Automated Epileptic Seizure Detection using Improved Crystal Structure Algorithm with Stacked Autoencoder

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***Abstract*—Epilepsy can be referred to as a neurological disorder, categorized by intractable seizures with serious consequences. To forecast such seizures, Electroencephalogram (EEG) datasets should be gathered continuously. EEG signals were recorded by using numerous electrodes fixed on the scalp that cannot be worn by patients continuously. Neurostimulators can intervene in advance and ignore the seizure rate. Its productivity is increased by using heuristics such as advanced seizure prediction. In recent times, several authors have deployed various deep learning approaches for predicting epileptic seizures, utilizing EEG signals. In this work, an Automated Epileptic Seizure Detection using Improved Crystal Structure Algorithm with Stacked Auto encoder (AESD-ICSASAE) technique has been developed. The presented AESD-ICSASAE technique executes a three-stage process. At the initial level, the AESD-ICSASAE technique applies min-max normalization approach to normalize the input data. Next, the AESD-ICSASAE technique uses ICSA based feature selection method for optimal choice of features. Finally, the SAE based classification process takes place and the hyperparameter selection process is performed by Arithmetic Optimization Algorithm (AOA). To depict the enhanced classification outcomes of the AESD-ICSASAE technique, series of experiments was made. Furthermore, the proposed method's results have been tested utilizing the CHB-MIT database, with results indicating an accuracy of 98.9%. These results validate the highest level of accuracy in seizure classification across all of the analyzed EEG data. A full set of experiments validated the AESD-ICSASAE method's enhancements.**

Keywords*—*Deep learning; EEG signals; epileptic seizure detection; hyperparameter tuning; stacked autoencoders

I. Introduction

Epilepsy is a disease of the central nervous system caused by irregularities in brain electricity [1]. Seizures occur often and often without notice, making this a diagnosis. Epilepsy manifests itself with episodes of temporarily diminished or suspended consciousness, brief periods of unconsciousness, and abrupt, severe convulsions [2]. Epilepsy has a significant effect on people's life since it may result in catastrophic events, mental decline, and restrictions on routine tasks. Patients with epilepsy would benefit more from a method to predict when they will have seizures so that they can avoid injury and begin treatment immediately [3]. In addition, it lays the way for seizure intervention mechanisms to be used to prevent impending seizures and individualized epilepsy treatment (tailored medicine with minimal side-effects). Numerous studies have recently shown that the onset of epileptic seizures may be predicted with some degree of accuracy [4], suggesting that individuals with epilepsy might benefit from seizure prediction methods. The EEG is now the most widely used instrument for seizure detection [5]. Examining pre-seizure EEG activity for specific patterns that signal future seizures was the key challenge, and this was overcome in the reported study [6]. Epileptic seizures lead to a rapid increase in electrical disturbances in brain of patients, which is measured utilizing the EEG approach [7]. Generally, EEG signal recordings were scrutinized by neurologists for determining different levels of epilepsy such as interictal (in-between seizures), ictal (on-going seizures), post-ictal (after seizure onset period), and preictal (just before seizure onset) [8]. But this process can be time-taking, and arduous, which results in the need for automated epileptic seizure predictive mechanism. Deep learning (DL) was another pattern in this regard, which can manage the large signal dataset produced by wearable IoT sensing gadgets such as EEG headsets for epilepsy [9]. The methods depend on DL methods solve the restrictions of conventional Machine Learning (ML) methods by providing less processing duration and ability of managing big data of multichannel biomedical signals. Accordingly, such methods serve promising roles in offering real time solutions in healthcare field [10].

In this paper, an Automated Epileptic Seizure Detection using Improved Crystal Structure Algorithm with Stacked Auto encoder (AESD-ICSASAE) technique has been developed. The presented AESD-ICSASAE technique executes a three-stage process. The AESD-ICSASAE methodology begins with a min-max normalization stage to standardize the input data. After that, an ICSA-based feature selection methodology is used by the AESD-ICSASAE method to choose the best features. In the end, the SAE-based method of classification is carried out, and the AOA is the one responsible for carrying out the hyperparameter selection procedure. Multiple computations have been performed to show how the AESD-ICSASAE technique improves classification accuracy.

A. Key Contributions

The work presented here introduces an automated system for identifying epileptic seizures termed AESD-ICSASAE. The methodology employed by the authors involves the utilization of deep learning methodologies, particularly stacked autoencoders (SAEs), for the purpose of examining EEG data.

Here we propose using the AOA to choose appropriate the hyperparameters and a modified version of the crystal structure algorithm (ICSA) to choose appropriate attributes. The AESD-ICSASAE approach greatly enhances classification accuracy, providing a possible choice for real-time seizure forecasting and tailored epilepsy therapy, according to the experimental findings.

The following outline describes how the remaining parts of this work are structured: Section II demonstrates current and significant work. The conceptual design of the proposed system is presented in Section III. Both findings and analysis of the simulations are discussed in Section IV. Challenges and limitations are discussed in Section V. The work is concluded in Section VI.

