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Research Article

Efficient Epileptic Seizure Detection with Optimal Channel Selection and FIXUPPACTBI-LSTM Deep Learning Model

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Abstract: Epilepsy is a neurological condition prevalent worldwide, affecting millions of people. Standard procedures for detecting epilepsy frequently produce suboptimal results due to variability across EEG channel. Therefore, this research aimed to use a well-organized FixupPACTBi-LSTM-based method to detect epilepsy with optimal channel selection as an effective way of identifying and eliminating disturbances from unwanted channel. The proposed method prioritized stability in channel selection by using networks with the lowest standard deviation as the fitness criteria. Additionally, the Linear Memory Controlled Water Wave Optimization (LMC-WWO) process enhances this selection through interactive optimization at the propagation, refraction, and breaking stages. By integrating memory-based searches, Gaussin functions, and solitary wave adaptions, the model effectively improved accuracy. After the optimal channel was identified, the selected signals went through segmentation and prep-processing before being converted into images and scalogram using Coco-GASF and CWT methods. These images were then resized and normalized through min-max normalization, producing grayscale representations for extracting signal rhythms. Features from the normalized scalograms and signal rhythms were extracted using Cas-GoogleNet, and the most relevant features were selected with Fisher's score method. Following this, classification was conducted using FixupPACTBi-LSTM classifier to ensure high precision in epilepsy detection. Finally, comparative analysis showed that this method performed better than existing model with a substantially shorter channel selection time of 8769 ms, followed by accuracy, sensitivity, and specificity rates of 97%, 98%, and 97%, respectively.

Keywords: Cascaded googlenet; Continuous wavelet transform; Covariance correlation coefficient; Electroencephalogram; Epilepsy; Water wave optimization

1. Introduction

Epilepsy is a neurological condition affecting people of all ages, and is characterized by a persistent tendency to experience recurring seizure (Whulanza et al., 2024; Rasheed et al., 2020). The condition is caused by a sudden and excessive electrical discharge in brain neurons, which disrupt the body's ability to function properly (Jiwani et al., 2022). This abnormal activity creates a highly excitable neural network, primarily affecting the cerebrum (Radman et al., 2021). Given these challenges, developing an effective model for early and reliable epileptic seizure detection is necessary for accurately identifying and categorizing the condition (Anuragi et al., 2021).

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Manually detecting epileptic seizure is an extremely time-consuming and laborious task process (Gupta et al., 2020). To address this challenge, various diagnostic methods including Magneto-Encephalography (MEG), Magnetic Resonance Imaging (MRI) scan, Positron Emission Tomography (PET), and Electroencephalography (EEG), have been developed to facilitate automatic epilepsy detection. However, these methods can be complex, time-consuming, and prone to errors (Nkengfack et al., 2020). Among the methods, EEG is widely recommended by neurologists for monitoring seizure frequency, as it records neuronal electrical activity and ensures accurate classification of seizure patterns (Aayesha et al., 2021; Jana et al., 2019).

Research has explored various domains and methods for automatic epileptic seizure detection, including time, frequency, time-frequency analysis, and empirical mode decomposition (EMD) (Saminu et al., 2021). However, non-linear methods, EMD, frequency spectrum analysis, and time-frequency methods have showed limitations in accurately identifying epilepsy. Given these challenges, an effective system should be designed to meet real-time application requirements by minimizing processing time (Brari and Belghith, 2021). Epileptic seizure are characterized by changes in EEG signal oscillation, shifting from stable to unstable state over time (Sagga et al., 2020). Over the past few decades, significant advancement has been made in detecting EEG abnormalities (Romahadi et al., 2024). Machine learning (ML) has played a crucial role in improving automatic seizure identification and predict other events (Sari et al., 2023; Roy et al., 2020). In addition, deep neural network model have enhanced accuracy by automatically selecting relevant features (Nugroho et al., 2023; Maulana and Sari, 2022). A combination of CNN and LSTM has been used to extract relevant features from time-frequency representation (Abdullah et al., 2023). Building on this, multi-Layer perceptron (MLP) network has also been applied for epileptic seizure identification using one-dimensional EEG signals (Alshebeili et al., 2020). Pattern-matching model achieved F1 score of 94.86% and an accuracy of 92.66% (Das et al., 2020). In this context, seizure detection framework incorporating EEG channel selection and features extraction was proposed for epilepsy treatment. However, this method faced challenges in accurately predicting normal cases (Ein Shoka et al., 2021). To improve performance, Nonlinear Mode Decomposition (NMD) was combined with a sliding window method to categorize EEG data into short, two-second epochs. Despite its potential, this method was unreliable for diagnosing other conditions, as the model was limited to detecting a single type of illness.

Stein kernel-based SR method was developed to distinguish epileptic seizure (Peng et al., 2021) achieving an accuracy of 98.21%. In line with this, predictive model using K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) methods showed that SVM slightly outperformed KNN in seizure detection (Savadkoohi et al., 2020). This method included a two-phase comprehensive method for early seizure recognition and evaluation (Chen et al., 2020). A new framework was introduced to automatically predict and classify epilepsy from EEG signals, achieving classification accuracies of 76.70%, 82.50%, and 81.40% after normalizing EEG dataset using Medium Absolute Deviation (MAD) method (Polat and Nour et, 2020). Additionally, a wide-scale mixed distribution-based stochastic EEG model was developed to capture fluctuations in non-Gaussianity caused by stochastic EEG variations (Yang et al., 2021). However, the model failed to remove artifacts present in the signal during epileptic convulsions.

Neural networks and adaptive neuro-fuzzy inference systems (ANFIS) have been used to automatically detect and diagnose epilepsy from EEG signal, achieving an impressive 98.05% categorization accuracy (Deivasigamani et al., 2021). EEG signals were characterized as focal or non-focal based on extracted features. In line with the discussion, preprocessing and classification of EEG data that using a combination of Deep Learning (DL) and ML algorithms, such as Random Forest, TabNet, XGBoost, as well as 1D CNN led to improved accuracy, recall, and F1-score (Kode et al., 2024). Two advanced DL model, Network 1D Raw, and 2D Conv, were proposed for the classification of seizure types (Rivera et al., 2024). In similar expression, a Transformer-based DL model achieved classification results with 85% accuracy, 87% specificity, and 82% sensitivity, respectively (Lih et al., 2023). However, the multi-channel structure of EEG signal, increased processing costs and decreased operating efficiency, posing a challenge for epilepsy detection. The complexity of precise feature selection and computations required made the process more difficult for the mode to differentiate between seizure, non-seizure, and pre-seizure phases.

This research proposed an improved detection framework using FixupPACTBi-LSTM for seizure classification. The analysis followed two-step procedure, including adaptive channel selection strategy, called Linear Memory Controlled Water Wave Optimization (LMC-WWO) used to eliminate unwanted EEG channel while ensuring optimal data quality. After the initial step, the research then used Fixed-update Parameterized Clipping Activation Function (PACF)-induced Bi-directional Long Short-Term Memory (FixupPACTBi-LSTM) model for epilepsy detection. During this process, RGB image and scalograms of EEG signal were generated to improve seizure EEG signal as well as the representation of normal. EEG data were converted into RGB image using Coco-GASF method, while scalograms were produced using CWT (Continuous Wavelet Transform). Cas-GoogleNet model was then used to extract features from these representations for efficient learning. Finally, FixupPACTBi-LSTM model was designed to accurately recognize different types of epilepsy seizure, including clonic, atonic, and tonic types. The classification criteria for seizure types were based on Scalogram Characteristics and Frequency Band Analysis. This comprehensive strategy incorporated advanced methods to increase the accuracy and reliability of epilepsy diagnosis. Subsequently, this research is categorized into different section, with Section 2 presenting the proposed method. Meanwhile, Sections 3 and 4 detail3ed the experimental analysis and review of the findings, respectively.

