University of Southern Queensland

EPILEPTIC SEIZURE PREDICTION WITH MACHINE LEARNING ON EEG DATA

A Thesis submitted by

Jee Sook Ra
M.Sc.

For the award of

Doctor of Philosophy

2025

ABSTRACT

Epilepsy affects over 50 million people globally, posing a significant challenge due to the unpredictability of seizures, which impacts patients' quality of life. Predicting epileptic seizures in advance can improve living standards through timely interventions and risk reduction. However, accurate seizure prediction remains unsolved. This research aims to enhance seizure prediction accuracy using machine learning methods applied to epileptic electroencephalography (EEG) signals. Key methods developed include personalized channel selection, efficient feature extraction, and accurate classification models. Three predictive models were developed, each showing a remarkable performance in terms of accuracy, sensitivity, and specificity, leading to notably enhanced epileptic seizure prediction rates. The first model employs a permutation entropy-based personalized channel selection, significantly improving accuracy but requiring careful consideration of factors that influence the channel selection. The optimal channels for predicting seizures may vary across different stages of the condition. Hence, the second model employs a personalized classification for the entire channels from each patient, emphasizing the superiority of Synchroextracting Transform (SET) over the popular short-time Fourier transform for accurately extracting information. SET, when combined with a one-dimensional convolutional neural network (1D-CNN), achieves a 100% accuracy, sensitivity, and specificity for the Bonn University database (82800 datapoints), surpassing a multilayer perceptron with a quicker computational speed. Meanwhile, when considering real-time monitoring of epileptic EEG, CNNs may not be suitable due to their computational costs and substantial memory requirements. Therefore, in the third model, a sparse representation combined with SET and basic traditional machine learning techniques like k-nearest neighbors are adopted. This approach has also been proven to be notably effective, with a 100% accuracy on the Bonn University database for seizure prediction. The three models developed in this research address the challenges arising from individual variability in brain functions and the high-dimensional nature of EEG data for epileptic seizure prediction. Future research should focus on optimizing these models for specific real-time EEG monitoring systems and conditions.

CERTIFICATION OF THESIS

I, Jee Sook Ra, declare that the PhD Thesis entitled *Epileptic seizure prediction with machine learning on EEG data* is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

This Thesis is the work of Jee Sook Ra except where otherwise acknowledged, with the majority of the contribution to the papers presented as a Thesis by Publication undertaken by the student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Date: 15/01/2025

Endorsed by:

[redacted]

Professor Yan Li

Principal Supervisor

[redacted]

Dr Tianning Li

Associate Supervisor

Student and supervisors' signatures of endorsement are held at the University.

STATEMENT OF CONTRIBUTION

Paper 1:
Jee Sook Ra, Tianning Li, & Yan Li (2021). A Novel Permutation Entropy-Based EEG Channel Selection for Improving Epileptic Seizure Prediction, Sensors, 21(23), 7972. https://doi.org/10.3390/s21237972.

Jee Sook Ra contributed 80% to this paper. Collectively Tianning Li, & Yan Li contributed the remainder.

Paper 2:
Jee Sook Ra, Tianning Li, & Yan Li (2023). A novel epileptic seizure prediction method based on synchroextracting transform and 1-dimensional convolutional neural network. Computer Methods and Programs in Biomedicine, 240, 107678. https://doi.org/10.1016/j.cmpb.2023.107678

Jee Sook Ra contributed 80% to this paper. Collectively Tianning Li, & Yan Li contributed the remainder.

Paper 3:
Jee Sook Ra, Tianning Li, & Yan Li (2024). Epileptic Seizure Prediction based on Synchroextracting Transform and Sparse Representation. IEEE Access, 12, 187684-187695. https://doi.org/10.1109/ACCESS.2024.3514859

Jee Sook Ra contributed 80% to this paper. Collectively Tianning Li, & Yan Li contributed the remainder.

ACKNOWLEDGEMENTS

I extend my heartfelt gratitude to my dedicated supervisor Professor Yan Li for her unwavering guidance, invaluable insights, and continuous support throughout the duration of my research. Her mentorship has been instrumental in shaping the course of my academic journey.

I would also like to express my sincere appreciation to my associated supervisor Dr Tianning Li for his valuable contributions, encouragement, and expertise that significantly enriched the quality of my work.

Their collective guidance has been a source of inspiration, and I am truly fortunate to have had such committed mentors.

This research has been supported by Sage Athena Swan Scholarship at the University of Southern Queensland which I appreciate very much.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1. Significance of research on seizure prediction

Epilepsy is a serious neurological disease, affecting more than 50 million people, both young and old, worldwide [1]. The ability to predict seizures holds immense potential for enhancing those affected individuals' safety and well-being. Seizures can occur unexpectedly, leading to dangerous situations, injuries, and a diminished quality of life for individuals with epilepsy. By developing reliable seizure prediction models, researchers aim to provide individuals with timely warnings, allowing them to take precautionary measures and reduce the risk of injury during a seizure. This aspect of research aligns with the broader goal of improving patient treatment outcomes and minimizing the negative impact of epilepsy on daily life.

Moreover, research in seizure prediction contributes to the advancement of personalized medicine in epilepsy management. Each person's experience with epilepsy is unique, and the factors influencing the occurrence of seizures can vary widely. Through in-depth research and the use of advanced technologies, scientists can identify individualized patterns and triggers leading to seizures. This personalized approach enables the development of tailored interventions, including optimized medication regimens and lifestyle modifications, thereby improving the effectiveness of epilepsy treatment.

Conventional diagnostic techniques involve electroencephalography (EEG) and high-resolution magnetic resonance imaging (hr-MRI) to identify symptoms following the initial epileptic seizure occurrence [2]. EEG and hr-MRI serve different purposes in neuroscience and clinical practice. EEG is particularly well-suited for real-time monitoring of brain activity and functional assessments, while hr-MRI excels in providing detailed structural information about the brain. The choice between the two depends on the specific goals of a study or clinical evaluation.

For example, when it comes to the management of seizures, EEG monitoring plays a significantly more crucial role, especially in situations like status epilepticus, where prolonged seizure activity or recurrent events without recovery pose a substantial risk of cerebral damages [3]. However, a survey conducted globally, with many responses from the USA, regarding continuous EEG availability in specialty ICUs found that only 32% had rapid access and interpretation capabilities [4].

Therefore, patients with epilepsy are at risk of premature death and sudden unexplained death (SUD) [5]. In addition, many individuals with epilepsy experience various concurrent symptoms, making it challenging to attribute or justify the elevated risk associated with epilepsy [6]. Therefore, accurate diagnosis is crucial in epilepsy management.

Moreover, the primary challenge for epilepsy patients is the unpredictability of seizures, significantly impacting their quality of life [7]. Although individuals with epilepsy can lead a relatively normal life during most of the time when seizures are not occurring, the uncertainty surrounding seizure episodes remains a profound concern. If seizures could be predicted in advance, patients would have the opportunity to take preventive measures, thereby improving their overall living standards. This has substantial implications for enhancing patient safety and well-being by enabling timely interventions and reducing the risks associated with unexpected seizures [8]. Despite its potential, seizure prediction remains an unsolved problem in the field.

Within this background, research in seizure prediction based on EEG has been focused as a critical area of study within the field of neuroscience and clinical neurology. Seizure prediction research can advance personalized medicine in epilepsy management by recognizing the uniqueness of each person's experience with epilepsy. Factors influencing seizure occurrences vary widely among individuals [9]. Through in-depth analysis of EEG, scientists can uncover individualized patterns and triggers leading to seizures. This personalized approach facilitates the development of tailored interventions, encompassing optimized medication regimens and lifestyle modifications. Consequently, this approach enhances the overall effectiveness of epilepsy treatment.

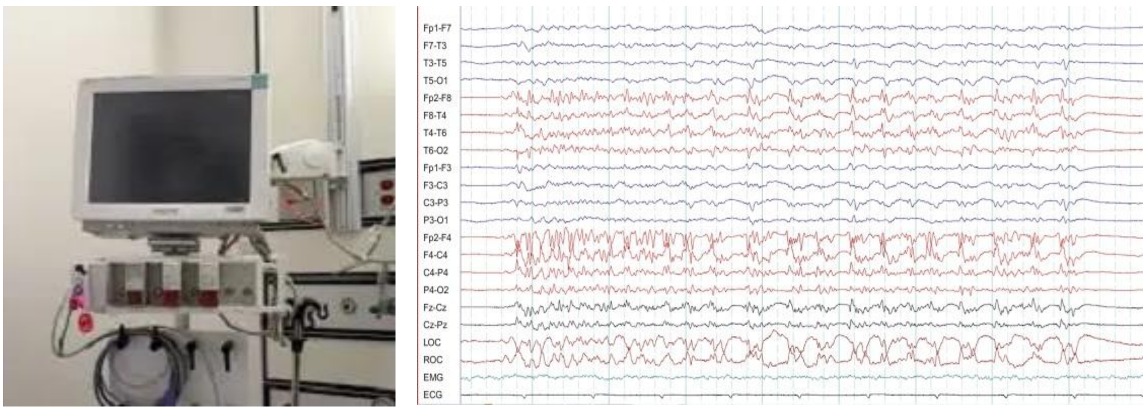
Furthermore, implementing effective seizure prediction technologies can mitigate healthcare costs associated with emergency care, providing a cost-effective solution, and enabling more efficient resource allocation in healthcare systems globally because it can lighten the economic burden linked to epilepsy by reducing unplanned emergency room visits, hospitalizations, and the need for constant supervision, which are common in the lives of individuals with uncontrolled seizures [10].

In summary, research on seizure prediction holds paramount significance for addressing epilepsy's challenges, enhancing safety, advancing personalized medicine, and reducing healthcare costs. Beyond the lab, it brings hope and tangible improvements for those with epilepsy. The primary objective of this research is to make a valuable contribution by creating a model capable of accurately and rapidly predicting epileptic seizures before they occur in real-time monitoring.

1.2. Brain electroencephalography (EEG)

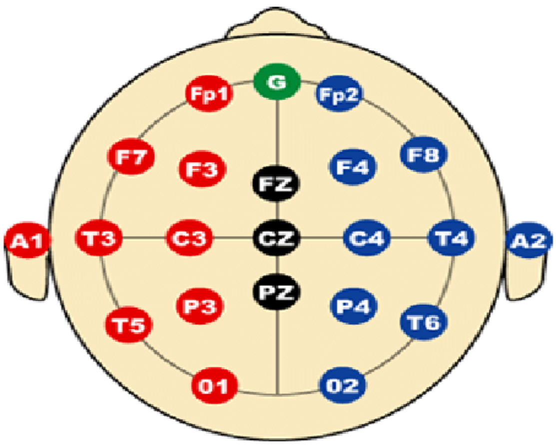
Epileptic EEG analysis based on machine learning has gained significant attention in recent years. EEG is a method used to monitor and record its electrical activity [11] (Figure 1). This procedure entails the positioning of electrodes on the scalp to identify and gauge voltage variations arising from the electrical impulses generated by neurons in the brain. To effectively capture the rapid changes in brain functions, these signals are usually sampled at a high frequency. The coordinated activity of numerous neurons generates these signals, which can be assessed by placing electrodes on the scalp. EEG signals are commonly defined by their frequency, amplitude, and waveform attributes [12, 13].

Electrodes are strategically positioned on the scalp following established electrode placement systems (Figure 2). The most widely adopted system is the International 10-20 System [14], which prescribes electrode positions based on specific distances between anatomical landmarks on the scalp [14]. The number of electrodes used can vary significantly, ranging from just a few to potentially dozens or even hundreds [15].



(a) **(b)**

Figure 1. Image of (a) an EEG monitor and (b) a printed EEG graph [16]



The letters used are:
F: Frontal Lobe
T: Temporal lobe
C: central lobe
P: parietal lobe
O: occipital lobe

Figure 2. The brain surface map of EEG electrodes [17]

To facilitate the diagnosis of epilepsy through EEG signals, a minimum of 23 electrodes are positioned across the scalp, leading to the generation of an immense volume of data [18]. Researchers may appreciate the richness of information within their dataset. However, they must deal with the complex nature of high-dimensional data structures and the complexities inherent in time-dynamic data.

Typically, EEG signals are categorized into distinct frequency bands, each corresponding to specific brain states or activities. These frequency bands include delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (above 30 Hz) [19]. Each of these frequency bands is associated with distinct cognitive and behavioural processes [20]. Artifacts, such as muscle activity (e.g., eye blinks or jaw clenching), movements, electrical interference, and environmental noise, have the potential to contaminate EEG signals [21]. To mitigate or eliminate these artifacts and enhance signal quality, preprocessing techniques such as filtering, artifact rejection, and referencing are employed [22]. There are also many data loss or vitiated data in EEG recordings due to limitations of scalp electrodes which can hinder the performance of processing algorithms [23]. These artifacts should be minimized to reduce the influence in feature extraction.

Within clinical practice, unusual EEG patterns have the potential to signal underlying pathological conditions, including epileptic seizures, sleep disorders, or cerebral dysfunctions [24]. The comprehension of the human brain through EEG can be significantly enhanced through advancements in EEG decomposition and analytical methods, alongside the integration of machine learning [23, 25-28]. Integrating appropriate machine learning algorithms with EEG analysis can automate the detection, classifying, and interpretation of EEG patterns. This integration enhances the possibility of faster and more accurate diagnosis and monitoring of neurological disorders, including seizure prediction.

1.3. Feature extraction in EEG analysis

EEG signal feature extraction is a vital process in comprehending and distilling meaningful insights from the brain's recorded electrical activity while also reducing data dimensionality. Its primary objective is to extract meaningful information from EEG signals rather than directly removing artifacts. However, the extracted features are designed to indirectly identify and eliminate artifacts, making the noise removal process unnecessary in this study. Two stages, EEG signal transformation and features selection, are combined in the process of feature extraction (Figure 3).

Figure 3. The process of feature extraction

In this study, the synchroextracting transform (SET) is employed for its effective decomposition of epileptic EEG signals. When employing decomposition approaches for signal processing, their effectiveness becomes particularly noticeable, especially when handling signals with artifacts and noise. The SET excels at removing the most diffused time-frequency energy, leaving behind only the time-frequency information associated with the signal's time-varying features, specifically the instantaneous frequencies (IF) [29]. However, it's important to note that such transformations can yield a substantial volume of decomposed signal data. Efficient selection of representative features becomes crucial in this context, as it allows for dimension reduction while preserving all essential information required for classification.

1.4. Feature selection

The signal transformation can be challenged by the issues of high-dimensional data [30]. In other words, machine learning models can be overfitting and therefore have a poor capability of classification by the signal decomposition [31]. Feature selection tools are crucial particularly when dealing with datasets with a large number of features or when there is a need to simplify models for better interpretability or computational efficiency. There are some methods developed for data dimensionality reduction. For example, backward selection is a feature selection technique commonly used in statistical modelling to choose the most relevant subset of features from a larger set of candidate features. The process involves starting with all available features and iteratively removing less important ones until the desired subset is achieved. Researchers can retain a subset of the most significant values and their corresponding spatial and temporal components. This reduces the dimensionality of the data while preserving the most critical information.

Singular Value Decomposition (SVD) is a mathematical technique commonly used in EEG analysis with signal transformation. SVD decomposes transformed data into its constituent parts, allowing to identify patterns and gain insights into brain activity. SVD can also help identify and remove noise components in EEG data. By analysing the singular values and vectors, artifacts and noise can be separated from meaningful brain signals. Sparse representation (SR) involves a parsimonious principle that a sample can be approximated by a sparse linear combination of basis vectors [32]. The benefit of the SR lies not only in its capability to handle a high volume of features but also in its robustness to redundancy, as it selects only a few features from all its basis vectors. Additionally, It is also highly resilient to noise [33].

When the entropy transform is employed for analysis, backward selection is used for feature selection. However, to address the challenges of high dimensionality, this research proposes using SVD and SR for epileptic EEG signals with a high volume of features after the SET transform. This approach, which involves classification based on feature selection methods, requires fewer data points while highlighting the crucial features within the signals.

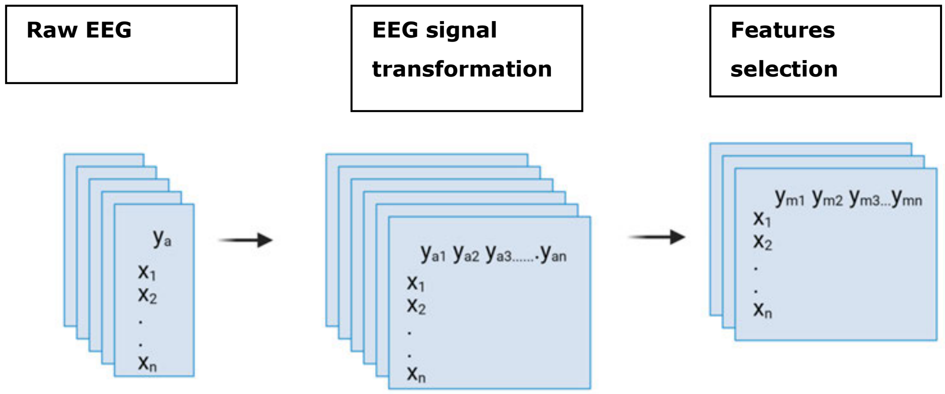


Figure 4. Reduction of EEG sub signals dimension by features selection

1.5. Channel selection for EEG analysis

Channel selection in EEG analysis is an optional step aimed at choosing the most relevant EEG electrode channels for a specific research or clinical objective. EEG data are typically recorded using an array of electrodes placed on the scalp, and not all channels may be necessary for a particular analysis.

The EEG International 10-20 System is a widely adopted standard for electrode placement on the scalp during EEG recordings, ensuring consistency across studies. Electrode sites are labelled with letters and numbers, representing brain regions and positions. The choice of electrodes depends on the research question and regions of interest. EEG data from this system supports various analyses, including brain activity mapping and cognitive neuroscience research. However, the impact of channel selection on predicting epileptic seizures through EEG analysis is still uncertain.

This research applies permutation entropy (PE) from EEG signals to select the effective functional channels of epileptic EEG signals collected from the human scalp. Following thorough experimentation, it has been determined that PE serves as an efficient indicator for representing epileptic conditions.

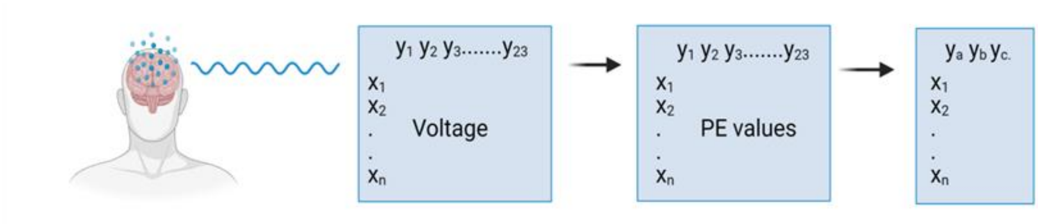


Figure 5. The process of channel selection based on the PE

1.6. Epileptic seizure prediction by machine learning

The process of EEG analysis typically encompasses several key stages, including data collection, feature extraction, model training, and model evaluation. To enable classification by machine learning algorithms, numerical features are used as input. EEG signal decomposition provides a variety of potential features that can be extracted, such as time-frequency features, time-domain features, statistical features, wavelet coefficients, and entropy features. Features play a crucial role in capturing different aspects of brain activity, aiding in the classification process.

Different machine learning algorithms can be used for EEG analysis, including support vector machines (SVMs), random forests, deep learning models like convolutional neural networks (CNN) or recurrent neural networks (RNN), and ensemble methods. The training data, which consists of selected features of EEG decomposition and corresponding labels (for example, inter-ictal, pre-ictal or ictal states), are used to train the models. The trained models are evaluated using validation or test datasets. Common evaluation metrics include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC), depending on the specific task (e.g., binary classification, multi-class classification, or regression).

1.7. Research objectives

The primary objective of this research is to develop a model that can accurately and efficiently predict epileptic seizures in advance during real-time monitoring. Despite decades of research, seizure prediction remains a challenging and unsolved problem. This study seeks to make significant progress in accurately predicting epileptic seizures before their occurrence, addressing key challenges in data analysis and model development. To achieve this main objective, the following sub-objectives are defined:

1. Advanced Feature Extraction:
   - Develop robust feature extraction methods capable of generating outcomes highly correlated with distinct pre-seizure stages observed in EEG signals.

- Address challenges posed by subtle fluctuations in EEG signals, noise, and artifacts.

2. Noise and Artifact Minimization:
   - Minimize the impact of noise and artifacts, such as those caused by muscle movements and environmental factors, to improve the reliability of extracted features.
   - Mitigate data loss or corruption during EEG recording caused by scalp electrode limitations and frequency-selective filtering.
3. Exploration of Machine Learning Techniques:
   - Leverage classical machine learning algorithms for their interpretability, computational efficiency, and suitability for smaller datasets.
   - Explore deep learning models for their ability to learn complex data representations, particularly in unstructured data scenarios.
   - Balance the trade-offs between classical and deep learning techniques to enhance seizure prediction accuracy.
4. System Evaluation:
   - Evaluate the robustness, computational efficiency, and real-time applicability of the developed model for epileptic seizure prediction.
   - Ensure that the system is scalable and reliable for practical diagnostic use.

By systematically addressing these sub-objectives, the study aims to advance the performance of seizure prediction systems, contributing to the development of robust diagnostic tools that improve the quality of life for individuals with epilepsy.

1.8. Proposed methods

To achieve precise seizure prediction, this study adopts a systematic approach. Initially, channel selection is employed to distinguish channel usage based on EEG signals from individual patients. For effective discrimination of channels, permutation entropy (PE) and genetic algorithm (GA) are utilized. Following this, the focus shifts to enhancing signal transformation, and suitable feature extraction techniques post the time-frequency (TF) transformation are applied. To enhance the resolution of EEG signal decomposition, the research incorporates a synchroextracting transformation (SET), and for extracting useful features from the transformed data, singular value decomposition (SVD) or sparse representation (SR) methods are applied.

The classification method is adapted to suit diverse conditions and scenarios, employing 1D-CNN or classical machine learning with SVM and kNN in this research. The development of a real-time mobile epileptic EEG monitor is yet to be realized. The specific type of epileptic EEG data has not been conclusively determined, requiring consideration of various circumstances before deciding on the classification platform. Classical machine learning and deep learning each come with their advantages and disadvantages. This research aims to identify the optimal classification method for both cases, striving for the most effective solution. The overall flow chart of this research is as follows (Figure 7).

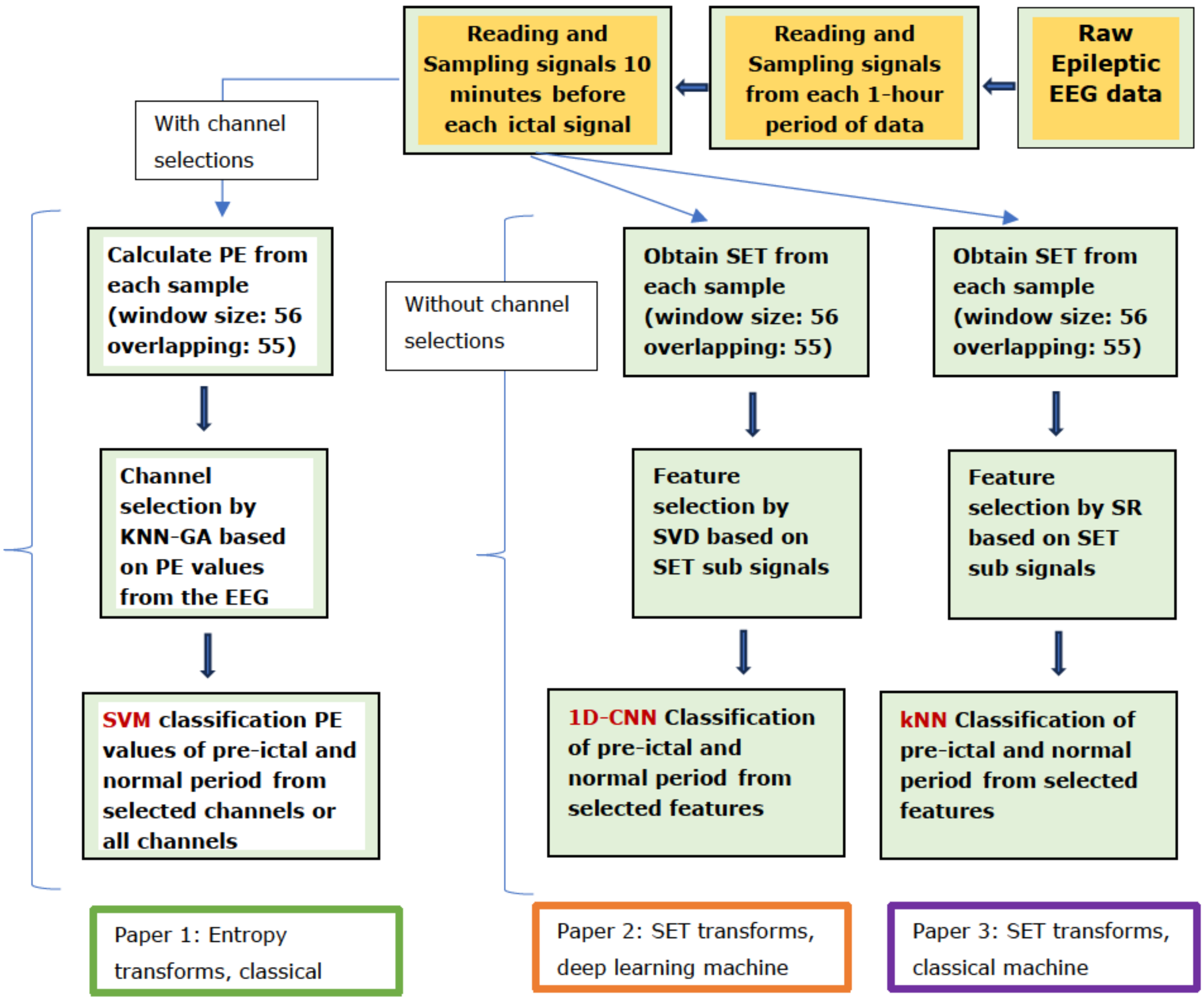


Figure 6. The process of seizure prediction methods based on EEG

1.9. Thesis structure

The structure of the remaining portion of this thesis is outlined as follows:

- Chapter 2 provides a comprehensive literature review covering epileptic EEG feature selections, classifications, and limitations of current research on seizure prediction.
- The subsequent chapters, namely 3, 4, and 5, contain three distinct research papers (refer to Figure 7). The first paper (chapter 3) presents a patient-specific optimization technique for EEG channel selection, based on the evaluation of permutation entropy (PE) values of EEG. The second paper (chapter 4) investigates the use of synchroextracting transformation (SET) and singular value decomposition (SVD) to achieve a higher-resolution decomposition of epileptic EEG signals. The third paper (chapter 5) employs SET and sparse representation (SR) techniques to enhance feature extraction in the analysis of epileptic EEG signals.
- In Chapter 6, the findings of this research are thoroughly discussed, leading to the final conclusions of the study.

