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A Signal-Based One-Dimensional Convolutional Neural Network (SB 1D CNN) Model for Seizure Prediction

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Abstract

Convolutional Neural Networks (CNNs) have become increasingly popular in seizure detection and prediction research. While traditional CNNs are effective in image classification tasks, applying them to seizure signal analysis requires specific architectures. In this study, we propose a Signal-Based One-Dimensional Convolutional Neural Network (SB 1D CNN) model that is customized for seizure signals. The SB 1D CNN model replaces traditional ReLU and Pooling layers with counterparts that are better suited to negative signal fluctuations and adjusts the training procedure accordingly. Additionally, the model introduces time/frequency-sensitive kernels in the initial convolution layer to capture significant features across time and frequency domains. To evaluate the proposed SB 1D CNN model, we conducted experiments using epileptic EEG signals from the CHB-MIT database. We carried out two sets of experiments: the first to identify optimal EEG channels through single-channel evaluations, and the second to train a robust SB 1D CNN model for seizure prediction. Comparative analysis with a traditional 1D CNN with a similar structure revealed that the SB 1D CNN model excels in feature extraction and classification of epileptic EEGs. Notably, training 1D CNNs exclusively with relevant data significantly enhances their performance. Overall, this study highlights the importance of tailored architectures in improving the effectiveness of 1D CNNs in seizure prediction tasks. The proposed SB

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1D CNN model offers a promising avenue for enhancing the accuracy and reliability of seizure prediction systems, with potential implications for improving patient care and management in epilepsy.

Keywords Epilepsy · Electroencephalogram (EEG) · Seizure prediction · Signal-based convolutional neural network

1 Introduction

Epilepsy is a neurological disorder that causes unpredictable and frequent seizures in the brain [25]. It affects people of all ages, races, and nationalities, making it a critical global health concern [4]. According to the World Health Organization (WHO), approximately 70 million people worldwide suffer from epilepsy [37]. Seizures disrupt normal brain function, making it difficult for those affected to lead normal lives [29]. It also results in elevated socio-economic costs and lower rates of employment and income [17]. While medication or surgery can sometimes manage epilepsy, there is no universally effective cure [25]. Over 30% of patients are resistant to treatments [7], indicating the need for accurate and automated systems to monitor and predict seizures [3]. Hence, there is a need for automated and accurate systems that can monitor and predict seizures.

In the past two decades, considerable studies have been conducted to create effective systems for predicting epileptic seizures [1, 7, 10, 13, 36]. These studies have introduced electroencephalogram (EEG) signals as potent tools for devising predictive devices [6, 19, 27]. EEG signals offer several advantages, including acceptable time accuracy, ease of use, affordability, and non-invasiveness [11]. Epileptic seizures manifest in EEG signals across four phases: Interictal, Preictal, Ictal, and Postictal (as shown in Fig. 1a). The Interictal phase signifies normal brain activity preceding a seizure, while the Preictal phase denotes the period just before seizure onset, characterized by emerging signs indicating changing brain functions. The Ictal phase corresponds to the seizure itself, marked by intense electrical activity in the brain, followed by the Postictal phase, during which brain activity returns to normal [22].

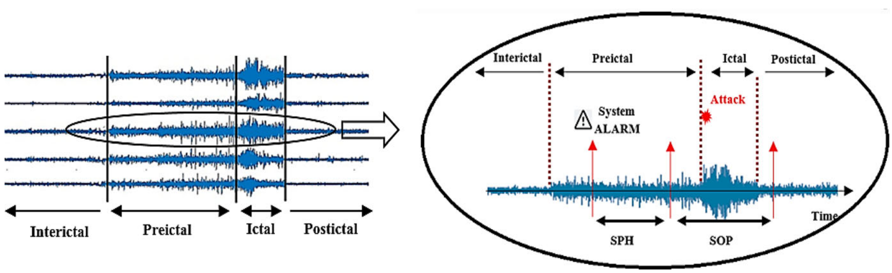

Fig. 1 **a** The occurrence of epileptic seizures on EEG signals consists of four phases: Interictal, preictal, Ictal, and postictal. **b** Seizure Occurrence Period (SOP) and Seizure Prediction Horizon (SPH). (MIT-CBH database signal (chb01_18))

Predicting the precise moment of a seizure remains challenging [25]. Existing algorithms typically provide an interval, termed the "Seizure Occurrence Period" (SOP), during which a seizure is expected. Moreover, there must be sufficient time between the system's alert and seizure onset for medical intervention or preventative measures, referred to as the "Seizure Prediction Horizon" (SPH), as depicted in Fig. 1b. A robust seizure prediction system should aim for a short SOP and a long SPH.

These systems must accurately predict seizure attacks by continuously monitoring EEG signals and detecting changes indicative of impending seizures. This involves extracting features from EEG signals and classifying them into interictal and preictal classes. Essentially, predicting an epileptic seizure is similar to detecting the entry of EEG signals from the interictal to the preictal stage. Most seizure prediction algorithms segment long-term EEG signals using temporal sliding windows and then extract features and classify them to determine whether the segment belongs to the interictal or preictal class. If a temporal window belongs to the preictal stage, a seizure attack can be anticipated. Identifying and extracting features predictive of the preictal stage is a complex process, and various strategies have been employed to enhance the accuracy of EEG-based seizure prediction methods [2, 9, 20, 21, 25, 28]. These strategies have shown that increasing the number of extracted features improves the precision of seizure prediction [28]. However, challenges such as the non-static nature of EEG signals, noise, artifacts, variability of epilepsy characteristics among patients, and distortions caused by external factors require tailored approaches for individual cases [12]. Existing methods are often time-consuming, require sophisticated implementation, and involve manual steps for feature extraction, selection, and classification [23]. Therefore, contemporary research focuses on fully automated methods for epileptic seizure prediction, such as CNN-based methods, aiming to achieve high accuracy, sensitivity, and reliability with minimal computational complexity [8].

Convolutional Neural Networks (CNNs) have shown promising results in seizure detection and prediction studies [28]. Unlike many artificial neural networks (ANNs) that only classify input data, CNNs perform feature extraction and selection, making them suitable for direct classification of raw EEG signals [8]. However, traditional CNNs are designed for processing 2D images and may require modifications to optimize their efficiency for EEG-based seizure prediction. Furthermore, the efficacy of CNNs depends on the quality and relevance of the training data. the primary objectives of this study are:

1. To design a Signal-Based 1D CNN tailored to the unique characteristics of EEG signals.
2. To evaluate and compare the classification accuracy of the proposed SB 1D CNN model against a traditional 1D CNN with identical configurations. This evaluation involves training both models using single-channel EEG data and meaningful channels EEG data.

