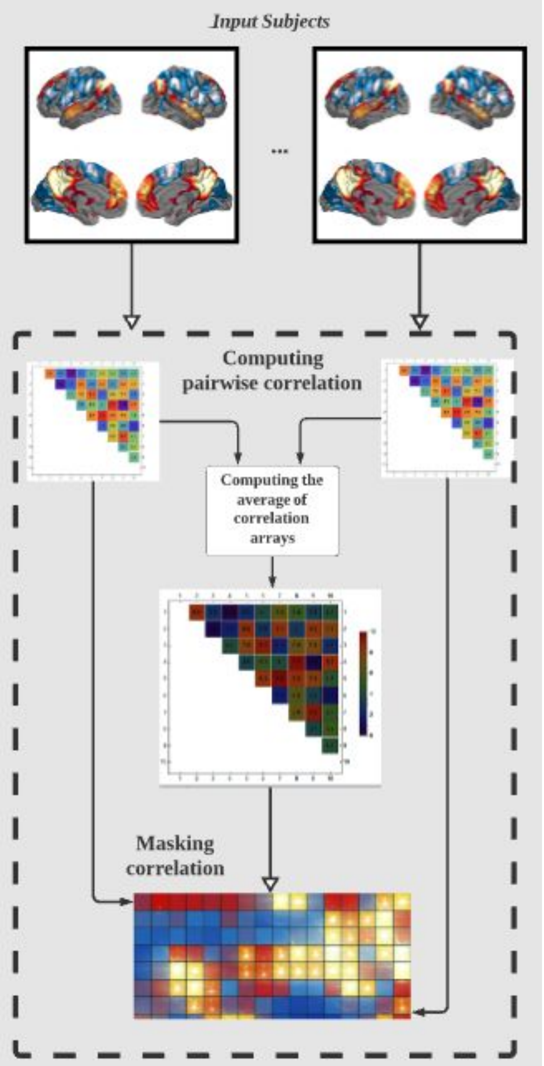
Functional connections

Correlation Measure

- Pearson correlation
- Spearman correlation

Feature Extraction

- CC200 atlas divides the brain into n = 200 regions, it then generated a matrix of 200 × 200.
- Only consider the strictly upper triangle of the matrix, and flatten it to one-dimensional vector as features.
- To reduce the dimensionality of the input, we adopted the same technique as in [Eslami et al. (2019)](#) and only considered 1/4 largest and 1/4 smallest of the average correlations.resulting in a feature vector of 9,950 values.



Data Augmentation using Linear Interpolation

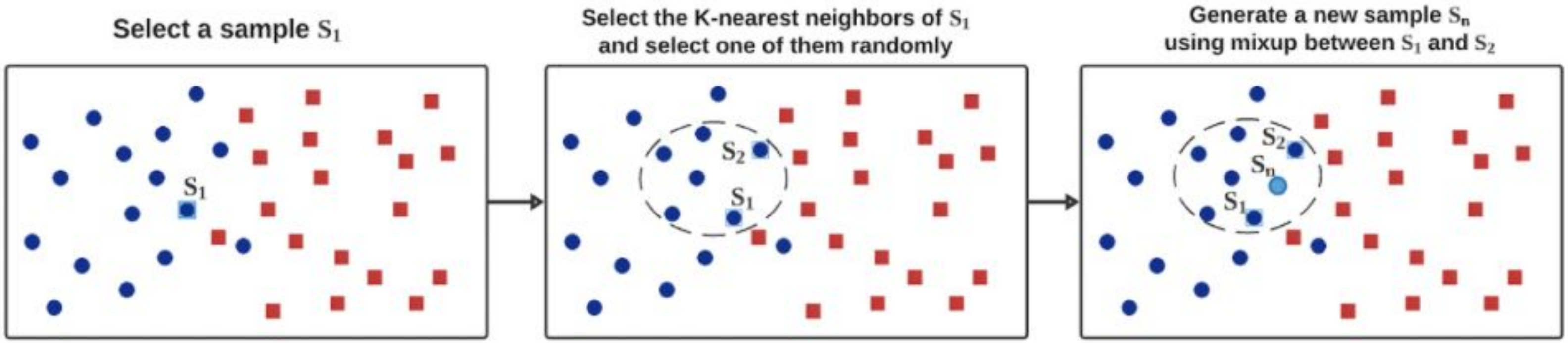
Linear Interpolation Method - - Mixup

- Mixup is a data augmentation method proprosed by MIT,which uses linear interpolation to obtain new sample data.The formula of Mixup(x represent data of samples,y represent their labels):

