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Deep learning for EEG Channel Selection for Epilepsy Detection and Classification

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Abstract
Recent and past researches have shown an increasing number of patients who are affected by epilepsy or epileptic seizure, which is a neurological disorder. Electroencephalogram (EEG) is a well-known technique or procedure that is effective, non-invasive, and widely used in many studies for detection and classification of Epilepsy. Continuous recording of EEG data provides opportunity for further analysis to better manage epilepsy by both the clinicians and patient's family. As per the present clinical practice, neurologists spend significant time to analyze each channel manually to identify the presence of the epileptic events in the hours of the recording. This challenge has motivated the development of automatic detection systems for epilepsy detection and classification. Though there are existing many approaches for epilepsy detection and classification, with the recent history still it is a problem due to its large amount of non-stationary data. Recently, Deep Learning (DL) has shown very high accuracy for the image classification and time series analysis. DL has also been used for many other Brain Signal Processing applications giving promising results. So, this paper considers the review of DL applications for Epilepsy detection and Classification to understand the scope, improvements and limitations. This will help the research community to identify the research gaps and future research directions.
Keywords— Epilepsy, Seizure, EEG, Machine Learning, Deep Learning

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I. INTRODUCTION

Elliptic seizure is one of the profound disorder symptoms, which impacts human brain. It is a serious brain disorder, which influences the overall behavior of people with some of recurrent seizures. Seizures are due to sudden rush of electrical signal activity in the brain that causes traumatic brain injury. These injuries exist from a few seconds to minutes based on the severity of the seizure impact. The impact of the seizures can be seen for any age groups [1]. Normal flow of electrical signals is disturbed in the brain and lead to many health issues by disturbing the functioning of various body parts of a human body [2]. Seizures result in creating an electrical disturbance in the brain and it shows various other physical symptoms. Patients with such disorders tend to display changing behavior, movements, feelings, confused speech, loss of hearing, and some lose their consciousness for seconds to moments. There is a constant need to control the occurrence of seizures based on the variations as it differs from person to person. Some of the other serious ailments observed for the people suffering from epileptic seizure include inability to move hands due to insufficient stamina, failure of balder and inability to hold urine due to lack of sufficient pelvic muscle strength [3]. In certain cases, patients face the breathing problem and their breathing stops suddenly during sleep or during awake hours. Some of the precautionary steps to avoid serious health problems due to seizures include to have timely food intakes, appropriate sleeping habits, regular medical checkups, and to avoid stressful works at different occasions in the life-style.

The probability of being attacked by seizure effects is high when the patients are suffering with high fever. Most of the times having bad eating habits found to be one of the reasons for seizure attacks. Few people have a bad habit of eating ice creams and drinking the cold water/beverages during the night times [4]. In India, more than 10 million people are affected with epileptic seizure and it is about 1% of the population [5]. In some scenarios flashing lights found to be the reason for epileptic seizures. Apart from these low sodium levels in the body takes place due to diuretic therapy causes the dizziness and constant fever may also cause the seizure effects. Classification of seizure is based on two types, i.e., focal and generalized as shown in Fig. 1.

