Functional EEG Network Analysis for Cognitive Diagnosis of Alzheimer's Disease

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Abstract

Electroencephalogram (EEG) is to test electrical activity in the brain. Using Machine Learning approaches, we construct a causality network to analyze cognitive function of EEG of a group of 15 normal control (NC) subjects, 16 mild cognitive impairment (MCI) patients, and 17 Alzheimer's Disease (AD) patients. The functional EEG network of each subject is represented by a 30x30 matrix, where each element depicts a causal relation between two EEG channels. The cognitive state (NC, MCI, or AD) of a subject is classified using color maps and features of the functional EEG Network.

Introduction

Objectives:

- Build Reconstruction models using data from other patients' data and adjacent channels
- Use Principal Component Analysis and Support Vector Machines to accurately predict a patient's cognitive state
- Create visual diagrams using color maps to observe common patterns in brain activity and perform image classification to predict a patient's cognitive state

Methods

- Subject data is separated into three training sets based on cognitive group
- Build Reconstruction models and create correlation matrix between reconstructed and raw EEG data
- Visualize the matrices using color maps to show the causality relationship between the channels
- Use image classification on the graphs to achieve accuracy greater than or equal to previous research[1]

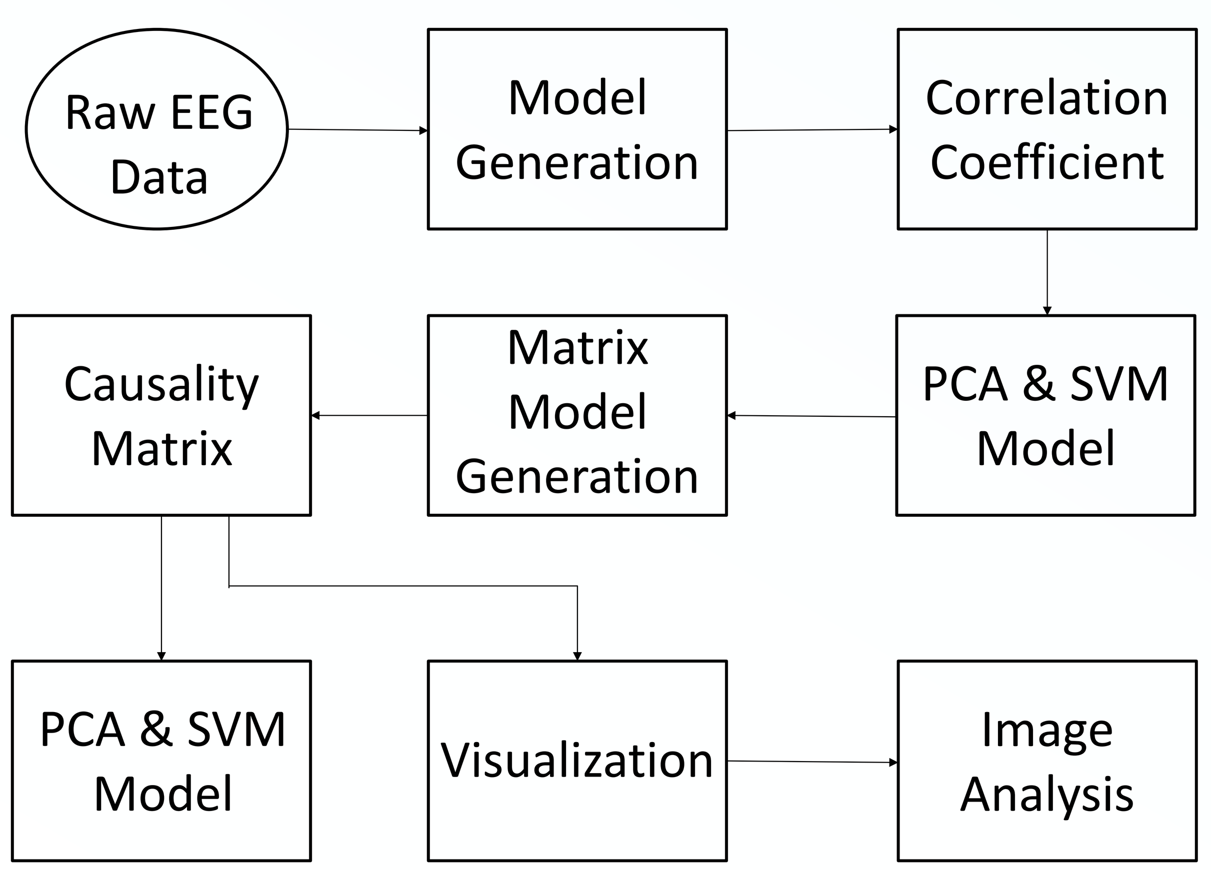

Figure 1: Outlined workflow of research process

Models

Pre-processing

- A 60 Hz notch filter for power line noise and a 2nd order low-pass butterworth filter were applied to the data before the initial start of the research

