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INFORMATICS

A novel moving window-based power spectrum features for single-channel EEG classification using machine learning

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ABSTRACT. Electroencephalogram (EEG) signal classification is a crucial and very difficult task. Meanwhile, extracting features that are representative and able to discriminate different types of EEG signals is a complex task. Such features are usually fed to machine learning algorithms to classify the EEG signals based on the extracted features. This paper proposed a highly accurate and real-time features extraction method that can be used to help physicians in detecting different types of seizures and states in EEG signals characterized by a set of features extracted from the power spectrum of the EEG window. This is achieved by applying the following four steps. First, the EEG signals dataset contains different classes of EEG signals: Normal Eye Closed, Normal Eye Opened, Focal Seizure, Non-Focal Seizure, and Ictal Seizure activities. Second, each EEG signal has a length of 4097 samples sampled with a sampling frequency of 173.6 Hz which resulted in 23.6 seconds in length, this signal will be truncated into windows (Sub-signals) with a length of 349 samples (Approximately 2 seconds) with a total number of 12 windows for each signal. Afterward, the Fourier Transform (FT) based power spectrum will be computed for each window, then a set of different features are extracted from each window's FT power spectrum, and these features are classified using different Machine Learning (ML) algorithms. The results showed that the proposed methodology yields around 98% accuracy for the five different classification scenarios using different ML algorithms. The suggested method is hence robust, fast, real-time, accurate, and simple.

Keywords: EEG; fourier transform (FT); power spectrum; moving window; machine learning; classification.

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Introduction

The electrical activity of the brain is represented by the electroencephalogram (EEG) signals. Electroencephalography (EEG) is an investigative non-invasive method that provides information for the classification, diagnosis, and therapy of brain conditions (Guo, Rivero, Dorado, Rabunal, & Pazos, 2010b; Oweis & Abdulhay, 2011; Li, Zhou, Yuan, Geng, & Cai, 2013; Pramanick, 2013). The information about the type and nature of diseases that affect the brain are studied from the frequency and energy contents of the EEG signals (Al-Fahoum & Al-Fraihat, 2014). The EEG signal contains a time series of potentials that is caused by the systematic neural activities in a brain. The EEG signal collected by placing the electrodes on the scalp is plotted as a voltage magnitude against time 6. In general, the voltage range of the scalp EEG is between 10 and 100 micro-volts (Pramanick, 2013; Sinha, 2008). The EEG frequency range of interest for the classification purpose lies between 0.1Hz and 100Hz. The main important components that are used to characterize the EEG are delta rhythm (0.5 - 4) Hz, theta rhythm (4 -8) Hz, alpha rhythm (8 - 13) Hz, and beta rhythm (13 - 30) Hz (Pramanick, 2013; Al-Fahoum & Al-Fraihat, 2014; Sinha, 2008; Kumar, Kanhangad, & Pachori, 2015).

The changes in the electrical activity of the brain can cause dramatic, noticeable symptoms or no symptoms at all. Neurologists use the EEG signals to detect and categorize the patterns of the neurological disease and abnormal behaviors such as pre-ictal spikes, seizures Hz (Guo et al., 2010; Oweis & Abdulhay, 2011; Li et al., 2013; Pramanick, 2013; Al-Fahoum & Al-Fraihat, 2014; Sinha, 2008; Kumar et al., 2015) sleep apnea (Yulita, Rosadi, Purwani, & Suryani, 2018), sleep stages (Fonseca, den Teuling, Long, & Aarts, 2018; Chambon, Galtier, Arnal, Wainrib, & Gramfort, 2018) and drowsiness detection (Nguyen, Ahn, Jang, Jun, & Kim, 2017). The analysis of the patient's EEG signal is time-consuming and laborious, and it requires the services of an expert (Ullah, Hussain, & Aboalsamh, 2018). A lot of research work has been done in recent years to detect epileptic and non-epileptic signals as a classification problem (Guo et al., 2010; Oweis &

Abdulhay, 2011; Li et al., 2013; Pramanick, 2013; Al-Fahoum & Al-Fraihat, 2014; Sinha, 2008; Kumar et al., 2015; Ullah et al., 2018). An epileptic form pattern represented by the presence of spikes in EEG signals has become a valuable tool for assessing brain disorders, especially epileptic seizures (Ray, 1994; Mukhopadhyay & Ray, 1998; Molla, Islam, Hassan, Islam, & Tanaka, 2020). Most of the existing methods depend on decomposing the EEG signal into several levels with various feature parameters to attain better classification results (Molla et al., 2020).

There is not many much available for training a classifier, so recognition of epileptic and non-epileptic EEG signals using ML algorithms is a challenging task. Moreover, the noise and artifacts present in the data in addition to the inconsistency in seizure morphology among patients create difficulty in learning the brain patterns associated with normal and abnormal cases (Guo et al., 2010; Oweis & Abdulhay, 2011; Li et al., 2013; Pramanick, 2013; Al-Fahoum & Al-Fraihat, 2014; Sinha, 2008; Kumar et al., 2015; Ullah et al., 2018; Molla et al., 2020). Seizure sometimes causes unusual behavior, sensations, and loss of awareness (Molla et al., 2020;) and the number of seizure patients in the world starts to increase in the last years. Therefore, a robust automatic system with good performance even with fewer training samples is needed to help and assist neurologists in classifying epileptic and non-epileptic EEG brain signals. Signal processing (SP) and ML techniques are traditionally used for the existing automatic seizure detection. However, these techniques might show good accuracy for one problem but fail to accurately perform other problems (Mukhopadhyay & Ray, 1998; Molla et al., 2020; Khushaba, Takruri, Miro, & Kodagoda, 2014; Khushaba, Al-Ani, Al-Timemy, & Al-Jumaily, 2016; Al-Timemy, Khushaba, Bugmann, & Escudero, 2015; Zhang & Chen, 2017)

In this paper, a highly accurate and real-time new method based on a set of features extracted from the power spectrum of the EEG window is proposed. This method can be used to help physicians in detecting different types of seizures and states in the EEG signal. The EEG signal dataset contains different classes of EEG signals: Normal Eye Closed, Normal Eye Opened, Focal Seizure, Non-Focal Seizure, and Ictal Seizure activities. This signal will be truncated into windows (Sub-Signals), then the Fourier Transform (FT) based power spectrum is computed for each window. Each EEG signal has a length of 4097 samples sampled with a sampling frequency of 173.6 Hz which results in 23.6 seconds in length, and each signal was truncated into 23 windows. Finally, a different set of features will be extracted from each window's FT power spectrum and these features are classified using different ML algorithms. In this work, we employed the support vectors machine (SVM), extreme learning machine (ELM), and K-nearest neighbors (KNN) algorithms. The results have shown that our suggested method is robust, fast, real-time, accurate, and simple. This method can be implemented in embedded systems and clinical applications.

The analysis of the brain signal using a computer interface system and intelligent signal segmentation have very important applications in medicine and military objectives (Al-Hudhud, 2014; Kotchetkov, Hwang, Appelboom, Kellner, & Connolly Jr., 2010.). To simplify the assembly of the brain-computer interface, a professional method is needed to extract features from EEG signals. The EEG signal has many sources of artifacts and noise which affect the main and useful features we are interested to extract from the original signal (Ullah et al., 2018; Ray, 1994; Mukhopadhyay & Ray, 1998; Molla et al., 2020). These artifacts are caused during the signal acquisition procedure due to the activities of muscles, eyes blinking, and the electrical noise from the power line (Al-Fahoum & Al-Fraihat, 2014; Molla et al., 2020).

