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Original Article

Robust Epileptic Seizure Recognition using Dimensionality Reduction with Deep Learning on EEG Signals

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Abstract - *An epileptic seizure is a sudden surge of electrical activity in the brain, disrupting normal brain function and often resulting in loss of consciousness or convulsions. The most important diagnostic test for epilepsy is the Electroencephalogram (EEG). Usually, the recognition of epileptic activity is based on finding specific patterns in the multimodal EEG and is done by the human expert. This is a time-consuming and difficult process; therefore, numerous attempts have been made to automate it using both Deep Learning (DL) and conventional methods. Epileptic seizure detection using DL includes training neural networks for analyzing the EEG signal and detecting patterns indicative of seizures with a high level of accuracy for earlier diagnosis and treatment. This study introduces a Robust Epileptic Seizure Recognition using Metaheuristics-based Dimensionality Reduction with Deep Learning (RESR-MDRDL) technique on EEG signals. The RESR-MDRDL technique concentrates on accurately identifying epileptic seizures utilizing EEG signals. In a preliminary stage, the RESR-MDRDL technique performs data pre-processing to standardize the input data. Also, a Salp Swarm Algorithm (SSA)-based technique is utilized for optimum Feature Selection (FS). For seizure recognition, the RESR-MDRDL technique employs a Deep Autoencoder (DAE) model, and its efficiency is improved using a Tunicate Swarm Algorithm (TSA). The simulation of the RESR-MDRDL methodology is examined by using an EEG dataset. The experimental validation of the RESR-MDRDL methodology indicated a superior accuracy value of 94.14% over existing techniques.*

Keywords - *Epileptic seizure, Metaheuristics, EEG signals, Tunicate Swarm Algorithm, Feature selection, Deep learning.*

1. Introduction

There are numerous kinds of neurological disorders, namely degenerative, neurogenetic disorders, and convulsive diseases. Many convulsive disorders arise due to unequal electrical activity in the brain, which results in intense body shivering [1]. Even though seizures are fragments of epilepsy, not every seizure is an outcome of epilepsy. Worldwide, approximately 1% of the population suffers from epilepsy [2]. It is the most prevalent neurological condition, which is fatal, occurs repeatedly and is unpredictable. However, with the aid of medicines, epilepsy is prevented and surgical treatment when a patient doesn't react to medicine [3]. EEG is a brain signal processing method that perceives the compound inner device of abnormal and normal brain waves. It is employed to analyze brain disease [4]. Almost epileptic seizures are an anomalous, automatic drive or modification of consciousness allied to anomalous EEG changes. Since epilepsy illustrates anomalous EEG signal variations, intra-cranial EEGs are employed to analyze, distinguish and categorize epileptic seizures [5]. Visual assessment for seizure recognition in EEG signals is time-consuming and leads to error. Therefore, a more accurate automatic structure for seizure recognition is vital. Machine Learning (ML) techniques are employed to predict epileptic seizures. On the other hand, DL methods become more general and have been discovered to be beneficial in assorted applications [6].

The FS task involves the exploration of an optimum feature sub-set, which signifies an assumed set of data and enlarges the classifiers' performance. FS technique provides numerous attractive benefits. Besides removing the irrelevant and redundant features, the developed feature sub-set, with fewer features, will not directly cut down computation time and cost [7]. Furthermore, the featured features are beneficial for data analysis and mining. The concluding output of the FS model will specify which features are significant in describing the complete dataset. Noticeably, the word FS denotes the models that yield input features subset. In contrast, the word feature extraction involves the methods employed to originate novel features from the novel dataset [8]. This pre-processing stage is generally achieved over numerical changes. The dual above-mentioned words, FS and feature extraction are binarily allied but dissimilar study areas. This work attention to the prior algorithm [9]. Epileptic seizures pose a major health risk, mitigating accurate and timely detection for effective management. Conventional methods mainly rely on manual observation, which is error-prone. Automated systems utilizing advanced techniques like DL can provide reliable, real-time seizure detection, improving patient care and outcomes [10].

This study introduces a Robust Epileptic Seizure Recognition using Metaheuristics-based Dimensionality Reduction with Deep Learning (RESR-MDRDL) technique on EEG signals. The RESR-MDRDL technique concentrates on accurately identifying epileptic seizures utilizing EEG signals. In a preliminary stage, the RESR-MDRDL technique performs data pre-processing to standardize the input data. Also, a Salp Swarm Algorithm (SSA)-based technique is utilized for optimum Feature Selection (FS). For seizure recognition, the RESR-MDRDL technique employs a Deep Autoencoder (DAE) model, and its efficiency is improved using a Tunicate Swarm Algorithm (TSA). The simulation of the RESR-MDRDL methodology is examined by using an EEG dataset. The major contribution of the RESR-MDRDL method is listed below.

- The RESR-MDRDL technique performs pre-processing by removing noise and irrelevant data, ensuring that the data is ready for additional analysis. This step improves the overall accuracy and efficiency of the seizure detection process. By refining the input data, the model can concentrate on more relevant patterns in the EEG signals.
- The RESR-MDRDL model employs SSA-based feature selection to detect and prioritize the most crucial features from EEG signals. This method mitigates dimensionality and concentrates on relevant data, improving the model's processing speed and accuracy. By choosing the optimal features, the model improves its capability to detect seizures effectively.
- The RESR-MDRDL method implements the DAE technique to recognize seizures by learning intrinsic patterns. This method improves the capability of the model to identify subtle and complex features within the signals. Capturing these patterns significantly enhances the accuracy of seizure classification.
- The RESR-MDRDL methodology utilizes the TSA model for fine-tuning the hyperparameters of the technique, optimizing the learning process. This approach assists in improving the generalization capability of the model, resulting in more accurate and reliable results. Refining the hyperparameters enhances the overall performance of the system.
- The RESR-MDRDL method's novelty stems from incorporating SSA-based feature selection, DAE-based seizure recognition, and TSA-based hyperparameter tuning into a unified framework. This integration optimizes the overall process, from feature extraction to classification, improving the model's efficiency and accuracy. By utilizing these advanced techniques, the method improves the performance of epileptic seizure detection.

