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Ictal-Interictal Epileptic State Classification with Traditional and Deep Learning Architectures

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A B S T R A C T

Epileptic seizures are caused by disturbances in the electrical activity of the brain. Failure to correctly classify epileptic forms may result in inappropriate treatment. Activities occurring prior to ictal activity may be causal and require further investigation. Therefore, it is important in the diagnosis of epilepsy to distinguish between ictal and interictal EEG using Electroencephalography (EEG) signs. In this study, ictal (absence seizure) and interictal EEG recordings were scored using 4 bipolar (C3-P3, T5-O1, FP2-F8, C4-T4) channel EEGs from Temple University Hospital (TUH) EEG Seizure Corpus (TUSZ) data. The data were divided into 3-second epochs and various features were obtained from the data. The data in each epoch were filtered using the Discrete Wavelet Transform (DWT) Daubechies-2 wavelet and were 0-32 Hz. range has been studied. Feature selection was made with Correlation based Feature Selection (CFS). The performances of traditional and deep learning classifier algorithms (Support vector machine (SVM), Long Short-term Memory (LSTM)) were compared and the results were discussed. The highest success rate was 96.96% in 84.86 seconds with the LSTM classifier model and 96.36% in 0.05 seconds with the SVM classifier algorithm

Keywords:Classification, Deep Learning, EEG, Epilepsy, Ictal, Interictal, Long short-term memory, Support Vector Machine, TUSZ.

1. INTRODUCTION

Epilepsy is a neurological disorder that develops when nerve cells in the brain perform electrochemical discharges in a different way than normal (Sanei & Chambers, 2007). Electroencephalography (EEG) signals are used to diagnose epileptic signals, to illuminate the causes behind various nervous system diseases, and to investigate the functioning of the brain. EEG is an important subject that enables the brain's responses to different stimuli to be researched according to their content in the time or frequency plane. Advanced technology facilities are used in different areas such as engineering, industrial, biomedical application areas (Coskun & Comlekci, 2011).Although the ways of diagnosing various diseases have improved, some techniques are now used to easily interpret the data obtained with certain devices (Alkalin & Veranyurt, 2021).Artificial intelligence techniques are mostly used for this purpose. Machine learning techniques, one of these techniques, are used in the analysis of EEG signals that allow the recording of electrical potential during the activity of the brain.Epilepsy is one of the most common, recurrent, non-infectious diseases affecting nearly 50 million people worldwide. While epilepsy is not a disease that can be completely cured, some of the sick individuals can continue their lives without having a seizure as a result of the use of the right drugs.In order to make the correct diagnosis and to determine the correct drug, it is necessary to distinguish the epileptic activity from other activities correctly. It is very difficult and laborious to continuously monitor and score long and complex EEG signals by the specialist.Therefore, detection of seizure activity with artificial intelligence techniques is very important (Tonge et al., 2022, Daftari,et al., 2022).

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2. METHODOLOGY

In this study, ictal EEG data and interictal EEG data were classified. 4 bipolar electrode connections were used and the data collected from these channels were classified into three-second epochs. Before the classification process, EEG data were reduced to lower frequency bands by discrete wavelet transform and features were extracted from the obtained wavelet coefficients.Distinctive features are selected with the Correlation based Feature Selection (CFS) feature reduction algorithm. The performances of classifiers are compared using both deep learning and traditional classification algorithms. The process flow of the proposed classification is shown in Figure 1.

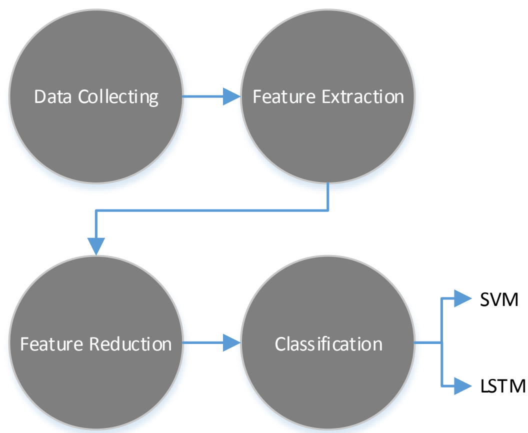

Fig. 1 - Proposed flow for this study.

