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Article

An Xception Spiking Fractional Neural Network-Based Framework for Accurate Detection and Classification of Epileptic Seizures in Electroencephalogram Signals

Pallavee Pravin Bavane[1], Padma Dandannavar[2], Sachin Subhash Patil[3]

[1]Department of Computer Science and Engineering, D. Y. Patil Technical Campus, Talsande, Kolhapur, Maharashtra, India; Research Scholar, KLS Gogte Institute of Technology (KLS GIT), Visvesvaraya Technological University (VTU), Belagavi, Karnataka, India.
[2]Department of MCA, Anuvartak Mirji Bhartesh Institute of Technology, Belagavi, Karnataka, India.
[3]Department of Computer Science and Engineering, Rajarambapu Institute of Technology, Rajaramnagar, Maharashtra, India.

Abstract: -Epileptic Seizures in Electroencephalogram Signals (EEG) is a neurological disorder that can be detected by continuous observation of the brain signals using EEG, allowing for early treatment and personalized care. The conventional approach for seizure detection, including visual analysis and manual analysis of EEG signals, offers useful information but is prone to limitations like noise in signals, inter individual variability, and the need for correct diagnosis during seizures. To address these challenges, an xception spiking fractional neural network-driven framework for accurate detection and classification of epileptic seizures in electroencephalogram signals (DCES-EEG-XSFNN) is proposed. At first, input data is gathered from Bangalore EEG Epilepsy Dataset. These data are pre-processed utilizing Robust Maximum Correntropy Kalman Filter (RMCKF) which is used for data normalization. Then the pre-processed data are given to Convolutional Variational Attention Transformer (ConVAT) for feature extraction, which is employed to extract relevant features. The extracted features are fed to Xception Spiking Fractional Neural Network (XSFNN) for detection and classification, which is used to detect epileptic seizures and classify such as seizure events, focal seizures, generalized seizures and healthy. To further improve the performance of XSFNN during detection and classification, the Superb Fairy-wren Optimization Algorithm (SFOA) is utilized. The proposed technique implemented in python, demonstrates substantial improvements in accuracy, precision, recall, F1-Score and Confusion matrix. The proposed achieves the best results accuracy of 97.67%, precision of 99.34%, recall of 97.67%, and an F1-score of 97.5% for Seizure compare with existing methods such as Enhanced EEG Signal Processing for Accurate Epileptic Seizure Detection (EEG-ESD-SVM), Epileptic Seizure Detection in EEG Signals Using Machine Learning and Deep Learning Techniques (ESD-EEG-1DCNN), and Epileptic Seizure Detection in EEG Signals Using Machine Learning and Deep Learning Techniques (DES-EEG-LSTM).

Keywords: Epileptic Seizures, Electroencephalogram, Robust Maximum Correntropy Kalman Filter, Convolutional Variational Attention Transformer, Xception Spiking Fractional Neural Network, Superb Fairy-wren Optimization Algorithm.

1. INTRODUCTION

Epileptic seizures occur due to abnormal electrical disturbances in the brain, leading to considerable interruptions in the normal functioning of the brain in patients [1]. The electroencephalogram recording of the brain wave patterns represents the complex neural activity in the brain, which is crucial for understanding the disturbances caused by epilepsy in patients [2]. Epilepsy is a considerable neurological disorder prevalent among millions of people worldwide, posing a challenge to the timely detection of seizure-related disturbances in the healthcare system [3]. The EEG signal is highly variable due to individual physiological differences, making it difficult to interpret consistently in clinical settings where prolonged recordings are analyzed daily by clinicians [4]. Seizures may occur unexpectedly without warning, requiring continuous observation to detect important abnormalities in prolonged neurological monitoring sessions [5]. The EEG signal often contains noise due to movement, environment, and biological artifacts, making it difficult to detect abnormal brain activity characteristics [6]. Artifacts caused by eye blinking, muscle activity, or external disturbances make it difficult to distinguish signal patterns for seizure detection during monitoring sessions [7].

The large amount of data generated by long-term EEG recordings requires a lot of effort from medical professionals to analyze the minute neurological differences associated with epilepsy [8]. Small seizure events can be easily missed in long recordings, making it even more challenging to identify unusual patterns of electrical activity in the brain associated with seizures [9]. Variations in electrode positioning among patients add to the inconsistencies in EEG signal patterns, making it even more challenging to interpret the patterns in a standardized manner, especially in relation to seizure-related neurological changes [10]. Medical professionals are required to distinguish between normal and abnormal brain activity patterns, which is even more challenging due to large variations in signal patterns associated with different physiological and environmental factors [11]. Individual differences in neurological fluctuations are quite large, making it challenging to identify seizure events based on a clear understanding of patient-specific patterns in complex EEG activity patterns [12]. Seizure events vary among different age groups due to differences in developmental and physiological factors, which also affect EEG patterns identified during clinical scenarios [13-14].

The misinterpretation of minute EEG signal variations can lead to a delay in clinical decision-making, thereby underlining the importance of understanding neurological anomalies related to epilepsy disorders [15]. The large amount of EEG signal data can pose a challenge to clinicians, as the continuous monitoring of the brain can result in the observation of different physiological processes that are not related to seizure occurrences [16]. Different types of seizures have different durations and magnitudes, thereby adding to the complexity of EEG signal anomaly interpretation during neurological assessments of patients [17]. The interpretation of clinical data is highly dependent on the interpretation of EEG signal patterns, thereby making it crucial for signal clarity to be achieved in the identification of abnormal neurological signals associated with epilepsy disorders [18]. Unexpected anomalies in the brain's electrical activity require close monitoring, particularly in situations where abnormalities related to seizures are observed for a short duration in a complex EEG signal environment [19]. Seizure detection is crucial in neurological research, as factors outside the research environment can influence EEG signal patterns among the monitored population globally [20].

A lot of research has been done in the seizure of the epilepsy through the use of different methods. Some of them are discussed below.

Kode, H. et al. [21] have provided EEG signals that were transformed to image and/or time-frequency features to classify them. Dwelling on categorizing time-series EEG representations based on deep learning-based One-Dimensional Convolutional Neural Network (1D CNN) representations and machine learning classifiers with tunable parameters. The focus was on managing time changes in EEG records to identify important tendencies which can be attributed to sleep-related states. The lack of consistency in the environment of EEG acquisition, electrode placement, and signal variations in subjects was a significant limitation that induces variability that makes it difficult to obtain consistent behavior of the model, but also decreases the similarity between datasets.

Kunekar, P. et al. [22] have offered a way of detecting epileptic episodes based on the EEG data which records the necessary electrical activity of the brain. Previous methods relied on the manual feature design, whereasDL allows the complete automated feature extraction and classification, which advances epilepsy detection. The given work focuses on automated epileptic seizure recognition using ML and DL approaches based on comparative analysis on UCI-Epileptic Seizure Recognition dataset, using various traditional models and an LSTM-based model to identify the most efficient one. There was also the limitation on the use of only one benchmark dataset, which can limit the diversity of patterns, as well as can limit generality to a broader range of EEG conditions.

