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Using scalp EEG and intracranial EEG signals for predicting epileptic seizures: review of available methodologies

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Abstract

Patients suffering from epileptic seizures are usually treated with medication and/or surgical procedures. However, in more than 30% of cases, medication or surgery does not effectively control seizure activity. A method that predicts the onset of a seizure before it occurs may prove useful as patients might be alerted to make themselves safe or seizures could be prevented with therapeutic interventions just before they occur. Abnormal neuronal activity, the preictal state, starts a few minutes before the onset of a seizure. In recent years, different methods have been proposed to predict the start of the preictal state. These studies follow some common steps, including recording of EEG signals, preprocessing, feature extraction, classification, and postprocessing. However, online prediction of epileptic seizures remains a challenge as all these steps need further refinement to achieve high sensitivity and low false positive rate. In this paper, we present a comparison of state-of-the-art methods used to predict seizures using both scalp and intracranial EEG signals and suggest improvements to

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existing methods.

Keywords: Epilepsy prediction, Preictal state, Scalp EEG, Intracranial EEG

1. Introduction

Epilepsy is a common neurological disorder in which patients suffer seizures. Being able to predict the onset of a seizure before it occurs is important since this may facilitate the prevention of accidents and injury that can occur during seizures and additionally may help with pre-seizure delivery of medication or other interventions [1]. Electrical activity in the brain can be monitored using electroencephalogram (EEG) signals [2], which can be recorded from the scalp of patients, referred to as scalp EEG [3], or by implanting electrodes inside brain tissues during surgery, referred to as intracranial EEG signals (iEEG) [4]. During any seizure, electrical activity in the brain changes abruptly and can be monitored using EEG signals.

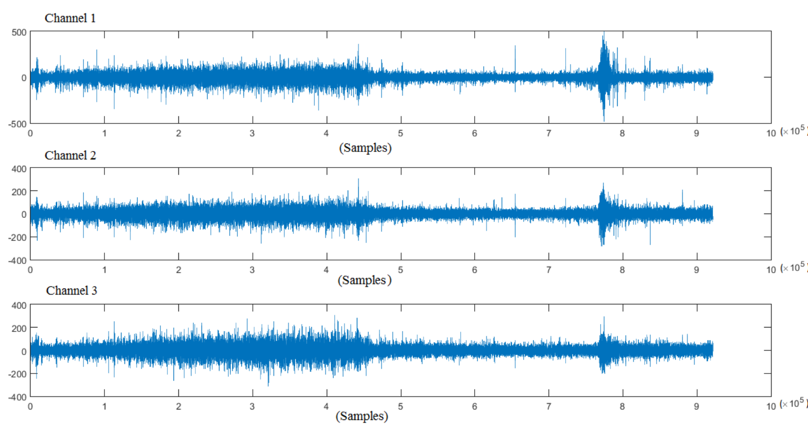

Figure 1: Interictal, preictal, ictal and postictal states of seizures from three channels of 1-hour recordings.

Figure 1 shows plots of multiple-channel EEG signals of 1-hour recordings of the first three channels of recordings. The preictal state is of interest as it starts some minutes before the seizure and the timely detection of the start of the preictal state may be used to help prevent seizures [5]. Detecting the preictal state involves a distinction between the interictal state and the preictal state [6]. In a typical seizure prediction system, EEG signals are sampled at a rate of 200 Hz [7] to 5000 Hz [8] within a window of 1-5 seconds. When an EEG signal is classified as preictal, an,alarm can be generated to trigger medication, stimulation or to take physical measures to prevent injury [9]. Researchers [10–25] have proposed a variety of machine learning methods for the prediction of seizures. However, obtaining a high sensitivity rate of classification between the interictal and the preictal state and low false positives remain a major challenge. A typical model for predicting seizures consists of preprocessing of EEG signals for (i) noise removal, (ii) feature extraction and selection for reducing large amounts of data, (iii) classification for differentiating between the preictal and the interictal state and (iv) postprocessing for decreasing false positives. Researchers have used the Butterworth filter [17], notch filter [18, 26–30], and common spatial pattern filter [31] in pre-processing to remove noise from the EEG signals that appeared during the recording of these signals. Many studies have also applied empirical mode decomposition [31], continuous wavelet transforms [32], and discrete wavelets transform [33] in preprocessing. Multiple features in the time domain have been extracted by a variety of methods, including statistical moments [31], spectral entropy [34], approximate entropy [35][36], and Hjorth parameters [37], including mobility and complexity. Frequency domain features include power spectral density, signal energy, and spectral moments [31]. A few studies have used Principle Component Analysis (PCA) [38–41] for feature selection. Once features have been extracted, classification between the interictal and the preictal state is required. Different studies have shown that Support Vector Machine (SVM) [17][41–48] has performed as a better classifier than others for differentiating the preictal and the interictal states. However, current studies have also successfully used convolution neural networks (CNN) [19] for classification. For postprocessing methods different researchers have applied Kalman filtering [10][49][50][44], and statistical validation methods, including random predictor [51], bootstrapping [32], and Poisson predictor, have been used as postprocessing methods.

