

# An Empirical Investigation of Reconstruction-Based Models for Seizure Prediction from ECG Signals

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## Abstract

Epileptic seizures are sudden neurological disorders characterized by abnormal, excessive neuronal activity in the brain, which is often associated with changes in cardiovascular activity. These disruptions can pose significant physical and psychological challenges for patients. Therefore, accurate seizure prediction can help mitigate these risks by enabling timely interventions, ultimately improving patients' quality of life. Traditionally, EEG signals have been the primary standard for seizure prediction due to their precision in capturing brain activity. However, their high cost, susceptibility to noise, and logistical constraints limit their practicality, restricting their use to clinical settings. In order to overcome these limitations, this study focuses on leveraging ECG signals as an alternative for seizure prediction. In this paper, we present a novel method for predicting seizures based on detecting anomalies in ECG signals during their reconstruction. By extracting time-frequency features and leveraging various advanced deep learning architectures, the proposed method identifies deviations in heart rate dynamics associated with seizure onset. The proposed approach was evaluated using the Siena database and could achieve specificity of 99.16%, accuracy of 76.05%, and false positive rate (FPR) of 0.01/h, with an average prediction time of 45 minutes before seizure onset. These results highlight the potential of ECG-based seizure prediction as a patient-friendly alternative to traditional EEG-based methods.

**Keywords** Anomaly Detection; Autoencoders; Deep Learning; Electrocardiogram; Epilepsy; Seizure Prediction.

## 1 Introduction

Epilepsy is a neurological disorder characterized by recurrent, unprovoked seizures caused by sudden and excessive electrical discharges in the brain. Seizures have a wide range of characteristics, differing

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in form, frequency, and intensity, which can make the task of diagnosis and prediction challenging. Despite advances in medical therapies, a significant proportion of epileptic patients continue to experience seizures even after receiving medical treatment. This is known as drug-resistant or intractable epilepsy [1]. As a result, many patients struggle to achieve full seizure control, which profoundly impacts their quality of life by increasing the risk of injury, limiting daily activities, and exacerbating mental health issues [2, 3].

Taking into account the uncontrollable nature of epilepsy, effective seizure management and prediction have become critical areas of research. Seizures typically progress through distinct phases, including inter-ictal (between seizures), pre-ictal (before seizure onset), ictal (seizure onset), and post-ictal (recovery) [4]. It should be noted that since the inter-ictal phase represents baseline physiological conditions, data from this phase can be utilized as a normal reference for the identification of deviations from the pre-ictal phase. The ability to anticipate an impending seizure could enable early intervention measures, significantly enhancing safety, autonomy, and quality of life for epileptic patients. Traditionally, seizure prediction approaches relied on electroencephalogram (EEG) recordings to detect abnormal brain activity [5, 6]; however, practical challenges with EEG, such as its limited portability, discomfort in long-term use, and susceptibility to motion artifacts, have driven interest in alternative, more accessible biomarkers like electrocardiogram (ECG) signals. Recent research suggests that ECG-based approaches may provide valuable insights into pre-ictal states, offering a promising non-invasive option for seizure prediction [7]. Recent comprehensive reviews further emphasize the potential of ECG-driven seizure prediction, highlighting the successful application of machine learning techniques as a viable and scalable alternative to EEG-based approaches [8, 9].

This growing interest in ECG-based seizure prediction is rooted in physiological findings that demonstrate how epileptic seizures interfere with autonomic nervous system (ANS) function, leading to distinct and measurable changes in cardiac dynamics. During seizures, autonomic imbalances can cause abrupt heart rate fluctuations. This results in sudden tachycardia or bradycardia, irregular rhythms, and even transient asystole in severe cases. Notably, these cardiac disturbances are not limited to the seizure itself but can also occur in the pre-ictal phase, where subtle changes in heart rate and other ECG-derived parameters have been observed as potential precursors to seizure onset [10, 11]. These pre-ictal cardiac signatures offer a promising non-invasive avenue for seizure prediction, especially in cases where traditional EEG monitoring is impractical due to its limited mobility and setup requirements.

Numerous studies have demonstrated the potential of analyzing heart rate fluctuations to predict epileptic seizures. These studies primarily focus on the analysis of Heart Rate Variability (HRV) features as indicators of ANS dysregulation. The research studies such as [12–17] have highlighted that HRV features in various domains—including time, frequency, and non-linear measures—can reveal patterns indicative of upcoming seizure onset. These changes reflect physiological shifts within the ANS, specifically sympathetic and parasympathetic activity, which are common during the pre-ictal stage. Such findings underscore the promise of HRV-based analysis as a non-invasive method for seizure prediction.

However, despite these promising findings, HRV-based approaches have limitations that impact their applicability in real-time settings. One primary challenge is the requirement of a sustained data window over a relatively long period of time—typically two to three minutes—to extract reliable HRV metrics. This introduces a delay, making HRV-based methods less practical for immediate seizure prediction. This limitation implies that patients must wait several minutes while features are extracted and algorithms are fine-tuned, causing delay in timely intervention in dynamic, real-world environments.

Taking into account these timing constraints, Ode et al. [18], developed a rapid-response model using a Self-Attentive Autoencoder (SA-AE) designed for detecting anomalies in heart rate patterns with minimal latency. By focusing on reconstruction error as an anomaly score, their SA-AE model enables quick classification of pre-ictal signals without the lengthy preprocessing typically required for HRV analysis. Their results demonstrated that deep learning architectures like the SA-AE are highly effective at detecting early signs of seizures from physiological data, thereby enabling more responsive seizure prediction.

Building on the work by Ode et al. [18], this study expands the analysis of ECG data beyond traditional HRV metrics through the utilization of time-frequency transformations. These transformations allow for a more detailed examination of both temporal and spectral characteristics, capturing subtle and transient variations in cardiac dynamics that are often overlooked by conventional HRV methods. By applying these domain transformations, we aim to develop a robust, near-real-time seizure prediction model that overcomes the latency limitations of standard HRV methods and provides timely warnings to patients, ultimately enhancing the safety and quality of life for epileptic patients.

In response to the critical challenges of seizure prediction, this study introduces the following significant contributions:

- The proposed model leverages Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Short-Time Fourier Transform (STFT) to extract time-frequency features from ECG signals, enhancing the detection of transient anomalies linked to pre-ictal states.
- By employing deep learning models such as Autoencoders and Transformer-based architectures, the framework reconstructs input signals and identifies seizure precursors based on deviations between input and reconstruction, enabling unsupervised anomaly detection.
- Taking into account the individual differences in ECG patterns, all models are trained using patient-specific characteristics to ensure personalized seizure prediction.
- After training is completed, a moving average is used to smooth the reconstruction error, improving the signal-to-noise ratio and reducing the number of false positives.
- Afterwards, we compute a statistical threshold based on the mean and standard deviation of the training error distribution, which enables patient-specific prediction.
- Finally, the proposed methodology is evaluated on the Siena Scalp EEG database using clin-

cally relevant metrics to demonstrate its real-world effectiveness.

