Using Sparse Representation of EEG Signal from a Shallow Sparse Autoencoder for Epileptic Seizure Prediction

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Abstract: Patients with epilepsy are affected with unexpected seizure events, which significantly diminish their quality of life. It is crucial to evaluate whether an epileptic patient's brain state is indicative of a possible seizure occurrence so that necessary therapy or alarm can be generated on time. If seizures could be predicted before the onset, interventions may be applied to avoid further damage during seizure attack, and patients could take medications or other treatments to prevent seizures from occurring. This research describes a patient-specific technique for predicting epileptic seizures based on a hybrid model. Single layer sparse autoencoder is trained to obtain a aparse representation of the scalp electroencephalogram (EEG) signals. SVM classifier is used to categorize the sparse signal as inter-ictal or pre-ictal. Individual EEG channel analysis for seizure prediction are presented. In addition, various hidden sizes of the autoencoder for optimal sparse representation are anlyzed.The proposed model evaluates 13 patients from the CHB-MIT dataset and obtains a sensitivity of 98% and an area under the curve (AUC) of 98%. We have evaluated the performance of our hybrid strategy to both deep learning models and conventional procedures. The proposed method outperforms current seizure prediction techniques, proving its efficacy.

1 INTRODUCTION

Epilepsy is a prevalent neurological disorder classified as the second most likely neural disease of the brain, and the number of epileptic patients has increased dramatically in recent years. A spontaneous epileptic seizure is characterized by the transient and instantaneous abnormal disruption of brain neurons (Yang et al., 2021b). Seizures caused by epilepsy can produce serious disruptions in a patient's emotions, behavior, movements, and awareness, and can result in severe damage or even death. The premature death rate of these patients is two to three times that of disease-free persons, placing a significant burden on the patients, their families, and the community (Rasheed et al., 2021).

The hypothesis underlying seizure prediction is that there exists a transition state (preictal) between the interictal (normal state) and the ictal (seizure state) (Truong et al., 2018). This notion is supported by an abundance of clinical evidence. Consequently, researchers have devoted a substantial amount of effort over the past few decades to attempting to anticipate epileptic seizures based on intracranial EEG and scalp EEG signals, with the latter being more practical for clinical application (Zhang and Li, 2022).

Early prediction of epileptic seizures provides sufficient time before the seizure really occurs; this is extremely important because the treatment can prevent the attack. The problem of seizure prediction (or forecasting) is detecting seizure symptoms and determining if the patient is on the verge of an attack (Ryu and Joe, 2021). Detecting seizure symptoms is analogous to identifying the inter-ictal and pre-ictal phases, according to the phase distinction.

Therefore, similar to conventional signal classification, numerous methods for seizure prediction have been proposed in the literature based on feature extraction and classification. For forecasting epileptic seizures from EEG readings, machine learning approaches and computational algorithms are applied with different feature extraction techniques. For example, (Usman et al., 2017) used empirical mode decomposition (EMD) for preprocessing and retrieved time and frequency domain information for training a prediction model. A patient-specific technique for predicting epileptic seizures based on the common spatial pattern (CSP) feature extraction of scalp EEG signals is presented in (Alotaiby et al., 2017). Seizure prediction framework using bag-of-wave (BoWav)

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feature extraction and synchronization patterns is proposed by (Cui et al., 2018). However, conventional features are generally chosen empirically after a brief period of time, therefore the key characteristics may be ignored (Cui et al., 2018).

In a relatively new trend, deep learning algorithms are being used in medical image and signal processing. Interest has been drawn to deep learning techniques due to their robust feature extraction capacity. This is possible because of advances in computing power and the availability of big data. These algorithms have a lot of potential and can have a big impact because, in most cases, their performance is better than what was possible with traditional machine learning techniques. Researchers have mostly been interested in convolutional neural networks (CNNs) for seizure prediction (Truong et al., 2018). This is likely because CNNs have been extensively used in image processing and are therefore better known and more established in the research community. Moreover, Long Short-Term Memory (LSTM), stacked autoencoders (SAE) and convolutional autoencoders (CAE) are developed for classifying EEG data resulting in high accuracy systems (Ryu and Joe, 2021), (Tautan et al., 2019). These methods, however, have a significant energy consumption as well as a huge number of parameters and hardware resources (Zhao et al., 2020). Therefore, these techniques cannot be used with small, low-power wearable or implantable medical equipment. To continuously update the epileptic patients, the devices should run in real-time.

