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Research paper

Presenting a technique for identifying and diagnosing epileptic seizures using nonlinear feature extraction based on DT-CWT coefficients of brain EEG signals with a deep learning approach

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Abstract

Epilepsy is a type of brain disease that can be diagnosed by observing EEG signals. The disease often occurs in children. However, some cases are also seen in adults. Diagnosing this disease in the early stages is a challenging task for doctors. In this work, the authors have classified epileptic and normal EEG signal by adopting deep learning approach. To achieve the efficient features, the dual tree complex wavelet (DTCWT) is considered. Then, the decomposed wavelet coefficients are applied to nonlinear feature extraction. These features are used as input to the Radial Hybrid Basis Function (RBF) class. Using the proposed method, about 99% classification accuracy is observed. This requires significant improvement of the proposed algorithm compared to other previously presented algorithms. It is the first time that nonlinear feature extraction on DT-CWT coefficients of an EEG signal is used to diagnose epilepsy.

Introduction

Epilepsy is a chronic neurological disease that can be diagnosed [1-4]. There are more than 60 million epilepsy patients in the world and more than 80% of these patients live in developing countries. According to the World Health Organization (WHO), epilepsy is one of the most common neurological disorders in the world. Scientific research on epilepsy, its causes and treatment often focuses on specific areas of the brain [5-7].

Epilepsy patients are subject to sudden and unpredictable seizures, so that they cannot protect themselves and may die from fainting, death, or injuries in traffic accidents [8, 9]. . The first step in patient evaluation is to determine whether epileptic seizures have a clinical picture or not [10]. Currently, anticonvulsant therapy is not completely effective for all types of epilepsy [11]. Currently, epilepsy is diagnosed by a neurologist or an epilepsy specialist through clinical examination and visual observation of the electroencephalogram (EEG) signal.

The normal EEG signal is the most important test in the diagnosis of epilepsy and epileptic seizures. Investigation of asymmetry or significant reduction in surface activity provides important information about electro-clinical syndromes. It should be remembered that a normal EEG does not rule out epilepsy, and not every EEG abnormality indicates epilepsy. The EEG signal is very important for the diagnosis of epilepsy, because it provides valuable spatial and temporal information about the brain by measuring sensory-dependent ion currents in brain neurons and the potential difference between electrodes along the patient's scalp [12, 13]. .

Diagnosing epilepsy abnormalities in EEG requires examination by trained neurologists and epileptologists and can be time-consuming. In addition, experts with different diagnostic experiences may have different opinions about the diagnostic results [14, 15]. For this reason, the development of an automated computerized

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system for the diagnosis of epilepsy is of great importance [16-18]. Nearly two decades ago, in an important work, Adeli et al. [19] built the work on automatic EEG that diagnoses epilepsy by providing a model for automatic detection of hidden seizures. Subsequently, Adeli et al. [20] and Ghosh Dastidar et al. [21] presented automatic diagnosis of temporomandibular epilepsy based on EEG. Temporal epilepsy is a challenging diagnosis even for trained epileptologists. Since then, many studies have been conducted in this field and various methods have been proposed to diagnose seizures and epilepsy [22-24]. A wavelet-based EEG processing study has been used by Fawcett et al. [25] to aid in seizure diagnosis, and computer-based epilepsy and automatic seizure prediction by Acharya et al. [26]. Feature extraction is one of the most important steps in many existing methods for epilepsy diagnosis. Among recent works, Acharya et al. [28] have used seven different machine learning methods for epilepsy diagnosis by reducing entropy features from EEG signals [27, 28], which include: Sugeno fuzzy classifier, support vector machine (SVM) SVM) [29], K Nearest Neighbor (KNN), Probabilistic Neural Network, Decision Tree (DT), Gaussian Mixture Model [30] and Naive Bayesian Classification (NBC). . Bandarabadi et al. [31] have proposed the prediction of epileptic seizures using power spectral features supported by the feature selection method, and based on the relative combination of spectral powers under electroencephalogram bands. Samii et al. [32] have proposed the classification of epileptic seizures using Fourier transform of discrete-time logic and multilayer perceptron (MLP) classifier [33]. Fu et al. [34], applied Hilbert marginal spectrum, entropy and energy characteristics of EEG signals in frequency band, and SVM to automatically detect seizures in EEG signals. Hasan et al [36] have presented the detection of epileptic seizures in EEG signals using tunable Q-factor wavelet transform and binning [35, 36]. Giswal and Banka [37] used locally derived features, i.e. descriptive neighborhood pattern and one-dimensional local gradient pattern to classify epileptic EEG signals using four different models, which are ML: nearest neighbor, SVM, DT, and Artificial Neural Network (ANN).