Many datasets of EEG signals for humans and canine are publicly available, including scalp EEG dataset and intracranial EEG signals. We will compare methods on two datasets only. Features are extracted by dividing the samples into groups of multiple seconds known as windows, which are selected from a fixed length of EEG signals (one second to a few minutes). A nonoverlapping window is more suitable in many cases for the prediction of seizures.

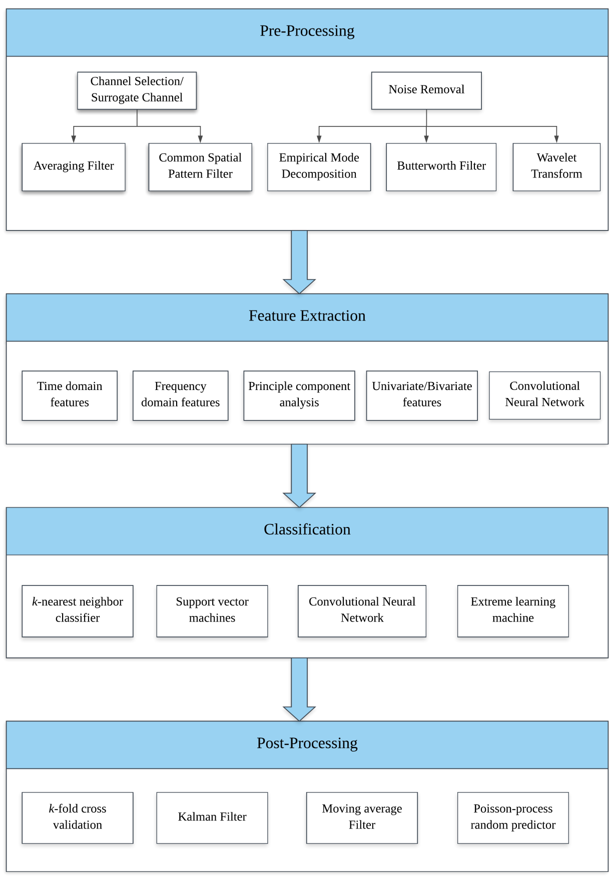

Figure 2: Epileptic seizure prediction system

In this paper, we present a comparison between multiple epileptic seizure prediction methods using scalp EEG and iEEG datasets. Section 2 discusses the latest developments in seizure prediction methods. Section 3 presents a detailed overview of publicly available EEG datasets, Section 4 explains the measures of evaluating the methods, Section 5 gives a detailed analysis of existing methods, and Section 6 summarises the existing methodology and suggests potential improvements to current techniques.

2. Epileptic Seizures Prediction Methods

EEG signals can be divided into two types based on the method of recordings: scalp EEG signals [52], which are recorded by placing electrodes on the scalp of the subjects, and intracranial EEG (iEEG) [53, 54] signals, in which electrodes are implanted on the brain by performing surgery. Figure 2 shows a flowchart of a typical epileptic seizure prediction system. The phases of the prediction system are (i) data acquisition, (ii) preprocessing of EEG signals, (iii) feature extraction, (iv) classification, and (v) validation of results in the postprocessing step. We will discuss each part in detail in the following subsections.

2.1. Preprocessing

Preprocessing of EEG signals is required to remove noise and can be achieved by converting a multiple channel EEG signal into a surrogate channel [55, 56] or by applying band-pass filters. A surrogate channel can be obtained by averaging or by applying Common Spatial Pattern (CSP) filtering [31][57]. Researchers have also applied the Butterworth bandpass filter [17][58–60], notch filter [18], wavelet transform [33][61–64], and empirical mode decomposition as preprocessing of EEG signals. Chu et al. [12] and Truong et al. [13] have used the Fourier transform to remove noise from EEG signals. Teixeira et al. [23] have selected a few channels instead of using all channels for seizure prediction in their proposed model. However, channel selection works in focal epilepsy cases in which a specific portion of the brain is affected.

Usman et al. [31] have applied empirical mode decomposition for removing noise from EEG signals. Sharma et al. [65] have applied the wavelet transform for noise removal. It has been observed that the Butterworth filter, wavelet transform, and Fourier transform give a better Signal to Noise Ratio (SNR) when applied to seizure prediction from EEG signals . However, another important factor that can give better SNR and also decrease computational cost by reducing the number of channels is Common Spatial Filtering (CSP). CSP converts multiple channels into a single surrogate channel with increased SNR and between class variance. In the future, CSP may be applied in its different variants to increase performance. The following subsections explain CSP and the wavelet transform.