II. Related Works

In [11], Epilepsy convulsions using EEG recordings were detected using the wavelet transform and then classified using ML algorithms as either not a seizure or a seizure. In all, 48 occurrences were selected from the collected EEG signals obtained via the CHB-MIT scalp EEG data. Hence, this data was segmented using Tuneable Q-Wavelet Transform (TQWT), and time-frequency characteristics like entropy were extracted. and temporal parameters were extracted to provide a huge dataset for accurately identifying epilepsy occurrences. Utilizing Random Forest (RF) and Support Vector Machine (SVM) classifiers, the dataset is further processed for classifying epilepsy. Jaiswal and Banka [12] proposed 2 effectual methods including Subpattern related PCA (SpPCA) and cross-subpattern correlation-related PCA (SubXPCA) includes SVM for automated seizure recognition in EEG signals. Feature extraction has been executed utilizing SubXPCA and SpPCA. Both methods explore sub pattern relation of EEG signals, which aids in making decisions.

By focusing on what makes seizures unique, Qureshi et al. [13] were able to develop a system for Epileptic Seizure Detection (ESD) that uses both traditional ML algorithms and fuzzy-based approaches. In this work, the raw input divides unknown EEG input segments into interictal and ictal groups. Bairagi and Harpale [14] introduced a novel technique, Singular Spectrum Empirical Mode Decomposition (SSEMD) for effectual categorization of Epileptic and Normal EEG Signals. For classifying EEG signals in normal and epileptic classes, high-performance ML classifiers were employed. In [15], an end-to-end ML method was modelled for recognition of epileptic seizures utilizing the pretrained deep 2D-CNN and concept of Transfer Learning (TL).

In [16], a Principal component analysis (PCA) with Genetic Algorithm (GA) related ML method can be advanced for classifying binary epileptic seizures out of EEG dataset. The presented method leverages PCA for minimizing the count of attributes for binary classification of epileptic seizures and can be implemented in the prevailing ML techniques for assessing model performance compared with more features. In this study, GA was used for tuning the hyperparameters of ML methods to detect the optimal ML method. To find the best SVM parameters for categorizing EEG recordings, Subasi et al. [17] develop a hybrid strategy for ESD using GA and Practical Swarm Optimization (PSO). SVMs are one of robust ML approaches and were widely leveraged in several application zones. The kernel parameter's setting for SVMs in training effects the classifier accuracy. The authors employed GA- and PSO-related techniques for optimizing the SVM parameters.

The AESD-ICSASAE method represents a notable advancement over prior methodologies for the automated detection of epileptic seizures, exhibiting superior performance in multiple aspects. The approach employed involves the utilization of deep learning techniques, particularly stacked autoencoders (SAEs), to more efficiently capture intricate patterns present in EEG signals compared to conventional ML methods. The utilization of an enhanced crystal structure algorithm (ICSA) facilitates superior feature selection, thereby tackling the difficulty of discerning pertinent features from voluminous EEG datasets. Furthermore, the AOA facilitates the optimization of hyperparameter selection, thereby augmenting the efficacy of the overall model. The suggested system exhibits superiority over prior approaches due to its ability to achieve greater categorization accuracy, enhanced computational efficiency, and increased interpretability, all of which are attributed to the recent advances.

III. The Proposed Model

A novel AESD-ICSASAE technique for reliable ESD on EEG data was developed in this paper. The presented AESD-ICSASAE technique executes a three-stage process.

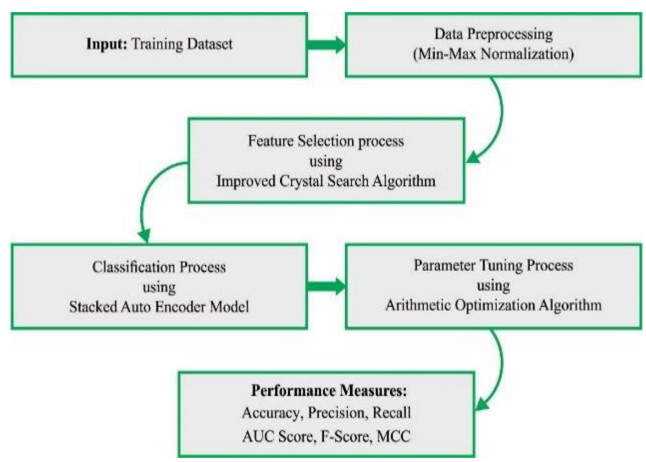

Fig. 1. Structure of the AESD-ICSASAE scheme.

As a first step, the AESD-ICSASAE method uses a min-max normalization methodology to standardize the input data. After that, an ICSA-based feature selection strategy is used by the AESD-ICSASAE method to choose the most relevant characteristics. At last, the AOA with SAE based classification process takes place. Fig. 1 represents the workflow of AESD-ICSASAE model.

