ANALYSIS OF EEG SIGNALS USING MACHINE LEARNING

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***Abstract*—The examination of electroencephalogram (EEG) signals has emerged as a fundamental component in the diagnosis of neurological illnesses and the comprehension of brain function. The intricate and high-dimensional characteristics of EEG signals present considerable obstacles for effective and precise abnormality detection. This proposal presents an enhanced EEG signal processing framework utilising feature extraction and threshold-based classification to facilitate precise and efficient detection of abnormalities. The suggested method entails the pre-processing of EEG signals to eliminate noise, succeeded by the extraction of features to encapsulate the complex dynamics of cerebral activity. Classification was executed via a threshold-based methodology, aimed at ensuring simplicity, interpretability, and real-time application. Performance parameters such as accuracy, power, signal bandwidth, skewness, kurtosis, and energy efficiency were utilised to meticulously assess the system. Experimental results demonstrate the framework's capacity to attain high classification accuracy, efficiently identifying brain anomalies like epilepsy, sleep problems, and other irregularities. The work highlights the importance of effective feature extraction in reducing the high-dimensional complexity of EEG signals, enabling swift and accurate diagnosis. The approach is engineered for efficiency and adaptability, rendering it appropriate for portable devices or distant healthcare systems. Future enhancements intend to employ more sophisticated feature extraction methods, improved thresholds, and advanced machine learning algorithms to increase the system's accuracy and versatility.**

***Keywords*— EEG, brainwave recognition, machine learning, feature extraction, Abnormality Detection.**

I. INTRODUCTION

EEG signals are intricate and susceptible to noise from factors such as muscle contractions, eye blinks, and environmental disturbances, complicating real-time processing and anomaly detection. These artefacts hinder the extraction of significant patterns, which are essential for detecting disorders like early seizure onset or cognitive deficits. Creating an effective real-time system necessitates the preprocessing of EEG signals to eliminate noise, the extraction of pertinent features, and the implementation of classification methods such as threshold-based models or machine learning algorithms for precise anomaly identification [1].

This technology can deliver prompt alerts and practical insights, aiding physicians in detecting neurological problems and facilitating early intervention [2]. This method can improve detection accuracy and facilitate continuous monitoring, hence enhancing patient health management and yielding superior outcomes in neurological care.

Electroencephalography (EEG) is an essential instrument for observing and evaluating cerebral activity, providing significant insights into neurological function. It has proven essential in detecting illnesses including epilepsy, sleep problems, and various cerebral anomalies. EEG data is intricate and comprises diverse waveforms, including delta, theta, alpha, and beta waves, each associated with distinct brain states [3]. We extract pertinent elements such as power, amplitude, and frequency band information that can function as dependable markers of normal or aberrant behaviour. These attributes diminish the data's dimensionality, facilitating more effective classification of signals by machine learning algorithms.

The complexity of EEG signals, characterised by high dimensionality, non-linearity, and noise susceptibility, renders human analysis both time-consuming and error-prone. This requires the creation of automated techniques to effectively and precisely analyse EEG data. Machine learning (ML) has surfaced as a viable method for tackling these difficulties. Support Vector Machines (SVMs) have garnered attention for their capacity to manage intricate datasets and categorise patterns with exceptional accuracy. Utilising SVMs for EEG analysis entails a sequence of procedures, including the preprocessing of raw signals, the extraction of significant features, and the implementation of classification models to differentiate between normal and pathological activity [4].

The proposal presents a framework based on SVM for the analysis of EEG signals and the detection of abnormalities. The methodology employs feature extraction techniques to obtain statistical and spectral attributes of the signals, while dimensionality reduction guarantees computational efficiency. The model is assessed by various performance metrics, such as accuracy and F1-score, to confirm its efficacy in detecting anomalies in EEG data.

A performance matrix offers a comprehensive assessment of a system's precision and efficacy by examining critical parameters, such as accuracy, power, energy, peak-to-peak amplitude, skewness, kurtosis, and F1 score. These criteria guarantee the system's dependability in differentiating between healthy and pathological EEG readings. The technique offers a comprehensive framework for evaluating performance, enhancing diagnostic accuracy and facilitating practical healthcare applications, hence allowing for more precise and prompt identification of neurological problems.

II. LITERATURE SURVEY

Recent research have thoroughly investigated EEG preprocessing, feature extraction (including skewness, kurtosis, energy, bandwidth, entropy), and threshold-based classification to identify neurological abnormalities such as epilepsy and sleep disorders.

