Valence State Analysis Using Discrete Wavelet Transform Features for Early Detection of Autism Spectrum Disorder in Young Kids

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Abstract

Autism spectrum disorder is a developmental disorder that has affected many children around the globe in recent years. It is possible to reduce the severity of the symptoms when the affected children are identified and treated early. Hence, early detection and treatment of this neurodevelopmental disorder significantly help the patient's (young ASD kids) well-being. In this regard, the research has been initiated by developing an algorithm based on a neural network that can efficiently differentiate the brain activity of a normal young subject and an autistic young subject. In this research, Electroencephalography (EEG) data were collected from normal kids and kids with ASD from age 4 to 6. Discrete Wavelet Transform (DWT) is used for feature extraction of EEG data for valence state analysis on younger kids. It was inferred that there is a linear increase in Power Spectral Density (PSD) irrespective of age during valence state analysis of various EEG bands such as gamma, beta, alpha, and theta. When comparing the PSD of normal subjects with subjects of ASD, the PSD of ASD subjects is comparatively higher than the PSD of normal subjects. The trained network can classify the EEG data as normal subjects and subjects with ASD with good accuracy from the datasets.

Keywords

Autism Spectrum Disorder, Electroencephalography, Discrete Wavelet Transforms, Neural Network, Space Invariant Artificial Neural Networks.

Introduction

Social disconnection and communication impairment with various severity are the main characteristics of Autism Spectrum Disorder (ASD) (Bosl *et al.*, 2011). The children affected by ASD show noticeable challenges in developing social and cognitive functions. These children cannot focus on activities that may require shared attention. Moreover, the co-occurrence of ailments such as depression, Tourette's syndrome, learning disability, dyspraxia, epilepsy, Attention Deficit Hyperactivity Disorder (ADHD), Obsessive-Compulsive Disorder (OCD), and generalized anxiety disorder can occur along with ASD (Ahmadlou, Adeli and Adeli, 2010; Eldridge *et al.*, 2014; Jeste, Frohlich and Loo, 2015).

Recent research in the field of ASD has grown exponentially. Brain Computer Interface (BCI) system connected with Electroencephalography (EEG) were used to interpret the signals received from the brain to study the behavior of people and also to analyze causes of sleep disorder (Dhongade and Rao, 2017; Hernandez-Gonzalez *et al.*, 2017). Experimental models were built to classify emotional activities like smiles, genuine smiles, fake/acted smiles, and neutral expressions. Several methods were proposed to understand intrinsic human behavior from three different emotional expressions like genuine, neutral, and fake/acted smile as well as analyze symptoms of epileptic seizure (Luo *et al.*, 2020; Mardini *et al.*, 2020). EEG features were extracted using three time-frequency analysis methods like Discrete Wavelet Transforms (DWT), Empirical Mode Decomposition (EMD), and incorporating DWT into EMD (DWT-EMD) at three frequency bands (Alex *et al.*, 2020; Chowdhury, Poudel and Hu, 2020; Das *et al.*, 2020). DWT blended with Artificial Neural Network (ANN) was adopted to improve the classification accuracy while studying the behavioral patterns of several test subjects (Deng *et al.*, 2021; Fayaz *et al.*, 2021; Uysal and Filik, 2021).

Many promising rehabilitative approaches have been developed to improve the social understanding, communication, and repetitive routines and behaviors of the children affected by ASD. Societal attitudes and support extended by local and national authorities play a prominent role in improving the quality of life of autistic people (Subasi, 2007; Liu *et al.*, 2012; Peker, Sen and Delen, 2016). Electroencephalography is a non-invasive technology that records the spontaneous electrical activity of the brain. It significantly helps to analyze the electrophysiological measures between different parts of the brain. It is possible to pick up EEG signals from the electrodes placed on the scalp by adopting various available montages and electrode setups. In this study, a neurosky mind waves mobile reader EEG with a single electrode is placed on the forehead of the test subjects

(Du and Swamy, 2006; Yusaf, Nawaz and Iqbal, 2016; Lu *et al.*, 2017; Bosl, Tager-Flusberg and Nelson, 2018). Different functional connectivity parameters are determined from EEG signals that show the cognitive network behavior of individuals showing symptoms of ASD during specific tasks.

