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Original Article

Epileptic Seizure Recognition Utilizing Improved Chimp Optimization Algorithm with Deep Learning on EEG Signals

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Abstract *- Epileptic seizure detection utilizing Electroencephalogram (EEG) signals is a significant application in medical diagnostics and healthcare. The EEG signals are electrical recordings of brain activity mainly utilized to monitor functions in the brain. Epileptic seizure detection in EEG aids in the analysis as well as management of epilepsy, a nervous disorder considered by existing seizures. Seizure detection using EEG signals is a very complex task that needs collaboration among medical specialists and Deep Learning (DL), Machine Learning (ML), and Neural Network (NN) experts to guarantee the reliability and accuracy of the recognition method for patients with epilepsy. DL methods, such as Convolutional NNs (CNNs) and Recurrent NNs (RNNs), are given training on labelled EEG repositories containing seizure and non-seizure parts. This article presents an Epileptic Seizure Recognition using an Improved Chimp Optimization Algorithm with DL (ESR-ICOADL) technique on EEG signals. The ESR-ICOADL technique aims to examine the EEG signals for detecting and classifying epileptic seizures. At a preliminary stage, the ESR-ICOADL technique applies the data preprocessing stage for converting the input data into valuable formats. For epileptic seizure recognition, the ESR-ICOADL technique applies a Bidirectional Gated Recurrent Unit (BiGRU) approach. Lastly, the hyperparameter tuning of the BiGRU approach could be boosted by utilizing ICOA, which supports accomplishing improved classification efficiency. The investigational analysis of the ESR-ICOADL approach is investigated on EEG datasets, and the simulated outputs illustrate the ESR-ICOADL model's significant results in diverse strategies.*

Keywords *- Epilepsy, Seizure detection, EEG signals, Chimp optimization algorithm, Deep learning.*

1. Introduction

Epilepsy is a prevalently seen brain disorder that contains frequent seizures in the brain owing to abandoned electrical movement [1]. This affects uninhibited jerking movement as well as temporary loss of consciousness. This disease is theoretically dangerous because it causes failure of the brain and lungs, heart failure, and sudden deaths caused by accidents. Because of this, it is vital to identify epilepsy [2]. The signal that records electrical movement and activity in the brain is called an EEG signal. The electrodes are positioned on different elements of the scalp at the time of procedure and provide multichannel data [3]. It is a non-invasive and low-cost model and a practical data resource in neurological analysis, like seizure detection. Typically, medical workers gather recordings by visually reviewing the long-term EEG [4]. This technique consumes more time, is prone to errors, and needs an assured level of human knowledge. So, it is highly recommended to use an automatic epilepsy seizure detection framework [5]. EEG detection needs a straight analysis by a physician and an essential extent of time and work [6]. Moreover, medical professionals with various stages of analytical capability sometimes report discrepant views on the analytic outcomes. Therefore, the improvement of an automatic CAD for diagnosing epilepsy can be immediately required. Many detection methods have been proposed in past research for epileptiform EEG [7]. Current techniques for seizure detection employ hand-engineered methods for feature extraction from EEG signals like nonlinear signal analyses, frequency, time, and time-frequency domain. To determine the classification, feature extraction is a primary step because it highly controls its accuracy [8]. Confidently predicts that a detection method is executed without difficult feature extraction, and the latest growth of DL has proposed a novel manner of encountering this problem. Over the last few years, DL has arrived normal in computer vision and ML, showing superhuman and near-human capability to perform several tasks like sequence learning and object detection [9]. Feature extraction earlier to classification looks to be a better option when compared to directly entering raw EEG samples into the classification algorithm. However, in some recent research, DL techniques were trained with raw EEG signals where the feature extraction was not executed [10]. This article presents an Epileptic Seizure Recognition using an Improved Chimp Optimization Algorithm with DL (ESR-ICOADL) technique on EEG signals. The goal of the ESR-ICOADL technique is to examine the EEG signals for detecting and classifying epileptic seizures. At a preliminary stage, the ESR-ICOADL technique applies the data preprocessing stage to convert the input data into valuable formats. For epileptic seizure recognition, the ESR-ICOADL technique applies the Bidirectional Gated Recurrent Unit (BiGRU) method. Lastly, the hyperparameter tuning of the BiGRU model could be boosted by employing ICOA, which supports accomplishing improved classification outcomes. The investigational analysis of the ESR-ICOADL technique is examined on EEG datasets.