## 2 Materials and Methods

The proposed seizure prediction framework, as illustrated in Fig. 1, follows a structured pipeline that includes data acquisition, preprocessing, feature extraction, modeling, post-processing, and performance evaluation. First, raw ECG signals are collected and preprocessed through noise filtering and segmentation to ensure consistency. Next, time-frequency transformation techniques—Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Short-Time Fourier Transform (STFT)—are applied to extract transient and steady-state features crucial for identifying preictal patterns. These features are then analyzed using three deep learning models: LSTM Autoencoder (LSTM-AE), Multi-Head Convolutional LSTM Autoencoder (MH-C-LSTM-AE), and Transformer Encoder-Encoder (T-EE), which are designed for reconstruction-based anomaly detection. Afterward, post-processing steps are applied to refine predictions by mitigating noise and distinguishing normal segments from anomalous ones. Finally, the framework is evaluated using standard performance metrics to ensure robustness across patient datasets.

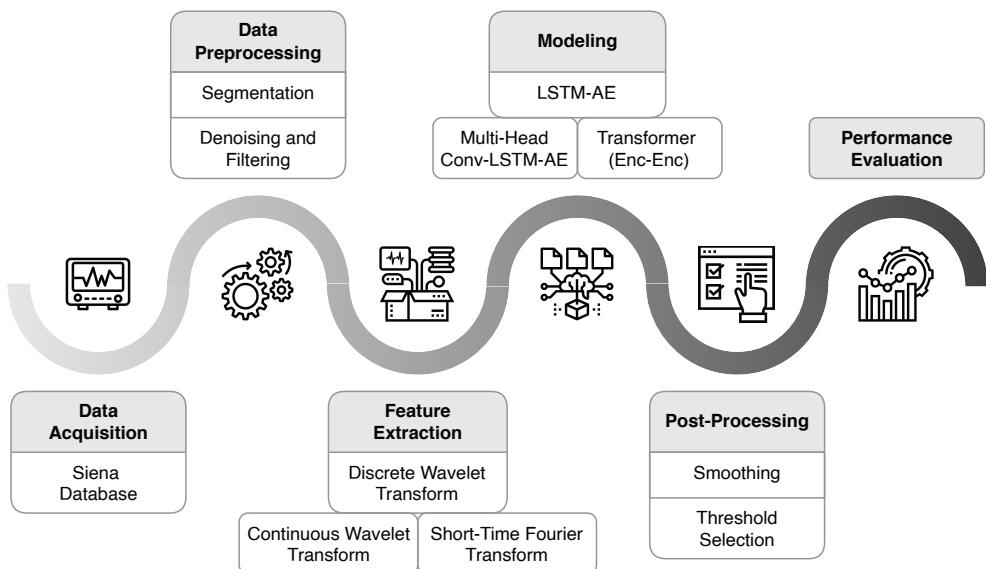


Figure 1: Overall components of the proposed approach for Epileptic Seizure Prediction.

### 2.1 Data Acquisition

In this study, the data were acquired from the Siena Scalp EEG Database [19], a comprehensive, open-access dataset provided by the University of Siena, Italy. This dataset contains simultaneous scalp EEG and ECG recordings from 14 epilepsy patients, primarily diagnosed with focal epilepsy and with some cases exhibiting generalized tonic-clonic seizures. Each patient recording captures at least one complete seizure event. A summary of the demographic data of the patients and a selection of clinical characteristics are provided in Table 1.

The ECG signals in the Siena Database are recorded at a high sampling rate of 512 Hz, ensuring

sufficient temporal resolution to capture subtle cardiac rhythm variations that may indicate impending seizure onset. Furthermore, annotations are provided for each seizure event, marking the onset and offset times, which allows for accurate identification of cardiac events associated with seizures [20, 21].

Table 1: Characteristics of the patients included in the study.

Patient ID	Age	Gender	Seizure Type	Seizures #	Recording (Min)
PN00	55	Male	IAS	5	198
PN01	46	Male	IAS	2	809
PN03	54	Male	IAS	2	752
PN05	51	Female	IAS	3	359
PN06	36	Male	IAS	5	722
PN07	20	Female	IAS	1	523
PN09	27	Female	IAS	3	410
PN10	25	Male	FBTC	10	1002
PN11	58	Female	IAS	1	145
PN12	71	Male	IAS	4	246
PN13	34	Female	IAS	3	519
PN14	49	Male	WIAS	4	1408
PN16	41	Female	IAS	2	303
PN17	42	Male	IAS	2	308

IAS is focal onset impaired awareness; WIAS is focal onset without impaired awareness; FBTC is focal to bilateral tonic-clonic; T is temporal; F is frontal; R is right; L is left; and B is Bilateral.

## 2.2 Data Preprocessing

In the preprocessing stage of this study, the primary aim is to enhance the quality of ECG signals by applying segmentation and denoising techniques to prepare the data for feature extraction and model training. Therefore, the ECG signals are first segmented into manageable time windows, and then, denoising techniques are applied to minimize noise and artifacts present in ECG recordings. This preprocessing steps enhances signal clarity and reliability, providing a cleaner input for downstream feature extraction and model training.

### 2.2.1 Segmentation

In the segmentation phase, the ECG data is divided into well-defined time windows to enable analysis of temporal patterns leading up to seizure events. This segmentation strategy is critical for isolating distinct segments within the continuous ECG signal. In this way, it is feasible to capture pre-ictal and ictal characteristics that may signal impending seizures. In order to capture the dynamic nature of ECG signals, we employed a range of window sizes—1, 5, and 10 seconds—each at different

overlap levels, including 0 (no overlap) and partial overlaps of 1, 3 or 5 seconds. Through the use of these varied configurations, we are able to examine the impact of window size and overlap on prediction accuracy and feature stability. In analyzing a signal over a wider window, we may be able to detect broader patterns, which might provide reliable information regarding changes in heart rate. Conversely, smaller windows with partial overlaps can provide a higher level of temporal resolution, which is crucial when detecting rapid, transient fluctuations associated with pre-ictal states. Additionally, the overlapping segments provide sequential continuity, which ensures that no critical data is lost at the boundaries between segments.

### 2.2.2 Denoising and Filtering

In ECG signal processing, denoising plays a crucial role in accurate feature extraction and prediction of medical conditions, including epileptic seizures. The primary artifacts in ECG signals include power line interference, motion artifacts, and baseline wander. In seizure prediction, the baseline wander artifact, which is often triggered by respiration or body movements, might provide valuable information about the underlying physiological conditions related to the connection between the ANS and the cardiovascular system during a seizure. Eliminating it completely can lead to the loss of subtle seizure-related patterns embedded in low-frequency oscillations. Preserving this component allows feature extraction methods to capture both high-frequency and low-frequency dynamics, enhancing predictive performance.

Accordingly, a low-pass filtering strategy was employed to keep slow-changing components like baseline wander while suppressing high-frequency noise that can obscure signal interpretation. By maintaining this balance, we are able to ensure that noise reduction does not compromise predictive information, resulting in more reliable and accurate seizure forecasting models.

## 2.3 Feature Extraction

In order to accurately predict seizure onsets, reliable feature extraction is necessary to transform input ECG signals into meaningful representations that capture significant patterns, temporal trends, and characteristics relevant to seizure prediction. The intricate and high-dimensional nature of ECG data necessitates extracting features that capture subtle pre-ictal dynamics, as these are vital for accurate and effective seizure prediction. To address this complexity, several techniques have been investigated. These include the set of features created by concatenating the coefficients derived from the discrete wavelet transform, the scalogram representation generated by the Continuous Wavelet Transform, and the spectrogram representation produced by the Short-Time Fourier Transform. To assess whether each method was effective in improving signal representation and its impact on model performance, each method was investigated independently. In the following, we provide a detailed overview of each technique, the motivation behind the chosen parameters, and their significance in the context of seizure prediction.

