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RESEARCH ARTICLE

Epileptic Seizure Prediction Based on Synchroextracting Transform and Sparse Representation

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the University of Southern Queensland Human Research Ethics Committee (UniSQ HREC).

ABSTRACT Feature extraction is crucial in machine learning and EEG analysis, where raw data often contains excess information. The prominence of machine learning has led to the development of numerous feature extraction methods over the past decade. This paper introduces an efficient feature extraction method that demonstrates superior experimental results. We employed the Synchroextracting Transform (SET) and Sparse Representation (SR) for enhanced feature extraction in epileptic EEG analysis. SET is a recently developed signal transformation technique, and SR effectively extracts information from multi-dimensional data. Our goal is to enhance time-frequency (TF) resolution using the SET-SR method, which offers a TF representation more concentrated with energy than traditional TF analysis methods. SR decomposes SET multi-dimensional sub-signals to accurately predict epileptic seizures. The significance of this feature extraction method was evaluated using a k-Nearest Neighbor (k-NN) algorithm, a traditional machine learning technique. Applying the SET-SR with the k-NN, we achieved an average accuracy of 99.48% on the CHB-MIT database and 100% accuracy on the Bonn University database in classifying pre-seizure signals. The SET-SR effectively detects pre-seizure signals, showing promise for developing an efficient patient-specific seizure prediction algorithm based on EEG data. Our findings demonstrate that enhanced feature extraction can reliably identify pre-seizure signals with high precision, even when using classical machine learning methods like k-NN. This research underscores the importance of feature extraction in EEG signal analysis and suggests that diverse classification methods can be employed for real-time seizure prediction while maintaining high accuracy.

INDEX TERMS EEG analysis, synchroextracting transform (SET), sparse representation (SR), kNN, epileptic seizure prediction.

I. INTRODUCTION

Due to the unpredictability of epileptic seizure activity and the lack of effective treatments for people with drug-resistant epilepsy, it is imperative to study accurate, sensitive, and patient-specific seizure prediction. According to the general classification of seizure stages, there are three types of seizures: namely, interictal (normal), preictal (pre-seizure) and ictal (seizure active). Meanwhile, seizure prediction is one of the most complex predictive signal analyses, as electroencephalogram (EEG) signal fluctuations are tiny in the microvolt range [1]. However, accurate seizure prediction can be enabled by leveraging improved yet computationally effective machine learning algorithms, optimized electronic hardware, and reliable sensors. In this article, we propose an approach that can detect EEG pre-seizure signals accurately without a complicated feature- extracting process that may delay the alarm before the seizure episodes. This research employs sparse representation (SR) and

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synchroextracting transform (SET) to analyze EEG signals. The SR is compatible with capturing the sparsity of EEG signals and temporal dynamics [2], which involves expressing a signal or data in few coefficients that are not equal to zero [3]. In other words, it represents data as a linear combination of a few essential elements rather than many with varying degrees of importance. One application of sparse representation is in signal processing, where it can be used to compress and reconstruct signals efficiently [4]. There are various methods for obtaining sparse representations, including optimization algorithms such as lasso [5], ridge regression [6], matching pursuit [7], and the active set method [8]. These methods work by minimizing the number of non-zero coefficients needed to represent the data while also ensuring that the representation accurately shows the data's structure. Furthermore, the SR can reduce computational complexity and memory requirements by reducing the coefficients representing a signal or data, leading to faster and more efficient algorithms [9].

EEG signals are sparse [2] and typically high-dimensional and complex [10], [11], [12], [13], [14]. The SR can identify and capture these sparse components, which can be important for identifying relevant features and patterns in the data [2]. Thus, it can decrease the data's dimensionality, making it easier to analyze and interpret [15]. Also, EEG signals often contain a large amount of noise, and the SR can filter out this noise by identifying the signal's most relevant and informative components [16].

The SET is a mathematical tool used to analyze signals contaminated with noise or interference [17]. It is a relatively new method that has been developed to address some of the limitations of other signal processing methods, such as Fourier transforms. The SET method works by identifying and extracting the periodic components of a signal that are synchronized with a reference signal while filtering out non-synchronized components [18]. This characteristic can help analyze signals with multiple periodic components, as the SET method can selectively isolate and analyze each component. The fundamental concept underlying the SET method is to use a reference signal known to be synchronized with the periodic components of the signal of interest. This reference signal could be a simple periodic waveform, such as a sine or cosine wave, or a more compl ex signal synchronized with the specific periodic components of interest [18]. The advantage of the SET method is that it can selectively extract and analyze individual periodic components of a signal, even when the signal is contaminated with noise or interference. Therefore, the SET can efficiently uncover the subtle, hidden patterns of EEG variations.

The primary findings of this research can be outlined as follows:

- By employing the proposed method (SET and SR), it becomes possible to achieve a high detection rate of pre- ictal signals using only a limited number of epileptic EEG signals.
- The suggested approach significantly decreases computational classification time, thereby facilitating real-time seizure prediction.

The rest of this paper is organized as follows. Section II provides an overview of previous works related to seizure prediction. In Section III, we describe the CHT-MIT and Bonn University databases utilized in this study, along with data preparation and the proposed signal transformation techniques (SET and SR) and classification methods. Section IV elaborates on the experimental setup and presents the results. The discussion of the research findings is presented in Section V. Finally, Section VI outlines the conclusions drawn from this study.

