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A Multi-Fusion Model for Seizure Prediction Through Electroencephalogram Signal Analysis Using HTT-RNN and Long Short-Term Dependencies Model

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ABSTRACT

A shift in electrical impulses in the brain causes epilepsy seizures. One percent of people worldwide suffer from seizures, which can lead to disability of the person. The electroencephalogram (EEG) signal is often used to measure brain activity. Prediction of seizures in earlier stages is still a challenging task in the existing system. The concept of a multimethod fusion technique for early seizure prediction was sparked by EEG data. The proposed model uses various techniques, such as a Bandpass filter, a Notch filter for filtering the Signal, and windowing techniques for data segmentation. The most effective method for handling nonlinear data is independent component analysis (ICA), which eliminates artefacts from the signals. Seizure features are examined using Hilbert-Huang Transform (HHT) techniques along with recurrent neural networks (RNNs) and long short-term dependencies model (LSTM), which uses time-frequency analysis to extract and perform the classification of the seizures. EEG signals divide seizure stages into three categories: preictal, ictal, and interictal. Early seizure prediction aids in giving the patient a preventative mechanism. The comparison is made with different algorithms such as RNN, LSTM, decision tree, and random forest concerning performance metrics such as precision, recall, F1 score, accuracy, and specificity. The proposed Hilbert Transform Technique-Recurrent Neural Network-Long Short-Term Memory (HTT-RNN-LSTM) model performs better than other existing algorithms with an F1 score rate of 92.2%, a recall value of 92.6%, a higher accuracy of 93.8%, and a higher precision of 93.0%.

1. INTRODUCTION

Epileptic seizures are a neurological condition that affects more than 50 million people globally and is brought on by aberrant electrical discharges in brain neurons. They cover a broad spectrum of challenges that might result in disability and significantly reduced quality of lifespan [1]. Epilepsy seizures will affect human behavior, and people with epilepsy are unable to live normal lives. Seizures can cause patients to faint, and there is a chance they could get hurt or even die. The recurrent occurrence of seizures is the cause of epilepsy, which is a condition of the neurological system [2]. There is still no known cure for seizures, despite tremendous medical progress, including the creation of several medications and treatments. The prediction of seizures is important for early diagnosis.

To acquire neurological signals from the brain, various methods can be incorporated, such as surgical (invasive) or nonsurgical (non-invasive) methods. To record brain impulses directly from the cortex's surface, microelectrodes are surgically inserted using an invasive technique [3]. The drawback of surgical implantation of electrodes on the brain may cause damage to the nervous system. Electroencephalograms (EEGs), Magnetoencephalograms (MEGs), FMRIs, and NIRS are popular invasive techniques used to extract brain signals [4]. An EEG-based methodology was the most effective and least expensive to set up among all the noninvasive techniques [5]. In this research, the prediction of seizure events using EEG signals was examined. EEG signals are recorded digitally to enable enhanced interpretation and analysis. EEG is useful in identifying the onset of epileptic seizures, as the normal activity of numerous brain cells becomes disrupted during a seizure [6].

According to numerous research studies, conventional EEG signal classification entails the following steps: Signal preprocessing, extraction of the features, and classification of the signals. Many research articles employ only one or two preprocessing methods for handling the original EEG signals, while some studies proceed without any signal preprocessing [7]. The electrodes were attached to the human scalp to record EEG signals, and there is a possibility of recording unwanted signals that could lead to incorrect seizure predictions. The system took into consideration the Limitations of the existing system. The proposed work concerns some preprocessing methods, such as filtering, artefact removal, Data segmentation, and signal normalization.

EEG recordings often contain multiple channels with signals originating from various regions of the human brain. Some channels must be selected in EEG seizure detection for special applications because the computational load of a seizure algorithm is proportional to the number of channels [8, 9]. The signals are essential for building a support system for seizure patients, and fewer channels are most important, since they enable real-time responses and low power consumption, both of which are essential, as is the system's operating time. The right channel selection techniques are very important for accurate seizure prediction. The most suitable channel selection methodologies are used in our proposed system to eliminate bad channels from EEG signals [8-10].

EEG signal analysis includes a significant contribution of the feature extraction of the EEG signal. Within the medical file, EEG signals from Multiple channels, along with the time of EEG signal acquisition, are available. Reducing dimensionality and compressing data are thus some of the ultimate purposes of feature extraction. Frequency and time-domain analysis, Spatial-Domain Analysis, Time-Frequency analysis, nonlinear features, and connecting features were the techniques applied in the study to differentiate brainwave patterns (alpha, beta, theta, and delta) and artefacts [11-13]. Although such methods demonstrate a significant improvement in EEG feature extraction, problems concerning the uniformity of methods such as wavelet transformation, even across a range of applications and in terms of noise and artifact resistance, still remain. The suggested system incorporates a hybrid model for extracting features from the signals.

The seizures can be classified into various stages, including the preictal stage, ictal stage, and postictal stage. A short period before the epileptic seizure (preictal) shows a slight deviation between normal and abnormal signals, followed by the seizure, which is the ictal stage. The stages directly after the ictal stage are known as the postictal stage, which lasts up to 10 minutes. The ictal stage is a period of intense electrical activity in the brain that follows the pre-ictal stage, which may present with symptoms such as headache and fatigue. This is followed by the post-ictal phase, during which the patient recovers their previous state before the ictal and endures symptoms such as headache, drowsiness, and confusion [6, 14-17].

The following are the main contributions of the work:

- A comprehensive preprocessing methodology was implemented for EEG signal analysis, utilizing ICA for enhanced artifact removal.
- Time-frequency analysis facilitated the localization of nonstationary and nonlinear real-time signals, with the HHT offering advantages over classical methods like Fourier and Wavelet transforms (WTs) by employing EMD and IMF for feature extraction.
- Deep learning techniques, specifically RNN and LSTM networks, were proposed for effectively learning, extracting, and classifying seizure stages with predictive capabilities.