In general, EEG signal processing goes through several common steps: the step of preprocessing includes the signal acquisition, artifacts removal, averaging of the signal, the output thresholding, then the resulting signal will be enhanced, and finally, the edge detection is done for the signal after the enhancement step (Khushaba et al., 2016; Al-Timemy et al., 2016; Zhang & Chen, 2016). The discriminative feature extraction step is used to determine the most important features or information for the classification exercise (Al-Fahoum & Al-Fraihat, 2014; Molla et al., 2020). In the final step, signal classification can be done by exploiting the algorithmic characteristics of the feature vector using different methods including, adaptive algorithms, clustering and fuzzy techniques, linear analysis, nonlinear analysis, and neural networks (Sun, Wang, Min, Zang, & Wang, 2018; Bhowmick, Abdou, & Bener, 2018; Sriraam et al., 2018; Kumar, Sharma, & Tsunoda, 2019).

The EEG signal is a nonstationary signal with non-linear properties (Pachori & Patidar, 2014; Abdulhay Alafeef, Abdelhay, & Al-Bashir, 2017; Panahi, Aram, Jafari, Ma, & Sprott, 2017; Wang et al., 2018; Sun et al., 2018; Bhowmick et al., 2018; Sriraam et al., 2018; Kumar et al., 2019). Several methods have been proposed to do feature-extraction of the EEG signals for automated detection of epileptic seizures. The most common methods used for feature extraction include the Fast Fourier transform (Polat & Güneş, 2007; Cerna & Harvey, 2000; Subasi, Kiymik, Alkan, & Koklukaya, 2005; Faust, Acharya, Allen, & Lin, 2008) Wavelet transform (WT) (Guo et al., 2010; Wang, Miao, & Xie, 2011; Nicolaou, & Georgiou, 2012; Kumar, Dewal, & Anand, 2014; Tawfik, Youssef, & Kholief, 2016) Eigenvectors (Übeyli, 2009; Awang, Paulra, & Yaacob, 2012), Time-Frequency Distributions (Guerrero-Mosquera, & Vazquez, 2009; Tzallas, Tsipouras, & Fotiadis, 2009), and Autoregressive Methods (AR) (Subasi et al., 2005; Faust et al., 2008).

(Polat & Güneş, 2007) have proposed A hybrid system of two stages where FFT was used for feature extraction and a decision tree classifier was used for decision-making and seizure detection. They have achieved 98.72% classification accuracy, but their method is not compatible with EEG characteristics since they considered that EEG is stationary for a short duration. (Tzallas et al., 2009) have performed time-frequency representation based on the Fourier transform method considering that in a short duration the EEG is nonstationary. They used the fractional energy of each window as a feature, and they have done the classification using a neural network and achieved an average classification accuracy of 89.1%.

(Guo, Rivero, & Pazos, 2010a) decomposed EEG signal into multiple sub-bands using multiple orthogonal and symmetric wavelet functions. They have extracted the approximate entropy from each sub-band and used them in an artificial neural network for seizure detection and achieved a classification accuracy of 98.27%. The feature extraction using wavelet packet entropy has been used in epilepsy recognition effectively with a 99.44% average classification accuracy (Wang et al., 2011). Moreover, a support vector machine (SVM) (Zhang & Chen, 2017) with permutation entropy (PE) implementation of a short-term EEG segment has been used for automated epileptic seizure detection and 86.10% accuracy was achieved (Nicolaou & Georgiou, 2012). In using permutation entropy, it was noticed that the value for epileptic EEG is less than that for non-epileptic EEG.

Wavelet-decomposition-based sub-band fuzzy approximate entropy (fAPE) (Kumar et al., 2014) and the weighted permutation entropy (WPE) (Tawfik et al., 2016) were used as potential features with SVM for seizure event recognition. The classification accuracy of sub-band fAPE is 98.45% and it is higher than that of 93.37% for WPE. However, not all features of EEG can be detected using the entropy-based implementation, and hence other features need to be introduced. (Übeyli, 2010) used the Burg autoregressive (AR) coefficients as features for epilepsy detection, they considered that the short-term window of EEG is stationary. They achieved an accuracy of 99.56% in implementing the least square SVM in epilepsy classification. Genetic programming (GP)-based feature extraction was used with a k-nearest neighbors (KNN) classifier for seizure detection (Guo, Rivero, Dorado, Munteanu, & Pazos, 2011). In recent years, the 1-D convolutional neural network architecture of deep learning algorithm has been used for seizure detection and it provides greater accuracy and sensitivity compared with the methods that involve manual feature selection (Chowdhury, Hossain, Fattah, & Shahnaz, 2019; Xu et al., 2019; Zhang, Guo, Yang, Chen, & Lo, 2019).

Ullah, Hussain, & Aboalsamh (2018) have implemented an ensemble model for seizure detection based on a pyramidal one-dimensional convolutional neural network (P-1D-CNN). The learning of this model was implemented with a low number of parameters and a classification accuracy of 99.10% was attained. (Raghu, Sriraam, Hegde, & Kubben, 2019) have implemented epilepsy recognition by arranging artifact-free filtered EEG time series sequentially to form a square matrix for computing the matrix determinant feature, and they have employed a multilayer perceptron as a classifier and achieved an accuracy of 97.15%. 1D-local binary pattern-based features were derived using a Gabor filter bank (Kumar et al., 2015), and seizure events in recorded EEG were recognized using a KNN classifier. (Molla et al., 2020) have divided the EEG signal into short time frames and used the discrete wavelet transform to decompose each frame of EEG into a number of sub-bands. To characterize the spike events, a group of features was extracted from each sub-band signal of a specific frame. a high-dimensional feature vector was created, and a graph Eigen decomposition (GED)-based approach was used to select a discriminative subset of features that are effective in characterizing the EEG signals to recognize seizure events from non-seizure events using a feedforward neural network. Their method can be used for EEG-based seizure detection with a classification accuracy of 99.55% which is higher than the accuracies of 98.72% for linear discriminant analysis and 99.39%, for support vector machine classifiers.

Material and methods

This section gives information about the used dataset, non-overlapping moving window principle, power spectrum FT, features extraction, classifier, and the performance evaluation criteria used in this study. Figure 1 shows the block diagram of the proposed methodology.

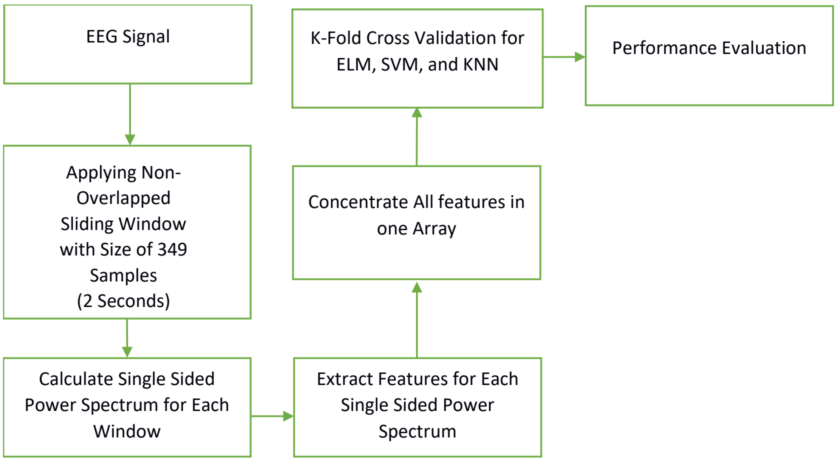

Figure 1. The proposed methodology block diagram.

