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NEURAL NETWORK BASED CLASSIFICATION OF EEG SIGNALS FOR DIAGNOSIS OF AUTISM SPECTRUM DISORDER

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ABSTRACT

Autism Spectrum Disorder(ASD) and its diagnosis is one of the streams where extensive researches are being carried out. Early diagnosis of autism can lead to better analysis and treatment of the person who suffers from autism. The idea that the same regions of brain are activated at or near the same time when the processing and/or execution of a specific task occurs is the basis for research using several forms of neuro-imaging and recording technology. As a step to develop an autism diagnosis system, 4 AR feature extraction algorithms are implemented on Electroencephalogram (EEG) signals of normal and autistic children. Moreover, 2 neural networks namely Cascade forward back propagation neural network model (CFBPNN) and Elman neural network (ENN) are used to identify the combination with highest classification accuracy. Network and Subject based classification is performed on the dataset. AR Burg and ENN combination were found to have the highest classification accuracy rate of 95.63%. Based on this research, a Human Machine Interface can be designed for the diagnosis of ASD.

KEYWORDS: ***Autism Spectrum Disorder, Electroencephalogram, Auto Regressive Features, Elman Neural Network, Cascade Forward Back Propagation Neural Network***

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INTRODUCTION

Autism Spectrum Disorder(ASD) is a disorder where children suffer from communication and social interaction disability since birth. Moreover, thoughts and actions become rigid and repetitive. The three core symptoms of autism are social interaction difficulties, communication challenges and repetition of behavior which are also known as the triad of impairments. ASD diagnosis concentrates mainly on these symptoms.[1] ASD can be broadly classified as Autistic Disorder, Asperger's Disorder, Pervasive-Developmental Disorder – Not Otherwise Specified (PDD-NOS), Childhood Disintegrative Disorder and Rett's Disorder.[2] Figure 1 shows the signs and symptoms of autism.

