IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

IJARSCT
Impact Factor: 6.252

Volume 2, Issue 1, September 2022

Review on Epileptic Seizure Detection using Machine Learning Concepts

Drisya Krishna K and Anoop S Pillai
Department of Electronics and Communication Engineering
NSS College of Engineering, Palakkad, Kerala, India

Abstract: *Epilepsy is one of the chronic severe non-communicable brain disorder and it is characterized by unprovoked recurrent seizures. A seizure is a burst of uncontrolled electrical activity between neurons that causes temporary abnormalities in muscle tone behaviors, sensations or states of awareness. The most common tool that is used for the determining epileptic seizure is the electroencephalogram (EEG).These signals are complex, noisy, non-linear, non-stationary and produce a high volume of data. Hence, the detection of seizures and discovery of the brain-related knowledge is a challenging task. Over the years, research is going in this domain to develop algorithms that can differentiate between seizure and non-seizure phases and develop mechanism that can detect and predict seizure before its onset. In this paper, we have extensively studied different soft computing techniques that have been developed over the years and have addressed the major singular problem of detection and prediction of an epilepsy seizure before its manifestation so that the after effects of the seizure can be minimized. Epilepsy research is a fascinating area that comes with numerous potentials for developing auto- mated systems that would open new avenues for treating the patient. The presented state-of-the-art methods and ideas will give a detailed understanding about seizure detection and classification, and research directions in the future.*

Keywords: Epilepsy

I. INTRODUCTION

Epilepsy is a group of neurological disorders that are characterized by recurrent seizures and can affect individuals of any age. Epilepsy arises from the gradual neurobiological process of 'epilepto- genesis' [1], which causes the normal brain net- work to fire neurons in a self-sustained hyper- synchronized manner in the cerebral cortex. More than 50 million people worldwide have epilepsy and nearly 80% them live in low- and middle- income countries. The main symptom of epilepsy is to experience more than one seizure by a patient. It causes a sudden breakdown or unusual activity in the brain that impulses an involuntary alteration in a patient's behaviour, sensation and loss of momentary consciousness. Classification of epilepsy can be done in two distinct ways. Figure 1 shows the detailed classification of seizure. One based on the origin or location of the seizure such as temporal, frontal, parietal or occipital lobes of the brain, where the seizure manifests [12]. And the other classification based on the type of seizures, focal or partial seizures and generalized seizures. Epileptic seizures can be detected using EEG signals by identifying certain abnormal brain ac- tivities associated with epileptic seizures, such as sharp spikes. As shown in Figure 2,The brain activity of patients with epilepsy can be categorized as different states: preictal, seizure orictal, postictal, and interictal. Preictal is the time before seizure occurrence, which lasts around fifty minutes to one hour, postictal is the time right after a seizure, interictal is the time between preictal and postictal stages, and ictal refers to the phase when a seizure takes place. Electroencephalography (EEG) is a particularly effective diagnostic tool to study the functional anatomy of the brain during an ES at- tack. EEG signals are complicated biomedical signals and difficult to investigate manually. Epileptic Seizure (ES) prediction is a classification problem focused on differentiating between the preictal and interictal states. Due to the recurrent nature of epilepsy, ES occurs in groups and patients afflicted from seizure clusters can acquire advantage through the forecasting of follow-on seizures. The prediction and medication of epilepsy have been broadly studied through EEG. EEG signals, which are non-Gaussian and non-stationary, measure the electrical activity in the brain which are in turn used to diagnose the type of the brain disor- ders. The analysis of EEG measurements helps segregate normal and abnormal function of the brain. For an accurate

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prediction of epilepsy, it is necessary to examine EEG recordings of longer duration. Expert neurologists examine epilepsy by studying continuous EEG signals recorded over several days, weeks, or even months, which re- quires a huge amount of human effort and time.

The detection and prediction of seizures differ according to the type of state detected. In detection, the ictal and interictal features are extracted, while in prediction the pre-ictal features are detected. Prediction of epileptic seizures is hard to detect compared to detection. Meanwhile, the prediction of seizure is highly beneficial for the patient's safety. Over the years, various studies have employed machine learning (ML)-based prediction and detection methods to address this issue. Deep learning (DL) is an advanced ML technology that is capable of learning patterns more precisely from large collections of data by processing it through a multi-layer hierarchical architecture. The ability of DL to produce very accurate results has influenced the researchers for the ES prediction in the last five to six years.

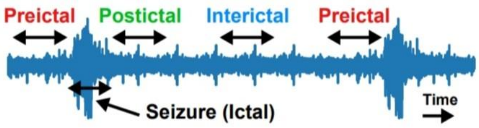

Fig. 1. Various stages of EEG signal in epileptic patients

The general workflow of a seizure detection model is as follows. First is data acquisition. The acquired signal has to be preprocessed by re- moving redundant and irrelevant data. The signal is then filtered to remove noise. The most discriminant features are derived from the filtered signal. Finally, a classifier is used to detect whether the processed signal is classified as one of the seizure states or a normal state. These phases are illustrated in the upcoming sections.