2 Related Works

This section provides an overview of recent studies on seizure detection and prediction using Convolutional Neural Networks (CNNs), which are categorized into two groups: one-dimensional CNNs (1D CNNs) and multi-dimensional CNNs (MD CNNs). In both approaches, a time-sliding window is extracted from epileptic EEGs and inputted into CNNs for feature extraction and classification. However, in MD CNNs, the time window is first transformed into a multi-dimensional shape, typically two or three-dimensional, to align with the CNN structure. Various approaches have been proposed to accomplish this conversion. For instance, Wei et al. [36] converted EEG time series into two-dimensional images for multichannel fusion and proposed a long-term recurrent convolutional neural network (LRCNN) for predicting epileptic seizures using a spatiotemporal deep learning model. Shahbazi and Aghajan [30] utilized Short-Term Fourier Transform (STFT) to fabricate multi-channel images from EEG signals and trained a CNN-LSTM network on the STFTs to classify EEG segments into preictal or interictal stages. Prathaban and Balasubramanian [23] introduced an adaptive optimization approach using the non-linear conjugate gradient technique alongside Sparsity-based EEG Reconstruction (SER) and a three-dimensional Optimized Convolutional Neural Network (3D OCNN) classifier for seizure prediction. They deployed the FR algorithm with the deep neural network architecture to accelerate the convergence rate and to reduce the complexity of the proposed non-linear model, and finally, a Phase Transition Kullback–Leibler divergence (PTB-KL) predictor was used for obtaining the Optimal Seizure Prediction Horizon (OSPH). Truong et al. [33] proposed a generalized retrospective and patient-specific seizure prediction method based on 2D CNNs, leveraging short-time Fourier transform on EEG windows for feature extraction. Hu et al. [14] employed 2D CNNs to predict seizures by computing the amplitude spectrums of EEG signals and forming feature maps for classification. They first calculated the amplitude spectrums of EEG signals from 18 channels and divided them into 19 frequency sub-bands. Then the mean amplitude spectrum on each of the 19 frequency sub-bands was computed for each channel and formed a feature map of size 18×19. Finally, their MAS map was fed to a 2D CNN for feature extraction and a support vector machine (SVM) for the epileptic state classification. Yu et al. [39] introduced a method for epileptic seizure prediction based on local mean decomposition and 2D CNN. Hussein et al. [15] proposed a data pre-processing method using continuous wavelet transform to map time-series EEG signals into "scalograms" before classification with a semi-dilated convolutional network (SDCN).

Additionally, CNNs can be implemented in a one-dimensional manner for seizure prediction. In this case, the separated time windows are directly injected into the network. Wang et al. [35] proposed a channel selection strategy in 1D CNN networks for predicting epileptic seizures. Jana et al. [16] developed a 1D CNN network to detect epileptic seizures from EEG signal spectrograms. Chirasani and Manikandan [8] introduced a novel architecture for 1D CNNs, comprising feature extraction layers, hierarchical attention layers, and classification layers, aimed at improving efficiency in seizure classification. In the feature extraction layers, two parallel convolution blocks were fed with two individual EEG channels to extract the feature map. Then extracted feature maps were given to the attention layer, where the output was a hierarchical weighted attention feature set. These weighted features were fed into a fully connected layer for classification. Other researchers, including Sagga et al. [26], Khalilpour et al. [18], Xu et al. [38], Zhao et al. [40], and Wang et al. [34], have also utilized 1D CNN networks for epileptic seizure detection/prediction in recent years. The related works in the field of seizure detection and prediction by CNNs are summarized in Table 1.

3 Materials and Methods

3.1 Dataset

This study used the CHB-MIT scalp EEG dataset, which is publicly available and was collected at the Children's Hospital Boston [31]. The dataset consists of recordings from 22 subjects, with 5 males and 17 females, grouped into 23 cases. One patient was recorded twice, hence the total number of cases is 23. The dataset includes 969 h of scalp EEG recordings, including 182 seizures, all of which were sampled at 256 samples per second with 16-bit resolution. Most recordings are one hour long and consist of 23 channels, although some recordings last for two or four hours or have 18, 24, or 38 channels. The dataset's files have annotations that show the start and end times of seizures, as determined by clinical experts. The CHB-MIT database used the international 10–20 system for electrode placement on the scalp, as shown in Fig. 2. However, the order of electrode placement varied among patients. To ensure consistency, in this work, the electrode placement in all patients was adjusted according to Table 2.

3.2 Data Preparation

The Seizure Prediction Horizon (SPH) was set to 27 min in this study, based on research conducted by Shokouh Alaei et al. [32]. The interictal period was defined as 60 min, and two different periods were investigated for the preictal period: 30 min and 60 min Interictal intervals were considered to occur between 2 and 3 h before seizures. We excluded cases where signal recordings were lost before a seizure, where the number of channels was fewer than 23, or where consecutive seizures occurred less than one hour apart. We applied several preprocessing steps to the separated recordings. Firstly, we normalized them to a range of 0–1, de-averaged them (with the DC value set to zero), and filtered them using a 0.5–120 Hz bandpass filter and a 50 Hz notch filter to eliminate potential noise and artifacts. To achieve a balanced distribution of training samples across each class and generate equal pairs of preictal-interictal inputs, we extracted non-overlapping 30s windows from one-hour signals for both interictal and 60 min preictal periods. For half-hour signals (30 min preictal), we utilized 30s windows with a 15s overlap. Figure 3 provides a visual representation of the oversampling technique described above. Based on these data selection criteria and the two different preictal time durations, we summarized the final selected EEG signals for this study in Table 3. Out of the 182 epileptic seizures recorded in the

Table 1 The related works in the field of seizure detection/prediction by CNNs

References	Year	Algorithm	detection/ prediction	Technique/scheme used	Performance Metrics
Wei et al. [36]	(2019)	2D CNN	prediction	LRCNN	accuracy = 93.40; sensitivity = 91.88; specificity = 86.13; FPR = 0.04 Fp/h
Shahbazi et al. [30]	(2018)	2D CNN	prediction	STFT & CNN-LSTM	sensitivity = 98.21; FPR = 0.13 Fp/h
Prathaban et al. [23]	(2021)	3D CNN	prediction	non-linear conjugate gradient technique & SER & 3D OCNN & FR	accuracy = 98; sensitivity = 99; FPR = 0.07 Fp/h
Truong et al. [33]	(2018)	2D CNN	prediction	STFT & 2D CNNs	sensitivity = 75 up to 81.40; FPR = 0.06—0.21 Fp/h
Hu et al. [14]	(2019)	2D CNN	prediction	MAS map & 2D CNNs & SVM	accuracy = 86.25
Hussein et al. [15]	(2021)	2D CNN	prediction	CWT & SDCN	sensitivity = 88.45 up to 98.90;
Wang et al. [35]	(2022)	1D CNN	prediction	channel selection & 1D CNNs	accuracy = 98.60; sensitivity = 98.85; FPR = 0.01 Fp/h
Jana et al. [16]	(2020)	1D CNN	detection	Spectrogram & 1D CNNs	accuracy = 77.57
Khalilpour et al. [18]	(2020)	1D CNN	prediction	Raw EEG data & 1D CNNs	accuracy = 97; sensitivity = 98.47; specificity = 98.50
Xu et al. [38]	(2020)	1D CNN	prediction	Raw EEG data & 1D CNNs	sensitivity = 93.50 up to 98.80; FPR = 0.063—0.074 Fp/h

