CHARACTERIZATION OF EPILEPSY PHASES FROM EEG SIGNALS USING SPECTRAL ANALYSIS, KATZ FRACTAL DIMENSIONS, AND SHANNON ENTROPY

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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 her **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

Epilepsy is known as a nervous system disorder often disguised as abnormal recurrent neuronal activity in the brain. In earlier times epilepsy was frequently misunderstood by society. The stigma around epilepsy is that it is contagious or happens because of demonic possession. An estimated 65 million people worldwide suffer from epilepsy. In most cases, the seizures got worse with time because of the failure of detection. And when it is diagnosed, the patient usually develops intractable seizures which are not well treated with anti-epileptic drugs. In this experimental work, a methodology was designed to reduce the detection time and increase the accuracy of prediction for the future.

In the first chapter, a brief introduction to epilepsy has been given. The different lobes of the brain, their structure, and function were compared with those of epileptic patients. The different waves generated by the brain were explored. The need for detection was raised and the different feature extraction methods were briefly explained.

In the second chapter, a thorough literature review has been provided.

In the third chapter, the methodology has been explained. This thesis aims to develop a detection method. Epileptic seizure has 3 distinguished phases such as pre-ictal, ictal, and post-ictal phases. This work focuses on the pre-ictal phase and employs signal processing methods to identify a seizure before its occurrence. In this work, both Linear and Non-Linear methods were employed. The signals were collected from online databases. Then the signal power was analyzed using various power spectral density methods. One good method was Welch PSD. After that, the signal was expressed in both time-frequency domains. And for that wavelet transform was used. Using wavelet transform, denoising of the data was performed. For denoising, Daubechies 6 wavelet was used. After denoising, feature extraction was done, first using linear methods of spectral analysis of the Alpha-Beta Ratio and Delta-Theta Ratio. Then non-linear methods such as Katz fractal dimension and Shannon entropy were chosen.

The fourth chapter contains the results of the experiment conducted.

The final chapter explores the result of the experiment conducted. Among all the methods employed, it was found that Katz FD outperforms Shannon entropy and other linear method such as ABR and DTR in the detection of seizure in the pre-ictal phase. From this, the

conclusion reached is that katz FD when used in any prediction model can detect epilepsy in its primitive stages. This detection will help those suffering from epilepsy and will make sure that their seizures are manageable with medications.

CONTENTS

PUBLICATION V

PREFACE VI

CONTENTS VIII

LIST OF FIGURES XII

LIST OF TABLES XIV

CHAPTER 1 1

INTRODUCTION 1

1.1. HISTORY OF EPILEPSY 1

1.2. NORMAL BRAIN - STRUCTURE AND FUNCTION 2

1.3. GENERATION OF WAVES 3

1.4. DIFFERENCES BETWEEN NORMAL BRAIN AND EPILEPTIC BRAIN 6

1.4.1 . DIFFERENCES IN STRUCTURE 6

1.4.2. FUNCTIONAL LIMITATIONS 6

1.5. NEED FOR DETECTION 7

1.6. DETECTION OF FEATURES 8

1.7. DETECTION OF FEATURES BY SIGNAL PROCESSING 10

1.7.1. PREPROCESSING 10

1.7.2. FEATURE EXTRACTION TECHNIQUES 10

1.7.2.A. LINEAR METHODS 10

1.7.2.A.1. TIME DOMAIN ANALYSIS 10

1.7.2.A.2. FREQUENCY DOMAIN ANALYSIS 10

1.7.2.A.3. FAST FOURIER TRANSFORM (FFT) 11

1.7.2.A.4. POWER SPECTRAL DENSITY (PSD) 11

1.7.2.A.5. PERIODOGRAM 11

1.7.2.A.6. WELCH'S PSD METHOD 11

1.7.2.A.7. BAND POWER ANALYSIS 11

1.7.2.B. NON-LINEAR METHODS 11

1.7.2.B.1. SHORT-TIME FOURIER TRANSFORM (STFT) 11
1.7.2.B.2. WAVELET TRANSFORM 12
1.7.2.B.3. FRACTAL ANALYSIS 12
1.7.2.B.4. ENTROPY 12
1.8. MOTIVATION AND OBJECTIVE 13

CHAPTER 2 15

LITERATURE REVIEW 15

CHAPTER 3 20

METHODOLOGY 20
3.1. EEG DATA ACQUISITION 21
3.2. SAMPLING FREQUENCY 22
3.3. TIME DOMAIN ANALYSIS 22
3.4. FREQUENCY DOMAIN ANALYSIS 23
3.4.1. FFT(FAST FOURIER TRANSFORM) 24
3.4.1.A. COOLEY-TUKEY METHOD: 25
3.4.2. POWER SPECTRAL DENSITY 25
3.4.3. PERIODOGRAM 27
3.4.4. WELCH PSD METHOD 28
3.5. TIME-FREQUENCY DOMAIN 29
3.5.1. SHORT-TIME FOURIER TRANSFORM 30
3.5.2. WAVELET TRANSFORM 32
3.6. FEATURE EXTRACTION 35
3.6.1. LINEAR METHOD 36
3.6.1.A. ALPHA - BETA RATIO 36
3.6.1.B. DELTA -THETA RATIO 36
3.6.2. NON-LINEAR METHOD 37
3.6.2.A. SHANNON ENTROPY 37
3.6.2.B. KATZ FRACTAL DIMENSIONS 39
3.7. SOFTWARE AND TOOLS 41

CHAPTER 4 ..... **42**

RESULTS **42**

4.1. BANDPOWER CALCULATION OF DELTA-THETA RATIO 42

4.1.1. DTR VARIATION OF ALL SUBJECTS 42

4.1.2. DTR VARIATION OF NORMAL TO PRE-ICTAL 46

4.1.3. DTR VARIATION OF NORMAL TO ICTAL 47

4.1.4. DTR VARIATION OF NORMAL TO POST-ICTAL 47

4.2. BANDPOWER CALCULATION OF ALPHA BETA RATIO 50

4.2.1. ALPHA BETA RATIO OF ALL SUBJECTS 50

4.2.2. ALPHA BETA RATIO OF NORMAL TO PRE-ICTAL 54

4.2.3. ABR RATIO OF NORMAL TO ICTAL 54

4.2.4. ABR OF NORMAL TO POST-ICTAL 55

4.3. SHANNON ENTROPY 58

4.3.1. SHANNON ENTROPY OF ALL SUBJECTS 58

4.3.2. SHANNON ENTROPY VARIATION OF NORMAL TO PRE-ICTAL 62

4.3.3. SHANNON ENTROPY VARIATION OF NORMAL TO ICTAL 62

4.3.4. SHANNON ENTROPY VARIATION OF NORMAL TO POST-ICTAL 63

4.4. KATZ FRACTAL DIMENSION 67

4.4.1. KATZ FD VARIATION AMONG ALL SUBJECTS 67

4.4.2. KATZ FD VARIATION OF NORMAL TO PRE-ICTAL 71

4.4.3. KATZ FD VARIATION OF NORMAL TO ICTAL 71

4.4.4. KATZ FD VARIATION OF NORMAL TO POST-ICTAL 72

CHAPTER 5 ..... **75**

DISCUSSION **75**

5.1 . DELTA THETA RATIO VARIATION 75

5.2 . ALPHA BETA RATIO VARIATION 76

5.3. SHANNON ENTROPY 77

5.4. KATZ FRACTAL DIMENSION 78

CHAPTER 6 ..... **80**

CONCLUSION **80**

CHAPTER 7 ..... **82**

FUTURE SCOPE **82**

CHAPTER 8 ..... **84**

REFERENCES **84**

LIST OF FIGURES

FIG. 1 DIFFERENT BRAIN LOBES 2
FIG. 2 DIFFERENT BRAIN WAVES[11] 4
FIG. 3. ELECTROENCEPHALOGRAM(EEG) [41] 8
FIG. 4 SPLITTING OF EEG SIGNAL ANALYSIS INTO TWO GROUPS - LINEAR AND NON-LINEAR ANALYSIS 20
FIG. 5 10-20 ELECTRODE SYSTEM[91] 21
FIG. 6 TIME DOMAIN ANALYSIS OF EEG SIGNAL 23
FIG. 7 EEG SIGNAL AND THEIR RESPECTIVE PSD IN VARIOUS PHASES 29
FIG. 8 SHORT-TIME FOURIER TRANSFORM[112] 31
FIG. 9 COMPARISON AMONG TIME DOMAIN, FREQUENCY DOMAIN, STFT AND WAVELET TRANSFORM[113] 32
FIG. 10 WAVELET TREE REPRESENTATION-DECOMPOSITION WAS DONE TILL LEVEL 6. 34
FIG. 11 ORIGINAL AND DENOISED EEG SIGNAL 34
FIG. 12 ANALYSIS OF THE DENOISED EEG SIGNAL USING WELCH PSD 35
FIG. 13 FEATURE EXTRACTION USING LINEAR AND NON-LINEAR METHODS 35
FIG. 14 DTR VARIATION OF SUBJECT 1 42
FIG. 15 DTR VARIATION OF SUBJECT 2 43
FIG. 16 DTR VARIATION OF SUBJECT 3 43
FIG. 17 DTR VARIATION OF SUBJECT 4 44
FIG. 18 DTR VARIATION OF SUBJECT 5 44
FIG. 19 DTR VARIATION OF SUBJECT 6 45
FIG. 20 DTR VARIATION OF SUBJECT 7 45
FIG. 21 DTR VARIATION OF SUBJECT 8 46
FIG. 22 DTR VARIATION OF NORMAL TO PRE-ICTAL PHASE OF ALL SUBJECT 46
FIG. 23 DTR VARIATION OF NORMAL TO ICTAL PHASE OF ALL SUBJECT 47
FIG. 24 DTR VARIATION OF NORMAL TO POST-ICTAL PHASE OF ALL SUBJECT 47
FIG. 25 ABR VARIATION OF SUBJECT 1 50
FIG. 26 ABR VARIATION OF SUBJECT 2 50
FIG. 27 ABR VARIATION OF SUBJECT 3 51
FIG. 28 ABR VARIATION OF SUBJECT 4 51
FIG. 29 ABR VARIATION OF SUBJECT 5 52

FIG. 30 ABR VARIATION OF SUBJECT 6 _____52
FIG. 31 ABR VARIATION OF SUBJECT 7 _____53
FIG. 32 ABR VARIATION OF SUBJECT 8 _____53
FIG. 33 ABR VARIATION OF NORMAL AND PRE-ICTAL OF ALL SUBJECT _____54
FIG. 34 ABR VARIATION OF NORMAL AND ICTAL OF ALL SUBJECT _____54
FIG. 35 ABR VARIATION OF NORMAL AND POST-ICTAL OF ALL SUBJECT _____55
FIG. 36 ShE VARIATION OF SUBJECT 1 _____58
FIG. 37 ShE VARIATION OF SUBJECT 2 _____58
FIG. 38 ShE VARIATION OF SUBJECT 3 _____59
FIG. 39 ShE VARIATION OF SUBJECT 4 _____59
FIG. 40 ShE VARIATION OF SUBJECT 5 _____60
FIG. 41 ShE VARIATION OF SUBJECT 6 _____60
FIG. 42 ShE VARIATION OF SUBJECT 7 _____61
FIG. 43 ShE VARIATION OF SUBJECT 8 _____61
FIG. 44 ShE VARIATION OF NORMAL TO PRE-ICTAL OF ALL SUBJECT _____62
FIG. 45 ShE VARIATION OF NORMAL AND ICTAL OF ALL SUBJECT _____62
FIG. 46 ShE VARIATION OF NORMAL AND POST-ICTAL OF ALL SUBJECT _____63
FIG. 47 KFD VARIATION OF SUBJECT 1 _____67
FIG. 48 KFD VARIATION OF SUBJECT 2 _____67
FIG. 49 KFD VARIATION OF SUBJECT 3 _____68
FIG. 50 KFD VARIATION OF SUBJECT 4 _____68
FIG. 51 KFD VARIATION OF SUBJECT 5 _____69
FIG. 52 KFD VARIATION OF SUBJECT 6 _____69
FIG. 53 KFD VARIATION OF SUBJECT 7 _____70
FIG. 54 KFD VARIATION OF SUBJECT 8 _____70
FIG. 55 KFD VARIATION OF NORMAL AND PRE-ICTAL OF ALL SUBJECT _____71
FIG. 56 KFD VARIATION OF NORMAL AND ICTAL OF ALL SUBJECT _____71
FIG. 57 KFD VARIATION OF NORMAL AND POST-ICTAL OF ALL SUBJECT _____72

LIST OF TABLES

Table 1 FREQUENCY DOMAIN ANALYSIS TECHNIQUES USED_____23
Table 2 SHANNON ENTROPY PROPERTIES FOR EACH PHASE _____39

CHAPTER 1

INTRODUCTION

In the middle of difficulty lies opportunity

- Albert Einstein

1.1. HISTORY OF EPILEPSY

Epilepsy as known today is a neurobiological disorder where the brain generates abnormal recurrent unprovoked signals[1].

Recent statistics show that an estimated 50 million people worldwide are affected by epilepsy. And with each year 5 million more are diagnosed. The majority of these are due to genetic factors. The other cause of epilepsy is accidents, where the brain gets damaged and the brain function gets unpredictable.

For a long time, epilepsy was not seen as a medical condition affecting the brain, and disrupting neural functioning and general wellbeing.

Famous personalities like Julius Caesar, Napoleon Bonaparte, Sir Isaac Newton, Charles Dickens, and Vincent Van Gogh amongst several others were suffering from epilepsy.

Epilepsy at those times was seen as a symptom of demonic influence, and it has a lot of stigma around it. People have the belief that it is contagious. Their work was not considered as their creativity but was rather observed as a result of their disease. They couldn't accept the fact that they suffered from epilepsy due to societal pressure. But to change this, there is a need to delve further into understanding the brain and what happens with the neurons when a person is suffering from epilepsy.

This work intends to find a sustainable method to help in diagnosis. The brain during an epileptic fit undergoes three different phases. These are the pre-ictal, ictal, and post-ictal phases. In the ictal phase, the patient usually faces a convulsive attack or sometimes goes blank and stares into something without knowing. Our method focuses on the pre-ictal phase. This experiment aims to identify the upcoming seizure while analyzing the pre-ictal phase.

For this study, 8 subjects who suffer from intractable epilepsy were studied. Then a comparison of the pre-ictal and ictal phases with normal was made. Then both types of methods - linear and non-linear methods were used to identify changes from normal to pre-ictal. These changes are expected to be relatively similar to ictal phases and could indicate the progression of a seizure.

1.2. NORMAL BRAIN - STRUCTURE AND FUNCTION

The below diagram shows how a normal brain looks structurally and acts functionally.

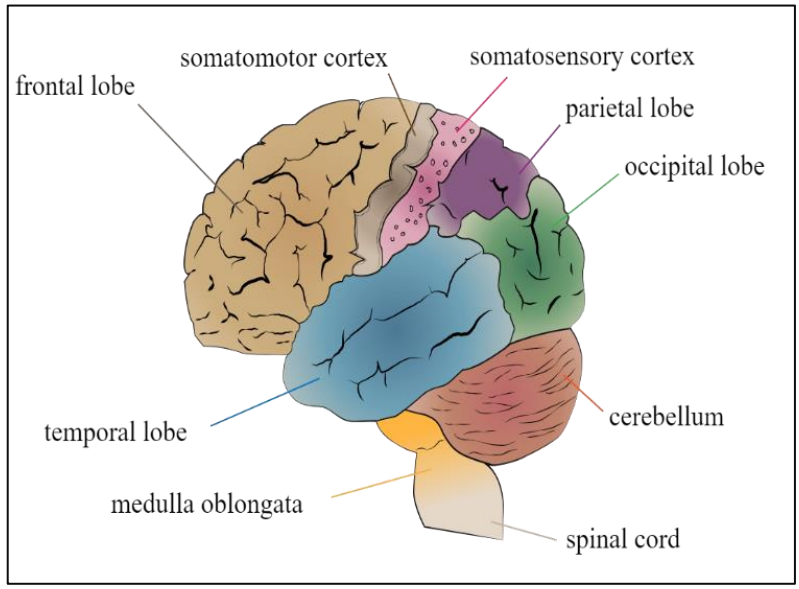


FIG. 1 DIFFERENT BRAIN LOBES

MAJOR LOBES AND THEIR FUNCTION -

Frontal Lobes – This lobe is located at the front of the brain. This controls the voluntary movement and cognitive processes like planning, problem-solving, and decision-making and motor movement. It also instruct social behavior and personality and helps produce language[2].

Temporal Lobes – This is located on both sides of the brain beneath the skull's temples, and is mostly involved in memory recollection and auditory processing such as processing of speech, and visual perception such as recognition of objects and understanding of language[3], [4].

Parietal Lobes – This lobe is located behind the frontal lobe, and is responsible for handling perceptual data and is vital for concentration and spatial cognition such as the

detection of touch, pain, and temperature and awareness of and perception of space combining sensory data to fully understand one's own body's location in space (proprioception). This lobe also helps in the understanding of numbers as well as arithmetic[5], [6]

Occipital Lobes – This lobe is located at the extreme back of the brain. The occipital lobes help in visual data analysis, which refers to interpreting stimuli perceived by the eyes. By doing this, the neurons in the occipital lobe help in the perception and recognition of color and differentiating visual data to understand depth and movement[7]

1.3. GENERATION OF WAVES

The brain generates waves from neuronal interaction, also known as brain waves or neural oscillations, as a result of the coordinated activity of neurons interacting with one another. Neuronal coordination is an essential component of brain activity and is responsible for a variety of physiological and cognitive functions.

Some explanations behind why the brain produces waves are as follows:

The Interaction between neurons:

Brain neurons interact with each other through electrical impulses known as action potentials. The activation of brain cells in coordination, produces a pattern of electrical activity known as brain waves. These waves allow communication between various areas of the brain.[8], [9], [10]

The Coordination of Brain Activity:

Brain waves aid in regulating the activity of different parts of the brain, allowing them to function more efficiently. Synchronized brain waves, for example, allow complicated activities requiring attention, memory, and sensory processing to interact and integrate information effectively.[9]

Control of Consciousness and Sleep:

Different kinds of brain waves are related with distinct states of awareness and sleep phases.

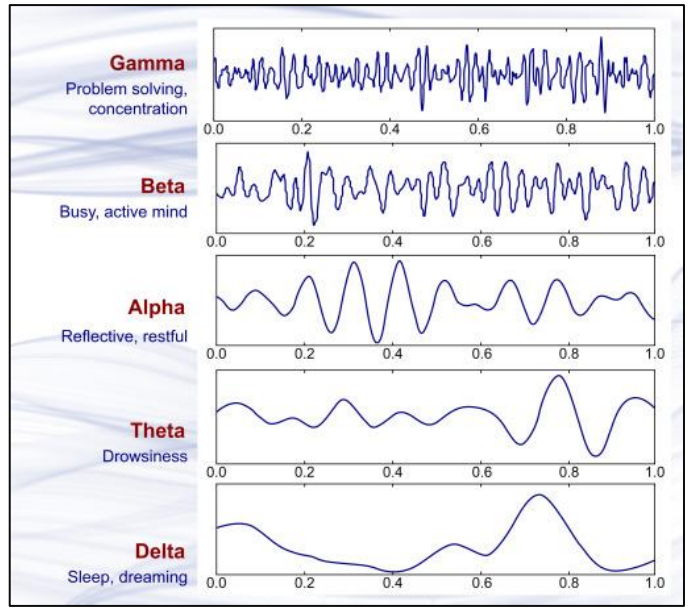


FIG. 2 DIFFERENT BRAIN WAVES[11]

- *Alpha Waves (8-12 Hz) :*

At 8 and 12 Hz, oscillatory neural activity is captured by alpha waves. They tend to occur in people who are awake but relaxed, with their pupils closed, indicating a reduced degree of cerebral arousal. Relaxed attention, meditative states, and internally guided cognitive processes have all been associated with alpha-wave activity. In addition, inhibitory neural networks that influence cognitive regulation and sensory processing are linked to alpha oscillations.[12], [13]

- *Beta Waves (12-30 Hz) :*

Neural waves in the 12–30 Hz range of frequencies are referred to as beta waves. They are prevalent during wakeful and alert states, particularly when engaged in cognitive tasks that require intense attention and active processing of thoughts. Elevated cortical arousal, cognitive function, and motor planning are linked to beta wave activity. The beta oscillation spectrum includes low-frequency beta waves, which are associated with states of relaxation and attentiveness, as well as high-frequency beta waves, which are associated with higher levels of cognitive demands and persistent focused attention.[12]

- *Delta Waves (0.5-4 Hz) :*

Neural waves of a slow frequency, between 0.5 and 4 Hz, are indicated as delta waves. They typically appear in stages 3 and 4 of non-rapid eye movement (NREM) sleep, which are deep sleep phases. Reduced sensory awareness along with substantial cortical suppression have

been demonstrated by delta wave activity. These oscillations are necessary for the consolidation of declarative memories, restorative processes, and sleep homeostasis.[12], [14], [15]

- *Theta Waves (4-8 Hz) :*

Neural oscillations with frequency between 4 and 8 Hz are depicted by theta waves. They are characteristic of low-arousal states including meditative practices light sleep, and relaxation. Internally directed cognitive activities, such as short-term memory retrieval, spatial awareness, and artistic ideation, are linked to theta wave activity. The acquisition of sensory information during cognitive activities and the regulation of psychological responses are additional functions connected with theta oscillations.[12]

- *Gamma Waves (30-100 Hz) :*

High-frequency neural waves between 30 and 100 Hz are referred to as gamma waves. They have been connected to elevated levels of mental engagement and brain activity. When performing activities involving pattern binding, processing information across dispersed brain networks, and sensory integration, gamma wave activity is seen. In addition, gamma oscillations are linked to several cognitive processes, such as memory retention, heightened awareness, and attentional selection. Cognitive deficits and neuropsychiatric conditions have been linked to altered gamma wave activity.[12], [14]

Brain waves also influence the processing of emotions. As an example, alpha waves are connected with relaxation and a good mood, but irregularities in other wave patterns might be related to worry, anxiety, and other emotional states.[15]

Brain waves assist in processing sensory information from the environment. For instance, alpha waves assist in sorting unwanted sensory information, allowing us to concentrate on essential signals.[16], [17]

Movement development and execution involve the use of certain brain waves. Beta waves, for instance, have been linked to motor control and active task performance.[18], [19], [20]

Brain waves are rhythms that occur when a significant amount of neurons fire in synchrony.A loop connecting the thalamus and brain generates rhythmic patterns. Loops like this are necessary for processes like sleep and focus. [10]

Interactions among excitatory and inhibitory receptors:

The brain creates patterns of rhythm by regulating excitatory and inhibitory signals. In particular, excitatory neurons' activity may be regulated by inhibitory interneurons, leading to the generation of certain brain waves. [10], [21], [22]

1.4. DIFFERENCES BETWEEN NORMAL BRAIN AND EPILEPTIC BRAIN

In epileptic patients, the changes are inevitable. Both structurally and functionally the brain looks different. The normal of an epileptic patient is different from the normal of a selected subject.

1.4.1 . DIFFERENCES IN STRUCTURE:

The loss of nerve cells is typical in epileptic brains, notably in regions such as the hippocampus. In reaction to loss of neurons and injury, there may be an increase in the number and diversity of glial cells, or gliosis.[23], [24], [25]

Studies have shown an irregular growth of the cerebral cortex that leads to disorganized neurons and cell layers is known as focal cortical dysplasia (FCD). The area of the hippocampus that shrinks and becomes bruised is frequently associated with temporal lobe epilepsy.[26]

Some other studies have shown significant atrophy in some parts of the brain, such as the temporal lobes. More widespread brain atrophy is seen occasionally.[27], [28], [29], [30]

1.4.2. FUNCTIONAL LIMITATIONS

Distinctive Electrical Activity –

Sharp recognizable spikes happen in between seizures. The presence of unexpected, uncontrolled neuronal electrical discharges indicates a seizure.[31], [32], [33], [34], [35], [36]

Modified Brain Waves-

The onset of convulsions may be linked to increased gamma waveform. [14]People with epilepsy often have reduced alpha wave activity.[13]

Dysfunction of the Network-

During seizures, the coordinated firing of neurons occurs as a result of overactive networks of neurons. There is usually an interruption in the physiological and functional connection between the various brain areas.[21], [37] Every epileptic patient is different. For different patients, different brain regions get activated.

1.5. NEED FOR DETECTION

The ancient disease termed epilepsy has long both fascinated and terrified experts and ordinary individuals. Seizures were mysterious until the central nervous system was well understood. The illness was associated with gods and demonic possession in antiquity, which made epileptics fearful and secluded. Until the middle of the 20th century, discrimination against people with epilepsy persisted. This discrimination included forced sterilizations as well as barriers to employment, marital equality, and health insurance. Even with the advancements, there are still a lot of false beliefs about epilepsy in the world. Research indicates that epileptic patients who live in communities that comprehend the pathophysiology and origin of seizures tend to do better in social and educational settings[38], [39]. Even though there has been improvement, more has to be done to inform people on the pathophysiology of epilepsy everywhere in the world. It has been evident that people who suffer from epilepsy are often misdiagnosed. There have been cases of false positives (normal abrupt unknown variation in the brain) and false negatives (actual presence of a seizure, often misdiagnosed as random variation). These lapses in diagnosis need attention. To overcome these challenges proper research needs to be conducted with a large number of both subjects and diagnosed patients. As of now, there are very few features that help in the diagnosis of epilepsy. Usually, by then it is too late and the patient needs Anti-Epileptic Drugs(AEDs) and sometimes even brain lobe surgeries to manage epilepsy. For the cases of false negatives, where the presence of epilepsy is often misdiagnosed, the need to identify features contributing to epilepsy needs to be established. This will result in receiving faster and more effective treatment plans.

1.6. DETECTION OF FEATURES

EEG is the earliest tool used to diagnose epilepsy.[40] This tool is used in the understanding of a normal brain from an epileptic brain.

ELECTROENCEPHALOGRAM(EEG)

In EEG, electrodes made of Ag/Agcl(silver/silver chloride) are applied to the scalp to record the alteration of neuronal activity. EEG is useful in neuroscience because it helps in the evaluation and tracking of neurological variables. This method is non-invasive. The electrodes pick up minute electrical fluctuations in brain activity, which are subsequently digitalized and amplified for examination. The method of recording this activity is called electroencephalography.

Different frequency bands, such as Delta, Theta, Alpha, Beta, and Gamma, are associated with distinct brain states or activities in EEG data. This technique offers insightful information on brain health and function by detecting patterns in brain wave activity. The four different phases of epileptic activity in the brain are inter-ictal(normal or absence of seizure), ictal, pre-ictal, and post-ictal. Every phase has distinct clinical and electroencephalogram features, and it symbolizes various cerebral activity patterns.

