Spectral and Nonlinear Analysis of Neural Dynamics during Cognitive Load Using EEG Signal Processing Techniques

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In

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Submitted by

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CERTIFICATE OF RECOMMENDATION

This is to certify that the thesis entitled **"Exploring Spectral and Nonlinear Characteristics of Neural Dynamics during Cognitive Loading"** is a bona fide work carried out by **SAMBIT SAHA** under my supervision and guidance for partial fulfillment of the requirement for Post Graduate Degree of Master of Engineering (Biomedical Engineering) in School of Bioscience and Engineering during the academic session 2022-2024.

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis contains a literature survey and original research work by the undersigned candidate, as part of his **Master of Engineering** in **Biomedical Engineering** studies during the academic session 2022-2024.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

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PREFACE

Understanding the neural dynamics of cognitive tasks is the back bone of modern neuroscience. This thesis investigates how the brain responds to cognitive loading during arithmetic tasks by examining both linear and nonlinear features of electroencephalography (EEG) signals. The study aims to shed light on the intricate neural mechanisms underlying cognitive effort.

Electroencephalography (EEG) is a non-invasive method that records electrical activity in the brain. This research focuses on extracting and analyzing spectral features—specifically the alpha, beta, delta, theta, and gamma band powers. In addition to these traditional linear functions, we discuss non-linear functions such as the Higuchi fractional form, model entropy and spectral entropy to understand neural responses.

The first step of our method is to denoise the EEG signals using a discrete noise transform. This important pre-processing step ensures the correct extraction and subsequent analysis. By examining the EEG data by channel, we can identify specific neural activations related to cognitive load. Our findings show significant changes in power across all frequency groups in response to cognitive load. In particular, non-linear processes provide a deeper understanding of how the brain adapts to these demands. This adaptation is not uniform in different brain regions. However, the frontal and temporal regions are the most active in cognitive processes.

The activities analyzed in this study clearly determine the neural changes associated with cognitive load. This observation has important implications for future research, especially in educational environments where an understanding of cognitive responsibility can inform teaching strategies and learning outcomes. This thesis thus contributes to the broader field of neuroscience by enhancing our understanding of how the brain processes and responds to cognitive challenges.

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Chapter-1

Introduction

Cellular electrical activity originates from the voltage differentials between the intracellular and extracellular environments of cells. This voltage difference, known as the membrane potential, is maintained by ion channels and transporters within the cell membrane. When certain conditions are met, this membrane potential can generate an action potential, a transient voltage change that propagates along the cell membrane.

The underlying physiology of electrophysiological signals (bio-signals) involves the specialized properties of the cell membrane, which regulates ion distribution and maintains the membrane potential. In single-cell measurements, microelectrodes capture the action potential as the primary bioelectric signal. For broader measurements, surface electrodes detect the electric field generated by the collective activity of multiple cells.

These electrical fields circulate through biological systems and allow non-invasive signals to reach the body's surface. Transducers or transducers convert the electrical current in the environment to conduct electricity in measurement systems and facilitate accurate signal recording. In recent times, biomarkers have enabled a detailed description of the human body from the outside and inside, to improve the efficiency of clinical diagnosis and biological research.

Action potentials act as important electrochemical signals in the human body, similar to small electrical impulses that move across the membranes of nerve cells and muscle fibers. They play an important role in facilitating the communication between nerves and organizing the muscle contractions necessary for movement. Visualize them as intricate bursts of electrical impulses, instigating a myriad of physiological responses throughout our systems. They happen because certain channels in the cell membranes open and close at just the right times, letting in sodium ions to kickstart the signal, then potassium ions to calm things down again. It's like a well-choreographed dance where ions move in and out, creating this wave of energy that moves in one direction along the cell. In our nerves, action potentials help messages zip from one end of a nerve cell to another, kind of like how a whisper travels down a line of people. And in our muscles, they're the spark that starts a contraction, helping us move and do all sorts of things. The timing and pattern of these action potentials are super important for how our nervous and

muscular systems work together, sort of like the rhythm and beat in a song that keeps everything in sync.

Cumulative bio-signals offer a comprehensive perspective on physiological processes by summing electrical activity from multiple cells or tissues. It is mostly complex and diverse signals, which reflect the synchronous and dyssynchronous activities of many biological origins. EEG (electroencephalography), EMG (electromyography), ECG (electrocardiography): These are technologies that measure aggregate bio-signals (i.e., from the brain, muscles and heart, respectively).

The acquisition of the data externally, from the surface of the human body or internally, from within the internal monitoring system is achieved by sensors and transducers. They turn the ionic currents which have been generated by the activities of the cell into electronic signals that are then able to be measured and analyzed. Surface electrodes, which include the fingertip sensors, are most frequently used to record bioelectric fields that originate deeper than one layer of epithelial cells. These electrodes are constructed to make excellent skin contact and to reduce noise and artefacts. Sophisticated transducer technologies—including capacitive, piezoelectric, and optical sensors—have been developed to increase the sensitivity and specificity of the detection of bio-signals, thereby allowing an improved accuracy and depth of monitoring physiological status.

Signal Acquisition Methods for Different Bio-signals

1. **ECG**:
    - **Non-Invasive**:
        - Attach electrodes to the skin surface (chest, arms, legs).
        - Detect heart's electrical signals during contraction and relaxation.
        - Amplify and record using an ECG machine.
    - **Invasive** (Rarely used):
        - Insert electrodes directly inside the heart (e.g., during cardiac catheterization).
        - Provides detailed information but riskier.



Figure.1 A regular ECG wave [1]

2. **EOG**:
    - **Non-Invasive**:
        - Position electrodes near eye corners.
        - Track eye movements (left, right, up, down).
        - Study eye behaviour during various activities.
    - **Invasive** (Not applicable):
        - EOG primarily remains external.

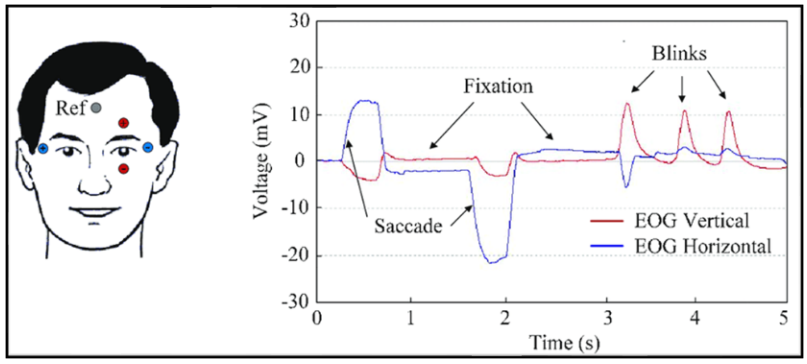


Figure.2 A regular EOG wave [2]

3. **EMG**:
    - **Non-Invasive**:
        - Apply surface electrodes over specific muscles.
        - Record muscle electrical activity during contraction.
        - Diagnose neuromuscular disorders.

- **Invasive** (Rarely used):
    - Insert needle electrodes into muscle tissue (intramuscular EMG).
    - More precise but invasive.

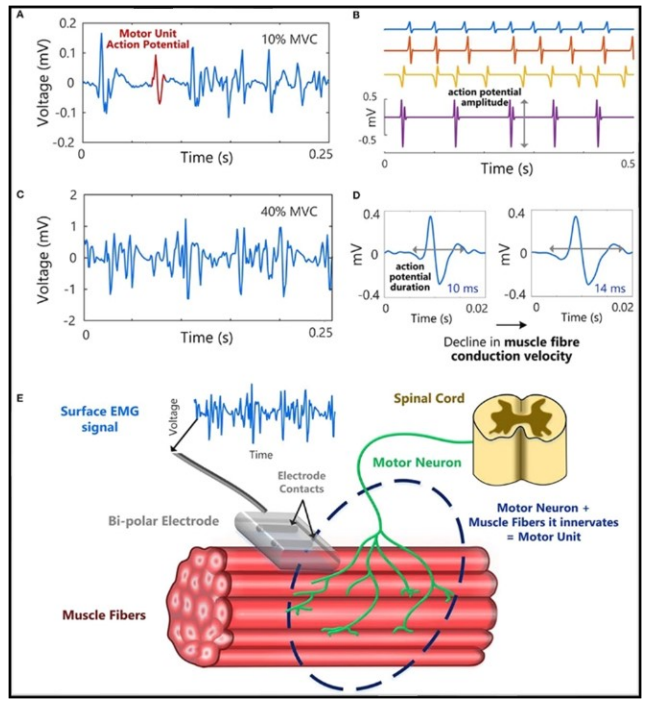


Figure.3 Generation of an EMG wave [3]

4. **EEG**:
    - **Non-Invasive**:
        - Wear a cap with scalp electrodes.
        - Record brain's electrical activity.
        - Useful for diagnosing neurological conditions.
    - **Invasive** (Research or surgery):
        - Place electrodes directly on brain's surface (intracranial EEG).
        - Provides precise data.

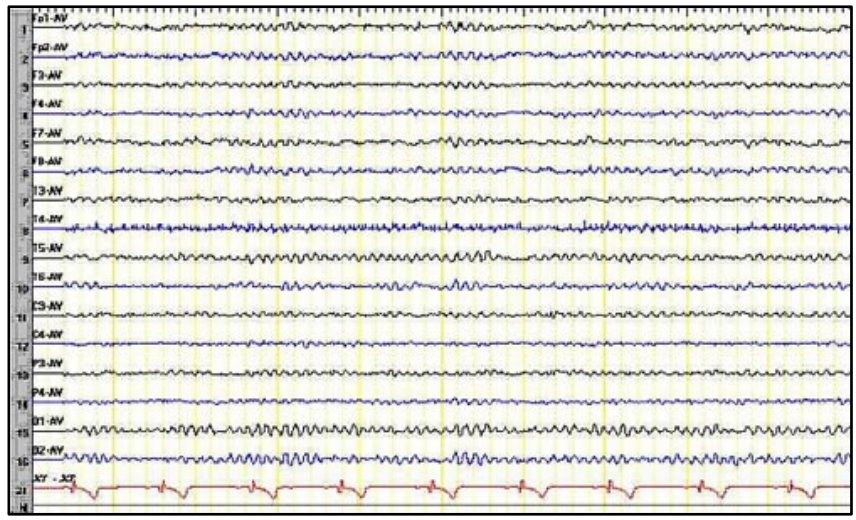


Figure.4 A regular EEG wave [4]

Brain Lobes are distinct regions of the cerebral cortex responsible for specialized functions such as sensory perception motor control and higher-order cognition [1]. The brain is divided into four main lobes. Each has distinct functions.

Frontal Lobe: This lobe plays crucial role in decision-making. It's also involved in planning personality expression and voluntary movement. Often likened to the CEO of the brain. It oversees executive functions.

Parietal Lobe: Responsible for processing sensory information the parietal lobe helps understand touch. Temperature and pain. It's also involved in spatial awareness and attention.

Temporal Lobe: Imagine temporal lobe as your personal concert hall. It handles auditory processing memory formation and language comprehension. It's where memories groove to the beat.

Occipital Lobe: Located at the back of your head. This lobe is all about visual processing. Think of it as theatre where brain watches world unfold.

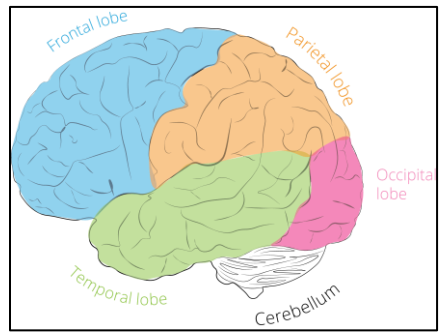


Figure.5 Different segments of a human brain [5]

Brain Structures and EEG Correlation

1. Cerebral Cortex

- **Function:** The outer layer of the brain responsible for higher-order thinking, sensory perception, motor control, and memory.
- **Associated EEG Signals:** Alpha waves (8-13 Hz) during relaxed wakefulness and beta waves (13-30 Hz) during active thinking.

2. Frontal Lobe

- **Function:** Responsible for decision-making, planning, personality, and voluntary movement.
- **Associated EEG Signals:** Beta waves, especially prominent over the prefrontal cortex.

3. Parietal Lobe

- **Function:** Involved in sensory processing (touch, temperature, pain), spatial awareness, and attention.
- **Associated EEG Signals:** Alpha and beta waves.

4. Temporal Lobe

- **Function:** Handles auditory processing, memory, and language comprehension.
- **Associated EEG Signals:** Theta waves (4-7 Hz) and gamma waves (30-100 Hz).

5. Occipital Lobe

- **Function:** Primarily engaged in visual processing and interpretation.
- **Associated EEG Signals:** Alpha waves, dominant at the back of the head.

6. Hippocampus

- **Function:** Essential for memory formation and spatial navigation.
- **Associated EEG Signals:** Theta waves, particularly significant during memory tasks.

7. Amygdala

- **Function:** Processes emotions, particularly fear and pleasure.
- **Associated EEG Signals:** While not directly measured by EEG, its activity influences overall brain activity.

8. Thalamus

- **Function:** Acts as a relay station for sensory information.
- **Associated EEG Signals:** Modulates overall cortical activity.

9. Basal Ganglia

- **Function:** Responsible for motor control and habit formation.
- **Associated EEG Signals:** While not directly measured by EEG, it plays a role in overall brain function.

10. Brainstem (Midbrain, Pons, Medulla)

- **Function:** Regulates vital functions such as breathing, heart rate, and consciousness.
- **Associated EEG Signals:** The reticular activating system (RAS) within the brainstem influences overall arousal levels.

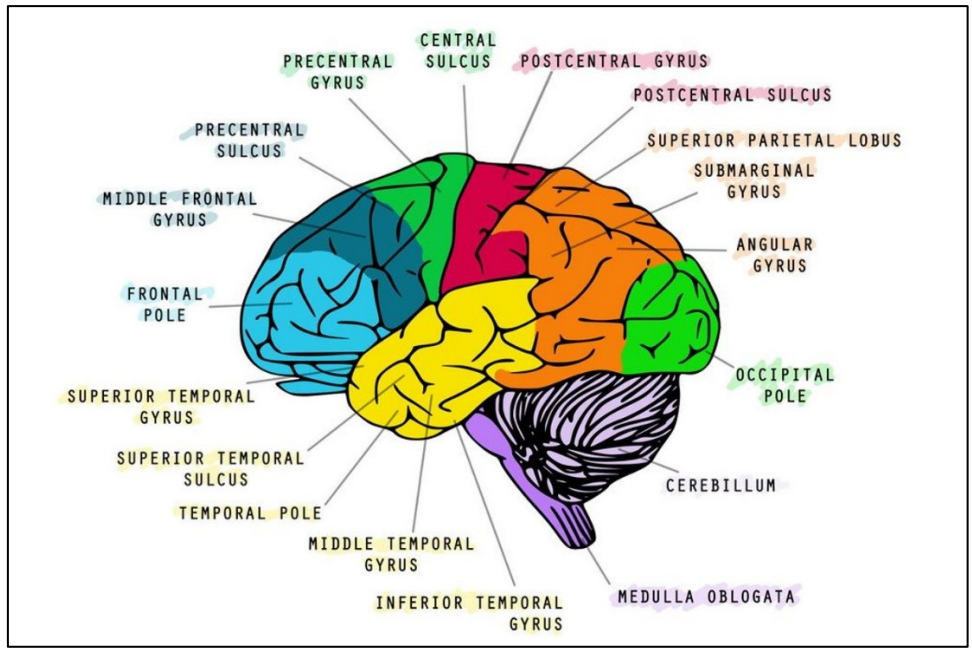


Figure.6 Physiology of a human brain [1]

Understanding the Brain with fMRI (Functional Magnetic Resonance Imaging)

Functional Magnetic Resonance Imaging (fMRI) is powerful tool used to study brain activity by measuring changes in blood flow and oxygen levels. It allows researchers to map brain activity. They can target specific regions. It also helps to understand how different areas of brain contribute to various cognitive processes and behaviours. Here's how fMRI helps in understanding different brain areas.

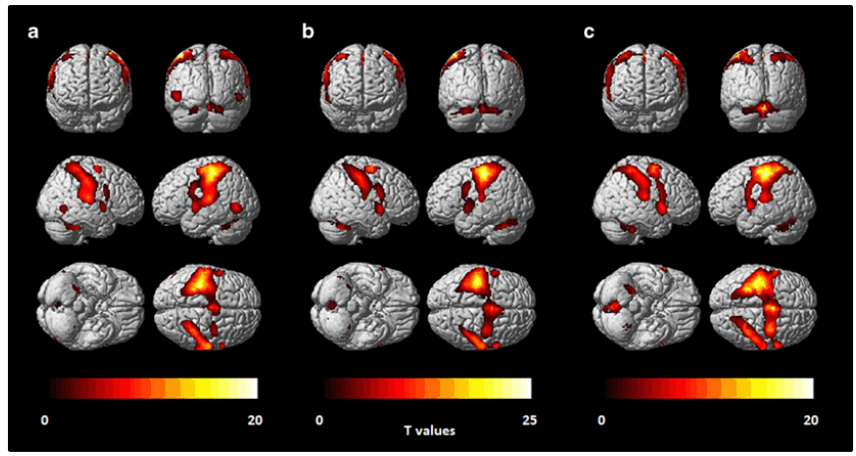


Figure.7 fMRI of a human brain [4]

Cerebral Cortex Mapping:

fMRI enables researchers to map activity in cerebral cortex. The outer layer of brain is responsible for higher-order thinking. It is responsible for sensory perception. It is also responsible for motor control. By correlating brain activity with cognitive tasks [5]. Scientists identify which areas of cortex are involved in specific functions. These functions include language processing memory retrieval and decision-making.

Limbic System Exploration:

The limbic system often referred to as the "emotional brain," includes structures like amygdala and hippocampus. fMRI studies revealed how these regions respond to emotional stimuli. They regulate memory. And emotional processing. Understanding limbic system's role helps in comprehending emotions memory formation. And stress responses.

Motor Cortex Investigation:

By analyzing fMRI data during motor tasks researchers can pinpoint regions of motor cortex responsible for planning and executing movements. This information aids in

understanding motor control. It also helps in understanding coordination. It also helps in understanding motor learning processes.

Visual and Auditory Processing:

fMRI studies of occipital and temporal lobes shed light on visual and auditory processing. These investigations reveal how brain processes visual stimuli. It recognizes objects. Interprets auditory information. Mapping visual and auditory cortex activity helps in understanding perception memory encoding. And sensory integration.

Prefrontal Cortex Functioning:

The prefrontal cortex located in frontal lobe, plays crucial role in executive functions. These functions include decision-making. It also helps with planning. Impulse control is another critical role. fMRI studies illustrate how this region responds during tasks. These tasks require cognitive control attention and working memory. They provide insights. Insights into cognitive flexibility and goal-directed behaviour.

Default Mode Network (DMN) Analysis:

The DMN is network of brain regions active during rest. It is also active during self-referential thinking. fMRI investigations of the DMN reveal its involvement in introspection. Mind-wandering and autobiographical memory retrieval are also linked. Understanding DMN's activity patterns helps in comprehending consciousness. Self-awareness and mental health disorders are connected as well.

Invasive ECoG (Electrocorticography)

Invasive ECoG involves placement of electrodes directly onto brain's surface or within brain tissue. Enabling high-resolution neural recordings. This technique differs from non-invasive methods. Because it offers superior spatial and temporal resolution. Crucial for comprehensive studies of brain activity in clinical and research settings.

Applications:

Epilepsy Monitoring: Invasive EEG/ECoG precisely localizes seizure foci in drug-resistant epilepsy [2]. This facilitates targeted surgical interventions

Brain Mapping: During neurosurgical procedures it maps functional brain areas. This minimizes postoperative deficits.

Brain-Computer Interfaces (BCIs): It enables control of external devices using brain activity. This benefits individuals with severe motor disabilities.

Basic Neuroscience Research: Invasive EEG/ECoG provides unprecedented access to neural activity in animal models This allows detailed investigations into brain function and circuitry

Procedure:

During procedures electrodes implanted subdurally or intra-cortically. They are connected to external recording equipment. For continuous monitoring.

Considerations:

Invasive EEG/ECoG procedures carry inherent risks. These include infection bleeding and tissue damage. This necessitates meticulous attention to patient safety. Ensuring long-term stability of implanted electrodes is crucial. This is for obtaining reliable recordings over extended periods. Additionally, there are ethical considerations. These include patient consent privacy and use of neural data. They must be carefully addressed. This upholds ethical standards in both researches and clinical practice.

EEG or Electroencephalography is a non-invasive neuroimaging technique used to measure and record electrical activity in brain. It involves placing electrodes on scalp. These electrodes detect electrical signals produced by brain neurons. Signals known as brainwaves are recorded as wave patterns. They are categorized into different frequency bands. Some of these bands are alpha beta. Theta and delta waves. EEG is used in clinical settings. It helps to diagnose and monitors various neurological conditions. Including epilepsy, sleep disorders and brain injuries. It is used in research. Researchers study brain function cognitive processes and mental states.

Action potentials (APs) are rapid changes in membrane potential. They occur due to opening and closing of voltage-gated ion channels in neurons. This propagates along axons. It leads to neurotransmitter release at synapses. However, APs are not directly responsible for signals measured by electroencephalography (**EEG)**. **Local field potentials (LFPs)**, on other hand refer to electric potentials in extracellular space surrounding neurons. This results from synchronized postsynaptic potentials, both excitatory and inhibitory. These arise from cortical neurons. LFPs are essential for diagnosing and classifying epileptic seizures. They provide fine temporal resolution. EEG measures electrical activity on scalp. This reflects summation of

LFPs from large populations of neurons. While APs contribute indirectly to EEG signals via synaptic activity. It is collective LFPs that primarily shape patterns observed in EEG recordings. This reflects synchronized neuronal activity.

The **Hodgkin-Huxley model**, formulated by Alan Hodgkin and Andrew Huxley in the 1950s through their research on the squid giant axon, is a seminal mathematical framework that elucidates the generation of action potentials in neurons. This model comprises differential equations that depict variations in membrane potential in response to ionic concentration changes across the neuronal membrane. Central components include sodium (Na+), potassium (K+), and M-type potassium (K+) ion channels, each characterized by specific conductance and reversal potentials, with gating probabilities dependent on membrane potential. The membrane potential is expressed by $\frac{dV}{dt} = \frac{1}{Cm}(Iion + Isyn)$, where V represents the membrane potential, C_m is the membrane capacitance, I_{ion} is the ionic symbol which represents current, and I_{syn} represents the synaptic current. The model accurately predicts potential action potentials, including depolarization, repolarization, threshold, and relaxation times. In addition, when the injection time changes, it enters the Hopf bifurcation, which indicates a low injection rate. Later developments of the model include other ion channels, complex geometries, and stochastic behaviour, which emphasize its central role in computational neuroscience and neural network simulation, thus advancing the understanding of neural information processing and functional capacity control.

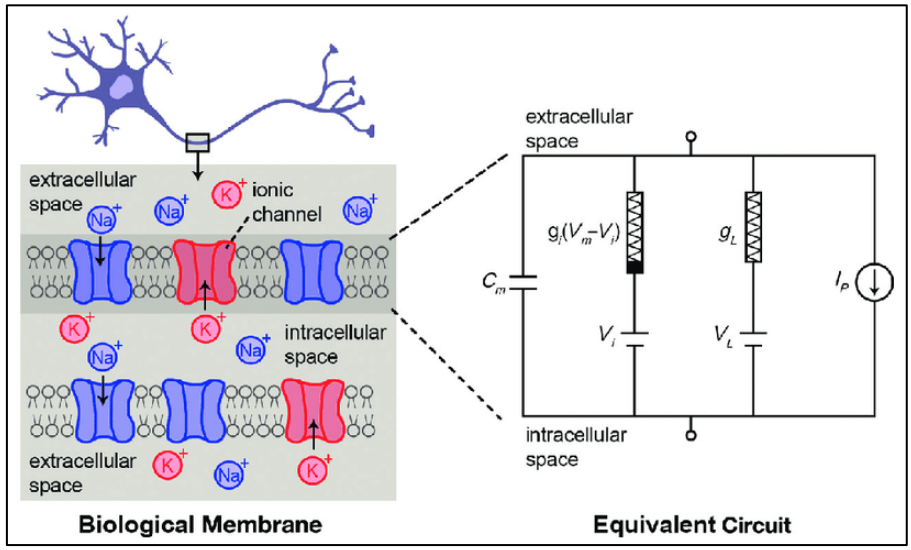


Figure.8 Hodgkin-Huxley model of biological neurons [6]

Brain imaging includes the scientific study of the shape and structure of the brain, including the measurement and analysis of various morphological parameters such as cortical

thickness, surface area and volume. These measurements are important for identifying and understanding differences in brain structure between individuals and groups, and are used to compare groups of individuals or to track long-term changes in structure of the brain. The study of brain morphology is very important for explaining individual differences in brain function, and it is also very important for the diagnosis and classification of many neurological and psychiatric diseases. The integration of brain morphology with models like Hodgkin-Huxley offers a comprehensive approach to neuroscience, where understanding the macroscopic structural differences complements the microscopic insights into neuronal activity and action potential generation. This holistic perspective is essential for advancing our knowledge of brain function and dysfunction, providing a robust framework for both theoretical research and clinical applications.

Bio-signal measurement techniques offer a variety of advantages and disadvantages that are necessary for a choice of the method to be used for specific applications. EEG yields high temporal resolution insights into cognitive and affective processes, but is expensive, and its spatial resolution is low. EDA offers continuous real-time assessment of the sympathetic nervous system noninvasively but is sensitive to environmental noise and cannot discern between types of stress. HRV reflects ANS balance and emotional states but requires accurate R-R interval detection and may be affected by some factors that have nothing to do with stress. Respiratory rate monitoring is accessible and non-invasive but is sensitive to physical activity and special tools for accuracy. Pupillometry correlates to cognitive processes with lower visual noise susceptibility but requires controlled lighting and takes personal context into account. Biometric wearables allow for continuous monitoring at lower costs, although sensor accuracy and placement are still issues. Computer vision provides non-invasive, real-time facial analysis but depends on the context and is also sensitive to environmental conditions; hence, privacy issues arise. Speech tonality analysis detects stress and cognitive load, but the estimation remains sensitive to speech variability and noise. Advanced biometric signal processing offers noise reduction techniques with strengths and limitations.

EEG (electroencephalography) is an excellent tool for analyzing electrical brain signals and detecting changes in brain activity under mental load due to several important advantages. As a non-invasive technique, EEG avoids invasive procedures or interventions, ensuring safety and comfort for both patients and researchers. High temporal resolution and recording of fast neural circuits are necessary for studying cognitive processes such as attention and memory. A comprehensive EEG can measure a variety of brain functions, including cognitive functions,

emotional states, and activity in the autonomic nervous system, which is useful for a variety of research studies. In addition, EEG is cost-effective compared to other neuroimaging methods such as fMRI, and its use is carried out in different areas, from clinical trials to home monitoring. Its ease of use, with minimal training and preparation, increases its accessibility to researchers and clinicians. Feedback capabilities are important for applications such as brain-computer interface (BCI) and neurofeedback training. Additionally, EEG integrates seamlessly with other neuroimaging techniques, providing insight into brain function and structure. Advances in signal processing, including machine learning and deep learning, have improved the accuracy and reliability of EEG analysis. Clinically, EEG is invaluable for diagnosing and monitoring neurological disorders such as epilepsy and assessing cognitive and emotional states.