Karthik, S.A. et al. [23] Have introduced Electroencephalography (EEG) as a basic method of detecting epileptic seizures since it was capable of recording the brain activity with great temporal detail. The paper shows the potential of symmetry/asymmetry features in the diagnosis of epilepsy. Discrete Wavelet Transform (DWT) and the Improved Feature Space Method (ICFS) which identifies the important features in the frequency, entropy, and time domain improve detection accuracy. A number of Support Vector Machine (SVM) settings were then applied to a set up of ensembles to process these features. One weakness was the difference in the quality of EEG signals produced by different subjects, and it may cause slight inconsistencies in features representation.

Shawly, T. and Alsheikhy, A.A. [24] have introduced a developed DL method of automated epilepsy prediction by improving the extraction of EEG features by adding a newly constructed attention module (NAM) to a specially designed convolutional neural network (CNN). Fourier Transform was applied in derivation of frequency-domain properties and Principal Component Analysis (PCA) was employed in dimensionality reduction. The system was trained, validated, and tested on three publicly available EEG datasets of PhysioNet and ResearchGate, providing the possibility of a good generalization of the system to a wide range of sources of data. One constraint has been identified to be associated with the use of these datasets and might not capture some complex clinical signal variations.

The article by Khan, F.A. et al. [25] has offered the accent on the necessity of eXplainable Artificial Intelligence (XAI) in precision healthcare, epilepsy management in the Internet of Medical Things (IoMT). The methodology uses band-pass filtering and epoch segmentation to improve the quality of Electroencephalograph (EEG) and then statistical feature extraction of the patterns of seizure and non-seizure. One of the limitations was based on the fact that different people will have varying EEG signals which might affect pattern separation consistency.

Cao, X. et al. [26] have introduced a hybrid framework of deep learning, which involves fusion of features to detect seizure effectively. Initially, the raw EEGs were separated into five levels using the Discrete Wavelet Transform (DWT), then timefrequency and nonlinear descriptors were extracted in each of the subbands. The Support Vector Machine-Recursive Feature Elimination (SVM-RFE) was used to eliminate redundant information, only representing the most significant descriptors to be fused. One of the weaknesses identified was the use of handcrafted descriptors prior to fusion, which limits flexibility in cases of highly diverse or noisy EEG recordings.

Halimeh, M.et al. [27] have made video-EEG measurements of 166 PWE as ground-truth to epileptic seizures forecasting, along with electrodermal activity (EDA), peripheral body temperature (TEMP), blood volume pulse (BVP), and accelerometry (ACC). The evaluation was done using brier skill score (BSS) that indicates the extent to which the NN Brier score has improved compared to a rate-matched random (RMR) forecast and improvement compared to chance (IoC). One of the limitations was that the quality of physiological signals varies among subjects, and they affect forecasting consistency.

Recent studies in epileptic seizure detection using EEG signals have been accelerating towards more advanced machine learning (ML) and deep learning (DL) paradigms, including 1D-CNN models trained on time frequency EEG transformations, LSTM-driven automated seizure recognition networks, DWT-SVM ensemble models which take into account symmetry and asymmetry patterns, attention-enhanced CNN models with new attention modules, XAI-supported statistical classifiers to help understand the predictions, hybrid CNN-Bi-LSTM models which use combination of temporal and spectral descriptors, and multimod Though the methods have considerable advantages that include the ability to capture complex temporal variations, learn robust frequency-based markers, autopilot discriminative patterns, and improve clinical transparency they nevertheless have important limitations that include the sensitivity to heterogeneous acquisition conditions of EEG, the limited generalization when trained on single datasets, sensitivity of handcrafted features to noise and subject variability, and inconsistent performance in multimodal models because their physiological measures vary, as well as the partial reliance of handcrafted features in hybrid systems and the unreliable performance of attention-based models. All these negatives serve as a clear indication that a more adaptable, noise-tolerant, and generalizable EEG seizure detector framework is urgently required that can surmount cross-subject variability, lessen feature engineering reliance, and grant consistent, clinically dependable classification across various EEG settings.

The aim is to study epileptic seizures in EEG signals, enhancing the knowledge of seizure patterns and enabling informed clinical decisions for the treatment of epilepsy.

In the proposed study, the DCES-EEG-XSFNN model tackles the most important issues in the detection of epileptic seizures, including signal noise, personal differences, and the need for precise and on-time diagnosis. The approach improves the accuracy of detection and classification by utilizing the XSFNN for efficient seizure detection. Moreover, the SFOA is used to optimize the parameters of the model, enhancing its performance. This technique enables highly accurate, reliable, and scalable seizure detection and classification, facilitating early interventions and personalized treatments for epilepsy patients.

Main contribution of this work is abridged as follows,

- Developed an XSFNN framework integrating RMCKF, ConVAT, and SFOA to enhance epileptic seizure detection and classification in EEG signals.
- Applied RMCKF for pre-processing normalizing EEG data, and enhancing signal quality to improve model performance.

➢ Optimized XSFNN parameters using SFOA, improving detection accuracy for accurate classification of focal seizures, generalized seizures, and healthy states.
➢ The obtained outcomes of the proposed DCES-EEG-XSFNN algorithm is comparing to the existing methods like ESD-EEG-1DCNN, DES-EEG-LSTM and EEG-ESD-SVM respectively

The balance paper is ordered as follows: Part 2 clarifies proposed methodology, Part 3 results with discussions, and Part 4 concludes the paper.

2. PROPOSED METHODOLOGY

In this section an xception spiking fractional neural network-based framework for accurate classification and detection of epileptic seizures in electroencephalogram signals (DCES-EEG-XSFNN) is proposed. Data collection, pre-processing, detection and classification, feature extraction, and optimization are the five steps in the process. The Bangalore EEG Epilepsy Dataset is first gathered and pre-processed utilizing the RMCKF. In order to extract pertinent features, the pre-processed data is then fed into feature extraction. The features that have been extracted are then used for classification and detection. The SFOA is used to optimize the parameters of XSFNN in order to enhance its performance. Figure 1 shows the Block Diagram of the proposed DCES-EEG-XSFNN.

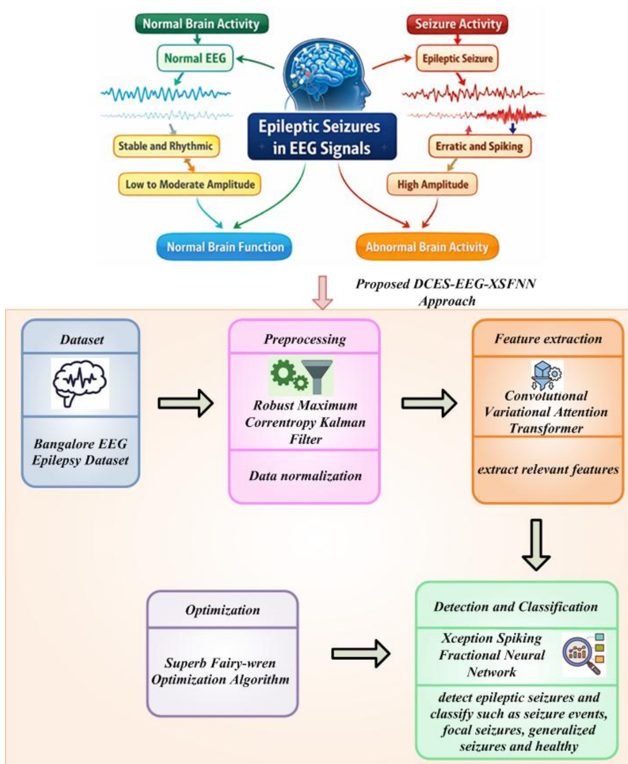

Figure 1: Block Diagram of the proposed DCES-EEG-XSFNN

2.1.Data Acquisition

Firstly the input data is collected from Bangalore EEG Epilepsy Dataset [28]. The Bangalore EEG Epilepsy Dataset is a collection of electroencephalogram (EEG) data used for studying epilepsy and detecting seizures. It contains EEG recordings from subjects, including both epileptic and non-epileptic individuals. The dataset includes time-domain and frequency-domain features extracted from the EEG signals, making it useful for classification tasks aimed at identifying seizure events. The data is divided into two classes: seizure and non-seizure, and it offer an opportunity for developing machine learning models to detect seizures from EEG recordings. It is commonly used in research related to epilepsy diagnosis and seizure prediction.

