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Epileptic Spike Detection in EEG Signals Using a Hybrid Wavelet–RLS Denoising and Probabilistic Neural Classification

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ABSTRACT

Accurate detection of epileptic spikes in electroencephalography (EEG) signals is essential for reliable epilepsy diagnosis but is often hindered by ocular, muscular, and power-line artifacts. This paper presents a hybrid framework for epileptic spike detection that integrates multiresolution wavelet decomposition with Recursive Least Squares (RLS) adaptive filtering for spike-preserving EEG denoising. Unlike generic artifact-suppression methods, the proposed preprocessing stage is designed to enhance transient epileptiform activity while preserving spike morphology. Statistical features extracted from wavelet subbands are subsequently classified using a Probabilistic Neural Network (PNN), enabling fast and probabilistically interpretable decision-making. Experimental evaluation on real EEG recordings demonstrates effective artifact suppression and an average classification accuracy of 91.86%, indicating that the proposed approach provides a computationally efficient and reliable solution for epileptic spike detection.

Keywords: *Epilepsy, EEG signal processing, Adaptive filtering, Wavelet-RLS, Probabilistic neural network (PNN)*

1. Introduction

Epilepsy is a chronic neurological disorder characterized by recurrent seizures arising from abnormal electrical discharges in the cerebral cortex [1]. Electroencephalography (EEG) is the primary non-invasive modality for detecting such abnormalities, particularly through epileptic spikes and sharp waves, which serve as key diagnostic biomarkers [2]. Since not every spike is pathological, accurate interpretation requires consideration of waveform morphology, frequency of occurrence, and clinical context [3]. However, EEG recordings are frequently contaminated by ocular, muscular, and power-line artifacts that can mimic epileptiform transients, making robust denoising a prerequisite for reliable clinical evaluation [4].

Over the past two decades, numerous signal-processing techniques have been developed for EEG artifact suppression, including wavelet-based approaches, Independent Component Analysis (ICA), adaptive filtering, and their various hybrids [5-7]. Further advances have explored wavelet-driven feature extraction and probabilistic classification [8], wavelet-based EEG classification schemes [9], and time–frequency analysis tools such as the Hilbert–Huang transform [10]. Foundational studies also established wavelet analysis as a principled framework for EEG processing and highlighted the impact of noise and artifacts on EEG interpretation [11-13]. More recent classical approaches improved denoising performance via DWT-based compression and scalar quantization [14], as well as hybrid Wavelet–FastICA strategies with adaptive thresholding to enhance separation between neural activity and artifacts [15, 16].

More recently, deep-learning-based frameworks have gained prominence for EEG denoising and artifact suppression. Frequency-domain learning and time–frequency reconstruction networks, as well as CNN/Transformer and GAN-based models, have demonstrated strong performance for multi-artifact suppression and EEG reconstruction [17-20]. Despite their success, these methods often require large training datasets and substantial computational resources, and they are generally designed for generic signal enhancement rather than spike-oriented denoising tailored to epileptic EEG analysis.

In this work, we address this gap by proposing a hybrid preprocessing and classification framework specifically designed for epileptic spike detection. The core contribution lies in a spike-preserving denoising stage that integrates multiresolution wavelet decomposition with Recursive Least Squares (RLS) adaptive filtering. While wavelet decomposition provides time–frequency localization of transient EEG components, the RLS filter adaptively suppresses structured and recurring noise with minimal distortion of spike morphology. Following denoising, statistical features extracted from wavelet subbands are classified using a Probabilistic Neural Network (PNN), enabling fast and probabilistically interpretable decision-making. The remainder of this paper is organized as follows: Section 2 describes the proposed methodology, Section 3 presents experimental results, and Section 4 concludes the study.

2. Methodology

This section presents the proposed epileptic spike detection framework, which consists of four main stages: EEG signal acquisition and preprocessing, spike-oriented denoising using a hybrid Wavelet–RLS filter, feature extraction in the wavelet domain, and probabilistic classification using a Probabilistic Neural Network (PNN). An overview of the complete processing pipeline is illustrated in Figure 1.

