Epileptic Seizure Localization from EEG Signals

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Abstract

Epileptic seizures represent a significant neurological challenge, characterized by abnormal brain activity due to excessive neuronal discharges. Electroencephalography (EEG) provides a non-invasive method to monitor such electrical activity, aiding in the detection and localization of seizures. This study utilizes EEG signals from pediatric patients to explore the ictal (seizure) and preictal (pre-seizure) stages, aiming to enhance seizure prediction and localization. Power Spectral Density (PSD) and Relative Power were the key features used to analyze brain wave patterns, particularly focusing on alpha and delta frequencies. Results indicate a significant increase in delta power during ictal stages, correlating with seizure activity. Additionally, the study highlights an alpha slowing phenomenon as patients approach seizure onset. These findings underscore the importance of focusing on preictal patterns for improving seizure prediction accuracy.

Keywords— EEG, Epileptic Seizures, Power Spectral Density, Ictal, Preictal, Alpha Slowing, Seizure Localization

I. INTRODUCTION

A "seizure" is a paroxysmal disruption of brain activity resulting from an excessive, hypersynchronous discharge of neurons in the brain [1]. In other words, it is a temporary, abnormal surge of electrical activity in the brain that can cause a variety of symptoms [2]. It can vary from the briefest lapses of attention or muscle jerks to severe and prolonged convulsions [3]. During a seizure, neurons in the brain send signals at the same time, much faster than normal [4]. It can cause a range of symptoms, from momentarily staring blankly to a loss of awareness and uncontrollable twitching. Some seizures can be milder than others, but even minor seizures can be dangerous if they occur during activities like swimming or driving. They manifest through sudden extension or flexion of the extremities. Moreover, they can reoccur in clusters [5].

Epilepsy is a chronic neurological condition that occurs when a person has two or more unprovoked seizures that happen more than 24 hours apart [2]. It is characterized by erratic signals from groups of neurons in the brain. Epilepsy has numerous causes, each reflecting an underlying brain dysfunction [1]. It can begin at any age. Worldwide, a quarter of all newly diagnosed cases of epilepsy are in children, especially under the age of 2, and in adults aged 65 or older [5]. Approximately 75% of epilepsy begins during childhood, reflecting the heightened susceptibility of the developing brain to seizures [1]. According to the World Health Organization (WHO), around 50 million people worldwide have epilepsy, making it the fourth most common neurological disease globally after migraines, strokes, and Alzheimer's [6]. The risk of premature death in people with epilepsy is up to three times higher than for the general population. Globally, an estimated 5 million people are diagnosed with epilepsy each year, with an incidence of approximately 50 new cases per year per 100,000 population [1].

An electroencephalogram is a painless medical test that measures the electrical activity of the brain by recording brain wave patterns. It can be used to diagnose and monitor epilepsy. Small metal discs with thin wires (electrodes) are attached to the scalp of the person, and the signals are sent to a computer to record the results [7]. Signals monitor the brain's electrical activity through the available 16 electrodes and 256 channels. EEG's high temporal resolution allows researchers to track real-time neural activity, proving invaluable in studying cognitive processes and neural dynamics. This allows us to study the dynamics of brain processes and how they relate to different stimuli and tasks [8]. Keeping track of seizures is the best way to know how many seizures a person has, what type, and how they affect them. This information helps the epilepsy team know what treatment may be best [9].

Normally, an EEG recording could take up to 10–15 hours. Each second is further divided into numerous parts based on the sampling rate of the dataset. Medical practitioners normally take a huge amount of time to manually traverse through this vast amount of data and detect the occurrence of a seizure [10]. Our aim is to aid them in identifying the important points of seizure in the EEG dataset while highlighting them. This seizure localization can be done by identifying the features in the dataset. This involves dividing the EEG files into separate ictal and preictal stages, hence helping in understanding the variations. The motivation behind this is the urgent need to improve the management and treatment of epilepsy.

II. Literature Review

G. Yogarajan et al. (2023) proposed an EEG-based, improved automatic seizure detection system using a deep neural network (DNN) and binary dragonfly algorithm (BDFA). Initially, the stationary wavelet transform is used to extract nine distinct statistical and Hjorth parameters from different levels of decomposed signals, which are then used to teach the DNN model the properties of the EEG signals. After that, the extracted features were reduced using the BDFA, which speeds up and enhances the DNN's performance during training [11]. Amirsalar Mansouri et al. (2019) did their research on "Online EEG Seizure Detection and Localization." A tunable, non-patient, and non-seizure-specific method was proposed to detect the presence and locality of a seizure using electroencephalography (EEG) signals [12]. Mohammad Khubeb Siddiqui et al. (2018) did their research on reducing seizure detection time while maintaining high accuracy and locating the brain hemisphere that is mostly affected by seizures. They did it using a decision forest on an ECoG brain dataset [13]. Jennifer L. DeWolfe et al., in Therapy in Sleep Medicine (2012), took an approach to discussing "Sleep-related seizure identification and its management." M. R. Newton et al. (1995) compared the yield of ictal, postictal, and interictal single-photon emission computed tomography (SPECT) in the localization of seizure foci in 177 patients with partial epilepsy [14]. A SPECT scan is a type of imaging test that uses a radioactive substance and a special camera to create 3D pictures [15]. F.H. Lopes da Silva et al. (1976) detected the occurrence of transient non-stationarities using a new method of automatic EEG analysis (ASD, or Automatic Non-Stationarity Detection). This method is derived from a parametric EEG model, which is also known as the autoregressive filter model and is based on inverse filtering. This is then applied to the scalp and subdural EEGs of epileptic patients [16].

