ISSN: 2229-6956 (ONLINE)
DOI: 10.21917/ijsc.2025.0517

A NON-FEEDBACK EEG-BASED BRAIN COMPUTER INTERFACE (BCI) FOR COGNITIVE STATE CLASSIFICATION IN TIME DOMAIN

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Abstract
This paper introduces an innovative EEG-based Brain-Computer Interface (BCI), aiming to discern two cognitive states experienced by students during learning sessions. Focusing on "Relaxation" and "Engagement in learning tasks", the study identifies attentive students and students exhibiting disengagement. Utilizing single EEG channel and signals from the fronto-polar region, it aims to develop a real-time engagement detection system compatible with portable devices. Employing a basic machine learning pipeline, the research focuses on time-domain feature extraction and capturing heterogeneous high-level features. Through feature analysis, selection, and support vector machine(SVM) classification, the BCI system differentiates between relaxed and learning states, achieving 60.36% accuracy with 10-fold cross-validation. The subject-wise analysis yields impressive results, reaching up to 93% accuracy. Despite challenges in EEG signal non-stationarity, the model's accuracy underscores the efficacy of the time-domain parameters.

Keywords:
Cognitive Computing, Brain Computer Interface, EEG Analysis, Machine Learning, Time-Domain Analysis

1. INTRODUCTION

Within the realm of cognitive computing, Brain-Computer Interface (BCI) stands out as a captivating field under the broader Human-Computer Interface domain. In recent years, EEG-based BCI systems have emerged as promising tools for understanding and interpreting cognitive states in various domains. By capturing and analyzing brain activity, these systems offer insights into the cognitive processes underlying human behavior. In educational settings, where effective learning strategies are paramount, the ability to assess and classify cognitive states in real-time holds significant potential for enhancing learning outcomes. As such, the development of EEG-based BCI systems tailored specifically for educational environments represents a promising avenue for advancing educational research and practice, particularly in online mode learning.

Cognitive state classification using EEG signals involves the identification and interpretation of patterns in brain activity associated with different mental states, such as attention, relaxation, and engagement [1]. There are various methods for assessing cognitive states, ranging from questionnaire-based self-reported assessments to ones based on neurophysiological signals [2]. EEG signals offer a non- invasive means of accessing neural activity, making them particularly well-suited for studying cognitive processes. Researchers can extract important information from EEG data and develop models capable of accurately classifying cognitive states in real-time by using machine learning algorithms and sophisticated signal processing techniques. These models hold promises in personalized learning interventions, and student support mechanisms in educational settings.

This paper aims to contribute to the burgeoning field of EEG-based BCI research by proposing a novel framework for cognitive state classification in educational settings. By harnessing the power of EEG technology, we seek to develop a system capable of accurately detecting and classifying cognitive states relevant to learning and educational engagement. Our proposed methodology seeks to give educators important insights into students' cognitive states during learning activities by combining machine learning and signal processing technologies, ultimately leading to more effective teaching and learning experiences.

We reviewed the existing literature on cognitive state detection using portable EEG devices and related papers in the domain. An investigation on the feasibility of using the wearable EEG device (MUSE) [3] [4] [5] for assessing the cognitive states of students is also carried out. The details and results regarding these works are as follows: A series of reading and responding to questions tasks are connected to the work. It identifies the comprehension and concentration levels employing the L1-regularized logistic regression. It has been noted that the accuracy of the concentration level prediction is 81%, with the subject-wise model producing the highest accuracy. The prediction of concentration level resulted in the highest accuracy of 67%.The paper [3] conducts a classification of five cognitive tasks: Think, Count, Recall, Breathe, and Draw. The work explored a set of machine learning algorithms, and the results show that Random Forest and RBF SVM perform well with the accuracy of 63% and 61% for different cognitive classification tasks. The study [5] focuses on classifying cognitive tasks relaxing and focus using probability distributions in a user study. The Tsallis entropy measure performed best for the focus score, with a sensitivity of 82.0% and specificity of 82.8%, while the Renyi entropy measure performed best for the relax score. Both studies highlight the importance of machine learning in cognitive task classification. In a study on motor movement imagination tasks, a single-trial-based mental state classification [6] was conducted. This study utilized an ensemble of classifiers, incorporating subject-specific temporal and spatial filters, and applied quadratic regression with 'L1' regularization. The results demonstrated comparable accuracy to techniques using pre-calibrated subject-specific data, highlighting the effectiveness of subject-independent procedures in BCI experiments. The pilot's EEG potentials in a simulated flight environment were the focus of the study [7], which classified the pilot's mental state into three categories: rest mode, navigation flying mode, and dogfight mode. Upon utilizing 10 different statistical features and employing the Random Forest classification algorithm achieved 81.7% accuracy.

