Impact of Signal Segmentation on EEG-Based Seizure Detection: A Comparative Time-Frequency Analysis

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Abstract: Accurate and timely detection of epileptic seizures from EEG signals is essential for reliable clinical decision support and patient monitoring. In this study, the impact of data segmentation on seizure detection performance is systematically investigated using the publicly available EEG dataset from the University of Bonn. Two commonly applied feature extraction methods, Discrete Wavelet Transform and Power Spectral Density, are evaluated in combination with a Random Forest classifier across multiple segmentation levels. A fully automated experimental framework is developed in MATLAB, and classification tasks of varying complexity, including binary and multi-class problems, are considered. The results reveal that signal segmentation significantly affects classification performance, with moderate segmentation generally improving accuracy for both Discrete Wavelet Transform and Power Spectral Density features. While excessive segmentation degrades performance in the Discrete Wavelet Transform based approach, the Power Spectral Density based method demonstrates greater robustness across segmentation levels. These findings underline the critical role of segmentation strategy in EEG-based seizure detection and highlight the importance of optimizing this parameter based on the chosen feature extraction technique. The insights obtained from this study can guide the development of more efficient, real-time, and clinically applicable seizure monitoring systems.

1 INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures resulting from abnormal electrical activity in the brain. Affecting over 50 million individuals worldwide, epilepsy significantly impairs quality of life and, in severe cases, poses life-threatening risks (World Health Organization, 2025). Accurate detection and monitoring of epileptic seizures are essential for effective disease management, yet conventional diagnosis heavily relies on manual inspection of electroencephalogram (EEG) recordings by trained specialists. This process is time-consuming, labour-intensive, and prone to subjective interpretation, especially in long-term monitoring scenarios (Milligan, 2021).

To address these challenges, automated seizure detection systems based on EEG signal analysis have been extensively investigated in recent years (Naidu and Zuva, 2023). Numerous studies have explored different approaches for extracting discriminative features from EEG recordings, ranging from time-domain methods to advanced time-frequency and spectral techniques. Among these, Discrete Wavelet Transform (DWT) and Power Spectral Density (PSD) have gained significant attention due to their ability to capture both transient and stationary characteristics of EEG signals associated with seizure activity (Liu et al., 2023, Kinaci et al., 2024).

In parallel, various machine learning algorithms, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and ensemble classifiers such as Random Forests, have been employed to classify extracted features with promising results (Siddiqui et al., 2021). Despite these advancements, many existing studies rely on pre-segmented datasets or fixed-length signals, often overlooking the critical

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role of signal segmentation strategy in the overall classification performance (Thangavel, 2022).

Moreover, the selection and configuration of segmentation parameters remain largely empirical in literature, and their interaction with feature extraction techniques is not systematically explored. This gap is particularly relevant for real-world clinical applications, where signal length, processing time, and system responsiveness are key considerations.

The aim of this study is to systematically investigate how different signal segmentation strategies affect seizure detection performance using two widely adopted feature extraction methods, DWT and PSD, in combination with Random Forest classification. To ensure comprehensive evaluation, experiments were conducted on the well-established University of Bonn EEG dataset, which is frequently utilized as a benchmark in the field.

Unlike many previous studies, this work focuses specifically on the relationship between segmentation granularity, feature extraction approach, and classification accuracy. The results demonstrate that appropriate segmentation can significantly enhance detection performance, while suboptimal segmentation may degrade system reliability. These findings not only contribute to a better understanding of the signal processing pipeline for EEG-based seizure detection but also provide practical insights for developing more robust, real-time, and clinically applicable monitoring systems.

2 MATERIAL AND METHODS

Block diagram of proposed study is given in Figure 1.

2.1 EEG Dataset

This study utilizes the publicly available EEG dataset provided by the Department of Epileptology at the University of Bonn, which has been extensively used for seizure detection research. The dataset consists of five subsets, each containing 100 single-channel EEG recordings. Sets A and B represent surface EEG recordings from healthy individuals with eyes open and eyes closed, respectively. Sets C, D, and E contain intracranial EEG recordings from epilepsy patients, with set E specifically representing seizure activity (Andrzejak et al., 2001).

