

# Epileptic seizure prediction on EEG signal using multiscale intrinsic mode fluctuation-based dispersion entropy

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## ABSTRACT


Fluctuation-based dispersion entropy (FDE) has emerged as a robust method for analysing biological signals. To improve its adaptability across multiple time scales, this study introduces a novel feature extraction technique, Intrinsic Mode Fluctuation-Based Dispersion Entropy (IMFDE), which combines empirical mode decomposition (EMD) and multiscale FDE. The electroencephalogram (EEG) signals were pre-processed, decomposed into intrinsic mode functions (IMFs), which were then used to compute IMFDE features. The proposed method was validated on a short-term dataset (Bonn University) and long-term dataset (Temple University Seizure Corpus – TUSZ). On the Bonn dataset, IMFDE achieved 99% accuracy, 100% sensitivity, and 98% specificity, and thus selected for subsequent testing for seizure prediction on TUSZ. On the TUSZ, IMFDE maintained a low false prediction rate ( $0.53 \text{ h}^{-1}$ ) and 100% sensitivity for 2- and 4-min seizure prediction horizons. These results demonstrate that IMFDE outperforms existing entropy-based methods, offers an adaptive and reliable approach for epileptic seizure forecasting.

**Keywords:** Electroencephalogram, Empirical mode decomposition, Epilepsy, Fluctuation-based dispersion entropy, Intrinsic mode fluctuation-based dispersion entropy.

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## 1. INTRODUCTION

Epilepsy attacks an estimated 5 million people every year, with roughly one-third suffering from seizures that cannot be controlled (Cherian and Kanaga, 2022; WHO, 2024). The occurrence of more than two seizures abruptly and lasts for several mins with varying severity is one of the symptoms in epilepsy that increases the threat of critical injuries and even sudden death (Rasheed et al., 2020). Early prediction of seizures has a major impact on life quality of epileptic patients. However, until now, seizure prediction is still manually undertaken which has a high possibility of misinterpretation (Gadhoumi et al., 2016; Assi et al., 2017). Thereby, automatic prediction of epileptic seizures is highly necessary to avoid harm to the patients.

Epileptic seizures on the brain signals of people with epilepsy can be analyzed using the recordings of various instruments, but the most common is the electroencephalogram (EEG) (Siuly et al., 2020). By analyzing the EEG signals, previous studies discovered that the occurrence of seizures show a specific process before clinical changes within

several minutes to hours (Li et al., 2013). This process is considered as pre-ictal condition. There are three other states of condition of epileptic patients, such as ictal, postictal, and interictal which is the time where seizure occurs, after seizure occurred, and between two seizures occur, respectively (Chiang et al., 2011). In this study, the epileptic seizures were predicted by detecting pre-ictal states on the recorded EEG signal.

Automated detection and prediction system using machine learning (ML) has been widely applied in biomedical engineering research field (Laghari et al., 2023; Wang et al., 2024; Yin et al., 2024; Munir et al., 2025; Qin, 2026). Concurrently, the development of seizure prediction system has been started since the 1970s using ML and focused on feature extraction (Tzallas et al., 2009). Accordingly, feature representation critically shapes model architecture and training strategy (Laghari et al., 2022). Entropy analysis outstands other methods in handling the high level of complexity of the EEG signals (Rasheed et al., 2020). In the previous study, the application of entropy in seizure prediction have worked on one scale only so it has not fully represented the dynamic of EEG signals (Singh et al., 2021). Then, a new method has been developed, namely multiscale entropy (MSE) which considers correlations on several spatial-temporal scales of the time series so that it is easier to distinguish every seizure state (Ouyang et al., 2009; Popov et al., 2020). However, MSE has not met the complexity criteria because of its unstable features (Shannon, 2001). Further, Singh et al. (2021) and Azami et al. (2019) showed that the use of multiscale dispersion entropy (MDE) and multiscale fluctuation-based dispersion entropy (MFDE) were able to overcome the shortcomings of MSE. They implemented a coarse-graining (CG) process in MDE and MFDE which resulted in significantly different feature values and led to more accurate seizure predictions. Despite these improvements, CG still employs fixed frequencies, which limits its adaptability to various forms of signals. CG decomposes the signals into some scales depending on the signal's sampling frequency and reduces the length for every scale, which is called down-sampling process. Down-sampling process leads to unstable entropy values since different signals might have different sampling frequencies (Azami and Escudero, 2018a). These choices can introduce information loss and limited sensitivity to transient pre-ictal dynamics, which hampers robust seizure forecasting and reproducibility on long-term EEG signal recordings. Motivated by these limitations, we pursue an intrinsic, data driven multiscale strategy that avoids coarse-graining and preserves frequency-specific information. This approach seeks to generate stable and interpretable features from short-term to long-term EEG.

We propose not only a new method, but also a comparative evaluation against prior entropy-based technique, multiscale PE as a precursor to FDE. Hence, the goal is set to develop an applicable multiscale-based seizure prediction system. Unlike conventional MSE and its derivatives that rely on fixed CG processes, the proposed

IMFDE replaces the coarse-graining with the adaptive decomposition using EMD to address the limitations. This improvement empowers the dynamic adjustment for the EEG non-stationary signal in the feature extraction process by computing FDE on IMFs instead of uniformly down-sampled signals. This combination is done to capture real oscillatory components of brain activity which maintains feature stability across sampling frequencies and provides a basis that is not only interpretable but also robust for epileptic seizure prediction. Therefore, IMFDE offers higher sensitivity, improved resilience, and enhanced separability between pre-ictal and normal states.

Therefore, in this study, seizure prediction is performed automatically using ML for the short-term and long-term dataset. Long-term datasets can capture more information so that the prediction results become more precise. Previous studies have successfully detected seizures on the short-term and long-term dataset, such as the Bonn University and CHB-MIT dataset (Wijayanto et al., 2019; Humairani et al., 2021). Therefore, this study continued to work on seizure prediction using Bonn University dataset and Temple University Hospital EEG Seizure Corpus (TUSZ), which is one of the largest open EEG datasets. The proposed feature extraction method is fluctuation-based dispersion entropy (FDE) since it is able to estimate the dynamic variability of signal fluctuations, so it is suitable for epilepsy prediction based on EEG signals (Wijayanto et al., 2019). FDE is combined with a multiscale empirical mode decomposition (EMD) approach to span multiple scales and get more information adaptively. This prediction system ends with the classification of pre-ictal states by support vector machine (SVM). Our findings denote that the system is adaptive to various forms of signals and ready to be evaluated with more subjects to predict seizures automatically.