Table 1 Comprehensive research on the identification of epilepsy using DL method and EEG inputs

Author (citation)	Methods	Dataset	Challenges	Achievement
(Varlı and Yilmaz, 2023)	2D CNN +LSTM	CHB MIT, Bonn dataset	Multiple type classification is not done	Accuracy = 95.46% Accuracy = 96.23%
(Ahmad et al., 2023)	Integrated 1D CNN with Bi LSTM	UCI epileptic data set	The classifier required adequate training.	Accuracy = 84.10%
(Chanu et al., 2023)	Multilayer perceptron	Bonn University dataset	The feature selection model should be optimized and increase accuracy.	Accuracy = 96.2% precision = 98%
(Sagga et al., 2022)	CNN model, Xception model	CHB MIT dataset	The model had to be improved to identify seizure with high precision.	Accuracy = 96.47% Precision = 99.79%
(Qiu et al., 2023)	ResNet-LSTM network (DARLNet)	Bonn University dataset	Multichannel EEG recordings were needed for detection.	Accuracy = 90.17% Precision = 90%
(Jiwani et al., 2022)	Conv-LSTM	Bonn University dataset	It was possible to interpret the facts incorrectly, leading to an inability to make a decision.	Accuracy = 96%

2. Proposed Automated Epileptic Seizure Detection and Classification System Using FIXUPPACTBI-LSTM Method

During the research, an efficient architecture named LMC-WWO and FixupPACTBi-LSTM-based automatic epilepsy seizure detection were implemented using optimal EEG channel as shown in Figure 1.

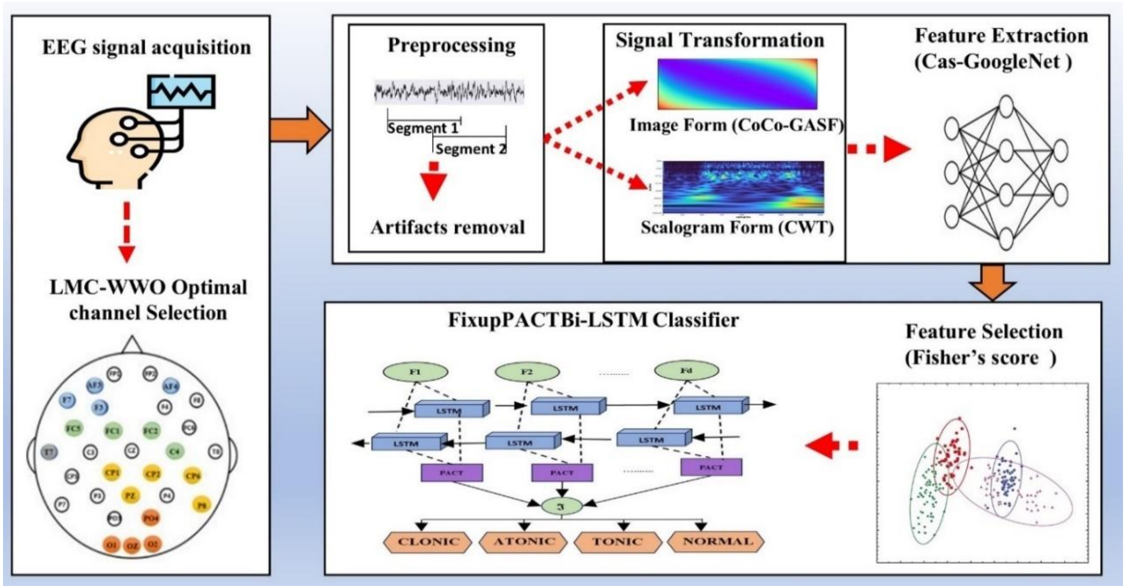


Figure 1 Proposed FIXUPPACTBI-LSTM framework for detection and classification of epilepsy

2.1. Dataset Description

CHB-MIT dataset used in this analysis (Guttag, 2010), is publicly available and consists of EEG recordings from 22 teenagers who experienced uncontrolled seizures, totaling 182 complete recording. Among these recordings, 80% were used for training, while the remaining 20% were reserved for testing. The dataset includes EEG signals captured from 23 or 24 scalp electrodes, positioned according to International 10-20 system.

2.2. Initialization

EEG waves from multiple channels (z_a) were mathematically represented by equation (1),

$$z_{ab} = \{z_1, z_2, z_3, \dots\dots\dots z_{nm}\}, a = 1,2,3, \dots\dots\dots\dots n, b = 1,2,3 \dots\dots\dots m \quad (1)$$

Where a was the n number of EEG signals, and b represented the m number of channel. For example, when n=2 then there were two EEG signal (a=1,2), and when m=3 then each EEG signal was recorded from three channels (b=1,2,3). Therefore $z_{ab} = \{z_{11}, z_{12}, z_{13}, z_{21}, z_{22}, z_{23}\}$.

2.3. Optimal Channel Selection

EEG data collected from multiple channels (z_a) were processed using an optimal channel selection. LMC-WWO method was used to select the best channel while reducing interference from unwanted signals. Water Wave Optimization (WWO) (Kaur and Kumar, 2022) was a novel evolutionary method used to resolve global optimization issues. To improve performance during the propagation and refraction phases of WWO, Memory-based search mechanism and linear control parameter were introduced to mitigate previously mentioned constraint. In this process, EEG data from multiple channels (z_a) were considered as water waves, and channel with the lowest standard deviation was considered fit during the process. Following this discussion, the fitness function $[f_{\min}(\alpha)]$ was defined by equation (2),

$$f(\alpha)\sqrt{\frac{\sum_{a=1}^{n}(z_a - \bar{z})^2}{n-1}} \quad (2)$$

Where $\bar{z}$ represented the mean of all channel of EEG signal. In propagation phase, a new wave $(\beta)$was created using a memory-based search mechanism $\beta(c,d)$, which was shown in equation (3),

$$\beta(c,d) = 1 - \left(\frac{h_{cd}}{n}\right) \tag{3}$$

Where c and d represented the water waves, and $h_{cd}$was the number of common edges. When the fitness of $[f(\beta)]$ was more than the capability of $f(\alpha)$, then the old wave(α) was replaced with the new wave(β) and reset the height to λ_{max}, else, the wave height was drop by one. As the wave height approached zero, the refraction operator was applied. In line with this process, the linear control parameter in refraction phase was given by equation (4),

$$\vec{\varepsilon}(w) = 2 - 2\left(\frac{w}{w_{max}}\right)^r \tag{4}$$

Where $\vec{\varepsilon}(w)$ was the linear control parameter, w represented the current iteration, w_{max} was the total number of iterations, and r signified the constant.

During the analysis, the breaking operator broke the wave(α) when it reached a better location than the best solution available (s_{best}). The solitary wave(β') was shown in equation (5),

$$\beta' = \alpha + G(0,1) \times \delta \times l_d \tag{5}$$

Where δ represented the breaking coefficient, and l_d was the length for the d^{th} dimension of search space. The optimal channel was signified as(ϕ_i), and the pseudo-code was given as follows.