Methodology

The data collection from subjects aged between four and six was carried out successfully in the special schools and hospitals in and around Bangalore. While conducting these studies, the subjects were engaged in various activities like listening to their favorite rhymes, playing with toys, and singing songs. Feedback was taken from their respective therapists. Their EEG signals were extracted using the electrodes placed on their forehead. The signals were extracted from the kids in the presence of their behavioral therapist. Figure 1 represents the proposed block diagram where EEG signals are extracted from the subject (normal and confirmed abnormal subjects). Preprocessing (PP) is done for removing artifacts, various filters like bior 2.2, bior 4.4, DB2, DB4, haar filters were used. Out of them, DB2 yielded the best results. DWT method was employed for feature extraction. Features extracted were classified using Feed forward back propagation neural network classifier. This classified normal subjects and abnormal subjects.

Figure 2 represents DWT-based three-level sub-band decomposition block diagrams. In existed method DWT feature extraction method yields five distinctive energy bands. During valance state analysis, the existing method could not significantly differentiate between normal subjects and abnormal subjects. In DWT based three-level sub-band decomposition method, the first level decomposition method yielded eight energy bands. The second-level decomposition method yielded ten energy bands. The third level decomposition method yielded twenty energy bands. During the third level decomposition, there was a significant difference in PSD level of normal subjects and abnormal subjects.

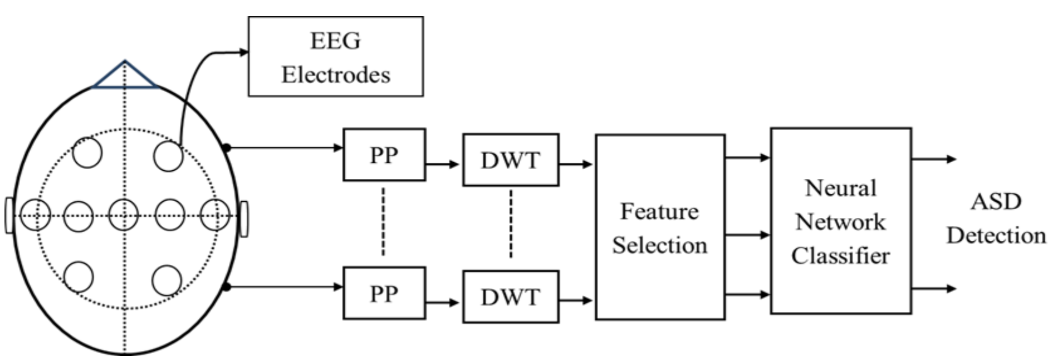

Figure 1 Block diagram of DWT based ASD detection and classification

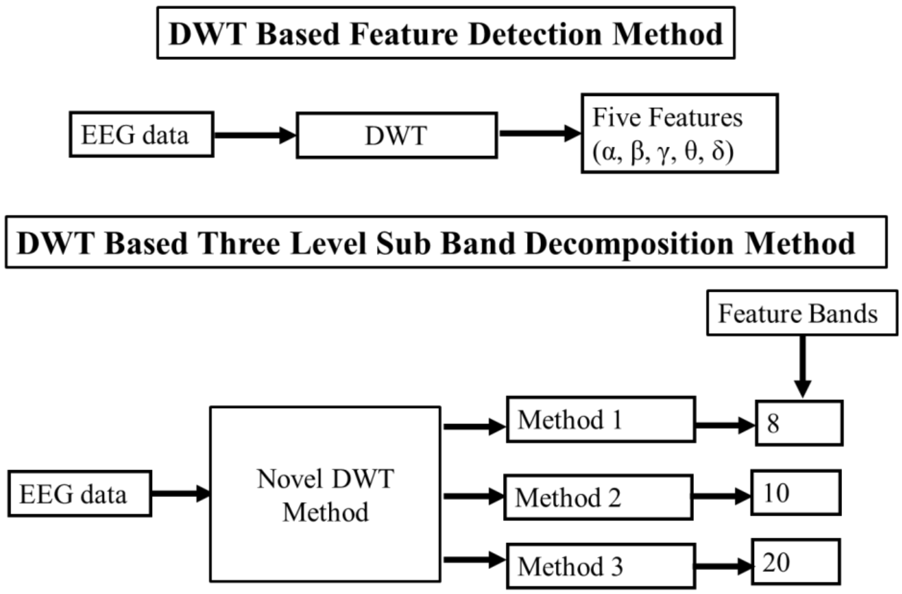

Figure 2 Three-level sub-band decomposition method block diagram

Result and Discussion

During the feature extraction and valance state analysis, power spectral density is one of the salient features to identify the differences in the brain electrophysiological processing. Table 1 shows the comparison of the energy levels of subjects with ASD (A1, A2, A3) and normal subjects (N9, N4, N5) between the age group of four and six years and D1to D8 represents the energy bands obtained during the first level decomposition.

