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Early Epileptic Seizure Prediction Using EEG Signals with Machine Learning

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***Abstract* -** Epilepsy is a chronic disease that dates back to ancient times and affects people only during seizures. Since the onset of seizures is unknown, it heavily poor affects the living standards of patients. If seizure onset can be predicted in sufficient advance, seizures can be prevented with drugs to be used or an opportunity can be provided for patients who cannot be stopped with drugs to move to a safe zone. For this purpose, to predict an epileptic seizure, before a certain period of time happens, frequency-based feature extraction is applied with the use of recorded EEG data. Bases of the study rely on creating time for patients to reach necessary medications approximately ahead 30-60 minutes before having an epileptic seizure. In this respect, an open-access dataset with 24 pediatric patients' EEG recordings was used and frequency-based feature extraction was performed using wavelet transformation. Afterward, classification performances of the features are compared for a k-nearest neighbor (k-NN), random forest algorithm (RF), support vector machine (SVM), and J48 which are extensively used machine learning techniques. In accordance with the classification results, the average highest accuracy was acquired as 99.87% with the SVM classifier.

***Keywords*:** Epileptic Seizure, Machine Learning, Feature Extraction, Classification, Wavelet Spectrum

1. Introduction

Epilepsy is a chronic noncommunicable disease also known as falling sickness. In an epileptic seizure, sudden and uncontrolled electrical discharges occur in neurons and consequently changes in consciousness, involuntary contractions, and emotional changes arise in the patient. Epilepsy is a disease which only affects the patient during the seizures and patients continue to live their lives in a healthy way between those seizures. Approximately 65 million epileptic patients are called in the world and epilepsy is known as the most common neurological disease in childhood and adolescence period, as the second most common neurological disease in adults after cerebrovascular diseases. Lots of different reasons (age, brain Infections, childhood seizures, dementia, hereditary family history, vascular disorders, and head traumas) may contribute to the development of seizures. Although there exists no currently available definitive treatment for epilepsy, it is a disorder that can be controlled with anti-seizure strategies and medications.

The first known epileptic observations in history were seen approximately 3000 years ago in the Babylonian period. Babylonians named this disease "Miqtu", and it was believed that Miqtu was caused by mystical beings attacking humans at that time [1]. For the first time, Hippocrates declared that the center of epilepsy was in the brain, and he named it "Mal Caduque" [2]. In the 1960s, the classification studies of epileptic seizures started, and the Classification and Terminology Commission was established [3]. At the present time, although the change in electroencephalography (EEG) signals during epileptic seizures is noticeable even with the bare eye, computer-assisted expert systems are necessarily needed to be used for detailed analysis and early prediction. Therefore, methods such as machine learning and deep learning are used extensively in the analysis of epileptic EEG signals [4–9].

The fundamental aim of the study is to predict the seizures before 30-60 minutes of the onset. In this way, patients would be able to take their medicine in time which will reduce the overall number of seizures they have and significantly improve their quality of life by preventing accidents and injuries. For this purpose, frequency-based feature extraction wavelet transform was used on the "CHB-MIT Scalp EEG Database" [10], which is available as open source in PhysioNet ("https://physionet.org/ content/chbmit/1.0.0/"), to obtain an automated seizure onset prediction system based on EEG measurements. The brain wave power values for delta (δ,0.5–4Hz), theta (θ,4–8Hz), alpha (α,8–12Hz) and beta (β,12–30Hz), and gamma (γ, >30Hz) bands were obtained from wavelet spectrum and these features were employed in a 3-class classification as pre-ictal, ictal, and inter-ictal output using the machine learning methods kNN, Random Forest, SVM, and J48.

The rest of the paper is designed as Figure 1; Section 2 Pre-processing EEG dataset with filters, intuitions of the feature extraction, and 3-class classification applications, Section 3 shows the classification accuracy results and Section 4 provides the conclusions.

