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EVALUATION OF FEATURE EXTRACTION AND CLASSIFICATION TECHNIQUES FOR EEG-BASED SUBJECT IDENTIFICATION

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Abstract

The ability to identify a subject is indispensable in affective computing research due to its wide range of applications. User profiling was created based on the strength of emotional patterns of the subject, which can be used for subject identification. Such system is made based on the emotional states of happiness and sadness, indicated by the electroencephalogram (EEG) data. In this paper, we examine several techniques used for subject profiling or identification purposed. Those techniques include feature extraction and classification techniques. In the experimental study, we compare three techniques for feature extraction namely, Power Spectral Density (PSD), Kernel Density Estimation (KDE), and Mel Frequency Cepstral Coefficients (MFCC). As for classification we compare three classification techniques, they are; Multilayer Perceptron (MLP), Naive Bayesian (NB), and Support Vector Machine (SVM). The best result achieved was 59.66%, using the MFCC and MLP-based techniques using 5-fold cross validation. The experiment results indicated that these profiles could be more accurate in identifying subject compared to NB and SVM. The comparisons demonstrated that profile-based methods for subject identification provide a viable and simple alternative to this problem.

Keywords: Subject Identification, Power Spectral Density, Kernel Density Estimation, Mel Frequency Cepstral Coefficients, Multilayer Perceptron, Naive Bayesian, and Support Vector Machine

1.0 INTRODUCTION

Brain Computer Interface (BCI) has been investigated as an alternative communication channel that utilizes the brain activity to control the computer [1]. A BCI system can be classified by the way it records the brain activity; either invasive or non-invasive. In an invasive system, the device to record the brain activity is placed under the skull whereas in a non-invasive system, such device is placed outside the head, e.g., magneto-encephalography (MEG), Functional magnetic resonance imaging (fMRI), and electroencephalograph (EEG).

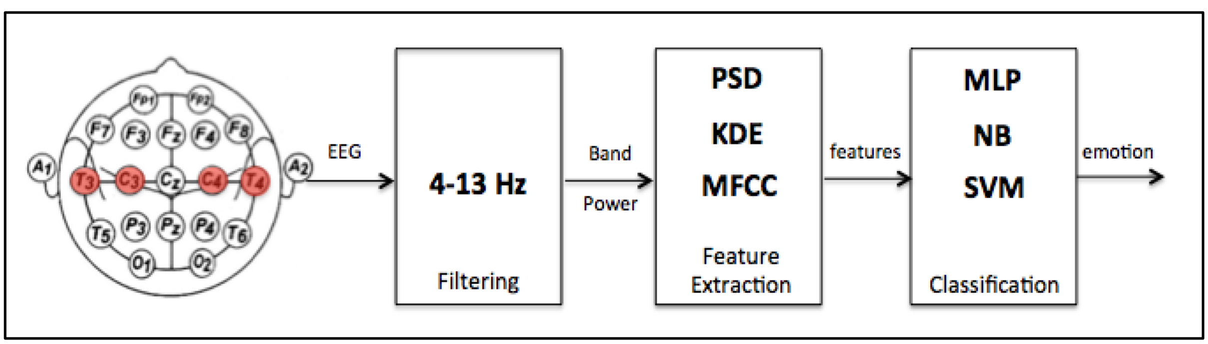

Figure 1 Experimental Setup

In affective computing research field, EEG data is widely adopted for recognizing emotions. Furthermore, EEG captures brain activities at the highest temporal resolution, cheaper, safer, and more portable compared to other neuron-imaging techniques. In this research, EEG data are recorded based on happy and sad emotions for generate the user profiling. User profiling helps to summarize the large amount of information obtained from a subject. Such system can be used for subject identification. Subsequently, the subject identification can be implemented through classification of emotion by using various supervised machine-learning techniques.

Thus, in this preliminary experiment, a fundamental set of features from three feature extraction techniques were analyzed. Moreover, computational models of emotion profiling based on the three classification techniques were compared. Subsequently, the performances of emotion profiling based on different feature extraction techniques and classifiers were evaluated.

