Detection of Abnormalities based on Gamma Wave EEG Signal for Autism Spectrum Disorder

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***Abstract*—Diagnosing Autism Spectrum Disorder (ASD) by using the traits of abnormalities in their gamma waveform has been proposed in this study to suggest an objective method to detect the disorder using Electroencephalography (EEG) signal. Gamma waveform plays an important role in learning, memory and information processing where it shows slower activities in ASD person compared to a normal person, thus, causing the patients to have trouble in processing knowledge, communicate and pay attention. This study applies Probabilistic Neural Network (PNN) and General Regression Neural Network (GRNN) to classify the data into normal and abnormal classes. Classification algorithm by PNN was used as a benchmark for the outcomes. The results show that even though PNN and GRNN have similar architecture, but with fundamental difference, the outcomes are different. In this case, PNN performs better than GRNN. To obtain the desired results, we used three and four statistical features (mean, minimum, maximum and standard deviation) for both methods. The outcomes of using PNN with four features are more accurate (99.5% for normal class and 80.5% for abnormal class) compared to only three features. Furthermore, the outcomes of using GRNN with four features also have improvement (95% for normal class and 63.5% for abnormal class) compared to only three features.**

***Index Terms*—ASD; EEG; Gamma Wave; GRNN; PNN.**

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex disorder of brain development. It is a neuro-developed mental disorder characterized by impaired social interaction, verbal and non-verbal communication, and restricted and repetitive behavior [1]. The signs usually can be noticed in the first two or three years of a patient's life [2]. These signs develop gradually though some children with autism reach their developmental milestones at a normal pace and then regress. Symptoms become apparent in early childhood, typically before the age of three. Autism has a strong genetic basis, although the genetics of autism are complex and it is unclear whether ASD is explained more by rare mutations with major effects, or by rare multigene interactions of common genetic variants. Although there is actually no known single cause for ASD, it is generally accepted that it is caused by abnormalities in brain structure or function. Brain scans show differences in the shape and structure of the brain in ASD children compared to normal children [3].

Autism is diagnosed based on a patient's behavioral characteristics and symptoms. The assessments can be highly subjective and require a tremendous amount of clinical expertise. We need a more objective way to diagnose and classify this disorder. Electroencephalography (EEG) is a medical imaging technique that reads the scalp electrical activity generated by brain structures after being picked up by metal electrodes and conductive media. Due to the capability to reflect both normal and abnormal electrical activity of the brain, EEG has been found to be a very powerful tool in the field of neurology and clinical neurophysiology [4-6]. Thus, the study on EEG signal for ASD patients would help to detect abnormal brain waves activity. The brainwave recordings could potentially reveal how severely the ASD individuals are affected. Before the use of EEG detection, the condition of ASD patients' brain activity could not be identified.

This study focuses on how to analyse EEG brain signal activity for ASD, especially gamma waves which include collecting datasets of ASD and normal patients, sub-band decomposition and feature extraction focuses only on gamma waves using Wavelet Toolbox to get mean, minimum, maximum and standard deviation for 10 channels of each subject and lastly classification of the features using Probabilistic Neural Network and General Regression Neural Network. This study does not include the raw materials from ASD patients. The importance of the study is to suggest that EEG is an important tool to diagnose ASD based on the abnormalities of gamma waves since EEG is widely used to investigate brain functions in healthy individuals and in those with medical and psychiatric problems. It can also be used to examine brain activity either during rest, or during evoked brain responses. The study can be assumed to be related to children and adolescents. Since EEG is non-invasive, it is ideal for the younger patients.