2.1.1. Common Spatial Filtering

The common spatial pattern filter [66] converts a multiple- channel EEG signal into a single-surrogate-channel EEG signal, thus increasing SNR [67] and potentially resulting in higher discrimination between multiple EEG states. which could lead to better classification between multiple states of EEG signals. The CSP method increases SNR by increasing variance between multiple states. Assume that X_1 and X_2 represents signals from two different states of EEG signals then filter coefficients can be computed as follows:

$$R_1 = \frac{(X_1 X_1^t)}{trace(X_1 X_1^t)} \tag{1}$$

$$R_2 = \frac{(X_2 X_2^t)}{trace(X_2 X_2^t)} \tag{2}$$

$$R = R_1 + R_2 \tag{3}$$

$$[Evec, Eval] = eig(R) \tag{4}$$

$$w = \sqrt{D^{-1}} Evec^t \tag{5}$$

$$S_1 = w R_1 w^t \tag{6}$$

$$S_2 = wR_2w^t \tag{7}$$

$$[B, D] = eig(S_1, S_2) \tag{8}$$

$$Filter = \beta^t w \tag{9}$$

Eq. (9) gives the coefficients of the common spatial filter. Multiple-channel EEG signals can be converted into a surrogate channel by multiplying a signal with filter coefficients.

2.1.2. Wavelet Transform

Wavelets [33] are defined as sharp waves with zero mean values. Wavelets have localization capability in both time and frequency domain. The wavelet transform is a very effective tool for signal processing due to it localization property. Many researchers have used the wavelet transform for the preprocessing of EEG signals. The wavelet transform can be divided into two types: including Continuous Wavelet Transform (CWT) [68] and Discrete Wavelet Transform (DWT) [7]. In CWT, signals are convolved and matched with a wavelet basis function in continuous time and frequency. Signals in CWT also need to be converted into digital signals. The original signal is the weighted sum of a wavelet basis function in continuous domain. If $f(t)$ is a continuous function in time t, then CWT is defined as:

$$W_{a,b} = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{|a|}} \psi^*(\frac{t-b}{a}) dt \tag{10}$$

where a and b are a set of real numbers, * represents complex conjugation, and ψ is the mother wavelet. Wavelet function can be defined as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi(\frac{t-b}{a}) \tag{11}$$

Combining Eq. (10) and Eq. (11), we get the following expression.

$$W_{a,b} = \int_{-\infty}^{+\infty} f(t)\psi_{a,b}(t)d(t) \tag{12}$$

The wavelet function becomes narrower with the increase of a and is displaced in time with varying values of b. Therefore, a is a scaling factor and b is a localizing factor.

2.1.3. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) [69][70] decomposes a signal into oscillatory functions called Intrinsic Mode Function (IMF). This decomposition of a signal into multiple IMFs is similar to the Fourier transform and wavelet transform. As noise in the signal is present in high frequency components, EMD is applied to get relatively low-frequency components. Let $x(t)$ be referred to as signal, and for every IMF, it must fulfill these two conditions:

1) The total count of peak values and zero crossings must be equal, or differ by only one.

2) At any point given in the signal, the average envelope defined by local minima and local maxima is zero.

Algorithm 1 shows how an IMF is obtained from the given signal $f(t)$.

Algorithm 1: Intrinsic mode function

Input: Signal $f(t)$

Output: Intrinsic mode function

initialize. Interpolate between minima and maxima to generate envelopes $e_l(t)$ and $e_m(t)$;

Compute the local mean. Extract $h_1(t)=x(t)-a(t)$; Apply the two conditions to determine whether it is a valid IMF;

Repeat the above steps till a valid IMF is obtained.

2.2. Feature Extraction

Many univariate [5] and multivariate features [75] can be extracted for

Table 1: Description of features of a seizure prediction system

Feature	**Description**
Statistical moments [17][71–73]	These include mean, variance, skewness, and kurtosis. Variance represents the spread of the data, skewness gives information about the symmetry of the data and kurtosis gives information about peaks in the data.
Spectral moments [12][18]	Frequency domain features include spectral centroid, variational coefficient, and spectral skewness, which gives us useful information about variation in the data.
Hjorth parameters [74][17][23]	Famous in extracting features from EEG signals, they include mobility and complexity. Mobility gives average frequency, whereas, complexity represents variation in frequency.
Entropy [62]	Entropy provides mutual information between samples and is considered to be a good feature in discrimination between multiple states of seizures in EEG signals.
Approximate entropy [17][23]	It quantifies the irregular behaviour of signals.
Lyapunov exponent [17][22][23]	It characterize the separation rate between close trajectories.
PCA [21][38–41]	Principal component analysis reduces dimensions of data into principal components with higher variance.

classification between the preictal and the interictal states. These features include Hjorth parameters [71][76], Lyapunov exponent [77–79], spectral entropy [34, 79, 80], approximate entropy [35], correlation [1], spectral power [49], statistical [71–73] and spectral moments [81][82]. Hjorth parameters include complexity and mobility. Statistical features extracted in time domain include mean, standard deviation, skewness, and kurtosis. Spectral moments are frequency domain features consisting of spectral centroid, variational coefficients, and spectral skewness. Researchers [83][84] have also applied PCA for feature extraction. Table 1 shows a brief description of several features.

