Journal of Computer Science

Original Research Paper

Epileptic Seizure Detection Using Integrated Decomposed Features from EEG Signal

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Article history
Received: 24-02-2024
Revised: 01-04-2024
Accepted: 03-04-2024

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Abstract: The root cause of the seizure is a sudden abnormal excessive electrical discharge in the brain and it is an Epileptic Seizure (ES) when such abnormal electrical activity arises particularly for epilepsy. Recognizing ES is crucial for effective treatment as it often repeats and can lead to serious outcomes. Since epilepsy is a neurological issue, detecting ES by analyzing brain signals is the preferred method, with Electroencephalogram (EEG) being the most reliable approach for this purpose. Different Machine Learning (ML) and Deep Learning (DL) methods are extensively used in ES detection from EEG signals. Existing methods first extract features from EEG signals using different methods and then classify ES using appropriate ML/DL methods. This study investigates ML-based ES detection where feature extraction from decomposed EEG signals using various methods and integrating the extracted features to classify ES are the main attractions. Empirical Mode Decomposition (EMD) is employed to systematically break down EEG signals into Intrinsic Mode Functions (IMFs), with the earlier IMFs containing more information than the later ones. From the initial six IMFs, three distinct features named Fluctuation index (F), Variance (V) and Ellipse Area (EA) of the second-order difference plot are extracted. Neural Network (NN), the well-known ML method, is employed in this study for ES classification from extracted F, V and EA features individually and integrating these (i.e., F + V + EA). The experimental analysis is conducted on the benchmark CHB-MIT dataset and the integrated feature set shows promising performance over individual feature sets. The proposed NN-based ES detection with integrated decomposed features outperforms prominent existing methods, showing an accuracy of 99.80%.

Keywords: Electroencephalogram, Epilepsy, Seizure, Empirical Mode Decomposition, Neural Network

Introduction

A seizure refers to a sudden and brief episode where there is involuntary movement, potentially impacting the body. At times, this might also involve a quick change in behavior, sensations, or consciousness. These changes occur due to unusual electrical impulses in the brain. Epileptic Seizure (ES) is a common type of seizure characterized by abnormal electrical activity originating from the underlying condition of epilepsy. ES is one of the most common neurological diseases among 50 million people around the world (Epilepsy, 2022); therefore, it is a major health concern. Epilepsy diagnosis typically relies on analyzing an individual's seizure patterns, medical background and outcomes of neurological assessments and imaging procedures. Detecting Epileptic Seizures (ES) is crucial due to their likelihood of recurrence, necessitating appropriate treatment and management. The serious potential consequences of Epileptic Seizures (ES) underscore the urgency of developing an effective detection method. Es detection with Electroencephalogram (EEG) is the most promising due to its affordability and simplicity in measuring brain activity.

Over the past few decades, epilepsy has garnered considerable attention in computational intelligence research (OK and Rajesh, 2020; Pattnaik *et al.*, 2022; Sameer and Gupta, 2022; Nogay and Adeli, 2020; He *et al.*, 2022), particularly for automating the detection of ES. In recent years, Machine Learning (ML) and Deep Learning (DL) techniques have become significant in EEG analysis for diagnosing various neurological disorders, including seizures. EEG stands out as a preferred modality for identifying abnormal brain signals due to its non-invasive and cost-effective nature (Hassan *et al*., 2022; Das *et al*., 2023). Despite its nature, the analysis of EEG signals presents challenges related to their non-stationary and non-linear behavior (Aayesha *et al*., 2022). However, EEG signals have become a highly promising avenue for recognizing and analyzing ES. During seizures, EEG signals typically manifest abnormal and synchronized spikes and sharp wave discharges.

Previous studies on EEG-based Epileptic Seizure (ES) detection have investigated a range of methods for EEG signal processing, transformation, feature extraction and the application of diverse ML/DL approaches. For instance, Empirical Mode Decomposition (EMD) is used in OK and Rajesh (2020); Das *et al.* (2024) to decompose EEG signals. Tunable Q-Wavelet Transform (TQWT) and Wavelet transformation are utilized by Pattnaik *et al*. (2022); Hassan *et al.* (2019) to divide into frequency sub-bands. Some studies have used raw EEG signals (Sameer and Gupta, 2022; He *et al*., 2022; Kaziha and Bonny, 2020; Gómez *et al*., 2020). As an example, a Convolutional Neural Network (CNN) is applied to the raw signals to create convolved features in Sameer and Gupta (2022) and Graph Attention Networks (GAT) are used to extract spatial features in He *et al.* (2022). Moreover, recent research has investigated diverse techniques for extracting features that can effectively capture distinctive information from raw EEG signals (Pattnaik *et al*., 2022; Hassan *et al*., 2019; Mahmoodian *et al*., 2019; Tapani *et al*., 2019; Nandini *et al*., 2022). Recent studies in EEG-based Epileptic Seizure (ES) detection have prioritized signal decomposition and feature extraction methods for enhancing ES detection through ML/DL approaches.

