Epileptic Seizure Detection in SEEG Signals using a Unified Multi-scale Temporal-Spatial-Spectral Transformer Model

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Abstract. High-performance methods for automated detection of epileptic stereo-electroencephalography (SEEG) have important clinical research implications, improving the diagnostic efficiency and reducing physician burden. However, few studies have been able to consider the process of seizure propagation, thus failing to fully capture the deep representations and variations of SEEG in the temporal, spatial, and spectral domains. In this paper, we construct a novel long-term SEEG seizure dataset (LTSZ dataset), and propose channel embedding temporal-spatial-spectral transformer (CE-TSS-Transformer) framework. Firstly, we design channel embedding module to reduce feature dimensions and adaptively construct optimal representation for subsequent analysis. Secondly, we integrate unified multi-scale temporal-spatial-spectral analysis to capture multi-level, multi-domain deep features. Finally, we utilize the transformer encoder to learn the global relevance of features, enhancing the network's ability to express SEEG features. Experimental results demonstrate state-of-the-art detection performance on the LTSZ dataset, achieving sensitivity, specificity, and accuracy of 99.48%, 99.80%, and 99.48%, respectively. Furthermore, we validate the scalability of the proposed framework on two public datasets of different signal sources, demonstrating the power of the CE-TSS-Transformer framework for capturing diverse temporal-spatial-spectral patterns in seizure detection. The code is available at https://github.com/lizhuoyi-eve/CE-TSS-Transformer.

Keywords: Seizure detection · Multi-scale analyse · Transformer

1 Introduction

Epilepsy is a chronic neurological disorder caused by sudden abnormal discharges of brain neurons, affecting approximately 70 million people worldwide [1,2]. As a minimally invasive method, stereo-electroencephalography (SEEG) is widely used in the diagnosis and treatment of epilepsy [3]. However, current clinical practice still requires physicians to visually observe and analyse long-term SEEG signals, which is very subjective and time-consuming. Therefore, leveraging computer-assisted diagnoses for intelligent recognition of epileptic SEEG signals is an effective alternative to manual seizure detection.

Many machine learning methods have been proposed [4,5,6]. For instance, Zubair *et al.* [7] used discrete wavelet transform for extracting time-frequency features and the variants of principal component analysis for dimensionality reduction to achieve epilepsy detection. Li *et al.* [8] proposed a method combining multi-scale Radial Basis Function networks with Fisher Vector encoding for extracting EEG epilepsy features from the time-frequency domain. In recent years, deep learning methods have also been explored [9,10,11]. Yu *et al.* [12] proposed a SEEG classification method based on an epilepsy domain adversarial network, which uses an adversarial network to learn SEEG features.

Although these methods have shown promising results, they are limited in their ability to fully capture the complex patterns of epileptic neural activity. Specifically, referring to their propagation process, seizures are caused by clustered abnormal discharges of brain neurons, generating high-frequency, transient spike waves, and transmitting them to different brain regions [13]. This process produces oscillatory signals with different spectra over time, during the ictal and interictal periods, which are transmitted to different brain spatial regions. Therefore, multi-scale temporal, spatial, and spectral analyses of long-term epilepsy data can provide insights into ictal and interictal state features. However, previous research has not adequately considered the propagation process of seizures, failing to fully capture the associated neural activity variation across temporal, spatial and spectral domains. Also, few studies have designed seizure detection methods specific for SEEG.

To address aforementioned problems, this paper designs an interpretable channel embedding temporal-spatial-spectral transformer (CE-TSS-Transformer) framework for detecting seizures on a novel long-term seizure SEEG dataset. Its main contributions are as follows:

1) A novel channel embedding (CE) module is designed to address the often overlooked temporal patterns and randomness in the original SEEG signals. It reduces feature dimensions and provides an adaptive optimal representation for subsequent multi-scale analyses.

2) A multi-scale temporal-spatial-spectral (TSS) convolution network is designed to comprehensively capture the specific representations of different time, channels and SEEG rhythms in a uniform manner.