Level- 1

During valance state analysis, a linear increase in Power Spectral Densities (PSD) of EEG bands gamma, beta, alpha, and theta is observed during the first level decomposition. In the case of the theta band to the delta band, there is a significant rise in PSD values from the first energy band to the eighth band at level 1. Table 1 presents the energy levels of subjects with ASD and normal subjects of 4 to 6 years.

During valance state analysis, when comparing the PSD of normal subjects with subjects of ASD, the PSD of ASD subjects is comparatively higher than the PSD of normal subjects. However, as seen in the table above normal subjects at the eighth energy band, PSD is significantly lower than PSD of ASD subjects. Figure 3 shows the graph plotted with PSD in the y-axis and energy bands in the x-axis for subjects in the age group of 4-6 years (Level 1).

Table 1 Energy levels of subjects with ASD vs normal subjects

	D1	D2	D3	D4	D5	D6	D7	D8
N9	-3.52594	2.348022	7.883919	12.46726	16.62408	19.61439	24.97971	46.99022
N4	-1.34527	5.655867	10.37533	15.25241	17.14037	21.47814	25.23978	49.56009
N5	-3.08743	1.409837	6.736787	11.21493	15.79248	19.09183	25.29444	48.04176
A1	6.932983	12.9604	18.47084	23.05811	27.06864	31.82856	32.076	67.76394
A2	9.497077	15.23507	20.12333	24.51286	28.40417	30.57102	31.96233	61.86347
A3	6.268371	12.5249	18.00833	21.61636	27.80194	30.36592	11.23784	62.52733

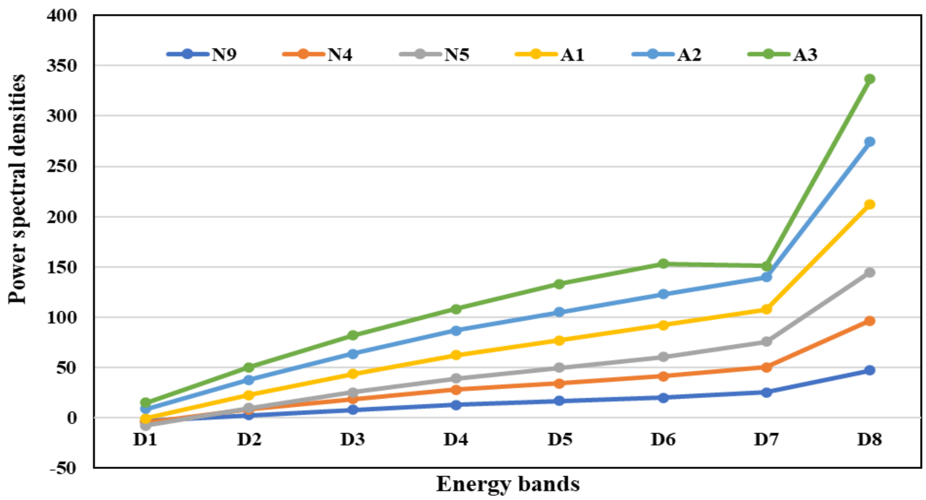

Figure 3 Graph of PSD Vs Energy Band (Level-1)

Level -3

During valance state analysis, in Power Spectral Densities (PSD) of EEG bands gamma, beta, alpha, theta, there is a linear increase, and from theta band to delta band, there is a significant.