The rest of the paper is presented as follows. Literature surveys of the existing methodology are discussed in Section 2. The proposed methodology and its architectural flow are given in Section 3. Experimental results and discussion of findings are described in Section 4. The conclusion of the study and future work is given in Section 5.

2. LITERATURE SURVEY

Sharma et al. [18] also suggested a seizure detection system of nonstationary EEG signals using Adaptive Time Frequency Flexible Wavelet Transform (ATFFWT) with Fractal Dimension (FD) feature extraction.

The article by Übeyli [19] proposed a new multiclass seizure classification strategy based on SVM with an error-correction mechanism. In this study [20], neural-network-based EEG pattern recognition was investigated, in which the multilayer backpropagation network was incorporated with automated artifact-detection and artifact-removal methods to facilitate the segmentation of the signal and subsequent feature-extraction.

Yan et al. [21] used Short-Time Fourier Transform (STFT) to extract time-frequency features and proposed a three-transformer-tower model equipped with attention mechanisms to overcome the limitations of the signal length and enhance the accuracy of categorization. A convolutional network with a CGRNN was suggested in Affes et al. [22], where time-frequency EEG characteristics of the Boston Children's Hospital database are used to predict seizures.

Cui et al. [23] described a Bag-of-Wavelet model that was coupled with Extreme Machine Learning, where interictal and preictal codebooks were built through clustering. In this study [24], the Shannon entropy method is combined with the KNN classifier to classify pre-seizure and non-seizure states. This research article used the Children's Hospital Boston – Massachusetts Institute of Technology (CHB-MIT) datasets in its study. Perez-Sanchez et al. [25] have used the Discrete Wavelet Transform (DWT) and fractal dimension features with SVM and other machine learning classifiers in the detection of seizures.

The seizure prediction method using high-frequency oscillation (HFO) was reported in this study [26], where an automated detector was developed to show an ROC greater than 0.80 in either preictal or interictal phases. Song et al. [27] suggested a single-channel seizure recognition system based on ONASNet and brain rhythmic recurrence biomarkers, which is compared to the architecture models. Other researchers used Morlet wave transforms on CNNs [28], line-length features based on wavelets and ANN classifiers [29], hybrid wavelet and empirical mode decomposition (EMD) methods [30], CNN-based prediction of the seizure onset zone [31], BiLSTM+attention mechanisms [32], wavelet-filtered Bi-Gradient Recurrent Networks [33], and RCMDE-based complexity of the EEG [34].

3. PROPOSED METHODOLOGY

Despite the many advancements in the study of EEG data processing, seizure prediction remains a challenging task. Three phases of brain activity are distinguished in epilepsy: preictal, ictal, and postictal states. Research aims to identify the preictal stages of epileptic seizures. The time right before a seizure begins is known as the preictal stage. If seizures are identified before they occur, drugs can be provided to prevent the occurrence of seizures in a patient.

The Dataset used for the research is the CHB-MIT Scalp EEG Database, which was collected at the Children's Hospital Boston. The EEG recording is collected from 22 patients, consisting of 17 females and 5 male patients, with an age range of 1 to 22 years. 22-channel scalp data are recorded for each patient with several trials. The sampling rate of recorded EEG signals at 256 samples per second was analyzed.

Figure 1 shows the architecture diagram of the Hilbert

Transform Technique-Recurrent Neural Network-Long Short-Term Memory (HTT-RNN-LSTM) Multi-fusion model. EEG signals are given as the input to the model. Various techniques are applied to the preprocessing of EEG signals, the channel selection method is applied to select the appropriate channel for seizure prediction, and after that, feature extraction and classification are done by HTT, RNN, and LSTM multi-fusion method to predict the seizure.

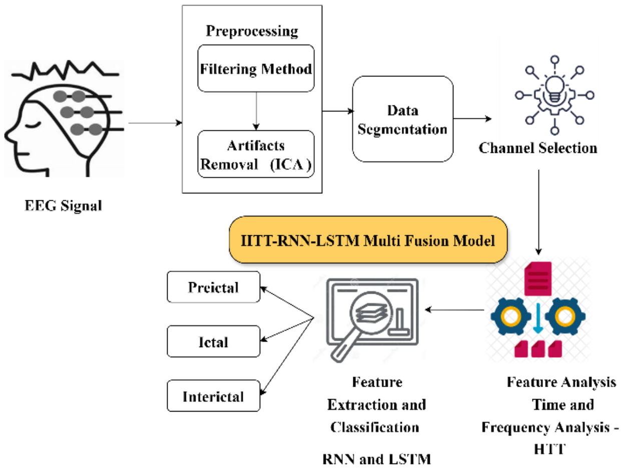

Figure 1. Architecture diagram of the Hilbert Transform Technique-Recurrent Neural Network-Long Short-Term Memory (HTT-RNN-LSTM) multi fusion model

3.1 Electroencephalogram preprocessing

The data preprocessing techniques are used to enhance the signal quality of the EEG signals. This includes noise reduction, baseline correction, and filtering to eliminate artefacts and to improve the SNR.

3.1.1 Filtering techniques

In EEG Signal processing, the filtering process involves extracting or altering the signal components while suppressing others. The bandpass filter and a notch filter were applied to the EEG data in this investigation.

Bandpass filter. The bandpass filter allows EEG signals within the 1 Hz to 100 Hz range to pass through, attenuating frequencies outside this range.

$$y[n] = \sum_{f=0}^{L-1} h\,[f].x[-f] \qquad (1)$$

From Eq. (1), the length of the filter kernel is given as L and the filter coefficients as h[f].

Notch filter. Applying a notch filter at 60 Hz targets narrow frequency bands by removing the power line noise but maintaining the originality of the EEG signal while reducing interference. As a result, data cleanliness is improved.

$$H(s) = \frac{s^2 + \omega_0^2}{s^2 + \frac{\omega_0}{Q}s + \omega_0^2} \qquad (2)$$

From Eq. (2), where ω_0 is the notch frequency, and Q is the quality factor, which determines the width of the notch.