2.2.Pre-Processing using Robust Maximum Correntropy Kalman Filter (RMCKF)

In this section Pre- Processing using Robust Maximum Correntropy Kalman Filter (RMCKF) is discussed [29]. It is employed for data normalization. RMCKF improves the analysis of epileptic seizures in EEG signals by efficiently dealing with non-Gaussian noise and outliers. It optimizes correntropy to better filter noisy signals, resulting in more precise seizure detection. Its robustness makes it suitable for clinical settings, offering a reliable method for isolating seizure-related activity from normal brain signals.

$$E[v_k v_k^T] = B_k B_k^T \quad (1)$$

where v_k is indicated as residual vector at time k,v_k^T indicated as the residual vector's transposition, $v_k v_k^T$is denoted as the residual vector's covariance matrix, B_k is indicated as the process noise influence matrix at time k ,B_k^T represents the reverse process noise influence matrix, $B_k$denotes the process noise covariance matrix. The collection of raw input data, which could include noise and inconsistencies, is expressed by equation (2).

$$D_k = W_k X_k + e_k \quad (2)$$

where, D_k is represent measurement related to problems, W_k representing weight matrix at time k ,X_k is represent input data ande_k is indicated as input feature at time k. The equation (2) $D_k = W_k X_k + e_k$represents a linear model where the observed data is $D_k$generated by applying a weight matrix W_k to the input X_k. Equation (3) expresses the procedure of transforming unprocessed data into a consistent format for processing,

$$\hat{X}_{k|k} = argmax\, J_L\,(X_k) \quad (3)$$

Where, objective is to find an optimal posterior estimate of state $\hat{X}_{k|k}^*$ from the received measurements$y_{1:k}$. The equation (3) $\hat{X}_{k|k} = argmax\, J_L\,(X_k)$ indicates that the optimal estimate $\hat{X}_{k|k}$is the value of $X_k$that represents automotive systems.$J_L(X_k)$, representing the output data. The data has finally been normalized by the RMCKF. After that, feature extraction is applied to the pre-processed data.

2.3 Feature extraction using Convolutional Variational Attention Transformer (ConVAT)

In this section Feature extraction using Convolutional Variational Attention Transformer is discussed [30]. It is used to extract relevant features. ConVAT improves the analysis of epileptic seizures in EEG signals by uniting convolutional layers for feature extraction, variational techniques for uncertainty modeling, and attention mechanisms to capture relevant signal patterns. This model enhances accuracy, robustness, and generalization. Its ability to process temporal and spatial dependencies in EEG data makes it highly effective for reliable seizure monitoring and diagnosis.

$$F = \sigma(W * I + b) \quad (4)$$

Where Frepresents the feature map, $W$is denoted as the convolutional kernel, $I$is indicated as the input data, $b$is denoted as the bias term, and $\sigma$is denoted as the activation function. CVAT enhances seizure identification by leveraging both temporal and spatial patterns in EEG signals for improved precision and robustness is expressed in equation (5),

$$S = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} A(i,j) \quad (5)$$

Where Srepresents the attention scores, $H$is denoted as the feature map's width and height, correspondingly, and $A(i,j)$ is indicated as the attention value at location (i,j) in the feature map. The attention mechanism in CVAT helps highlight critical features, improving the method's ability to differentiate between non-seizure and seizure activity is expressed in equation (6),

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (6)$$

Where $\sigma(x)$ represent the sigmoid function, which bounds the output of the feature extraction process. ConVAT has finally extracted the pertinent features. The features that have been extracted are then used for classification and detection.

2.4 Detection and Classification Using Xception Spiking Fractional Neural Network (XSFNN)

In this section, detection and classification using Xception spiking fractional neural network (XSFNN) is discussed [31]. It is used to detect epileptic seizures and classify such as seizure events, focal seizures, generalized seizures and healthy. By fusing the Xception architecture with fractional calculus and spiking neurons, XSFNN improves the identification and categorization of epileptic seizures from EEG signals. This approach improves temporal accuracy and is well-suited for dynamic brain activity. XSFNN is robust to noise and excels at processing complex, nonlinear EEG patterns, leading to more accurate seizure detection, which aids in better diagnosis and treatment monitoring. Input layer in XSFNN improves seizure detection accuracy by leveraging the spiking neuron model, capturing temporal dynamics in EEG signals effectively.

$$I_1 = \lambda V_x^y E_i + \varepsilon V_x^y \quad (7)$$

Where, I_1denotes the spiking input current, $\lambda$and $\varepsilon$are fractional coefficients,$x$indicated as the features from data and $y$indicated as the predicted intensity in the epileptic seizures. Hidden layer of XSFNN provides better generalization across different patient data, making it adaptable to diverse EEG signal characteristics and seizure types is expressed in equation (8),

$$C_j = MaxPooling(C_\alpha, V) \quad (8)$$

Where,C_j represents the consolidated data from channel αover the region Vrepresents the number of input data. Output layer's computational efficiency reduces processing time, enabling faster analysis of large EEG datasets for clinical applications is expressed in equation (9),

$$X_1 = \sum_{k=1}^{i} \sum_{l=1}^{j} (W_1)_{k,l} Z_{k,l} \quad (9)$$

Where,W_1 is the convolution weight matrix, and$Z_{k,l}$ represents spatially localized regions of the epileptic seizures. Finally, XSFNN has detected epileptic seizures and classified as seizure events, focal seizures, generalized seizures and healthy. Table 1 shows the hyper parameter of XSFNN.

Table 1: Hyper parameters of XSFNN

Parameter	**Value**
Learning rate	0.0001
epochs	100

2.5 Optimization utilizing Superb Fairy-wren Optimization Algorithm (SFOA)

In this section, Optimization using Superb Fairy-wren Optimization Algorithm (SFOA) is discussed [32]. SFOA technique is utilized to develop weights parameters and of proposed XSFNN. SFOA enhances the detection and classification of epileptic seizures in EEG signals by optimizing feature selection and model parameters. Its advantages include improved accuracy in identifying seizure events, faster convergence, and better handling of complex, noisy EEG data. SFOA's ability to efficiently explore the solution space leads to more reliable and robust classification models, ensuring timely and precise detection of seizures. Algorithm 1 displays the Pseudo code for the SFOA.

