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Classification of Epileptic EEG Signals Using Improved Atomic Search Optimization Algorithm

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Abstract: Epilepsy is a neurological disorder that is distinguished by the presence of seizures, which are caused by abnormal brain activity. On average, about 60% of epilepsy cases are due to focal seizures, which affect a specified part of the cerebrum. Epileptic seizures can be cured at the initial stage, but untreated seizure for a long time cause severe effect and sometimes leads to death. Therefore, accurate classification of the epileptic Electroencephalogram (EEG) signal is an essential step in the diagnosis of epilepsy, aiding physicians in making the diagnosis. This research presents an effective classification of epileptic EEG signals using the improved atomic search optimization (IASO) algorithm and the random search strategy (RSS). The IASO is used to select the appropriate features but has a high probability to enhance the convergence rate. However, due to a lack of population variety and exploratory capabilities and this convergence rate may decrease in some circumstances. As a result, the RSS is offered to enhance the solution and improvise the exploration capabilities. The raw data of EEG signals are obtained from TUH, BONN, and BERN datasets. The raw data is pre-processed using an adaptive filtering method. The IASO is utilized in selecting the relevant features which ease the process of classification using LSTM. The results show that IASO attained better classification accuracy of 98.40% for TUH dataset which is comparatively lower than the existing Deep network model with 97%.

Keywords: Adaptive filtering, Classification of EEG signals, Electroencephalogram, Epilepsy, Improved atomic search optimization.

1. Introduction

Sudden abnormal synchronous discharge behaviour in the neural cell groups of the brain causes epilepsy which is a chronic neurological illness that affects brain function. This disease affects 1% of the world's population on average. The intracranial or scalp EEG is generally utilized as a clinical method for diagnosing epilepsy [1, 2]. Epilepsy may lead to a lack of consciousness, affects the psychological and neurological condition of the person, and a severe case of epilepsy causes death [3]. This disorder doesn't specify particular age groups and causes brain malformations, intracranial haemorrhage, or tumors in the brain [4]. Epilepsy-affected people get injured by falling and biting their tongues [5]. The detection and recognition of EEG signals are significant measures for an epilepsy diagnosis. Feature extraction and intelligent recognition are utilized to classify epileptic EEG signals. The information of the EEG signals is in the form of frequency domain and wavelet form [6]. The timely treatment of epilepsy aids in the effective diagnosis of the condition, which is usually done through the interpretation of EEG signals by a radiologist or doctor [7].

In general, epilepsy is categorized into two significant classes based on the brain region which is stimulated at the time of seizures, the two classes include partial and generalized. The partial one starts from a specified area of the brain and lies on one side of the cerebral column but the generalized one is initiated in the entire brain [8]. Researchers are keen to identify a reliable solution to predict and classify the patient's EEG with epilepsy [9, 10]. The EEG signals have a high-frequency range which is higher than mV in the steps of epileptic seizures. These high-frequency waves with appearances of epileptic seizure are known as waves. There are particular methodologies based on feature extraction to diagnose the spikes obtained from the report of brain EEG data [11, 12]. The EEG signals are generally non-linear and dynamic, so it is essential to perform non-linear analysis based on a wavelet, fractal, and theories based on entropy [13]. Feature extraction and selection is considered important area in the classification of EEG signals. Specifically, the image features are provided as an input for the classifier in the classification of epileptic EEG signals [14,15].

The main contribution of this research paper is listed as follows:

1. Since ASO is not efficient in providing enough solutions for small dimensional problems, IASO is proposed. Here, a random search strategy is used for converting the ASO into IASO which is used to enhance the exploitation.
2. IASO's ability to select features more effectively makes it simpler to choose relevant features for classification.
3. From various optimization methods, the proposed IASO achieved the highest metrics during evaluation and attained comparatively better results than the existing methods.

The remaining paper is organized as follows, Section 2 represents the related works. The proposed method is discussed in Section.3. The results and discussion are provided in Section.4. The conclusion of this research is presented in Section 5.

