Differential Sequence Analysis of EEG Brain Signals for Emotional and Cognitive Assessment

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To improve mental health and wellness and create specific solutions, it is essential to comprehend how individuals feel and brain functions. In this study, we present a novel approach for emotion recognition and analysing electroencephalography (EEG) data for cognitive evaluation. EEG data were collected from 30 participants using non-invasive electrodes positioned at AF3, AF4, T7, T8, and Pz, corresponding to the frontal, temporal, and parietal lobes. We have obtained real-time EEG data from participants during various tasks, including as rest, listening to music, answering questions, and completing mathematical puzzles. Our goal was to investigate the brain correlates of different emotional and cognitive states. The recorded signals were pre-processed using a 4–8 Hz digital Butterworth bandpass filter targeting theta waves, followed by Fast Fourier Transform (FFT) and sequence pattern mapping. Statistical significance of variations between brain states was confirmed using ANOVA ($p < 0.05$). A supervised machine learning classifier (Random Forest) achieved 89.2% prediction accuracy, with precision = 0.87, recall = 0.90, and F1-score = 0.885, demonstrating robust differentiation between emotional and cognitive states. We have developed prediction models for emotion recognition and cognitive assessment using linear regression classification based on EEG features extracted from multiple brain areas. Using statistical analysis and graphical representation techniques, the EEG data was visualized and analyzed, revealing a variety of patterns associated with different tasks and stimuli. Our study demonstrates that emotional states and cognitive activity may be accurately identified from EEG signals. More specifically, we observed significant differences in EEG patterns between tasks, suggesting that real-time tracking of human emotions and mental processes can be achieved with EEG-based techniques. Applications in human-computer interaction, mental health monitoring, and tailored interventions to improve well-being are possible with the suggested methodology.

Povzetek: Raziskava kaže, da je mogoče s pomočjo EEG signalov in strojnega učenja prepoznati čustvena in kognitivna stanja človeka.

1 Introduction

It's critical to understand the complex connections between human emotions and mental functions in order to explore the depths of human psychology and advance general wellness. Our attitude, decisions, and behaviours are mostly shaped by our emotions, but our cognitive processes provide the basis for our ability to perceive, interpret, and interact with our environment. The development of non-invasive techniques for the real-time monitoring and assessment of these internal states has therefore been given priority by developments in affective computing and cognitive neuroscience. The advancement of biomedical technology and our increasing comprehension of the brain have made brain science an indispensable field of study to solve the riddles of life Jahankhani, [15]. Because of this, the electroencephalogram, or EEG, is crucial for examining brain science and is frequently employed in a range of brain-related study fields Acharya, [1], Essa, [7]. The complex structure of the brain has been researched since the mid-1900s, and brain science has remained a popular area of study in recent years. Furthermore, in order to gain a deeper understanding of brain structure and function, EEG signals may be combined with other imaging modalities such as positron emission tomography (PET) Winterhalder, [26], functional near-infrared spectroscopy (fNIRS) Negrescu, [20], Essa, [10], and magnetic resonance imaging (MRI) Albatrookh, [2], Oxley, [21]. The spontaneous biological potential of the brain is amplified and recorded on the scalp to create the EEG signal pattern. This potential, which is usually obtained by placing noninvasive electrodes on the scalp, has been demonstrated to represent the macroscopic activity of the brain surface. The intrinsic and recurring electrical impulses produced by groups of brain cells are recorded by these devices Erman, [9]. One of the primary topics of interest in brain science is the examination of brain electrical activity Williamson, [27]. Electrodes are applied to the scalp during the noninvasive neuroimaging procedure known as EEG in order to record the electrical activity of the brain Essa, [16]. EEG is currently widely utilized in neuroscience and has the potential to improve brain–computer interfaces, make emotion detection easier, and aid in the rehabilitation of people with partial paralysis Shah, [23], Binnie, [3]. This enables researchers to measure and analyze the electrical signals generated by the brain. These signals offer valuable information on the operating mechanisms of the brain, covering the identification of various neurological disorders and the exploration of cognitive processes such as perception, attention, and memory. EEG has gained widespread popularity as a means of investigating electrical activity of the human brain, due to its noninvasive and safe characteristics Shih, [23]. In addition, EEG is a useful diagnostic and research tool for disorders linked to brain dysfunction, such as Alzheimer's disease Khoo, [16], Siuly, [25], epilepsy, schizophrenia, Creutzfeldt-Jakob disease Wang, [28], cerebral palsy Essa, [17], and cognitive impairment Essa, [17]. In order to recognize and analyze EEG signals accurately, one must have a solid understanding of their intricate theoretical aspects and be able to extract the elements that are pertinent to the task at hand. However, because of their distinct qualities, EEG signals present serious difficulties. One such difficulty, according to Lun, [17], is their sensitivity to noise interference, which can lead to a low signal-to-noise ratio. It is noted in Mahmud, [19] that the distinct characteristics of EEG signals make it difficult to directly extract relevant information about certain tasks from them. As highlighted in Mahmud, [19], Essa, [18], accurate EEG signal recognition and interpretation are essential to expanding our knowledge of how the brain functions. Its nonlinearity and nonconformity to a normal distribution further set them apart from traditional signals. Furthermore, individual variables like age, psyche, and testing setting can significantly alter EEG signals da Silva Louren, [6]. To better interpret EEG data, it is therefore essential to create diverse methodology for signal analysis and look into machine learning techniques for signal analysis Giri, [14]. It takes careful study of their unique characteristics and the development of advanced signal analysis algorithms to accurately extract useful information on particular tasks from EEG signals. Our paper presents a novel contribution through a comprehensive description of denoising techniques, which includes mathematical formulations with pseudo codes. In addition, we report the recent advancements in the field of EEG, while highlighting current challenges and discussing future trends. This paper's main contributions can be summed up as follows. We provide a thorough analysis of the steps involved in EEG signal processing, such as feature engineering, denoising, and signal acquisition. The procedure used to denoise the EEG signal is described in full, along with the accompanying evaluation standards. We examine feature engineering in detail in this paper, looking at time–frequency, high-order spectral, and nonlinear dynamic analysis. We give a thorough analysis of both traditional and deep learning methods for categorizing EEG signals. We also provide an overview of the typical datasets utilized for EEG signal processing. We highlight current issues with EEG signal processing techniques and offer potential solutions as well as future research prospects.