3) A TSS-Transformer network is designed to address the local sensory domain of convolutional neural network. The network learns the global correlation of local features, enhancing the representation capability of SEEG signals.

4) In addition to the novel SEEG dataset, the proposed method is capable of dealing with a variety of multi-scale temporal, spatial and spectral patterns from other neural activity modalities, including depth electrodes, strip electrodes and EEGs. The method is also capable of dealing with inter-patient heterogeneity.

2 Materials and Methods

2.1 Epilepsy Datasets

LTSZ dataset. The dataset for this paper is collected from the neurosurgery department of a hospital that monitored the clinical epilepsy SEEG of five patients, which we also refer to as the long-term SEEG seizure dataset (LTSZ dataset). The SEEG signals of all patients are obtained using the Neruacle Digital EEG Machine (NSH0256) with a sampling frequency of 4000 Hz. Each patient have an individualised surgical pathway, and each SEEG have a different number of contacts, each of which represented SEEG channel. The SEEG data are reviewed and approved by the ethical committee of the hospital. Ictal and interictal data are manually labelled by two physicians with extensive clinical experience. General information of all patients is shown in Table 1.

Table 1. General information of epileptic patients of the LTSZ dataset.

Patient ID	Gender	Age	SEEG electrodes	SEEG contacts	Seizure events	Total seizure time(s)	Total time(h)
01	Female	33	9	127	146	4380	384
02	Female	5	10	132	65	10549	154
03	Female	11	8	126	138	2438	94
04	Male	15	13	196	12	2430	237
05	Female	10	11	142	16	1067	92

Bonn Dataset. The public dataset consists of five sets (A-E), each containing 100 segments of neural activity with length of 23.6s and frequency of 173.61 Hz. Specifically, sets C and D contain signals from depth electrodes recorded during interictal periods of five epilepsy patients, while set E contains signals from depth and strip electrodes recorded during ictal periods [14].

CHB-MIT Dataset. The public dataset consists of scalp EEG signals from 22 paediatric epilepsy patients at Children's Hospital Boston. The dataset totalled 961 hours and contained 198 seizures. The EEG electrodes are placed according to the International 10-20 system with a sampling frequency of 256 Hz [15].

2.2 Preprocessing

Preprocessing helps improve the quality of signals, making them more suitable for subsequent epilepsy detection [16,17]. The two public datasets have already been preprocessed [14,18]. We perform the following steps of the LTSZ dataset:

1) *Downsampling*: Reduce the original sampling frequency from 4000 Hz to 1000 Hz to retain essential information while decreasing data volume and improving computational efficiency.

2) *Bandpass and Notch Filtering*: Apply bandpass filtering to the SEEG signals within the range of 0.5-70 Hz to eliminate noise. Implement notch filtering on the SEEG signals to remove powerline interference.

3) *Normalization*: Utilize z-score normalization to reduce the fluctuation and nonstationarity of SEEG signals.

For the LTSZ, Bonn, and CHB-MIT datasets, continuous brain activity records are pre-organized into non-overlapping 2s epoch segments before being input into CE-TSS-Transformer.

2.3 Architecture of the CE-SST-Transformer Framework

The overview of the proposed model framework of CE-TSS-Transformer is shown in Fig. 1. Components of this framework is detailed in the following sections and Fig. 2. As the inputs, the SEEG dataset are defined as $D_i = \{(x_1, y_1), ..., (x_{N-1}, y_{N-1}), (x_N, y_N)\}$, where y represents labels for ictal or interictal periods. N represents the total number of SEEG segments. $x_j \in \mathbb{R}^{E \times P}$ represents SEEG segments with E channels and P sampling points at a sampling rate of s_i. Similar definition applies to the other two public datasets.