2. Related works

Fu [16] introduced an automatic detection and classification of EEG signals using the sparse common spatial pattern (SCSP) and Fisher linear discriminant analysis (FLDA) algorithm. The vital features were extracted using the SCSP algorithm and the classification of EEG signals was performed using the SCSP pattern. These methodologies neglect the recurrent features and decrease the issues related to singularities. The dimensional features were reduced using the SCSP which helps to escalate the process of EEG signal classification using FLDA. However, the classification results were not based on the age group of people since SCSP-FLDA does not focus on validating different ages.

Duan [17] introduced a methodology for the classification of epilepsy by utilizing the combination of feature extraction and the spiking swarm intelligent optimization (SSIO) algorithm. The features were extracted using the time-frequency features and the features of the principal component. The classification of epilepsy takes place using the SSIO algorithm which completely contemplates the cooperation of individuals with communication among the intervention. The time-frequency features were utilized in the extraction of features that were utilized to de-noise the repeated EEG signals. The spiking neuron model present in SSIO needs to be operated each time to attain a certain energy level for every iteration.

Saric [18] suggested an MLP ANN, approach for identifying generalized and localized epileptic seizures, including the scenario with no seizure incidence. 822 samples of EEG signals from the temple university hospital seizure detection corpus (TUH EEG Corpus) collection were used to create the algorithm. Such MLP ANN-based FPGA solutions are scalable and portable, making them extremely useful for real-time epileptic seizure identification in both clinical and non-clinical settings. After the generated ANN model was successfully implemented, the FPGA chip's resource use must be taken into consideration because of the high FPGA resource utilization. However, the device has a variety of issues with connection size, speed, clock dispersion, and I/O capacity.

Liu [19] have developed a unique hybrid bilinear model and show how these models may be used to categorize seizures based on EEG data with little feature extraction. The EPILEPSIAE dataset and the Temple University Hospital (TUH) Seizure Corpus dataset were both utilized in this method. On the EPILEPSIAE dataset, where hybrid design outperformed symmetric networks substantially, the benefits of the hybrid network were more obvious. On the EPILEPSIAE and TUH datasets, the hybrid bilinear network performs at a comparable level, demonstrating the generalizability of the model. However, without including these extra-sensory data, there was a significant gap in the accuracy of the diagnosis.

Sheykhivand [20] developed sparse representation-based classification (SRC) using dictionary learning to detect epileptic seizures

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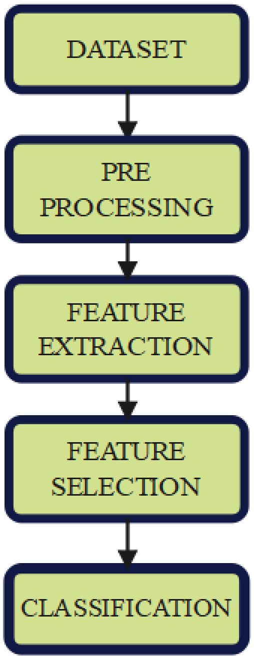

Figure. 1 The process involved in the classification of EEG classification

efficiently. The discriminative characteristics of each class are automatically learned during dictionary learning in SRC, making it an end-to-end classifier that does not need a feature extraction technique. The SRC was used to reduce the workload on medical practitioners by performing visual analysis of huge amounts of data. However, SRC can automatically identify non-convulsive status epilepticus (NCSE), a disease that was challenging for doctors to diagnose.

Shruti Mishra [21] have introduced a discrete wavelet transform (DWT) and moth flame optimization (MFO) on the basis of extreme learning machine (ELM) referred as DM-ELM to categorize the EEG signal to detect the epileptic seizures. The signal was decomposed using the DWT and the classification was performed by evaluating the optimal parameters using MFO algorithm. However, imbalance occurs among the phases of exploration and exploitation with trapping of local optima.

Hend Alshaya and Muhammad Hussain [22] have introduced an effective deep network model which was on the basis of ResNet and long short term memeory (LSTM) to categorize the epileptic seizures. The deep network was based on ResNet module which was used to train the model without overfitting. Moreover, the LSTM module helps to learn about the long term dependencies in a short period of time and helps in effective classification. However, the issues related to vanishing gradient occurs which effects the overall classification performance.

