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Epilepsy detection using wavelet transform, genetic algorithm, and decision tree classifier

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ABSTRACT

This work presents a unique detection approach for classifying epilepsy using the CHB_MIT dataset. The suggested system utilizes the discrete wavelet transform (DWT) technique, genetic algorithm (GA), and decision tree (DT). This model consists of three distinct steps. In the first one, we present a feature extraction method that uses a DWT of four levels on electroencephalogram (EEG) and electrocardiogram (ECG) signals. The second step is the process of feature selection, which entails the elimination of irrelevant features in order to produce datasets of superior quality. This is achieved via the use of correlation and GA techniques. The reduction in dimensionality of the dataset serves to decrease the complexity of the training process and effectively addresses the problem of overfitting. The third step utilizes a DT algorithm to make predictions based on the data of epileptic patients. The performance evaluation layer encompasses the implementation of our prediction model on the CHB-MIT dataset. The results achieved from this implementation show that using feature selection techniques and an ECG signal as additional information increases the detection model's performance. The averaging accuracy is 98.3%, the sensitivity 96%, and the specificity is 99%.

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1. INTRODUCTION

Epilepsy is a significant neurological illness impacting an estimated global population of over 50 million individuals [1]. People with epilepsy are prone to unpredictable seizures, which are caused by a sudden, abnormal discharge of nerve cells in the brain. Hence, the precise identification and prognosis of epilepsy have considerable importance. The assessment of neural activity in the brain is often conducted via the use of electroencephalogram (EEG) data. The data obtained from electrodes fixed to the scalp has the ability to indicate the condition of the cerebral neurons at a particular moment. The EEG signals that are recorded exhibit complexity, nonlinearity, instability, and randomness due to the intricate interconnections among billions of brain neurons. Numerous researchers have concentrated their attention on the analysis and processing of EEG signals as a means to assist in the detection and treatment of epilepsy [2].

Several studies have been proposed to build an automated system for seizure identification. For example, Wen and Zhang [3] used a genetic algorithm (GA)-based frequency-domain feature exploration for epileptic EEG multiclassification. Hassan *et al.* [4] use a full ensemble empirical mode decomposition with adaptive noise for epilepsy detection. Sanchez *et al.* [5] achieved good performance using a wavelet transform-based statistical time feature-based methodology for epileptic seizure detection in an EEG signal. Yazid *et al*. [6] suggested a new method that merges a discrete wavelet transform (DWT) and a local binary pattern transition for feature extraction. Iloon *et al*. [7] use the Siamese network to improve seizure detection performance. [8] examined various classification techniques to minimize the dimension of EEG data and fused the EEG signal with principal component analysis (PCA).

Many researchers have focused on feature extraction processes for EEG analysis. These methods are based on domains such as time domain analysis and frequency domain analysis. They are used to extract low- and high-frequency features of the signal, which are then fed into a classifier [9]. Signal adaptation techniques such as wavelet transform and wavelet packet have also been widely used for seizure recognition [10], [11]. Feature selection is the purpose of picking a subset of relevant attributes, which has rarely been considered in existing studies. Some characteristics obtained from EEG signals are redundant or unimportant, and feature reduction methods can eliminate unnecessary features and avoid the loss of relevant data [12]. Feature selection approaches have many benefits, such as making models simpler and clearer for researchers or users to understand, cutting down on the number of dimensions, making learning models more compatible with classification data, and encoding the input space's natural symmetries [13], [14]. Alsakaa *et al*. [15] used a combination of discrete wavelet decomposition and support vector machine (SVM) for feature extraction and classification to detect epileptic seizures from the EEG signal and achieved significant accuracy.

The objective of this research is to develop a system and algorithm with higher achievement in terms of specificity, sensitivity, and accuracy. We focus on a feature extraction method by using DWT and a decision tree (DT) classifier with feature selection. Most of the existing researchers have considered only the EEG signal; this work uses a combined EEG and electrocardiogram (ECG) signal. We combine ensemble learning with GA and correlation feature selection to increase the performance of epileptic seizure identification. We provide two major contributions. First, taking features from 23 EEG channels and 1 ECG channel and combining subsets of those features to get new samples during the learning process makes the chosen features more specific, sensitive, or accurate. Second, we fed the newly obtained features to a DT classifier and evaluated the performance of the algorithm.

