Received: February 24, 2023. Revised: March 20, 2023.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Improved Artificial Bee Colony Based Feature Selection for Epileptic Seizure Detection

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Abstract: According to WHO, 6 million people are affected by an epileptic seizure every year as per a survey carried out in 2019. At the moment, doctors use direct observation of the electroencephalogram (EEG) signal to determine the presence of an epileptic seizure. However, epileptic detection in most of the previous research works suffers from low accuracy and is unsuitable for processing large datasets. In this work, the seizure EEG signal is effectively detected and enhanced using Chebyshev normalization. Additionally, the signals are decomposed by applying fast empirical mode decomposition (EMD). Then, entropy features are extracted and effective selection is obtained by using the improved artificial bee colony (ABC) optimization algorithm. Finally, a stacked autoencoder (SAE) is used for better EEG classification. The existing researches such as MCAFF, CNN-RNN, ESSA, SVM and 1D-CNN are used for comparing the IABC-SAE method. The proposed IABC-SAE method gained better performance in seizure EEG signal identification and achieves higher classification accuracy (CA) of 99.98% in TUH-EEG database compared to the existing ESSA.

Keywords: Epileptic seizure, EEG signal, Chebyshev normalization, Fast empirical mode decomposition, Improved ABC optimization, Stacked auto encoder.

1. Introduction

According to the world health organization (WHO), epilepsy affected 50 million people worldwide in that 70% live seizure-free with proper analysis and action. On the contrary, 30% of people who are having epilepsy remain to suffer unidentifiable frequent seizures [1]. Epilepsy is one of the brain neurological chronic diseases that affect brain cells' electrical activities. The symptoms of the neurological disorder are muscle weakness, broken bones, loss of sensation, bleeding into the brain and breathing difficulties [2-3]. Epilepsy affects the brain as well as the nerves throughout the human body and spinal cord. Epilepsy is a very serious and most commonly occurring neurological syndrome [4]. Epilepsy is occurred because of the hyper-synchronous and excessive irregular electrical activities of neuron cells, which impact the both physical and mental health of the patient [5].

Epilepsy disease is characterized by paroxysmal events which are disrupted the neurons and neurotransmitters known as seizures which is growing from the irregular activation of neuronal networks [6-7]. Although it is rare, it is genuinely tough, and people need to be aware of the risk. [8]. Epilepsy is divided into two categories: focal and non-focal. In a focused disorder, only one hemisphere of the brain or another specific area of the brain is damaged. However, even though they were not directly impacted by the seizures, non-focal epilepsy has an impact on numerous brain regions. [9-10]. Therefore, they need surgical interference to treat the seizures as well as reduce the risks accompanied by invasive interference with the brain [11]. The electroencephalogram (EEG) signal is generally used golden standard method for epileptic detection as it is a condition related to the brain's electrical activity. It is the evaluation of brain electrical action by recording on the mainframe using small metal electrodes placed on the scalp [12-13]. EEG allows for obtaining focal and non-focal signals and provides effective brain records for examination as well as detection the neurological syndrome [14-15]. Therefore, this manuscript is mainly based on the feature selection and segmentation of the relevant aspects in the EEG-signal image classification.

The main contribution of the research is given as follows:

- In this recognition, a stacked auto-encoder classifier is used for classifying epilepsy seizures. In addition, it is handling high-dimensional data and extracted features help to overcome imbalanced data problems.
- Improved ABC optimization algorithm evaluates every fitness function to get the global optimal solution.

The remaining part of this work is arranged as follows: the existing work related to Seizure EEG signal classification is given in section 2. A clear explanation of the IABC-SAE is given in section 3 whereas the results and discussions of the existing and proposed work are given in section 4. Finally, the conclusion is presented in section 5.

2. Literature survey

This section provides a literature survey about the different techniques used in seizure EEG signal development. The following section presents the literature survey along with its advantages and limitations.

Darshana Priyasad [16] represented a novel deep learning based interpretable seizure organization using unprocessed EEG and multi-channel attentive feature fusion (MCAFF). In this work, the direct use of EEG signals supports the network to learn rich aspects as well as develop the rhythmic activity of the seizure. Additionally, the convolution block and SincNet filter were applied after the EEG wave of each chosen channel to offer a compact and personalized filter during model training. Finally, the selected fusion aspects were delivered to the classification network over the high-level features of the system. Therefore, architecture could easily extend the different frequency distribution of new channels along with retraining to the fusion and classify the sub-models of the function. Although, it takes much computation time and costs the function.

Anand Shankar [17] demonstrate the analysis and organization of epileptic seizures using the EEG recurrence plot (RP) images and CNN. It is possible to analyze non-linear, non-stationary, and brief data of the function using the RP. After that, the RP was directly fed into the CNN for performing the different kernel functions and analysis of the quality assessment of the system therefore, it would increase the error rate of the system.

Anis Malekzadeh [18] introduced a computer-aided diagnosis system for the automatic analysis of epileptic seizures in EEG signals using a fusion of handcrafted and deep learning aspects. Additionally, Bonn and Freiburg datasets were used to enhance the performance of the EEG detection including pre-processing, feature extraction, and classification of the system. First, they applied a band-pass filter with 0.5 to 40 Hz incidence for the elimination of substances in the EEG datasets and Tunable-Q Wavelet Transform for EEG signal rotting of the system. Then the CNN–RNN-based DL method improved the coherence and accuracy of the system detection of epileptic seizures from EEG signals. However, it was difficult to apply the signal band system of the function.

T. J. Rani, and D. Kavitha, [19] presented the deep learning based automatic discovery of normal and abnormal EEG signals. The artifacts from the EEG signals were removed by using the 8th order butter worth filter followed by the signal decomposition was achieved by using the swarm decomposition. Next, the multidimensional features were obtained by semantic feature extraction and enhanced salp swarm algorithm (ESSA) was used to choose an appropriate feature for classification. The utilization of hand-crafted features was not effective while classifying the signals.