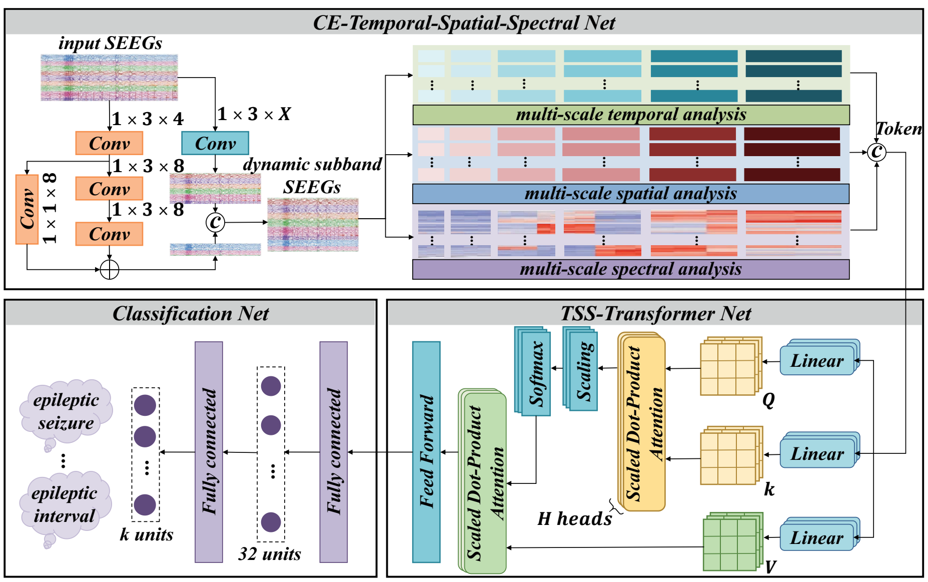
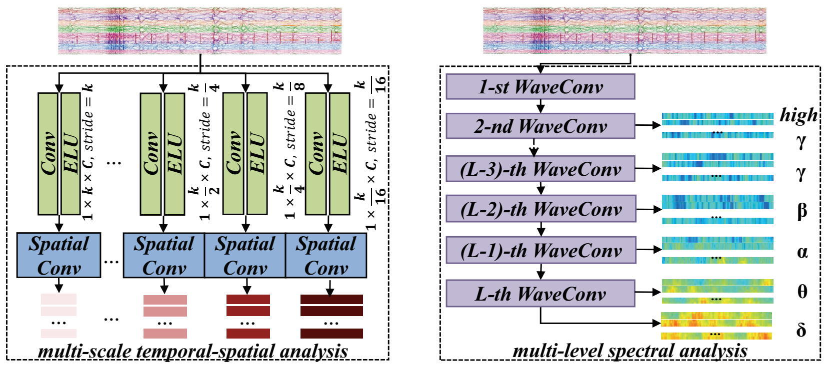


Fig. 1. Architecture of the proposed CE-TSS-Transformer framework.

CE-Temporal-Spatial-Spectral Net. To construct optimal representations for subsequent TSS analyses, we set up a CE module. This module first embeds the original SEEG segments of size $E \times 1 \times T$ into a set of $8 \times 1 \times T$ time-series



(a) (b)

Fig. 2. Schematic of the multi-scale temporal-spatial-spectral analysis. (a) multi-scale temporal-spatial analysis; (b) multi-scale spectral analysis.

representations. The first two temporal convolution layers perform convolution and batch normalization, with a kernel size of 1×3, stride of 1, and padding of 1. The dimensionality of time-series-like embedding is reduced in the final convolutional layer and the residual module using the exponential linear unit (ELU) and average pooling. Meanwhile, the original SEEG segments undergoes convolution, ELU, and average pooling to retain its main features. The '$1 \times 3 \times 4$' and '$1 \times 3 \times 8$' denote dilation rates of 4 and 8, respectively, while 'X' in '$1 \times 3 \times X$' denotes the number of SEEG contacts for different patients. Finally, the processed SEEG input signal is concatenated with the time-series-like embedding to create the dynamic subband matrix $\mathbf{M} \in \mathbb{R}^{C \times 1 \times T}$, where $C = E + 8$.