Table 1 (continued)

References	Year	Algorithm	detection/ prediction	Technique/scheme used	Performance Metrics
Zhao et al. [40]	(2020)	1D CNN	prediction	Binary Single-dimensional CNN (BSD CNN)	sensitivity = 89.26 up to 94.69; FPR = 0.095—0.117 Fp/h
Wang et al. [34]	(2021)	1D CNN	detection	RS-DA & 1D CNNs	accuracy = 99.54; sensitivity = 88.14; specificity = 99.62;

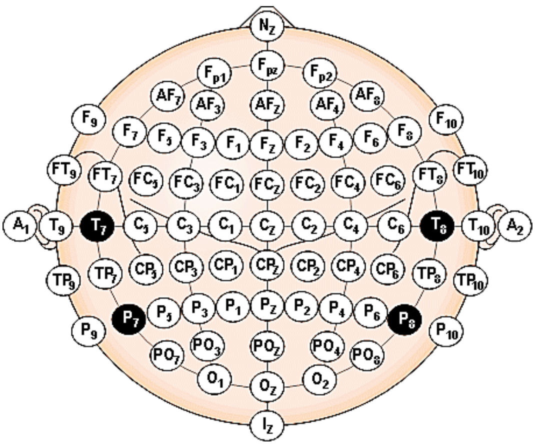

Fig. 2 The International 10–20 system of EEG electrode positions [31]

database, we utilized information from signals corresponding to 60 and 70 seizures to train the proposed models.

3.3 The Traditional Model of 1D CNNs

Convolutional Neural Networks (CNNs) are a type of deep neural network that is widely used in computer vision applications such as image classification, object detection, and face recognition [5]. Unlike traditional Artificial Neural Networks (ANNs), CNNs are very good at processing raw image data, automatically identifying features, and training the model. Similar to ANNs, CNNs adjust the weights and parameters of the network based on input–output pairs. While initially structured as 2D networks, 1D CNNs have gained popularity in recent years. Figure 4 displays the primary layers of a traditional 1D CNN network. These layers include three fundamental layers: the convolutional layer, the pooling layer, and the Fully Connected (FC) layer. Depending

Table 2 The electrode adjustment in this work

# Channel	Electrode placement	# Channel	Electrode placement
# 1	FP1-F7	# 13	FP2-F8
# 2	F7-T7	# 14	F8-T8
# 3	T7-P7	# 15	T8-P8
# 4	P7-O1	# 16	P8-O2
# 5	FP1-F3	# 17	FZ-CZ
# 6	F3-C3	# 18	CZ-PZ
# 7	C3-P3	# 19	P7-T7
# 8	P3-O1	# 20	T7-FT9
# 9	FP2-F4	# 21	FT9-FT10
# 10	F4-C4	# 22	FT10-T8
# 11	C4-P4	# 23	T8-P8
# 12	P4-O2		

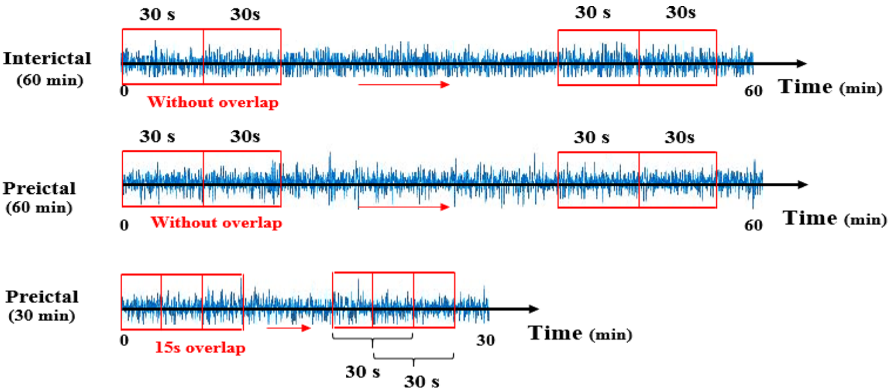

Fig. 3 Illustration of the oversampling technique used in this work

on the complexity of the classification problem, specific networks may incorporate additional layers such as Rectified Linear Unit (ReLU), Local Response Normalization (LRN), and Dropout. The complexity and arrangement of these layers determine the design of the network.

3.4 The Proposed Seizure Prediction Framework

Figure 5 provides an overall block diagram of the proposed seizure prediction framework. In the initial stage of the framework, we developed a Signal-Based (SB) 1D CNN model and a traditional 1D CNN model. Both models were trained using single-channel EEG data, and their performance was compared. We then selected specific channels that consistently demonstrated superior accuracy in predicting epileptic seizures based

Table 3 The details of the selected EEG signals for each patient

Case	Sex	Age	No. of Channels	No. of Seizures		
				All	Preictal (30 min)	Preictal (60 min)
Chb01	F	11	23	7	4	2
Chb02	M	11	23	3	2	2
Chb03	F	14	23	7	5	3
Chb04	M	22	23/24	4	2	2
Chb05	F	7	23	5	3	2
Chb06	F	1.5	23	10	4	3
Chb07	F	14.5	23	3	2	2
Chb08	M	3.5	23	5	4	4
Chb09	F	10	23	4	2	2
Chb10	M	3	23	7	2	2
Chb11	F	12	23	3	–	–
Chb12	F	2	23/24/25	40	–	–
Chb13	F	3	18/20/23	12	–	–
Chb14	F	9	23	8	4	3
Chb15	M	16	26/32	20	10	8
Chb16	F	7	18/23	10	7	5
Chb17	F	12	18/23	3	3	3
Chb18	F	18	18/23	6	4	4
Chb19	F	19	18/23	3	3	3
Chb20	F	6	23	8	6	5
Chb21	F	13	23	4	3	3
Chb22	F	9	23	3	2	2
Chb23	F	6	23	7	–	–
Total	–	–	–	182	70	60

on the obtained results and a thorough review of prior research focused on identifying optimal channels within the CHB-MIT database. In the subsequent stage of the framework, the proposed SB 1D CNN model was implemented and trained with the final selection of channels. Its performance was then compared to that of a traditional 1D CNN model with the same structure in the Final Evaluation stage.