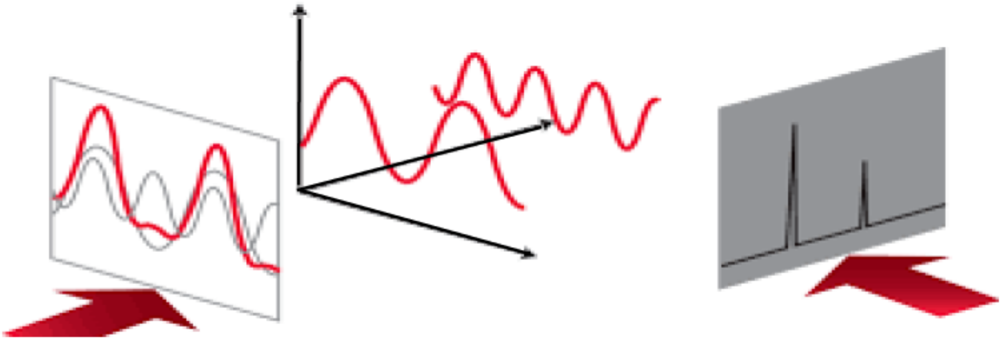
CHAPTER 2: LITERATURE REVIEW

2.1. EEG signal analysis

Feature extraction before classification of epileptic EEG signals is an important area of research. Numerous machine learning models often struggle to accurately classify unknown samples, primarily due to the presence of a substantial amount of unrelated information or noise [34]. There has been intensive research on the time domain, frequency domain and time-frequency domain of EEG signal analysis (Figure 4). The raw EEG data is a time-domain signal, which means it's a function of time. It's essentially a continuous stream of voltage values recorded over a specific period. Initially, EEG data are analysed in the time domain. Time-domain features from EEG signals are statistical values of amplitude and their variances, skewness, and kurtosis analysis. These features capture basic statistical properties of the signal over time. Examples of the feature extraction methods in the time domain are AR Modelling [35, 36], Cepstrum analysis [37], linear predictive coding (LPC) [38] and kernel-based modelling [39]. However, the information obtained from the time-domain analysis is not sufficient for obtaining useful information [40].

Therefore, frequency domain analysis or spectral analysis of raw EEG signals is required for obtaining pertinent information from a signal. Various signal transformation techniques are available for converting a signal from time-domain to frequency-domain, such as Fourier transform [41]. Other frequency-domain feature extraction methods are discrete cosine transform [42], spectral estimation [43], and the Hilbert transform [44]. EEG signals can be decomposed into different frequency bands (e.g., delta, theta, alpha, beta, gamma) and features related to spectral power, frequency peaks can be extracted. However, only spectral information about a signal is available but not time-domain information concurrently if Fourier transform is used [45].

To overcome the limitation of frequency-domain feature extraction methods, signal analysis has undergone significant advancements, particularly in the realms of time and frequency domains over the past few decades [46]. Time-frequency (TF) analysis methods have been developed over many years. A short term Fourier transform (STFT) [47] and wavelet transform (WT) [48] were developed to be used for time-domain as well as frequency analysis of EEG signals. These time-frequency analyses (TF) methods are extensively used in de-noising [49], signal processing and data compression [50], but they require intensive computation with complex signals [29]. One of the drawbacks of TF analysis is to be curtailed by the Heisenberg uncertainty principle or unexpected cross-terms [51]. Hence, the TF analysis methods experience low time-frequency resolution [52]. In addition, these methodologies yield output coefficients that exhibit a strong correlation, resulting in diminished signal classification rates [29]. Consequently, the TF analysis methods are hampered by their limited time-frequency resolution, which hinders their ability to accurately characterize the nonlinear behaviours inherent in non-stationary signals. In an effort to conduct efficient real-time signal analysis, a novel approach known as time-frequency–energy (TFE) analysis was introduced [53].



(a) (b)

Figure 7. EEG signal (a) time domain analysis and (b) frequency domain analysis

In recent times, numerous decomposition techniques for EEG TFE analysis have emerged to address these challenges, proving to be valuable in deciphering patterns within EEG signals. These include empirical mode decomposition (EMD) [54], Tensor decomposition [55], as well as TFE Analysis methods such as synchrosqueezing transformation (SST) [56] and synchroextracting transformation (SET) [57]. The SET stands out as a TFE representative method that relies more on energy-based principles compared to traditional TF analysis techniques, allowing for an effective portrayal of time-frequency characteristics [57].

2.2. EEG Pre-Processing techniques

EEG signals are highly sensitive and often subject to contamination from noise sources such as eye blinks, muscle movements, and environmental interference. Effective pre-processing is crucial to improving the quality of EEG signals and ensuring reliable analysis. Recent research highlights several advanced pre-processing techniques for artifact removal, including independent component analysis (ICA) [58-60], principal component analysis (PCA) [61], wavelet transform (WT) [62, 63], regression-based techniques [63, 64], adaptive filtering [65, 66], artifact subspace reconstruction (ASR) [59, 67], deep learning-based approaches [68-70], and hybrid methods [71-74] that combine multiple strategies for enhanced performance.

ICA is a widely used blind source separation technique that decomposes EEG signals into statistically independent components [58]. Artifacts can be identified and removed by excluding specific components associated with noise [58]. WT decomposes EEG signals into different frequency bands, enabling selective denoising. Artifacts are identified and suppressed in specific frequency bands without affecting the underlying signal [63]. Deep learning-based approaches such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders are increasingly being used for artifact removal [75]. These models learn to distinguish artifacts from neural signals based on labelled datasets [68]. Hybrid methods combine traditional and modern techniques (e.g., ICA with deep learning or wavelet transform with regression) to leverage the strengths of each approach [74].

The choice of artefact removing technique depends on the type of noise, dataset characteristics, computational resources, and intended application. Traditional methods like ICA and WT remain widely used, but modern deep learning approaches hold significant promise for addressing complex artifacts in EEG data. Future research should focus on developing robust hybrid models that integrate these techniques to enhance artifact removal in both offline and real-time EEG applications.

Another crucial pre-processing step is the window sampling technique, which is commonly employed in EEG signal processing. This method segments long, continuous EEG recordings into smaller, manageable intervals, or windows, for analysis [76]. This approach allows for isolating specific time intervals of interest, applying localized signal processing, and enhancing computational efficiency. Recent studies, including Asymmetric Windowing Recurrence Plots (AWRP) [77], Overlapping Sliding Window (OSW) Method [78], Window Stacking Meta-Models

[79], and Impact of Time Window Length [80], have introduced innovative windowing techniques to refine EEG signal analysis. These methods have been particularly impactful in areas such as emotion recognition and clinical classification tasks. These advancements underscore the significant role of windowing techniques in advancing EEG signal processing, with applications spanning emotion recognition, biometrics, and clinical diagnostics.

2.3. Entropy measurements in EEG signal analysis

Meanwhile, the utilization of entropy measurements in EEG signal analysis finds applicability across various domains. In statistical terms, entropy serves as a means to quantify the degree of stochasticity and regularity present within signal processes [81, 82]. Grounded in information theory, it offers another pathway to gain insights into the intricate patterns and dynamics inherent in EEG data. Employing a signal's entropy is a powerful means to quantify the uncertainty or randomness in any domain of EEG datasets [83]. Entropy measures divide a signal into segments and then compare analogy directly or after some signal transformation. Approximate entropy, sample entropy and permutation entropy (PE) are usually applied to signals in the time domain [84].

Entropy measures involve segmenting a signal and subsequently making direct comparisons, either in the time domain or following specific signal transformations. The selection of a transformation and the associated parameters imposes underlying assumptions about what patterns showing in the signal, potentially yielding significantly different outcomes [85]. PE, for instance, evaluates the predictability of a time series by assessing the order of data points within a sliding window. The PE proves particularly valuable for characterizing the temporal dynamics embedded within EEG signals, enabling the detection of alterations in the pattern of brain activity over time. In addition, spectral entropy (SE) quantifies how uniformly the power or energy is distributed across different frequency bands within a signal's spectrum [86]. A signal with a more evenly distributed spectral power will have higher spectral entropy, indicating greater complexity or randomness in its frequency content. Conversely, a signal dominated by specific frequencies will have lower spectral entropy, suggesting a more ordered or predictable frequency structure.

Two commonly used options in the domain of frequency domain analysis are spectral entropy and total wavelet entropy. It's common practice to convert a time-domain signal into a frequency-domain representation through methods like Fourier transform or wavelet analysis when working with frequency-domain entropy [87]. Early efforts in seizure prediction research involved the application of EEG entropy. Research cantered on PE has demonstrated high sensitivity, around 80-90% of accuracy for detecting seizure EEG signals [88].

2.4. Feature selection

Reducing feature dimensionality while preserving vital information from sub-signals after EEG transformation or decomposition presents a significant challenge. Feature selection techniques aim to address this challenge by summarizing the essential characteristics of the original signals. Additionally, the implementation of feature selection contributes significantly to lowering the computational cost associated with classifying high-dimensional data.

In the early 2000s, conventional approaches like backward selection or forward selection were widely used to differentiate the features of EEG signals. There has been prior research on feature selection algorithms with diverse performance levels and computational complexities. For instance, Burrell et al. (2007) compared classical feature selection methods, a forward selection method, and the bound algorithm for classifying pathological events in intracranial EEG. The findings suggest that the forward technique outperforms the other methodologies specifically for their datasets [89].

Over the recent decades, sparse representation (SR) methods have emerged as a research focus for data processing across various fields [90]. The SR is applied to represent data with minimal atoms in each overcomplete dictionary. This allows for a concise representation of data and facilitates the extraction of valuable information. [29]. In essence, SR can be viewed as a brief demonstration of complex, time-varying, nonlinear signals, capturing distinctive patterns inherent to the signal and facilitating reconstruction when necessary [29]. Yuan et al. applied a classification method utilizing kernel SR and kernel collaborative representations. The classification accuracy in detecting seizures achieved 98.63% and 99.99%, respectively. The rapid computation speed contributes to real-time monitoring of epilepsy [91]. Wang and Guo (2011) also proposed SR based on matching pursuit and selected decomposition coefficients and atom parameters as features. The experiment results showed 100% of accuracy in seizure detection classification [92]

In the meantime, singular value decomposition (SVD) [93] method to analyse EEG and induced potential data has given rise to a theory about how EEG data from different channels might be structured. Haddad et al. (2015) suggested a way, using SVD, to divide multi-channel EEG data into time blocks. These time blocks are periods when the patterns of active brain cells causing the EEG signals remain consistent [94]. Xia et al. (2015) employed SVD and achieved a sensitivity of 96.40% and a specificity of 99.01%, with a false detection rate of 0.16/h. for the seizure detection based on EEG signals [95]. Furthermore, Judith et al. (2022) successfully removed the artifacts present in the acquired EEG signals [96].

A genetic algorithm (GA), developed by John Holland et al in 1970s [97] is also frequently used in the signal analysis. A GA is a search heuristic that imitates the process of Charles Darwin's theory of natural selection, in areas such as inheritance, mutation, selection, and crossover. Alyasseri et al. (2021) proposed genetic algorithm (GA) is efficient to find the optimal WT parameters for EEG signal denoising [98]. Albasri et al. (2019) determined the minimum set of electrodes required for optimum identification accuracy in each EEG sub-band of both stimuli by GA algorithm [99].

2.5. Machine learning for seizure prediction

Common machine learning models used in epileptic EEG classification include support vector machine (SVMs), linear regression, linear discriminant analysis (LDA), k-nearest neighbors algorithm (kNN), random forests, convolutional neural network (CNNs), recurrent neural networks (RNNs). Maimaiti et al. (2022) outlined two primary categories of automated techniques. The first category involves traditional machine learning (TML) models, which include algorithms such as the SVM, k-NN or LDA. The second category encompasses deep learning (DL) methods, such as the bi-directional long short-term memory network (Bi-LSTM), the CNN, RNN or the long short-term memory network (LSTM) [100].

The majority of EEG applications typically involve the use of features with high dimensions. Both k-NN and SVMs have been applied in EEG classification, demonstrating effective discrimination of features within EEG datasets. Nonetheless, it's worth noting that varying outcomes have been observed across different EEG applications [101]. Especially, SVMs, initially introduced by Vapnik in 1999 [102], has become widely recognized as one of the frequently employed classifiers in studies related to seizure detection [103]. The reason for the SVM popularity lies in its effectiveness in minimizing structural risks and balancing the trade-off between training errors and model complexity. Originally designed as a neural network model, SVM was designed to perform exceptionally well in scenarios marked by restricted sample sizes and rare events like onsets of seizures [102]. Cura et al. (2021) employed an SVM in their seizure detection study, achieving an accuracy rate of 95.1% [104].

In recent times, there has been a growing number of research focused on epileptic EEG analysis using DL techniques. Among these studies, approximately 14% have been directed towards the detection or prediction of seizures [105]. Especially, CNN-based approaches have gained significant popularity recently. Zhou et al. (2018) used a CNN based on raw EEG signals instead of manual feature extraction to distinguish ictal, preictal, and interictal segments for epileptic seizure detection [106]. The results showed average accuracies of 96.7, 95.4, and 92.3% for the three experiments.

Seizure prediction using EEG remains a challenging problem to be resolved. A summary of recent research for seizure prediction (or detection) based on EEG is as below (Table 1).

Table 1: The summary of recent research for seizure prediction or detection based on EEG

Title of paper	features	classifier	accuracy	sensitivity
The automatic **detection** of seizure based on tensor distance and bayesian linear discriminant analysis [107]	WT, TD	BLDA	97.60%	95.12%
Classification of epileptic EEG signals using synchrosqueezing transform and machine learning [104]	SST	SVM, KNN	95.13%	90.30%
Early **prediction** of refractory epilepsy in children under artificial intelligence neural network [108]	Raw EEG data	SVM	77.80%	82.60%

Dissimilarity-based time–frequency distributions as features for epileptic EEG signal classification [109]	TFD	ANN	97.60%	NA
		SVM	94.20%	NA
Patient specific epileptic seizures **prediction** based on support vector machine. [110]	FD, FI, VC, and Kurtosis.	SVM	96.2%	95.7%
Intelligent seizure **prediction** system based on spectral entropy [111]	SpE	MLP	91.14%	91.37%
Probabilistic **prediction** of epileptic seizures using SVM [112]	Power spectrum	SVM	NA	78%

Table 1: The summary of recent research for seizure prediction or detection based on EEG

Title of paper	**features**	**classifier**	**accuracy**	**sensitivity**
Epilepsy seizure **detection** using akima spline interpolation based ensemble empirical mode kalman filter decomposition by EEG signals [113]	ASI-EEMKFD	LSTM	98.20%	94.96%
Epileptic seizure **prediction** based on permutation entropy [88]	PE	SVM	NA	94%
Epilepsy **prediction** through optimized multidimensional sample entropy and Bi-LSTM [114]	SampE	Bi-LSTM	80.09%	NA
Epileptic seizure **prediction** using scalp electroencephalogram signals [115]	EMD	LSTM	NA	93%
Dynamic learning framework for epileptic seizure **prediction** using sparsity based EEG reconstruction with optimized CNN classifier [116]	Sparsity based EEG reconstruction	3D-CNN	98.86%	99.25%
Cross-subject seizure **detection** in EEGs using deep transfer learning [117]	CSP	CNN	90%	92.2%

Epileptic seizure **detection** using multi-channel EEG wavelet power spectra and 1-D convolutional neural networks [118]	WT	CNN	97.5%	97.5%
Deep learning approach to **detect** seizure using reconstructed phase space images [119]	Reconstructed phase space	CNN	98.5%	NA
Seizure **prediction** using directed transfer function and convolution neural network on intracranial EEG [120]	DTF	CNN	90.8%	NA

Table 1: The summary of recent research for seizure prediction or detection based on EEG

Title of paper	**features**	**classifier**	**accuracy**	**sensitivity**
Automatic seizure **detection** based on S-transform and deep convolutional neural network [121]	wavelet packet decomposition	CNN	95.45%	NA
A multi-view deep learning framework for EEG seizure **detection** [122]	STFT	CNN	93.97%	NA
Early **prediction** of epileptic seizures using a long-term recurrent convolutional network [123]	Raw EEG	CNN	93.40%	91.88%
Scalp EEG classification using deep Bi-LSTM network for seizure **detection** [124]	LMD	Bi-LSTM	NA	93.61%

2.6. Limitations of current research on seizure prediction.

Achieving consistently accurate predictions well before a seizure remains a substantial challenge. The primary obstacle stems from a limited comprehension of the complicated dynamics of EEG signals, particularly during the preictal phase, delaying the development of robust prediction models.

The time-frequency (TF) analysis method has evolved over several decades to gain insights into the mechanisms of EEG signals. Classical techniques like the short-time Fourier transform (STFT) and wavelet transform (WT) TFA proves to be an effective tool in describing the time-varying features of nonstationary signals, aiding in a clearer interpretation of these signals. However, classical methods have drawbacks, such as low time-frequency resolution due to the Heisenberg uncertainty principle and unexpected cross-terms, leading to an inaccurate characterization of nonlinear behaviours in time-varying signals.

Moreover, the application of signal transformations or signal decomposition results in the generation of numerous sub-signals, causing significant time consumption and computational expenses. Furthermore, this procedure can impede accurate classification performance due to the heightened number of dimensions. Ensuring swift predictions in real-time epileptic seizure prediction systems is imperative. However, the use of signal transformation can escalate the signal dimensions, thereby disrupting the effectiveness of real-time seizure prediction. Consequently, contemporary research trends lean towards avoiding transformations that could elevate feature dimensionality.

In addition, the presence of unique variations in seizure patterns and brain activity presents obstacles in constructing universal models capable of accurately forecasting seizures across diverse patient groups. One approach to address this challenge involves pre-selecting channels for pre-seizure classification, providing a means to develop a generalized model while accommodating individual patterns. Despite its potential, channel selection has not received sufficient attention in the field of seizure prediction research.

In the meantime, the progress in portable EEG devices and wearable EEG headsets allows for the capture of real-time EEG data outside typical laboratory settings. This approach supports the collection of information on real-time brain activity providing a more dynamic and ecologically valid understanding of neural patterns. However, as of now, there is a lack of research utilizing real-time EEG data, resulting in limited information about its characteristics. It is crucial to recognize that classification performance may vary compared to static data. Seizure prediction research needs to account for diverse scenarios based on the nature of the data.

2.7. Summary

This chapter reviews key advancements in EEG signal analysis for epileptic seizure prediction. It highlights the importance of feature extraction, starting with time-domain, frequency-domain, and time-frequency domain methods, which address the limitations of raw EEG data by providing valuable insights into its temporal and spectral characteristics. Advanced techniques like synchroextracting transform (SET) have emerged to overcome challenges in traditional methods, such as low time-frequency resolution and computational complexity. The chapter also explores entropy measurements for quantifying randomness in EEG signals and their application in seizure prediction. Feature selection methods, such as sparse representation (SR) and genetic algorithms, are discussed for reducing dimensionality and improving classification efficiency. Machine learning and deep learning models, including SVMs, CNNs, and Bi-LSTMs, are examined for their efficacy in seizure detection and prediction. Finally, the limitations of current research are addressed, emphasizing the need for real-time analysis, personalized models, and improved handling of EEG signal variability, along with the potential of wearable EEG devices for future advancements.

CHAPTER 3: PAPER 1 – A NOVEL PERMUTATION ENTROPY-BASED EEG CHANNEL SELECTION FOR IMPROVING EPILEPTIC SEIZURE PREDICTION

3.1 Introduction

This paper published in Sensors (21(23), p7972) develops a highly effective and accurate algorithm to enhance seizure prediction precision by optimizing EEG channel selection. Using permutation entropy (PE) values, K nearest neighbors (KNN), and a genetic algorithm (GA), the method significantly reduces computational complexity. Employing a support vector machine (SVM) classifier, the algorithm achieves a 92.42% average prediction rate from EEG data of 22 patients, compared to 71.13% using all channels. The selected channels improve accuracy by 10.58%, sensitivity by 23.57%, and specificity by 5.56%. Exceptional results are achieved for four patients, with accuracy, sensitivity, and specificity exceeding 90% and lower standard deviations, demonstrating the robustness and efficacy of this approach.

3.2 Published paper

sensors

MDPI

Article

A Novel Permutation Entropy-Based EEG Channel Selection for Improving Epileptic Seizure Prediction

Jee S. Ra, Tianning Li * and Yan Li

School of Sciences, University of Southern Queensland, Toowoomba, QLD 4350, Australia; jee.ra@usq.edu.au (J.S.R.); Yan.Li@usq.edu.au (Y.L.)
* Correspondence: Tianning.Li@usq.edu.au

Abstract: The key research aspects of detecting and predicting epileptic seizures using electroencephalography (EEG) signals are feature extraction and classification. This paper aims to develop a highly effective and accurate algorithm for seizure prediction. Efficient channel selection could be one of the solutions as it can decrease the computational loading significantly. In this research, we present a patient-specific optimization method for EEG channel selection based on permutation entropy (PE) values, employing K nearest neighbors (KNNs) combined with a genetic algorithm (GA) for epileptic seizure prediction. The classifier is the well-known support vector machine (SVM), and the CHB-MIT Scalp EEG Database is used in this research. The classification results from 22 patients using the channels selected to the patient show a high prediction rate (average 92.42%) compared to the SVM testing results with all channels (71.13%). On average, the accuracy, sensitivity, and specificity with selected channels are improved by 10.58%, 23.57%, and 5.56%, respectively. In addition, four patient cases validate over 90% accuracy, sensitivity, and specificity rates with just a few selected channels. The corresponding standard deviations are also smaller than those used by all channels, demonstrating that tailored channels are a robust way to optimize the seizure prediction.

Keywords: EEG channel selection; permutation entropy; K nearest neighbors (KNN); support vector machine (SVM); genetic algorithm (GA)

Citation: Ra, J.S.; Li, T.; Li, Y. A Novel Permutation Entropy-Based EEG Channel Selection for Improving Epileptic Seizure Prediction. *Sensors* **2021**, *21*, 7972. https://doi.org/10.3390/s21237972

Academic Editor: Manuchehr Soleimani

Received: 31 October 2021
Accepted: 25 November 2021
Published: 29 November 2021

1. Introduction

Epilepsy is a serious brain disorder, second only to strokes in its effect. More than 50 million people worldwide are affected by epilepsy, and the symptoms of one-third of those are not controlled by anticonvulsant medication. Therefore, one of the critical objectives in seizure management in epileptic patients is its early detection and prediction to provide well-timed preventive interventions [1]. If epileptic seizures can be predicted in advance, the patients' unfortunate consequences can be alleviated. Unfortunately, despite decades of international efforts devoted to predicting seizures, seizure prediction remains an unsolved problem [2].

Two key components in research into seizure detection and prediction using epileptic electroencephalography (EEG) signals are feature extraction and classification [3,4]. Most of the existing research is patient-independent and trains models for all types of patients [5–10], while some EEG-based seizure detection algorithms are patient-dependent and are adaptive to individual patients. In order to reduce the computational load for a real-time seizure prediction using EEG data, identifying the most relevant channels for the seizure prediction is both important and effective. It can make seizure-predicting wearable or implantable devices with less complicated feature extraction during the process of developing machine learning algorithms for the real-time analysis. In addition, a decreased number of EEG channels may deliver more convenience to the patients.

However, selecting channels in epileptic features extraction is often not considered necessary. As to patient-specific feature extraction, although the benefits of patient-specific seizure prediction research have not yet been identified, we believe that discovering well-chosen channels tailored to an individual can lead to the uncovering of behavioral patterns in seizure activity through relations between neurophysiological characteristics and EEG channels [11], given the complex aspects of seizure onsets.

Even though much epileptic EEG feature-extraction research has been published, not many papers related to EEG channel selection have been reported over the last decades. Furthermore, the research about machine learning performance comparisons between results with selected channels and all channels is seldom found. Chang et al. [12] proposed that channel selection reduced the channel number from 22 to fewer than 6 channels, and it also saved 93.73% of the computation time. The best result showed a success rate of 70% in three-channel cases of the EEG database. Ibrahim et al. [13] also showed the seizure prediction probability by the selected channel, and the selected feature was higher than 70%, while the false-alarm probability was less than 30%. The channels were classified by a statistical frame. Chakrabarti et al. [14] applied an artificial neural network (ANN) and a principal component analysis (PCA) for the selection of epileptic EEG channels. The results revealed that the accuracy decreased simultaneously as the number of channels decreased. The highest accuracy of 86.7% was achieved with 18 channels out of 23 channels.