2.1. Dataset

The EEG data used in this study were taken from the Temple University Hospital (TUH) database. EEG data collected from Temple University Hospital are publicly defined as TUH-EEG Corpus. Each EEG retrieved was manually matched with the corresponding clinician report.The dataset is based on the placement of the international 10-20 system electrodes from the scalp at 250 Hz. recorded at the sampling frequency. Recordings were taken from 19 unipolar channels (FP1, FP2, F7, F3, FZ, F4, F8, T7, C3, CZ, C4, T8, P7, P3, PZ, P4, P8, O1 and O2) (Tuncer & Bolat, 2022a).In total, 495 seconds of interictal and 495 seconds of ictal EEG data from 7 patients were used. The description of the dataset (v1.5.2/edf/train/) is given in Table 1.

Table 1 -Dataset description.

Dataset	Patient File
Ictal interictal	/train/02_tcp_le/014/00001413/
	/train/02_tcp_le/026/00002657/s001_2006_03_23/
	/train/02_tcp_le/017/00001795/s001_2004_08_05/00001795_s001_t001
	/train/02_tcp_le/011/00001113/s002_2004_08_31/00001113_s002_t001
	/train/02_tcp_le/030/00003053/s001_2006_08_01/00003053_s001_t001
	/train/02_tcp_le/024/00002448/s001_2006_01_26
	/train/01_tcp_ar/086/00008608/s001_2012_01_30/00008608_s001_t000
	/train/02_tcp_le/014/00001413/
	/train/02_tcp_le/026/00002657/s001_2006_03_23/

2.2.Feature extraction

Effective feature extraction is extremely important for the classification of the signal with high accuracy. At this stage, various features are extracted from the epoched signals. Feature extraction is a method used to obtain useful information contained in the data. There are many methods proposed in the literature to extract features from EEG signals (Fang Y. et al., 2015).In this study, EEG data were analyzed in lower frequency bands using 5-level discrete wavelet transform. Wavelet transform is a type of transform used for time-frequency analysis of a signal. Wavelet transform is done with the help of wavelets.The most important parameter of the wavelet transform is the wavelet. The function of the window function in the Fourier transform is performed by the main wavelet functions in the wavelet transform. There are many main wavelets with different properties and uses (Guo T. et al., 2022, Suhail et al., 2020).Some main wavelet functions (Daubechies (Db), Symlets (Sym), Coiflets (Coif)) used in wavelet transform are given in Figure 2. In this study, Db 2 wavelet was preferred because of the similarity of instantaneous peaks in seizure EEG data.

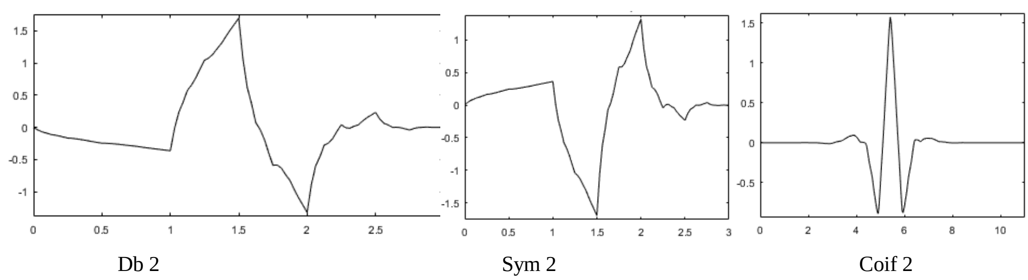

Fig. 2 - Example Wavelet Shapes.