Giswal and Banka [37] used locally derived features, i.e. descriptive neighborhood pattern and one-dimensional local gradient pattern to classify epileptic EEG signals using four different models, which are ML: nearest neighbor, SVM, DT, and Artificial neural network (ANN). Wang et al. [38], from multivariate feature extraction and nonlinear analysis and five different classification models ML, KNN, linear resolution analysis, NBC, logistic regression and SVM for automatic detection Epileptic seizures were used in EEG signals. Tzimurta et al. [39] have investigated the automatic detection of seizures based on discrete wavelet transform [39, 40]. In this method, five-level analysis is applied to each part of the EEG and five features are extracted from the wavelet coefficients. The extracted feature vector is used to train a random forest that performs classification to distinguish octal (during seizures) from interictal (between seizures) EEG data. The above methods all require manual modification of feature extraction methods to better perform the next steps, i.e. effective classification [41, 42]. Recent advances in deep learning (DL) [46–43] provide a way to eliminate the need for manual changes in feature extraction methods [47]. For example, in Hasanpour et al.'s paper [48], a zero-to-hundred DL method for multi-class classification of visual-motor EEG signals is presented. One of the most effective DL methods is the Convolutional Neural Network (CNN) [51-49], which has recently been used to predict epilepsy and mental disorder [52, 53]. Finally, in reference [54], CNN is used to improve the diagnosis of epileptic seizures and high percentages are presented in this field.

Feature extraction and selection

The proposed general method of epilepsy diagnosis based on EEG signals is shown in Figure 1. After feature extraction, we use the spectral regression discriminant analysis (SRDA) algorithm to reduce the number of features and computational load, and use a hybrid network for classification, which has not been used in the diagnosis of epilepsy [55-56]. . Also, we use the hybrid RBF network for EEG classification for the first time.

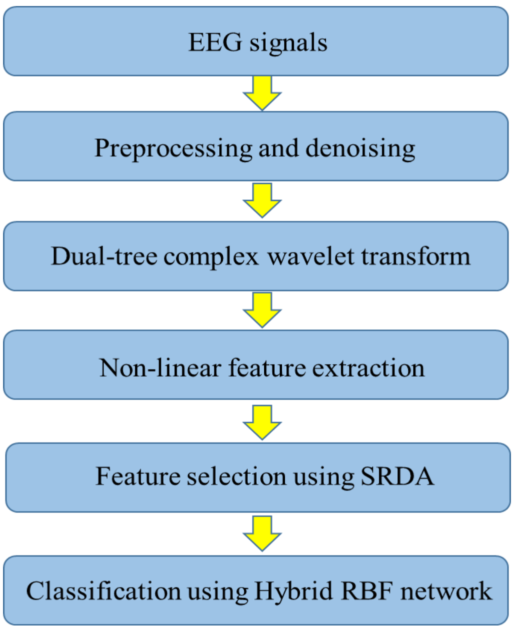

Fig. 1: Block diagram of the proposed epilepsy diagnosis scheme.

