EEG BASED DIAGNOSIS OF AUTISM SPECTRUM DISORDER USING STATIC AND DYNAMIC NEURAL NETWORKS

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ABSTRACT

Electroencephalography (EEG) signals can be used to monitor the brain activities of all human beings. As a result, it can be used to detect abnormalities in the brain functioning. In this study, using Artificial Neural Network (ANN) EEG signals of children with Autism Spectrum Disorder (ASD) and non-ASD children were classified. Two neural network models namely Pattern Recognition Neural Network (Pattern Net) and Layered Recurrent Neural Network (LRN) were used. Auto regressive (AR) Burg and LRN combination were found to have the highest classification accuracy rate of 94.62%. Moreover, Bit Transfer Rate (BTR) of the signals were calculated for each network in order to evaluate the Human Machine Interface system performance. Maximum BTR of 6.08 bit/sec was achieved for AR Burg and LRN combination. The proposed method has obtained promising results. For the study, real-time dataset which was obtained from ASD children of various special schools in Coimbatore has been used.

Keywords: autism spectrum disorder, electroencephalography, auto regressive features, layered recurrent neural network, pattern recognition neural network.

1. INTRODUCTION

Mental health disorders affect approximately 20% of children and adolescents worldwide [1, 2]. Autism Spectrum Disorder (ASD) is one of the most common neuro-developmental disorders (NDD) with a global prevalence estimate of 1 to 2% in children [3]. 90% of people with ASD live in low and middle-income countries where there is a significant demand for screening tools that do not require highly trained professionals [4]. There has been growing interest in electroencephalography (EEG) as an investigational tool for biomarker development in NDD. However, one of the key challenges lies in the identification of appropriate multivariate, next-generation analytical methodologies that can characterize the complex, nonlinear dynamics of neural networks in the brain [5, 6].

The EEG has been used as a tool for examining the brain since 1924 (Berger, 1924; as cited in Pizzagalli, 2007. It 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 (Elul, 1972; Speckmann & Elger, 1982). 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 (Kandel, Schwartz & Jessel, 2000). 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, bandwidths of different frequencies have been associated with development, states of consciousness, and various cognitive activities.

The ultimate goal of this study is to develop a robust and reliable early biomarker of ASD risk that can be implemented as a simple laboratory-type test by community healthcare workers in low-resource environments where expert knowledge and skilled staff are often not accessible. The study aims to investigate a new ASD diagnosis system based on Auto Regressive (AR) features and Artificial Neural Network (ANN) models.

2. LITERATURE SURVEY

Many researchers have carried out diagnostic procedure to analyze EEG behaviour of ASD patients. Some of such studies are as follows:

In the work presented by A. Sheikhani *et al.* [7], the dataset were recorded by 21 electrodes with both earlobes chosen as common referential electrodes and EEG signals were extracted from two groups: 10 (9 boy and 1 girl) ASD and 7 (4 boys and 3 girls) non-ASD children. A short time Fourier transform technique was used to extract EEG signal features and then applied as an input to k-nearest neighbours (KNN) classifier to get classification accuracy up to 82.4%. In their later paper [8], the authors improved the method and used larger data for testing (17 ASD and 11 normal subjects) which obtained up to 96.4% distinction level.

Ahmadlou *et al.* [9] investigated fractal dimension to measure complexity and dynamical changes in ASD brain. The method was tested on a database of eyes-closed EEG data which was obtained from two groups namely 9 ASD and 8 non-ASD children. The dataset were recorded according to 10-20 international system, each consisting of 19 channels and sampling rate of 256 Hz. An accuracy of 90% was achieved with a radial basis function classifier. Later, the same group also presented ASD diagnosis using visibility graph [10] and fuzzy synchronization likelihood and enhanced probabilistic neural network classifier [11]. Both the proposed methods obtain around 95.5 % accuracy.

J. Fan *et al* [12] presented spectral features of EEG signals from a 14-channel EEG neuro headset, together with therapist ratings of behavioural engagement, enjoyment, frustration, boredom and difficulty to train a group of classification models. They used seven classification techniques and compared the results. Bayes network, naive Bayes, Support Vector Machine, multilayer perceptron, KNN, random forest and decision tree classifier (J48) were used to obtain the classification accuracy ranged between 75-85 %.

It was reported by Bosl et al. [5] that an EEG dataset was collected from 79 subjects: 46 ASD and 33 non-ASD subjects. The EEG dataset was recorded by a 64-channel Sensor Net System and Net Station software, amplified, band-pass filtered at 0.1 to 100 Hz and sampled at a frequency of 250 Hz. They used minimum mean square error as a feature vector and then, the multiclass KNN, the support vector machine and Naive Bayesian classification algorithms have been applied to classify typical signal and autistic signal. The classification accuracy is over 80% at age of 9 months. Classification accuracy for boys was close to 100% at age of 9 months and ranged between 70% to 90% at 12 and 18 months. For girls, classification accuracy was highest at age of 6 months, but declines thereafter.