For example, Albaqami [5] et al. employed wavelet packet decomposition alongside statistical features (such as skewness, kurtosis, energy, and entropy) and classified EEG data using gradient boosting decision trees, attaining approximately 88% accuracy, thereby underscoring the effectiveness of interpretable, rapid methodologies appropriate for real-time applications.

Omerhodzic [6] et al. employed DWT-based energy characteristics across EEG sub-bands and a neural network classifier to effectively differentiate epileptic signals, indicating the viability for portable detection systems.

Additional research has highlighted higher-order moments, such as skewness and kurtosis: a study utilising maximal overlap wavelet distributions demonstrated that skewness characteristics can differentiate seizure types, with SVM classification achieving up to 96% accuracy when optimised [7].

Furthermore, investigations of intracranial EEG and MEG in paediatric epilepsy revealed that diseased regions displayed markedly increased skewness and kurtosis relative to controls, demonstrating high sensitivity (~ 88 %) and specificity (~ 89 %) in identifying the epileptogenic lobe [8].

Comprehensive evaluations highlight that attributes such as variance, energy, nonlinear energy, entropy, skewness, kurtosis, line length, and wavelet-derived features are regularly efficacious in seizure detection tasks, frequently diminishing Bayesian error by 5 to 13% and enhancing classifier performance. Additional studies emphasise energy efficiency through mechanisms such as differential energy and derivatives, which minimise error rates while maintaining computational simplicity for real-time implementation.

Beyond epilepsy, comprehensive EEG analyses highlight how extensive feature extraction alleviates the high dimensionality of EEG data, enabling swift and reliable classification. The literature endorses your emphasis on interpretable threshold-based classifiers with efficient feature sets, optimally designed for portable or remote healthcare systems.

The suggested future approach of including advanced feature extraction and adaptive thresholds corresponds with growing trends in hybrid or ensemble classifiers that maintain real-time practicality while enhancing accuracy and adaptability.

III. METHODOLOGY

A. *Block Diagram*

Figure 1 depicts a systematic method for identifying anomalies in EEG signals through machine learning. Electroencephalogram (EEG) data is initially acquired with the conventional 10-20 electrode placement approach. The raw signals are subjected to preprocessing to eliminate noise and artefacts, so ensuring the data is clean and appropriate for analysis. After pre-processing, essential features are retrieved from the signals, encompassing significant time-domain, frequency-domain, or nonlinear attributes. The features are subsequently input into a machine learning model, which is taught to identify patterns linked to atypical brain activity. The model's analysis identifies irregularities in the EEG signals. The technique incorporates a feedback loop whereby the outcomes of anomaly detection can inform and enhance subsequent preprocessing steps, establishing an iterative and adaptive detection system.

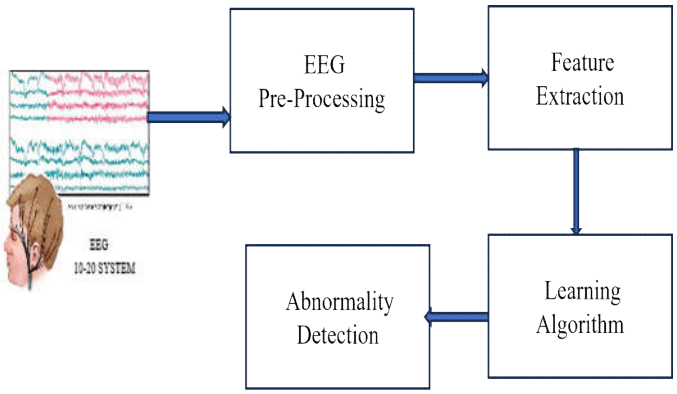


Figure1: Proposed Block Diagram

B. *Data Collection and Analysis*

Retrieved publicly accessible EEG datasets from online repositories such as PhysioNet. The datasets comprise EEG signals from both healthy subjects and patients with neurological disorders, establishing a basis for model training and evaluation. A collection of 64-channel EEG recordings from participants engaged in various motor imagery tasks has been provided to PhysioNet by the creators of the BCI2000 instrumentation system for brain-computer interface research. Subjects executed various movement and visual activities while 64-channel EEG data were obtained using the BCI2000 device. Each participant completed 14 experimental trials: two one-minute baseline trials (one with eyes open and one with eyes closed), and three two-minute trials for each of the following four tasks:

A target manifests on either the left or right side of the screen. The subject repeatedly opens and shuts the designated fist until the target vanishes. Subsequently, the individual attains a state of relaxation.

