Classification of Coherence Indices Extracted from EEG Signals of Mild and Severe Autism

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***Abstract*—Autism spectrum disorder is a debilitating neurodevelopmental illness characterized by serious impairments in communication and social skills. Due to the increasing prevalence of autism worldwide, the development of a new diagnostic approach for autism spectrum disorder is of great importance. Also, diagnosing the severity of autism is very important for clinicians in the treatment process. Therefore, in this study, we intend to classify the electroencephalogram (EEG) signals of mild and severe autism patients. Twelve patients with mild autism and twelve patients with severe autism with the age range of 10-30 years participated in the present research. Due to the difficulties of working with autism patients and recording EEG signals from these patients in the awake state, the Emotiv Epoch headset device was utilized in this work. After signal preprocessing, we calculated short-range and long-range coherence values in the frequency range of 1-45 Hz, including short- and long-range intra- and inter-hemispheric coherence features. Then, statistical analysis was conducted to select coherence features with statistical differences between the two groups. Multilayer perceptron (MLP) neural network and support vector machine (SVM) with radial basis function (RBF) kernel were used in the classification stage. Our results showed that the best MLP classification performance was obtained by selected inter-hemispheric coherence features with accuracy, sensitivity and specificity of 96.82%, 97.82% and 96.92%, respectively. Also, the best SVM classification performance was obtained by selected inter-hemispheric coherence features with accuracy, sensitivity and specificity of 94.70%, 93.85% and 95.55%, respectively. However, it should be noted that the MLP neural network imposes a much higher computational cost than the SVM classifier. Considering that our simple system gives promising results in diagnosing autistic patients with mild and severe severities from EEG, there is scope for further work with a larger sample size and different ages and genders.**

Keywords—Autism spectrum disorder; electroencephalography (EEG); classification; neural network; support vector machine; coherence feature

I. Introduction

Autism spectrum disorder is a debilitating neurodevelopmental illness characterized by serious impairments in communication and social skills. Patients with autism manifest repetitive and restricted behavior [1-3]. The prevalence of autism has increased considerably from 0.67% in 2000 to 2.58% in 2016 in the United States [4-6]. Therefore, in recent years, researchers emphasized different approaches to early diagnosis of this disorder to provide timely intervention and achieve better treatment outcomes [7, 8]. In this regard, it is also very important to determine the severity of the disease in autism spectrum disorder because it leads to changing treatment approaches due to the level of brain disorders [9]. Brain images have shown abnormalities in brain and head size and limbic and cerebellar structure in autistic patients [10]. Magnetic resonance imaging (MRI) studies have shown that autistic patients have serious disturbances in the functional connectivity between different brain regions [11, 12]. fMRI and diffusion tensor imaging (DTI) studies also showed that patients with autism had reduced long-range functional connectivity at rest and during different executive cognitive tasks [13]. However, due to its high availability, cheapness, and ease of use, many researchers have analyzed the electroencephalogram (EEG) signals of autism patients to study their brain function [14-18]. For instance, in a recent study, Hadoush et al. [19] analyzed and compared the brain complexity of children with mild and severe autism through multiscale entropy analysis of EEG signals. They found that the brain complexity of children with mild autism is higher than that of children with severe autism in the right parietal, right frontal, left parietal and central cortices. Finally, they concluded that EEG multiscale entropy could serve as a sensitive index to detect the level of autism severity. In a review study, Wang et al. suggested excessive power in low- and high-frequency EEG bands and impaired functional connectivity as common EEG abnormalities in autism spectrum disorders [20]. The organization of this article is as follows. In Section II, we briefly review some related work in autism diagnosis through EEG analysis. In Section III, the proposed system for preprocessing the EEG signal and extracting and classifying the EEG features of autism patients is presented. Then the obtained results are presented in Section IV. Section V discussed the obtained results. Finally, in the last section, the conclusion of this work is presented.