2. Related Works

In [11], the research proposes an approach using time series and time-frequency-image conversions of time-reliant EEG. The STFT and CWT models are utilized to change signals to images. These two methods have generated distinct images using CWT and STFT techniques. Singh and Malhotra [12] developed a cloud-fog-united smart neuro care technique employing DL. It uses the highest variance-based network selection process. Dissanayake et al. [13] presented a model utilizing the Geometric-DL (GDL) technique. Initially, the research employed graphs that were classified from physical links in the EEG network. Then, the study pursues the manufacture of subject-specific graphs by using DL. Kumar et al. [14] developed a BiLSTM system. Two separate Long Short-Term Memory (LSTM) systems with opposite propagation orders are joined in the deep framework. In [15], an Automated DL-assisted Brain Signal Classification (ADLBSC) model is developed. The research contains the structure of the Improved TLBO (ITLBO) methods to pick out features. Additionally, the DBN method is mainly utilized for detection, and then DBN model hyperparameters are ideally adjusted by applying the Swallow Swarm Optimization Algorithm (SSA). Ahmad et al. [16] developed a hybrid DL model. A K-means SMOTE is employed to balance sample info. Then, 1-D CNN is combined with the BiLSTM system depending on the Truncated Backpropagation Through Time (TBPTT) model. Finally, the method uses softmax and sigmoid classification approaches. Qiu et al. [17] designed a LightSeizureNet (LSN) model. Kernel-wise pruning, Global average pooling, and Dilated 1D convolution are also used. In [18], an advanced DL model is proposed. This model uses an autoencoder for feature extraction and Relief-F feature ranking to mitigate computational load. The Hybrid Deep Scheme (HDS) combines LSTM and MSA-DCNN, which are used for seizure detection, while the Adaptive Spider Monkey Black Widow Optimization (ASMBWO) model is used for optimization. Chanu [19], an optimized NN model is introduced. Discrete Wavelet Transform (DWT) is utilized to extract features, and the samples are classified using a fusion method that integrates Self-Organizing NN (SONN) and Multi-Layer Perceptron (MLP) models. Abdulwahhab et al. [20] propose a unified deep ML method which integrates CNN and LSTM-RNN techniques. Short-Time Fourier Transform (STFT) and Continuous Wavelet Transformation (CWT) are also utilized.

3. The Proposed Model

This work has developed an automatic Epileptic Seizure Recognition employing the ESR-ICOADL technique. The ESR-ICOADL method aims to examine the EEG signals for detecting and classifying epileptic seizures. It involves three-phase procedures, namely preprocessing, BiGRU categorization, and ICOA-based tuning. Figure 1 depicts the structure of the ESR-ICOADL method.

3.1. Data Preprocessing

Initially, the ESR-ICOADL approach applies this stage to convert the given data into valuable formats. Here, low and high-level values are considered. All the data is regularized in the order of zero to one. The major reason for this model is to simplify low value to zero as well as high value to one, but it allows the value from zero to one. For simplification purposes, the Z-score normalization technique is used.

3.2. Seizure Detection using BiGRU

In this section, the BiGRU model is employed to detect and classify seizures. The LSTM module contains multiple gates, namely memory units, input, output, and forget gates, while the GRU is composed of an activation function, update, and reset gates [21]. The LSTM is relatively more computationally intricate than GRU concerning the count and development of the gating mechanism, resulting in comparatively more complex requiring high computational resources. Thus, the study proposes a BiGRU flow of learning algorithms that are learned efficiently from the encoded unknown sequences. The BiGRU contains forward and backward layers, which they process in identical order in different sequences. The forward layer is used to read the input series from the direction of left to right, viz., from X_{t-1} to X_n but the sequence length is n. Concurrently, the backward layer is used to read the input series order from right to left, viz., from X_{t+n} to X_{t-1}. Both GRU layers have GRU units, where each unit comprises two gates, such as reset and update, depicted as r and μ, with Tanh and sigmoid activation functions. The r determines which part of the data is to be retained or forgotten. If the value of the output of r is nearer to 0, then r forgets the data from the prior sequence part; if the value is closer to 1, then r retains the prior part of the sequence.