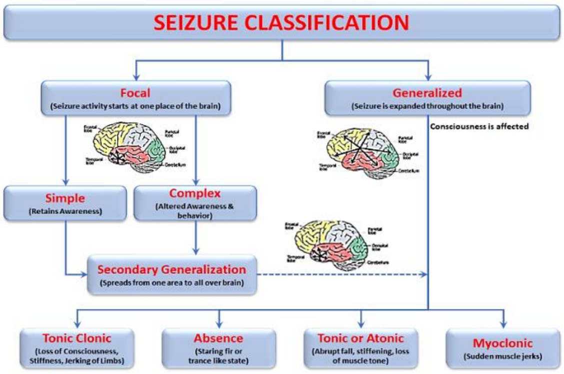

Figure 1 Seizure Classification

A. Focal and Non-Focal Epilepsy

These are the two types of seizures, where one side of the brain gets affected with seizure results in focal epilepsy [6]. Reasons for the occurrence of focal seizures are due to brain tumours, heat stock and low blood sugar. Most teenagers get addicted to illegal drugs and the use of such drugs can also lead to the formation of focal epilepsy. Heavy consumption of alcohol and smoking are also some of the reasons for seizures. Patients with epilepsy are most probably treated with antiseptic drugs. Antiseptic drugs can control epilepsy depending upon the type of seizure [7]. Better treatment and diagnosing helps in the reduction of the number of focal seizure cases. By having appropriate treatment, the people with seizures can have normal life. Focal seizure is also known as partial seizure as it occurs in one area of the brain's hemisphere. Focal seizure changes to generalized seizure which affects the entire brain. Focal awareness and focal impaired awareness are the two types of focal epilepsy [8].

Table I: The Comparison of Different Input Modalities and Network Structures for Deep Learning-Based Seizure Detection

		Visible Symptoms	Duration	EEG Response	Genetics	Response to Treatment
Partial	**Simple Partial**	alter emotions or change the way things look, smell, feel, taste or sound	10-30 seconds	Maximum phase reversal in the right temporal lobe	Genetic contribution is much smaller	Yes
	Complex Partial	Amnesia, Saying words repetitively, scream, laugh, cry, unable to respond	30 seconds to 3 minutes	3-5 Hz spike waves	Genetic contribution is much smaller	Yes
Generalized	**Absence**	Staring with unresponsiveness	3-20 seconds	Generalized 3 Hz spike wave discharges	Genetic contribution is high	Yes
	Myoclonic	brief loss of postural tone, often resulting in falls and injuries	Usually, 1 second or rarely more than 1 minute	Slow spike wave sudden diffuse attenuation or generalized polyspike-wave	Genetic contribution is high	Yes

	Atonic	loss of muscle control	**2-20 Seconds**	Sudden attenuation with generalized, low-voltage fast activity (most common) or generalized polyspike-wave.	Genetic contribution is high	Yes
	Tonic	muscle stiffness, jerking movements	1-3 minutes	Rapid changes in polarity	Genetic contribution is high	Yes
	Tonic-Colonic	Muscle tightening, unusual head movements, numbness, hallucinations	10-30 seconds	Maximum phase reversal in the right temporal lobe	Genetic contribution is much smaller	Yes

Generalized seizure (non-focal epilepsy) affect the total hemisphere (brain) [8]. The impact of seizure can be seen with the help of electroencephalography (EEG). Different symptoms of epileptic seizures are listed in Table I. The patients suffering from severe epilepsy in the last stage of treatment found to have non-focal epilepsy. Change in the structure of the brain, genetic issue and infection in the brain such as meningitis are the major reasons for generalized seizures. The symptom of the generalized seizure is included with the changes in the eyes colour that turns into blue and losing control of the bladder [9]. People with such seizure attacks won't be able to remember anything which is happening around them. Similarly, the atonic seizure occurs when muscles in the body become stiff and it happens when there is calm down in the muscle movement. Similarly, myoclonic seizures occur when there is a little jerk in the body parts. However, a clonic seizure occurs only when there is a period of shaking in the parts of the body.

B. Electroencephalogram (EEG) in Diagnosis of Epilepsy

EEG is used in the detection of interictal epileptic form activity (IEA) [10]. It is an electronic tool, which helps widely in the detection of epilepsy. Large amount of EEG data is stored by the long-term EEG recording of epileptic patients [11]. The output of an EEG includes spikes, sharp-and-slow wave complexes, and some of the poly spikes as shown in Fig. 2.

