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Cumulant feature extraction based on the DT-CWT for EEG brain signals to diagnose epileptic seizures

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***Abstract*— Epilepsy, a form of brain disorder, can be detected by analyzing EEG signals. Although this condition commonly affects children, it can also be found in adults in certain cases. Early diagnosis of epilepsy poses a challenge for medical professionals. In this research, the authors have employed a deep learning approach to classify EEG signals as either epileptic or normal. To enhance the effectiveness of the analysis, the Dual-Tree Complex Wavelet Transform (DT-CWT) is utilized. Subsequently, the DT-CWT coefficients are disintegrated to extract cumulant features. These features undergo dimensionality reduction using spectral regression discriminant analysis (SRDA) and are then employed as input for the Radial Basis Function (RBF) hybrid kernel classifier. The proposed method demonstrates an impressive classification accuracy of approximately 99.8%, showcasing a significant improvement overpreviously proposed algorithms. Notably, this study pioneers the use of nonlinear feature extraction on DT-CWT coefficients of EEG signals for epilepsy diagnosis.**

***Keywords*— Epilepsy, k-means algorithm, nonlinear features, radial basis function networks, EEG brain classification , feature reduction.**

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I. INTRODUCTION

Epilepsy, a chronic neurological disorder, can be diagnosed through various methods [1-4]. It affects more than 60 million individuals worldwide, with over 80% of patients residing in developing countries. The World Health Organization (WHO) identifies epilepsy as one of the most prevalent neurological disorders globally. Extensive scientific research investigates the causes and treatment of epilepsy, often focusing on specific brain regions [7-5]. Epileptic seizures result from abnormal electrical discharges in the brain. Detecting and predicting these seizures is crucial for enhancing the quality of life for individuals with epilepsy. Traditional seizure detection methods involve visual analysis of electroencephalogram (EEG) signals by expert neurologists. However, this approach is time-consuming and subjective. Alternatively, automated seizure detection systems employing signal processing and machine learning techniques offer a more efficient and objective approach.

Individuals with epilepsy face the potential danger of sudden and unpredictable seizures, which can render them unable to safeguard themselves and lead to injuries, fatalities, or impairments resulting from motor vehicle accidents [8, 9]. The initial stage of assessing a patient involves determining the presence or absence of clinical seizure activity [10]. Although anticonvulsant therapy is not universally effective for all forms of epilepsy at present [11], the diagnosis of epilepsy is typically performed by a neurologist or epilepsy specialist through clinical examination and visual scrutiny of electroencephalogram (EEG) signals.

Electroencephalogram (EEG) signals play a vital role in diagnosing epilepsy and epileptic seizures. Analyzing asymmetry or significant reduction in surface activity yields essential insights into electro-clinical syndromes. It is important to note that a normal EEG does not exclude the possibility of epilepsy, and an abnormality in the EEG does not necessarily indicate epilepsy. EEG signals are highly valuable for epilepsy diagnosis as they provide spatial and temporal information about the brain by measuring ion-dependent currents in brain neurons and potential differences between electrodes placed on the patient's scalp [12, 13]. The examination of epileptic abnormalities in EEG requires the expertise of trained neurologists and seizure specialists, which can be a time-consuming process. Moreover, different diagnosticians with varying levels of experience may offer differing opinions on the diagnostic outcomes [14, 15]. Consequently, the development of an automatic computer system for epilepsy diagnosis holds great significance [16-18]. Adeli et al. made a significant contribution two decades ago by constructing an automated EEG system that served as a model for detecting concealed seizures. Subsequent works by Adeli et al. [20] and Qoshdast-Ahmadi et al. [21] introduced fuzzy logic-based automated epilepsy diagnosis methods utilizing EEG data. Even for trained epilepsy specialists, diagnosing transient epilepsy poses a challenging task. Since then, numerous studies have been conducted in this field, proposing various methodologies for seizure and epilepsy diagnosis [22-24].

