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Comparison of Various Empirical-Mode Decomposition Techniques of EEG for the Diagnostics of Epilepsy

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One of the most prevalent neurological conditions of the human brain, epilepsy, can be identified mostly with electroencephalogram (EEG) signals. Complex and non-stationary brain signals captured by EEG recordings can be used to identify epileptic episodes. Our study is aimed at constructing a model for epilepsy diagnostics based on the characteristics of decomposed EEG signals. Several features from the EEG signal are extracted, including spectral power, spectral entropy, spectral centroid, peak amplitude, peak frequency, skewness, kurtosis, Hjorth mobility, Hjorth complexity, amplitude modulation, and frequency modulation. Three decomposition approaches have been compared, i.e., empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD), and complete ensemble empirical mode decomposition (CEEMD). The three phases of investigation include ictal seizures, interictal seizures free of epilepsy manifestations, and healthy (normal) EEG signals. The signals are broken down using various decomposition techniques; features are generated and then fed to a classifier based on the multi-head attention mechanism. The suggested model has been examined using the EEG dataset provided by Bonn University, and its performance has been assessed.

Keywords: epilepsy, electroencephalogram (EEG), ensemble empirical mode decomposition (EEMD), complete ensemble empirical mode decomposition (CEEMD), empirical mode decomposition (EMD), multi-head attention mechanism

INTRODUCTION

EEG analysis is a frequently used method for the diagnostics of epilepsy. The EEG signals can mark many potential issues with the brain cells. Neurologists typically diagnose epilepsy by visually examining the EEG data. However, deciphering incredibly intricate, and nonlinear EEG data takes much time and effort. Additionally, the nonlinear features cannot be recovered solely through the eye inspection. Therefore, neurologists must have access to signal processing methods to aid in this diagnosis [1]. Based on the EEG signal, numerous automatic epileptic seizure detection techniques have been created. Figure 1 illustrates how the human brain electrical activity manifests as brain wave patterns. As is usually accepted, delta (<4 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), and gamma (>30 Hz) are the five frequency bands of human brain waves (Fig. 1). As EEG signal recording is a non-invasive procedure, it is preferred in neurology as a diagnostic tool.

Recurrent convulsions (seizures) are the defining feature of epilepsy [1, 2]. As should be taken into account, epilepsy and seizures are two different medical conditions [3]. Epileptic seizure disorders are challenging to quantify because they cause abrupt alterations in a typical brain network. Both focal and generalized variants are usually present. A patient with epilepsy can manifest seizures (an ictal phase), and also the patient may not have clear seizures (an interictal phase) [4, 5].

A seizure is brought on by a sudden outburst of electrical activity in the brain and affects the entire body. It results in brief bewilderment, loss of awareness or consciousness, uncontrollable jerking motions of the limbs and legs, etc. The type of epileptic seizure is crucial in the management of epileptic patients. Depending on the patient's level of awareness, focal seizures may only affect

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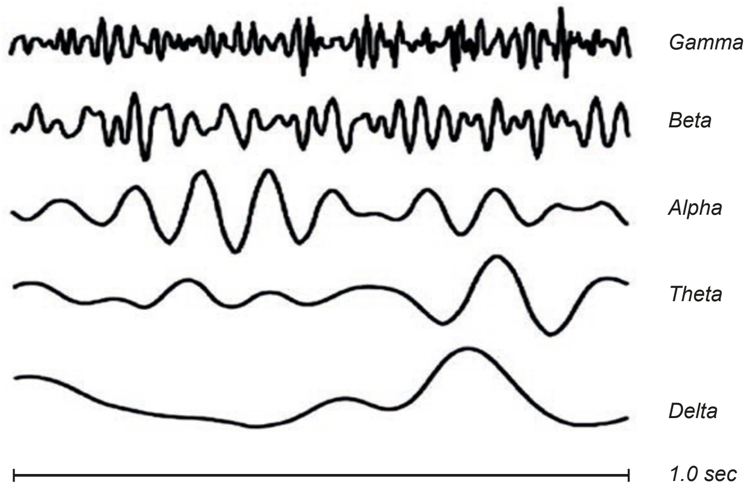

Fig. 1. A simplified presentation of the five main frequency components (manifestations) of the human EEG. Time scale is the same in Figs. 3–5.