$$x_n = \lambda x_i + (1-\lambda)x_j \quad y_n = \lambda y_i + (1-\lambda)y_j$$

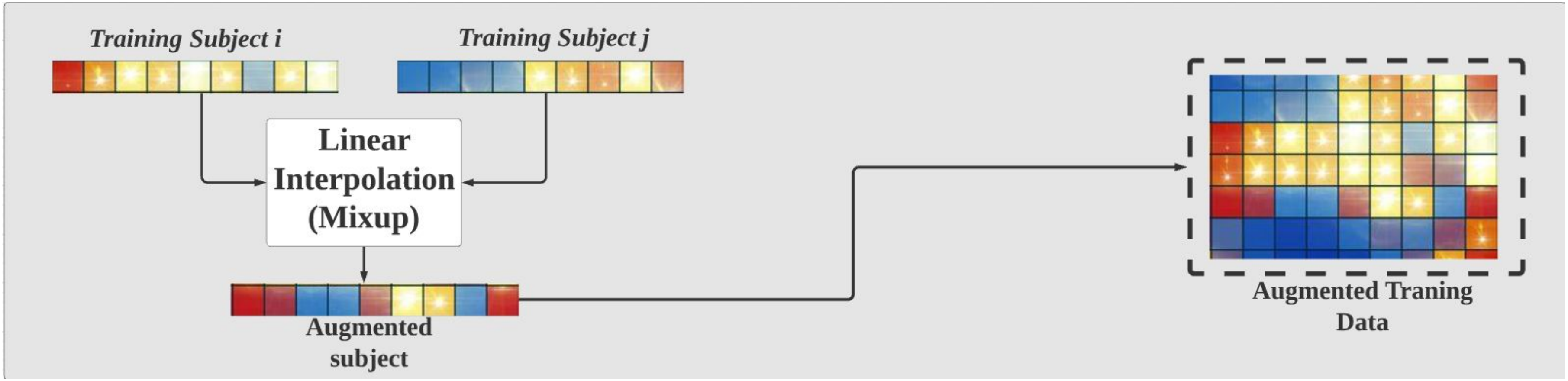
Two options for interpolation

- Interpolate between two random samples.
- interpolate between two nearest neighbors.



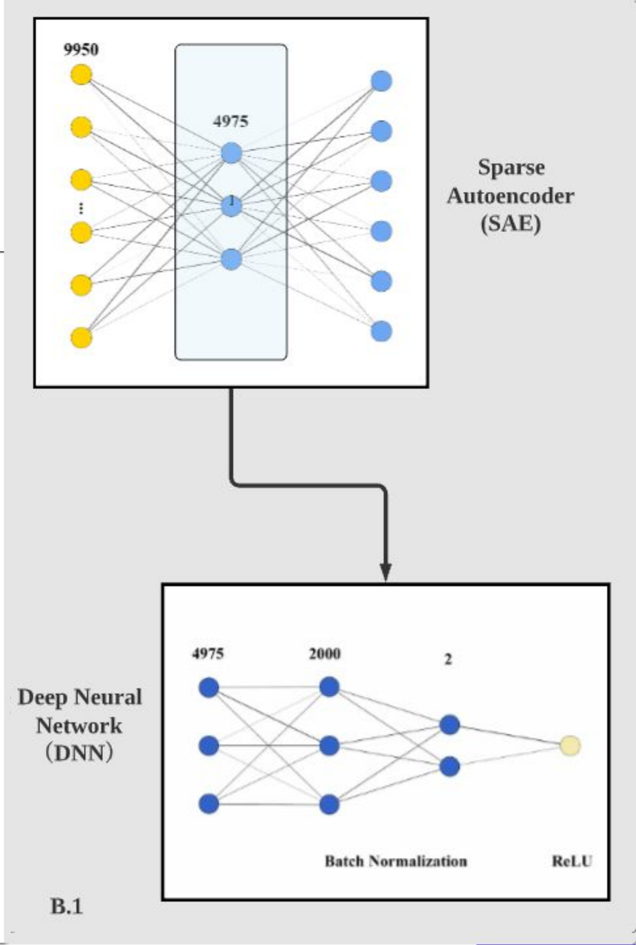
Results of Data Augmentation

- subject i and subject j are the feature vectors of the random sample we selected in the datasets and its random neighbor.
- We use these two feature vectors to generate new feature vectors of training samples by linear interpolation.Since each sample in the dataset will be used to generate a new sample, the size of our dataset will be doubled after data augmentation.



