AN EFFICIENT EPILEPTIC SEIZURE DETECTION USING ENTROPY FEATURES WITH OPTIMAL NEURAL NETWORK

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ABSTRACT

The planning of electroencephalogram (EEG) signal location is a difficult errand because of the need of removing delegate designs from multidimensional time arrangement created from EEG estimations. Productively recognizing epileptic seizure EEG signals is helpful in taking care of neurological variations from the norm and furthermore in assessment of the physiological condition of the mind for a wide scope of utilizations in the field of biomedical. The electrical activity of the brain is indicated by the EEG signals and also it contains useful information about the state of the brain for studying brain function. In the manual scoring there is always a chance for human errors, also it consumes a lot of time, process is costly and not sufficient enough for reliable information. This developed a need of designing an automatic system for evaluating and diagnosing epileptic seizure EEG signals to eliminate the chance of the analyst missing data. An Adaptive artificial neural network (AANN) is used in the proposed approach to detect normal or epileptic signal. Also, oppositional crow search algorithm (OCSA) is used for optimal designing of the epileptic seizure detection system. The proposed method is to be implemented using Matlab software. The simulation results are to be compared with existing approaches to calculate its effectiveness.

1. INTRODUCTION

Epilepsy is the second most common brain disorder after migraine. The defining characteristic of epilepsy is recurrent seizures that strike without warning. Symptoms may range from brief suspension of awareness to violent convulsions and sometimes loss of consciousness. Automatic detection of epileptic seizures can considerably improve the patients' quality of life [1]. Electroencephalogram (EEG) is the prime signal that has been widely used for the diagnosis of epilepsy. Current EEG-based seizure detection systems encounter many challenges in real-life situations [2]. The EEGs are non-stationary signals and seizure patterns vary across patients and recording sessions. Moreover, EEG data are prone to numerous noise types that negatively affect

the detection accuracy of epileptic seizures. The visual inspection of EEG is unfortunately labor and time consuming [3].

A vast number of methods were developed for automatic seizure detection using EEG signals. Extracting features that best describe the behavior of EEGs is of great importance for automatic seizure detection systems' performance. Several feature extraction and selection techniques are reported in the researches [4]. Most of them use hand-wrought features in the time-domain, frequency-domain, time-frequency domain or sometimes in a combination of two domains. However, these domain-based methods encounter three main challenges [5]. First, they are sensitive (not robust enough) to acute variations in seizure patterns. This is because the EEG data is non-stationary and its statistical features change across different subjects and over time for the same subject. Secondly, EEG data acquisition systems are very susceptible to a diverse range of artifacts such as muscle activities, eye-blinks, and environmental white noise. All these sources of noise can alter the genuine EEG features and hence seriously affect the performance accuracy of seizure detection systems. Finally, most existing seizure detection systems were trained on small-scale EEG datasets collected from few specific patients, making them less practical in clinical applications [6]. So as to handle some of these issues and challenges a new epileptic seizure detection method is presented.

Nowadays lot of researchers has analyzed epileptic seizure detection in EEG signal. Among them some of the papers are analyzed here; by analyzing high dimensional phase space via Poincaré section, R. Shantha Selvakumari and M. Mahalakshmi [7] have presented an Epileptic seizure detection approach. Though the results have shown promises, the sensitivity could have been further increased for better performance. Based on empirical mode decomposition, Varun Bajaj and Ram Bilas Pachori [8] have presented a new approach for detection of epileptic seizures. The presented method has provided an effective result by detecting the changes because of epileptic seizure in the EEG signals which could have been further improved with noise reduced EEG signal. Bogaarts et al. [9] have proposed a new method in which the importance of training dataset selection has been shown by Optimal training dataset composition for SVM-based, age-independent, automated epileptic seizure detection. The outcomes have guaranteed that the proposed technique has beated the vast majority of the current strategies [13, 14]. Orhan et al. [10] have exhibited another component extraction strategy known as likelihood circulation dependent on equivalent recurrence discretization. The outcomes have indicated that the exhibited strategy can be utilized as opposed to measurable parameters for the extraction of the highlights of EEG signals for the contributions of classifiers. By deteriorating EEG flag up to six wavelet scales without down inspecting, Chen et al. [11] have proposed a methodology for seizure recognition. The outcomes have demonstrated that the proposed methodology is aggressive with a large portion of the current EEG seizure location strategies. Kabir et al. [12] have displayed a novel examination framework for distinguishing epileptic seizure from EEG signals which uses factual highlights relying upon ideal portion system with calculated model

trees. The Presented method has been able to achieve better results in terms of classification accuracy and sensitivity.