Each EEG recording is composed of 4096 samples, acquired at a sampling frequency of 173.61 Hz. To investigate the effect of signal segmentation on classification performance, the recordings were divided into smaller, equally sized segments. Different segmentation scenarios were applied, including 1 (no segmentation), 2, 4, 8, and 16 segments per signal, allowing for a systematic evaluation of how segment length influences feature extraction and subsequent classification.

Segmenting the signals into smaller portions provides both an increased number of training examples and an opportunity to capture localized signal variations, which is particularly relevant for the detection of transient events such as epileptic seizures.

2.2 Data Segmentation

Signal segmentation was performed by evenly dividing each 4096-sample EEG recording into smaller non-overlapping segments based on the chosen segmentation factor. For instance, applying a segmentation factor of 2 results in segments of 2048 samples each, whereas a factor of 16 yields segments of 256 samples.

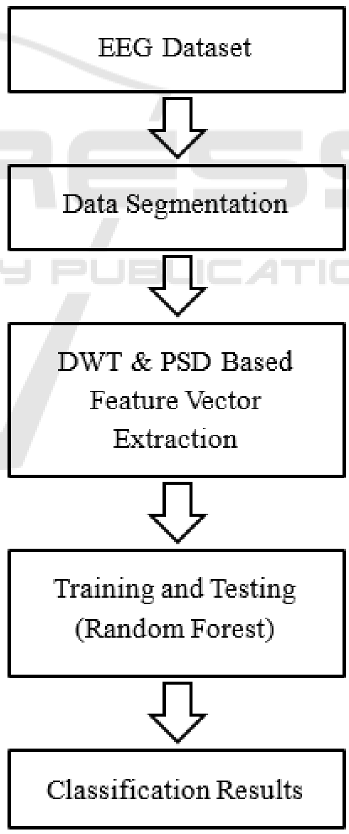

Figure 1: Block diagram of proposed study.

This segmentation process serves multiple purposes. Firstly, it increases the total number of available data samples, which is beneficial for training machine learning models and reducing the risk of overfitting. Secondly, it allows for finer temporal analysis by focusing on shorter signal windows, which can reveal localized patterns and frequency components that may be less visible in longer segments. Importantly, the segmentation strategy can influence the ability of feature extraction methods to capture relevant information, making its optimization a critical step in EEG-based classification tasks (Zhou et al, 2024).

2.3 Feature Extraction

Two distinct feature extraction techniques were applied to characterize the EEG signal segments: Discrete Wavelet Transform (DWT) and Power Spectral Density (PSD) analysis. Both approaches aim to quantify the essential temporal and spectral properties of the EEG signals by generating 10-dimensional feature vectors for each segment.

2.3.1 Discrete Wavelet Transform Features

Discrete Wavelet Transform (DWT) provides a multiresolution time-frequency analysis of the EEG signals, effectively capturing both low and high frequency components (Almahdi et al., 2021, Subekti et al., 2024). In this study, each EEG segment was decomposed into four levels using the Daubechies 4 (db4) mother wavelet. From the resulting approximation and detail coefficients, the following 10 statistical features were extracted to form the DWT-based feature vector:

- D_1: Mean of the approximation coefficients at level 4.
- D_2: Standard deviation of the approximation coefficients at level 4.
- D_3: Mean of the detail coefficients at level 4.
- D_4: Standard deviation of the detail coefficients at level 4.
- D_5: Mean of the detail coefficients at level 3.
- D_6: Standard deviation of the detail coefficients at level 3.
- D_7: Mean of the detail coefficients at level 2.
- D_8: Standard deviation of the detail coefficients at level 2.
- D_9: Mean of the detail coefficients at level 1.
- D_{10}: Standard deviation of the detail coefficients at level 1.

These features collectively capture signal energy distribution, variability, and frequency content across multiple scales, which are essential for distinguishing seizure activity from normal brain signals.

2.3.2 Power Spectral Density Features

To characterize the frequency-domain properties of the EEG segments, the Welch method was applied to estimate the PSD of each segment and its corresponding reference signal. Based on the PSD distributions, the following 10 features were calculated to construct the PSD-based feature vector:

- P_1: Kullback-Leibler divergence between the segment PSD and the reference PSD.
- P_2: L2-norm (Euclidean distance) between the segment PSD and the reference PSD.
- P_3: Difference in total spectral power between the segment and reference PSD.
- P_4: Difference in spectral entropy between the segment and reference PSD.
- P_5: Difference in spectral flatness between the segment and reference PSD.
- P_6: Difference in spectral bandwidth between the segment and reference PSD.
- P_7: Frequency corresponding to the maximum power in the segment PSD.
- P_8: Median frequency of the segment PSD.
- P_9: Variance of the segment PSD.
- P_{10}: Maximum absolute difference between the segment PSD and the reference PSD.

