ORIGINAL ARTICLE

Mental state classification based on electroencephalogram (EEG) using multiclass support vector machine

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ABSTRACT

Introduction: Mental state refers to a person's state of mind from various perspectives, including consciousness, intention, and functionalism. Mental states closely related to everyday life include the concentrating state, neutral state, and relaxation state. Concentration is vital for cognitive tasks, while relaxation is crucial for comfort. However, individuals with mental disorders or neurological conditions often struggle to achieve these states, requiring effective detection and intervention. One method for detecting mental states is by using brainwave signals obtained through electroencephalogram (EEG). EEG has been widely used in neuroscience and clinical settings to objectively assess mental states by analyzing brainwave signals. Previous studies have demonstrated the potential of EEG-based mental state classification in stress detection, cognitive workload analysis, or depression detection.

Materials and Methods: The data used in this research is secondary data in the form of recorded brainwave signals using EEG from 2018. and utilises self-reported data obtained from locally validated personal stress inventory questionnaires. The data used was obtained from four participants, including two females and two males. For pre-processing, this study uses the Hamming Windows Finite Impulse Response filtering method to extract features from each wave band. Additionally, feature selection methods are applied to choose the most relevant predictor features. Multiclass Support Vector Machine (SVM) with One-Against-One (OAO) and One-Against-All (OAA) approaches are used for classification.

Results: The feature selection process reduced the number of predictor variables from 160 to 40, focusing on minimum and maximum feature values. Multiclass SVM classification using 40 predictor variables achieved an AUC range of 0.907–0.922 (OAA) and 0.854–0.927 (OAO), while classification using all predictor variables yielded an AUC range of 0.898–0.927 (OAA) and 0.917–0.941 (OAO). Comparative performance analysis indicates that the OAA approach is superior to the OAO approach.

Conclusion: This study highlights the effectiveness of EEG-based classification of mental states using the Multiclass SVM method. The findings reinforce the role of EEG as an objective tool for mental state assessment, supporting its potential application in clinical and cognitive research for early detection of mental health disorders.

KEYWORDS:
Mental States, Electroencephalogram (EEG), Brainwaves, Multiclass SVM

INTRODUCTION

Mental state refers to the state of the mind that can be observed from various perspectives, such as consciousness-based, intentionality-based, and functionalism-based.[1] Mental states that are closely related to everyday life are concentrating states, relaxed states, and neutral states. Mental states, particularly concentration and relaxation, play an important role in everyday life. Concentration is particularly needed in cognitively demanding activities, such as studying and working. The inability to achieve a state of concentration at the right time can have a negative impact on information processing, memory retrieval and problem-solving decision-making. On the other hand, relaxation also plays a crucial role in maintaining psychophysiological balance. In a relaxed state, the body is calm, not tense, and recovers from fatigue, which is important for overall mental and physical health.

Along with increasing demands in education and work, the complexity of modern life has led to the emergence of various mental health problems. Disorders such as anxiety, depression, bipolar, post-traumatic stress disorder (PTSD), and insomnia can prevent a person from achieving an ideal state of concentration or relaxation.[2] For example, individuals with anxiety disorders often have difficulty relaxing, sleeping, and maintaining focus, which in turn impairs their productivity and well-being. In addition to mental disorders, neurological diseases such as Alzheimer's, stroke, vascular dementia and Parkinson's disease can also impact one's ability to concentrate or achieve a relaxed state.[3-5] The inability to manage both conditions is often an indication of a mental or neurological health disorder that needs to be addressed.

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A person's condition, both neurologically and mentally, can influence the frequency and type of brain waves that appear, this is the basis for detecting mental conditions based on brain waves.[6] Electroencephalography (EEG) is a widely used tool to objectively analyze brain activity, as the frequency and type of brain waves that appear can reflect a person's mental state.[7,8] The diagnosis of EEG recordings is often done in the time domain by examining the waveforms, wave sharpness, and wave complexity9. Conventional methods in EEG analysis still rely on manual observation of brain wave patterns, which can be time-consuming and subjective. Therefore, faster and more accurate automated techniques are needed to evaluate a patient's mental state.

Machine learning methods have been developed to identify brain activity patterns related to a person's mental state. This study focuses on applying machine learning techniques to classify EEG signals into concentration, relaxation and neutral categories. Using this method, this study aims to support medical personnel in understanding patients' mental states more objectively, which in turn can improve the accuracy of diagnosis and the effectiveness of clinical interventions.

