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The multimodal parameter enhancement of electroencephalogram signal for music application

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ABSTRACT

Blinding of modality has been influenced decision of multimodal in several circumstances. Sometimes, certain electroencephalogram (EEG) signal is omitted to achieve the highest accuracy of performance. Therefore, the aim for this paper is to enhance the multimodal parameters of EEG signals based on music applications. The structure of multimodal is evaluated with performance measure to ensure the implementation of parameter value is valid to apply in the multimodal equation. The modalities' parameters proposed in this multimodal are weighted stress condition, signal features extraction, and music class. The weighted stress condition was obtained from stress classes. The EEG signal produces signal features extracted from the frequency domain and time-frequency domain via techniques such as power spectrum density (PSD), short-time Fourier transform (STFT), and continuous wavelet transform (CWT). Power value is evaluated in PSD. The energy distribution is derived from STFT and CWT techniques. Two types of music were used in this experiment. The multimodal fusion is tested using a six-performance measurement method. The purposed multimodal parameter shows the highest accuracy is 97.68%. The sensitivity of this study presents over 95% and the high value for specificity is 89.5%. The area under the curve (AUC) value is 1 and the F1 score is 0.986. The informedness values range from 0.793 to 0.812 found in this paper.

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1. INTRODUCTION

The modalities' understanding is described as a consideration process from separation of data that can be visible for one modality while blind to others. From the origin, separate unimodal data, then the multimodal will gather information into extracted features and decision part [1]. The multimodal also will be divided into three-stage which is early, intermediate, and late stage. Early-stage is a combination of different feature modalities into a single group before passing the learning phase. The solution to improve these imperfect data functions by categorizing the classification during intermediate stage. The modalities of semantic information can be decoded at the decision level which occurs during the late-stage category [2]. The multimodal approach measured the stress condition in an impaired mobility data such as the brain response and peripheral bio-signals reported by Kalimeri and Saitis [3]. The construct of hate speech classification in social media based on text and photo will be fragmented using multi classes of fusion groups in the deep multimodal fusion technique [4]. During the late stage, the emotional responses by using fractal dimension (FD) features approach is estimated to find the effect of weighting factors in electroencephalogram (EEG) signal contribution [5]. Therefore, the EEG signal executes the imperfect data result of reliability and asynchronous features among different modalities; and become a familiar signal method in exploit multimodal function. Similar work has also been pursued in this similar research area in order to classify the human stress level using an EEG signal. Here, self-stress questionnaire assessment and music application is utilized as the basis for our initial works.

Sometimes, the modalities' functions may omit certain imperfect modalities' parameter of the EEG signal by ignored or uncounted them which obstructed the path in obtaining an excellent performance measurement. This issue is found as a crucial limitation contains in this functional approach. Consequently, the multimodal function was used in this study in order to solve and improve the function by considering poor or unbalanced data such as the EEG signals. The idea is to enhance the multimodal data in EEG data by improving some numerical value in the multimodal (1), as mentioned in the equation.

$$p_{multimodal}^{x} = \alpha p_{eeg}^{x} + (1-\alpha) p_{music}^{x} \quad (1)$$

In medical and bio-signal applications, the EEG is a part of the electrophysiological signal. The electrophysiological signal from brain waves can be monitored, measured, and analyzed for the characteristics in the EEG frequency range. This approach used the international 10/20 system of electrode placement to relocate the electrode channel position via relative distance for monitoring, measurement, and recording the EEG signal properly. In the example, the recognition of high arousal degree in the EEG signal for the intention complex task used 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) are collected by Emotiv headband [6]. In signal processing, a bandpass filter in the EEG signal processing analysis is practically applied to obtain the EEG frequency range from 0.01 Hz until 100 Hz with an approximate amplitude of 100 µV [7]. Then the comprehensive features of EEG signals were extracted into various connectivity functions based on primary frequency bands which are delta, theta, alpha, beta, and gamma [8]. Similar with Al-shargie *et al.* works [9], applied the frequency band range from 0.5-30 Hz to measure the EEG signal in multilevel mental stress assessment.