Faust et al. [25] utilized wavelet analysis-based EEG signal processing to assist in the diagnosis of seizures and epilepsy, while Achari et al. [26] proposed computerized methods for automatic seizure prediction. Feature extraction plays a crucial role in many existing seizure detection approaches. Achari et al. [28] employed seven different machine learning techniques to reduce entropy features from EEG signals for seizure detection [27, 28]. These methods included the Sugeno fuzzy classifier, support vector machine (SVM) [29], K nearest neighbor (KNN), probabilistic neural network, decision tree (DT), Gaussian mixture model [30], and simple Bayesian classifier (NBC). Bandarabadi et al. [31] suggested seizure prediction by utilizing spectral power features with the support of a feature selection method, employing relative combinations of spectral powers within EEG sub-bands. Samaei et al. [32] proposed seizure classification using the discrete-time Fourier transform and a multi-layer perceptron (MLP) classifier [33]. Foong et al. [34] employed Hilbert marginal spectrum, entropy, and energy features of EEG signals in frequency bands, along with support vector machines (SVM), for automatic seizure detection. Hassan et al. [36] introduced adjustable Q-factor wavelet transform and packaging for seizure detection in EEG signals [35, 36]. Gissual and Banca [37] utilized local derivative features such as descriptive adjacency patterns and one-dimensional local gradient patterns for epileptic EEG signal classification. They employed four different models: k-nearest neighbor (k-NN), support vector machine (SVM), decision tree (DT), and artificial neural network (ANN).

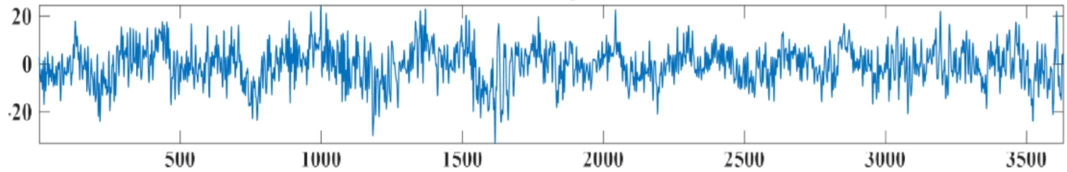
Wang et al. [38] employed multi-variable feature extraction and nonlinear analysis, along with five different classification models (ML, KNN, linear discriminant analysis, NBC, logistic regression, and SVM) for automatic seizure detection in EEG signals. Testa et al. [39] investigated automatic seizure detection based on discrete wavelet transform [39, 40]. Their method involved applying a five-level decomposition to each EEG segment and extracting five wavelet coefficient features. A random forest classifier was then trained using the extracted feature vector to classify epileptic EEG data as interictal (between seizures) or ictal (during a seizure). These methods typically require manual adjustments in feature extraction for improved performance during subsequent stages, particularly effective classification [41, 42]. Recent advancements in deep learning (DL) [46-43] offer a solution to bypass the need for manual feature extraction adjustments [47]. For instance, Hassani et al. [48] proposed a zero-to-one DL approach for multi-class classification of visual motor EEG signals. One of the most effective DL methods is the convolutional neural network (CNN) [51-49], which has recently been utilized for seizure and psychiatric disorder prediction [52, 53]. Furthermore, CNN has been employed in reference [54] to enhance seizure detection, resulting in high detection rates.

2.Proposed Method: Epileptic Seizure Detection Framework

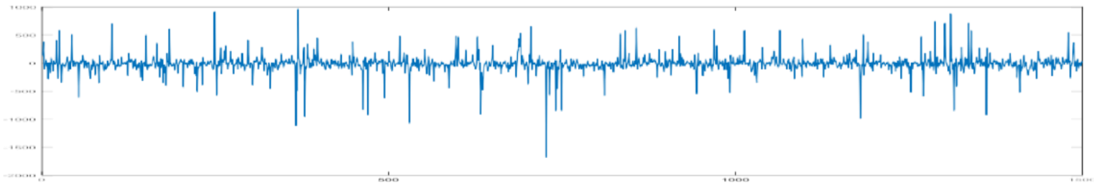
The proposed method for epileptic seizure detection combines the DT-CWT-based feature extraction and the Hybrid- RBF classifier. The framework consists of the following steps:

1. Data Acquisition and Preprocessing: EEG signals are acquired and preprocessed to remove artifacts and noise.
2. Feature Extraction using DT-CWT: The preprocessed EEG signals are decomposed using the DT-CWT, extracting relevant frequency and time-domain information.
3. Calculation of Cumulants from DT-CWT Coefficients: The cumulants are computed from the DT-CWT coefficients, capturing the higher-order statistics.
4. Feature reduction using SRDA.
5. Training the Hybrid-RBF Classifier: The extracted features are used to train the Hybrid-RBF classifier using labeled data.
6. Testing and Evaluation: The trained classifier is tested on new EEG signals to detect epileptic seizure activity.
7. Results and Discussion: The performance of the proposed method is evaluated and compared with existing approaches.