A target manifests on either the left or right side of the screen. The patient envisions repeatedly opening and shutting the appropriate fist until the target vanishes. Subsequently, the individual attains a state of relaxation.

A target manifests at either the upper or lower portion of the screen. The subject alternately clenches both fists (when the target is above) or both feet (when the target is below) until the target vanishes. Subsequently, the individual attains a state of relaxation.

A target manifests at either the upper or lower portion of the screen. The subject envisions opening and closing either both fists (if the target is positioned above) or both feet (if the target is positioned below) until the target vanishes. Subsequently, the subject becomes relaxed.

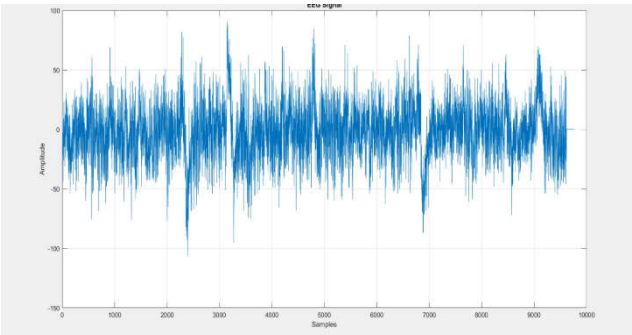


Figure2: Channel 1 EEG Signal

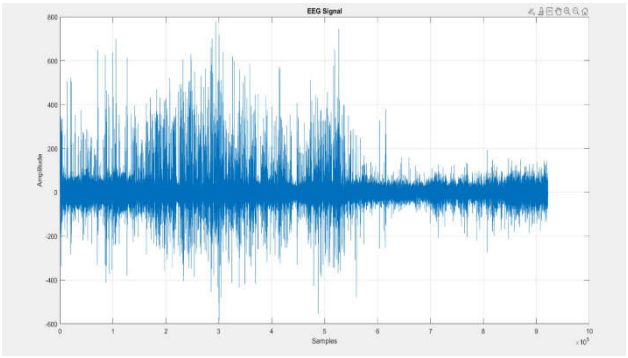


Figure3: Channel 2 EEG Signal

C. *Pre-processing of Raw Data*

The raw EEG signal is non-stationary and has limited spatial resolution. EEG signals are vulnerable and significantly influenced by artefacts and noise. These artefacts may influence the information and analysis of the collected signals. Consequently, the detection and elimination of artefacts, whether in clinical diagnosis or practical applications, constitutes the most critical pre-processing step prior to their use to mitigate their influence on the feature extraction phase. At this stage, it is essential to determine the frequency and channel from the EEG, as it is generated by multiple electrodes.

Filters are implemented by mathematical methodologies. This phase purges the data by excluding frequencies beyond the specified range. A high-pass filter eliminates gradual signal fluctuations, such as baseline drift resulting from perspiration or electrode displacement. Standard cutoff: 0.5 Hz to 1 Hz. A low-pass filter eliminates high-frequency noise from muscle movement, power line interference, or environmental disturbances. Standard cutoff: 30 Hz to 50 Hz. A band-pass filter integrates high-pass and low-pass filtering to preserve only the pertinent EEG frequency range. The filtered signals are illustrated in Figures 4 and 5.

Standardising the signal amplitude to provide uniformity between electrodes and recording sessions. Normalisation modifies the signal to ensure it resides within a standardised range, often characterised by a mean of 0 and a standard deviation of 1. Muscle contractions generate high-frequency noise in EEG data. Employ a low-pass filter with a cutoff frequency of 40–50 Hz to attenuate muscular noise. The general frequencies of interest in EEG are specified by

- Delta (0.5–4 Hz): Deep sleep or unconsciousness.
- Theta (4–8 Hz): Drowsiness or meditation.
- Alpha (8–13 Hz): Relaxed, wakeful state.
- Beta (13–30 Hz): Active thinking, motor activity.
- Gamma (30–100 Hz): Higher cognitive functions.

