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Research Article

Detection of Epileptic Seizures with Different Machine Learning Algorithms Using EEG Signals in Daily Life

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Abstract—**Today, Electroencephalography (EEG) is commonly used as a diagnostic tool for epilepsy. In this study, an effective method for diagnosing epileptic seizures in non-clinical settings is proposed. To evaluate the performance of this method, EEG data from 7 pediatric patients at Boston Children's Hospital were analyzed using Decision Tree (DT), Linear Discriminant (LD), Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). The time and frequency characteristics of the EEG signals were compared. Experimental results show that epileptic seizures can be determined effectively with 100% accuracy by using only 3 channels (FP1-F7, FP2-F4 and T8-P8) with mean amplitude, mean frequency, median frequency and variance features with SVM, KNN or DT.**

Index Terms—**Electroencephalography, epileptic seizure, machine learning, median frequency, time domain analysis.**

I. INTRODUCTION

EPILEPTIC SEIZURE is known as the unusual electrical activities of the brain that occur in the central nervous system. During these activities, patients may experience loss of consciousness, confusion, tongue biting, falling down and related injuries [1]. It is not easy to detect when seizures will start. Seizures can be occurred unexpectedly in every moment of daily life, so this situation is pretty troubling especially for children and people with mental disabilities. It can be classified using machine learning algorithms for electrical activities that lead to the emergence of symptoms that occur during seizures [1], [2] and [3]. However, it is still difficult to diagnose. In this context, researchers have worked on the determination of deterministic features with a series of non-linear time series analyzes based on EEG measurements of seizures [4], [5] and [6].

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EEG signals are uninterrupted waveforms composed of fluctuations in potential differences across time. EEG plots depict a voltage signal that varies over time. Each data point represents the instantaneous voltage value at evenly spaced time intervals [2] and [7]. In this system, 21 electrodes are placed around the skull [8].

In the literature, there are investigations focused on identifying epileptic seizures through EEG measurements employing these electrode structures. Notably, various convolutional neural network (CNN) architectures rooted in deep learning have been utilized for this purpose [9]. From these CNN structures, 95% accuracy performances can be obtained with AlexNet and 94.17% accuracy performances with GoogleNet [2] and [10]. However, the seizure moment can be detected with 100% accuracy in EEG signals by obtaining many frequency and time characteristics from many different channels of EEG signals with different frequency regions. Especially K-nearest neighbour (KNN) and SVM algorithms are successful in this regard [11], [12] and [13]. One of the most important advantages of this study in comparison with the similar studies in the literature is the ability for determining the instantaneous seizures that patients may encounter in daily life with high accuracy by using the time and frequency characteristics obtained from the most effective frequency range of the EEG signals with the least effective number of channels and the most effective frequency range of these channels. Therefore, in cases of seizures that may occur in the daily life of the patients, a 1 second delay is also important in terms of performing the transactions quickly with even less storage space. In this way, using EEG data obtained by sampling rate of 256 Hz from 16 different channels of 7 pediatric epilepsy patients by Children's hospital of Boston-MIT, each signal was divided into one second segment. The time and frequency characteristics of the signals were obtained for each separated second segment. These were obtained as mean absolute value (MAV), mean frequency (MNF), median frequency (MDF) and variance (VAR) [11], respectively. Pearson correlation relationships were examined for each channel by applying comparatively statistical analysis of data. Thus, the most effective features for each channel were determined and their performances for determining seizure occurrence moments were comparatively determined by employing 5 different machine learning algorithms (DT, SVM, LD, NB and KNN) [14]. By using the achieved

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statistics of most effective 3 channels FP1-F7, FP2-F4 and T8-P8, seizure occurrence moments can be determined with 100% efficiency with MNF, MDF, MAV and VAR features, SVM, KNN, DT and LD.

The structure of this article is outlined as follows: Section 2 introduces the materials and methods employed in identifying epileptic seizure states. Experimental results, depicted through graphs and tables, are presented in Section 3, while Section 4 delves into the implications of these findings. Section 5 serves as the conclusion of the article.

II. Materials and Methods

A. EEG Dataset and Preprocessing

In this study, the EEG data of 7 patients in Boston-MIT Children's hospital with ages between 1.5 and 22 were investigated. These records consist of EEG data from 16 different channels with the sample rate of 256 Hz. The delta, theta, alpha and beta components of an example signal taken from the data set are given in Figure 1.