### 2.3.1 Discrete Wavelet Transform

In the first approach, DWT was used to decompose the ECG signal into time-frequency components, enabling simultaneous analysis of transient and steady-state features. In contrast to Fourier Transform, DWT provides both time and frequency information, making it effective for ECG signals with abrupt changes. The DWT of a signal  $x[n]$ , sampled at discrete points, is computed using a mother wavelet  $\psi(n)$ , scaled and translated as follows:

$$W_{j,k} = \sum_n x[n] \cdot \psi_{j,k}(n) \quad (1)$$

where:

$$\psi_{j,k}(n) = 2^{-j/2} \psi(2^{-j}n - k) \quad (2)$$

Here,  $j$  denotes the scale index,  $k$  is the translation index, and  $\psi(n)$  is the mother wavelet. These coefficients  $W_{j,k}$  encapsulate both the temporal and spectral characteristics of the signal.

In this study, the sym4 wavelet was selected due to its symmetry and structural similarity to ECG waveforms. This will help in minimizing distortion while effectively capturing both rapid changes (e.g., arrhythmias) and smooth trends (e.g., heart rate variability) [22, 23]. The decomposition was performed up to level 3, balancing the preservation of high-frequency components, such as noise and rapid fluctuations, with low-frequency trends that reflect broader physiological changes [24]. The decomposition process at each level involved applying low-pass and high-pass filters, yielding approximation ( $c_{A_j}$ ) and detail ( $c_{D_j}$ ) coefficients:

$$\begin{aligned} c_{A_j}[n] &= \sum_k h[k] \cdot c_{A_{j-1}}[2n - k] \\ c_{D_j}[n] &= \sum_k g[k] \cdot c_{A_{j-1}}[2n - k] \end{aligned} \quad (3)$$

where  $h[k]$  and  $g[k]$  denote the low-pass and high-pass filter coefficients, respectively. After decomposition, the coefficients  $c_{A_3}, c_{D_3}, c_{D_2}, c_{D_1}$  were normalized to mitigate differences in signal magnitude across patients, ensuring comparability across datasets. Finally, the normalized coefficients were concatenated into a feature vector, creating a compact and robust representation of ECG signals for subsequent analysis.

### 2.3.2 Continuous Wavelet Transform

In the second approach, the CWT was employed to analyze the energy distribution of the ECG signal across both the time and frequency domains. Unlike traditional methods, CWT provides a detailed time-frequency representation, making it highly effective for detecting transient features in non-stationary biomedical signals such as ECG. The CWT of a signal  $x(t)$  is defined as:

$$C(a, b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}^*(t) dt \quad (4)$$

where:

$$\psi_{a,b}^*(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad (5)$$

Here,  $a > 0$  indicates the scale parameter, controlling frequency variations, while  $b$  denotes the translation parameter, governing time localization. The function  $\psi^*(t)$  is the complex conjugate of the mother wavelet. This decomposition enables precise analysis of signal variations at different time instances and frequency bands.

In this study, the Mexican hat wavelet (mexh) was selected as the mother wavelet due to its strong resemblance to QRS waves and excellent localization properties in both the time and frequency domains. The mathematical definition of the Mexican hat wavelet is given by:

$$\psi(t) = (1 - t^2) e^{-t^2/2} \quad (6)$$

This wavelet is particularly well-suited for identifying transient energy shifts in ECG signals, which are crucial for detecting pre-ictal activity preceding seizure events. Prior research has demonstrated that mexh effectively captures subtle energy variations in biomedical signals, making it a reliable tool for analyzing rapid transitions in ECG signals [25].

To achieve an optimal balance between resolution and computational efficiency, we selected a scale range of  $a = 128$ . This range enables capturing both low-frequency trends (e.g., heart rate variations) and high-frequency changes (e.g., noise or sharp bursts). The scalogram, which represents the energy distribution of the signal across different scales and time instances, is computed as:

$$E(a, b) = |C(a, b)|^2 \quad (7)$$

where  $E(a, b)$  denotes the energy at scale  $a$  and translation  $b$ . Following the decomposition, to ensure consistency across datasets, scalogram energy was normalized, enhancing seizure prediction by identifying subtle pre-ictal patterns.

### 2.3.3 Short-Time Fourier Transform

In the third approach, the STFT was employed to analyze the time-frequency characteristics of ECG signals, capturing both steady-state trends and transient variations in ECG signals. These variations often include abrupt spectral energy shifts, which are critical indicators of pre-ictal states. The STFT of a signal  $x(t)$  is defined as:

$$X(t, f) = \int_{-\infty}^{\infty} x(\tau)w(\tau - t)e^{-j2\pi f\tau} d\tau \quad (8)$$

where  $w(\tau - t)$  denotes a window function that selects a segment of the signal centered at time  $t$ , and  $f$  indicates the analyzed frequency component. This equation demonstrates that the signal is divided into short segments via the window function  $w$ , and the Fourier Transform is then applied to each segment, providing a localized frequency analysis.

In this study, a window size of 512 samples was selected to balance temporal and spectral resolution, ensuring the detection of both rapid transitions (e.g., arrhythmic events) and long-term variations (e.g., heart rate trends). A smaller window improves temporal resolution at the cost of frequency accuracy, while a larger window enhances frequency resolution but reduces time localization. This

window size aligns well with the typical ECG sampling rate, effectively capturing both low and high-frequency features [26].

Once the STFT coefficients are obtained, the spectrogram is computed by computing the squared magnitude of the STFT:

$$S(t, f) = |X(t, f)|^2 \quad (9)$$

where  $S(t, f)$  denotes the signal's energy distribution across time and frequency. This spectrogram provides a visual representation of how the power of different frequency components varies over time. Next, to ensure consistency across various patient datasets, the spectrogram energy was normalized, reducing the impact of inter-ictal variability while preserving the most relevant pre-ictal characteristics.

## 2.4 Modeling

In seizure prediction, the ability to detect anomalies in physiological signals is an essential component of early warning systems. These anomalies often manifest as subtle deviations from normal patterns during the pre-ictal phase, which precedes seizure onset. In this study, we present a reconstruction-based anomaly detection approach that can be used to predict the onset of epileptic seizures in an unsupervised manner. By analyzing signal representations produced through feature extraction, the approach minimizes reliance on labeled data, thereby enhancing its adaptability and scalability across diverse patient profiles.

The core idea of this study is based on the reconstruction error generated by models trained exclusively on normal segments of ECG signals. These models learn to represent the baseline patterns of the signal, capturing its inherent characteristics under typical, non-seizure conditions. However, during the pre-ictal phase, subtle yet significant deviations emerge in the signal's characteristics as the heart responds to physiological changes preceding a seizure event. These deviations, often undetectable through direct observation, lead to higher reconstruction errors when the signal is passed through models. This phenomenon makes reconstruction error a reliable indicator for identifying potential pre-ictal activity, serving as an indicator of imminent seizure onset.

In order to investigate these anomalies, three reconstruction-based models were used: the LSTM Autoencoder, the Multi-Head Convolutional LSTM Autoencoder, and the Transformer-Based Anomaly Detection Model. Each model is meticulously crafted to address distinct challenges inherent in ECG signal processing. These challenges include capturing long-term temporal dependencies, modeling complex spatial relationships, and identifying sequential patterns with high fidelity. By independently evaluating these models, the study rigorously evaluates their individual contributions to anomaly detection, providing insights into their effectiveness in advancing seizure prediction.