Figure 1 shows a sample EEG signal from our used database in this paper [66]. This signal is pre-processed.



(a) Normal ECG signal



(b) Epileptic ECG signal

Fig. 1. Sample ECG signal.

The general proposed method for seizure detection based on EEG signals is shown in Figure 2. After feature extraction, we use the spectral regression discriminant analysis (SRDA) algorithm to reduce the number of features and computational burden, and for classification, we employ a hybrid network that has not been used for seizure detection [55-56]. Additionally, we use the hybrid RBF network for the first time in EEG classification.

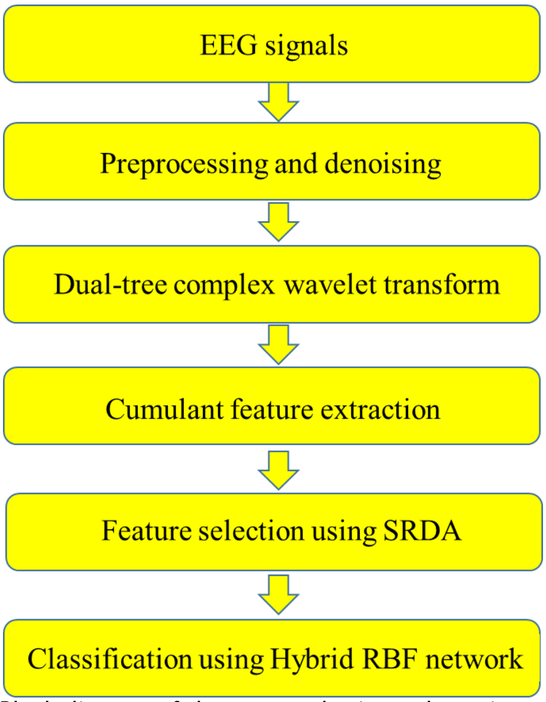


Fig.2. Block diagram of the proposed seizure detection scheme.

2.1 TheDual-Tree complex wavelet Transform (DT-CWT)

The Dual-Tree Complex Wavelet Transform (DT-CWT) is a powerful signal processing technique used for analysing EEG signals. It provides a multi-resolution analysis by decomposing EEG signal into different frequency subbands. The DT-CWT overcomes some limitations of the traditional Discrete Wavelet Transform (DWT) by providing better time-frequency localization and directional selectivity.

In reference [38], it was proposed to utilize the DT-CWT for extracting features from EEG signals. In our study, we follow a similar procedure, but with a different approach. We use the coefficients obtained from this transform to extract nonlinear features. The DT-CWT involves two real filter trees, namely Tree A and Tree B, as depicted in Figure 3. The formulation of the second-order mirror filters (square mirror filter) can be found in reference [30]. These two trees correspond to the real and imaginary components of the complex wavelet transform. The DT-CWT performs the transformation of EEG signals using two parallel sampled Discrete Wavelet Transform (DWT) systems, which capture the same information. The filters are specifically designed to interpret the upper DWT sub-band signals as the real part of the complex wavelet transform and the lower DWT sub-band signals as the imaginary part. Consequently, the DT-CWT enables continuous changes in the transformed representation.5 subbands are extracted and selected from the EEG signal namely Delta (0~4Hz), Theta (4~8Hz), Alpha (8~15Hz), Beta (15~30 Hz) and Gamma (30~60Hz) as in [65]. From these subbands we extract 5 cumulants.

