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# Machine Learning-Integrated EEG Signal Analysis to Assess Mental Arithmetic Task Difficulty Levels

**Md. Mushfikur Rahman Khan[1*], Md. Nazmul Islam[1], Md. Mahmudul Hasan Rashed[1], Afzal Hossen[1]**

*[1]Department of Electrical and Electronic Engineering, Faculty of Electrical and Computer Engineering, Bangladesh Army University of Engineering & Technology (BAUET), Qadirabad Cantonment, Natore-6431, Bangladesh*

**Abstract:** In this research, a method for automatically detecting mental arithmetic problems and evaluating their difficulty level is presented. This method uses single-channel EEG signals. It is essential to comprehend the effects of varying task difficulty on the cerebral cortices and to quantitatively evaluate the operation of different brain waves during cognitive tasks. A filter bank divides the EEG data into different rhythms (gamma, beta, alpha, theta, and delta). Following that, each rhythm is assessed according to several factors, including energy, entropy, mean, L2 norms, skewness, kurtosis, relative power, and absolute power. Metrics like precision, recall, F1 score, and confusion matrix are computed using the SVM classifier, a machine learning classifier. The program effectively distinguishes between the brain's active and resting states during the specified cognitive task. The maximum accuracy of 86.67% was obtained while employing 4 characteristics for subject F8 and the delta sub-band. The maximum accuracy of 86.67% was obtained for subject Fp1 and the beta sub-band when 8 characteristics were used.

**Keywords:** *Mental arithmetic task, brain cortices, brain waves, machine learning, Electroencephalogram*

**Introduction:** A fascinating study area that integrates the fields of neuroscience and machine learning examines the automatic detection of mental arithmetic exercises and establishes their degree of difficulty. Calculations must be made mentally, without the use of external equipment like calculators or writing implements, in mental arithmetic. Cognitive abilities including attention, working memory, and numerical processing are required for this mental activity. The electrical activity of the brain is measured with electrodes placed on the scalp using electroencephalography (EEG), a non-invasive neuroimaging technique. Studies on cognitive neuroscience have extensively used EEG to directly measure cerebral activity and examine a variety of cognitive processes, including mental arithmetic. Over 300 million individuals worldwide, or 4.4% of the world's population, are thought to experience depression. People from Southeast Asia had a wide range of health problems as a result of mental stress or despair (7%). Suicide is a possibility for those with severe depression. Approximately 800,000 people die by suicide each year.  Therefore, stress or depression is a serious problem that needs to be identified and addressed at a young age to reduce suicide risk and improve quality of life. The goal of using EEG signals to automatically identify mental arithmetic operations is to develop a system that can accurately identify when someone is engaged in mental calculations and distinguish them from other cognitive activities. Many applications have made extensive use of the analysis of electroencephalography (EEG) signals, such as the detection of epileptic seizures [1], prediction of seizures [2], identification of emotions [3], classification of sleep stages [4], and detection of cognitive workload [5-8].

The effects of various cognitive activities on brain activity have also been studied using EEG signals [9, 10]. Additionally, cognitive tasks have been categorized using the task engagement index. The purpose of this work is to explore the application of machine learning algorithms to classify stress levels from EEG signals, building on previous studies. The degree of difficulty of these mental arithmetic exercises can also reveal important details regarding cognitive load and individual differences in mathematical aptitude.

**Literature Review:** This study's goal is to appropriately classify EEG data, which necessitates an understanding of brain physiology and the link between various cognitive tasks and distinct cortical regions. For applications like biofeedback systems and the identification of learning issues, this categorization is crucial [11–13]. In prior work [14], gamma, beta, alpha, theta, and delta rhythms were extracted from the decomposed EEG signals using a filter bank approach. For each of these rhythms, many characteristics like energy, entropy, mean, and L2 norms were assessed. Support vector machines, decision trees, and quadratic discriminant analysis were three machine learning classifiers whose performance was compared. Each of the four lobes of the cerebral cortex—frontal, parietal, temporal, and occipital—plays a unique function in processing sensory data. For instance, cognitive processes including memory, language, judgment, emotional expression, problem-solving, and sexual behavior are controlled by the frontal lobe. Processing of visual information is done by the occipital cortex, processing of auditory information is done by the temporal lobe, and processing of spatial orientation is done by the parietal lobe. These four cortices' electrical activity is captured by EEG signals, which offers important information about how they work [15]. Following the International 10/20 system, which specifies the positions and names of these electrodes for both clinical and research purposes, electrodes put on the scalp are frequently used to record EEG.A