In Alhaddad *et al.* [13] the dataset were collected from 12 children: 8 (5 boys and 3 girls) with ASD and 4 (all of them are boys) with non-ASD. The dataset was recorded by G.tech EEG acquisition system which has 16 channels with AFz electrode as ground and right ear lobe as Reference and then filtered using band pass filter with a frequency band (0.1-60) Hz and digitized at 256Hz. The notch filter was also used at 60Hz. Optimum pre-processing techniques were used in this study. They used two feature extraction techniques: time and frequency domains (raw data and FFT). Fisher linear discriminant is used as classifier. They obtained classification accuracy up to 90%. Later E. Alsaggaf *et al*. [14] used the same dataset and processing techniques that was used by J. Alhaddad for autism disorders diagnosis and obtained 80.27% accuracy.

From the survey, it can be concluded that classification accuracy is proportional to the number of channels used for EEG data acquisition. The motive of this study is to develop an EEG based ASD diagnosis system which gives maximum classification accuracy with minimum possible EEG channels.

3. METHODOLOGY

EEG based ASD diagnosis for children consist of four steps such as EEG Data Acquisition, Data Preprocessing, Feature Extraction and Classification [15] as shown in Figure-1.

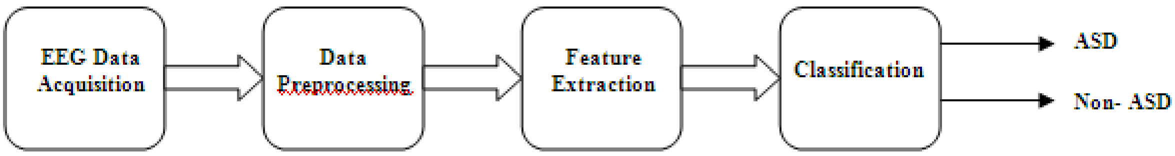

Figure-1. Block diagram of EEG Based ASD Diagnosis for Children Using ANN.

3.1 EEG Data acquisition

ASD dataset used in this study was collected from ASD children of various special schools in Coimbatore, India. Non-ASD dataset was collected from non-ASD children of neighbourhood who were ready to volunteer. To ensure the anonymity of the subjects, no personal information is published (name, photo, address, symptoms, etc). Sample size included 4 (3 boys and 1 girls) non-ASD children and 6 (4 boys and 2 girls) children with ASD. Age group of 6-12 years was chosen. The non-ASD children group consisted of children with no past or present neurological disorders.

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, O1, O2, T3, T4, C3, C4, Fp1 and Fp2 according to 10-20 International System.

Each EEG recording was taken for 30 seconds. 12 such trials were taken for each state. A break of 2 minutes was given between each trial as children can get easily stressed. Readings were recorded in different sessions and on different days.

Datasets were recorded in the following 4 states for both groups:

- **a. Relax:** The subjects were asked to stay in a relaxed state. As both ASD and non-ASD children were found to be easily distracted, they were asked to limit their activities as much as possible.
- **b. Flashcards read and spell:** The children were shown alphabets A-Z as black bold capital letters. Each alphabet was printed in individual A4-size white sheets. Each sheet was shown and spelled at the same time by a volunteer. The child was asked to simultaneously listen and read the alphabet and then spell it loudly. Learning disability if any can be noticed by this task.
- **c. Video read and spell:** The children 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 is found to be liked and more responded by both ASD and non-ASD children as compared to spelling of flashcards shown manually. Learning disability if any can be noticed by this task.

d. **Video hand movement imitation:** The children 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 can be noticed.

3.2 Data Preprocessing

Raw EEG signals were processed to extract the features. EEG signals related to this study was 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 was used to extract the required frequency. This process also removes the artifacts due to ambient noise and transducer noise. Digitization was done at 256Hz. 50 Hz notch filter was also used. The preprocessed EEG signals were then applied to the feature extraction stage.

3.3 Power Spectral Density (PSD) features and their estimation

The parametric spectrum estimation depends on the previous information of the system. Generally used parametric method is the AR method. For the AR method, the coefficient of a signal at particular instance is derived by adding the coefficient of the past samples and summing the error estimation. P^{th} model order of Autoregressive (AR) process is given by

$$x[n] = -\sum_{k=1}^{p} a_k \; x[n-k] + e(n) \qquad (1)$$

Where a_k indicates AR coefficients, p indicates the model order, x(n) represents EEG signal at the sample point n and e(n) indicates the error term independent of previous samples. Thus, in order to obtain the estimates of AR coefficient a_k we have used six feature extraction algorithms such as AR Burg, AR Modified Covariance, AR Covariance, AR Yule Walker, Levinson Durbin Recursion and Linear Prediction Coefficient.