Algorithm 1 Pseudocode for LMC-WWO

Input: EEG signals (z_a)
Output: Selected optimal channel (ϕ_i)

Begin
  Initialize maximum iteration (Y_{max}), new wave (β), and Gaussian function (G)
  Compute fitness, $[f(\alpha)]$
  Set iteration $Y = 1$
  While $(Y \le Y_{max})$ **do**
  For each wave **do**
  Compute a new wave using memory-based search mechanism, $\beta(c,d) = 1 - \left(\frac{\hbar_{cd}}{n}\right)$
  If $(f(\beta) > f(\alpha))$\{
    Reset height to λ_{max}
  \} **Else** \{
    Decrease the height by one
  \} **End if**
  Evaluate wavelength of each wave, $\aleph = \aleph \times \chi^{\frac{(-f(\alpha) - f_{min} + \phi)}{(f_{max} - f_{min} + \phi)}}$
  Compute linear control parameter in the refraction phase $\vec{\varepsilon}(w)$
  Calculate a new wave using$(\boldsymbol{G})$
  Evaluate the new wavelength, $\aleph' = \frac{f(\alpha)}{f(\beta)}$
  Compute solitary wave,$\boldsymbol{\beta}' = \boldsymbol{\alpha} + \boldsymbol{G}(\mathbf{0},\mathbf{1}) \times \boldsymbol{\delta} \times \boldsymbol{l_d}$ **and** $\phi_i = \{\phi_i, \phi_i > T\}$
  End for
  End while
   Set $Y = Y + 1$
  Return selected optimal channel(ϕ_i)
End

2.4. Signal Partitioning

The signals in the optimal channel(ϕ_i) were given for the process of signal partitioning using windowing method. During the process, the partitioned signals were given in equation (6),

$$\lambda = \{\phi_1, \phi_2, \phi_3, \ldots\ldots. \phi_{ab}\} \tag{6}$$

Where λ represented the a number of partitioned signals from the b number of channel.

2.5. Pre-Processing

The section showed the partitioned signals(λ) experienced pre-processing to increase quality of the signal. It was necessary to remove the artifacts and noises using bandpass filter during the process. Therefore, the signal was pre-processed and was represented by equation (7),

$$\nu = \{\lambda_1, \lambda_2, \lambda_3, \ldots\ldots\ldots. \lambda_j\} \tag{7}$$

where ν was the j number of pre-processed signal.

2.6. Signal Transformations

The phase showed the pre-processed signals(ν) were transformed into image and scalogram form. This step included conversion of raw EEG signal into scalogram form using CWT method which combined frequencies of low and high. The wavelet transforms [$\varpi_\nu(e, f)$] of a continuous signal(ν) concerning the wavelet function was provided by equation (8),

$$\varpi_\nu(e, f) = \int_{-\infty}^{\infty} \nu(h)\, \rho_{e,f}^*(h) dh \tag{8}$$

Where $\nu(h)$ was the time-domain signal, $\rho_{e,f}(h)$ represented the mother wavelet scaled by factor e, as well as expanded by a factor f, and $*$ was the complex conjugate. Following the analysis, the wavelet as in equation (9),

$$\rho_{e,f}(h) = \frac{1}{\sqrt{e}} \rho\left(\frac{h-f}{e}\right) \tag{9}$$

Substituting (8) in (9), the CWT was given by equation (10),

$$\varpi_\nu(e, f) = \frac{1}{\sqrt{e}} \int_{-\infty}^{\infty} \nu(h)\, \rho^*\left(\frac{h-f}{e}\right) dh \tag{10}$$

The generated scalogram was resized into 224×224 which was high to preserve important features. The resized scalogram was represented as ϑ, which passed through min-max normalization. In the context of this research, min-max normalization was a popular method for normalizing data, mitigating the redundant data that led to achieving effective handling. The expression for min-max normalization(ς) was represented by equation (11),

$$\varsigma = \frac{\vartheta - \vartheta_{min}}{\vartheta_{max} - \vartheta_{min}} \tag{11}$$

Where ϑ_{min} was the minimum and ϑ_{max}represented the maximum feature value of the signal. In the Image form section, pre-processed signal (ν) was transformed into RGB image using Coco-GASF method. During the analysis, the scaled time-series signal was transformed from Cartesian co-ordinate to polar co-ordinate in conventional GASF (Thanaraj et al., 2020). To overcome this changes, Covariance Correlation (CoCo) coefficient was calculated. The pre-processed signal (ν) was rescaled to have the interval$[-1,1]$, which was given in equation (12),

$$\tilde{\nu}_0 = \frac{t_m - min(\nu)}{max(\nu) - min(\nu)} \tag{12}$$

Where $\tilde{\nu}_0$ was the rescaled pre-processed signal, t_m represented the m number of scaled signals, $min(\nu)$ was the lowest, and $max(\nu)$ the highest value of the signal. The angle(ω) was computed using CoCo coefficient, which was given by equation (13)(14),

$$\omega = arc\psi(\tilde{\nu}_0) \tag{13}$$

$$\psi = \frac{C_{cov}(M,N)}{\upsilon_M \upsilon_N} \tag{14}$$

Where ψ was CoCo Coefficient, υ_M signified the standard deviation of point M , υ_N represented the standard deviation of point N , and $C_{cov}(M,N)$ was the covariance. Moreover, the temporal correlations of the adjacent points (M,N) were computed by determining the summation of the angle to obtain Gram matrix called GASF, which was given by equation (15),

$$\zeta = [\psi(\omega_M, \omega_N)] \tag{15}$$

Where ζ represented the image formats during the calculation in the research. In grayscale conversion sub-phase, the obtained image formats(ζ) were converted into gray-scaled image. At this point, the image was converted into 8-bit grayscale where each pixel value was represented by 8 bits. During the process, R,G, and b values were extracted for each pixel then an intensity standard formula was used to compute grayscale intensity. The gray-scaled image was shown by equation (16),

$$\Phi_y = \{\zeta_1, \zeta_2, \zeta_3, \ldots\ldots\ldots \zeta_y\} \tag{16}$$

Where Φ_y represented the y number of gray-scaled images during the analysis. From gray-scaled image (Φ_y), five rhythms were extracted corresponding to the frequency bands. The main EEG rhythms, including Delta(x_1), Theta(x_2), Alpha(x_3), Beta(x_4), and Gamma(x_5) were extracted from the gray-scaled image, which was mathematically represented by equation (17),

$$R_{rhythms} = \{x_1, x_2, x_3, x_4, x_5\} \tag{17}$$

Where $R_{rhythms}$ was the extracted rhythms in this research.