Nevertheless, none of those studies showed the machine learning validating performance comparisons between results with selected channels and results with all channels. Moctezuma and Molinas [15] decomposed the EEG data from each channel into different frequency bands using the empirical mode decomposition (EMD) or the discrete wavelet transform (DWT) for the channel selection. The results showed accuracies of up to 100% with only one EEG channel in the epileptic seizure classification, while all the test results of channels were less than 100%; however, this research only classified the seizure and non-seizure signals, not the pre-ictal signals. The classification performance to detect seizure EEG signals usually achieves high accuracy. Prasanna et al. [16] examined recent research to classify between seizure and non-seizure EEG signals. According to their review, the accuracy range that recent studies achieved was from 90% to almost 100%. This research, however, focuses on seizure prediction instead of seizure detection.

In this research, we confine the features to the channels, and present a patient-dependent optimization method for EEG channel selection based on the permutation entropy (PE) values, and employing K nearest neighbors (KNN) combined with a genetic algorithm (GA) for epileptic-seizure prediction. In the last few decades, some seizure prediction studies have applied the GA to generate solutions to search features derived from EEG signals [17–22]. For example, Firpi et al. [23] employed a GA to create artificial features from EEG signals. In their experiment, three patients' datasets were used, and the validation was performed by the KNN, achieving an average of 83.33% seizure prediction. KNN is one of the most widespread methods in the machine learning techniques. As medical facilities require minimal computational time, the KNN has been used as a seizure prediction algorithm in many recent studies [24–27]. For instance, Wang et al. [27] proposed a KNN analysis on EEG data from 10 patients with epilepsy, achieving 73% sensitivity and 67% specificity on average using a 150-min prediction horizon.

The classifier in this research is the SVM, as the SVM classification complexity does not depend on the feature dimension, and it provides a global solution [28–30], which might be appropriate for epileptic EEG classification. Shiao et al. [31] showed that the SVM-based seizure prediction system could achieve a robust prediction for preictal period and normal period iEEG signals from dogs with epilepsy. The sensitivity was 90–100%, and the false-positive rate was about 0–0.3 times per day. However, SVM does not always seem suitable for the epileptic EEG signals classification. Direito et al. [32] used massive data from 216 patients from the European Epilepsy Database, including 185 patients with scalp EEG recordings and 31 with intracranial data. They tested their method over a total of 16,729.80 h with inter-ictal data, including 1206 seizures using the SVM. The method achieved an overall sensitivity of 38.47% and a false-positive rate per hour of 0.20 (statistical significance only in 11% of the patients). This disproved the importance of proper feature extractions.

This research is the first study to compare the effectiveness of EEG channel selection with that before channel selection. It also aims to reveal that patient-specific channel selection can contribute to a more efficient seizure prediction. The remainder of this paper is arranged as follows. Section 2 presents the details of the proposed techniques for the EEG channels selection and classifications. Section 3 explains the datasets used in this paper, experimental setup, and results. Section 4 discusses the findings of this research. Finally, the conclusions of this study are drawn in Section 5.

2. Methodology

The goal is to construct a less complicated seizure prediction system with less computational load but high accuracy for real-time seizure prediction. The PE values differentiated by KNN combined with a GA (KNN-GA) are employed in this research to select channels for efficient analysis and seizure prediction. The overall process is divided into three steps: PE calculation and data sampling, channel selection by KNN-GA, and test modelling by the machine learning method, SVM. Firstly, the raw EEG signals without noise-filtration, segmented into time windows, are directly used to acquire the PE values, which are the parameters obtained by feature extraction. Secondly, the selected PE values of each channel are used for selecting the most pre-ictal related channels through KNN-GA, which is executed repeatedly (maximum number of executions is 30 in this study). Finally, the effect of the selected channels is validated and compared using the SVM classification with all 23 channels. The primary process of the method is illustrated below (Figure 1).

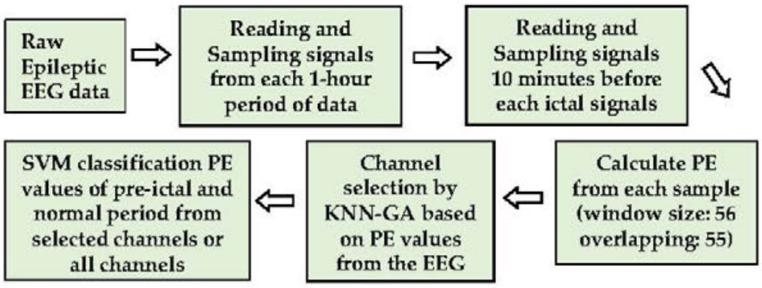


Figure 1. The main process of methods.

2.1. Permutation Entropy

For the proper channels to be selected efficiently from EEG signals in the dataset, the collected original data samples are used as the input to obtain the PE values to measure the detailed variations in the EEG signals by expressing the signal in multi-scale time-frequency domains. The PE provides a quantity measure of the complexity of a dynamic system by capturing the order relations on time-series signals and their probability distribution of the ordinal patterns [33].

The first step is to convert a one-dimensional time series into a matrix of overlapping column vectors. Then, M-dimensional vectors are mapped into unique permutations that achieve the ordinal rankings of the data. These permutations are the values that are associated with each partitioned vector based on the ordinal position of the values within the vector. Then, the relative frequency of each permutation is calculated by counting the number of times the permutation is found in the signals divided by the total number of sequences [34]. Finally, the relative frequency of each permutation is used to compute the PE of the order M of the signals, which is given by Equation (1) [34]:

$$PE_M = -\sum_{i=1}^{M!} P_i \log_2 P_i \quad (1)$$

The smaller the value of PE_M, the more regular and more deterministic is the time series. Contrarily, the closer to 1 PE_M is, the noisier and more random the time series is.

2.2. Channel Selection by KNN Based on Genetic Algorithm

Noise and redundant data points in signals can render information on the training of the method irrelevant. For effective and efficient EEG signal analysis, identifying the channels that contribute most to the prediction outcomes is crucial. A genetic algorithm (GA), developed by John Holland et al. in 1970s [35] is also applied in this research. A GA is a search heuristic that imitates the process of Charles Darwin's theory of natural selection, in areas such as inheritance, mutation, selection, and crossover.

For feature selection, 'mutation' in GA means switching features on and off. 'Crossover' means interchanging the used features. In this paper, the selection is based on the accuracy of the KNN classification performance. KNN is a supervised learning algorithm, and it is one of the most important non-parameter algorithms in the pattern recognition field [36]. The training samples themselves generate the classification rules without any additional data. The KNN classification algorithm predicts the test sample's category according to the K training samples, which are the nearest neighbors to the test sample, and judges the category with the most significant probability [36].

The overall process of KNN-GA for a channel selection works as follows in this study (Figure 2):

1. Load the PE values (Section 2.2) of each channel.
2. KNN-GA begins with a set of individual subjects, which are the total population (all individuals). A subject is described by a set of parameters (channels in this research) noted as Genes. Genes are combined into a string to form a Chromosome (any possible solution). The population size is 20, and the minimum number of Genes is one.
3. Then each Chromosome in the population is evaluated by the fitness function (KNN in this paper) to test how well it predicts pre-ictal periods. It gives a fitness score (maximum: infinity) to each subject.
4. Now the selection operator chooses some of the Chromosomes for reproduction based on a probability distribution. We set 0.9 for the initial probability. For example, if $f(x)$ is a fitness function, then the probability that chromosome C_X is chosen to reproduce is:
$$p(C_x) = \frac{f(C_x)}{\sum_{i=1}^{N_{pop}} f(C_i)} \quad (2)$$
where *Npop* is the number of Chromosomes in the population.
5. Next, we mix Chromosomes for crossover (type: uniform, crossover probability: 1.0). Each Gene is selected randomly from one of the corresponding genes of the parent Chromosomes.
6. The final step is to apply random mutations. For each Gene that we are to copy to the new population, we allow a small probability of error (0.01 in this paper).
7. Repeat from step 2 until the population converges (does not produce offspring which are significantly different from the previous generation). It can then be said that the genetic algorithm has provided a set of solutions to our problem (maximum number of generations: 30).

2.3. Selected Channels Validation by a SVM Model

Following channel selection, a SVM is used to classify the patterns into pre-ictal and normal periods. There are three types of optimization method for the SVM used in this research: Lagrange multiplier (LM), evolutionary and Particle Swarm Optimization (PSO). The PE values of the selected channels by KNN-GA were trained and tested for each of the three types of SVMs, and the best result was selectively adopted. The PE values of all channels were also derived through the same process. The detailed steps are demonstrated below (Figure 3).

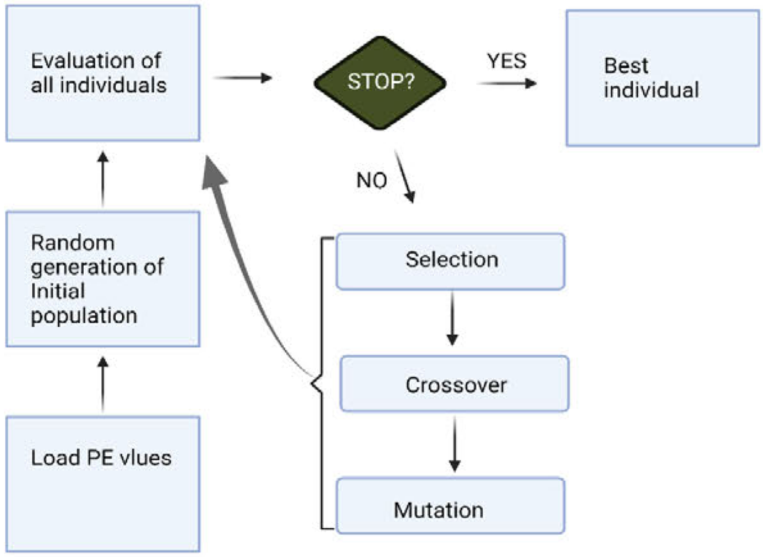


Figure 2. The process of KNN-GA.

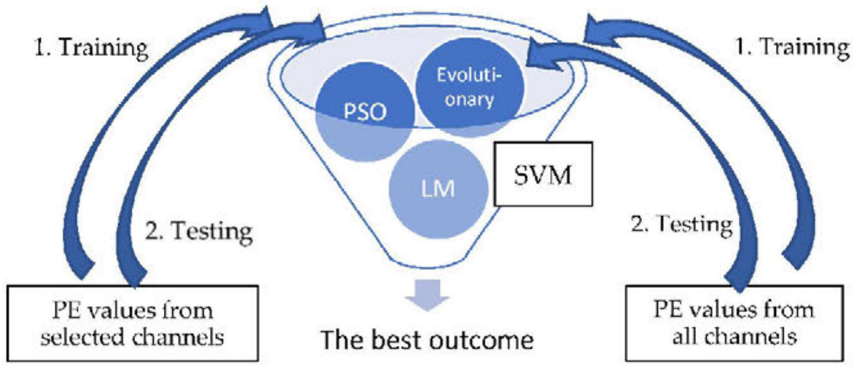


Figure 3. SVM classification.

3. Results

3.1. The Experimental Data and Clinical Consideration

The experimental data came from CHB-MIT Scalp EEG Database [37]. This the data of this database is collected at the Children's Hospital Boston. It consists of EEG recordings from pediatric subjects with intractable seizures. Subjects were monitored for several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention. Recordings, grouped into 24 cases, were collected from 24 subjects (5 males, ages 3–22; 18 females, ages 1.5–19). Each case (chb01, chb02, etc.) contains 9 to 42 continuous *.edf* files from a single subject. The characteristics of each patient and the patient's data are summarized below (Table 1).

The 24 patients' EEG signals with a 256 Hz sampling rate were recorded using 23 channels which are FP1-F7 (1), F7-T7 (2), T7-P7 (3), P7-O1 (4), FP1-F3 (5), F3-C3 (6), C3-P3 (7), P3-O1 (8), FP2-F4 (9), F4-C4 (10), C4-P4 (11), P4-O2 (12), FP2-F8 (13), F8-T8 (14), T8-P8 (15), P8-O2 (16), FZ-CZ (17), CZ-PZ (18), P7-T7 (19), T7-FT9 (20), FT9-FT10 (21), FT10-T8 (22), and T8-P8 (23). The letter notations are—FP: frontopolar, F: frontal, T: temporal, O: occipital, C: central, and P: parietal (Figure 4).

Table 1. The characteristics of each patient and the patient's data.

Patient ID	Gender	Age	Number of Seizures	Length of Records (Hours)
1	F	11	7	45.00
2	M	11	3	39.57
3	F	14	7	57.87
4	M	22	4	154.41
5	F	7	5	38.09
6	F	1.5	10	89.25
7	F	14.5	3	67.23
8	M	3.5	5	26.38
9	F	10	4	65.92
10	M	3	7	72.49
11	F	12	3	73.30
12	F	2	40	NA
13	F	3	12	NA
14	F	9	8	41.50
15	M	16	20	62.29
16	F	7	10	17.03
17	F	12	3	34.11
18	F	18	6	62.85
19	F	19	3	61.58
20	F	6	8	41.43
21	F	13	4	55.71
22	F	9	3	75.93
23	F	6	7	70.90
24	NA [1]	NA	16	NA

[1] Not available. Not specified.

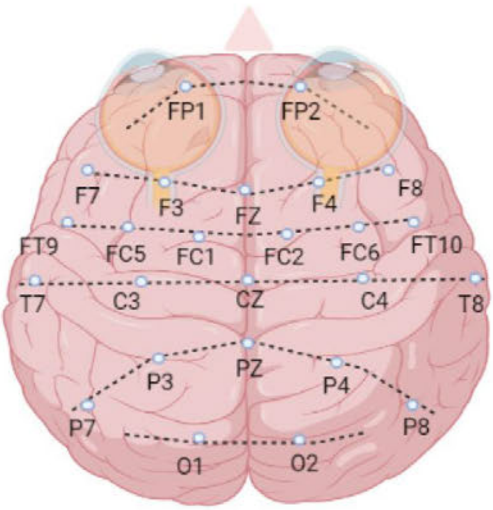


Figure 4. The brain surface map of EEG channels.

Epileptic EEG signals are typically classified into four periods: normal, pre-ictal, ictal, and post-ictal periods (as shown in Figure 5). In some experimental results, the high accuracy rate might not be impressive when available normal period data are surplus and the pre-ictal period signals occupy only a tiny fraction of the testing dataset. Thus, this research restricts the ratio of normal to pre-ictal training/testing data up to 10:1. Selecting segments of EEG signal recording for the analysis is one of the significant problems of seizure prediction research. The seizure prediction horizon (SPH) is the period between the seizure alarm sign and the beginning of seizure occurrence. Therefore, the SPH prerequisites are to be designated before assessing the analysis. The size of the SPH has been reported to be between a few minutes and several hours before a seizure onset. The standard size is still a debatable question. This research set an SPH of 10 min (2.8 s duration) for both training and testing.

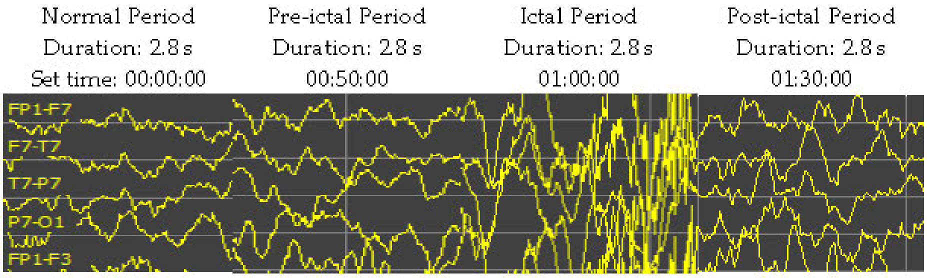


Figure 5. An example of EEG recordings (Patient ID 1, channels of FP1-F7, F7-T7, T7-P7 and P7-O1) over time showing the activity from the EEG signals at the normal, pre-ictal, ictal, and post-ictal periods. The patient was an 11-year-old female. The sampling rate is 256 Hz. The vertical scale is 50 μV.

Each patient dataset contains data points of 17–154 h. Data samples of a normal period (2.8 s duration) are randomly selected in each hour of the 17–154 h duration. In summary, the samples are collected from:

- Pre-ictal period: 10 min before a seizure onset.
- Normal period: between pre-ictal and post-ictal periods (30 min after a seizure onset).

3.2. *Validation of the Channel Selection Technique*

The KNN-GA algorithm selected three to eight channels among 23 channels based on the PE values from each patient's EEG signals. The most frequently selected channels are P7-O1 (10 times), P8-O2 (9 times), C3-P3 (8 times) and CZ-PZ (8 times) from 22 patient datasets (Figure 6).

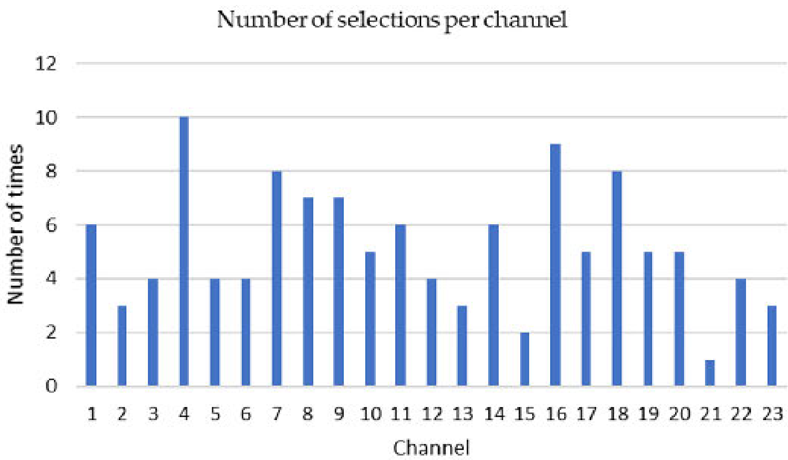


Figure 6. The number of times and each channel from 1 to 23 has been selected. The vertical axis shows how many times one given channel has been selected. Channel 1: FP1-F7, 2: F7-T7, 3: T7-P7, 4: P7-O1, 5: FP1-F3, 6: F3-C3, 7: C3-P3, 8: P3-O1, 9: FP2-F4, 10: F4-C4, 11: C4-P4, 12: P4-O2, 13: FP2-F8, 14: F8-T8, 15: T8-P8, 16: P8-O2, 17: FZ-CZ, 18: CZ-PZ, 19: P7-T7, 20: T7-FT9, 21: FT9-FT10, 22: FT10-T8, 23: T8-P8.

The efficiency of a seizure prediction algorithm is determined by the prediction rate, accuracy, sensitivity, and specificity. The prediction rate refers to how many predictions are correctly made out of the total number of ictal occurrences in the testing set. Sensitivity is the percentage of the true pre-ictal prediction, and specificity is the percentage of the true normal period prediction (Table 2). Table 3 presents the performance of the selected channels and all channels based on the SVM classification testing for the 22 patients in the CHB-MIT Scalp EEG Database.

Table 2. Accuracy, sensitivity, and specificity.

	True Pre-Ictal Period	True Normal Period
Predict pre-ictal period	I	II
Predict normal period	III	IV

Accuracy = (I + IV)/(I + II + III + IV). Sensitivity = I/(I + III). Specificity = IV/(II + IV).

The prediction rate average of the selected channels from 22 patients is 92.42%, while that of all channels from 22 patients is only 71.13%, an improvement of 29.93%. The accuracy average of the selected channels is 74.60%, and that of all channels is 67.46%. The sensitivity and specificity completed by the selected channels testing also show a higher rate (average 69.51% and 73.14%, respectively) than all channels testing (average 56.25% and 69.29%, respectively). On average, the accuracy, sensitivity, and specificity with selected channels are improved by 10.58%, 23.57%, and 5.56%, respectively. The analysis of variance (ANOVA) tests also confirm that the accuracy and sensitivity using the selected channels from the SVM testing result are significantly higher than those using all channel testing results (at $p < 0.01$ and $p < 0.05$, respectively) (Table 4). The standard deviations of the accuracy, sensitivity, and specificity from the selected channels testing for the 22 patients are smaller (15.36, 25.03, and 20.81, respectively) than from all channel testing (Table 4). In addition, the execution time of the SVM model is almost instantaneous (10–500 milliseconds) in many patients' cases. Nevertheless, the average percentage of computational runtime saved by channel selection is 42%.

Two-dimensional area graphs are also added to view the numerical results visually (Figure 7). In Figure 7a,b, the blue shapes with red outline (pre-ictal period) of "Real status" are closer to the blue shapes of "Prediction using the selected channels" than the black shapes of "Prediction using all channels". Thus, the figures demonstrate that using the selected channels can better predict the pre-ictal period than using all channels.

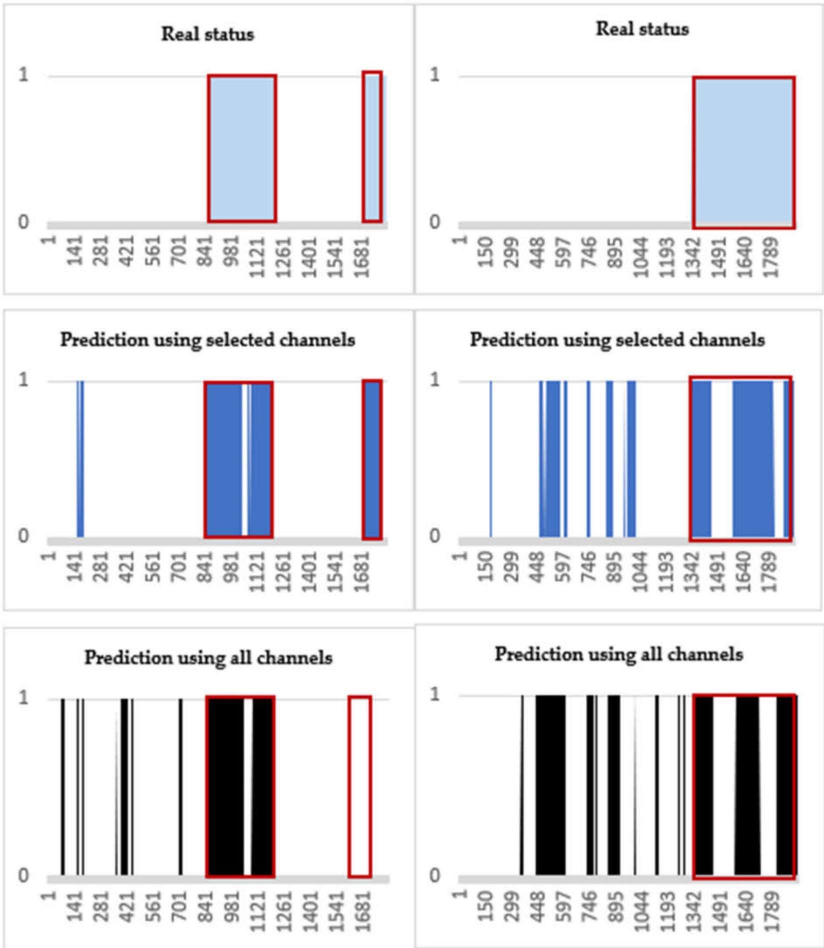
Table 3. The performance of the selected channels and all channels based on the SVM classification testing for 22 patients.