Preprocessing of the EEG signals plays a vital role in the analysis of EEG signals for the prediction of the disease. However, preprocessing must be done in an appropriate way, as it preserves brain-related information in the EEG.

3.1.2 Artifacts removal

The artifacts induced in the EEG, such as eye blinks, power line interference, and muscle movements, must be identified and removed to achieve good EEG decoding performance. Removal of artifacts can often require varying degrees of human expert involvement. Some methods require human expertise, such as visual inspection, while others require minimal input for adjusting hyperparameters in wavelet-based ICA [35]. Techniques leveraging human knowledge include a threshold of the amplitude, segments with high variance are identified, and high amplitude EoG segments are responsible for noise-related EEG blink [36]. Many studies highlight the effectiveness of ICA in reducing human intervention while ensuring reliable artifact separation [36-39]. For removing the EEG signals, this paper also uses techniques such as independent component analysis (ICA).

Let *X* = [x1, x2…. xn] represent the mixed signals. The matrix is represented as *X*, with $N_{datapoints}$ * $M_{Channel}$, and then calculate the *Mean* (*X*) and then subtract the *Mean* (*X*) for each Signal *X*.

$$XY = X - Mean(X) \qquad (3)$$

From Eq. (3), represent the signals and then perform the whitening of data to get the components that are uncorrelated, with a covariance between any two elements is zero, and each component has a variance of 1.

$$X \text{ whitening} = WX \qquad (4)$$

From Eq. (4), where W is the whitening matrix. W is $M_{channel}$ * $M_{Channel}$ and is typically initialized with random values. The linear transformation of ICA makes the resulting components as independent as possible. To achieve this process, maximize the non-Gaussianity of the components. The value of W is updated through higher-order moments (kurtosis) or mutual information using the FastICA algorithm to obtain the EEG without artifacts. The original EEG signals, which are now free of noise and artifacts, are restored by reconstructing the remaining subcomponents after the noise-prone and artifact-prone components have been eliminated.

EEG preprocessing is carried out as follows: filtering, artifact removal, and data segmentation. Before ICA, bandpass (1–100 Hz) and 60Hz notch filtering are used to improve the signal-to-noise ratio and separation between components. ICA is applied to the FastICA algorithm, with the number of components equal to the number of EEG channels, and artifact-related components are defined based on abnormal amplitude and spectral properties. ICA-based artifact-removal quantitatively measured by SNR, Signal-to-Artifact Ratio (SAR), and correlation coefficient is compared with the WT, Adaptive Filtering, and Principal Component Analysis (PCA). The findings support the claim that ICA with filtering is the most effective at denoising, as visual analysis suggests.

3.1.3 Data segmentation

The Signals of individual channels were segmented with a 5-second window for the CHB-MIT dataset. Continuous EEG signals can be separated into fixed-length signals for feature extraction with the aid of data segmentation. A 5 s window was selected because it allows for more precise classification. It can successfully record the preictal, ictal, and postictal stage transitions. If the segment window is large, it might dilute the correct pattern of the data, and feature extraction using too small segments is sufficient to identify the useful patterns. With a window size of 5 seconds and a sampling rate of 256, there are 1280 samples per window. This length had positive results in several investigations [40-42].

3.2 Channel selection

An electrode that is delivering faulty or distorted data is referred to as a "bad channel." The quality of recorded EEG signals might be adversely affected by poor channels, which can also lead to inaccurate or deceptive analysis. The Bad channels are identified by using different methods such as Kurtosis, Variance, and Correlation. Kurtosis is employed to quantify the impulsiveness and presence of abnormal spikes in EEG signals and is defined as Eq. (5).

$$Kurtosis(K) = \frac{1}{n}\sum_{i=1}^{n}(\frac{(xi-\mu)}{\sigma})^4 \tag{5}$$

where, n denotes the number of samples in a given EEG channel, xi represents the EEG signal amplitude, μ is the mean value, and σ is the standard deviation of the channel signal.

Statistically, the value of kurtosis of 3 implies a normal (Gaussian) distribution. EEG channels with kurtosis values much larger than 3 are due to heavy-tailed distributions caused by impulsive noise, motion artifact, or electrode failure. In this respect, channels with kurtosis K > 3 are considered abnormal and are eliminated. This statistical threshold choice is both statistically justified and consistent with the literature on EEG artifact detection. Moreover, using the CHB-MIT EEG dataset empirically showed that channels with such artifacts consistently had kurtosis values above this threshold, thus confirming its applicability to real-life EEG channel screening.

Variance-based filtering is employed to eliminate low-information channels, enhancing system robustness by setting thresholds for channels with variance below 50% of the global channel variance. This decision is made since low variance indicates a channel's minimal contribution to the signal or possible detachment of the electrode. To further reduce redundancy, Pearson's correlation analysis is utilized, excluding channels that show correlation coefficients exceeding 0.95 with other channels, thus preserving discriminative content while minimizing redundancy. The effectiveness of this channel selection strategy is assessed by comparing seizure prediction results pre- and post-channel removal. Experimental results demonstrate that the optimized channel set leads to improved classification stability and increases average seizure prediction accuracy by approximately 2, underscoring the significant positive impact of statistically justified channel selection on model performance.

3.3 Feature analysis

The preprocessed EEG signals are used to extract the features from the de-noised signals for further processing of the signals. The method for feature extraction can be divided into single-dimensional and multidimensional feature extraction methods. Examples of single-dimensional feature extraction techniques are time, frequency, or spectral domain, and decomposition domain [43]. A statistical method called time-domain analysis offers an in-depth understanding of changes in signal amplitude, whereas frequency-domain analysis identifies patterns in the data. The Decomposition domain is the practice of breaking down a signal into its constituent elements using certain mathematical techniques or algorithms. The multi-dimensional Feature Extraction Techniques involve combining more features to extract features with more, such as the time-frequency domain retrieved based on suggestions from several research papers.