2. Related Works

Pouryosef et al. [11] propose a pipeline built on genetic and Bat techniques for feature creation and size decrease of EEG signal. After the wavelet segmentation and extraction, the Bat model recognizes the most appropriate feature. This method employs these factors and a genetic model united with the neural networks model to mechanically categorize the parts of the EEG signal. In [12], the ensemble technique is measured for seizure identification and recognition. At first, Wavelet transform is utilized to remove the related feature. The factors are decreased utilizing Linear Discriminant Analysis (LDA). Divya and Devi [13] project a Hybrid Grey Wolf Optimizer-Improved Sine Cosine Algorithm with SVM (HGWOISCA-SVM) for classification. The EEG signal is mainly denoised by applying a more excellent wavelet threshold function. Next, three kinds of features are calculated. Then, the Enhanced Grasshopper Optimizer Algorithm (EGOA) was implemented to pick the optimum feature with a higher distinctive influence and decrease the dimensional. Lastly, the nominated features are sent to the model to distinguish the signals. In [14], a hyperparameter tuning with Zebra Optimizer Algorithm (ZOA) is presented to fine-tune features from EEG signals. Then, they are pre-processed utilizing the swarm decomposition model. The removed features then experience hyperparameter tuning by employing ZOA tracked by FS utilizing Enhanced Spatial bound Whale Optimizer Algorithm (WOA) with the mixture of SSA hybridized with Lens Opposition-Based Learning (LOBL) device. The features attained from the selection model are then served to hyperparameter enhanced LSTM classifier.

Thakare et al. [15] projected a novel hybrid technique to pick the optimum features that contain the PSO model, the recently Proposed Probabilistic PSO (PPSO) model and the Sequential Differential Evolution (SDE) method. The EEG data were employed to assess the model. Then, the features are removed by Discrete Wavelength Transform (DWT). Sharma and Meena [16] projected a new real model to enhance the recognition of attacks utilizing the spectral feature of non-stationary signals. The DWT-based feature does not reflect the inter-relationship between modules of EEG signals. This inter-relationship was seized by the new EEG sign using the graph signal method. Next, GFT-based features were nominated and served into dissimilar classification algorithms for analysis. Gowda et al. [17] presented an effectual identification of epileptic EEG signals utilizing the Improved Atomic Search Optimizer (IASO) model and the Random Search Strategy (RSS). The IASO is employed to pick suitable features, but it is more likely to improve the convergence rate. The RSS is presented to enhance the solution and create exploration skills. The raw data is pre-processed utilizing an adaptive filtering model. The IASO is applied to pick the related features, a simple identification procedure utilizing LSTM. Guhdar, Mstafa, and Mohammed [18] developed an automatic framework in order to improve patient care and address employment challenges faced by individuals with epilepsy.

Ahmad et al. [19] introduce the Advanced Multi-View Deep Feature Learning (AMV-DFL) model by integrating FFT-based frequency domain features, raw time domain features, and 1D CNN-extracted deep features for improved EEG signal analysis. A multi-view forest classifier and SHAP explainability are utilized for robust classification and interpretation. Qin et al. [20] present an Adaptive Dual-Modality Learning Model (ADML) method by incorporating time series imageries with a Transformer-based model. Prasad and Ramkumar [21] propose the Deep Neural Optimum Transformation (DNOT) method for epileptic seizure prediction, incorporating CNN for spatial feature extraction, LSTM for temporal modelling, and AutoEncoder for dimensionality reduction. Mekruksavanich, Phaphan, and Jitpattanakul [22] present a hybrid DL methodology by integrating DL models for optimized EEG pattern recognition. Kode, Elleithy, and Almazedah [23] present a novel approach to epileptic seizure detection by utilizing ML and DL methods on EEG signals, focusing on classifying time-series data with 1D CNN and parameter tuning. Ghasemloo and Gholami [24] introduce a method for modelling preictal periods utilizing probabilistic dispersions and autoencoders, detecting change points in EEG signals. Mallick and Baths [25] introduce a novel epileptic seizure detection method using 1D Convolutional layers, Bidirectional LSTM, GRU, and Average pooling layers for extracting features, which are then passed through Dense layers for classification. Kumar and Upadhyay [26] propose a DL model integrating 1D-ResCNN with LAMB and AdamW optimization approaches to extract features from EEG data and accelerate convergence efficiently. Nikoupour, Keyvanpour, and Shojaedini [27] present a multi-label classification approach for epileptic seizures utilizing DL methods.

Despite the progress in epileptic seizure detection utilizing various ML and DL methods, multiple challenges remain. Many approaches still face difficulty handling noisy or incomplete EEG data, restricting their generalization to real-world scenarios. Moreover, most models depend heavily on handcrafted features or fixed parameters, making them less adaptable to varying patient conditions. There is also a need for more effectual techniques to capture long-term dependencies in EEG signals and more robust methods for handling imbalanced datasets in seizure classification. Additionally, integrating real-time monitoring and personalized prediction remains an area for additional improvement.

3. Methodology

This work presents a new RESR-MDRDL approach to EEG signals. The technique concentrates on accurately identifying epileptic seizures utilizing EEG signals. Figure 1 demonstrates the overall workflow of the RESR-MDRDL methodology.

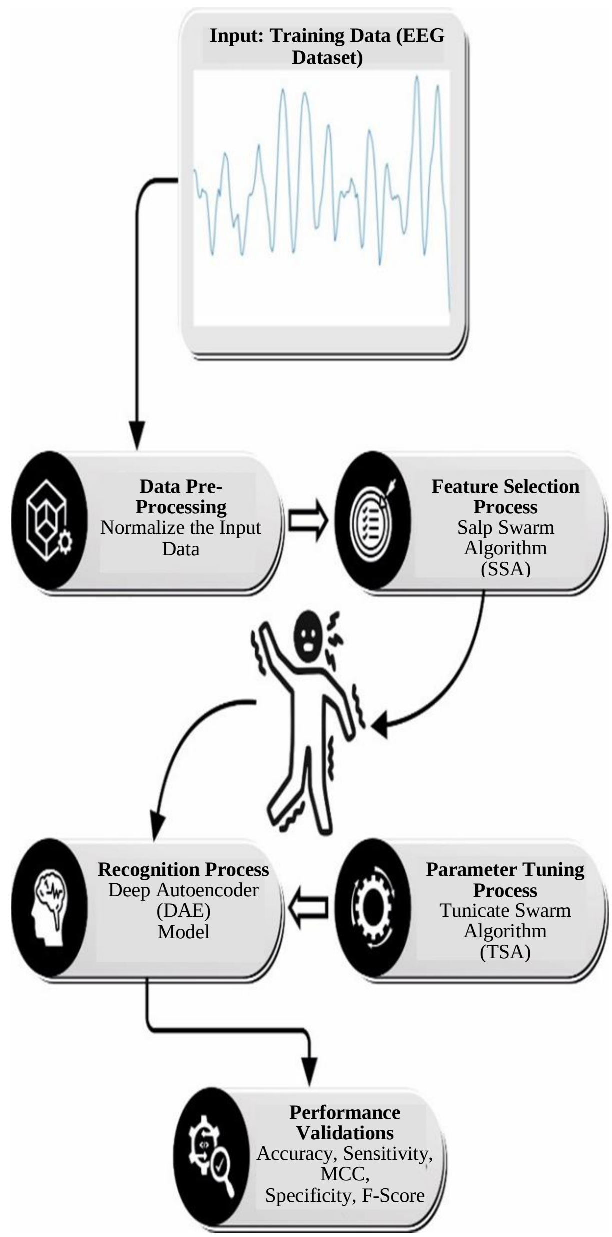

Fig. 1 Overall workflow of the RESR-MDRDL methodology

3.1. Pre-Processing

Initially, the RESR-MDRDL method employs a data pre-processing stage to transform the input information into useful formats. Here, high—and low-level values are considered. Each piece of information is standardized in zero-to-one order. The leading cause simplifies the lowest value to zero and the highest values to one; however, it permits the values from zero to one. The Z-score normalization model is utilized for simplification purposes.