These features collectively reflect both absolute and relative spectral characteristics, providing a robust representation of the signal's frequency content and its deviation from baseline patterns (Ikizler and Ekim, 2025a, Ikizler and Ekim 2025b).

2.4 Classification and Performance Evaluation

A Random Forest (RF) classifier was employed to distinguish between different EEG classes based on the extracted features. RF is an ensemble learning method known for its robustness in overfitting and its ability to handle high-dimensional, complex data structures. Its use in EEG signal classification has been well documented due to these advantages (Kode et al., 2024, Kunekar et al., 2024).

The classification performance was assessed using standard metrics, including accuracy and precision, across both binary and multi-class classification tasks. These metrics provide a reliable indication of the model's ability to correctly identify seizure-related activity and differentiate it from non-seizure EEG patterns (Farawn et al., 2025).

All feature extraction, segmentation, and classification procedures were implemented in MATLAB within a fully automated framework, ensuring consistency and reproducibility across all experiments. To ensure a reliable and unbiased evaluation of the proposed classification framework, a 10-fold cross-validation strategy was adopted in all experiments. In this approach, the dataset was randomly partitioned into 10 equal-sized folds, with each fold serving as a test set exactly once while the remaining nine folds were used for training. This process was repeated iteratively to guarantee that all data samples contributed to both training and testing, providing a comprehensive estimate of the model's generalization ability. The reported accuracy and precision results represent the average performance across all 10 folds.

3 RESULTS

In this study, the publicly available EEG dataset provided by the University of Bonn was utilized to evaluate the impact of data segmentation on the classification performance of epileptic seizure detection. The dataset consists of five distinct classes (A, B, C, D and E), containing both healthy and epileptic EEG recordings. Various binary and multi-class classification tasks were designed by combining different subsets of these classes to comprehensively assess the system's effectiveness.

All experimental procedures, including signal preprocessing, segmentation, feature extraction, classification, and performance evaluation, were implemented entirely in a MATLAB environment using a custom-developed program. This program was designed to perform the entire experimental workflow in a fully automated manner, ensuring consistency and repeatability across all tests.

In the experimental setup, the effect of signal segmentation was investigated by dividing each EEG recording into 1, 2, 4, 8, and 16 equal-length segments. Two widely used feature extraction techniques were employed separately for each scenario: DWT and PSD. The extracted features were subsequently classified using a Random Forest algorithm, which has been shown to be effective for EEG based classification tasks due to their robustness and ensemble learning capabilities.

For each segmentation level and classification task, both accuracy and precision metrics were calculated to evaluate the system's performance. The entire set of experiments, covering 16 different classification tasks and five segmentation levels for both DWT and PSD-based feature sets, was conducted on a personal computer equipped with an Intel 12th Generation i5 processor and 16 GB of RAM, running a standard Windows 11 operating system. The computational environment provided sufficient processing power to efficiently handle the relatively large number of experiments without introducing hardware-related performance limitations.

The following sections present detailed experimental results, including quantitative tables and visual analyses, to reveal the effect of segmentation on classification accuracy for both feature extraction approaches.

The effect of data segmentation on the classification performance was systematically evaluated using both DWT-based, and PSD-based feature extraction approaches combined with Random Forest classification. The detailed results for each classification task and segmentation level are presented in Table 1 (DWT) and Table 2 (PSD), respectively.

In general, increasing the number of segments applied to the EEG recordings leads to noticeable changes in classification accuracy. This effect is evident across both feature extraction strategies, though with slight differences in magnitude and behaviour depending on the method.

