Robust feature learning method for epileptic seizures prediction based on long-term EEG signals

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***Abstract*—Deep learning (DL) has been expensively applied in multiple fields like computer vision, speech recognition and natural language processing. The field of Epileptic seizure prediction didn't receive the deserved attention by DL community, even though, deep neural networks can handle the challenging task of onsets prediction whilst achieving the highest rates of sensitivity, despite the complex nature of EEG signals. In the literature, this issue was addressed differently most of the time using handcrafted temporal and spectral features, machine learning techniques and rarely deep learning with extracted features. In this paper, we introduce an LSTM model designed to address the chaotic nature of an EEG signal in order to predict pre-ictal and inter-ictal states. Our model is evaluated on the publicly available CHBMIT database. We achieved an average sensitivity rate of 0.84 using a Raw EEG data segment as input to the LSTM model.**

***Index Terms*—feature learning, feature extraction, epileptic seizures prediction, raw EEG data, long-short term memory**

I. Introduction

Electroencephalogram (EEG) is the most reliable tool used by clinicians during the diagnosis process of epileptic patients. It helps to discern borders of pre-ictal, ictal, post-ictal and inter-ictal periods. The differentiation between these periods is very crucial to answer some clinicians' questions like the detection of seizures triggers.

The international league against epilepsy [1] defines epileptic seizures as a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. The common words employed in several definitions of epileptic seizures ([2], [3] and [4]) are: sudden, excessive, abnormal, paroxysmal, neural discharge.

Intracranial electroencephalography (iEEG) uses electrodes placed directly onto the exposed surface of the brain. This type of recordings contribute to the outline of a larger area, defined as irritative zone, that generates abnormal inter-ictal events/potentials. It is employed to discern the epileptogenic zone in order to proceed to surgery. While scalp EEG is recorded by using electrodes placed onto the scalp, this type is more susceptible to artifacts/noise than iEEG. The scalp EEG is a practical complement to the diagnosis of seizure disorders, but it is not clear that an EEG pattern should be essential to seizures definition [5]. The advantage of scalp EEG resides in its ease of use. Elaborating a comparison between these two types of sensors, [6] shows that the overall average of prediction sensitivity for iEEG is around 80.5-98.8%, although, it sits around 74-99.1% for scalp EEG.
The evolution of both frequency and amplitude over time should be analyzed to distinguish seizures from other abnormal activity in an EEG signal.

The capability of seizures prediction refers to the existence of a preseizure state [7]. For such approach, ictal segments (when the seizure occurs) are excluded from the processing. The objective is to differentiate between the pre-ictal and the inter-ictal states in order to prevent an incoming seizure.

Mainly, we can define two different approaches. The first one is based on thresholds of one or multiple calculated features. When the threshold value is exceeded, an alarm will be generated to indicate an incoming seizure. This approach was used by some researches for the aim of seizures prediction [8], [9] and [10]. In the other approach, the use of machine learning techniques shows a good efficiency to detect an incoming seizure [11] [12] [13]. Various features can be extracted from the EEG signal that is labeled based on the type of segment and passed as a feature vector to classifiers to perform the learning task [14] [15] [16].
During the past decades, machine learning techniques were the only option for seizure prediction, since it can handle the

high complexity of an EEG signal. In our case, we study the differentiation between these two states in order to prevent seizures attacks. Recently, researches in this field are giving more importance to deep learning approaches. Seeing that the latter showed high performances for images/identity and speech recognition. The only disadvantage is the need of a larger amount of data in order to perform the learning phase of DL techniques.

Convolutional Neural Networks are the most used DL technique for epilepsy prediction for its capability to process images and signals exceedingly well. Due to the availability of big data for epileptic patients, some researchers tested Long Short-Term Memory (LSTM) to predict seizures. Performances are close to those achieved by CNNs. Furthermore, the time of execution and the required resources are considerably less compared to CNNs requirements.