The purpose of the proposed article is to enhance epilepsy treatment strategies by offering a comprehensive analysis aimed at comprehending the onset of seizure activity and enhancing the precision of pinpointing the precise regions causing seizures. For this purpose, the data is split into two files: preictal, which is the data before the seizure, and ictal, which is the data during the seizure. The relative power of the brain waves in ictal and preictal regions is then determined using the Welch method for power spectral density. Our primary focus is on the preictal stage of epileptic seizures in order to find the early markers of seizure onset. We have made important discoveries that may improve early detection techniques. We have also provided a visual representation in the form of graphs through a Graphical User Interface (GUI) where the user can upload a dataset in Comma-Separated Values (CSV) or European Data Format (EDF). In this way, we extract the features and provide seizure localization.

III. DATA DESCRIPTION

The study utilizes the CHB-MIT dataset collected from the Children's Hospital at Boston, available in an online public repository [17], consisting of EEG recordings from pediatric subjects with intractable seizures. The EEG recordings are grouped into 23 cases (chb01, chb02,..chb23), which were collected from 22 subjects (5 males, ages 3–22 and 17 females, ages 1.5–19), case chb21 was obtained from the same subject 1.5 years after chb01. The EEG recordings are present in the European Data Format (.edf) and contain EEG signal recordings that range between one and four hours. The sampling rate of the signals is 256 Hz (ie. 256 samples per second). Most of the cases contain 23 EEG channels, where an EEG channel is formed by taking the difference between potentials measured at two adjacent electrodes (bi-polar montage).The International 10-20 system of EEG electrode positions and nomenclature was used for these recordings as given in Figure 1.

IV. METHODOLOGY

This study aims to identify distinct features in EEG signals of patients experiencing epileptic seizures. Typically, medical practitioners spend considerable time analyzing entire datasets of recordings. However, understanding these specific features can greatly aid them by allowing a focused examination of points where seizure activity initiates. By pinpointing the onset of seizures, the analysis process becomes more efficient, enabling quicker diagnosis and better-targeted treatments for patients. The feature extraction process is preceded by the data preprocessing stage where the files are segmented into separate ictal and preictal files. These segmented files are easier to manipulate and process, and reduce computational strain. It also allows focusing on specific segments of data, making targeted analysis more manageable. An EEG is composed of various frequency components, and in order to identify different features, the frequency components of the EEG signals must be analyzed. This is done using the Welch's Method for Power Spectral Density and Relative Power, thereby determining the variation of the brain waves activity between the ictal and the preictal stages. The architecture diagram of the proposed methodology is shown in Figure 2.

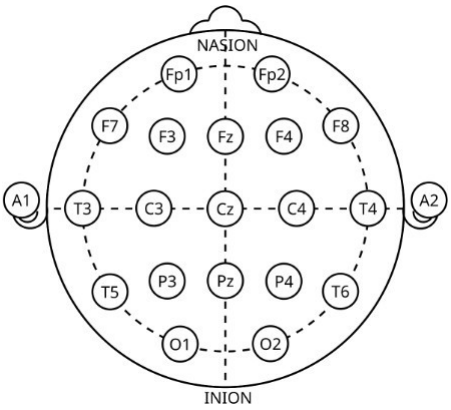

Fig. 1. The international 10-20 system of electrode placement. [18]