1) Multi-scale temporal analysis. Considering the non-stationary and heterogeneity of SEEG in epilepsy patients, we proposed multi-scale temporal to capture SEEG features across different time scales. This process is shown in Fig. 2(a). We used six independent temporal convolution layers, each including temporal convolution of different sensory domains, batch normalization, and ELU to extract SEEG features. Each layer can be expressed as:

$$t_i = ELU(BN(Conv(x_{CE}))) \tag{1}$$

where, x_{CE} denotes the dynamic subband SEEGs. t_i is the feature obtained from each layer, $i \in \{1, 2, 3, 4, 5, 6\}$. The size of six convolution kernels is set to $\{k, k, \frac{k}{2}, \frac{k}{4}, \frac{k}{8}, \frac{k}{16}\}$, $k = 2^{\lfloor \log_2 s_i \rfloor - 3}$. Considering s_i=1000 Hz, it can be calculated that $k = 64$, i.e., the size of six convolution kernels is set to $\{64, 64, 32, 16, 8, 4\}$.

2) Multi-scale spatial analysis. Considering the spatial propagation during seizures, we reveal the features of brain activity at different scales through multi-scale spatial analysis. The features after multi-scale temporal analysis undergoes spatial convolution along the electrode channel, retaining k convolution kernels of size $C \times 1$ with a stride of 1. This layer acts as a spatial filter, learning the features between different channels after multi-scale temporal analysis.

3) Multi-scale spectral analysis. Multi-scale spectral analysis is helpful for studying the dynamic changes of different frequency components during ictal and interictal states. This process is shown in Fig. 2(b). We propose a multi-layer wavelet convolution method to extract different SEEG rhythms. The definition of a wavelet convolutional layer can be expressed as:

$$\begin{aligned} x_p = x_{CE}(N-\tfrac{R}{2}+1), \ldots, x_{CE}(N-1) \copyright x_{CE}(0), \\ \ldots, x_{CE}(N-1) \copyright x_{CE}(0), \ldots, x_{CE}(\tfrac{R}{2}-2) \end{aligned} \tag{2}$$

$$\begin{aligned} y_A(t) = \textstyle\sum_{r=0}^{R} x_p(s \times i - r) \times g(r) \\ y_D(t) = \textstyle\sum_{r=0}^{R} x_p(s \times i - r) \times h(r) \end{aligned} \tag{3}$$

where, $\copyright$ denotes the concatenating operation. N denotes the length of the SEEG segments. The 1-D signal of length N from each channel in x_{CE} is taken as input, resulting in x_p after periodic padding. R, s denote the size of the convolution kernel and stride, respectively. $y_A(t)$ and $y_D(t)$ denote the approximate wavelet coefficients and fine wavelet coefficients, respectively. g, h are a pair of wavelet convolution kernels.

In order to obtain the wavelet coefficients of different SEEG rhythms, i.e. 0-4 Hz (δ rhythm), 4-8 Hz (θ rhythm), 8-12 Hz (α rhythm), 13-30 Hz (β rhythm), 30-50 Hz (γ rhythm), and $>$50 Hz (high γ rhythm), we choose the Db4 wavelet basis function for spectral feature extraction. The stride and kernel size of WaveConv are set to 2 and 8. The number of layers of the wavelet convolution $L = 2^{\lfloor \log_2 s_i \rfloor - 3}$, which can be calculated as $L = 6$.

TSS-Transformer Net. CE-TSS net concatenates the multi-scale features to obtain six sets of hybrid features as shown in Fig. 1. We input the concatenates features into the transformer encoder to better capture long-distance dependencies and structural information, and the process can be expressed as:

$$Attention(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = Softmax(\frac{\mathbf{Q}\mathbf{K}^{\mathrm{T}}}{\sqrt{k}})\mathbf{V} \tag{4}$$

where, k denotes the length of the token. Matrix $\mathbf{Q}$, $\mathbf{K}$ and $\mathbf{V}$ denotes the query, key and value.

$$\begin{aligned} MHA(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = [head_0; \ldots; head_{H-1}] \\ head_n = Attention(\mathbf{Q_n}, \mathbf{K_n}, \mathbf{V_n}) \end{aligned} \tag{5}$$

where, MHA denotes the multi-head attention. H denotes the number of heads. $\mathbf{Q_n}, \mathbf{K_n}, \mathbf{V_n}$ denotes the query, key, and value of the n-th head after linear transformation.

