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Autoencoder-based subtyping of eating behaviors using functional MRI

Hyoungshin Choi, Bo-yong Park, and Hyunjin Park*

Abstract— **Eating behaviors are related to both obesity phenotypes and brain function, but brain function does not per se mediate eating behaviors in individuals with obesity. Here, we identified subgroups of eating behaviors using functional connectivity and autoencoder-derived latent features. We found three subgroups in eating behaviors, where disinhibition and hunger factors showed significant differences among the groups.**

I. INTRODUCTION

Studies on resting-state functional magnetic resonance imaging (rs-fMRI) found that eating behaviors are associated with brain function [1], but the relationships across brain function, eating behaviors, and obesity phenotypes are not fully explained. Here, we investigated functional connectivity analysis combined with autoencoder (AE) to identify subgroups of eating behaviors regardless of obesity phenotypes. Specifically, we calculated connectome gradients [2] and latent features in the hidden layer of AE. We then defined subgroups of eating behaviors based on these features to assess differences in the traits across the subgroups.

II. METHODS

We obtained a total of 424 rs-fMRI data from the enhanced Nathan Kline Institute-Rockland Sample database (47.06±18.89 years, 67% female), and preprocessed the data using the Fusion of Neuroimaging Preprocessing pipeline [3]. We constructed functional connectivity using Pearson's correlation of time series between different brain regions defined using Brainnetome atlas. The correlation coefficients were z transformation and thresholded leaving the top 10% elements per row. We calculated functional gradients using diffusion map embedding [2] for each individual and aligned them to the template gradients defined using 488 subjects obtained from Human Connectome Project (28.19±3.93 years, 48% female). After controlling for age and sex from the gradients, we concatenated three principal gradients and fed them to the AE model, which contained five hidden layers with 420, 200, 120, 200, and 420 units, respectively. Tanh as activation function, Adam optimizer, weight decay of 0.1, learning rate of 0.0001, and dropout rate of 0.3 for the input data were used. Mean squared error was used as a loss function. We divided subjects into 60, 20, 20% for train, validation, and test datasets. The model with the smallest error in the validation dataset was applied to the test dataset. Within the test dataset, we applied K-means clustering to gradients as well as latent features calculated from the third hidden layer to identify subgroups of eating behaviors. The optimal K was selected using the consensus clustering algorithm [4]. We compared eating behaviors assessed using a three-factor eating questionnaire (TFEQ) [5] across the subgroups.

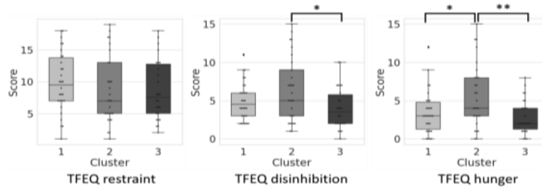

Figure 1. TFEQ scores of subgroups

III. RESULTS

While subgroups defined using gradients did not show significant differences in TFEQ scores, those defined using latent features showed significant differences (false discover rate < 0.05) in disinhibition and hunger scores in the second subgroup compared to other groups. The body mass index did not show significant differences among the groups.

IV. DISCUSSION & CONCLUSION

Sub-groups defined using latent features revealed significantly different eating behavior traits although they did not differ in obesity phenotype. Our results provide new insights for understanding the relationship between brain function and eating behaviors.

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Hyoungshin Choi is with Department of Electrical and Computer Engineering, Sungkyunkwan University and Center for Neuroscience Imaging Research, Institute for Basic Science (email: gudtls17@naver.com). Bo-yong Park is with Department of Data Science, Inha University (email: boyong.park@inha.ac.kr). *Hyunjin Park is with Center for Neuroscience Imaging Research, Institute for Basic Science and School of Electronic and Electrical Engineering, Sungkyunkwan University (corresponding author; email: hyunjinp@skku.edu).