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MULTICLASS EPILEPSY CLASSIFICATION USING WAVELET DECOMPOSITION, DIRECT QUADRATURE, AND SHANNON ENTROPY

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Abstract

Computerized disease diagnosis tools based on electroencephalography analysis has come to play an important role in improving the accuracy and speed of the disease investigation rate, speed up the diagnosis process, and drastically eliminate the need for the tedious electroencephalography visual inspection. Seizure is one of the neurological disorders that can benefit from such systems. Pre-emptive epilepsy detection in inter-ictal states is a challenging task in seizure detection. In this paper, we propose an automated system for normal, ictal, and inter-ictal EEG signals classification. The method provides an accurate diagnosis tool even when faced with temporal and spectral disturbances. The proposed method works by partitioning the electroencephalography signals (normal, ictal, and inter-ictal) into sub-bands using discrete wavelet transform decomposition. Then, Direct Quadrature calculates the instantaneous frequency of the resulting components rather than traditional methods. Thus, shielding the instantaneous frequency calculation from the effects of amplitude modulation. Moreover, we used a neural network-based machine-learning model using features of the Shannon Entropy of instantaneous frequency, the maximum, minimum, and standard deviation values of the decomposition. The proposed model yields 100% accuracy for the healthy vs. ictal, healthy vs. ictal vs. inter-ictal (epileptic zone), and healthy vs. ictal vs. inter-ictal (opposite hemisphere). The suggested technique outperforms the previous results in the literature, which suffer with more than two mixed classes.

Keywords: Discrete wavelet transforms, Electroencephalography, Entropy, Epilepsy, Pattern classification.

1. Introduction

The importance of the brain as a major part of the central nervous system (CNS) cannot be overstated. The working of the brain involves biopotential activities of the neurons, which enables the transfer of information. Such electrical activities open a window to study the brain functions by monitoring the ongoing brainwaves. Electroencephalography (EEG) is a medical signal obtained by tapping into the neurological pathways of the human brain. It is capable of recording the brain cortical activity with millisecond temporal resolution. EEG-based diagnosis and monitoring is typically conducted by neurologists, who investigate the health status of the human brain and the accompanying abnormalities and markers of diseases (e.g., Parkinson’s, seizures, etc.).

Epilepsy is one of the complex brain abnormalities caused by a disturbed electrochemical release in a major cell population, which can be detected by EEG [1, 2, 3]. Epilepsy attacks cause seizures that impair the patient, increase the risk of death, and lead to adverse social effects [4, 5]. Long-term EEG recording and analysis is a well-known technique for seizure diagnosis. However, the detection and classification of seizure states require elaborate efforts [1]. Moreover, tools for EEG analysis have come to play an important role in improving the accuracy and speed of the disease investigation rate, speed up the diagnosis process, and drastically eliminate the need for the tedious EEG visual inspection [6]. Patients suffering from neurological disorders (e.g., seizures) can greatly benefit from computerized diagnostic tools [3].

The processing and analysis of EEG signals can reveal different characteristics of the seizure states (i.e., healthy, ictal, inter-ictal). This paper provides a highly accurate method for multiclass epilepsy classification that can handle temporal and spectral disturbances in the EEG signal.

The proposed method works by partitioning the electroencephalography signals (normal, ictal, and inter-ictal) into sub-bands using discrete wavelet transform (DWT) decomposition. Then, the instantaneous frequency of the resulting components is calculated using direct quadrature (DQ), thus shielding the instantaneous frequency calculation from the effects of amplitude modulation. Moreover, the method employs neural network-based machine-learning model using features of maximum, minimum, and standard deviation values of the DWT decomposition, as well as Shannon Entropy of instantaneous frequency. Figure 1 shows a graphical representation of the proposed diagnosis system.

The contributions of this paper are as follows:

- We analyse EEG signals containing more than two classes of seizure cases.
- We used DQ to rectify the effect of amplitude modulation on the spectral information in the EEG signal, which improves the accuracy of the classification process.
- We extract indicative features based on SE of the instantaneous frequency in addition to the common statistical parameters of the DWT.
- We develop a classification model based on Artificial Neural Networks (ANN) that handles the classification of two, three, and four seizure cases (including normal) while matching the high accuracy of the latest literature.