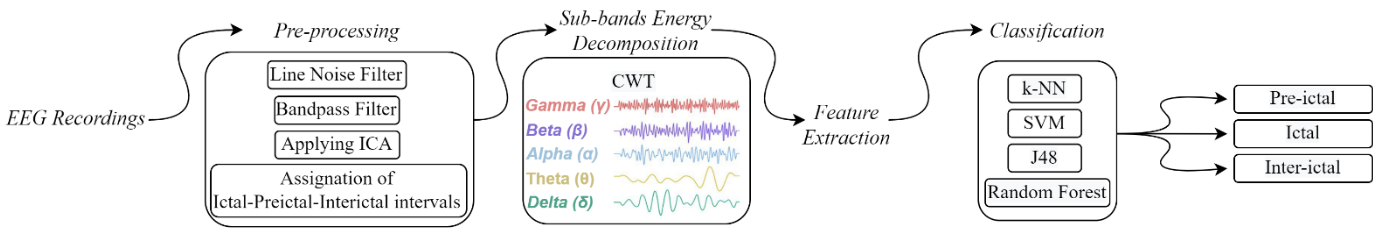

Fig. 1: General view of the flowchart in the study.

2. Materials and Methods

2.1. EEG Recordings

In this study, the publicly available CHB-MIT database [10] was used. With the cooperation of the Massachusetts Institute of Technology (MIT) and Boston Children's Hospital (CHB), 950 hours of raw EEG data were recorded from 23 channels according to the international 10-20 electrode positioning system. Data were recorded with a sampling frequency of 256Hz. The data includes EEG signals recorded from 23 pediatric patients with 185 severe epileptic seizures. The 24th patient, whose gender and age information was not specified, was added to this data set later. The cases were divided into consecutive 1-hour recordings (with the exception of consecutive recordings of 2 or 4 hours for just a few patients). For the recordings that include ictal activity, start-end times of the seizures were specified in detail.

2.2. Pre-processing

In this section, it is explained how to clean the EEG signals by applying various filters and how to determine the 3-class classification outputs (Interictal, Preictal, and Ictal) from the cleaned EEG signals. While recording EEG data, it is exposed to some internal or external noise, which may be caused by the recorded device or from the person whose EEG data is received. In this study, bandpass filtering, line noise removal, and Independent Component Analysis (ICA) filtering were used for artifact removal.

2.2.1. Line Noise Filter

Powerline noise is characterized by a sinusoidal 50/60Hz element observable in raw recordings of biomedical data. It is usually the result of using devices that use alternating currents as a power source. The standard type of electrical transport in the United States is 120V and 60Hz. Since the EEG data were recorded in the USA, the noise line was removed at 60Hz. Figure 2 shows the clearing of sinusoidal noise at 60Hz from an EEG signal.

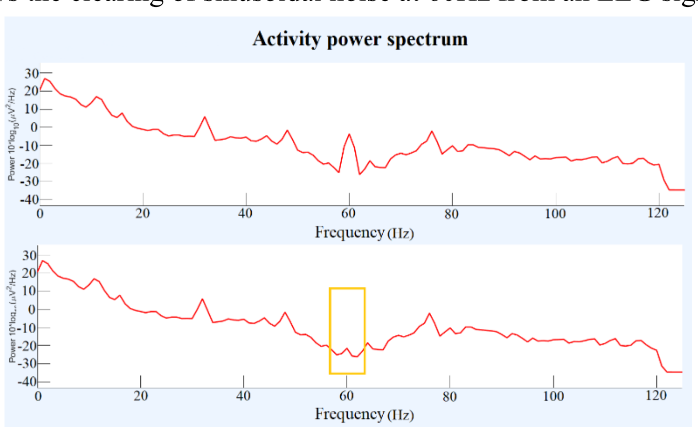

Fig. 2: Applying line noise filter at 60Hz.

2.2.2. Bandpass Filter

It is known that EEG signals include certain frequency range; delta wave (0.1-3.5Hz) with the slowest oscillation of brain signals to the gamma wave (30-100Hz) with the highest oscillation [11]. In this study, a high pass filter at 0.1Hz and a low-pass filter at 120Hz were used. The higher cut-off frequency is set to 120Hz, because epileptic seizures emit high frequencies, and they are mostly observed in the gamma band, and we want to capture the possible high frequencies due to epileptic seizures.