There have been significant advancements in the field of epileptic seizure prediction, with promising outcomes reported by various methodologies. However, these existing systems typically utilize multichannel EEG signals for pre-ictal and inter-ictal recognition. These methods extract features from multiple EEG channels or analyse all available channels collectively in order to categorize multi-channel epochs of short time intervals as pre-ictal or interictal for seizure prediction. Existing approaches do not analyze individual EEG channels for the identification of abnormalities or signal variations that lead to these state shifts. This also holds true for epileptic seizure detection techniques. EEG analysis at the level of a single channel is important for various reasons: Initially, a neurologist would like to construct his analysis of multi-channel EEG input bottom up (from individual signal to group level). The individual signal-level evidence builds the multichannel epoch-level determination. Second, analysis at the level of individual signals can reveal the potential of each EEG channel for seizure prediction depending on the type of seizure. Exploring multi-channel EEG analysis by combining single channel evaluations is an effective approach. This technique also presents the possibility of exploring the use of minimal EEG channels for seizure prediction (or detection) rather than using data from the entire scalp. In addition, the advancement of such a system is advantageous for the creation and usage of wearable devices and sensor networks, resulting in greater wearing comfort and a more compact form factor due to a reduction in processing demand.

This paper presents an approach for epileptic seizure prediction using a hybrid model comprising of a shallow sparse autoencoder (AE) and support vector machine (SVM) classifier. We therefore elaborate these methods as follows:

1.1 Shallow Sparse Autoencoder

The basic components of an AE are: an encoder and a decoder. To rebuild the original dataset x from the encoder's representation y, the decoder is configured to minimize the difference between x and $\hat{x}$, as shown in Fig. 1. The encoder's output y represents the reduced representation of x, which consists of n samples. To be more precise, an encoder is a function $f(.)$ that converts a given input x into some unknown representation y. The procedure is stated as follows:

A shallow AE with a single hidden layer comprising of n neurons in the input/output layer and m hidden neurons is developed with $m < n$ as shown in Fig. 1. Encoder layer is evaluated with sharing weights $W^E \in \mathbb{R}^{n\times m}$ and biases vector $b_x \in \mathbb{R}^m$. The decoder layer reconstructs the signal with weights $W^D \in \mathbb{R}^{m\times n}$ and biases vector $b_y \in \mathbb{R}^n$. These weights and biases of the model are calculated over signal reconstruction error instead of classification results. The scaled conjugate gradient (SCG) was designated to update these weights and bias values. Encoding process for input EEG signal $x \in \mathbb{R}^n$ is modeled as:

$$y = f(W^E x + b_x) \tag{1}$$

Where $f(\cdot)$ represents the activation function in the encoder neurons. Two inputs, a bias vector b and a matrix W, are used to configure the decoder. In most cases, the activation function is selected based on the characteristics of the available data (Meng et al., 2017). However, in contrast to non-linear functions, linear activation helps in building a system with low computational cost. For this reason, both the encoding and decoding procedures will use linear activations. For the encoder's activation function, the saturating linear transfer function (Satlin) is described as:

$$satlin(x) = \left\{ \begin{array}{ll} -1 & x < -1 \\ 0 & -1 \leqslant x \leqslant 1 \\ 1 & x > 1 \end{array} \right\} \quad (2)$$

Finding the values of the training parameters $\theta = (W, b_x, b_y)$ that minimize the reconstruction loss for a given dataset is the goal of AE training.

$$\Theta = min_{\theta} L(x, \hat{x}) = min_{\theta} L(x, f(W^T x + b)) \quad (3)$$