3.2. FS Using SSA

Next, the RESR-MDRDL technique designs an SSA-based FS technique for selecting an optimum feature set. Mirjalili et al., 2017, proposed SSA, a nature-inspired approach that emulates the swarm behaviours of salps in the Deep Ocean [28]. Similar to jellyfish, salps form a group known as a salp chain.

The salp chain has a leader and followers.

Step 1: Randomly produce the initial salp in the search space between the bounds of the variable:

$$S(j,i) = rand(j,1) * (UP\_i - LP\_i) + LP\_i \qquad (1)$$

In Equation (1), i and j are correspondingly variable numbers.

Step 2: The location of the salp represents the problem solution that is formulated as follows:

$$S = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1i} \\ S_{21} & S_{22} & \cdots & S_{2i} \\ \vdots & \vdots & \ddots & \vdots \\ S_{m1} & S_{m2} & \cdots & S_{mi} \end{bmatrix} \qquad (2)$$

Step 3: Assess the fitness for every location of salps:

$$OS = [OS_1 OS_2 OS_3 \cdots\cdots\cdots OS_m] \qquad (3)$$

Step 4: Sort the salp location based on the fitness value:

$$L = \begin{Bmatrix} L_{11} & L_{12} & \cdots & L_{1d} \\ L_{21} & L_{22} & \cdots & L_{21} \\ \vdots & \vdots & \ddots & \vdots \\ L_{n1} & L_{n2} & \cdots & L_{nd} \end{Bmatrix} \qquad (4)$$

Step 5: Arrange the objective function of the salp location:

$$OL = [OL_1 OL_2 OL_3 \cdots\cdots\cdots OL_m] \qquad (5)$$

Step 6: Upgrade the leading salp location based on the swarm's target as follows:

$$S_{1,j\_new} = \begin{cases} F_j + c_1((Up_j - Lp_j)c_2 + Lp_j) \; c_3 \geq 0 \\ F_j - c_1((Up_j - Lp_j)c_2 + Lp_j) \; c_3 < 0 \end{cases} \qquad (6)$$

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \qquad (7)$$

Where c_2 and c_3 are random values amongst $[0,1]$, F_r is the swarm's target, $and\, m$ and M are the existing and optimum iteration values.

Step 7: Update the follower salp location based on Equation (8):

$$s_{i,j\_\text{new}} = \frac{1}{2}(s_{i,j\_\text{new}} + s_{i-1,j\_new}) \qquad (8)$$

The fitness function considers the classifier outputs and the chosen attribute quantity. It improves the classifier outcomes and lessens the chosen attribute size. Therefore, the FF is applied to compute the outcomes.

$$Fitness = \alpha * \; ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F} \qquad (9)$$

Error Rate infers the classifier error rate by utilizing the attributes chosen and assessed as the proportion of incorrect classification to the amount of classifier made within the range [0,1]. ($ErrorRate$ shows the complement of classifier accuracy), $\#SF$ specifies the chosen attribute number, and $\#All\_F$ shows the comprehensive number of attributes in the original data. α controls the prominence of classifier quality and subset length and is fixed at 0.9.

3.3. Seizure Recognition Using DAE

For seizure recognition, the RESR-MDRDL technique employs the DAE model. An AE is a kind of NN that encrypts input information for reconstructing as resultant data [29]. The AE must acquire and collect the vital input features to implement this method. An instance of AE with input, output, and hidden layer (HL). For training set $\{x(1), x(2), \ldots x(n)\}$ so that $x(i)Rd$, the primary step of the AE methodology is to encrypt the input $x(i)$ to HL $y\big(x(i)\big)$ based on Equation (10), this state is decoder as resultant state $z\big(x(i)\big)$ based on Equation (11) as:

$$y(x) = f(W_1 x + b) \qquad (10)$$

$$z(x) = g(W_2 x + c) \qquad (11)$$

W_1 denotes the weighted matrix for the optimizer method, b signifies the encoded bias vector, W_2 implies the decoded matrix of the resultant layer, and c represents the decoded bias vector. During this case, the logistic sigmoid function $1/(1 + \exp(x))$ is executed to $f(x)$ and $g(x)$.

The AE approach utilizes a vector input state (x) and encoded function $\wp$) to estimate another vector (y); in the reconstruction, the decoded function (g) is executed to vector y to restructure vector x; the ensuing resultant state in the use of (g) is vector z. Reconstruction error is defined by scaling with loss function $LH(x,z)$; this function can minimalize as $L(X,Z)$ to find optimum parameter rates as:

$$\theta = arg_{\theta}\min L(X,Z)$$
$$= arg_{\theta}\min \frac{1}{2}\sum_{i=1}^{N}\left\|x^{(i)} - z\left(x^{(i)}\right)\right\|^{2} \quad (12)$$

One crucial difficulty in applying AE approaches is the dimensional of HL, which is fixed as equivalent to or superior to the resultant state. In this case, a non-linear AE with HL that is one unit superior to the input state is utilized by executing the sparsity restriction approach, such that the AE technique is changed into a sparse AE. To attain sparse representation, it is executed sparsity restriction for minimizing reconstruction error as:

$$SAO = L(X,Z) + \gamma \sum_{i=1}^{H_D} KL(\rho||\hat{\rho}) \quad (13)$$

$$\hat{\rho}_j = \left(\frac{1}{N}\right)\sum_{i=1}^{N} y_j\left(x^{(i)}\right) \quad (14)$$

In which γ implies the weight, H_D signifies the count of hidden units, ρ denotes the sparsity parameter, and H_D defines the count of hidden units. In Equation (14), the average rate of activation function for hidden unit j under the train set is the KullbackLeibler (KL) divergence for ML that $KL(\rho||\hat{\rho})$ is measured as:

$$KL(\rho||\hat{\rho}_j) = \rho\log\frac{\rho}{\hat{\rho}_i} + (1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_i}. \quad (15)$$

KL divergence determines the parameter $KL(\rho||\hat{\rho}_j) = 0$ if $= \hat{\rho}_j$. To modify this task, the sparsity restriction on the input model and the backpropagation (BP) approach is executed. Figure 2 represents the DAE structure.