a single region of the brain. Focal seizures are classified into those without loss of consciousness and focal seizures with impaired awareness. Focal seizures without loss of consciousness, also known as partial seizures, result in various symptoms, including spontaneous sensory abnormalities and the uncontrollable jerking of one or another body area. Complex partial seizures (focal seizures accompanied by altered awareness) produce several symptoms, including hand rubbing, swallowing, and chewing; this is related to a loss of consciousness or awareness. Frontal lobe, temporal lobe, and occipital lobe seizures are examples of different focal seizure types. Seizures starting in the frontal parts of the brain and called frontal lobe seizures are related to the initiations of movements. Seizures in the temporal lobes significantly impact short-term memory. Occipital lobe seizures induce blinking of the subject's eyes and impair the eyesight. Generalized seizures affect all parts of the brain. They are manifested as absence seizures, tonic–clonic seizures, atonic seizures, clonic seizures, and/or myoclonic seizures [6, 7].

Our study was aimed at constructing a model for epilepsy diagnostics based on the characteristics of decomposed EEG signals. Three decomposition approaches have been compared, i.e., i) empirical mode decomposition (EMD), ii) ensemble empirical mode decomposition (EEMD), and iii) complete ensemble empirical mode decomposition (CEEMD).

The suggested model has been examined using the EEG dataset provided by the Bonn University, and its performance has been assessed.

DATA COLLECTION

The Bonn dataset that became available (https://ebrary.net/59044/education/details_ public databases) was used for application of the suggested method. This dataset includes five sets, namely A, B, C, D, and E, each comprising 100 single-channel EEG segments; the length of each segment is 23.6 sec. In total, 4097 samples were analyzed. The sampling rate was 173.61 sec^{-1}; only clean signals after removing muscle contraction- and eye movement-related artifacts were selected. This database included normal healthy control EEGs with the eyes open and closed, A and B respectively. The EEG segments in sets C and D corresponded to the intervals preceding a seizure (interictal ones). The E set was taken during the ictal phase, with the preference of seizure activity of the patients with clinically diagnosed epilepsy [8]. In this study, we considered Set A (EEG samples recorded from subjects with the eyes open), Set D (interictal EEG recordings from an epileptogenic cortical region during seizure-free periods), and Set E (EEG recordings coinciding with the seizure episodes). With a sampling rate of 173.61 sec^{-1}, 12-bit ADCs were used for the data capture. Each dataset contained 100 EEG signals, with 4097 samples per epoch.

METHODS

Thus, our study develops a framework for classifying EEGs of the ictal and interictal phases, and those recorded from normal healthy subjects. It involves signal decomposition, feature extraction, selection, standardization, and classification based on a multi-head attention mechanism. Figure 2 explains the suggested methodology. Different decomposition techniques used here were empirical mode decomposition (EMD), ensemble empirical decomposition (EEMD), and complete ensemble empirical mode decomposition (CEEMD). The signal was divided into intrinsic mode functions (IMFs) via an algorithm known as empirical mode decomposition (EMD), which is non-linear and non-stationary. Many studies have reported EMD as an effective approach for EEG signal decomposition [9]. To overcome the issue of mode mixing in EMD, ensemble empirical decomposition (EEMD) was proposed by adding white noise to the EMD approach. Thus, EEMD is a noise-assisted data analysis technique. An upgraded form of the EEMD approach is complete ensemble empirical mode decomposition (CEEMD), which provides good spectral separation of intrinsic mode functions (IMFs) at various frequencies.

Following decomposition of the EEG signal, the features of various EEG segments were computed. The features extracted for this study included spectral power [10], spectral entropy [11, 12], spectral centroid [13], peak amplitude, peak frequency, skewness, kurtosis [14], Hjorth mobility, Hjorth complexity [14], amplitude modulation bandwidth, and frequency modulation bandwidth [15, 16]. The best features were selected based on recursive feature elimination [17, 18]. This was then followed by feature standardization [19], modifying data with a zero mean and a single unit of variance. The model based on the multi-head attention temporal convolution neural network was then developed using training data. The performance of the model was then assessed based on the accuracy, precision, recall, specificity, and F1 Score.

