Comparison between KNN and ANN Classification in Brain Balancing Application via Spectrogram Image

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Abstract: In this paper, the comparison between K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) algorithm for classifying the spectrogram images in brain balancing is presented. After producing spectrogram image from Electroencephalogram (EEG) signals, Gray Level Co-occurrence Matrix (GLCM) texture feature were extracted. These features produced huge matrices, therefore to reduce the size of matrices; the Principal Component Analysis (PCA) is applied. The results show that the KNN and ANN were able to classify the spectrogram image with 87.5% to 90% accuracy for the brain balancing application.

Keywords: EEG, spectrogram image, GLCM, PCA, KNN, ANN.

1. Introduction

K-Nearest Neighbour (KNN) is known as a simple but robust classifier and is capable to produce high performance results even for complex applications [1, 2]. The KNN uses a distance of features in a data set to determine which data belongs to which group. A group is formed when the distance within the data is close while many groups are formed when the distance within the data is far. In Electroencephalogram (EEG) research, KNN is widely used as a classifier to classify the EEG signals. For example, KNN was used to classify epileptic and normal brain activities through EEG signals [3]. In another example, KNN was used to classify ten samples of EEG signals for individual biometric purposes [4].

Artificial Neural Network (ANN) is a well-known classifier used to process feature rich data [5-7]. ANN is also extensively used as classifier for analysing the EEG signals, similar to KNN. For example, in EEG signals research, the ANN is employed to analyse anaesthesia depth monitoring [8], Parkinson disease [6] and epileptic seizure [5]. The KNN and ANN are widely used as classifiers in EEG signals classification. From the previous literature, the KNN and ANN are able to classify the EEG signals with accuracy rate of 75% to 98 % [4, 9-11].

Compared to the KNN, ANN is a more complex algorithm, because it has several parameters that should be set before designing the ANN model. The network model, network size, activation function, learning parameters, and the number of training samples are among these parameters. For example, a feed-forward ANN trained with Levenberg-Marquardt algorithm was used to classify brain related diseases such as Amyotrophic, Parkinson and Huntington [6].

EEG is always used in diagnosing brain-related disease such as Alzheimer [12] and Epilepsy [13]. However, its application is not limited to the brain related diseases it is also used for other applications such as Brain-Computer Interfacing (BCI) [14] and Intelligence Quotient (IQ) [15]. There are also studies in brainwave balancing application but the number of published papers is too few. For example, visual and sound effect of 3-dimensional (3D) game was used to stimulate balanced brainwave for BCI application [16]. Another example is producing a balance brainwave by using EEG biofeedback [17]. A balance brainwave promotes happy lifestyle and good health while unbalance brain will cause physical aches and problem in psychology such as sleep difficulties and lack of patience [18].

The original EEG signals are in terms of amplitude (Voltage) and frequency (Hertz). The signals are 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) [19]. However, these signals can be converted into frequency-based parameters using the Fourier Transform technique. In this paper, EEG signals were analysed based on the time-frequency image processing technique, also known as spectrogram. As an example, the Short Time Fourier Transform (STFT) technique is used to produce spectrogram. The STFT technique is employed to perform the Fourier Transform on the signal, followed by mapping the signal into a two-dimensional function of frequency and time. There are studies on mapping signal into spectrogram by employing STFT in Electrocardiogram (ECG) signals [20, 21]. The STFT spectrogram is used to detect heart abnormalities [20]. In [21], the spectrogram from ECG is used to detect respiratory disease in sleep. This paper is an improvement of the previous study that classifies spectrogram image from EEG signals [22]. The objective of this paper is to compare classification of spectrogram image for brainwave balancing application between KNN and ANN.

2. Methods

The experiments initiated with the collection of EEG signals from 51 volunteer participants, in which the data preceded a series of processes as shown in Figure 1.Then, the EEG signals were pre-processed to produce clean signals. Next, the EEG spectrogram images was produced from clean EEG signals and the Gray Level Co-occurrence Matrix (GLCM) texture features were extracted from EEG spectrogram image. This is followed by using the PCA to reduce the GLCM texture features. Finally, two classification algorithms were used; KNN and ANN to classify the EEG spectrogram image. Collection and processing of the EEG signals utilized the intelligent signal processing technique developed in SIMULINK and MATLAB.