Recent investigations have demonstrated that the primary EEG signal frequency bands are compatible to implement in signal processing. Moreover, the feature extraction technique can rely on the signal processing domain analysis which consists of time domain, frequency domain, and time-frequency domain. EEG signal should be seen in spectral mode and analyzed using power spectral density (PSD) for frequency domain analysis. The PSD estimated the power and coherence value in high-frequency resolution of the frequency range corresponding to the EEG signal [10]. Moreover, PSD can find the power peak value and mean value [11], standard deviation, skew, kurtosis, and root means square (RMS) [12]. The Time-frequency domain is the relation between the time and frequency domain. Therefore, the Time-frequency domain can be represented as the combination of time and frequency into single features function. The idea of time-frequency is by carried out any EEG signal in respect of frequencies for the time to be realized using continuous wavelet transform (CWT) and short time Fourier transform (STFT) methods. The energy distribution value from the EEG signal was found in time-frequency domain analysis [13]. Similar findings from the frequency domain also found in the time-frequency domain [14], [15]. The approach method in time-frequency is widespread likes STFT methods. Many of the features in the EEG signal is derived from the STFT methods have been shown by proficient features such as minimum, maximum, and median value [16]. Likewise, some researchers agree with the method in finding the entropy, Hjorth mobility, and complexity feature which will be calculated from the energy distribution [17], [18]. These common methods mention that exploited from the EEG signal can be used as the EEG probability parameter in this research.

Aside from the EEG probability parameter, there is a slew of other variables to consider which include weighting and application factors. The stress level was employed as a weighting element, while music was used as an application factor. Due to both elements may be stated in numerical terms, the stress level and music application were chosen as multimodal parameters for this study. The manifest of stress is recognized when there is an interruption which caused some pressure to mental and physical to human that can lead to a beneficial or non-beneficial to the human body. If the human is able to manage the stress and the external pressure for improvement and gains, then this stress will be considered as good stress level due to the beneficial in overcoming the stress factors. On the other hand, the non-beneficial stress mainly causes a depression, mental problem and critical illness. Therefore, the self-stress assessment is required to identify the stress level by answering a stress questionnaire. Moreover, recognising one's stress level can assist people in managing stress before it worsens and leads to a protracted stress state. The self-stress assessment methods are potentially of questionable accuracy and reproducibility to be measured, proved by works of [19], [20]. The study by Olaitan [21] used the self-stress assessment with the clinical assessment, and identify the hypertension of health workers. This shows that the several of physiological assessment and self-stress assessment can be implemented in stress level measurement. Hence, in this research, the physiological measurement and a self-stress assessment questionnaire were applied to obtain the stress level classification. The result will be performed as the weighting factor for this research in multimodal function.

Several studies such as Paszkiel *et al.* [22] explored the impact of music applications on stress and identified the stress level through music. Conceptually similar works have also been carried out in [23] which it can observe the effectiveness of mental and stress condition. In addition, application of music can reduce stress in cancer patient because music can be a part of therapy treatment [24]. This is generally accepted in the literatures from which it can be concluded that the music application can be considered as a part of component in multimodal in order to determine the human stress level. Therefore, various types of music are utilized to examine the effects of stress levels such as low rhymes and high rhymes.The contribution of this studying this paper is summarized as: i) the proposed of EEG features extraction as EEG probability parameter based on low rhymes and high rhymes, and ii) to enhance the multimodal function equation in order to determine the stress level classification by using the physiological measurements and a self-assessment stress questionnaire.