Sriraam [20] represented the classification of focal and non-focal epileptic seizures using the application of multi-aspects and SVM classifiers. In this application, initially, the EEG seizure signal information was acquired from the Bern Barcelona database which obtain focal and non-focal signal recordings from five epilepsy patients for effective classification. Then outlier removal approach was performed to decrease the change of the trailing data as well as improve the classification level using Turkey's range test and standardized before classification. After removal, the SVM classifier was used to improve the EEG seizure classification productivity along with fewer false positives

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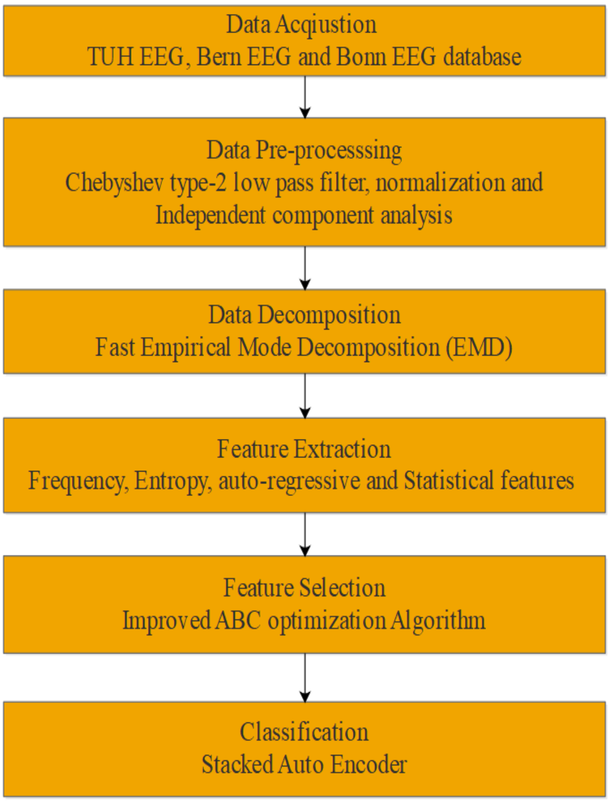
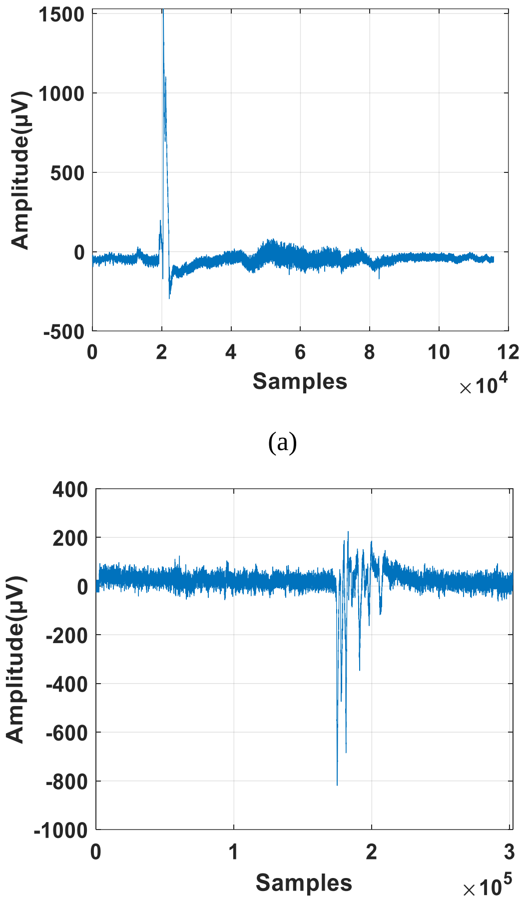


Figure. 1 The Block Diagram of proposed IABC-SAE method



(a)

(b)

Figure. 2 The sample: (a) FNSZ and (b) GNSZ signals of the TUH EEG dataset

therefore, the application accuracy was insufficient.

Sunaryono [21] developed the integration of one-dimension convolution neural network (1D-CNN) and majority voting and deep neural network (MVDNN) for automatic discovery of seizure. The discrete wavelet transform and discrete Fourier transform were used to obtain the features of EEG signals. Subsequently, the features were reduced using XGBoost for classifying the signals using 1D-CNN. Therefore, the combination 1D-CNN and MVDNN was improved the classification performances. However, the classification of seizure using 1D-CNN was mainly based on wavelets.

3. Proposed methodology

In this research, the EEG seizure signal based Epilepsy detection and classification is performed using IABC- SAE of the function. Initially, the seizure data are acquired based on three datasets thus performing the effective feature extraction and selection of the epileptic seizure. The block diagram of the IABC-SAE method is shown in Fig. 1.

3.1 Data acquisition

In this proposed method, the Epilepsy seizure detection and classification is done using EEG signals based on three main datasets namely; Temple University Hospital (TUH-EEG) database, Bonn University EEG and Bern-Barcelona EEG database. The TUH EEG dataset obtains 2,012 seizure information from various patients [17]. The sample TUH EEG signal datasets are shown in Fig. 2.

The Bern-EEG dataset contains 7500 signal groups from 5 epilepsy patients, and it is classified into two groups of EEG signals namely; focal and non-focal signals. The sample Bern EEG signal images are shown in Fig. 3.

