

POWER SPECTRAL ANALYSIS OF VARYING COMPLEXITY TASKS USING EEGLAB

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Abstract

Analysis of the effects of increasing degrees of complexity on students' brains is the primary topic of this research. Therefore, this study aims to use Electroencephalography (EEG) to determine the task's difficulty level. This research examined assertions of broad mathematical and logical difficulty that can be addressed with the "C programming language." The EEGLAB software has been used to analyze brain waves' power spectrums while solving problem statements of different degrees of complexity. Most significantly, we discovered that as problem statements get more complicated, the strength of the Alpha, Beta, and Theta bands rises. Input features for machine learning classifiers have included descriptive statistical metrics such as mean, standard deviation, skewness, and kurtosis. Specifically, we have compared and analyzed the efficacy of four ML classifiers: Logistic Regression, Neural Network, Decision Tree, and Support Vector Machine. To classify EEG data into "easy" and "hard" categories for C programming problem statements, the DT classifier has been found to perform better with a 69.23% accuracy. The results of this research can be used to generate test questions for open-book exams, and higher-order laboratory experiments.

Keywords: Brain Signals; Complexity Level; Electroencephalogram (EEG); Machine Learning Classifiers; Power Spectral Analysis

Introduction

The effects of increasing degrees of complexity on students' brains have been a subject of significant research interest. Understanding how the brain responds to tasks of varying difficulty can provide valuable insights into cognitive processes and educational methodologies. This study mainly focuses on analyzing task difficulty levels using Electroencephalography (EEG), a non-invasive technique that measures electrical brain activity. To assess task difficulty, we employed the

"C programming language" to create a problem statements with varying mathematical and logical complexity levels. The "C programming" language offers a versatile platform for developing and implementing tasks that require computational thinking and problem-solving skills. By leveraging the capabilities of the C language, we aimed to investigate the relationship between task complexity and brain activity patterns. Assessing complexity task levels in C-language is important for several

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reasons, and it can provide various benefits in the real world. The combination of C language-based tasks and EEGLAB software is of the most academic interest in this paper because it allowed the researchers to study the neural correlates of cognitive tasks more precisely than possible with other methods. C is a low-level language that gives researchers much control over how code is executed, which can help identify specific neural signatures of different cognitive processes. EEGLAB is a powerful software package that can be used to record and analyze EEG data, which can then be used to correlate neural activity with specific cognitive tasks. Using these two tools together, the researchers got a more in-depth look at the brain activity that underlies cognitive tasks of varying complexity. Overall, assessing complexity task levels in C-language is a valuable tool for facilitating skill development, tracking progress, personalizing instruction, preparing students for future careers, enhancing project planning, and ensuring code quality. It empowers students with the necessary knowledge and abilities to tackle real-world programming challenges, contributing to their success in computer science and related industries.

EEGLAB software has been utilized to analyze the EEG data collected during task-solving. EEGLAB provides a comprehensive set of tools and algorithms for processing and analyzing EEG signals, including power spectrum analysis. By examining the power spectra of brain waves, we aimed to identify patterns that correlate with the complexity of the problem statements. Our investigation revealed a significant finding: as the complexity of C programming problem statements increased, we observed an increase in the strength of the Alpha, Beta, and Theta bands in the brain wave power spectra. These frequency bands are associated with different cognitive processes, and their heightened activity suggests higher engagement and cognitive load when tackling more complex tasks. The use of EEG in educational studies is relatively new. This

research aims to see if using EEG data to assess students' problem-solving abilities would be beneficial. Human cognition may be impacted by varying degrees of challenge. This study aimed to examine broad classes of solvable mathematical and logical problems in C. Easy problems are explored while more challenging ones are outlined. The student's brain activity was monitored as they read problem statements of progressively greater difficulty. The problem statements that were considered for the study are depicted in Blocks: **Problem Statement: 1 (Easy)** and **Problem Statement:2 (Hard)**. Using a five-channel Emotive Insight EEG system, we could record the subject's brain activity as they read the problem statements (Figure 1). The power in each frequency band of an EEG waveform may be represented by isolating its components. Theta (4-8 Hz), Alpha (8-12 Hz), Beta (13-30 Hz), and Gamma (30-43 Hz) are the five frequency bands often detected in the EEG spectrum. In this work, we create an AI-based complexity prediction method that leverages EEG brain wave data to assess the difficulty of problem statements. This research aims to accomplish the following goals:

1. To conduct power spectrum analysis of the user's brain waves while addressing C programming problem statements of varied difficulty.
2. Apply machine learning classifiers to categorize the different levels of complexity.

The following outline illustrates how the remaining parts of the paper are structured. Section II will delve into the related work, while Section III will expound on the EEG in brain analysis. Section IV will detail the proposed methodology and experimental procedures, and Section V will discuss an analysis of the results and model assessment.

Finally, the concluding remarks will be presented in the last section.