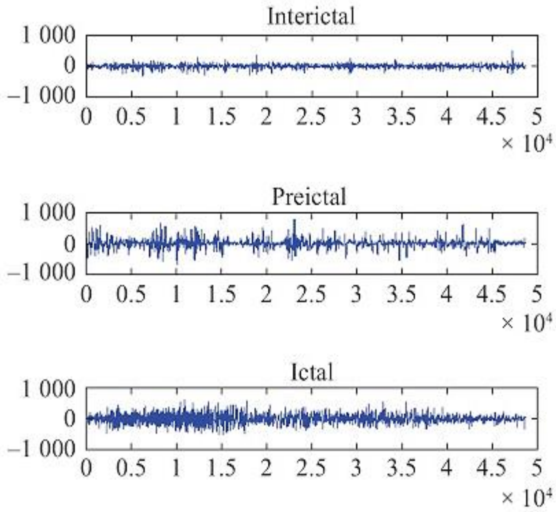

Figure 2 Interictal, Preictal and Ictal Signal

There will be a highly positive value for the identification of epilepsy if there is a presence of IEA in a mental neurologically and normal subject and also in a proper clinical perspective. The ictal signal is defined as periods of seizures in the EEG and the epileptic form activity has been considered as ictal [12]. The difference between the interictal and ictal signals is during the seizure considering as post-ictal and the also after the seizure is consider as an interictal signal. Preictal stage is the middle stage of a seizure, which includes the time between the first symptom to the last stage of the seizure activity.

A comparison table drawn in Table II for the data duration and detection of number of seizures from various authors in the previous research. It is seen that the number of hours spent on different patients is proportional to the number of seizures detected.

Table II The Comparison of Different EEG Types and Data duration for Seizure Detection

References	EEG type	No. of patients	No. of seizures	Data duration		FDR	Mean detection delay
				Ictal	Interictal		
Saab and Gotman [52]	Scalp	44	195	1012h	1012h	0.34/h	9.8s
Kuhlmann *et al.* [53]	Scalp	21	88	554h	552h	0.60/h	16.9s
Wang *et al.* [54]	Scalp	10	44	72min	121h	99.3%	-
Zabihi *et al.* [55]	Scalp	24	161	2.55h	169h	93.1%	-
Fatichah *et al.* [56]	intercranial	-	-	39.3min	2.62h	98.4%	-
Hills [57]	intercranial	12	48	41min	6.5h	94%	3.17s
Parvez and Paul [58]	intercranial	21	87	58h	490h	97%	-
P.LeVan *et al.*[59]	Scalp	46	205	-	-	-	2s
R.Hopfengartner *et al.*[60]	Scalp	159	794	25,278h	25,278h	0.22/h	-
K.Kelly *et al.*[61]	Scalp	47	141	3653h	3653h	2/h	-
R. Hopfengartner *et al.* [62]	Scalp	19	148	3248h	3248h	0.29/h	-

II. EXISTING METHODS FOR SEIZURE DETECTION

In this Section, a detailed review on detection of epileptic seizure using different types of technologies is discussed in detail with the help of existing literature. Some of the topics included in this section are machine learning (ML), deep learning (DL), and channel selection in EEG have been discussed from the recent studies. Machine learning plays an important role in the assessment and belief process on neurological issues. It can be correlated to the classification of EEG data. It helps in recognizing the seizures with patterned results. It is applied with a wide range of classifiers to detect seizures and authorize the outcomes. Therefore, a brief explanation was given about the detection of seizures using machine learning and also includes a detailed review on detection of seizure using deep learning as well. Deep learning is one of the useful techniques to reduce the manual extraction of features and selection process. Convolution neural network (CNN), recurrent neural network (RNN) and fully connected neural network (FCNN) are some of the DL techniques that are used widely in most of the medical applications [13]. Finally, a complete view about the channels of EEG and the performance in detecting the epileptic seizure has been explained.

A. Channel Selection in EEG

The selection of channel is one of the key tasks because out of 64 channels of EEG, it is very important to identify the pinpoint locations of the hemisphere (brain) that is generating the fluctuated electrical signals from brain to detect the seizure. It is important to minimize the number of channels that are not required to improvise the performance. There are various approaches used in channel selection such as filtering, hybrid and human-based techniques. EEG signals are tested for various brain related issues and are obtained from multiple channels [13].The seizure detection mainly depends on the inputs obtained from features of multi-channels and categorization of these signals plays a significance role in the seizure detection. The channel reduction may be possible by keen observation of EEG outputs by an automated learning model to detect the seizures in a meaningful manner. This helps to reduce over-fitting and overall process time to train the model for the prediction purpose [14]. This in turn helps to improve the classification accuracy. The processing of channel selection is based on selecting the specific features and a set of channels are required to obtain the features from different channels [15]. Therefore, the brain activity is examined and evaluated based on the information obtained from these EEG channels by using different types of modelling techniques.