Table 2 Energy levels of subjects with ASD vs normal subjects (4 to 6 years)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	D16	D17	D18	D19	D20
N9	14.4	14.1	13.2	10.4	18.2	18.5	16.4	15.2	20.7	23.5	21.8	20.9	30.6	26.8	28.7	28.7	29.6	24.8	28.1	28.4
N4	17.8	15.7	13.9	14.1	18.4	20.2	17.3	15.6	25.6	27.8	18.5	22.2	31.1	28.6	30.0	27.1	30.0	30.4	27.8	26.5
N5	11.6	12.7	11.1	10.2	18.1	16.4	17.4	14.8	22.4	23.6	19.8	18.2	25.3	31.6	22.9	30.8	31.0	30.3	24.7	26.2
A1	24.4	24.7	23.7	21.1	30.1	31.0	26.2	26.1	36.1	36.3	33.3	33.0	38.7	41.5	41.4	36.4	42.9	40.7	40.0	37.2
A2	25.4	27.0	25.6	23.2	30.0	30.3	30.0	29.1	33.0	32.7	32.9	34.6	41.1	35.1	36.6	37.2	37.5	36.5	36.3	33.0
A3	23.7	23.4	22.2	20.5	28.9	30.6	28.0	28.8	32.4	33.3	33.9	32.2	39.9	38.6	36.4	37.2	39.5	38.4	37.4	37.0

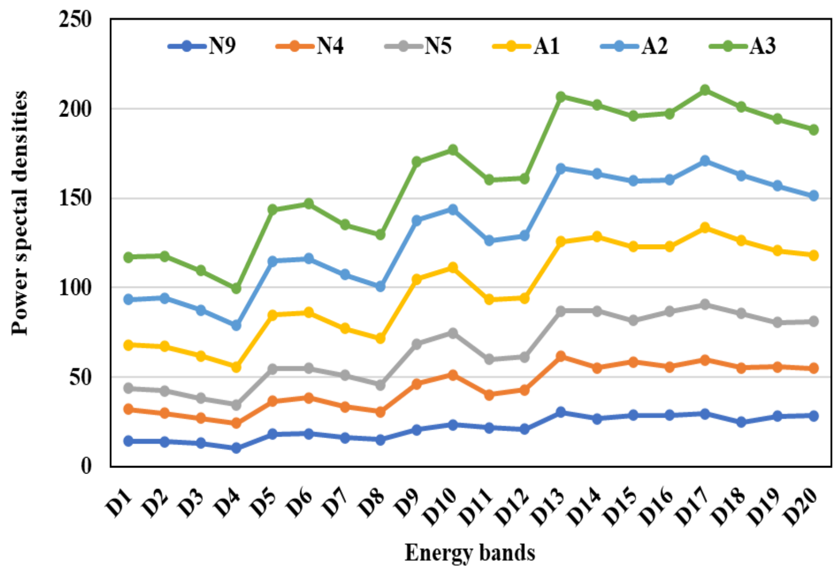

Figure 4 Graph of PSD Vs Energy Band (Level-3)

Jump in PSD from the first energy band to the 20th band at level 3. When comparing the PSD of normal subjects with subjects of ASD, the PSD of ASD subjects is comparatively higher than the PSD of normal subjects. At the 20^{th} energy band, it is seen that normal subject PSD is significantly lower than PSD of ASD subjects as shown in Figure 4. Table 2 presents the energy level of subjects with ASD and normal subjects of four to six years at level 3. D1to D20 represents the 20 energy bands obtained during third-level decomposition.

Neural Network

Classification of normal and autistic subjects is carried out using Feed Forward Back Propagation Neural Network (FFBPNN). The NN model employs 'TANSIG PURELIN' as a network activation function. Three normal subjects of age four to six years and three abnormal subjects of age four to six are considered for training. In the NN training stage, input data and sampling data are fed to the NN classifier, where targets are set as 0.2 for normal and 0.8 for autistic subjects. The input values are shown in Table 3.

Table 3 Input Values

Epoch	27 iterations
Performance	0.000393 to 0=3.45e-13
Gradient	0.000546 to 1.00e-07=1.48e-08
Mu	0.00100 to 1.00e+10=1.00e-1
Validation checks	0 to 6= 0