EEG dataset

The EEG dataset used in this paper has been acquired at the Epilepsy Center of the Bonn University Hospital of Freiburg (Andrzejak et al., 2001). The dataset consists of five different subsets (A-E) which are denoted as Z, O, N, F, and S. Each subset consists of 100 single-channel EEG signals with a duration of 23.6 seconds recorded using an analog-to-digital (A/D) converter of 12-bit resolution and a sample rate of 173.61 Hz. Subsets A and B are collected extracranially, while the other subsets (C, D, and E) are captured intracranially. Both A and B sets are recorded from five different healthy volunteers using a standard 10-20 electrode placement while their eyes open and closed. The other remaining three sets are gathered from another five epileptic patients. More specifically, both sets C and D are collected from the epileptogenic zone (D) and hippocampal formation of the opposite hemisphere of the brain (C) respectively during the seizure-free intervals (i.e., inter-ictal EEG). Finally, set E only contains seizure signals corresponding to seizure attacks (i.e., ictal EEG), and it is recorded from all the recording sites exhibiting ictal activity (Andrzejak et al., 2001). Figure 2 shows samples of signals from the used dataset.

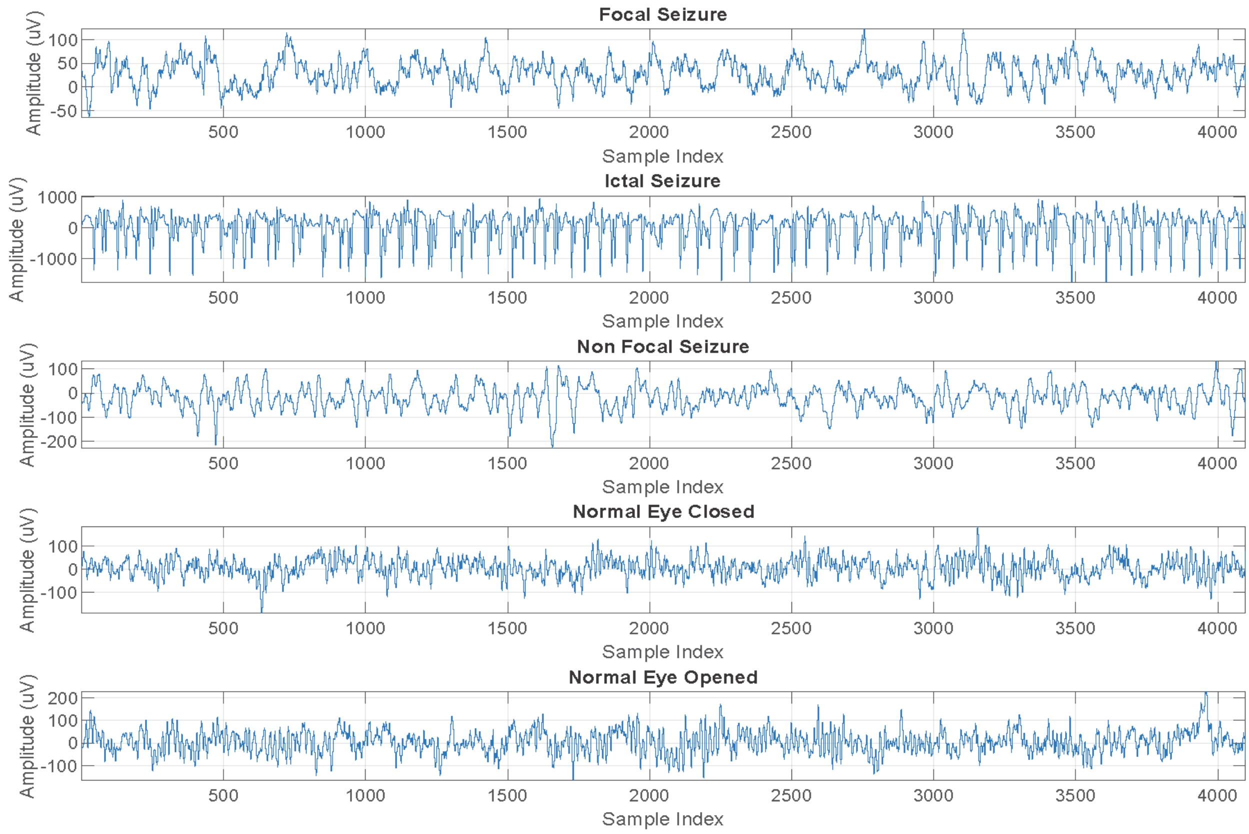

Figure 2. Sample signals from the used dataset.

The used dataset is unbalanced; this is the nature of the brain-related diseases where there are not enough patients to collect more data. One of the solutions recently appeared is the augmentation of the dataset to become balanced (Helwan, & Uzun Ozsahin, 2017). This solution has many drawbacks such as it requires an extra evaluation system quality of augmented datasets, it needs new research to create new or synthetic data with an advanced application, the application of few data augmentation techniques like GANs is quite challenging, and identification of optimal data augmentation strategy is another challenge, and finally, if real data contains biases the augmented data may contain same biases (Alqudah & Alqudah, 2022). Finally, to avoid these problems and make the research more practical we keep the dataset without augmentation.

Moving window principle

In this paper, we have applied the non-overlapping moving window technique. In this technique, a window with a predefined size usually in seconds is selected to slide over the EEG signal, the window size was converted to samples using equation 1.

$$WL_{Time} = \frac{\mathrm{WL}_{Samples}}{F_s} \quad (1)$$

where WL_{Time} is the window length in seconds, $\mathrm{WL}_{Samples}$ is the window size in samples, and Fs is the sampling frequency. The chosen window size must be suitable for the signal length, enough to extract features from the signal, and does not require zero padding (Helwan & Uzun Ozsahin, 2017; Alqudah & Alqudah, 2022). The non-overlapping moving window technique is used to ensure that the feature extraction methods are paying attention to every detail in the EEG signal and its corresponding FT. Also, splitting the EEG signal into sub-signals using this technique will result in increasing the number of signals that will be used in building the classification model (Alqudah & Alqudah, 2022). Figure 3 shows an example of the proposed non-overlapping moving window technique over the EEG signal. This example shows a signal with a length of 4188 samples using a window of the length of 2 seconds (349 samples).

