DPML: Derivative-Based EEG Preprocessing for Enhanced Epileptic Seizure Detection Using Machine Learning

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***Abstract*—This paper presents a comparative study for epilepsy monitoring using EEG signals along two main axes. The first axis consists of comparing the performance of the differentiation technique, which is known to be very important for the study of non-stationarity, with wavelet transform, which is widely used for detecting different brain rhythms. The second part aims to compare the performance of different machine learning algorithms, including k-Nearest Neighbors (k-NN), Decision Trees, Random Forest, and Support Vector Machines (SVM). Used features are statistical and higher order statistics characteristics such as mean, standard deviation, median, Min-Max, Kurtosis and Skewness. We tested our approach on publicly available and widely used datasets in the literature, namely the University of Bonn dataset and the Bern-Barcelona dataset. The experimental results demonstrate the effectiveness of the differentiation method as an important tool for EEG preprocessing, leading to very high performance.**

***Index Terms*—Epilepsy, EEG, classification, wavelet, derivative, machine learning.**

I. Introduction

Epilepsy is a chronic neurological disorder characterized by recurrent seizures resulting from abnormal electrical activity in the brain. This condition significantly affects patients' daily lives, as they must take specific precautions, particularly during activities that pose potential safety risks, such as driving. Given the frequency and unpredictability of epileptic seizures, timely and accurate detection is essential to minimize risks [1].Moreover, the interpretation of EEG recordings is time-consuming, which highlights the importance of an automated tool for monitoring and detecting epileptic seizures.

Consequently, the development of reliable automatic seizure detection systems is crucial to support clinical decision-making and improve patient safety [2].

Traditional epilepsy detection approaches rely heavily on expert visual inspection of EEG signals, which is labor-intensive, prone to human error, and was not suitable for continuous or real-time monitoring. Nowadays, machine learning (ML) techniques have emerged as effective tools for automating EEG analysis. However, the performance of ML-based seizure detection systems strongly depends on the quality of signal preprocessing and feature extraction, particularly when dealing with non stationary EEG signals and limited datasets. This highlights the need for robust preprocessing strategies that can enhance the discriminative information available to ML classifiers through the use of both statistical features (mean, median, standard deviation, maximum, and minimum) and higher-order statistical features (kurtosis and skewness).

This research will only focus on machine learning-based epileptic seizure detection andwill provide details of a new derivative-based preprocessing approach (DPML) aimed at enhancing seizure-related signal characteristics. In addition to the proposed derivative-based method, wavelet transform is employed as a comparative preprocessing technique. The main objective is to evaluate the impact of these preprocessing strategies on the performance of conventional ML classifiers when applied to both raw and preprocessed EEG data.

Several machine learning algorithms are investigated, including k-Nearest Neighbors (KNN), Decision Trees (DT), Random Forest (RF), and Support Vector Machines (SVM). The proposed framework is evaluated using the Bonn and Bern Barcelona datasets. Experimental results demonstrate that derivative-based preprocessing significantly improves classification performance, highlighting its effectiveness as a powerful and computationally efficient alternative for ML-based EEG seizure detection systems.

The main contributions of this study are summarized as follows:

- Proposal and evaluation of a novel derivative-based EEG preprocessing approach (DPML), used in combination with machine learning classifiers, for epileptic seizure detection.
- A comparative study of two EEG signal preprocessing techniques: derivative-based preprocessing and wavelet transform using statistical and higher-order statistical features for epilepsy monitoring.
- Comprehensive performance assessment of several machine learning classifiers, including KNN, Decision Trees, Random Forest, and SVM, using raw and preprocessed EEG data.
- Detailed description of the experimental framework and evaluation protocol based on the *Bonn* and *Bern Barcelona* datasets.

The remainder of this paper is structured as follows: Section 2 reviews related work, while Section 3 details our proposed approach. In Section 4, we present and discuss the results. Finally, Section 5 concludes the paper and outlines potential directions for future research.

II. Related work

The classification of EEG signals for epilepsy detection has been extensively addressed in the literature using both public and private datasets. Among these datasets, The Bonn EEG database which is one of the most studied and used benchmark datasets when evaluating detection methods for epileptic seizures, due to its well-structured recordings and clear distinction between seizure and non-seizure states. Numerous studies have explored a variety of preprocessing, feature extraction, and classification strategies on this dataset [3], [4].