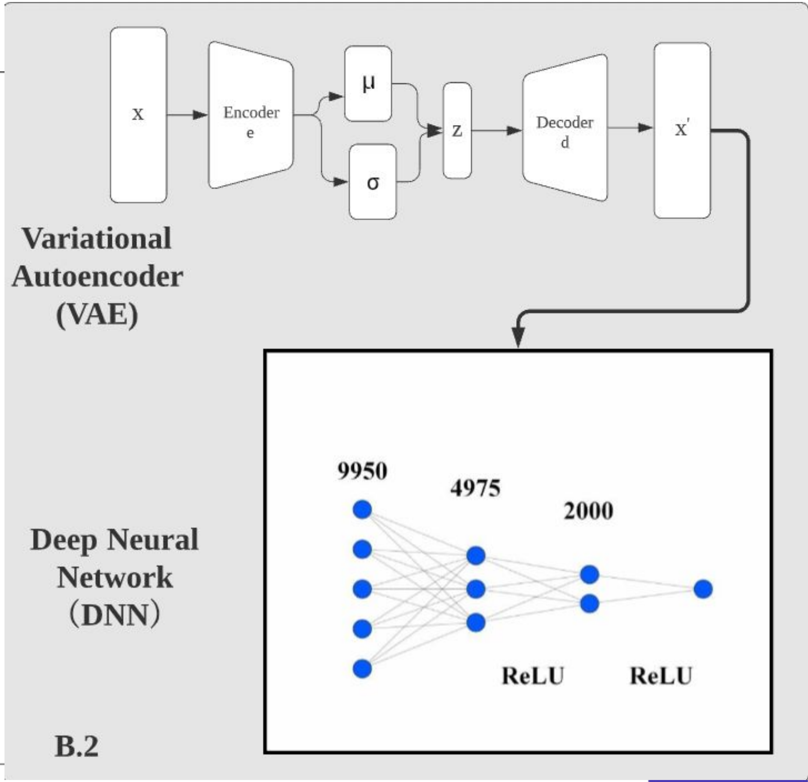
Method-Deep Neural Network behind Sparse Autoencoder

- Input Layer
  - 4,975 units
  - The bottleneck of the Sparse Autoencoder
- Hidden Layers
  - Two fully-connected layers
  - 2,000 and 2 units respectively
  - Rectified Linear Unit as the activation function
- Output Layer
  - One unit
  - Represent the predicted label of each of the input samples