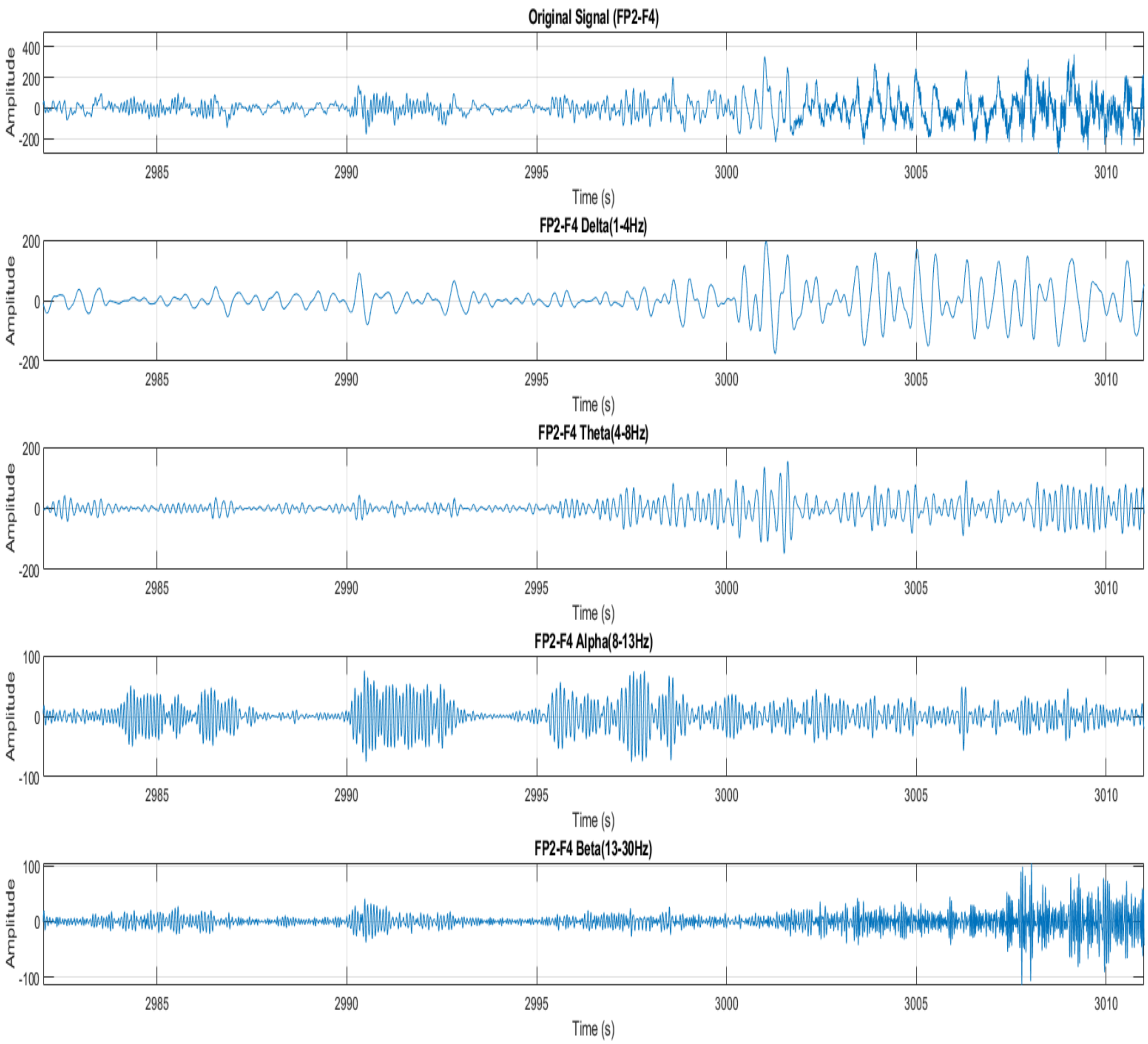

Fig.1. Time-frequency plots illustrating the EEG signal obtained from the FP2-FP4 channel during an epileptic seizure, depicting different frequency regions [2]

Beta waves (12-30Hz) typically manifest during periods of wakefulness and intense cognitive activity, characterized by their high frequency. Alpha waves (8-12Hz) are commonly observed when the brain is in a state of relaxation, displaying a lower frequency [2] and [15]. Theta waves (4-8Hz) are generally present during light sleep, while Delta waves (0.1-4Hz) exhibit the lowest frequency and are typically associated with deep sleep. The human EEG predominantly encompasses signals within the 1-30Hz frequency range. Although there is some indication that higher frequencies may convey significant neurophysiological information, the majority of EEG studies focus on signals within the 1-30Hz frequency range [2] and [15].

