Advances in Computing and Intelligent System, Vol. 1 No. 1 (2019) p. 1-7

ACIS

FAZ Publishing

Advances in Computing and Intelligent System

Journal homepage: www.fazpublishing.com/acis

e-ISSN : 2682-7425

ANN Classification for the Analysis of 3D EEG Data in BBI

N. Fuad[1,4*], M. N. Taib[2], R. Jailani[2], M. E. Marwan[3,4]

[1] Computational Signal, Imaging and Intelligence (CSII),
Universiti Tun Hussein Onn Malaysia, 86400 Johore, MALAYSIA.
[2]Advanced Signal Processing Research Group (ASPRG), Faculty of Electrical Engineering,
Universiti Teknologi MARA, 40450 Selangor, MALAYSIA
[3]Department of Computer Science, Kolej Poly-Tech MARA Batu Pahat,Bangunan Tabung Haji, Jalan Timah Sari, 83000 Johore, MALAYSIA
[4]Mentor Solution, Taman Koperasi Bahagia, Batu Pahat, 83000 Johore, MALAYSIA (JR0041306-H)

* Corresponding Author

[1]norfaiza@uthm.edu.my

Received 20 November 2018; Accepted 20 January 2019; Available online 10 March 2019

Abstract: In this paper, the Artificial Neural Network (ANN) algorithm is used for classifying the 3D EEG PSD in brain balanced index (BBI) is presented. The EEG signal recording was conducted on 96 healthy subjects. Development of 3D EEG models involves pre-processing of raw EEG signals and construction of spectrogram images. The maximum PSD values were extracted as features from the model. There are three indexes for balanced brain; index1, index2, index 3, index 4 and index 5. There are significant different of the EEG signals due to the BBI. Theta-θ (4-8 Hz), Delta-δ (0.5-4 Hz), Alpha-α (8–13 Hz) and Beta-β (13–30 Hz) were used as input signals for the classification model. This result has shown that the ANN classifier managed to produced accuracy rate, sensitivity rate and specificity with small classification errors for the 3D EEG PSD inputs. The overall classification accuracy of 88.89%, classification sensitivity within range 87.50% to 92.31% and classification specification within range 94.92% to 98.82% were obtained.

Keywords: Electroencephalogram (EEG), Artificial Neural Networks (ANN), Power Spectrum Density (PSD), brain balanced index (BBI).

1. Introduction

Artificial Neural Network (ANN) is well known classifier to process feature rich data [1-3]. ANN is also extensively used as classifier for analyzing the EEG signals for example, in EEG signals research, the ANN is employed to analyze an aesthesia depth monitoring [4], Parkinson disease [2] and epileptic seizure [5].

ANN is a complex algorithm because it has few parameters that need to be set before designing the ANN model. Among these parameters are as network model, network size, activation function, learning parameters, and number of training samples. For example, a feed-forward ANN, and trained with Levenberg-Marquardt algorithm was used to classify brain related diseases such as Amyotrophic, Parkinson and Huntington [2]. EEG always used in diagnosing brain-related disease such as Alzheimer [6] and Epilepsy [7]. However, it is not limited to brain related diseases but also used for other applications such as Brain-Computer Interfacing (BCI) [8] and Intelligence Quotient (IQ) [9]. There are also studies in brainwave balancing application but the number of published papers is too little. The disadvantages of unbalanced brain are physical aches and problem in psychology while balance brain promotes happy lifestyles and good health [10]. There is study stimulate balanced brainwave using 3-dimensional (3D) game. Visual and sound effects were induced in 3D game to produce balanced brainwave for BCI application [11]. The other method to produce balance brainwave is called EEG biofeedback which is popular method now days [12].

