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A novel approach based on wavelet analysis and arithmetic coding for automated detection and diagnosis of epileptic seizure in EEG signals using machine learning techniques

Hafeez Ullah Amin, Mohd Zuki Yusoff*, Rana Fayyaz Ahmad

Centre for Intelligent Signal & Imaging Research (CISIR), Department of Electrical & Electronic Engineering, Universiti Teknologi PETRONAS, 32610 Bandar Seri Iskandar, Perak, Malaysia

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ABSTRACT

Epilepsy, a common neurological disorder, is generally detected by electroencephalogram (EEG) signals. Visual inspection and interpretation of EEGs is a slow, time consuming process that is vulnerable to error and subjective variability. Consequently, several efforts to develop automatic epileptic seizure detection and classification methods have been made. The present study proposes a novel computer aided diagnostic technique (CAD) based on the discrete wavelet transform (DWT) and arithmetic coding to differentiate epileptic seizure signals from normal (seizure-free) signals. The proposed CAD technique comprises three steps. The first step decomposes EEG signals into approximations and detail coefficients using DWT while discarding non-significant coefficients in view of threshold criteria; thus, limiting the number of significant wavelet coefficients. The second step converts significant wavelet coefficients to bit streams using arithmetic coding to compute the compression ratio. In the final step, the compression feature set is standardized, whereupon machine-learning classifiers detect seizure activity from seizure-free signals. We employed the widely used benchmark database from Bonn University to compare and validate the technique with results from prior approaches. The proposed method achieved a perfect classification performance (100% accuracy) for the detection of epileptic seizure activity from EEG data, using both linear and non-liner machine-learning classifiers. This CAD technique can thus be considered robust with an extraordinary detection capability that discriminates epileptic seizure activity from seizure-free and normal EEG activity with simple linear classifiers. The method has the potential for efficient application as an adjunct for the clinical diagnosis of epilepsy.

1. Introduction

Epilepsy is a common brain disorder that affects people of all ages. It is a chronic neurological disorder in which recurrent seizures occurs due to abnormal neuronal activities within the human brain and affects the sensorium, mood and/or movement of the human body [1]. World Health Organization statistics indicate that approximately 50 million people currently live with epilepsy worldwide and an estimated 2.4 million people are diagnosed with epilepsy each year [2]. The incidence of the malady is higher in developing countries; i.e., between 7 and 14 per 1000 people. Treatment mostly comprises antiepileptic drugs and/or surgery [3].

The electroencephalogram (EEG) commonly detects seizure activity as it reflects electrophysiological conditions of the brain at a given time [4] and is widely used for diagnostic due to its low cost. EEG signals, enhanced with physiological and pathological data, are employed to evaluate and assess the treatment and progress of epileptic patients. Typically, clinicians evaluate EEG signals for three types of activity: (i) normal EEG activity that records healthy subjects with eyes open or closed; (ii) inter-ictal/seizure-free EEG activity that may contain small spikes and/or subclinical seizures that occur between two clinical episodes in epileptic patients; (iii) and *ictal* EEG activity containing sudden spikes.

Generally, EEG recordings are lengthy (hours to days) and contain a huge amount of data collected from patients. A visual inspection of such recordings is slow, time-consuming, vulnerable to errors, and subject to inter-observer variability [5]. Hence, several automated Computer Aided Diagnostic (CAD) techniques have been developed to help diagnose epileptic seizures [1,5–27]. CAD

* Corresponding author.
E-mail address: mzuki_yusoff@utp.edu.my (M.Z. Yusoff).

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techniques are based on the extraction of linear, non-linear, and time and/or frequency domain features from EEG signals. Further, machine-learning classifiers are employed to detect and characterize seizure activity. Details of related CAD techniques reported by previous studies are presented in the 'related-work' section where prior results are discussed and compared with the proposed technique. The literature review demonstrates the need for a highly accurate and more efficiently automatic EEG seizure detection system that differentiates seizure (ictal) from seizure-free (inter-ictal) or normal EEG readings with faultless accuracy.

The main objective of this work is to develop an efficient and robust automated computer-aided diagnostic (CAD) technique that mines a compact set of significant data (EEG signals) for utilization as a cost-effective feature involving simple linear classifiers to accurately differentiate seizure activity from seizure-free or normal EEG segments. The present study employed discrete wavelet decomposition (DWT) of EEG signals to obtain wavelet coefficients for different levels of decomposition. Although many studies have applied wavelet transforms to EEG signals, they either used an advanced wavelet transform, such as wavelet packet decomposition [5] and the complex wavelet transform [12], or a non-linear feature extraction method [6,7,28] along with non-linear classifiers [29], which are not always feasible for 1D signal decomposition and which demand additional loading and processing time. Furthermore, few studies only classified normal and seizure EEG activity [20,30] but did not classify seizure-free (inter-*ictal*) intervals. The present work combines the discrete wavelet transform with arithmetic coding to extract more robust features that efficiently and better segregate seizure activity (*ictal* EEG) from seizure-free (inter-*ictal* EEG) and normal EEG activity. Both linear and non-linear classifiers were applied to compare our results with those from the previously reported relevant studies that either employed non-linear or linear classifiers. In addition, the proposed method can aid real-time clinical diagnosis of epilepsy with EEG signals.

Fig. 2 shows a block diagram of the proposed method. We initially applied DWT to the EEG datasets and decomposed the obtained signals to approximations and detail coefficients. We then extracted the most significant coefficients by discarding non-significant coefficients using threshold criteria in such a way that the reconstructed signal's total energy was retained by >99%. Significant coefficients were next encoded to a bit-stream by employing an arithmetic coding algorithm and computing the compression ratio for the EEG dataset. Finally, the computed compression ratio (CR) was standardized and used as a feature to train machine-learning classifiers to identify optimal classifier-model parameters for classification purposes. The performance of these classifiers was then evaluated by using a 10-fold cross-validation technique. A portion of the extracted features (dataset) was used to train classifiers while the remaining data was utilized to assess the classifiers. Averaged performance measures for the 10-fold validation were also determined (see 'results section' for accuracy, sensitivity, and specificity).

