RESEARCH PAPER

EEG Signal Analysis for Neurorehabilitation: Current Landscape and a Novel Engagement Prediction Framework

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ABSTRACT
Electroencephalography (EEG) is accepted as an objective and non-invasive approach to measure cognitive effort and fatigue. These two are important components in the monitor-ing of mental engagement in neurorehabilitation practices. This article reviews recent research studies that utilized EEG-based feature extraction methods combined with machine learning techniques to interpret brain activity associated with cognitive tasks. A major aim of these studies has been to recognize and identify mental task type (i.e., resting, engaged, varying degrees of task complexity). Preprocessing techniques like Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) and feature extraction techniques that include Power Spectral Density (PSD) and Spectral Edge Frequency (SEF). In this article, it was revealed that EEG power ratios (alpha/beta, theta/beta) and the power in the beta and gamma frequency ranges were significant markers of cognitive effort. The information provided by entropy and statistical features derived from multiple bands of EEG data would be useful for classifying mental state and task difficulty. Models such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) used to analyze these features has resulted in classification accuracy rates of 96.8% and 98.6% respectively. Mental arithmetic is a good indicator for being able to investigate cognitive load. Overall, this article indicates that EEG is a viable tool for monitoring cognitive engagement as it varies dynamically.
Keywords: *electroencephalography, cognitive engagement, mental arithmetic, feature extraction, task classification*
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INTRODUCTION

Neurorehabilitation is essential when it comes to helping people recover from conditions like stroke, brain injury, or other neurological disorders. The patient's mental engage-ment—that is, their level of focus and cognitive involve-ment during therapeutic activities—is a critical component of successful rehabilitation. This engagement is subjective and subject to variation in the majority of clinical settings because it is evaluated indirectly through behavioral cues or therapist judgment. More objective methods of tracking engagement using neurophysiological signals like electroencephalography (EEG) have been made possible by recent developments in wearable technology and neuroscience. Electroencephalogra-phy is a neuroimaging technique that is used to record spon-taneous electrical activity in the brain by placing electrodes on the scalp. EEG is frequently used to diagnose a variety of neurological conditions.However, it also gaining popularity as a tool in neurorehabilitation owing to its non-invasive nature, fine temporal resolution, simplicity and portability [1]. Additionally, EEG helps record patterns of brain activity that indicate mental fatigue, cognitive workload, and attention. This review of the literature looks at EEG-based research that analyzes and categorizes brain signals and cognitive states associated with stress, mental effort, and processing during task performance. Our objective is to demonstrate the usefulness of EEG in evaluating and tracking participation during structured tasks and to investigate its possible uses in assisting neurofeedback and neurorehabilitation systems.

LITERATURE SURVEY

Tee Yi Wen and Siti Mariyam Shamsuddin Aris [2] looked into using EEG power ratios as a more objective way to measure stress. Power spectral density (PSD) was computed using the Fast Fourier Transform (FFT) after 40 participants' EEG signals were recorded in response to virtual reality (VR)-based stimuli. Alpha/beta and theta/beta ratios from the prefrontal cortex were the main focus of the study. Both ratios significantly decreased after the stimulus, indicating higher stress levels marked by decreased relaxation and increased focus or exhaustion. Future research will examine the efficacy of using features derived from the Alpha/Beta and Theta/Beta ratios to categorize stress levels.

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The problem of accurately classifying EEG signals corresponding to different cognitive loads during mental arithmetic tasks, differentiating between no task, normal, and difficult levels, was addressed by Kiran Nirde et al. [3] with 91%, 89%, and 65% accuracy, statistical features taken from EEG data were applied to classifiers like SVM, KNN, and Decision Tree.When tuned deep learning models, such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks, were fed raw EEG signals, the accuracy was 96.80% and 94%, respectively. The outcomes showed that ANN and LSTM performed better. These results demonstrate how well deep learning captures intricate EEG patterns better than classifiers associated with mental workload.