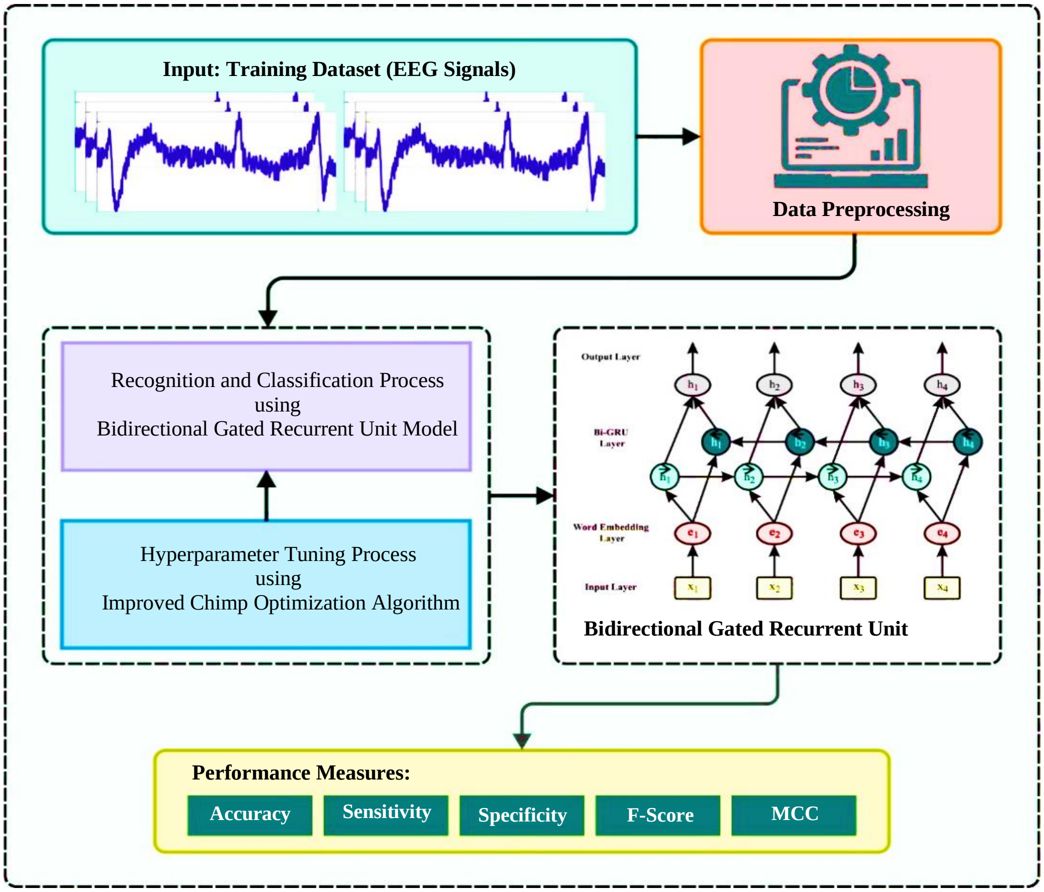

Fig. 1 Structure of the ESR-ICOADL system

The μ determines how much data from the prior Hidden Layer (HL) is to be retained in the existing HL. Once the μ value is closer to 0, μ forgets the part of data from the prior HL and maintains the parts of data from the before the existing HL if the values are near 1. The functions of these gates are mathematically modelled below:

$$r_t = \sigma(w_r \cdot x_t + u_r \cdot h_{t-1}), \tag{1}$$

$$\mu_t = \sigma(w_\mu \cdot x_t + u_\mu \cdot h_{t-1}), \tag{2}$$

$$h_t = \tanh(w \cdot x_t + r_t \cdot u \cdot h_{t-1}), \tag{3}$$

$$h_t = (1 - \mu_t) \cdot h_{t-1} + \mu_t \cdot \tilde{h}_t, \tag{4}$$

$$y_t = \sigma(w_o \cdot h_t), \tag{5}$$

Where the reset and update gates are r_t and μ_t, correspondingly, within [0,1], the weight parameters are w, and u, and the input given to GRU is x_t, the weight parameter among input and output layers is w_0, and the node of the output layer at the t time stage is y_t. The candidate, HL of the existing node, is denoted as $\tilde{h}_t$, the existing HL is h_t, and the HL of the previous node is h_{t-1}.

3.3. Hyperparameter Tuning by Employing ICOA

In the final phase, the ICOA can be exploited for the optimum hyperparameter selection method. COA is a revolutionary optimizer approach whose main idea originates from the hunting strategy of chimpanzees [22]. Attackers (prey survival space), Drivers (next prey), Barriers (restrictive prey escape space), and Chasers (over-taking prey) are different groups of the COA. During chimpanzee hunting, there is an occurrence of social incentive".

Furthermore, this social incentive results in chimpanzees performing so incomprehensibly at the end of the attacking procedure that chimpanzees escape their tasks to frantically obtain meat. Chimpanzee hunts for meat in place of social benefits, namely mate choice, ethnic support, or their strength. During hunting, attackers are satisfied with additional pieces of meat, which is generally considered to be a process that needs further information to forecast the prey's action. It is a significant contribution that is certainly related to physical ability, age, and intelligence. Generally, the hunting process of chimpanzees is classified into two phases. The former can be used to intercept, drive, and chase prey and the latter can be used to attack prey.

3.3.1. Surround Prey

The action of chimpanzees encircling the prey during hunting can be described as follows:

$$d = |c.xrey\ (t) - m.xhimp\ (t)| \tag{6}$$

$$x_{chimp}(t+1) = x_{prey}(t) - a \cdot d. \qquad (7)$$

The distance between the chimp and the prey is given in Equation (6). The position update formula of chimpanzees is shown in Equation (7); the number of existing iterations is t; a position vector for chimpanzees is x_{chimp}; and a vector of prey position is x_{prey}. The vectors m and c are evaluated using the following expression:

$$a = 2f \cdot r_1 - f. \qquad (8)$$

$$c = 2r_2. \qquad (9)$$

$$m = Chaotic\text{-}value, \qquad (10)$$

In the equations, the convergence factor is f dropped linearly from 2.5 to 0. The modulus of r_1 and r_2 are random numbers in [0, 1]; c is the randomization value within [0, 2]; and a chaos vector evaluated in different graphs is m.