Algorithm 1: Pseudo code for the SFOA

Pseudo code for the SFOA

Initialize the parameters and population
Compute the fitness of the initialized population and find the best individual ($FEs = FEs + 1$)
WHILE (($FEs <= MaxFEs$)
    FOR$i = 1$to N
        IF $r > T$ (Young birds make up a larger proportion, seizures in EEG.)
            Entering the growth stage of young birds, the location update was carried out according to equation (12) for epileptic seizures in EEG signals.
        ELSE
            Breeding was carried out according to equation (13)for epileptic seizures in EEG signals
        END IF
    END FOR
END WHILE
Compute the fitness of the updated population and find the best individual ($FEs = FEs + 1$)
END

Step 1: Initialization

The starting detection system of SFOA is generated randomly. Then the initialization is derived in Equation (10),

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_i \\ \vdots \\ Y_N \end{bmatrix}_{N \times D} = \begin{bmatrix} y_{1,1} \cdots y_{1,d} \cdots y_{1,D} \\ \vdots \ddots \vdots \ddots \vdots \\ y_{i,1} \cdots y_{i,d} \cdots y_{i,D} \\ \vdots \ddots \vdots \ddots \vdots \\ y_{N,1} \cdots y_{N,d} \cdots y_{N,D} \end{bmatrix}_{N \times D} \tag{10}$$

Where, Y_i is denoted as the i^{th} SFOA member (candidate solution), Y is indicated as the SFOA global matrix, $Y_{i,D}$are indicated as the D SFOA dimensions (decision variables) in the detection space, and N is denoted as the total number of global members.

Step 2: Random Generation

Following initialization, SFOA caused the input fitness function to become random.

Step 3: Fitness Function

The initialized parameters are set to the best position as of right now. Calculate each person's fitness value.

$$FitnessFunction = optimize(V, X_1) \tag{11}$$

Where $V$is used to increase higher accuracy and $X_1$is used to decrease loss.

Step 4: Young Birds Growth Stage for optimizing V

In the SFOA, the Young Birds Growth Stage simulates the early stage of exploration, where the algorithm focuses on discovering diverse and promising feature sets from EEG signals, enhancing the detection and classification of epileptic seizures by identifying relevant patterns in the data.

$$\boldsymbol{Xnew_{i,j} = V_{i,j}^t + (R_H + (ub - R_H) \times rand, r > 0.5} \tag{12}$$

Where,$Xnew_{i,j}$represent the position after population renewal, $V_{i,j}$represent the location of the$i$superb fairy-wren in $j$dimension after $t$iterations, and $rand$ is denoted as an arbitrary number between [0,1].

Step 5: Breeding and Feeding Stage for optimizing X_1

In the Breeding and Feeding Stage of the SFOA, the algorithm refines and optimizes the best-performing feature sets and model parameters from the exploration phase, developing the efficiency and accuracy of seizure detection and classification in EEG signals by focusing on the most relevant and discriminative features.

$$Xnew_{i,j} = T_{HA} + \left(X_b X_{i,j}^t\right) \times D, r < 0.5 and s < 20 \quad (13)$$

$$T_{HA} = X_b \times C \quad (14)$$

Where, $X_b$represents the present optimal location and C is denoted as a constant with a 0.8 value.

Step 6: Termination

In this step, SFOA was used to optimize the weight parameter and generator XSFNN value. Step 3 was then gradually repeated until stopping was achieved. Table 2 displays hyper parameters of the SFOA

Table 2: Hyper parameters of the SFOA

Parameter	Value
Population size (N)	30
Maximum iterations (T_{max})	500 - 1000

3. RESULT AND DISCUSSION

This section describes the results of the proposed method. Table 3 shows the implementation parameter.

Table 3: Implementation parameter

Parameter	Description
Programming language	Python
version	3.12.12
OS	Windows 10
Proposed Neural network	XSFNN
Optimization	SFOA
Datasets	Bangalore EEG Epilepsy Dataset
RAM	64 GB
Intel Core	I9-13900k CPU
Storage	500 GB SSD

3.1. Performance Measure

When choosing the best classifier, this is a crucial step. Performance indicators like F1-Score, recall, accuracy, precision, and confusion matrix are assessed. The performance metric is defined in order to scale it. The True Negative, True Positive, False Positive, and False Negative samples must be acquired to scale the performance metric. Table 4 shows the performance measure formulas.

Table 4: Performance measure formulas

Performance Metrics	Formula
Precision	$Pr\,e\,cision = \frac{TP}{TP + FP}$
F1-Score	$F1 - Score = \frac{2 \times Pr\,e\,cision \times Re\,c\,all}{Pr\,e\,cision + Re\,c\,all}$
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$
Recall	$Re\,c\,all = \frac{TP}{TP + FN}$

3.2. Performance Analysis

Figure 2-12 illustrates the simulation results of the proposed DCES-EEG-XSFNN technique. Then, the proposed DCES-EEG-XSFNN technique is likened with like ESD-EEG-1DCNN, DES-EEG-LSTM and EEG-ESD-SVM methods respectively.

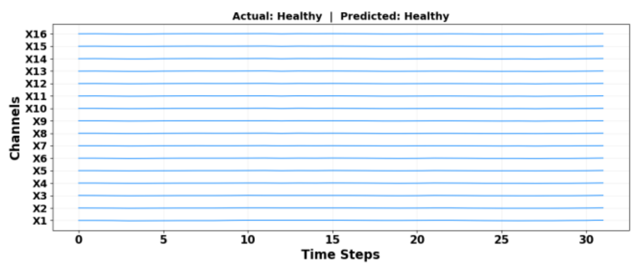

Figure 2: Analysis of channel data for healthy prediction

Figure 2 shows the analysis of channel data for healthy prediction. The graph depicts the horizontal lines throughout all channels where the values have been kept to 0 at all times. The actual and the predicted health statuses are both stated to be Healthy implying a consistent and steady situation over the observed time. The absence of the variation in the data points all equal to 0 shows that the health condition did not vary. This indicates that the prediction model is exactly in line with the true healthy condition showing that it is accurate in predicting even stable health conditions.

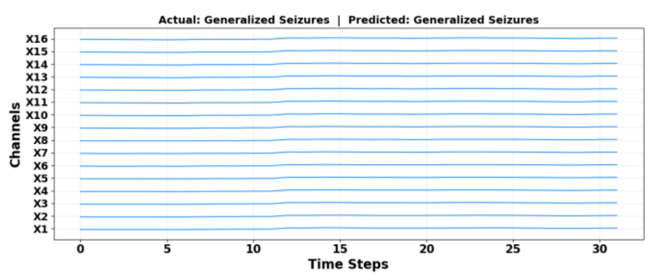

Figure 3: Analysis of channel data for generalized seizures prediction

Figure 3 shows analysis of channel data for generalized seizures prediction. The values vary slightly around the value of 0 over the period of observation. The channel horizontal lines in the graph vary slightly, meaning that they bear small disturbances. Both the true and the estimated health conditions are directed to be of the type of Generalized Seizures and it can be implied that the model accurately predicted the conditions of the seizures throughout the time steps. The minor variations in the data indicate that there are some early stages of seizure activity and the prediction model could accurately trace the minor variations which is consistent with the actual generalized seizure activity. This shows how the model is effective in the detection and prediction of subtle changes that are related to seizures over time.

