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PREDICTING THE ONSET OF EPILEPTIC SEIZURES IN INDIVIDUAL PATIENTS USING DEEP NEURAL NETWORK

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Abstract

Epilepsy is the most prevalent neuro disorder in the world, may impair brain function or even put the patient's life in peril. Seizure control requires epilepsy prediction, which enables preventative actions to lessen harm or manage seizures. It has been shown that abnormal brain activity begins in the pre-ictal state, that occurs before a seizure begins. In this research, the pre-ictal period's temporal span was reevaluated and split into many temporal windows. Then it was suggested to use deep neural network to create a specific seizure prediction method. By making use of the strategy, the temporal dependence of the signal across several time frames throughout the pre-ictal phase is represented. Additionally, by implementing a soft threshold blurring and focusing procedure inside the neural network, seamless feature extraction is made possible. The outcomes of our approach are contrasted with those of more contemporary epilepsy prediction techniques. Our approach still has certain shortcomings when compared to the finest methods, but it also exhibits several novel ideas and benefits.

Keywords: Epileptic seizure, Seizure detection, Deep learning, Convolutional neural networks Scalp electroencephalogram.

1.Introduction

Epilepsy, a brain illness, affects all ages. Epilepsy is world's most prevalent neurological illnesses, affects millions of individuals worldwide. If detected and treated with anti-epileptic medications, 70% of epilepsy patients might live seizure-free.Mostly drug-resistant patients need surgery and/or electrical stimulation.This disease's cause is unknown. Seizures may be treated if caught early. Patients cannot drive or work due to this ailment. Thus, a device that predicts seizure could improve their lives. This warning gadget alerts the patient to prevent mishaps or take seizure-suppressing medicines when it anticipates a seizure.Epilepsy diagnosis relies on the electroencephalogram (EEG). Electrodes on the patient's scalp capture brain impulses for EEG recordings[1]. Experts visually evaluate seizure signals obtained during EEG sessions to diagnose utilizing EEG signals. This method is costly, error-prone, and sluggish. Two independent specialists often view the same electroencephalogram differently. This might lead to mistreatment.

Gibbs' electroencephalogram (EEG) of the scalp has been used to detect partial-onset seizures (PWE) since its invention in 1935.[2]. Long-term clinical significance requires several days of observation. It requires experience for an epileptologist to interpret an EEG and detect a seizure. Therefore, it is crucial for EEG reading efficiency to have automatic seizure detection. With automated seizure detection, neurostimulation and medication delivery on demand may be feasible.

Time-frequency analysis, wavelet transform, and nonlinear analysis may depict seizures in EEG signals. The success of most of these conventional techniques is patient-specific since epileptic EEG patterns vary[3-5]. Seizure identification by EEG is difficult since seizures are usually recorded for just a few minutes in 24 h because EEG includes noise and abnormalities. Thus, no hand-crafted features seem universal yet. Deep learning technology automatically learns important features in supervised learning to tackle these challenges. Recent research showed that deep learning can classify EEG data[6-9].

We hypothesized that experienced epileptologists, rather than relying on automatic seizure diagnosis using spectro-temporal or complicated, non-stationary EEG signals, would perform visual analysis of EEG plot images to detect seizure states[10,11]. If this is the case, CNNs that mimic the performance of human visual recognition experts might be useful in the identification of seizures. In this study, epileptologists manually categorized EEG data into seizure and non-seizure categories before feeding them into a CNN.Predicting seizures was first studied in the 1970s.Epileptic EEGs have four phases: preictal, ictal, postictal, and interictal is illustrated in figure 1.