Several works have focused on advanced signal preprocessing techniques to enhance seizure-related EEG patterns. For instance, Butterworth filtering has been commonly applied to reduce noise and artifacts prior to classification [5]. Other approaches have relied on spectral and time–frequency transformations, such as wavelet transform, to capture the non-stationary characteristics of EEG signals [6]. Feature extraction strategies often include statistical measures, entropy-based features, and fractal dimensions, which are then combined with conventional machine learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees (DT), and Random Forest (RF) [7], [8].

More complex hybrid frameworks have also been proposed, integrating signal decomposition methods with extensive feature extraction and selection pipelines. Ahmad et al. [9], for example, combined wavelet-based decomposition with linear and non-linear features, followed by feature selection using distance correlation coefficients and classification using ensemble machine learning models. These studies demonstrate that appropriate preprocessing and feature engineering play a critical role in improving seizure detection performance, often more significantly than the choice of classifier itself.

The related work includes many methods; however a major challenge still lies in developing preprocessing techniques capable of enhancing the discriminative information contained in EEG signals while preserving low computational cost and robustness, especially when dealing with limited datasets. Although wavelet-based and frequency-domain approaches have demonstrated good effectiveness, they often involve high computational requirements and strong dependence on parameter tuning.

This study proposes and investigates a novel derivative-based EEG preprocessing framework (DPML) for epileptic seizure detection using machine learning algorithms. The proposed approach is designed to better characterize local temporal changes in EEG recordings, thereby generating a more compact and discriminative representation that is well suited for statistical feature extraction.

III. Proposed approach

Our proposed methodology, which outlines the various steps detailed in the following sections, is illustrated in Figure 1.

In our approach, we conduct a comparative study of machine learning models where feature extraction is applied to raw, derivative-based, and wavelet-transformed data.

Preprocessing : EEG signals are often non-stationary, and their characteristics vary over time. This makes analysis complex. However, a non-stationarity study is essential to study temporal and dynamic variations in brain activity. According to a literature review, wavelet differentiation and decomposition are two important tools for detecting rapid variations in brain activity [10].

1) Wavelet transform : This technique is used to analyze both the frequency and temporal aspects of the signal at different time and frequency scales, facilitating the detection of transient phenomena. Furthermore, each frequency band can be isolated based on its frequency and duration, which allows efficient identification of different cerebral rhythms .
   - *Alpha* α (8 - 12 Hz): By studying the frequency range around 10 Hz, wavelet transform allows alpha waves determination.
   - *Beta* β (13 - 30 Hz): Wavelets identify faster oscillations, characteristic of beta waves.
   - *Theta* θ (4 - 8 Hz): wavelets allow to detect the slower oscillations associated with theta waves.
   - *Gamma* γ (30 - 100 Hz): High-frequency wavelets are particularly effective at isolating gamma oscillations.
   - *Delta* δ (0.5 - 4 Hz): By analyzing low frequencies, wavelets can capture the slow oscillations characteristic of delta waves.

   Considering these rhythms, we will use a new data vector defined as:

$$WT_{EEG} = \begin{bmatrix} \alpha \\ \beta \\ \theta \\ \gamma \\ \delta \end{bmatrix} \quad (1)$$

2) Differentiation: George Box and Gwilym Jenkins (1976) [11] showed that differentiation is an interesting tool for transforming a non-stationary process into a stationary one. Since then, differentiation and derivative determination have been applied to the study of several types of non stationary time series in various fields, including finance, economics, chemistry, ecology,... In particular, derivation is used for the preprocessing of several classes of biological signals such as Electromyography (EMG) [12], Electrocardiography (ECG) [13] and EEG in our previous works [14], [15].

We will use a new form of data D_{EEG} which includes EEG and its derivatives as follows:

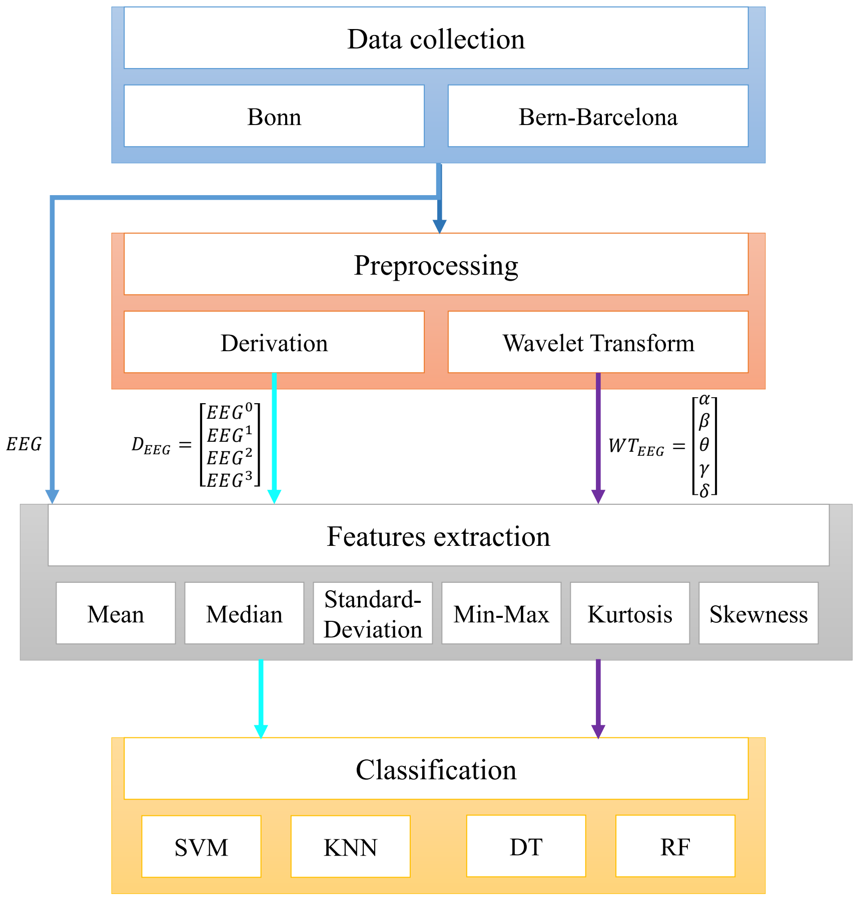

Fig. 1: Comparison of EEG preprocessing methods: Raw EEG, Wavelet (WT), and Derivative (DERV).

$$D_{EEG} = \begin{bmatrix} EEG^0 \\ EEG^1 \\ EEG^2 \\ EEG^3 \end{bmatrix} \tag{2}$$

where : EEG^i represents the derivative of order i.

We extract meaningful features from raw data EEG, derivative-based data D_{EEG}, and wavelet-transformed data WT_{EEG} to enhance the model learning process. The following section introduces the statistical features employed in this study.

Features Extraction :

Let's consider a dataset $\{X_1, X_2, \ldots, X_n\}$, where n represents the number of data points. The vector of given data is denoted as $\mathbf{X} = [x_1, x_2, \ldots, x_n]$.

We will present now how to calculate several statistical features of this dataset.

- ***Mean*** (μ): The mean of a dataset represents the average value of the all value dataset. It is calculated as :

$$\mu = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{3}$$

- ***Stanard Deviation*** (σ): The STNard deviation measures the spread or dispersion of data points around the mean. It's provide a measure of the dataset's variability.

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2} \tag{4}$$

- ***Median***: The median is the middle value in a dataset when arranged in increasing order.

$$\text{Median} = \begin{cases} x_{\frac{n+1}{2}}, & \text{if } n \text{ is odd} \\ \frac{x_{\frac{n}{2}} + x_{\frac{n}{2}+1}}{2}, & \text{if } n \text{ is even} \end{cases} \tag{5}$$

- ***Min-Max***: the maximum and minimum values in the dataset. It gives a simple measure of the extent of the dataset.

$$\text{Min-Max} = [\min(x), \max(x)] \tag{6}$$

- ***Kurtosis***: Kurtosis measures the degree of peakedness or flatness in the distribution of data compared to a normal distribution (a value of 0 is normal)

$$\text{Kurtosis} = \frac{n(n-1)}{(n-2)(n-3)} \cdot \frac{\sum_{i=1}^{n} (x_i - \mu)^4}{\left(\sum_{i=1}^{n} (x_i - \mu)^2\right)^2} - 3 \tag{7}$$

- ***Skewness***: Skewness measures the asymmetry of the data distribution. A skewness of 0 indicates a perfectly symmetrical distribution, while positive or negative skewness indicates a distribution with a longer tail on the right or left, respectively.

$$\text{Skewness} = \frac{n}{(n-1)(n-2)} \cdot \frac{\sum_{i=1}^{n}(x_i-\mu)^3}{\left(\sum_{i=1}^{n}(x_i-\mu)^2\right)^{3/2}} \quad (8)$$

Our work focuses on machine learning methods. In fact, the feature vectors obtained after the feature extraction stage were used in the classification process by applying machine learning models. We conduct a series of experiments to evaluate the performance of our approach.

