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# Identification of Autism Spectrum Disorder (ASD) using Autoencoder

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***Abstract:** Deep Learning (DL) techniques are computational models based on representation learnings. They are demonstrated to be the best reasonable strategies to deal with information with various portrayals and with numerous degrees of reflection. Recognizable proof of ASD has been a test as there is no demonstrated reason for it. The issue has been tended to by numerous specialists with the utilization of fMRI. As MRI and its varieties have 3D representations, Machine Learning and Deep Learning techniques are appropriate to deal with and handle them. This paper extends the recognizable proof of ASD from fMRI pictures utilizing Autoencoder organize. The examinations are led on the benchmark dataset ABIDE II. Results uncover that DL strategies are bringing out better classifiers delivering a great degree of arrangement exactness.*

***Keywords:** ASD, ABIDE, Deep Learning, Machine Learning*

## I. INTRODUCTION

ASD is a condition identified with mental health that affects how an individual sees and associates with others, messing up social connection and correspondence. The confusion likewise incorporates constrained and monotonous examples of conduct. The expression "Spectrum" in the ASD issue alludes to the wide scope of indications and seriousness. ASD incorporates conditions that were recently viewed as an independent spectrum, Asperger's disorder, youth disintegrative issue and an undefined type of inescapable developmental disorder. ASD starts in early youth and in the end, causes issues working in the public eye socially, in school and at work, for instance. Regularly kids show indications of mental imbalance inside the primary year. Few youngsters seem to grow typically in the main year, and afterward experience a time of relapse somewhere in the range of 18 and two years of age when they create chemical imbalance side effects. The indications in ASD shifts with the sex [1]. While there is no solution ASD, serious, early treatment can have a major effect on the lives of numerous kids. A few youngsters give indications of mental imbalance range issues in early earliest stages, for example, diminished eye to eye connection, absence of reaction to their name or lack of concern to parental figures.

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Other youngsters may grow regularly for the initial barely any months or long stretches of life, yet then all of a sudden become pulled back or forceful or lose language aptitudes they've just procured. Signs normally are seen by age 2 years. Every kid with a ASD is probably going to have an interesting example of conduct and level of seriousness from low working to advanced. A few kids with ASD experience issues learning, and some have indications of lower than typical insight. Other youngsters with the turmoil have ordinary to high knowledge they adapt rapidly, yet experience difficulty conveying and applying what they know in regular daily existence and changing in accordance with social circumstances. Due to the special blend of side effects in every youngster, seriousness can here and there be hard to decide. It's commonly founded on the degree of impedances and how they sway the capacity to work.

Existence of ASD has no single known reason. Given the unpredictability of the disorder and the way that side effects and seriousness change, there are likely numerous causes. Both hereditary qualities and the earth may assume a job. Specialists analyze ASD by taking a gander at an individual's conduct and advancement. ASD can, for the most part, be dependably analyzed by the age of two. It is significant for those with worries to search out evaluations as quickly as time permits so a finding can be made. According to now, there is no specific immaculate therapeutic fix or treatment as it is a psychological issue. Along these lines, our fundamental test here is to check a patient whether is an ASD type or not. There are numerous ways like utilizing EEG/Transfer Entropy [2], utilizing restorative pictures alongside Deep Learning and Machine Learning calculations to anticipate an ASD quiet.

In section 2, we present an extensive literature study on this domain in recent years. Section 3, explains the autoencoder framework used and section 4 carries the details of experiments conducted and their results.

## II. LITERATURE SURVEY

The existing ASD screening tools for early detection of autism are expensive, time-sensitive and less efficient. So we use intelligent methods based around Machine learning and Deep learning. The main goals of these methods are to speed up the screening time and to improve sensitivity and accuracy of the diagnosis process.

### A. Machine Learning Algorithms

Lot of research works were done in the field of ASD identification with machine learning algorithms. Ismail et. al [3] had designed a novel diagnostic tool to identify ASD based on cerebral white matter segmented form brain image and an adaptive spatial model to account for data inhomogeneity's.

With this, they reconstructed CWM meshes and estimated 3 shape features. This was experimented on 20 ASD controls and used K-Nearest Neighbour (KNN) classifier. They had presented that the classifier brings out 95% accuracy. However this work is not done using bench mark datasets. Gajendra Katuwal et. al. [4] had reported that from ABIDE dataset brain morphometric features were derived with the help of FreeSurfer and were applied on 3 classifiers namely Random Forest (RF), Support Vector Machine (SVM) and Gradient Boosting Machine (GBM). Experiments were conducted on datasets of individual sites and were showing higher accuracy of 97%. However, overall classification accuracy was found to be 67%. They also presented that important features of classification were observed in frontal and temporal regions and these regions has high impact of ASD. H. Choi has presented his work on identification of ASD using variational autoencoder (VAE). He had presented the functional connectivity matrix into 2 features. The extracted features were visualized by VAE and connectivity matrices were generated. This data driven feature extraction based on deep learning was proved to discover highly complex patterns of abnormalities. Majority of the studies made use of brain imaging for the identification ASD. However, for identification of ASD, EEG data can also be used. This unexplored area is studied by Ali et. al. [1]. It makes use of EEG data, nonlinear effective connectivity measures and graph theory. [1] used EEG data, transfer entropy with self-prediction optimality, and four graph theoretic parameters to compare the effective connectivity networks of ASD youths with those of healthy controls (HCs) during a passive face processing task. Results of the study shows a significant difference in average degree of differentiation between ASD affected and normal controls. Rajarajan [2] had presented a simple artificial neural network (ANN) model to work on brain images. He had presented that Back Propagation Network (BPN) works on small data set. The Machine learning algorithms used for prediction of ASD are Multilayer perceptron, Functional trees, Logistic model trees, LDA, KNN, Random forest etc. These all algorithms support Support Vector Machine (SVM) [7].

