Brain disease classification using multi-channel 3D convolutional neural networks

Thesis Proposal Seminar

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- Brain diseases (e.g. Alzheimer, Mild Cognitive Impairment (MCI), Attention Deficit Hyper Activity Disorder (ADHD), Autism Spectrum Disorder (ASD)) are well-known for their the difficulty in diagnosing
- Lots of complex symptoms and often overlapping with other psychiatric disorders (e.g. Depression, Anxiety)
- Traditional way of diagnosis on observatory methods and interview evaluation of symptoms as described in *DSM-5 2013* is very objective and requires a lots of expertise with misdiagnosis danger
- How can we achieve a more automate and quantifiable diagnosis?
- Brain image data (e.g. MRI, fMRI, X-rays, computed tomography (CT) e.t.c.) have been used to offer a more quantifiable measure. Deep Learning (DL) algorithms have utilized to extract features and automate the diagnosis

Thesis Focus

- This project is focusing on diagnosing ASD from fMRI[1] images with DL
- ASD is a developmental disorder with a wide-range of symptoms associated with damages and deficits in social communication and restrictive and repetitive behaviours
- According to WHO[2], one in 160 children has an ASD
- Symptoms appear during early childhood and tend to develop over time
- So timely diagnosis is important for the relief of symptoms

[1] Functional magnetic resonance (fMRI)
[2] World Health Organization

- People with ASD have distinct and differing patterns of brain connectivity that can be reflected in fMRI images
- fMRI images are able to measure the brain functionality though changes in blood flow between different brain regions (during resting or activity)
- More oxygenated blood in a brain part means this part is more active, this is known as the Blood-Oxygenation Level Dependent response (otherwise known as BOLD)
- The images are created as brain slices that typically are taken on 1 or 2 seconds resulting in a 4-D data product, 3-D of the brain, and 1-D of time
- It is a non-invasive method but expensive and data collection might be slow due to its temporal resolution[3]

[3] blood flow takes several seconds to change

fMRI data time series

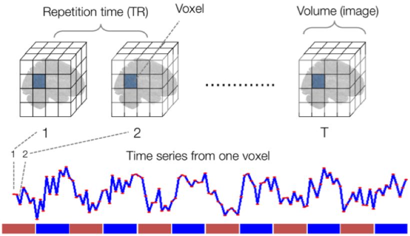

Figure: Each voxel holds a time-varying signal(BOLD) and can be interpreted as a time series signal over time

1 Problem Definition
2 Data overview
3 Aim
4 Research Questions
5 Methods

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- Data : resting state fMRI (rs-fMRI) image data with their phenotypic information provided by ABIDE [4]
- All images are anonymous, with no protected health information included
- They come from aggregation of 17 image centers and are publicly available
- Image volumes from 539 individuals diagnosed with autism spectrum disorder (ASD) and 573 typical controls (CON)
- A typical fMRI dataset size : 61 x 73 x 61, i.e. 73 brain slices, where each slice is 61 x 61 pixels

[4] Autism Brain Imaging Data Exchange (ABIDE)

Data preprossesing

- Preprocessing of rs-fMRI signals is required to clean confounding variation due to physiological processes (heart beat and respiration), head motion, and low frequency scanner drifts
- The preprocessing has already been made using 4 different pipelines:
  - Connectome Computation System (CCS)
  - Configurable Pipeline for the Analysis of Connectomes (CPAC)
  - Data Processing Assistant for Restin by five different teams g-State fMRI (DPARSF)
  - Neuroimaging Analysis Kit (NIAK)
- The different pipelines have implemented different processing steps like Slice timing correction, Motion realignment, Low-frequency drifts e.t.c

- Moreover, different methods have been used in the preprocessed brain volumes to reduce time component while preserving the 3D dimensions
- These different methods extract different aspects of the time series and are commonly known as statistical derivatives (ALFF, ReHo, e.t.c.)
- For example amplitude of low-frequency fluctuation (ALFF) is calculated independently for each voxel as the ratio of spectral power in two distinct frequency ranges
- Regional homogeneity (ReHo), is the temporal coherence or synchronization of the BOLD time series within a set of a given voxel's nearest neighbors
- (see here for more information about the prepossessing pipelines and derivatives)