The original EEG signals are in terms of amplitude (voltage) and frequency. The signal is grouped into frequency bands. There are four frequency bands, Delta, Theta, Alpha and Beta. Each frequency varies in each band; Delta (0.5 to 4Hz), Theta (4 to 8Hz), Alpha (8 to13Hz) and Beta (13 to 30Hz) [13]. However, these signals can be converted into frequency based by using Fourier Transform. In this paper, EEG signals were analyzed based on time-frequency image processing technique or called spectrogram. One example to produce spectrogram is the Short Time Fourier Transform (STFT). The STFT technique is to perform a Fourier Transform on the signal, followed by mapping the signal into a two-dimensional function of frequency and time. In [14, 15] employ STFT in Electrocardiogram (ECG) to generate spectrogram. The STFT spectrogram is used to detect heart abnormalities [14]. In [15], the spectrogram from ECG is used to detect respiratory disease in sleep. This paper is an improvement

**Corresponding author: norfaiza@uthm.edu.my*

from the previous study that classifies spectrogram image from EEG signals [16]. The objective of this paper is to classify of PSD from 3D EEG for brainwave balancing application by using ANN.

2. Methodology

Figure 1 shows the flow diagram of methodology. Initially, EEG signals were collected from 96 volunteers. Then, the EEG signals were pre-processed to produce clean signals and filtering into four band frequencies delta, theta, alpha and beta. Next, the 2D image was produced from clean EEG signals and 3D EEG model have been developed from EEG spectrogram using image processing techniques.

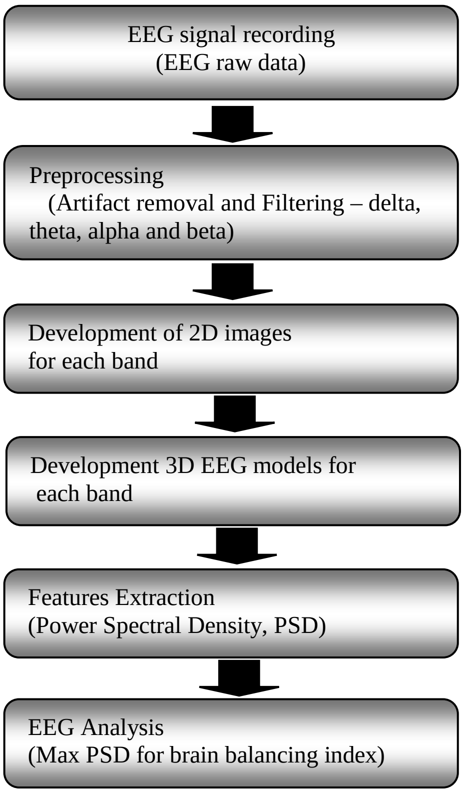

Figure 1. Flow diagram of methodology

2.1 Subjects and Data Collection

The samples are among 96 volunteers with an average age of 21.7. The data are collected from Biomedical Research and Development Laboratory for Human Potential, Faculty of Electrical Engineering, Universiti Teknologi MARA Malaysia (UiTM). All volunteers are healthy and not on any medication before the tests. These are performed and have fulfilled the requirement provided by ethics committee from (UiTM).

Figure 2 shows the experimental setup for EEG signal recording. There were two channels and one reference to two earlobes used to collect or record EEG signal. These channels connected to gold disk bipolar electrode that complied with 10/20 International System. The sampling rate is 256Hz. Channel 1 positive was connected to the right hand side (RHS), Fp_2. The left hand side (LHS), Fp_1 was connected to channel 2 positive. Fp_Z is the point at the center of forehead declared as reference point. MOBIlab was used in wireless EEG equipment and the EEG signal was monitored for five minutes. The Z-checker equipment was used to maintain the impedance to below than 5kΩ. The MATLAB and SIMULINK are used to process the data with the intelligent signal processing technique.

The volunteers are required to answer the fifteen questions in Brain Dominance Questionnaires [17] prior to EEG recording. Then, the score is calculated after the questionnaires are completed. The score will determine the group or balanced brain index of each sample. This balanced brain index is produced from the previous experiment. Table 1 shows the balanced brain index with the descriptions.