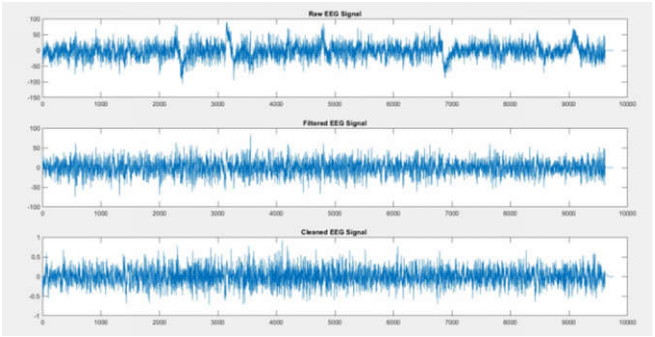


Figure 4: Filtered EEG Signal 1

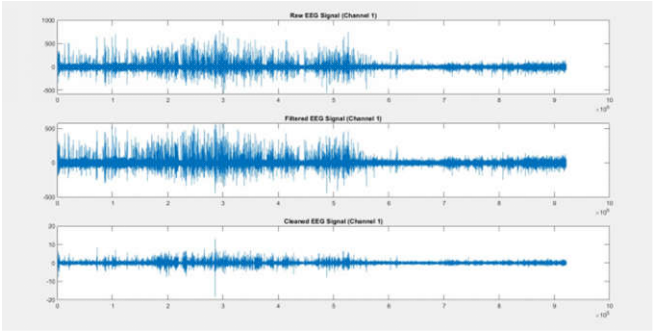


Figure 5: Filtered EEG Signal2

An artifact-free EEG signal is achieved by eliminating disturbances such as eye blinks, muscle contractions, and external interference by methods like bandpass filtering, Independent Component Analysis (ICA), and notch filtering, as seen in figures 7 and 8.

This guarantees that the signal precisely represents cerebral activity. Segmentation entails isolating a certain segment of the processed signal according to temporal or sample indices (e.g., samples 8300–8500). This approach concentrates analysis on the area of interest while eliminating noise and artefacts, rendering it appropriate for subsequent feature extraction or classification tasks.

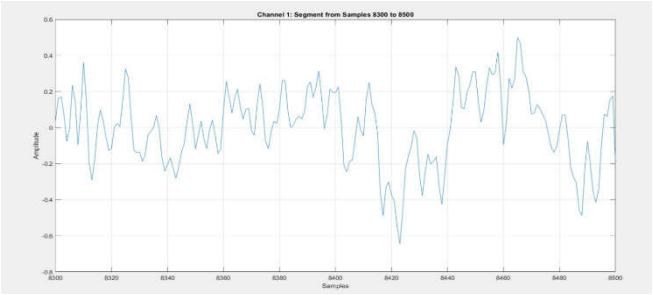


Figure 6: Noise Free Channel1

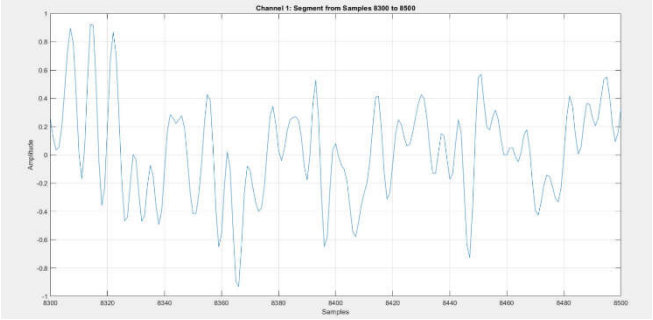


Figure 7: Noise Free Channel2

D. *Performance Evaluation*

In the analysis of EEG signals for abnormalities, a range of statistical and signal-derived parameters are typically employed, such as mean, variance, power, energy, skewness, kurtosis, peak-to-peak amplitude, and bandwidth. These attributes define the EEG signal and are essential for detecting anomalies. The following is a framework for evaluating the performance of these features:

Mean

The mean amplitude of the EEG signal throughout a temporal duration. Denotes the fundamental activity level of the signal, crucial in identifying anomalies such as spikes or bursts. Analyse the average of normal and abnormal signals to detect substantial discrepancies.

$$Mean = \left(\frac{1}{N}\right) \sum_{n=1}^{N} (x_n)$$

Where N = Number of data points; x_n= Individual data point in the signal

Variance

The variability or dispersion of signal amplitudes relative to the mean. Elevated variance may signify anomalies or atypical cerebral activity, such as epileptic spikes. Examine the standard deviation to evaluate signal variability. Utilise variance ratio tests to differentiate between normal and abnormal groups.

$$Variance = \left(\frac{1}{N}\right) \sum_{n=1}^{N} (x_n - \mu^2)$$

Where x_n = Individual data point in the signal; N = Number of data points

Power

The aggregate signal power inside a designated frequency band, typically computed using the Power Spectral Density (PSD). Illustrates the energy allocation among brainwave frequencies (delta, theta, alpha, beta, gamma). Conduct band-specific power analysis to identify anomalies in frequency domains. Utilise metrics such as relative power or power ratio for comparisons across frequency bands.

$$Power = \left(\frac{1}{N}\right) \sum_{n=1}^{N} x_n^2$$

Where x_n = Individual data point; N = Number of data points.