A. Data Normalization

In the beginning, the AESD-ICSASAE method utilizes a min-max normalization strategy in order to standardize the input data. The process of Min-Max normalization involves applying a linear transformation to the original dataset. $MaxA$ and $MinA$ represent the upper and lower bounds of attribute A, accordingly. The process of Min-Max normalization involves mapping the value of variable A to a new value, denoted as v', within a specified range. This is achieved by computing the difference between the new_MinA and new_MaxA. The threshold value for Min-Max range was fixed as [0,1]

$$V' = \frac{V - \text{Min } A}{\text{Max } A - \text{Min } A}(new\_MaxA - new\_MinA) + new\_MinA \quad (1)$$

B. Feature Selection using ICSA Technique

The AESD-ICSASAE method currently employs an ICSA-based strategy for selecting features. The mathematical modeling of CSA is developed where the aim is to utilize crucial modification [18]. Now, all the candidate solutions of optimization technique are considered as a single CSA in the space. CSA counts are determined at random for the initialization of iteration purposes.

$$Cr = \begin{bmatrix} Cr_1 \\ Cr_2 \\ \vdots \\ Cr_i \\ \vdots \\ Cr_n \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^j & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & x_2^j & \dots & x_2^d \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_i^1 & x_i^2 & \dots & x_i^j & \dots & x_i^d \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \dots & x_n^j & \dots & x_n^d \end{bmatrix} \begin{cases} i = 1,2,\dots,n \\ j = 1,2,\dots,d \end{cases} \quad (2)$$

In Eq. (2), n indicates the CSA count and d designates the problem dimension. The initial location of CSA can be determined at random in the searching space as follows:

$$x_i^j(0) = x_{i,\min}^j + \xi\left(x_{i,\max}^j - x_{i,m\dot{m}}^j\right), \begin{cases} i = 1,2,\dots,n \\ j = 1,2,\dots,d \end{cases} \quad (3)$$

Now, $x_i^j(0)$ correspondingly represents the initial CSA position, $x_{i,\min}^j$ and $x_{i,\max}^j$ shows the minimal and maximal permissible values for j^{th} variable of i^{th} solution candidate and ξ indicate random number within [0, 1]. All the CSA at the corner can be assumed as the main CSA related to the concept of 'basis' in CSAlography, in which Cr_{main} is determined at random by assuming the initially made CSA. Note that arbitrary selection for every step can be determined by ignoring current Cr. The CSA with optimum formation can be determined as Cr_b while mean value of arbitrarily selected CSA is signified by F_c.

In order to upgrade the location of solution candidate in searching space, fundamental principle was deliberated:

a) Simple cubicle:

$$Cr_{new} = Cr_{old} + rCr_{main}, \quad (4)$$

b) Cubicle with the best CSAs:

$$Cr_{new} = Cr_{old} + r_1 Cr_{main} + r_2 Crb, \quad (5)$$

c) Cubicle with the mean CSAs:

$$Cr_{new} = Cr_{old} + r_1 Cr_{main} + r_2 F_c, \quad (6)$$

d) Cubicle with the best and mean CSAs:

$$Cr_{new} = Cr_{old} + r_1 Cr_{main} + r_2 Crb + r_3 F_c, \quad (7)$$

Now, the novel location is denoted by Cr_{new}, the older location can be represented by c_{rold}, and r, r_1, r_2 and r_3 denotes the random number. To provide the best possible results from the classifier, the CSO technique includes a fitness function (FF) whose values are skewed towards the positive to highlight the superiority of the candidates.

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \quad (8)$$

The fitness function (FF) employed in the ICSA method was developed to have a balance between classifier accuracy (maximum) and the number of chosen features in all solutions (min) obtained by using such selected features, Eq. (9) denotes the FF for evaluating solutions.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \quad (9)$$

Whereas $\gamma_R(D)$ signifies the classifier error rate of presented techniques. $|C|$ is total number of features in the dataset, $|R|$ denotes the cardinality of the selected subset, α and β were two parameters that match the importance of subset length and classification quality. $\in$ [1, 0] and $\beta = 1 - \alpha$.

In order to create the ICSA, the chaos theory was used in the design process. The evolution of chaos exhibits regularity, nonrepeat ergodicity, and unpredictability, and it is a nonlinear process that may be sensitive to the starting state. Such attributes enable particles to hasten the convergence speed of method, escape from local optimization, and establish good spatial distribution. To participate in population initialization, chaotic series related to Tent map was employed and it can be formulated below.

$$f(x) = \begin{cases} 2x & 0 \le x \le 0.5 \\ 2(1-x) & 0.5 < x \le 1 \end{cases} \quad (10)$$

The formula of Tent map afterward Bernoulli transform can be expressed:

$$f(x) = \begin{cases} 2x & 0 \le x \le 0.5 \\ 2x - 1 & 0.5 < x \le 1 \end{cases} \quad (11)$$

