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Development of Segmentation Method to Localize Epileptic Symptoms in EEG Signal

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Abstract.
Purpose: Epilepsy is a chronic neurological disorder that affects more than 50 million people worldwide, where early detection through EEG signal analysis is crucial for proper management. However, the quality of EEG signals is often affected by noise and artifacts, which can lead to diagnostic errors of up to 30% in the early stages. This study aims to develop an EEG signal preprocessing method to improve the classification performance of epileptic symptoms through preprocessing, segmentation, and seizure interval analysis approaches.
Methods: The preprocessing stage involved applying a 50 Hz notch filter and a 0.5–60 Hz bandpass filter. The contribution of this work is in the development of hybrid segmentation based on frequency and amplitude analysis, while seizure intervals were identified using distances criteria between consecutive spikes detected on signals. The method was tested using the CHB-MIT dataset consisting of 23 EEG channels.
Result: The results showed that the system successfully identified seizure segments with an average accuracy of 62.09%, and 9 out of 23 channels achieved accuracies above 70%. Channels Ch08 (86.60%), Ch09 (86.36%), and Ch19 (80.51%) achieved the highest accuracies. The results also showed high specificity(99.85%) and low False Positive rate(0.15%) indicating the system's effectiveness to reduce falase positive.
Novelty: This method proved effective in detecting epileptiform activity and shows potential as an EEG-based early detection tool for epilepsy, although further optimization is needed to improve accuracy on channels with low signal-to-noise ratio (SNR).

Keywords: Epilepsy, EEG, Signal pre-processing, Segmentation, Interval analysis
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INTRODUCTION

Epilepsy stands as one of the most prevalent chronic neurological disorders globally, affecting over 50 million individuals [1]. Early and accurate detection is essential for effective management and improving patient quality of life. Electroencephalography (EEG) plays a central role in epilepsy diagnosis by providing critical insights into brain activity. However, EEG signals are frequently corrupted by biological and environmental artifacts, which can lead to diagnostic errors of up to 30% in early assessments [2].

The main challenge arises from the high noise levels and complexity of raw EEG signals, which obscure subtle epileptiform patterns. This makes seizure detection particularly difficult for short-duration or interictal events [3]. Conventional preprocessing techniques, such as simple bandpass or notch filters, often fail to sufficiently enhance signal quality. Furthermore, existing detection methods typically focus on isolated seizure segments, neglecting their temporal relationships. This oversight increases false positives, whereas seizures are clinically characterized by temporally clustered and evolving abnormal discharges. Several studies have addressed these limitations with advanced approaches. Mahjoub et al. [4] combined Tunable-Q Wavelet Transform (TQWT) with a Support Vector Machine (SVM), achieving high accuracy but at significant computational cost, reducing real-time applicability. Urigüen and García-Zapirain [5] reviewed artifact removal techniques, emphasizing both the utility and limitations of filtering methods. Garcés Correa et al. [6] developed an adaptive filtering method suitable for real-time detection, yet its sensitivity and specificity still fall short of robust clinical standards. Kaya et al. [7] introduced the use of enhanced Local Ternary Patterns (LTP) to extract stable features from EEG signals in epilepsy patients. This technique focuses on signal preprocessing to reduce noise and artifacts, which can compromise signal quality, before classification. Mamatha and Hariprasad [8] discussed various artifact removal techniques in

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EEG signals used for epilepsy diagnosis, focusing primarily on ICA as a leading method for removing artifacts from EEG signals. They explained that ICA is effective in separating independent signals from ocular, muscular, and cardiac artifacts, which often interfere with EEG signal analysis, without requiring prior knowledge of the contaminating components. Savadkoohi et al. [9] developed a machine learning-based approach for epileptic seizure prediction using EEG signals. They tested the SVM technique to classify EEG signals that had been preprocessed to remove artifacts and noise. This study demonstrated that SVM yielded very high accuracy in detecting epileptic seizures, thanks to its ability to maximize the margin between positive and negative classes. Jebelli et al. [10] highlighted the importance of preprocessing EEG signals to address noise from portable devices, particularly in real-world work environments. They adopted ICA to produce cleaner EEG signals, allowing them to be used in further analysis without compromising data validity. Schlink et al. [11] demonstrated the effectiveness of ICA methods in separating EEG signal sources to detect cortical changes due to acute stress. This approach is relevant as a reference for EEG signal processing using ICA, particularly for applications requiring artifact separation and identification of specific cortical activity. Saputro et al. [12] demonstrated EEG signal processing for seizure classification utilizing feature extraction methods such as MFCC, Hjorth Descriptor, and ICA, aimed at improving data quality prior to classification. This approach supports the accuracy of SVM-based classification models, although suboptimal pipeline design can impact analysis results. Fasil and Rajesh [13] explored a feature extraction approach from short EEG signal segments for epilepsy classification. Using approximate entropy and sample entropy as primary features, this study demonstrated that short-duration segments can reduce computation time without sacrificing classification accuracy, making it an efficient method for EEG signal processing.