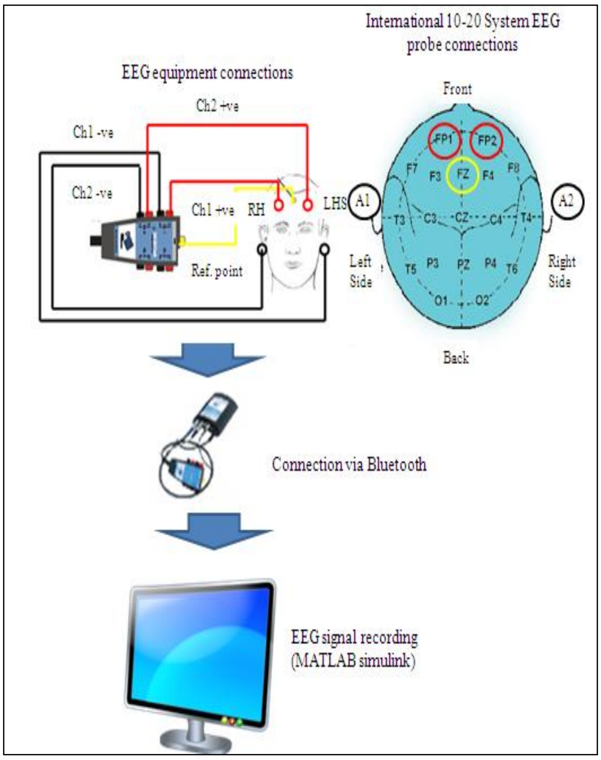

Figure 2. Experimental setup

Table 1: The index level for balanced brain

Index level	Description
Index level 1	Unbalanced brain
Index level 2	Less balanced brain
Index level 3	Moderately balanced brain
Index level 4	Balanced brain
Index level 5	Highly balanced brain

2.2 Signal Preprocessing

The EEG raw data was processed separately after data collection. The filter of band passes and artifact removal was included in EEG signal pre-processing. The artifacts may be produced when the eyes of volunteer's blink. The artifacts can be removed by setting a threshold value in MATLAB tools. The setting of threshold values was below than -100μV and greater than 100μV. Only the meaningful and informatics signal were occurred within -100μV to 100μV. The Hamming windows were used to design the band pass filter with the rate of overlapping of 50% for the frequency; 4-8 Hz is theta-θ band, 0.5-4 Hz (delta-δ band), 8-13 Hz (alpha-α band) and 13-30 Hz (beta-β band).

2.3 2D EEG image

The STFT was used to produce the spectrogram image in 436x342 pixels of image size for Fp1 and Fp2 channel. Each band of frequency was set in a spectrogram image. The theta-θ band was set from 4Hz to 8 Hz, 0.5-4 Hz (delta-δ band), 8-13 Hz (alpha-α band) and 13-30 Hz (beta-β band).

This method was used for motor imagery EEG signal classification [18,19] and epileptic seizures detection using EEG signal. [20,21]. Equation 1 was implemented to analysis the signal in time frequency domain. The EEG signal, x(t), the window function, w(t) and signiture of complex conjugate, * are stated in STFT. The signal changed in time and performed using STFT. The small window of data in one time was used to map the signal to 2D function of time and frequency. Then the Fourier Transform (FT) would be multiplied with window function to yield the STFT.

$$STFT_x^{(w)}(t, f) = \int_{-\infty}^{\infty} [x(t).(t-t').e^{-j2\pi ft}\, dt] \quad (1)$$

2.4 3D EEG model

3D EEG models have been developed from EEG spectrogram using image processing techniques. Some techniques or algorithms such as gradient, color conversion, optimization and mesh algorithms were integrated to developed this model, while the spectogram images are represented in RedGreenBlue (RGB) color. Color conversion was implemented to transform spectogram of RGB to spectogram of gray scale. Gray scale images were used in a data matrix (I) which the values represent intensity within some range which are 0 (black) and 255 (white). Gray scale is the most commonly used images within the context of image processing.