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**Corresponding author details:** Md. Mushfikur Rahman Khan
*E-mail address: mushfikur4@gmail.com*
*Tel: +8801521329766*

setup of 19 electrodes, a ground electrode, and a system reference electrode is used to capture the signals [16]. Analyzing EEG signals to differentiate between the brain's resting state and active engagement during mental arithmetic tasks has been the topic of several investigations. These studies examined the operation of several brain cortices, brain wave patterns, and the brain's reaction to various situations, such as task failure. We will briefly discuss a couple of these studies here: In [17], the authors examined the causal connection between the frontal lobe rhythm and the parieto-occipital lobe rhythm in order to explore the performance of mental task activities. During mental arithmetic workouts, Yu et al. [18] looked at the relationship between cerebral cortices and cardiac autonomic nerve activity. The filter packet parameters and approximative entropy were included in the feature set utilized in their analysis.

According to the research's conclusions, a rise in cerebral awareness was accompanied by a decline in parasympathetic activity and an increase in sympathetic activity. EEG signals were used in a study by Dornhege et al. [19] to identify excessive mental workload in drivers navigating actual traffic conditions. Authors in [20] and [21] were able to discriminate between the resting state and task state by using statistical features acquired from filter decomposition of EEG signals and applying machine learning techniques. The alpha rhythm was taken into account by the authors of [22] when assessing the task's difficulty. They used Welch's periodogram to calculate the alpha wave's power. Similar to [23], alpha and theta wave analysis were used to determine the effort level. The spectrum properties of the EEG waves were used by Rebsamen et al. [24] to classify various workload levels. To determine the mental arithmetic problem, Wang et al. [25] used the generalized Higuchi fractal dimension spectrum, power spectral density, autoregressive model, and spectral features of EEG signals. With a single channel, they attained an accuracy of 84.15%, and with many channels, 97.87%. In a different study [26], frontal EEG signals from 20 healthy volunteers were captured as they performed four cognitive and motor activities, including lexical judgment tests, finger tapping, mental rotation, and arithmetic operations. The results showed that task complexity was correlated with an increase in theta activity. The amount of mental workload for each individual was classified with an accuracy of 65% to 75% using the support vector machine method. Alpha rhythm was used in [27] to determine how difficult it was to do a mental arithmetic problem. The dataset used in their analysis contained the EEG signals from 18 male patients.

The EEG data in this study is divided into five separate sub-bands that correspond to the five natural brain waves: delta, theta, alpha, beta, and gamma using a series of digital filters. The EEG data is then classified into the rest or active states using a machine learning classifier, specifically the SVM (Support Vector Machine). The confusion matrix, F1 score, and various performance indicators are taken into account, and each sub-band's mean, energy, and entropy are retrieved as features. We learn more about the relationship between each brain wave and cognitive activity by examining the simulation's results. This page also offers a quantitative examination of how each cortical region functions when doing cognitive activities. The research also discusses the classification of EEG signals into two categories based on task complexity, using information from both the active and resting stages.

**Data Collection:** In the present study, a publicly available dataset from MIT PhysioNet [28] was employed to explore a widespread EEG-based depression or stress detection system. The collection includes 36 participants' artifact-free EEG recordings from 36 different subjects. The Neurocom monopolar EEG device, which has twenty-three channels, was used to record the signals at a sampling rate of 500 Hz. The symmetrical anterior-frontal, central, parietal, occipital, and temporal regions, as well as other places chosen in accordance with the international 10/20 approach, were electrode locations. Students from Kyiv's Taras Shevchenko National University who were aged 18 to 26 participated in this study as participants. The only pupils who were considered did not have any visual impairments and showed no clinical signs of mental, cognitive, linguistic, or non-verbal learning problems. For performance analysis and to gauge the degree of task complexity, the number of operations finished within a 4-minute time frame and the accuracy of the computation were recorded for each participant. If the computed result differed from the true value by no more than 20%, the task complexity level was deemed low.

**Materials & Methodology:** When the body is moving during data collection, noise is frequently added to the EEG signal. Due to its low amplitude and the interference from the electrodes on the headsets that pick up brain signals, removing this noise from the EEG data can be difficult.