The rest of the paper is organized as follows: In Section 2, related works on the computational models of subject identification were described. Section 3 defines the material used for this research. Whereas in Section 4, methodology were explained. In section 5, the comparison results are discussed. Finally, limitations and future work are described in conclusions.

2.0 RELATED WORK

Several researchers have studied the computational model on subject identification, as shown in Table 1. Recently, the empirical research on subject identification is characterized by a wide variety of methodologies. Subject identification can be done through explicit and implicit approaches.

Typical explicit measurement is done by direct self-assessment using Self-Assessment Manikin (SAM) forms and questionnaire of subject identification; it had been done in [2]–[9].

The implicit approach is an automatic inference of emotional information based on the measurement of the behavioral and physiological signals from the subject [10]. Studies had been done in this approach using different physiological conditions, such as EEG [1]–[9], [11]–[25], facial expression [5], and eye activity [7].

The computational model of subject identification had been evaluated with various techniques as described in Table 1. Numerous feature extraction techniques were selected from previous study, such as statistical features [22], fast fourier transform (FFT) [11], [21], PSD [4]–[6], [13], [14], [17], [26], higher order crossings (HOC) [24], [26], KDE [15], [16], [18], [20], common spatial patterns (CSP) [6], [8], [19], and MFCC [1], [18].

With regard to the classification techniques that were employed from previous studies were adaptive network-based fuzzy inference system (ANFIS) [2], NB [2], [7], [11], [16], [17], [19], SVM [1]–[4], [6]–[9], [12], [17], [19], [22], [23], [25], [27], [28], k-nearest neighbor (KNN) [7], [17], [22], [23], [26], [28], hidden Markov models (HMM) [5], MLP [7], [15], [18], [20]–[22], Gaussian mixture model (GMM) [16], One-Rule [16], linear discriminant function (LDF) [7], and Decision tree [23].

Hence, this motivates us to explore the techniques for subject identification. For the purpose of this research, the feature extraction techniques PSD, KDE, and MFCC were compared. Complementary to this, the classification techniques MLP, NB, and SVM were also compared.

3.0 MATERIALS

In this section, details of the stimuli used, data collection procedure, and electrode locations are briefly described.

3.1 Stimuli

The commonly used stimuli database that contains facial images eliciting emotions, the International Affective Picture (IAPS) [29], was used to invoke emotion from the subject.

3.2 Data Collection

Five young and healthy participants volunteered to participate in the experiment at International Islamic University of Malaysia (IIUM). The subjects were briefed about the experiment and their rights through a consent form and a verbal explanation. The subjects watched the emotional images from IAPS [1] that refer to affective states, namely 'happy', and 'sad' emotions; one minute long for each emotion.

3.3 Electrodes Location

Four EEG electrodes (C3, C4, T3, and T4) were placed on their scalps, at the specific regions using the International 10-20 system depicted in red, as shown in Figure 1. The electrodes were connected to the EEG head box to enhance the signals with the sampling rate frequency of 250 Hz.

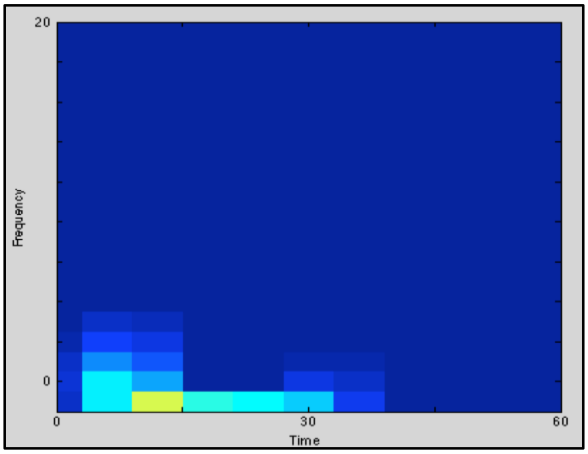

Figure 2 PSD features from 1 channel of EEG data during elicitation of happy emotion of a subject 1

4.0 METHODOLOGY

This section discusses the signal preprocessing, feature extraction, and classification techniques.

