Detection of focal electroencephalogram signals using higher-order moments in EMD-TKEO domain

Soumya Chatterjee ✉

Department of Electrical Engineering, Jadavpur University, Kolkata 700032, India
✉ *E-mail: chapeshwar@gmail.com*

Detection of epileptogenic focus based on electroencephalogram (EEG) signal screening is an important pre-surgical step to remove affected regions inside the human brain. Considering the fact above, in this work, a novel technique for detection of focal EEG signals is proposed using a combination of empirical mode decomposition (EMD) and Teager–Kaiser energy operator (TKEO). EEG signals belonging to focal (Fo) and non-focal (NFo) groups were at first decomposed into a set of intrinsic mode functions (IMFs) using EMD. Next, TKEO was applied on each IMF and two higher-order statistical moments namely skewness and kurtosis were extracted as features from TKEO of each IMF. The statistical significance of the selected features was evaluated using student's *t*-test and based on the statistical test, features from first three IMFs which show very high discriminative capability were selected as inputs to a support vector machine classifier for discrimination of Fo and NFo signals. It was observed that the classification accuracy of 92.65% is obtained in classifying EEG signals using a radial basis kernel function, which demonstrates the efficacy of proposed EMD-TKEO based feature extraction method for computer-based treatment of patients suffering from focal seizures.

1. Introduction: Epilepsy is a major neurological disorder which affects people of all ages across the world. About 1–2% of the entire population on the globe is affected by epilepsy. Epilepsy can be differentiated into two types: Generalised and partial epilepsy [1]. Generalised epileptic seizures affect almost the entire region of the human brain, whereas partial epilepsy affects certain localised regions of the human brain. Partial epilepsy can be classified into two types: (a) focal (Fo) and (b) non-focal (NFo). Diagnosis of focal epilepsy is preliminarily done through analysis of electroencephalogram (EEG) signals since it has a better time resolution and is much more cost effective than other means of diagnosis such as function magnetic resonance imaging (fMRI), diffusion magnetic resonance imaging (dMRI) and so on. EEG signals collected from those areas inside the brain, where first seizure inception is observed to Fo group. On the other hand, those signals which do not take part in seizure onset is categorised as NFo group. Earlier mode of detection of Fo EEG signal was through visual analysis, which is susceptible to human error and also quite time-consuming. Therefore, diagnosis of focal seizure based on computer-aided detection of Fo and NFo EEG signals has been a major area of research of the past few years [2–6].

Automated detection and classification of Fo and NFo EEG signals based on entropy features extracted from the multi-resolution analysis of EEG signals using discrete wavelet transform (DWT) have been reported in [2]. In [3], detection of Fo and NFo signals employing a combination of delay permutation entropy and support vector machine (SVM) classifier has been proposed. Recently, detection of Fo and NFo EEG signals using empirical mode decomposition (EMD) has been presented in many existing works. Entropy features extracted from IMFs for classification of Fo and NFo signals have been reported in many existing kinds of literature [4]. Classification of Fo and NFo EEG signals using entropy features on a hybrid EMD-DWT domain and area of phase plane reconstruction of empirical wavelet transform has been reported in [5, 6]. Non-linear analysis of EEG signals using entropies [7] continuous wavelet transform, higher-order spectra and texture parameters [8], cumulants [9], recurrence quantification analysis [10] and so on has been reported in the existing literature. Along with signal processing, machine learning

techniques [11] such as deep learning [12, 13] have been implemented by the researchers to classify EEG signals with reasonable accuracy.

In this Letter, a novel method based on a combination of EMD and Teager–Kaiser energy operator (TKEO) is proposed to distinguish between Fo and NFo EEG signals. Since EEG signals during seizure activity reveal a high degree of fluctuations and non-linearity. Hence non-linear energy tracking operator (TKEO) can be used to quantify the changes in energy for the discrimination of focal seizures from the non-focal one. Although predominantly used in speech processing applications, the application of TKEO in the detection of focal seizures in EEG signals is not yet reported in any existing kinds of literature. Therefore, in this study, a new method has been proposed to detect focal epilepsy based on EEG signals analysis using features extracted in the EMD-TKEO domain.