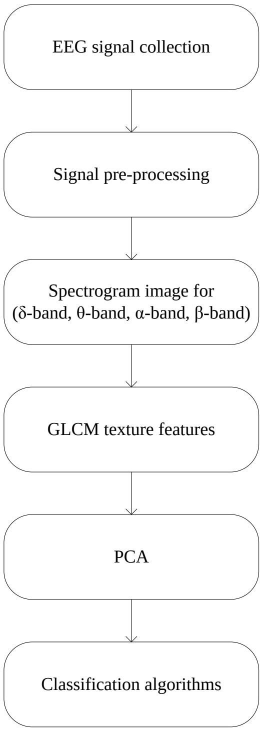

Figure 1. Experiment methodology.

2.1 EEG signal collection

The samples were collected from 28 males and 23 females at the Biomedical Research and Development Laboratory for Human Potential, Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM). The experiment procedure used was approved by the ethics committee of the UiTM. The EEG signals were recorded using g.MOBIlab via wireless connection for duration of 5 minutes. The impedance is set below 5kΩ and checked with Z-checker equipment. The standard gold disc electrodes with bipolar connection are used in accordance to 10-20 international system. Two channels are used; Fp1 and Fp2 with reference earlobes A1, A2 and Fpz. The sampling rate is 256Hz. The volunteers are required to answer fifteen questions in Brain Dominance Questionnaires prior to EEG recording [23]. 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 [24]. Table 1 shows the balanced brain index with descriptions.

2.2 Signal pre-processing

EEG signal pre-processing involves artefact removal and band pass filter. The artefacts occurred when volunteers move or blink their eyes and are removed by setting threshold value. The threshold was set to remove signals when the signals peaks are greater than 100μV and smaller than -100μV. The band pass filter is designed from frequency range of 0.5Hz to 30Hz with 50% overlapping in Hamming window.

Table 1: Balanced brain index

Index	Description
Index 1	unbalanced brain
Index 2	less balanced brain
Index 3	moderately balanced brain
Index 4	balanced brain
Index 5	highly balanced brain

2.3 Spectrogram image

The spectrogram image is produced using STFT for both Fp1 and Fp2 channels with image size of 436x342 pixels. The STFT is generated by multiplying Fourier Transform (FT) of the EEG signal with window function. The spectrogram is produced according to the frequency band. The Delta band is set from 0.5Hz to 4Hz, Theta band is set from 4Hz to 8Hz, Alpha band is set from 8Hz to 13Hz and Beta band is set from 13Hz to 30Hz.

2.4 GLCM texture features

The GLCM is generated with 0^0, 45^0, 90^0 and 135^0 orientations. The grey level is set at 32 and displacement is set at 1. Consequently, texture feature were extracted for each GLCM. In this experiment, texture features are the combination of Haralick [25], Soh [26] and Clausi [27] techniques. The 20 texture features are Autocorrelation, Contrast, Correlation, Cluster prominence, Cluster shade, Dissimilarity, Energy, Entropy, Homogeneity, Maximum probability, Variance, Sum average, Sum variance, Sum entropy, Different variance, Different entropy, Information of correlation 1, Information of correlation 2, Inverse difference normalized, and Inverse difference moment normalized.

2.5 Principal Component Analysis (PCA)

The GLCM texture features resulted in a big matrix of data. The PCA was employed to reduce this matrix. In addition, PCA is able to find the optimum features in which it accelerates the execution time for the classification process. In general, the first few principal components are accepted while the last few principal components are removed. This is the reason why a large data matrix can be reduced. In this paper, two criteria were used by PCA in selecting the best components, which are known as the Kaiser-rule [28] and Scree-rule [29]. The Kaiser-rule solely uses the eigenvalue, while the Scree-rule employs graph of eigenvalue versus principal components.

2.6 Classification algorithms

In this paper, two classification algorithms were used; the KNN and 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 the classifiers were verified together with brain dominance questionnaire [23]. The best model for both classifiers is selected based on the highest accuracy and the lowest mean square error (MSE). In KNN algorithm, there are two parameters to be varied, distance and k variable. At first, the distance is varied and k variable is fixed. Then, the k variable is varied and the distance is fixed. There are four distances used, Euclidean, City block, Cosine and Correlation. The k variable is varied from 1 to 15. 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. Finally, the KNN and ANN model is compared to find the best model for this experiment.