Empirical mode decomposition. One of the most effective methods for isolating non-linear and non-stationary signals is empirical mode decomposition (EMD) [20]. This is a data-driven technique that calculates intrinsic mode functions to estimate the signal subbands. Intrinsic mode functions (IMFs) are oscillatory functions with variable amplitude and frequency. IMFs are highly beneficial for simultaneous analysis in the time and frequency domains.

$$\mathrm{x(t)} = \sum_{m=1}^{k} IMF_m(t) + r_k(t), \quad (1)$$

where k is the IMF number and r_k is the final residual value.

The intrinsic mode function meets two essential requirements.

i) There should be an equal number of zero crossings and extrema, or they should vary by one.

ii) The upper and lower envelope mean values should both be equal to zero [21].

One of the main drawbacks of EMD is the mode-mixing issue. Mode mixing is defined as merging oscillations from distinct modes and the dispersion of oscillations from the same mode.

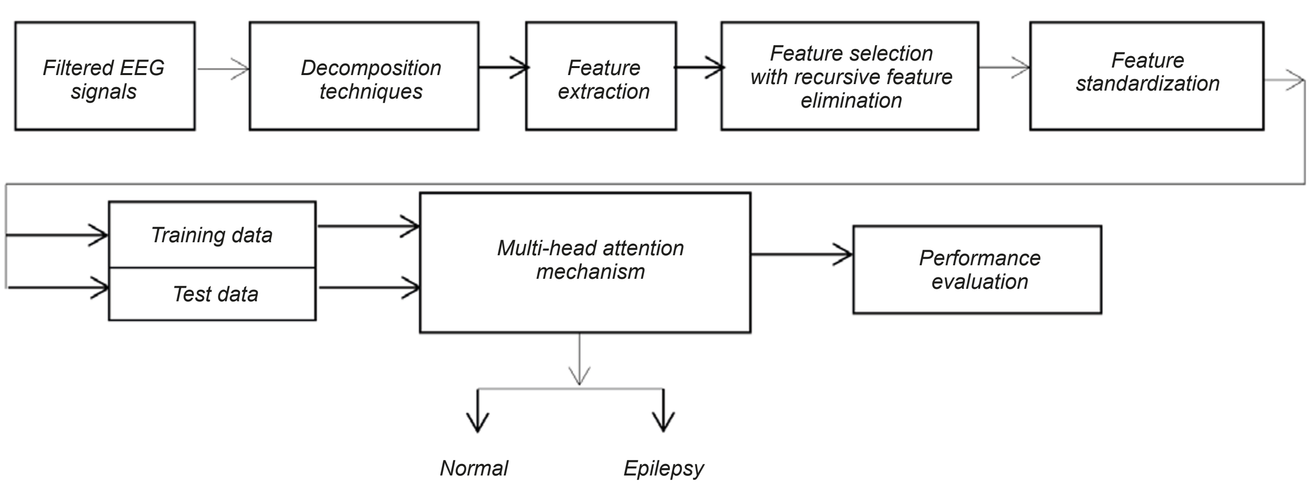

Fig. 2. Scheme of the proposed methodology.

Ensemble empirical mode decomposition (EEMD) has been proposed to solve the mode-mixing issue.

Ensemble empirical mode decomposition. The main drawback of EMD is frequent mode mixing. This issue arises when separate IMFs produce multiple scales of signals, and IMF does not accurately reflect the properties of the original signal because some IMF components may include the characteristic components of several time scales [22]. Another method, ensemble empirical mode decomposition (EEMD), was proposed for the data analysis, with noise embedded to solve the mode-mixing issue. Averaging the final results, EEMD performs the decomposition over a group of noisy replicas of the original signal. An ensemble refers to the signal's addition of white noise. To get meaningful IMFs from EMD, it is crucial to introduce noise into the signal [23]. The steps of EEMD are listed below:

(i) Add white noise to the targeted input signal $x(m)$ in i^{th} steps

$$x^i(m) = x(m)+a_0 w^i(n) \text{For i=1}\ldots l, \quad (2)$$

where $w^i(n)$ is white noise and α_0 is the amplitude.

ii) Decompose the resulting signal-noise to IMFs based on EMD

iii) Repeat steps (i) and (ii) with different white noise series

Calculate the ensemble means of corresponding IMFs of the decomposition as the final result.

The average $k^{th}\overline{IMF_K}$ can be defined as

$$\overline{IMF_k} = \frac{1}{l}\sum_{i=1}^{l} IMF_K^i, \quad (3)$$

where l is the number of white noise.

