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CNN-based classification of epileptic states for seizure prediction using combined temporal and spectral features

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ABSTRACT

Reliable prediction of epileptic seizures is of paramount importance in reducing the serious consequences of seizures by detecting their onset and warning patients early enough to take prompt and effective intervention measures, thereby ensuring the safety of patients who cannot be treated with pharmaceutical treatments or surgery. Indeed, the classification of epileptic states by deep learning methods based on electroencephalography (EEG) signals has attracted much attention in recent years. Nevertheless, the performance of classification of these states is strongly related to the preprocessing phase. The study of stability and detection of transitions between epileptic states is paramount to improve prediction algorithms. In this work, a stability index (SI) based on multivariate autoregressive modeling, capable of quantifying the phenomena observed during transitions between epileptic states and indicating the stability state of the epileptic neural system, is computed and fed to a convolutional neural network model among other known features in order to improve the learning performance of high-level features of the EEG signal and thus the classification of epileptic states. The experimental results highlight that the integration of the SI can stabilize the implemented learning model, satisfactorily improve the classification of epileptic states and permit our model to be competitive, based on many performance measures, to the state-of-the-art studies. Regarding the distinction between preictal and interictal states, our proposed model achieved an average accuracy of 90.1% to 94.5% and an average sensitivity of 88.6% to 92.8% for preictal interval durations of 30 and 60 min, respectively, on the CHB-MIT data set.

1. Introduction

Epilepsy is a neurological disease which is known and characterized by the appearance of spontaneous seizures that cause an alteration in the normal electrical activity between brain neurons, and cause also significant disturbances of the cognitive and emotional states. This chronic disorder affects nearly 1 % of the current population. The majority of seizures are controlled by drug therapy. Although, anti-epileptic medication and surgery can somehow alleviate symptoms, these treatments remain ineffective for about 30 % of cases. Therefore, concerns about epilepsy could be significantly reduced by the establishment of reliable seizure prediction systems, since early prediction of epileptic seizures ensures sufficient time before their onset, thus enabling the complete treatment or prevention of seizures through the use of the appropriate medication. Over the last few years several approaches have been developed to automatically predict seizures. Most of these approaches have been based on the analysis of the electroencephalogram (EEG), which represents the electrical recording of cerebral activities and is regarded as the most robust diagnostic and analytical device for epilepsy due to its high temporal resolution[1–13]. Experts classify the cerebral activity of epileptic patients based on EEG recordings into four main states: the preictal state, which is a transient state, usually lasts from a few minutes to a few hours before the onset of the seizure, the ictal state, which represents the seizure, the postictal state, which is attributed to the period after the seizure has occurred, and finally the interictal state, which refers to the normal state that takes place between seizures. This

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state begins after the postictal state of the first seizure and lasts until the appearance of the preictal state of the next seizure. The problem of prediction of epileptic seizures involves the detection of the preictal state. It has therefore been considered in the majority of studies in the literature as a classification task between preictal and interictal states. In fact, advances in artificial intelligence (AI) techniques, and in particular machine learning (ML) has greatly improved the field of epileptic seizures prediction by providing tools to deal with the large complexity of EEG signals and to facilitate big data management and multivariate analysis. As examples of some of these works: In[14], Büyükçakır et al, developed a non-specific seizure prediction system based on the Hilbert vibration decomposition (HVD) method for feature extraction from EEG recordings of 10 subjects from the CHB-MIT database. These features were fed into an MLP classifier to achieve a sensitivity of 89.8 % and a false alarm rate of 0.081/h. In[15], Messaoud et al applied the Random Forest classifier to classify a set of linear and non-linear features into preictal and interictal states with the aim of predicting seizures occurrence. The suggested method was tested on 20 patients from the CHB-MIT dataset and achieved a sensitivity of 82.07 % and a low false positive rate (FPR) of 0.0799 /h. In [16] Song et al used sample entropy-based features and extreme learning machine (ELM) model to classify interictal and preictal states. The proposed method was tested on 21 patients from the Freiburg dataset and achieved a specificity of 83.80 % and a sensitivity of 86.75 %. In[1] Cho et al examined the phase lock value (PLV) calculated using noise-assisted multivariate empirical mode decomposition (NA-MEMD) to classify interictal and preictal states using support vector machine (SVM). The proposed method was tested on 21 patients from the CHB-MIT dataset and achieved a specificity of 82.76 %, a sensitivity of 82.44 %, and an accuracy of 83.17 %. In[4], a bag-of-waves (BoWav) based features extraction was proposed and the ELM method was used to classify the features sequence. The approach achieved 88.24 % of sensitivity across 9 patients from the CHB-MIT dataset. In[17], Abbaszadeh et al examined multiple univariate linear measures extracted from intracranial EEG (iEEG) signals and SVM as a classifier to predict seizures. The proposed approach was validated on 6 patients from the Freiburg EEG database and exhibited a sensitivity of 78 % and a specificity of 100 %.