Conventional time-frequency analysis methods like FT and STFT struggle with the dynamic nature of epileptic EEG signals [44, 45], which are nonstationary due to sudden neuronal discharges. To address this, adaptive analysis techniques are necessary. The Hilbert-Huang Transform (HHT) offers a parametric approach for such analysis, decomposing EEG signals into Intrinsic Mode Functions (IMFs) through EMD and Hilbert spectral analysis. These IMFs represent narrow-band oscillatory components that help localize seizure patterns, revealing strong correlations between their instantaneous properties and neurophysiological indicators such as epileptiform spikes and preictal energy accumulation.

3.3.1 Empirical mode decomposition

EEG measurements of epileptic activity are inherently nonlinear and nonstationary, as bursts of neuronal synchronization, short-lived oscillatory outbursts, and rapid spectral energy fluctuations occur abruptly. The traditional time-frequency analysis methods, like Fourier and wavelet analysis, assume some predefined basis functions and a predetermined resolution, and this restricts their capability to describe the dynamics of seizures effectively. Conversely, the EMD is a purely data-driven, adaptive algorithm that splits a signal according to its local time-scale features, which makes it very convenient for the analysis of epileptic EEG.

<u>Algorithm for EMD</u>:

Step 1: EEG signals $E(t)$

Step 2: Evaluate all peaks and troughs of $E(t)$

Step 3: To calculate upper envelope $X_{max(t)}$ and lower envelope $X_{min(t)}$ assign the peak

Step 4: Calculate the Envelope's mean E_{Mean} with respect to time in Eq. (6)

$$\left(\frac{X_{Max(t)}+X_{min(t)}}{2}\right) = E_{Mean(t)} \tag{6}$$

Step 5: Subtract the E_{Mean} from the signal as $Y(t)$

IMF Conditions

(i) The number of zero crossings and extrema of the Signal must differ by at most one.

(ii) The local average of the upper and lower envelopes should be approximately zero.

This step is taken to ensure that every extracted IMF is a narrow-band oscillatory component with a discrete instantaneous frequency.

Step 6: Check $Y(t)$ satisfies IMF conditions

If condition is True:

It is accepted as an IMF, and the sifting process stops for that component

If condition is False:

Repeat the above process until the IMF is satisfied.

Step 7: To extract more IMFs, subtract the IMF from the current signal and repeat. Signals are reconstructed using Eq. (7).

$$X_m = E(t)\sum_{i=1}^{n} \mathrm{IMF}_i(t) + r(t) \tag{7}$$

after extracting all IMFs, where $r(t)$ is the residual signal.

Each IMF receives an application of the HT to determine the signal's immediate frequency and amplitude. For an IMF $\mathrm{IMF_i(t)}$, compute for the signal in Eq. (8):

$$Z_m(t) = IMF_i(t) + jH[IMF_i(t)] \tag{8}$$

where, $H(.)$ denotes the Hilbert Transform operator and j is the imaginary unit. This analytic representation allows the calculation of the instantaneous amplitude and instantaneous frequency of EEG signals, providing high-resolution time-frequency characterization. These representations have been beneficial for identifying transient epileptic characteristics, seizure-onset patterns, and abnormal rhythmic oscillations, thereby providing a solid theoretical basis for combining EMD with Hilbert-based time-frequency analysis in the processing of epileptic EEG signals.

3.4 Feature extraction and classification

In the proposed framework, seizure prediction is formulated as a multiclass temporal classification problem comprising interictal, preictal, and ictal EEG states. To effectively capture the complex temporal dynamics preceding seizure onset, an HTT–RNN–LSTM multi-fusion model is developed, in which time–frequency representations obtained from the HTT are exploited for hierarchical temporal feature learning and classification.

3.4.1 Input representation

EEG signals are split into overlapping, 5-10 seconds time windows after preprocessing and HTT-based time frequency decomposition. A single EEG segment is modeled as a two-dimensional feature matrix of size (time steps, num features), where time steps equals the size of a temporal sample window and num features equals the number of EEG channels and the number of extracted features of the HTT. Both frequency-localized seizure features and temporal continuity are maintained in this representation.

3.4.2 Complementary RNN–LSTM feature learning

RNNs are naturally sequential processing machines and perform better on short-term periodicities in EEG signals. The RNN component in the proposed architecture captures sudden changes and transient epileptic form discharges that often occur during early preictal changes. The property of having a hidden state that recurs periodically ensures that the RNN acquires temporal correlations of short length that are important in identifying abrupt variations in brain activity.

Nonetheless, standard RNNs are prone to vanishing gradients, limiting the model's capacity to capture long-term dependencies. To overcome this drawback, Long Short-Term Memory Model (LSTM) networks are introduced as a supporting learning concept. LSTMs have gated memory cells that selectively retain and forget information, making them especially useful for modelling low-rate, evolving preictal dynamics and long-term abnormal oscillations in EEG signals.

The following model takes advantage of the complementary capabilities of these architectures:

- RNN layers accentuate high-frequency temporal variations, which are short-term,
- The LSTM layers can capture long-term temporal structure and the cumulative progression of seizures.

3.4.3 Fusion strategy and network architecture

The proposed HTT-RNN-LSTM model will incorporate feature-level fusion, rather than direct model aggregation. EEG sequences created by HTT are then fed into an RNN layer to clean up the short-term time-coded representations. The RNN output sequence is then passed through a stack of LSTM layers, enabling hierarchical temporal abstraction.

The LSTM module has three layers with 128, 64, and 32 hidden units, respectively. This gradual decline in the number of neurons helps refine features in a hierarchy and control the model's complexity. A dropout rate of 0.2 is used, with dropout applied after each LSTM layer to prevent overfitting and retain temporal dynamics associated with seizures. The hidden state computation at time step t is expressed as Eq. (9):

$$r = f(W_{\mathrm{hx}}x_t + W_{hh}\, h_{t-1} + b_h) \tag{9}$$

where, x_t is the input feature vector, h_{t-1} is the previous hidden state, W_{hx} and W_{hh} are the input and recurrent weight matrices, b_h is the bias term, and $f(.)$ denotes the Rectified Linear Unit (ReLU) activation function.