Furthermore, this EEG-based modeling of mental states can be a preliminary study for further research in understanding a person's psychological or clinical condition. The inability to achieve a situationally appropriate state of concentration, relaxation or neutrality could be an early indication of a more serious psychological or neurological disorder. With this modeling, the potential for developing early screening methods for mental health disorders becomes more open, which in turn can help in prevention efforts and the design of more targeted interventions.

In the organization of this review, section 2 the adopted research method is presented. The results of the study are shown in section 3. In section 4, a discussion and comparison between studied papers are provided. Section 5 at the end is devoted to the conclusion.

MATERIALS AND METHODS

Data Source

The data used in this research is secondary data in the form of recorded brainwave signals using Electroencephalography (EEG), which was obtained through GitHub using the following link https://github.com/jordan-bird/eeg-feature-generation/tree/master/dataset/original_data.[10] The data used in this study was obtained from four participants, consisting of two females and two males who performed the mental state recording process (relaxed, neutral, and concentrated) several times. The conditions imposed when recording are as follows: In the relaxed mental state, subjects were listened to low-tempo music and sound effects designed for meditation while being instructed to relax their muscles and rest. In the neutral mental state, a similar test was conducted but without any stimulus. This test was conducted before the other mental state tests to prevent the lasting effects of relaxation and concentration. As for the concentration mental state, subjects were instructed to run a "shell game" in which a ball was hidden under one of three cups which were then randomized, then the subject's task was to determine which cup had the ball in it.

Each participant made two recordings for each mental state resulting in a total of 24 data recordings. However, in this study only data with a minimum duration of 40 seconds was used so that 22 raw data were used and the recording duration was cut to 40 seconds. From these 22 data, the signal was cut into several signal pieces within a time span of 10 seconds and overlapping 5 seconds so that the data used in the classification analysis was 154 sample data. The recording data used in this study came from four channels: AF7, AF8, TP9, and TP10.[10]

Research Steps

The research steps (shown by Figure 1) are as follows:
1. Brain Activity Analysis: Examines brain wave patterns to understand the characteristics of EEG signals related to mental states.
2. EEG Data Processing: Filtering the signals based on relevant frequency ranges to extract meaningful information according to the type of wave subband as each wave subband is associated with a specific mental state.
3. Data Segmentation: Dividing the EEG signal into time segments to observe changes in brain activity within a certain period.
4. Feature Extraction: Retrieving characteristic features i.e. key information from the EEG signal that can reflect a person's mental state.
5. Feature Selection: Selecting the aspects of the signal characteristics that are most influential in distinguishing mental states.
6. Data Normalization: Scaling the data to make it more consistent in the classification process.
7. Mental State Classification: Analyzing brain activity patterns with machine learning models to classify mental states based on EEG data.
8. Model Evaluation: Comparing multiple analysis approaches to determine the best method for detecting mental states based on EEG.

Pre-processing data

The signal processing process begins with signal filtering. Signal filtering is used to separate signal waves based on frequency ranges, namely delta waves (0.1-3.5 Hz), Theta (4-7.5 Hz), Alpha (8-13 Hz), Beta (13.5-30 Hz), Gamma (30.5-100 Hz). The filtering method used is a Finite Impulse Response (FIR) Filter which has a limited impulse response because there is no feedback in the filter, giving results that tend to be stable compared to Infinite Impulse Response (IIR). Signal data tends to be stationary for a short duration, so the time epoch method will be more effective in reducing the variation of signal.[10] Time epoching is the segmentation of data into several epochs based on time intervals determined by the researcher. Each epoch segment can overlap with other segments, which is known as overlap. The common overlapping used in EEG analysis is 50% of the epoch size.[11]

Feature Extraction and Feature Selection

Features are unique characteristics of an object. Feature extraction is a step to obtain features that will be used in the classification process as predictor variables. The following features can be extracted from EEG recording signals[10-16]:

1. Minimum: The smallest sample value.
2. Maximum: The largest sample value.
3. Variance: A measure of how spread out the data is.
4. Skewness: A measure of the asymmetrical of the data distribution.
5. Kurtosis: A measure of the peakedness of the data distribution.
6. Energy: A quantitative measure of electrical activity in the brain.
7. Entropy: A nonlinear measure that quantifies the complexity and randomness of the data.
8. Zero Crossing Band: The number of sign changes (from positive to negative and vice versa) in the signal data fluctuations.