A successful EEG-based BCI system relies on the extracted EEG features and the algorithm used for classification. One study

[2] aimed to classify three mental states—neutral, relaxed, and concentrated—using EEG signals. It employed short-term windowing to extract statistical features and applied feature selection algorithms to identify relevant features. Testing various classifiers, the study found that the random forest classifier, based on an attribute selected by the OneR rule set, achieved a prediction accuracy of 87.16%.Another study [8] identified mind-wandering states using EEG markers from sustained attention and visual search tasks. The study uses a support vector machine classifier and single-trial ERP methodology, with alpha power as the most predictive marker. The study [9] employs a long short-term memory (LSTM) based deep ensemble model and the filter bank common spatial pattern approach in conjunction with EEG-based deep neural network models to evaluate cognitive performance. The model achieved a classification accuracy of 87.04% during a mental arithmetic experiment. Finally, the review [10] provides a thorough analysis of classification algorithms used in EEG-based BCIs over a decade until 2017. It identifies key challenges such as low signal-to-noise ratio, and non-stationarity of EEG signals over time or between users. A key finding of the review is the effectiveness of adaptive classifiers (adaptive LDA/QDA,SVM) in addressing these challenges. They are capable of adjusting feature weights over time, ensuring BCI performance even with changing signal distributions.

A thorough examination of EEG literature revealed a prevalent reliance on traditional feature extraction techniques like autoregressive models and power spectral density models. These methods operate under assumptions of linearity, Gaussian distribution, and minimum phase within EEG signals. However, as EEG signals are essentially products of nonlinear systems, these conventional approaches may fall short in capturing the intricate interactions among sinusoidal components at different frequencies. To address this limitation, incorporating time domain analysis emerges as a valuable addition, offering a more holistic understanding of EEG signals by accounting for their temporal characteristics and nonlinear interactions. This integration of time domain analysis into EEG feature extraction methods holds promise for enhanced capturing complex dynamics and nonlinear behaviors inherent in EEG signals[11].

This paper proposes a hybrid set of time-domain features for an EEG-based non-feedback BCI system, which includes low-order and higher-order statistics-based features, and other features like Hjorth and entropy parameters. Also, the study tries to minimize to single channel so that a kind of wearable, portable EEG device can be utilized during real-time implementation. The study delves this feature set into the task of discerning between states of relaxation and performing mathematical work. The research encompasses both subject-level and group level analyses and extends its application to the assessment of student engagement in both classroom and self-paced learning environments. Distinguishing between a relaxed state and active mathematical work engagement aids in identifying students immersed in learning. This distinction helps to implement feedback mechanisms, such as sending alerts or employing gamification methods through learning management systems.

The rest of this article is organized as follows. In Section 2, a comprehensive overview of the data used in the study, detailing its source, characteristics, and preprocessing steps are discussed. Additionally, it delves into the proposed method, elucidating the theoretical framework and methodologies employed for the research. In Section 3, the article presents the results obtained from the experiments conducted. This section aims to provide a robust analysis of the results, addressing their significance and implications. Furthermore, the section outlines the potential directions for future research and areas that merit further exploration. Finally, Section 4 offers a concise summary and implications of the work accomplished in the article.

2. MATERIALS AND METHODS

The proposed system includes three segments: EEG data acquisition and preparation, feature extraction, and cognitive state classification. The Fig.1 describes the diagrammatic representation of the proposed model.

2.1 DATASET USED

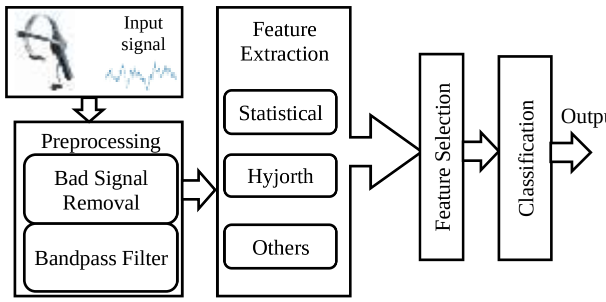

Fig.1. BCI System Architecture

The dataset employed in this study originates from [12] and is publicly accessible from the School of Information, UC Berkeley. It was curated using the Neurosky Mindwave, a consumer- grade brainwave sensing headset, following the 10-20 international electrode placement system. The EEG signals were captured from the fronto-polar lobe position (FP1) at a sampling rate of 512 Hz. The dataset encompasses readings from 30 students concurrently exposed to different stimulus presentations such as relaxation, math work, music listening, video watching. The data is collected in a synchronized manner from all the 30 students. Since the current work focuses on educational scenarios, this work utilizes the data from the relaxed period and math work stimuli period only. The Fig.2 provides the statistics of the dataset pertinent to this investigation.