In this work, we present for the first time, an LSTM learned with Raw EEG signals (no pre-processing for noise and no feature extraction/selection) for the prediction of epileptic seizures. We evaluate our model on the CHB-MIT dataset. It is a publicly available dataset that contains continuous long term scalp EEG data for pediatric subjects from the Boston Children's Hospital. Since this work is about a challenging sequence labeling with LSTM, it requires special handling. Despite the fact that the proposed model achieved great results, it consumed a lot of resources and time. We tried to handle this problem by controlling the time steps limit fed into the LSTM model.

The rest of this paper is divided into 3 main sections. Related papers to the field of epileptic seizures detection/prediction are presented in the section II. In section III, we describe the used dataset and the proposed methodology for seizure prediction. Results are discussed in section IV. And finally, the work is concluded by presenting perspectives for future contributions.

II. Related works

In order to get a complete overview of the state, we selected more recent papers elaborated for seizures classification. This part resumes popular researches in this field and does not exclude any methodology.

Bhattacharyya et al. [17] proposed a multivariate approach for patient specific EEG seizure detection. They employed a multivariate extension of the Empirical Wavelet Transform. The proposed architecture consists of selecting only 5 channels out of the 23 from the CHB MIT database in order to reduce the computation cost. The channel with the least standard deviation was regarded as reference to calculate the mutual information of other channels. The four channels with the highest MI are selected with the reference channel. Then EMD was applied to the selected 5 channels and instantaneous amplitudes and frequencies were calculated for each MODE. The three features extracted are: Mean, Mean monotonic absolute AM and Variance monotonic absolute AM. The Synthetic Minority Over-sampling Technique (SMOTE) was used as a technique to resolve the problem of imbalanced data. Authors used three classifiers with a view to evaluate the proposed system performances: RF, Linear Naive Bayes and K-NN. The method proposed has achieved a max average sensitivity equal to 97.91% and a max average specificity equal to 99.57% using the RF classifier, with five adaptively selected EEG channels.

Lasitha *et al.* in their work used both Bonn and CHB MIT databases to evaluate their work aiming to detect seizure onsets based on both Fractal Dimension and Harmonic Wavelet Packet Transform. Energy features from HWPT and FD are extracted for all channels and epochs to construct the feature vector passed to a Relevance Vector Machine (RVM) to achieve classification.

Antoniades et al. in their work [18] proposed a system to detect inter-ictal discharges from intracranial EEG signal. 18 subjects assessed for temporal lobe epilepsy at King's College Hospital were included in this study. EEG data was recorded using 13 electrodes during alertness and sleep periods. Scores for each trial of 325ms can be attributed from 0 to 4. This task was performed by an expert epileptologist. By adding a 1-D filter to every electrode signal as well as adding a bias term in order to generate the feature map. A logistic regression is applied to the output of this CNN's hidden layer to classify intracranial EEG features into non-IED, IED1, IED2 and IED3 classes. To resolve the problem of unbalanced data, authors employed the undersampling method for the non-IED class. Best accuracy obtained in this study is 89% achieved by the multi-class CNN approach.

A time-frequency analytic algorithm, denoted by LMD for Local Mean Decomposition, was applied to the EEG signal in order to detect seizure activity in [19]. LMD decomposes the EEG signal into several Product Functions (PFs). Maximal amplitude, minimal amplitude, average absolute value are three time-domain features. Maximum, skewness and kurtosis of PF's power spectral density are three frequency-domain features. Fractal Dimension, Renyi Entropy and Hurst Component are also extracted for the first five PFs. Features are passed to different types of classifiers: K-Nearest Neighbor, Back Propagation Neural Network, Linear Discriminant Analysis, un-optimized Support Vector Machine and Genetic Algorithm optimized SVM. Authors performed five classification cases of the Bonn epilepsy dataset and presented the obtained accuracy of all classifiers. The average accuracy for all cases of the proposed approach is about 98.10%.