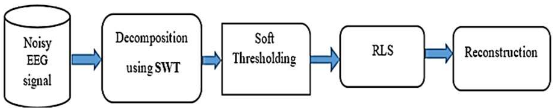

Figure 1. Diagram of Wavelet-RLS method

2.1. *EEG Signal Acquisition and Preprocessing*

In this study, EEG signals were obtained from the publicly available University of Bonn EEG dataset [21], which consists of three distinct groups: recordings from healthy individuals (Group 1), recordings from epileptic patients during seizure-free intervals (Group 2), and recordings acquired during seizure episodes (Group 3). Each group contains 4,000 signal segments, providing a balanced dataset suitable for both denoising and classification tasks.

To ensure consistency across recordings and improve classification robustness, each EEG segment was normalized with respect to its maximum amplitude, thereby preserving relative signal energy while enabling fair inter-sample comparison. Artifact suppression was initially performed using the Stationary Wavelet Transform (SWT), selected due to its shift-invariance and superior performance compared to the Discrete Wavelet Transform (DWT) in biomedical signal denoising. Subsequently, a Recursive Least Squares (RLS) adaptive filtering algorithm was applied in the wavelet domain to dynamically update filter coefficients and further suppress structured noise components [22]. The general SWT-based denoising procedure is illustrated in Figure 2 [23].

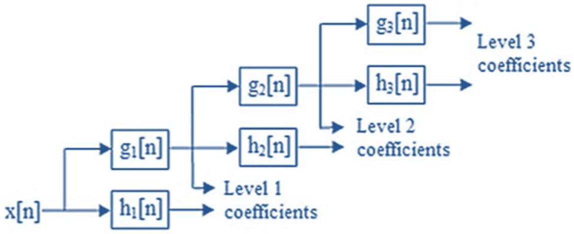

Figure 2. SWT algorithm [23]

2.2. *EEG Signal Denoising Using Wavelet-RLS Filter*

The proposed Wavelet–RLS filter combines the multiresolution analysis capability of the wavelet transform with the fast-converging adaptive tracking properties of the Recursive Least Squares algorithm. Initially, the EEG signal is decomposed into multiple sub-bands using the Stationary Wavelet Transform (SWT), allowing signal components to be isolated across different time–frequency scales. An adaptive RLS filter is then applied independently to each sub-band to suppress noise while preserving diagnostically relevant EEG features [22].

Adaptive filtering techniques have been widely studied for signal enhancement in the presence of colored noise, particularly in recursive identification frameworks [24]. Motivated by these results, the RLS algorithm is employed in this work to achieve fast convergence and robust noise suppression.

Figure 3 illustrates the structure of the adaptive filtering stage [25].

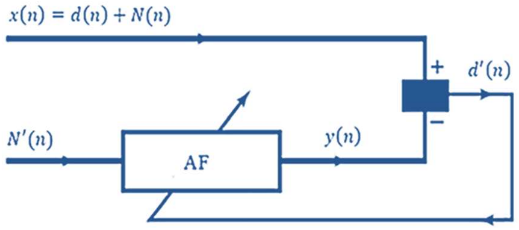

Figure 3. RLS algorithm [25]

The observed signal $x(n)$ is modeled as the sum of the clean EEG signal $d(n)$ and additive noise $N(n)$, such that:

1. $x(n) = N(n) + d(n)$ 2. (1)

The input vector $N'(n)$, composed of current and previous samples or extracted features, is fed into the adaptive filter (AF). The filter output $y(n)$ represents an estimate of the noise component, which is subtracted from the observed signal $x(n)$ to obtain the error signal:

3. $d'(n) = x(n) - y(n)$ 4. (2)

Ideally, $y(n) \approx N(n)$ resulting in $d'(n) \approx d(n)$, i.e., the noise is effectively removed. The error signal $d'(n)$ is used to recursively update the RLS filter weights, enabling continuous adaptation to nonstationary noise conditions.

