Epilepsy detection has been studied extensively since the 1970s. Early, statistical methods and classical machine learning techniques were used for Epilepsy classification. But due to the data complexity, the researchers started applying deep learning to this problem. Since 2016, many deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Belief Networks (DBN), Autoencoders (AE), Long short-term memory (LSTM), and generative adversarial networks (GAN) have been used to identify epilepsy.

Classification of EEG signals into epileptic and nonepileptic involves extracting features from the EEG signals and using these features in training a machine learning model. In the literature, several feature extraction approaches and several classification methods are used. Several groups used the Discrete Wavelet Transform for feature extraction and then they applied different machine learning algorithms.

In 2017, Sandeep Kumar Satapathy and Alok Kumar Jagadev decided to use a semi-automatic tool in the framework of machine learning to understand the EEG signals and to predict epilepsy seizures. Using Bonn University—EEG Dataset, their primary focus was on two main techniques: neural networks and support vector machine (SVM); for neural network approach probabilistic neural network, radial basis function neural networks, and recurrent neural networks are taken into consideration for empirical analysis on EEG signal to detect epilepsy seizure. Furthermore, for SVM, several kernel methods were studied such as linear, polynomial, and RBF during empirical analysis. With wavelet transform as the data analysis technique and some of the statistical features of many have been extracted from the signals such as Minimum (MIN), Maximum (MAX), MEAN, and Standard Deviation (SD), the efficiency of different machine learning techniques like MLPNN, RBFNN, RNN, PNN, and SVM have been compared, and concluded that SVM is the most efficient and powerful machine learning technique for the purpose of classification of the EEG signal with accuracy of 99.1% but extremely high detection time.[2.1]

Later that year, another study done by Duo Chen et al. in the hope for developing a framework for automatically searching the adequate DWT settings to improve accuracy and to reduce computational cost of seizure detection, they developed a method to decompose EEG data into 7 commonly used wavelet families. The selection of frequency bands and features removed approximately 40% of redundancies. With two different datasets Bonn University and Children’s Hospital Boston and the Massachusetts Institute of Technology (CHB-MIT) EEG-Datasets, their proposed algorithm is constructed by two main selection blocks, a Wavelet-Level Selection (DWT coefficient features from several frequency bands construct the feature vector of one EEG signal segment) and a Band-Feature Selection. A support vector machine (SVM) and RBF kernel was used as the classifier. To assess the performance of the approach, especially its ability to overcome individual difference, they used leave-one-subject-out cross-validation on MIT dataset which was a fair evaluation scheme to truly reveal the robustness of the classifier on overcoming the individual difference. Since UBonn dataset did not separate the data from different patients, 10-fold cross validation was used instead of leave-one-subject-out. On MIT dataset, decomposition level affects the accuracy substantially regardless of the mother wavelets. On UBonn dataset wavelets could achieve high accuracy (above 95%) at low decomposition level (less than 2). UBonn dataset, Compared with the results in MIT dataset, EEG segments in UBonn could be accurately classified at very low decomposition level, however, in other cases, including this work, these properties of wavelet do not matter at all. On dataset having complex EEG signals (contain hidden information distribution in several frequency bands), like MIT dataset, decomposition level influences accuracy substantially regardless of the mother wavelet and running the process is very time-consuming, especially when using various wavelet families and long-time continuous EEG segments.[2.2]

Shuang X. Wang et al. on the other hand involved a novel random forest model combined with grid search optimization in the proposed automatic detection framework in 2019. The short-time Fourier transformation visualizes seizure features after normalization and used to conduct the time-frequency analysis of non-stationary EEG signals. The dimensionality of features is reduced through principal component analysis before feeding them into the classification model which was used to classify 500 samples of raw EEG data. In this study, the time-frequency analysis method is used to extract the time-frequency characteristics of EEG signals. At the same time, the statistical characteristics of EEG signals are extracted by statistical techniques, thus the best combination of feature extraction and feature classification is realized. Noninvasive EEG data was obtained at Bonn University from 25 patients with medically intractable partial epilepsy, the dataset was divided into five groups of ictal scalp EEG signals. And EEGLAB toolbox of Matlab was used to preprocess the cEEG. To ensure the credibility of the test results, they performed an arithmetic average processing. This paper uses the improved GSO to identify RF by computer. The GSO algorithm refers to meshing the variable regions, then traversing all the grid points, solving the objective function values satisfying the constraints, and selecting the optimal values. Although the proposed RF-GSO classification model has excellent classification performance with accuracy of 96.7 the model had low sensitivity and specificity for multi-class.[2.3]