Problem Statement: 1 (Easy)

Given a positive Integer denoting n , do the following:

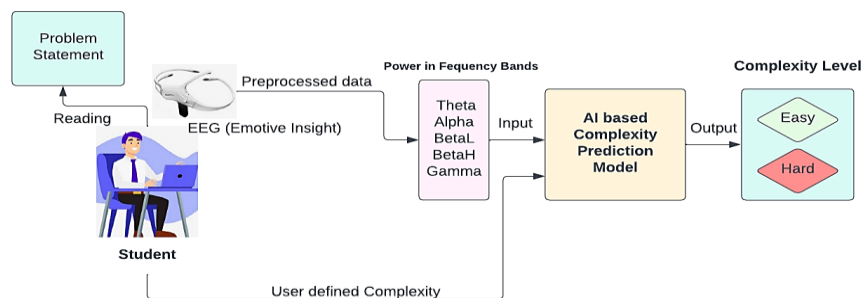


Figure 1. Programming Task's Complexity Prediction Model

If $1 \leq n \leq 9$ print the lowercase English word corresponding to the number (e.g., one for 1, two for 2) If $n > 9$ print Greater than 9

Sample Input	Sample Output
5	five
8	eight
44	Greater than 9

Problem Statement:2 (Hard)

The students have an entry in the library only if they enter a four-digit security number assigned to them. Note every student has a unique four-digit security number. Write a Program in C to check whether a security number entered by the student is correct or not. If it satisfies the following criterion, then print a message “**You are allowed to enter in the library**” otherwise, print a message “**Sorry security number is not valid**”. The security number is valid only if it satisfies the following conditions: Number must be 4 digits long and if we perform repeatedly addition of the square of each digit it ends up in digit 1.

Sample Input	Sample Output
1033	You are allowed to enter in Library
417	Sorry security number is not valid

Related Work

Numerous cognitive architectures have been put forth to model and comprehend the human mind. Considerable research from the last 20 years has already identified various EEG patterns associated with cognition. To work on various cognitive elements such as memory, emotion, etc., Dahal, Nandagopal, Nafalski and Nedic (2011). suggested extracting distinct characteristics from visual, tactile, auditory, and psychomotor stimuli and evaluating their impact on the EEG. Jaušovec (2000) outlined the distinctions in cognitive processes between gifted, intelligent, creative, and average people when solving complex problems. The author established that various respondents' approaches to solving closed and open tasks would change depending on their degrees of intellect and creativity. These variations would represent EEG patterns. Numerous studies have looked at EEG patterns throughout various task complexity levels, (Kirschner *et al.*, 2012; Tianchen *et al.*, 2016; Bricker, 2020; Jianyu *et al.*, 2020). The design problem-solving process was examined using EEG by Liu *et al.* (2018) from the standpoint of cognitive science. They tried to look at the effects of various problem statements from the angles of divergent thinking, convergent thinking, and mental workload

to understand how designers' cognitive activities were affected. Jaušovec and Jaušovec (2000) looked at how different cognitive processes connected task complexity. A novel conception for complex thinking was put out by Pacheco and Herrera (2021) through the synthesis and conjugation of many mental views. Numerous studies have concentrated on EEG analysis for the complexity of arithmetic tasks (Federico and Carole, 2012; Spüler *et al.*, 2016; Al-Shargie *et al.*, 2018; Lokare and Netak, 2020). According to Karkare *et al.* (2009) research, task-specific skills and demands might alter the temporal scale-free dynamics of brain responses. Winnie *et al.* (2017) created an EEG-based mental workload-detection tool by developing a generalized model for four different cognitive and motor activities. Different parameters Lokare *et al.* (2022) and Chang *et al.* (2013) have been considered for measuring cognition, including Bloom's levels and language complexity. How effectively an electroencephalogram and an eye-tracker can be used to predict programmer competence (novice/expert) and task complexity (easy/complex) was examined by Seolhwa *et al.* (2018). The Consequences and Downfalls of Block Design for EEG Classification Experiments were outlined by Ren *et al.* (2020). A few number of researchers Bridwell *et al.* (2018) and Turner *et al.* (2016) concentrated on the investigation of behavioral aspects using EEG. Therefore, preliminary findings indicate that EEG might be a valuable technique for directly determining a student's level of cognitive exertion.

As a result, it may be stated that an EEG analysis for programming language courses is completely missing from the research. The present study is one of the first attempts to identify correlations between cognitive tasks (problem-solving activities of varied complexities in C programming) and the brain's functioning.

EEG Signal Analysis using EEGLAB

The EEG power spectrum analysis for the prediction of the complexity level may be completed in six steps, as depicted in Figure 2.1. It includes data gathering, loading an Edf file, importing channel locations, data filtration, Artefact removal using independent component analysis (ICA), and spectral power analysis.