Energy

The cumulative energy of the signal over time, determined by the summation of squared amplitudes. Denotes the aggregate signal strength and is responsive to bursts or high-amplitude fluctuations. Evaluate the overall energy of signals in both normal and pathological conditions. Employ statistical normalisation to ensure equitable comparison among people.

$$\text{Energy} = \sum_{n=1}^{N} x_n^2$$

Where x_n = Individual data point in the signal; N = Number of data points.

Skewness

The asymmetry of the signal amplitude distribution relative to the mean. Facilitates the identification of anomalies, as skewness diverging from zero may signify irregular patterns. Positive skew: Signifies extended tails towards elevated amplitudes. Negative skew: Signifies extended tails towards lower amplitudes

$$Skewness = \left(\frac{1}{N}\right) \sum_{n=1}^{N} \left(\frac{(x_n - \mu^2)}{\sigma}\right)^3$$

Where μ = Mean of the signal; σ = Standard deviation of the signal; N = Number of data points; xi = Individual data point

Kurtosis

The kurtosis of the signal amplitude distribution. Elevated kurtosis levels may signify significant peaks or temporary irregularities in the signal. Analyse the kurtosis values of normal and aberrant signals. Identify epileptic spikes or other brief high-amplitude occurrences.

$$Kurtosis = \left(\frac{1}{N}\right)\sum_{n=1}^{N} \left(\frac{(x_n - \mu^2)}{\sigma}\right)^4 - 3$$

Where μ = Mean of the signal; σ = Standard deviation of the signal; N = Number of data points; x_n= Individual data point

Peak-to-Peak Amplitude

The disparity between the maximum and minimum amplitude of the signal. Detects significant amplitude fluctuations, frequently associated with artefacts or pathogenic occurrences. Threshold-based analysis for identifying anomalously high or low values. Temporal domain comparisons for baseline normalisation

$$\text{Power} = \max(x) - \min(x)$$

Where max(x) = Maximum value of the signal; min(x) = Minimum value of the signal.

$$\frac{\sqrt{\sum_{n=1}^{N} fi^2 P(fi)}}{\sum_{n=1}^{N} P(fi)}$$

Where fi = Frequency component; P(fi) = Power at frequency; N=Number of frequency bins

IV. Results

A. *Classification Analysis*

Electroencephalogram (EEG) signals serve as a crucial diagnostic instrument in neurology, facilitating the detection of anomalies including epileptic seizures, sleep problems, and cerebral traumas. Signal classification is a crucial phase in EEG data processing, wherein segments of the signal are examined for their attributes and juxtaposed with established thresholds to assess their condition. Threshold matching classification is a simple yet effective technique for evaluating the health of EEG signal segments. Threshold matching analysis for signal categorisation is a key methodology that harmonises simplicity and effectiveness. Comparing retrieved signal properties to predefined criteria enables excellent discrimination between healthy and pathological brain activity. This methodology is extensively employed in EEG analysis for several clinical applications, including seizure detection, brain-computer interfaces, and diagnostic tools.

Table 1: Analysis based on Performance metrics

Parameter	**Channel 1**	**Channel 2**	**Normal Range**
MEAN	0.1866	0.0899	Close to zero (after normalization)
VARIANCE	1.1517	0.2173	Indicative of signal variability, with higher values potentially linked to abnormal brain activity.
SKEWNESS	0.3682	-0.3042	Healthy signals usually have low skewness, indicating symmetry in the signal.
KURTOSIS	2.5683	2.6222	Values close to 3 are typical of Gaussian-like distributions; deviations may indicate abnormal spikes or artifacts
POWER	1.1815	0.2243	Elevated power may indicate excessive brain activity, often linked to seizures
ENERGY	237.4874	45.0781	Elevated energy may indicate excessive brain activity, often linked to seizures
BANDWIDTH	48.3980 HZ	50.9453 Hz	Higher bandwidths might reflect pathological activity or noise.