Finally, Bonn-EEG datasets are including 500 signal information with five subsets such as; S, N, F, Z and O and these signals are verified from 128 channel amp and 12-bit analog to digital transmute. In this order S, N and F are containing intracranial epileptic activity of EEG signals. Therefore, seizure events will help to effectively extract from the

 DOI: 10.22266/ijies2023.0630.27

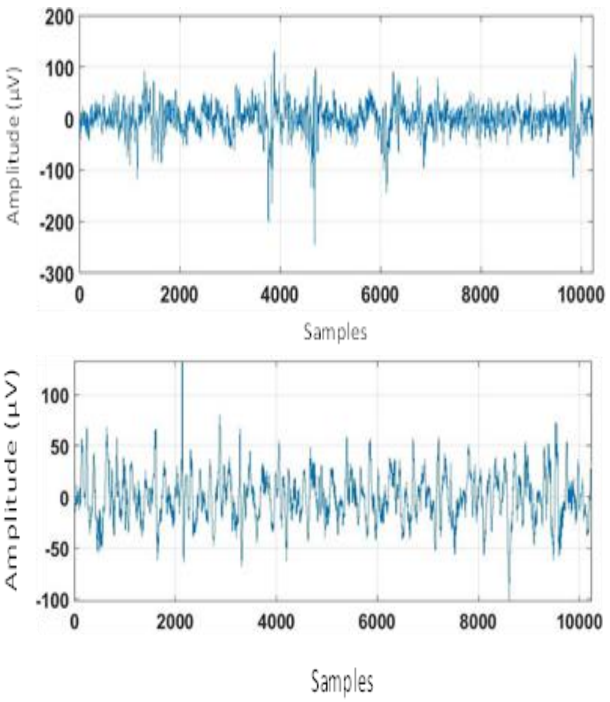


Figure. 3 The sample Bern EEG signals

original EEG based on the time duration and the sampling level.

3.2 Data pre-processing

After the data collection, a pre-processing step is required to extract efficient information from EEG signals. In this step, the EEG signal is commonly based on several objects such as; muscle activity, eye movement, etc. However, hence these relics must be removed before pre-processing the EEG signal. To extract more suitable features, each signal segment is disintegrated into incidence subbands by three methods of incidence spectrum decay, discrete wavelet transform, and empirical mode decomposition. Moreover, min-max methods are applied to normalize the datasets. The process of mini-maxi normalization is defined by Eq. (1) and the error is diminished among the idealized filter based on the characteristics range of filter. Chebyshev type 2 low pass filters are stated using the Eq. (2).

$$Mini - Maxi.Norm = \frac{z_i - z_{mini}}{z_{maxi} - z_{mini}} \quad (1)$$

where, z_i is input, and z_{mini} & z_{maxi} defines the minimum and maximum value of input respectively.

$$Chebyshev\ type\ 2\ low\ pass\ filter = \frac{1}{\sqrt{1+\rho^2 T_n^2(\frac{w}{w_0})}} \quad (2)$$

From Eq. (2), ρ is the ripple factor, w is angular frequency, w_0 is cut-off frequency at 60 Hz and T_n Chebyshev polynomial of the 6th order.

3.3 EEG signal data decomposition using FEMD

After the EEG signals are pre-processed, the signals are fed into the decomposition by using the FEMD technique, which decomposed the non-stationary EEG signals into oscillatory modes called as IMFs and satisfies every following condition. The empirical mode decomposition produces a group of intrinsic mode activity with '0'oscillations and time-frequency circulation using hilbert-huang transform. The principle of the EMD is that provides the sum of obtained IMFs given to the original signal. The IMF satisfies two conditions: (1) the amount of '0' crossing and extrema should be equivalent or differs with one, and (2) the mean value of the upper and lower coverings should be zero.

IMF is stated as $z_i = \{z_1, z_2, \dots . z_n\}$ at $n - point$ data and local minima $Localm_i, i = 1,2, \dots$ and local maxima $Localz_j, j = 1,2, \dots$ are using to input signal values $z[n]$.

Calculation of upper $U[n]$ and lower envelopes $L[n]$ by using cubic interpolation thereby evaluating the mean of the envelopes values of the function shown in Eq. (3).

$$M_n[n] = \frac{(U[n] - L[n])}{2} \quad (3)$$

Fig. 4 shows the FEMD - EEG signals taken from TUH EEG dataset.

Calculate the difference among input and mean of envelope value i.e., $d_1[n] = z[n] - M_n[n]$ and IMF, $d_1[n] = IMF_1[n]$ of the function. After obtaining the $IMF_1[n]$ evaluate the residue $R_i[n] = z[n] - IMF_1[n]$ if the residue signal value has more than zero return and calculate the new IMF of the function. This process continues until it achieves last residue $R_L[n]$ which has a non-zero cross and reformulates the $z[n]$ as shown in Eq. (4).

$$z[n] = (\sum_{i=1}^{L} IMF_1[n]) + R_L[n] \quad (4)$$

Where L is the number of IMF_s and $R_L[n]$ is the residue.

3.4 Feature extraction

The signals were first decomposed and fed into the feature extraction process, which extracts the Hjorth parameters based on entropy features. Moreover, the selected features are fed into the