Probabilistic Neural Network (PNN) and General Regression Neural Networks (GRNN) have similar architectures, but with a fundamental difference: Probabilistic networks perform classification where the target variable is categorical, whereas general regression neural networks perform regression where the target variable is continuous. The architecture of PNN and GRNN is illustrated in Figure 1. The PNN was introduced by Specht (1990) and have gained interest since they offer a way to interpret the network's structure in the form of probability density function (PDF). PNN also put the statistical kernel estimator into the framework of Radial Basis Function (RBF) compared to classical RBFs; PNNs are used for classification only [7]. PNN is mainly a classifier which can map any input pattern to a number of classifications and can be forced into a more general function approximator. It is an implementation of a statistical algorithm called kernel discriminant analysis in which the operations are organized into a multilayered feed-forward network with four layers or nodes; input, hidden, class and decision nodes [8]. While General Regression Neural Network (GRNN) is a variation of the radial basis neural networks, which is based on kernel regression network. GRNN does not require an iterative training procedure as a back propagation network [9]. It can approximate any arbitrary function between input and output vectors, and draw the function's estimate directly from the training data. GRNN is consistent in which as the training set size becomes large, the estimation error approaches zero with only a little bit of restrictions on the function. The GRNN is used especially for estimation of continuous variables as in standard regression techniques [10].

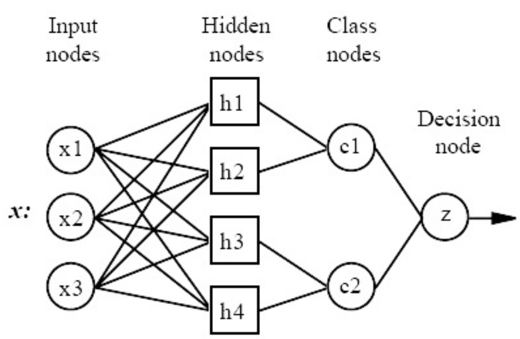

Figure 1: Architecture of PNN and GRNN

i. Input nodes – where the inputs are applied.
ii. Hidden nodes – where a nonlinear transformation is applied on the data from the input space to the hidden space; in most applications the hidden space is of high dimensionality.
iii. Class nodes – For PNN networks, there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored within each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category. The pattern neurons add the values for the class they represent. For GRNN networks, there are only two neurons in the pattern layer. One neuron is the denominator summation unit and the other is the numerator summation unit. The denominator summation unit adds up the weight values coming from each of the hidden neurons. The numerator summation unit adds up the weight values multiplied by the actual target value for each hidden neuron.
iv. Decision node - For PNN networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category. For GRNN networks, the decision layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value [11].

II. METHODOLOGY

A. Research Design and Procedure

This experiment used datasets which distinguished two groups: children formally diagnosed with ASD and an age and gender matched control group. In the control group, a neurological or psychiatric disorder was excluded and all received a normal education. In both the ASD as well as the normally developing group, epilepsy was excluded on the basis of medical history, follow-up of the paroxysmal events and EEG recording. The diagnosis of ASD was confirmed by a child and adolescent consultant psychiatrist and was made according to DSM IV guidelines.

B. Subjects or Data Sources

Routine EEG recordings were performed according to the international 10–20 system against G2 as a reference electrode (placed between Cz and Fz). The impedance of each electrode was kept below 5 kΩ. Data were high- and low-pass filtered at 0.008 and 70 Hz, respectively, with a sampling frequency of 512 Hz. All EEG recordings contained 21 standard scalp electrodes. Electrodes Fp1, Fp2, A1 and A2 were left out of the analysis to minimize eye-induced movement and ECG artifacts. We included 19 patients with autism (mean age 10.6 ± 4.1 years, 16 boys) and 19 age- and gender-matched controls (mean age 10.1 ± 3.8 years, 16 boys).

C. Instrumentation and Data Analysis

a. Sub-band decomposition

The EEG contains information about the brain, thus, the sub-band decomposition of EEG can be used to analyze many brain diseases. Sub-band decomposition means to extract brain waves into different frequency bands (alpha, beta, delta, theta and gamma). The frequency bands of EEG signal provide a lot of useful information that can be interpreted using several methods. Sample frequency of 512Hz was used in this work.

Figure 2 shows the EEG sub-band decomposition using daubechies at level 8. This decomposition is repeated up to level 8 to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters. At each level, the signal is decomposed into low and high frequencies. High pass filters produce the detail wavelet coefficient, D1 to D8 while low pass filters produce approximation wavelet coefficients, A1 to A8. Single level decomposition composition computes the approximation coefficients vector cA and detail coefficients vector cD which are obtained by the wavelet decomposition of vector X. The EEG decomposition levels and its frequency band are tabulated in Table 1.