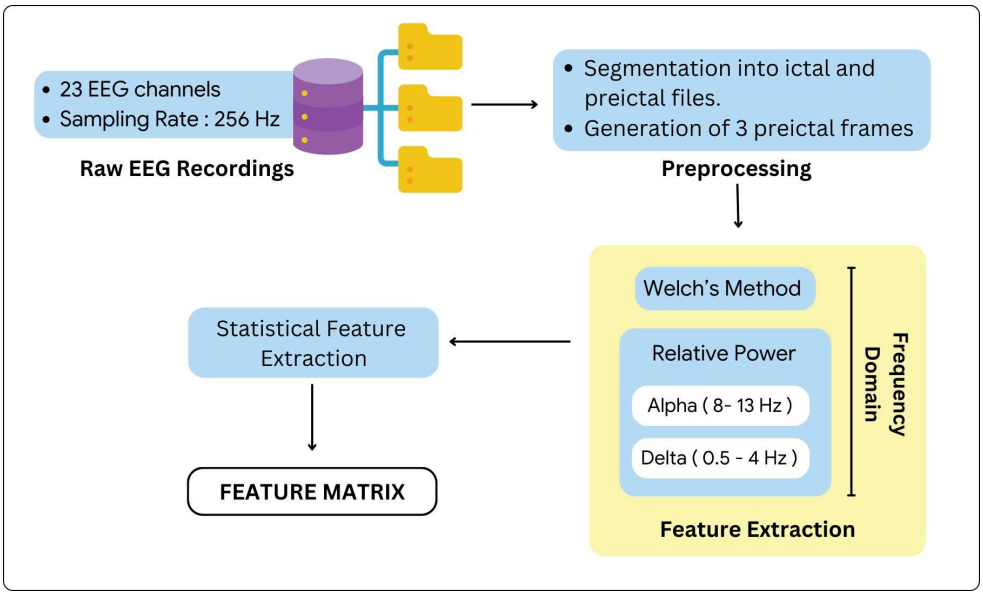

Fig. 2. Feature Extraction Process

A. Data Preprocessing

The preprocessing of the dataset included the segmentation of the available data into two different data files - the ictal data files and the preictal data files. Separating the EEG dataset into ictal (seizure) files and preictal (pre-seizure) files is critical for several reasons related to the analysis, diagnosis, and potential prediction of epileptic seizures. The ictal files were created for each of the seizures, that contain all the data points between the seizure start time and seizure end time, ie. it contains the EEG recordings during a seizure. Analyzing this data helps in identifying the specific patterns and characteristics of brain activity that occur during a seizure. Secondly, three preictal frame files were generated for every seizure which represents the EEG recordings just before the onset of a seizure. A gap of 10 seconds is left between the start of the ictal stage and the end of preictal frame 1 to avoid any crossovers in brain wave behavior during the ictal and preictal stages. Preictal frame 1 includes the 10 seconds before the start of the earlier gap. Frame 2 includes the 10 seconds before start of frame 1, and Frame 3 includes the 10 seconds before start of frame 2. This data is crucial for understanding the changes in brain activity that precede a seizure. Further analysis is performed based on these files created.

B. Feature Extraction

For the purpose of extracting features, power spectral density and relative power have been employed in quantifying the distribution of power across different frequency bands, which is critical for identifying physiological brain activities. Power Spectral Density helps in detecting dominant frequency components, while relative power highlights the proportionate

power of specific frequency bands, and this study specifically focuses on the behavior of alpha and delta waves. These features are essential for diagnosing neurological conditions as they provide insights into abnormal brain activities.

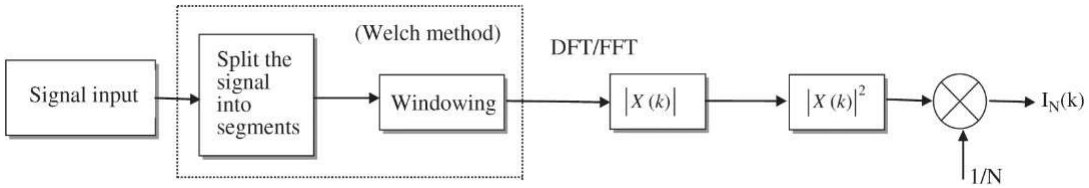

Fig. 3. Flowchart of the Welch Method with windowing [20]

1) Power Spectral Density: Welch's method is a periodogram approach for estimating the power spectral density of a signal. The power spectral density or power spectrum represents the proportion of the total signal power contributed by each frequency component of a voltage signal [19]. PSD of a signal means the distribution of power over its frequency components, that represents the impact of the frequency components included in the signal. Welch's method helps in determining the underlying frequency components, leading to a better understanding of the various brain signals and their associated physiological states. Through averaging, this method reduces variance and provides a more accurate PSD estimate. The method includes segmentation, windowing and averaging, by which it reduces variance. During the segmentation process, the data segments with overlapping points are identified, which are further split into segments having equal length. Using a window function - Hann window the segments are windowed, thus minimizing discontinuities at segment boundaries. For each segment, the DFT is computed, to convert the time domain data into frequency domain data, resulting in the formation of periodograms for each segment, followed by the computation of the mean squared amplitude for each segment. The final PSD estimate is obtained by averaging all the periodograms. The flowchart of the described methodology is provided in Figure 3[20].
The PSD is estimated in the following way: [21]