A. wo-tree complex wavelet transform (DT-CWT)

In reference [38], it is suggested to use DT-CWT in EEG

feature extraction. Here, we adopt the same procedure, but as we will explain, we use the coefficients of this transformation to extract non-linear features. DT-CWT uses two real filter trees (tree A and tree B) as shown in Figure 1. In reference [30], the formulation (h.g) of quadratic mirror filters (squared filter) is given. Two trees are related to the real and imaginary part of the transmission of the imaginary wave. DT-CWT transforms EEG signals using two DWTSs that are sampled in parallel for the same information. The filters are designed to interpret the high DWT subgroup signals as the real part of the mixed wavelet transmission and the low DWT subgroup signals as the imaginary part. The DT-DWT changes continuously when the transition is designed to this mode. The optional converted coefficients are:
LL_{1a}،LL_{2a}،LH_{2a}،LL_{3a}،LH_{1b}،HL_{2b} و HL_{3b}

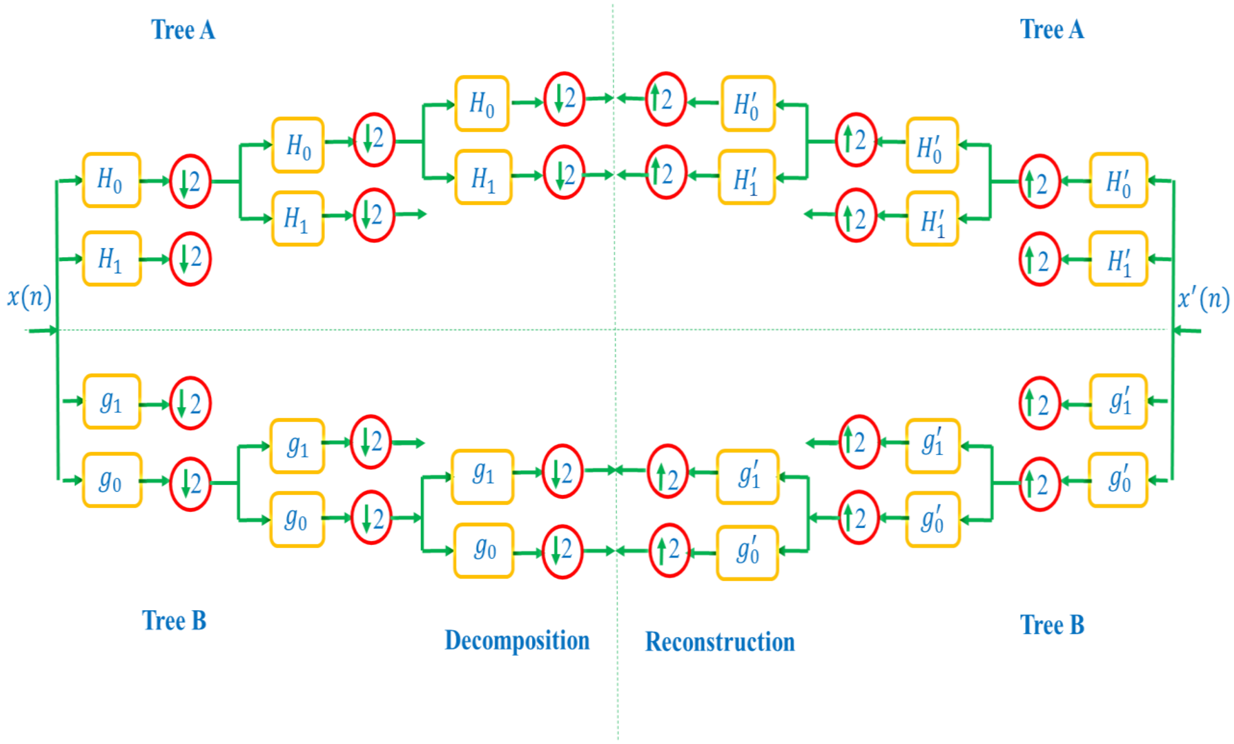

Fig. 2: Three levels of two-dimensional DT-CWT applied to preprocessed brain EEG

After three steps of DT-CWT, subgroup LL3 is obtained. By choosing the coefficients of this subgroup as features, we have 1024 primary features. In this case, the obtained initial feature vector has 1024 entries. Large-scale classification of such a vector has unacceptable computational complexity, and there are features that do not provide any useful information for classification. Therefore, feature selection and reduction is necessary. We want to reduce these features to seven or less. Here we will explain how to choose the right feature and its benefits.