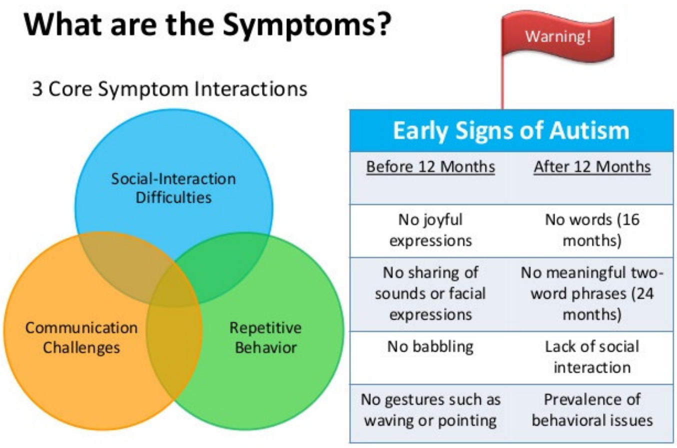

Figure 1
Signs and Symptoms of Autism

The idea that the same regions of brain are activated at or near the same time when the processing and/or execution of a specific task occurs is the basis for research using several forms of neuro-imaging and recording technology. The Electroencephalogram (EEG) has been used as a tool for examining the brain since 1924.[3] The EEG is a dynamic measure of the electrical activity present on the scalp. The electrical activity recorded from a given region on the scalp represents the fluctuation of the underlying field potentials for that region across time. Its specific properties (i.e. amplitude and frequency) depend among other things, on the temporal synchrony and spatial location of its underlying generators. As cortical pyramidal neurons reside near the scalp and have the characteristics necessary to generate potentials including parallel alignment and synchronized activity, they are thought to be the primary generators of the EEG.[4] Thus, the electrical activity recorded by the EEG reflects the extracellular potentials of nearby cortical pyramidal neurons, whose activity may be modulated by a wide range of cortical and sub cortical inputs.[5] Rhythmic oscillations have been observed consistently across several frequency bandwidths in different regions of the brain. The primary frequency bandwidths examined include delta (1 – 3 Hz), theta (4 – 7Hz), alpha (8 – 12 Hz) and beta (13 – 30 Hz). Using EEG, the bandwidths of different frequencies have been associated with the development, states of consciousness, and various cognitive activities.ASD is usually diagnosed by inspecting and analyzing the behavioral aspects of children.[6] Parents are being interviewed and along with the observation of the child's behavior, the diagnosis is performed and interpreted. As a result, the diagnosis can be subjective to the clinician's interpretation and may vary from person to person. As a result, a standard diagnostic tool is the requirement of the day. W. Bosl et al. developed a biomarker for autistic infants. He used multi-scale entropy (mMSE) as a feature extraction algorithm and multiclass Support Vector Machine (SVM) on EEG signals of children (6-24 months) at resting state. 70% to 90% accuracy was found for children between 12 and 18 months.[7] Oberman et al. suggested in a study that dysfunctional mirror activity was shown by individuals with ASD which was reflected by mu(μ) wave suppression. They collected EEG data during four conditions namely self hand movement, hand movement video observation, 2 bouncing balls video observation and visual white noise observation. μ waves were not suppressed while the ASD group performed hand movement task, showing that mirror neuron system dysfunction may be present.[8] A. Sheikhani et al. performed a study and EEG was evaluated using spectrogram and coherence values. Highest classification accuracy was found in alpha frequency of 96.4% when the children performed in a relaxed eye-opened condition.[9] Elizabeth Milne et al. performed data acquisition when the children were asked to watch Gabor patches in computer screen. A zebra grey-scaled image was also present in the screen to amplify the stimulus. Children were asked to press the response button as soon as the zebra was seen. P1 amplitude was higher in ASD children as compared to controls. Meanwhile, in α-band inter-trial ASD children showed lesser phase coherence. This showed that synchronisation of stimulus-related cell assemblies were low in ASD children.[10]Wafaa Khazaal Shams et al. classified EEG signals of normal and autistic children using Principle Component Analysis (PCA) and Multilayer Perception Neural network (MLP). Data acquisition was performed when the children performed eye-open tasks and motor tasks. 90-100% accuracy was found for ASD data while control data produced an accuracy of 90% for eye-open tasks.[11] Uvais Qidwai et al. performed classification of ASD and control children while performing 2 tasks namely eyes-open task and eyes-closed task using EEG signals. Multilayer Perception and Time Difference of Arrival (TDOA) was applied on the data in time domain. Features were clearly distinguished with 90% classification accuracy.[12] Few other studies applied fisher linear discriminant analysis FLDA[13], Wavelet transform coherence[14] and hand gestures using Artificial neural networks[15] gave good classification too.

MATERIALS AND METHODS

EEG Data Acquisition

Participants

Sample size included 4 (3 boys and 1 girls) normal children and 6 (4 boys and 2 girls) children with autism. Age group of 6-12 years was chosen. The normal children group consisted of children with no past or present neurological disorders. Many studies similar to this study were analyzed and this sample size was decided to obtain statistical significance. Informed consent form was obtained from parents/guardians of all participants and EEG were taken by a trained EEG technician under supervision of neurologist.

Electrode Placement

Since the EEG signals of children were only taken into consideration, paediatric montage was chosen for the study. The paediatric montage consists of electrodes A1, A2(reference electrodes-not shown in picture), O1, O2, T3, T4, C3, C4, Fp1 and Fp2 according to 10-20 International System as shown in Figure 2 below.

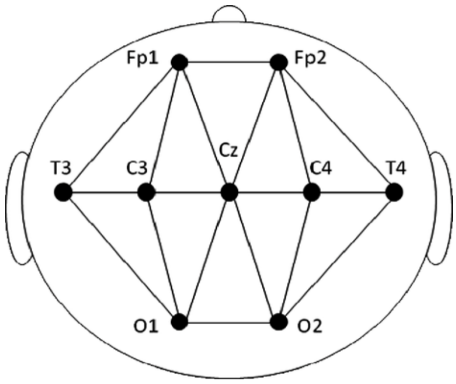

Figure 2
Paediatric Montage Using 10- 20 International Electrode Placement

Experimental Protocol

Relax

The subjects were asked to stay in a relaxed state. As both normal and autistic children were found to be easily distracted, they were asked to limit their activities as much as possible without being very strict.

Flashcards read and spell

The subjects were shown alphabets A-Z as black bold capital letters. Each alphabet was printed in individual A4-size white sheets. The researcher showed the sheet and spelled the corresponding alphabet at the same time. The subject was asked to simultaneously listen and read the alphabet and then spell it loudly. Learning disability if any could be noticed by this task.

Video read and spell

The subjects were asked to repeat alphabets A-Z and small words related to each letter shown in the form of audio visual clip. As our study involved only children, we have used child animation video which was found to be liked and more responded by both normal and autistic children as compared to spelling of flashcards shown manually. Learning disability if any could be noticed by this task.

Video hand movement imitation

The subjects were asked to imitate hand movements shown in an audio visual clip. As it involved simultaneous watching and performing the hand movements, dysfunction of mirror neurons if any could be noticed. Each recording was taken for 30 seconds. 12 such trials were taken for each task. A break of 2 minutes was given between each trial as children could get easily stressed. Readings were recorded in different sessions and on different days.