The alpha, theta, delta, and beta frequency bands were analyzed for signals with a sample rate of 256 Hz for each patient. To remove high-frequency components from the EEG data in these signals, a 2nd-order low-pass Butterworth digital filter was applied. However, for EEG recordings, the frequency regions of occurring seizures were determined using Fast Fourier Transform (FFT) and significant frequency regions were determined using MATLAB R2021b software. The block diagram of the proposed algorithm is given in Figure 2.

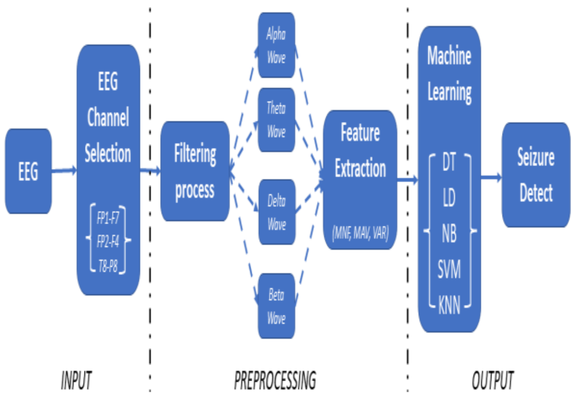

Fig.2. Block diagram of the system

B. E Feature Extraction of EEG Signals

Four distinct features were derived from the filtered EEG signals. MNF and MDF primarily encompass information associated with the amplitude and frequency of a signal [14], [16], [17] and [18].

$$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j \,, \qquad (1)$$

In Eq. (1), MNF is an average frequency value calculated by dividing the sum of the multiplications of the power spectrum intensity values of the signal up to J=1, 2,…,M' and the values of each instantaneous frequency by the intensity values of the same spectrum. fj represents its frequency in the jth frequency band, Pj is the power spectrum of the signal in the jth frequency band, and M is the length of the frequency band. MDF is a frequency where the spectrum is divided into two regions with equal amplitudes [2] and [19].

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \,, \qquad (2)$$

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |X_i| \,, \qquad (3)$$

Another widely employed parameter is MAV, which encapsulates crucial information regarding the average amplitude of the signal [14]. The MAV features of EEG signals are computed using Eq. (3). VAR is another significant feature used to assess the power of signals, defined as the mean square of the deviation values of signals [11], [14], [19] and [20].

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} X_i^2 \,, \qquad (4)$$

In Eq. (3) and (4), X_i represents the signal in segment i, N denotes the length of the EEG signal [14]. These obtained features MNF, MDF, VAR and MAV are classified in two classes as non-seizure (0) and seizure (1), in terms of entry features.

C. Classification of EEG Signals

In this study, five different machine learning algorithms (KNN, DT, NB, SVM, and LD) [14] are employed for the classification of EEG signals [21] and [22]. MNF, MDF, VAR, and MAV inputs are classified into two classes: non-seizure (0) and seizure (1). Each classifier undergoes training through cross-validation with a k-fold value of 5. To assess the performance of the introduced method, classification accuracy was calculated using Eq. (5) [14] and [23].

$$Accuracy(\%) = \frac{1}{N}\sum_{k=1}^{N}\left[\frac{TP+TN}{TP+TN+FP+FN}\right]\times 100 \,, \qquad (5)$$

In this context, N represents the number of classes. True positive (TP) and true negative (TN) denote the number of correctly classified samples, while false positive (FP) and false negative (FN) represent the number of misclassified samples [11] and [23].

III. Results and Discussing

The received signals were plotted for 15 seconds before the seizure and 15 seconds at the time of the seizure. The EEG signals of all channels for the sample patient are given in Figure 3. The obtained results show that the amplitude of the EEG signals increases at the time of the seizure. Recently studies show that the moment of seizure can be detected with 100% accuracy by employing EEG signals, specially by using the K-nearest neighbor (KNN) and SVM algorithms [10] and [11]. Also, there are studies based on deep learning architecture (CNN) [9] and [10].

However, all these studies are clinical studies for the use of channels collectively. In this study, all channels were already examined separately and together, and there were significant increases in the amplitude values of all channels at the time of seizure. However, the primary objective of this study is to determine the most effective channels (FP1-F7, FP2-F4 and T8-P8) taken from the frontal and temporal regions of the human brain, which will not disturb the person in daily life, to determine the seizure quickly and without requiring storage space. The frequency analysis of the original signal of the sample patient taken from the FP2-F4 channel and the frequency analysis of the delta, theta, alpha and beta components of this signal are given in Figure 4.