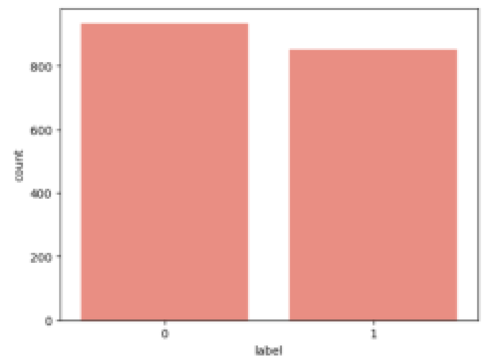

Fig.2. Data Statistics: Relax (0) & Mathwork (1)

Each subject's dataset consists of continuous segments lasting between 26 and 29 seconds for the math-doing state and between

27 and 31 seconds for the relaxation state, except Subject 29, which contains 60 seconds of relaxation data and 54 seconds of math-doing data. The dataset considers one epoch duration as one second.

2.2 EEG SIGNALS

EEG signal refers to a continuous, non-linear, non-stationary, time-varying signal that captures the electrical activity of the brain. This signal is characterized by amplitudes ranging from microvolts to a few millivolts. The frequency spectrum of an EEG signal extends from 0.1 Hz to around 50 Hz. The EEG signal's frequency spectrum is split into several bands, including delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz). The time-varying and non-stationary nature of EEG signals helps to process from the time domain and frequency domain to get valuable insights into cognitive processes and neurological conditions. Time domain analysis of EEG signals focuses on the temporal characteristics and dynamics of brain activity while frequency domain analysis provides information about different frequency components present in the signal.

2.3 TIME-DOMAIN ANALYSIS

Temporal analysis observes the changes in signal amplitude over time, offering insights into and patterns, trends, temporal relationships within the signal. Specific mental states or neurological conditions like seizure activity exhibit characteristic temporal patterns. In BCI systems, where real-time monitoring is critical, time domain analysis promptly furnishes information about the ongoing brain activity, facilitating timely interventions or feedback. This study concentrates on a set of sophisticated features derived from time-domain analysis to discern distinct cognitive states. The statistical characteristics of the EEG signal, such as mean, median, variance, standard deviation, skewness, kurtosis, etc. are the most basic properties. Some non-statistical linear features in time domain includes Peak-to-Peak Amplitude, Signal Magnitude Area,Mean Absolute Value, Zero crossing rate etc. The nonlinear feature set includes entropy and Hjorth values. The Hjorth parameters are based on the variance of the derivatives of the EEG signal. Hjorth parameters most frequently utilized are mobility, activity, and complexity. Entropy measures the degree of randomness in the EEG signal by quantifying the distribution of signal amplitudes or frequencies. Lower values of entropy suggest more regular or predictable patterns [13].

2.4 FREQUENCY-DOMAIN ANALYSIS

Frequency domain analysis techniques focus on discerning characteristics derived from the sinusoidal components inherent in the data. Typically, this involves initially converting the data from the time domain to the frequency domain. EEG signals exhibit distinct activity within specific frequency bands. Consequently, analyzing the frequency spectrum of EEG signals is pivotal for identifying these bands and categorizing brainwaves. It is observed that during cognitive tasks requiring focused attention or sustained mental effort, alpha power typically decreases. Conversely, during tasks involving relaxation, meditation, or mind-wandering, alpha power is found increasing. Beta oscillations are associated with active cognitive engagement. Tasks requiring active problem-solving, decision-making often exhibit increased beta power over frontal and central brain regions. During tasks involving working memory, increase in gamma power is observed over prefrontal and parietal regions. Delta and theta oscillations play a role in memory encoding, retrieval, and attentional processes [14].

In the frequency domain, power spectral density (PSD) is a powerful metric that provides a multitude of properties, including intensity-weighted mean frequency (IWMF), intensity-weighted bandwidth (IWBW), and spectral edge frequency (SEF) [15]. Additionally, assessing the band power of each stimulus frequency is another prevalent mechanism for feature extraction in the frequency domain. In this work, we conducted an analysis on the absolute and relative power spectrum values for the major frequency bands α, β, γ, δ and θ for the cognitive state prediction.

2.5 PREPROCESSING

In the preprocessing step, the dataset's raw EEG voltage values are converted according to Neurosky Support Guide[16]. Next, bad signals are removed from the dataset by checking the signal quality value with the quantification that, the value 0 indicates optimal quality, and values exceeding 128 suggest improper headset placement. Finally, the band pass filter is applied to filter the signals in the 1-40 Hz range.