3.3.2. Attack Prey

The f value gradually decreases to simulate the strategy of chimpanzees towards the prey. Hence, the fluctuation range also reduces. At each iteration, if the number of f linearly dropped from 2.5 to 0, then the respective value of a also varies between $[-f, f]$. If the value lies in the $[-f, f]$ interval, then the next location of the chimpanzee can be anywhere within its existing and the prey locations. If $|a| < 1$, then the chimpanzee attacks the prey.

3.3.3. Search for Prey

Based on the locations of $x_{Attacker}$, $x_{Barrier}$, x_{chaser}, and x_{Driver}, chimpanzees hunt for the prey. Chimpanzees separately move while finding the prey but round up to hunt once they spot the prey. If $|a| > 1$ or $|a| < -1$ then separate chimpanzees from the prey with random values dependent on the divergence of scientific modelling, which highlights the exploration process and enables COA to search globally for optimum outcomes. If $|a| > 1$, then the Chimp is separated from the target (local optimum solution) to search for the best prey (global optimum solution). The COA has a c parameter to find new solutions. Where the random integer within [0,2] is c. The influence weight is larger if $|c| > 1$; otherwise, it is smaller. The new COA employs an initialization technique because it produces chimpanzee individuals in the search space randomly. The stochastic method does not guarantee that the individuals can be equally spread in the primary search space and, occasionally, with overlapping places of any prepared individuals that may be absent of the search space. Most significantly, the first populace disturbs the effectualness of the optimizing process. Due to this purpose, the Sine chaotic map approach could be utilized in this research to modify the Chimp's populace. Hence, the Sine chaotic 1-D self-map mathematical equation is given below Equation (11).

$$\begin{cases} x_{i+1} = \dfrac{k}{4}\sin(\pi \cdot x_i)\,, \\ k \in (0,4] \end{cases} \qquad (11)$$

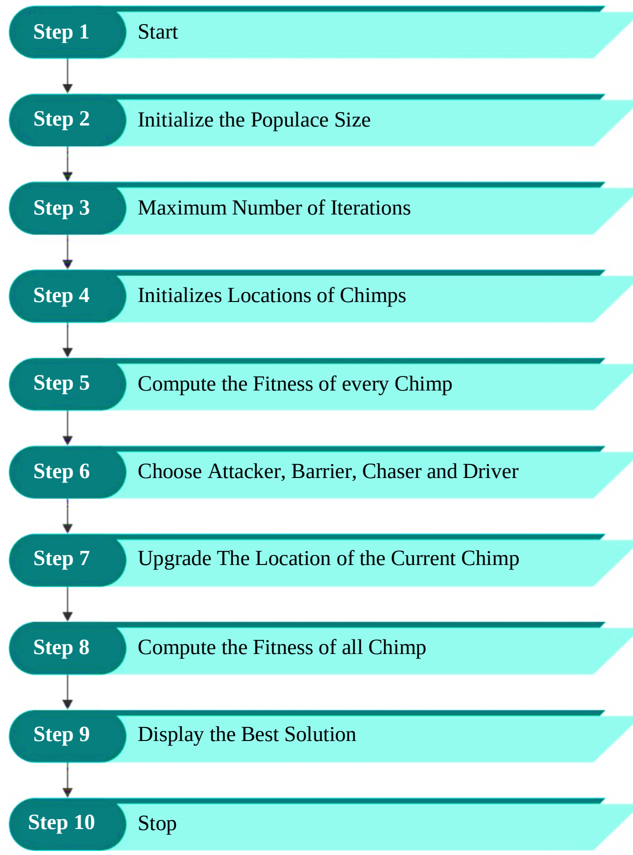

Fig. 2 COA steps

Where x_j is the value of the iterative sequence; i is known as a positive numeral; $x_0 \in (0,1)$; and k is a network parameter in (0,4). As mentioned above, the initialization of the sine chaotic map permits a further even dispersion of chimpanzees in the search space with traversal as well as non-repeatability.

This makes sure that the initial space is amply explored to improve the quality and assortment of the early population. During the exploration method, avoid the algorithm problem, which falls into a local optimal, thus enhancing the effectiveness of the algorithm. Figure 2 represents the steps utilized in COA. The ICOA approach constructs an FF to gain greater classification performance. This concludes with a positive number to portray the optimum candidate solutions. The mitigated error rate of the classification can be said to be the FF, which is shown in Equation (12).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{No.of\ misclassified\ samples}{Overall\ samples} \times 100 \qquad (12)$$

4. Results and Discussion

In this research, the seizure-recognizing values of the ESR-ICOADL model are examined on the EEG dataset [23], as portrayed in Table 1.

