Assessing Autism Spectrum Disorders sby Deep Learning Using MRI

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INTRODUCTION

Autism spectrum disorder (ASD) is a group of developmental disabilities characterized by impaired social communication and interaction accompanied by restricted, repetitive patterns of behavior, interests, or activities (1). It was once estimated to be a rare disorder affecting fewer than 1 in 1000 children, but recent studies have estimated the prevalence to be as much as 1 in 68 (2). Even though our understanding and clinical characterization of these disorders have progressed immensely since it was first described in 1943, the fundamental molecular pathways involved in ASD are still largely unknown (3). Consequently, the diagnostic gold standard remains as clinical diagnosis based on behavior. Therefore, an objective diagnostic tool based on physiologic changes is still lacking.

The spatial and temporal resolution of functional magnetic resonance imaging have proven to be useful in providing physical evidence of physiologic differences in people with ASD compared to the general population and mechanistic insight to the pathophysiology of ASD (4). **Therefore, we proposed to use a deep learning model to classify autism spectrum disorder using fMRI and MRI images**. Our work will pave the way for a more robust, objective diagnostic methodology that is based on pathophysiology of the disorders. In addition, we may also uncover features that provide mechanistic hypothesis to the pathogenesis in terms of brain regions, neurological circuits, or cellular pathways.

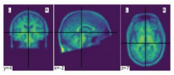

Figure 1. Smoothed MRI Image from Three Different Planes for a Single Subject.

METHODS

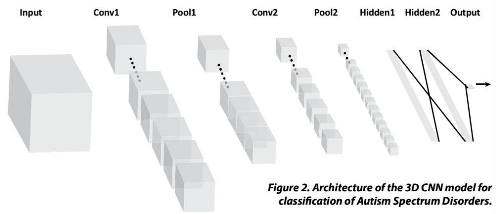

Figure 2. Architecture of the 3D CNN model for classification of Autism Spectrum Disorders.

Other Model Architectures Evaluated
Recurrent 3D Convolutional Neural Networks
2D Convolutional Neural Networks on multiple slices of MRI
3D Convolutional Neural Networks on videos of a single slice of fMRI
2D Convolutional Neural Networks on a single slice of MRI
Traditional Deep Neural Networks

Table I. Deep Learning Strategies Evaluated Prior to the Developement of the Final Model. *As a proof-of-concept, we used a small portion of the dataset (taken from a single site with consistent sizing) to allow us to rapidly develop working models and evaluate each of our strategies. Within this small dataset, we use 80% of the data as the training set and 20% as a test set.*

Num	Type	Channels	Filters	Kernal Size	Stride
0	Input	1		128x128x128	
1	Conv3D	1	16	5x5x5	3
	ReLU				
2	MaxPooling			2x2x2	
3	Conv3D	1	32	5x5x5	3
	ReLU				
4	MaxPooling			2x2x2	
	Flatten				
5	Dense (Fully Connected)			100	
	ReLU				
	Dropout (r=.15)				
6	Dense (Fully Connected)			100	
	ReLU				
7	Output (Sigmoid)			1	

Table II. Detailed Description of the Best Network of the Set.

CONCLUSION

- After a number of experimentations, we arrived at our current 3D CNN model which appeared to capture the most information from the MRI scans. The relative simplicity of the layers allowed us to build a deeper model with the available resources.

- We achieved results of 65-70% on both our training and validations sets with near perfect performance on our training set. This signifies some overfitting in our model. It was difficult to lower variance without sacrificing accuracy. This could be due to the size of the dataset (~1300 images) and the limited depth of our model. We addressed the issue of overfitting as much as possible using dropout and cross-validation.

FUTURE DIRECTIONS

- Try other deep learning architecture (recurrent convolutional neural network) if we have more processing power
- Apply our model to a broader dataset, encompassing a wider distribution of ages. This would help us reduce overfitting and create a more broadly generalizable model for autism classification
- Examine the activations to search for the part of the input that is responsible for the output and investigate the roles of a given neuron, filter, and layer
- Explore additional feature spaces (adding features such as connectomes) strongly contributing features

DATA

ABIDE (Autism Brain Imaging Data Exchange) is a publicly available dataset with 1114 subjects. It contains data from 521 patients (ASD positive) and 593 controls (ASD negative) with ages ranging from 5 - 64 years. It contains MRI and resting state fMRI data for most examples. ABIDE is an amalgamation of data from 19 research labs across the world, as such, the dimensions of data are not entirely consistent between labs due to the difference in equipment used.

Accurate labeling is available categorizing subjects into ASD and non-ASD categories. Further information such as demographic data, "handedness" (left or right), medications etc. are also available.

RESULTS

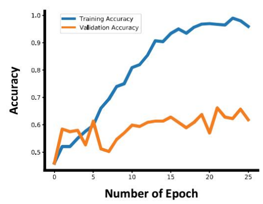

Figure 3. Training and Validation accuracies

	Training Set	Dev Set	Test Set
Loss	0.13	2.7	-
Accuracy	96%	62%	56%
Precision	-	.55	.53
Recall	-	.53	.56
F1-Score	-	.54	.55

Table III. Final Model Results

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