The rest of this paper is arranged as follows. Section 2 contains the materials and methods applied in this study, such as the dataset used, pre-processing, decomposition, feature extraction, and classification methods. The results and discussion of the findings are presented and well written in Section 3. The last section, Section 4, concludes the paper.

In 2017, Sharma et al. (2017) developed an EEG signals automated detection model using new approach combining non-linear feature extraction with advanced wavelet analysis, tested on Bonn University dataset. Their model decomposes and extracts the discriminating features of EEG signals using the Adaptive Tunable Fractional Fourier Wavelet Transform Sub Bands (ATFFWT SBs) and fractal dimensions (FDs). The features are able capture the underlying complexity of the EEG signals. Then, Least Squares Support Vector Machine (LS-SVM) is used to classify the features, resulting in a noteworthy performance with a sensitivity of 100% across seven out of eight classification problems (CPs). For one CP, FN-OZ, which involves pre-ictal and normal EEG signals, the model achieved a sensitivity of only 90%. Nevertheless, this relatively lower performance reflects the challenge of

predicting seizures.

Continuing the study, Azami et al. (2018b) contributed an alternative approach to extracting the complexity features of EEG signals with CG process as the multiscale method. The proposed models were performed on two different datasets, Gait in Aging and Disease Database and The Bern-Barcelona EEG database. The introduction and evaluation of enhanced multiscale entropy methods, including MDE and MFDE are well-presented to investigate the impact of down-sampling and other filtering strategies on the reliability of entropy measurement. Their findings are quite interesting since CG decomposes signals into multiple scales based on the sampling frequency and performs down-sampling at each scale. This down-sampling procedure can result in unstable entropy values, as variations in sampling frequencies across signals may affect the consistency of feature extraction. However, the entropy-based approaches offer robustness and stability improvement of EEG signal complexity analysis with various signal conditions.

Extending the development of EEG signals analysis, Savadkoobi et al. (2020) introduced another approach using multiscale, focused on the epileptic seizure detection of Bonn University dataset. The study implemented statistical feature extraction, i.e., mean, variance, skewness, and kurtosis, after the signals are decomposed through three domains, which are time domain (TD), frequency domain (FD), and time-frequency domains (TFDs), Fourier Transform and wavelet transform. These two stages produce 60 features to be further selected using T-test and sequential forward floating selection (SFFS). Then, the selected features are fed into two classifiers, K-nearest neighbor (KNN) and SVM with k-fold cross-validation. The highest sensitivity obtained was 100% for five out of six CPs aligned with 100% of accuracy and specificity. The sixth CP, FN-OZ, obtained lower sensitivity, accuracy, and specificity in 95%, 95%, and 94%, respectively. Nonetheless, these results surpass the previous study (Sharma et al., 2017) by adding feature selection stage, indicating a strong potential for innovation in epileptic seizure prediction.

Building upon earlier studies, Wijayanto et al. (2021) proposed the combination of multi-distance fluctuation-based dispersion entropy (MFDispEn), multi-distance fluctuation-based dispersion fractal (MFDF), Higuchi's based MFDF (MFDFa), Katz's based MFDF (MFDFb) as the new multiscale methods for feature extraction. Their proposed methods' performances were evaluated using Bonn University dataset, applying SVM as the classifier with three scenarios, e.g., seizure detection, seizure prediction, and three classes problem. From the sensitivity point of view, the highest result was achieved using MFDFa in classifying F-O, which are 100% sensitivity, 98% accuracy, and 97% specificity. Meanwhile, by assessing the overall score percentage, the authors concluded that MFDF achieved the highest average performance. This is attributed to the integration of Higuchi's and Katz's methods, which resulted in greater differentiation than MFDFa and MFDFb. These findings demonstrate a promising direction for

improving classification performance in predicting epileptic seizure.

Further advancing EEG-based seizure prediction, Lopes et al. (2023) explored the impact of deep convolutional neural network (CNN) to remove EEG signals artefact, assessed based on scalp EEG data in the EPILEPSIAE database. Their model starts with standard EEG signals preprocessing using band-pass and notch filtering. Then, the process branches into two cases, one pipeline proceeds with physiological artefacts removal using CNN to generate denoised EEG time series, while the other retains the noisy EEG time series. The outputs from both cases are extracted using TD, FD, and TFDs to derive the features as inputs of CNN connected to a bidirectional long short-term memory layer (CNN-BiLSTM). Crucially, artefact removal contributed to better performance, with an average seizure sensitivity and false prediction rate (FPR) per hr of 0.34 and 0.90, respectively. The outcomes show a significant improvement path for enhancing epileptic seizure prediction systems.

In another relevant approach, Dong et al. (2025) addressed the limitations of single-scale features to discriminate EEG epileptic pre-ictal and ictal signals using multiscale spatio-temporal attention (MSAN), validated on CHB-MIT and Kaggle EEG datasets. Their method integrates a spatial attention backbone using the Swin Transformer, a spatial pyramid module to extract multiscale spatial information, and a sequential aggregation module that utilizes multiple LSTMs for temporal modeling as the main modules. In order to address the class imbalance and improve feature discriminability, a dual-loss training strategy, which included a combination of triplet loss and focal loss, is introduced. This novel approach reached a remarkable sensitivity of 96% and an FPR of 0.00, demonstrating the superiority of MSAN and revealing a significant advancement in the model development of predicting epileptic seizures.

The aforementioned studies deploy various multiscale algorithms on different short-term EEG datasets achieving promising results for epileptic seizure prediction. Despite that, the methods still suffer from poor interpretability and generalizability due to reliance on short-term datasets. This evolution reveals a high potential to develop and find new approach of multiscale methods combination in predicting epileptic seizure on long-term dataset. Therefore, the main contributions of this study lie in below points.

- i. The new IMFDE framework which involves the combination of EMD with PE and FDE to produce interpretable and distinctive features in the system.
- ii. Throughout the pre-processing stage, the standard EEG signal pre-processing techniques are used to eliminate noise, along with segmentation to reduce the computational cost.
- iii. The features produced from noise-free and segmented EEG signals were utilized as inputs for SVM classifier. The validation of the proposed methodology was evaluated with several evaluation metrics.

iv. Cross-dataset validation is done to evaluate the system on short-term dataset using Bonn University dataset and long-term using TUSZ.