For the DWT-based feature extraction, the segmentation process initially contributes positively to classification performance. Specifically, segmenting the signals into 2 and 4 parts often results in improved accuracy compared to the non-segmented scenario, particularly for complex classification tasks such as multi-class problems (e.g., A-B-C, A-B-C-D-E). However, excessive segmentation (i.e., 16 segments) tends to degrade performance, especially in binary tasks such as A-B and A-C, where a decline in accuracy is observed. This suggests that excessive division of signals may disrupt the temporal structure and statistical characteristics captured by the DWT, negatively impacting the representational power of the extracted features.

On the other hand, the PSD-based feature extraction exhibits a more consistent and stable improvement trend with increasing segment count. In particular, the classification accuracy for difficult tasks such as C-D, C-D-E, and A-B-C-D-E shows substantial gains as the number of segments increases. Notably, even at 16 segments, no severe performance degradation is observed, indicating that PSD features can benefit from finer temporal resolution without sacrificing signal integrity. This can be attributed to the frequency-domain nature of PSD, which allows for effective characterization of spectral content even in short signal segments.

When comparing the two methods, it is evident that while both DWT and PSD benefit from moderate segmentation (2 to 4 segments), PSD-based features demonstrate greater robustness to higher segmentation levels, particularly in multi-class and challenging binary classification scenarios. In contrast, the DWT-based approach appears to be more sensitive to over-segmentation, emphasizing the need to carefully select the segmentation parameter based on the chosen feature extraction method.

Overall, these results highlight the critical role of segmentation in optimizing the classification performance of EEG signals, as well as the interaction between segmentation strategy and feature representation. The findings suggest that an optimal segmentation level exists that maximizes classification accuracy, and that this optimum may vary depending on the feature extraction technique applied.

In addition to the tabular results, Figures 2 and 3 visually illustrate the impact of data segmentation on the mean classification accuracy across all 16 tasks for both DWT-based and PSD-based feature extraction methods, respectively.

Table 1: Classification performance (Accuracy and Precision) of Random Forest for different segment counts and classification tasks using DWT-based features.

Tasks	Metric	DWT-based Feature Vector				
		1 segment	2 segment	4 segment	8 segment	16 segment
A-E	Accuracy %	99,50	99,50	100,0	100,0	99,78
	Precision %	99,55	99,52	100,0	100,0	99,78
A-D	Accuracy %	96,50	97,25	97,75	96,69	94,34
	Precision %	96,89	97,38	97,79	96,74	94,36
A-C	Accuracy %	98,50	97,75	98,12	97,12	94,75
	Precision %	98,64	97,85	98,16	97,17	94,79
A-B	Accuracy %	92,00	93,75	92,63	91,75	89,41
	Precision %	92,72	94,01	92,80	91,80	89,49
C-D	Accuracy %	68,00	76,50	77,75	77,25	74,97
	Precision %	68,95	77,20	78,11	77,34	75,03
C-E	Accuracy %	97,50	98,25	98,37	98,81	98,53
	Precision %	97,88	98,38	98,42	98,82	98,54
B-E	Accuracy %	97,50	98,75	99,12	98,25	97,84
	Precision %	97,94	98,79	99,15	98,26	97,86
B-C	Accuracy %	97,50	97,50	98,38	98,31	96,97
	Precision %	97,73	97,61	98,40	98,35	96,99
B-D	Accuracy %	97,00	98,75	98,00	98,06	97,03
	Precision %	97,35	98,83	98,04	98,11	97,05
A-B-C	Accuracy %	92,67	93,83	93,17	92,04	88,67
	Precision %	93,23	94,11	93,30	92,18	88,74
A-B-D	Accuracy %	93,00	92,67	93,42	91,58	88,71
	Precision %	93,69	93,19	93,69	91,76	88,86
A-B-E	Accuracy %	94,33	94,83	94,08	93,25	91,40
	Precision %	94,78	95,07	94,29	93,31	91,48
C-D-E	Accuracy %	73,33	81,83	83,92	83,29	81,33
	Precision %	73,29	82,13	84,08	83,29	81,21
A-B-C-E	Accuracy %	94,00	94,25	94,38	93,03	89,97
	Precision %	94,71	94,51	94,56	93,14	90,05
A-B-C-D	Accuracy %	78,50	82,38	83,69	82,16	77,73
	Precision %	79,08	82,72	83,97	82,20	77,74
A-B-C-D-E	Accuracy %	82,40	84,60	85,60	84,22	79,96
	Precision %	82,80	84,63	85,76	84,16	79,86

Table 2: Classification performance (Accuracy and Precision) of Random Forest for different segment counts and classification tasks using PSD-based features.

