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EEG Signal Analysis for Epilepsy Patterns Using EDFBrowser

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Abstract: Background- In the healthcare system, biomedical signals are significant. It aids in diagnosing medical conditions and offers valuable information about a patient's health. Neurologists can find meaningful information and patterns by carefully examining electroencephalogram (EEG) data, which enables sufferers to receive proper care at the right time.

Objective- Biomedical EEG signals can be used to study the neurological condition known as epilepsy. Signals from an EEG can be used to study brain activity and identify neurological disorders. Recurrent seizures are a sign of epilepsy that affects the brain.

Methods- A medical history, neurological examination, and diagnostic EEG tests are frequently used to identify seizures. EEG bio-signals can be viewed and analyzed using an open-source software program called an EDFBrowser.

Results- This research defines the various ways, including visual inspection, frequency analysis, time-frequency analysis, and spike detection, to read EDF (European Data Format) for epileptic patterns. Also, to define the amplitude-frequency relationship, analyze EEG signals, and examine brain activity in different frequency bands, like Delta, theta, alpha, beta, and gamma, employing Fast Fourier Transform (FFT).

Conclusion- In neuroscience, it must correctly interpret the EEG signal patterns to analyze the condition of the brain.

Keywords: *Electroencephalogram (EEG) Signal, neurological disorder, epilepsy, seizure, EDFBrowser, European Data Format (EDF) files.*

1. Introduction

A biomedical signal refers to any measurable physiological activity or change in the body that can be detected and recorded. These signals can be obtained from various parts of the body, such as the brain, heart, muscles, and other organs. Examples of biomedical signals include electrocardiogram (ECG) signals, electroencephalogram (EEG) signals [1], electromyogram (EMG) signals, and electrooculogram (EOG) signals [2], [3]. The distinguishable signals are generated by distinct body parts in living beings and aid in inspecting body organs' condition [3].

Biomedical signals can be acquired using various techniques such as electrodes, sensors, and imaging equipment, and they are often analyzed using advanced signal processing algorithms to extract useful information [4]. An EEG, or neurobiological signal, measures the brainiac's electrical movement. It is a non-harmful technique that employs electrodes applied to the scalp to track the electrical impulses generated by the brain. These signals assist in diagnosing neural conditions [5]. Overall, EEG signals provide valuable insights into brain function and can be used to diagnose and study neurological disorders and cognitive processes. Epilepsy is a non-invasive neurological disorder that affects the brain and is observed by recurrent seizures. Epileptic seizures are provoked by weird electrical action in the brain, which can render changes in behaviour, consciousness, and motor function. Epilepsy can affect any age, from neonatal to older adults, but it is most commonly diagnosed in children and seniors [6]. The causes of epilepsy can vary, but they may include genetic factors, head injury, brain tumors, infections, or developmental disorders. The reason for the illness is unclear in approximately fifty percent of cases, though [7], [8]. Different types of seizures and regions of the brain can cause a wide range of symptoms for those living with epilepsy. A recursive seizure is an uncontrollable electrical disturbance in the nervous system that can change behaviour, body movements, sensations, or consciousness. Seizures are the hallmark of epilepsy, but they can also occur in other conditions, such as high fever, head injury, or stroke [6]. Generalized seizures and partial seizures are the two basic seizure types. Generalized seizures affect the whole brain and can result in convulsions, loss of consciousness, or muscle spasms. Furthermore, it is split into subtypes such as (a) absence seizures, (b) myoclonic seizures, (c) tonic-clonic seizures, and (d) atonic seizures. On the other hand, partial seizures are restricted to a specific region of the brain and, depending on which section of the brain is damaged, might result in various symptoms. Alterations in consciousness, strange feelings, the movement or twitching of particular body parts, and changes in mood or behavior are all potential signs of partial seizures [6], [9], [10], [11]. Seizures can be triggered by various factors, such as flashing lights, loud noises, stress, or sleep deprivation. However, in many cases,

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the cause of seizures is unknown. Diagnosing seizures typically involves a medical history, neurological examination, and diagnostic tests such as an EEG, MRI, or CT scan. Treatment options for seizures may include medication, surgery, or implanted devices that can help control seizures [5], [12]. EDFBrowser is a free open-source software application for viewing and analyzing bio-signals, including EEG, ECG, EMG, and other physiological signals [13]. The software was developed by Teunis van Beelen and is available for download on his website (https://www.teuniz.net/edfbrowser/). This work describes classifying and analyzing patterns for non-epileptic and epileptic subjects using EEG data in EDF format from CHB-MIT Dataset [14], a benchmark for scalp long-term EEG database. Following the first section, the introduction and the rest of the paper are organized as tracks such as previous work; epilepsy versus seizure; spikes and sharp waves discharges (SWD); EDFBrowser; applied classification mechanism; experiments and results; discussion; conclusion; and then references.