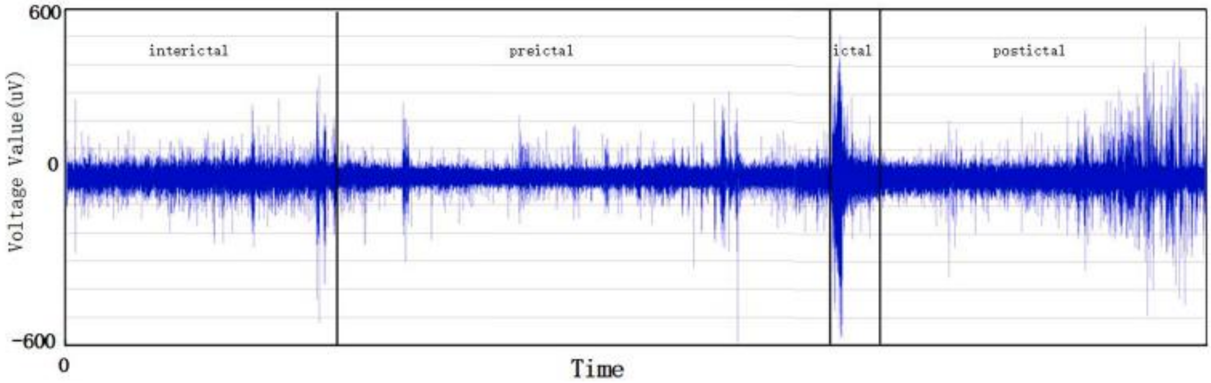

Fig. 1: Epileptic EEG activity States.

The preictal phase is before the seizure start, the ictal phase is the seizure itself, and postictal period is immediately after, and another interictal phase is the seizure-free time between one seizure and the next. Interictal-to-preictal transition detection predicts seizures. Electroencephalograms have been employed in many brain activity investigations [12-15]. Seizure prediction algorithms were first threshold-based, raising warnings when an EEG biomarker (feature) exceeded a threshold. However, these linear models based on just one characteristic may not be enough to understand pre-seizure activity.Later, basic machine learning methods worked for some patients. These algorithms might create relationships between EEG biomarkers, helping models discover pre-seizure tendencies. Deep learning architectures are being employed in more research fields[16-20]. These architectures may extract information straight from the data without computing created characteristics before categorization. These models choose the finest features, involving fewer feature design and domain knowledge to build intelligent systems. Although beneficial without physiological grounding, machine learning models are black boxes. Thus, academics are exploiting EEG signals or their various aspects to build seizure prediction systems. While using deep learning, some researchers still use traditional signal processing to extract features. Other issues are as important as seizure prediction algorithm complexity. EEG preprocessing. Researchers are using non-invasive EEG to predict seizures. These transmissions generally have artifacts reduce false alarms by removing EEG distortions before building seizure prediction models. Low-pass filters diminish high-frequency noise while high-pass filters remove DC noise. Das wavelet-decomposed noise. Usman reduced artefacts using empirical mode decomposition. Prathaban pioneered sparsity-based EEG reconstruction. All authors improved seizure prediction by removing artefacts[21-25]. No work tested noisy and denoised models for data prediction.

Typically, seizure prediction models are trained on initial chronological episodes and evaluated on subsequent seizures without taking concept drifts through time into account. These variations in data distribution may be brought on by seizure activity, changes in antiepileptic medication type or dose and biological cycles such as circadian rhythms, which may affect brain dynamics. For training computational models, a different strategy is needed to handle concept drifts. Many authors put forth solutions that relied only on routinely updating the models. Kiral-Kornek made use of EEG data gathered over a period of time. They allowed the machines to adjust over time by retraining them each month and removing old data after a particular number of months[26,27]. Pinto made advantage of EEG data gathered before to surgery. As a result, they only used information spanning a few days and not data from many months. After testing with a fresh seizure, they retrained their models. Only Nejedly was able to confirm that there had been an improvement in prediction performance, despite the fact that those investigations had attempted to address concept drifts. The current work discusses several significant issues that must be resolved while creating seizure prediction algorithms. We tested a deep neural network-based EEG glitch reduction model that replicated expert manual preprocessing on prediction performance. We also examined how updating models over time affected idea deviations. In conclusion, denoising and idea drifts in homemade feature-based learning systems and models fed EEG time data are comprehensively evaluated.