In general, a variable is said to be good if it has a high correlation with its class but has a low correlation with other variables. In general, a variable is said to be good if it has a high correlation with class variables but has a low correlation with other variables. Therefore, the Fast Correlation Based Filter (FCBF) feature selection method is used[17] to select several features that have a high correlation with class variables.

Multiclass SVM

Support Vector Machine (SVM) is a machine learning method based on the principle of Structural Risk Minimization and can be used for solving classification problems in high-dimensional feature spaces.[18] In nonlinear cases, a kernel function is used to map the input space to a higher-dimensional feature space. Parameter selection is a step to obtaining the most optimal hyperparameters for the SVM model, which results in the best classification performance. One of the methods that provide satisfactory results is Grid Search[19], The determination of parameters C and γ can be done using an exponential pattern.[20] The method for determining parameter is based on research conducted by Liu, Zhang, Qu, and Bell.[21] Multiclass SVM is an extension of the SVM method, which was originally designed for binary data classification. Multiclass SVM is applied by decomposing multiclass data into a series of binary classification problems, making it possible to apply standard SVM. There are two approaches to Multiclass SVM namely One-Against-All and One-Against-One. In the OAA approach, each class p is compared with all other classes22. To classify data into e classes/categories, e binary SVM models need to be built. However, In the OAO approach, each class is compared with every other class.[13] To classify data into e classes/categories, e(e-1)/2 binary SVM models need to be built.

Classification Performance Evaluation

Classification performance can be evaluated using a confusion matrix. The confusion matrix is a table that presents the results of classification for measuring the classification performance. Measures that can be used to evaluate classification performance include accuracy, sensitivity, and specificity. Besides using the confusion matrix, classification performance can also use the area under curve (AUC). AUC is a method that measures the area under the Receiver Operating Curve (ROC) graph to assess prediction performance.

RESULTS

The total number of recordings is 22, consisting of seven Concentrated mental conditions, seven neutral mental conditions, and eight relaxed mental conditions. Power Spectral Density (PSD) plots display the spectral power density of brainwave signals and depict the frequency energy distribution in brainwave signals. An example of one of the PSD plots is shown in Figure 2. The PSD plots containing signal frequencies from 0 to 120 Hz indicate that brainwave signals for Concentrated, neutral, and relaxed conditions have delta, theta, alpha, beta, and gamma wave sub bands. Therefore, the preprocessing stage will start with filtering, where the data will be separated into five wave sub bands.

Filtering

The Finite Impulse Response (FIR) Hamming Windows filtering method is used to separate the signal into five wave sub bands. Each mental condition contains five sub bands: delta, theta, alpha, beta, and gamma. The higher the frequency range, the higher the signal density. Therefore, delta will have the lowest signal density, while gamma will have the highest signal density.

Segmentation

Brainwave signals tend to be stationary over short periods. Therefore, time epoching or data segmentation based on time duration is performed to reduce signal waveform variation. The data is divided into ten-second epochs with a five-second overlap, resulting in seven epochs for each recording data.

Signal Feature Extraction

After data segmentation, the next step is feature extraction to capture the characteristics of the signal data. Feature extraction is performed on the five wave sub bands, with each sub band having eight features. Therefore, for one channel, there will be a total of 40 features. This study uses four channels, resulting in a total of 160 features entering the classification stage. The feature extraction results show that there are striking differences in the range of signal features. Therefore, Z-Score Normalization is used to balance the impact of variables in the data modeling process.

Feature Selection

Feature selection using Fast Correlation Based Filter (FCBF) results in 40 selected features. These features include the minimum and maximum features from the delta, theta, alpha, beta, and gamma waves in channels AF7, AF8, TP9, and TP10. These 40 selected features are used as predictor variables in the classification analysis.

Classification Mental State Using the OAA Multiclass SVM

In the One-Against-All (OAA) approach, the class p data is compared with all other data except class p. As a result, three binary models are formed. The Multiclass SVM modeling is performed with optimal parameters obtained from Grid Search. The best model is selected based on the highest Area Under the Curve (AUC) value. The evaluation of the OAA approach with all variables is shown in Table I. Table I shows