The filter output is given by:

5. $y(n) = W^T(n).N'(n)$ 6. (3)

The weight vector $W(n)$ is updated at each iteration by minimizing the squared error $[d'(n)]^2$, allowing the filter to track variations in the EEG signal characteristics more effectively than static filtering techniques.

To quantify denoising performance, Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR), are employed:

7. $MSE = \frac{\sum_{i=1}^{N}[e(n)-x(n)]^2}{N}$ 8. (4)
9. $SNR = 20 * log_{10}\left(\frac{\sqrt{mean(e(n))^2}}{\sqrt{mean(e(n)-x(n))^2}}\right)$ 10. (5)

where $e(n)$ is the denoised output, $x(n)$ is the reference signal (when available), and N is the number of samples. Lower MSE and higher SNR indicate more effective noise reduction.

In practical scenarios where a clean reference signal is unavailable, the correlation coefficient is used to evaluate similarity between the noisy input and the denoised output:

11. $corr(x.y) = \frac{cov(x.y)}{\sigma_x \sigma_y}$ 12. (6)

Here, μ_X and μ_Y are the mean values of X and Y, and σ_X , σ_Y are their standard deviations. Higher correlation values indicate successful noise suppression while preserving the underlying EEG structure.

2.3. *Statistical Properties of Brain Signals*

Statistical analysis of EEG signals enables discrimination between normal and epileptic brain activity. Variations in amplitude distribution, energy concentration, and temporal dynamics provide informative descriptors that capture seizure-related abnormalities. These statistical properties form the basis for feature extraction and subsequent classification.

2.4. *Feature Extraction via Wavelet Transform*

In addition to denoising, the wavelet transform facilitates the extraction of discriminative statistical features from EEG signals. Its joint time–frequency representation enables localization of transient epileptiform patterns. Features such as energy distribution, spectral power, and entropy are computed from wavelet sub-bands and used as inputs to the classification stage.

2.5. *Classification Using Probabilistic Neural Networks (PNN)*

Following feature extraction, EEG segments are classified using a Probabilistic Neural Network (PNN) due to its rapid training, robustness with limited data, and probabilistic interpretation of outputs. As a Bayesian feedforward classifier, the PNN estimates class-conditional probability density functions and assigns each segment to seizure or non-seizure classes accordingly [26].

2.6. *Evaluation Criteria*

The performance of the proposed framework was evaluated using real EEG recordings. Denoising effectiveness was assessed using SNR and MSE, while classification performance was quantified based on accuracy derived from extracted statistical features. The proposed approach achieved an average classification accuracy of approximately 91.86%, demonstrating its effectiveness for automated epileptic spike detection.

Figure 4 summarizes the complete processing pipeline of the proposed Wavelet–RLS-based framework.

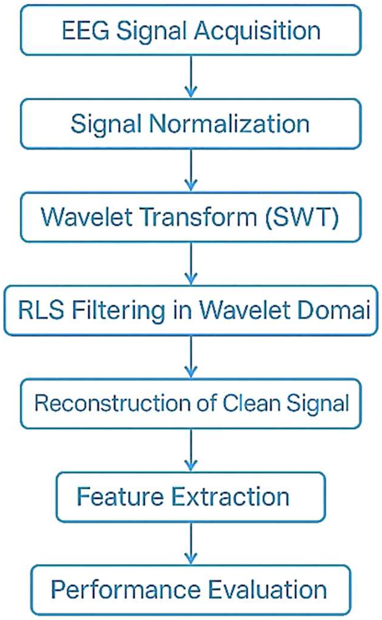

Figure 4. Flowchart of the proposed noise removal algorithm for epileptic EEG signals using the hybrid Wavelet–RLS method

3. Simulation Results

This section presents the experimental setup, dataset characteristics, implementation details of the proposed Wavelet–RLS filtering framework, feature extraction procedure, and the evaluation metrics used to assess denoising and classification performance.

3.1. *Dataset and Experimental Setup*

Three EEG datasets corresponding to different subject groups—healthy individuals, epileptic patients during seizure-free intervals, and epileptic patients during seizure activity—were used in this study. The EEG signals were recorded from 10 scalp channels following the international 10–20 system, with a sampling frequency of 173.61 Hz [21].