IV. Experiments

In this section, we present the used database and the studied cases, as well as the obtained experiments.

The performance of our approach is comprehensively evaluated for each classification task using the following metrics:

- ***Accuracy***(ACC):

$$ACC(\%) = 100 \cdot \frac{TP}{TP+FN+FP+TN} \quad (9)$$

The Accuracy metric quantifies the proportion of correct predictions (both positive and negative) out of all predictions made.

- ***Recall*** (REC):

$$REC(\%) = 100 \cdot \frac{TP}{TP+FN} \quad (10)$$

Recall, also known as **True Positive Rate (TPR)**, measures the ability of the model to correctly identify positive instances. It focuses on minimizing false negatives and is particularly important when detecting rare events such as seizures.

- ***Specificity*** ($SPEC$):

$$SPEC(\%) = 100 \cdot \frac{TN}{TN+FP} \quad (11)$$

Specificity, also referred to as the True Negative Rate (TNR), measures the model's capacity to correctly identify negative samples. A higher specificity value reflects a lower number of false positives, which is important in medical diagnosis tasks where avoiding incorrect positive predictions is critical.

Where:

- TP (True Positive) denotes the number of correctly identified positive instances.
- TN (True Negative) represents the number of correctly identified negative instances.
- FP (False Positive) corresponds to instances that are incorrectly classified as positive.
- FN (False Negative) corresponds to instances that are incorrectly classified as negative.

These metrics provide a detailed assessment of the classification model's performance.

A. Used database

The data set used in this paper was the Bonn and Bern Bercelona datasets.

Bonn database

It comprises 100 single channels EEG of 23.6s. It was taken from five patients named A, B, C, D and E. Sets A and B are the surface EEG recorded during eyes closed and open situations of healthy patients (Hp). Set C and D are the intracranial EEG recorded during a seizure-free (Ep) from within the seizure-generating area and from the outside the seizure-generating area of epileptic patients respectively. Set E is the intracranial EEG of an epileptic patient during epileptic seizures (Sp).

Classification problems related to Bonn database are presented in the Table I.

TABLE I: Studied cases related to the BONN database

Experiments	Studied case
1	Hp vs Ep
2	Ep vs Sp
3	Hp vs Sp
4	Hp and Ep vs Sp
5	Ep and Sp vs Hp
6	Hp vs Ep vs Sp

HE: Healthy, EP: Epileptic, ES: Epileptic Seizures

Bern Bercelona database

The Bern–Barcelona EEG dataset consists of 3,000 single-channel EEG segments, equally divided into 1,500 focal and 1,500 non-focal recordings. Each segment has a duration of 20 seconds and is sampled at 512 Hz, resulting in 10,240 samples per segment [16]. Focal EEG segments correspond to signals recorded from brain regions associated with the epileptogenic focus responsible for the generation of seizures. In contrast, non-focal EEG segments are acquired from brain areas not involved in epileptic activity and are therefore considered non-epileptogenic.

B. Results

The present work is mentioned to study the interest of using the derivatives compared to the wavelets using Machine learning, four algorithms are tested SVM, KNN, DT and RF, based on feature engineering, statistical features.

In Table II, the derivative-based representation (DERV) consistently achieves high accuracy across most experimental settings, particularly with classifiers such as KNN and SVM.

Figure 2 presents the mean classification accuracy on the Bonn dataset using three EEG representations: raw signals, wavelet transform (WT), and derivative-based (DERV) features. Overall, the derivative-based approach consistently outperforms both raw EEG and wavelet-based representations, indicating its effectiveness in enhancing seizure-related patterns for machine learning models.

On the Bern–Barcelona dataset, notable improvements are observed for the Random Forest (0.75) and Decision Tree (0.67) classifiers as shown by Figure 3 and Table III.

