Neuroscience 577 (2025) 12–24

Contents lists available at ScienceDirect

Neuroscience

journal homepage: www.elsevier.com/locate/nsc

Research Article

Entropy-driven deep learning framework for epilepsy detection using electro encephalogram signals

Sandeep Singh Sikarwar [a], Arun Kumar Rana [b], Sandeep Singh Sengar [c,*]

[a] *Galgotia College Of Engineering And Technology, Central University of Haryana, Greater Noida, India*
[b] *Galgotia College Of Engineering And Technology, Greater Noida, India*
[c] *School of Technologies, Cardiff Metropolitan University, CF5 2YB, United Kingdom*

ARTICLE INFO

Keywords:
Epilepsy detection
Multiple variable entropy
Deep Learning
EEG signals
Neurological disorder
Temporal dynamics

ABSTRACT

Epilepsy is one of the most frequently occurring neurological disorders that require early and accurate detection. This paper introduces a novel approach for the automatic identification of epilepsy in EEG signals by incorporating advanced entropy-based measures with modern pre-processing techniques. The objective is to develop a robust and effective epilepsy detection method. EEG data were pre-processed using adaptive wavelet denoising models to suppress noise while preserving signal integrity. Multivariate entropy features, including Multiple Variable Permutation Entropy (mvMPE) and Multiple Variable Multi-Scale Fuzzy Entropy (mvMFE), were extracted to capture both complexity and frequency-specific variations. Additionally, Uniform Manifold Approximation and Projection (UMAP) was applied for non-linear dimensionality reduction, enhancing the discriminative power of features. A Residual Convolutional Neural Network (ResNet) integrated with Bi-Directional Long Short-Term Memory (Bi-LSTM) was employed to capture both temporal dynamics and spatial features. The proposed model demonstrated superior classification accuracy compared to traditional approaches. Implemented using Python, the model achieved an accuracy of 94%, F1-Score of 96%, recall of 93%, specificity of 87.70%, and precision of 82.21%. This study highlights the synergy between advanced entropy measures and cutting-edge deep learning architectures for robust and accurate epilepsy detection.

Introduction

Epilepsy, derived from the Greek word ‘epilepsia’ meaning ‘to attack,’ is a chronic neurological disorder affecting millions globally. Another words, Epilepsy is a chronic neurological disorder characterized by sudden, recurrent seizures caused by abnormal brain activity. It affects millions of people worldwide, and early diagnosis is crucial for effective management. While antiepileptic drugs and surgical interventions can help control seizures, accurately detecting epilepsy remains a challenge. Electroencephalography (EEG) is commonly used to monitor brain activity and detect seizures. However, analysing EEG signals manually is difficult due to their complex, non-linear, and noisy nature, which makes automated methods essential. Artificial Intelligence (AI) has revolutionized healthcare by providing advanced diagnostic tools and intelligent systems for various medical conditions. Artificial intelligence techniques, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Graph Neural Networks (GNNs), have shown significant effectiveness in recognizing patterns within intricate medical datasets. Additionally, emerging transformer models and hybrid architectures have shown enhanced capabilities in recognizing intricate temporal and spatial relationships in data. These techniques have been successfully utilized in diagnosing various conditions, such as attention deficit hyperactivity disorder (ADHD), COVID-19, and diabetes. In ADHD diagnosis, AI models analyze behavioral and neuron imaging data for early detection. For COVID-19, AI-powered radiological imaging analysis has accelerated diagnosis and monitoring. Similarly, AI systems for diabetes management predict blood glucose levels, detect complications, and provide personalized care recommendations. Despite these advancements, current methods still face limitations. Many systems struggle to balance accuracy and computational efficiency, especially when data is limited. Models that require large datasets often underperform in real-world scenarios where training data is scarce. Moreover, relying on a single type of feature extraction can lead to low classification accuracy, as important seizure information may be missed. Additionally, noise interference in EEG signals remains a

* Corresponding author.
E-mail addresses: arunkumar@galgotiacollege.edu (A.K. Rana), SSSengar@cardiffmet.ac.uk (S.S. Sengar).

https://doi.org/10.1016/j.neuroscience.2025.05.003
Received 15 February 2025; Accepted 2 May 2025
Available online 5 May 2025

challenge, reducing the reliability of predictions. To address these limitations, this study proposes a novel approach that integrates advanced entropy-based feature extraction with effective noise reduction and feature selection. Adaptive wavelet denoising is applied to reduce noise while maintaining essential signal information. For robust feature extraction, two multivariate entropy measures are introduced: Multivariate Permutation Entropy (mvMPE) and Multivariate Multi-Scale Fuzzy Entropy (mvMFE). These measures capture both the complexity and frequency-specific patterns in EEG data. Further, Uniform Manifold Approximation and Projection (UMAP) is employed for non-linear dimensionality reduction, enhancing the discriminative power of the extracted features.

A hybrid model combining Residual Convolution Neural Networks (ResNet) and Bi-LSTM networks is proposed for classification. This architecture leverages ResNet's ability to extract spatial features and Bi-LSTM's strength in capturing temporal dependencies, providing a comprehensive understanding of EEG patterns. The proposed method achieves higher accuracy compared to conventional approaches. The main contributions of this study include:

- Design framework of mvMPE and mvMFE for advanced feature extraction, capturing complex seizure characteristics.
- Applying UMAP for efficient dimensionality reduction, improving the clarity of feature representations.
- Developing a hybrid ResNet-Bi-LSTM model that enhances classification accuracy and robustness.
- Conducting comprehensive experiments demonstrating significant improvements in accuracy, F1-Score, recall, specificity, and precision compared to existing methods.

The remainder of the paper is organized as follows. Section 2 reviews related work in the field of epilepsy detection using AI and deep learning. Section 3 describes the proposed methodology, including data pre-processing, feature extraction, dimensionality reduction, and model design. Section 4 presents the experimental results and evaluates the model's performance. Finally, Section 5 concludes the paper with a discussion of findings and future research directions.

Literature survey

In this section literature review of current research efforts concerning epilepsy detection, emphasizing novel techniques and models that enhance both efficiency and accuracy. The studies concentrate on utilizing advanced computational methods to examine EEG data and distinguish between epileptic and non-epileptic states. Ilias et al. (2023) proposed two techniques for differentiating ictal, interictal, and healthy instance, without feature extraction. Initially, single-channel EEG data has been altered into a three-channel image utilizing the Fourier transform in a short time. This image is then fed into pre-trained models such as ResNet18, Efficient Net, DenseNet201, and AlexNet. Next, technique introduces a multimodal deep neural network (DNN), using two CNN branches to process every single-channel EEG input to extract characteristics of low and high-frequency. Sunaryono et al. (2022) describe method's classification for the automatic Epilepsy diagnosis from EEG information. EEG signals were classified using a combination of two-class and three-class gradient boosting machines, based on certain statistical and crossing frequency characteristics. Prominent traits are selected through a Genetic Algorithm (GA). Three kinds of EEG signals (normal, interictal, and ictal) from the University of Bonn's EEG dataset were used to assess the suggested approach. Beeraka et al. (2022) implemented a short-time Fourier transform block in DL models with Field-Programmable Gate Array (FPGA) to increase the number of epileptic seizures detected. The following stages have been utilized for the detection of seizures: (1) application of short-time Fourier transform (STFT) for evaluation of EEG segments in terms of time and frequency; (2) extraction of the relevant characteristics and frequency ranges; and (3) CNN and Bi-LSTM to detect seizures. Tawhid et al. (2022) have focused on designing an efficient framework to identify epileptic seizures employing EEG data by using a convolution long short-term memory (ConvLSTM) network. Standard 19-channel EEG data that has been subdivided into 3 s time frames and resampled to 256 Hz is utilized in the model. Further, the ConvLSTM model is applied to separate epileptic patients from healthy ones. UFP and TUEP are the two datasets are taken for testing with techniques of leave-one-out cross-validation and five-fold cross-validation. The findings unequivocally indicate that the model exceeds the state-of-the-art in performance, so it is qualified for automatic Epilepsy diagnosis. Mallick and Baths (2024) proposed a radical approach toward epileptic seizure detection by putting together the strength of Bi-LSTM, Average Pooling Layer, 1-D convolutional layers (1D-CNN), and GRU in a single component. The EEG waveform's classification is then obtained by sending the features to dense layers. The recommended model's efficiency is validated by using the Bonn dataset. Using five-fold cross-validation, resilience and generalizability of the suggested architecture are examined. Kumar et al., (2023) introduced the concept of seizure detection using a Bi-LSTM network. Therefore, by using statistical feature extraction methods and LMD, Bi-LSTM decreases the processing costs while keeping the unpredictable character of EEG data. The deep design combined with two different LSTM networks propagating in opposite ways. In order to determine the output state, the deep model can utilise data from both before and after the present the period of study. Al-Qazzaz et al. (2024) used two sessions to automatically distinguish between children who have epileptic seizure and typical children. In the first session, machine learning based models, like, SVM, KNN, and decision tree were used to classify the extracted features from the EEG dataset. In the next session, deep learning based on RNN classifiers, such as, gated recurrent unit (GRU), LSTM, and BiLSTM were used to classify the dataset. Islam et al. (2022) suggested a dynamic approach for identify the epileptic seizures that makes use of a deep learning model called Epileptic-Net. The hyper column technique (HT), residual blocks (RB), feature attention modules (FAM), and dense convolution blocks (DCB) make up the mainly diverse suggested approach. First, the EEG data set' discriminative characteristics are extracted using dense convolution blocks. The samples' key characteristics are then extracted via feature attention modules. Following that, when it fully utilizes the convolution layer's input, residual blocks learn more crucial components. Lastly, hyper column technique preserves the effective local characteristics that were taken from the layers located at the various model levels. Zhang et al. (2022) proposed a Bi-GRU neural network-based automated identification of seizures method that aids in EP diagnosis and treatment. First, the EEG records are filtered and pre-processed using wavelet transforms. Following that, the signals' relative energies in many specific frequency bands are supplied to the Bi-GRU system. The resultant products of the Bi-GRU network are then input into the threshold comparison, seizure merging, and moving average filtering procedures to produce outcomes that are discriminate and indicate whether or not the tested EEG is seizure-related. Shoka et al. (2023) offered a novel, effective system for classifying and recognizing data from an EEG that has been encrypted by applying CNNs with the Arnold Transform and Chaotic Baker Map techniques. The suggested solution uses the Arnold Transform and Chaotic Baker Map techniques to encrypt the EEG period of the channel series after converting it into an image of a 2D spectrogram and then sends information to CNN-based models for Transfer Learning (TL). Ahmed et al. (2023) introduced a novel method called the InvBase method for removing baseline power from EEG signals before feature extraction. This approach ensures that the extracted features remain invariant across different subjects, thereby improving the robustness of emotion classification in terms of valence and arousal. The proposed scheme was evaluated against subtractive and no-baseline-correction methods, demonstrating its effectiveness. Similarly, Islam et al. (2020) proposed a motion artefact removal technique specifically designed for epilepsy monitoring using wearable EEG headsets. In their work, motion

Table 1
Research gaps from the existing works.

