Autism Spectrum Detection using FMRI data

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***Abstract*— ASD (Autism Spectrum Disorder) is an underestimated neurological disorder that has the capacity to destroy the social life of an individual. Therefore, the detection of this disease at an early age is very crucial for human kind. With the advancements in various machine learning and deep learning algorithms, it has now been possible to detect ASD in patients based on the earlier records of various patients. We have introduced a ANN model that is capable of predicting ASD based on FMRI data, since FMRI data is widely used for studying different brain activities. WE have used ABIDE dataset that are primary source of FMRI data. We have also compared our proposed model with the different machine learning algorithms like KNN, Random forest, etc. that had previously been used for ASD detection.**

Keywords— FMRI data, ABIDE dataset, ANN (Artificial Neural Network), Autism Spectrum Disorder (ASD)

I. INTRODUCTION

ASD (Autism Spectrum Disorder) is a condition that affects children aged six to seventeen years old. Individuals with ASD have issues with their social skills, behavioural skills, and communication skills. Patients with ASD are much more likely to exhibit abnormal social behaviour and repetitive behaviour, which can negatively impact their social experiences. According to the statistics given by WHO, 1 child in 160 children suffer with ASD. So, it becomes very crucial to detect ASD at an early age, so the standard of lifetime of children is also improved. The models for early detection of ASD are supported functional and structural relationships of human brains. Therefore FMRI (Functional resonance Imaging), are utilized in the training of ASD models, because it will be accustomed study structures of brain and show the correlated fluctuations in BOLD (Blood oxygen level-dependent) signals from different brain regions. ABIDE is one among the foremost commonly used dataset in training of models designed for detection of autism. it's been observed that ASD affects the functional connectivity between different regions of the brain. So works are being done to spot ASD supported neural patterns of functional connectivity. during this paper we've got proposed a ASD detection model supported FMRI data, that's able to detect ASD in subjects/patients.

II. EXPERIMENTAL DATASET AND BASELINE METHODS

A. Experimental dataset

Selection of proper dataset is one of the crucial steps of any experiment, because the training of the model is determined by the selected dataset. We have used FMRI dataset for the training of our model. FMRI is non-invasive technique (i.e., scans done on humans to obtain FMRI data, have no side-effects on human health), for studying brain activities. FMRI data has FMRI signals extracted on different brain parcellations and atlases and a set of confound signals. In-order to collect FMRI data, series of brain images are acquired while subject performs a set of tasks. Changes in the measured signals between individual images are used to make inferences regarding task related activities in the brain. Each image consists of 100000 voxels, which correspond to a spatial location and has number associated with it that represents intensity. Each voxel has its own time series. Goals of FMRI data analysis:

- **Localization**: Determine which regions of the brain are active during a specific task.
- **Connectivity**: Determine how different brain regions are connected with one another
- **Prediction**: Use a person's brain activity to predict their perceptions, behavior, or health status.

B. ABIDE DATASET

The Autism Brain Imaging Evidence Exchange is a compilation of anatomical and functional brain image data provided by 24 international brain imaging laboratories. It is the most widely used dataset for autism diagnosis. The ABIDE dataset is split into two parts: ABIDEI and ABIDEII. The data in ABIDEI comes from 1112 people, with 539 of them having ASD and 573 were normal taken from 17 sites, whereas ABIDE Ⅱ 593 normal individuals and 521 with ASD, taken from 19 sites.

PRE-PROCESSING OF DATASET

The different tools available for pre-processing of FMRI data are CCS, CPAC, DPARSF, NIAK, etc. We have used CPAC (Configuring Pipeline of Analysis of Connectome) with nuisance signal removal, motion alignment, low frequency drift as parameters. FILT_Global i.e. Band Pass Filtering and Global Signal Regression were used as processing strategy. The data that is obtained after processing strategy and registration technique, are further treated by calculating the derivatives based on the region of interest. The different region of interests is namely aal (automated

anatomical labeling), ez(eickhof-zilles), ho, TT, dosenach 160 as well as cc200.
After all the above-mentioned pre-processing techniques, the desirable dataset is obtained.