Then, Optimization Options Reference (OOR) was implemented to gray scale pixels' image for optimization technique. There were severals options in OOR using MATLAB software but for this research, DiffMaxChange (Maximum change in variables for finite differencing) option have been chosen. The natural shape can be found from pixels' value. This shape related to the maximum of certain energy function computed from the surface position and squared norm. A finite number of points were generated for the height of the optimized surface. Then the matrices of pixels value were resized using Gradient and Mesh algorithm into vectors. Two vector arguments replaced the first two matrix arguments, length(x) = n and length(y) = m where [m, n] = size (z). A vectors x is included matrix X (rows) and a vectors y is for matrix Y (columns). Matrix X and Y can be evaluated as features using array module in MATLAB's software.

2.5Classification algorithms

The classification algorithms used is ANN. The ratio used for training and testing process was 80:20. The ratio 80:20 means that 80% of the data is selected for training process, while 20% of the data is selected for testing process. The outputs of classifiers were verified together with brain dominance questionnaire [17]. The best model for both classifiers is selected based on the highest accuracy and lowest mean square error (MSE). In ANN algorithm, a feed-forward was used with 8 inputs and 1 output. The sigmoid was used for the ANN activation function. There are three parameters to be optimized, namely number of neurons in the hidden layer, learning rate, momentum and epoch. In each experiment, the parameter to be optimized is varied while the two parameters were fixed.

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The interval activity of the neurons shown in Equation 2;

$$v_k = \sum_{j=1}^{n} w_{kn} x_n \quad (2)$$

where;

w_{kn} is weight, x_n is inputs, v_k is activation of neuron.

Typically, the activation functions are linear, sigmoid and hyperbolic tangent. In this thesis use sigmoid function. The sigmoid function is shown in Equation 3.

$$f(x) = 1 / (1 + e^{-x}) \quad (3)$$

3. **Results and Discussions**

3D EEG models were produced using optimization; gradient and mesh algorithms as depict in Figure 3 (a)-(h). These show each of frequency bands for Fp1 and Fp2 channels. The 3D signal is spectral of PSD and a different maximum PSD produced by each frequency band. Eight 3D signals for channels Fp1 and Fp2 are produced by EEG sample. The 3D EEG model produced as depicted in Table 2.