The study aims to develop an effective ES detection method by integrating features extracted from decomposed EEG signals using various techniques. The main steps include EEG signal decomposition, feature extraction, integration and ML-based classification. EMD is employed to iteratively decompose the EEG signal into Intrinsic Mode Functions (IMFs), with the initial IMFs containing the most information. Three key features-Fluctuation Index (F), Variance (V) and Ellipse Area (EA) of the second-order difference plot-are extracted from the first six IMFs. The feature values for all EEG channels are arranged, placing the features of the channels one after another for the feature set for methods F, V, or EA. Features using the three individual methods are concatenated (i.e., F + V + EA) for an integrated feature set. For ES recognition, a Neural Network (NN) is employed. The experimental analysis is conducted on the CHB-MIT benchmark dataset. In the context of ES detection, the key contributions are:

1. The CHB-MIT benchmark dataset is analyzed in depth. EMD is applied to decompose into IMFs
2. F, V and EA features are extracted from the first six IMFs. An integrated feature set is constructed by concatenating individual features (i.e., F + V + EA)
3. ES classification is performed by NN using individual and integrated features and subsequent analysis is presented on outcomes

The remainder of the paper provides a concise overview of prior studies applying ML/DL techniques to ES detection, introduces the proposed method with its framework and components, reports experimental findings and compares the method to state-of-the-art approaches. Finally, the paper offers a summary of the study's contributions and achievements, followed by a discussion of emerging future research directions stemming from this study.

Literature Review

Several EEG-based ES studies have been investigated in recent years, employing a variety of techniques. Several prominent ES studies are reviewed below.

EMD was utilized for EEG signal decomposition, followed by extracting fractal dimension, entropy, exponential energy, statistical energy and classification using a Support Vector Machine (SVM) to distinguish seizure signals from the Bern-Barcelona dataset in OK and Rajesh (2020). Cross-bi-spectrum analysis of EEG signals, accompanied by linear and nonlinear features, was employed for ES classification using SVM in Mahmoodian *et al.* (2019), on the Freiburg iEEG (Ihle *et al*., 2012) dataset. Moreover, SVM was utilized to detect neonatal seizures (Tapani *et al*., 2019) along with the correlation features in the time domain and time-frequency domain.

EEG decomposition using TQWT of CHB-MIT, alongside temporal, nonlinear, statistical feature extraction and classification with Random Forest (RF) and SVM in Pattnaik *et al*. (2022). Parameters of hybrid SVM were refined by Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) in Subasi *et al*. (2019) for the Bonn dataset. In Nandini *et al*. (2022), a variety of classifiers including RF, K Nearest Neighbors (KNN), Naive Bayes (NB), Logistic Regression (LR), SVM, Decision Tree (DT), etc., used two-time domain features. In Sun and Chen (2023), Variational Modal Decomposition (VMD) was used on the CHB-MIT dataset to extract High-Frequency Detection (HFD) Differential Entropy (DE) for ES detection using the SVM classifier. Another method, the Hilbert-Huang Transform (HHT), along with spectral entropies, sub-band energies and higher-order statistics as features from CHB-MIT and SVM, LR and KNN as classifiers was used in Abdellatef *et al*. (2023).

DOI: 10.3844/jcssp.2024.1270.1280

Several recent DL-based studies showed promising outcomes for EEG-based ES detection. CNN was used to detect Seizures without extracting features in Kaziha and Bonny (2020). Image-based EEG signals were classified using CNN by Gómez *et al*. (2020) from CHB-MIT. For ES detection of the Bonn dataset, CNN was used by Sameer and Gupta (2022) for raw EEG. In He *et al*. (2022), spatial feature extraction was conducted using GAT and classification using Bi-directional Long Short-Term Memory (BiLSTM) from raw EEG signals of TUH (Obeid and Picone, 2016) and CHB-MIT. A CNN-based model was also proposed by Qiu *et al*. (2023). The study by Deepa and Ramesh (2022) examined the impacts of MinMaxScaler normalization on the results of LSTM, BiLSTM, etc. In Dang *et al*. (2021), another CNN-based ES detection on the CHB-MIT dataset involved the utilization of frequency bands.

The ML/DL-based methods discussed above vary in their utilization of decomposed EEG signals, raw signals and feature extraction. Recognition performance with decomposition with empirical mode (i.e., EMD) was better as shown in OK and Rajesh (2020). Hence, the main motivation of the study is to achieve better EEG-based ES recognition by developing a model using features from decomposed EEG signals by EMD.

Materials and Methods

The novel aim of the present study is to develop an ML ML-based well-performed ES detection method from EEG signal. Fig. 1 illustrates the proposed ES detection framework, outlining key steps including EEG signal preprocessing, signal decomposition using EMD, feature extraction, feature integration and finally, classifying ES using NN. Subsequent sections detail each step of the framework.

Data Collection and Processing

This study is performed with a well-studied, publicly available CHB-MIT dataset (Shoeb, 2009). It has 24 EEG recordings of 23 subjects (i.e., patients) from CHB. Among 23 subjects, five are males (ages 3-22) and 17 are females (ages 1.5-19). A summary of the patients is demonstrated in Table 1. Here, case no. 1 and case no. 21 are from the same patient but signal collection time is different and subject information is not available for case no. 24. EEG signals from individual subjects are stored in individual. Edf format files. There are some gaps of 10 sec or more in the continuous signal due to some hardware inconvenience and privacy maintenance. The sampling rate of the signals is 256 samples per second with 16-bit resolution. This study takes common 22 channels' data for each case which are "FP1-F7", "F7-T7", "T7-P7", "P7-O1", "FP1-F3", "F3-C3", "C3-P3", "P3-O1", "FP2-F4", "F4-C4", "C4-P4", "P4-O2", "FP2-F8", "F8-T8", "T8-P8", "P8-O2", "FZ-CZ", "CZ-PZ", "P7-T7", "T7-FT9", "FT9-FT10", "FT10-T8". Additional details regarding the CHB-MIT dataset can be found at: (https://physionet.org/content/chbmit/1.0.0/).