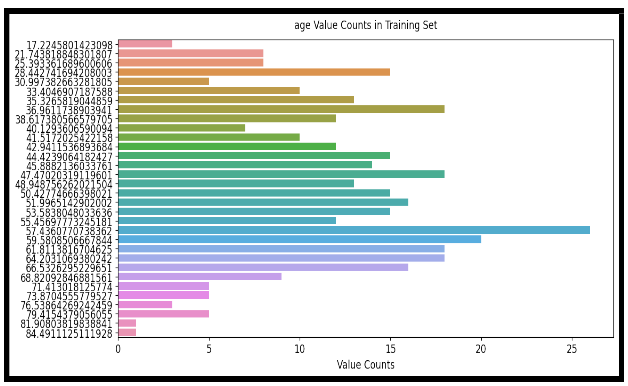
C. Baseline Methods

Recently, the utilization of ANN (Artificial Neural Network), has gained lots of recognition, in coping with classification and learning problems. ANNs are capable of handling free parameters and also give better accuracy. ANNs have the power to detect brain biomarkers (capable of early detection of ASD) in patients laid low with ASD, using the FMRI data. The proposed method is predicated on detection of ASD using ANN, supported FMRI data. The trained model may be evaluated supported its performance, using different supervised algorithms. The algorithms used are KNN (K-nearest neighbor), SVM (Support Vector Machine) and Random Forest. These evaluations are made on Abide dataset. After performing hyper-parameter tuning and different optimization techniques, the results obtained are 67% accuracy just in case of SVM, 60% in KNN also as 55% in Random forest.

D. Data Visualization

1) Comparisions b/w subjects

We have compared all the subjects according to their ages because age is the biggest factors in these types of neurological diseases.



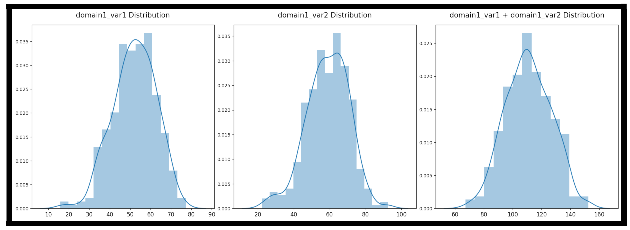
2) Statistical feature of TARGET features

We have calculated the Feature analysis in Subjects.

```
Target feature domain1_var1 Statistical Analysis
------------------------------------------------
Mean: 52.09  -  Median: 52.42  -  Std: 10.5
Min: 15.77  -  25%: 45.29  -  50%: 52.42  -  75%: 59.79  -  Max: 77.29
Skew: -0.3113  -  Kurtosis: -0.01612

Target feature domain1_var2 Statistical Analysis
------------------------------------------------
Mean: 58.92  -  Median: 59.53  -  Std: 11.75
Min: 22.19  -  25%: 51.62  -  50%: 59.53  -  75%: 67.36  -  Max: 92.55
Skew: -0.34  -  Kurtosis: 0.2999

Target feature domain1 Statistical Analysis
--------------------------------------------
Mean: 111.0  -  Median: 110.6  -  Std: 15.81
Min: 67.19  -  25%: 99.58  -  50%: 110.6  -  75%: 122.7  -  Max: 152.6
Skew: 0.0374  -  Kurtosis: -0.3281
```