This paper is organized as follows: Section 2 presents related work; Section 3 explains the proposed method and clinical database used for this study. Section 4 presents the experimental results. Section 5 discusses experimental results and a comparison with present state-of-the-art techniques. Section 6 provides the concluding remarks.

2. Related work

This section presents a detailed discussion of previous related research on feature extraction using linear and non-linear methods along with different machine-learning classifiers.

Presently, numerous studies have been reported epileptic seizure detection methods depending on EEG signals applying linear and non-linear techniques [7,9,14,25,26,28,31,32]. Feature extraction techniques are the key focused on the methods proposed by these studies to differentiate between seizure-free, seizure and standard EEG activities together with machine learning algorithms. These techniques incorporate the frequency sub-bands extraction, entropy analysis, use of wavelet decomposition, largest Lyapunov exponent, fractal measurement, Hurst exponent and higher-order cumulants [33,34]. These studies reported the use of machine learning algorithms, such as an artificial neural network (NN), fuzzy classifier, Gaussian mixture model, k-nearest neighbor (k-NN), support vector machine (SVM), and naïve Bayes classifier.

Generally, time and frequency-based methods are useful for feature extraction in EEG signals, and the mined attributes of the signals are further utilized as inputs into the classifiers [32]. Besides, frequency-based features, scientists have analyzed EEG signals by using discrete wavelet transform (DWT). Time-frequency analysis can be accomplished for EEG signals using DWT decomposition. An automated seizure detection method initially proposed by Gotman et al. [35] have been widely adopted. Features such as peak amplitude, sharpness, time interval, and slope were used for seizure activity detection after the decomposition of the EEG signals. Likewise, Khan et al. [36] decomposed EEG signals by employing the DWT and computed features, such as energy and coefficients variation in sub-frequency bands for the detection of the epileptic seizure activity. Similarly, Adeli et al. [8,9] tested and illustrated the epileptic seizure discharge being a 3 Hz spike using wavelet transform. Features related to transients were computed and located over time and frequency space. Subasi et al. [37] suggested a system based on wavelet transform and artificial neural networks (ANN) to classify EEG seizure signals. Subasi's team [27] implemented dynamic fuzzy neural networks, and thus, improved their developed method. Guo et al. [16] utilized genetic programming and proposed an automatic feature extraction scheme for the classification of epileptic seizure activity. Recently, fuzzy approximate entropy (fApEn) and discrete wavelet transformation based EEG feature extraction method were proposed by Kumar et al. [38]. In addition, Senhadji and colleagues [32] have analyzed the spectral content of EEG signals as a function of time by using wavelet transformation for 'time vs. duration' analysis and 'time-frequency' approach. The authors have adopted both the analyses approaches to detect inter-ictal spikes and ictal duration. Studies also suggested a method to overcome the computational load for classical wavelet transform; likewise, Chen et al. [12] reported artificial neural networks (ANNs) and logistic regression for the classification of epileptic seizure activity. Further, artificial neural networks (ANNs) and logistic regression were used to classify epileptic seizure activity. Xie and Krishnan [39] proposed a method known as the sparse functional linear model, to represent EEG signals based on wavelets, that is, wavelet variance to detect discriminative components of EEG signals. Acharya and colleagues [7] have used wavelet packet decomposition for EEG decomposition and principal component analysis (PCA) to discard the eigenvalues from these wavelet coefficients. Further, they have utilized ANOVA analysis to identify significant eigenvalues and employed a 10-fold cross-validation approach to train the classifiers. The Gaussian mixture model (GMM) was utilized to achieve highly correct results of classification for epileptic signals. Wang and colleagues [40] extracted EEG features by using wavelet package entropy that reported a hierarchical classification strategy. Recently, a wavelet-based fuzzy-approximate entropy (fApEn) method was reported by Kumar et al. [41] along with support vector machine (SVM) for classification functions. The EEG was decomposed into sub-bands with discrete wavelet transforms and then computed fApEN of each sub-band to rate the chaotic behavior of EEG signals. The authors have reported the highest classification accuracy with SVM classifier along with the RBF.

The literature review shows that majority of the studies were incapable to attain perfect results using signal processing techniques with machine learning methods for seizure activity from seizure-free EEG signals or seizure-free EEG activity from healthy EEG recordings.

3. Materials and method

3.1. Dataset

EEG data used for this analysis is a publicly available database at the University of Bonn as first reported by Andrzejak et al. [31]. This database contains five sub data sets labeled as A, B, C, D and E. There are 100 single channel EEG segments in each dataset with a length of 23.6 s, and a total of 4097 samples per channel. Five healthy subjects' Eyes open (EO) and eyes closed scalp EEG recordings were labeled as Sets A and B, respectively. EEG readings at various spatial locations of five epileptic patients were denoted as Datasets D, C and E. Dataset C includes EEG recordings from the hippocampal formation from the hemisphere opposite the epileptogenic zone. Dataset D includes EEG records of the epileptogenic zone. The recordings C and D both were collected during the seizure-free time. Set E is a collection of seizure activity recorded by the hippocampal focus. Data sets were recorded using 128 channels with average reference. Channels with pathological activities were removed from the average common reference computation. Eye movement artifacts were removed from scalp EEG sets (A and B). The data were acquired using 12-bit analog-to-digital converts with a sampling frequency of 173.61 Hz. Further, a band-pass filter (0.53 to 40 Hz with a 12 dB/oct filter roll-off) was applied on raw EEG data [31]. According to the original source of this dataset, EEG data comprises 5 (classes) × 100 (observations per class) × 4097 (23.6 s per observation).