4.1 Signal Preprocessing

In this step, filtering was applied to eliminate noises and artifacts. The signals were taken from the theta (4-8 Hz) and alpha bands (8-13 Hz) that correlate with emotional experiences [30].

4.2 Features Extraction

Emphasizing on literatures on computational model as shown in Table 1, many feature extraction techniques had been adopted in EEG-based researches. In this research, three feature extraction techniques will be evaluated; the details are explained and illustrated with examples in the following section.

4.2.1 Power Spectral Density (PSD)

PSD is one of the many methods applied in the characterization of patterns of brain activities present in EEG signals and it is used in studies of subject identification [4]–[6], [13], [14], [17], [26]. EEG signals are normally represented in the form of electrical voltage over a time period. PSD can be calculated based on the average of energy density over a selected frequency range.

PSD from different bands were computed using short-time fourier transform (STFT). The small window of data over a time period was used to map the signals to a 2D function of time and frequency. Then the Fourier transform (FT) would be multiplied with the window function to yield the STFT. The STFT may then be defined using the following equation (Equation 1).

$$\mathrm{STFT}_f^u(t', u) = \int_t [f(t).W(t - t')].e^{-j2\pi ut} \qquad (1)$$

Where

t	time
u	frequency
f(t)	EEG signal
W	window

As a result, the total number of EEG features derived from PSD in one-minute window and 50% overlapping is 1032 as shown in Figure 2.

4.2.2 Kernel Density Estimation (KDE)

KDE is a widely used method in several processes in affective computing research study [15], [16], [18], [20]. KDE, also known as the Parzen Window method, is a non-parametric approach in the sense that it makes no assumption regarding the distributions of data samples [18]. The probability distribution function is explicitly determined by the training data. KDE has an advantage in the ability to accurately model the brain wave patterns.

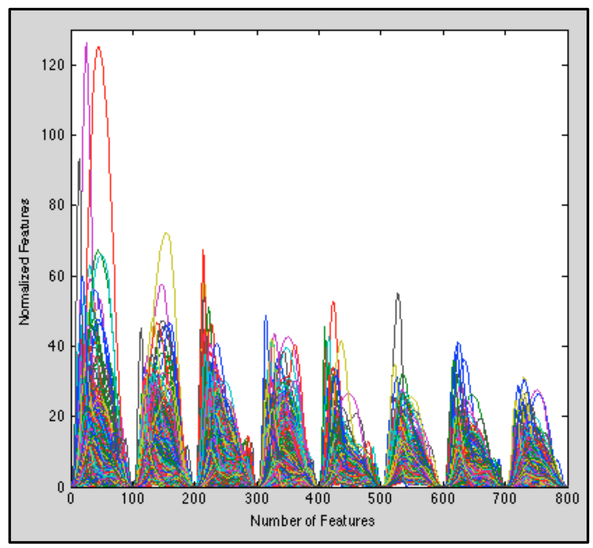

Figure 3 800 features from KDE for frequency ranged from 4Hz to 13 Hz (theta, alpha) during elicitation of sad emotion of a subject 2

KDE can be defined with the following equation (Equation 2).

$$\hat{p}(X; h) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - x_i}{h}) \qquad (2)$$

Where

K	kernel function centers at the data points x_i
n	number of sample per frame
h	window width or bandwidth

An 800-feature matrix was obtained from this extraction method as shown in Figure 3.