The reconstruction loss L in AE's training phase is typically derived from the square of the error:

$$L(\theta) = \frac{1}{n} \sum_{k=1}^{n} (x - \hat{x})^2 \quad (4)$$

Here, both the n and m represents the number of samples in the signal. The decoder layer reconstructs the sparse vector $y \in \mathbb{R}^m$ to its original form as:

$$\hat{x} = W^D y + b_y \quad (5)$$

AE's objective function reconstructs the input to its original form. High weights of hidden layers make the generated features more dependent on the network structure rather than the input data. Therefore, to avoid this complexity, sparse AE imposes weight-decay regularization so as to keep neuron weights small.

$$\Theta = \alpha min_{\theta} L(x, \hat{x}) + \lambda ||W||^2 \quad (6)$$

Here, α is the scale parameter to control the weights of the data reconstruction loss. We used L_2 regularization $||W||^2$ to ensure weight matrix W having small elements. Hyper parameter λ is incorporated to control the regularization strength. Transfer function to compute decoder layer's output is linear function (Purelin) $f(x) = x$. These functions are applied to each signal sample using the Mean Square Error (MSE) loss function, presented in equation 4. MSE is used in the AE's training phase to compare the original and reconstructed signals. Encoding yields a sparse representation of the signal, while decoding generates a reconstruction of the signal to its original form. The decoding is only added in training phase to ensure the best sparse representation of the data possible.

Sparsity level of the AE for input signal of length n and hidden size m is given as:

$$SparsityLevel = \frac{n}{m} \quad (7)$$

1.2 Gaussian SVM

The Gaussian kernel SVM is frequently employed due to its excellent performance, and is frequently regarded as one of the most effective techniques when it comes to supervised learning (Yang et al., 2021a). To ensure that models perform well, it is necessary to precisely determine hyper-parameters such kernel width and penalty factor. The performance of the Gaussian kernel SVM is thoroughly examined in (Yang et al., 2021a) when the hyper-parameters are set to their most extreme values (0 or ∞). The Leave-One-Out (LOO) approach's local density and precision serve as the cornerstone of the parameter optimization strategy, which is suggested to increase computing efficiency. The kernel width of each sample is dependent on the local density necessary to ensure a higher separability in feature space, and the LOO approach refines the grid search to identify the ideal penalty value. The proposed method is evaluated for validity by comparison to the grid method (Yang et al., 2021a).

The impact of various kernel functions on SVM characteristics is highly variable (Yang et al., 2021a). Here, we used the Gaussian kernel presented in equation 8. An optimized hyperplane in kernel space is generated by a Gaussian function of kernel scale 4 and kernel offset 0.1. Training instances are separable for these parameters and yield optimal results. The feature space that training data is mapped to is determined by the kernel width. As a result, the success of an SVM's training procedure is profoundly affected by its accuracy.

$$k(x_i, x_j) = exp(-\frac{||x_i - x_j||^2}{2\sigma^2}) \quad (8)$$

Some of the key contributions of the proposed method are:

- We have used sparse representation generated by the AE for seizure prediction
- Our framework provides individual EEG channel analysis for seizure prediction
- Using autoencoder with only one hidden layer will reduce the computational complexity of the algorithm
- Multiple Hidden sizes of autoencoder are analyzed to obtain optimum sparse representation capable of effectively classifying the data as interictal or pre-ictal
- Our method outperforms state of the art seizure prediction techniques

2 PROPOSED METHODOLOGY

AE based feature extraction method achieved great success in generating implicit features of high dimensional data (Meng et al., 2017). AE use artificial neural networks to reduce dimensionality by minimizing the reconstruction loss. Due to this, AE and its extensions demonstrate a promising ability to extract meaningful features, particularly in signal processing domain (Meng et al., 2017).