The network can thus automatically learn the relative strengths of short-term RNN-derived features and long-term LSTM-derived features through end-to-end backpropagation; therefore, the fusion coefficients do not need to be set manually.

3.4.4 Hyperparameter selection rationale

The choice of the most essential architectural hyperparameters in the proposed HTT-RNN-LSTM implementation is informed by empirical tests, architectural stability principles, and previous deep learning experience with EEG time-series modeling. The three-layer LSTM architecture is used to enable hierarchical temporal abstraction, with the low-level capturing short-term temporal changes and the high-level capturing long-term changes in the seizure pattern. The gradual decrease in the number of neurons (128, 64, and 32 units) is intended to balance representational capacity and model complexity, avoiding over-parameterization while maintaining discriminative features related to seizures. The dropout rate of 0.2 is chosen after initial experiments to alleviate overfitting without attenuating clinically meaningful temporal dynamics, which are essential for effective seizure forecasting.

3.4.5 Classification layer

The resulting temporal features are given to a fully connected dense layer of 128 neurons, which serves as a high-level feature integrator. The last output layer uses a Softmax activation function, which produces probabilistic predictions for the three seizure states: interictal, preictal, and ictal. This multiclass classification scheme enables early seizure prediction by correctly identifying preictal EEGs before seizure onset.

4. RESULTS AND DISCUSSIONS

In this section, a detailed analysis of the proposed HTT-RNN-LSTM model for predicting epileptic seizures is presented. The study of experimental results is conducted through various validation plans designed to ensure that the results are based on a solid statistical foundation, clinically relevant, able to withstand inter-patient variability, and amenable to real-time implementation.

4.1 Performance metrics

The Evaluation metrics used for the HTT-RNN-LSTM proposed model, in terms of accurate prediction of seizure, Sensitivity of data, Specificity of prediction, Precision, Recall, and F1-score, are computed.

Accuracy measures a test's effectiveness in distinguishing patients and healthy cases by considering true positives and negatives. It measures the model's overall performance as in Eq. (10).

$$Accuracy = \frac{Correct\ positive\ state + Correct\ negative\ state}{Total\ samples} \quad (10)$$

Test Precision is measured by the given Eq. (11).

$$Precision = \frac{Correct\ positive\ state}{Correct\ positive\ state + False\ positive\ state} \quad (11)$$

Test specificity evaluates its accuracy in identifying healthy cases by measuring the proportion of true negatives among all healthy cases. It is referred to as the true negative rate represented in Eq. (12).

$$Specificity = \frac{Correct\ negative\ state}{Correct\ negative\ state + False\ positive\ state} \quad (12)$$

Seizure prediction's true positive rate is determined when the system failing to predict a seizure (false negative) can have severe consequences for the patient, as represented in Eq. (13).

$$Recall = \frac{Correct\ positive\ state}{Correct\ positive\ state + false\ negative\ states} \quad (13)$$

The combination of Precision and recall is used to obtain the $F1$ score and is represented in Eq. (14).

$$F1 = 2.\frac{Precision * Recall}{Precison\ + Recall} \quad (14)$$

When the $F1$ Score is 1, it indicates a model is perfect with high precision (correct seizure predictions), high recall (correctly identifies all seizures), with no false positives or false negatives. If the $F1$ Score is 0, the model fails to make correct predictions.

4.2 Cross-validation performance analysis

In this experiment, 80 percent of the EEG data is used for training, and the remaining 20 percent for testing. To achieve statistical reliability and eliminate bias introduced by the train-test split, several validation strategies are used. Besides the traditional split, the five-fold cross-validation scheme (random shuffling) is used, and all reported performance measures are averages across the five folds. This plan improves the accuracy and the statistical stability of the evaluation during the experiment.

Table 1 reveals the performance of the proposed model with five-fold cross-validation. The consistency across all folds and the slight standard deviation of assessment measures demonstrate the statistical consistency of the proposed framework and indicate that a particular data split does not drive the findings.

Table 1. Performance of the proposed Hilbert Transform Technique-Recurrent Neural Network-Long Short-Term Memory (HTT–RNN–LSTM) model under five-fold cross-validation on the Children's Hospital Boston – Massachusetts Institute of Technology (CHB-MIT) dataset

Fold	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
Fold 1	93.6	92.4	94.3	92.0
Fold 2	93.9	92.7	94.6	92.3
Fold 3	94.1	92.9	94.8	92.5
Fold 4	93.7	92.5	94.4	92.1
Fold 5	93.8	92.6	94.5	92.2
Mean ± Std	93.8 ± 0.19	92.6 ± 0.19	94.5 ± 0.18	92.2 ± 0.19

Table 2. Subject-wise performance of the proposed Hilbert Transform Technique-Recurrent Neural Network-Long Short-Term Memory (HTT–RNN–LSTM) model under leave-one-subject-out validation (Children's Hospital Boston – Massachusetts Institute of Technology (CHB-MIT) dataset)

Subject ID	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
chb01	93.5	92.3	94.1	92.0
chb02	94.0	92.8	94.7	92.4
chb03	93.6	92.5	94.4	92.1
chb04	93.9	92.7	94.6	92.3
chb05	93.8	92.6	94.5	92.2
chb06	94.0	92.9	94.8	92.5
Mean ± Std	93.8 ± 0.18	92.6 ± 0.18	94.5 ± 0.17	92.2 ± 0.18

4.3 Patient-independent validation (Leave-One-Subject-Out)

To evaluate model generalization more thoroughly, patient-independent validation is conducted on the CHB-MIT data using a leave-one-subject-out (LOSO) protocol. Here, the EEGs of one subject would be used for testing, and the other subjects would be trained. This is done for every subject, and the proposed model is tested on entirely unknown patient data, providing a stringent measure of its generalization capability across subjects.