In this Letter, EEG signals belonging to Fo and NFo group were taken from an online database and at first, EMD was applied to the respective EEG signals to extract different IMFs. After the extraction of the IMFs for both Fo and NFo EEG signals, TKEO was applied to each set of IMFs. Higher-order statistical moments such as skewness and kurtosis of TKEO of each IMF were extracted as features, and their statistical significances were evaluated using student's *t*-test. Finally, the feature vectors from most statistically significant IMFs were selected as inputs to the classifier. To classify Fo and NFo EEG signals, SVM classifier was used. It was observed that the proposed EMD-TKEO methodology delivered reasonably accurate results in discriminating between Fo and NFo signals. A brief outline of the proposed method is illustrated in Fig. 1.

2. EEG database description: In this Letter, Fo and NFo EEG signals are taken from a publicly available database. Detailed information of the database can be found out in [14]. The database comprises of EEG signals recorded intra-cranially from five patients suffering from temporal lobe epilepsy. Each EEG signal consists of two pairs recorded from two adjacent electrodes *x* and *y*, respectively. Each signal consists of 10,240 data points. The sampling frequency is kept at 512 Hz. In this work, a total number of 100 EEG signals (with 50 EEG signals each for both
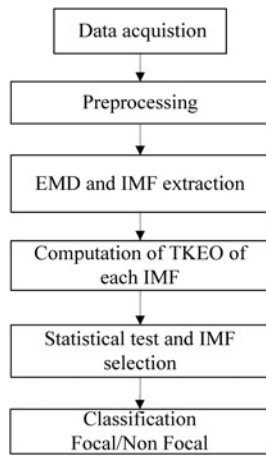
Fig. 1 *Outline of the proposed methodology*

Fo and NFo groups) are selected from the database for detection and classification of EEG signals. Besides, the performance of the proposed model is also evaluated using 3750 signals.

3. Working methodology

3.1. Empirical mode decomposition: The EMD decomposes any signal $f(t)$ into a set of zero mean band limited oscillation modes known as intrinsic mode functions (IMFs) $c_m(t)$, using a shifting algorithm [15]. Each IMF must satisfy the following conditions: (i) the number of maxima and of zero-crossings must either be equal or differ from each other at most by one and (ii) the mean value of the envelope defined by the local maxima and the local minima, respectively, at any instant, is zero. The steps involving EMD are as briefly described as follows:

1. Determine local extremum of function $f(t)$.
2. Compute the top and bottom envelopes using cubic spline inter-polation of maximum and minimum points.
3. Determine the mean of the top and bottom envelopes.
4. Calculate deviation, check if the deviation is a zero-mean function, then stop iteration and accept deviation function as first IMF.
5. Otherwise, treat deviation function as the new data and repeat steps (1)–(4) until an IMF is obtained.

The above process is repeated until the final residue is a constant or a function from which no more IMFs can be derived. At the end of the decomposition, the decomposed signal $f(t)$ taken in this particular study can be written as

$$f(t) = \sum_{m=1}^{L} c_m(t) + r_L(t) \tag{1}$$

where L is the total number of IMFs, $c_m(t)$ is the mth IMF, and $r_L(t)$ is the final residue.

3.2. Non-linear energy operator: In this study, a non-linear energy tracking operator TKEO was used to characterise the instantaneous energy of non-linear and non-stationary EEG signals. For any continuous signal $f(t)$, TKEO can be mathematically expressed as follows:

$$\psi\big(f(t)\big) = \dot{f}(t) - f(t)\ddot{f}(t) \tag{2}$$

Here $\dot{f}(t)$ and $\ddot{f}(t)$ are the first and second derivatives of $f(t)$, respectively. For a discrete signal, the derivatives can be replaced

with their respective time differences. Therefore, TKEO for a discrete signal $f[n]$ is expressed as

$$\psi\big(f[n]\big) = f^2[n] - f[n-1]f[n+1] \tag{3}$$

The advantage of using TKEO is discussed briefly. It can be pointed out from (3), that to compute the energy of discrete signals, any instant of time, on three sample points are necessary. Therefore, TKEO makes use of a small time window, enabling it to be the ideal candidate to track local fluctuations in amplitude and frequency of a time series more effectively, compared to Hilbert transform (HT) [16]. Besides, compared to the wavelet transform, the energy operator is also independent of the type of mother wavelet to be used. Further, this energy operator is simple and easy to implement. Therefore, it has been used in several signal processing applications including ECG beat classification [17], speech processing [18] and gearbox fault monitoring [19] and so on. In this Letter, TKEO is applied to each IMF to extract suitable features for discrimination of Fo and NFo EEG signals.