3.5 The Proposed SB 1D CNN Model

Convolutional Neural Networks (CNNs) were originally introduced with a 2D structure, simulating the behavior of the brain's visual cortex. In image classification tasks, raw images are inputted, features are extracted using convolutional layers, relevant features are selected through pooling layers, and classification is performed using a

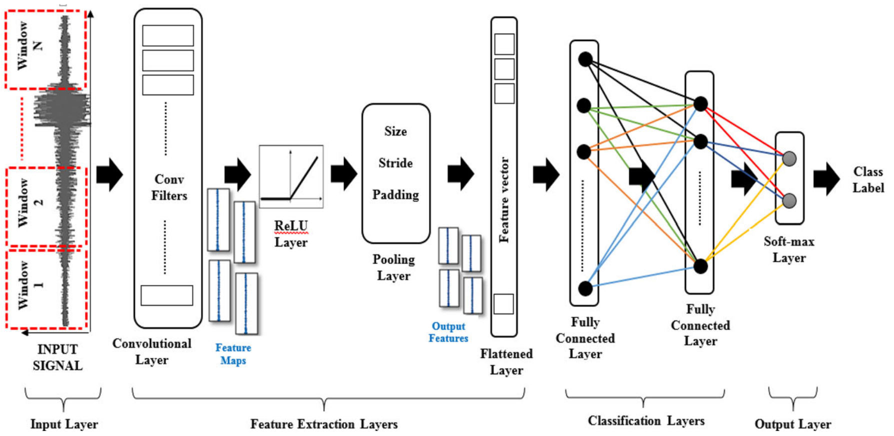

Fig. 4 Layers of a traditional 1D CNN

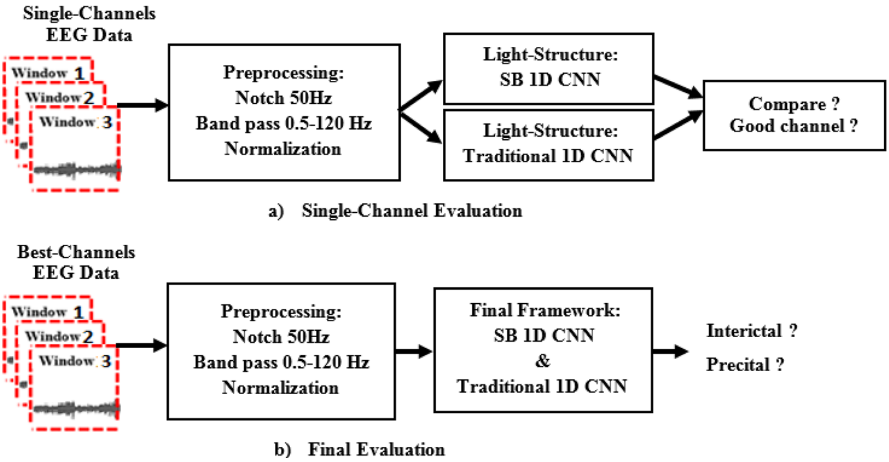

Fig. 5 Overall block diagram of the proposed seizure prediction framework

fully connected classifier. However, some of these layers may not be optimal for signal classification tasks. Our experiments have shown that ReLU and Pooling layers in traditional 2D CNNs tend to emphasize positive values while suppressing negatives. While this behavior is suitable for images, it may overlook the significance of minimum values in signals. Consequently, feature maps produced by these layers may not accurately represent signal characteristics. Moreover, signals exhibit distinct characteristics from images, requiring the use of more effective kernels in the feature extraction layers of 1D CNNs. To address these challenges, the proposed SB 1D CNN model replaces ReLU and Pooling layers with layers that are more sensitive to negative fluctuations in signals. Time/frequency-sensitive kernels are employed in the first convolutional layer to extract meaningful features in both time and frequency domains.

Additionally, the training procedure is modified to accommodate these optimizations. In the following sections, the key components of the proposed SB 1D CNN model will be described in detail to enhance comprehension of the topic.

3.5.1 Input Layer

In this study, 30s sliding windows were used as inputs for the proposed SB 1D CNN model. These inputs were represented as 1×7680 vectors, directly extracted from long-term EEG signals, and fed into the model.

3.5.2 Convolution Layer

The convolution layers serve as the foundation of the 1D CNN architecture, bearing the majority of the computational workload of the network. These layers extract features from the inputs using trainable kernels of specific dimensions. In convolution layers, each kernel convolves with the input, selectively extracting particular characteristics from the input signal [28]. Two crucial parameters in the convolution operation are the "Stride" and "Padding." The Stride determines the step size that the kernel takes after each convolution, while Padding involves adding extra samples at the beginning and end of the input vector before convolution. The output of a convolution layer is referred to as a "feature map". Each feature map is a vector containing specific characteristics of the input signal, and its size diminishes as it traverses through the network. Ultimately, this vector is converted into a collection of significant features ready for classification. Therefore, the number of feature maps at the output of each convolution layer equals the number of kernels in that layer. The dimensions of the feature maps depend on the size of the input, kernels, Stride, and Padding and can be calculated using Eq. (1).

$$N_{out} = \left\lfloor \frac{N_{in} + 2P - K}{S} \right\rfloor + 1 \tag{1}$$

The following is a technical explanation of convolution layers and how they work. The output feature map vector's dimensions (Nout) depend on the input vector's dimensions (Nin), padding dimensions (P), stride dimensions (S), and kernel dimensions (K). The effectiveness of convolution layers depends on the number, size, and coefficients of the kernels. Kernel coefficients directly affect feature extraction. In 1D CNNs, kernel coefficients are typically initialized randomly. However, this method has limitations. For example, it can produce kernels with uniform coefficients that extract similar characteristics from the input signal. Randomly initialized kernels may also not effectively extract all fundamental features from the signal, leading to a time-consuming training process that could result in classification failure. To address these challenges, we designed time/frequency-sensitive kernels for use in the first convolution layer of the proposed SB 1D CNN model. These specialized kernels enabled the extraction of more meaningful characteristics in both time and frequency domains without increasing the computational burden. For time domain analysis, we used Gaussian windows with varying sigma values to calculate the weighted average of the signals over different time intervals. The coefficients of Gaussian windows were computed from Eq. (2).

$$W[n] = \exp\left(-\frac{1}{2}\left(\frac{n-\frac{N}{2}}{\sigma\frac{N}{2}}\right)^2\right), \text{ where}\begin{cases} 0 \le n \le N \\ \sigma \le 0.5 \end{cases} \tag{2}$$

The proposed SB 1D CNN model uses sine wave coefficients in different frequency bands for convolution to extract features from input signals. These specially designed kernels are capable of capturing unique characteristics of EEG signals across various frequency bands, including delta, theta, alpha, beta, and gamma subbands. Figure 6 provides a comparison between the traditional random kernels and the proposed time/frequency-sensitive kernels, illustrating the feature maps they generate. By utilizing domain-specific knowledge in kernel design, the proposed model can efficiently extract relevant features from EEG signals and enhance prediction performance for epileptic seizures.

