CS-671 Deep Learning and its Applications
Autism Classification on rs-FMRI

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May 20, 2019

Overview

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1. Autism spectrum disorder (ASD) is characterized by qualitative impairment in social reciprocity, and by repetitive, restricted, and stereotyped behaviors/interests.
2. ASD is recognized to occur in more than 1continuing research advances, their pace and clinical impact have not kept up with the urgency to identify ways of determining the diagnosis at earlier ages, selecting optimal treatments, and predicting outcomes. For the most part this is due to the complexity and heterogeneity of ASD.

Motivation

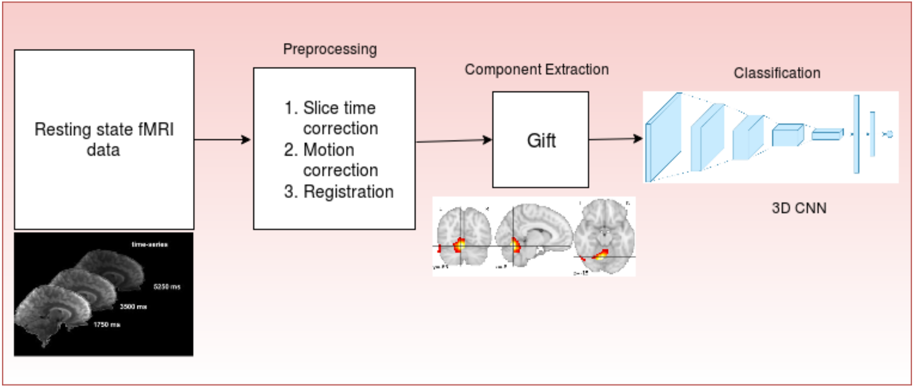
1. Autism Spectrum Disorder (ASD) is due to impairments in social deficits and communication.
2. ASD is highly heritable and the diagnosis is vital
3. As of 2015, autism is estimated to affect 24.8 million people
4. The traditional diagnosis methods are based on clinical interviews and behavior observation
5. Use of deep learning algorithm can improve the accuracy of diagnosis based on previous experiences.
6. The algorithm can detect signs of autism before they are diagnosed.

Dataset

Autism Brain Imaging Data Exchange (ABIDE) offers two large-scale collections: ABIDE I and ABIDE II. The model will be employed so as to focus on the combination of resting-state fMRI (rs-fMRI), gray matter (GM), and white matter (WM) data.

1. ABIDE-I Collection
   Total Number of Subjects : 1112
   Affected : 539
   Normal : 573

Pipeline


Preprocessing
Component Extraction
Classification
Resting state fMRI data
1. Slice time correction
2. Motion correction
3. Registration
Gift
3D CNN
time-series
5250 ms
3500 ms
1750 ms

Implementation Strategies

The strategy is three-fold, being performed concurrently:

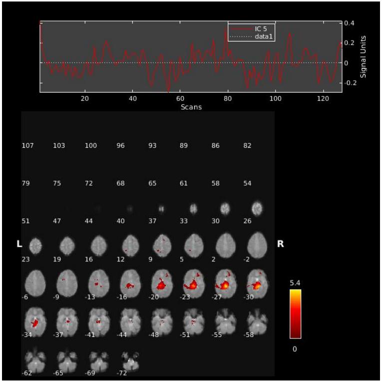
- Classification on components obtained
- Averaging out 4D Data in time and perform classification
- Classification on MRI Anatomical 3D Data after performing registration

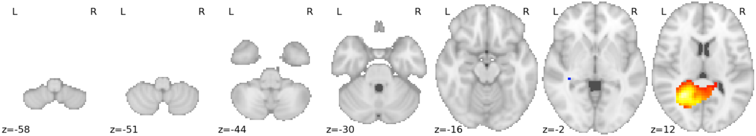
Components and Classification I

Group ICA of fMRI Toolbox (GIFT):
GIFT is an application developed in MATLAB that enables group inferences from fMRI data using Independent Component Analysis (ICA)
Steps to extract 3D components from fMRI data:

1. Organize the data (.nii) files generated post FSL preprocessing and registered data in to normal and patient, then perform the group level analysis on the these 2 groups i.e., normal and patient by combining all the preprocessed data from sites.
2. While doing group level analysis we went with all default values provided with GIFT except below 2:
    1. Number of IC : 20
    2. ICA algorithm : Infomax

Components and Classification II





Components and Classification III

3. Files generated for each group:
    1. Group level:
        - agg_component_ica.nii
        - mean_component_ica.nii
        - std_component_ica.nii
    2. subxxx_component_ica.nii file for each subject in that group with 20 components in each .nii file
4. 2 Class Classification using 3D CNN for each component
    - Extracted single component from all subjects (subxxx_component_ica.nii) and trained 3D CNN for 2 class classification i.e., normal and patient.
        - Training sample size: 758
        - Validation sample size: 163
        - Test sample size: 163

Results Obtained

Classification accuracy for each component:

component 00	93.86
component 01	98.15
component 02	93.86
component 03	97.54
component 04	95.09
component 05	95.09
component 06	94.47
component 07	96.93
component 08	96.31
component 09	92.63
component 10	95.09
component 11	96.93
component 12	91.41
component 13	99.38
component 14	90.79
component 15	97.54
component 16	93.86
component 17	94.47
component 18	93.86
component 19	87.11

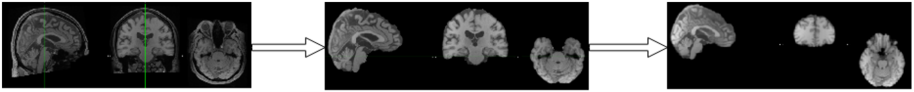
Problem with this approach: high accuracy but no proper justification

Approach 2 - Training model on 1-component and tested with different components from all subjects:

We obtained a classification accuracy of 46%

Classification on MRI Anatomical Data

1. We took all the 3D Anatomical MRI data and applied Brain Extraction, followed by Registration
2. We split the data to 70% train, 15% test and 15% validation, with class labels: Controlled and Patient, and trained a 3D CNN as well as a 3D Autoencoder (detached Decoder and added 2 FCs for classification).



Results Obtained

- 3D-CNN : We did not get appreciable results : classification accuracy of 56% on validation data in each epoch. The model was not learning features well.
- 3D-Autoencoder : Trained Autoencoder on 3D data and used it as a Classifier, we got 52% validation accuracy across all epochs.

Targets

- Train a 2D Autoencoder on Anatomical MRI Data and use Majority Voting for Classification
- Searching for a pre-trained 3D Classifier and fine-tune it
- Extract slices of all subjects. This returns a 3D volume (Total No. of Subjects = No. of Subjects x Volumes in each Subject).
  1. Train an autoencoder for the volumes
  2. Get latent representation for each 4D Data
  3. Train a GRU for this representation to learn the temporal information
  4. Perform classification for test subjects

The End