Interestingly, our approach represents strong prospects in epileptic seizure prediction, harnessing developments in EEG signal processing and machine learning for medical use.

## 2. MATERIALS AND METHODS

### 2.1 Proposed Model

Figure 1 represents the block diagram of our proposed method. We used datasets from Bonn University and TUSZ v1.5.0 as the EEG dataset. The short-term EEG recordings in Bonn University dataset were fed to a pre-processing stage to reduce noise. Signal normalization, a fourth-order Butterworth bandpass filter (BPF), and 30 sec windowing were applied at this stage. Each window was decomposed using EMD that produced intrinsic mode functions (IMFs). PE and FDE were computed from the decomposed signals of IMF 1 to IMF 5, denoted them as intrinsic mode permutation entropy (IMPE) and intrinsic mode fluctuation-based dispersion entropy (IMFDE). Then, the features (PE, FDE, IMPE, and IMFDE) were classified using linear SVM to discriminate pre-ictal and normal states. After successfully predicting seizures in Bonn University dataset, the study continued to evaluate the system on TUSZ v1.5.0 as the long-term dataset following the same stages. We used one seizure type, Generalized Non-specific Seizure (GNSZ), with the number of patients studied was 37. In this study, the seizure prediction horizon (SPH) for TUSZ was set up to 4 mins. After the classification phase, a prediction system was made by detecting the pre-ictal states.

### 2.2 EEG Datasets

In this study, two EEG datasets were used to evaluate the performance of the proposed seizure prediction system. The first dataset contains EEG signals that were recorded at the University Hospital Bonn, Germany, and published publicly under the name of Bonn University dataset (Andrzejak et al., 2001). Five sets of EEG signals were included in Bonn University dataset, identified as F, N, O, S, and Z. Each set consists of 100 segments using a single channel that lasts for 23s at 173 Hz of sampling frequency. The set of Z and O represent normal EEG signals from healthy patients with different conditions which are eyes-opened and eyes-closed, respectively. The F, N, and S sets consist of EEG signals from epileptic patients recorded by intracranial electrodes where set F and N were collected during pre-ictal condition while set S from ictal condition.

The second dataset used in this study was one of the largest open datasets of EEG signals from Temple University Hospital (TUH), namely TUSZ in v1.5.0. TUSZ presents an accurate annotation of the clinical condition of patients with epileptic seizures (Shah et al., 2018). The EEG signals were recorded using a sampling frequency of 256 Hz following the international 10-20 configuration system.

TUSZ includes 822 sessions (280 sessions with epileptic seizures) of 315 patients. EEG signal recordings are annotated according to electrographic, electroclinical, and clinical embodiments. Based on the results of examination and testing by a neurologist, TUSZ consists of ten types of seizures, namely GNSZ, Focal Non-Specific Seizure (FNSZ), Simple Partial Seizure (SPSZ), Complex Partial Seizure (CPSZ), Absence Seizure (ABSZ), Tonic Seizure (TNSZ), Clonic Seizure (CNSZ), Tonic Clonic Seizure (TCSZ), Atonic Seizure (ATSZ), and Myoclonic Seizure (MYSZ). TUSZ has been divided into two datasets, namely training and testing data to facilitate seizure research using ML. Training and testing data contains 265 and 50 patients, respectively. The duration of each file is no more than one hour and is stored in European Data Format (EDF) with at least one seizure.

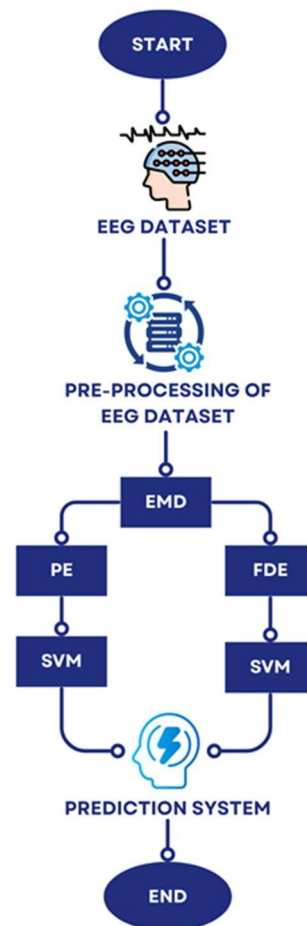


Fig. 1. The workflow of proposed seizure prediction system

### 2.3 Pre-processing of EEG Dataset

Pre-processing stage was performed to synchronize the information and reduce the noise in the dataset (Solaija et al., 2018). The EEG signals were filtered and normalized to reduce noise that appeared while recording (Das et al., 2023). In this study, we applied a fourth-order BPF filter in

frequency of 0.3–60 Hz for both datasets with 173,61 Hz and 256 Hz of sampling frequency for Bonn University dataset and TUSZ. However, in TUSZ, the number of channels used to record the EEG signals is varied. These channels had to be converted into bipolar montages which represented the difference between two adjacent electrodes. In this study, the bipolar montage resulted in 18 channels, which are utilized in every patient. Pre-processing stage was ended in the normalization process for Bonn University dataset, but TUSZ needed to proceed with the process of windowing stage that windowed the filtered signals into 30 sec windows.

## 2.4 Empirical Mode Decomposition

As a non-stationary and nonlinear signal analysis method, EMD belongs to a range of methods commonly used to analyze biomedical signals, such as lung sound classification, detection of seizures, and elimination of artifacts. EMD removes local oscillations of the signal to decompose the signal into several IMFs, then residue. Each IMF fulfills two conditions. First, the number of extreme and zero crossing values in the dataset must be the same or at least one different. Second, the local maxima define the mean value of the envelope and the local minima is equal to zero at any point. So, if the input signal is  $z(t)$ , it undergoes a decomposition process consisting of the following steps to derive its IMFs (Huang et al., 1998; Goncalves et al., 2003).

- 1) Detect all local maxima and minima (extrema) in  $z(t)$ .
- 2) Generate the envelopes by interpolating between the extrema, resulting  $e_{max}(t)$  and  $e_{min}(t)$ .
- 3) Compute the local mean function  $m(t)$  as the average of these envelopes.
- 4) Obtain the detail component as  $d_1(t) = z(t) - m(t)$ .
- 5) Assess whether the resulting  $d(t)$  adheres to the defined IMF conditions.
- 6) Re-execute steps 1 to 4 until an IMF is extracted.