Data acquisition

Collecting and recording brain data from individuals who participated in an experiment is called data acquisition. Both invasive and noninvasive methods may be utilized to record the

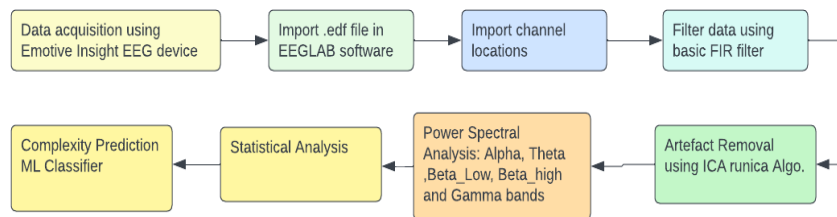


Figure 2. Steps in the EEG signal analysis for complexity level prediction of C programming question

complexity prediction dataset. The noninvasive approach is known as electroencephalography (EEG), while the invasive method is called electrocorticography (ECoG). Subjects in experiments are asked to read problem statements of different complexity.

Participant's Details: A total of 30 students' EEG data were gathered while solving simple and difficult problem statements in the C programming language. Thirty undergraduates from Rajarambapu Institute of Technology (07 girls, 23 boys, mean age = 21.1 years, age range = 18-26) took part in this research on problem-solving.

Preparation: Before data acquisition, the subject's scalp is cleaned to remove any dirt, oil, or residue that may affect electrode contact. Electrode gel or paste is applied to the predetermined electrode locations on the scalp according to the International 10-20 system, a standard electrode placement method. The subject may also be instructed to relax and remain still during the recording to minimize artifacts.

Electrode Placement: EEG electrodes are attached to the scalp using adhesive collars or caps with predetermined electrode sites. The electrodes are positioned at specific locations based on the research or clinical question of interest. Common electrode placements include AF3, AF4, T7, T8, and Pz, depending on the desired brain regions to be recorded.

Signal Acquisition: The EEG device, typically an amplifier, is connected to the electrodes via conductive cables. The amplifier amplifies the weak electrical signals picked up by the electrodes and converts them into digital signals for further processing. The sampling rate, which determines the number of data points collected per second, is set according to the research or clinical requirements.

Recording: The EEG data acquisition is initiated, and the subject is instructed to remain still and relaxed during the recording session. The recording duration can vary depending on the study design or clinical protocol, ranging from a few

minutes to several hours. Maintaining a quiet environment and minimizing any potential sources of electrical interference is important to obtain clean and reliable EEG data.

Data Storage: The recorded EEG data are stored digitally, usually in a computer or a data storage device. Proper data labeling and documentation should be maintained for data analysis and interpretation, including subject information, electrode placement, and recording parameters.

EEG Data Collection: Five active electrodes (AF3, AF4, T7, T8, and Pz) are connected to the scalp and arranged according to the expanded international electrode 10-20 system for EEG data collection. AF3 and AF4 electrodes are associated with the frontal cortex, whereas T7 and T8 are associated with the temporal lobe. Pz electrode is present to gather data from the parietal lobe. We did not deploy an electrode for the occipital lobe since we employed a five-channel emotive insight device. In line with the Declaration of No Objection, all participants were granted a written informed agreement to have their brains used for research. Participants were set up for EEG recording after filing a consent form. Participants filled out many questionnaires before the setup, including their name, address, class, age, and knowledge of the programming course in percentage. The experimental work was done in a computer laboratory at Rajarambapu Institute of Technology, Sakharale, INDIA.

Preprocessing

Preprocessing data reduces computing complexity and improves classifier effectiveness since artifacts and noise corrupt EEG data during capture. ECG, EOG, EMG, electrode failures, power lines, and equipment and device interference create these artifacts as mentioned by Dipali *et al.* (2019), Ying *et al.* (2021), and Brian *et al.* (2017). EEG artifacts have two sources. Interior artifacts come from biological processes inside the body, whereas exterior artifacts come from outside. Table 1,

summarises artifact kinds. Downsampling, windowing, and filtering are necessary to preprocess EEG data due to its poor signal-to-noise ratio.

Power Spectral Analysis

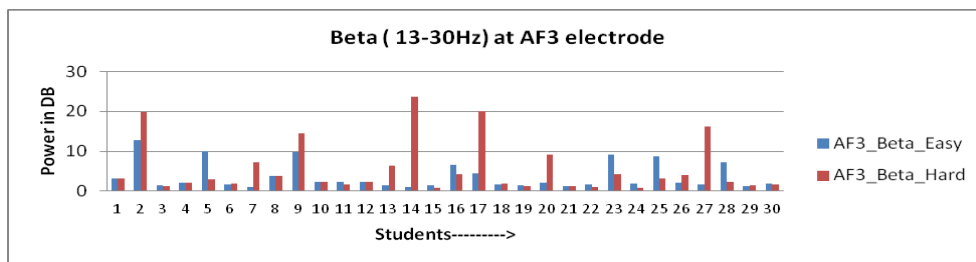
The EEG data were gathered from each of the thirty subjects at all five locations of electrodes, namely AF3, AF4, T7, T8, and Pz. After preliminary processing of the raw EEG data by rejecting artifacts and filtering out the noise, a plot of the power spectrum of various frequency bands, namely Alpha(4-8Hz), Theta(4-8Hz), Beta(13-30Hz), Gamma(>30Hz) is been created. At first, an activity power spectrum and an independent component analysis were carried out on each of the five channels' worth of data to determine which brain regions performed better during the various activities. After completing an independent component analysis on each channel, it was determined that more research should be conducted on three-channel locations. These three channel locations were situated on the frontal and temporal regions of the brain, respectively (AF3, AF4, and T8). The graph 1, shows the beta-band at AF3