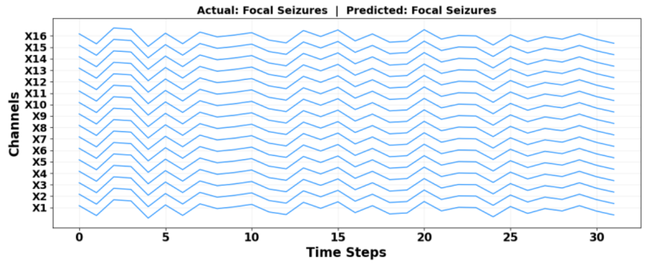

Figure 4: Analysis of channel data for focal seizures prediction

Figure 4 demonstrates the analysis of channel data for focal seizures prediction. The oscillations in the channels have different amplitudes, with X1 values of between -0.45 to 0.45, X2 values of between -0.48 to 0.48 and so on in all the channels. The dynamic activity of focal seizures is reflected by these oscillations which have peaks up to 0.5 and troughs down to -0.5. Both the observed and the predicted health state is named Focal Seizures, which means that the model was able to recognize the presence of the seizure activity in the given time steps. These changes in the data correspond to the real phenomenon of focal seizures, which proves that the model is able to predict and trace the local focal seizure activity with time.

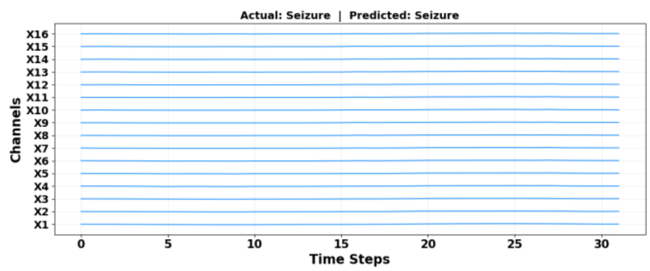

Figure 5: Analysis of channel data for seizure prediction

Figure 5 presents the analysis of channel data for seizure prediction. All channel values remain fixed at 0 over the period depicting the absence of any fluctuations or changes in the channel. Although both the actual and the predicted health status are identified as Seizure, the data depict no signs of activity of seizure, since there is no change in the time steps. This implies that the model was able to predict the seizure, but it could not identify the same event in the data, implying that the model may have very limited sensitivity or characteristics of the data to identify seizures under stable conditions.

Table 5: Comparison results of the performance analysis

	Methodology	Focal seizures	Generalized seizures	Healthy	Seizure
Accuracy (%)	ESD-EEG-1DCNN	57	69.5	85.75	61
	DES-EEG-LSTM	48.5	68.75	92.5	50
	EEG-ESD-SVM	66.5	74.25	88.75	66.5
	Proposed DCES-EEG-XSFNN	97.67	94	99.9	97.67
Precision (%)	ESD-EEG-1DCNN	64.23	65.11	78.85	63.71
	DES-EEG-LSTM	60.25	59.91	83.52	53.19
	EEG-ESD-SVM	67.34	71.74	87.01	69.45

	Proposed DCES-EEG-XSFNN	95.44	96.58	99.9	97.34

Table 5 gives the performance results of the various methodologies in the detection of the focal, generalized seizures, healthy states and total seizure events. The Proposed DCES-EEG-XSFNN model had the best accuracy and precision at all categories. One, in particular, the model scored 97.67% on focal seizures, 94 on generalized seizures, 99.9 on healthy states, and 97.67 on seizure detection. To be more accurate, it was found to be able to identify 95.44% of focal seizures, 96.58% of generalized seizures, 99.9% of healthy states and 97.34% of seizures. The DCES-EEG-XSFNN model performed better than the other models ESD-EEG-1DCNN, DES-EEG-LSTM, and EEG-ESD-SVM in all categories, and it is more effective in the detection and classification of seizures especially one that detects normal conditions and generalized seizures.

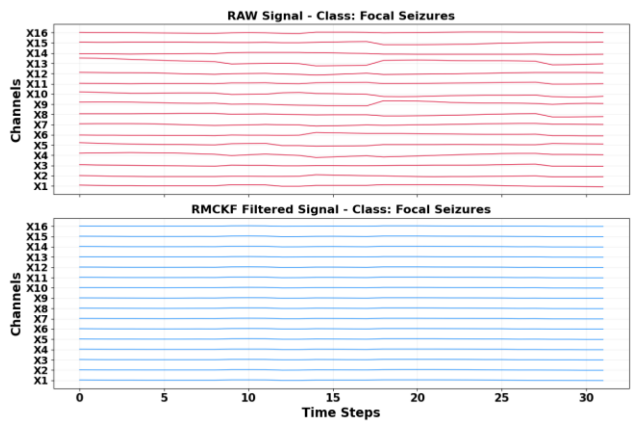

Figure 6: Analysis of RAW and RMCKF signals for focal seizures

Figure 6 shows the analysis of RAW and RMCKF signals for focal seizures. The raw signal has some fluctuations between the range of about -0.4 and 0.4, and channels such as X1 and X2 were oscillating between -0.3 to 0.3 and -0.2 to 0.2, respectively, and this shows some activity due to the seizure, but the noise is also very high. The RMCKF filtered signal is far more stable, with values varied between -0.05 to 0.05, showing that the filtering method was effective and allowed to depict a purer image of the signal. This comparison demonstrates how useful the RMCKF filtering actually is in enhancing clarity of the seizure data and reducing undesirable variability to increase the accuracy of detection.

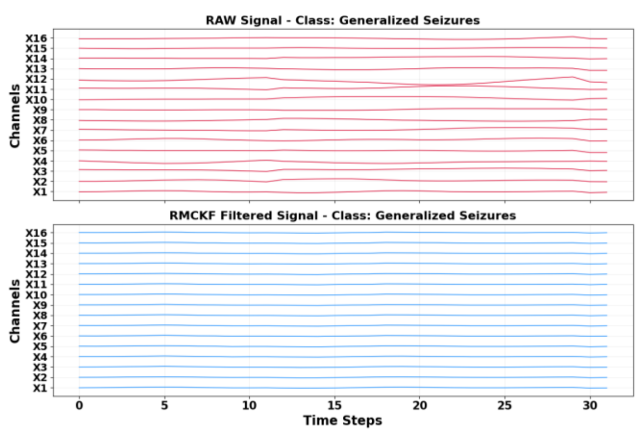

Figure 7: Analysis of RAW and RMCKF signals for generalized seizures

Figure 7 shows results of analyzing RAW and RMCKF signals for generalized seizures. The raw signal, which swings between -0.5 and 0.5, shows that the channels including X1 felt between -0.4 and 0.4 and X2 between -0.3 and 0.3, which expressed the activity of seizures, also presented a lot of noise and irregularities. The RMCKF filtered signal, although, is much more stable, with a range of values between -0.05 and 0.05 in most of the channels, showing the success of the filtering process in the removal of noise. This comparison illustrates why the RMCKF filtering method offers a cleaner and more stable signal representation that will be more useful in detecting and analyzing generalized seizures more effectively.