Define  $k_1(t) = d_1(t)$  as the smallest intrinsic time scale in the input signal after the first IMF is obtained. Then, the process continues to the calculation of residual signal as  $re_1(t) = z(t) - k_1(t)$ . EMD treats residue as the next input signal to repeat the above process until no more IMFs resulted which means that the ultimate residue is constant. Upon completion of the decomposition,  $z(t)$  is represented as (1).

$$x(t) = \sum_{n=1}^N k_n(t) + re_N(t) \quad (1)$$

where  $N$  is the number of IMFs,  $k_n(t)$  is the  $n$ -th IMF, and  $re_N(t)$  is the ultimate IMF residue.

## 2.5 Permutation Entropy

PE calculates chaotic and non-stationary signals in the time domain. The measure of complexity is calculated by comparing the neighboring values. All values in the time domain are mapped to symbols that represent the relationship between current and past time. This mapping is

assumed to be the  $m$ -dimensional space which is calculated using (2).

$$H_p(m) = -\frac{1}{\ln(m)} \sum_{i=1}^I p_i \ln(p_i) \quad (2)$$

where  $I$  is the number of distinct symbols for the known embedding dimensions ( $I \leq m!$ ).

The  $m$  leads to various conditions. If the EEG signal is dominated by high frequencies, the permutations of probability  $m$  will be identical. Meanwhile, if the EEG signal is dominated by low frequencies, the permutations of the probability  $m$  will be distinct (Nicolaou and Georgiou, 2012). The recommended value of  $m$  for EEG signals is  $m = 3, \dots, 7$  (Bandt and Pompe, 2002).

## 2.6 Fluctuation-based Dispersion Entropy (FDE)

The irregular fluctuations in EEG signals obscure the distribution pattern which highlights the need for signal characterization. FDE provides a dynamic and nonlinear approach to signal complexity by computing the local signal fluctuations to detect the differences between adjacent elements (Li et al., 2019). Therefore, FDE was chosen as the main method because it shows high potential in characterizing various biomedical signals with large dimensions (Azami et al., 2019).

FDE is an extension of Shannon entropy (ShEN) and PE, with its algorithm grounded in the normal distribution function. In the beginning of calculation, a time series is defined, for example  $x = \{x_j, j = 1, 2, \dots, N\}$  and  $x$  is mapped to  $y = \{y_j, j = 1, 2, \dots, N\}$  where  $y_j$  is the normal distribution function. Then, the signals are calculated using (5) (Azami et al., 2019; Li et al., 2019).

$$FDE(x, m, c, d) = -\sum_{a\pi=1}^{(2c-1)^{m-1}} p(\pi_{v_0, v_1, \dots, v_{m-1}}) \ln(p(\pi_{v_0, v_1, \dots, v_{m-1}})) \quad (3)$$

where  $m$  is the embedded dimension,  $c$  is the number of classes in FDE,  $d$  is the mapping approach, and  $p(\pi_{v_0, v_1, \dots, v_{m-1}})$  is the relative frequency of each distribution pattern.

## 2.7 Support Vector Machine

SVM was first introduced by Vapnik (1992) and has been widely used in different research areas, such as classification, regression, prediction, and estimation because of its faultless performance (Alickovic et al., 2018; Hadiyoso et al., 2021). SVM for classification and prediction uses the concept of supervised learning that analyzes data and distinguishes patterns. The models built by the SVM training algorithm, such as hyperplane splitting, from the training data provide new examples as single categories (Alturki et al., 2020). So, the main principle of SVM is to find an imaginary hyperplane to separate the classes defined in the dataset. There are two types of SVM, namely linear and nonlinear which are marked by the kernel

functions (Rayatnia and Khanbabaie, 2019). There are a lot of nonlinear kernel functions, for instance radial basis functions (RBF) and polynomials (Kehri and Awale, 2020). In this study, the classification process on Bonn University dataset was carried out with 10-fold cross-validation. Additionally, the linear SVM was applied TUSZ as well.

2.8 Evaluation Metrics

The performance of the proposed method was evaluated by defining the seizure prediction horizon (SPH), followed by calculating accuracy (ACC), sensitivity (SE), seizure SPH sensitivity (SSS), specificity (SP), and FPR.

For seizure prediction using the Bonn University dataset, performance was assessed using ACC, SE, and SP as defined in equation (4), (5), and (6) where TP is true positive, TN is true negative, FP is false positive, and FN is false negative (Halim et al., 2025). In contrast, evaluation on the TUSZ dataset was based on SPH, FPR, and SSS. SPH is an area with a certain time span just before the occurrence of a seizure. FPR is defined as the ratio of false pre-ictal detections in an hour (Alotaiby et al., 2017). Since SPH was explicitly set in the TUSZ evaluation, SSS was defined as the percentage of seizures for which at least one pre-ictal state was correctly detected within the SPH. This study adopted the SSS calculation method defined by Alotaiby et al. (2017), in which a seizure is considered to have been successfully predicted if at least one pre-ictal detection occurs within the SPH.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$SP = \frac{TN}{TN+FP} \tag{5}$$

$$SE = \frac{TP}{TP+FN} \tag{6}$$

3. RESULTS AND DISCUSSION

3.1 Results using Bonn University Dataset

This study proposed the new method that was applied to Bonn University dataset. The signals were filtered and normalized at the beginning. After that, the features were extracted using FDE and PE, then IMFDE and IMPE as the multiscale features. Each EEG dataset was decomposed by the EMD algorithm using a stopping criterion [0.01,0.05,0.05] and a maximum of one iteration per mode. The first five intrinsic mode functions (IMFs 1–5) were retained, corresponding approximately to the delta–gamma EEG frequency bands (Huang et al., 1998). These parameters prevent over-sifting and ensure computational efficiency while preserving physiologically meaningful oscillations. For every IMF, FDE was calculated with an embedding dimension  $m = 3$ , number of classes  $c = 5$ , a logistic-sigmoid (“LOGSIG”) mapping function, and time delay  $d = 1$ . These settings follow the recommendations of Azami and Escudero (2018a) and Li et al. (2019), providing a balance

between sensitivity and robustness. In parallel, PE features were computed with  $m = 4$  (Nicolaou and Georgiou, 2012; Echegoyen et al., 2020). Feature values were classified using SVM with 10-fold cross-validation to distinguish normal and pre-ictal states. Therefore, the sets used were F, N, O, and Z which then grouped into a scenario including seven classification problems (CPs) (Wijayanto et al., 2021). Table 1 displays all set pairs of the CPs. The scenarios were classified severally. The detailed process is shown in Algorithm 1 as the pseudo code below. The prediction results for one scale and multiscale features are displayed in Table 2 and Table 3, respectively.

