Classification of Normal and Stress between Female based on EEG Signals by using Artificial Neural Network

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***Abstract*— This paper focuses on the analysis of EEG signals to classify female with and without stress. Stress is an emotional state that is common to each and every one of us. Moderate level of stress can lead to positive effects such as motivation booster but too much of stress may lead to negative effect that may harm our body. This study is to explore an alternative method to identify the sign of stress among female individuals by analyzing the EEG signals among normal subjects and subjects with stress. This EEG analysis is based on the classification of EEG signals to distinguish subjects with and without stress. Our research work includes performing classification of EEG signals by using two different types of Artificial Neural Network (ANN) classifier known as Scaled Conjugate Gradient and ANN with Resilient Back Propagation. The inputs fed to these classifiers are either in the form of Power Spectral Density (PSD) features or Energy Spectral Density (ESD) features extracted from the EEG signals. The aim of this study is to determine which one among of these two classifiers can perform better in distinguishing EEG signals of female with and without stress. In addition, the suitable type of EEG features as inputs to the classifier will also be studied. Based on the conducted analysis, it is shown that ANN with Resilient Back Propagation and Scaled Conjugate show high accuracy for PSD features, however only Scaled Conjugate Training obtained better accuracy in classifying based on ESD features in classifying females with and without stress.**

***Index Terms*—ANN, Resilient Back Propagation, Scaled Conjugate Gradient, Classification, EEG signals, PSD, ESD**

I. INTRODUCTION

Stress or also known as tension is one of emotional states that frequently happen to everyone. Psychiatry researches [1-3] have shown that women are suffering more depression than men and they are more susceptible to the emotional states called stress. Stress is a kind of pressure that can give positive or negative effects. Stress is a part of natural methods on how our body reacts to a challenge. Looking from the positive side of stress, it will make the individuals to prepare themselves for incoming challenges and to avoid any danger. While looking at its negative side, if stress continues to be experienced without relief, it may lead to distress. Based on the information from The American Institute of Stress (AIS) [4] , there are 50 common signs and symptoms of stress such as chest pain, excess anxiety and insomnia.

Stress sprouts because of many thoughts. The outcome of how our body responds to challenge will head towards stressful or stress-free. Stress can causes depression, which requires proper medical establishment to alleviate it. Therefore, it is crucial to have early-detection of stress. Observation is one of the methods to detect early signs of stress. We can detect it through observing an emotional and physical signs of stress. However the result is not straight forward. Another method is by answering stress questionnaires and yet we can only get an overview or a subjective result. This is because everyone responds to stress in different way. Such questionnaires can be used as initial diagnosis of stress level. To have a more detailed analysis of stress condition, the affected individuals will have to meet the consultant. Hence, a new type of diagnosis is needed for detecting stress.

Electroencephalography (EEG) is a test that detects electrical activity in brain and has been used in research on brain function. EEG is one of the methods that have been used in a hospital for screening for epilepsy and in diagnosing neurological disorder or brain death. EEG can be described in term of rhythmic activities. Looking at EEG rhythmic activities, the signals can be divided into bands by frequency and typically called as brainwaves. Each band has its own range of frequency and correlate with different mind and physiological states.

TABLE I. EACH BAND FREQUENCIES RANGE LINKS WITH DISTINCT MIND AND PHYSIOLOGICAL STATES [5, 6].

Bands and its Frequency	Amplitude (μV)	Mind State
Delta (0.5-4Hz)	Highest	Deepest stages of sleep
Theta (4-8Hz)	High	Experiencing emotions, relaxation, daydreaming, intuition, and have subconscious mind
Alpha (8-13Hz)	Low	Relaxation, drowsiness and sleep.
Beta (13-32Hz)	Lowest	Logical Thinking , Conscious Thought and Concentration or anxiety

Based on Table I, the spectral component in EEG alpha waves and beta waves are in frequency range of (8-13 Hz) and frequency range of (13-32 Hz) respectively. People that have anxiety, high stress or insomnia have the probability of having low alpha band frequency and high beta band frequency. Phenomenon that is called the "alpha blocking" may occur to the stress subject. This is due to excessive beta activity and very low delta. EEG or brainwave test can be used to detect stress and to classify an individual is with and without stress.