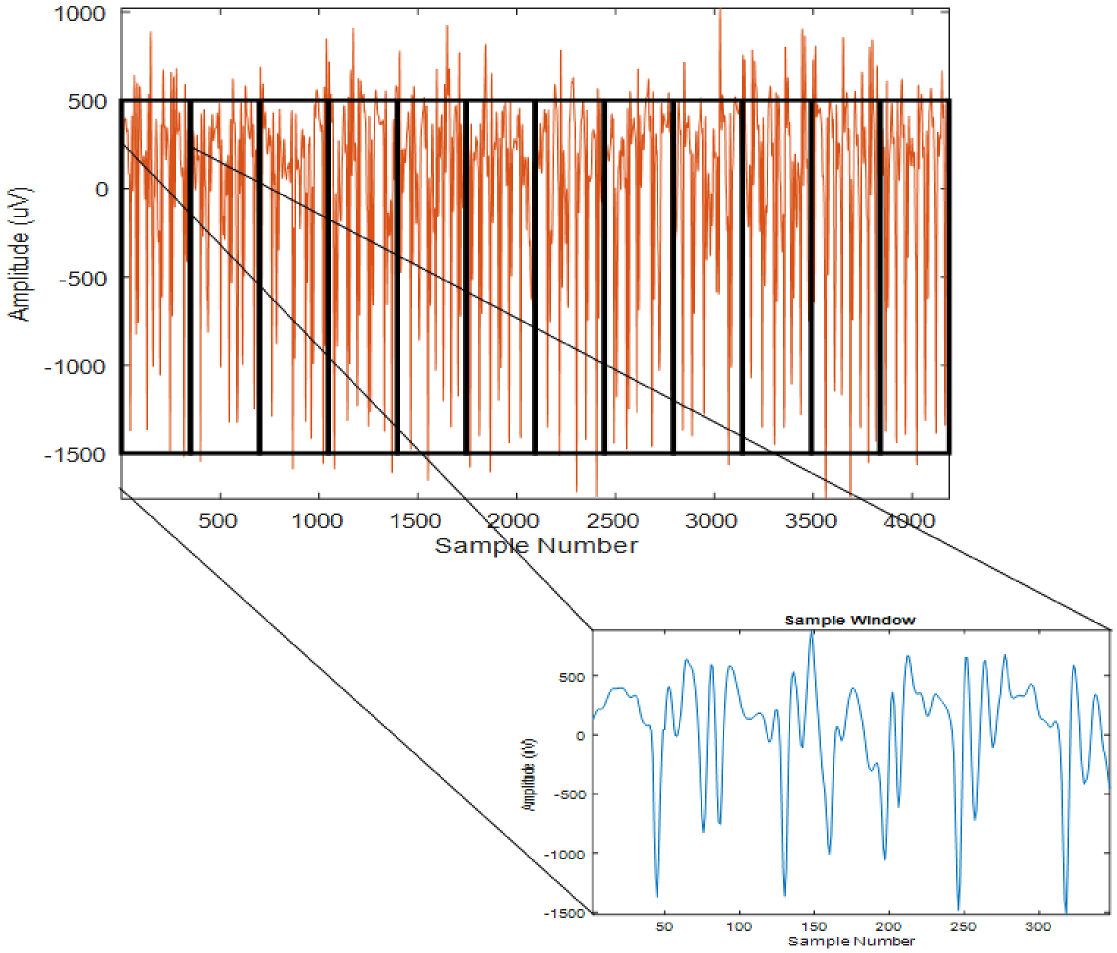

Figure 3. An example of the Non-overlapping sliding window over the EEG signal.

The power spectrum based on FT

The FT is one of the common methods used for analyzing signals in general and especially biomedical signals. It is basically defined as the Fourier transform of the autocorrelation function of a signal (Alqudah, 2019b). It can be defined in the continuous and discrete time domain as follows:

$$PS(f) = \frac{1}{T}\int_0^T r_{xx}(t)\, e^{-j2\pi ft}\, dt \qquad m = 1,2,3,\ldots, \tag{2}$$

$$PS[m] = \sum_{n=1}^{N} r_{xx}[n]\, e^{\frac{-j2\pi mn}{N}} \qquad m = 1,2,3,\ldots,N \tag{3}$$

where $r_{xx}(t)$ and $r_{xx}[n]$ are the autocorrelation functions applied on the signal.

The autocorrelation functions have an even symmetry property, the sine terms in the expansion of the Fourier series will be all zeros, and equations 2 and 3 can be simplified to include only real (cosine) parts which are known as cosine transforms as shown in equations 4 and 5.

$$PS(f) = \frac{1}{T}\int_0^T r_{xx}(t)\, cos(-j2\pi ft)\, dt \qquad m = 1,2,3,\ldots, \tag{4}$$

$$PS[m] = \sum_{n=1}^{N} r_{xx}[n]\, cos\left(\frac{-j2\pi mn}{N}\right) \qquad m = 1,2,3,\ldots,N \tag{5}$$

These definitions are not very popular, other popular definitions are used for finding the power spectrum in a direct method. This direct method is mainly based on the fact that the energy contained in an analog signal is directly proportional to the integration of the magnitude of the signal squared over time (Helwan & Uzun Ozsahin, 2017) as shown in equation 6.

$$E = \int_{-\infty}^{\infty} |x(t)|^2\, dt \tag{6}$$

By applying the Parseval theorem, this method can be extended as shown in equation 7.

$$E = \int_{-\infty}^{\infty} |X(f)|^2\, df \tag{7}$$

Hence that $|X(f)|^2$ is the same as the energy density function over frequency which is also known as the power spectral density (PSD) or what we defined before as the power spectrum (PS). Using the direct method, we can calculate the power spectrum as the squared magnitude of the Fourier transform of any signal (El-Shennawy, 2014) as in equation 8.

$$PS(f) = |X(f)|^2 \tag{8}$$

Unlike the conventional FT, since the power spectrum is defined as a magnitude, it does not have any information related to the phase (Alqudah & Alqudah, 2022). So, in general, the power spectrum is a non-invertible transformation which means it is not possible to reconstruct the original signal from the power spectrum. Moreover, the power spectrum has a wider application range than FT and can be applied in situations where the phase is not useful or can be ignored or in case the data contains a lot of noise (since the phase is easily corrupted by noise) (Alqudah & Alqudah, 2022). Figure 4 shows an example of EEG signals in different Power spectrums.

Power spectrum features from moving window

In this section, the power spectrum is calculated for each extracted non-overlapping window, then a set of features are extracted. The EEG Features in this paper are extracted from the frequency domain (power spectrum) only and explained in detail in the following sub-sections (Khazaee & Ebrahimzadeh, 2010).

The mean absolute value (MAV)

The MAV is one of the popular power spectrum features that have been widely applied in power spectrum pattern recognition (Khazaee & Ebrahimzadeh, 2010). MAV is defined as the average absolute signal value. It can be expressed as

$$MAV = \frac{1}{L}\sum_{i=1}^{L} |X_i| \tag{9}$$

The wavelength (WL)

The WL is a frequently used power spectrum feature, which represents the cumulative length of the waveform over time (Khazaee & Ebrahimzadeh, 2010). WL can be formulated as

$$WL = \frac{1}{L}\sum_{i=1}^{L}|X_i - X_{i-1}| \quad (10)$$

where $|X_i|$ is the power spectrum of the signal and L is the length of the power spectrum.

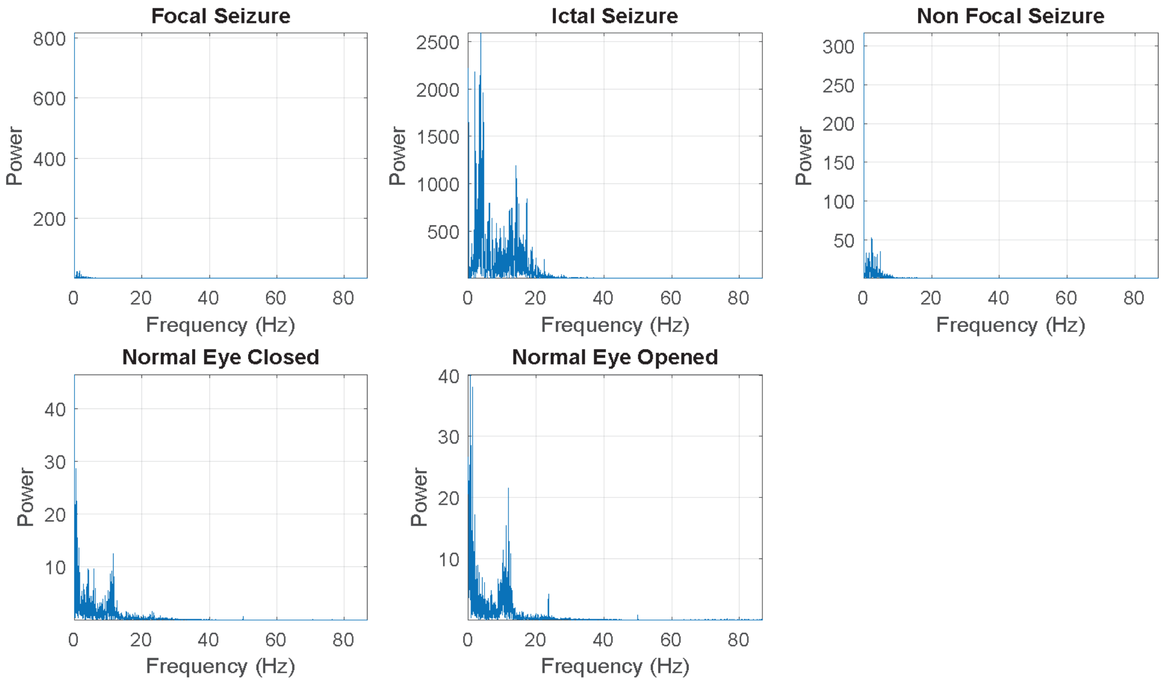

Figure 4. An example of EEG signal different power spectrums.

