A review of usable EEG-based solutions for epileptic seizure prediction

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Abstract
An epileptic seizure is a sudden event caused by an abnormal activity of the brain leading to severe consequences for affected patients, such as serious injuries and even sudden death. Therefore, it is crucial to predict epileptic seizures using wearable sensors. Electroencephalography (EEG) signals are the most adequate sensor signals leading to an accurate prediction. However, EEG sensors contain several electrodes, making them not usable on a daily basis. To solve this issue, researchers opted to reduce the number of electrodes by selecting the most pertinent EEG channels. In this paper, we present a literature review of epileptic seizure prediction approaches. We consider the different steps along the pathway, from data preprocessing to classification and performance evaluation. In addition, with the aim of a final product that can be worn daily for continuous monitoring, we study existing works that are related to EEG channel selection. We also discuss possible future studies to design a usable and efficient seizure prediction system.

Keywords
Epileptic seizure prediction, EEG channel selection, Deep learning, Electroencephalogram

1. Introduction

Epilepsy is a neurological disease that causes epileptic seizures, accompanied by a loss of consciousness, leading to serious injuries [1]. Therefore, it is necessary to propose a usable solution that can be worn daily by affected patients for continuous monitoring, which predicts seizures before they happen. This is a challenging problem attracting researchers from several disciplines.

In the last years, epilepsy-related research has matured thanks to the availability of data and the shown transition between the seizure phases. Furthermore, advanced analytics has attracted the attention of researchers to use predictive modeling, machine learning algorithms, and deep learning methods in detecting and predicting epileptic seizures.

This paper presents a literature review of existing approaches to predict epileptic seizures. Our study starts by discussing data preprocessing that is essential for algorithms to operate efficiently

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and fulfil the intended purpose. We also compare the performance of prediction systems based on standard popular algorithms or novel methods. We describe the used data, the proposed methods dealing with the problem and their related results. Existing studies demonstrate that the records of the electrical activity of the brain (EEG) are the most informative data items that can be used to predict epilepsy seizures. However, EEG sensors cannot not be worn on a daily basis due to high number of electrodes, which is related to the number of channels (i.e., one channel corresponds to two electrodes). Thus, researchers proposed novel approaches that deal with EEG channel selection. These approaches allow us to reduce the number of electrodes composing an EEG sensor to make it suitable for daily use. This paper discusses these approaches and presents future research leading to the development of usable EEG-based systems for epileptic seizure prediction.

The remainder of this paper is organized as follows. Section 2 describes and discusses some related approaches that were developed in the context of seizure prediction. Section 3 presents and discusses relevant studies that deal with EEG channel selection. Section 4 discusses the objectives and challenges related to the development of a usable EEG-based system for epileptic seizures prediction. Section 5 summarizes the paper.

2. Epileptic seizure prediction

Uncontrolled seizures are a major handicap for people with epilepsy in their daily life. The difficulties encountered by these people can be mitigated by developing algorithms capable of anticipating epileptic episodes. Aimed at enhancing the patients's life quality, several algorithms were proposed for the detection and prediction of seizures. Recent research has principally focused on advancing the prediction of an episode, aiming to allow enough time to take necessary precautions before seizures start. In the following, we discuss several published approaches of seizure prediction.

2.1. Approaches to epileptic seizure prediction

For epileptic seizure prediction, Truong et al. [2] used three databases: (1) the Freiburg Hospital intra-cranial EEG (iEEG) data set, (2) the CHB-MIT data set, and (3) the American Epilepsy Society Seizure Prediction Challenge data set. They selected 13 out of 24 patients from the CHB-MIT database and 13 out of 21 patients from the Freiburg iEEG database. The continuous data was segmented into 30-seconds windows. To deal with imbalance between classes, Truong et al. [2] generated more preictal segments. The authors first applied the Short-Time-Fourier-Trasnform (STFT) to transform raw data into spectrograms. Then, they proposed a CNN that automatically extracts features and classifies the data in a patient-oriented manner. As a post-processing configuration, the authors set an alarm only if 240 seconds per 300 seconds positive predictions were generated. The proposed model achieved a sensitivity of 81.4%, 81.2%, and 75%, and a FPR of 0.06/h, 0.16/h, and 0.21/h, with the 3 databases, respectively. The seizures were predicted at most 5 minutes before the onset.