The fundamental processing architecture employed in this paper to predict epileptic seizures is depicted in Figure 1. Firstly, a sparse AE with only one hidden layer is trained to obtain a sparse signal directly from the raw EEG data. SVM classifier processes these sparse signal samples to categorize the data as inter-ictal or pre-ictal. Ability of various hidden sizes of the AE are analyzed for seizure prediction.

Using the raw EEG data directly without any transformation or feature extraction and AE with only one hidden layer will reduce the computational complexity of the algorithm. Avoiding the complicated process for extracting features, a lot of memory for storing high-precision parameters, and complex arithmetic computations will reduce the hardware resources requirement. It is desirable in wearable devices that demand low-power consumption and real-time operation. Therefore, the proposed methodology is computationally efficient, and its classification performance is comparable to that of existing seizure prediction techniques.

EEG data is divided into 1-second segments for each channel. These 1-second segments are fed into the AE. Different seizure prediction methods in the literature commonly use EEG data segments ranging from 1 to 30 seconds in length (Zhang and Li, 2022), (Khan et al., 2021). The proposed algorithm processes one-second EEG segments using a single EEG channel. The EEG dataset used in this work has previously been preprocessed for noise and artifact removal. As a result, to minimize the computational overhead of preprocessing, we use raw EEG data directly.

AE with single hidden layer processes each 1-sec EEG trial to produce its sparse representation. In the training phase, an encoder is used to determine a sparse representation of the signal, and a decoder is designated to restore the signal to its original form. The sparse signal samples are used as input to classifier model to categorize the data as inter-ictal or pre-ictal. However, the decoder part of the AE is discarded in the testing phase and only the encoder is utilized for seizure prediction. Numerous hidden sizes of AE are analyzed to obtain an optimum sparse signal samples capable of classifying the data precisely.

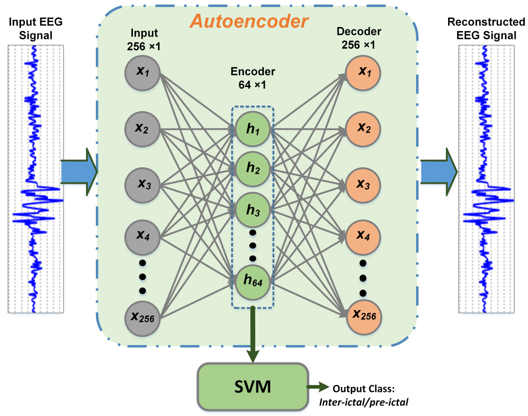

Figure 1: Work flow architecture of the proposed seizure prediction method.

2.1 Evaluation Data

In order to evaluate the effectiveness of the proposed seizure prediction system, we experimented with the Children's Hospital Boston-collected PhysioNet scalp EEG database CHB-MIT. There are 163 seizure occurrences recorded from 23 pediatric patients with 916 hours of continuous scalp EEG (sEEG) monitoring. Recordings from 22 participants are organized into 23 cases and sampled at 256 Hz.

We evaluate the common 18 channels for each patient to ensure model consistency and patient wise uniformity as in (Ryu and Joe, 2021), (Sun et al., 2021), (Gao et al., 2022). Because there are numerous patients in the experiment using different channels, we used the same 18 channels that all patients had. Therefore, we utilize 18 channels ("FP1-F7", "F7-T7", "T7-P7", "P7-O1", "FP1-F3", "F3-C3", "C3-P3", "P3-O1", "FP2-F4", "F4-C4", "C4-P4", "P4-O2", "FP2-F8", "F8-T8", "T8-P8", "P8-O2", "FZ-CZ", "CZ-PZ").

2.2 System Parameters

We experimented the proposed seizure prediction algorithm with various hidden sizes of the AE. For a an input size of 256, the encoder layer length varies from 64 to 8, corresponding to the sparsity levels 4 to 32 as demonstrated in equation 7. Reducing the AE's hidden size will decrease the computational cost of the algorithm. In addition, analyzing the EEG signals towards seizure prediction with different hidden sizes of the AE will help to select an optimum hidden size as we do not have a specific formula to build an AE with the most appropriate hidden size.

