# Autism Spectrum Disorder (ASD) Detection Using Machine Learning Algorithms

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**Abstract.** Some diseases are characterized by persistent deficits in brain activity. Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder. It appears in early childhood and evolves throughout life and needs to be detected early to accelerate the treatment and recovery process. These deficits may be detected using medical imaging techniques. In this paper, we present machine learning algorithms allowing to detect peoples with ASD from normal peoples. We used data from the ABIDE dataset. We tested 3 algorithms: Support Vector Machines (SVM), Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). The best result was obtained using CNN algorithm with an accuracy equal to 95%.

**Keywords:** Autism · Machine learning · CNN · LSTM · SVM · ABIDE · fMRI

## 1 Introduction

In the recent decades, the medicine industry has adopted numerous approaches and methods to discover or predict many diseases [1, 2]. In this context, researches are focusing on developing machine learning algorithms in order to improve their accuracy [3].

Brain diseases such as Autism Spectrum Disorder (ASD) have been of increasing interest to researchers over the past few years. ASD is known as a cerebral disease that involves impairments in cognitive functions, communication/social interactive, cognitive and adaptive skills. Studies from the neuroscience domain indicate that the biomarkers of ASD are still unknown however the corpus callosum and intracranial brain volume holds significant information for its detection. Based on these conclusions, we suggested machine learning models for automatic ASD detection. The proposed algorithms were tested and evaluated on the ABIDE[1] dataset. Since autism is a brain dysfunction disorder, we will use functional Magnetic Resonance Images (fMRI) which better describe this disorder.

In this paper three algorithms were presented: Support Vector Machine (SVM), Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). The comparison of results showed that CNN performs better than SVM and LSTM with an accuracy equal to 95%.

[1] ABIDE dataset: https://fcon_1000.projects.nitrc.org/indi/abide/.


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## 2 State of Art

ASD is a brain-based disorder marked by social deficits and repetitive behaviors. The main aim of psychiatric Neuroimaging research is to identify objective bio-markers that may inform the diagnosis and treatment of brain-based disorders. ASD is associated with a range of phenotype that vary in severity of social, communicative and sensory motor deficits. Recently, Machine Learning (ML) algorithms have been applied to brain imaging data to extract brain function patterns. These algorithms can retrieve robust neural patterns from brain imaging data of psychiatric disorder patients.

In their work, Omar et al. [4] proposed an effective prediction model based on ML technics in order to develop a mobile application for predicting ASD for people of any age. The model was developed by merging Random Forest-CART and Random Forest-Iterative Dichotomiser3. The proposed model was evaluated with AQ-10 dataset and 250 real dataset collected from people with and without autistic traits [4].

In another work, Kuper et al. [5] focused on adolescents and adults. They used SVM to examine whether ASD detection can be improved by identifying a subset of behavioral features from the ADOS Module 4 in a routine clinical sample. They identified reduced subsets of 5 behavioral features for the whole sample as well as age subgroups. The results of evaluation may help to improve the complicated diagnostic process of ASD by encouraging future efforts to develop novel diagnostic instruments for ASD detection based on the identified constructs as well as aiding clinicians in the difficult question of differential diagnosis [5]. In the work of [6], authors explore the possibility to test Naïve Bayes, Support Vector Machine, Logistic Regression, KNN, Neural Network and Convolutional Neural Network for predicting and analysis of ASD problems. They evaluate the proposed methods on publicly available three different non-clinically ASD datasets for children, adolescents and adults. The results suggest that CNN based prediction models work better on all these datasets.

Knowing that the Functional Magnetic Resonance Imaging (fMRI) helped to identify and detect the ASD, Dvornek et al. [7] proposed a model based on Recurrent Neural Networks with Long Short-Term Memory for classification of individuals with ASD and typical controls from the resting-state fMRI time-series. They used the ABIDE-I dataset for training and testing the LSTM models. Results with a cross-validation framework showed an accuracy of 68.5% on the whole ABIDE cohort.