2. MATERIEL AND METHOD

This section contains a description of the EEG and ECG data sets used and an explanation of the techniques used to process these signals. In order to create an automated system for diagnosing medical neurological brain disorders, a series of four primary stages were undertaken, as shown in Figure 1. These phases include the acquisition of EEG and ECG data, data preprocessing, extraction of relevant features, and subsequent classification and decision processes. A pre-processing module first processes, manipulates, and segments the acquired EEG and ECG data. The DWT method is applied to break the signal down into its individual frequency sub-bands, which are D1, D2, D3, D4, and an approximation. Then, the feature vectors were derived by calculating several measures, including energy, standard deviation (SD), variance (VAR), and entropy. DT algorithm was used to sort the extracted features into groups. Finally, the whole range of different combinations of the suggested methods were executed and validated. The proposed methods were also validated using MATLAB software. The following sections provide a more comprehensive analysis and elaboration of each step, including the data description and the categorization process.

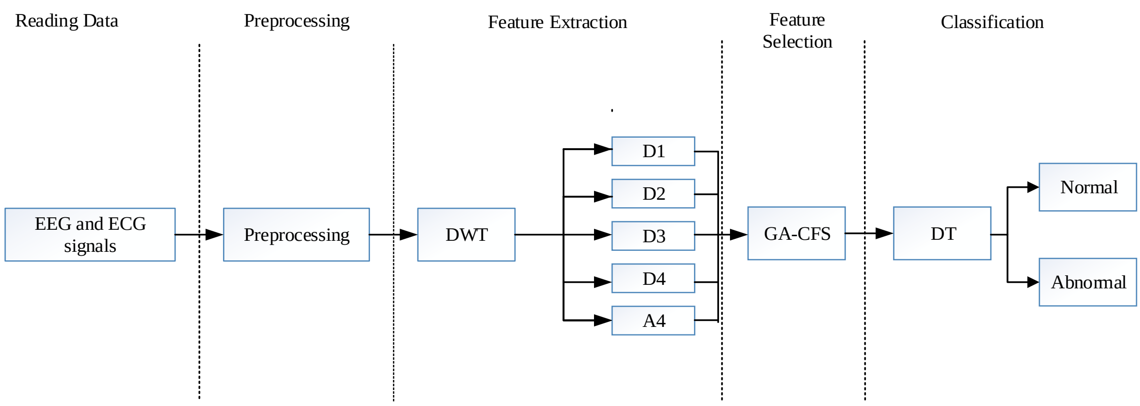

Figure 1. Block diagram of the suggested approach

2.1. Data description

This work utilizes a publicly accessible EEG dataset generated by Children's Hospital Boston, USA, usually designated as CHB-MIT [16]. The CHB-MIT dataset comprises data taken from patients with intractable seizures [17]. The dataset has a total of 24 instances, which were gathered from a sample of 23 participants. The cases, labeled 'chb01',..., 'chb24', consist of many days of EEG recordings of participants who were examined for possible eligibility for surgical intervention. Each individual instance includes many consecutive EEG recordings, saved in.edf file format. The recordings adhered to the International 10-20 system of EEG electrode placements, with a sampling frequency of 256 Hz and a 16-bit resolution. In some instances, supplementary signals such as ECG were included in the recordings. The recordings used in this research consist of 23 EEG channels and an ECG channel taken from a patient named 'chb04'. To make the proposed automated system more balanced, we chose to use EEG and ECG signals from the CHB-MIT EEG dataset that were both epileptic and nonepileptic.

2.2. Feature extraction

2.2.1. Discrete wavelet transform

This method uses DWT to build a single vector that represents the shape of the ECG and EEG signals and performs a unified time-frequency representation of the data [18]. The segmentation is performed by calculating coefficients using wavelets of different orders and types. The segments are then broken into four levels. To get four specific pieces of information and an estimated value for each channel of the 24 channels. The DWT separates the ECG and EEG data into subband signals that reflect different time scales. This is done by running the signals through a series of iterative filters, as seen in Figure 2.