2. Literature Review

In the field of medicine, biomedical signals have significance since they can be used to glean useful information about a patient's health status and contribute to the diagnosis of medical disorders. For example, an ECG signal can be used to detect irregular heartbeats and diagnose heart disease, while an EEG signal can be used to study brain activity and diagnose neurological disorders [3], [15], [16]. EEG signals are characterized by their frequency content, which can be categorized into unique frequency bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (>30 Hz) [2], [17]. Each frequency band is associated with different states of brain activity and cognitive functions. For example, the alpha frequency band is associated with relaxed wakefulness, while the beta frequency band is associated with focused attention. EEG signals can be used to diagnose a wide range of brainiac disorders, such as epilepsy, bedtime disturbances, and brain tumors. Additionally, cognitive processes, including attention, perception, and memory, can be studied using EEG [5], [8]. To extract useful information from EEG signals, advanced signal processing techniques are often used, such as time-frequency analysis, filtering, and artifact removal [3], [5], [18]. An envelope low-pass filter is used in signal processing to extract a signal's envelope while suppressing high-frequency noise and other unwanted bio-signals [1]. The envelope of a signal is the fluctuating part of the signal that varies more slowly than the carrier wave, which can be thought of as the "envelope" that surrounds the carrier. Envelope low-pass filters perform by passing only the low-frequency components of a signal through while attenuating or blocking the high-frequency components [4]. These techniques can help identify important features in the EEG signal that are relevant to a particular application. One common type of non-epileptic pattern is a psychogenic non-epileptic seizure (PNES). PNES is a state identical to seizure-like activity caused by psychological aspects, such as concussion or stress. PNES can be challenging to identify because the symptoms can resemble epileptic seizures but have a distinct underlying cause [11], [19], [20]. Another type of non-epileptic pattern is a movement disorder, such as a tremor or myoclonus. These movements can be mistaken for seizures, but they are caused by problems in the motor system, rather than abnormal brain activity [3], [21], [22], [23]. There are several types of epileptic patterns that can be seen on an EEG: Interictal epileptiform discharges (IEDs) [24] are abnormal spikes or sharp waves that are seen on an EEG when the patient is not experiencing a seizure. IEDs are often used to diagnose epilepsy and to identify the location of the seizure focus [6], [11], [25]. Ictal patterns refer to the EEG changes that occur during an epileptic seizure. These changes can include rhythmic spikes or sharp waves that are synchronous and occur in a specific region of the brain [6], [9], [11], [25], [26]. Post-ictal patterns refer to the EEG changes that occur immediately after an epileptic seizure. These changes can include slowing of the EEG activity or a burst of high frequency activity [25], [27]. Status epilepticus patterns is a prolonged seizure that lasts for more than five minutes, or a series of seizures that occur without a return to consciousness between seizures. EEG patterns during status epilepticus can include continuous or nearly continuous spike and wave discharges [21], [28]. Thus, each medical contact should be described and made as safe as possible so that the benefits outweigh any possible health risks. All tests must be done in the same room with the digital EEG machine, which keeps track of many different things [29].

3. Materials and Methods

The methodology describes epilepsy versus seizure, spikes and wave discharges, and the EDFBrowser tool for understanding the rhythms of EEG signals.

3.1. **Epilepsy versus Seizure:** Epilepsy and seizures are often used interchangeably, but they are not the same thing. Epilepsy is due to recurrent seizures that cause neurological disturbance. On the other hand, a seizure is a sudden, uncontrollable electrical disturbance in the brain that can alter consciousness or induce changes in movement, sensation, or behaviour [12]. Seizures can occur in anyone, regardless of whether they have epilepsy or not. Seizures can be caused by various factors, such as high fever, head injury, or stroke. However, epilepsy is a specific diagnosis that requires the presence of recurrent seizures without an underlying cause [7], [12]. Depending on the type of seizure and the area of the brain affected, the symptoms of a seizure can change. Generalized seizures, which affect the entire brain, and partial seizures, which affect only a portion of the brain, are the two basic forms of seizures. Generalized seizures may cause the person to lose consciousness and experience muscle spasms, convulsions, or rhythmic movements[33][34]. In contrast, partial seizures can cause a range of symptoms, including altered consciousness, unusual sensations, movement or twitching of specific body parts, or changes in mood or behavior [7], [10], [12].