EEG data from all 24 cases were analyzed for ES detection. Individual data points in EEG are electric voltage measures from the skull through channel leads. Figure 2 shows a portion of 22 channels' EEG signal values having epileptic spikes for a sample case, with one-half of the area highlighted in red. The red-marked region indicates abnormal signals containing epileptic spikes, visually distinguishable from the unmarked area. EEG signal value ranges are diverged among the individual subjects. For better understanding, the chart in Fig. 3 shows a comprehensive visualization of the minimum and maximum voltage measured values in different channels of seizure and non-seizure periods for individual subjects.

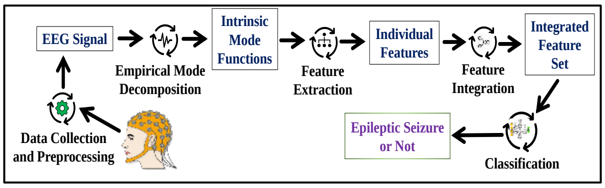

Fig. 1: Proposed framework for Epileptic Seizure (ES) detection

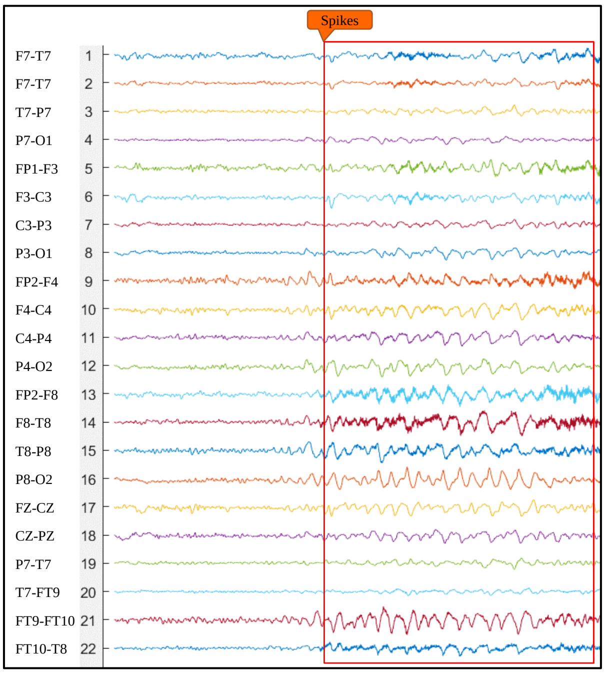

Fig. 2: Sample epileptic spike of a patient

Table 1: Summary of the CHB-MIT dataset

Case No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Age (year)	11	11	14	22	7	1.5	14.5	3.5	10	3	12	2	3	9	16	7	12	18	19	6	13	9	6	-
Gender	F	M	F	M	F	F	F	M	F	M	F	F	F	F	M	F	F	F	F	F	F	F	F	-

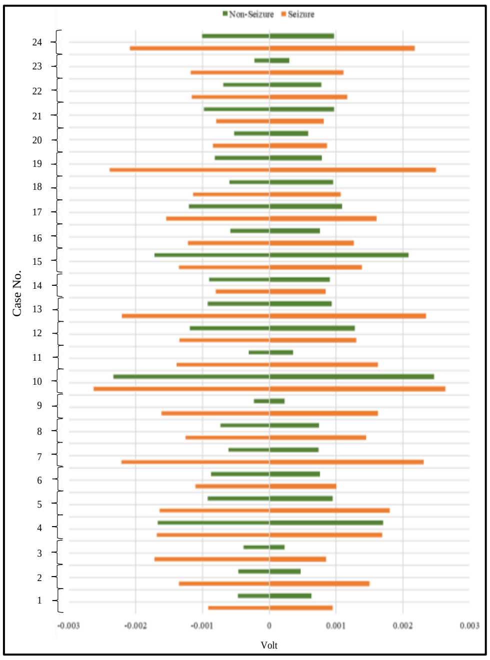

Fig. 3: Individual patients' minimum and maximum EEG responses (unit-volt) for seizure and non-seizure cases

It is observed from Fig. 3 that the seizure period voltage range is larger than the non-seizure period in general for a particular subject. Seizure symptoms can vary in voltage dynamics, potentially showing greater fluctuations. Occasionally, non-seizure periods, while relatively stable, might register higher voltages than certain seizure phases due to transient influences like background brain activity, environmental factors, or physiological changes for a particular subject (Aurlien *et al*., 2004). Sometimes, the non-seizure voltage ranges of several subjects are higher than the seizure voltage values of a few other subjects. For instance, the non-seizure voltage range for case 4 is larger than the seizure range of cases 1, 2, 5-9 and a few others. Such voltage range variation among individual subjects depicts the complexity of subject-independent seizure detection. For such a complicated scenario, sophisticated techniques with feature extraction, as well as appropriate ML/DL algorithms, are necessary for proper discrimination between seizure and non-seizure states.