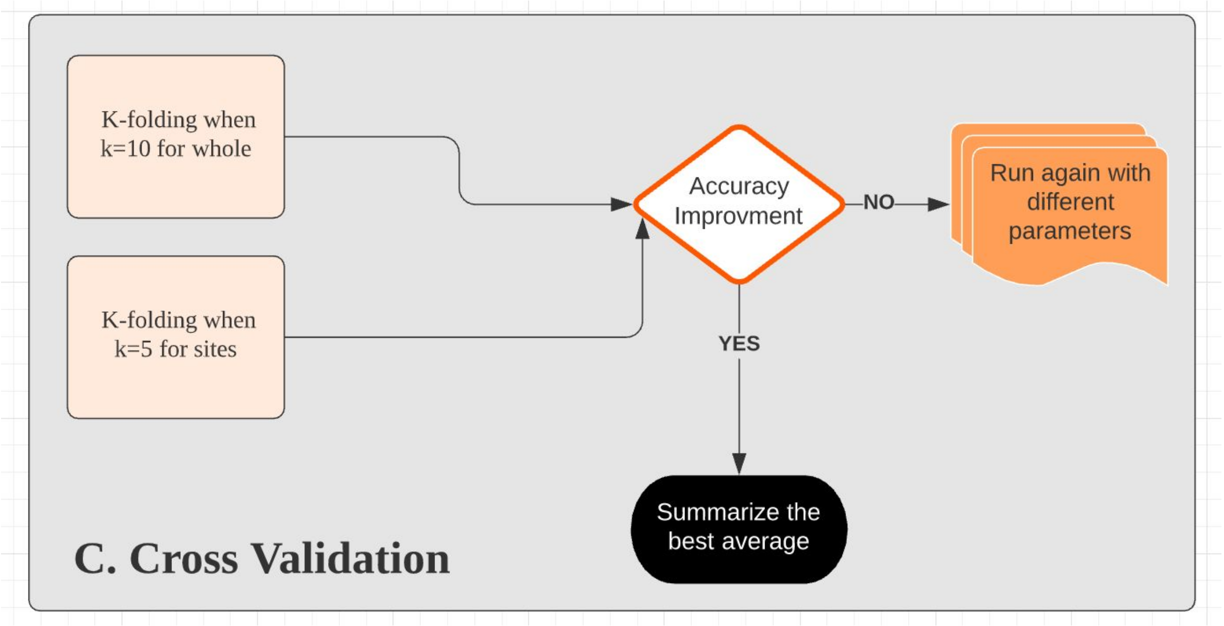
Method-Deep Neural Network behind Variational Autoencoder

- Input Layer
  - 9,950 units
  - The filtered input data with some random variables processed by the Variational Autoencoder
- Hidden Layers
  - Two fully-connected layers
  - 4,975 and 2,000 units respectively
  - Rectified Linear Units as activation function between the fully-connected layers
- Output Layer
  - One unit
  - Represent the predicted label of each of the input samples



Cross Valiadation: K-folding

- The validation set is extracted from training set data, without training it;
- The original data is divided into several K folds;
    - when k=10 to calculate the accuracy for the whole data running 10 times in the algorithm,
    - when k=5. calculate the sites due to smaller sample sizes.
- Each of k set evaluate the final result and calculate the Mean Squared Error with the means.



Result: General Accuracy

- Accuracy: determines the percentage of correctly classified subjects, whether or not the actual ASD is classified as ASD and the control group is classified as healthy.

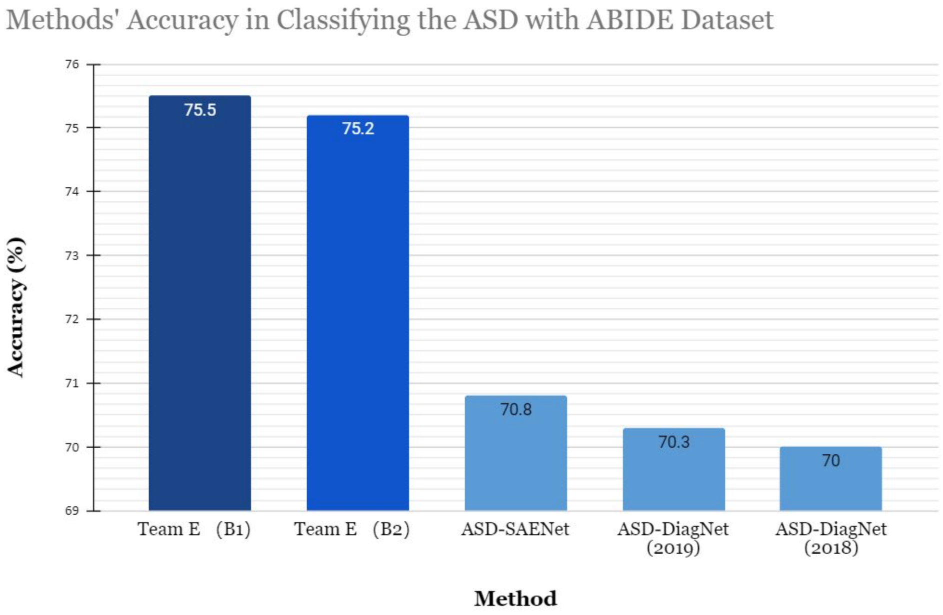
- Sensitivty: measures the percentage of actual ASD patient subjects which are accurately classified as ASD.