### B. Deep Learning

Deep learning techniques are representation learning strategies with different degrees of representation yet non-direct modules that each changes the representation at one level into a representation at a higher, somewhat progressively unique level. Our writing overview distinguished that Autoencoder and its variety are the broadly utilized profound learning model for this issue. Convolution Neural Network (CNN) and 3D CNN are also proved to be promising models by researchers to address the problem of identifying ASD.

## III. AUTOENCODER AND TRANSFER LEARNING

An autoencoder is a kind of artificial neural framework used to learn data coding in an effective way. The purpose of an autoencoder is to get comfortable with a portrayal (encoding) for a great deal of data, customarily for dimensionality decline, by means of setting up the framework to neglect signal "upheaval". Nearby the lessening side, a duplicating side is discovered, where the autoencoder endeavors to make from the decreased encoding a depiction as close as possible to its extraordinary data, thusly its name. A couple of varieties exist to the fundamental model, with the purpose of convincing the educated portrayal of the commitment to acknowledge supportive properties. Models are the regularized autoencoders (Sparse, Denoising and Contractive autoencoders), showed convincingly in learning depictions for resulting request tasks, and Variational autoencoders, with their continuous applications as generative models. Autoencoders are suitably used for handling many applied issues, from face acknowledgment to verifying the semantic hugeness of words. An autoencoder is a neural framework that makes sense of how to copy its commitment to its yield. It has an inside (concealed) layer that portrays a code used to address the data, and it is built up by two guideline parts: an encoder that maps the commitment to the code, and a decoder that maps the code to a propagation of the primary data. Playing out the recreating task perfectly would basically duplicate the sign, and this is the explanation autoencoders when in doubt, are limited inhabits that power them to imitate the data generally, protecting only the most relevant pieces of the data in the copy. The probability of autoencoders has been well known in the field of neural frameworks for an extensive time allotment, and the fundamental applications return to the '80s. Their most ordinary application was dimensionality reduction or feature adjusting, anyway more starting late the autoencoder thought has gotten even more commonly used for learning generative models of data. Presumably, the most predominant AIs during the 2010s included small autoencoders stacked inside profound neural frameworks. The simplest type of an autoencoder is a feedforward, non-intermittent neural system like single-layer perceptrons that partake in multilayer perceptrons (MLP) – having an information layer, a yield layer and at least one concealed layers interfacing them – where the yield layer has a similar number of hubs (neurons) as the info layer, and to recreate its sources of info (limiting the distinction between the information and the yield) rather than anticipating the objective Y given data sources X. In this manner, autoencoders are unaided learning models (don't require named contributions to empower learning). An autoencoder consists of two parts, the encoder and the decoder, which can be defined as transitions $\phi$ and $\Psi$ such that

$$\phi : X \rightarrow F \qquad (1)$$

$$\Psi : F \rightarrow X \qquad (2)$$

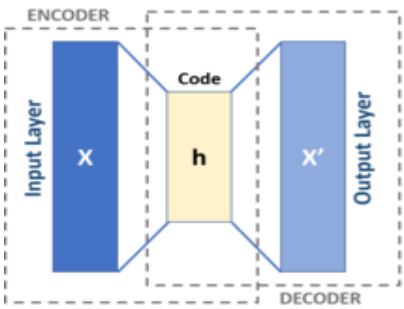



**Fig. 1 Architecture of Autoencoder**

Transfer learning is an AI system where a model prepared on one errand is re-purposed on a second related undertaking. Transfer learning is an enhancement that permits fast progress or improved execution when demonstrating the subsequent assignment. Transfer learning is identified with issues, for example, perform various tasks learning and idea float and isn't only a territory of concentrate for deep learning. In any case, transfer learning is main stream in deep learning given the gigantic assets required to prepare deep learning models or the huge and testing datasets on which deep learning models are prepared. Transfer learning possibly works in deep learning if the model highlights gained from the primary assignment are general. Transfer learning is advancement, an easy route to sparing time or showing signs of improvement execution. In general, it is not obvious that there will be a benefit to using transfer learning in the domain until after the model has been developed and evaluated.

The classifier model used in the present work is same as given by Heinsfeld et. al. [5]. Denoising autoencoders were used to train the predictive model for better generalization; i.e. accurate classification of new subjects outside the initial pool of participants. Details of the classifier and dataset are given in the subsequent section.