This work resolves significant problems with seizure prediction models. An expert-like deep multilayer deep neural network-based EEG deformation reduction model was used to examine the performance of predictions. Models were retrained to solve idea drifts. A simple artificial neural network trained on handmade features was contrasted to a deep convolutional neural network learned on EEG time data.

2.Proposed Methodology

In the seizure forecasting pipeline, EEG data is preprocessed using digital frequency filtering and testing mistakes. Following this, the pipeline splits into two different paths: one that produces denoised EEG time-series data, which is free of physiological artifacts, and another that does not. From the data, we obtained both clean and noisy EEG measures. Both EEG time series and EEG features are used by deep neural networks. Separate training and testing sets are then created from each dataset. Both the standard strategy, which learns once and tests on the rest of the epileptic fits, and the chronological method, which updates after each test seizure, are employed on the datasets to generate seizure prediction models. Figure 2 shows the research pipeline. Since each model is patient-specific, this pipeline is run for each patient.

2.1.Preprocessing

Lopes' approach was based on the three-stage model used in professional hand signal preparation. The first filtering was done using a second-order notch filter at 50 Hz and a fourth-order bandpass filter at 0.5-100 Hz. The program then got rid of things like high amplitude data, saturated sections, and flatlines that were deemed to be experimental errors. Elements known to contain artifacts were also removed. The first 30 minutes of each epileptic signal were discarded to eliminate postictal effects. Ten second EEG windows were developed at last. The entire time spent on data preparation is 4650 hours.

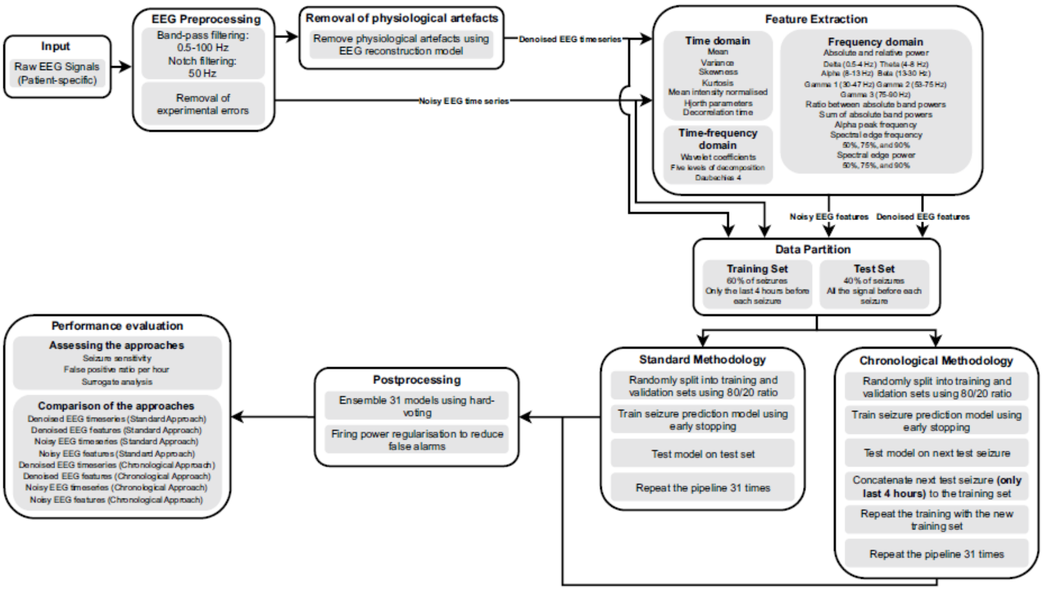

Figure 2. Seizure prediction pipeline

2.2.Feature extraction

We recovered EEG features using signal processing on previously collected data. Time-domain linear univariate features included skewness, mean, normalized mean intensity, variance, kurtosis, Hjorth parameters, and decorrelation. Frequency-domain linear single-variate characteristics included absolute and relative band powers (delta: 0.7-3.9 Hz, theta: 3.9-8.5 Hz, alpha: 13.6-13.8 Hz, beta: 13.6-30.8 Hz, gamma 1: 47.5-52.5 Hz, gamm Time constraints meant that only linear, univariate features could be analyzed.