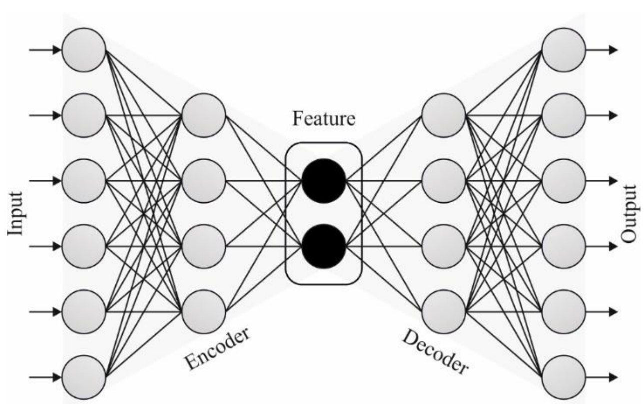

Fig. 2 Architecture of DAE

Deep or stacked AE approaches are among the most influential NN structures. The DAE approach starts from the pre-training input state and then HLs, so the result of k^{th} HL is utilized as input for $(k+1)^{th}$ HL. Therefore, HLs are stacked hierarchically in the DAE; thus, the last HL is a high-level representation of each input state and is utilized in predicting.

A DAE approach is sufficiently executed in this case by adding a typical forecaster at the maximum model state. The forecast is then executed using the LR method. The DAE approach is integrated with a dropout procedure to manage numerous faults in the presented approach.

3.4. Parameter Selection

Finally, the parameter selection is enhanced by the TSA design. The authors proposed a new metaheuristic model named the TSA, which imitates the social hunting nature of bioluminescent tunicates [30]. Every tunicate is tubular and displays a jellylike tunic, which helps link every other tunicate. On the other hand, TSA was stimulated by dual different behavioural designs of tunicates in the deep ocean. To convey the computation term of the jet propulsion model, it is highly essential to fulfil the below-mentioned restrictions:

- Averting crashes among the search individuals.
- Moving to the Finest Search Individuals (FSI).
- Unite in the area near the FSI.

The swarm intellect device helps upgrade the location of tunicates, which depends on the finest optimum solution. The calculations are defined in the following subsections.

3.4.1. Averting Crashes among Search Individuals

To avert crashes among the search individuals, the $\vec{A}$ vector was utilized to describe the upgraded location of the searched individual, which was demonstrated as follows:

$$\vec{A} = \frac{\vec{G}}{\vec{M}} \quad (16)$$

$$\vec{G} = r_2 + r_3 - \vec{F} \quad (17)$$

$$\vec{F} = 2 * r_1 \quad (18)$$

$$\vec{M} = \lfloor P_{\min} + r_1.(P_{\max} - P_{\min})\rfloor \quad (19)$$

Meanwhile, the vectors $\vec{G}$ and $\vec{F}$ correspondingly signify the deep ocean's gravitational force and water flow rate. r_1, r_2 and r_3 are evenly distributed randomly produced integers within the interval of $[0\ and\ 1]$. Similarly, $\vec{M}$ specifies the collective forces among the searched individual. Here, $P_{\min}$ and $P_{\max}$ are fixed to one and four correspondingly, and the initial and second velocities of the searched individual are designated.

3.4.2. Moving Towards the FSI Direction

After averting the crash, everyone must continue near the track of the FSI. The numerical formula for impending the optimum search individual was definite below:

$$S^{\rightarrow}D = |F_{best} - rand * X(t)| \tag{20}$$

Here, $S^{\rightarrow}D$ depicts the spatial distance from the tunicate to its prey, $X(t)$ denotes the tunicate location, F_{best} portrays the food location, and $rand \in [O, 1]$.

3.4.3. Unite with the FSI Surrounding Area

The tunicates meet near the location of the finest individual, defined as follows:

$$X(t) = F_{best} + \vec{A}.S^{\rightarrow}D, \qquad if\ rand \geq 0.5 \tag{21}$$

$$X(t) = F_{best} - \vec{A}.S^{\rightarrow}D, \qquad if\ rand < 0.5 \tag{22}$$

Here, $X(t)$ specifies the upgraded location of every tunicate relative to the food location F_{best}.

3.4.4. Tunicate Swarming Behaviour

During the swarm intellect device, the tunicates' locations are upgraded depending upon the locations of the primary dual finest tunicates. The mathematical calculation is mentioned below.

$$X_i(t+1) = \begin{cases} \dfrac{X_i(t) + X_{i\text{-}1}(t+1)}{2 + r_1} \\ X_i(t) \end{cases} if i = 1 if i > 1 \tag{23}$$

Whereas $i = 1,2, \ldots N$, N denotes the size of the population, $X_i(t+1)$ and $X_{i-1}(t+1)$ refer to the upgraded present and prior search individual location of the subsequent iteration, respectively, and $X_i()$ is defined by Equation (21) and (22).

The FS is the key factor affecting the TSA's performance. The hyperparameter selection technique has a solution encoding methodology for assessing the effectiveness of the solution candidate. Now, the TSA considers performance a primary criterion for developing the FF.

$$Fitness = \max(P) \tag{24}$$

$$P = \frac{TP}{TP + FP} \tag{25}$$

Where TP and FP are the true and false positive values.

4. Results and Discussion

The RESR-MDRDL model's simulation validation is examined under epileptic seizure recognition and UCI datasets [31]. The dataset description is illustrated in Table 1. The simulation is performed by employing the Python 3.6.5 tool on a PC with an i5-8600k, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. The parameter settings are as follows: learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5.

Table 1. Dataset description

Classes	Class Label	Instance Numbers
"Recording of seizure activities"	Class 1	2300
"Recording of EEG from the area where the tumour is located during a non-seizure period"	Class 2	2300
"Recording of EEG from a healthy part of the brain during a non-seizure period"	Class 3	2300
"Recording of EEG with the patients' eyes closed during a non-seizure period"	Class 4	2300
"Recording of EEG with the patients' eyes open during a non-seizure period"	Class 5	2300
Overall Instances		**11500**

Figure 3 illustrates the performance of the RESR-MDRDL method on 80:20 of TRAS/TESS. Figures 3(a)-3(b) represents the confusion matrices presented by the RESR-MDRDL method. The figure indicates that the RESR-MDRDL method recognizes and classifies each class. Also, Figures 3(c)-3(d) depict that the RESR-MDRDL methodology attained the highest PR and ROC under diverse classes.