Author's Name	Aim	Methods	Advantages	Disadvantages
Ilias et al. (2023)	To propose and evaluate methods for classifying EEG signals into healthy, interictal, and ictal cases,	AlexNet, DenseNet201, Efficient Net, ResNet18, CNN	Robust Evaluation,	Imbalanced Data, Complexity of Multimodal Models
Sunaryono et al. (2022)	To develop and evaluate a reliable classification technique for automatically identifying epilepsy in EEG recordings.	GBM, GA	Effective Preprocessing Techniques	High computational complexity, Lack of Generalizability
Beeraka et al. (2022)	To improve EEG signal recognition of epileptic seizures by employing DL in combination with hardware implementation.	Bi-LSTM, CNN	Cross-validation for Small Dataset, Generalizability	Limited Clinical Validation
Tawhid et al. (2022)	To develop a generalizable and effective approach for detecting epilepsy from EEG signals	ConvLSTM	Real-Time Application Potential, Extensibility	Data Dependency requires more computational resources
Mallick, and Baths, (2024)	To establish an automated technique for identifying epileptic seizures based on EEG	LSTM, GRU, 1D-CNN	Generalizability, Extensibility	Lack of Real-Time Validation, Complexity of Model
Kumar et al. (2023)	To boost the precision and effectiveness of detecting seizures by addressing the fact that EEG data is not stationary	Bi-LSTM, LSTM	Effective Handling of Non-linear EEG Signals	Complexity of Implementation
Al-Qazzaz et al. (2024)	To develop an automatic technique for anticipating epileptic seizures by analyzing EEG signals	SVM, RNN, KNN, DT	Potential for Real-Time Detection	Dataset Limitations
Islam et al. (2022)	To introduce a dynamic method, Epileptic-Net, which uses the DL model for the automatic identification of epileptic seizures.	DCB, FAM, RB, HT	Reliable Diagnosis, Scalability	Limited Labeled Data
Zhang et al. (2022)	To create a computerized approach for detecting seizures based on the Bi-GRU neural network to aid in the diagnosis and management of EP	Bi-GRU	Low Computational Demand, Scalability	Noise and Artifact Sensitivity
Shoka et al. (2023)	To enhance encrypted EEG classification using deep learning for secure diagnosis	CNN, TL	Security Enhancement	Dataset Dependency, Computational Complexity

artifacts were artificially introduced in a controlled lab environment to simulate real-world scenarios. The contaminated signals underwent temporal and spectral analysis, followed by artifact removal using Independent Component Analysis (ICA), resulting in cleaner EEG data. In another advancement, Phadikar et al. (2022) presented a multi-stage EEG denoising method aimed at removing muscle artifacts without compromising the integrity of EEG information. The process involved identifying artifact-laden signals using a pre-trained classifier, followed by wavelet packet decomposition (WPD) and subsequent correction using a modified non-local means (NLM) algorithm. The final artifact-free EEG signal was reconstructed using inverse WPD. Additionally, *meta*-heuristic algorithms were employed to optimize filter parameters, further enhancing the denoising performance. Collectively, these studies contribute significantly to the field of EEG signal processing by addressing baseline power, motion artifacts, and muscle artifacts through innovative methodologies. Table 1 addresses the aim, methods, advantages, and disadvantages of the existing works.

Research gaps

Problem statement

Epileptic seizures significantly affect the quality of life of patients, so reliable and time-efficient detection methods are essential. Traditional approaches for detecting epilepsy using EEG signals rely on manual feature extraction, which is time-consuming and prone to errors. In recent years, deep learning has made automatic epilepsy diagnosis possible. However, developing optimal models for multi-class classification and creating scalable models for real-time use remains a challenge. Newer approaches using entropy-driven frameworks (Ilias et al., 2023), hybrid models of CNN-DNN networks (Beeraka et al., 2022) and Bi-LSTM Architectures (Mallick & Baths, 2024), have promising results but don't yet have complete implementation on a variety of testing datasets. Encryption-based approaches for pre-processing EEG signals (Shoka et al., 2023) and adaptive feature extraction methods (Islam et al., 2022) add further computational overload. To address these limitations, this study proposes an innovative, efficient, and generalized framework to improve the accuracy of epilepsy detection while ensuring robustness, scalability, and real-time application feasibility across

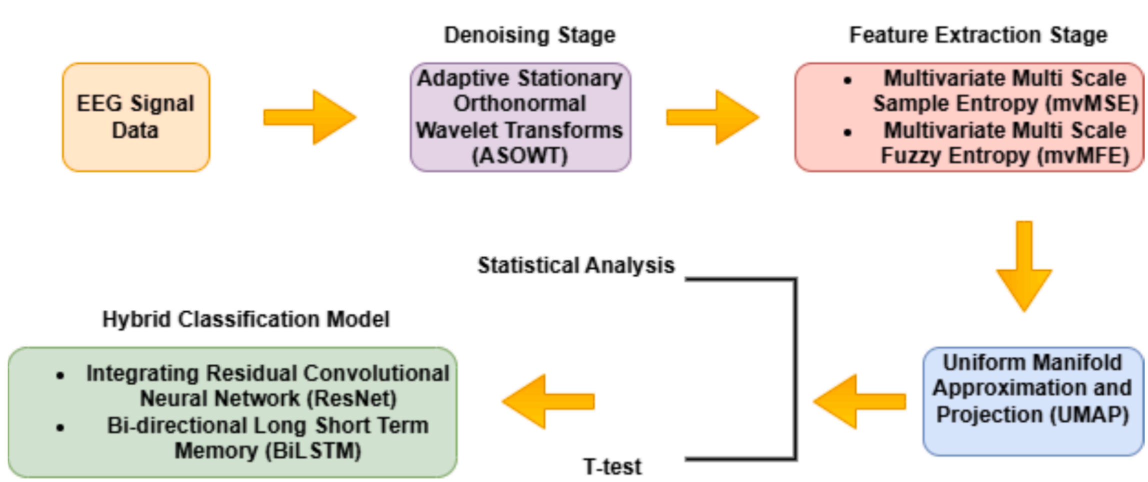

Fig. 1. The proposed methodology.

diverse patient populations.

Propose methodology

Epilepsy is a common neurological disorder that requires proper and timely diagnosis. This paper presents a new approach that combines advanced entropy measures with modern pre-processing techniques for EEG-based epilepsy detection. Adaptive wavelet denoising effectively removes noise without affecting the signal's integrity, while Multivariate Permutation Entropy (mvMPE) and Multivariate Fuzzy Entropy (mvMFE) capture signal complexity and frequency-specific patterns. Uniform Manifold Approximation and Projection (UMAP) is used to reduce dimensionality and improve the discriminative power of the features. A hybrid Residual Convolution Neural Network (ResNet) and Bi-LSTM model combines spatial dynamics with temporal dynamics to establish superior classification accuracy more than traditional methods. With this approach, there lies a robust framework for the precise diagnosis of epilepsy. The workflow for the proposed methodology is demonstrated in the subsequent Fig. 1.

EEG data description

This study uses a publicly available benchmark EEG dataset from Bonn University to analyze epileptic seizure prediction and detection over time. The data was collected by the Neurophysics Research Group, led by Prof. Dr. Klaus Lehnertz, which focuses on the complex dynamics of the human brain, particularly epilepsy. Their research explores seizure onset, spread, and termination through neural dynamics, synchronization, and network-based methods. The EEG signals were sampled at 173.61 Hz, but the recordings are influenced by the system's spectral bandwidth of 0.5 Hz to 85 Hz. As described in the manuscript, a low-pass filter at 40 Hz was applied as the first step of analysis; however, this filtering was not applied to the downloadable dataset.