3.2. **Spikes and Sharp Waves Discharges (SWD):** These are abnormal electrical discharges that are often associated with neurological disorders such as epilepsy [9], [10], [11]. In addition to these patterns, EEG signals can also contain artifacts, which are unwanted signals that can arise from sources such as muscle activity, eye movements, and environmental interference. Advanced signal processing techniques are often used to remove these artifacts and extract useful information from the EEG signal [11].

3.3. **EDFBrowser:** In reference [13], EDFBrowser allows users to load and visualize bio-signal data in a variety of formats, including EDF, EDF+, BDF, and BDF+. The software provides a range of features for signal visualization and analysis, including adjustable time scales, signal filtering, and the ability to mark and annotate events in the signal. One of the unique features of EDFBrowser is its ability to handle multiple signals at once, which can be helpful when analyzing data from multiple channels. The software also includes a number of advanced features, such as the ability to perform time-frequency analysis using the continuous wavelet transform and the ability to export data in various formats for use with other software tools. EDFBrowser is a powerful tool for visualizing and analyzing bio-signals and is widely used in research and clinical applications[37][38][39]. Its open-source nature and active developer community make it a valuable resource for researchers and clinicians working with bio-signals (https://www.teuniz.net/edfbrowser/).

3.4. **Algorithm applied for classification mechanism:** The mathematical equation for the Fast Fourier Transform (FFT) algorithm is:

$$\mathbf{X(k) = \sum [n=0 \text{ to } N\text{-}1]\ x(n) * exp[-j(2\pi nk/N)]}$$

where:

X(k) is the frequency-domain representation of the signal, also known as the spectrum

x(n) is the time-domain signal

k is the index of the frequency component being calculated, ranging from 0 to N-1

N is the total number of samples in the time-domain signal

j is the imaginary unit (√-1)

π is the mathematical constant pi (3.1415926...)

exp is the exponential function e raised to the power of the argument.

In words, the equation states that the frequency-domain representation of a signal can be obtained by multiplying each sample of the signal in the time domain by a complex exponential function, summing these products over all the samples in the signal, and repeating this for all frequency components from 0 to N-1 [35][36].

4. Experimental

The CHB-MIT data collection includes EEG recordings performed on children who suffered from uncontrollable seizures. Subjects were observed over a while to evaluate their seizure episodes. Twenty-three patients are spread throughout 24 instances in the collection, such as each patient has two recordings, each one and a half years apart. The dataset comprises nine hundred sixty-nine hours of scalp EEG recordings with 173 seizures. Seizures of various sorts (clonic, atonic, and tonic) are included in the dataset. The variety of patients (Male, Female, 10–22 years old) and various attack types present in the datasets make it possible to evaluate the effectiveness of seizure detection in practical contexts for non-epileptic and epileptic subjects [14]. The CHB-MIT database, an EEG data used in this paper, can be downloaded from the PhysioNet website (https://physionet.org/content/chbmit/1.0.0/). In this article, for classifying and analyzing EEG signals, EDF (.edf file-extension) format data through the EDFBrowser tool by following various options like high-pass band, low-pass band filters, amplitude and power-spectrum of a movement. These are the following results of no-seizure activity and seizure activity for Subject-A and Subject-B, respectively. Here, Subject-A is a non-epileptic, and Subject-B is an epileptic patient. Now it shows non-epileptic EEG signal patterns for Subject-A and epileptic patterns for Subject-B. It mentions apparent differences between no-seizure and seizure patterns from EEG signals for epilepsy [40][41]. It categorized into two parts, the detail bio-signal patterns as shown in section-4, as results for the experiments.

5. Results

Non-epileptic pattern: A non-epileptic pattern refers to a pattern of brain activity that resembles an epileptic seizure, but is not caused by abnormal electrical activity in the brain. Non-epileptic patterns can be caused by a variety of factors, such as medication side effects[42], metabolic disorders, or changes in blood flow to the brain, as shown in Figure-1.