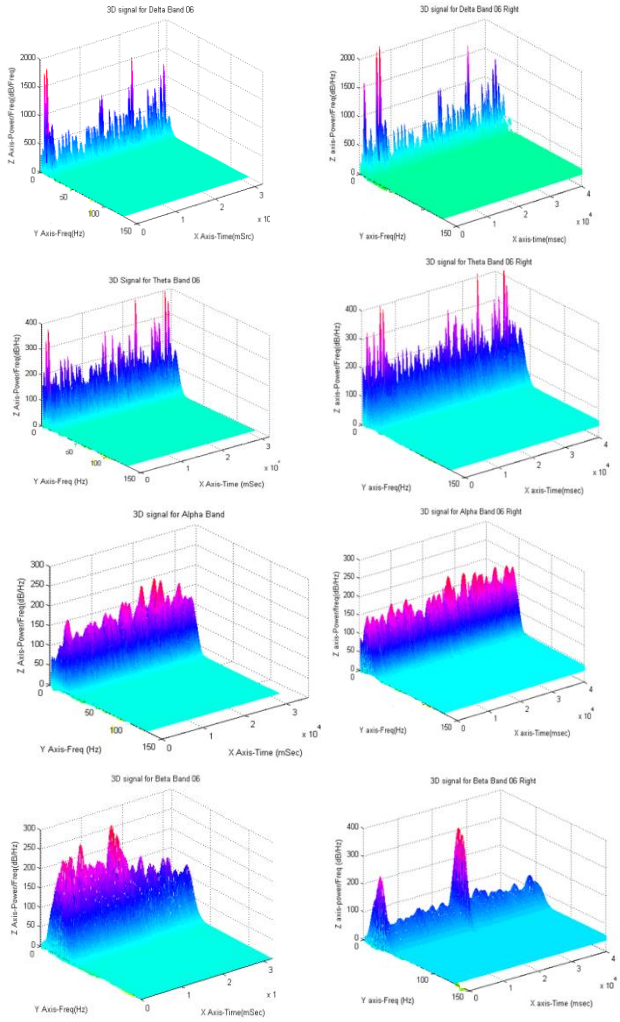


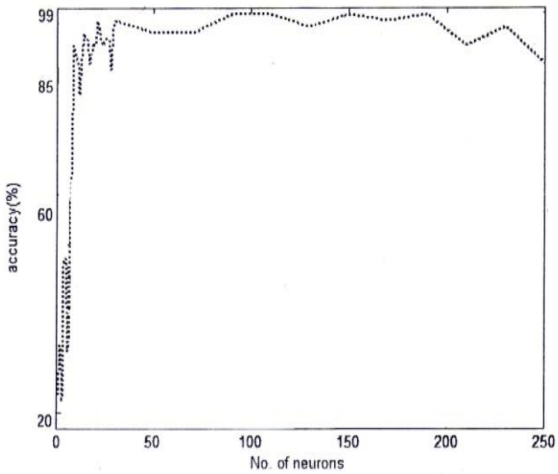
Figure 3. Three Dimension (3D) model for (a) Delta band from Fp1 channel (b) Delta band from Fp2 channel (c) Theta band from Fp1 channel (d) Theta band from Fp2 channel (e) Alpha band from Fp1 channel (f) Alpha band from Fp2 channel (g) Beta band from Fp1 channel (h) Beta band from Fp2 channel

Table 2: Data sample per index

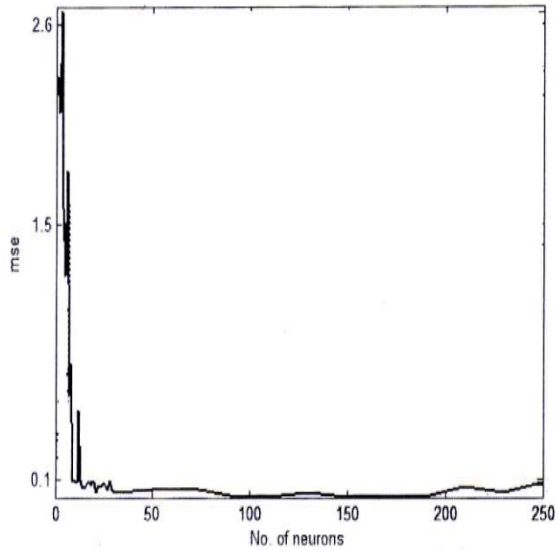
Index	Samples	3D EEG model
Index 1	19	152
Index 2	8	64
Index 3	15	120
Index 4	37	296
Index 5	17	40

Performance of optimization of the ANN has been presented in Figures 4 to 7 for data. There are two figures for each parameter (hidden layer, learning rate, momentum rate and epoch) which presented accuracy percentage and mean squared error (MSE). The activation function controls the amplitude with range 0 to 1. There are 768 samples as inputs to classifier.

Figure 4 illustrates the result for the optimizing number of neurons in hidden layer. In the figure, it was found that the hidden layer 14, 20 and 21 may produce a good prediction outcome. In the experiment, the network with hidden layer 20 with an accuracy rate of 92.68% in Figure 4(a) and 0.0852 MSE in Figure 4(b) was selected.



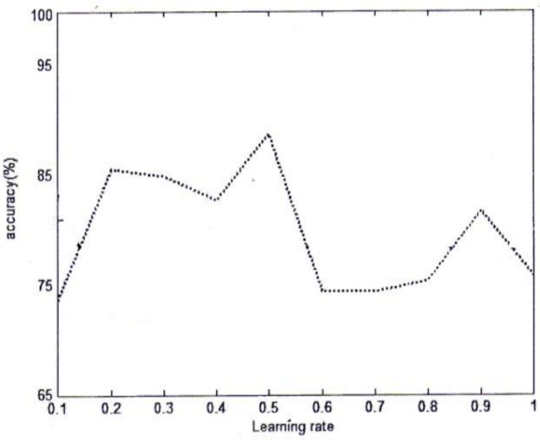
(a)