The primary goal of the current study is to classify ASD patients and control participants based on their neural patterns of functional connectivity using resting state functional magnetic resonance imaging (rs-fMRI) data. Supervised ML algorithms were used and applied to a large population sample of brain imaging data extracted from the ABIDE dataset.

# 3 Methods

## 3.1 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is a deep learning neural network that has shown excellent performance in many computer vision and machine learning problems. It is designed to learn automatically spatial hierarchies of features through back-propagation. It uses the multiple building blocks, such as the convolution layers, the pooling layers and the fully connected layers [8]:

**Convolution Layer.** This layer is a fundamental component of the CNN architecture. It performs feature extraction using a combination of linear and nonlinear operations, i.e. convolution operation and activation function.

**Pooling Layer.** This layer provides a down sampling operation which reduces the dimensional of the feature maps and identify invariance to translation, shift and distortions. The filter size, stride and padding are the hyper-parameters in pooling operations, similar to convolution operations.

**Fully Connected Layer.** The features extracted by the convolution layers and then downsampled by the pooling layers are mapped using a subset of fully connected layers to the final outputs of the network. The fully connected layer is followed by a nonlinear function, such as ReLU. When the input data are transformed into output through the different layers, it is called the forward propagation. We build a CNN network with 8 convolution layers, 4 pooling layers and a fully connected layer.

## 3.2 Long Short Term Memory (LSTM)

Long Short Term Memory (LSTM) network is a special kind of Recurrent Neural Networks that is capable of learning long-term dependencies. LSTM can be used to model univariate time series forecasting problems. These problems are comprised of a single series of observations and a model is required to learn from the series of past observations to predict the next value in the sequence. The LSTM model learn a function that maps a sequence of past observations as input to an output observation. As such, the sequence of observations must be transformed into multiple examples from which the LSTM can learn [7].

In our paper, we extracted mean time-series from regions of interest defined by several atlases. Each time course was normalized to represent percent change from the average signal for that region of interest.

## 3.3 Support Vector Machines (SVM)

Support Vector Machine (SVM) is a classical binary classification algorithm, particularly adapted for big data. The SVM method was proposed by “Vapnik” [9] and has been widely used for medical image processing.

Given a set of training examples features $\{x_i\}_{i=1}^{l}$, and their labels $\{y_i\}_{i=1}^{l}$, a Support Vector Machine (SVM) builds a prediction model that assigns new examples into one class or the other depending on the side of the learned separating hyperplan on which they stand.

The decision function of the SVM is given in (1) where k is a given positive kernel.

$$f(x) = \sum_{i=1}^{l} \alpha_i^* k(x, x_i). \tag{1}$$

The dual learning optimization problem form is given in (2). C>= 0 is the regularization parameter related to the misclassified samples.

$$\begin{aligned} &\max_{\alpha_i} \sum_{i=1}^{l} \alpha_i - \tfrac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j k(x_i, x_j), \\ &s.t \quad 0 \le \alpha_i \le C \end{aligned} \tag{2}$$

The linear kernel was used and the one-vs-the-rest scheme was adopted in our work. For dimensionality reduction we used PCA to keep 99% of variance then we transformed the phenotypic data into a dataset and determined the target.

## 4 Material and Results

### 4.1 Material

This study is performed using the ABIDE dataset which is an online sharing consortium that provides imaging data of ASD and control participants with their phenotypic information. The ABIDE dataset includes two large-scale collections: ABIDE I and ABIDE II. ABIDE I includes 1112 subjects aged between 7 and 64: 539 subjects with ASD and 573 subjects with typical controls.

The ABIDE dataset includes functional and structural brain imaging data collected from laboratories around the world to ensure data diversity and to understand the complexity of the disease to be able to make the diagnosis at earlier ages, to select optimal treatments and to predict outcomes.

Structural imaging [9] is used to visualize and analyze anatomical properties of the brain and are particularly useful for detecting brain damage and abnormalities. Functional imaging [9–11] is used to identify brain areas and underlying brain processes that are associated with performing a particular cognitive or behavioral task. It can be used to investigate the functional anatomy of the brain by identifying the parts of the brain with critical functions, to evaluate the effect of many diseases such as stroke and to brain treatment.