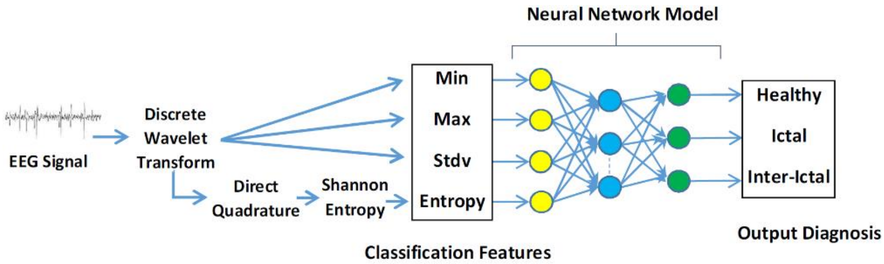

Fig. 1. A graphical representation of the proposed diagnosis system.

2. Related Work

The identification of seizure phases as normal, pre-ictal, ictal, or inter-ictal is a problem that received great attention in the EEG analysis literature. The research landscape can generally be categorized into EEG analysis methods or machine learning techniques. EEG analysis aims at extracting the best features to be fed to the machine learning models. In this regard, pre-processing of the EEG signals to supress noise and remove artefacts is a major research avenue.

The EEG signal recording process is affected my multiple sources of noise (e.g., ambient electrical current, muscles and heart activities). These sources can greatly affect the quality of the recording and distort the extracted features [7]. Thus, de-noising and artefact removal are necessary to truly capture the most accurate features and characteristics of the EEG recording. More specifically, in WT-based features extraction techniques, the choice of the mother wavelet and thresholding function plays a major role in improving the quality of the EEG signal. To this end, several studies have been conducted to compare the efficiency of different choices.

Al-Qazzaz et al. [8] compared the capabilities of forty-five mother wavelets and four thresholding methods to de-noise 60-second EEG recordings from one normal and one post-stroke subjects. In another study [9], they combined automatic independent component analysis (AICA) and WT to improve the quality of the EEG signal recordings from 35 subjects (15 health and 20 unhealthy). Both results showed an improved EEG signal quality in terms of noise-related metrics (e.g., cross correlation and peak signal to noise ratio), and were combined with machine learning techniques to discriminate stroke-related cognitive impairment and vascular dementia from healthy recordings [10, 11]. Such research can be readily expanded to include seizure classification.

The EEG signal can be analysed in frequency domain, time domain, or combination of both techniques. The usefulness of any feature extraction method depends on how indicative or informative it is of the seizure phase as well as its resilience in dealing with noisy signals. Moreover, EEG analysis techniques must be capable of dealing with the nonstationary and nonlinear brain activity patterns. A comparison of seizure and seizure-free EEG signals in [12] noticed different synchronization levels. This is due to the fact that spatial and temporal shifts in synchronization are strongly dependent on the pathological brain's activity. The seizure-free EEG segments were more random, less stationary with comparatively different amplitude levels, and exhibited less nonlinear dependency [13-17]. Thus, these identified differences should be taken into account in seizure prediction and classification.

Several studies in the literature utilized various combinations of the time and frequency domain features to identify normal, ictal and inter-ictal activities based on EEG recordings [1, 3, 18-29]. In [19], Short Fourier Transform (SFT) windowing was applied to the EEG, and then the classification features were extracted by computing the fractional energy of specific SFT windows. The authors in [30, 31] used empirical mode decomposition (EMD) of EEG signals [31], which produced intrinsic mode functions (IMF). The mean frequencies of the resulting IMFs constituted the main feature of their seizure classification technique. In [32], the features were produced by computing the fractional energy values of the EEG components using the pseudo-Wigner-Ville distribution.

In other studies, Lyapunov exponents of EEG records were used as features for seizure pattern recognition [33]. In [20, 34-37], Wavelet Transform (WT) was used to calculate EEG signal sub-bands. In [38, 39], the matrix features were extracted by computing the entropy values of EEG components as obtained from WT.

Recent efforts in seizure classification and prediction have moved toward employing deep learning techniques [11]. Gomez et al. [40] used fully convolutional networks of imaged EEG to automatically detect seizures and achieve a 99.6% average accuracy. Similarly, Nogay and Adeli [41] used pre-trained deep convolutional neural networks (CNNs) and transfer learning and reported 100% accuracy for both binary and ternary classification. However, these approaches rely on converting the EEG signal into visual data in the form of a spectrogram image [42], which may be computationally intensive. In another study, Hossain et al. [43] used CNNs to classify EEG signals as seizure or no seizure. They achieved an accuracy of 99.65%. However, such binary classification is an easier problem due to the limited output choices [41]. Akut [44] used WT for pre-processing the EEG signal and convolutional neural networks (CNN) for classification, which achieved a 99.4% accuracy. A review and more details of these methods among others can be found in the survey by Taeho et al. [45].

