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Classification of Human Concentration Levels Based on Electroencephalography Signals

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***Abstract*—Concentration denotes the capability to direct one's attention to a specific subject matter. Presently, within the era characterized by an overwhelming abundance of information inundating human existence, distractions frequently impede human concentration, thereby influencing the depth of knowledge acquisition. Various elements contribute to the decline in human concentration, including diminished metabolic states, inadequate sleep, and engaging in multiple tasks simultaneously. The cognitive state of an individual during the process of thinking can be assessed through the analysis of electroencephalography signals. The primary objective of this investigation is to facilitate experts' interpretation of electroencephalography signal outcomes for categorizing concentration levels. The dataset utilized in this examination comprises unprocessed EEG data obtained from observing individuals in both relaxation and concentration states. After data preprocessing, feature extraction is executed, and classification is performed using the Support Vector Machine technique. The outcome of this study reveals an accuracy rate of 84%. These developments allow for continual monitoring of brain function, an enhanced comprehension of cerebral activities, and increased operational efficacy of end-effectors. The implications of these advancements on prospective research opportunities are evident in the potential for more accurate diagnosis of neurological disorders and the progression of sophisticated BCI applications designed to support healthcare and monitor cognitive states. The evolution of EEG technology is paving the way for novel research pathways in neuroscience and human-computer interaction.**

***Keywords*— Human concentration; support vector machine; brain wave; electroencephalography.**

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I. INTRODUCTION

Concentration is the ability to focus entirely on an object. A person's state of mind when thinking can be determined by using electroencephalography (EEG) signals. EEG signals can be detected by the state of mind, even without physical movement. EEG signals are used to provide information on brain function. EEG signal cannot be viewed directly because it has a small electric wave size. EEG signal recording includes information on electrical activity in the brain. EEG can provide convenience in signal recording because it can detect a person's state of mind, such as concentration [1]. Every human being needs concentration when doing an activity. Many factors affect concentration loss, such as reduced metabolic states, drug consumption, sleep deprivation, and multitasking. Therefore, a system is needed that can read brain wave signals by classifying concentration levels. Numerous studies have been conducted on electroencephalographic signals, including one that determined a person's emotional state by Liu et al. [2] using a library of emotional video clips chosen in real-time from over a thousand film clips. The accuracy rate for classifying the three positive emotions was 86.43%, whereas the accuracy rate for classifying the four negative emotions was 65.09%. The accuracy for emotions as a whole was 92.26%.

Saha et al. [3] conducted follow-up research in 2017 by employing signals from the EEG with alert and non-alert categories for online detection of cognitive failure while driving. The type-2 fuzzy method defines a neural classifier that removes uncertainty in motor planning categorization. The accuracy obtained is 88%. Utilizing the discrete wavelet transform to analyze EEG signals, Chiang et al. [4] diagnosed epilepsy patients and minimized entropy using Fuzzy for the characteristics of each brain wave, and the classification used was the associative Petri net. The accuracy obtained reached 98.6%. Furthermore, Krishna et al.'s [5] study from 2019 classified the four fundamental emotions—happy, fearful, sad, and relaxed—by breaking down the EEG data into time domain feature extraction. The retrieved characteristics are fed into the extreme learning machine classifier to classify emotions such as happiness, fear, sorrow, and relaxation. The accuracy obtained from this investigation reached 87.1%. In a follow-up study published in 2015, Cheong et al. [6] used the discrete wavelet transform to examine EEG signals from autistic individuals and trained the multilayer perceptron (MLP) neural network to categorize signals into three severity levels of autism (mild, moderate, and severe). The accuracy obtained reached 92.3%.

A prediction model was created in 2023 due to research by Zhou et al. to determine a regression relationship between the EEG signals from many different channels and the EEG signals from a select few. Instead of directly employing recorded multiple-channel EEGs, estimated full-channel EEGs enable acquiring additional MI-related data and improved classification accuracy. The regression model can calculate other channel EEGs from multiple-channel EEGs acquired. The suggested approach produces equivalent or even better performance compared to the conventional way using directly recorded full-channel EEG and achieves significant accuracy improvements over the standard method using directly recorded multiple-channel EEG [7].