2.2.3. Applying ICA

EEG data is extremely susceptible to artifacts, or external noise of non-cerebral origin. To distinguish mixing artifacts and independent signals of interest from the signal, a sophisticated statistical analytic technique known as Independent Component Analysis has been used in this study [12]. The main purpose of this method is to recover a version of the original sources by multiplying the data with a matrix that does not mix.

During the elimination of the artifacts, the data in the recorded trails and the data from each channel are preserved. The ICA technique separates the multi-channel EEG data into components that are spatially fixed and temporally independent. In this study, we apply FastICA [13], a very efficient method for maximizing non-Gaussianity measures for the blind source separation problem. This method is a version of the ICA algorithm that can also be described as a neural network. Figure 3 shows an example for application of FastICA on EEG signal:

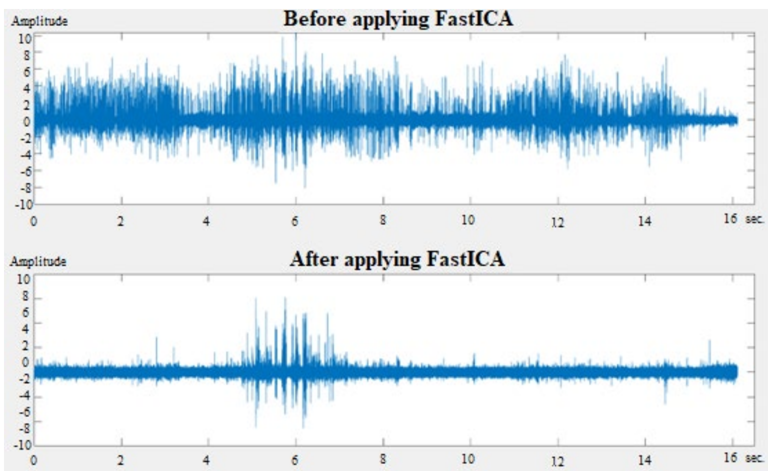

Fig. 3: Applying ICA filter to epileptic EEG signal.

2.2.4. Assignation of Ictal-Preictal-Interictal Intervals

In order to extract features from the data set and make a 3-class classification, ictal, preictal, and interictal regions must be determined. Preictal is expressed as activities that occur before the onset of the seizure. Ictal refers to the recordings during the seizure, while interictal refers to normal brain activities except for the other two states. The starting and ending time intervals of the ictal activity are detailed in the patient record folders [10]. Preictal regions cover the recordings at 15 to 60 minutes intervals prior to the seizure onsets. If the interval between two seizures is less than 15 minutes, these ictal activities are combined and recorded as a single seizure. The interictal region covers the time interval between the two seizures, excluding the preictal region, 5 minutes after the seizure, and 5 minutes before the preictal region. The 5 minutes intervals are separators between the interictal-ictal and interictal-preictal parts respectively.

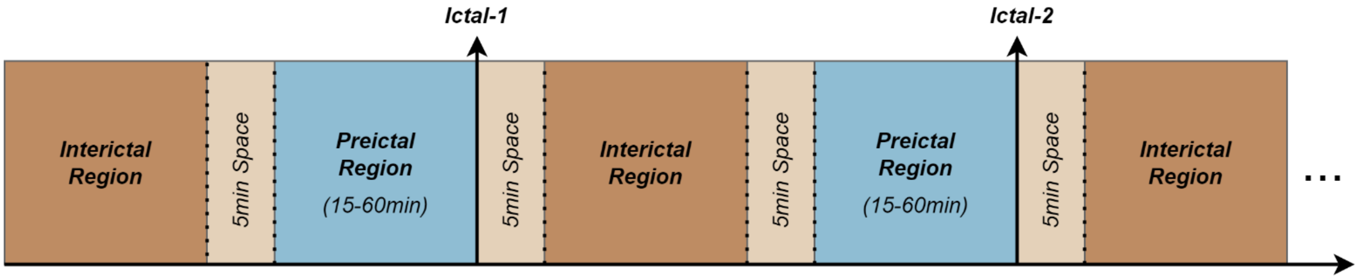

Fig. 4: Representation of Ictal, Preictal, and Interictal parts on the EEG timeline.