II. RELATED WORK

According to Maimaiti et al., automated methods for seizure prediction can be categorized into two groups: traditional machine learning (TML) methods (for example, support vector machine (SVM), k-nearest neighbors algo- rithm (k-NN) or linear discriminant analysis (LDA)) and deep learning (DL) methods (for example, bi-directional long short term memory network (Bi- LSTM), convolutional neural network (CNN) or long short-term memory network (LSTM)) [19]. An increasing number of EEG analysis studies using DL have been published lately, and 14% of them were to find or predict seizures [20]. The most popular DL in recent years, CNN-based research, achieved the specificity of the EEG classification performance for seizure prediction in the range of 86.13% [21] to 99% [22] (Table 1).

Feature extraction from EEG data has been pivotal in enhancing the accuracy of seizure prediction models. For instance, time-frequency analysis techniques like the short-time Fourier transform (STFT) have been widely used due to their ability to capture both temporal and spectral information from EEG signals. However, traditional approaches like the STFT often face limitations in resolving non-stationary signal components [23], [24], [25], which are critical for early seizure prediction.

Sparse representation (SR) has emerged as a powerful mathematical tool with extensive applications in signal processing, including feature extraction for EEG analysis. Although SR-based methods have primarily been explored for seizure detection, their potential for seizure prediction is promising. Li et al. introduced a seizure detection technique utilizing SR with online dictionary learning and elastic net constraint, achieving significant sensitivity (95.45%) and specificity (99.08%) in long-term intracranial EEG recordings [26]. Similarly, Peng et al. employed SR-based methods for epileptic seizure classification, demonstrating high accuracy using a dictionary learning with homotopy (DLWH) algorithm [27]. Other researchers, like Yuan et al., have leveraged SR techniques with specialized kernels (e.g., log-Euclidean Gaussian) to detect seizures, further underscoring the versatility of SR in feature extraction [28].

TABLE 1. Overview of the CNN-based research for seizure prediction.

Author (year)	Methods	Dataset	Accuracy	Sensitivity	Specificity
Wei et al. (2019) [21]	CNN, LRCN [1]	15 Clinical data Scalp EEG	93.40%	91.88%	86.13%
Usman et al. (2021) [32]	EMD [2], CNN, LSTM	CHB-MIT [3]	NA	93%	92.5%
Prathaban & Balasubramanian (2021) [33]	CNN	CHB-MIT, SRM [4]	98%	99%	90%
Jana & Mukherjee (2021) [34]	CNN	CHB-MIT	99.47%	97.83%	92.36%
Zhang et al. (2020) [22]	CSP [5], CNN	CHB-MIT	90%	92.2%	NA
Sharan & Berkovsky (2020) [35]	WT [6], CNN	CHB-MIT	97.25%	97.25%	97.25%
Li et al. (2020) [36]	CNN, LSTM	CHB-MIT	95.29%	95.42%	95.29%
Assali et al. (2023) [37]	CNN	CHB-MIT	94.5%	92.8%	NA
Shahbazi & Aghajan (2018) [38]	CNN, LSTM	CHB-MIT	NA	98.21%	NA
Ozcan & Erturk (2019) [39]	3D-CNN	CHB-MIT	NA	85.7%	NA
Li et al. (2022) [40]	Transformer Guided CNN	CHB-MIT	NA	93.5%	NA
Khalilpour et al. (2020) [41]	1D-CNN	CHB-MIT	97%	98.5%	98.47%
Zhang et al. (2019) [42]	CNN	CHB-MIT	NA	92.2%	NA
Zhang et al. (2024) [43]	MFCC-CNN	CHB-MIT	96%	92%	84%
Quadri et al. (2024) [44]	Stacked CNN-BiLSTM	CHB-MIT	NA	97.63%	NA

[1] Long-term recurrent convolutional network. [2] Empirical mode decomposition. [3] Children's Hospital Boston (CHB) and the Massachusetts Institute of Technology (MIT) Scalp EEG Dataset.

In addition to SR, synchroextracting transform (SET) has recently gained attention for its superior performance in capturing fine-grained temporal and spectral features from EEG data. Although the SET has been relatively underutilized in EEG signal analysis, preliminary studies, such as those by Ra et al., indicate that SET-based pre-seizure classification can outperform traditional STFT-based methods, offering higher accuracy [29]. Jiang et al. and Rajinikanth et al. also applied SET for epileptic EEG classification, achieving impressive accuracy, specificity, and sensitivity rates of 99% across various seizure stages [30], [31].

In summary, while machine learning classification methods play a crucial role in seizure prediction, the effectiveness of these models is fundamentally driven by the underlying feature extraction techniques. SR and SET, among others, represent promising directions for enhancing the accuracy and reliability of epileptic seizure prediction systems.

III. METHOD

A. DATABASE OVERVIEW

Over the past decade, extensive research on EEG-based seizure prediction has been conducted, largely due to the availability of open-access databases provided by hospitals and research institutions [19]. This study utilizes two well-known databases: the Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) scalp EEG database and the Bonn University epilepsy database, both of which are publicly accessible and widely used for comparative research.