2. RESEARCH METHOD

The method proposed to achieve the study aims are contained in four major steps as shown in Figure 1. The figure shows the four major steps are self-assessment, signal processing, features extraction, multimodal performance. The research method began by self-stress assessment which includes music and the EEG signal measurement processes. Next, the signal is processed and the features being extracted to arrive at the multimodal performance. The signal processing can be explained as the technique to gain a standard EEG signal from the raw EEG signal, while features extraction is described as features applied in the multimodal function. The multimodal performance was presented as the best measurement result achieved based on multimodal parameter application.

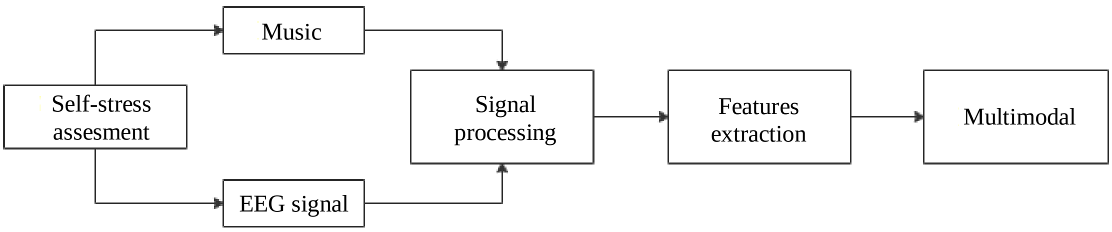

Figure 1. The structure of multimodal

2.1. Self-stress assessment

The self-stress assessment is tested using a questionnaire format and measured based on the quantities' scale provided by the International Stress Management Association UK (ISMAUK). The scales of ISMA stress questionnaire show in three stress classes which is low stress (0), medium stress (1) and high stress (2). These three stress classes are categorized based on the total score value from the question answer. In calculation technique, yes answers contribute to 1 score and no answers equal 0 score; which means that the question answer is derived purely based on the total number of yes. The score will then be added together to determine the subjects' stress classes. The score value and stress level are described in Table 1.

Table 1. Level of the stress score value and the conditions

Total Score	Stress classes	Description
0-4	0	Mild stress-related illness.
5-13	1	Medium experience stress
14-25	2	Medium experience stress leads to creating unhealthy behaviours

2.2. Music

Music is performed using voice vocal or sound to present the harmony, melody, or rhythm. Music is very wide to be described but can be categorized in empathizing and systemizing music described by [25]. The sharing and understanding about other people feeling can be expressed in the lyric, video clips or music rhythms. These mechanisms influence people while listening to the music. On the other hand, there is no noticeable influence that there is an impact of reaction to the style of music based on gender [26]. However, the selection of music is still important and become a critical part during collecting the EEG signal because it causes an impact on the brain waves. In this research, it used a different of music types which are low rhymes and high rhymes. Low rhymes for the baby rhythm song and high rhymes for pop-punk song. Pop-punk is categorizes as systemizing type because it presents in intense dimension; while baby rhythm is a relaxing music and can be classified in empathizing type. The selection of this music due to it contains an empathizing and systemizing in the music which easy to identify the EEG signal performance.

2.3. EEG signal

In this section describes about the experimental procedure in the EEG signal data collection. The experiment procedure to the subject is operated under ethic identity number IREC 2021-039 approved by IIUM Research Ethics Committee (IREC). The subject must have good health and hearing, not taking any prescription medicine (include antidepressants) and is not pregnant. In addition, subject is required to understand, read and write in English language. Next, thirty-four subjects which were involved in this experiment data collection have equal number of genders. The standardized period of this experiment was conducted from 9 AM to 5 PM. Each of the experiment will take 20 minutes and all the process detail shown in Figure 2.

In the beginning of the data collection, subject is located in the quiet room and was asked to be relaxed while sitting on the chair. Then, subject needs to answer all self- stress assessment questionnaires. After that, subject was asked to have little movement as possible until the experiment is completed. EEG Emotiv EPOC+headset is used for capturing the EEG signal in the offline mode. The advantage of using this headset is that the headset is a wireless device and able to connect to EmotivPro software for recording the EEG signal without any interruption. In this research, ten targeted channels (AF3, F7, F3, FC5, T7, AF4, F4, F8, FC6, and T8) be applied. Earphone device is used during listening the music.