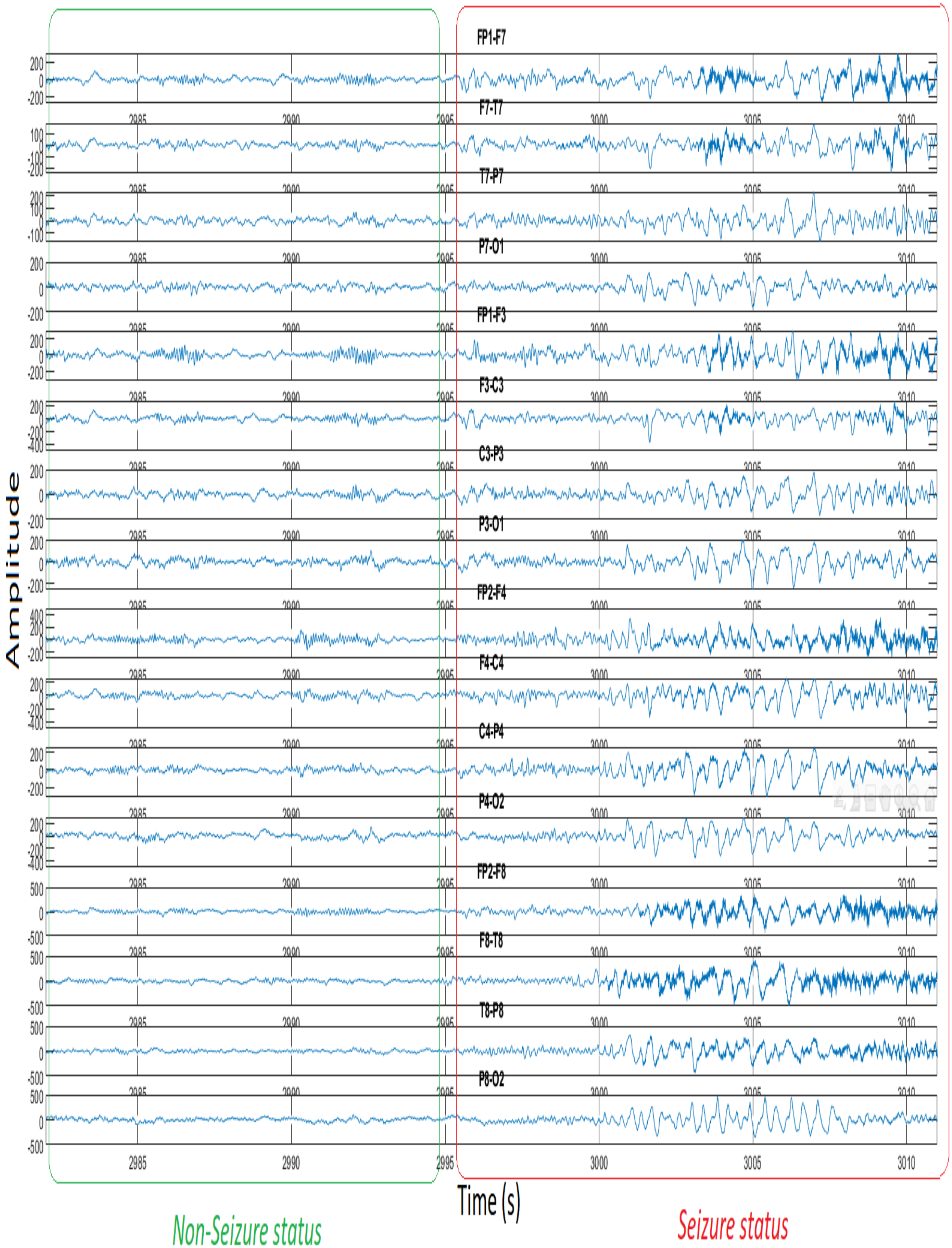

Fig.3. Amplitude-time graphs of EEG signals of all 16 channels of an 11-year-old girl with epilepsy