Tasks	Metric	PSD-based Feature Vector				
		1 segment	2 segment	4 segment	8 segment	16 segment
A-E	Accuracy %	100,0	99,75	99,75	99,94	99,88
	Precision %	100,0	99,76	99,76	99,94	99,88
A-D	Accuracy %	99,00	99,25	98,62	97,88	96,37
	Precision %	99,09	99,29	98,65	97,89	96,42
A-C	Accuracy %	96,50	98,50	96,62	96,62	93,88
	Precision %	96,88	98,55	96,73	96,65	93,92
A-B	Accuracy %	91,50	92,75	91,88	95,63	96,56
	Precision %	91,97	93,17	92,05	95,64	96,60
C-D	Accuracy %	83,00	92,75	87,75	90,00	90,75
	Precision %	83,91	93,06	87,90	90,10	90,81
C-E	Accuracy %	98,50	99,50	99,63	99,94	99,88
	Precision %	98,55	99,50	99,63	99,94	99,88
B-E	Accuracy %	98,50	99,00	99,88	99,88	99,62
	Precision %	98,64	99,09	99,88	99,88	99,63
B-C	Accuracy %	97,50	98,75	98,62	99,31	97,94
	Precision %	97,63	98,83	98,66	99,32	97,95
B-D	Accuracy %	99,00	99,75	99,12	98,64	98,06
	Precision %	99,09	99,76	99,16	98,96	98,08
A-B-C	Accuracy %	91,33	95,33	93,25	95,21	93,50
	Precision %	92,65	95,64	93,42	95,29	93,53
A-B-D	Accuracy %	94,67	94,50	93,75	95,52	94,62
	Precision %	95,01	94,71	93,93	95,44	94,68
A-B-E	Accuracy %	94,33	95,50	94,92	97,25	97,52
	Precision %	94,78	95,74	95,03	97,27	97,54
C-D-E	Accuracy %	87,33	93,00	91,17	93,08	93,23
	Precision %	88,34	93,16	91,49	93,09	93,25
A-B-C-E	Accuracy %	93,25	95,88	94,37	96,12	95,00
	Precision %	93,63	96,50	94,46	96,19	95,02
A-B-C-D	Accuracy %	86,00	92,50	88,75	90,66	89,73
	Precision %	86,39	92,76	88,96	90,72	89,78
A-B-C-D-E	Accuracy %	87,20	93,00	90,15	92,33	91,36
	Precision %	88,11	93,37	90,30	92,39	91,39

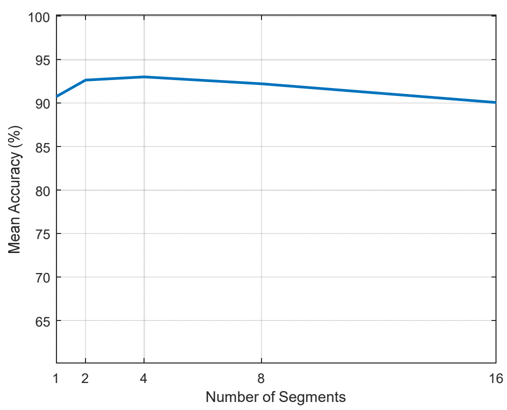

Figure 2: The effect of the number of segments on the mean classification accuracy across 16 classification tasks using Random Forest and DWT-based features.

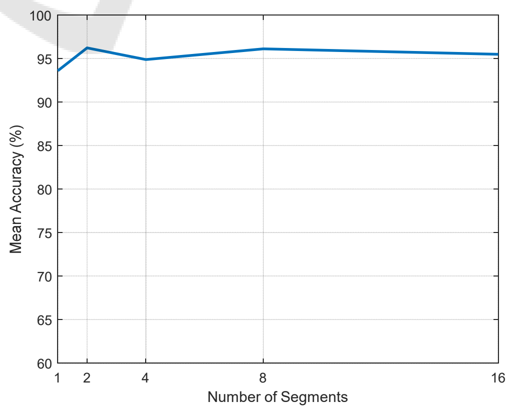

Figure 3: The effect of the number of segments on the mean classification accuracy across 16 classification tasks using Random Forest and PSD-based features.