Another approach done by Paschalis Bizopoulos et al. in 2020, beside the choice of the EEG epileptic seizure recognition dataset from University of California, Irvine (UCI) for EEG classification, the implications of this study could be generalized in any kind of signal classification problem. Here we also refer to CNN as a neural network consisting of alternating convolutional layers each one followed by a Rectified Linear Unit (ReLU) and a max pooling layer and a fully connected layer. For the CNN modules with one and two layers, the input is converted to an image using learnable parameters. They restricted the output for the model to a 178 × 178 image to enable visual comparison. CNN DenseNet201 achieved the best accuracy of 85.3% with training time 70seconds/epoch on average. The two layer CNN S2I achieved worse even compared with the 1D variants. Another outcome of these experiments is that increasing the depth of the base models did not increase the accuracy which is inline with previous results.[2.4]

Until recently, the general belief in the medical community was that epileptic seizures could not be anticipated. Seizures were assumed to be abrupt transitions that occurred randomly over time. However, theories based on reports from clinical practice and scientific intuition, like the “reservoir theory” postulated by Lennox, existed and pointed out to the direction of seizure predictability. Various feelings of auras, that is, patients’ reports of sensations of an upcoming seizure, exist in the medical literature.[2.5] Even though seizure detection and prediction is an ongoing research. So far many different approaches using machine learning and deep learning have been tried by several researchers on seizure prediction.

In 2017, U. Rajendra Acharya et al. developed a computar-aided diagnosis (CAD) system to distinguish the class of EEG signals from Bonn University, Germany if normal, preictal, or seizure class using machine learning techniques. The EEG signals were normalized with Z-score normalization, zero mean and standard deviation of 1,then they were divided into 10 equal portions, nine out of ten were used to train the CNN while the one tenth was used to test the performance of the system. The model achieved 88.67% accuracy.[2.6]

Thara D Ka, B G PremaSudhab, and Fan Xiongc in 2019 experienced epileptic seizure detection using Long Short Term Memory (LSTM) approach on BONN university dataset resulting in 99.08% accuracy. Meanwhile seizure prediction was conducted using the same dataset by classifying preictal states of EEG from interictal and ictal states and the model could identify the pre-ictal state with the overall sensitivity: 89.21% and false prediction rate: 0.06.[2.7]

In this study, I Wijayanto, S Hadiyoso, S Aulia, and B S Atmojo in 2020 extracted the EEG signal pattern by using the Higuchi fractal dimension to classify the ictal and interictal conditions of EEG signals from Bonn University Dataset. The features were extracted from five EEG sub-bands, delta, theta, alpha, beta, and gamma band and fed to support vector machine model. The experiment shows that the use of HFD and the quadratic kernel is suitable for ictal detection with average accuracy of 91.1%. While the use of cubic kernel and HFD is suitable for detecting interictal conditions with average accuracy of 94.1%.[2.8]

Meanwhile, in 2021, Adnan Salman offers a model based on a two-dimensional Convolution Neural Network (CNN), that provides a reliable strategy for both preprocessing and feature extraction. The model is used to categorize EEG signals from university of Bonn dataset into normal vs intericatl vs ictal instance, and in order to improve training and generalization accuracy, they adopted an augmentation technique to expand the size of the data set. This model achieved 97.8% accuracy.[2.9]

In this research, H O Lekshmy, Dhanyalaxmi Panickar and Sandhya Harikumar focused on the performance of various machine learning techniques (Logistic regression, Naive Bayes, Random Forest, and K- Nearest neighbor, Artificial neural network, Convolutional neural network, Long short term Memory technique and Auto Encoder) on EEG data to find the best algorithm that perform well on the Bonn university dataset as the primary dataset and CHB-MIT dataset to validate the results. The EEG signals shows different potential at different frequencies, so a conversion from the time- amplitude domain into the frequency-time domain was needed using Wavelet transform (WT). Random Forest classifier has performed remarkably well in terms of specificity, sensitivity and with 97%accracy. Among deep learning algorithms, Long Short Term Memory (LSTM) is the best performing model with 98% accuracy. Random Forest is less computationally expensive when compare with the Long Short-Term Memory (LSTM) model. Long Short-Term Memory (LSTM) model performance can be effectively increased with the help of GPU acceleration. Random Forest supports variability of data, while LSTM is more suitable for time-series data. Long ShortTerm Memory (LSTM) model has a provision for avoiding long dependencies this makes our predictions more accurate when compared with other models. The main problem with Long ShortTerm Memory (LSTM) model is, it requires a large amount of data for training purposes.[2.10]

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