In this study, 11,122 sec of seizure signal and 11,122 sec of non-seizure signal are collected from 23 patients/24 cases. The EEG signal is divided into consecutive segments using a 10-sec window with a 70% overlap (3-sec step size). Each segment contains 10 sec of data and the consecutive segments have an overlap of 7 sec (10 sec * 70% overlap = 7 sec), leading to a partially shared time domain between adjacent windows. This ensures that all information remains intact during segmentation, enabling a more comprehensive analysis of the EEG signal, especially in scenarios where the events of interest, such as seizures, occur in shorter durations. A total of 3707 segments are generated for Seizure and an equal number for non-seizure, resulting in a combined sample size of 7414 for further steps.

Empirical Mode Decomposition (EMD)

Signal decomposition allows for deeper analysis by breaking down signals into simpler components. In the proposed method, EEG signal decomposition using EMD is crucial. EMD is also able to handle non-stationary and non-linear signals (Huang *et al*., 1998), which are common in many real-world applications, such as biomedical signal analysis. Seizure signals often contain complex patterns with non-stationary and non-linear characteristics, so EMD can be used to reduce noise, enhance the quality of the signal and make it easier to extract relevant information (OK and Rajesh, 2020). Algorithm 1 shows the process of EMD followed by OK and Rajesh (2020).

Algorithm 1: Empirical Mode Decomposition

Initialization: Start with the original EEG signal and set the residue to be equal to the original signal [EEG segment of a channel]

$$r(t) = x(t).$$

Step 1. IMF extraction: Repeat the following steps if the residue can be decomposed and the IMF count is less than six:

a) Identify the local maxima and minima of the residue, $y\_max(t)$ and $y\_min(t)$, respectively.
b) Fit cubic spline interpolating functions to the local maxima and minima to obtain the upper, $u(t)$ and lower, $l(t)$ envelopes by:
$$u(t) = spline\ (t, y\_max(t))$$
$$l(t) = spline\ (t, y\_min(t))$$
c) Calculate the mean $c(t)$ of the upper and lower envelopes and subtract the mean from residue as $d(t)$:
$$c(t) = (u(t) + l(t))/2$$
$$d(t)) = r(t) – c(t)$$
d) If $d(t)$ does not satisfy the conditions of IMFs, repeat the procedure defined in (a) to (c). Whenever $d(t)$ satisfies the conditions, define IMF:
$$IMFn = d(t)$$
e) Subtract the current IMF component from the residue to obtain the new residue:
$$r(t) = r(t) – IMFn$$

Step 2. Stop if the residue can no longer be decomposed and the IMF count is six

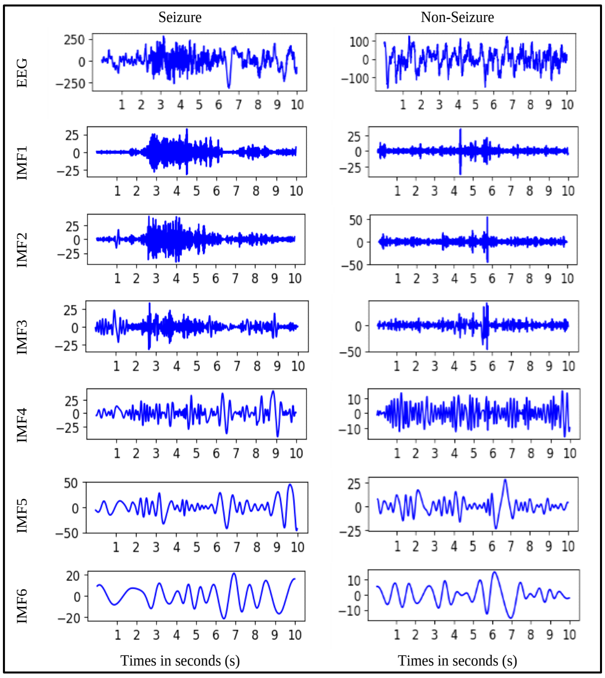

Fig. 4: Six IMFs of seizure and non-seizure sample

The core concept of EMD is to iteratively extract IMFs from the signal until a non-decomposable residue remains (Das *et al*., 2024). In this study, the first six IMFs are considered as the initial ones that carry more information. Step 1 of Algorithm 1 is the main component of individual IMF generation, which is repeated six times (directed in step 2) for six IMFs. In the first iteration, IMF1 is generated from the original signal. IMF1 is subtracted from the original signal to form the new residue. This residue is used for further iteration and IMF2 is generated. This is how the iterations go on four more times. Seizure and non-seizure IMFs are shown in Fig. 4. The figure demonstrates that seizure IMFs display abrupt, high-frequency patterns indicating erratic neuronal firing, while non-seizure IMFs are smoother and more consistent, reflecting normal brain activity.