In Figure 4, categorized EEG activities are shown in a timeline. On the other hand, the duration of the interictal, preictal, and ictal states in each patient is given in Table 1. Each segment length (Sample frequency was 256Hz) in the recordings was determined as 1 second. According to the table, most of the EEG recordings (86.27%) are interictal. This is followed by preictal (13.38%) and ictal (0.35%).

Table 1: Durations of the regions.

	Total duration of Instances (in seconds)								
Subjects	**Interictal**	**Preictal**	**Ictal**	**Total (hh:mm:ss)**	Sub13	86281	24300	547	**30:52:08**
Sub01	120252	21386	449	**39:28:07**	Sub14	66011	20942	177	**24:12:10**
Sub02	114726	10260	175	**34:46:01**	Sub15	83052	45738	2012	**36:20:02**
Sub03	113475	19021	409	**36:55:05**	Sub16	42128	15497	94	**16:01:59**
Sub04	546855	12500	382	**155:28:57**	Sub17	62271	9457	296	**20:00:24**
Sub05	119447	17400	563	**38:10:10**	Sub18	110985	13620	323	**34:42:08**
Sub06	200264	34123	253	**65:10:40**	Sub19	95800	10260	239	**29:31:39**
Sub07	228460	10800	328	**66:33:08**	Sub20	75174	18963	302	**26:13:59**
Sub08	51331	17069	924	**19:15:24**	Sub21	103264	12334	203	**32:10:01**
Sub09	227259	14400	280	**67:12:19**	Sub22	98754	10800	207	**30:29:21**
Sub10	150591	24840	454	**48:51:25**	Sub23	71932	18900	431	**25:21:03**
Sub11	113771	8880	809	**34:17:40**	Sub24	30365	37079	527	**18:52:51**
Sub12	40072	29620	1016	**19:38:28**	**Total**	**820:08:40**	**127:16:29**	**03:10:00**	**950:35:09**

2.3. Feature Extraction

Wavelet transform is a method that allows signals to be gradually separated into high and low-frequency components [14, 15]. Since frequency information can be obtained in nonstationary signals with wavelet transform, this method can provide optimum time-frequency resolution in all frequency ranges. In order to determine the energy distribution over frequency bands within the data array, the Morlet wavelet was utilized. For each EEG channel, power values in 5 frequency bands (delta, theta, alpha, beta, and gamma) were acquired as features. The formula used to extract the EEG features is given below:

$$F_i^j = \frac{1}{N}\int_{f\in f_i}\int_{\tau} |\, S_i(f,\tau)|^2 \, d\tau \, df, \qquad i \in (\delta,\theta,\alpha,\beta,\gamma), \quad and \quad j = (1,..,23) \tag{1}$$

where, F_i^j is the extracted feature of jth channel and ith sub-band and $S_i(f,t)$ is the wavelet spectrum of the jth channel.

2.4. Classification

In this study, k-NN Random Forest, J48, and SVM algorithms, which are frequently used in analysing EEG signals, were exercised in the classification process. In order to implement these classification algorithms Waikato Environment for Knowledge Analysis (WEKA) was used [16]. This program is a set of machine learning algorithms to answer data mining problems.

2.4.1. k-Nearest Neighborhood (kNN) Algorithm

Among the classification algorithms, kNN [17] is one of the most widely used algorithms. The principle behind the algorithm is to determine the test sample's class considering the classes of k closest samples in the training set. The proximity of the samples is calculated by any distance metric, such as euclidean, manhattan and minkowski. The euclidean distance was used in this study and the formula is below:

$$D_i = \sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{2}$$

2.4.2. Random Forest (RF) Algorithm

RF is one of the supervised learning algorithms [18] and it generates various trees and merges them with possible combinations toward gaining further prediction. The aim is the process of choosing the highest scoring value among the classification decision trees. RF algorithm provides various models and classifications by training each decision tree on a different sample over multiple decision trees. Therefore, the classification value is increased by generating more than one decision tree during the classification process.

2.4.3. J48 (C4.5 Algorithm)

J48 is an ID3 algorithm that creates a decision tree that is widely used by machine learning in the WEKA program [19]. The C4.5 tree is an enhancement of the ID3 tree, also known as a statistical classifier. In the C4.5 tree, it is possible to move subtrees to different levels according to their entropy values. In addition, another feature of the C4.5 tree is that it performs the pruning operation of the sub-trees for which sufficient information cannot be obtained. The working steps are as follows: At each step, all entropies are calculated and controlled, the normalized information gain of each feature is calculated, the feature that gives the best information gain is moved as a decision in the decision tree, and then a sub-decision tree is constructed by creating a sub-list under this new decision node.