For denoising evaluation, five representative EEG recordings containing epileptic spike activity were selected. Performance was quantitatively assessed using Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR). The proposed Wavelet–RLS filtering approach was compared against a reference Wavelet–Independent Component Analysis (Wavelet–ICA) method to highlight improvements in artifact suppression and signal preservation.

3.2. *Wavelet-RLS Filtering Method*

The Wavelet–RLS denoising framework is implemented through the following steps:

a) Applying the Stationary Wavelet Transform (SWT) to decompose the noisy EEG signal into multiple wavelet coefficients across different frequency bands.
b) Processing the decomposed coefficients using the Recursive Least Squares (RLS) algorithm for adaptive noise estimation.
c) Applying soft thresholding to the estimated coefficients to suppress noise while preserving diagnostically relevant EEG components.
d) Reconstructing the denoised signal using the Inverse Wavelet Transform (IWT).

Figures 5 and 6 illustrate the SWT decomposition of a noisy epileptic EEG signal. Prior to decomposition, signal extension is applied where necessary to standardize segment length and mitigate boundary artifacts.

In this study, the SWT was performed using four decomposition levels with the Symlet-3 mother wavelet. This configuration provides an effective balance between frequency resolution and preservation of epileptic spike morphology.

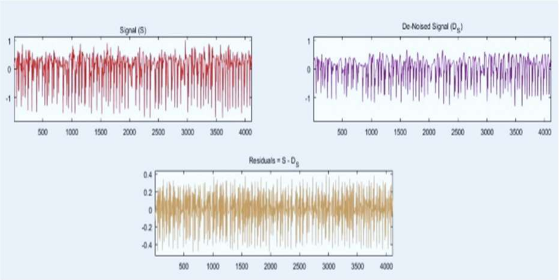

Figure 5. Application of the stationary wavelet transform (SWT) to a noisy signal

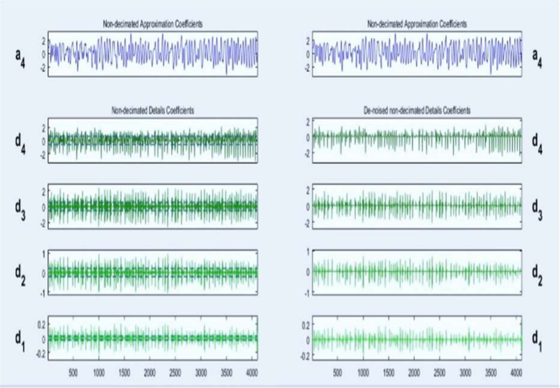

Figure 6. Decomposition of the noisy signal into wavelet coefficients using SWT

During the soft-thresholding stage, each wavelet coefficient is compared against a level-dependent threshold. Coefficients exceeding the threshold are retained, while those below it are attenuated. Threshold values were individually tuned based on estimated noise variance within each sub-band, with empirical validation performed on the reconstructed signal to maximize noise reduction without distorting spike characteristics.

Figure 7 illustrates the subsequent RLS-based adaptive filtering applied to the thresholded wavelet coefficients, showing the desired clean signal, noise-corrupted input, denoised output, and the corresponding error signal.

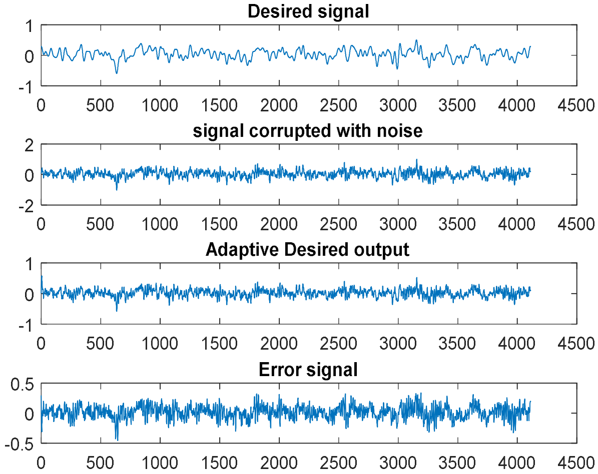

Figure 7. Application of the RLS filter to the wavelet coefficients within the desired frequency bands