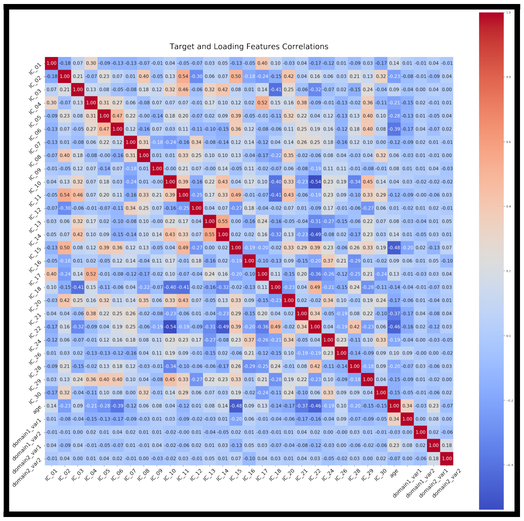


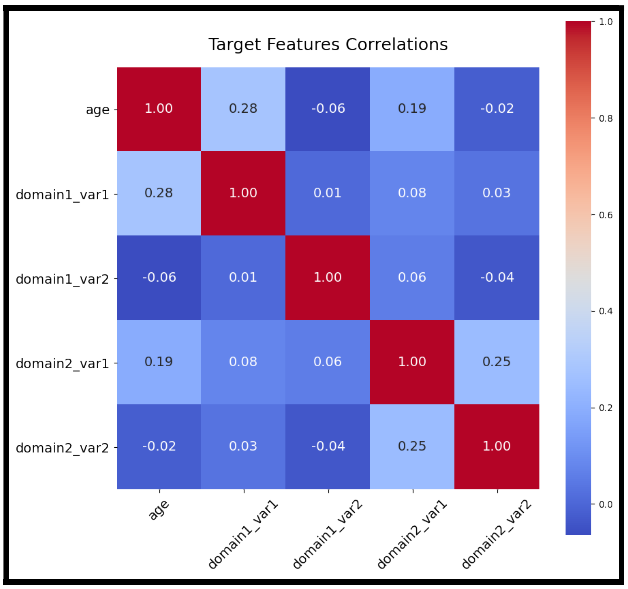
3) Co-relation b/w different features

Features

1. **Source-based Morphometry Loadings Features-**

IC_01 - Cerebellum
IC_02 – ACC (Agenesis of corpus callosum) + mpfc (Medial prefrontal cortex)
IC_03 - Caudate
IC_04 - Cerebellum
IC_05 - Calcarine
IC_06 - Calcarine
IC_07 – Precuneus +PCC (The posterior cingulate cortex)
IC_08 - Frontal
IC_09 – IPL (Inferior Parietal Lobule) +AG (angular gyrus)
IC_10 – MTG (Human Middle Temporal Gyrus)
IC_11 - Frontal
IC_12 – SMA (supplementary motor area)
IC_13 - Temporal Pole
IC_14 - Temporal Pole + Fusiform
IC_15 – STG (Superior temporal gyrus)
IC_16 - Middle Occipital
IC_17 - Cerebellum
IC_18 - Cerebellum
IC_20 – MCC (anterior midcingulate cortex in cognitive motor control)
IC_21 - Temporal Pole + Cerebellum
IC_22 - Insula + Caudate
IC_24 – IPL (Inferior Parietal Lobule +Postcentral
IC_26 – Inf +Mid Frontal
IC_28 - Calcarine
IC_29 – MTG (Human Middle Temporal Gyrus)
IC_30 - Inf Frontal