II. Related Work

As mentioned, due to the increasing prevalence of autism worldwide, the development of a new diagnostic approach for autism spectrum disorder is of great importance. Several studies have shown significant differences between various EEG features of individuals with autism and normal individuals [21-23]. These studies mainly focused on the spectral power of EEG frequency bands, connectivity and coherence between cortical areas, and hemispheric activity asymmetry [24, 25]. For instance, Jamal et al. obtained an accuracy, sensitivity and specificity of 94.7%, 85.7% and 100%, respectively, in autism diagnosis using connectivity features and a support vector machine (SVM) with the polynomial kernel [26]. Sheikhani et al. used spectral power features and K-nearest neighbours and reported a classification accuracy of 82.4% for autism diagnosis [27]. Fan et al.

proposed a similar framework for EEG classification of autism and non-autism subjects and reported an accuracy of 85% for this purpose [28].

On the other hand, several recent studies have investigated the nonlinear features of EEG for autism diagnosis. Bosl et al. reported good EEG classification results for autism diagnosis using multiscale entropy and SVM [29]. Ahmadlou et al. used the fractal dimension of EEGs and radial basis function neural network and achieved a classification accuracy of 90% for autism diagnosis [30]. Djemal et al. proposed an EEG-based computer-aided diagnosis of autism through entropy and wavelet-based features as well as an artificial neural network and achieved a classification accuracy of 99.71% [31]. Abdulhay et al. proposed a computer-aided autism diagnosis system through second-order plot area and empirical mode decomposition and achieved a classification accuracy of 94.4% for autism diagnosis [24].

Although several studies have been published in the field of computer-aided diagnosis of autism using EEG signals, very few studies have paid attention to the fact that in autism, we are dealing with a relatively wide range of patients with different behavioral and cognitive symptoms. Meanwhile, diagnosing the severity of autism is very important for clinicians in the treatment process. Therefore, in this study, we intend to classify the EEG signals of mild and severe autism patients using coherence indices and machine learning approaches (i.e., SVM and artificial neural networks).

III. Materials and Methods

A. Patients

Twelve patients with mild autism and twelve patients with severe autism were participated in the present research. All participants with autism were diagnosed by psychiatry experts according to the diagnostic criteria of DSM-5 [32]. Also, the severity of autism was determined through psychiatric interviews with specialists. The age range of the selected patients was 10-30 years. During the selection stage, patients with autism who had other neurological conditions, such as epilepsy or head trauma, were excluded. The patient enrollment was administered in a psychiatric clinic. The research project was done in accordance with the principles of the Declaration of Helsinki (1996) and the current Good Clinical Practice guidelines. The goal and an overview of the project were characterized by the participants and their parents during the initial contact. For those who agreed to participate, all the necessary information was provided prior to signing written informed consent. Information about the subjects was utilized anonymously and for the purpose of the study.

B. Data Acquisition and Cleaning

Previous studies have shown that resting with eyes open is the best EEG recording condition for EEG classification of autism from healthy subjects. Hence, in the current work, EEG recordings were performed while the patients were awake with their eyes open and sitting comfortably in an armchair without any stimuli. Depending on the subject's cooperation, EEG was recorded for 12-20 minutes for each patient in one session. Due to the difficulties of working with autism patients and recording EEG signals from these patients in the awake state, the Emotiv Epoch headset device was utilized in this work. Since the Emotiv Epoch headset is a wireless EEG device, the signal recording was conducted in autistic patients more easily. This EEG device uses a Bluetooth module for wireless communication. The Emotiv Epoch headset and Software Development Kit include 14 electrodes (AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1, O2 based on 10-20 international system) along with DRL/CMS references at P4/P3 locations. As depicted in Fig. 1, the EEG headset is wireless and has a large lithium-based battery for 12 hours. The sampling rate in this device is 128 Hz. The electrode impedance is reduced through the saline liquid and alcohol pads until the circles shown in Fig. 1 turn green. Emotive software was utilized to record EEGs and convert their format to MATLAB format.