For this study, the analysis is focusing on female gender. EEG signals may differ between genders based on the research conducted by [7, 8]. This is due to the reason, as stated earlier that female have more tendency to become stress. In addition, female subjects who involved in the experiment are mostly students, who we believe exposed to the academic pressure on campus as well outside the campus. In order to determine the presence of stress, the relation of alpha-beta waves and brain activity are used in this study.

Stress may lead to an asymmetry brain activity. Research work [9] is focusing on classifying the EEG signals between individuals with and without depression based on Frontal Brain Asymmetry (FBA) technique. An alpha-band characteristic has been used in diagnosis of depression by determining the FBA. Subject with stress is found to have more activation at left frontal asymmetry [10]. In [11], the stress subjects were asked to listen to binaural beat sound to induce relaxation onto the subject. The result has shown that EEG frontal alpha asymmetry of the stress subject increased. This shows the relationship between brain asymmetry and the mental state. Another study was done to see the EEG Alpha Asymmetry behavior when stress is induced [12]. In the study, after stress is induced, alpha wave was found to be affected and there was a different in their alpha level on both hemispheres. Based on research [13], there is high activity on left frontal in depression. These studies have shown that EEG Brain asymmetry holds an essential role in detecting stress. Alpha band of EEG signals is regarded as the most significant band to represent people with anxiety, stress or depression. Those mental states are commonly associated with low alpha waves and high beta waves. The increment of beta waves and decrement of alpha waves happen when stress occurred [14] .These studies further emphasized that alpha and beta wave are vital elements that need to scrutinize.

Artificial Neural Network (ANN) is a complex interconnected group of network that is similar to human biological neural network. ANN is a mathematical and computational model, from which the outcome or output is based on the input with a computational processing. The application of ANN has been widely used in many studies as a method for classification [15-18], estimation[19], pattern recognition [20] and controlling. Fig. 1 shows the basic architecture of neural network model that comprises the input layer, number of hidden layer and output layer.

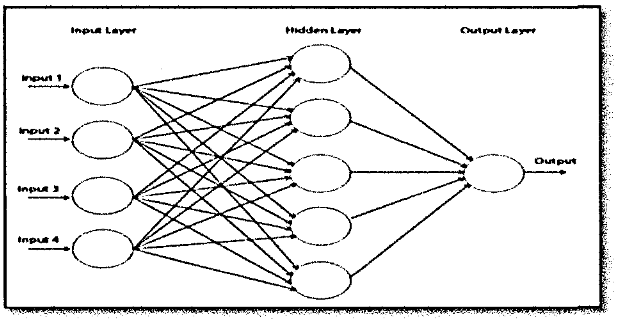

Fig. 1 General architecture of ANN modeling

For multilayer network category, Multilayer Back Propagation Neural algorithm is found to be useful for this study. With this algorithm various training functions can be used for classification. By using different training algorithms, we can get more accurate result. A study [21] was conducted on comparison analysis between four training methods which are Gradient De-scent Back Propagation, Levenberg-Marquardt, Conjugate Learning Gradient Back Propagation and Gradient Descent Back Propagation with movement, and Resilient Back Propagation. This study shows that the Resilient Back Propagation method has brought perfect accuracy and gave better performance than others. Resilient back propagation algorithm is a complex algorithm but in the context of our study, it is better than the others in the sense that it does not require an estimation or empirically determination of step size parameter. This algorithm will determine an appropriate step size values by itself and can thus be applied "as is" to a variety of problems without significant loss of efficiency [22].For this study, the performance of Resilient Back Propagation will be compared with Scaled Conjugate Gradient approach. Scaled Conjugate Gradient approach is a supervised learning algorithm for feed forward neural networks that updates weight and bias values based on conjugate gradient methods[23].