In specific applications related to cognitive load measurement, EEG power spectrum analysis is widely utilized to assess cognitive demands by analyzing power in different frequency bands, including alpha, beta, and theta. Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) techniques provide insights into brain activity changes during cognitive tasks, with ERD indicating power decreases and ERS indicating power increases, aiding in understanding neural mechanisms underlying cognitive load. Machine learning and classification techniques enhance the quantification of cognitive load by extracting features from EEG signals and training classifiers to predict cognitive load based on brain activity. These advancements underscore EEG's pivotal role in both research and clinical settings, offering a robust framework for studying and interpreting brain function and cognitive processes.

EEG band control is a basic function of EEG signal processing and analysis that involves the decomposition of EEG signals into a number of frequency bands characterized by unique functional characteristics. These groups are important to the study of brain function and neural mechanisms because they reflect insights into various mental processes and neural excitations in brain regions and their functions.

Frequency Bands and their Functional Properties:

Delta Band (0.5–4 Hz): This frequency band represents deep sleep, unconsciousness, and relaxation with slow waves. This is primarily used to determine the quality and depth of sleep, thus being an essential metric for sleep research.

Theta Band (4–8 Hz): This band is concerned with drowsiness, sleep, meditation, and memory consolidation. Used widely in many studies about cognitive development and memory processes in infants and children.

Alpha Band (8–12 Hz): The alpha band is related to relaxation, closed eyes, and decreased cortical activity. It is often used to test the extent of relaxation and the level of stress an individual is exposed to, thus being a relevant metric in neurofeedback training and stress research.

Beta Band (13–30 Hz): Beta represents active thinking, problem-solving, and motor activity. It is used as a measure of cognitive load and attention, hence being a relevant metric in cognitive development and neurofeedback training.

Gamma Band (30–100 Hz): A gamma band is responsible for higher cognitive processes, such as attention, work memory, and decision-making. It is used to determine cognitive performance and neural activity, thus being an essential metric in cognitive neuroscience and brain-computer interfaces.

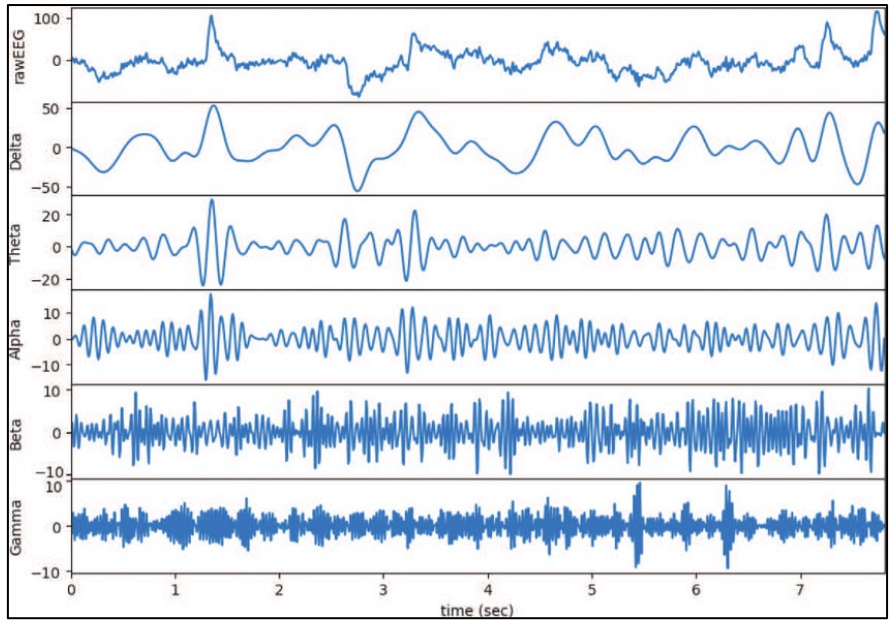


Figure.9 Different frequency Bands of an EEG signal [7]

Applications of EEG Band-Powers:

Sleep research: EEG recordings are used to determine the quality, depth and stages of sleep. Therefore, the delta group is important.

Cognitive development: EEG band energies, especially the theta and alpha bands, are used to study cognitive processes such as memory consolidation and attention in infants and children.

Neurofeedback Training: EEG tapes are used to help people control brain activity and optimize cognitive performance.

Brain-computer interface (BCI): The power of the EEG band is also being used in the development of brain-controlled devices that can be used in video games, communication and rehabilitation.

Neurological diseases: EEG group control is a very important tool in the diagnosis and monitoring of neurological diseases such as epilepsy, Alzheimer's disease [3] and Parkinson's disease [4].

Insights to Brain Functions and Neural Processes:

The potential of the EEG band provides important insight into brain activity and neural processes. It provides an explanation for the neural impulses associated with cognitive processes such as attention, memory and decision-making. By identifying specific brain regions and their associated functions, such as the default mode network in the alpha band of self-referential thinking, we can better understand brain functions.

The potential of EEG bands is also used to study cognitive processes, and to understand how the brain processes information and makes decisions. In addition, they also help to study neuroplasticity, the ability of the brain to adjust itself in response to experiences and learning.

Motivation and Objective

Cognitive load refers to the amount of mental effort required to perform a task and may vary depending on the difficulty and novelty of the task. EEG, which measures the brain's electrical activity and provides insight into neural processes and mental states.

Here's why studying cognitive load is crucial in EEG:

1. Understanding cognitive processes: The goal of researchers to study cognitive load is to understand what works differences in mental performance. This knowledge can help optimize work design, training strategies, and even work environments to increase performance and reduce stress.

2. Monitoring the brain activity: EEG allows researchers to examine moment-to-moment changes in brain activity related to cognitive processes. When cognitive load increases (eg, during a complex problem-solving task), specific patterns in EEG signals may indicate increased neural activity or changes in attention and memory.

3. Applications in cognitive science: The study of cognitive load and EEG can make progress in cognitive science, neuroscience and psychology. A deeper understanding of how the brain adapts to different mental needs may help treat mental illnesses or improve cognitive training programs.

4. Practical applications: From a practical point of view, the knowledge of the effect of mental load on EEG readings can be used in different areas. For example, in educational settings, it can guide teachers to change teaching methods to better engage students without overwhelming them. In clinical settings, it can help diagnose and monitor conditions such as ADHD or Alzheimer's disease.

The motivation behind this work is rooted in the critical need to understand cognitive processes, particularly under conditions of cognitive loading, using an arithmetic dataset and advanced EEG signal analysis techniques. By investigating both linear features, such as alpha, beta, theta, delta, and gamma powers, and nonlinear features, including Higuchi's Fractal

Dimension (HFD), Sample Entropy (SampEn), and Spectral Entropy (SpecEn), the study aims to elucidate how different neural dynamics correlate with cognitive engagement. The choice of arithmetic tasks provides a structured cognitive challenge, allowing for precise measurement of cognitive stress and engagement levels. Through a comprehensive analysis that integrates traditional spectral analysis with advanced nonlinear measures, this research seeks to identify distinct EEG patterns associated with varying levels of cognitive load. Ultimately, the study aspires to deepen our understanding of brain function during cognitive tasks, paving the way for enhanced cognitive load management and optimized educational methodologies.

Chapter-2

Literature Review

1. Temporal Dynamics of Brain Activation

Previous research has explored the potential role of brain activity in cognitive functions. Cognitive processes are a combination of past experiences and new information [6]. Understanding the complex neural dynamics underlying these processes allows us to understand how we respond to mental stress, make decisions and adapt to new situations [7]. These motivations vary according to the functional needs of the context [8].

2. EEG in Characterizing Cognitive Activities

Researchers have used EEG signals to describe various mental activities, such as gaming, driving and sleeping [9], logical analysis of program components [10] and advances in technology. knowledge. For instance, during cognitive tasks such as gaming, there is typically an increase in alpha power relative to theta power, with alpha predominating over beta frequencies. Spectral analysis of EEG signals has shown variations in workload-related frequency dynamics and distinct spatial patterns, while event-related spectral perturbations have revealed task-induced modulations in neural energy and phase. These findings underscore the importance of alpha oscillations in cognitive engagement. A study on neural correlations and cognitive load classification found that EEG band powers showed significant variation between rest and task states [11].

3. Nonlinear and Nonstationary Characteristics of EEG

While spectral features of EEG have received considerable attention in the classification of cognitive tasks, the nonlinear and nonstationary characteristics of EEG signals, such as fractal, chaos, and entropy features, have been found to be more effective in characterizing different states. The efficacy of nonlinear features can be attributed to the fact that biological processes are irregular, nonstationary, and nonlinear.

4. Changes in Linear and Nonlinear EEG Measures as a Function of Task Complexity: Evidence for Local and Distant Signal Synchronization

This study delves into the variations in EEG measures associated with task complexity in both visual and auditory modalities. Previous studies have shown that changes in gamma power occur when performing manual tasks, suggesting that these changes are not situation-specific and are related to presentation of abstract works. Nonlinear algorithms were used to evaluate the complexity and synchrony of the EEG signals and to show significant changes in signal and synchrony at different electrical sites. These findings emphasize the importance of considering local and remote signal synchronization when examining EEG changes related to task complexity [34].

5. The Persistence of Experience: Prior Attentional and Emotional State Affects Network Functioning in a Target Detection Task

This study examines how past and emotional situations affect brain network activity during search tasks. Subjects participated in internal (IF) and external (EF) tasks before participating in the detection task. The results showed increased brain activity in frontal, parietal and temporal regions during the search task following EF tasks, especially after IF tasks. In particular, the dorsolateral prefrontal cortex shows distinct connectivity patterns based on previous attentional states, indicating a significant influence of previous experience on network dynamics during task performance [35].

6. Behavioural States, Network States, and Sensory Response Variability

This study examines the relationship between behavioural characteristics, network characteristics and response variability in the context of EEG changes in tasks of varying complexity in visual and listen. Previous studies have identified the role of changes in gamma power during manual tasks, suggesting involvement in abstract task representation. Through the use of non-linear algorithms, the researchers found changes in EEG complexity and synchrony that reflect changes in signalling and synchrony across electrical domains. These findings provide an important understanding of the interaction between behavioural characteristics, network dynamics, and response variability [36].

7. EEG Correlates of Cognitive Load in a Multiple-Choice Reaction Task

This study investigates the EEG correlates of cognitive load in a multiple-choice response task, focusing on changes in theta, alpha and beta power. Theta energy is found in tasks with high demands on working memory (WM), which indicate the organization of information processing. Low alpha power is associated with activation of wider cortical regions in complex WM tasks. Beta activity, especially in the beta-2 range, is associated with motor cortex activation during the preparation and execution of motor responses. These findings provide insight into the neural mechanisms underlying cognitive load and task performance [28].

8. Tracking of Mental Workload with a Mobile EEG Sensor

A study on tracking mental stress using an EEG sensor shows the importance of changes in theta, alpha and beta power. Increased theta activity is seen in tasks with a high demand for WM, which controls information processing. Low alpha power is associated with cortical activation in complex WM tasks. Beta activity, especially in the beta-2 range, may indicate activation of the motor cortex during the preparation and execution of a motor response. This study highlights the potential of mobile EEG sensors to monitor cognitive activity in real-time environments [29].

9. Moment-to-Moment Variability in Functional Brain Networks During Cognitive Activity in EEG Data

This study examines the time-to-time variability in functional brain networks during cognitive tasks using EEG data. Theta energy is associated with higher WM demands and facilitates information processing. Reduced alpha power corresponds to general cortical reactivity during complex WM tasks. Beta activity, especially in the beta-2 range, may be associated with the activation of the motor cortex for the preparation and performance of the motor response. These findings show the importance of brain network activity in cognitive functions and the relevance of EEG components to follow these changes [30].

10. Monitoring Working Memory Load During Computer-Based Tasks with EEG Pattern Recognition Methods

Investigating EEG-based monitoring of working memory load during computer-based tasks, this study examines changes in theta, alpha, and beta power. Theta power increases with high WM demands, aiding information processing. A reduction in alpha power is linked to widespread cortical activation during complex WM tasks. Beta activity, particularly in the beta-2 range, may relate to motor cortex activation during motor response preparation and execution. The study emphasizes the utility of EEG pattern recognition methods in assessing cognitive load during computer-based tasks [31].

11. EEG-Based Prediction of Cognitive Load in Intelligence Tests

This study focuses on EEG-based cognitive load prediction in cognitive tests, the influence of EEG measurements, network connectivity and signal complexity. Brewer et al. (2012) and Mills et al. (2017) investigated cognitive workload in tasks with different question types. Soler et al (1998) and Logan (1985) indicated a reduction in cognitive performance as skill acquisition increased. Stevens et al. (2006) and Mack et al. (2013) showed that practice and skill acquisition reduce psychological stress. The use of machine learning models and EEG features in mental load prediction is promising, although the number of channels is limited, and personal neural networks for each subject have increased the accuracy of the prediction [32].

12. EEG-Related Changes in Cognitive Workload, Engagement, and Distraction as Students Acquire Problem-Solving Skills

This study examines EEG-related changes in cognitive workload, engagement, and distraction as students acquire problem-solving skills. Brewer et al. (2012) and Mills et al. (2017) studied cognitive workload in tasks with different question types. Soler et al (1998) and Logan (1985) found that increased job skills reduce mental workload. Stevens et al. (2006) and Mack et al. (2013) showed that getting used to working and acquiring skills reduces psychological stress. This paper discusses EEG-based cognitive load prediction using measurements of network connectivity and signal complexity. Machine learning models and EEG features have shown effectiveness in predicting cognitive load, with neural networks adapted for each subject improving prediction accuracy [33].

These findings demonstrate the dynamic nature of EEG responses to external stimuli in different states of consciousness.

Chapter-3

Methodology

The methodology used in this experiment is shown in Figure. 1.

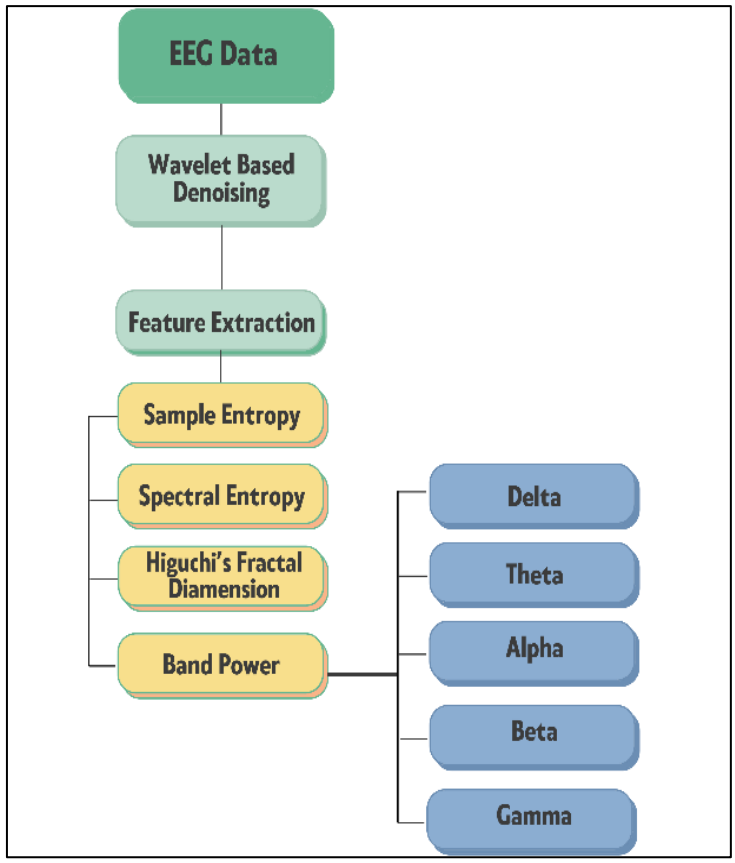


Figure.10 Block diagram of the Methodology of the whole process

Data Acquisition

The dataset used in this study, entitled "Electroencephalogram during mental calculation", provides a comprehensive record of electroencephalographic (EEG) signals. EEG data were captured using the Neurocom 23-channel unipolar EEG system, developed by XAI-MEDICA, Ukraine [13]. This system is known for its accuracy and reliability in recording neural activity, making it ideal for cognitive neuroscience research.

Electrode Configuration and Placement

For precision and standard measurements, silver/silver electrodes were used. These electrodes were placed symmetrically on the participants' scalp according to the international 10-20 system, an accepted method for EEG electrode placement. This system will organize the electrode position in different subjects and ensure the comparison of EEG data. All electrodes were referenced to ear pin reference electrodes to maintain a common reference signal and reduce noise.

Impedance and Signal Quality

Maintaining low electrical impedance is important for quality EEG recordings. In this study, the electrode impedance was kept below 5 kΩ to ensure optimal signal quality. Low impedance reduces artifacts and improves the accuracy of recorded neural signals.

Signal Digitization and Filtering

EEG signals were digitized at a sampling rate of 500 Hz, providing high temporal resolution capturing rapid changes in neural activity. To increase the recording quality, several filters were used. A high-pass filter with a cut-off frequency of 0.5 Hz was used to remove slow transients and linear variations. A low-pass filter with a cut-off frequency of 45 Hz was used to remove high-noise and complex artifacts. Additionally, a notch filter at 50 Hz was used to reduce interference from power lines, which are common in EEG recordings.

Recording Protocol and Conditions

The EEG recording duration varied across assessment types and implemented settings. Recorded segments were designed to ensure that no artifacts were present. In the case of the resting-state assessments, every recording extended to a length of 180 seconds. Therefore, the recorded data could be seen as a fundamental measure of neural activity without any imposed tasks. In the case of the mental arithmetic tasks, data was recorded for 60-second intervals, so as to capture the activity levels and responses associated with cognitive load and performed mental effort.

Participant Demographics and Data Collection

The sample for the study constituted 36 people. Each subject provided EEG data under two conditions, that is, before and after they performed cognitive tasks. For each condition, the twenty-minute data trace contained one sixty-second trace. This design allowed for a

comparative analysis of neural conditions ascribable to both the performance of a cognitive task and resting.

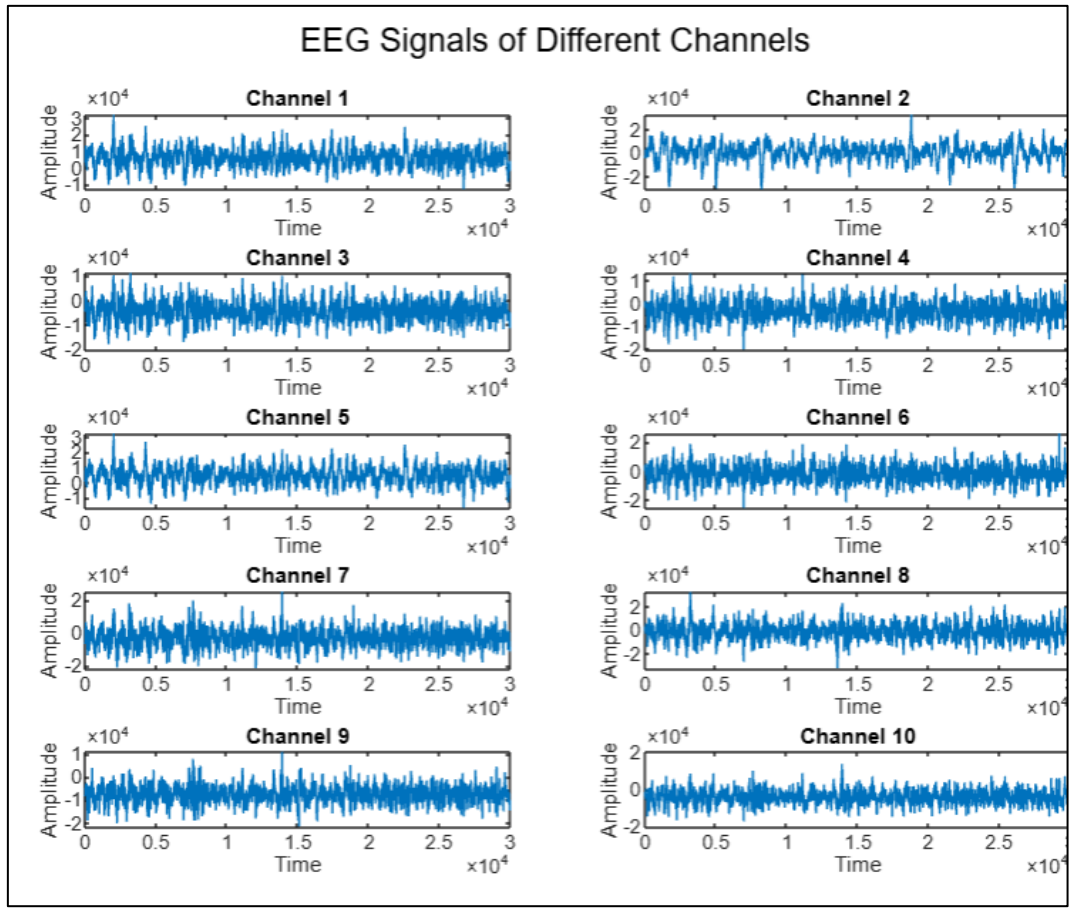


Figure.11 Graphical representation of a raw EEG of a subject of first 10 channels

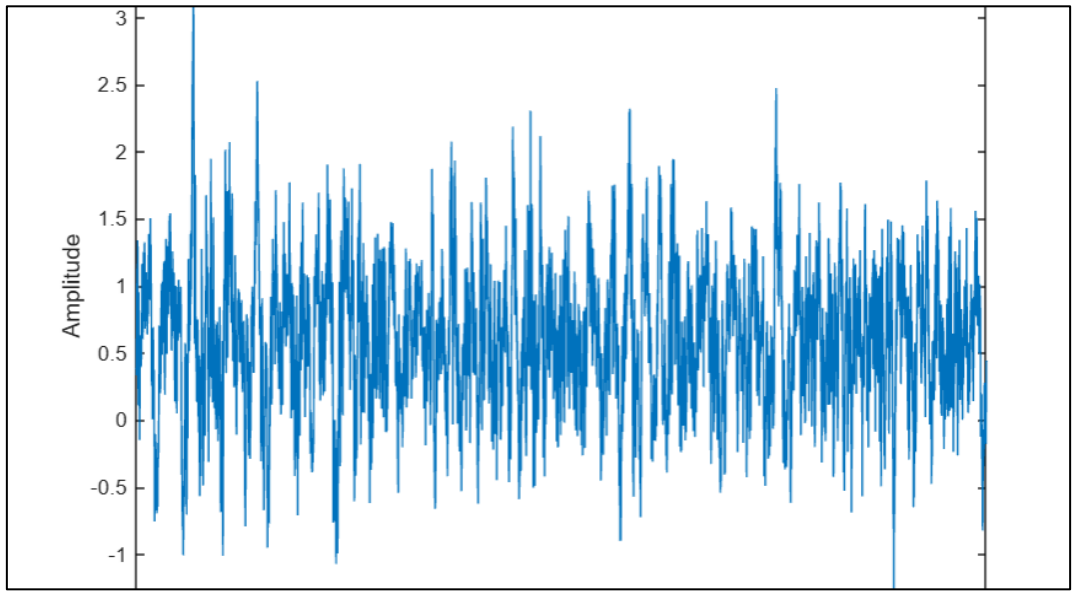


Figure.12 Graphical representation of a raw EEG of a Subject of a particular channel C1

Denoising of EEG Signals

For the purpose of improving quality of the EEG signals and reducing noise, the technique based on discrete wavelet transform was employed. Since this method is a rather sophisticated one, it was used in the current project to take advantage of the capability, which is inherent to wavelet transforms, to decompose signals into different frequency bands, as shortest wavelets are used to distinguish detail signals from approximation signals of twice smaller frequency band.

Discrete Wavelet Transform (DWT) Methodology

The DWT method composes the EEG signal into a set of coefficients that represent proximal and detailed components at different levels of decomposition. This analysis is performed using a filter bank from MATLAB online that accurately displays information in different bands of the EEG signal. The ability of the wavelet transforms to identify time and frequency information makes it ideal for processing non-linear signals such as EEG [12].

Wavelet Selection and Decomposition Levels

For this study, we chose the Daubechie 6 (db6) wavelet for its balance between time and frequency resolution, making it a powerful choice for EEG signal analysis. An 8-level decomposition was performed, which accurately represents the signal at multiple scales. Each level of decomposition produces coefficients corresponding to different components of the original signal.

Thresholding and Noise Reduction

High values of DWT indicate a strong correlation with the mother wave, indicating important features of the EEG signal. However, low coefficient values are associated with noise. For effective signal extraction, threshold value was applied to these coefficients.

Threshold values were determined manually for each excitation level by careful inspection of the power dynamic density (PSD) and signal parameters. Manual adjustment of the thresholds ensures an accurate estimate, consistent with the noise features observed in the dataset. A simple threshold was used, which preserves the characteristics of the original signal while maintaining noise immunity, focusing on high-frequency components associated with noise in the EEG recordings.

Power Spectral Density (PSD) Analysis

To evaluate the effectiveness of the denoising process, PSD analysis was performed before and after the DWT-based denoising application. The PSD filter provides a comprehensive view of the frequency distribution of the signal, which allows us to measure the amount of noise reduction. By comparing the PSD plots before and after the denoising, we were able to confirm that the large noise components are significantly reduced while preserving the integrity of the underlying neural signals.

Fourier Transform and Its Applications in EEG Signal Processing

The Fourier Transform (FT) is a mathematical technique that decomposes a time-domain signal into its constituent frequencies. This powerful tool transforms a signal from the time domain to the frequency domain, enabling the analysis of its frequency components. The FT is defined for a continuous signal x(t) as:

$$X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-j2\pi ft} dt$$

where X(f) represents the frequency domain representation of the signal, f is the frequency, and j is the imaginary unit.

Discrete Fourier Transform (DFT)

In practical applications, especially for digital signals like EEG, the Discrete Fourier Transform (DFT) is used. The DFT transforms a sequence of N discrete time-domain samples x[n] into N frequency components. The DFT is given by:

$$X[k] = \sum \int_{n=0}^{N-1} x[n]\, e^{-j\frac{2\pi}{N}kn}$$

for k=0, 1, 2……. N−1. The inverse DFT (IDFT) reconstructs the time-domain signal from its frequency components:

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k]\, e^{j\frac{2\pi}{N}kn}$$

Fast Fourier Transform (FFT)

The Fast Fourier Transform (FFT) is an efficient algorithm for computing the DFT, reducing the computational complexity from $O(N^2)$ to O(NlogN). This efficiency is crucial for real-time processing and analysis of EEG data, which typically involves large datasets.

Applications in EEG Signal Processing

1) **Power Spectral Density (PSD) Analysis**: The PSD quantifies the power distribution of an EEG signal across different frequencies. By applying the FT to EEG signals, the PSD can be computed, providing insights into the brain's rhythmic activities and aiding in the identification of different brain states (e.g., sleep stages, seizure detection).

$$\text{PSD}(f) = \frac{1}{N}|X(f)|^2$$

2. **Filtering**: The FT facilitates the design of frequency filters (e.g., low-pass, high-pass, band-pass) to isolate specific frequency components or remove noise from EEG signals. By transforming the signal to the frequency domain, applying the filter, and transforming back to the time domain, unwanted components can be effectively removed.