Recently, Deep Learning (DL) approaches, which represents enhanced ML technologies capable of learning patterns more accurately from huge amounts of data by processing it through multilayered hierarchical architectures, have become indispensable in the field of signal processing, for automatic features extraction as well as for classification and thus for seizures prediction, with performances exceeding the levels previously achieved by traditional ML techniques. To mention a few works, in[2], Truong et al proposed a Convolutional Neural Network (CNN) model for both features extraction and classification with the aim of separating preictal from interictal segments. Preprocessing with short-time Fourier transform (STFT) on 30-second EEG windows was applied to extract data in frequency and time domains. Across the CHB-MIT dataset, the implementation results achieved a sensitivity of 81.2 %. In[5] Khan et al applied the wavelet transform (DWT) to convert EEG signals from time-based view to a combination of time- and frequency-based view and CNN to extract features and to distinguish between preictal, ictal, and interictal states. The proposed approach was evaluated on 15 patients in the CHB-MIT dataset and reached a sensitivity of 87.8 % and an FPR of 0.142 /h. In[6], Zhang et al proposed an approach for seizure prediction based on wavelet packet decomposition and common spatial pattern (CSP) to extract features in the time domain and frequency domain, as well as a CNN model to distinguish between preictal and interictal states. The approach was assessed on 23 patients from the CHB-MIT dataset and reached a sensitivity of 92.2 % and an FPR of 0.12/h. In[7], Ozcan et al evaluated the spatiotemporal correlation in features, extracted from multichannel EEG signals, consisting of spectral band power, statistical moment and Hjorth parameters, as well as a multiframe 3D CNN model for classification. The proposed approach attained a sensitivity of 85.7 % and an FPR of 0.096/h, across tests performed on 16 patients in the CHB-MIT dataset. In[18], Liu et al, proposed a multi-view CNN architecture to predict seizures onset by using time domain and frequency domain features. By performing experiments on 2 patients from the CHB-MIT dataset, the proposed approach achieved a sensitivity of 91.5 % and a specificity of 79.5 %. In [1], Hu et al put forward a new epileptic states classification approach to predict seizures, in which they partition further the preictal interval to many subintervals, using values of a Mean Amplitude Spectrum (MAS). Such values were retrieved from the EEG signals in the feature extraction phase. After that, the features were fed to a CNN-SVM model to classify the respective epileptic states. Experiments have shown that for a three-subinterval partition of the preictal state, a classification accuracy of 86.25 % was achieved on the CHB-MIT dataset. In[9], Romney et al applied empirical ensemble mode decomposition (EEMD) and Relief methods for features extraction and a deep neural network (DNN) model to predict seizures. The model was evaluated on 23 patients from the CHB-MIT dataset and returned a sensitivity and a specificity of 86.7 % and 89.5 %, respectively. In[10], Toraman et al converted EEG signals to spectrograms via STFT and used the spectrogram images as features to differentiate between preictal and interictal states by means of three different pre-trained CNN models (VGG19, ResNet, DenseNet). These models were finally compared for the determination of the best results. The classification was carried out based on 20 cases from the CHB-MIT dataset and reached a sensitivity of 92.32 %, a specificity of 89.76 % and an accuracy of 91.05 %. In[11], Usman et al applied STFT in the preprocessing phase, a CNN architecture to automatically extract features, and an SVM classifier to identify preictal state segments from interictal ones. The proposed method was successfully implemented and achieved 92.7 % of sensitivity and 90.8 % of specificity across the CHB-MIT dataset. In[12] Yang et al also applied STFT to convert the original EEG signals into spectrograms that map time–frequency features, but they were hallmarked by the use of a dual self-attentive residual network (RDANet) for classification. The proposed approach attained a sensitivity of 89.33 %, a specificity of 93.02 %, an AUC of 91.26 %, and an accuracy of 92.07 % over 13 patients derived from the CHB-MIT dataset. In[19], Gao et al put forward an approach for seizure prediction based first on transforming EEG signals into power spectrum energy density diagrams (PSDEDs), and then applying deep convolutional neural networks (DCNNs) and transfer learning for automatic PSDED features extraction and classification. The proposed method achieved an accuracy of 92.5 % and a sensitivity of 92.6 % in a case study of 11 patients from the CHBMIT dataset. In[13] Usman et al applied a customized three-layer convolutional neural network to retrieve automated features from preprocessed EEG signals via empirical mode decomposition with subsequent bandpass filtering, and merged them with handcrafted features to provide a full feature set. This feature set was subsequently used to train an ensemble classifier that mixed the outputs of SVM, CNN and LSTM using agnostic meta-learning. The proposed method yielded an average sensitivity of 96.28 % and a specificity of 95.65 % across all CHB-MIT patients. In[20], Ryu et al proposed a DWT-based approach for time–frequency domain conversion of EEG data and a novel hybrid DL model that couples a dense convolutional network (DenseNet) and LSTM for the classification of epileptic states. The proposed approach was tested on 24 cases from the CHB-MIT dataset and yielded a prediction accuracy of 93.28 %, a sensitivity of 92.92 %, a specificity of 93.65 %, an FPR of 0.063/h, and an F1-score of 0.923.

The fundamental premise of seizures prediction is the existence of a difference in brain waves between the interictal and preictal states, but a general and specifiable definition of the phase transition between these two states is still lacking. This is due to the fact that the dynamics of the various epileptic states are quite different from one patient to another, so that the specific characteristics of seizures in particular patients may not necessarily be relevant to other patients. Preprocessing and extraction of patterns that accurately reflect EEG behavior in epilepsy is therefore a crucial step to ensure the effectiveness of automatic seizure prediction systems. Motivated by these challenges, in this paper we investigated three types of features in the preprocessing phase, a time-varying spectral feature of epileptic EEG signals generated by STFT that have been proven in many works in the literature to be highly relevant for the identification of EEG waveforms variations during epilepsy[2,7,8,11,12], a non-linear feature, the sample entropy(SampEn), which has demonstrated a significant potential according to the literature[21–25] in quantifying the complexity of time series and more precisely the discrimination between multiple seizure states in EEG signals, but also a new time-varying feature; a stability index (SI) calculated using a multivariate autoregressive model (MVAR) that has been successfully shown in our recently published research[26] to be able to follow the temporal evolution of the stability state of the neural system, permitting the quantification of epileptic electrical activities and the analysis of the changing dynamics of EEG signals before, during and after seizures. The seizure prediction problem is treated in this work as a classification task between interictal and preictal brain states using a CNN-based DL model, and a true alert is regarded once the preictal state is detected within the predetermined preictal horizon. The remaining sections of this paper are organized as follows: Section 2 presents the proposed approach, where we introduce the dataset used, the preprocessing phase that integrates the calculation of the SI based on MVAR modeling, and the CNN architecture used to analyze the generated features and classify epileptic states. Section 3 presents the experimental setup, the evaluation results of the suggested approach, and a discussion and comparison with existing researches in the literature. The last section provides a conclusion and some future perspectives of our work.

2. Materials and methods

The preictal state is the inception of the ictal state, it holds the process of seizure development. The challenge of seizure forecasting is to recognize the symptoms of seizures and to anticipate whether the patient is on the verge of a seizure attack. In the present paper, we propose a method of prediction of epileptic seizures based on the differentiation between preictal and interictal states using scalp EEG signals derived from the publicly available CHB-MIT database. For this purpose, a preprocessing step is required in which three types of features are extracted, a frequency feature which is the relative power spectral density (RPSD) obtained using STFT, a nonlinear feature for estimating time series complexity which is the SampEN and a temporal feature that allows to follow the evolution of the epileptic electrical activity over time, which is the SI generated by MVAR modeling. Once these features are generated, they are injected to the CNN model to perform the classification task. A general flow chart of the proposed approach is presented in Fig. 1.

2.1. Dataset

The EEG signals used in this work are derived from the “CHB-MIT” database available in open access on “PhysioNet.org”. This database contains 24 sets of continuous long-term, multichannel scalp EEG recordings acquired from 22 patients, recorded at the Children’s Hospital in Boston. These recordings were performed on pediatric patients suffering from epileptic seizures (5 males, aged 3–22 years; 17 females, aged 1.5–19 years; and 1 subject with no age and sex information) to assess their fitness for surgery. The EEG signals were recorded according to the international 10–20 electrodes positioning system with a sampling rate of 256 and a resolution of 16 bits.

From this dataset, we selected a subset of recordings appropriate for our study; these are the recordings that comprise at least 1 h of pre-seizure EEG data. Since full use of EEG scalp electrode channels is impractical for real-time seizure prediction, the electrodes used in this work are specific to each patient and are selected by an expert as being the most sensitive electrodes and reflective of the patient’s epileptic state (see Table1).

2.2. Preprocessing of EEG signals

As mentioned earlier, EEG recordings of epileptic seizures consist of four epileptic states: interictal, preictal, ictal and postictal (as shown in Fig. 2). Seizures prediction involves anticipating the onset of a seizure before it occurs, which refers to the recognition of the preictal activity. Thus, identifying the ictal state is meaningless for seizure prediction. So, in this study, we discard the ictal state and combine postictal and interictal states to perform a binary classification between preictal and interictal states.