H. Anila Glory [23] have introduced a hybridized adaptive haar wavelet-based binary grasshopper optimization algorithm and deep neural network (AHW-BGOA-DNN) to detect the epileptic seizures. The AHW-BGOA was used in optimization of hyperparameters and the informative features are extracted using the deep learning model. Moreover, the deep learning model adjust the weighted fitness functions. However, dropout rate influenced the overall performance of the model.

3. Classification of EEG signal using Improved atom search optimization algorithm as a feature selector:

The classification of EEG signals involves four steps such as pre-processing, feature extraction, selection of features, and classifying the epileptic EEG signals. The input samples of EEG signals are collected from temple university hospital (TUH), the BONN dataset from the University of Bonn, and the BERN-BARCELONA dataset. In the stage of pre-processing, an adaptive filtering method is utilized which operates at the frequency range from 30 Hz to 80 Hz. The pre-processed output is provided as input for the stage of the feature extraction method. The selected features are extracted using the IASO algorithm and finally, classification is performed using the LSTM classifier. The process of classifying the EEG signal is represented in Fig. 1 as follows:

3.1 Dataset

This paper utilized three datasets such as TUH, BONN, and BERN which contain raw data from EEG signals. This section describes the datasets utilized in this research.

- **TUH dataset [24]:** This is a publicly accessible dataset that consists of around 30,000 EEG signals. The data about the EEG clinical settings for 10,874 patients are utilized. The dataset helps researchers to improve their research in the field of neuroscience.
- **BONN dataset [25]:** This dataset consists of 100 single-channel EEG signals with a sampling rate of 173.61 Hz. The range of spectral bandwidth is between 0.5 Hz to 85 Hz. Each set consists of 100 files and each file has 4097 samples of EEG time series in ASCII code.
- **BERN dataset [26]:** This dataset consists of data obtained from multichannel EEG signals which are captured using specialized

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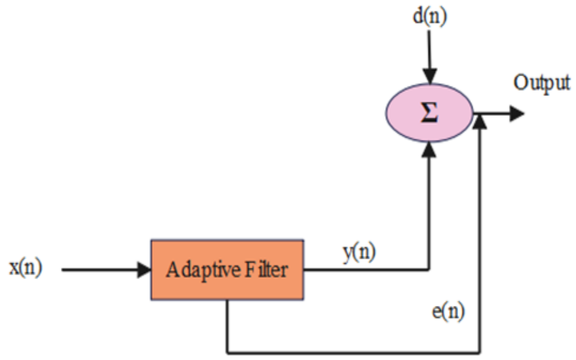

Figure. 2 Adaptive filtering method

electrodes and patients suffering from temporal lobe epilepsy. Based on the channel size of the EEG system, the sample size varies from 512 or 1024 Hz. There are two types of EEG signals present in this dataset which include focal and non-focal signals. Every individual file consists of around 10240 samples with a period of 20 seconds.

3.2 Pre-processing

The EEG samples obtained from the datasets are pre-processed using the adaptive filtering technique. Since raw EEG signals consist of artifacts and noises, it is necessary to remove those noises for better diagnosis and classification of EEG signals. The filtering is an essential process to remove the noises that occur from power line, the patient's muscular activities and components which produce low frequencies. The adaptive filter utilized a fixed range of frequencies and modifies the weight of frequencies. Moreover, it cleaned the EEG signals by eliminating the artifactual constituents present in the signal. The residual error obtained from the adaptive filtering method is computed using Eq. (1).

$$e(n) = d(n) - y(n) \tag{1}$$

Where the desired signal is denoted as $d(n)$, the reference signal is denoted as $x(n)$ and $y(n)$ is denoted as a residual error. The adaptive filtering technique utilizes optimization algorithms to get optimal filter co-efficient.

