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Compendium Juxtapose of Algorithmic Ingress to Evaluate Performance of Brain Signals in Seizure Detection

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Abstract: Brain signals are imperative for the human body's regular neuronal functioning. Epilepsy is a neural detriment that can cause severe morbidity and paralytic seizures that injure an individual's efficient quotidian operability. The Electroencephalogram (EEG) indicators have been proven to corroborate the disorders in the human body through the signal fluctuations and volatilities that indicate the damages that may likely be persistent or risks that may be triggered in the future. The method of EEG analysis is most successful in neoteric times due to its property of non-invasiveness that aids in increasing traffic amongst users to take up the tests. This paper proposed a novel framework comprising various methods to process the EEG input signal, from preprocessing to predicting seizure availability. Initially, The Linear Filter was employed in the previous system. In terms of accuracy and detecting morbidity, this filtering technique is inefficient. As a result, the distinctive research of Least Square Generative Adversarial Network techniques can be used to denoise the input signal, improving its quality. The Multilevel decomposition method is used to breakdown the input signal to speed up the process and increase the accuracy of signal processing to the next level. The Higuchi Fractal Dimension model is used from the decomposed signal to extract the features and cluster using the K-Means clustering method. Finally, the cluster data is analyzed and classified as seizure and non-seizure using SVM, ANN, CNN, and E-CNN models. These algorithms are implemented, experimented with, and the results are verified. The results are compared with the other algorithms, and it is found that the proposed framework outperforms earlier methods in classification.

Keywords: *EEG Signal Processing, Seizure Detection, Machine Learning Algorithms, Deep Learning Algorithms, Signal Processing, Preprocessing, Signal Data Analytics.*

1. Introduction

Epilepsy, a neurological disorder characterized by recurrent seizures, presents significant challenges to individuals' daily functioning and overall quality of life. Understanding and accurately diagnosing epileptic activity are crucial for effective management and treatment. Electroencephalogram (EEG) signals serve as a valuable tool in this regard, offering insights into brain activity and facilitating the detection of abnormalities associated with epilepsy. However, the complexity and variability of EEG signals often pose challenges in accurate interpretation and diagnosis. In recent years, advancements in signal processing techniques have revolutionized EEG analysis, offering promising avenues for enhanced detection and prediction of epileptic seizures. Traditional methods, such as linear filtering, have demonstrated limitations in terms of accuracy and sensitivity to pathological signals. Consequently, there is a growing need for innovative approaches capable of improving signal quality and extracting meaningful features for precise classification. This research endeavours to address these challenges by proposing a novel framework for EEG signal analysis, encompassing a comprehensive methodology from pre-processing to seizure prediction. Central to this framework is the integration of advanced signal processing techniques, including Least Square Generative Adversarial Network (LS-GAN) denoising and multi-level decomposition, aimed at enhancing signal fidelity and efficiency. Moreover, the incorporation of feature extraction methods, such as the Higuchi Fractal Dimension model, enables the extraction of distinctive features crucial for distinguishing between seizure and non-seizure states. The subsequent utilization of clustering techniques, particularly K-Means clustering, facilitates the organization and classification of extracted features, laying the groundwork for accurate seizure detection. Furthermore, the classification stage employs a diverse set of machine learning algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Enhanced Convolutional Neural Networks (E-CNN). These algorithms are rigorously implemented and evaluated to assess their efficacy in accurately classifying EEG signals. Through comprehensive experimentation and validation, this research demonstrates the superior performance of the proposed framework in comparison to existing methods. By leveraging advanced signal processing techniques and machine learning algorithms,

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this framework offers a promising avenue for enhancing the diagnosis and management of epilepsy, ultimately improving the overall well-being and quality of life for individuals affected by this debilitating disorder.