Despite the huge amount of researches on seizure prediction, there is no standard duration for the preictal state and even the CHB-MIT dataset does not provide any information on the duration of this state. In our experiment, we therefore tested our approach using two different preictal horizons of 30 min[2,6,10–12,15,19] and 60 min[3,7,8,18] respectively since they represent the most used horizons in the

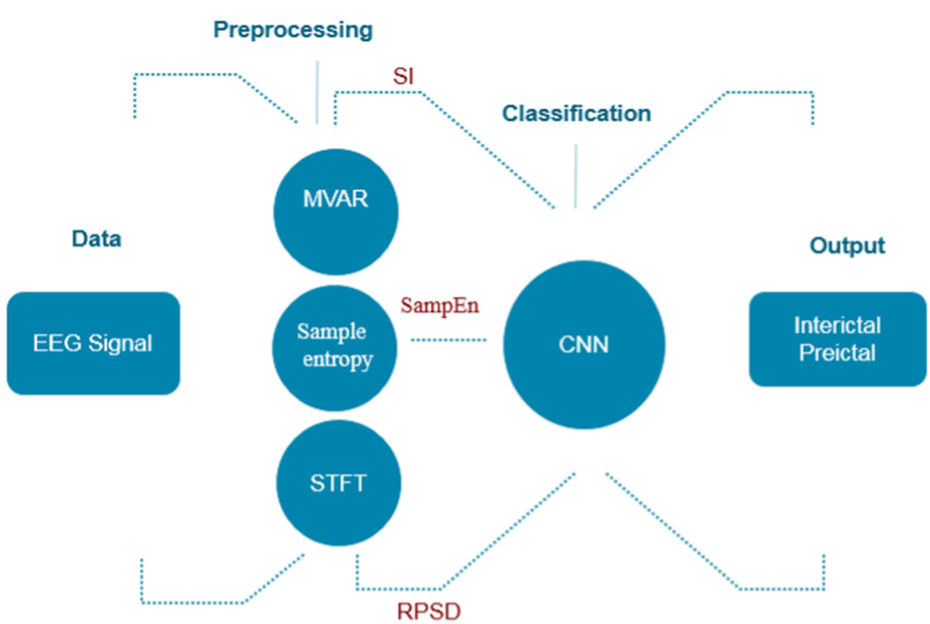

Fig. 1. Proposed process of classifying epileptic states.

Table 1
Selected patients from the CHB-MIT dataset.

Patients	Gender	Age	N° seizures	Electrodes
Chb01	F	11	4	Fp1-F7, F3-C3
Chb02	M	11	2	F7-T7, T7-P7
Chb03	F	14	3	T7-P7, P7-O1
Chb04	M	22	3	P7-O1, P3-O1
Chb06	F	1.5	7	F7-T7, T7-P7
Chb07	F	14.5	2	F3-C3, F8-T8
Chb08	M	3.5	4	F7-T7, T7-P7
Chb09	F	10	3	FP2-F4, F4-C4
Chb10	M	3	4	P7-O1, T7-FT9
Chb12	F	2	6	T7-P7, P7-O1
Chb14	F	9	3	F7-T7, T7-P7
Chb15	M	16	8	FP1-F3, F3-C3
Chb16	F	3	3	P7-O1, P3-O1
Chb18	F	2	2	FP1-F7, FP1-F3
Chb19	F	3	3	T7-P7, P7-O1
Chb20	F	3	3	F7-T7, T7-P7
Chb22	F	1	1	P8-O2, P7-O1
Total			61	

literature.

2.2.1. Relative power spectral density

The frequency domain of the EEG signal is generally separated into 5 well-known spectral bands: δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz) and γ (up to 30 Hz). The spectral features of interest in this work are the relative power spectral densities of these five sub-bands. Instead of investigating the energy of the whole EEG signal, the distribution of energy across frequency bands allows characterization of the variation in signal energy in the frequency domain and thus provides a more robust measure for revealing the preictal state. In order to calculate them, we adopted the STFT transform[2,10–13] which is a local Fourier transform (on a portion of the signal) that maps the frequency variations over time. This transformation is applied after dividing the signal into short consecutive segments of 2 s using a non-overlapping sliding window (Hamming window), then calculating the Fourier transform of each segment. The STFT then relies on two variables: a frequency variable and a time location variable of the frequency component. This transformation thus makes it possible to achieve the required goal, namely to have information on the signal both in time and in frequency.

The square of the averaged STFT calculated for each frequency band gives its power spectral density (PSD). The relative power spectral density (RPSD) is defined as the ratio of the band PSD to the total PSD, as follows:

$$\mathrm{RPSD}_i = \frac{\mathrm{PSD}_i}{\mathrm{PSD}_T}\ ,\ \mathrm{i} \in \{\delta, \theta, \alpha, \beta, \gamma\} \tag{1}$$

PSD_T represents the spectral power of the entire frequency band of the EEG signal ranging from 0.5 Hz to 32 Hz[8].

2.2.2. Sample entropy

Entropy approaches have revealed significant potential in the analysis of EEG signals and notably in the identification of epileptic seizures. This is mainly related to the high complexity of the human brain and the non-linear interactions among neurons, leading to a signal whose dynamics can be further characterized using entropy algorithms [27,28]. Over the past few years, various estimators have been purported to quantify the entropy of EEG signals. SampEn is a widespread entropy algorithm that fits into the category of embedding entropies, those that seek to quantify the complexity of a time series through comparing it to a lagged version of itself. SampEn is derived from the approximate entropy (ApEn) but it has been shown in the literature that it is more robust than ApEn in several aspects; it is less susceptible to noise and is applicable to short time series data. Moreover, it is resistant to short and strong transient disturbances such as spikes[21–23,29]. These properties make SampEn an interesting feature for the nonlinear analysis of physiological signals such as EEG. Therefore, SampEn has been used in this study as one of the features for preictal state recognition.

To compute SampEn, consider N samples of a time series: $\{x(n)\} = x(1), x(2), x(3), \cdots, x(N)$ and follow the subsequent algorithmic steps [22]:

1. Form m-vectors: $X_m(1), X_m(2), \cdots, X_m(N-m+1)$ with $X_m(i) = [x(i), x(i+1), \cdots, X(N-m+1)]$ et $i = 1, \cdots, N-m+1$; each vector $X_m(i)$ stands for m consecutive values of x, starting with the i$^{\text{th}}$ sample. The distance between two vectors $X_m(i)$ and $X_m(j)$ is defined by the following formula:

$$d[X_m(i), X_m(j)] = Max_{k=1,\cdots,m}(|x(i+k-1) - x(j+k-1)|) \tag{2}$$

2. For a vector $X_m(i)$, count the number of j $(1 \le j \le N-m,\ j \ne i)$ denoted B_i, so that the distance between $X_m(i)$ and $X_m(j)$ is lower or equal to r (threshold).

$$B_i^m = \frac{1}{N-m-1} B_i \tag{3}$$

With $1. \le i \le N-m$

3. Set $B^m(r)$ as follows:

$$B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r) \tag{4}$$

4. Expand the dimension to $m+1$ and then calculate the vector N-m (i ≠ j) designated by $A_i^m(r)$ and computed as follows:

$$A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r) \tag{5}$$

With.$A_i^m(r) = \frac{1}{N-m-1} A_i$

Finally, SampEn is computed as shown below:

$$SampleEn(m, n, N) = -\ln\left[\frac{A^m(r)}{B^m(r)}\right] \tag{6}$$

For m samples, the vectors $B^m(r)$ report the probability that two sequences correspond. Similarly, for m + 1 samples, the vectors $A^m(r)$ report the probability that two sequences correspond.