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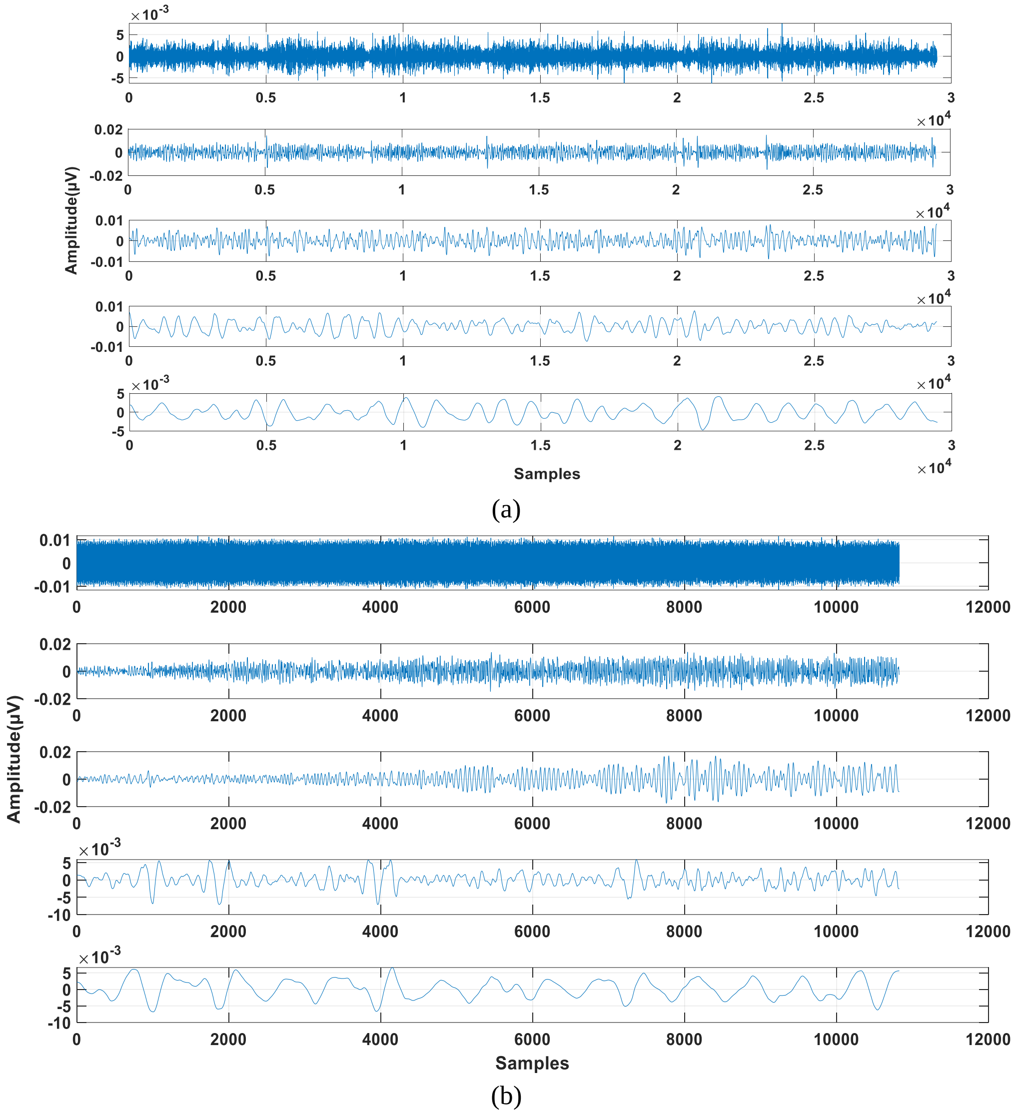

Figure. 4: (a) TUH-EEG dataset signals are decomposed into FNSZ class and (b) TUH EEG dataset signals decomposed into GNSZ class

Improved ABC optimization method, which extracts the features and uses them as input to better obtain the ideal feature for classification.

Entropy:

Entropy is a measure of the amount of information that can be utilized to distinguish between desirable information gathered from the environment. The consistency or degree of ambiguity using different levels of EEG signal and signal instability were assessed utilizing approximate entropy $(ApEn)$. In where the signal with N sample points repeats itself along with the tolerance of $r\ for\ m$ points and $m+1$ was demonstrated in entropy. $ApEn$ was given in Eqs. (5) and (6).

$$ApEn(m, r, N) = \emptyset^{m}(r) - \emptyset^{m+1}(r) \quad (5)$$

$$\phi^{m}(r) = \frac{1}{(N-m+1)} \sum_{i} In(C_i^d(r)) \quad (6)$$

where C_i^d is a correlation integral indicating the probability of a vector $Y(i)$, which remains related to $Y(j)$ within tolerance range r.

3.5 Feature selection using improved artificial bee colony (ABC) algorithm:

A population-based stochastic optimization technique is known as artificial bee colony (ABC) algorithm. It can be applied to function categorization, clustering, and optimization. An artificial collection of bees in the ABC algorithm contains three various groups such as scout bees, onlooker bees and employed bees. The number of bees betrothed in the colony and the number of observers are same in this procedure. Moreover, the massive number of resources is correlated to the fitness value of the solution. Three main bees operations are used while the iteration which was the initial swarm has SN

solution and initial population $X_i = x_{i,1}, x_{i,2}, x_{i,3} \ldots\ldots, x_{i,D}$, where SN is the size of the swarm and D is the dimension. The detailed operation of the improved ABC algorithm is as follows.

3.5.1. Employed bee search

An employed bee slightly adjusts its posture as a result of a new source which is added to the local knowledge stored in its memory. This bee compares the amount of nectar that was produced by a new source (fitness amount) and the nectar amount of the prior source and determines which is superior to the function. In this stage, the employed bees search each resolution of $X_i = 1,2,3 \ldots\ldots, SN$ and effort to determine improved resolutions as shown in Eq. (7);

$$v^*_{i,jr} = x_{ib.jr} + \phi_{i.jr}\left(x_{ib.jr} - x_{k.jr}\right) + \phi_{i.jr}.\left(x_{best.jr.}x_{ib.jr}\right) \quad (7)$$

Here, where $\phi_{i.jr}$ is random number among $[-1, 1]$ and $x_{ib.jr}$ are the highest resolution data from the k-region of X and [0, C] are taken at random from the entire swarm ($x_{ib.jr} = x_i$), and jr is a random number in the range $[1, D]$.