C. Seizure Recognition using Optimal SAE

In this work, the SAE based classification process takes place. The SAE method obtains the feature vector as input to assign appropriate class labels. AE was a kind of unsupervised learning framework which has 3 states namely input, hidden states and output [19]. The process of AE trained includes encoded and decoded parts. Fig. 2 depicts the infrastructure of SAE. The encoded part is used for mapping the input dataset to hidden demonstration and decoded part is used to regenerate input dataset in hidden demonstration. To give the unlabeled source dataset $\{x_n\}_{n=1}^{N}$, while $x_n \in R^{m\times 1}$, h_n signifies hidden encoded vector analyzed in x_n, and $\hat{x}_n$ indicates decoded vector of final state and encoder procedure can be defined in such a way:

$$h_n = f(W_1 x_n + b_1) \quad (12)$$

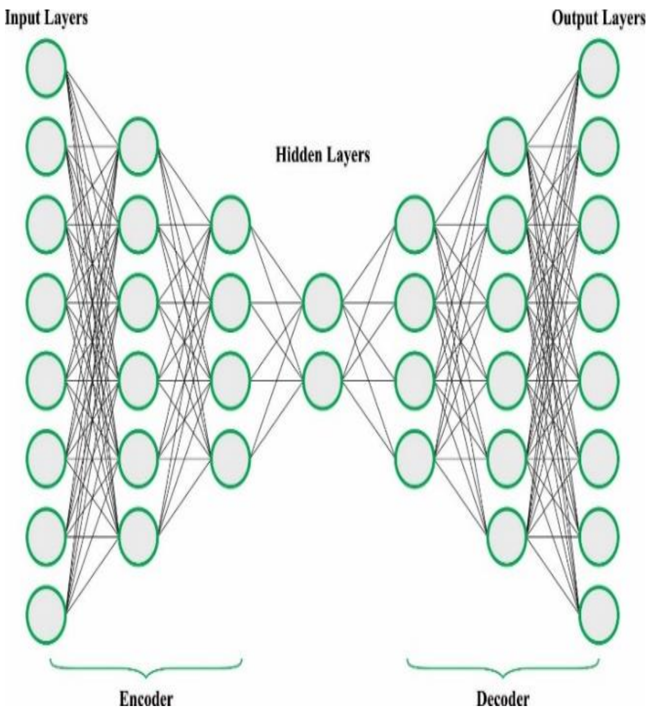

Fig. 2. Architecture of SAE.

While f represents the encoded operation, W_1 stands for the weighted matrix associated with the encoded, and b_1 displays the bias vector. This method of decoding may be characterized as follows:

$$\hat{x}_n = g(W_2 h_n + b_2) \quad (13)$$

The decoded perform is denoted by g, while the weighted matrix of decoding are represented by W_2, and the bias vector is denoted by b_2. To reduce the amount of inaccuracy in the reconstruction, AE's collection of variables was fine-tuned.

$$\emptyset(\Theta) = \arg\min_{\theta,\theta'} \frac{1}{n}\sum_{i=1}^{n} L\left(x^i, \hat{x}^i\right) \quad (14)$$

While L denotes a loss function $L(x, \hat{x}) = \|x - \hat{x}\|^2$.

SAE uses a stacking technique to map n AEs to n hidden states using an unsupervised state-wise learning approach, before tuning using a supervised technique. Because of this, we may classify the SAE-based technique in the following ways:

1) The first step was to train the first AE using the input dataset to produce a feature vector;

2) The second phase was to use that feature vector as input for the next stage, and so on, until the process stopped.

3) Afterwards, all hidden states are trained, and the BP technique is used to minimize the cost function and improve the weight using labelled trained sets to achieve tuning.

Finally, the hyperparameter selection process is performed by the AOA resulting in enhanced performance. This optimization technique primarily relies on exploration and development stages [20]. The searching space for candidate solutions can be covered generally to break deadlock of method falling into search stagnation in exploration stage.

In the preliminary step of AOA's optimized approach, the sequence of potential solutions was constructed randomly.

$$X = [_{\chi_{N-1,1}}\chi_{N,1}\chi_{2,\cdot\cdot,1}\chi 1,1\ \chi_{N-1,j}\chi_{N,j}\chi_{2,j}\chi 1,j\ \chi_{N,n-1}\chi_{1,\cdot,\cdot n-1}\ \chi_{N-l,n}\chi_{1,n}\chi_{N,n}\chi_{2,\dots,n}{}']$$

$$X = \begin{bmatrix} x_{1,1} & \cdots & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots & \cdots & x_{2,j} & \cdots & x_{2,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots & \cdots & x_{N-1,j} & \cdots & x_{N-1,n} \\ x_{N,1} & \cdots & \cdots & x_{N,j} & x_{N,n-1} & x_{N,n} \end{bmatrix} \quad (15)$$

Before the AOA can put the optimized method into action, it must complete the searching phase based on the resultant value of the Math Optimizer Accelerated (MOA) functioning, which may be calculated using the formula below.

$$MOA(C\_Iter) = \text{Min} + C\_Iter \times \left(\frac{Max - \text{Min}}{M\_Iter}\right) \quad (16)$$

We may see the function's value after $\_Iter$ iterations by looking at $MOA(C\_Iter)$; C_Iter shows the existing iteration; M_Iter indicates the maximal iteration amount; Min and Max stand for the minimum and maximum values of the accelerated function, respectively.