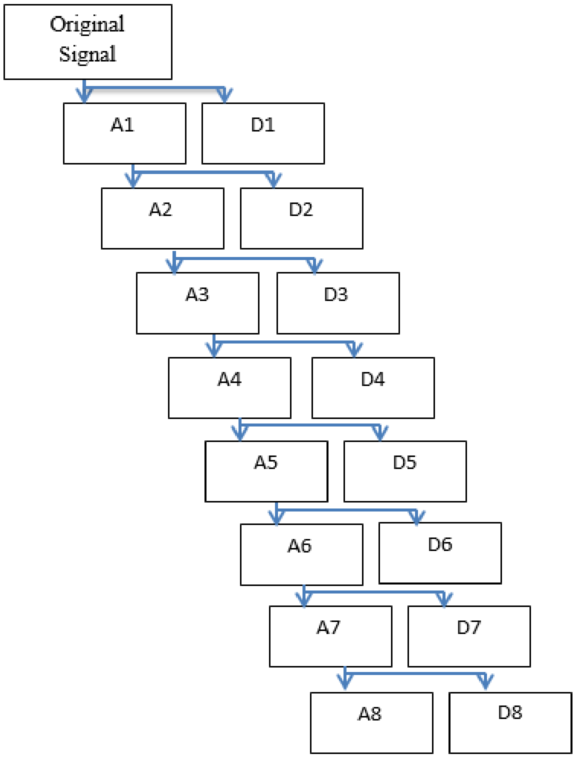

Figure 2: EEG sub-band decomposition

Table 1
EEG Decomposition Level and its Frequency Band

Frequency Level (Hz)	Decomposition Level	Frequency Band
100 - 512	D1 – D4	Noises
30 – 100	D5	Gamma
16 – 30	D6	Beta
8 – 16	D7	Alpha
4 – 8	D8	Theta
0 – 4	A8	Delta

b. *Wavelet Toolbox*

In this work, Wavelet 1-D from Wavelet Toolbox in MATLAB® version r2015a was used for gamma waves feature extraction. By using gamma waves data from the previous step for each channel in each subject, one dimensional wavelet transform was used to get the value of mean, median and standard deviation. Based on the extracted features, the abnormality in gamma waveform of ASD patients was compared with the gamma waveform of a normal person. Figure 3 shows the wavelet decomposition at level 4 for db4 for Gamma waves. Decomposition at level 4 contains of s = A4 + D4 + D3 + D2 + D1. S represents the original signal; A4 is approximation at level 4, while D4, D3, D2 and D1 are details at levels 4, 3, 2 and 1 respectively. However, only S, A4, D4 and D1 were used in this experiment since the peak to peak value of A4, D4 and D1 showed a significant difference from the original signal, s. While Figure 4 below shows an example result of the original signal by using Wavelet 1-D.

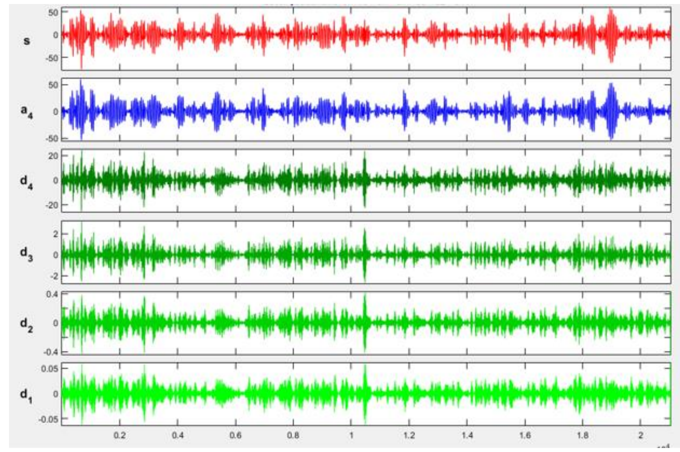

Figure 3: Wavelet at db4 level 4 (s=A4+D4+D3+D2+D1)