Denoising of EEG signal based on adaptive stationary Orthonormal wavelet transforms (ASOWT)

EEG signals with a sample frequency of 173.61 Hz and a frequency rate between [0.50 to 85] Hz were used. Noise in the original signal influenced the accuracy of the ground subsidence data as well as the raw monitoring data. With these nonlinear signals, the wavelet transform is a useful tool for identifying system signals, minimising or removing random noise, and supplying more precise data for predicting deformation. To solve this, filters were used to exclude undesired frequencies, concentrating exclusively on the EEG data's medically recognized range. Signals in the frequency domain are represented across time using wavelet transformations. A wavelet is often defined by the following Eq. (1).

$$\varphi_{k,m}(m) = |k|^{\frac{1}{2}}\omega\left\{\left(\frac{M-m}{k}\right)\right\} \tag{1}$$

where m and $k \neq 0$ stand for the translation and scaling parameters. The wavelet transform used in this study is the Discrete Wavelet Transform (DWT), specifically the Stationary Wavelet Transform (SWT). This procedure entails the use of low-pass and high-pass filters to break down the signals into detailed coefficients and approximation coefficients at every level. In the first stage of SWT, the approximation coefficient is obtained by convolution of the input signal $y[l]$ with $k_1(n)$, and the detail coefficient is obtained by convolution with $h_1(n)$, as described in Eqs. (2) and (3) respectively. $s_1(n)$ represents the filtered signal obtained by convolving $y(n)$(input signal) with $h_1(n)$ (filter kernel), emphasizing specific signal features. $f_1(n)$ represents the feature-extracted signal, derived by convolving $y(n)$ with $k_1(n)$, highlighting key patterns or components for further analysis. The length of the input signal $y[l]$ is a multiple of M when $M = 2^j$, where j is an integer. For the high-pass filter, this is $k_1(n)$, and for the low-pass filter, it is $h_1(n)$.

$$s_1(n) = h_1(n)*y(n) = \sum h_1[n-l]y[l] \tag{2}$$

$$f_1(n) = k_1(n)*y(n) = \sum k_1[n-l]y[l] \tag{3}$$

The approximation coefficient $f_1(n)$ and the detail coefficient $s_1(n)$ have lengths equal to the input signal M. By convoluting them with modified versions of the high-pass filter $h_2(n)$ and low-pass filter $k_2(n)$, the approximation coefficient $f_1(n)$ used in the next step to produce $f_2(n)$ and $s_2(n)$. Additionally, SWT has been utilized in this work to eliminate the down-samplers to overcome the WT's lack of translation invariance, and in the WT, employing up-samplers. An EEG signal sample undergoes stationary wavelet decomposition using an Orthonormal wavelet, which captures both time and frequency information, allowing for the extraction of relevant signal features and reducing noise while maintaining signal integrity. A mathematical representation of the ASOWT approximation and detailed coefficients is described in Eqs. (4) and (5) respectively.

$$s_{j+1}(n) = h_{j+1}(n)*f_j(n) = \frac{1}{2^j}\sum h_{j+1}\varnothing[n-l]f_j[l] \tag{4}$$

$$f_{j+1}(n) = k_{j+1}(n)*f_j(n) = \sum k_{j+1}\varnothing[n-l]f_j[l] \tag{5}$$

The equations describe the SWT process, where signals are decomposed into approximation coefficients $s_{j+1}(n)$ and detail coefficients f_{j+1}. At each level of decomposition, high-pass filters $h_{j+1}(n)$ and low-pass filters $k_{j+1}(n)$ are up sampled from the previous level j to extract finer details and low-frequency components, respectively. The resulting coefficients capture different levels of resolution, providing both smooth approximations and detailed features of the signal at various scales.

Feature extraction

It's crucial for brain-computer interface applications. This study used pre-processed, noise-free EEG data to improve the training efficiency and data understanding. To extract the important information from EEG data, multivariate multi-scale entropy approaches (mvMPE and mvMFE) were used. Additionally, UMAP was used to minimise data dimensionality, allowing for accurate categorisation and overall efficiency.

Multiple variables and scale permutation entropy

Permutation Entropy is a statistical metric employed to assess the complexity or randomness inherent in time-series dataset. It examines the relationships in order between adjacent data points, creating patterns and determining their probabilities. PE is known for its computational efficiency, resilience to noise, and is extensively utilized in EEG analysis to identify variations in signal dynamics.

Multiple Variables: To analyse data effectively, it is crucial to examine multiple variables or dimensions at the same time to uncover relationships and dependencies among them. This approach is particularly important in situations where the interactions between variables influence the results, offering a deeper insight into complex systems. For instance, in the study of EEG signals, data from various electrodes (channels) are analysed collectively to understand the brain's spatial and temporal dynamics. Methods such as Multivariate Time Series Analysis, Principal Component Analysis, and Canonical Correlation Analysis are frequently employed to identify significant patterns and correlations within high-dimensional datasets.

Multi Scale: In orders to analysing data with different scales to understand patterns that vary with scale. It is essential to capture dynamics that may only become evident at specific levels of detail. In EEG studies, multi scale entropy or wavelet transforming decompose signals into components across time–frequency scales, revealing hide temporal and spatial structures. This approach improves robustness and ensures broader insights.

A coarse-grained time series $Y = \left\{y_{l,a}\right\}_{a=1,2...M}^{l=1,2...q}$ is q-channel produce time series $V = \left\{v_{l,b}\right\}_{b=1,2...K}^{l=1,2...q}$ with the data length K as shown in Eq. (6):

$$y_{l,a}{}^{(n)} = \frac{1}{n}\sum_{b=(a-1)n+1}^{an} v_{l,b}, 1 \le l \le q, 1 \le a \le \left\lfloor \frac{K}{n} \right\rfloor = M \tag{6}$$

The scaling factor is represented by n. For coarse-grained time-series Y, the multiple variables embedding vector Xm(i) in Eq. (7)

$$Y_c(j) = [y_{1,j}, y_{1,j+e_1}, \ldots y_{1,j+(c_1-1)e_1}, y_{2,j}, y_{2,j+e_2}, \ldots y_{2,j+(c_2-1)e_2}, \cdots, y_{q,j}, y_{q,j+e_q}, \ldots y_{q,j+(c_q-1)e_q}, \tag{7}$$

Whereas the embedding dimension c_l and time delay e_l of each channel may have various values, set the same values for the embedded dimension of every channel. c and delay e forsimplicity, and $h = c \times e$, $j = 1, 2, M - h$. Determine the Chebyshev distance e_{jx}^{c} between $Y_c(j)$ and $Y_c(x)$, the multivariate embedding vectors, using the Eq. (8)

$$e_{jx}^{c} = e[Y_c(j), Y_c(x)] = \max_{g=1,2\cdots c}(|y(j+g-1) - y(x+g-1)|), j \ne x \tag{8}$$

Given the similarity tolerance r, $\varphi_j^c(r) = \frac{1}{M-h-1}Q_j$ is enhance that $e_{jx} \le r$, $j \ne x$. Construct a global quantity in Eq. (9)

$$\varphi^c(r) = \frac{1}{M-h}\sum_{j=1}^{M-h}\varphi_j^c(r) \tag{9}$$

Extension of the embedding dimension from c to c + 1 can be done in q ways, and the process of expansion can be articulated as $[c_1, c_2, \ldots, c_q]$ to $[c_1, c_l + 1, \ldots, c_q]$. $Y_{c+1}(j)$ are the new multivariate embedding vectors that were obtained as a result. The overall quantity with the embedding factor c + 1 received as follows in Eq. (10)

$$\varphi^{c+1}(r) = \frac{1}{q^*(M-h)}\sum_{j=1}^{q^*(M-h)}\varphi_j^{c+1}(r) \tag{10}$$

According to Shannon's theorem, the multivariate multi-scale permutation entropy is as in Eq. (11)

$$mvMPE(V, c, e, r) = -\ln\left(\frac{\varphi^{c+1}(r)}{\varphi^{c}(r)}\right) \tag{11}$$

The entropy of a multivariate sample may be found by first applying a scale factor to coarsen a time series, and then calculating the multivariate sample entropy of the processed series. Using various scale factors, the entropy may be computed on many scales.

The complexity of mvMPE is measured by multivariate time series across multiple scales, but its sensitivity to noise and outlier's affects reliability. To address this, the Cauchy Mean Value Theorem is selected, which effectively balances variations, improving mvMPE's stability and accuracy. Cauchy Mean Value Theorem is expressed in Eq. (12)

$$S'(c) = \frac{S(y) - S(x)}{T(y) - T(x)}T'(z) \tag{12}$$

To improve the robustness and reliability of mvMPE against outliers and noise, CMVT was introduced (Nazra & Syafwan, 2023) to enhance the stability and accuracy of entropy computation in noisy environments. Eq. (13) solves the intricacy of multivariate time series in mvMPE across several scales.

$$mvMPE(V, c, e, r) = -\ln\left(\frac{\varphi^{c+1}(r)}{\varphi^{c}(r)}\right)^{*}w'S'(c) \tag{13}$$

Multivariate Multiscale Permutation Entropy (mvMPE) quantifies the complexity of multivariate time-series data V across scales c, using embedding dimension e and similarity threshold r. It analyzes ordinal patterns, computes the logarithmic ratio of probability distributions $\varphi^{c+1}(r)$ and $\varphi^{c}(r)$, and incorporates weighted significance $w'S'(c)$ for multivariate contributions, capturing multi scale randomness and dynamics, especially in signals like EEG (Fig. 2).

Multiple variable and scale fuzzy entropy (mvMFE)

The fuzzy function that replaces the unit step function in sample entropy is the exponential function $e^{-\left(\frac{f}{r}\right)^{h}}$. This results in fuzzy entropy (FE), which performs better than sample entropy. This replacement guarantees the continuation of entropy values and maximizes the vectors' self-similarity values.

(1) Finding the vector dimension m is the first step for a long-time series M, expressed as $v(j) = \{v(1), v(2), \ldots, v(M)\}$. To create a new sequence, recreate the time series v in Eq. (14)

$$Y_j{}^c = v(j), v(j+1), \cdots v(j+c-1) - v_0(j), j = 1, 2\cdots M - c + 1 \tag{14}$$

Let c represent the embedding dimension. A continuous series of c elements starting at the j-th point is adjusted by subtracting the mean value $v_0(j)$, where

$$v_0(j) = \frac{1}{c}\sum_{l=0}^{c-1} v(j+1) \tag{15}$$

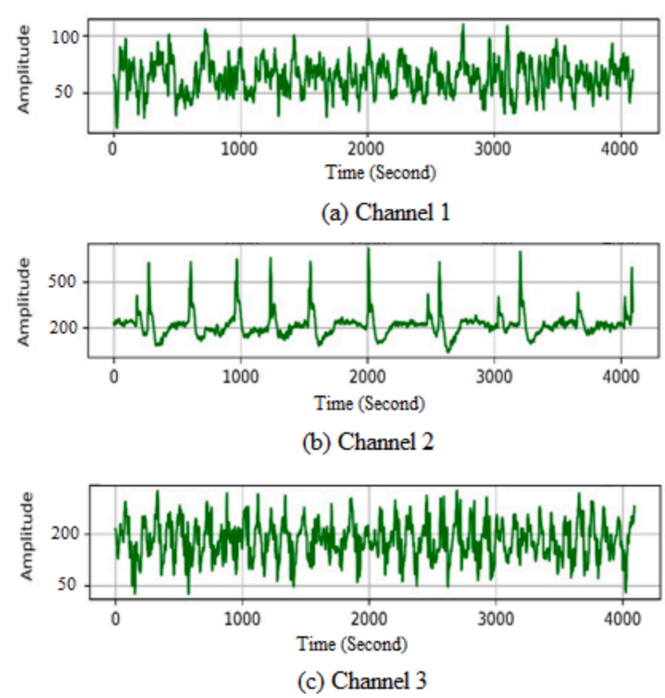

Fig. 2. Visual illustration of the mvMPE in (a) channel 1 (b) channel 2 and (c) channel 3.