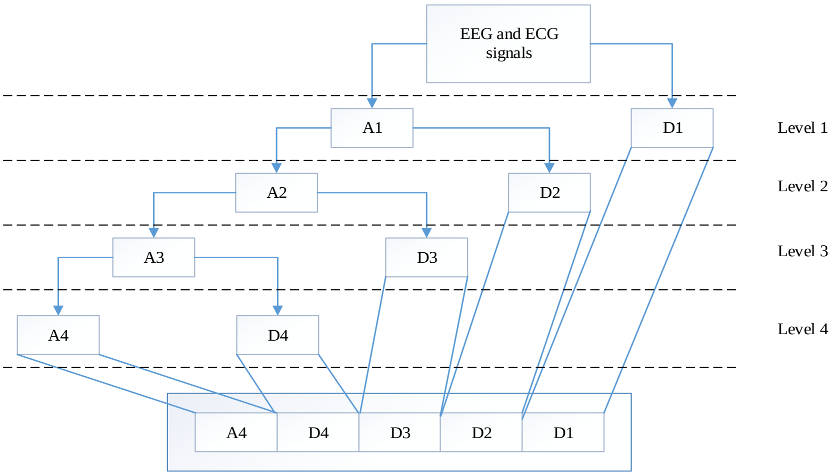

Figure 2. DWT procedure

The DWT divides EEG and ECG signals using the mother function as a single function into several functions, as defined by (1):

$$\psi(t) = \frac{1}{\sqrt{2}}\psi\left(\frac{t-b}{a}\right) \qquad a, b \in S, a > 0 \tag{1}$$

The scaling and shifting parameters, denoted as a and b, respectively, are defined in relation to the space of the wavelet, denoted as S. The (2) representing the wavelet transform is shown in (2).

$$F(a, b) = \frac{1}{\sqrt{a}}\int \psi\left(\frac{t-b}{a}\right)\, dt \tag{2}$$

In (3) describes how the DWT can produce a very efficient representation, which justifies its use in this work. The DWT was applied to split the EEG-filtered signal into high-pass and low-pass filters. This decomposition allowed the signal to be represented as approximation (A1) and detail (D1) coefficients at the first level.

$$F(t) = \sum_{m=-\infty}^{m=+\infty} D_{n,m}\phi\,(2^{-n}t - m) + \sum_{m=-\infty}^{m=+\infty} 2^{\frac{-j}{2}} A_{j,m}\psi(2^{-j}t - m) \tag{3}$$

The symbols Aj,m and Dn,m denote the approximate and detailed coefficients, respectively. Here, n represents the scale, and ψ represents the scale function. In the subsequent level, the approximate coefficients derived from the initial stage (A1) will undergo a decomposition into approximate (A2) and detailed (D2) coefficients. The iterative process continues until the attainment of the approximation (An) and detail (Dn) coefficients at the final level. The calculation of the EEG signal characteristics included determining the detail coefficients at each level and the approximation coefficients at the final stage. In this study, the (db4) wavelet function was used as the mother wavelet function, with a decomposition level of 4. Many statistical traits have been looked at to see if they can be used with the DWT method. The goal is to create feature vectors and make diagnostic systems work better. This procedure has been replicated using other single statistical features. Nonstationary and nonlinear signals, like EEG and ECG signals, are hard to describe with standard statistical features because they are not linear or stationary. The focus of this study shifts to other features and important parameters that help explain how EEG signals are distributed, such as the standard deviation, mean, minimum value, maximum value, variance, and energy. The classification of such traits may be achieved with high accuracy and ease by using machine learning techniques, as shown in our current research.

2.2.2. Feautres

Feature extraction is a primary method in data preparation and machine learning, which entails recognizing and choosing the most significant and useful elements of unprocessed data. The objective of this process is to convert the original data into a concise and controllable representation, known as features, while retaining its fundamental information. Feature extraction is crucial in several data processing tasks, including binary classification. That allows for distinguishing between two different classes. Before starting the classification procedure, there is a characteristic step. Which consists of extracting the set of significant features and transforming them into vectors [19]. The following features used in this study are extracted from the time domain: entropy, standard deviation, energy, minimum value, maximum value, and heart rate, and from the frequency domain: power spectral density and coherence.

In (4) and (5) define the measured energy for an EEG and ECG segment, respectively.

$$E\text{EEG10 (i,n)} = \sum_{K=1}^{L} |EEG(i,K)|^2 \tag{4}$$

$$EECG10\ (n) = \sum_{K=1}^{L} |ECG(K)|^2 \tag{5}$$

Where L is the record's length (10*256=560 samples) and i represents the channel number in the EEG signal (1–23). $\sigma EEG10$ and $\sigma ECG10$ are the standard deviations of the EEG and ECG signals, respectively, calculated using the following expression:

$$\sigma_{EEG10}(i,n) = \left(\frac{1}{L}\sum_{K=1}^{L}(EEG(i,K) - \overline{EEG(i)})^2\right)^{\frac{1}{2}} \tag{6}$$

$$\sigma_{ECG10}(n) = \left(\frac{1}{L}\sum_{K=1}^{L}(ECG(K) - \overline{ECG(n)})^2\right)^{\frac{1}{2}} \tag{7}$$