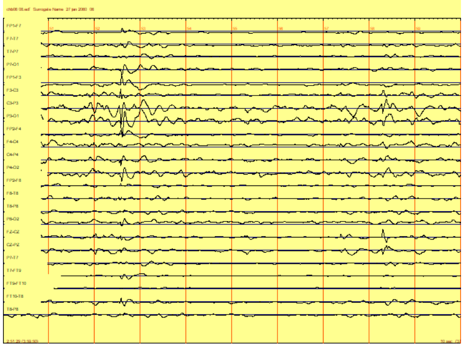

Fig. (1). EEG Signals of non-epileptic Subject-A for 23 Channels (or features) in Wave forms.

In the subsequent plots named Figure-2, all of the required EEG Signals of non-epileptic Subject-A. Here, in detail, such as four Channels (or features) in Waveforms for ten (10) seconds with a range of -100 micro-Volts (µV) to +100 µV; shows eye-blink artefact; four Channels in Waveforms for five (05) seconds with a range of -200 µV to +200 µV; and plots EEG amplitudes for all four features with a segment length of 10 seconds, bandpass filter 50.0 to 120.0 Hz and envelope lowpass filter 5.00 Hz.

Here from Figure-1, 2[a], 2[b] and 2[c], it is clear that non-epileptic patterns are regular in nature. The patient may have a psychogenic non-epileptic seizure (PNES). These seizures are recognized according to the standard convention at all stages, like interictal, ictal and post-ictal patterns [16].

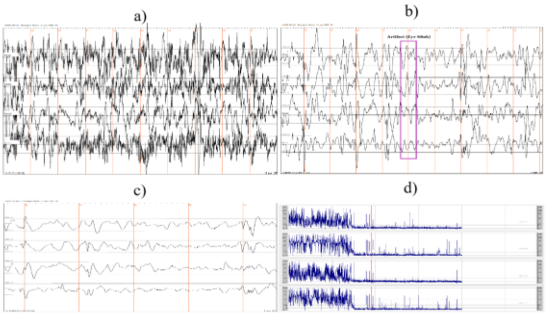

Fig. (2). EEG Signals of non-epileptic Subject-A a) four Channels (or features) in Waveforms for ten (10) seconds with a range of -100 µV to +100 µV; b) shows eye-blink artefact; c) four Channels in Waveforms for five (05) seconds with a range of -200 µV to +200 µV; and d) plots EEG amplitudes for all four features with a segment length of 10 seconds, bandpass filter 50.0 to 120.0 Hz and envelope lowpass filter 5.00 Hz

Epileptic pattern: Epileptic patterns refer to abnormal electrical activity in the brain that can cause epileptic seizures. Epileptic patterns can be identified, in Figure-3, by analyzing EEG signals, which record the electrical activity of the brain.

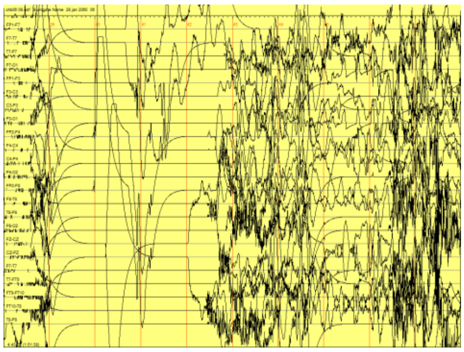

Fig. (3). EEG Signals of epileptic Subject-B for 23 Channels (or features) in Wave forms.

In the following plots, named Figure-4, all the needed EEG Signals of epileptic Subject-B. Here, in particular, it shows a sharp Waveforms pattern for four features in ten (10) seconds with a range of -200 µV to +200 µV; displays a spike Waveform pattern for four channels in five (05) seconds with the energy of -200 µV to +200 µV; exhibits a slow Waveforms pattern for four Channels in five (05) seconds with a capacity of -200 µV to +200 µV; and plots EEG amplitudes for all four features with a segment length of 10 seconds, bandpass filter 50.0 to 120.0 Hz and envelope lowpass filter 5.00 Hz.

Here from Figure-3, 4[a], 4[b] and 4[c], it is clear that epileptic patterns are irregular in nature. The patient may have an abnormal epileptic seizure pattern. These seizures are identified according to the irregularity and abnormality routine at all stages, like interictal, ictal and post-ictal patterns.