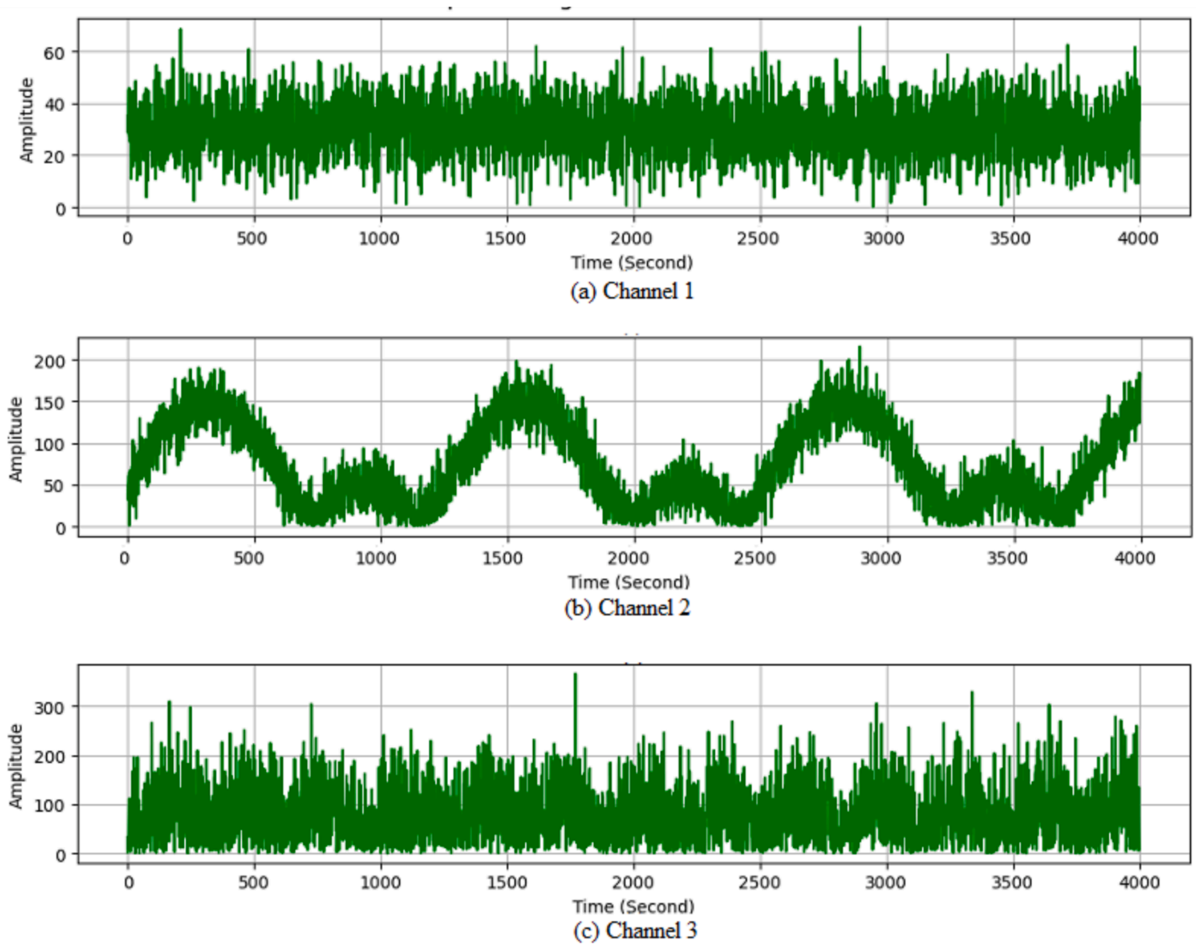

Fig. 3. Visual illustration of the mvMFE image in (a) channel 1 (b) channel 2 and (c) channel 3.

(2) The formula for the maximum distance e^c_{jx} between two reconstruction vectors, Y^c_j and Y^c_x, is $e^c_{jx} = e\left[Y^c_j, Y^c_x\right]$.

$$e^c_{jx} = e\left[Y^c_j, Y^c_x\right] = \max_{l\in(0,c-1)} |(v(j+l) - v_0(j)) - (v(x+l) - v_0(x))| \tag{16}$$

$$j, x = 1, 2, ..M - c, j \neq x \tag{17}$$

(3) Fuzzy membership function is defined as in Eq. (18)

$$F^c_{jx} = e^{\left[-\left(\frac{e^c_{jx}}{r}\right)^h\right]} \tag{18}$$

Fuzzy membership functions are exponential, with h representing the fuzzy membership function's border gradient and r representing the similarity tolerance, which is often chosen to be between 0.1 and 0.25 times the original data's standard deviation (SD).

(4) The function is defined as follows,

$$D^c_j h, r = \frac{\sum_{x=1,x\neq1}^{M-c+1} F^c_{jx}}{M-c} \tag{19}$$

(5) Therefore, we obtain Eq. (20), to generate $\varphi^{c+1}(h, r, M)$, Once the vector dimension has been increased, repeat earlier steps to c + 1.

$$\varphi^c(r) = \frac{\sum_{j=1}^{M-c+1} D^c_j(h, r)}{M - c + 1} \tag{20}$$

$$\varphi^{c+1}(r) = \frac{\sum_{j=1}^{M-c+1} D^c_j(h, r)}{M - c + 1} \tag{21}$$

(6) Multivariate multiscale fuzzy entropy is defined as follows:

$$\mathrm{mvMFE}(V, c, r, e) = -\ln\left(\frac{\varphi^{c+1}(r)}{\varphi^c(r)}\right) \tag{22}$$

In addition, by considering the continuous changes in similarity over the break, the Mean Value Theorem (MVT) can be applied to fuzzy entropy to improve the feature of epilepsy detection and continuity. In this way, the MVT ensures that, within the interval, the average rate of change.

$$d'(c) = \frac{d(x) - d(y)}{x - y} \tag{23}$$

Thus, to improve the estimation of fuzzy similarity between vectors, introduce a weighted mean similarity function over a range of vector distances which is denoted by w'. The Eq. (24) provides a continuous approximation of the fuzzy entropy and minimizes abrupt changes in similarity (Fig. 3).

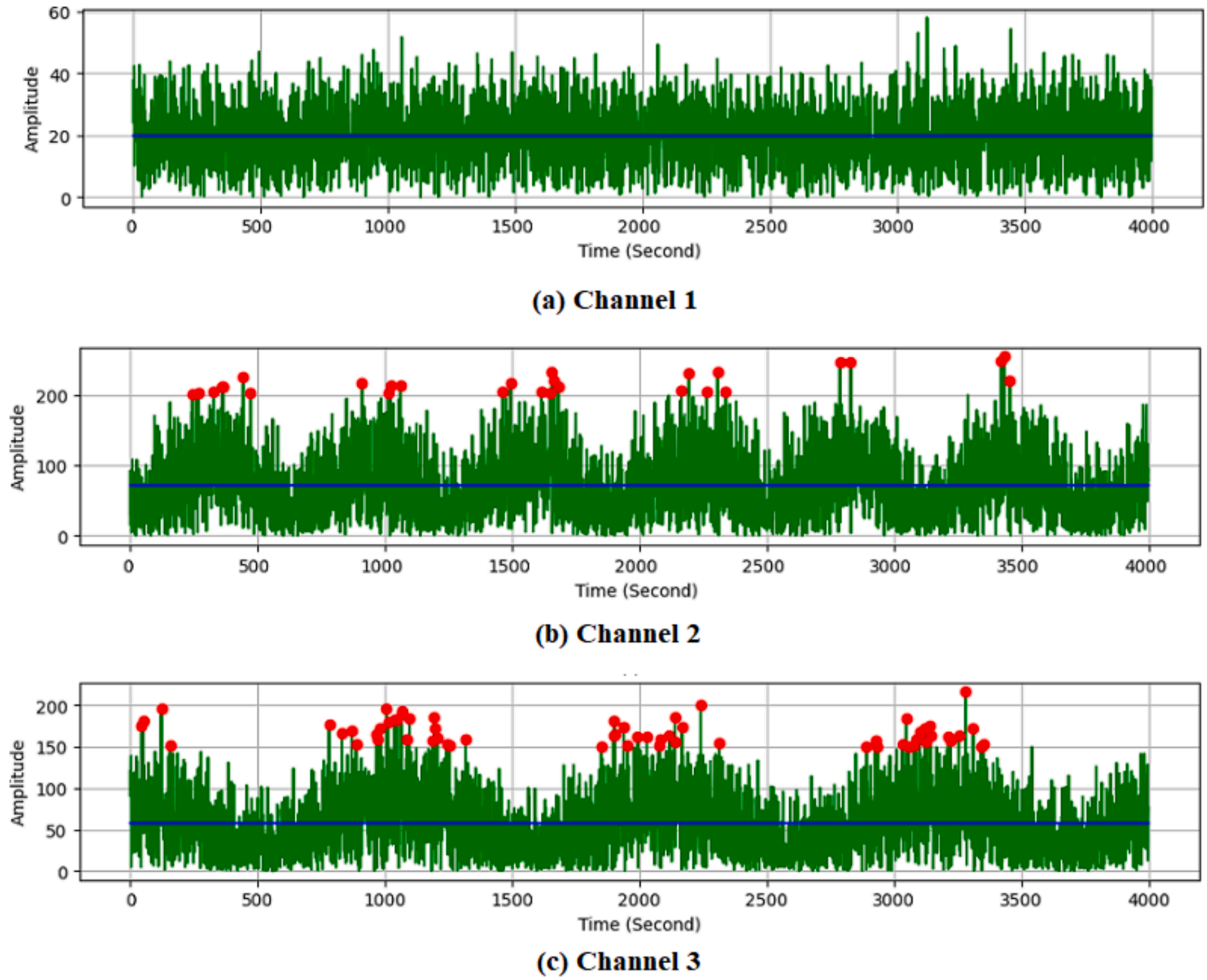

Fig. 4. Uniform Manifold Approximation and Projection Image in (a) channel 1 (b) channel 2 and (c) channel 3.