Figure 6 shows six rows of normalized coefficients used in a convolutional layer. The first two rows are coefficients of two sinusoidal signals with frequencies of 2 and 6 Hz. These coefficients were used as an initial input for the convolutional layer kernels. The kernels were then convolved with a 20s window of the input signal, creating two feature maps that highlight frequencies in the alpha and theta bands. The third and fourth rows show two time-sensitive kernels, generated using Gaussian windows with

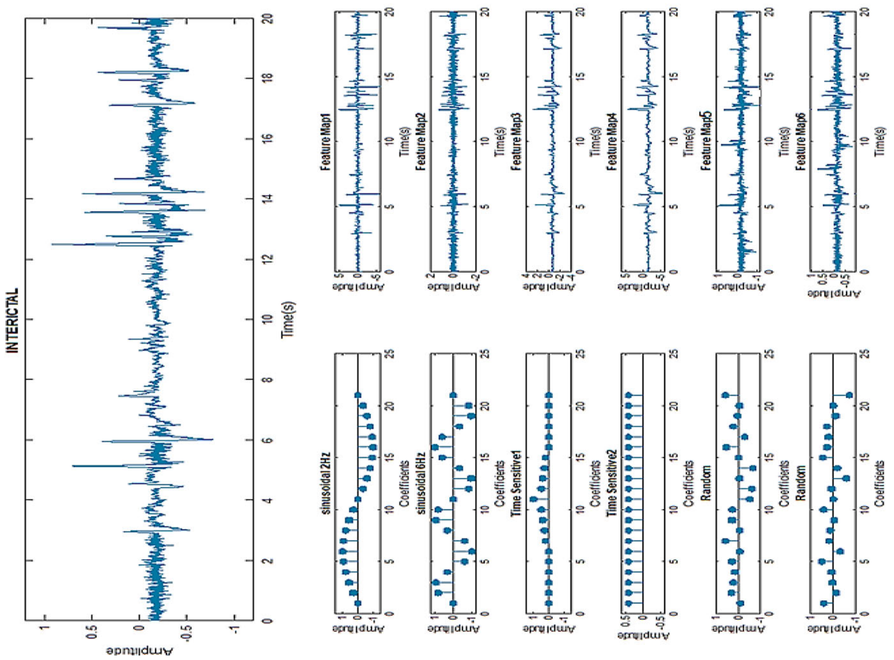

Fig. 6 Examples of proposed time/frequency-sensitive kernels and their corresponding feature maps

different sigma coefficients. These kernels were also convolved with a 20s window of the input signal, enhancing the temporal features in the resulting feature maps. The last two rows contain kernels with random coefficients, commonly used in traditional CNN architectures. These kernels were also convolved with a 20s window of the input signal. The extracted feature maps from these kernels appear entirely random and fail to capture any temporal or frequency characteristics of the input signal. Our experiments suggest that using kernels with more effective coefficients at the outset of training can significantly enhance the convergence speed of the network and reduce training time.

3.5.3 ReLU Layer

In a standard 1D CNN architecture, a Rectified Linear Unit (ReLU) is usually added after each convolution layer. This layer performs a non-linear operation on its input, where any negative values are changed to zero. This non-linear activation function helps the model to learn and represent more complex relationships within the data, resulting in better performance in tasks like feature extraction and classification. The ReLU layer's function is shown in Fig. 7, and its transformation function is represented by Eq. (3).

$$f(x) = \max(0, x) = \begin{cases} x \text{ if } x > 0 \\ 0 \text{ if } x \leq 0 \end{cases} \tag{3}$$

In the field of EEG signals, both negative and positive values contain important information. However, traditional ReLU layers are not ideal as they discard negative values. To overcome this limitation, we have introduced a new layer called "RELU_Z" in our SB 1D CNN model. The function of the RELU_Z layer is explained in Fig. 8, and its transformation function is represented by Eq. (4).

$$f(x) = \begin{cases} x \text{ if } x > T \text{ or } x < -T \\ 0 \quad \text{if } -T \leq x \leq T \end{cases} \tag{4}$$

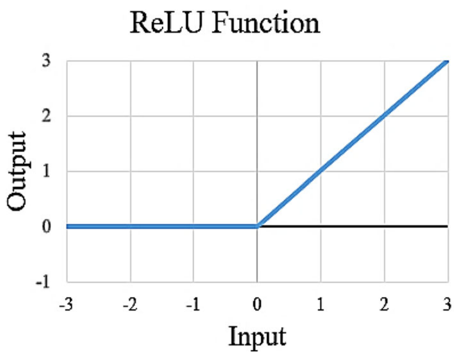

Fig. 7 The function of the ReLU layer

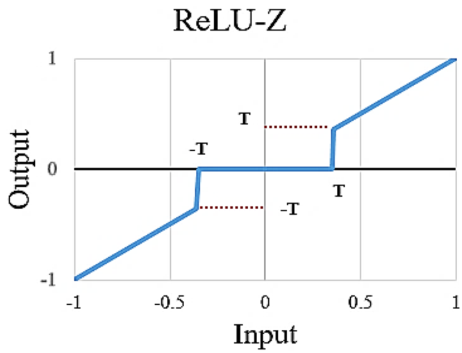

Fig. 8 The function of the proposed ReLU-Z layer

In the RELU_Z layer, the input value is represented by "x" and the output value after applying the transformation function is represented by "f(x)". The parameter "T" determines the threshold value between 0 and 1. This threshold value decides at which point the input values will be transformed to zero in the output. Unlike traditional ReLU layers, the RELU_Z layer sets both positive and negative values smaller than T to zero. This modification ensures that the output feature maps retain the maximum and minimum values of the signals. In our proposed model, we conducted experiments to determine the optimal value of T by systematically exploring different T values and observing their impact on the model's performance metrics through an iterative process. After conducting these experiments, we tuned the value of T to 0.35.

3.5.4 Pooling Layer

The pooling layer is a crucial component of 1D CNNs, which is usually placed after convolution and ReLU layers in the network architecture. The primary function of these layers is to reduce the dimensions of the feature maps, which helps decrease computational complexity and prevent overfitting. During the pooling process, the feature map is divided into smaller sections, and a representative value is chosen or calculated for each section to form the output. Max-pooling is a popular technique for downsampling in 1D CNNs, which involves selecting the maximum value within each section. However, Max-pooling can ignore extreme minimum values present in the signals. To address this limitation, we have modified the pooling layer in the proposed SB 1D CNN model by introducing an "ABS-Pooling" layer. The ABS-Pooling layer computes the maximum absolute value within each section, aligning with the principles of the RELU_Z layer and ensuring that negative values are not overlooked. Consequently, the output of this layer represents the most prominent peak, whether positive or negative, in the feature map.