Patient ID	Recording Duration (Hours)	Number of Seizures		Selected Channels [1]	Test Results (Selected Channels/All Channels) [2]				Execution Time s: Second(s) ms: Milli-Second(s)	SVM Optimization Methods
		Train	Test		Prediction Rate (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)		
1	45.00	4	3	*4, 11, 16, 18*	**100**/100	**97.28**/100	**93.66**/100	**100**/100	**32 ms** (30% [4])/46 ms	LM
2	39.57	1	2	*5, 6, 8, 11*	**100**/75	**54.27**/30.85	**50.00**/38.02	**56.40**/27.27	**47 ms** (40%)/78 ms	Evolutionary
3	57.87	4	3	*4, 8, 14, 16, 18, 19, 20, 23*	**100**/67	**77.89**/70.51	**70.91**/62.81	**81.07**/74.00	**121 s** (24%)/159 s	Evolutionary
4	154.41	2	2	*8, 10, 14, 17, 18, 19*	**100**/50	**80.79**/76.82	**45.45**/24.79	**84.71**/82.60	**44 s** (15%)/52 s	PSO
5	38.09	2	3	*1, 7, 9, 13, 16*	**100**/50	**58.19**/55.19	**90.12**/46.88	**38.65**/60.27	**1 s** (80%)/5 s	Evolutionary
6	89.25	6	4	*6, 9, 14, 16, 18*	**100**/75	**66.04**/58.38	**71.19**/59.27	**57.02**/56.82	**250 ms** (33%)/375 ms	LM
7	67.23	1	2	*4, 11, 16, 18*	**100**/50	**83.61**/80.17	**99.17**/0.00	**80.50**/96.20	**16 ms** (48%)/31 ms	LM
8	26.38	2	3	*8, 14, 17, 19*	**100**/100	**95.73**/65.56	**87.19**/74.38	**100**/62.40	**16 ms** (48%)/31 ms	LM
9	65.92	3	1	*4, 11, 16, 18, 20*	**100**/100	**69.01**/61.98	**34.71**/68.60	**72.82**/61.25	**31 ms** (83%)/187 ms	LM
10	72.49	3	4	*4, 8, 11, 16, 18, 20*	**75**/75	**65.97**/44.03	**80.17**/74.10	**60.64**/61.98	**17 s** (29%)/24 s	PSO
11	73.30	1	1	*3, 4, 7, 8, 10, 17, 21*	**100**/0	**84.55**/71.98	**50.41**/0.00	**88.34**/47.70	**16 ms** (36%)/47 ms	LM
12	NA [3]	NA	NA	*NA*	NA	NA	NA	NA	NA	NA
13	NA [3]	NA	NA	*NA*	NA	NA	NA	NA	NA	NA
14	41.50	5	3	*1, 2, 3, 5, 7, 9, 23*	**33.3**/33.3	**61.67**/60.27	**32.51**/18.73	**70.41**/72.73	**64 s** (11%)/72 s	Evolutionary
15	62.29	6	7	*1, 7, 17, 10, 16, 22, CP2 Ref*	**100**/42.9	**75.48**/63.87	**69.42**/22.41	**80.33**/97.02	**1 s** (80%)/5 s	LM
16	17.03	2	3	*1, 2, 5, 7, 9, 10, 15, 16*	**100**/100	**69.97**/69.83	**100**/100	**54.96**/54.75	**93 ms** (69%)/297 ms	LM
17	34.11	2	1	*1, 9, 12*	**100**/100	**45.45**/46.38	**100**/87.60	**37.66**/40.50	**31 ms** (34%)/47 ms	LM
18	62.85	2	4	*4, 7, 13, 20, 22*	**75**/75	**71.63**/66.39	**42.77**/50.00	**86.05**/74.59	**15 s** (6%)/16 s	PSO
19	61.58	1	1	*4, 6, 14*	**100**/100	**94.86**/96.05	**90.08**/100	**95.45**/95.56	**16 ms** (57%)/37 ms	LM
20	41.43	4	4	*3, 4, 6, 7, 12, 15*	**100**/75	**94.63**/87.02	**90.63**/88.43	**96.34**/86.42	**20 s** (9%)/22 s	PSO
21	55.71	2	2	*4, 7, 13, 19, 20, 22*	**50**/50	**69.35**/49.44	**42.15**/23.14	**75.39**/55.28	**297 ms** (62%)/781 ms	LM
22	75.93	2	1	*1, 2, 9, 12, 23*	**100**/100	**88.55**/80.05	**24.79**/22.31	**99.17**/89.67	**16 ms** (48%)/31 ms	LM
23	70.90	4	3	*8, 10, 14, 17, 18, 19*	**100**/100	**87.40**/100	**96.69**/100	**59.50**/100	**15 ms** (6%)/16 ms	LM
24	NA	10	5	*3, 5, 9, 11, 12, 23*	**80**/80	**48.91**/49.44	**67.27**/76.03	**33.61**/27.27	**312 ms** (38%)/500 ms	LM

[1] Channels, 1: FP1-F7, 2: F7-T7, 3: T7-P7, 4: P7-O1, 5: FP1-F3, 6: F3-C3, 7: C3-P3, 8: P3-O1, 9: FP2-F4, 10: F4-C4, 11: C4-P4, 12: P4-O2, 13: FP2-F8, 14: F8-T8, 15: T8-P8, 16: P8-O2, 17: FZ-CZ, 18: CZ-PZ, 19: P7-T7, 20: T7-FT9, 21: FT9-FT10, 22: FT10-T8, 23: T8-P8. [2] Bold represents the testing results of the selected channels. [3] Not available. Not possible to match training and testing sets as the channels were frequently changed during the EEG recording—the recordings may be contaminated. [4] The percentage of computational runtime saved by channel selection. The average is 42%.

Table 4. The ANOVA test results by the SVM classification.

	Accuracy		Sensitivity		Specificity	
	Selected Channels	**All Channels**	**Selected Channels**	**All Channels**	**Selected Channels**	**All Channels**
N	22	22	22	22	22	22
$\sum X$	1641.23	1484.21	1529.29	1237.50	1609.02	1524.28
Mean	74.60	67.46	69.51	56.25	73.14	69.29
σ	15.36	18.36	25.03	33.44	20.81	22.52
p-value	0.002699		0.033532		0.339937	
F-ratio	11.5588		5.17403		0.95353	
	significant at $\alpha = 0.01$		significant at $\alpha = 0.05$		not significant at $\alpha = 0.05$	



(**a**) (**b**)

Figure 7. Visual comparisons for the SVM testing results. Blue-colored area with red outlines represents the SPH (10 min), i.e., alarming at 10 min before the seizure onsets. (**a**) Patient ID 20: a total of 4 seizure occurrences in a period of 24 h. (**b**) Patient ID 3: a total of 3 seizure occurrences.

4. Discussion

Seizures can occur anywhere in the brain, but for children, they frequently occur in the temporal and frontal lobes, affecting the functions these regions control [38]. Three to eight channels among 23 channels were selected for each subject by KNN_GA based on PE values of epileptic EEG signals. The most frequently selected channel was P7-O1 (10 times), which is located at the scalp of the parietal and occipital lobes of the brain. However, the total number of channels connected to the frontal and temporal lobes region is much higher than that of the parietal and occipital region channels. Consequently, the number of selected frontal and temporal lobes region channels is higher.

The patient-specific channel selection technique improves the prediction rate by 29.93% and the accuracy, sensitivity, and specificity by 10.58%, 23.57%, and 5.56%, respectively. The average accuracy, sensitivity, and specificity of the SVM testing are 74.60%, 69.51%, and 73.14%, respectively, and with all channels, they are 67.46%, 56.25%, and 69.29% in this research into epileptic seizure prediction. In particular, the true pre-ictal prediction rate (sensitivity) of the classification with the selected channels is considerably higher than that with all channels. The corresponding standard deviations are also smaller than those using all channels, demonstrating that tailored channels are more robust in optimizing seizure prediction rates. With the selected channels, the highest accuracy, sensitivity, and specificity rates are 97.28% (patient ID 1), 99.17% (patient ID 7), and 100% (patient ID 1), respectively. On the other hand, patient ID 17 and ID 24 cases achieved poor accuracy (under 50%) despite having high sensitivity.

There are a couple of limitations for the proposed approach. (1) Based on the results from different subjects (such as Patients 17 and 24), it is observed that the patterns of PE values during the nighttime are similar to the patterns of PE values during the pre-ictal period. This phenomenon may affect the predication accuracy. In reality, it is difficult to verify whether a patient is sleeping or just at rest during the nighttime. (2) It is possible that the starting point of the preictal periods are likely not the same for all patients. In this research, the SPH is set to 10 min for all subjects during the model training, while the SPH could be any time period (e.g., several hours).

This research aims to reduce the complexity of feature extraction and classification steps in predicting seizures while a high accuracy is retained and the computation time is significantly reduced. The average execution time by using the selected channels was only 47.09% of that by all channels. For Patient IDs 1, 8, 19, and 20, more than 90% validation accuracy, sensitivity, and specificity rates with just a few selected channels are obtained in this research method. The results demonstrate that the proposed EEG channel selection method with a suitable classification algorithm (SVM in this paper) can increase real-time seizure prediction accuracy.

5. Conclusions

In this paper, we recognize that the patterns of epileptic seizure occurrences are patient specific. The key issue is to discern which regions of the brain are most relevant to the seizure onsets for a specific patient. The most frequently selected channel was P7-O1 (10 times). However, many EEG channels were connected to the temporal and frontal lobes, which frequently causes seizures in children.

After finding the suitable channels for each patient through the KNN-GA algorithm, the SVM training and testing based on PE values of epileptic EEG signals exhibit more accurate outcomes of seizure prediction and less computation load than with all 23 channels. Consequently, fewer patient-dependent EEG channels can contribute to essential aspects of seizure prediction analysis, such as less EEG electrodes required on the scalp and more accurate mobile real-time seizure predictions.

Author Contributions: J.S.R. presented the project idea and completed the modelling, experiments and the writing of this manuscript, while T.L. and Y.L., being supervisors, contributed to the design of the study, the completion of the project and the editing of this manuscript. All authors read and approved the final. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethical review and approval were waived for this study, due to the secondary data are used in this research. The data used are publicly available through the link 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 20 October 2021).

Informed Consent Statement: The data used is from the CHB-MIT Scalp EEG Database which was made publicly available online. The detailed information is in the link 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 20 October 2021).

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.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Epilepsy, Key Facts. Available online: https://www.who.int/news-room/fact-sheets/detail/epilepsy (accessed on 12 July 2021).
2. Kuhlmann, L.; Lehnertz, K.; Richardson, M.P.; Schelter, B.; Zaveri, H.P. Seizure prediction—Ready for a new era. *Nat. Rev. Neurol.* **2018**, *14*, 618–630. [CrossRef] [PubMed]
3. Liu, X.; Fu, Z. A Novel Recognition Strategy for Epilepsy EEG Signals Based on Conditional Entropy of Ordinal Patterns. *Entropy* **2020**, *22*, 1092. [CrossRef] [PubMed]
4. Krishna, N.M.; Sekaran, K.; Vamsi, A.V.N.; Ghantasala, G.S.P.; Chandana, P.; Kadry, S.; Blazauskas, T.; Damasevicius, R.; Kaushik, S. An Efficient Mixture Model Approach in Brain-Machine Interface Systems for Extracting the Psychological Status of Mentally Impaired Persons Using EEG Signals. *IEEE Access* **2019**, *7*, 77905–77914. [CrossRef]
5. Yang, S.; Li, B.; Zhang, Y.; Duan, M.; Liu, S.; Zhang, Y.; Feng, X.; Tan, R.; Huang, L.; Zhou, F. Selection of features for patient-independent detection of seizure events using scalp EEG signals. *Comput. Biol. Med.* **2020**, *119*, 103671. [CrossRef] [PubMed]
6. Sridevi, V.; Machireddy, R.; Srinivasan, K.; Radhakrishnan, K.; Rathore, C.; Nayak, D.S. Improved Patient-Independent System for Detection of Electrical Onset of Seizures. *J. Clin. Neurophysiol.* **2019**, *36*, 14–24. [CrossRef] [PubMed]
7. Bogaarts, J.G.; Gommer, E.D.; Hilkman, D.M.W.; Van Kranen-Mastenbroek, V.H.J.M.; Reulen, J.P.H. Optimal training dataset composition for SVM-based, age-independent, automated epileptic seizure detection. *Med. Biol. Eng. Comput.* **2016**, *54*, 1285–1293. [CrossRef] [PubMed]
8. Ra, J.S.; Li, T.; Li, Y. A novel spectral entropy-based index for assessing the depth of anaesthesia. *Brain Inform.* **2021**, *8*, 1–12. [CrossRef] [PubMed]
9. Li, S.Y.; Wen, P. Identification of motor imagery tasks through CC–LR algorithm in brain computer interface. *Int. J. Bioinform. Res. Appl.* **2013**, *9*, 156–172.
10. Nguyen-Ky, T.; Wen, P.; Li, Y. Consciousness and Depth of Anesthesia Assessment Based on Bayesian Analysis of EEG Signals. *IEEE Trans. Biomed. Eng.* **2013**, *60*, 1488–1498. [CrossRef]
11. Shen, C.-P.; Liu, S.-T.; Zhou, W.-Z.; Lin, F.-S.; Lam, A.Y.-Y.; Sung, H.-Y.; Chen, W.; Lin, J.-W.; Chiu, M.-J.; Pan, M.-K.; et al. A Physiology-Based Seizure Detection System for Multichannel EEG. *PLoS ONE* **2013**, *8*, e65862. [CrossRef]
12. Chang, N.-F.; Chen, T.-C.; Chiang, C.-Y.; Chen, L.-G. Channel selection for epilepsy seizure prediction method based on machine learning. In Proceedings of the 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Diego, CA, USA, 28 August–1 September 2012; pp. 5162–5165.
13. Ibrahim, F.; El-Gindy, S.A.-E.; El-Dolil, S.M.; El-Fishawy, A.S.; El-Rabaie, E.-S.M.; Dessouky, M.I.; Eldokany, I.M.; Alotaiby, T.N.; Alshebeili, S.A.; El-Samie, F.E.A. A statistical framework for EEG channel selection and seizure prediction on mobile. *Int. J. Speech Technol.* **2019**, *22*, 191–203. [CrossRef]
14. Chakrabarti, S.; Swetapadma, A.; Pattnaik, P.K. A Channel Selection Method for Epileptic EEG Signals. In *Emerging Technologies in Data Mining and Information Security*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 565–573.
15. Moctezuma, L.A.; Molinas, M. EEG Channel-Selection Method for Epileptic-Seizure Classification Based on Multi-Objective Optimization. *Front. Neurosci.* **2020**, *14*, 593. [CrossRef]
16. Prasanna, J.; Subathra, M.S.P.; Mohammed, M.A.; Damaševičius, R.; Sairamya, N.J.; George, S.T. Automated Epileptic Seizure Detection in Pediatric Subjects of CHB-MIT EEG Database—A Survey. *J. Pers. Med.* **2021**, *11*, 1028. [CrossRef]
17. Assi, E.B.; Sawan, M.; Nguyen, D.K.; Rihana, S. A hybrid mRMR-genetic based selection method for the prediction of epileptic seizures. In Proceedings of the 2015 IEEE Biomedical Circuits and Systems Conference (BioCAS), Atlanta, GA, USA, 22–24 October 2015; pp. 1–4.
18. Ataee, P.; Yazdani, A.; Setarehdan, S.; Noubari, H. Genetic Algorithm for Selection of Best Feature and Window Length for a Discriminate Pre-seizure and Normal State Classification. In Proceedings of the 4th International Symposium on Image and Signal Processing and Analysis, Zagreb, Croatia, 15–17 September 2005; pp. 107–112.

19. D'Alessandro, M.; Vachtsevanos, G.; Hinson, A.; Esteller, R.; Echauz, J.; Litt, B. A genetic approach to selecting the optimal feature for epileptic seizure prediction. In Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Berlin, Germany, 23–27 July 2005; pp. 1703–1706.
20. Thorbole, P.S.; Kalbhor, S.D.; Harpale, V.K.; Bairagi, V. Hardware Implementation of Genetic Algorithm for Epileptic Seizure Detection and Prediction. In Proceedings of the 2017 International Conference on Computing, Communication, Control and Automation (ICCUBEA), Pune, India, 17–18 August 2017; pp. 1–5.
21. Banupriya, C.V.; Devi Aruna, D. Robust Optimization of electroencephalograph (EEG) Signals for Epilepsy Seizure Prediction by utilizing VSPO Genetic Algorithms with SVM and Machine Learning Methods. *Indian J. Sci. Technol.* **2021**, *14*, 1250–1260. [CrossRef]
22. Al Ghayab, H.R.; Li, Y.; Siuly, S.; Abdulla, S.A. Epileptic seizures detection in EEGs blending frequency domain with information gain technique. *Soft Comput.* **2019**, *23*, 227–239. [CrossRef]
23. Firpi, H.; Goodman, E.; Echauz, J. Genetic Programming Artificial Features with Applications to Epileptic Seizure Prediction. In Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, Shanghai, China, 1–5 September 2005; pp. 4510–4513.
24. Ghaderyan, P.; Abbasi, A.; Sedaaghi, M.H. An efficient seizure prediction method using KNN-based undersampling and linear frequency measures. *J. Neurosci. Methods* **2014**, *232*, 134–142. [CrossRef]
25. Ibrahim, S.W.; Djemal, R.; Alsuwailem, A.; Gannouni, S. Electroencephalography (EEG)-based epileptic seizure prediction using entropy and K-nearest neighbor (KNN). *Commun. Sci. Technol.* **2017**, *2*, 6–10. [CrossRef]
26. Savadkoohi, M.; Oladunni, T.; Thompson, L. A machine learning approach to epileptic seizure prediction using Electroencephalogram (EEG) Signal. *Biocybern. Biomed. Eng.* **2020**, *40*, 1328–1341. [CrossRef]
27. Wang, S.; Chaovalitwongse, W.A.; Wong, S. Online Seizure Prediction Using an Adaptive Learning Approach. *IEEE Trans. Knowl. Data Eng.* **2013**, *25*, 2854–2866. [CrossRef]
28. Bonev, B.; Escolano, F.; Cazorla, M. Feature selection, mutual information, and the classification of high-dimensional patterns. *Pattern Anal. Appl.* **2008**, *11*, 309–319. [CrossRef]
29. Al Ghayab, H.R.; Li, Y.; Siuly, S.; Abdulla, S. Epileptic EEG signal classification using optimum allocation based power spectral density estimation. *IET Signal Process.* **2018**, *12*, 738–747. [CrossRef]
30. Li, Y.; Wen, P. Classification of EEG Signals Using Sampling Techniques and Least Square Support Vector Machines. In Proceedings of the International Conference on Rough Sets and Knowledge Technology, Gold Coast, Australia, 14–16 July 2009; pp. 375–382.
31. Shiao, H.-T.; Cherkassky, V.; Lee, J.; Veber, B.; Patterson, E.E.; Brinkmann, B.; Worrell, G.A. SVM-Based System for Prediction of Epileptic Seizures From iEEG Signal. *IEEE Trans. Biomed. Eng.* **2017**, *64*, 1011–1022. [CrossRef] [PubMed]
32. Direito, B.; Teixeira, C.; Sales, F.; Castelo-Branco, M.; Dourado, A. A Realistic Seizure Prediction Study Based on Multiclass SVM. *Int. J. Neural Syst.* **2017**, *27*, 1750006. [CrossRef]
33. Henry, M.; Judge, G. Permutation Entropy and Information Recovery in Nonlinear Dynamic Economic Time Series. *Econometrics* **2019**, *7*, 10. [CrossRef]
34. Bandt, C.; Pompe, B. Permutation Entropy: A Natural Complexity Measure for Time Series. *Phys. Rev. Lett.* **2002**, *88*, 174102. [CrossRef] [PubMed]
35. Holland, J.H. Genetic Algorithms and the Optimal Allocation of Trials. *SIAM J. Comput.* **1973**, *2*, 88–105. [CrossRef]
36. Guo, G.; Wang, H.; Bell, D.; Bi, Y.; Greer, K. KNN Model-Based Approach in Classification. In *On the Move to Meaningful Internet Systems*; Springer: Berlin/Heidelberg, Germany, 2003; Volume 2888.
37. Shoeb, A.H. *Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment*; Massachusetts Institute of Technology: Cambridge, MA, USA, 2009.
38. Childhood Epilepsy: The Brain. Massachusetts General Hospital. Available online: https://www.massgeneral.org/children/epilepsy/education/the-brain (accessed on 10 October 2021).

3.3 Links and implications

The research confirmed that personalized epileptic EEG channel selection significantly increased the prediction rate by 29.93% and improved accuracy, sensitivity, and specificity by 10.58%, 23.57%, and 5.56%, respectively. In SVM classification of pre-ictal and inter-ictal, average accuracy, sensitivity, and specificity with selected channels were 74.60%, 69.51%, and 73.14%, compared to 67.46%, 56.25%, and 69.29% using all channels for predicting epileptic seizures in this study.

However, opting for channel selection in EEG analysis for seizure prediction comes with certain drawbacks. It can lead to limited spatial coverage, potentially overlooking crucial information from other brain regions. Moreover, the ideal channels for predicting seizures might vary depending on individual conditions. EEG patterns are dynamic, the most effective channels for prediction could change across different stages of epilepsy or the selected channels may be more prone to artifacts such as muscle activity or electrical interference. Furthermore, integrating patient-specific channel selection methods may introduce complexity to the model development process.

Therefore, the forthcoming research paper on seizure prediction will utilize a novel signal transformation instead of entropy transformation and implement 1D-CNN without the channel selection step to create a more simplified model.

CHAPTER 4: PAPER 2 – A NOVEL EPILEPTIC SEIZURE PREDICTION METHOD BASED ON SYNCHROEXTRACTING TRANSFORM AND 1-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK

4.1 Introduction

This paper, published in Computer Methods and Programs in Biomedicine (volume 240, page 107678), explores enhanced methodologies for epileptic seizure prediction using EEG signals. It introduces synchroextracting transformation (SET) and singular value decomposition (SET-SVD) to achieve higher-resolution decomposition of EEG signals, surpassing the limitations of the short-term Fourier transform (STFT). The study acknowledges the dynamic nature of EEG patterns and the need for patient-specific channel selection, despite its complexity. Overall, the findings demonstrate that SET-SVD offers a promising approach for more accurate epileptic seizure prediction, with the 1D-CNN model proving effective for fast and precise patient-specific EEG classification.

4.2 Published paper

Computer Methods and Programs in Biomedicine 240 (2023) 107678

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

A novel epileptic seizure prediction method based on synchroextracting transform and 1-dimensional convolutional neural network

Jee Sook Ra*, Tianning Li, YanLi

School of Mathematics, Physics and Computing, University of Southern Queensland, Toowoomba, QLD 4350, Australia

ARTICLE INFO

Article history:
Received 23 December 2022
Revised 7 June 2023
Accepted 12 June 2023

Keywords:
EEG analysis
Synchroextracting transform (SET)
Singular value decomposition (SVD)
1-dimensional convolutional neural network (1D-CNN)
Epileptic seizure prediction

ABSTRACT

Background and objective: Epilepsy is a serious brain disorder affecting more than 50 million people worldwide. If epileptic seizures can be predicted in advance, patients can take measures to avoid unfortunate consequences. Important approaches for epileptic seizure predictions are often signal transformation and classification using electroencephalography (EEG) signals. A time-frequency (TF) transformation, such as the short-term Fourier transform (STFT), has been widely used over many years but curtailed by the Heisenberg uncertainty principle. This research focuses on decomposing epileptic EEG signals with a higher resolution so that an epileptic seizure can be predicted accurately before its episodes.

Methods: This study applies a synchroextracting transformation (SET) and singular value decomposition (SET-SVD) to improve the time-frequency resolution. The SET is a more energy-concentrated TF representation than classical TF analysis methods.

Results: The pre-seizure classification method employing a 1-dimensional convolutional neural network (1D-CNN) reached an accuracy of 99.71% (the CHB-MIT database) and 100% (the Bonn University database). The experiments on the CHB-MIT show that the accuracy, sensitivity and specificity from the SET-SVD method, compared with the results of the STFT, are increased by 8.12%, 6.24% and 13.91%, respectively. In addition, a multi-layer perceptron (MLP) was also used as a classifier. Its experimental results also show that the SET-SVD generates a higher accuracy, sensitivity and specificity by 5.0%, 2.41% and 11.42% than the STFT, respectively.

Conclusions: The results of two classification methods (the MLP and 1D-CNN) show that the SET-SVD has the capacity to extract more accurate information than the STFT. The 1D-CNN model is suitable for a fast and accurate patient-specific EEG classification.

1. Introduction

Epilepsy is characterized by aberrant brain activity that results in seizures or episodes of abnormal behaviors, sensations, and occasionally loss of consciousness. If epileptic seizures can be predicted in advance, unfortunate consequences for the patient can be mitigated. One important area of seizure prediction research is feature extraction and classification based on electroencephalography (EEG) signals, which are various electrical activities measured across the scalp using small metal discs (electrodes). While some EEG-based seizure prediction algorithms are patient-independent, this study customizes experimental methods to individual patients' EEG signals (patient-dependent).

Signal processing is employed in many applications to provide underlying information on specific problems so that useful features can be extracted. There has been intensive research on the time domain, frequency domain and time-frequency domain for EEG signal analysis. Time domain analysis often is not sufficient for obtaining all useful information. Frequency domain analysis generates only spectral information about the signal but not the time-domain information at the same time. Therefore, EEG data in the time domain are often transformed into the time-frequency (TF) domain using various different methods, such as short-time Fourier transform (STFT) [1], wavelet analysis (WA) [2,3] or multiresolution Fourier transform (MFT) [4]. However, despite decades of development, the TF analysis method has been constrained by the Heisen-

* Corresponding author.
E-mail addresses: jee.ra@usq.edu.au (J.S. Ra), Tianning.Li@usq.edu.au (T. Li), Yan.Li@usq.edu.au (YanLi).

https://doi.org/10.1016/j.cmpb.2023.107678

Table 1
Overview of the reviewed articles.

Author	Methods	Dataset	Accuracy	Sensitivity	Specificity
Khalilpour et al. (2020) [16]	Raw EEG data, 1-D CNN	CHB-MIT [1]	97%	98.5%	98.5%
Prathaban & Balasubramanian (2021) [17]	Sparsity based EEG reconstruction, 3-D CNN	CHB-MIT, SRM [2], NINC [3]	98%	99%	90%
Wang et al. (2021) [18]	STFT, 3-D CNN	CHB-MIT	80.5%	85.8%	75.1%
Truong et al. (2017) [12]	STFT, 2-D CNN	CHB-MIT, Freiburg [4], KSPC [5]	NA	NA	81.4%
Chen and Parhi (2021) [13]	STFT, 2-D CNN	AESPC [6]	NA	NA	82%
Sun et al. (2021) [14]	STFT, Channel attention dual-input CNN	CHB-MIT	NA	97.1%	95.6%
Shahbazi and Aghajan [19]	STFT, 2-D CNN + LSTM	CHB-MIT	NA	98.2%	NA

[1] Children's Hospital Boston and the Massachusetts Institute of Technology Scalp EEG Dataset.
[2] Private SRM dataset.
[3] Neonatal EEG recordings with seizure annotations of Neonatal Intensive Care Unit acquired from Helsinki University Hospital.
[4] Freiburg iEEG dataset.
[5] Kaggle seizure prediction competition dataset.
[6] The American Epilepsy Society Prediction Challenge dataset.

berg uncertainty principle [5,6] or unanticipated cross-terms [7]. Since TF-based analysis methods use wide bandwidth in the TF domain, the energy of the generated TF representation smears heavily according to the Heisenberg uncertainty principle. In addition, when there are many components in the input signal, which is similar to frequency beats in time, a cross-term occurs. As a result, TF-based analysis methods experience a low TF resolution [5,8]. In recent years, many signal transformation methods were developed to overcome those issues, which are instrumental in decrypting patterns from epileptic EEG signals. One of them is synchroextracting transform (SET) [9], the novel TF analysis method which improves the energy concentration in the TF representation [9]. Meanwhile, one of the restraints of applying the SET is generating many sub-signals that can cause significant time consumption and computational cost or sometimes inhibit accurate classification performance due to many dimensions. After a SET decomposition, the singular value decomposition (SVD) is applied to minimize a large number of sub-signals without losing the crucial information in the SET preserves (SET-SVD). The last step of this study is the classification of the pre-ictal period and normal period using two types of neural networks (NNs), multi-layer perceptron (MLP) and 1-dimensional convolutional neural network (1D-CNN), to compare with the performances of the SET and STFT resolutions. A convolutional neural network (CNN) is a common term used to describe a 2-dimensional CNN (2D-CNN) used for image classification and signal processing, given that the kernel moves along the data in two dimensions. In many situations, however, a 2D-CNN may not be feasible for 1-dimensional signals (such as time series signals), particularly if the training data are limited or time-corresponding. In this study, a 1D-CNN is used to reduce processing time and accomplish more effective classification, and the outcomes are compared to those of a multi-layer perceptron (MLP). The following is a summary of the major contributions of this study:

- With the proposed method, pre-ictal signals in epileptic EEG signals can be accurately detected.
- The proposed method reduces the classification computational time. Real-time seizure prediction can, therefore, be enabled.
- A better signal transformation method can be discovered by contrasting different signal transformation methods with the same classification algorithms. Nevertheless, this procedure takes a considerable amount of time and effort, and this study can be used as a benchmark reference for different types of signal analysis.