In a paper published in 2023, Harvey and Shahwan recommended that the authors concentrate on assessing facts and information on potential drivers or factors that may impact the result and prognosis, notably by thoroughly examining all research on EEG data in particular. The clinical characteristics of the IGE syndromes that make up TAS share a lot of similarities, the authors found, which often complicates prognostication. TAS's clinical and EEG diagnostic characteristics are well recognized, but little is known about the prognosis characteristics of each syndrome, whether clinically or electroencephalographically connected. In addition, the authors found that the predictive value of EEG in TAS is unknown in clinical practice and that prognostic markers, especially those associated with EEG, are rarely adequately studied. The authors came to the conclusion that factors that might influence the treatment response, result, or natural history of TAS are not well understood or supported by research as a result of conflicting findings and varied study techniques [8].

In 2023, Parsa et al. [9] concluded that deep learning algorithms are incredibly effective at categorizing different neuropsychiatric diseases from EEG patterns. The review highlights the effects of several parameters, such as subject count, network design, and frequency bandwidth, on how well deep neural networks do in classifying EEG. This work highlights the significance of EEG feature extraction in enhancing classification accuracy. To increase the effectiveness of deep neural networks in classifying EEG, the authors propose that future research should concentrate on creating new techniques to automatically learn relevant and interpretable aspects of input signals. Deep learning criteria in EEG classification are also necessary for better clinical communication and implementation.

A deep learning-based neural decoder leveraging pre-motion EEG inputs for 3D hand kinematics was proposed by Jain and Kumar [10]. This work investigates the feasibility of using EEG signals during reach and handheld activities to decipher intersubject 3D hand movements. In intra-subject and between-subject settings, the proposed CNN-LSTM decoder can achieve significant correlations in the three axes of up to 0.730 and 0.627, respectively. Therefore, it can offer helpful information regarding hand position decoding of premovement EEG signals for real-world Brain-Computer Interface (BCI) applications. This study finds that numerous EEG pause windows have been used to determine trajectory intentions, and premovement neural signals contained in electrical brain waves can be used to decode hand trajectories effectively.

EEG reactivity with electrical stimulation and quantitative analysis, according to Liu et al.'s [11] analysis may be a promising predictive indicator for neurologic prognosis in critically ill patients with severe hemispheric infarction. The study demonstrates that electrical stimulation and quantitative analysis can significantly enhance prognosis accuracy in clinical practice. Gallotto et al. [12] discussed the need for precise and rapid EEG biomarkers to identify epilepsy. Epilepsy is a prominent comorbidity with several neurological diseases in elderly people. Interictal epileptiform discharge (IED), a well-known epilepsy biomarker, is only found in a small portion of EEGs. Thus, identifying additional trustworthy biomarkers will aid clinicians in diagnosing illnesses absent overt epileptic activity, permitting prompt prescription of the necessary treatments.

A more precise understanding of the relative contribution of different brain inputs to the EEG signal was provided by Thio and Grill [13]. EEG modeling, analysis, and interpretation can be made more accurate with the help of this information. This further highlights the significance of considering all brain activity sources when interpreting EEG measurements. This publication can benefit researchers and medical professionals who utilize EEG to diagnose and treat neurological problems. A method to enhance EEG/ERP signals using Kalman filters and metaheuristically tuned parameters was published by Yadav et al. [14]. The social mimic optimization method optimizes the adaptive Kalman filter parameters. The suggested approach was evaluated in various chaotic conditions before being compared to industry-standard optimization techniques. The outcomes demonstrate that the proposed approach performs better than existing methods in the literature and can be applied to improve EEG/ERP signals. The proposed methodology may thus be a helpful tool for enhancing EEG/ERP signals, as this paper says.

According to Dash et al. [15], a new filter-bank-based hybrid technique has been developed to eliminate ocular aberrations from EEG signals. The suggested method is based on a dyadic cutoff point based on empirical wavelet transform and a Savitzky–Golay-driven total variation filter. The proposed technique's effectiveness in removing ocular artifacts caused by blinking and eye movements was proven. The suggested approach has also been verified using wearable EEG with sensor inputs by ocular artifact removal. Existing techniques for eradicating eye motion and eye blinking anomalies from EEG recordings were compared to the proposed technique's denoising performance.