### 2.4.1 Training and Testing Methodology

In order to develop a stable and personalized seizure prediction framework, a short segment is selected from the initial portion of each patient's ECG recording. This segment represents a typical, non-

seizure baseline signal, ensuring that the model is trained exclusively on normal patterns. By focusing on these baseline characteristics, the models develop a comprehensive understanding of the patient’s unique ECG dynamics. This enables them to identify subtle deviations from normality during the prediction phase.

Once trained, the models are applied to the entire patient dataset (except the portion selected for training) to identify anomalies indicative of seizure activities. This approach is particularly advantageous for patient-specific analysis, as it inherently accounts for individual variations in ECG morphology and rhythm. By tailoring the models to each patient’s data, the framework achieves a high degree of personalization, which is critical for accommodating the diverse physiological characteristics of epileptic patients. Furthermore, the reliance on patient-specific training segments eliminates the need for generalized assumptions, enhancing the performance of anomaly detection [27, 28].

#### 2.4.2 LSTM Autoencoder

The LSTM-AE is a neural network designed for sequential data, using an encoder-decoder structure. The encoder, composed of stacked Long Short-Term Memory (LSTM) layers, generates a compact latent representation, which captures long-term dependencies within the input data. In order to ensure robust training and to prevent overfitting, optimization layers—Batch Normalization and Dropout—were applied. The decoder, mirroring the encoder, reconstructs the input signal to match the original as closely as possible. Fig. 2 illustrates the LSTM-AE architecture, highlighting its layers and structure.

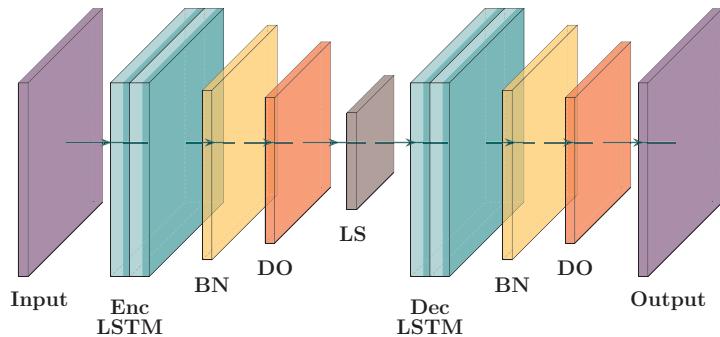


Figure 2: Schematic Diagram of LSTM-AE. Enc is Encoder; Dec is Decoder; BN is Batch Normalization; DO is Dropout; LSTM is Long Short-Term Memory; and LS is Latent Space.

#### 2.4.3 Multi-Head Convolutional LSTM Autoencoder

MH-C-LSTM-AE is a hybrid model that integrates convolutional layers, LSTM layers, and multi-head attention mechanisms to effectively capture both spatial and temporal complexity. In this model, the encoder begins with 1D convolutional layers, which identify localized features such as QRS complexes and waveform patterns. These layers use dilation factors to expand the receptive field, allowing the model to capture both fine-grained and broader patterns. Next, LSTM layers model temporal dependencies, tracking periodic trends and abrupt transitions. Additionally, in order to enhance the

efficiency of the encoder, multi-head attention mechanisms are integrated into the model, enabling the model to dynamically focus on the most critical regions of the signal representations. This attention-based feature enhances the detection of subtle, localized anomalies indicative of pre-ictal states, even with complex background patterns. The decoder, mirroring the encoder, reconstructs both temporal and spatial signal features, ensuring accurate anomaly detection. The architecture is motivated by the need to comprehensively capture the multiscale nature of ECG-derived representations, which often contain both localized events (e.g., QRS complexes) and long-term dependencies (e.g., heart rate variability) [29]. The architecture of this model is illustrated in Fig. 3.

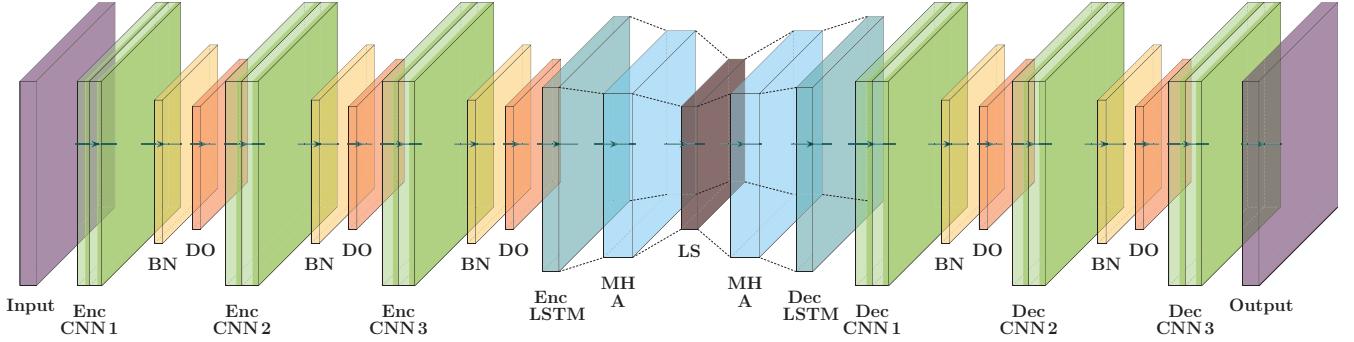


Figure 3: Schematic Diagram of Multi-Head-Conv-LSTM-AE. Enc is Encoder; Dec is Decoder; BN is Batch Normalization; DO is Dropout; CNN is Convolution Layer; LSTM is Long Short-Term Memory; MH is Multi-Head Attention Layer; and LS is Latent Space.

#### 2.4.4 Transformer-Based Anomaly Detection Model

Transformers are highly effective for seizure prediction due to their ability to model long-range dependencies in ECG signals. Unlike RNNs and LSTMs, which process data sequentially, transformers operate in parallel, significantly improving efficiency and scalability—critical for analyzing continuous ECG recordings. The proposed transformer-based model leverages two transformer encoder layers to process ECG signal representations. Each layer employs a multi-head self-attention mechanism, allowing the model to capture key dependencies and relationships within the signal, regardless of their position in the sequence. This capability enables the model to focus on different signal segments at various time steps, offering a flexible and adaptive approach to interpreting complex, non-linear interactions. Following self-attention, a feedforward network refines the learned representations by capturing higher-order feature relationships, further enhancing the model’s ability to detect seizure-related patterns. The overall architecture is depicted in Fig. 4.

