Predicting Autism using Machine Learning and Neural Networks

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Abstract

Advances in medicine have helped improve effective diagnosis of autism spectrum disorder (ASD) over the years, but still in majority of the cases the diagnosis cannot be made early enough to drastically improve the prognosis of the disorder. Current diagnosis methods are based on a set of behavioral criterion and not on any biological indicator and thus are subjective, error prone and time consuming. Machine Learning has the potential to overcome these deficits and predict autism accurately. Accumulation of 3D fMRI brain scans and clinical phenotype data of ASD and non-ASD patients have led to increased possibility of using machine learning for diagnosis purposes. This paper applies and evaluates deep learning models to predict ASD and learn important features from the fMRI scans. The methodology includes a Convolutional AutoEncoder, and a Convolution neural network to learn features and make predictions. Regression analysis is also applied on clinical phenotype data of ASD and non-ASD patients. It is seen that our Deep Models on fMRI data are not predictive of ASD but simple regression analysis classifies correctly with an accuracy of 70% showing that normal features collected in clinics can be used to diagnose autism accurately and quickly.

Project Code:
`https://github.com/samiragarwala/autism_prediction`

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1. Introduction

Autism is a highly prevalent neuro-development disorder across the world. In developing countries such as India, proper large-scale diagnostic and treatment facilities for such disorder are not present. This makes the accurate diagnosis of autism an important problem to address since currently diagnosis of autism is based on a behavioral criteria and not on any bio-markers. A medical professional assesses a patient for the disorder using the prescribed norms, but in the process a substantial amount of misdiagnoses and late diagnoses occur. This leads to most autism cases being diagnosed after the age of 5 [1], whereas early intervention could significantly improve the autistic person's life. Due to this, it is important to find a way to accurately detect autism using some bio-markers.

Considering the difficulty of autism diagnosis, it is important to find a way to solve it. A step in the right direction would be to apply machine learning techniques such as deep learning to detect autism using fMRIs and other biological data.

Deep Learning is a branch of machine learning which is used to model high level abstractions in data. These models are some of the most accurate machine learning algorithms in modern times. These models are applied everywhere - from search engines and recommender systems to cancer detection [2]. Due to this, they have huge potential in accurately diagnosing autism. Hence, experimentation must be done with these models to find a way to detect autism accurately.

In this report, we examine the use of deep learning models to detect autism using fMRI scans, while also using regression analysis on phenotype data of autistic patients for the same purpose. We believe that by addressing such an important challenge through a machine learning approach, we will be able to contribute constructively to research on accurate autism diagnosis.

2. Training Dataset

The ABIDE data is a consortium of resting-state functional magnetic resonance imaging (R-fMRI) data sets from individuals with ASD collected by UCLA, Caltech and CMU over a period of few years. Multiple datasets are available on the ABIDE website, including phenotype and Region-of-Interest (ROI) data, but for our purposes, we only use the fMRI and the phenotype data. There is a 55% - 45% split between patients with and without autism. The age of patients ranges from 10 months to 16 years old. Each fMRI image is a 91x108x91 3D image of the patients' brain and there are 1071 images in the dataset.

The phenotype data contained multiple attributes such as *DSM-IV TR* Diagnostic Criteria, age, gender, handedness, FIQ (Full-scale IQ), VIQ (Verbal IQ) and PIQ (Performance IQ) standard score, and various Autism Diagnostic Interview scores.

There are only 1071 images in the dataset, and since neural networks need large amounts of data, data augmentation is essential. Let us take 2 autistic brains. Our hypothesis is that autism, in general, affects similar regions of the brains, though it might be to different extents. We take corresponding regions of the 2 brains and randomly swap about 25% of the fMRI brain regions to create a new brain, which should also be autistic. Following this pattern, we can keep randomly swaping a different 25% brain regions to create new brain samples that should be autistic. Using this methdology, we use different combinations of the autistic and control brains to create 4815 fMRI images, that increases our training and test set.

3. Methodology

3.1. Convolutional Neural Network

A Convolution Neural Network (CNN) was used to learn spatial features across the image data. The CNN was used to take images from the Convolutional Autoencoder. Our architecture was as follows: each convolution unit had a micro-architecture of Convolution $\rightarrow$ Batch Normalization $\rightarrow$ ReLU.

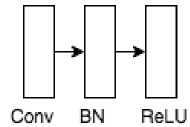


Figure 1: Micro-architecture of CNN : One Convolutional Unit, containing Convolution3D (Conv), Batch Normalization (BN) and ReLU (Rectified Linear Unit) layers

The convolution units were repeated 8 times in the macro-architecture of Convolution Unit $\rightarrow$ Convolution Unit $\rightarrow$ Max Pool. The first two convolution units had $5 \times 5 \times 5$ filter size while the rest had $3 \times 3 \times 3$ filter size.