2.3. Feature selection based on genetic algorithm

Feature selection is a technique that involves picking a subset of essential characteristics from the initial collection without making any transformations. The process of subset selection is considered optimal when it adheres to certain criteria that are used to assess the discriminative capability of the subset [20]. GA is a heuristic optimization framework that exploits the principles of natural behavior. It has shown significant efficacy in the identification of important characteristics inside search spaces characterized by high dimensionality [21]. Consequently, the use of GA is a viable approach for the exploration of optimum solutions in the analysis of epileptic seizure data [22].

GA = {P (0), N, g, s, l, p, f, t}

Where P (0) represents the initial population; N represents the size of the population; G represents the generation number; s represents the selection process; l represents the crossover operation; f represents the fitness function [f ∶ I → R+]; and t represents the termination condition [t ∶ IN → {0, 1}].

The presence of excessive and unnecessary features in medical datasets decreases the effectiveness of current data analysis techniques, resulting in incomprehensible outcomes. However, selecting appropriate attributes can produce informative and valid results [23]. This emphasizes the importance of a preprocessing phase. To address the issues raised by the Hughes phenomenon, the proposed model employs attribute subset selection [24]. Within this method, feature selection is performed using correlation-based feature selection (CFS)-GA. CFS is a feature selection approach that determines the optimal subset of features through heuristic evaluation for each category. In (8) denotes the evaluative approach used for the CFS method.

$$CFS(S) = \frac{K.\overline{MCD_{ij}}}{\sqrt{k+K(K-1)+\overline{MCD_{ii}}}} \tag{8}$$

Where K: the number of features; MCDij: the mean of the correlation between feature and class; MCDii: the mean of the pairwise correlations between every two features.

The correlation is determined by information gain, as given in (9) and (10). where a represents any value of the category H(A) and H(A|B) denote A's entropy and A's conditional entropy given B, respectively.

$$H(A) = \sum_{a\in A} p(a) \times \log_2(p(a)) \tag{9}$$

$$H(A|B) = \sum_{b\in B} p(b) \sum_{a\in A} p(a|b) \times \log_2(p(a|b)) \tag{10}$$

Era in (11) indicates the value of information driven by features A and B; a higher value of ERa shows a high correlation between these features.

$$ER_a = H(A) - H(A|B) \tag{11}$$

While the algorithm has superior performance in reducing dimensions, it fails to get a global optimal outcome. GA serves as a wrapping technique for size reduction due to its capacity to do global searches. The proposed approach integrates GA and CFS to create a combined CFS-GA technique. This algorithm consists of four components: a coding scheme that encodes each entity through binary codes; a selection operator that utilizes the roulette wheel procedure; a crossover operator that generates novel entities by exchanging cross points; and a mutation operator that uses mutation in binary encoding. The combined CFS-GA method is described in Algorithm 1.

Algorithm 1: CFS-GA pseudo-code

```
//P: Initial amount of population
// g: Iteration number of population
// A(t): Off springs in t generation
//P(t): Parents in t generation
// R_mut: Mutation rate
// R_cro: Crossover rate
Input : P, g, A(t), P(t), R_mut, R_cro
Output: Selected features
    Start
    t ← 0
    Initialize g, R_mut, and R_cro
    Initialize P(t)
    Evaluate fitness of P(t)
     While (not terminating criteria) do
            Generate A(t) from P(t) through crossover operation
            Generate A'(t) from A(t) through mutation operation
            Evaluate fitness of A'(t)
      P(t+1) from P(t) and A'(t)
      t ← t + 1
   end While
   Return selected features
   END
```

2.4. Classification

The DT approach is used for the purpose of classification by constructing a hierarchical structure in the shape of a tree [25]. The DT consists of three main nodes: the root node, internal nodes, and leaf nodes. The application of classification criteria occurs at internal nodes along the routes from the root to the leaves. The complexity of the current challenge will determine whether the structure of the tree grows or shrinks. The root node serves as the first node of a tree structure, from which all other nodes originate [26]. The internal nodes of a DT algorithm execute decision rules, also known as tests, on characteristics. These tests generate branches that lead to either additional internal nodes or leaf nodes. The leaves of the tree serve as representations of the terminal nodes, which ultimately determine the tree's final categorization outcome [27]. In this research, the C4.5 DT methods are used, which utilize the information gain ratio as a criterion for feature selection as presented in Algorithm 2. The algorithm in use efficiently addresses the issue of overfitting and demonstrates proficiency in handling continuous characteristics.