1) THE CHB-MIT DATABASE

The CHB-MIT database contains EEG recordings from pediatric patients with intractable seizures, captured at a 16-bit resolution and 256 Hz sampling frequency. Twenty-two out of 24 recordings from the CHB-MIT database were selected for analysis. Two recordings (chb13 and chb24) were excluded due to frequent channel changes that affected data quality. The database provides a comprehensive collection of recordings, as detailed in Table 2, for the study of seizure prediction

2) THE BONN UNIVERSITY DATABASE

The Bonn University epilepsy database consists of five datasets (A to E) with 100 single-channel EEG segments per dataset, each lasting 23.6 seconds [46]. These segments were recorded with a 173.61 Hz sampling rate and passed through a bandpass filter covering 0.53 Hz to 40 Hz. Table 3 summarizes the characteristics of each dataset.

B. FEATURE EXTRACTION

1) SYNCHROEXTRACTING TRANSFORM (SET)

The short-time Fourier transform (STFT) is a widely used technique for analyzing non-stationary signals but suffers from an equilibrium between temporal and spectral precision trade-offs. It is difficult to accurately localize the frequency content of a signal in time, especially for signals that exhibit highly variable frequency content over time [47]. The SET method offers a solution to this issue as the SET uses the instantaneous frequency (IF) information to reassign the STFT coefficients to their accurate frequencies [18], [48]. Ra et al. demonstrates that the SET method achieves higher accuracy than the STFT method [29].

According to Li et al, calculating the STFT is the first step of a SET method. Next, the IF is estimated as follows [49]:

$$\hat{\omega}_f(\eta, t) = \begin{cases} Re\left\{\frac{\delta_t s_f^g(\eta,t)}{2i\pi s_\pi^g(\eta t)}\right\}, & \left|s_f^g(\eta,t)\right| > \gamma \\ \infty, & \left|s_f^g(\eta_7 t)\right| \le \gamma \end{cases} \tag{1}$$

$$\gamma = \sqrt{2\, log_2\, N} \cdot \sigma \tag{2}$$

TABLE 2. The features of each recording and the patient's data [45] utilized in this study.

RECORDING ID	AGE	GENDER	NUMBER OF SEIZURES	LENGTH OF RECORDS (HOURS)
chb01	11	F	7	45.00
chb02	11	M	3	39.57
chb03	14	F	7	57.87
chb04	22	M	4	154.41
chb05	7	F	5	38.09
chb06	1.5	F	10	89.25
chb07	14.5	F	3	67.23
chb08	3.5	M	5	26.38
chb09	10	F	4	65.92
chb10	3	M	7	72.49
chb11	12	F	3	73.30
chb12	2	F	40	NA[1]
chb14	9	F	8	41.50
chb15	16	M	20	62.29
chb16	7	F	10	17.03
chb17	12	F	3	34.11
chb18	18	F	6	62.85
chb19	19	F	3	61.58
chb20	6	F	8	41.43
chb21	13	F	4	55.71
chb22	9	F	3	75.93
chb23	6	F	7	70.90

[1]. Not available

TABLE 3. The characteristics of each dataset within the Bonn University database.

Dataset	Information about the subjects	Account of the recordings	Count of files (time in seconds)
A	Five individuals without any health conditions (normal)	EEG recordings captured from the surface with the individual's eyes open	100 (23.6)
B		EEG recordings captured from the surface with the individual's eyes closed	100 (23.6)
C	Five individuals diagnosed with epilepsy	EEG recordings from the hippocampal formation in the hemisphere opposite the region where seizures originate, obtained during periods when no seizures were present	100 (23.6)
D		EEG readings from the area where seizures originate. Recorded during periods without any occurrence of seizures.	100 (23.6)
E		EEG recordings capturing epileptic seizure activity originating from the hippocampal focus.	100 (23.6)

where N represents the length of the signal and $\sigma = median$ $(|s_f^g(\eta,t) - median\left(s_f^g(\eta,t)\right)|)/0.6745$. $\hat{\omega}_f(\eta,t)$ is the IF and $s_f^g(\eta,t)$ is the STFT within a sliding window $g(t) \in L^2(R)$. Finally, the extraction of energy can be defined as shown below.

$$Te_f(\eta,t) = s_f^g(\eta,t)\ \delta(\eta - \hat{\omega}_f(\eta,t)) \tag{3}$$

where $\delta(\eta - \hat{\omega}_f(\eta,t))$ is referred to as the synchroextracting operator (SEO) and can be understood as:

$$\delta(\eta - \hat{\omega}_f(\eta,t)) = \begin{cases} 1, & \eta = \hat{\omega}_f(\eta,t), \\ 0, & otherwise, \end{cases} \tag{4}$$

From (4), the SEO solely extracts the time-frequency coefficients at the instantaneous frequency (IF) position $\eta = \hat{\omega}_f(\eta,t)$ and the remaining is discarded. which derives the following capability of extracting:

$$Te_f(\eta,t) = \begin{cases} s_f^g(\eta,t), & \eta = \hat{\omega}_f(\eta,t), \\ 0, & otherwise, \end{cases} \tag{5}$$

As a result, we can obtain a time-frequency (TF) representation that clearly shows the concentration of energy. Unlike STFT, which may spread a signal's energy across neighboring TF bins, SET reallocates the energy to the correct TF bins based on the instantaneous frequency. This process ensures that the energy is concentrated around the true frequency components of the signal.

2) SPARSE REPRESENTATION (SR)

Generally, in mathematics, when many elements of a vector or matrix are 0, it is termed to be sparse. SR deals with sparse solutions for systems of linear equations. Supposing 100 datapoints from the SET dataset (Section B) are selected to construct a training set, listing the features (2944 features in this research) in rows with a column vector (2944 × 1) creates a matrix whose size is 2944 × 100 (Figure 1). D in Figure 1 is called a dictionary. Each column vector in a dictionary is called an atom. In this case, there are 100 atoms in the dictionary. The principle of sparse representation (SR) entails that a signal can be estimated by forming a limited and sparse linear combination of atoms from a dictionary (Figure 1).