The average amplitude change (AAC)

The AAC is another power spectrum feature that calculates the average number of changes in the power spectrum (Khazaee & Ebrahimzadeh, 2010). AAC can be formulated as:

$$ACC = \frac{1}{L-1}\sum_{i=1}^{L}|X_{i+1} - X_i| \quad (11)$$

The log detector (LD)

The LD is a feature that is good at estimating the exerted force (Too, Abdullah, Saad, & Tee, 2019a). LD can be defined as:

$$\text{LD=exp}\left(\frac{1}{L}\ \sum_{i=1}^{L}\{log|X_i|\}\right) \quad (12)$$

The root mean square (RMS)

The RMS is one of the popular features that are useful in describing muscle information (Khazaee & Ebrahimzadeh, 2010). Mathematically, RMS can be calculated as:

$$RMS = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(X_i)^2} \quad (13)$$

The difference absolute standard deviation (DASD)

The DASD is another frequently used power spectrum feature (Khazaee & Ebrahimzadeh, 2010). It can be expressed as:

$$DASD = \sqrt{\frac{1}{L-1}\sum_{i=1}^{L-1}(X_{i+1} - X_i)^2} \quad (14)$$

The signal percentage rate (SOP)

The SOP is defined as the mean of the signal output in which the absolute value of the power spectrum exceeds a pre-defined threshold value (Khazaee & Ebrahimzadeh, 2010). SOP can be given as follows:

$$SOP = \frac{1}{L}\sum_{i=1}^{L}f(X_i) \quad (15)$$

$$F(X_i) = \begin{Bmatrix} 1 & X_i \geq T \\ 0 & \text{otherwise} \end{Bmatrix} \quad (16)$$

The AAC changes

The AAC Changes is a power spectrum feature that acts as an indicator of the abrupt changes in the power spectrum (Khazaee & Ebrahimzadeh, 2010). AAC changes can be computed as:

$$AACC = \sum_{i=1}^{L-1} f(X_i) \quad (17)$$

$$F(X_i) = \begin{Bmatrix} 1 & |X_i - X_{i+1}| \geq T \\ 0 & \text{otherwise} \end{Bmatrix} \quad (18)$$

The simple square integral (SSI)

The SSI is defined as the summation of square values of the power spectrum amplitude (Khazaee & Ebrahimzadeh, 2010). It can be computed as:

$$SSI = \sum_{i=1}^{L} X_i^2 \quad (19)$$

The variance of signal (VAR)

It is good at measuring the signal power (Khazaee & Ebrahimzadeh, 2010). It can be expressed as:

$$VAR = \frac{1}{L-1} \sum_{i=1}^{L} X_i^2 \quad (20)$$

The modified mean absolute value (MMAV)

The MMAV is an extension of the MAV feature in which the weight window function is assigned mathematically (Khazaee & Ebrahimzadeh, 2010). It can be computed as:

$$MMAV = \frac{1}{L} \sum_{i=1}^{L} W_i |X_i| \quad (21)$$

$$W_i = \begin{Bmatrix} 1 & 0.25L \leq i \leq 0.75L \\ 0.5 & \text{otherwise} \end{Bmatrix} \quad (22)$$

The modified mean absolute value 2 (MMAV2)

The MMAV2 is another extension of the MAV feature in which the continuous weight window function is assigned (Khazaee & Ebrahimzadeh, 2010). and it can be expressed as follows:

$$MMAV2 = \frac{1}{L} \sum_{i=1}^{L} W_i |X_i| \quad (23)$$

$$W_i = \begin{Bmatrix} 1 & 0.25L \leq i \leq 0.75L \\ \frac{4i}{L} & i < 0.25L \\ \frac{4(i-L)}{L} & \text{otherwise} \end{Bmatrix} \quad (24)$$

The slope sign change (SSC)

The SSC generally is a common feature of a signal that is widely used to determine the number of power spectrum changes (Khazaee & Ebrahimzadeh, 2010). and can be calculated as:

$$SSC = \sum_{i=2}^{L-1} f(X_i) \quad (25)$$

$$f(X_i) = \begin{Bmatrix} 1 & (((X_i > X_{i-1})(X_i > X_{i+1})) \,||\, (((X_i < X_{i-1})(X_i < X_{i+1})) \\ & \text{and } ((|X_i - X_{i-1}| \geq \text{Th})||(|X_i - X_{i+1}| \geq \text{Th})) \\ 0 & \text{otherwise} \end{Bmatrix} \quad (26)$$

Energy

It Provides the sum of squared elements in the power spectrum (Khazaee & Ebrahimzadeh, 2010). Also, known as uniformity or the angular second moment and can be expressed as:

$$En = \sum_{i=1}^{L} X_i \quad (27)$$

Entropy

The Entropy measures the randomness of intensity distribution (Too et al., 2019a) and can be expressed as:

$$Ent = -\sum_{i=1}^{L} P(i) Log_2 P \quad (28)$$

The moment based features

In this part, the moment-based features are extracted (Khazaee & Ebrahimzadeh, 2010). The normalized root squared zero-order moment can be expressed as:

$$m_0 = \left(\sqrt{sum_{i=1}^{L} X_i 2}\right)^{\frac{1}{Th}} \quad (29)$$

where Th is a predefined threshold value which is selected to be 0.1 in this paper, next we will calculate the first (d_1) and second (d_2) derivatives for higher-order moments. After that the normalized root squared 2nd (m_2) and 4th (m_4) order moments are calculated as follows:

$$m_2 = \sqrt{um_{i=1}^{L} \frac{d1_i 1}{L-1}}^{\frac{1}{Th}} \quad (30)$$

$$m_4 = \sqrt{um_{i=1}^{L} \frac{d1_i 2}{L-1}}^{\frac{1}{Th}} \quad (31)$$

After calculating the root squared moments values, we can calculate the features using values called sparseness (SPR) and irregularity factor (IRF) (Khazaee & Ebrahimzadeh, 2010) as follows:

$$SPR = \frac{\sqrt{|(m_0 - m_2) \odot (m_0 - m_4)|}}{m_0} \quad (32)$$

$$IRF = \frac{m_2}{\sqrt{m_0 \odot m_4}} \quad (33)$$

The extreme learning machine (ELM)

The ELM is a type of non-linear and feed-forward network with one hidden layer classifier which is scalable and fast-to-train. The ELM structure consists of an input layer with signals connected to a large number of non-linear hidden neurons using the tanh function as the activation function. These connection weights are randomly initialized with values set to random values between-1.5 and 1.5. In the definition of the ELM, there is a ratio called the fan-out ratio, which represents the number of the input layer neurons to the hidden layer neurons, and a single iteration can be used to calculate the number of the output neurons and the optimizing values for the output weights. The definition of extremes in the ELM is referred to a high-speed network in the classification with low training error (Phung, Tran, Ma, Nguyen, & Pham, 2014; Alqudah, 2019a).