Rasekhi et al. [17] and Teixeira et al. [23] have extracted 22 univariate features, including statistical and spectral moments, entropy, Hjorth parameters, and Lyapunov exponent. It has been observed that statistical features perform better in both scalp EEG and intracranial EEG signals. However, spectral features perform better only in the case of scalp EEG signals. Howbert et al. [20] have extracted spectral features for an iEEG dataset and have obtained a sensitivity of 73%, whereas, Chu et al. [12] have observed a sensitivity of 86.67% on a scalp EEG dataset with spectral features. Convolutional neural networks are proving to be good feature extraction methods as features extracted through CNN give better sensitivity. Xiang et al. [85] have achieved 90% sensitivity with fuzzy entropy. We have observed that spectral features and those extracted from CNN give better inter-class separability. In future, if we use these features with better classification methods, we should be able to achieve better sensitivity.

Statistical and spectral moments and univariate features can be extracted as follows: statistical moments include, mean, standard deviation, and skewness which can be computed through Eq. (13), Eq. (14), and Eq. (15), respectively.

$$\mu = \frac{1}{N}\sum_{i=1}^{N}(x_i) \tag{13}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{14}$$

$$\beta = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3 \tag{15}$$

where x_i is the EEG signal and N is the number of samples.

Spectral features are frequency domain features and include spectral centroid, variational coefficient, and spectral skewness. These features can be computed easily with the help of power spectral density. Power spectral density is computed by Eq. (16).

$$P(w) = \sum_{n=1}^{N} r_y[n]e^{-jwn} \tag{16}$$

where, r_y denotes autocorrelation of the signal x_n. Spectral centroid, variational coefficient, and spectral skewness can be computed by Eq. (17), Eq. (18), and Eq. (19), respectively.

$$C_s = \frac{\sum_w wP(w)}{\sum_w P(w)} \tag{17}$$

$$\sigma_s^2 = \frac{\sum_w (w - C_s)^2 P(w)}{\sum_w P(w)} \tag{18}$$

$$\beta_s = \frac{\sum_w ((w - C_s)/\sigma_s)^3 P(w)}{\sum_w P(w)} \tag{19}$$

Lyapunov exponents [77] are useful in determining the aperiodic behavior of signals. Assume that $||\delta x_i(0)||$ and $||\delta x_i(t)||$ are the distances of two points in i^{th} direction. Then the Lyapunov exponent can be computed as:

$$\lambda_i = \lim_{t\to\infty}\frac{1}{t}log_2\frac{||\delta x_i(t)||}{||\delta x_i(0)||} \tag{20}$$

Hjorth parameters include mobility and complexity, which are useful for the classification of EEG signals[76]. Hjorth activity can be defined as variance of EEG signal in time.

$$Activity = var(t) \tag{21}$$

$$Mobility(y(t)) = \sqrt{\frac{Activity(\frac{dy(t)}{dt})}{Activity(y(t))}} \tag{22}$$

$$Complexity(y(t)) = \frac{Mobility(\frac{dy(t)}{dt})}{Mobility(y(t))} \tag{23}$$

2.3. Classification

Support Vector Machine (SVM) [86] has been widely used for the classification of EEG signals. Other classifiers that can be used include the k-nearest neighbor classifier [87] and the Gaussian mixture model (GMM)[88]. Convolutional neural networks (CNN) [89] are also useful for classification. SVM and CNN perform well in classification between multiple states of seizures. However, GMM, logistic regression, and ensemble classifiers have also been used. Figure 3 shows a comparison of the classification sensitivity and specificity of different methods in using scalp EEG signals, whereas; Figure 4 compares the sensitivity and specificity obtained by applying different methods on intracranial EEG signals. Similarly, Figure 5 compares the False Positive Rates (FPR) of different seizure prediction methods on scalp EEG datasets, and Figure 6 compares the FPR of seizure prediction methods on intracranial EEG. We have concluded from these graphs that methods that have used SVM and CNN for classification have achieved greater sensitivity, specificity and lowest false positive alarms.

2.3.1. Convolutional Neural Networks

Convolutional Neural Networks (CNN) [89] and extreme learning machines [90][91] give better classification sensitivity for both scalp and intracranial EEG datasets. Hussein et al. [92] and Truong et al. [13] have applied convolutional neural networks and have observed a sensitivity of 93% and 81.2%,respectively,