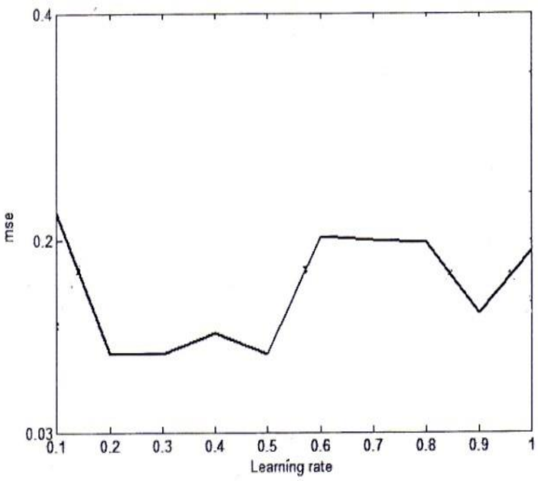
(b)

Figure 4: Training performance and prediction accuracy with varying
hidden layer size (a) accuracy rate (b) MSE

Figure 5 presents the result of finding the optimum leaning rate. From the figure, learning rate of 0.5 produces good outcome. The learning rate of 0.5 was found to be optimum accuracy 88.81% in Figure 5(a) and MSE 0.0995 in Figure 5(b).

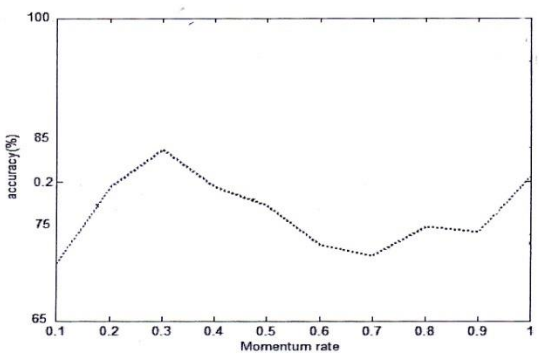


(a)

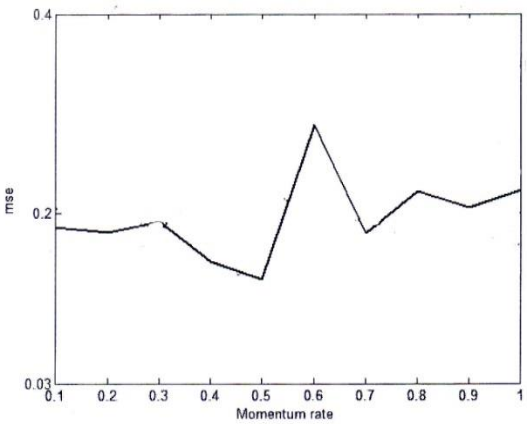


(b)
Figure 5: Training performance and prediction accuracy with varying learning rate (a) accuracy rate (b) MSE

Figure 6 illustrates the result of finding the optimum momentum. From the figure, it showed that the momentum rate of 0.5 has been produced good outcome. The momentum rate of 0.5 was found to be optimum accuracy 84.78% in Figure 6(a) and MSE 0.1344 in Figure 6(b).

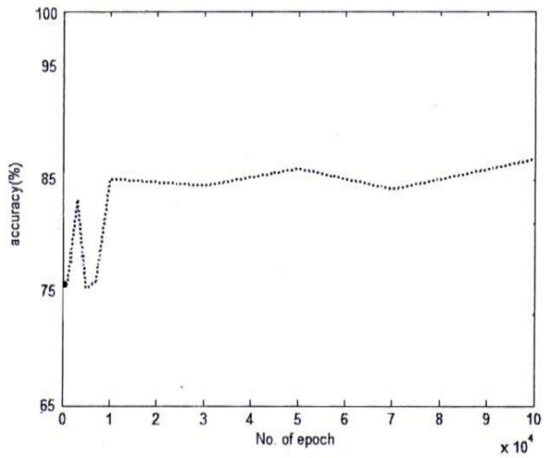


(a)