B. Channel Placement

The placement of the channels based on the brain-related areas is interconnected to the performance of the brain activity. In such scenarios, BCI plays a major role in performing brain activities and examine the signals of the brain [16]. The electrode placement is based on the standardized procedures that are popularly used in the electrode positioning at an exact location of the scalp. The polarity of all these electrodes is indicated with a circle to estimate the location of the electrodes as shown in Fig. 3. The electrode positions are estimated by the systems which are categorized as 10-20 and 10-5 systems, in which the electrodes are placed in an order. This defines the system range efficiently for the placement of the electrodes.

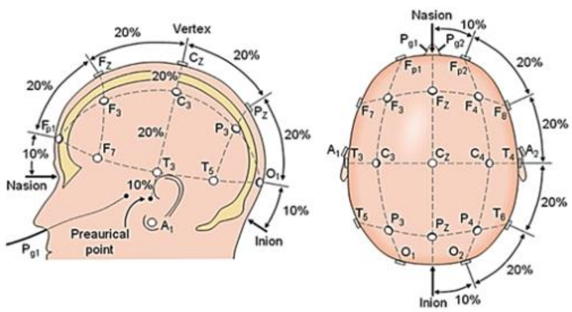

Figure 3 Placement of Different Electrodes (Channels) over the Scalp using the international 10-20 system

The tracking of the EEG signals is one of the complicated topics to understand the patient condition in real-time scenarios. The real-time applications will require only a few electrodes for understanding the brain functional properties and evaluation is based on the techniques adopted for accessing the brain signals.

C. Seizure Detection based on Machine Learning Techniques

Machine learning plays an essential role in the evaluation and estimation processing of neurological issues. Seizure prediction is one of the most advanced versions and it is one of the important applications in the real world. Recent studies proved that seizure prediction is validated to predict the significant aspects of the applications. The epileptic seizure prediction is evaluated and proved in a varied range of applications such as neuroscience, statistics and machine learning [20]. Epilepsy can be detected by evaluating the signals produced by the brain neurons. These neurons play a vital role in communicating and generating the signals in a defined manner. The detection of seizures and brain-related concerns is the most complicated and challenging task. ML classifiers can be related to the classification of EEG data and used to identify the seizures with patterned results. The brain signals are used by ECG and Electrocorticography (ECoG) media, which produces complex noisy signals. Based on the statistical features and machine learning techniques the black-box and non-black-box techniques were introduced in the recent times [21]. The ML classifiers are the approximate classifiers that provides high accuracy levels and estimate the processing of the classifiers. There are different types of classifiers for examining the stages and their accuracy levels. The process of adopted using EEG for seizure detection cannot validate a detection process. However, using the ML based on seizure detection techniques once can validate and confirm the existence of seizures in a human brain [22]. There are different types of ML techniques available to identify the seizures. However, they proved to be very critical and involve complicated processing procedures. The features which are selected and extracted based on the EEG signals consists of amplitude and duration. The accuracy and seizure detection can be evaluated using supervised and unsupervised ML techniques [23]. Classification and evaluating the performance plays an important role in machine learning techniques that are used to detect seizures. These classifiers play a major role in defining the seizure and examining the accuracy levels of the performance. Some of the popularly used classifiers include Support Vector Machine (SVM) and decision tree. These classifiers are applied to validate the EEG dataset for the seizure detections. The classifiers with datasets cannot particularly produce patterned features, which is a complicated task because the signals are complex in nature [24]. The datasets used with the machine learning classifiers will be able to detect and identify the neuro problems related to the brain in a determined manner. The neurological problems are examined at various stages include predicting the type and occurrence of seizure and calculates the seizure accuracy levels for better results.