The exploration phase is realized mainly by the two operators namely Division (D) and Multiplication (M). In mathematical computation, these two operators are accomplished tremendously distributing value, for the considerable amount of candidate solutions were covered. In exploration technique, the position of candidate solution can be considerably upgraded by the following expression:

$$x_{i,j}(C\_Iter + 1) = \begin{cases} best(x_j)/(MOP + \varepsilon) \times ((UB_j - LB_j) \times \mu + LB_j) & r_2 < 0.5 \\ best(x_j) \times MOP \times (UB_j - LB_j) \times \mu + LB_j & otherwise \end{cases} \quad (17)$$

Now $\chi_{i,j}(C\_Iter + 1)$ denotes the j^{th} location of i^{th} solution in $(C\_Iter + 1)th$ iteration; ε represents the small value; The UB and LB indicate the maximum and minimum possible distances to a proposed solution; μ is applied to regulate exploration stage that was set to 0.5.

$$MOP\ (C\_Iter) = 1 - \frac{C\_Iter^{\frac{1}{\alpha}}}{M\_Iter^{\frac{1}{\alpha}}} \quad (18)$$

The variable α is utilized to establish the degree of effectiveness of the exploitation process during each iteration, where α is assigned a value of 5. The utilization of the exploitation process is contingent upon two operators, specifically Addition (A) and Subtraction (S), which are conducive to minimizing dispersion in candidate solutions and can be implemented through extensive search techniques with a heightened likelihood of approximating the best possible solution.

$$x_{i,j}(C_{Iter} + 1) = \begin{Bmatrix} best(x_j) - MOP \times ((UB_j - LB_j) \times \mu + LB_j, & r_3 < 05 \\ best(x_j) + M0P \times ((UB_j - LB_j) \times \mu + LB_j, & otherwise \end{Bmatrix} \quad (19)$$

Algorithm 1: Pseudo code for AOA

Populace size (N) and maximum iterations (T) are set to their default values.
The starting position of each individual searching agent, $X_i(i = 1,2, \ldots, N)$
Input values are $\alpha, \mu,$ Min, and Max
While $(t \le T)$
Assess the fitness of every search agent, Upgrade best Fitness, X_b
Assess the MOP
Assess the MOA
For every search agents
If $rand > MOA$
Upgrade position
Else
Upgrade position
End if
End for
$$t = t + 1$$
End While
Return best Fitness, X_b

The flexible changes between the exploration and utilization steps enable the AOA approach to finding the best answer and remain to offer a wide range of options for a broad search.

IV. Results and Discussion

In this section, we verify the AESD-ICSASAE technique's experimental outcome evaluation on a dataset [21,22], of 40000 observations and two categories of classes, illustrated in Table I. The AESD-ICSASAE method has chosen a set of 7 features out of 23 features.

TABLE I. A Comprehensive Overview of the Dataset

Type of Classes	Total number of Observations
Seizure	20,000
NonSeizure	20,000
Overall Observations	**40,000**

In Fig. 3, the confusion matrices of the AESD-ICSASAE model are demonstrated. The results demonstrated that the AESD-ICSASAE model has shown accurate classification of seizure and no seizure class samples.

Table II presents the comprehensive outcomes of detecting seizures achieved by the AESD-ICSASAE approach, utilizing 60% of the Training set (TR) and 40% of the Testing set (TS) records. The AESD-ICSASAE method's brief findings for classification using 60% of the TR dataset are shown in Fig. 4. Samples belonging to the seizure and no seizure classes were correctly recognized using the AESD-ICSASAE methodology. In addition, it is noticed that the AESD-ICSASAE model at training phase has attained overall accu_bal of 98.70%, prec_n of 98.70%, reca_l of 98.70%, F_score of 98.70%, AUC_score of 98.70%, and MCC of 97.41%.