In this regard, the goal of our research is to use the analysis of EEG data to create models for cognitive evaluation and emotion recognition. We obtained real-time EEG data from participants in a range of experimental settings, including rest intervals, visual stimulus exposure, auditory experiences, cognitive tasks, and problem-solving exercises. Through a methodical examination of EEG patterns during these episodes, we aim to clarify the brain markers linked to various emotional and cognitive conditions. We can create predictive models that can precisely identify emotional states and cognitive processes based on neurophysiological variables taken from various brain regions by using linear regression classification algorithms to EEG data. Furthermore, the visualization and understanding of intricate brain events are made possible by statistical analysis and graphical representation techniques, which offer insightful information on the temporal and spatial dynamics of EEG data. Our aim is to promote the development of new methods for mental health monitoring, well-being, and human-computer interaction through the application of EEG data analysis. The previous methods such as CNN-BiLSTM and Graph CNN have achieved high classification accuracies (up to 91.3%), that typically require dense electrode setups and intensive computational resources, limiting real-time applicability. In contrast, our study employs a minimal 5-channel EEG configuration and introduces Differential Sequence Analysis (DSA) alongside ANOVA for statistically validated feature extraction.

2 Methodology

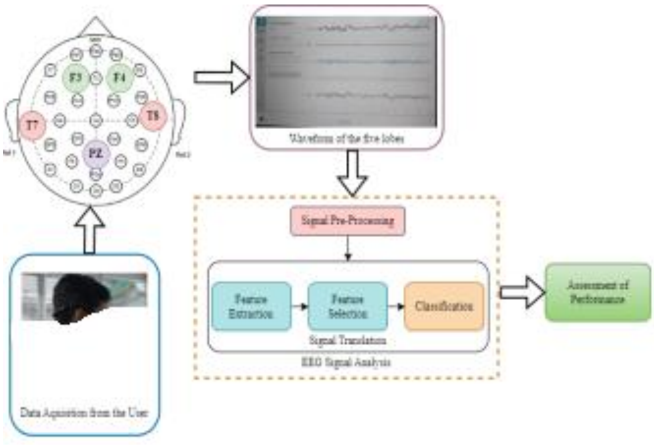


Figure 1: Process Flowchart of our present work

Figure 1 shows the overall process flowchart of our present work. Nowadays, electroencephalography (EEG) is a commonly used standard method to assess brain electrical activity. Typical EEG equipment components include an amplifier, display unit, data storage device, and electrodes. For the purpose of gathering data, we used an Emotiv Insight EEG headset with five channels. These electrodes are non-invasive, and they are attached to the patient's scalp. We recorded EEG data from five lobes: T7 (left temporal lobe), T8 (right temporal lobe), AF3 (left prefrontal cortex), and PZ (parietal-midline) using this headset. Signal improvement and filtering are the main concerns of pre-processing. Since EEG signals are fundamentally weak, noise from both internal and external sources can rapidly contaminate signals. The preprocessing pipeline involved a bandpass filter ranging from 0.5 to 40 Hz to remove baseline drift and high-frequency noise, ensuring retention of relevant cognitive and emotional frequency components (e.g., theta, alpha, beta). Artifacts such as eye blinks and muscle movement were attenuated using an adaptive thresholding technique based on amplitude and variance criteria. Feature extraction focused on relative power spectral densities across standard EEG bands (theta: 4–8 Hz, alpha: 8–13 Hz, beta: 13–30 Hz), with emphasis on frontal (AF3, AF4) and temporal (T7, T8) asymmetries. These spectral features were computed using Fast Fourier Transform (FFT) and normalized across subjects to reduce inter-individual variability. Frequency band filters are used to reduce artifacts that are occur due to movements and electrode displacements. The next step is to extract features after preprocessing and noise reduction. Finding information that accurately captures the subject's emotional state is the main objective of feature extraction. Statistical analysis is used for feature extraction, shown in Table (1-5). Reducing the quantity of data processing needed to efficiently achieve the best results is the aim of feature selection. We chose five sequences for the feature selection step, and we gathered data from each subject in a separate sequence. We took data while the subjects were at rest, we played music and posed illogical questions to get data on memory recall, and we gave them math’s problems to do to get data on attentiveness. We employed a linear regression model for emotion analysis in the categorization process.