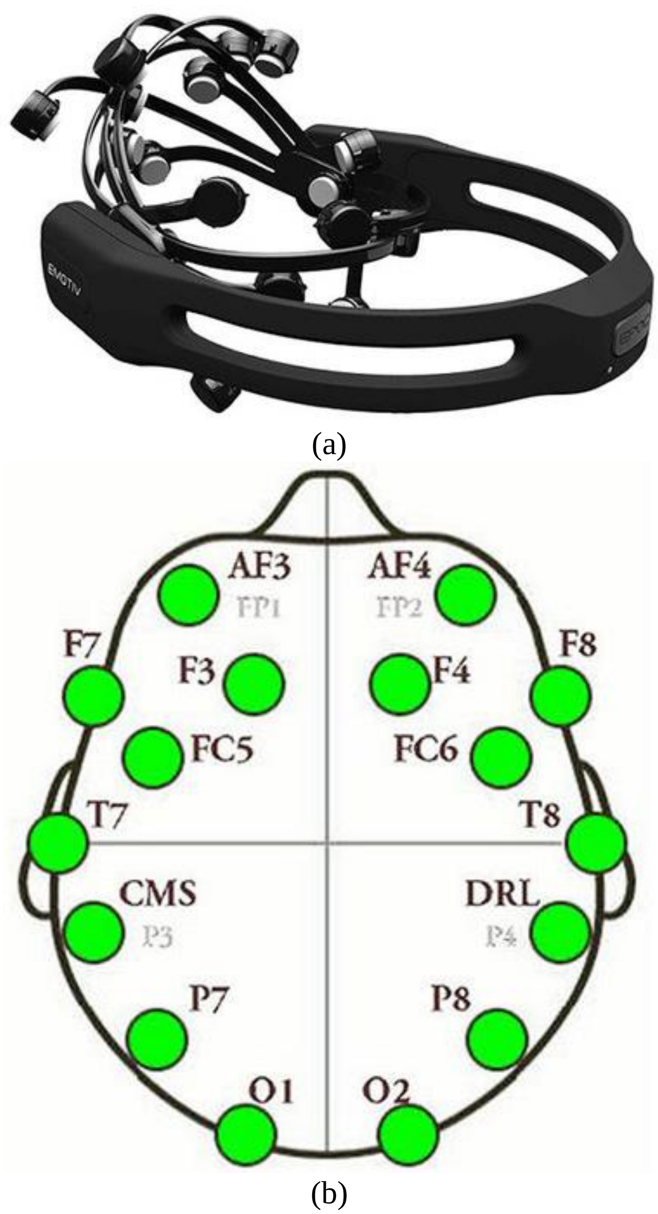


Fig. 1. Emotiv Epoch device and sensors organization. (a) headset and sensors, (b) 10-20 EEG international protocol.

Emotiv Epoch utilizes a 50 Hz notch filter to eliminate the main power line component. After EEG recording, in the signal preprocessing and conditioning stage, a band-pass Hanning window with a finite duration and frequency range of 1-45 Hz was applied to the signals via MATLAB software [33-35]. In addition, we performed electrode interpolation using adjacent channels for low-quality electrodes. EEGs were re-referenced to the common average and then were decomposed via independent component analysis (ICA). Components with motion and muscle artifacts were recognized by ICA and were then removed based on time courses and frequency scalp maps. The cleaned components were reconstructed, and a 50-second cleaned EEG signal was prepared for each patient.

C. Coherence Features

EEG coherences measure the level of synchronization between two channels (i.e., two brain regions) in terms of EEGs recorded at different regions of the scalp. The coherence function gives information about the functional connectivity of the brain [36]. The value of the coherence function is in the range of zero to one, which shows the correlation of two signals in terms of frequency. If the value of the coherence function is zero, it means that the two channels are independent of each other, and the value of one indicates a high correlation between the two channels. The coherence function of two signals, i and j, at frequency f, is calculated as follows:

$$COH_{i.j}(f) = \frac{|S_{i.j}(f)|^2}{S_{i.i}(f) \cdot S_{j.j}(f)} \qquad (1)$$

Where, $S_{i.j}(f)$ is the cross-spectrum of the two signals, and $S_{i.i}(f)$ and $S_{j.j}(f)$ are auto-spectrum of the two signals. Fig. 2 shows the EEG coherence visualization method through matrix representation and node-link diagram.