The remainder of this paper is arranged as follows. In Section 2, related works are discussed. Section 3 presents the details of the datasets used in this paper, data preprocessing, the proposed techniques for signal transformation (SET, STFT and SVD) and classification (MLP and 1D-CNN). Section 4 explains the experimental setups and results. Section 5 discusses the findings of this research. Finally, the conclusions of this study are drawn in Section 6.

2. Related works

The STFT has been widely used for EEG signal analyses as it is simple and adaptive to be implemented [10]. For example, Gorur et al. (2002) achieved an accuracy of 88.7% by applying a STFT and neural network (NN) method for the sleep spindles detection [11]. Some research applying the STFT for seizure prediction, especially using a CNN, has shown desirable results. Truong et al. (2017) applied a STFT with a CNN for seizure prediction [12] and reached a sensitivity of 81.4%. Chen and Parhi (2021) also used a STFT and a CNN and achieved an overall sensitivity of 82% [13]. A STFT with a channel attention dual-input CNN showed a better sensitivity of 95.6% [14]. On the other hand, so far, no study has applied the SET for seizure prediction yet. Kiranyaz et al. (2015) developed the first adaptable 1-dimensional CNN (1D-CNN) model for a fast and accurate patient-specific electrocardiogram (ECG) classification, and achieved 99% of accuracy [15]. Khalilpour et al. (2020) used a seven-layer 1D-CNN to detect pre-ictal and normal periods in the brain signals, where the performance was evaluated in terms of accuracy, specificity, and sensitivity which resulted in 97%, 98.47%, and 98.5%, respectively. Table 1 summarizes the reviewed articles that employed CNNs or STFT for the prediction of epileptic seizures (detection of pre-ictal signals).

3. Methodology

This study aims to find an excellent accurate epileptic seizure prediction method. Comparison is a way to justify that our method is optimum. As a result, this comparison may help establish a less complex seizure prediction system with a higher resolution of EEG signal transformation. In this research, the raw EEG signals without noise removal are converted using the SET and STFT respectively, and the dimensionality of the results obtained by the SET is reduced by a SVD. The decomposed and chosen values of the signals are then classified using two types of neural networks, the MLP and 1D-CNN, and their classification performances are then compared. The fundamental procedure of the proposed method is illustrated in Fig. 1.

3.1. Experimental data

Long-term annotated data are required for the development of seizure prediction algorithms. Hospitals and research institutions have created open-access databases, and two well-known epilepsy datasets (the Bonn University (Bonn) database and the Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) scalp EEG database) are accessible online. This study evaluates the

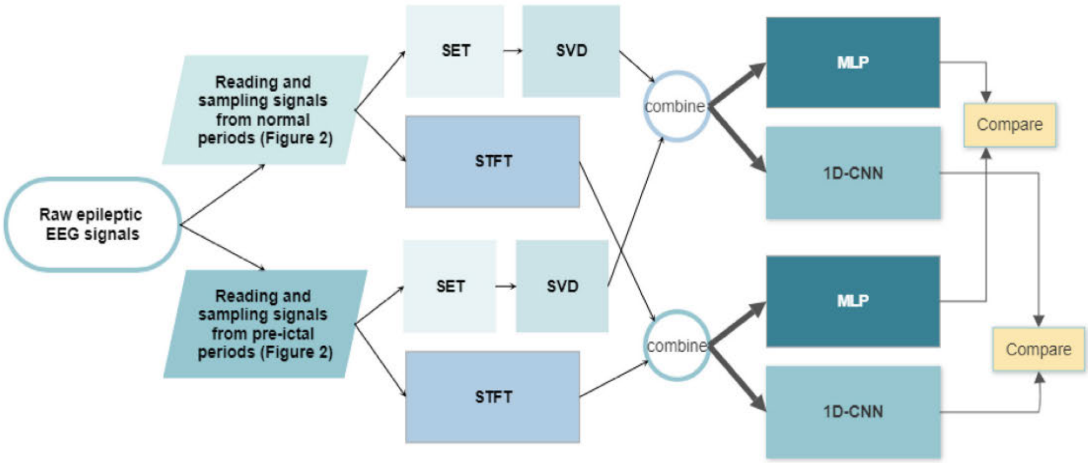


Fig. 1. The main processing diagram of the proposed methodology.

Table 2
The characteristics of each patient and the patient's information data used in this paper [20].

Recording number	Patient ID	Gender	Age	Number of seizures	Length of records (Hours)
chb01	1-1	F	11	7	45.00
chb02	2	M	11	3	39.57
chb03	3	F	14	7	57.87
chb04	4	M	22	4	154.41
chb05	5	F	7	5	38.09
chb06	6	F	1.5	10	89.25
chb07	7	F	14.5	3	67.23
chb08	8	M	3.5	5	26.38
chb09	9	F	10	4	65.92
chb10	10	M	3	7	72.49
chb11	11	F	12	3	73.30
chb12	12	F	2	40	NA[1]
chb14	14	F	9	8	41.50
chb15	15	M	16	20	62.29
chb16	16	F	7	10	17.03
chb17	17	F	12	3	34.11
chb18	18	F	18	6	62.85
chb19	19	F	19	3	61.58
chb20	20	F	6	8	41.43
chb21	1-2	F	13	4	55.71
chb22	21	F	9	3	75.93
chb23	22	F	6	7	70.90

[1] Not available. Not specified.

proposed method on the two publicly available databases (Bonn and CHB-MIT). The information about the two databases is provided below.

3.1.1. CHB-MIT database

EEG recordings of pediatric patients with uncontrollable seizures are available in the CHB-MIT database [16]. Twenty-four recordings were collected from 23 patients (5 males (ages 3–22) and 17 females (ages 1.5–19); information for Patient ID 23 is not specified). Recordings chb01 (Patient ID 1-1) and chb01 (Patient ID 1-2) were obtained from the same female patient. A single recording is represented by nine to forty-two continuous *.edf* files (chb01, chb02, or others). Patients were monitored for up to several days after stopping anti-seizure medication in order to describe their epileptic seizures and determine whether they were a good candidate for surgery. In this study, 22 out of 24 recordings are analyzed. Two recordings (chb13 and chb24) are excluded from this study because they are unsuitable for experimentation due to frequent channel changes during the EEG recording; Table 2 provides information about 22 recordings.

3.1.2. Bonn database

This EEG database is publicly available and provided by the University of Bonn as acquired by Andrzejak et al. [21]. It consists of five datasets: A, B, C, D, and E. Each dataset consists of 100 single-channel EEG files with a duration of 23.6 seconds and a total of 4097 samples as shown in Table 3. 12-bit analogue-to-digital converters sampling at 173.61 Hz were used. The EEG database consists of 5 classes x 100 files x 4097 data points (23.6 seconds).

3.2. Epileptic EEG data pre-processing

Four stages are commonly used to categorize epileptic EEG signals: normal, pre-ictal, ictal, and post-ictal periods (Fig. 2). To avoid a relatively high ratio of normal period data in the classification, the normal to pre-ictal training/testing data ratio is capped at 10:1 [20]. One issue with seizure prediction studies is how to select

Table 3
The descriptions of each dataset in the Bonn University database [21].

Dataset	File name	Subject details	Description	Number of files (duration in seconds)
A	Z001.txt to Z100.txt	Five healthy subjects (normal)	Surface EEG recordings with eyes open	100 (23.6)
B	O001.txt to O100.txt		Surface EEG recordings with eyes closed	100 (23.6)
C	N001.txt to N100.txt	Five epilepsy patients	EEG readings of hippocampal formation in the hemisphere opposite the epileptogenic zone. Recorded during seizure-free periods.	100 (23.6)
D	F001.txt to F100.txt		EEG recordings of the epileptogenic zone. Recorded during seizure-free periods.	100 (23.6)
E	S001.txt to S100.txt		EEG recordings of epileptic seizure activity from the hippocampal focus.	100 (23.6)

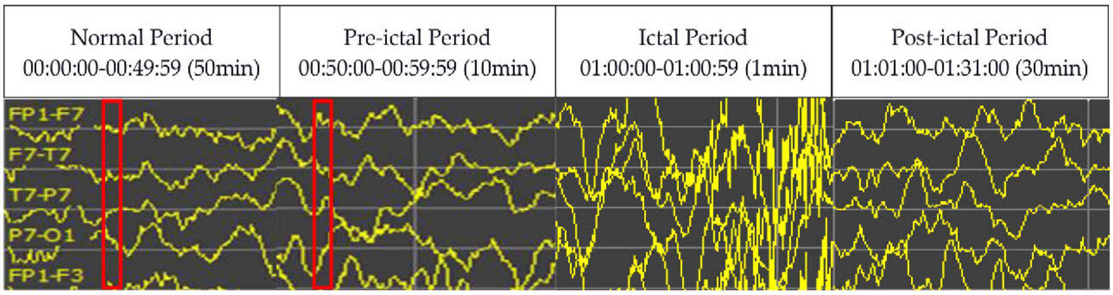


Fig. 2. An example of EEG signals sampling (Patient ID 1-1, channels of FP1-F7, F7-T7, T7-P7 and P7-O1). The red windows are the sampling signals (2.8 seconds of length in normal and pre-ictal periods). Yellow lines/waves over time show the activity from the EEG signals at the normal period (50 min), pre-ictal (10 min before the ictal period starts), ictal (1 min) and post-ictal (30 min after the ictal period) periods. The patient was an 11-year-old female. The recording rate is 256 Hz. The vertical scale is 50 μV.

pre-ictal EEG signal recording segments. The time between a prognostic symptom of a seizure and the start of a seizure is defined as the seizure prediction horizon (SPH), which has been reported to be between a few minutes and several hours. For both training and testing datasets, the SPH in this study is set at 10 minutes (2.8 seconds in duration). Therefore, pre-ictal samples are collected 10 minutes before seizure onsets. Data samples for a normal period (in 2.8-second duration and one-hour interval) are randomly selected in between pre-ictal and post-ictal periods (30 min after a seizure) (Fig. 2).

However, the SPH cannot be applied to the Bonn database because its ictal (dataset E) and non-ictal (dataset A-D) recordings are separated. Regarding the EEG signals from any specific area on the scalp, all electrode channels attached to the scalp are equally weighted, and EEG signals from all channels are evenly used.

3.3. Short time Fourier transformation (STFT)

STFTs are widely used for denoising time-dependent signals. The Fourier transform (FT) of function $f(x)$ is function $F(\omega)$, where:

$$F(\omega) = \int_{\infty}^{-\infty} f(x)e^{-i\omega t}dx \tag{1}$$

$$f(x) = 2\pi \int_{\infty}^{-\infty} F(\omega)e^{-i\omega t}d\omega \tag{2}$$

The fast Fourier transform (FFT) is a fast algorithm for computing the discrete FT. The FFT is a method for converting a signal's information into its frequency information where the time information cannot be recovered after the transformation. The STFT of a signal consists of the FFT of crossing windowed blocks of the signal (Fig. 3). The STFT, however, provides both information in a time-frequency domain as shown in Fig. 3. This study sets the window length as the FFT length, which is 10, and the overlap length is 5.

3.4. Synchroextracting transform (SET)

For a complex signal $s(t)$, which is the sum of n non-stationary modes, its expression is as follows [9]:

$$s(t) = \sum_{k=1}^{n} s_k(t) = \sum_{k=1}^{n} A(t)e^{i\varphi_k(t)} \tag{3}$$

where $\varphi'_{k+1}(t)$ - $\varphi'_k(t) > 2\Delta$, s_k, A_k, φ_k, denote the k_{th} mode, the corresponding instantaneous amplitude, and instantaneous phase, respectively. $\varphi_k{}'$ is the first-order derivative of φ_k and denotes instantaneous frequency; Δ is the frequency support of a window function. The STFT representation of $Ge(t, \omega)$ for the original signal $s(t)$, which forms the foundation of the SET, is displayed in the following form [9]:

$$Ge\ (t,\ \omega) = \sum_{k=1}^{n} A_k(t)\hat{g}\left(\omega - \varphi'_k(t)\right)e^{i\varphi_k(t)} \tag{4}$$

where $\hat{g}$ denotes the Fourier transform of the window function g, $g \in L_2(R)$. According to Eq. (4), the instantaneous frequency can be calculated by

$$\varphi'(t,\ \omega) = \sum_{k=1}^{n} \varphi' k(t,\ \omega) = -i\frac{\sigma_t G_e(t,\ \omega)}{G_e(t,\ \omega)} \tag{5}$$

Yu et al. (2017) developed an operator to only retain the time-frequency information from the STFT representation that is most related to the time-frequency characteristics of the target signal, which may remove the irrelevant interference and smeared time-frequency energy. The formula for the SET [9] is:

$$T_e(t,\ \omega) = G_e(t,\ \omega)\delta\left(\omega - \varphi'(t,\ \omega)\right) \tag{6}$$

where

$$\delta\left(\omega - \varphi'(t,\omega)\right) = \begin{cases} 1, & \omega = \varphi'(t,\omega) \\ 0, & else \end{cases} \tag{7}$$

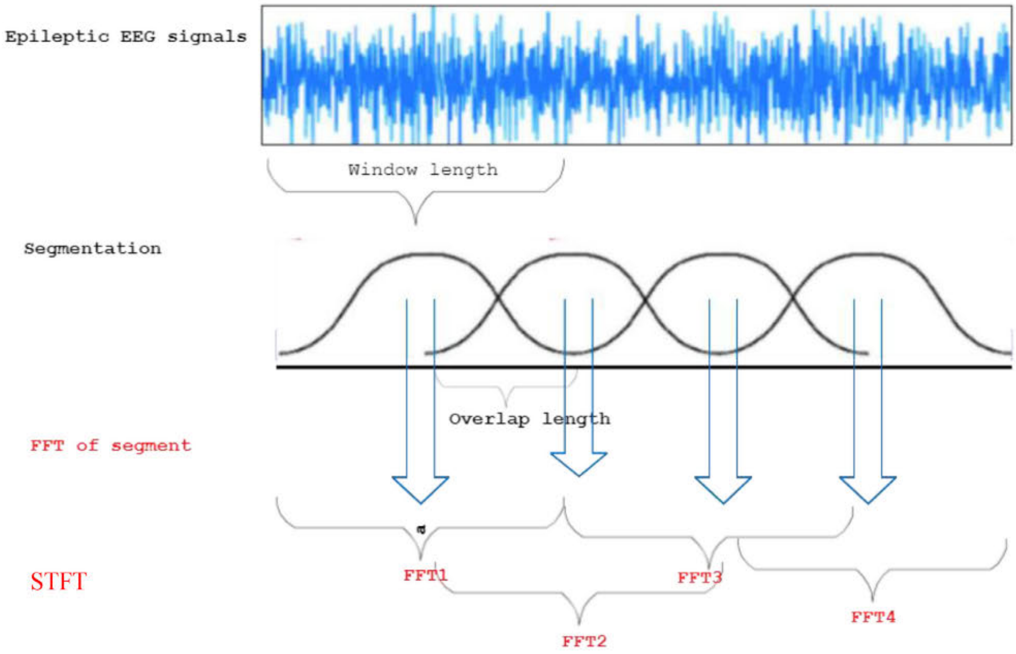


Fig. 3. The STFT of a signal consists of the FFT of crossing windowed blocks of the signal.

which is the synchroextracting operator (SEO). According to Eqs. (5) and (6), $Te(t, \omega)$ in SET can be deduced through Eq. (7) [9]:

$$Te(t,\omega)\big|_{\omega-\sum_{k=1}^{n}\varphi'_k(t)=0} = Ge(t,\ \omega)\big|_{\omega-\sum_{k=1}^{n}\varphi'_k(t)=0} \approx \sum_{k=1}^{n} A_k(t)\hat{g}(0)e^{i\varphi_k(t)} \tag{8}$$

In this way, a sharper time-frequency representation than the STFT can be obtained, and instantaneous frequency (IF) with a highly precise degree can be extracted.

3.5. Singular value decomposition of synchroextracting transform

The singular value decomposition (SVD) was developed by Eugenio Beltrami and Camille Jordan in 1873. An SVD is a matrix factorization into three matrices. It has intriguing algebraic properties and transmits essential geometrical and theoretical insights regarding linear transformations [22]. An SVD of an $\boldsymbol{M} \times \boldsymbol{N}$ matrix $\boldsymbol{X}$, representing the SET values (Section 3.4) of the EEG signals is given by

$$X = USV^T \tag{9}$$

where $\boldsymbol{U(M \times M)}$ and $\boldsymbol{V(N \times N)}$ are orthonormal matrices, and $\boldsymbol{S}$ is an $\boldsymbol{M} \times \boldsymbol{N}$ diagonal matrix of singular values ($\sigma_{ij} = 0$ if $i \neq j$ and $\sigma_{11} \geq \sigma_{22} \geq \cdots \geq 0$). The columns of the orthonormal matrices $\boldsymbol{U}$ and $\boldsymbol{V}$ are called the left and right singular vectors, respectively. An important property of $\boldsymbol{U}$ and $\boldsymbol{V}$ is that they are orthogonal to one another. The singular values (σ_{ii}) represent the significance of singular vectors in the matrix's composition. In other words, singular vectors corresponding to larger singular values contain more information than other singular vectors regarding the content of patterns embedded in the matrix. In this study, 10 singular values (SET-SVD) are selected and employed.

3.6. Neural networks-based classification

Neural networks (NNs) process information using a mathematical or computational model, which is a network of simple processing elements capable of complex overall performance, as determined by the connections between processing elements and element parameters. This study applies two types of NNs, a multi-layer perceptron (MLP) and a convolutional neural network (CNN) to classify normal and pre-ictal stages of the STFT (Section 3.3) or SET-SVD (Section 3.5) of epileptic EEG signals.

3.6.1. Multi-layer perceptron (MLP)

The MLP, in this research, is learned using the backpropagation algorithm, where the errors of the hidden layer units are determined by back-propagating the errors of the output layer units. Its network consists of an input layer, a hidden layer, and an output layer. The activation function of the hidden layer is the sigmoid function, and its equation is given below.

$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1} \tag{10}$$

Each connection between a node in the hidden layer and a node in the input layer has a weight. The backpropagation technique repeatedly modifies the weights of the links in the network to reduce the difference between the expected output vector of the network and the predicted output vector [23]. Each layer has a cost function, which is designated as follows and has its own least minimum error value:

$$C = cost\ (s,\ y) \tag{11}$$

where s is a predicted output value and y is an expected output value. The following describes the backpropagation algorithm to minimize the cost function:

1. The initial values of weight (w) and bias (b) are randomly chosen.
2. w and b are matrix representations of the weights and biases. Derivative of C in w or b can be calculated using partial derivatives of C in the individual weights or biases.
3. The termination condition is met once C is minimized to a threshold.

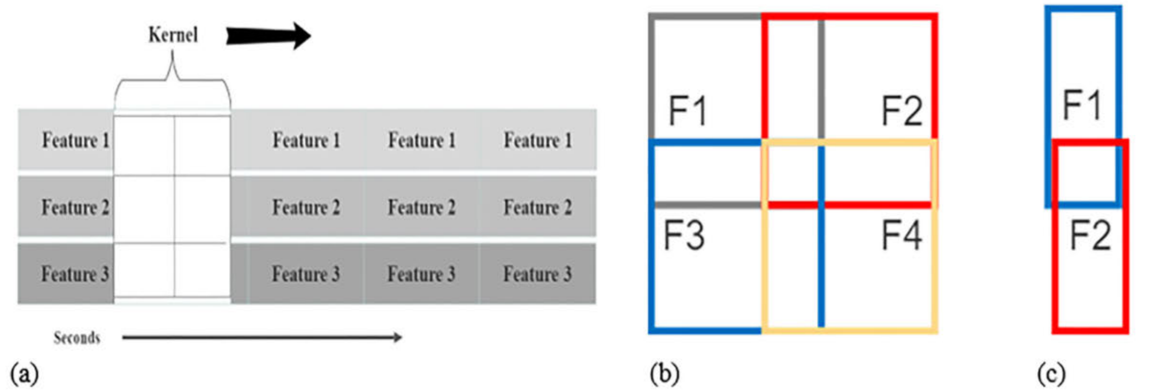


Fig. 4. (a) and (c) In 1D-CNN, the convolutional layer's kernel slides along one dimension; (b) In 2D-CNN, the convolutional layer's kernel moves along two dimensions.

Table 4
1D-CNN Structure Information.

1D-CNN Model structure layer	Kernel size	Activator	Output shape	Number of parameters
Convolutional 1D	2	ReLu	229×64	192
Dense	-	ReLu	229×16	1040
Max Pooling 1D	2		114×16	0
Flatten	-		1824	0
Dense	-	softmax	3	5475

Table 5
The confusion matrix of the classification performance of pre-ictal/normal period signals.

	True pre-ictal period	True normal period
Predicted pre-ictal period	A	B
Predicted normal period	C	D

Accuracy = (A + D) / (A + B + C + D).
Sensitivity = A / (A + C).
Specificity = D / (B + D).

3.6.2. 1-dimensional convolutional neural networks (1D-CNNs)

CNNs are a subclass of neural networks, which have at least one convolutional layer. Like MLPs, CNNs consist of an input layer and an output layer, and hidden layers. The main benefit of employing a CNN is that it can use its kernel to retrieve spatial information from the data. In 1D-CNN, the kernel slides along one dimension instead of two dimensions as shown in Fig. 4.

In this research, the first step of the 1D-CNN model is to rearrange the input data by creating one-dimensional vectors from each row of the input data. The input data dimension, 1430×230, is composed of 1430 steps with 230 features per step. And then, one convolutional layer, two dense layers, one max-pooling 1D layer and one flattened layer are added into the model structure. The convolutional layer consists of kernels that slide through the 1-dimensional data. The pooling layer (max-pooling layer in this study) is used to decrease the size of the convolutional layer outputs. This step involves sliding a window to take the maximum values in each window. The rectified linear unit activation function (ReLu) is used in the dense layer which is also called a fully connected layer. A summary of the proposed 1D-CNN model structure information is listed in Table 4. Kernel and max-pooling have a size of 2 and are used to decrease the size of neurons to 114×16.

4. Experimental results

The EEG signals are successfully decomposed by the SET-SVD and STFT, and they are classified into two groups of data, pre-ictal period and normal period. The scalograms illustrate that the SET method can generate more energy-concentrated TF results than the STFT (Fig. 5).

The efficiency of a seizure prediction algorithm (detecting pre-ictal signals) is determined by the accuracy, sensitivity, and specificity. Sensitivity is the percentage of the true pre-ictal prediction, and specificity is the percentage of the true normal period prediction (Table 5).

4.1. The CHB-MIT database

Table 6 presents the performance of the STFT and SET-SVD based on the MLP, and 1D-CNN classification tested using the 22 recordings in the CHB-MIT Scalp EEG Database. 720 datapoints (2.8 seconds of duration) are selected from each file. However, some files are excluded because interictal signals should be at least one hour ahead or after ictal signals. In addition, pre-ictal signals should be between suitable interictal signals. As the result, the total number of the data points is 5464800. 70% of the data are randomly selected for training (3825360 samples) and the remaining 30% are used for testing (1639440 samples). Fig. 6 illustrates the accuracy, specificity, and sensitivity of the related articles for comparisons.

In the MLP classification, the average accuracy by the SET-SVD is 94.73%, and that of STFT is 89.73%. The sensitivity and specificity of the MLP with the SET-SVD are higher (average 96.85% and 88.51%, respectively) than those with STFT (average 94.44% and 77.09%, respectively). The accuracy, sensitivity and specificity of the SET-SVD are improved by 5.0%, 2.41% and 11.42%, respectively. The average false positive rates (FPR) by the SET-SVD and STFT are 10.59% and 22.21%, respectively (average FPR = 1 – average specificity).

Based on the 1D-CNN, the average accuracy by the SET-SVD is 99.71%, and that of STFT is 91.59%. The sensitivity and specificity obtained by the 1D-CNN with the SET-SVD also show a higher rate (average 99.75 % and 99.56 %, respectively) than those with the STFT (average 93.51% and 85.65%, respectively). On average, the accuracy, sensitivity and specificity by the SET-SVD are increased by 8.12%, 6.24% and 13.91%, respectively. The average FPR by the SET-SVD and STFT are 0.44% and 14.35%, respectively.

Fig. 6 shows the comparison of the classification results by the proposed method and the methods from the reviewed studies that also applied the STFT and CNN to the CHB-MIT database. The p-values also confirm that the classification performances using the SET-SVD are significantly higher than those using the STFT (at $p < 0.05$) (Table 6).