- Specificity: represents the percentage of actual healthy subjects which are successfully classified as healthy.

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Team E（B1）	75.5	72.8	78.1
Team E（B2）	75.2	72.3	78.1
ASD-SAENet	70.8	62.2	79.1
ASD-DiagNet (2019)	70.3	68.3	72.2
ASD-DiagNet (2018)	70	74	63

- The proposed B.1 method has significantly improved the previous studies' accuracy.

- Running Time is relative fast:
  1. ASD-DiagNet(2019) 41 min
  2. B.1 runs 2 h 38 mins
  3. B.2 runs 3 h 19 mins
  4. ASD-DiagNet(2018) 6 h

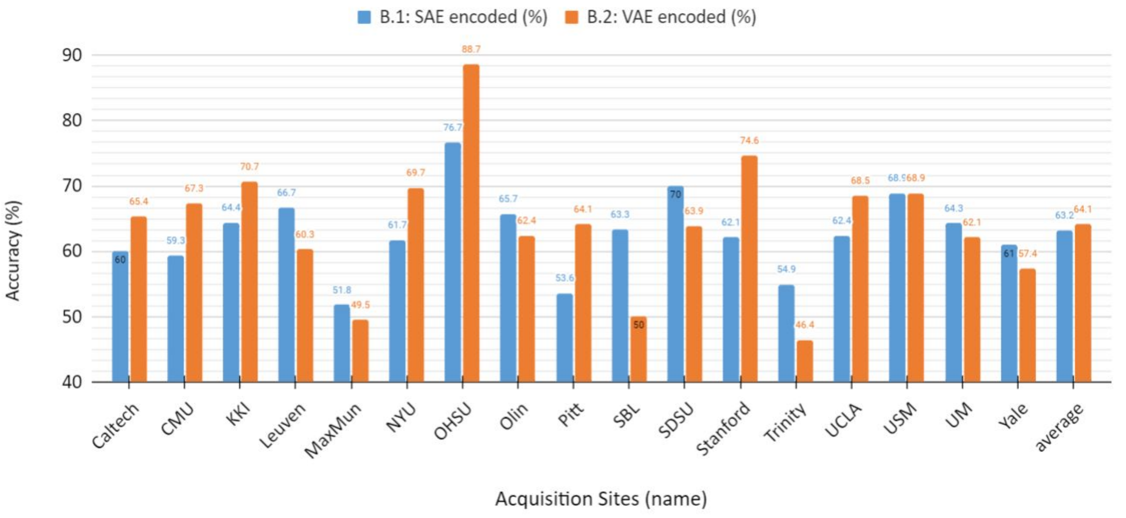


Result: Acquisition Site Accuracy

Sites	B.1: SAE encoded (%)	B.2: VAE encoded (%)
Caltech	60	65.4
CMU	59.3	67.3
KKI	64.4	70.7
Leuven	66.7	60.3
MaxMun	51.8	49.5
NYU	61.7	69.7
OHSU	76.7	88.7
Olin	65.7	62.4
Pitt	53.6	64.1
SBL	63.3	50
SDSU	70	63.9
Stanford	62.1	74.6
Trinity	54.9	46.4
UCLA	62.4	68.5
USM	68.9	68.9
UM	64.3	62.1
Yale	61	57.4
average	63.2	64.1

- The MaxMun: Ludwig Maximilians University Munich and Trinity: Trinity Centre for Health Sciences both have more people in the control group than the targeted autism group, the imbalance between the two might cause the accuracy to be lower as well.