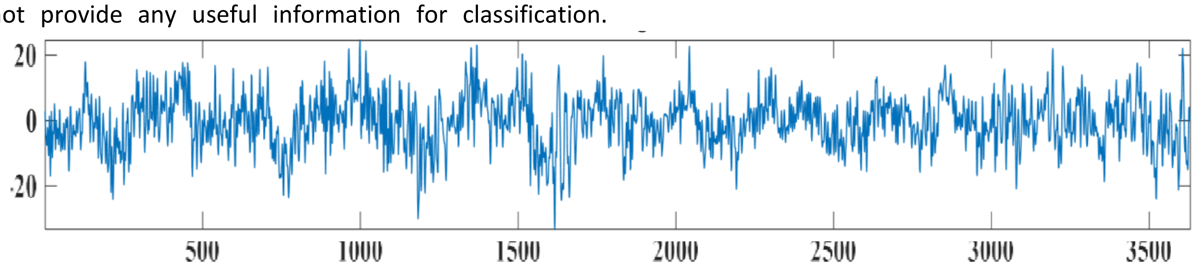

Fig. 3: Normal EEG signal

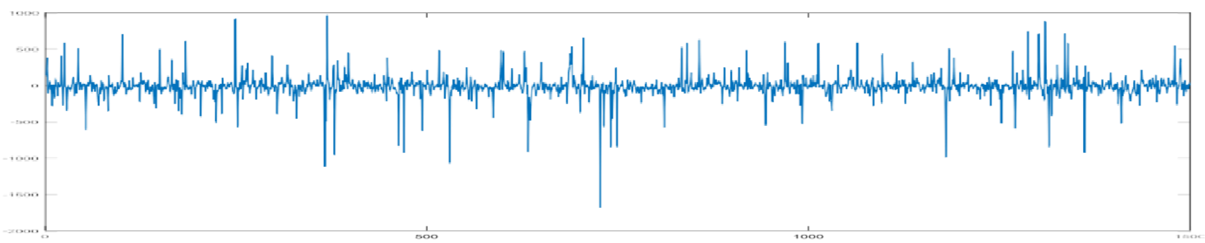

Fig. 4: Epileptic EEG signal

B. Extraction of non-linear features from DT-CWT coefficients

After extracting the DT-CWT coefficients from the selected EEG, we calculate the nonlinear features. For the first time, we have used the nonlinear features of ApEn, FE and IQR, [59, 25], for EEG classification in this paper. These features are completed in Table 1 and explained in reference [25]. Its calculations are not mentioned in this section.

Table1. Non-linear features extracted from DT-CWT coefficients

Features	Description
FE	Fuzzy Entropy
ApEn	Approximate Entropy
IQR	Interquartile Range

It is important to mention that to extract nonlinear features from DT-CWT coefficients, first convert the input data into a 1x1024 vector and then apply the nonlinear feature extraction formula described in references [25] and [29] to it. We have applied By using these three feature extraction methods and with the eight selection coefficients of DT-CWT described in the third section, 24 features are obtained for each EEG included in the classification. However, we have used feature reduction to reduce these features as much as possible.