Bandwidth

The spectrum of frequencies where the signal energy is focused. Denotes the dispersion of frequency components, facilitating the differentiation between normal and pathological brainwave activity. Determine bandwidth from the frequency spectrum with parameters such as -3dB cutoff points. Associate variations in bandwidth with clinical circumstances (e.g., constriction during seizures)

Threshold Matching:
For the investigation, we selected two EEG channels that are filtered and devoid of noise. The signals are divided into segments of 10 seconds, ranging from 8000 samples to 9600 samples. The performance metric features are extracted for each filtered and normalised segment, and the threshold ranges are created accordingly. Each extracted feature is tested against specified threshold ranges that signify normal (healthy) or abnormal (unhealthy) situations. The threshold values denote the anticipated range for each feature in healthy, artifact-free signals.

- **Mean:** [-0.5, 0.5]
- **Variance:** [0.1, 2.0]
- **Skewness:** [-1, 1]
- **Kurtosis:** [2.5, 4.5]
- **Bandwidth:** is within [1 Hz, 30 Hz]

Table 2: Comparison & Analysis

Parameter	Channel 1	Channel 2	Analysis	Comparison
MEAN	0.0899	0.1866	Channel 1lightly deviates from zero, but within reasonable bounds for a normalized EEG. The other deviates from zero, suggesting potential abnormality or artifact	Signal 2 shows a greater deviation, possibly abnormal
VARIANCE	0.2173	1.1517	Low variance indicates limited variability, possibly normal activity. The channel 2 high variance indicates elevated variability, possibly abnormal.	Signal 2 have high variability, a potential indicator of abnormal activity
SKEWNESS	-0.3042	0.3682	Mild negative skewness suggests slight asymmetry but not significant. Mild positive skewness; may indicate slight asymmetry in the signal.	Both within typical bounds but signal 2 shows more asymmetry.
KURTOSIS	2.6222	2.5683	1 is Close to 3 consistent 2 is slightly below 3, but not significantly abnormal.	Both close to near three, suggesting near GD.
POWER	0.2243	1.1815	Elevated power indicates excessive brain activity, often linked to seizures or artifacts.	signal2 exhibits evaluated power potentially linked to abnormal activity
ENERGY	237.4874	45.0781	Low energy is typical of normal EEG segments. High energy supports the interpretation of elevated activity	Signal 2 have high energy, further supporting abnormality.
BW	50.9453	48.3980	Bothe are High but still plausible, possibly reflecting noise or sharp waveforms	Both high but Signal 2 aligns with pathological characteristics.

The performance metrics of the two channels is given above in Table 2

B. *Classification Logic*

Healthy Signal:
A signal segment is deemed healthy if all extracted features conform to the established thresholds. This indicates that the section demonstrates typical, consistent brain activity devoid of substantial disruptions. If the mean is within the interval [-0.5, 0.5] and the variance is between 0.1 and 2.0, the signal can be deemed normal.

Unhealthy Signal:
Should any features exceed the threshold range, the section is deemed unhealthy. This may signify the existence of atypical cerebral activity, including seizures, muscular artefacts, or other neurological disorders. If the kurtosis surpasses 4.5 or the bandwidth is beyond the 1 Hz to 30 Hz range, the signal may be deemed irregular. The classification of EEG signals is

accomplished by feature extraction and a predetermined threshold range.