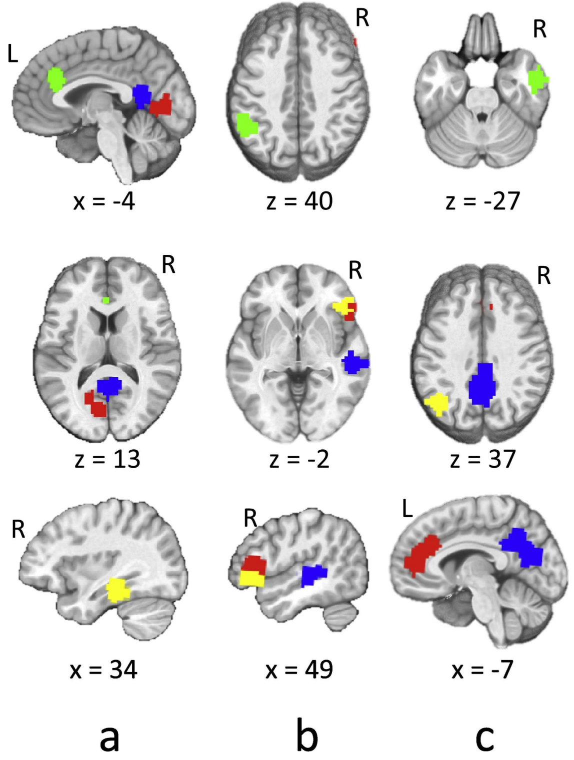
- For the OHSU: Oregon Health and Science University site includes data that is suitable to the model of VAE after the reconstructed input, the accuracy is higher.



Result: Anticorrelation Biomarkers on fMRI

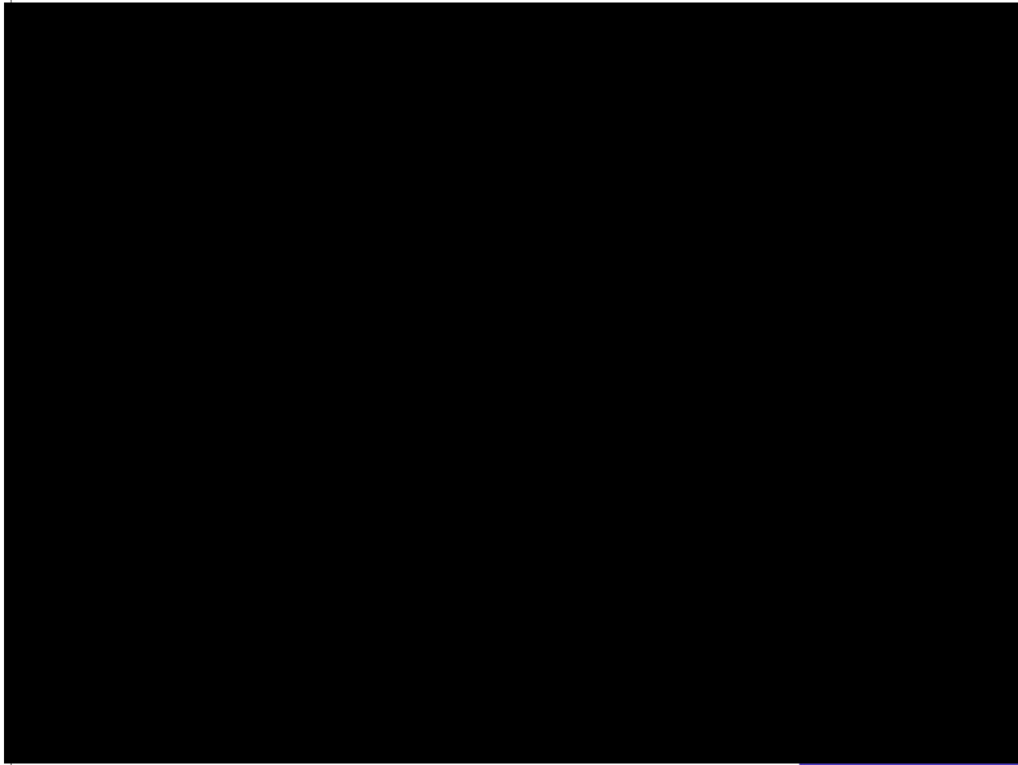
- The anterior (paracingulate gyrus), posterior (supramarginal gyrus) and of frontal-temporal areas (e.g. middle temporal and inferior frontal; fusiform gyrus and orbital cortex);
- Areas of the ASD subjective brains important features for classification model;
- Anticorrelation that reflects underconnectivity.