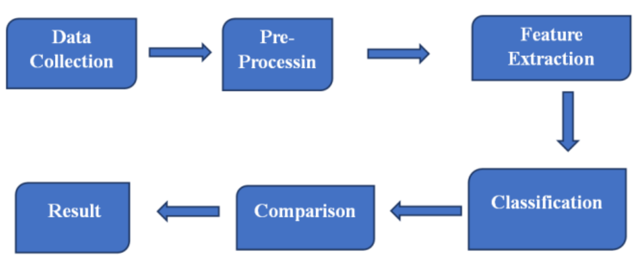
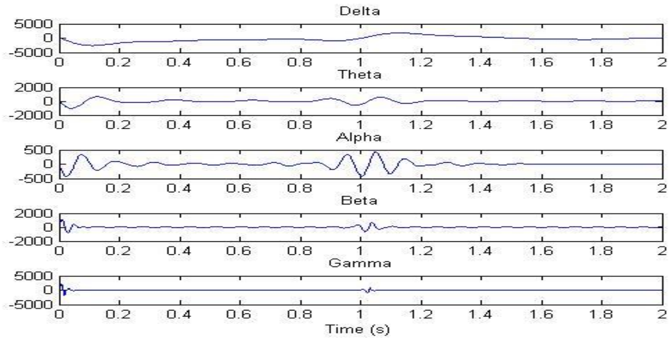



**Fig. 1:** Overview of the methodology.

In the discipline of signal processing, a filter is a device or technique used to exclude specific undesired components or features from a signal. The primary characteristic of filtering, which is a subset of the broader field of signal processing, is the selective reduction or removal of particular portions of the signal.