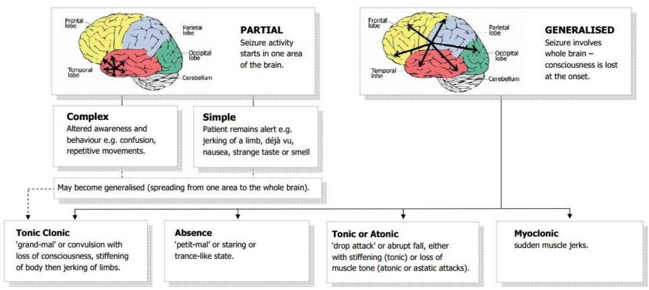

Fig. 2. Seizure classification

The main aim of this paper is to bring forth various commendable and notable works of re- searchers that have been done over the years to develop efficient epilepsy detection and prediction systems using EEG signals that have proved to work significantly with high accuracy and low false alarm per patients. The remaining of the pa- per is organized in the following manner: different processing techniques have been outlined which is followed by classifiers that are generally used for epilepsy seizure detection. A comparison table has been included that gives a summarized view of the different review work.

Contribution of this paper:

1. EEG signal and the information on available public and private datasets.
2. Comparison about the preprocessing of available datasets
3. Detailed description of ongoing feature ex- traction methods
4. Performance Evaluation of different classification process used for epileptic seizure detection

This study will help the researchers with their data science backgrounds to identify which statistical and machine learning classifiers are more relevant for further improvement to the existing methods for seizure detection. The study will also help the readers for understanding about the publicly available epilepsy datasets and their limitations.In the end this paper provides a future direction for the development of better seizure detection and prediction algorithm with better accuracy than that of existing method

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II. ANALYSIS OF EEG DATASETS FOR EPILEPTIC SEIZURE PREDICTION

2.1 EEG Signal

There are two types of EEG signals: Scalp EEG (sEEG) and intracranial EEG (iEEG). sEEG is recorded using electrodes that are placed on the scalp of the subject, as shown in Figure 3a. sEEG is noninvasive and easy to place; however, it cannot be used to record data for a long time. sEEG can be contaminated with different types of artifacts, including motion artifacts. Further, sEEG uses a lower number of electrodes compared to iEEG but covers a larger brain surface iEEG signals are recorded using invasive electrodes placed directly on the brain. As illustrated in Figure 3b, these electrodes can either be subdural or depth. The first is placed on the brain as grids or strips and covers a larger surface area, whereas the latter is inserted deep into the brain, thereby providing higher ac- curacy . iEEG provides 20 to 100 times higher

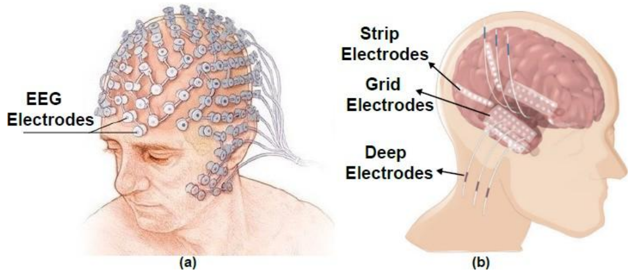

Fig. 3. Scalp EEG and Intracranial EEG

signal quality than sEEG, more immune to motion artifacts, and provides better seizure localization. The drawbacks of using invasive electrodes are the need for surgery and the risk of complications after the surgery. EEG data can also be classified as long-term or shortterm based on the dura- tion of the recordings. Short-term EEG recordings are similar to routine EEG scans, whereas long- term EEG recordings span for extended periods, from months to years. Long-term EEG is usually performed to correlate clinical behavior with an EEG phenomenon. EEG recordings may contain unusable data, called dropout. They are caused by a machine-related error and should be removed for better processing. Dropout could be a constant value, a constant pattern, or low amplitude values and may span from a few seconds to a couple of hours. Small intervals of dropout data can be ignored.