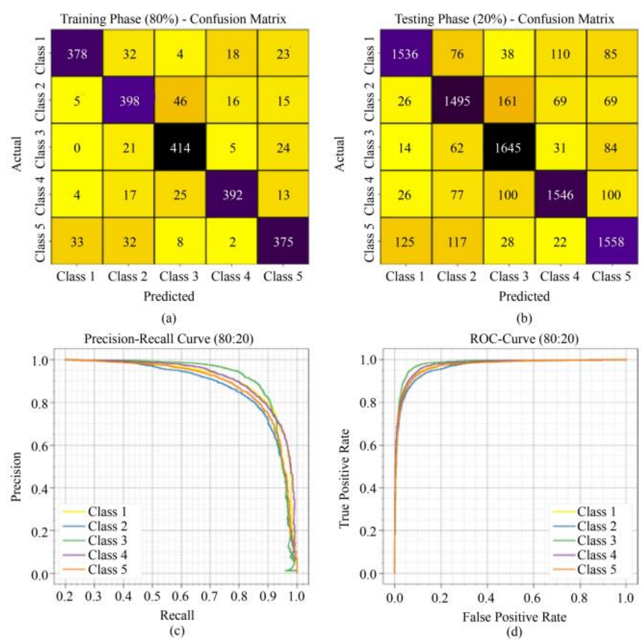

Fig. 3 80:20 of TRAS/TESS (a-b) confusion matrices, and (c-d) PR and ROC curves.

Table 2 and Figure 4 highlight the experimental results of the RESR-MDRDL methodology on 80:20 of TRAS/TESS. The outputs demonstrate that the RESR-MDRDL methodology precisely detected the classes. On 80%TRAS, the RESR-MDRDL methodology reaches an average $accu_y$ of 93.83%, $sens_y$ of 84.56%, $spec_y$ of 96.14%, F_{score} of 84.56%, and MCC of 80.74%. Additionally, on 20%TESS, the RESR-MDRDL model attains an average $accu_y$ of 94.03%, $sens_y$ of 85.09%, $spec_y$ of 96.27%, F_{score} of 85.16%, and MCC of 81.48%.

Table 2. Classifier output of RESR-MDRDL method on 80:20 of TRAS/TESS

Classes	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	MCC
TRAS (80%)					
Class 1	94.57	83.25	97.40	86.00	82.70
Class 2	92.86	82.14	95.50	81.99	77.53
Class 3	94.37	89.60	95.56	86.40	82.94
Class 4	94.18	83.61	96.84	85.25	81.65
Class 5	93.15	84.22	95.40	83.18	78.89
Average	**93.83**	**84.56**	**96.14**	**84.56**	**80.74**
TESS (20%)					
Class 1	94.83	83.08	97.72	86.40	83.31
Class 2	92.00	82.92	94.40	81.22	76.17
Class 3	94.22	89.22	95.48	86.16	82.59
Class 4	95.65	86.92	97.78	88.69	86.03
Class 5	93.48	83.33	95.95	83.33	79.28
Average	**94.03**	**85.09**	**96.27**	**85.16**	**81.48**

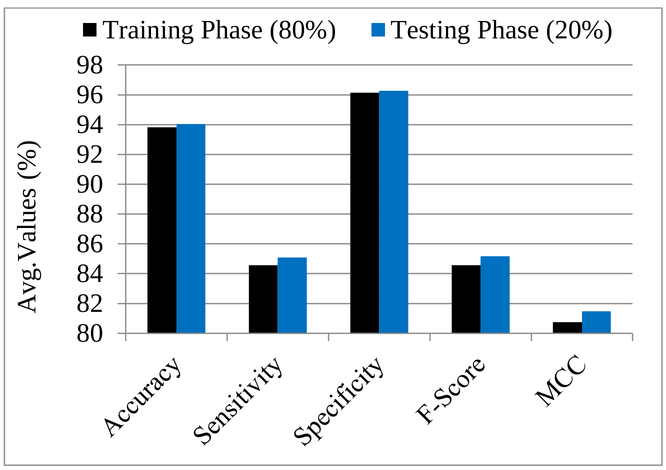

Fig. 4 Average outcome of RESR-MDRDL method on 80:20 of TRAS/TESS

In Figure 5, the Training (TR) and Validation (VL) accuracy outputs of the RESR-MDRDL methodology on 80:20 of TRAS/TESS are demonstrated and analyzed within 0-25 epochs. The figure showed that the values exhibited higher values over multiple iterations. Also, the accuracy increases over epochs, depicting reduced overfitting and enhancing the RESR-MDRDL method's accomplishment, exhibiting consistent prediction on unseen samples.

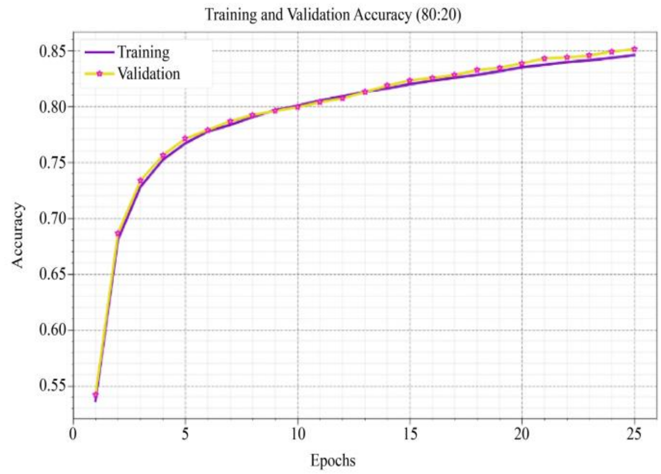

Fig. 5 $Accu_y$ curve of RESR-MDRDL method on 80:20 of TRAS/TESS

Figure 6 depicts the TR/VL loss of the RESR-MDRDL technique on 80:20 of TRAS/TESS. The loss is computed within the range of 0-25 epochs. The TR/VL accuracy shows a lessening trend, highlighting the technique's ability to balance data fitting and generalization. The continuous decline in loss accentuated the superior accomplishment of the RESR-MDRDL method, progressively refining the prediction outputs.