In additionally, for the ith onlooker bee $x_{ib.jr}$ is chosen from the k-region of X_i and improved search strategy as shown in Eq. (8) and (9).

$$v^*_{ib,jr} = x_{ib.jr} + \phi_{i.jr}.\left(x_{ib.jr} - x_{k.jr}\right) \quad (8)$$

And

$$v^*_{ib,j} = \{\ v^*_{ib,jr},\ if\ j = jr\} \quad (9)$$

$x_{ib.jr}$, otherwise

where $j = 1, 2, \ldots, D$. shows modified search strategy resolution selection of the onlooker bee search phase of v_{ib} and X_{ib}, the better one is selecting according to Eq. (10):

$$x_{ib} = \begin{cases} v_{ib}, & if\ f(v_{ib}) < f(X_{ib}) \\ X_{ib,} & otherwise \end{cases} \quad (10)$$

3.5.2. Scout bee search

The counter $trail_i$ keeps track of the search status for the solution Xi. The abandoned Xi is then replaced by a brand-new one that is created at random and the swarm is convergent as the iteration rate rises. In addition, three solutions created in scout bee search, $U1, U2$, and $U3$, are created when Xi is given up. Then, to replace the discarded Xi, the best option among $U1, U2, and\ U3$ is chosen. Like the originally improved $ABC, U1$ is created randomly by $U2$, the best resolution X_{ib} is selection in the k-region of Xi. Then, $U2$ is produced around X_{ib} if $trail_i$ is greater than a parameter, and the corresponding solution of Xi is abandoned thus new one is created in Eq. (11)

$$U_{2.j} = X_{ib.j} + rand(0,1).\left(x_{r1.j} - x_{r2.j}\right) \quad (11)$$

Where $j = 1, 2, \ldots, D$, X_{r1} and X_{r2} are two various resolutions which are generally selected from the whole swarm, and $r1 \neq r2 \neq ib$. Opposition-Based Learning (OBL) is a powerful technique that can increase the likelihood of discovering superior candidate solutions. The OBL then produces the third answer, $U3$. In the k-region of the abandoned solution Xi, the best neighbour X_{ib} is identified. The following is the generation of an opposite solution $U3$ based on X_{ib} as follows;

$$U_{3.j} = x_j^{min} + x_j^{max} - x_{ib.j} \quad (12)$$

$$x_j^{min} = min\{x_{i,j}\},\ x_j^{max} = max\{x_{i,j}\} \quad (13)$$

$i = 1, 2, \ldots, SN, j = 1, 2, \ldots, D$, Where [$x_j^{min}$, x_j^{max}] is the limit of the current swarm, and it is dynamically updated by Eq. (15). As can be observed, for each dimension, | $X_{ib.j}\ x_j^{min}$ | and | $x_j^{max}\ U_{3.j}$ | are equivalent. We attempt to verify the opposite side of the current X_{ib} when it is stationary ($U3$). This may make it more likely to come across superior potential solutions for the function. A straightforward elite approach is applied after the generation of the three new solutions $U1, U2, and\ U3$. The most effective answer among $U1, U2, and\ U3$ is chosen to take the place of the discarded answer Xi.

3.6 Classification

Once the feature selection is performed it requires the classification of the EEG signals to provide effective results for diagnosis. Stacked auto-encoder technique is used for performing the classification of epilepsy disease into ictal, interictal, and normal cases.

Stacked auto encoder classifier:

The Stacked Sparse Auto-Encoder (SSAE) is a neural network technique connecting an amount of auto-encoders that signifies a layer and is trained in unlabeled data. The training of an auto-encoder estimates the optimum parameters using various algorithms which reduce the deviation between input and output. The coding among input and output is represented by the eqs. (14-16) illustrated below. Here, the input path $x = (1, 2, 3, 4 \ldots, N)$, is transformed into hidden representation " x ", by employing a nonlinear model which is shown as Eq. (14) to Eq. (16).

$$x = f(x) = M_f(W_1 x + b_1) \tag{14}$$

$$n_1^{(1)} = M_f(w_{11}^{(1)} x_1 + \cdots w_{15}^{(1)} x_5 + b_1^{(1)} \tag{15}$$

$$n_i^{(1)} = M_f(w_{i1}^{(1)} x_1 + \cdots w_{i5}^{(1)} x_5 + b_i^{(1)} \tag{16}$$

Here, $n_i^{(1)}$ denotes the ith neuron in the SSAE architecture's first layer, M denotes an activation function, and w_i and b_i stand for the weight matrix and the bias parameter.

4. Results and discussions

In this section, the outcomes of the proposed IABC-SAE method using TUH, Bern, and Bonn signal datasets are presented. The implementation and simulation of the IABC-SAE method are done using MATLAB R2022 software. The system configuration used for this research is an i5 processor with 8GB of RAM. All analysis and assessment trials are performed on public field databases, widely used in the related works datasets and output limits are utilized to construct the results of the function. The dataset used to analyze the IABC-SAE method and performs best in Seizure signal classification where 80% of training and 20% of testing the function. In that, the data is randomly taken for training and testing based on the iteration. The performance of the IABC-SAE method is analyzed in terms of CA, sensitivity, specificity, Positive Predictive Value (PPV) and Negative Predictive Value (NPV).

The classification accuracy of the method is shown in Eq. (17)

$$CA = \frac{TP}{TP+FP+TN+FN} \tag{17}$$

The sensitivity of the method is shown in Eq. (18)

$$sensitivity = \frac{TP}{TP+FN} \tag{18}$$

The specificity of method is shown in the Eq. (19)

$$Specificity = \frac{TN}{TN+FP} \tag{19}$$

The Positive predictive value of the method is defined in Eq. (20)

$$PPV = \frac{TP}{TP+FP} \tag{20}$$

The Negative predictive value of the method is defined in Eq. (20)

$$NPV = \frac{TN}{T|N+FN} \tag{21}$$

Where, TP, TN, FP and FN denotes the true positive, true negative, false positive and false negative respectively.

4.1 Performance analysis of IABC-SAE methods:

This section shows the performance of the Epilepsy Seizure EEG signal detection and classification using Bern, TUH, and Bonn EEG datasets. In Epilepsy Seizure EEG, the improved ABC optimization algorithm achieves an effective EEG signal's accuracy of 99.98%. in TUH-EEG database. Additionally, the performance of IABC-SAE optimization method helps to improve the effective detection and classification using seizure EEG signals.