electrode EEG data for 30 students, measured on easy and hard programming tasks. The beta band is a frequency band of brain waves that ranges from 13 to 30 Hz. It is associated with attention, focus, and processing of information. Overall, the data shows that the students' beta band activity is more active during the hard task than during the easy task. This is evident in the higher values for AF3_Beta_Hard in all cases.

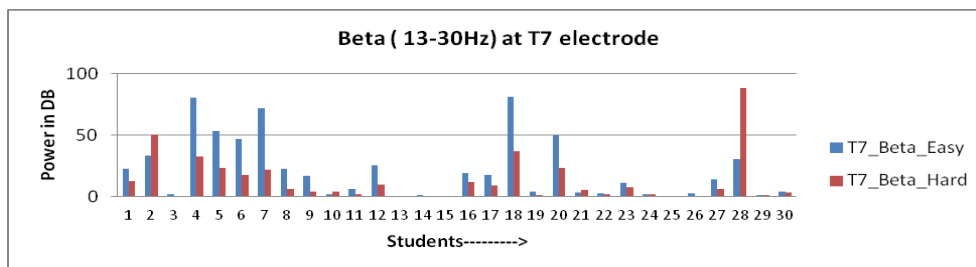
There are some interesting differences between the two tasks regarding the beta band. For example, the difference between AF3_Beta_Easy and AF3_Beta_Hard is larger for some students than others. This suggests that there may be individual differences in how people process information. The data provide interesting insights into students' beta-band EEG activity during different cognitive tasks. The data suggest that the beta band is more active during challenging tasks and that different brain waves are involved in different types of cognitive processing. The data also shows individual beta band activity variations between students. Graph 2 represents the values of T7 Beta wave measurements for easy and hard tasks. The Beta wave measurements vary across different

Table 1. Power in Frequency bands: Theta, Alpha, and Gamma

Brain Lobes->	Frontal Lobe		Temporal Lobe		Parietal Lobe
Electrode->	AF3	AF4	T7	T8	Pz
Alpha_Easy	7.39	2.78	34.72	6.02	2.68
Alpha_Hard	10.89	9.74	81.5	12.18	0.81
Theta_Easy	37.53	13.01	242.4	29.12	8.9
Theta_Hard	60.38	50.56	447.76	60.37	2.08
Gamma_Easy	1.58	0.72	6.23	2.39	1
Gamma_hard	1.57	1.48	9.08	3.54	0.52



Graph 1. Power in Beta Frequency band at AF3 electrode for Thirty Students



Graph 2. Power in Beta Frequency band at T7 electrode for Thirty Students

participants and tasks. In some cases, the Beta wave measurements are higher for easy tasks than hard ones (e.g., student 1, 4, 6). Conversely, for other participants, the Beta wave measurements are higher for hard tasks compared to easy tasks (e.g., students 2, 3, 9).

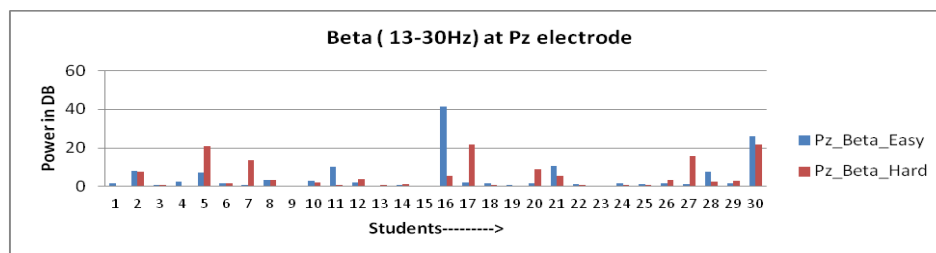
There are instances where the Beta wave measurements for both easy and hard tasks are relatively low (e.g., students 7, 10, 14). Some participants exhibit a significant difference in Beta wave measurements between easy and hard tasks (e.g., student 27). It's worth noting that the magnitude of the Beta wave measurements varies widely among participants, ranging from very low to relatively high values.