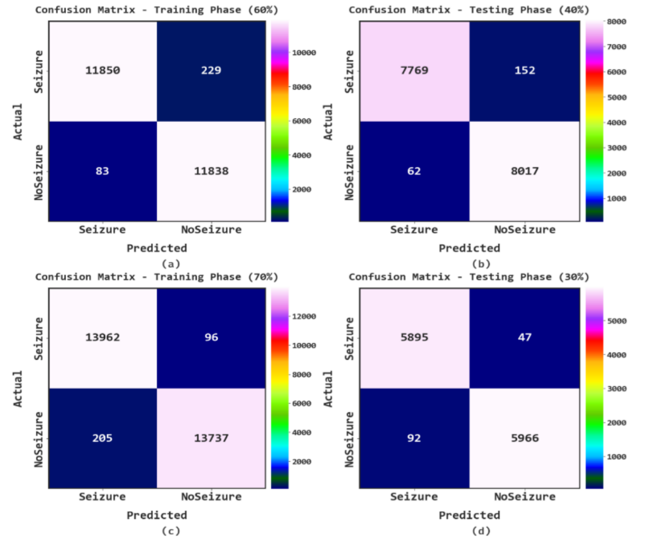

Fig. 3. Confusion matrix of the AESD-ICSASAE approach for the training (TR) and testing (TS) databases with a ratio of 60:40 and 70:30, respectively.

TABLE II. Presents the Findings of Detecting Seizures using the AESD-ICSASAE Approach with a 60:40 Ratio of Training to Testing Databases

Training / Testing (60:40)						
Class	$\boldsymbol{Accu_{bal}}$	$\boldsymbol{Prec_n}$	$\boldsymbol{Reca_l}$	$\boldsymbol{F_{score}}$	**Score of AUC**	**MCC**
Training Set						
Seizure	98.10	99.30	98.10	98.70	98.70	97.41
NoSeizure	99.30	98.10	99.30	98.70	98.70	97.41
Average:	**98.70**	**98.70**	**98.70**	**98.70**	**98.70**	**97.41**
Testing Set						
Seizure	98.08	99.21	98.08	98.64	98.66	97.33
NoSeizure	99.23	98.14	99.23	98.68	98.66	97.33
Average:	**98.66**	**98.67**	**98.66**	**98.66**	**98.66**	**97.33**

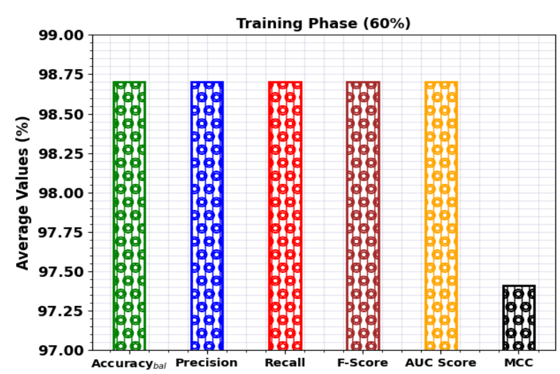

Fig. 4. Average outcome of AESD-ICSASAE approach under 60% of TR.

Table II presents the comprehensive outcomes of detecting seizures achieved by the AESD-ICSASAE approach, utilizing 60% of the Training set (TR) and 40% of the Testing set (TS) records. Fig. 5 presents the detailed classification outcomes of the AESD-ICSASAE method with 40% of TS database. The AESD-ICSASAE technique has properly identified the seizure and no seizure class samples. Moreover, it is visible that the AESD-ICSASAE methodology at testing phase has attained an average $accu_{bal}$ of 98.66%, $prec_n$ of 98.67%, $reca_l$ of 98.66%, F_{score} of 98.66%, AUC_{score} of 98.66%, and MCC of 97.33%.

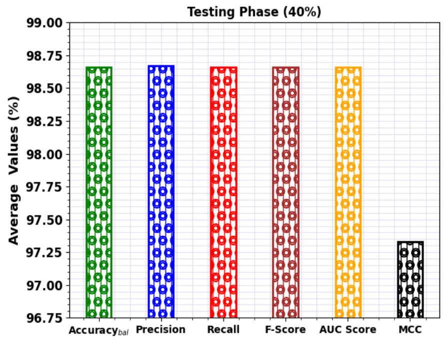

Fig. 5. Average outcome of AESD-ICSASAE approach under 40% of TS database.

Table III provides an overview of the AESD-ICSASAE method's detection findings for seizures using 70% of TR and 30% of TS datasets. The AESD-ICSASAE approach's quick classification results using 70% of the TR dataset are shown in Fig. 6. The AESD-ICSASAE technique has properly recognized the seizure and no seizure class samples. Also, it is noted that the AESD-ICSASAE method at training phase has acquired average $accu_{bal}$ of 98.92%, $prec_n$ of 98.93%, $reca_l$ of 98.92%, F_{score} of 98.92%, AUC_{score} of 98.92%, and MCC of 97.85%.