This study addressed the development of a preprocessing and analysis framework designed for both effectiveness and computational efficiency. The proposed approach integrates noise reduction using notch and bandpass filters, hybrid segmentation combining frequency and amplitude thresholds, and seizure interval analysis for characterizing temporal patterns.

The novelty of this work lies in achieving temporal seizure detection without reliance on computationally intensive machine learning classifiers. By combining hybrid segmentation with interval analysis, the method provides a transparent, interpretable, and efficient solution that demonstrates strong potential as an early detection tool for clinical EEG applications.

METHODS

The proposed method follows a systematic pipeline consisting of four main stages: data acquisition, signal preprocessing, hybrid seizure segmentation, and seizure interval analysis, as illustrated in Figure 1. The entire workflow was implemented in Python, utilizing libraries such as MNE-Python for data handling, SciPy for signal processing, and Pandas for data manipulation.

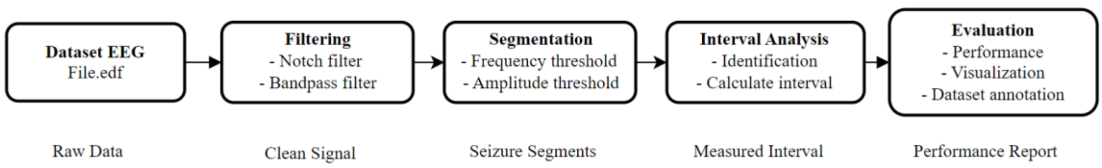

Figure 1. The overall workflow of the system, from raw EEG data to final classification

Signal Preprocessing

The raw EEG signals were first subjected to a two-step filtering process to remove noise and artifacts. First, a 50 Hz notch filter was applied to eliminate power-line interference. Subsequently, a fourth-order Butterworth bandpass filter was used to retain frequencies within the 0.5 Hz to 60 Hz range. This step effectively removes low-frequency baseline drift and high-frequency muscle artifacts (EMG) while preserving the relevant brainwave frequencies (Delta, Theta, Alpha, Beta, and Gamma) crucial for seizure analysis. The frequencies involved in this scheme were derived from information in [14]. Zero-phase filtering was implemented to prevent phase distortion.

Hybrid Seizure Segmentation

Following preprocessing, a two-steps segmentation algorithm was developed to identify potential seizure segments. The first one was based on frequency analysis and the second one was based on amplitude analysis.

In [14], the authors stated that EEG signal with high spike (>100μV) in high frequencies (>30Hz) indicates a key characteristic of epileptiform discharges. This step identifies segments having high power signals in high frequency (>30 Hz). We adopted Welch's method (also called the periodogram method) to identify the segments. For clarity, the Welch's method is rewritten here [15]. Let $x_m(n) \triangleq w(n)x(n+mR), n = 0,1,2,\dots,N-1,\ m = 0,1,2,\dots,M-1$, be the m-th windowed, zero-padded segment from the signal x. where R is the window hop size, and M is the number of available frames. Then the periodogram (or the power) of the m-th segment is given by

$$P_{x_m}(\omega) \triangleq \frac{1}{N}\left|\sum_{n=0}^{N-1} x_m(n) e^{-\frac{j2\pi n\omega}{N}}\right|^2 \tag{1}$$

where ω is sample's index in frequency domain while n is index in time domain. In symmetric Fourier transformation, the sequence of indexes and their lengths are identical. Therefore, in this paper, index n is used for both domains. The total power of the signal is given by equation (2).

$$P_x \triangleq \sum_{m=0}^{M-1} P_{x_m} \tag{2}$$

Then the segment m with high power in high frequency contents was flagged as expressed in equation (3).

