Graph Neural Network on Decomposed fMRI Data

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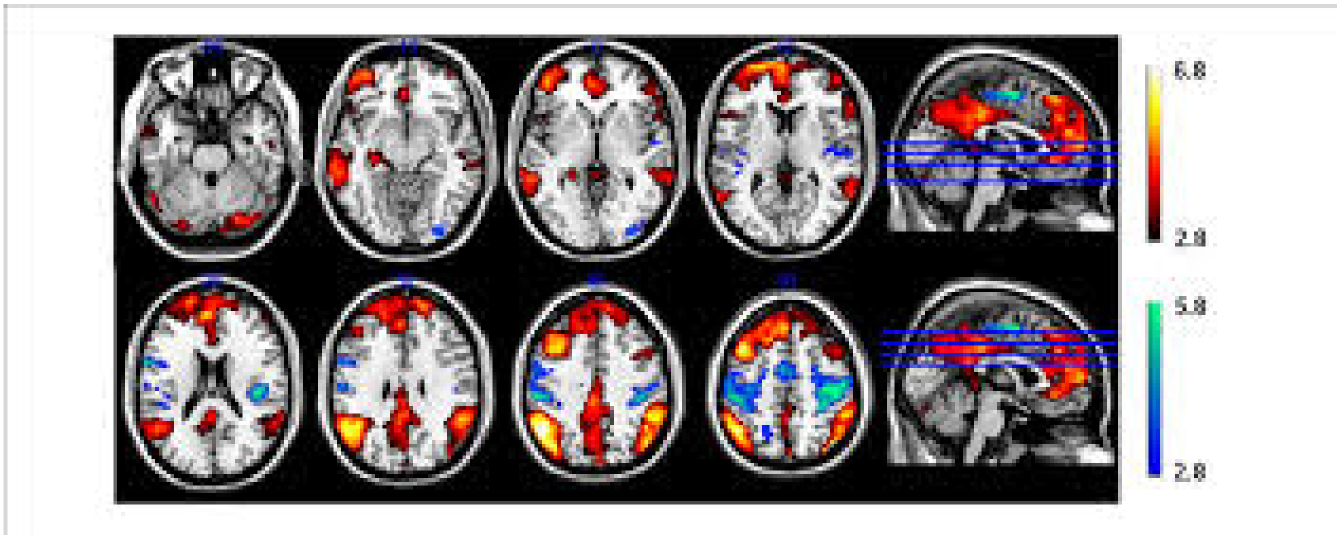

Figure 1: fMRI visualization

ABSTRACT

fMRI has proven to be an excellent measurement to understand the inner working of the brain. Many models have used this 3d imaging of the brain to diagnose diseases like cancer detection. It has also been shown that fMRI can be fed into deep learning models to predict psychological disorders like ADHD. However, these models are convolutional neural network models and are very hard to interpret. In this project, fMRI data is put in a graph format, and a graph neural network has been trained to predict whether a person has ADHD or not.

KEYWORDS

fMRI, neural networks, Canonical Independent Component Analysis, graph neural networ

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1 INTRODUCTION

Functional magnetic resonance imaging or functional MRI(fMRI) is a brain activity measurement paradigm of the brain. This technique relies on the fact that when there is more neuronal activity, the blood circulation is higher. fMRI tries to capture this change of blood circulation level when a brain region is more active. This contrast of blood circulation is called blood-oxygen-level-dependent (BOLD) contrast. This is a very noisy measure because of head motion, breathing, and heartbeat. Different methods have been developed to reduce the noise[3]. Fig. 1 is showing fMRI data for one patient.

Different machine learning techniques have been deployed to predict psychological conditions like depression and ADHD[5]. One of the problems of this type of black-box method is that it is hard to determine exactly what is causing the machine learning model to make specific predictions. As a result, it is hard to find causal relationships from the convolutional neural network models.