In this work, the performance evaluation of three different EEG signal datasets is evaluated with various classifiers such as; K-Nearest Neighbor (KNN), Multiclass Support Vector Machine (MSVM), Decision Tree (DE), Random Forest (RF) along with graphical comparison which is shown below. From the analysis, it is concluded that the IABC- SAE classifiers achieve a higher classification accuracy of 99.98%. in the TUH-EEG database than the other. Tables 1, 2 and 3 show the performance analysis of Bern-EEG Seizure signals without feature selection, with feature selection, and with different optimization algorithms respectively. A graphical comparison of the Bern datasets for various classifiers without feature selection is shown in Fig. 5. A graphical illustration of the Bern datasets for various classifiers with feature selection is shown in Fig. 6. A graphical representation of the Bern datasets with various optimization algorithms is illustrated in Fig. 7.

The performance of the proposed IABC-SAE method is analyzed with different optimization algorithms in terms of particle swarm optimization (PSO), grey wolf optimizer (GWO), whale optimization algorithm (WAO), and slap swarm algorithm (SSA).

Received: February 24, 2023. Revised: March 20, 2023.

Table 1. Performance analysis of Bern-EEG Seizure signals without feature selection

Classifiers	CA (%)	Sensitivity (%)	Specificity (%)	NPV (%)	PPV (%)
KNN	82.04	78.76	76.46	70.98	82.46
MSVM	86.47	80.47	81.10	82.45	85.10
DE	89.61	82.45	84.07	85.80	88.46
RF	90.32	89.05	85.45	86.43	89.44
Proposed SAE	91.66	90.44	89.59	90.45	90.99

Table 2. Performance analysis of Bern-EEG Seizure signals with feature selection

Classifiers	CA (%)	Sensitivity (%)	Specificity (%)	NPV (%)	PPV (%)
KNN	89.58	78.57	79.80	90.88	82.46
MSVM	90.68	89.46	88.80	90.78	84.51
DE	91.35	92.59	89.69	91.58	89.69
RF	92.90	93.68	93.66	92.46	91.48
Proposed IABC-SAE	99.42	99.08	98.69	98.69	99.05

Table 3. Comparison of Bern-EEG Seizure signals with different performance metrics and various optimization algorithms

Optimization algorithm	CA (%)	Sensitivity (%)	Specificity (%)	NPV (%)	PPV (%)
PSO	88.45	90.65	90.43	91.35	90.49
GWO	92.4	89.43	89.45	91.94	91.49
WAO	93.09	91.45	93.46	93.57	91.96
SSA	94.45	93.43	92.46	94.46	92.45
Proposed SAE	99.42	99.08	98.69	98.69	99.05

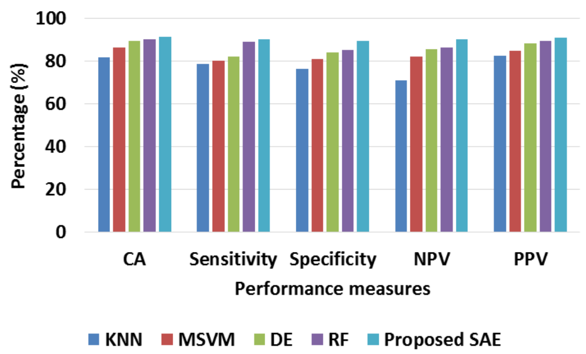

Figure. 5 Graphical comparison of the Bern datasets without feature selection

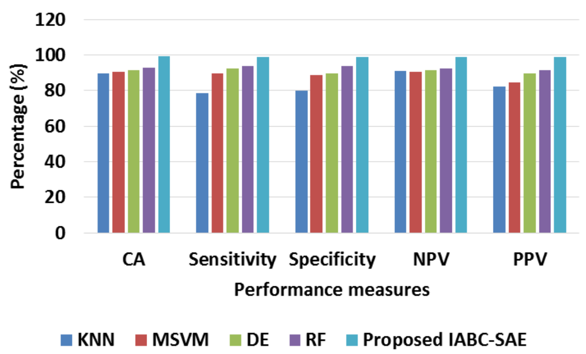

Figure. 6 Graphical comparison of the Bern datasets with feature selection

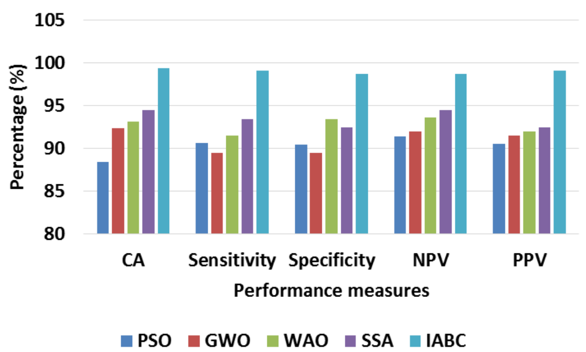

Figure. 7 Graphical comparison of the Bern datasets with various optimization algorithms.

Tables 4, 5, and 6 show the performance analysis of TUH-EEG Seizure signals without feature selection, with feature selection and with different optimization algorithms respectively. A graphical comparison of the TUH-EEG datasets for various classifiers without feature selection is shown in Fig. 8. A graphical illustration of the TUH datasets for various classifiers with feature selection is shown in Fig. 9. A graphical representation of the TUH datasets with various optimization algorithms is illustrated in Fig. 10.

From the analysis, the proposed IABC-SAE provides higher accuracy to effectively extract the unbalanced features compared to the others.

Received: February 24, 2023. Revised: March 20, 2023.

Table 4. Performance analysis of TUH-EEG Seizure signals without feature selection in different performance metrics.