3. Results and Discussion

Table 2 displays the EEG spectrograms generated for Index 3, 4, and 5. Index 1 and Index 2 refer to the samples with unbalance brain signals, thus the samples and the EEG spectrograms for both indices are not available because the samples were collected from university students who commonly have high rates of brain balance. From the table, each sample produced eight EEG spectrograms from Delta, Theta, Alpha, and Beta bands for each Fp1 and Fp2 channels. A total of 408 images were generated by the EEG spectrograms.

Table 2. EEG spectrograms generated from STFT.

Index	Samples	EEG spectrogram
Index 3	9	72
Index 4	37	296
Index 5	5	40
TOTAL	51	408

Figure 2 illustrates the EEG spectrograms generated by STFT. The images shown are for Delta, Theta, Alpha, and Beta bands for both Fp1 and Fp2 channels. The images projected texture-like shaped and each frequency band produces a unique and different texture and shapes.

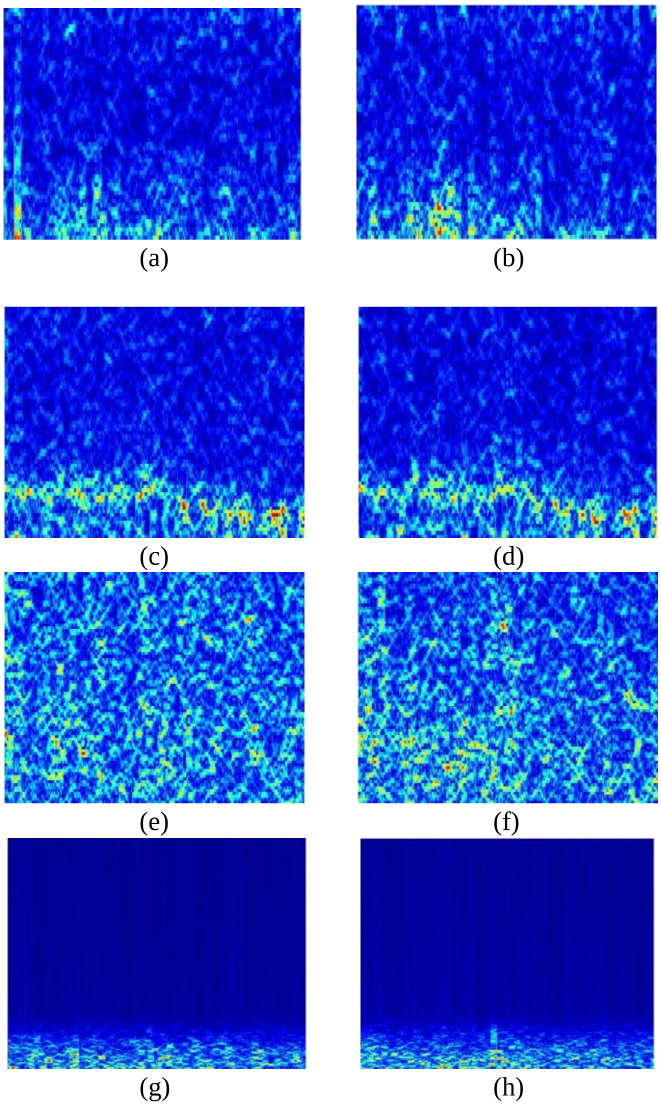

Figure 2. EEG spectrograms for (a) Delta band from Fp1 channel (b) Delta band from Fp2 channel (c) Theta band from Fp1 channel (d) Theta band from Fp2 channel (e) Alpha band from Fp1 channel (f) Alpha band from Fp2 (g) Beta band from Fp1 channel (h) Beta band from Fp2 channel.

The accuracy and MSE result for varying distances in KNN algorithms is shown in Table 3. From the table, Euclidean distance shows the highest accuracy among the other distance at 90% with MSE value of 0.1. The Cosine and Correlation distance gave same results in terms of accuracy and MSE.

Table 3. Accuracy in percentage and MSE with varying distances for KNN algorithm.