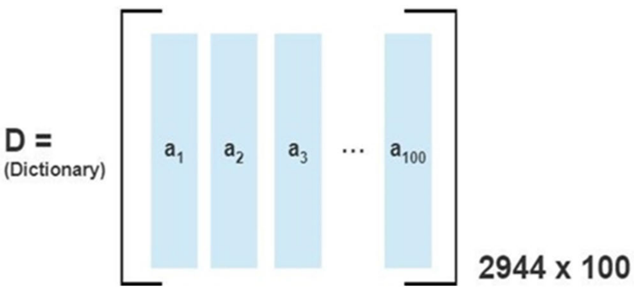

FIGURE 1. Dictionary structure of sparse representation. a1, a2, a3 ... a100 are called atoms.

The subsequent formulation of the SR model is as follows [50].

$$(b|D, x, k) = a1x1 + \cdots + akxk + \varepsilon = Dx + \varepsilon \tag{6}$$

where D, x, and k are the model parameters. b is a new sample, x is a sparse coefficient vector, D is a dictionary, ai is a dictionary atom, and ε is an error term (Figure 2).

The constraints imposed by the SR model are as follows:

1. The error term, denoted as ε, follows a normal distribution with a mean of zero and a spherical covariance matrix.

2. The coefficient vector x is independent of the error term ε.

3. The distribution of the coefficient vector x must promote sparsity.

4. Dictionary atoms are typically assumed to follow a normal distribution.

The process of obtaining the sparse coefficients x, given a new signal b and a dictionary D, is referred to as sparse coding. SR can be approached through two primary methods: (1) sparse coding, which involves obtaining the coefficients x for a given signal using a fixed dictionary, and (2) dictionary learning, where the basis vectors (dictionary atoms) are learned from training data. In this study, the l1-non-negative least squares (l1-NNLS) sparse coding model is employed, as shown below [50]:

$$\frac{1}{2}\,\|b - Dx\|_2^2 + \lambda^T x \text{ subject to } x \geq 0 \tag{7}$$

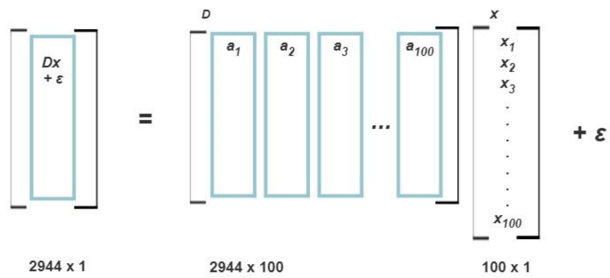

FIGURE 2. A sparse representation model example with 100 dictionary atoms.

where $\lambda = \frac{\phi}{\gamma}$ with covariance matrix Φ and regularization parameter γ.

The SR procedure in this study is implemented as follows:

1. Dictionary Construction and Normalization: The training instances are first collected and normalized to form a dictionary. The normalization technique applied is unit l2-norm, which is computed as follows:

$$\|x\| = \sqrt{x^T x} = \sqrt{\Sigma_{=1}^{d} x_i^2} \tag{8}$$

2. Sparse Coding: After normalization, sparse coding is performed to estimate the sparse coefficients for a new signal. This is achieved through non-negative quadratic programming (NNQP) optimization, which minimizes the following cost function:

$$\min \frac{1}{2} x^T Hx + g^T x \text{ subject to x} \geq 0 \tag{9}$$

where $g = -A^T b + \lambda$ and $H_{k\times k} = A^T A$.

3. Optimization via active-set algorithm: The optimization is conducted using an active-set algorithm [51]:, which follows this general procedure:

1. Identify a feasible starting point.
2. Iteratively solve the optimization problem until a satisfactory solution is reached:
    1. Approximate the solution for the current active set of constraints.
    2. Calculate the Lagrange multipliers for the active set.
    3. Remove any constraints associated with negative Lagrange multipliers.
    4. Check for and address any infeasible constraints.
3. Repeat the process until convergence.

This approach ensures the effective sparse approximation of the signal, resulting in the extraction of sparse coefficients that are critical for the classification and prediction tasks in the context of seizure prediction.

C. SPH and SOP

Epileptic seizures can be classified into three states: interictal (normal), preictal (pre-seizure), and ictal (seizure active). The goal of this study is to distinguish between the interictal and preictal states in epilepsy patients using SR coding applied to EEG data. For seizure prediction to be clinically useful, there must be a sufficient interval between the prediction alert and the actual seizure onset to allow for appropriate intervention or safety measures. However, this interval should not be so long that it increases patient anxiety [52]. Before assessing the performance of seizure prediction models, it is essential to define two key concepts: the Seizure Prediction Horizon (SPH) and the Seizure Occurrence Period (SOP). As outlined by Maiwald et al. [53], the SOP refers to the time window during which a seizure is expected to occur, while the SPH represents the time between the prediction alert and the beginning of the SOP (Figure 3). For accurate predictions, the seizure onset must occur after the SPH and within the SOP. In this research, we use an SPH of 10 minutes and an SOP of one hour to balance timely intervention with reducing patient anxiety.