In 2023, Frescura et al. [16] investigated how nearby sounds affected EEG alpha waves, revealing individual preferences and relaxed moods. The study's results demonstrated that participants' alpha wave reactions to noise from neighbors were significantly higher in those with low noise sensitivity and favorable sentiments toward neighbors than in those with high noise sensitivity and unfavorable attitudes. The study also discovered that music played through a wall partition with minimal sound attenuation elicited a significantly higher alpha wave response than footsteps audible through the floor at a low-impact sound pressure level. The autocorrelation function's practical duration was established to research subjective preferences. Speech and music sounds heard at varied SPLs differed significantly from one another. An enormous alpha wave response is produced by footsteps in combination with an air source rather than by single footsteps.

Sarma and Barma [17] proposed an emotion recognition technique using an EEG signal by selecting the appropriate EEG segment for the target emotion. The matching EEG segments were identified using random matrix theory and a multivariate systems analysis framework. The proposed method achieves high accuracy for emotion analysis on two EEG data sets—SEED and DEAP. Features and channels of CWT in the brain's frontal, temporal, and occipital regions match the k-NN classifier exceptionally well. Furthermore, the chosen EEG segments with the lowest entropy variation coefficient attained the maximum classification accuracy. Numerous analyses—in particular, the appropriate EEG segment length, channel choice, and chosen segment characteristics—have been looked into.

Mumtaz et al. [18] outlined the shortcomings of EEG artifact reduction methods in 2021 and provided recommendations for improvement. This study outlines the general and algorithm-specific difficulties associated with EEG artifact reduction techniques. The MATLAB and Python-based toolbox developed for EEG preprocessing is also covered in this publication. This study also gives an overview of EEG artifact removal techniques and briefly describes the many kinds of EEG artifacts. The recommendations provided in the paper can be used as a reference when selecting the best instruments and methods for eliminating EEG artifacts. This study suggests that the EEG artifact reduction approach can be used to its full potential while effectively addressing the problems that may cause the inferred interference from EEG data to rise.

A new automatic ICA classifier algorithm named iMARA was presented by Haresign et al. [19]. It was created specifically to work with infant EEG data and EEG data gathered during parent-infant naturalistic interactions. The iMARA classifier outperforms the original MARA, an adult-trained classifier, in terms of classification accuracy and is superior at eliminating stereotype artifacts from simple visual attention ERP studies. Researchers studying EEG development now have a versatile tool for automatically detecting and eliminating fake ICA components, thanks to this new method.

In 2021, Chen et al. [20] develop a general framework for accurately identifying sleep spindles using features in the sleep EEG's macroscale and microscale entropy. This system uses a compact convolutional neural network with spatial pyramid coupling to infer deeply controlled aspects of variable-length EEG epochs and an "elastic" time window to adjust to changing spindle durations in EEG. The classification of spindles is then supported by combining these depth features and EEG-age entropy. The suggested framework performs better than its cutting-edge competitors with an F1-score of 0.66 while adding 0.034 more information entropy to the equation. Generally speaking, the framework's essential nature opens the door to general recognition of complex EEG waveforms or time series.

In 2021, Rahman et al. [21] analyzed studies that employed EEG signals to find potential links between emotional state and brain activity. The authors explain basic emotions theoretically and discuss the appropriate feature extraction, selection, and classification procedures used. Additionally, they go through structured methods for selecting subjects, stimuli, feature extraction, and selection procedures. A discussion of possible future approaches and the main challenges for researchers developing EEG-based emotion analysis tools concludes the report.

Min et al. [22] created a portable driver tiredness detection framework in 2021 using prefrontal EEG signals and a hybrid model that is rapid and effective on entropy analysis methodologies to boost detection quality significantly. By using a multi entropy measure, this study shows how the proposed method may analyze a very robust representation of single-channel EEG data. The trial outcomes show a notable improvement in the model's performance and show how effective and practical the suggested method is for detecting driver fatigue. This study presents a novel approach for real-time single-channel signal analysis with enormous potential: using prefrontal brain waves to create a highly efficient system to detect driver fatigue.