2.7. Feature Extraction

During the analysis, characteristics were obtained from the extracted rhythms $(R_{rhythms})$ and the normalized scalogram(ς). Therefore, the process was mathematically represented by equation (18),

$$F_V = \{R_{rhythms}, \varsigma\} \tag{18}$$

Where F_V was the input of feature obtaining phase in this research. At this point, the features were collected using Cas-GoogleNet model. The input $(F_V)$was given to CL, composing of several learnable filters known as kernels with bias value. Relating to the process, the output (F_t) was given in equation (19),

$$\frac{F_t = [(F_V + 2p - K)]}{SS} \tag{19}$$

Where P represented the convolution padding size, K was the convolution kernel size, and SS represented the convolution stride size, respectively. During this analysis, the pooling layer performed down sampling to reduce the size of the convoluted output. PL used the max-pooling to scale the dimension of B_{cas} in equation (20)

$$\chi_{pool} = \tau_{max}(B_{cas} * \theta) \tag{20}$$

Where τ_{max} was the max function, B_{cas} represented the input feature map and χ_{pool} signified the PL output. In context of this research, final CL and PL output was converted into a one-dimensional numerical array represented as χ_{arr}. Fully connected layer (FCL) gave the probabilities of each input being in a specific feature by connecting the input to another output with a learnable weight. Moreover, the output of FCL(χ_{full}) was calculated in equation (21),

$$\chi_{full} = K_c \cdot \chi_{arr} + \varrho \tag{21}$$

Where K_c was learnable weight matrix and ϱ represented the bias value. The output of the feature extraction was mathematically represented as $\mathcal{R}$.

2.8. Feature Selection

The extracted features($\mathcal{R}$) were selected for the process of feature selection. In this section, optimal features were selected using Fisher's score $[F_d]$ method, computed in equation (22),

$$F_d = F_d(\mathcal{R}) = tr\{(\bar{p}_b)(\bar{p}_t + \tau I)^{-1}\} \tag{22}$$

Where $\bar{p}_b$ was the between-class scatter matrix, d signified the number of selected features, and $\bar{p}_t$ represented the total scatter matrix. $I$was the identity matrix, tr represented the variance between scatter matrix, and τ was the positive regularization parameter.

2.9. Classification

The optimally selected features $[F_d]$ were selected for the classification process. During this stage, FixupPACTBi-LSTM was used for detection of epilepsy seizure. Conventional Bi-LSTM (Imrana et al., 2021) sequentially processed temporal information at a certain duration and generated a single output.

Bi-LSTM was a slower model and required more time for training. Consequently, fixed-update initialization (Fixup) for weight initialization and PACT were used to overcome the mentioned limitations. Figure 2 showed the construction of FixupPACTBi-LSTM during the process. Initially, the received output$[F_d]$ was sent to the input layer (π), expressed by equation (23),

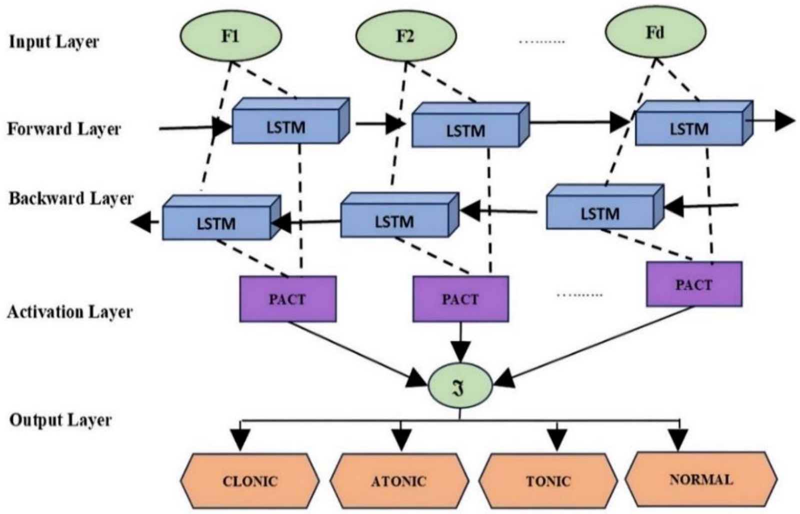


Figure 2 Architecture of FixupPACTBi-LSTM model

$$\left(\pi_{m\epsilon[h_q][n]}\right) F_d = O\left(\frac{1}{\sqrt{K}}\right) \; Where\; n\; \epsilon\; argminF_d \tag{23}$$

where K signified the residual branch, O represented the Fixup initialization parameter, and m and n were the layers. Subsequently, model calculated the forward layer $(\vec{h}_q)$ and backward layer hidden sequence$(\overleftarrow{h}_q)$ from the opposite direction, which were given by equation (24) (25),

$$\vec{h}_q = D\left(U_{\vec{h}\gamma}\gamma_n + U_{\vec{h}h}\vec{h}_{n-1} + o_{\vec{h}}\right) \tag{24}$$

$$\overleftarrow{h}_q = D\left(U_{\overleftarrow{h}\gamma}\gamma_n + U_{\overleftarrow{h}\overleftarrow{h}}\overleftarrow{h}_{n-1} + o_{\overleftarrow{h}}\right) \tag{25}$$

where $U_{\vec{h}\gamma}$and$U_{\overleftarrow{h}\gamma}$ were the forward and backward input-hidden weight matrices, $\vec{h}_{n-1}$and $\overleftarrow{h}_{n-1}$ were the previous forward as well as backward hidden sequence. $o_{\vec{h}}$ and $o_{\overleftarrow{h}}$ represented the bias vectors in both directions. Therefore, the encoded vector (g_w) was formed by the combination of final forward and backward layer output with PACT activation function, given by equation (26)(27),

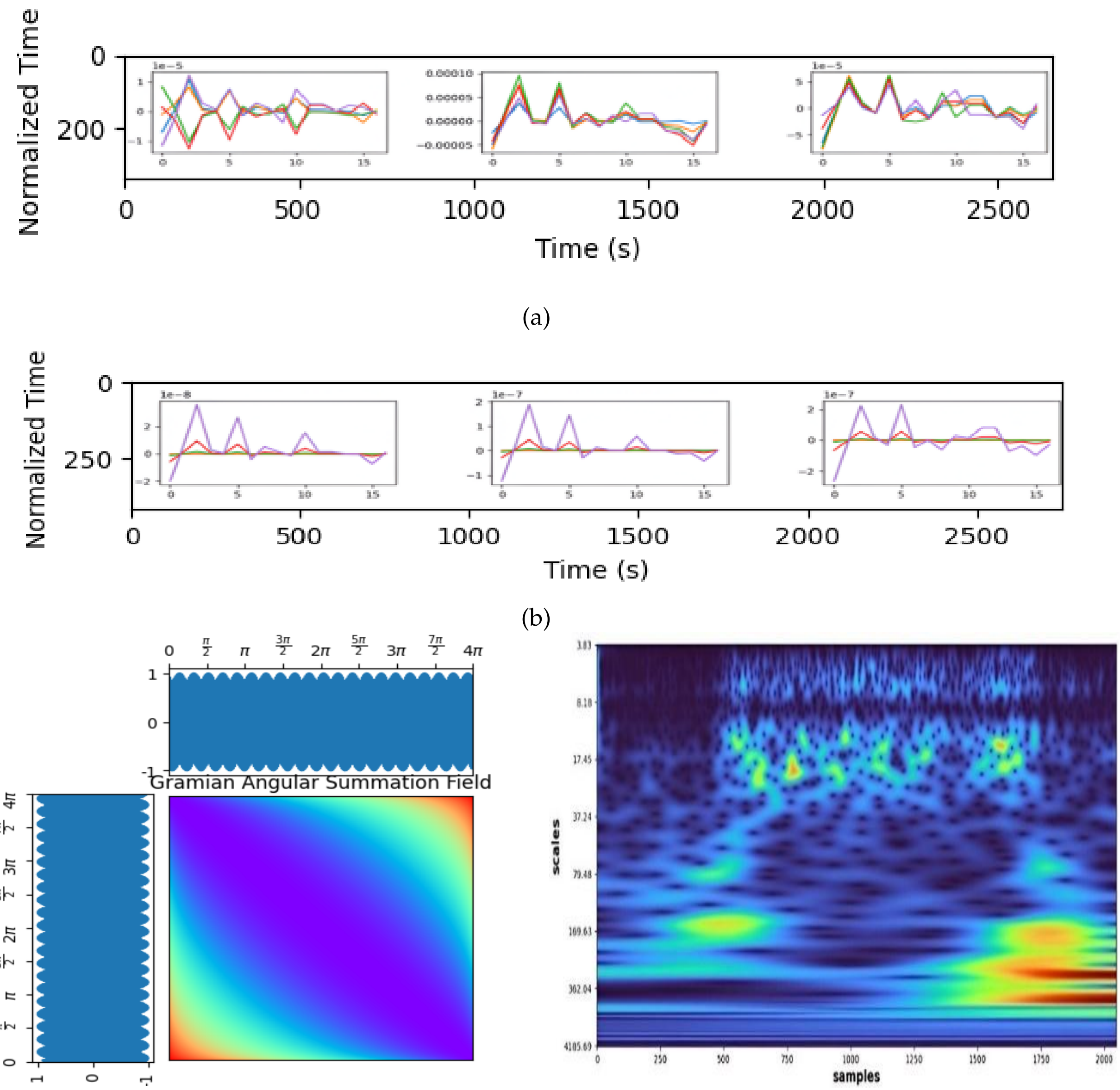
$$g_w = W_f\left[U_{r\vec{h}}\vec{h}_q + U_{r\overleftarrow{h}}\overleftarrow{h}_q + o_r\right] \tag{26}$$