3.3. Feature extraction from EMD-TKEO: As highlighted in this Letter, in the initial step of this research work, EEG signals representing both Fo and NFo categories were decomposed using EMD to extract different IMFs. Then, TKEO of IMF was computed to determine their instantaneous energy. From the TKEO of each IMF, higher-order statistical moments such as skewness (third statistical moment) and kurtosis (fourth statistical moment) are extracted as features to distinguish between of Fo and NFo signals. Similarly, a set of features were found to yield reasonably a high degree of accuracy in healthy and seizure EEG signal classification in [19]. Hence, these features are chosen primarily in this work. Mathematically, these features can be expressed as follows.

The skewness of TKEO of each IMF =

$$F_1 = \text{TKEOskewness} = \frac{1}{K}\sum_{i=1}^{K}\left(\frac{f_i - \mu}{\nu}\right)^3 \tag{4}$$

Kurtosis of TKEO of each IMF =

$$F_2 = \text{TKEOkurtosis} = \frac{1}{K}\sum_{i=1}^{K}\left(\frac{f_i - \mu}{\nu}\right)^4 \tag{5}$$

where $\mu = (1/K)\sum_{i=1}^{K} f_i$ denotes the mean and $\nu = (1/K)\sum_{i=1}^{K}(f_i - \mu)^2$ denotes the variance for 'K' number of data points $K \in F\{f_1, f_2, f_3, \ldots, f_K\}$.

3.4. Student's t-test and IMF selection: After extraction of the higher-order moments from the TKEO of each IMF, the discriminative capability of the selective features was assessed using Student's t-test. For a binary class problem, a t-test is similar to an analysis of variance (ANOVA) test. The outcome of the t-test yields a 'p' value which is an indicator of the discriminative ability of the selected features. It is believed that low 'p' values indicate that the selected features are statistically significant with a very high discriminative capability [20]. After conducting t-test, it was observed that the features extracted from the TKEO of first three IMFs of Fo and NFo EEG signals, were found to more statistically significant, satisfying null hypothesis testing compared to other IMFs. Hence, in this study, features based on TKEO of first three IMFs were selected to classify Fo and NFo EEG signals. Figs. 2a and b show the variation of TKEO for the first three IMFs for typical Fo and NFo signals. Tables 1 and 2 present the results of the t-test along with the mean values of the selected features for the first three IMFs belonging to Fo and NFo groups.
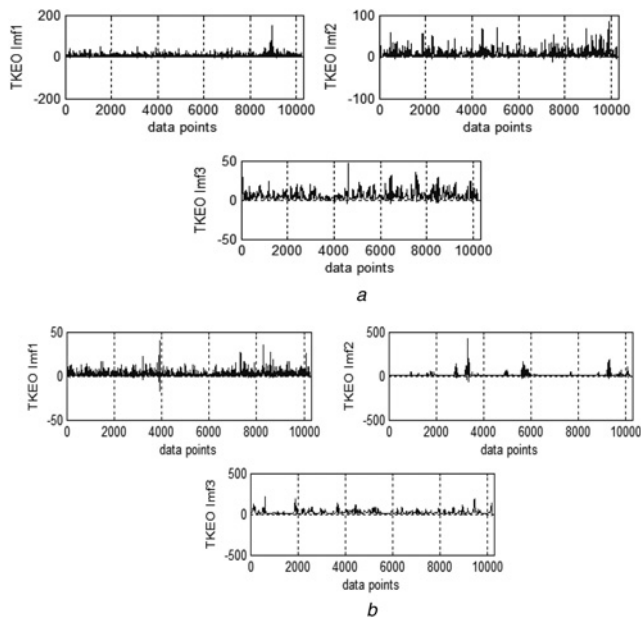
Fig. 2 TKEOs computed from the first three IMFs of a typical EEG signal
a Fo
b NFo of electrode x