The data suggest that the Beta wave activity at the T7 electrode location can vary depending on the task difficulty and individual differences. These variations' specific patterns or significance would require further analysis, such as statistical tests or comparisons with other variables, to draw more definitive conclusions. Graph 3 shows the Pz_Beta values for Easy and Hard tasks. Pz_Beta is a measure of cognitive engagement, and the higher the value, the greater the level of cognitive

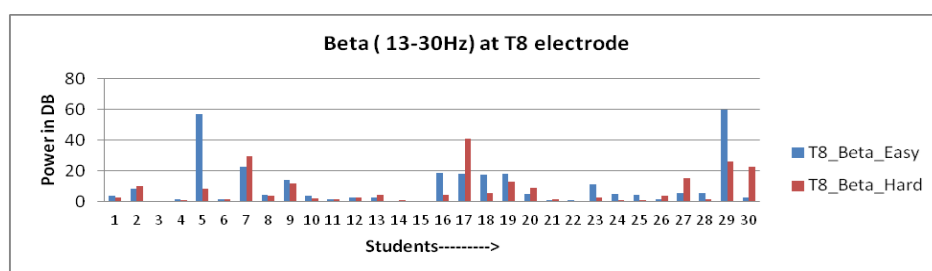
engagement. As you can see, the Pz_Beta values are significantly higher for Hard tasks than for Easy tasks. This suggests a greater level of cognitive engagement is required for Hard tasks. The graph3 also shows that the Pz_Beta values are more variable for Hard tasks than for Easy tasks. This suggests that a wider range of cognitive engagement levels is required for Hard tasks, with some participants requiring more engagement than others.

Overall, the table suggests that a greater level of cognitive engagement is required for Hard tasks. Graph 4 shows the T8_Beta values for Easy and Hard tasks. T8_Beta is a measure of cognitive engagement, and the higher the value, the greater the level of cognitive engagement. As you can see, the T8_Beta values are significantly higher for Hard tasks than for Easy tasks. This suggests that a greater level of cognitive engagement is required for Hard tasks. The graph also shows that the T8_Beta values are more variable for Hard tasks than for Easy tasks.

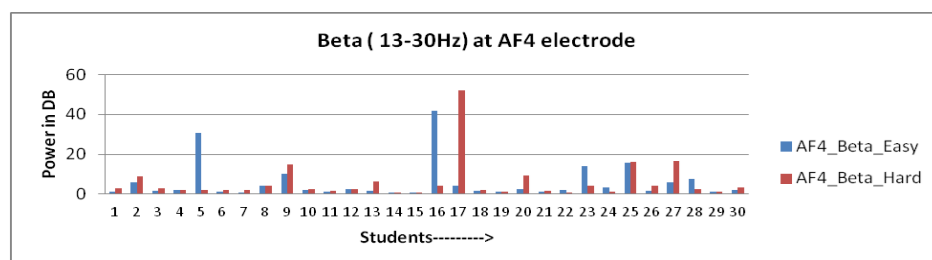
This suggests that a wider range of cognitive engagement levels is required for Hard tasks, with some participants requiring more engagement than



Graph 3. Power in Beta Frequency band at Pz electrode for Thirty Students



Graph 4. Power in Beta Frequency band at T8 electrode for Thirty Students



Graph 5. Power in Beta Frequency band at AF4 electrode for Thirty Students

others. Graph 5 shows the AF4_Beta values for Easy and Hard tasks. AF4_Beta is a measure of cognitive engagement, and the higher the value, the greater the level of cognitive engagement. The AF4_Beta values are significantly higher for Hard tasks than for Easy tasks. This suggests that a greater level of cognitive engagement is required for Hard tasks. Graph 5 also shows that the AF4_Beta values are more variable for Hard tasks than for Easy tasks. This suggests that a wider range of cognitive engagement levels is required for Hard tasks, with some participants requiring more engagement than others. Overall, the table suggests a greater level of cognitive engagement is required for Hard tasks. The higher mean, median, mode, standard deviation, variance, range, and interquartile range values for Hard tasks support this.

The table1 presents recorded power values (in DB) for different brain lobes (Frontal Lobe, Temporal Lobe, and Parietal Lobe) and corresponding electrode locations (AF3, AF4, T7, T8, and Pz) across various frequency bands (Alpha, Theta, and Gamma) during easy and hard tasks. Analyzing the data, we can observe the following patterns:

Alpha Power: The Alpha power values generally increase from the easy to the hard tasks across all brain lobes and electrodes. This suggests an increase in cortical inhibition and relaxation during more challenging tasks.

Theta Power: Similar to Alpha power, Theta power increases overall from easy to hard tasks. This suggests greater mental effort and cognitive engagement during more complex tasks.

Gamma Power: The Gamma power values are relatively low compared to Alpha and Theta. However, there is a slight increase in Gamma power from easy to hard tasks, indicating higher neuronal activation during more challenging tasks.