$$W_f = C(|h_q| - |h_q - \Omega| + \Omega) \tag{27}$$

where W_f was the PACT activation function, C signified a constant, Ω represented the parameterized clipping level, and o_r was the total bias vectors. h_q was the total of forward and backward layer hidden sequence, and $U_{r\vec{h}}$ and $U_{r\overleftarrow{h}}$ were the forward as well as backward weight matrices. Following this process, the output of the classifier was mathematically represented as $\Im$. Therefore, the classifier detected the signal as clonic, tonic, atonic, and normal.

3. Results and Discussion

By comparing the outputs, the result showed the efficiency of the proposed model against current model. The sample proposed outputs in line with these findings were shown in Figure 3. The result of EEG signal partition, preprocessed indication, and signal transformation such as image format, as well as scalograms used to graphically represent cerebral activity were shown in Figure 3.



(a)

(b)

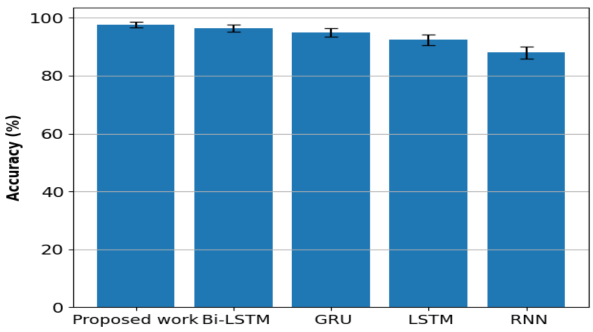
(c) (d)

Figure 3 Sample result of the proposed methodology (a) partitioned signals, (b) Pre-processed signals, (c) Image form, (d) Scalogram form

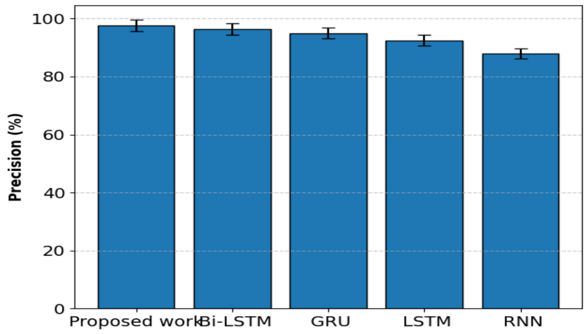
3.1. Performance Analysis

In the context of this analysis, the performance of the proposed methodology was assessed by comparing the method to other pertinent model to determine consistency of model. During performance evaluation, the efficiency of the proposed FixupPACTBi-LSTM classifier was examined using the current method, including Recurrent Neural Network (RNN), Bi-LSTM, Gated Recurrent Unit (GRU) & Long Short-Term Memory (LSTM). The proposed method was compared based on quality metrics during the process.

Figure 4 showed that proposed classifiers outperformed existing classifier in this research. FixupPACTBi-LSTM with PACT function, achieved higher accuracy (97.99%), precision (98.0039), and recall (98.003%). Consequently, existing RNN recorded lower performance of 88.933% recall, 88.93% precision, and 89% accuracy, respectively. Comparison with Table 1 further showed that proposed classifier outperformed existing model in terms of accuracy and also effectively categorized various seizure types while maintaining computational efficiency.



(a)



(b)

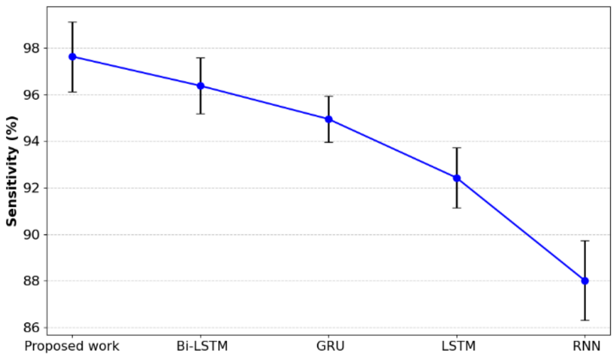
Figure 4 Analysis of the proposed system's performance FixupPACTBi-LSTM method based on (a) Accuracy, (b) Precision

Table 2 showed that Higher TPR and TNR described superiority of the recommended model. For instance, when compared to the current methods, TPR of the proposed model was higher at 98.003%. Similarly, proposed FixupPACTBi-LSTM achieved the highest TNR of 97.991%.

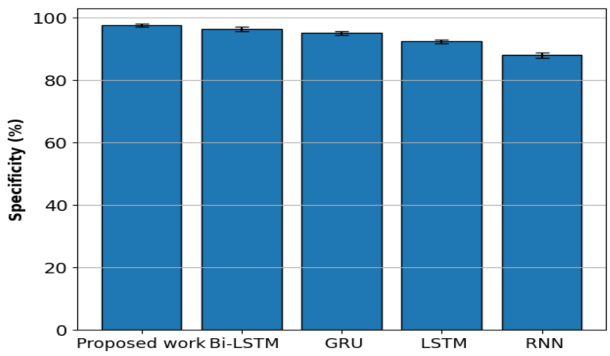
Table 2 Performance comparison of the proposed model based on TPR & TNR

Metrics	Algorithms				
	Proposed FixupPACTBi-LSTM	Bi-LSTM	GRU	LSTM	RNN
TPR (%)	98	95.57	94.34	92.74	88.93
TNR (%)	97.99	95.61	94.03	92.43	89.06

Figure 5 showed the performance analysis of proposed FixupPACTBi-LSTM with the current methods based on (a) sensitivity and (b) specificity. In line with these results, existing Bi-LSTM, GRU, LSTM, and RNN methods offered a sensitivity of 95.57, 94.34, 92.74, as well as 88.93%. However, a very high sensitivity of 98% was achieved by the proposed strategy, as the specificity was 97%.