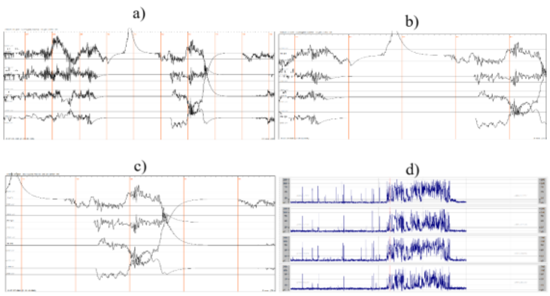

Fig. (4). EEG Signals of epileptic Subject-B a) a sharp Waveforms pattern for four features in ten (10) seconds with a range of -200 µV to +200 µV; b) displays a spike Waveform pattern for four channels in five (05) seconds with the energy of -200 µV to +200 µV; c) exhibits a slow Waveforms pattern for four Channels in five (05) seconds with a capacity of -200 µV to +200 µV; and d) plots EEG amplitudes for all four features with a segment length of 10 seconds, bandpass filter 50.0 to 120.0 Hz and envelope lowpass filter 5.00 Hz.

Fast Fourier Transform (FFT) is commonly used in neuroscience to analyze electroencephalogram (EEG) signals and study brain activity[43] in different frequency bands. The FFT algorithm takes a time-domain bio-signal, which is a function of time, and transforms it into its frequency-domain representation, which is a function of frequency. This transformation allows us to identify the individual frequency components of a signal and their respective amplitudes and phases. An FFT results in a spectrum that displays the signal's frequency content.

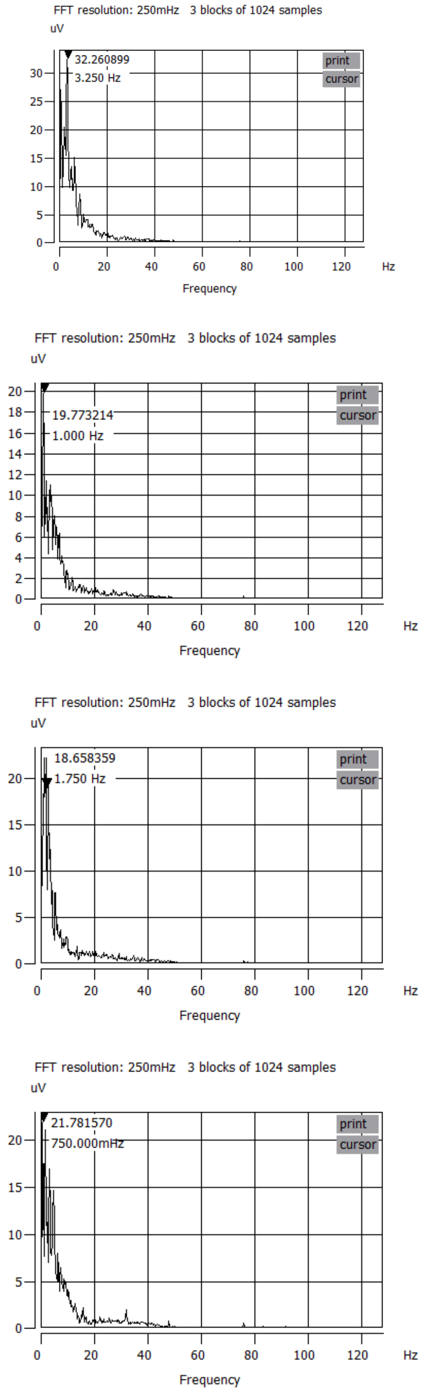

Fig. (5). FFT Results of EEG Signals for non-epileptic Subject-A for four features.

