Deep Learning for Epilepsy monitoring: A survey

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Abstract. Diagnosis of epilepsy can be expensive, time-consuming, and often inaccurate. The gold standard diagnostic monitoring is continuous video-electroencephalography (EEG), which ideally captures all epileptic events and dis-charges. Automated monitoring of seizures and epileptic activity from EEG would save time and resources, it is the focus of much EEG-based epilepsy research. The purpose of this paper is to provide a survey in order to understand, classify and benchmark the key parameters of deep learning-based approaches that were applied in the processing of EEG signals for epilepsy monitoring. This survey identifies the availability of data and the black-box nature of DL as the main challenges hindering the clinical acceptance of EEG analysis systems based on Deep Learning and suggests the use of Explainable Artificial Intelligence (XAI) and Transfer Learning to overcome these issues. It also underlines the need for more research to recognize the full potential of big data, Computing Edge, IoT to implement wearable devices that can assist epileptic patients and improve their quality of life.

Keywords. Epilepsy, Deep learning, Electroencephalography, EEG signal analysis.

1 Introduction

As defined by the International League Against Epilepsy, epilepsy is a temporary occurrence of signs and symptoms caused by abnormally synchronized and rapidly changing activity of neurons in the brain. [1]. About 50 million people worldwide are affected by this chronic neurological brain disorder [2] which is characterized by epileptic seizures that can lead to significant social, cognitive, physiological, and neurological consequences and may lead to death if not monitored and diagnosed appropriately [3].
The Electroencephalographic signals (EEG) can provide key information to identify neurological conditions and should be recorded to localize epileptic seizures. EEG is the most efficient method of recording and analyzing brain activity regardless of its sensitivity to noise, its key advantages are non-invasiveness, portability, cost-effectiveness, relative ease of use, and exceptional sub-millisecond temporal resolution[4]. Diagnosing epilepsy using EEG signals is time-consuming and takes a lot of effort and it is prone to human error, as the neurologist has to carefully examine many hours of EEG signal recording. Computer-Aided Diagnosis (CAD) solutions are needed to assist neurologists and patients in the identification of seizures. Generally, a CAD system to EEG signal analysis follows a four steps process:
(i) Signal acquisition: This step involves capturing electrical activity on the scalp using EEG recording methods.
(ii) Preprocessing: since the raw EEG data are subject to artifacts and noise [5]. Such artifacts must be identified and eliminated using a set of manipulations for the subsequent processing steps.
iii) Feature extraction: This step aims to analyze the preprocessed signal and decrease the number of features in it by creating new features from the existing ones which then should summarize most of the information in the original feature set.
(iv) Feature classification: This step involves designing a properly structured and well-defined model for disease detection or prediction or pattern recognition in the signal.
Automatizing the previous steps of EEG signal analysis using DL is an important stage towards building more

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practical EEG applications relying less on human professional capacities requiring longer training and expertise. The purpose of this paper is to provide a survey in order to understand, classify and benchmark the key parameters of deep learning-based approaches that were applied in the processing of EEG signals for epilepsy monitoring. In this sense, we make two main contributions:

- Based on literature analysis, we give a structured overview of the existing approaches with respect of the four steps process of analyzing EEG signals.
- We spot and discuss future research avenues and trends in this field that we filtered from the survey of literature.

The rest of this paper is organized as follows. A survey based on the epilepsy monitoring automation process is presented in section 2. The potential research directions and open problems are summarized in section 3. Finally, the conclusion is delineated in section 4.

2 Survey on DL for epilepsy: a process-based perspective

In the quest to digitalize epilepsy monitoring, several DL methods have been proposed in the literature. Based on the conducted survey of the literature, we noted that the existing approaches vary mainly on the aim of using DL techniques, for example, to reduce noise, to augment data, to extract features, or to decode the neurologic disorder. Hence, we choose to arrange the included studies according to the stages of EEG analysis process described in the previous section. Prior to this paper, we know of few works that tried to study the issue from this standpoint. For example, the review of Shoeibi et al. [6] adopted a technical viewpoint and focused on the type of DL architectures, in addition, it focused only on epileptic seizure detection problems.