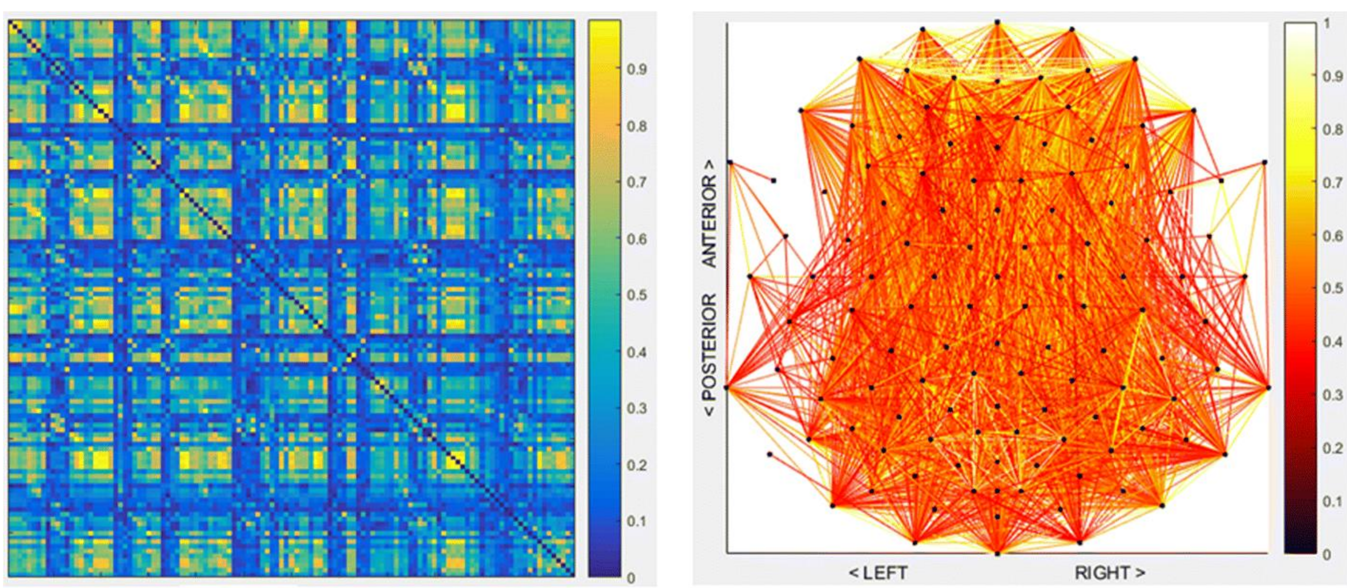
In this work, we calculated short-range and long-range coherence values in the frequency range of 1-45 Hz, including short- and long-range intra- and inter-hemispheric coherence features. Totally, 89 coherence features were calculated.

D. Feature Selection and Classification

To avoid the curse of dimensionality, statistical analysis was applied to the calculated coherence features to select features with significant differences between the two groups of patients with autism. Statistical analysis was also performed in MATLAB software. After performing the Shapiro-Wilk test to confirm the normality of the data, repeated measures analysis of variance (ANOVA) was used to handle the multiple comparison problems and the independent t-test was used as a post hoc analysis to compare the mean of the extracted features between the two groups [37-40]. $P < 0.05$ was considered as the threshold of significance.

E. Multilayer Perceptron (MLP) Neural Network

The selected coherence features through a statistical analysis were applied to suitable classifiers to classify the feature set into mild and severe autism. SVM and artificial neural networks are common classifiers in biomedical applications. Neural networks have been utilized in classification and pattern recognition for different research projects because of their unique properties, such as self-organizing, adaptability, and robustness [41]. There are three layers in a feed-forward neural network like MLP: an input layer, a hidden layer, and an output layer. In the current research, the supervised learning network was utilized to classify mild and severe autism. The architecture of the network is depicted in Fig. 3.



a b

Fig. 2. EEG coherence visualization method. (a) matrix representation, (b) node-link diagram [43].