Area Number	Source Green Area	Red Marker Area	Blue Marker Area	Yellow Marker Area
a	Paracingulate Gyrus	Middle Temporal Gyrus; posterior division	Precuneous Cortex	Temporal Fusiform Cortex; posterior division
b	Supramarginal Gyrus	Inferior Frontal Gyrus	Superior Temporal Gyrus	Frontal Orbital Cortex
c	Middle Temporal Gyrus	Paracingulate Gyrus	Precuneus Cortex, Cingulate Gyrus	Lateral Occipital Cortex



Future Goals

- Interpret the results from the medical perspective with more Region of Interest Connectivity.
- Apply this model to the data of other brain disorders

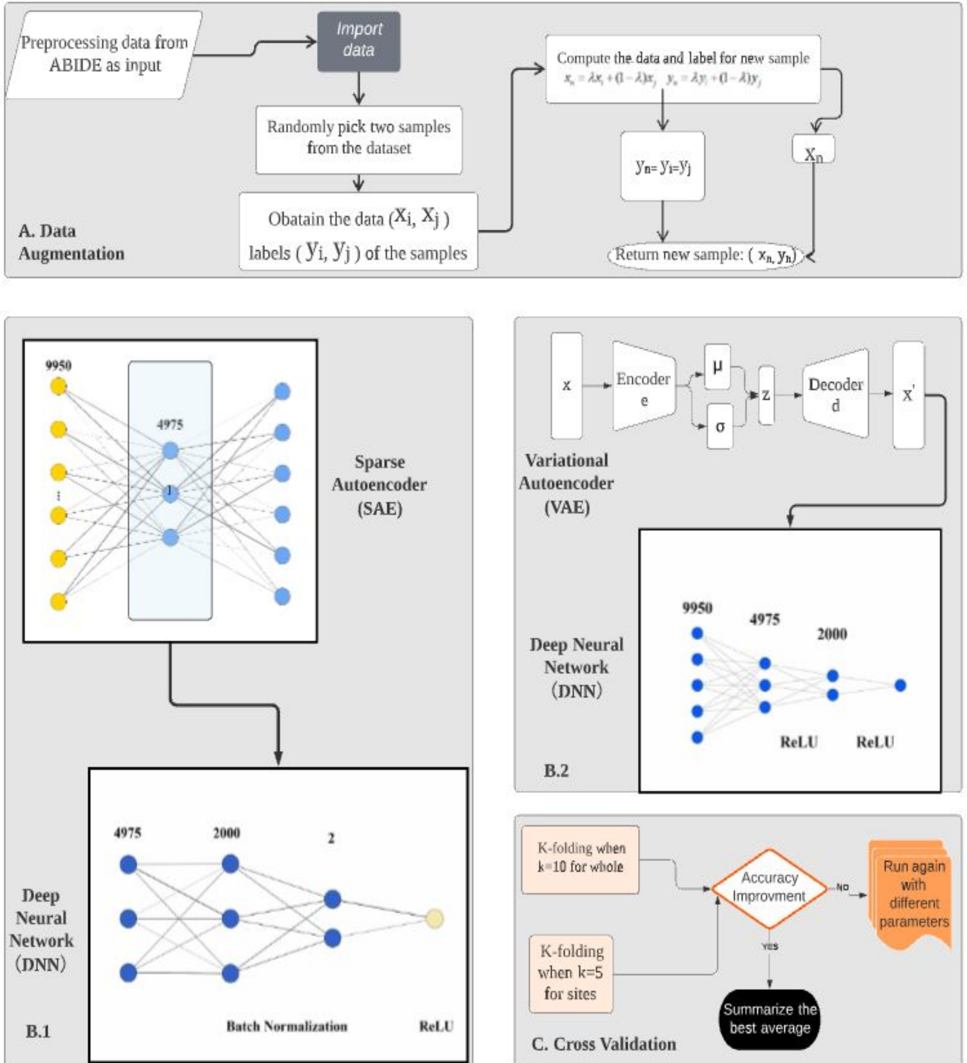


Commentary

overall experience & peer review

Division of labor

Hans Han	Stephanie Shao	Yaluo Wang
• Dataset preprocess • Data augmentation with mixup • Final report & slides	• Deep Neural Network Algorithm Implementation • Final report & slides	• Autoencoder Algorithm Implementation • Data and other Visualizations • Final report & slides



Summary

"Classifying Autism Spectrum Disorder Using Machine Learning through ABIDE Dataset"

- Whole: B.1 is better with 75.5%
- Sites: B.2 is better with 88.7%
- Generally, Team E proposed result have better accuracy than the previous studies.

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