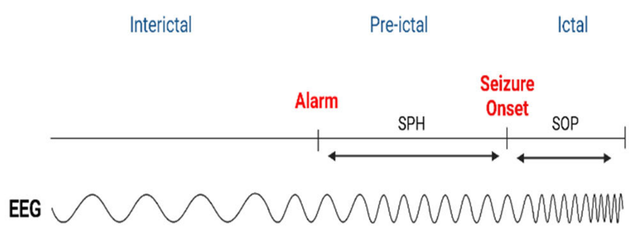

FIGURE 3. SPH and SOP on the timeline of epilepsy EEG.

D. SYSTEM EVALUATION

This study employs the k-nearest neighbors (k-NN) algorithm to classify the sparse coefficient vectors generated by the active set algorithm for new instances. The k-NN algorithm works by calculating the distances between data points to determine their proximity and predicting the class based on the labels or values of the nearest neighbors [54]. Specifically, the nearest neighbors for each test point are identified from the training dataset, and the test point is classified based on the majority vote of the k-nearest neighbors. Parameter tuning, such as adjusting the value of k, is achieved through cross-validation to optimize the model's performance for the given dataset.

The evaluation process involves four-fold cross-validation, repeated over 20 iterations, in which the dataset is divided into training and test sets. Following this, each new instance is assigned a label (either interictal or preictal) based on the classification outcome.

Table 4 presents four key evaluation metrics used to assess the classification performance: accuracy (Acc), specificity (Spe), sensitivity (Sen), and balanced accuracy (BAcc).

Additionally, the area under the curve (AUC) is provided as a measure of the model's ability to differentiate between classes. The AUC quantifies the degree of separability, indicating how well the model distinguishes between different categories. A higher AUC reflects greater accuracy in distinguishing between classes. The receiver operating characteristic (ROC) curve visualizes this by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR), with TPR on the y-axis and FPR on the x-axis. An AUC value of 0.5 indicates no ability to differentiate between classes (random performance), while a value between 0.7 and 0.8 is considered satisfactory, 0.8 to 0.9 is regarded as excellent, and values above 0.9 are considered exceptional [55].

TABLE 4. The performance metrics.

Metrics	Formalism
Acc	(TP[1]+TN[2]) / (TP+TN+FP[3]+FN[4])
Sen	TP / (TP+FN)
Spe	TN / (TN+FP)
BAcc	(Sen + Spe) / 2

[1] true positive (interictal), [2] true negative (preictal), [3] false positive, [4] false negative

IV. EXPERIMENTS AND RESULTS

All the experiments are implemented on the same PC with 12th Gen Intel(R) Core (TM) i7-1255U 1.70 GHz processor-based machine with 16.0 GB (15.7 GB usable) RAM using MATLAB. Figure 4 depicts the proposed experimental procedure for predicting epileptic seizures.

A. CHB-MIT DATABASE

For a reliable evaluation, in each subject, 3 × 256 data points from 23 channels in SPH (pre-seizure) are randomly chosen, and 5 × 256 data points are also selected randomly from 23 channels at the interictal (normal stage). Each extracted data sample (8 × 256 × 23) is decomposed by the Set algorithm to acquire the corresponding SET, and then 2944 - 3456 features are generated. After that, a SET dictionary matrix is constructed. The sparse coding performs feature extraction from the SET. The sparse coefficients can then be used for classification.

Once the classifier (k-NN) has been trained, it is applied to the testing data to evaluate its performance. This process involves applying the classifier to the test data and comparing the predicted class labels to the true labels. Finally, the performance of the classifier is evaluated using metrics such as accuracy (Acc), specificity (Spe), sensitivity (Sen), balanced accuracy (BAcc) and AUC. The k-NN classification results of the SET-SR for the EEG signals from the 22 patients in the CHB-MIT Database are presented in Table 5. Figure 5 exhibits the ROC curves of k-NN classification for the SET-SR from EEG signals of Recording ID chb01 and chb12. 5464800 data points were analyzed, 3825360 samples (70%) of them were randomly selected for training, and the remaining 1,639,440 samples (30%) were allocated for testing. In this research, the average Acc by