3. **Event-Related Potentials (ERPs)**: FT is used to analyze ERPs, which are brain responses that are time-locked to specific sensory, cognitive, or motor events. By examining the frequency components of these responses, researchers can identify characteristic patterns associated with different stimuli or cognitive processes.

4. **Coherence Analysis**: Coherence measures the correlation between EEG signals at different scalp locations as a function of frequency. It provides insights into functional connectivity and the synchronization of neural activities across different brain regions.

$$\text{Coherence}(f) = \frac{\left|S_{xy}(f)\right|^2}{S_{xx}(f)S_{yy}(f)}$$

where $S_{xy}(f)$ is the cross-spectral density of signals x and y, and $S_{xx}(f)$ and $S_{yy}(f)$ are the power spectral densities of x and y, respectively.

5. **Frequency Band Analysis**: The FT allows the decomposition of EEG signals into standard frequency bands (e.g., delta, theta, alpha, beta, gamma). These bands are associated with different cognitive and physiological states, and their analysis can provide valuable information about brain function and pathology.

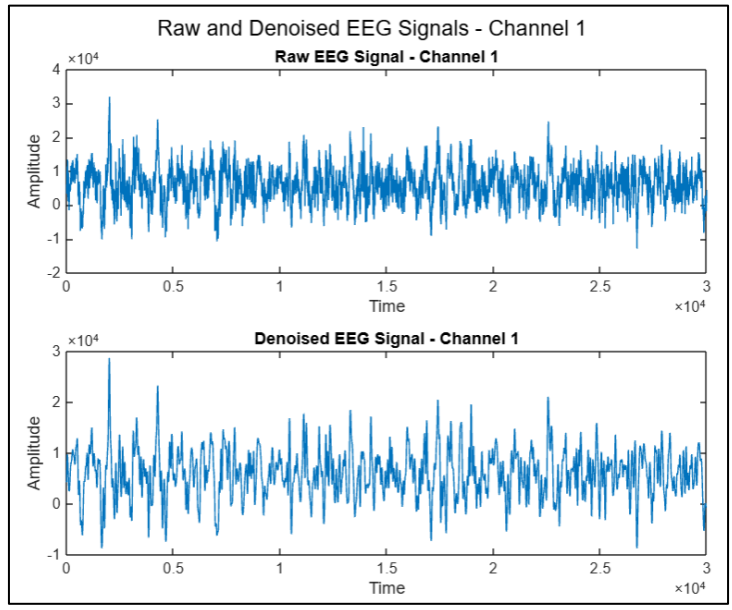


Figure.13 Graphical representation of a raw EEG vs a denoised EEG

Feature Extraction

In the analysis of EEG signals, feature extraction plays an important role in identifying patterns and important features in the data. This study used image extraction techniques from both spatial and non-spatial regions for signal analysis [14]. Spectral functions show rhythmic patterns in the frequency domain, while non-linear functions capture complex patterns and arrhythmias, thus providing a better understanding of EEG signals.

1) Spectral Features

By analyzing the frequency content, visualization techniques provide valuable insight into the rhythmic patterns of EEG signals. One of the primary methods of spectral analysis in this study is the estimation of Welch Power Spectral Density (PSD).

Welch Power Spectral Density (PSD)

The Welch method is a well-established method for estimating the power spectral density of a signal. This involves decomposing the signal into overlapping segments, applying

a fast Fourier transform (FFT) to each segment, and averaging the resulting power spectrum. This approach smooths the power density estimation, reduces the noise variance and provides a more reliable representation of the frequency components of the signal [15].

In this study, the Welch PSD was used to calculate electrical power in different EEG frequency bands. The EEG frequency bands analyzed were:

• **Delta waves (0.5-4 Hz):** These waves are associated with deep sleep and are characterized by high intensity and low frequency.

• **Theta waves (4-8 Hz):** These waves occur during light sleep, relaxation and meditation.

• **Alpha waves (8 to 13 Hz):** These waves are seen when a person is awake but relaxed, and seen when their eyes are closed.

• **Beta Waves (13-30 Hz):** These waves are associated with active mental activity, concentration and problem solving.

• **Gamma Waves (30 Hz and higher):** These waves are associated with higher mental functions such as vision and cognition.

Cognitive power was calculated in these frequency groups to evaluate different cognitive characteristics and cognitive functions. For example, an increase in alpha wave power may indicate relaxation, while an increase in beta wave power may indicate an increase in mental load or concentration. This analysis is particularly important for brain-computer interface (BCI) applications [16], where understanding these frequency bands helps interpret and respond to neural signals.

2) Nonlinear Features

In addition to critical features, non-linear features were extracted to capture complex patterns and arrhythmias in the EEG signals. Nonlinear analysis methods, such as entropy measurement, fractional measurement, and Lyapunov flow, provide a deeper understanding of the dynamic behaviour of EEG signals, which are not only visible in the frequency domain..

Higuchi's Fractal Dimension (HFD)

Higuchi fractal dimension (HFD) is a key method for measuring the fractal dimension of time series data, and is particularly applied to the analysis of electroencephalogram (EEG)

signals. HFD is a measure of the non-linear, complex, and self-similar nature of EEG signals. Higher HFD values indicate greater complexity, which indicates complex and adaptive brain functions. Conversely, lower HFD values indicate less muscle stiffness, which may be associated with more neural activity.

Calculation of HFD

HFD is calculated by dividing the time series into segments based on the parameter k. For each segment k, the length $L(k)$ of the curve is measured as:

$$L(k) = \frac{1}{k}\sum_{m=1}^{k}\left(\frac{N-1}{\left(\frac{N-m}{k}\right)k}\sum_{i=1}^{\left(\frac{N-m}{k}\right)}|x(m+i\cdot k)-x(m+(i-1)\cdot k)|\right) \quad (1)$$

Where, N is the total number of data points, and x represents the signal values. The HFD is derived from the slope D of the log-log plot of the average curve length against k:

$$D = \lim_{k\to k_{\max}}\left(\log\left(\frac{L(k)}{k}\right)\right) \quad (2)$$

Optimizing $k_{\max}$, the maximum segment interval, is crucial for accurately characterizing the signal's complexity. This optimization involves plotting HFD values against different k values and selecting the k at which the HFD values reach a point of saturation. This ensures that the calculated fractal dimension reliably reflects the intricacies of the signal [17].

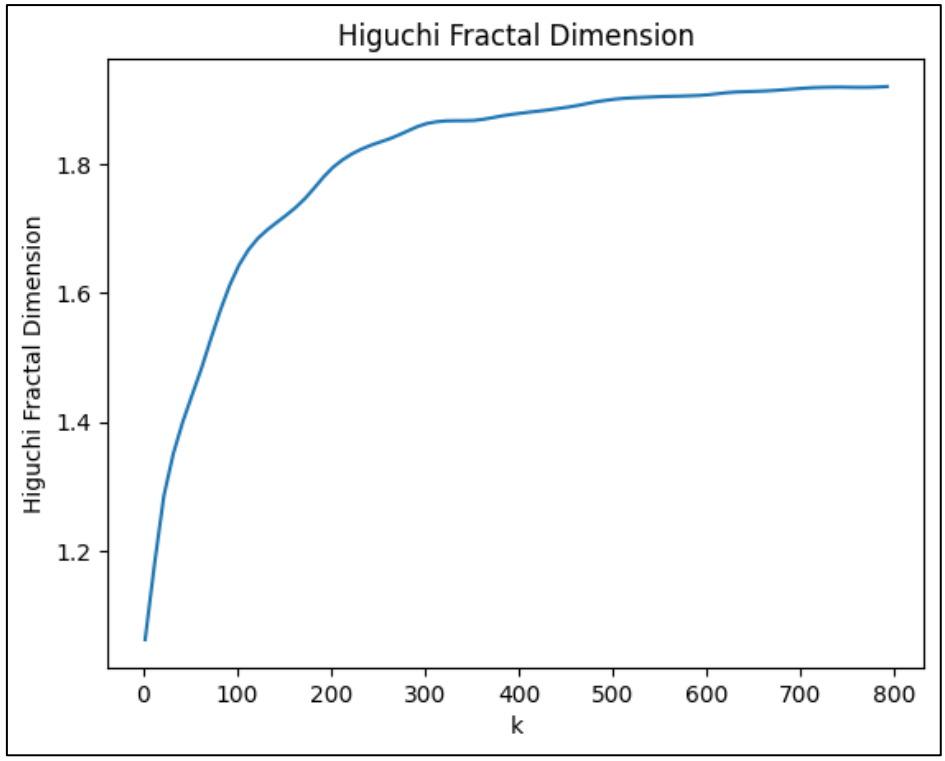


Figure.14 Graphical representation of the HFD

Significance in EEG Analysis

In EEG analysis, HFD provides important insight into the functional state of the brain. By evaluating fractional volume, researchers can determine the degree of complexity and consistency of brain activity. High values of HFD indicate a healthy and adaptive brain that is able to respond to various stimuli, while low values of HFD are associated with neurological diseases and conditions that are more difficulty of neural activity. Therefore, the use of HFD in EEG signal processing provides a powerful framework for understanding the dynamic behaviour of the brain, facilitating the identification of pathological conditions and contributing to advances in neurophysiological research.

Sample Entropy (SampEn)

The sample entropy (SampEn) is a very important measure for evaluating the consistency or predictability of time-series data, and is often used in the analysis of physical signals and biomarkers, including heart rate variability and EEG. The uncertainty of differences in neural activity is determined, with higher SampEn values indicating complexity and variability, and lower values indicating regular, predictable patterns.

Calculation of Sample Entropy

SampEn is determined by comparing segments of the time series, counting the occurrences of matching sequences of specified lengths mmm and m+1m+1m+1, and then calculating the logarithmic ratio of these counts:

$$\text{SampEn}(m, r) = -\log\left(\frac{A^m(r)}{B^m(r)}\right) \qquad (3)$$

In this context:

- ‘m' represents the sequence length, indicating the number of data points in each compared sequence.
- ‘r' denotes the tolerance or similarity threshold, which is the maximum allowable difference between two sequences for them to be considered a match.
- ‘$B^m(r)$’ is the probability that two sequences of length mmm match within the tolerance r, capturing short-term patterns.

- ‘$A^m(r)$’ is the probability that two sequences of length (m+1) match within the same tolerance r, considering longer sequences.

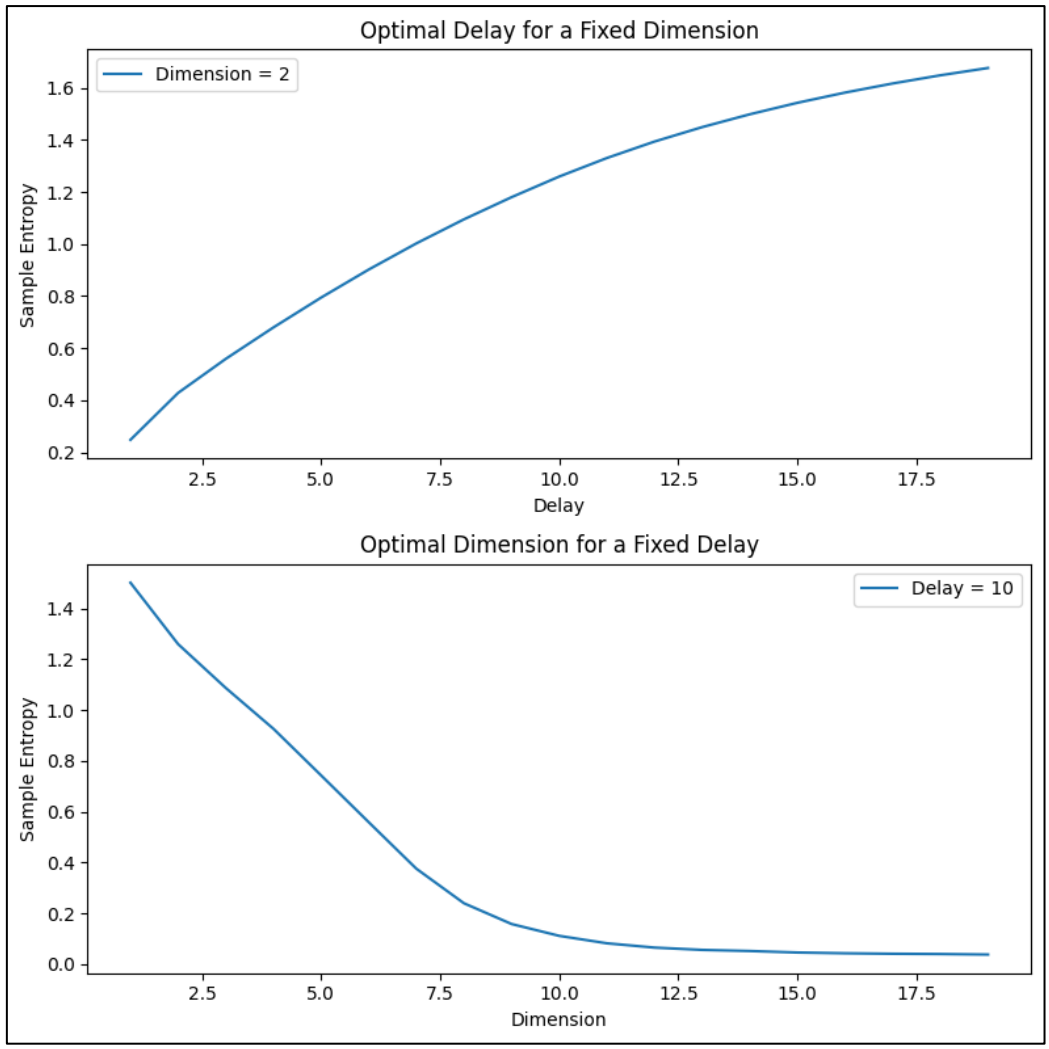


Figure.15 Graphical representation of the Sample Entropy

Importance of Parameters m and r

The parameters m and r are critical to accurately represent signal dynamics and control the sensitivity of SampEn to underlying neural activity. These parameters must be chosen carefully to ensure a robust analysis. This selection process involves setting SampEn to various values of mmm and r and identifying the point where the measurement stabilizes, indicating saturation. Such optimization ensures that the derived SampEn values accurately reflect the complexity of the neural signals [18].

Significance in EEG Analysis

In EEG analysis, SampEn provides valuable insights into the complexity of neural dynamics. By measuring the regularity and predictability of EEG signals, SampEn helps researchers understand the degree of neural complexity and variability. High SampEn values typically indicate a healthy, adaptive neural system capable of responding to diverse stimuli, while low values may be associated with more regular and less adaptable neural patterns, potentially linked to neurological disorders or specific brain states.

Through its application in EEG signal processing, SampEn enhances our understanding of neural complexity, facilitating the identification of pathological conditions and contributing to advancements in neurophysiological research. This measure's ability to quantify the unpredictability of neural activity makes it a powerful tool in the study of brain function and dysfunction.

Spectral Entropy (SpecEn)

Spectral Entropy (SpecEn) is an important measure for analyzing the distribution of energy or power at different frequencies in a signal. This criterion can be used in time intervals and frequency. Higher SpecEn values indicate a distribution of power across frequencies, indicating more complex and less predictable neural activity. In contrast, low SpecEn values indicate an energy distribution, which is often associated with highly visible and coordinated neural behaviours.

Calculation of SpecEn

The process of calculating SpecEn involves several steps. Initially, the Power Spectral Density (PSD) of the signal is obtained. The PSD represents how the power of a signal is distributed across different frequency components [19]. Once the PSD is computed, it is normalized so that the total power sums to one, transforming the PSD into a probability distribution. Using these normalized values, the spectral entropy is then calculated:

$$\text{SpecEn} = -\sum_{i=1}^{N} P(i) \log\big(P(i)\big) \qquad (4)$$

Here:

- P(i) denotes the normalized power at the i^{th} frequency.
- N represents the total number of frequency bins.

Importance in EEG Analysis

In the context of EEG analysis, SpecEn is very important because it provides insight into the complexity of neural signals. A higher SpecEn indicates a distribution of neural activity at different frequencies, indicating a more complex and adaptive nature of the brain. In contrast, SpecEn is less likely to indicate that neural activity is multi-modal and to indicate a more consistent and coordinated neural pattern.

Applications and Implications

By comparing the SpecEn of EEG signals, researchers can benefit a deeper expertise of the mind's practical state. For instance, a extra uniform strength distribution (better SpecEn) may be related to lively cognitive procedures and alert states, at the same time as a focused strength distribution is probably found at some point of sleep or in sure neurological disorders. This makes SpecEn a effective device for distinguishing among distinctive mind states and expertise the underlying neural mechanisms.

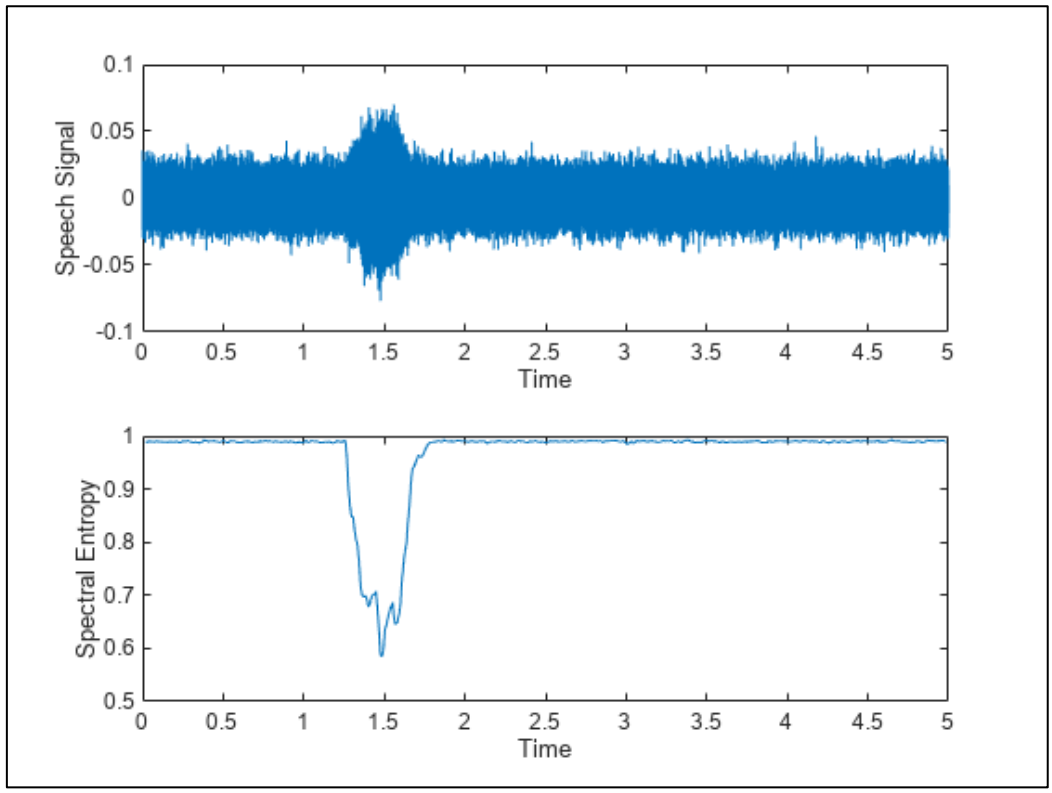


Figure.16 Graphical representation of Spectral Entropy [38]

Chapter-4

Results

I. Comparison the different features across all the subjects before and during the tasks

A. Comparison of Spectral Features

1) Comparison of the Alpha Powers across all subjects

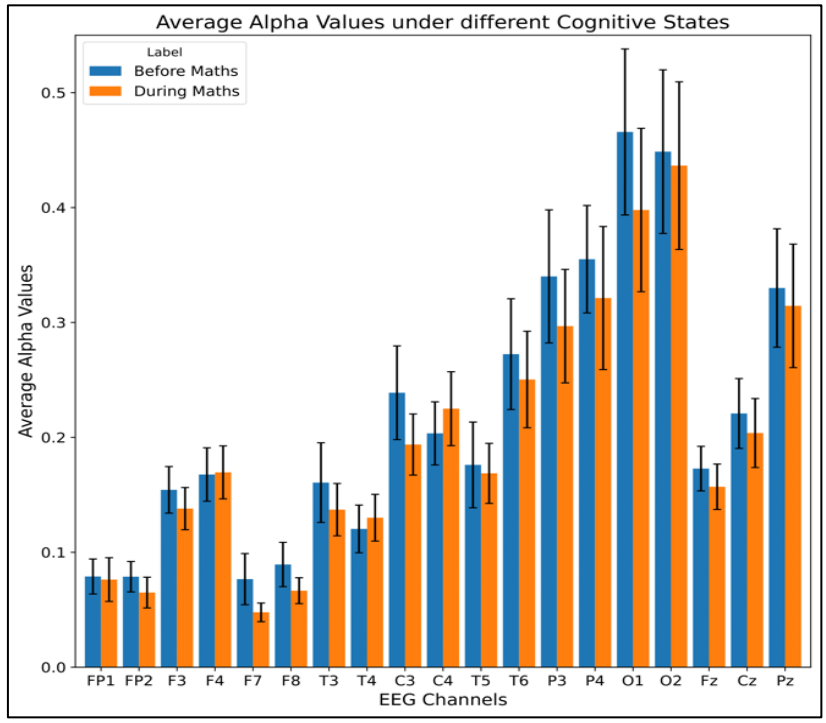


Figure. 17. Variation in alpha power averaged across all subjects before and during the tasks.

Figure 17 illustrates a marked decrease in average alpha power across all subjects while performing arithmetic tasks, suggesting a negative correlation with cognitive workload. Alpha power, indicative of cortical inactivity or a state of calm alertness, diminishes with increased cortical engagement. This observation is consistent with previous studies, which report alpha power reductions during cognitive loading.

During the arithmetic tasks, distinct patterns of alpha power changes were observed across different brain regions. Notably, alpha power decreased across nearly all EEG channels, with a more pronounced reduction in the left hemisphere compared to the right. Specifically, electrodes F3 and T3 demonstrated significant decreases, while F4 and T4 exhibited slight increases. Similarly, a decrease

was observed at C3, whereas C4 showed an increase. Additionally, O1 experienced a more substantial decrease in alpha power than O2. In the parietal region, all channels consistently demonstrated reductions in alpha activity. Overall, the left hemisphere showed a greater reduction in alpha power relative to the right hemisphere [20].

2) Comparison of the Beta Powers across all subjects

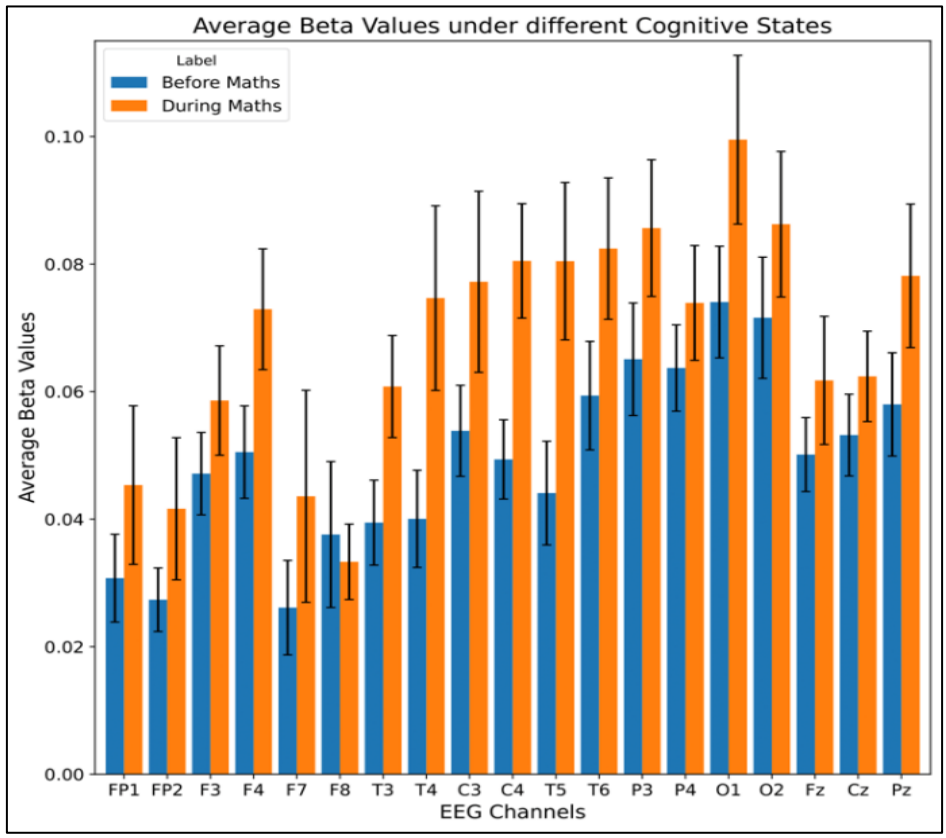


Figure. 18 Variation in beta power averaged across all subjects before and during the tasks.

Figure 18 reveals a significant increase in beta activity from the pre-task state during mathematical tasks, underscoring the responsiveness of beta waves to cognitive engagement. Beta activity, associated with heightened alertness, active cognitive processing, and complex task participation, contrasts with alpha waves that denote relaxation.

During the tasks, an increase in beta activity was observed across all EEG channels. The most pronounced increases were noted in the frontal, central, occipital, and parietal regions. These findings align with previous research indicating that elevated beta activity is linked to heightened cognitive activity and sustained attention [21].

2) Comparison of the Delta Powers across all subjects

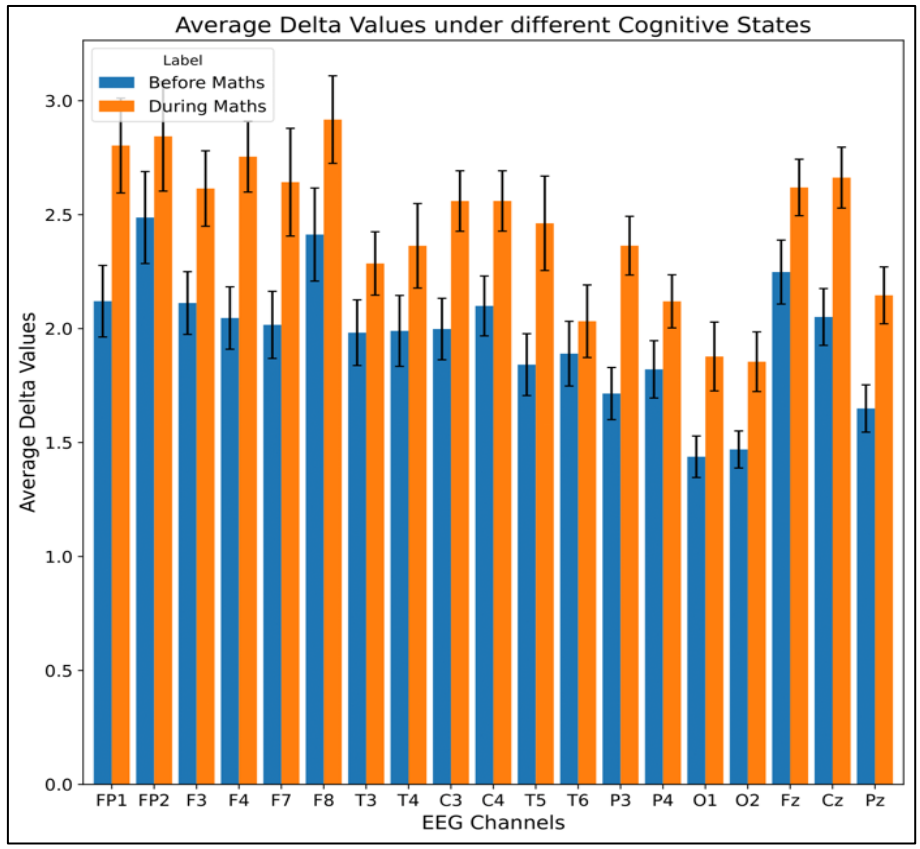


Figure. 19 Variation in delta power averaged across all subjects before and during the tasks.