Algorithm 1 Pseudo code for seizure prediction using PE, FDE, IMPE, and IMFDE features implemented on the Bonn University dataset.

Table 1. Scenario for the classification stage

Classification problem	Pairs of set
CP1	N–Z
CP2	N–O
CP3	F–Z
CP4	F–O
CP5	N–OZ
CP6	F–OZ
CP7	FN–OZ

INPUT:

```

Bonn sets: {F, N, O, Z}
CP_pairs ← list of seven classification problems from Table 1
Fs_target = 173.61 Hz
BPF = Butterworth 4th order, passband = [0.3, 60] Hz
EMD_params: STOP = 0.01, 0.05, 0.05,
MAX_ITERATIONS = 1, NUM_IMF = 5
FDE_params: m = 3, c = 5, mapping = "LOGSIG", d = 1
PE_params: m = 4
CV_FOLDS = 10
FUNCTION EXTRACT_FEATURES (signal):
// 1) Pre-processing
x ← BANDPASS_FILTER (signal) // as specified in Methods
x ← NORMALIZE(x) // zero-mean, unit-variance (or as specified)
// 2) Single-scale features on x
fde_single ← FDispEn (x; m, c, mapping, d)
pe_single ← PE (x; m_PE)
// 3) Multiscale features via EMD
IMFs ← EMD (x; STOP, MAX_ITERATIONS) // keep the first NUM_IMF components (IMFs 1–5)
IMFs ← IMFs [1..NUM_IMF] // approx. delta–gamma bands
fde_multi ← []
pe_multi ← []
FOR each IMF in IMFs:
fde_multi.APPEND(FDispEn(IMF; m, c, mapping, d))
pe_multi.APPEND(PE(IMF; m_PE))
    
```

```
// 4) Concatenate feature sets as needed
IMFE_vector ← CONCAT (fde_multi) // IMFDE
features_SINGLE_vector ← [fde_single, pe_single] //
optional single-scale baseline
RETURN {SINGLE_vector, IMFE_vector, IMPE_vector}
IMPE_vector ← CONCAT (pe_multi) // IMPE features
```

**MAIN:**

```
FOR each (SET_A, SET_B) in CP_pairs:
// Build dataset for this CP
X ← []; y ← []
FOR each recording r in (SET_A SET_B):
feats ← EXTRACT_FEATURES(r.signal)
// Choose which feature variant(s) to evaluate:
// feats.SINGLE_vector // PE/FDE single-scale
// feats.IMFE_vector // IMFDE (FDE on IMFs 1-5)
// feats.IMPE_vector // IMPE (PE on IMFs 1-5)
X.APPEND (SELECT (feats)) // pick one or evaluate all
three separately
y.APPEND (LABEL(r, SET_A, SET_B)) // binary label for
```

```
this CP // 10-fold cross-validation with SVM scores ← []
SPLITS ← K_FOLD_SPLIT (X, y, k = CV_FOLDS)
FOR each (X_tr, y_tr; X_te, y_te) in SPLITS:
clf ← TRAIN_LINEAR_SVM (X_tr, y_tr)
y_pred ← PREDICT (clf, X_te)
scores.APPEND (METRICS(y_te, y_pred)) // e.g., ACC,
SE, SP
REPORT_MEAN_STD (scores) // per CP and per feature
variant (SINGLE, IMFDE, IMPE)
```

All scenarios were classified severally with linear SVM. The seizure prediction results are displayed in Table 2. IMFDE achieved the highest result in CP4 with ACC, SE, and SP of 99%, 100%, 98%, respectively. The second-best results were achieved in CP2 using IMPE with 98% of ACC, SE, and SP. IMPE obtained slightly different results with IMFDE. In contrast, the results obtained by PE and FDE were significantly lower. Thus, the IMFDE and IMPE were tested further on long-term dataset, the TUSZ, to specify the best combination of multiscale methods.

**Table 2.** One scale features prediction result using Bonn University dataset

CP	PE			FDE		
	ACC (%)	SE (%)	SP (%)	ACC (%)	SE (%)	SP (%)
CP1	79	70	83	89	89	90
CP2	59	34	64	80	87	73
CP3	67	68	88	94	94	95
CP4	67	70	83	85	82	88
CP5	72	38	76	83	75	87
CP6	79	69	95	89	77	94
CP7	71	65	96	84	86	82

**Table 3.** Multiscale features prediction results using Bonn University dataset

CP	IMPE			IMFDE		
	ACC (%)	SE (%)	SP (%)	ACC (%)	SE (%)	SP (%)
CP1	91	91	92	94	90	98
CP2	98	98	98	97	96	98
CP3	90	90	90	95	95	95
CP4	96	94	98	99	100	98
CP5	95	93	97	96	90	97
CP6	94	88	97	96	93	97
CP7	96	96	96	96	94	95

**3.2 Results using TUSZ**

The study aims to develop an applicable multiscale-based seizure prediction system. Hence, the TUSZ, as the long-term dataset, was used to validate the performance of IMFDE and IMPE. GNSZ was chosen out of the ten types of seizures in TUSZ with a total of 37 patients, which were divided into 28 training and 9 testing data. TUSZ was required to go through more pre-processing steps since the TUSZ is longer, larger, and more complicated than Bonn University dataset. After setting ground truth of the seizures from the provided information in a dataset, the channel was converted by bipolar montage and constructed 18 channels. However, to predict seizures in long-term dataset, every

EEG signal recording should start with normal conditions. Therefore, the recordings were processed after the first 5 mins to make sure that the initial condition of the recording was not included in the processed signal. Then, the signals were normalized and filtered to eliminate the noise in 0.3–60 Hz using Butterworth BPF. The sampling frequency was set to 256 Hz. The selected cutoff frequencies retain slow pre-ictal trends (above 0.3 Hz) and low-gamma information (below 60 Hz) relevant to the features analysis. This is supported by the frequency sampling used which keeps ample headroom below Nyquist while focusing on physiologically meaningful scalp EEG content.