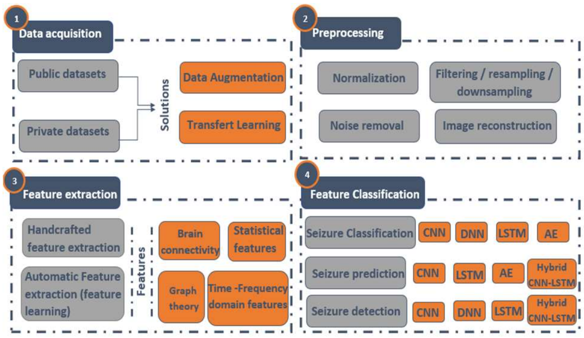

Fig. 1. Classification of DL based epilepsy monitoring methods according to the stages of EEG signal analysis process

Figure 1 provides a classification of existing approaches; the proposed taxonomy is structured following the EEG analysis process. To describe this classification in detail, we devote a subsection to each step of the process.

2.1. Data acquisition

- Public datasets:

Epilepsy databases are important in the design of accurate and robust CADs. Several EEG datasets were used by the included studies., namely, Freiburg [7], CHB-MIT [8], Intracranial EEG dataset Kaggle [9], Bonn [10], Bern-Barcelona [11], Epileptic seizure recognition dataset [12], TUH abnormal EEG corpus [13]. Although the number of data sets in this area is quite large, they cannot be mixed easily due to different frequency sampling and other parameters. In addition, many of the public datasets suffer from the quality of data.

- Private datasets:

Private datasets are gathered by scholars in their laboratory, hospital, or institution. While private datasets contain relatively a better quality of data, they remain limited in quantity. Additionally, private databases are not made available online so that other researchers can benefit from them, thus reproducibility remains questionable.

- Data augmentation and transfer learning approaches:

A common issue of the public and the private datasets is the small sample data, in this sense, DL techniques have extensively been used in the stage of data acquisition to overcome this issue. Either by augmenting artificially data or by using prior knowledge. For instance, due to lack of datasets, Liu et al. [14] and Liang et al. [15] developed a technique of data augmentation that consists of splitting and overlap-ping consecutive segments using Principal Component Analysis (PCA) and Fast Fourier Transform (FFT) to obtain more training data. Wei et al. [16] used Wasserstein Generative Adversarial Nets (WGANs) as a data augmentation technique. Further-more, Daoud and Bayoumi [17] used a semi-supervised approach based on Deep convolutional Autoencoder (DCAE) and on transfer learning technique to enhance the model optimization. Toraman [18] used transfer learning which has enabled more efficient feature extraction from small datasets and also allows the learning of small dataset with low computational cost.

2.2. Preprocessing

In general, biomedical signals are subject to artifacts and noise during their acquisition and processing, which strongly affects the quality of feature extraction techniques. These disturbances are detected and removed in preprocessing stage using DL.
Generally, preprocessing is performed using statistical methods such as the z-score normalization technique [19] to normalize EEG signal, downsampling, resampling, and

filtering [20], and noise removal using Short Time Fourier Transform (STFT) [21].
Some research made use of deep architectures to preprocess EEG data, Li et al. [22] used CNN to construct an optimal filter band.
In the studied works, we observed that many works used preprocessing methods while considerable works skip this stage. By comparing the performance of the two classes of approaches, we noted that the accuracy range of the studies that used preprocessing is [82.27%-98%]. The accuracy of the studies that used the raw EEG signal without preprocessing is [90%,99. 6%]. This leads us to state that DL models can select meaningful information and automatically apply filters to the raw data without the need for an additional method, so the use of preprocessing does not impact the performance of the model, rather it impacts the computational resources. Because with the use of preprocessing, the dimension of the input is reduced, hence the time and computation are also decreased, as result the learning time is shorter and the resources are less required.

2.3. Feature extraction

Features are retrieved from the preprocessed EEG signals using different feature extraction procedures to prepare the signals for the deployment of deep networks. In the surveyed literature, we distinguished between (i) works that used handcrafted features to extract features related to time, frequency, brain connectivity, graph-theoretic measures to describe the functional connectivity between EEG channels, and other statistical features (mean, variance, skewness, kurtosis) that provide information about the symmetry and the peaks in the EEG data [23]. Fast Fourier Transform, discrete wavelet transform, and Wavelet Decomposition method are the most used methods in this type of approach. (ii) works that used DL models for automatic feature extraction. For instance, Truong et al. [21] used an unsupervised feature extraction technique based on GAN. Daoud and Bayoumi [17], Wei et al. [24], and Xu et al. [25] used CNN to extract the significant spatial features from different scalp positions. Xu et al. [25] used long short-term memory (LSTM) to further extract the temporal features in addition to the deep features extracted by CNN.
By comparing the effectiveness of handcrafted and DL features extraction in the studied works, we clearly noted that the latter outperforms the former. However, in the learned feature extraction, there is no control on what features the model will extract from the data (in many cases the extracted features have no real-world interpretation).