Table 2 shows subject-wise seizure predictions using an LOSO validation scheme. The high accuracy, sensitivity, and specificity maintained across subjects, as well as the low standard deviation, demonstrate that the proposed model is resistant to inter-patient variation and has the potential to generalize efficiently to previously unseen patient data.

4.4 Clinical performance indicators

False positives and false negatives present significant challenges in medical seizure prediction systems. This study evaluates the HTT-RNN-LSTM framework's practical utility using clinically meaningful metrics alongside standard classification measures. The False Positive Rate (FPR), crucial for minimizing unnecessary alarms that can increase patient anxiety, is kept low in this model, demonstrating a balance between early detection and alarm reliability. The model's efficiency is quantifiable through prediction delay time, indicating its ability to timely identify the preictal phase before seizure onset, thus allowing for preventive measures like warnings or medication adjustments. Additionally, sensitivity remains consistent across various prediction horizons, ensuring detection accuracy even with extended early warning periods. Overall, the HTT-RNN-LSTM model successfully balances the need for early seizure alerts with the management of false alarms, indicating potential utility in real-world epilepsy monitoring.

Table 3. Comparison of the false alarm rate and prediction delay is made with the existing system

Model	FAR/h	Prediction Delay
Decision tree	1.2–2.0	18–30 s
Random forest	0.3–0.8	10–20 s
RNN	0.15–0.5	5–12 s
Proposed model	0.05–0.2	2–6 s

Note: RNN = Recurrent neural network

In Table 3, the proposed model has 0.05–0.2 FAR/h and prediction delay from 2s-6s, which is higher when compared to existing models. In medical seizure prediction systems, both false positives and false negatives have serious clinical consequences. Therefore, in addition to conventional classification metrics, clinically relevant indicators are evaluated to assess the practical applicability of the proposed HTT–RNN–LSTM framework.

4.5 Signal preprocessing and feature robustness analysis

Consider the original signals from the CHBMIT dataset given in Figure 2, which depicts the EEG non-seizure signals, and Figure 3, which depicts seizure EEG signals.

Figure 4 illustrates the EEG signals in blue, showing their temporal and amplitude variations. After applying filtering techniques to remove power line interference, the refined signals are shown in red. Figure 5 represents the artifact removal process using ICA combined with filtering methods. The two extracted components with respect to time and amplitude are highlighted in blue and green, demonstrating the effectiveness of the technique. Figure 6 shows the Fast ICA components in terms of frequency and power spectral density.

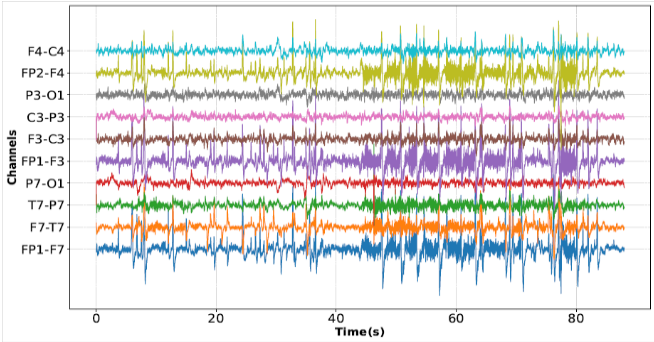

Figure 2. Electroencephalogram (EEG) signal with non-seizure

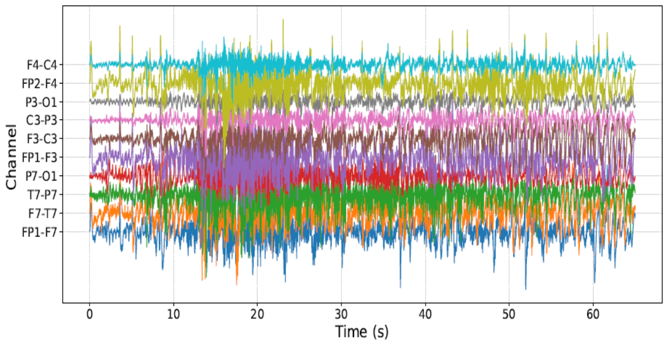

Figure 3. Electroencephalogram (EEG) signals with seizure

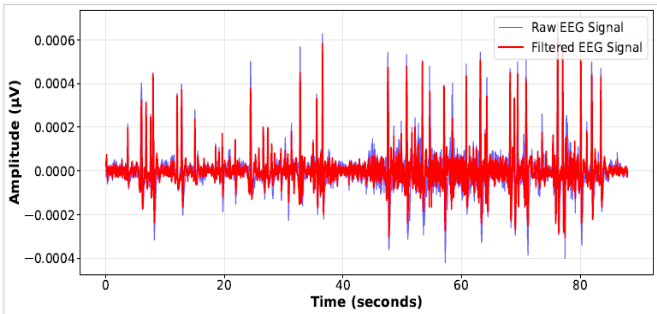

Figure 4. Original electroencephalogram signals vs. filtered electroencephalogram (EEG) signal

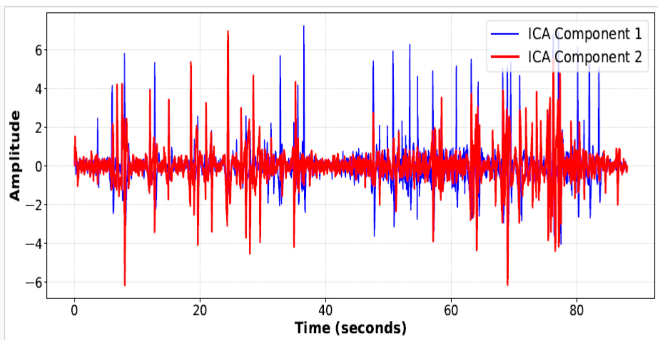

Figure 5. Fast independent component analysis (ICA) components

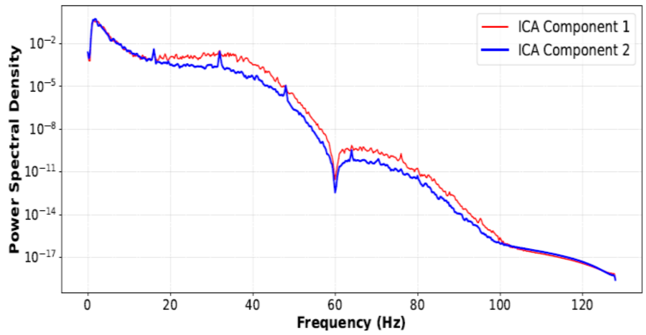

Figure 6. Independent component analysis (ICA) components with frequency and power spectral density