Electrode Variations: Across the different frequency bands, there are variations in power values based on electrode location. For example, in the Alpha and Theta bands, the Parietal Lobe (Pz) consistently exhibits higher power values than other electrodes. It shows the involvement of the Parietal Lobe in the cognitive processes associated with the tasks.

The recorded power values provide insights into the neural activity and cognitive processes associated with varying task complexities. The increases in Alpha and Theta power suggest increased cognitive load and engagement, while the variations in electrode-specific power values indicate the involvement of specific brain regions in processing the tasks. Beta waves are fast brain waves with a frequency of 13-30 Hz. They are associated with focused attention, problem-solving,

and decision-making. Theta waves are slow brain waves with a 4-8 Hz frequency. They are associated with deep sleep, meditation, and creativity. Alpha waves are slower brain waves with a frequency of 8-12 Hz. They are associated with relaxed wakefulness, daydreaming, and visualization. As the complexity of a programming task increases, there is a corresponding increase in beta, theta, and alpha power. This suggests that these brain waves support the cognitive processes involved in programming, such as problem-solving, planning, and creativity. Beta waves may promote a state of focused attention, which is conducive to problem-solving. Theta waves, on the other hand, may facilitate the collection of information from different brain regions, which is essential for complex problem-solving. Alpha waves promote a relaxed focus, which is conducive to creative thinking. The findings suggest that beta, theta, and alpha power play an important role in supporting the cognitive processes involved in programming. This research could have implications for developing training programs and interventions that can help improve the programming skills of students and professionals. The increase in beta, theta, and alpha power is related to engaging in more creative and divergent thinking as the complexity of a programming task increases.

The increase in beta, theta, and alpha power is related to managing and coordinating multiple tasks and subtasks as the complexity of a programming task increases. The findings suggest that programmers may benefit from activities promoting focused attention, integrating information from different brain regions, and relaxed focus, such as meditation, mindfulness, and exercise.

Features extraction

Statistical characteristics such as the mean, standard deviation, skewness, and kurtosis are derived from the data using the equations 1 to 4 as mentioned by Nagabushanam, Perattur (2020). The mean, standard deviation, kurtosis, and skewness are commonly chosen as features in statistical analysis for several reasons:

Mean: It provides information about the typical value or level of the variable. In the context of the given data, comparing the means of Pz Beta waves during easy and hard tasks helps understand the average differences between the two conditions.

$$Mean = \frac{\sum_{i=1}^N x_i}{N} \quad (1)$$

Standard Deviation: The standard deviation measures dispersion or variability in the dataset. It indicates how much the values deviate from the mean. By calculating the standard deviation, we can assess the spread of the data and determine if there are notable differences in variability between easy and hard tasks.

$$\text{Standard Deviation (SD)} = \sqrt{\frac{\sum (xi - \text{mean})^2}{N}} \quad (2)$$

Kurtosis: Kurtosis measures the shape of the distribution and determines the presence of heavy or light tails compared to a normal distribution. Positive kurtosis indicates a more peaked distribution with heavy tails, while negative kurtosis indicates a flatter distribution with light tails. Examining the kurtosis can provide insights into the Pz Beta wave data distribution and any departure from a normal distribution.

$$\text{Kurtosis} = \frac{\sqrt{\frac{\sum (xi - \text{mean})^4}{N}}}{SD} \quad (3)$$

Skewness: Skewness measures the asymmetry of the distribution. By analyzing the skewness, we can identify any skewness in the Pz Beta wave data and understand if it is positively or negatively skewed.

These features (mean, standard deviation, kurtosis, and skewness) collectively provide valuable information about the data distribution's central tendency, variability, shape, and symmetry. They allow us to gain insights into the dataset's characteristics and compare different conditions or groups.

$$\text{Skewness} = \frac{\sqrt{\frac{\sum (xi - \text{mean})^3}{N}}}{SD^3} \quad (4)$$

Where N = Number of items
i = 1 to N

Result Analysis

The dataset information and a description of the experimental setup are shown in Table 2.

The dataset is well-balanced, with 23 male and seven female students. The problem statements are of two levels of difficulty, easy and hard. The EEG signals were collected using a 5-channel Emotive Insight device. The input features are mean, standard deviation, kurtosis, and skewness for Easy and Hard C programming Problem statements of a total Thirty students. The output features are the user-defined complexity level and the predefined complexity level. The machine learning models are logistic regression, neural network, decision tree, and support vector machine. The measuring parameters are accuracy, precision, sensitivity, specificity, and F1 score. The train-test split is 70% training and 30% testing. The dataset is a valuable resource for researchers interested in developing machine learning models to predict the complexity of a problem from EEG signals.