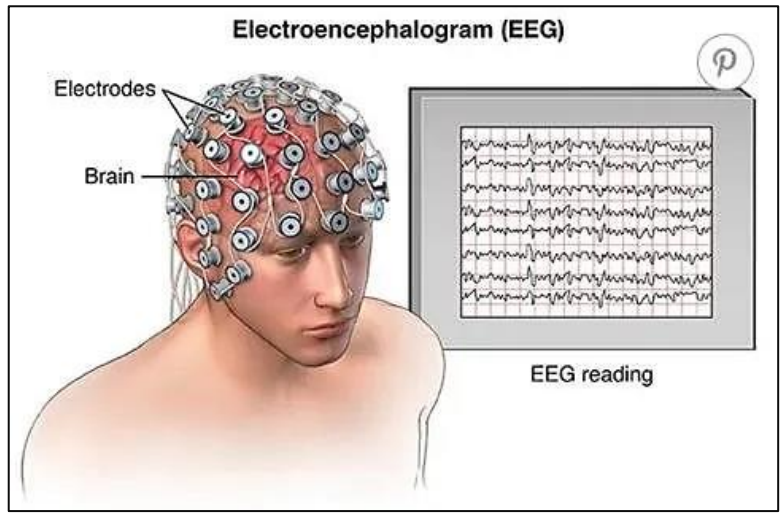


FIG. 3. ELECTROENCEPHALOGRAM(EEG) [41]

Interictal Phase

The interval between consecutive seizures is known as the interictal period. It is characterized by a somewhat normal level of brain activity, therefore also called the normal phase, however, EEG frequently reveals some atypical patterns. On an EEG, there are abrupt,

brief variations in brain activity that resemble spikes or sharp waves. These point to hyperexcitability in specific brain areas. With occasional interictal spikes, the background EEG activity is usually rather normal. [31]The localization of seizure foci and diagnosing epilepsy are made easier by interictal EEG patterns. Keeping records on variations in interictal activity can reveal information about how well a treatment is working.

Ictal Phase

The ictal phase is the time during which a seizure occurs. The brain generates strong, unpredictable electrical activity. These activities are the primary characteristics of a seizure disorder. Sudden onset of periodic discharges at a high frequency. Over time, the EEG pattern changes. It usually originates locally and can eventually spread to other areas.[42]There is an increase in the EEG signals' amplitude.[42], [43]Concerning the kind of seizure and the areas of the brain affected, symptoms often vary. Tremors, a state of unconsciousness, sensory issues, and changes in conduct are a few signs of these.[42]The total duration of a seizure may range from a few seconds to several minutes.

Pre-ictal Phase

The period preceding a seizure is known as the preictal phase. Slight behavioral and neurological changes are frequently associated with it, and they could represent an upcoming seizure. Before a seizure occurs, there may be gradual changes in the EEG, such as an increase in the frequency or amplitude of brain waves. Change from regular interictal rhythms to more structured, seizure-inducing activity. Perceptual, motor, or psychological signs that some patients perceive just before a seizure starts. Unusual scents, déjà vu sensations, and distortions of vision are a few examples of these auras. The preictal state may include anxiousness, agitation, or other abnormalities in behavior.[44]

Post-ictal Phase

The phase that follows after a seizure known as the postictal period is marked by a return to normal brain activity, although it is sometimes accompanied by momentary weaknesses.The brief period of decreased electrical activity that happens just after a seizure. As the brain recovers, EEG patterns gradually return to their baseline.[45], [46], [47], [48]Patients frequently express feeling tired, confused, and disoriented. This could go on for a few minutes or hours. Patients might suffer from headaches, painful muscles, and weakness.The patient get momentary memory loss, trouble speaking, and mood swings.[45]

1.7. DETECTION OF FEATURES BY SIGNAL PROCESSING

1.7.1. PREPROCESSING

To distinguish among the interictal, ictal, preictal, and postictal stages of epilepsy from EEG data, methods of signal processing are used for analysis. These approaches assist in identifying, explaining, and interpreting the patterns associated with every stage. Before utilizing sophisticated signal processing methods, EEG data is usually preprocessed to eliminate noise and artifacts that mask the actual brain signals. Frequency components beyond the area of interest are removed by high-pass and low-pass filters (usually 0.5-70 Hz for EEG).[48], [49] Artifacts from eye blink, muscle movements, and other non-involuntary sources are separated and eliminated using methods such as Wavelet Transform.

1.7.2. FEATURE EXTRACTION TECHNIQUES

The methods of feature extraction were categorized as *linear* and *non-linear* methods

1.7.2.A. LINEAR METHODS

Linear methods are simpler to implement and analyze since they presume a linear connection in the data. They are frequently applied when linear equations or transformations provide an adequate explanation of the signal or system behavior. This experiment deals with EEG signals, which are known to be non-stationary. The purpose of using this method is to check the dominance of different waveforms.

1.7.2.A.1. Time Domain Analysis

In Time Domain analysis the signal characteristics are observed directly over time. This experiment used this to study amplitude, power, and signal shape analysis. These methods were used for Initial data inspection, detecting trends and spikes.[50], [51]

1.7.2.A.2. Frequency Domain Analysis

In Frequency Domain Analysis signal characteristics in the frequency domain are studied. In this study, the methods used are Spectral Analysis, Fourier Transform, Power Spectral Density (PSD), and Periodogram. These methods were used for identifying dominant frequencies, filtering, and frequency-based feature extraction.[51]

1.7.2.A.3. Fast Fourier Transform (FFT)

FFT is the competent computation of the Discrete Fourier Transform (DFT). FFT was used for transforming signals from time to frequency domain, and for signal processing.[51], [52], [53]

1.7.2.A.4. Power Spectral Density (PSD)

Power Spectral density is the measure of power distribution over frequency. This was done with the methods of periodogram and Welch's method. This is used for analyzing signal strength at different frequencies, and noise analysis.[54], [55], [56]

1.7.2.A.5. Periodogram

A periodogram is the estimate of the spectral density of a signal by squaring the magnitude of its Fourier Transform.[57], [58] These are frequently used for identifying dominant frequencies and analyzing spectral content.

1.7.2.A.6. Welch's PSD Method

WELCH improved the estimation of PSD by segmenting the signal, windowing each segment, computing periodograms, and averaging. Welch's method was used for reducing noise in spectral estimates and analyzing steady-state signals.[54], [55]

1.7.2.A.7. Band Power Analysis

Band Power is the total power within a specific frequency range, calculated by integrating the PSD over that range. Bandpower is used for EEG analysis (e.g., alpha, beta bands), and feature extraction in biomedical signals.[12], [14]

1.7.2.B. NON-LINEAR METHODS

When linear models are insufficient to effectively represent the data or the behavior of the system, non-linear approaches are employed. These techniques work well for extracting more intricate, non-linear correlations from the data. Since EEG signals are non-stationary, these methods are more effective.

1.7.2.B.1. Short-Time Fourier Transform (STFT)

STFT does an analysis of frequency content over time by segmenting the signal and applying FFT to each segment. STFT is used for Time-frequency analysis.[59]

1.7.2.B.2. Wavelet Transform

Wavelet transform helps in the decomposition of a signal into components with both time and frequency information using wavelets.

There are two types in which wavelet transform is characterized

- Continuous Wavelet Transform (CWT)
- Discrete Wavelet Transform (DWT)

Wavelet Transform is used for denoising and transient event detection.[60]

1.7.2.B.3. Fractal Analysis

Fractal analysis is the analysis of self-similar patterns and complex structures within signals using fractal metrics. The method in which the fractal analysis is performed is Katz's Fractal dimension. These are used for physiological signal analysis, and analyzing similar natural phenomena.[61]

1.7.2.B.4. Entropy

Entropy is used for the measurement of complexity or randomness in a signal. Various types of entropies are Shannon entropy, Sample entropy, and Approximate entropy. Entropies are used for complexity analysis, EEG signal analysis, and biomedical signal processing.[62]

The goal here has been to create a tool that will help in epilepsy diagnosis in the future by utilizing all of these strategies. This study shows a range of pre-ictal seizure diagnostic techniques, from the least to the most effective. Every technique adds special benefits and insights to a complete strategy for recognizing and evaluating seizure activity. Suppose any patient is suffering from a disease that also constitutes a seizure disorder and has certain characteristics that set it apart from other neurological problems. In that case, it must be classified as a separate disease; some parameters are needed for that. In this work, an attempt has been made to determine that parameter using different linear and non-linear methods. Determining an accurate diagnosis is essential to ensure that patients receive the most effective care.

The aim is to develop a diagnostic tool that combines the most effective methods from both linear and non-linear signal processing approaches, hence enhancing the precision efficiency

Through the use of leading-edge signal processing methods to study epileptic EEG data and to have a clear distinction between the interictal, pre-ictal, ictal, and post-ictal phases, this experiment seeks to bridge this gap in research. To be more accurate, here exploration of both linear and non-linear techniques is performed to capture the distinct features of EEG signals linked to each phase. This experiment can increase seizure prediction accuracy and deepen the understanding of epileptic brain activity by utilizing the strategies.

1.8. MOTIVATION AND OBJECTIVE

The disease epilepsy has mostly been misunderstood due to various societal factors with inadequate information on epilepsy that it is communicable and that it impairs memory or intelligence. Due to this, people face discrimination in places of employment, educational institutions, and social situations.

There are many different kinds of epileptic fits, ranging from reduced attention spans to convulsive attacks. Seizures could go undetected by observers, which might cause panic or unsuitable reactions.

Unusual behaviors such as directionless roaming, disorientation, or repeated motions caused by certain seizures might be misinterpreted for purposeful activities, mental health problems, or intoxication. Usually, seizures don't happen during medical examinations such as Electroencephalography tests(EEG) and the symptoms of epilepsy might coexist with other illnesses, detecting the disorder can be challenging. Improper therapy is a result of frequent misdiagnosis or delayed diagnosis. Several factors that might cause seizures are stress, lack of sleep, and flashing lights. Additionally, each person will experience seizures differently. Stress and worry can be greatly increased by not knowing when a seizure can happen. Not to mention, the prejudice and social stigma attached to epilepsy can cause low self-esteem, sadness, and feelings of loneliness. Friends and family are overly protective of the affected person or in some cases do not comprehend the disease, which can cause misunderstandings or even strained relationships. A lot of persons with epilepsy have legal limitations on their ability to drive, which affects their independence and social and professional opportunities. Employers and coworkers may discriminate against people with epilepsy because they misunderstand the condition and may have doubts about the person's ability. Increasing public understanding via campaigning and education is essential to debunking falsehoods and lowering stigma. This involves teaching people in communities, businesses, and schools about epilepsy and how to

help individuals who are impacted by it. Promoting the growth of resources like accessible healthcare and support groups for people with epilepsy can help these people live more fulfilled lives. Epilepsy is a rare event that occurs randomly, and not all individuals exhibit the same neural patterns. Normal variations in brain activities can sometimes be mistaken for seizures (false positive), and actual seizures go undetected (false negative). These challenges can be addressed by a procedure that detects a seizure before its occurrence. Identifying the right algorithms to incorporate into diagnostic tools is essential for improving our abilities in the field of epilepsy diagnosis. Emphasis is placed here on how selecting suitable algorithms may greatly improve epilepsy detection, particularly concerning the more recent and advanced non-linear techniques. Diagnoses made with algorithms designed particularly for epilepsy detection are more accurate and precise. When it comes to capturing the intricate, non-linear patterns seen in EEG data during epileptic episodes, non-linear techniques like the Wavelet Transform, Fractal dimensions, and Entropy analysis are advantageous. Compared to conventional linear approaches, advanced non-linear algorithms are more successful at identifying tiny patterns and aberrations in EEG data that may indicate preictal or ictal phases. For seizure prediction to be precise and timely, this sensitivity is essential.

Non-linear techniques are frequently more stable when it comes to managing the non-stationarity and variability of EEG signals, which can change dramatically during epileptic episodes. Because of its resilience, the diagnostic tool is more reliable when used to a variety of patient profiles and situations. The development of new approaches in non-linear signal processing is being driven by ongoing research and innovation. For example, new approaches to identifying minute alterations in EEG data linked to epilepsy are being made possible by developments in fractal analysis and machine learning techniques.

CHAPTER 2

LITERATURE REVIEW

Study the past if you would define the future.

- Confucius

This paper shows Hans Berger's 1924 discovery of electroencephalography (EEG) was a crucial turning point in our understanding of the electrical activity of the brain. The German psychiatrist Berger first became interested in exploring the potential for brain wave telepathy. Nevertheless, his research resulted in the creation of the EEG as a method for examining the electrical activity of the brain, which eventually helped to recognize epilepsy as an independent medical illness.[63]

This study shows how conventional approaches to epilepsy diagnosis rely upon electroencephalogram (EEG) data made by trained healthcare professionals. This may be a tedious and unreliable process. Automated seizure detection techniques are becoming more and more necessary as a result of the shortcomings of manual diagnosis. The diversity and clinical significance of the data were impaired by the use of small and confined datasets in previous algorithms in this field. The current work used power spectral density and connectivity analysis to extract characteristics from the TUEP dataset to address these problems. This technique of feature extraction produced very accurate findings, with 90% or more of the EEG signals being classified as non-epileptic. By using these cutting-edge techniques, the experiment not only enhances seizure detection accuracy but also provides a better and more reliable alternative to traditional diagnostic approaches. To improve and enhance automated epilepsy detection systems, future research projects may investigate the fusion of machine learning and deep learning methodologies. [2]

This paper introduces us to how EEG helps identify brain waves associated with various areas of the scalp, aiding in the detection of epilepsy. Machine learning algorithms and deep learning models are used in predicting epilepsy by choosing features with the help of a particle swarm optimization algorithm. The models Vgg16, Vgg19, and Inception V3 are employed for

detecting epilepsy, with Inception V3 achieving the top accuracy of 97.87%. The most recent version shows a 5.1% increase in accuracy compared to current methods, proving its efficacy in identifying epilepsy. Validation on Kaggle and CHB-MIT datasets has shown a boost in accuracy by 0.7% and 0.13% respectively, providing further evidence of its effectiveness. [64]

Automatic seizure detection can be facilitated by identifying the unique properties that differentiate the PSD of EEG phases during seizures from the ones without seizures. [65], [66]

This assessment of PSD analysis shows how essential it is for DSP operations including modulation, filtering, and spectral analysis. To ensure accuracy, efficiency, and resilience in the estimation of PSD from digital data, researchers design and study methods.[54]

This study showed how PSD analysis paired with high-frequency oscillations (HFOs) in EEG data provides the precise detection of epileptic seizure patterns. [67]

In this investigation, the result showed how Periodic synchronous discharges (PSD) with sharp waves or sharp and slow waves were seen in certain EEG instances with secondary generalized epilepsy.[68]

In this study, the result showed that certain epileptic symptoms solely emerge during sleep, and seizures are often the result of non-rapid eye movement (NREM) sleep.[69]

The research paper employs Thomson's multitaper spectral estimation as the PSD estimation method. By taking the median of estimates from numerous tapers applied to the same window, it minimizes bias and variance in EEG signals. This method makes use of orthogonal, uncorrelated Discrete Prolepian Spheroidal Sequences (DPSS) tapers, which minimize variation in spectral estimations. [70], [71]

Several studies have used PSD analysis to accurately identify epileptic episodes. For instance, a research that used PSD characteristics taken from EEG data was able to detect seizures with an accuracy of 99.6% and 99.7%. [72]

PSD may be applied to differentiate between healthy, pre-seizure, and seizure signals, according to another research. The PSD of the epileptic signal is much greater than that of the healthy signal. [67]

This work showed that Welch's approach is a variation on the periodogram method that uses an average across overlapping signal segments to lower the estimate's variance.

Neural signals, which frequently contain non-stationary components, benefit greatly from this. [73]

The study addresses the difficulties in interpreting EEG data and contrasts a novel methodology for recurrence quantification analysis (RQA) that uses the Short-term Fourier transform (STFT) with the conventional embedding technique. [74]

It draws attention to the complexity of interpreting nonstationary EEG data and the challenge of choosing the best embedding conditions for various frequency bands. The authors highlight the value of feature-based methods for comprehending neurological processes and propose that STFT-based recurrence analysis may provide more accurate information on broader brain states in contrast to microstate dynamics. Additionally, they discuss how deep neural networks may be used to analyze two-dimensional time-frequency pictures of EEG data in a variety of illnesses, including severe depression, epilepsy, schizophrenia, and autism.[74]

The research study compares basic thresholding methods with the Short-Time Fourier Transform (STFT) for spike recognition in peripheral neural captures. Previous research has shown that poor signal-to-noise ratios, irregular spiking patterns, and electromyographic data contamination from nearby muscles make it difficult to isolate neural events from peripheral nerve recordings.
To create signals from physiological recordings and serve as a ground truth for the spike detection algorithm's validation, the paper presents a quasi-simulation framework. The results show that by lowering the false detection rate, the STFT-based method works better than simple thresholding, especially in recordings with somewhat low SNR. [75]

This study focuses on determining analgesic depth by evaluating nonstationary data stored in electroencephalograph (EEG) data using the Wavelet Transform (WT). It highlights the Wavelet Transform's self-evolving window structure, which offers a time-scale representation of spectral components with varying resolutions, by contrasting it with more conventional techniques like the Short-Time Fourier Transform and Gabor Transform. The work shows how Wavelet Transform may be used to identify and examine background and transitory processes in both awake and sleeping states, revealing variations in the way the brain reacts to external inputs depending on the subject's level of consciousness. According to the study, there exists a continuous brain function that keeps a check on external or environmental stimuli while the person is awake or asleep. [73], [76], [77], [78], [79]

This study shows that patients with epilepsy had higher alpha power in their left hemisphere nodes and lower high beta power in the epileptic left parietal lobe. [80]

This analysis unveils Theta, alpha, and delta band frequencies are higher in epilepsy. The amygdala, piriform cortex, and medial septum have a lower correlation. [81]

This research has demonstrated that the EEG signal of individuals with epilepsy, especially those with focal epilepsy, has elevated alpha power. It is believed that the existence of interictal spikes and sharp waves, together with enhanced cortical activity, are associated with this higher alpha power.

This research highlights that individuals with epilepsy, especially those with generalized epilepsy, frequently experience a drop in beta power. It is suspected that the existence of interictal spikes and sharp waves, together with reduced cortical activity, are associated with this lower beta power. [82], [83]

Patients with TLE(Temporal Lobe Epilepsy) had lower alpha-delta and alpha-theta ratios. [84]

This investigation depicts that Shannon entropy includes the EEG range of 0.8 to 32 Hz. Renyi entropy utilizes multiscale permutation. Although these entropies are capable of measuring signal complexity, they are not very good at differentiating between signals. [85]

Some studies have used entropy analysis on EEG data to examine its performance in epilepsy detection based on short-term analysis. In a comparative study between Shannon's Entropy (ShEN) and Renyi's Entropy (RE), ShEN showed higher accuracy. [60]

This work focuses on the complicated nature of non-linear patterns in information presents a challenge for conventional linear techniques like the Fourier transform. A key tool for examining patterns of human behavior is Shannon's entropy, which data-driven quantifies uncertainty and complexity. Reflecting shifts in activity patterns, it calculates the likelihood of various activities in a participant's routine. Lower entropy levels reflect regular and predictable patterns, whereas higher values indicate more diverse and unexpected activity. [50]

According to a paper, where four different nonlinear feature extraction methods such as the Higuchi method (HFD) and Katz method (KFD), Hurst exponent, and L-Z complexity measure were studied, KFD was marked as the highest-ranking non-linear method [6].

However, in another study, Katz's, Higuchi's, and the k-nearest Neighbor (k-NN) algorithms were compared regarding their ability to detect the onset of epileptic seizures. KFD ranked lower in performance[86], [87]

This work highlights that Katz's technique transforms FD values exponentially, it is robust and noise-insensitive, making it the ideal method for differentiating between epileptic states in intracranial EEG (IEEG). Because of this, it works especially well in the noisy environments that are typical of IEEG recordings. [87]

In this paper, Higuchi's approach is more noise-sensitive even if it yields more accurate FD predictions on synthetic data. Despite its theoretical accuracy, this sensitivity might cause issues in real-world applications where data quality changes, making it less dependable for EEG analysis.[88]

This assessment indicates Petrosian's approach may be straightforward and computationally effective, but has trouble reproducing the dynamic range of synthetic FDs, which makes it difficult to employ for analog signal analysis. This restricts its use in situations when precise recording of a broad range of FD values is required.

This research demonstrates that overall, Katz's algorithm's balance between accuracy and robustness in noisy environments makes it the most suitable for analyzing epileptic states in EEG, while Higuchi's and Petrosian's methods have their respective strengths and limitations depending on the specific application and noise conditions.[87], [88], [89]

All these research studies suggested that Power spectral density using Welch PSD gives a clear idea about the power shared by various frequencies. A more refined method for analyzing and removing artifacts from the EEG signal would be to use Wavelet Transform. The Theta-Delta ratio is usually computed in various papers. In this study, an attempt has been made to study the Delta-Theta Ratio of epileptic EEG signal. Also, the fast waves, Alpha and Beta are studied in ratio form. From other non-linear features, Shannon Entropy and Katz Fractal Dimension of the EEG signal will be evaluated to explore a method that could help in the pre-ictal diagnosis of epilepsy.

CHAPTER 3

METHODOLOGY

A dream doesn't become reality through magic; it takes sweat, determination, and hard work

– Colin Powell

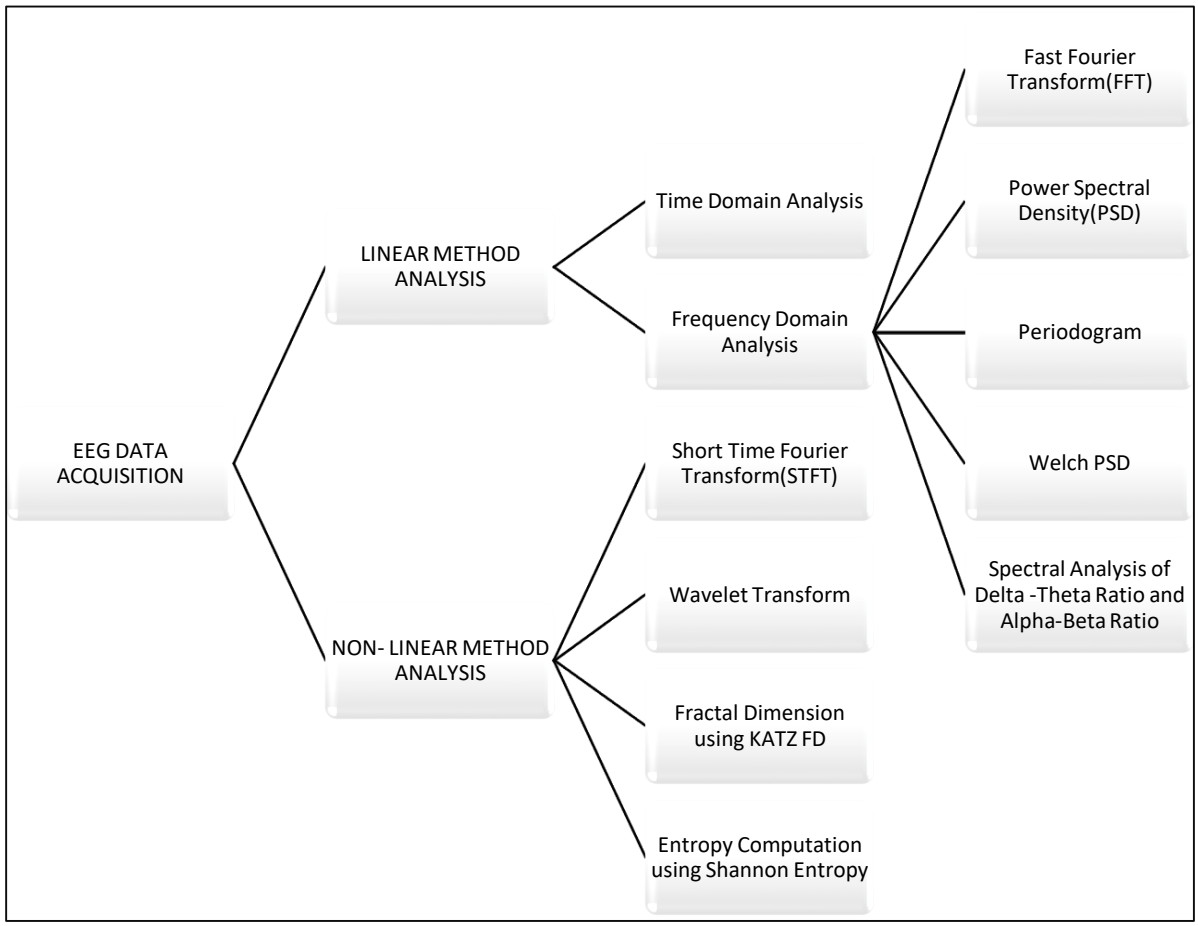


FIG. 4 SPLITTING OF EEG SIGNAL ANALYSIS INTO TWO GROUPS - LINEAR AND NON-LINEAR METHOD ANALYSIS

3.1. EEG DATA ACQUISITION

This experiment was carried out using data from a reputed online source. For this experiment that requires Electroencephalogram(EEG) data, the data was taken from PHYSIOBANK DATABASE[90]. PhysioBank includes a huge collection of physiological data of subjects including clinical and waveform information. It also includes long-term recording that helps us in better analysis of the data.

For this particular experiment, data were taken from the CHB-MIT Scalp EEG Database. This database is contained in the Neuroelectric and Myoelectric Databases. It contains recordings of 22 pediatric epileptic patients. The pediatric patient has intractable epilepsy. Intractable epilepsy means that these patients were given AED(Anti-Epileptic Drugs), to control the seizures, but these drugs failed their purpose. The database is collected from Children's Hospital Boston, where the patients were admitted.

Out Of the 22 subjects, it has the recording of 5 males in the age range of 3 to 22 years and of 17 females, in the age range of 1.5 years to 19 years. Out of all these randomly 8 subjects were chosen, and the features were extracted. In the database, the channels were labeled as Fp1 as Left frontopolar region, Fp2 as the Right frontopolar region, F3 as the Left frontal region, F4 as Right frontal region, C3 as the Left central region, C4 as the Right central region, P3 as the Left parietal region, P4 as Right parietal region, O1 as Left occipital region, O2 as Right occipital region, T3 as Left temporal region, T4 as Right temporal region, F7 as Left lateral frontal region, F8 as Right lateral frontal region, T5 as Left posterior temporal region, T6 as Right posterior temporal region, Pz as Midline parietal region, Cz as Midline central region, Oz as Midline occipital region.

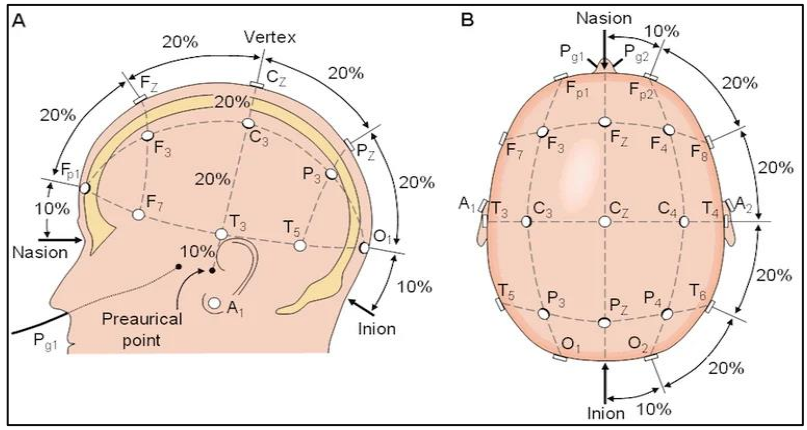


FIG. 5 10-20 ELECTRODE SYSTEM[91]

An organized procedure in EEG that ensures uniform electrode placement across investigations is the 10–20 electrode placement system. The placement of electrodes on the scalp is determined by the percentage of distances between significant head landmarks. In front-back placement, for example, the "10" and "20" indicate the distances between the nasion and inion, and for right-left placement, the distances between preauricular positions. With the use of this method, precise electrode localization about brain areas is made possible, allowing for reliable and accurate EEG recordings for use in clinical and scientific settings.