Cross-validation

- Leave One Out (LOO) principal was used to separate subjects into training and test sets

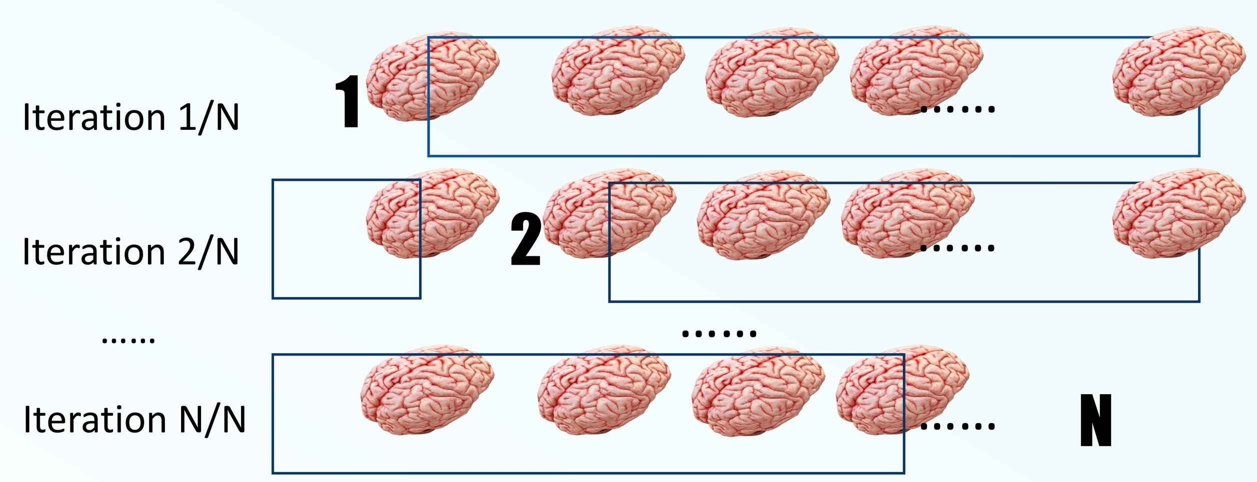

Figure 2: Leave-one out cross validation

- Subject Data was also split into training/testing sets based off of a 75/25 rule[2]

Feature Extraction

- Principal Component Analysis (PCA) was used to reduce the dimensions of the data to 2 features

Neural Networks

- Reconstruction models were built using Keras[2]
- Classification models were built using the Deep Neural Network Toolbox in Matlab

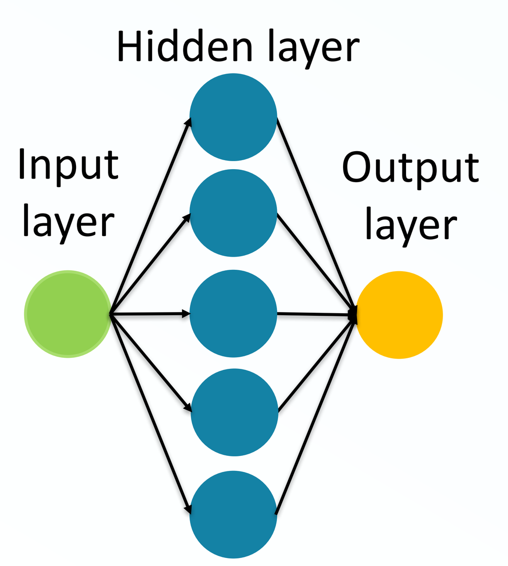

Figure 3: A generic neural network model

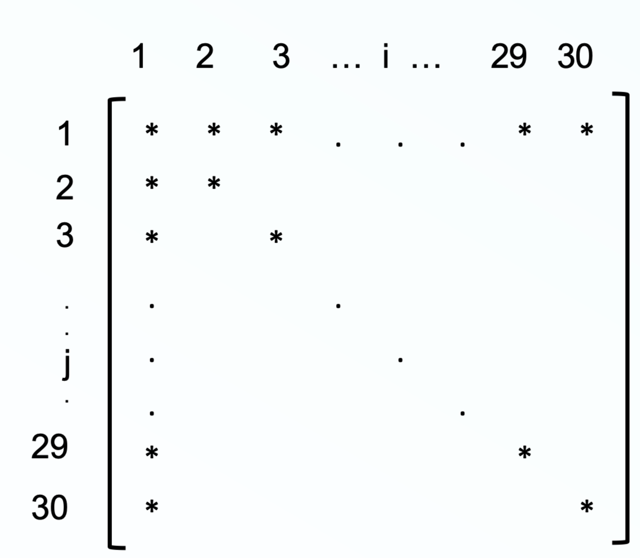

Figure 4: Functional EEG Network represented by a 30x30 matrix

Formulas

Mathematical equations used include:

- Correlation Coefficient

$$r = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \qquad (1)$$

- Solving for eigenvalues and eigenvectors

$$Ax = \lambda x \qquad (2)$$

Results

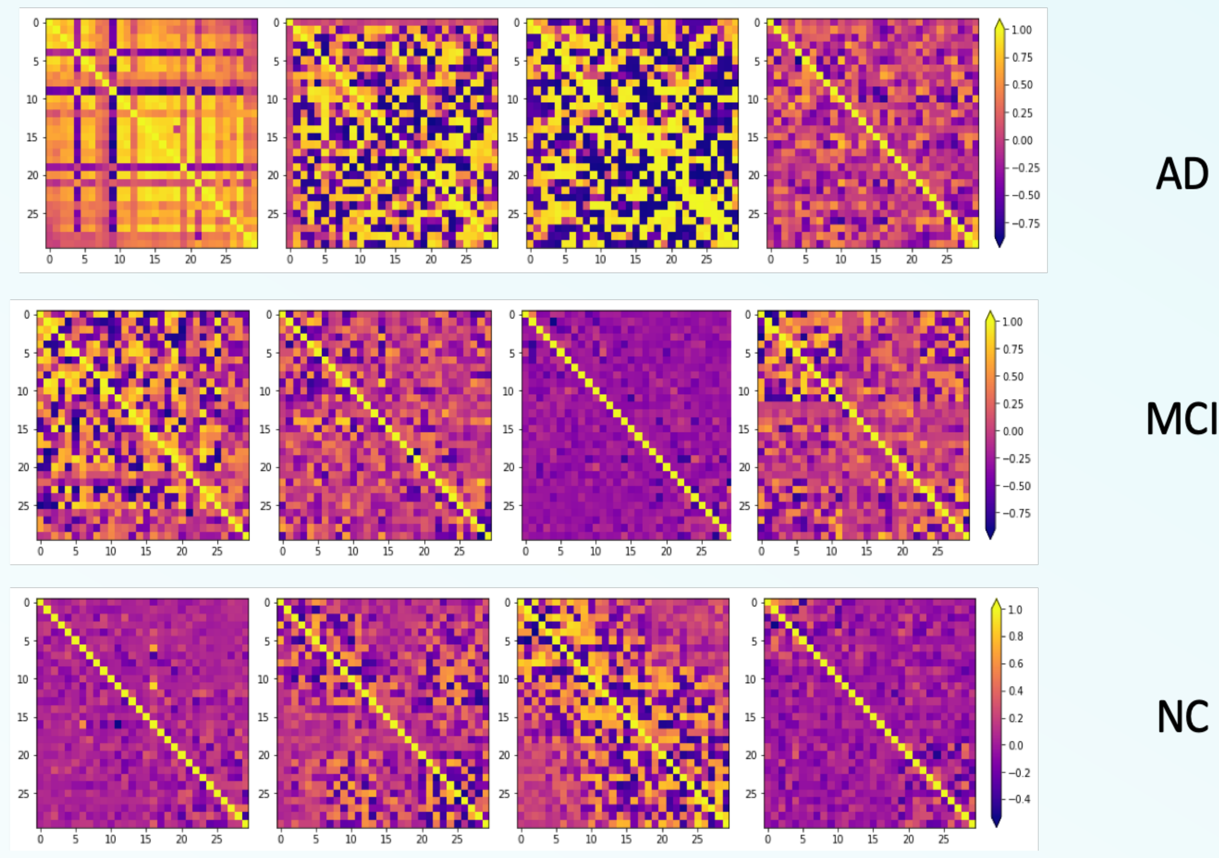

Figure 5: Sample visuals of causality network for each cognitive group

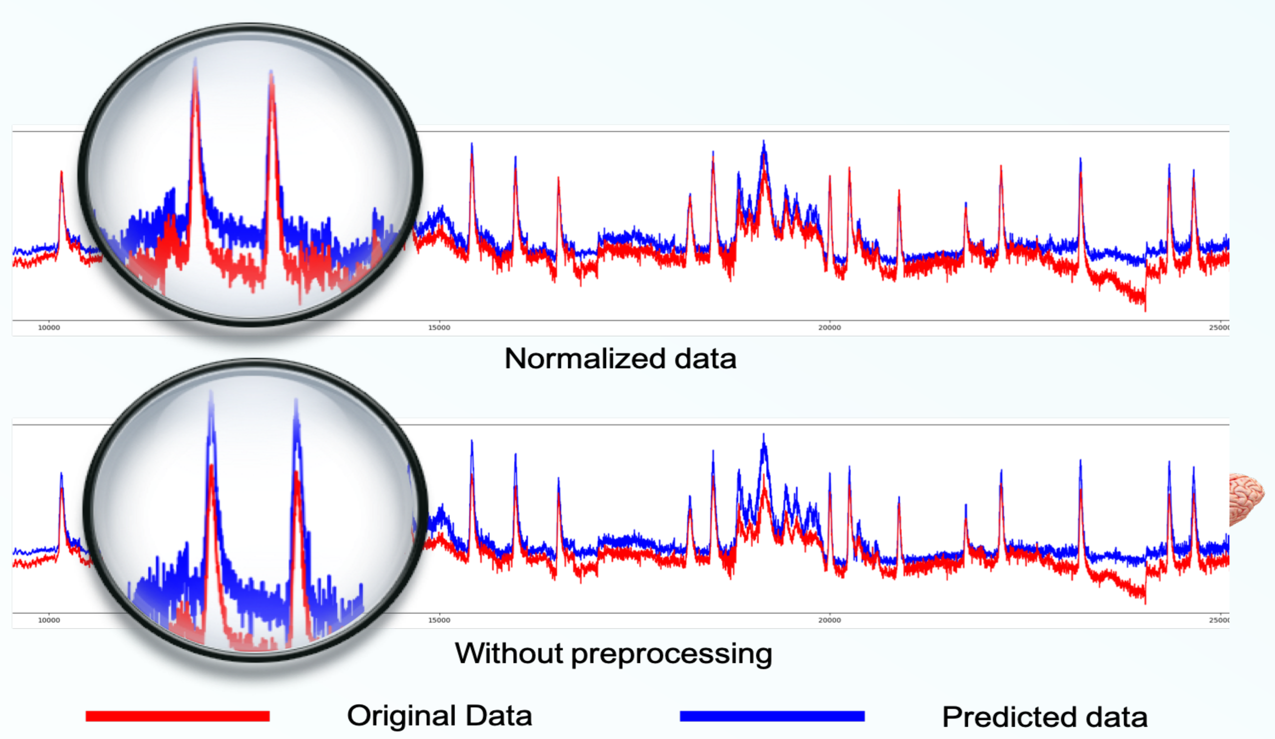

Figure 6: Graph of reconstructed data w/ normalization

Discussion

		Predicted classes			
		NC	MCI	AD	
True classes	NC	5	4	6	33.3%
	MCI	3	10	3	62.5%
	AD	2	8	7	41.2%
		50%	45.5%	43.8%	Overall Acc: 45.8%

Figure 7: Confusion matrix of the results from the image classification model

Based on the confusion matrix in Figure 7, the generated model only reached 45.8% accuracy. Compared to previous research[1], the model produced less-than half the desired results. The accuracy obtained could be due to a multitude of factors, including a small EEG data set or non-optimal parameters for model training.

Many approaches were taken to increase the classification accuracy of subjects into their respective cognitive group. Among these were performing PCA on a matrix of eigenvalues for both a square and symmetric matrix, and computing channel averages for correlation matrices and using the channel averages as features in an SVM model.

Improvements

1. Correlate EEG Causality Network to fMRI
2. Collect EEG data from more subjects
3. Real-time diagnosis of cognitive deficit

Acknowledgement

This project was sponsored by the National Science Foundation through Research Experience for Undergraduates (REU) award, with additional support from the Joint Institute of Computational Sciences at University of Tennessee Knoxville. This project used allocations from the Extreme Science and Engineering Discovery Environment (XSEDE), which is supported by the National Science Foundation. In addition, the computing work was also performed on technical workstations donated by the BP High Performance Computing Team

References

[1] Joseph C. McBride, X. Z., Nancy B. Munroc, Gregory A. Jichad, Frederick A. Schmittd, Richard J. Krysciod, Charles D. Smithd, Yang Jiang. (2015). Sugihara causality analysis of scalp EEG for detection of early Alzheimer's disease. NeuroImage: Clinical, 7, 8. doi:10.1016/j.nicl.2014.12.005

[2] Joseph McBride, A. S., Henian Xia, Adam Petrie and Xiaopeng Zhao. (2011). Reconstruction of physiological signals using iterative retraining and accumulated averaging of neural network models. Physiological Measurement, 32(6), 15. doi:10.1088/0967-3334/32/6/004