2.4.4. Support Vector Machine (SVM) Algorithm

SVM is one of the most used supervised machine learning techniques [20, 21]. This technique detects the ideal bound among the practicable outputs and their expected classes in a high-dimensional feature space. Hence, even when the data cannot be split into categories linearly, data points can be classified. In this part, the objective is to classify 3 outputs (Pre-ictal, Ictal, and Inter-ictal). Normally, SVM cannot manage multiclass classification. It manages binary classification by default. The method for classifying multiple outputs is to split each of the 3 outputs into binary. This method is named the One-to-One (or One vs One) approach [22, 23], which separates multiclass into multiple binaries.

The 10-fold cross-validation approach was used for performance evaluation. This approach uses a dataset that is split into 10 parts at random. One part of each fold is utilized for testing, while the combination of the remaining parts is used for training. To test each part, this procedure is performed ten times, and the total accuracy is determined by averaging all of the values.

3. Results

In this study, frequency-based features were extracted using Wavelet Transform. kNN, Random Forest, SVM, and J48 classifiers were used to calculate the 3-class classification accuracy. The results obtained are shown in Table 2, which shows weighted and unweighted average accuracies. The unweighted average accuracy is known as the arithmetic mean, which treats all recall values equally without considering the sample numbers. The weighted average accuracy is produced by multiplying each component by a coefficient favouring the values for classes with a higher number of samples. Table 2 shows that the weighted average results are close to each other for all patients. The highest average accuracy value belongs to SVM with 99.87%. This accuracy value is followed by kNN, RF, and J48 with values of 99.41%, 99.39%, and 98.82% respectively. It is worth noting that individual accuracies are above 96% for all results.

Table 2: 10-fold cross-validation method accuracy results.

Weighted Average Accuracy Results				
Subjects	**kNN**	**RF**	**J48**	**SVM**
Sub01	99.78%	99.56%	99.23%	99.95%
Sub02	99.74%	99.74%	99.28%	99.97%
Sub03	99.49%	99.60%	98.99%	99.95%
Sub04	99.77%	99.69%	99.54%	99.95%
Sub05	*96.54%*	99.71%	99.33%	99.98%
Sub06	98.89%	98.49%	98.68%	99.86%
Sub07	99.74%	99.81%	99.53%	99.98%
Sub08	99.03%	99.74%	98.75%	99.96%
Sub09	98.97%	99.83%	***99.63%***	99.97%
Sub10	99.46%	99.21%	98.46%	99.86%
Sub11	99.50%	99.54%	99.05%	99.97%
Sub12	99.37%	99.19%	97.69%	99.66%
Sub13	97.78%	*97.84%*	98.04%	99.74%
Sub14	***99.91%***	99.79%	99.35%	99.90%
Sub15	98.38%	99.50%	97.88%	99.70%
Sub16	99.82%	97.97%	98.16%	*90.79%*
Sub17	***99.91%***	99.63%	99.16%	99.94%
Sub18	99.60%	99.64%	99.22%	99.93%
Sub19	99.90%	99.61%	99.33%	99.89%
Sub20	99.69%	99.67%	99.51%	99.33%
Sub21	99.76%	99.60%	99.12%	99.96%
Sub22	99.77%	***99.84%***	99.35%	***99.99%***
Sub23	99.32%	98.79%	97.62%	99.93%
Sub24	99.79%	99.04%	*96.71%*	99.76%
Average	**99.41%**	**99.39%**	**98.82%**	**99.87%**