Table I: Model Evaluation of All Variables

Kernel	AUC	Accuracy	Sensitivity	Specificity
One Against All Approach Model				
Linear	0.927	0.902	0.901	0.952
Polynomial d=2	0.922	0.896	0.895	0.949
Polynomial d=3	0.926	0.902	0.900	0.952
Polynomial d=4	0.912	0.883	0.882	0.942
RBF	0.907	0.876	0.875	0.939
Sigmoid	0.898	0.864	0.862	0.933
One Against One Approach Model				
Linear	0.941	0.922	0.920	0.962
Polynomial d=2	0.927	0.902	0.901	0.952
Polynomial d=3	0.922	0.896	0.895	0.949
Polynomial d=4	0.931	0.909	0.907	0.955
RBF	0.927	0.902	0.902	0.952
Sigmoid	0.917	0.889	0.889	0.946

Table II: Prediction results using the best model

Recording Data Number	Actual Class	Prediction Class
5	Concentrated	Concentrated
	Concentrated	Concentrated
	Concentrated	Concentrated
	Concentrated	Concentrated
	Concentrated	Concentrated
	Concentrated	Concentrated
	Concentrated	Concentrated
12	Neutral	Concentrated
	Neutral	Concentrated
	Neutral	Neutral
	Neutral	Neutral
	Neutral	Neutral
	Neutral	Neutral
	Neutral	Neutral
19	Relaxed	Relaxed
	Relaxed	Relaxed
	Relaxed	Relaxed
	Relaxed	Relaxed
	Relaxed	Neutral
	Relaxed	Relaxed
	Relaxed	Relaxed

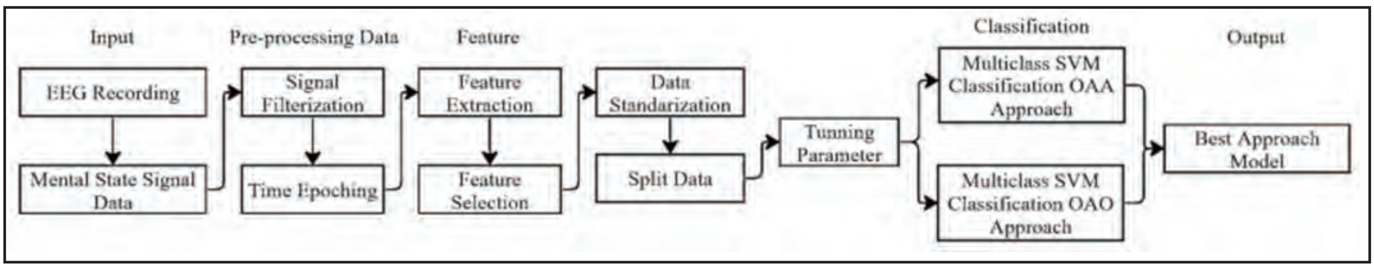

Fig. 1: Research Step

that the linear kernel has the highest AUC compared to other kernels. Therefore, the best model in the OAA approach with all predictor variables is the model with the linear kernel with a parameter C of 0.0625. The AUC value of 0.927 indicates that the classification performance falls into the Excellent Classification category. The accuracy value shows that the model can correctly classify 90.2% of the data into their respective classes.

The OAA approach with predictor variables from feature selection has the best kernel performance, which is Polynomial degree 4 with an AUC of 0.922, indicating that the classification performance is in the Very Good Classification category. The accuracy value of 0.896 indicates that the model can correctly classify 89.6% of the test data using the best kernel and parameters.

The best OAA model is obtained by comparing the AUC between the OAA model with all variables and the OAA