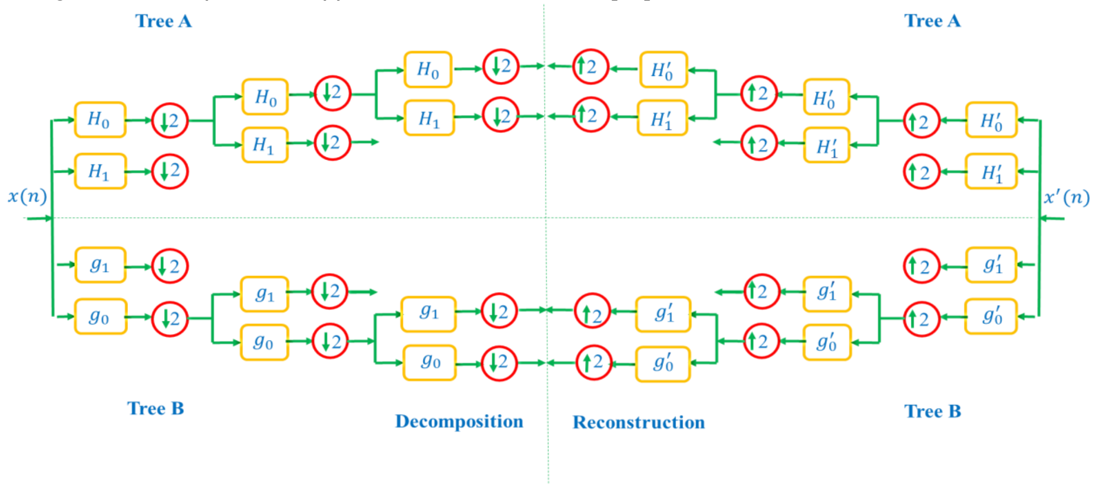


Fig. 3. Three levels of the DT-CWT applied to pre-processed brain EEG.

Figure 2 shows three levels of DT-CWT applied to pre-processed EEG data. By selecting the coefficients of this subgroup as features, we have 5 subbands. Classification on such a vector at a large scale has unacceptable computational complexity, and there are features that provide no useful information for classification. Therefore, feature selection and reduction are necessary. We want to reduce these features to seven or less. Here, a method for selecting suitable features and its benefits will be described.

2.2 Higher order Cumulants

Once the DT-CWT coefficients are extracted from the chosen EEG data, we proceed to compute their cumulants. Cumulants are statistical measures that describe the shape of a distribution. They not only indicate the level of high-order correlation but also quantify the deviation of a random process from a Gaussian process. Cumulants are nonlinear combinations of moments. The i-th moment of a real-valued random variable X can be calculated as follows:

$$M_i = E\,[X^i] \quad (1)$$

Where, E[.] represents the mathematical expectation operator. For each subband, we calculate the cumulants C2, C3, C4, C5, and C6, which are obtained as

$$C_2 = M_2 - M_1^2 \quad (2)$$
$$C_3 = M_3 - 3M_2M_1 + 2M_1^3 \quad (3)$$
$$C_4 = M_4 - 4M_3M_1 - 3M_2^2 + 12M_2M_1^2 - 6M_1^4 \quad (4)$$
$$C_5 = M_5 - 5M_4M_1 - 10M_3M_2 + 20M_3M_1^2 + 30M_2^2M_1 - 60M_2M_1^3 + 24M_1^2 \quad (5)$$
$$C_6 = M_5 - 6M_5M_1 - 15M_4M_2 + 30M_4M_1^2 - 10M_3^2 + 120M_3M_2M_1 - 120M_3M_1^3 + 30M_2^3 - 270M_2^2M_1^2 + 360M_2M_1^4 - 120M_1^6 \quad (6)$$

The computation of cumulants for the DT-CWT coefficients allows us to capture the higher-order statistical characteristics of the EEG signal. These cumulant features are particularly sensitive to the presence of seizure activity, aiding in the differentiation between normal brain activity and epileptic seizures. It is important to note that the first cumulant, C1 (also known as M1), represents the mean and does not provide significant discriminatory information for classification purposes. By employing 5 feature extraction methods and selecting five specific DT-CWT subbands, as explained in section three, a total of 25 features are considered for each EEG signal during classification. However, we have applied feature reduction techniques to minimize the number of features as much as possible.