(a)



(b)

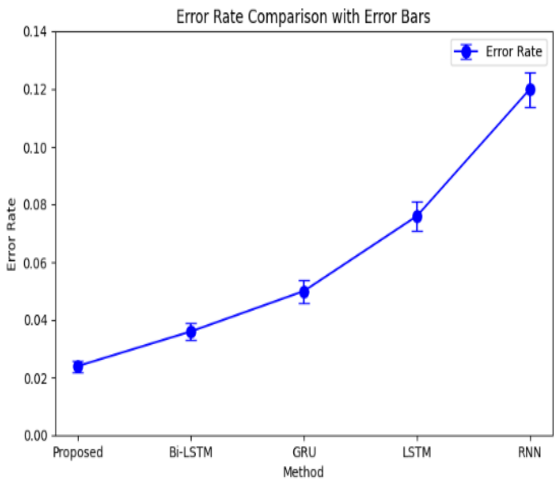
Figure 5 Performance analysis based on (a) Sensitivity and (b) Specificity

Table 3 showed FNR & FPR analysis for proposed FixupPACTBi-LSTM and existing algorithms. When the values of FNR & FPR were low, then the method had good predictive results. Table 3 showed that recommended FixupPACTBi-LSTM achieved the lowest FNR & FPR values of 1.99 and 2.00. Relating to this outcome, the proposed method was an error-prone model.

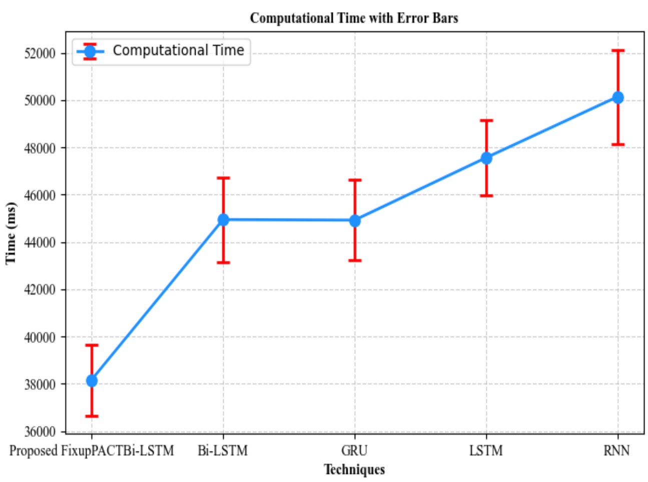
From the graph in Figure 6(a), the readings showed that the lower error rate value of FixupPACTBi-LSTM (0.024) allowed model to be more suitable for epileptic seizure classification. Figure 6(b) showed comparative performance research of proposed FixupPACTBi-LSTM with other methods. During the analysis, model consumed a training time of 38173.97192ms, while existing methods showed an increased time. The outcome was given by 44946.83789ms for Bi-LSTM, 44923.48999ms in favor of GRU, 47562.27197ms for LSTM, and RNN had 50137.44238 ms.

Table 3 FNR & FPR analysis

Algorithms	FNR	FPR
Proposed FixupPACTBi-LSTM	1.996	2.008
Bi-LSTM	4.426	4.382
GRU	5.653	5.967
LSTM	7.254	7.566
RNN	11.06	10.934



(a)



(b)

Figure 6 Graphical representation (a) Error Rate representation, (b) computational time

Figure 7 showed that PACT Activation Function in Bi-LSTM had efficiently reduced training time to a greater extent. Table 4 compared the proposed method to existing model using F-Measure. During the analysis, F-Measure values of existing Bi-LSTM, GRU, LSTM, and RNN were 95.57344, 94.34698, 92.7451, as well as 88.9336%. Bi-LSTM method associated with Fixup achieved a higher F-Measure of 98.00399%.

Table 4 Performance analysis of Proposed FixupPACTBi-LSTM

Algorithm	F-Measure (%)
Proposed FixupPACTBi-LSTM	98.00399
Bi-LSTM	95.57344
GRU	94.34698
LSTM	92.7451
RNN	88.9336

The comparison of proposed method with existing model based on AUC was shown in Figure 7. AUC values of existing Bi-LSTM, GRU, LSTM, and RNN were 0.95, 0.94, 0.92, as well as 0.89, respectively. Meanwhile, the proposed method achieved 0.97, showing that model performed exceptionally well in differentiating between seizure and non-seizure events. The proposed method achieved the linear curve between (0.2-0.4) of false positive rate.

Optimal channel selection sub-phase compared the performance of proposed LMC-WWO against the current algorithms. These systems included WWO, Coyote Optimization Algorithm (COA), Energy Valley Optimization (EVO), and Black Widow Optimization (BWO) which were based on channel selection time. During the research, minimum standard deviation of channel was used to determine fitness in the proposed model. For the recommended system, when the number of iterations varied from 10 to 50, the fitness value was between 0 and 2500. Meanwhile, existing BWO signified a gradual increase and provided high-range values for different iterations. This outcome showed that the usage of a memory-based search mechanism with a linear control parameter in the proposed system had improved the optimal channel selection process.

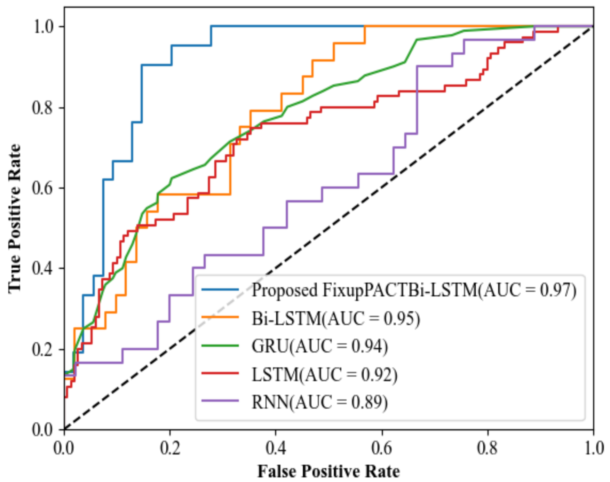


Figure 7 AUC curve analysis

Figure 8 showed that the proposed model reached superior performance compared to conventional methods. Recommended LMC-WWO achieved the lowest channel selection time of 8769.83 ms. However, existent methods required an average of 33757.61 ms to train the data. The analysis showed that the proposed model had a low time complexity.