The structural diagram of the adaptive filter is represented in Fig. 2 as follows:

3.3 Feature extraction

The pre-processed output obtained from the adaptive filtering technique proceeds with the extraction of features which eases the process of classifying the EEG signals. In this research various feature extraction methods such as statistical features, frequency features, entropy features, spectral features, power spectral features, and multi-scale wavelet transform are utilized for extracting the features from EEG signals.

Statistical features: Ratio of largest absolute to root mean squared value, kurtosis, mean length of the curve, log root sum of the variations in sequences [27].

Frequency features: Frequency of the mean value

Entropy features Multiscale permutation entropy, Shannon entropy, tsallis entropy, and sure entropy [28].

Spectral features: Band power alpha, spectral flux, spectral flatness, band power beta.

Power spectral features: Density of the spectral power.

3.4 Feature selection using IASO

The extracted features using the various feature extraction methods are provided as input for the stage of feature selection using the IASO algorithm. The IASO algorithm is a hybrid of the region search strategy (RSS) and atom search optimization (ASO) algorithms.

3.4.1. Atom search optimization (ASO) algorithm

ASO is a type of metaheuristic algorithm that is inspired by the motion of atoms. The mathematical representation of the atomic system by Newton's second law is provided in Eq. (2) as follows:

$$a_i = \frac{F_i + G_i}{m_i} \tag{2}$$

Where the force of interaction is denoted as F_i and the constraint of an operating atom is denoted as G_i. The atom's acceleration is denoted as a_i and the atom's mass is denoted as m_i.

The force of interaction among the atom i and j is obtained from the Lennard-Jones potential is denoted in Eq. (3).

$$F_{ij}^{t}(t) = -\eta(t)\left[2\left(h_{ij}(t)\right)^{13} - \left(h_{ij}(t)\right)^{7}\right] \tag{3}$$

Where the depth function is denoted as $\eta(t)$ and the value is denoted in Eq. (4) as follows:

$$\eta(t) = \alpha\left(1 - \frac{t-1}{T}\right)^{3} e^{-\frac{20t}{T}} \tag{4}$$

Where the weight of the depth function and maximum iteration is represented as α and T

correspondingly. The function which is utilized to adjust repulsion or attract the regions is denoted as $h_{ij}(t)$ which is represented in Eq. (5) as follows

$$h_{ij}(t) = \begin{cases} h_{min}, \frac{r_{ij}(t)}{\sigma(t)} < h_{min} \\ \frac{r_{ij}(t)}{\sigma(t)}, h_{min} \leq \frac{r_{ij}(t)}{\sigma(t)} \leq h_{max} \\ h_{max}, \frac{r_{ij}(t)}{\sigma(t)} > h_{max} \end{cases} \quad (5)$$

Where r is denoted as the distance between two atoms, the lower region is denoted as h_{min} and the upper region is denoted as h_{max}.

The function $h_{ij}(t)$ represented in Eq. (5) helps the occurrence of repulsion, attraction, or equilibrium. The value of h_{min} is represented in Eq. (6) as follows:

$$h_{min} = g_0 + g(t), h_{max} = u \quad (6)$$

Where the values of g_0 and $g(t)$ is 1.1 and 1.24 respectively and g is known as the drift factor which is represented in Eq. (7) as follows:

$$g(t) = 0{,}1 \times sin\left(\frac{\pi}{2} \times \frac{t}{T}\right) \quad (7)$$

The algorithm gets drifted to the stage of exploration by using this factor. The drifted length of the atom is represented as $\sigma(t)$ which is denoted in Eq. (8) as follows:

$$\sigma(t) = \left\| x_{ij}(t), \frac{\sum_{j \in Kbest} x_{ij}(t)}{K(t)} \right\|_2 \quad (8)$$

Where the population of the atom with the best function is denoted as $Kbest$. The total force that occurs in the atom i is represented in Eq. (9).

$$F_i^d(t) = \sum_{j \in Kbest} rand_j \, F_{ij}^d(t) \quad (9)$$

The random number representation among the range [0,1] is represented as $rand_j$. The geometrical alignment has a great impact on the atomic motion. In ASO, the bond occurred among the atoms is considered a covalent bond which is represented in Eq. (10) as follows:

$$\theta_i(t) = \left[|x_i(t) - x_{best}(t)|^2 - \left(b_{i,best}\right)^2\right] \quad (10)$$