This paper discusses on the classification analysis based on alpha and beta band of EEG signals between female subjects to detect one is with or without stress. Alpha and beta bands are selected because both bands are prognostic indicator for the existence of stress[14]. The classification analysis is executed by using the Scaled Conjugate Gradient Training and Resilient Back Propagation Training in Artificial Neural Network (ANN). In this analysis, two types of features are extracted from the EEG signals specifically the Power Spectral Density (PSD) and Energy Spectral Density (ESD) features.

PSD value is selected from the maximum power or energy at the peak frequency. While ESD value is the area under the PSD curve over frequency range [14]. The two features are then applied with EEG Asymmetry formula [11]. The comparison is made based on the accuracy measures of different training types, the adopted features type, the selected bands of EEG signals and the selected EEG channels (electrode).

The raw EEG data was recorded by using Emotiv EPOCH device [24], which has 14 EEG channel locations: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The EEG channel location is based on the International 10-20 system. Fig. 2 shows the scalp location covered by Emotiv EPOCH. Each side of brain is covered by 7 placements of electrodes where 4 of them are covering the frontal side of the brain.

The ability of ANN in learning and predicting the set of data is helpful for this study especially to classify alpha and beta waves to distinguish subjects with stress and without stress .Table II shows twelve groups that have been analyzed using both training method to find the best classification result. 4E means the EEG data being employed for the analysis are the reading from frontal left or right region, meanwhile 7E means the EEG readings are from the whole left or right region of the brain.

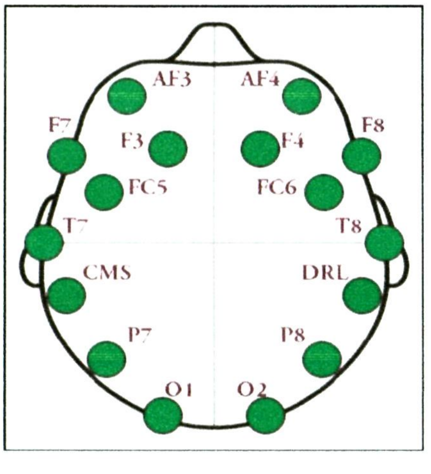

Fig. 2. 14 EEG channel locations with 2 reference points covered by Emotiv Epoch[24, 25].

TABLE II. GROUPS FOR SCALED CONJUGATE GRADIENT TRAINING AND RESILIENT BACK PROPAGATION TRAINING

Group	EEG sub band	Placement of electrode
ESD	Alpha	4E
		7E
	Beta	4E
		7E
	Alpha And Beta	4E
		7E
PSD	Alpha	4E
		7E
	Beta	4E
		7E
	Alpha And Beta	4E
		7E

II. METHODOLOGY

A. Introduction

The classification process is executed on Matlab software. There are three main steps in the classification processes. They are pre-processing, main-processing and post-processing.

B. Pre-processing step

The input data is from 48 female subjects. Each subject need to answer DASS questionnaire [26] and from the result the subject is divided between stress and non-stress group. For normal female subjects which we labeled as non-stress group assigned with '0'tag. As for subjects with mild, severe and moderate stress level. We labeled them as stress group and we assigned this group with '1'tag. Table III shows the number of subject in each category.

TABLE III. THE NUMBER OF STRESS AND NORMAL SUBJECTS.