Feature Extraction

The goal of feature extraction is to extract the most relevant information from the data. Reduction in dimensionality, improvement of classification accuracy and enhancement of computational efficiency are some contributions of feature extraction (Boonyakitanont *et al*., 2020). In this study, from each IMF, three features are extracted: The Fluctuation Index, Variance and Ellipse Area of SODP. The Fluctuation Index, which measures the degree of change in signal amplitude, typically indicates higher fluctuation in Seizure EEG compared to Non-Seizure EEG, reflecting the erratic nature of epileptic discharges. Variance, representing the extent of variability in relation to the mean of signal amplitude, is elevated in epileptic signals due to the dynamic nature of seizure activity. Additionally, the SODP provides a visual representation of the differences between consecutive signal points and is particularly adept at capturing signal variability. The areas of elliptical structures produced by Seizure signals' SODP are higher. Collectively, these features offer valuable insights into the unique patterns and characteristics of epileptic activity, facilitating accurate differentiation between seizure and non-seizure signals. A brief demonstration of the extracted features is given below:

1. Fluctuation index (F): The fluctuation index serves as a valuable metric for assessing the degree of variability within a dataset, particularly in the context of time series (here an IMF) analysis. A heightened fluctuation index signifies a greater level of variability within the dataset, suggesting that the data exhibits more pronounced fluctuations over time. Conversely, a lower fluctuation index implies a greater degree of stability, indicating that the dataset experiences fewer and less significant fluctuations
2. Variance (V): Variance serves as a crucial statistical metric, offering insights into the extent of distribution or scattering within a dataset, a characteristic pivotal in tasks such as classification and clustering. Computed by averaging the squared disparities between each data point and the mean, variance provides a nuanced understanding of how data values deviate from the overall average, thus portraying the overall data dispersion
3. Ellipse Area (EA) of second-order difference plot: The dispersion or variability in a time series dataset is measured by calculating the Ellipse Area (EA) in the Second Order Difference Plot (SODP). Here, SODP provides a visual representation of a time series of second-order statistics and serves as a valuable tool for identifying trends and outliers within the dataset. *EA* of the SODP encapsulates a concise portrayal of the dataset's variability and distribution, offering a comprehensive insight into the nuanced patterns and spread inherent in the temporal data. The necessary equations for calculations are explained below from (Pachori and Patidar, 2014):

$$d_1(x) = t_i(x+1) - t_i(x) \quad (1)$$

$$d_2(x) = t_i(x+2) - t_i(x-1) \quad (2)$$

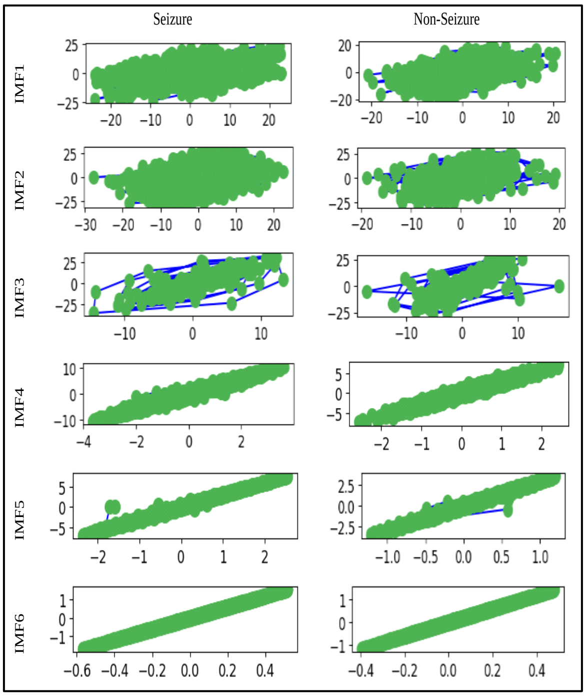

Fig. 5: SODPs of seizure and non-seizure sample cases of a channel of patient 1

In this context, where $t_i(x)$ specifically represents an IMF, the assessment of SODP involves plotting $d_2(x)$ against $d_1(x)$. The SODP samples of seizure and non-seizure IMFs are demonstrated in Fig. 5. Upon visual examination, it becomes evident that the initial IMFs of the Seizure data display a more widespread distribution. As an example, in Fig. 5, the SODP of IMF1 varies vertically from -25 to +25 for seizure and the values vary from -20 to +20 for non-seizure cases. This allows us to compute the area of the elliptical structure formed by the SODP. Notably, the SODPs demonstrate that the areas of the elliptical structures generated by the seizure-related IMFs are notably larger compared to those of the non-seizure IMFs, particularly for the lower index *IMFs*. The *EA* of SODP is defined by:

$$EA = \pi ab \tag{3}$$

where, a represents the semi-major and b represents the semi-minor axes.

Feature Integration

From 22 channels of the CHB-MIT dataset, there is a total of 132 = (22×6) IMFs extracted. The extracted features for all IMFs are arranged, placing one after another for the feature set for a particular method, *F*, *V*, or *EA*. Features using the three individual methods are concatenated (i.e., *F* + *V* + *EA*) for an integrated feature set. The feature values are characterized to distinguish an EEG segment as seizure or non-seizure. To explore the combined impact of individual features (which is the main significance of the present study), a new feature set was generated by integrating *F*, *V* and *EA* into a single feature set. The integrated feature set holds 396 = (3×22×6) features concatenating *F*, *V* and *EA* features. For better understanding, Fig. 6 visually demonstrates feature set formations using individual methods (Figs. 6a-c) and finally integrating individual methods (Fig. 6d).

Classification

Integration of features from decomposed *EEG* signals using different methods to achieve better *ES* recognition is the main attraction of this study. Among different *ML* models, *NN* is considered in this study. *NN* is the most studied *ML* method due to its ability to learn and make good classification predictions. To observe the effectiveness of feature integration over individual methods, four different *NN* models are tested in this study: three models for individual feature sets (by *F*, *V* and *EA*) and a model with the integrated feature set.