As observed in Figure 2, the DWT-based approach exhibits a characteristic trend where the mean accuracy initially improves with segmentation but shows a gradual decline beyond a certain point. Specifically, segmenting the EEG signals into two parts yields a noticeable improvement in overall accuracy, suggesting that limited segmentation helps capture localized temporal patterns more effectively. However, as the number of segments increases beyond four, the mean accuracy begins to deteriorate. This indicates that excessive segmentation may fragment the temporal structure of the signal, reducing the ability of the DWT to extract meaningful features, especially for complex classification tasks.

In contrast, Figure 3 demonstrates a more stable behaviour for the PSD-based approach. Although slight fluctuations are present, the mean accuracy remains consistently high across different segmentation levels, with the best performance generally achieved between two and eight segments. This suggests that the PSD method, being inherently focused on frequency domain information, is less sensitive to signal segmentation and can maintain high classification performance even with finer temporal resolution. Furthermore, the relatively flat accuracy curve indicates that PSD-based features are more robust to variations in the segmentation parameter compared to DWT-based features.

These graphical results confirm that while segmentation is a valuable strategy for enhancing classification performance, its optimal configuration depends significantly on the chosen feature extraction method. The DWT method benefits from moderate segmentation but is more vulnerable to over-segmentation, whereas the PSD approach demonstrates greater resilience across a wider range of segmentation levels.

4 DISCUSSION

The results of this study provide important evidence regarding how the segmentation strategy directly shapes the performance of seizure detection systems utilizing EEG signals. While the technical aspects of the experimental design are described earlier, it is crucial to emphasize the broader implications of the observed trends.

The most striking finding is the clear dependence of classification success on the interplay between segmentation and feature extraction technique. The DWT-based method exhibited notable sensitivity to the segmentation parameter. Moderate segmentation levels contributed positively by enhancing the system's ability to capture transient patterns characteristic of epileptic seizures. However, excessive segmentation led to performance degradation, highlighting a potential trade-off between temporal resolution and the preservation of signal integrity.

On the other hand, the PSD-based approach demonstrated greater stability across different segmentation levels. The ability to extract consistent spectral information even from short signal segments explains the more gradual variations in classification accuracy observed in this method. This robustness makes PSD-based features particularly attractive for real-time seizure detection applications, where short analysis windows and rapid decision-making are required.

These findings carry direct implications for practical, clinically oriented EEG monitoring systems. Particularly in portable or continuous monitoring setups, signal segmentation becomes inevitable due to hardware limitations, memory constraints, or the need for prompt seizure detection. The results suggest that careful selection of segmentation parameters, aligned with the characteristics of the chosen feature extraction approach, can maximize detection reliability without sacrificing system efficiency.

Furthermore, the observed differences between DWT and PSD approaches highlight that there is no universal segmentation strategy suitable for all signal processing pipelines. Instead, a task-specific optimization process is required, especially for systems intended for deployment in critical care environments where false positives or delayed detections may have severe consequences.

5 CONCLUSIONS

This study provides a comprehensive analysis of how EEG signal segmentation influences seizure detection performance, offering valuable insights for the development of reliable, real-world clinical decision support systems.

The findings demonstrate that segmentation is not merely a technical preprocessing step but a decisive factor that interacts with the feature extraction strategy to shape classification success. Moderate segmentation enhances performance, particularly for methods that exploit time-frequency characteristics, such as DWT. Meanwhile, PSD-based approaches offer greater flexibility and resilience to segmentation, making them promising candidates for continuous, real-time monitoring scenarios.

These insights lay the groundwork for future research directions. Moving forward, extending the analysis to more heterogeneous and clinically realistic EEG datasets is essential to validate these findings under practical conditions. Furthermore, incorporating advanced deep learning architectures capable of learning optimal segmentation schemes adaptively, rather than relying on fixed segment counts, may yield further improvements in both accuracy and system efficiency.

In addition, future work should investigate the trade-offs between segmentation, classification performance, and computational cost to ensure that proposed methods are not only effective but also suitable for deployment in low-power, wearable, or mobile seizure detection platforms. Ultimately, this line of research contributes to the development of more accessible, accurate, and patient-friendly solutions for epilepsy monitoring and management.

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