Group	Normal	Stress
No. of subjects	28	20
Target	0	1

The recorded EEG signal is filtered in order to acquire all sub-band wave data. The filtered EEG data is used as inputs to the ANN for classification purpose. The process starts with the raw EEG data obtained from the experiment to undergo artifacts removal process. Artifacts removal process is crucial to obtain good quality of EEG data which is clear from any noise or unwanted signal. After artifacts removal the EEG data will undergo the filtering process. Hamming band pass filter is applied to divide the signals into 4 frequency bands as stated in Table I. The features are then extracted using Fast Fourier Transform to obtain the PSD and ESD values. The ESD and PSD values are then utilized in calculating the asymmetry of the brain. The EEG Asymmetry is calculated by using (1) and (2) for PSD and ESD[11].

$$\ln(ESD_{right}) - \ln(ESD_{left}) \quad (1)$$

$$\ln(PSD_{right}) - \ln(PSD_{left}) \quad (2)$$

The next main process will be considering using two groups of preprocessed data, i.e. the first analysis is based on 4 electrodes placement (frontal region) and the second analysis is based on 7 electrodes placement (whole brain region)

C. Main processing step

An Artificial Neural Network (ANN) emulates the simplified model of the biological neurons. ANN is capable of solving a problem that has complex connectivity and can be employ as techniques for classification and pattern recognition analysis [27]. In the context of this study, recorded EEG signals of both subject groups with and without stress will be fed to the ANN for training purpose. In this study to apportion training and testing data, we used the 80:20 ratio. 80% of data is used for training, while the other 20% of data is used for testing. In this type of training, input and output are provided. Therefore the learning algorithm for this study is categorized as supervised learning. Supervised learning model of an ANN is effective to find clarification for a linear and non-linear problems, for example, order, plant control, anticipating, forecast, and robotics[28]. Scaled Conjugate Gradient and Resilient Back Propagation algorithms are condign choices for classification. Even though their memory requisites are small but they are much faster.

D. Post-processing step

Post-processing step is an interpretation process of results to see the data is correctly classified or misclassified. Confusion matrix is the visualization diagram of the overall results which contains the accuracy, precision, sensitivity and specificity measures of the perform classification. Below are the equations and Table IV shows the term used for accuracy, precision, sensitivity and specificity.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (5)$$

$$Specificity = \frac{TN}{TN+FP} \quad (6)$$

Where;

TP: true positive

TN: true negative

FP: false positive

FN: false negative

TABLE IV. TERMS USED TO DEFINE SENSITIVITY, PRECISION, SPECIFICITY AND ACCURACY

		Actual	
		Normal	**Stress**
Predicted	**Normal**	TP	FP
	Stress	FN	TN

This study aims to obtain the measure of classification accuracy, precision, sensitivity and specificity value for analysis purpose i.e. in the context of detecting stress. If the subject is correctly classified as normal, then the diagnosis result will show that the subject was previously labeled as normal and this is considered as true positive (TP) case. If the subject was previously labeled as stress and correctly classified, then the diagnosis result will show that subject is classified as stress and this is considered as true negative (TN) case. For a misclassified case, an example is where the subject was labeled as normal but wrongly classified as stress where the test result is said to be false positive (FP).Otherwise, if the subject was labeled as normal then the test result is said to be false negative (FN). True Positive and True Negative are called as the standard truth, meanwhile False Positive and False Negative are the opposite of earlier data labeling.

The value of accuracy represents the proportion value of true results (TP and TN). Sensitivity value here is represents accurate classification of normal subject, while specificity value here represents accurate classification of stress subject. Lastly precision value is the percentage of normal subjects that actually are normal subject.

III. RESULT AND DISCUSSION

In this section, the result starts with comparison between both trainings based on the extracted features of PSD and ESD. The ANN classification is used for both different trainings, specifically the Scaled Conjugate Gradient (trainscg) and Resilient Back Propagation (trainrp)[29]. Next part for this section is to analyze the results of classification by using trainscg and trainrp function with same number of hidden layer based on the measures of accuracy, precision, sensitivity and specificity.

Table V and Table VI shows the result of classification accuracy based on input on PSD and ESD features using different training algorithms. From the result, trainscg function gives more accuracy with minimum number of hidden layer compared to trainrp function where it achieved highest percentage of accuracy with big number of hidden layer. Both trainings show high accuracy measures based on inputs from the alpha and beta values.