One of the important features of the discrete wavelet transform is that it passes the signal through high-pass and low-pass filters. In each filtering, the time series is decomposed into low and high frequency components. These components are called approximations (A) and details (D) components. Here, the approximation component represents the low frequency values in the time series.The detail components represent the high frequency values of the time series (Xin Q., 2022). Figure 3 shows the lower frequency bands obtained by the discrete wavelet transform of the EEG dataset.

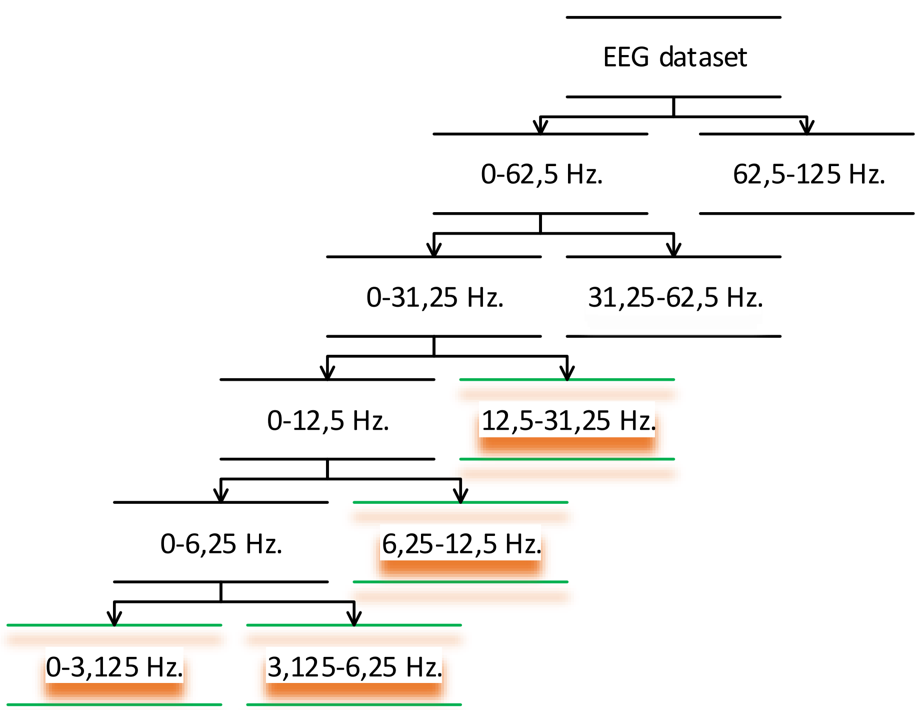

Fig. 3 - Components formed by filtration.

0-31.25 Hz for each channel in the 3-second epoch. 8 different features were obtained from the wavelet coefficients in the frequency band. Obtained features are shown in Table 2. A total of 32 statistical features (4 channels x 8 features) were calculated, 8 from each channel.

Table 2 - An example of a table.

Wavelet components	Feature name
(A5+D5+D4+D3)	Variance, total energy, max. amplitude, min. amplitude
D3	Standard Deviation
D4	Standard Deviation
D5	Standard Deviation
A5	Standard Deviation

As seen in Table 2, variance, total energy, max. amplitude, min. amplitude features were obtained. Standard deviation values were obtained from D3, D4, D5, A5 wavelet coefficients.

2.3.Feature selection

The large number of features causes the complexity and processing load of the classifier to increase. In addition, the training of the classification process with so many features will take a long time. For this reason, it is necessary to make feature selection in order to make an effective and fast classification. Data that is reduced in size as a result of feature selection should ideally preserve essential information with high discriminatory power and high reliability. Thus, simpler and more understandable classification models with good classification performance are created (Cai J. et al., 2018).One of the feature algorithms frequently used in the literature is CFS. Correlation-based feature selection is a filter algorithm that sorts subsets of features according to their function. This algorithm is inferred by looking at the correlation levels between the features.If the values of the features change symmetrically with each other, it is accepted that the features are related to each other, otherwise the features are considered to be unrelated to each other.The correlation between X and Y can be calculated using Eq.1, with H(X) being the entropy of the X feature and H(X|Y) being the entropy of the X feature according to the case of selecting the Y feature(Tuncer & Bolat, 2022a).

$$C(X/Y) = \frac{H(X) - H(X/Y)}{H(Y)} \quad (1)$$

The features selected to be given to the classifier algorithm with the CFS algorithm are given in Table 3.