3.5.5 Fully Connected Layer

Fully connected layers are a crucial component of 1D CNNs, particularly for classification tasks. These layers consist of neurons with adjustable weights and biases that can learn intricate patterns from extracted features. The number of neurons and network depth in the fully connected layers are determined by the complexity of the problem and the desired number of output classes. In our proposed SB 1D CNN model, the fully connected layers retain their original functionality of processing extracted features and making predictions for classification tasks.

3.5.6 Output Layer

The output layer is the final stage in 1D CNNs and is responsible for generating predictions based on input data processed by preceding layers. This layer synthesizes the information learned by the network and produces the final output. In our proposed SB 1D CNN model, the output layer comprises two neurons, each representing a distinct class: interictal and preictal. These neurons use a Softmax activation function to compute the probability distribution across the output classes, making it easier to classify input signals into the respective categories.

3.5.7 Training the Proposed Model

Training 1D CNNs involves adjusting weights, biases, and convolution kernel coefficients to minimize computed output error. This optimization process is accomplished through iterative updates using gradient descent and its variants, including stochastic gradient descent (SGD), batch gradient descent, mini-batch gradient descent, and vanilla gradient descent methods. These methods are commonly utilized in artificial neural networks (ANNs) [23]. In the case of our proposed SB 1D CNN model, we used the conventional backpropagation (BP) method with a batch size of 10. Backpropagation involves computing the gradient of the loss function concerning the weights by propagating error signals backward through the network during training. This gradient information is then utilized to update the weights in a manner that minimizes the overall loss.

4 Implementation and Experiments

We implemented the models proposed in our study using MATLAB R2021b on a system with an 8 GB Intel Core i5 dual-core processor running at 3.40 GHz. Our models utilized time/frequency-sensitive kernels in the first convolution layer and replaced the conventional ReLU and Pooling layers with RELU_Z and ABS-Pooling layers, which required modifications to the training algorithm. Therefore, we manually implemented the models and adjusted the training procedures accordingly in the RELU-Z and ABS-Pooling layers. We conducted two sets of experiments to compare the proposed SB 1D CNN model against a traditional 1D CNN with the same structure. These experiments included single-channel experiments and final evaluation experiments. To conduct these experiments, we used data from 60 seizure events when the preictal interval was set to 60 min and data from 70 seizure events when the preictal interval was set to 30 min. In the case of the 60 min preictal scenario, the dataset comprised 14,400 30s windows of preictal and interictal signals. We allocated 11,520 windows for training and used the remainder for testing. In the 30 min preictal scenario, the dataset included

16,400 30s windows, with 13,120 windows used for training and the remaining for testing. In all experiments, we set the maximum number of epochs to 50, and the dataset was split into an 80–20 ratio for training and testing the implemented models.

4.1 Single-Channel Experiments

The single-channel experiments were conducted to assess the effectiveness of a streamlined architecture in the proposed SB 1D CNN model compared to a traditional 1D CNN with a similar structure. Both models were trained using one channel of EEG data and consisted of eight layers: input, 1D convolution, ReLU (or RELU-Z), Pooling (or ABS-Pooling), Flatten, dropout, fully connected (FC), and output layers. To ensure sufficient data for training, a streamlined network structure was employed. The interictal and preictal periods were set to 60 min and 30 min, respectively. The input data consisted of 1×7680 vectors. The convolution layer featured 10 kernels with dimensions of 1×129, a stride of 3, and no padding. The Pooling layer utilized kernels with dimensions of 1×3, a stride of 3, and no padding. A dropout layer with a dropout rate of 20% was incorporated to prevent overfitting. The FC layers comprised 300 and 100 nodes with ReLU activation functions, and the output layer consisted of 2 nodes with a softmax activation function. In the convolution layer of the proposed SB 1D CNN model, five time-sensitive and five frequency-sensitive kernels were utilized. In contrast, the kernels in the convolution layer of the traditional 1D CNN were initialized randomly, as per standard practice.

4.2 Final Evaluation Experiments

In the final evaluation experiments, both the proposed SB 1D CNN and traditional 1D CNN models were equipped with a more complex structure comprising 12 layers. The detailed parameters of these models are outlined in Table 4. Similar to the previous experiments, the SB 1D CNN model utilized 5 time-sensitive and 5 frequency-sensitive kernels in the first convolution layer, while the traditional 1D CNN initialized its convolution layer kernels randomly. During these experiments, insights gained from the initial trials guided the training of both networks. This training process was conducted twice: once using data exclusively from the top 10 channels and another time employing data from all channels. The term 'top channels' refers to those channels with an accuracy exceeding 70%. We conducted a comparative analysis of these channels against previous studies focusing on optimal channel selection within the CHB-MIT database. Our investigation led to the identification of the top 10 channels, which were meticulously chosen for subsequent experimental trials [24, 41]. Additionally, we explored two different durations for the preictal period: 60 min and 30 min.

5 Results and Discussion

In this study, we validated the proposed models by using four indexes: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). TN and

Table 4 The parameters of the proposed seizure prediction model

Number	Layer name	Kernel size Number	Layer parameters	Output shape
0	Input	–	–	1 × 7680
1	Conv1D	1 × 129 10	Stride = 3, Padding = 0	1 × 2518 × 10
2	ReLU-Z	–	–	1 × 2518 × 10
3	ABS-Pooling	1 × 3 1	Stride = 3, Padding = 0	1 × 840 × 10
4	Dropout	–	0.2	1 × 840 × 10
5	Conv1D	1 × 11 10	Stride = 3, Padding = 0	1 × 278 × 100
6	ReLU-Z	–	–	1 × 278 × 100
7	ABS-Pooling	1 × 10 1	Stride = 2, Padding = 0	1 × 135 × 100
8	Flatten	–	–	1 × 13,500
9	FC	200	Activation = Relu	200
10	FC	50	Activation = Relu	50
11	Output	2	Activation = Softmax	2

TP represent the number of accurately detected seizure-free events and seizure events in EEG, respectively. On the other hand, FP and FN indicate the total number of incorrectly detected seizure-free events and false seizure events in EEG. To evaluate the performance of our prediction models, we formulated the performance metrics using these four metrics as shown in Eq. (5–9).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5}$$

$$\text{Sensitivity y} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{Specificit y} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{7}$$

$$\text{Selectivit y} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{8}$$

$$\text{F1} - \text{Measure} = \frac{2 * \text{Selectivity} * \text{Sensitivity}}{\text{Selectivity} + \text{Sensitivity}} \tag{9}$$

Accuracy represents the model's ability to correctly classify both interictal and preictal segments. Specificity refers to the model's capability to accurately detect the interictal segments, while Sensitivity represents the model's ability to detect the preictal segments. Selectivity is the model's ability to avoid erroneous detections of preictal segments. F1-Measure is a single metric that balances both sensitivity and selectivity, offering an overall assessment of the model's ability to detect preictal segments while minimizing false positives.