C. Spectral regression discriminant analysis algorithm (SRDA) [13]

SDRA is one of the most powerful feature reduction algorithms. For this reason, we have used this technique in our proposed method. For SDRA, a set of data $x_1.\dots x_m \in R^N$ are considered. So, they belong to Nc different classes and m_k is assigned to a number of training samples from the kth class $(\sum_{k=1}^{Nc} m_k = m)$. The stages of SDRA are summarized as follows [4]:

1. $$\boldsymbol{y}_k = \Bigg[\underbrace{0.\dots.0}_{\sum_{i=1}^{k-1} m_i}.\underbrace{1.\dots 1}_{m_k}.\ \underbrace{0.\dots.0}_{\sum_{i=k+1}^{Nc} m_i}\Bigg]^T \qquad k = 1.\dots.Nc \qquad (1)$$

And $y_0 = [1.1.\dots.1]^T$ represents the vector of ones. Since $y_0$is described in the subspace as $\{y_k\}$, the vectors Nc-1 are obtained by the following relations:

$$\{\underline{y}_k\}_{k=1}^{Nc} \quad . \quad \left(\underline{y}_i^T y_0 = 0 \; where \; \underline{y}_i^T \underline{y}_j = 0.i \neq j\right) \qquad (2)$$

2. At this point, a new entry "I" is added to each x_i that is still assigned to x_i. Therefore, the vectors Nc-1 $\{a_k\}_{k=1}^{Nc-1} \in R^{N+1}$are created, such that a_k is a solution to the regularized least squares problem as follows It is defined as:

$$a_k = \left(\sum_{i=l}^{m}\left(a^T x_i - \underline{y}_i^k\right)^2 + \alpha\|a\|^2\right) \qquad (3)$$

Here, $\underline{y}_i^k$ is the mnk element of $\underline{y}_k$ and α≥0 is a parameter to control the reduction rate.

3. The vectors $Nc - 1\ \{a_k\}$ are the basic vectors of SRDA. Suppose $A = [a_1.\dots.a_{Nc-1}]$ is a $(N+1) \times (Nc-1)$ transformation matrix. x can be determined in z and in the next $(Nc-1)$ subspace by the following relation:

$$z = A^T[x\ 1\ ] \qquad (4)$$

4. Using SRDA, we reduce the features of each EEG to 1 and 7 according to the number of classes.

RBF classifier with combined learning "K-means, RLS"

In this section, we describe the RBF classifier (Figure 3) with the hybrid learning method, which is our proposed classification tool. We call the proposed classifier hybrid RBF because the hybrid learning method has two steps in the following order [29]: Step 1: The algorithm uses K-means classification to train the hidden layer in unsupervised mode. Typically, the number of categories and thus the number of computational sections in the hidden layer is generally less than the sequential sample. Step 2. Regular Least Squares (RLS) algorithm is used to calculate the weight vector of the linear outer layer. This two-stage design method has a pair of desirable features, namely computational simplicity and accelerated convergence.

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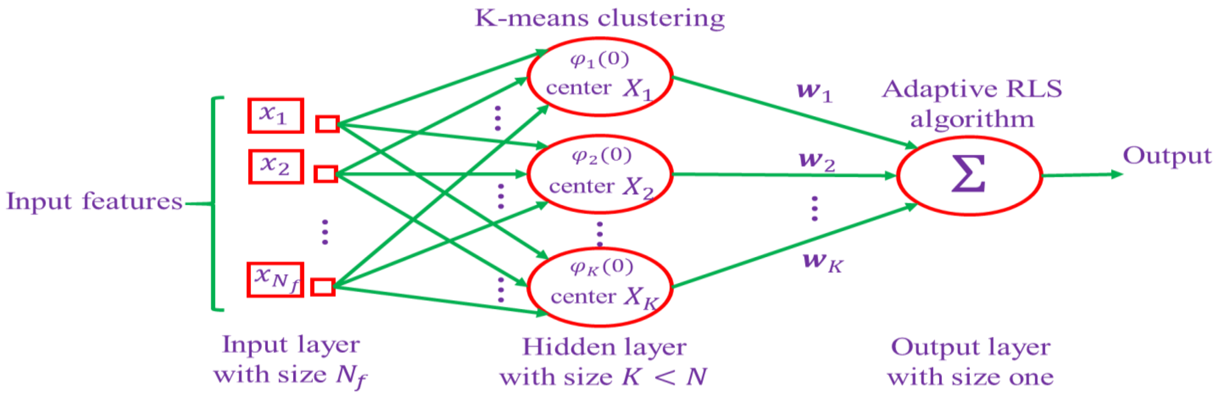