2. PROPOSED EPILEPTIC SEIZURE DETECTION

The main purpose of proposed methodology is to effectively identify the seizure using optimal neural network. The overall structure of the proposed methodology is given in figure 1. The proposed work compressed into three modules, namely preprocessing, feature extraction and epileptic seizure detection.
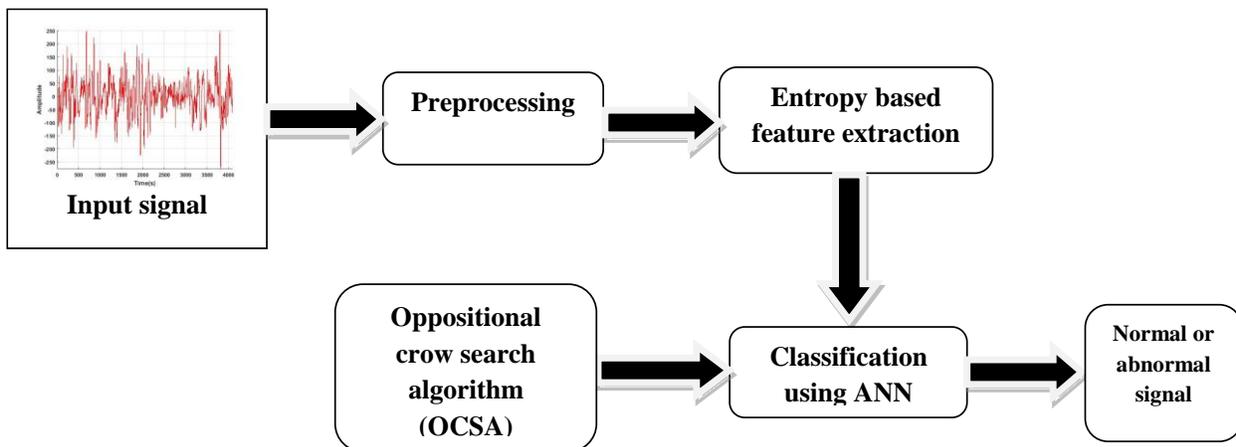
Figure 1: Overall structure of proposed epileptic seizure detection

2.1 Preprocessing:

Initially, the collected EEG signals are given to the preprocessing stage to remove the noise and artifacts from each input signal. In this paper, for preprocessing band pass filter is utilized. After noise removal, the signals are decomposed into high frequency channel (HH band) and low frequency channel (LL band) with the help of discrete wavelet transforms (DWT). Here, the extracted HH band is utilized for further processing.

2.2 FEATURE EXTRACTION:

After the preprocessing stage, the significant highlights are extricated from HH band. The EEG signal is of non direct and non stationary in its property. In this manner, non direct parameter, for example, entropy expands the power of separating typical and unusual EEG signals. The

randomness in a system is known as the entropy. The randomness and complexity of a signal can be measured using entropy. Such non linear features are detailed below:

❖ **Approximate entropy:** Approximate entropy (AE) is a feature which is used to quantify the amount of predictability and randomness of a signal. The AE is calculated using equation (1).

$$AE(p,q,\tau,N)=\varphi^P(q)-\varphi^{m+1}(r) \tag{1}$$

$$\phi^P(q)=\frac{1}{N-(p-1)\tau}\sum_{i=1}^{N-(p-1)\tau}\log C_i^P(q) \tag{2}$$

Where, p,q,τ,N represents the embedding dimension, data points, vector comparison distance and time delay. For each I, correlation dimension $C_i^P(q)$ are computed using equation (2).

$$C_i^P(q)=\frac{1}{N-(m-1)\tau}\sum_{j=1}^{N-p+1}\theta(q-d(y(i),y(j))) \tag{3}$$

In above equation (3), the value of $\theta(y)$ is set to zero when y is not greater than 0.

❖ **Sample entropy:** The example entropy highlight is applied to short length time arrangement information and for evaluating the multifaceted nature of sign by keeping up the inclination limit. The SE can be calculated using equation (4).

$$SE(p,q)=\ln\left[\frac{E^p(q)}{D^p(q)}\right] \tag{4}$$

Here, $E^p(q)$ represents the Here, speaks to the likelihood of coordinating two successions for focuses and speaks to the likelihood of coordinating two groupings for focuses. The estimation of and are set 2 and 0.2 occasions the standard deviation of the data.