The support vector machine (SVM)

The SVM is one of the most widely used classifiers in the medical field. It is a type of supervised machine learning technique that is used to solve both problems, classification, and regression. But the main use of the SVM is for classification problems, especially for two classes classification or what is known as binary classification. SVM uses the training subset of data and marks them to which labels they belong then use them to build a hyper line for two classes or a hyperplane for more than two classes to separate between data. During the testing, the SVM uses the same hyper line or hyperplane to decide to which class the new unlabeled data belong, this is making the SVM a non-probability binary classifier (Alqudah & Alqudah, 2022).

The K-nearest neighbor (KNN)

The KNN method is one of the oldest and most widely used machine learning algorithms which is very simple to understand. KNN's basic principle is to classify any feature vector input using the majority voting technique of the testing input by finding the distances between the nearest neighbor labeled data to find the final class. The distance which is usually a Euclidean distance is used as a weight and it must be adapted for each problem being solved. The KNN performance can be improved by using a large dataset for learning the distance metric (Alqudah, 2019b; Alqudah, Qazan, Alquran, Qasmieh, & Alqudah, 2020)

K-fold cross-validation

Due to differences in the quantity of the dataset utilized, evaluating any machine learning or deep learning model will be difficult in general. Typically, machine learning experts divide the data set into training and testing sets with various ratios, using the training set to train the model and the testing set to test the model, and then assessing the model's performance using the accuracy metric (Alqudah & Alqudah, 2022). However, this method is unreliable because the accuracy gained for one test set may differ significantly from that obtained for another. As a result, K-fold Cross-Validation gives an ideal solution to this problem: the answer is acquired by folding the data and guaranteeing that each fold is used as a testing set at some time (Alqudah & Alqudah, 2022). A block diagram of K-fold cross-validation is shown in Figure 5.

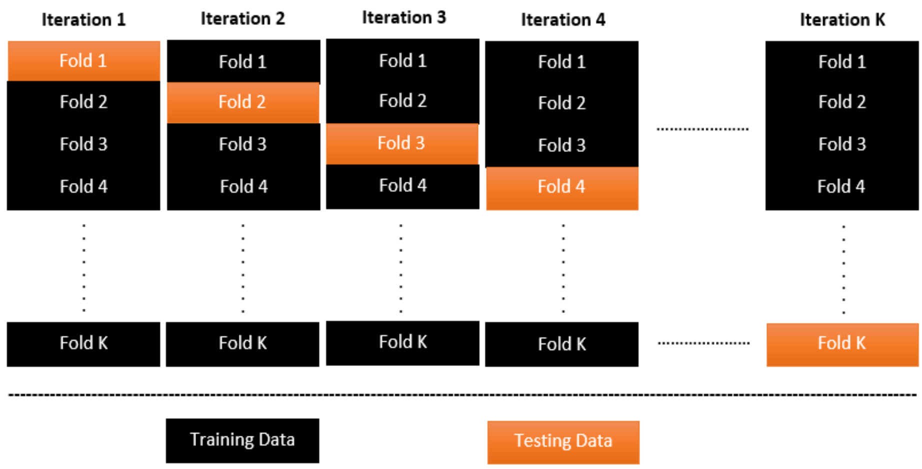

Figure 5. Block diagram of K-fold cross-validation.

Performance evaluation

After training and testing the classifiers we can generate the confusion matrix, this matrix represents the relationship between the original class (target class) of the data with the generated class (predicted class) using the used classifiers. Using this matrix, we can find four main statistical values called true positive (TP), true negative (TN), false positive (FP), and false-negative (FN). Then to find the efficiency and performance of the proposed method, six different statistical values including accuracy, sensitivity, specificity, precision, F-measure, and Matthew correlation coefficient (MCC) were calculated (Alqudah, 2019b; Alqudah et al., 2020; Alqudah & Alqudah, 2022). These values are calculated as follows.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (34)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (35)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (36)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (37)$$

$$\text{F1} - \text{Measure} = \frac{2TP}{2TP+FP+\text{FN}} \quad (38)$$

$$\text{MCC} = \frac{\text{TN}*\text{TP}-\text{FN}*\text{FP}}{\sqrt{(\text{TP}+\text{FP})(\text{TP}+\text{FN})(\text{TN}+\text{FP})(\text{TN}+\text{FN})}} \quad (39)$$

Results and discussion

In this section, the experimental results of the proposed methodology will be shown. Five different scenarios with five different sets of classes have been used as shown in Table 1. The proposed methodology with the five scenarios was tested on a computer of Intel core i5-2410M/2.3 GHz and 12 Gb of RAM computer. The results demonstrate the performance evaluation of all extracted features and classifiers. Figure 6 shows the violin plot for a subset of features (4 out of 28). Based on Figure 6, we can notice that the extracted features can be used efficiently to discriminate between the classes. Where the range of holder exponents in the features and the other features were far away from each other, which means that the proposed moving windows features extraction is suitable for EEG signals classifications. All classifiers have been evaluated using the 10-K fold cross-validation technique. This technique is generally used to ensure that the classifier model is generalized. Table 2 shows the performance of the three classifiers used (ELM, SVM, and KNN). The results are obtained with ELM that has 20000 hidden layers, C with a value of 100e7, and Alpha with a value of 0.0001, while SVM has radial basis function (RBF) kernel, and finally, KNN using 1 as a number of neighbors (NN). These hyperparameters were selected after testing different sets of them and then choosing the ones with the highest performance. Figure 7 shows the confusion matrices for the best classifier among all scenarios. To check if the proposed methodology can be used in a real-time manner, the time consumption of the features extraction was measured. It starts from the time of the power spectrum calculation until the time of calculating features among all scenarios. The time consumption for each classifier is measured in all scenarios. Figure 8 shows the time consumption for feature extraction and classifiers among all scenarios.

Table 1. Summary of the used dataset.

Scenario Number	Number of Classes	Class Names	Number of Signals	Number of Windows
1	3	Ictal Inter-Ictal Normal	300	3600
2	3	Focal Seizure Non-Focal Seizure Normal	300	3600
3	4	Focal Seizure Ictal Seizure Non-Focal Seizure Normal	400	4800
4	5	Focal Seizure Ictal Seizure Non Focal Seizure Normal Eye Closed Normal Eye Opened	500	5000
5	2	Normal Abnormal	500	5000