TABLE III. SEIZURE DETECTION OUTCOMES OF AESD-ICSASAE APPROACH UNDER 70:30 OF TR/TS DATASET

Training / Testing (70:30)						
Type of Class	$\boldsymbol{Accu_{bal}}$	$\boldsymbol{Prec_n}$	$\boldsymbol{Reca_l}$	$\boldsymbol{F_{score}}$	**Score of AUC**	**MCC**
Seizure_Training Set						
Seizure	99.32	98.55	99.32	98.93	98.92	97.85
NoSeizure	98.53	99.31	98.53	98.92	98.92	97.85
Average	**98.92**	**98.93**	**98.92**	**98.92**	**98.92**	**97.85**
Seizure_Testing set						
Seizure	99.21	98.46	99.21	98.83	98.85	97.69
NoSeizure	98.48	99.22	98.48	98.85	98.85	97.69
Average	**98.85**	**98.84**	**98.85**	**98.84**	**98.85**	**97.69**

Fig. 7 portrays brief classification outcomes of the AESD-ICSASAE methodology with 30% of TS database. The AESD-ICSASAE technique has properly identified the seizure and no seizure class samples. Additionally, it is noted that the AESD-ICSASAE technique at testing phase has achieved average $accu_{bal}$ of 98.85%, $prec_n$ of 98.84%, $reca_l$ of 98.85%, F_{score} of 98.84%, AUC_{score} of 98.85%, and MCC of 97.69%.

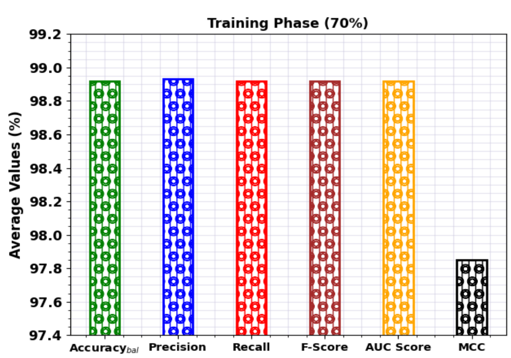

Fig. 6. Average outcome of AESD-ICSASAE technique under 70% of TR database.

Examining the AESD-ICSASAE approach's Training Accuracy (TACC) and Validation Accuracy (VACC) for seizure detection efficiency is shown in Fig. 8. The graph shows that greater TACC and VACC values result in greater efficiency for the AESD-ICSASAE method. The AESD-ICSASAE model is clearly the most successful in terms of TACC results.

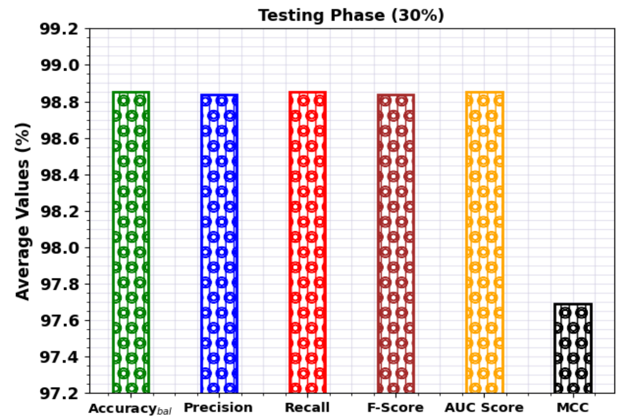

Fig. 7. Average outcome of AESD-ICSASAE approach in 30% of TS database.

Fig. 8. Depicts the TACC and VACC analyses of the AESD-ICSASAE approach.

In Fig. 9, the TLS and VLS of the AESD-ICSASAE model is put to the test in terms of their ability to identify the onset of a seizure. Based on the graph, it seems that the AESD-ICSASAE method performs better when TLS and VLS are kept to their absolute minimums. It has been shown that the AESD-ICSASAE method leads to diminished VLS results.

Fig. 9. TLS and VLS analysis of AESD-ICSASAE approach.

Fig. 10 presents the results of a clear precision-recall analysis of the AESD-ICSASAE database used to evaluate the tested methods. The results showed that the AESD-ICSASAE method improved precision-recall values across the board.

Fig. 11 displays the results of a comprehensive ROC analysis performed on the AESD-ICSASAE test database. That number meant the AESD-ICSASAE algorithm had successfully clustered together a number of different types.

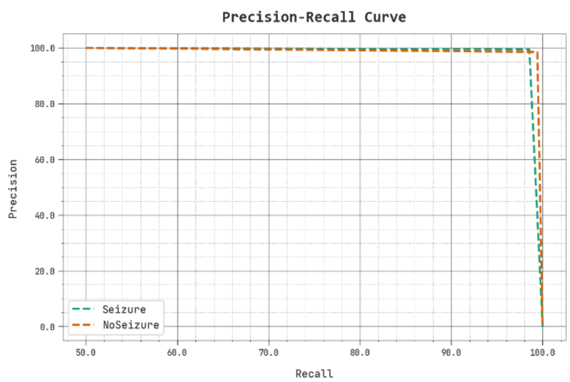

Fig. 10. Precision-recall analysis of AESD-ICSASAE method.