3 Data representation

Table 1: Statistic values in rest position

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4225.2	4199.7	4250.6	4225.2	35.9	25.4
AF4	4209.7	4189.9	4229.5	4209.7	28	19.8
T7	4312.6	4331.9	4293.2	4312.6	27.4	19.4
T8	4167.1	4161.3	4172.9	4167.1	8.2	5.8
PZ	4057.4	4052.9	4061.8	4057.4	6.3	4.4

Table 2: Statistic values in listening song position

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4241.5	3614.1	5009.9	4239.5	106.5	106.5
AF4	4234.9	3686.4	4780.1	4233.5	78.5	78.5
T7	4288	38880.3	4527.9	4288.7	48.3	48.3
T8	4161.9	3709.7	4479.6	4161.2	56.9	56.9
PZ	4093.1	3631.4	4350.8	4094.2	50.6	50.6

Table 3: Statistic values in random question-answer session

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4249.6	4193.5	4305.6	4249.6	79.3	56.1
AF4	4299.9	4190	4409.7	4299.9	155.3	109.9
T7	4340.6	4386.9	4394.2	4340.6	75.9	53.7
T8	4206.9	4197.3	4216.4	4206.9	23	9.6
PZ	4127.4	4106.4	4148.5	4127.4	29.7	21

Table 4: Statistic values in math solving position

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4190.4	4096	4284.9	4190.4	133.5	94.4
AF4	4170.6	4085.8	4255.5	4170.6	120	84.9
T7	4222.2	4161.5	4282.9	4222.2	85.8	60.7
T8	4084.1	4036.8	4131.4	4084.1	66.9	47.3
PZ	4032.5	3975.1	4089.9	4032.5	81.1	57.3

We used a range of statistical measures, including mean, median, average, maximum, minimum, and standard deviation, to analyze brain signal data collected while the subject was at different position. This enabled us to accurately describe the dynamics of the signals in key regions of the brain, including the AF3, AF4, T7, T8, and PZ lobes. Following data collection, the raw EEG signals underwent preprocessing steps, including filtering and artifact removal. Relevant features were then extracted from each lobe to quantify their activity. To find the average intensity of the signal in each lobe, the mean, or average, was calculated. This provided a measure of central tendency that was sensitive to extreme values. Simultaneously, the median was utilized as an effective replacement for the mean, particularly beneficial in situations where high values can distort the perception of central tendency. The term "average" was used to refer to the overall signal distribution and was employed interchangeably with the mean. To determine the maximum and minimum lowest levels of signal intensity—a critical step in locating possible outliers with clinical or scientific significance—maximum and minimum values were computed. Lastly, the standard deviation was calculated to measure the data's dispersion around the mean and offer insights into the stability and consistency of each lobe's brain activity. Together, these extensive statistical measurements allowed for a more sophisticated understanding of the variability, fundamental patterns, and range of signal intensities of regional brain dynamics. The deep learning models offer higher accuracy in some cases, they often lack interpretability and require extensive training data, GPU support, and hyperparameter tuning so we have used linear regression model. The statistical outcomes presented in Tables 1–4 reveal meaningful distinctions in EEG signal patterns corresponding to varying emotional and cognitive states. For instance, increased activation in the AF3 and AF4 regions during task-induced cognitive load aligns with heightened frontal theta and alpha desynchronization, a well-documented neural signature of working memory and attention processes. Conversely, variations in T7 and T8 activity during emotion-eliciting stimuli—particularly in the theta and low-beta bands—correspond to known lateralized emotional processing, with heightened right temporal activation associated with negative affect.