When talking about Deep learning, Convolutional Neural Networks have attracted the most interest in seizure prediction. Yuan *et al.* proposed in [20] a new approach to the detection of epileptic seizures based on the attentive representation of the different channels of an EEG signal. The authors assume that, in the field of epileptic seizure detection from multiple-channel signals, several channels are unimportant and do not give any information about the activities, but they add a lot of noise to the signal which degrades the performance of a detection system. Based on these facts, they proposed a multi-view deep learning model that can accurately detect the onset of epileptic seizures from multiple-path EEG signals. A deep Convolutional Neural Network is proposed by the authors in this paper. Comprising of 13 layers (5-convolutional layer, 5-

max-pooling and 3-fully connected).
A CNN of 3 blocks implementing normalization, convolution and max pooling layers was used in [21]. The spectrum obtained from the spectral information of the raw EEG signal was fed to the CNN. Evaluated with only 13 cases of the CHB-MIT database (a total of 64 seizures), it achieved an average sensitivity of 81.2% with FPR at 0.16/h.
Khan et al. proposed a CNN architecture that contains six convolutional layers. Extracted features were used to label EEG segments (pre-ictal, inter-ictal and ictal classes) [22]. Wavelet transform was applied to each channel and for all EEG bands. The output was then passed to the CNN. 15 cases from the same database were used for the evaluation. 3 seizures out of 18 were not predicted, which resulted in an average FPR of 0.142/h.

One one side, Fourati *et al.* [23] showed the effectiveness of recurrent neural networks in their initial work for SVM learning. To add, the authors in [24] and [25] used Echo State Network for EEG feature representation to discriminate between calm and stress states.

On the other side, some studies evaluated LSTM for the aim of seizures detection. In order to classify two states: seizure and non-seizure, the LSTM model with a maxpooling and softmax layers was proposed in [26]. The system was evaluated with two types of EEG signals (clean and noisy), and showed good results for both cases. Bonn dataset was used for the performances evaluation. But since it does not contain a long-term EEG data, it is not considered as a reliable dataset to compare our results with for this study.
Yao et al. [27] proposed a model which combine an attention mechanism and a Bidirectional Long Short-Term Memory (BiLSTM) in order to exploit both spatial and temporal features. This model aims to overcome seizure variabilities, thus capturing essential seizure patterns. The system was validated on the noisy data of CHB-MIT. Mean values of sensitivity and specificity are 87.00% and 88.60% respectively, noted as the highest rates of the current modern methods.
iEEG was employed by [28] to check for seizures related-events (Spikes, RonS, Ripples and Baselines). Since they are the clearest, it gives prominent results when processed with an LSTM model.
The first authors who introduced LSTM deep learning models for epileptic seizure prediction were Tsiouris *et al.* in their work [29]. Various time and frequency domain features were investigated in this study. In addition, correlation between channels and graph theory measures were also calculated and combined with the aforementioned features to construct the feature vector which presents the input for 3 different LSTM architectures. Tsiouris also studied the impact of the pre-ictal window and the LSTM input size on the performance of the proposed system. Unlike other studies using the CHB-MIT databse, the evaluation was performed on the entire amount of its data, achieving a very high level of sensitivity (0.990) and low FPR (0.02/h) with a pre-ictal window of 120 min.
Hussein *et al.* deployed an LSTM network in order to extract the most discriminative features related to series of onsets [26]. The proposed architecture consists of a 3 layers LSTM model with a softmax classification layer on top of them. A perfect accuracy was achieved for the binary classification of normal and seizure EEG segments.
This work [30] proposes the implementation of deep learning for the detection of normal, predictive and epileptic EEG signals (normal, inter-ictal, ictal), without characteristics extraction nor selection. The system automatically learns and discovers the characteristics necessary for classification from input data processing through multiple layers. System performance is validated by the Bonn database, achieving 88.67% accuracy, 95.00% sensitivity and 90.00% specificity.
Recalling information for long periods of time is basically the default behavior of LSTMs, rendering them the best option for long-term EEG signals processing.