## 3 Post-Processing

### 3.1 Smoothing

In the post-processing stage of our seizure prediction framework, smoothing the reconstruction error is a critical step that enhances the robustness and accuracy of predictions. Raw reconstruction error

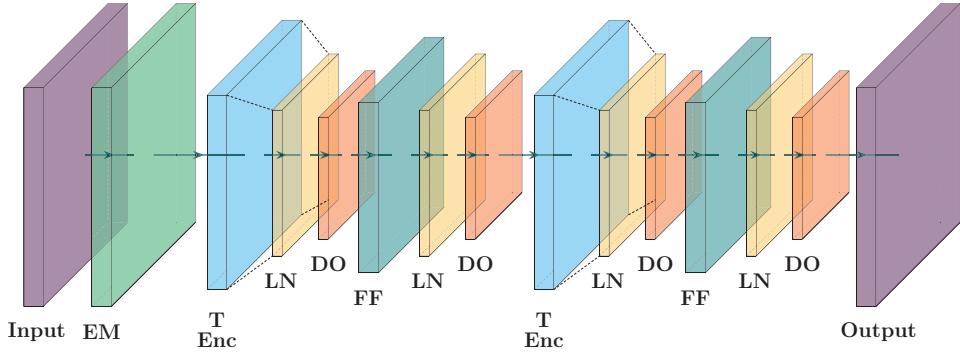


Figure 4: Schematic Diagram of Transformer (Enc-Enc). EM is Embedding; T-Enc is Transformer Encoder; LN is Layer Normalization; DO is Dropout; and FF is Feed-Forward Layer.

values, derived from comparing the model’s output with the original signal, often exhibit significant variability due to noise and transient fluctuations in ECG data. Without adequate smoothing, these variations could lead to false positives, reducing the predictive accuracy and reliability of the model. In order to resolve this, we apply a moving average technique with a fixed window size, where each point in the smoothed reconstruction error sequence is computed as the mean of its surrounding values. This reduces noise while retaining significant variations associated with seizure events. Specifically, the smoothed reconstruction error  $E_{\text{smoothed}}(i)$  at index  $i$  is given by:

$$E_{\text{smoothed}}(i) = \frac{1}{n} \sum_{j=\max(0, i-\frac{w}{2})}^{\min(N, i+\frac{w}{2})} E(j), \quad (10)$$

where  $E(j)$  represents the raw reconstruction error at point  $j$ ,  $w$  is the window size, and  $N$  is the total number of points. This technique effectively reduces short-term variability while preserving the overall trend of the reconstruction error curve, which is essential for robust anomaly detection. In order to maintain consistency, we apply smoothing to both the training and testing reconstruction error sequences. Importantly, the smoothed error distribution from the training set serves as the foundation for threshold selection. By leveraging statistical properties of these smoothed errors, we define an adaptive threshold for anomaly detection, ensuring that test samples are evaluated against a stable and noise-filtered baseline.

As a result of this post-processing step, the signal-to-noise ratio of the system is significantly improved, resulting in improved reliability and stability during the prediction phase. It helps to mitigate the risk of false positives caused by transient spikes in error values, ensuring that the model only flags events that exceed a well-defined and smoothed threshold. By integrating this smoothing process, our approach achieves a more balanced performance, critical for real-time seizure prediction applications.

### 3.2 Threshold Selection

The statistical thresholding method employed in this study provides a robust and dynamic mechanism for identifying anomalies by leveraging statistical properties of reconstruction errors. Specifically, this

approach calculates the threshold based on the mean and standard deviation of the reconstruction errors derived from the training dataset. This ensures adaptability to patient-specific data distributions and robustness against noise.

The statistical threshold is mathematically defined as follows:

$$\mu = \frac{1}{N} \sum_{i=1}^N E_{\text{Train}}(i), \quad \sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (E_{\text{Train}}(i) - \mu)^2} \quad (11)$$

where  $\mu$  represents the mean reconstruction error, and  $\sigma$  is the standard deviation of reconstruction errors in the training data. Accordingly,  $\tau$  denoted as the threshold is defined as:

$$\tau = \mu + k\sigma \quad (12)$$

where  $k$  is a tunable parameter that determines the sensitivity of the anomaly detection system. A higher  $k$  reduces false positives by requiring larger deviations to classify an event as anomalous, while a lower  $k$  increases sensitivity but may result in more false positives.

In this study,  $k$  was conservatively set to 2, striking a balance between minimizing false positives and ensuring the detection of meaningful anomalies.

This method offers significant advantages:

- The inclusion of the standard deviation ensures the method is resilient to outliers and irregularities in the training data.
- The adjustable  $k$ -parameter allows flexibility for different application requirements, such as prioritizing high specificity or sensitivity.

By employing this statistical thresholding technique, the study ensures that anomalies are detected effectively, providing a foundation for the development of reliable ECG-based seizure prediction systems.

## 4 Performance Evaluation

Accurately assessing a seizure prediction model requires a comprehensive evaluation framework that ensures reliability, robustness, and clinical viability. This section outlines the key performance metrics used to quantify predictive accuracy, specificity, and false alarm rates. Additionally, to account for seizure rarity, a class weighting mechanism is applied, preventing model bias toward non-seizure intervals. Another critical aspect is the definition of the pre-ictal interval, which determines the valid window for seizure predictions and ensures a fair assessment across different datasets. By incorporating these evaluation strategies, we establish a well-balanced and interpretable performance analysis.

## 4.1 Evaluation Metrics

In order to fully assess the performance of seizure prediction models, a variety of evaluation metrics should be used. These metrics are based on four fundamental components of a confusion matrix:

**TP** These are instances where the model correctly predicted seizures.

**FP** These are instances where the model incorrectly predicted a seizure.

**TN** These are the predictions where the model identified normal behavior correctly, avoiding false alarms.

**FN** These are missed seizures, where the model failed to predict the seizure onset.

These components form the basis for key performance metrics such as specificity, accuracy, and FPR.

Seizure prediction models often face a significant class imbalance between seizure intervals (positive class) and normal intervals (negative class). Since seizures are relatively rare compared to normal intervals, this imbalance can distort performance metrics. To address this challenge, a weighting mechanism is employed to adjust the relative importance of each class. Therefore, the weight for the negative class (normal intervals) is set to 1, while the positive class (seizure intervals) is assigned a weight inversely proportional to its frequency. This ensures that the model is penalized more heavily for missing seizures (FN) or falsely predicting seizures (FP), reflecting the critical nature of these errors. Accordingly, the model becomes more sensitive to the minority class, improving its ability to detect seizures without being overly biased by the abundance of normal intervals.

Another vital aspect of seizure prediction evaluation is defining the pre-ictal interval—the period preceding a seizure during which predictions are considered valid. This interval determines the temporal window in which the model's predictions are analyzed. In this study, the pre-ictal interval is dynamically adapted based on the length of the dataset, so for a longer dataset, an hour-long pre-ictal interval is used, while for shorter datasets, a proportionately shorter interval of 30 minutes (half of the standard interval) is applied. Adjusting the pre-ictal interval dynamically ensures that evaluation metrics remain clinically meaningful and consistent across datasets of varying durations. Without this adaptation, models trained on shorter datasets might exhibit artificially high sensitivity, while those trained on longer datasets might fail to detect shorter pre-seizure patterns. This approach offers multiple advantages:

- By adjusting the pre-ictal interval to the length of each record, the evaluation ensures that longer or shorter records do not skew performance metrics.
- The model is better equipped to handle diverse ECG signal durations, leading to more reliable predictions across varying scenarios.

As a consequence, in order to maintain consistency in evaluations, pre-ictal intervals must align with the segmentation window size used in data processing. For instance, if the pre-ictal interval is defined as 3600 samples with a 1-second segmentation window, it must be reduced to 360 samples when a

10-second segmentation window is applied. This adjustment ensures that predictions remain precise and consistent with the scaled data, preventing inaccuracies caused by mismatched intervals and segmentation lengths. Allowing the above strategies, various evaluation metrics are computed to assess the model’s performance:

- Accuracy: Represents the proportion of correct predictions (TP and TN) out of all predictions.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (13)$$

- Specificity: Measures the model’s ability to correctly identify normal activities (non-seizures).

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (14)$$

- False Positive Rate (FPR): Indicates the proportion of normal activities incorrectly classified as seizures, helping to assess the model’s false alarm rate.