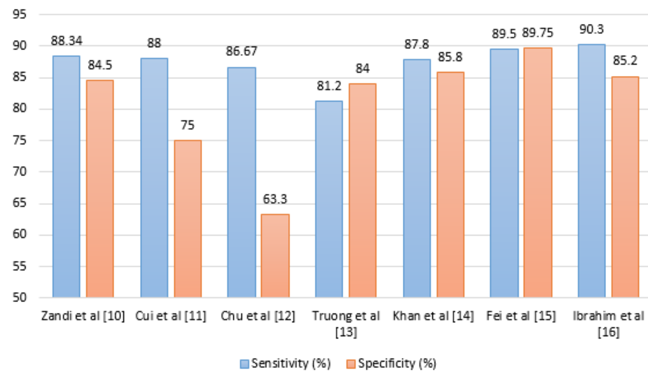

Figure 3: Comparison of seizure prediction methods using scalp EEG signals

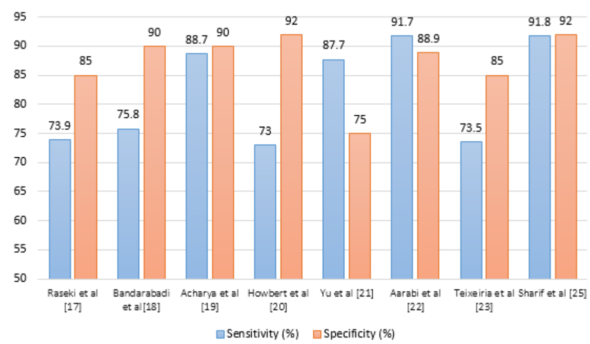

Figure 4: Comparison of seizure prediction methods using iEEG signals

in a scalp EEG dataset. Acharya et al. [19] have applied CNN to iEEG dataset and classified it with a 95% sensitivity. In the following subsections, we explain covolutional neural networks and support vector machine in detail.

Artificial Neural Networks (ANN) [93] have been designed like the complex neural network of the human brain. They are made as a result of connecting neurons. Similarly, like biological neurons, artificial neural networks take inputs and combine them into outputs. However, the output of each layer of artificial neural networks is the weighted sum of the previous layer. Distortion in layers because of translation may lead to poor accuracy of these artificial neural networks. Therefore, convolutional neural networks are widely used as they are

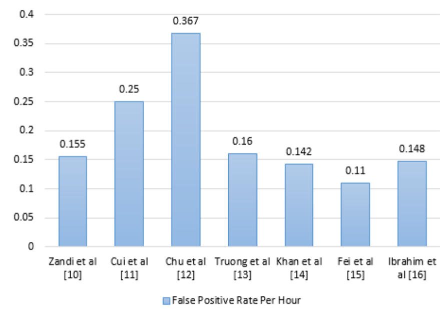

Figure 5: Comparison of false positive rates of seizure prediction methods using scalp EEG signals

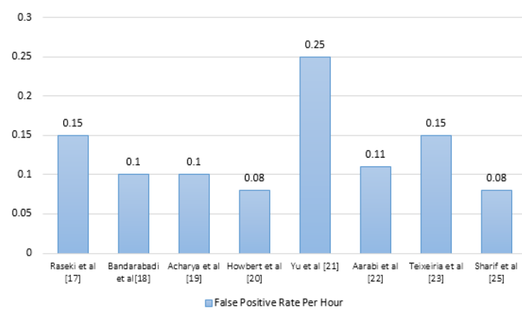

Figure 6: Comparison of false positive rates of seizure prediction methods using intracranial EEG signals

shift and translation invariant. Figure 7 shows three layers of ANN, including input layer, hidden layer, and output layer.

CNN is a subset of deep learning [95][96] widely used for medical signal processing such as MRI and tomography analyses. In CNN, like ANN, the output of the current layer is computed with the help of weights and bias of the previous layer. Weights and bias may be computed for each layer with the help of Eq. (24) and Eq. (25).

$$\Delta W_l(t+1) = -\frac{x\lambda}{r} W_l - \frac{x}{n}\left(\frac{\partial C}{\partial W_l}\right) + m\Delta W_l(t)) \tag{24}$$

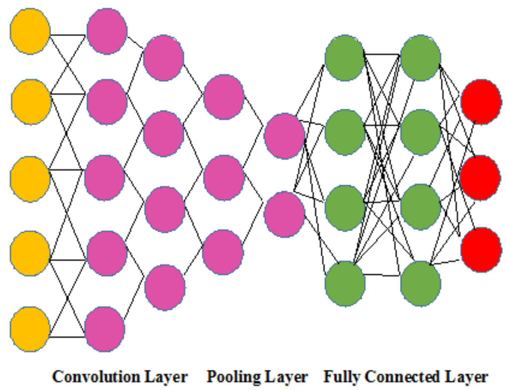

Figure 7: Convolutional neural networks [94]

$$\Delta B_l(t+1) = -\frac{x}{n}\left(\frac{\partial C}{\partial B_l}\right) + m\Delta B_l(t) \tag{25}$$

where, W represent weights, l is the layer number, B denotes bias, and x, n, m, t are regularization parameters. Convolutional neural networks consists of three types of layers: convolutional layer, pooling layer, and fully connected layer.

Convolutional layer: This layer consists of multiple filters known as "filter". These filters are convolved with EEG signals, and this layer controls how much filter must be convolved. Eq. (26) shows the convolution between input signal and filter. The output of convolution is a feature map.

$$y_k = \sum_{n=0}^{N-1} x_n h_{k-n} \tag{26}$$

where h is filter and N represents number of elements of x.