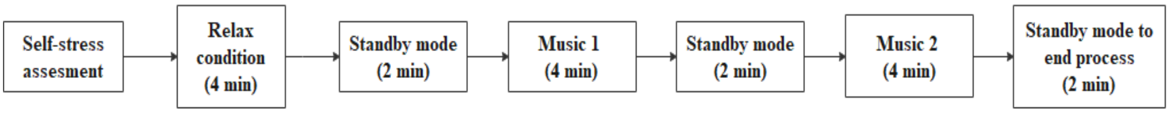

Figure 2. Data collection process for music application

2.4. Signal processing

Multiple signals were produced during capturing and recording the EEG signal. Therefore, the purposed of signal processing step is to ensure that the undesired and interrupted signal is eliminated. The process of removing the unwanted signal is required in this research in order to obtain the standard EEG signal in the range of -100 µV to 100 µV in frequency domain. The band-pass filter technique approach is used to gain the standard EEG signal. This approach used is based on the works of [27], [28]. Then, the EEG frequency bands of delta, theta, alpha and beta will be separated to the targeted frequency range in this research which are (0 Hz to 4 Hz), (4 Hz to 7 Hz), (8 Hz to 12 Hz) and (12 Hz to 25 Hz) respectively. The process of signal processing is expressed in Figure 3.

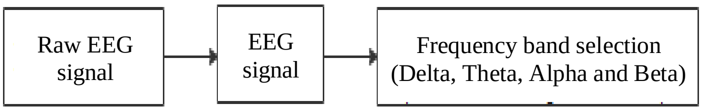

Figure 3. The block diagram for the EEG signal processing

2.5. Features extraction

The extraction of features is a method to gain the specific features of the EEG signal. The frequency and time-frequency domain analysis are the most conventional and standard practice for analyzing the EEG signals. These domains analysis show the potential features in each of frequency band used for this research. For the frequency domain analysis used PSD, while for time-frequency domain used STFT and CWT. The purposed of using these two domains is to compare the features performance in EEG signal. This technique is supported by Rahman *et al.* [28] that applied in their research to determine the features in EEG signal.

2.5.1. Power spectral density (PSD)

In signal processing, the common practice of the PSD technique is the conversion of the time domain to the frequency domain. Nevertheless, it could identify the power value in minimum, maximum and average power values. The familiar function as a feature extraction is being used in EEG signals are mean, standard deviation, RMS, standard deviation error, median, mean deviation, and coefficient of mean deviation. Skew, variance, and kurtosis are a part of the statistical features function is used. The extension of statistical features is calculated in power relative and entropy. The purposed of power relative is added into the features to determine the highest power concentration of a specific frequency range. For entropy, an algorithm is used in analyzing the EEG signal. The justification of using entropy in this paper is to identify the probability density function of power value in the EEG signal. In addition, magnitude square coherence and magnitude cross power spectral density can also be applied as a feature in the frequency domain.

2.5.2. Short time Fourier transform (STFT)

The STFT technique was performed to analyse the sinusoidal signal frequency in the EEG signal. The EEG signal is represented in sinusoidal waves with the content of complex exponential data is commonly related to the transformation domain. Therefore, it can measure and analyse the variety of features in the data signal. The determination of various features will contribute to improve the function of signal representation. This paper found the energy value from the EEG signal, and used it to measure the minimum, maximum, and average features. Moreover, the energy value to determine the mean, standard deviation, RMS, standard deviation error, median, mean deviation, coefficient of mean deviation, variance, skew, and kurtosis as the function of a feature. Besides, the advanced mathematical features comprise two features which are entropy and recursive energy efficiency (REE). The purpose of the additional two features is to identify the existing concentration of the energy result in signal processing.