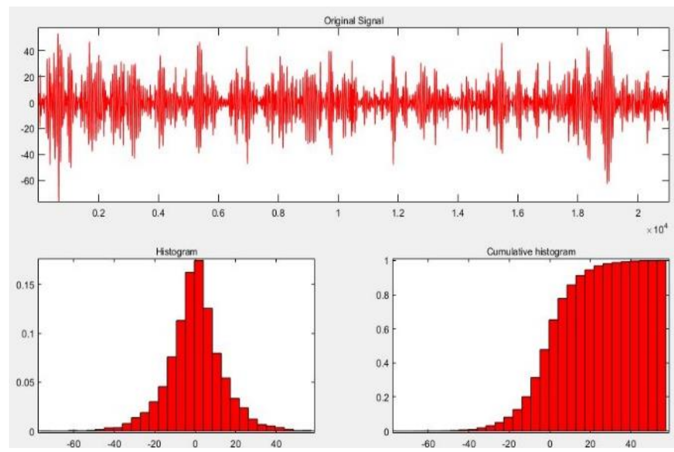

Figure 4: Result of original signal using wavelet 1-D

c. *Probabilistic Neural Network*

For this experiment, there are four features at the input layer which are mean, minimum, maximum and standard deviation using 400 data of 10 subjects with two target classes; I and II. Target I represents a normal class while target II represents an abnormal class. Each of the subject has 40 data with 10 channels (F7, F6, F4, F3, T13, T19, T9, T15, P18 and P16) at four cases of original, approximation at level 1 (A4), details at level 4 (D4) and details at level 1 (D1) by using the Wavelet toolbox on previous feature extraction.

The PNN coding contains 400 data with the features of mean, minimum, maximum and standard deviation with two target classes. Table 2 shows some example of data classification using PNN for all four features (mean, minimum, maximum and standard deviation). Normal class should be target I while abnormal class is target II as shown in the table below. In the table, the outcomes for control subject, C1 is I which is normal class and ASD subject, A1 is II for abnormal as expected. The classification was performed by using three features (mean, maximum and standard deviation) on PNN.

Table 2
Example of Data Classification using PNN with 4 Features

Subject	Feature Mean	Min	Max	Std. Dev	Target	Class
C1	0.000668	-13.62	16.42	3.847	1	Normal
	0.000153	-12.30	14.90	3.421	1	Normal
	-0.002820	-17.76	15.57	3.719	1	Normal
	-0.001500	-19.96	18.39	4.300	1	Normal
	0.001868	-26.49	25.35	6.149	1	Normal
	-0.003720	-34.91	28.35	6.989	1	Normal
A1	0.005872	-76.10	57.39	13.680	11	Abnormal
	-0.000410	-106.40	90.59	15.000	11	Abnormal
	-0.001350	-45.17	46.13	10.150	11	Abnormal
	0.008823	-80.74	77.14	13.850	11	Abnormal
	0.010550	-77.10	53.75	14.820	11	Abnormal
	0.001476	-91.34	83.29	17.350	11	Abnormal

d. General Regression Neural Network

For the classification using GRNN, firstly, we use three features at the input layer (mean, maximum and standard deviation) using 400 data of 10 subjects. Each of the subjects has 40 data with 10 channels (F7, F6, F4, F3, T13, T19, T9, T15, P18 and P16) at four cases of original, approximation at level 1 (A4), details at level 4 (D4) and details at level 1 (D1) by using the Wavelet toolbox on previous feature extraction.

Classification using GRNN is slightly different from PNN since there is no specific target class. Instead, GRNN classifies the data based on the value of the output, v. For three features, the output value for normal has to be between 1 and 6 while for abnormal, the value is between 8 and 15. There is a gap between 6 and 8 to avoid collisions between the classes. Table 3 shows some example for data on control subject, C1 and ASD subject, A1. There is one data on subject C1 misclassified as abnormal since the output is over the range of 1 to 6.