Unweighted Average Accuracy Results				
Subjects	**kNN**	**RF**	**J48**	**SVM**
Sub01	91.33%	75.10%	86.33%	97.53%
Sub02	86.93%	75.70%	83.47%	96.90%
Sub03	85.93%	75.30%	84.00%	97.37%
Sub04	90.33%	70.87%	75.63%	93.83%
Sub05	*80.60%*	90.23%	89.97%	99.43%
Sub06	92.10%	*68.43%*	*75.47%*	*79.30%*
Sub07	93.03%	76.83%	84.33%	98.30%
Sub08	91.50%	***95.77%***	***94.70%***	99.63%
Sub09	92.37%	72.20%	79.17%	91.17%
Sub10	94.33%	82.30%	84.13%	95.43%
Sub11	93.27%	92.97%	92.77%	99.53%
Sub12	94.57%	89.03%	90.23%	96.60%
Sub13	90.33%	84.70%	88.70%	93.60%
Sub14	89.43%	80.17%	83.50%	90.20%
Sub15	94.83%	94.17%	90.83%	97.50%
Sub16	89.57%	69.17%	*75.47%*	82.83%
Sub17	***99.77%***	84.33%	87.00%	98.77%
Sub18	89.27%	80.43%	83.83%	96.90%
Sub19	95.77%	77.43%	81.90%	93.80%
Sub20	86.70%	77.13%	89.10%	97.60%
Sub21	89.50%	72.90%	80.07%	94.23%
Sub22	94.57%	84.60%	89.37%	***99.67%***
Sub23	89.27%	76.77%	81.43%	98.10%
Sub24	95.00%	75.53%	79.17%	93.13%
Average	**91.26%**	**80.09%**	**84.61%**	**95.06%**

Examining the unweighted average accuracies, the results have quite a wide range compared to weighted average recall. The highest average accuracy is obtained by SVM as 95.06%. The average accuracy results for kNN, J48, and RF are 91.26%, 84.61%, and 80.09% respectively. When the table is analysed on a per-subject basis, the lowest accuracy values are as follows: RF (68.43%), J48 (75.47%), SVM (79.30%), and kNN (80.06%). The highest accuracy values, in decreasing order, are: kNN (99.77%), SVM (99.67%), RF (95.77%), and J48 (94.70%). The remarkable difference in values and ranges for weighted and unweighted accuracies is due to the uneven distribution of samples in classes. Since the area occupied by the ictal data, as shown in Table 1, on the whole dataset is very small (0.35%), the margin of error factor of ictals in the weighted average recall table is ineffective compared to preictal and interictal. For this reason, weighted average accuracy values are much higher than the unweighted accuracy values. The unweighted average accuracy is used to justify this problem for unevenly distributed classes. In this way, the ictal classification accuracies are reflected in average results more accurately. Another point to be noted is that, although the age range is very high (from an 18-month-old baby to a young person at 22 years old) the accuracy results are very promising.

4. Conclusion

Epilepsy is a disease that affects people only during seizures. However, the moment of the seizure onset is unknown, and this reduces the quality of life for people with epilepsy, also increasing their life-threatening risks. There are medicines to prevent the seizure if taken before the onset, and early prediction could allow the time interval needed for taking the necessary medicines. In this study, we present a model for classifying the preictal, ictal, and interictal regions. Using the model, a seizure could be predicted 30-60 minutes before the onset for minimizing the total number of seizures and increasing the quality of life for the patient. In literature, some effective epileptic studies were performed with the dataset that is used in this study. Fahd A. Alturki et al. in [24], proposed a single system that can diagnose 2-class and 3-class neurological diseases simultaneously. E Alickovic et al. [25], provided 3-class classification with a new model of automated seizure detection. For feature extraction, discrete wavelet transform (DWT), wavelet package decomposition (WPD) empirical mode decomposition (EMD) was utilized. The DWT and WPD features were classified with KNN and provided the best results with 100% and 99.95 respectively. For EMD features, the RF classifier was applied and 94.3%. accuracy result obtained. A. Bhattacharyya et al. [26] obtained the features in EEG signals using EWT and observed the patient-based accuracy result over 6 different classifiers (RF, C4.5, (functional tree) FT, Bayes-net, Naive-Bayes and K-NN). By making dual classification as seizure and seizure-free, they achieved the highest accuracy value as 99.71% with RF. D. Chen et al. [27], proposed 2 class classification as seizure and non-seizure. DWT was used to extract the features. By using leave-one-subject-out cross validation with SVM classifier, an average accuracy value of over 90% was obtained.

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