Background Study

Seizures most commonly occur when abnormalities and signal volatilities are observed in the EEG rate compared to the normal range in an individual [1]. This non-invasive and less painstaking mode of analysis has proved to be a prominent diagnostic tool in the health industry to identify the various neurological detriments a likely human faces. The dynamic signal processing framework is a popular domain and an area of interest that is progressively updated continually. The explicit identification of the precise waveform or phase in which the EEG signals must be tapped to organize the abnormality is a constant challenge that many researchers strive to establish [2], [3]. Nevertheless, the epileptic recognition through waveforms proves idiosyncratic rather than generalized to specific attributes or ranges. An individual's brain holds a unique system of connecting with each neuron and therefore is a complex architecture to be decrypted holistically. The frequency ranges in each waveform phase tend to enlighten the signal-wave-frequency processing method using simulative-algorithmic approaches [3]. A global survey by the World Health Organization (WHO) delineates the approximation of nearly a quarter of the population suffers from brain disorders [4]. The survey also explicates the various root causes of these detriments and the lifestyle changes that may be necessitated to create a paradigm shift toward healthy living. The EEG data in an individual is most commonly procured through the Brain Computer Interface (BCI) tools, with the distance placement of electrodes within the cerebral cortex of an individual. The signal waves through this method are captured through the explicit maintenance of odd-even electrodes on the Frontal-Central-Temporal-Parietal-Occipital (FCTPO) regions of the cortex [5] and are further augmented for its precision using computerized algorithmic approaches. The data signals thus obtained are further stratified and filtered based on their frequency into alpha, beta, delta, theta, and gamma shifts [6], each holding significant prominence in the determination of diverse activities in that an individual is involved. The signal frequency waveforms delineate a large amount of information regarding the interictal, ictal [7], and postictal continuum that further elaborates the patterns of EEG signals for each individual, thereby helping in the accurate classification of the normal and abnormal clusters. The authors in [8] proposed a GAN model for enhancing the speech signal data. The author used 30 subjects with 40 noise voice data to check the performance of the GAN method. Finally, the author compared the classified output with the state-of-the-art methods. At the same time, the issues and challenges regarding scalability were not discussed. This paper contributes a novel framework to provide better classification accuracy, and it involves: A linear filter and LS-GAN model are designed for denoising the EEG input signal. A multilevel decomposition model is created for decomposing the EEG signal. The Higuchi Fractal Dimension method is implemented for learning and extracting the features from the decomposed signals. The feature data is clustered using the K-means clustering model. Finally, various machine learning models are used for classifying the clustered data, and their performance is compared. Various simulative studies have broadly analyzed the glitches and disruptions in the signals in the EEG. The quondam research relevant to this domain of interest has provided crucial elaboration on seizure processing and epileptic identification through automated and manual methodologies. These methods have been implemented through various simulative platforms such as deep learning, Artificial Neural Networks, machine learning, and data mining [9]. However, the motivation of this study remains to provide a collection of algorithms that separate the specificity, sensitivity, precision, and accuracy [10] of signal wave processing in the identification of seizures through a cluster of algorithms such as SVM [11], ANN, CNN [8] and Equitorial-CNN [11]. The method of using a CNN based on raw EEG signals for detecting epileptic seizures is effective and has the potential to improve the accuracy and efficiency of epileptic seizure detection [12]. It uses multilevel wavelet decomposition and feature extraction methods that provides a comprehensive outlook on the various algorithmic performance concerning the linear filter, along with the Least Square GAN (LS-GAN) algorithm [13] and the Higuchi Fractal dimension measure [14]. A light weight CNN architecture for automatic seizure detection using EEG signals [16] also proposed optimum results. Before implementing the proposed model, it is essential to understand the standard and seizure EEG signal. The frequency level of the seizure signal is higher than the standard signal, as shown in Figure-1. Thus, it is clear that the abnormal peak values and the time interval help to detect the seizure signal. In addition to this, to increase the accuracy, the signal data is analyzed, and the features-based classification is applied using deep learning algorithms.

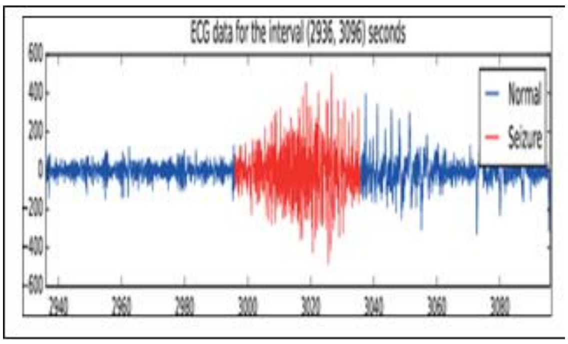


Fig 1. Normal versus Seizure EEG Signal

2. Proposed Novel Framework

This paper has aimed to propose a novel framework for analyzing and predicting seizure signals from a large amount of EEG signals. Figure-2 illustrates the overall logical functionality of the proposed novel framework. It shows the various stages of the framework, such as preprocessing, denoising, decomposing, feature extraction, and classification using machine learning and deep learning algorithms.

2.1 Input Signal

Compared to the existing methods [8] and to increase the scalability of the proposed model, this paper uses 100 EEG signals dataset taken from the Kaggle website. The dataset is already used by several earlier research methods and is considered a benchmark dataset. The data comprises preprocessed and non-preprocessed. All the 100 EEG data are stored in five different folders, each representing a separate person and subject. The EEG data record shows human brain activity for 24 seconds. The dataset is considered a time-series data with 4100 data points representing the EEG values at different times. Hence, the data size is taken for 500 individuals, with 4100 data points obtained in 23.5 seconds. The entire dataset is represented in Y for the exploratory variable X.