According to Shoeb and Guttag, there are well-equipped techniques that are used in machine learning for the detection of the seizure by selective and extraction methods [24]. The neurological order severely affects the trauma of the brain and it is the most serious condition across the world. It cannot be predicted and examined in detail using the EEG due to the complex nature and massive data outputs, seizures cannot be identified at one go. A supervised machine learning classifier can identify and examine the seizure types depending on their approximate results. These classifiers are prominently performed in detecting the seizure phase and category for the detailed examination of the performance. Sahu *et al.* considered the statistical features to validate the results using ML techniques while using them on the given datasets [25]. Most of the complicated tasks such as performance detection and examining epilepsy are performed using ML techniques take a long duration for training the datasets and for validating the trained data. Training dataset plays an important role in ML techniques and it is easy to estimate the results based on the validation. Estimation of the disease and training datasets will be using unsupervised learning and it is used in neurological patterns. Apart from these, reinforcement learning (RL) is one of the advanced technologies used in neuroscience and it plays a vital role in the development of the customized detection methods for wide range of datasets. There are different types of algorithms that plays a crucial role to design the ML models for variety of applications in the medical sciences [26]. These models are applied to solve most complicated tasks and evaluate the performance [27]. Many challenges were faced in seizure detection to find the enhanced accuracy levels and prediction models. Later, many improvised techniques were proposed by Wikström *et al.* to easily extract and select the model to obtain the better results out of the model [28].

The highlights of a review by Assi *et al.* on the prediction of seizures were to look into the signal processing techniques and different methods to assess the prediction study, where each component of the framework is discussed and more improvement opportunities were identified ML considerations to increase forecasting the epileptic seizure capabilities from the given model [29]. Epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain [30]. Therefore, it requires long-term medication and only about 60-70% can handle the seizures. Coming to numbers per 1000 in population 5.59-10 of prevalence is seen to have epilepsy. Among 70 million people with epilepsy worldwide, 12 million are expected from India [31]. The combination of two fractal features were implemented using SVM to achieve the accuracy of 97.13% [32]. Preictal state is important feature for the seizure detection and this starts before the seizure. The work carried out by Usman *et al.* using machine learning to predict the state with 23 electrodes on the head of 22 subjects as an experiment [33]. The EEG signals were converted to a single channel to improve the Signal to Noise Ratio (SNR). The classifiers like k-nearest neighbor and SVM were used and SVM seem to produce the better results. The proposed model detects and for the given dataset it took 33.46 minutes to predict the seizure effect, which is far better as compared to other models. The expected outcome of this research is to implement a novel model to detect and classification based on deep learning. However, some models proposed by Mormann *et al.* [31] and Meier *et al.* [35] are based on modes that are sensitive to different acute variations in patterns. This happens because EEG data is not stationary and the features changes according to the subjects and the noise can change the features itself due to changes in the acquisition system of EEG. Some models were implemented by Abualsaud *et al.* reduce the noise in EEG, resulted in the 10% drop of detection accuracy [36]. Hence, to overcome these limitations a deep learning approach was recommended by many authors to detect and classify the seizure. In this direction Hussein *et al.* implemented seizure detection for noisy EEG dataset with an accuracy of 99% [37]. A model with low false prediction rates of 0.11-0.02 was proposed to find seizures by Tsiouris *et al.* is based on LSTM learning methods [38]. It was seen to provide best results compared to other studies using the same dataset. Under ideal and real-life conditions, the model proposed by Hussein *et al.* achieves a robust seizure detection performance using deep neural network architecture and from the results the authors claimed to achieve 100% accuracy using a clinical dataset by eliminating most of the background noise [39]. The algorithm proposed by these authors combines the domain-based implementation with infoGain technique to detect the seizure from EEG data. In this technique, the data was decomposed to frequency bands and transformations like Fast Fourier transform (FFT) and discrete wavelet transform (DWT) were applied. It is then passed to least-square support vector machine (LS-SVM) for classification with an accuracy of 95.63% when the data was divided into five (5) different pairs i.e., healthy people with open eyes, epileptic patients with active seizures, healthy people with eyes closed, epileptic patients with free seizures [40]. The non-linear techniques proposed by Birjandtalab *et al.* detect seizures and non-seizure episodes automatically predicted with an accuracy of 95% [41].