4.2.3 Mel Frequency Cepstral Coefficients (MFCC)

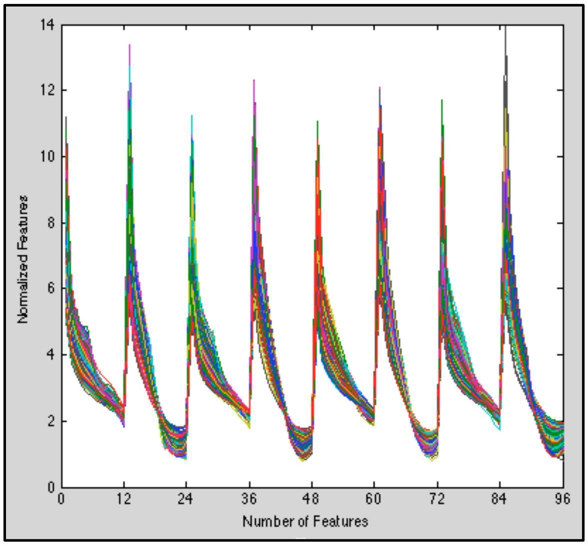

Figure 4 96 features from MFCC for frequency ranged from 4Hz to 13 Hz (theta, alpha) during elicitation of sad emotion of a subject 3

MFCC are commonly used method to extract features from speech data. It is based on the behavior of the mel-frequency that follows a linear spacing below 1 kHz and a logarithmic spacing above 1 kHz. Here, the EEG sampling rate frequency is 250 Hz, which is compatible with a linearity assumption.

The filters used are triangular and they are equally spaced along the mel-scale as cited from [1]:

$$\mathrm{Mel(f)} = 2595\log_{10}\left(1+\frac{f}{700}\right) \quad (3)$$

MFCC were calculated from the log filterbank amplitudes m_j using the Discrete Cosine Transform

$$c_i = \sqrt{\frac{2}{N}}\sum_{j=1}^{n} m_j \cos\left(\frac{\pi i}{N}(j-0.5)\right) \quad (4)$$

Where

N the number of filterbank channels

c_i the cepstral coefficients

Accordingly, 96 features were obtained from this feature extraction method as shown in Figure 4.

4.3 Classification

As indicated in the previous studies on computational model as shown in Table 1, many classification techniques had been used for EEG-based researches. Here, three classification techniques were evaluated. The performance of each classifier was validated through 5-fold cross validation. The details are described below.

4.3.1 Multilayer Perceptron (MLP)

MLP is a variant of artificial neural network, which is inspired by the biological nervous system. MLP structure consists of three layers, specifically an input layer, a hidden layer, and an output layer, as illustrated in Figure 5. Input layer consists of features extracted from the brain signals. The hidden layer contains the neurons that map the input towards the intended output. While the output layer is the result of the classification.