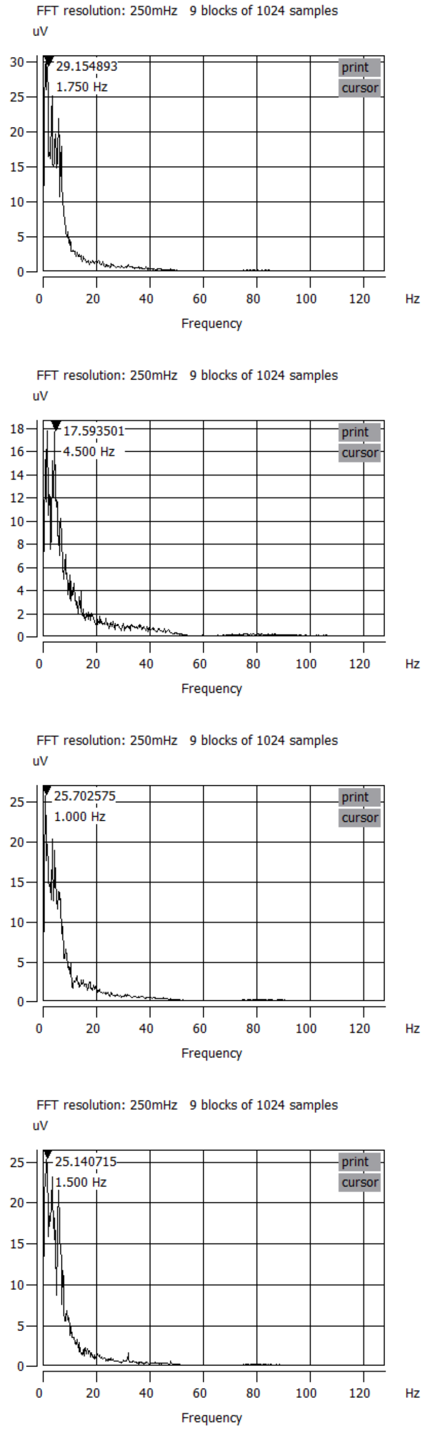

Fig. (6). FFT Results of EEG Signals for epileptic Subject-B for four features.

The FFT algorithm efficiently computes this equation by exploiting symmetries in the complex exponential function and by recursively breaking the computation down into smaller sub-problems. Here, it is considered that for Subject-A, N = 1024 samples, k = 3. Whereas for Subject-B, N = 1024 samples, k = 9. Then, simultaneously, the FFT algorithm was applied to find the following results, shown on the left-hand and right-hand sides of Figure-5 and Figure-6, respectively. Different frequency bands in the spectrum are analyzed to differentiate between epileptic and non-epileptic seizures. For example, in epileptic seizures, the power in the high-frequency bands (gamma and beta) is increased, while in non-epileptic seizures, the power in the lower frequency bands (delta and theta) is increased. Removing noise from EEG signals is essential in analyzing and interpreting the signal. Filtering involves removing unwanted frequencies from the EEG signal, as shown in Figure-7.

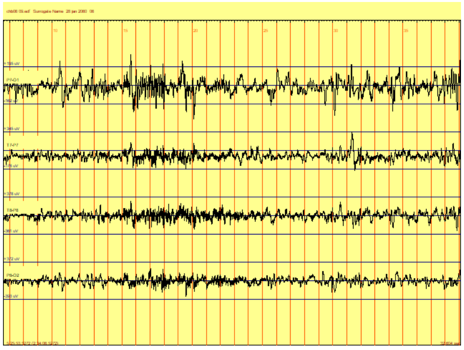

Fig. (7). EEG Signals filtering shows raw bio-signals

Two filters can be applied to EEG signals: high-band-pass and low-band-pass. Low-pass filters remove high-frequency noise, such as muscle artefacts and high-frequency noise, while high-pass filters remove low-frequency noise, such as drifts and slow waves, as shown in Figure-8 and Figure-9, respectively.

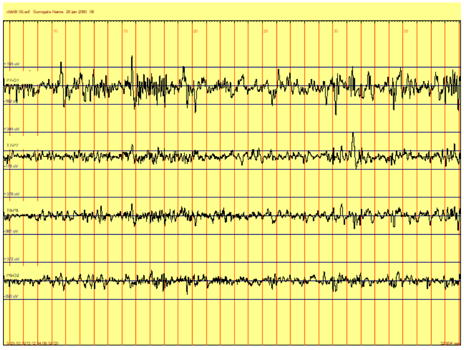

Fig. (8). EEG Signals filtering displays a Waveform pattern after applying low-band-pass filter.