2.4. Feature classification

Feature classification is the end process of EEG signal analysis. It is arguably the stage where deep architectures are most used. Various DL architectures are used to decode different epileptic disorders. Decoded epileptic disorders include detecting the ictal or preictal phase of the seizure, identifying types of seizure such as focal, tonic, clonic, or myoclonic seizure, and predicting high-risk clinical symptoms of epilepsy, just to name a few. By analyzing the problems being decoded in this stage, we can classify them into three main groups of tasks, namely, classification, detection, and prediction. Hence, we choose to categorize the DL models based on the decoding problem. Table 1. Illustrates each decoded problem with the implemented DL models and their performance.

Table 1. Feature classification based on decoding epileptic problems

Decoded problem	DL model	Accuracy range	Main Works
Classification	CNN	[88.76% - 98.9%]	[26] [27] [28]
	Deep Neural network (DNN)	[90%-96%]	
	LSTM	96.54%	
	AE	95%	
Prediction	CNN	[98% - 99.5%]	[17] [24] [29]
	LSTM	[96.08% - 99.08%]	
	AE	88%	
	Hybrid CNN-LSTM	[93.4% - 99.6%]	
Detection	CNN	[74.8% - 99.5%]	[19] [30] [22]
	DNN	[97.21% - 98.3%]	
	LSTM	95.5 %	
	Hybrid CNN-LSTM	95.42%	

The task of classification is based on the categorization of seizures according to the type of epilepsy: focal/generalized, nonspecific seizure, Simple/Complex, partial seizure, Absence/tonic/tonic-clonic/ myoclonic seizure. CNN was used by the majority of classification studies and has achieved the highest accuracy that reached 98.9%.
Concerning the task of prediction, it relies on triggering the alarm at the detection of the preictal period. It requires identifying the existence and duration of the preictal period. Hybrid CNN-LSTM was the most used in prediction studies and has achieved the highest accuracy that reached 99.6%.
Regarding the task of detection that is mostly performed, it is based on the identification of patients with epilepsy and the recognition of epileptiform EEG discharges. CNN was used by the majority of detection studies and has achieved the highest accuracy that reached 99.5%.

3 Discussion

We propose in this section to emphasize some research pathways which, based on the conducted survey, hold the potential to define the research landscape related to DL-based Epilepsy monitoring.

- Managing small sample datasets: Data is a key issue in computer-based EEG analysis. Numerous studies use relatively small and private data, whereas DL algorithms perform more efficiently with a larger and more varied dataset. EEG Data-efficient methods are expected to be of a central focus in neuroscience in order to harness the power of artificial learners while achieving good results with less training data and in particular less human supervision [31].
- Explainable models: Though accurate in their predictions and classifications, DL-based approaches suffer from the lack of interpretability. In this sense, Explainable AI [32] is seen as a promising mechanism to increase algorithmic transparency and accountability. And hence to improve the clinical acceptance of these DL-based EEG.
- Computational resources: DL models are highly resource-consuming. Unfortunately, these resources are not affordable for everyone. Therefore, researchers need to work towards resource optimization. required by leveraging the potential of cutting-edge Big Data, IoT, and Edge Computing tools for real-time processing and safe storage of EEG data. The use of such technologies helps to enable handling patients with neurological disorders at anytime, anywhere.
- Teleneurology: Neurology telemedicine can be used to support patients who are unable to consult experts and patients with neurological impairment or who require urgent care. [33]. Neurology is one of the most difficult practices to manage remotely since it requires specific devices to monitor brain activity. However, given the implications of the current health crisis (Covid-19 pandemic), teleneurology is identified as a priority in the research agendas. DL-based wearable devices can revolutionize this innovative healthcare practice. Indeed, deep intelligent architectures can facilitate, optimize, and secure the communication, transfer, and processing of the different biosignals received from mobile or wearable devices, enabling the patient to receive treatment from his own home [34].

4 Conclusion

From the performed review, it can be concluded that automated EEG analysis systems based on DL have shown their potential success in epilepsy monitoring. Many Deep neural network architectures have already been explored to design such systems. However, hybrid architectures showed a significant performance comparing to mono-architectures. The accuracies obtained for seizure monitoring are fair, and work in this area needs to focus more on the use of clinical datasets and seizure prediction.

Our findings identified data availability and the black-box nature of DL as the main challenges hindering the clinical acceptance of EEG analysis systems based on DL and suggest the use of transfer learning and XAI to overcome these issues. Further research should be conducted to optimize resources to move forward in the field of teleneurology and to implement wearable devices that can be user-friendly with less reliance on trained professionals.

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