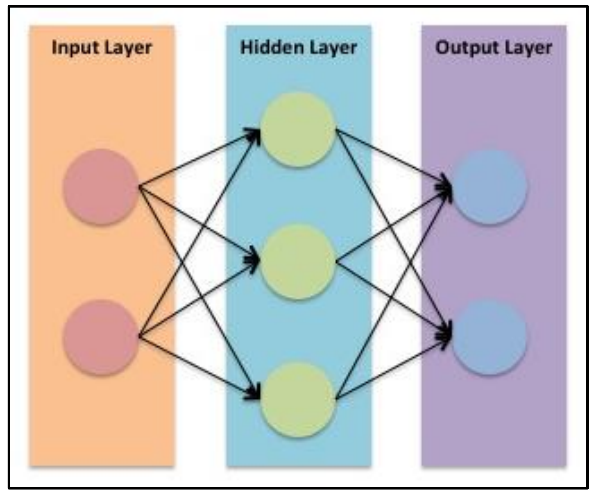

Figure 5 General MLP Network Structure

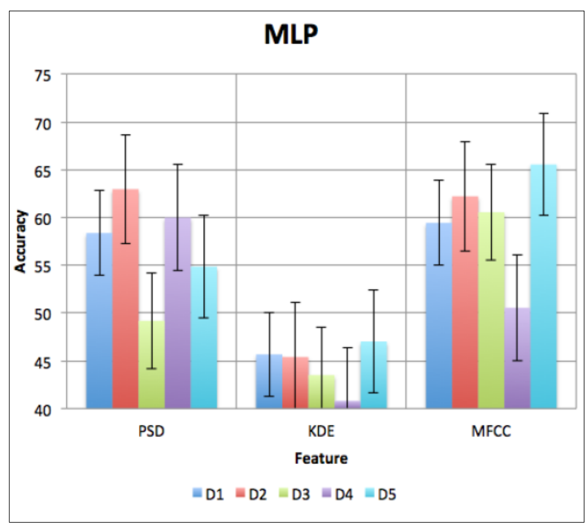

Figure 6 Result for classification 5-fold cross validation using MLP. Error bars shown correspond to the standard error of the mean

MLP was trained and tested with the data in a set of iterations, commonly known as epochs. The vector of the synaptic weights (w) of MLP was upgraded in each iteration to maximize the correct classification rate and to minimize the classification errors [31]. The function of classification error was derived from mean-squared error (MSE).

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \quad (5)$$

Where

$\hat{Y}$ vector of n predictions, and Y is the vector of the true values.

The MLP parameter configuration that was used in this research is shown in Table 2.

Table 2 Parameters for MLP

Parameters	Values
No. of hidden layer	1
No. of neurons in hidden layer	30
No. of neuron in output layer	1
Mean-square error goal	0.1

The results of 5-fold cross validation testing for identifying subject using features that were extracted from PSD, KDE, and MFCC are shown in Figure 6.

The MLP results show that the accuracies from all features are above 40%. The accuracy of classifying PSD features ranges from 44.59% to 67.56%. Furthermore, the accuracy of features extracted from KDE ranges from 32.43% to 54.05%. Likewise, the accuracy of featured extracted from MFCC range from 50% to 72.22%.

In brief, the subject identification using MLP performed well on the features that were extracted from MFCC while the result was poor when the features were extracted using KDE.

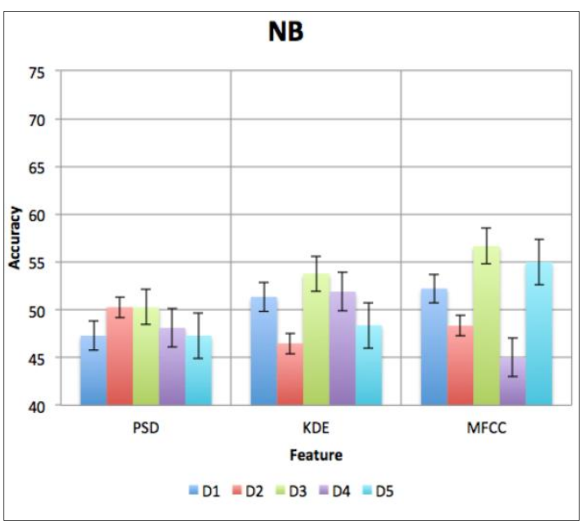

Figure 7 Result for classification 5-fold cross validation using NB. Error bars shown correspond to the standard error of the mean

4.3.2 Naïve Bayesian (NB)

NB is a method to classify the input data using the concept of probability. The output of the classification process is based on the maximum of posterior probability, where the features in the feature matrix are considered to be conditionally independent of each other. With regard to this approach, the prior probability and the corresponding likelihood probability were calculated by the following equation (Equation 6).

$$\hat{y} = \arg\max_{k\in\{1,\ldots,K\}} P(h)\prod_{i=1}^{n} P(x_i|h) \quad (6)$$

Where

$\hat{y}$ naïve bayesian classification output

P(h) Prior probability of the corresponding class target h in the training data

P(x|h) Likelihood probability of each feature in feature set x if target h is true in the training

h target

X feature set of {x1, …, xi}

The NB results for subject identification with 5-fold cross validation using features that were extracted from three different feature extraction techniques are shown in Figure 7.

The NB classification results show that the accuracies from PSD, KDE, and MFCC features are above 40%. The classification result from PSD features is from 44.59% to 55.45%. While the result from KDE features ranges from 40.54% to 55.40%. Lastly, classification result from MFCC features ranges from 36.11% to 61.11%.