Complete-ensemble empirical mode decomposition. The CEEMD technique has enhanced the EEMD algorithm. It provides effective spectrum separation of the modes at various frequencies [24]. This one is one of the adaptive, non linear, and non-stationary signals broken down into intrinsic mode functions. The problem of mode mixing of EMD may be eliminated using EEMD by adding white noise to the signal. The CEEMD approach decomposes the original signal into N distinct noise levels by using both positive and negative white noise. It does not have any complications, issues, or solutions.

The CEEMD consists of the following steps with the calculation of IMFs.

(i) The first residue is represented as

$$r_1(m) = x(m) - \overline{IMF_1}, \quad (4)$$

where $\overline{IMF_1}$ is the first average IMF obtained by EEMD.

The second average IMF is calculated as

$$\overline{IMF} = \frac{1}{l}\sum_{i=1}^{l} E_1\left(r_1(m) + a_0 E_1\left(w^i(m)\right)\right), \quad (5)$$

and k+1 average IMF can be represented as

$$\overline{IMF}_{k+1} = \frac{1}{l}\sum_{i=1}^{l} E_1\left(r_k(m) + a_k E_k\left(w^i(m)\right)\right), \quad (6)$$

where $E_k(.)$ is the k^{th} EMD mode extracted from the signal, and α_k is the amplitude.

Features extracted. The crucial step in the processing of EEG signals is feature extraction. It pinpoints the most crucial aspects of signals. The most important task is to extract usable information from the data. It aids in lowering the dataset's redundant data content. Machine learning using only raw signals produces relatively poor outcomes owing to the high data rate and information redundancy. By removing the unused and redundant data, feature extraction reduces noise. Spectral entropy, spectral power [25], spectral centroid, amplitude and frequency modulation, skewness, kurtosis, peak amplitude and peak frequency, Hjorth mobility, and Hjorth complexity [26] are the features retrieved [27].

Feature selection. The process of selecting features from a dataset involves deciding, which attributes are the most pertinent. It aids in removing the extraneous, pointless, or unnecessary elements. Among other benefits, it minimizes the training time, prevents overfitting, and escapes the dimensionality curse. Using feature selection, it is possible to decrease and increase irrelevant features in the overall process. The technique employed in our work is feature selection with recursive feature elimination. The latter is one of the wrapper-based feature selection techniques. Selecting relevant features from the dataset and removing the less significant ones is helpful. Identifying the number of features to select and the algorithms utilized to aid in feature selection are two crucial alternatives for recursive feature elimination [28].

Classification with a multi-head attention mechanism. The model can concentrate on the essential data, whereas it processes the input by using attention techniques to identify dependencies between the sequence elements. Multiple attention heads are used in a multi-head attention scenario to learn various facets of the input representation. Three vectors make up the input to the multi-head attention mechanism: those are i) the query vector

(Q), ii) the critical vector (K), and iii) the value vector (V) [29, 30]. These vectors are typically obtained using linear transformations from the input sequence. Utilizing learned linear projections, the input vectors Q, K, and V are changed to provide various input representations. The learnt projections matrices for each head of the multi-head attention mechanism are distinct. Context vectors are produced for each head by computing weighted sums of the value vectors using the attention weights. These context vectors extract the pertinent data from the input sequence and weight it based on the attention mechanism. The multi-head attention mechanism's ultimate output concatenates and linearly projects the context vectors from each attention head. Usually, the output is passed into the model's last layers for additional processing. The model can capture various dependencies and patterns in the input sequence to use numerous attention heads, improving its capacity to recognize complicated relationships.

$$Attention\,(Q,K,V) = softmax\left(\frac{Qk^T}{\sqrt{d}_k}\right)V. \quad (7)$$

Three vectors, the key, value, and query, play critical roles in the multi-head attention process. The key vector represents the data used to calculate the attention weights. It stores the information needed for the attention mechanism to assess the value or relevance of each element of the input sequence. A learnt linear transformation is often used to extract the key vector from the input representation. The actual data of the input sequence is contained in the value vector. It stands for the result that the attention mechanism will give attention to. Another method uses a learnt linear transformation to derive the value vector from the input representation. In order to calculate the weights, the query vector is compared with the key vector. It is the component for which the attention mechanism looks for the most pertinent data. For each head of the multi-head attention mechanism, the key, value, and query vectors are typically modified separately using various learning projection matrices. This enables the attention mechanism to simultaneously learn many viewpoints of the input sequence.