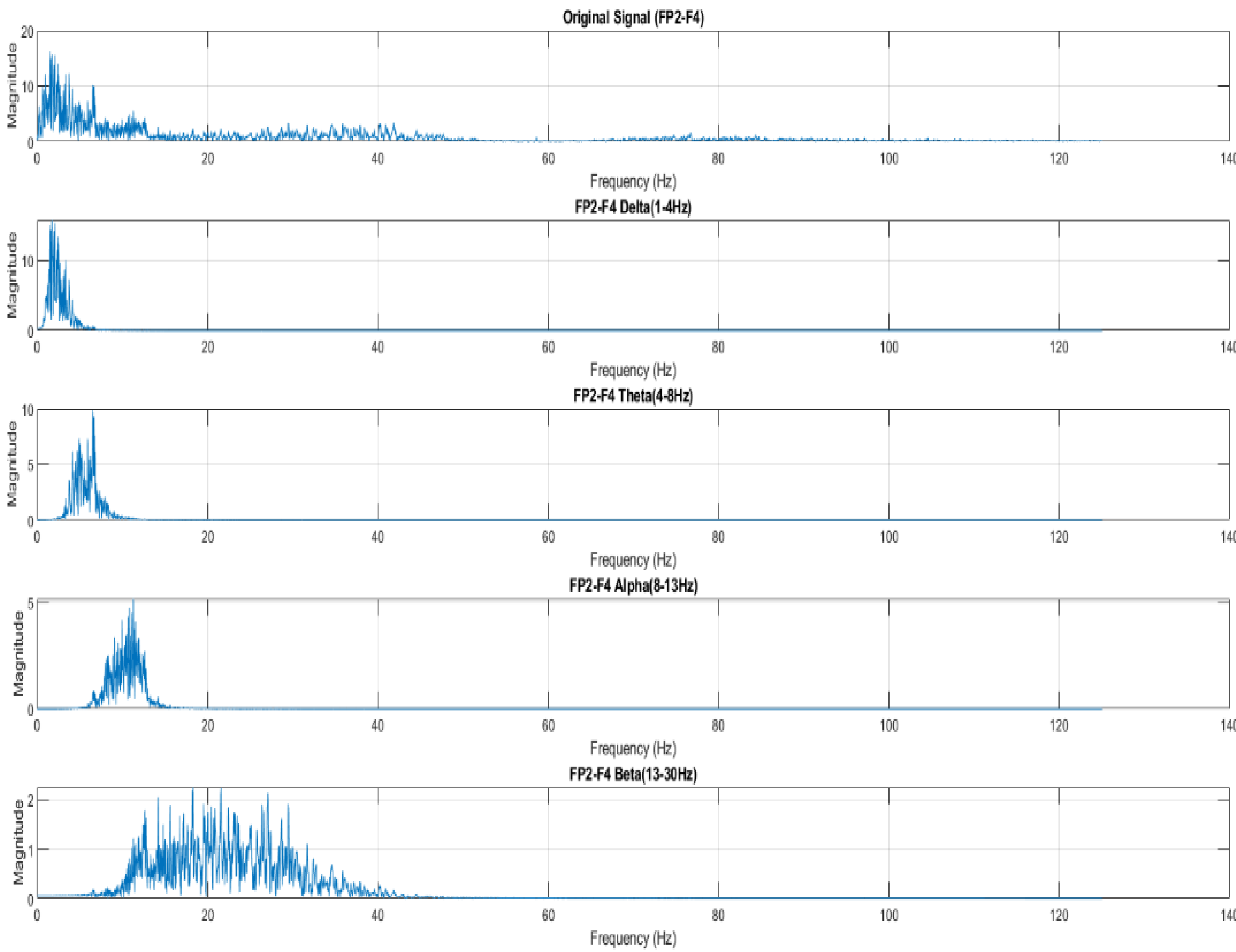

Fig.4. EEG frequency spectrum depicting the different frequency regions of the FP2-F4 channel during an epileptic seizure in a patient

As seen in Figure 4, this study investigates distinctive features of frequency spectra to achieve effective classification by analyzing all channels for each patient across various frequency ranges. Upon scrutiny of this figure, it becomes apparent that the notable frequency range extends up to the corner frequency (Fc) of 30 Hz.

The results of Pearson correlation for the selection of the most effective channels in terms of the impact of input features on the output are presented in Table I.

The obtained results indicate that the FP2-F4 channel and the T8-P8 channel are the most prominent channels showing rhythmic activations, while the FP1-F7 channel is sensitive to high-amplitude deviations [26]. When examining the frequency spectra in this study, these three channels are prominently observed. Statistically, in Pearson correlation analysis, it is observed that the features MAV, MNF, MDF, and VAR, which are solely utilized with these three channels, exhibit high correlation in determining seizure and non-seizure states.

Frequency spectra of EEG recordings containing all channels for each patient have been obtained. Figure 5 displays the frequency spectra encompassing a total of 30 seconds, including the first 15 seconds before the seizure, the seizure moment, and the last 15 seconds after the seizure, from EEG recordings of a sample patient comprising FP1-F7, FP2-F4, and T8-P8 channels.