Pre-processing

The raw EEG signals were processed to extract the features. EEG signals related to this study falls in the range of 0.1-100 Hz, however the predominant frequency lies in the interval of 0.1-60 Hz. A band pass filter is used to extract the required frequency. This process also removes the artifacts due to ambient noise and transducer noise. Digitization is done at 256Hz. 50 Hz notch filter was also used. The preprocessed EEG signals were then applied to the feature extraction stage.

Feature Extraction

In the study, Four Auto Regressive Feature extraction algorithms are used.

AR Burg Method

This method uses least squares sense techniques to minimize the forward and backward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. The major benefits of the AR Burg estimation are high frequency resolution, stability and very efficient computation. The AR burg method generates the reflection coefficient automatically without the interference of autocorrelation function.

AR Modified Covariance Method
This method uses least squares sense techniques to minimize the forward and backward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. The results of the modified covariance techniques are obtained below.

$$qx(k,l) = \frac{1}{N}\sum_{n=p}^{N-1}[x(n-l)x*(n-k) + (n-p+l)x*(n-p+k)] \quad (1)$$

AR Covariance Method
This method uses least squares sense techniques to minimize the forward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. When comparing the Yule-Walker AR estimation, Covariance AR estimation produces higher resolution spectrum for short data records. The linear equations are solved in order to obtain the results of the covariance techniques.

$$\begin{bmatrix} q_x(1,1)q_x(2,1)\dots q_x(p,1) \\ q_x(1,2)q_x(2,2)\dots q_x(p,2) \\ \vdots\vdots\vdots\vdots \\ q_x(1,p)q_x(2,p)q_x(p,p) \end{bmatrix}\begin{bmatrix} a_p(1) \\ a_p(2) \\ \vdots \\ a_p(p) \end{bmatrix} = -\begin{bmatrix} q_x(0,1) \\ q_x(0,2) \\ \vdots \\ q_x(0,p) \end{bmatrix} \quad (2)$$

Where,

$$qx(k,l) = \frac{1}{N}\sum_{n=p}^{N-1} x(n-l)x*(n-k);\ k = 0,1,\dots,p \quad (3)$$

In this method, for calculating autocorrelation matrix windowing is not necessary.

AR Yule-Walker Method
This method uses least squares sense techniques to minimize the forward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. Biased estimates of the signal's autocorrelation function are also used to calculate coefficients. AR Yule Walker technique gives a stable output for all pole models. The AR coefficients are extracted by solving the following normal equations.

$$\begin{bmatrix} q_x(0)\,q^*_x(1)q^*_x(2)\dots q^*_x(p) \\ q_x(1)q_x(0)q^*_x(1)\dots q^*_x(p-1) \\ q_x(2)\,q_x(1)q_x(0)\dots q^*_x(p-2) \\ \vdots\vdots\vdots\vdots \\ q_x(p)\quad q_x(p-1)\quad q_x(p-2)\dots q_x(0) \end{bmatrix}\begin{bmatrix} 1 \\ a_p(1) \\ a_p(2) \\ \vdots \\ a_p(p) \end{bmatrix} = -b(0)\begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad (4)$$

Once the AR parameters have been estimated, then the AR spectral estimate is computed as

$$\hat{p}_{AR}(e^{jw}) = \frac{b(0)}{1+\sum_{k=1}^{p} a_p(k)e^{-jkw}} \quad (5)$$

$$qx(k) = \frac{1}{N}\sum_{n=0}^{N-1-k} x(n+k)x*(n);\ k = 0,1,\dots,p \quad (6)$$

Where,

$$b(0)=qx(0) + \sum_{k=1}^{p} a_p(k)q_x(k) \quad (7)$$

Signal Classification
Artificial neural networks (ANNs) provide a "system level transform" by studying the activity of a given system through training and testing process for a given set of inputs and outputs. Moreover, it utilises less amount of representative data (measured or simulated).In this study, we use Cascade forward back propagation neural network model (CFBPNN) and Elman neural network (ENN) to classify the EEG data signals.

Cascade forward back propagation neural network model (CFBPNN)
CFBPNN shown in Figure3 is analogues to Cascade feed forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. Cascade forward back propagation artificial neural network model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, however, the most significant symptom of this network is that every layer of neurons is associated with all previous layer of neurons.