4 Mathematical statement

4.1 Equations

$$\blacksquare \mathbf{Y_i} = (\boldsymbol{\beta_0} + \boldsymbol{\beta_1}.\mathbf{X_{i1}} + \boldsymbol{\beta_2}.\mathbf{X_{i2}} + \ldots\ldots.. + \boldsymbol{\beta_k}.\mathbf{X_{ik}}) + (\boldsymbol{\varepsilon_i}) \qquad (1)$$

From the equation (1),

Y_i = Outcome or characteristic to predict a cognitive state for the ith observation.

X_{i1}, X_{i2},……., X_{ik} = The features extracted from the brain signal data for the ith observation, power in different frequency bands, coherence between brain regions.

β_0 = the y-intercept or constant term. In our result the value of y-intercept is -1.69718E9 and slope 1 for AF3, AF4, T7, T8, and PZ in all sequence.

β_1, β_2,……., β_k = The coefficients associated with each feature. They represent the change on the predicted outcome for a one-unit change in the corresponding feature.

ε_i = The error term for the ith observation, representing the difference between the observed and predicted values. ε_i value in rest position is 32560, when subject listening a song that position the ε_i value is 27392, in random or frequent question answer sequence ε_i value is 49740 and, in the math, solving position the ε_i value is 26239.

Cognitive $\text{State}_i = \beta_0 + \beta_1$ ………… (2)

Power in Theta $\text{Band}_i + \beta_2$ ………… (3)

Coherence between Frontal, Temporal and Parietal $\text{Lobes}_i + \varepsilon_i$

In this case,

The equation (2) that is Cognitive State_i is measured based on cognitive performance or a categorical variable that is representing the different cognitive states. The equation (3) Power in Theta Band_i is a feature representing the power in the theta frequency band extracted from the brain signal.

Coherence between Frontal, Temporal and Parietal Lobes_i is another feature representing the coherence between brain regions β_0, β_1, β_2 are the coefficients to be estimated through the regression analysis.

5 Results

The feelings Bouazizi, [4] are essential to daily life and have a big impact on how people connect with one another, deeply influencing them. The main novelty of the Berlin Brain-Computer Interface Blankertz, [5] is its non-invasive EEG-based BCI system, which uses advanced machine learning techniques to automatically adjust to each user's distinct brain patterns without the need for any prior training. Classification algorithms are play important role to identified different disease Li, Dingkun, [18] and for various application we can used classification.