Albaqami et al. [23] presented a computerized binary categorization system to classify brain signals in multichannel EEG scans using the wavelet packet decomposition (WPD) method in 2021. This technique divides an EEG signal into frequency sub-bands and obtains statistical properties for every selected coefficient. The obtained features are categorized utilizing CatBoost, XGBoost, and LightGBM, examples of frameworks based on gradient-boosting decision trees. On identical datasets, the suggested approach outperforms existing methods regarding sensitivity and precision by more than 1 percentage point and 3 percentage points, respectively. It also obtains 87.68% accuracy in binary classification. Researchers conclude that the findings of this study offer important insights into the classification effectiveness of WPD, the extraction of features, and the gradient-boosting decision tree classification algorithm for EEG.

A novel method for identifying aberrant EEG signals is presented by Tuncer et al. [24]. It integrates WPD and chaotic one-dimensional local binary pattern (CLBP) methods. This technique extracts features by first applying CLBP to the decomposed signal after applying WPD to the EEG signal. Minimum redundancy reduction maximum relevancy was employed to select clinically significant characteristics, and a support vector machine (SVM) classifier was utilized to divide them into normal and abnormal EEG classifications. The built model has the best performance to date with this database, with

98.19% accuracy for the PZ channel. Advanced approaches are outperformed by the suggested strategy.

Several recent studies related to the use of EEG have been published, including research conducted by Monge et al. that illustrates the potential of wireless EEG devices in educational settings, shedding light on students' cognitive and emotional states. This facilitates collaboration between educators and researchers. The discourse delves into the equilibrium between the advantages of EEG utilization in the academic domain, such as gaining fresh perspectives on the learning processes, and the obstacles encountered, including disruptions to regular classroom activities and financial constraints. The study presents empirical support indicating that despite the disruptions to the daily school routine, integrating EEG devices could pave the way for advancements in pedagogy and learning methodologies, ultimately benefiting all stakeholders [25].

Ruchika et al. [26] emphasize the significance of EEG in managing individuals with neurological disorders, a diagnostic tool that monitors the brain's electrical functions. It discusses the recent advancements in EEG technology that enable neurosurgeons to closely observe brain activity during surgical procedures, enhancing their clinical judgment and ensuring brain safety. Furthermore, the study anticipates the development of wearable devices in the future, facilitating continuous monitoring of brain health and potentially expediting patient recovery processes. Johri et al. propose a method for recognizing brain activity through EEG signals, categorizing it into listening to music, watching movies, and meditating. They use a convolutional neural network with Temporal, Spatial, and Separable convolutions to effectively analyze and interpret complex brain signals. The study showcases the effectiveness of Depthwise Convolution and Separable Convolutions in EEG signal processing.

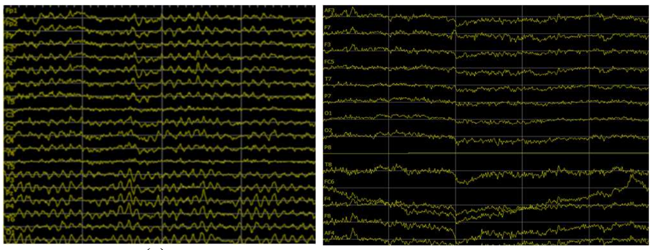
Comparing different networks like EEGNet, EEGNet-SSVEP, and DeepConvNet, it emphasizes the significance of adding more layers to achieve higher accuracy, with DeepConvNet reaching 99.94% accuracy [27]. Volkova et al. [28] present a review on decoding movements from brain activity using electrocorticography (ECoG) for assistive devices. ECoG offers advantages like better temporal/spatial resolution and lower risks, making it a promising neuroprosthetic solution. The authors discuss how decoding algorithms extract relevant information from ECoG for BCIs. They also stress the importance of generalization in decoding algorithms and the need for regularization methods to prevent overfitting in ECoG-based BCIs. Patel et al. [29] present an extensive overview of advancements in BCI technology, emphasizing its significance for assisting disabled individuals and enabling innovative applications such as hands-free game playing and controlling home appliances using brain signals. The text explains the process of capturing and processing brain signals, including signal acquisition, data preprocessing, feature extraction, and classification, to facilitate beginner comprehension regarding BCI system workflow. The study thoroughly examines diverse BCI applications, demonstrating various techniques for feature extraction and classification and elucidating the adaptability and potential of BCI technology across different domains.