TABLE II: Performance of machine learning classifiers on Raw, Derivative (DERV), and Wavelet (WT) EEG signals on Bonn Dataset

		KNN				SVM				DT				RF			
		ACC	Recall	SPC	T (min)	ACC	Recall	SPC	T (min)	ACC	Recall	SPC	T (min)	ACC	Recall	SPC	T (min)
Exp.1	EEG	61.00	61.00	46.67	0.3	66.00	66.00	50.00	0.6	70.00	70.00	66.67	0.42	82.00	83.00	74.63	0.20
	DERV	96.00	96.00	95.00	1.71	98.00	98.00	96.67	0.51	93.00	93.00	95.00	0.51	97.00	98.00	96.77	0.28
	WT	93.00	93.00	96.67	2.11	97.00	100.00	97.00	2.57	93.00	93.00	95.00	0.94	96.00	96.00	93.55	0.28
Exp.2	EEG	90.00	89.00	91.67	0.24	94.00	93.00	98.33	0.4	92.00	89.00	98.33	0.38	91.00	89.00	93.65	0.15
	DERV	92.00	93.00	91.67	1.72	96.00	95.00	96.67	0.4	97.00	96.00	98.33	0.41	97.00	96.00	98.41	0.17
	WT	91.00	90.00	93.33	2.25	97.00	97.00	96.67	1.89	97.00	97.00	96.67	0.73	96.00	96.00	95.24	0.18
Exp.3	EEG	94.00	93.00	96.67	0.23	98.00	97.00	100.00	0.39	96.00	94.00	98.33	0.4	94.00	92.00	98.41	0.14
	DERV	96.00	94.00	98.33	0.97	95.00	100.00	36.00	0.96	94.00	98.33	97.00	0.4	97.00	97.00	100.00	0.18
	WT	98.00	97.00	100.00	6.39	99.00	100.00	98.00	1.98	100.00	100.00	100.00	0.71	99.00	98.00	100.00	0.18
Exp.4	EEG	66.00	63.00	48.33	0.32	66.00	61.00	33.33	0.62	71.00	70.00	61.67	5.25	85.00	83.00	73.85	0.28
	DERV	94.00	93.00	86.67	1.74	98.00	98.00	96.67	0.63	95.00	95.00	91.67	0.61	99.00	99.00	98.39	0.33
	WT	91.00	91.00	91.67	1.68	93.00	94.00	95.00	4.24	95.00	96.00	96.67	1.14	97.00	96.00	91.94	0.29
Exp.5	EEG	96.00	95.00	96.67	0.4	95.00	91.00	98.33	0.55	97.00	97.00	97.50	0.38	95.00	89.00	98.32	0.1637
	DERV	98.00	97.50	99.00	1.67	97.00	92.00	100.00	0.48	99.00	98.00	99.17	0.55	97.00	93.00	99.16	0.2169
	WT	97.00	95.00	97.50	6.49	97.00	97.00	96.67	2.1	98.00	95.00	100.00	1	98.00	98.00	98.32	0.3456
Exp.6	EEG	100.00	100.00	81.00	0.17	71.00	75.00	83.00	0.78	76.00	97.00	86.00	0.47	84.00	84.00	91.00	0.2275
	DERV	93.00	93.00	96.00	1.65	97.00	96.00	97.00	0.75	95.00	96.00	96.00	0.60	96.00	95.00	97.00	0.2785
	WT	91.00	91.00	94.00	6.48	93.00	92.00	95.00	3.40	93.00	92.00	95.00	1.16	97.00	98.00	98.00	0.324

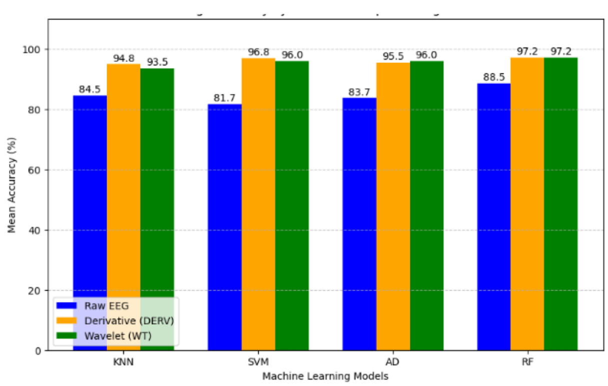

Fig. 2: Comparison of EEG preprocessing methods on Bonn dataset: Raw EEG, Wavelet (WT), and Derivative (DERV).