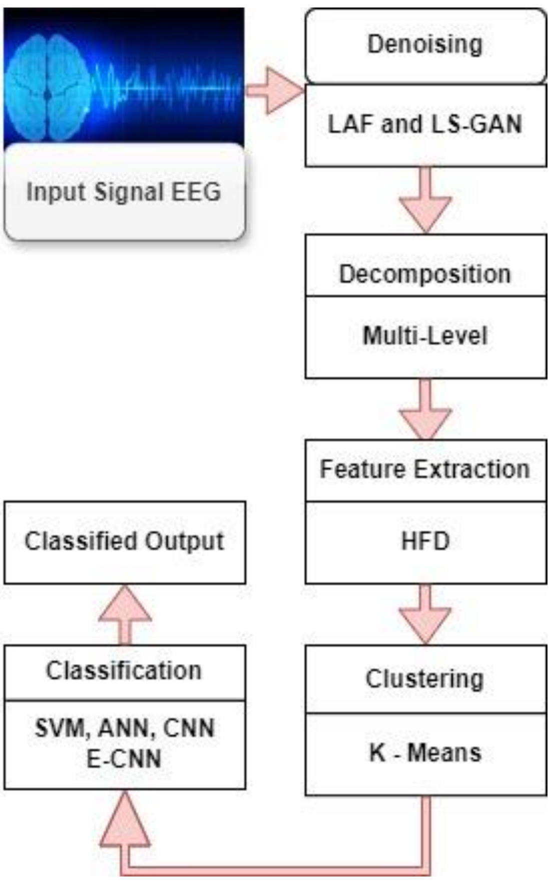


Fig 2. Framework for Performance Evaluation of Brain Signals in Seizure Detection

2.2 LF and LS-GAN Based Signal Denoising

One of the mathematical-model-based filters used mainly in image processing, control systems, and signal processing is called a linear filter. It is a function that maps the input and output signal and provides an output signal as a linear combination of the input signal and the filter coefficients. In image processing, linear filters enhance or modify images to sharpen, blur, or remove noise. A linear filter moves a window over the image, computes the weighted sum of the pixel values within the window, and assigns the result to the center pixel. The mathematical calculation of the linear filter is given in equation-(1).

$$LAF = \frac{Ones(i(1), i(2))}{i(1) * i(2)} \qquad \textbf{(1)}$$

For example, Figure-3 shows how the linear filter compares and filters the data. The weights in the sum are the filter coefficients, which determine the filter's effect. In signal processing, linear filters are used to analyze and modify signals, such as removing noise, extracting features, or isolating components. A linear filter operates on the signal in the time or frequency domain, depending on the type of filter. Linear filters have some desirable properties, such as linearity, shift invariance, and time invariance, which make them well-suited for many applications. However, linear filters may not always be appropriate for all applications, and other filters, such as nonlinear or adaptive filters, may be required. The Least Square Generative Adversarial Network (LS-GAN) is a variant of the Generative Adversarial Network (GAN) architecture for generative models. LS-GAN was introduced as a modification to the original GAN framework to address some challenges, such as stability issues during training and difficulties in generating high-quality images. This paper uses LS-GAN and LS filters to increase the input signal quality for denoising. In LS-GAN, the loss function used to train the generator and discriminator networks is based on Least Squares instead of the original binary cross-entropy loss.

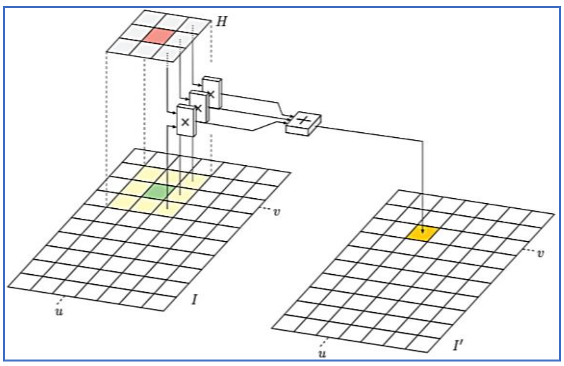


Fig 3. Linear Filter Process

The Least Squares loss is designed to provide a smooth and continuous gradient, making it easier for the generator and discriminator to learn. The LS-GAN also uses a linear activation function for the discriminator network, which helps to mitigate some of the instability issues that can occur in traditional GANs. LS-GAN has been used in various applications, including image synthesis, super-resolution, and style transfer. In some cases, LS-GAN has produced high-quality results and improved training stability compared to traditional GANs. However, LS-GAN is still a relatively new approach, and more research is needed to fully understand its strengths and limitations and compare its performance to other generative models. The LS-GAN used for removing the noise from the input signals $\{S^{(1)}, S^{(2)}, \ldots, S^{(n)}\}$ for the noise Pg(S). The data value distributed in n signals is $\{x^{(1)}, x^{(2)}, \ldots, x^{(n)}\}$ obtained from the entire data distribution Pd(x). The discriminator is updated using ascending stochastic gradient formula given below

$$\nabla_{\theta d} \frac{1}{n} \sum_{i=1}^{n} [\log D(x^{(i)}) + \log(1 - D(G(S^{(i)})))] \qquad (2)$$

The main objective of the LS-GAN method is to reduce noise. E-CNN is implemented as an efficient Convolutional Neural Network in our suggested system. Because we use the LS-GAN technique, which uses the Least Squares loss function for the discriminator, we consider CNN technique is efficient. The experimental findings show that LS-GAN produces more realistic pictures than normal GAN.