5.1 Single-Channel Evaluations

In the single-channel evaluations, we trained our proposed lightweight SB 1D CNN model using single-channel EEG data and twenty-three-channel EEG data. We compared its performance with a traditional 1D CNN model in predicting seizures. Table 5 presents a comparison of the two models, reporting the average sensitivity, selectivity, specificity, accuracy, and F1-Measure over five runs.

The proposed SB 1D CNN model exhibits superior classification performance compared to traditional 1D CNNs, as demonstrated in Table 5. This performance improvement is attributed to the adjustments made to specific layers within the SB 1D CNN to tailor them to the characteristics of the signals. The SB 1D CNN model preserves the negative peaks of the signals and uses time/frequency-sensitive kernels in the initial convolution layer, enabling the extraction of a broad range of signal features. This also results in convergent responses being generated with each re-training, which is an advantage in practical applications. Table 5 shows that the maximum sensitivity, selectivity, specificity, and accuracy achieved by single-channel data in a traditional 1D CNN were 74.21, 71.30, 75.70, and 74.96, respectively. However, the proposed SB 1D CNN achieved higher values of 80.35, 76.65, 81.71, and 80.53 (for channel 21), suggesting that certain channels were more effective in predicting epileptic seizures, with accuracies exceeding 70%. Channels 21, 22, 6, 11, 7, 12, 17, 4, 2, and 1 demonstrated particularly high accuracies, as illustrated in Fig. 9. Furthermore, when trained with data from all channels, the proposed SB 1D CNN model achieved a sensitivity of 88.77, selectivity of 83.21, specificity of 87.28, and accuracy of 89.02. In comparison, the traditional 1D CNN achieved slightly lower values of 82.46, 79.15, 81.06, and 83.26, respectively. These results further emphasize the superior performance of the SB 1D CNN model in predicting epileptic seizures.

5.2 Final Evaluations

We started by conducting initial experiments to determine the optimal channels for our seizure prediction model. We selected 10 channels and built a more advanced SB 1D CNN model with two convolution layers for the final evaluations. During the final evaluations, we trained the model using the best channels of EEG data and twenty-three-channel EEG data. We tested two different preictal period durations, 60 min and 30 min, and compared the SB 1D CNN model to a traditional 1D CNN with the same structure. Tables 6 and 7 present a comparison between the two networks in terms of seizure prediction, showing the average sensitivity, selectivity, specificity, and accuracy over 5 runs.

Several trends emerge from the data presented in Tables 6 and 7. Firstly, the proposed SB 1D CNN model outperformed traditional 1D CNNs in all experiments, indicating the effectiveness of modifications made to the 1D CNN architecture. Secondly, the

Table 5 Comparison of the lightweight SB 1D CNN and traditional 1D CNN model in predicting seizures by single-channels data (preictal = 30 min)

# Channel	Proposed SB 1D CNN					Traditional 1D CNN				
	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1-Measure (%)	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1-Measure (%)
1	73.75	72.06	75.5	74.63	75.06	67.36	65.14	68.5	67.93	68.21
2	71.09	73.33	76.71	75.9	76.30	68.32	69.09	69	69.16	69.08
3	58.33	52.74	57.08	58.7	57.88	53.07	50.51	52.01	52.54	52.27
4	77.7	72.9	77.73	78.21	77.97	70.45	66.53	66.18	69.81	67.95
5	60.24	58.51	60.69	62.46	61.56	57.1	55.59	57.95	57.52	57.73
6	78.77	74.37	77.52	78.14	77.83	73.48	70.85	72.97	72.73	72.85
7	75.61	70.88	76.95	77.78	77.36	70.34	66.28	72.95	71.64	72.29
8	63.86	59.5	63.29	63.58	63.43	55.91	52.45	55.08	55.49	55.28
9	61.56	58.57	64.73	63.14	63.93	55.94	53.08	54.38	56.16	55.26
10	59.96	54.46	58.12	59.54	58.82	54.13	52.44	55.91	55.52	55.71
11	79.73	76.4	76.53	79.13	77.81	73.4	70.7	71.8	72.6	72.20
12	78.59	72.69	76.72	78.65	77.67	70.01	69.28	69.38	71.19	70.27
13	58.65	51.93	59.11	58.88	58.99	52.46	50.58	52.69	52.57	52.63
14	58.97	53.77	58.64	58.8	58.72	53.17	50.31	53.43	53.3	53.36
15	55.9	51.77	54.55	54.73	54.64	52.04	50.48	51.9	51.47	51.68
16	58.05	55.71	59.18	58.61	58.89	51.15	51.58	51.99	51.57	51.78
17	78.65	74.07	79.81	78.73	79.27	73	70.27	73.36	71.18	72.25
18	60.76	58.67	63.8	64.28	64.04	57.13	54.37	55.78	57.45	56.60

Table 5 (continued)

# Channel	Proposed SB 1D CNN					Traditional 1D CNN				
	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1-Measure (%)	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1-Measure (%)
19	57.57	54.22	56.73	57.15	56.94	52.02	51.42	52.78	53.4	53.09
20	63.48	60.73	63.88	64.68	64.28	57.59	57.36	57.19	57.39	57.29
21	80.35	76.65	81.71	80.53	81.12	74.21	71.3	75.7	74.96	75.33
22	79.06	75.46	80.53	81.29	80.91	74.06	70.52	74.67	74.37	74.52
23	66.65	60.47	66.34	66.49	66.41	63.66	57.11	64.49	64.07	64.28
all	88.77	83.21	87.28	89.02	88.14	82.46	79.15	81.06	83.26	82.15

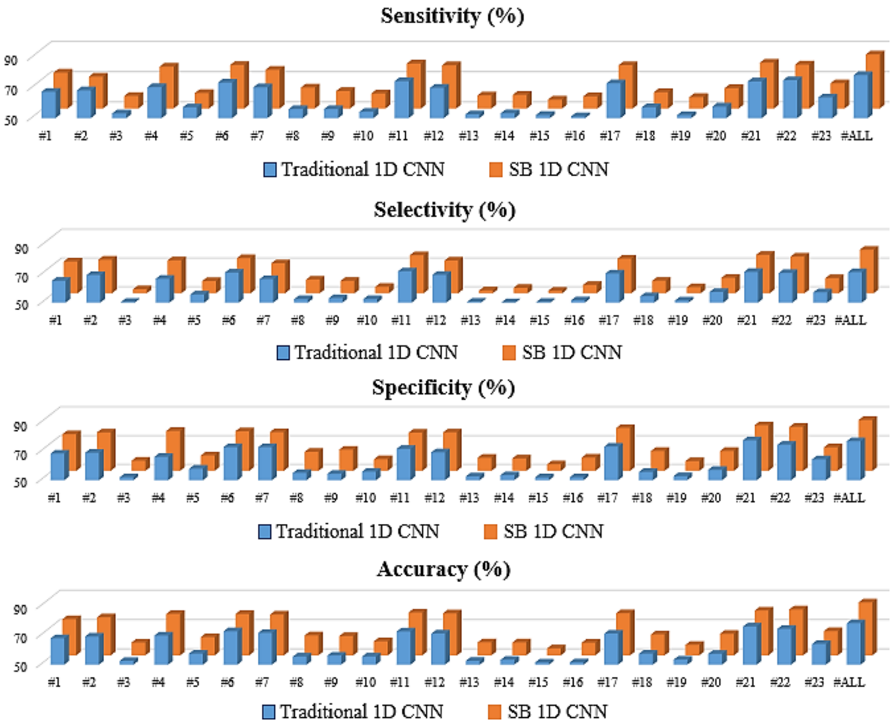

Fig. 9 Sensitivity, selectivity, specificity, and accuracy comparison between the proposed SB 1D CNN and a traditional 1D CNN using single-channel and all-channel EEG data