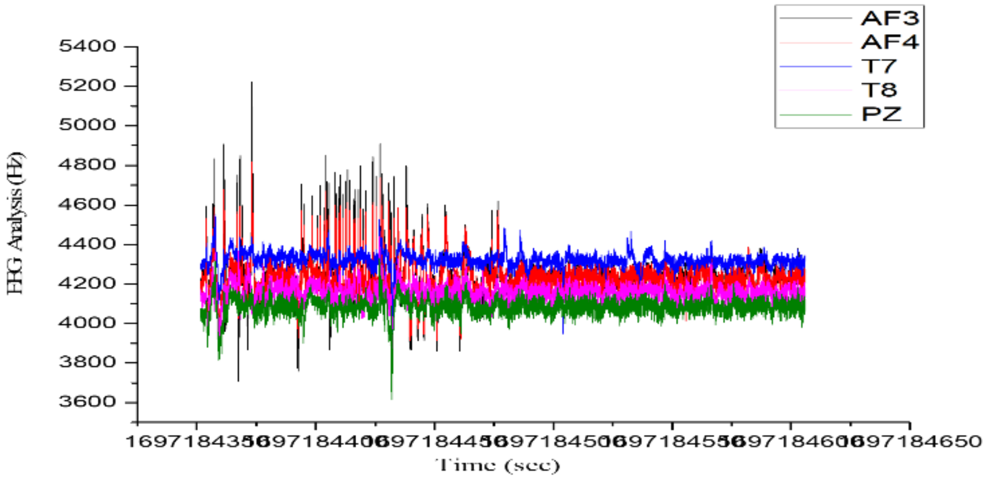
5.1 Dataset description

Table 5: Collecting EEG data using an emotiv five channel device

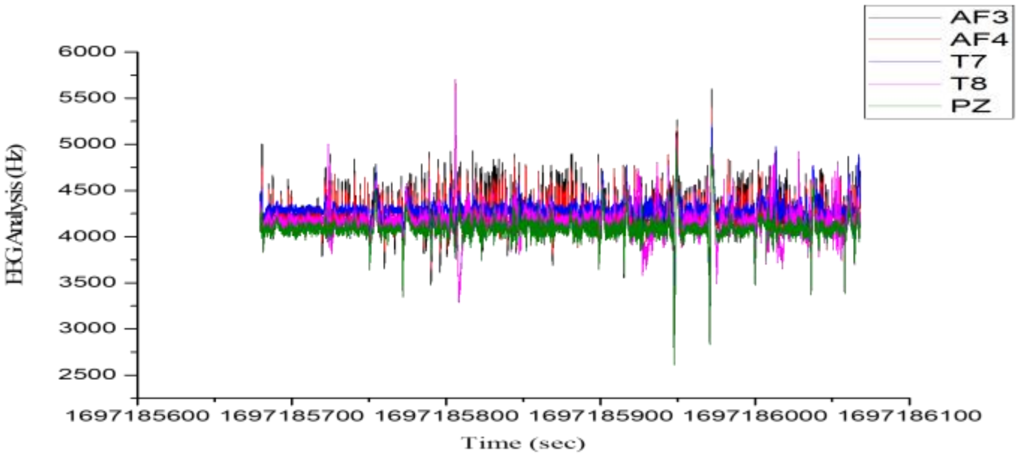
Subject Description	Sequence	AF3 (µV)	AF4 (µV)	T7 (µV)	T8 (µV)	PZ (µV)
Male Age: 30	Rest	4199.7	4189.8	4293.2	4161.3	4052.9
	Listening song	4578.6	4448.9	4285.6	4156	4099.4
	Random question-answer	4193.5	4190	4286.9	4216.4	4106.4
	Maths solve	4096	4085.7	4161.5	4036.8	3975.1
Female Age: 26	Rest	4242.8	4305.2	4382.9	4202.4	3945.6
	Listening song	4300.1	4354.6	4536.9	4286.3	3960.1
	Random question-answer	4200.9	4312.7	4434.7	4266.5	3829.2
	Maths solve	4025	4099.8	4381.9	3741.8	3904.5
Male Age: 20	Rest	4251.5	4858.2	4881.2	4806.6	4121.6
	Listening song	4290.7	5175.5	5452.3	5103.5	4224.1
	Random question-answer	4210.8	4250.6	4330.5	4196.3	4168.5
	Maths solve	4117.4	4257.3	4051.2	3948.5	4079.5
Female Age: 20	Rest	4219.7	4077.5	4603.9	4065.6	4307.5
	Listening song	4225.3	4141.3	4646.2	4097.9	4252
	Random question-answer	4248.9	4601.4	4891.2	5362.2	3808.1
	Maths solve	4206.7	4242.1	4772.9	4171.7	4121.2

An Emotiv 5-channel device has been used to collect EEG data from a group of sixteen people, both male and female, ages ranging from twenty to thirty years. Microvolts (µV) serve as the unit of measurement for the electrical activity from significant brain lobes such as AF3, AF4, T7, T8, and PZ in the dataset. The dataset includes a vast amount of data, with more than 120 data points collected per second from each brain lobe. Real-time data collection allowed for the immediate measurement of brain activity responses. The dataset's subjects are a mixture of our institute's faculty and students, providing a varied picture of brain activity responses across various demographic characteristics. These individual EEG data give insightful information about brain activity and functioning, which advances our knowledge of neural dynamics and cognitive processes. The tables have been updated with concise footnotes and annotations where necessary. To strengthen their interpretability, accompanying textual analyses have been added to the results and discussion sections, highlighting key observations—for instance, performance variation across subjects or channels, and the relationship between classifier accuracy and EEG band power. These improvements aim to make the visual data more self-explanatory while aligning them more closely with +the study's core objectives.