3.2. SAMPLING FREQUENCY

The recorded data has a sampling frequency of 256 Hz with 16-bit resolution. This information is important in the recording of the EEG signals. A higher sampling frequency in EEG means more details of brain signals are captured and frequent changes are seen more clearly. But, a higher sampling rate also implies more data are present.

According to the Nyquist criterion, noise can be minimized by ensuring that the sampling frequency is at least twice as high as the highest frequency that is present in the signal. The highest possible frequency that may be reliably recorded in an EEG is constrained by the Nyquist frequency, which is half of the sampling frequency.

Nyquist Equation-

$$f_s \geq 2.f_{max}$$

f_s = sampling frequency

f_{max} = maximum frequency component of the signal[92]

Temporal resolution and frequency features are affected by sampling frequency. Elevated levels of sampling improve frequency resolution, aiding the highly accurate detection of EEG components. Additionally, they enhance temporal resolution, making it feasible to precisely recognize rapid variations in neurological signals, such as epileptic spikes.[93]

3.3. TIME DOMAIN ANALYSIS

In Time domain analysis, the EEG signals from the 8 subjects are downloaded and plotted against time in seconds.

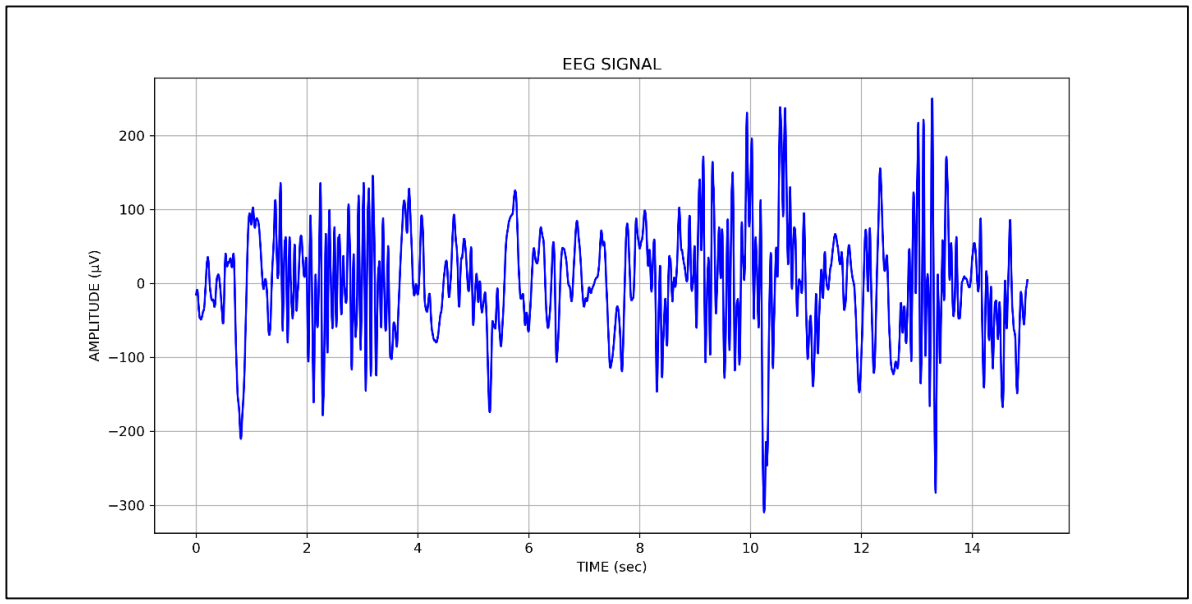


FIG. 6 TIME DOMAIN ANALYSIS OF EEG SIGNAL

3.4. FREQUENCY DOMAIN ANALYSIS

For the Frequency domain analysis, the EEG signal collected from 8 subjects was downloaded. This was done to observe the following changes. In the table below the different methods used for the analysis of the EEG Signal are given.

Table 1 FREQUENCY DOMAIN ANALYSIS TECHNIQUES USED

METHOD	DOMAIN	DESCRIPTION
FFT	Frequency Domain	Efficiently computes the DFT, transforming time-domain signal to the frequency domain.
Periodogram	Frequency Domain	Estimates PSD by squaring the magnitude of the FFT.
PSD	Frequency Domain	Describes power distribution over frequency.
Welch's Method	Frequency Domain	Estimates PSD by averaging periodograms of overlapping segments.
STFT	Time-Frequency Domain	Analyzes frequency content over time by computing Fourier Transform on short segments.
Wavelet Transform	Time-Frequency Domain	Decomposes signal into components at different scales using wavelets.
Bandpower Spectral Analysis	Time-Frequency Domain	Measures power within a specific frequency band from the PSD.

EEG signals show predictable electrical patterns in the brain known as neural oscillations. Neural oscillations allow different parts of the brain to interact with each other and coordinate brain activity. Identifying how these oscillations interact through frequency domain analysis provides insights into how the brain works during seizure activities.

EEG frequency bands of Alpha, Beta, Delta, Theta, and Gamma reveal variability in the dynamics and processes of the brain. Whereas beta waves indicate high alert requiring activity, alpha waves signify a state of calmness. How these bands interact to regulate neuronal activity and brain behavior can be understood by frequency domain analysis.

Based on EEG research, neural rhythms have an integral part in neurological diseases. To better comprehend how oscillations promote synaptic remodeling and the creation of abnormalities, frequency-specific EEG changes are analyzed before, after, and during seizure activities.

Complex networks of neurons are dependent on neural oscillation. By assessing neural space coherence, synchronization, and connection, frequency domain study exposes network dynamics. Deciphering the brain systems underlying cognition and behavior depends on this understanding.[51], [94], [95]

Following is how the EEG signals were analyzed in the frequency domain.

3.4.1. FFT(FAST FOURIER TRANSFORM)

Signals and data in the frequency domain are efficiently analyzed computationally using the Fast Fourier Transform (FFT). It is based on the Discrete Fourier Transform (DFT), which separates a signal or function into its frequency components from its temporal or spatial domain. This is to obtain important insights into the signal's underlying frequencies.[52]

FFT makes sure to quickly carry out this transition. [52] Conventional techniques for computing the DFT have an $O(N^2)$ computational complexity, where N is the total number of data points. Nevertheless, its complexity is greatly reduced to $O(N \log N)$ using FFT techniques, which makes it considerably quicker and more beneficial for real-world applications.[53]

The algorithm commonly used behind FFT computation is the Cooley-Tukey method, which was developed in 1965 by J.W. Cooley and J.W. Tukey.

3.4.1.A. COOLEY-TUKEY METHOD:

For computing the FFT, the Cooley-Tukey method uses a divide-and-conquer strategy.

The DFT computation is iteratively broken down into smaller components by making use of the periodicity and symmetry of sinusoidal functions.

The approach attains a computational complexity of $O(N \log N)$, where *N* is the number of data points, by breaking the issue down into smaller parts.

The Discrete Fourier Transform (DFT) yields the formula for the Fast Fourier Transform (FFT), which describes a series of complex integers as the sum of complex exponential functions: $x_0, x_1 \ldots\ldots x_{N-1}$. The definition of a DFT of length *N* is:

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i\frac{2\pi}{N}k_n}$$

Where,

- X_k is the k-th frequency component of the signal in the frequency domain.
- x_n is the n-th sample of the signal in the time domain.
- k_n ranges from 0 to N-1, representing the frequencies at which the signal is analyzed.
- $e^{-i\frac{2\pi}{N}k_n}$ is the complex exponential function representing the sinusoidal waveform at frequency k. [96], [97], [98], [99], [100], [101]

3.4.2. POWER SPECTRAL DENSITY

Power Spectral Density (PSD) in signal analysis shows how a signal's power is expressed across various frequencies. It measures a signal's power or intensity at every single frequency component.

PSD analysis is used in this research to examine Electroencephalograph(EEG).The need for this feature extraction method for PSD estimation, feature extraction, and pattern identification.

The PSD shows how a signal's power, or energy, is distributed over each frequency unit.

$$P = \int_{-\infty}^{\infty} S_x(f)df$$

In mathematics, it is commonly represented as $S(f)$, where f is the frequency, and $S_x(f)$ is the PSD of the signal $x(t)$.

The PSD calculates a signal's power distribution over the spectrum range, revealing the frequencies that contribute most to the signal's total power. While studying the PSD, the understanding of which frequencies are dominant over which phases of seizure, gives us insight on which waves are more activated in that phase. Sudden outbursts of some waves are sometimes seen. These are the unpredictability that need thorough research.

Units of PSD: The PSD's units are determined by the units of the signal under study. For instance, the PSD would use units of volts squared per Hertz (V2/Hz) if the signal was in volts.To offer a logarithmic scale for simpler comprehension, the PSD is frequently given in decibels (dB) in practical applications.

There are several methods for estimating the PSD, such as Welch's method and Periodogram. The PSD techniques split the signal into segments, calculating the Fourier transform individually for each segment, and then averaging the power spectra, and then normalizing it.

PSD measures the distribution of signal power

$P = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} |x_T(t)|^2 dt = \int_{-\infty}^{\infty} S_x(f)df$ over frequency domain.

Here,

P = total power of the signal

$x_T(T)$ = time-limited version of the signal $x(t)$, truncated to a window of duration $2T$.

$|x_T(t)|^2$ = instantaneous power of the signal at the time t

$\frac{1}{2T}$ = normalizes the integral over the time window of length $2T$

T = approaches infinity, this expression gives the average power of the signal over all time.

Properties of PSD :

- $S_x(f) \geq 0$
- $S_x(-f) = S_x(f)$

[102], [103], [104], [105], [106]

3.4.3. PERIODOGRAM

A periodogram representation is a way of the PSD whose visual presentation helped us identify the dominant frequencies for EEG classification. [57], [70], [107]

From our understanding, the Periodogram is computed as follows,

In the first step, a discrete-time signal is obtained. Then the signal is frequently amplified by a window function before generating the periodogram. This reduces the spectral leakage. Then windowed signal's DFT is computed to convert the time domain to the frequency domain.

Then the DFT's magnitude is squared to obtain squared amplitude. This squared amplitude is normalized by dividing by the signal's length or by a scaling factor. The periodogram's x-axis shows frequency, which is often defined as cycles per sample or units of time. Each frequency's power is shown on the y-axis. The prominent frequencies in the signal are shown as peaks in the periodogram. The relative power or energy present at certain frequencies is shown by the height of these peaks.

A smoother representation is done for continuous data, even if the periodogram by itself can approximate the power spectrum. This can be achieved by averaging many periodograms or by using techniques like Welch's method, which produces a smoother estimate of the PSD.

FORMULA

The formula for the periodogram $P_{xx}(k)$ of a signal $x(n)$of length N is:

$$P_{xx}(k) = \frac{1}{N} |X[k]|^2$$

Where where $X[k]$ is the Discrete Fourier Transform (DFT) of the signal $x(n)$]

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

Here, k represents the frequency bin index, and the DFT converts the time-domain signal $x(n)$into its frequency components $X[k]$. [57], [58], [70], [107]

3.4.4. WELCH PSD METHOD

Welch PSD techniques are used to determine the PSD of a signal by averaging customized periodograms. This method helps us by reducing the variance of the estimate by dividing the signal into overlapping or non-overlapping portions and computing periodograms for each segment. This is very helpful for handling non-stationary signals. The noise is then reduced by averaging. Welch PSD gives choices between variance reduction and frequency resolution by providing control over parameters like the overlap and segment length. While shorter segments offer lower frequency resolution but reduce variation, longer segments offer better frequency resolution but may result in increased variance. Welch's technique is more resilient to non-stationarities because it computes several periodograms spanning various signal segments, giving it insights into how the signal's spectral content varies over time. Welch's method works well for instantaneous mode or scarce resources applications since its computing complexity is often lower than that of other methods for calculating the PSD. [54], [55], [70], [107]

$$P_{x(f)} = |X(f)|^2$$

where, $P_{x(f)}$ is the periodogram, $|X(f)|$ is the Fourier Transform of the signal.

$$P_{welch(f)} = \frac{1}{M}\sum_{k=1}^{M} P_{x_k}(f)$$

Where $P_{welch\,(f)}$ is the Welch PSD estimate, $P_{x_{(k)}}(f)$ is the periodogram of the kth segment, and M is the total no. of segments. [105], [108], [109], [110]

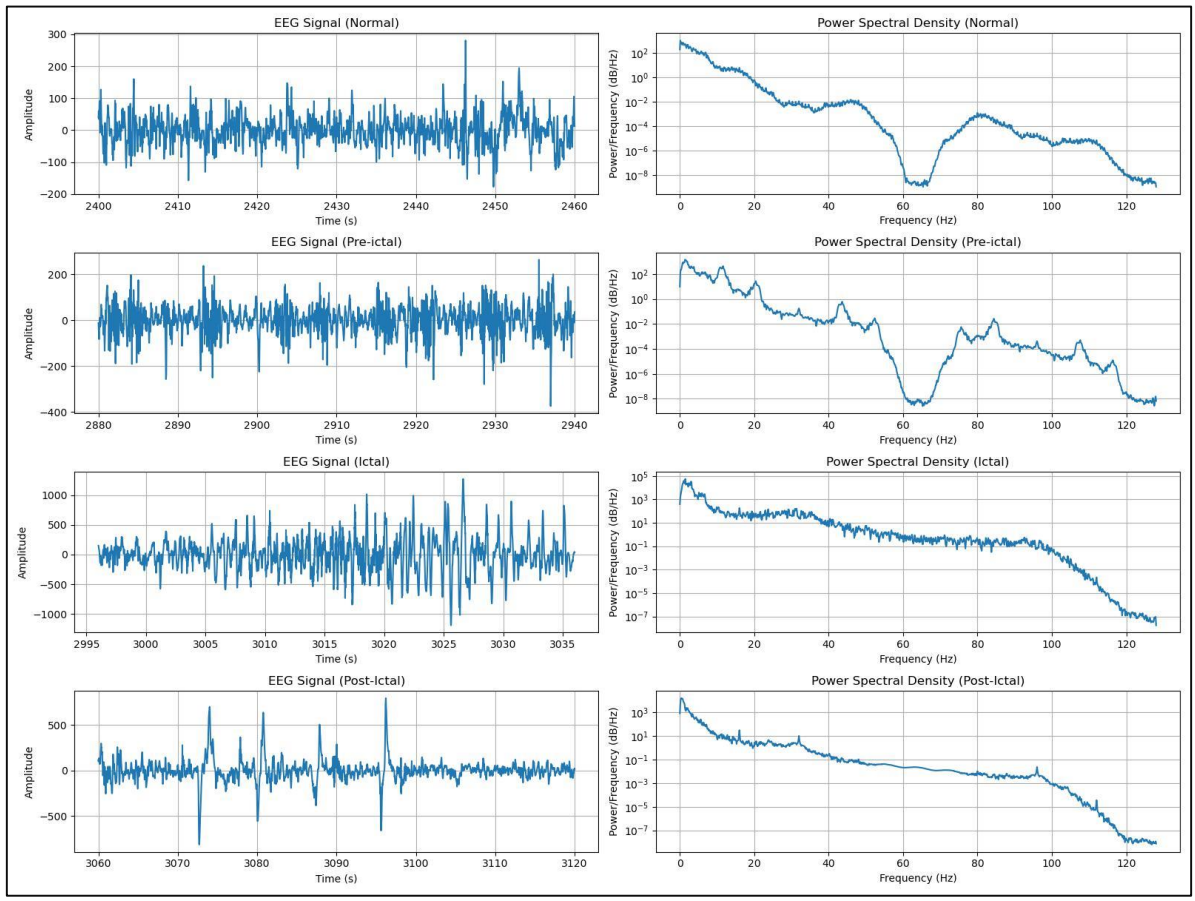


FIG. 7 EEG SIGNAL AND THEIR RESPECTIVE PSD IN VARIOUS PHASES

3.5.TIME-FREQUENCY DOMAIN

The main information obtained via Welch's approach is the frequency content of a signal. When used with time-domain analysis approaches, Welch's method provides indirect insights into the time-frequency properties of a signal, even if it does not directly provide time-domain information.

The time-frequency information is extracted from signals using Welch's approach in conjunction with time-domain analysis techniques, even if the method itself primarily gives frequency-domain information.

When compared to methods that just concentrate on one domain, methods that combine time and frequency information offer an in-depth understanding of a signal's behavior. Few explanations behind this:

- Detailed Analysis: Time-varying frequency features such as spectrograms, wavelet transforms, and the Short-Time Fourier Transform (STFT), provide a more thorough investigation of the signal's temporal evolution and frequency content changes.
- Segmentation of Events: Events can be localized in the frequency and time domains using time-frequency analysis techniques. This enables us to identify the precise moment at which a given frequency component appears in the signal, giving significant information about brief occurrences or spectral character alterations.
- Features of Dynamic Events: The statistical characteristics of many real-world signals are dynamic and non-stationary, meaning they fluctuate with time. Techniques that treat signals as stationary are incapable of capturing these changes than those that combine time and frequency information.
- Better Resolution: Compared to evaluating each domain alone, these techniques can provide greater clarity in terms of both time and frequency through the integration of data from both domains. This is especially helpful when working with signals that have several overlapping frequency components or when exact event localization is needed.
- Improved Interpretability: Time-frequency integrated visualization methods, such as spectrograms or scalograms, offer comprehensible depictions of signal properties. These graphical tools can make it easier to identify important details and help in the interpretation of complicated data.[51], [111]

3.5.1.SHORT-TIME FOURIER TRANSFORM

An approach used for time-frequency analysis of signals is the Short-Time Fourier Transform (STFT), which makes it easier to examine the way the frequency components of a signal change with time. This approach divides the signal into brief, often overlapping segments and reduces spectral loss by applying a window function to each segment. The STFT then uses these windowed segments to carry out the Fourier transform, which generates a localized frequency representation for every time segment.

The final result is often displayed as a spectrogram, a representation of a matrix with two dimensions, with the vertical plane representing frequency and the horizontal plane representing time. Each point's magnitude indicates the signal's strength or amplitude at that particular frequency and time. The degree of overlap between segments and the window

function selection are important factors that affect the time-frequency representation's resolution and accuracy.[59]

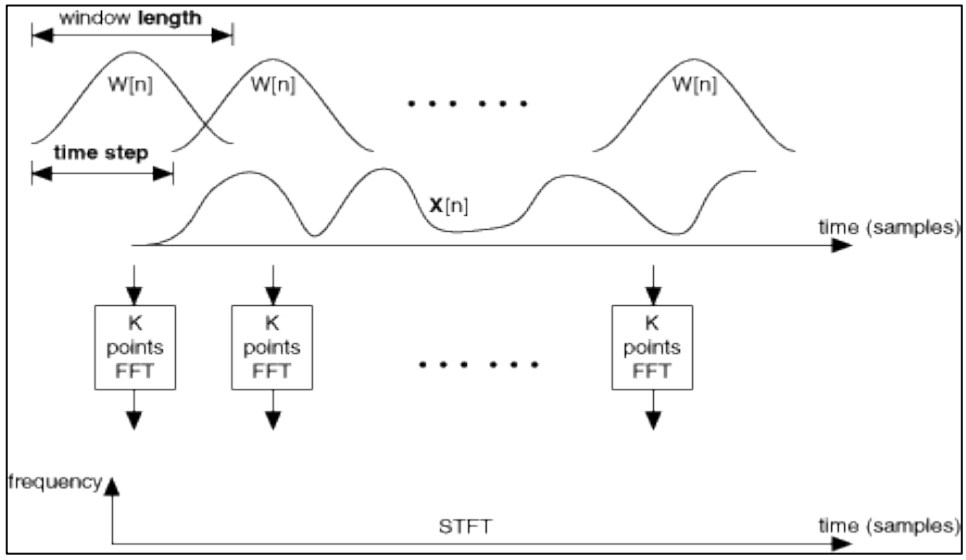


FIG. 8 SHORT-TIME FOURIER TRANSFORM[112]

The formula for STFT of a discreet time signal $x_{[n]}$ is given by

$$STFT\{x_{[n]}\}(m,\omega) = X(m,\omega) = \sum_{n=-\infty}^{\infty} x_{[n]}\, \omega[n-m] e^{-jwn}$$

$x_{[n]}$ = Discreet time signal

$\omega[n-m]$ = a window function, which is centered around $[n=m]$. This window function is typically a short-duration window that slides along the signal.

m = the time shift, indicating the center of the window at a specific point in time.

ω = is the angular frequency variable

$X(m,\omega)$ = represents the STFT, which is a function of both time shift m and frequency ω. [59]

3.5.2. WAVELET TRANSFORM

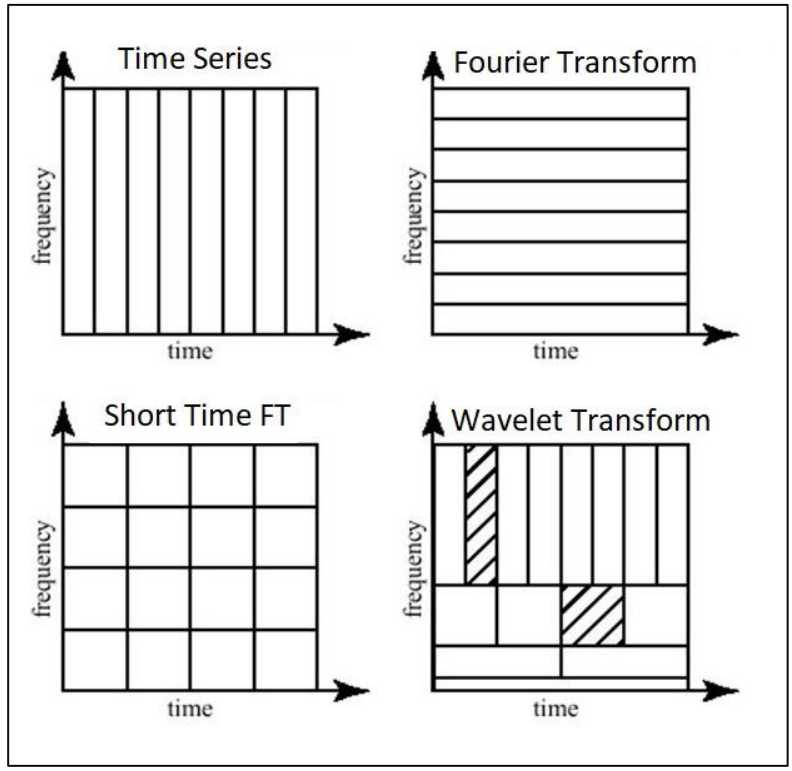


FIG. 9 COMPARISON AMONG TIME DOMAIN, FREQUENCY DOMAIN, STFT AND WAVELET TRANSFORM[113]

A signal can be broken down into wavelets—small, time- and frequency-localized waves—by the wavelet transform. Because of its localization, the wavelet transform can give a thorough time-frequency analysis that captures both the signal's stationary and transient characteristics.

1. Time- Frequency localization
    a. Wavelet Transform analyzes transient events easily by capturing both the time and frequency information.
    b. With WT, it can be easily identified which frequency components are occurring in which time.
2. Multi-Resolution Analysis
    a. Scales – scales in wavelet show how much compression or dilation has been applied to the mother wavelet

        Low scale –

        i. Compressed wavelet – wavelet is highly compressed or narrow in time
        ii. High frequency – since the wavelet is narrow it can capture rapid changes
        iii. Fine detail – sensitive to fine details and transient features such as spikes, sharp transitions, and other rapid variations.

High scale –

i. Dilated wavelet – wavelet stretched or wide in time.
ii. Low frequency – wider wavelet captures slower or more gradual changes
iii. Coarse detail – sensitive to overall trends and long-term behavior such as baseline shift and slow oscillations. [76], [77]

b. Hierarchical decomposition - decomposing a signal into various levels of detail facilitates studying the signal's specific characteristics as well as its general patterns.

Time-series data such as in EEG is complex and contains information at various scales and resolutions. This decomposition method represents signals in terms of their respective component at different levels of detail. [60]

Level Of Decomposition –

There are mainly two levels of decomposition -

- *Approximate Coefficient* (low-frequency components)-

These represent the signal's coarsest scale or smoothed form. They record the signal's low-frequency components or the general trend.

- *Detailed Coefficient* (high-frequency components)-

These stand for the remaining or finer features of the signal that the approximations cannot capture. They line up with the signal's high-frequency elements or abrupt shifts.

Mathematical framework

This hierarchical decomposition is achieved using DWT and CWT.

In DWT, the signal is successively decomposed by applying a series of High Pass(detail) and low-pass (approximations) filters.[60]Then the signal is downsampled to extract the different levels of detail. Each level of decomposition results in a set of approximations coefficient and detail coefficient. These are further used for signal compression and denoising.

Daubechies 6 level 6 was chosen. Db6 effectively captures both high and low frequencies.The thresholds were set manually for all the subjects. This ensures precision and accuracy.

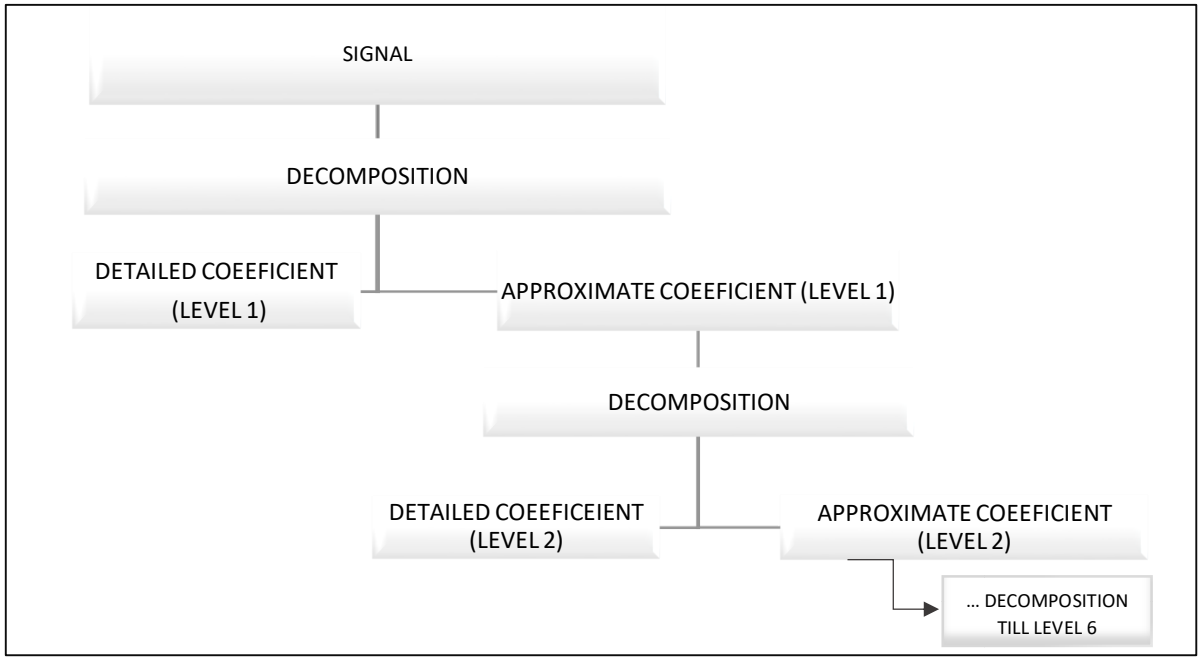


FIG. 10 WAVELET TREE REPRESENTATION-DECOMPOSITION WAS DONE TILL LEVEL 6.