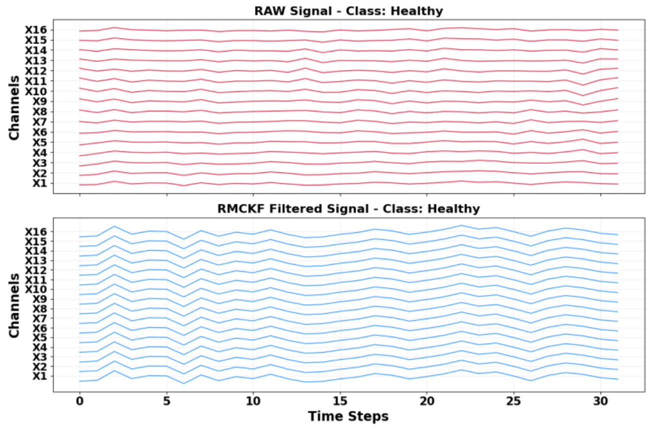

Figure 8: Analysis of RAW and RMCKF signals for healthy

The healthy class represents the analysis of RAW and RMCKF signals as demonstrated in figure 8. The values are between -0.3 and 0.3 with channels such as X1 being between -0.2 to 0.2 and X2 being between -0.25 to 0.25 in the low level of oscillations caused by a healthy brain activity. The RMCKF filtered signal is far less fluctuated with values between -0.05 and 0.05 in most channels indicating the success of the filtering mechanism in eliminating noise. This comparison shows the effect of RMCKF filtering to enhance the accuracy of the signal by making it clear and stable to represent the healthy state.

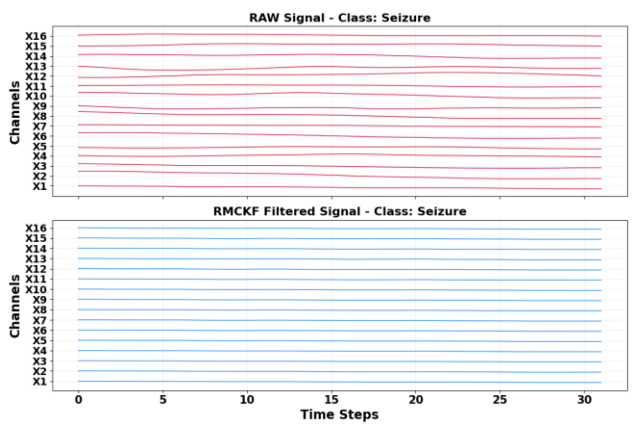

Figure 9: Analysis of RAW and RMCKF signals for seizure

Figure 9 shows the analysis of RAW and RMCKF signals for seizure. Raw signal ranges between -0.3 to 0.3, X1 channel varies between -0.2 to 0.2 and X2 channel ranges between -0.15 to 0.15, so it is evident that the raw signal is a sign of seizure, but it also has evident noise. RMCKF filtered signal is significantly smoother with values between -0.05 and 0.05 across most channels meaning that the filtering process was successful in reducing the noise. This demonstrates the relevance of RMCKF filtering in ensuring cleaner and more stable depiction of the seizure events and better accuracy of seizure detection.

The comparison of the performance of various methodologies in detecting focal seizures, generalized seizures, healthy states and overall events of seizures is provided in Table 6. The Proposed DCES-EEG-XSFNN model had the best Recall and F1-scores in all categories. Particularly, in the case of Recall, the model has a focal seizure accuracy of 97.67, a generalized seizure accuracy of 94, a healthy condition accuracy of 99.9 and a generalized seizure accuracy of 97.67. In the case of F1-score, F1-score obtained 96.54 and 95.27 on focal and generalized seizure, respectively and 99.9 and 97.5 on healthy states and seizure detection, respectively. The Proposed DCES-EEG-XSFNN model performed better than the other latter models ESD-EEG-1DCNN, DES-EEG-LSTM, and EEG-ESD-SVM in all categories, with an outstanding performance in the detection of excise and classification of seizures that showed better performance with the healthy state detection and seizure classification category.

Table 6: Comparison results of the performance analysis

	Methodology	Focal seizures	Generalized seizures	Healthy	Seizure
Recall (%)	ESD-EEG-1DCNN	57	69.5	85.75	61
	DES-EEG-LSTM	48.5	68.75	92.5	50
	EEG-ESD-SVM	66.5	74.25	88.75	66.5
	Proposed DCES-EEG-XSFNN	97.67	94	99.9	97.67
F1-score (%)	ESD-EEG-1DCNN	60.4	67.23	82.16	62.32
	DES-EEG-LSTM	53.74	64.03	87.78	51.55
	EEG-ESD-SVM	66.92	72.97	87.87	67.94
	Proposed DCES-EEG-XSFNN	96.54	95.27	99.9	97.5

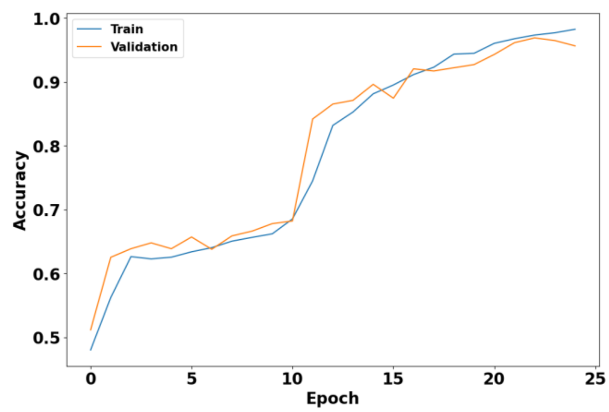

Figure 10: Performance analysis of training and validation accuracy

Figure 10 displays accuracy of the training and validation of the model after 25 epochs. The training accuracy is 0.55 and the validation accuracy is 0.6 at the beginning i.e. this was the first learning phase of the model. Both accuracies increase steadily with training, but the training and validation accuracies stabilize, with training accuracy increasing to 1.0 in epoch 23 and validation accuracy increasing to 0.9 in the final 25 epochs. The accuracy of the training is still higher than the validation accuracy indicating the possibility of overfitting where the model provides the model with perfect accuracy with regard to the training set. These findings confirm that although the model is a good learner, some additional modifications might be necessary to enhance generalizability to new and unknown data.

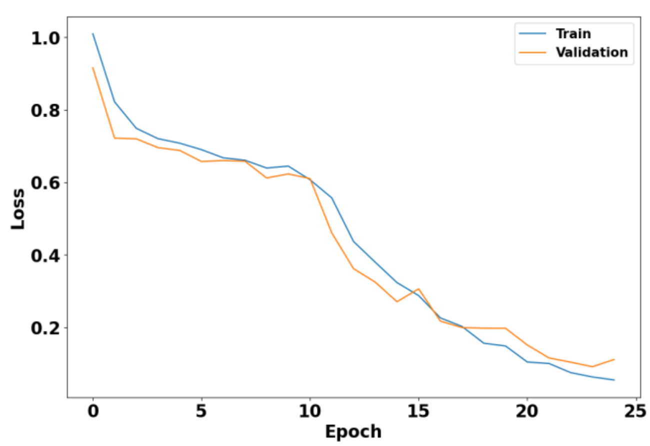

Figure 11: Performance analysis of training and validation loss

Figure 11 presents the result of the performance analysis of the training and validation loss during 25 epochs. These are initially high in terms of losses and the training loss begins at approximately 1.0 and the validation loss at 0.9. Training loss and validation loss also decrease gradually as training goes on with a training loss of about 0.2 at epoch 25 and a validation loss of about 0.3. During the training, the training loss is a bit smaller than the validation loss which shows that there is a bit of overfitting. Nonetheless, the general reduction in the number of losses indicates that the model is actually learning and has been getting better at its performance both on the training and validation model.