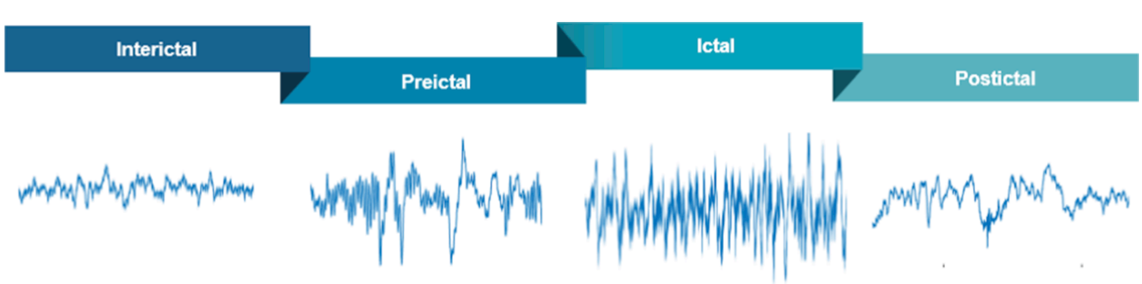

Fig. 2. Epileptic seizure states.

2.2.3. Stability index

In the human brain, the epileptic neuronal network is characterized by the generation of epileptic seizures, which are reflected on the EEG by sinusoidal waveforms of large amplitudes and rapid propagation speed, demonstrating significant synchronization within the neuronal network. The epileptic network can then be assimilated to a dynamic system with stability properties that evolve over time. The study of stability and the understanding of the mechanism of transitions between epileptic states is essential to improve prediction algorithms. Multivariate autoregressive modeling (MVAR) is chosen in the present study to quantify epileptic electrical activity and analyze the changing dynamics of EEG signals during seizures, by evaluating a stability index whose temporal variation is an indicator of the stability state of the system[26,30].

In this paper, the SI is calculated [26] and is added as a feature in the preprocessing phase in order to improve the classification performance. In fact, MVAR modeling is usually applied on stationary processes. To deal with such a non-stationarity problem of an EEG signal, this signal is decomposed into short time segments using a non-overlapping sliding window. The duration of each segment is equivalent to 2 s, which is similar to the durations of the EEG segments used by STFT and SampEn methods. Each EEG segment Y is in fact presented via a series of state variables, according to equation (7).

$$Y = \begin{pmatrix} y_1(1) & \cdots & y_d(1) \\ \vdots & \vdots & \vdots \\ y_1(N) & \cdots & y_d(N) \end{pmatrix} \tag{7}$$

Where d is the electrode number, and N is the number of samples.

The whole Auto-Regressive (AR) parameters are estimated through the application of MVAR modeling. The p order MVAR model of each segment estimates each sample as a weighted sum of the previous p samples, as provided in equation (8).

$$Y_n = \sum_{r=1}^{p} A_r(n) Y_{n-r} + W(n) \tag{8}$$

where Y_n is the time series estimated by the use of sum of linear combinations of previous EEG signals, $W(n)$ is a white noise with a null average, $n \in \{1, ..., N\}$ refers to the index of the samples, $r \in \{1, ..., p\}$, p is the optimal order of our model, and $A_r(n) \in R^{d\times d}$ is the AR matrix built with estimated parameters. The coefficients $A_r(n)$ from the MVAR model are estimated by Yules Walker's equations[30].

The optimal order p of our AR model is selected using the Shwartz Baysian Criterion (SBC) whose formula is presented by equation (9), and it corresponds to the minimal SBC value calculated over several time windows for each patient.

$$SBC = \log\hat{\sigma}^2(p) + \frac{p\log N}{N} \tag{9}$$

where: N is the sample size, p is the AR-process order and $\hat{\sigma}^2$ is the prediction-error variance.

The parameters of the AR system are then updated with the Kalman filter with the goal of reducing the estimation error. As a matter of fact, the general Kalman-filter model was defined in[26]. The calculation of the SI of a population system is based on extracting the MVAR-matrices eigenvalues, which represent indicators of the stability state of the underlying system. To compute them, the system in fact needs to be represented in state variables, as given in equation (10).

$$\widehat{Y_n} = J.\widehat{Y_{n-1}} + \widehat{W}(\mathrm{n}) \tag{10}$$

where: $\widehat{Y_n} = [Y_n^T, Y_{n-1}^T, \cdots, Y_{n-p+1}^T]^T \in R^{dp\times 1}$ is a state vector, $\widehat{W}(n) = [W(n)^T, 0, \cdots, 0]^T \in R^{dp\times 1}$ is a noise matrix, and J is a state-system expression, as given in equation (11).

$$J = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1p} \\ \vdots & \vdots & \vdots & \vdots \\ A_{d1} & A_{d2} & \cdots & A_{dp} \\ I & 0 & 0 & 0 \\ 0 & I & 0 & 0 \\ 0 & 0 & I & 0 \end{bmatrix} \in R^{dp\times dp} \tag{11}$$

The J matrix system can be written as follows:

$$J = VLV^{-1} \tag{12}$$

where the columns of $V \in R^{dp\times dp}$ are independent eigenvectors V_j and L is a diagonal matrix made with eigenvalues as given in equation (13).

$$L = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 & 0 \\ 0 & 0 & \lambda_3 & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & \lambda_{dp} \end{bmatrix} \in R^{dp\times dp} \tag{13}$$

The modules of the maximums of the eigenvalues λ_{max}, computed for each segment provide information about the stability of the described system and thus constitute a stability index (SI) variable over time. The SI is then represented as a vector $[\lambda_{max_1}, \ldots, \lambda_{max_j}]$ where j is the number of segments. According to our previous research work[26], if the SI is less than 1, no upcoming seizure will be detected, but if the SI is greater than 1, the system is unstable, thus predicting an epileptic seizure. Fig. 3 illustrates an example of a stability index for an epileptic patient (Chb06_09). The stability index is below 1 during the interictal state, which represents the normal state. During the transition to the preictal state, the index starts to increase until it exceeds the threshold defined by the value 1 to indicate the arrival of a seizure.

2.3. Epileptic-states classification

2.3.1. CNN model

The classification of the epileptic EEG-based state requires sophisticated approaches to cope with the great complexity of this signal to set the best prediction performances. The DL model is fully developed in the world today, and it utilizes characteristics obtained from EEG signals in the preprocessing phase, thus automatically producing more characteristics at high levels of abstraction[31,32]. In addition, the last DL approaches, which are as well known for their big number of hidden layers, give really very effective solutions to well classify the epileptic

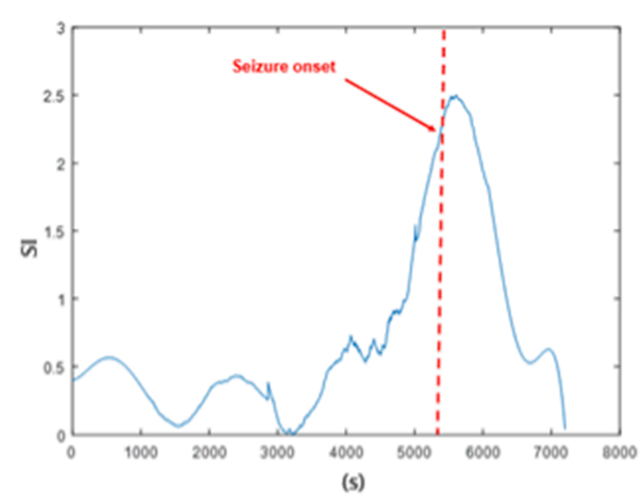

Fig. 3. Stability index for an epileptic patient (Chb06_09).

states. A CNN is a very powerful DL model, in particular the 1D-CNN which has been well adopted in the literature for the treatment of EEG signals[32–34]. Its architecture is usually composed of a series of 1D convolutional, pooling, normalization and fully connected layers.