The performance evaluations of various classes are represented in a confusion matrix. The confusion matrix contains true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) connections. It helps us to know how many sample predictions are correct and incorrect per class. In our work, the performance evaluation parameters are precision, recall, F1 score, and accuracy.

Precision, also known as a positive predictive value, represents the number of true-positive prediction samples to the total number of positive samples.

$$\text{Precision} = \frac{TP}{TP+FP}. \quad (8)$$

Recall, also known as sensitivity, represents the number of true-positive samples:

$$\text{Recall} = \frac{TP}{TP+FN}. \quad (9)$$

Specificity represents the number of true-negative samples.

$$\text{Specificity} = \frac{TN}{TN+FP}. \quad (10)$$

F1 Score is the mean of precision and recall:

$$\text{F1 Score} = \frac{2\times Precision\times Recall}{Precision + recall}, \quad (11)$$

and accuracy represents the number of correctly identified samples to the total number.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}, \quad (12)$$

RESULTS

The EEG signals were decomposed using the EMD, EEMD, and CEEMD approaches. Figures 3, 4, and 5 represent decomposed EEG signals with the CEEMD technique (mode 4) of ictal, interictal, and normal EEGs, respectively.

Table 1 displays the level-2 EMD decomposition. Using the Bonn EEG dataset, the performance evaluation of several decomposition algorithms has been determined. Calculations were made to compare normal, epileptic seizure-free samples, and various kinds of epilepsy seizures. As shown in Table 1, several level-2 decomposition algorithms have a range of the precision, recall, and F1 score.

EMD mode-2 and EEMD mode-2 accuracy values are decreased by 93% and 95%, respectively. A high accuracy rating of 97% is achieved by CEEMD mode-2 decomposition. Class F, S, and Z predictions in EMD and EEMD modes-2 were incorrect. The categorization contains a false prediction; S, F, and Z are incorrectly predicted in CEEMD mode-2. Therefore, CEEMD mode-2 is the best compared with other level-2 decompositions. Many studies have reported discrete wavelet transform (DWT), which was commonly employed for EEG signal decomposition to EEG sub-bands delta, theta,

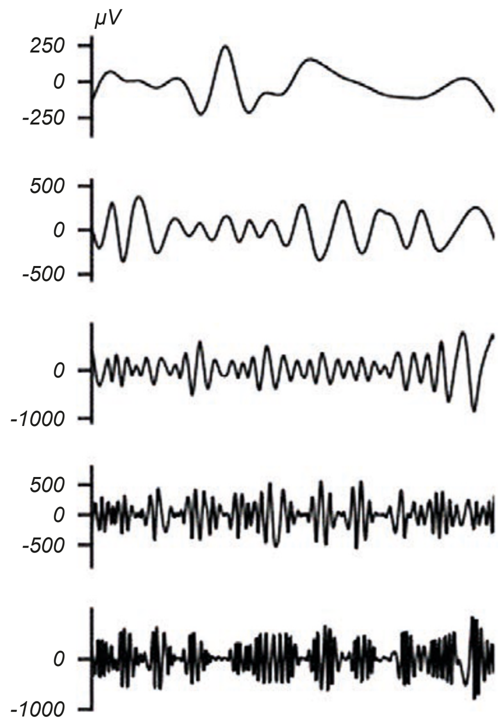

Fig. 3. CEEMD mode-4 decomposition of EEG signals using an ictal signal. The time scale in this and analogous subsequent illustrations is similar to that in Fig. 1.

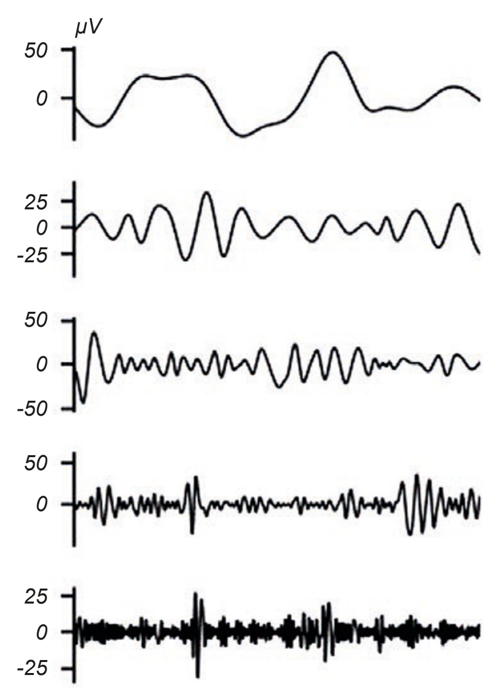

Fig. 4. CEEMD mode-4 decomposition of EEG signals using an interictal signal.