Wavelet Tree plot - The wavelet tree is plotted to visualize the hierarchical decomposition of the signal into different frequency bands.

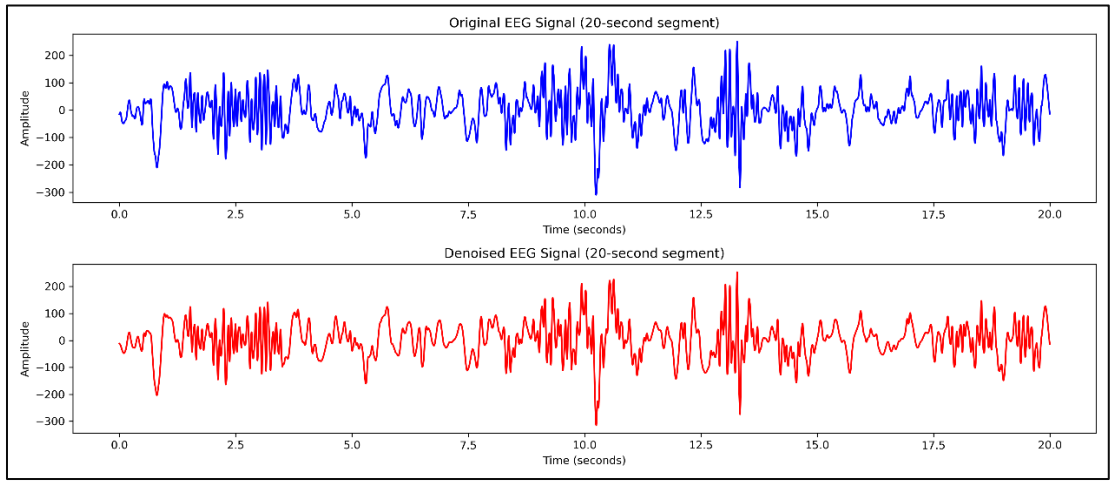


FIG. 11 ORIGINAL AND DENOISED EEG SIGNAL

Denoising -Plot

The above figure shows the original EEG signal in blue and the denoised EEG signal in red. The denoised signal is free from any artifact. This way the DWT provides a structured approach to understanding signal dynamics. So, the EEG signal was denoised using wavelet transform of Daubechies 6, level 6, and then the feature extraction methods were applied.

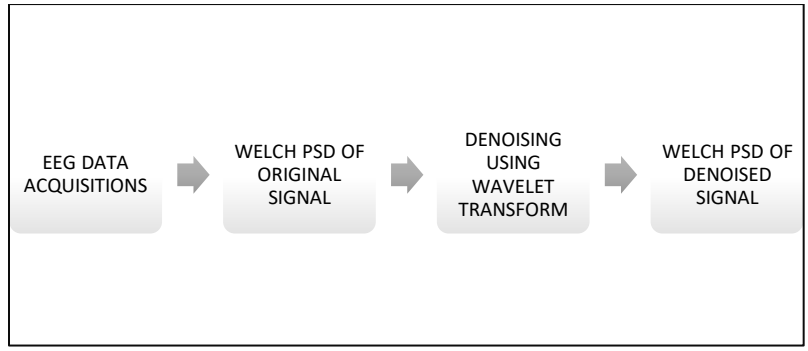


FIG. 12 ANALYSIS OF THE DENOISED EEG SIGNAL USING WELCH PSD

The EEG signal was analysis Using Welch PSD, before and after wavelet denoising. This was done to extract information on the power of the signal still present after denoising.

3.6.FEATURE EXTRACTION

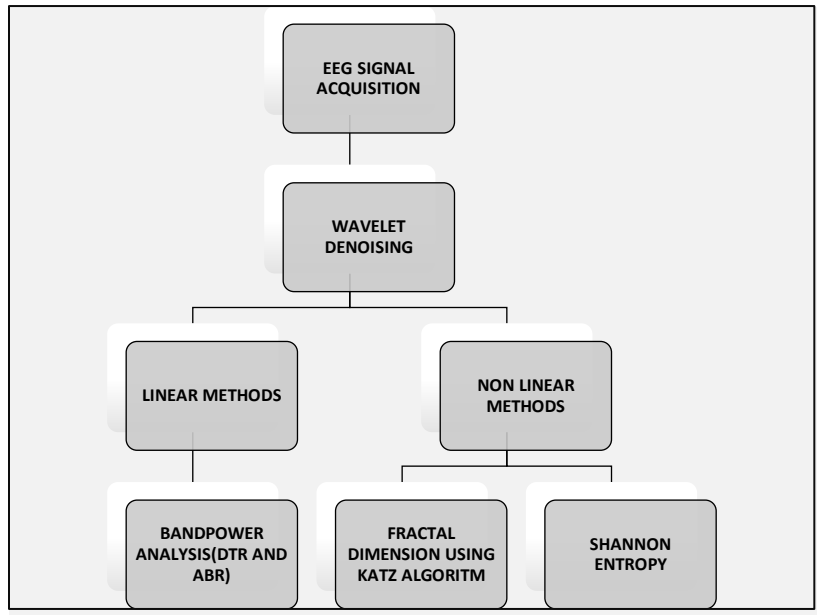


FIG. 13 FEATURE EXTRACTION USING LINEAR AND NON-LINEAR METHODS

The feature extraction was done after preprocessing methods of wavelet transform, for denoising the acquired signal. The features were extracted and studied with the help of 4 methods, 2 linear and 2 non-linear. These methods were found to be the most appropriate for studying the neural dynamic that takes place in the brain of an epileptic patient.

3.6.1. LINEAR METHOD

3.6.1.A. ALPHA – BETA RATIO(ABR)

This process was started with EEG data that had been denoised (noise and artifacts removed using wavelet transform). The band power for the Alpha (8–12 Hz) and Beta (12–30 Hz) frequency bands were calculated after denoising. To find the power in each band was accomplished by calculating the Power Spectral Density (PSD) and integrating it over the appropriate frequency ranges. The deviation from normal to pre-ictal, ictal, and post-ictal was then investigated by computing the alpha-beta ratio for each subject. The intention behind calculating these was to check the domination of a specific waveform over the other band. Alpha and Beta, both are fast waves but both relate to different activities. The changes in power ratio are a reflection of seizure onset or offset. A shift from the alpha to beta power, i.e. alpha power is diminishing and beta power increases, indicates that the brain is shifting to a more stressed or alert stage from a relaxed stage. These changes if present, will be seen mostly in a shift from normal to pre-ictal, and in the ictal stage, this change will be more prominent. In the post-ictal stage, as expectedly the alpha power increases, as the seizure is less evident.

3.6.1.B. DELTA THETA RATIO(DTR)

This process was started with EEG data that had been denoised (noise and artifacts removed using wavelet transform). The band power for the Delta (0.5–4 Hz) and Theta (4–8 Hz) frequency bands were calculated after denoising. To find the power in each band was accomplished by calculating the Power Spectral Density (PSD) and integrating it over the appropriate frequency ranges. The deviation from normal to pre-ictal, ictal, and post-ictal was then investigated by computing the delta-theta ratio for each subject. The increased delta-theta ratio represents slow-wave activity. The location of these activities gives insights into the seizure origination sight. In kids, these delta-theta activities are usually high, which represents a higher delta power than theta power. But, if this activity is still observed in adulthood, then that is a reflection of focal epilepsy or other neurological abnormalities. A higher delta-theta ratio is associated with impaired brain activities. A brain lobe mostly generating 0.5-4 Hz of frequency most times is not considered normal. These activities are usually seen in long-term epilepsy, intractable seizures, and frequent seizures.

3.6.2.NON-LINEAR METHOD

3.6.2.A. SHANNON ENTROPY

Entropy is a measure of the randomness and uncertainty of a signal. The higher the entropy, the more complex the signal is. More complex means a more chaotic system and therefore the predictability decreases.

Shannon entropy is also called information entropy. It is a non-linear measure quantifying the degree of complexity in a signal.

Claude Shannon in 1948 published a paper "A Mathematical Theory of Communication". This paper was published in the 'Bell System Technical Journal". This paper introduced the concept of Shannon entropy, which determines the uncertainty in a message.

According to Claude Shannon,

When X is a set of decreet EEG signal variables.

$X = \{ x_1, x_2, \ldots\ldots, x_n \}\,;\; x_i \epsilon R^d$

Now, the Shannon entropy is defined as :

$$\text{SE} = -\sum_{i=1}^{n} p(x_i) \ln p\,(x_i)$$

where $p(x_i)$ is the probability of $x_i \in X$ satisfying $\sum_{i=1}^{n} p(x_i) = 1$.[114]

Shannon entropy analysis of EEG signals helps us understand the electrical activity of the brain. These provide us with information such as the

- The Brain waves, Alpha (α), Beta(β), Delta(δ), Theta (θ), Gamma(γ). The amplitude and frequency of these waves give us insights into the brain's state and function
- Normal and abnormal brain
- Presence of tumors, head injuries, brain damage, sleep disorders
- Neurodegenerative diseases such as Alzheimer, Epilepsy, Parkinson, etc.

ShE gives all this information from an EEG signal about the brain state. But after that, some other methods are needed to study the pattern. These pattern recognition methods help in designing algorithms for automated identification.

ShE quantifies the unpredictability and randomness in the EEG signal. It gives us a value of the signal complexity. The more complex a signal is, the less predictable it becomes and it has a higher entropy. So, the lesser entropy often signifies a less complex signal and more predictable system.

Normal Phase – EEG signals in a healthy brain have high entropy because of the complex and diverse neural activity present. The brain's capacity to process a wide variety of information and respond adaptively to events is reflected in its high entropy, which is a result of its varied and unsynchronized firing patterns. Normal brain function is characterized by considerable diversity and unpredictability, in contrast to seizures, when neuronal activity becomes coordinated and predictable (low entropy). The increased entropy during normal activity contrasts sharply with the decreased entropy observed during the pre-ictal and ictal phases. Interictal Phase (in between seizures), EEG findings show increased entropy, suggesting more complex and diverse electrical activity, while brain activity is generally normal.

Pre-ictal Phase (Before a seizure): The brain becomes less arbitrarily engaged and more regulated as the seizure approaches closer. As a result, entropy begins to decrease as electrical activity gets more coordinated.

Ictal Phase(during a seizure): In this stage of a seizure the peak of neuronal firing synchronization occurs during the actual seizure. Entropy significantly decreases as a result of the EEG signals being extremely regular and predictable.

Post-ictal Phase(after a seizure): Following a seizure, the brain progressively reverts to its normal state. The entropy rises to pre-seizure levels, and the EEG signals resume their complexity and unpredictability.

Table 2 SHANNON ENTROPY PROPERTIES FOR EACH PHASE

PHASE	ENTROPY	COMPLEXITY	PREDICTABILITY
Normal	High	High	Low
Pre-ictal	Low	Low	High
Seizure	Low	Low	High
Post-ictal	High	High	Low

The following are the Steps involved

- Loading the EEG data from CSV files.
- Defining segment ranges and labels.
- Iterating over each file and segment to calculate Shannon Entropy.
- Plotting the results with appropriate labels, titles, and annotations.

3.6.2.B. KATZ FRACTAL DIMENSIONS

Fractals are signals that show self-similarity and complexity at several scales in signal processing. Fractal geometry techniques can be used to these signals to extract useful information about their underlying dynamics and structures. Signals with fractal characteristics frequently point to intricate, non-linear processes that are difficult for conventional linear techniques to fully understand.

Properties of Fractals :

Self-Similarity: At various time scales or resolutions, the signal displays identical patterns. Long-Range Dependence: The signal exhibits correlations over extended time intervals, indicating that its activity at one point in time is connected to its behavior at a different, distant time.

Non-Integer Dimensions: Using a fractal dimension, which is typically a non-integer value, can be used to quantify the signal's complexity.

Leonard Katz

The main area of interest for Leonard Katz's research was the analysis of complex signals, especially those coming from biological systems, using fractal geometry. His treatment of fractal dimension, best shown by the Katz fractal dimension, provided an easy way to measure signal complexity, making it useful for a wide range of applications, such as signal processing in healthcare.

Analyzing brain wave patterns can reveal fractal features that help explain brain function and identify neurological conditions like epilepsy.

By analyzing the relationship between the curve's length and the distance it covers, the Katz fractal dimension (KFD) is used to quantify the complexity of a discrete curve. Katz's fractal dimension may be calculated as follows:

$$D = \log(N) / \log(N) + \log\left(d/L\right)$$

where:

- N is the total number of points in the curve.
- d is the diameter of the curve, which is the distance between the first and the farthest point on the curve.
- L is the total length of the curve.[115]

Katz's FD here is utilized to examine the electroencephalograms (EEGs). When KFD is computed, the complexity of these signals identified shows typical and unusual patterns.

Katz's fractal dimension has been utilized to investigate the dynamics of numerous biological processes, yielding information about their underlying mechanisms.

Katz's approach is a common choice for signal processing applications that need a comprehension of a signal's complexity and unpredictability. It is simple and effective.

Formula :

Considering a simple time series or curve defined by points (x_i, y_i) for $i = 1, 2, \ldots\ldots, N$.

The steps to calculate the Katz fractal dimension are as follows:

Calculate ***L***: Compute the total length of the curve by summing the Euclidean distances between consecutive points.

$$L = \sum_{i=1}^{N-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}$$

Calculate ***d***: Determine the diameter d of the curve, which is the maximum distance from the first point to any other point on the curve.

$$d = max\{\sqrt{(x_i - x_1)^2 + (y_i - y_1)^2} \mid i = 1, 2, \ldots, N\}$$

Compute the Katz Fractal Dimension ***D***:

$$D = \log(N) / (\log(N) + \log(d/L))$$

The Katz fractal dimension provides a single numerical value that captures the complexity of the signal, with higher values indicating more complexity. [87], [88], [89], [115]

The following are the Steps involved:

- Loading the EEG data from CSV files.
- Defining segment ranges and labels.
- Iterating over each file and segment to calculate Katz Fractal Dimension.
- Plotting the results with appropriate labels, titles, and annotations.

3.7.SOFTWARE AND TOOLS

Programming Language: Python 3.11.7 was used for all calculations.

Libraries and Packages: pandas, numpy, and matplotlib.pyplot and SciPy.fft were used for numerical computations.

Hardware: Calculations were performed on a standard desktop computer with an Intel i7 processor and 16GB RAM.

RESULTS

> *Knowing is not enough; we must apply. Willing is not enough; must do.*
>
> *- Bruce Lee*