2.2 Available Datasets

1. **CHB-MIT sEEG Dataset:** The CHB-MIT dataset contains sEEG data recorded at a sampling rate of 256 Hz from 23 epileptic patients at the Children's Hospital of Boston.The dataset is di- vided into cases, each representing one patient, except for case 1 and case 21, where the data are recorded from the same patient with a gap of 1.5 years. Although the number of channels varies from 23 to 26, the following 18 channels are common among all patients: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FZ-CZ, CZ-PZ, FP2-F4, F4- C4, C4-P4, P4-O2, FP2- F8, F8-T8, T8-P8, and P8-O2.It doesnot contain preictal or interictal labels but can be extracted using seizure timings provided in meta-data files of every patient. This can be applied for all cases except case 24, where the start and the end time of the file are not specified. The dataset has 198 seizures, and the files are in .edf format
2. **Bonn Dataset:** The Bonn EEG dataset con- tains sEEG and iEEG from 5 subjects with a sampling rate of 173.61 Hz. The data are collected from patients experiencing a seizure-free interval (folders N and F), from patients having a seizure (folder S), and from healthy patients at rest (folders Z and O). There are 100 samples in each folder where every sample has a record duration of 23.6 seconds. Unlike other available datasets, the Bonn dataset contains healthy labels. However, due to the short total duration of 3.3 hours and the use of a single channel to record the data, the Bonn dataset is not preferred for epilepsy prediction algorithm development.
3. **American Epilepsy Society Dataset:** The American Epilepsy Society dataset contains iEEG data of 7 subjects (2 humans and 5 dogs) with a total duration of 1,333.7 hours. The number of channels varies from 15 to 24 among the subjects, while the sampling rate is 5000 Hz and 400 Hz for humans and dogs, respectively. The recordings are structured similar to the Melbourne dataset, with 1 hour of recordings divided into six 10-minute files and a seizure horizon onset of five minutes. Interictal files from the dogs have

a week gap with seizures, while interictal files from humans have a gap of 4 hours . Several hours of iEEG data for the first human subject contain dropout data across all channels, caused by 60 Hz noise coupled through recording machines. Notch filters could be used to remove this noise.

4. **The European Epilepsy Dataset (Private):** The European Epilepsy dataset is the largest avail- able EEG dataset, including data for 30 invasive patients over multipledays of recording and a total duration of 6,488 hours. Although there are two packages, scalp and intracranial EEG, this paper only refers to the intracranial EEG package of the European Epilepsy dataset. The number of channels and sampling rate varies widely among the patients ranging from 31 to 124 and 256 Hz to 2500 Hz, respectively, which is much higher than other available datasets. The dataset includes a few scalp electrodes for Electrooculography (EOG) and Electrocardiogram (ECG), which record the elec- trical activity of the eyes and heart, respectively. The files of this dataset are not labeled as pre- ictal or interictal, however, they can be extracted using the timing information of the 590 seizures present in the dataset. Further, the dataset provides information about seizure types and the origin of the seizures. Finally, the dataset includes details about subclinical seizures, which show abnormal electrical activity in the brain with no physical symptoms.

III. PREPROCESSING OF EEG DATA

Electroencephalogram (EEG) is one of the emerging as key tools help us to explore and under- stand the functionality and dynamics of the brain. The noninvasiveness, portability, low cost, and high temporal resolution make EEG the most preferred brain-imaging method. It measures the joint electrical activity of a population of neurons. Its many advantages aside, EEG has a drawback, in that it is always contaminated with artifacts. Artifacts are undesirable signals that arise from sources other than neurons; they distort the original EEG activity and hence make its analysis more difficult. Whereas EEG ideally should include only neuronal activity, unfortunately it is often contaminated by eye movements, eye blinks, muscle activity, and cardiac activity. Since artifact contamination alters the true EEG signal, it also affects the results of the desired application. It is therefore mandatory, in either clinical or practical research, to deal with these artifacts prior to the analysis of EEG signals. To do so, a method is required that not only can remove artifacts efficiently but at the same time, can preserve the true, distortion-free EEG signals. For these purposes, several manual and automated methodologies have been developed and utilized.

3.1 Types of Artifact

Basic knowledge on the different types of artifacts is necessary in order to develop suit- able algorithms for removal of artifacts from EEG signals. Broadly, artifacts in EEG can be classified into two types, physiological and nonphysiological. Non-physiological artifacts include electrode displacement, interference from the environment, and movement artifacts. These artifacts can be reduced in number by proper subject instruction and experimental setup. On the other hand, physiological artifacts include ocular artifacts, muscle artifacts and cardiac artifacts. In contrast to nonphysiological artifacts, removal or reduction of these artifacts requires the use of a suitable handling algorithm. Here we are looking different types of methods to remove artifact.