Figure 7 represents the Time and frequency representation of the EEG signals with respect to the spectrogram for ICA components analysis for the removal of artifacts in the signals. Figure 8 represents the PCA component analysis for the removal of the artifacts present in the EEG signals.

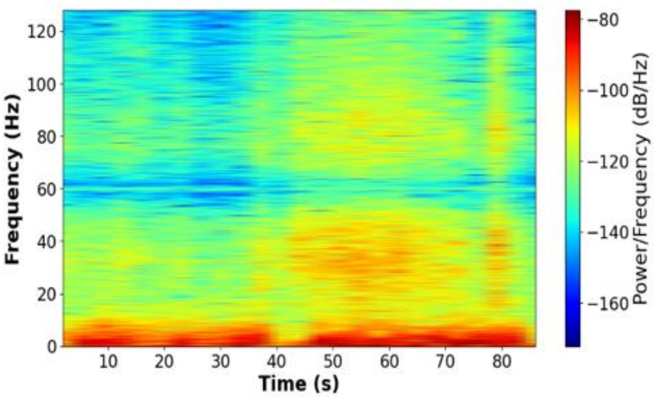

Figure 7. Time and frequency representation in a spectrogram

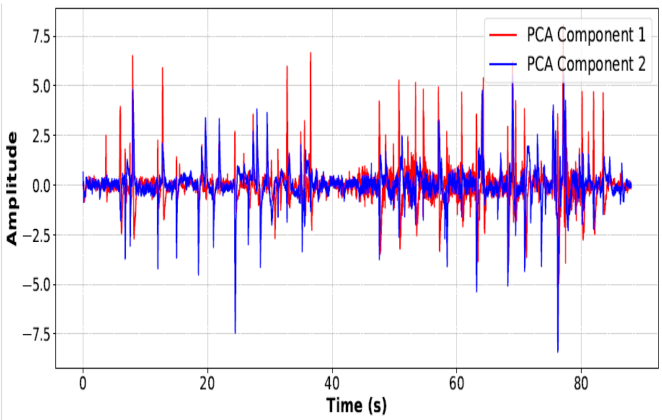

Figure 8. Principal Component Analysis (PCA) components for artifacts removal

Figure 9 demonstrates that the artefact removal methods, such as ICA and filtering methods, WT, Adaptive filtering, and PCA, are compared with respect to Signal with respect to Noise Ratio (SNR), Signal concerning Artefacts Ratio (SAR), and Coefficient of Correlation. The proposed ICA and Filtering method gives the highest value of 14.2 of SNR, whereas other methods give a lesser value, such as 13.5, 12.8, and 11.9. The correlation coefficient is higher at 95% when compared with other models.

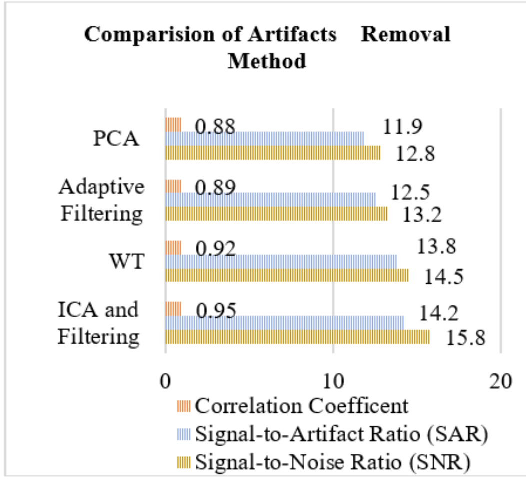

Figure 9. Comparison of various artifact removal methods

Table 4. Quantitative comparison of feature extraction methods

Feature Extraction Method	Feature Dimension	Accuracy (%)	F1-Score (%)
Power Spectral Density (PSD)	High	87.4	86.9
Wavelet Transform (WT)	Medium	90.1	89.6
HTT (Proposed)	Reduced	93.8	92.2

A comparative analysis reveals that the HTT-based feature extraction significantly improves classification performance and reduces dimensionality compared to conventional techniques like WT and PSD. The method enhances classification accuracy and F1-score, demonstrating superior pattern separability for seizure-related patterns and increased robustness in seizure prediction.

Table 4 compares HTT-based feature extraction with conventional PSD and WT methods, showing that HTT delivers higher classification accuracy and F1-scores while using fewer features. This indicates HTT's superior ability to retain seizure-relevant information compared to traditional time-frequency features.

4.6 Robustness to patient variability, signal quality, and boundary conditions

Epileptic EEGs show significant variability influenced by patient differences, recording equipment, electrode placement, and signal quality. A systematic study evaluated the robustness of the HTT-RNN-LSTM framework against these variabilities, focusing on inter-patient differences, noise interference, and sensitivity to parameters. The framework's inter-patient robustness was assessed via a LOSO validation, demonstrating high accuracy and sensitivity, signifying that seizure temporal patterns can be generalized across patients, thus indicating that the model is not tailored to individual cases. Furthermore, the model's resilience to noise and signal quality degradation was tested on EEG segments affected by artifacts and low signal-to-noise ratios common in clinical recordings. By integrating artifact removal methods with HTT-based feature extraction, the model maintained its predictive performance even with increasing noise levels. A parameter sensitivity analysis was conducted, varying hyperparameters like learning rate, dropout rate, and LSTM hidden units, showing that performance differences were minimal, suggesting the framework operates effectively within set parameters without requiring fine-tuning. Overall, the findings confirm that the HTT-RNN-LSTM model is stable amidst patient variability, recording condition discrepancies, and parameter disturbances, validating its practical application for epilepsy monitoring.

