Using EEGs to Diagnose Autism Disorder by Classification Algorithm

Ebtehal A Alsaggaf[1], MSCS; Mahmoud I. Kamel [2], Ph.D.

Department of Computer Science, Faculty of Computing and Information Technology,
King Abdulaziz University, Jeddah, Saudi Arabia.
[1.]Email: eaalsaggaf@kau.edu.sa
[2.]Email: miali@kau.edu.sa

Abstract: The classification algorithm is a new trend to discover autism disorder using Electroencephalography (EEG) signal of normal and autistic subjects. This paper is presented methods to detect autism disorders from normal subjects and to evaluate the ability of using filtering and windsorizing techniques supervised learning model. The Fast Fourier Transform (FFT) features with 30 ensembles average are applied. Fisher Linear Discriminant (FLD) classifier and 18 Subjects with cross-validation are combined to estimate the classification's accuracy and reached (80.27%) for all subjects.

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1. Introduction

Autism or Autism Spectrum Disorders (ASD) is a social development disorder that is marked by a distinct lack of social and language skills. The cause of autism is not known and approximately 1 in 88 children born are diagnosed with autism (Baio, 2012). There is not a medical test for autism; a diagnosis is based on observed behavior and educational and psychological testing.

In previous years, either a psychologist or psychiatrist experienced with ASD could make a diagnosis. Currently, doctors use a psychiatric manual, the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV),to diagnose psychiatric disease. It can be far from accurate as so many mental illnesses are complex disorders with a multitude of symptoms that can ebb and flow and even change over the years.

Therefore, Scientists of AI, including pattern recognition, work for supporting the idea that computer science can be used to help them (Alsaggaf & Gamalel-Din, 2011). Fortunately, with the advancements in technology, there is a lot of research going on around using neuroscience with EEG analysis to apply machine learning methods to automated detection of autism using cross-validation methods (Stahl, Pickles, Elsabbagh, Johnson, & The BASIS Team, 2012; Bosl, Tierney, Tager-Flusberg, & Nelson, 2011). EEG signals analysis based machine learning method is part of typical Brain computer Interface (BCI) algorithms and have three main steps preprocessing, feature extraction, and classification (L. Thompson, & M. Thompson, 2010).Therefore, there is a lot of research going on around the world today trying to use Neuroscience to treat and diagnosis children with ASD. The analysis and classification of EEG signals will properly diagnose the patient (Fabricius, 2010).

FLD and regularized Fisher Linear Discriminant (RFLD) were demonstrated by reanalyzing an EEG dataset from autistic children. Using 10 cross-validations, both methods successfully discriminated between groups of autistic and normal children. They were studied the optimum preprocessing, as well as, optimum features extraction which give the highest classification accuracy using MALAB functions and the BCI2000 tools. FFTextracted features were classified to estimate average classification accuracy of both classifiers. Windsor Filtered Data sets gave the best accuracy 91% fromother combined preprocessing operations data sets in FLD. On the other hand, The RFLD was improved the classification performance of the FLD and its result was 92% (Kamel et al., 2012; Alhaddad et al., 2012).

The goal of this study is to evaluate the ability of using filtering and windsorizing techniques to detect ASD disorders from normal subjects. The FFT features with 30 ensembles average is applied .FLD classifier and 18 Subjects -fold cross-validation are combined to estimate average classification accuracy of our supervised learning model.

2. Material and Methods

The goal of our supervised learning model is to determine and to classify the pattern of EEG signals of two classes' labels in terms of predictor features. The performance of the current model depends on the accuracy of the employed classifiers in which EEG signal processing algorithms are used to learn and model the input relationship of the BCI application (i.e. BCI2000) as described in papers (Kamel et al., 2012; Alhaddad et al., 2012). FLDA classifier was applied with 30 ensample average and FFT as feature extraction technique. When constructing the final model, 18 Subjects-fold cross-validation is used to estimates the accuracy of model.

Below the process of applying supervised learning modelis describedstep by step:

1. Apply the type of preprocessing operations used (i.e., filtering, windsorizing) for all subjects. Before doing anything else, we applied FFT features and decimation number is not used.

2. Prepare training data by building input vectors from both groups to be appropriate for feeding into our supervised learning algorithm after doing data acquisition and pre-processing modulesas described in papers (Kamel et al., 2012; Alhaddad et al., 2012). Training data sets contained 1800 epochs for each class and the validation data sets depended on the number of ensemble30 as describe in step 4(b).

3. Determine the structure of the learned function and corresponding learning algorithm as flow :

a. Choose the FLDA classifier as learning algorithm.

b. Create a training data and a testingdata by splitting the universe of data. The training data is the data that the classifier uses to learn how to classify the data, whereas the testing(validation)data is used to feed the already trained model in order to get an error rate that can help us identify the classifier's performance and accuracy form step 2. The method is trained 18subjects using 1 distinct subject for testing and remaining 17 subjectsfor training. The final performance of the method is obtained by averaging.