Table 1: Subjects information used in this study from the CHB-MIT database.

Patient ID	No. of seizure events	Inter-ictal Duration (hrs)
1	7	14
2	3	23
3	6	22
5	5	14
9	4	46
10	6	26
13	5	14
14	5	5
18	6	24
19	3	25
20	5	20
21	4	22
23	5	13
Total	64	268.6

The time interval between at least 4 hours (hrs) before the start of a seizure and 4 hrs after it has ended is known as the inter-ictal phase. CHB-MIT dataset demonstrates that many seizures can take place near together. In the seizure prediction task, we are interested in forecasting a seizure episode that will occur within roughly 30 minutes of the previous one. As a result, we treat seizures that happen within 30 minutes of one another as a single seizure, with the first seizure's onset serving as the start of the combined seizure. Additionally, we only take into account patients with less than 10 seizures per day for the prediction task because it is not necessary to predict seizures occurrence for patients experiencing seizures on average every 2 hours. These parameters indicate that 13 participants have sufficient data (at least three primary seizures and three hrs of interictal recording). The subject ID, total number of seizure occurrences, and length of the inter-ictal period for each subject are included in the Table 1 thorough description of each subjects' information.

The Seizure Prediction Horizon (SPH) is the time between the alert triggered in anticipation of the seizure occurrence and the actual ictal state onset. For an accurate forecast, a seizure must occur after the SPH and before the Seizure Occurrence Period (SOP), which is the estimated time span for seizure occurrence. A false alarm will be generated if the prediction algorithm produces a positive signal (a seizure is imminent) but there is no seizure during the SOP. After the alert has been triggered, the ideal therapeutic application of SPH is giving the patient sufficient time to take preventative measures. A patient's SPH must be lengthy enough to allow for adequate safety measures once the alarm is activated. To comfort the patient, however, the SOP should not be overly lengthy. In this research, we employ the SPH period of 10 minutes and the SOP period of 30 minutes.

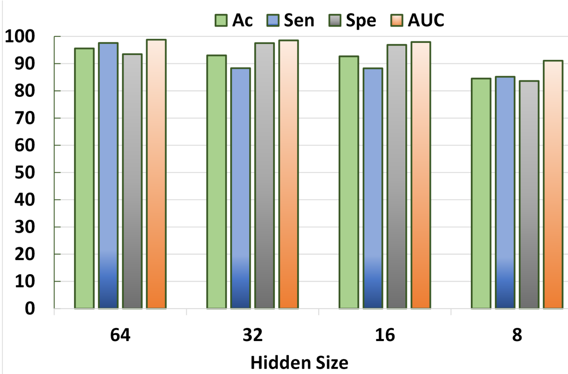

Figure 2: Variations in Seizure prediction performance of the proposed method using different hidden sizes (Sparsity Levels) of the AE for channel 'FzCz' (best case).

Inter-ictal EEG recordings are more prevalent than pre-ictal EEG recordings because the ictal state is uncommon across lengthy hours of EEG recordings. In machine learning methods, it is commonly assumed that data from different classes should be distributed uniformly (Rasheed et al., 2021). A classifier trained on a greater number of examples for one class in comparison to other classes will be biased and prefer an uneven decision. To overcome the class imbalance problem, numerous strategies are discussed in the literature, including overlapping window (Truong et al., 2018),(Dissanayake et al., 2021), generative adversarial network (GAN) (Rasheed et al., 2021), and synthetic minority over-sampling technique (SMOTe) (Usman et al., 2021). We utilize SMOTe to produce additional pre-ictal data during the training phase, hence addressing the issue of data imbalance as described in (Usman et al., 2021). By supplementing pre-ictal state data with an overlapping window, SMOTe can alleviate the class imbalance issue.