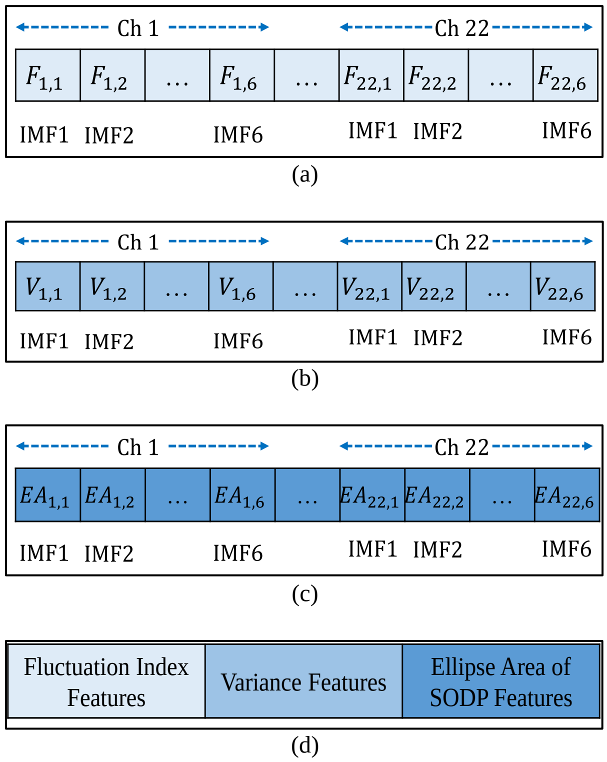

Fig. 6: Feature set formation using individual methods and concatenation of those for integrated feature set. Here, *F*: Fluctuation Index, *V*: Variance, *EA*: Ellipse Area of SODP; (a) Fluctuation (*F*) feature set having 132 = (22×6) Fluctuation Index; (b) Variance (*V*) feature set having 132 = (22×6) Variance values; (c) Ellipse Area (EA) feature set having 132 = (22×6) ellipse areas of SODP; (d) Integrated feature set having 396 = (3×22×6) features concatenating *F*, *V* and *EA* features

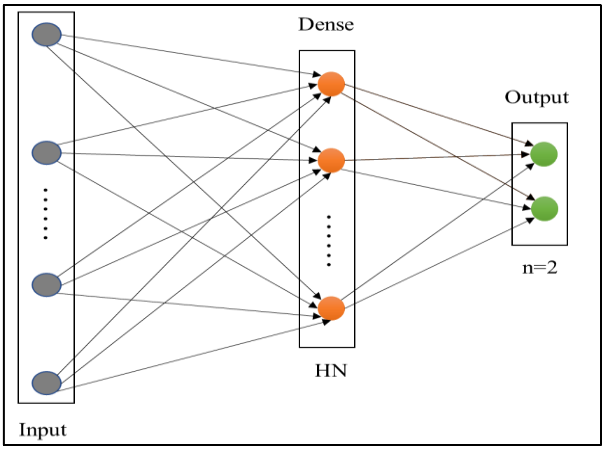

Fig. 7: Neural network structure considered to classify seizure. The number of output neurons is two (n = 2) for seizure and non-seizure cases activation. Input sizes are 132 and 396 for individual and integrated feature sets. The model tested for different h

The NN structure considered to classify ES using features demonstrated in the previous section is shown in Fig. 7. It consists of an input layer, one hidden layer and an output layer. Neurons within each layer are fully connected to neurons in the subsequent layer (Alkan *et al.*, 2005). The number of output neurons is two (n = 2) for seizure and non-seizure cases activation. The input size is 132 for the feature set of F, V, or EA; the size is 396 for the integrated feature set. The number of Hidden Neurons (HN) is a user-defined parameter and a model tested for different HNs. ReLU and softmax activation functions are used in the hidden and output layers, respectively.

Experimental Studies

This section first presents an experimental evaluation of NN. However, the experimental setup is given first.

Experimental Setup

The experiments, including feature extraction and classification, are conducted using Python. To perform the experiment, 80% of samples from the prepared 7414 samples are used to train a model and the remaining 20% are used to test (i.e., measure generalization) the model.

The number of HN in the NN (Fig. 7) is a user-defined parameter; and the four models are tested with varying hidden neurons 10, 20, 50 and 75 to observe the recognition ability for a particular model. The well-known Adam optimization algorithm is used to train the NN with a learning rate is 0.001.

Experimental Evaluation

At first, a rigorous analysis is presented for HN = 50 and then performance is compared among four individual methods for different HNs. Figure 8 shows the training loss curves for *HN* = 50 of NN models with feature sets of *F*, *V*, *EA* and integrated these (i.e., *F* + *V* + *EA*). Consequently, Figs. 9-10 show the training and test sets accuracy curves for the same NN with HN = 50. It is observed from Fig. 8 that models are converged after 50-100 epochs. Training set accuracy is smoothly inverse correlated with the loss curve of a particular model; such correlation is justified as the training samples used to train a model. After 100 epochs, all the models show near or equal 100% training set accuracies.