Pooling layer: This layer performs a down sampling of the signal. It reduces the neurons' dimensions from a convolutional layer to reduce computational cost and avoid overfitting. The max. pooling method is used in this layer to select a feature map and to reduce output neurons.

Fully connected layer: This layer consists of connections to all activations of previous layers. The activation function can be a rectified linear unit or softmax.

2.3.2. Support Vector Machines

Bandarabadi et al. [18] have applied support vector machines but have not performed preprocessing of the intracranial EEG dataset; therefore, a low sensitivity of 75.8% has been observed by the authors. Similarly, Raseki et al. [17] have applied SVM on an iEEG dataset and have observed a sensitivity of 73.9%. We have concluded that SVM do not perform well for intracranial EEG signals. However, for scalp EEG signals, SVM give better sensitivity. Xiang et al. [85] have applied SVM for the classification of a scalp EEG dataset and have observed a sensitivity of 90%.

Support Vector Machine (SVM) [86] was introduced in the 1990s as a set of algorithms for two-class classification. SVM has been widely applied for different classification problems, including biometric recognition, text classification, data analysis, face classification, and biomedical signal processing for the classification of multiple diseases. SVM can be classified into two types: one is linear SVM and the other is nonlinear classification.

Linear SVM. The aim of SVM is to map the given features into a higher dimensional feature space and find a good hyperplane. This hyperplane gives optimal separation between two classes. This optimal separation is known as hard margin SVM. These hard margins are good only for the classification of linear data. Assume that we have training data that are linearly separable $S = (x_1, y_1), \ldots, (x_l, y_l)$, where X denotes the input space and $Y = -1, +1$ is the binary classification. The class of the feature vector is determined based on $<w,x>+b=0$ and $f(x)=\text{sign}<w,x+b>$, where w is perpendicular to hyperplane, while the changing values of b are parallel to the hyperplane. This hard-margin classification is not suitable for real-world applications as it perfectly trains the classifier for training data and real-world data contains noise; therefore, to get a better performance against test data, we need soft margins. To get a soft-margin classification, we introduce a term C, which is a penalizing factor for every misclassification.

Nonlinear SVM:. Many real-world applications of classification cannot be performed with the help of linear SVM. Therefore, we need to map the data into higher-dimension feature space and replace the inner product of these features with a kernel function. In this way, with the help of a kernel function, the data becomes linearly separable. The most popular kernel functions include the radial basis function and the multilayer perceptron.

2.4. Postprocessing

Many methods used for seizure prediction have been proposed by various authors, but only a few have done statistical validation. This postprocessing step is necessary for validating the classification results. These statistical validation techniques include the Poisson process random predictor [97][98], k-fold validation [99], moving average filter [100], and Kalman filtering[49]. In k-fold cross validation, data are divided into k different sets and the classifier is trained using k-1 sets and tested with one set. The Poisson predictor random processor creates chance predictors for a comparison with a seizure prediction model. If the model predicts a seizure, then it must perform better than the chance predictors of the Poisson-process. Only in this case, the model is validated to have a correct classification. The Kalman filter is also used as postprocessing step to remove false alarms generated by classifiers. Truong et al. [13] and Teixeria et al. [23] have applied the Kalman filter as postprocessing for scalp EEG and iEEG signals, and it has been observed that the Kalman filter provides better validation against false alarms for scalp EEG signals than for iEEG signals. Howbert et al. [20] have used the Poisson process random predictor on iEEG signals but could not achieve good results. On the other hand, Xiang et al. [85] and Acharya et al. [19] have applied k-fold cross validation and have achieved good results on both scalp EEG and iEEG signals.

3. Datasets

EEG signals can be recorded in two ways. One is by placing multiple electrodes on the scalp of patients and the other, intracranial EEG, is by placing electrodes within the brain during surgery. Many researchers have worked on two famous datasets that are publicly available. Table 2 compares scalp EEG and intracranial EEG datasets.

3.1. CHB-MIT Dataset

EEG data collected from Children's Hospital Boston and the Massachusetts Institute of Technology [101] are publicly free and available on www.physionet.org. This dataset consists of continuous recordings of EEG signals of 22 subjects, including 5 male and 17 female patients. The ages of the female patients range from 1.5 to 19 years, whereas the ages of the male patients range from 3 to 22 years. Data have been recorded by placing 23 electrodes on the scalp of each subject. This scalp EEG dataset has been sampled at 256 Hz. It has been recorded and saved in European data format (EDF), which can be converted into .mat files in MATLAB. All files have been annotated for ictal states and give information about the start and end of the seizure state. The preictal state can be assumed as the state before the start of the ictal state[102].

3.2. American Epilepsy Society Dataset

This dataset has been recorded by the American Epilepsy Society in collaboration with the University of Freiberg [103]. The dataset consists of intracranial EEG recordings of 7 subjects, including 5 dogs and 2 humans. An intracranial dataset is recorded by implanting electrodes inside the brain through surgical procedures. The data recorded from dogs have been acquired using 16 electrodes and sampled at 400 Hz, whereas the data recorded from humans have been acquired using 16 electrodes and sampled at 5000 Hz. The data have been annotated for the interictal and the preictal state and are saved in .mat files.