Table 1. Specification of dataset

Class Labels	Classes	Instance Numbers
EEG signals with seizure	Activity	2300
EEG signals without seizure	Non-Activity	9200
Total Number of Instances		**11500**

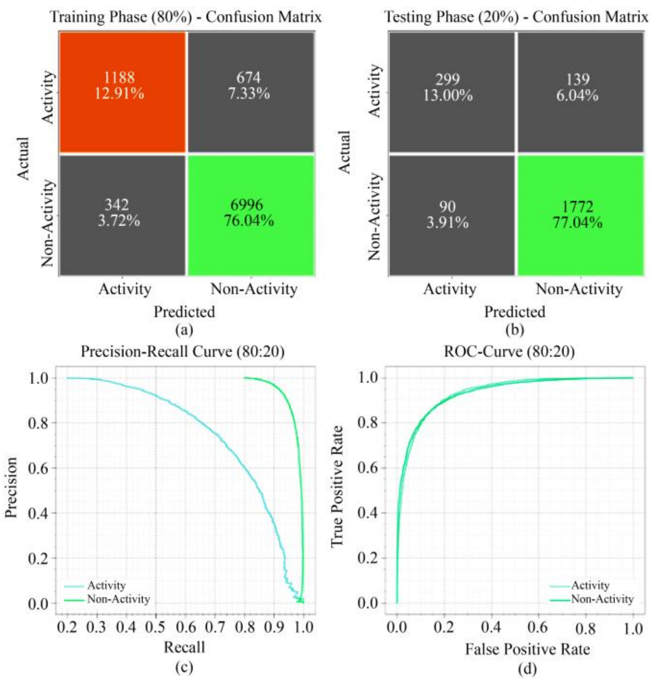

Fig. 3 (a-b) Confusion matrices, (c-d) PR and ROC curve under 80:20 of TR/TS phase

Figure 3 portrays the classifier evaluation of the ESR-ICOADL approach with the TR dataset. Figures 3a and 3b illustrate the confusion matrices of the ESR-ICOADL approach at 80:20 of TR/TS. The figure shows that the ESR-ICOADL method can be correctly classified and identified into two classes. Also, Figure 3c portrays the PR accomplishment of the ESR-ICOADL technique. The figure shows that the ESR-ICOADL technique achieves greater PR accomplishments in each class. Furthermore, Figure 3d signifies the ROC assessment of the ESR-ICOADL technique. This figure revealed that the ESR-ICOADL technique paves the way to capable outputs with enriched values of ROC with each class. In Table 2 and Figure 4, the overall seizure detection outputs of the ESR-ICOADL methodology are portrayed. The evaluation outputs illustrate that the ESR-ICOADL methodology appropriately recognized two classes. On 80% TR, the ESR-ICOADL method presents an average $accu_y$ of 88.96%, $sens_y$ of 79.57%, $spec_y$ of 79.57%, F_{score} of 81.64%, and MCC of 63.82%. Also, with 20% TS, the ESR-ICOADL model presents an average $accu_y$ of 90.04%, $sens_y$ of 81.72%, $spec_y$ of 81.72%, F_{score} of 83.12%, and MCC of 66.44% corresponding.

Table 2. Seizure detection output of ESR-ICOADL technique under 80:20 of TR/TS phase

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}	MCC
80% TR					
Activity	88.96	63.80	95.34	70.05	63.82
Non-Activity	88.96	95.34	63.80	93.23	63.82
Average	**88.96**	**79.57**	**79.57**	**81.64**	**63.82**
20% TS					
Activity	90.04	68.26	95.17	72.31	66.44
Non-Activity	90.04	95.17	68.26	93.93	66.44
Average	**90.04**	**81.72**	**81.72**	**83.12**	**66.44**