A wide range of classification algorithms were used in combination with feature extraction methods [12]. The simple random sampling (SRS) method was used for feature extraction from EEG time series, which fed the feature to a least square support vector machine (SVM) classifier [46]. In [47], sample entropy (SampEn) and distribution entropy (DistEn) were computed from 5 sec EEG segments. In [48], approximate entropy (ApEn) values were extracted as classification features, as in [24, 38, 39]. Whereas in [49], different entropy estimators were used for the extraction of features for the Artificial Neural Network Fuzzy Inference System (ANFIS) classifier. The discrete wavelet transform (DWT) is typically used for EEG signal analysis and the statistical features of the results are used for classification [18, 49].

In the aforementioned studies, seizure EEG data exhibit nonstationary and nonlinear characteristics encapsulated in nonlinear relationships [29, 39, 49]. However, Fourier Transform (FT) is based on stationary characteristics. Whereas Short-Fourier Transform (SFT) assumes linear properties. Moreover, EMD suffers from mode mixing (i.e., oscillations of different time scales are assigned to the same IMF or oscillations of the same time scale are in different IMFs) and mode intermittency, which limits its applications [34]. Mode mixing may distort the understanding of the physiological seizure process. In addition, methods to improve the mode intermittency (e.g., ensemble EMD and masking) has been shown to be time consuming and/or unstable [36]. Compensating for these weaknesses will incur high complexity in these solutions. On the other hand, wavelet transform can adaptively represent nonstationary signals and adjust itself based on the input data. Furthermore, the computational time of WT is low in comparison to EMD, which is a huge advantage if the EEG analysis tool is to be deployed in real-time applications.

3. Materials and Methods

The following subsections provide the details of the system in terms of the input dataset, mathematical analysis, classification features, and performance evaluation methods.

3.1. Dataset

In this subsection, we go through the details of the EEG (i.e., normal, ictal, and inter-ictal) records, their decomposition into sub-bands using multilevel wavelet transform, and the instantaneous frequency computation using DQ. In addition, we describe in detail the extraction of the classification features (i.e., the wavelet output minimum, maximum, and standard deviation, and the Shannon Entropy of the instantaneous frequency), and the classification using ANN.

The dataset is publicly available and fully described in [37]. It consists of single channel EEG recordings of healthy and seizure signals, and was divided into five sets A_Z, B_O, C_N, D_F and E_S. All of the recordings were obtained using the same 128-channels cap and amplifier system, with an average common reference, a sampling frequency of 173.61 Hz, and 12-bit resolution.

Each set contains 100 23.6 second-segments. Artefacts were removed using visual inspection. Sets A_Z and B_O consist of recordings of five healthy volunteers in awake-state extra-cranially using surface EEG. Set A_Z is for open eyes recording and B_O is used for closed eyes. Whereas the inter-ictal sets, C_N and D_F contain seizure-free activity recordings of the hippocampal formation of five patients. The set C_N is for the opposite brain hemisphere and DF is for the epileptic zone. Set E_S conveys seizure signs extracted from all regions of ictal activity.

3.2. EEG analysis using multilevel wavelet decomposition

The EEG signal is spectrally decomposed using wavelet analysis into a set of coefficients called wavelet coefficients. The transformation is reversible if a sufficient number of coefficients is calculated. This can be accomplished by a linear combination of the wavelet functions and their coefficients. Such analysis offers the advantage of revealing time as well as frequency information embedded in the signal. Thus, wavelet transform is an efficient tool for the extraction of features in both the frequency and time domains [50-53]. The continuous wavelet transform (CWT) is computed by Eq. (1) as follows:

$$CWT(a,b) = \int_{-\infty}^{+\infty} x(t) * \psi_{a,b}(t)dt \qquad (1)$$

where $x(t)$: is the EEG signal to be analysed. a: is the dilation/compression factor. b: is the translations coefficient. $\psi_{a,b}(t)$: is the function resulting from scaling the mother wavelet, $\psi(t)$ using Eq. (2).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi(\frac{t-b}{a}) \qquad (2)$$

A The CWT incurs a large overhead due to the large number of the a and b factors required for a continuous representation, and the abundance of the generated redundant data. Thus, it is often disregarded in favour of the more efficient discrete wavelet transform (DWT) [53, 54].