TABLE V. THE NUMBER OF HIDDEN LAYER AND ACCURACY VALUE FOR SCALED CONJUGATE GRADIENT.

Scaled Conjugate Gradient			
PSD	**No. Hidden Layer**	**threshold**	**Accuracy%**
A4E	8	0.6	81.25
A7E	18	0.7	81.25
B4E	12	0.4	81.25
B7E	22	0.2	81.25
AB4E	6	0.1	87.5
AB7E	6	0.2	81.25
ESD	**No. Hidden Layer**	**threshold**	**Accuracy%**
A4E	25	0.2	81.25
A7E	14	0.6	81.25
B4E	11	0.4	68.75
B7E	11	0.4	77.08
AB4E	15	0.6	81.25
AB7E	8	0.6	81.25

TABLE VI. THE NUMBER OF HIDDEN LAYER AND ACCURACY VALUE - RESILIENT BACK PROPAGATION.

Resilient Back Propagation			
PSD	**No. Hidden Layer**	**threshold**	**Accuracy%**
A4E	20	0.3	81.25
A7E	27	0.4	85.42
B4E	13	0.6	81.25
B7E	24	0.7	81.25
AB4E	6	0.2	89.5
AB7E	7	0.6	87.5
ESD	**No. Hidden Layer**	**threshold**	**Accuracy%**
A4E	24	0.4	79.17
A7E	19	0.5	81.25
B4E	11	0.5	66.67
B7E	28	0.3	77.08
AB4E	19	0.4	75
AB7E	16	0.5	81.25

From the Table above, it is shown that the PSD feature for Alpha-Beta 4 electrodes placement (AB4E) for both training algorithms has helped to achieve the best accuracy. However another variable that we need to look at is the number of hidden layer. Hidden layer does affect the training error and test set error. Low number of hidden layer aims for high training error and test error set due to under-fitting, while high number of hidden layer aims for low training error and can have perfect accuracy of train set. However with many hidden layers, it causes less effectiveness in the back-propagation algorithm and shoot up test error set due to over-fitting[30]. In order to shelter the competency of the network to conclude, the number of hidden layer has to be kept as low as possible. Resilient Back-Propagation and Scaled Conjugate Gradient trainings show high accuracy for PSD features, however only Scaled Conjugate Training obtained better accuracy in classifying based on ESD features.

All the training parameters are set with default value for Resilient Back propagation and Scaled Conjugate Gradient based on [29]. The input nodes are set to 2, representing the value of alpha EEG signal along with beta EEG signals. The output is 1, representing the diagnosed result of each subject (stress and non-stress) which is converted into binary number. In order to see the performance of ANN classification between 2 different training algorithms, 4 groups are considered. They are:

i) PSD features for Alpha-Beta 4 electrodes (AB4E)

ii) ESD features for Alpha-Beta 4 electrodes (AB4E)
iii) PSD features for Alpha-Beta 7 electrodes (AB7E)
iv) ESD features for Alpha-Beta 7 electrodes (AB7E)

Table VII, VIII, IX and X display confusion matrix produced based on the classification. All tables contain predicted information by ANN using hidden layer equal to 6. The value of hidden layer is acquired from the rule of thumb for supervised learning networks as stated below.

$$N_h = \frac{N_s}{\alpha(N_i + N_o)} \qquad (7)$$

Where:
N_h : Number of hidden layer
N_i : Number of input neurons.
N_o: Number of output neurons.
N_s = number of samples in training data set.
alpha = an arbitrary scaling factor usually 2-10.

Table VII shows information of PSD feature based on Alpha-Beta with 4 electrode placement. The percentage of results that are misclassified for trainscg and trainrp are 12.5% and 10.42% respectively. Table VIII shows information of PSD feature based on Alpha-Beta with 7 electrode placement. The percentage of results that are misclassified for trainscg and trainrp are 18.25% and 20.8% respectively. Table IX shows information of ESD feature based on Alpha-Beta with 4 electrode placement. The percentage of results that are misclassified for trainscg and trainrp are 22.92% and 37.5% respectively. Table X shows information of ESD feature based on Alpha-Beta with 7 electrode placement. The percentage of results that are misclassified for trainscg and trainrp are 25% and 33.33% respectively.