$$\mathrm{mvMFE}(V, c, r, e) = -\ln\left(\frac{\varphi^{c+1}(r)}{\varphi^{c}(r)}\right) * w'd'(c) \tag{24}$$

Feature dimensionality reduction

Further, the Manifold Approximation and Projection (UMAP) model is performed to minimize the data dimensions to prepare data for accurate classification results. UMAP is a dimensionality reduction technique based on fuzzy topology. It groups signals with similar properties and separates those with distinct features by constructing the topology of the data in its original high-dimensional space and projecting it place in lower-dimensional space. UMAP excels in computational performance, scalability, and visualization. It uses a fuzzy topological of high-dimensional space data points to represent that manifold and it uses an exponential probability distribution with assumptions and edge weights to determine how similar the points are:

$$q_{x|y} = \exp\left(-\frac{g(u_x, u_y) - \beta_x}{\alpha_x}\right) \tag{25}$$

Distance between the x-th and y-th data points is denoted by $g(u_x, u_y)$, while β distance calculates between the x-th data point and its closest point. When the graph's weight between nodes x and y isn't equal to graph's weight node between y and x. Asymmetrization of the high-dimensional probability is used by UMAP:

$$q_{xy} = q_{x|y} + q_{y|x} - q_{x|y}q_{y|x} \tag{26}$$

UMAP builds a low-dimensional imitation of the high-dimensional graph and optimizes its arrangement to be as comparable as possible. To model distance in small dimensions,

$$p_{xy} = \left(1 + b(v_x - v_y)^{2a}\right)^{-1} \tag{27}$$

For default UMAP, $b \approx 1.93$ and $a \approx 0.79$. Because binary cross-entropy (CE) may capture the global data structure, it is used as a cost function in UMAP:

$$U_{map}(Q, P) = \sum_x \sum_y \left[q_{xy} \log\left(\frac{q_{xy}}{p_{xy}}\right) + (1 - q_{xy}) \log\left(\frac{1 - q_{xy}}{1 - p_{xy}}\right) \right] \tag{28}$$

where P represents the low-dimensional data points and Q represents the high-dimensional data points' probabilistic similarity. Thus, the CE function optimizes projection space by updating low-dimensional data points' coordination using a cross-entropy derivative. UMAP uses stochastic gradient descent (SGD) for faster convergence and less memory, maintaining correlation between high- and low-dimensional distances for both small and large distances.

We specifically employed mvMPE and mvMFE due to their unique advantages in capturing both the complexity and frequency-specific variations in EEG signals. The selection of these methods was based on their ability to provide comprehensive information about brain dynamics by analysing nonlinear and multichannel data. Unlike traditional entropy measures, mvMPE and mvMFE effectively capture multiscale dependencies, making them highly suitable for complex biomedical signals. Additionally, these methods offer enhanced noise robustness and computational efficiency, ensuring reliable performance in real-time application. Their ability to extract interpretable features has been validated in existing studies; next support their suitability for epilepsy detection. While other entropy measures, such as Approximate Entropy and Sample Entropy, are available, it will not provide the same level of robustness and interpretability for multichannel EEG data (Fig. 4).

Statistical analysis

The statistical analysis presented in this paper focuses on assessing the significance and reliability of the identified features. A *t*-test with a significance level set at $p < 0.05$ is utilized to evaluate the differences between groups, ensuring that the findings are statistically valid. Additionally, to validate the model, a 10-fold cross-validation method is implemented. This technique involves dividing the dataset into ten segments, using each segment for testing while training on the others. This thorough methodology ensures that the model's performance is innovative and not biased by any specific data subset.

Hybrid classification model

In order to this classification stage, the proposed Hybrid Self-Attention ResNet with BiLSTM (HSAR-BiLSTM) techniques combines the ResNet with a Bi-LSTM network. This integration leverages both temporal dependencies and spatial feature extraction to improve accuracy of EEG signal classification for epilepsy detection.

The proposed HSAR-BiLSTM framework

- **Residual Convolutional Neural Network (ResNet)**

CNNs are widely used in image processing, defect diagnosis, and other domains due to their robust feature extraction capabilities. However, training deep CNNs architectures with various parameters can lead to over fitting. To address this issue, ResNets are recommended. ResNets utilize residual blocks to establish cross-layer connections within the network, enabling the preservation of original input data while extracting features. This approach prevents information loss in deep networks. A residual network is composed of multiple residual blocks working together to enhance performance. The expression for a residual block is in Eq. (29)

$$r_{k+1} = r_k + \xi(r_k, W_k) \tag{29}$$

where $\xi(r)$ is the residual mapping function and r_{k+1} and r_k stand for the residual block's input and output respectively. This study introduces an enhanced residual block capable of generating feature maps with time-series information by performing a time-dimensional convolution. Because it maintains the integrity of time-series data, this method is beneficial for forecasting data quality and guarantees that the complete epilepsy dataset makes a significant contribution to the classification job. ResNet extracts features from each local region of the input spectral data by using a collection of convolutional filters to produce feature maps. This may be seen in Eq. (30)

$$(s_k)_{ij} = (W_k \otimes r)_{ij} + a_k \tag{30}$$

where $(s_k)_{ij}$ denotes (i, j) element of k th output feature map, W_k and a_k represent the k th filter and bias, respectively, and r represents input feature maps, and convolution operation as $\otimes$. The proposed HSAR-BiLSTM model uses fewer residual blocks to reduce number of trainable parameters. Each residual block contains same number of layers, and a batch normalization (BN) layer is added to each residual module. The BN layer connects every sample in a mini batch, ensuring that output of a given training sample is influenced not only by that sample but also by other samples in same batch. This prevents network from producing a definitive result based solely on a single training sample. Consequently, when network processes a random batch, it learns more effectively, reducing the risk of over fitting. Fig. 6 depicts the Structure of the suggested HSAR-BiLSTM framework.

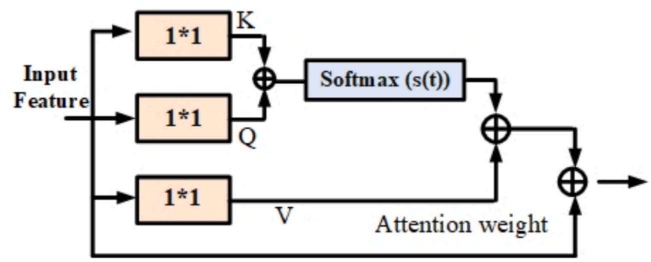

Fig. 5. Pictorial representation of the self-attention mechanism.

- **Bi-LSTM**

LSTM is a type of RNN designed to address the issue of long-term dependency, which is a limitation of traditional RNNs. This problem arises due to the repeated neural network modules in RNNs, which struggle to retain information over long sequences. LSTM calculates the following for each layer at time t:

$$h_t = \sigma_s(W_h y_t + F_h v_{t-1} + a_h) \tag{31}$$

$$m_t = \sigma_s(W_m y_t + F_m v_{t-1} + a_m) \tag{32}$$

$$k_t = \sigma_s(W_k y_t + F_k v_{t-1} + a_k) \tag{33}$$

$$e_t = h_t e_{t-1} + m_t \sigma_s(W_e y_t + F_e v_{t-1} + a_e) \tag{34}$$

$$b_t = k_t \sigma_b(e_t) \tag{35}$$

where a sigmoid function is represented by σ_s, hyperbolic tangent function by σ_s and σ_b, internal cell states by e, hidden states by b, and gates by h, m, and k. BiLSTM, which incorporates both forward and backward LSTM, is more effective at capturing information from both directions compared to LSTM, which is limited to encoding information from front to back. To generate feature maps, the backward pass reverses the forward pass by changing all instances of $t-1$ to $t+1$ in Eqns. (31)–(35). The forward and backward outputs are then concatenated as follows.

$$t = [t_k w : t_a w] \tag{36}$$

where the forward and backward outputs are denoted by $t_k w$ and $t_a w$, respectively. Consequently, the BiLSTM mechanism has demonstrated efficacy in the evaluation of epilepsy.

- **Attention Mechanism:**

The use of attention mechanisms has produced significant results across various fields. The attention mechanism is modelled after the human brain's resource allocation system. The brain processes information by focusing more on what is important and paying less or no attention to other areas, effectively discarding irrelevant information, suppressing unnecessary data, and highlighting what requires attention.