The process continued to a 30 min windowing, EMD, and

feature extraction using PE and FDE, with the exact same parameters applied in Bonn University dataset. IMF 1 to 5 were carried out to the feature extraction stage and ignored the IMF 6 or higher since they produced considerable different signals from the original signals, so it was very difficult to interpret. After that, each IMF feature was calculated using PE and FDE, independently. Each method produces five features. In addition, since each window consisted of 18 channels, we calculated the average feature value to be fed into SVM.

Our seizure prediction focused on the normal and pre-ictal states. The length of the pre-ictal state was determined by the duration of SPH. In this study, the SPH for 28 training data and 9 test data were 4 mins and 2 mins, respectively. After the SPH was defined, the mean features of IMPE and IMFDE were classified by SVM separately. The following pseudocode illustrates the detailed procedure. Table 4 shows the prediction results on test data using IMPE and IMFDE evaluated by FPR and SE. IMFDE achieved an average FPR 0.53 h<sup>-1</sup> and SSS 100%. Meanwhile, IMPE had an average FPR 0.8 h<sup>-1</sup> and SSS 100%.

Algorithm 2 Pseudo code for seizure prediction using IMPE and IMFDE features evaluated on the TUSZ.

**INPUT:**

*TUSZ dataset (EDF + seizure annotations)*  
*Seizure type = GNSZ*  
*Patient split: TRAIN = 28 patients, TEST = 9 patients*  
*F<sub>s\_target</sub> = 256 Hz*  
*BPF = Butterworth 4th order; passband = [0.3, 60] Hz*  
*Montage = bipolar → 18 channels*  
*Window length = 30 minutes (non-overlapping)*  
*EMD params: STOP = 0.01, 0.05, 0.05,*  
*MAX\_ITERATIONS = 1, NUM\_IMF = 5*  
*FDE params: m = 3, c = 5, mapping = "LOGSIG", d = 1*  
*PE params: m = 4*  
*SPH: TRAIN = 4 mins, TEST = 2 mins*

**OUTPUT:**

*Feature sets and labels for IMPE and IMFDE; trained SVM; test metrics*

**PROCEDURE MAIN:**

```

records ← SELECT (TUSZ where seizure_type == GNSZ)
(train_patients, test_patients) ← SPLIT_PATIENTS (records, 28, 9)
//---- Build TRAIN set (SPH = 4 min) ----
(X_train_IMPE, y_train), (X_train_IMFDE, y_train) ← BUILD_DATASET (train_patients, SPH = 4)
//---- Build TEST set (SPH = 2 min) ----
(X_test_IMPE, y_test), (X_test_IMFDE, y_test) ← BUILD_DATASET (test_patients, SPH = 2)
//---- Train and evaluate SVM separately for IMPE and IMFDE ----
svm_IMPE ← TRAIN_SVM (X_train_IMPE, y_train, CV = 10-fold)
svm_IMFDE ← TRAIN_SVM (X_train_IMFDE,

```

```

y_train, CV = 10-fold)
y_pred_IMPE ← PREDICT (svm_IMPE, X_test_IMPE)
y_pred_IMFDE ← PREDICT (svm_IMFDE, X_test_IMFDE)
REPORT_METRICS (y_test, y_pred_IMPE) // e.g., accuracy, sensitivity/specificity, FPR, SSS
REPORT_METRICS (y_test, y_pred_IMFDE)
FUNCTION BUILD_DATASET (patients, SPH_minutes):
X_IMPE ← []
X_IMFDE ← []
y ← []
FOR each patient in patients:
FOR each recording r in patient.recordings:
//--- Load & resample/confirm Fs ---
(sig_raw, ann, Fs_in) ← READ_EDF_WITH_ANNOTATIONS(r)
IF Fs_in ≠ Fs_target: sig_raw ← RESAMPLE (sig_raw, Fs_target)
//--- Exclude initial 5 minutes to ensure normal start ---
sig_raw ← DISCARD_INITIAL (sig_raw, 5 minutes, Fs_target)
ann ← SHIFT_ANNOTATIONS (ann, -5 minutes)
//--- Bipolar montage to 18 channels ---
sig_bip ← APPLY_BIPOLAR_MONTAGE (sig_raw, target_channels = 18)
//--- Normalize & band-pass filter 0.3–60 Hz ---
sig_norm ← ZSCORE_CHANNELWISE (sig_bip)
sig_filt ← BUTTERWORTH_BPF (sig_norm, order = 4, passband = [0.3, 60], Fs = Fs_target)
// --- Segment into 30-minute windows (non-overlapping) ---
windows ← SEGMENT (sig_filt, length = 30 mins)
//--- Build pre-ictal labels by SPH ---
preictal_intervals ← []
FOR each seizure onset time t_on in ann:
preictal_intervals.APPEND([t_on - SPH_minutes, t_on])
FOR each window w in windows:
// Label = 2 if window overlaps any pre-ictal interval; else 1 (normal)
label ← (OVERLAPS (w.time_range, preictal_intervals)) ? 2 : 1
//--- Feature extraction per window ---
(f_IMPE, f_IMFDE) ← EXTRACT_FEATURES_WINDOW(w)
//--- Average across 18 channels (per method) ---
f_IMPE_mean ← MEAN_ACROSS_CHANNELS(f_IMPE) // 5 features (PE on IMFs 1..5)
f_IMFDE_mean ← MEAN_ACROSS_CHANNELS(f_IMFDE) // 5 features (FDE on IMFs 1..5)
X_IMPE.APPEND(f_IMPE_mean);
X_IMFDE.APPEND(f_IMFDE_mean)
y.APPEND(label)
END FOR
END FOR

```

```

END FOR
RETURN ( (X_IMPE, y), (X_IMFDE, y) )
FUNCTION      EXTRACT_FEATURES_WINDOW
(window_signal):
// window_signal: shape [channels=18, time]
features_IMPE ← []
features_IMFDE ← []
FOR each channel c in window_signal:
x ← window_signal[c, : ]
// EMD with STOP criterion and max 1 iteration per
mode
IMFs ← EMD (x; STOP = <as specified>,
MAX_ITERATIONS = 1)
IMFs ← KEEP_FIRST_N (IMFs, N = 5) // IMFs 1-5
(≈ delta-gamma)
// Compute PE and FDE independently on each IMF
pe_vec ← []
fde_vec ← []
FOR each IMF in IMFs:
pe ← PERMUTATION_ENTROPY (IMF; m =
<m_PE>)
fde ← FDISPERSION_ENTROPY (IMF; m =
<m_FDE>, c = <c_FDE>, mapping = "LOGSIG", d =
<d_FDE>)
pe_vec.APPEND(pe)
fde_vec.APPEND(fde)
END FOR
features_IMPE.APPEND(pe_vec) // length = 5
features_IMFDE.APPEND(fde_vec) // length = 5
END FOR
RETURN (features_IMPE, features_IMFDE)
    
```