In DWT, the signal is decomposed into two coefficients: Approximate (A) and Detailed (D). Approximate coefficients are obtained by convoluting the original signal with a low pass filter, whereas the detailed coefficients result from convoluting the signal with high pass filter. The process for both types is followed by down sampling. The resulting approximation coefficient are further splits into similar parts using the same procedure, which provides two coefficients in place of the first approximation coefficient. For example, if level K of the wavelet transform is used to decompose the signal, then the output will have the structure [A_K, D_K, D_{K-1}, D_{K-2},..., D_2, D_1]. In this work, the number of decomposition levels is chosen based on the dominant frequency components of the EEG signal. The most useful spectral information of EEG signals lies within 30 Hz. Thus, the number of decomposition levels was chosen to be 4 (i.e., D_1-D_4 and one final approximation, A_4). An order 2 Daubechies wavelet (db2) was selected as mother wavelet function because of its smoothing feature [53].

3.3. Direct Quadrature

Direct Quadrature is required for the correct calculation (i.e., countering the effect of modulation) of the instantaneous frequency classification feature [35]. Normalization is used to filter out the effect of the amplitude module. It is performed by applying the envelope of the wavelet decomposition output at the maximum of the frequency-modulated part as in Eq. (3). This step is followed by taking the Hilbert transform to find the instantaneous frequency [54, 55]. The process is applied to all decompositions, with $x(t)$ as the real part, and $y(t)$ is the imaginary part obtained by Eq. (4).

$$f_1(k) = \frac{C_W(k)}{e_1(k)}, f_2(k)\frac{f_1(k)}{e_2(k)}, \dots, f_n(k) = \frac{f_{n-1}(k)}{e_n(k)} \quad (3)$$

where N: is the number of normalizations. $C_w(k)$: is the k^th wavelet transform output, $f_n(k)$: is the frequency modulation part. $e_n(k)$: is the n^th envelope function.

$$y(t) = \frac{1}{\pi}\lim_{\epsilon\to 0}\left(\int_{t-\frac{1}{\epsilon}}^{t-\epsilon}\frac{x(\tau)}{t-\tau}d\tau + \int_{t+\tau}^{t+\frac{1}{\tau}}\frac{x(\tau)}{t-\tau}d\tau\right) \quad (4)$$

3.4. Shannon entropy

The Shannon Entropy, $\eta(x)$, of the instantaneous frequency is another feature used for the classification and is given by Eq. (5), where P_i is the probability of finding the corresponding data point, i, in the stream.

$$\eta(x) = -\sum_{i=0}^{N-1}\log_2 P_i \quad (5)$$

3.5. Classification features

The four features extracted from the wavelet decomposition form the input to the ANN classification model. These are the entropy of the instantaneous frequency, maximum, minimum, and standard deviation. The entropy of the instantaneous frequency was computed as the Shannon Entropy of the instantaneous frequency of every detail wavelet output. The instantaneous frequency is the result from the Direct Quadrature. The maximum represents the maximum value of every detail wavelet outputs (D_1, D_2, D_3, D_4). Whereas the minimum and standard deviation values represent the minimum value and the standard deviation of the EEG components excluding the approximation wavelet output corresponding to the frequency range (0.5-5.3Hz). The approximation features contained no useful spectral information of the EEG signal and caused a reduction in the classification accuracy. Table 1 shows the statistical parameters (i.e., the min, max, and standard deviation) and Shannon Entropy of sample EEG signals after the DWT decomposition and DQ normalization.

3.6. Classification and validation

The machine-learning model is comprised of an artificial neural network (ANN). The structure of the network is built using processing units, called neurons, and are arranged in input, hidden, and output layers. The inter-layer connections are adaptable synaptic weights that are adjusted through the learning and training process. The input propagates through the network structure from the input layer, and the output layer provides the output. The network iteratively adjusts the weights to store the learnt knowledge to reach the minimum square difference [51, 52].

The model was constructed, trained, and tested using MATLAB software 2018a. The four feature types result in sixteen classification features (four for each of the four detailed outputs). The training and testing and were done using 5-fold cross validation and similar results were obtained when the data was divided randomly into 70% and 30% for training and validating/testing, respectively. The Levenberg-Marquardt learning function was used in the supervised learning.

Table 1. Example of the entropy of the instantaneous frequency, maximum, minimum, and standard deviation values for the different EEG sub-bands and classes. Z: healthy, S: ictal, F: inter-ictal (epileptic zone), N: inter-ictal (opposite hemisphere), Entropy of INF: Shannon Entropy of instantaneous frequency, SD: standard deviation.