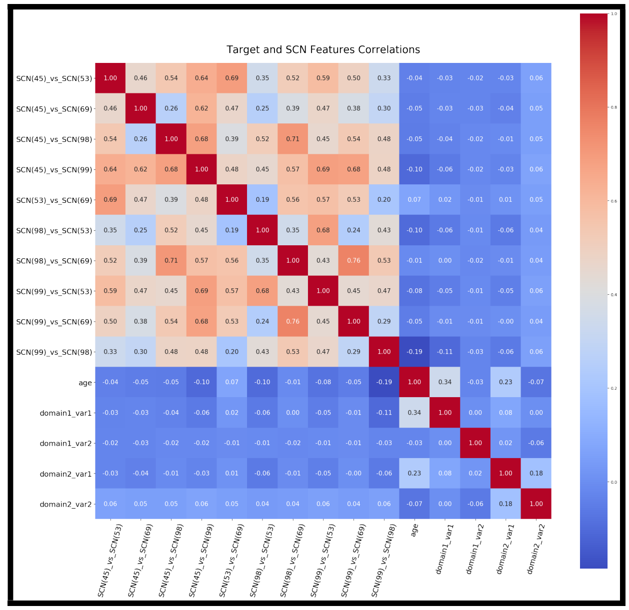




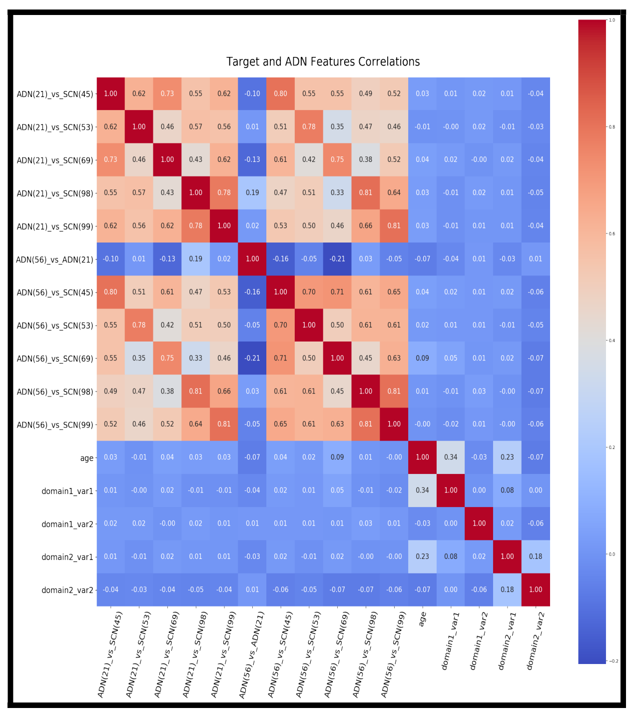
2. Static Functional Network Connectivity Features

SCN - Sub-cortical Network
ADN - Auditory Network
SMN - Sensorimotor Network
VSN - Visual Network
CON - Cognitive-control Network
DMN - Default-mode Network
CBN - Cerebellar Network

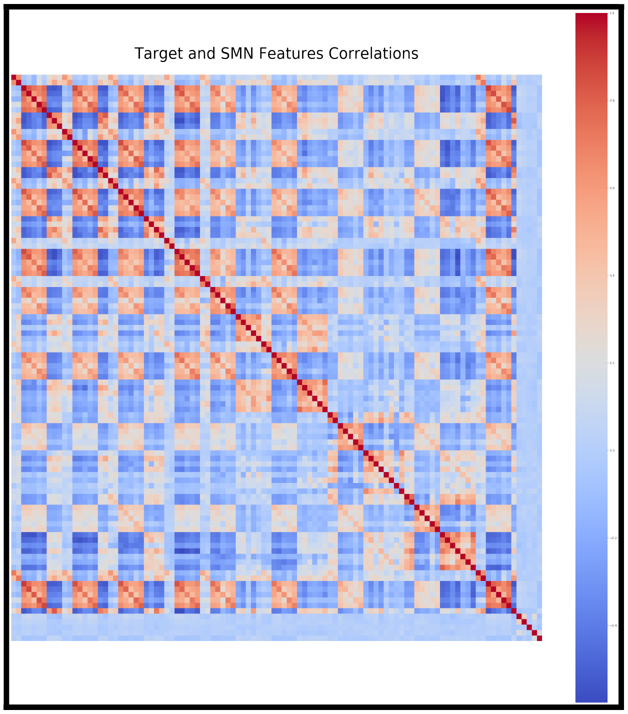
SCN - Sub-cortical Network-



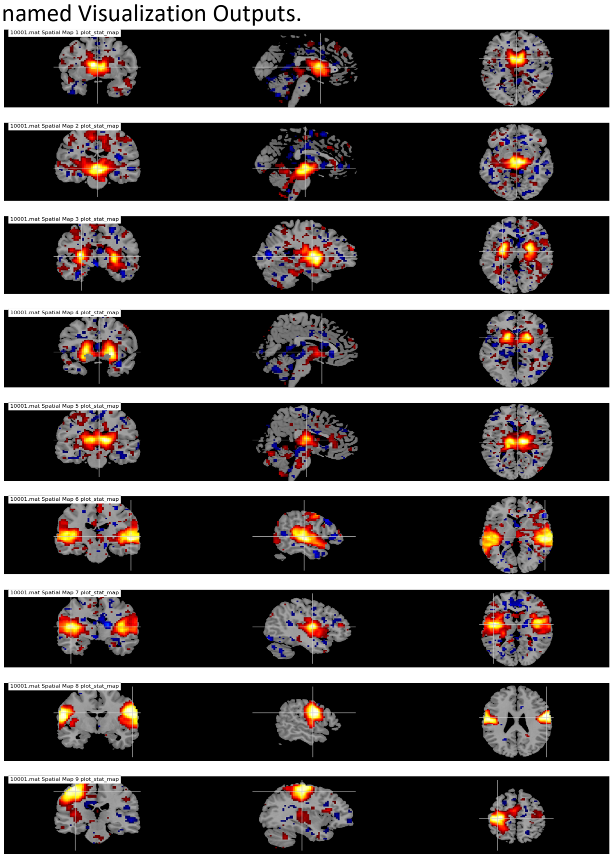
ADN - Auditory Network-



SMN - Sensorimotor Network



We have attached all the Co-relation Matrix in a document named Visualization Outputs.