**Table 1** t-Test results of the selected features for the first three IMFs of Fo and NFo signals of electrode x

EEG signal	No. of IMFs	F_1 (mean value)	'p' value	F_2 (mean value)	'p' value
Fo	IMF_1	11.021	5.94×10^{-4}	253.75	5.94×10^{-4}
NFo		5.75		98.43	
Fo	IMF_2	8.40	9.98×10^{-6}	124.67	1.21×10^{-4}
NFo		4.65		46.66	
Fo	IMF_3	5.66	6.30×10^{-4}	54.52	5×10^{-4}
NFo		3.90		30.71	

Table 2 t-Test results of the selected features for the first three IMFs of Fo and NFo signals of electrode y

EEG signal	No. of IMFs	F_1 (mean value)	'p' value	F_2 (mean value)	'p' value
Fo	IMF_1	11.88	9.88×10^{-5}	271.83	2×10^{-4}
NFo		6.06		108.36	
Fo	IMF_2	7.60	6.26×10^{-4}	101.04	6×10^{-4}
NFo		4.89		53.32	
Fo	IMF_3	5.70	4.28×10^{-5}	57.55	6.31×10^{-4}
NFo		3.63		26.12	

From the tables, it can be seen that the extracted features have high statistical significance with 'p' values <0.001. In addition to t-test, a box plot is also analysed in Figs. 3a and b, which illustrates the difference between the chosen features for first three IMFs in between two classes. It is evident from Figs. 3a and b that for the selected features, a wide variation in average values and quartiles is observed between Fo and NFo classes, which further indicate that the selected features a very high discrimination capability.

3.5. Support vector machines: To assess the performance of the proposed method, an SVM classifier is implemented. An SVM classifier is a popular machine learning algorithm aimed to solve any binary classification task. It aims to reduce the classification
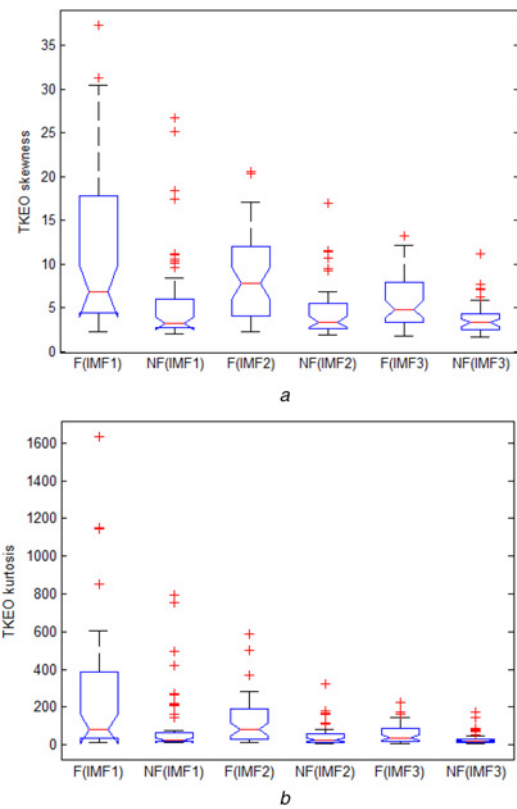
Fig. 3 Boxplot of the extracted features
a TKEO skewness
b TKEO kurtosis for the first three IMFs of Fo and NFo signals of electrode x

error by finding an optimum separating hyperplane with a maximum margin in other words the distance between any one of the classes with the hyperplane. Mathematical details of SVM classifier were reported in [21]. There are different kernel functions exist in an SVM which maps the training data from input to a feature space of higher dimension, using some kernel functions such as linear, polynomial, radial Basis function (RBF) functions. Among different kernel functions of SVM classifier, the RBF kernel function has been found to deliver better result and hence the performance of the SVM classifier has been evaluated in this study using RBF kernel functions. Mathematically, RBF kernel can be expressed as [22]

$$RBF = e^{(-\gamma \| f - g \|^2)} \tag{6}$$

where (f, g) is a linearly separable training data, and $\gamma = 1/2\sigma^2$ is the parameter of the RBF kernel and σ is the width. The choice of optimum width σ is particularly important since the performance of the SVM classifier depends on it. The optimum value of σ yielding maximum classification accuracy is obtained in this work using a grid search algorithm.