Where $x_{best}(t)$ is denoted as the best position of the atom at iteration t. The distance between the atom i and $best$ is represented as $b_{i,best}$. The force of the atom due to constraint is denoted in Eq. (11)

$$G_i^d(t) = \lambda(t)(x_{best}^d(t) - x_i^d(t)) \quad (11)$$

Where $\lambda(t)$ is represented as a Langrangian multiplier and it is described in the following Eq. (12).

$$\lambda(t) = \beta e^{-\frac{20t}{T}} \quad (12)$$

Where the weight of the multiplier is denoted as β. The acceleration of the atom i in a time period t is denoted in Eq. (13) as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{m_i^d(t)} + \frac{G_i^d(t)}{m_i^d(t)} \quad (13)$$

Where $m_i(t)$ is represented as the mass of the atom i.

3.4.2. Improved atomic search optimization (IASO) algorithm

The IASO is a combination of ASO and random search strategy which is applied to choose relevant features to ease the process of classification. For a wrapper based feature selection, the threshold is considered as 0.5 to verify the selection of features. Similar to other global-level optimizing techniques, ASO doesn't provide an effective solution for small dimensional problems. This problem can be overwhelmed using a random search strategy and it enhances the efficiency of ASO in selecting the features.

In the proposed IASO algorithm, the ASO algorithm is utilized for the stage of exploration and the random search strategy is utilized for the stage of exploitation. In the random search strategy method, the initialization of random solutions takes place in a specified search space. The solution for the problem is created and accepted or rejected based on the neighboring solutions. The search space is explored by means of shifting to the better neighboring solution. This strategy is utilized to assist ASO and neglect local minimum. IASO performs the capability of fast-optimal search with the feature of Random Search Strategy (RSS).

Random search strategy (RSS)

The ASO algorithm is updated by evaluating the current solution and the velocity of the atom which has a high probability to enhance the convergence rate. However, due to a lack of population variety and exploratory capabilities, this convergence rate may decrease in some circumstances. As a result, the RSS is offered to enhance the solution and improvise the exploration capabilities.

1. In individual solution, a vector of a random number in generated within the interval of [-1,1], and establish the unit vector is represented in Eq. (14):

$$u = \frac{\{r_{1,}r_{2,\dots,}r_n\}}{\sqrt{r_1^2+r_2^2+\dots+r_n^2}} \tag{14}$$

Where u is the unit vector and the random numbers are denoted as $r_{1,}r_{2,\dots,}r_n$

2. The solution is updated for a defined step length which is represented in Eq. (15) as follows

$$x_i' = \begin{cases} x_i + \lambda * u \ \ iff(x_i') < f(x_i), \ \lambda = \frac{U_i+L_i}{2}, \tau = (0.95)^t \\ x_i + \lambda * \tau * u \ otherwise \end{cases} \tag{15}$$

Where the shrinking parameter is represented as τ and it gets decreased to an increasing iterated number. The lower and upper bounds are represented as U_i and L_i respectively.

Different values are evaluated as 0.95, 0.9, and 0.85 to change the variable $\tau = \theta^t$, which is responsible for exploration and exploitation skills and the performance of the IASO algorithm is monitored during numerous separate trails. Based on the results of the trials, the value of θ is set to 0.95, resulting in an efficient performance. The RSS may be used to optimize the balance between exploration and exploitation skills.

Fitness function

Each atom is assessed using a predetermined fitness function for the selection of wrapper features. Reducing the number of characteristics and improving prediction accuracy are the major objectives of feature selection. The fitness function can be evaluated using the Eq. (16) as follows:

$$Fit = \gamma E_R + (1-\gamma)\frac{|F|}{|R|} \tag{16}$$

Where the classification error rate is defined as E_R and it is represented in Eq. (17) as follows:

$$E_R = \frac{No.of\ wrongly\ predicted\ instances}{Total\ number\ of\ instances} \tag{17}$$

The number of features is represented as $|F|$, the actual length of the feature set is denoted as $|R|$. The parameter γ is utilized to enhance the size of the feature and the performance.