2.3.Seizure Prediction pattern

Developing and testing seizure prediction models requires SOP and SPH. Fig. 2a shows that the SPH gives the patient time to take precautions before a seizure occurs, whereas the SOP is the seizure itself. Preictal samples, obtained before the seizure, match the SOP during training. The SPH samples from the preliminary preictal samples until the seizure start are not analyzed. In the event of a real alert, the individual in question will have a time frame equivalent to the SPH to take remedies before the predicted seizure, which will occur inside the SOP. The best SOP has never been agreed upon. Grid search or unsupervised research has been done to discover it. The articles above suggest a SOP of 30–60 minutes. Researchers have been employing a 30-minute SOP because it is within the ideal range of SOPs found in prior studies and is short enough to reduce patient worry. Our research employed a 30-minute SOP. Patients might use a seizure-suppressing medicine since the SPH was 10 minutes. Up until forty minutes before the onset of a seizure, all samples had been categorized as interictal (class 0). Class 1 learning SOP samples were preictal. Rejected SPH training samples. Figures 3 depicts a valid alert as well as two false alarms.

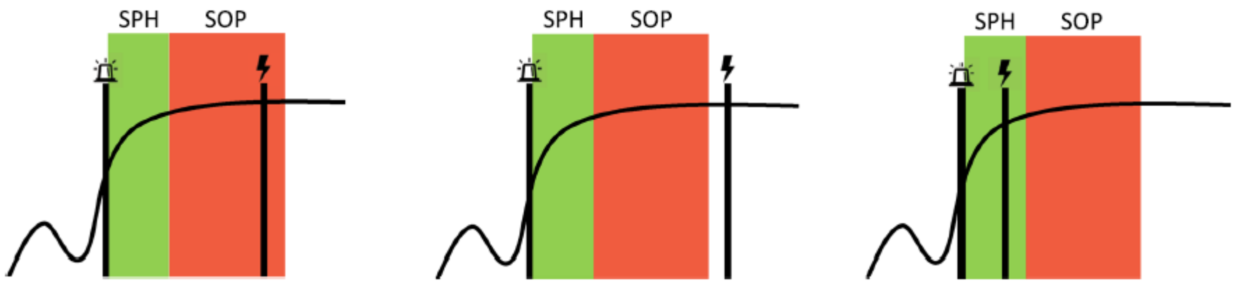

Figure 3. Representation of seizure prediction model training and alert criteria.

2.4.Experimental Data Usage

The first 60% of the seizures were used as training for this division, which was carried out chronologically. As previously mentioned, data pretreatment entailed removing certain data that couldn't be utilized. Because of this, it was unable to accurately forecast certain seizures during testing due to a lack of preictal data. In order to preserve the 60/40 ratio, one test seizure from patient had to be eliminated, and both sets from that patient were updated. Finally, we only utilized the four hours before to the commencement of each seizure during the training phase to shorten the calculation time. For each seizure in the test set, all the data from 30 minutes from the start of the preceding seizure to the start of the seizure under examination were included.