Figure 19 demonstrates an increase in delta power during arithmetic tasks compared to the pre-task state, indicating heightened neural activity during task execution. The rise in delta power suggests enhanced cognitive activity and sustained attention during cognitive efforts.

During the tasks, an increase in delta activity was observed across all EEG channels, likely due to an overall increase in cortical activity associated with cognitive loading. This finding is consistent with previous studies, which have reported that delta power augmentation is linked to increased cognitive demands and sustained attention during challenging tasks [22].

4) Comparison of the Theta Powers across all subjects

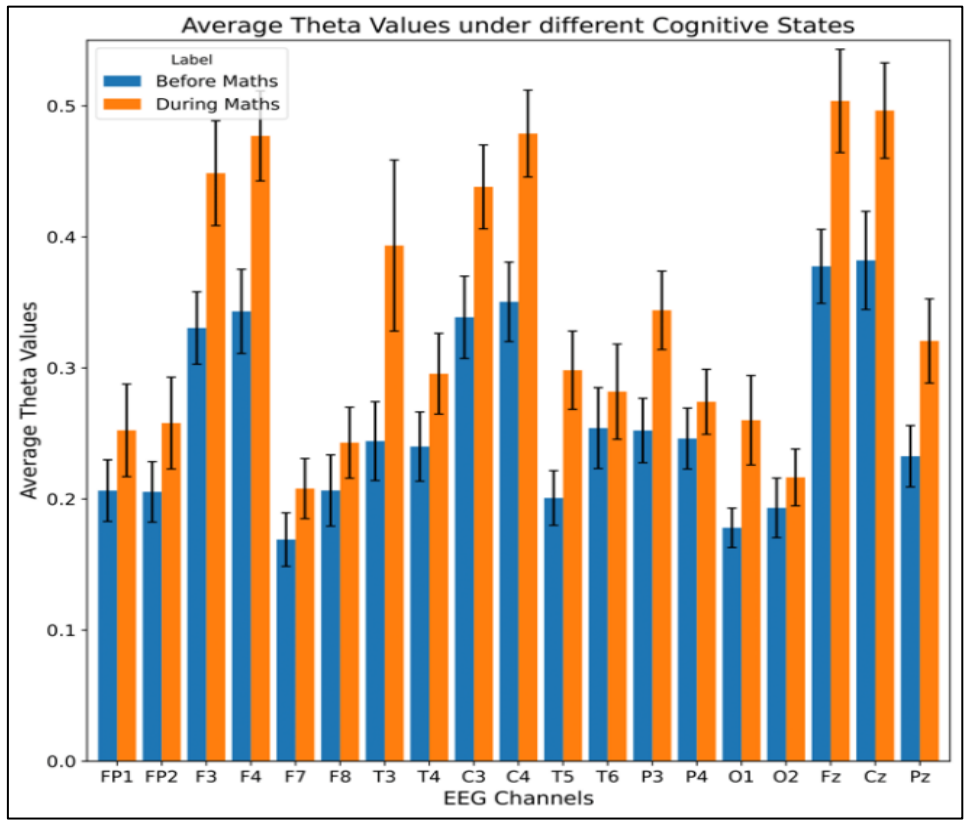


Figure. 20 Variation in theta power averaged across all subjects before and during the tasks.

Figure 20 shows the increase in mean theta power in all subjects under mental load compared to pre-workout levels, indicating a relationship between high mental workload and theta power. While beta waves are associated with alertness and stronger mental processing during complex tasks, increased theta power reflects increased cognitive performance and focus during tasks. mind.

Theta values showed significant changes in different brain regions during exercise. In the frontal region, a significant increase was found in the dorsolateral prefrontal cortex (F3 and F4), while the inferior frontal cortex (F7 and F8) showed a smaller increase in theta power. In addition, a significant increase was observed in the left hemisphere, the left hemisphere and areas of the brain. These findings are consistent with previous research linking theta power with cognitive needs and attention in challenging tasks [23].

5) Comparison of the Gamma Powers across all subjects

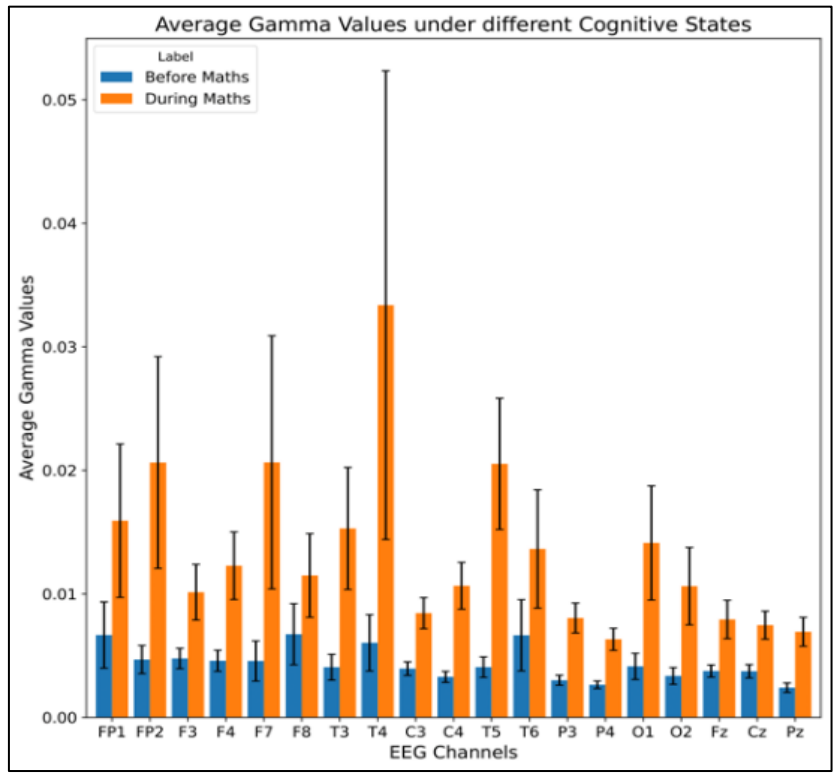


Figure. 21 Variation in gamma power averaged across all subjects before and during the tasks.

Figure 21 shows a significant increase in gamma activity during index tasks compared to baseline before the task, indicating increased neural activity. While beta waves are associated with increased alertness and active mental processing during complex tasks, increased gamma energy indicates increased mental activity and attention. continue mental activities.

During activity, gamma power increases in all EEG channels, with peaks most evident in the frontal, frontal, and occipital regions. These findings are consistent with previous studies that have linked increased gamma activity with cognitive needs and increased attention during challenging tasks [24].

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B. Comparison of nonlinear features

1) Comparison of the Higuchi's Fractal Dimension

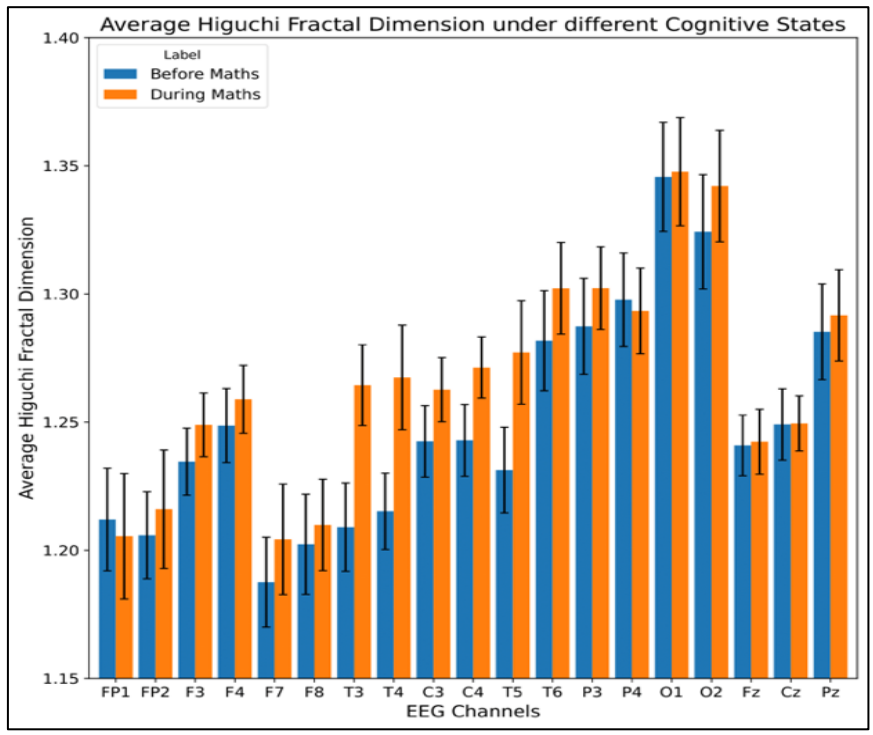


Figure. 22 Variation in HFD averaged across all subjects before and during the tasks.

Figure 22 shows the increase in Higuchi Fractal Dimension (HFD) values during the statistical operations in contrast to the low values before the operations. Higher HFD values indicate more complex EEG signals, reflecting increased neural activity and adaptation to task demands. Computing often involves higher cognitive functions such as working memory, attention and problem solving. As brain connections become stronger and more interconnected in response to mental demands, the complexity of the EEG signals increases, and the HFD values increase.

During the calculations, almost all EEG channels showed an increase in HFD, with the most significant changes observed in the temporal domain. The middle and early stages showed an increase, albeit to a lesser extent. These changes were similar across both hemispheres, indicating neural complexity during the task. This pattern is similar to the adaptation of brain activity to cognitive challenges, which is reflected in the increase in fractional dimensions.

2) Comparison of the Sample Entropy across all subjects

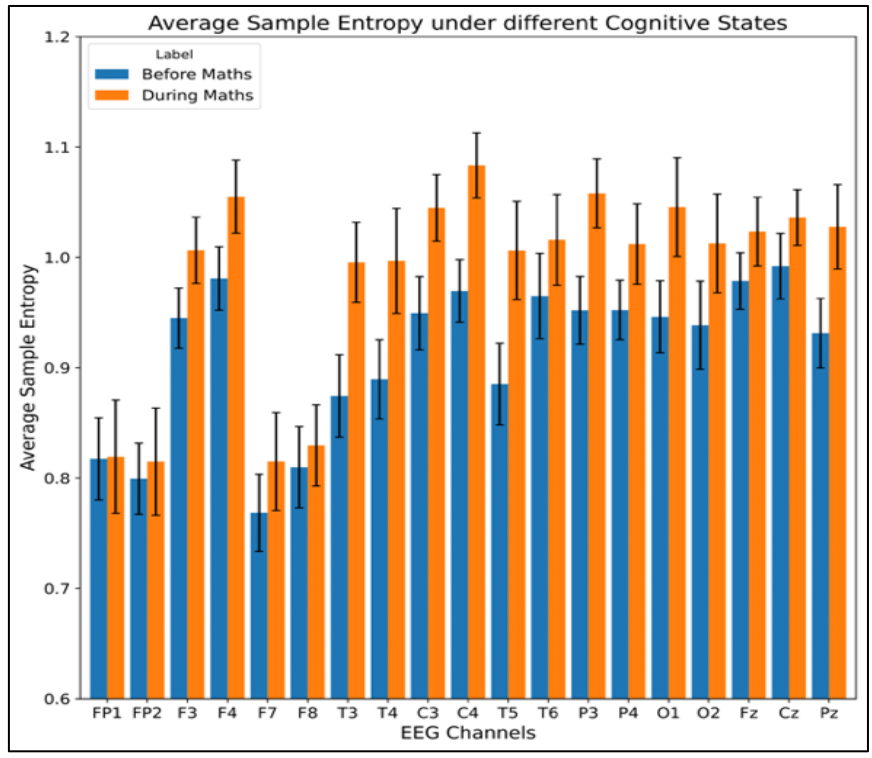


Figure. 23 Variation in SampEn averaged across all subjects before and during the tasks.

Figure 23 shows the increase in sample entropy (SampEn) during the tasks, indicating a more complex neural activity in response to cognitive input. Cognitive tasks, such as arithmetic or problem solving, require the simultaneous activation of multiple brain regions, increasing neural complexity.

Higher SampEn values were observed in all EEG channels, indicating parallel processing of information across brain regions during cognitive tasks. In particular, the frontal area (F7 and F8) and frontal area (FP1 and FP2) showed a lower increase in SampEn compared to the frontal area and other brain regions. This model emphasizes the role of these regions in processing complex cognitive needs [25].

3) Comparison of the Spectral Entropy across all subjects

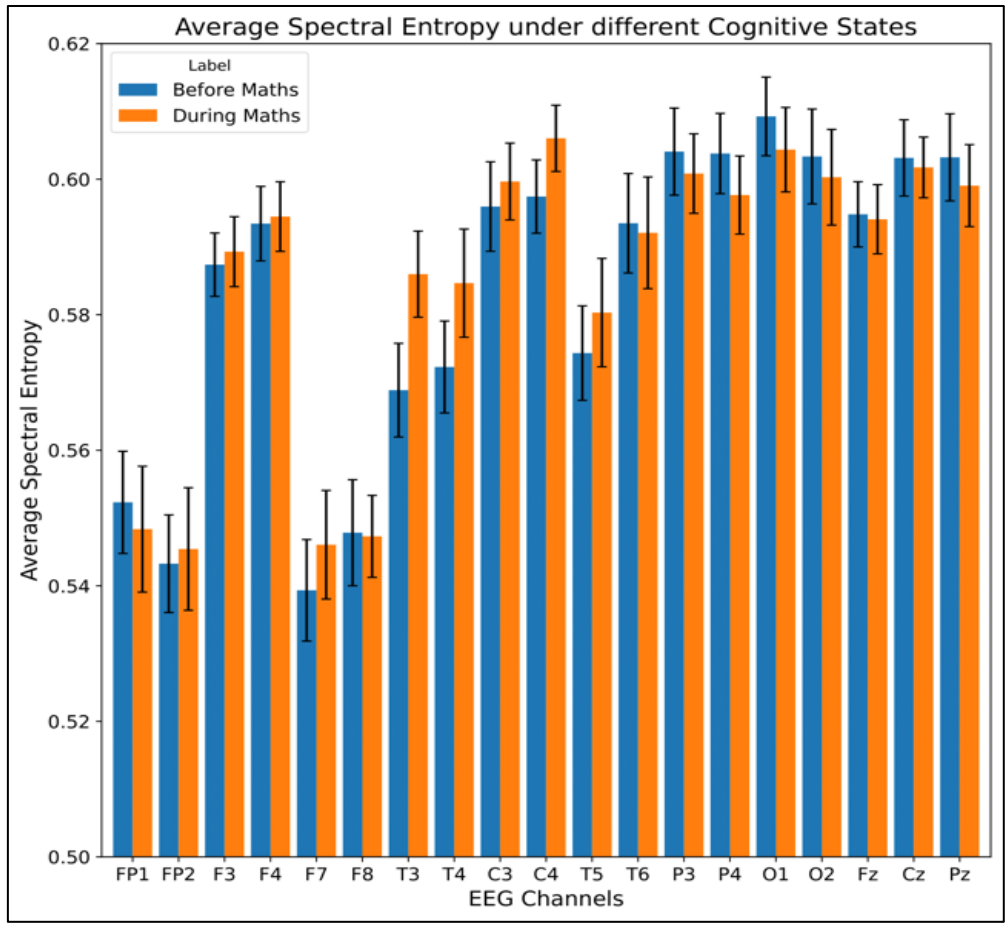


Figure. 24 Variation in SpecEn averaged across all subjects before and during the tasks.

Figure 24 shows the specific changes of spectral entropy values (SpecEn) in different EEG channels. There was a significant increase in SpecEn in temporal and central regions, indicating a distribution of power across EEG bands. In contrast, SpecEn was reduced in the parietal and occipital regions, indicating a stronger energy distribution associated with or predicted neural activity.

The non-uniform variation in SpecEn across different brain regions may result from the involvement of specific frequency bands in response to cognitive loading or from ongoing background activity in certain frequency ranges. Additionally, different neural networks may be recruited by individuals for the same cognitive task, leading to diverse patterns of SpecEn across channels. This variability highlights the complex interplay between cognitive demands and regional brain activity [26].

II. Comparison the different features across the subjects who have done the task correctly before and during the tasks

A. Comparison of Spectral Features

1) Comparison of Alpha Powers of the subjects who have done the task correctly

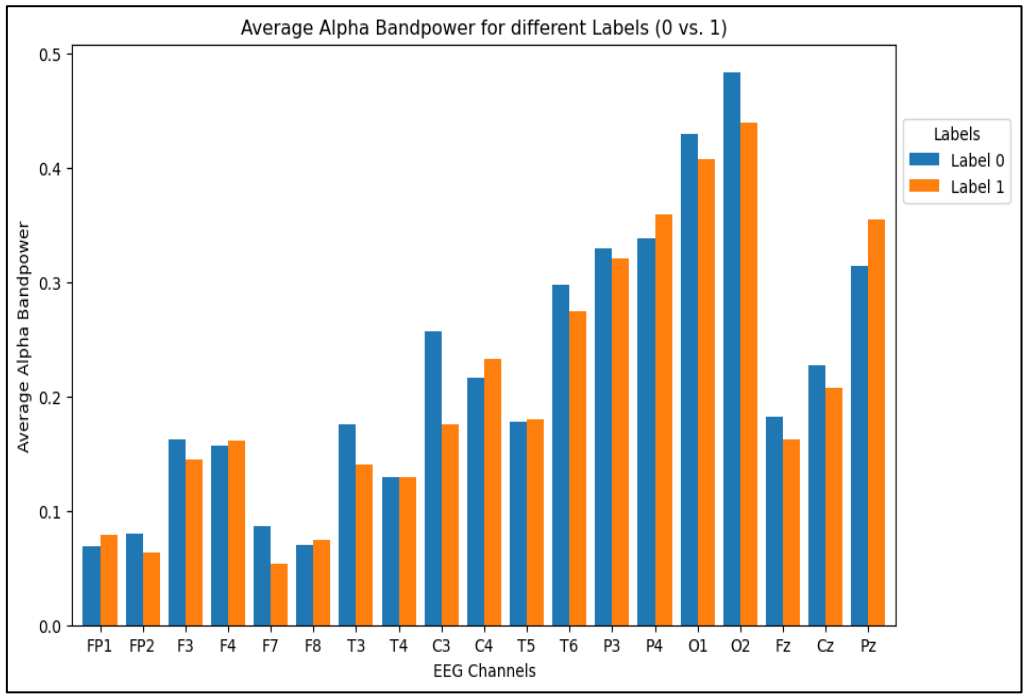


Figure. 25 Variation in alpha power averaged across all subjects before task [Label 0] and during the tasks [Label 1]

Based on the alpha power results before and during the task for students who performed correctly Figure 25 illustrates:

1. Frontal regions (FP1, FP2, F3, F4, F7, F8) generally show moderate alpha activity.
2. Temporal channels (T3, T4, T5, T6) exhibit varied alpha power, with some showing higher activity during the task.
3. Central channels (C3, C4, Cz) display significant alpha power, especially in C3.
4. Parietal channels (P3, P4, Pz) demonstrate high alpha power, particularly in P3 and P4.
5. Occipital channels (O1, O2) exhibit the highest alpha power during the task.

Findings suggest differential activation across brain regions, with pronounced activity in parietal and occipital areas during task performance, indicating these regions are particularly engaged in correct task execution.

2) Comparison of Beta Powers of the subjects who have done the task correctly

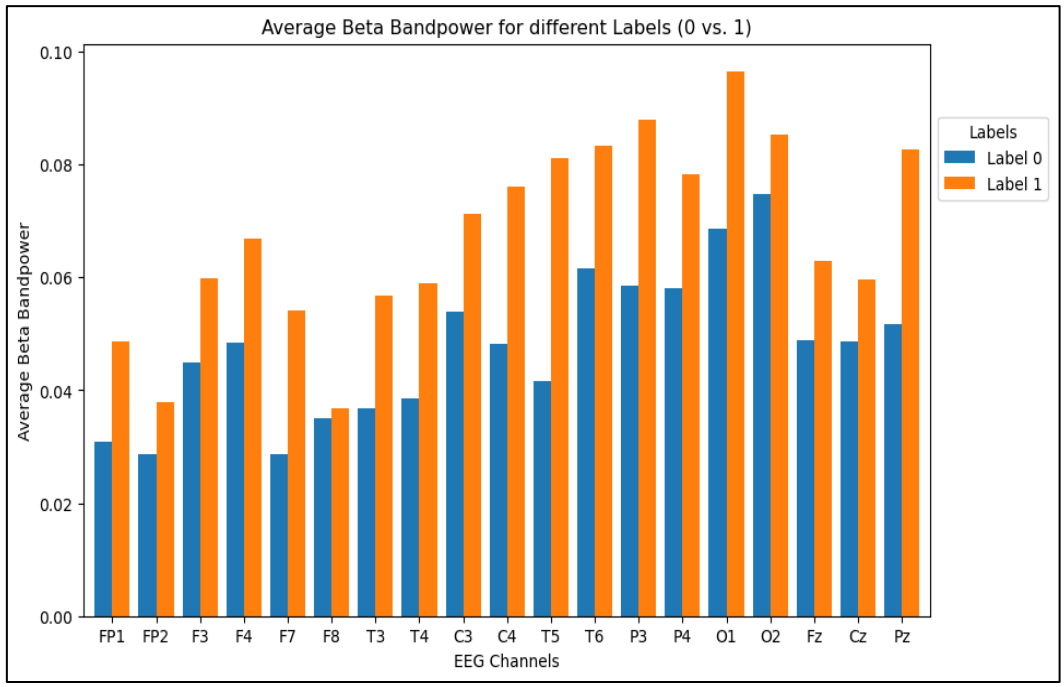


Figure. 26 Variation in beta power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the beta power results before and during the task for students who performed correctly Figure 26 illustrates:

1. Frontal channels (FP1, FP2, F3, F4, F7, F8) generally show moderate to high beta activity during the task.
2. Temporal channels (T3, T4, T5, T6) display varied beta power, with T6 showing notably higher activity.
3. Central channels (C3, C4, Cz) exhibit moderate beta power, especially in C3 and C4.
4. Parietal channels (P3, P4, Pz) demonstrate considerable beta power, particularly in P3 and P4.
5. Occipital channels (O1, O2) also show significant beta power, especially O1.

Findings indicate differential activation across brain regions during task performance, with pronounced beta activity in frontal, parietal, and occipital areas, suggesting these regions are notably engaged in correctly performing the task.

3) Comparison of Delta Powers of the subjects who have done the task correctly

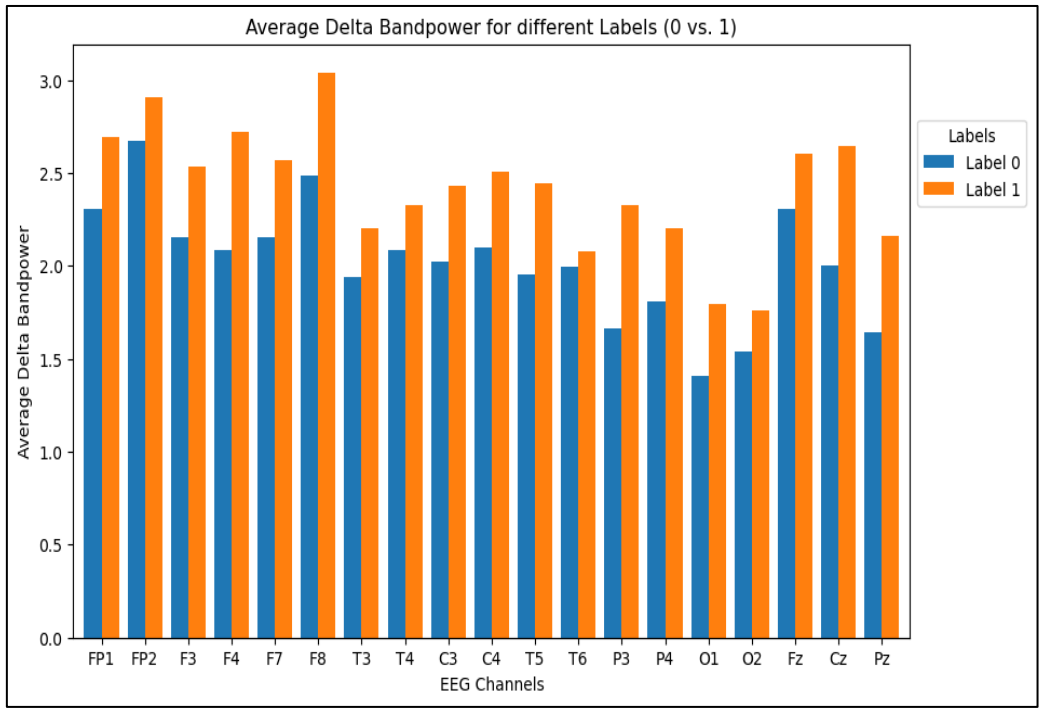


Figure. 27 Variation in delta power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the delta power results before and during the task for students who performed correctly Figure 27 illustrates:

1. Frontal channels (FP1, FP2, F3, F4, F7, F8) generally show moderate to high delta activity during the task.
2. Temporal channels (T3, T4, T5, T6) exhibit varied delta power, with T6 showing notably lower activity.
3. Central channels (C3, C4, Cz) demonstrate moderate delta power, especially in C4.
4. Parietal channels (P3, P4, Pz) display moderate delta power, particularly in P3 and P4.
5. Occipital channels (O1, O2) also show moderate delta power during the task.

Findings indicate widespread delta activity across frontal, central, parietal, and occipital regions during task performance, suggesting general engagement of these areas in cognitive processes associated with task execution.