$$F_m(n) = \begin{cases} 1 & \frac{p_{x_h}}{P_x} > \tau, n = 0,1,2,\dots,N-1 \\ 0 & else \end{cases} \tag{3}$$

$$p_{x_h} = \sum_{n>\omega_h} P_{x_m,M}(n) \tag{4}$$

where τ is a threshold of ratio of high power parts of the signal compared to the total power, and ω_h is the threshold of the high frequency. In our scheme, we conducted 2 segmentations on the same signal, one with N_1 window size, and another one with N_2 window size, $N_2 > N_1$. Therefore, we have 2 periodograms $P_{x_{m_1}}(n)$ and $P_{x_{m_2}}(n)$ and τ_1 and τ_2 are the threshold ratio of high power parts of the signal compared to the total power ($\tau_1 > \tau_2$), and ω_h is the threshold of the high frequency. Using equation (3), we have flagged segments ($F_{m_i}(n)$=1, i=1, 2) with high power contents from both 2 segmentation processes. Then, we proposed the final flagging process to decide the segments with high power in high frecuency as follows. First, we extend the size of the flagged segments $F_{m_1=1}(n)$=1 with k unit samples to the left and right of the segments. Therefore, we now have $F'_{m_1}(n) = k||F_{m_1}(n)||k$, all contain unit samples, where | | is a concatenate operation. Then we perform bitwise operation as expressed in equation (5).

$$F(n) = F_{x_{m_1}}(n) \vee (F'_{x_{m_1}}(n) \wedge P_{x_{m_2}}(n)) \tag{5}$$

We have found out that this operation can reduce false positive.

The second step is to flag the signal's samples absolute amplitude which exceeds 100 μV, corresponding to the high-voltage spikes and sharp waves typical of seizures as expressed in equation (6).

$$V(n) = \begin{cases} 1 & |x(n)| > v \\ 0 & else \end{cases} \tag{6}$$

where $x(n)$ is the signal obtained from preprocessing, and v is the amplitude threshold.

Now, we have 2 sets of signals: $F(n)$ representing frequency content of the signals (indicated as 1 in high frequency contents of the signal), and $V(n)$, representing amplitude of the signals (indicated as 1 in high amplitude parts of the signal). The next step is to classify signal samples based on both criteria. Equation (7) was used to identify both high frequency and high amplitude of the segments $S(n)$ in a bitwise scheme.

$$S(n) = S_b(n) \vee F_{lp}(n) \vee V_{lp}(n) \tag{7}$$

$$S_b(n) = F(n) \wedge V(n) \tag{8}$$

$$F_{lp}(n) = V(n) \wedge \left([F(n) \circledast H_{lp}] \geq c_{off}\right) \tag{9}$$

$$V_{lp}(n) = F(n) \wedge ([V(n) \circledast H_{lp}] \geq c_{off}) \tag{10}$$

where $\circledast$ is a convolution operator, H_{lp} is a low pass filter and c_{off} is filter's cutoff level, usually is set as 0.707. Equation (8) is a direct combination of both frequency and amplitude criteria. However, to anticipate misidentification caused by various waveforms in the signals we add equation (9) and (10) to add smooth transition between flagged and non-flagged segments. A segment was classified as a "seizure" if it met both the frequency and amplitude criteria, or if it met a strong criterion for one while receiving minimal support from the other. This hybrid approach enhances detection robustness by leveraging complementary signal characteristics.

Seizure Interval Analysis

The final stage analyzes the temporal distribution of the detected seizure segments to differentiate between true epileptic events and sporadic, non-epileptic activities. ALGORITHM 1 indicated the detail description of the algorithm.

ALGORITHM 1: EPILEPTIC SEGMENTATION

```
Input: binary signal S(n) with length N-1
Output: epileptic segments
% list all flagged segments
set j = 0
from n = 0 to N-1
    find 0->1 transition, record n to Raise(j)
    find 1->0 transition, record n to Fall(j)
    increase j
    set state(n) = 'normal'
end
set c = 0
set J = j
% analyze consecutive and epileptic spikes
set(m)=0
set j =0
do
    start(c) = Raise(j)
    interval(j) = Raise(j+1) - Fall(j)
    if interval(j) < th1,
        from n = Raise(j) to Fall(j)  set state(n)  'spike',
        increase c
        increase j
    end
    else    %distance between consecutive spikes>th1
        if c>th2
            Finish(m) = Fall(j)
            from n = start(m) to Finish(m) state(n) = 'epileptic'
        end
```