2.3 Spectral regression discriminant analysis (SRDA) algorithm

The objective of feature vector dimensionality reduction is to find compact representations that retain the essential information from the primary features. These primary features are then transformed into a new set of features known as secondary features. In this study, Spectral Regression Discriminant Analysis (SRDA) is utilized to eliminate the redundancy present in the primary features. SRDA aims to identify projection axes where data points from different classes are far apart, while data points from the same class are close together. Since the original extracted features, i.e., cumulants, may have varying dynamic ranges, they need to be normalized to the [0, 1] range prior to being input to SRDA. SRDA is considered one of the most effective algorithms for feature reduction, which is why we have incorporated it into our proposed method. In SDRA, a set of data points $x_1.\dots x_m \in R^N$ is considered, where they belong to *Nc* different classes, and m_k is the number of training samples from class $k(\sum_{k=1}^{Nc} m_k = m)$. The steps of SDRA can be summarized as follows:

1.

$$\boldsymbol{y}_k = \left[\underbrace{0.\dots.0}_{\sum_{i=1}^{k-1} m_i}.\underbrace{1.\dots1}_{m_k}.\underbrace{0.\dots.0}_{\sum_{i=k+1}^{Nc} m_i}\right]^T \qquad k = 1.\dots.Nc \qquad (7)$$

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

$$\left\{\underline{y_k}\right\}_{k=1}^{Nc} \ . \left(\underline{y_i^T} y_0 = 0 \ where\ \underline{y_i^T}\,\underline{y_j} = 0.\, i \neq j\right) \qquad (7)$$

2. At this stage, the new input "l" is added to each $x_i$that has not yet been assigned. Therefore, *N*c-1 vectors $\{a_k\}_{k=1}^{Nc-1} \in R^{N+1}$are created, where $a_k$is defined as a solution to the regularized least squares problem as follows:

$$a_k = \left(\sum_{i=l}^{m}\left(a^T x_i - \underline{y_i^k}\right)^2 + \alpha\|a\|^2\right) \qquad (9)$$

Here is the translation of the passage to English:

Here, $\underline{y_i^k}$is the k-th element of $\underline{y_k}$ and α≥0 is a parameter for controlling feature size.

2. The vectors *Nc*-1 $\{a_k\}$are the basis vectors of SRDA. Let $A = [a_1.\dots.a_{Nc-1}]$be a transformation matrix of size (*N*+1)×(*Nc*-1). x can be represented in z and in the sub-space of dimension (*Nc*-1) using the following equation:

$$z = A^T[x\ 1\,] \qquad (10)$$

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

3. RBF classifier with hybrid 'K-means, RLS' learning

The Hybrid Radial Basis Function (Hybrid-RBF) classifier is a machine learning algorithm that combines the strengths of two classifiers: the Radial Basis Function (RBF) and the k-Nearest Neighbors (k-NN). By integrating these two approaches, the Hybrid-RBF classifier benefits from the RBF's ability to model complex decision boundaries and the k-NN's robustness in handling noisy data and making classifications based on local information.

In this section, we present the Hybrid-RBF classifier (shown in Figure 3) using our proposed hybrid learning method, which serves as our recommended classification tool. We refer to our classifier as "hybrid" because the learning method comprises two stages:

Stage 1: The algorithm employs K-means clustering for unsupervised training of the hidden layer. Typically, the number of clusters, and consequently the number of computational partitions in the hidden layer, is set to be smaller than the number of sequence samples.

Stage 2: The regularized least squares (RLS) algorithm is utilized to calculate the weight vector of the linear outer layer. This two-stage design method possesses two desirable features: computational simplicity and accelerated convergence.