4.1.BANDPOWER CALCULATION OF DELTA-THETA RATIO

4.1.1. DTR VARIATION OF ALL SUBJECTS

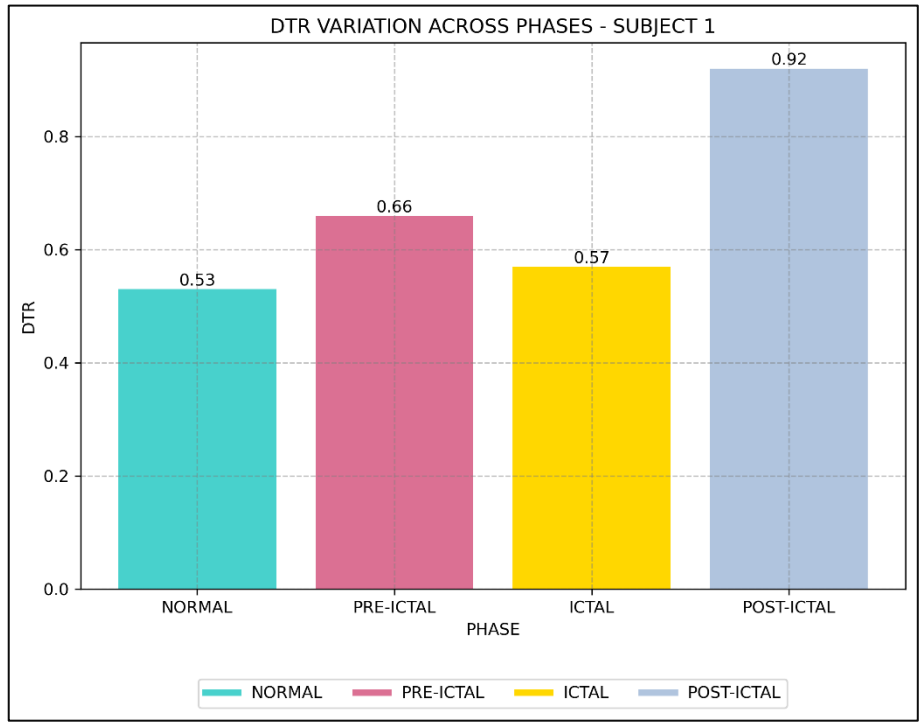


FIG. 14 DTR VARIATION OF SUBJECT 1

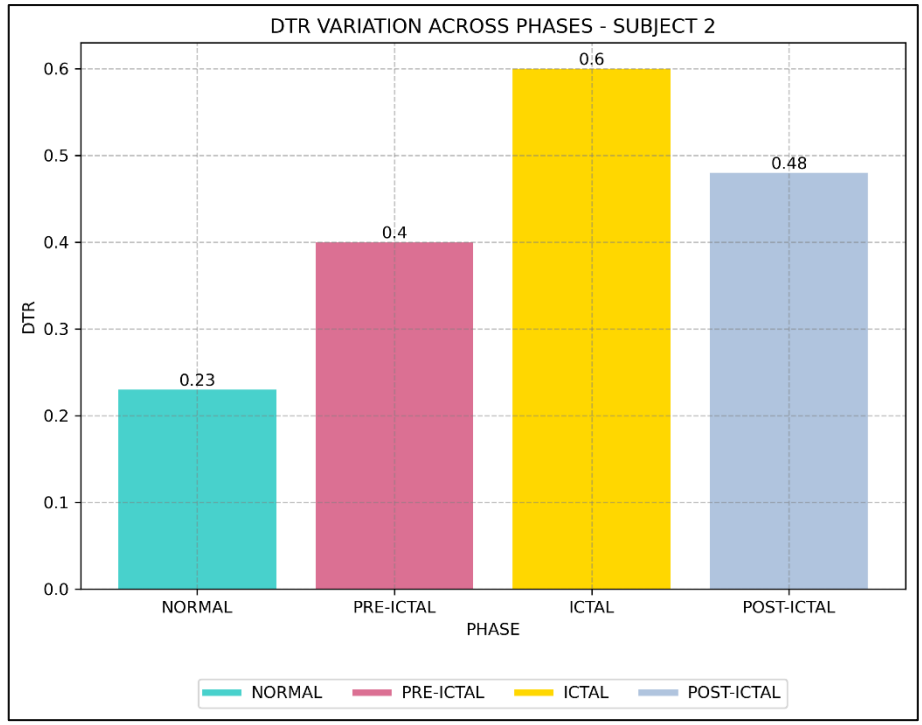


FIG. 15 DTR VARIATION OF SUBJECT 2

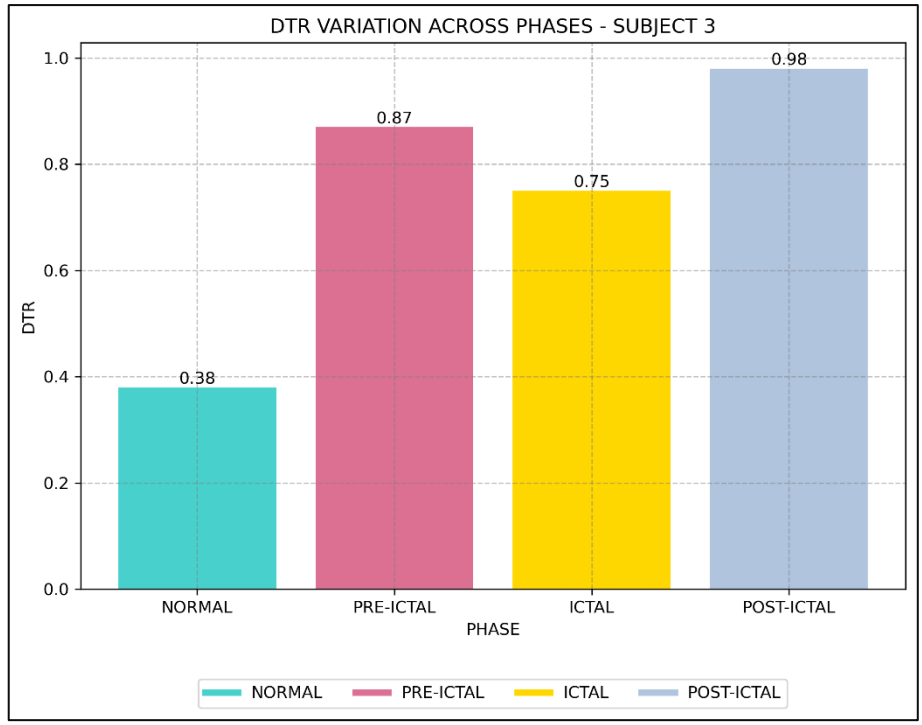


FIG. 16 DTR VARIATION OF SUBJECT 3

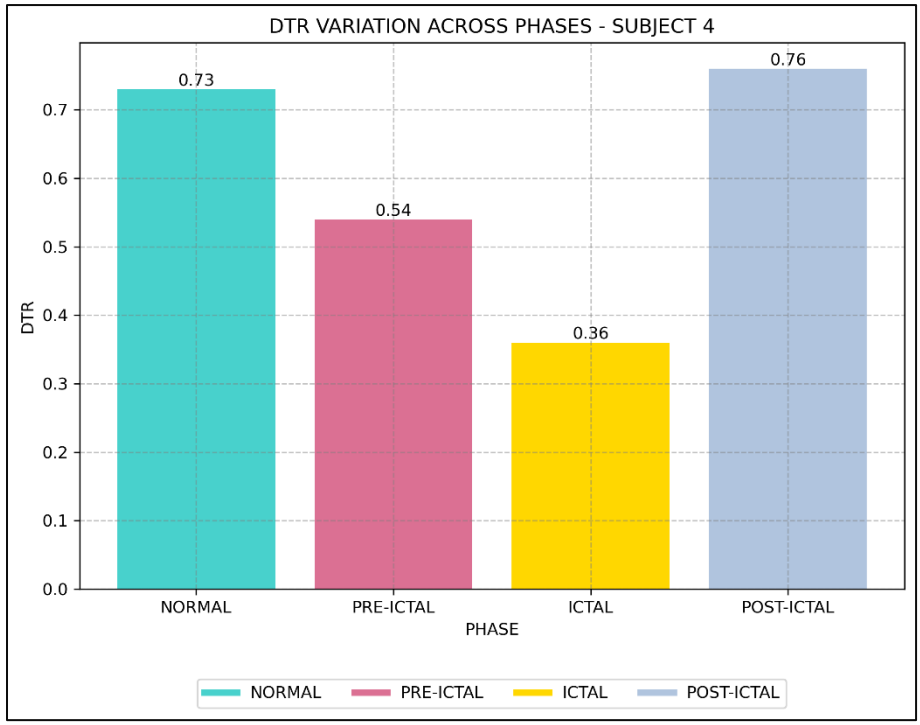


FIG. 17 DTR VARIATION OF SUBJECT 4

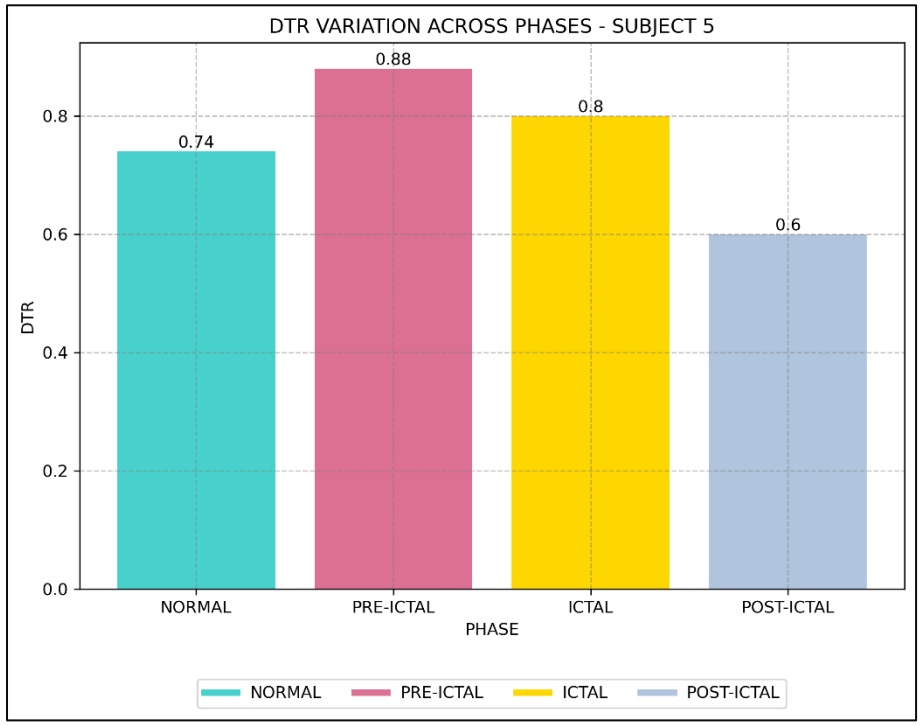


FIG. 18 DTR VARIATION OF SUBJECT 5

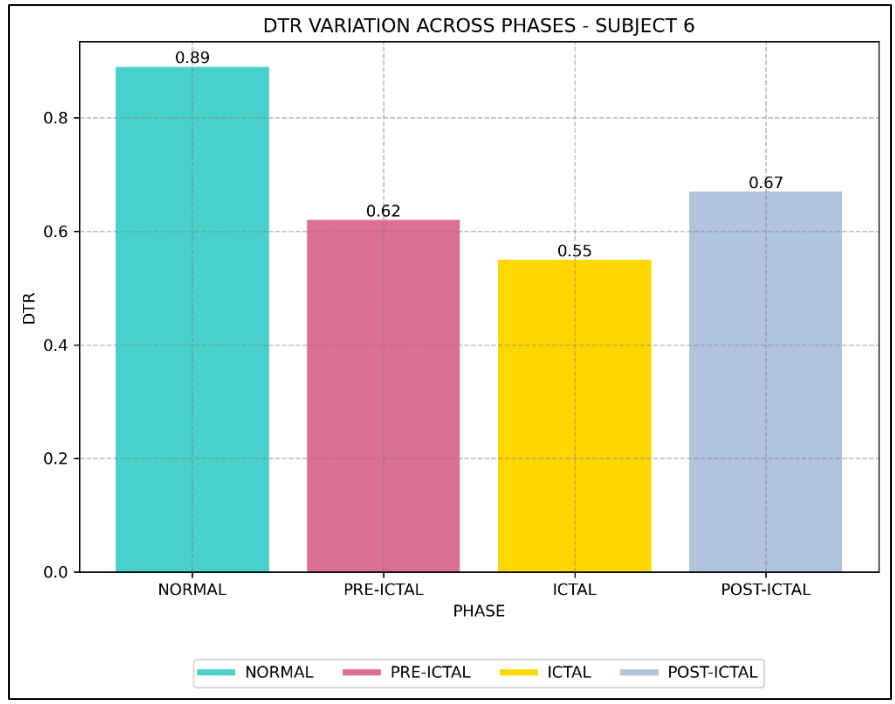


FIG. 19 DTR VARIATION OF SUBJECT 6

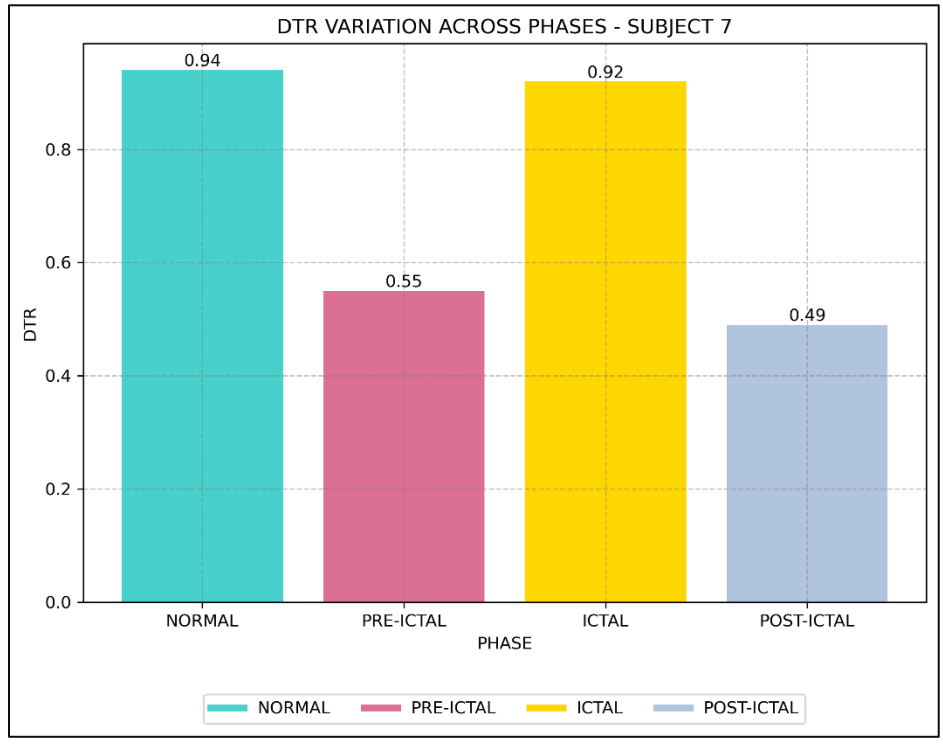


FIG. 20 DTR VARIATION OF SUBJECT 7

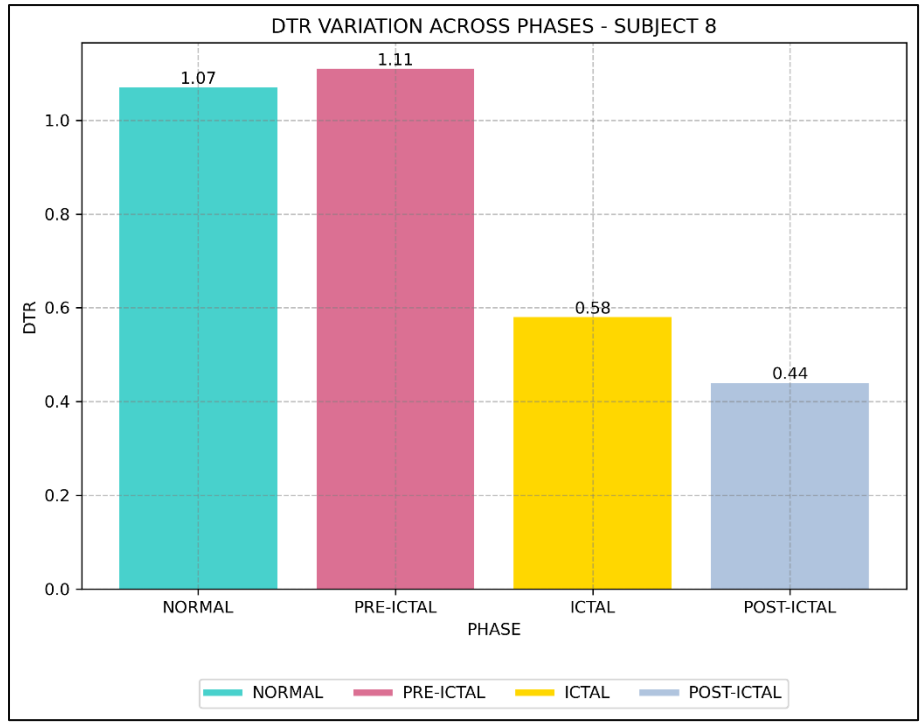


FIG. 21 DTR VARIATION OF SUBJECT 8

4.1.2. DTR VARIATION OF NORMAL TO PRE-ICTAL

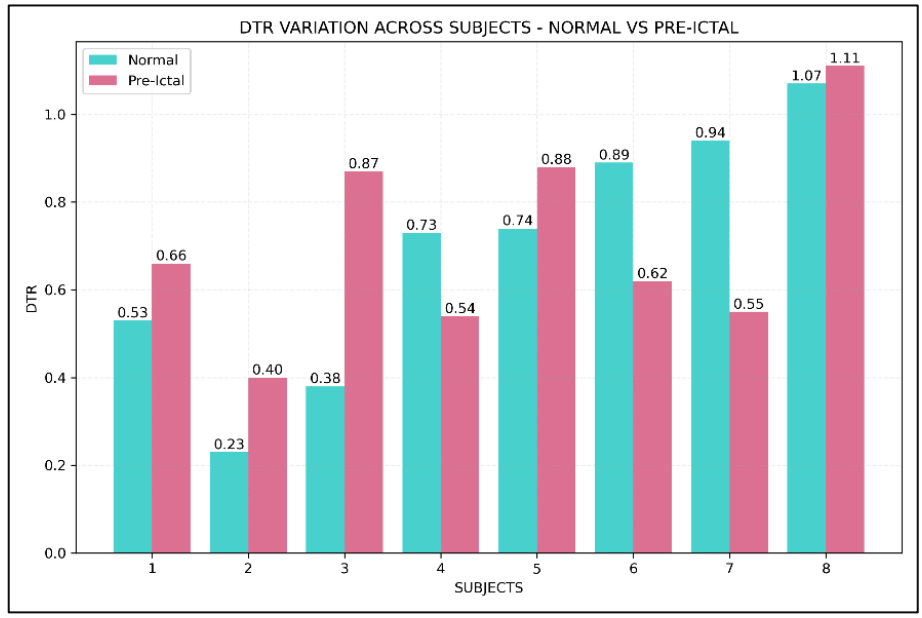


FIG. 22 DTR VARIATION OF NORMAL TO PRE-ICTAL PHASE OF ALL SUBJECT

4.1.3. DTR VARIATION OF NORMAL TO ICTAL

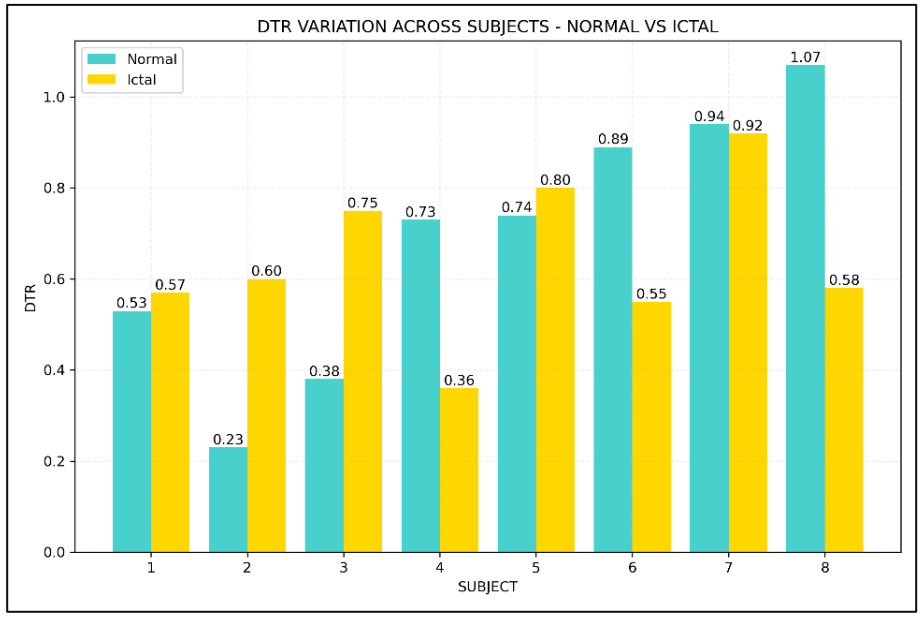


FIG. 23 DTR VARIATION OF NORMAL TO ICTAL PHASE OF ALL SUBJECT

4.1.4. DTR VARIATION OF NORMAL TO POST-ICTAL

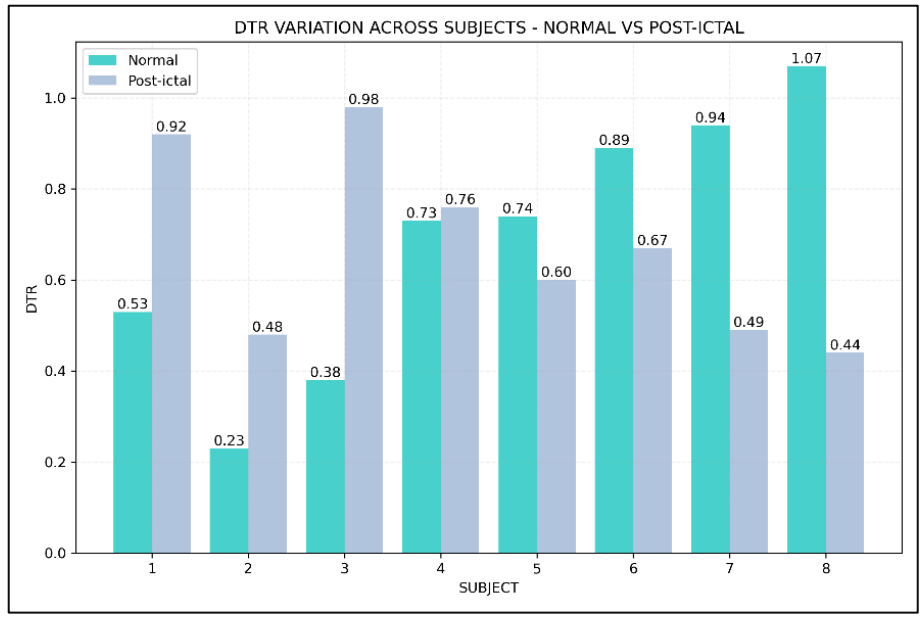


FIG. 24 DTR VARIATION OF NORMAL TO POST-ICTAL PHASE OF ALL SUBJECT

Observations from the DTR Variations Across All Subjects

- Subject 1
  - The DTR value starts at 0.53 in the normal phase.

- It increases to 0.66 in the pre-ictal phase, indicating heightened activity before the seizure.
- During the ictal phase, the DTR decreases slightly to 0.57, suggesting a reduction in dynamic temporal response during the seizure.
- In the post-ictal phase, the DTR value rises significantly to 0.92, which may indicate recovery or balancing activity after the seizure.

- Subject 2
  - The DTR begins at 0.23 in the normal phase.
  - There is a steady increase to 0.40 in the pre-ictal phase and further to 0.60 in the ictal phase, showing a progressive increase in brain activity as the seizure develops.
  - In the post-ictal phase, the DTR decreases to 0.48, possibly reflecting the brain's return to a more stable state after the seizure.
- Subject 3
  - The DTR is 0.38 in the normal phase.
  - It rises sharply to 0.87 in the pre-ictal phase, suggesting a significant increase in brain activity before the seizure.
  - The DTR then decreases in the ictal phase to 0.75 but again rises to 0.98 in the post-ictal phase, which might indicate fluctuating brain activity levels during and after the seizure.
- Subject 4
  - The DTR is relatively high at 0.73 in the normal phase.
  - It decreases to 0.54 in the pre-ictal phase and further drops to 0.36 in the ictal phase, indicating a marked reduction in brain activity leading up to and during the seizure.
  - In the post-ictal phase, the DTR increases to 0.76, surpassing the normal phase value, suggesting a possible recovery effect in brain activity after the seizure.
- Subject 5
  - The DTR is 0.74 in the normal phase.
  - It increases to 0.88 in the pre-ictal phase, indicating a rise in brain activity as the seizure approaches.

    - During the ictal phase, the DTR slightly decreases to 0.80 and then drops further to 0.60 in the post-ictal phase, reflecting a gradual decline in activity after the seizure.
- Subject 6
    - The DTR is 0.89 in the normal phase.
    - It decreases to 0.62 in the pre-ictal phase and further to 0.55 in the ictal phase, indicating reduced brain activity as the seizure develops.
    - The DTR increases to 0.67 in the post-ictal phase, suggesting a partial recovery in activity after the seizure.
- Subject 7
    - The DTR starts high at 0.94 in the normal phase.
    - It drops to 0.55 in the pre-ictal phase, rises again to 0.92 during the ictal phase, and finally decreases to 0.49 in the post-ictal phase, indicating fluctuating brain activity levels during different seizure phases.
- Subject 8
    - The DTR is notably high at 1.07 in the normal phase.
    - It increases slightly to 1.11 in the pre-ictal phase but decreases significantly to 0.58 during the ictal phase and further to 0.44 in the post-ictal phase, showing a substantial reduction in brain activity after the seizure.

Most subjects show increased DTR during the pre-ictal phase, suggesting heightened brain activity before the seizure onset. The ictal phase generally sees a decrease in DTR, which may reflect the seizure's impact on brain dynamics. Post-ictal phase DTR values vary widely among subjects, indicating different recovery patterns or compensatory mechanisms in the brain after a seizure. The fluctuation in DTR across different phases highlights the complex nature of brain activity in epilepsy and the potential for DTR as a marker of seizure progression and recovery.