3.3.1 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. The PSD by AR Burg method is obtained by solving the normal equations (2).

$$\hat{p}_{burg}(f) = \frac{\hat{e}_p}{\left|1+\sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \qquad (2)$$

3.3.2 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 PSD by AR Modified Covariance method is obtained using the normal equation (3).

$$\hat{p}_{mcov}(f) = \frac{\hat{\sigma}^2}{\left|1+\sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \qquad (3)$$

3.3.3 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. In this method, for calculating autocorrelation matrix windowing is not necessary. The PSD by AR Covariance method is obtained using the normal equation (4).

$$\hat{p}_{cov}(f) = \frac{\hat{\sigma}^2}{\left|1+\sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \qquad (4)$$

3.3.4 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 model at all times. The PSD by AR Yule-Walker method is obtained by solving the normal equations (5).

$$\hat{p}_{yule}(f) = \frac{\hat{\sigma}^2}{\left|1+\sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \qquad (5)$$

3.3.5 Levinson-Durbin recursive algorithm

An alternative technique of evaluating the AR coefficients is provided by Levinson-Durbin recursive algorithm. The method utilizes the important property that the coefficient of an AR (k) process can be evaluated from the parameters of the AR (k-1) plus k value of the auto correlation function. First order AR coefficient of the signal is first obtained and from these, the algorithm proceeds recursively up to the order *p*.

3.3.6 Linear Prediction Coefficient Analysis (LPC)

In EEG modelled LPC, every coefficient is evaluated as linear weighted sum of the previous *p* coefficients, where *p* indicates prediction order. If x (n) is the current coefficient, then it is foreseen by the previous *p* coefficients as

$$\hat{x}(n) = -\sum_{k=1}^{p} a_k \, x(n-k) \qquad (6)$$

Levinson-Durbin recursive algorithm is used to calculate a linear prediction coefficient which is known as LPC analysis.

In all the six feature extraction techniques model order is fixed as 4 for better accuracy based on trial and

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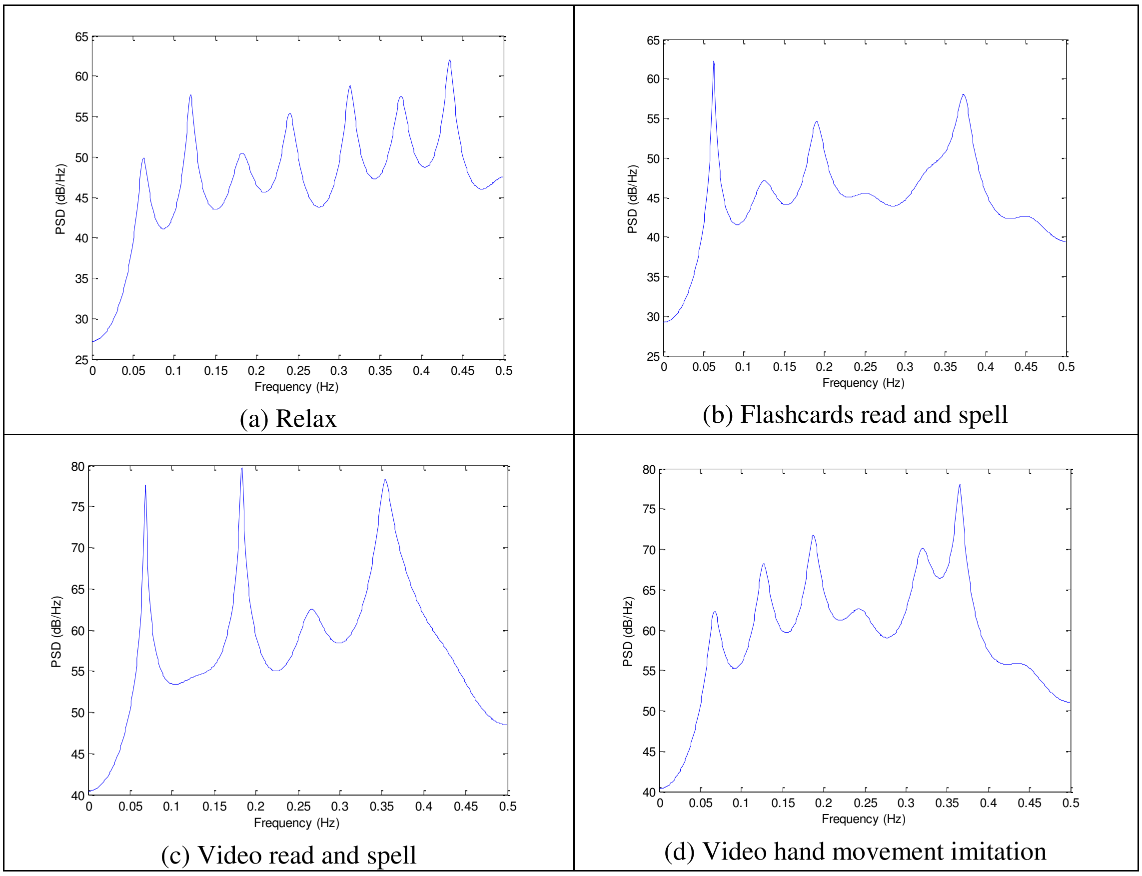
error process. Sixteen features are extracted for each task per trial. A total dataset consisting of 48 data samples for each subject is obtained to train and test the neural network. Figure-2 shows the PSD plots for 4 different tasks performed by Subject N2 using AR Burg. Subject N2 is a non-ASD child. Figure-3 illustrates the PSD plots using AR Burg performed by Subject A5 who is an ASD child. From all the PSD plots displayed, it can be observed that every task taken into this experiment have unique patterns and there is noticeable difference between PSD plots of non-ASD and ASD children.