Convolution layer: It applies filters to receive the field data through the adjustment of three parameters which impact the size of the layer: the strides, the size of filters, and the number of filters. Every filter is composed of a K_x coefficient. The latter presents a subset of synaptic layer weights. Indeed, to cover various areas of input feature maps, many filters use stride S_x. Added to that, the output neurons are produced forming the output feature maps (in other words the input feature maps of the next layer). At position (x), we compute in a formal way the output feature map f_0 using equation (14):

$$out_x^{fo} = f\left(\sum_{f_i \in A_{fo}} \left(\beta^{f_i,f_o} + \sum_{i=0}^{k_x-1} w_i^{f_i,f_o} \times In_{xS_x+i}^{f_i}\right)\right) \tag{14}$$

where A_{f_o} indicates the input feature maps generally used to produce the output feature maps, f_0, w^{f_i,f_o} and β^{f_i,f_o} respectively represent the kernel and bias values between the f_o output feature map and the f_i input one, and f(*) denotes a non-linear active function such as a sigmoid, a tanh or a Rectified Linear Unit (ReLU)[35].

Pooling layer: This layer permits condensing the information into a smaller size of the intermediate input (sub-sampling). As a consequence, it decreases the number of network parameters. Usually, the maximal or average input neurons are selected by a pooling layer. These latter are then partitioned into non-overlapping pooling windows. With a pooling window of Kx size, the outputs can be computed using equation (15):

$$out_x^{fo} = \max_{0 \le i \le K_x} In_{xK_x+i}^{f^i} \tag{15}$$

where f_0 is equal to f_i as a one-to-one mapping relationship between input and output feature maps.

Fully connected layer: This layer can run the classification of features through the use of multiple Fully Connected (FC) hidden layers. In fact, computing such layers corresponds to matrix multiplication, as depicted in equation (16). The last layer gives a loss function that will specify how the network will reduce the difference between the predicted state and the real one.

$$out^{no} = f\left(\sum_{n_i=0}^{N_i-1} w^{n_i,n_o} \times In^{n_i}\right) \tag{16}$$

where $f(*)$ is a Softmax function estimating on the output a probability distribution, w^{n_i,n_o} is the synaptic weight, and N_i is the number of neurons in the input layer *In*.

Dropout layer: This layer is a very promising technique that is based on setting a fraction rate of input units to 0 at each update in a random way during the training time. Its use consists in preventing overfitting.

2.3.2. Proposed 1D-CNN architecture

In this paper, we propose a 1D-CNN architecture as shown in Fig. 4, in which a set of seven features corresponding to the RPSD of the five frequency sub-bands (δ,θ,α,β,γ) of the signal EEG, SampEN and SI are considered as inputs, respectively. This architecture comprises three repeated applications of convolution operations running with a kernel-size 3. Every of them is followed by a ReLU operation. Moreover, the second and third convolution operations are here followed by size-2 max-pooling operations. Using this architecture, we can also reduce the spatial information, while increasing its feature (this information begins by 64 filters; and the number of filters doubles until 256 filters at every down-sampling step). After these convolutions and max-pooling operations, basically-three FC layers are applied to learn global features. Furthermore, the dropout layer is performed after the first FC layer with the objective of preventing overfitting. The two first FC layers are fixed to 100 and 5 neurons, respectively. The last FC layer is followed by a Softmax function to derive the probability distribution among multiple and various classes that correspond to different epileptic states.

3. Experiments and results

As described in Section 2.2.1, the five PSD features corresponding to the frequency sub-bands of the EEG signal, the SampEn, as well as the SI, are computed respectively to observe the frequency variations over time, to assess the complexity and measure the randomness of the EEG signal, and to analyze the stability state. The min–max normalization is then applied to these features to standardize the set of features within the interval [01] in order to prevent the high features from being influenced by the low ones. The formula for min–max normalization of each feature × is given as follows:

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{17}$$

Where x_{min} and x_{max} are separately the minimum and maximum of the feature x.

3.1. Experiment setting

A DL architecture is developed using the Keras library written in Python[36]. The experiments are performed on a Gaming Laptop PC with i7-10750H processor 2.60 GHz CPU equipped with an NVIDIA GeForce GTX 1650 graphics card. Table 2 shows the main hyper-parameters used in order to train and predict the model during

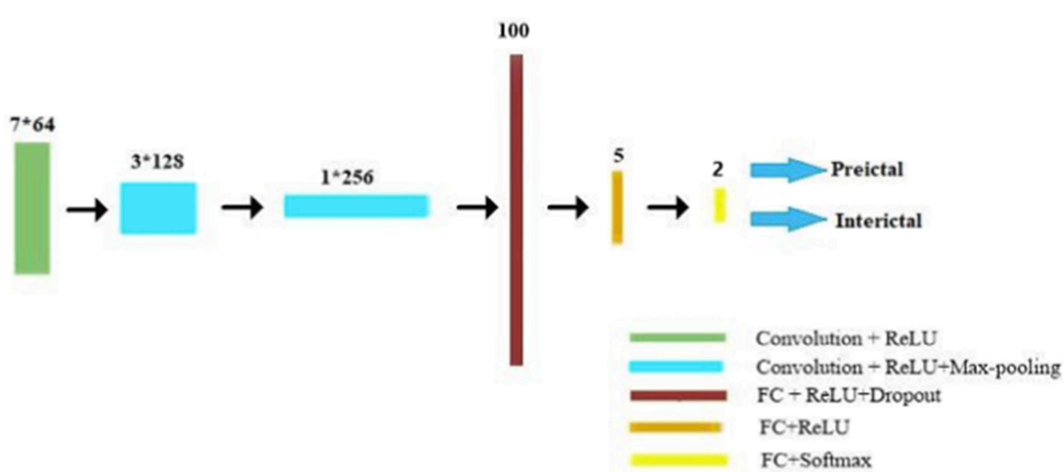

Fig. 4. Proposed 1D-CNN architecture.

Table 2
Hyper-parameter values of the implemented CNN model.

No.	Hyper-parameter	Valeur
1	Optimizer	Adam
2	Learning rate	0.001
3	Loss function	Categorical cross entropy
4	Batch size	512
5	Metrics	Accuracy
6	Epochs	200

execution. Part of this experiment, an adaptive moment estimation (Adam) optimizer has been utilized to learn weight parameters, which is known as an efficient optimizer, in particular as regards models having nonstationary and noisy data[37]. Furthermore, the hyper-parameters such as learning rate, number of epochs for training and batch size are empirically set to 0.001, 200 and 512 respectively to ensure the convergence of the network and avoid the overfitting problem.

In this paper, we focus upon seven patients from the CHB-MIT dataset to detect the epileptic states. In addition to that, we evaluate the classification performance by the within-subject method where every subject is taken in a separate way and partitioned respectively to 80 % and 20 % of observations for training and test.

3.2. Results

The performance of our seizure prediction model is evaluated by computing four statistical metrics such as accuracy, sensitivity, precision and F1-score as shown below. Where TP, FP,TN and FN represent the number of true positives, false positives, true negatives and false negatives, respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{19}$$

$$Precision = \frac{TP}{TP + FP} \tag{20}$$

$$F1 - Score = 2 \times \left(\frac{Precision \times Sensitivity}{Precision + Sensitivity}\right) \tag{21}$$

Furthermore, to better demonstrate the effectiveness of our approach and to enable a better comparison with the literature, we tested our approach using the two most commonly used preictal intervals in the literature, which, as mentioned earlier, are 30 min and 60 min, respectively. Moreover, to study the impact of the SI on the improvement of the classification process, we tested our model for two cases, without (- SI) and with (+SI) the integration of the stability index in the feature map.