III. Materials and methods

A. EEG data

We evaluated performances of our proposed method using data from the CHB-MIT scalp long-term EEG dataset [31]. Data was recorded from 23 pediatric patients with intractable seizures at Boston Children's Hospital. Table I presents details of the 24 cases (2 cases recorded for the same patient). In this dataset, we found about 983 hours of EEG recordings annotated by experts to identify the beginning and the end of onsets in epochs with ictal activities. As shown in the Table I, seizures are minor in duration compared with total EEG duration of each case, leading to a very imbalanced data distribution making the classification exceedingly challenging. 256 Hz was the sampling frequency of all recorded signals, with 16-bit resolution. For electrode positioning, the international 10–20 system was chosen.
Analysing files of all cases summary, we note that the montage of channels changes within the case, so we opt for a manual channel selection process to discern the common montage over all epochs. Finally, we discern the 18 channels to be used in this work: FP1, T7, P7, O1, F3, C3, P3, FP2, F4, C4, P4, O2, F8, T8, P8, FZ, CZ and PZ. We used the complete amount of data from CHB-MIT dataset (except three segments from the case 12: chb12-27/28/29 since we can't found the common montage of selected channels in these epochs [29]).

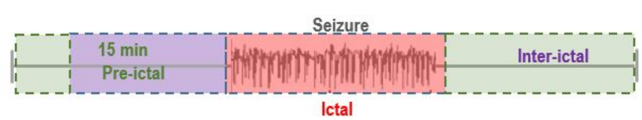

Fig. 1. Different states representation of an epileptic patient's EEG segment

B. Methodology

For the aim of seizure prediction, our deep network is deployed to accomplish the high-level characteristics learning of pre-ictal and inter-ictal states. Tsiouris tested four windows to extract pre-ictal states: 15-30-60-120 minutes and compared the obtained results. Since there are not a lot of differences

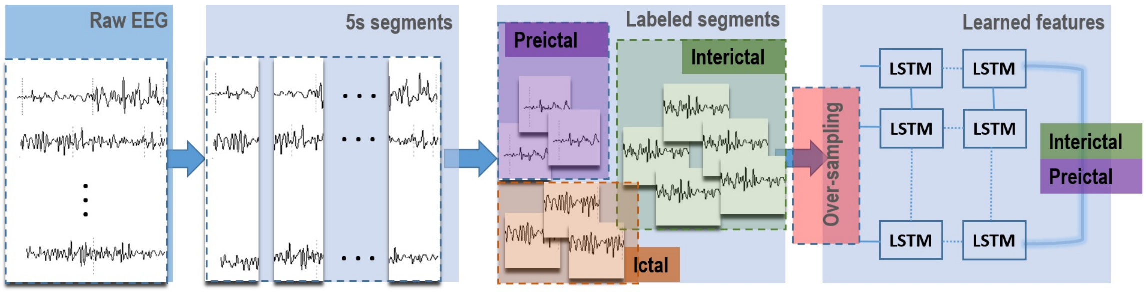

Fig. 2. Architecture of the proposed system

TABLE I
DETAILS OF ALL 24 CASES INCLUDED IN THE CHB-MIT DATABASE

Case	#seizures	Seizures duration (mm:ss)	EEG duration (hh:mm)
1	7	07:20	40:30
2	3	02:52	35:00
3	7	06:42	38:00
4	4	06:18	156:00
5	5	09:18	39:00
6	10	02:33	66:30
7	3	05:25	67:00
8	5	15:19	20:00
9	4	04:35	68:00
10	7	07:27	50:00
11	3	13:26	35:00
12	27	17:36	21:00
13	12	08:55	33:00
14	8	02:49	26:00
15	20	26:55	40:00
16	10	01:24	19:00
17	3	04:53	21:00
18	6	05:17	35:30
19	3	03:56	30:00
20	8	03:49	27:30
21	4	03:19	33:00
22	3	03:24	26:30
23	7	05:30	26:30
24	16	08:31	21:00

between the average rate of sensitivity of all tested windows, we decided to choose one window for the rest of the analysis. Leafing through all annotation files, we discover that some seizures occur in the beginning of the epochs, thus, there is not a sufficient duration to extract pre-ictal segments with a 60-120 windows. Furthermore, some seizures occur consecutively with an interval of less then 60-120 minutes. For these reasons, we opt to test our method using a pre-ictal window of 15 minutes.