❖ **Fuzzy entropy:** In fuzzy entropy, instead of using the two value function in sample entropy, the fuzzy concepts are utilized for measuring unpredictability. The FE can be calculated using equation (5).

$$FE(p,n,q,N)=\ln\varphi^{p+1}(n,q) \tag{5}$$

Here, $\varphi^p(n,q)=\frac{1}{N-m}\sum_{i=1}^{N-p}\left[\frac{1}{N-p-1}\sum_{j=1}^{N-p}F_{ij}^p\right] \tag{6}$

p, q and N are same as in approximate entropy. The F_{ij}^{p} is a degree of similarity calculated for a given value of q and n. 4, 2 and 0.2 are the values of p, n and q respectively as chosen for detecting focal and non focal EEG signals.

❖ **Permutation entropy:** For calculating the complexity of a time series, the neighborhood values are compared. The PE can be calculated using equation (7). The time lag (τ) and embedding dimension (p) values are set to 1 and 3 respectively. Every permutation can be taken as a symbol and the overall sum of symbols depends on p.

$$PE = -\sum_{k=1}^{k} r_k \log r_k \tag{8}$$

$$\text{Here, } r_k = \frac{s_k}{N-p+1} \tag{9}$$

Also, occurrence of kth symbol in time series is represented as s_k and probability of occurrence of kth permutation is represented by r_k.

❖ **Rényi entropy:** A signal's spectral complexity is quantified using the entropy measure. It is the generalized form of Shannon entropy. It is calculated using (10).

$$RE = \frac{1}{1-\beta}\left(\sum_{i=1}^{k} t_i^{\beta}\right), \beta \neq 1 \tag{10}$$

Here, t_i^{β} is a ith sample of signal (t) and β is a positive constant such that $\beta \neq 1$. RE approaches Shannon entropy when β approaches 1. Here, the β is set to 2.

❖ **Tsallis entropy:** The sudden change in the signal is measured using Tsallis entropy. It is calculated using equation (11).

$$RE = \frac{1}{b-1}\left(\sum_{i=1}^{k} t_i^{b}\right), b \neq 1 \tag{11}$$

Here, t_i^{b} is the signal and b is a non-extensively index. The value of b is set to 2.

❖ **Wavelet entropy:** The information on the dynamics of a signal is provided by wavelet entropy. Also, it helps in recognizing the intermittent characteristics of a signal. It is calculated using equation (12).

$$WE = -\sum_{y<0} \alpha_y \ln \alpha_y \tag{12}$$

Here, $\alpha_y = \dfrac{G_y}{G_s}$, G_y is the energy of ith sub band and G_s is the overall signal energy.

❖ **Hjorth parameter:** The statistical character of signals is measured using Hjorth parameter. It consists of three parameters namely mobility, activity and complexity. Mobility alone is considered here. Parameter is considered for the characterization of seizure inclined sign that is characterized as the square base of proportion of subsidiary of the sign to that of the first sign which is appeared in condition (13).

$$\text{❖ } Mob = \sqrt{\frac{\text{var}(z'(s))}{\text{var}(z(s))}} \tag{13}$$

❖ **Shannon entropy:** The dynamics and the spread of a signal is measured using Shannon entropy. Utilizing signal amplitude, the spectral entropies are measured. It can be calculated using equation (14).

$$ShE = \log_2 \frac{1}{p(y)} \tag{14}$$

Here, the power in every frequency band is represented as $p(y)$.

❖ **Multiscale permutation entropy:** MPE can be calculated by constructing multiple coarse grained time series and averaging of data points in non overlapping windows of increasing length τ. Each coarse grained is constructed using equation (15).

$$z_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} y_i \tag{15}$$

Here, τ is the scale factor $1 \le j \le N/\tau$.

2.3 EPILEPTIC SEIZURE DETECTION USING OPTIMAL NEURAL NETWORK:

After the feature extraction process, the extracted features are given to the input of artificial neural network to classify a signal as normal or epileptic. In this to increase the convergence