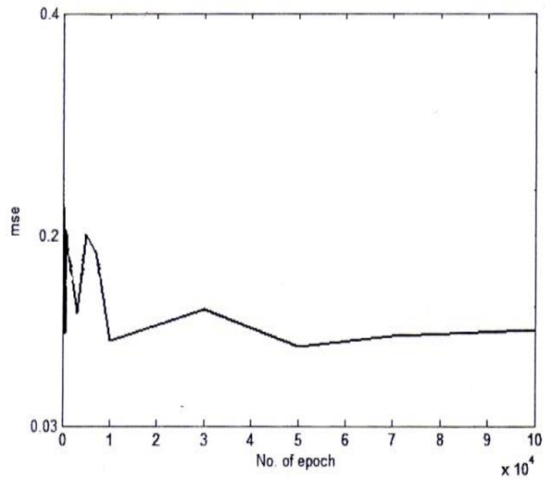


(b)
Figure 6: Training performance and prediction accuracy with varying momentum rate (a) accuracy rate (b) MSE

Figure 7 shows the result of finding the optimum epoch. From this figure, it was found that the epoch value of 500, 10000 and 100000 may produces good outcome. The epoch 10000 was found to be optimum accuracy 85.06% in Figure 7(a) and MSE 0.1057 in Figure 7(b).



(a)



(b)
Figure 7: Training performance and prediction accuracy with varying epoch (a) accuracy rate (b) MSE

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Table 3 shows the best network for the training to testing was defined by 20 hidden neurons layer, 0.5 learning rate, 0.5 momentum rate and epoch of 10000.

Table 3 The best network for training to testing.

Parameter	Value
Hidden neuron layer	20
Learning rate	0.5
Momentum	0.5
Epoch	10000

3.1 Accuracy, sensitivity and specificity

In order to calculate the overall accuracy, sensitivity and specificity of the classification, the confusion matrix was employed as illustrated in Table 4. For this study, the testing data were tested for accuracy, sensitivity and specificity. There are 768 samples and only 153 as testing samples. From the confusion matrix, there are 136 samples classified and 17 samples misclassified.

Table 4 Confusion matrix

	Actual Class						Total
	Group	Index1	Index2	Index3	Index4	Index5	
Target Class	Index1	27	1	1	0	1	**30**
	Index2	0	12	0	0	1	**13**
	Index3	2	0	21	1	0	**24**
	Index4	1	1	1	52	4	**59**
	Index5	0	1	2	0	24	**27**
Total		**30**	**15**	**25**	**53**	**30**	**153**

Besides the overall classification performance in term of accuracy, sensitivity and specificity, the classification performance by group were also measured as depicted in Table 5. The classification performance of all group were good. The overall classification accuracy for all groups was 88.89%.

Table 5: Classification performance by group index

Group	Index1	Index2	Index3	Index4	Index5
Accuracy	88.89	88.89	88.89	88.89	88.89
Sensitivity	90.00	**92.31**	**87.50**	88.14	88.89
Specificity	97.32	97.64	96.65	**98.82**	**94.92**

The ANN model produced results of sensitivity within range 87.50% to 92.31%. Index 2 was the highest percentage (92.31%) and index 3 was the lowest percentage (87.50%). The model able to test correctly identifies the true positive pattern for BBI especially for index 2.

For specificity, ANN model produced results within range 94.92% to 98.82%. Index 4 was the highest percentage (98.82%) and index 5 was the lowest percentage (94.92%). The model able to test correctly identifies the true negative or those data without the BBI pattern especially for index 4.

4. Conclusion

The results discussed about the ANN model produced results of sensitivity within range 87.50% to 92.31% and specificity within range 94.92% to 98.82%. Test sensitivity is the ability of a test to correctly identify those with the pattern (true positive rate). Test specificity is the ability of the test to correctly identify those without the pattern (true negative rate).

Acknowledgement

Author would like to thank the members of Biomedical Research Laboratory for Human Potential, FKE, UiTM for their cooperation and kindness. Appreciation also goes to Advanced Signal Processing Research Group (ASPRG) for their support.

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