As stated by Matthew Mead, CNN and LS-GAN can collaborate to deliver better outcomes. Because CNNs are so effective at image processing, LS-GAN's generator and discriminator are both the default CNNs. LS-GAN is often used with image data and can employ CNN as a discriminator.

2.3 Multilevel Decomposition Model for EEG Signal Decomposition

Multilevel decomposition is a signal processing technique used to decompose a signal into multiple levels of detail. The idea behind multilevel decomposition is to represent a signal at different scales or levels of resolution, from coarse to fine. It allows for more detailed and nuanced signal analysis and more effective processing and compression (Figure-4). In this paper, upsampling-based signal decomposition is used. The signal length determines the decomposition level. The highpass g(j) and lowpass h(j) filters provide the coefficients c(j) obtained from the input signal S.

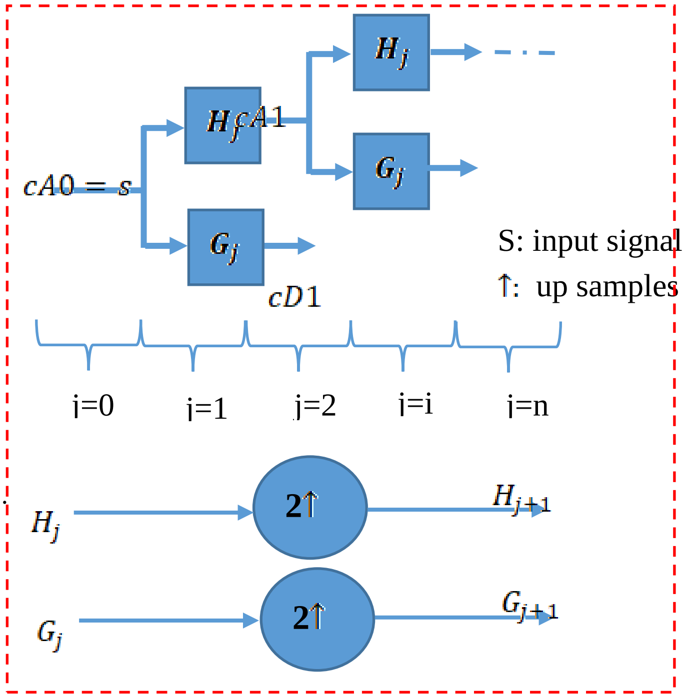


Fig 4. Multilevel Decomposition

Multilevel decomposition is typically achieved through a sequence of filtering and down-sampling operations. The first step is to apply a low pass filter to the signal, which removes high-frequency components and provides a coarser representation of the signal. This filtered signal is then down-sampled, reducing the number of samples in the signal and providing a coarser representation of the signal. The process is then repeated, applying a low pass filter and down-sampling the signal multiple times until a desired level of decomposition is achieved. At each level, the filtered signal can be represented as a wavelet, representing the difference between the original signal and the filtered signal at that level. Multilevel decomposition is widely used in various applications, such as image processing, video compression, speech processing, and biomedical signals. It is a powerful tool for analyzing signals, extracting information, and compressing signals for storage and transmission. The spatial-temporal features are extracted from each scale for further classification. To demonstrate the effectiveness of EEG Wave Net [18]. Overall, multilevel decomposition provides a flexible and effective way to decompose signals into multiple levels of detail, enabling a more detailed and nuanced analysis of signals and more effective processing and compression of signals.

2.4 HFD Based Feature Extraction

The Higuchi Fractal Dimension (HFD) is a mathematical algorithm used to quantify the fractal dimension of a time series or a signal. The fractal dimension measures the complexity of a signal or a pattern and provides information about the scaling properties of the signal. The HFD is based on the fractal dimension and calculates the fractal dimension of a time series by counting the number of times a curve must be broken into smaller parts to fit within a certain length. The HFD is calculated by determining the number of curves required to cover the entire time series as the length of the curves decreases. The HFD has been widely used in various applications, such as biomedical signals, speech processing, and image analysis. It has been used to analyze signals to extract information about the underlying complexity and to quantify the level of irregularity in signals.

The HFD is also used as a feature extraction technique for machine learning algorithms, where it is used as a feature in combination with other features to develop models for classification and regression tasks. Overall, the Higuchi Fractal Dimension is a valuable tool for analyzing and quantifying the fractal dimension of signals and time series, providing insights into signals' complexity and scaling properties. The HFD model receives an input $\{x^{(1)}, x^{(2)}, \ldots, x^{(n)}\}$, having N points. A new data sequence x_k^m is obtained by HFD is:

$$x_k^m = \left\{x(m), x(m+k), x(m+2k), \ldots, x\left(m + \left[\frac{N-m}{k}\right]k\right)\right\} \quad (3)$$

Where the data inside the square brackets [ ] represents the integer part, k is the initial time, and m is the initial time interval. The slope of the signal $L_m(k)$ in the above equation, concerning the logarithmic value and HFD process,

$$L_m(k) = \left\{\frac{N-1}{\left[\frac{N-m}{k}\right]k}\left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} |x(m+ik) - x(m+(i-1)k)|\right)\right\}/k \quad (4)$$