Fujiwara et al. [3] aimed to predict epileptic seizures using heart rate variability (HRV) analysis. First, HRV features were extracted from the data of epileptic patients. Then, an anomaly monitoring technique called multivariate statistical process control (MSPC) was implemented to predict the seizures. Fujiwara et al. [3] used ECG data collected from 11 patients. They defined the preictal episode to be 15 min before and 5 min after the seizure's onset. The interictal data was recorded at least 50 min before or after the seizure's onset. The advantage of using MSPC was the fact that, for modeling, it only needs the interictal data considered as the normal data. The proposed approach was not efficient with the seizures that happened during sleep. Considering the 8 patients with wakening preictal episodes, it achieved an average sensitivity of 91% with a FPR of 0.7/h. Fujiwara et al. [3] showed that for seizure prediction, HRV individuality must be considered among the patients.

Khan et al. [4] used a CNN to predict focal epileptic seizures. Their model was evaluated using data from 28 patients from the Mount Sinai Hospital and data from the CHB-MIT database. Only the records including one single seizure were considered. The data was first transformed using continuous wavelet transform applied to each channel. This step permits to exploit both time and frequency information. The proposed model is a CNN with six convolutional layers, two dense layers and a softmax layer that outputs the probability distribution of the input data. The seizure prediction problem is defined as a multi-class classification (i.e., the target output is either interictal, preictal, or ictal labels). To deal with the imbalanced data sets, Khan et al. [4] selected random examples from the interictal data set, so the classes were balanced. One challenge presented in this study is to estimate the optimal length of preictal period also considered as the prediction horizon (SPH) in a patient-independent way. During the learning process, a grid search on many possible values and cross-validation were used to select the appropriate preictal period. The final length was set to be 10 min before the seizure onset. The proposed model achieved a sensitivity of 87.8% and a FPR of 0.142/h during the test phase. The correctly predicted seizures were reported 4 to 10 min before the seizure onset.

Shahbazi and Aghajan [5] developed a CNN-LSTM network to predict seizures in a patient-specific manner. To evaluate the model, the authors considered 14 out of 24 cases from the CHB-MIT database. The records were segmented into windows with 10-seconds length. Preictal data was extracted from the 30 min that precede the seizure's onset. To deal with imbalanced sets, only a number of the interictal segments equal to the preictal segments was considered. Shahbazi and Aghajan [5] initially applied STFT to transform the raw data segments into multichannel images. The features from spectral, spatial, and temporal domains were then learned by the CNN-LSTM model to classify the segments into preictal and interictal data. The CNN was initially pre-trained to classify the data. Then, the whole CNN-LSTM was trained using the initialized CNN weights. To obtain an effective prediction, the event was reported only if 8 of 10 successive samples are classified as preictal segments. The evaluation results were, on average, a sensitivity of 98.21% and a FPR of 0.13/h. The mean prediction time was 44.74 minutes.

Shasha et al. [6] proposed a lightweight solution for the epileptic seizure prediction problem, which can efficiently operate on edge computing platforms. They considered 19 patients from the CHB-MIT database to validate their approach. Shasha et al. [6] chose the preictal data to be the 15 min preceding the ictal phase. First, the EEG recordings were transmitted to the edge computing platform. After segmentation, the correlation matrices were extracted using Pearson correlation coefficient (PCC). These features represent the synchronization strength between all pairs of EEG channels, during the different brain states. Then, the matrices were fed into a simple CNN to classify the preictal and interictal signals. The prediction results were 92.91% of sensitivity and 89.98% of accuracy.

Zhang et al. [7] presented an approach based on a bidirectional long short-time memory (Bi-LSTM) for the prediction of the epileptic seizure. They selected 13 patients from the CHB-MIT database to evaluate their method. First, they segmented the signals into 5 seconds windows. Then, for the feature extraction, Zhang et al. [7] calculated an optimized multidimensional sample entropy that considers all the 23 EEG channels. For the classification step, the Bi-LSTM network was trained using data from the 13 patients and then, tested on each patient individually. The proposed method achieved, on average, 80% of accuracy, 86.67% of sensitivity and a FPR of 0.26/h. The authors also compared 3 intervention times equal to 2, 5 and 10 min. Based on the model performance, they finally chose the prediction time to be 5 minutes.

2.2. Discussion

The previously discussed approaches that deal with the prediction of epileptic seizures are shown in Table 1. In addition to the details about the considered data and the analysis process, we also specify if the proposed solution can be a real life practical product, i.e., the proposed approach involving the data type can be convenient to use in real life. Furthermore, if many algorithms were tested, only the results corresponding to the best performance are indicated in the tables.