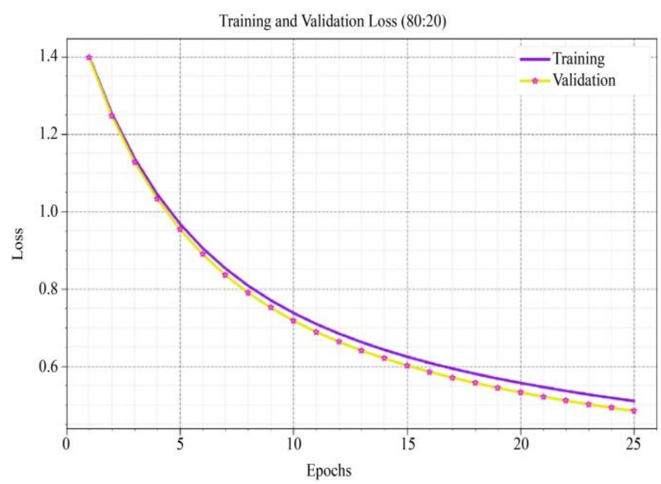

Fig. 6 Loss curve of RESR-MDRDL method on 80:20 of TRAS/TESS

Figure 7 shows the performance of the RESR-MDRDL approach at 70:30 of TRAS/TESS. Figures 7(a)-7(b) depict the confusion matrices. The figure indicates that the RESR-MDRDL approach detected and classified each class. Also, Figures 7(c) infers the PR inspection of the RESR-MDRDL approach.

The figure showed that the RESR-MDRDL technique attained high PR under overall classes. Finally, Figure 7(d) exhibits the ROC of the RESR-MDRDL technique. The RESR-MDRDL technique exhibited a promising solution with high ROC under varying classes.

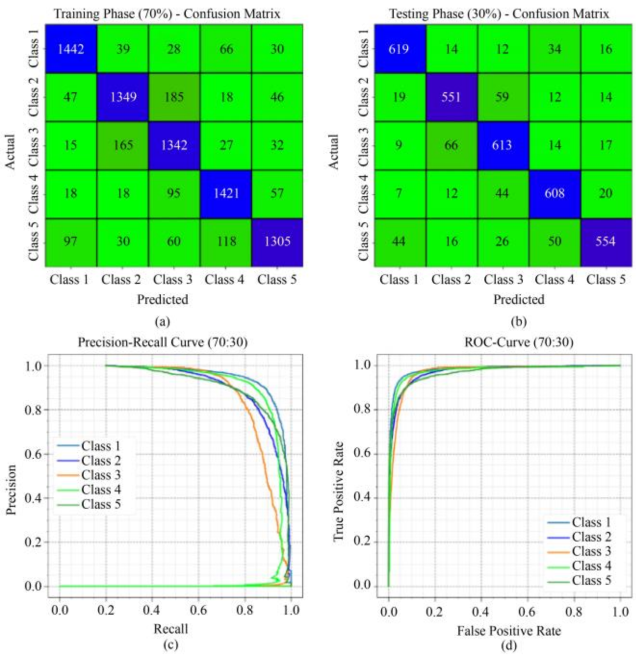

Fig. 7 70:30 of TRAS/TESS (a-b) confusion matrices and (c-d) PR and ROC curves

Table 3 and Figure 8 highlight the experimental outputs of the RESR-MDRDL method on 70:30 of TRAS/TESS. The outputs establish that the RESR-MDRDL method precisely detected the classes. On 70%TRAS, the RESR-MDRDL approach attains average $accu_y$ of 94.08%, $sens_y$ of 85.22%, $spec_y$ of 96.30%, F_{score} of 85.21%, and MCC of 81.57%. Moreover, on 30%TESS, the RESR-MDRDL approach reaches an average $accu_y$ of 94.14%, $sens_y$ of 85.34%, $spec_y$ of 96.34%, F_{score} of 85.36%, and MCC of 81.75%.

Table 3. Classifier output of RESR-MDRDL methodology on 70:30 of TRAS/TESS

Classes	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	**MCC**
TRAS (70%)					
Class 1	95.78	89.84	97.25	89.45	86.81
Class 2	93.19	82.01	96.07	83.12	78.87
Class 3	92.46	84.88	94.31	81.56	76.92
Class 4	94.82	88.32	96.44	87.20	83.97
Class 5	94.16	81.06	97.44	84.74	81.27
Average	**94.08**	**85.22**	**96.30**	**85.21**	**81.57**
TESS (30%)					
Class 1	95.51	89.06	97.13	88.87	86.06
Class 2	93.86	84.12	96.14	83.87	80.07
Class 3	92.84	85.26	94.84	83.23	78.72
Class 4	94.41	87.99	96.01	86.30	82.81
Class 5	94.12	80.29	97.57	84.52	81.07
Average	**94.14**	**85.34**	**96.34**	**85.36**	**81.75**

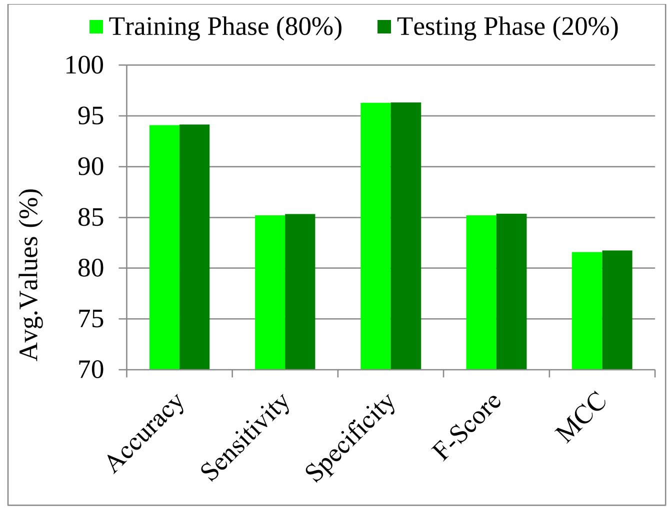

Fig. 8 Average outcome of RESR-MDRDL methodology on 70:30 of TRAS/TESS

In Figure 9, the TR/VL accuracy outputs of the RESR-MDRDL methodology on 70:30 of TRAS/TESS are established and computed within 0-25 epochs. The figure also depicts growth, which represents the ability of the RESR-MDRDL method to perform well over various iterations.

Furthermore, the values enhance over epochs, portraying enhanced performance and minimal overfitting of the RESR-MDRDL method, exhibiting consistent prediction on hidden samples.

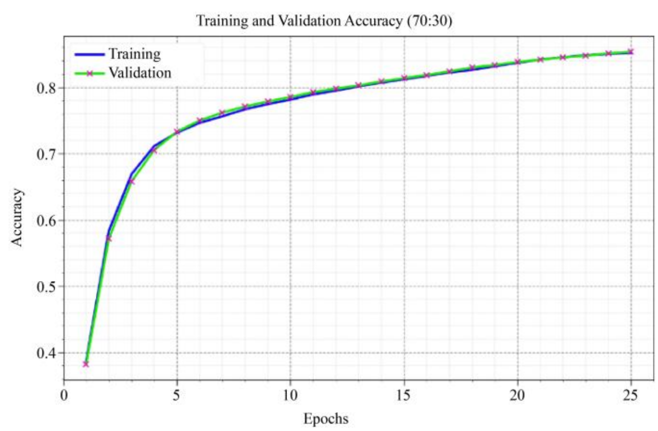

Fig. 9 $Accu_y$ curve of RESR-MDRDL method on 70:30 of TRAS/TESS

In Figure 10, the TR/VL loss of the RESR-MDRDL approach at 70:30 of TRAS/TESS is displayed. The loss is computed over 0-25 epochs, with accuracy decreasing, highlighting the RESR-MDRDL approach's balance between data fitting and generalization.