Fig. 5: "k-means, RLS" class of hybrid RBF [8, 29]

The RBF network consists of three layers, which can be seen in Figure 3, and their tasks are:

1. The input layer includes the source nodes that connect the network to its environment. Grid entries are for feature classification.
2. The hidden layer contains the hidden parts that use the hidden transfer from the input space to the hidden space. For most applications, dimensions are just the hidden layer of the upper network. This training layer is the only unsupervised mode that uses phase 1 of the hybrid learning method. Each segment in the hidden layer is mathematically described by a basic radial function:

$$\varphi_j(x) = \varphi(\|x - x_j\|) \qquad j = 1.2. \ldots . N \qquad (5)$$

The j th input data point $x_j$defines the center of the radial basis function and the vector x is the signal (pattern) applied to the input layer. Therefore, unlike the multilayer perceptron, the links connecting the source nodes to the hidden parts are unweight direct links. There are several radial functions to use in the hidden layer, but we use the Gaussian function to compare between SVM and RBF as in reference (16).

3. The output layer is linear and is designed to provide the network response to the activation pattern used for the input layer. This layer is trained in supervised mode by two stages of the hybrid process. There is no limit to the size of the output layer except to say that typically the size of the output layer is much smaller than the hidden layer. Here we explain the RBF learning algorithm:

A. K-means clustering

K-means is an algorithm that uses distances (as KNN) for clustering with two steps:

Step 1: The cluster variance is minimized according to the assigned set of the cluster mean $\{\hat{E}\}_{j=1}^{K}$, the following minimization should be done:

$$\min_{\{\hat{\mu}\}_{j=1}^{K}} \sum_{j=1}^{K} \sum_{C(i)=j} \left\|\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_j\right\|^2 \qquad for\ a\ given\ C \qquad (6)$$

Step 2: Calculate the optimized cluster, i.e. $C(i) = arg \min_{1\le j\le K} \left\|\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_j\right\|^2$, we optimize the encoder as follows:

$$C(i) = arg \min_{1\le j\le K} \left\|\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_j\right\|^2 \qquad (7)$$

B. RLS algorithm in hybrid learning Adaptive algorithms

RLS algorithm in hybrid learning Adaptive algorithms are designed to converge with specific weights. These weights are adjusted in the RBF network during the learning phase. RLS algorithm is one of the most powerful adaptive algorithms. In this part, we describe the role of RLS in the output layer of the RBF network [8]. Consider the $K \times 1$vector:

$$\boldsymbol{\Phi}(\boldsymbol{x}_i) = \begin{bmatrix} \varphi(\boldsymbol{x}_i.\boldsymbol{\mu}_1) \\ \varphi(\boldsymbol{x}_i.\boldsymbol{\mu}_2) \\ \vdots \\ \varphi(\boldsymbol{x}_i.\boldsymbol{\mu}_K) \end{bmatrix} \qquad (8)$$

We specify the output of K units in the hidden layer. This vector is produced in response to the stimulus $\boldsymbol{x}_i. i = 1.2. \ldots . N$. Therefore, the training sample as far as the supervised training of the output layer is concerned, is defined by $\{\boldsymbol{\Phi}(i). d(i)\}_{i=1}^{N}$. so that d_i is the optimal response in the overall output of the RBF network for the input $\boldsymbol{x}_i$. This training is done using the RLS algorithm described below [8]: According to the training sample