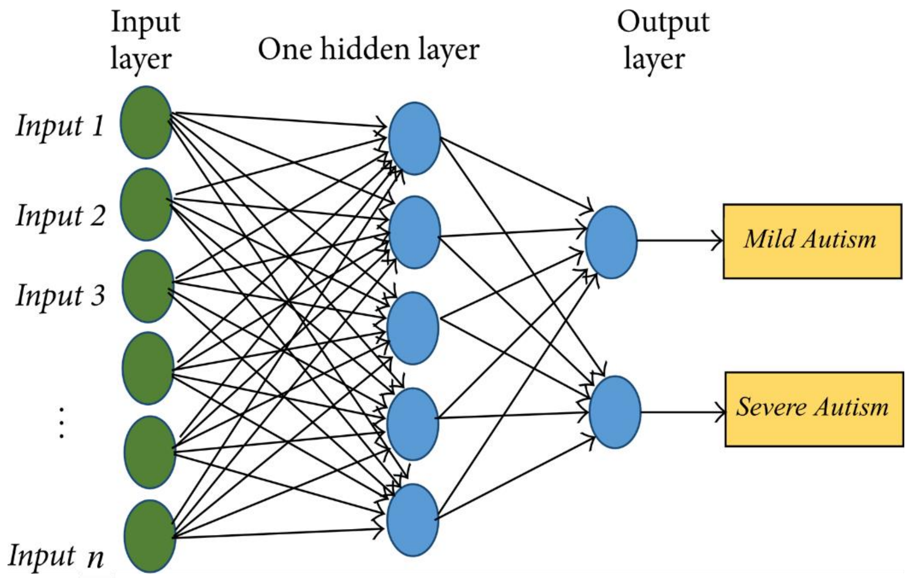


Fig. 3. Artificial neural network architecture.

The neural network was configured with n neurons (based on the number of selected features) in the input layer, five neurons in the hidden layer, hyperbolic tangent hidden transfer function, softmax output transfer function, and backward propagation training algorithm. The bias and weights for the network were initialized through the Nguyen-Widrow method. The neurons of each layer are connected to the next layer with a certain weight, which is defined as follows:

$$\Delta W_{ij} = \eta \delta_j(n) y_i(n) \tag{2}$$

The above equation is known as the delta law, through which weight correction is done from neuron i to neuron j. η, $\delta_j(n)$ and $y_i(n)$ are the learning rate parameter, local gradient and input signal of neuron j, respectively. If j is a neuron in the hidden layer, then $\delta_j(n)$ is obtained by:

$$\delta_j(n) = \varphi_j^{'}\big(v_j(n)\big) \sum_k \delta_k(n) W_{kj}(n) \tag{3}$$

Where, k is a neuron in the output layer, and $\varphi_j^{'}\big(v_j(n)\big)$ denotes the activation function to characterize the input-output relationships of the non-linearity to neuron j.

F. SVM with Radial Basis Function (RBF) Kernel

SVM has been widely utilized by researchers to solve various nonlinear problems and classification tasks with small data samples [42]. We used SVM in this study because this classifier minimizes the expected risk in the test data and considers a margin around the class boundaries, which leads to increased generalizability of the results. SVM uses a kernel function to transform the nonlinear classification problem into a linear one by increasing the dimensionality of the dataset. In this work, we used the RBF kernel. The RBF kernel is the most widely utilized kernel in SVMs. The RBF kernel has good performance in various classification problems. It is expressed as:

$$\big(x_i . x_j\big) = \exp\left(-\gamma \|x_i - x_j\|^2\right) . \gamma > 0 \tag{4}$$

Where, γ is the free parameter to scale the extent of influence, two samples have on each other.

IV. Results and Evaluation

The coherence features were calculated from every 14 channels of EEG signals. Fig. 4 shows an example of recorded EEG signals of mild autistic and severe autistic patients for the right and left hemispheres after preprocessing. After feature extraction, the feature selection process was done through statistical analysis. Fig. 5 shows box plots for short-range and long-range intra-hemispheric coherence features with significant differences ($P < 0.05$) between mild and severe autism groups. As shown, there were significant differences in both the left and right hemispheres. In addition, Fig. 6 shows box plots for short-range and long-range inter-hemispheric coherence features with significant differences ($P < 0.05$) between mild and severe autism groups. These 10 coherence features with significant differences between the two groups were considered as selected features for the classification step. In the classification step, based on the results obtained from the statistical analysis, we considered four feature sets as input to the classifiers: all coherence features, all selected features, selected intra-hemispheric features, and selected inter-hemispheric features. It should be noted that the training and testing processes of the classifier were carried out with the four-fold cross-validation method.