3.2. Discrete wavelet transform

The inner product of a given signal $[x(t)]$ with dilated and translated versions of the wavelet function $[\psi_{a,b}(t)]$ is the wavelet transform denoted as follows:

$$W_{\psi}X(a,b) = \left\langle x, \psi_{a,b} \right\rangle, \tag{1}$$

$$\psi_{a,b} = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right), \tag{2}$$

Scale and translation parameters are represented as $[a, b \in \Re]$ in the above equations, respectively. The scaling parameter dilates or compresses the wavelet function and the translation parameter changes its location [42]. The low or high frequency components can be obtained from the correlation of the signal $[x(t)]$ with dilated or contracted versions of the wavelet function $[\psi_{a,b}(t)]$, respectively. Practically, the wavelet transform is defined at discrete scales ($a_j = 2^j$) and times ($b_{j,k} = 2^j k$), called the discrete wavelet transform (DWT). The DWT successfully divides a given signal into approximations and detailed coefficients at different scales. Lower scales provide information for high frequency components and higher scales provide information for low frequency components. DWT decomposition results for the present study are provided in the description of the proposed method section.

3.3. Arithmetic coding

Arithmetic coding is a technique primarily used in data compression. It maps data and produces non-block codes in such a way that the original data can be obtained from the generated code. This is to say that a one-to-one correspondence between source data (symbols) and the code does not exist. Hence, each source symbol is not individually converted to a codeword in contrast to previous coding algorithms such as Huffman coding. In arithmetic coding, a complete sequence of source symbols is allocated to a single arithmetic codeword. The codeword expresses an interval of real numbers between 0 and 1. When the number of symbols in the source data increases, then the interval used to denote it turns smaller and the number of bits essential to denote the interval grow larger [43]. Moreover, in arithmetic coding, each source symbol does not involve in symbolizing an integral number of code symbols. Thus, each symbol of the source data reduces the interval size according to its probability of occurrence.

Consider a sequence of five symbols ($x_1x_2x_3x_3x_4$) from a four-symbol source with encoded probabilities (0.2, 0.2, 0.4, and 0.2) (Fig. 1). First, the complete sequence is considered to occupy the entire half open interval [0, 1). This interval is subdivided into four parts based on the probabilities of the source symbols. The first symbol of the sequence (x_1) is associated with subinterval (0, 0.2); the sequence interval is narrowed to [0, 0.2). The subinterval [0, 0.2) is then stretched to the full height of the entire half-open interval [0, 1) and labeled with end points that hold narrowed range values [0, 0.2). Again, the narrowed range [0, 0.2) is then subdivided according to the original source symbol probabilities, whose process continues with the next symbol. Accordingly, x_2 contracts to (0.04, 0.08), x_3 narrows to (0.056, 0.072), and so on until the last symbol. The last symbol is used as a special indicator marking the end of the sequence, which narrows the range to (0.06752, 0.0688). At this point, any number with an interval, say 0.068, can represent the entire sequence.

3.4. Proposed computer aided diagnostic technique

Fig. 2 shows a block diagram of the proposed Computer Aided Diagnostic (CAD) technique, which comprises the following three steps.

1 Wavelet Decomposition
- Decomposition of EEG signals via discrete wavelet transform.
- Apply threshold to coefficients such that reconstructed signal energy remains ~99%, rounded to the nearest integer.

2 Feature Computation
- Encode DWT coefficients using Arithmetic coding.
- Compute compression features.
- Standardize extracted features.

3 Feature Classification
- Classify features using machine-learning classifiers.
- Evaluate performance via *k-fold* cross-validation and EEG classification results.

Initially, using DWT with Daubechies wavelet, EEG signal x[n] is decomposed up to level 4 to 'approximation' and 'detail' coefficients. We selected the db4 wavelet in this analysis; as previously reported by Adeli et al. [9], db4 is best suited for the decomposition of EEG signals due to its orthogonality property and efficient filter implementation, particularly, for epileptic EEG signals. DWT uses a succession of high pass g(n) and low pass h(n) filters. The discrete mother wavelet is described by the high pass filter g(n) ; while the low pass filter h(n) represents its mirror version [30]. Cutoff frequencies for h(n) and g(n) filters equal one-fourth the sampling frequency of EEG signal inputs. In the first level decomposition, input signals are simultaneously filtered through h(n) and g(n) filters resulting in corresponding outputs called 'approximation' (A1) and 'detail' (D1) coefficients, respectively. Approximation coeffi-

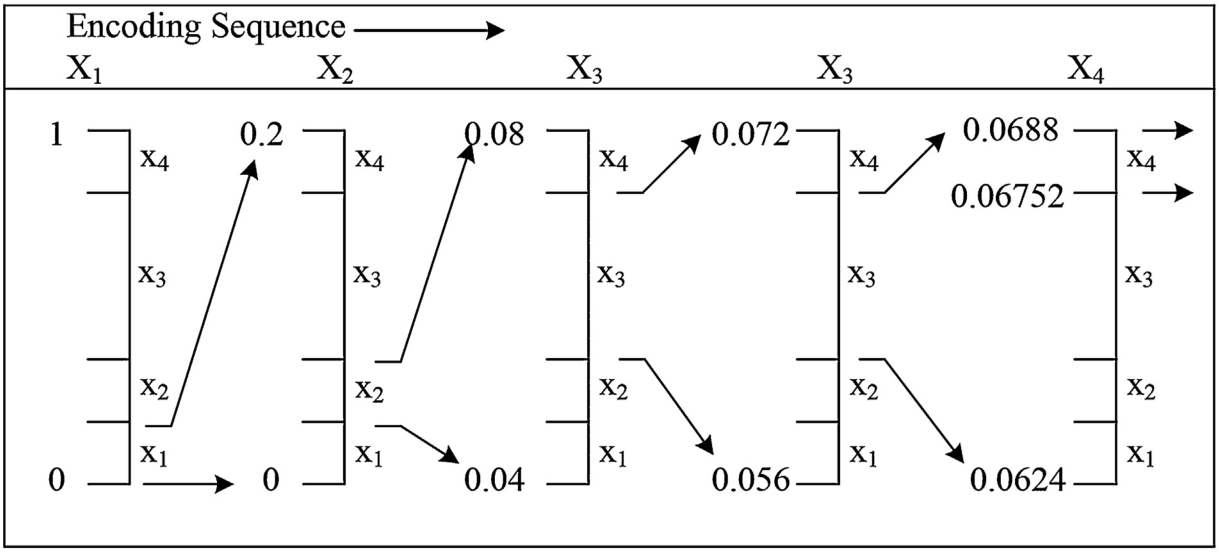

Fig. 1. Simple Arithmetic Coding Procedure with Example.