For the purpose of this study, ictal segments (when the seizure occurs, annotated on SEIZURES-INFO file) are not included. For each case, we extract pre-ictal and inter-ictal epochs, then we apply a segmentation script in order to obtain epochs of 5 seconds duration. This segmentation window was proved by [29] [32] to be the best for epileptic seizures analysis. All obtained epochs were labeled based on the annotation files accompanied with the database.

The Figure 1 shows how to differentiate between pre-ictal, ictal and inter-ictal periods. The borders are generally identified by epileptologists. In the case where two onsets occur consecutively, the set of segments between the first and second onsets can be miss-labeled as inter-ictal and pre-ictal states. To resolve this problem, all consecutive seizures should be processed separately to ensure a correct labeling of the overlapped segments.

To overcome the imbalanced aspect of data, we carried out an over-sampling augmentation technique to expand the amount of samples in the pre-ictal class. The ratio of pre-ictal:inter-ictal class differs between cases. Thus, for each case, we tried to reach the ratio 1:1 or 1:2 to guarantee a significant classification rate. Duplicated trials were selected randomly, then the resulted set was shuffled.

We contribute by proving that the seizures prediction can be carried out with a raw EEG signal. Thus, reducing extra-time of feature extraction and making it suitable for a real time application.

We conceptualize an LSTM model adapted to the nature of the EEG signals with two LSTM Layers. Since the input signal is a complex time series of 18x1280 time points, we fixed the number of memory units at 500 for both LSTM layers. We included a dropout layer with a probability of training equal to 0.2. Two layers follow the LSTM layers: a fully connected layer activated with ReLu function, and a dense layer to discriminate between the pre-ictal and inter-ictal states. which are The "softmax" activation was used as function in the dense layer. We personalized the model parameters using the popular Adaptative Moment Estimation (Adam) optimizer. The LSTM network was built on Matlab environment using the deep learning toolbox.

The training and testing phases are performed separately for every subject, therefore making a subject-dependent approach. This selection was predicated in line with our review of recent studies on onsets prediction and the insufficient subject-independent studies. Furthermore, carrying out a subject-dependent experiments allows to handle the variability and specificity of each subject and to compare the obtained results with existing ones.

The evaluation of our model was elaborated through a 10-folds cross-validation. For each case, trials were shuffled and divided into 10 groups. One group was designed to hold-out set and the remaining groups were used as training sets.

IV. Results and discussion

Deep Learning methods offer an automatic learning of temporal dependency. In this work, we implemented a deep architecture of an LSTM model for features learning applicable for epileptic seizures prediction. The model was tested on the CHB-MIT database and with only Raw data. As it is known, neural networks are invulnerable to the noise in the input data and in the mapping function, and can carry out the tasks of learning and prediction even if some values are missing. Neural networks have a high capacity to readily learn linear and nonlinear relationships. For these reasons, we have chosen to feed our LSTM with raw EEG segments with no pre-processing against noise and artifact. Keeping the noise has the advantage of guaranteeing that all ictal segments will be retained because pre-processing may affect them since shapes of the latter and artifacts can be similar.

In the other hand, we are facing the problem of imbalanced data since the number of pre-ictal segments for each case are minimum compared to the amount of pre-ictal segments (For example: For the chb024, the ratio of interictal-class to preictal-class instances is 5:1; for some other cases it is even more imbalanced). This problem can affect notably the classification rate, in the case where the accuracy measures indicate excellent rates (such as 90%). However, the accuracy is really only reflecting the underlying class distribution.

To resolve this problem, we chose to deal with it by an over-sampling technique which consists of adding copies of instances from the under-represented preictal-class.