2.5.3. Continuous wavelet transform (CWT)

There are various methods to obtain features function in the time-frequency domain such as continuous wavelet transform which are used in this paper. The distribution energy in CWT may found the peak minimum, maximum and average value. Similar to the STFT method, the energy value can measure the mean, standard deviation, RMS, standard deviation error, median, mean deviation, coefficient of mean deviation, variance, skew, and kurtosis. All the functions are also counted as feature functions in the CWT method. The EEG signal is capable of extracting more features comprises two features which are entropy and REE.

2.6. Multimodal

The most significant contribution of this study is the enhancement of multimodal parameter function by applying EEG features extraction based on music application to identify stress levels between physiological data and a self-assessment stress questionnaire. Refer to the (1) and previous explanations about the multimodal parameter describe α is the weighted factor, while $p\,^{x}_{eeg}$is the EEG signal features extraction and $p\,^{x}_{music}$ is the music class. The weighting option has three values in total (0,1,2). Three values are derived from the stress classes, which are detailed in Table 1. Next, the EEG signal features extraction value produced from the features' extraction result discussed in the features' extraction section is $p\,^{x}_{eeg}$. These characteristics are classified into two domains: frequency domain and time-frequency domain. Lastly, the music class parameter $p\,^{x}_{music}$ is divided into two classes (1,2) based on music types. Therefore, the improvement of parameter in multimodal function is measured in various techniques such as accuracy, sensitivity, specificity, area under the curve (AUC), F1 score and informedness. This performance of measurement technique was present as the significance of the improvement methods.

3. RESULTS AND DISCUSSION

In line with the findings of this paper about the ability to enhance the multimodal parameter in the EEG signal based on music application for thirty-four subjects. The multimodal parameter contains weighted stress classes, EEG signal features, and music categories. The result of the parameter obtained be discussed detail in this sections 3.1 to 3.3.

3.1. Self-stress assessment

The weighted stress classes can be known from the sum of score by using the calculation method. Based on the total score from the seventeen male and seventeen female subjects in a range of nineteen to thirty years old can be summarised in the stress classes in percentage as shown in Figure 4. From the figure, it describes that the high percentage score can be found in class 2 compare to other classes. From our finding, it shows that no result was obtained from class 0 in self-stress assessment. 35%±5% from total percent of stress score present in class 1 proved that this group has experience with stress. However, there is not much of a difference between male and female stress groups in terms of percentages for classes 1 and 2. It shows that, most people must having a stress experience in medium and high stress level with overall result shows 33% for class 1 and 67% for class 2. These stress levels were demonstrated that the human have an experience of fatigue and pressure situation in order to achieve goals in their life [29]. In a positive opinion, stress may encourage people to be more independent, control their emotion, and enhanced creative thinking to make a decision.