Finally, it addresses the current challenges and limitations hindering the effectiveness of BCI systems, highlighting areas requiring enhancement for future BCI technology development. Lahane et al. [30] present an extensive overview of BCI technology advancements, emphasizing its significance for aiding disabled individuals and creating innovative applications such as hands-free game playing and controlling home appliances through brain signals. The article elucidates capturing and processing brain signals, including signal acquisition, data preprocessing, feature extraction, and classification, to facilitate comprehension for novices in BCI system workflow. A thorough examination of diverse BCI applications demonstrates various feature extraction and classification techniques, thus illustrating the adaptability and potential of BCI technology across different domains. Lastly, the paper outlines the current challenges and limitations affecting BCI system efficiency, highlighting areas requiring enhancement for future BCI technology progress.

II. Materials and Methods

A. Dataset

This research processed two types of EEG data: low concentration and high concentration. The data used is in the form of an EEG signal dataset sourced from the Mendeley databases [31]. Figure 1 (a) shows Examples of EEG signal data in humans at low concentrations, and Figure 1(b) shows EEG signal data at high concentrations.



(a) (b)

Fig. 1 Example of human EEG signal data with (a) low concentration and (b) high concentration

Out of 250 data, 200 are used to train and 50 for assessment. Table 1 depicts the distribution of these points.

TABLE I
Allocation of Dataset

Dataset	Training data	Test data	Total
Low concentration	100	25	125
High concentration	100	25	125
Total	200	50	250

B. General Architecture

In this investigation, there are multiple stages of the technique. A high-pass filter filters the EEG's frequency at the beginning of the process, preprocessing. The second stage is feature extraction utilizing PyEEG [32]Then, enter the classification stage using the SVM approach. After going through all these stages, the resulting output is high and low concentration levels. The phases are arranged in a general architecture, as seen in Figure 2.

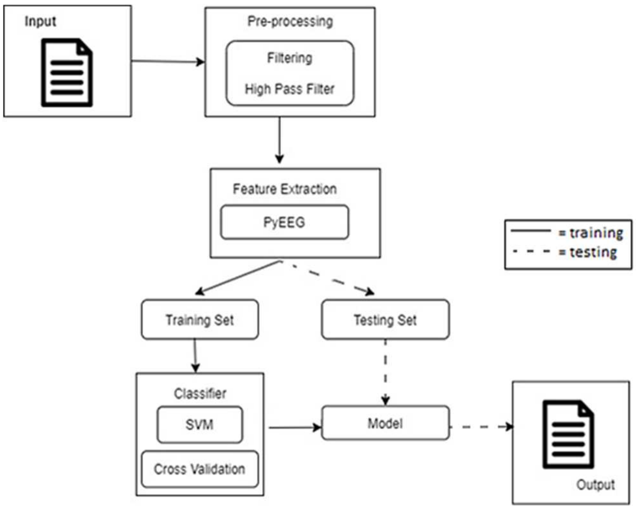
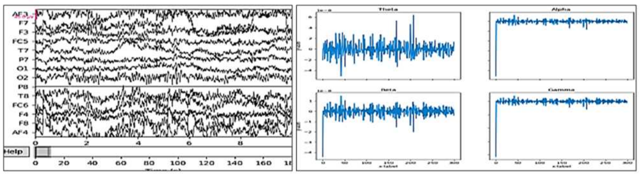


Fig. 2 General architecture

C. Preprocessing

At this preprocessing stage, the EEG signal data is processed to remove unnecessary signals that can interfere with data processing so that the required data can be produced. The EEG signal is subjected to the signal-filtering process, which is a filter that passes high frequencies and rejects low frequencies. The findings obtained in this process are to segregate the delta, theta, alpha, and beta signals. Figure 3 depicts EEG signals before and after applying the high-pass filter.