Accuracy, sensitivity and specificity were calculated in this study to measure classification performance. These metrics were calculated based on the concepts of false negative (FN), false positive (FP), true negative (TN), and true positive (TP), which represent cases that were incorrectly or correctly identified as negative or positive cases.

$$Accuracy = \frac{TP+TN}{N+P}$$
$$Sensitivity = \frac{TP}{TP+FN} \ . \tag{5}$$
$$Spesificity = \frac{TN}{TN+FP}$$

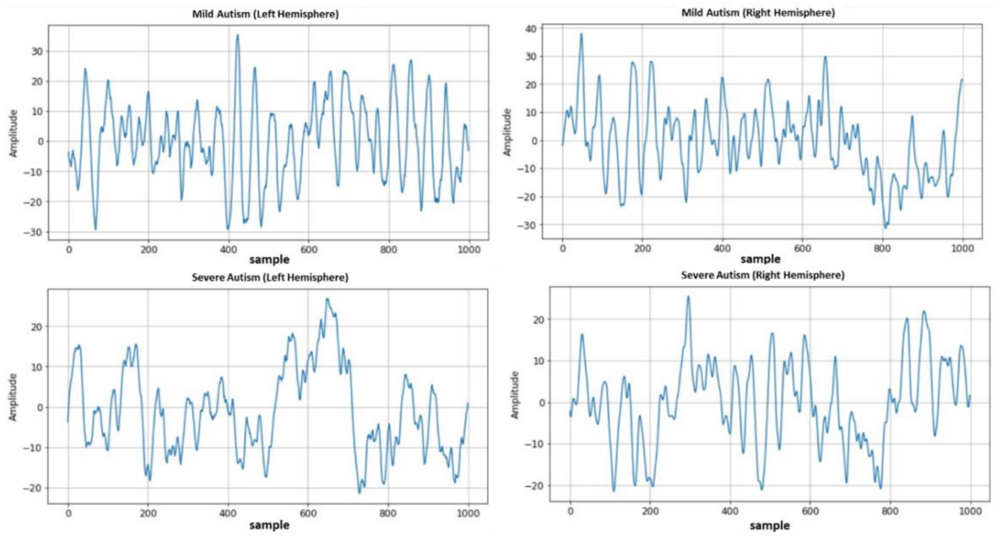


Fig. 4. Sample EEG signals of mild autistic (top) and severe autistic (bottom) patients for right and left hemispheres.

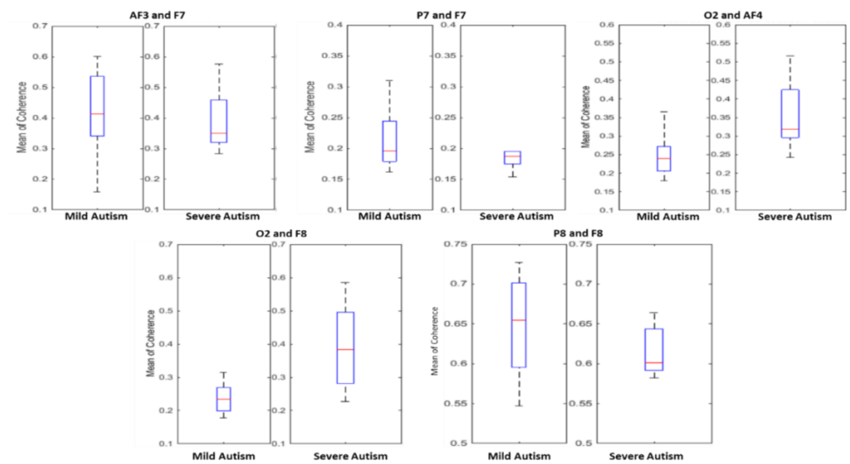


Fig. 5. Box plots for short- and long-range intra-hemispheric coherence features with significant differences (P < 0.05) between mild and severe autism groups.