Type	Name	Origin
Physiological	Ocular	Eye blink, eye movement, eye flatter
	Muscle	Chewing, swallowing, clenching, sniffing, talking
	Cardiac	ECG pulse
Non-physiological	Instrumental	Electrode misplacement and cable movements
	Interferences	High voltage machines in surroundings
	Movements	Head and body movement
	Volume Conduction and Superposition	Measurement of neuronal activities from single brain region at multiple electrode

Fig. 4. Types of Artifacts in EEG

1. **Artifact avoidance:** The most straight forward way to reduce artifacts in EEG signals is to avoid movements that can incur them. For example we can remove ocular artifact by controlling eye movements. But it is not practically possible especially in the case of epileptic patients. It is because of any human can't control its pulse activity for long time.
2. **Artifact segment rejection:** Here we remove all epochs that are highly affected by signals from non-neuronal sources.The most difficult part of this method is to identify artifactual epochs from large EEG datasets, as it requires much expertise in anal- ysis of EEG data as well as a significant amount of time, making it unsuitable for applications like BCI. A major drawback of using this method, moreover, is the loss of important neuronal information present in artifactual epochs, which might lead to erroneous conclusions. In any case, due to the recent development of automatic artifact removal algorithms, the use of epoch rejection these days is not preferred.
3. **Regression Methods:** Regression algorithm is common and simple method used to remove artifactual contamination. Regression methods are based on a simple methodology entailing the subtraction of artifactual signals from EEG signals after estimation of artifact propagation coefficients. These propagation coefficients can be estimated using measured reference signal for particular type of artifacts i.e electrooculography (EOG) signals for ocular artifacts and electrocardiography (ECG) signals for ECG artifacts. Regression method require an reference channel so it limit it application to EOG and ECG removal. Fig shows artifact removal based on regression method.
4. **Filtering algorithms:** Different filtering tech- niques are used to remove the artifacts present in EEG signals. The common noise is powerline noise (50/60 Hz interferences).For to remove this noise commonly notch filter is used. Adaptive filtering is the common approach used to remove the artifacts from EEG signals. Adaptive filtering assumes that there is no correlation between the true EEG signal and artifactual activities . A reference signal is used to estimate the artifactual signal that is correlated with an artifact. Then, the estimated signal is subtracted from the recorded EEG signal to obtain the artifact-free EEG signal. Achieving the best results using adaptive filtering is highly dependent on the choice of the reference signal. For instance, EOG signals can be used to remove ocular artifacts from EEG data and/or ECG can be used to measure the reference signal that can be used to remove cardiac artifacts . Finally, an optimization algorithm can be used to obtain an optimal set of parameters that best estimates the artifacts present in EEG signals. The least mean squares (LMS) algorithm is the most commonly employed adaptive algorithm for adjustment of a weight vector. Another most commonly used algorithm is recursive least squares (RLS)-based adaptive filtering . RLS algorithms perform better than LMS-based filters but also incur high computational cost relative to LMS. Online implementation, no preprocessing/calibration and ease of use are the few advantages of adaptive filters, whereas the requirement of a reference signal using extra sensors is the limitation.
5. **Blind source seperation:** BSS is one of the most popular and widely used techniques for re- moval of artifacts from EEG data by separating source signals of neuronal activity from artifacts . One of the major advantages of BSS is that it does not require any prior information (in some cases very limited information) about the mixing of different sources. There are many BSS algorithms developed to remove artifacts from EEG signals, including independent component analysis (ICA), principal component analysis (PCA), canonical correlation analysis (CCA), and morphological component analysis (MCA)
6. **Empirical Mode Decomposition:** Empirical mode decomposition (EMD) is a data-adaptive multiresolution technique to decompose a signal into physically meaningful components.EMD can be used to analyze non-linear and non-stationary signals by separating them into components at different resolutions.EMD has been successfully used to remove artifacts from EEG data and also in combination with other methods. Furthermore, EMD, as it is very sensitive to noise, has been modified to deal with modemixing complications. Enhanced EMD (EEMD) is developed that has the average number of IMFs from EMD as the opti- mal IMFs providing a noise-assisted data analysis method So many hybrid methods also used for the artifact removal like Adaptive Filtering and Blind source seperation, EMD and BSS, Wavelet trans- form and BSS etc.

IV. FEATURE EXTRACTION METHODS

The feature extraction step aims to extract the discriminating features from the EEG representation allowing to characterize the seizure activity pattern. In order to detect the epilepsy correctly we should find important features. Considering every channel for epileptic seizure detection leads to an over fitting problem. So channel selection and feature extraction are important steps in epilepsy detection. We can classify features based on 3 domains such as time domain, frequency domain and time frequency domain. Time-domain features (TDFs) are those calculated on raw EEG signals or on pre-processed signals done in the time domain, such as empirical mode decomposition (EMD). Frequency-domain features (FDFs) are computed on discrete-Fourier transform of raw EEG signals. Time-frequency-domain features (TFDFs) are de- fined on transformed EEG signals that contain both time and frequency characteristics, such as short-time Fourier transform (STFT) spectrogram or DWT.