Gang Li et al. [4] investigated the effects of mental exhaustion on EEG signals during tasks and at rest. In order to induce mental fatigue, 20 male participants were given a series of mental arithmetic tasks at the same time. EEG recordings were made prior to and following arithmetic tasks, with an emphasis on alpha sub-bands (alpha1, alpha2) and delta-beta bands. When in a resting state as opposed to a task state, the relative power for evaluating mental fatigue was higher. In the resting state, alpha1 increased and alpha2 decreased significantly, with overall alpha decreasing in both states, according to an ANOVA with FDR correction. The findings show minute EEG alterations associated with mental exhaustion.

Bushra Fatimah et al. [5] intended to use EEG to assess task difficulty and identify whether the brain is engaged in mental tasks or at rest. The suggested methodology yields two results: the first experiment examined the function of each cortex in cognitive tasks, and the second experiment categorized the EEG signals according to task difficulty. SVM, Decision Tree, and Quadratic Discriminant Analysis (QDA) were used to classify features such as entropy, energy, mean, and L2 norm that were extracted from filtered sub-bands. On certain channels, QDA was able to distinguish between rest and task and difficulty levels with up to 100% accuracy approximately. In the future, more raw EEG datasets gathered at various sampling rates will be used to test the robustness of the suggested algorithm.

Qun Wang and Olga Sourina [6] presented a lightweight and effective machine learning framework for real-time EEG-based mental math task recognition. Ten participants had their EEG signals recorded while they alternated between mental math and rest. Power Spectral Density (PSD), Auto-Regressive (AR) coefficients, statistical features, and a new descriptor set known as Generalized Higuchi Fractal Dimension Statistics (GHFDS) were used to extract features from the data. Support Vector Machines (SVM) were then used to classify these features. The system showed great promise for real-time task recognition, achieving a high classification accuracy of 97.87% using all feature sets from just four EEG channels.

The research encourages the creation of inexpensive, portable EEG-based devices for neurofeedback and cognitive monitoring.

Aminul Islam et al. [7] proposed an EEG-based system to detect mental stress during arithmetic tasks using wavelet and statistical feature analysis. EEG signals were decomposed using Discrete Wavelet Transform (DWT), and 60 statistical features were extracted. Neighborhood Component Analysis (NCA) was used to select the top 4 features. Ensemble Subspace KNN model was used for classification, achieving 77.3% accuracy, with 91% sensitivity, 64% specificity, and an F1-score of 80%. The study highlights the value of wavelet-based features and efficient selection methods in identifying stress during cognitive tasks.

Pavithara et al.v [8] centered on using Field Programmable Gate Array (FPGA) implementation of wavelet transforms to improve EEG analysis for the diagnosis of neurological disorders. Low pass and high pass filters, followed by down-sampling by a factor of two, comprise the decomposition of an EEG signal. On a Basys 3 board, EEG signals were broken down using DWT and WPT, and Daubechies-4 wavelets were used to extract features like mean, variance, and peak-to-peak. Different levels of decomposition of DWT (4 levels) and WPT (3 levels) yield the five EEG sub-bands. WPT used more resources while providing lower latency (6.7µs vs. 13.1µs for DWT), with the delta band exhibiting the largest variance. Consequently, at the cost of resources used, the WPT decomposition is more effective than DWT.

Aslam et al. [9] tackled the challenges of limited explainability and inter-subject variability in EEG-based mental task classification. Features were extracted using Mahalanobis Distance (MD) and refined via RF-RFE. Classifiers including RF, SVM, kNN, and LDA were used. This work successfully classified the mental arithmetic tasks from EEG, achieving an 99.30 % and 98.33 % better classification accuracies for resting vs calculation and good vs bad calculation states, respectively, after a systematic comparison with existing techniques and state of the art we got a better conclusion.