(a) Relax (b) Flashcards read and spell

(c) Video read and spell (d) Video hand movement imitation

Figure-2. PSD Plots for 4 tasks performed by subject N2 using AR Burg.

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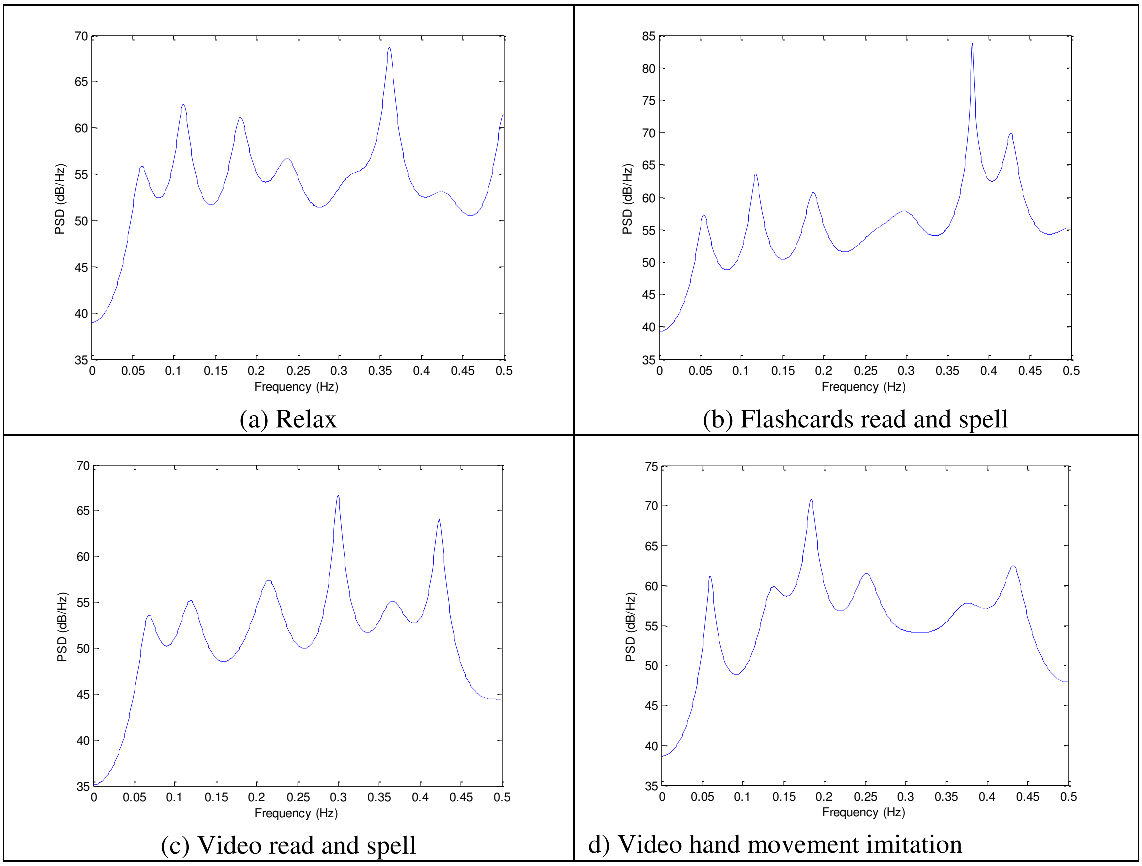

(a) Relax (b) Flashcards read and spell

(c) Video read and spell d) Video hand movement imitation

Figure-3. PSD plots for 4 tasks performed by subject A5 using AR Burg.

3.4 Classification

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 Pattern Recognition Neural Network model (Pattern Net) and Layered Recurrent Neural Network model (LRN) to classify the EEG data signals.