Classifiers	**CA (%)**	**Sensitivity (%)**	**Specificity (%)**	**NPV (%)**	**PPV (%)**
KNN	78.04	74.76	76.46	70.98	82.46
MSVM	82.47	80.47	81.10	82.45	85.10
DE	84.61	82.45	84.07	85.80	88.46
RF	89.32	89.05	85.45	86.43	90.44
Proposed SAE	89.66	90.24	88.79	88.25	90.46

Table 5. Performance analysis of TUH-EEG Seizure signals with different performance metrics with feature selection

Classifiers	**CA (%)**	**Sensitivity (%)**	**Specificity (%)**	**NPV (%)**	**PPV (%)**
KNN	87.58	79.57	80.80	91.88	83.46
MSVM	89.68	89.96	89.00	90.98	85.51
DE	92.35	91.59	90.69	92.58	89.79
RF	93.90	93.99	92.66	92.46	91.48
Proposed IABC-SAE	99.98	98.78	99.87	99.57	99.90

Table 6. Comparison of TUH-EEG Seizure signals with different performance metrics and optimization algorithm

Optimization algorithm	**CA (%)**	**Sensitivity (%)**	**Specificity (%)**	**NPV (%)**	**PPV (%)**
PSO	84.58	80.57	84.50	91.88	84.56
GWO	89.8	88.69	88.00	92.56	85.52
WAO	90.35	90.35	91.69	94.25	90.90
SSA	94.90	94.99	95.66	93.15	92.48
IABC	99.98	98.78	99.87	99.57	99.90

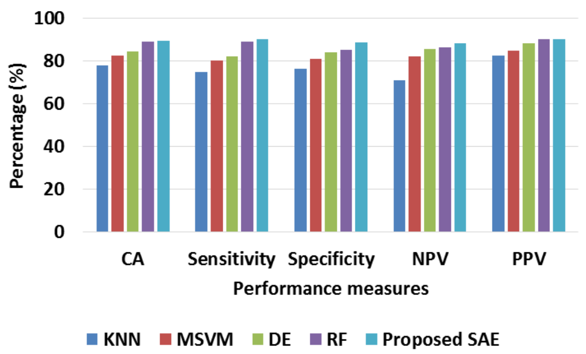

Figure. 8 Graphical comparison of the TUH datasets without feature selection

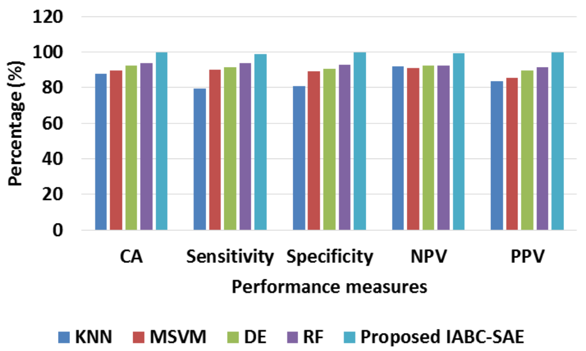

Figure. 9 Graphical comparison of the TUH datasets with feature selection

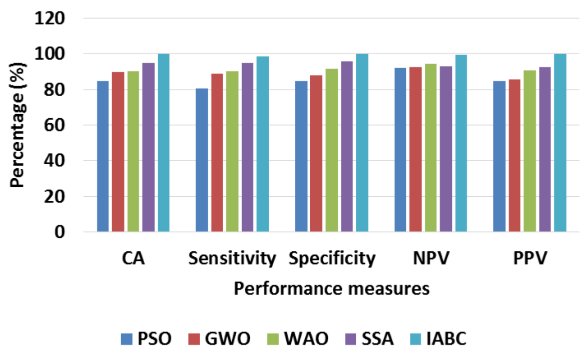

Figure. 10 Graphical comparison of the TUH datasets with various optimization algorithms

Tables 7, 8, and 9 show the performance analysis of Bonn-EEG Seizure signals without feature selection, with feature selection and with different optimization algorithms respectively. A graphical comparison of the Bonn-EEG datasets for various classifiers without feature selection is shown in Fig. 11. A graphical illustration of the Bonn-EEG datasets for various classifiers with feature selection is shown in Fig. 12. A graphical representation of the Bonn datasets with various optimization algorithms is illustrated in Fig. 13.

According to the investigation, the suggested IABC-SAE provides greater accuracy than the others.

Received: February 24, 2023. Revised: March 20, 2023.

Table 7. Performance analysis of Bonn-EEG Seizure signals without feature selection in different performance metrics

Classifiers	**CA (%)**	**Sensitivity (%)**	**Specificity (%)**	**NPV (%)**	**PPV (%)**
KNN	78.04	74.76	76.46	70.48	82.46
MSVM	82.47	80.47	81.1	82.45	85.1
DE	84.61	82.45	84.07	85.8	88.46
RF	89.32	89.05	85.45	86.43	90.44
Proposed SAE	89.66	90.24	88.79	88.25	90.46

Table 8. Performance analysis of Bonn-EEG Seizure signals with feature selection in different performance metrics.

Classifiers	**CA (%)**	**Sensitivity (%)**	**Specificity (%)**	**NPV (%)**	**PPV (%)**
KNN	88.45	80.58	81.24	92.78	86.25
MSVM	89.68	90.46	91.19	93.65	86.24
DE	93.52	93.82	91.02	92.00	90.23
RF	95.06	94.25	91.85	92.31	92.81
Proposed IABC-SAE	99.73	98.37	99.88	99.01	99.22

Table 9. Comparison of Bonn-EEG Seizure signals with different performance metrics and optimization algorithm.