## IV. EXPERIMENTS AND RESULTS

Experiments were carried out using rs-fMRI data from the Autism Imaging Data Exchange (ABIDE I). ABIDE is a consortium that provides previously collected rs-fMRI ASD and matched controls data for the purpose of data sharing in the scientific community by Di Martino et al., in 2014. We included data from 505 ASD individuals and 530 matched controls (typical controls, TC). The ABIDE datasets were collected at 17 different imaging sites and include rs-fMRI images, T1 structural brain images and phenotypic information for each patient. It contains key phenotypical information, including distribution of ASD and TC by sex and age and the ADOS score for ASD subjects, as well as the Mean FRAME WISE Displacement (FD) quality measure. Previously preprocessed rs-fMRI data was downloaded from the Preprocessed Connectomes Project (http://preprocessed-connectomesproject.org/). Data was selected from the C-PAC preprocessing pipeline. In the present study, we used two stacked DENOISING autoencoders for the unsupervised pre-training stage to extract a lower-dimensional version from the ABIDE data. We achieved the best optimization for the validation set using reconstruction loss (mean squared error); the following configuration was used in a cross-validation k-fold schema. The input and output layers have 19,900 features fully connected to a bottleneck of 1000 units from the hidden layer. We conducted 2 experiments. These experimental setups are different from the one proposed by Heinsfield et. al [5] in the following aspects viz., i) we used ReLU (Rectified Linear Units) as activation functions ii) ADAM optimizer iii) for data corruption is using Gaussian distribution. In contrast, Heinsfield et. al. [5] used binomial distribution. The second autoencoder maps 1000 inputs from the output of the previous autoencoder to outputs through a hidden layer of 600 units. Experiment 1 was done for 100 iterations on MLP layer and 700 and 2000 iterations on Autoencoder 1 and Autoencoder 2 respectively. In order to arrive at average result of experiments, we performed 10 fold cross validation testing. Mean Squared Error (MSE), Mean Absolute Error (MAE) and Classification Accuracy of experiment 1 is given below.

**Table- I: Experiment 1: Results of experiments on 10 fold cross validation**

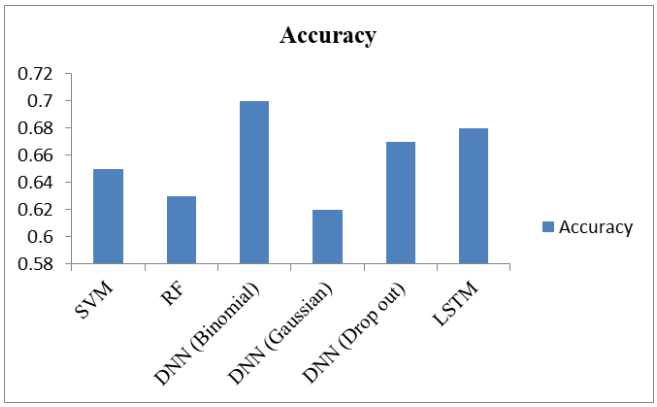
| Fold No | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Accuracy | 0.6987 | 0.6923 | 0.6602 | 0.6794 | 0.6858 |
| **Fold No** | **6** | **7** | **8** | **9** | **10** |
| Accuracy | 0.6987 | 0.6602 | 0.6474 | 0.6474 | 0.7051 |

Experiment 2 was conducted by introducing a drop out layer in MLP. Dropout is one way of regularization that helps the model to avoid overfitting. The results of experiment 2 are given in Table II.

**Table- II: Experiment 2: Results of experiments on 10 fold cross validation**

| Fold No | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Accuracy | 0.6666 | 0.6666 | 0.6666 | 0.6731 | 0.6859 |
| **Fold No** | **6** | **7** | **8** | **9** | **10** |
| Accuracy | 0.6474 | 0.6859 | 0.6859 | 0.6923 | 0.6731 |

Experiment 2 gives an average accuracy of 67.34% whereas Experiment 1 gives 62%. The results of the experiments are compared with the classification accuracy from various other Machine Learning and Deep Learning models on same ABIDE dataset and given in Figure 2. Though the result of experimentation is not higher than that of Heinsfield et. al. [5], this work gives an insight that modifications in autoencoders are not giving any improved performance. However, this may be due to the size of the data set.




## V. CONCLUSION

The present study is an attempt to improve the performance of autoencoder based deep learning model presented by Heinsfield et. al. [5]. The classification accuracy on an average of 70% was the result of the experimentation. To improve the performance, we tried by introducing few changes viz., increase in number of layers, increase in number of iterations.

However, the experiments on ABIDE dataset has resulted in classification accuracy of 67% on average. This is less when compared to test results of [5].

But these experimental results make us to draw few findings viz., i) increase in number of layers of autoencoder model does not bring in any improvement in performance ii) usage of computational resources in terms of GPUs are essential for these kind of applications and iii) increase in number of iterations also does not have any impact. However, the scope of further work in this direction is to try with different activation functions, and models like CNN, 3D CNN and LSTM.

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