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A Review on Machine Learning Techniques for Predicting Seizures Using EEG Signals

[1]Vetrikani R, [2]Yogesh G S

[1,2]Department of Electronics and Communication Engineering East Point College of Engineering and Technology, Bangalore, India

Abstract – With the recent development in machine learning (ML) techniques, many advancements are striving toward clinical practice for the benefit of human society. One of such key objectives is the early prediction of seizures to provide preventive interventions promptly. Because of the electrifying new enhancements in machine learning-based algorithms, there is a paradigm shift in the early prediction of seizures. Here we deliver a methodical review of machine learning techniques for the early prediction of seizures using EEG signals. In this paper, we discussed the main symptoms and classification of seizures along with the development of EEG signals in the field of neuroscience, and the measures used for the prediction of seizures. Also, we elaborated on various stages involved in the machine learning techniques for the prediction.

Keywords – Seizure, EEG signals, Machine Learning Techniques

I. INTRODUCTION

A sudden and uncontrolled disturbance of electrical activity in the brain results in a seizure. It is a temporary disruption of functions in the brain due to excessive neuronal discharge, also called an electrical storm in the brain. Around 65 million people in the world are identified to have seizure symptoms [1]. The cost of treatment for 5 million cases is estimated to be 0.5% of GDP in India. In the world, nearly 40-50% of people are at the risk of more seizures within two years from the first seizure. In India, about 1 in 3 people has a seizure that is not cured by anti-epileptic drugs and the mortality rates are 4 to 7 times higher [2]. If a person's seizure is diagnosed and treated properly in time it is assessed that 70% of people could live seizure-free. Unconsciousness and Bizarre behaviors were the only symptoms considered in ancient times and their belief was seizure occurs due to the possession by evil spirits.

A person with provoked seizure has a reoccurrence rate to be less but a high risk of a death rate. Based on the type and severity, seizure types will vary. Mild seizures can be treated and prevented with prescribed medications whereas a seizure that lasts for more than five minutes is an emergency that led to life-threatening situations if not treated properly. If the seizures are not predicted or treated early, they may lead to status epilepticus or seizure-related disorders. With status epilepticus, the mortality rate is between 10% and 40%. To determine the seizure type it is recommended to take electroencephalography (EEG). Identification of seizures refers to seizure forecasting focused on EEG before they occur. Using Machine learning algorithms and computational methods, seizures can be identified from EEG or electrocorticography (ECoG) signals which are multifaceted, noisy, non-linear, and produce a high amount of data.

A. Symptoms

The main symptom of seizures is controlling or blocking the normal function of the brain. It diverges based on the infected area of the brain. Other symptoms include various motor manifestations (positive manifestations), loss of self- awareness, transient blindness, paralysis, etc, (negative manifestations).

B. Classification of Seizure

The classification of seizures is followed for 35 years with the old method and revised in the year 2017 which includes unclassified seizures and simplifying JARGON to improve communication between the physician and the patient. Based on ILAE 2017, seizure types are classified into focal onset (seizure starts at any area of the brain), generalized onset (seizure starts at the center of the brain), and unknown onset (seizure starting position is not known).

According to the EEG signal change that is reflected as transient high peaks, it is observed that for generalized seizure signal will have a sharp wave; for absence seizure signal will reflect as a wave with a sharp edge; if the signal has high amplitude without sharp edge, it is defined as photo-convulsive response and if the reflection of signal with high peaks is only on the right side or not spreading, it is defined as a focal type.

II. EEG SIGNALS

In 1923, Hans Berger recorded the first human EEG from multiple electrodes placed on the scalp that measures the voltage variations from the ionic current inside the brain neurons.