**Table 4.** Prediction results of the multiscale features using TUSZ

Record	Seizure type	FPR ( $h^{-1}$ )		SSS (%)	
		IMPE	IMFDE	IMPE	IMFDE
1	GNSZ	1	0.4	100	100
2		1	1	100	100
3		1	1	100	100
4		1	0.4	100	100
5		1	1	100	100
6		0.4	0.2	100	100
7		0	0.4	100	100
8		1	0.4	100	100
9		1	0	100	100
Average		0.82	0.53	100	100

### 3.3 Discussion

The prediction performance results using short-term dataset, Bonn University, claims that the one scale methods were trounced by the multiscale methods. PE and FDE were incapable of reflecting dynamics of EEG signals completely because they measured the EEG signals on the single scale (Singh et al., 2021). The seizure prediction system worked on the pre-ictal and normal states which had more similar dynamics than normal and ictal states. As a result, IMPE and IMFDE were more powerful in collecting more information from the decomposition stage that led to higher prediction results.

Table 5 shows the performance comparison of this study and previous studies that predicted seizures using Bonn University. Sharma et al. (2017) predicted seizures by classifying the set pairs of FN–OZ using the combination of analytic time-frequency flexible wavelet transforms (ATFFWT), FD, and least squares SVM (LS SVM). The highest results that they obtained were 92%, 90%, and 94% for ACC, SE, and SP, respectively. The next study conducted by Savadkoohi et al. (2020) combined four statistical features (SF), wavelet transform, feature selection, KNN, and SVM to classify the same set pairs as Sharma et

al. They achieved higher results with SVM in 96% for all performance evaluators. Furthermore, Wijayanto et al. (2021) classified exactly the same CPs as this study, yet they combined MFDispEn, MFDF, MFDFa, MFDFB, and SVM. The best results occurred in F–O with various numbers of ACC, SE, and SP detailed in Table 5. However, our multiscale combination using IMPE and IMFDE improved the performance of seizure prediction system up to 99%, 100%, and 98% of ACC, SE, and SP, respectively, in CP4.

The seizure prediction results of the short-term dataset indicate development and improvement with IMPE and IMFDE. Both methods were implemented to predict seizures in the long-term TUSZ dataset. As shown in Table 4, IMFDE outperformed IMPE at the same IMF level, obtaining a lower FPR. Notably, both methods reached a perfect score of sensitivity, 100%.

Fig. 2 and Fig. 3 show the average feature values for IMPE and IMFDE from one of the recording files (file 4 of data train) in 5 IMFs, respectively. Based on SPH that was set in file 4 of data train, the pre-ictal state occurred for 4 minutes in the 29<sup>th</sup> to 36<sup>th</sup> window. The IMFDE resulted up to 0.1 difference in value, while the IMPE feature produced only up to 0.01 when entering the pre-ictal state. The gap in

feature values between normal and pre-ictal states produced by IMFDE is wider ranging than IMPE. This happened since FDE calculated the fluctuations that occurred in the local signal which made the changes in amplitude and frequency were clearly seen so that it could recognize the pre-ictal patterns conveniently. The use of IMFDE also overcame IMPE's problem by specifying the number of classes to map the data based on signal amplitude values. IMFDE was able to mitigate the instability caused by the coarse-graining down-sampling step by introducing adaptive decomposition using EMD, enabling each IMF to represent specific oscillatory modes and providing better capture of transient neural fluctuations preceding seizures. This advantage of IMFDE strengthened the robustness of entropy features and made the seizure prediction system able to produce higher SSS and lower FPR because the classification process performed using SVM became easier.

Previous works have successfully detected the seizures and classified the ten types of seizures, yet none of them predicted the seizures in TUSZ (Albaqami et al., 2022; McCallan et al., 2023; Akor et al., 2025). Therefore, this study marked the first seizure prediction system that was evaluated on TUSZ as the long-term dataset with competitive average results achieved by IMFDE in  $0.53 \text{ h}^{-1}$

of FPR and 100% of SE.

Although the proposed IMFDE method resulted superb and low FPR on both Bonn University and TUSZ EEG datasets, several limitations remain. First, since the evaluation relied on public datasets recorded under controlled experimental conditions, the result may not fully represent the variability of EEG data acquired in real-world hospital settings. Second, the IMFDE calculation is computationally demanding making the current implementation unsuitable for real-time seizure forecasting on resource-limited devices. In line with this, the validation for real-time continuous monitoring has not been executed using the proposed model. Consequently, a fruitful line of inquiry involves algorithmic optimization, such as applying ensemble EMD variants and additional methods to reduce the computational complexity of entropy estimation (Liu et al., 2022; Berg et al., 2025). Other than that, further validations of IMFDE model on larger and more diverse EEG datasets, including multi-institutional datasets, are required to confirm its generalizability. Moreover, integrating the IMFDE framework into edge-AI EEG acquisition systems would pave the way for real-time seizure warning tools and broader clinical applications in digital healthcare.