4.2. BANDPOWER CALCULATION OF ALPHA BETA RATIO

4.2.1. ALPHA BETA RATIO OF ALL SUBJECT

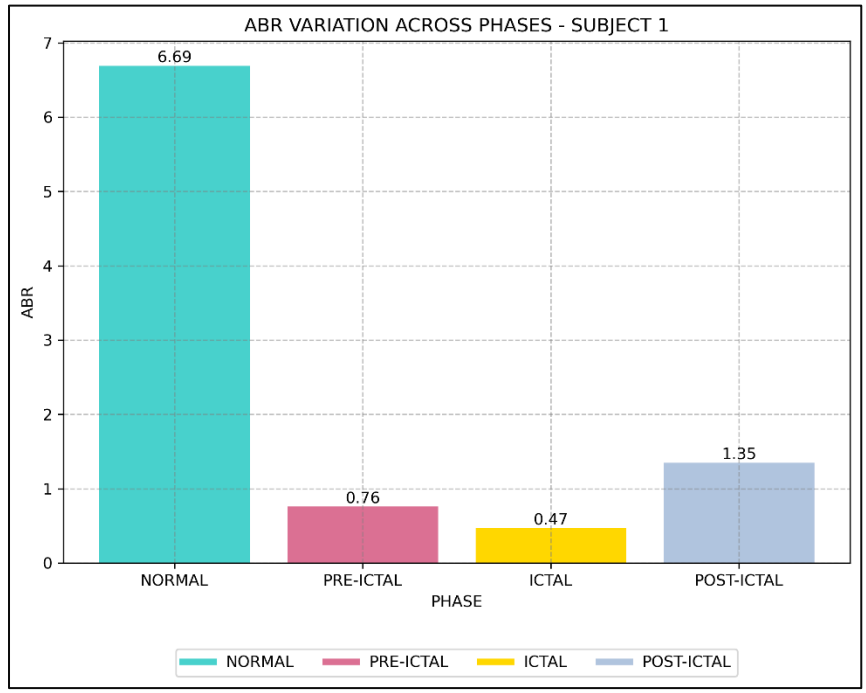


FIG. 25 ABR VARIATION OF SUBJECT 1

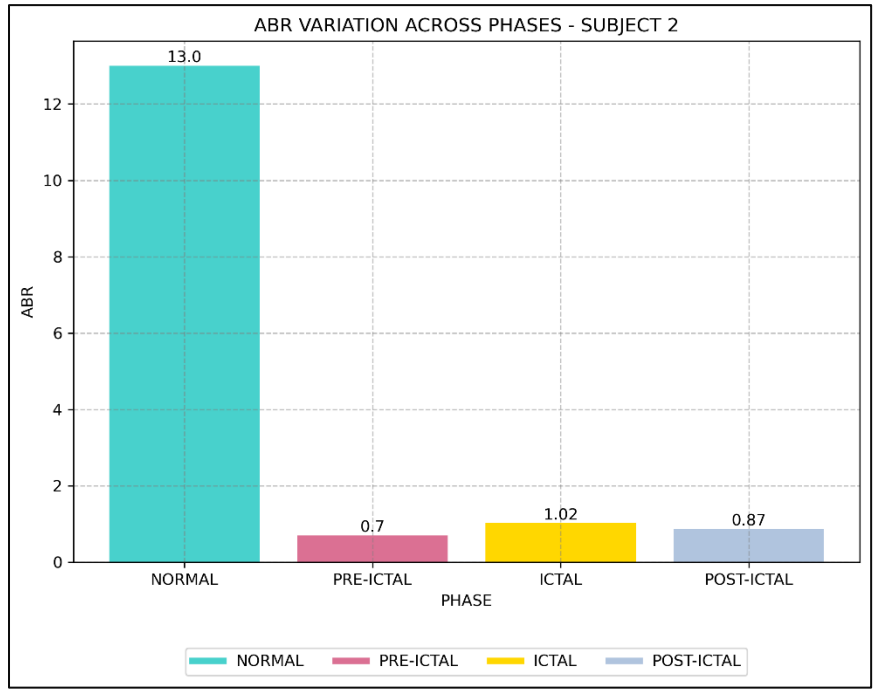


FIG. 26 ABR VARIATION OF SUBJECT 2

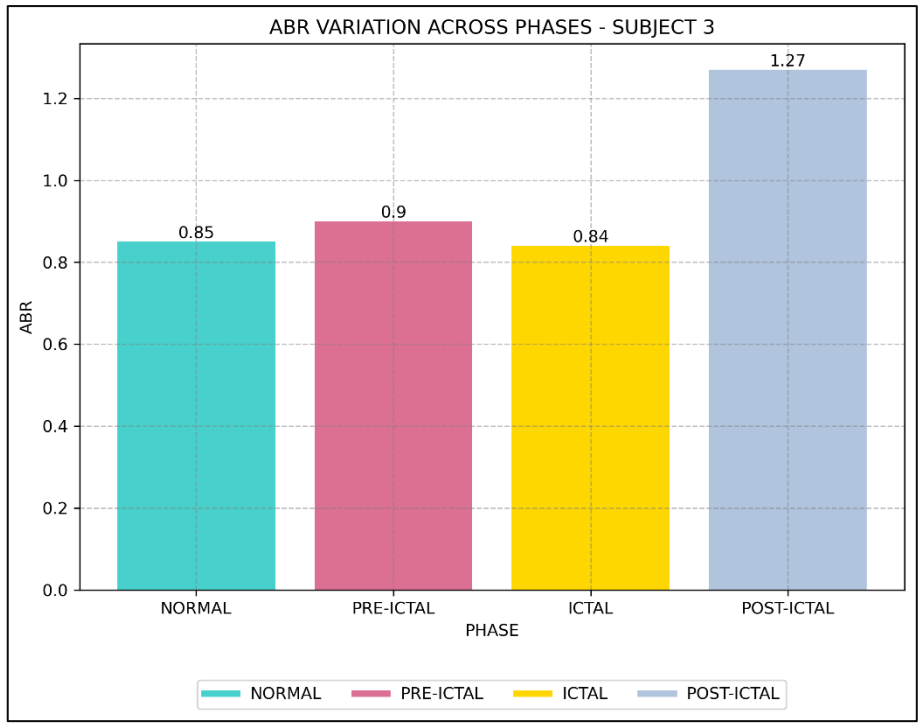


FIG. 27 ABR VARIATION OF SUBJECT 3

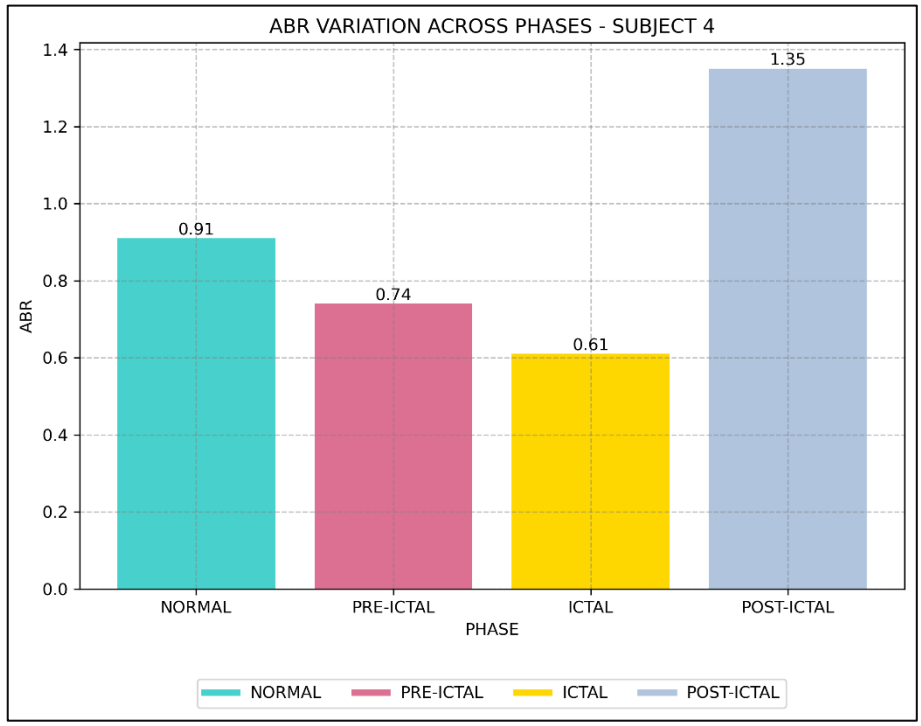


FIG. 28 ABR VARIATION OF SUBJECT 4

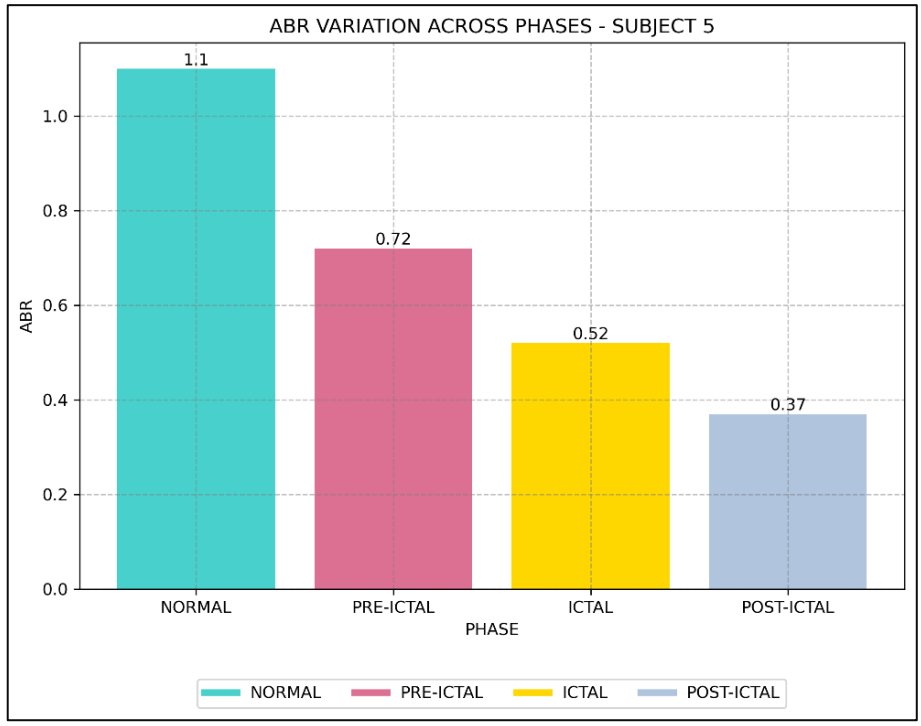


FIG. 29 ABR VARIATION OF SUBJECT 5

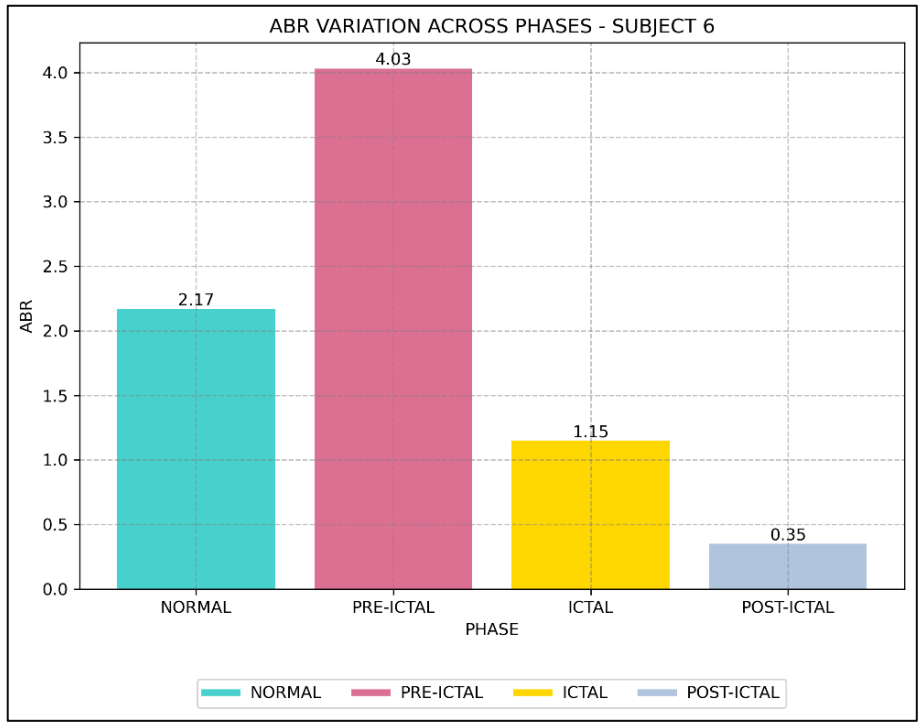


FIG. 30 ABR VARIATION OF SUBJECT 6

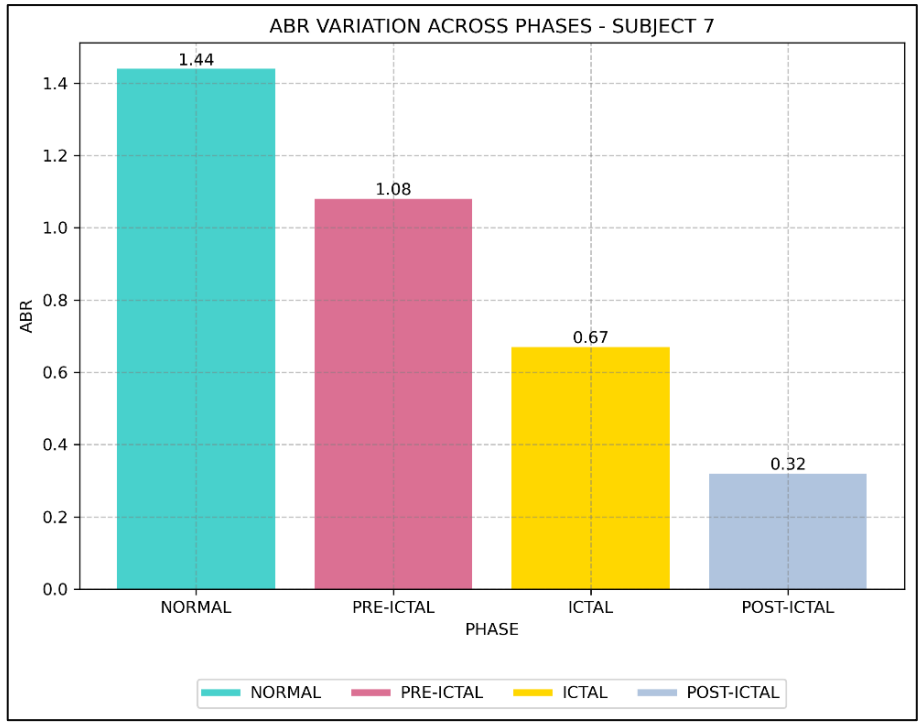


FIG. 31 ABR VARIATION OF SUBJECT 7

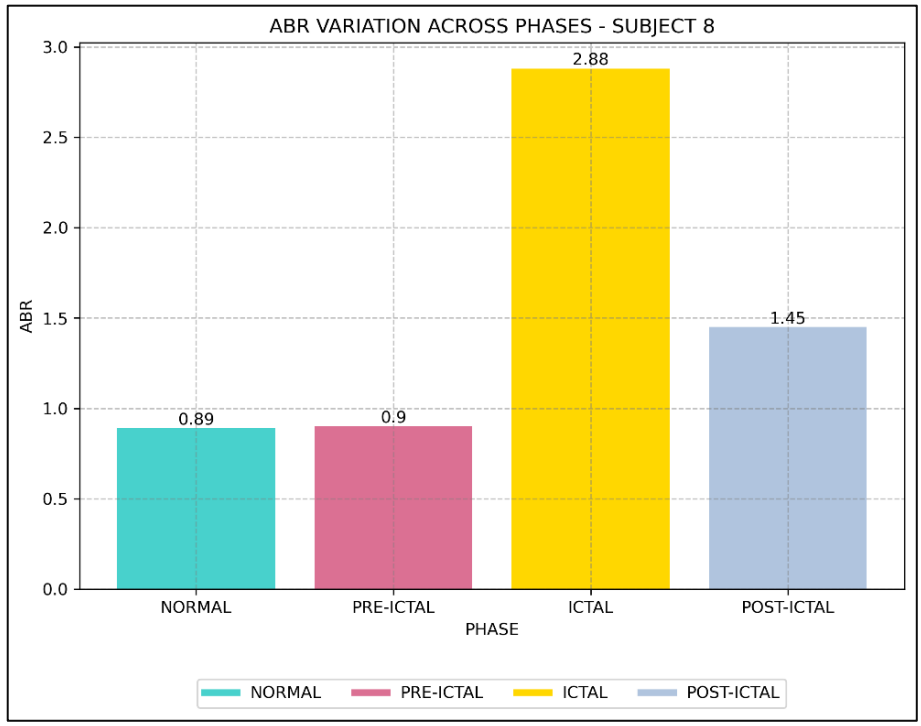


FIG. 32 ABR VARIATION OF SUBJECT 8

4.2.2. ALPHA BETA RATIO OF NORMAL TO PRE-ICTAL

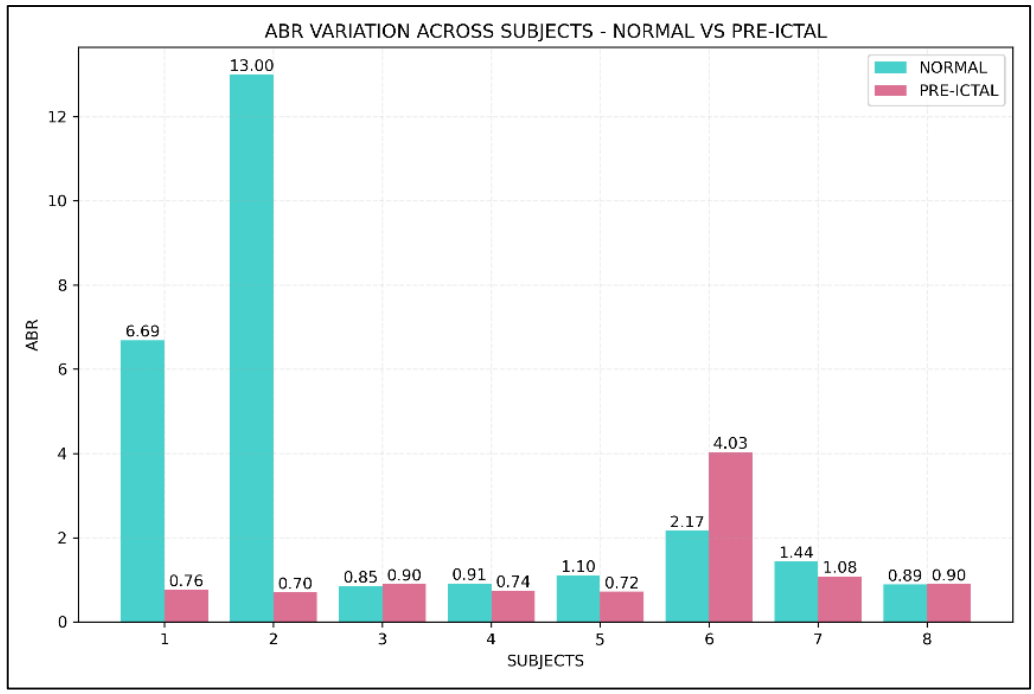


FIG. 33 ABR VARIATION OF NORMAL AND PRE-ICTAL OF ALL SUBJECT

4.2.3. ABR RATIO OF NORMAL TO ICTAL

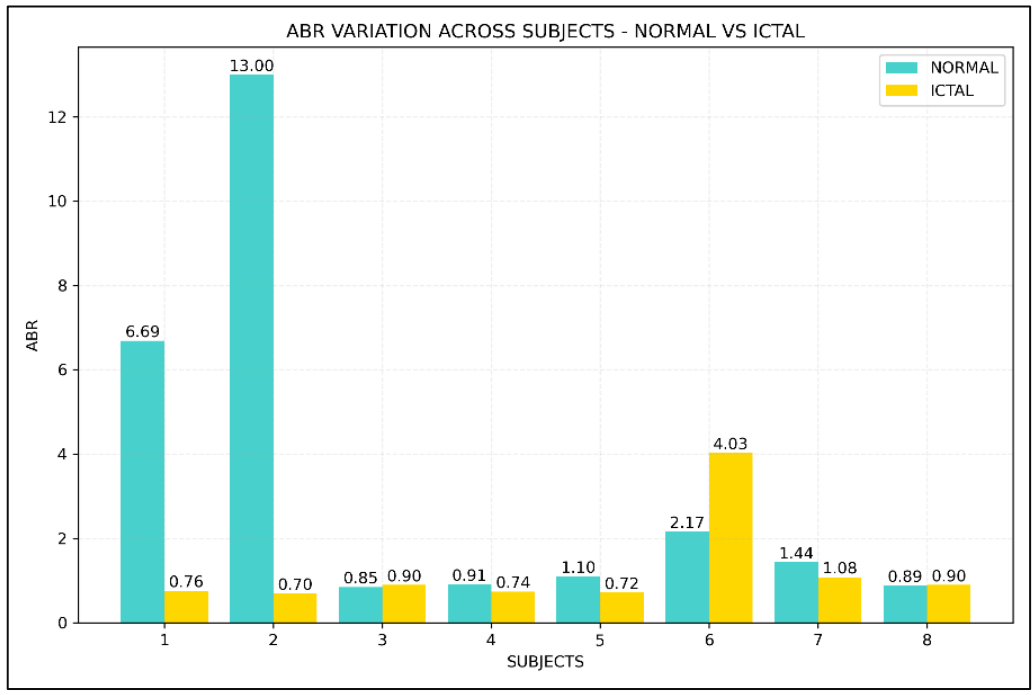


FIG. 34 ABR VARIATION OF NORMAL AND ICTAL OF ALL SUBJECT

4.2.4. ABR OF NORMAL TO POST-ICTAL

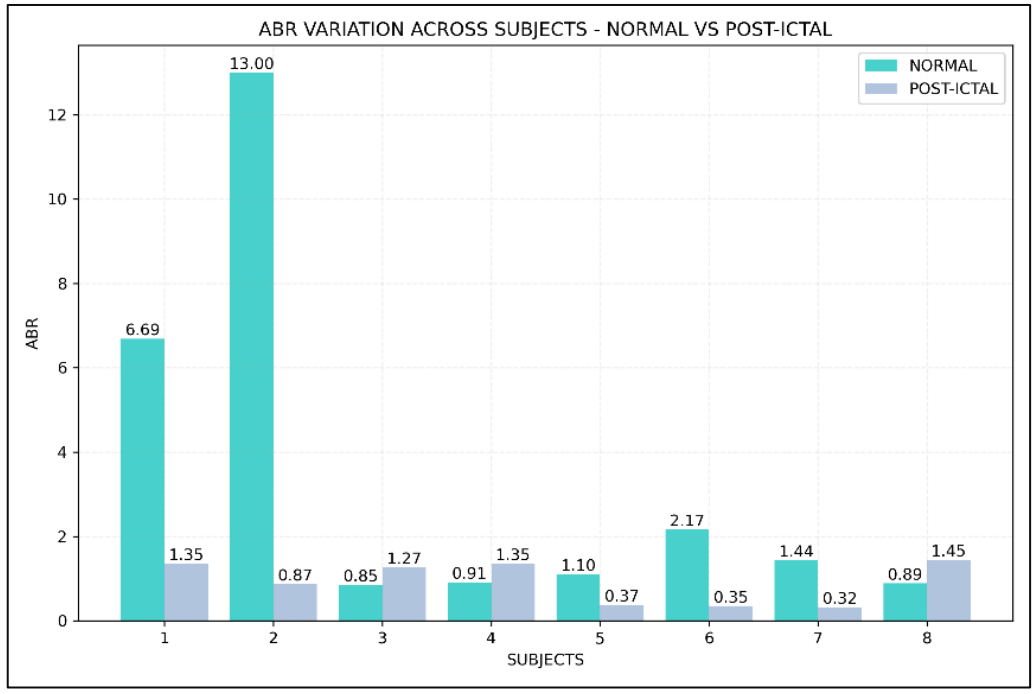


FIG. 35 ABR VARIATION OF NORMAL AND POST-ICTAL OF ALL SUBJECT

Observations from the ABR Variations Across All Subjects

- Subject 1
  - The ABR value starts at 6.69 in the normal phase.
  - It decreases significantly to 0.76 in the pre-ictal phase, indicating a reduction in ABR before the seizure.
  - During the ictal phase, it further decreases to 0.47, suggesting a continued decline in ABR activity during the seizure.
  - In the post-ictal phase, the ABR rises to 1.35, reflecting a recovery or compensatory response after the seizure.
- Subject 2
  - The ABR begins at 13 in the normal phase.
  - It drops to 0.70 in the pre-ictal phase, showing a substantial decrease in ABR before the seizure.
  - In the ictal phase, it increases to 1.02, indicating a rise in ABR activity during the seizure.

- The value recedes to 0.87 in the post-ictal phase, reflecting a partial recovery after the seizure.

- Subject 3
  - The ABR is 0.85 in the normal phase.
  - It increases to 0.90 in the pre-ictal phase, suggesting a slight rise in ABR as the seizure approaches.
  - During the ictal phase, it decreases slightly to 0.84, indicating a minor reduction in ABR.
  - In the post-ictal phase, it rises to 1.27, showing a notable increase after the seizure.
- Subject 4
  - The ABR is 0.91 in the normal phase.
  - It decreases to 0.74 in the pre-ictal phase, followed by a further decrease to 0.61 during the ictal phase, indicating a significant reduction in ABR leading up to and during the seizure.
  - In the post-ictal phase, the ABR rises to 1.27, surpassing the normal phase value, which suggests a recovery effect after the seizure.
- Subject 5
  - The ABR is 1.10 in the normal phase.
  - It decreases to 0.72 in the pre-ictal phase, showing a reduction in ABR before the seizure.
  - During the ictal phase, it drops further to 0.52 and continues to decrease to 0.37 in the post-ictal phase, reflecting a continuous decline in ABR.
- Subject 6
  - The ABR is 2.17 in the normal phase.
  - It rises significantly to 4.03 in the pre-ictal phase, indicating a notable increase in ABR before the seizure.
  - During the ictal phase, it decreases to 1.15, followed by a drop to 0.35 in the post-ictal phase, suggesting a substantial reduction after the seizure.
- Subject 7
  - The ABR starts at 1.44 in the normal phase.
  - It decreases to 1.08 in the pre-ictal phase and further drops to 0.67 during the ictal phase.

- In the post-ictal phase, it decreases to 0.32, indicating a reduction in ABR following the seizure.

- Subject 8
  - The ABR is 0.89 in the normal phase.
  - It increases slightly to 0.90 in the pre-ictal phase.
  - During the ictal phase, it rises significantly to 2.88, and then decreases to 1.45 in the post-ictal phase, reflecting a high fluctuation in ABR activity.

The ABR values across different phases of the seizure cycle reveal substantial changes in brain activity and responsiveness. In the normal phase, the ABR values are relatively high, indicating a stable level of brain responsiveness. As subjects approach the pre-ictal phase, there is a notable decrease in ABR, suggesting that brain responsiveness diminishes in anticipation of a seizure. During the ictal phase, the ABR decreases dramatically, reflecting the severe impact of the seizure on brain function and the impairment of normal processing and response to stimuli.ABR values show considerable variation in the post-ictal phase. Some subjects experience a recovery effect with an increase in ABR, indicating a compensatory response, while others exhibit only slight increases or continued low values, highlighting different recovery patterns. Overall, these observations show significant disruption caused by seizures and the varied recovery responses, emphasizing the potential of ABR as a marker for understanding seizure impacts and recovery dynamics.