2.6 FEATURE EXTRACTION

The feature extraction process aims to select information crucial for classification. This study focuses on the time domain and adopts statistical methods, a conventional feature extraction modality in signal processing. Additionally, methods encompassing entropy value, signal energy, and Hjorth parameters calculation are employed to construct the feature set. Additionally, we employed the power spectrum values to identify the significance of frequency domain features in the cognitive state classification.

2.6.1 Statistical Features:

Statistical feature extraction of EEG signals involves quantifying key statistical properties, such as mean, variance, kurtosis, and skewness to provide a concise numerical representation of the signal's distribution. These features play a crucial role in characterizing the central tendencies, variability, and shape of EEG waveforms, enabling effective pattern recognition and classification [17]. This work concentrates on the following 9 statistical parameters as summarized in Table I.

Table.1. Statistical Features

Item	Parameter	Description
1	mean(x)	mean of the signal segment
2	std(x)	standard deviation of the signal segment
3	var(x)	variance of the signal segment
4	min(x)	minimum value in the signal
5	max(x)	maximum value in the signal
6	argmin(x)	index of minimum value
7	argmax(x)	index of maximum value
8	skewness(x)	returns the symmetry of signal
9	kurtosis(x)	returns the peakedness of signal

2.6.2 Time Domain Features: Beyond Statistical Measures:

Other than statistical parameters, we considered a set of descriptors from the time domain. The different signal dynamics included in the feature set are detailed below.

- *Peak-to-Peak Amplitude*: It returns the amplitude difference between the maximum and minimum values from the signal. It provides a measure of variability. Refer to Eq.(1).

$$P_{tP} = X_{max}\text{-}X_{min} \tag{1}$$

- *Signal Magnitude Area*: Signal magnitude area is a measure of the magnitude of a varying quantity and is calculated as given in Eq.(2). It is the area under the absolute value of the signal. It quantifies the overall magnitude of the signal.

$$SMA = \sum_{i=1}^{N} | x[i] | \tag{2}$$

- *Mean Absolute Value*: The mean absolute value of a signal is computed using Eq.(3) by taking the average of the absolute values of the samples. For a given signal x of length N,

$$\text{MAV} = \frac{1}{N}\sum_{i=1}^{N} | x[i] | \tag{3}$$

- *Zero Crossing Rate*: It is a measurement that reflects the times that signs of two adjacent values in a signal change from positive to negative and vice versa. It can provide insights into the frequency and dynamics of the signal. Refer Eq.(4).

$$\text{ZCR} = \frac{1}{2}\sum_{i=2}^{N} | \text{sign}(x_i) - \text{sign}(x_{i-1}) | \tag{4}$$

- *Waveform Length*: It is the total length of the waveform. It is calculated using Eq.(5) as the sum of the absolute differences between consecutive data points. It is useful for capturing the rate of change or variability in a signal.

$$\text{WL} = \sum_{i=1}^{N} | x_i - x_{i-1} | \tag{5}$$

- *Power of the Signal*: In signal processing, energy is defined as the measure of signal strength. Power is defined as the amount of energy consumed per unit time. In the discrete domain, the energy of the signal is calculated by Eq.(6) and power of signal is calculated as Eq.(7).

$$E_x = \sum_{n=-\infty}^{\infty} | x(n) |^2 \tag{6}$$

$$P_x = \lim_{N\to\infty} \frac{1}{N}\sum_{n=0}^{N-1} | x(n) |^2 \tag{7}$$

where $x(n)$ represents the value of signal at n^{th} instant and N is the number of sample per epoch.

- *Root Mean Square*: Another parameter that represents the power within the signal is termed as the root mean square (RMS) value. It characterizes the average power or amplitude of a signal. Refer Eq.(8).

$$\text{RMS} = \sqrt{\sum_{n=0}^{N-1} x(n)^2} \tag{8}$$

- *Hyjorth Parameters*: Hjorth parameters are indicators of three properties in EEG signal processing: Activity, Mobility, and Complexity. They describe the overall energy of the EEG signal, its activity, changes, and complexity. The activity parameter represents the signal power, indicating the variance and surface of the power spectrum in the frequency domain as in Eq.(9)

$$\text{Activity} = \text{var}(x(t)) \tag{9}$$

The mobility parameter, defined in Eq. (10), is the mean frequency or rate of signal change, calculated by dividing the variance of the first derivative of the signal by the variance of the signal.

$$\text{Mobility} = \sqrt{\frac{\text{var}\left(\frac{dx(t)}{dt}\right)}{\text{var}(x(t))}} \tag{10}$$