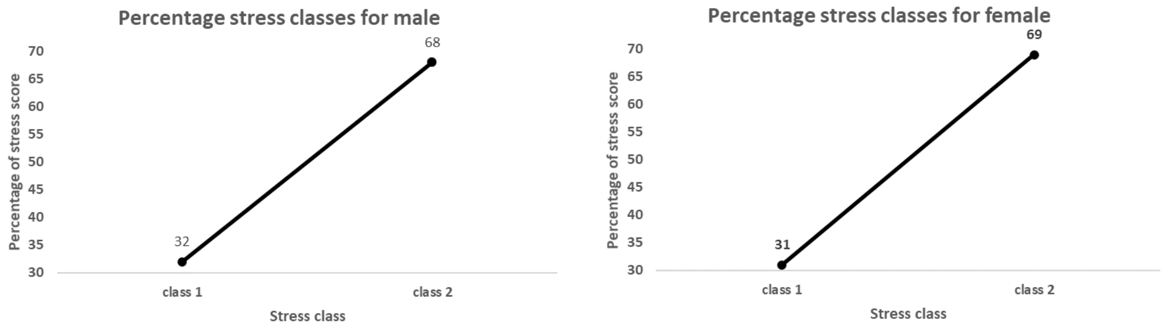

Figure 4. Stress classes in percentage for male and female

3.2. Features extraction and multimodal

For EEG signal features extraction is gained from the features extraction method in frequency and time-frequency domains, respectively. PSD approach is used to analyze the EEG signal in frequency domain. Nevertheless, the EEG signal in time-frequency domain analysis is a process using STFT and CWT techniques from nineteen features for both domain analysis. In the frequency domain, features in the power value were measured; while in the time-frequency domain, features in the energy distribution value were evaluated. The features extraction is subdivided into three conditions which are resting state (RS), pop-punk (M1), and baby rhythm (M2) condition. The average feature extraction result for the analysis domain with three conditions is present in the Table 2. In both domains, music 1 or pop-punk was demonstrated as a high value of features extraction result compared with resting state and music 2 or baby rhythm. The differences of features extraction result caused by the chosen music type. Music 1 is the combination of power pop and pop music in a fast rock tempo with melodies and chord progression while music 2 is a low tempo melody and known as relaxing music. The relaxing music effect can calm and help the human toward the relaxed mental state condition [30].

Table 2. The average of features extraction result

Method	Condition	Result
PSD	RS	3.875835 µv
	M1	5.348473 µv
	M2	4.029015 µv
CWT	RS	3.79981 (J/Hz)
	M1	5.348725 (J/Hz)
	M2	4.867353 (J/Hz)
STFT	RS	3.891119 (J/Hz)
	M1	5.391332 (J/Hz)
	M2	4.783486 (J/Hz)

3.3. Multimodal

The contribution of low values was found in features extraction average result before applied the multimodal function. Different with relaxing state, human is in relax condition to listen to any music genre. The consistency of the subject in relax condition is provable to be found in the low value of feature extraction. The multimodal result was performed using a stress class and features extraction parameter value. This result shows in the Table 3. However, the observation is made that there is no significant between this domain and technique used.

Table 3. The average of multimodal

Method	Condition	Result
PSD	RS	42.03393 μv
	M1	46.40736 μv
	M2	41.05527 μv
CWT	RS	41.93819 (J/Hz)
	M1	43.59026 (J/Hz)
	M2	43.01139 (J/Hz)
STFT	RS	45.49176 (J/Hz)
	M1	40.86589 (J/Hz)
	M2	41.31803 (J/Hz)

The average of the multimodal result is measured using six performance measurement techniques. The six techniques listed as accuracy, sensitivity, specificity, AUC, F1 score, and informedness. The result for accuracy, sensitivity, and specificity are shown in Figure 5. The validation of using stress classes and average features extraction in multimodal fusion was performed when the highest accuracy is 97.68%. The measurement of sensitivity and specificity is to identify the proposition of positive correctly and the possibility of an optimal result. The sensitivity of this study presents over 95% and the high value for specificity is 89.27%. The underlying of the obtained high percentage of sensitivity and specificity will prove that this measurement technique is acceptable to be a potential testing measurement technique in the parameter value multimodal result. Futhermore, the result measurement for PSD and CWT are obtained the same pattern with STFT and attempt to performed a high accuracy result.