TABLE I
THE PEARSON CORRELATION RELATIONSHIPS OF EEG CHANNELS

EEG Channel Selection	FP1-F7 F7-T7 T7-P7 P7-O1 FP1-F3 F3-C3 C3-P3 P3-O1 FP2-F4 F4-C4 C4-P4 P4-O2 FP2-F8 F8-T8 T8-P8 P8-O2	FP1-F7 T7-P7 FP1-F3 FP2-F4 C4-P4 FP2-F8 F8-T8 T8-P8	FP1-F7 FP1-F3 FP2-F4 T8-P8	FP1-F7 FP2-F4 T8-P8
Signal Features	***Pearson Coef.***	***Pearson Coef.***	***Pearson Coef.***	***Pearson Coef.***
MAV	0,789	0,881	0,964	0,999
MNF	0,147	0,394	0,599	0,949
MDF	0,394	0,708	0,977	0,999
VAR	0,494	0,704	0,676	0,854

The obtained results indicate that the FP2-F4 channel and the T8-P8 channel are the most prominent channels showing rhythmic activations, while the FP1-F7 channel is sensitive to high-amplitude deviations [26]. When examining the frequency spectra in this study, these three channels are prominently observed. Statistically, in Pearson correlation analysis, it is observed that the features MAV, MNF, MDF, and VAR, which are solely utilized with these three channels, exhibit high correlation in determining seizure and non-seizure states. Frequency spectra of EEG recordings containing all channels for each patient have been obtained. Figure 5 displays the frequency spectra encompassing a total of 30 seconds, including the first 15 seconds before the seizure, the seizure moment, and the last 15 seconds after the seizure, from EEG recordings of a sample patient comprising FP1-F7, FP2-F4, and T8-P8 channels. While the seizure states are pronounced in these channels, the frequency response results, particularly in the low-frequency regions (up to 10 Hz), are provided in Figure 6.

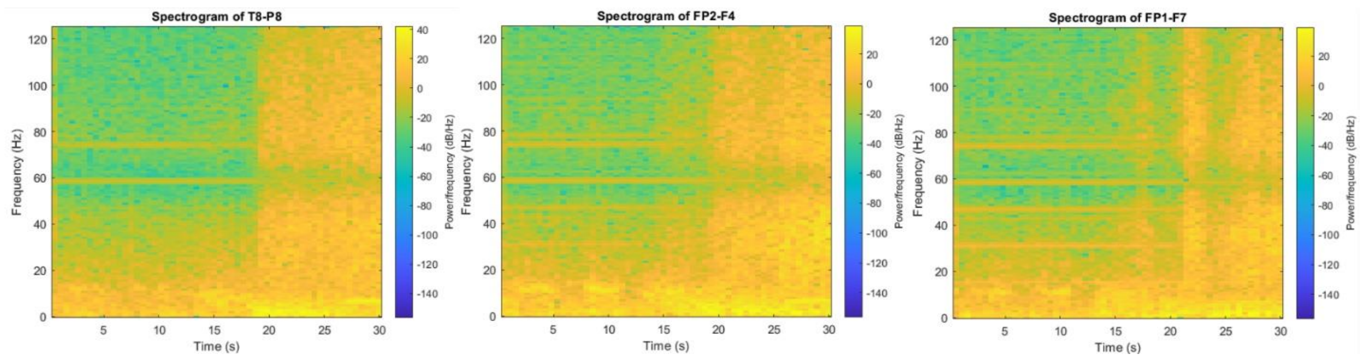

Fig.5. Frequency spectrums of 3 channels showing the seizure moment and pre-seizure situation