TABLE I Frequency bands of EEG signal

S No	Frequency Bands	Frequency Range
1	Delta	Up to 4 Hz
2	Theta	4 Hz to 8 Hz
3	Alpha	8 Hz to 12 Hz
4	Beta	12 Hz to 26 Hz
5	Gamma	26 Hz to 1000 Hz

Table I shows the typical five frequency bands used for analyzing EEG signals. Up to 4 Hz that is predominantly

found in infants and deep sleep stages of normal adults are called the Delta band; from 4 Hz to 8 Hz the signal is in the theta band that is observed in the sleeping stage; the Alpha band is taken in between the frequency range of 8 Hz to 12 Hz usually present in the posterior region of the brain and normal awake and resting stage; frequency range in between 12 Hz and 26 Hz is called the beta band that is present in the frontal region of the brain and awake stage with mental activity; the last band is gamma in between 26 Hz and 1000 Hz frequency range that is predominantly found in stressed, happy or aware person [3].

EEG signal electrodes are placed on the human scalp on an international 10-20 system used for the recording of brain activity with an amplitude of 10 µV – 100 µV. The drawback of scalp EEG is that owing to a large distance between neurons inside the skull and the electrodes, the recorded signals become distorted. Scanning EEG signal recordings visually is complicated and long. So, for better treatment, there is a need for a consistent and computerized system to predict, and classify seizures [4].

A. Analysis of EEG Signals

There are four classifications in EEG analysis, i) time domain, ii) frequency domain, iii) time-frequency domain, and iv) non-linear domain [5].

i) Time-domain: There are four methods in the time-domain analysis of EEG, a) linear prediction – output is calculated from the input and earlier outputs, b) principal component analysis (PCA) –high-dimensional data is transformed into a low dimensional data, c) linear discriminant analysis (LDA) – reduce dimensions of feature sets by finding a linear combination of feature measures, d) independent component analysis (ICA) –high dimensional data is decomposed into linear statistically independent components used to eradicate noise and artifacts.

ii) Frequency-domain: There are two methods in frequency- domain analysis, a) parametric methods- which provide better frequency resolution. Parametric methods that are usually applied are auto-regression (AR), moving average (MA), and auto-regressive moving average (ARMA), b) non-parametric methods – periodogram method used for the valuation of power spectral density (PSD).

iii) Time-frequency domain: Used to obtain a multi- resolution decomposition of sub-band signals by passing EEG signals through filter banks. The time-frequency domain that is commonly used in EEG signals is wavelet transform (WT).

iv) Non-linear domain: used to detect coupling among harmonics in the spectrum of signals. Widely used non- linear parameters in EEG signals are higher-order spectra (HOS), approximate entropy (ApEn), Kolmogorov entropy, sample entropy (SampEn), Hurst exponent (H), largest Lyapunov exponent (LLE).

B. Characteristics of EEG Signal

It is observed that the characteristics of EEG signals are used to identify the different stages of seizure are described below in four states [6]:

a) Pre-ictal state: The initial stage of a seizure, also called an aura occurs immediately before the ictal stage of a seizure. It can last from a few seconds to an hour in duration. It has to be early detected to avoid false warning times.

b) Pro-ictal state: Stage where seizures are more likely to occur but not guaranteed to happen.

c) Ictal and Interictal state: the ictal state is the period of a seizure and the interictal state is the period between two seizures.

d) Post-ictal state: the state after the occurrence of a seizure.

To diagnose a disease, first EEG data is to be decoded and features are extracted by applying Fourier transform (FT) or wavelet transform (WT). These features extracted from the EEG signal pattern models are then used to train a machine learning-based classifier.

C. Development of EEG measures used for seizure prediction

Initially, from 1970 to 1979 seizure prediction was carried out by using linear approaches to identify pre-ictal patterns [7]. Then the development of non-linear methods was employed in 1981 for feature extraction, to identify pre-ictal patterns of EEG signals [8]. In 1983 researchers exposed the change in spike rate before seizure onset [9]. A contradiction to the change in spike rate before seizure onset was raised in 1985 [10].