Sharma et al. [10] addressed the low accuracy of existing non-invasive stress detection methods. EEG data from 20 subjects was processed using Savitzky–Golay filtering and SWT decomposition. Entropy based features were extracted followed by F-score selection and classification using Bayesian-optimized KNN method. The model achieved 96.07% accuracy and 0.97 AUC using 10-fold cross-validation. Nadiya et al. [11] used Spectral Edge Frequency (SEF50) to examine EEG changes during mental arithmetic in 36 subjects. Six brain regions and five frequency bands were used to calculate SEF50. The beta/gamma and theta/alpha bands had higher and lower SEF50, respectively. Using single-channel EEG, Fatimah et al. [12] sought to categorize brain activity during mental arithmetic tasks. The Fourier Decomposition Method (FDM) was used to break down the signals. The Kruskal-Wallis test was used to choose features. For classification, SVM, KNN, and logistic regression were used. SVM outperformed previous techniques on channel C3, achieving 98.6% accuracy. Future research will examine the connections between various brain regions and how they react to different cognitive tasks.

Gashaj et al. [13] studied the differences in students' understanding of symbolic versus non-symbolic mathematical proofs. They examined the beta and gamma activity of the frontal and parietal regions. The findings revealed symbolic reasoning was related to gamma band activation and that symbolic proofs were considered to be more familiar and easier to understand. A transparent method for identifying mental states from EEG, without the use of black-box models, was put forward by Daniela Andreea Coman et al. [14]. PhsyioNet data were analyzed for spectral peak and Pearson correlation were performed for the theta, alpha, and beta bands. The method achieved high accuracy on the F7/Fz channels (theta/beta) with a high F1 score, MCC, and specificity.

It was pointed out by Azizi [15] that recording nonlinear, time-varying EEG dynamics during mental tasks is very important. To analyze the EEG dataset of 36 participants executing mental math, Discrete Wavelet Transform (DWT) and spectral entropy were employed. Subsequently, frequency and complexity-based features were derived. The research found differences between task and rest conditions, thereby highlighting the importance of entropy in recognizing changes in the cognitive state. The approach is still a few steps away from being utilized in a real-time mental workload monitoring system for everyday use, as further validation is required in future.

During the Alternative Uses Task (AUT) Yin et al. [16], an investigation was conducted to find out if there are neural cognitive differences between engineers and artists using EEG. After EEG preprocessing in EEGLAB, ERP, PSD, and brain state analysis were performed. Compared to the art students, the engineering ones were faster in their responses and more extensive cortical activation, especially in the temporal and parietal regions is what we could be observed. The comparison of the two groups of students showed that the artists had more pronounced frontal activation, thus indicating different patterns of cognitive engagement. The research findings suggest that EEG is a viable tool in distinguishing differences in problem-solving approaches due to educational background.

Cao et al. [17] investigated brain activity associated with design fixation in creative tasks. 21 student's EEGs were examined using BrainVision Analyzer, PCA, and FFT. Alpha synchronization, a measure of internal focus, was higher in low-fixation individuals and alpha desynchronization in high-fixation individuals.

Additionally, the low-fixation group showed more flexibility in their ideation.

Dattola et al. [18] localized brain activity during mental math using eLORETA and EEG. Statistical non – Parametric Mapping analysis of 35 participant's EEG signals showed that high performers had higher beta activity in left limbic regions. There were no differences between the performance groups in other frequency bands. Dlamini et al. [19] performed a systematic review of EEG studies examining brain activity during code and art reviews. Wavebands, stress-related markers, and EEG techniques.

Singh and Krishnan [20] looked at more than 20 studies on EEG feature extraction techniques in time, frequency, spatial, and decomposition domains. The classification accuracies varied from 70% to 98.6%. In their study, they concluded that spatial and decomposition features were the most stable and adaptable features for different EEG applications. Negi provided a comprehensive review of EEG processing pipelines for clinical and BCI use. The paper described in detail the stages of signal acquisition, preprocessing, feature extraction methods (FFT, WT, CSP), and classifiers (SVM, kNN, CNN). The performance figures that were mentioned in the paper and that ranged from 70% to 98.6% put a strong emphasis on the fact that the choice of techniques is of utmost importance for giving the right solution to the problem at hand as best as posssible.