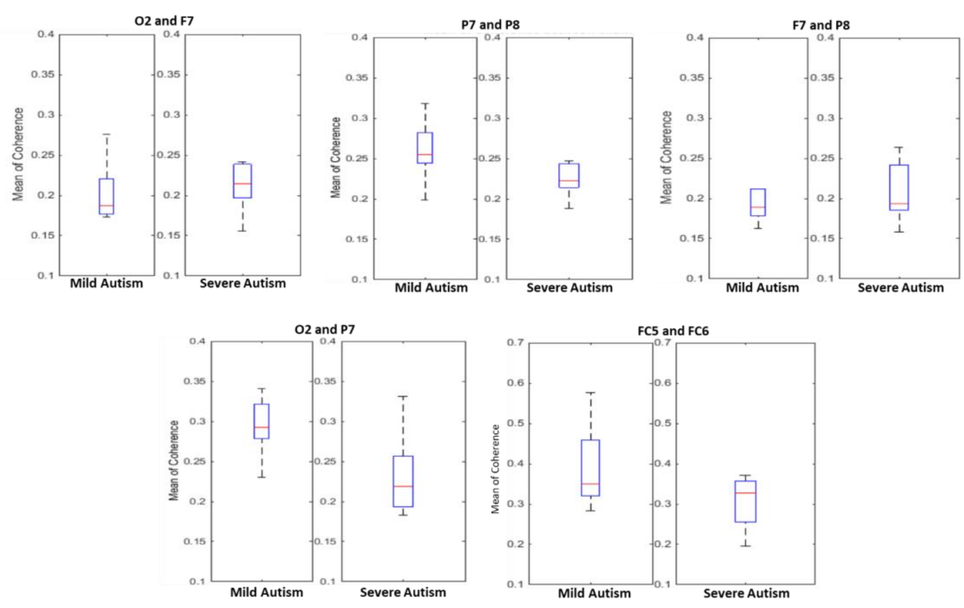


Fig. 6. Box plots for short- and long-range inter-hemispheric coherence features with significant differences (P < 0.05) between mild and severe autism groups.

The performance of the MLP and SVM classifiers is evaluated based on the above indices, as depicted in Tables I and II.

Table I shows the performance of the MLP neural network in the classification of coherence features using the four mentioned feature sets. According to this table, the best classification performance was obtained by selected inter-hemispheric coherence features with accuracy, sensitivity and specificity of 96.82%, 97.82% and 96.92%, respectively. Furthermore, Table II shows the performance of the SVM classifier with RBF kernel in the classification of coherence features using the four mentioned feature sets. Again, the best classification performance was obtained by selected inter-hemispheric coherence features with accuracy, sensitivity and specificity of 94.70%, 93.85% and 95.55%, respectively.

Fig. 7 compares the accuracy rates obtained by MLP and SVM for coherence features extracted from EEG signals for mild and severe autism classification. As shown, the MLP neural network has performed better in classifying coherence features and distinguishing mild autism from severe autism compared to the SVM classifier with the RBF kernel. However, it should be noted that the MLP neural network imposes a much higher computational cost than the SVM classifier. Table III shows the average time of classification operations (in terms of seconds) using MLP and SVM classifiers with and without feature selection.

TABLE I. PERFORMANCE OF MLP NEURAL NETWORK IN THE CLASSIFICATION OF COHERENCE FEATURES

Feature set	Accuracy (%)	Sensitivity (%)	Specificity (%)
All coherence features	88.94	85.90	89.36
All selected features	92.25	91.45	92.99
Selected intra-hemispheric features	93.68	93.70	92.51
Selected inter-hemispheric features	96.82	97.82	96.92

TABLE II. PERFORMANCE OF SVM CLASSIFIER WITH RBF KERNEL IN THE CLASSIFICATION OF COHERENCE FEATURES

Feature set	Accuracy (%)	Sensitivity (%)	Specificity (%)
All coherence features	86.39	84.10	87.91
All selected features	91.12	90.34	92.02
Selected intra-hemispheric features	91.97	89.63	92.69
Selected inter-hemispheric features	94.70	93.85	95.55

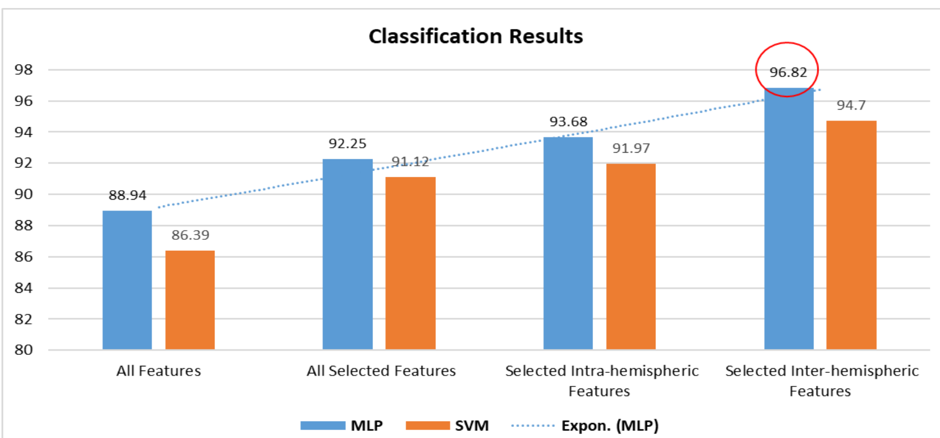


Fig. 7. Average accuracies obtained by MLP and SVM for coherence features extracted from EEG signals for mild and severe autism classification.