Algorithm 2: Pseudo-code of DT algorithm

```
Input: Subset of classified instances, S;
Output: DT
procedure BuildDT(S)
    if homogenous(S) then
        return createLeafNode(label(S))
    end if
    maxInformationGain ← 0
    splitFeature ← null
    e ← entropy(S)
    for each feature (EEG, ECG) in features(S) do
        gain ← informationGain (e, S, features)
        if gain > maxInformationGain then
            maxInformationGain ← gain
            splitFeature ← (features)
        end if
  end for
  if splitFeature = null then
      return createLeafNode (majority Label(S))
  end if
  DT ← createDecisionNode(splitFeature)
  partitions ← partition (S, splitFeature)
  for each partition in partitions do
      subtree ← BuildDT(partition)
      addBranchToNode (DT, subtree)
  end for
  return DT
```

3. RESULTS AND ANALYSIS

We have successfully executed the algorithm to carry out binary classification, distinguishing between seizure and non-seizure instances. The categorization is conducted on a specific 900-second portion of ECG and EEG data, which is separated into a series of segments, resulting in a total of 90 segments. 30 recordings are allocated to the learning stage, which accounts for one-third of the total recordings. The remaining 60 recordings are reserved for the test and classification stages, making up 2/3 of the total. A total of 24 signals were used to examine the algorithm. Out of these, 11 signals exhibited seizure signs, while the other 13 signals showed normal signs. After doing the discrete wavelet decomposition mentioned earlier, we will establish five vectors: DT D1, DT D2, DT D3, DT D4, and DT A4. These vectors correspond to detail 1, detail 2, detail 3, detail 4, and approximation, respectively [28]. At this stage, the learning process has been finished. The next step is to evaluate the ability of the algorithm to distinguish between the two classes by adding additional segments. In order to achieve this objective, a collection of 60 instances is used, with 23 instances resembling epileptic cases and the rest, 37 instances, belonging to the non-epileptic category. The detection performance is examined on the basis of specificity, sensitivity, and accuracy, which are expressed as follows:

$$Sensitivity = \frac{TP}{TP+FN} \tag{12}$$

$$Specificity = \frac{TN}{TN+FP} \tag{13}$$

$$Accuracy = \frac{TN+TP}{TN+TP+FP+FN} \tag{14}$$

With TP: denote true positives, FP: denote false positives TN: denote true negatives, and FN: denote false negatives.

Table 1 shows the performance of the algorithm before applying the feature selection technique. The highest accuracy was obtained for DT-$D1$, which corresponds to the feature vector of the first detail coefficient of the wavelet decomposition, which can be translated by saying that the detail 1 coefficients are the coefficients most affected by the effects of the crisis. Table 2 shows the performance of the algorithm after applying the combined GA and CFS for feature selection. The highest accuracy is still obtained on DT-$D1$, which corresponds to the feature vector of the first detail coefficient of the wavelet decomposition.

According to the analysis results, generally, the use of GA-CFS as a feature selection method shows better achievement in terms of improving accuracy ratios. We have determined the importance of the most significant parameters among the attributes used in the classification to find out if all the features are important for the accuracy of our classifier. The results are shown in Figure 3.

The feature extraction phase concerns all channels, which means that all 24 channels have undergone an extraction of the same parameters. To do this, we proposed to average the importance of each parameter over the 24 channels. The new importance curve is shown in Figure 4. The combined GA-CFS algorithm and DT classifier outperformed the other approaches in the literature in terms of accuracy performance. Table 3 shows the comparison of the proposed method with other existing approaches in the field.