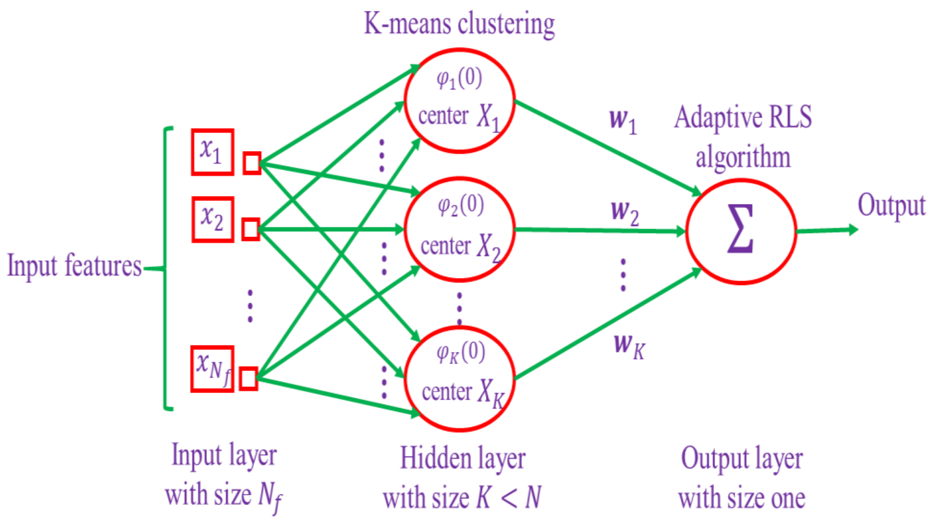


Fig. 4. Hybrid "k-means, RLS" RBF classifier.

The RBF network is composed of three layers, as depicted in Figure 4, each serving a specific purpose:

1. The input layer comprises input nodes that establish connections between the network and its environment. The inputs provided to the network are the features used for classification.
2. The hidden layer consists of hidden units responsible for transferring information from the input space to the hidden space. In most cases, only the top layer of the network serves as the hidden layer and has a reduced number of dimensions. This layer is trained in an unsupervised manner, utilizing stage 1 of the hybrid learning method. Each component within the hidden layer is mathematically represented by a primary radial function:

$$\varphi_j(x) = \varphi\left(\|x - x_j\|\right) \qquad j = 1.2.\dots.N \tag{11}$$

The jth input data point, xj, serves as the center of the radial basis function in the hidden layer. The vector x represents the signal or pattern that is inputted to the input layer. Unlike in multilayer perceptrons, the connections linking the source nodes to the hidden units are direct and weightless. Various radial basis functions can be used in the hidden layer, but in our case, we employ the Gaussian function for comparison with SVM (Support Vector Machine) as mentioned in reference [56].

The output layer is linear and responsible for producing the network's response to the activated pattern from the input layer. In the supervised mode, this layer is trained using two stages of the hybrid learning process. The size of the output layer is not restricted, although it is typically much smaller than the hidden layer size. Here, we outline the RBF learning algorithm:

The jth 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. So unlike a multilayer perceptron, links that connect source nodes to hidden parts are weightless direct connections. 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 [56].

3. The output layer is linear and is designed to provide a network response to activate the pattern used for the input layer. This layer is trained in supervised mode using 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:

3.1. K-means clustering for hidden layer

The K-means algorithm is a clustering algorithm that operates in two steps, similar to the K-nearest Neighbors (KNN) algorithm, using distances as a measure:

Step 1: Minimizing the variance of each cluster with respect to the assigned set of cluster means $\{\hat{E}\}_{j=1}^{K}$. This involves performing the following minimization:

$$\min_{\{\hat{\boldsymbol{\mu}}\}_{j=1}^{K}} \sum_{j=1}^{K} \sum_{C(i)=j} \left\|\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_j\right\|^2 \qquad for\ a\ given\ C \tag{12}$$

Step 2: The optimized cluster is computed, which means that $C(i) = arg\ \min_{1\le j\le K} \left\|\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_j\right\|^2$. We optimize the encoder as follows:

$$C(i) = arg\ \min_{1\le j\le K} \left\|\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_j\right\|^2 \tag{13}$$

3. 2 The RLS algorithm for output layer

Adaptive algorithms are specifically designed to converge to specific weights. These weights are adjusted during the learning phase of the radial basis function (RBF) network. One of the most powerful adaptive algorithms is the Regularized Least Squares (RLS) algorithm. In this section, we explain the role of RLS in the output layer of the RBF network. Let's consider a K×1 vector:

:

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

(14)

We calculate the outputs of the K units in the hidden layer, which are generated in response to the stimulus $\boldsymbol{x}_i$, where i takes values from 1 to N. The training sample is defined in relation to the supervised training of the output layer using $\{\boldsymbol{\Phi}(i).d(i)\}_{i=1}^{N}$for i ranging from 1 to N, where d_i represents the desired overall network output for input $\boldsymbol{x}_i$. This training process utilizes the Regularized Least Squares (RLS) algorithm, which is described below: For each iteration n, starting from 1 and going up to N, we perform the following calculations:

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

(15)

$$\boldsymbol{g}(n) = \boldsymbol{P}(n)\boldsymbol{\Phi}(n) \qquad (16)$$

$$\alpha(n) = d(n) - \widehat{\boldsymbol{w}}^T(n-1)\boldsymbol{\Phi}(n) \qquad (17)$$

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

(18)

In the initial value assignment of the algorithm, we set $\widehat{\boldsymbol{w}}(0) = \boldsymbol{0}$ and $\boldsymbol{P}(0) = \lambda^{-1}\boldsymbol{I}$where λ is a small positive constant. This ensures proper initialization of the RLS algorithm. Reference [9] provides a detailed analysis that demonstrates the superiority of the hybrid RBF network compared to SVM classifiers in terms of computational efficiency and accuracy. In the upcoming simulation section, we will compare the performance of the RBF hybrid network with that of SVM and KNN classifiers for the classification of brain diseases.

4. *Simulation and Classification Results*

Here we describe the data set and the simulation setup of this paper:

4.1. Data set description

This research paper utilizes publicly available EEG data from the University of Bonn, Germany [66]. The dataset comprises five subsets labeled as A, B, C, D, and E. Each subset consists of 100 single-channel EEG signals with a duration of 23.6 seconds. The EEG signals were recorded using a 128-channel amplifier system with an average common reference. The data was digitized at a sampling rate of 173.61 samples per second, with a 12-bit A/D resolution.

In this study, the focus is specifically on the classification problem presented in subsets A, D, and E, which aligns with practical requirements. Previous research has also investigated this particular classification problem. Therefore, subsets A, D, and E have been selected for further analysis in this study.

4.2 results for the A-D-E set

For comparing the results of the proposed method, we adopt the three-class scenario and give the results in Table 2.

TABLE. 2. Comparison of different classification methods in the three-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	2023	DT-CWT + Cumulants + SRDA + Hybrid RBF	99.84

4-3 results for other sets (two and three class scenarios)

In this section, we present the simulation results to showcase the effectiveness of the proposed algorithm. We evaluate the classification accuracy of the proposed method by considering different combinations of subsets A, B, C, D, and E. To obtain reliable results, we employ ten-fold cross-validation, which involves dividing the data into ten subsets and performing the classification process ten times, each time using a different subset as the testing set.

To account for the random selection of partitions in cross-validation, we repeat the ten-fold cross-validation procedure 30 times and calculate the average results. We examine several scenarios, including A-E, AB-E, A-C-E, A-D-E, CD-E, and AB-CD-E. The classification accuracy results are presented in Table 3.

The obtained results demonstrate the efficiency of the proposed method in detecting epileptic seizures from EEG signals, as it achieves high classification accuracy across various combinations of the dataset subsets.

TABLE. 3.The results of the proposed method for various scenarios.

DATA SET	**A-E**	**AB-E**	**A-C-E**	**A-D-E**	**CD-E**	**AB-CD-E**
CLASSIFICATION WITH PROPOSED METHOD	100	100	99.84	100	100	99.81

As we can see, our proposed method gives perfect results for the two class scenarios.

5. CONCLUSION

Automatic disease classification is a significant area of research in bioinformatics, and in the context of early detection of epilepsy, an efficient approach for EEG signal classification has been proposed. The proposed method utilizes a hybrid RBF classifier with DTCWT features, which outperforms a simple SVM model in terms of classification performance. The Hybrid RBF classifier serves as a validation tool, and the results obtained from it are compared with previous works, further confirming the effectiveness of the proposed method in EEG classification.The results obtained from the Bonn University epileptic seizure dataset demonstrate the potential of using the cumulants of DT-CWT coefficients and the Hybrid-RBF classifier for automated and objective detection of epileptic seizures. By leveraging advanced signal processing techniques and machine learning algorithms, this method achieves accurate and efficient seizure detection, thereby assisting in the diagnosis and treatment of epilepsy.As a future direction, optimizing the network structure can potentially improve the classification accuracy of the proposed method. This optimization effort can be explored in subsequent studies to further enhance the performance of the approach.

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