Classification Net. The detection of epileptic seizure onset in SEEG signals utilizes a multilayer perceptron (MLP) as a classification net. The final output is the classification result, indicating the probability of input SEEG segments belonging to the ictal or interictal periods.

3 Experiments and Results

3.1 Experimental Settings

Our method is implemented based on Python 3.8.10 using PyTorch 1.8.1 and GeForce RTX 3090 GPU. The training epoch is set to 2000, the learning rate to 0.0002, β_1 to 0.9, and β_2 to 0.999. In addition, the number of heads H is set to 10, and the number of layers is set to 6 in the TSS-Transformer net. Classification sensitivity (SEN), specificity (SPE) and accuracy (ACC) are used as the metrics to evaluate the performance of clinical epilepsy seizure detection [19].

The experiments used cross-entropy to train the network and the leave-one-out method for n seizure data of each patient, i.e., the SEEG data of one seizure is selected as the test set each time, and the data of the remaining $n-1$ seizures are selected as the training set, and the experiments are repeated for n times, and the final average result on the test set is taken as the final result.

3.2 Experimental Results

Detection Performances. Using the LTSZ dataset for single-patient seizure detection, the model is trained sequentially, and the final detection results are shown in Table 2. The detection results on the SEEG signals of five patients with epilepsy show that our proposed model achieves high detection accuracy, with SEN, SPE and ACC reaching 99.48%, 99.80% and 99.48%, respectively.

Table 2. The performance of seizure detection on the LTSZ dataset.

Patient ID	SEN(%)	SPE(%)	ACC(%)
1	100.00±0.00	100.00±0.00	100.00±0.00
2	97.38±0.44	98.98±0.41	97.40±0.44
3	100.00±0.00	100.00±0.00	100.00±0.00
4	100.00±0.00	100.00±0.00	100.00±0.00
5	100.00±0.00	100.00±0.00	100.00±0.00
Mean	**99.48±0.09**	**99.80±0.08**	**99.48±0.09**

We conducted comparisons with other detection algorithms, following the same experimental procedures as our proposed CE-TSS-Transformer network. As shown in Table 3, our method outperforms the other methods by improving 3.15%, 2.88% and 2.81%, respectively.

Ablation Study. Multi-scale division uses 6 SEEG rhythms because single-scale analysis can't fully capture brain activity, so features from all rhythms are needed. To further validate the effectiveness, we compare the CE-TSS-Transformer with five simple structures. As shown in Fig. 3, our proposed framework outperforms the other five baselines in all classification scenarios.

Table 3. The performance comparison of different methods for seizure detection.

Method	LTSZ dataset		
	SEN(%)	SPE(%)	ACC(%)
EMD+SVM	93.32±0.52	96.35±0.47	94.76±0.12
CWT+SVM	96.77±0.32	97.83±0.18	94.92±0.46
Deep ConvNet	97.23±0.41	96.08±0.37	98.07±0.48
Transfomer	98.02±0.11	97.41±0.27	98.93±0.18
CE-TSS-Transformer	**99.48±0.09**	**99.80±0.08**	**99.48±0.09**

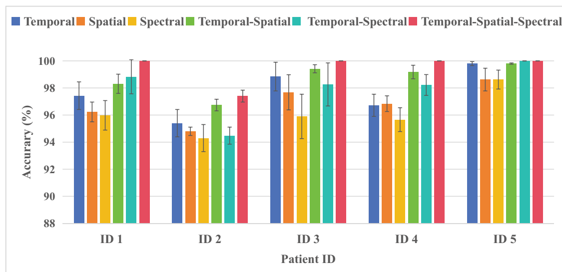


Fig. 3. Comparison of classification performance by multi-scale TSS analysis.