The Complexity parameter measures the signal's complexity or irregularity by comparing it to a pure sine wave. It converges to 1 if the signal is more similar, calculated in Eq.(11) as the square root of the first derivative's mobility to the signal's mobility.

$$\text{Complexity} = \frac{\text{Mobility}\left(\frac{dx(t)}{dt}\right)}{\text{Mobility}(x(t))} \tag{11}$$

- *Entropy Feature*: Entropy is a crucial time domain feature in EEG data processing and statistics, used to measure the regularity and unpredictability of fluctuations over time-series data. Shannon entropy quantifies uncertainty or disorder, calculated using Eq.(12), where n is the number of intervals, x_i is the signal value in the interval, and $p(x_i)$ is the probability of x_i.

$$H(x) = \sum_{i=1}^{N} p(x_i)\log_2 p(x_i) \tag{12}$$

In summary, the work extracts a total of 20 features: nine statistical features, seven non-statistical, linear features, and four non-linear features from the raw EEG values for the cognitive state classification.

2.7 FEATURE SELECTION

Feature selection is a vital step in data preprocessing that identifies critical features and also helps in the dimension reduction of the feature set. In this work, we apply two feature selection strategies sequentially on the feature set to find the best parameters yielding maximum classification accuracy. The selection of features is performed through mutual information analysis and sequential feature selection method to select the best 'K' features.

2.7.1 Mutual Information Gain:

Mutual information is a symmetrical measure of dependence between variables, based on entropy values. It is a univariate filter method that can capture linear and nonlinear relationships between variables.

$$I(X,Y) = H(X) - H(X/Y) \tag{13}$$

Eq.(13) represents the mutual information calculation. Here $I(X,Y)$ represent mutual information, $H(X)$ represents entropy, and $H(X/Y)$ represents conditional entropy. This study conducted a mutual information analysis on different linear and non-linear features. The result has shown that the features “skewness”, “minimum” possess the least information gain (0.0) with the classification label, so these features are eliminated from the feature list. The Fig.3 highlighted the significance of parameters in the study.

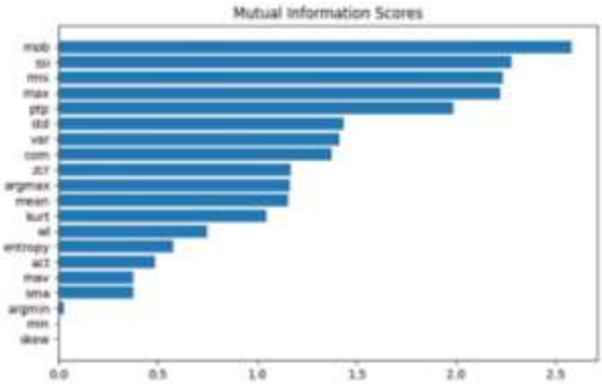

Fig.3. Mutual Information Gain Analysis

2.7.2 *Sequential Forward Selection:*

- Sequential Forward Selection (SFS) algorithm is a greedy approach for sequential feature selection. This method iteratively adjusts the feature set to enhance the predictive model’s performance by adding or removing features. In the context of this study, SFS is employed to determine the scale of feature importance and assess model performance. The feature set after mutual information gain analysis has undergone a forward selection method and identified the most significant feature in each iteration. Acknowledging the limitation of the SFS algorithm, where the order of features can influence the final selected set, we approached the process iteratively to mitigate the issue. In each iteration, the best features are removed from the set and selected the best remaining features. This iterative approach enhances the algorithm’s consistency. The feature importance resulting from this analysis is depicted in Fig.4.

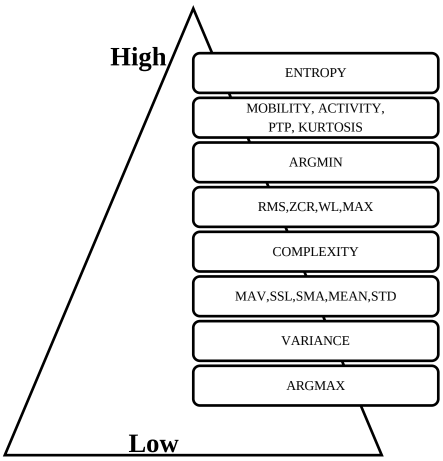

Fig.4. Feature Importance from SFS (Bottom to Top)

2.8 CLASSIFICATION

Support Vector Machine (SVM) stands out as a robust machine learning algorithm extensively utilized in EEG classification tasks, primarily due to its capability to manage high-dimensional data, address nonlinearity with kernel tricks, and handle multiclass classification scenarios. SVM employs a discriminant hyperplane to identify classes and maximize margins, which enhances generalization capabilities. The regularization parameter C allows accommodation of outliers. While SVM typically uses linear decision boundaries, it can create nonlinear decision boundaries through the “kernel trick.” In BCI research, the Gaussian or Radial Basis Function (RBF) kernel is commonly used, both of which yield excellent results for BCI applications [18]. SVM has demonstrated considerable success across a spectrum of EEG applications, spanning from motor imagery classification and mental state recognition to various Brain-Computer Interface (BCI) implementations [19].