5.2 Time series analysis of sensor usage



(a)



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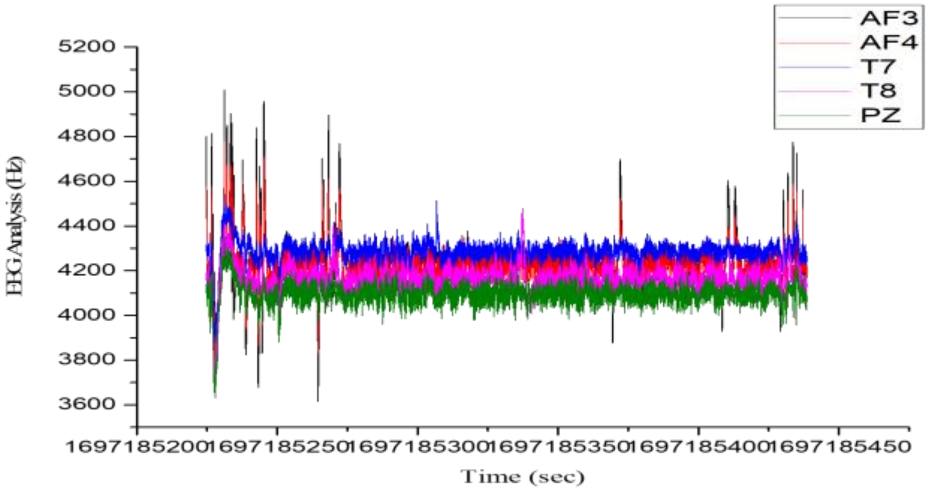