The continuous mitigation of loss confirms the superior accomplishment of the RESR-MDRDL method, progressively fine-tuning the prediction outputs as the model gradually increases.

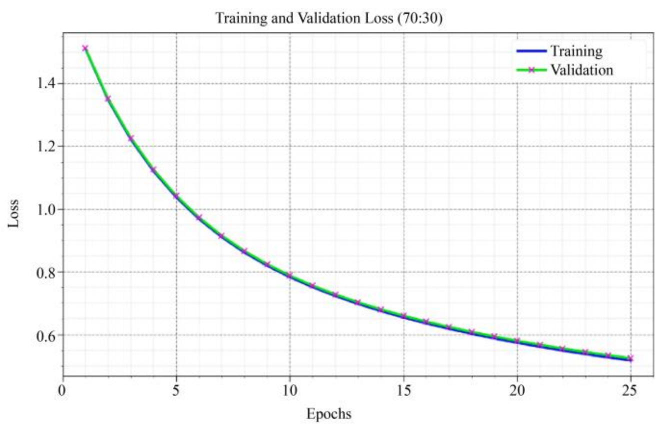

Fig. 10 Loss curve of RESR-MDRDL method on 70:30 of TRAS/TESS

In Table 4 and Figure 11, the outputs of the RESR-MDRDL method are compared with recent models. The outputs highlighted that the linear SVM, KNN, and MLP models accomplished poor performance with the least $accu_y$ values of 76.70%, 76.00%, and 78.00%, respectively. In the meantime, the KELM, SA-KELM, and M-Gaussian-SVM methods have reported nearer performance with $accu_y$ values of 80.53%, 82.49%, and 81.40%, subsequently. However, the RESR-MDRDL technique performs better with a maximum $accu_y$ of 94.14%. Thus, the RESR-MDRDL technique is applied for automated epilepsy detection on EEG signals.

Table 4. $Accu_y$ the outcome of the RESR-MDRDL technique is compared with recent models

Methods	Accuracy (%)
RESR-MDRDL	94.14
KELM	80.53
SA-KELM	82.49
M-Gaussian-SVM	81.40
Linear SVM	76.70
KNN	76.00
MLP	78.00

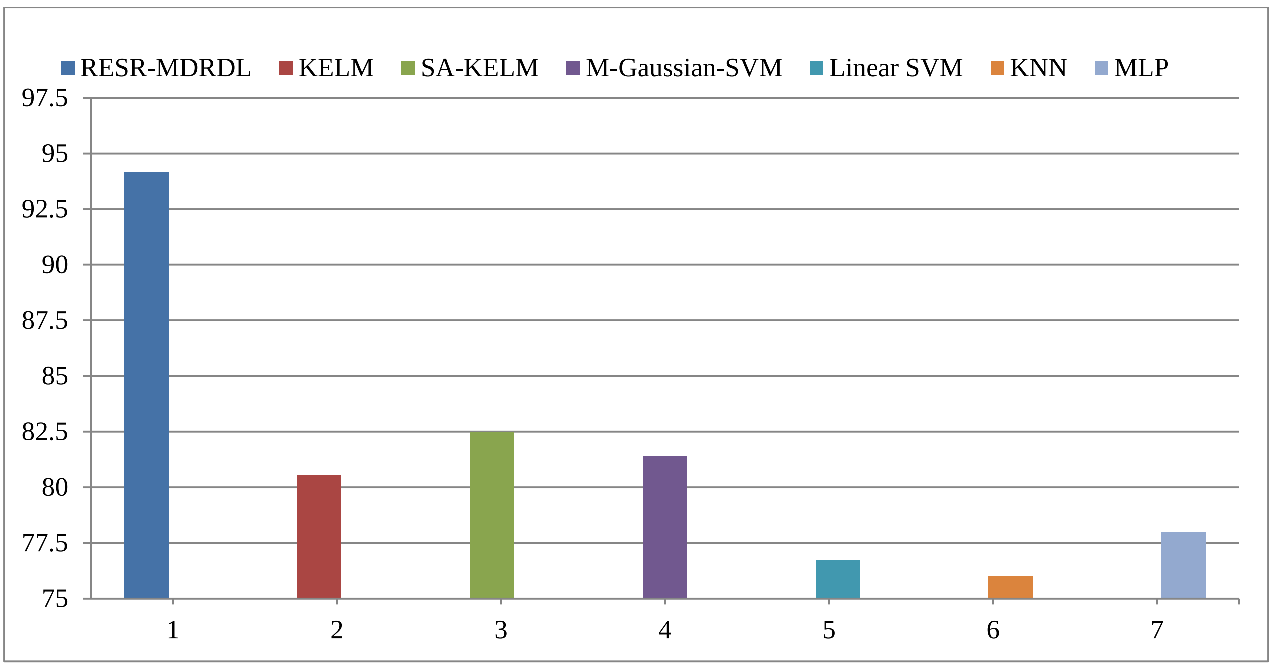

Fig. 11 $Accu_y$ the outcome of the RESR-MDRDL technique is compared with recent models

5. Conclusion

In this study, a new RESR-MDRDL approach to EEG signals is presented. The RESR-MDRDL approach concentrates on accurately identifying epileptic seizures using EEG signals. It contains various kinds of stages involved. In a preliminary stage, the RESR-MDRDL technique performed data pre-processing to normalize the input dataset. Besides, the RESR-MDRDL technique utilized an SSA-based FS approach for optimal feature sets. The RESR-MDRDL technique employed the DAE model for seizure recognition, and TSA improved its efficiency. The simulation of the RESR-MDRDL method is examined by using an EEG dataset. The experimental validation of the RESR-MDRDL methodology indicated a superior accuracy value of 94.14% over existing techniques.