3.3. Feature Extraction for Neural Network Classification

In the feature extraction stage, the Discrete Wavelet Transform (DWT) is employed using the Daubechies-3 (db3) mother wavelet, selected due to its strong correlation with the temporal morphology of epileptic spikes. This enables effective decomposition of EEG signals into approximation (A) and detail (D) coefficients.

Initially, ten statistical features were extracted from each EEG segment, including:

- Mean and variance of approximation coefficients (A)
- Mean and variance of the detail coefficients (D)
- Total power of wavelet coefficients
- Mean energy of the Fourier-transformed wavelet coefficients
- Median of A
- Maximum of D
- Entropy
- Skewness of D

Table 1 summarizes the extracted features. Following feature-importance evaluation, four features—median, maximum, skewness, and entropy—were identified as degrading classification performance and were excluded. Consequently, a refined subset of six statistical features was selected for classification using the PNN.

Table 1. Extracted features from each segment of the EEG signal

Title	features
Mean(A)	Average approximate wavelet coefficients
Mean(D)	Average partial wavelet coefficients
VAR(A)	Variance of approximate coefficients of wavelet
VAR(D)	Variance of partial Violet coefficients
abs(FFT(D))	The power of wavelet's coefficients
Mean(abs(FFT(D)))	Average energy corresponding to the Fourier transform of the wavelet's coefficients
entropy(D)	entropy
median(A)	The mean of the approximate coefficients of wavelet
Max(D)	Maximum partial coefficients of wavelet
skewness(D)	skewness

Feature selection was performed empirically based on classification performance.

3.4. Evaluation Metrics for the Proposed Method

The denoising performance of the proposed method was quantitatively evaluated using Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR) [27].

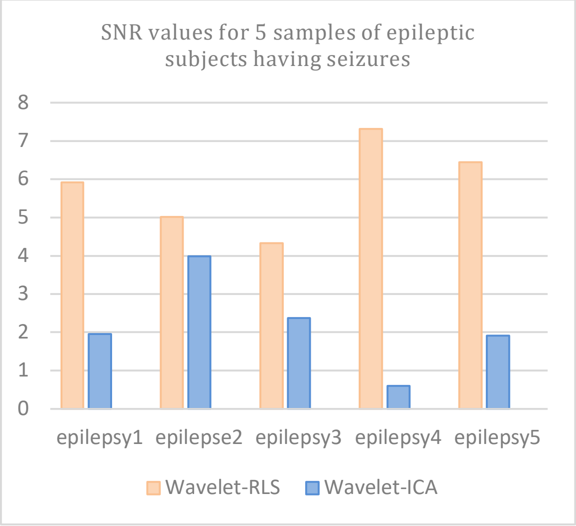

Figure 8. SNR values for 5 samples of epileptic subjects during seizure activity

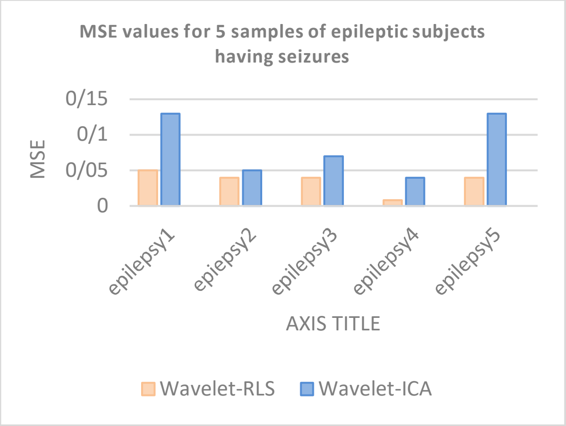

Figure 9. MSE values for 5 samples of epileptic subjects during seizure activity

Figure 8 presents the SNR values obtained from five epileptic EEG recordings, while Figure 9 illustrates the corresponding MSE results.