Performance on Other Neural Activity Modalities. Deep electrodes, strip electrodes, and EEG signals are important means for detecting epileptic seizures. Similar to SEEG signals, they record the neuronal firing process in the brain, accompanied by temporal, spatial, and spectral changes.

To validate the scalability of our proposed method, we compared it with two public datasets. On the Bonn dataset, similar to the CD-E classification task in the LTSZ dataset, we achieved recognition rates of 98.69% for SEN, 99.68% for SPE, and 99.00% for ACC. On the CHB-MIT dataset, comprehensive evaluation showed average SEN, SPE, and ACC values of 99.76%, 99.93%, and 99.83%, respectively. Compared to other studies, our epileptic seizure detection results are superior. Detailed experimental results are shown in Table 4, demonstrating the scalability of our proposed CE-TSS-Transformer detection method.

Table 4. Comparison with other related work on the Bonn and CHB-MIT dataset

Dataset	Author	SEN(%)	SPE(%)	ACC(%)
Bonn	Atal *et al.* [20]	98.66	98.50	98.50
	Lian *et al.*[21]	-	-	98.03
	Liu *et al.*[22]	97.00	99.50	98.70
	This work	**98.69**	**99.68**	**99.00**
CHB-MIT	Jiang *et al.*[23]	98.36	99.32	99.45
	Qureshi *et al.*[24]	97.17	99.72	99.62
	Liu *et al.*[25]	97.10	97.77	97.18
	This work	**99.75**	**99.93**	**99.83**

4 Conclusion

In this paper, we constructed a epilepsy SEEG dataset–LTSZ dataset and proposed a novel CE-TSS-Transformer framework for detecting seizures. Firstly, we proposed a CE module to reduce dimensionality and adaptively construct optimal representations for subsequent analysis. Secondly, we proposed unified multi-scale TSS to capture multi-layered features. Finally, we used the Transformer encoder to learn the global dependency of features. Experiments show that on the LTSZ dataset, the framework achieves SEN of 99.48%, SPE of 99.80%, and ACC of 99.48%. Additionally, we validate the effectiveness of our method through experiments on ablation study and its scalability on public datasets.

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References

1. Koutlis, C., Kimiskidis, V.K., Kugiumtzis, D.: Identification of hidden sources by estimating instantaneous causality in high-dimensional biomedical time series. Int. J. Neural Syst. **29**(04), 1850051 (2019)
2. Thijs, R.D., Surges, R., O'Brien, T.J., Sander, J.W.: Epilepsy in adults. Lancet **393**(10172), 689–701 (2019)
3. Herff, C., Krusienski, D.J., Kubben, P.: The potential of stereotactic-eeg for brain-computer interfaces: current progress and future directions. Front. Neurosci. **14**, 123 (2020)
4. Abbasi, B., Goldenholz, D.M.: Machine learning applications in epilepsy. Epilepsia **60**(10), 2037–2047 (2019)
5. Diykh, M., Miften, F.S., Abdulla, S., Deo, R.C., Siuly, S., Green, J.H., Oudahb, A.Y.: Texture analysis based graph approach for automatic detection of neonatal seizure from multi-channel eeg signals. Measurement **190**, 110731 (2022)
6. Anuragi, A., Sisodia, D.S., Pachori, R.B.: Epileptic-seizure classification using phase-space representation of fbse-ewt based eeg sub-band signals and ensemble learners. Biomed. Signal Process. Control **71**, 103138 (2022)
7. Zubair, M., Belykh, M.V., Naik, M.U.K., Gouher, M.F.M., Vishwakarma, S., Ahamed, S.R., Kongara, R.: Detection of epileptic seizures from eeg signals by combining dimensionality reduction algorithms with machine learning models. IEEE Sens. J. **21**(15), 16861–16869 (2021)
8. Epileptic seizure detection in eeg signals using sparse multiscale radial basis function networks and the fisher vector approach. Knowledge-Based Systems **164**, 96–106 (2019)