4) Comparison of Theta Powers of the subjects who have done the task correctly

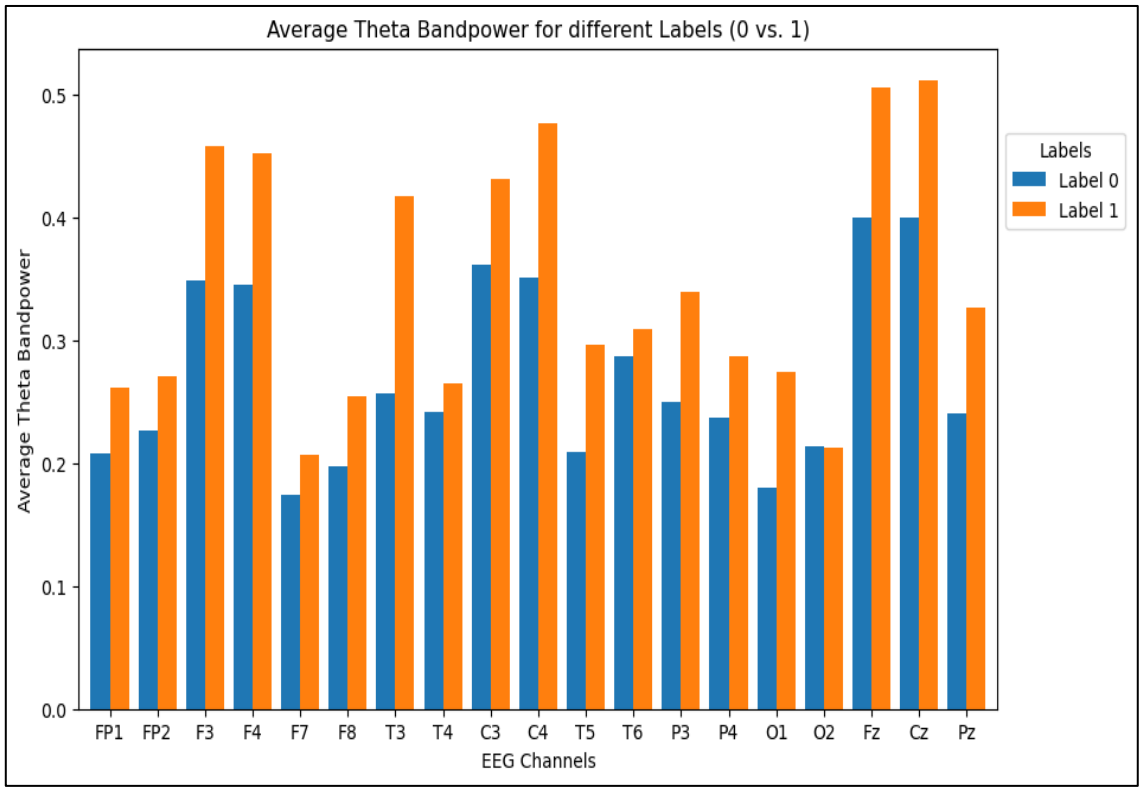


Figure. 28 Variation in theta power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the theta power results before and during the task for students who performed correctly Figure 28 illustrates:

1. Frontal channels (FP1, FP2, F3, F4, F7, F8) generally exhibit moderate to high theta activity during the task.
2. Temporal channels (T3, T4, T5, T6) show varied theta power, with T3 and C4 displaying notably higher activity.
3. Central channels (C3, C4, Cz) demonstrate significant theta power, especially in C3 and C4.
4. Parietal channels (P3, P4, Pz) display moderate theta power, particularly in P3 and P4.
5. Occipital channels (O1, O2) also show moderate theta power during the task.

Findings indicate widespread theta band activity across frontal, central, parietal, and occipital regions during task performance. This suggests engagement of these areas in cognitive processes such as attention, working memory, and decision-making associated with task execution.

5) Comparison of Gamma Powers of the subjects who have done the task correctly

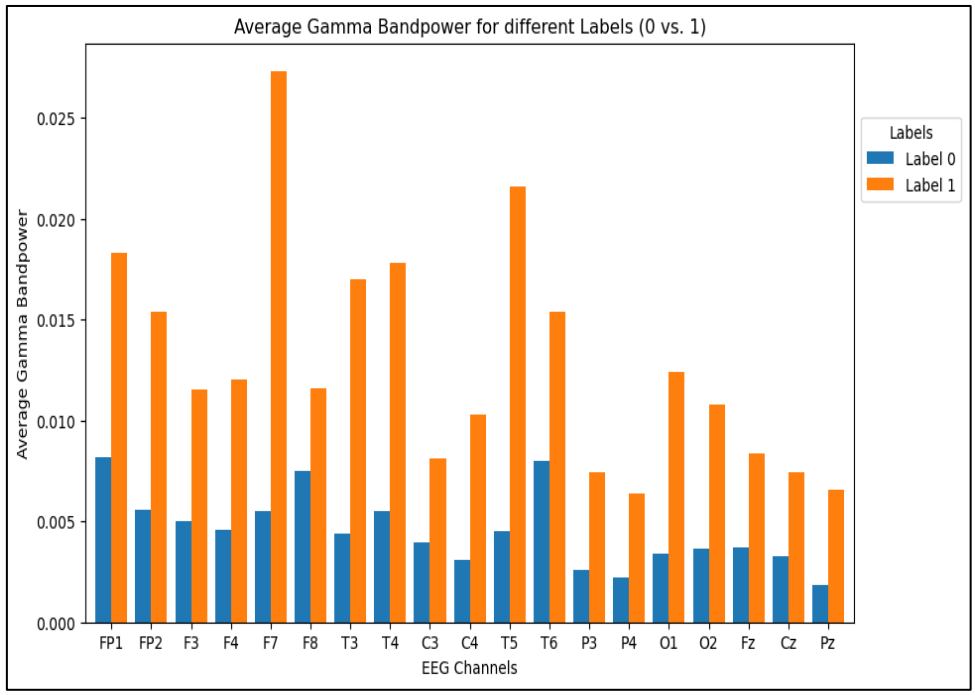


Figure. 29 Variation in gamma power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the gamma power results before and during the task for students who performed correctly the Figure 29 illustrates:

1. Frontal channels (FP1, FP2, F3, F4, F7, F8) generally exhibit low to moderate gamma activity during the task.
2. Temporal channels (T3, T4, T5, T6) show varied gamma power, with T6 displaying relatively higher activity.
3. Central channels (C3, C4, Cz) demonstrate low to moderate gamma power, particularly in C3.
4. Parietal channels (P3, P4, Pz) display low gamma power, with P3 and P4 showing minimal activity.
5. Occipital channels (O1, O2) also exhibit low gamma power during the task.

Findings suggest that gamma activity is generally lower compared to alpha and beta bands across all brain regions during task performance. However, there is noticeable variation, with some frontal and temporal regions showing slightly higher gamma activity, indicating potential localized cognitive processing during task execution.

B. Comparison of nonlinear features

1) Comparison of Higuchi's Fractal Dimension of the subjects who have done the task correctly

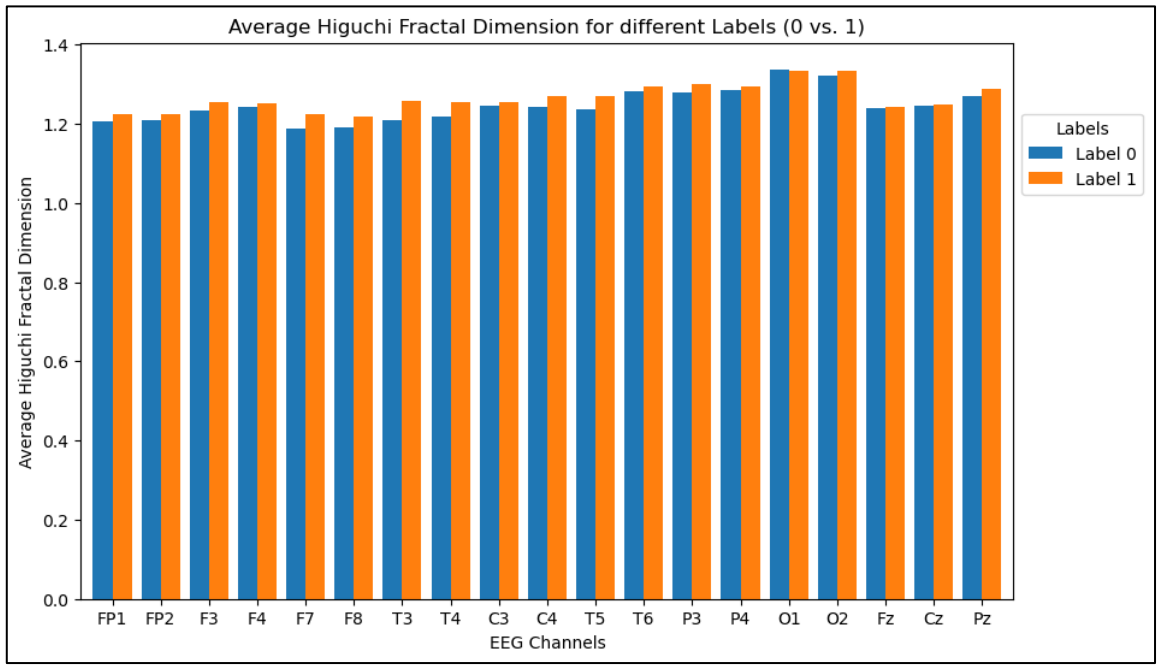


Figure. 30 Variation in HFD averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the Higuchi's Fractal Dimension (HFD) results before and during the task for students who performed correctly the Figure 30 illustrates:

1. Frontal channels (FP1, FP2, F3, F4, F7, F8) generally exhibit consistent HFD values during the task.
2. Temporal channels (T3, T4, T5, T6) show moderate to high HFD values, particularly T6.
3. Central channels (C3, C4, Cz) demonstrate relatively high HFD values, especially in C3 and C4.
4. Parietal channels (P3, P4, Pz) display moderate to high HFD values, particularly in P3 and P4.
5. Occipital channels (O1, O2) also show moderate HFD values during the task.

Findings suggest that frontal, central, parietal, and occipital regions exhibit varying degrees of complexity or irregularity in the signal patterns as measured by HFD during task performance. Higher HFD values typically indicate more complex or irregular signal dynamics, which can relate to the complexity of cognitive processes involved in task execution.

2) Comparison of Sample Entropy of the subjects who have done the task correctly

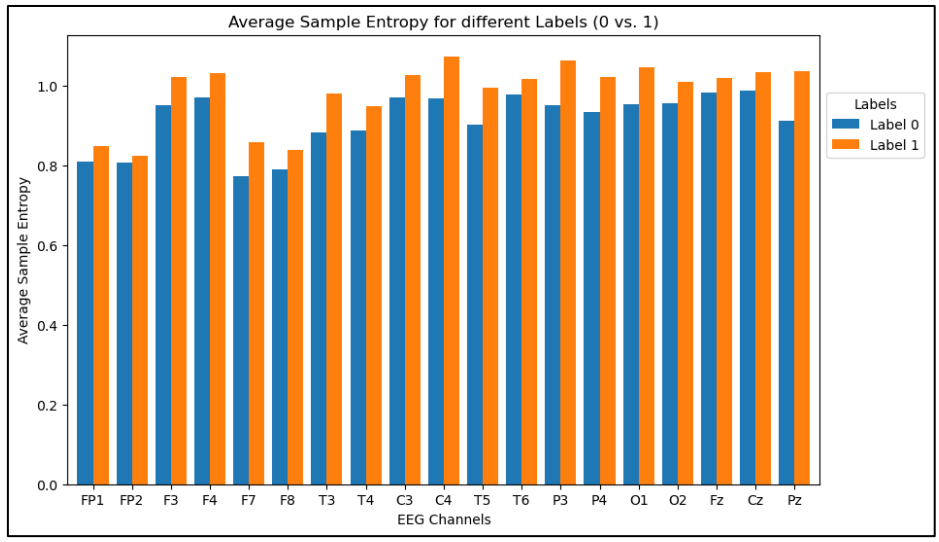


Figure. 31 Variation in SampEn averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the Sample Entropy (SampEn) results before and during the task for students who performed correctly the Figure 31 illustrates:

1. Frontal channels (FP1, FP2, F3, F4, F7, F8) generally show consistent SampEn values during the task.
2. Temporal channels (T3, T4, T5, T6) exhibit moderate to high SampEn values, with T6 showing higher complexity.
3. Central channels (C3, C4, Cz) demonstrate relatively high SampEn values, especially in C4.
4. Parietal channels (P3, P4, Pz) display moderate to high SampEn values, particularly in P3 and P4.
5. Occipital channels (O1, O2) also show moderate to high SampEn values during the task.

Findings suggest that central, parietal, and occipital regions exhibit higher complexity or irregularity in signal patterns as measured by SampEn during task performance. Higher SampEn values typically indicate greater irregularity or complexity in neural activity, which can reflect increased cognitive processing demands during task execution.

3) Comparison of Spectral Entropy of the subjects who have done the task correctly

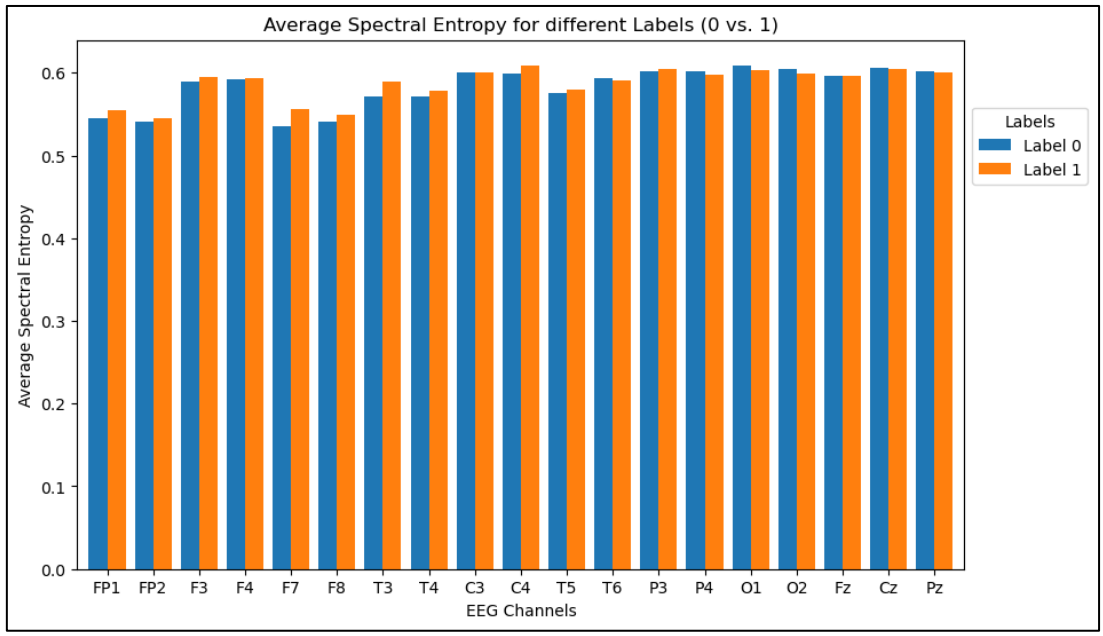


Figure. 32 Variation in SpecEn averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the Spectral Entropy (SpecEn) results before and during the task for students who performed correctly the Figure 32 illustrates:

1. Frontal channels (FP1, FP2, F3, F4, F7, F8) generally show consistent SpecEn values during the task.
2. Temporal channels (T3, T4, T5, T6) exhibit moderate to high SpecEn values, with T3 showing slightly higher entropy.
3. Central channels (C3, C4, Cz) demonstrate relatively stable SpecEn values, with C4 showing slightly higher entropy.
4. Parietal channels (P3, P4, Pz) display moderate to high SpecEn values, particularly in P3 and P4.
5. Occipital channels (O1, O2) also show moderate to high SpecEn values during the task.

Findings suggest that temporal, parietal, and occipital regions exhibit higher entropy or unpredictability in spectral patterns as measured by SpecEn during task performance. This may indicate greater variability or diversity in neural activity, potentially reflecting different stages or aspects of cognitive processing during task execution.

III. Comparison the different features across the subjects before and during the tasks who couldn't do the task correctly before and during the tasks

A. Comparison of Spectral Features

1) Comparison of Alpha Powers of the subjects who couldn't do the task correctly

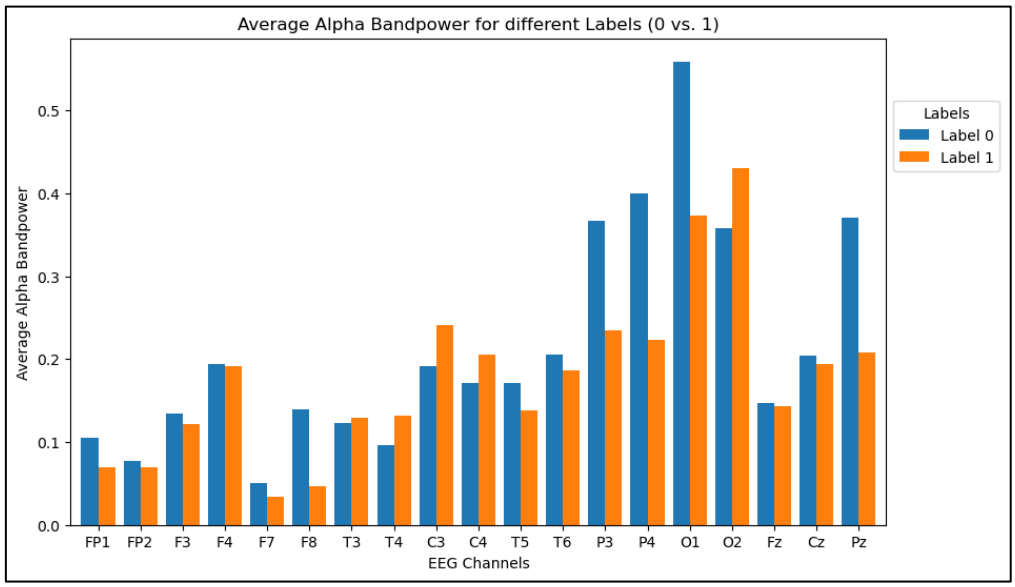


Figure. 33 Variation in alpha power averaged across all subjects before task [Label 0] and during the tasks [Label 1]

Based on the alpha power results before and during the task for students who struggled, the findings in the Figure 33 suggest:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: Channels across the frontal lobe exhibit varying levels of alpha power, indicating different states of cortical activity related to cognitive processing. Notably, FP1 and FP2 show relatively lower alpha power during the task, suggesting increased cognitive engagement and reduced resting states.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T6 and T4 demonstrate notable changes in alpha power, potentially reflecting modulation of auditory and language processing during the task.

3. **Central (C3, C4, Cz)**: Channels C3 and C4 show significant variations in alpha power, indicating involvement in motor coordination and sensorimotor integration. Cz also exhibits moderate alpha power changes, suggesting engagement in attentional processes.

4. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 exhibit higher alpha power, indicative of reduced cortical activation during task engagement, possibly related to states of relaxation or reduced sensory processing.

5. **Occipital Lobe (O1, O2)**: Channels O1 and O2 show varied alpha power patterns, potentially reflecting visual processing demands and cognitive states during the task.

These findings underscore differential alpha power activity across various brain regions, highlighting the involvement of frontal, temporal, central, parietal, and occipital areas in cognitive tasks. Each region shows distinct patterns of alpha power, reflecting their specific roles in neural processing and cognitive function during task performance.

2) Comparison of Beta Powers of the subjects who couldn't do the task correctly

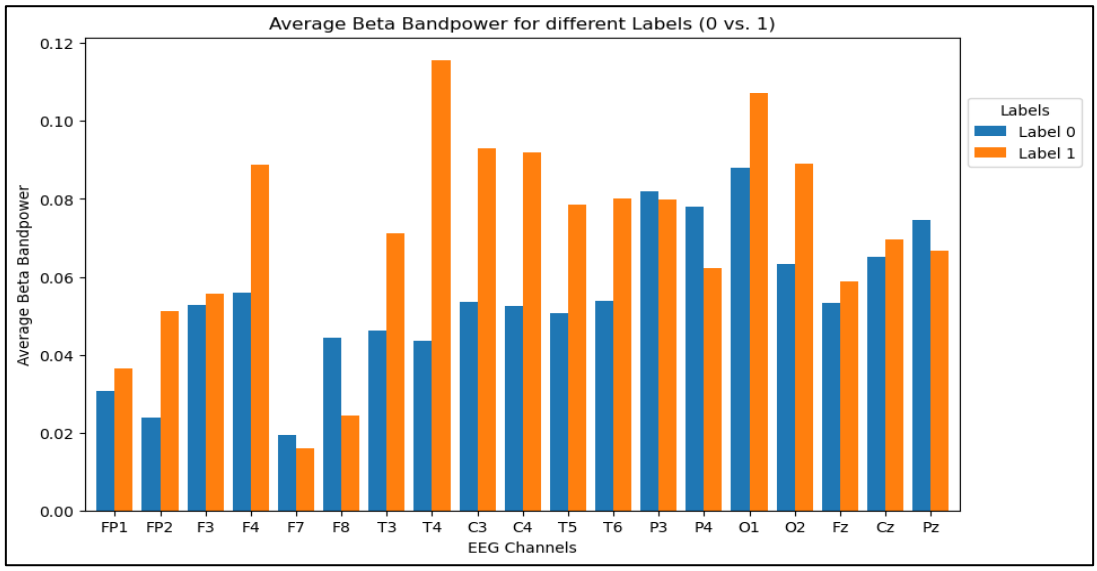


Figure. 34 Variation in beta power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the beta power results before and during the task for students who struggled, the findings in the Figure 34 suggest:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: Channels across the frontal lobe exhibit varying levels of beta power, indicating different states of cortical activation related to cognitive processing. Notably, F4 and FP2 show higher beta power during the task, suggesting increased engagement in executive functions and task-related processing.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T4 and T6 demonstrate notable changes in beta power, potentially reflecting modulation of auditory processing and sensorimotor integration during the task.

3. **Central (C3, C4, Cz)**: Channels C3 and C4 show significant variations in beta power, indicative of motor planning and sensorimotor integration. Cz also exhibits moderate beta power changes, suggesting involvement in attentional processes.

4. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 exhibit moderate to high beta power, indicative of active engagement in sensory integration and attentional processes during the task.

5. **Occipital Lobe (O1, O2)**: Channels O1 and O2 show varied beta power patterns, potentially reflecting visual processing demands and cognitive states during the task.

These findings highlight differential beta power activity across various brain regions, emphasizing the involvement of frontal, temporal, central, parietal, and occipital areas in cognitive tasks. Each region shows distinct patterns of beta power, reflecting their specific roles in neural processing and cognitive function during task performance.

3) Comparison of Delta Powers of the subjects who couldn't do the task correctly

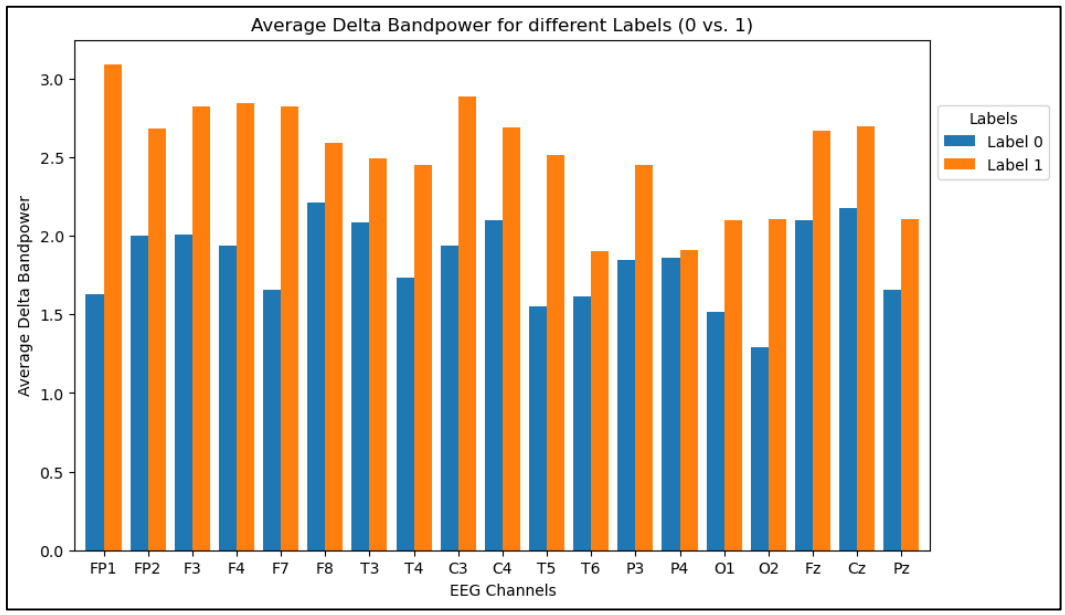


Figure. 35 Variation in delta power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the delta power results before and during the task for students who struggled, the findings in the Figure 35 suggest:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: Channels across the frontal lobe show varying levels of delta power, indicating different degrees of slow wave activity during the task. Notably, FP2 and F4 exhibit consistent patterns of delta power, suggesting increased neural activity associated with cognitive control and attentional processes.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T6 and T4 show notable changes in delta power, indicating increased neural synchronization during the task, possibly related to auditory processing and memory consolidation.

3. **Central (C3, C4, Cz)**: Channels C3 and C4 demonstrate significant delta power variations, reflecting engagement in motor planning and sensory processing tasks. Cz also shows moderate delta power changes, suggesting involvement in overall cognitive processing.

4. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 exhibit moderate to high delta power changes, indicating active engagement in sensory integration and attentional processes during the task.

5. **Occipital Lobe (O1, O2)**: Channels O1 and O2 demonstrate consistent patterns of delta power, potentially reflecting sustained processing related to visual attention and perception during the task.

These findings highlight differential delta power activity across various brain regions, underscoring the involvement of frontal, temporal, central, parietal, and occipital areas in cognitive tasks. Each region exhibits distinct patterns of delta power, reflecting their specific roles in neural processing and cognitive function during task performance.

4) Comparison of Theta Powers of the subjects who couldn't do the task correctly

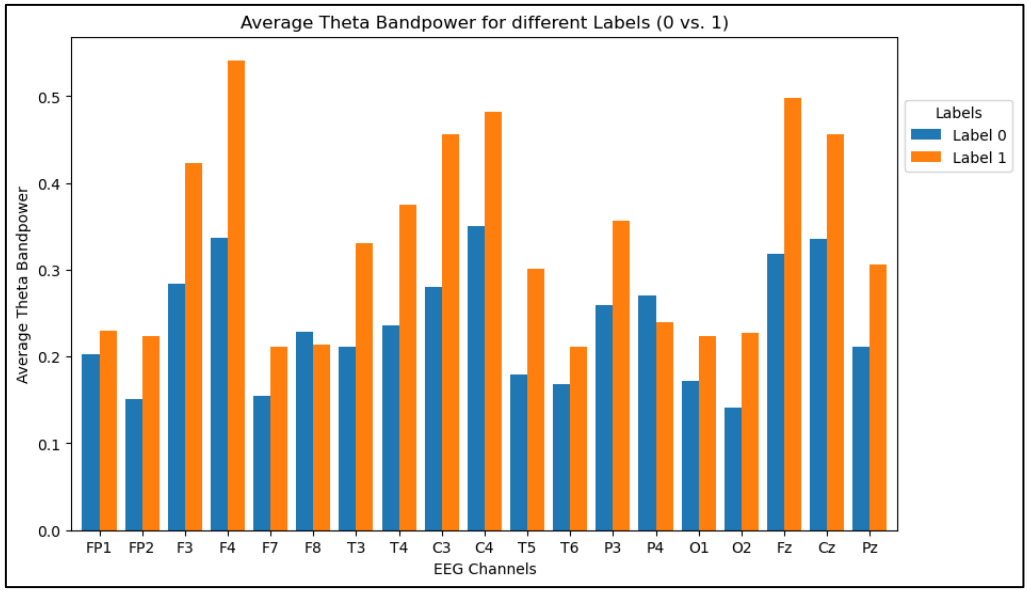


Figure. 36 Variation in theta power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the theta power results before and during the task for students who struggled, the findings in the Figure 36 indicate:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: Channels across the frontal lobe show varying levels of theta power, suggesting differential engagement in cognitive processes during the task. Notably, F3 and F4 exhibit consistent patterns of theta power, indicating increased neural activity associated with working memory and attentional control.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T4 and T3 show notable changes in theta power, suggesting increased theta synchronization during the task, potentially linked to auditory processing and memory encoding.