EEG Component	Features				Class
	Entropy of INF	Max	Min	± SD	
D_1	-12.18	41.8	-42.43	11.93	Z
D_2	-5.51	96.54	-98.29	31.19	Z
D_3	-2.84	289.37	-204.17	57.45	Z
D_4	-1.45	213.41	-270.15	71.27	Z
A_4	-1.45	366.76	-430.19	111.34	Z
D_1	-11.07	258.08	-351.09	66.12	S
D_2	-6.013	928.56	-1263.37	277.07	S
D_3	-2.65	1974.56	-2425.31	724.62	S
D_4	-1.3	1783.89	-2714.46	862.94	S
A_4	-1.54	2768.58	-2991.06	1231.84	S
D_1	-11.79	12.99	-11.76	2.91	F
D_2	-5.6	33.82	-30.83	7.72	F
D_3	-2.65	91	-99.02	19.46	F
D_4	-1.44	114.33	-100.92	37.69	F
A_4	-1.37	409.75	-175.77	102.92	F
D_1	-12.22	9.24	-11.28	2.79	N
D_2	-5.92	31	-40.26	9.68	N
D_3	-2.91	115.36	-109.29	31.39	N
D_4	-1.3	249.47	-352.34	88.53	N
A_4	-1.39	370.44	-782.44	169.37	N

3.6.1. Healthy vs. ictal classification

This classification employed 100 record of healthy subjects and 100 seizure records. Every EEG signal was decomposed into five frequency sub-bands (i.e., four detail and one association), see Table 2. However, only the detail components were used for the calculation of features. We calculated the statistical features and the entropy of the instantaneous frequency for the four detail EEG sub-bands. This resulted in the full features matrix of dimensions 200×16 corresponding to theta, alpha, beta, and gamma brain waves. The feature matrix was classified into two classes: ictal and normal using an ANN with the Levenberg-Marquardt training function and 11 neurons in the hidden layer.

3.6.2. Healthy vs. ictal vs inter-ictal (F) classification

Similar to the previous subsection, this classification utilized 100 inter-ictal signals in addition to the 200 records used in the previous subsection. The classification works for the three classes; healthy, ictal, and epileptic zone inter-ictal. The features matrix associated with details EEG components has a dimension of 300× 16 and fed into the same ANN structure.

3.6.3. Healthy vs. ictal vs inter-ictal (F) classification

An all-combined matrix including 100 records belonging to healthy subjects combined with 100 ictal signal, 100 inter-ictal (epileptic zone), and 100 (opposite hemisphere) with a total of 400 EEG records have been utilized. The same decomposition and ANN were used with a feature matrix of dimension 400×16. The output represents the classification of three classes: inter-ictal (epileptic zone) with inter-ictal (opposite hemisphere), ictal, and normal.

3.7. Performance metrics

The resulting confusion matrices were analysed to produce several standard performance measures. These include accuracy, specificity, sensitivity, positive and negative predictive values, and class prevalence, as defined in Eqs. (6) to (11). Where: t_p: true positive is the number of subjects correctly classified in predefined (positive) class. f_n: False negative is the number of subjects misclassified in negative class. f_p: False positive, the number of subjects misclassified to be in the positive class. t_n: True negative, represents the subjects correctly classified in the negative class.

Table 2. Frequency range of each EEG component resulting from the DWT decomposition.

Decomposed Signal	Frequency Range (Hz)
D_1	42.5-85
D_2	21.25-42.5
D_3	10.625-21.25
D_4	5.3125-10.625
A_4	0.5-5.3125

$$Accuracy = \frac{t_p + t\_n}{t_p + f_n + f_p + t_n} \tag{6}$$

$$Sensitivity = \frac{t_p}{t_p + f_n} \tag{7}$$

$$Specificity = \frac{t_n}{t_n + f_p} \tag{8}$$

$$Class\ Prevalence = \frac{t_p + f_n}{t_p + f_n + f_p + t_n} \tag{9}$$

$$Positive\ predictive\ value = \frac{t_p}{t_p + f_p} \tag{10}$$

$$Negative\ predictive\ value = \frac{t_n}{f_n + t_n} \tag{11}$$

4. Results and Discussion

The approximation coefficient represents the low frequency content of the signal. Since DWT analysis can provide both time and frequency information contained with the EEG records, it reveals the difference in the EEG signal synchronization values between normal and epileptic subjects. This was captured in the classification model by examining the maximum temporal and spectral information. By comparing the classification accuracy in the presences and absence of approximation features, we found that those features contain no meaningful information to the seizure pattern recognition. This may result from the nature of frequency contained within the approximation coefficient, which represents the slow and baseline waves. Thus, we excluded the approximation coefficient features in the matrix of features used for seizure classification. Figure 2 illustrates the EEG components resulting from the DWT decomposition of an ictal signal.