2.5 Clustering EEG Feature Data

The features extracted from the EEG data are clustered using the K-Means clustering algorithm before feeding into the E-CNN model. K-Means is an unsupervised machine learning algorithm for cluster analysis used to find patterns and group similar data points together in clusters. The "K" in K-Means represents the number of clusters desired. The algorithm works by initializing K centroids, randomly chosen from the data points, then iteratively assigning each data point to the nearest centroid, and finally recalculating the new centroids as the mean of all data points assigned to it. The process is repeated until the centroids no longer change or reach maximum iterations. The Euclidean distance among the data points is calculated using the following equation:

$$\mathbf{dist}(\mathbf{x}, \mathbf{center-point}) = \sqrt{\sum \mathbf{n}(\mathbf{x} - \mathbf{center-point})^2} \quad (5)$$

The new centroid is calculated and repeats the entire process until all data points are completed. The resulting clusters can then be used for various tasks such as data compression, classification, and pattern recognition.

K-Means clustering can be applied to EEG (Electroencephalogram) data to cluster similar EEG features. EEG data records the brain's electrical activity and can be processed to extract various features such as frequency, amplitude, and power. K-Means clustering can be used to group EEG features with similar properties into the same cluster, providing a more compact representation of the data and facilitating further analysis. Sometimes, EEG Saclograms [17] also used to predict epileptic seizures. In EEG feature clustering, the data points are the extracted EEG features, and the number of clusters (K) is usually chosen based on prior knowledge or empirical experimentation. The algorithm then groups the EEG features into K clusters so that the features in the same cluster are more similar to those in other clusters. This type of clustering can be helpful in various EEG analysis tasks, such as identifying patterns in brain activity and classifying EEG signals into different states (e.g., sleep vs. wakefulness). However, the success of K-Means clustering for EEG feature clustering depends on the quality of the EEG features and the choice of the number of clusters.

2.5.1 K-Means Based CNN

K-Means clustering can be integrated with the proposed Effective - Convolutional Neural Networks (E-CNNs) in various ways to improve their performance. Some of the common ways are:

2.5.2 Feature extraction

The K-Means clustering is performed on the activations of a pre-trained network to obtain compact and discriminative representations. K-Means can be used to extract features from images before feeding them into a E-CNN. The extracted features can be used to initialize the weights of the E-CNN, providing a better starting point for training.

2.5.3 Weight quantization

K-Means can be used to quantize a E-CNN's weights, reducing the network's memory and computation requirements. The quantization is performed by similar grouping weights together and replacing them with their centroid, which is calculated using K-Means.

2.5.4 Clustering-Based Regularization

K-Means clustering can be used to add a clustering-based regularization term to the loss function of the E-CNN. The regularization term encourages the feature representations learned by the E-CNN to form clusters that are similar to those obtained by K-Means clustering.

2.5.5 Data augmentation

K-Means clustering can generate additional training data by transforming the original data points into the centroids obtained from K-Means clustering. It can help increase the training set's size, leading to better performance of the E-CNN. A three stage “Concealed Information Test” using Wavelet transform, k-means clustering and multi-layer feed forward neural network [15] is also produces optimum results. Overall, integrating K-Means clustering with E-CNNs can help to improve their performance, efficiency, and robustness.

In this paper, the output obtained from the K-Means clustering algorithm is fed to E-CNN. Once the clustering process is done through the k-mean cluster and then combined with being segregated into appropriate testing and training samples, the sample sets are then stratified into 70% of training and 30% of testing data to be effectuated into various classification algorithms to analyze the precision of seizure identification. The classification algorithms that play a significant role in analyzing the identification performance are effectuated and compared in the next phase of the study. The features extracted from the fractal dimension of the Higuchi subsample set indicate that the parametric frequency spectrums are similar in evincing the abnormal waveforms from the processed signal waves. The semantics of a Convolution Neural Network [8] consists of input, output, and a fully connected layer. The model is designed with odd S-layers, which consists of information on the subsampling layers with computation of parity, even C-layers and F-layer, with all the performance computed using the mean square error method. The model uses the Hessian diagonal approximation method that aids in the computation of misclassifications. The Levenberg-Marquardt stochastic coefficient with increase and theta decrease rates are established for each epoch, with its maximum number set to 50. The activation function used for this model is the 'Hyperbolic tangent sigmoid function, which is computed in the following equation:

$$tansig\ (m) = \frac{2}{(1+\exp(-2*m))-1} \qquad \textbf{(6)}$$

The input signal is represented m. The K performance evaluation compares the classification accuracy with the other classifiers, such as SVM and ANN. The K-means-based E-CNN can provide better accuracy since the complexity level of classification is reduced by the K-means algorithm.

3. EEG Classification Using E- Convolution Neural Network

A Convolutional Neural Network (CNN) model can be used for processing Electroencephalogram (EEG) signals for various applications, such as sleep stage classification, seizure detection, and brain-computer interfaces. In our proposed indagation, we propel the concept of E-CNN which is efficient in analysing the accuracy, sensitivity and specificity.