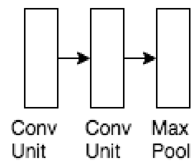


Figure 2: Macro - Architecture of CNN

Thus, we finally decided to use the following architecture:

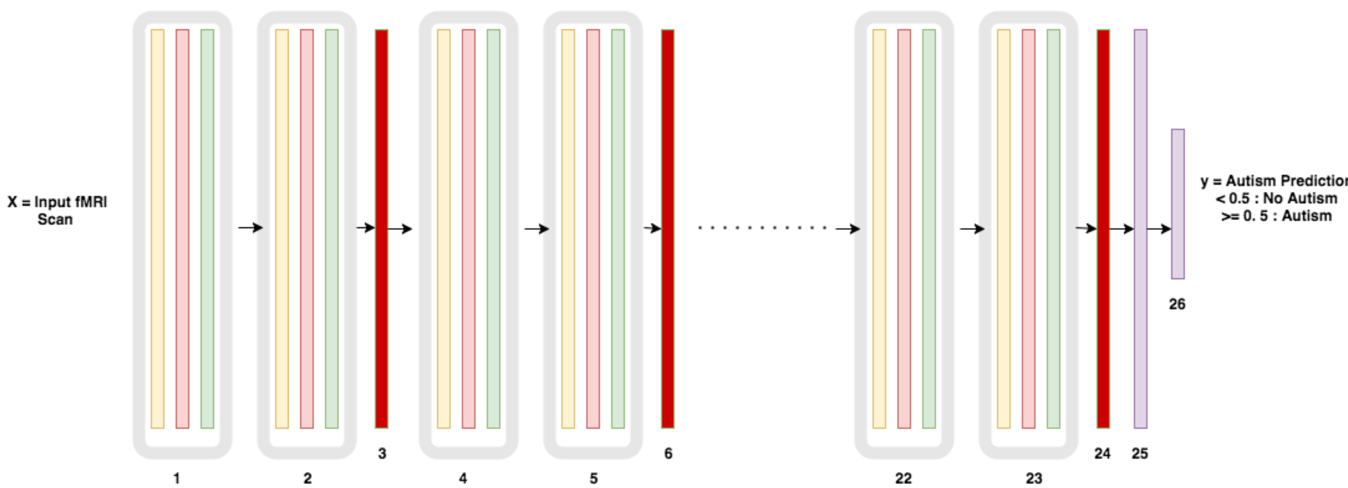


Figure 3: Overall Architecture of the Convolutional Neural Network

1 Yellow is Convolutional Layer, having 5x5x5 filters with stride of 1.
Light red is Batch-Normalization layer.
Green is ReLU Layer

2 Yellow is Convolutional Layer, having 5x5x5 filters with stride of 1.
Light red is Batch-Normalization layer.
Green is ReLU Layer.

3 Dark Red is Max-Pool layer of stride 1

4 Yellow is Convolutional Layer, having 3x3x3 filters with stride of 1.
Light red is Batch-Normalization layer.
Green is ReLU Layer

5 Yellow is Convolutional Layer, having 3x3x3 filters with stride of 1.
Light red is Batch-Normalization layer.
Green is ReLU Layer.

6 Dark Red is Max-Pool layer of stride 1

$\vdots$ (The above 3 blocks of layers repeated 6 more times)

$\vdots$

25 Fully Connected layer with 32 hidden neurons

26 Fully Connected layer with 1 neuron, having a sigmoid loss function. If the output is < 0.5, then the image is not an Autistic scan. If the output is ≥ 0.5, then the image is an Autistic scan.

Again, a lot of different Convolutional Neural Network architectures were tried:

- Instead of having 8 blocks of the Convolutional Unit, we tried to have blocks ranging from 2-7, but these architectures gave lower test-set accuracies that the one given by the above shown architecture.
- we also tried to have $10, 12$ and 14 Convolutional Units in the network, but the increase in test-set accuracy was negligible ($< 0.3\%$). Hence we decided to go with the network which had lower computational cost to save on training time and also lower the number of variables for the most compact model.
- Instead of defining the macro-architecture as Convolution Unit $\rightarrow$ Convolution Unit $\rightarrow$ Max Pool, we tried defining the macro-architecture as Convolution Unit $\rightarrow$ Max Pool. In fact, this macro-architecture gave much worse results since there were not enough convolutions before the max-pool layers to extract relevant features before choosing the important features.
- On removing Batch-Normalization, the results of the model were much worse. This might be because of the regularizing effect of Batch-Normalization, coupled with the acceleration of training. Maybe if we had left the model to train for many more hours/days, a model without Batch-Normalization might have reached the same accuracies.