The new datasets are fed to the LSTM model with a sequence of 18 channels x 1280 time points.

To introduce the metrics used to evaluate performances of our system, we define these items as:

- The number of segments properly detected as pre-ictal state is noted True Positive rate (TP).
- The number of segments properly detected as inter-ictal is noted True Negatives (TN).
- The number of segments incorrectly designated as pre-ictal is noted False Positives (FP).
- The number of segments improperly classified as inter-ictal is noted False Negatives (FN).

The well known expressions of these metrics are:

- Sensitivity (SENS) = TP/(TP + FN)
- Specificity(SPEC) = TN/(TN + FP)
- Accuracy = TP/ (TP+TN)*100%
- False Prediction Rate per hour (FPR (h^{-1}))= FP/ Total of hours

All obtained rates are presented in the Table II.

For the 24 cases in CHB-MIT, the average SENS, SPEC and ACC are 84.60%, 90.16% and 88.89%, respectively. The model provides a low FPR of 0.27 false alarms per hour. The minimum FPR is obtained for the cases Chb04, Ch07 and Chb11. The standard deviations of sensitivity, specificity and accuracy are 0.11, 0.08, and 0.09, respectively. As it can be seen in Table II, using raw EEG samples of every 5-s segments, we can achieve high performances varying across cases. The best sensitivity attained for cases chb07 and chb11 is 0.98. On the other hand, we have obtained as worst result a 0.67 sensitivity rate for the case chb24. We deduce that when seizures number exceeds 10, LSTM network underperforms in prediction seizures, which can be justified by a high number of non-spaced seizures causing a miss-classification of adjacent states as explained in the Subsection III-B .

Cross-patient sensitivity, specificity and accuracy results over all cases were illustrated on the Bar Chart 3. We can notice a degradation of rates that affects some specific cases, mainly Ch012 and Chb24. Many reasons can justify the under-performances such as: signals with high signal to noise ratio, number of consecutive seizures and the patients medical history (we can't confirm this fact since patients' personal information are private and cannot be accessed by the database users).

In order to defend their methodology choice, Tsiouris *et al.* [29] applied the proposed architecture on raw EEG data for only 3 cases (Chb01,Chb02 and Chb14) and showed that the results accuracy are better with feature extraction against feature learning. They obtained an average accuracy of 74.00% since their architecture failed to deal with the character of a Raw EEG signal because it doesn't include a sufficient number of hidden memory units.

Along with their hypothesis, we decided to investigate more in this direction and conceptualize a model adequate to receive a raw EEG signal as input.

Since we didn't find an other research that deploys LSTM with a raw EEG segments for the aim of seizures prediction, we compared our method with three different approaches proposed recently by [27] in order to detect seizures and no-seizures segments. The comparison focuses on this study which was evaluated with the complete volume of CHB-MIT database, being the premier public database consisting of long-term EEG signals. Recently, the TUH EEG Corpus database [33] became openly accessible letting easier validation. As shown in Table III, our system outperforms the three aforementioned models. in terms of specificity and accuracy. Thus, the projected LSTM model is ready to produce higher seizure prediction performance as compared with the work of Yao *et al.*.

Assuming once again that the proposed deep LSTM model is conceptualized to handle the complex nature of the EEG signal, using two LSTM layers and more hidden memory units allowing for better feature learning. Our model is more appropriate for real time applications than other based on feature extraction techniques requiring high level of expertise and familiarity with epileptic seizures characteristics.

Typical feature representation is learned by our model leading to very satisfying results for seizures prediction. Furthermore, we can apply the same architecture for seizures detection by including ictal segments to the overall process.