1) The signal $x(n), n = \{0, 1, \ldots, N-1\}$ is divided into L segments. Each segment has M points, and the data in the i-th segment can be expressed as:

$$x_i(n) = x(n + iM - M), \qquad 0 \le n \le M, \quad 1 \le i \le L \tag{1}$$

2) The Fast Fourier Transforms of these sequences are taken and the i^{th} periodogram is

$$I_i(\omega) = \frac{1}{U}\left|\sum_{n=0}^{M-1} x_i(n)w(n)e^{-j\omega n}\right|^2, \quad i = 1, 2, \ldots, M-1 \tag{2}$$

where,

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n) \tag{3}$$

3) The PSD is obtained as:

$$PSD(e^{j\omega}) = \frac{1}{L}\sum_{i=1}^{L} I_i(\omega) \tag{4}$$

2) Relative Power: The relative power of brain signals is a measure used to understand the distribution of power across different frequency bands in EEG data. Relative power helps to identify dominant brain waves and their associations with various cognitive states. The EEG signal is divided into several standard frequency bands:

- Delta (δ) : 0.5 – 4 Hz
- Theta (θ) : 4 – 8 Hz
- Alpha (α) : 8 – 13 Hz
- Beta (β) : 13 – 30 Hz
- Gamma (γ) : 30 – 100 Hz

Relative power expresses the power in a frequency band as a percentage of the total power of the signal. It quantifies the relative contribution of different frequency bands to the overall power of a signal [22]. Powerful insights on the underlying physiological or functional processes can be derived by understanding the relative contribution of different frequency bands to the overall signal power [22]. The relative power for a particular frequency band is calculated as given (5):

$$\text{Relative Power} = \frac{\text{Band Power}}{\text{Total Power}} \tag{5}$$

Analyzing relative power helps identify which frequency bands are most active or disrupted. Increased relative power in specific frequency bands during seizure onset (ictal phase) or before seizure onset (preictal phase) can aid in diagnosis and monitoring. For example, high relative power in the delta band is associated with deep sleep stages and elevated beta relative power indicates active thinking and concentration.

V. Results and Discussions

This section discusses the key findings gained from our analysis of EEG data during the preictal and ictal stages of a seizure. We employed the technique of Relative Power calculation to gain a deeper understanding of how the brain responds to an epileptic seizure event. Our investigation primarily focused on the aspect of spectral power distribution examined through relative power calculations for alpha and delta waves. When considering epileptic seizures, analyzing the patterns of alpha and delta power can offer insights into the brain's electrical changes prior to the onset of the seizure as well as during the seizure event. The study by Smith SJM[39] underlines the importance of the alpha rhythm in neurological disease, where it typically slows down and loses its characteristic anterior- to-posterior gradient – changes that are usually commensurate with clinical severity and therefore useful to monitor neurological dysfunction.

A. Increased Relative Delta Power in Comparison to Relative Alpha Power During Epileptic Seizure

The delta waves are high-amplitude waves located frontally in adults and posteriorly in children. Pathologically, delta waves occur in metabolic encephalopathy, hydrocephalus, subcortical lesions, diffuse lesions and deep midline lesions [27]. The delta oscillations have been proved to have a high correlation with epilepsy. The asymmetry of the delta signals can be used as a biomarker to identify the epileptogenic zone [2]. Hence a higher concentration of delta waves could be an indicative of suspected seizure activity. Fig.4 provides the average of the relative delta and alpha powers of all ictal time periods of a given patient. The x-axis provides the range of average relative powers and the y-axis consists of column graphs of 19 patients. The red columns represent the average relative delta power of a given patient whereas the blue columns represent the average relative alpha power of a given patient. We have observed that the relative delta power is higher than the relative alpha power during the ictal stage. An average increase of 90.87% was observed from the relative alpha power to the relative delta power during these periods. This significant increase that has been consistent across 19 patients can underline the potential of delta power as a strong indicative of suspected seizure activity. Thereby monitoring and analyzing the delta waves could provide a crucial role in the diagnosis of an epileptic activity. The distinct increase in relative power of delta waves when compared to the alpha wave could highlight the importance of these waves in accurately localizing the epileptogenic zones.