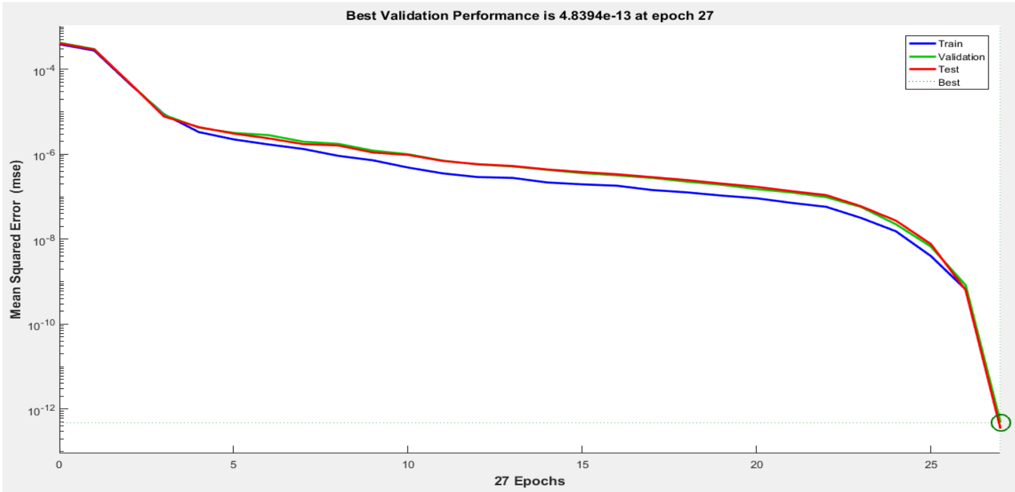

Figure 5 The best validation performance plot

Figure 5 reveals the best validation performance. The best mean squared error expected is around 10^{-5}. The best validation performance was achieved at the 27th epoch. Test input performance at the 27th epoch is around 10^{-12}. Training performance was around 10^{-12}. This shows the system state after training based on plot regression, which shows the plot between training samples, output data, validation samples, and test samples.

The trained network is evaluated for its performance, considering gradient, Mu, and MSE. Figure 6 shows that the minimum gradient was achieved at the 27th epoch. At zeroth epoch, the sensitive factor is decreasing till the 3rd epoch. From the 27th epoch, it is observed that there is a steep fall in the sensitive factor. Error histogram reveals that at zero error, 35 instances of training, 10 instances of validation, and 10 instances of the test are observed, which is shown in Figure 7.