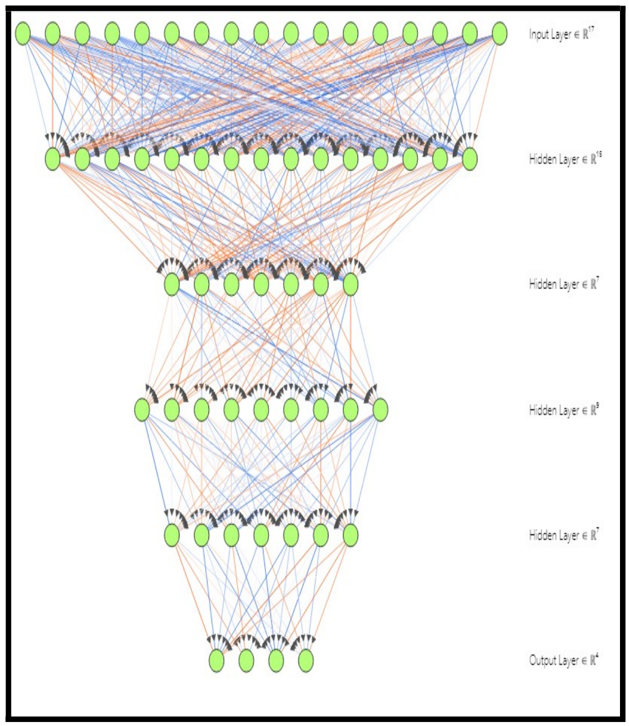


III. Proposed Approach/Method

With the surge in popularity of Artificial neural Network (ANN), we have used ANN to detect ASD in patients. The training of the model has been done using ABIDE dataset

A. Network Architecture

The input and output layers are two of the six layers in the network. There are 17 neurons in the input layer and four neurons in the output layer. There are 15, 7, 9, and 7 neurons in each of the four hidden layers. After every level in the network, there is a dropout layer with the dropout rate equal to 0.1. The dropout layer is used to drop the unnecessary features with are irrelevant in the prediction. ReLU activation function is used in all the layers except the output layer in which SoftMax is used. ReLU (Rectified Linear Activation Function) is a linear activation function that will output the given as it is, if the input is positive otherwise output zero. On the other hand SoftMax is used to allocate probabilities to each class in a multiclass classification.



B. Training of the model

- For the training of the model, ADAM is used as the SGD optimizer.
- Categorical Cross-entropy is used the loss function, because the input dataset have categorical data.
- Since categorical data is present in input, so one hot encoding technique is used. The different categorical

data present are namely autism, non-autism, inconsistent value and missing value.

IV. Result

We developed a model that can predict Autism Spectrum Disorder using the ABIDE dataset, keeping in mind the success of ANN. The sample size during learning was 25, the dropout rate was 0.1, and the number of epochs was 200. The total time taken for execution of this model is around 12-15 hours with specification **i7 10750H Nvidia 1660Ti (GDDR6 VRAM 6GB) Memory 16 Gb(2933MHz).** The obtained accuracy is 90.62 %.

V. Comparison with existing schemes approaches

Many researchers have already built many methods/models for detecting ASD. We compared our findings to several machine learning algorithms such as random forest, logistic regression, KNN, SVM rbf, and XGBoost, which have already been used in the detection of ASD. For 200 epochs, the model was trained.