Table 3
Example of Data Classification using GRNN for 3 Features

Subject	Feature Mean	Max	Std. Dev	Output	Class
C1	0.000668	16.42	3.847	5.3115	Normal
	0.000153	14.90	3.421	5.5095	Normal
	-0.002820	15.57	3.719	5.8904	Normal
	-0.001500	18.39	4.300	3.9542	Normal
	0.001868	25.35	6.149	**6.9297**	**Abnormal**
	-0.003720	28.35	6.989	4.8770	Normal
A1	0.005872	57.39	13.68	10.9994	Abnormal
	-0.000410	90.59	15.00	11.0000	Abnormal
	-0.001350	46.13	10.15	8.3061	Abnormal
	0.008823	77.14	13.85	11.0000	Abnormal
	0.010550	53.75	14.82	10.8810	Abnormal
	0.001476	83.29	17.35	11.0000	Abnormal

Meanwhile, when using 4 features (mean, minimum, maximum and standard deviation), all six data on C1 were correctly classified as normal. Instead of 6.9297 on previously misclassified data, the new output after adding one more feature became 5.9389, which in the range of a normal class. Table 4 shows the data classification using GRNN with four features.

Table 4
Example of Data Classification using GRNN for 4 Features

Subject	Feature Mean	Min	Max	Std. Dev	Output	Class
C1	0.000668	-13.62	16.42	3.847	5.319	Normal
	0.000153	-12.30	14.90	3.421	3.656	Normal
	-0.002820	-17.76	15.57	3.719	3.523	Normal
	-0.001500	-19.96	18.39	4.300	5.063	Normal
	0.001868	-26.49	25.35	6.149	**5.939**	**Normal**
	-0.003720	-34.91	28.35	6.989	1.313	Normal
A1	0.005872	-76.10	57.39	13.68	11.000	Abnormal
	-0.000410	-106.40	90.59	15.00	11.000	Abnormal
	-0.001350	-45.17	46.13	10.15	10.996	Abnormal
	0.008823	-80.74	77.14	13.85	11.000	Abnormal
	0.010550	-77.10	53.75	14.82	11.000	Abnormal
	0.001476	-91.34	83.29	17.35	11.000	Abnormal

III. Results and Discussion

Results of data classification are different between using three and using four features for both PNN and GRNN. Table 5 and Table 6 show the overall results of data classification between three features and four features using PNN and GRNN, respectively.

The overall results for PNN based on the table above show that all control subjects except C4 have low percentage of abnormality in his/her gamma waves, which is at 2.5% when three features were used. When four features were used, C2 have 2.5% abnormalities in his/her gamma waves. However, since the percentage of both subjects are low, they are not considered as ASD. For ASD subjects, all of them have a high percentage of abnormal with 95% for A1 at the highest and 67.5% for A4 at the lowest. The results of three and four features for ASD subjects were uniform except for A4, which shows a modification of 67.5% abnormalities to 82.5%.

Table 5
Results of Data Classification using PNN with 3 and 4 Features

Method	PNN (3 Features)		PNN (4 Features)	
Subject	Normal (%)	Abnormal (%)	Normal (%)	Abnormal (%)
C1	100	0	100	0
C2	100	0	97.5	2.5
C3	100	0	100	0
C4	97.5	2.5	100	0
C5	100	0	100	0
A1	5.0	95.0	5	95.0
A2	25.0	75.0	25	75.0
A3	25.0	75.0	25	75.0
A4	32.5	67.5	17.5	82.5
A5	25.0	75.0	25	75.0

Table 6
Results of Data Classification using GRNN with 3 and 4 Features

Method	GRNN (3 Features)		GRNN (4 Features)	
Subject	Normal (%)	Abnormal (%)	Normal (%)	Abnormal (%)
C1	85.0	15.0	92.5	7.5
C2	92.5	7.5	90.0	10.0
C3	85.0	15.0	100.0	0.0
C4	95.0	5.0	97.5	2.5
C5	85.0	15.0	95.0	5.0
A1	10.0	90.0	10.0	90.0
A2	57.5	42.5	42.5	57.5
A3	52.5	47.5	47.5	52.5
A4	65.0	35.0	45.0	55.0
A5	65.0	35.0	37.5	62.5