3 SYSTEM EVALUATION

3.1 Experimental Setup

Using the CHB-MIT database, the AE model for sparse representation of the input signal is trained using 10 minutes of pre-ictal EEG data (1-second duration segments) for each seizure. For example, as indicated in Table 1, Patient 1 has experienced seven seizures. Therefore, we extract 70 (7×10) minutes of pre-ictal data and the same amount of data for the inter-ictal phase for this patient. Various model assessment strategies have been presented in the lit-

Table 2: Patient wise classification results of the proposed seizure prediction method with AE's hidden size 64.

Patient ID	Channel 'FzCz' (Best Case)				Channel 'FP1F7' (Worst Case)			
	Ac	Sen	Spe	AUC	Ac	Sen	Spe	AUC
1	99.0	100	97.8	100	92.6	89.2	96.1	97.0
2	93.8	98.7	91.8	98.0	89.7	85.8	93.4	94.0
3	96.3	98.1	93.0	99.0	88.0	97.4	78.4	89.0
5	96.1	98.1	95.0	99.0	83.4	74.7	92.2	92.0
9	97.5	98.3	94.6	99.0	89.2	82.4	95.9	90.0
10	95.0	99.3	91.0	100	91.9	86.0	97.8	94.0
13	95.7	99.4	91.8	98.0	88.0	87.2	88.9	94.0
14	94.1	91.2	98.0	99.0	87.2	78.3	96.9	95.0
18	95.4	99.1	91.3	100	86.8	86.5	87.1	88.0
19	94.1	97.0	91.5	98.0	94.0	97.8	90.3	95.0
20	97.0	99.0	96.1	100	97.1	96.0	98.2	95.0
21	95.8	99.3	92.5	99.0	87.1	85.3	88.8	91.0
23	92.0	91.0	92.0	95.0	86.1	84.6	87.7	90.0
Average	**96.0**	**98.0**	**93.5**	**98.8**	**89.3**	**87.1**	**92.0**	**92.6**

erature, including patient-wise data partitioning into train and test sets (Zhang et al., 2021a), k-fold CV (Rasheed et al., 2021), (Ryu and Joe, 2021), and LOO CV (Gao et al., 2022). As a result, for a fair comparison and to avoid over-fitting, we evaluated the performance of the proposed seizure prediction model using the same 10-fold CV as the majority of existing approaches. Raw trials/segments of duration 1 second were utilized without any preprocessing. The compressed form of these segments was utilized to train the 10-fold CV-based classifier.

3.2 System Performance

The sampling rate of the dataset is 256, while the hidden size of AE is 64 (at sparsity level 4). This implies that the sparse signal length is 64, which the SVM classifier uses to identify the data as pre-ictal or inter-ictal. Among the 18 available EEG channels of the dataset, we present the results of best and worst performing channels. Channel 'FzCz' corresponds to the the best case providing the highest average classification results for all the patients, whereas, channel 'FP1F7' is the worst case. Table 2 provides a summary of the patient-specific seizure prediction results achieved with these two channels. Performance metrics include prediction accuracy (Ac), sensitivity (Sen), specificity (Spe), and area under the curve (AUC). Even when using a single EEG channel, the proposed approach can produce results comparable to those of previous studies on the prediction of seizures. The prerequisite is the Neurologist's selection of the channel.

The proposed classification approach is also evaluated using an AE with variable hidden sizes that generates sparse signals of varying lengths. Figure 2 illustrates the average Ac, Sen, Spe, and AUC of the proposed method for seizure prediction at each sparsity level. Statistical analysis of performance evaluation demonstrates that the proposed classification model can be utilized in a variety of system-required scenarios. The highest sparsity level reported is 32, which corresponds to compressing an input signal of length 256 to merely 8 samples.

3.3 Performance Comparison

Table 3 illustrates the performance comparison between the proposed algorithm and other existing epileptic seizure prediction approaches for the CHB-MIT dataset. However, even if the same datasets were used, the model performance would be affected by the selection of samples by different methods, the wide variety of channel configurations, the division of data, the duration of the pre-ictal period, and training approaches (such as processing for unbalanced data) and evaluation techniques (LOO, k-fold CV etc). We used a framework that is quite relevant to the existing high performance approaches in order to achieve a comparative analysis that is pretty fair.