TABLE VII. CONFUSION MATRIX FOR PSD, AB4E

PSD/AB4E		Normal	Stress
Scaled Conjugate Gradient	Normal	26	4
	Stress	2	16
Resilient Back Propagation	Normal	25	2
	Stress	3	18

TABLE VIII. CONFUSION MATRIX FOR PSD, AB7E

PSD/AB7E		Normal	Stress
Scaled Conjugate Gradient	Normal	19	0
	Stress	9	20
Resilient Back Propagation	Normal	19	1
	Stress	9	19

TABLE IX. CONFUSION MATRIX FOR ESD, AB4E

ESD/AB4E		Normal	Stress
Scaled Conjugate Gradient	Normal	21	4
	Stress	7	16
Resilient Back Propagation	Normal	18	8
	Stress	10	12

TABLE X. CONFUSION MATRIX FOR ESD, AB7E

ESD/AB7E		Normal	Stress
Scaled Conjugate Gradient	Normal	20	4
	Stress	8	16
Resilient Back Propagation	Normal	20	8
	Stress	8	12

The overall performance of the classification process of female subjects with and without stress based on Alpha-Beta bands of EEG signal is displayed in Table XI and Table XII for trainscg and trainrp respectively .Both tables present the value of accuracy, precision, sensitivity and specificity .Table XI and Table XII shows the performance of the classification of female with and without stress based on Alpha-Beta bands of EEG signal based on different training algorithm. From both tables below, the performance of classification based on PSD feature shows better accuracy for 4 electrode placements (frontal brain region), while classification based on ESD feature shows better accuracy for 7 electrode placements (whole brain region). From the overall result, it can be observed that classification based on PSD feature has achieved higher accuracy when compared to classification based on ESD feature.

TABLE XI. PERFORMANCE OF THE CLASSIFICATION OF FEMALE WITH AND WITHOUT STRESS BASED ON ALPHA-BETA BANDS OF EEG SIGNAL FOR SCALED CONJUGATE GRADIENT

Scaled Conjugate Gradient				
	PSD		ESD	
	AB4E(%)	AB7E(%)	AB4E(%)	AB7E(%)
Accuracy	87.5	81.25	77.08	75
Precision	92.86	67.85	75	71.43
Sensitivity	86.67	100	84	83.33
Specificity	88.89	68.97	69.57	66.67

TABLE XII. PERFORMANCE OF THE CLASSIFICATION OF FEMALE WITH AND WITHOUT STRESS BASED ON ALPHA-BETA BANDS OF EEG SIGNAL FOR RESILIENT BACK PROPAGATION

Resilient Back Propagation				
	PSD		ESD	
	AB4E(%)	AB7E(%)	AB4E(%)	AB7E(%)
Accuracy	89.58	79.2	62.5	66.67
Precision	89.29	67.86	64.28	71.43
Sensitivity	92.59	95	69.23	71.43
Specificity	85.71	67.86	54.55	60

IV. CONCLUSION

Based on recorded EEG readings, we can analyze the signals and use it to detect stress by classifying EEG signals of individuals with and without stress. The experiment is conducted started by applying the network growing technique to determine optimize number of hidden layer to 12 group as stated in Table II. The result shows high accuracy with two inputs based on reading of alpha and beta bands. The selection of inputs fed to these classifiers between in the form of Power Spectral Density (PSD) features or Energy Spectral Density (ESD) features extracted from the EEG signals, PSD features is found to be better since it has shown to give higher accuracy when compared to ESD feature using both training. Based on this study both trainings have shown to give high accuracy based on input of PSD feature, but for ESD feature as input Scaled Conjugate Training has shown to give a better performance than Resilient Back Propagation.

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