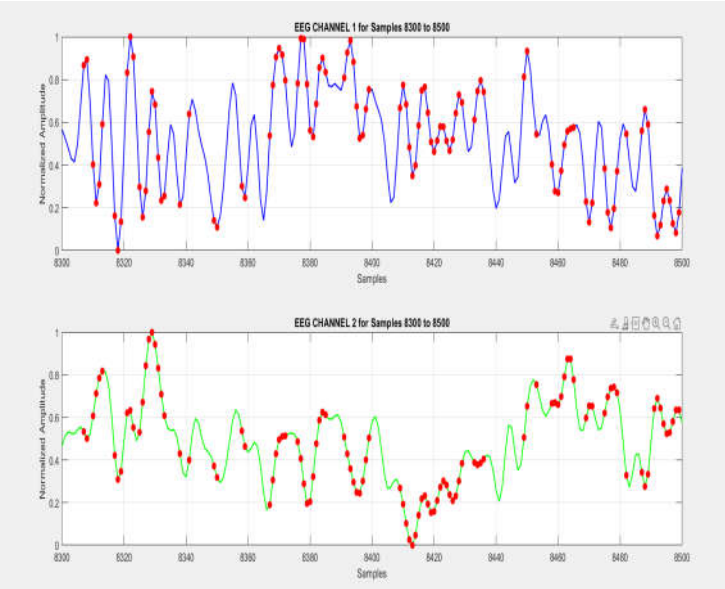


Figure8: EEG Abnormality Identification

The analysis in Figure 9 illustrates the anomaly between the two channels. The red spots depicted in the graph represent anomalous data that surpass the typical range of many metrics, including amplitude, power, mean, and energy. The red points presumably denote data points identified as anomalous according to specific criteria, such as amplitude thresholds or deviations from anticipated patterns. In channel 2, the red dots exhibit a higher density in regions with rapid variations, indicating that these segments of the signal may substantially diverge from anticipated patterns. This may result from the existence of artefacts, noise, or genuine neurological problems. The anomalous pattern in channel 2 may result from noise or artefacts disrupting the standard EEG rhythm.

Channel 1 exhibits a more constant and rhythmic pattern, while EEG Signal 2 displays more erratic variations. The irregularities may indicate an abnormality or interference in Signal 2. In a clinical context, these aberrations may signify areas of potential seizure activity, artefact interference, or other unusual occurrences.

Channel 1 seems to represent a normal EEG segment, while Signal 2 presumably denotes an abnormal EEG segment, potentially signifying irregular brain activity (e.g., seizure activity, artefact, or sharp waves). We have compared the signal segments of the channels based on the established threshold of the performance metric. Channel 1 displayed a singular healthy EEG segment subsequent to the comparison. The threshold range has aligned with the performance values of the segments between indices 8000 and 8200.

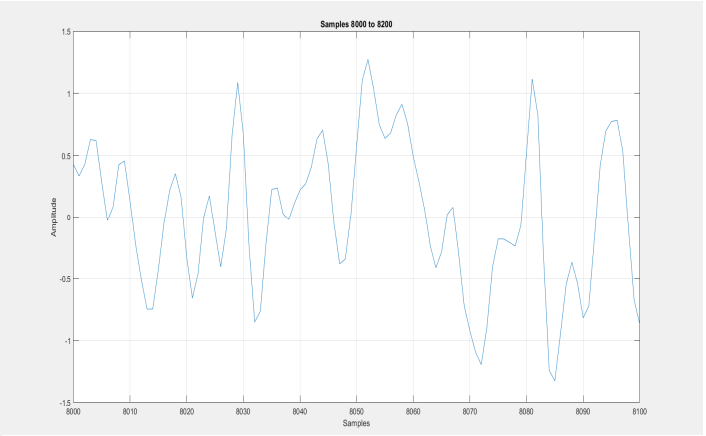
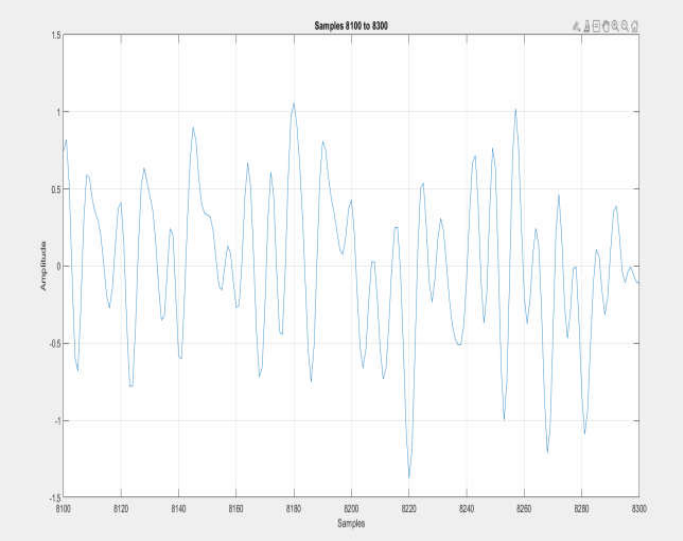


Figure 9: EEG Segments from 8000-8200

For the segment (8000-8200)
Mean: -0.0795
Variance: 0.6358
Skewness: 0.0676
Kurtosis: 2.5252
Peak-to-Peak Amplitude: 3.6944
Power: 0.6389
Energy: 128.4204
Bandwidth: 50.9453 Hz

Channel 2 exhibited no healthy EEG segments, as all noise-free segment features failed to align with the established threshold range. The performance measure values of channel 2 significantly surpassed expectations, indicating an anomaly in the channel.



