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.

Methods

- Subject data was separated into three training sets based on the 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]

Neural Networks

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

Classification models were built using the Deep Neural Network Toolbox in Matlab.

Mathematical equations used include:
- Correlation Coefficient
  \[ r = \frac{Cov(X,Y)}{\sigma_x \sigma_y} \] (1)
- Solving for eigenvalues and eigenvectors
  \[ Ax = \lambda x \] (2)

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.

Feature Extraction

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

Discussion

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.

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

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References


Figure 1: Outlined workflow of research process
Figure 2: Leave-one-out cross validation
Figure 3: A generic neural network model
Figure 4: Functional EEG Network represented by a 30x30 matrix
Figure 5: Sample visuals of causality network for each cognitive group
Figure 6: Graph of reconstructed data w/ normalization
Figure 7: Confusion matrix of the results from the image classification model

Appendix

Table 1: Predicted classes

<table>
<thead>
<tr>
<th>Cognitive State</th>
<th>True classes</th>
<th>NC</th>
<th>MCI</th>
<th>AD</th>
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</thead>
<tbody>
<tr>
<td>NC</td>
<td>5</td>
<td>4</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>MCI</td>
<td>3</td>
<td>10</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>AD</td>
<td>2</td>
<td>8</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>3</td>
<td>4</td>
<td>7</td>
<td>62.5%</td>
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<tr>
<td>Acc.</td>
<td></td>
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<td>45.8%</td>
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</tbody>
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Table 2: Parameters for model training

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<th>Cognitive State</th>
<th>Model parameters</th>
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</thead>
<tbody>
<tr>
<td>NC</td>
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<td></td>
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</tr>
<tr>
<td>MCI</td>
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<tr>
<td>AD</td>
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