Our imaging data is composed of functional Magnetic Resonance Imaging from ABIDE I that allows a better description of the brain-related dysfunction. We extracted features using each correlation matrix extracted from the dataset. For dimensionality reduction, we used a PCA to keep 99% of variance.

An example of F-MRI images is shown in Fig. 1.

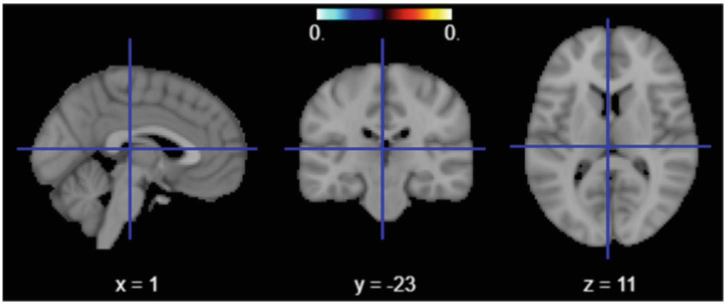


**Fig. 1.** Example of F-MRI images

Our proposed algorithms have been tested on a dataset of 500 patients. 51.2% of the base are subjects with ASD while 48.8% are subjects with typical controls (Fig. 2). We can say that our dataset is balanced. We assign 70% of our modeling dataset to the train and the remaining 30% to the test.

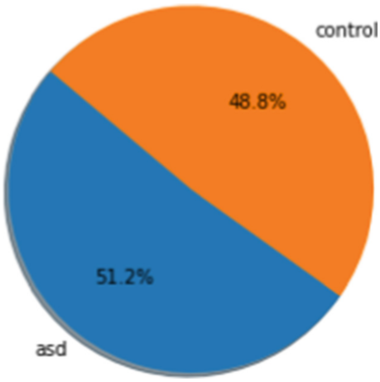


**Fig. 2.** Diagram of ASD distribution in the ABIDE dataset

For gender distribution (Fig. 3), we can see that our dataset is mainly composed of males with a rate = 84%. To understand the reason behind this, we need to know that ASD affects females less frequently than males. Of course several sex-differential genetic and hormonal factors may contribute in the appearance and the development of this disease.

While visualizing the age distribution (Fig. 4), it's clear that the most of patients are very young (aged from 5 to 15 years). This may be justified by the fact that this disease is more frequent among children than among adults and emphasizes the importance of early ASD diagnosis for children to accelerate treatment and recovery.

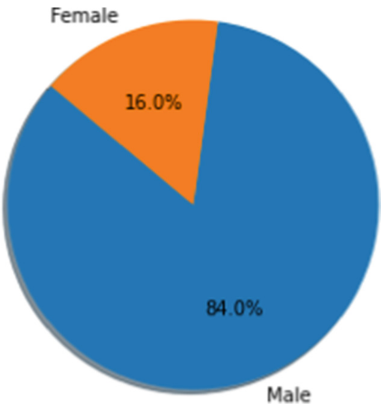


**Fig. 3.** Diagram of gender distribution in the ABIDE dataset

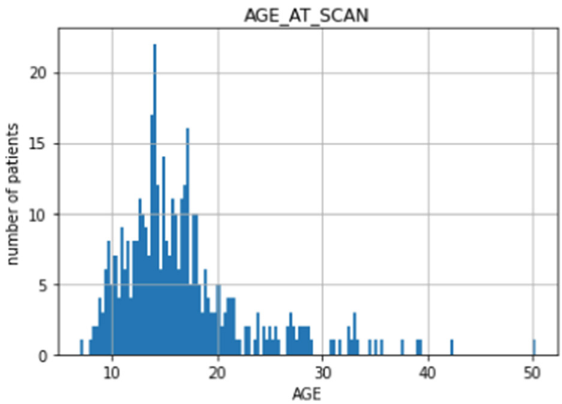


**Fig. 4.** Age distribution in ABIDE dataset

### 4.2 Results and Discussion

The performance of the proposed methods has been evaluated using the accuracy score.