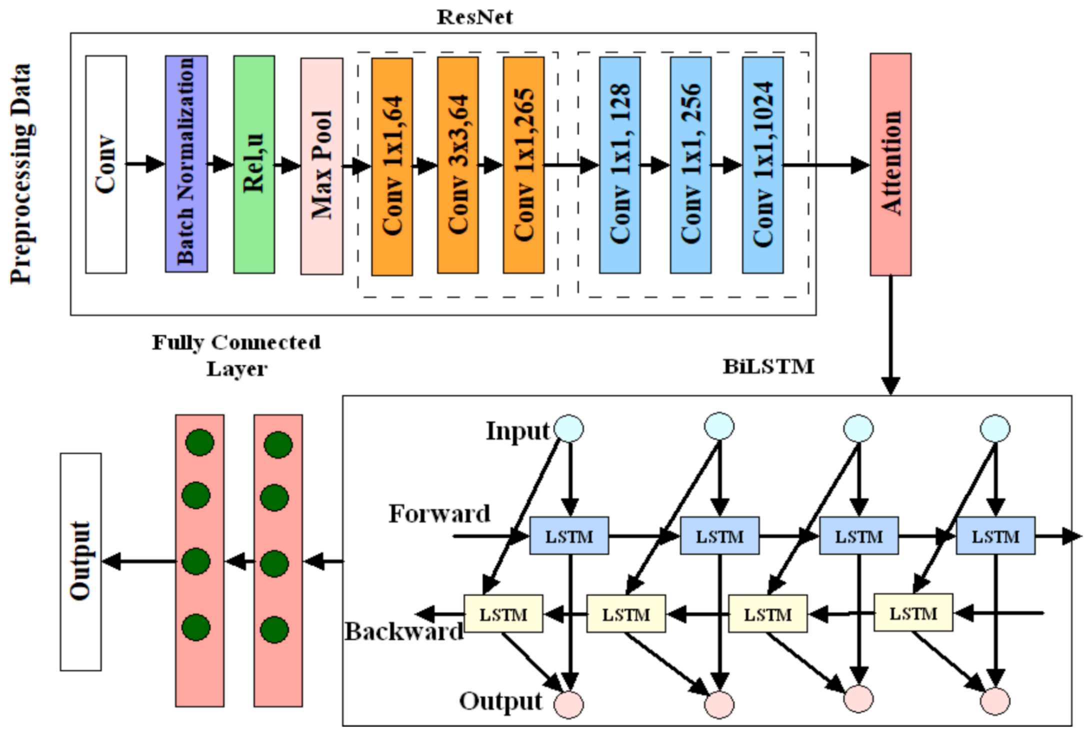

Fig. 6. The architecture of the proposed HSAR-BiLSTM framework.

The drawback of conventional encoder-decoder designs, which depend on a fixed-length vector inside the code, is addressed by this method. To enhance model accuracy, the attention mechanism leverages properties that significantly affect output variables, such as those found in EEG recordings. A self-attention strategy is employed to generate score able weights, using the same input to determine pairs of dot-product attention mechanisms involving query Q_l, key K_l, and value V_l, as illustrated in Fig. 5.

$$a_t = tanl(W_l h_l + b_l) \tag{37}$$

where W_l is the weight of attention

$$B_{attention}(Q_l, K_l, V_l) = softmax\left\{\frac{Q_l K_l^t}{\sqrt{e_l}}\right\} V_l \tag{38}$$

1. The dimension of Q_l, K_l, and V_l is denoted by e_l. W^Q is the matching projection weight, and the query is $Q_l = lW^Q$. For K_l and V_l, similar outcomes can be achieved with the right projection weights, W^V and W^K. Eq. (37), finally, can be used to obtain the attention vector.

$$b = B_{attention}(V_l) \tag{39}$$

- **Fully Connected Layer (FC)**

The fully connected layer in a convolution neural network is the final layer. After the attention mechanism, all nodes in the fully connected layer are directly connected to all other nodes in the previous $t-1$ and subsequent $t+1$, layers, with the input being flattened. The fully connected layer also contains the parameters due to its fully connected nature. To reduce the dimensionality, the linking layer can be mapped to a lower dimension. Eq. (40) enables the use of multiple fully connected layers within the same network.

$$u_t = \sum_{i=1}^{j} W_{i,t} q_i + b_l \tag{40}$$

A neuron's bias value is denoted by b_l, its input value is denoted by q_i, its weight value for the i th input is denoted by t, and its output value is denoted by u_t.

- **Classification**

SoftMax is a commonly used function in DL and machine learning, particularly in multi-class classification tasks. It maps the input into a real number between 0 and 1. The classifier must generate the probability for each class in a multi-class scenario, with the sum of all probabilities being equal to 1. To compare magnitude of probabilities and weight coefficient s_t, the calculation is performed as follows

$$s(t) = softmax(a_t) \tag{41}$$

Results and discussion

This paper describes the DL Framework Driven by Entropy for Epilepsy Detection EEG signals are used. Many matrix, including recall, accuracy, and F1-score are utilized to assess the effectiveness of the suggested strategy. The recently developed framework is linked to a number of models, such as RNN, Bi-GRU, DenseNet201, and ConvLSTM, and it is suggested to ascertain the extent to which its performance has increased.

Evaluation setup

The system runs on a 64-bit Windows 10 Pro operating system with an Intel Core i3-8100 processor and 8 GB of RAM. The dataset used for the experiments is publicly available and linked in the bibliography. Simulations were carried out using the Python programming language in the Jupyter Notebook environment. OpenCV (cv2) was used for image processing and computer vision tasks, while key libraries like TensorFlow were used to build and train machine learning models. This setup enables efficient development and testing of many machine learning models and computer vision algorithms.

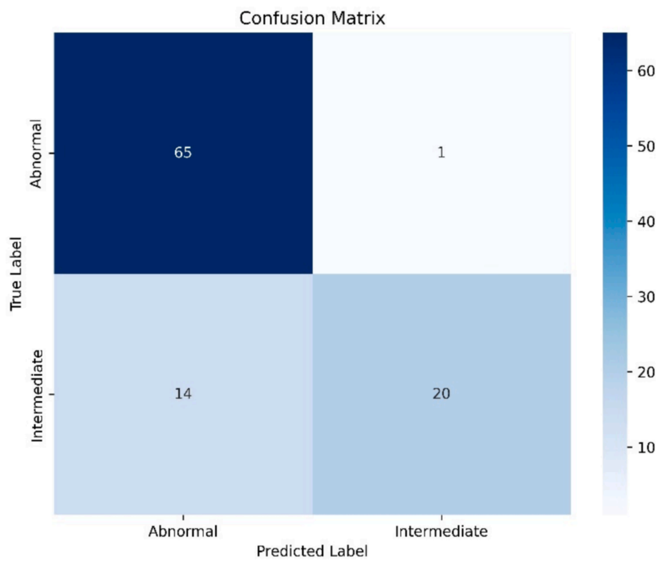

Fig. 7. Confusion Matrix.

Table 2
Comparative analysis of the performance metrics.

	Recall	Accuracy	F1-Score
RNN	0.84	0.85	0.85
Bi-GRU	0.84	0.85	0.85
DenseNet201	0.87	0.88	0.87
ConvLSTM	0.82	0.83	0.83
Proposed	**0.93**	**0.94**	**0.96**

Performance evaluation

Accuracy, recall, F1-score, specificity, and precision are used as evaluation metrics to assess performance.

- **Accuracy:** It is the degree to which a quantity's measurements match its real, or actual, value.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \tag{42}$$

- **F-Score**

The F-Score number carefully balances the requirement to completely identify every data piece to guarantee that each definition defines a single type of information item.

$$\text{F} - \text{Score} = 2 \times \frac{\text{Presision. Recall}}{\text{Presision} + \text{Recall}} \tag{43}$$

- **Recall**

A performance statistic called recall is used to assess how well a classification model finds every pertinent event in a dataset. It is defined as the ratio of TP to the sum of FN and TP.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{44}$$

where,FP = False positive,TP = True positive, FN= False negative, TN=True negative,

Performance results

Fig. 7 illustrates how the confusion matrix compares predicted labels with true labels to assess the performance of a classification model. In this case, the matrix shows that the model correctly classified 65 instances as Abnormal (True Positive, TP), but incorrectly labeled 14 instances as Intermediate when they were actually Abnormal (False Negative, FN). This analysis helps evaluate the accuracy of the model and identify areas for improvement.

The comparative analysis of the proposed model is shown in Table 2. It outperforms all other models, achieving 94 % accuracy, 93 % recall, 96 % F1-Score, 87.70 % specificity, and 82.21 % precision, demonstrating superior performance. The DenseNet201 model follows with 88 % accuracy, 87 % recall, and 87 % F1-Score. Both the RNN and Bi-GRU models achieve 85 % accuracy, 84 % recall, and 85 % F1-Score. The ConvLSTM model has the lowest performance, with 83 % accuracy, 82 % recall, and 83 % F1-Score.

Table 3 highlights the key differences in methodologies, feature extraction techniques, classifiers, datasets used, and performance metrics.

The performance metrics, including accuracy, F1-score, recall, specificity, and precision, are graphically represented in Figs. 8 to 10. These metrics are compared across various techniques, including RNN, Bi-GRU, DenseNet201, ConvLSTM, and the proposed model. The figures also visualize the differences between epileptic and non-epileptic EEG signals using entropy-based feature extraction methods (mvMPE and mvMFE).

Fig. 11 clearly shows the distinction between the entropy values of epileptic and non-epileptic signals. For epileptic signals, both mvMPE and mvMFE values are generally higher, indicating greater complexity and irregularity in brain activity, which is characteristic of seizures. The increased entropy values suggest heightened neural activity and chaotic patterns during seizures. In contrast, non-epileptic signals show lower entropy values, indicating more regular and predictable brain activity. Non-epileptic brain signals maintain a more stable and controlled dynamic, as reflected in their lower entropy.

Fig. 12 presents box plots that provide a statistical summary, including the median, quartiles, and potential outliers. For epileptic signals, both mvMPE and mvMFE show significantly higher median entropy values compared to non-epileptic signals. A wider interquartile range (IQR) indicates greater variability in epileptic EEG patterns. In contrast, for non-epileptic signals, entropy values are more concentrated, reflecting stable brain activity. Fewer outliers suggest more consistent signal characteristics across non-epileptic data. The clear separation between epileptic and non-epileptic signals in both entropy

Table 3
Comparative Analysis of Epileptic Seizure Detection Methods.