3.2.1. States performance computed based on preictal state of 30 min.

Performance metrics obtained for classification of epileptic states into two classes (preictal, interictal) for a preictal interval set to 30 min are presented in Table 3. Our proposed approach reached, within this case, an average accuracy of 81 %, an average sensitivity of 71.4 %, an average precision of 73.2 %, and an average F1-score of 72.3 % using a feature map excluding the SI. Our results also revealed that with the inclusion of the SI as a feature, the average accuracy, sensitivity, precision, and F1- score increased to 94.5 %, 92.8 %, 91.5 % and 92.2 %, respectively, demonstrating the effectiveness of the SI in distinguishing epileptic states. Comparing the different evaluation metrics achieved with and without the SI, shown in Fig. 5, performance is clearly superior with the SI across all patients and in all metrics. Fig. 6 depicts the average gain between the two cases. This gain can exceed 13.5 % for accuracy, 21.4 % for sensitivity, 18.3 % for precision and 19.8 % for F1-score, which proves the importance of the SI.

Table 3
Classification results for a test performed with a preictal interval duration of 30 min.

Patient	Accuracy (%)		Sensitivity (%)		Precision (%)		F1_score (%)	
	−SI	**+SI**	**−SI**	**+SI**	**−SI**	**+SI**	**−SI**	**+SI**
Chb01	85.3	97.9	74.8	98.8	77.8	94.8	76.3	96.8
Chb02	80.4	90.7	75.1	87.8	74.8	91	74.9	89.4
Chb03	83.7	95.1	82.5	95.8	82	96.3	82.2	96
Chb04	64.6	96.5	69.6	97.2	65.4	92.5	67.4	94.8
Chb06	90.1	99.6	68.9	93.3	70	94.8	69.4	94
Chb07	89.8	94.8	66.6	82.4	70.4	88.8	68.4	85.5
Chb08	79.8	96.3	71.5	93.7	68	93.9	69.7	93.8
Chb09	83.3	90.1	66.8	85.9	74.3	85.4	70.4	85.6
Chb10	83.9	93.6	69.2	91.3	69.6	88.2	69.4	89.7
Chb12	83.7	96.4	83	98.8	80.6	95.3	81.8	97
Chb14	82.4	89.4	67.7	85.1	67.5	83.5	67.6	84.3
Chb15	85.1	94.9	65.3	88.5	79.7	93.6	71.8	91
Chb16	85.7	96.5	67.2	93.8	76.3	93.2	71.5	93.5
Chb18	77.9	96.3	81.9	91.9	73.2	94.4	77.3	93.1
Chb19	74.2	89.9	73.3	94.6	74.2	89.1	73.7	91.8
Chb20	66.6	93.9	63.4	99.7	77.6	92.3	69.8	95.9
Chb22	80.3	93.9	67.2	99.4	62.2	88.7	64.6	93.7
Average	81	94.5	71.4	92.8	73.2	91.5	72.3	92.2

3.2.2. States performance computed based on preictal state of 60 min

Table 4 presents the results obtained upon a binary classification of the epileptic states into interictal and preictal states, for a preictal interval set to 60 min. For this preselected interval, our proposed approach achieved an average accuracy of 73.4 %, an average sensitivity of 68.9 %, an average precision of 71.9 %, and an average F1-score of 70.4 % without the inclusion of the SI in the set of features used for classification. With the integration of the SI, these metrics increased to reach an average accuracy of 90.1 %, an average sensitivity of 88.6 %, an average precision of 91.4 %, and an average F1-score of 90 %. Fig. 7 shows that this improvement in the performance metrics after the inclusion of the SI has been detected among all treated patients and in all metrics. This provides further evidence that the SI has an enhancing effect on overall seizure prediction performance, regardless of the length of the preselected preictal interval. This enhancement is more strongly demonstrated by the calculated average gain depicted by Fig. 8 which amounts to 16.7 %, 19.7 %, 19.5 % and 19.6 % respectively for accuracy, sensitivity, precision and F1-score respectively.

3.3. Discussion

As noted, the performance of the classification approach of epileptic states depends on the used dataset, the preprocessing techniques, the extracted features, the preictal interval and the classifier architecture. The results presented previously revealed that the duration of the preictal interval is an important factor influencing the classification process and that a 30-minute preictal interval was more appropriate than a 60-minute preictal interval for better classification of epileptic states and thus for seizure prediction. These results are intuitively expected, because the more we move back in time from the onset of the seizure, the more the appearance of signs of epileptic activity decreases.

In order to compare our results with other research works in this area, a summary of the best ML and DL based approaches for seizure prediction that have been evaluated on the CHBMIT dataset is presented in Table 5. A wide range of techniques has been employed in these studies to analyze EEG signals during the preprocessing phase in order to extract the most appropriate features for better classification of epileptic states, and thus seizure prediction. For this purpose, STFT represents the most used method, either to extract features in the time–frequency domain or to convert EEG signals into spectrogram images, to fed them to a DL model for classification. In our study, the main novelty is the

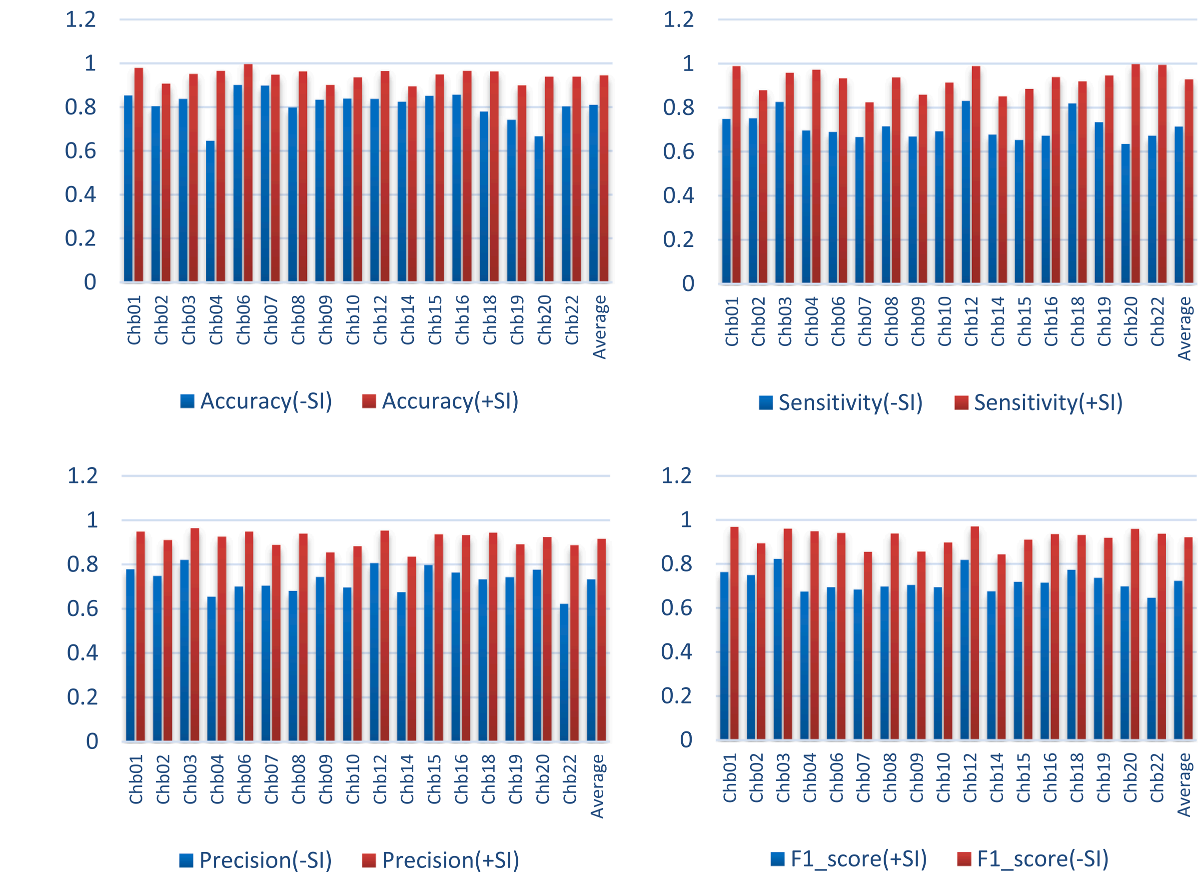

Fig. 5. Classification results per patient using a 30 min preictal interval duration.