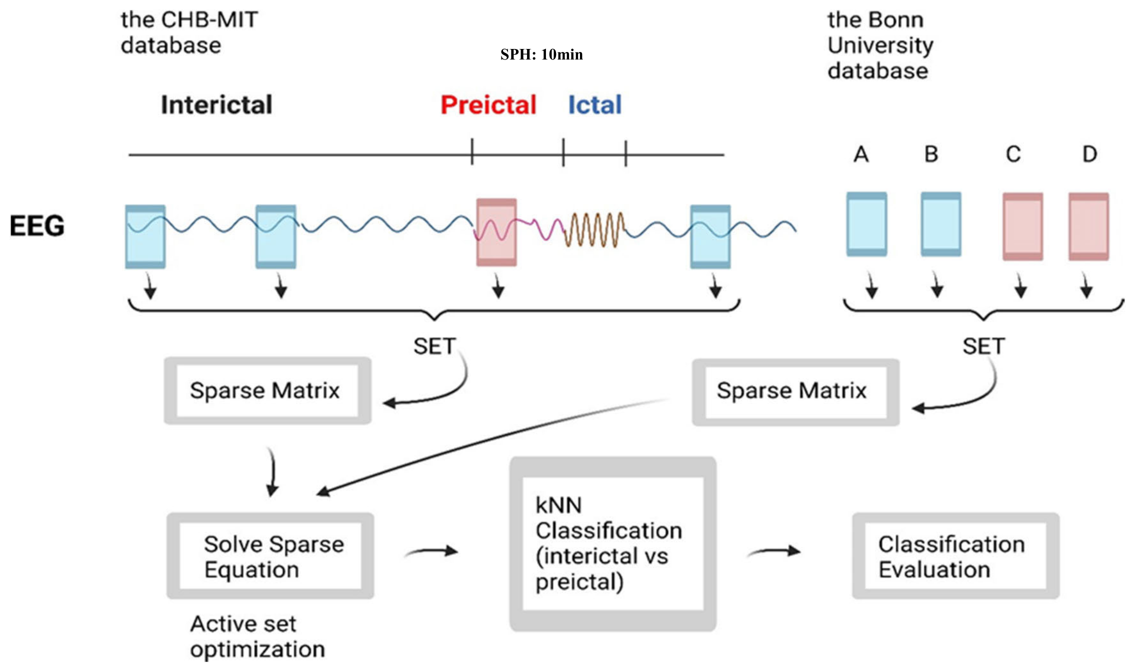

FIGURE 4. The experiment process of the proposed method.

the k-NN classification is 99.48%. The average Spe, Sen, and BAcc are 98.75%, 99.85%, and 99.30%, respectively. The average AUC is 0.8529. The variances are so small that they can be considered insignificant. The exceptional results demonstrate that based on the SET-SR, the proposed framework can effectively perform classification tasks for epilepsy prediction with a high accuracy, which is closely aligned with clinical practice. Figure 6 illustrates the Acc, Sen, and Spe comparisons with the results from the relevant studies [21], [22], [32], [33], [34], [35], [36].

B. THE BONN UNIVERSITY DATABASE

$100 \times 5 \times 173$ data points are selected randomly from healthy subjects (A, B, or both), and $100 \times 3 \times 173$ data points are selected randomly from epilepsy patients during seizure-free periods and seizure-active periods (C, D and E) and. Table 6 presents the k-NN classification results based on the SET-SR method for a combination of a set of experiments (A:C, A:D, B:C, B:D, AB:C, AB:D, AB:E, CD:E, ABC:E, and ABCD:E). Of 692000 samples, 484400 samples (70%) were randomly selected for training, and the remaining 207600 samples (30%) were selected for testing. The average Acc by the k-NN classification is 100%. The average Spe, Sen, BAcc, and AUC are all 100%. The average computation time for the classification is 2.7508 seconds. The ROC curves by the k- NN classification based on the SET-SR for datasets A, B, and C are illustrated in Figure 7.

The SPH is not applicable to the Bonn University datasets because the ictal signals are recorded and stored as separate, time-discrete files, meaning they do not include signals within the SPH. The datasets are individually recorded without temporal continuity, limiting their use for seizure prediction compared to databases like the CHB-MIT, which have continuous recordings. However, we still used the Bonn University database to complement our model alongside the CHB-MIT database. The observed 100% accuracy is likely due to each dataset being recorded from different individuals, potentially making it easier for the model to identify person-specific patterns rather than general seizure predictors. Despite the lack of temporal correlation, tests on various combinations of datasets can provide a high possibility of seizure prediction ability.

V. DISCUSSION

Without using deep learning methods, this study successfully shows high interictal and preictal classification accuracy using the SET-SR and k-NN methods. The STFT is a signal processing technique that allows us to analyze a signal in the time-frequency domain. One drawback of the STFT is that the time-frequency resolution is fixed and depends on the choice of the analysis window. For example, we obtain a good time resolution with a short analysis window but a poor frequency resolution, and vice versa. This trade-off is known as the uncertainty principle [56]. One way to overcome this limitation is by squeezing the STFT coefficients along the contours of constant frequency in the time-frequency plane. The SET method squeezes the STFT coefficients along the contours of constant frequency, and it can achieve better frequency resolution and concentrate the energy of the signal around its actual frequency components, thereby improving the ability to analyze the signal in the time-frequency domain [49].

TABLE 5. The performance of the k-NN classification based on the SET-SR for the epileptic EEG signals from the 22 recordings in the CHB-MIT database (note that: Recording ID chb13 and chb24 are excluded as mentioned in section III).