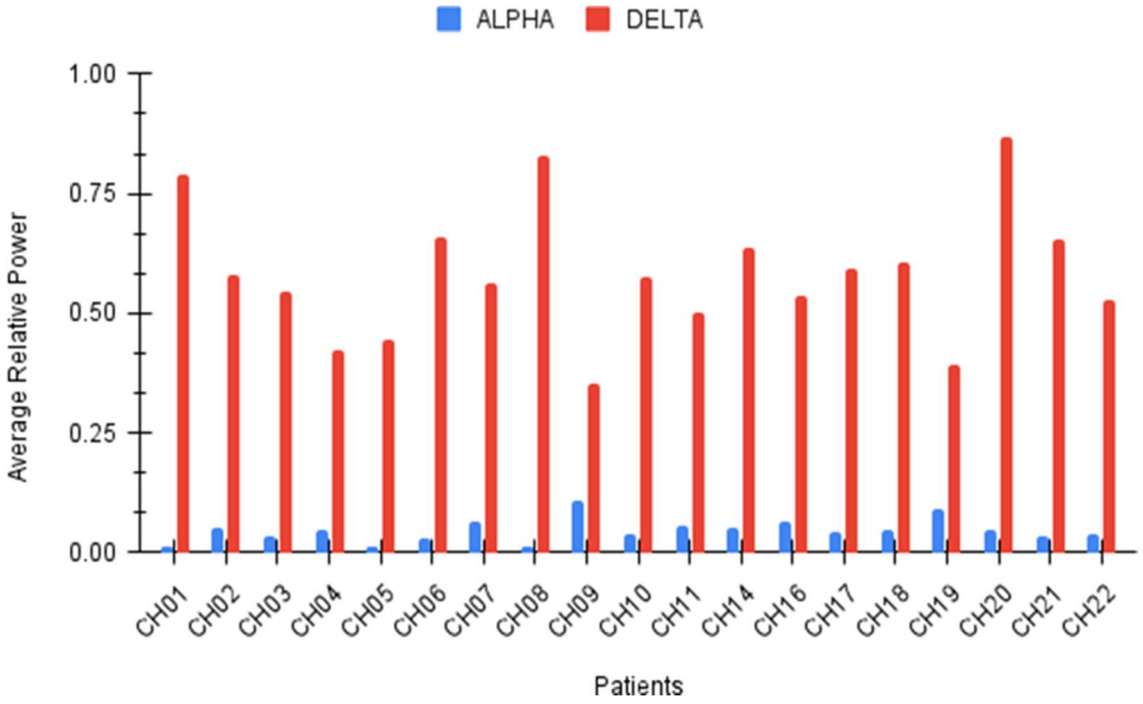

Fig. 4. Comparison between relative alpha and delta values during ictal stage

B. Higher Relative Delta Power In Ictal Stage Than In Preictal Frames

Delta waves, one of the slowest brain oscillations in the EEG spectrum, are often observed in healthy individuals during deep sleep but can also be pathological when present in awake states. These waves, typically ranging between 0.5 to 4 Hz, have been widely studied for their association with various neurological conditions, including epilepsy. In adults, delta waves are predominantly recorded from the frontal cortex, while in children, they are more posteriorly located [27]. Delta wave abnormalities are linked to disorders such as metabolic encephalopathy, brain injuries, and deep midline lesions [27].

From the line graph provided in Fig.5, it can be seen the relative delta power of the ictal stage is higher than the plotted lines indicating relative delta of the preictal frames. The relative delta power of the ictal stage is denoted in the red line graph whereas the green, yellow and blue line graphs indicate the frame 1, frame 2, frame 3 respectively. The higher delta power trend in the ictal stage could be suggestive of correlation between delta waves and epileptic seizure occurrences.