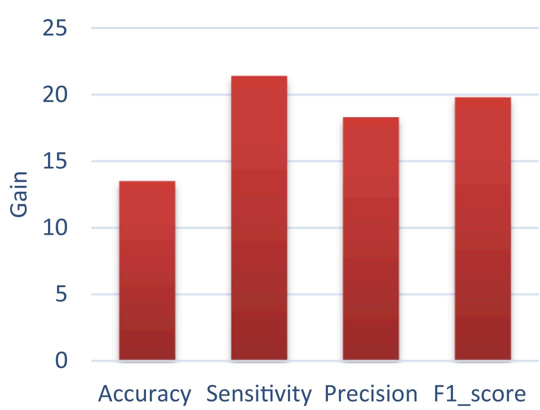

Fig. 6. Average performance gain (Preictal interval duration = 30 min).

integration of the SI, retrieved through the application of the MVAR modeling, as a feature with the target of improving model performance in learning the high-level EEG-signal features and classifying the epileptic state by a CNN model.

Determining which approach is better is difficult, because even though they were evaluated on the same dataset, they were tested with different patients, different numbers of recordings, as well as different preictal interval durations. Our results achieved with the integration of the SI and using the two most used preictal interval durations in the literature (30 min and 60 min) showed that our proposed approach performed relatively well compared to other studies in this research area reported in Table 5 in terms of both accuracy and sensitivity. We also have an additional consideration, which is the use of the minimal number of derivations compared with other presented works, i.e., 2

Table 4
Classification results for a test performed with a preictal interval duration of 60 min.

Patient	Accuracy (%)		Sensitivity (%)		Precision (%)		F1-score (%)	
	−SI	+ SI	−SI	+ SI	−SI	+ SI	−SI	+ SI
Chb01	79.5	94	79.2	93.8	79.7	94.7	79.4	94.2
Chb02	81.7	95.2	78.4	93.4	79	94.6	78.7	94
Chb03	80.2	93.9	65.3	91.8	76.1	91.3	70.3	91.5
Chb04	72.5	93.2	61	90	66.5	93.7	63.6	91.8
Chb06	79	88.5	68.8	84	72.6	88.6	70.6	86.2
Chb07	80.3	68.8	80.9	85.1	80.1	84.4	80.5	84.7
Chb08	70.8	86.1	70.7	86.1	71.1	86.4	70.9	86.2
Chb09	76.8	82.1	74.7	80.5	79.7	84.7	77.1	82.5
Chb10	76	92.4	76	92.4	76.1	92.6	76	92.5
Chb12	88.7	97.3	80.3	93.7	88.3	96.4	84.1	95
Chb14	58.3	82.3	59.4	81.8	59.4	82.1	59.4	81.9
Chb15	64.5	83	64	82.8	68	84.2	65.9	83.5
Chb16	70.5	90.2	70.5	90.2	70.9	90.5	70.7	90.3
Chb18	54.4	98.2	54.4	98.2	41.6	98.2	47.1	98.2
Chb19	92.4	95	70.2	75.6	90.3	97.1	79	85
Chb20	62	96.2	60.2	91.5	57.1	96.5	58.6	93.9
Chb22	60.7	95.9	58	95.3	66.4	97.7	61.9	96.5
Average	73.4	90.1	68.9	88.6	71.9	91.4	70.4	90

patient-specific derivations.

Indeed, works tested with a preictal interval duration shorter than or equal to 30 min[1,2,5,6,9–12,15,19,20] averaged no more than 93.28 % in accuracy and 92.92 % in sensitivity. On the other hand, with our approach, we managed to reach an average of accuracy of 94.5 % and an average of sensitivity of 92.8 %. For works tested with a duration of preictal interval ranging from more than 30 min to 60 min[3,4,7,8,18], the maximum averages of accuracy and sensitivity reached are respectively 86.25 % and 91.5 %. Whereas this average of sensitivity was

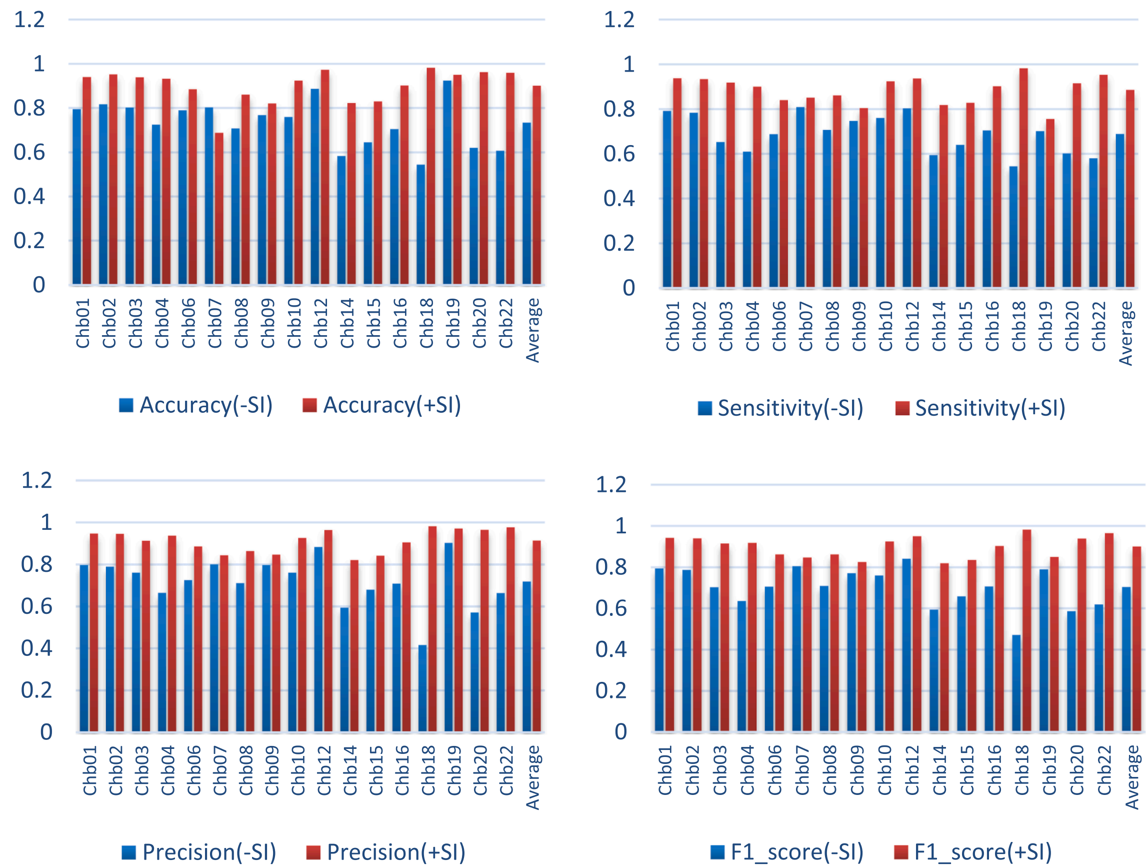

Fig. 7. Classification results per patient using a 60 min preictal interval duration.