Existing studies have demonstrated the feasibility of epileptic seizure monitoring. Prediction systems aim to improve the life quality of patients with refractory epilepsy (i.e., drug-resistant). Although the precital period is not visually recognizable when analyzing the related data, state-of-the-art research studies have shown the transition between the interictal and the ictal state and have shown the possibility of predicting epileptic seizures. A perfect prediction is not reached yet, but with the currently achieved performance, patients can still be warned for the majority of their seizures.

Regarding the used parameters, Fujiwara et al. [3] used ECG to monitor the epileptic seizures. The advantage of using non-EEG solutions is that they are more promising with regard to their practical use in daily life. Using the HR variable, Fujiwara et al. [3] obtained a good performance. However, they defined the preictal period to last from the 15 min before the seizure until 5 min after the actual onset. This way, predicting a seizure at a time close or matching the onset can not be counted as a successful prediction. On the other hand, unlike non-EEG solutions that are usually associated to specific types of seizures, EEG solutions were tested with a variety of seizures that encompasses focal and generalized seizures, with or without motor symptoms. Therefore, EEG is proven to be the most valuable source for epilepsy monitoring. Making the EEG a daily life tool that will be worn continuously by the patients is not realistic. Consequently, it is important to transform the conventional EEG-based solutions into a minimalistic and portable product. Indeed, the main objective is to reduce the number of EEG channels to the minimum and keep the same performance. We need to further investigate this issue.

In almost all the studied approaches that use EEG data [2, 8, 9, 4, 5], the authors used techniques such as STFT, DFT, and wavelet transforms to convert the raw data into a form that reveals the frequency aspect in addition to the temporal aspect. They have shown the efficiency of using time-frequency features in comparison with using the raw data.

Some of the studies relied on handcrafted feature extraction, while others used intelligent

Table 1
Related work on epileptic seizure prediction

Related work	Data	Real life practical product	Seizure's type	Patient-specific vs cross-patient	Features engineering	Classifier	Performance*
[3]	ECG / HR	yes	Focal seizures	patient-specific	handcrafted extraction	MSPC anomaly detection	sen = 91%, FPR = 0.7/h
[4]	EEG	no	variety*	cross-patient	CNN	CNN	sen = 87.8%, FPR = 0.142/h
[5]	EEG	no	variety	patient-specific	CNN	CNN+LSTM	sen = 98.21%, FPR = 0.13/h
[2]	EEG + iEEG	no	variety	patient-specific	CNN	CNN	3 databases: sen = 81.4% & 81.2% & 75%, FPR = 0.06/h & 0.16/h & 0.21/h
[6]	EEG	no	variety	cross-patient	PCC	CNN	Ac = 89.98%, sen = 92.91%
[7]	EEG	no	variety	cross-patient	entropy method	Bi-LSTM	sen = 86.67%, FPR = 0.26/h

variety : focal, lateral, and generalized seizure onsets.
Performance: sen = sensitivity/recall; FPR = False Positive Rate; prec= precision; spec = specificity; Ac = Accuracy.

techniques for automatic feature extraction. They commonly used CNNs [8, 4, 5, 2] to learn and extract the most relevant information.

For data classification, the majority of the approaches used ML algorithms that have shown optimistic results. In the related work on seizure prediction, the majority of the approaches are essentially based on the use of a single type of DL network, such as a CNN or an RNN variant (e.g., RNN vanilla, LSTM, GRU). Epileptic seizures are temporal intervals or events characterized by their sequential phases. Hence, during a seizure, the signal segments are correlated. Consequently, previous studies demonstrated the effectiveness of the recurrent aspect in DL models used to analyze the EEG data. One approach [5] is based on a combination of a CNN and an LSTM. It achieved promising results. In this work, preictal data was choosen to be at most 30 minutes before the seizure onset. However, for 12 among 14 patients, their model predicted the seizure before an horizon going from 32 to 103 minutes. Thus, the reported predictions are likely not correct classifications. Based on the different RNNs proposed in [10, 11, 12, 13, 9], the GRU network is shown to be adequate to analyze the EEG data in the context of seizure prediction. It has shown good results in temporal sequence modeling and especially in the detection of different seizure phases [11, 9, 14].

3. EEG channel selection

Contrary to the other eventual measurements, EEG can effectively describe all the seizure types, either with hidden symptoms or with apparent altered behavior. It is up to now the most adequate tool to use for seizure prediction task. In the literature, many researchers addressed the problem of EEG channel selection with regard to epilepsy disorder. In general, their aim is to reach the same or better classification results while using a reduced number of EEG channels compared to using all the initial channels.