(a) (b)

Fig. 3 EEG signals: (a) before being given a high-pass filter and (b) after being given a high-pass filter

The frequency of the EEG signal is divided into four parts: delta, theta, alpha, and beta. Delta is in the 0.5Hz–4Hz range, theta is in the 4Hz–7Hz range, alpha is in the 7Hz–12Hz range, and beta is in the 12Hz–30Hz range.

D. Feature Extraction

Moreover, the feature extraction procedure uses PyEEG on the EEG signal. In the filtering stage, the EEG signal has been separated into four parts: delta, theta, alpha, and beta. The following code contains the PyEEG script for this research:

```
FUNCTION def extract_features(signal):
    a = pyeeg.bin_power(signal,[0.5,4,7,12,30],173)
    aa = list(a)
    aa[0] = aa[0].tolist()
    aa[1] = aa[1].tolist()
    b = [[hfd(signal,Kmax=5),
        svd_entropy(signal,Tau=4,DE=10),
        fisher_info(signal,Tau=4,DE=10),
        dfa(signal)]]
    return list(chain.from_iterable(b))
ENDFUNCTION
```

The explanation for the script is as follows: The code defines a function called *extract_features* that accepts a *signal* as input and extracts specific features. The *bin_power* function from the *pyeeg* module is called the *signal* input, a frequency range list [0.5, 4, 7, 12, 30], and a sampling rate of 173. The power is calculated within designated frequency ranges [0.5–4Hz, 4–7Hz, 7–12Hz, 12–30Hz]. The result of *bin_power* is converted to a list, and the first and second elements of the list (*aa[0]* and *aa[1]*) are converted to lists as well using the *tolist()* method. This step seems unnecessary since *bin_power* likely returns the results as listed already. A nested list *b* is created, which contains the results of four different functions: *hfd*, *svd_entropy*, *fisher_info*, and *dfa*. These functions are applied to the *signal* input. The specific parameters used for each function are *Kmax=5*, *Tau=4*, and *DE=10* for *svd_entropy* and *fisher_info*. It's thought that the other functions (*hfd* and *dfa*) use default parameter values. The nested list *b* is flattened using *chain.from_iterable*, and the flattened list is returned as the function's result.

E. Classification

Modeling in SVM is to find the best-dividing line, also known as a hyperplane, by maximizing the distance between classes, which is utilized for categorizing high-dimensional classes. The kernel used in this research is the RBF kernel. The dataset is subsequently partitioned into K subsets using K-fold cross-validation. The K value used in this study is 5, which is fivefold.

III. Results and Discussion

Figure 4 illustrates some examples of datasets that show low-concentration and high-concentration conditions.

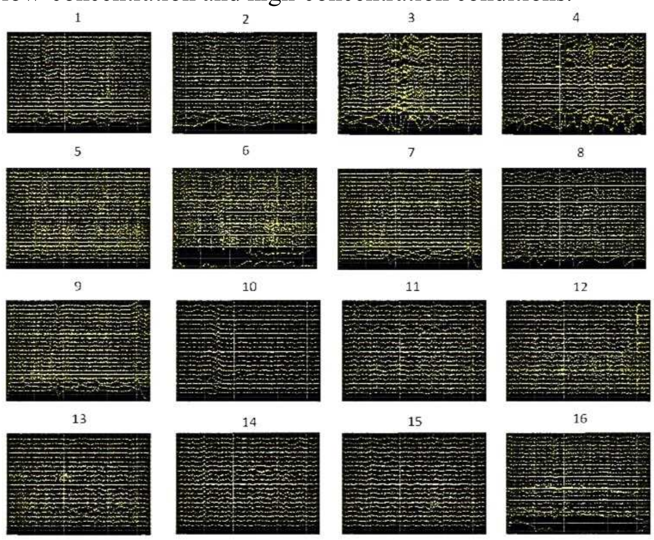


Fig. 4 Part of the dataset with low-concentration conditions

This stage is a system test to see the results of the preprocessing process, feature extraction, and classification using the SVM method. The EEG signal is categorized into two parts: high and low concentrations. Testing the system in the classification process using SVM. The data used is 250 EEG data consisting of 200 training data and 50 test data. Table 2 displays some of the examination results.