3.4.1 Pattern recognition neural network

A feed forward back propagation based pattern recognition neural network is used in this study for classifying and recognizing the 4 different tasks of ASD and non-ASD children as shown in Figure-4. While Pattern Net can be created for pattern recognition problems, it is a feed forward network that can be trained to classify inputs according to target classes. The target data for pattern recognition networks should be composed of vectors. This is a static network.

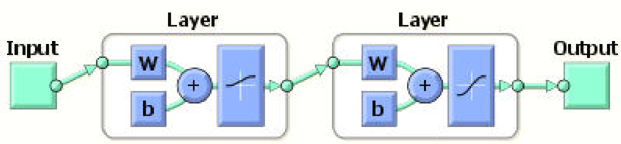

Figure-4. Pattern Recognition Neural Network Model.

3.4.2 Layered recurrent neural network

Layered recurrent neural networks are alike feed forward networks, apart from the condition that each and every layer has an intermittent linking with a tap interruption connected with it which makes the network to have a boundless active reaction to input data. This network resembles the time delay and the distributed delay neural networks, which have fixed input reactions. This is a dynamic network.

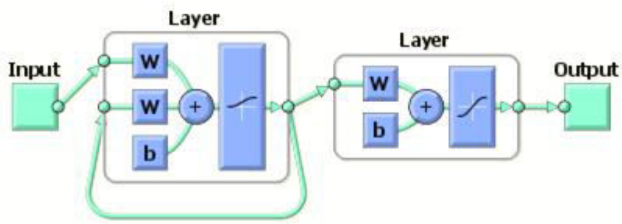

Figure-5. Layered recurrent neural network model.

16 features have been given for each EEG signal. These values become the input to the neural network. Sixteen input neurons, 3 output neurons and 10 hidden neurons are used to design the Pattern Net and LRN. Trial and error method is used to select the values for hidden neurons. Testing and training of the network are performed using 75% and 100% of the data set respectively. 0.001 is fixed as training error tolerance rate. Error tolerance rate for testing is 0.6.

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4. RESULTS AND DISCUSSIONS

4.1 Network based classification

The performance of the Pattern Net for the six AR feature sets is shown in Figure-6. It is observed that AR Burg outdid the other feature sets with the highest classification accuracy of 93.87% for Subject A5 and the lowest classification accuracy of 88.46% for Subject N2. AR Burg is found to be the best feature extraction technique in this study due to its high resolution for short data records and its ability to always produce a stable model. The next best performance is observed for the AR modified Covariance feature sets at 93.37% for Subject A5 and the lowest classification accuracy for the same feature set was 88.32% for Subject N2. Figure 7, depicts the classification accuracy of LRN for the six AR features. It is evident from the result that AR Burg again outperformed other feature sets with the highest classification accuracy of 94.62% for Subject A5 and the lowest classification accuracy of 89.17% for Subject N2. The next best performance is observed for the AR modified Covariance feature sets at 94.37% for Subject A5 and the lowest classification accuracy for the same feature set was 89.02% for Subject N2. In network based classification, LRN has well identified the pattern. LRN has performed better because of its dynamic properties versus static Pattern Net. Here, Subject N1 to Subject N4 are non-ASD children while Subject A1 to Subject A6 are children with ASD.