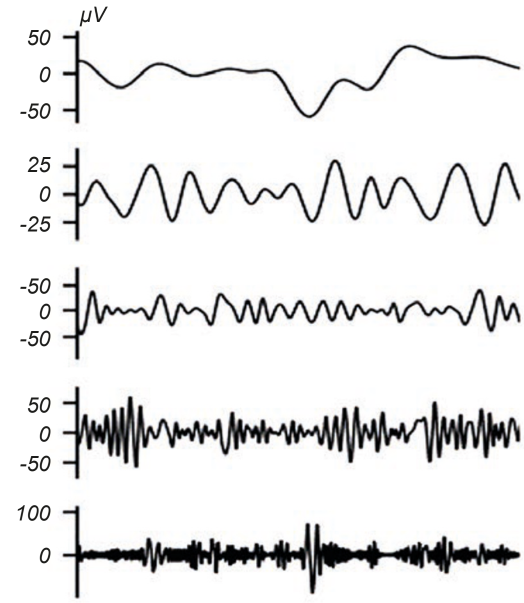

Fig. 5. CEEMD mode-4 decomposition of EEG signals using a normal (healthy) signal.

alpha, and beta brain waves [4, 31].

The numerous classes of precision, recall, F1 score, specificity, and accuracy three-level decomposition are listed in Table 2. Classes F, S, and Z stand for the absence of epileptic seizures during EEG recordings, the occurrence of epilepsy seizures during EEG recordings, and normal EEG recordings, respectively.

Different classes of three-level decomposition system precision, recall, F1 score, specificity, and accuracy are compared. EMD mode-3 and EEMD mode-3 provide 95% and 97% accuracy, respectively. The 98% accuracy is available in CEEMD modes-3. There is no incorrect prediction in the classification class F in CEEMD mode-3. Seizure-free was accurately predicted by CEEMD mode-3. When evaluating several decomposition methods, CEEMD mode-3 comes out on top.

Different decomposition performance evaluations for four-level decomposition approaches have been compared. As shown in Table 3, several classes of precision, recall, F1 score, specificity, and accuracy have been determined.

Table 3 gives the performance of the classifier for mode-4 decomposition. The EMD mode-4 and EEMD mode-4 gave an accuracy of 97% and 98% respectively. The CEEMD mode-4 demonstrated 100% accuracy, and no incorrect predictions exist

Table 1. Precision, Recall, F1 Score, Specificity, and Accuracy of Various Decomposition Techniques for Level-2 Decomposition

Decomposition techniques	Class	Precision	Recall	F1 Score	Specificity	Accuracy (%)
EMD mode-2	Interictal	0.92	0.92	0.92	0.94	93
	Ictal	0.87	0.92	0.90	0.95	
	Normal	1.00	0.95	0.97	1.0	
EEMD mode-2	Interictal	0.89	0.94	0.91	0.95	95
	Ictal	0.95	1.0	0.98	0.97	
	Normal	1.00	0.90	0.95	1.0	
CEEMD mode-2	Interictal	0.93	0.92	0.93	0.97	97
	Ictal	1.00	0.96	0.98	1.0	
	Normal	0.95	1.0	0.97	0.97	

Table 2. Precision, Recall, F1 Score, Accuracy, and Specificity of Various Decomposition Techniques for the Level-3 Decomposition

Decomposition techniques	Class	Precision	Recall	F1 Score	Specificity	Accuracy (%)
EMD mode-3	Interictal	0.96	0.95	0.96	0.97	95
	Ictal	1.00	0.88	0.94	1.0	
	Normal	0.91	1.0	0.95	0.95	
EEMD mode-3	Interictal	0.96	0.95	0.96	0.97	97
	Ictal	1.00	1.0	1.00	1.0	
	Normal	0.95	0.95	0.95	0.97	
CEEMD mode-3	Interictal	0.94	1.0	0.97	0.97	98
	Ictal	1.00	1.0	1.00	1.0	
	Normal	1.00	0.95	0.98	1.0	