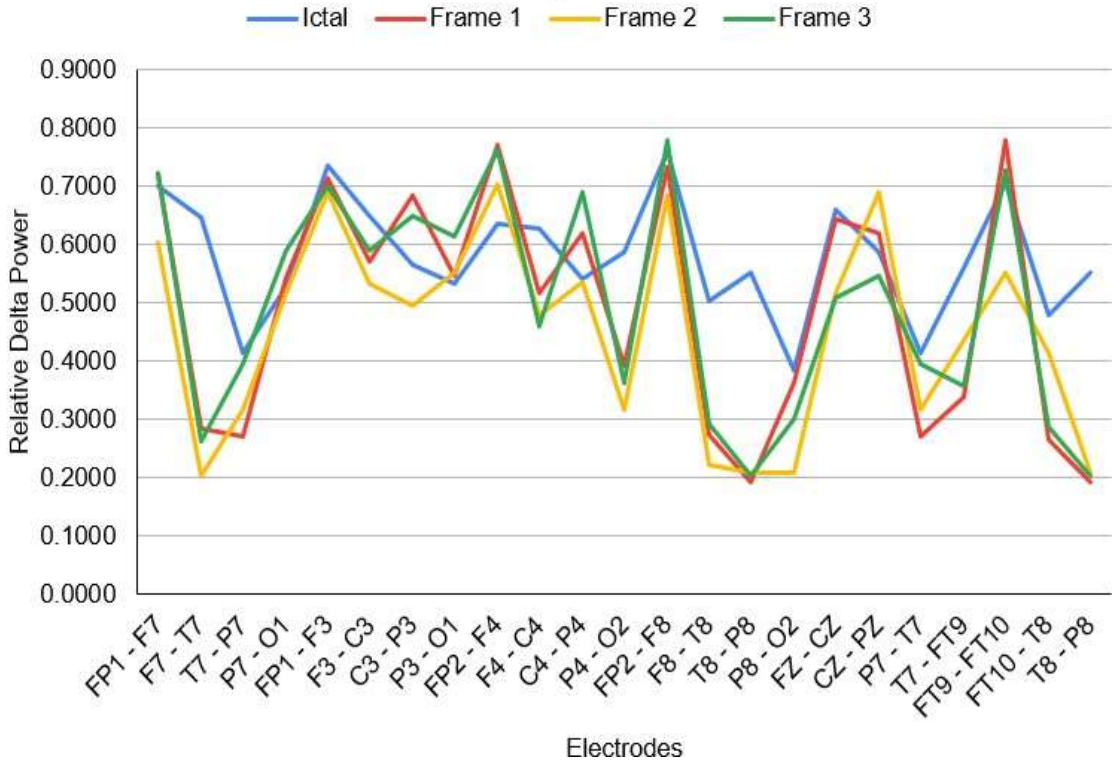

Fig. 5. Comparison between relative delta during ictal and preictal stages

C. Numerical evidence of possible Alpha Rhythm slowing phenomenon

Alpha slowing refers to the phenomenon where the higher frequency power of alpha waves gradually shifts to lower frequency ranges, resembling those of delta waves. This gradual conversion can be observed as the patient approaches the ictal stage. Interframe dependencies were used to demonstrate the relative increase in delta power compared to alpha power as the patient neared the ictal stage. This was achieved by calculating the relative alpha and delta power in each frame: frame 1, frame 2, frame 3, and the ictal stage.

Fig. 6 presents these calculations for Patient1, who experienced three recorded seizure attacks. For example, when considering the frame combination of the ictal stage and frame 1 in Fig. 6, the values listed under the row for relative alpha during Seizure 1 represent the difference in relative alpha power calculated for the electrodes during the ictal and frame 1 periods. Similarly, the row for relative delta during Seizure 1 contains the difference in relative delta power calculated for the electrodes during the same periods. In the row labeled 'Percent difference of delta and alpha', the relative difference between the delta and alpha power values during Seizure 1 was calculated for each electrode. This process was repeated for every seizure and for all the frame combinations considered.

Fig. 6 shows that, in combinations where the initial concentration of alpha waves is higher than that of delta waves, the relative difference in a given electrode gradually decreases as the ictal stage approaches, ultimately resulting in a higher concentration of delta waves than alpha waves. A negative sign in the percentage increase field indicates that the relative concentration of delta waves was lower compared to the relative power of alpha waves. High positive values indicate a higher concentration of delta waves compared to alpha waves. This observation aligns with our earlier findings, showing a significant increase in relative

delta power during the ictal stage, indicating that alpha waves convert into delta waves as a seizure occurs. The highlighted cells are the points where a gradual increase in delta wave concentration could be noticed. For interpreting the alpha slowing phenomenon, we consider frame 3 to be the frame farthest from the ictal stage and frame 1 to be nearest to the ictal stage. Hence, in the event of alpha slowing, the concentration of alpha waves would be the highest in frame 3 and the lowest in the ictal stage. Considering seizure 1 of the patient 1, we observe that in the frame 2 and 3 combination under electrode F4-C4, the percent difference of delta and alpha is -33.33, indicating that the concentration of alpha waves is higher than that of delta waves during that time frame. In the same electrode for the same seizure, considering the values under the frame combination frame 1 and 2, we see the percent difference of delta and alpha as 14.29, suggesting a higher concentration of delta waves than alpha waves during that period. Similarly, in the frame combination ictal and frame 1, the percent difference of delta and alpha is 75.00, showing that the electrode has a predominant concentration of delta waves compared to alpha waves.

Figure 7 summarizes the results observed in seven patients (Refer supplementary material). The values under each selected frame combination indicate the potential occurrence of the alpha slowing phenomenon. The electrode field denotes the electrode in which the observation was found. This could serve as a suggestive point from where the epileptogenic activity started. This detailed analysis can help in understanding the progression of seizure activity and improve the accuracy of identifying epileptogenic zones, enhancing treatment strategies for epilepsy.