Optimization algorithm	**CA (%)**	**Sensitivity (%)**	**Specificity (%)**	**NPV (%)**	**PPV (%)**
PSO	87.58	79.57	80.8	91.88	83.46
GWO	89.68	89.96	89	90.98	85.51
WAO	92.35	91.59	90.69	92.58	89.79
SSE	93.9	93.99	92.66	92.46	91.48
Proposed SAE	99.73	98.37	99.88	99.01	99.22

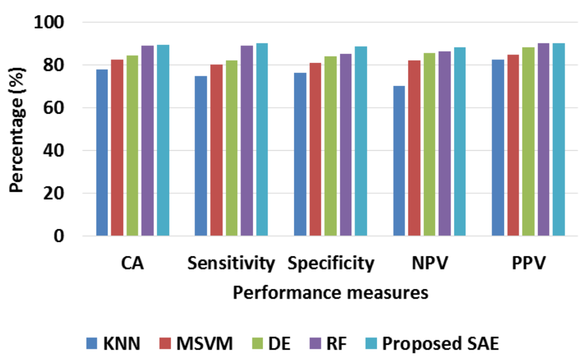

Figure. 11 Graphical comparison to Bonn datasets without Feature selection

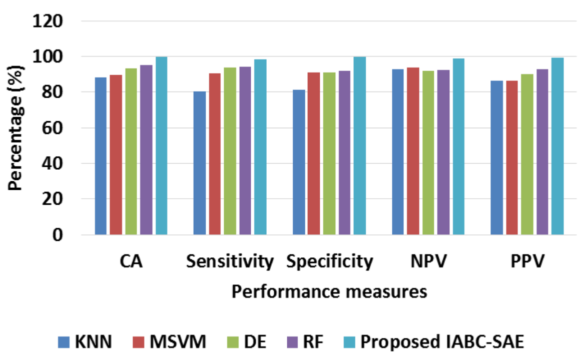

Figure. 12 Graphical comparison to Bonn datasets with Feature selection

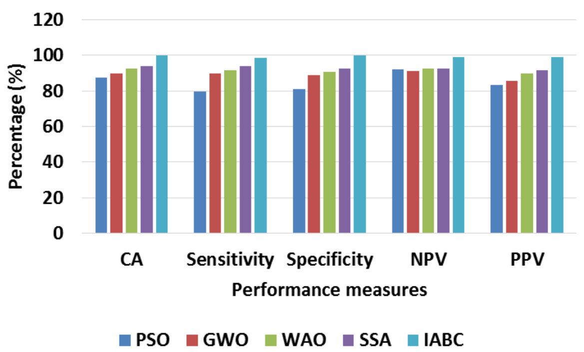

Figure. 13 The Graphical comparison to Bonn datasets with various optimization algorithms.

4.2 Comparative analysis

This section shows the comparative analysis of the Improved ABC Optimization for EEG signal classification. The dataset used for the seizure signal classification is TUH, Bonn and Bern EEG where the performance of the stacked autoencoder is compared with the MCAFF [16], CNN-RNN [18], ESSA [19], SVM [20] and 1D-CNN [21]. The comparative analysis between the MCAFF [16], CNN-RNN [18], ESSA [19], SVM [20] and 1D-CNN [21] with IABC-SAE is shown in Table 10. From the analysis, it is known that the Improved ABC Optimization with Stacked autoencoder provides better performance than others. For example, the accuracy of the IABC-SAE is 99.98% in TUH-EEG database due to its optimal feature selection using IABC.

Table 10. Comparative analysis of existing and proposed classifiers

Datasets	Methods	CA (%)	Sensitivity (%)	Specificity (%)	NPV (%)	PPV (%)
TUH-EEG	MCAFF [16]	NA	96.5	NA	NA	96.4
	ESSA [19]	99.20	98.99	99.01	NA	NA
	IABC-SAE	99.98	98.78	99.87	99.57	99.90
Bonn-EEG	CNN-RNN [18]	99.71	99.61	99.79	NA	99.68
	ESSA [19]	97.84	97.34	97.56	NA	NA
	1D-CNN [21]	98	NA	NA	NA	NA
	IABC-SAE	99.73	98.37	99.88	99.01	99.22
Bern -EEG	SVM [20]	92.15	NA	NA	NA	NA
	ESSA [19]	99.32	98.20	98.60	NA	NA
	IABC-SAE	99.42	99.08	98.69	98.69	99.05

5. Conclusion

This research work is directed towards the detection and classification of epileptic seizures using EEG signals. In this research, different algorithms are proposed to classify epileptic and non-epileptic seizures. From these three different datasets such as TUH-EEG, Bonn University EEG and Bern-Barcelona EEG, the recorded EEG signal noise is eliminated using a Chebyshev type 2 low pass filter and by using ICA. Then, the signal is decomposed into Fast Empirical Mode Functions using EMD. From the IMFs, hybrid features are extracted and the proposed improved artificial bee colony feature selection method is introduced to eliminate the irrelevant features or to select the optimum aspect values. By utilizing values, the abnormality and normality of epileptic seizure disease were classified by using a Stacked autoencoder. The proposed method showed an improvement in the accuracy of 99.98% for the TUH-EEG database when compared with the existing ESSA. In the future, a hybrid optimization can be used for improving the classification of an epileptic seizure.

Notation

Parameter	Description
z_i	Input
z_{mini} & z_{maxi}	Minimum and maximum value of input
ρ	Ripple factor
w	Angular frequency
w_0	Cut-off frequency
T_n	Chebyshev polynomial of the 6th order
$Localm_i$	Local minima
$Localz_j$	Local maxima
$U[n]$	Upper envelopes
$L[n]$	Lower envelopes
$M_n[n]$	Mean of the envelopes value
$d_1[n]$	Difference among input and mean of envelope value
$IMF_1[n]$	Intrinsic mode functions
$R_i[n]$	Residue
$R_L[n]$	Last residue
N	Sample Points
r	Tolerance
m	Points
$ApEn$	Approximate entropy
C_i^d	correlation integral indicating the probability
SN	Size of the swarm
X_i	Initial population
D	Dimension
$\phi_{i.jr}$	Random number among $[-1, 1]$
$trail_i$	Counter
$U1, U2,$ and $U3$	Solutions created in scout bee search
$n_i^{(1)}$	ith neuron in the SSAE architecture's first layer
M	Activation function
w_i	Weight matrix
b_i	Bias parameter
CA	Classification accuracy
PPV	Positive predictive value
NPV	Negative predictive value
TP	True positive
TN	True negative
FP	False positive
FN	False negative

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

For this research work all authors' have equally contributed in Conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review and editing.

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