4. Train the model. We take the training data and we feed it into the algorithm as shown in Figure 1.

5. Validate the model's performance. To estimate the accuracy classification for each subject,the results of cross-validation method is calculated depending on the average numberof the projected samplesfor each class.

6. Finally, weapplied the decision rule where each test subject is placed in the class from which it has the smallest number; if average numberof the projected samplesof normal less than autism, then subject is autism. Otherwise, the subject is considered in normal.

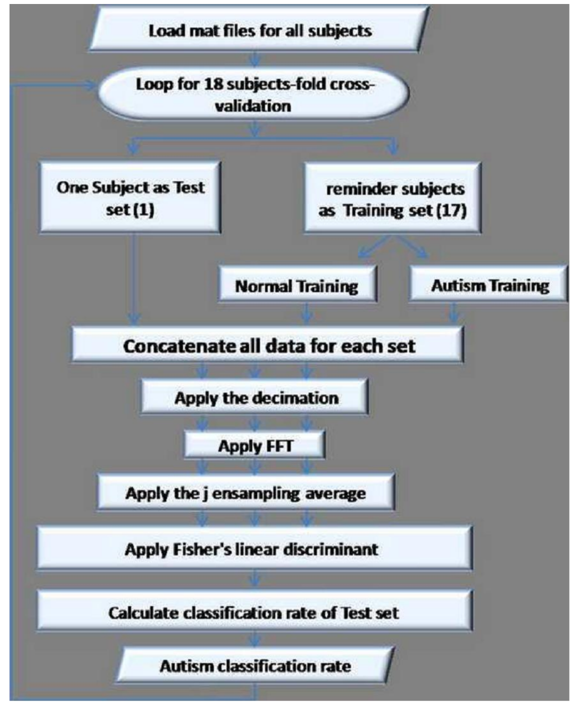

Figure 1: Flow chart outlining the FLD classification and 18 subjects-fold cross-validation process used for data analysis and estimating the accuracy of the classify Normal an Autism subjects.

3. Summary of Results

3.1 Classification Results using 18 Subjects-fold cross-validation

In this experiment, 18 Subjects -fold cross-validation is used to estimate average classification accuracy of FLDA. Table 1 illustrates the classification results for each subject using FFT features and 30 ensembles average.

We evaluated the ability of Windsor Filtered Data set to discriminate ASD disorders from control subjects in which significant differences are found using FLD classifier which it has (80.27%) average classification accuracy for 18 subjects.

Table 2 summarizes the classification results using 18 Subjects-fold cross-validations. Moreover, an 87.5% of original grouped cases correctly classified.

Table 1: Classification results for each subject using 18 Subjects-fold cross-validations

Subject	The classification result		Possible Diagnosis
	Normal	Autism	
Autism#1	0%	100%	Autism
Autism#2	0 %	100%	Autism
Autism#3	10%	90%	Autism
Autism#4	0 %	100%	Autism
Autism#5	30%	70%	Autism
Autism#6	46%	54%	Autism
Autism#7	37%	63%	Autism
Autism#8	54%	46%	Normal
All Autism Subjects averaged	22.125 %	77.875%	
Normal#1	88%	12%	Normal
Normal#2	100%	0%	Normal
Normal#3	55%	45%	Normal
Normal#4	88%	12%	Normal
Normal#5	93%	7%	Normal
Normal#6	77%	23%	Normal
Normal#7	50%	50%	--------
Normal#8	100%	0%	Normal
Normal#9	71%	29%	Normal
Normal#10	100%	0%	Normal
All Normal subjects averaged	82.2%	17.8 %	
The average classification (mean ± S.D)		80.3±19.8	

Table 2: Classification Results using 18 Subjects-fold cross-validation

Cases	Predicted group membership		Total
	Normal	Autism	
Normal	9	1	10
Autism	1	7	8
Normal	90%	10%	100%
Autism	12.5%	87.5%	100%

4. Conclusion and Recommendations:

This paper gives a brief description of our intended final model algorithm in order to discriminate between autistic and normal children. In this model, the feature extraction and classifier learning are combined, thus the ability of Windsor Filtered Data sets are evaluated by choosing FLDA classifier. The model's accuracy is calculated by the 18 subjects-fold cross-validation process depending on the number of 30ensampling to estimate the accuracy classification for each subject.

The average classification accuracy is closed to (77.875%) for autism subjects and (82.2%%) for each normal subject.On the other hand,the average classification accuracy for 18 subjects is (80.27%). These findings prove that the classification algorithm with EEG signal processing is the way to solve the problem of autism diagnosis. This can be seen as the ground work for applying new BCI applications for further development diagnosis of the autism to see how the treatment will be working in future. To validate the current model, more experimentation should be performed with more subjects to obtain more accurate results.

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Corresponding Author:
Mrs. Ebtehal A Alsaggaf
Department of Computer Science, Faculty of Computing and Information Technology, King Abdulaziz University,

Jeddah, Saudi Arabia.
Email: eaalsaggaf@kau.edu.sa

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