RECORDING ID	Sen.	Spe.	Acc.	BAcc	Computing time (seconds)	AUC
chb01	1.0000	0.9926	0.9972	0.9963	4.2517	0.9490
chb02	1.0000	0.9714	0.9918	0.9857	4.4503	0.8954
chb03	0.9992	0.9957	0.9979	0.9974	6.5653	0.7844
chb04	0.9969	0.9978	0.9972	0.9974	6.6943	0.8925
chb05	0.9992	0.9918	0.9964	0.9955	7.6127	0.7836
chb06	0.9961	0.987	0.9922	0.9915	5.9232	0.8611
chb07	1.0000	0.9905	0.9964	0.9952	5.7754	0.9172
chb08	0.9997	0.9991	0.9995	0.9994	7.5463	0.7948
chb09	1.0000	0.9421	0.9834	0.971	6.0021	0.7998
chb10	0.9979	0.9974	0.9977	0.9977	5.9471	0.8882
chb11	0.9984	0.972	0.9909	0.9852	6.3571	0.9135
chb12	0.9996	0.9987	0.9991	0.9991	8.2200	0.9418
chb14	1.0000	0.9922	0.9971	0.9961	5.8319	0.8033
chb15	0.9953	0.9961	0.9956	0.9957	4.1532	0.7184
chb16	0.9995	0.9922	0.9967	0.9958	9.6510	0.8586
chb17	0.9964	0.9744	0.9881	0.9854	4.3093	0.7543
chb18	0.9951	0.9965	0.9956	0.9958	4.1405	0.8356
chb19	1.0000	0.9961	0.9989	0.998	7.4632	0.9820
chb20	1.0000	0.9792	0.9922	0.9896	5.8349	0.9311
chb21	0.9995	0.9839	0.9937	0.9917	4.1687	0.8722
chb22	0.9953	0.9883	0.9927	0.9918	6.2783	0.8225
chb23	0.9995	0.9900	0.9959	0.9947	4.9566	0.7649
count	**22**	**22**	**22**	**22**	**22**	**22**
average	**0.998527**	**0.9875**	**0.994827**	**0.9930**	**6.0061**	**0.8529**
Variance, σ^2	**0.000003**	**0.0002**	**0.00001**	**0.00004**	**2.0972**	**0.0049**

However, the SET-based methods generate numerous sub- signals that contain many zero values, which reduce the accuracy of machine learning outcomes. A suitable and effective solution to address this issue is the SR. The SR retains only critical information and discards redundant or irrelevant information, which enhances its algorithm efficiency by reducing the processing of unimportant data. After reducing the dimensionality of the SET sub-signals by SR, the k-NN classification results reached an average accuracy of 99.48% for the EEGs from the CHB-MIT database and100% for the Bonn University EEG database.

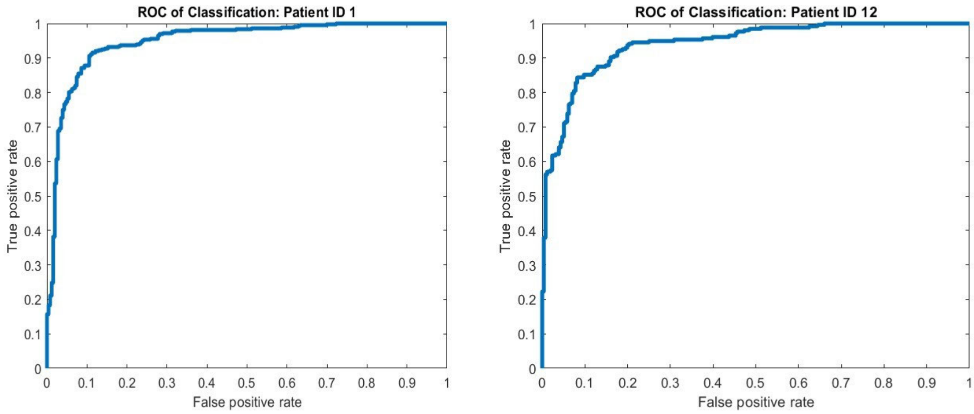

FIGURE 5. ROC curves (blue) by k-NN classification based on the SET-SR for recording ID chb01 and ID chb12 EEG signals in the CHB-MIT database.

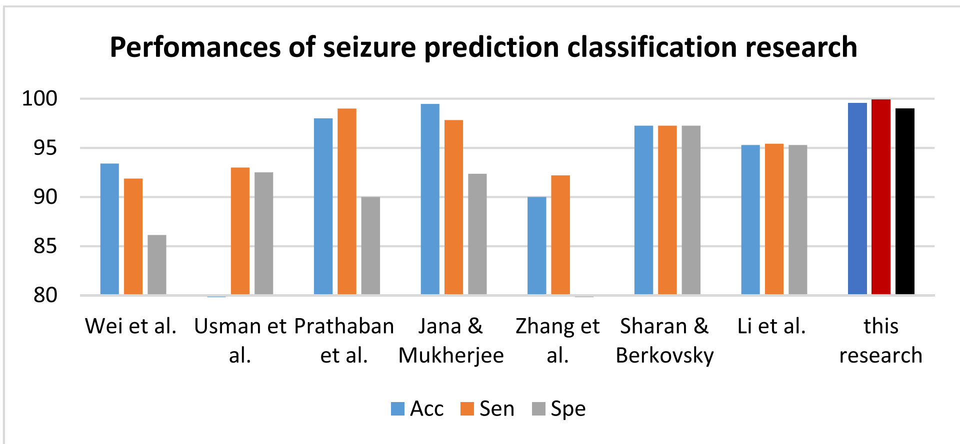

FIGURE 6. Acc, Sen, and Spe comparison of the seizure prediction classification performances among recent CNN-based studies.

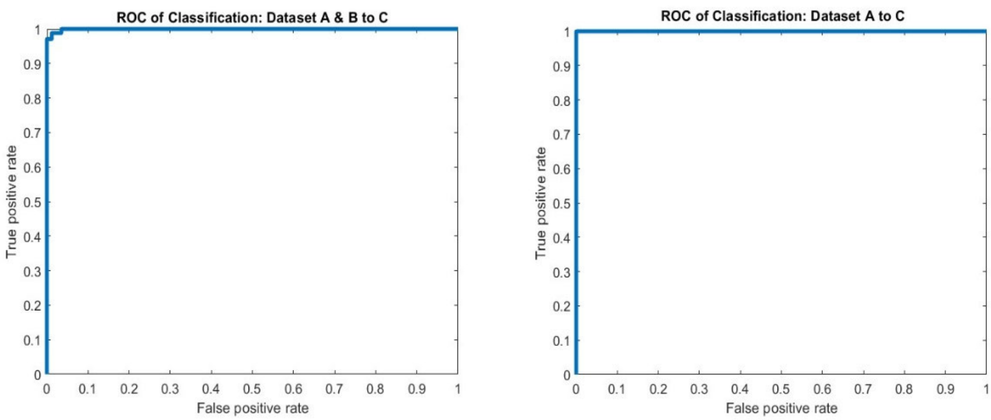

FIGURE 7. ROC curves (blue) by the k-NN classification based on the SET-SR for the Bonn University database.