In short, the result of subject identification using NB is of the highest accuracy when the features extracted from MFCC were used.

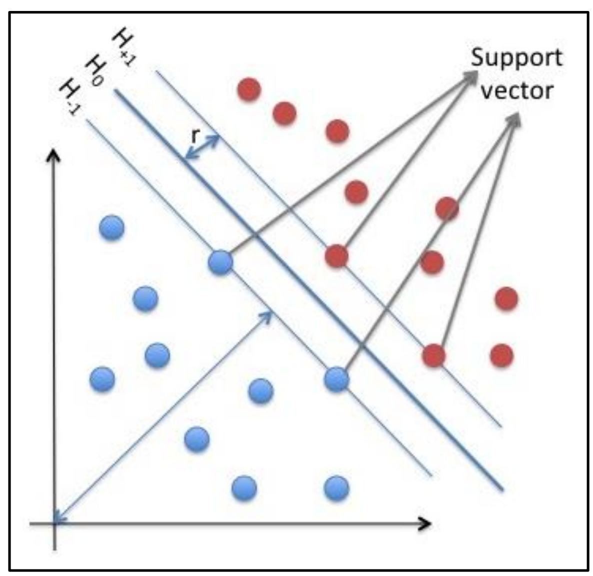

Figure 8 Simple illustration for linearly separable input with H0 as the optimum hyperplane

4.3.3 Support Vector Machines (SVM)

SVM is one of the most popular supervised techniques for solving the subject identification problem. The basic idea is to transform the input data into a higher dimensional plane through either linear or non-linear kernel functions [32].

In a binary class problem, the two groups of feature data are separated in a higher-dimension hyperplane. Hyperplane with the maximum margin between the parallel hyperplanes from both sides is selected as the optimal solution as illustrated in Figure 8.

The results of subject identification using SVM classification are all above 50%. The accuracy of classifying using the features extracted from PSD ranges from 51.35% to 64.86%. The accuracy of classifying using the features extracted from KDE ranges from 50% to 52.70%. For features extracted from MFCC, the accuracy ranges from 52.77% to 58.33%.

Thus, the results shows that SVM classification using features that were extracted using PSD produced the best result compared to those using features derived from KDE and MFCC.

5.0 RESULTS AND DISCUSSION

The classification results from three different classifier and three feature extraction techniques are illustrated in Figure10.

In the classification results based on features extracted from PSD, the mean (M) and standard deviation (SD) of the accuracy were 54.48% and 5.06%, respectively. The highest accuracy was achieved by SVM and the lowest was by NB.

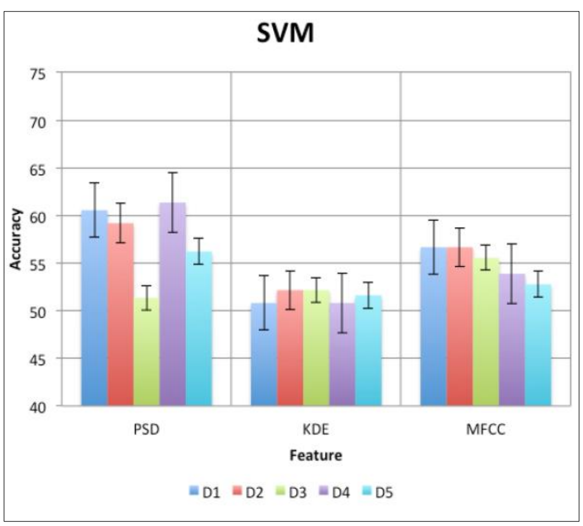

Figure 9 Result for classification 5-fold cross validation using SVM. Error bars shown correspond to the standard error of the mean

The classification results based on KDE features were obtained with M 48.79% and SD 3.77%. The highest accuracy was achieved by SVM and the lowest was by MLP.

Finally, the classification results based on MFCC features were obtained with M 55.40% and SD 4.11%. The highest accuracy was obtained by MLP and the lowest was by NB.