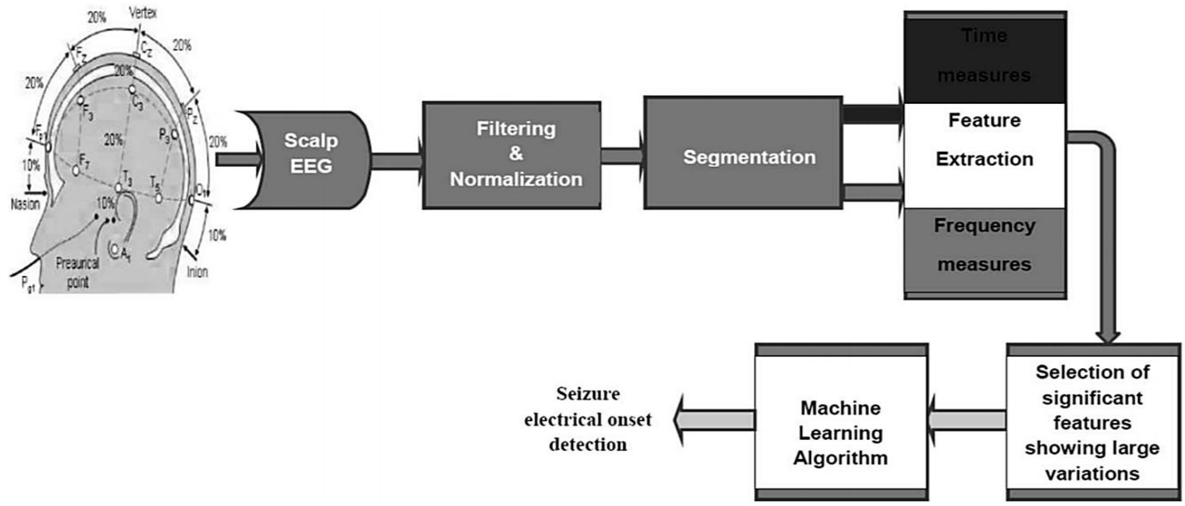

Figure 4 Different Steps involved in Automated Seizure Detection using ML Techniques

Source: *Adopted from Sridevi et al. [42, p. 17]*

Different types of steps involved in EEG data collection are shown in Fig. 4. Ahead of applying the machine learning algorithms for the EEG data, so many pre-processing techniques are applied to ensure that the ML model is trained and validated properly with the available dataset. Some of the steps involved in this process included with filtering and normalization of data, segmentation, feature extraction, identifying the desired features, and finally applying the ML algorithms for the prediction of seizures [42]. The raw data from the scalp of the subjects are sent for neural networks and feature extraction using spectral analysis and then classified using deep neural networks (DNN). The best results [43] were found using the neural networks to classify the spatially represented seizure patterns in 2D from the raw EEG images. 249 images which contained 249 human-annotated seizure events ranging from 8.34 to 61.25 s was used as training part and a set of 4,272h of EEG recordings containing 324 seizure events were mentioned as test sets. Most of the studies carried out for automatic detection of epileptic seizure were carried out using ML techniques, but now deep learning techniques are adopted to reduce the manual extraction of features and selection process. Different combinations of input structures on dataset. Therefore, the biggest disadvantage using a ML based model is to deal with huge datasets with careful pre-processing methods. Also, they need to have quality input datasets with adequate training time and resources to adopt the model. Moreover, they need special training facilities even for narrow application as well. Some of the other constrains using ML includes the need of structured training datasets, require supervised learning, require tagging, and they do not learn interactively in the real-time environments. Therefore, there is a need of alternate method for solving all the above issues.