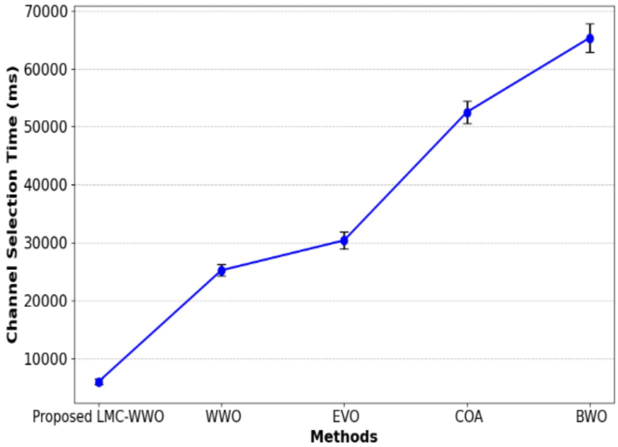


Figure 8 Graphical representation of channel selection time

Table 5 Analyzing the proposed model in comparison

Methods	Methods used	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)
Proposed work	LMC-WWO and FixupPACTBi-LSTM.	CHB-MIT	97	98	97
(Lih et al., 2023)	Transformer model	-	85	87	82
(Shoka et al., 2023)	Convolutional Neural Network (CNN).	CHB-MIT	86.11	-	-
(Sunaryono et al., 2022)	Gradient Boosting Machines (GBM) fusion.	University of Bonn (UoB), CHB-MIT	96.53	-	-
(Jibon et al., 2023)	Linear graph CNN and DenseNet	CHB-MIT	96	97	98
(Ilias et al., 2023)	Short time-Fourier transform and gated multimodal unit.	University of Bonn	95.33	-	-

4. Conclusions and Future Scope

In conclusion, this research introduced an automatic epileptic seizure detection framework using FixupPACTBi-LSTM method. Experimental evaluation showed the effectiveness of the proposed method in improving seizure detection. During the research, CHB-MIT dataset was used to assess the performance of the model, showing that FixupPACTBi-LSTM achieved a high accuracy (97.99%), precision (98%), and specificity (97%) signifying its reliability. Building on this discussion, proposed LMC-WWO reduced channel selection time of 8769ms, while FixupPACTBi-LSTM classifier achieved a minimal computational time of 3817ms, justifying high efficiency. The proposed system was evaluated with accurate results by classifying the types of epilepsy. However, this research did not focus on assessing severity of epilepsy. Future research should address this aspect to further improve epilepsy diagnosis and treatment.

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Author Contributions

The authors contributed significantly to the conceptualization and design of the research. The authors are also fully responsible for the analysis, interpretation, and discussion of the results. In addition, all authors reviewed and approved the final version of the manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

References

Aayesha, Qureshi, MB, Afzaal, M, Qureshi, MS & Fayaz, M 2021, 'Machine learning-based EEG signals classification model for epileptic seizure detection', *Multimedia Tools and Applications*, vol. 80, no. 12, pp. 17849-17877, https://doi.org/10.1007/s11042-021-10597-6

Abdullah, MSN, Karim, HA & AlDahoul, N 2023, 'A combination of light pre-trained convolutional neural networks and long short-term memory for real-time violence detection in videos', *Methods*, vol. 400, article 4000, https://doi.org/10.14716/ijtech.v14i6.6655

Ahmad, I, Wang, X, Javeed, D, Kumar, P, Samuel, OW & Chen, S 2023, 'A hybrid deep learning approach for epileptic seizure detection in EEG signals', *IEEE Journal of Biomedical and Health Informatics*, pp. 1-12, https://doi.org/10.1109/JBHI.2023.3265983

Alshebeili, SA, Sedik, A, Abd El-Rahiem, B, Alotaiby, TN, El Banby, GM, El-Khobby, HA, Ali, MA, Khalaf, AA & Abd El-Samie, FE 2020, 'Inspection of EEG signals for efficient seizure prediction', *Applied Acoustics*, vol. 166, article 107327, https://doi.org/10.1016/j.apacoust.2020.107327

Anuragi, A, Sisodia, DS & Pachori, RB 2021, 'Automated FBSE-EWT based learning framework for detection of epileptic seizures using time-segmented EEG signals', *Computers in Biology and Medicine*, vol. 136, article 104708, https://doi.org/10.1016/j.compbiomed.2021.104708

Brari, Z & Belghith, S 2021, 'A novel Machine Learning approach for epilepsy diagnosis using EEG signals based on Correlation Dimension', *IFAC-PapersOnLine*, vol. 54, no. 17, pp. 7-11, https://doi.org/10.1016/j.ifacol.2021.11.018

Chanu, MM, Singh, NH & Thongam, K 2023, 'An automated epileptic seizure detection using optimized neural network from EEG signals', *Expert Systems*, vol. 40, no. 6, article e13260, https://doi.org/10.1111/exsy.13260

Chen, Z, Lu, G, Xie, Z & Shang, W 2020, 'A unified framework and method for EEG-based early epileptic seizure detection and epilepsy diagnosis', *IEEE Access*, vol. 8, pp. 20080-20092, https://doi.org/10.1109/ACCESS.2020.2969055

Das, K, Daschakladar, D, Roy, PP, Chatterjee, A & Saha, SP 2020, 'Epileptic seizure prediction by the detection of seizure waveform from the pre-ictal phase of EEG signal', *Biomedical Signal Processing and Control*, vol. 57, article 101720, https://doi.org/10.1016/j.bspc.2019.101720

Deivasigamani, S, Senthilpari, C & Yong, WH 2021, 'Machine learning method based detection and diagnosis for epilepsy in EEG signal', *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 4215-4221, https://doi.org/10.1007/s12652-020-01816-3

Ein Shoka, AA, Alkinani, MH, El-Sherbeny, AS, El-Sayed, A & Dessouky, MM 2021, 'Automated seizure diagnosis system based on feature extraction and channel selection using EEG signals', *Brain Informatics*, vol. 8, pp. 1-16, https://doi.org/10.1186/s40708-021-00123-7

Gupta, S, Bagga, S, Maheshkar, V & Bhatia, MPS 2020, 'Detection of epileptic seizures using EEG signals', *2020 International Conference on Artificial Intelligence and Signal Processing (AISP)*, pp. 1-5, https://doi.org/10.1109/AISP48273.2020.9073157

Guttag, J 2010, 'CHB-MIT Scalp EEG Database', *PhysioNet*, https://doi.org/10.13026/C2K01R

Ilias, L, Askounis, D & Psarras, J 2023, 'Multimodal detection of epilepsy with deep neural networks', *Expert Systems with Applications*, vol. 213, article 119010, https://doi.org/10.1016/j.eswa.2022.119010

Imrana, Y, Xiang, Y, Ali, L & Abdul-Rauf, Z 2021, 'A bidirectional LSTM deep learning approach for intrusion detection', *Expert Systems with Applications*, vol. 185, article 115524, https://doi.org/10.1016/j.eswa.2021.115524

Jana, GC, Sharma, R & Agrawal, A 2020, 'A 1D-CNN-spectrogram based approach for seizure detection from EEG signal', *Procedia Computer Science*, vol. 167, pp. 403-412, https://doi.org/10.1016/j.procs.2020.03.248

Jibon, FA, Miraz, MH, Khandaker, MU, Rashdan, M, Salman, M, Tasbir, A, Nishar, NH & Siddiqui, FH 2023, 'Epileptic seizure detection from electroencephalogram (EEG) signals using linear graph convolutional network and DenseNet based hybrid framework', *Journal of Radiation Research and Applied Sciences*, vol. 16, no. 3, article 100607, https://doi.org/10.1016/j.jrras.2023.100607

Jiwani, N, Gupta, K, Sharif, MHU, Adhikari, N & Afreen, N 2022, 'A LSTM-CNN model for epileptic seizures detection using EEG signal', *2022 2nd International Conference on Emerging Smart Technologies and Applications (eSmarTA)*, pp. 1-5, https://doi.org/10.1109/eSmarTA56775.2022.9935403

Kaur, A & Kumar, Y 2022, 'A new metaheuristic algorithm based on water wave optimization for data clustering', *Evolutionary Intelligence*, vol. 15, no. 1, pp. 759-783, https://doi.org/10.1007/s12065-020-00562-x

Kode, H, Elleithy, K & Almazedah, L 2024, 'Epileptic Seizure detection in EEG signals using Machine Learning and Deep Learning Techniques', *IEEE Access*, vol. 12, pp. 80657 – 80668, https://doi.org/10.1109/ACCESS.2024.3409581