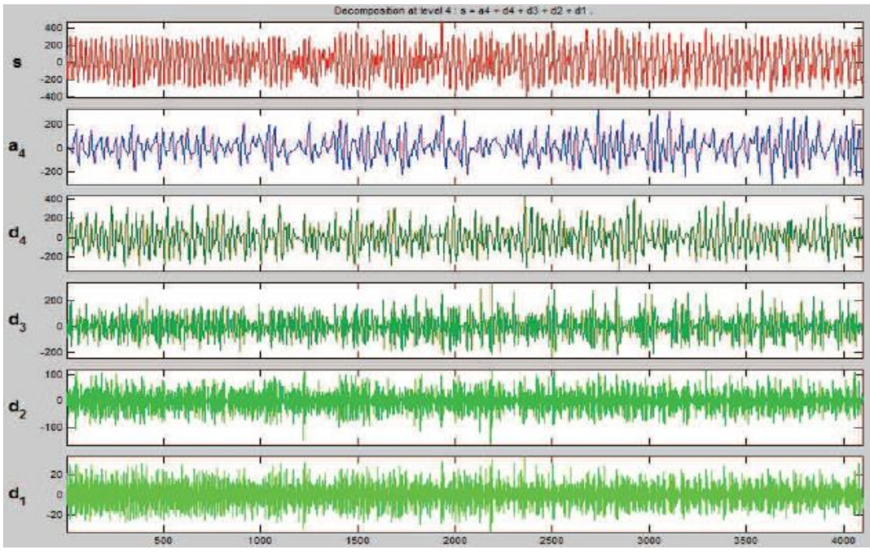

Fig. 2. Example of EEG sub-bands resulted from dwt decomposition applied on EEG signal of class S. S is the original EEG signal, *a*4 represents the approximation output, d_1-d_4 represent the detail output of DWT.

Tables 3 to 5 reveals that classification accuracy, sensitivity, and specificity were all 100%. These values surpass the highest accuracies in the literature [19, 32, 48, 56] for the same dataset, see Figs. 3, 4 and 5. Although similarly high accuracies were achieved in the literature, using DWT for EEG sub-bands calculation gives us the advantages of time-frequency analysis in terms of speed and accuracy when classifying greater number of classes. Furthermore, the use of DWT combined with DQ, statistical features, and ANN is simpler and faster than the methods employed in seizure detection with 100% accuracy (i.e., the work in [47]). In [47], 100% accuracy was obtained using Wigner-Ville distribution. However, this tool cannot provide good results in non-linear situations. Moreover, adjusting the time windows and resolution in this method are based on trial-and error, which represent a major shortcoming in the method implementation. The use of wavelet decomposition combined with approximated entropy in [17] led to 100% accuracy, but the accuracy dropped significantly when the number of classes increased. Other works [32, 57, 58], which utilize the wavelet transform, achieved lower accuracy as they ignored the amplitude modulation effect in the spectral information of the resulting components. In our study, this was tackled by the use of DQ, which retains relevant non-overlapping spectral features. The information embedded in the seizure spikes are represented in the extract features vector, which is able to discern between seizure and non-seizure states.

Table 3. Classification of normal vs. ictal EEG. Testing accuracy is 100%.

Class	Sensitivity	Specificity	Class Prevalence	+ve Predictive Value	-ve Predictive Value
Healthy	100%	100%	40.28%	100%	100%
Ictal	100%	100%	59.72%	100%	100%

Table 4. Classification normal vs. ictal vs. inter-ictal EEG. Testing accuracy is 100%

Class	Sensitivity	Specificity	Class Prevalence	+ve Predictive Value	-ve Predictive Value
Healthy	100%	100%	32.11%	100%	100%
Ictal	100%	100%	38.53%	100%	100%
Inter-Ictal	100%	100%	29.36%	100%	100%

Table 5. Classification of normal vs. ictal vs. inter-ictal (F) vs. inter-ictal (N) EEG. Testing accuracy is 100%.