Fink and Benedek [21] related the alpha-band activity (8–12Hz) with creativity in ideation tasks such as the AUT and the Consequences Task. ERD / ERS method is focused on EEG alpha power (8–12 Hz) that is further split into lower and upper alpha bands and phase-locking value (PLV). Authors suggested that increased alpha synchronization may reflect the generation of original ideas and internally focused thought and thus support alpha as an indicator of creative cognition. No mentions of accuracy measures were made. The present review considers alpha power as the most consistent neural marker of creative ideation in spite of the neuroscientific creativity literature that has presented results contradictory to this one. It highlights the necessity of more tightly focused studies with lucid concepts and consistent methods to get deeper insights of brain functions in the field of creativity.

Chaddad et al [22] explored EEG handling methods involving classical and deep learning models like SVM, KNN, CNN, ICA, and DWT. The research ventured into noise removal strategies with their implementations through datasets like CHB-MIT and BCI. Achieved accuracies were close to 98%, and AUC, SNR, and MSE were among the metrics used for performance evaluation. The paper consolidates the outcomes of various EEG studies and asserts that they are extremely precise in detecting epilepsy (up to 98%), depression, and sleep disorders. It highlights the successful application of both traditional machine learning and deep learning models in EEG analysis. Ram´ırez-Arias et al.[23] assessed various machine learning models for motor imagery EEG classification, utilizing features derived from fractal analysis (DFA, Hurst) and power spectral density (PSD). We tested models like ANN and SVM on the PhysioNet dataset. The medium-sized ANN had an accuracy of 98.57 percent, an AUC of 0.9998, and an F1 score of 0.9855.

EEG bands were successfully employed to categorize movement types (hands, feet, relaxation), demonstrating significant efficacy in motor task detection. Its shortcomings include the absence of real-time data utilization, an exclusive focus on motor movements rather than cognitive domains, and the lack of rehabilitation recommendations or correlations to mental tasks.

Valentim et al. [24] examined 36 participants' EEG signals while they completed mental tasks. They employed fractal dimensions, the Hurst exponent, Welch's PSD, and Detrended Fluctuation Analysis (DFA). In order to better understand cognitive activity, this paper focuses on the necessity of analyzing EEG signals from multiple areas. In order to find patterns in mental tasks, it recommends combining fractal methods with PSD. This study did not employ any machine learning models. The findings showed a stronger alpha wave at rest and increased beta and gamma activity during tasks. Classification metrics were not included in this exploratory study, but statistical trends were reported. The approach lacks real-time application and customized modifications, and it is restricted to exploratory and statistical analysis. The fractal indices were not very good at differentiating between performance groups.

Constant Therapy [25] emphasized the importance of math exercises in stroke and traumatic brain injury patients' cognitive rehabilitation. The report highlights increased accuracy and quicker reaction times in math tasks based on user data from its digital therapy platform. For instance, one user achieved 92% accuracy in subtraction with a 10-second average, demonstrating the value of arithmetic as a rehabilitation tool.

Flint Rehab [26] outlined cognitive rehabilitation strategies for individuals with deficits in processing speed, attention, and memory brought on by traumatic brain injury or stroke. The article highlights mental arithmetic as an important task involving multiple brain regions to improve working memory and information processing. No quantitative data was provided, despite being based on clinical insight and neuroplasticity principles. A list of therapist-recommended cognitive exercises to aid in stroke recovery was given in the article [27], which focused on abilities like attention, problem-solving, and numeracy. It was emphasized how crucial mental math is for fostering different cognitive domains and aiding in numeracy rehabilitation. Although the benefits were qualitatively described, there was no statistical or experimental validation.