TABLE III. AVERAGE TIME OF CLASSIFICATION OPERATIONS USING MLP AND SVM CLASSIFIERS WITH AND WITHOUT FEATURE SELECTION

Operation	Time (s)
MLP classification without feature selection	40.82
MLP classification with feature selection	5.16
SVM classification without feature selection	0.62
MLP classification with feature selection	0.28

V. Discussion

In the present work, we attempted to investigate the potential of EEG coherence features in the classification of mild from severe autism and compare the ability of the MLP neural network and SVM classifier with RBF kernel to classify these features. Our findings showed that the MLP neural network has a better classification performance than the SVM classifier in the task of classifying the coherence features extracted from the EEG signals of two patient groups (96.82% versus 94.70%) at the cost of a more complicated computational process. The computation time of MLP classifier implementation was much longer than that of SVM. Very few similar studies have been published to date to classify mild from severe autism through brain signal analysis. For this reason, it is very challenging to compare the results of this research with other methods based on engineering algorithms. Cheong et al. applied wavelet transform to feature extraction from EEG signals and MLP classifier and reported an accuracy of 92.3% for classifying mild autistic patients from severe autistic patients [44]. In a three-class problem, Howell et al. [45] proposed a general linear model for feature extraction, a recursive feature elimination method for feature selection, and a random forest classifier to classify fMRI data into mild, moderate, and severe autism. They reported 72% accuracy on this three-class problem. Therefore, compared to the previous limited works in this field, our neural network-based system performs better. This can be due to the use of coherence features in the present work. Many electrophysiology and neuroimaging studies on autism spectrum disorders have shown that abnormality and impairment in brain connectivity are one of the most reported neuropathological mechanisms of autism [46-48]. Therefore, the coherence feature, which expresses the degree of coupling of different brain regions with each other, can be one of the strengths of our proposed system for classifying different severities of autism. In addition, it should be noted that most coherence impairments are located in the frontal region, consistent with previous neurophysiological works [49, 50].

Although SVM is a powerful classifier for two-class classification problems, MLP neural network was able to show better performance in the present work. However, the high computational cost of neural networks can limit their practical application in clinical systems [51-54]. Therefore, it is recommended to optimize the MLP neural network in order to reduce the calculation cost and improve the classification performance in future research. In addition, the investigation of other SVM kernels (such as linear, polynomial or sigmoid kernels) can also be done in future research. Furthermore, our results showed that feature selection through statistical analysis is a suitable approach to optimize the two-class classification problem of autism spectrum disorders. In fact, the feature selection approach adopted in this study led to improved classification performance and a significant reduction in computational cost. Therefore, future studies should do more research on the feature selection stage extracted from the EEG signals.

The strength of our study is to propose a simple semi-automatic system based on coherence features and a neural network for classifying mild autistic patients from severe autistic patients from EEG signals. However, limitations such as the small sample size could reduce the generalizability of the results of the current research. Furthermore, in this work, the resting state EEG was analyzed, while previous neurophysiological studies have demonstrated that patients with autism spectrum disorders exhibit important neuropathological mechanisms in different states of arousal. Therefore, different EEG recording protocols should be considered in future studies.

VI. Conclusion

In this paper, the classification of mild and severe autism from EEG signals was investigated by coherence features with MLP neural network and SVM classifier with RBF kernel. The effectiveness of these features was investigated via statistical analysis, and it was seen that coherence features with significant differences between the two groups have more discrimination in diagnosing autistic patients with different severities. In addition, the effectiveness of MLP and SVM was compared, and the MLP neural network yielded the maximum classification accuracy, sensitivity, and specificity. Considering that our simple system gives promising results in diagnosing autistic patients with mild and severe severities from EEG, there is scope for further work with a larger sample size and different ages and genders.

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