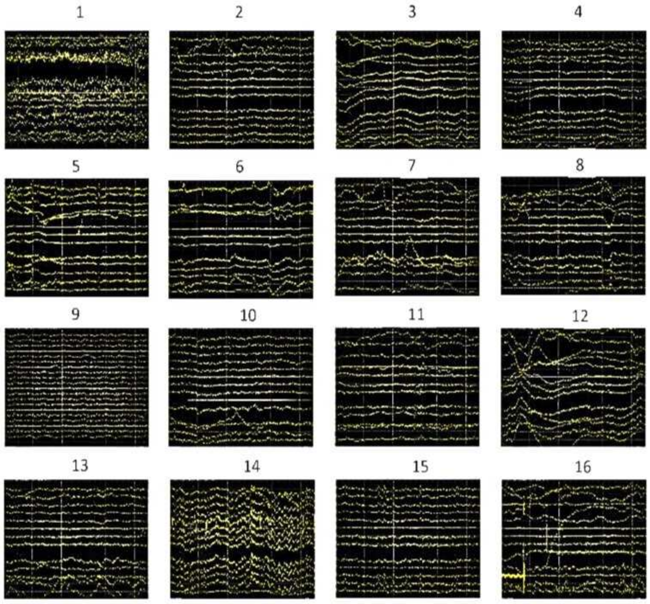
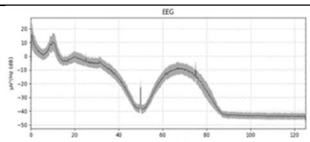
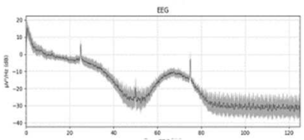
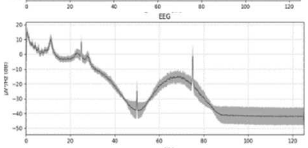
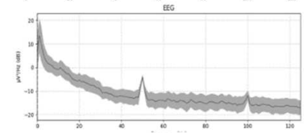
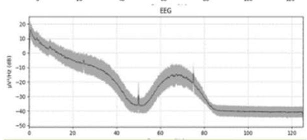
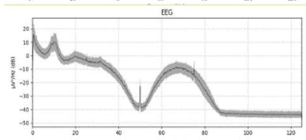
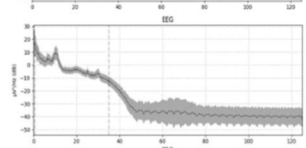
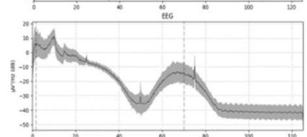
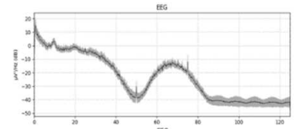
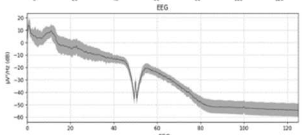
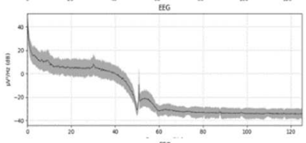
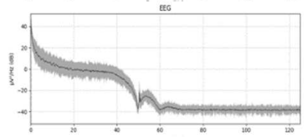
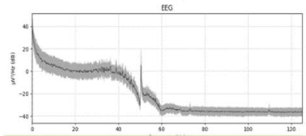
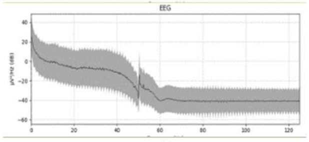
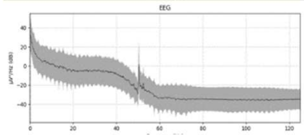
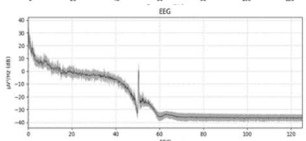
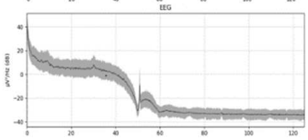
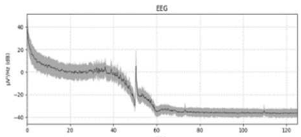
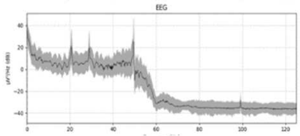
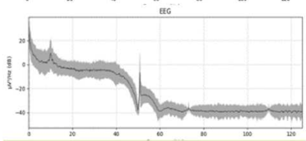