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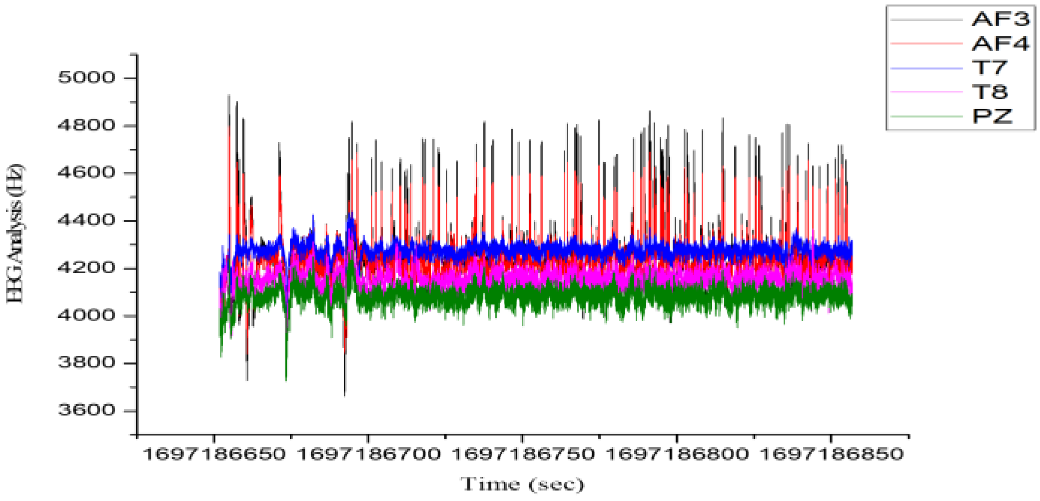
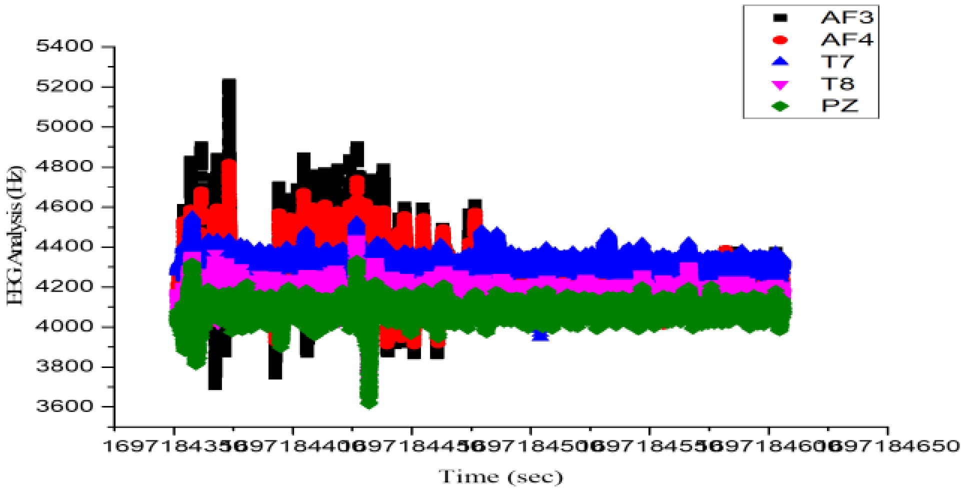
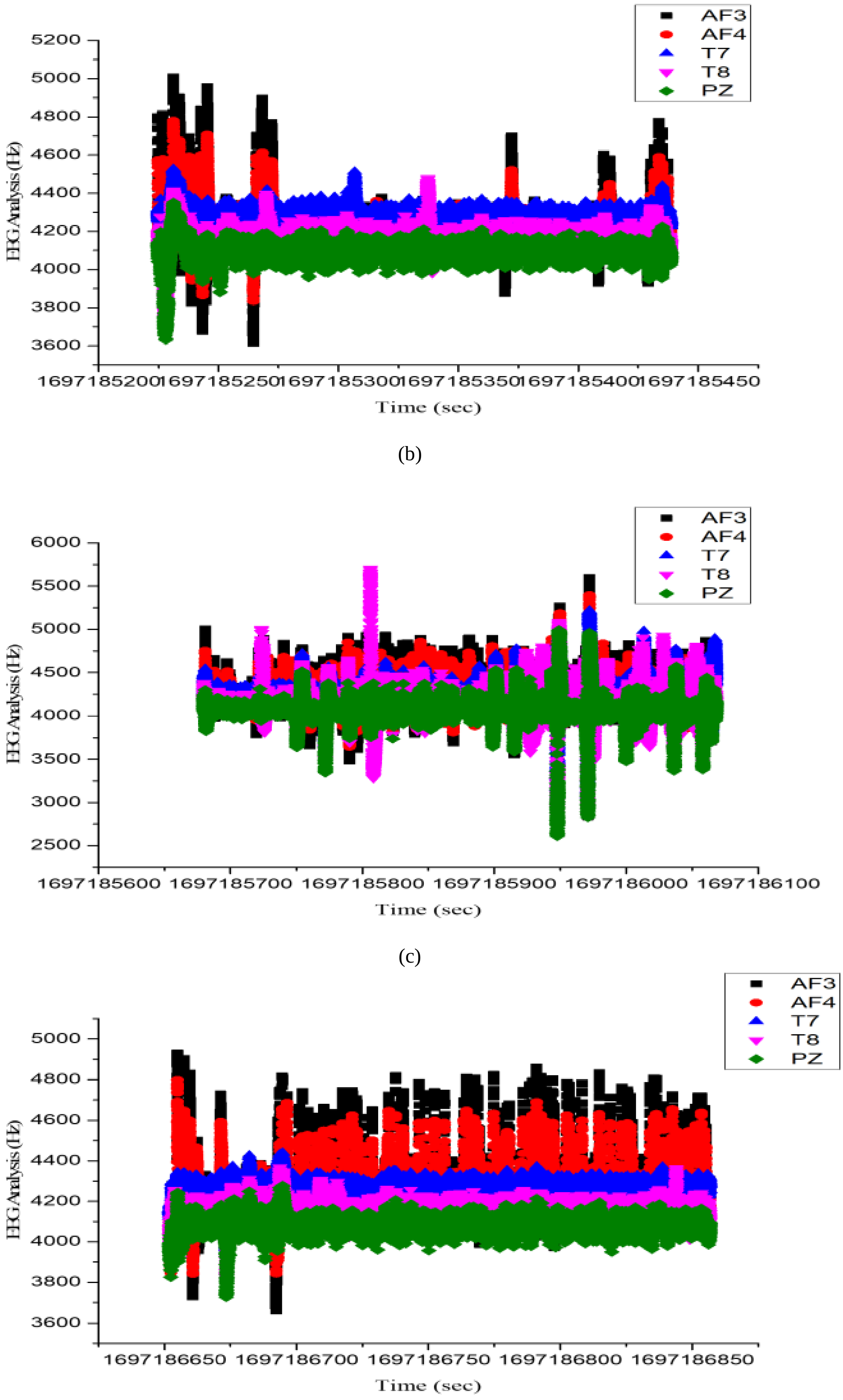


(d)

Figure 2: Line Plot of different lobes. (a) When subject was in resting position, (b) when subject listening the song, (c) when we asked the random question to the subject and answered frequently, (d) when the subject was solving the mathematical problems.



(a)



(b)

(c)

(d)

Figure 3: Scatter Plot of different lobes. (a) When subject was in resting position, (b) when subject listening the song, (c) when we asked the random question to the subject and answered frequently, (d) when the subject was solving the mathematical problems.