3.2. Convolutional AutoEncoder

Autoencoders are used to perform dimensionality reduction on inputs. Additionally, autoencoders preserve important features in the original data, hence information which may be important in predictions is not lost while encoding images using autoencoders [2]. fMRI images are high dimensional images. Due to this, convolutional autoencoders are used to effectively encode and perform dimensionality reduction on the images.

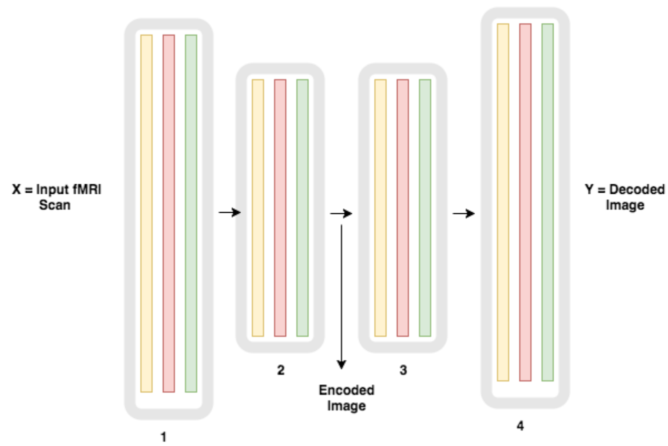


Figure 4: Overall Architecture of the AutoEncoder designed for best results and efficiency

The Convolutional autoencoders are based on autoencoders but have an important difference. Similar, to convolutional neural networks, convolutional autoencoders (CAE's) make the use of convolutional filters to take advantage of the spatial structure in the input. Thus, as CAE's perform dimensionality reduction on data while at the same time preserving spatial relationship, the reduced data obtained from CAE's can be used as inputs to the Convolutional Neural Networks.

3.3. Regression

Regression is a linear model that we can use to find direct relationships between the features (phenotype data) and the prediction (autism or no-autism). Since linear regression involves linear algebraic calculations and not complex training procedure such as neural networks, it is less computationally expensive than the latter and runs faster. Regression results in better predictions than neural networks when less data is available. Consequently, we decided to use this model for prediction of autism using the phenotype data.

4. Programming Implementation

4.1. Pre-processing

The ABIDE Data was stored as RData, which is the file extension used to store data processed by the R programming language. RData cannot be easily processed in python, the language the models are being implemented in. Consequently, an R Script was written to save the data in the numpy format which can easily be used in python.

While building the models, it was evident that the numpy file size was too large and the program was taking time to process the data. Hence, the numpy files were compressed to HDF5 files which are smaller in file size, allowing faster processing. This was done by writing a python script in which the numpy data was loaded and then the h5py python package was used to save the data as HDF5 files. To ensure that the models train properly, all the data is normalized before it is used i.e. all the fMRI scan inputs have a mean of 0 and a variance of 1.

4.2. Models and Algorithms

The AutoEncoder to reduce the dimensionality of the fMRI brain scans was implemented in python using the Keras [3] neural network package. To ensure that dimensionality reduction was adequately taking place in the AutoEncoder, a custom activity regularizer had to be designed and implemented using TensorFlow package to be used in the AutoEncoder.

To check if the dimensionality reduction was performed correctly, the original brain scan, the encoded image and the decoded image were all visualized using a function we wrote in python and compared. This was done by using the matplotlib package. After this, the reduced data was saved to train and test the convolutional neural network.

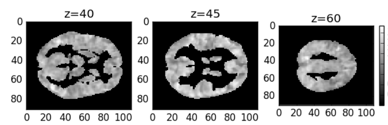
The CNN to train and make predictions for autism diagnosis was implemented in python using the Keras [3] neural network package. After the CNN finished training on the train data, the model had to be tested to check its accuracy. This was done by designing and writing a test function in python which compared the predictions of the model and the true data values to find the overall test and train accuracy of this model.

Before implementing the regression model, the phenotype data had to be processed. This was essential since a lot of the features in the dataset were incomplete and thus we manually processed the 1071 different examples in the CSV data to include only a few relevant features and examples for training and testing purposes. After this processing, the features in the processed dataset had to be encoded into a numpy array. Hence, we wrote a function to load the data and perform the encoding on the data before using it for regression analysis.

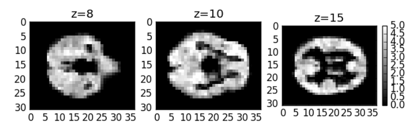
The regression model was programmed and implemented using the scikit-learn package [4]. Several types of regression models were programmed and before being tested using a test function we wrote.