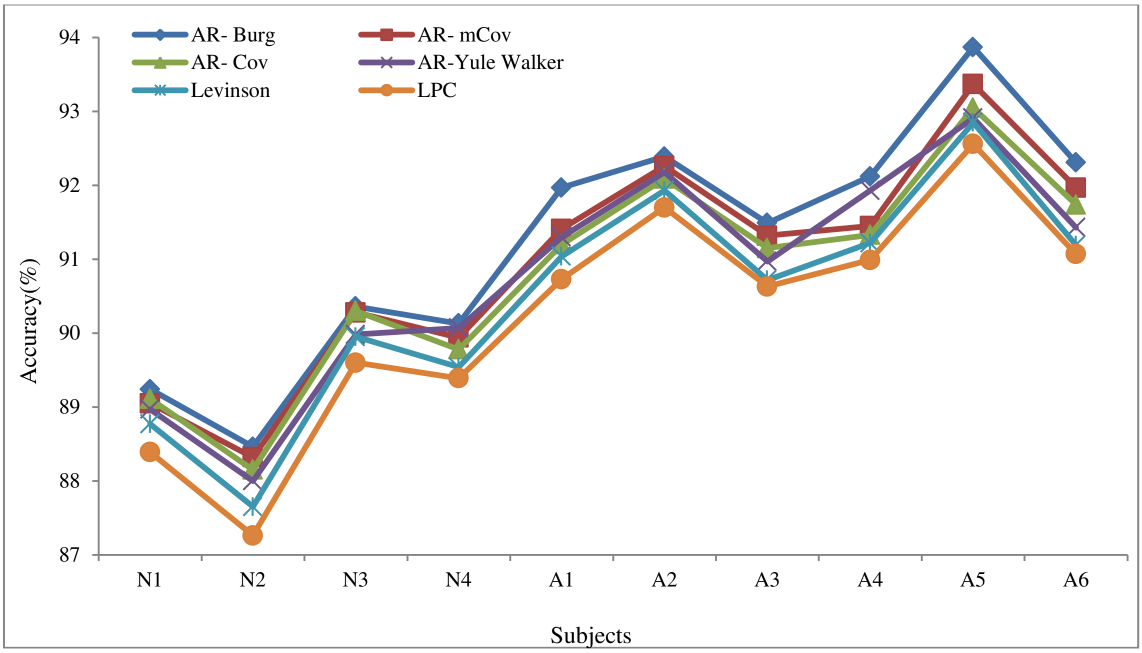

Figure-6. Pattern net classification performance.

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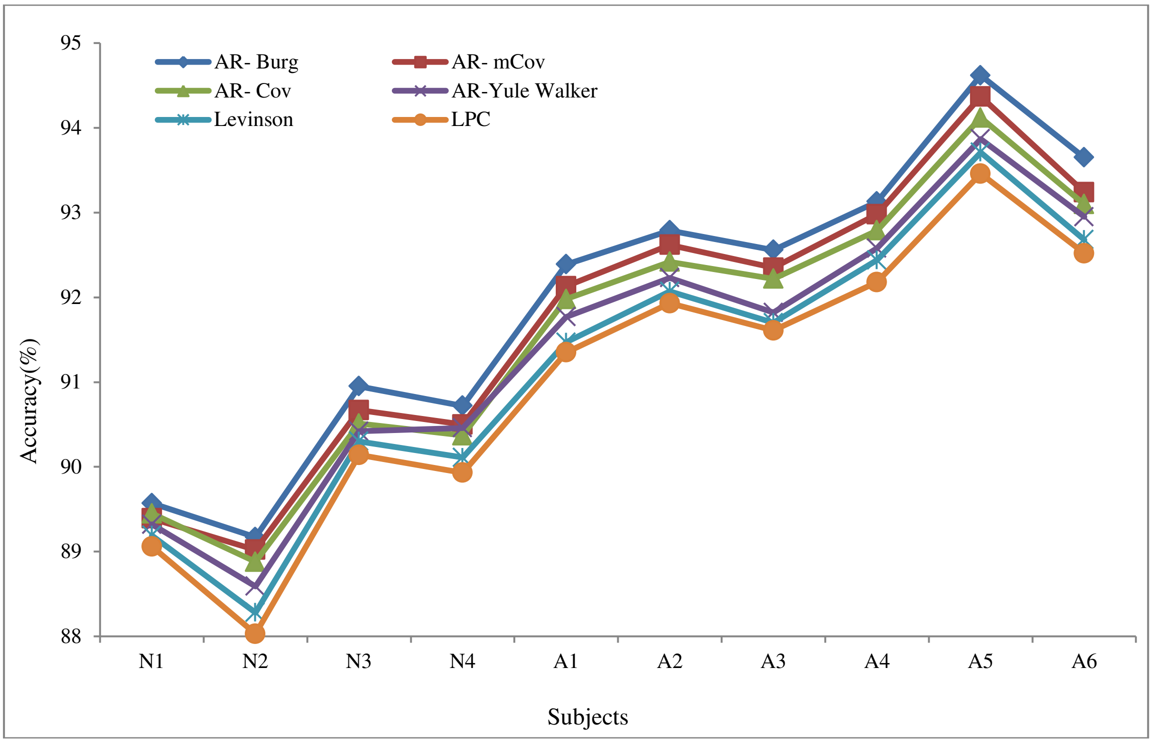

Figure-7. Layered recurrent neural network classification performance.

4.2 Subject based classification

From the network models developed, it is seen that the data from Subject A5 has obtained highest accuracy levels in the range of 92.56% to 94.62%. The least performance accuracy is observed for Subject N2 with a range of 87.26% to 89.16%. Here, Subject N1 to Subject N4 are non-ASD children while Subject A1 to Subject A6 are children with ASD. Subject A5 had slightly more degree of ASD as compared to other ASD children. Moreover, he participated in the experiments for a long period as compared to other subjects. As a result, maximum accuracy was obtained for Subject A5 for all tasks.

The subject based classification results for Pattern Net and LRN are shown in Figures 8 and 9 respectively. Mean accuracy range using Pattern Net for the ASD children varies from 91.28% to 92.36% and mean accuracy range for the non-ASD children varies from 88.66% to 89.55%. Similarly, mean accuracy range using LRN for ASD children varies from 92.18% to 93.19% and mean accuracy range for the non-ASD children varies from 89.29% to 90.10%. It is observed from the results that higher classification accuracy was found in children with ASD as compared to non-ASD children. This emphasises the fact that more difference of behaviour of neurons under each task were found in children with ASD as compared to non-ASD children.