Table 2: CHB-MIT and American Epilepsy Society datasets

Dataset	No. of Subjects	Type	No. of channels	Sampling rate (Hz)	No. of seizures	Recording (Hrs.)
CHB-MIT [101]	22 humans	Scalp EEG	23	256	198	644
American Epilepsy Society [103]	5 dogs	iEEG	16	400	-	658
	2 humans	iEEG	16	5000	-	21.3

4. Evaluating the Performance of Methods

Sensitivity and specificity are important measures in assessing the performance of a seizure prediction method. Sensitivity measures the True Positive Rate (TPR), whereas specificity gives the True Negative Rate (TNR). We can define sensitivity and specificity through Eq.(27) and Eq.(28).

$$Sensitivity = TP/(TP + FN) \tag{27}$$

$$Specificity = TN/(TN + FP) \tag{28}$$

where TP is true positive, that is correctly classified positive classes, TN is true negative, which denotes correctly classified negative classes. Similarly, FP is false positive, a negative class predicted as positive, and FN is false negative, which is positive class predicted as negative. In seizure prediction, the preictal state is considered to be positive class and the interictal state a negative class. It is extremely important that a proposed method predicts a preictal class correctly for prevent the seizure, but it is also important that the method does not predict a preictal class incorrectly. Therefore, upon evaluation, a seizure prediction method must achieve high sensitivity as well as specificity.

Table 3: Comparison of seizures prediction methods using scalp EEG signals

Method	Preprocessing	Features	Classifier	Postprocessing	Sensitivity (%)	Specificity (%)	Avg. Anticipation Time (min.)
Zandi et al. [10]	Zero crossings	Histogram bins	Variational GMM	Similarity index	88.34	84.5	22.5
Cui et al. [11]	Codebook	Bag of waves	Extreme learning machine	-	88	75	1
Chu et al. [12]	Fourier transform	Spectral features	Thresholding	-	86.67	63.3	45.3
Truong et al. [13]	Short-time Fourier transform	Window of 30 sec.	Convolutional neural networks	Kalman filter	81.2	84	5
Khan et al. [14]	Wavelet transform	CNN	CNN	-	87.8	85.8	5.83
Fei et al. [15]	Butterworth filter	Fractional Fourier transform	BPNN	-	89.5	89.75	25.5
Ibrahim et al. [16]	Derivative, local mean,variance, median	PDF bins	Thresholding	-	90.32	85.2	22.63

5. Comparison of Existing Methods

Table 3 and Table 4 compare epileptic seizure prediction methods using scalp EEG signals and intracranial EEG signals, respectively. It has been observed that prediction involves effective preprocessing, feature extraction, and classification. These three steps play a vital role in the sensitivity of the system.

Table 4: Comparison of seizures prediction methods using intracranial EEG signals

Method	**Preprocessing**	**Features**	**Classifier**	**Postprocessing**	**Sensitivity (%)**	**Specificity (%)**	**Avg. Anticipation Time(min.)**
Rasekhi et al. [17]	Butterworth filter	22 univariate features, normalization	SVM	Outlier processing, smoothing	73.9	85	-
Bandarabadi et al. [18]	-	Spectral features	SVM	-	75.8	90	-
Acharya et al. [19]	Z-score normalization	CNN	CNN	K-fold validation	88.7	90	-
Howbert et al. [20]	-	Spectral power	Logistic regression	Poisson process chance prediction	73	92	-
Yu et al. [21]	Local mean decomposition	PCA+CNN	Bayesian linear discriminant analysis	Moving average filter	87.7	75	21
Aarabi et al. [22]	Butterworth filter	Correlation dimension Lyapunov exponent, nonlinear interdependence	Rule-based decision-making	Repeated random cross validation	91.7	88.9	14.33
Teixeira et al. [23]	Electrodes selection	22 univariate features	MLP	Kalman filtering	73.5	85	15.58
Yuan et al. [24]	Wavelet transform	Diffusion distance	Bayesian linear discriminant analysis	Smoothing and thresholding	85.11	92	17.67
Sharif et al. [25]	Chebyshev filter	Fuzzy rules	SVM	Prediction score	91.8	92	21