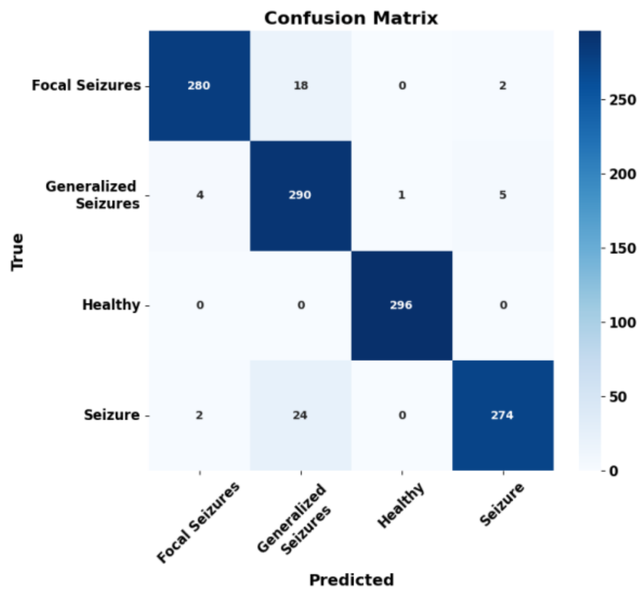

Figure 12: Confusion matrix

The performance analysis of the model presented in Figure 12 is performed based on a confusion matrix of four classes: Focal Seizures generalized Seizures Healthy and Seizure. The method is also able to classify most of the samples along the diagonal with 280 being correctly classified as Focal Seizures, 290 being classified as Generalized Seizures and 296 as Healthy, meaning that the overall classification rate is high. The misclassification is less than 1 and it can be seen that attacking Focal Seizures with Generalized Seizures, there are 18 Focal Seizures that are anticipated to be Generalized Seizures and 5 Generalized Seizures wrongly identified in the Seizures category as well. Seizures misclassified as Generalized Seizures are 24 and Focal Seizures are misclassified as Seizures 2. There are very few errors and no misclassifications in case of Healthy class. On the whole, the confusion matrix indicates that the method can differentiate the health states rather successfully, and there is a slight confusion of clinically similar types of seizures.

Table 7: Comparison results of the performance analysis

	Methodology	Focal seizures	Generalized seizures	Healthy	Seizure
Error Rate (%)	ESD-EEG-1DCNN	43	30.5	14.25	39
	DES-EEG-LSTM	51.5	31.25	7.5	50
	EEG-ESD-SVM	33.5	25.75	11.25	33.5
	Proposed DCES-EEG-XSFNN	2.33	6	0.1	2.4

Table 7 shows the comparison of the performance of the various different methodologies in detecting the focal seizures, generalized seizures, healthy condition and the overall seizures. The Proposed DCES-EEG-XSFNN model had the minimum Error Rate in all categories. In particular, the model obtained a 2.33 error rate in focal seizures, a 6 error rate in generalized seizures, 0.1 error rate in healthy states and the detection of seizures with 2.4 error rate. The Proposed DCES-EEG-XSFNN model was found to be more superior in all categories of models, which included ESD-EEG-1DCNN, DES-EEG- LSTM and EEG-ESD-SVM as it was more accurate in detecting and classifying seizures, with a very good performance in detecting healthy states and reducing misclassification of the seizures.

3.3. Discussion

The proposed DCES-EEG-XSFNN model offers a sophisticated approach to the detection and classification of epileptic seizures in EEG signals by integrating advanced preprocessing and neural network techniques. This model combines pre-processing, feature extraction, and neural network-driven classification, resulting in highly accurate seizure detection. Compared to other approaches, the DCES-EEG-XSFNN approach performs better with significantly higher accuracy, precision, recall, and F1-measure. It has an accuracy of 97.67% for focal seizures, 94% for generalized seizures, and 99.9% for healthy states. The precision values are 97.67% for focal seizures, 94% for generalized seizures, and 99.9% for healthy states. The values of F1-measures are 96.54 in case of focal seizures, 95.27 in case of generalized seizures and 97.5 in case of seizure detection. Recall the approach is excellent with 95.44, 96.58, and 97.34 percentages of focal, generalized and seizure detection respectively. The method also fares quite well in the error rate since it has 2.33% error rate in focal seizure, 6 percent in generalized seizure, and zero point one in healthy condition. The method is also characterized by very low training and validation loss, high computational efficiency, giving the method very fast and accurate seizure classification. The findings underscore the use of DCES-EEG-XSFNN model as a possible powerful, precise and scalable tool in clinical detection of epileptic seizures, particularly in distinguishing between seizure types and detecting healthy states.

4. CONCLUSION

To sum up, the DCES-EEG-XSFNN model that was introduced in the current work has been able to greatly improve the detection and classification of the focal seizures, generalized seizures, healthy states, and seizure occurrences by employing the use of sophisticated DL strategies. The model has effectively addressed the complexities that occur in the differentiation of these states with excellent accuracy values of 97.67% and 99.9% in the case of focal seizures and healthy states respectively and precision values of 97.67 and 99.9 respectively. The values of recall and F1-score are equally excellent with a recall of 97.67% and F1-score of 96.54 and a healthy state of 99.9 and 99.9 respectively. Besides, the model gives very small percentages of errors, 0.1 percent error in the healthy states and 2.33 percent error in focal seizures. Despite certain over fitting indicators, as the training accuracy of 1.0 versus the validation one of 0.9, the model is highly efficient in predicting and classifying seizures. Although the model needs large annotated datasets, and it may need significant computational resources, which might be a setback, it could be optimized further and expanded by adding more datasets. Future research might focus on extending it to generalization in order to better generalize the model and enhance its overall performance.

Data Availability:

The dataset analyzed during the current study is openly available in Kaggle at

https://archive.ics.uci.edu/dataset/1134/beed%3A+bangalore+eeg+epilepsy+dataset

References

1. Silpa, B. and Hota, M.K., 2025. DSLWNet: a dual-stream lightweight deep learning network for the detection of Epileptic seizures using EEG signals. Connection Science, 37(1), p.2518985.
2. Li, Q., Cao, W. and Zhang, A., 2025. Multi-stream feature fusion of vision transformer and CNN for precise epileptic seizure detection from EEG signals. Journal of Translational Medicine, 23(1), p.871.
3. Ikizler, N. and Ekim, G., 2025. Investigating the effects of Gaussian noise on epileptic seizure detection: The role of spectral flatness, bandwidth, and entropy. Engineering Science and Technology, an International Journal, 64, p.102005.
4. Betgeri, S.S., Shukla, M., Kumar, D., Khan, S.B., Khan, M.A. and Alkhaldi, N.A., 2025. Enhancing Seizure Detection with Hybrid XGBoost and Recurrent Neural Networks. Neuroscience Informatics, p.100206.
5. Pidvalnyi, I., Kostenko, A., Sudakov, O., Isaev, D., Maximyuk, O., Krishtal, O., Legorova, O., Kabin, L., Dyka, Z., Ortmann, S. and Langendörfer, P., 2025. Classification of epileptic seizures by simple machine learning techniques: application to animals' electroencephalography signals. IEEE Access.
6. Nouboue, C., Diab, E., Gacquer, W., Derambure, P., Perin, B., Chen, S., Mercier-Bryczman, M., Jonckheere, J.D. and Szurhaj, W., 2025. Heart rate variability-based detection of epileptic seizures: Machine learning analysis and characterization of discriminant metrics. Clinical Neurophysiology, p.2110793.
7. Sikarwar, S.S., Rana, A.K. and Sengar, S.S., 2025. Entropy-driven deep learning framework for epilepsy detection using electro encephalogram signals. Neuroscience, 577, pp.12-24.