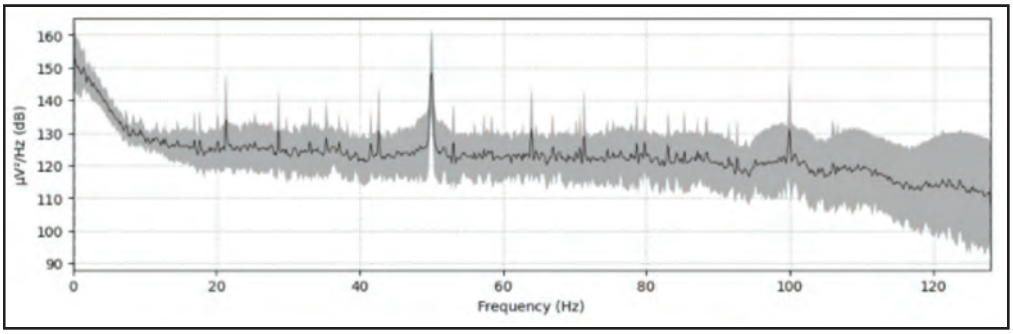

Fig. 2: PSD Plot of Signal Data for Concentrated Mental Condition

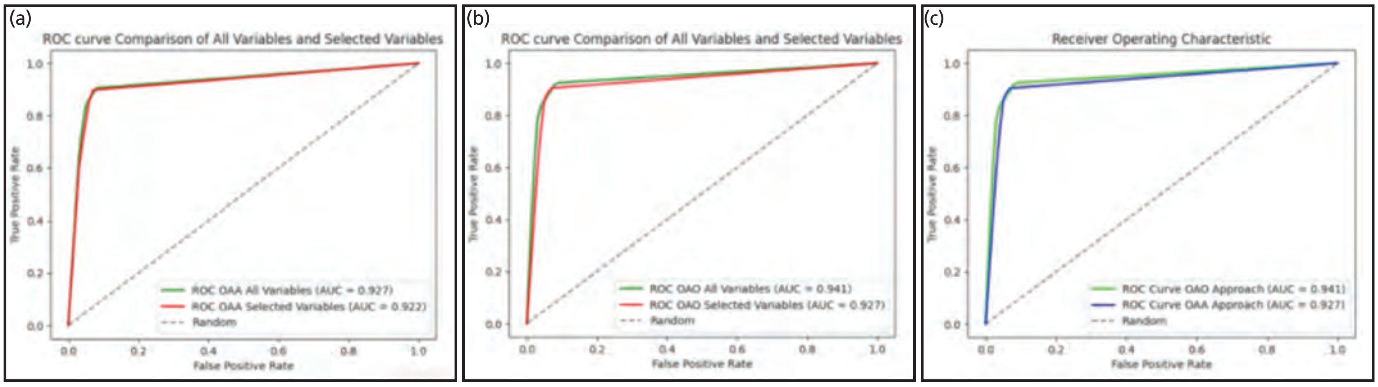

Fig. 3: Comparison ROC curve (a) OAA Model with All Variables and Selected Variables, (b) OAO Model with All Variables and Selected Variables, (c) OAA Approach and OAO Approach

model with selected variables. The OAA model for all variables has an AUC of 0.927, higher than the kernel AUC value of the OAA model for selected variables, which is 0.922. This shows that the model with all variables is better than the model with selected variables. A comparison of the ROC curve between all variables and selected variables in the OAA model is shown in Figure 3 (a). The difference in AUC values of 0.005 means that visually there is no significant difference between the two graphs.

Classification Mental State Using the OAO SVM

In the One-Against-One (OAO) approach, one class is compared with every other class. Like the OAA approach, modeling was performed on linear, polynomial, RBF, and sigmoid kernels using the best parameters according to Grid Search. The model evaluation results of the OAO approach using all feature predictor variables are shown in Table I.

The best kernel is the Linear kernel with the C parameter of 0.031256. The AUC value of 0.941 also implies that the classification ability is in the Excellent Classification category. The accuracy value on the optimal kernel of 0.922 indicates that the model can classify 92.2% of the testing data correctly.

The OAO approach with selected predictor variables has the best kernel performance, which is polynomial degree 3 with an AUC value of 0.922 shows that the classification level reaches the Excellent Classification category. The accuracy value of 0.902 shows that the model can classify 90.2% of the testing data correctly.

The highest AUC in the model with All Variables was 0.941 but the highest AUC in the model with Selected Variables was 0.927. So, it can be concluded that in the OAO approach, the best model is the model with all predictor variables. The ROC curve showing the comparison between the ROC of all variables and the selected variables is shown in Figure 3(b). Visually, the ROC of all features is higher than the ROC of the selected features, this is in accordance with the computational results which state that the area under the curve for all variables is larger than the area under the curve of the selected variables.

Selection of the Best Classifier

The selection of the best classifier between the OAA approach and the OAO approach in the Multiclass SVM method is done by comparing the performance of the best model of each approach. The comparison of the two models is shown in Table I. Table I shows that the AUC, accuracy, sensitivity, and specificity of the best model multiclass SVM OAO approach are higher than the best model multiclass SVM OAA approach. The comparison of the ROC curves between the two approaches is shown in Figure 3(c). Figure 3(c) shows that the area under the OAO curve is larger than the area under the OAA curve. This is in accordance with the results of mathematical calculations.

The higher AUC value of the OAO approach indicates that the Multiclass SVM OAO approach is better at classifying mental state data from electroencephalogram than the Multiclass SVM OAA approach

An example of predicting subjects using the best model is carried out on the 5th recording data for the Concentrated class, the 12th recording data for the neutral class, and the 19th recording data for the relax class. Each recording data has 7 epochs and 160 extracted features.