**LSTM.** We used the binary cross-entropy loss function and the Adadelta optimizer with the default parameter values. During the training, we fixed the dropout rate during training to 0.4. The impact of parameters and variations of the proposed architecture were explored as well as training conditions. We tested the data while varying the number of hidden nodes (8, 16, 32, or 64) in the LSTM, and removing dropout. We also tested variations on the base network: connecting only the final LSTM cell's output to a single dense node and stacking LSTM layers. The variation of Loss and Accuracy rates are presented in Fig. 5. We got an accuracy equal to 76.25%.

**CNN.** CNN is typically a repetitions of a stack of several convolution layers and pooling layers, followed by one or more fully connected layers. The CNN that we have worked


**Fig. 5.** Accuracy and loss depending on the number of epoch for LSTM model

on has 8 convolutional layers, 4 max pooling layers and one sigmoid output layer. The input consists of three (316, 70, 1) patches from axial, sagittal and coronal image slices centered on the target voxel. We used Adam as optimizer algorithm. We fit the model and set the number of epochs at 60, so we got an accuracy value equal to 95% (Fig. 6).

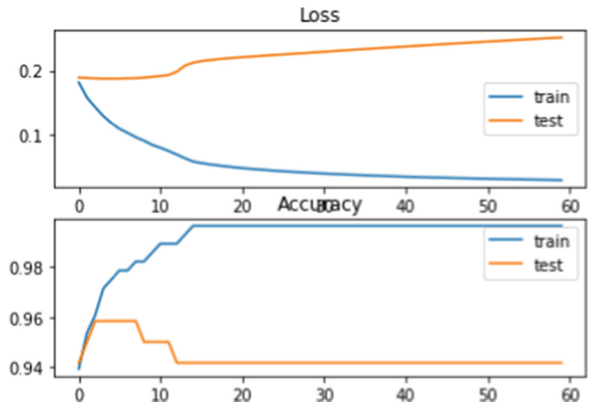


**Fig. 6.** Accuracy and loss depending on the number of epoch for CNN model

**SVM.** The obtained results show good performance of our SVM based method with an accuracy rate equal to 88%. The feature reduction step based on PCA allowed to keep 99% of variance. Our results exceed those of Eslami et al. [12] who combined SVM with a deep learning algorithm. We can say also that our SVM based method performs better than the method presented in [13] for male subjects since our base is male oriented. The Linear SVM method presented in [14] reaches an accuracy equal to 69% and the Gaussian SVM method presented in [15] reached 66%. These two methods are less efficient than our method.

In the Table 1, we summarize the obtained results for the trained algorithms. We conclude that CNN gives the best accuracy rate.

**Table 1.** Accuracy rate of ASD detection in ABIDE dataset using different algorithms.

| Algorithm | Accuracy (%) |
|---|---|
| **CNN** | **95** |
| SVM + PCA | 88 |
| LSTM | 76.25 |
| SVM + Deep learning [12] | 80 |
| SVM + GARCH [13] | 71 |
| Linear SVM [14] | 69 |
| Gaussian SVM [15] | 66 |

## 5 Conclusion

ASD is a brain disease that it is notoriously difficult to diagnose, especially for children. It is associated with significant brain structure changes, which can be measured by magnetic resonance imaging (MRI) scan.

In this paper, we presented three algorithms to generate a model for ASD detection using image classification tools: Convolutional Neural Network, Support Vector Machines and Long Short Term Memory.

These methods for automatic ASD detection were tested on the ABIDE dataset. The performance of algorithms was evaluated throw the accuracy. The best result was obtained using the CNN algorithm with a rate equal to 95%.

In order to achieve better recognition of ASD, other modalities i.e. EEG, speech or kinesthetic modalities can be analyzed simultaneously.

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