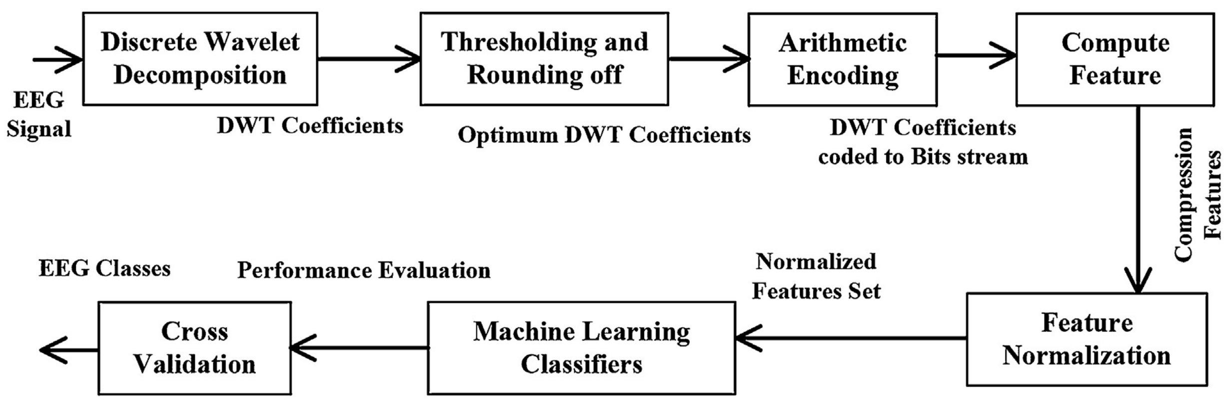

Fig. 2. Block diagram of the proposed CAD technique for EEG epileptic seizure classification.

cients (A_i) and detail coefficients (D_i) at (i^{th}) level are represented as follows:

$$A_i = \frac{1}{\sqrt{M}} \sum_n x(n).\varphi_{j,k}(n) \quad (3)$$

where: $\varphi_{j,k}(n) = 2^{-j/2} h\left(2^{-j} n\text{-}k\right)$ is scaling function, and

$$D_i = \frac{1}{\sqrt{M}} \sum_n x(n).\psi_{j,k}(n) \quad (4)$$

where: $\psi_{j,k}(n) = 2^{-j/2} g\left(2^{-j} n\text{-}k\right)$ is the wavelet function.

Here: $n = 0, 1, 2, \ldots, M-1$; $j = 0, 1, 2, \ldots, J-1$; $k = 0, 1, 2, \ldots, 2^j - 1$; $J = 4$; M is the length of the EEG discrete signal x[n].

DWT coefficients D_{jk} (approximation $A_{i=3}$ and details ($D_{i=0,\,1,\,2,\text{ and }3}$) are compacted by eliminating non-significant coefficients with implementation of certain threshold value (α) defined as follow:

$$\hat{D}_{jk} = \begin{cases} D_{jk}, & \left|D_{jk}\right| \geq \alpha, \\ 0, & \left|D_{jk}\right| < \alpha, \end{cases} \quad (5)$$

The specification of the threshold value (α) ensured the reconstructed signal has enough energy, i.e., energy >99%.

$$energy(E) = \frac{100 \times \|X_r\|_2^2}{\|X\|_2^2} > 99\% \quad (6)$$

where (X_r) denotes the reconstructed signal and (X) represents the original signal.

The computation of threshold value (α) is based on the method of Donoho and Johnstone [44] where the last level of the detailed coefficients vector is considered for the estimation of the standard deviation of the noise (unwanted signal). Here, hard thresholding is used and the threshold value (α) is defined as:

$$\alpha = \hat{\sigma}\sqrt{2logN} \quad (7)$$

Here, N denotes the number of wavelets coefficients in the last level of the detailed coefficients.

Based on the median absolute deviation,

$$\hat{\sigma} = \frac{\text{median}\left(\left|\sim D_{jk}\right|\right)}{0.6745} \quad (8)$$

Here, the number in the denominator denotes the scale factor, depending on the distribution of $\sim D_{jk}$, and equal to 0.6745 for normal distributed data. $\sim D_{jk}$ denotes the wavelet coefficients in the last level of the detailed coefficients.

The computed threshold value is changed if the energy criteria mentioned in Eq. 6 is not met. This is to ensure that the quality of the signal is not compromised among the datasets.

This process ensures the quality of the signal after disregarding the non-significant coefficients. The DWT coefficients $\hat{D}_{jk}$ subjected to threshold are rounded to the nearest integer and represented as $(\bar{D}_{jk})$.

The second step includes encoding the rounded DWT coefficients $(\bar{D}_{jk})$ into bitstreams by applying the arithmetic coding technique. Arithmetic coding has two strategies to reduce data: *static* and *adaptive*. Here, static arithmetic coding is used because the number of wavelet coefficients and their probability of occurrence is known. The adaptive strategy is useful when the distribution of the source in the form of cumulative counts is unknown [45].

Accordingly, DWT coefficients' size is compacted and the signal is consequently compressed. The arithmetic coding output bits' stream provides the compression feature denoted as follows:

$$CR = \frac{\text{Size of Original Signal } X}{\text{Size of Compressed Signal } X_c} \tag{9}$$

The third step includes the standardization of the extracted CR features to zero mean and unit variance by the following equation.

$$\hat{x}_i = \frac{x_i - \bar{x}}{\sigma} \tag{10}$$

Here, $i = 1, 2, \ldots, N$; where N reflects the number of instances in a specific feature x; σ and $\bar{x}$ are the standard deviation and the mean of (x_i), respectively; and $(\hat{x}_i)$ is the standardized feature value.