5. Results

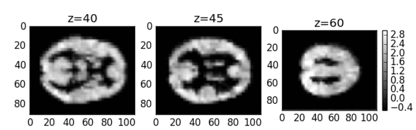
5.1. Neural Network



(a) Input Image



(b) Encoded Image



(c) Decoded Image

Figure 5: Results of CAE

We see that the convolution auto-encoder was able to reduce the dimensionality of the fMRI 3-D scan from 91x108x91 to 31x37x31 clearly. The input image in many cases was also blurry, yet the output image was clear, as seen in the figure below.

After training the convolution neural network on the fMRI brain scans, the train and test accuracy were obtained.

Train Accuracy	**Test Accuracy**
0.9863	0.5486

Table 1: Accuracy of Convolution Neural Network

From table 1, we see that although the convolution neural network is able to learn the features for the train set which is signalled by its high train accuracy, it is not able to generalize what it has learnt, resulting in a low test accuracy. This also shows us the complexity of diagnosing autism and how brain structure can vary substantially for individuals

5.2. Regression

Several types of regression such as polynomial and linear regression were performed on the processed phenotype data. This resulted in various diagnosis accuracies depending on the type of regression used.

Regression Type	Train Accuracy	Test Accuracy
Linear Regression	0.5568	0.6315
Polynomial Regression (Power = 2)	0.6045	0.6315
Polynomial Regression (Power = 3)	0.6386	0.6140
Polynomial Regression (Power = 4)	0.6772	0.7017
Polynomial Regression (Power = 12)	0.7	0.6842

Table 2: Accuracies of different types of Regression

From table 2, we can see that polynomial regression can be used to predict autism with an accurate diagnosis rate of around 70%, which is significant as currently majority of autism cases are diagnosed after the age of 5 [1].

6. Analysis and Implications

6.1. Convolution Neural Network (CNN)

The CNN did not perform very well for the Brain fMRI scans. Looking back at the results and experiments tried, it could be as a result of the following:

1. There is a CNN architecture that has not been explored but might work well for this dataset. There are innumerable architectures that can be tried, and more study needs to be done as to what kind of architectures could be used and work best. Better models could be found out by doing a statistical analysis of how each neuron fired when an image was inputted, but such a study is beyond the scope of this project.
2. The dataset was not large enough, as a result of which the CNN could not learn relevant features and patterns to predict a complex condition like ASD. Maybe we need more augmentation and a larger supervised dataset.

The failure of the CNN model does not mean that a CNN cannot be used later. It just hints at the need for further and more detailed study, which we have managed to narrow down the search space to.

6.2. Regression

A regression analysis managed to give us results better than modern clinical success rates. Surprisingly, only simple and few features were needed to get these results. This means that maybe just a few well-filtered features are good enough indicators. This being said, it must be noted that autism may manifest itself in a similar way to other developmental disabilities in the phenotype data and hence the regression model needs to be tested on datasets of other disorders to ensure that it predominantly gives a unique prediction for autism.

On one hand, regression is less computationally expensive and easier to use than Deep Networks, but creating the required features requires manual human effort, which is tedious and might be inconsistent across different doctors. On the other hand, CNNs are more computationally expensive but since fMRI scans are standardized across the world and no features need to be created, the predictions are accurate and consistent.

7. Conclusion

In order to improve the life of autistic people, it is important to diagnose ASD early. This early diagnosis, leads to an early intervention which has been proven to improve the prognosis of the disorder. Based on this paper, it can be said that polynomial regression on patient phenotype data has a huge potential in the early detection of ASD as results are quite accurate. On the other hand deep learning on fMRI scans was not able to diagnose autism accurately. Over here, there is scope for further research by training and testing the convolution neural network on fMRI scans of autistic and non-autistic people of a small age range such as 0-2,2-4, 4-6 years. This may lead to better results as a result of more similar brain structures.

Accurate and early diagnosis of ASD not only improves the life of autistic people due to early start of therapy but also reduce the overall costs of life-long support of these people by $\frac{2}{3}$ [5]. Though we did not get good results through the use of fMRI scans, they still have a lot of potential in autism diagnosis research, if sufficient data is available. This is not only due to the fact that fMRI scans are relatively safe as they use magnetic fields and not radiation to produce images, but also as fMRI scans can potentially reduce the time and effort needed to diagnose ASD and instead of a team of medical professionals diagnosing a person with ASD over multiple sessions, a diagnosis can be made accurately using neural networks on a scan. Thus use of fMRI scans and phenotype data in ASD detection should be further explored in research using more specific machine learning algorithms and a larger dataset while also experimenting with new techniques in the field.

8. References

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