3.1. Approaches to EEG channel selection for seizure monitoring

In the context of epileptic seizure prediction, Jana and Mukherjee [15] presented a patient-specific solution to select the best EEG channels. The proposed algorithm was based on the use of a CNN for automatic feature extraction and EEG data classification. The CHB-MIT database was used to validate the approach. The proposed channel reduction algorithm proceeded by elimination. First, the authors calculated the average classification accuracy using all channels. Then, they reduced each channel temporally and checked the average classification accuracy using the remaining channels. The channel was permanently removed if it did not affect the accuracy result. The first iteration reduced the number of channels to 15. Using the same technique, two other iterations reduced the total number to 6 most important channels. The selection was stopped when removing any of the remaining channels provided less accuracy. The proposed method achieved 99.47%, 97.83% and 92.36% in terms of average classification accuracy, sensitivity and specificity, respectively. The procedure reduced the EEG channels by 72.73%. The proposed method was designed to reduce the channels while keeping the same accuracy as using all the channels.

Shoka et al. [16] aimed to detect the epileptic seizure. They presented a five-step algorithm to analyze EEG data. The first step was dimensionality reduction. It consisted of selecting the most relevant EEG channels. The next steps were feature extraction from the selected channels, feature averaging, classification using seven different classifiers, and finally testing using a cross-validation method. The proposed method was evaluated using the CHB-MIT data set. To select the most important channels that reveal the seizure, the variance of the signal amplitude was calculated from the several channels. Then, only the data from the three channels with the maximum variance was analyzed and considered for seizure detection. The authors set a fixed number of channels to select for all the patients.

In the context of epileptic seizure detection, Karimi and Kassiri [17] proposed a patient-specific approach that includes channel selection. The solution consisted of three main steps: (1) EEG channel reduction toward dimensionality reduction, (2) feature extraction, and (3) data classification using a non-linear SVM. The authors selected 5 (out of 23) channels for every patient that can determine the seizure state from the non-seizure state. In fact, the selection was based on the ratio between the average energy of the wideband ictal signal and interictal signal. The proposed algorithm was validated on the CHB-MIT data set. The model achieved a detection sensitivity of 96.87% and a specificity of 99.95%. With only 5 selected channels, the authors reduced the processing power/time by a factor of 4.6 for univariate feature extraction and 25.3 for bivariate features. The results showed that the proposed automatic patient-specific channel selection method improved the seizure detection performance. However, the authors statically set the number of channels to select.

To improve the seizure detection performance, Jana et al. [18] proposed an EEG channel selection algorithm. It also allowed to decrease the computational cost. The approach was based on binary particle swarm optimization (BPSO) integrated with the extreme learning machine (ELM) classifier. To determine the best size of channels set and identify the best combination for seizure detection, the authors measured a value called fitness function of 50 random combinations of channels for 100 iterations. The fitness function assumed a balanced relation between the classification accuracy and the number of channels. Jana et al. [18] defined their fitness function with weights equal to 0.7 and 0.3 for the accuracy and the channels reduction, respectively. To evaluate the proposed approach, the data from two patients from the CHB-MIT data set was processed. After channel optimization, the ELM classifier tested the final set of channels to estimate the seizure detection performance. For the first subject, the proposed solution improved the accuracy by approximately 3% after reducing the number of channels to 6. For the second subject, the model achieved an accuracy of 75.47% after the channel selection compared to an accuracy of 73.69% with all the channels. In this approach, the authors needed to choose the weights of the fitness function. Furthermore, testing many combinations can be time consuming for real applications.

Towards an efficient seizure prediction, Daoud and Bayoumi [19] included in their study an algorithm that selects the most important EEG channels. In fact, they proposed several DL models to classify preictal and interictal signals and then compared the results before and after reducing the channels. They chose the preictal signal to be one hour before the seizure onset and the interictal phase to be at least four hours away from the seizures. They considered raw EEG data as their input without preprocessing. The four proposed models are (1) a simple MLP, (2) a CNN to extract spatial features from the electrodes' locations followed by an MLP for classification, (3) an ensemble of a CNN and a Bi-LSTM and (4) a deep convolutional autoencoder (DCAE). Daoud and Bayoumi [19] have shown results indicating enhancements after using the CNN and the Bi-LSTM instead of MLP. To select the channels, they calculated the product of variance and entropy of the preictal signals for each channel. Indeed, the authors selected the 8 channels with the highest values and test the selection. The prediction results were compared to the ones using all the channels. Iteratively, in case of a decreased performance, the next high-rated channel was added to the selection. Daoud and Bayoumi [19] considered 8 patients to evaluate their approach. Using only 10 channels on average among the considered subjects, they achieved the same performance as all the channels. Indeed, the three presented models (1) CNN-BiLSTM, (2) DCAE-BiLSTM and (3) DCAE-BiLSTM with channel selection achieved the same prediction performance in terms of accuracy, precision, sensitivity, and FPR. The benefits of channel selection were a reduced training time and using less parameters. On the other hand, the authors had to fix the number of channels to test at first.