2.5.Artificial neural network architectures

Figure 4 shows CNN-BiLSTM architecture. It has three convolutional blocks and another bidirectional LSTM layer. Each block features two layers of convolution, one of which is a capable of learning pooling layer with stride 2. Each block also has a 50% spatial dropout layer, a swish activation layer, and a batch normalization layer. Eq. 1 describes the swish function.

$$f(x) = x \times \text{sigmoid}(x) \quad (1)$$

The numerical values for each property were discovered using a grid search process.There was no attribute selection performed before classification, thus the little neural network had no way of knowing which features may boost its prediction accuracy the most. To prevent overfitting caused by the limited size of the training data, dropout layers at a 50% rate were used for both neural networks.

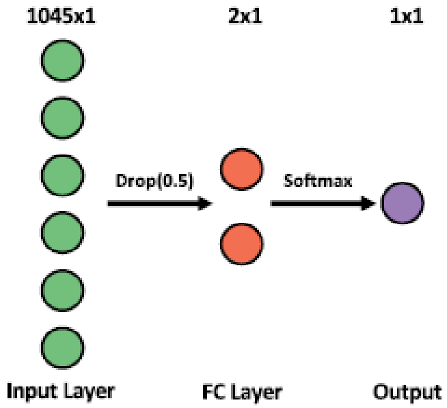

Figure 4. Architecture of Neural Network

Both grid searches utilized the same training sample of 10 patients. We estimated the geometric averages of specificity and sensitivity using the most recent seizure data from the training set to evaluate the hyperparameters. For each possible permutation and patient training set, the grid search was run three times to evaluate results and choose the best hyperparameters. The data was averaged out. All the models developed for the patient used the selected attributes.

3.6.Training Strategy

Standard and chronological methods were used to train our patient-specific models. Epilepsy prediction models were traditionally built using a static training set and evaluated on new seizure data. Learning seizure prediction models using one set of epileptic fits, testing on the next seizure, merging the new seizure (EEG signal and labels) with the old training set, and so on, constituted the chronological training. Partitioning and standardizing the data was done whenever the training set was changed. We ran both procedures 30 times each, yielding 30 models for use in a resounding voting ensemble, the size of which is sufficient to exclude the possibility of a tie. Furthermore, in a practical setting, it is impractical to have 30 unique displays for each patient. The majority vote ensemble helped minimize the variance across the seizure prediction models, narrowing the field from 30 models down to just one.

We created neural networks with 64-sample batches of 32 interictal and 32 preictal datasets. Duplicating preictal samples overestimated the minority class to even out the classes. Early halting normalization with a 40-epoch patience prevented overfitting after 500 training epochs. Adam, with a 3e4 starting learning rate, was the optimization method. Binary cross-entropy was the loss function. Early stopping requires a validation set to continually assess model overfit. Thus, we randomly split the training set into a new training set and a validation set 4/1. The samples were divided 4/1, unlike the seizure-level data partitioning. A training-derived z-score normalized training, validation, and test sets. Table 1 summarizes training conditions. Firepower regularization decreased false alarms. A SOP-sized moving window collects sample projections.

Table 1. Parameters for training Neural Network

Attributes	**Value**
Data Set	4/1
Function Used	Adam
Rate of Learning	3e−4
Error function	Binary cross-entropy
Epochs	400
Patience epochs (early stopping)	40
Runs	30

The movable window alarms when the preictal instant ratio surpasses 0.5. We employed a 40-minute refractory period after each alert. Models did not alarm throughout this time. Refractory intervals protect the individual from being flooded with alerts.

3.7.Post-processing

The method involves employing a window that is shifting with a dimensions equivalent to SOP, that collects the predicted output of multiple samples. The movable window alarms when the preictal instant ratio surpasses 0.5. The SPH and SOP periods were concatenated to create a 40-minute refractory time after each alert. Models did not alarm throughout this time. Refractory intervals protect patients from being overloaded with alerts. Our firing power implementation is adapted from Teixeira et al. We adjusted the approach to manage temporal gaps from disconnected windows after preprocessing. Thus, the firing power treats gaps as many windows that have a null value, reducing until it reaches zero.