4. Performance evaluation

4.1. Performance analysis: The performance of the proposed methodology based on higher-order statistical moments extracted from TKEO of first three IMFs for detection of Fo and NFo signals are discussed in this section. Since the present study involves a typical binary classification problem. Hence SVM classifier is used in this Letter. To assess the performance of the SVM classifier, the following parameters described in (4)–(6)

were evaluated:

$$\mathrm{CAC} = \left(\frac{\mathrm{True\ postive + True\ negative}}{\mathrm{True\ negative + False\ negative + True\ positive + False\ positive}} \times 100 \right)$$
(7)

$$\mathrm{CSE} = \left(\frac{\mathrm{True\ positive}}{\mathrm{True\ positive + False\ negative}} \times 100 \right) \quad (8)$$

$$\mathrm{CSP} = \left(\frac{\mathrm{Truen\ egative}}{\mathrm{Truen\ egative + False\ positive}} \right) \times 100 \quad (9)$$

In (7)–(9), true positives, true negatives, false positives, and false negatives are computed from the confusion matrix. In this study, two types of experiments are conducted. In the first experiment, the performance of SVM classifier is evaluated at each level of decomposition using the features extracted from TKEO of first three IMFs for discrimination of Fo and NFo signals. The number of signals used in this work is 100 with 50 EEG signals for each class (Fo and NFo) and two higher-order moments are selected from TKEO of each IMF. Therefore, input feature vector size is 2×50. To avoid over fitting and assess, reliable performance of SVM classifier, the ten-fold cross-validation technique is adopted in this work. In ten-fold cross-validation, the ratio of training to testing data is kept 9:1. The performance of the SVM classifier in classifying Fo and NFo signals for both electrodes x and y for the first three levels of IMF decomposition is reported in Tables 3 and 4, respectively. In each case, the value of the optimised kernel width σ of the RBF is also indicated in the respective tables. It is to be noted that the optimum value of σ for each case is obtained using a grid-search algorithm based optimisation technique.

From Tables 3 and 4, it can be pointed out that the classification accuracies are different for each IMF. The highest CAC of 88.75% is obtained for features extracted from TEKO of IMF_2 for classification of EEG signals of electrode x. For electrode y, the highest CAC of 87.75% is achieved for IMF_1. For classification of EEG signals of electrode y, the performance of IMF_1 and IMF_3 is almost similar. Also, it can be pointed out from Tables 3 and 4, that the performance of the SVM classifier is reasonably satisfactory and consistent for each IMF. However, to improve the accuracy of the proposed model further, the second set of experiments are conducted in this Letter. In the second experiment, the overall performance of SVM classifier is re-evaluated by selecting two features from all three IMFs (IMF_1–IMF_3) together, hence, in the second case, the size of the feature vector is 6×50. Finally, based on these entire set of features, the CAC, CSE, and CSP in differentiating between Fo and NFo signals are reported in Table 5. It is to be noted that in the second experiment, the performance of the proposed model is assessed independently of each IMF. Here also,

Table 3 Performance analysis of electrode x for the first three IMFs

IMF number	CAC, %	CSE, %	CSP, %	σ
IMF_1	87.25	86.50	88.25	2.8
IMF_2	88.75	87.25	89.50	1.4
IMF_3	86.50	87.50	87.25	1.2

Table 4 Performance analysis of electrode y for the first three IMFs

IMF number	CAC, %	CSE, %	CSP, %	σ
IMF1	87.75	87.0	89.75	1.6
IMF2	86.50	87.50	88.75	2.4
IMF3	87.50	87.25	89.25	3.2

Table 5 Performance analysis of SVM classifier including all features

| Electrode	CAC, %	CSE, %	CSP, %	σ
x	91.50	88.50	91.75	1.8
y	90.25	87.25	90.50	2.6
overall	90.87	87.87	91.12	—

ten-fold cross-validation with training to testing ratio kept 9:1 is used to evaluate the classifier performance.

From Table 5, it can be seen that the CAC of 91.50 and 90.25% is obtained in the classification of Fo and NFo signals for electrodes x and y, respectively. Finally, the overall classification accuracy in differentiating Fo and NFo EEG signals is calculated by taking the mean of classification accuracies obtained for electrodes 'x' and 'y', respectively. As it can be pointed out from Table 5, that the overall CAC accuracy of 90.87%, CSE of 87.87% and CSP of 91.12% is achieved in this work in classifying Fo and NFo EEG signals. Moreover, it can be observed that overall CAC, CSE, and CSP in distinguishing Fo EEG from NFo signals in the second experiment is better than the first experiment.