speed of ANN; he weights are optimally selected with the help of oppositional crow search algorithm (OCSA). For classification, the dataset signals are split into two types such as training dataset and testing dataset. For training process, 80% of signals are used and remaining 20% of signals are used for the testing process. The artificial neural network is a classifier which is used for many applications namely, recognition, prediction classification etc. Normally, the neural network consist of three layers namely, input layer, hidden layer and output layer and each layer consist of n neurons. The number of input neuron is based on the input data and the number of neurons of the hidden layer is selected empirically by the user. Lastly, the output layer comprises c neurons for the c classes. Each connection between two neurons is connected with a weight factor. At first, the weight values are randomly assigned. Then, this weight is optimally selected using OCSA during the training of the network according to input and output data. The structure of AANN is given in figure 2.
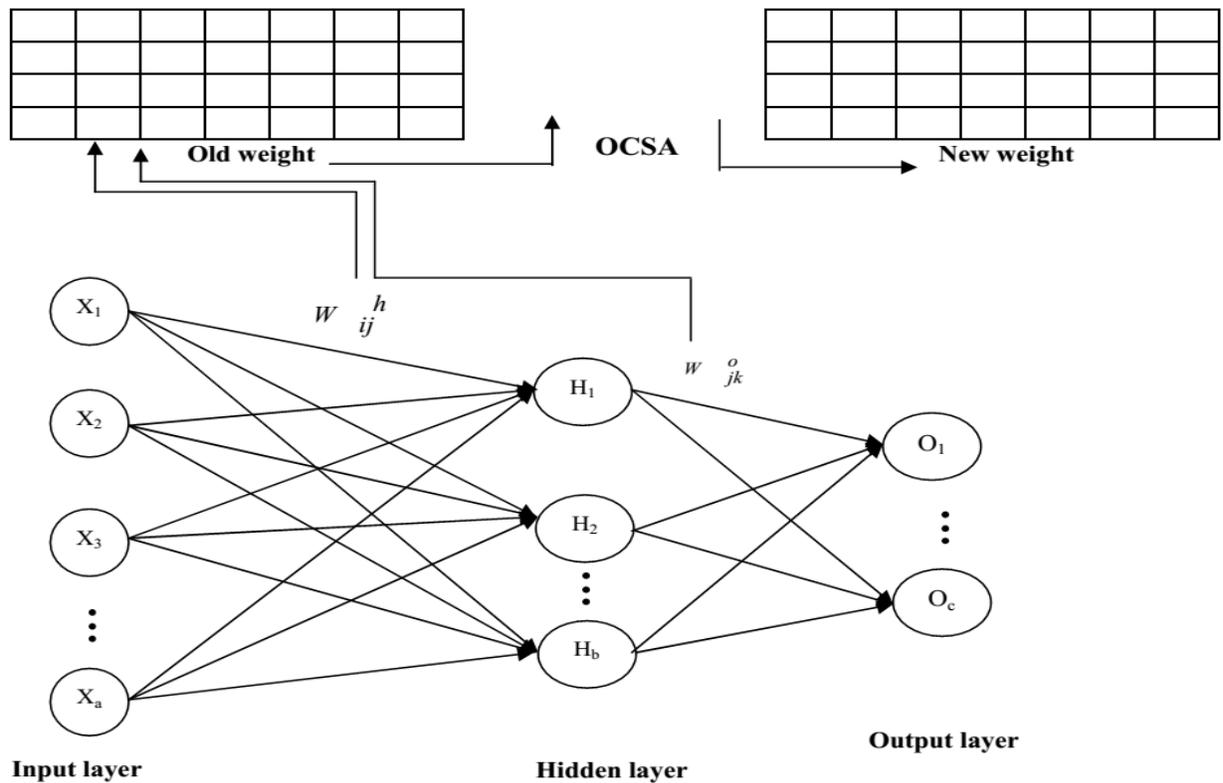

Figure 2: Structure of adaptive artificial neural network (OANN)

Training process:

Consider a neural network with a-b-c- configuration. Here, the input layer nodes are represented as $X_1, X_2, \ldots, X_a$, the hidden layer nodes are represented as $H_1, H_2, \ldots, H_b$ and the value of output

nodes are $O_1, O_2, \ldots, O_c$. W_{ij}^h represents the weight connecting the input layer node i and the hidden layer node j. W_{jk}^o denotes the weight connecting hidden node j and the output layer node k, where $1 \le h \le a; 1 \le j \le b; 1 \le i \le c$.