4.1 Time Domain Features((TDFs)

Groups of statistical parameters have been frequently used to discriminate between ictal and normal patterns, because it is assumed that EEG statistical distributions during a seizure and normal periods are different. These parameters are mean, variance, mode, median, skewness (third moment describing data asymmetry), and kurtosis (fourth moment determining tailedness of the distribution). The minimum and maximum values are also used to quantify the range of data or the magnitude of signal baseline. Other statistical parameters include coefficient of variation (CV) defined as the ratio of the standard deviation (SD) to the sample mean that explains the dispersion of the data in relation to the population mean. In figure 5 important statistical parameters are listed whereas z is the analytical signal of a real discrete time EEG signal x, obtained using the Hilbert transform. $F^{(t)}$stands for the EEG features computed from z Energy, average power, and root mean squared value (RMS) are mutually relevant to amplitude measurements. The energy is a summation of a squared signal, the average power is the signal mean square, and the RMS is the square root of the average power.

(1) Features based on statistical moments:

- First moment and second central moment of EEG signal [15], [12]

Mean: $F_1^{(t)} = \mu = \frac{1}{N}\sum_{n=1}^{N} |z[n]|$

Variance: $F_2^{(t)} = \sigma^2 = \frac{1}{N}\sum_{n=1}^{N} (\mu - |z[n]|)^2$

- Normalised moments: third and fourth central moments of EEG signal [15], [12]

Skewness: $F_3^{(t)} = \frac{1}{N\sigma^3}\sum_{n=1}^{N} (|z[n]| - \mu)^3$

Kurtosis: $F_4^{(t)} = \frac{1}{N\sigma^4}\sum_{n=1}^{N} (|z[n]| - \mu)^4$

- Coefficient of variation of the EEG signal [15]

$$F_5^{(t)} = \frac{\sigma}{\mu} = \frac{\sqrt{F_2^{(t)}}}{F_1^{(t)}}$$

Fig. 5. Important Statistical Features

(2) Features based on amplitude:

- Median absolute deviation of EEG amplitude [12]

$$F_6^{(t)} = \frac{1}{N}\sum_{n=1}^{N} (|z[n] - \mu|)$$

- Root mean square amplitude [13]

$$F_7^{(t)} = \sqrt{\frac{\sum_{n=1}^{N} z[n]^2}{N}}$$

- Inter-quartile range [14]

$$F_8^{(t)} = z[\frac{3(N+1)}{4}] - z[\frac{N+1}{4}]$$

Fig. 6. Amplitude based Features

[11pt] article Regarding features used to characterize EEG, nonlinear properties have attracted increasing attention nowadays since nonlinearity is believed to be inherent in physiological processes. So entropy is one of the best feature

to analyse EEG signals. Various type of entropy are listed below

Shannon entropy (ShEn) [30] reflects the un- certainty in random process or quantities. It is defined

$$ShEn(X) = -\sum_i p_i log p_i$$

where $p_i$is the probability of an occurrence of each of value in X

Approximate entropy (ApEn) [33] is a measure of the regularity and fluctuation in a time series derived by comparing the similarity patterns of template vectors. The template vector of size m is defined as a windowed signal: u[i] $=[x[i]x[i+1].....x[i+m\text{-}1]^T$ and

we first consider the self-similarity of the template vector u[i] with a tolerance r as

$$\text{ApEn}(X,m,r) = \frac{1}{N-m+1}\sum_{i=0}^{N-m}\log C_i^m(r) - \frac{1}{N-m}\sum_{i=0}^{N-m-1}\log C_i^{m+1}(r)$$

Sample entropy (SampEn) [34] is based upon a concept similar to the ApEn, where the SampEn compares the total number of template vectors of size m and m + 1. The SampEn differs from the ApEn in that the self-similarity of all pairs of template vectors u[i] and u[j] with a tolerance as

$$\phi^m(r) = \sum_{j=0, j\neq i}^{N-m}\sum_{i=0}^{N-m}\Theta(r - ||u[i] - u[j]||_\infty).$$

Fuzzy entropy, permutation entropy, weighted permutation entropy, distribution entropy are all notable features to classify EEG signals

EEG frequency-domain features ($F^{(f)}$)
(1) Feature based on power spectrum: • maximum power of the frequency bands [15], [13] $F_1^{(f)} = \sum_{k=1}^{\delta} \|Z[k]\|^2$ $F_2^{(f)} = \sum_{k=\delta+1}^{M} \|Z[k]\|^2$ M corresponds to the maximum frequency
(2) Features based on spectral information: • Spectral centroid: average signal frequency weighted by magnitude of spectral centroid [12] $F_3^{(f)} = \frac{\sum_{k=1}^{M} k\|Z[k]\|}{\sum_{k=1}^{M}\|Z[k]\|}$ • Spectral flux: difference between normalized spectra magnitudes [12] $F_4^{(f)} = \sum_{k=1}^{M}\left(Z^{(l)}[k] - Z^{(l-1)}[k]\right)^2$ where $Z^{(l)}$ and $Z^{(l-1)}$ are normalized magnitude of the Fourier transform at l and $l-1$ frames • Spectral flatness: indicates whether the distribution is smooth or spiky [12] $F_5^{(f)} = \left(\prod_{k=1}^{M} Z[k]\right)^{\frac{1}{M}}\left(\sum_{k=1}^{M} Z[k]\right)^{-1}$ • Spectral Roll-Off: spectral concentration below threshold λ [12] $F_6^{(f)} = \lambda\sum_{k=1}^{M}\|Z[k]\|$
(3) Feature based on entropy: • Spectral entropy: measures the regularity of the power spectrum of EEG signal [13] $F_7^{(f)} = \frac{1}{\log(M)}\sum_{k=1}^{M} P(Z[k])\log P(Z[k])$