The SVM model is used in binary classification to create a hyperplane that best divides data points into one of the two classes. The hyperplane’s distance from the closest data points on each side is maximized. Eq.(14) defines the general form of hyperplane for linearly separable datasets.

$$w^T x + b = 0 \tag{14}$$

where w is the normal vector to the hyperplane, and b is the bias term. We need to select a classifier, $d=\text{sign}(w^T x+b)$ for each data point x_i, such that the Eq.(15) holds.

$$d_i(w^T x_i + b) \geq 1, \text{where} 1 \leq i \leq n \tag{15}$$

Finally, w and b are optimized to set an optimal separating hyperplane, and the margin between the two classes is maximized. The hyperparameters of the SVM algorithm considered for performance optimization include kernel, *C*, and gamma values.

2.8.1 *Gridsearch Algorithm:*

The Gridsearch algorithm is an optimization technique used for machine learning model hyperparameter tuning . It chooses the optimal settings for your model optimization.

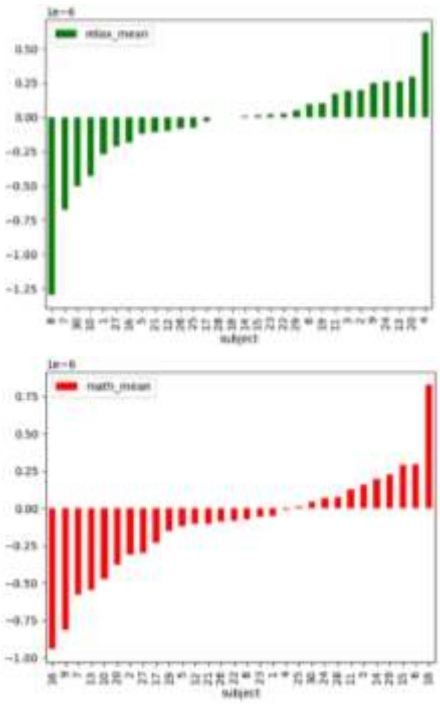

Fig.5. Whole subjects Mean EEG: The graph on the left indicates Relax state and on the right indicates Math doing state

Grid Search utilizes an exhaustive search approach, methodically examining different combinations of designated hyper parameters and their initial values. Using a cross validated model to evaluate performance at various parameter values, this method entails fine-tuning parameters. Grid Search can, however, become time- and resource-intensive due to its exhaustive nature, especially as the number of hyper parameters increases.

3. RESULTS AND DISCUSSIONS

Using a binary SVM classification model, the study analyzes 30 students' EEG readings in relaxed and mathwork doing states. The classification is conducted in two methods: subject-wise and subject-independent, using a comprehensive set of parameters. The study develops a generalized model across subjects. Also it helps to study the inter subject and intra subject variability across the two states in time domain. Refer to Fig.5 for a comparison of EEG values during the two events considered in this research.

We employed the Support Vector Machine algorithm for distinguishing the two cognitive states. To enhance the robustness of the model developed, we executed a 10-fold cross-validation (CV) during the model-building process. To evaluate the performance of the model, Accuracy and F1 score are adopted as metrics and are calculated according to the Eq.(16) and Eq.(17).

$$F1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \tag{16}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

Here the variables TP, FP, TN, FN indicate the number of true positive, false positive, true negative, and false negative values after classification. Using the different sets of features from SFS, we derived different models. The level of importance of features from SFS is indicated in Table.2.

Table.2. Feature Importance Levels

Level	Parameters
1	Entropy
2	Mobility, Activity, PtP, Kurtosis
3	Argmin
4	RMS,ZCR,WL,MAX
5	Complexity
6	MAV,SSI,SMA,MEAN,STD
7	Variance
8	Argmax

The 10-fold CV accuracy scores of different models constructed based on feature importance are presented in Table.3. The results demonstrate the highest average accuracy of 59.02% and F1 score of 58.87 with the feature set containing all the feature values. Notably, the statistical features yielded a lesser feature importance but contributed to classification in a fare manner. Based on these results, the decision is made to employ the model with all feature set for the classification task of distinguishing two different cognitive states relaxed and math work processing. This proves the importance of hybrid feature sets in the EEG classification for differentiating cognitive states.