References

[1] Muhammad Haseeb Aslam et al., “Classification of EEG Signals for Prediction of Epileptic Seizures,” *Applied Sciences*, vol. 12, no. 14, pp. 1-15, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Anis Malekzadeh et al., "Epileptic Seizures Detection in EEG Signals using Fusion Handcrafted and Deep Learning Features," *Sensors*, vol. 21, no. 22, pp. 1-28, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] K. Polat, and M. Nour, "Epileptic Seizure Detection based on New Hybrid Models with Electroencephalogram Signals," *IRBM*, vol. 41, no. 6, pp. 331-353, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Abeg Kumar Jaiswal, and Haider Banka, "Epileptic Seizure Detection in EEG Signal using Machine Learning Techniques," *Australasian Physical & Engineering Sciences in Medicine*, vol. 41, pp. 81-94, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[5] Muhammet Varlı, and Hakan Yılmaz, "Multiple Classification of EEG Signals and Epileptic Seizure Diagnosis with Combined Deep Learning," *Journal of Computational Science*, vol. 67, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] José Escorcia-Gutierrez et al., "An Automated Deep Learning Enabled Brain Signal Classification for Epileptic Seizure Detection on Complex Measurement Systems," *Measurement*, vol. 196, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Kuldeep Singh, and Jyoteesh Malhotra, "Smart Neurocare Approach for Detection of Epileptic Seizures Using Deep Learning Based Temporal Analysis of EEG Patterns," *Multimedia Tools and Applications*, vol. 81, pp. 29555-29586, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Anwer Mustafa Hilal et al., "Intelligent Epileptic Seizure Detection and Classification Model Using Optimal Deep Canonical Sparse Autoencoder," *Biology*, vol. 11, no. 8, pp. 1-18, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Theekshana Dissanayake et al., "Geometric Deep Learning for Subject Independent Epileptic Seizure Prediction Using Scalp EEG Signals," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 2, pp. 527-538, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Mohammad Karimi Moridani, Seyed Sina Jabbari Behnam, and Mahdyar Heydar, "Automatic Epileptic Seizure Detection Based on EEG Signals Using Deep Learning," *Artificial Intelligence Evolution*, pp. 96-106, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Mahrad Pouryosef, Roozbeh Abedini-Nassab, and Seyed Mohammad Reza Akrami, "A Novel Framework for Epileptic Seizure Detection Using Electroencephalogram Signals Based on the Bat Feature Selection Algorithm," *Neuroscience*, vol. 541, pp. 35-49, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Sreelekha Panda et al., "Seizure Detection Using Integrated Metaheuristic Algorithm Based Ensemble Extreme Learning Machine," *Measurement: Sensors*, vol. 25, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] P. Divya, and B. Aruna Devi, "Hybrid Metaheuristic Algorithm Enhanced Support Vector Machine for Epileptic Seizure Detection," *Biomedical Signal Processing and Control*, vol. 78, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] T. Jhansi Rani, and D. Kavitha, "Classification of Epileptic Seizures Using LSTM Based Zebra Optimization Algorithm with Hyperparameter Tuning," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 3, pp. 80-91, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Anuradha Thakare, Ahmed M. Anter, and Ajith Abraham, "Seizure Disorders Recognition Model from EEG Signals Using New Probabilistic Particle Swarm Optimizer and Sequential Differential Evolution," *Multidimensional Systems and Signal Processing*, vol. 34, pp. 397-421, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ramnivas Sharma, and Hemant Kumar Meena, "Enhanced Epileptic Seizure Detection through Graph Spectral Analysis of EEG Signals," *Circuits, Systems, and Signal Processing*, vol. 43, pp. 5288-5308, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Madhu Belur Gopala Gowda et al., "Classification of Epileptic EEG Signals Using Improved Atomic Search Optimization Algorithm," *International Journal of Intelligent Engineering & Systems*, vol. 16, no. 6, pp. 134-144, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mohammed Guhdar, Ramadhan J. Mstafa, and Abdulhakeem O. Mohammed, "Hybrid Deep Learning Model for Epileptic Seizure Classification by Using 1D-CNN with Multi-Head Attention Mechanism," *Arxiv*, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] Ijaz Ahmad et al., "Robust Epileptic Seizure Detection Based on Biomedical Signals Using an Advanced Multi-View Deep Feature Learning Approach," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 10, pp. 5724-5754, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Jiahao Qin et al., "Dual-Modality Transformer with Time Series Imaging for Robust Epileptic Seizure Prediction," *Applied Sciences*, vol. 15, no. 3, pp. 1-25, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[21] Himayavardhini Jagath Prasad, and G. Ramkumar, "A Robust Deep Learning Model to Predict Epileptic Seizures Based on Electroencephalographic (EEG) Signals," *9th International Conference on Communication and Electronics Systems*, Coimbatore, India, pp. 1393-1399, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Sakorn Mekruksavanich, Wikanda Phaphan, and Anuchit Jitpattanakul, "Epileptic Seizure Detection in EEG Signals via an Enhanced Hybrid CNN with an Integrated Attention Mechanism," *Mathematical Biosciences and Engineering*, vol. 22, no. 1, pp. 73-105, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[23] Hepseeba Kode, Khaled Elleithy, and Laiali Almazaydeh, "Epileptic Seizure Detection in EEG Signals using Machine Learning and Deep Learning Techniques," *IEEE Access*, vol. 12, pp. 80657-80668, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[24] Mohammadmahdi Ghasemloo, and Hadi Gholami, “Deep Learning for Preictal Change Point Detection: Enhancing Seizure Prediction in EEG Signals,” *Authorea*, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[25] Sayani Mallick, and Veeky Baths, “Novel Deep Learning Framework for Detection of Epileptic Seizures Using EEG Signals,” *Frontiers in Computational Neuroscience*, vol. 18, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Priyaranjan Kumar, and Prabhat Kumar Upadhyay, “A Hybrid Optimization-Enhanced 1D-ResCNN Framework for Epileptic Spike Detection in Scalp EEG Signals,” *Scientific Reports*, vol. 15, pp. 1-20, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[27] Maryam Nikoupour, Mohammad Reza Keyvanpour, and Seyed Vahab Shojaedini, “A Robust Framework for Epileptic Seizure Diagnosis: Utilizing GRU-CNN Architectures in EEG Signal Analysis,” *20th CSI International Symposium on Artificial Intelligence and Signal Processing*, Babol, Iran, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[28] Hussein Abdel-Mawgoud et al., “Hybrid Salp Swarm Algorithm for Integrating Renewable Distributed Energy Resources in Distribution Systems Considering Annual Load Growth,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 1, pp. 1381-1393, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[29] Thanongsak Xayasouk, HwaMin Lee, and Giyeol Lee, “Air Pollution Prediction Using Long Short-Term Memory (LSTM) and Deep Autoencoder (DAE) Models,” *Sustainability*, vol. 12, no. 6, pp. 1-17, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[30] Vanisree Chandran, and Prabhujit Mohapatra, “A Novel Multi-Strategy Ameliorated Quasi-Oppositional Chaotic Tunicate Swarm Algorithm for Global Optimization and Constrained Engineering Applications,” *Heliyon*, vol. 10, no. 10, pp. 1-42, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] Harun-Ur-Rashid, Epileptic Seizure Recognition, Kaggle, 2018. [Online]. Available: https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure-recognition