4.3. SHANNON ENTROPY

4.3.1. SHANNON ENTROPY OF ALL SUBJECTS

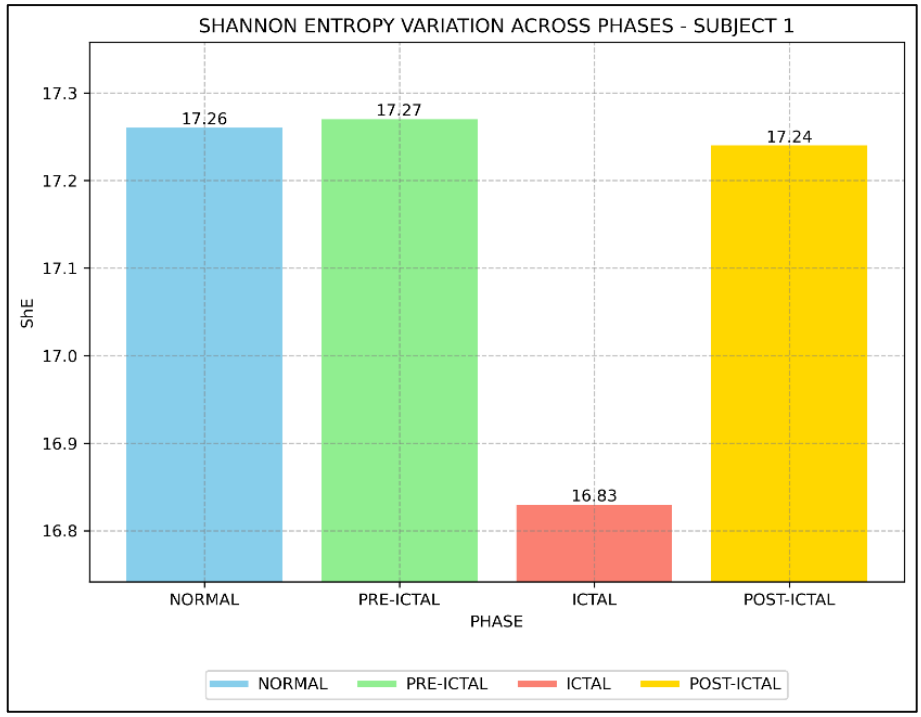


FIG. 36 ShE VARIATION OF SUBJECT 1

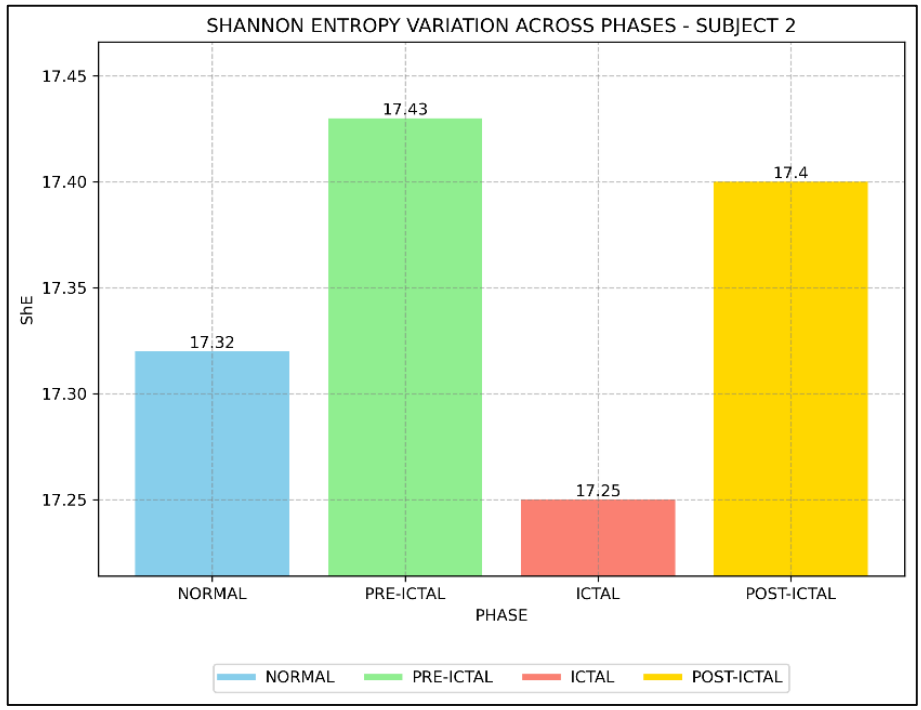


FIG. 37 ShE VARIATION OF SUBJECT 2

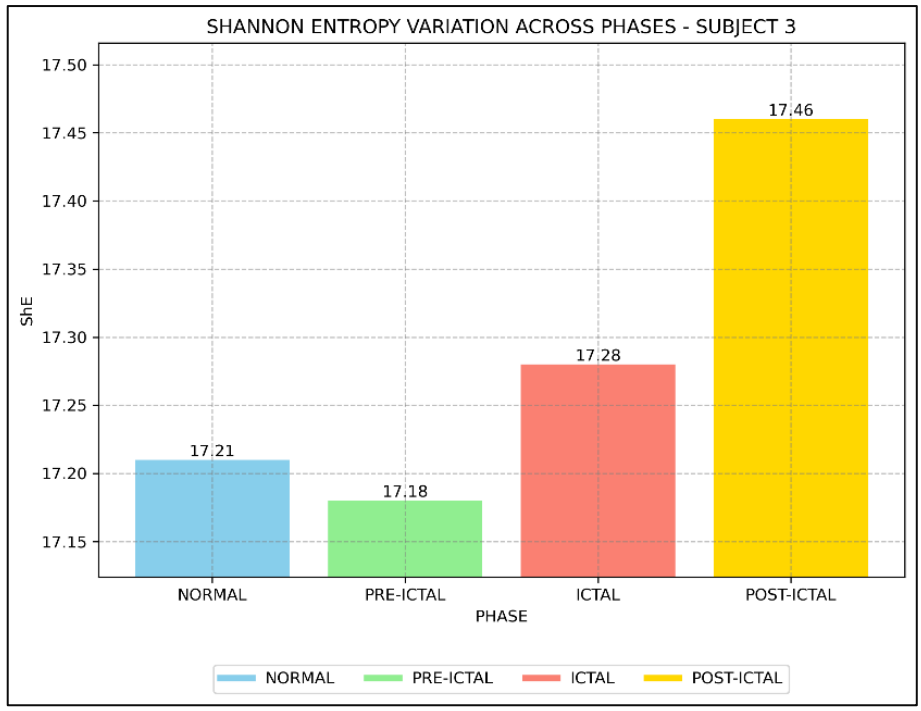


FIG. 38 ShE VARIATION OF SUBJECT 3

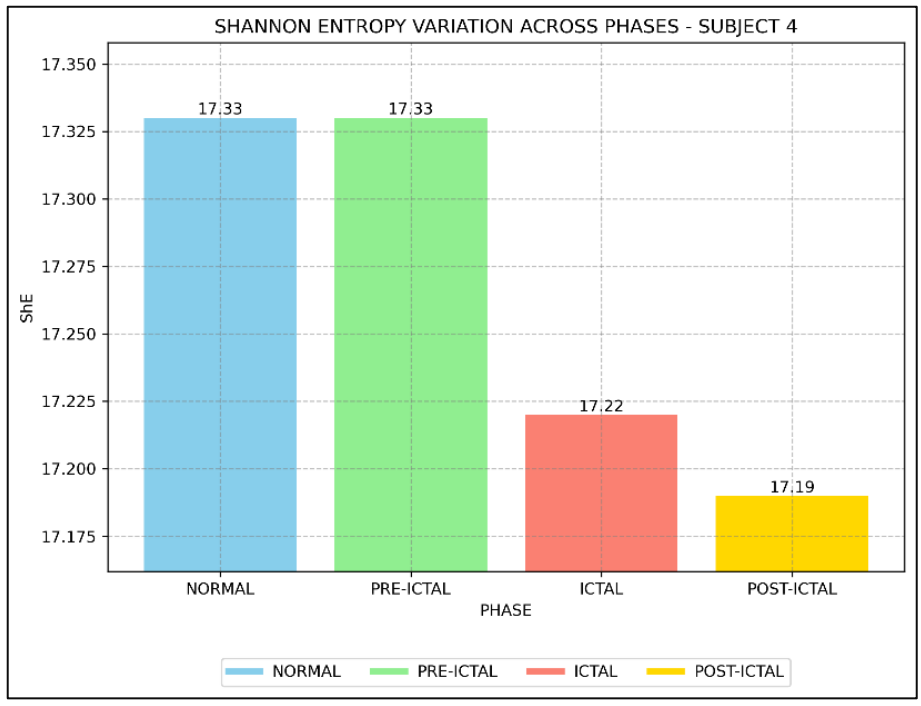


FIG. 39 ShE VARIATION OF SUBJECT 4

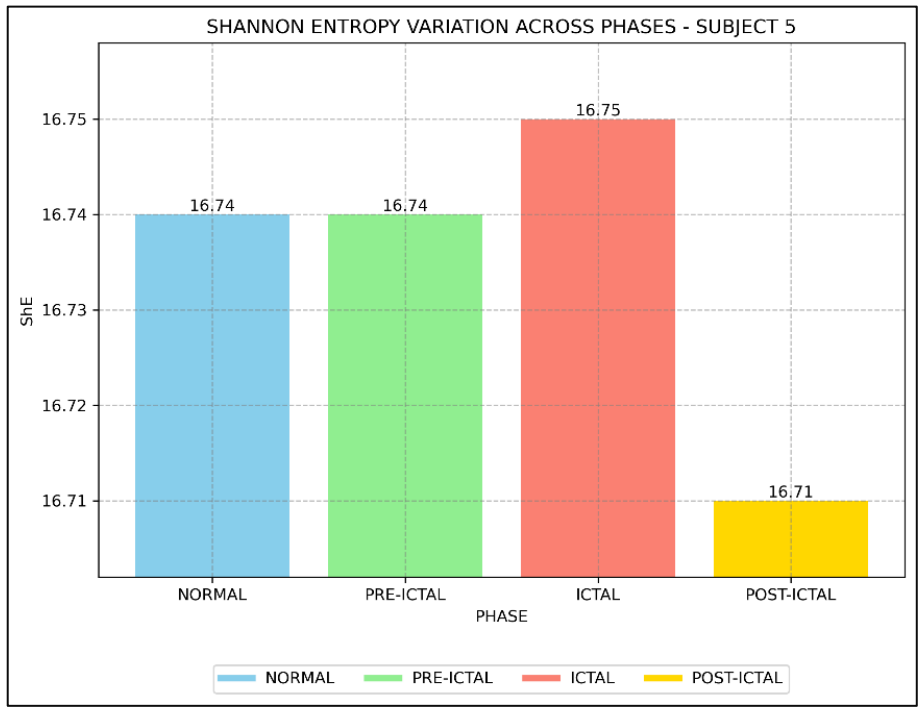


FIG. 40 ShE VARIATION OF SUBJECT 5

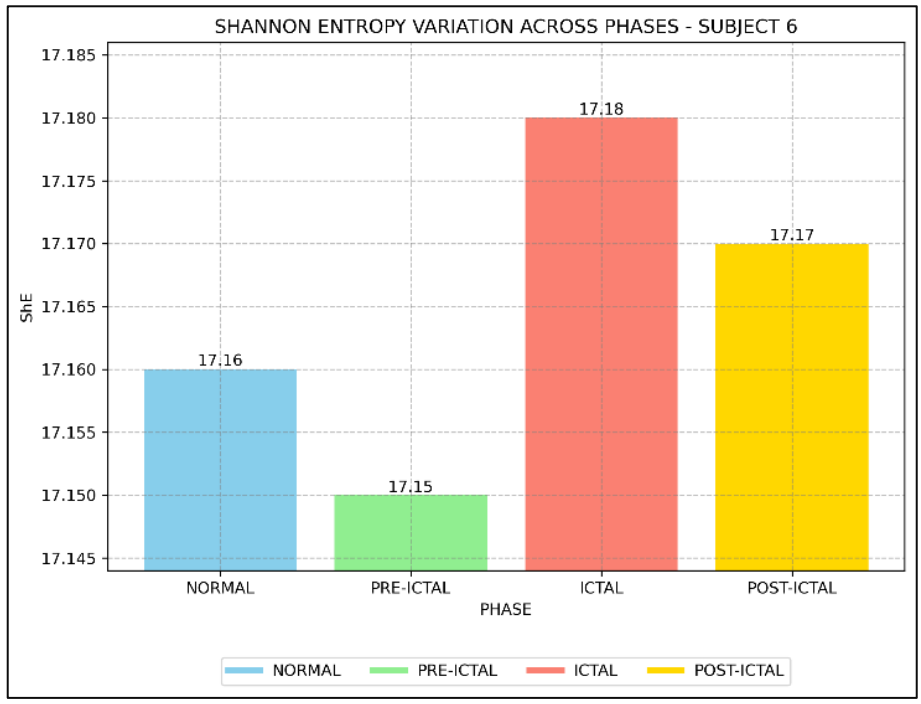


FIG. 41 ShE VARIATION OF SUBJECT 6

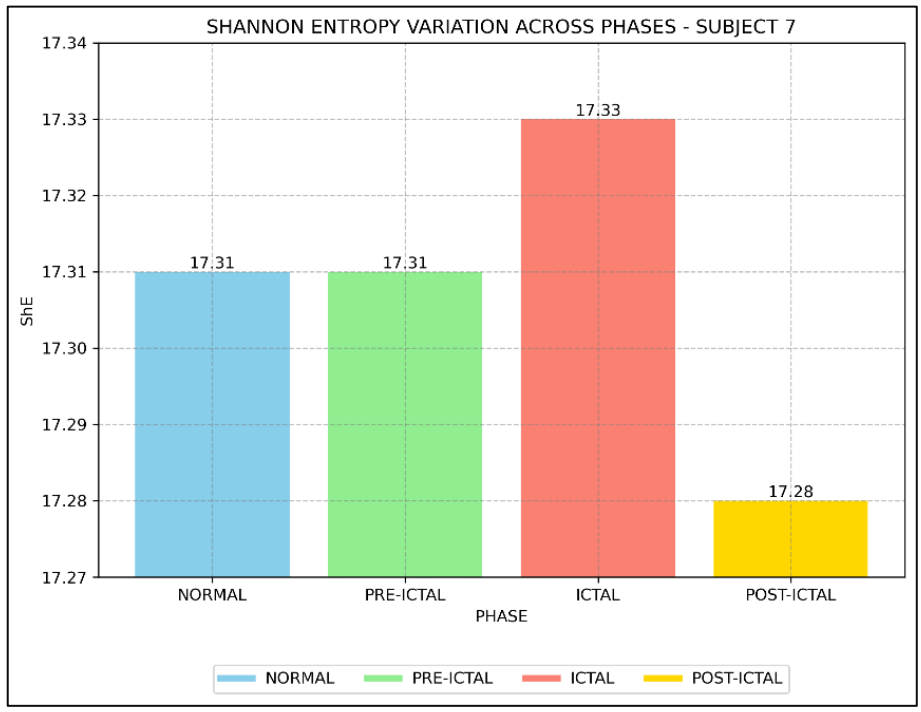


FIG. 42 ShE VARIATION OF SUBJECT 7

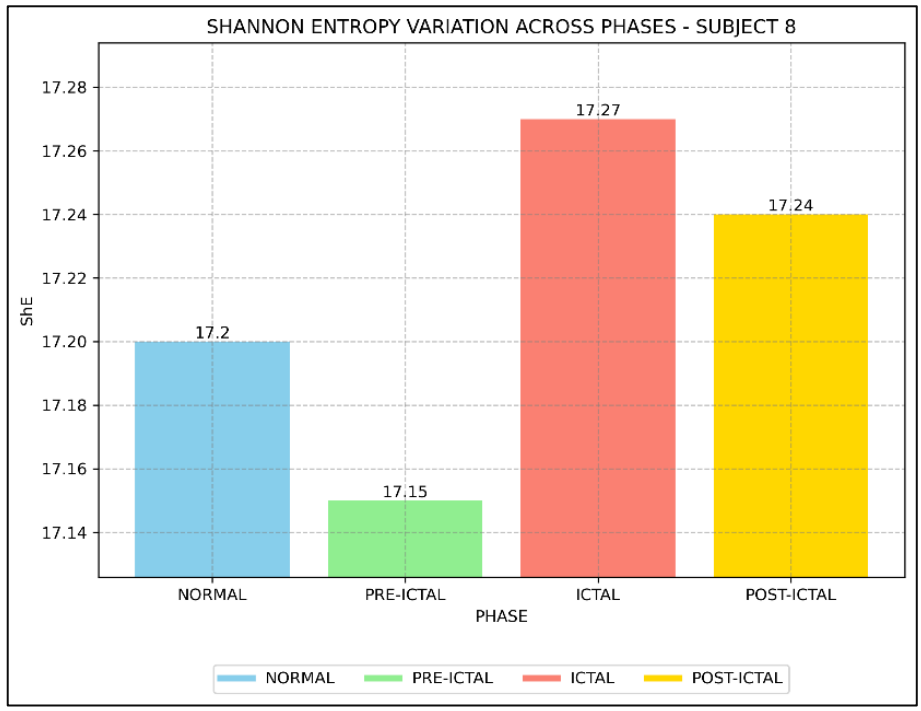


FIG. 43 ShE VARIATION OF SUBJECT 8

4.3.2. SHANNON ENTROPY VARIATION OF NORMAL TO PRE-ICTAL

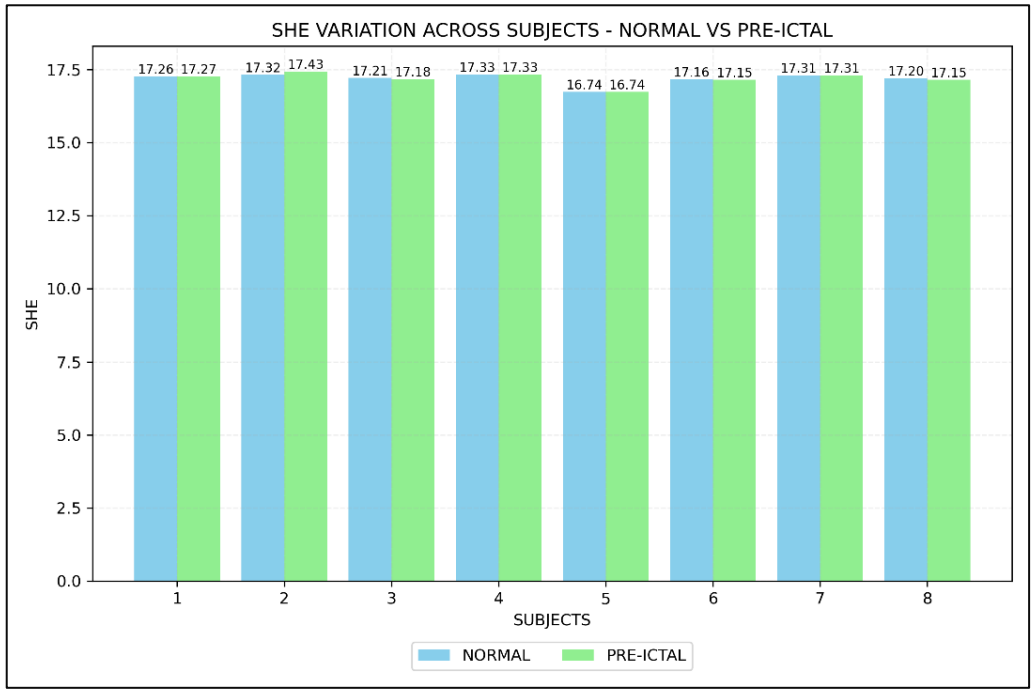


FIG. 44 ShE VARIATION OF NORMAL TO PRE-ICTAL OF ALL SUBJECT

4.3.3. SHANNON ENTROPY VARIATION OF NORMAL TO ICTAL

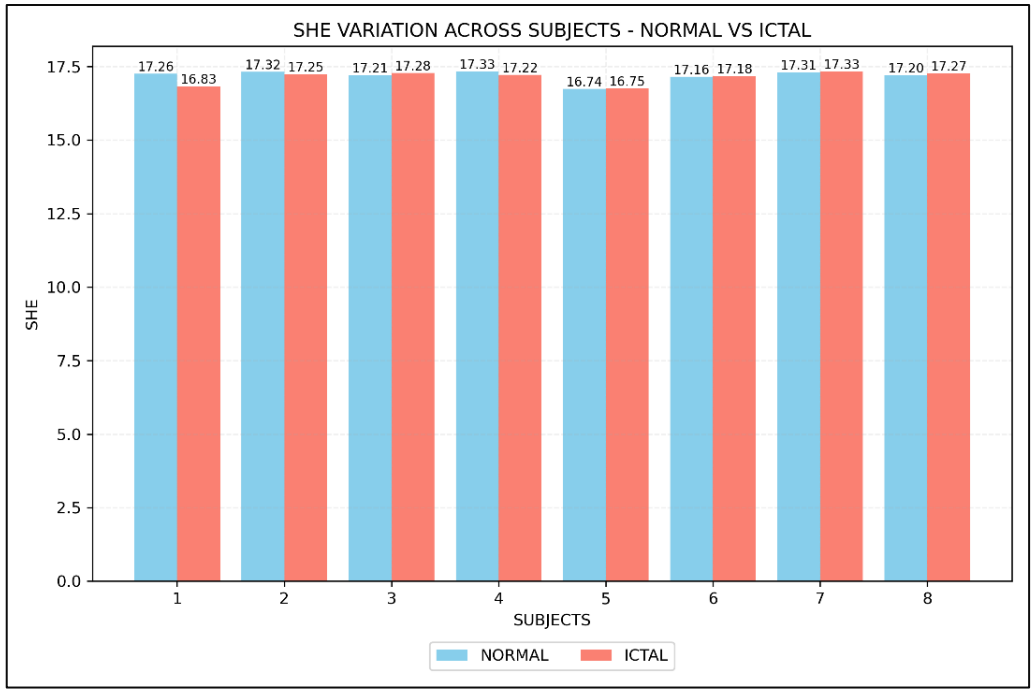


FIG. 45 ShE VARIATION OF NORMAL AND ICTAL OF ALL SUBJECT

4.3.4. SHANNON ENTROPY VARIATION OF NORMAL TO POST-ICTAL

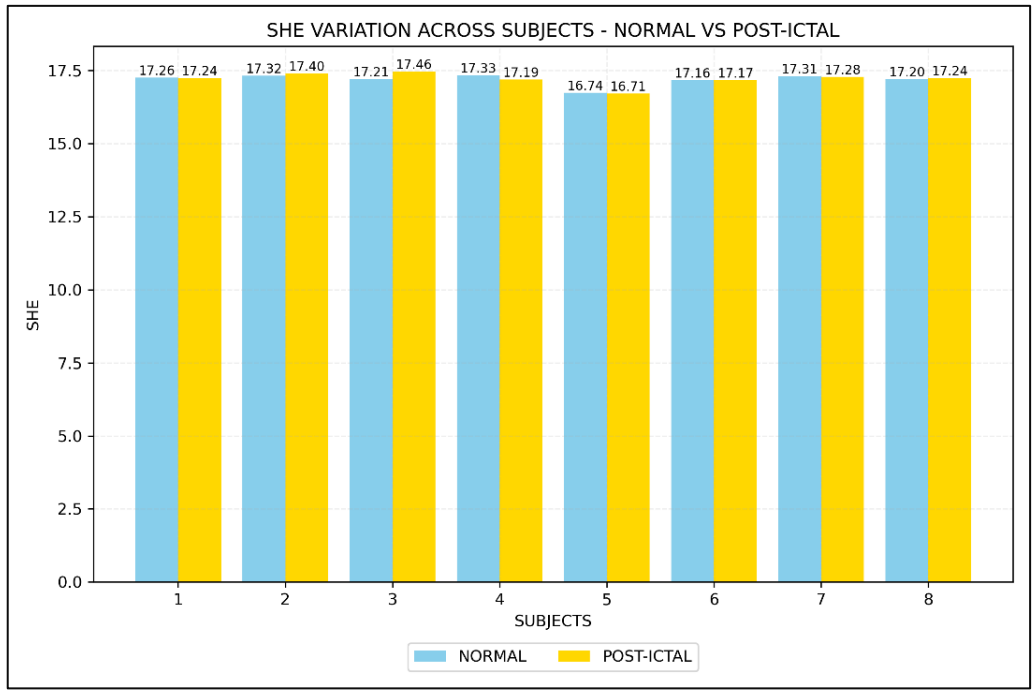


FIG. 46 ShE VARIATION OF NORMAL AND POST-ICTAL OF ALL SUBJECT

Observations from the Shannon Entropy (ShE) Variations Across All Subjects

- Subject 1
  - The ShE value starts at 17.26 in the normal phase.
  - It increases slightly to 17.27 in the pre-ictal phase, indicating a minimal rise in entropy before the seizure.
  - During the ictal phase, the ShE value decreases to 16.83, reflecting a reduction in complexity and information processing during the seizure.
  - In the post-ictal phase, the ShE value rises again to 17.24, showing a partial recovery in complexity and information processing.
- Subject 2
  - The ShE value is 17.32 in the normal phase.

- It increases to 17.43 in the pre-ictal phase, suggesting a rise in entropy as the seizure approaches.
- The ShE value decreases to 17.25 during the ictal phase, indicating a decrease in entropy during the seizure.
- It then increases to 17.40 in the post-ictal phase, reflecting a recovery in entropy following the seizure.

- Subject 3
  - The ShE value in the normal phase is 17.21.
  - It decreases slightly to 17.18 in the pre-ictal phase, showing a small drop in entropy before the seizure.
  - During the ictal phase, the ShE increases to 17.28, suggesting a temporary rise in complexity during the seizure.
  - The ShE value continues to increase to 17.46 in the post-ictal phase, indicating a further recovery in entropy.
- Subject 4
  - The ShE value is 17.33 in the normal phase.
  - It remains unchanged at 17.33 in the pre-ictal phase, indicating stability in entropy before the seizure.
  - During the ictal phase, the ShE decreases to 17.22, reflecting a drop in complexity during the seizure.
  - In the post-ictal phase, it further decreases to 17.19, showing a continued decrease in entropy.
- Subject 5
  - The ShE value starts at 16.74 in the normal phase.
  - It remains constant at 16.74 in the pre-ictal phase, indicating no change in entropy before the seizure.

- The ShE increases slightly to 16.75 during the ictal phase, suggesting a small rise in complexity during the seizure.
- It then decreases to 16.71 in the post-ictal phase, reflecting a reduction in entropy after the seizure.

- Subject 6
  - The ShE value is 17.16 in the normal phase.
  - It decreases slightly to 17.15 in the pre-ictal phase, showing a minimal drop in entropy before the seizure.
  - During the ictal phase, the ShE decreases further to 17.18, indicating a temporary rise during the seizure.
  - It continues to decrease to 17.17 in the post-ictal phase, reflecting a slight decrease in entropy after the seizure.
- Subject 7
  - The ShE value is 17.31 in the normal phase.
  - It remains at 17.31 in the pre-ictal phase, indicating stable entropy before the seizure.
  - During the ictal phase, the ShE increases to 17.33, reflecting a rise in complexity during the seizure.
  - It decreases to 17.28 in the post-ictal phase, showing a slight reduction in entropy after the seizure.
- Subject 8
  - The ShE value is 17.20 in the normal phase.
  - It decreases to 17.15 in the pre-ictal phase, indicating a drop in entropy before the seizure.
  - During the ictal phase, the ShE increases to 17.27, suggesting a temporary rise in complexity during the seizure.
  - It decreases again to 17.24 in the post-ictal phase, reflecting a slight reduction in entropy following the seizure.

The Shannon Entropy (ShE) values across different phases of the seizure cycle show variability in brain complexity and information processing. In the normal phase, ShE values are relatively stable, reflecting a consistent level of brain activity complexity. As the pre-ictal phase approaches, there is a combination of slight increases and decreases in ShE, suggesting subtle changes in brain dynamics before the seizure. During the ictal phase, ShE values generally decrease, indicating a reduction in complexity and information processing during the seizure. In the Post-ictal phase, ShE values exhibit varied recovery patterns: some subjects experience an increase in entropy, reflecting a recovery or compensatory response, while others show a decrease, indicating a different recovery pattern. These observations highlight the complex nature of brain entropy dynamics during and after seizures and suggest that ShE can be a useful marker for understanding changes in brain activity across different seizure phases.