In the case of scalp EEG signals, Turong et al. [13] have used convolutional neural networks for classification (CNN) and have achieved only an 81.2% sensitivity. Preprocessing and feature extraction are the main reasons for the low performance of CNN. On the other hand, Al Hussein et al. [92] have extracted features with the help of CNN and performed classification with the same to achieve a sensitivity of up to 93%. Similarly, Yu et al. [21] and Acharya et al. [19] have applied CNN for feature extraction on intracranial EEG signals and have observed a sensitivity of 87.7% and 88.7% after training the CNN with 150 epochs. Xiang et al. [85] have proposed a model for predicting of seizure using scalp EEG signals with the help of SVM and fuzzy entropy as features to get a 90% sensitivity. However, Raseki et al. [17] and Bandarabadi et al. [18] could only achieve a sensitivity of 73.9% and 75.8% respectively, for intracranial EEG signals. These results show that SVM have not performed well in the case of intracranial EEG signals. Figure 8 compares ROC the curves of multiple methods of scalp EEG signals, and Figure 9 compares the ROC curves of intracranial methods. The method proposed by Ibrahim et el. [16] proves to perform well for scalp EEG signals, and the model of Sharif et al. [25] gives a better sensitivity as well as less false positive alarms per hour in the case of intracanial EEG signals. Another important measure in evaluating a seizure prediction method is average anticipation time. The method proposed by Chu et al. [12] has successfully predicted the preictal state with an average prediction time of 45.3 minutes. However, FPR has been increased, which makes the proposed method not suitable. The methods proposed by Ibrahim et al.

[16] and Sharif et al. [25] have successfully predicted seizures with average an anticipation time of 22.63 minutes and 21 minutes, respectively, with relatively low false positive alarms, which makes these methods suitable for preventing seizures. All these studies clearly explain that a system that predicts seizures with a higher sensitivity must be able to preprocess EEG signals effectively. Moreover, multivariate features must be extracted, and classification must be done with the help of CNN or SVM as these two classifiers give better detection provided that preprocessing and features extraction have been done in an effective manner. However, there is a trade-off between sensitivity, specificity, and average anticipation time. It has been seen that methods with a greater anticipation time results in increased false alarms, which is not desirable and could have negative affects on a patient's health. Therefore, we must choose an optimal setting to get a better sensitivity and average anticipation time with minimum false alarms.

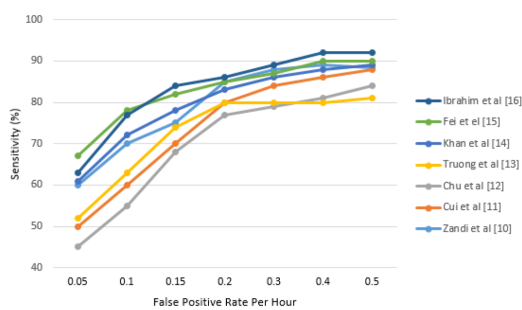

Figure 8: Comparison of the ROC curves of Scalp EEG methods

6. Conclusion and Future Work

In recent studies, it has been observed that epileptic seizures can be prevented by detecting the start of the preictal state. This can be done by recording EEG signals either by placing electrodes on the scalp of patients or by implanting electrodes inside the skull. However, prediction with high sensitivity and less false positive rate remains a challenge. Effective preprocessing methods are

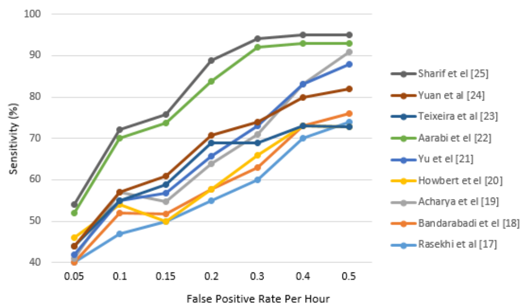

Figure 9: Comparison of the ROC curves of intracranial EEG methods

required so that noise induced during the recording of EEG signals is removed. Selecting a few channels instead of using all channels or converting them into a single surrogate channel is also a big challenge in the preprocessing. Feature extraction and selection is also a major challenge in seizure prediction systems. A smaller number of features with high interclass variance must be selected so that the overall system detects seizures effectively without increasing the complexity of the overall system. In the classification phase, SVM and CNN have been proved to perform well in terms of both sensitivity and specificity. Many researchers have achieved better sensitivity but have not validated their results using any standard validation method. Therefore, a postprocessing method also needs to be incorporated into the system, and results must be validated by more than one method so that the performance of the classifier is validated effectively. With the help of these modifications, we can predict epileptic seizures more effectively with greater anticipation time, increased sensitivity, and a very low false positive rate. Table 3 shows a comparison of epileptic seizures prediction methods on a scalp EEG dataset, while Table 4 compares seizures prediction methods on an intracranial EEG dataset. By comparing multiple methods, we have been able to conclude that the channel selection for scalp EEG signals and the Butterworth filter for iEEG signals are good for the preprocessing of EEG signals. For extracting features, convolutional neural networks, entropy and the instantaneous amplitude gives good features for scalp EEG signals, while for iEEG signals, correlation dimension Lyapunov exponent and nonlinear interdependence in addition to CNN, provide good features. Random forests, SVM, and stacked autoencoders have been proved to be better classifiers for scalp EEG signals, and CNN also gives better classification for iEEG signals, however, SVM do not perform well in the case of iEEG signals. In the future, by combining all of the best techniques, we should be able to design a model that will increase the true positive rate of classification between interictal and preictal state and reduce false positive rates.

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