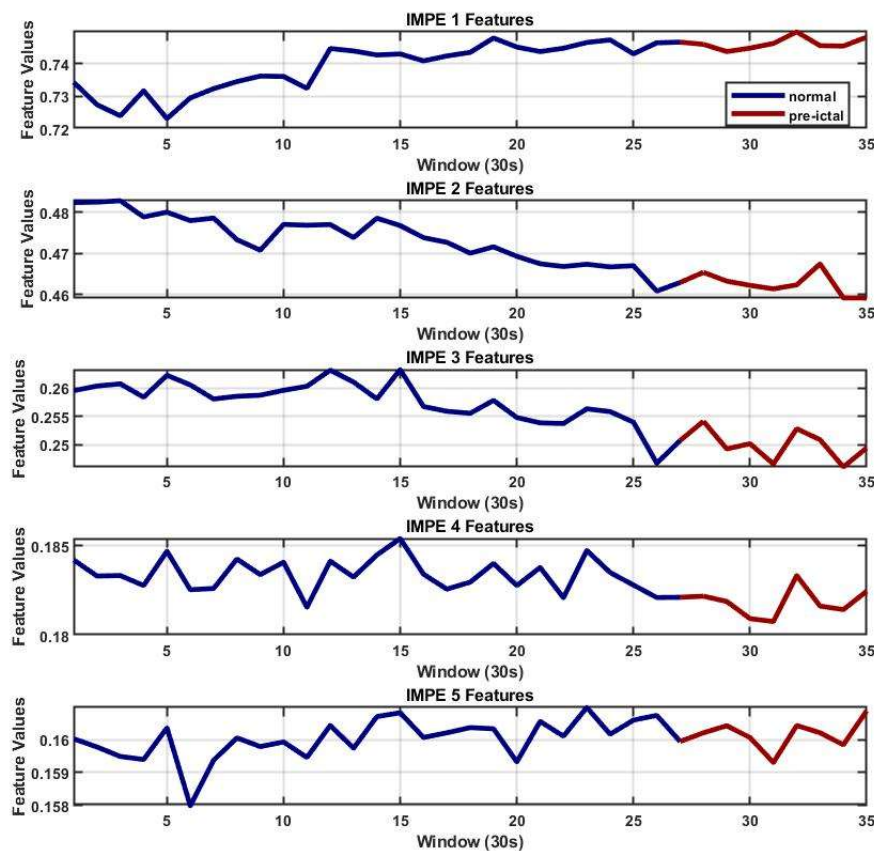


Fig. 2. Sample of IMPE mean values in 5 IMFs

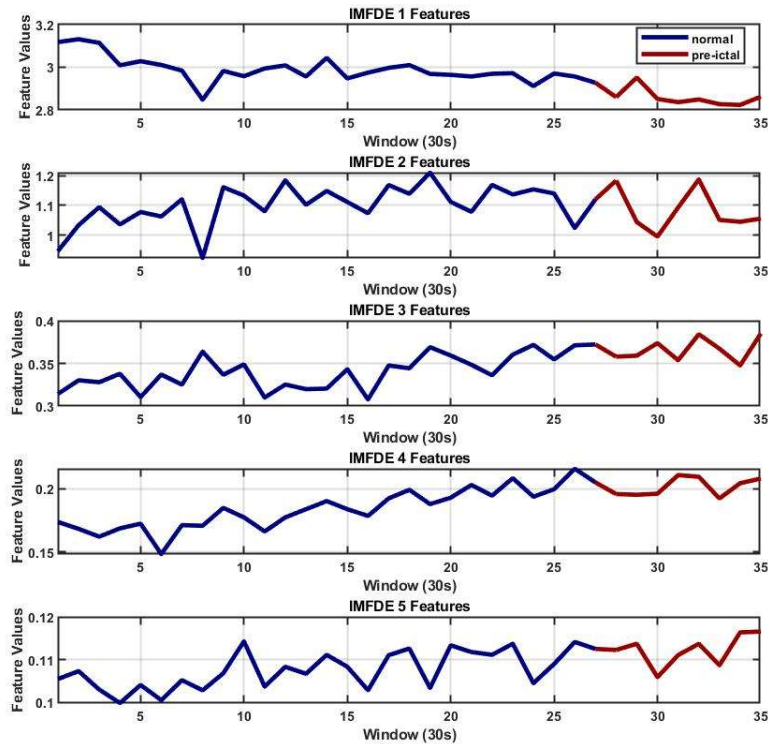


Fig. 3. Sample of IMFDE mean values in 5 IMFs

Table 5. Performance comparison with previous studies using Bonn University dataset

References	Multiscale methods	CP	ACC (%)	SE (%)	SP (%)
Sharma et al. (2017)	ATFFWT, FD, and LS SVM	FN-OZ	92	90.5	94
Savadkoohi et al. (2020)	Four SF, wavelet transform, feature selection, and KNN	FN-OZ	89	87	91
	Four SF, wavelet transform, feature selection, and SVM	FN-OZ	96	96	96
Wijayanto et al. (2021)	MFDispEn and SVM	F-O	97	98	97
		FN-OZ	95	96	94
	MFDFa and SVM	F-O	98	100	97
		FN-OZ	96	96	97
	MFDFB and SVM	F-O	97	100	94
		FN-OZ	97	99	95
MFDF and SVM	F-O	98	99	98	
	FN-OZ	98	98	98	
This study	IMPE and SVM	F-O	96	94	98
		FN-OZ	96	96	96
		N-Z	91	91	92
		N-O	98	98	98
	IMFDE and SVM	F-Z	90	90	90
		N-OZ	95	93	97
		F-OZ	94	88	97
		F-O	99	100	98
		FN-OZ	96	94	95
		N-Z	94	90	98
IMFDE and SVM	N-O	97	96	98	
	F-Z	95	95	95	
	N-OZ	96	93	97	
	F-OZ	96	94	95	

#### 4. CONCLUSION

In this study, a new combination of multiscale method using EMD with FDE, under the name of IMFDE, was proposed to predict epileptic condition in EEG signal recordings. Pre-processed EEG signals were decomposed using EMD, then 5 IMFs were fed to the feature extraction stage. The FDE values were calculated for each IMF and resulted in 5 IMFDE features. The robustness of the proposed methods was examined by comparing with the former method of FDE, PE, which resulted in 5 IMPE features. Additionally, the one scale methods, FDE and PE, were estimated to see the advantages from the multiscale methods. The proposed method was evaluated on Bonn University and TUSZ. The results from Bonn University dataset claimed that the multiscale methods were more capable of seizing the dynamics of EEG. The highest results were achieved using IMFDE with 99%, 100%, and 98% of ACC, SE, and SP, respectively. Therefore, the TUSZ was used to test the IMFDE and IMPE further in predicting seizure to reach the goal in developing an applicable multiscale-based seizure prediction system. The performance evaluation of IMFDE and IMPE on TUSZ was different seeing that the recordings contain longer duration. The best results showed an FPR of  $0.53 h^{-1}$  and SE of 100% for TUSZ using IMFDE. Our experimental results signify that IMFDE is all set to be evaluated on more subjects to predict seizures automatically since it is adaptive to various forms of signals. Despite these promising results, future extensions will aim to optimize computational efficiency and extend validation to larger EEG databases. These advances would make IMFDE-based seizure forecasting viable for real-time and mobile healthcare deployment.

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