4.4. KATZ FRACTAL DIMENSION

4.4.1. *KATZ FD VARIATION AMONG ALL SUBJECTS*

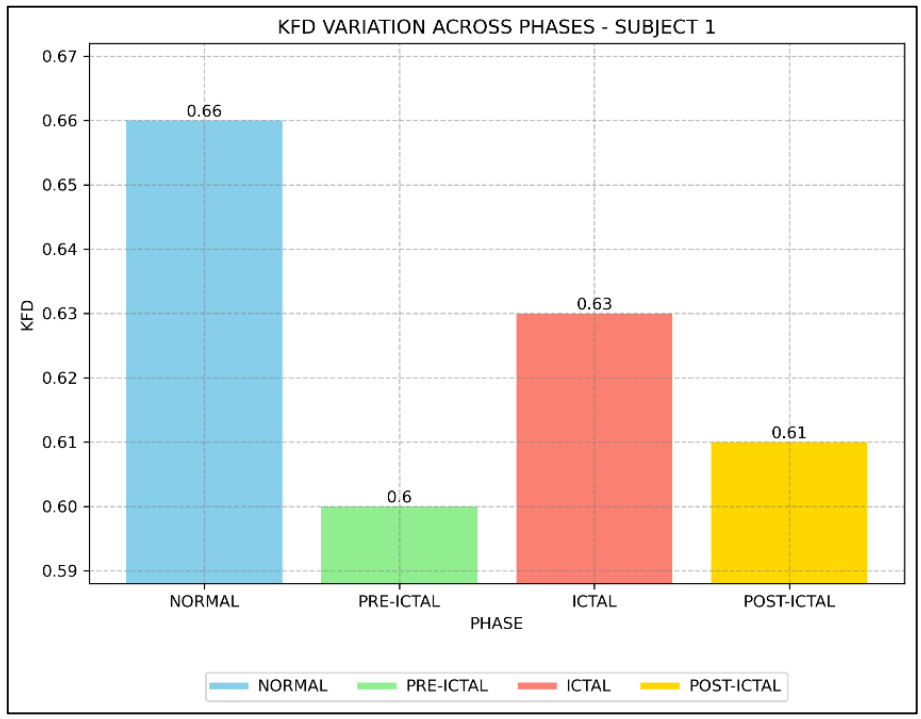


FIG. 47 KFD VARIATION OF SUBJECT 1

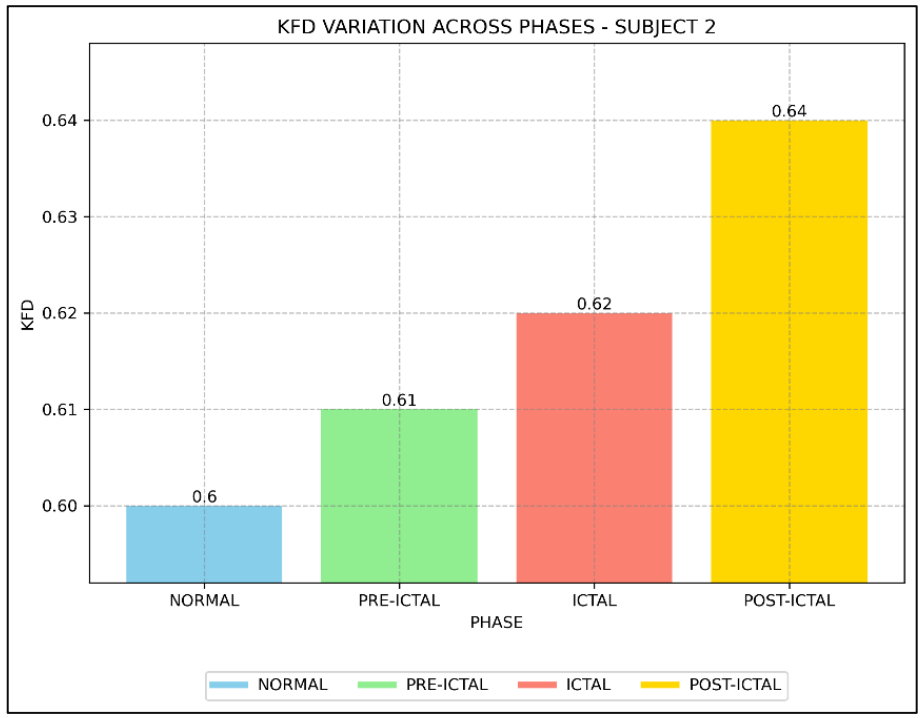


FIG. 48 KFD VARIATION OF SUBJECT 2

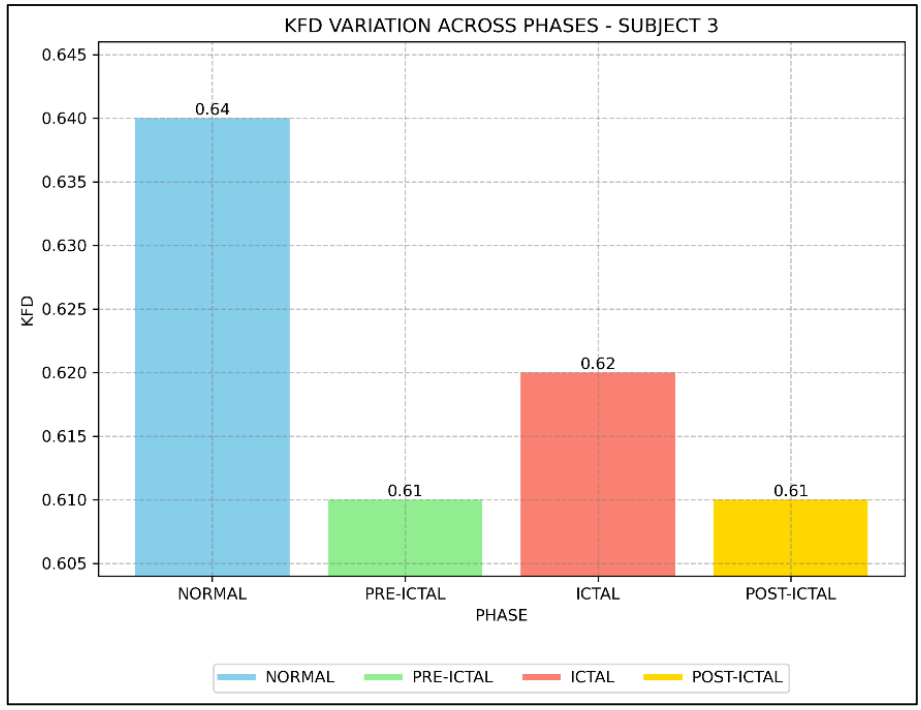


FIG. 49 KFD VARIATION OF SUBJECT 3

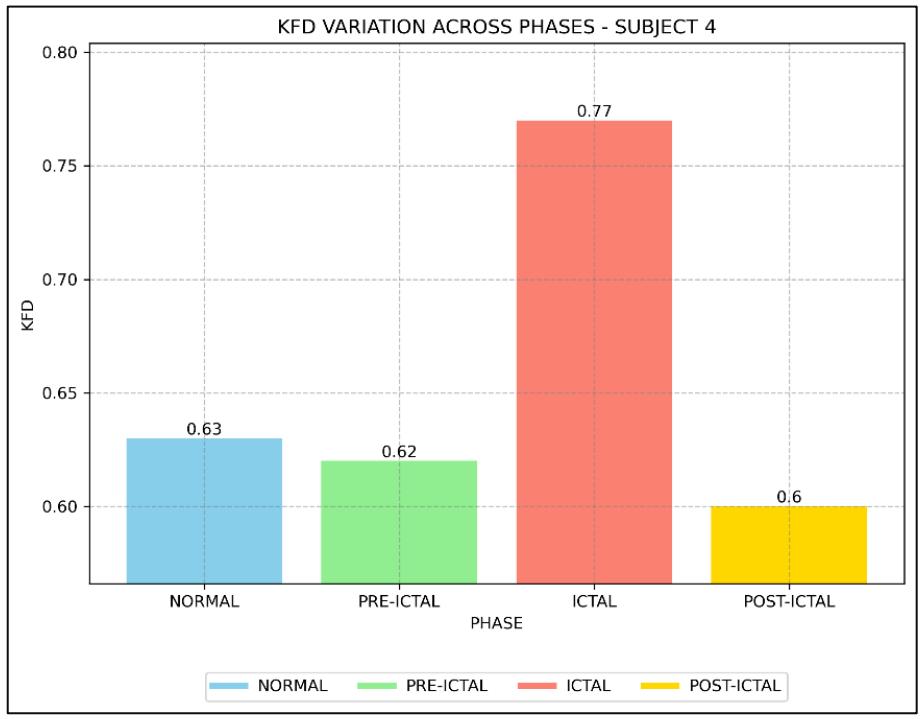


FIG. 50 KFD VARIATION OF SUBJECT 4

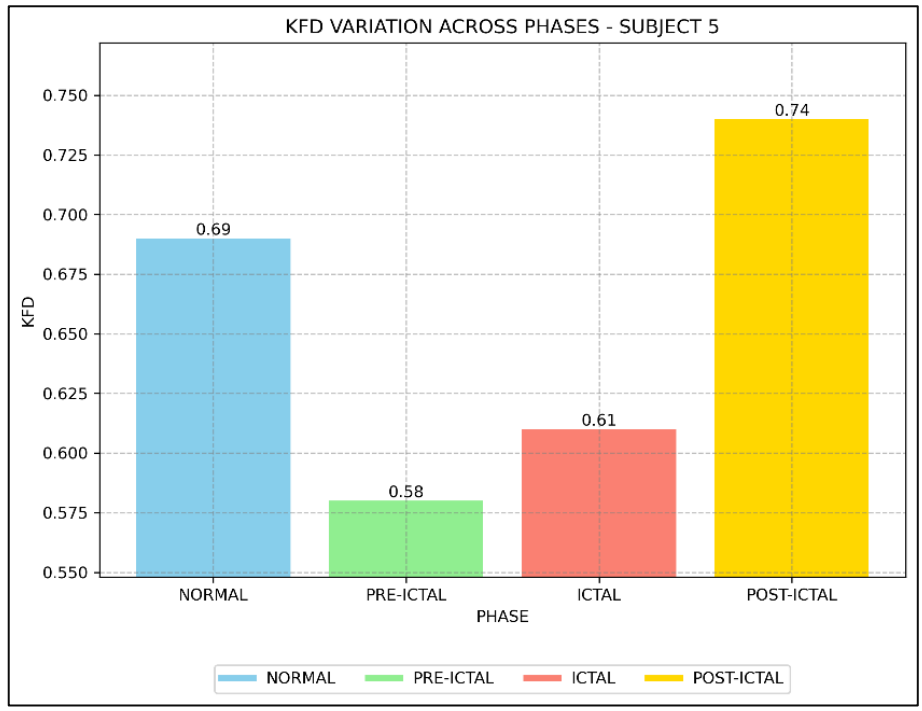


FIG. 51 KFD VARIATION OF SUBJECT 5

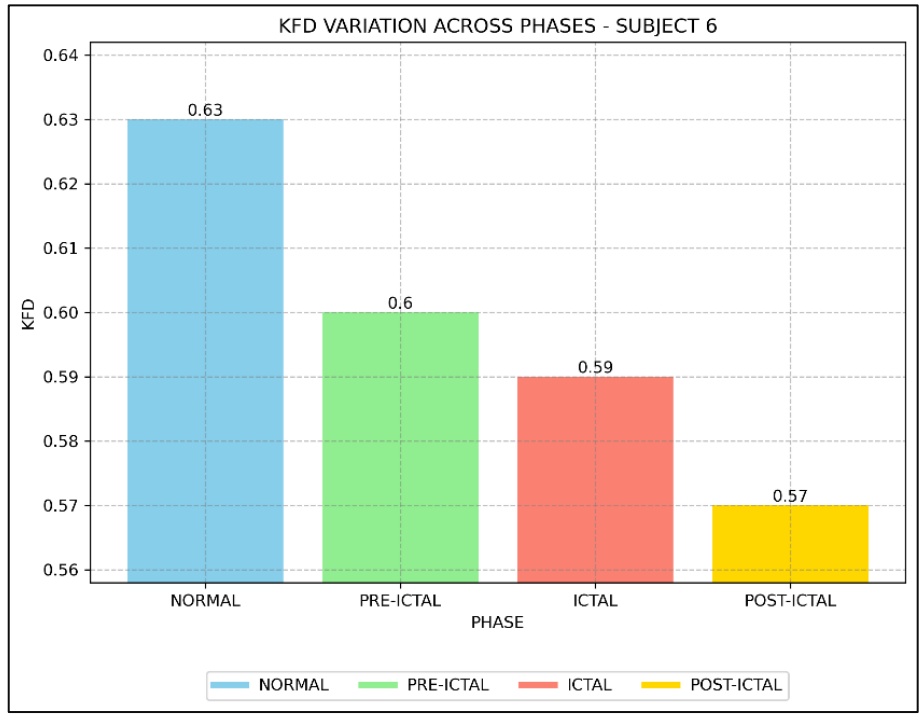


FIG. 52 KFD VARIATION OF SUBJECT 6

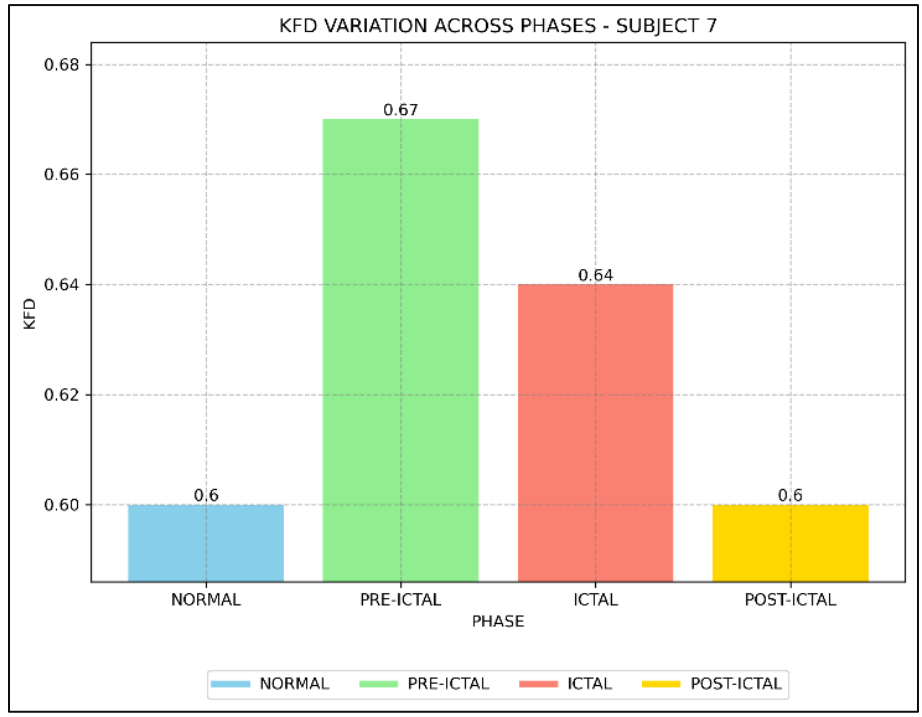


FIG. 53 KFD VARIATION OF SUBJECT 7

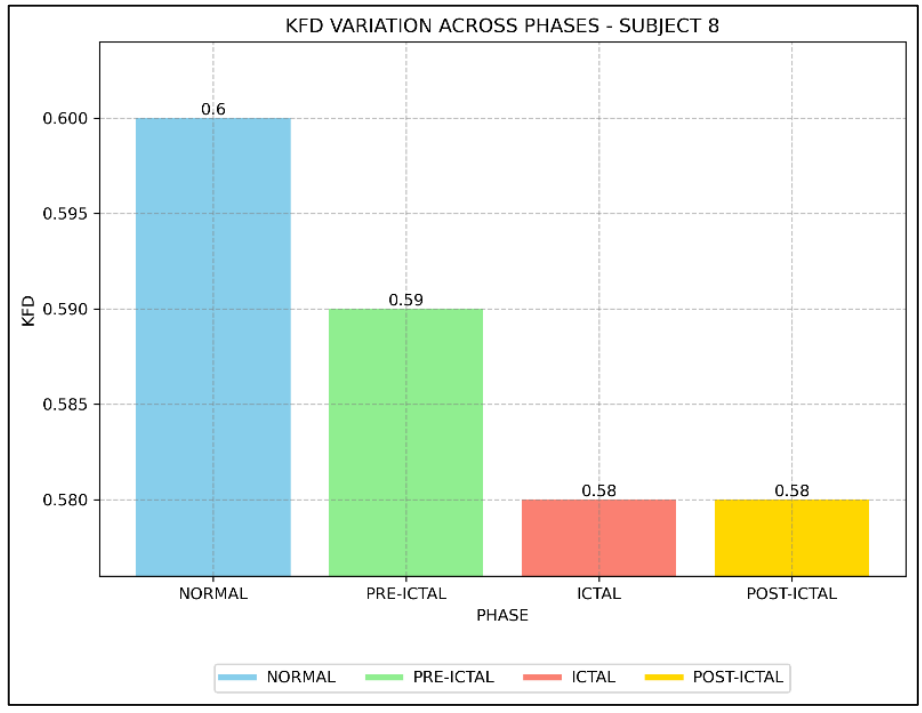


FIG. 54 KFD VARIATION OF SUBJECT 8

4.4.2. KATZ FD VARIATION OF NORMAL TO PRE-ICTAL

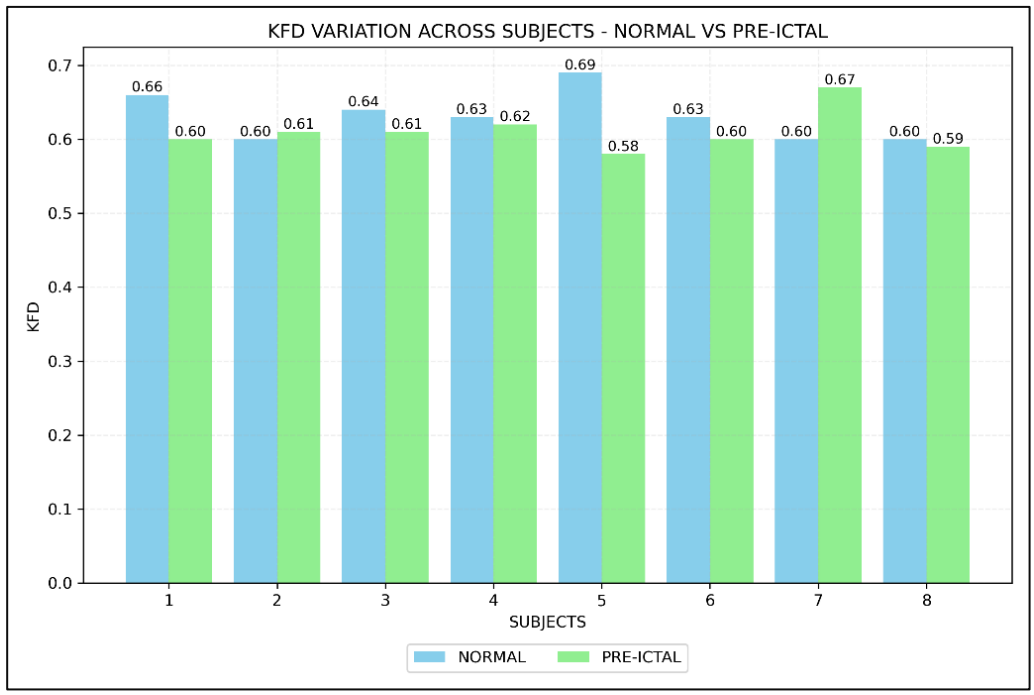


FIG. 55 KFD VARIATION OF NORMAL AND PRE-ICTAL OF ALL SUBJECT

4.4.3. KATZ FD VARIATION OF NORMAL TO ICTAL

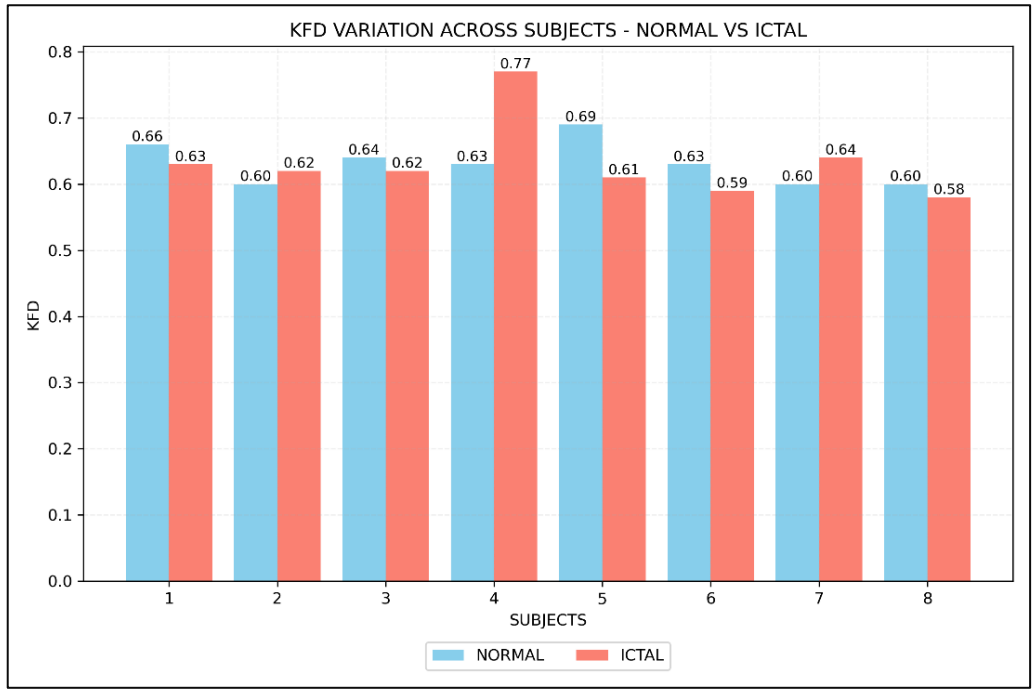


FIG. 56 KFD VARIATION OF NORMAL AND ICTAL OF ALL SUBJECT

4.4.4. KATZ FD VARIATION OF NORMAL TO POST-ICTAL

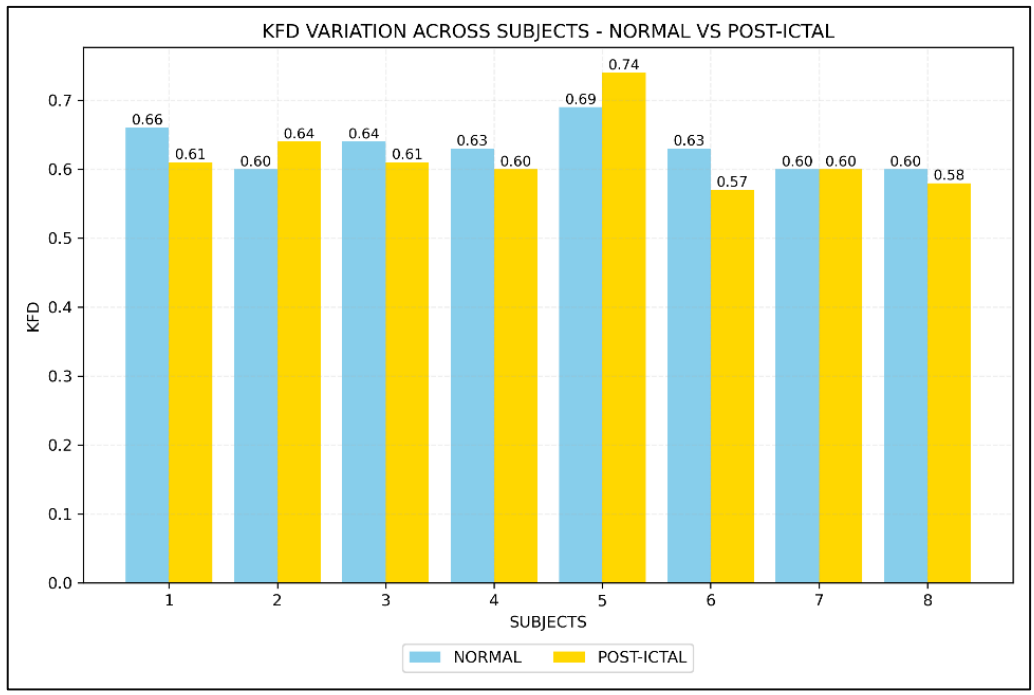


FIG. 57 KFD VARIATION OF NORMAL AND POST-ICTAL OF ALL SUBJECT

Observations from the KFD Variations Across All Subjects

- Subject 1

  - The KFD value starts at 0.66 in the normal phase.
  - It decreases slightly to 0.60 in the pre-ictal phase, indicating a reduction in fractal dimension before the seizure.
  - During the ictal phase, the KFD increases to 0.63, reflecting a rise in complexity during the seizure.
  - In the post-ictal phase, the KFD decreases to 0.61, showing a partial return to lower complexity after the seizure.

- Subject 2

  - The KFD value is 0.60 in the normal phase.
  - It increases to 0.61 in the pre-ictal phase, suggesting a slight rise in complexity before the seizure.

- The KFD value continues to increase to 0.62 during the ictal phase and further rises to 0.64 in the post-ictal phase, indicating a continued increase in complexity throughout the seizure and recovery phases.

- Subject 3

  - The KFD value starts at 0.64 in the normal phase.
  - It decreases to 0.61 in the pre-ictal phase, reflecting a drop in fractal dimension before the seizure.
  - During the ictal phase, the KFD increases slightly to 0.62, then decreases again to 0.61 in the post-ictal phase, showing fluctuating complexity around the seizure period.

- Subject 4

  - The KFD value is 0.63 in the normal phase.
  - It decreases slightly to 0.62 in the pre-ictal phase, suggesting a minor reduction in complexity before the seizure.
  - During the ictal phase, the KFD rises significantly to 0.77, indicating a substantial increase in complexity during the seizure.
  - In the post-ictal phase, the KFD decreases to 0.60, reflecting a reduction in complexity after the seizure.

- Subject 5

  - The KFD value is 0.69 in the normal phase.
  - The KFD decreases to 0.58 in the pre-ictal phase, showing a marked reduction in complexity before the seizure.
  - During the ictal phase, the KFD increases to 0.61, and significantly rises to 0.74 in the post-ictal phase, suggesting a significant increase in complexity during and after the seizure.

- Subject 6

  - The KFD value is 0.63 in the normal phase.
  - It decreases to 0.60 in the pre-ictal phase, reflecting a reduction in fractal dimension before the seizure.

- During the ictal phase, the KFD decreases slightly to 0.59, then drops further to 0.57 in the post-ictal phase, indicating a continued decrease in complexity.

- Subject 7

  - The KFD value starts at 0.60 in the normal phase.
  - It increases to 0.67 in the pre-ictal phase, showing a rise in complexity before the seizure.
  - The KFD decreases to 0.64 during the ictal phase and further drops to 0.60 in the post-ictal phase, reflecting fluctuating complexity during and after the seizure.

- Subject 8

  - The KFD value is 0.60 in the normal phase.
  - It decreases to 0.59 in the pre-ictal phase, indicating a slight reduction in complexity before the seizure.
  - The KFD value decreases to 0.58 during the ictal phase and remains at 0.58 in the post-ictal phase, showing a stable low complexity throughout the post-seizure period.

The KFD values across different phases of the seizure cycle exhibit varied patterns of complexity and fractal dimension. In the normal phase, KFD values generally reflect stable complexity levels. As the pre-ictal phase approaches, there is a mix of increases and decreases in KFD, suggesting changes in complexity before the onset of seizures. During the ictal phase, KFD values fluctuate, with some subjects showing an increase in complexity while others experiencing a decrease. This indicates a dynamic shift in brain activity during the seizure. In the post-ictal phase, KFD values show a range of responses: some subjects experience a return to normal or lower complexity, while others show continued increased complexity. These variations highlight the complex nature of brain dynamics during and after seizures and suggest that KFD could be a valuable marker for assessing changes in brain activity across different seizure phases.

CHAPTER 5

DISCUSSION

It always seems impossible until it's done.

– Nelson Mandela

Among the different domains explored, the study first proved that the Time-Frequency domain is the best method for analyzing EEG signal characteristics. Among the frequency domains, the Welch PSD method was known to provide good results for understanding the power distribution in the frequency domain of the different phases of the seizure cycle. Wavelet Transform of db 6 level 6 denoised the EEG signal effectively. Following denoising, the feature extraction method provided an important insight into the various neural dynamics. The four different observations from feature extraction are explained below.

5.1 . DELTA THETA RATIO VARIATION

The Delta-Theta Ratio (DTR) across the eight subjects displays unique traits throughout the different phases of the seizure duration.

Subjects 1, 2, and 3 demonstrated an increase in DTR from the normal baseline to the pre-ictal, ictal, and post-ictal phases. This trend indicates a higher dominance of delta power relative to theta power across these phases compared to the interictal period.

Subjects 6 and 7 showed a decrease in DTR through the pre-ictal, ictal, and post-ictal phases, which indicates greater dominance of theta waves over delta waves in these subjects during seizure activity.

In the pre-ictal phase, a noticeable increase in DTR from normal levels was observed in subjects 1, 3, 5, and 8. However, in the ictal phase, DTR decreased from this elevated pre-

ictal level. This pattern indicates that while delta power increases relative to theta in the pre-ictal phase, it diminishes during the ictal phase.

Conversely, in subjects 4 and 6, the pre-ictal DTR was lower than during the ictal phase, whereas subject 7 showed a high DTR in the pre-ictal phase that decreased during the ictal phase.

These results highlight the variability in DTR patterns among subjects, which reflects different dynamics of delta and theta wave dominance throughout the seizure cycle. These findings reflect variable dominance of DTR and can be used for understanding individual differences in seizure activity

5.2 . ALPHA BETA RATIO VARIATION

The Alpha-Beta Ratio (ABR) in this study gives an image of the relative dominance of beta waves (high-frequency) over alpha waves (lower frequency). This ratio is important in interpreting neural activity during different phases of epileptic events.

These subjects displayed a consistent pattern of decreasing ABR from the pre-ictal to ictal to post-ictal phases. This reduction in ABR indicates that beta-wave activity was more dominant than alpha-wave activity throughout these phases.

The decrease in ABR suggests a progressive decline in the frequency and amplitude of alpha waves relative to beta waves, reflecting changes in neural dynamics associated with seizure activity. All subjects, except subject 8, exhibited a decrease in ABR from the baseline normal phase to the ictal phase.

This overall reduction highlights a shift towards higher beta wave activity, which is often associated with increased cortical excitability and seizure propensity.

When examining the pre-ictal phase for potential seizure prediction, most subjects showed similar ABR patterns in both the pre-ictal and ictal phases.

This consistency suggests that analyzing the pre-ictal phase can be a reliable indicator of impending seizure activity.

Subject 8, however, exhibited a notable exception where the ABR value in the ictal phase significantly dropped, nearly halving, indicating a unique neural response compared to other subjects.

The ABR analysis provided information into the neural activity patterns associated with different seizure phases. The consistent decrease in ABR from pre-ictal to ictal to post-ictal phases across subjects 1, 2, 5, and 7 shows the predominance of beta-wave activity during seizures. The unique case of subject 8, with a marked reduction in ABR during the ictal phase, highlights the variability in seizure dynamics among individuals.

This experiment states the potential of ABR as a diagnostic tool for predicting seizures, emphasizing the importance of phase-specific analysis to capture the nuances of neural activity in epileptic patients. Further studies and usage of advanced signal processing techniques are required to enhance the predictive capabilities of ABR and enhance seizure diagnosis.

5.3. SHANNON ENTROPY

Shannon Entropy (ShE) quantifies the unpredictability and randomness within the EEG signal. Higher entropy values indicate increased complexity and reduced predictability, whereas lower entropy values reflect reduced complexity and improved predictability of neural activity.

In the ictal phase, subjects 1, 2, and 4 exhibited low entropy, indicating reduced signal complexity and increased predictability of neural dynamics. Conversely, the remaining subjects displayed high entropy in the ictal phase, indicating heightened complexity and reduced predictability.

In the pre-ictal phase, subjects 1 and 2 showed higher entropy than the inter-ictal phase, suggesting increased complexity and reduced predictability of neural activity. Subjects 4, 5, and 7 displayed entropy levels nearly equal to the inter-ictal phase, indicating a stable

complexity level. The remaining subjects showed lower entropy, reflecting reduced complexity and increased predictability.

For the post-ictal phase, subjects 1, 4, 5, and 7 demonstrated lower entropy, signifying reduced complexity and increased predictability of neural activity. The other subjects displayed variable entropy levels.

Shannon Entropy effectively differentiates between normal subjects and epileptic patients by highlighting the complexity and predictability of neural activity. However, its ability to distinguish between different seizure phases is limited. Lower entropy in the ictal phase for some subjects suggests a more organized and predictable neural state during seizures, whereas higher entropy indicates chaotic and less predictable neural activity.

While Shannon Entropy is useful in identifying the general complexity and predictability of neural activity in epileptic patients, its utility in distinguishing between different seizure phases is limited. The variations in entropy across subjects and phases highlight the need for other methods to understand and predict seizure dynamics fully. Further research and advanced signal processing techniques, such as non-linear dynamic analysis and machine learning, are required to enhance the diagnostic capabilities for epilepsy using entropy measures.

5.4. KATZ FRACTAL DIMENSION

The Katz Fractal Dimension (KFD) is a measure of the complexity and irregularity in a time series. The computation of KFD for the EEG signals of subjects 1, 3, 6, and 8 showed a predictable decrease across all three phases (pre-ictal, ictal, and post-ictal) from the baseline normal phase. This decline indicates a reduction in signal complexity during these phases.

In subject 7, KFD increased during the pre-ictal and ictal phases, suggesting increased signal irregularity, but returned to baseline normal values in the post-ictal phase, indicating a normalization of brain activity.

Subjects 4 and 5 exhibited contrasting patterns. In subject 4, during the pre-ictal phase, the KFD initially declined, then increased during the ictal phase, followed by another decline

in the post-ictal phase. Whereas, subject 5 experienced a decrease in KFD during the pre-ictal phase, which continued to drop in the ictal phase before rising again in the post-ictal phase. This uniform decrease in KFD across all phases in subjects 1, 3, 6, and 8 suggests a reduction in signal complexity and irregularity during seizure activity. This indicates a more synchronized and less chaotic brain state.

In subject 7, the increase in KFD during the pre-ictal and ictal phases suggests heightened irregularity and complexity in brain activity, which then normalizes post-seizure.

The contrasting patterns in subjects 4 and 5 highlight the variability in seizure dynamics across individuals. These variations in KFD reflect different responses of brain activity to seizure onset and recovery.

Katz Fractal Dimension proves to be the best method for analyzing seizure activity. The consistent patterns identified in the pre-ictal and ictal phases across all 8 subjects suggest its potential to identify seizure onset before its progression to a more serious seizure type. The capability of Fractal Dimensions using KATZ to detect changes in signal complexity and irregularity makes it an important aid in the pre-ictal diagnosis and supervising of epilepsy.

CHAPTER 6

CONCLUSION

All's well that ends well.

– William Shakespeare

This study analyzed EEG signals through four different approaches for detecting seizures and identifying phases: two linear techniques, Delta-Theta Ratio (DTR) and Alpha-Beta Ratio (ABR), and two non-linear techniques, Shannon Entropy and Katz Fractal Dimension (KFD). The findings indicated that the non-linear methods were more successful in recognizing the pre-ictal phase, which serves as a biomarker for predicting seizures.

DTR measures the power ratio between delta and theta waves. While it showed changes across seizure phases, the variations were not consistent across all subjects, limiting its reliability.

ABR measures the power ratio between alpha and beta waves. Subjects 1, 2, 5, and 7 showed a consistent decrease in ABR from normal through pre-ictal, ictal, and post-ictal phases, indicating beta wave dominance. However, ABR alone did not effectively distinguish between pre-ictal and ictal phases for early diagnosis.

Shannon Entropy assesses the unpredictability of the EEG signal. Lower entropy in the ictal phase was observed in subjects 1, 2, and 4, suggesting lower complexity. Only subjects 1 and 2 showed higher entropy in the pre-ictal phase, indicating limited consistency across subjects. Entropy such as Shannon entropy can distinguish between epileptic patients and normal subjects, but can hardly tell the differences between different phases. As earlier mentioned, the sub-types of Shannon entropy can help in the identification of different seizures if and when applied.

KFD measures signal complexity and irregularity. Subjects 1, 3, 6, and 8 showed a consistent decrease in KFD across all phases, indicating reduced complexity during seizures.

Subject 7 showed increased KFD in the pre-ictal and ictal phases, normalizing post-ictal. This consistency in KFD changes suggests its potential for early seizure detection.

As per the literature survey, these findings indicated the Fractal dimension as a better method than Entropy measures. Non-linear methods, particularly Katz Fractal Dimension, demonstrated superior performance in identifying the pre-ictal phase for seizure prediction. The consistent patterns in KFD indicate its strength in detecting early seizure activity, making it a valuable tool for improving the accuracy and reliability of seizure prediction and enhancing patient outcomes. Katz Fractal Dimension was a promising method used in various other non-linear signal studies. In this study, for identification of the different phases, especially the pre-ictal, Katz Fractal Dimensions outperformed other methods.

CHAPTER 7

FUTURE SCOPE

The future scope of building a seizure detection system using Katz Fractal Dimension (KFD) involves hopeful advancement. One key area is the implementation of real-time monitoring systems that continuously compute KFD from EEG signals. This would allow for the early detection of seizures, providing timely alerts to patients and other aid, thereby preventing injuries and enabling immediate intervention.

Integrating machine learning algorithms to analyze KFD patterns over time could enhance the system's ability to accurately differentiate between normal and seizure states, creating a more personalized and robust detection system.

Additionally, the development of wearable EEG devices with embedded processors capable of calculating KFD in real time would increase convenience and enable continuous monitoring outside of clinical settings. This would improve patient management and also facilitate the collection of data for long-term monitoring and research. Utilizing cloud-based platforms for storing and analyzing EEG data can further support large-scale data collection and KFD computation, helping to identify patterns and improve predictive modeling. Enhancing the focus on KFD calculation during the pre-ictal phase could provide early and accurate identification of impending seizures, offering critical time for preventive measures.

In improving other methods, several strategies could be employed. For the Delta-Theta Ratio (DTR), combining it with other EEG features and integrating machine learning techniques can enhance its predictive power, making it more reliable in identifying seizure phases. Developing adaptive thresholding techniques that adjust DTR thresholds based on individual patient data can increase sensitivity and specificity in seizure detection. For the Alpha-Beta Ratio (ABR), adjusting the frequency bands used for its calculation can help better capture seizure-related changes, while applying temporal analysis methods to study changes in ABR over time can improve early detection by identifying trends and patterns.

Shannon Entropy could be enhanced by merging multi-scale entropy analysis to capture complexity at different time scales, providing a more detailed understanding of the EEG signal.

Additionally, entropy-based feature selection methods could be used to identify the most relevant features for seizure prediction, focusing on the most informative aspects of the EEG signal and thereby enhancing predictive models.

The integration of live feedback, machine learning, and wearable technology with KFD analysis holds significant potential for advancing seizure detection and prediction. By refining linear methods such as DTR and ABR and enhancing Shannon Entropy analysis, to develop a comprehensive and reliable diagnostic tool for epilepsy treatment. These advancements promise to improve patient outcomes and provide deeper insights into seizure dynamics.

CHAPTER 8

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