Time Domain Representation        Frequency Domain Representation

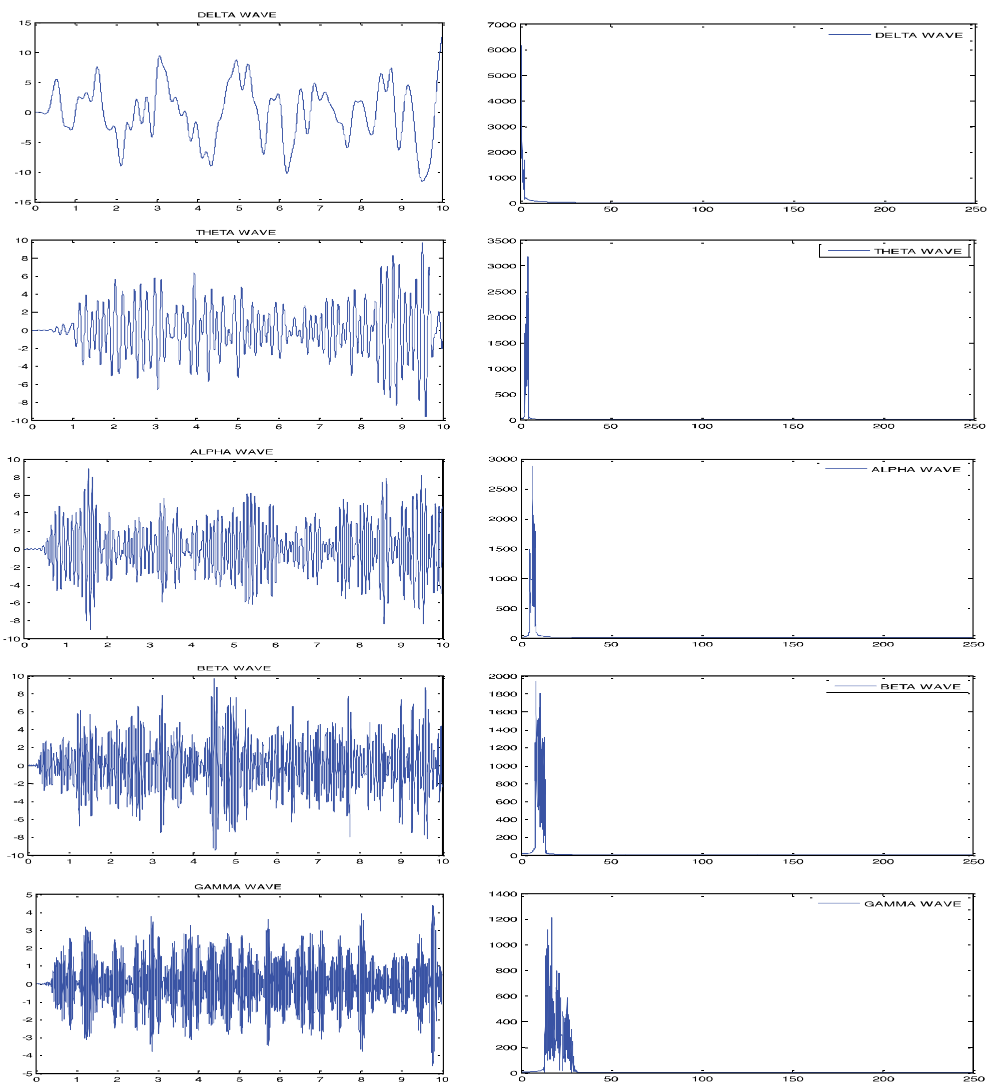



**Fig. 3:** Representation of extracted five EEG Rhythms in both the time domain as well as frequency domain.

Ocular noise and power line noise are two different types of noise that must be taken into account during the pre-processing step. The EEG signal is subjected to pre-processing techniques to address these issues. High-pass filters with a cutoff frequency of 0.5 Hz are used to remove low-frequency noise, and low-pass filters with passband edges set at 45 Hz are used to remove high-frequency noise. A particular filter is also used to get rid of power-line interference. Here in this study, we used a total of 11 electrode data, As the temporal lobe and frontal lobe were more active at the time of computational work or study, we selected 11 EEG channels for this study and also aimed to experiment with different types of permutation of channels. The EEG data is further divided into several brain rhythms, such as gamma, beta, alpha, theta, and delta, using a bank of digital filters. Fig. 1. represents the extracted five EEG Rhythms in both the time domain as well as frequency domain. The original EEG signals are broken down into their component frequencies to produce these sub-band signals. From 440 datasets gathered from a total of 36 participants, various variables like energy, entropy, mean, L2 norms, kurtosis, skewness, relative power, and absolute power were retrieved.

$$Entropy = -\sum_{n=0}^{N-1} p(x_i[n]) \log_2 \left(p(x_i[n])\right) \qquad \text{eq. 1}$$

Where $p(x_i[n])$ is the discrete probability of $x_i[n]$

$$Energy = \sum_{n=0}^{N-1} |x_i[n]|^2 \qquad \text{eq. 2}$$

$$L2\ norms = \left(\sum_{0}^{N-1} |x_i[n]|^2\right)^{\frac{1}{2}} \qquad \text{eq. 3}$$

$$Mean = \frac{1}{N} \sum_{n=0}^{N-1} (x_i[n]) \qquad \text{eq. 4}$$

$$Kurtosis = \frac{\sum (X - X')^4}{n s^4} \qquad \text{eq. 5}$$

$$Skewness = \frac{\sum_{i=1}^{N} (X_i - X')^3}{(N-1) S^3} \qquad \text{eq. 6}$$

Here,

$p_1 = Power\ in\ the\ specific\ frequency\ band$

$p_2 = Total\ Power$

So, $Power\ \ P = \frac{1}{N} \sum_{k=1}^{N} (d_j(k)^2)$ eq. 7

$$\text{Relative power} = 10 \log_{10} \frac{p_2}{p_1} \qquad \text{eq. 8}$$

$$\text{Absolute power} = 10 \log_{10} \frac{P}{1mW} \qquad \text{eq. 9}$$

Here,

$$Power\ \ P = \frac{1}{N} \sum_{k=1}^{N} (d_j(k)^2) \qquad \text{eq. 10}$$

These extracted features are then given to SVM a machine learning classifier.

**Simulation:** Two results that were attained by using our suggested methodology are presented in this section. In the first experiment, we look at how much each cortical region participates in cognitive activities. The results of categorizing EEG signals from various cortices into two classes—active and rest—are specifically presented. Using metrics like accuracy, precision, recall, F1 score, and the confusion matrix, we assess the effectiveness of the machine learning classifier SVM for this classification job. The experiment's dataset consists of 440 instances, each with 8 rows and 3960 columns. Several processes, including signal preprocessing, feature extraction, and the classification of the active and resting stages, were applied to the gathered EEG data. These procedures were used to examine and interpret the EEG data gathered during our trials.