In EEG signal processing, a E-CNN model can learn to identify patterns and features in the EEG signals that are indicative of specific brain states or events. It is achieved by training the E-CNN on a large dataset of EEG signals and the corresponding labels, such as the sleep stages, the presence or absence of seizures, or the user's intent in a brain-computer interface. The EEG signals are transformed during training into spectrograms or other image-like representations that a E-CNN can process. The model then learns to recognize patterns indicative of the corresponding labels in these representations. Once trained, the E-CNN can process new EEG signals and predict the corresponding brain states or events. This process is often faster and more accurate than traditional signal processing methods, as E-CNN can learn to identify complex patterns in the EEG signals that might not be easily discernible using traditional methods.

The entire feature dataset is divided into two parts: training and testing. 80% data is used for training the proposed E-CNN model, whereas 20% is used for testing the model. Some of the data is selected randomly for cross-validation. The total number of learning layers in the E-CNN is 5, and several pooling layers are 4 to reduce the dimensionality. The fully connected layer has four components, they are ***Left – fist, both – feet, right – fist and both – fists***. The optimal value is selected by comparing the output labels obtained from the above-said components. Finally, using the validation and testing process. This paper uses a 10-fold verification for validating the model.

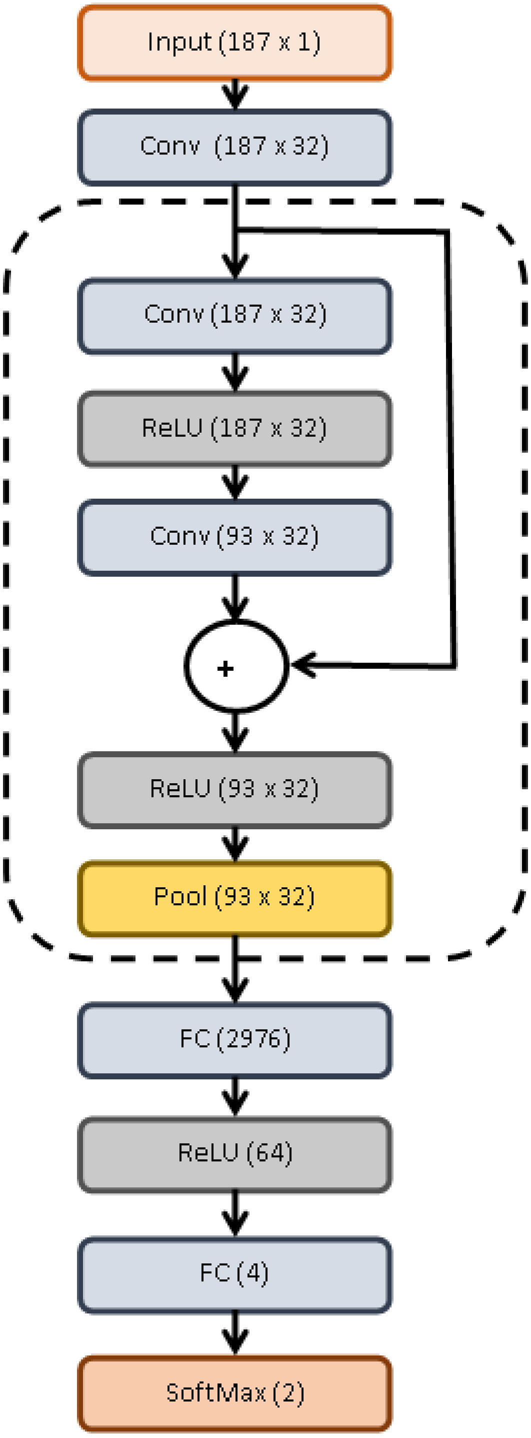
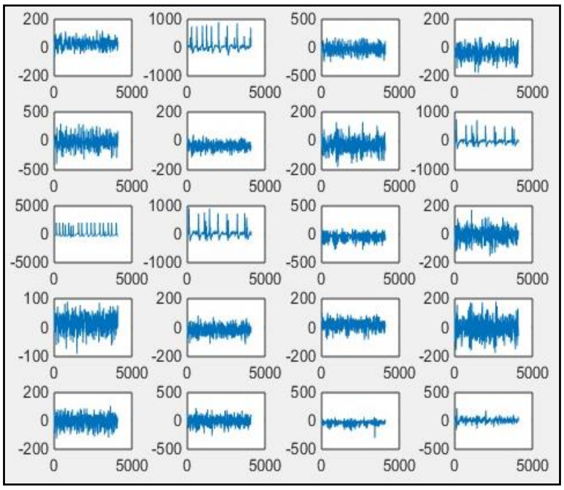


Fig 5. E-CNN Model for Feature Classification

4. Experimental Results and Discussion

The proposed novel framework explained in Section-3 is implemented in Python software, and the results are verified. The input data is visualized and shown in Figure-6 to understand the paper's workflow easily. Figure-6 shows 20 EEG data recorded for different people at different times, like sleep, wakeup, tension, etc. Figure-7 depicts the signal wave obtained through the Least Square Generative Adversarial Network Technique (LS-GAN).