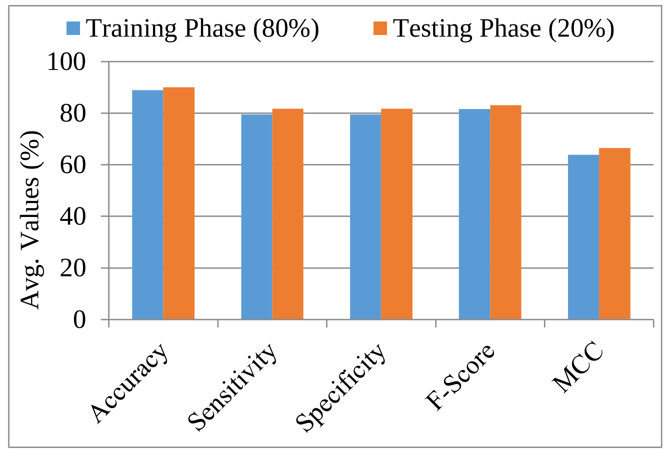

Fig. 4 Average of ESR-ICOADL technique under 80:20 of TR/TS phase

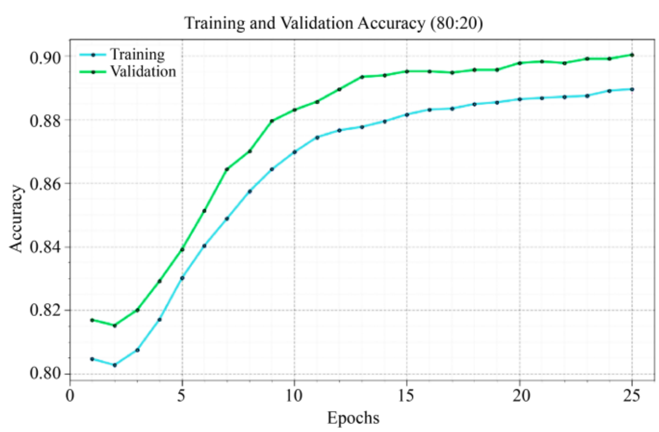

Fig. 5 $Accu_y$ the curve of the ESR-ICOADL technique under 80:20 of the TR/TS phase

To determine the accomplishment of the ESR-ICOADL method at 80:20 of TR/TS and the $accu_y$ curves with several epochs are evaluated, as depicted in Figure 5. This figure provides useful evidence with regard to the generalization proficiencies and learning processes of the ESR-ICOADL approach. Thereby, an improvement in epochs could be seen, which resulted in boosted TR/TS $accu_y$ curves. It is perceived that the ESR-ICOADL approach gains enhanced TR accurateness that can detect the designs under TR/TS. Figure 6 portrays a complete loss outcome of the ESR-ICOADL approach with 80:20 of TR/TS. The TR evaluation shows that epochs mitigate the attained loss. Majorly, the loss outcomes are lessened as the approach changes the weight to lower anticipative errors on the TR/TS datasets. This loss outcome establishes the range where the method is fitted to the TR dataset. It is noted that the loss is slowly mitigated, and it has been revealed that the ESR-ICOADL system efficiency gains the designs represented in the TR/TS datasets. Also, it could be observed that the ESR-ICOADL system changes the measurements to lessen the discrimination amid the actual and anticipated TR classes.