Our goal is to divide the dataset's EEG signals into the two states of rest and activity. Table 1 displays the SVM classification results, including the confusion matrix, F1 score, recall, accuracy, and precision metrics. Entropy, energy, mean, kurtosis, skewness, relative power, and absolute power produced from data across all sub-bands make up the feature set utilized for categorization. F stands for frontal lobe, T for temporal lobe, P for parietal lobe, and O for occipital lobe when referring to the channels.

**Table 1.** Classification of SVM for detection of the mental arithmetic task for FP1 beta using 8 features of brain rhythms.

<table>
<tr><td colspan="7">SVM</td></tr>
<tr><td>Channel</td><td>Sub-bands</td><td>Accuracy</td><td>Recall</td><td>Precession</td><td>F1 Score</td><td>Confusion Matrix</td></tr>
<tr><td>FP 1</td><td>beta</td><td>86.67</td><td>0.90</td><td>0.90</td><td>0.90</td><td><table><tr><td>8</td><td>2</td></tr><tr><td>0</td><td>5</td></tr></table></td></tr>
</table>

Table 1, for example, shows that subject Fp1 and the beta sub-band have an accuracy of 86.67%, precision of 0.90, recall of 0.90, and F1 score of 0.90. The values of the confusion matrix are as follows: true positive = 8, false negative = 2, false positive = 0, and true negative = 5.

The values for the 11 channels (Fp1, Fp2, F3, F4, F7, F8, T3, Cz, P4, O1, and O2) are listed in the tables in Appendix A and B. The tables show the outcomes for four and eight features for each of the five sub-bands that each channel is linked with.

Table 1 presents the SVM findings, including the confusion matrix, F1 score, recall, accuracy, and precision metrics. Utilizing 8 features for the Fp1 channel and the beta sub-band resulted in the highest accuracy of 86.87% out of all the different feature and channel combinations. The F1 score, recall, and precision all add out to 0.90 for this accuracy number. These numbers were chosen because the confusion matrix displays a real positive value of 8 as the greatest and a false positive value of 0 as the lowest.

**Result Discussion:**

**Feature Extraction across Sub-bands:** By identifying and using entropy, energy, and mean, three crucial aspects from decomposed EEG signals, we made a substantial contribution. The five EEG sub-bands that these attributes were generated from were beta, gamma, theta, alpha, and beta. This methodical technique to feature extraction improved the study's depth compared to earlier studies that frequently concentrated on particular brainwave patterns (e.g., solely theta or alpha). It also allowed for a full analysis of cognitive and resting states.

**Comprehensive Analysis of Cortical Regions:** In contrast to earlier research that concentrated on certain brain regions or rhythms, we conducted a thorough analysis of the contributions made by the frontal, temporal, parietal, and occipital lobes, among other cortical regions, to cognitive activities. This more comprehensive perspective advances our knowledge of the relationship between cortical activity and cognitive states by providing fresh perspectives on how the entire brain functions during mental math activities.

**Method of Classification Using SVM:** Although prior research has classified EEG data using a variety of machine learning models (including decision trees, quadratic discriminate analysis, and support vector machines), As EEG signal has non-linear characteristics, so we worked with a semi-parametric model (SVM) also we focused especially on the SVM model for splitting EEG data into two states: activity and rest. Their research demonstrated the effectiveness of SVM in differentiating mental states, particularly in the context of mental math exercises. Additionally, we offered comprehensive performance indicators such as recall, precision, F1 score, and confusion matrix.

**Comparison with Previous Research:** In this study we offered a direct comparison with previous studies in the field, demonstrating that our proposed method produced accuracy that was either better or equivalent (See Table II). As an illustration, we reported an accuracy of 86.67% using 8 features, which is in line with earlier research by Wang et al. that found an accuracy of 84.15% using a single channel. Our enhanced methodology's significance is made clearer by this benchmarking.

In this study, we only experimented with a Support vector machine (SVM). We reviewed literature that already conducted classifier comparisons (including decision trees, quadratic discriminant analysis, and support vector machines). As those investigations have previously examined the distinctions among classifiers, we chose not to replicate the identical examination but rather to expand on those discoveries, particularly emphasizing on showcasing the effectiveness of feature extraction and SVM technique. Also, we planned to experiment hybrid model for a similar dataset shortly.

**Discussions& Result:** In this study, we performed tests on a particular mental arithmetic problem to determine how challenging it was. EEG signals were gathered, processed using a variety of methods, and then categorized using various machine learning techniques. The best procedure with the highest level of accuracy was what we were trying to find. We also noticed that the categorization process's outcomes could change based on how many features are used.