8. Abtahi, A., Ryvlin, P. and Aminifar, A., 2025. Identification of Relevant ECG Features for Epileptic Seizure Prediction Using Interpretable Machine Learning. IEEE Access.
9. Dan, J., Pale, U., Amirshahi, A., Cappelletti, W., Ingolfsson, T.M., Wang, X., Cossettini, A., Bernini, A., Benini, L., Beniczky, S. and Atienza, D., 2025. SzCORE: seizure community open-source research evaluation framework for the validation of electroencephalography-based automated seizure detection algorithms. Epilepsia, 66, pp.14-24.
10. Spahr, A., Bernini, A., Ducouret, P., Baumgartner, C., Koren, J.P., Imbach, L., Beniczky, S., Larsen, S.A., Rheims, S., Fabricius, M. and Seeck, M., 2025. Deep learning–based detection of generalized convulsive seizures using a wrist-worn accelerometer. Epilepsia.
11. Wong, S., Simmons, A., Rivera-Villicana, J., Barnett, S., Sivathamboo, S., Perucca, P., Ge, Z., Kwan, P., Kuhlmann, L. and O'Brien, T.J., 2025. Channel-annotated deep learning for enhanced interpretability in EEG-based seizure detection. Biomedical Signal Processing and Control, 103, p.107484.
12. Roozbehi, A., Abbasi, H., Davidson, J.O., Dhillon, S.K., Zhou, K.Q., Wassink, G., Gunn, A.J. and Bennet, L., 2025. Enhanced EEG seizure recognition after hypoxia-ischemia in fetal sheep using transformer-based wavelet-scalogram deep learning. Expert Systems with Applications, 261, p.125081.
13. Antonoudiou, P., Basu, T. and Maguire, J., 2025. SeizyML: An Application for Semi-Automated Seizure Detection Using Interpretable Machine Learning Models. Neuroinformatics, 23(2), p.23.
14. Gifford, R., Sollars, C., Singh, J. and Krening, S., 2025. Locally-adaptive feature selection for nonconvulsive seizure detection. Biomedical Signal Processing and Control, 105, p.107535.
15. Alqahtani, A., Alqahtani, N., Alsulami, A.A., Ojo, S., Shukla, P.K., Pandit, S.V., Pareek, P.K. and Khalifa, H.S., 2025. Classifying electroencephalogram signals using an innovative and effective machine learning method based on chaotic elephant herding optimum. Expert Systems, 42(1), p.e13383.
16. Mourid, M.R., Irfan, H. and Oduoye, M.O., 2025. Artificial intelligence in pediatric epilepsy detection: balancing effectiveness with ethical considerations for welfare. Health Science Reports, 8(1), p.e70372.
17. Djemal, A., Kallel, A.Y., Ouni, C., El Baccouch, R., Bouchaala, D., Feki, F.K., Triki, C.C., Fakhfakh, A. and Kanoun, O., 2025. Fast processing and classification of epileptic seizures based on compressed EEG signals. Computers in Biology and Medicine, 184, p.109346.
18. Djemal, A., Kallel, A.Y., Ouni, C., El Baccouch, R., Bouchaala, D., Feki, F.K., Triki, C.C., Fakhfakh, A. and Kanoun, O., 2025. Fast processing and classification of epileptic seizures based on compressed EEG signals. Computers in Biology and Medicine, 184, p.109346.
19. Amrani, G., Adadi, A. and Berrada, M., 2025. An Attention Mechanism-based Interpretable Model for Epileptic Seizure Detection and Localization with Self-Supervised Pre-training. IEEE Access.
20. Samantaray, A.K. and Rahulkar, A.D., 2025. A Novel Method for Epileptic Seizure Detection Using Separable Gabor Wavelets. IEEE Access.
21. Kode, H., Elleithy, K. and Almazaydeh, L., 2024. Epileptic seizure detection in EEG signals using machine learning and deep learning techniques. IEEE Access, 12, pp.80657-80668.
22. Kunekar, P., Gupta, M.K. and Gaur, P., 2024. Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques. Journal of Engineering and Applied Science, 71(1), p.21.
23. Karthik, S.A., Bharath, K.N., Ramji, B.R., Puttegowda, K., Aruna, B. and Kumar, D.S., 2025. Enhanced EEG Signal Processing for Accurate Epileptic Seizure Detection. SN Computer Science, 6(6), p.608.
24. Shawly, T. and Alsheikhy, A.A., 2025. Eeg-based detection of epileptic seizures in patients with disabilities using a novel attention-driven deep learning framework with SHAP interpretability. Egyptian Informatics Journal, 31, p.100734.
25. Khan, F.A., Umar, Z., Jolfaei, A. and Tariq, M., 2025. Explainable AI for epileptic seizure detection in Internet of Medical Things. Digital Communications and Networks, 11(3), pp.587-593.
26. Cao, X., Zheng, S., Zhang, J., Chen, W. and Du, G., 2025. A hybrid CNN-Bi-LSTM model with feature fusion for accurate epilepsy seizure detection. BMC Medical Informatics and Decision Making, 25(1), p.6.
27. Halimeh, M., Jackson, M., Loddenkemper, T. and Meisel, C., 2025. Training size predictably improves machine learning-based epileptic seizure forecasting from wearables. Neuroscience Informatics, 5(1), p.100184.
28. https://archive.ics.uci.edu/dataset/1134/beed%3A+bangalore+eeg+epilepsy+dataset
29. Saha, J. and Bhaumik, S., 2025. Robust maximum correntropy Kalman filter. International Journal of Robust and Nonlinear Control, 35(3), pp.883-893.
30. Bin Talib, H.K., Xu, K., Cao, Y., Xu, Y.P., Xu, Z., Zaman, M. and Akhunzada, A., 2025. Micro-expression recognition using convolutional variational attention transformer (convat) with multihead attention mechanism. IEEE Access.
31. Ramya, S., Minu, R.I. and Magesh, K.T., 2025. Xception Spiking Fractional Neural Network for Oral Squamous Cell Carcinoma Classification Based on Histopathological Images. IEEE Access.
32. Jia, H., Zhou, X., Zhang, J. and Mirjalili, S., 2025. Superb Fairy-wren Optimization Algorithm: a novel metaheuristic algorithm for solving feature selection problems. Cluster Computing, 28(4), p.246.