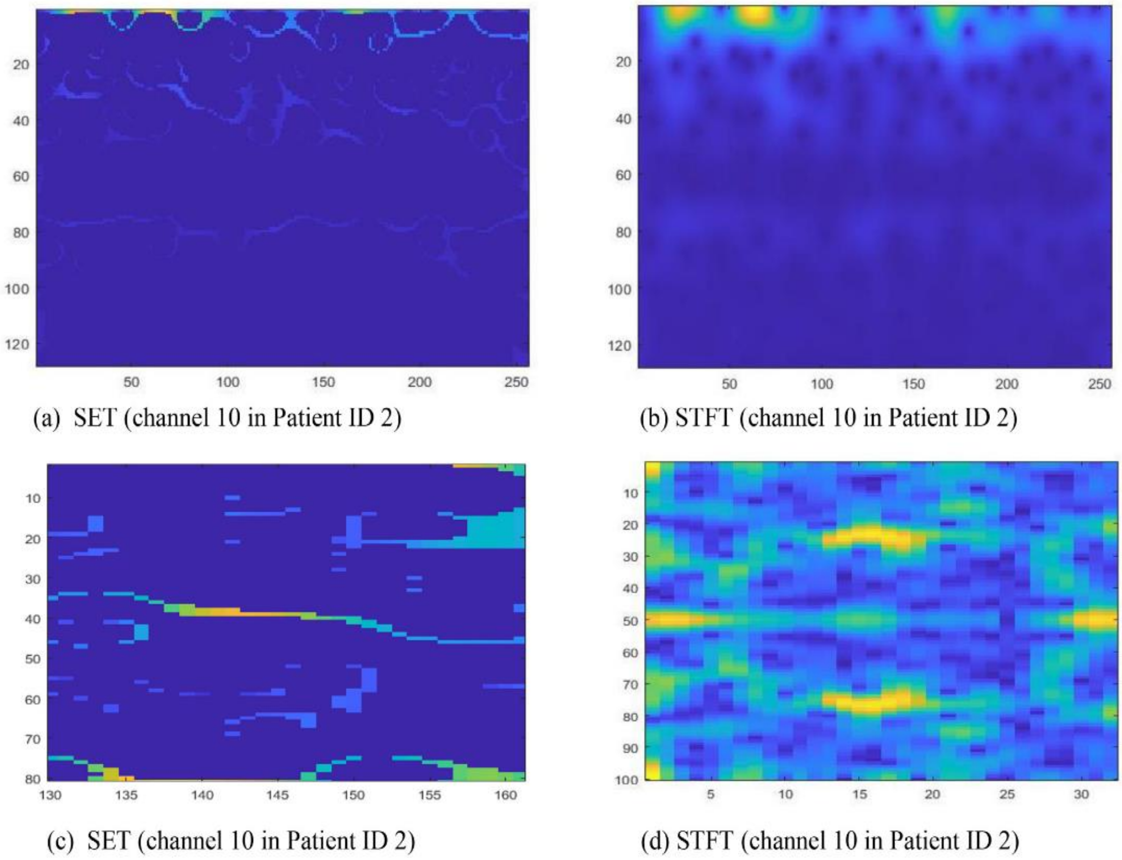


Fig. 5. Scalograms of the SET (a), (c) and STFT (b), (d) transform results. x-axis: time (1/256 seconds), y-axis: frequency (Hz). (c) and (d) are enlarged by zooming in of one sector of (a) and (b).

Table 6
The performance of the SET-SVD and STFT based on the MLP, and 1D-CNN classification tested on 22 recordings.

Patient ID	MLP						1D-CNN					
	Accuracy (%)		Sensitivity (%)		Specificity (%)		Accuracy (%)		Sensitivity (%)		Specificity (%)	
	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT
1-1	93.84	93.99	87.47	96.98	91.17	87.35	100	98.9	100	99.08	100	98.54
2	99.59	96.89	99.87	97.19	98.62	95.45	100	98.71	100	99	100	97.7
3	98.36	89.19	99.26	95.26	93.94	70.04	99.83	92.9	99.84	95	99.76	86.16
4	97.01	83.87	98.95	99.77	91.07	28.8	99.75	99.1	99.77	100	99.67	95.76
5	93.5	88.83	97.8	92.17	76.77	72.41	99.85	88.93	99.84	92.01	99.89	68.15
6	97.11	86.99	96.94	93.67	97.35	77.67	99.69	89.32	99.74	90.97	99.62	87.22
7	91.99	89.78	95.22	89.38	89.91	91.2	99.61	88.89	99.63	93.06	99.54	76.43
8	98.05	96.34	98.76	96.83	96.79	95.52	99.8	98.34	99.95	98.25	99.55	98.51
9	97.78	91.45	99.15	99.81	94.89	52.63	99.66	96.27	99.81	97.4	99.01	90.48
10	89.74	84.2	97.18	94.81	75.56	64.58	99.87	82.41	99.88	85.61	99.85	75.51
11	98.26	90.68	99.35	94.17	93.06	73.26	99.65	89.71	99.77	93.01	99.08	73.26
12	98.52	96.5	99.39	97.17	97.21	95.6	99.63	97.2	99.54	96.62	99.77	97.92
14	95.93	81.8	86.93	95.28	95.28	71.01	99.75	79.81	99.72	86.67	99.81	65.55
15	89.41	76.36	95.26	86.39	86.39	45.04	99.38	84.63	99.47	89.06	99.26	77.69
16	94.62	77.06	82.83	87.33	87.33	62.96	99.57	77.60	99.65	82.85	99.39	65.55
17	94.33	94.37	98.17	81.79	81.79	83.46	99.46	95.15	99.74	95	98.61	95.65
18	92.77	94.04	95.96	84.58	84.58	87.64	99.72	91.98	99.83	93.32	99.33	86.79
19	96.62	99.04	98.84	88.16	88.16	100	99.89	100	99.87	100	100	100
20	92.98	94.73	93.37	84.05	84.05	100	100	98.89	100	100	100	96.14
1-2	87.3	85.28	93.55	80.25	80.25	60.92	99.58	83.55	99.57	88.45	99.59	69.32
21	96.49	94.56	94.24	87.04	87.04	95.49	99.73	95.53	99.79	97.06	99.53	91.49
22	96.11	88.11	91.39	95.72	95.72	85	99.17	87.18	99.18	84.86	99.15	89.57
Mean	**95.01**	**89.73**	**96.85**	**94.44**	**89.41**	**77.09**	**99.71**	**91.59**	**99.75**	**93.51**	**99.56**	**85.65**
standard deviation	**3.30**	**6.30**	**4.64**	**5.90**	**6.81**	**19.06**	**0.20**	**6.26**	**0.19**	**4.92**	**0.38**	**11.37**
standard error	**0.70**	**1.35**	**0.99**	**1.26**	**1.45**	**4.06**	**0.04**	**1.37**	**0.04**	**1.07**	**0.08**	**2.48**
p-value	**0.00**		**0.02**		**0.01**		**0.00**		**0.00**		**0.00**	

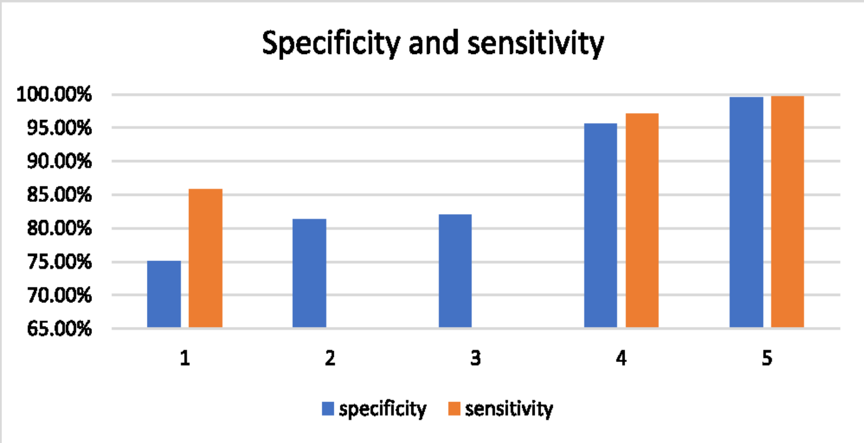


Fig. 6. Specificity and sensitivity of the related studies that applied the STFT and CNN with the CHB-MIT database. 1. Wang et al. (2021); 2. Truong et al. (2017); 3. Chen and Parhi (2021); 4. Sun et al. (2021); 5. The proposed method.

Table 7
The performance of the SET-SVD and STFT based on the MLP, and 1D-CNN classification tested using the Bonn University database.

	MLP						1D-CNN					
	Accuracy (%)		Sensitivity (%)		Specificity (%)		Accuracy (%)		Sensitivity (%)		Specificity (%)	
	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT	SET-SVD	STFT
A:B	100	98.70	100	97.37	100	100	100	98.45	100	98.23	100	98.62
A:C	100	99.57	100	99.12	100	100	100	100	100	100	100	100
A:D	100	98.26	100	96.49	100	100	99.78	99.22	100	100	99.57	98.59
B:C	100	99.13	100	100	100	98.28	100	99.61	100	99.15	100	100
B:D	100	99.78	100	100	100	99.57	100	100	100	100	100	100
AB:C	100	97.68	100	98.70	100	97.18	100	99.74	100	100	100	99.19
AB:D	100	99.42	100	99.13	100	99.57	100	100	100	100	100	100
C:D	100	99.35	100	99.12	100	99.57	100	98.84	100	100	100	97.67
Mean	**100**	**98.99**	**100**	**98.74**	**100**	**99.27**	**99.97**	**99.48**	**100**	**99.67**	**99.95**	**99.26**
standard deviation	**0.00**	**0.72**	**0.00**	**1.23**	**0.00**	**1.02**	**0.08**	**0.60**	**0.00**	**0.65**	**0.15**	**0.89**
standard error	**0.00**	**0.27**	**0.00**	**0.46**	**0.00**	**0.38**	**0.03**	**0.22**	**0.00**	**0.25**	**0.06**	**0.34**

In addition, the standard deviations (SDs) of both results from the 1D-CNN and MLP using the SET-SVD are meaningfully lower than those using the STFT. With the 1D-CNN, the SDs of accuracy, sensitivity and specificity from the results by the SET-SVD are lower by 6.06, 4.73 and 10.99 compared to those by the STFT, respectively, while with the MLP, they are lower by 3.00, 1.26 and 12.25, respectively).

4.2. The Bonn University database

The performances of the STFT and SET-SVD based on the MLP, and 1D-CNN classification tested on the Bonn EEG Database are presented in Table 7. 720 data points (4.15 seconds of duration) from each of 23 files per dataset (A, B, C or D) are analyzed. The total number of data points is 82800: Randomly selected, 70% of the data (57960 samples) were used for training, while the remaining 30% (24840 samples) were used for testing.

The classification outcomes for the SET-SVD sets exhibit nearly 100% accuracy, sensitivity, and specificity (99.95 – 100%). For classifying the STFT sets, the 1D-CNN (accuracy: 99.48%, sensitivity: 99.67%, specificity: 99.26%) is marginally superior to the MLP (accuracy: 98.99%, sensitivity: 98.74%, specificity: 99.27%). The SPH is not applicable to the Bonn database, but the accuracy performance obtained from various combinatory experiments suggests that the proposed method can predict seizures.

5. Discussion

There has been a paradoxical problem reported in signal analysis using the STFT. A longer window length results in a better frequency resolution but with a worse time resolution, while a shorter window length results in a better time resolution but would have a worse frequency resolution [24–28]. To improve the TF resolution as high as possible, one of the advanced post-processing methods, the SET, is successfully applied to the raw EEG signals, and it extracts useful information to predict the epileptic pre-seizure status. To the best of our knowledge, the SET has never been applied to analyze EEG signals for the prediction of pre-seizure status previously.

The SET represents only the TF information related to signal time-varying features [9]. It is clearer and more concentrated than the STFT (Fig. 5). Followed by the SVD, the SET can effectively describe the time-frequency characteristics of epileptic EEG signals. The experiments on the Bonn University database show that both the 1D-CNN and MLP can discriminate the SET-SVD sets with almost a zero-standard error. Tested on the CHB-MIT database, the average accuracy, sensitivity, and specificity by the 1D-CNN classification with the SET-SVD are 99.71%, 99.75% and 99.56%, respectively, which are 8.12%, 6.24% and 13.91% higher than the results by the STFT. Another classification method in this study, the MLP, also shows that the results by the SET-SVD are higher by 5.0%, 2.41% and 11.42% than those by the STFT in accuracy, sensitivity and specificity, respectively.

In addition, the SET shows more reliable test results than the STFT in this research. A high SD means that there is a large variance between the data and the mean. The SDs from the 1D-CNN results using the SET-SVD are lower than those by using the STFT (Table 6). The SDs of results from the MLP also confirm lower SDs from the SET-SVD, which indicates that the STFT is not as reliable as the SET-SVD. Da Silva et al. [29] showed that the STFT generates more significant data variability, resulting in less accurate classification performance than wavelet transform (WT) based methods. Oliveira et al. [30] also supported this conclusion using the results of variance, indicating less accuracy in terms of variability in data obtained from the analysis by the STFT. The STFT shows a large dispersion of individual values within the temporal window of processing and over time (successive windows), and consequently would result in larger measurement errors in dynamic situations, as suggested by Karlsson et al. [31].

This research also aims to reduce computational time for real-time seizure prediction while maintaining high accuracy in feature extraction and classification processes. EEG signals can be transformed from a wireless and/or portable EEG monitor to the necessary peripherals for acquisition alarms without sacrificing critical time [32]. The proposed 1D-CNN model is compact and has only one convolutional layer, which can reduce the processing time immensely. Recent studies [33–36] showed that the majority of 1D-CNN applications have employed a shallow structure that has one or two CNN layers and the number of parameters is less than 10000 (6707 in this research as shown in Table 4), while nearly all 2D-CNN applications have used architectures with more than one million parameters. Consequently, a 1D-CNN has a lower computational complexity than a 2D-CNN, and the testing time takes less than one second in this research.

6. Conclusion

In this research, the training and testing processing in the classification are patient-specific as the patterns of epileptic seizure occurrences are patient-dependent [20]. The experiments on two epileptic EEG databases (the Bonn and CHB-MIT) show that the SET-SVD has the capacity to extract more accurate information than the STFT. Especially, the SET-SVD with 1D-CNN can provide almost 100% of accuracy, sensitivity and specificity for predicting seizure status in both databases.

The performances by the STFT have a larger SD than those of the SET-SVD, which means that the STFT is less reliable. Using the STFT with the 1D-CNN, the specificity for Patient ID 5 in the CHB-MIT database is 68.15%, while the specificity for the same Patient ID by the SET-SVD with 1D-CNN achieved 99.89%. This type of weakness for the STFT is also found in other studies [29–31].

The effectiveness of the 1D-CNN in this research is promising. Compared with the MLP, the computational speed is much faster (more than 1000 times) and the accuracy is more than 10% higher. Although the experiments using a 2D or 3D-CNN were not conducted in this study, it was concluded from the literature review that the 1D-CNN would be faster (100 times lesser number of parameters) and more accurate (1-10%) than the 2D or 3D-CNN.

Declaration of Competing Interest

No conflict of interest is involved in this research.

Funding

This research received no external funding.

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.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).

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.

References

[1] J. Allen, Short term spectral analysis, synthesis, and modification by discrete Fourier transform, IEEE Transactions on Acoustics, Speech, and Signal Processing 25 (3) (1977) 235–238.

[2] P. Kumar, E. Foufoula-Georgiou, Wavelet analysis for geophysical applications, Reviews of geophysics 35 (4) (1997) 385–412.

[3] M. Qatmh, et al., Detection of epileptic seizure using discrete wavelet transform on gamma band and artificial neural network, in: 2021 14th International Conference on Developments in eSystems Engineering (DeSE), IEEE, 2021.

[4] R. Wilson, A.D. Calway, E.R. Pearson, A generalized wavelet transform for Fourier analysis: the multiresolution Fourier transform and its application to image and audio signal analysis, IEEE Transactions on Information Theory 38 (2) (1992) 674–690.

[5] P.J. Loughlin, J.W. Pitton, L.E. Atlas, Proper time-frequency energy distributions and the Heisenberg uncertainty principle, in: [1992]Proceedings of the IEEE-SP International Symposium on Time-Frequency and Time-Scale Analysis, IEEE, 1992.

[6] P. Busch, T. Heinonen, P. Lahti, Heisenberg's uncertainty principle, Physics Reports 452 (6) (2007) 155–176.

[7] E.P. Wigner, On the quantum correction for thermodynamic equilibrium, Physics Review 40 (1932) 749–759.

[8] P. Laplante, ACM SIGSOFT Software Engineering Notes, Heisenberg uncertainty 15 (5) (1990) 21–22.

[9] G. Yu, M. Yu, C. Xu, IEEE Transactions on Industrial Electronics, Synchroextracting transform 64 (10) (2017) 8042–8054.

[10] E. Sejdić, I. Djurović, J. Jiang, Time–frequency feature representation using energy concentration: An overview of recent advances, Digital signal processing 19 (1) (2009) 153–183.

[11] D. Gorur, et al., Sleep spindles detection using short time Fourier transform and neural networks, in: Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No. 02CH37290), IEEE, 2002.

[12] N.D. Truong, et al., A generalised seizure prediction with convolutional neural networks for intracranial and scalp electroencephalogram data analysis, 2017. arXiv preprint arXiv: 1011.3382.

[13] R. Chen, K.K. Parhi, Seizure prediction using convolutional neural networks and sequence transformer networks, in: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), IEEE, 2021.

[14] B. Sun, et al., Seizure prediction in scalp EEG based channel attention dual-input convolutional neural network, Physica A: Statistical Mechanics and its Applications 584 (2021) 126376.

[15] S. Kiranyaz, et al., Convolutional neural networks for patient-specific ECG classification, in: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2015.

[16] S. Khalilpour, et al., Application of 1-D CNN to predict epileptic seizures using EEG records, in: 2020 6th International Conference on Web Research (ICWR), IEEE, 2020.

[17] B.P. Prathaban, R. Balasubramanian, Dynamic learning framework for epileptic seizure prediction using sparsity based EEG Reconstruction with Optimized CNN classifier, Expert Systems with Applications 170 (2021) 114533.
[18] Z. Wang, J. Yang, M. Sawan, A novel multi-scale dilated 3D CNN for epileptic seizure prediction, in: 2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS), IEEE, 2021.
[19] M. Shahbazi, H. Aghajan, A generalizable model for seizure prediction based on deep learning using CNN-LSTM architecture, in: 2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP), IEEE, 2018.
[20] J.S. Ra, T. Li, Y. Li, A novel permutation entropy-based EEG channel selection for improving epileptic seizure prediction, Sensors 21 (23) (2021) 7972.
[21] R.G. Andrzejak, et al., Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state, Physical Review E 64 (6) (2001) 061907.
[22] Chowning, S., *The Singular Value Decomposition*. 2020.
[23] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning representations by back--propagating errors, nature 323 (6088) (1986) 533–536.
[24] A. Zabidi, et al., Short-time Fourier Transform analysis of EEG signal generated during imagined writing, in: 2012 International Conference on System Engineering and Technology (ICSET), IEEE, 2012.
[25] S.-H. Cho, G. Jang, S.-H. Kwon, Time-frequency analysis of power-quality distuvvvrbances via the Gabor–Wigner transform, IEEE transactions on power delivery 25 (1) (2009) 494–499.
[26] A. Chakraborty, D. Okaya, Frequency-time decomposition of seismic data using wavelet-based methods, Geophysics 60 (6) (1995) 1906–1916.
[27] H.R. Al Ghayab, et al., Epileptic seizures detection in EEGs blending frequency domain with information gain technique, Soft Computing 23 (1) (2019) 227–239.
[28] T. Nguyen-Ky, P. Wen, Y. Li, Consciousness and depth of anesthesia assessment based on Bayesian analysis of EEG signals, IEEE Transactions on Biomedical Engineering 60 (6) (2013) 1488–1498.
[29] R. Da Silva, et al., The comparison of wavelet-and Fourier-based electromyographic indices of back muscle fatigue during dynamic contractions: validity and reliability results, Electromyography and clinical neurophysiology 48 (3/4) (2008) 147.
[30] R.S. Oliveira, et al., Spectral analysis of electromyographic signal in supramaximal effort in cycle ergometer using Fourier and Wavelet transforms: a comparative study, Revista Andaluza de Medicina del Deporte 5 (2) (2012) 48–52.
[31] S. Karlsson, J. Yu, M. Akay, Time-frequency analysis of myoelectric signals during dynamic contractions: a comparative study, IEEE transactions on Biomedical Engineering 47 (2) (2000) 228–238.
[32] O. Kaziha, T. Bonny, in: *A convolutional neural network for seizure detection*. in *2020 Advances in Science and Engineering Technology International Conferences (ASET)*, IEEE, 2020.
[33] Y. Zhang, et al., Vibration-based structural state identification by a 1-dimensional convolutional neural network, Computer-Aided Civil and Infrastructure Engineering 34 (9) (2019) 822–839.
[34] O. Yildirim, et al., Automated detection of diabetic subject using pre-trained 2D-CNN models with frequency spectrum images extracted from heart rate signals, Computers in biology and medicine 113 (2019) 103387.
[35] J. Rahul, L.D. Sharma, Automatic cardiac arrhythmia classification based on hybrid 1-D CNN and Bi-LSTM model, Biocybernetics and Biomedical Engineering 42 (1) (2022) 312–324.
[36] M. Salem, S. Taheri, J.S. Yuan, ECG arrhythmia classification using transfer learning from 2-dimensional deep CNN features, in: 2018 IEEE biomedical circuits and systems conference (BioCAS), IEEE, 2018.

4.3 Links and implications

In this study, the classification processes for training and testing are tailored to each patient due to the patient-dependent nature of epileptic seizure patterns. Results from experiments conducted on two epileptic EEG databases, namely the Bonn and CHB-MIT databases, reveal that SET can extract more accurate information compared to STFT. Specifically, SET with 1D-CNN demonstrates nearly 100% accuracy, sensitivity, and specificity in predicting seizure status in both databases.

The efficacy of 1D-CNN in this research is promising. In comparison to MLP, it offers significantly faster computational speed (over 1000 times) and higher accuracy (more than 10%). While experiments with 2D or 3D-CNN were not conducted in this study, the literature review suggests that 1D-CNN would be faster (with 100 times fewer parameters) and more accurate (1-10%) than 2D or 3D-CNN.

However, CNNs often demand substantial labelled data for effective training, posing challenges in scenarios where obtaining extensive labelled datasets is difficult. This can render training CNNs impractical, leading to potential struggles in generalizing well to unseen data. Moreover, the intricate internal workings of CNNs make interpretation complex, especially in fields like brain disorders where interpretability is vital. The memory requirements of CNNs, particularly with EEG data from many channels can be significant, limiting their deployment on devices with constrained memory, such as edge or IoT devices.

As a result, upcoming research is turning to Sparse Representation (SR) and k-Nearest Neighbors (k-NN) to manage the large volume of data inherent in EEG. Despite the nature of EEG data, which is voluminous, this approach still achieves high accuracy and swift analysis. SR's ability to quickly select sparse data, rather than incorporating a vast amount of data in calculations, contributes to the efficiency of the analysis.

CHAPTER 5: PAPER 3 – EPILEPTIC SEIZURE PREDICTION BASED ON SYNCHROEXTRACTING TRANSFORM AND SPARSE REPRESENTATION

5.1 Introduction

The paper submitted to IEEE Access in 2024 highlights the importance of feature extraction in EEG signal analysis for epileptic seizure prediction. It introduces synchroextracting transformation (SET) and sparse representation (SR) to enhance this process, overcoming limitations of traditional methods. The combined SET-SR approach improves time-frequency resolution and achieves high classification accuracy using the k-nearest neighbors algorithm (k-NN), with 99.48% on the CHB-MIT database and 100% on the Bonn University database. These results showcase the SET-SR model's effectiveness in detecting pre-seizure signals, advancing the field of seizure prediction.

5.2 Published paper

IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 13 November 2024, accepted 4 December 2024, date of publication 11 December 2024,
date of current version 19 December 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3514859

RESEARCH ARTICLE

Epileptic Seizure Prediction Based on Synchroextracting Transform and Sparse Representation

JEE SOOK RA, TIANNING LI, AND YAN LI
School of Mathematics, Physics and Computing, University of Southern Queensland, Toowoomba, QLD 4350, Australia
Corresponding author: Jee Sook Ra (jee.ra@unisq.edu.au)

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

The associate editor coordinating the review of this manuscript and approving it for publication was Tony Thomas.

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]:

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

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

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.

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

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).

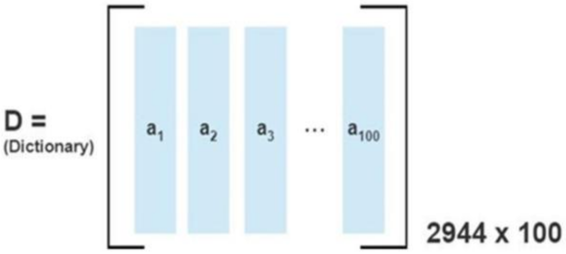


FIGURE 1. Dictionary structure of sparse representation. a1, a2, a3 ... a100 are called atoms.

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

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

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]:

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

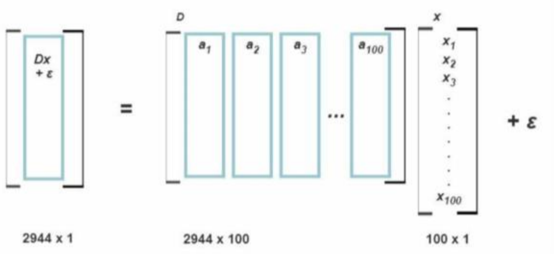


FIGURE 2. A sparse representation model example with 100 dictionary atoms.

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:

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

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:

$$\min \frac{1}{2} x^T H x + g^T x \text{ subject to x} \geq 0 \quad (9)$$

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.

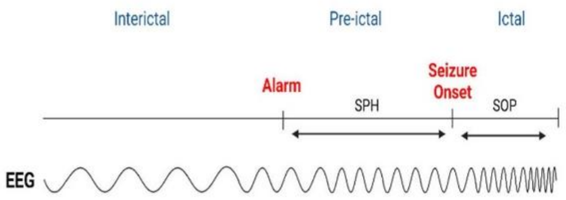


FIGURE 3. SPH and SOP on the timeline of epilepsy EEG.