29. increase m
30. until $j = J$

The algorithm first identifies groups of consecutive seizure segments. Then, it calculates the time interval between the end of one segment and the start of the next. An interval is considered "valid" if its duration is less than 2 seconds (classified by th_1 in the algorithm), indicating a high temporal correlation. The segments is ultimately classified as "EPILEPTIC" if it contains a sequence of at least 100 consecutive valid intervals (classified by th_2 in the algorithm). This criterion ensures that the classification is based on sustained, rapidly recurring epileptiform patterns, which are clinically more significant than isolated abnormal discharges, thereby minimizing false positives.

RESULTS AND DISCUSSIONS

This study utilized the publicly available CHB-MIT Scalp EEG Database, a standard benchmark for epilepsy research [16]. The dataset includes multi-channel EEG recordings from pediatric subjects with intractable seizures. For this research, recordings were processed in their original European Data Format (EDF), featuring 23 bipolar montage channels sampled at 256 Hz. Each recording is accompanied by clinical annotations detailing the onset and offset times of seizure events, which serve as the ground truth for evaluating the system's performance.

Table 1. Parameters used in the experiment

Category	Parameter	Value	Unit	Description
Dataset	Dataset	CHB-MIT Scalp EEG	-	Boston Children’s Hospital
	Duration	1 – 4	Hour	-
	Sampling rate	256	Hz	Standard EEG sampling rate
	Amount of Channels	23	Channels	Bipolar montage configuration
Preprocessing	Low cutoff frequency	0.5	Hz	baseline drift
	High cutoff frequency	60	Hz	line noise
	Notch filter	50	Hz	Electricity line frequency
Segmentation	Window size	0.124	second	~32 samples @ 256 Hz
	Window overlap	0.063	second	~16 samples overlap
	Amplitude threshold (th1)	0.0001	V	100 µV for spike detection
	Frequency threshold	30	Hz	Cutoff for spectral analysis
Interval Analysis	Interval threshold (th1)	2	second	Maximum inter-seizure interval
	Minimum consecutive (th2)	100	high samples	Distance between 2 conscutive high samples

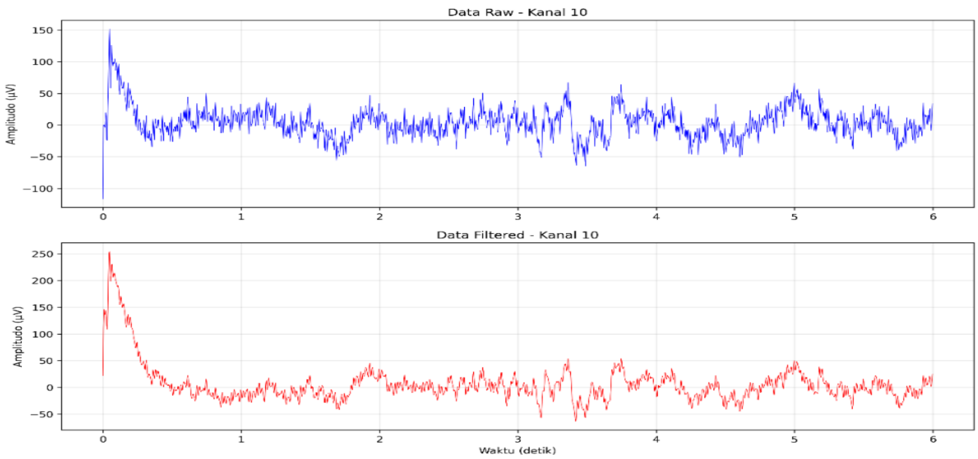

Figure 2. Comparison of a raw EEG signal segment vs. the same segment after filtering

System Performance

Table 1 shows the parameters used in the experiment. The preprocessing stage was effective in enhancing signal quality, as illustrated in Figure 2, which shows a clearer distinction of signal events after filtering. The hybrid segmentation successfully identified seizure periods, with an average of 0.48% of total segments being classified as seizure, consistent with the sporadic nature of epilepsy. In segmentation step, figure 3 provides a visual example of how the algorithm identifies seizure segments based on combined frequency and amplitude criteria.