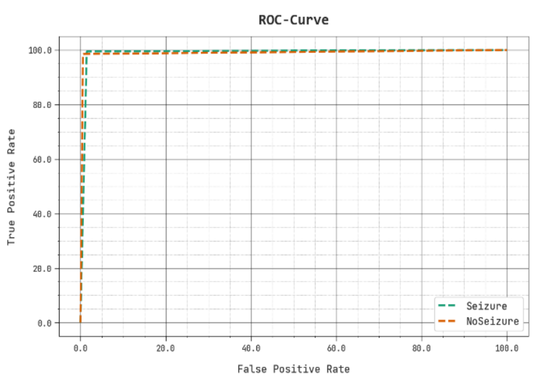

Fig. 11. ROC curve analysis of AESD-ICSASAE method.

Finally, the AESD-ICSASAE strategy superior accuracy may be verified at the ending phase through a comparative analysis, as depicted in Table IV and Fig. 12. The depicted figure indicates that the AESD-ICSASAE approach has exhibited enhanced efficacy, achieving an accu_y of 98.92%.

TABLE IV. COMPARISON OF THE AESD-ICSASAE SYSTEMS TO ALTERNATIVE METHODOLOGIES

Methodology used	$Accu_y$ **(%)**
AESD-ICSASAE	**98.92%**
DCAE-MLP	98.17%
SVM Model	82.39%
LR Model	81.32%
ResNet-152	90.63%
Inception-V3 Model	91.89%
EESC Model	93.92%

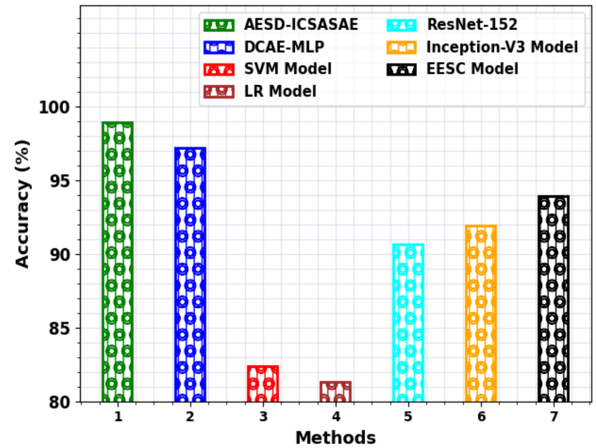

Fig. 12. Comparative analysis of AESD-ICSASAE system with other approaches.

In contrast, the existing models such as DCAE-MLP, SVM, LR, ResNet-152, Inception-v3, and EESC models have demonstrated certainly reduced accu_y of 97.17%, 82.39%, 81.32%, 90.63%, 91.89%, and 93.92% respectively. These results assured the supremacy of the AESD-ICSASAE model on seizure detection and classification.

V. Challenges and Limitations of Proposed Work

There are currently a number of restrictions and difficulties in the area of automated epileptic seizure identification. Several challenges arise in the application of EEG data analysis, such as inter-individual variability, the trade-off between sensitivity and specificity, poor generalization of current methods across different datasets and patient groups, the requirement for immediate implementation with high accuracy, interpretation of deep learning models, and a lack of data for training and evaluation purposes. To surmount these obstacles, it is necessary to undertake investigation efforts that are geared towards developing the applicability of findings, minimizing erroneous positive and negative outcomes, refining instantaneous being processed, augmenting comprehensibility, and broadening the availability of varied and inclusive datasets.

VI. Conclusion

This paper presents the AESD-ICSASAE algorithm, a novel method for performing precise ESD on EEG data. The described AESD-ICSASAE method is a three-step procedure. The first step of the AESD-ICSASAE method is to normalize the input data using a min-max normalization strategy. After that, an ICSA-related feature selection procedure is used by the AESD-ICSASAE method to choose the best features. Finally, improved performance is achieved by the AOA's hyperparameter selection process and categorization of SAE-related data. Experiments were conducted to illustrate the improved classification results achieved using the AESD-ICSASAE method. The simulations covered every possible scenario, ensuring that the AESD-ICSASAE method would improve. To boost the efficiency of the AESD-ICSASAE method, a fusion system based on ensemble voting may be developed in the future.

Additionally, there exist numerous elements that could be examined in the work. Initially, an inquiry into the generalizability of the AESD-ICSASAE methodology across diverse datasets and patient cohorts would offer valuable perspectives on its potential utility above the particular dataset employed. Furthermore, conducting an analysis of comparison with established methodologies could simplify an analysis of the merits and limitations of the suggested approach. Improving the comprehensibility of the outcomes through the identification of the influential characteristics or trends could improve its medical significance. Enhancing the real-time validity of the approach could be achieved through enhancing its efficiency in computing, particularly in managing substantial amounts of EEG data. Performing verification tests on additional data sets would confirm the efficacy and dependability of the aforementioned. Ultimately, an evaluation of the viability of executing the proposed methodology in real-time will determine its practicability in facilitating prompt seizure forecasts and strategies. Incorporating considerations related to generalization, effectiveness, comprehension, productivity, verification, and real-time accessibility would enhance the effectiveness of the AESD-ICSASAE methodology.

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