Figure: fMRI Image of ASD from ALFF derivative with CPAC preprocessing

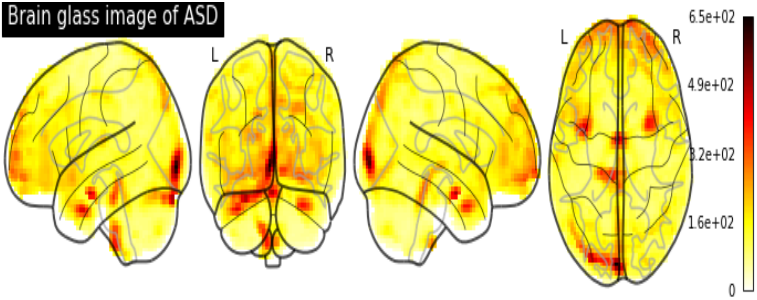
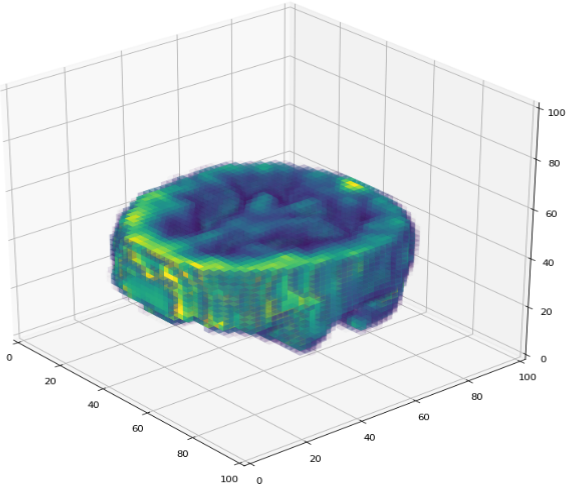


Figure: 3D slice of fMRI image volume



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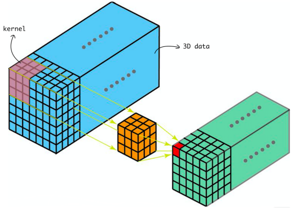
- The main aim is training a classifier to distinguish between 2 classes: ASD or control using the rs-fMRI image data.
- Which structure should we use?
- Convolutional Neural Networks (CNNs) are the backbone of DL in image analysis
- Multiple kernels can generate multiple feature images that can identify patterns, lines, and edges so on
- Since our image data are 3D, 3D-CNN's is the most proper structure



- CNNs can have a lot of layers and train a lot of parameters but are data hungry
- Medical data are expensive to find and annotation is difficult
- Use data augmentation techniques to increase size (e.g. rotation, scaling e.t.c)
- The calculated derivatives can be used to increase the channels in the CNNs. If we refer to colored image it has 3 channels RBG, each derivative has one, we can combine the derivatives to make inputs to CNNs with more channels.
- We have the following available derivatives :
  [alff, degree binarize, degree weighted, dual regression (10 volumes), eigenvector binarize, eigenvector weighted, falff, lfcd, reho ,vmhc]

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Questions of interest

During the project we are also interesting in answering the following questions:

Role of derivatives

What is the relation of the derivatives in the classification? We are interested to know if a certain derivative or derivative combination gives better classification

Data augmentation

What kind of 3D augmentation (e.g. rotations, scaling of each volume) are most important in the 3D CNN training?

Architecture

What is the best architecture of the 3D CNN? We wish to know how many layers to use and number of filters in each layer in the model architecture.

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- Research using 3D CNNs on ABIDE dataset has already be done, *Thomas et al. 2020* proposed a network architecture with an average pooling layer as first layer followed by 3 3D CNN layers with ELU activation a maxpooling layer and flatten layer with ELU and finally a FC layer with one node for final labels classification.
- in their training they tested either one or 9 derivatives with one preprocessing pipeline and evaluated with 2 cross-validation mehtods: i) five-fold cross-validation (CV) and ii) a leave-site-out CV procedure
- The number of layers in our architecture is to be discussed but we are planning to use Dropout (*Srivastava et al. 2014*) in each CNN layer to avoid over-fitting and speed the training
- Monte Carlo dropout can also be used to obtain the uncertainty of the classifier

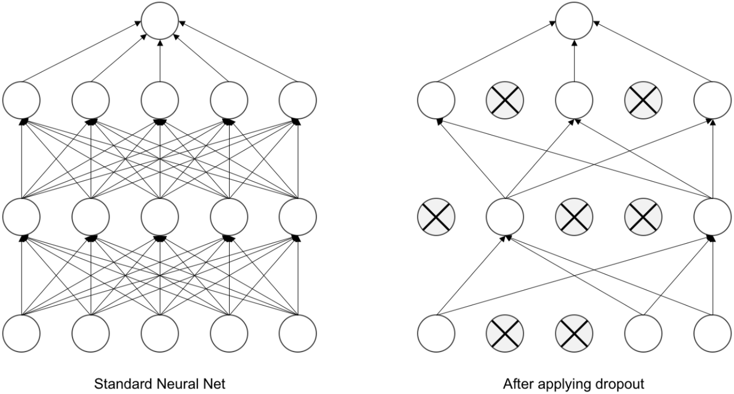

Figure: Illustration of Dropout in Neural Network

- As stated in the Thesis aim we plan to use data augmentation to increase the training size using different methods
- Also, different combinations of the derivatives will be investigated to see if a certain derivative or combination results more accurate classification
- Another method that might be deployed is ensemble learning where we aim to combine different classifiers to a majority voting
- Finally, for statistical evaluation or our model we are going to use statistical metrics like accuracy, F1-score and ROC

References

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- Srivastava, Nitish et al. (June 2014). "Dropout: A Simple Way to Prevent Neural Networks from Overfitting". In: *Journal of Machine Learning Research* 15, pp. 1929–1958.
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