Primary estimation of seizure almost 6 sec before the seizure onset was developed in 1998, using Kolmogorov entropy [11,12]. In 2003, phase synchronization of different EEG channels was found to decrease before seizure onset [13]. Bi or multivariate measures showed improved results in the seizure prediction during 2005-to 2006 [14,15,16]. Results of seizures predicted by employing bivariate measures and convolutional neural network (CNN) were presented in 2009 [17].

The use of long short-term memory (LSTM) for automatic feature learning from EEG data for predicting a seizure was developed in 2018 [18]. An unsupervised method for seizure prediction using a generative adversarial network (GAN) was proposed in 2019 [19].

III. MACHINE LEARNING TECHNIQUES

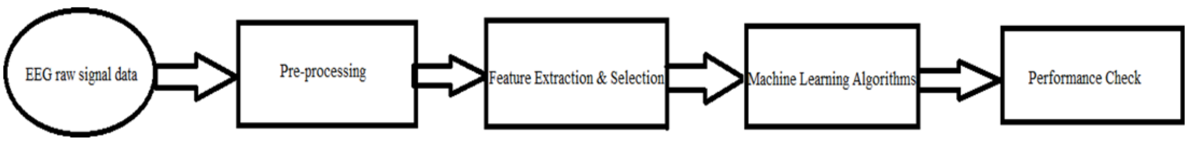

Fig. 1 Process of seizure prediction using a machine learning approach

The various machine learning techniques used in the field of neuroscience are i) supervised learning – used in the field of theoretical and computational neuroscience [20], ii) unsupervised learning – used in the identification and classification of diseases through perceptions [21], and iii) reinforcement learning – the process of developing a policy to maximize the rewards of interaction between an agent and its environment [22].

Using a support vector machine (SVM) to classify preictal and ictal states of EEG signals sensitivity to predict a seizure is 73.9% [23]. Other classification methods in machine learning algorithms are radial basis function (RBF), multilayer perception (MLP), etc. After removing artifacts by pre-processing step using filtering techniques sensitivity is increased to 75.8% [24]. The sensitivity is improved to 88% by using wavelet energy and wavelet entropy features to train the neural network [25]. Based on zero-crossing by EEG scalp signals with 22.5 minutes predicted time, the sensitivity is improved by 88.3% [26].

A. Seizure Prediction using Machine Learning Approach

For the machine learning approach, EEG raw data signal is pre-processed by using filtering techniques to remove noise and artifacts as shown in fig.1. Band-pass filter, wavelet filter, finite impulse response filter, and adaptive filter are some of the common techniques used in the signal processing stage. Chebyshev filtering method enhances seizure prediction among other filtering methods.

Based on univariate and multivariate features, all reliable features are predicted with pre-ictal and interictal stages. For pre-ictal changes, bivariate measures are categorized to perform better than univariate measures. Similarly, the performance is better in linear measures compared to non- linear measures [27]. Various numerical methods like linear predictive coding (LPC), kurtosis, mean, auto-correlation, and PCA are considered to train the neural network for further EEG signal classification. These features are extracted by using EEG signal analysis methods. Extracted features are selected then by using reduced dimensions.

Various machine learning algorithms are used to classify the pre-ictal and interictal patterns from EEG data signals. The machine learning algorithms that are frequently used in the classification for predicting seizures are back-propagation, K- nearest neighbor (KNN), learning vector quantization (LVQ), self-organizing map (SOM), feed-forward, normalized correlation, hamming distance, SVM, weighted
Euclidean distance, artificial neural network (ANN), k- means clustering, fuzzy logic.

IV. CONCLUSION

In this paper, we systematically reviewed the context of seizures, analysis of EEG signals, processes involved in the prediction of seizures by using machine learning algorithms, and the evaluation of algorithms. We also discussed the various survey papers focused on EEG signals with specific sensitivity rates for predicting a seizure. We also tried to provide some insights into the aspects of pre-processing, feature extraction, feature selection, and prediction techniques using machine learning models, etc,

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