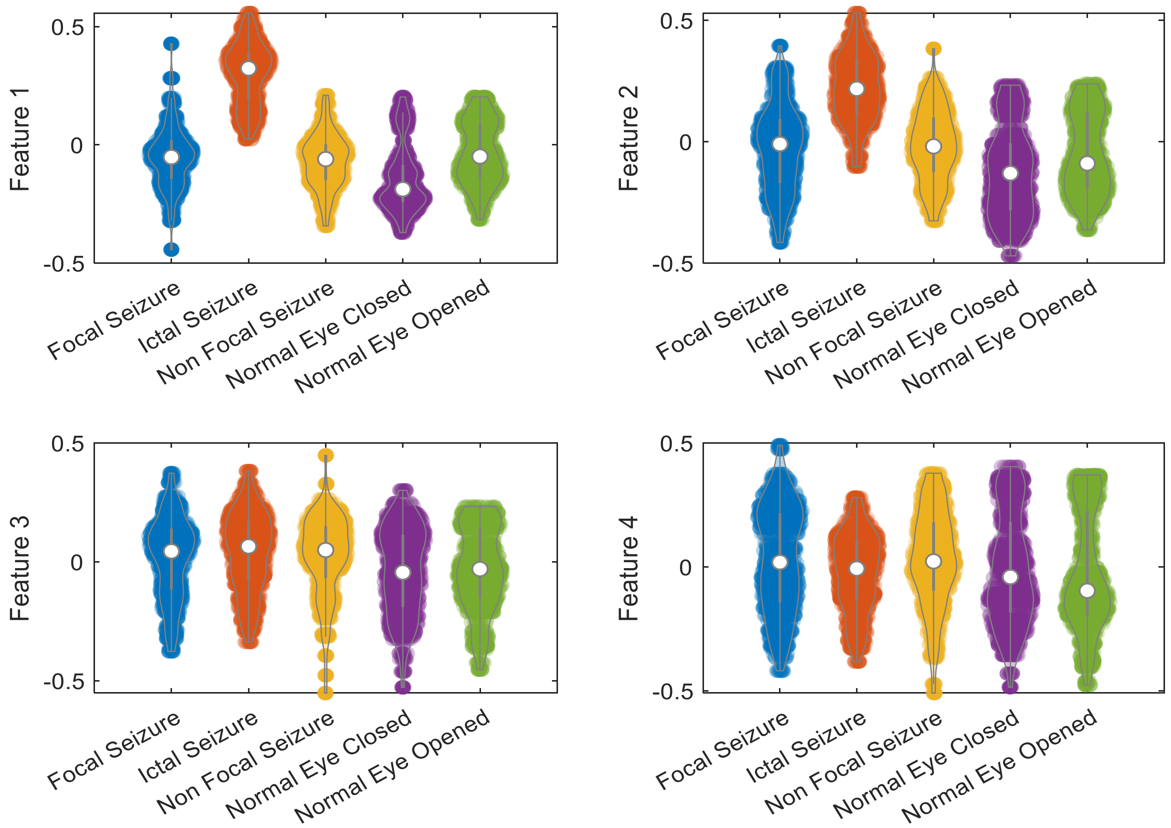

Figure 6. Violine plot for subset of features among all classes.

Table 2. The results of all used classifiers among all scenarios.

Scenario Number	Classifier	Accuracy %	Sensitivity %	Specificity %	Precision %	F1-Score %	MCC
1	ELM	99.0±0.2	98.0±0.77	98.0±0.77	98.01±0.74	98.0±0.02	0.96±0
	SVM	90.7±0.9	91.2±2.56	90.2±2.6	90.39±2.1	90.74±0.93	0.81±0.02
	KNN	95.65±0.41	91.3±0.82	100±0	100±0	95.45±0.45	0.92±0.01
2	ELM	98.5±0.5	98.1±0.74	98.9±0.74	98.9±0.73	98.49±0.01	0.97±0
	SVM	88.2±1.68	85.38±2.07	93.84±0.95	86.67±1.76	85.9±1.96	0.8 ±0.03
	KNN	95.2±0.4	95.7±1.73	94.7±1:35	94.79±1.23	95.22±0.43	0.9±0.01
3	ELM	97.6±0.32	97.7±0.95	97.5±0.85	97.52±0.81	97.6±0.32	0.95±0.01
	SVM	87.28±1.16	85.68±1.4	95.6±0.44	86.25±1.24	85.82±1.31	0.82±0.02
	KNN	95.7±0.33	91.4±0.66	100±0	100±0	95.51±0.36	0.92±0.01
4	ELM	97.6±0.32	97.8±1.55	97.4±1.35	97.44±1.3	97.6±0.32	0.95±0.01
	SVM	85.9±1.95	85.9±1.98	96.48±0.5	85.88±2.03	85.74±2.01	0.82±0.02
	KNN	95.1±0.3	95.4±1.43	94.8±1.33	94.86±1.18	95.11±0.32	0.9±0.01
5	ELM	100±0	100±0	100±0	100±0	100±0	100±0
	SVM	96±1	96±1	96±1	97±1	96±1	0.91± 0.02
	KNN	99.8±0.19	99.67 ±0.314	100±0	100±0	99.83 ±0.16	0.9959 ±0.0039

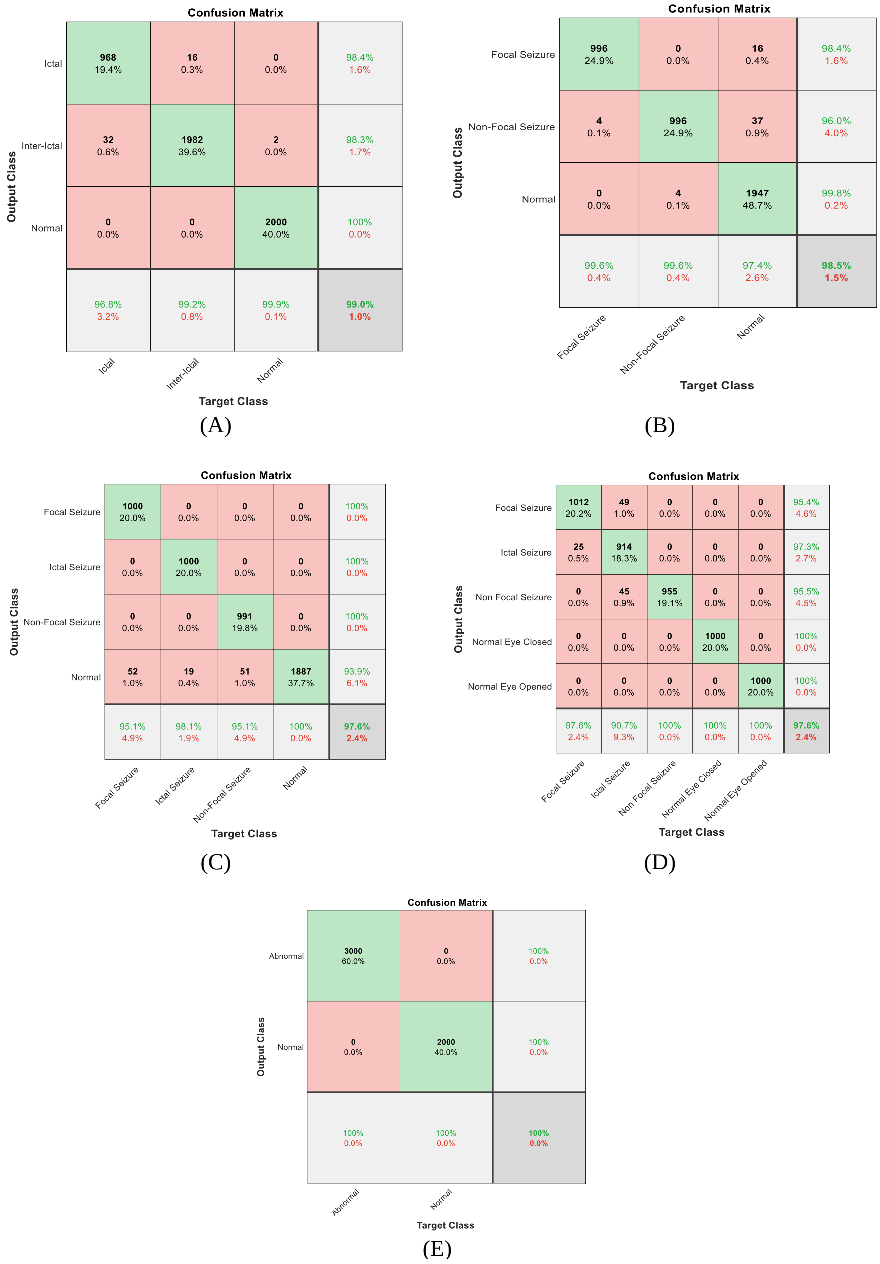

Figure 7. Confusion matrices of the best classifier for A) Scenario 1, B) Scenario 2, C) Scenario 3, D) Scenario 4, and E) Scenario 5.