3.5 Classification of EEG signals using LSTM

The final stage in the process is the classification of EEG signals. The feature selected using IASO is provided as input for the stage of classification. This research utilizes a long short-term memory network (LSTM) as a classifier. LSTM is a special type of recurrent neural network (RNN), which can learn long-term dependence. The LSTM consists of a central component known as cell state which can add or remove information from cells and selectively permit information to pass through the door mechanism to accomplish this. The forget gate, input gate, and output gate make up an LSTM. The input gate chooses what information to add to the cell state after the forget gate has decided which information to remove from the cell state. The cell state can be updated once these two points have been established. The output gate, in the end, determines the network's ultimate output.

The process of the node present in LSTM is described in Eqs. (18-23) as follows:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{18}$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{19}$$

$$\tilde{C}_t = tanh(W_C.[h_{t-1}, x_t] + b_C) \tag{20}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{21}$$

$$o_t = \sigma(W_0.[h_{t-1}, x_t] + b_0) \tag{22}$$

$$h_t = o_t * tanh(C_t) \tag{23}$$

Where the hidden state of the prior layer is denoted as h_{t-1}, input for the current layer is denoted as x_t. The weight and biased state are denoted as W and b respectively. The sigmoid function is denoted as σ and the output of the forget gate is denoted as f_t. The output from the input gate is represented as i_t and the intermediate temporary state is denoted as $\tilde{C}_t$. The state of the cell present in the prior layer is denoted as C_{t-1} and the state of the cell present in the next layer is denoted as C_t. The output from the output gate and the hidden state of the succeeding layer is denoted as o_t and h_t respectively.

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Table 1. Performance analysis of various classifiers with feature selection for TUH dataset

Classifier	Accuracy(%)	Sensitivity(%)	Specificity(%)	F1-score(%)
SVM	93.23	91.79	95.91	93.93
KNN	94.28	90.96	92.79	91.82
RF	94.55	95.49	92.96	94.24
DT	95.28	91.80	94.74	91.03
LSTM	98.40	98.00	97.91	98.46

Table 2. Performance analysis of various classifiers without feature selection for TUH dataset

Classifier	Accuracy(%)	Sensitivity(%)	Specificity(%)	F1-score(%)
SVM	84.82	85.38	83.65	86.29
KNN	91.69	90.77	92.71	90.26
RF	89.32	87.80	88.75	89.01
DT	88.95	91.19	89.28	90.85
LSTM	94.44	92.45	93.66	92.67

Computing the output of the input and output gate individually doesn't provide better performance so, the output from the input and output gate can be distinguished using the factor $1 - f_t$. This helps to improve the cell state for the next layer in the input and output gate, it is represented in Eq. (24) as follows:

$$C_t = f_t * C_{t-1} + (1 - f_t) * \tilde{C}_t \tag{24}$$

4. Results and analysis

This section provides the results and analysis of this research. The result portion is classified into performance analysis and comparative analysis which are represented in the following sections. The performance of the proposed approach is evaluated with the existing approaches by considering the performance metrics such as accuracy, sensitivity, specificity and F-1 score which is defined as follows:

Accuracy: It is defined as the ratio of correctly classified EEG signals from total number of observations. It is mathematically evaluated using the Eq. (25).

$$Accuracy = \frac{T\,P + T\,N}{(T\,P + T\,N + F\,P + F\,N)} \tag{25}$$

Sensitivity: It is defined as the proportion of correctly predicted positive classes which is predicted as positive. It is mathematically evaluated using the Eq. (26).

$$Sensitivity = \frac{T\,P}{(T\,P + FP)} \tag{26}$$

Specificity: It is defined as the proportion of actual negative which is predicted as positive. It is mathematically evaluated using the equation (27).

$$Specificity = \frac{T\,N}{(T\,N + FP)} \tag{27}$$

F-1 score: It is defined as the average value which is obtained from recall and precision and it is mathematically evaluated using the Eq. (28).

$$F1\ score = 2 \times \frac{(Recall \times Precision)}{(Recall + Precision)} \tag{28}$$

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

4.1 Performance analysis

The performance of the LSTM classifier with feature selection and without feature selection is compared with the existing classifiers such as support vector machine (SVM), K-nearest neighbor (KNN), random forest (RF) and decision tree (DT). The performance analysis of the classifier with feature selection is represented in Table 1.