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (15)$$

## 5 Experimental Results

In this section, the results obtained through implementation of the proposed approach are presented and analyzed using the evaluation metrics discussed previously. Based on the fundamental steps of the proposed method, the results can be examined from three perspectives: the length of signal segmentation windows, the type of extracted features and representations, and the architecture used for modeling the seizure prediction process. Accordingly, the following analysis of the results is conducted with these considerations in mind.

### 5.1 Seizure Prediction Performance

For a better understanding of the results, it is important to understand how the proposed approach works and what are the preliminary steps to improve prediction performance.

The proposed approach is designed to predict seizures onset by monitoring and analyzing the reconstruction loss of ECG signals, which serves as an indicator of abnormal patterns in the data. The approach involves extracting meaningful features using time-frequency methods and analyzing them through sequence-to-sequence models. These models are trained to reconstruct ECG signals from normal, non-seizure segments. During this process, the reconstruction loss indicates how well the model can predict the original signal based on its learned patterns. Higher reconstruction errors typically correspond to anomalies, such as those occurring during the pre-ictal phase, which precedes a seizure. However, as observed in the raw reconstruction error values (Fig. 5), the presence of noise can lead to false positives, where the model identifies certain points as anomalies, even when they

are not indicative of seizure activity. These noise-induced fluctuations complicate the interpretation of the data and decrease the trustworthiness of the predictions.

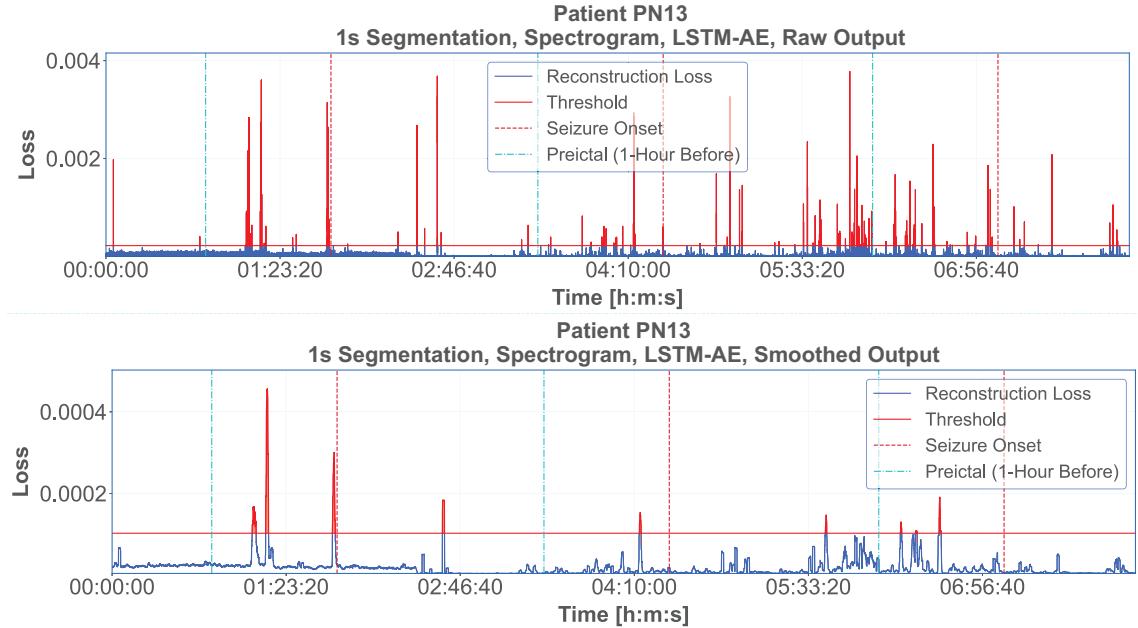


Figure 5: Comparison of Raw and Smoothed Reconstruction Loss (Patient PN13, 1s segmentation, Scalogram, LSTM-AE). In the plots, the blue curve represents the reconstruction error, the red horizontal line indicates the threshold, the red dashed lines mark the seizure onset points, and the turquoise dash-dotted lines, highlight the pre-ictal period.

This is where the post-processing step becomes critical. During this step, a smoothing technique is applied to reduce high-frequency noise in order to allow the model to identify more meaningful anomalies. As shown in the lower part of Fig. 5, after smoothing, the reconstruction error values are significantly more stable, with fewer false anomalies identified. This improves the model’s ability to accurately detect the true pre-ictal phase, reducing the number of incorrect predictions and providing a more reliable prediction method.

In the example shown in Fig. 5, three out of three seizures were correctly predicted. However, it is important to note that this approach heavily depends on the patient’s ECG signal, and in some cases, it may fail to accurately predict impending seizures, as demonstrated in Fig. 6. In this case, the first two seizure onsets were successfully predicted, while the third attack was missed.

## 5.2 Results Based on Segmentation Window Lengths

The length of segmentation windows is crucial in seizure prediction, directly impacting model performance and reliability. Longer windows capture richer temporal dynamics, enhancing feature stability and accuracy but increasing computational cost and response time. Conversely, shorter windows improve efficiency but may lack sufficient data representation, limiting generalization. This study analyzed segmentation windows of 1, 5, and 10 seconds with varying overlap levels (none, 1, 3, and 5 seconds).

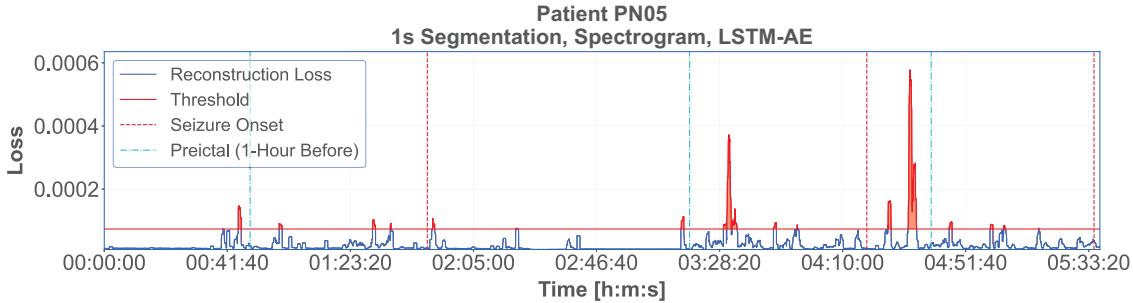


Figure 6: The Reconstruction Loss of Patient PN05 (Patient PN05, 1s segmentation, Scalogram, LSTM-AE). In this case, two out of the three seizures were correctly predicted, while the third attack was missed.

Results showed that a 1-second window without overlap achieved the best results, offering high accuracy and low variability across patients. This setup effectively balances temporal information capture with computational efficiency. In contrast, the 5-second segmentation window, when used with partial overlaps (e.g., 1 or 3 seconds), showed moderate performance. Although the overlaps enhanced temporal continuity, the results were less consistent than with the 1-second window, as indicated by increased standard deviations. This suggests that while partial overlaps may provide some advantages in terms of continuous data representation, they also introduce more variability, leading to reduced robustness in comparison. Finally, the 10-second segmentation windows, whether used with no overlap or partial overlap, exhibited the lowest performance and highest variability across patients. This performance drop can be attributed to over-aggregation of data, which may obscure the short-term patterns critical for accurate seizure prediction.