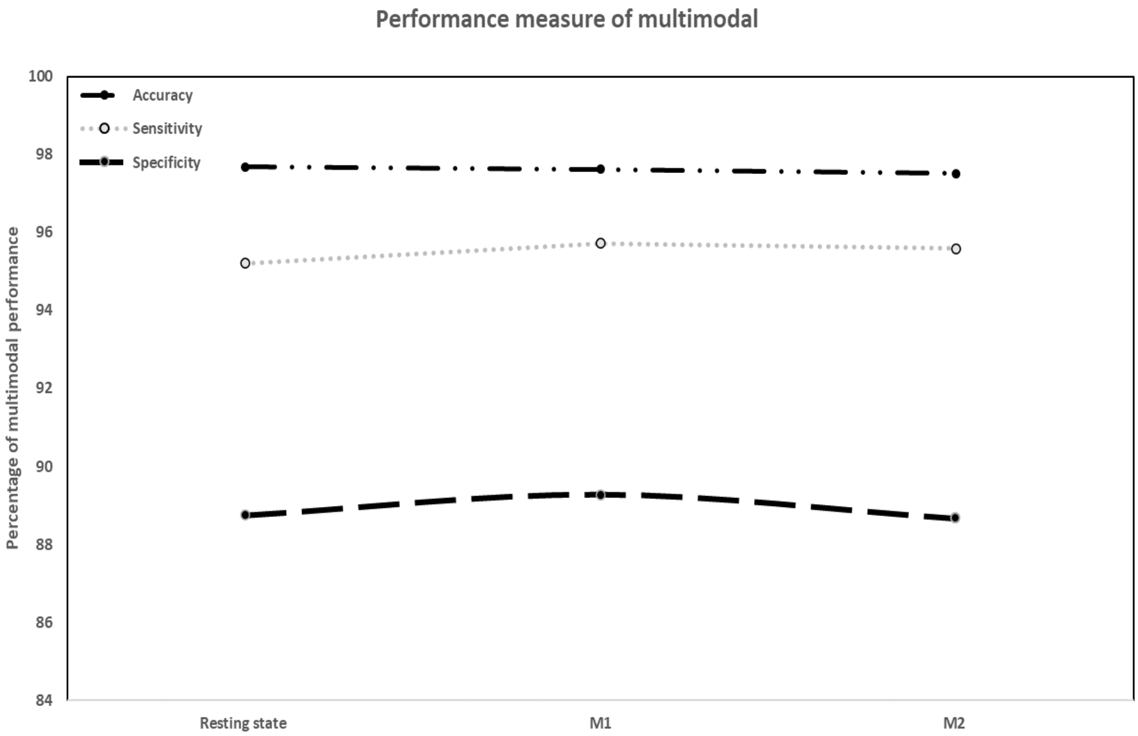

Figure 5. The result for accuracy, sensitivity, and specificity in percentage

In addition, the AUC, F1 score and informedness result make up a contribution towards the solution to determine the parameter value in multimodal reported in Table 4. The AUC is to determine the precise integration under to function of features results. The highest score for this AUC is 1 in this paper shows the perfect score and the nearest value to 1 is a more reliable performance [21]. The F1 measurement provided proof that the solution enhanced the multimodal when the result shows high value because F1 measurement has the same task as the accuracy function. An informedness measure the result in the range of -1 to 1 with the value of 1 is correct, -1 is incorrect and 0 is being changed [31]. The informedness values show the result in range 0.793 to 0.812 were described that the value is presenting a closely correct.

Table 4. Additional performance measurement of multimodal

Method	PSD (RS)	PSD (M1)	PSD (M2)	CWT (RS)	CWT (M1)	CWT (M2)	STFT (RS)	STFT (M1)	STFT (M2)
AUC	0.982	0.999	0.969	1	1	0.991	0.991	1	0.986
F1 SCORE	0.982	0.986	0.901	1	1	0.986	0.958	1	0.958
Y (informedness)	0.795	0.794	0.807	0.799	0.789	0.797	0.801	0.797	0.812

4. CONCLUSION

Overall, it is permissible to apply a conceptually comparable technique from the previous in addition to the approach of combining physiological measures and a self-assessment stress questionnaire in the multimodal parameter. The outcome of the study contribution shown that the highest accuracy is 97.68% and informedness is 5.7 while AUC and FI score produce 1 as a result. The result of sensitivity and specificity produces 95.81% and 89.5%. Based from the result finding, the proposed parameter and method used capable of performing a good result using EEG signal based on music application in multimodal function for thirty-four subjects. In this study, the stress level is identified as an area that needs to be investigated more in order to learn more about human stress.

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