ML Models

Logistic Regression: LR is a classification algorithm commonly used for binary classification problems. It applies the logistic function to model the relationship between the independent variables and the binary outcome. In predicting the difficulty

Table 2. Experimental Setup

Dataset Description	EEG Signals have been collected from Thirty college students while they perform problem-solving tasks of various complexities
Number of Students	30 (Male=23, Female=07)
Name of College	Rajarambapu Institute of Technology, Sakharale, Maharashtra, INDIA
Problem statements	02 (Easy and Hard)
EEG Device	5 Channel Emotive Insight
Implementation of Problem Statements	C Programming Language
Input Features	Mean, standard deviation, kurtosis, and skewness for Easy and Hard C programming Problem statement of total Thirty students
Output Features	User defined complexity level and Predefined Complexity level Easy=0, Hard =1
Machine Learning Model	Logistic Regression, Neural Network, Decision Tree, Support Vector Machine
Measuring Parameters	1. Accuracy 2. Precision 3. Sensitivity 4. Specificity 5. F1 Score
Train Test Split	70% Training and 30% Testing

level of C programming problem statements, logistic regression estimates the probability that a problem statement is either easy or hard. It calculates a weighted combination of the input features and applies a sigmoid function to produce a probability score. The decision boundary is typically set at a probability threshold of 0.5, where values above the threshold indicate a “hard” prediction and below indicate an “easy.”

Neural Network: Neural Networks, special fiscally Multilayer Perceptron (MLP), consists of interconnected layers of artificial neurons. They are well-suited for complex pattern recognition tasks and can learn non-linear relationships in the data. In predicting the difficulty level of C programming problem statements, a Neural Network model is trained with multiple hidden layers to capture intricate relationships between the input features and the problem difficulty. The network learns to optimize the weights and biases to classify problem statements as easy or hard. The output layer typically uses a sigmoid activation function to produce a probability score, and a threshold is applied to make the final prediction.

Decision Tree: A DT is a supervised learning algorithm that uses a tree-like flowchart structure to make decisions. Every internal node represents a feature, and each leaf node represents a class label or outcome. The DT is constructed by recursively splitting the dataset based on the key values of the input features that result in the best separation of the classes. In predicting the difficulty level of C programming problem statements, a Decision Tree model is built by selecting the most informative features and creating decision rules that determine the difficulty level. The model uses a set of if-else conditions based on the feature values to classify the problem statement as easy or hard.

Support Vector Machine (SVM): A Support Vector Machine is a powerful supervised learning algorithm for classification and regression tasks. It separates data points into different classes by finding an optimal hyperplane that maximizes the margin between the classes. In predicting the

difficulty level of C programming problem statements, SVM constructs a decision boundary by mapping the input features to a high-dimensional space and finding a hyperplane that maximally separates the easy and hard problem statements. The model identifies support vectors, the closest data points to the decision boundary, and uses them to make predictions. SVM aims to balance maximizing the margin and minimizing the classification errors.

These models, Logistic Regression, Neural Network, Decision Tree, and Support Vector Machine, are popular for predicting the difficulty level of C programming problem statements. Each has strengths and weaknesses, and its performance depends on the dataset, feature selection, and model hyperparameters.

Observations

Based on Figure 3, we can make the following observations for the prediction of C programming problem statement difficulty (either easy or hard) using different machine learning models:

Accuracy: The accuracy represents the overall correctness of the predictions made by the model. The Decision Tree model achieved the highest accuracy of 69%, followed by the Support Vector Machine with 61%, Neural Network with 53%, and Logistic Regression with the lowest accuracy of 46%.

Precision: Precision measures the model’s ability to correctly identify positive instances (in this case, classifying a problem statement as hard). The Decision Tree, Neural Network, and Support Vector Machine models achieved a precision of 1, indicating no false positives in their predictions. Logistic Regression achieved a precision of 0.66, correctly classifying 66% of the hard problem statements.

Sensitivity: Sensitivity, also known as recall or true positive rate, measures the model’s ability to correctly identify positive instances among all actual positive instances. The Decision Tree and Neural Network models had a sensitivity of 0.5,

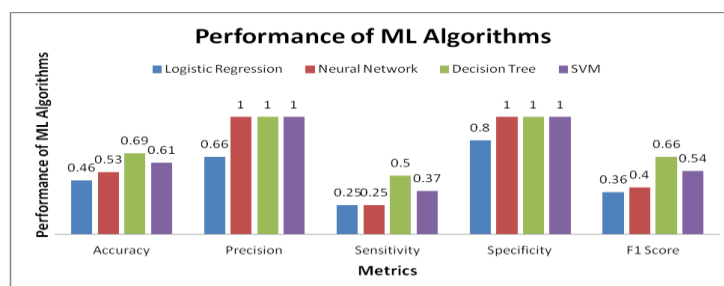


Figure 3. Programming Task’s Complexity Prediction Model

indicating that they correctly classified 50% of the hard problem statements. The support Vector Machine had a sensitivity of 0.37, while Logistic Regression had the lowest sensitivity of 0.25.