**Table 2.** Comparison and Result Table.

| No | Authors | No. of tasks | No. of channels | Accuracy |
|---|---|---|---|---|
| 1 | Ramaswamyet et.al. [29] | 2 | 6 | 94.4% |
| 2 | Del R Millan et.al. [30] | 3 | 8 | 70% |
| 3 | Wang et.al. [31] | 2 | 1 | 84.15% |
| 4 | Anderson et.al. [32] | 2 | 6 | 91.4% |
| 5 | Liang N et al. [33] | 5 | 6 | 51% |
| 6 | Binish Fatimahet et.al. [34] | 1 | 11 | 80.6% |
| **7** | **Ours Proposal** | 1 | 11 | 86.67% (4 features) |
| | | 1 | 11 | 86.67% (8 features) |

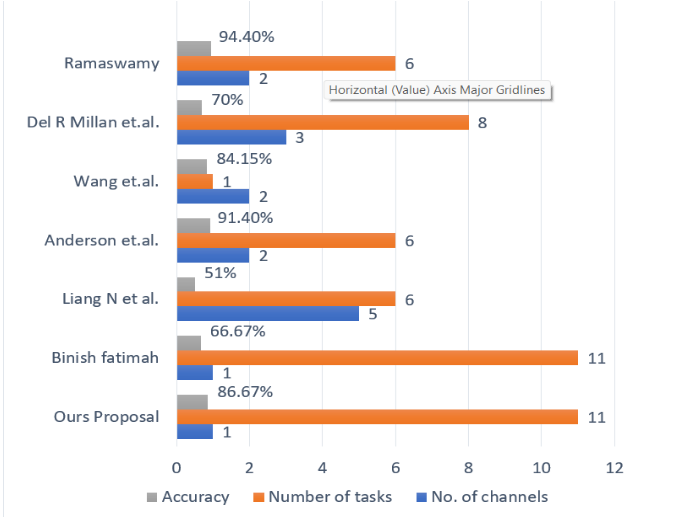



**Fig. 4:** Bar chart representation of accuracy comparison.

In this study, EEG signals were gathered, processed using a variety of methods, and then categorized using various machine learning techniques. The best procedure with the highest level of accuracy was what we were trying to find. We also noticed that the outcomes of the categorization process could change based on how many features are used. Using parameters such as entropy, energy, and mean retrieved from the EEG signal, we categorize the supplied EEG signal into rest state and active state. The data is further divided into five sub-bands using a set of digital filters, allowing us to record the delta, theta, alpha, beta, and gamma rhythms of the brain. The accuracy was found to be 94.4% in [29] and 91.4% in [32] for six channels in both cases. Here in this study, by performing SVM we got the accuracy of 86.67% for 11 channels. As go through (Appendix-A), it shows their classifier results (For 4 features). Similarly, we also evaluate, the result for 8 features. In Fig. 4 we presented the comparison analysis of our proposed model with state of art techniques. Our proposed method showed better performance compared to other literature.

**Conclusion:** Diseases due to mental illness are becoming increasingly commonplace globally, making it harder for doctors to diagnose patients by using a patient classification system. Through the integration of feature extraction techniques that capture many EEG rhythms relevant to cognitive stress, the proposed method improves classification accuracy. The method uses sophisticated machine learning methods, such as Support Vector Machines, to distinguish between different task difficulties. Robust assessment measures are incorporated to guarantee noteworthy improvements in accuracy, and stringent noise reduction techniques enhance the quality of the EEG signals analyzed. Cross-validation is another technique used to assess the model's performance and provides a more broadly applicable accuracy metric than more conventional approaches. In order to identify the resting and active states of the brain during a certain cognitive task, this study examines the function of each brain rhythm. In addition, we offer a method for evaluating the imposed task's difficulty using EEG data. This study may advance our knowledge of how the brain reacts to different learning deficits and aid in the development of brain-computer interface algorithms.

**Future Work:** In our upcoming research, we'll use more unprocessed EEG datasets with various sampling rates to test the suggested algorithm's robustness. To obtain more accurate results, we will use hybrid models like Random Forest and additional machine learning algorithms, as well as a greater number of electrodes. To choose the best feature, we shall employ "Uncertainty Calculation".

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