3. **Central (C3, C4, Cz)**: Channels C3 and C4 demonstrate significant theta power variations, reflecting engagement in motor planning and sensory integration tasks. Cz also shows moderate theta power changes, indicating involvement in cognitive processing and attention.

4. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 exhibit moderate to high theta power changes, indicating active engagement in sensory integration and attentional processes during the task.

5. **Occipital Lobe (O1, O2)**: Channels O1 and O2 demonstrate consistent patterns of theta power, potentially reflecting sustained processing related to visual attention and perceptual tasks during the task.

These findings highlight differential theta power activity across various brain regions, emphasizing the involvement of frontal, temporal, central, parietal, and occipital areas in cognitive tasks. Each region shows distinct patterns of theta power, reflecting their specific roles in neural processing and cognitive function during task performance.

5) Comparison of Gamma Powers of the subjects who couldn't do the task correctly

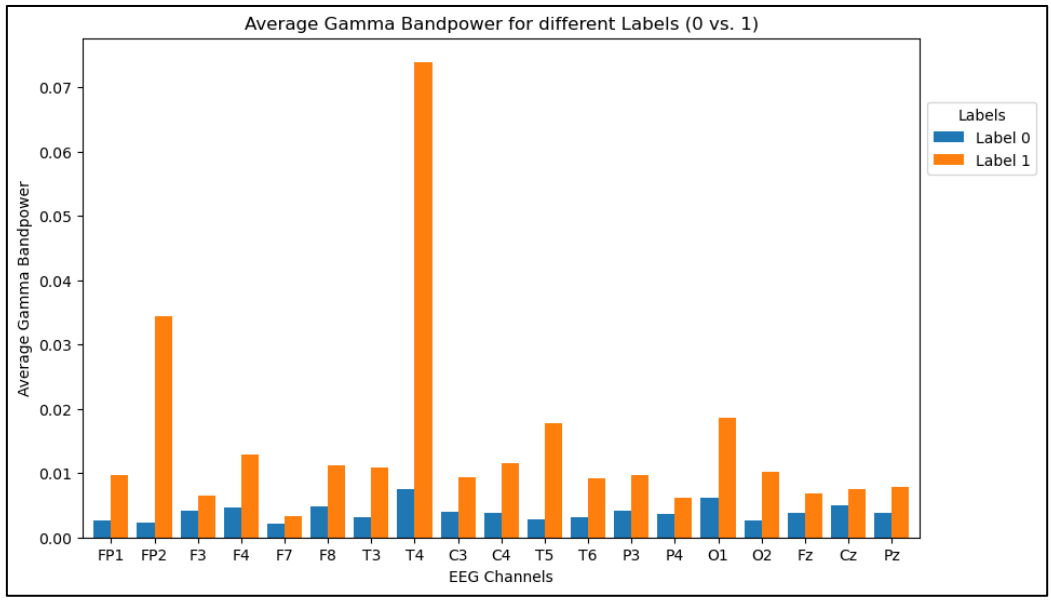


Figure. 37 Variation in gamma power averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the gamma power results before and during the task for students who struggled, the findings in the Figure 37 suggest:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: Channels across the frontal lobe exhibit varying levels of gamma power, indicating different levels of cortical activation related to higher cognitive functions. Notably, FP2 and F4 show higher gamma power during the task, suggesting increased engagement in executive functions and cognitive control processes.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T4 and T6 demonstrate notable changes in gamma power, potentially reflecting modulation of auditory processing and language functions during the task.

3. **Central (C3, C4, Cz)**: Channels C4 and C3 show significant variations in gamma power, indicative of motor planning and sensory integration. Cz also indicates moderate gamma power changes, suggesting involvement in attention and cognitive processing.

4. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 indicate moderate gamma power, indicative of active engagement in sensory integration and attentional processes during the task.

5. **Occipital Lobe (O1, O2)**: Channels O1 and O2 indicate varied gamma power patterns, potentially reflecting visual processing demands and cognitive states during the task.

These findings show different gamma power activity in different brain regions and emphasize the involvement of frontal, temporal, central, parietal and occipital regions in cognitive functions. Each region shows distinct patterns of gamma power, reflecting their specific roles in neural processing and cognitive function during task performance.

B. Comparison of nonlinear features

i. Comparison of Higuchi's Fractal Dimension of the subjects who couldn't do the task correctly

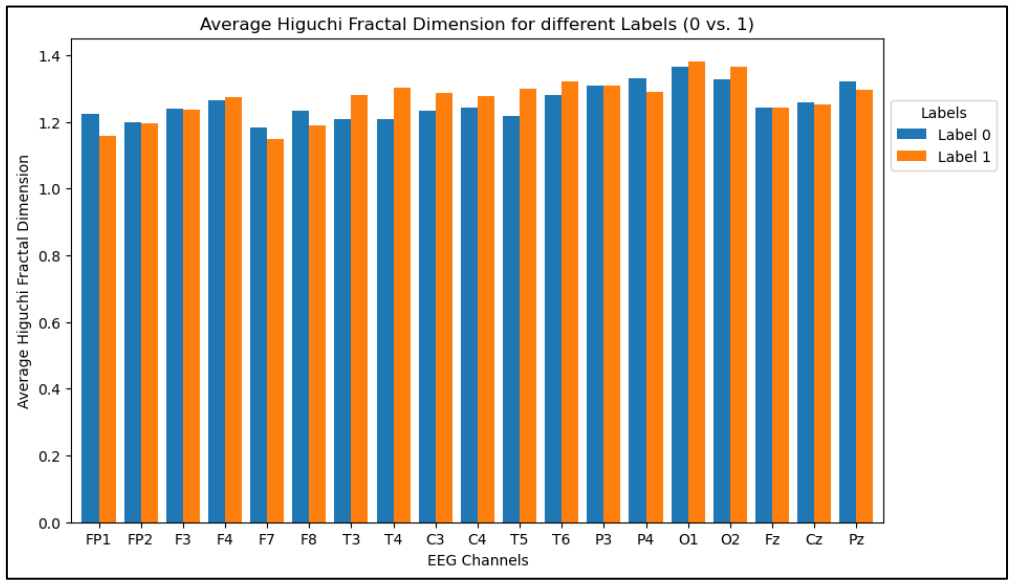


Figure. 38 Variation in HFD averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the Higuchi's Fractal Dimension (HFD) results before and during the task for students who struggled, several findings in the Figure 38 emerge:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: These channels show varied activity, suggesting engagement during the task. Notably, FP1 and FP2 indicate significant changes, possibly indicating increased cognitive processing.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T3 and T4 exhibit notable shifts in HFD values, implying heightened activity during the task, potentially related to auditory and memory processing.

3. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 demonstrate distinct changes, indicating involvement in sensory integration and attention processes during the task.

4. **Occipital Lobe (O1, O2)**: Channels O1 and O2 exhibit consistent patterns, potentially linked to visual processing demands during the task.

5. **Central Midline (Fz, Cz)**: Channels Fz and Cz show moderate changes, indicating general cognitive engagement and attentional processes across tasks.

These findings suggest differential activation across brain regions, highlighting the involvement of frontal and temporal regions in cognitive tasks, with varying degrees of engagement observed in parietal and occipital areas.

ii. Comparison of Sample Entropy of the subjects who couldn't do the task correctly

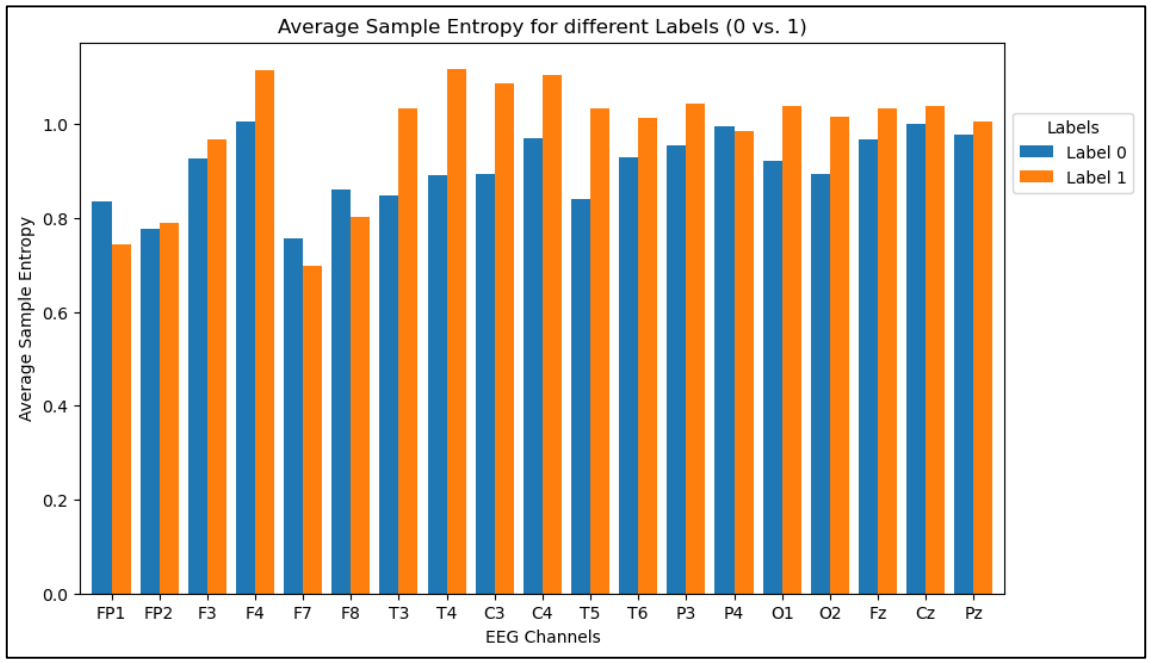


Figure. 39 Variation in SampEn averaged across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the Sample Entropy (SampEn) results before and during the task for students who struggled, the findings in the Figure 39 highlight:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: Channels across the frontal lobe show varied levels of entropy, suggesting differential complexity and irregularity in neural activity during the task. Notably, F3 and F4 exhibit significant changes, indicating increased processing demands.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T3 and T4 demonstrate pronounced changes in SampEn, suggesting heightened neural complexity during the task, possibly related to auditory and language processing.

3. **Central (C3, C4, Cz)**: Channels C3 and C4 show notable variations in entropy, reflecting engagement in motor and sensory integration processes. Cz also exhibits increased entropy, indicating involvement in attention and cognitive processing.

4. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 show moderate to high entropy changes, implying active engagement in sensory integration and attentional processes during the task.

5. **Occipital Lobe (O1, O2)**: Channels O1 and O2 demonstrate increased entropy, suggesting heightened visual processing demands during the task.

These findings indicate differential activation and complexity across various brain regions, highlighting the involvement of frontal, temporal, central, parietal, and occipital areas in cognitive tasks.

iii. Comparison of Spectral Entropy of the subjects who couldn't do the task correctly

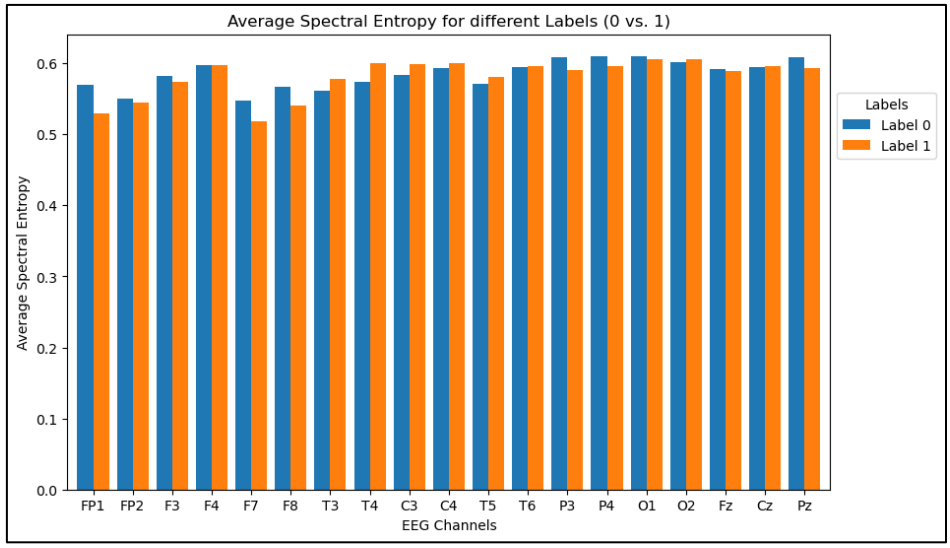


Figure. 40 Variation in average SpecEn across the subjects before task [Label 0] and during the tasks [Label 1]

Based on the Spectral Entropy (SpecEn) results before and during the task for students who struggled, the findings in the Figure 40 reveal:

1. **Frontal Lobe (FP1, FP2, F3, F4, F7, F8)**: Channels across the frontal lobe show varying levels of spectral entropy, indicating different degrees of spectral complexity during the task. Notably, F3 and F4 exhibit consistent patterns of spectral entropy, suggesting active involvement in executive functions and decision-making processes.

2. **Temporal Lobe (T3, T4, T5, T6)**: Channels T4 and T6 show notable changes in spectral entropy, indicating increased neural processing complexity during the task, possibly related to auditory and memory functions.

3. **Central (C3, C4, Cz)**: Channels C3 and C4 indicate significant spectral entropy variations, reflecting engagement in motor coordination and sensory integration processes. Cz also shows

moderate spectral entropy changes, indicating involvement in attention and cognitive processing.

4. **Parietal Lobe (P3, P4, Pz)**: Channels P3 and P4 exhibit moderate to high spectral entropy changes, suggesting active engagement in sensory integration and attentional processes during the task.

5. **Occipital Lobe (O1, O2)**: Channels O1 and O2 demonstrate consistent spectral entropy patterns, possibly indicating sustained visual processing demands during the task.

These findings indicate differential spectral complexity across various brain regions, highlighting the involvement of frontal, temporal, central, parietal, and occipital areas in cognitive tasks. Each region shows distinct patterns of spectral entropy, reflecting their specific roles in cognitive and sensory processing during task performance.

IV. Comparison the different features across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

A. Comparison of Spectral Features

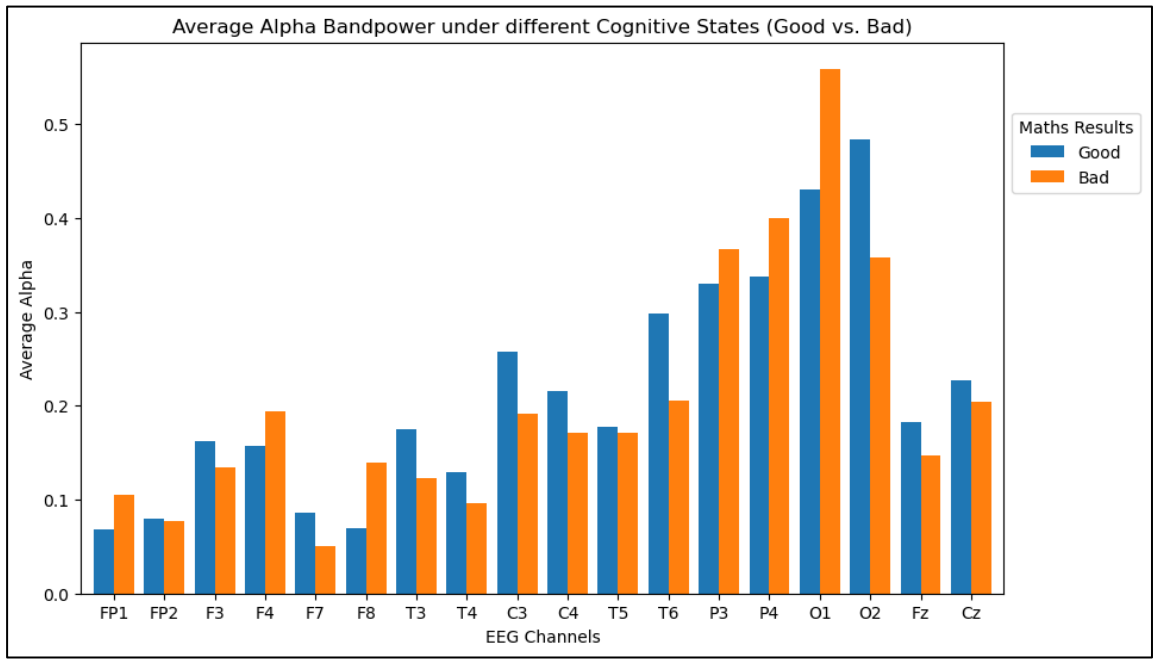


Figure. 41 Variation in average alpha power across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

1) **Comparison of Alpha Powers across all the subjects**

1. **Frontal Channels (FP1, FP2, F3, F4, F7, F8)**:
    - For FP1, FP2, F3, and F7, alpha power is higher in students who did not complete the task correctly.
    - For F4 and F8, alpha power is higher in students who completed the task correctly.
2. **Temporal Channels (T3, T4, T5, T6)**:
    - For T3 and T4, alpha power is higher in students who completed the task correctly.
    - For T5, there is a small difference, with slightly higher alpha power in students who did not complete the task correctly.
    - For T6, alpha power is higher in students who completed the task correctly.
3. **Central Channels (C3, C4, Cz)**:

- For all central channels (C3, C4, Cz), alpha power is higher in students who completed the task correctly.

4. **Parietal Channels (P3, P4, Pz)**:
    - For P3, P4, and Pz, alpha power is higher in students who did not complete the task correctly.
5. **Occipital Channels (O1, O2)**:
    - For O1, alpha power is higher in students who did not complete the task correctly.
    - For O2, alpha power is higher in students who completed the task correctly.

Active Channels

Based on the alpha power values, the following observations can be made about channel activity:

- **Higher Activity in Correct Task Completion**:
    - Channels with notably higher alpha power in students who completed the task correctly are C3, C4, T6, and O2.
- **Higher Activity in Incorrect Task Completion**:
    - Channels with notably higher alpha power in students who did not complete the task correctly are FP1, P3, P4, Pz, and O1.

2) Comparison of Beta Powers across the subjects

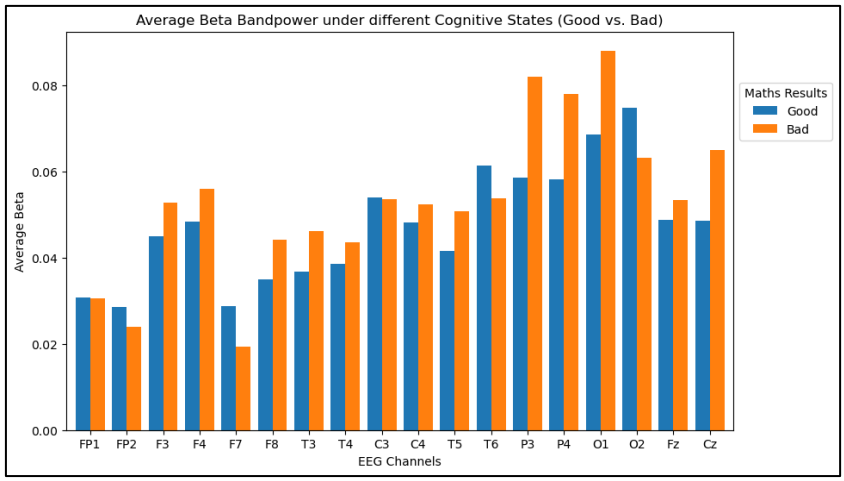


Figure. 42 Variation in average beta power across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

- **Frontal Channels (FP1, FP2, F3, F4, F7, F8, Fz)**:
    - FP1 and FP2: Slight decrease in beta power for students who did not complete the task correctly.
    - F3, F4, F8, and Fz: Increase in beta power for students who did not complete the task correctly.
    - F7: Decrease in beta power for students who did not complete the task correctly.
- **Temporal Channels (T3, T4, T5, T6)**:
    - T3, T4, and T5: Increase in beta power for students who did not complete the task correctly.
    - T6: Decrease in beta power for students who did not complete the task correctly.
- **Central Channels (C3, C4, Cz)**:
    - C3: Slight decrease in beta power for students who did not complete the task correctly.
    - C4 and Cz: Increase in beta power for students who did not complete the task correctly.
- **Parietal Channels (P3, P4, Pz)**:
    - P3, P4, and Pz: Increase in beta power for students who did not complete the task correctly.
- **Occipital Channels (O1, O2)**:
    - O1: Increase in beta power for students who did not complete the task correctly.
    - O2: Decrease in beta power for students who did not complete the task correctly.

Active Channels Based on Beta Power

- More Active Channels in Students Who Did Not Complete the Task Correctly:
    - Parietal (P3, P4, Pz), Occipital (O1), and Central (Cz) regions show higher beta power.
- Less Active Channels in Students Who Did Not Complete the Task Correctly:

- Frontal (FP1, FP2, F7) and Temporal (T6) regions show lower beta power.

3) Comparison of Delta Powers across the subjects

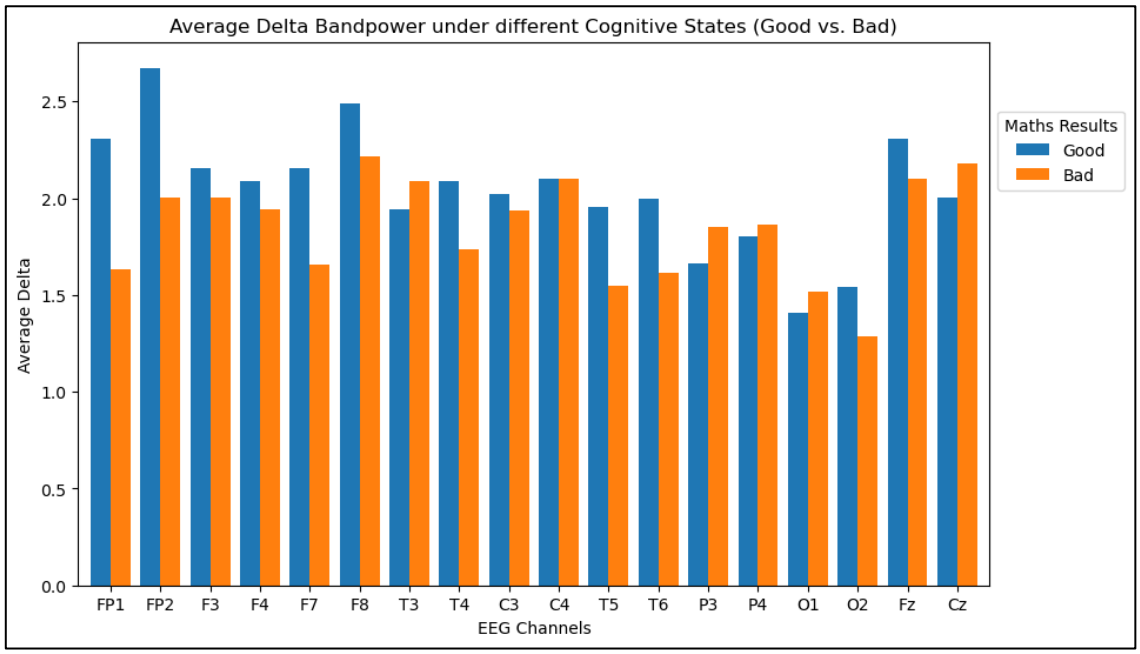


Figure. 43 Variation in average delta power across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

1. **Frontal Channels (FP1, FP2, F3, F4, F7, F8, Fz)**:
    - FP1, FP2, F3, F4, F7, F8, and Fz: Decrease in delta power for students who did not complete the task correctly.
2. **Temporal Channels (T3, T4, T5, T6)**:
    - T3: Increase in delta power for students who did not complete the task correctly.
    - T4, T5, and T6: Decrease in delta power for students who did not complete the task correctly.
3. **Central Channels (C3, C4, Cz)**:
    - C3: Decrease in delta power for students who did not complete the task correctly.
    - C4 and Cz: Slight increase in delta power for students who did not complete the task correctly.

4. **Parietal Channels (P3, P4, Pz)**:
    - P3, P4, and Pz: Increase in delta power for students who did not complete the task correctly.
5. **Occipital Channels (O1, O2)**:
    - O1: Increase in delta power for students who did not complete the task correctly.
    - O2: Decrease in delta power for students who did not complete the task correctly.

Summary of Changes

- **Increases in Delta Power for Students Who Did Not Complete the Task Correctly**:
    - Notable increases are observed in T3, P3, O1, Cz, Pz, and C4.
    - Moderate increases are observed in P4.
- **Decreases in Delta Power for Students Who Did Not Complete the Task Correctly**:
    - Significant decreases are observed in FP1, FP2, F7, T5, T6, and T4.
    - Moderate decreases are observed in F3, F4, F8, Fz, C3, and O2.

Active Channels Based on Delta Power

- **More Active Channels in Students Who Did Not Complete the Task Correctly**:
    - Temporal (T3), Parietal (P3, P4, Pz), Central (C4, Cz), and Occipital (O1) regions show higher delta power.
- **Less Active Channels in Students Who Did Not Complete the Task Correctly**:
    - Frontal (FP1, FP2, F3, F4, F7, F8, Fz), Temporal (T4, T5, T6), Central (C3), and Occipital (O2) regions show lower delta power.