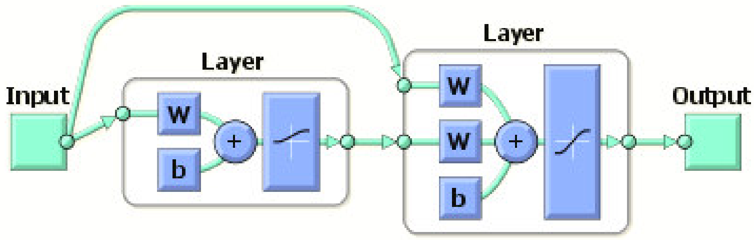

Figure3
Cascade Forward Back Propagation Neural Network Model (w=weight of network, b=bias)

Elman neural network (ENN)

ENN is illustrated in Figure 4. ENN is a type of the dynamic recurrent neural network, which consists of two-layer back propagation networks with an additional feedback connection from the output of the hidden layer to its input. ENN with one or more hidden layers can learn any dynamic input-output relationship arbitrarily well while enough neurons are given in the hidden layers.

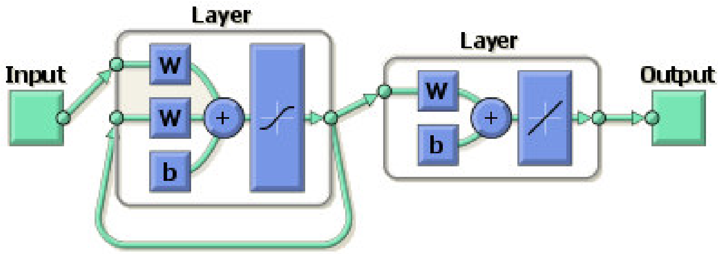

Figure4
Elman Neural Network Model(w=weight of network, b=bias)

The following were based on methodology of Charlyn et al [16]. For each EEG signal, 16 features have been given whose values become the input to the selected neural network. To Design the CFBPNN and ENN, 16 input neurons, 3 output and 10 hidden neurons were used. values for hidden neurons were selected based on trial and error. The training and testing of these neural networks were performed using 75% and 100% of the dataset respectively. The training and testing error tolerance rate were fixed as 0.001 and 0.6 respectively. . In the study, subject 1 to subject 4 are normal subjects while subject 5 to subject 10 are autistic subjects..

RESULTS AND DISCUSSION

Network based classification

The performance of the Cascade neural network is shown in Figure 5,for the four AR feature sets. It is observed that AR Burg out did the other feature sets with the highest classification accuracy of 95.21% for subject 9 and the lowest classification accuracy of 91.36% for subject 2.The next best performances observed for the AR modified Covariance feature sets at 94.79% for subject 9 and the lowest classification accuracy for the same feature set was 91.15% for subject 2. Figure 6, depicts the classification accuracy of ENN for the four AR features, from which it is evident from the result that AR Burg again outperformed other feature sets with the highest classification accuracy of 95.63% for subject 9 and the lowest classification accuracy of 92.92% for subject 2. The next best performance is observed for the AR modified Covariance feature sets at 95.31% for subject 9 and the lowest classification accuracy for the same feature set was 92.40% for subject 2.In network based classification, ENN is well identified pattern. This is because of the advantages of easy design, dynamic nature, good generalization ability and a good tolerance to input noise.