Table 6 shows different outcomes for all the subjects using three features GRNN and four features GRNN. With three features, control subjects, C1 to C5 have 5 to 15% abnormalities in his/her gamma waves. Compared to using four features, the highest percentage of abnormalities in the control subject is at 10% for C2 with the lowest percentage of abnormalities at 2.5% for C4. It shows improvement, especially on C3 that has 100% normal percentage compared to 85% when classified with three features only. Meanwhile, for ASD subjects, with only three features, except A1, all of them have a higher normal percentage compared to abnormal with 65% being the highest. However, with four features, except A1 that statistically shows 90% abnormalities in his/her gamma wave, the other four subjects changed drastically. They have a higher percentage of abnormalities compared to normal with the lowest at 52.5% and the highest at 62.5%.

IV. Conclusion

In this experiment, 400 data were used and the results using PNN are as expected. ASD has higher abnormalities in gamma waves compared to control subjects. Classification by PNN with three features (mean, maximum, standard deviation) shows among ASD patients, all of them have a high percentage of abnormalities (lowest at 67.5% and highest at 95%) where control subjects have 100% normal gamma waves except for control subject 4 which contains 2.5% abnormalities in his/her gamma waves but it is still at normal range. While classification by PNN with four features (mean, minimum, maximum, standard deviation) shows ASD patients have high percentage of abnormalities between 75% and 95% with control subjects except C2 (2.5% abnormal) have 100% normal gamma waves. Meanwhile by using GRNN with three features, the results are varied. In control subjects, C1, C3 and C5 there are about 15% in abnormal class which is quite high for control subjects, yet in ASD patients especially A4 and A5 show high percentage of normal Gamma waves at 65% respectively. However, GRNN with four features shows improvement when control subjects only have 0% to 10% abnormalities in his/her gamma waves with ASD patients have high percentage of abnormalities from 52.5% to 95%. Thus, the results using PNN are more accurate compared to when using GRNN. The overall classification results for each classifier are shown in the Figures 5 and 6.

Gamma waves are closely associated with sensory processing, working memory, attention and many other cognitive domains thus it gives impact on ASD patient based on how severe the abnormalities in their gamma waves. Compared to control, the alpha, beta, theta and delta in ASD also show different waveforms, the study is focused on gamma solely to prove the importance of gamma waves activity in detection of ASD using EEG.

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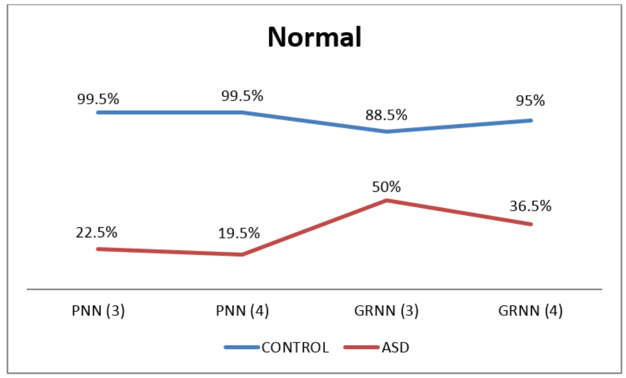

Figure 5: Classification results for normal class

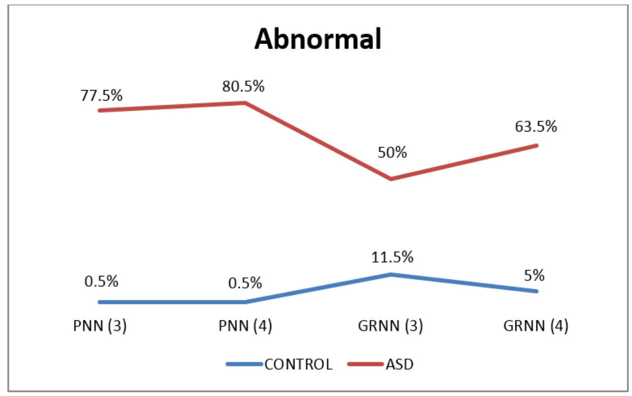

Figure 6: Classification result for abnormal class

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