4.2. Performance evaluation with different kernel functions of the SVM classifier: Fig. 4 shows the variation of CAC obtained using various kernel functions of SVM. It is evident from Fig. 4, that among various kernel functions the RBF kernel function yields the highest CAC in discriminating between Fo and NFo signals. The lowest CAC is achieved in the case of polynomial kernel function while that of the linear kernel function lies in between. For polynomial kernel function, the CAC for index '3' is reported in Fig. 4. A most important observation is that the performance of different kernel functions of SVM classifier is relatively consistent, which indicates the fact that the proposed model has a high degree of reliability and stability.

4.3. Performance analysis with different training to the testing ratio: As mentioned in Section 4.1 that to ensure the robust performance of SVM classifier, a ten-fold cross-validation technique is used in this Letter, with the ratio of training data to testing data is kept 9:1. In this section, the performance of the SVM classifier is also evaluated by changing the ratio of training data to testing data during ten-fold cross-validation. The variation in the CAC in differentiating between Fo and NFo EEG signals for different training to testing ratios is portrayed in Table 6.

From Table 6, it can be seen that as the ratio of training to testing data increases, the performance of the SVM classifier improves. The highest classification accuracy is achieved during ten-fold cross-validation when the ratio of training to testing data is kept 9:1. Although ten-fold cross-validation is generally used for analysing the performance of a classifier, yet another method of selecting training and testing data for assessing classifier performance is a
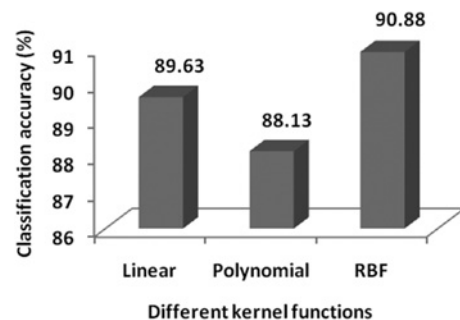
Fig. 4 *Performance evaluation employing various kernel functions*

hold-out technique. In the next section, the performance of SVM classifier utilising proposed set of features is also assessed using the hold-out technique.

4.4. Performance analysis using a hold-out technique: Table 7 reports the performance of the SVM classifier evaluated using the hold-out technique, with the ratio of testing to training data again varied from 5:5 to 9:1.

It can be seen from Table 7, that the CAC increases as the ratio of training to testing data points is increased from 5:5 to 9:1, in case of the holdout technique. Comparing the results presented in Tables 6 and 7, it can be said that the highest CAC of 90.875% is achieved in case of ten-fold cross-validation, whereas CAC of 89.625% is

Table 6 Performance analysis of SVM with different training to testing ratios for ten-fold cross-validation

Training: Testing ratio	CAC (%) x	CAC (%) y	CAC (%) overall
5:5	73.50	72.25	72.875
6:4	78.25	77.50	77.875
7:3	83.50	82,75	83.125
8:2	87.75	86.50	87.125
9:1	91.50	90.25	90.875

Table 7 Performance analysis of SVM classifier with different training to testing ratios for hold-out technique

Training: Testing ratio	CAC x	CAC y	CAC (%) overall
5:5	71.25	70.50	70.875
6:4	75.75	74.25	75.000
7:3	81.50	80.75	81.125
8:2	86.25	85.25	85.75
9:1	89.75	89.50	89.625

Table 8 Performance comparison with other classifiers

Classifier	CAC, %	CSE, %	CSP, %
kNN ($k=5$, Euclidean distance)	89.25	88.125	90.875
Naïve Bayesian	87.00	88.75	85.125

Table 9 Performance analysis using 3750 pairs of EEG signals including all features

Electrode	CAC, %	CSE, %	CSP, %	σ
x	92.85	91.00	93.45	2.2
y	92.45	90.40	92.80	3.6
overall	92.65	90.70	93.15	—

achieved in the case of hold-out technique when the ratio of training to testing data is kept 9:1. Hence, it can be inferred that the performance of the SVM classifier in the case of ten-fold cross-validation is slightly superior as compared to hold-out technique even when the ratio of training to testing data points are kept identical in both cases.