D. Seizure Detection based on Deep Learning Techniques

The deep neural networks also represent a ML system but with many layers and nodes for deriving the high-level functions from the given inputs. Using deep learning (DL) techniques for seizure detection resulted to obtain numerous advantages in the medical sciences. In the recent times, robust features of DL techniques are applied to EEG data and to detect seizures automatically [44]. Thodoroff *et al.* considered to capture the spectral, temporal and spatial information from their recurrent neural network (RNN) model. Considering the EEG data in real-time always thrown a challenge for the engineers to deal with huge amount of nonstationary data that has been generated in the process of observing the patient brain condition. To deal with such nonstationary data Hosseini *et al.* suggested cloud-based DL for the EEG data that is used for seizure detection [45]. In this work, the authors considered to increase the classification accuracy by developing the dimensionality-reduction technique. DL techniques are applied to train the autoencoder in two steps for unsupervised feature extraction and to perform the classification. For the purpose of classification, a gradient-log-normalizer was used over the probability distribution as a softmax layer for preictal signals in the last layer. By combining all these steps, the authors developed a brain-computer interface (BCI) to detect seizures from the cloud-based environment. This method allowed the authors to obtain 94% accuracy as compared to 71 to 78% by using the SVM of ML techniques. The authors extended this work of seizure prediction BCI using the internet of things (IoT) by optimizing the DL techniques [46]. A lot of work towards auto-detection of epileptic seizure detection has been carried out by using deep neural networks [41] and DL methods [43]. CNN based on the raw EEG signals were used to classify the ictal, preictal and interictal segments of the seizure detection by Zhou *et al.* [47]. The authors compared the overall performance of the time and frequency domain signals that were used for the seizure detection. The average accuracies in frequency domain found to be in the range of 92.3% to 97.5% from their experiment on the Freiburg database. Daoud and Bayoumi put their effort to enhance the accuracy to a maximum rate of 99.6% with lowest false alarm rate of 0.004 h^{-1} with overall seizure prediction time of 1 hour [48]. Later, S-Transform and deep CNN were used for the automatic seizure detection by Liu *et al.* [49]. In this work, the authors used smoothing and collar techniques for the outputs of the CNN model to enhance the detection accuracy and to minimize the false detection rate (FDR).

The main disadvantage of EEG signals is that they are noisy, non-stationary, and produces high volume of data. Hence, to detect them is a high risk and challenging process. A model presented by Jang and Cho is efficient enough to detect the events of the EGG monitoring using deep neural networks. The discrimination of 5s EGG segments for pulsive seizures are trained with only 6 positive false events, 98% of positive predicted value with 100% of sensitivity was achieved [50]. Here, a classifier was built to distinguish total 5,000 raw EEG inputs from 5-sec EEG segments was used with 100 periodogram results between 0 to 99 Hz. The best method is to avoid the overfitting of data into the training set while using deep networks. Though the detection systems sometimes give high sensitivity it is very helpful as they give some False positive results which helps the neurologists differentiate true and falsely positive points among the classifier output [52]. Deep learning makes more progress than machine learning in the field of image recognition, video mixing, a model proposed to automatically detect the seizures using deep learning [51] experimented on signal channel is found to acquire 86% of accuracy. The EEG signals are processed using FFT or Wavelet decomposition to eliminate and increase the SNR of the model, the database used is of CHB-MIT. The comparison of different input modalities and network structures are seen for different deep learning parameters that are used for seizure detection. These parameters shown in Table III are considered for the multi-channel human iEEG dataset by Chao and Jang for the challenge conducted by Kaggle Seizure Detection, and the summary of their work is given in the table III [43].