Convolutional Neural Networks (CNNs) have been most extensively applied in seizure prediction research due to their high accuracy. However, CNNs may still face certain challenges. CNNs can be computationally intensive and require significant amounts of computing power and time to train. This can make them challenging for large-scale datasets or real-time applications [57]. In addition, CNNs are often seen as "black boxes," making it difficult to understand how they

TABLE 6. The performance by the k-NN classification based on the SET-SR for the Bonn University database.

	Sen.	Spe.	Acc.	BAcc.	Compute time (seconds)	AUC
A:C	1.00	1.00	1.00	1.00	1.8879	1.00
A:D	1.00	1.00	1.00	1.00	2.2233	1.00
B:C	1.00	1.00	1.00	1.00	2.5389	1.00
B:D	1.00	1.00	1.00	1.00	1.9601	1.00
AB:C	1.00	1.00	1.00	1.00	4.3686	0.9994
AB:D	1.00	1.00	1.00	1.00	3.5260	1.00
AB:E	1.00	1.00	1.00	1.00	3.5858	1.00
CD:E	1.00	1.00	1.00	1.00	4.1219	1.00
ABC:E	1.00	1.00	1.00	1.00	5.9867	1.00
ABCD:E	1.00	1.00	1.00	1.00	6.7144	1.00
count	10	10	10	10	10	10
Average	1.00	1.00	1.00	1.00	3.6914	1.00

make their predictions, which can be a limitation in applications where interpretability is essential [58]. Conversely, SR and k-NN make interpreting the data flow and understanding the underlying patterns easier because this approach simplifies the identification of factors that contribute to a specific outcome by highlighting the most significant features.

VI. CONCLUSION

The k-NN classification results from this study confirm that the SET-SR method is highly effective in extracting accurate information from EEG data, supporting the potential for real-time seizure prediction. This research aligns with our primary objective of achieving a high detection rate of pre-ictal signals using a limited number of epileptic EEG signals while significantly reducing computational classification time. While CNN-based methods have been shown to outperform traditional ML algorithms in various studies [21], [59], [60], the performance of a model is contingent on several factors such as data quality, model complexity, and parameter optimization.

Our findings suggest that when the signal analysis and feature extraction methods are well-suited to the data, traditional ML techniques like k-NN can deliver high accuracy, particularly in challenging tasks like seizure prediction. The success of the proposed SET-SR method in achieving average accuracy, specificity, sensitivity, balanced accuracy, and AUC of 100% with the Bonn University database and 99.48%, 98.75%, 99.85%, 99.30%, and 0.8529, respectively, with the CHB-MIT databases, demonstrates its potential.

To further enhance this research, future work could explore integrating larger and more diverse datasets to improve model generalizability. Investigating hybrid approaches that combine traditional ML and deep learning techniques could also yield better performance. Additionally, refining the feature extraction process and optimizing model parameters could further reduce computational time, making real-time

applications more feasible. Testing the method in real-world clinical environments would be crucial to validate its effectiveness in practical scenarios, ultimately advancing the goal of reliable and timely seizure prediction.

CONFLICT OF INTEREST STATEMENT

None of the authors have potential conflicts of interest to disclose.

INSTITUTIONAL REVIEW BOARD STATEMENT

Ethical review and approval were waived for this study due to the secondary data used in this research. The data used are publicly available through the links below.

https://scholar.google.com.a u/scholar?q = Ali + Shoeb. +Application+of+Machine+Learnin g+to+Epileptic+ Seizure+Onset+Detection+and+Treatment+ PhD+Thesis +Massachusetts+Institute+of+Technology+September +2009&hl=en&as_sdt=0,5 (accessed on 23 October 2022).

https://repositori.upf.edu/handle/10230/42894?show=full (accessed on 21 October 2020)

INFORMED CONSENT STATEMENT

The data are from the CHB-MIT Scalp EEG Database and the Bonn University epilepsy database. They were publicly available online. The detailed information is in the links below.

https://scholar.google.com.au/scholar?q=Ali+Shoeb+ Application+of+Machine+Learning+to+Epileptic+ Seizure+Onset+Detection+and+Treatment+PhD+ Thesis+Massachusetts+Institute+of+Technology+

September+2009&hl=en&as_sdt=0,5 (accessed on 23 October 2022).

https://repositori.upf.edu/handle/10230/42894?show=full (accessed on 21 October 2020)

DATA AVAILABILITY STATEMENT

The data and materials used in this study are available at the University of Southern Queensland under the research data management policy.

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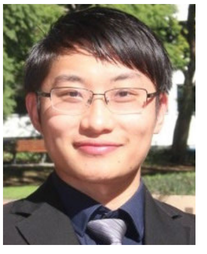

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