3.8. Performance Assessment

We used three metrics—seizure sensitivity, false alarms per hour (FAPH), and the number of people with above-chance performance as measured by surrogate analysis—to evaluate the accuracy of the seizure model's predictions. Using Equations 2 and 3, the sensitivity to seizures and FAPH were calculated.The ratio of the total number of real alarms to the total number of experimental seizures is known as sensitiveness of seizure (SS).

$$\text{Sensitiveness of Seizure(SS)} = \frac{Real\ Alarms}{Total\ Experimental\ Seizures} \qquad (2)$$

The rate of false alarms per hour is the ratio of the number of alarms that are false (#FalseAlarms) to the whole length of the interictal phase (InterictalDuration) without the intervals soon after false alarms when no new alarm may be triggered (#FalseAlarms × RefractoryDuration).

$$\text{FAPH} = \frac{Alarm_{false}}{Length_{\mathrm{InterIctal}} - \mathrm{Alarm}_{\mathrm{false}} \times \mathrm{Length}_{\mathrm{Refraction}}} \qquad (3)$$

The substitute analysis uses the technique of Monte Carlo and moves seizure at random.This approach is used to see if the models do better than what would be expected by chance. When a level of significance of 0.05 is used, seizure forecasting techniques are said to perform better than chance if their results are statistically significant and better than the results of the substitute. The results of the analysis is tabulated in table 2.

Table 2. Prediction of seizures algorithms' average outcomes

Approach	Sensitivity of Seizure	FAPH	Above Borderline (%)
Standard Denoised EEG	0.17±0.23	0.29±0.45	13 (0.27)
Chronological Denoised EEG	0.19±0.21	0.21±0.21	16 (0.41)
StandardDenoised Features	0.32±0.32	0.88±0.94	22 (0.52)
ChronologicalDenoised Features	0.35±0.34	0.84±0.73	23 (0.56)

StandardNoisy EEG	0.12±0.22	0.32±0.55	9(0.21)
ChronologicalNoisy EEG	0.16±0.21	0.23±0.21	15 (0.36)
StandardNoisy Features	0.33±0.35	0.91±1.07	21 (0.47)
ChronologicalNoisy Features	0.31±0.33	0.81±0.61	22(0.53)

Denoising EEG data and retraining the algorithms were examined to generate patient-specific seizure prediction models. Deep neural networks and shallow neural networks were employed to create the prediction models.Lopes et al. designed and tested the EEG artefact reduction model for EEG signal reconstruction. Next, we wanted to see whether artefact reduction might enhance seizure prediction. The artefact removal model denoised EEG data before generating seizure prediction models, improving seizure sensitivities, FAPH values, and patient performance above chance level in most situations.