From Table 1 and Table 2, it is concluded that the performance of the LSTM classifier provides better results with both feature selection and in absence of feature selection. In presence of feature selection, the LSTM classifier achieves better classification accuracy of 98.40% and without feature selection, it achieved 94.44%. The better result is due to the presence of multiple numbers of hidden layers in the structure of LSTM. When the selected features pass through the layers of LSTM, it keeps the relevant data and discards the irrelevant one from each cell.

Table 3 represents the performance of the optimization algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Fruit fly Optimization algorithm (FOA), Atomic Search Optimization (ASO) algorithm, and the proposed IASO.

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Table 3. Evaluation of optimization algorithms

Algorithms	Accuracy (%)	Sensitivity(%)	Specificity(%)	F1-score(%)
PSO	86.66	89.27	88.93	89.49
ACO	91.35	90.70	89.99	90.34
FOA	93.78	92.36	91.16	92.73
ASO	93.96	93.25	92.25	93.91
IASO	98.40	98.00	97.91	98.46

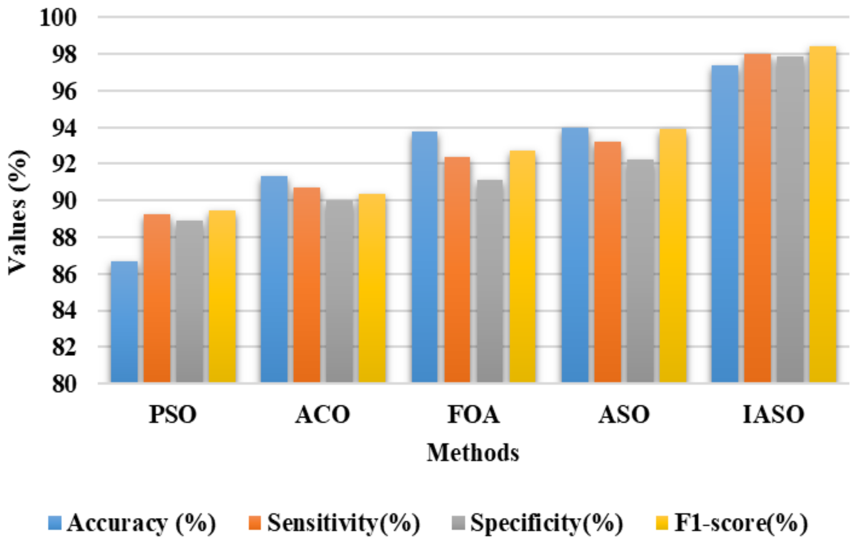

Figure. 3 Graph of performance evaluation of optimization algorithms

From Table 3, it is concluded that the proposed IASO has the highest evaluation metrics compared with other optimization algorithms for feature selection. IASO algorithm is a combination of a random search strategy and ASO. The ASO algorithm alone is not effective to provide an efficient solution for dimensional problems. So, a random search strategy is utilized in ASO to improve its performance of ASO. Thus, IASO aids in better classification accuracy of 98.40% while FOA (94.78%) and ASO (94.96%) attained less accuracy while selecting the relevant features. The graphical representation of the performance of the optimization algorithm is represented in Fig. 3.