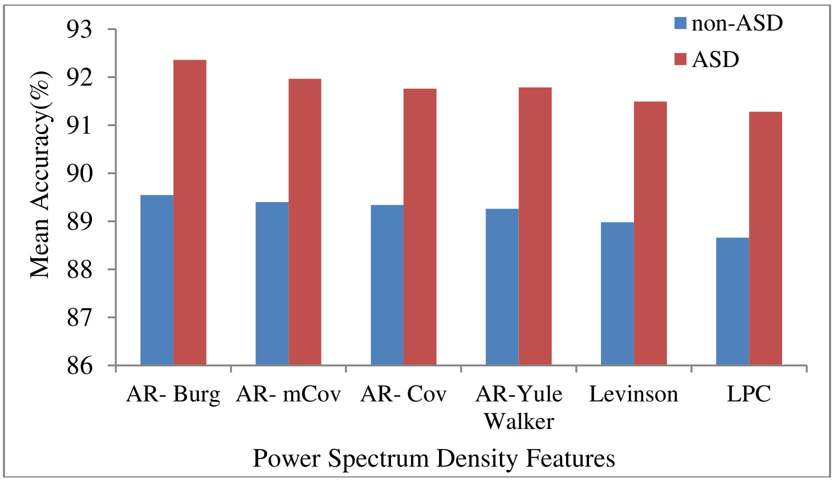

Figure-8. Subject based mean classification accuracy for 6 AR-features using pattern net.

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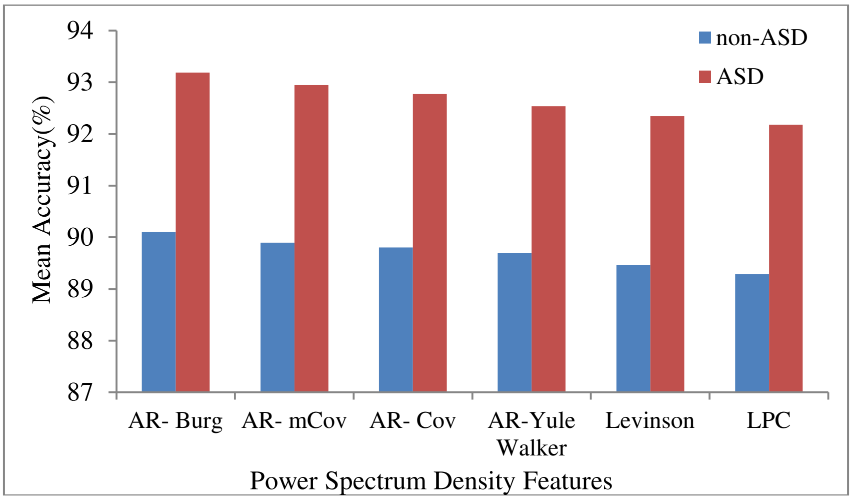

Figure-9. Subject based mean classification accuracy for 6 AR-features using LRN.

4.3 Bit Transfer Rate (BTR)

The classification accuracy was calculated in each neural network model for each subject. Then, BTR was calculated to evaluate the Human Machine Interface (HMI) system performance. The BTR is defined as the amount of information communicated per unit of time. This parameter encompasses speed and accuracy in a single value. The BTR can be used for comparing the different HMI approaches and for the measurement of system improvements. The BTR has been calculated from equation given below.

$$BTR=\frac{60}{T_{act}}\left[\log_2 n + p_a \log_2 p_a + (1\text{-}p_a)\log_2 \frac{1\text{-}p_a}{n\text{-}1}\right] \quad (7)$$

Where,

n = Number of Hand Movement
p_a = Mean Accuracy
$1\text{-}p_a$ = Mean Recognition Error
T_{act} = Action Period (in seconds)

The BTR for Pattern Net and LRN for six parametric features are shown in Figures 10 and 11 respectively. From the results, it is observed that the highest BTR is achieved for LRN using AR Burg with the rate of 6.08 bits/sec. Overall BTR ranges from 4.30 bits/sec to 6.08 bits/sec for LRN. Similarly Pattern Net has also performed well with BTR varying from 4.11 bits/sec to 5.86 bits/sec