Standardized features are then used as input for the machine-learning classifier. To demonstrate the proposed CAD system's effectiveness, we used four machine-learning classifiers: (i) support vector machine (SVM) with radial basis function (RBF) [46]; (ii) multi-layer perceptron (MLP) with 3 hidden layers [47]; (iii) Naïve Bayes (NB) [48]; and (iv) K-nearest neighbors (k-NN) with k = 5—for machine learning classifier details, see [49]. A 10-fold cross-validation method was adopted to evaluate classifier performances using average accuracy, sensitivity and specificity computed as estimated results [49].

3.5. *k-Fold cross-validation*

In machine learning, k-fold cross-validation (CV) is a common procedure to evaluate the efficiency of classification algorithms on a given data [50]. In this procedure, a given dataset is divided into 'k disjoint folds' of equal size. Then, at each fold, k-1 folds are utilized for training purpose and one fold is reserved as a validation set to evaluate the classification model. Accordingly, it is repeated k times with each k-fold used exactly once as validation data. Then, the k-accuracies from k-fold CV are averaged to evaluate the efficiency of the classifier. The key advantage of this CV is that all instances in a given dataset are used for training and testing; while each instance is used for validation exactly once. Variance in the resulting estimate can be reduced as the value of k increases. However, running the training algorithm k times can increase computational costs, which can be reduced by adopting a reasonable k value (e.g. 5-fold or 10-fold).

4. Experimental results

Beginning with the experimental setup, we now present experimental validation results compared to state-of-the-art methods. All the analysis in our experiments was performed on a desktop computer with 2.4 GHz Intel Core i5 processor, 4GB memory and 64 bit Windows 7 ultimate operating system. The feature extraction and standardization part were completed with MATLAB and the classifiers were employed from Weka 3.6.9 toolbox. For the five datasets of EEG, five different cases of classification are considered (Table 1). These cases are selected based on previous studies to facilitate comparison.

Table 1
Experimental Cases for Classification.

Case	Datasets	Description
1	A and E	Normal and seizure (*ictal*) EEG recordings
2	AB and E	Normal and seizure (*ictal*) EEG recordings
3	C and E	Seizure-free (*inter-ictal*) and seizure EEG recordings
4	CD and E	Seizure-free (*inter-ictal*) and seizure EEG recordings
5	ABCD and E	Normal, seizure-free and seizure EEG recordings

Table 2
Quality of reconstructed EEG signals for all datasets (A–E).

Set	Energy %	Zero Ratio %	MSE	PSNR (dB)
A	99.13 (0.67)	68.20 (5.52)	24.04 (3.56)	55.64 (1.98)
B	99.37 (0.40)	61.95 (5.62)	24.03 (6.69)	58.84 (2.16)
C	99.02 (0.79)	78.43 (8.12)	24.02 (7.11)	57.44 (3.04)
D	99.05 (0.84)	79.28 (5.91)	24.03 (6.24)	58.62 (5.61)
E	99.25 (0.05)	50.22 (12.21)	24.02 (3.80)	70.68 (4.52)
AB	99.24 (0.35)	65.12 (3.91)	24.03 (3.66)	60.52 (1.94)
CD	99.25 (0.46)	78.91 (5.34)	24.03 (4.96)	61.99 (4.54)
ABCD	99.33 (0.27)	72.09 (3.28)	24.03 (2.77)	64.63 (3.80)

Note: The facts are represented as mean (standard deviation).

Table 3
Threshold values for data set A–E while controlling for MSE.

Datasets	A	B	C	D	E	AB	CD	ABCD
Threshold	15.35	15.5	16.77	17.84	17.00	15.42	17.27	16.24

Note: Values reported in Table 3 are subject to a dataset, wavelet type, decomposition levels, and retained quality of reconstructed signals.

We used 100 EEG segments from each of the five datasets. The proposed CAD technique employed DWT up to 4th level data decomposition to extract wavelet coefficients, after which non-significant coefficients were discarded as previously explained. After discarding the non-significant wavelet coefficients, the quality of reconstructed signals was ensured by retaining signal energy at >99% while controlling the mean square errors (MSEs) for all the five datasets (A–E) (Table 2 demonstrates the quality of the reconstructed datasets; Table 3 reports the threshold values used to reduce non-significant wavelet coefficients). Retaining certain percent energy while controlling the MSEs ensures that criteria for discarding wavelet coefficients over all datasets were balanced and fair. Only significant wavelet coefficients for all five datasets were used to compute compression (compression ratio - CR) features via the arithmetic-coding algorithm. After feature extraction, machine-learning classifiers were trained and tested for all datasets using the 10-fold cross-validation method. This method divided 'features sets' into 10 subsets of equal size, using nine subsets for classifier training and one subset for testing. Averages for accuracy, sensitivity, and specificity were then computed for final classifier performances [49].

Classifier performances were evaluated using sensitivity, specificity, and accuracy as follows:

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100\% \tag{11}$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \times 100\% \tag{12}$$

Table 4
Classification accuracy results for datasets A–E of the University of Bonn database.