The results demonstrate that the Wavelet–RLS framework significantly improves signal quality compared to the reference method, thereby enabling more reliable feature extraction and classification.

3.5. Classification using PNN

The classification stage employs a Probabilistic Neural Network (PNN) to categorize EEG segments into epileptic spike and non-epileptic classes.

Wavelet-based methods have also been widely used for detecting transient and localized patterns in noisy signals, owing to their strong time–frequency localization capability [28, 29].

Classification performance was evaluated using accuracy, sensitivity, and specificity, defined as:

13. *Accuracy*= $\frac{(TP+TN)}{(TP+FN+FP+TN)} \times 100\%$ 14. (7)

15. *Sensitivity*= $\frac{(TP)}{(TP+FN)} \times 100\%$ 16. (8)

17. *Specificity*= $\frac{TN}{TN+FP} \times 100\%$ 18. (9)

where:

- TP (True Positive) is the number of correctly detected epileptic spikes
- TN (True Negative) is the number of correctly identified non-epileptic events

- FP (False Positive) is the number of non-epileptic segments misclassified as epileptic
- FN (False Negative) is the number of epileptic spikes misclassified as non-epileptic

The classifier was initially evaluated using a three-class model; however, this approach yielded unstable performance. Consequently, a binary classification strategy was adopted, resulting in more robust and reliable outcomes.

The proposed Wavelet–RLS + PNN framework achieved a classification accuracy of 91.86%, as illustrated in Figure 10.

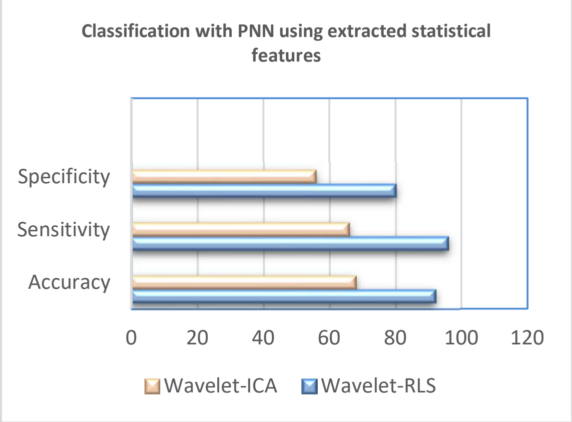

Figure 10. Classification results using the Probabilistic Neural Network (PNN) based on extracted statistical features.

Table 2 presents a quantitative comparison between the proposed Wavelet–RLS feature extraction method and the conventional Wavelet–ICA approach in terms of classification accuracy. As shown, the Wavelet–RLS framework achieves an accuracy of 91.86%, which is substantially higher than the 67.76% obtained using Wavelet–ICA. This improvement highlights the effectiveness of RLS-based adaptive denoising in preserving epileptic spike characteristics that are critical for reliable classification.

Table 2. Result of performed method

Methods	Accuracy
Wavelet-RLS	91.86%
Wavelet-ICA	67.76%

Table 3 provides a comparative analysis of representative EEG-based seizure detection and artifact removal methods reported in the literature. The comparison focuses on classification accuracy (when available), preservation of spike morphology, computational complexity, and reported limitations.

As summarized in Table 3, many existing approaches primarily emphasize artifact suppression or end-to-end seizure detection, often without explicitly considering preservation of epileptic spike morphology. Deep-learning-based methods demonstrate strong performance but typically require large training datasets and high computational resources, limiting their suitability for real-time or resource-constrained clinical environments. In contrast, the proposed Wavelet–RLS + PNN framework explicitly preserves spike morphology while achieving competitive classification accuracy and maintaining low computational complexity. These characteristics make the proposed method particularly well suited for practical EEG analysis and real-time epileptic spike detection.