4.2 Comparative analysis

This section provides a comparative analysis of various methods utilized for selecting the features and a valid comparison is performed with the existing methods to prove the efficiency of the proposed IASO algorithm. The performance of the proposed approach is evaluated with different approaches such as AHW-BGOA-DNN, DM-ELM and Deep Neural Network (DNN) model to compute the performance based on accuracy, sensitivity, specificity and F1-score. Table 4 shows the comparative analysis of the proposed IASO with different approaches for various datasets. The overall results from the table 4 shows that the proposed IASO-LSTM have achieved better results when compared with the existing methods. For TUH dataset, the proposed approach achieved classification accuracy of 98.40% whereas the DNN model achieved classification accuracy of 97%. For BONN dataset, IASO-LSTM have achieved classification accuracy of 95.89% where the existing DM-ELM achieved accuracy of 92%. At last, the performance of the proposed approach is evaluated for BERN dataset with AHW-BGOA-DNN. For BERN dataset, IASO-LSTM achieved accuracy of 96.81% whereas the existing AHW-BGOA-DNN achieved classification accuracy of 93.13%. The better result is due to the capability of IASO in performing exploration in untested regions and providing satisfactory performance. In IASO, the exploitation is performed using a random search strategy which is utilized in neglected the redundant features and ease the process of classifying epileptic EEG signals.

5. Conclusion

A precise classification of the epileptic EEG signal is an essential step in the diagnosis of epilepsy that aids physicians in making the diagnosis. In this research, the improved atomic search optimization algorithm is proposed to effectively classify the

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Table 4. Comparison of the proposed approach for various dataset with the existing approaches

Dataset	Methods	Accuracy(%)	Sensitivity(%)	Specificity(%)	F1-score(%)
TUH	DNN model [21]	97	98	-	97.4
	IASO-LSTM	98.40	99.00	97.91	98.46
BONN	DM-ELM [22]	92.00	91.00	93.00	94.00
	IASO-LSTM	95.89	94.11	97.56	98.10
BERN	AHW-BGOA-DNN [23]	93.13	93.46	95.93	-
	IASO-LSTM	96.81	97.11	98.33	95.46

epileptic EEG signals. Since LSTM is organized with multiple hidden layers, it meritoriously classifies the epileptic EEG signal. The features are extracted using the proposed IASO algorithm which is a combination of ASO and random search strategy. In IASO, ASO is utilized in the stage of exploration and random search strategy is utilized in the stage of exploitation. In pre-processing, the adaptive filter is utilized to de-noise the EEG artifacts and redundant signals. The experimental findings show that the proposed IASO performs better than the existing methods such as SSIO and FPGA in classifying the epileptic EEG signals. The proposed IASO attained better accuracy of 98.40% for TUH dataset whereas DNN model achieved classification accuracy 97%. In the future, the efficiency of the proposed methodology can be evaluated with machine learning classifiers.

Notation list

Parameter	Description
$y(n)$	Residual error
$d(n)$	Desired signal
F_i	Force of interaction
G_i	Constraint of an operating atom
a_i	Acceleration of the atom
m_i	Mass of the atom
$\eta(t)$	Depth function
α	Weight of the depth function
T	Maximum number of iterations
$h_{ij}(t)$	Function used for repulsion or attraction of the regions
r	Distance among the atoms
h_{min}	Lower region
h_{max}	Upper region
g	Drift factor
$\sigma(t)$	Drifted length of the atom
$Kbest$	Population of the atom with best function
$rand_j$	Random number which lies in the range of [0,1]
$x_{best}(t)$	Best position of the atom at iteration t
$b_{i,best}$	Distance between normal and the best atom
$\lambda(t)$	Langrangian multiplier
β	Weight of the Langrangian multiplier
i	Acceleration of the atom
t	Time period
$m_i(t)$	Mass of the atom at time t
u	Unit vector
$r_1, r_{2,\dots,} r_n$	Random number
τ	Shrinking parameter
U_i	Upper bound of the atom
L_i	Lower bound of the atom
$\lvert F \rvert$	Number of features
$\lvert R \rvert$	Actual Length of the feature set
γ	Parameter used to enhance feature's size
x_t	Input for the current layer of LSTM
h_{t-1}	Hidden state of the prior layer
σ	Sigmoid function
i_t	Output from the input gate
$\tilde{C}_t$	Intermediate temporary state
C_{t-1}	Cell present in the prior layer

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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