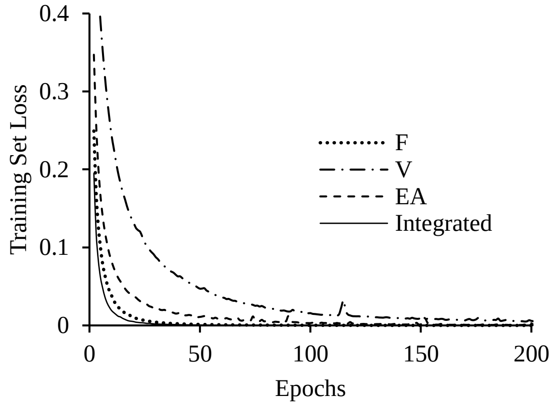

Fig. 8: Training set loss vs. Epochs curves for HN = 50

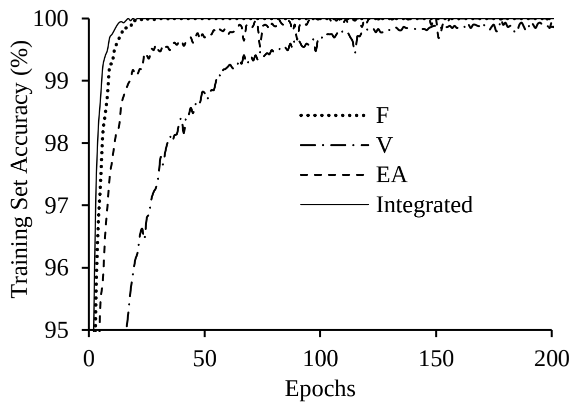

Fig. 9: Training set accuracy vs. Epochs curves for HN = 50

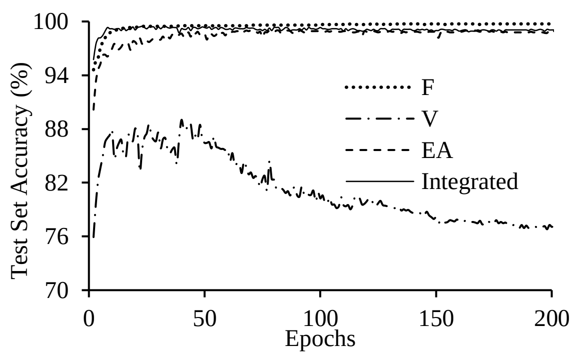

Fig. 10: Test set accuracy vs. Epochs curves for HN = 50

Most importantly, for HN = 50, notable differences in test set accuracies are observed among the models, as seen in Fig. 10. Test set accuracy reflects the generation ability of an *ML* model, which is the main performance indicator. According to Fig. 10, classification accuracies are different for different feature sets. Among individual feature sets, the *F* feature set achieves the highest accuracy, reaching 99.73%. In contrast, the *V* feature set yields a lower accuracy of 89.01%, while the *EA* feature set shows a slightly better accuracy of 99.12%. On the other hand, the integrated feature set (combining *F*, *V* and *EA*) performs well with an accuracy of 99.46%. It is also observed from the figure that the V feature is not only the worst among the four models, but also its performance degrades significantly after 50 epochs. Again, the *F* feature set is the most discriminative, closely followed by the integrated feature set and outperforms the EA feature aset. Although the integrated feature is not found to be effective in improving performance for HN = 50, their loss convergence (Fig. 8) and accuracy improvement with respect to training epochs are better than models with individual feature sets. These results demonstrate the NN architecture's effectiveness in identifying patterns and achieving high accuracy.

NN models with three individual features and an integrated feature set are trained for HN values 10, 20, 50 and 70. The histogram in Fig. 11 depicts the test set classification accuracies among models with *F*, *V*, *EA* and integrated feature sets for different HNs. The histogram suggests that a higher HN is generally associated with improved classification accuracy. Although accuracy improves for the V feature set with respect to HN values, its highest accuracy, 89.48 for HN = 75, is worse than any other values for other feature sets. For HN = 75, EA also achieved the highest accuracy, but the values are lower than the F feature set with any HN values. It is also remarkable for the F feature set that although it is the best-performed individual method, showing 99.73% accuracy for HN = 50, its performance did not improve further for HN = 75. On the other hand, performance with an integrated future set is inferior to the F for lower HN values (e.g., HN 10, 20), increases gradually and shows the best performance of 99.80% for HN = 75. As features in the integrated feature set are larger than individual methods, better performance with larger HN values is logical for the NN model. On the other hand, while performance for *V* is very low for lower HN values, its involvement in the integrated set hinders achieving good performance. While the performance of individual V and EA feature sets improves for HN = 75, the performance with integrated feature sets outperforms any individual methods. Briefly, the integrated feature set underscores the potential benefits of feature integration, despite the limitations of certain feature components of individual feature sets, especially the *V* feature set.

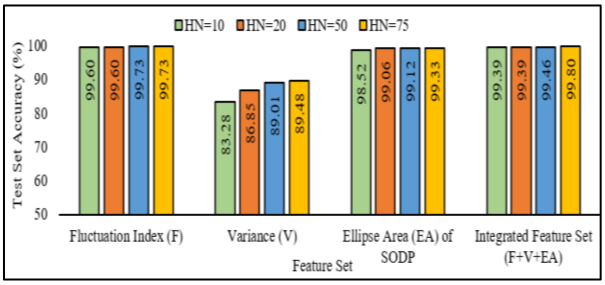

Fig. 11: Test set accuracies across distinct feature sets for different Hidden Neurons (HNs) in the neural network