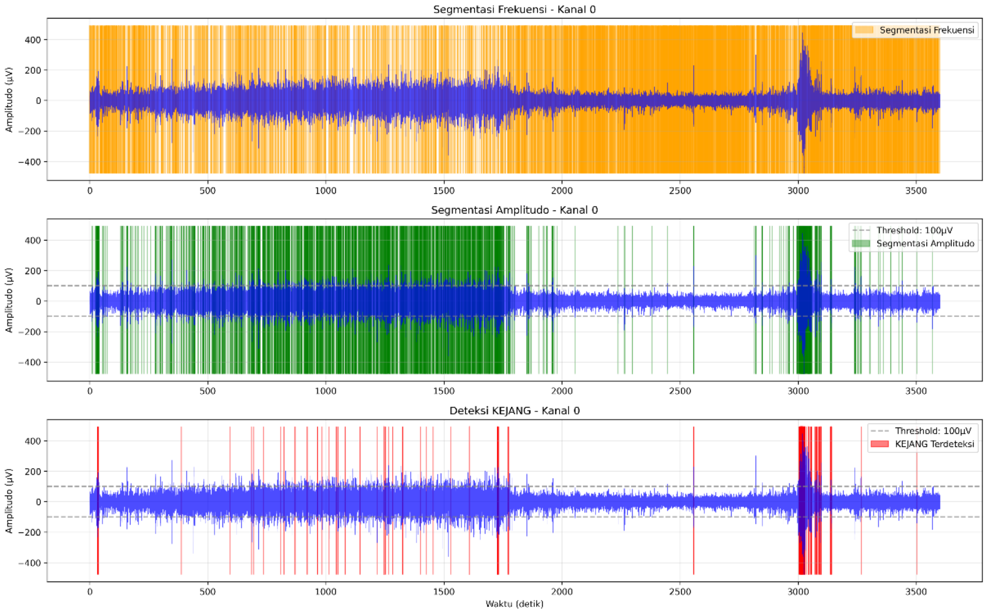

Figure 3. Example of seizure segmentation on a single channel

The performance of the system was validated against the manual annotations provided in the dataset. To evaluate the performance, we adopted commonly used metrics such as Accuracy=$TP/(TP+TN)$, Sensitivity=$(TP/(TP+FN))$, Specificity = $TN/(TN+FP)$, False Positive Rate=$(FP/(FP+TN)$, and *F1-*score = 2*(Precision * Sensitivity/ (Precision + sensitifity), with Precision=$TP/(TP+FP)$. In this work, *TP* is defined as the location of 'epileptic' segments obtained from the algorithm which are matched with the location of '*seizure*' labels provided by the dataset, while TN is defined the location of 'normal' segments obtained from the algorithm which are matched with those provided by the dataset.

Table 2. Seizure detection accuracy per channel compared to manual annotations

Channel	Sensitivity (%)	Specificity (%)	False Positive Rate (%)	F1-Score (%)	Accuracy (%)
Ch0	78.64	99.88	0.1216	83.02	79.29
Ch1	80.98	97.70	0.0214	88.56	76.59
Ch2	29.12	99.97	0.0283	44.24	78.43
Ch3	19.05	99.97	0.0335	31.23	55.43
Ch4	73.96	99.92	0.0816	81.62	79.23
Ch5	86.05	99.84	0.1625	85.83	76.18
Ch6	66.03	99.97	0.0330	78.15	83.84
Ch7	75.14	99.75	0.2542	75.99	40.16
Ch8	77.91	99.97	0.0330	86.16	86.60
Ch9	80.33	99.99	0.0055	88.85	86.36
Ch10	81.23	99.92	0.0799	86.26	30.34
Ch11	77.02	99.74	0.2604	76.95	4.49
Ch12	85.02	99.90	0.1019	87.61	83.12
Ch13	87.76	99.74	0.2582	83.29	73.09
Ch14	86.41	99.82	0.1815	85.31	76.19
Ch15	64.63	99.53	0.4725	62.54	6.82
Ch16	12.33	99.98	0.0213	21.60	41.67
Ch17	6.32	99.98	0.0185	11.70	18.31
Ch18	29.12	99.97	0.0283	44.24	78.43
Ch19	80.84	99.95	0.0459	87.43	80.51
Ch20	87.08	98.95	1.0547	61.99	38.32
Ch21	87.08	99.90	0.0986	88.92	78.52
Ch22	86.41	99.82	0.1815	85.31	76.19
Average :	66.89 %	99.85%	0.15%	70.73%	62.09

After obtaining a tentative model, parameter estimation is performed on the ARIMA model using the maximum likelihood estimation method. This parameter significance test is useful for determining whether the parameters generated in the ARIMA model are significant or not by considering P>|z|. Parameters with a P value <0.05 are considered significant and can be retained in the model. Figure 4 result for significane parameter.