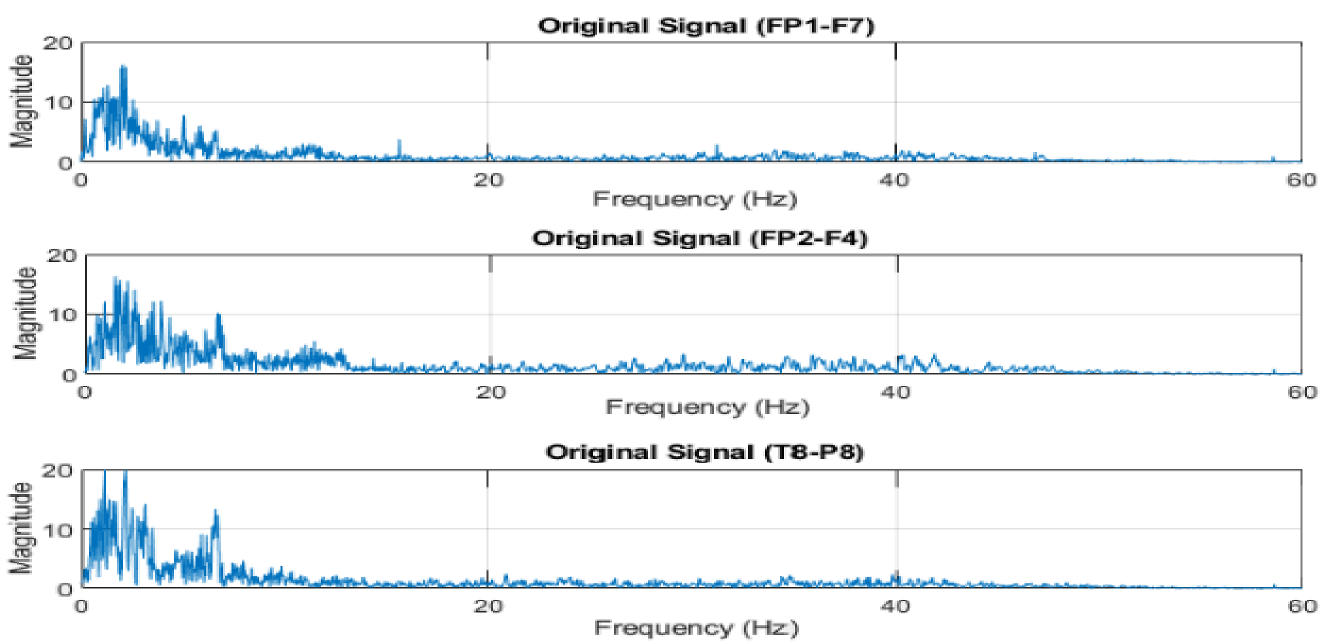

Fig.6. Frequency domain FFT graphs of 3 channels showing the seizure moment and pre-seizure situation

As observed in Figure 6, High amplitudes are present in low frequencies during seizure moments, accompanied by a significant variation in amplitude values. Therefore, MAV, MNF, MDF, and VAR features have been selected. Thus, with minimal features and considering the minimum number of channels, effective seizure detection has been achieved. The recordings obtained for pre-seizure and seizure states have been classified using Machine Learning algorithms in 1-second segments. This is because the primary aim of this study is to detect seizure states in real-time data with 1-second intervals, considering daily life scenarios. For this purpose, different classifiers have been employed and compared using the FP1-F7, FP2-F4, and T8-P8 channels. During the training of these classifiers, cross-validation (k-fold: 5) has been chosen. Subsequently, performance metrics have been determined using 1000 different data points representing seizure and non-seizure states that were reserved for testing. The test results are provided in Table 2.

The accuracy performance of classifications increases as the number of features increases. By utilizing all four of these features together, KNN, SVM, and DT classifiers can achieve 100% performance. The performance results, including ROC curves and Confusion matrices obtained by using these four features together, are further depicted in Figure 7.

While the performance values in Figure 7(b) and (c) are lower when using LD and NB, as observed in Figure 7(a), when SVM, KNN, or DT are used, seizure states have been accurately detected with 100% accuracy using the MAV, MNF, MDF, and VAR features. Upon examining the ROC curves, it is evident that the area under the curve (AUC) values are 1.0, indicating the most effective classification performance.

This is particularly significant for wearable headgear systems in everyday life. Notably, even though this study utilizes a ready-made EEG dataset comprising 16 channels obtained from 7 pediatric patients by Children's Hospital Boston, and employs MATLAB R2021b, the data has been transformed into 1-second segments with time and frequency features (MAV, MNF, MDF, and VAR) to simulate real-life scenarios. The resulting model, trained with K-fold: 5 cross-validation, is well-suited for testing with structures that mimic real-world conditions.

TABLE II

ACCURACY PERFORMANCES USİNG DİFFERENT CLASSİFİERS WİTH FP1-F7, FP2-F4, T8-P8

Used Classifier	Accuracy (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)
Fine Tree	*100%**	*90,5%***	*97,6%****	*99,8%*****	*100%******
Medium Tree	*100%**	*90,5%***	*97,6%****	*99,8%*****	*100%******
Coarse Tree	*100%**	*90,5%***	*97,6%****	*100%*****	*99,9%******
Linear Disc.	*71,4%*	*71,4%***	*95,2%****	*92,9%*****	*100%******
Gaussion NB	*85,7%**	*81%***	*100%****	*100%*****	*97,6%******
Kernel NB	*85,7%**	*78,6%***	*100%****	*97,6%*****	*90,5%******
SVM Linear	*100%**	*88,1%***	*97,6%****	*97,6%*****	*100%******
SVM Qaudratic	*100%**	*83,3%***	*100%****	*100%*****	*100%******
SVM Fine Gausion	*100%**	*90,5%***	*99,8%*****	*100%*****	*99,8%******
SVM Medium Gausion	*100%**	*88,1%***	*97,6%****	*97,6%*****	*100%******
SVM Coarce Gausion	*100%**	*69%***	*92,9%****	*88,.1%*****	*100%******
SVM Kernel	*100%**	*83,3%***	*97,6%****	*100%*****	*99,9%******
KNN fine	*100%**	*88,1%***	*97,6%****	*97,6%*****	*97,6%******
KNN medium	*100%**	*85,7%***	*97,6%****	*100%*****	*100%******
KNN weighted	*100%**	*90,5%***	*97,6%****	*100%*****	*99,8%******