Datasets	Accuracy %			
	Naïve Bayes	KNN (k = 5)	MLP (Hidden Layers:3)	SVM (RBF)
A-E	100	100	100	100
AB-E	100	100	100	100
C-E	100	100	100	100
CD-E	100	100	100	100
ABCD-E	100	100	100	100

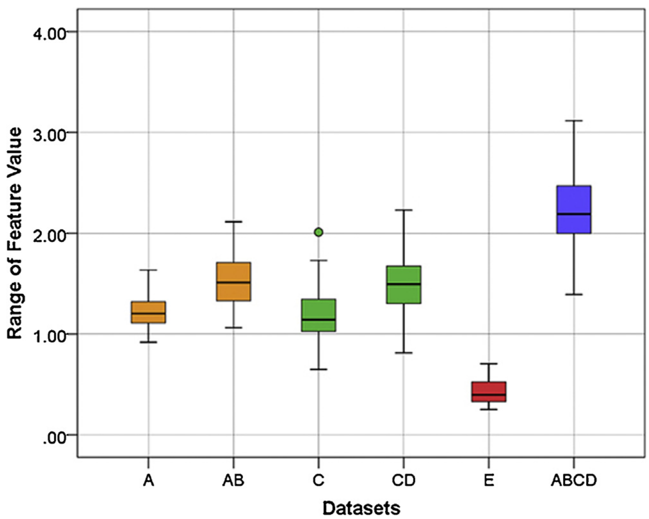

Fig. 3. Box plot of feature values. The normal (A, AB) and inter-ictal (C, CD) datasets are clearly different than the ictal dataset (E).

$$\text{Accuracy} = \frac{\text{Correctly classified (True Positive + True Negative)}}{\text{Total Cases}} \times 100\% \tag{13}$$

The number of seizures correctly identified by the proposed CAD system are represented as 'true positive' (TP); the number of normal segments correctly identified as 'normal' are referred to as 'true negative' (TN); the number of incorrectly identified EEG segments as seizures are referred to as 'false positive' (FP); and the number of missed seizures events as 'false negative' (FN).

Table 4 presents computed values for classification accuracy for all the four machine-learning classifiers in the proposed CAD system, which achieved perfect classification accuracy (100%) for datasets A-E, AB-E, C-E, CD-E, and ABCD-E. Besides, all the four classifiers achieved 100% sensitivity and specificity for the above mentioned datasets. Since the proposed technique achieved perfect accuracy for sensitivity and specificity results, only classification accuracy is reported below.

To justify the differences between the datasets achieved with the proposed feature extraction method, a one way ANOVA was applied to the features extracted from all the datasets. There was a statistically significant difference between datasets as determined by one-way ANOVA, $F(5,594) = 547.23$, $p < 0.0001$. A Tukey post hoc analysis showed that datasets A (normal EEG pattern), AB, C (inter-ictal), CD and ABCD (normal and inter-ictal together) were statistically significantly different than the dataset E (ictal), p-value<0.0001. In addition, Fig. 3 shows a box plot of all the datasets to display the distribution of feature values.

5. Discussion

This section provides a detailed comparison with previous methods as reported in the EEG literature and summarizes the robustness of the proposed technique. Only the recent studies that employed the Bonn EEG database were included.

In signal processing, a completely periodic signal repeats itself with a constant period and can be mathematically defined, such as sin(x) [51]. However, in the case of EEG signal, it is not completely periodic like sin(x), but there is some periodicity, see Fig. 4. In this implementation, the idea is to consider the redundant information that resides in the EEG in different conditions, like normal, inter-ictal, and ictal EEG. The elimination of redundant information from the EEG signals leads to EEG compression. The potential of EEG compression is related to the brain neuronal processes. It is obvious that the EEG signals recorded over the scalp are dependent on whatever neural processes that are occurring inside the brain which reflect directly the electrical activity of the neuronal communications [52,53]. When the active neuronal networks of the brain during certain tasks fire and produce a smooth rhythm (e.g., EEG in resting-state eyes-closed condition), this will result in fewer fluctuations in the scalp electrical potential and certain EEG rhythms such as alpha waves will be dominant [54] – producing high redundant information in the EEG signal, and increasing the potential of EEG compressibility [55]. Similarly, when the active neuronal networks of the brain in a certain mental task are firing with rapid changes over time [56] (e.g., EEG in the working memory task), then there is a possibility of relatively high fluctuations in the scalp electrical potential, which would result in low redundant information in the EEG signal. It can be interpreted that when an individual is feeling relax during a certain situation or the brain is not involved in complex processing such as cognition, the recorded EEG signal will have a high amount of redundant information, the reverse of such situation will lead to a very minimum redundant information in the EEG signal.

In the case of EEG analysis, where normal, inter-ictal, and ictal conditions are involved. The idea of compression in these conditions helps to separate the ictal EEG from the non-ictal one. The ictal and inter-ictal EEG have high randomness and are lacking in structure, which give relatively low or no potentials of compressibility.

In this work, static arithmetic coding was introduced for feature extraction of EEG signals in combination with the discrete wavelet transform to detect the epileptic seizures in EEG recordings. Our proposed approach is based on discrete wavelet transform (DWT) decomposition of EEG signals, extraction of features from the significant DWT coefficients using static arithmetic coding, and classification of the EEG segments using linear (kNN and Naïve Bayes) and non-linear (MLP and SVM) classifiers. The use of DWT with static arithmetic coding is evaluated using five classification problems (see, Table 1). Several previous DWT studies identified the most appropriate technique to handle with the non-stationary transient events in the EEG signals, especially for epileptic EEG data [4,9]. To our knowledge, there is no study in the literature related to feature extraction with static arithmetic coding for epileptic seizure detection with computationally efficient and perfect classification results. Our proposed technique's results were compared with the previously reported automated seizure detection techniques. Table 5 shows our classification results for (i) normal (sets A and B) versus seizure/*ictal* (set E); (ii) seizure-free/inter-*ictal* (sets C and D) versus seizure/*ictal* (set E); and (iii) normal + seizure-free/inter-*ictal* (sets A–D) versus seizure/*ictal* (set E). The proposed technique achieved perfect classification results (100%) for normal EEG and epileptic seizure patterns (sets A or B vs. set E), compared to numerous prior studies using simple machine-learning algorithms (Naïve Bayes or k-NN). The few studies that did report

Table 5
Comparisons with previously reported automated detection studies of Epileptic EEG signals using different feature extraction methods and machine learning classifiers (classifying epileptic EEG vs. seizure-free EEG vs. normal EEG patterns).