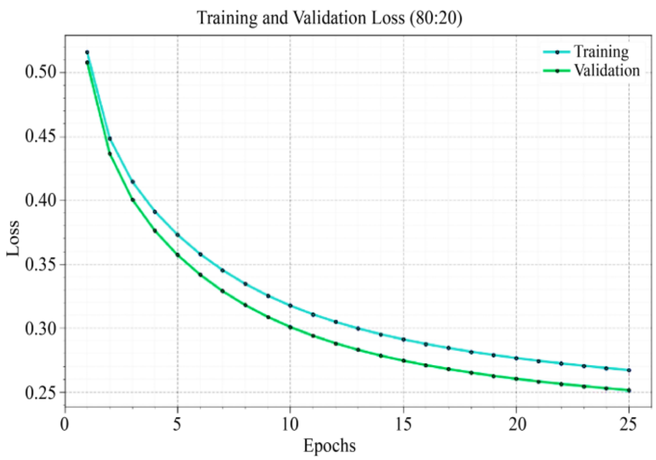

Fig. 6 Loss curve of ESR-ICOADL technique under 80:20 of TR/TS phase

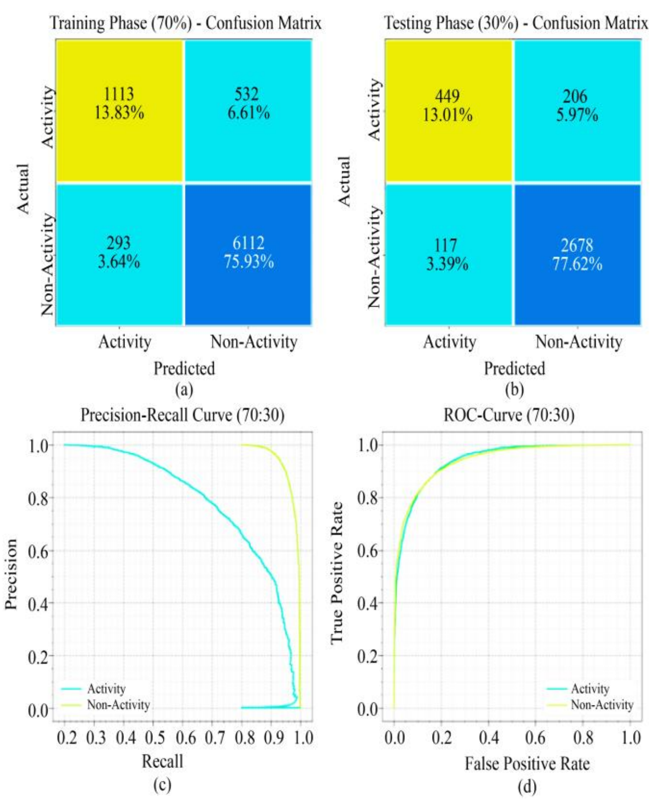

Fig. 7 (a-b) Confusion matrices, (c-d) PR and ROC curve under 70:30 of TR/TS phase

Figure 7 portrays the classifier evaluation of the ESR-ICOADL methodology with TR databases. Figures 7a and 7b illustrate the confusion matrices of the ESR-ICOADL approach under 70:30 of TR/TS. The figure depicted that the ESR-ICOADL approach could be classified and identified into two classes. Additionally, Figure 7c portrays the PR accomplishment of the ESR-ICOADL methodology. The figure indicates that the ESR-ICOADL methodology acquires superior PR accomplishment with each class. Also, Figure 7d indicates the ROC assessment of the ESR-ICOADL approach. This figure revealed that the ESR-ICOADL approach leads to effectual outputs with improved ROC with every class. In Table 3 and Figure 8, the complete seizure detection evaluation of the ESR-ICOADL approach is portrayed. The simulated outputs portrayed that the ESR-ICOADL approach properly recognized two classes. According to 70% TR, the ESR-ICOADL model presents an average $accu_y$ of 89.75%, $sens_y$ of 81.54%, $spec_y$ of 81.54%, F_{score} of 83.32%, and MCC of 67.00%. Also, on 30% TS, the ESR-ICOADL approach gives an average $accu_y$ of 90.64%, $sens_y$ of 82.18%, $spec_y$ of 82.18%, F_{score} of 83.93%, and MCC of 68.16% subsequently. To calculate the performance of the ESR-ICOADL approach with 70:30 of TR/TS, the $accu_y$ curves can be determined, as revealed in Figure 9. The $accu_y$ curves denote the output of the ESR-ICOADL approach over several epochs. This figure presents eloquent data concerning the generalization proficiencies and learning processes of the ESR-ICOADL system. By raising the epochs, the TR/TS $accu_y$ curves acquire improved results. Also, the ESR-ICOADL method improves TR accuracy, which can detect designs in the TR/TS datasets.

Table 3. Seizure detection output of ESR-ICOADL technique under 70:30 of TR/TS phase

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}	MCC
70% TR					
Activity	89.75	67.66	95.43	72.96	67.00
Non-Activity	89.75	95.43	67.66	93.68	67.00
Average	**89.75**	**81.54**	**81.54**	**83.32**	**67.00**
30% TS					
Activity	90.64	68.55	95.81	73.55	68.16
Non-Activity	90.64	95.81	68.55	94.31	68.16
Average	**90.64**	**82.18**	**82.18**	**83.93**	**68.16**