Output obtained after overall cleaning:

	Classifiers	Accuracy score	AUC-ROC Score
0	Random Forest	0.840764	0.735244
1	Logistic Regression	0.668790	0.599839
2	kNN	0.687898	0.619831
3	SVM_rbf	0.796178	0.694598
4	ANN	0.837585	
5	XGBoost	0.847134	0.747647

Output obtained after sample wise cleaning:

	Classifiers	Accuracy score	AUC-ROC Score
0	Random Forest	0.840764	0.735244
1	Logistic Regression	0.668790	0.599839
2	kNN	0.687898	0.619831
3	SVM_rbf	0.796178	0.694598
4	Our Deep Neural Network	0.906212	
5	XGBoost	0.847134	0.747647

Random Forest- A comparison of machine learning algorithms for the surveillance of autism spectrum disorder Scott H. Lee
Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques Author-Suman Raja,Sarfaraz Masood

Further Comparisons without Aug. –

Site	ASD-DiagNet	ASD-DiagNet (no aug.)	Heinsfeld et al., 2018	SVM	Random-Forest
Caltech	52.8	49.9	52.3	46.9	**54.2**
CMU	**68.5**	67.4	45.3	66.6	62.4
KKI	**69.5**	68.6	58.2	66.4	66.6
Leuven	**61.3**	57	51.8	59.8	59.8
MaxMun	48.6	51.4	**54.3**	53.8	49.2
NYU	68	65.1	64.5	**71.4**	61.8
OHSU	**82**	71.9	74	79.4	54.3
Olin	**65.1**	58.8	44	59.5	52.2
Pitt	**67.8**	65.9	59.8	66.3	59.9
SBL	51.6	47.5	46.6	**60**	48.3
SDSU	63	61.3	**63.6**	58.7	62.7
Stanford	**64.2**	53	48.5	51.4	62.1
Trinity	54.1	51.2	**61**	53.1	54.5
UCLA	**73.2**	70.3	57.7	72.1	69.3
USM	68.2	65.1	62	**73.2**	58
UM	63.8	**65.7**	57.6	64.2	64.8
Yale	**63.6**	61.7	53	61.6	55.3
Average	**63.8**	60.7	56.1	62.6	58.6

Bold and color values corresponds to highest accuracy achieved among all datasets.

ROC Curve for all the available models –

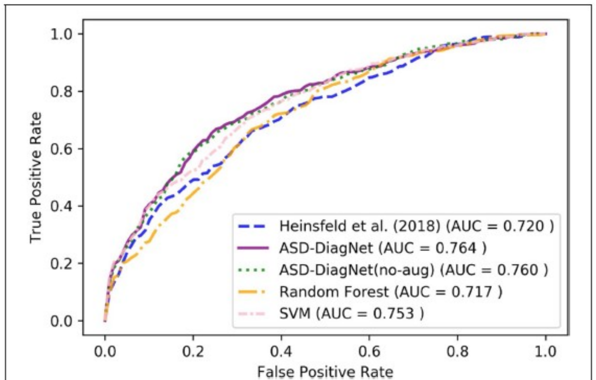


FIGURE 4 | ROC curves of different methods for classification of whole dataset using CC-200 parcellation.

Further Comparisons with Aug. –

Method	Accuracy	Sensitivity	Specificity
ASD-DiagNet	**67.5**	63.4	71.5
ASD-DiagNet (no aug.)	64.5	60.9	68
SVM	**67.5**	63.9	70.9
Random forest	65	56.8	72.7
Heinsfeld et al., 2018	63.3	58.6	67.8

Bold values show the highest accuracy among all methods.

Method	Accuracy	Sensitivity	Specificity
ASD-DiagNet	65.3	63.4	66.9
ASD-DiagNet (no aug.)	65.2	61.1	69
SVM	**66.4**	61.6	71
Random forest	65.1	60.3	69.7
Heinsfeld et al., 2018	63.2	59.8	66.4

Bold values show the highest accuracy among all methods.

VI. Conclusion

The proposed model is ANN architecture that is capable of classifying ASD patients based on FMRI data. We have also compared the accuracy of our model with the other algorithms like KNN, SVM, random forest, and logistic regression. The result depicted that average accuracy of our model is 90.62 %.

VII. Future Scope

Our model has shown promising results in the task of predicting ASD, but there is always a scope of improvement and enhancement in the proposed model. This can be achieved by training the model on aggregated collection of FMRI and phenotypic data. This could help in improving the performance and accuracy of the model. In some cases, the data augmentation is helpful, but in fewer cases, this has also led to decrement in accuracy of model. So, it is required to propose better data augmentation methods and generating new samples of data by taking into consideration structural and phenotypic data of subjects.

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