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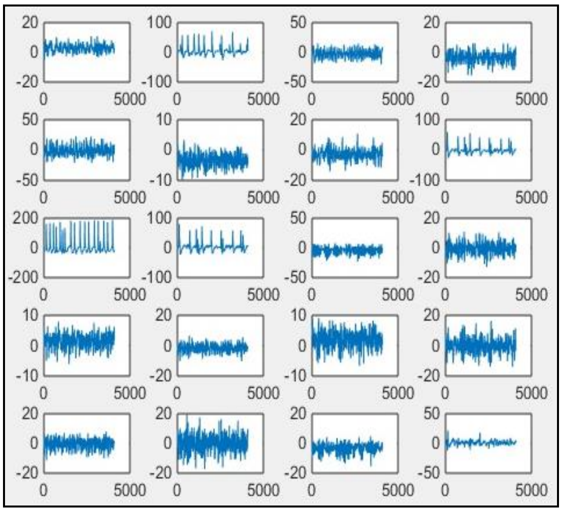

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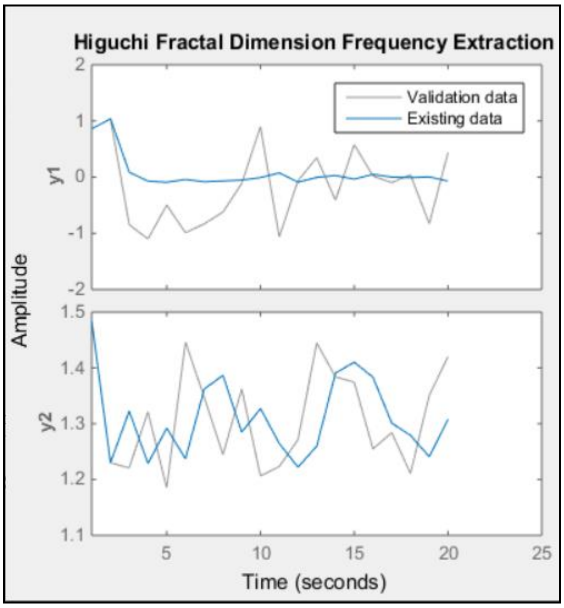

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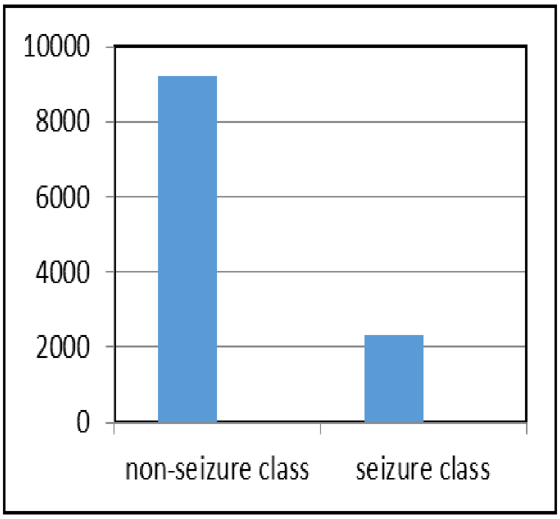
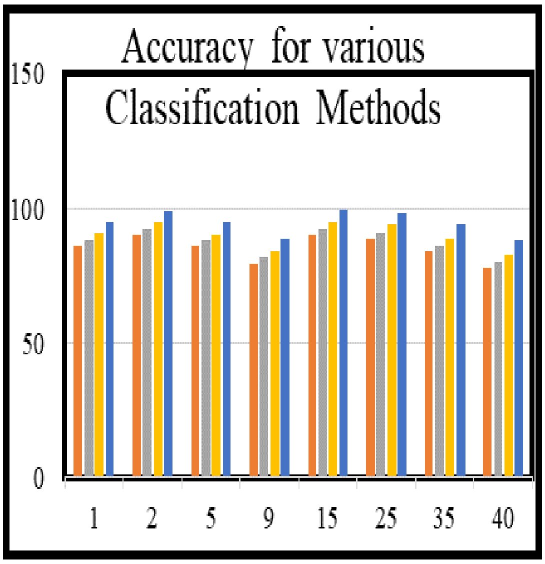


Fig 5. E-CNN Model for Feature Classification

Table-1. E-CNN Architecture Implemented in Python

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 187, 1)]	0
conv1d (Conv1D)	(None, 187, 32)	128
re_lu_4 (ReLU)	(None, 187, 32)	0
max_pooling1d (MaxPooling1D)	(None, 93, 32)	0
flatten (Flatten)	(None, 2976)	0
dense_6 (Dense)	(None, 64)	190528
dense_7 (Dense)	(None, 1)	65