### 5.3 Results Based on Extracted Feature Types

The quality and diversity of extracted features are crucial for the success of seizure prediction models. Transforming input ECG signals into meaningful representations enables better analysis of the underlying patterns. In this study, we used three feature extraction methods: Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Short-Time Fourier Transform (STFT), which capture time, frequency, and scale-based features which are useful for predicting seizures.

The performance of each feature extraction method was assessed individually for each patient, and the mean performance across all patients alongside the standard deviation was reported. The standard deviation provides a comprehensive view of the model's robustness across different patients, highlighting variability in performance. The results are summarized in Tables 2, 3, and 4.

Table 2: Summarized results from the DWT representation

Models	Specificity	Accuracy	FPR (/h)
LSTM-AE	$98.16 \pm 0.009$	$75.48 \pm 0.125$	$0.018 \pm 0.009$
MH-C-LSTM-AE	$98.13 \pm 0.009$	$75.46 \pm 0.125$	$0.019 \pm 0.009$
T-EE	<b><math>98.32 \pm 0.01</math></b>	<b><math>75.54 \pm 0.126</math></b>	<b><math>0.017 \pm 0.01</math></b>

Table 3: Summarized results from the Scalogram representation

Models	Specificity	Accuracy	FPR (/h)
LSTM-AE	$98.8 \pm 0.005$	$75.67 \pm 0.13$	$0.012 \pm 0.005$
MH-C-LSTM-AE	<b><math>98.98 \pm 0.006</math></b>	<b><math>75.74 \pm 0.129</math></b>	<b><math>0.01 \pm 0.006</math></b>
T-EE	$98.72 \pm 0.004$	$75.62 \pm 0.13$	$0.013 \pm 0.004$

Table 4: Summarized results from the Spectrogram representation

Models	Specificity	Accuracy	FPR (/h)
LSTM-AE	$98.76 \pm 0.008$	$75.95 \pm 0.128$	$0.011 \pm 0.006$
MH-C-LSTM-AE	<b><math>99.16 \pm 0.006</math></b>	<b><math>76.05 \pm 0.127</math></b>	<b><math>0.01 \pm 0.005</math></b>
T-EE	$98.76 \pm 0.008$	$75.62 \pm 0.126$	$0.016 \pm 0.009$

Analysis shows that the STFT-derived spectrogram slightly outperforms other methods, suggesting that frequency-domain information offers more discriminative features for seizure prediction. However, as illustrated in Fig. 7, scalogram and spectrogram, displayed similar trends, indicating that pre-seizure anomalies occurred at consistent intervals. These points could potentially aid in early seizure detection, though further clinical validation is needed.

In conclusion, while all feature extraction methods show potential, the STFT-based spectrogram offers the most promising results for seizure prediction, guiding future research in selecting the most effective techniques.

#### 5.4 Results Based on Designed Models

In the final step, architectures play a crucial role in transforming the extracted features into actionable predictions. In this study, a wide range of neural network architectures were employed, including feedforward networks, convolutional networks, recurrent networks, autoencoders, and transformer models. The results of these models are presented cumulatively in Table 5.

Table 5: Final Results

Models	Specificity	Accuracy	FPR (/h)
LSTM-AE	$98.76 \pm 0.008$	$75.95 \pm 0.128$	$0.011 \pm 0.006$
MH-C-LSTM-AE	<b><math>99.16 \pm 0.006</math></b>	<b><math>76.05 \pm 0.127</math></b>	<b><math>0.01 \pm 0.005</math></b>
T-EE	$98.76 \pm 0.008$	$75.62 \pm 0.126$	$0.016 \pm 0.009$

Based on the data shown in Table 5, it is evident that among the proposed architectures, the MH-C-LSTM-AE model achieved the highest performance, successfully predicting 45 out of 47 seizures with specificity of 99.16%, accuracy of 76.05%, and FPR of 0.01/h. Following closely, the T-EE model also demonstrated high performance, predicting 44 seizures, and finally, the LSTM-AE model

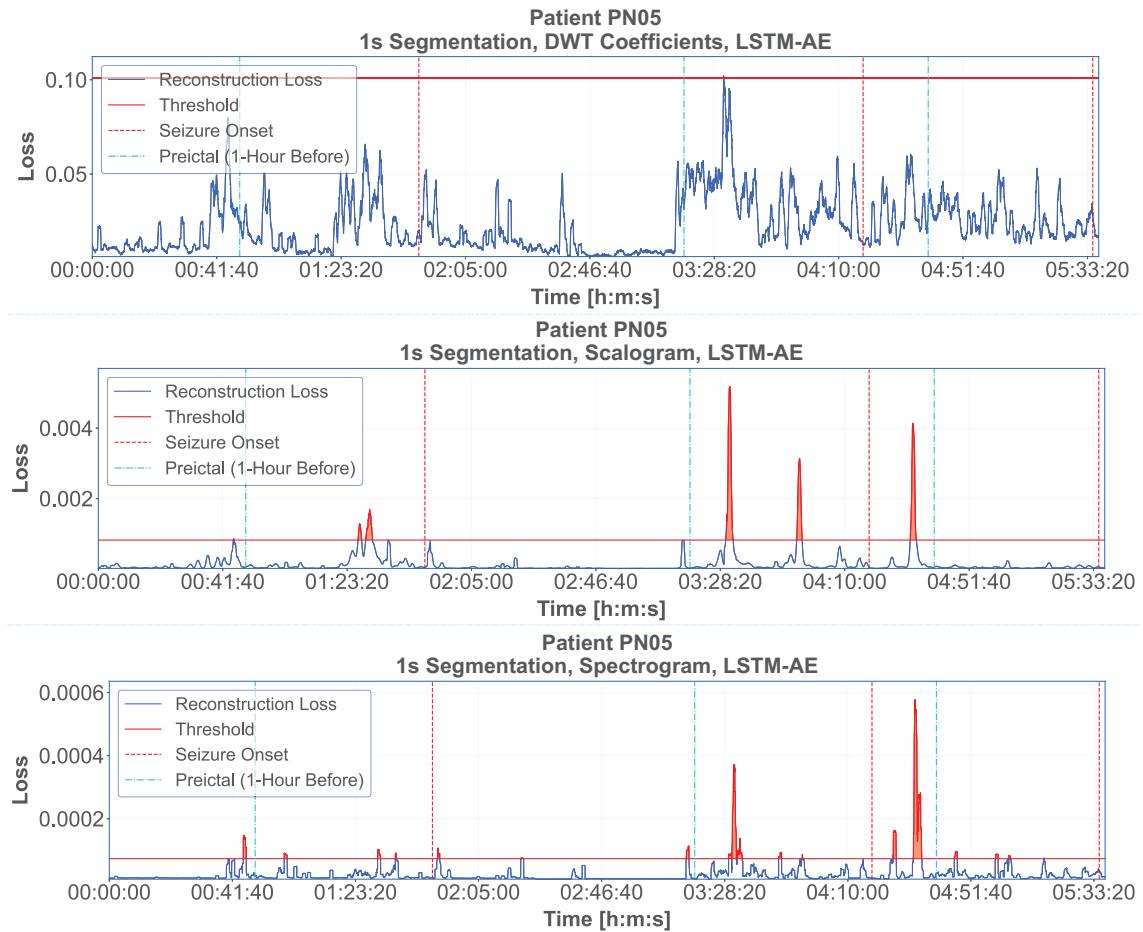


Figure 7: Results of reconstruction loss for seizure prediction (Patient PN05, 1s segmentation, LSTM-AE). The first plot shows the reconstruction loss using combined coefficients from the DWT, the second plot displays results from the scalogram representation derived from the CWT, and the final plot presents the reconstruction loss based on the spectrogram representation from the STFT.

predicted 43 seizures. Additionally, it can be observed that all three models were able to predict seizures approximately 40 minutes in advance, indicating their potential for early seizure prediction.