Table 3. Comparative Analysis of Artifact Removal and Denoising Techniques for Epileptic EEG Signals

Ref.	Method / Technique	Accuracy (if reported)	Spike Morphology Preservation	Processing Speed / Complexity	Limitations
[15]	Wavelet–ICA + PNN	Accuracy 67.76%	Not explicitly reported by the authors	Moderate; ICA computationally expensive	Incomplete artifact removal; spike distortion possible
[30]	Wavelet threshold denoising + Time-Frequency Peak Filtering	Not explicitly reported by the authors	Excellent preservation of waveform shape	Efficient and stable	No explicit limitations report; still requires proper parameter selection
[31]	DWT + Bandpass Filtering + ML Classifier	Not explicitly reported by the authors	Not explicitly reported by the authors	Standard ML pipeline; no embedded implementation	Focused on feature extraction and detection; no detailed metrics publicly available
[32]	Evidential Multi-View Learning (EEG seizure detection)	Not explicitly reported by the authors	Not explicitly reported by the authors	End-to-end multi-view deep learning; runtime not reported	End-to-end multi-view deep learning; runtime not reported
[33]	1D CNN-LSTM + DWT denoising	Not explicitly reported by the authors	Partial / not explicitly reported	High complexity; GPU required	Requires large datasets; spike preservation not guaranteed
[34]	ICA, Wavelet, Filtering	Not explicitly reported by the authors	Not explicitly reported by the authors	Moderate; ICA computationally expensive	Focused on artifact removal; spike detection not evaluated

This Work	Wavelet–RLS + PNN	Accuracy 91.86%	Explicitly preserved	High speed; adaptive filtering; suitable for real-time	Needs careful RLS parameter initialization & parameter tuning; evaluated on multiple EEG segments

4. Conclusion

In this study, a hybrid framework for epileptic spike detection from EEG signals was presented, combining wavelet-based multiresolution analysis with Recursive Least Squares (RLS) adaptive filtering and probabilistic classification. The proposed Wavelet–RLS preprocessing stage was specifically designed to suppress ocular, muscular, and power-line artifacts while preserving the transient morphology of epileptic spikes, which is critical for reliable clinical interpretation.

Experimental results demonstrated that the proposed method significantly outperforms the conventional Wavelet–ICA approach in both denoising and classification tasks. The Wavelet–RLS framework achieved a classification accuracy of 91.86%, compared to 67.76% obtained using Wavelet–ICA, confirming the effectiveness of adaptive filtering in enhancing spike-related features. In addition to improved accuracy, the proposed method offers faster convergence and lower computational complexity, making it suitable for real-time or resource-constrained EEG analysis environments.

Compared with recent deep-learning-based EEG denoising and seizure detection approaches, the proposed method provides a competitive balance between performance and efficiency. While deep neural networks often require large annotated datasets and high computational resources, the Wavelet–RLS framework maintains high accuracy with a lightweight and interpretable structure, making it more practical for clinical deployment.

Beyond algorithmic performance, this study emphasizes the importance of clinical context in EEG interpretation. The presence of epileptic spikes alone is insufficient for a definitive diagnosis; waveform morphology, anatomical localization, and correlation with patient symptoms must also be considered. The proposed method can therefore serve as a supportive tool for neurologists, assisting in automated screening, spike highlighting, and prioritization of EEG segments for expert review.

Future work will focus on extending the proposed framework to incorporate additional epileptiform patterns, such as sharp waves and background abnormalities, and evaluating its performance across broader age groups and larger, multi-center EEG datasets. Integration with clinical workflows and real-time monitoring systems also represents a promising direction for further research.

Authors' Contributions

All authors equally contributed to this study.

Declaration

The authors affirm that all scientific content and conclusions presented in this article are their own. A language model (ChatGPT) was used exclusively to refine the English grammar and improve the clarity of writing. The model was not used for generating ideas, interpreting results, or performing data analysis.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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We would like to express our gratitude to all individuals helped us to do the project. The simulations and analyses were carried out using MATLAB, which provided essential tools for implementing and evaluating the proposed method.

Declaration of Interest

The authors declare that they have no conflict of interest. The authors also declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Ethical Considerations

Not applicable.

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