Fig. 7. Important Frequency Domain Features

4.2 Frequency-Domain Features (FDFs)

Frequency domain analysis is also crucial, since a frequency representation of an EEG signal pro- vides some useful information about patterns in the signal. The PSD and the normalized PSD (by the total power) are mostly used to extract features that represent the power partition at each frequency. figure 7 describes the relevant and discriminant frequency EEG features that we have identified. These features are based on spectral in- formation of EEG signal such as power spectrum, spectral flux, spectral Roll-Off, spectral centroid, spectral entropy and spectral flatness. As shown in the figureZ is the Fourier transform of the analytic signal z of a real discrete time EEG signal x. $F^{(}f)$stands for the EEG features computed from Z)

4.3 Time-Frequency-Domain Features (TFDFs)

Time domain analysis can provide better spatial information thus poor in frequency content infor- mation required for EEG classification. Frequency domain can provide temporal information but only after windowing the function. Selection of window size is a biggest challenge in frequency analysis. Time frequency analysis is resolving both of these problems. Recent research refers wavelet analysis and short time Fourier transform are best methods for time frequency analysis.

4.4 Time-Frequency Analysis with Gabor Transform (Short Time Fourier Transform)

Fourier transform can't solve the time varying features of an EEG signals. This problem can be partially resolved by Gabor transform also called as Short Time Fourier Transform. This is widowed Fourier Transform in which Fourier Transform is progressively taken over a time window of a few seconds with stationary window length. Thus non stationary signal is divided in time segment and the FT is successively applied to each segment. EEG analysis with Gabor Transform facilitates iden- tification of Tonic-Clonic seizures and provides quantitative measures of the dynamics of epileptic seizures. Gabor Transform has a limitation that its window length is predefined and cannot have variation as per the requirement so window se- lection is a challenge in Gabor transform. Narrow window size gives poor frequency resolution and wide window size causes the time localization non- precise. This actually causes uncertainty in data analysis

4.5 Time-Frequency Analysis with Wavelet Transform

Limitation of STFT related to selection of window size can be overcome by wavelet transform (WT). The WT has facility of varying frequency based on frequency component such as narrow window size for high frequency and broad for low frequency. This facilitates optimal time frequency resolution in all frequencies and it eliminates the requirement of signal stationary. The continuous wavelet transform (CWT) is correlation between signal and the wavelet function. Calculating wavelet coefficients with CWT for every possible scale needs more efforts and result in a huge data. Therefore Discrete Wavelet Transform (DWT) is preferable choice for EEG signals. The Discrete Wavelet Transforms (DWT) means choosing subsets of the scales (time and frequency) and positions of the wavelet mother function The feature vectors are calculated on the basis of approximated wavelet coefficients of the EEG signals. Discrete wavelet transform (DWT) decomposes the signal into time frequency representations to depict their distribution. This time– frequency distribution of the EEG signals can be characterized by minimum, maximum of the wavelet coefficients, Mean and Standard deviation of the wavelet coefficients in each sub band.

V. ML APPROACHES FOR ES PREDICTION

The seizure prediction problem is formulated as a classification task between interictal and preictal brain states. ML is proliferating across research areas over the past few decades by using statistical methods to recognize patterns in large collections of data.The availability of large-scale biomedical data is turning over a new leaf for healthcare re- searchers. Development of effective medical tools relies on data analysis approaches and the advancements of ML techniques. In this section, we provide a comprehensive review of the literature using ML-based methods for ES prediction. We can categorise ML in to 3 group such as supervised learning, unsupervised learning, and reinforcement learning.