Chakrabarti et al. [20] tested different configurations of artificial neural networks (ANN) to detect epileptic seizures. For feature extraction and channel reduction, they applied PCA. It was used to reduce high-dimensional data sets while keeping the most relevant information. The proposed approach was evaluated using 10 patients' records from the CHB-MIT data set.

Based on PCA and the channels' contributions, several combinations were tested. The number of selected channels ranges from 3 to 19. The 3-layer ANN achieved the best performance with 85.6% accuracy when using all initial channels. After applying the channel selection algorithm, the 4-layer ANN achieved 86.7% accuracy using only 18 among the 23 channels.

Yuan et al. [21] considered an SSDA-based approach to select the EEG channels by looking for correlation between them. They ranked the channels based on a zero-stimulus method. Half of the number of initial channels that were high-rated was selected and considered in seizure detection. The presented results showed an improvement of the accuracy by 2% after the channel reduction. In the next research, Yuan et al. [22] proposed an approach that considers the contribution of each channel when classifying the data. They introduced two attention-based models. The first one considered local-based attention that measures the energy independently for each channel. The second model, named global-based attention, was an MLP model that consider the relation between all channels. Next, Yuan et al. [23] introduced a novel attention-based model called MuVAN. Yuan et al. [23] used three data sets with a similar data structure for three different applications: (i) epileptic seizure detection, (ii) sleep stage classification, and (iii) physical activity recognition. Knowing that intended patterns are related to an interval rather than to a point, the authors divided data into many multivariate temporal records that are fed into a 2-layer bidirectional gated recurrent unit (Bi-GRU). Two attention mechanisms were proposed: (i) a location-based and (ii) a context-based mechanism. The first mechanism does not capture any existing correlation between the views, while the second algorithm captures the hidden connections. With a conventional softmax operation, the elements were rated, so that important ones are top-ranked and irrelevant elements have close-to-zero scores. However, instead of ignoring the impertinent elements, Yuan et al. [23] took into account the contribution of some irrelevant views in the decision making. For all considered data sets, the MuVAN model outperformed the baseline approaches. The methods proposed in Yuan et al. [22, 23] consider each of the available channels when taking the final decision (i.e., without reducing the number of channels).

Shah et al. [24] aimed to reduce spatial information (i.e., reducing the number of EEG channels) to minimize the EEG signal artifacts. The proposed channel selection was based on testing many configurations and evaluate their performance to detect the epileptic seizure. The authors used epilepsy domain knowledge to designate the subsets of channels whose sizes range between a minimum of 8 channels and a maximum of 20. To compare the performance of the different configurations, the authors used a DL algorithm that consists of a CNN and a BiLSTM. The 8-channel configuration presented a tolerable reduction in performance compared with a all channels configurations, with 33.44% of sensitivity, 85.51% of specificity, and 38.19 FA per day.

In [25], an EEG channel selection method was proposed not only in the context of seizure detection, but also for other applications that use EEG records. The authors applied the Gumbel-softmax trick to develop their concrete selector layer. The layer was composed of K neurons. Based on the Gumbel-softmax measures, each neuron selected one single channel with the highest probability from all the input channels. To address the problem of duplicate channel selection, Strypsteen and Bertrand [25] created a dependency between layer's neurons by employing a regularization function. Consequently, the selected channels were distinct and their number corresponded to the neurons number which was set by the researchers. To validate the channel selection layer, two EEG-related data sets were tested. The first one was associated to a classification task for motor execution. The authors tested different number of neurons (i.e., number of channels to be selected). Selecting 50 out of 128 channels achieved the best performance. Moreover, with only 8 channels, the model's performance decreased by only 5% compared to the best performance. The second data set was related to a regression problem for auditory attention decoding. With only 10 per 64 channels, the model achieved an accuracy close to that with the all-channel baseline. The proposed selection method achieved the same or better performance as the baseline approaches. It also requires less computations and hence, less processing time. However, the number of the selected channels depends on the researchers' decision (the size of the channels subset is equal to the number of neurons in the Gumbel-softmax layer).