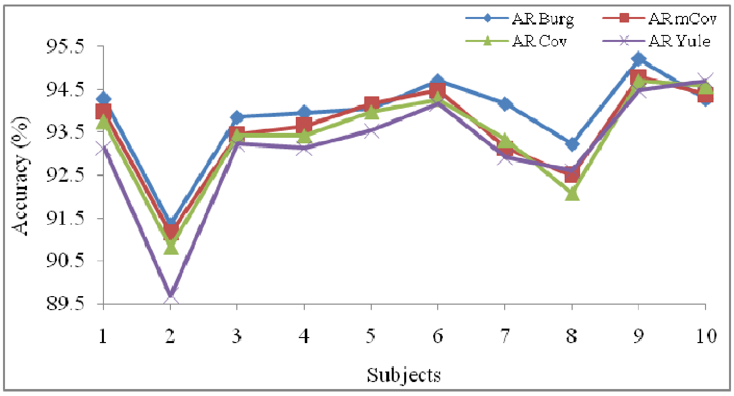

Figure 5
CFBPNNClassification Performance

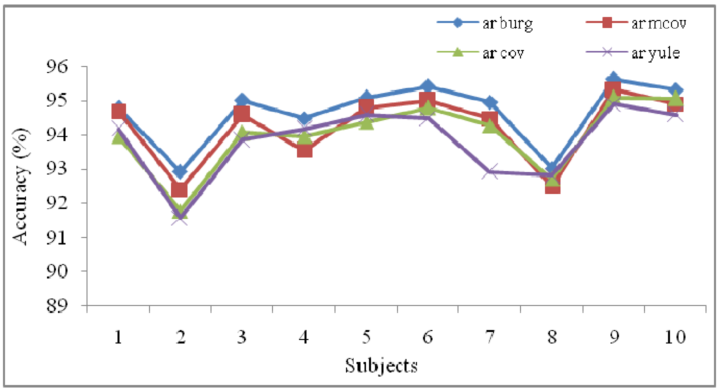

Figure 6
ENN Classification Performance

Subject based classification

From the network models developed, it is seen that the data from subject 9 has obtained highest accuracy levels in the range of 94.48% to 95.63%. Theleast performance accuracy is observed for subject 2 witha range of 89.69% to 91.56%. Subject 1 to subject 4 are normal subjects, while subject 5 to subject 10 are subjects with autism. Subject 9 had slightly more degree of autism as compared to other children with autism. Moreover, subject 9 participated in the experiments for a long period as compared to other subjects. As a result, maximum accuracy was obtained for Subject 9 for all tasks.The subject based classification results for two neural networks are shown in Figure 7 and 8. Mean accuracy range using CFBPNN for the autistic subjects varies from 93.73% to 94.27% and mean accuracy range for the normal subjects varies from 92.29% to 93.36%.Similarly, mean accuracy range using ENN for the autistic subjects varies from 94.04% to 94.91% and mean accuracy range for the normal subjects varies from 93.43% to 94.29%. It is observed from the results that higher classification accuracy is found for autistic children as compared to normal children. This emphasises the fact that more difference of behaviour of neurons under each task are found in children with autism as compared to normal subjects.

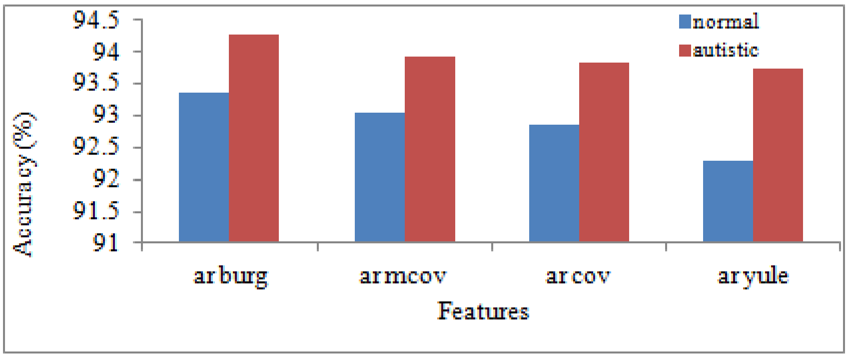

Figure 7
Subject Based Mean Classification Accuracy of 4 AR-Features for CFBPNN

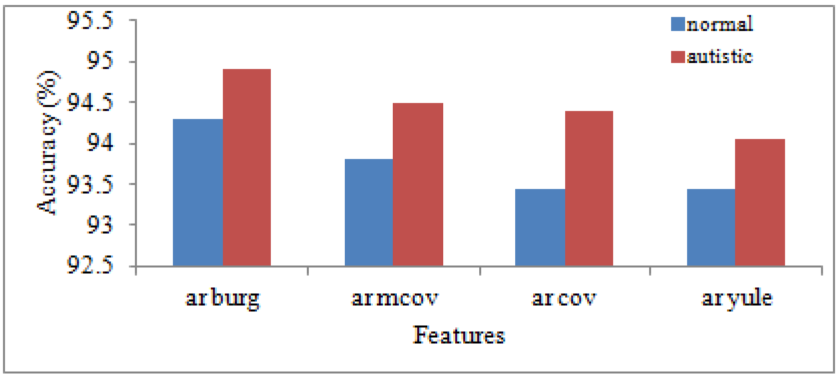

Figure 8
Subject Based Mean Classification Accuracy of 4 AR-Features for ENN

CONCLUSION

In this paper, the feasibility of diagnosing autism based on 4 different taskswere performed using EEG signals and neural networks. Four auto regressive feature extraction algorithms and two neural networks were used to design a suitable algorithm. EEG data from ten subjects were collected which was used in the experiments. It was observed from the empirical results that the AR Burg and ENN combination had the highest recognition accuracy rate of 95.63%. Investigations also proved that classification accuracy of EEG signals were higher for subjects with autism as compared to normal subjects due to more difference of behaviour of neurons under each task. However, the study is required to verify the performance of the proposed algorithms in online recognition of EEG signals which can be applied to develop an automated autism diagnosis system.

CONFLICT OF INTEREST

Conflict of interest declared none.

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