In a different article, Wykes et al. [28] carried out a multisite randomized trial with 377 patients/participants to evaluate how cognitive remediation (CR) should be given in early psychosis. Participants could choose between group CR, one-on-one CR, independent CR, or treatment-as-usual (TAU) as they wish . Therapist-led CR was more engaging and cost-effective than the independent format, and it significantly improved cognitive and functional outcomes.

METHODOLOGY

The proposed methodology focuses on estimating men-tal engagement from electroencephalography (EEG) signals recorded during mental arithmetic tasks. The method is intended to be data-driven, comprehensible and appropriate for

Table 1: Exhaustive review on existing works

Ref.	*Dataset*	*Models*	*Results*
[2]	Research er-generated	FFT	Decline in Al-pha/beta and theta/beta ra-tio
[3]	Public dataset from PhysioNe t	ANN, LSTM	Accuracy: 96.80%, 94%
[5]	Data set from PhysioNet	SVM, Decision Tree, QDA	Highest accu-racy of QDA upto 100%
[6]	Public dataset from PhysioNe t	Features: PSD, GHFDS; Classifiers: SVM	Accuracy: 97.87%
[7]	Public dataset from PhysioNe t	DWT, NCA, Ensemb le KNN model	Accuracy: 77.3%
[10]	Public dataset from PhysioNe t	Bayesian KNN	Accuracy: 96.07%
[12]	Public dataset from PhysioNe t	Features: FDM, Classifiers: SVM, KNN	Accuracy of SVM: 98.60%
[15]	Continuo us-time integrable signalus-ing	FFT	Accuracy: 96.80%, 94%
[21]	Pub lic EE G dataset from University of Bonn	Event-Related Desynchro-nization (ERD) / Syn-chronizati on (ERS)	alpha syn-chronization (increase inalpha power)%

[24]	PhysioNe t data of 36 partici-pants	Detrended Fluctuation Analysis (DFA), Hurst exponent,	Good performers had lower high-frequency power

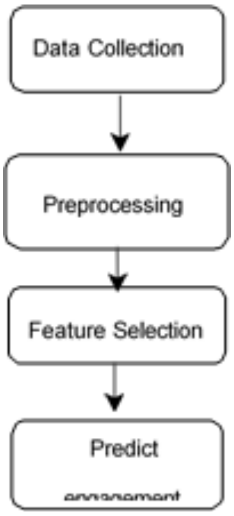

Figure. 1. Methodology

analysis focused on neurorehabilitation. We collect the EEG signals from a dataset pertaining to signals during a mental arithmetic task. We proceed to subject the EEG signals to bandpass filtering and subsequent preprocess-ing using Power Spectral Density. The extracted features will be fed into a machine learning model. The model will predict the continuous engagement score of the subject and provide feedback for neurorehabilitation.

CONCLUSION

With an emphasis on the extraction of significant features and their interpretation using machine learning models, we examined recent developments in EEG-based cognitive engagement evaluation in this survey. The examined studies consistently show that EEG signals are trustworthy markers of mental effort and task complexity, especially frequency-domain features like alpha/beta and theta/beta ratios, PSD-based measures, and gamma-band activity. The quality of EEG-derived insights is further improved by combining entropy and statistical features with preprocessing techniques like DWT and FFT. These results provide compelling evidence that EEG offers an objective, real-time assessment of cognitive states, surpassing conventional behavioral methods, which are frequently subjective and inconsistent.

Overall, the data demonstrates that EEG can classify mental tasks with up to 96–98% accuracy when combined with machine learning methods like ANN and SVM. This demon-strates its potential for use in neurorehabilitation, where on-going engagement monitoring is crucial for individualized treatment. Particularly, mental math exercises remain useful stimuli for assessing cognitive load. EEG-based engagement monitoring is set to become a useful and significant tool in clinical rehabilitation, cognitive training, and human-machine interaction systems as wearable EEG technology becomes more widely available and computational models become more advanced.

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