Table 3 - An example of a table.

Selected channel name	Selected feature name
C3-P3	Standard Deviation (D5)
T5-O1	Total Energy Standard Deviation (D5) Standard Deviation (A5)
FP2-F8	Standard Deviation (D4) Standard Deviation (D5)
C4-T4	Max. Amplitude Standard Deviation (D4) Standard Deviation (D5)

2.4.Classfication

Useful and practical techniques are needed to solve classification problems. The features obtained in the previous stage are given as input to the classifiers at this stage. In this article, the success rates of SVM and LSTM classification algorithms are compared to choose the best result. Support vector machines are a learning method that emerged in the field of statistical learning theory.It can be used for linear or non-linear separable problems. In linearly separated problems, data can be separated by many lines, but kernel functions are used in problems that cannot be separated linearly (Guerrero MC, 2021). In this article study, the Polykernel kernel function expressed in Equation 2 is used.

$$k(x,y) = \left(a(x)^T y + c\right)^d \quad (2)$$

Here; α is the slope, c is the constant term and d is the polynomial degree. In this study, the default values of the SVM kernel function are used.

LSTM is a special type of Recurrent Neural Networks (RNN). LSTM network has a complex structure called LSTM cell in its hidden layer (Tuncer & Bolat, 2022b). In this study, a 4-layer structure was used, with 16 neurons in the LSTM layer and 32 neurons in the dropout layer. The created LSTM architectural structure is given in Table 4 in detail.

Table 4 - An example of a table.

Classifier	Learning Parameters
LSTM	Optimizer : ADAM, Learning Rate: 0,01 Dropout Rate : 0,2 Batch size : 10 Epoch : 50 32 memory units Layers: LSTM, Dropout, Activation, Output

10-fold cross validation approach was used in training the data. The accuracy, sensitivity, specificity percentages according to the classifier algorithms and the time spent by the classifier models to finalize the problem are given in Table 5.

Table 5 - The results of the classifier algorithms and the time spent by the algorithms.

Classifier	Sen. (%)	Spec. (%)	Acc. (%)	Duration(sn)
SVM	96.36%	96.36%	96.36%	0.05
LSTM	96.96%	96.96%	96.96%	84.86

According to Table 5, 96.96% success rate was achieved in 0.05 seconds with the SVM classifier, while 96.96% success rate was achieved in 84.86 seconds with the LSTM classifier. Considering the time cost of the model, it showed a much more successful performance of 0.05 seconds compared to the deep learning architecture of the SVM model. In the LSTM model, this time was determined as 84.86 seconds.Calculations were made on a computer with "Intel(R) Core (TM) i3-6006U CPU @ 2.00 GHz. 4 GB Ram".

III.CONCLUSION

In this study, two different approaches were used to classify ictal and interictal EEG data, which are important in the detection of epileptic seizures. Although most of the studies in the literature have been done on single-channel EEG, multi-channel EEG data was used in this study. In this way, classifier models are simulated with EEG data similar to real-world problems. The features that are correlated with each other were removed from the model by selecting the feature with CFS among 32 features.In this way, it is aimed to reach higher accuracy rates in a shorter time. While the number of features was 32 at the beginning, the number of features decreased to 9 after feature selection. It has been observed that deep learning architecture is more effective when classifier algorithms are considered according to accuracy rates.When the classifier algorithms are considered according to the processing cost times, it is concluded that the SVM algorithm is a faster algorithm. Since the success rate difference between both classifier algorithms is 0.6% and the processing time difference is 84.81 seconds, it has been concluded that the SVM algorithm is the optimum classifier algorithm when the classifier algorithms are considered in terms of both processing cost and success rates.

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