3.2. Discussion

The previously discussed EEG channel selection approaches related to epilepsy disorder are summarized in Table 2.

Table 2
Related work on channel selection

Related work	Prior parameter specification	Patient-specific selection	Patient-specific number of channels	Number of channels	Detection (D) or Prediction (P)	Results	Channel selection method
[15]	no	no	no	6/23	P	same	Testing combinations and elimination
[16]	yes	no	no	3/23	D	-	Ranking and selection
[17]	yes	yes	no	5/23	D	improved	Ranking and selection
[18]	yes	yes	yes	average 5.5/23	D	improved	Testing combinations
[19]	yes	yes	yes	average 10/23	P	same	Ranking and selection
[20]	yes	no	no	18/23	D	improved	Testing combinations
[21]	yes	no	no	11/23	D	improved	Ranking and selection
[24]	no	no	no	8/22	D	decreased	Testing combinations

Prior parameter specification: selection related parameters are given to the algorithm.
Research line: D for epileptic seizure detection and P for prediction.
Model performance improvement: the performance after channel selection compared to the performance using all channels.

Using different methodologies, some researchers obtained the same results before and after channel reduction [15, 19, 26]. Others managed to improve their model performance after channel selection [17, 18, 20]. This indicates that some channels can be contaminated by noise or do not yield relevant information, which can significantly affect the performance of the model in detecting or predicting the seizures. Shah et al. [24] also obtained poorer values after reducing the number of EEG channels. This might be related to the elimination of pertinent channels.

The majority of existing approaches use channel selection as part of seizure analysis or seizure detection processes [16, 17, 18, 20, 21, 22, 24, 26]. They help medical staff in analyzing EEG data after the medical consultation. In particular, these approaches allow us to better localize past seizures that have already happened in short periods of time. Another main goal presented in related work is to reduce power consumption of seizure detection systems [18, 26].

In almost all existing approaches, the authors selected a specific number of channels based on personal choice, on a doctor's opinion, or based on previous research. They generally used different ways to rank the channels or test different combinations. This leads to select the same number of channels for all patients. However, epilepsy is a very distinctive condition that manifests itself differently and uniquely for each person. It can start from several locations and affect brain areas with different sizes. This makes the one-size-fits-all approaches inappropriate for epilepsy management. Additionally, a patient with epileptic disorder frequently undergoes the same type of seizures. Therefore, a channel selection method should be a patient-specific solution to get optimal parameters and best evaluations. On the other hand, testing multiple candidate channel combinations and all possible sizes of subsets with a DL approach for each patient is computationally very demanding and time-consuming for practical use.

4. Future prospects

Based on findings discussed above, some considerations that could improve the outcome of seizure prediction systems should be explored. In fact, to develop an optimal solution that accurately predicts all types of epileptic seizure with a minimum of discomfort to the patient, we present some research lines. In regard with the data, the first essential step is to select many databases and carry out data preprocessing to ensure a high-quality data. Also, it is important to determine the optimal feature extraction method. To get an accurate classification of the data, we must choose and design the right ML algorithm for the intended task and find the optimal hyperparameters that results in the best performance of the algorithm. In addition, to obtain a product that can be easily used by the patients for long periods of time, while achieving a high prediction performance, we must enhance the solution by reducing the used EEG channels, thereby reducing the number of electrodes. We confirm that testing different channel combinations is time-consuming. Consequently, we must consider an automated approach that minimizes the amount of time and effort and results in few selected channels. The exclusion of noisy and irrelevant channels must be studied in terms of the prediction performance as we need to target better prediction results. Also, the number of selected channels must be set automatically and distinctively for each patient based on his or her physiological signals.

5. Conclusion

In this paper, we first analyzed and discussed the most pertinent research works related to the prediction of epileptic seizures. Then, we presented the state of the art concerned with a specific type of data frequently used in the context of epilepsy, i.e., EEG. This study involved research work that deals with the selection of EEG channels. Based on our literature review, we defined several avenues to improve the outcome of the epileptic seizure predictors. In the future, we plan to implement a usable EEG-based system for epilepsy seizure prediction. The target system should solve the challenges identified in this work.

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