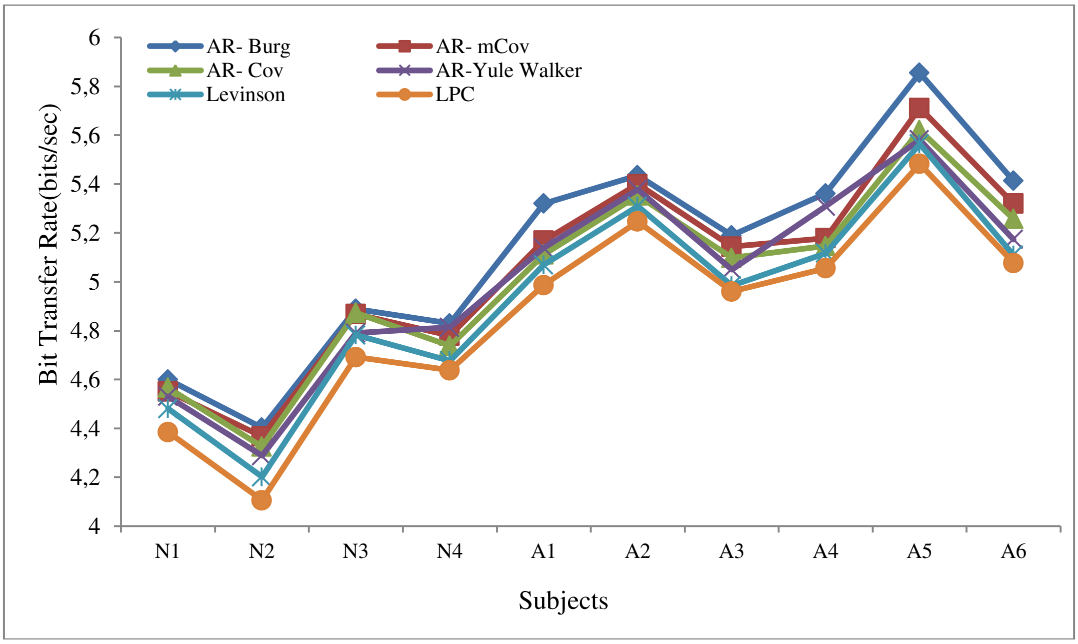

Figure-10. Bit transfer rate for pattern net using six parametric features.

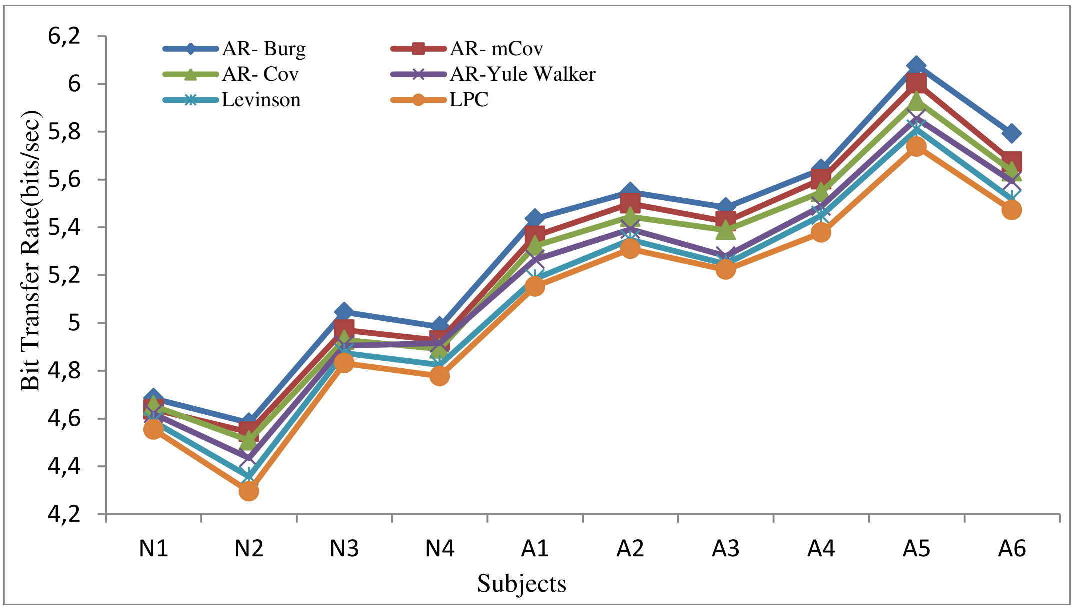

Figure-11. Bit transfer rate for LRN using six parametric features.

5. CONCLUSIONS

Diagnosing ASD based on 4 different tasks were performed using EEG signals and Artificial Neural Networks in this study. Data was collected from ten subjects for four tasks. Six Auto Regressive feature extraction algorithms namely the AR Burg, AR Modified Covariance, AR Covariance, AR Yule Walker, Levinson Durbin Recursion and Linear Prediction Coefficient were applied to the neural network for classification. It was observed from the empirical results that the AR Burg and LRN combination had the highest recognition accuracy rate of 94.62%. Investigations also proved that classification accuracy of EEG signals were higher for subjects with ASD as compared to non-ASD subjects due to more difference of behaviour of neurons under each task. It was also evident that maximum bit transfer rate of 6.08 bits/sec was achieved for LRN using AR Burg.

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