Class	Sensitivity	Specificity	Class Prevalence	+ve Predictive Value	-ve Predictive Value
Healthy	100%	100%	23.29%	100%	100%
Ictal	100%	100%	22.60%	100%	100%
Inter-Ictal	100%	100%	54.11%	100%	100%

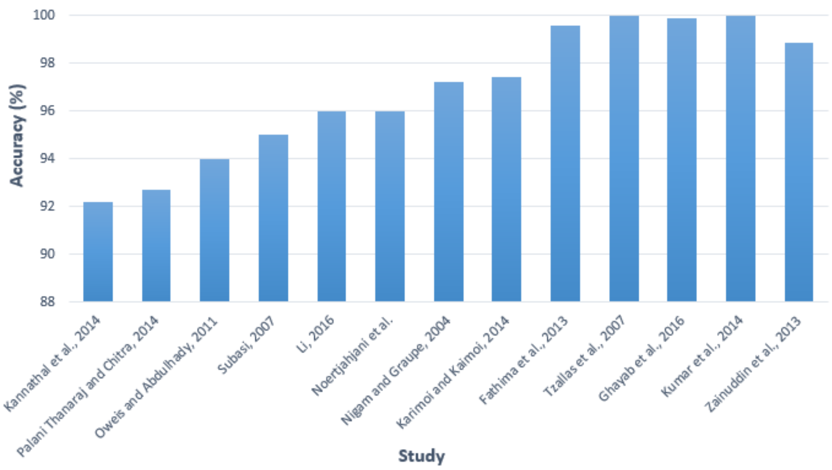

Fig. 3. Comparison to the related literature using the same dataset and classifying for normal vs. ictal EEG.

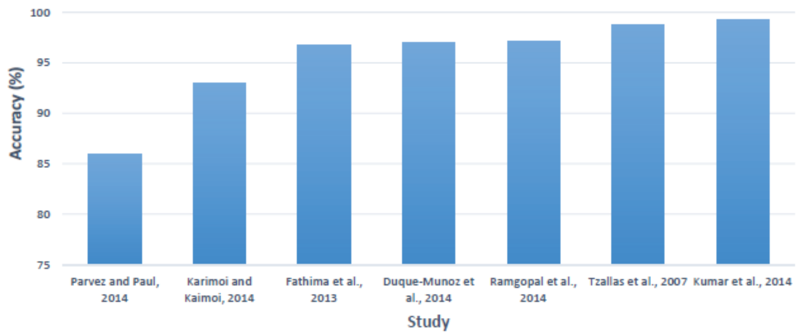

Fig. 4. Comparison to the related literature using the same dataset and classifying for normal vs. ictal vs. inter-ictal (F) EEG.

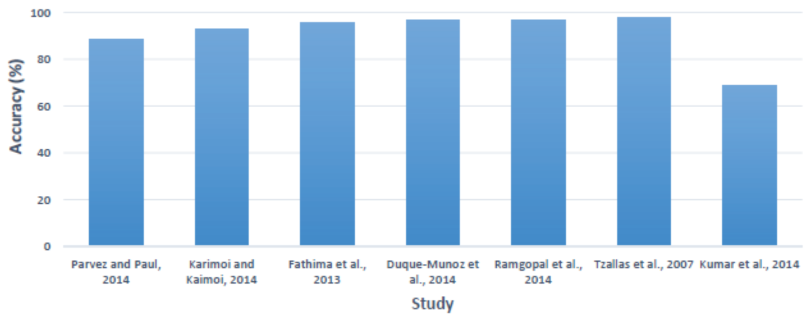

Fig. 5. Comparison to the related literature using the same dataset and classifying for normal vs. ictal vs. inter-ictal (F) vs. inter-ictal(N) EEG.

Fig. **6** shows results from recent studies that use deep learning techniques. Note that the datasets used in these studies are different from the one used by proposed model, which does not allow a fair comparison. Moreover, Emami et al. [42] report the results from binary classification (i.e., seizure/no seizure). Most of these methods rely on the computationally intensive deep learning, which maybe promising but it relies in theses specific methods on converting EEG signals into images by taking the EEG spectrogram, which may be impractical.

Table 6 shows the effect of using more EEG components from the DWT decomposition on the classification accuracy. The highest accuracy is achieved when all detail coefficients were used without the approximation features. Thus, the feature derived from high frequency EEG content (i.e., detail components) contain useful information that can significantly distinguish between normal, ictal and inter-ictal. More detail components will lead to higher accuracy. All EEG signal belonging to healthy, ictal, inter-ictal (F), inter-ictal (N) were correctly classified with 100% accuracy using the ANN model, see Table 4.