Time series analysis is crucial for understanding EEG data, revealing dynamic changes in brain activity over time, particularly for studying event-related potentials (ERPs), frequency components, and cognitive process patterns. Time series methods facilitate in recognizing abnormal EEG patterns linked to neurological disorders, aiding in the development of pattern recognition algorithms and understanding brain dynamic connectivity. They also play a crucial role in brain-computer interface (BCI) development, enabling real-time interpretation of EEG signals for applications like control interfaces and cognitive function studies. Figure 2(a) and Figure 3(a) are showing the graphical representation of the EEG signal amplitude over time during the resting period. During the rest sequence, the EEG signals display relatively low amplitude and stable patterns. We get low standard deviation values in different lobes such as F3, F4, T7 T8 and PZ (from Table1: 25.4, 19.8, 19.4, 5.8, 4.4) comparing to other sequences, indicating a relaxed and calm state of the subject. We observed slight fluctuations in the EEG signal, reflecting normal brain activity during rest. Figure 2(b) and Figure 3(b) are the graphical representation plots of EEG signal amplitude over time while the subject listens to music. During music listening, the EEG signals are exhibit dynamic changes reflecting auditory processing and emotional responses. Look for fluctuations in EEG signal amplitude synchronized with the rhythm and beat of the music. Additionally, observe changes in frequency bands associated with attention or arousal levels. Figure 2(c) and Figure 3(c) are the plots, showing the amplitude of the EEG signal across time during the question-answer interaction. Figures 2 and 3 have been revised to enhance clarity and visual comprehension. Each subfigure is now distinctly labeled (e.g., Figure 2a, Figure 2b) with consistent notation, and all axes include appropriate units (e.g., µV for EEG amplitude, Hz for frequency components) along with descriptive legends. The figure captions have been expanded to explain the observed patterns and trends, such as differential power distributions across emotional and cognitive tasks. During the question-answer sequence, we observed variabilities in EEG signal patterns corresponding to cognitive engagement and response generation. Look for peaks or changes in EEG signal amplitude coinciding with the presentation of questions and subjects' responses. Increased activity in frontal and prefrontal regions is indicating cognitive processing and decision-making. In the math problem-solving task, the EEG signal amplitude is plotted visually in Figure 2(d) and Figure 3(d). We saw alterations in EEG signal patterns during arithmetic problem-solving that were indicative of cognitive effort and problem-solving techniques. Examine the EEG signal for oscillations in both amplitude and frequency bands, particularly in regions linked to executive functioning (prefrontal cortex, AF3, AF4). Higher theta and gamma activity is a sign of engaged working memory and mental performance. When describing the graphical plots, be sure to discuss any notable trends, patterns, or differences observed across different sequences. Consider comparing the EEG signals between sequences and discussing how they reflect the cognitive and emotional states of the subjects during each task.

6 Conclusion

In conclusion, this study investigated the use of EEG data analysis and linear regression classification to explore human cognitive and emotional responses across different sequences of stimuli presentation. Through the collection and processing of EEG data during rest, music listening, question-answer sessions, and math problem-solving tasks, we gained insights into the dynamic nature of neural activity associated with various cognitive and emotional processes. The graphical representations of EEG signals revealed distinct patterns and trends during each sequence, reflecting the subjects' cognitive engagement, emotional responses, and task-specific neural processing. From the observed patterns, we identified significant fluctuations in EEG signal amplitude, frequency bands, and connectivity measures, providing valuable information about the underlying neural mechanisms involved in each task. Furthermore, the application of linear regression classification allowed us to establish predictive models for identifying cognitive and emotional states based on EEG features. By leveraging machine learning techniques, we demonstrated the feasibility of accurately classifying cognitive and emotional states across different individuals, paving the way for inter-subject independent emotion recognition and mental state monitoring. Overall, this research contributes to the growing body of knowledge in EEG-based cognitive and affective neuroscience, highlighting the potential of EEG data analysis for understanding human cognition, emotion, and mental well-being. The findings underscore the importance of integrating neuro imaging techniques with advanced analytical methods to unravel the complexities of the human brain and its responses to external stimuli.

Moving forward, future research endeavors may focus on refining and validating the predictive models developed in this study, exploring additional features and modalities for emotion recognition, and investigating the practical applications of EEG-based cognitive and emotional assessment in real-world settings. By continuing to advance our understanding of the brain-behavior relationship, we can develop innovative solutions for promoting mental health, enhancing human-computer interaction, and fostering well-being in diverse populations. We can use our project as a wearable healthcare device. We can also apply our innovation in IoT Neurotechnology Integration of emotional and cognitive detection. This idea can be used as a portable personalized stress monitoring device.

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