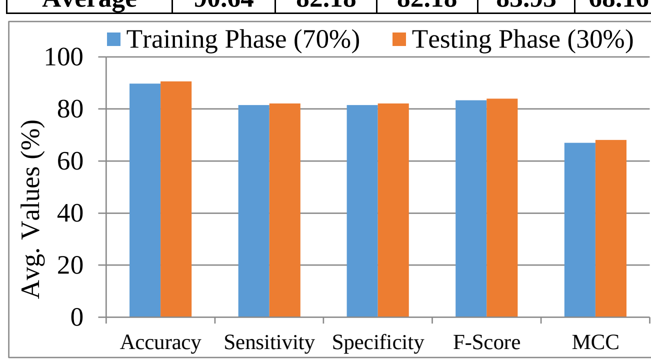

Fig. 8 Average of ESR-ICOADL technique in 70:30 of TR/TS phase

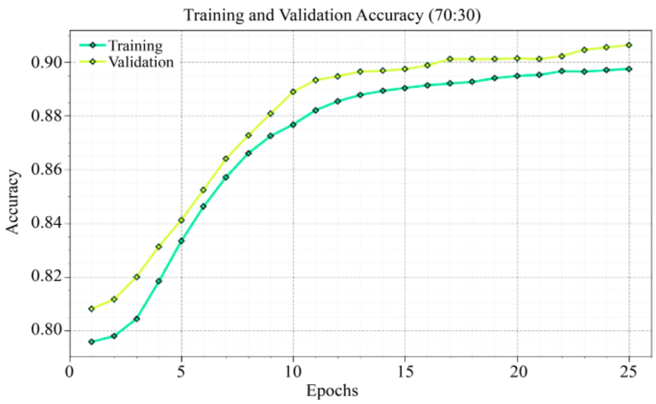

Fig. 9 $Accu_y$ curve of the ESR-ICOADL technique in 70:30 of the TR/TS phase

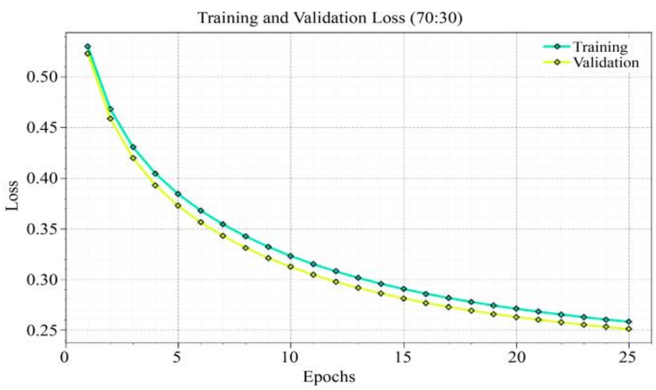

Fig. 10 Loss curve of ESR-ICOADL model in 70:30 of TR/TS phase

Figure 10 illustrates a complete TR/TS loss outcome of the ESR-ICOADL approach with 70:30 of TR/TS. Also, the TR loss illustrated that the method acquired lessened over epochs. Generally, the loss reduces as the method alters the weight to lessen the predictive errors with the TR/TS datasets. The outcome makes the level at which the method fits the trained datasets and could be slightly lessened, stating that the ESR-ICOADL model efficiently gains the pattern shown in the TR/TS datasets. Also, the ESR-ICOADL model alters the measurements to diminish the deviation between the initial and evaluated TR class. In Table 4 and Figure 11, the comparison outputs of the ESR-ICOADL approach are portrayed [24]. The obtained values depicted that the linear SVM, KNN, and MLP models showed poorer performance with $accu_y$ values of 76.70%, 76%, and 78%, while, the KELM, SA-KELM, and M-Gaussian-SVM models reported improved $accu_y$ values of 80.53%, 82.49%, and 81.40%, respectively. But, the ESR-ICOADL system depicted maximum performance with $accu_y$ of 90.64%. Thus, the ESR-ICOADL system can be utilized for precise seizure detection.

Table 4. $Accu_y$ output of the ESR-ICOADL technique with other models

Methods	Accuracy (%)
ESR-ICOADL	90.64
KELM	80.53
SA-KELM	82.49
M-Gaussian-SVM	81.40
Linear SVM	76.70
KNN	76.00
MLP	78.00

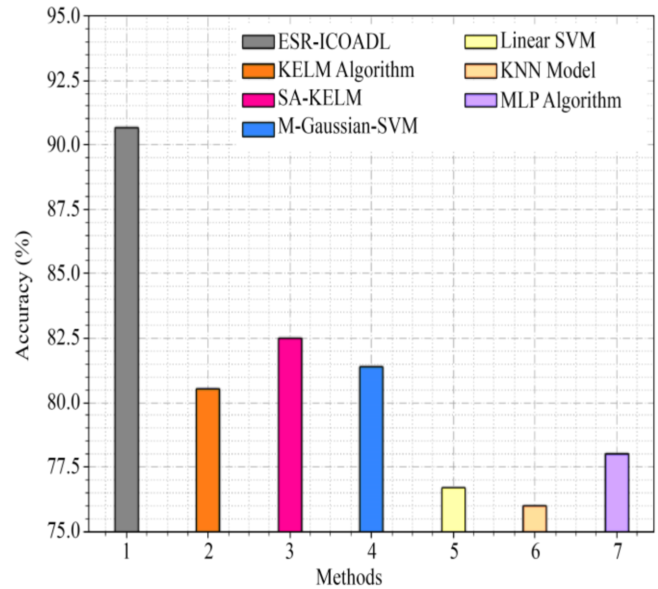

Fig. 11 $Accu_y$ outcome of the ESR-ICOADL approach with other models

5. Conclusion

This study has developed an automated Epileptic Seizure Recognition using the ESR-ICOADL technique on EEG. The ESR-ICOADL technique aims to investigate the EEG signals to detect and classify epileptic seizures. It involves a three-phase process, namely preprocessing, ICOA-based tuning, and BiGRU-based classification. Initially, the ESR-ICOADL approach applies the data preprocessing stage for converting the input data to a sensible format.

For epileptic seizure recognition, the ESR-ICOADL approach exploited the BiGRU method. Lastly, the tuning process of the BiGRU model could be boosted by employing ICOA, which supports accomplishing enhanced classifying outputs. The performance analysis of the ESR-ICOADL approach is investigated on EEG datasets, and the results illustrate the significant results of the ESR-ICOADL approach through diverse measures.

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