5.1 Supervised Learning

In supervised learning, training data accompanied by labels assigned by human experts is fed to the learning algorithm for extracting the relation between data and labels so that the system can classify the unseen data accurately to their respective categories. For instance, a training data consists of images with labels of house, a dog, a cat and we want an algorithm that can predict the label of an image previously unknown to the system. These algorithms have wide applications in the field of computational and theoretical neuroscience an example technique is support vector machine (SVM), a supervised learning algorithm generally used for prediction of ES (described in a latter section). Analysis of neural mechanisms under stress is carried out using a supervised ML approach

5.2 Unsupervised Learning

Our brain receives most of the information in a day without any guidance. The brain develops a working model from the repetition of information and uses this model to make a perception. This perception is then used for detecting the patterns in new information. Unsupervised learning algorithms are motivated by how the brain studies new things through perceptions. Unsupervised learning applies unclassified or unlabeled data for training of the algorithms. These algorithms are extensively used in the identification and classification of diseases from neurophysiological data

5.3 Reinforcement Learning

Animal psychology, how animals communicate with each other and with the environment, helped to develop reinforcement learning (RL) . RL is a significant illustration of the advancement of tech- nology due to the collaboration of neuroscience and AI. Reinforcement Learning is the process of developing a policy to maximize the rewards of interaction between an agent and its environment. Central factors of a reinforcement learning system are a policy, reward signal, value function, and model of the environment.

5.4 Classification Algorithms

Identification of pre-ictal and interictal patterns from EEG data is carried out using different types of ML algorithms, e.g, artificial neural network (ANN), k-means clustering, decision trees, SVM, and fuzzy logic etc Now a days research show that supervised learning model performs better in epileptic seizure prediction.SVM is one of the best method for preictal and ictal classification states. Most of the previous work proposed machine learning based prediction schemes like Support Vector Machine (SVM). SVM classifier is used in numerous studies like [7], [10], [11] to predict the epileptic seizures. SVMs achieved outstanding results over other types of classifiers in terms of specificity and sensitivity.ML classification algorithms use feature vectors, derived from traditional signal processing methods for training and provide good accuracy but a generalized model cannot be anticipated from these techniques. For seizure prediction through an ML approach, script writing requires feature extraction stage that takes a lot of time. The presence of noise and artifacts in data makes feature extraction very complex to handle. Hence it is a challenging problem to produce a generalized automatic system with loyal performance especially even when limited training samples are available. On the other hand, DL algorithms automatically learn features and give encouraging outcomes in ES prediction. Features learned through DL models are more distinguishing and robust than hand- crafted features. The recent advances in machine learning science and particularly the deep learning techniques breakthroughs have shown its superior- ity for automatically learning very robust features that outperformed the human-engineered features in many fields such as speech recognition, natural language processing, and computer vision as well as medical diagnosis (Wang et al., 2020). Multiple seizure detection systems that used artificial neural networks (ANNs) as classifiers, after traditional feature extraction, were reported in previous work. For instance (Orhan et al., 2011), used multilayer perceptron (MLP) for classification after using discrete wavelet transform (DWT) and K-means algorithm for feature extraction. Samiee et al. (2015) also used MLP as a classifier after using discrete short-time Fourier transform (DSTFT) for feature extraction. In Jaiswal and Banka (2017), ANNs were evaluated for classification after using the local neighbor descriptive pattern (LNDP) and one-dimensional local gradient pattern (1D-LGP) techniques for feature extraction. Yavuz et al. (2018) performed cepstral analysis utilizing generalized regression neural network for EEG signals classification. On the other hand, convolutional neural networks (CNNs) were adopted for both automatic feature learning and classification. For example (Acharya et al., 2018), proposed a deep CNN consisting of 13 layers for automatic seizure detection. For the same purpose (Abdelhameed et al., 2018a), designed a system that combined a one-dimensional CNN with a bidirectional long short-term memory (Bi-LSTM) recurrent neural network. Ke et al. (2018); Zhou et al. (2018), and Hossain et al. (2019) also used CNN for feature extraction and classification. In Hu et al. (2019), CNN and support vector machine (SVM) were incorporated together for feature extraction and classification of EEG signals.

In general, supervised learning is the most widely used technique for classifying EEG signals among all other machine learning techniques. Several researchers have recently experimented with semi-supervised deep learning strategies in which an autoencoder (AE) neural network can benefit from training using both unlabeled and labeled data to improve the efficacy of the classification process.(Gogna et al., 2017; Yuan et al., 2017; Ab- delhameed and Bayoumi, 2018, 2019; She et al., 2018).Now a days Recurrent neural networks also gain importance in epileptic seizure prediction.

VI. CONCLUSION

With the increase of epilepsy, its accurate detection becomes increasingly important. A major challenge is to detect seizures correctly from a large volume of data. Due to the complexity of EEG signals in such datasets, machine learning classifiers are suitable for accurate seizure detection. Selecting suitable classifiers and features are, however, crucial. So this paper help us to comprehensively analyse EEG seizure detection process such as data acquisition, important features associated with EEG data, noise removal and also discuss the ongoing trends in classification process. Earlier we analyse each EEG signal by extract features separately and given in to a machine learning model to detectictal or non ictal stages. But today they can focus on deep learning models and can provide full automation in epileptic seizure detection process and also can provide better accuracy.