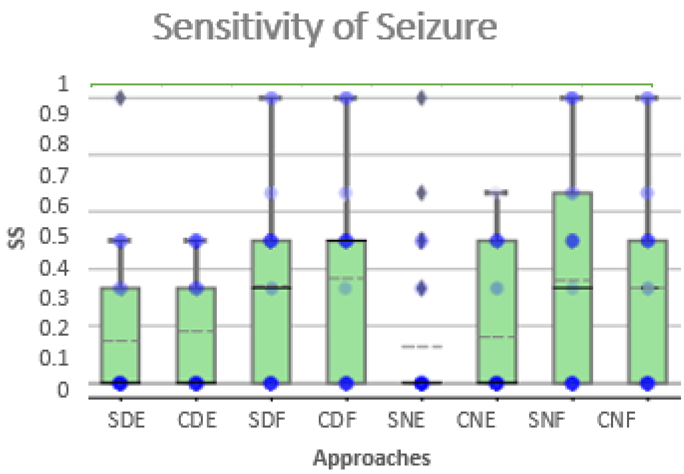

Fig. 5. Sensitivity of Seizure- A comparison of various approach

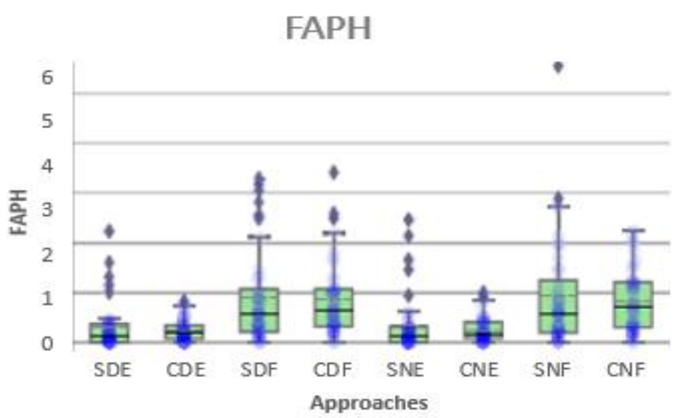

Fig. 6.FAPH- A comparison of various approach

Various measures showed various retraining behaviors. The seizure sensitivity as illustrated in figure 5. Retraining enhanced FAPH and the number of patients performing above chance were illustrated in figure 6 and 7 . Thus, chronological training helped models adjust to idea drifts or have more training data. This reduced false alarms and increased patient performance above chance level.Deep learning models have lower seizure sensitivity and FAPH values due to their cautious alarm firing. Due to their lesser sensitivity, deep learning models had fewer patients performing above chance.

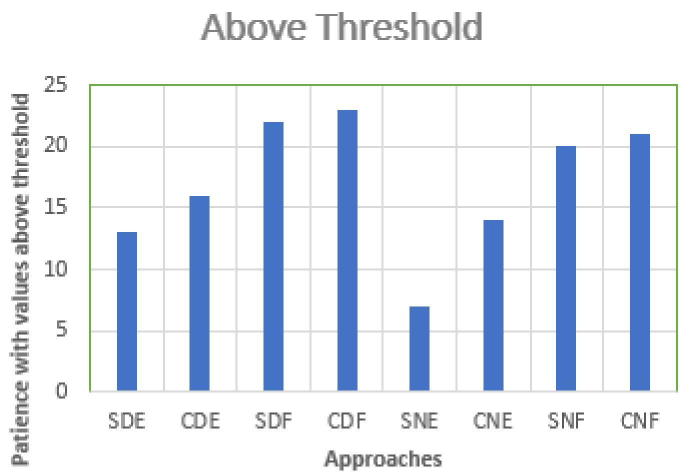

Fig. 7.Above Threshold- A comparison of various approach

Surrogate analysis could not verify models that failed to forecast test seizures, hence fewer patients performed above chance.After denoising technique and chronological training, deep learning models outperformed shallow neural networks. Data-driven deep neural networks.EEG time series characteristics are automatically retrieved. Feature-based models acquire knowledge utilizing equation values from years of study. Retraining just adjusts categorization model weights. Thus, deep learning architectures, adjusting to the input training data distribution, may be more impacted by input data amount, quality, and temporal closeness to the next seizure.

Conclusion

This paper discusses the importance of sturdy preprocessing for eliminating noisy artefacts from EEG signals, such as ocular artefacts, and the need to periodically retrain seizure forecasting algorithms to account for concept drifts. Denoising data and retraining models enhanced deep learning performance. Denoising and retraining had little impact on basic neural networks utilizing handmade features as input, suggesting that customized characteristics were more data-resistant. Shallow neural networks with handmade features predicted twice as many seizures as deep learning models. False alarms were four times greater than deep neural networks. Thus, comparing both models yields no clear winner. These methods should be evaluated with additional patients and prospective data. These methods should be tested with additional test seizures and extremely long-term acquisition system signals. This research examines epilepsy pre-seizure. A temporal window accurately predicted epilepsy. Many areas need upgrading. To increase results and forecast efficiency, the model might be parameterized or simplified. Non-patient-specific seizure prediction will be researched.

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