4) Comparison of Theta Powers across all the subjects

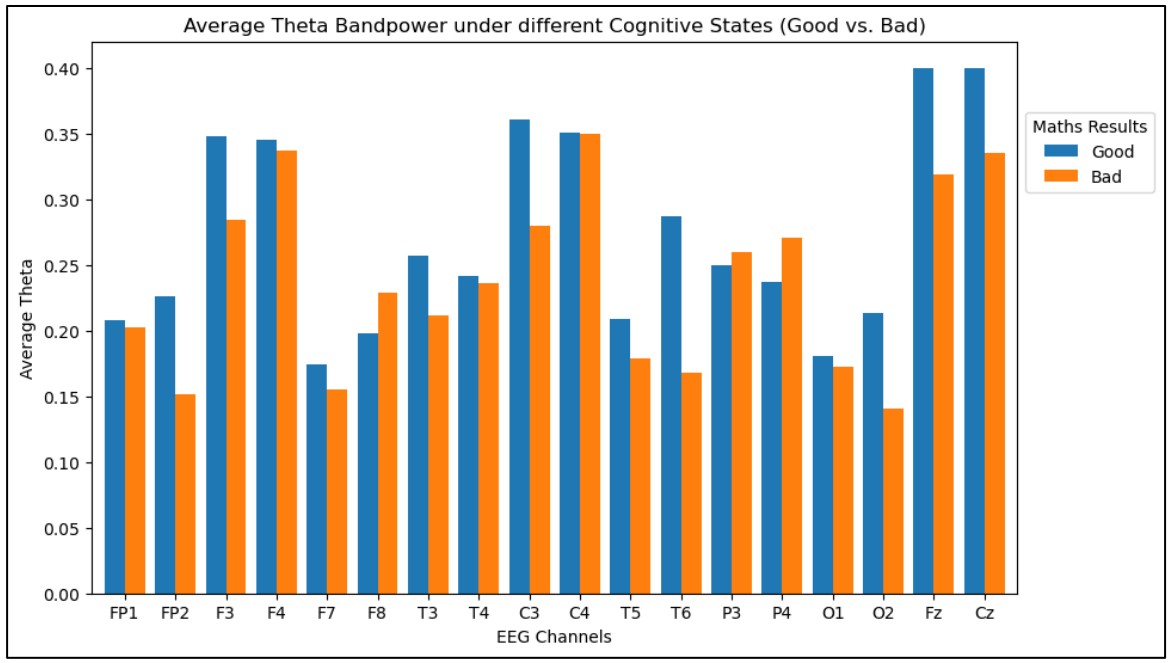


Figure. 44 Variation in average theta power across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

1. **Frontal Channels (FP1, FP2, F3, F4, F7, F8, Fz)**:
    - FP1, FP2, F3, F4, F7, and Fz: Decrease in theta power for students who did not complete the task correctly.
    - F8: Increase in theta power for students who did not complete the task correctly.
2. **Temporal Channels (T3, T4, T5, T6)**:
    - T3, T4, T5, and T6: Decrease in theta power for students who did not complete the task correctly.
3. **Central Channels (C3, C4, Cz)**:
    - C3 and Cz: Decrease in theta power for students who did not complete the task correctly.
    - C4: Slight decrease in theta power for students who did not complete the task correctly.
4. **Parietal Channels (P3, P4, Pz)**:

- P3 and P4: Increase in theta power for students who did not complete the task correctly.
- Pz: Decrease in theta power for students who did not complete the task correctly.

5. **Occipital Channels (O1, O2)**:
   - O1 and O2: Decrease in theta power for students who did not complete the task correctly.

Active Channels Based on Theta Power

- **More Active Channels in Students Who Did Not Complete the Task Correctly**:
  - Frontal (F8), Parietal (P3, P4) regions show higher theta power.
- **Less Active Channels in Students Who Did Not Complete the Task Correctly**:
  - Frontal (FP1, FP2, F3, F4, F7, Fz), Temporal (T3, T4, T5, T6), Central (C3, C4, Cz), and Occipital (O1, O2) regions show lower theta power.

5) Comparison of Gamma Powers across all the subjects

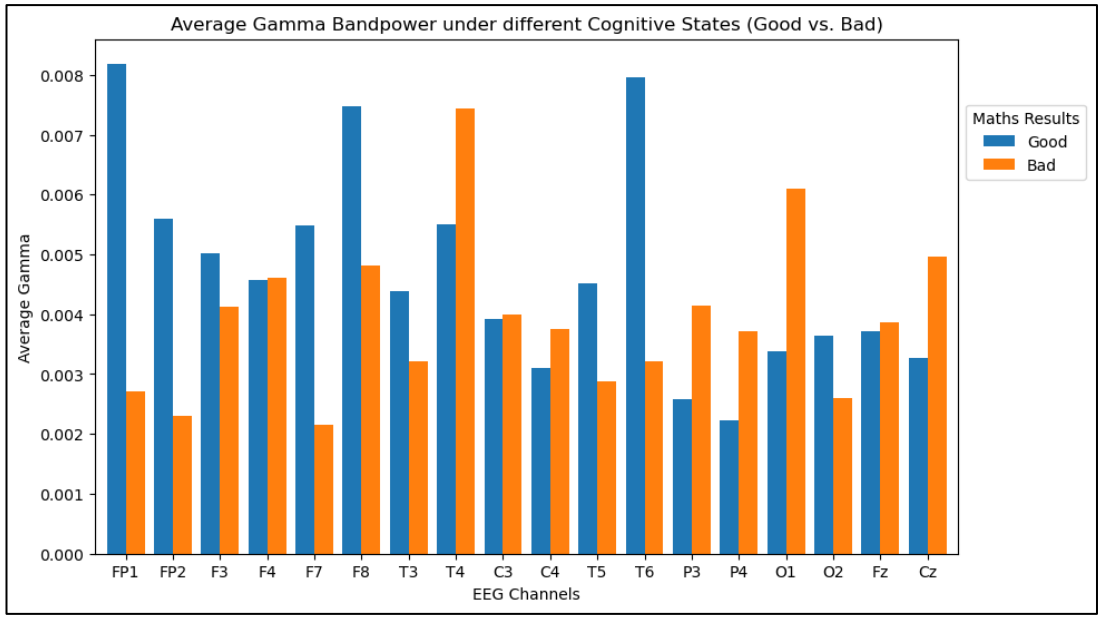


Figure. 45 Variation in average gamma power across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

1. **Frontal Channels (FP1, FP2, F3, F4, F7, F8, Fz)**:
   - FP1, FP2, F3, F7, and F8: Decrease in gamma power for students who did not complete the task correctly.

- F4 and Fz: Slight increase in gamma power for students who did not complete the task correctly.

2. **Temporal Channels (T3, T4, T5, T6)**:
    - T3 and T5: Decrease in gamma power for students who did not complete the task correctly.
    - T4: Increase in gamma power for students who did not complete the task correctly.
    - T6: Decrease in gamma power for students who did not complete the task correctly.
3. **Central Channels (C3, C4, Cz)**:
    - C3: Slight increase in gamma power for students who did not complete the task correctly.
    - C4 and Cz: Increase in gamma power for students who did not complete the task correctly.
4. **Parietal Channels (P3, P4, Pz)**:
    - P3, P4, and Pz: Increase in gamma power for students who did not complete the task correctly.
5. **Occipital Channels (O1, O2)**:
    - O1: Increase in gamma power for students who did not complete the task correctly.
    - O2: Decrease in gamma power for students who did not complete the task correctly.

Active Channels Based on Gamma Power

- **More Active Channels in Students Who Did Not Complete the Task Correctly**:
    - Occipital (O1), Parietal (P3, P4, Pz), Central (Cz), and Temporal (T4) regions show higher gamma power.
- **Less Active Channels in Students Who Did Not Complete the Task Correctly**:
    - Frontal (FP1, FP2, F7, F8), Temporal (T3, T5, T6), and Occipital (O2) regions show lower gamma power.

B. Comparison of nonlinear features

1) Comparison of Higuchi's Fractal Dimension of all the subjects

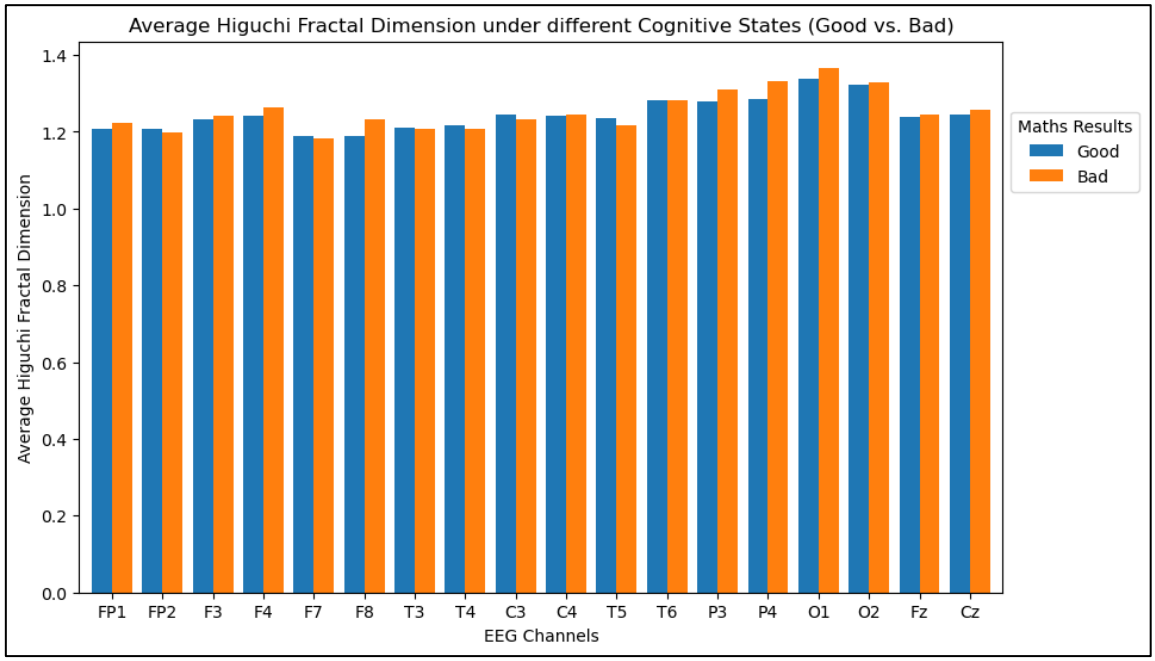


Figure. 46 Variation in average HFD across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

1. **Frontal Channels (FP1, FP2, F3, F4, F7, F8, Fz)**:
    - FP1, F8, P4, O1, Pz: Increase in Higuchi's Fractal Dimension for students who did not complete the task correctly.
    - FP2, F7, T5: Decrease in Higuchi's Fractal Dimension for students who did not complete the task correctly.
    - F3, F4: Slight increase in Higuchi's Fractal Dimension for students who did not complete the task correctly.
2. **Temporal Channels (T3, T4, T5, T6)**:
    - T5, P3, P4, O1: Increase in Higuchi's Fractal Dimension for students who did not complete the task correctly.
    - T3, T4, T6: Slight decrease in Higuchi's Fractal Dimension for students who did not complete the task correctly.
3. **Central Channels (C3, C4, Cz)**:

- P4, O1, Pz: Higuchi measurement fractional increase for samples that did not perform correctly.
- C3, Cz: There is a slight increase in the Higuchi's fraction measurement for students who did not perform correctly.
- C4: Slight decrease in Higuchi's Fractal Dimension for students who did not complete the task correctly.

4. **Parietal Channels (P3, P4, Pz)**:
   - P3, P4, Pz: Increase in Higuchi's Fractal Dimension for students who did not complete the task correctly.

5. **Occipital Channels (O1, O2)**:
   - O1: Increase in Higuchi's Fractal Dimension for students who did not complete the task correctly.
   - O2: Slight increase in Higuchi's Fractal Dimension for students who did not complete the task correctly.

Active Channels Based on Higuchi's Fractal Dimension

- **More Active Channels in Students Who Did Not Complete the Task Correctly**:
  - Parietal (P4, Pz), Occipital (O1, O2), and Frontal (FP1, F8) regions show higher Higuchi's Fractal Dimension.
- **Less Active Channels in Students Who Did Not Complete the Task Correctly**:
  - Frontal (FP2, F7), Temporal (T5, T3, T4, T6), and Central (C4) regions show lower Higuchi's Fractal Dimension.

2) Comparison of Sample Entropy across the subjects

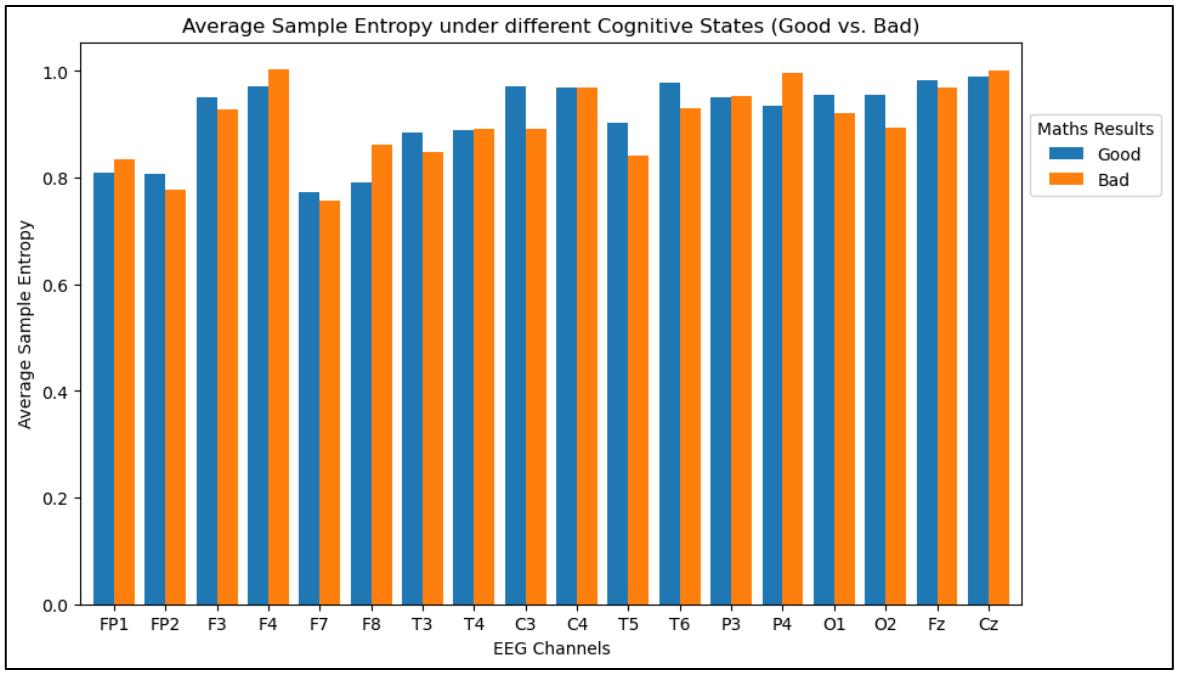


Figure. 47 Variation in Sample Entropy across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

1. **Frontal Channels (FP1, FP2, F3, F4, F7, F8, Fz)**:

   - FP1, F4, and F8: Increase in sample entropy for students who did not complete the task correctly.
   - FP2, F3, F7, and Fz: Decrease in sample entropy for students who did not complete the task correctly.

2. **Temporal Channels (T3, T4, T5, T6)**:

   - T4: Slight increase in sample entropy for students who did not complete the task correctly.
   - T3, T5, and T6: Decrease in sample entropy for students who did not complete the task correctly.

3. **Central Channels (C3, C4, Cz)**:

   - C4 and Cz: Slight changes in sample entropy for students who did not complete the task correctly.
   - C3: Decrease in sample entropy for students who did not complete the task correctly.

4. **Parietal Channels (P3, P4, Pz)**:

   - P4 and Pz: Increase in sample entropy for students who did not complete the task correctly.
   - P3: Slight increase in sample entropy for students who did not complete the task correctly.

5. **Occipital Channels (O1, O2)**:

   - O1 and O2: Decrease in sample entropy for students who did not complete the task correctly.

Active Channels Based on Sample Entropy

- **More Active Channels in Students Who Did Not Complete the Task Correctly**:
  - Frontal (FP1, F4, F8), Parietal (P4, Pz), and Central (Cz) regions show higher sample entropy.
- **Less Active Channels in Students Who Did Not Complete the Task Correctly**:
  - Frontal (FP2, F3, F7, Fz), Temporal (T3, T5, T6), Central (C3), and Occipital (O1, O2) regions show lower sample entropy.

3) Comparison of Spectral Entropy across the subjects

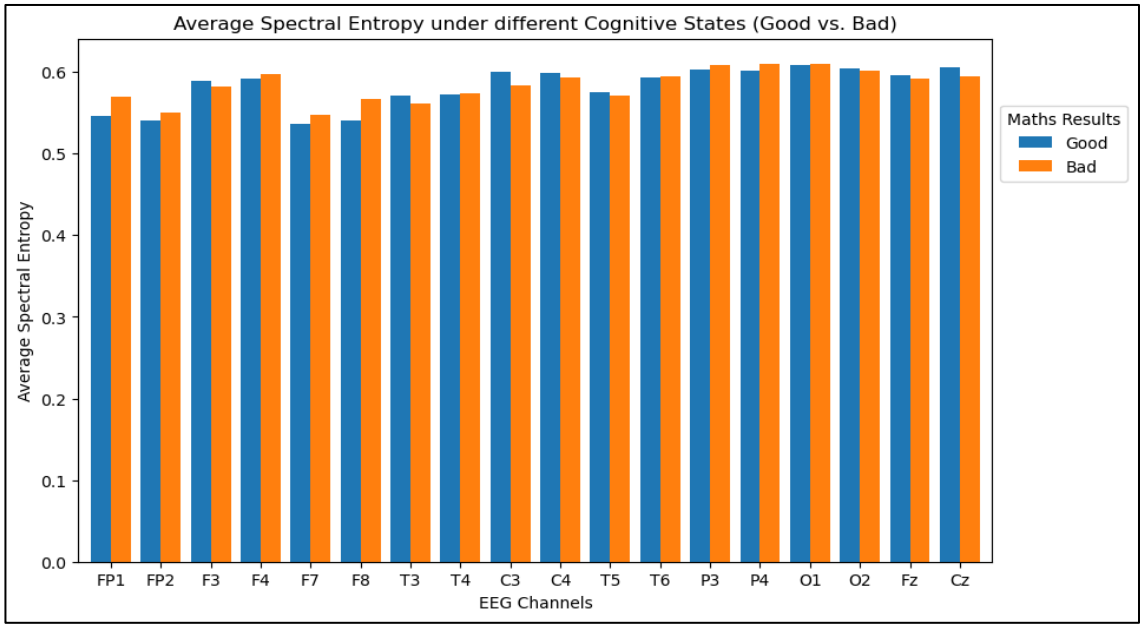


Figure. 48 Variation in average Spectral Entropy across all the subjects before the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

1. **Frontal Channels (FP1, FP2, F3, F4, F7, F8, Fz)**:
    - FP1, FP2, F4, F7, and F8: Increase in spectral entropy for students who did not complete the task correctly.
    - F3 and Fz: Decrease in spectral entropy for students who did not complete the task correctly.
2. **Temporal Channels (T3, T4, T5, T6)**:
    - T3: Decrease in spectral entropy for students who did not complete the task correctly.
    - T4 and T6: Slight increase in spectral entropy for students who did not complete the task correctly.
    - T5: Decrease in spectral entropy for students who did not complete the task correctly.
3. **Central Channels (C3, C4, Cz)**:
    - C3, C4, and Cz: Decrease in spectral entropy for students who did not complete the task correctly.
4. **Parietal Channels (P3, P4, Pz)**:
    - P3, P4, and Pz: Increase in spectral entropy for students who did not complete the task correctly.
5. **Occipital Channels (O1, O2)**:
    - O1: Slight increase in spectral entropy for students who did not complete the task correctly.
    - O2: Decrease in spectral entropy for students who did not complete the task correctly.

Active Channels Based on Spectral Entropy

- **More Active Channels in Students Who Did Not Complete the Task Correctly**:
    - Frontal (FP1, FP2, F4, F7, F8), Parietal (P3, P4, Pz), and Occipital (O1) regions show higher spectral entropy.
- **Less Active Channels in Students Who Did Not Complete the Task Correctly**:
    - Frontal (F3, Fz), Temporal (T3, T5), Central (C3, C4, Cz), and Occipital (O2) regions show lower spectral entropy.

V. Comparison the different features across all the subjects during the task who did the task correctly (Good) and who couldn't do the task correctly (Bad)

A. Comparison of Spectral Features

4) Comparison of Alpha Powers across all the subjects

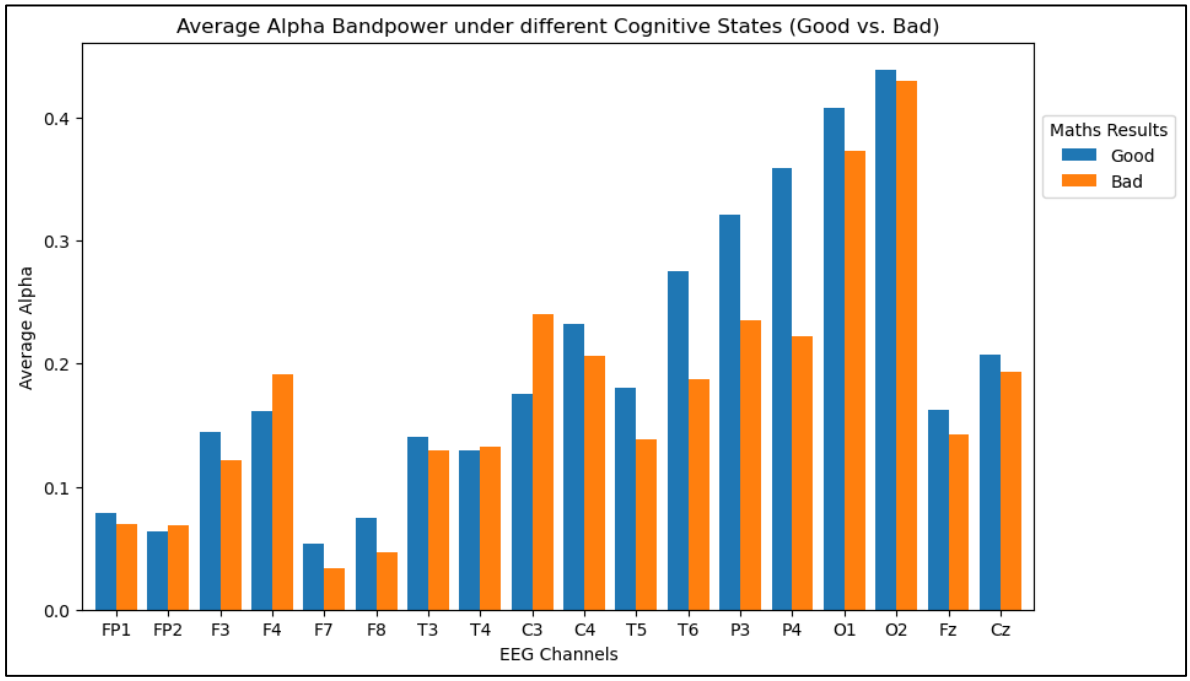


Figure. 49 Variation in average alpha power across the subjects before the task

Based on the comparison of alpha powers between students who completed the task correctly and those who did not, several findings can be highlighted:

1. **Frontal Lobe (F3, F4, F7, F8):**
    - There is notable activity in the frontal regions, particularly in channels F3 and F4.
    - Differences in alpha power suggest varying levels of engagement or cognitive processing related to task completion.
2. **Temporal Lobe (T3, T4, T5, T6):**
    - Channels T3 and T4 show significant differences in alpha power.
    - Activity in these temporal regions may indicate involvement in task-related processing or attentional mechanisms.

3. **Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):**
    - Channels C3 and C4 exhibit distinct patterns in alpha power, suggesting differential neural processing.
    - Parietal channels (P3, P4, Pz) also show varying levels of activity, potentially reflecting different cognitive states during task performance.
4. **Occipital Region (O1, O2):**
    - Channels O1 and O2 display noticeable differences in alpha power.
    - This indicates involvement of occipital areas, possibly related to visual processing or attentional modulation.

5) Comparison of Beta Powers across the subjects

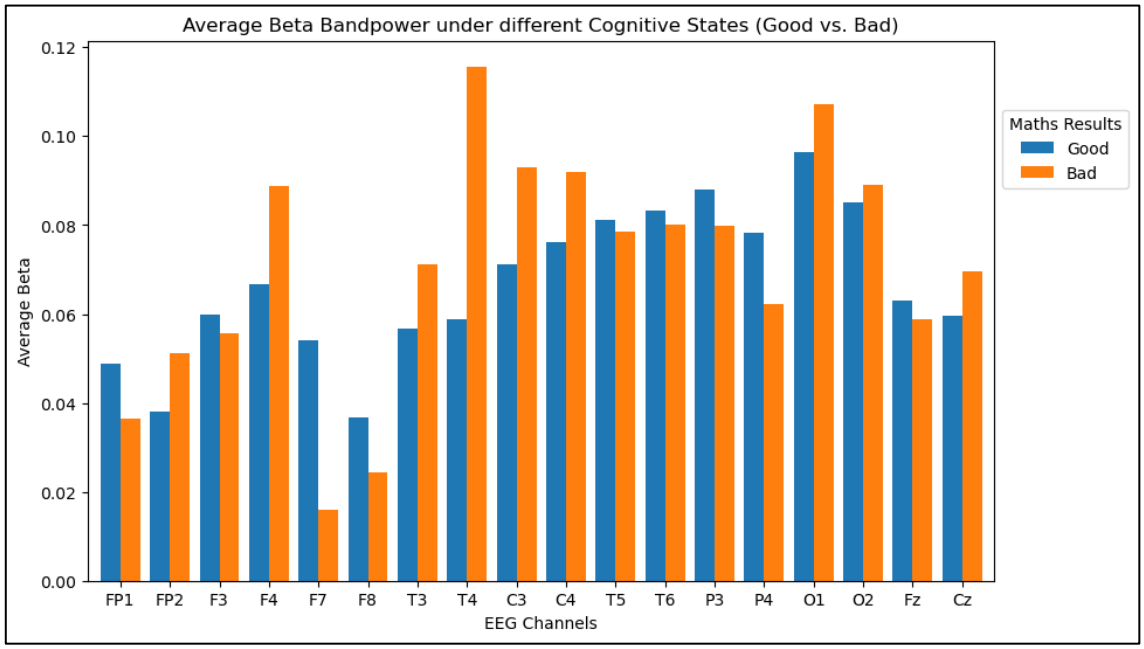


Figure. 50 Variation in average beta power across the subjects before the task

Based on the comparison of beta powers between students who completed the task correctly and those who did not, several findings can be highlighted:

1. **Frontal Lobe (F3, F4, F7, F8):**
    - Channels F4 and F7 show notable differences in beta power.
    - Activity in these frontal regions may indicate varying levels of cognitive engagement or executive function related to task performance.

2. **Temporal Lobe (T3, T4, T5, T6):**
    - Channels T4 and T5 exhibit distinct patterns in beta power.
    - This suggests involvement of temporal areas in cognitive processing or auditory stimuli processing during task execution.
3. **Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):**
    - Channels C3 and C4 display differential beta power, indicating varying neural processing.
    - Parietal regions (P3, P4, Pz) also show differing levels of beta activity, potentially reflecting attentional processes or sensory integration.
4. **Occipital Region (O1, O2):**
    - Channels O1 and O2 demonstrate differences in beta power.
    - This suggests involvement of occipital areas, potentially related to visual processing or attentional modulation during task performance.