The comparison between the actual class and the predicted class using the best model on the 5th recording data, 12th recording data, and the 19th is shown in Table II. Table II shows that there are three predicted incorrect data, namely two neutral class data but predicted as a concentrated class, and one relaxed class data but predicted as a neutral class.

DISCUSSION

The series of signal processing stages in this study demonstrates an improved accuracy compared to previous research using the same dataset10. The study by Bird, Manso, Ribeiro, Ekart, & Faria[10], which did not specify the employed filtering method, achieved the highest accuracy of 87.16% using the random forest method, whereas the accuracy of the SVM method was 75.24%. In this study, it achieved the highest accuracy value of 92.2%. This improvement confirms that the series of EEG waveform signal processing steps and the multiclass SVM approach used in this study can improve accuracy compared to processing from previous research with the same dataset.

The high classification performance indicates that EEG signals can effectively represent a person's mental condition. An accuracy of 92.2% implies that EEG-based models can distinguish between concentrated, neutral, and relaxed mental states with high reliability. Therefore, EEG analysis serves not only as a recording of brain activity but also as a practical tool for interpreting psychological states objectively. This capability opens opportunities for EEG-assisted applications in clinical environments, especially in supporting medical personnel to monitor, assess, and tailor treatments based on a patient's cognitive state.

Furthermore, the ability of the model to detect discrepancies between a patient's expected and actual mental state highlights its potential clinical relevance. For instance, if a subject is expected to concentrate but the model detects a relaxed or neutral state, it may suggest signs of cognitive decline, mental fatigue, or stress. Similarly, persistent tension detected during a supposed relaxation phase may indicate underlying conditions such as anxiety, insomnia, or chronic stress. These findings underscore the potential of EEG-based classification models as early screening tools for psychological or neurological disorders.

This study, therefore, lays the groundwork for future research aimed at integrating EEG-based monitoring into mental health diagnostics and personalized interventions, ultimately contributing to improved psychological well-being.

Despite the favorable results, several limitations must be acknowledged. First, this study employed publicly available data, thus future research is advised to utilize real data from EEG recordings in hospital settings to assess the generalizability of this method across different cases. Secondly, we solely utilized data sourced from four EEG channels—AF7, AF8, TP9, and TP10—while there remains a possibility that other EEG channels might be more optimal for classifying mental states such as concentration, neutrality, and relaxation. The signal filtering method in this study only focuses on segmenting the signal waveform into five sub bands, while there is no handling of noise generated when the recording is in progress such as eye blinks, muscle movements, or noise from the recording machine. Future studies may explore various filtering combinations to produce cleaner signals.

Furthermore, feature selection in this study was focused on the level of correlation between predictor variables and class variables without overcoming multicollinearity. Meanwhile, signal data is susceptible to multicollinearity. Therefore, it is suggested that further research apply feature extraction methods such as Principal Component Analysis (PCA) and factor analysis which are more effective in managing multicollinearity. In addition, in this study we use the Grid Search method to select the hyperparameters of the SVM model. However, this method has limitations, including requiring a long computation time, so future research needs to consider the parameter tuning method which has a shorter computation time.

CONCLUSION

This paper presented a study on mental state classification based on EEG signals. The signals go through the data pre-processing stages before finally several features from each wave sub band are extracted to be able to classify mental states of Concentrated, neutral, and relaxed. Through the multiclass SVM approach, the highest AUC value is 0.941 with an accuracy of 92.2% which indicates that the accuracy of the model in classifying data is an excellent classification. These good results indicate that signal processing using computation can support the medical team in classifying the patient's mental condition based on the electroencephalogram accurately, so that it can support medical personnel in clinical monitoring and decision-making.

An important implication of this study is its ability to detect mismatches between the expected and actual state of the patient. If a person is expected to be in a state of concentration but the model shows otherwise, this may indicate cognitive impairment, stress, or mental fatigue that requires further evaluation. Conversely, if the patient is supposed to be in a relaxed state but the model shows that he or she is still in a tense state or has difficulty achieving relaxation, this could be an indication of an anxiety disorder, insomnia, or chronic stress that requires further intervention.

As such, this method can serve as a preliminary study for further research in detecting indications of psychological or clinical disorders, as well as assist in the development of more targeted interventions to improve the quality of patients' mental health and well-being.

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DECLARATION OF INTEREST

The authors would like to disclose that they have no conflict of interests to declare and have no competing interests in this study.

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