Table 3. Precision, Recall, F1 Score, Accuracy, and Specificity of Various Decomposition Techniques for Level- Decomposition

Decomposition techniques	Class	Precision	Recall	F1 Score	Specificity	Accuracy (%)
EMD mode-4	Interictal	0.94	0.94	0.94	0.97	97
	Ictal	0.95	1.0	0.98	0.97	
	Normal	1.0	0.95	0.98	1.0	
EEMD mode-4	Interictal	1.00	0.94	0.97	1.0	98
	Ictal	0.95	1.0	0.97	0.97	
	Normal	1.00	1.0	1.00	1.0	
CEEMD mode-4	Interictal	1.0	1.0	1.0	1.0	100
	Ictal	1.0	1.0	1.0	1.0	
	Normal	1.0	1.0	1.0	1.0	

across all classes. The CEEMD mode-4-decomposition can be suggested to be the best for EEG classification for epilepsy diagnostics.

Figure 6 represents the accuracy values obtained with various levels of decomposition and with different decomposition techniques. EMD gave an accuracy of 93%, 95%, and 97% with modes-2, -3, and -4 respectively. EEMD gave an accuracy of 95%, 97%, and 98% with modes-2, -3, and -4 decomposition. CEEMD modes-2, -3, and -4 decomposition gave the highest accuracy of 97%, 98%, and 100%, respectively. Thus, CEEMD with mode-4 gave 100% accuracy, which can be reported to perform the best for EEG signal classification for the diagnosis of epilepsy.

CONCLUSION

This study was aimed at creating a model for diagnosing epilepsy based on the characteristics of the decomposed EEG signals. The suggested

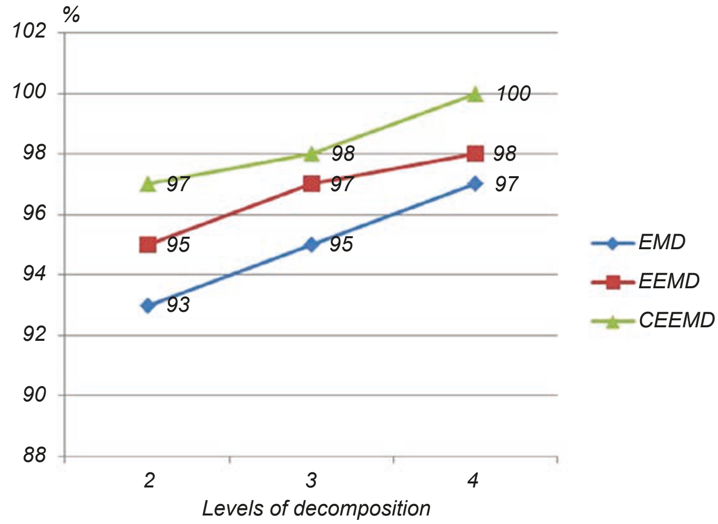

Fig. 6. Various levels of decomposition of EMD, EEMD, and CEEMD.

approach employed EMD, EEMD, and CEEMD decomposition, feature extractions, and feature selection, including recursive feature elimination, to identify important features and classification based on a multi-head attention mechanism. The Bonn EEG data set, open-access and widely utilized in similar studies, has been used to assess the performance of various decomposition approaches. The EEG signals were split into multiple levels of intrinsic mode functions (IMFs) using different decomposition techniques, such as EMD, EEMD, and CEEMD at levels 2, 3, and 4. Complete ensemble empirical mode decomposition (CEEMD) with mode-4 decomposition was found to give 100% accuracy when compared with other decomposition approaches in various modes. In upcoming work, we intend to evaluate the suggested approach to take into account higher-mode EEG signal decomposition and with real EEG signals and other EEG datasets available for epilepsy identification.

This is a theoretical study using an open EEG dataset. Thus, confirmation of the correspondence of the study to the internationally accepted ethical standards for experimental and medical research works is not necessary.

The authors, B. Gopika and J. E. Jacob, confirm the absence of any conflicts over commercial or financial relations, relations with organizations or individuals that could in any way be related to the study, and also in interrelations between the co-authors.

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