**Used with MAV, MNF, MDF and VAR*
***Used only MDF*
**** Used only VAR*
***** Used with MNF, VAR*
****** Used with MAV, MNF*

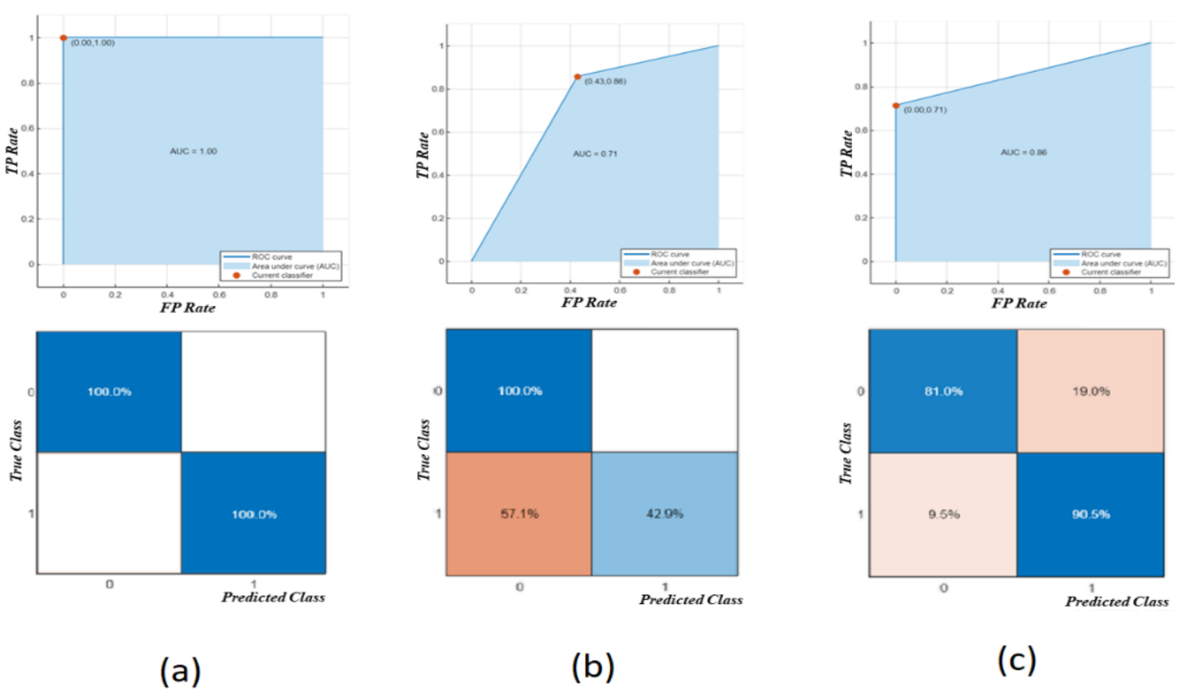

Fig.7. Accuracy performance results (with MAV, MNF, MDF and VAR features); (a) Results for SVM, KNN or DT, (b) Results for LD, (c) Results for NB

IV. Conclusion

In this study, EEG signals sampled at 256Hz were utilized from 7 child patients with ages ranging between 7 to 12 years, obtained by Children's Hospital Boston. Time and frequency features of these signals were comparatively examined. The experimental results demonstrate that epileptic seizures can be effectively identified with 100% accuracy using only 3 channels (FP1-F7, FP2-F4, and T8-P8) along with features like mean amplitude, mean frequency, median frequency, and variance, when employed with SVM, KNN, or DT. As a result, this allows for the diagnosis of daily occurring seizures without disturbing individuals, making it suitable for wearable systems geared towards instantaneous seizure detection with fewer channels, thereby requiring less storage space and enabling rapid real-time identification of seizures.

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Biographies

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From 1984 to 1993, he worked as a research assistant, from 1993 to 1999 as a lecturer, from 1999 to 2001 as an Assistant Prof. Dr., from 2001 to 2003 as an Associate Prof. Dr., from 2003 to 2014 as an Prof. Dr. in two departments for University of Marmara. Since 2015 he has been working as an Prof. Dr. for Electrical and Electronics Engineering Department of School of Engineering, also is Director of Vocational School of Halic University.

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