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$\{\boldsymbol{\Phi}(i).d(i)\}_{i=1}^{N}$, we perform the following calculations for iterations $n = 1.2. \ldots . N$:

$$\boldsymbol{P}(n) = \boldsymbol{P}(n-1) - \frac{\boldsymbol{P}(n-1)\boldsymbol{\Phi}(n)\boldsymbol{\Phi}^{\boldsymbol{T}}(n)\boldsymbol{P}(n-1)}{1+\boldsymbol{\Phi}^{\boldsymbol{T}}(n)\boldsymbol{P}(n-1)\boldsymbol{\Phi}(n)} \quad (9)$$

$$\boldsymbol{g}(n) = \boldsymbol{P}(n)\boldsymbol{\Phi}(n) \quad (10)$$

$$\alpha(n) = d(n) - \widehat{\boldsymbol{w}}^{T}(n-1)\boldsymbol{\Phi}(n) \quad (11)$$

$$\widehat{\boldsymbol{w}}(n) = \widehat{\boldsymbol{w}}(n-1) + \boldsymbol{g}(n)\alpha(n) \quad (12)$$

To initialize the algorithm, $\widehat{\boldsymbol{w}}(0) = \boldsymbol{0}$ and $\boldsymbol{P}(0) = \lambda^{-1}\boldsymbol{I}$ are considered, where λ is a small positive constant.
In reference [9], a thorough analysis is performed to demonstrate the superiority of the hybrid RBF over the SVM classifier both in terms of computation and accuracy. In the simulation part, we will compare the performance of RBF hybrid network with the performance of SVM and KNN classifiers in the classification of brain diseases..

Results of simulation and classification

In this study, the Boston Children's Hospital, Massachusetts Institute of Technology CHB-MIT data set, which is the most common data set in the field of epileptic seizures, is selected for model training and evaluation. The dataset consists of EEG signals from 23 patients admitted to Boston Children's Hospital. All patients are under 22 years old, 5 are male and 17 are female. In this dataset, there are between 24 and 70 hours of EEG signal recorded for each patient. The recorded signals of each patient in this dataset are continuous and uninterrupted, and each patient has at least 5 recorded seizures. The data of this data set have only two signs: convulsive and normal. The number of signal recording electrodes is between 18 and 23 channels (in some patients, the number of channels is less). The sampling frequency is 256 Hz and the bit resolution is 16 bits. An example of the signals of this database and the transformation applied on top of them: In the results section, in order to compare the proposed work with previous works done in this field, a table similar to the following table has been used:

Table. 2 Comparison of different classification methods in the two-class scenario

Authors	Year	Method	Accuracy (%)
Guo et al. [57]	2011	GP-based feature extraction + KNN	93.5
Du et al. [58]	2012	HOS + simple logistic regression	94.5
Acharya et al. [63]	2012	Entropies, HOS, FD and H + Fuzzy classifier	99.7
Martis et al. [59]	2013	ITD derived features + DT	95.6
Acharya et al. [60]	2013	CWT based HOS and textures + SVM	96.0
Kaya et al. [61]	2014	1-D local binary patterns + BayesNet	95.67
Martis et al. [64]	2015	WPD based non-linear features + SVM	98.0
Riaz et al. [62]	2015	EMD based temporal and spectral features + SVM	84.0
Li et al. [65]	2017	DT-CWT-based non-linear features + SVM	98.87
This work		DT-CWT-based non-linear features + Hybrid RBF	99.54

Conclusion

Automatic disease classification is one of the most important researches in the field of bioinformatics. A hybrid RBF classifier with DTCWT features is proposed for epilepsy classification for early detection, which is efficient for EEG signal classification. The hybrid RBF with DTCWT features performs better compared to the simple SVM model. Hybrid RBF class has been used to validate the result. In addition, the obtained result is also compared with some previous works and it can be confirmed that the proposed method is efficient for EEG classification. In addition, the classification accuracy can be improved by optimizing the network structure, and this is considered as a future work.

Conflict of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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