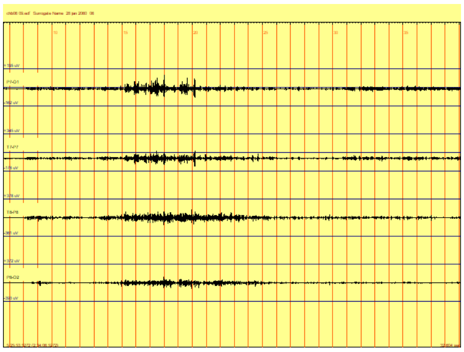

Fig. (9). EEG Signals filtering exhibits a Waveform pattern after applying high-band-pass filter**.**

Discussion

Analyzing non-epileptic and epileptic patterns with EEG signals can be challenging, as the patterns may be intermittent and difficult to capture. However, there are several approaches that can be used to analyze non-epileptic or epileptic patterns with EEG signals:

5.1. **Visual inspection:** One of the most straightforward methods for analyzing non-epileptic patterns is to use the EEG signal for irregular patterns or artefacts. In comparison, analyzing epileptic patterns scans the EEG signal for abnormal patterns, such as spikes and sharp or slow waves. It can be done by examining the raw EEG signal or applying filters to remove noise and other unwanted bio-signals.

5.2. **Frequency analysis:** EEG signals can be decomposed into different frequency bands using Fast Fourier analysis (FFT) or wavelet transforms. Changes in the power or frequency of the EEG signal[44] can be used to identify abnormal patterns, such as alpha or beta waves, high-frequency oscillations or rhythmic discharges.

5.3. **Event-related potential (ERP) analysis:** ERP analysis involves measuring the brain's electrical response to specific stimuli or events[45]. ERP analysis can be used to identify differences in brain activity between healthy individuals and those with non-epileptic patterns.

5.4. **Time-frequency analysis:** Time-frequency analysis involves analyzing the EEG signal in both the time and frequency domains. It can be done using methods such as spectrograms or wavelet transforms, which can help identify transient changes in frequency or power that may be associated with an epileptic activity.

5.5. **Spike detection:** Spike detection algorithms can be used to automatically identify spikes or sharp waves in the EEG signal. These algorithms use features such as amplitude, duration, and shape to identify potential epileptic patterns.

5.6. **EEG analysis using FFT:** It is just one tool among many that can be used to diagnose and treat patients with seizure disorders. It is typically used in conjunction with other diagnostic tests, such as neuroimaging and clinical assessments, to provide a comprehensive diagnosis and treatment plan.

6. Conclusion

Epilepsy is a neurological disorder characterized by recurrent seizures, while an attack is a sudden, uncontrolled electrical disturbance in the brain that can cause a range of symptoms. Analyzing non-epileptic and epileptic patterns with EEG signals requires careful examination of the signal for any irregular or abnormal patterns, as well as advanced techniques such as frequency analysis, time-frequency analysis, spike detection, ERP analysis, or machine learning. The choice of method will depend on the specific type of non-epileptic and epileptic patterns being analyzed and the available resources. It's essential to accurately diagnose the underlying cause of any seizure-like activity, as the treatment will depend on the underlying cause. If the pattern is non-epileptic, treatment may involve addressing the underlying medical or psychological condition. It is important to note that removing noise from EEG signals can be a challenging task, and different methods may be more effective for different types of noise. It is also critical to carefully evaluate the effects of noise removal on the EEG signal and to ensure that the signal is processed correctly and accurately. Analyzing epileptic patterns with EEG signals is vital for diagnosing and managing epilepsy. EEG can help identify the location of the seizure focus and guide treatment options, such as medication or surgery. EEG can also be used to monitor treatment effectiveness and identify any changes in seizure activity over time. For future work, to measure the performance of predefined multiple supervised machine learning algorithms to identify, analyze and classify specific EEG signals patterns associated with non-epileptic or epileptic patterns. This approach requires a large dataset, like CHB-MIT data of EEG signals from both healthy individuals and those with non-epileptic or epileptic patterns.

LIST OF ABBREVIATIONS

CHB-MIT	Children’s Hospital Boston and the Massachusetts Institute of Technology
ECG	ElectroCardioGram
EDF	European Data Format
EEG	ElectroEncephaloGram
EMG	ElectroMyoGram
EOG	ElectroOculoGram
ERP	Event-related potential
FFT	Fast Fourier Transform
PNES	Psychogenic Non-Epileptic Seizure
SWD	Spikes and Sharp Waves Discharges

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

All authors listed have made a significant, direct and scholarly contribution to the work and approved it for publication.

AVAILABILITY OF DATA AND MATERIALS

The CHB-MIT database, an EEG data used in this paper, can be downloaded from the PhysioNet website (https://physionet.org/content/chbmit/1.0.0/).

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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