## 6 Comparison with Previous Studies

Seizure prediction using ECG signals has been extensively explored in biological signal processing and machine learning. This section briefly reviews related studies and compares their results with the proposed approach.

In prior work, Billeci et al. [30] applied a classification-based approach to the Siena Database, reporting an accuracy of 88.86%, specificity of 89.32%, and FPR of 0.41/h. While these results represent an advancement over earlier efforts, the reliance on linear features and conventional classification methods may limit the ability to capture the non-linear dynamics presented in pre-seizure patterns, potentially hindering seizure prediction performance in real-world settings.

As previously mentioned, the proposed method builds upon the work of Ode et al. [18], who utilized

an attention-based autoencoder (SA-AE) model for seizure prediction based on RR interval (RRI) features. However, given the unavailability of their original dataset, we decided to ensure a fair and direct comparison by re-implementing their methodology using the publicly accessible Siena database. In our re-implementation, we trained the SA-AE model on RRI features, achieving specificity of 93.85%, accuracy of 67.13%, and FPR of 0.067/h, with a prediction time of 1 minute. This allowed us to validate their approach under consistent and controlled conditions. Despite these results, the exclusive reliance on RRI features may not fully capture the intricate pre-seizure dynamics, which are critical for accurate seizure prediction. Furthermore, the relatively high FPR observed in this model poses significant challenges for clinical applicability, as false alarms can lead to alarm fatigue and reduced trust in automated systems. In order to overcome these limitations, we explored the potential benefits of incorporating our proposed time-frequency features into the model. By training the re-implemented SA-AE model with these enhanced features, we observed notable improvements in specificity and accuracy. These findings suggest that time-frequency representations offer a more comprehensive view of the underlying ECG patterns, capturing temporal and frequency-domain information that RRI features alone may miss. However, despite these improvements, the performance of the time-frequency enhanced model still did not match the robustness of our proposed MH-C-LSTM-AE model. This difference could be attributed to differences in model architecture, extracted feature representations, and the level of optimization during the training process, which all influence the final performance.

Compared to Ode et al. [18], as shown in Table 6, the proposed method achieves substantially lower FPR, enhancing its reliability for clinical applications. By addressing these limitations, the proposed framework improves prediction while ensuring a better balance between accuracy and real-world applicability.

Table 6: Comparison with previous studies.

Previous Studies		Dataset	Specificity	Accuracy	FPR (/h)	Predicted Time (Min)
Billeci et al. [30]		Siena Database	89.34 %	<b>88.86 %</b>	0.41	13.7
Ode et al. [18]		Siena Database	93.85 %	67.13 %	0.067	1
SA-AE	DWT Coefficients	Siena Database	98.05 %	75.38 %	0.019	10
	Scalogram		91.94 %	74.09 %	0.081	21
	Spectrogram		95.73 %	74.51 %	0.043	22
Proposed Methods	LSTM-AE	Siena Database	98.76 %	75.95 %	0.011	43
	MH-C-LSTM-AE		<b>99.16 %</b>	76.05 %	<b>0.010</b>	<b>45</b>
	T-EE		98.76 %	75.62 %	0.016	44

## 7 Discussion

Seizure prediction remains a critical challenge in neurology, with significant implications for patient safety and quality of life. The findings of this study provide strong evidence for the effectiveness of an ECG-based anomaly detection framework for seizure prediction, with high accuracy and temporal sensitivity. The framework, grounded in time-frequency domain feature extraction and advanced sequence modeling coupled with reconstruction error analysis, enables the proposed approach to not only detect seizures accurately but also provide a dynamic, patient-specific solution using adaptive statistical thresholds. This is critical for real-world clinical applications, where individual variability in ECG signals often challenges the use of universal thresholds.

One of the critical elements contributing to the model's success was the smoothing of reconstruction errors using moving average filtering. This step was pivotal in enhancing the reliability of the model by effectively reducing transient fluctuations often inherent in ECG signals. By reducing these fluctuations, the model is able to maintain accuracy while decreasing false alarms, which is essential for clinical systems. Furthermore, the use of an adaptive statistical thresholding method, derived from the training set's distribution parameters, enables the creation of patient-specific decision boundaries. This method accounts for inter-patient variability in physiological signals, ensuring that the model can effectively adapt to the individual characteristics of each patient. Next, the choice of segmentation window length also played a crucial role in model performance. In particular, a 1-second window without overlap provided superior results, striking a balance between temporal granularity and computational efficiency. This setup allowed the model to capture fine-grained temporal features, which are essential for detecting the pre-ictal state. Longer windows, conversely, resulted in decreased performance, due to over-smoothing and the loss of temporal resolution, which is critical for identifying early pathological changes. The feature extraction methodology also influenced the system's accuracy. Among the methods evaluated, STFT demonstrated the highest discriminative capability, highlighting the importance of frequency-domain features in identifying pre-seizure ECG patterns. However, the relatively slight performance margin between STFT, CWT, and DWT suggests that a multi-representation ensemble could be a promising avenue for future research. Combining these techniques may enhance the model's ability to detect diverse pre-seizure signatures, potentially improving prediction accuracy. Finally, among the investigated models, the MH-C-LSTM-AE model achieved the best performance. It successfully identified 45 out of 47 seizures, exhibiting high specificity and FPR of only 0.01/h. The architecture's ability to integrate temporal dependencies (via LSTM layers), spatial hierarchies (via convolutional layers), and contextual attention (via multi-head attention) was crucial for capturing the complex ECG dynamics associated with seizure onset. Notably, the approach predicted seizure onset with an average prediction time of approximately 40 minutes, suggesting its potential for real-time, anticipatory intervention in clinical settings.

However, despite these successes, the model's sensitivity to inter-individual variability remains a limitation. This is a well-known challenge in biological signal-based prediction systems, where variability in individual data can impact the consistency and generalizability of predictions. This highlights the

need for patient-specific calibration or the incorporation of transfer learning strategies in future iterations. Additionally, while the system demonstrated promising results during retrospective analysis, its true potential will only be fully realized through prospective real-time deployment in clinical environments, which will help assess its robustness under actual clinical constraints. Furthermore, the methodology proposed in this study has significant potential for broader clinical applications. Given the reliance on ECG signals and reconstruction error-based anomaly detection, the framework could be adapted for the early detection or ongoing monitoring of various cardiovascular and neurological conditions. For example, this system could be adapted for arrhythmia classification [31], sleep apnea detection [32], and other cardiovascular or neurological conditions, with minimal modifications due to their similar temporal patterns in ECG and related signals.

## 8 Conclusion

In this study, we developed a comprehensive framework for seizure prediction using ECG signals. Through careful selection of time-frequency representations and the design of robust deep learning architectures, we identified key factors—such as a 1-second time-window, low-pass filtering, and Fourier-based spectrograms—that contributed to the best performance. However, challenges such as limited patient-specific data and the inability to accurately identify seizure phases pose significant barriers to improving both the accuracy and generalizability of the model. Moving forward, future research should focus on refining the framework to improve accuracy, particularly in scenarios with limited data.

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