Reference	Methodology	Feature Extraction Method	Classifier Used	Dataset Used	Accuracy (%)
Proposed method	Proposed Method (ResNet-BiLSTM with mvMPE&mvMFE)	Multivariate Entropy Features & UMAP	ResNet-BiLSTM	Bonn EEG Dataset	94.0
Malekzadeh et al (2021a)	CNN-RNN Fusion Model	TQWT, Statistical, Frequency, Nonlinear Features	CNN-RNN	Bonn & Freiburg	99.71
Malekzadeh et al (2021b)	CNN-AE with Fractal Features	DT-CWT, Fractal Dimension Features	CNN-AE	Bonn & Freiburg	99.73

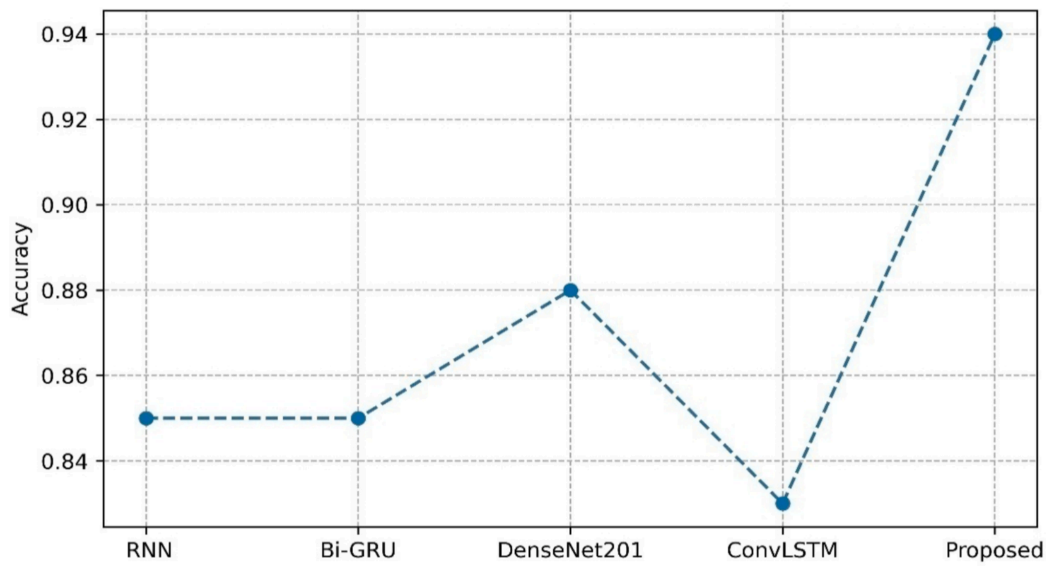

Fig. 8. Visual illustration of the Accuracy.

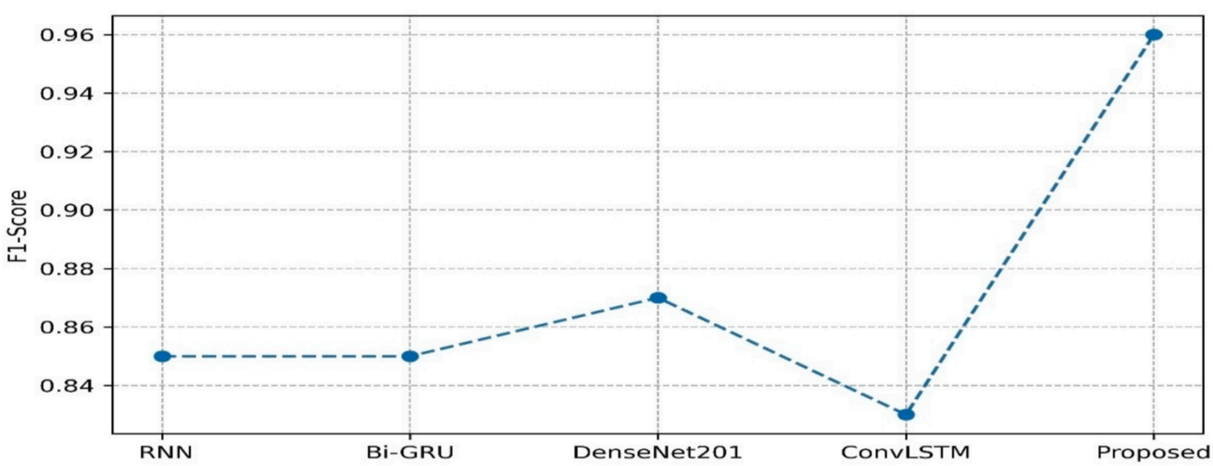

Fig. 9. Visual illustration of the F1-Score.

measures highlights the effectiveness of mvMPE and mvMFE as diagnostic features for epilepsy detection.

Limitations of the study

Our proposed entropy-driven deep learning technique for epilepsy detection through EEG signals has illustrative significant highly improvements in accuracy and reliability, there are certain limitations that should be acknowledged. Primarily relies on the publicly available Bonn University EEG dataset, which is not fully representing the diversity of real-world scenario. Evaluating on large and more heterogeneous datasets from different clinical settings would improvement generalization. Further, computational complexity of the proposed hybrid model Bi-LSTM and ResNet can limit its deployment on resource-constrained edge devices. Upcoming work could focus on reduce model size and inference time using techniques such as model compression and quantization. Next, we use of multiple variable entropy features has improved the model's ability to capture complex signal dynamics. It's still being sensitive to noise and artifacts in real-world dataset. However, implemented robust noise reduction techniques or include multimodal data, such as ECG or fMRI also enhance the model's reliability. Additionally, the interpretability of the model remains a challenge. Although deep learning models often provide high accuracy, they act as "black boxes," making it difficult for clinicians to trust predictions. Developing Ex-AI techniques to interpret model decisions would facilitate clinical adoption. Lastly, the proposed model has not been highly tested for real-time detection. Future research should emphasize the development of real-time monitoring systems with minimal latency to provide timely intervention for epilepsy patients. Addressing these limitations will contribute to the further advancement and practical implementation of AI-driven epilepsy detection systems.

Conclusion and future scope

This paper presents a robust and innovative framework for medical data, which often involves significant uncertainty that can impact the accuracy of diagnostic models. The combination of Type-2 fuzzy systems and fuzzy regression provides a powerful approach to address uncertainty by accurately representing data imprecision. These techniques enhance interpretability and offer more reliable predictions, facilitating better decision-making in epilepsy detection through EEG signals. By incorporating advanced pre-processing methods such as adaptive wavelet denoising and entropy-based feature extraction techniques like mvMPE and mvMFE, the framework effectively captures intricate,

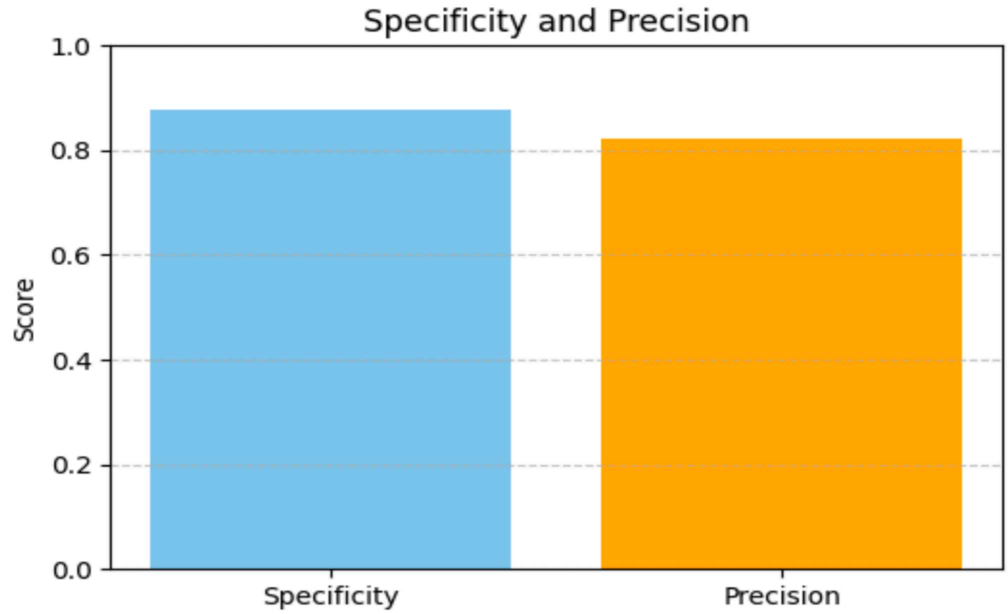

Fig. 10. Showing the Specificity and precision of proposed model.