Distance	Accuracy (%)	MSE
Euclidean	90.00	0.1000
City block	88.75	0.1125
Cosine	83.75	0.1625
Correlation	83.75	0.1625

Figure 3 depicts the accuracy and the MSE when k variables varied from 1 to 15. In the figure, the legend 'solid' line and 'dot' line represent the MSE and the accuracy percentage. From the figure, the solid line displays a decreasing trend, while the dot line shows an increasing trend until k=5 and at this point the solid and dot line are constant until k=15. In the figure, k=1 and k=2 produced the same accuracy of 90% and the same MSE value of 0.1. The k=1 is chosen as compared to k=2 for economical purpose.

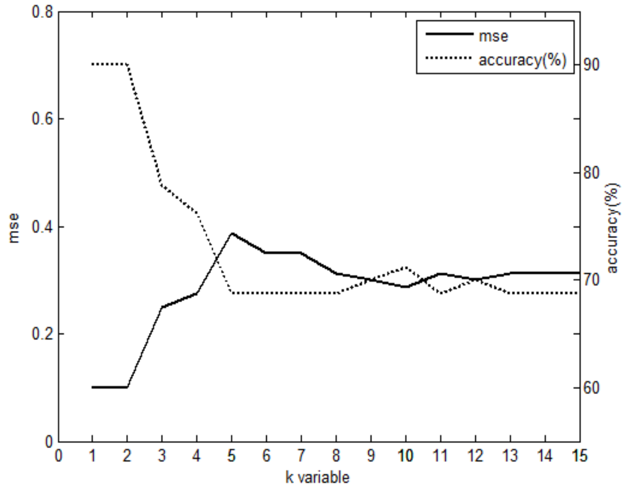

Figure 3. The accuracy in percentage and MSE with varying k variables for KNN algorithm.

The optimization of ANN parameters is presented in Figures 4 to 7. Figure 4 shows the results for optimizing the number of neurons in the hidden layer. From the figure, it was found that the hidden layers 17, 18 and 29 might produce a good prediction outcome. In the experiment, the network with the hidden layer 17 with an accuracy rate of 86.89% and 0.0926 MSE was selected.

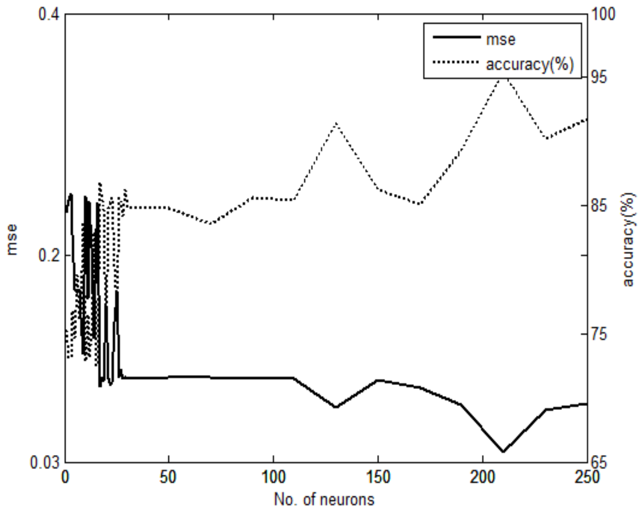

Figure 4. The accuracy and MSE on training performance with varying hidden layer size.

Figure 5 illustrates the results of finding the optimum learning rate. From the figure, a fluctuation trend is seen for both dot and solid lines. It clearly shows that 0.8 learning rate gave the highest accuracy and the lowest MSE. The learning rate of 0.8 was found to be the optimum accuracy 82.93% with MSE 0.1074.

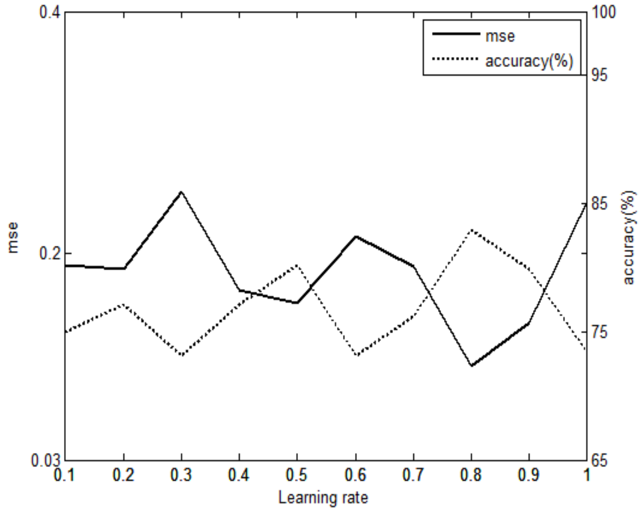

Figure 5. The accuracy and MSE on training performance with varying learning rate.