Methods for classifying EEG at the segment level (1-30 sec intervals) and providing classification results in terms of accuracy, sensitivity, specificity, and AUC are compared. In this table, we present the best single-channel results. The AE utilized sparsity level 4. Classification performance statistics demonstrate that our method yields comparable results to the state-of-the-art, particularly in terms of prediction sensitivity, which is the most crucial factor to ensure that no seizure event prediction is missed.

Table 3: Average classification results comparison with some recent seizure prediction methods for CHB-MIT database.

Ref. - Year	**No. of Patients**	**Channels**	**Segment Length**	**SPH (min)**	**Evaluation**	**Data balancing**	**Ac** (%)	**Sen** (%)	**Spe** (%)	**AUC** (%)
(Yang et al., 2021b)	13	22	5 sec	30	10-fold CV	Overlap window	92.0	87.8	92.8	91.3
(Rasheed et al., 2021)-2021	13	22	60 sec	10	10-fold CV	GAN	92.0	90.9	89	-
(Truong et al., 2018)	13	22	30 sec	30	LOO-CV Seizure wise	Overlap window		81.2	-	-
(Ryu and Joe, 2021)	23	18	10 sec	10	k-fold CV	-	92.6	91.2	94.1	-
(Zhang et al., 2021b)	19	23	8 sec	15	Train/Test split	Overlap window	89.9	92.9	87.0	-
(Usman et al., 2021)	22	23	29 sec	32	k-Fold CV	SMOTe	-	93	92.5	-
(Liang et al., 2022)	13	All	30 sec	30	LOO-CV Patient Wise	Overlap window	-	88.3	-	-
(Dissanayake et al., 2021)	24	23	10 sec	60	10-fold CV	Overlap window	91.5	92.4	89.9	96.9
(Zhang et al., 2021a)	13	23	5 sec	5	Test 1 patient; Train Rest	-	80.0	-	74.1	-
(Sun et al., 2021)	17	18	1.5 sec	30	4-fold CV	Overlap window	-	97.1	95.6	91.7
(Li et al., 2021)	19	All	5 sec	15	LOO-CV Seizure Wise	-	-	95.5 -	-	93.8 -
(Gao et al., 2022)	16	18	4 sec	30	LOO-CV	Overlap window	-	93.3	-	-
(Halawa et al., 2022)	16	18	10 sec	8	70% Train 30% Test	Overlap window	93.4	-	-	86.5
This_work (Channel ‘FP1F7’, Worst Case)	**13**	**1**	**1 sec**	**10**	**10-fold CV**	**SMOTe**	**89.3**	**87.1**	**92.0**	**92.6**
This_work (Channel ‘FzCz’ , Best case)	**13**	**1**	**1 sec**	**10**	**10-fold CV**	**SMOTe**	**96.0**	**98.0**	**93.5**	**98.8**

4 CONCLUSIONS

Using a single-layer autoencoder and SVM classifier, we introduced a hybrid method for developing a baseline model for the early prediction of epileptic episodes in this study. Two phases of EEG data processing are proposed for the prediction of seizures. First, a sparse signal is generated using a dimensionality reduction methodology based on a deep learning method for unsupervised learning. The SVM classifier is then trained to classify the data as either interictal or pre-ictal. Analysis of a single EEG channel are provided to predict the beginning of epileptic episodes. Evaluation at the level of individual signals reveals the seizure-predicting capability of each EEG channel. This method provides the possibility of combining analysis of fewer EEG channels to get reliable seizure prediction on their basis. The proposed method outperformed state-of-the-art methodologies, with an average prediction sensitivity of 98% percent and an area under the curve (AUC) of 98%. Developing such a high-performance system is beneficial for the construction and usage of wearable devices and sensor networks, making them more comfortable to use and smaller in size as a result of the decreased processing requirements. In the future, the current effort will be broadened to produce more exhaustive findings.

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