4.7 Hyperparameter sensitivity and performance impact analysis

A sensitivity analysis examined the effect of hyperparameters like LSTM layers, hidden neurons, and dropout rates on model performance under consistent training conditions. It evaluated configurations with 1 to 4 layers, finding that more layers minimally improved accuracy but raised computational demands and training instability. The tested architecture of 128-64-32 units balanced predictive accuracy and generalization, but larger sizes risked overfitting, and smaller ones reduced temporal representation. A dropout rate of 0.2 yielded stable validation results, while higher rates decreased sensitivity in preictal detection, and lower rates increased false positives. The analysis concluded that the hyperparameters remain within the model's stable operating range, highlighting the robustness of the HTT-RNN-LSTM model.

4.8 Comparative model performance analysis

Table 5 shows the classification of the different phases with an interictal precision of 95.6%, for preictal is 92.4%, and ictal is 94.9%. The early prediction of preictal seizure to give an alert warning, thereby improving the patient's health condition.

Table 5. Classification of the seizure phase and its metrics

Classification Phase	Precision (%)	Recall (%)	F1-Score (%)
Interictal	95.6	96.1	95.8
Preictal	92.4	91.8	92.1
Ictal	94.9	95.3	95.1

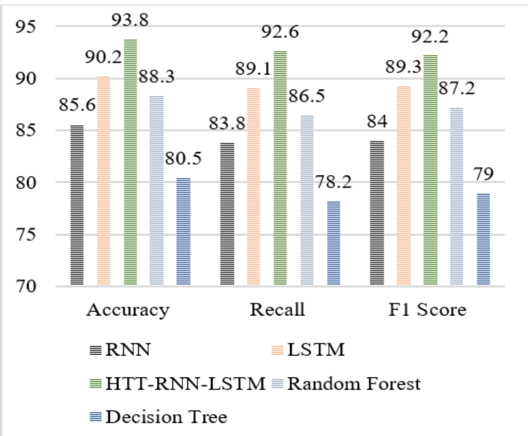

Figure 10. Comparison of Hilbert Transform Technique-Recurrent Neural Network-Long Short-Term Memory (HTT-RNN-LSTM) with existing methods

The proposed method, HTT-RNN-LSTM Model, achieves a greater accuracy of 93.8%, whereas the other models are RNN (85.6%), LSTM (90.2%), Decision Tree (80.5%), and Random Forest (88.3%). The proposed model achieves a precision of 93%, a recall of 92.6%, an F1 score of 92.2%, and a specificity of 94.5%, which outperforms the other model in predicting seizures from EEG signals are shown in Figure 10.

4.9 Clinical discussion and practical implications

Clinically, distinguishing EEG signals into preictal, ictal, and interictal phases greatly impacts seizure management. The preictal phase, acting as a warning before a seizure, allows for early interventions that can reduce risks. The ictal phase pertains to the active seizure, enabling real-time monitoring for timely medical responses. The interictal phase serves as a baseline to identify normal versus pathological EEG activity. The proposed HTT-RNN-LSTM model aims to concurrently analyze these phases, moving beyond binary seizure predictions. It considers clinical feasibility when designing prediction time windows, recommending that preictal horizons be several minutes to tens of minutes ahead of a seizure. This balance seeks to optimize warning signal detection while minimizing false alarms. Although the study does not evaluate specific prediction outcomes, it indicates robust performance against signal variations with controlled false alarm rates, suggesting it could serve as a decision-support tool in clinical settings, supporting but not replacing medical judgment. Future research will focus on clinical validation and developing real-time EEG monitoring systems for practical use in healthcare.

4.10 Computational complexity and real-time feasibility analysis

Real-time seizure prediction systems require low-latency processing and efficient resource utilization to allow prompt clinical interventions. The HTT-RNN-LSTM model is analyzed for its computational complexity and practical feasibility. The model employs EMD and HTT methods for each EEG channel, with EMD's complexity being $NlogN$, where N represents the number of samples in the analysis window, allowing for significant parallelization due to independent EEG window processing. The RNN-LSTM fusion network utilizes extracted temporal features with complexity $O(T \times H^2)$, where T is the sequence length, and H is the number of hidden units. By using a hierarchical LSTM structure with fewer layers (comprising 128, 64, and 32 units), the model effectively reduces computational costs while maintaining temporal modeling capabilities. In practical assessments, the mean processing time per EEG window is maintained below 5–10 seconds, enabling faster-than-real-time predictions. The model is executable on standard hardware without specialized acceleration, making it suitable for real-time deployment. Memory usage is moderate due to feature-level fusion and dimensionality reduction. While more advanced architectures could enhance prediction accuracy, they could also elevate computational costs. The current design represents a balance between quality and responsiveness, with future implementations aimed at lightweight model compression and edge-centric applications to improve deployment feasibility.

5. CONCLUSION

The proposed multimethod fusion model based on the HTT-

RNN-LSTM model for predicting seizures and classifying them into preictal, ictal, and interictal states by analyzing EEG signals provides better results. Filtering Techniques and ICA provide better performance than PCA and adaptive filtering methods for the removal of artefacts. The RNN and LSTM models are used to extract highly correlated features for additional seizure-stage classification; the dropout function helps prevent overfitting; and HTT and RNN extract features from both the time and frequency domains. The LSTM model helps identify long-term dependencies among the features. Compared with RNNs, LSTMs, Decision Trees, and Random Forests, the proposed model achieves 93.2% classification accuracy. The outcome was 22.8% better than the raw data classification. The false-positive prediction rate was lower than that of other algorithms. Future research will focus on integrating real-time data to predict seizures early and create preventive measures that will improve patients' daily lives.

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