Specificity: Specificity represents the model's ability to correctly identify negative instances (in this case, classifying a problem statement as easy). All the models achieved high specificity values, with Decision Tree, Neural Network, and Support Vector Machine achieving a specificity of 1, indicating no false negatives in their predictions. Logistic Regression achieved a specificity of 0.8, correctly classifying 80% of the easy problem statements.

F1 Score: The F1 score is a measure that combines precision and sensitivity to provide a single value that represents the model's overall performance. The Decision Tree model achieved the highest F1 score of 0.66, followed by the Support Vector Machine with 0.54, Neural Network with 0.4, and Logistic Regression with the lowest F1 score of 0.36.

Based on the given observations, the Decision Tree model performed the best overall in predicting the difficulty level of C programming problem statements, achieving the highest accuracy, precision, sensitivity, specificity, and F1 score. Further evaluation and comparison of the models may be required to make more robust conclusions.

The Decision Tree (DT) model is best for predicting programming difficulty due to its interpretability, feature importance analysis, ability to capture non-linear relationships, robustness to irrelevant features, handling of mixed data types, and scalability for large datasets.

Conclusion

The research provides valuable insights into the power spectral characteristics of different brain lobes and electrode locations across various frequency bands during easy and hard tasks. The findings indicate important patterns and variations in neural activity related to task complexity.

The increased Beta, Alpha, and Theta power from easy to hard tasks suggests heightened cognitive engagement, mental effort, and cortical inhibition during more challenging programming tasks. This implies that as the complexity of the tasks increases, individuals may require greater cognitive resources and focus on completing them. The slight increase in Gamma power during harder tasks indicates higher neuronal activation and potentially enhanced information processing. Although Gamma power values were relatively low compared to Alpha and Theta, they still provide

evidence of the involvement of the gamma frequency band in cognitive processing during programming tasks. Moreover, the variations in power values across different electrode locations highlight the role of specific brain lobes, such as the Parietal Lobe, in processing task-related information. The Parietal Lobe consistently exhibited higher power values in the Alpha and Theta bands, suggesting its importance in cognitive processes associated with the tasks. It is worth noting that the conclusions drawn from this analysis should be considered in the context of the specific experimental setup and the study's limitations. Further research and statistical analysis, including comparisons with control groups or baseline data, would provide more robust insights into the relationship between brain activity and programming task complexity. Overall, this analysis contributes to our understanding of the neural correlates of cognitive processes during programming tasks and highlights the importance of considering different frequency bands and brain lobes in studying cognitive workload and engagement.

In this study, EEG was utilized to evaluate how different levels of difficulty in C programming problem statements impacted the learners' brains. Thirty students are a part of this research. Research has been conducted using a 5-channel emotional insight device. The informed consent form is signed by each student who is taking part. The participants also rated the difficulty of each question. EEGLAB is used to do the power spectrum analysis. As the difficulty of a C programming problem statement grows, the strength of the associated alpha, theta, and beta frequencies also increases. Also, Electrodes in the frontal and temporal lobes were shown to be most impacted by task difficulty. We performed a descriptive statistical analysis of data from 30 students for feature selection. Mean, Standard Deviation, Kurtosis, and Skewness are the four parameters chosen as inputs to ML classifiers. Four machine learning classifiers, including logistic regression, neural networks, decision trees, and support vectors, were used to classify C programming problem statements into easy and difficult categories. The suggested Decision Tree approach aimed to improve performance, achieving an accuracy of 69.23% in the EEG categorization of simple and difficult C programming problem statements. The Decision Tree model's ability to capture complex relationships, handle mixed data types, and provide interpretable results makes it well-suited for predicting programming difficulty. Its performance highlights its potential as a valuable tool in educational settings and programming assessment platforms. The proposed approach will

aid in tailoring tasks to individual students' levels of cognitive ability. This idea may be used to create a Personalized Intelligent Tutoring System and generate assessment plans for higher-level tasks. Further improvements can be made by incorporating additional features that capture different aspects of programming difficulty, such as problem complexity, algorithmic complexity, and language-specific challenges. Additionally, ensemble methods like Random Forests or Gradient Boosting can be explored to enhance predictive performance. Furthermore, evaluating the model's performance on a larger and more diverse dataset can provide more robust insights into its effectiveness.

Declarations

Informed Consent: All participants provided informed consent prior to participating in the study. They were provided with comprehensive information regarding the nature of the research, its purpose, potential risks and benefits, and their rights as participants. Participants were given the opportunity to ask questions and clarify any concerns before providing their consent.

Ethical Approval: The research study and its procedures involving human participants and EEG data collection were reviewed and approved by the ethics committee of the *institutional review board: Dr. Babasaheb Ambedkar Technological University, Lonere, Raigad, INDIA*. The study was conducted in compliance with the guidelines set forth by the committee/IRB.

Conflict of Interests: The authors declare that there is no conflict of interest.

Data Availability Statement: Due to the absence of publications, the datasets created and analyzed during the current work are not publicly accessible. Still, they are available from the corresponding author upon justifiable request.

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