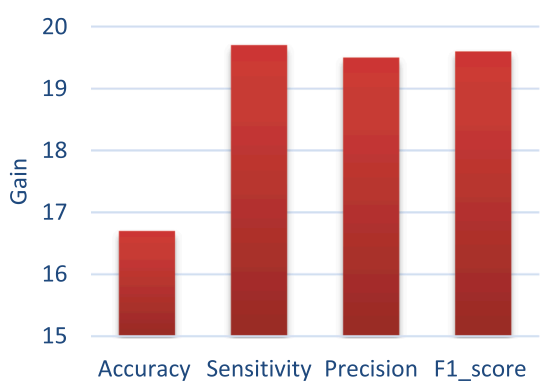

Fig. 8. Average performance gain (Preictal interval duration = 60 min).

reached by[18] and with a test carried out on only two patients. However, for this preictal interval range, we were able with our approach to attain an average accuracy of 90.1 % and an average sensitivity of 88.8 %. In[13], the average sensitivity obtained exceeded that attained with our work to reach 96.28 %, but with this study the comparison may not be quite convenient since the preictal interval duration was not provided.

In[38], the average sensitivity reached almost 100 %. In that work, authors divided the input signal into 5 s segments while our work was based on 2 s segments. To study the effect of the signal segmentation on the classification process, we partitioned the EEG signals into 5 s segments and rerun the hole process to predict seizures for a preictal state duration of 30 min and we noticed that there is an improvement in the classification results such as the average sensitivity which reached 94.8 % instead of 92.8 % and the average accuracy which reached 96.6 % instead of 94.5 %. These results reflect the impact of signal partitioning on seizure prediction. Moreover, in this same work[38], the number of electrodes used was 18 for each subject, whereas for our study we used only 2 electrodes for each subject, which are the most sensitive electrodes, i.e. the electrodes that most accurately reflect the epileptic activity. This choice to use only two electrodes is related to our future goal which is the development of a mobile application that predicts the onset of epileptic seizures and warns the patient himself as well as his doctor in order to take the necessary precautions. Therefore, we need to minimize the number of electrodes as much as possible, first to make the headset convenient and comfortable for the patient himself, but also to reduce the complexity and the material resources consumption.

These results are obtained given that the SI is a relevant feature which is integrated as input of CNN model. This latter has the capacity to extract more features within the network. The feature vector obtained after the convolution layers becomes the input of a fully connected network, which ultimately allows achieving high performance in seizure recognition.

4. Conclusion

The potential of the SI as a feature extracted from EEG signals based on MVAR modeling, has been presented and explored in this paper. This feature, capable of revealing the stability state of the neural system and therefore quantifying the epileptic electrical activities and analyzing the changing dynamics of the EEG signals during the seizures, has been fed into a CNN model along with other features widely used in the literature in this field, in order to improve the performance of the system in learning the high-level features of the EEG signals and classifying the epileptic states. The experimental results revealed that with a feature map including the SI, extracted using only two patient-specific EEG derivations, our model, which achieved average accuracies ranging from

Table 5
Comparison with state-of-the-art methods using the open CHB-MIT EEG database.

Author	Year	Preprocessing	Classifier	N° of cases	N° of EEG channels	EEG Segmetation window	Preictal state duration (min)	Accuracy (%)	Sensitivity (%)
Cho et al[1].	2017	PLV (NA-MEMD)	SVM	21	3	60	5	83.17	82.44
Alotaiby et al [3].	2017	CSP	LDA	24	18 to 23	3	60	–	81
Truong et al [2].	2017	STFT	CNN	13	6	30	30	–	81.2
Cui et al[4].	2018	BoWav	ELM	9	–	–	50	–	88.24
Khan et al[5].	2018	DWT	CNN	15	22	–	10	–	87.8
Tsiouris et al [38].	2018	Statistical moments, zero crossings, wavelet transform coefficients, PSD, cross-correlation, graph theory.	LSTM	24	18	5	15 30 60 120	–	99.28 99.38 99.63 99.84
Zhang et al [6].	2019	CSP	CNN	23	18	5	30	–	92.2
Ozcan et al [7].	2019	Spectral power, Statistical moments, Hjorth parameters	3D CNN	16	21	4	60	–	85.7
Liu et al [18].	2019	Time domain and frequency domain features	multi-view CNN	2	23	30	60	–	91.5
Hu et al[8].	2019	MAS	CNN-SVM	24	18	1	60	86.25	–
Romney et al [9].	2020	EEMD and relief	DNN	23	2	3.9	23	–	86.7
Toraman et al [10].	2020	STFT	CNN + SVM	20	18	5	30	91.05	92.32
Usman et al [11].	2020	STFT	CNN + SVM	24	–	30	30	–	92.7
Yang et al [12].	2020	STFT	RDANet	13	22	5 s	30	92.07	89.25
Büyükçakır et al [14].	2020	HVD	MLP	10	18	16 s	120	–	89.8
Gao et al [19].	2020	PSDED	DCNN	11	22	4	10 30	92.6 92.5	92.3 92.6
Messaoud et al [15].	2021	Linear and non-linear features	Random Forest classifier	20	18	15	30	–	82.07
Usman et al [13].	2021	CNN, Statistical and Spectral moments	Ensemble of SVM, CNN, LSTM	24	23	30	–	–	96.28
Ryu et al [20].	2021	DWT	DenseNet and LSTM	24	18	10	5 10 15	93.28 92.69 92.99	92.92 91.24 91.75
This work	2022	MVAR (SI)Sample entropy (SampEn) STFT	CNN	17	2	2	30 60	94.5 90.1	92.8 88.6

90.1 % to 94.5 % and average sensitivities ranging from 88.6 % to 92.8 %, respectively, depending on the duration of the preictal interval used in the experiment, was quite efficient compared with other works in this field. These results are relevant to our primary objective which is the prediction of epileptic seizures and illustrate the ability of our approach to predict seizures before 30 min and 60 min of their onset with accuracies of 90.1 % and 94.5 % respectively. In our future research, we aim to develop an appropriate unsupervised approach to automatically determine the most impactful electrodes and the duration of the preictal interval specific to each patient, since these informations are of great importance for the good classification of epileptic states and therefore for the robust prediction of epileptic seizures. Furthermore, we intend to develop a mobile application that will inform the patient's doctor about the seizure onset time for early intervention.

CRediT authorship contribution statement

Ines Assali: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Ahmed Ghazi Blaiech:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Asma Ben Abdallah:** Methodology, Validation, Supervision. **Khaled Ben Khalifa:** Methodology, Validation, Supervision. **Marcel Carrère:** Methodology, Validation, Supervision. **Mohamed Hédi Bedoui:** Conceptualization, Methodology, Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used in this study are available in open access on Physionet.

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