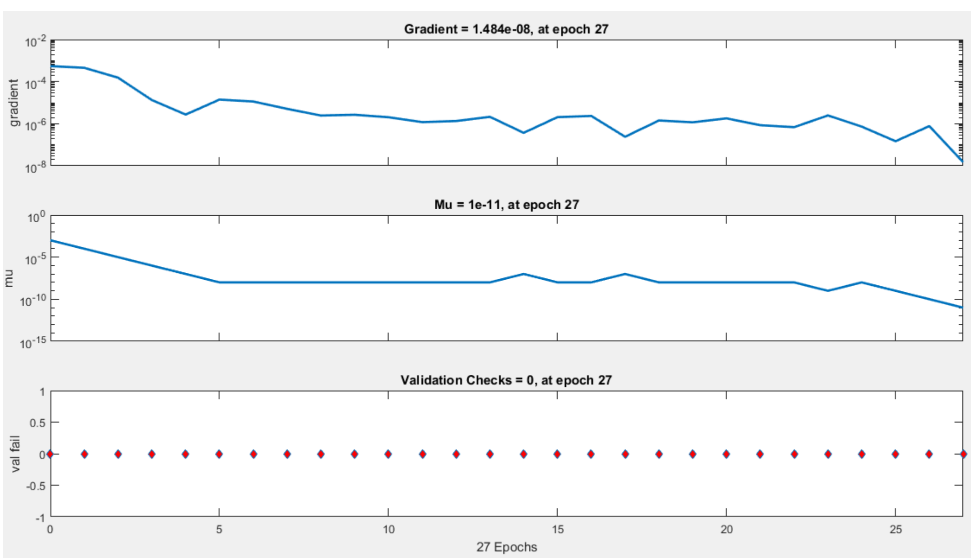

Figure 6 Minimum gradient achieved at 27th epoch

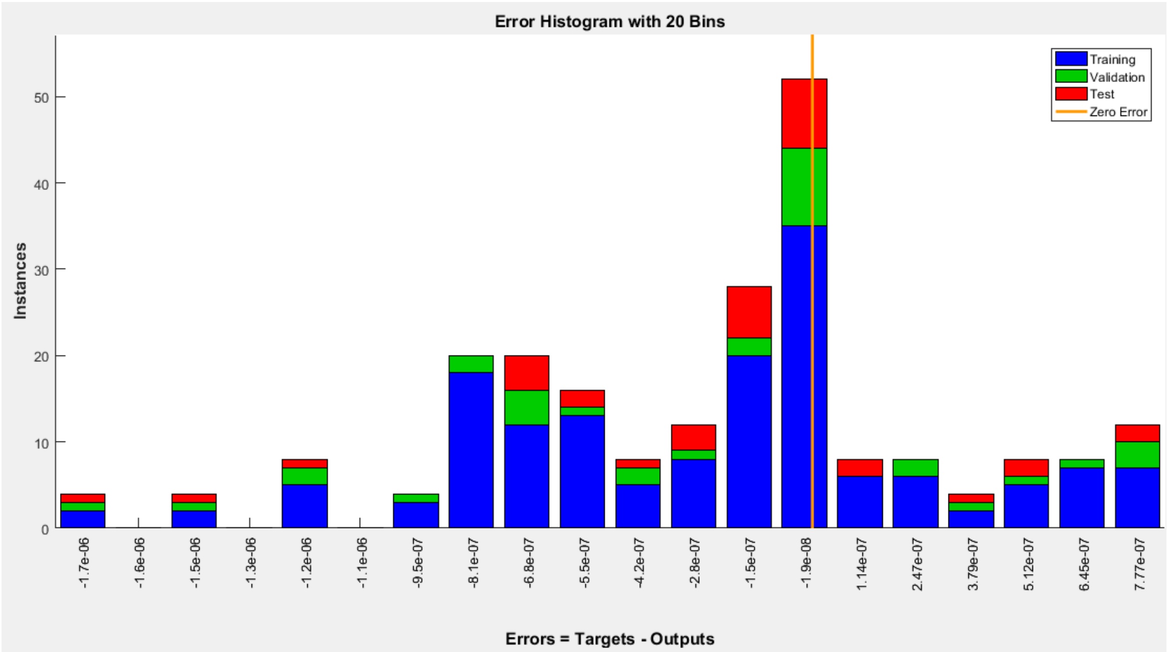

Figure 7 Error Histogram

The regression plot obtained from the confusion matrix provides the optimal solution for better classification accuracy. The confusion matrix as shown in Figure 8 shows that the neural network is trained to achieve the best regression, as the matrix indicates that the neural network is trained. The above neural network results indicate that the desired regression of one is achieved. Trained output matches the set targets of 0.2 and 0.8. The trained network could successfully classify the EEG data as normal subjects and subjects with ASD with good accuracy for the given datasets. It is vital to evaluate the performance of the network considering large EEG datasets for practical implementation.

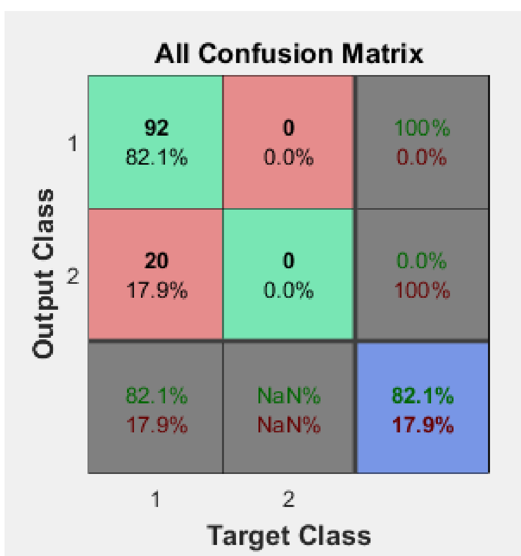

Figure 8 Confusion Matrix

Conclusion

This paper throws light on the suitability of an EEG biomarker to distinguish autistic individuals from neurotypical. The EEG signal data were extracted using a single electrode placed on the forehead of the subjects while performing various activities depending on the interest of the subjects. Validation of sensors has been carried out with EEG data analysis of different emotions. Feature extraction employed Discrete Wavelet Transform. During valance state analysis, our results reveal a linear increase in Power Spectral Density of EEG bands gamma, beta, alpha, and theta among subjects in the age group of four to six years.

A significant rise in PSD has been observed during valance state analysis from theta to delta band. Our studies reveal that the PSD of normal subjects is significantly lower than the PSD of ASD subjects. The trained network can classify the EEG data as normal subjects and subjects with ASD with good accuracy for the given datasets. Further evaluation of the neural network's performance with large EEG datasets is required. Thus, in the future, this type of neural network can be developed into a practically feasible tool for personalized treatments and performance evaluation of the therapies on the autistic brain.

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