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

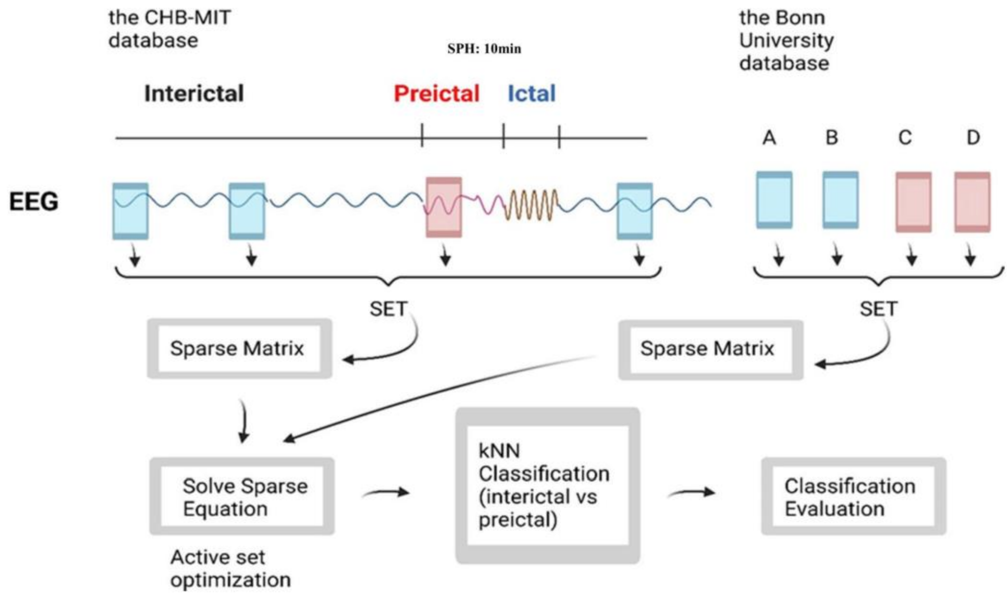


FIGURE 4. The experiment process of the proposed method.

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.

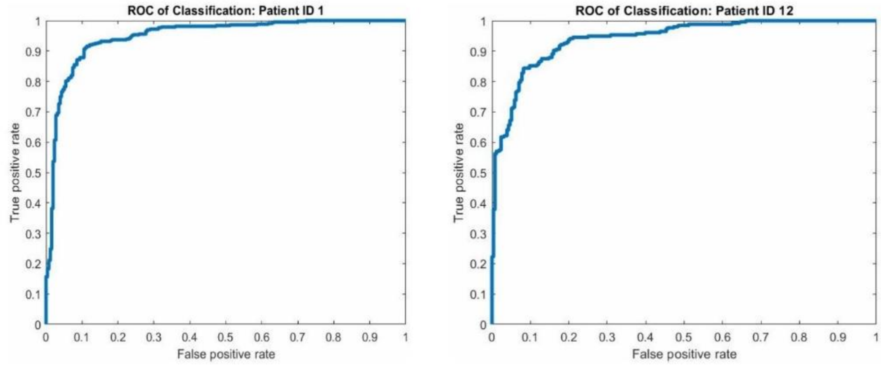


FIGURE 5. ROC curves (blue) by k-NN classification based on the SET-SR for recording ID chb01 and ID chb12 EEG signals in the CHB-MIT database.

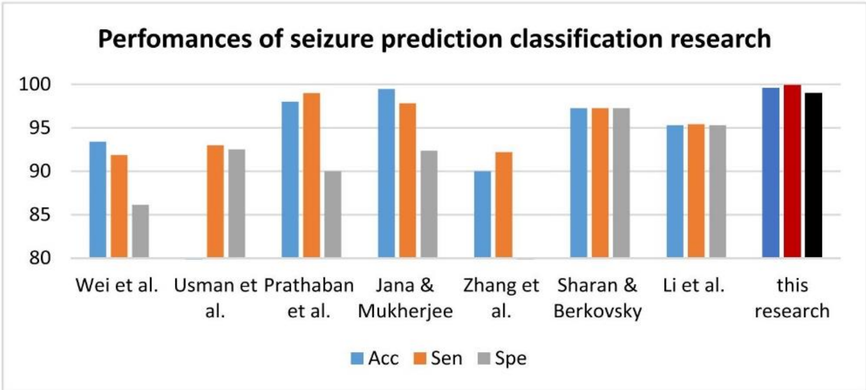


FIGURE 6. Acc, Sen, and Spe comparison of the seizure prediction classification performances among recent CNN-based studies.

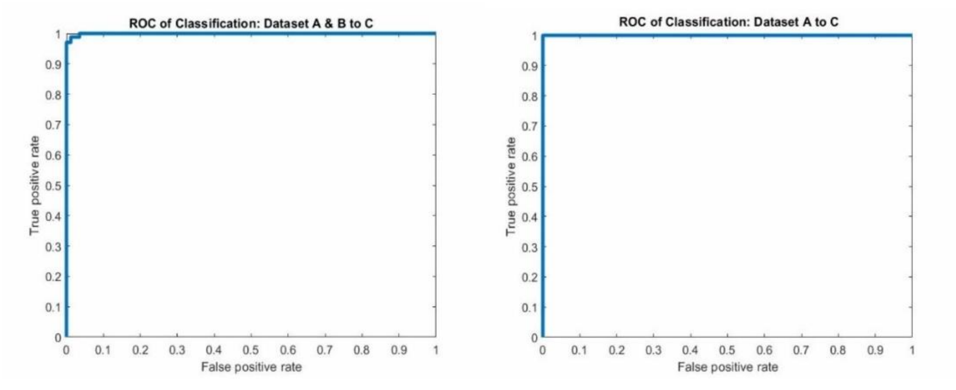


FIGURE 7. ROC curves (blue) by the k-NN classification based on the SET-SR for the Bonn University database.

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.

REFERENCES

[1] L. Sörnmo and P. Laguna, *Bioelectrical Signal Processing in Cardiac and Neurological Applications*, vol. 8. New York, NY, USA: Academic, 2005.

[2] Y. Li, "Sparse representation for high-dimensional data analysis. Sparse machine learning models in bioinformatics," Ph.D. thesis, School Comput. Sci., Univ. Windsor, Windsor, ON, Canada, 2013, pp. 41–57.

[3] C. Herzet and A. Drémeau, "Bayesian pursuit algorithms," in *Proc. 18th Eur. Signal Process. Conf.*, Aug. 2010, pp. 1474–1478.

[4] S. Aviyente, "Compressed sensing framework for EEG compression," in *Proc. IEEE/SP 14th Workshop Stat. Signal Process.*, Aug. 2007, pp. 181–184.

[5] A. Bonnefoy, V. Emiya, L. Ralaivola, and R. Gribonval, "A dynamic screening principle for the lasso," in *Proc. 22nd Eur. Signal Process. Conf. (EUSIPCO)*, Sep. 2014, pp. 6–10.

[6] C. Peng, Q. Zhang, Z. Kang, C. Chen, and Q. Cheng, "Kernel two-dimensional ridge regression for subspace clustering," *Pattern Recognit.*, vol. 113, May 2021, Art. no. 107749.

[7] X. Zhang, Z. Liu, Q. Miao, and L. Wang, "Bearing fault diagnosis using a whale optimization algorithm-optimized orthogonal matching pursuit with a combined time–frequency atom dictionary," *Mech. Syst. Signal Process.*, vol. 107, pp. 29–42, Jul. 2018.

[8] H. J. Ferreau, C. Kirches, A. Potschka, H. G. Bock, and M. Diehl, "QpOASES: A parametric active-set algorithm for quadratic programming," *Math. Program. Comput.*, vol. 6, no. 4, pp. 327–363, Dec. 2014.

[9] B. Wohlberg, "Efficient algorithms for convolutional sparse representations," *IEEE Trans. Image Process.*, vol. 25, no. 1, pp. 301–315, Oct. 2015.

[10] M. K. Delimayanti, B. Purnama, N. G. Nguyen, M. R. Faisal, K. R. Mahmudah, F. Indriani, M. Kubo, and K. Satou, "Classification of brainwaves for sleep stages by high-dimensional FFT features from EEG signals," *Appl. Sci.*, vol. 10, no. 5, p. 1797, Mar. 2020.

[11] Y. Li, "A novel statistical algorithm for multiclass EEG signal classification," *Eng. Appl. Artif. Intell.*, vol. 34, pp. 154–167, Sep. 2014.

[12] Y. Li and P. Wen, "Analysis and classification of EEG signals using a hybrid clustering technique," in *Proc. IEEE/ICME Int. Conf. Complex Med. Eng.*, Jul. 2010, pp. 34–39.

[13] T. Nguyen-Ky, P. Wen, and Y. Li, "Consciousness and depth of anesthesia assessment based on Bayesian analysis of EEG signals," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 6, pp. 1488–1498, Jun. 2013.

[14] M. Diykh, Y. Li, and S. Abdulla, "EEG sleep stages identification based on weighted undirected complex networks," *Comput. Methods Programs Biomed.*, vol. 184, Feb. 2020, Art. no. 105116.

[15] P. O. Hoyer, "Non-negative sparse coding," in *Proc. 12th IEEE Workshop Neural Netw. Signal Process.*, Sep. 2002, pp. 557–565.

[16] A. Hyvärinen, P. Hoyer, and E. Oja, "Sparse code shrinkage: Denoising by nonlinear maximum likelihood estimation," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 11, 1998.

[17] J. Li, D. Mba, X. Li, Y. Shang, S. He, and T. R. Lin, "An adaptive synchroextracting transform for the analysis of noise contaminated multi-component nonstationary signals," *Appl. Acoust.*, vol. 202, Jan. 2023, Art. no. 109169.

[18] G. Yu, M. Yu, and C. Xu, "Synchroextracting transform," *IEEE Trans. Ind. Electron.*, vol. 64, no. 10, pp. 8042–8054, Oct. 2017.

[19] B. Maimaiti, H. Meng, Y. Lv, J. Qiu, Z. Zhu, Y. Xie, Y. Li, Yu-Cheng, W. Zhao, J. Liu, and M. Li, "An overview of EEG-based machine learning methods in seizure prediction and opportunities for neurologists in this field," *Neuroscience*, vol. 481, pp. 197–218, Jan. 2022.

[20] A. Craik, Y. He, and J. L. Contreras-Vidal, "Deep learning for electroencephalogram (EEG) classification tasks: A review," *J. Neural Eng.*, vol. 16, no. 3, Jun. 2019, Art. no. 031001.

[21] X. Wei, L. Zhou, Z. Zhang, Z. Chen, and Y. Zhou, "Early prediction of epileptic seizures using a long-term recurrent convolutional network," *J. Neurosci. Methods*, vol. 327, Nov. 2019, Art. no. 108395.

[22] B. Zhang, W. Wang, Y. Xiao, S. Xiao, S. Chen, S. Chen, G. Xu, and W. Che, "Cross-subject seizure detection in EEGs using deep transfer learning," *Comput. Math. Methods Med.*, vol. 2020, pp. 1–8, May 2020.

[23] M. K. Kıymık, I. Güler, A. Dizibüyük, and M. Akın, "Comparison of STFT and wavelet transform methods in determining epileptic seizure activity in EEG signals for real-time application," *Comput. Biol. Med.*, vol. 35, no. 7, pp. 603–616, Oct. 2005.

[24] K. Sivasankari and K. Thanushkodi, "An improved EEG signal classification using neural network with the consequence of ICA and STFT," *J. Electr. Eng. Technol.*, vol. 9, no. 3, pp. 1060–1071, May 2014.

[25] S. Ali, "Time-frequency coherence of multichannel EEG signals: Synchrosqueezing transform based analysis," *Int. J. Comput. Sci. Trends Technol.*, vol. 4, no. 3, pp. 40–48, 2016.

[26] J. Li, W. Zhou, S. Yuan, Y. Zhang, C. Li, and Q. Wu, "An improved sparse representation over learned dictionary method for seizure detection," *Int. J. Neural Syst.*, vol. 26, no. 1, Feb. 2016, Art. no. 1550035.

[27] H. Peng, C. Li, J. Chao, T. Wang, C. Zhao, X. Huo, and B. Hu, "A novel automatic classification detection for epileptic seizure based on dictionary learning and sparse representation," *Neurocomputing*, vol. 424, pp. 179–192, Feb. 2021.

[28] S. Yuan, W. Zhou, Q. Wu, and Y. Zhang, "Epileptic seizure detection with log-Euclidean Gaussian kernel-based sparse representation," *Int. J. Neural Syst.*, vol. 26, no. 3, May 2016, Art. no. 1650011.

[29] J. S. Ra, T. Li, and YanLi, "A novel epileptic seizure prediction method based on synchroextracting transform and 1-dimensional convolutional neural network," *Comput. Methods Programs Biomed.*, vol. 240, Oct. 2023, Art. no. 107678.

[30] Y. Jiang, W. Chen, M. Li, T. Zhang, and Y. You, "Synchroextracting chirplet transform-based epileptic seizures detection using EEG," *Biomed. Signal Process. Control*, vol. 68, Jul. 2021, Art. no. 102699.

[31] V. Rajinikanth, S. Kadry, D. Taniar, K. Kamalanand, M. A. Elaziz, and K. P. Thanaraj, "Detecting epilepsy in EEG signals using synchro-extracting-transform (SET) supported classification technique," *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 8, pp. 10123–10141, Aug. 2023.

[32] S. M. Usman, S. Khalid, and Z. Bashir, "Epileptic seizure prediction using scalp electroencephalogram signals," *Biocybernetics Biomed. Eng.*, vol. 41, no. 1, pp. 211–220, Jan. 2021.

[33] B. P. Prathaban and R. Balasubramanian, "Dynamic learning framework for epileptic seizure prediction using sparsity based EEG reconstruction with optimized CNN classifier," *Expert Syst. With Appl.*, vol. 170, May 2021, Art. no. 114533.

[34] R. Jana and I. Mukherjee, "Deep learning based efficient epileptic seizure prediction with EEG channel optimization," *Biomed. Signal Process. Control*, vol. 68, Jul. 2021, Art. no. 102767.

[35] R. V. Sharan and S. Berkovsky, "Epileptic seizure detection using multi-channel EEG wavelet power spectra and 1-D convolutional neural networks," in *Proc. 42nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2020, pp. 545–548.

[36] Y. Li, Z. Yu, Y. Chen, C. Yang, Y. Li, X. Allen Li, and B. Li, "Automatic seizure detection using fully convolutional nested LSTM," *Int. J. Neural Syst.*, vol. 30, no. 4, Apr. 2020, Art. no. 2050019.

[37] I. Assali, A. G. Blaiech, A. Ben Abdallah, K. Ben Khalifa, M. Carrère, and M. H. Bedoui, "CNN-based classification of epileptic states for seizure prediction using combined temporal and spectral features," *Biomed. Signal Process. Control*, vol. 82, Apr. 2023, Art. no. 104519.

[38] M. Shahbazi and H. Aghajan, "A generalizable model for seizure prediction based on deep learning using CNN-LSTM architecture," in *Proc. IEEE Global Conf. Signal Inf. Process. (GlobalSIP)*, Nov. 2018, pp. 469–473.

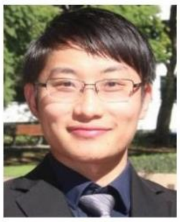
[39] A. R. Ozcan and S. Erturk, "Seizure prediction in scalp EEG using 3D convolutional neural networks with an image-based approach," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 11, pp. 2284–2293, Nov. 2019.

[40] C. Li, X. Huang, R. Song, R. Qian, X. Liu, and X. Chen, "EEG-based seizure prediction via transformer guided CNN," *Measurement*, vol. 203, Nov. 2022, Art. no. 111948.

[41] S. Khalilpour, A. Ranjbar, M. B. Menhaj, and A. Sandooghdar, "Application of 1-D CNN to predict epileptic seizures using EEG records," in *Proc. 6th Int. Conf. Web Res. (ICWR)*, Apr. 2020, pp. 314–318.

[42] Y. Zhang, Y. Guo, P. Yang, W. Chen, and B. Lo, "Epilepsy seizure prediction on EEG using common spatial pattern and convolutional neural network," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 2, pp. 465–474, Feb. 2020.
[43] F. Zhang, B. Zhang, S. Guo, and X. Zhang, "MFCC-CNN: A patient-independent seizure prediction model," *Neurolog. Sci.*, vol. 45, no. 12, pp. 5897–5908, Dec. 2024.
[44] Z. F. Quadri, M. S. Akhoon, and S. A. Loan, "Epileptic seizure prediction using stacked CNN-BiLSTM: A novel approach," *IEEE Trans. Artif. Intell.*, vol. 5, no. 11, pp. 5553–5560, Nov. 2024.
[45] J. S. Ra, T. Li, and Y. Li, "A novel permutation entropy-based EEG channel selection for improving epileptic seizure prediction," *Sensors*, vol. 21, no. 23, p. 7972, 2021.
[46] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 64, no. 6, Nov. 2001, Art. no. 061907.
[47] R. Jacob, A. Unnikrishnan, and T. Thomas, *Development of Time-frequency Techniques for Sonar Applications*. Cochin, India: Cochin Univ. Science and Technology, 2010.
[48] Z. Yan, Y. Xu, K. Zhang, A. Hu, and G. Yu, "Adaptive synchroextracting transform and its application in bearing fault diagnosis," *ISA Trans.*, vol. 137, pp. 574–589, Jun. 2023.
[49] Z. Li, J. Gao, H. Li, Z. Zhang, N. Liu, and X. Zhu, "Synchroextracting transform: The theory analysis and comparisons with the synchrosqueezing transform," *Signal Process.*, vol. 166, Jan. 2020, Art. no. 107243.
[50] Y. Li, Z. L. Yu, N. Bi, Y. Xu, Z. Gu, and S.-i. Amari, "Sparse representation for brain signal processing: A tutorial on methods and applications," *IEEE Signal Process. Mag.*, vol. 31, no. 3, pp. 96–106, May 2014.
[51] M. J. Best and N. Chakravarti, "Active set algorithms for isotonic regression; a unifying framework," *Math. Program.*, vol. 47, nos. 1–3, pp. 425–439, May 1990.
[52] E. Bou Assi, D. K. Nguyen, S. Rihana, and M. Sawan, "Towards accurate prediction of epileptic seizures: A review," *Biomed. Signal Process. Control*, vol. 34, pp. 144–157, Apr. 2017.
[53] T. Maiwald, M. Winterhalder, R. Aschenbrenner-Scheibe, H. U. Voss, A. Schulze-Bonhage, and J. Timmer, "Comparison of three nonlinear seizure prediction methods by means of the seizure prediction characteristic," *Phys. D, Nonlinear Phenomena*, vol. 194, nos. 3–4, pp. 357–368, Jul. 2004.
[54] K. Varmuza and K. Varmuza, "K—Nearest neighbour classification (KNN-method)," in *Pattern Recognition in Chemistry*. Berlin, Germany: Springer, 1980, pp. 62–71.
[55] S. Narkhede, "Understanding AUC-ROC curve," *Towards Data Sci.*, vol. 26, no. 1, pp. 220–227, 2018.
[56] L. Cohen, "Uncertainty principles of the short-time Fourier transform," *Proc. SPIE*, vol. 2563, pp. 80–90, Jun. 1995.
[57] J. Lee, J. Wang, D. Crandall, S. Šabanovic, and G. Fox, "Real-time, cloud-based object detection for unmanned aerial vehicles," in *Proc. 1st IEEE Int. Conf. Robotic Comput. (IRC)*, Apr. 2017, pp. 36–43.
[58] A. Adadi and M. Berrada, "Explainable AI for healthcare: from black box to interpretable models," in *Embedded Systems and Artificial Intelligence*. Fez, Morocco: Springer, 2020.
[59] M. Sun, F. Wang, T. Min, T. Zang, and Y. Wang, "Prediction for high risk clinical symptoms of epilepsy based on deep learning algorithm," *IEEE Access*, vol. 6, pp. 77596–77605, 2018.
[60] K. M. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A long short-term memory deep learning network for the prediction of epileptic seizures using EEG signals," *Comput. Biol. Med.*, vol. 99, pp. 24–37, Aug. 2018.

JEE SOOK RA received the bachelor's degree in information technology from RMIT and the master's degree in mathematics and applied statistics from the University of Technology Sydney, Australia. Since 2020, she has been contributing to teaching at the University of Southern Queensland. Her research interests include EEG analysis, signal processing, machine learning, and the application of embedded systems in multidisciplinary sciences in general.



TIANNING LI received the B.ISM. degree from Nanjing University, Nanjing, China, in 2009, the M.AccFin. degree from The University of Adelaide, Adelaide, SA, Australia, in 2012, and the Ph.D. degree from the University of Southern Queensland (UniSQ), Toowoomba, QLD, Australia, in 2015. He is currently a Computing Lecturer and the First Year Experience Lead with the School of Mathematics, Physics and Computing, UniSQ. His research interests include machine learning algorithms, signal processing, and electroencephalography (EEG) research.

YAN LI received the Ph.D. degree from Flinders University, Australia. She is currently a Full Professor in artificial intelligence (AI) in computer science discipline and the Associate Head (Research) and the Chair of the Research Committee, School of Mathematics, Physics and Computing, University of Southern Queensland (UniSQ), Australia. She has published more than 250 high-quality publications, supervised dozens of Ph.D. completions, and obtained more than $3.8 million research grants from Australia government, industry, and through international collaborations in recent years. Her research interests include AI, machine learning, big data, internet technologies, security, signal/image processing, and EEG research.

5.3 Links and implications

In this study, traditional machine learning (ML), specifically kNN classification with the SET-SR method, demonstrated outstanding performance with 100% average accuracy, specificity, sensitivity, balanced accuracy, and AUC on the Bonn University database. For the CHB-MIT databases, the averages were 99.48% accuracy, 98.75% specificity, 99.85% sensitivity, 99.30% balanced accuracy, and 0.8529 AUC.

The kNN classification results highlight the SET-SR method's ability to extract highly accurate information from the data. Recent studies have compared CNNs and traditional ML models in seizure prediction tasks, with CNNs often outperforming traditional ML algorithms. However, a model's accuracy depends on factors like input data quality, model size and complexity, optimization algorithm during training, and parameter settings.

In certain scenarios, traditional ML algorithms like kNN may be more suitable and efficient than CNNs, depending on the problem and available data. This study emphasizes that, with appropriate signal analysis and feature extraction methods, traditional ML techniques like kNN can achieve high accuracy in challenging areas like seizure prediction. On the other hand, CNNs have notable memory requirements, particularly with EEG data from numerous channels, limiting their deployment on devices with constrained memory, such as edge or IoT devices.

Future research should focus on comparing seizure prediction models with data in the real-time epileptic EEG measuring system, as this represents the ultimate goal of seizure prediction research.

CHAPTER 6: DISCUSSION AND CONCLUSIONS

6.1 Discussion and conclusions

The findings from the first paper (Chapter 3) highlight a significant 29.93% improvement in epileptic EEG prediction rates through personalized channel selection, with enhancements in accuracy (10.58%), sensitivity (23.57%), and specificity (5.56%). In the SVM classification, utilizing selected channels results in higher average accuracy (74.60%), sensitivity (69.51%), and specificity (73.14%) compared to using all channels (67.46%, 56.25%, and 69.29%) for predicting seizures. However, despite these improvements, channel selection in EEG analysis for seizure prediction may face challenges such as variability in optimal channels due to the individual's changing state over time. Additionally, selected channels may be more susceptible to artifacts like muscle activity or electrical interference across different epilepsy stages. Therefore, the channel selection method may add complexities to the process of developing the seizure prediction models.

To overcome these challenges associated with channel selection, the next study introduces a new signal transformation to replace entropy transformation and employs 1D-CNNs without the channel selection step, resulting in a more streamlined model. This study utilizes personalized classification processes tailored to individual patients due to the patient-dependent nature of epileptic seizure patterns. Experiments on the Bonn and CHB-MIT databases reveal that synchroextracting transformation (SET) outperforms short-time Fourier transform (STFT) in extracting more accurate information. Specifically, SET with 1D-CNN achieves nearly 100% accuracy, sensitivity, and specificity in predicting seizure status in both databases.

The advantages of 1D-CNN are clear, with its computational speed being over 1000 times faster and its accuracy more than 10% higher compared to multilayer perceptron (MLP). Although 2D or 3D-CNNs were not tested in this study, previous research suggests that 1D-CNNs would not only be faster, having 100 times fewer parameters, but also more accurate by 1-10% than 2D or 3D-CNNs.

While CNNs are highly capable, they face significant challenges in certain areas. One major issue is their reliance on large amounts of labelled data; when such data is limited, training becomes difficult, and their ability to generalize to new, unseen data is compromised. Additionally, the complex internal structure of CNNs creates substantial interpretability problems, which is particularly problematic in fields like brain disorder analysis, where understanding the decision-making process is crucial. Furthermore, the high memory requirements of CNNs, especially when processing multiple EEG channels, can hinder their use on devices with limited memory, such as edge or IoT devices.

Chapter 5 focuses on overcoming the challenges of handling extensive EEG data from real-time measurements by investigating sparse representation (SR) and k-nearest neighbors (kNN). This method not only enhances the accuracy but also accelerates the analysis process. The efficiency stems from SR's capability to rapidly identify and utilize sparse data, minimizing the volume of data required for calculations. The study demonstrated the remarkable performance of traditional machine learning, particularly kNN classification using the SET-SR method. On the Bonn University database, this approach achieved perfect scores, including 100% average accuracy, specificity, sensitivity, balanced accuracy, and AUC. For the CHB-MIT databases, the results were similarly impressive, with averages of 99.48% accuracy, 98.75% specificity, 99.85% sensitivity, 99.30% balanced accuracy, and an AUC of 0.8529.