The robust features, based on precise instantaneous frequency calculation supported by the EEG components statistical parameters is the paramount advantage of this work. The proposed model is fast with computational time of 0.1474 sec on an average specification machine (Intel i7 6th generation and 8GB RAM), which makes it suitable for real-time applications. It provides high accuracy in comparison to other works in the literature. Furthermore, the classification accuracy is does not drop with more than two classes as in other high accuracy studies [38, 59]. The main difference results from the calculation of the entropy features based on instantaneous frequency of the wavelet decomposition output rather than computing the entropy for wavelet decomposition results directly.

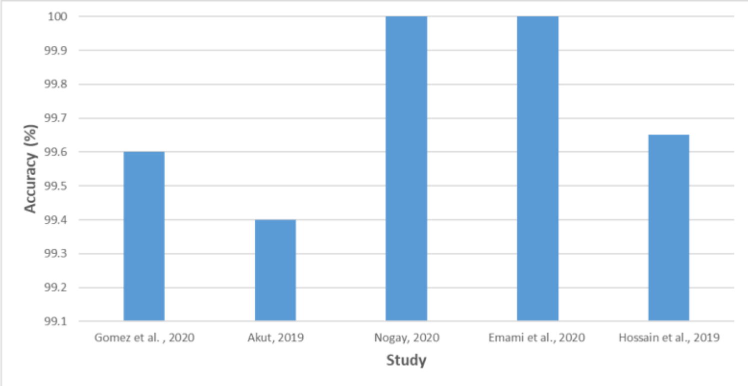

Fig. 6. Results from recent studies that use deep learning techniques.

Table 6. Classification results for normal vs. ictal vs. inter-ictal (F) EEG against the number of DWT sub-bands.

Decomposition Level	No. of Features	Accuracy			
		Healthy	Ictal	Inter-Ictal	Overall
$\boldsymbol{D_1}$	4	79.10%	94.10%	91.70%	87.70%
$\boldsymbol{D_1}$, $\boldsymbol{D_2}$	8	86.80%	97.90%	95.50%	93%
$\boldsymbol{D_1}$, $\boldsymbol{D_2}$, $\boldsymbol{D_3}$	12	85.30%	97%	91.20%	91%
$\boldsymbol{D_1}$, $\boldsymbol{D_2}$, $\boldsymbol{D_3}$, $\boldsymbol{D_4}$	16	100%	99%	100%	99.70%
$\boldsymbol{D_1}$, $\boldsymbol{D_2}$, $\boldsymbol{D_3}$, $\boldsymbol{D_4}$, $\boldsymbol{A_4}$	20	100%	100%	100%	100%

5. Conclusions

In this paper, we have tackled the problem of designing an automated system for seizure detection in EEG data. Although there exist numerous studies in the literature that produce high accuracy, they suffer from high computational overhead because of complicated analytic or perform badly with mixed EEG data containing more than two cases.

In this study a robust method for classify EEG into normal, ictal and inter-ictal has been proposed that achieve high accuracy for various mixture of classes. The potential of wavelet technique as a powerful time-frequency tool dealing with nonstationary signals, the advantages of DQ normalization, the measure of synchronization degree by the mean of entropy, the extraction of temporal data via statistical parameter computing, and the fast adaptable artificial neural network classifier are the main promising features of the presented work.

Nomenclatures

A_i	Approximate coefficients of the discrete wavelet transform at level i, time series signal
a	The dilation/compression factor, number
b	The translations coefficient, number
$C_w(k)$	The k^{th} wavelet transform output, time series signal

D_i	Detail coefficient of the discrete wavelet transform at level i, time series signal
$E_n(k)$	The n^{th} envelope function
f_n	False negative, number
f_p	False positive, number
$f_n(k)$	Frequency modulation part of the time series signal.
N	The number of normalizations
t_n	True negative, number
t_p	True positive, number
Greek Symbols	
$\psi(t)$	Mother Wavelet parameter, $\frac{1}{\sqrt{\lvert a \rvert}}\psi(\frac{t-b}{a})$
$\eta(x)$	Shannon Entropy number, $-\sum_{i=0}^{N-1}\log_2 P_i$.
Abbreviations	
AICA	Automatic Independent Component Analysis
ANFIS	Artificial Neural Network Fuzzy Inference System
ANN	Artificial Neural Network
APEn	Approximate Entropy
CNN	Convolutional Neural Network
CNS	Central Nervous System
DistEn	Distribution Entropy
DQ	Direct Quadrature
DWT	Discrete Wavelet Transform
EEG	Electroencephalography
EMD	Empirical Model Decomposition
FT	Fourier Transform
IMF	Intrinsic Mode Functions
SampEn	Sample Entropy
SFT	Short Fourier Transform
SRS	Simple Random Sampling
SVM	Support Vector Machine

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