Discussion

As shown in Table 2, performance varied between channels, with 9 channels achieving an accuracy above 70%. Notably, channels Ch08 (86.60%), Ch09 (86.36%), and Ch19 (80.51%) demonstrated the highest accuracy, indicating that the signal features in these channels strongly correlated with the annotated seizure events. False positive rates and specificity demonstrated that the system has been successful in reducing false positive events, thus proved that the system is potential to be implemented as diagnostic tools.

the variation in accuracy across channels suggests that the location of electrodes relative to the seizure's focal point plays a significant role. Channels with higher accuracy (e.g., Ch08, Ch09) likely captured the epileptiform activity more directly, resulting in clearer, more easily detectable patterns. These channels are located over the Temporal and Parietal-Occipital regions, which were identified as the primary zones of ictal electrical discharges (seizures) in this subject. The proximity of these electrodes to the seizure focus results in a higher Signal-to-Noise Ratio (SNR) and clearer spike-and-wave morphology.

The significantly lower accuracy in channels like Ch11 and Ch15 is due to two main factors: (a) Frontal electrodes are highly susceptible to eye blinks (EOG) and forehead muscle activity (EMG). These artifacts often produce high-amplitude spikes (>100 µV) that trigger false positives in rule-based segmentation, and (b) Bipolar Cancellation and Spatial Attenuation: In a bipolar montage, if seizure activity reaches both electrodes in a pair with similar phase and amplitude (common mode), the signals will partially cancel each other out. Furthermore, spatial attenuation (a decrease in signal strength) occurs as the electrical current propagates from the posterior focus to the distant frontal polar region.

The observed variation in per-channel accuracy (ranging from 4.49% to 86.60%) reflects the spatial distribution of ictal activity. High-performing channels correspond to seizure foci in the temporal-parietal region, while frontal channels suffer from artifact contamination and spatial attenuation.

The interval analysis proved crucial in reducing false positives and confirming sustained seizure activity. Based on this analysis, 16 out of 23 channels were classified as "EPILEPTIC," indicating widespread, temporally correlated abnormal brain activity consistent with a clinical seizure event. The channels with low accuracy but classified as "EPILEPTIC" by the interval analysis (e.g., Ch15) present an interesting case. This suggests that while the system detected sustained abnormal patterns, these patterns did not perfectly align with the precise start and end times of the manually annotated seizure. This highlights a key strength of the method: its ability to identify clinically relevant, sustained epileptiform activity even if it deviates slightly from the annotated event boundaries.

One of the primary limitations observed was the system's susceptibility to high-amplitude artifacts that were not fully eliminated during preprocessing, leading to some false positives. Additionally, the reliance on a minimum of 100 consecutive segments meant that very short seizure events could be missed. Despite these limitations, the study successfully demonstrates that a combination of robust signal processing and rule-based temporal analysis can provide a transparent and computationally efficient alternative to complex machine learning models for early epilepsy detection.

The results demonstrate the effectiveness of the hybrid segmentation and interval analysis pipeline in identifying epileptiform activity.

CONCLUSION

This study successfully developed and evaluated a non-machine learning framework for epilepsy detection from EEG signals. The proposed pipeline, which combines signal preprocessing, hybrid segmentation, and temporal interval analysis, proved effective in identifying epileptiform activity. The system achieved an average detection accuracy of 62.09% against clinical annotations, with key channels exceeding 80% accuracy. The interval analysis further confirmed sustained seizure patterns in 16 of the 23 channels, demonstrating the method's ability to distinguish clinically relevant events from sporadic abnormalities.

While the framework offers a transparent and computationally efficient alternative to complex models, limitations include susceptibility to artifacts and missing very short seizure events. Future work should focus on integrating advanced artifact removal techniques, such as Independent Component Analysis (ICA), and optimizing the algorithm to improve its robustness and accuracy for real-time clinical applications.

DATA AVAILABILITY

The data that support the findings of this study are openly available in PhysioNet at https://physionet.org/content/chbmit/1.0.0/.

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