Table.3. Different Model Accuracy

Model	Parameters	Accuracy	F1 Score
1	Level 1	56.89	47.32
2	Level 1,2	57.90	53.03
3	Level 1,2,3	57.0	53.40
4	Level 1,2,3,4	57.56	54.51
5	Level 1,2,3,4,5	57.22	55.19
6	Level 1,2,3,4,5,6	58.62	57.42
7	Level 1,2,3,4,5,6,7	58.57	57.61
8	**Level 1,2,3,4,5,6,7,8**	**59.02**	**58.87**
9	Statistical	53.86	54.99
10	Linear, Non-Statistical	55.72	58.71
11	Hyjorth	56.05	48.20
12	Non-Statistical	57.96	52.94
13	Non-Linear, Non-statistical	58.46	53.94

To improve the model performance, parameter tuning and 10-fold cross-validation approach is performed using the Grid search algorithm. it is found that the radial basis function is the best kernel, and the parameter 'C' when fine-tuned with values [0.1, 1, 10, 100], the optimal performance is achieved when set to 100. The gamma value is tested with values [1, 0.1, 0.01, 0.001, 0.0001], and it is found that 0.01 is the optimal value. Finally, the parameter-tuned SVM model achieves a mean accuracy of 60.36% and an F1 score of 58.87.

It has been observed that subject-specific differences influence EEG variability in synchronous tasks in brain structure, functionality, and behavior [20] [21]. Therefore, we conducted experiments to assess the effectiveness of the proposed method in predicting subject-specific cognitive states. We have built 30 subject-specific classification models utilizing the EEG data of every individual subject in two different cognitive states. The accuracy results from 10-fold CV of subject-wise models are depicted in Fig.6.

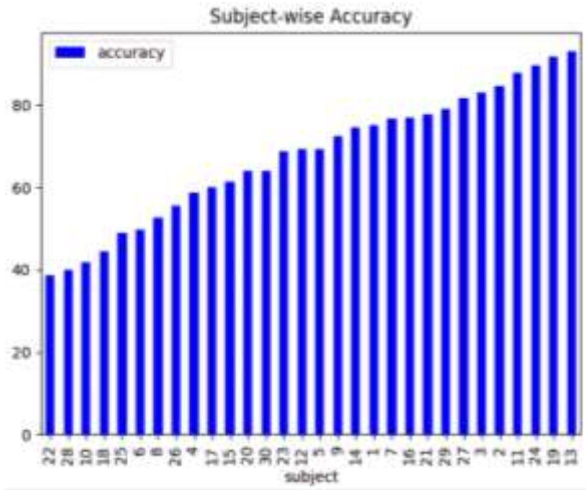

Fig.6. Subjectwise Study: 10-Fold CV Accuracy

The results suggest that the identified feature set is more effective in subject-wise studies distinguishing different cognitive states. On average, an accuracy of 67.69% is achieved in subject-wise study. Notably, Subject 22 exhibits a lower accuracy of 38.66%, which is very below the chance level, while Subject 13 achieves the highest accuracy of 93%. The variation in results is explored through a comparative analysis conducted on two proprietary values, “Attention” and “Meditation,” obtained from the EEG device. The objective was to explore whether subjects with lower classification accuracy might be experiencing disengagement or mental tension, reflected in non-calm states of mind. The graphs in Fig.7 depict a comparison of these values during the two cognitive states.

Since this analysis yielded minimal contribution to the drastic variation in subject-specific accuracy, we further explored the machine learning model by analyzing the accuracy values obtained from the 10-fold cross-validation results. It became apparent that there was significant variation in accuracy among the different folds. The Fig.8 illustrates the accuracy at each fold for subject 22 with the lowest accuracy. This indicates that the model cannot perform well on this small and imbalanced dataset and the classifier has not been able to learn the data adequately.