			ELECTRODES																							
FRAME COMBINATION	RELATIVE POWER	SEIZURE NO.	FP1 - F7	F7 - T7	T7 - P7	P7 - O1	FP1 - F3	F3 - C3	C3 - P3	P3 - O1	FP2 - F4	F4 - C4	C4 - P4	P4 - O2	FP2 - F8	F8 - T8	T8 - P8	P8 - O2	FZ - CZ	CZ - PZ	P7 - T7	T7 - FT9	FT9 - FT10	FT10 - T8	T8 - P8
ICTAL & FRAME 1	ALPHA	SEIZURE 1	0.02	0.03	0.12	0.02	0.03	0.01	0.01	0.04	0.04	0.02	0.02	0.05	0.02	0.05	0.05	0.06	0.02	0.03	0.12	0.05	0.04	0.05	0.05
		SEIZURE 2	0.03	0.01	0.09	0.02	0.05	0.06	0.06	0.04	0.09	0.05	0.01	0.04	0.02	0.06	0.06	0.05	0	0	0.09	0.05	0.03	0.06	0.06
		SEIZURE 3	0	0.03	0.12	0.02	0.01	0.01	0.07	0.09	0.01	0.03	0.03	0.02	0	0.01	0.04	0.05	0.02	0.05	0.12	0.04	0.01	0.02	0.04
	DELTA	SEIZURE 1	0.14	0.36	0.32	0.03	0.07	0.06	0.04	0.13	0.2	0.08	0.11	0.17	0.08	0.31	0.5	0.14	0.05	0.13	0.32	0.49	0.21	0.42	0.5
		SEIZURE 2	0.03	0.41	0.1	0.12	0.05	0.27	0.2	0.01	0.21	0.03	0.1	0.02	0.06	0.03	0.23	0.25	0.08	0.02	0.1	0.18	0.05	0.05	0.23
		SEIZURE 3	0.1	0.32	0.01	0.04	0.09	0.09	0.11	0.1	0.01	0.22	0.03	0.39	0.1	0.35	0.35	0.17	0.02	0.05	0.01	0.01	0.04	0.17	0.35
	PERCENT DIFFERENCE OF ALPHA AND DELTA	SEIZURE 1	85.71	91.67	62.50	33.33	57.14	83.33	75.00	69.23	80.00	75.00	81.82	70.59	75.00	83.87	90.00	57.14	60.00	76.92	62.50	89.80	80.95	88.10	90.00
		SEIZURE 2	0.00	97.56	10.00	83.33	0.00	77.78	70.00	-300.00	57.14	-66.67	90.00	-100.00	66.67	-100.00	73.91	80.00	100.00	100.00	10.00	72.22	40.00	-20.00	73.91
		SEIZURE 3	100.00	90.63	-1100.00	50.00	88.89	88.89	36.36	10.00	0.00	86.36	0.00	94.87	100.00	97.14	88.57	70.59	0.00	0.00	-1100.00	-300.00	75.00	88.24	88.57
FRAME 1& 2	ALPHA	SEIZURE 1	0	0.01	0	0.01	0.03	0.06	0.03	0.04	0.03	0.06	0.04	0.01	0.02	0.01	0.01	0.01	0.1	0.04	0	0	0.02	0.01	0.01
		SEIZURE 2	0	0.01	0.01	0.03	0.01	0.08	0.01	0.02	0	0.1	0.06	0.02	0	0.01	0	0.01	0.01	0	0.01	0.01	0.01	0.01	0
		SEIZURE 3	0	0.01	0.01	0.04	0.01	0.02	0.05	0.01	0.01	0.05	0.03	0.02	0.01	0.03	0.01	0.05	0.03	0	0.01	0.01	0.01	0.01	0.01
	DELTA	SEIZURE 1	0.09	0.17	0.03	0.09	0.1	0.09	0.01	0.03	0.18	0.07	0.11	0.03	0.16	0.19	0.03	0.01	0.24	0.19	0.03	0.02	0.27	0.02	0.03
		SEIZURE 2	0.24	0.02	0.14	0.31	0.07	0.07	0.42	0.18	0.02	0.09	0.3	0.23	0.06	0.01	0.08	0.34	0.02	0.08	0.14	0.25	0.31	0.34	0.08
		SEIZURE 3	0.03	0.09	0.03	0.14	0.1	0.09	0.15	0.17	0.04	0.05	0.16	0.03	0.05	0.05	0	0.11	0.12	0.06	0.03	0.02	0.1	0.12	0
	PERCENT DIFFERENCE OF ALPHA AND DELTA	SEIZURE 1	100.00	94.12	100.00	88.89	70.00	33.33	-200.00	-33.33	83.33	14.29	63.64	66.67	87.50	94.74	66.67	0.00	58.33	78.95	100.00	100.00	92.59	50.00	66.67
		SEIZURE 2	100.00	50.00	92.86	90.32	85.71	-14.29	97.62	88.89	100.00	-11.11	80.00	91.30	100.00	0.00	100.00	97.06	50.00	100.00	92.86	96.00	96.77	97.06	100.00
		SEIZURE 3	100.00	88.89	66.67	71.43	90.00	77.78	66.67	94.12	75.00	0.00	81.25	33.33	80.00	40.00		54.55	75.00	100.00	66.67	50.00	90.00	91.67	
FRAME 2&3	ALPHA	SEIZURE 1	0.02	0.01	0.01	0.02	0.01	0.01	0	0.01	0	0.04	0.05	0.01	0.01	0.01	0.01	0	0.05	0.03	0.01	0.01	0	0.03	0.01
		SEIZURE 2	0	0	0	0.02	0	0.03	0.02	0.01	0.01	0.11	0.01	0.03	0.01	0	0.02	0.03	0.02	0.01	0	0	0	0	0.02
		SEIZURE 3	0	0	0.02	0.02	0	0.03	0	0	0	0	0.01	0	0	0.01	0	0.01	0.08	0.3	0.02	0	0.01	0	0
	DELTA	SEIZURE 1	0.05	0.21	0.26	0.09	0.08	0.09	0.16	0.16	0.04	0.03	0.03	0.02	0.04	0.28	0.13	0.11	0.04	0.19	0.26	0.06	0.2	0.06	0.13
		SEIZURE 2	0.35	0.12	0.23	0.26	0.24	0.16	0.39	0.3	0.13	0.06	0.49	0.09	0.24	0.19	0.18	0.13	0.07	0.02	0.23	0.5	0.21	0.54	0.18
		SEIZURE 3	0.06	0.09	0.21	0.13	0.13	0.1	0.09	0.28	0.09	0.09	0.06	0.03	0.01	0.12	0.03	0.03	0.13	0.22	0.21	0.2	0.11	0.1	0.03
	PERCENT DIFFERENCE OF ALPHA AND DELTA	SEIZURE 1	60.00	95.24	96.15	77.78	87.50	88.89	100.00	93.75	100.00	-33.33	-66.67	50.00	75.00	96.43	92.31	100.00	-25.00	84.21	96.15	83.33	100.00	50.00	92.31
		SEIZURE 2	100.00	100.00	100.00	92.31	100.00	81.25	94.87	96.67	92.31	-83.33	97.96	66.67	95.83	100.00	88.89	76.92	71.43	50.00	100.00	100.00	100.00	100.00	88.89
		SEIZURE 3	100.00	100.00	90.48	84.62	100.00	70.00	100.00	100.00	100.00	100.00	83.33	100.00	100.00	91.67	100.00	66.67	38.46	-36.36	90.48	100.00	90.91	100.00	100.00