A brain is an idiosyncratic machine. It is never off, and there are different connections between different parts of the brain. Looking at one region of the brain and treat it as a signal processing box is not enough to understand the brain as a whole. The brain functions as a network and, network analysis is a significant part of understanding the brain from a neuroscience perspective. Standard graph methods are not equipped to handle high-dimensional networks with multiple features. Graph neural network has turned out to be an import method to handle high dimensional graph networks in recent researches [6].

In this project, fMRI data from ADHD 200 dataset [4] was decomposed into a network format using canonical Independent Component Analysis(canICA). Then a graph neural network(GNN) was trained to predict whether a person has ADHD or not from the network.

2 BACKGROUND

Different tools and techniques have been used in the project to decompose fMRI data and create connectivity network among different regions. GNN has been the focus of modeling in this project. All these are explained below.

2.1 Canonical Independent Component Analysis

This is the method used to decompose high dimensional fMRI signals into low dimensional regions[2]. The basic equation for canICA is given below:

y1 =$w_1 x_1 = \sum_j w_{1j} x_{1j}$
$y2 = w_2 x_2 = \sum_j w_{2j} x_{2j} (1)$

Where the goal is to find w1 and w2 such that it maximizes the correlation between y1 and y2.

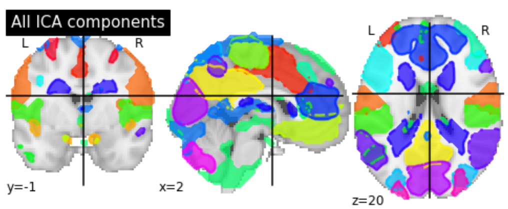

Figure 2: Reduced CanICA components in the Brain

The decomposition was done in nilearn package and it reduced the data into 20 dimensions as shown in Fig 2

2.2 Graph Convolutional Neural Network

Graph convolutional network is a type of neural network that can find embedded space of network features. It works exactly like a convolutional neural network but on a graph structure data.

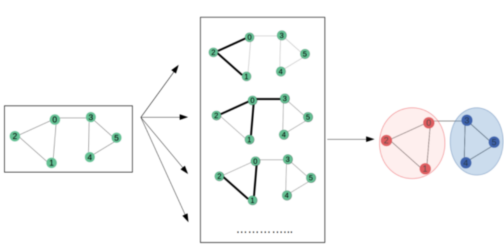

Figure 3: Illustrated Graph Neural Network

The Fig 3 shows illustrated graph neural network. The advantange of graph neural network is that it captures not only the node information for prediction but also the graph structure of the data

There is an alternative version of GCN that can also take in signed edge value [1]. fMRI connectivity was based on correlation and had both positive and negative edge.So, Signed GCN was delopyed for the network prediction too.

3 DATA AND PIPELINE

The dataset was from ADHD 200 data. To avoid loading the dataset manually through python, the dataset was loaded from python module named nilearn. Limitation of loading fMRI from nilearn is that it only allowed 40 subjects to be downloaded. For building an initial pipeline for analysis, this amount of data was enough.

The loaded data was fitted and transformed using canICA module in nilearn. The final data looked like this:

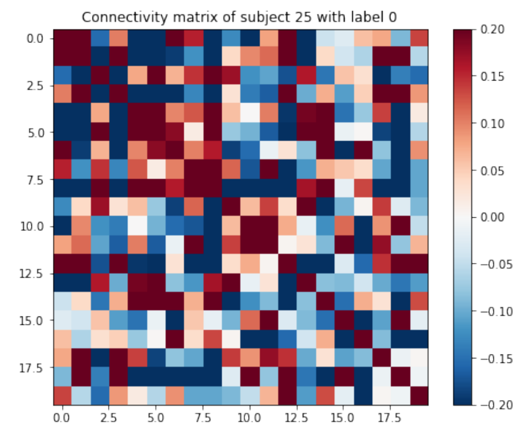

Figure 4: Correlation Matrix for one normal subject

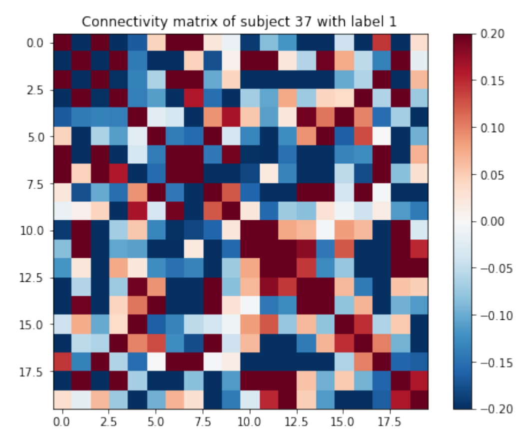

Figure 5: Correlation Matrix for one subject with ADHD

Each component of the matrix referred to connection between two regions as shown in Fig. 2. The edge attribute is the correlation between two regions and it can be seen from the figure that the relation can be positive or negative.

Each of the matrix was converted to a networkx format and of each node/region was put in as node attribute. Finally using a torch_geometric utlity the networkx data was converted into a torch_geometric format so that it can be trained on GNN.

There were 40 samples and train-test split was 70-30. No validation set was held out due to lack of data.The correlation between different regions can be seen in Fig. 6

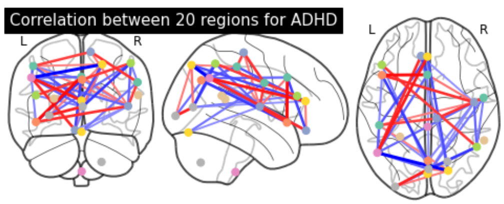

Figure 6: Correlation for subjects with ADHD

4 RESULT

Different Types of graph neural network was trained. The models and its results are explained below in the subsections.

4.1 Fully Connected Neural Network

For starter, the matrix shown in Fig. 4 was flattened and passed into two layer fully connected network for binary classification. The model accuracy was not very high and over 100 epochs there was no change in loss value. This indicated that the model did not learn anything over the epochs.

The final confusion matrix is shown in table 1

	Predicted ADHD	Predicted Non-ADHD
ADHD	5	0
Non-ADHD	7	0

Table 1: Confusion matrix for Fully Connected Network on test set

It seems that everything is getting predicted as ADHD.

4.2 Graph Neural Network With Weighted Edge

The edge of the network was very small. When passing the network through a two layer GCN, there was no ouput detected. So, the edge weights were normalized and fed into GCN to predict ADHD. The confusion matrix looked as shown in table below:

	Predicted ADHD	Predicted Non-ADHD
ADHD	0	5
Non-ADHD	0	7

Table 2: Confusion matrix for GCN with normalized weight

4.3 Graph Neural Network Without Weighted Edge

Since none of the methods were working, the edge weight was totally removed from the data for Graph convolutions. The results was slightly better than random prediction as shown in table below:

	Predicted ADHD	Predicted Non-ADHD
ADHD	4	1
Non-ADHD	5	2

Table 3: Confusion matrix for GCN without weight

4.4 Signed Graph Convolutional Neural Network

The edges were based on correlation. Signed GCN incorporates the polarity of weight of edges. The results from SGCN did not improve as shown in table below:

	Predicted ADHD	Predicted Non-ADHD
ADHD	5	9
Non-ADHD	7	0

Table 4: Confusion matrix for Singed GCN

Same result as before.

5 CONCLUSION

In this project fMRI data was converted into a network format and Graph Neural Network approach was applied for a binary classification problem. The problem was simplified and has a lot of implications. For example, fMRI is not the exact measure of how the brain is interacting within different regions. It is only a proxy. Also, canICA might not be the right algorithm for decomposition. However, the key takeaway was that a working pipeline was built in python to convert fMRI into a network format and successfully apply the graph convolutional network.

For future work different decomposition methods will be explored along with causality. Also, hyperparameter tuning will be conducted.

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