Author(s)	Year	Feature Extraction Methods	Classifier(s)	Datasets	Accuracy %
Song [23]	2012	Optimized sample entropy (O-SampEn) algorithm	Extreme learning machine (ELM)	D-E	97.50
Yatindra [18]	2012	Discrete wavelet transform (DWT) and approximate entropy (ApEn)	ANN, SVM	A-E	100
				B-E	92.5
				C-E	100
				D-E	95
				ABCD-E	94
Acharya [5]	2012	Wavelet Packet Decomposition and Principal component analysis	Gaussian Mixture Model (GMM)	Normal, inter-ictal, and ictal	99.00
Fernandez-Blanco et al [61]	2012	Automatic seizure detection based on star graph topological indices, General Discriminant Analysis (GDA)	GDA	A-E	99.00
Varun Bajaj [10]	2012	Empirical mode decomposition (EMD)	Least Squares SVM	ABCD-E	100
Satchidanada Dehuri [62]	2013	Differential evolution-Radial basis Function neural networks (DE-RBFNs)	NN	A-E	100
				ACD-E	98.98
				ABCD-E	98.46
Xie & Krishnan [39]	2013	Dynamic PCA + PCPEM	k-NN	A-E	100
				ABCD-E	100
Song et al. [24]	2013	Discrete Wavelet Transform with db4 + permutation and sample entropy + genetic algorithm	Extreme learning machine (ELM)	A-E	94.20
Joshi et al. [17]	2014	Fractional linear prediction (FLP) +SVM	SVM with RBF	C-E	95.33
				D-E	
Lee et al. [33]	2014	Wavelet transform, phase space reconstruction and Euclidean distance	weighted fuzzy membership function (NEWFM)	A-E	98.17
Kaya et al. [63]	2014	One-dimensional local binary pattern (1D-LBP)	BayesNet	A-E	99.50
				A-D	99.50
				D-E	93.00
				CD-E	95.66
				AB-CDE	93.00
Pachori & Patidar [21]	2014	Empirical mode decomposition (EMD) and second order difference plot (SODP) of intrinsic mode functions	ANN	Not reported	97.75
Guohun Zhu [57]	2014	Fast weighted horizontal visibility graph constructing algorithm (FWHVA)	*k*-NN	A-E	100
				ABCD-E	95.40
Yatindra Kumar [41]	2014	Wavelet based Fuzzy approximate entropy (fApEn)	SVM with RBF	A-E	100
				B-E	100
				C-E	99.6
				D-E	95.85
				ABCD-E	97.36
Fu et al. [14]	2014	Hilbert-hung transform based time-frequency image	SVM with RBF	A-E	99.12
Guangyi [12]	2014	Dual-tree complex wavelet (DTCWT)-Fourier features	k-NN	A-E	100
				A,B,C,D-E	100
Jose et al. [17]	2014	Fractional linear prediction	SVM with RBF	CD-E	95.33
Dhiman & Priyanka [64]	2014	Wavelet Packet + Genetic Algorithm	SVM	A-E	100
Yuan et al. [65]	2014	Kernal SRC	SVM with RBF	A-E	98.63
				D-E	98.63
Zhu et al. [57]	2014	FFT + sample entropy	KNN	A-E	99
				B-E	90
				C-E	97
				D-E	94
				ABCD-E	95
Kang et al. [59]	2015	FFT spectral analysis, AR model	Quadratic discriminant analysis (QDA)	A-E	99.78
				B-E	99.55
			MLPNN	C-E	99.62
				D-E	99.46
Sharma and Pachori [60]	2015	Phase space representation and intrinsic mode functions	Least Squares SVM	CD-E	98.67
Tawfik et al. [66]	2016	Wavelet Transform + Weighted Permutation Entropy algorithm	SVM, ANN	A-E	99.5
				B-E	85.00
				C-E	93.5
				D-E	96.5
				ABCD-E	93.75
Tiwari et al., [67]	2017	Key-point descriptors + Gaussian filters	SVM (RBF)	AB-E	100
				ABCD-E	99.31
Jesus et al., [68]	2017	DWT	SVM (RBF)	A-E	99.85
Ihsan et al., [69]	2018	P-1D- Convolutional Neural network (CNN)		AB-CDE	99.80
				AB-CD	99.95
Acharya et al., [70]	2018	13-layer Deep Convolutional Neural network		CD-E	88.7%
Present Work	**2019**	**Discrete Wavelet + Arithmetic coding**	**k-NN, Naïve Bayes, MLP, and SVM**	**A-E**	**100%**
				AB-E	**100%**
				C-E	**100%**
				CD-E	**100%**
				ABCD-E	**100%**