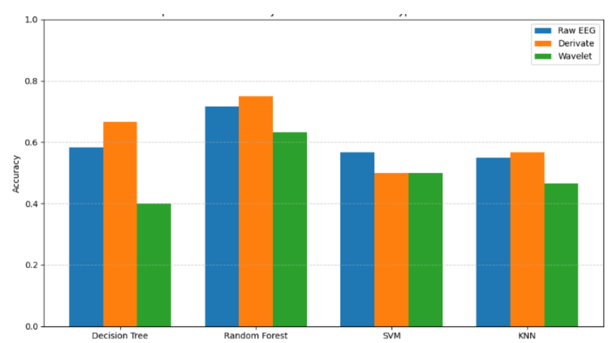

Fig. 3: Comparison of EEG preprocessing methods on Bern Barcelona dataset: Raw EEG, Wavelet (WT), and Derivative (DERV).

Overall, derivative-based preprocessing shows consistent effectiveness across most experiments, achieving competitive and, in some cases, superior classification performance compared to other feature representations.

As reported in Table II and Table III, the derivative-based approach reduces computational cost compared to wavelet-based methods. In addition, DERV achieves similar or better classification results than WT while significantly lowering processing time (0.28–1.72 min versus 0.71–6.49 min).

V. Discussion

This study presents a comprehensive comparative analysis between derivative-based preprocessing and wavelet transform, highlighting their respective strengths and limitations in the context of seizure detection. An in-depth performance evaluation of multiple machine learning classifiers following these preprocessing techniques is conducted to assess their impact on seizure detection accuracy.

The use of derivatives as a preprocessing step has been investigated in our previous work using fractal dimensions [14] and deep learning architectures [17].

In this study, derivative-based preprocessing is further integrated within the DPML framework, which combines temporal derivative representations with statistical and higher-order statistical feature extraction for machine learning-based EEG classification.

The experimental results highlight the influence of preprocessing strategies on EEG-based seizure classification. Compared to raw EEG signals, both derivative-based (DERV) and wavelet-based (WT) representations improve the discriminative quality of extracted features, emphasizing the importance of signal transformation prior to classification.

Across the Bonn dataset, derivative-based features show strong effectiveness when combined with classical machine learning models. This behavior is explained by their ability to emphasize local temporal variations, which are closely related to seizure dynamics, while preserving the intrinsic structure of the signal required for statistical feature extraction.

On the Bern Barcelona dataset, the variations across preprocessing methods are less pronounced, although derivative-based features remain consistently competitive, particularly with Random Forest classifier.

TABLE III: Performance of machine learning classifiers on Raw, Wavelet (WT), and Derivative (DERV) EEG signals on Bern/Barcelona Dataset

Method	**KNN**				**SVM**				**DT**				**RF**			
	ACC	Recall	SPC	T(s)	ACC	Recall	SPC	T(s)	ACC	Recall	SPC	T(s)	ACC	Recall	SPC	T(s)
EEG (Raw)	55.00	65.52	45.16	0.004	56.66	75.86	38.71	0.004	58.33	65.52	51.61	0.004	71.66	79.31	64.52	0.387
WT	46.67	100.00	5.88	0.110	50.00	84.62	23.53	0.570	40.00	53.85	29.41	2.150	63.33	84.62	47.06	0.670
DERV	56.66	58.62	54.83	0.005	50.00	79.31	22.58	0.006	67.00	65.51	67.74	0.007	**75.00**	75.86	74.19	0.167

Moreover, derivative-based preprocessing offers a computational advantage. In contrast to wavelet decomposition, it introduces minimal computational overhead, resulting in reduced processing time, which is particularly relevant for real-time EEG analysis applications.

In addition, derivative-based features enhance discriminability by emphasizing local variations in EEG signals, leading to a compact and efficient feature representation. As a result, the method maintains competitive classification performance while significantly improving computational efficiency, making it promising for seizure detection and monitoring applications.

VI. Conclusion

This work introduces a machine learning framework for epileptic seizure detection based on three EEG signal representations: raw EEG, derivative-based signals, and wavelet-transformed signals. Four classification methods KNN, SVM, Decision Tree, and Random Forest classifiers were employed. Our experiments were conducted on the Bonn and Bern–Barcelona datasets showing that derivative-based preprocessing enhances seizure detection performance in terms of accuracy, recall, and specificity compared with wavelet transform–based preprocessing, while preserving low computational requirements. DPML constitutes an effective and reliable preprocessing approach for machine learning-driven seizure detection. In addition, its low computational overhead makes it suitable for real-time implementations, including wearable and embedded monitoring systems that can continuously monitor patients and provide rapid seizure alerts, thus improving patient care and clinical response.

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