Recent studies have highlighted the advantages of CNNs over traditional ML models in seizure prediction tasks, with CNNs often achieving superior performance. However, factors such as input data quality, model size and complexity, optimization algorithms used during training, and parameter settings can significantly impact a model's accuracy. Despite the success of CNNs, traditional ML algorithms like kNN can sometimes outperform CNNs in specific scenarios. These scenarios include situations with limited labelled data, high-dimensional data, simple or linear relationships, and the need for model interpretability. Additionally, traditional ML models may be more suitable when computational resources are limited, making it ideal for real-time applications.

The choice between traditional ML and CNNs should be based on the specific characteristics of the data, the nature of the problem, and the available resources. Hybrid approaches that combine traditional ML algorithms with deep learning techniques can also be effective in certain situations. The kNN classification results in this study demonstrate the SET-SR method's ability to extract highly accurate information from the data, showcasing its potential as a viable alternative or complement to CNNs in various contexts.

6.2 Future work

Future research should prioritize comparing seizure prediction models using data from real-time epileptic EEG measuring systems, as this represents the ultimate goal of seizure prediction research. These models must operate accurately in real-world conditions, which involve continuous, dynamic data with numerous features. The channel selection method offers significant benefits by making the equipment more user-friendly for patients, and this research demonstrates higher accuracy compared to results without channel selection. However, the process of EEG channel selection requires extensive experimentation across various scenarios, such as when patients are sleeping, awake, or actively moving. Each of these states can significantly affect EEG readings, leading to variations in the effectiveness of seizure prediction models. For instance, the brain's electrical activity during sleep is markedly different from that during wakefulness or physical activity, which can impact prediction accuracy. Understanding how channel selection performs under these diverse conditions is crucial for developing robust and reliable models that can adapt to the dynamic nature of real-world applications. This knowledge will help optimize channel selection strategies, ensuring that the models remain effective regardless of the patient's state.

In future research, real-time seizure prediction may require a hybrid approach that combines various feature extraction methods and effective machine learning techniques tailored to different situations and individuals. Traditional ML algorithms offer the advantages of interpretability and computational efficiency, while deep learning techniques excel in feature extraction and pattern recognition. By integrating these approaches, researchers can develop models that are both powerful and adaptable to diverse conditions and patient-specific needs. Leveraging the strengths of each methodology, hybrid models can achieve higher accuracy and maintain robustness across various conditions. For example, during real-time EEG monitoring, the brain's electrical patterns can change considerably depending on different physiological states. A hybrid model can adapt to these variations more effectively than a single-method approach.

Moreover, hybrid approaches can balance the need for interpretability, crucial in medical applications, with the computational efficiency required for real-time deployment. This balance is essential because medical professionals must understand and trust the model's predictions, particularly regarding critical decisions like seizure prediction. At the same time, the models must operate efficiently on devices with limited processing power, such as IoT devices. Therefore, hybrid models, which combine the strengths of different machine learning techniques, ensure that seizure prediction remains practical and reliable, even in environments with constrained computational resources.

REFERENCES

1. Sirven, J.I., *Epilepsy: a spectrum disorder.* Cold Spring Harbor perspectives in medicine, 2015. **5**(9).
2. Pohlmann - Eden, B. and M. Newton, *First seizure: EEG and neuroimaging following an epileptic seizure.* Epilepsia, 2008. **49**: p. 19-25.
3. Meldrum, B.S. and J.B. Brierley, *Prolonged epileptic seizures in primates: ischemic cell change and its relation to ictal physiological events.* Archives of Neurology, 1973. **28**(1): p. 10-17.
4. Koffman, L., et al., *Continuous electroencephalographic monitoring in the intensive care unit: a cross-sectional study.* Journal of Intensive Care Medicine, 2020. **35**(11): p. 1235-1240.
5. Yang, H., J. Han, and K. Min, *A multi-column CNN model for emotion recognition from EEG signals.* Sensors, 2019. **19**(21): p. 4736.
6. Holst, A.G., et al., *Epilepsy and risk of death and sudden unexpected death in the young: a nationwide study.* Epilepsia, 2013. **54**(9): p. 1613-1620.
7. Freestone, D.R., P.J. Karoly, and M.J. Cook, *A forward-looking review of seizure prediction.* Current opinion in neurology, 2017. **30**(2): p. 167-173.
8. Le Van Quyen, M., et al., *Anticipation of epileptic seizures from standard EEG recordings.* The Lancet, 2001. **357**(9251): p. 183-188.
9. Faught, E., *Adherence to antiepilepsy drug therapy.* Epilepsy & Behavior, 2012. **25**(3): p. 297-302.
10. Sanchez Fernandez, I., et al., *The burden of decisional uncertainty in the treatment of status epilepticus.* Epilepsia, 2020. **61**(10): p. 2150-2162.
11. Britton, J.W., et al., *Electroencephalography (EEG): An introductory text and atlas of normal and abnormal findings in adults, children, and infants.* 2016.
12. Allen, P.J., et al., *Identification of EEG events in the MR scanner: the problem of pulse artifact and a method for its subtraction.* Neuroimage, 1998. **8**(3): p. 229-239.
13. Medithe, J.W.C. and U.R. Nelakuditi. *Study of normal and abnormal EEG*. in *2016 3rd International conference on advanced computing and communication systems (ICACCS)*. 2016. IEEE.
14. Morley, A., L. Hill, and A. Kaditis, *10-20 system EEG Placement.* European Respiratory Society, European Respiratory Society, 2016.
15. Herwig, U., P. Satrapi, and C. Schönfeldt-Lecuona, *Using the international 10-20 EEG system for positioning of transcranial magnetic stimulation.* Brain topography, 2003. **16**: p. 95-99.
16. Simma, L., et al., *Integrating Neuromonitoring in Pediatric Emergency Medicine: Exploring Two Options for Point-of-Care*

Electroencephalogram (pocEEG) via Patient Monitors—A Technical Note. Journal of personalized medicine, 2023. **13**(9): p. 1411.
17. Khalifa, W., et al. *A survey of EEG based user authentication schemes*. in *2012 8th International Conference on Informatics and Systems (INFOS)*. 2012. IEEE.
18. Shoeb, A.H., *Application of machine learning to epileptic seizure onset detection and treatment*. 2009, Massachusetts Institute of Technology.
19. Hamad, A., et al. *Feature extraction of epilepsy EEG using discrete wavelet transform*. in *2016 12th international computer engineering conference (ICENCO)*. 2016. IEEE.
20. Wagner, J., et al., *Distinct β band oscillatory networks subserving motor and cognitive control during gait adaptation.* Journal of Neuroscience, 2016. **36**(7): p. 2212-2226.
21. Peng, W., *EEG preprocessing and denoising.* EEG Signal Processing and Feature Extraction, 2019: p. 71-87.
22. Kaya, I., *A brief summary of EEG artifact handling.* Brain-computer interface, 2019(9).
23. Rasheed, K., et al., *Machine learning for predicting epileptic seizures using EEG signals: A review.* IEEE Reviews in Biomedical Engineering, 2020. **14**: p. 139-155.
24. Siuly, S., et al., *Electroencephalogram (EEG) and its background.* EEG Signal Analysis and Classification: Techniques and Applications, 2016: p. 3-21.
25. Safayari, A. and H. Bolhasani, *Depression diagnosis by deep learning using EEG signals: A systematic review.* Medicine in Novel Technology and Devices, 2021. **12**: p. 100102.
26. Signorino, M., et al., *EEG spectral analysis in vascular and Alzheimer dementia.* Electroencephalography and clinical neurophysiology, 1995. **94**(5): p. 313-325.
27. Šušmáková, K., *Human sleep and sleep EEG.* Measurement science review, 2004. **4**(2): p. 59-74.
28. Sharma, R. and H.K. Meena, *Emerging Trends in EEG Signal Processing: A Systematic Review.* SN Computer Science, 2024. **5**(4): p. 1-14.
29. Krishnan, S. and Y. Athavale, *Trends in biomedical signal feature extraction.* Biomedical Signal Processing and Control, 2018. **43**: p. 41-63.
30. Johnstone, I.M. and D.M. Titterington, *Statistical challenges of high-dimensional data*. 2009, The Royal Society Publishing. p. 4237-4253.
31. Srivastava, N., et al., *Dropout: a simple way to prevent neural networks from overfitting.* The journal of machine learning research, 2014. **15**(1): p. 1929-1958.
32. Li, Y. and A. Ngom, *Sparse representation approaches for the classification of high-dimensional biological data.* BMC systems biology, 2013. **7**(4): p. 1-14.

33. Wright, J., et al., *Robust face recognition via sparse representation.* IEEE transactions on pattern analysis and machine intelligence, 2008. **31**(2): p. 210-227.
34. Langley, P. *Selection of relevant features in machine learning*. in *Proceedings of the AAAI Fall symposium on relevance*. 1994. California.
35. Pardey, J., S. Roberts, and L. Tarassenko, *A review of parametric modelling techniques for EEG analysis.* Medical engineering & physics, 1996. **18**(1): p. 2-11.
36. Vaz, F., P.G. de Oliveira, and J. Principe, *A study on the best order for autoregressive EEG modelling.* International journal of bio-medical computing, 1987. **20**(1-2): p. 41-50.
37. Yavuz, E. and C. Eyupoglu, *A cepstrum analysis-based classification method for hand movement surface EMG signals.* Medical & biological engineering & computing, 2019. **57**: p. 2179-2201.
38. Anjum, M.F., et al., *Linear predictive coding distinguishes spectral EEG features of Parkinson's disease.* Parkinsonism & related disorders, 2020. **79**: p. 79-85.
39. Zhang, Y., et al., *Multi-kernel extreme learning machine for EEG classification in brain-computer interfaces.* Expert Systems with Applications, 2018. **96**: p. 302-310.
40. Subha, D.P., et al., *EEG signal analysis: a survey.* Journal of medical systems, 2010. **34**: p. 195-212.
41. Shaker, M.M., *EEG waves classifier using wavelet transform and Fourier transform.* brain, 2006. **2**(3): p. 169-174.
42. Birvinskas, D., et al. *EEG dataset reduction and feature extraction using discrete cosine transform*. in *2012 Sixth UKSim/AMSS European Symposium on Computer Modeling and Simulation*. 2012. IEEE.
43. Schmidt, A.L., et al., *Method for training material evaluation with method of EEG spectral estimation*. 1994, Google Patents.
44. Freeman, W.J., *Hilbert transform for brain waves.* Scholarpedia, 2007. **2**(1): p. 1338.
45. Harpale, V.K. and V.K. Bairagi. *Time and frequency domain analysis of EEG signals for seizure detection: A review*. in *2016 International Conference on Microelectronics, Computing and Communications (MicroCom)*. 2016. IEEE.
46. Flandrin, P. and P. Borgnat, *Time-frequency energy distributions meet compressed sensing.* IEEE Transactions on Signal Processing, 2010. **58**(6): p. 2974-2982.
47. Allen, J.B. and L.R. Rabiner, *A unified approach to short-time Fourier analysis and synthesis.* Proceedings of the IEEE, 1977. **65**(11): p. 1558-1564.
48. Antonini, M., et al., *Image coding using wavelet transform.* IEEE Trans. Image Processing, 1992. **1**: p. 20.5-220.
49. Madhale Jadav, G., J. Lerga, and I. Štajduhar, *Adaptive filtering and analysis of EEG signals in the time-frequency domain based on the*

local entropy. EURASIP Journal on Advances in Signal Processing, 2020. **2020**(1): p. 1-18.
50. Gröchenig, K. and K. Gröchenig, *Time-frequency analysis and the uncertainty principle*. 2001, Springer.
51. Ra, J.S. and T. Li, *A novel epileptic seizure prediction method based on synchroextracting transform and 1-dimensional convolutional neural network.* Computer Methods and Programs in Biomedicine, 2023. **240**: p. 107678.
52. Li, Y., et al., *Epileptic seizure classification of EEGs using time–frequency analysis based multiscale radial basis functions.* IEEE journal of biomedical and health informatics, 2017. **22**(2): p. 386-397.
53. Frei, M.G. and I. Osorio, *Intrinsic time-scale decomposition: time–frequency–energy analysis and real-time filtering of non-stationary signals.* Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2007. **463**(2078): p. 321-342.
54. Rilling, G., P. Flandrin, and P. Goncalves. *On empirical mode decomposition and its algorithms*. in *IEEE-EURASIP workshop on nonlinear signal and image processing*. 2003. Grado: IEEE.
55. Sidiropoulos, N.D., et al., *Tensor decomposition for signal processing and machine learning.* IEEE Transactions on signal processing, 2017. **65**(13): p. 3551-3582.
56. He, D., et al., *Time-reassigned synchrosqueezing transform: The algorithm and its applications in mechanical signal processing.* Mechanical Systems and Signal Processing, 2019. **117**: p. 255-279.
57. Yu, G., M. Yu, and C. Xu, *Synchroextracting transform.* IEEE Transactions on Industrial Electronics, 2017. **64**(10): p. 8042-8054.
58. Klug, M., T. Berg, and K. Gramann, *Optimizing EEG ICA decomposition with data cleaning in stationary and mobile experiments.* Scientific Reports, 2024. **14**(1): p. 14119.
59. Callan, D.E., et al., *Shredding artifacts: extracting brain activity in EEG from extreme artifacts during skateboarding using ASR and ICA.* Frontiers in neuroergonomics, 2024. **5**: p. 1358660.
60. Rashida, M. and M.A. Habib, *Feature Extraction from Regenerated EEG–A Better Approach for ICA Based Eye Blink Artifact Detection.* Frontiers in Biomedical Technologies, 2024. **11**(2): p. 199-206.
61. Zhao, Y., et al. *Methods for Removing Artifacts from EEG signals: A review*. in *2024 IEEE 24th International Conference on Software Quality, Reliability, and Security Companion (QRS-C)*. 2024. IEEE.
62. Nayak, A.B., et al., *An empirical wavelet transform-based approach for motion artifact removal in electroencephalogram signals.* Decision Analytics Journal, 2024. **10**: p. 100420.
63. Zhao, S., et al., *An outlier detection based two-stage EEG artifact removal method using empirical wavelet transform and canonical correlation analysis.* Biomedical Signal Processing and Control, 2024. **92**: p. 106022.

64. Gudikandula, N., et al. *Recent Advancements in Online Ocular Artifacts Removal in EEG based BCI: A Review*. in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*. 2024. IEEE.
65. JURCZAK, M., M. KOŁODZIEJ, and A. MAJKOWSKI, *Comparison of Independent Component Analysis, Linear Regression and Adaptive Filtering for Artifact Removal in SSVEP Registration.* Przeglad Elektrotechniczny, 2024. **2024**(5).
66. Yadav, S., S.K. Saha, and R. Kar. *A Metaheuristic Approach Based Adaptive Filter Design for EEG Noise Mitigation Application*. in *2024 Third International Conference on Power, Control and Computing Technologies (ICPC2T)*. 2024. IEEE.
67. Hazarika, D., et al., *Dynamical Embedding of Single-Channel Electroencephalogram for Artifact Subspace Reconstruction.* Sensors, 2024. **24**(20): p. 6734.
68. Bagheri, F. and B. TaghiBeyglou, *A Neural Learning-Based Approach for EOG Artifact Removal from EEG.* CMBES Proceedings, 2024. **46**.
69. Xiong, J., et al., *One-Dimensional EEG Artifact Removal Network Based on Convolutional Neural Networks.* 2024.
70. Akuthota, S., K.R. Kumar, and R. Janapati, *Artifacts removal techniques in EEG data for BCI applications: A survey*, in *Computational Intelligence and Deep Learning Methods for Neuro-rehabilitation Applications*. 2024, Elsevier. p. 195-214.
71. Mamatha, G. and S. Hariprasad, *Analysis and Comparison of Artifact Removal Techniques for Epilepsy EEG Signal.* Indian Journal of Science and Technology, 2024. **17**(23): p. 2370-2380.
72. Massar, H., et al., *EMD-BSS: A hybrid methodology combining Empirical Mode Decomposition and Blind Source Separation to eliminate the ocular artifacts from EEG recordings.* Biomedical Signal Processing and Control, 2024. **95**: p. 106475.
73. Massar, H., et al., *Improvements of EEG Signal Quality: A Hybrid Method of Blind Source Separation and Variational Mode Destruction to Reduce Artifacts.* International Journal of Online & Biomedical Engineering, 2024. **20**(8).
74. Agounad, S., et al., *Advanced Signal Processing and Machine/Deep Learning Approaches on a Preprocessing Block for EEG Artifact Removal: A Comprehensive Review.* Circuits, Systems, and Signal Processing, 2024: p. 1-49.
75. Xiong, W., L. Ma, and H. Li, *A general dual-pathway network for EEG denoising.* Frontiers in Neuroscience, 2024. **17**: p. 1258024.
76. Atyabi, A. and D.M. Powers. *The impact of Segmentation and Replication on Non-Overlapping windows: An EEG study*. in *2012 IEEE International Conference on Information Science and Technology*. 2012. IEEE.
77. Prabowo, D.W., et al., *Asymmetric Windowing Recurrence Plots on Input Formulation for Human Emotion Recognition.* IEEE Access, 2024.

78. Li, G. and X. Yu, *Sliding window-aided ordered statistics decoding for short LDPC codes.* arXiv preprint arXiv:2404.14165, 2024.
79. Zhu, Y., et al., *Window Stacking Meta-Models for Clinical EEG Classification.* arXiv preprint arXiv:2401.10283, 2024.
80. Yuvaraj, R., et al. *Optimal EEG Time Window Length for Boredom Classification Using Combined Non-Linear Features*. in *2024 32nd European Signal Processing Conference (EUSIPCO)*. 2024. IEEE.
81. Xie, H.-B., W.-X. He, and H. Liu, *Measuring time series regularity using nonlinear similarity-based sample entropy.* Physics Letters A, 2008. **372**(48): p. 7140-7146.
82. Pincus, S.M., *Approximate entropy as a measure of irregularity for psychiatric serial metrics.* Bipolar disorders, 2006. **8**(5p1): p. 430-440.
83. Zanin, M., et al., *Permutation entropy and its main biomedical and econophysics applications: A review.* Entropy, 2012. **14**(8): p. 1553-1577.
84. Richman, J.S. and J.R. Moorman, *Physiological time-series analysis using approximate entropy and sample entropy.* American journal of physiology-heart and circulatory physiology, 2000. **278**(6): p. H2039-H2049.
85. Krim, H. and M. Viberg, *Two decades of array signal processing research: the parametric approach.* IEEE signal processing magazine, 1996. **13**(4): p. 67-94.
86. Zhang, A., B. Yang, and L. Huang. *Feature extraction of EEG signals using power spectral entropy*. in *2008 international conference on BioMedical engineering and informatics*. 2008. IEEE.
87. Bein, B., *Entropy.* Best Practice & Research Clinical Anaesthesiology, 2006. **20**(1): p. 101-109.
88. Yang, Y., et al., *Epileptic seizure prediction based on permutation entropy.* Frontiers in computational neuroscience, 2018. **12**: p. 55.
89. Burrell, L., et al. *Evaluation of Feature Selection Techniques for Analysis of Functional MRI and EEG*. in *DMIN*. 2007.
90. Caiafa, C.F. and A. Cichocki, *Computing sparse representations of multidimensional signals using Kronecker bases.* Neural computation, 2013. **25**(1): p. 186-220.
91. Yuan, Q., et al., *Epileptic EEG classification based on kernel sparse representation.* International journal of neural systems, 2014. **24**(04): p. 1450015.
92. Wang, J. and P. Guo. *Epileptic Electroencephalogram Signal Classification based on Sparse Representation*. in *IJCCI (NCTA)*. 2011.
93. Bekara, M. and M. Van der Baan, *Local singular value decomposition for signal enhancement of seismic data.* Geophysics, 2007. **72**(2): p. V59-V65.
94. Haddad, A.E. and L. Najafizadeh. *Global EEG segmentation using singular value decomposition*. in *2015 37th Annual International*

Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2015. IEEE.

95. Xia, Y., et al., *Seizure detection approach using S-transform and singular value decomposition.* Epilepsy & Behavior, 2015. **52**: p. 187-193.
96. Judith, A.M., S.B. Priya, and R.K. Mahendran, *Artifact Removal from EEG signals using Regenerative Multi-Dimensional Singular Value Decomposition and Independent Component Analysis.* Biomedical Signal Processing and Control, 2022. **74**: p. 103452.
97. Holland, J.H., *Genetic algorithms and the optimal allocation of trials.* SIAM journal on computing, 1973. **2**(2): p. 88-105.
98. Alyasseri, Z.A.A., et al. *EEG signal denoising using hybridizing method between wavelet transform with genetic algorithm*. in *Proceedings of the 11th National Technical Seminar on Unmanned System Technology 2019: NUSYS'19*. 2021. Springer.
99. Albasri, A., F. Abdali-Mohammadi, and A. Fathi, *EEG electrode selection for person identification thru a genetic-algorithm method.* Journal of medical systems, 2019. **43**: p. 1-12.
100. Maimaiti, B., et al., *An overview of EEG-based machine learning methods in seizure prediction and opportunities for neurologists in this field.* Neuroscience, 2022. **481**: p. 197-218.
101. Sha'Abani, M., et al. *kNN and SVM classification for EEG: a review*. in *InECCE2019: Proceedings of the 5th International Conference on Electrical, Control & Computer Engineering, Kuantan, Pahang, Malaysia, 29th July 2019*. 2020. Springer.
102. Vapnik, V., *The nature of statistical learning theory*. 1999: Springer science & business media.
103. Sharif, B. and A.H. Jafari, *Prediction of epileptic seizures from EEG using analysis of ictal rules on Poincaré plane.* Computer methods and programs in biomedicine, 2017. **145**: p. 11-22.
104. Cura, O.K. and A. Akan, *Classification of epileptic EEG signals using synchrosqueezing transform and machine learning.* International journal of neural systems, 2021. **31**(05): p. 2150005.
105. Craik, A., Y. He, and J.L. Contreras-Vidal, *Deep learning for electroencephalogram (EEG) classification tasks: a review.* Journal of neural engineering, 2019. **16**(3): p. 031001.
106. Zhou, M., et al., *Epileptic seizure detection based on EEG signals and CNN.* Frontiers in neuroinformatics, 2018. **12**: p. 95.
107. Ma, D., et al., *The automatic detection of seizure based on tensor distance and bayesian linear discriminant analysis.* International journal of neural systems, 2021. **31**(05): p. 2150006.
108. Huang, Y., et al., *Early prediction of refractory epilepsy in children under artificial intelligence neural network.* Frontiers in Neurorobotics, 2021. **15**: p. 690220.
109. Ech-Choudany, Y., et al., *Dissimilarity-based time–frequency distributions as features for epileptic EEG signal classification.* Biomedical Signal Processing and Control, 2021. **64**: p. 102268.

110. Gabara, A., et al. *Patient specific epileptic seizures prediction based on support vector machine*. in *2020 32nd International Conference on Microelectronics (ICM)*. 2020. IEEE.
111. Rusnac, A.-L. and O. Grigore. *Intelligent Seizure Prediction System Based on Spectral Entropy*. in *2019 International Symposium on Signals, Circuits and Systems (ISSCS)*. 2019. IEEE.
112. Abbaszadeh, B., T. Haddad, and M.C. Yagoub. *Probabilistic prediction of Epileptic Seizures using SVM*. in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. 2019. IEEE.
113. Baskar, K. and C. Karthikeyan, *Epilepsy seizure detection using akima spline interpolation based ensemble empirical mode Kalman filter decomposition by EEG signals.* Journal of Medical Imaging and Health Informatics, 2019. **9**(6): p. 1320-1328.
114. Zhang, Q., et al., *Epilepsy prediction through optimized multidimensional sample entropy and Bi-LSTM.* Biomedical Signal Processing and Control, 2021. **64**: p. 102293.
115. Usman, S.M., S. Khalid, and Z. Bashir, *Epileptic seizure prediction using scalp electroencephalogram signals.* Biocybernetics and Biomedical Engineering, 2021. **41**(1): p. 211-220.
116. Prathaban, B.P. and R. Balasubramanian, *Dynamic learning framework for epileptic seizure prediction using sparsity based EEG Reconstruction with Optimized CNN classifier.* Expert Systems with Applications, 2021. **170**: p. 114533.
117. Zhang, B., et al., *Cross-subject seizure detection in EEGs using deep transfer learning.* Computational and Mathematical Methods in Medicine, 2020. **2020**.
118. Sharan, R.V. and S. Berkovsky. *Epileptic seizure detection using multi-channel EEG wavelet power spectra and 1-D convolutional neural networks*. in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. 2020. IEEE.
119. Ilakiyaselvan, N., A.N. Khan, and A. Shahina, *Deep learning approach to detect seizure using reconstructed phase space images.* Journal of biomedical research, 2020. **34**(3): p. 240.
120. Wang, G., et al., *Seizure prediction using directed transfer function and convolution neural network on intracranial EEG.* IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2020. **28**(12): p. 2711-2720.
121. Liu, G., W. Zhou, and M. Geng, *Automatic seizure detection based on S-transform and deep convolutional neural network.* International journal of neural systems, 2020. **30**(04): p. 1950024.
122. Yuan, Y., et al., *A multi-view deep learning framework for EEG seizure detection.* IEEE journal of biomedical and health informatics, 2018. **23**(1): p. 83-94.

123. Wei, X., et al., *Early prediction of epileptic seizures using a long-term recurrent convolutional network.* Journal of neuroscience methods, 2019. **327**: p. 108395.
124. Hu, X., et al., *Scalp EEG classification using deep Bi-LSTM network for seizure detection.* Computers in Biology and Medicine, 2020. **124**: p. 103919.

APPENDIX

Programming methods for each research paper are saved in the following addresses:

Paper 1: https://github.com/nicki1228/paper1/tree/main
Paper 2: https://github.com/nicki1228/Paper-2/tree/main
Paper 3: https://github.com/nicki1228/Paper-3