Lih, OS, Jahmunah, V, Palmer, EE, Barua, PD, Dogan, S, Tuncer, T, García, S, Molinari, F & Acharya, UR 2023, 'EpilepsyNet: Novel automated detection of epilepsy using transformer model with EEG signals from 121 patient population', *Computers in Biology and Medicine*, vol. 164, article 107312. https://doi.org/10.1016/j.compbiomed.2023.107312

Maulana, H & Sari, RF 2022, 'Authorship Obfuscation System Development based on Long Short-term Memory Algorithm', *International Journal of Technology*, vol. 13, no. 2, pp. 345-355. https://doi.org/10.14716/ijtech.v13i2.4257

Nkengfack, LCD, Tchiotsop, D, Atangana, R, Louis-Door, V & Wolf, D 2020, 'EEG signals analysis for epileptic seizures detection using polynomial transforms, linear discriminant analysis and support vector machines', *Biomedical Signal Processing and Control*, vol. 62, article 102141, https://doi.org/10.1016/j.bspc.2020.102141

Nugroho, HA, Subiantoro, A & Kusumoputro, B 2023, 'Performance Analysis of Ensemble Deep Learning NARX System for Estimating the Earthquake Occurrences in the Subduction Zone of Java Island', *International Journal of Technology*, vol. 14, no. 7, pp. 1517-1526, https://doi.org/10.14716/ijtech.v14i7.6702

Peng, H, Lei, C, Zheng, S, Zhao, C, Wu, C, Sun, J & Hu, B 2021, 'Automatic epileptic seizure detection via Stein kernel-based sparse representation', *Computers in Biology and Medicine*, vol. 132, article 104338, https://doi.org/10.1016/j.compbiomed.2021.104338

Polat, K & Nour, M 2020, 'Epileptic seizure detection based on new hybrid models with electroencephalogram signals', *Irbm*, vol. 41, no. 6, pp. 331-353, https://doi.org/10.1016/j.irbm.2020.06.008

Qiu, X, Yan, F & Liu, H 2023, 'A difference attention ResNet-LSTM network for epileptic seizure detection using EEG signal', *Biomedical Signal Processing and Control*, vol. 83, article 104652, https://doi.org/10.1016/j.bspc.2023.104652

Radman, M, Moradi, M, Chaibakhsh, A, Kordestani, M & Saif, M 2021, 'Multi-feature fusion approach for epileptic seizure detection from EEG signals', *IEEE sensors journal*, vol. 21, no. 3, pp. 3533-3543, https://doi.org/10.1109/JSEN.2020.3026032

Rasheed, K, Qayyum, A, Qadir, J, Sivathamboo, S, Kwan, P, Kuhlmann, L, O'Brien, T & Razi, A 2020, 'Machine learning for predicting epileptic seizures using EEG signals: A review', *IEEE reviews in biomedical engineering*, vol. 14, pp. 139-155, https://doi.org/10.1109/RBME.2020.3008792 10.1109/ACCESS.2024.3406332

Rivera, MJ, Sanchis, J, Corcho, O, Teruel, & Trujillo, J 2024, 'Evaluating CNN methods for epileptic seizure type classification using EEG data', *IEEE Access*, vol. 12, 10.1109/ACCESS.2024.3406332

Roy, S, Asif, U, Tang, J & Harrer, S 2020, 'Seizure type classification using EEG signals and machine learning: Setting a benchmark', *In 2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, pp. 1-6, https://doi.org/10.1109/SPMB50085.2020.9353642

Romahadi, D, Feleke, AG & Youlia, RP 2024, 'Evaluation of Laplacian Spatial Filter Implementation in Detecting Driver Vigilance Using Linear Classifier', *International Journal of Technology*, vol. 15, no. 6, https://doi.org/10.14716/ijtech.v15i6.7166

Sagga, D, Echtioui, A, Khemakhem, R & Ghorbel, M 2020, 'Epileptic seizure detection using EEG signals based on 1D-CNN Approach', *In 2020 20th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA)*, pp. 51-56, https://doi.org/10.1109/STA50679.2020.9329321

Sagga, D, Echtioui, A, Khemakhem, R, Kallel, F & Hamida, AB 2022, 'Epileptic seizures detection on EEG signal using deep learning techniques', *In 2022 6th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)*, pp. 1-6, 10.1109/ATSIP55956.2022.9805860

Saminu, S, Xu, G, Shuai, Z, Abd El Kader, I, Jabire, AH, Ahmed, YK, Karaye, IA & Ahmad, IS 2021, 'A recent investigation on detection and classification of epileptic seizure techniques using EEG signal', *Brain sciences*, vol. 11, no. 5, p. 668, https://doi.org/10.3390/brainsci11050668

Sari, M., Berawi, M.A., Larasati, S.P., Susilowati, S.I., Susantono, B. and Woodhead, R. 2023, 'Developing Machine Learning Model to Predict HVAC System of Healthy Building: A Case Study in Indonesia', *International Journal of Technology*, vol. 14, pp. 1438-1448. https://doi.org/10.14716/ijtech.v14i7.6682

Savadkoohi, M, Oladunni, T & Thompson, L 2020, 'A machine learning approach to epileptic seizure prediction using Electroencephalogram (EEG) Signal', *Biocybernetics and Biomedical Engineering*, vol. 40, no. 3, pp. 1328-1341, https://doi.org/10.1016/j.bbe.2020.07.004

Shoka, AAE, Dessouky, MM, El-Sayed, A & Hemdan, EED 2023, 'An efficient CNN based epileptic seizures detection framework using encrypted EEG signals for secure telemedicine applications', *Alexandria Engineering Journal*, vol. 65, pp. 399-412, https://doi.org/10.1016/j.aej.2022.10.014

Sunaryono, D., Sarno, R. and Siswantoro, J., 2022,'Gradient boosting machines fusion for automatic epilepsy detection from EEG signals based on wavelet features'*, Journal of King Saud University-Computer and Information Sciences,* vol. 34, pp.9591-9607. https://doi.org/10.1016/j.jksuci.2021.11.015

Thanaraj, KP, Parvathavarthini, B, Tanik, UJ, Rajinikanth, V, Kadry, S & Kamalanand, K 2020, 'Implementation of deep neural networks to classify EEG signals using gramian angular summation field for epilepsy diagnosis', *arXiv preprint arXiv:2003.04534*, https://doi.org/10.48550/arXiv.2003.04534

Varlı, M & Yılmaz, H 2023, 'Multiple classification of EEG signals and epileptic seizure diagnosis with combined deep learning', *Journal of Computational Science*, vol. 67, p.101943, https://doi.org/10.1016/j.jocs.2023.101943

Yang, Y, Sarkis, RA, El Atrache, R, Loddenkemper, T & Meisel, C 2021, 'Video-based detection of generalized tonic-clonic seizures using deep learning', *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 8, pp. 2997-3008, 10.1109/JBHI.2021.3049649

Whulanza, Y, Kusrini, E, Sangaiah, AK, Hermansyah, H, Sahlan, M, Asvial, M, Harwahyu, R & Fitri, IR 2024, 'Bridging human and machine cognition: advances in brain-machine interface and reverse engineering the brain', *International Journal of Technology*, vol. 15, no. 5, pp. 1194-1202, https://doi.org/10.14716/ijtech.v15i5.7297