Fig. 6. Alpha slowing observed in a patient

SEIZURE FILE	START TIME	END TIME	SEIZURE LENGTH	ELECTRODE	RELATIVE DIFFERENCE BETWEEN RELATIVE ALPHA AND DELTA			PERCENTAGE INCREASE
					FRAME 3 & 2	FRAME 2 & 1	FRAME 1 & ICTAL	
PATIENT 1								
FILE 1	130	212	82	F4 - C4	-33.33	14.29	75.00	144.44
FILE 2	2972	3053	81	CZ - PZ	50.00	100.00	100.00	50.00
FILE 3	3369	3378	9	F3 - C3	70.00	77.78	88.89	21.25
PATIENT 2								
FILE 1	7804	7853	49	F3 - C3	28.57	55.56	90.91	68.57
FILE 2	6446	6557	111	P4 - O2	-300.00	58.82	100.00	400.00
FILE 3	1679	1781	102	FT10 - T8	-50.00	0.00	56.52	188.46
FILE 4	3782	3898	116	T7 - P7	84.21	90.00	93.62	10.05
PATIENT 3								
FILE 1	4920	5006	86	P3 - O1	-75.00	66.67	88.24	185.00
FILE 2	3285	3381	96	P7 - O1	-400.00	88.89	91.43	537.49
FILE 3	13688	13831	143	FZ - CZ	78.57	92.00	100.00	21.43
PATIENT 4								
FILE 1	12231	12295	64	FP1 - F7	-250.00	47.37	92.00	371.74
FILE 2	2951	3030	79	C4 - P4	-200.00	12.50	95.45	309.53
FILE 3	9196	9267	71	C4 - P4	50.00	53.33	76.09	34.29
PATIENT 5								
FILE 1	298	320	22	P7 - O1	-100.00	60.00	81.82	222.22
FILE 2	1454	2206	752	F3 - C3	42.86	80.00	96.43	55.55
PATIENT 6								
FILE 1	2282	2372	90	F8 - T8	50.00	50.00	98.16	49.06
FILE 2	3025	3140	115	T7 - P7	0.00	76.92	93.33	100.00
FILE 3	3136	3224	88	FP2 - F4	-16.67	66.67	71.43	123.34
PATIENT 7								
FILE 1	299	377	78	C4 - P4	-100.00	22.22	76.00	231.58
FILE 2	2964	3041	77	F3 - C3	0.00	76.92	100.00	100.00
FILE 3	3159	3240	81	FP1 - F3	-33.33	50.00	92.31	136.11

Fig. 7. Summary on alpha slowing observed among patients

CONCLUSION

This study focused on the preictal stage of epileptic seizures to identify early indicators of seizure onset, with significant findings that could enhance early detection methods. Using the CHB-MIT dataset, which contains EEG recordings from paediatric subjects at Children's Hospital Boston, the data was divided into preictal and ictal segments. The relative power of various brain wave frequencies was computed for all cases, revealing a consistent transition from alpha to delta waves, known as alpha slowing, in most patients. These results suggest that a shorter, more immediate preictal window is essential for developing reliable seizure prediction models. The study highlights the importance of targeting the preictal stage, laying the groundwork for future research and advancements in seizure prediction technologies.

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