Comparison with Previous Studies

Numerous recent investigations have applied various ML/DL methods utilizing the CHB-MIT dataset. These studies have been consolidated, providing a summary and a performance evaluation is presented in Table 2, comparing the outcomes with the proposed method. The reported results in the respective articles serve as the basis for assessing the efficacy of the proposed approach in relation to existing studies. Some studies, such as Kaziha and Bonny (2020); (Gómez *et al*., 2020), used raw EEG signals. Kaziha and Bonny (2020) segmented the dataset into 100-sec intervals, achieving 96.70% accuracy with a CNN on a test set comprising 30% of the data. Similarly, Gómez *et al*. (2020) achieved 99.30% accuracy using raw EEG data along with CNN and a leave-one-patient-out evaluation strategy. Dang *et al*. (2021) achieved 99.56% accuracy by segmenting the dataset by 1 sec, dividing the signals into frequency bands and using CNN in a 10-fold CV. Qiu *et al*. (2023) segmented the dataset by 2 sec and used 1D CNN to extract features and classify them using them, achieving an accuracy of 97.09% in a 10-fold CV. Deepa and Ramesh (2022) achieved 99.55% accuracy using BiLSTM on a test set of 20% available data. He *et al*. (2022) achieved 98.52% accuracy using GAT and BiLSTM in a 5-fold CV. Some studies employed signal decomposition techniques like TQWT (Pattnaik *et al*., 2022) and VMD (Sun and Chen, 2023). Segmenting EEG signal by 2 sec, (Pattnaik *et al*., 2022) used TQWT to decompose EEG and achieved 93% accuracy using RF in a 10-fold CV. Sun and Chen (2023) used VMD to decompose and SVM to classify 10-fold achieving 98.3% accuracy. The proposed method outperforms all others, achieving a top accuracy of 99.80% on the CHB-MIT dataset through EMD decomposition, feature integration and NN classification (HN = 75). Finally, the proposed method is revealed as an effective ES detection method with an integrated feature set.

Table 2: Comparison of the proposed method with leading studies using CHB-MIT dataset

Study reference	Segmentation + overlap	Decomposition + feature extraction	Train-test split + classification	Classification accuracy (%)
Kaziha and Bonny (2020)	100 sec + N/A	N/A + N/A	70/30+ CNN	96.70
Gómez *et al.* (2020)	4 sec + N/A	N/A + N/A	Leave-one-patient - out + CNN	99.30
Dang *et al.* (2021)	1 sec + 50%	Frequency bands + N/A	10-fold CV + CNN	99.56
Pattnaik *et al*. (2022)	2 sec + N/A	TQWT + nonlinear, temporal, statistical feature	10-fold CV + RF	93.00
He *et al.* (2022)	1 sec + 50%	N/A + GAT	5-fold CV + BiLSTM	98.52
Deepa and Ramesh (2022)	N/A + N/A	N/A + N/A	80/20 + BiLSTM	99.55
Qiu *et al*. (2023)	2 sec + 50%	N/A + CNN	10-fold CV + CNN	97.09
Sun and Chen (2023)	2 sec + N/A	VMD + DE, HFD	10-fold CV + SVM	98.30
The proposed method	10 sec + 70%	EMD + integrated features of F, V, EA	80/20 + NN	99.80

Conclusion

Epileptic Seizure (ES) detection can help physicians accurately diagnose and monitor epilepsy and automatic ES detection from EEG signal is revealed as an open challenge in the ML/DL domain. This study investigates a novel strategy of ES detection from EEG signals through signal decomposition, feature extraction and feature integration. The well-known CHB-MIT benchmark EEG dataset is used in this study. EMD decomposes the raw EEG signals to extract essential components (i.e., IMFs) and uncover the underlying patterns that might be hidden in raw data. The fluctuation index (F), Variance (V) and Ellipse Area (EA) of SODP features are extracted from individual decomposed IMFs. The features were also concatenated to generate an integrated feature set, which is the main significance of this study. Finally, NN models are trained with individual and integrated feature sets. The performance of individual models is identified through a comprehensive analysis. Among individual methods, variance performs much worse than the fluctuation index or Ellipse area. The proposed method with an integrated feature set reveals an effective ES detection method that outperforms models with individual feature sets and prominent existing studies. However, it is noticeable that feature integration does not show significant improvement over the Fluctuation Index; the worst performed Variance features consideration in the integrated feature set might be the reason for that.

The findings and insights from this study open several future studies in ES detection. This study considers NN for classification and shows competitive performance with different DL methods (Table 2). However, the appropriate DL model (i.e., CNN) and other ML models (i.e., SVM) might perform well for features from decomposed signals and integrated feature sets. Thus, there is a scope for work remaining with other ML models using feature integration. In the present study, integration is performed considering all the individual features for simplicity. Appropriate selection of features might enhance performance further and remain an interesting but challenging future work.

Acknowledgment

The authors would like to thank anonymous reviewers for their constructive comments and suggestions to update the manuscript.

Funding Information

This research received no external funding.

Author's Contributions

Shupta Das: Developed the concept; conducted the experiments and result analysis; prepared the initial manuscript and contributed to edited and reviewed the manuscript.

Suraiya Akter Mumu: Developed the concept; conducted the experiments and contributed to edited and reviewed the manuscript.

M. A. H. Akhand: Developed the concept and result analysis; suggested initial manuscript preparation and contributed to edited and reviewed the manuscript.

Md Abdus Samad Kamal: Result analysis and contributed to edited and reviewed the manuscript.

Ethics

It has been testified by the authors that this article has not been submitted to be published in any other journal and contains no conflicts of interest or ethical issues.

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