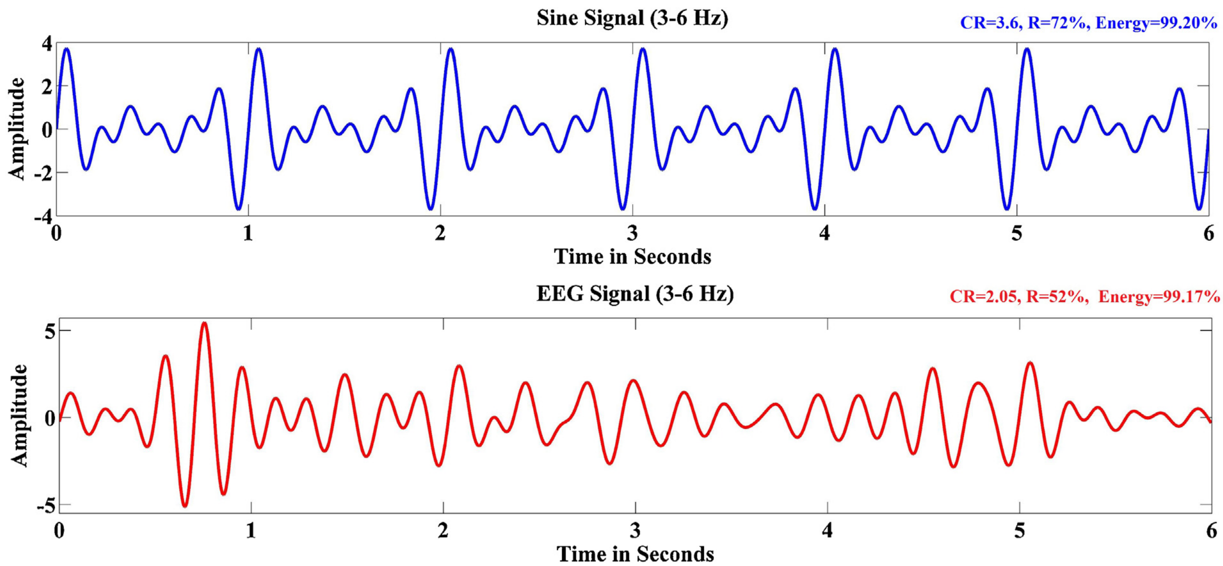

Fig. 4. Example of periodic sine signal and EEG signal of 3-to-6 Hz with redundant information, *CR* (compression ratio), *R* (percentage redundancy).

perfect classification results either employed complex methods for feature extraction [57,39] or non-linear classifiers (ANN and kernel SVM) [18,58]. The segregation of normal from epileptic EEG patterns was relatively easier than for seizure-free vs. epileptic EEG patterns. However, seizure-free/inter-*ictal* EEG patterns may contain spikes similar to those observed in seizure EEG patterns, which can create difficulties in the differentiation of seizure activity from non-seizure EEG readings in commonly used diagnostic tools. This can result in misclassifications reported by many studies Kang et al., [59] Zhu et al. [57], Kumar et al. [38], Sharma & Pachori [60], etc., as listed in Table 5. To justify the robustness of feature extraction of the proposed CAD technique, statistically, analysis (one-way ANOVA) was performed on the features extracted from all the datasets (A to E). The results indicated a statistically significant difference between normal vs. seizure, normal with seizure-free vs. seizure, and seizure-free vs. seizure datasets. The proposed technique, however, achieved satisfactory results for sets A-E, AB-E, C-E, CD-E, and ABCD-E, as shown in Table 5, using both machine learning algorithms and statistical analysis. Such findings, to our knowledge, have never been reported by any prior study.

The novelty of this study is the utilization of discrete wavelet transform with static arithmetic coding for the extraction of robust EEG features in the proposed CAD technique. The DWT with *db4* wavelet is proved as a most appropriate technique for non-stationary signals and is very effective in detecting sudden spikes that mark epileptic EEG signals, as reported by Adeli [9]. Further, DWT is capable of representing EEG signals in a compact manner as it limits the number of significant coefficients while retaining both time and frequency information. Combined with arithmetic coding, DWT locates signal compression (the limit to which a signal can be compressed), which is an important characteristic of EEG signal and varies with the brain's state. In addition, we decomposed signals up to the 4th DWT level of sub-bands. Moreover, both encoder and decoder of the arithmetic coding algorithm are in linear time; thus, indicating that the time complexity of the proposed technique is $O(N)$.

To compare the time computation of the proposed approach, time computations were determined for all the five datasets. The proposed feature extraction method requires 0.5 s for feature extraction from a segment of 23.5 s recording which is computationally faster than the time-frequency analysis based methods proposed by Tzallas et al., [71,72]. Further, our approach of feature extraction is also faster than the empirical mode decomposition (EMD) based method proposed by Alam and Bhuiyan [73], which required 0.2-0.6 s for processing 1.475 s recording, i.e., 23.6 s would require 3.2 to 9.6 s processing time. The classification algorithms k-NN, naïve Bayes, MLP, and SVM required 0.001$\sim$0.002 s, 0.001$\sim$0.002, 0.09$\sim$0.11 s and 0.01$\sim$0.05 s, time for testing, respectively. Thus, to detect the seizure, for example, 24 h continuous recordings of an epilepsy patient, the proposed CAD system can be expected to detect approximately 30 minutes. This means the proposed technique is exceptionally quick in terms of computational cost and thus, is suitable for implementation as a computer-aided, clinical diagnostic tool.

5.1. Limitations

A 100% correct classification rate was achieved for a relatively small database. Should we employ larger clinical databases, the proposed technique might or might not yield perfect classification accuracy. If not perfect, the proposed technique could be amended by adding a feature selection step after feature extraction. We recommend Fisher's Discriminant Ratio and Principal Component Analysis to be used as a feature selection method. The former is a feature ranking method, which can rank all the features according to their discrimination power; while the latter is a dimensionality reduction method, which transforms the features into a linear combination of mutually orthogonal new variables, representing the original features in a low dimensional space. Second, a lengthy feature extraction step via 10-fold cross-validation scheme could be computationally costly. However, we believe that with advanced high performance computational technology the additional feature extraction would not be a problem.

6. Conclusion and future direction

The proposed technique robustly outperformed those that were previously reported in the literature. Perfect seizure activity detection is highly desirable as a medical diagnostic system, which makes this technique a valuable supportive clinical tool for the diagnosis of epileptic seizures and subsequent clinical management. The present effort combined discrete wavelet transform (a basic preliminary wavelet analysis) with an arithmetic-coding algorithm to optimally extract EEG features. We then employed machine-learning classifiers to identify and differentiate seizure/*ictal* from seizures-free (inter-*ictal*) and normal EEG patterns. We submit that the combination of DWT with the arithmetic-coding algorithm better mines an EEG database for the most useful and most significant information which can then train machine learning classifiers for diagnostic purposes.

In the future, we intend to further validate the proposed CAD technique with high density, larger clinical EEG databases. A feature selection step may be added to select for highly seizure-contaminated segments of huge EEG databases for classification.

Ethical approval

In this study, a publically available EEG database is used, employed the University of Bonn as acquired by Andrzejak et al. [31]. Thus, the authors of this study did not practice the ethical approval and/or informed consent.

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Conflict of Interest

None.

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