REFERENCES

[1]. World Health Organization, Neurological Disorders: Public Health Challenges. World Health Organization, 2006

[2]. E. Bou Assi, D. K. Nguyen, S. Rihana, and M. Sawan, “Towards accurate prediction of epileptic seizures: A review,” *Biomed. Signal Process. and Control*, vol. 34, pp. 144–157, Apr. 2017

[3]. H. Daoud and M. Bayoumi, “Deep Learning based Reliable Early Epileptic Seizure Predictor,” *IEEE Biomedical Circuits and Systems Conference (BioCAS)*, Cleveland, OH, pp. 1–4, 2018.

[4]. H. G. Daoud, A. M. Abdelhameed, and M. Bayoumi, “Automatic epileptic seizure detection based on empirical mode decomposition and deep neural network,” *IEEE 14th International Colloquium on Signal Processing Its Applications (CSPA)*, pp. 182–186, 2018

[5]. S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997.

[6]. R. Cassani, T. H. Falk, F. J. Fraga, P. A. Kanda, and R. Anghinah,``The effects of automated artifact removal algorithms on electroencephalography-based Alzheimer's disease diagnosis," *Frontiers Aging Neurosci.*, vol. 6, p. 55, Mar. 2014.

[7]. C. Amo, L. de Santiago, R. Barea, A. López-Dorado, and L. Boquete, ``Analysis of gamma-band activity from human EEG using empirical mode decomposition," *Sensors*, vol. 17, no. 5, p. 989, 2017.

[8]. D. Labate, F. La Foresta, N. Mammone, and F. C. Morabito, ``Effects of artifacts rejection on eeg complexity in Alzheimer's disease," in *Advances in Neural Networks: Computational and Theoretical Issues*, Cham, Switzerland: Springer, 2015, pp. 129_136.

[9]. N. Mammone, ``Preprocessing the EEG of Alzheimer's patients to automatically remove artifacts," in *Multidisciplinary Approaches to Neural Computing*. Cham, Switzerland: Springer, 2018, pp. 279_287.

[10]. A. H. H. Al-Nuaimi, E. Jammeh, L. Sun, and E. Ifeachor, ``Complexity measures for quantifying changes in electroencephalogram in Alzheimer's disease," *Complexity*, vol. 2018, Mar. 2018, Art. no. 8915079.

[11]. H. Cai *et al.*, ``A pervasive approach to eeg-based depression detection," *Complexity*, vol. 2018, Feb. 2018, Art. no. 5238028

[12]. R. J. Croft and R. J. Barry, ``Removal of ocular artifact from the EEG: A review," *Neurophysiol. Clin./Clin. Neurophysiol.*, vol. 30, no. 1, pp. 5_19, Feb. 2000.

[13]. A. R. Teixeira, A. M. Tomé, E. W. Lang, P. Gruber, and A. M. da Silva, ``Automatic removal of high-amplitude artefacts from single-channel electroencephalograms," *Comput. Methods Programs Biomed.*, vol. 83, no. 2, pp. 125_138, Aug. 2006.

[14]. K. H. Ting, P. C. W. Fung, C. Q. Chang, and F. H. Y. Chan, ``Automatic correction of artifact from single-trial event-related potentials by blind source separation using second order statistics only," *Med. Eng. Phys.*, vol. 28, no. 8, pp. 780_794, 2006.

[15]. G. L. Wallstrom, R. E. Kass, A. Miller, J. F. Cohn, and N. A. Fox, ``Automatic correction of ocular artifacts in the EEG: A comparison of regression-based and component-based methods,'' *Int. J. Psychophysiol.*, vol. 53, no. 2, pp. 105_119, 2004.

[16]. A. Delorme, T. Sejnowski, and S. Makeig, ``Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis,'' *NeuroImage*, vol. 34, no. 4, pp. 1443_1449, 2007.

[17]. P. Jahankhani, V. Kodogiannis, and K. Revett, ``EEG signal classi_cation using wavelet feature extraction and neural networks,'' in *Proc. IEEE John Vincent Atanasoff Int. Symp. Mod. Comput. (JVA)*, Oct. 2006, pp. 120_124.

[18]. N. Kalchbrenner, E. Grefenstette, and P. Blunsom, ``A convolutional neural network for modelling sentences,'' Apr. 2014, *arXiv:1404.2188*. [Online]. Available: https://arxiv.org/abs/1404.2188

[19]. M. P. Kerr, ``The impact of epilepsy on patients' lives,'' *Acta Neurologica Scandinavica*, vol. 126, no. s194, pp. 1_9, 2012.

[20]. Y. Kim, ``Convolutional neural networks for sentence classi_cation,'' Aug. 2014, *arXiv:1408.5882*. [Online]. Available: https://arxiv.org/abs/ 1408.5882*Neural Inf. Pro-cess. Syst.*, 2012, pp. 1097_1105.