V. Conclusion

Thinking of the safety and an improved quality of life for epileptic patients, the need of predictive system is being very

TABLE II
EEG-BASED SEIZURE PREDICTION RESULTS

Case	#seizures	Pre-ictal window: 15min			
		RAW EEG			
		SENS	**SPEC**	**ACC**	**FPR** (h^{-1})
case01	7	0.92	0.94	93.42	0.12
case02	3	0.95	0.97	96.91	0.14
case03	7	0.93	0.93	93.53	0.11
case04	4	0.95	0.97	96.78	0.02
case05	5	0.88	0.90	89.48	0.25
case06	10	0.70	0.79	76.51	0.4
case07	3	0.98	0.98	98.74	0.02
case08	5	0.90	0.94	92.47	0.12
case09	4	0.92	0.97	95.53	0.03
case10	7	0.83	0.82	82.62	0.36
case11	3	0.96	0.99	98.24	0.02
case12	27	0.53	0.74	65.84	1.21
case13	12	0.82	0.87	84.96	0.37
case14	8	0.71	0.82	76.54	0.69
case15	20	0.73	0.81	78.09	0.47
case16	10	0.78	0.89	84.16	0.53
case17	3	0.96	0.99	97.99	0.03
case18	6	0.92	0.95	95.49	0.11
case19	3	0.95	0.96	96.04	0.12
case20	8	0.88	0.91	90.49	0.3
case21	4	0.95	0.95	95.49	0.13
case22	3	0.95	0.96	96.10	0.1
case23	7	0.88	0.88	88.21	0.45
case24	16	0.67	0.71	69.92	0.46
MEAN	–	0.84	0.90	88.89	0.27
STD	–	0.11	0.08	9.50	0.27

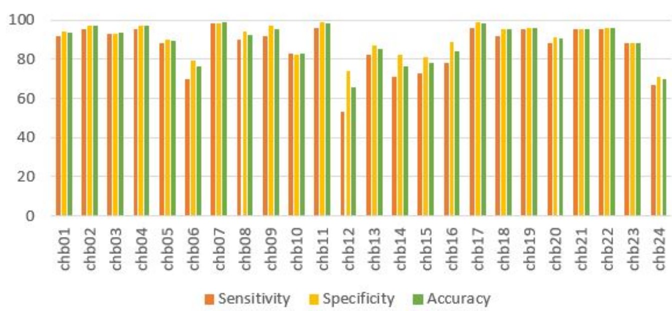

Fig. 3. Results of all cases grouped by SENS, SPEC and ACC

TABLE III
PERFORMANCE COMPARISON OF THE PROPOSED WORK WITH A RAW EEG-BASED APPROACH

Ref	**#Cases**	**#Channels**	**Method**	**Results**		
				SENS	**SPEC**	**ACC**
[27]	24	17	BILSTM	0.86	0.82	84.00
			Attention mechanism + LSTM	0.83	0.88	86 .00
			Attention mechanism + BILSTM	0.87	0.88	87.80
[29]	24	18	LSTM	–	–	74.00
Our work	24	18	Deep LSTM	0.84	**0.9**	**88.89**

crucial. As Electroencephalogram is mainly used to diagnose and detect seizures, researches in the field of onsets prediction are generally based on it. Since this latter is well-known by its complexity, it is important to adopt an adaptive model to handle its chaotic nature.

Deep learning networks showed great performance for clinical applications. For epileptic seizures prediction, LSTM has been used for classification after a feature extraction step that aims to reduce the high data dimensionality. LSTM as a deep network can handle the high temporal dimensionality of EEG signal and learn more relevant features than handcrafted extraction. In this paper, we showed how LSTM can perform feature learning achieving unusual sensitivity rates when using no pre-processed EEG signals. A Patient-specific approach was described and tested with a predefined LSTM architecture and some fixed parameters. As perspectives for future contributions, we intend to implement a subject-independent approach for epileptic seizure prediction which generalizes the learning process by the mean of a high level feature representation. Furthermore, we propose to investigate the impact of the pre-ictal window, the input size and the architecture complexity on the prediction performances. In order to handle the exceedingly long sequences of EEG signals with the proposed LSTM, we will focus on the possibility of implementing LSTM with an encoder-decoder architecture. This can reduce resources consumption and improve overall results at the same time.

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