Table 1. Performance of algorithm without feature selection

Results	Sensitivity (%)	Specificity (%)	Accuracy (%)
DT(D1)	94	97.2	96.2
DT(D2)	90.2	91	93.3
DT(D3)	92	7	86
DT(D4)	90	89.3	90.1
DT(A4)	91	94	93

Table 2. Performance of algorithm using feature selection

Results	Sensitivity (%)	Specificity (%)	Accuracy (%)
DT+GA-CFS(D1)	96	99	98.3
DT+GA-CFS (D2)	92	93	94
DT+GA-CFS (D3)	89.1	76	85.6
DT+GA-CFS (D4)	91.4	90	91.2
DT+GA-CFS (A4)	94	96.1	95

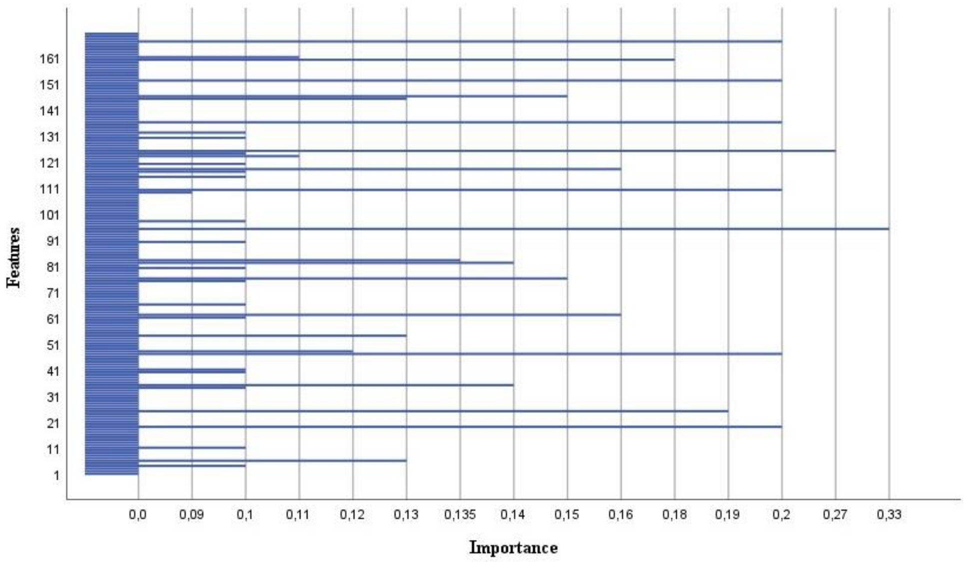

Figure 3. Histogram of the most important parameters

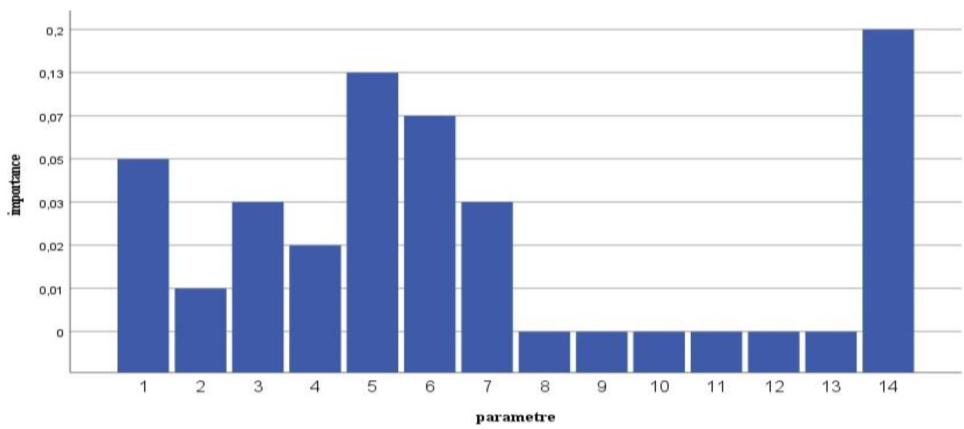

Figure 4. The mean value of importance of each feature over the 24 channels

Table 3. Comparison of the classification accuracy achieved by our approach to the diagnosis of epileptic seizures with previous methods available in the literature

Authors	Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Wang *et al.* [8]	PCA-GE+Kstar	-	-	94.5
Alsaaka *et al.* [15]	DWT+SVM	93.5	94.6	94.1
Albaqami *et al.* [25]	CatBoost +WPD	83.3	91.33	87.68
Our work	DWT+CFS-GA+DT	96	99	98.3

4. CONCLUSION

In this study, a new assisted diagnostic system for epileptic seizure recognition is designed based on the fusion of a DWT, GA, and DT. The DWT was adopted to extract features from EEG and ECG signals in both the frequency domain and the time domain. The ECG signal used as complementary data and the feature selection method presented by CFS-GA combined with a DT classifier prove to be excellent approaches, with improved sensitivity, specificity, and accuracy of 2%, 1.8%, and 2.1%, respectively. The research result shows that using a feature selection method reduces the dataset dimensionality and produces the best classification performance.

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