9. Shoeibi, A., Khodatars, M., Ghassemi, N., Jafari, M., Moridian, P., Alizadehsani, R., Panahiazar, M., Khozeimeh, F., Zare, A., Hosseini-Nejad, H., et al.: Epileptic seizures detection using deep learning techniques: A review. Int. J. Environ. Res. Public Health **18**(11), 5780 (2021)
10. Liu, G., Zhou, W., Geng, M.: Automatic seizure detection based on s-transform and deep convolutional neural network. Int. J. Neural Syst. **30**(04), 1950024 (2020)
11. Shi, Z., Liao, Z., Tabata, H.: Enhancing performance of convolutional neural network-based epileptic electroencephalogram diagnosis by asymmetric stochastic resonance. IEEE J. Biomed. Health Inform. (2023)
12. Yu, H., Hu, M.: Epilepsy seeg data classification based on domain adversarial learning. IEEE Access **9**, 82000–82009 (2021)
13. Jafarpour, S., Hirsch, L.J., Gaínza-Lein, M., Kellinghaus, C., Detyniecki, K.: Seizure cluster: definition, prevalence, consequences, and management. Seizure **68**, 9–15 (2019)
14. Andrzejak, R.G., Lehnertz, K., Mormann, F., Rieke, C., David, P., Elger, C.E.: 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 **64**(6), 061907 (2001)
15. Goldberger, A.L., Amaral, L.A., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K., Stanley, H.E.: Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. Circulation **101**(23), e215–e220 (2000)
16. Xiao, L., Li, C., Wang, Y., Chen, J., Si, W., Yao, C., Li, X., Duan, C., Heng, P.A.: Automatic localization of seizure onset zone from high-frequency seeg signals: A preliminary study. IEEE J. Transl. Eng. Health Med. **9**, 1–10 (2021)
17. Liu, S., Li, G., Jiang, S., Wu, X., Hu, J., Zhang, D., Chen, L.: Investigating data cleaning methods to improve performance of brain–computer interfaces based on stereo-electroencephalography. Front. Neurosci. **15**, 725384 (2021)
18. Prasanna, J., Subathra, M., 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. **11**(10), 1028 (2021)
19. Boonyakitanont, P., Lek-Uthai, A., Chomtho, K., Songsiri, J.: A review of feature extraction and performance evaluation in epileptic seizure detection using eeg. Biomed. Signal Process. Control **57**, 101702 (2020)
20. Atal, D.K., Singh, M.: A hybrid feature extraction and machine learning approaches for epileptic seizure detection. Multidimens. Syst. Signal Process. **31**(2), 503–525 (2020)
21. Lian, J., Shi, Y., Zhang, Y., Jia, W., Fan, X., Zheng, Y.: Revealing false positive features in epileptic eeg identification. Int. J. Neural Syst. **30**(11), 2050017 (2020)
22. Liu, S., Wang, J., Li, S., Cai, L.: Epileptic seizure detection and prediction in eegs using power spectra density parameterization. IEEE Trans. Neural Syst. Rehabil. Eng. (2023)
23. Jiang, Y., Chen, W., Li, M.: Symplectic geometry decomposition-based features for automatic epileptic seizure detection. Comput. Biol. Med. **116**, 103549 (2020)
24. Aayesha, Qureshi, M.B., Afzaal, M., Qureshi, M.S., Fayaz, M.: Machine learning-based eeg signals classification model for epileptic seizure detection. Multimed. Tools Appl. **80**, 17849–17877 (2021)
25. Liu, H., Gao, Y., Zhang, J., Zhang, J.: Epilepsy eeg classification method based on supervised locality preserving canonical correlation analysis. Math. Biosci. Eng. **19**(1), 624–642 (2022)