The total number of features that were derived from PSD was 1032, KDE 800, and MFCC 96. As shown in Figure 10, SVM achieved the highest accuracy with the features extracted from PSD and KDE. In short, SVM yielded the best accuracy from a large set of data.

On the contrary, NB and MLP classification results were not based on the number of features. As shown in Figure 10, NB yielded the lowest accuracy from the PSD-based features and moderate accuracy from the KDE-based features.

Lastly, the accuracy results from MLP classification were the lowest in the KDE-based features, moderate in PSD-based features, and highest in the MFCC-based features. The highest accuracy was achieved from MLP classification and MFCC-based features at 59.66%.

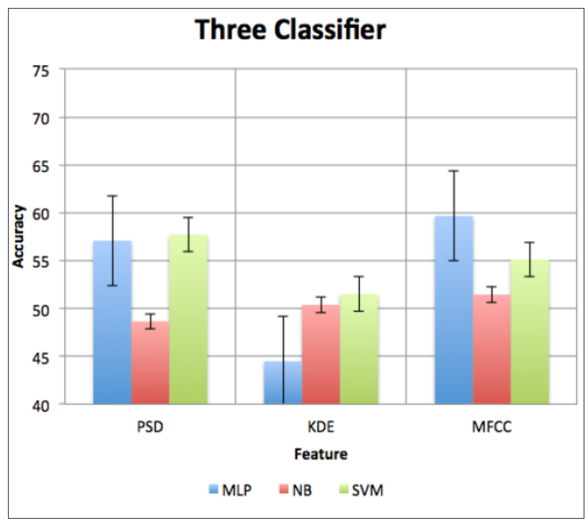

Figure 10 Result for classification 5-fold cross validation using three classifier. Error bars shown correspond to the standard error of the mean

6.0 CONCLUSIONS

From the results of this study, we can conclude that it is possible to implement a system for recognizing the emotions from EEG signals. However, to make it efficient to recognize the human emotion, the accuracy of the classification must be improved. Hence, it is necessary to test other features extraction techniques and use more sophisticated classifiers. To validate the techniques evaluated in this work, tests will be conducted to collect more data. Finally, to develop subject identification, it is important to correlate with the subject precursor emotion and other psychometric analysis results, to get more understanding on the subject behaviour.

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Table 1 Taxonomical Table on Computational Modeling on Subject Identification

No	Source	Measurement Tools	Feature Extraction	Classification
1	[2]	EEG and Questionnaire	-	ANFIS, NB, SVM
2	[11]	EEG and peripheral physiological signals	FFT	NB
3	[12]	EEG	-	SVM
4	[13]	EEG	PSD	-
5	[3]	Self Assessed and EEG	-	SVM
6	[26]	EEG and SAM	PSD, HOC	KNN
7	[14]	EEG	PSD	SVM
8	[4]	EEG and Questionnaire	PSD	SVM
9	[5]	Facial expression, EEG, Self assessed	PSD	HMM
10	[15]	EEG	KDE	MLP
11	[6]	Self Assessed, EEG, Peripheral Physiological Signals	PSD, CSP	SVM
12	[16]	EEG	KDE	GMM, BN, One-Rule
13	[17]	EEG	PSD	SVM, NB, KNN
14	[1]	EEG	MFCC	SVM
15	[18]	EEG	KDE, MFCC	MLP
16	[19]	EEG	CSP	SVM, NB
17	[20]	EEG	KDE	MLP
18	[7]	EEG, eye activity, and facial expressions	-	KNN, MLP, SVM, LDF, NB
19	[21]	EEG	FFT	MLP
20	[22]	EEG	Statistical Features	KNN, SVM, MLP
21	[23]	EEG	-	Decision tree, KNN, SVM
22	[28]	EEG	HOC	KNN, SVM
23	[25]	EEG	-	SVM
24	[8]	SAM and EEG	CPS	SVM
25	[9]	SAM and EEG	-	SVM