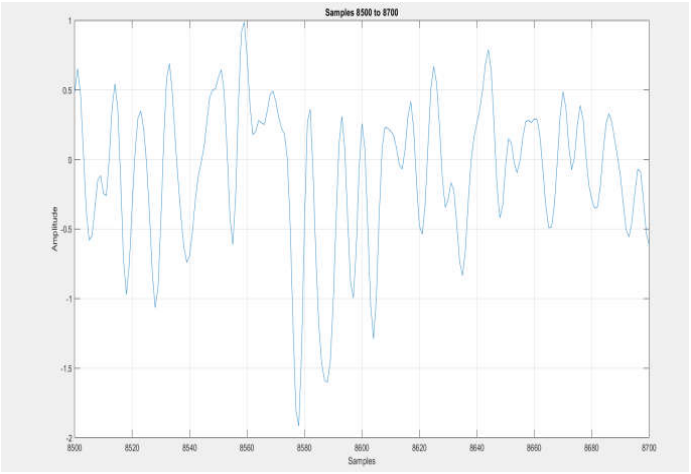
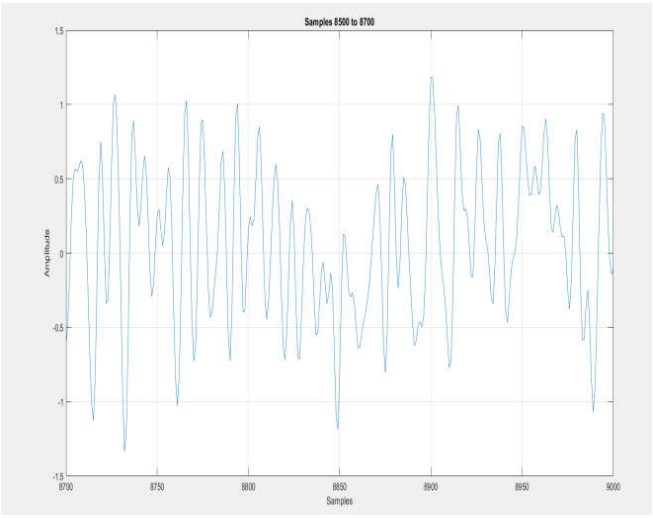


Figure 10: EEG Segments



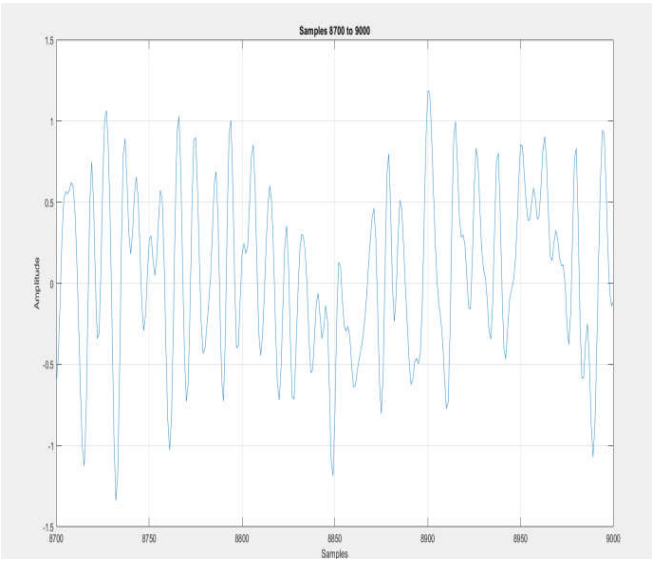


Figure 11: EEG Segments (For Reference)

Following the threshold-based categorisation, it is determined that channel 2 is partially normal, while signalling an unhealthy signal associated with a probability of epilepsy, seizures, and other neurological disorders.

V. Conclusions

The examination of EEG signals by feature extraction and threshold matching offers a methodical means to evaluate cerebral activity and identify irregularities. The approach captures basic aspects of the EEG signal by extracting key variables like mean, variance, skewness, kurtosis, peak-to-peak amplitude, power, energy, and bandwidth. This method is proficient at spotting anomalies, including seizures or artefacts, by recognising deviations from anticipated feature ranges. Healthy signals often reside within the defined thresholds, indicating consistent and normal cerebral activity. Conversely, unhealthy signals display feature levels over these thresholds, indicating potential problems that may necessitate additional examination.

The integration of preprocessing (filtering and normalisation), feature extraction, and threshold-based classification establishes a resilient framework for EEG analysis. It elucidates the interpretation of intricate cerebral signals, providing a dependable and effective instrument for therapeutic applications such as seizure detection, artefact removal, and diagnostic assistance. This approach establishes a basis for automated systems, enhancing precision and expediting decision-making in neurological evaluations.

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