Table III: The Comparison of Different Input Modalities and Network Structures for Deep Learning-Based Seizure Detection

Input Forms	Network Structures	Accuracy	Sensitivity	Specificity	F1 Score	AUC (Area under Curve)	FDR (False Detection Rate)
Raw time-series EEG	FCNN	0.985	0.963	0.985	0.031	0.983	0.020
	RNN	0.993	0.966	0.993	0.066	0.989	0.018
	1D CNN	0.996	0.965	0.996	0.118	0.990	0.015
Periodogram	FCNN	0.985	0.963	0.985	0.046	0.984	0.020
	RNN	0.982	0.967	0.982	0.026	0.985	0.024
	1D CNN	0.996	0.962	0.996	0.108	0.989	0.016
Image of STFT	2D CNN	0.998	0.967	0.998	0.194	0.991	0.011
40 × 250 image of EEG	2D CNN	0.999	0.966	0.999	0.407	0.993	0.009
40 × 750 image of EEG	2D CNN	0.999	0.969	0.999	0.492	0.998	0.008
Oshea *et al.* [74]	1D CNN	0.997	0.969	0.997	0.136	0.990	0.012
Zhou *et al.* [87]	1D CNN	0.995	0.967	0.995	0.089	0.989	0.017
Cao *et al.* [59]	2D CNN	0.997	0.962	0.997	0.136	0.990	0.015

III.RESULTS AND DISCUSSIONS

Along with the review the topics like seizure detection, classification and selection of channels, the motive of the research shows the summarized version of the evidences related to the accuracy of the seizure detection using EEG. Although many evidences show the efficiency and better placement methods to analyze the best area among the scalp, many modern problems associated with the EEG can be summarized as the unstable signals which are processed and the accuracy of the signals which is received as an output from the EEG. Most of the problems can be addressed by find out the accuracy of the EEG channel selection process and methods to amplify the process after the EEG signal is detection. In order to discuss these, detection methods using technologies like deep and machine learning are elaborated in the methodologies. Some of the methods regarding the seizure channel selection are discussed in Section II. A purposeful as well as systematic study related to these topics can be considered helpful in improvising the EEG signals and drives us towards the objective of this review. Many methods which involve mathematical rules like Fast Fourier Transform (FFT), Wavelet Transform (WT), Continuous Wavelet Transform (CWT) and many as a better approach [63, 68]. However, the paper is kept simple and easy to understand and evaluate a basic sense of the Objective.

A. Data Sources and Analysis, Studies Selections, and Data Extraction

The data collected and verified from different resources and considered for various ethical considerations which plays a vital role in scientific research. The data elaborated are collected from sources like Google Scholar, IEEE Xplore, Springer and Web of Sciences. The selection of the topics and data are based on the research topics and the studies of the latest reports under the similar study.

B. Research Gaps

It is seen that most of the features are not being identified by using single channel for EEG. It has got its own limitations towards obtaining accurate information and does not provide adequate efficiency. However, multi-channel selection is producing low efficiency due to complexity involved in the computational features. Therefore, optimal channel selection is much needed in the present conditions for improving computational speed and to increase the features. Apart from that class imbalance is one of the serious problems while using the machine learning classifiers. So far, the research has been carried out on the limited amount of data and on the homogeneous data. This is going to reduce the accuracy of the ML model as it is trained with less amount of data. However, it is seen that with the limited amount of homogeneous and specific data some of the ML classifiers are exhibiting the better accuracy and classification results. Such kind of practices may not deliver accurate information for the seizure detection. Therefore, it is very much essential to build a model which is quite capable of selection of EEG channels automatically for the efficient detection of seizure types.

IV. CONCLUSION

In this review article, a detailed discussion on epilepsy and various types of seizures and seizure detection techniques have been critically discussed. Due to the severity and highest rate of risk involved in the patients suffering from epileptic seizure, it has gained the importance and popularity among the research fraternity. Various articles and methodologies were discussed in the past to detect the seizures accurately from the scanning reports of the brain images. However, the abrupt nature of incidences that occur with the patients suffering with epileptic seizures, it is quite challenging to predict the root cause of the problem. From the brain signals obtained by EEG few researchers could summarize the seizure prediction models, but still, they need to enhance the accuracy of seizure detections. The channel selection and pre-processing of the EEG data becomes more complicated due to the involvement of massive recordings of brain signals from the monitoring devices. Therefore, this review paper included most of the channel selection procedures adopted by various researchers in the past. Finally, this article helps to establish a conclusive evidence to derive new strategies and deep learning methodologies for EEG channel selection and seizure identification in an efficient manner in a real-time environment.

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