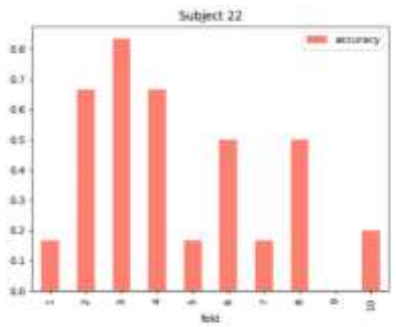

Fig.8. 10-Fold Accuracy Result: Subject 22

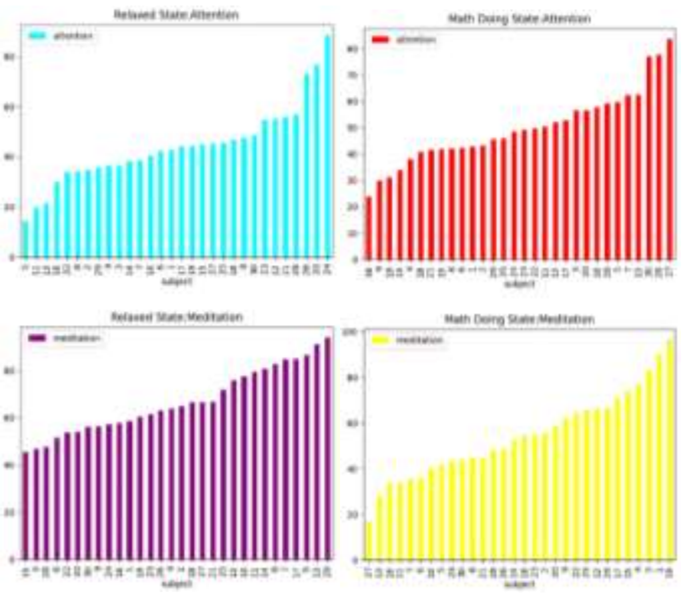

Fig.7. Attention-Meditation Analysis

In light of the limited discriminatory power observed in the time-domain model between the two cognitive states, we opted to explore the frequency domain through band power analysis. Leveraging the relative power values provided by the dataset, we conducted an in-depth examination to uncover potential distinctions during the different cognitive states. As depicted in the box plots illustrated in Fig.9, our findings revealed minimal discernible changes in band powers across the two cognitive states. We also carried out Wilcoxon rank sum tests with continuity correction to compare the distribution of various frequency band values (Delta, Theta, Alpha, Beta, and Gamma) between two different conditions. The results are summarized in Table.4.

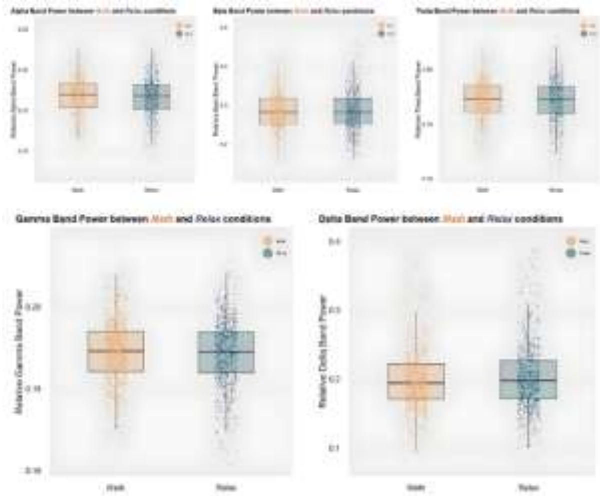

Fig.9. Band Power Analysis

Table.4. Wilcoxon Rank Sum Test Result

Frequency band	T-Statistics	p-Value
Delta	421099	0.1702
Theta	442206	0.6626
Alpha	453123	0.1703
Beta	435113	0.8641
Gamma	442206	0.8641

Despite the meticulous examination of time domain features and frequency band power features, our analysis did not yield significant insights into the differentiation between cognitive states. This outcome could potentially stem from various factors, including the relatively small subset of electrodes under investigation or the limited number of subjects included in the study. Also while observing the experiment paradigm; it is found that mathwork includes only the basic arithmetic operations that could be solved in a relaxed manner by the students of this age group. The easiness in the cognitive task can lead to poor classification between the two states under investigation. This underscores the complexity of distinguishing cognitive processes and highlights the challenges inherent in EEG-based cognitive state classification. The future directions of this research could possibly be using higher difficulty level math questions.

4. CONCLUSION

This study explores various EEG features for cognitive state classification, leveraging signals from a single electrode position. An SVM-based classification model distinguishes between relaxed and engaged learning states, achieving a peak accuracy of 60.36%. The subject-wise analysis demonstrates robustness, with individual accuracy reaching 93%, emphasizing the importance of cognitive state detection in E-Learning for enhancing student engagement and learning outcomes.

The proposed model integrates higher-order features and a machine learning classifier-based approach, reducing computational time and complexity. This approach holds promise for real-time engagement measurement in E-Learning. Though the model exhibits limitations, considering the usage of a single electrode for cognitive state classification, it shows promising results in subject-based and subject-independent analyses. It is believed that the precision of classification results could be improved by incorporating additional posterior lobe EEG data. Exploring more EEG features can provide more insights into neural activity during different cognitive states, and robust approaches like artificial neural networks can improve classification accuracy.

Future research will address limitations by expanding electrode coverage and diversifying the subject pool to enhance model discriminatory power. Advancements in this area could lead to more sophisticated tools for cognitive state detection, revolutionizing E-Learning.

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