6) Comparison of Delta Powers across the subjects

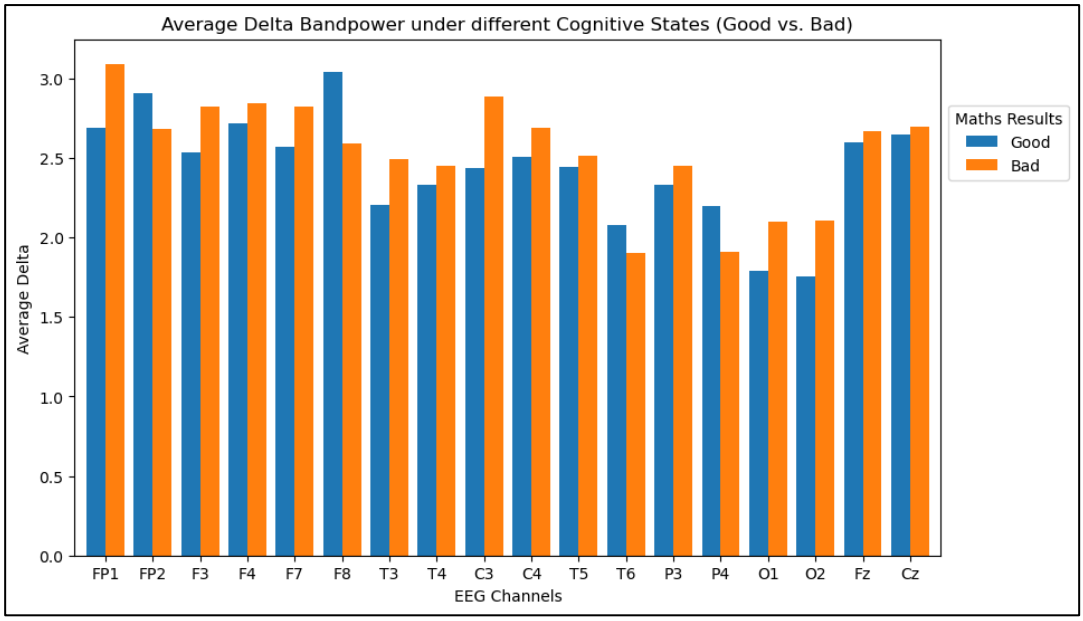


Figure. 51 Variation in average delta power across all the subjects before the task

Based on the comparison of delta powers between students who completed the task correctly and those who did not, several findings can be highlighted:

1. **Frontal Lobe (F3, F4, F7, F8):**

- Channels F8 show noticeable differences in delta power.
- Activity in these frontal regions may suggest varying levels of cognitive engagement or sleep-related processes during task performance.

2. **Temporal Lobe (T3, T4, T5, T6):**
   - Channels T6 exhibit distinct patterns in delta power.
   - This indicates involvement of temporal areas, potentially related to auditory processing or memory consolidation.
3. **Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):**
   - Channels C3 and C4 display differential delta power, suggesting varying neural processing.
   - Parietal regions (P3, P4, Pz) also show differences in delta activity, potentially reflecting attentional processes or sensory integration during task execution.
4. **Occipital Region (O1, O2):**
   - Channels O1 and O2 demonstrate differences in delta power.
   - This suggests involvement of occipital areas, possibly related to visual processing or relaxation states during task performance.

7) Comparison of Theta Powers across all the subjects

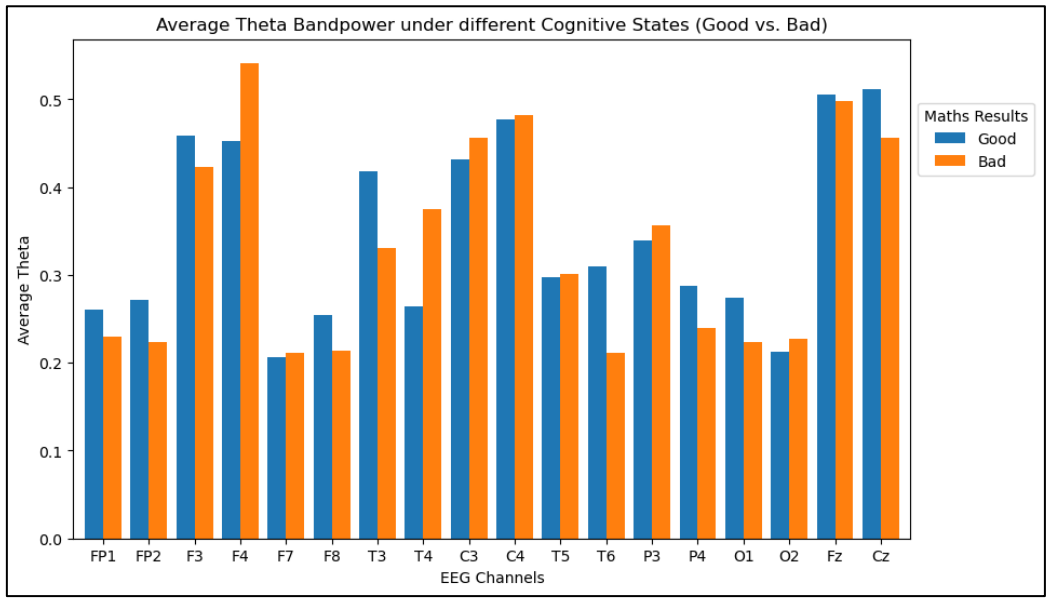


Figure. 52 Variation in average theta power across all the subjects before the task

Based on the comparison of theta powers between students who completed the task correctly and those who did not, several findings can be highlighted:

1. **Frontal Lobe (F3, F4, F7, F8):**
    - Channels F3 and F4 show significant differences in theta power.
    - Activity in these frontal regions may indicate varying levels of cognitive processing or attentional control during task performance.
2. **Temporal Lobe (T3, T4, T5, T6):**
    - Channels T3 and T4 exhibit distinct patterns in theta power.
    - This suggests involvement of temporal areas, potentially related to auditory processing or memory encoding during the task.
3. **Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):**
    - Channels C3 and C4 display differential theta power, indicating varying neural processing.
    - Parietal regions (P3, P4, Pz) also show differences in theta activity, potentially reflecting attentional processes or sensory integration during task execution.
4. **Occipital Region (O1, O2):**
    - Channels O1 and O2 demonstrate differences in theta power.
    - This suggests involvement of occipital areas, possibly related to visual processing or attention modulation during task performance.

8) Comparison of Gamma Powers across all the subjects

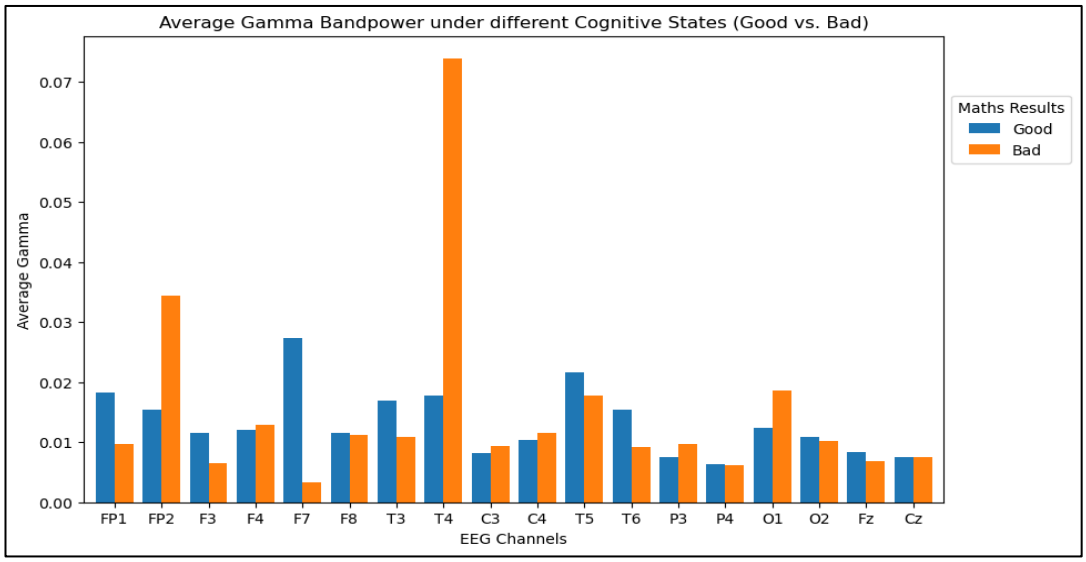


Figure. 53 Variation in average gamma power across the subjects before the task

1. Frontal Lobe (F3, F4, F7, F8):

- Channels F7 and F8 exhibit notable differences in gamma power.
- Activity in these frontal regions may suggest varying levels of cognitive processing or executive function during task performance.

2. Temporal Lobe (T3, T4, T5, T6):

- Channels T4 show distinct patterns in gamma power.
- This indicates involvement of temporal areas, potentially related to auditory processing or higher cognitive functions such as language processing.

3. Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):

- Channels C3 and C4 display differential gamma power, indicating varying neural processing.
- In Parietal regions (P3, P4, Pz) show differences in gamma activity, which may reflect attentional or spatial integration processes during the task.

4. Occipital Region (O1, O2):

- Channels O1 and O2 show differences in gamma power.
- This indicates the involvement of occipital areas, which may be related to visual processing or attentional modulation during the task.

B. Comparison of nonlinear features

9) Comparison of Higuchi's Fractal Dimension of all the subjects

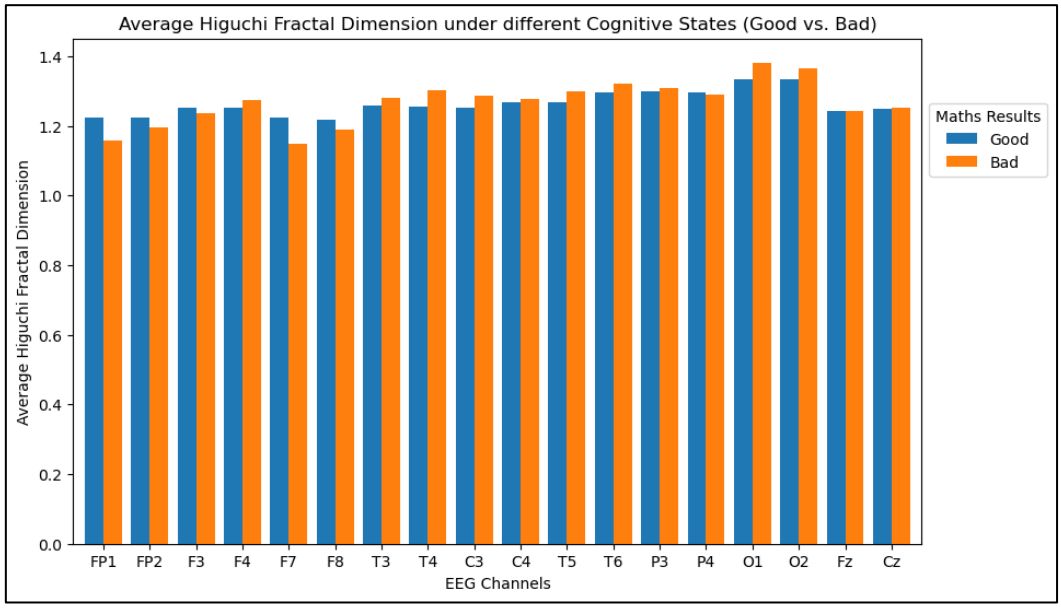


Figure. 54 Variation in average HFD across the subjects before the task

Based on the comparison of Higuchi's Fractal Dimension (HFD) between students who completed the task correctly and those who did not, several findings can be highlighted:

1. **Frontal Lobe (F3, F4, F7, F8):**
   - Channels F4 and F7 show noticeable differences in HFD.
   - Activity in these frontal regions may suggest varying levels of complexity or irregularity in neural oscillations related to cognitive processing during task performance.
2. **Temporal Lobe (T3, T4, T5, T6):**
   - Channels T6 exhibit distinct patterns in HFD.
   - This indicates varying fractal complexity in the temporal areas, possibly reflecting different levels of the neural dynamics related to the auditory processing or the memory functions during the task.
3. **Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):**
   - Channels C3 and C4 show different HFD, indicating different neural processing complexity.

- Parietal regions (P3, P4, Pz) also show differences in HFD, potentially reflecting differences in cognitive states or attentional modulation during task execution.

4. **Occipital Region (O1, O2):**

   - Channels O1 and O2 demonstrate differences in HFD.
   - This suggests varying fractal characteristics in occipital areas, possibly related to visual processing or attentional states during task performance.

10) Comparison of Sample Entropy across the subjects

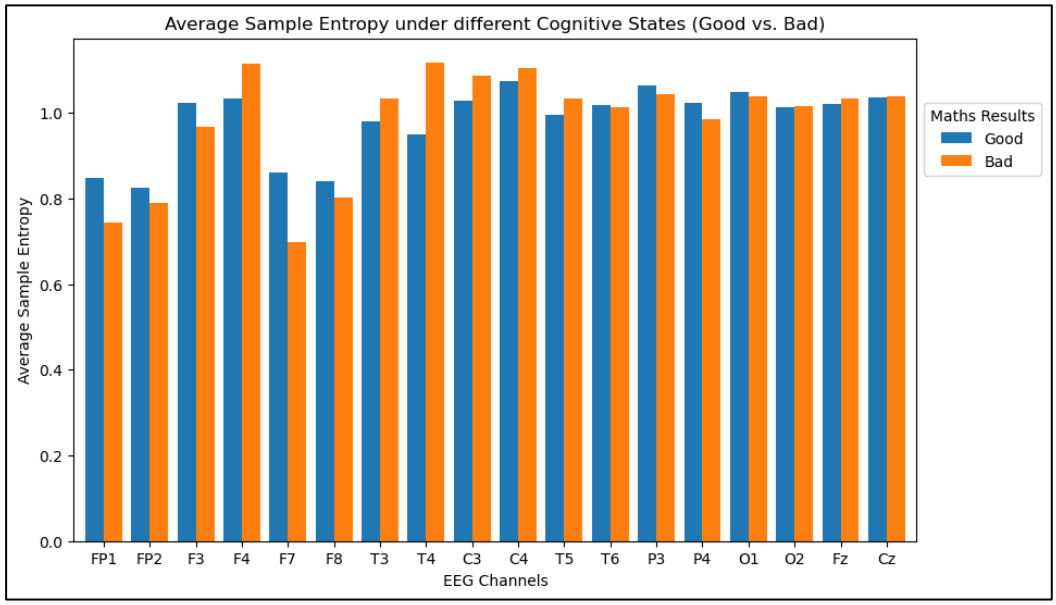


Figure. 55 Variation in average SampEn across the subjects before the task

Based on the comparison of Sample Entropy (SampEn) between students who completed the task correctly and those who did not, several findings can be highlighted:

1. **Frontal Lobe (F3, F4, F7, F8):**

   - Channels F4 and F7 exhibit noticeable differences in SampEn.
   - This suggests varying levels of complexity or irregularity in neural oscillations related to cognitive processing in the frontal regions during task performance.

2. **Temporal Lobe (T3, T4, T5, T6):**

   - Channels T4 and T5 show distinct patterns in SampEn.
   - This indicates varying entropy in temporal areas, potentially reflecting different levels of neural dynamics related to auditory processing or memory functions during the task.

3. **Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):**

   - Channels C4 and P3 display differential SampEn, indicating varying neural processing complexity.
   - Parietal regions (P3, P4, Pz) also show differences in SampEn, potentially reflecting differences in cognitive states or attentional modulation during task execution.

4. **Occipital Region (O1, O2):**

   - Channels O1 and O2 demonstrate differences in SampEn.
   - This suggests varying entropy in occipital areas, possibly related to visual processing or attentional states during task performance.

11) Comparison of Spectral Entropy across the subjects

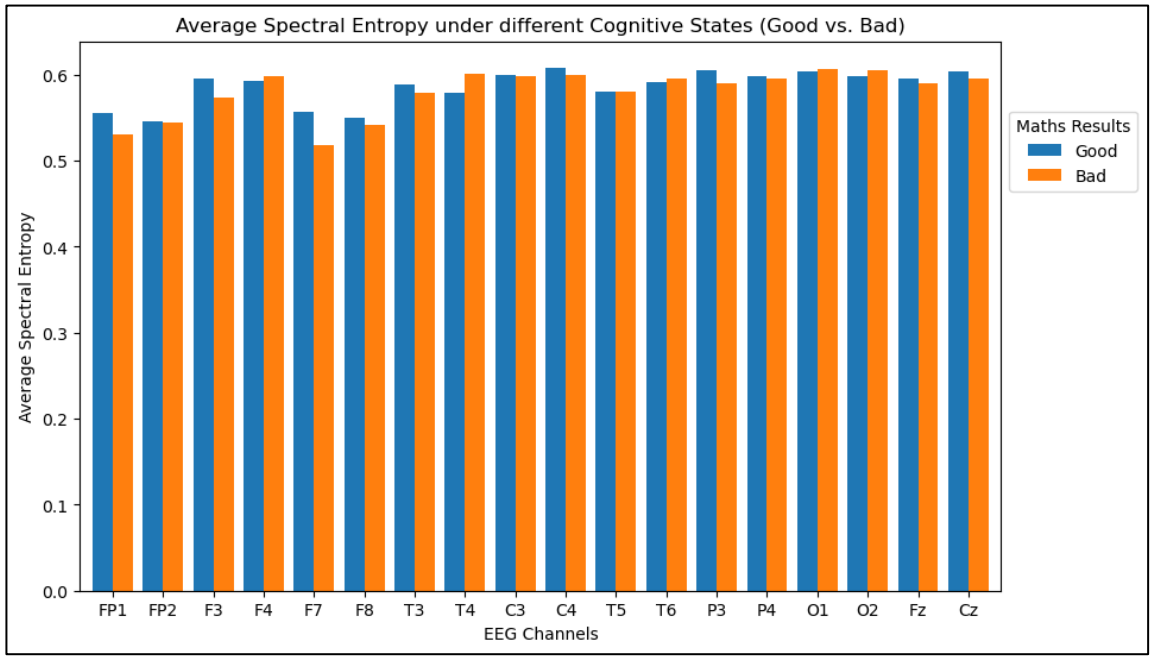


Figure. 56 Variation in average SpecEn across the students before the task

Based on the comparison of Spectral Entropy (SpecEn) between students who completed the task correctly and those who did not, several findings can be highlighted:

1. **Frontal Lobe (F3, F4, F7, F8):**

   - Channels F3 and F4 show noticeable differences in SpecEn.
   - This suggests varying levels of spectral complexity or irregularity in neural oscillations related to cognitive processing in the frontal regions during task performance.

2. **Temporal Lobe (T3, T4, T5, T6):**

   - Channels T4 and T6 exhibit distinct patterns in SpecEn.
   - This indicates varying entropy in temporal areas, potentially reflecting different levels of neural dynamics related to auditory processing or memory functions during the task.

3. **Central and Parietal Regions (C3, C4, Cz, P3, P4, Pz):**

   - Channels C3, C4, and P3 display differential SpecEn, indicating varying neural processing complexity.
   - Parietal regions (P3, P4, Pz) also show differences in SpecEn, potentially reflecting differences in cognitive states or attentional modulation during task execution.

4. **Occipital Region (O1, O2):**

   - Channels O1 and O2 demonstrate differences in SpecEn.
   - This suggests varying entropy in occipital areas, possibly related to visual processing or attentional states during task performance.

Summary of the Findings

The analysis revealed significant changes in EEG features when comparing pre-task and task states during arithmetic tasks. Alpha power decreased significantly across most EEG channels, especially in the left hemisphere, indicating increased cognitive workload. Beta power increased across all regions, reflecting heightened alertness and active cognitive processing. Delta and theta energies, related to attention and cognitive needs, increased during the task, especially in the frontal and left hemispheres. Gamma activity, which indicates significant cognitive involvement, increased throughout the cortex, particularly in the frontal, frontal, and occipital regions. Non-linear functions such as Higuchi fractal dimension (HFD) and sample entropy (SampEn) showed higher values during the exercise, indicating an increase in neural complexity, and clear changes in global regions and all channels, especially in the dorsolateral prefrontal cortex. Spectral entropy (SpecEn) describes regional changes and shows the complexity of neural responses to cognitive challenges.

In the analysis of subjects who performed the tasks correctly, specific patterns of regional neural activity were observed. Alpha power showed marked activity in parietal and occipital regions, while beta power showed significant elevations in frontal, parietal and occipital regions, indicating increased cognitive processing. Delta and theta activity increased in the frontal, middle, and parietal regions, indicating increased attention and the involvement of working memory. Gamma power showed an increase in the frontal and temporal regions, possibly related to cognitive performance. Non-spatial tasks such as HFD, SampEn, and SpecEn show greater complexity and unpredictability in neural signals, particularly in temporal, parietal, and occipital regions, and demonstrating complex mental processing when performing practical tasks.

For subjects who had difficulty performing the task, comparative analysis revealed distinct patterns of neural activity in different brain regions. Changes in alpha, beta, delta, theta and gamma power were observed in the frontal, temporal, central, parietal and occipital regions, indicating involvement different from mental and emotional processes. The frontal regions showed significant changes in dynamic power and entropy, indicating their role in executive functions and cognitive control. Time zones revealed clear changes in linear and non-linear tasks, especially in auditory processing and memory. Central regions showed similar changes related to motor planning and sensorimotor integration, while parietal and occipital regions were involved in sensory processing and visual perception. The HFD and entropy indices

showed complexity and disturbance in neural activity during the task, with specific channels in all areas showing significant involvement.

In comparing spectral and nonlinear EEG features between subjects who successfully completed a task and those who did not, distinct patterns were observed. Alpha power was higher in specific frontal, parietal, and occipital channels for students who performed poorly, while beta power increases were more prominent in the parietal and occipital regions of the same group. Delta and theta power exhibited a mixed distribution, with some regions showing higher power for students who failed the task, particularly in temporal and parietal channels. Gamma power was generally elevated in parietal and central regions among the unsuccessful group. Nonlinear features such as HFD and SampEn revealed increased complexity in the parietal and occipital channels of the unsuccessful group, whereas SpecEn was notably higher in the frontal and parietal regions for the same, suggesting different levels of cognitive processing and neural complexity between the two groups.

Comparison of visual and non-linear features between subjects who performed the task correctly and those who did not showed significant differences in the alpha, beta, delta, theta, and gamma bands at in different brain regions, including the frontal, temporal, and central. The parietal and occipital lobes. These differences in neural oscillatory patterns indicate different levels of cognitive engagement, attentional processing, and integration during task performance. In addition, non-invasive measures such as HFD, Sampen and Specen showed clear patterns between the two groups, especially in the frontal, temporal, parietal and occipital, indicating differential neural complexity, entropy and processing dynamics related to cognition and attention during wakefulness.

Chapter-5

Discussion & Conclusion

The aim of this study is to characterize the change in neural dynamics during mental engagement using linear and non-linear functions extracted from EEG signals. Our findings include the extracted features, especially the alpha, beta, theta, delta and gamma powers, as well as the Higuchi fractal dimension (HFD), sample entropy (SampEn) and spectral entropy (SpecEn), for example useful for mental load.

Alpha power exhibited a negative correlation with cognitive loading, with a more pronounced decrease observed in the left hemisphere, particularly in the left frontal, temporal, and central regions, compared to the right frontal, central, and temporal regions. In contrast, beta activity, a marker of cognitive function, showed a consistent increase across all channels. Additionally, the delta, theta, and gamma bands demonstrated increased activity, suggesting overall enhanced neural engagement during cognitive tasks, excluding the alpha band.

Nonlinear features, including HFD, SampEn, and SpecEn, also showed increases across channels, indicating heightened neural complexity and cognitive engagement. These changes in complexity were more pronounced in the frontal, central, and temporal regions. In particular, the prefrontal cortex showed marked changes compared to the inferior prefrontal cortex. Differences in SpecEn indicate that the distribution of frequency activity in different brain regions is not the same and show individual differences in neural responses to mental load. Although frequency domain complexity varies across EEG channels, there is a significant increase in self-similarity and complexity, as shown by HFD and SampEn functions across all channels.

To distinguish the samples that performed the task correctly from those that did not, we analyzed spectral and nonlinear features extracted from the EEG signals.

Non-linear Features

Non-linear functions, including Higuchi's fractional dimension (HFD), sample entropy (SampEn), and spectral entropy (SpecEn), showed significant changes that helped distinguish the cognitive integration levels of students. The HFD showed significant differences, especially in the frontal and temporal regions, indicating different complexity and different neural oscillations. SampEn changes were found in frontal and temporal lobes, indicating different

levels of neural activity related to cognitive processing and memory functions. SpecEn shows differences in the frontal, temporal, and occipital regions, which show changes in visual complexity and attentional characteristics. These non-linear measures emphasize the neural complexity and cognitive integration of students who have completed the task correctly.

Spectral Features

Specific characteristics, especially the alpha, beta, theta, delta and gamma bands, showed significant differences between the two groups. Alpha power showed a significant decrease, especially in the frontal, temporal and central areas of the left hemisphere, in students who performed the task correctly, indicating a reduction in cognitive load. However, beta power, an indicator of cognitive function, showed an increase in all channels, indicating an increase in cognitive involvement. Delta and theta powers show different patterns that reflect different levels of attention and neural processing processes. Variations in gamma power, particularly in frontal and temporal regions, indicate changes in cognitive processing and executive functioning.

Feature Comparison and Implications

Comparing the efficacy of spectral and non-linear features, it is evident that both offer valuable insights, but non-linear features provide a more nuanced understanding of neural complexity and cognitive engagement. HFD, SampEn, and SpecEn are particularly effective in capturing the intricate dynamics of brain activity, reflecting the heightened complexity and self-similarity in students who performed well on the task. These features help in distinguishing cognitive states with greater precision, offering a more comprehensive picture of cognitive loading. By utilizing these advanced metrics, we can better understand the neural mechanisms underlying successful task performance, which is crucial for applications in cognitive stress analysis and educational settings. This deeper insight into cognitive functioning can inform the development of machine learning models for more accurate cognitive load analysis and classification, ultimately contributing to improved educational strategies and interventions.

Chapter-6

Future Aspects

This research has significant implications for today's research landscape, particularly in academic fields. Potential applications include analyzing psychological stress in students, which may be particularly useful for identifying and addressing psychological stress in students who struggle or struggle with math. Such comparative analyzes can provide valuable insight into psychological burden and stress and enable targeted interventions.

In addition, the linear and non-linear features used in this study hold promise for the development of machine learning models aimed at analyzing and classifying cognitive load. These models can improve our understanding of cognitive processes and support the creation of adaptive learning environments that cater to individual cognitive needs. This study paves the way for future research to examine the complex dynamics of cognitive engagement and its effects on cognitive strategies and cognitive load management.

In the future, this research will have more applications, including helping students with brain development, intellectual disabilities, and gifted students. It can also help criminal investigations by examining how the brains of people with different cognitive abilities work. In addition, it can be used to test IQ by identifying brain regions that are more active in various cognitive tasks. Understanding the activation patterns of different brain regions can help solve cognitive problems better. Implementing these nonlinear and spectral features in an EEG machine can provide real-time data, and a proposed advancement is to integrate these features into a wearable device. This innovation would make the technology more accessible and user-friendly, eliminating the need for professional setup and enabling widespread use in various settings.

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