Fig. 5 Part of the dataset with high-concentration conditions

TABLE II
TEST RESULTS

No.	EEG data	Actual output	Desired output	Status
1		Low concern.	Low concern.	Succeed
2		Low concern.	Low concern.	Succeed
3		Low concern.	Low concern.	Succeed
4		Low concern.	Low concern.	Succeed
5		Low concern.	Low concern.	Succeed
6		Low concern.	Low concern.	Succeed
7		Low concern.	High concern.	Failed
8		Low concern.	Low concern.	Succeed
9		Low concern.	Low concern.	Succeed
10		Low concern.	High concern.	Failed
11		High concern.	High concern.	Succeed
12		High concern.	High concern.	Succeed
13		High concern.	High concern.	Succeed
14		High concern.	High concern.	Succeed
15		High concern.	High concern.	Succeed
16		High concern.	High concern.	Succeed
17		High concern.	High concern.	Succeed
18		High concern.	High concern.	Succeed
19		High concern.	High concern.	Succeed
20		High concern.	High concern.	Succeed

Based on the classification test of the EEG signal testing data in Table 2 using SVM, an accuracy value of up to 84% is obtained based on implementing the machine learning method, namely, the confusion matrix. Figure 6 illustrates the results of the EEG signal evaluation using the confusion matrix.

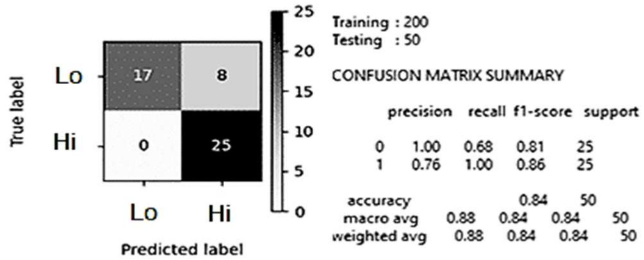


Fig. 6 The results of the confusion matrix on the EEG signal test data

In Figure 6, the 0th index is the testing data for the low-concentration class, and the 1st is the testing data for the high-concentration class. Table 3 presents the outcomes of the formulas for true positive, false positive, precision, macro averaged precision, and weighted averaged precision.

TABLE III
TP, FP, PRECISION, MAP, AND WAP VALUES

	Low	High
TP	17	25
FP	0	8
Precision: TP/(TP+FP)	1.00	0.76
Macro Averaged	0.88	
Weighted Averaged	0.88	

Recall is the percentage of anticipated positives from total positives. Calculations of true positive, false negative, recall, macro averaged recall, and weighted averaged recall can be seen in Table 4.

TABLE IV
TP, FN, RECALL, MAR, AND WAR VALUES

	Low	High
TP	17	25
FN	8	0
Precision: TP/(TP+FN)	0.68	1.00
Macro Averaged	0.84	
Weighted Averaged	0.84	

Table 5 displays the F1 score and accuracy.

TABLE V
F1-SCORE AND ACCURACY

	Low	High
F1-Score	0.81	0.86
Accuracy	0.84	

IV. CONCLUSIONS

The SVM method can accurately classify low and high concentration levels of EEG signals. The accuracy value obtained from the experimental findings is 84%. Explore how EEG can measure cognitive workload and mental fatigue, which are closely related to concentration levels. Research could concentrate on designing adaptive interfaces and environments that respond to a person's cognitive state. Future research should aim to develop personalized concentration level assessment models that account for these differences. Combine EEG with other physiological and behavioral data sources, including eye tracking, heart rate monitoring, and facial expression analysis, to provide a complete picture of concentration levels. This could lead to more accurate assessments.

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