models demonstrated improved performance when the duration of the preictal period was set to 30 min compared to 60 min, suggesting that epileptiform characteristics in EEG signals become more pronounced as the time to seizure onset decreases. Lastly, both models performed better when trained with relevant EEG channels rather than all channels, highlighting the importance of training 1D CNNs exclusively with pertinent data for enhanced performance. Based on these results, under optimal conditions (using the top ten EEG channels for training and a preictal duration of 30 min), the proposed SB 1D CNN model achieved an average sensitivity of 98.5%, selectivity of 96.16%, specificity of 95.24%, and accuracy of 98.22%. In contrast, a traditional 1D CNN yielded an average sensitivity of 92.04%, selectivity of 89.24%, specificity of 85.89%, and accuracy of 92.17%.

As previously discussed, our proposed model involves alterations to the internal structure of the 1D CNNs, specifically focusing on modifying the functions of ReLU and Pooling layers. Subsequently, we executed the proposed model with a simplified architecture comprising only two layers. The performance of this modified model was then compared with that of previous studies that exhibited a structural resemblance to our proposed model. The details of the previous studies and this work, including the dataset, number of convolution layers, preictal and SPH time, Novelty, and Performance Metrics were given in Table 8.

Table 6 Comparison of the proposed SB 1D CNN and traditional 1D CNN model in predicting seizures by best-channels and all channels data (preictal = 30 min)

# Channel	SB 1D CNN					Traditional 1D CNN				
	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1- Measure (%)	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1- Measure (%)
Best Channels	98.5	96.16	95.24	98.22	96.71	92.04	89.24	85.89	92.17	88.92
All Channels	94.36	91.95	89.87	94.77	92.25	88.57	86.63	85.71	89.07	87.36

Table 7 Comparison of the proposed SB 1D CNN and traditional 1D CNN model in predicting seizures by best-channels and all channels data (preictal = 60 min)

# Channel	SB 1D CNN					Traditional 1D CNN				
	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1- Measure (%)	Sensitivity (%)	Selectivity (%)	Specificity (%)	Accuracy (%)	F1- Measure (%)
Best Channels	94.66	93.55	91.27	95.24	93.21	89.32	87.59	87.40	91.67	89.48
All Channels	89.33	86.64	85.17	89.93	87.49	84.45	81.77	82.78	84.93	83.84

Table 8 Comparison of the results of the proposed model with some past studies having a structure close to the proposed model

References	dataset	N. of Conv. layers	Preictal Time	SPH Time	Novelty	Performance Metrics
Wang et al. [35]	CHB-MIT	4	30 min 60 min	5 min 5 min	Channel selection strategy	Acc = 98.60; Sens = 98.85 Acc = 98.32; Sens = 98.48
Khalilpour et al. [18]	CHB-MIT	2	30 min	10 min	individual & Grouped channel	Acc = 97; Sens = 98.5
Xu et al. [38]	Kaggle & CHB-MIT	5	60 min 30 min	5 min 5 min	Raw & 1D CNNs	Sens = 93.5 Sens = 98.8
Zhao et al. [40]	AES & CHB-MIT	5	60 min 30 min	5 min 5 min	BSDCNN	Sens = 89.26 Sens = 94.69
This work	CHB-MIT	2	30 min 60 min	27 min 27 min	SB 1D CNN	Acc = 98.22; Sens = 97.95 Acc = 94.85; Sens = 93.18

Compared to previous studies, our method shows similar performance with significantly less computational complexity. Wang et al. [35] proposed a method for selecting channels in 1D CNNs, achieving 98.6% accuracy and 98.85% sensitivity with four convolutional layers, using preictal intervals of 30 and 60 min. Khalilpour et al. [18] evaluated a 1D CNN with 2 convolutional layers across individual channels and all channels combined, achieving 97% accuracy and 98.5% sensitivity using data from all channels. Meanwhile, Xu et al. [38] and Zhao et al. [40] reported sensitivities of 93.5% and 98.8%, 89.26% and 94.69%, respectively, with 1D CNNs that used 5 convolutional layers across different datasets. In contrast, our method only uses two convolutional layers and achieves similar accuracy and sensitivity, while demonstrating its effectiveness with lower computational complexity.

6 Conclusion

For this study, we developed a new way to predict seizures by using a Signal-Based One-Dimensional Convolutional Neural Network (SB 1D CNN) that was specifically designed for classifying epileptic signals. Our goal was to improve accuracy by optimizing the architecture and training procedure of 1D CNNs to better match the characteristics of epileptic EEG signals. We made changes to the traditional ReLU and Pooling layers, replacing them with layers that are more responsive to negative signal fluctuations. Additionally, we used time/frequency-sensitive kernels in the convolution layer to extract meaningful features across time and frequency domains. We tested our proposed SB 1D CNN model extensively using epileptic EEG signals from the CHB-MIT database. We chose the best channels through single-channel evaluations and trained the final SB 1D CNN model using the data from these channels, which resulted in significant improvements in classification performance. Our results show that the SB 1D CNN model achieved superior sensitivity, selectivity, specificity, and accuracy compared to traditional 1D CNNs.

Specifically, the proposed SB 1D CNN model achieved an average sensitivity of 98.5, selectivity of 96.16, specificity of 95.24, and accuracy of 98.22, while a traditional 1D CNN yielded lower performance metrics. Our findings highlight the superior capability of the SB 1D CNN model in feature extraction and classification of epileptic EEG signals, emphasizing the importance of tailored architectures for improving model performance. Our study underscores the significance of training 1D CNNs with relevant data and optimizing their architecture for specific signal-processing tasks, such as epileptic seizure prediction. By facilitating timely interventions and improved management of the condition, our approach holds promise for enhancing the accuracy and efficacy of seizure prediction systems, ultimately benefiting individuals with epilepsy.

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Code Availability The code is a custom code. It was developed by using MATLAB software.

Declarations

Conflict of interest The authors declare no conflict of interest.

Human and Animal Rights This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent The authors declare that they have no consent.

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