Total params: 190, 721 ; Trainable params: 190, 721; Non-trainable params: 0



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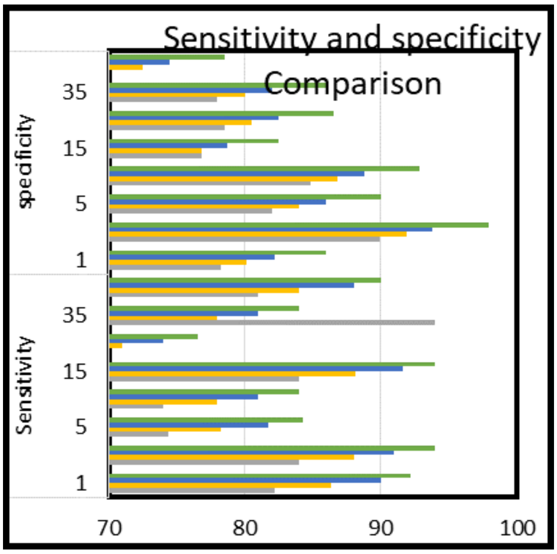

Fig 5. E-CNN Model for Feature Classification

Figure-8 evinces the result of feature extraction through the Higuchi fractal dimension, and the fit percentage in relevance to the validated input model. It should be noted that the lower fit percentage can indicate higher extracted features, while higher percentage can indicate that the features in the input signal hold higher precedence over the extracted frequency signal wave.

Figures 11 and 12 show the accuracy, sensitivity, and specificity assessments. The ability of a test to distinguish between sick and healthy persons influences its accuracy and diagnostic usefulness. The most accurate test should be used initially. In actuality, this does not occur since the accuracy of a test differs for predicting diseases and in different conditions. Accuracy, sensitivity, specificity, and positive and negative values are features of a test that represents the aforementioned qualities.

A test's accuracy is defined as its capacity to accurately distinguish between sick and healthy instances. To measure a test's accuracy, we must compute the fraction of true positives and true negatives in all analysed cases. This may be expressed mathematically as:

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad \textbf{(7)}$$

A test's sensitivity is its capacity to appropriately identify patient instances. We may measure it by calculating the proportion of true positives in patient instances. This may be expressed mathematically as:

$$\textbf{Sensitivity} = \frac{TP}{TP+FN} \qquad \textbf{(8)}$$

The specificity of a test is its capacity to accurately identify healthy instances; to assess it, compute the proportion of true negatives in healthy cases. This may be expressed mathematically as:

$$\textbf{Specificity} = \frac{TN}{TN+FP} \qquad \textbf{(9)}$$

This classification methodology is then applied and assessed with different epochs in terms of train accuracy, test accuracy, and cross-validation with different approaches to achieve the best results. The results are shown in the table below. While a combination of various epochs is implemented, the general pattern of the outcome evinces that the highest optimal result is obtained for overall accuracy to be at epoch 15 and the optimal maximal specificity and sensitivity percentage to be highest at epoch 3.

Table-2. Performance Evaluation in Terms of Accuracy

Method	Train Accuracy	Test Accuracy	Cross Validation
SVM [16]	98.16%	97.83%	0.975
DT [16]	100.00%	94.39%	0.9375
RF [16]	100.00%	97.87%	0.975
XG Boost [16]	100.00%	97.43%	0.97173913
K-Means E- CNN	100	98.2	99.13

5. Conclusion

Seizure detection is a burgeoning region of interest in the healthcare industry due to the escalated number of neurological disorders observed in the elderly, teens, and infants. Therefore, the constant pressure to construct a resilient exploratory solution is the motive behind the research in relevance to this field. The proposed indagation pivots to dissect the identification of seizure triggering in humans using the EEG signal waveforms. While various research has elaborated on diverse classification algorithms to analyze the performance of agnizing seizures, a compendium of classification algorithms instituted to anatomize the performance of the algorithms is a novel approach. The study further provides a comprehension of the necessity of entailing preprocessing and Denoising through LS-GAN, which assist in obtaining denoised signals for further feature extractions. The utilization of DWT for decomposing the signal wave and the HFD has rendered explicit features for accurate classification. The extracted features are made for classification performance through proposed E-CNN and other SVM, and ANN algorithms have established the juxtaposed results to clarify the simulative performance. The future study on seizure detection could attempt to employ a novel classification framework and analyze to dissect if the precision of performance surpasses the compendium of algorithms presented in this proposed study.

6. Future Works and Directions

The particular challenge with early seizure detection is the time insights in which the seizure may be recognized. Our proposed E-CNN method propels the results of accuracy, sensitivity, and specificity with different epochs. Further, we suggests some future works that can be done in the area which includes:

- Investigating the usage of various Deep Learning Models to increase seizure detection systems' effectiveness.
- Investigating the use of additional forms of EEG data, such as intracranial EEG, to increase seizure detection accuracy.
- Creating patient-specific seizure prediction algorithms that can provide advanced warning of an impending seizure.
- Evaluating seizure detection systems' performance on bigger datasets to establish generalizability and robustness.

Conflicts of interest

The authors declare no conflicts of interest.

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