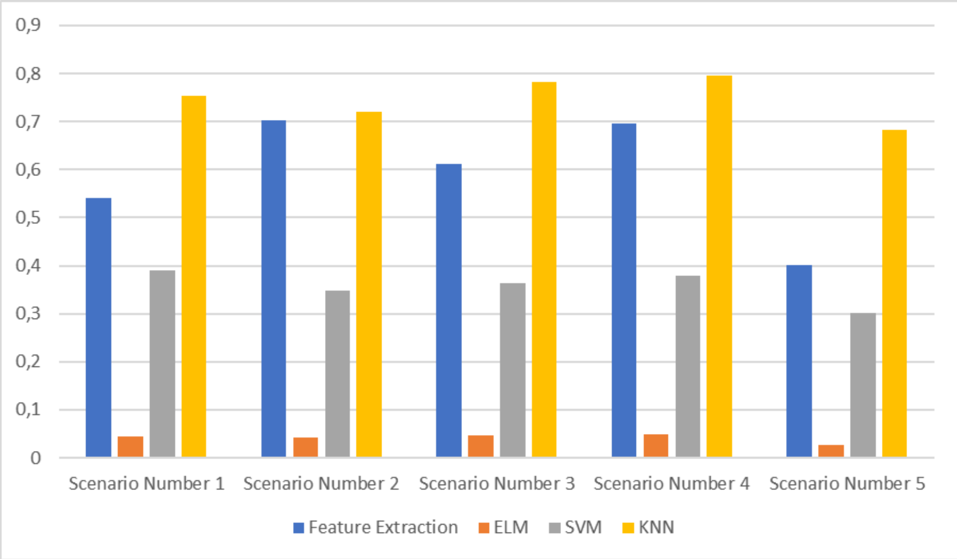

Figure 8. Time consumption for features extractions and classifiers.

The proposed methodology was successfully applied to the EEG signal dataset, the newly provided window-based power spectrum features extraction has been fed to three different types of classifiers namely: ELM, SVM, and KNN. The methodology was implemented in five different scenarios with different types of classes, the details of each scenario have been shown in Table 1. The proposed method was evaluated using 10 K-fold methodologies. The results in Table 2 show that the average achieved accuracy is 98, 90.7, and 95.65% for ELM, SVM, and KNN respectively in the first scenario, the average achieved accuracy is 98.50, 88.20, and 95.20% for ELM, SVM, and KNN respectively in the second scenario, the average achieved accuracy is 97.60%, 87.28%, and 95.70% for ELM, SVM, and KNN respectively in the third scenario, finally, the average achieved accuracy is 97.60, 85.90, and 95.10% for ELM, SVM, and KNN respectively in the fourth scenario. Moreover, for the fifth scenario (binary classification) it is also shown that the ELM classifier yields 100% accuracy, while the SVM and KNN achieved 96 and 99.8% respectively.

From the results shown in Table 2, we can conclude that the accuracy achieved when using an ELM classifier is higher than that achieved when SVM and KNN were used in all scenarios, this is because that ELM performs better than any other classification algorithm when it is fed with a large dataset as what we have used in our paper. ELM is a very fast and light classifier that can be used either in mobile or web applications. It saves the weight matrix that is multiplied by the input features which results in the output decision leading to the possibility of using it in a real-time manner which makes it superior to other types of classification algorithms. As shown in Table 3, ELM has the shortest time compared with all other classifiers. Also, we can notice that the total time required to provide a decision by the proposed methodology using ELM is less than 1 second which typically less than other methods such as wavelet transform. The fast classification process, the high accuracy for all scenarios, in addition to the ability to apply this methodology using embedded systems are the main advantages of the proposed methodology over other methods in the literature.

Finally, our method has a comparable accuracy with all previously published results in the literature as shown in Table 3. In our work, we have considered up to 5 scenarios in testing 5 classes of EEG signal. However, the maximum number of scenarios in the published literature was 3 and the number of EEG classes in most of the published research was only 2% (Nguyen et al., 2017; Molla et al., 2020; Guo et al., 2010a; Wang et al., 2011; Nicolaou & Georgiou, 2012; Übeyli, 2010; Raghuet al., 2019). This makes our method more accurate in terms of real time monitoring and so more applicable in clinical use. Moreover, we have achieved 100% accuracy in classifying normal EEG vs Abnormal one, but the accuracy achieved in most of the published literature was less than 99% (Nguyen et al., 2017; Molla et al., 2020; Guo et al., 2010a; Wang et al., 2011; Nicolaou & Georgiou, 2012; Übeyli, 2010; Raghuet al., 2019) and the maximum accuracy achieved was 99.56% by (Übeyli, 2010).

Table 3. Comparison between the related works and the proposed method.

Reference	Methodology	Number of Classes	Classes	Accuracy %
(Nguyen et al., 2017)	P-1D-CNN	2	Epileptic Seizure and Non-Epileptic Seizure	99.10
(Molla et al., 2020)	Wavelets Graph Eigen Decomposition with Artificial Neural Networks	2	Epileptic Seizure and Non-Epileptic Seizure	99.55 98.72 99.39
(Guo et al., 2010a)	Wavelets and Artificial Neural Networks	2	Epileptic Seizure and Non-Epileptic Seizure	98.27
(Wang et al., 2011)	Wavelets and SVM	2	Epileptic Seizure and Non-Epileptic Seizure	99.44
(Nicolaou & Georgiou, 2012)	Permutation Entropy and SVM	2	Epileptic Seizure and Non-Epileptic Seizure	86.10
(Übeyli, 2010)	AR and least square SVM	2	Epileptic Seizure and Non-Epileptic Seizure	99.56
(Raghu et al., 2019)	Matrix Determinant Features and Multilayer Perceptron	2	Epileptic Seizure and Non-Epileptic Seizure	97.15
This Paper	Power Spectrum Based Features with ELM	2	Ictal, Inter-Ictal, and Normal	98
		2	Focal Seizure, Non-Focal Seizure, and Normal	98.5
		4	Focal Seizure, Ictal Seizure, Non-Focal, Seizure, and Normal	97.6
		5	Focal Seizure, Ictal Seizure, Non Focal Seizure, Normal Eye Closed, and Normal Eye Opened	97.6
		2	Normal and Abnormal	100

Conclusion

In this paper, we implemented a full classifying system using features extracted from the power spectrum with three different classification algorithms. The proposed system is used to extract 2 seconds window from the EEG signal and then extract features from the calculated power spectrum to classify the EEG signal. The system was tested using the university of Bonn EEG signal database and five different scenarios with different sets and numbers of classes (2, 3, 4, and 5 classes) have been used. The methodology was applied then the accuracy, sensitivity, and precision were calculated. The results were compared with different scenarios and with previously used classification methods found in the literature. The results indicated that the best evaluation performance was obtained using an ELM classifier among all scenarios and when compared to other relevant studies in the literature the proposed methodology has the highest accuracy with the highest number of scenarios and classes. The future work will include applying the present algorithm with a larger dataset and adding a new type of EEG signals and diseases to be classified. Also, we can use the method proposed in this paper for clinical applications to diagnose related diseases from patients in a real-time manner. The main limitation of this paper that even though the results are promising, the main limitation of this study is the limited size of the used dataset. Also, the number of classes concerning the size of the dataset is low. Finally, the number of subjects included in the study is also low compared to other biomedical signals datasets.

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