Figure 6 shows the result for finding the optimum momentum. In the figure, it shows that momentum rate of 0.3 and 1 may produce a good prediction outcome. The momentum rate of 1 was found to be the optimum accuracy at 81.71% and with MSE at 0.1241.

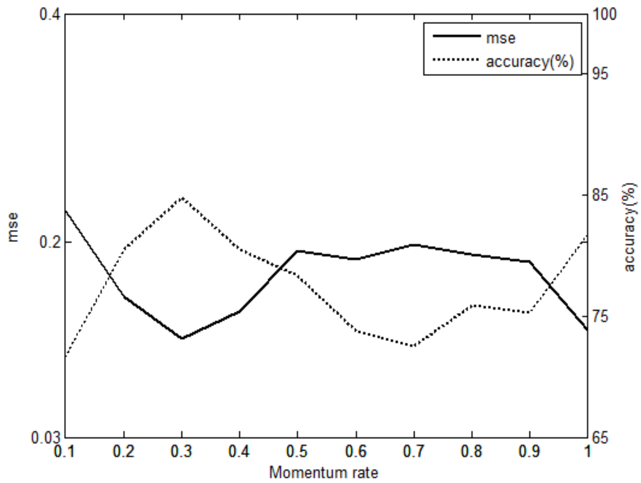

Figure 6. The accuracy and MSE on training performance with varying momentum rate.

Figure 7 shows the results to find the optimum epoch. From the figure, it is found that epoch values of 500, 10000 and 100000 might produce a good prediction outcome. The epoch of 10000 is found to be the optimum with an accuracy of 85.06% and an MSE of 0.1057. Finally, the best ANN network is defined by 17 hidden neurons, 0.8 learning rate, 1 momentum rate and epoch of 10000.

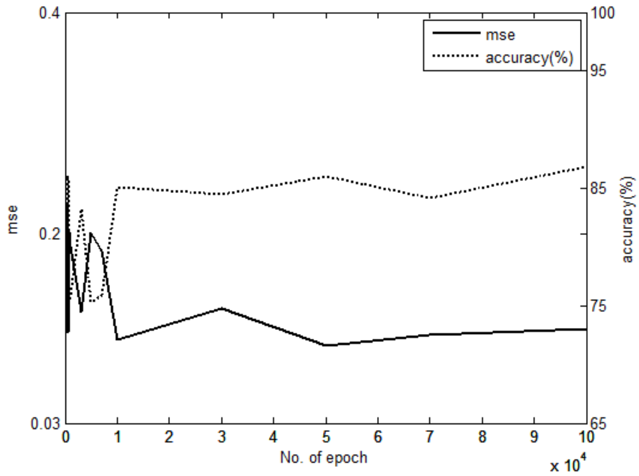

Figure 7. The accuracy and MSE on training performance with varying momentum epoch.

Table 4 illustrates the result of the accuracy percentage and the MSE, after the tests with ANN using the optimized parameters. From the table, this ANN model resulted in 87.5% accuracy and 0.7918 MSE.

Table 4. The accuracy and MSE on testing performance for ANN algorithm.

Accuracy (%)	MSE	Optimized parameter
87.50	0.7918	Hidden neurons – 17 Learning rate – 0.8 Momentum rate – 1 Epoch – 10000

The results of the comparison between KNN and ANN classifiers are shown in Table 5. Based on the results, the KNN model produces a better result with accuracy value of 90% and MSE 0.1. In contrast, the ANN model produces slightly lower result with 87.5% accuracy and MSE 0.7918.

Table 5. The comparison of the accuracy and MSE values for KNN and ANN.

Classifier	Accuracy (%)	MSE
KNN	90	0.1
ANN	87.5	0.7918

4. Conclusion

The results are discussed on the comparison of classification of the spectrogram image using either KNN or ANN for brainwave balancing application. The results were observed through percentage of the accuracy and the MSE for both classifiers. In conclusion, KNN gives better results in terms of accuracy and MSE compared to ANN for this application.

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