4.5. Performance comparison with other classifiers: To test the robustness and resiliency of the proposed model different classifiers namely k-nearest neighbour (kNN) and Naïve Bayesian classifiers were used to assess is reported in Table 8.

From the results presented in Table 8, the highest CAC, CSE, and CSP of 89.25, 88.125 and 90.875% are obtained using kNN classifier. For kNN classifier, the performance parameters based on $k=5$ and 'Euclidean' distance are reported in Table 8, since it is found to give better results compared to other parameters. The performance of NB classifier is relatively inferior yielding CAC of 87.00%, CSE of 88.75% and CSP of 85.125%. However, the performance of NB classifier is still reasonably satisfactory for the proposed model in comparison with some existing literature which are discussed in the next section. It is important to mention here, that performance parameters in Table 8, were computed considering ten-fold cross-validation with the ratio of training to testing data kept 9:1.

4.6. Performance analysis using a large number of EEG signals: In this section, the performance of the proposed method is evaluated using a large dataset, i.e. 3750 pairs of Fo and NFo EEG signals. The performance of the SVM classifier for electrodes 'x' and 'y' was computed separately as done earlier for the 50 pairs. Finally, the overall classification accuracy was computed by taking the mean of the classification accuracies obtained for electrodes 'x' and 'y' and the results are reported in Table 9. It can be observed that the overall classification accuracy of 92.65% is obtained in discriminating between Fo and NFo EEG signals considering 3750 pairs of EEG signals. Besides, investigations also reveal that the performance of the proposed method is better in the case of a large dataset of EEG signals in comparison with the small dataset (see Table 5) which further indicates the feasibility of the application of the proposed method in clinics for detection of focal seizures. It is to be mentioned here that the performance of the proposed model in the case of 3750 pairs of EEG signals is evaluated using ten-fold cross-validation with the ratio of training to testing data kept 9:1.

4.7. Comparative study with existing literature: The performance of the proposed method is compared with some existing state-of-the-art methods, and the results were compared in Table 10.

It is evident from Table 9 that the proposed model yields almost comparable and even better results in the classification of Fo and NFo signals, which further validates the capability of the proposed method in detecting epileptogenic focal regions inside the brain which can help in the treatment of patients suffering from focal epileptic seizures.

Table 10 Performance comparison with some recent methods

Reference no	Method	Cross-validation	EEG signal pairs	CAC, %
[3]	delay-permutation entropy + LS-SVM	no cross-validation	50	84
[4]	entropy-based features using EMD + LS-SVM	ten-fold cross-validation	50	87
[5]	area of phase space of EEG rhythms using EWT + LS-SVM	ten-fold cross-validation	50	90
[6]	entropy features in EMD-DWT domain + kNN and SVM	no cross-validation	3750	89.4
[23]	entropy feature of DWT + LS-SVM, PNN, kNN and fuzzy	ten-fold cross-validation	50	84
[24]	FAWT, fractal dimensions	ten-fold cross-validation	50	90.2
proposed work	higher-order moments in EMD and Teager–Kaiser energy operator domain + SVM	(ten-fold cross-validation training to the testing ratio 9:1)	3750	92.65

5. Conclusion: A novel feature extraction technique using a combination of EMD and TKEO was proposed for detection of Fo and NFo EEG signals. The proposed method was validated on an existing database of EEG signals. Investigations revealed that the proposed model was able to recognise Fo EEG signals and could effectively discriminate them from NFo EEG signals with a reasonably high degree of accuracy. Therefore, it can be concluded that the proposed technique can be effectively applied for identification of epileptogenic focus within the human brain to be used as a pre-surgical step especially for the diagnosis of those patients who are suffering from focal epileptic seizures. Besides, the proposed model utilised only two features for discrimination of EEG signals, hence in comparison with existing works, the proposed model is also computationally less burdensome. In the future, the proposed method will be tested on a large set of EEG signals, before it can be potentially applied in clinics. Moreover, the proposed method will be further extended as a potential feature extraction tool from several other biological signals like electromyogram, electrocorticogram and so on, to develop a computer-aided diagnostic system for fast and accurate treatment of different neurological disorders.

6. Funding and declaration of interests: Conflict of interests: none declared.

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