Lecture 1.4 (12:45-01:00)

Chaotic-Based Deep Learning for Major Depressive Disorder: Leveraging Neuronal Dynamics in Classification

Yi Ju Lee (ISSAS)

The complexity of Major Depressive Disorder (MDD) stems diverse underlying neurotransmitters, neural circuits, and hormonal systems, which makes it hard to diagnose relying on subjective self-reported symptoms. In the fields of physical statistics, artificial intelligence (AI), and medical research, the fusion of complexity science offers a robust method for extracting crucial health insights from complex medical data, especially in the study of psychiatry. Recent innovations such as Chaos Net, an AI model rooted in chaos theory, hold promise in authentically simulating human neuronal firing patterns at network scale. On the other hand, the power law scaling has been used to quantify the complexity of brain signal dynamics. In this research, based on fMRI data, we aim to exam the classification models for MDD diagnosis incorporating the concept of complex systems at different stages of the model analysis process, seeking a comprehensive approach to advance MDD diagnosis. Participants with structural and fMRI images, demographic and clinical data were selected from the Strategic Research Program for Brain Sciences (SRPBS) cohort. Brain imaging data of 400 age and sex-matched, right-handed MDD patients (age mean = 40.21 ± 7.35; male = 49.5%) and 400 health adults (age mean = 39.46 ± 8.01) were retrieved. The functional images were pre-processed. The power-law scaling of brain activity of each voxel was extracted and transformed into a heatmap for model training. The images were split randomly in the ratio of 8:1:1 for the training, testing, and validation data set. We use ChaosNet and DenseNet 121 as model backbone, and they were trained using Python 3.8 for 500 epochs with 1 Nvidia DGX A100 (40G) GPU. In contrast to using typical fMRI BOLD signal as input to DenseNet 121, our result has suggested that the complexity-transformed image data with ChaosNet show significant decreased training time from 48.3 hours to 1.12 hours with similar classification results. In the best-performing model, the average testing accuracy is 92.3. We also identified the key brain regions that is related to MDD, such as prefrontal cortex, hippocampus and amygdala. under Bonferroni correction. This study presents robust biological evidence surpassing previous methods in identifying MDD. We employ signal complexity within chaotic-based models to detect abnormal brain activities in MDD patients, necessitating expertise in statistical science, computer science, and neurosciences. The observed alterations in pathological hemodynamics in MDD suggest a significant loss of brain signal complexity, potentially contributing to precise clinical diagnosis. Our approach harnesses the unique properties of chaotic neurons, proving more efficient than alternative models. The future work will require exploring the integration of genetic data to subtype MDD patients, aiming to enhance our understanding of this complex disorder.