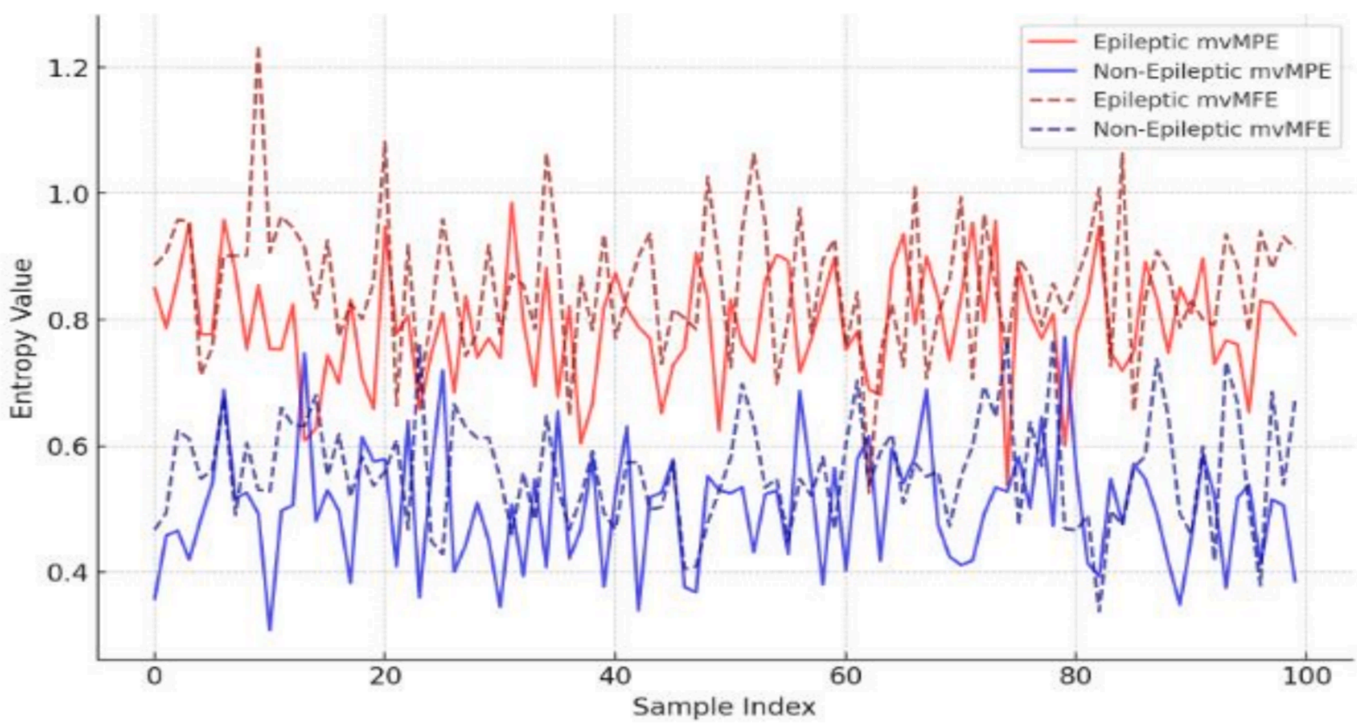

Fig. 11. Showing Comparison of mvMPE and mvMFE for Epileptic and Non-Epileptic EEG Signals.

frequency-specific variations in EEG signals. The use of UMAP for dimensionality reduction further enhances the discriminative power of the features. Additionally, the hybrid Bi-LSTM and ResNet classifier combines temporal and spatial feature extraction, leading to improved classification performance. The reliability of the proposed method is confirmed through statistical validation. The achieved accuracy underscores the effective collaboration between advanced entropy measurements and cutting-edge deep learning architectures, paving the way for more precise and dependable epilepsy detection. According to the experimental results, the proposed model achieved the highest F1-score (0.96), recall (0.93), accuracy (0.94), specificity (0.87), and precision (0.82).

Future advancements in patient monitoring aim to enhance outcomes and enable personalized epilepsy detection through lightweight deep learning models specifically designed for wearable devices. By incorporating multi-modal data, such as EEG, ECG, and fMRI, the predictive accuracy and robustness of these models can be significantly improved. Innovative deep learning frameworks, including transformers and graph neural networks, offer promising opportunities for better epilepsy detection by capturing complex temporal and spatial relationships. Furthermore, the development of lightweight models optimized for real-time use will support continuous monitoring through wearable technologies. The use of transfer learning and domain adaptation strategies can help address data scarcity issues and enhance model

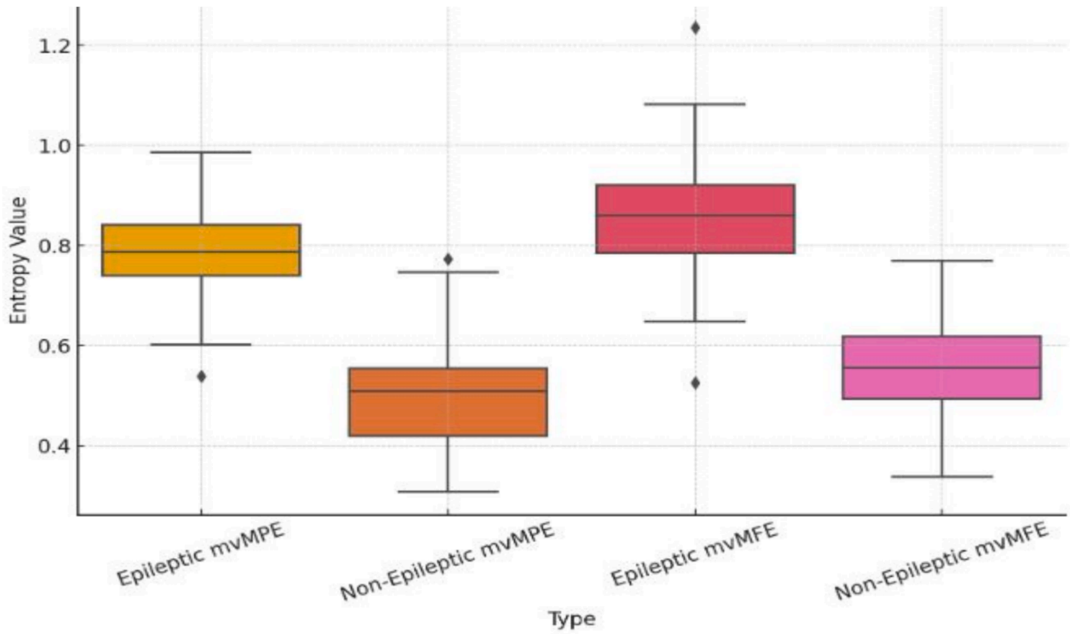

Fig. 12. Showing the Box Plot of mvMPE and mvMFE for Epileptic and Non-Epileptic Signals.

performance across various datasets. These advancements will contribute to more efficient, personalized, and accessible epilepsy management systems, ultimately improving patient care and outcomes.

CRediT authorship contribution statement

Sandeep Singh Sikarwar: Writing – review & editing, Writing – original draft, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Arun Kumar Rana:** Validation, Supervision, Resources, Formal analysis. **Sandeep Singh Sengar:** Visualization, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis.

References

Ahmed, M.Z.I., Sinha, N., Ghaderpour, E., Phadikar, S., Ghosh, R., 2023. A novel baseline removal paradigm for subject-independent features in emotion classification using EEG. Bioengineering 10 (1), 54.
Al-Qazzaz, N.K., Alrahhal, M., Jaafer, S.H., Ali, S.H.B.M., Ahmad, S.A., 2024. Automatic diagnosis of epileptic seizures using entropy-based features and multimodel deep learning approaches. Med. Eng. Phys. 130, 104206.
Beeraka, S.M., Kumar, A., Sameer, M., Ghosh, S., Gupta, B., 2022. Accuracy enhancement of epileptic seizure detection: a deep learning approach with hardware realization of STFT. Circuits Syst. Signal Process. 41, 461–484.
Ilias, L., Askounis, D., Psarras, J., 2023. Multimodal detection of epilepsy with deep neural networks. Expert Syst. Appl. 213, 119010.
Islam, M.S., El-Hajj, A.M., Alawieh, H., Dawy, Z., Abbas, N., El-Imad, J., 2020. EEG mobility artifact removal for ambulatory epileptic seizure prediction applications. Biomed. Signal Process. Control 55, 101638.
Islam, M.S., Thapa, K., Yang, S.H., 2022. Epileptic-net: an improved epileptic seizure detection system using dense convolutional block with attention network from EEG. Sensors 22 (3), 728.
Kumar, P.R., Shilpa, B., Jha, R.K., Mohanty, S.N., 2023. A novel end-to-end approach for epileptic seizure classification from scalp EEG data using deep learning technique. Int. J. Inf. Technol. 15 (8), 4223–4231.
Malekzadeh, A., Zare, A., Yaghoobi, M., Kobravi, H.R., Alizadehsani, R., 2021a. Epileptic seizures detection in EEG signals using fusion handcrafted and deep learning features. Sensors 21 (22), 7710.
Malekzadeh, A., Zare, A., Yaghoobi, M., Alizadehsani, R., 2021b. Automatic diagnosis of epileptic seizures in EEG signals using fractal dimension features and convolutional autoencoder method. Big Data Cogn. Comput. 5 (4), 78.
Mallick, S., Baths, V., 2024. Novel deep learning framework for detection of epileptic seizures using EEG signals. Front. Comput. Neurosci. 18, 1340251.
Nazra, A., Syafwan, M., 2023. The Cauchy Mean Value Theorem for Intuitionistic Fuzzy Functions. arXiv preprint arXiv:2312.09453.
Phadikar, S., Sinha, N., Ghosh, R., Ghaderpour, E., 2022. Automatic muscle artifacts identification and removal from single-channel eeg using wavelet transform with meta-heuristically optimized non-local means filter. Sensors 22 (8), 2948.
Shoka, A.A.E., Dessouky, M.M., El-Sayed, A., Hemdan, E.E.D., 2023. An efficient CNN based epileptic seizures detection framework using encrypted EEG signals for secure telemedicine applications. Alex. Eng. J. 65, 399–412.
Sunaryono, D., Sarno, R., Siswantoro, J., 2022. Gradient boosting machines fusion for automatic epilepsy detection from EEG signals based on wavelet features. J. King Saud Univ.-Computer Inf. Sci. 34 (10), 9591–9607.
Tawhid, M.N.A., Siuly, S., Li, T., 2022. A convolutional long short-term memory-based neural network for epilepsy detection from EEG. IEEE Trans. Instrum. Meas. 71, 1–11.
Zhang, Y., Yao, S., Yang, R., Liu, X., Qiu, W., Han, L., Zhou, W., Shang, W., 2022. Epileptic seizure detection based on bidirectional gated recurrent unit network. IEEE Trans. Neural Syst. Rehabil. Eng. 30, 135–145.