Initially, the input layer X_i node value is multiplied with weight value between the input layer and the hidden layer. Each node j present in the hidden layer receives the output H(j) using equation (16)

$$H_j = \alpha_j + \sum_{i=1}^{n} X_i W_{ij}^h \qquad (16)$$

Then, the output H_j passed through the tansig activation function. The Activation function is represented as a non-linear function which is given in equation (17).

$$F(H_j) = \frac{1}{1 + e^{-H_j}} \qquad (17)$$

After the active function calculation, we have to calculate the output value. The output function is described in the equation (18).

$$O_k = \alpha_k + \sum_{j=1}^{b} W_{jk}^o f(H_j) \qquad (18)$$

Where, α_j and α_k are the biases in the hidden layer and the output layer. Then, we calculate the learning error by means of the following equation;

$$E = \frac{1}{2n} \sum_{i=0}^{h-1} \sqrt{(T_i - O_i)^2} \qquad (19)$$

Where; n is the number of training parameters, O_i and T_i are the output value and the target value, respectively. Then, the error values are minimized based on the weight values. To minimize the error value, in this paper we optimally select the weight value using OCSA. The step by step process of optimal weight value selection is given below;

Step 1: Initialization: In ANN, at first the weight values are randomly assigned to each node. Here, weight values are represented as agent and solution is represented as crows. The crows consist of weight values of input neurons and output neurons.

Step 2: Opposite solution generation: For every solution C_i has a unique opposite solution OC_i. The opposite solution $OC(A'_1, A'_2, ..., A'_n)$ is calculated given as follow;

$$A'_i = a_i + b_i - A_i \qquad i \in 1,2,...,n \qquad (20)$$

$$OP_i = \begin{bmatrix} A'_{11} & A'_{12} & ....A'_{1D} \\ A'_{21} & A'_{22} & ....A'_{2D} \\ A'_{n1} & A'_{n2} & ....A'_{nD} \end{bmatrix} \qquad (21)$$

Step 3: Fitness calculation: After crow's initialization, fitness function of each crow is calculated. In this paper, the error value is considered as an objective function. The fitness function is shown in beneath,

$$\text{Fitness} = \min \{E\} \qquad (22)$$

$$E = \sum_i \sum_i (Y_i(t) - O_i(t)) \qquad (23)$$

Where, $Y_i(t)$ is represent a target and $Y_i(t)$ is a system output.

Step 4: Updation using CSA: After the fitness calculation, each crow are updated CSA. For updating the crows, two cases are available.

Case 1: The owner crow n of food source B_n^t doesn't realize the cheat crow m follows it so the cheat crow attains to the shroud location of owner crow. The thief crow position updation is provided in equation (24).

$$S_m^{t+1} = S_m^t + R_m \times FL_m^t \times (B_n^t - S_m^t) \qquad (24)$$

Where, R_m is a random number in range [0,1], FL_m^t is the flight length of crow m at iteration t.

Case 2: The proprietor crow n realize that the cheat crow m follows it therefore, the proprietor crow will mislead crow m by going to any another location of search space. In this case the position of crow m is updated by a randomly. The updation equation is given in equation (25).

$$S_m^{t+1} = \begin{cases} if \ R_n \geq P_n^t & update \ position by \ u\sin g \ equation(24) \\ else & update to \ random \ position \end{cases} \qquad (25)$$

Where, P_n^t is the probability of awareness of crow n at iteration t. The positions are updated using equation (25) and after that the latest objective function is evaluated, the attained fitness

function at iteration t is contrasted with earlier one and updating position of flock position is placed.

Step 5: Termination criteria: The optimization process terminates when it achieves the minimum error value or maximum number of iteration met. In this work, maximum number of iteration is used. The most extreme number of cycle set in this work is 40. The optimal selected weight values are assigned to artificial neural network and the corresponding weight is further utilized for the testing process.

Testing process:

After training process, the testing process is done with the help of remaining data. In this stage, the original input signal is classified as normal or epileptic signal. Here, at first, the features are extracted from each signal and extracted features are given ANN. The trained weights are assigned to the ANN. After the calculation, the corresponding score (S^{out}) is obtained for the input signal. Based on the score value, the signal is classified as normal or epileptic signal with the help of threshold value (T^H). For classification, the threshold value is depending upon the class value only. If the score value is above the threshold (T^H) means, the given signal is epileptic signal otherwise the signal is normal signal. The classification condition is given in equation (26).

$$output \in \begin{cases} epileptic, \ if \ S^{out} \geq T^H \\ normal, \ otherwise \end{cases} \tag{26}$$

3. RESULT AND DISCUSSION:

The proposed approach has used optimal Artificial Neural Network for epileptic seizure detection system. Here, the weights have been optimally selected by utilizing oppositional crow search algorithm. The presented epileptic seizure detection approach has been implemented in the platform of MATLAB7.0 atmosphere running in an Intel Pentium processor with 3.00 GHz. The dataset EEG signals are collected from the internet. The experimental used sample signals are given in figure 3.
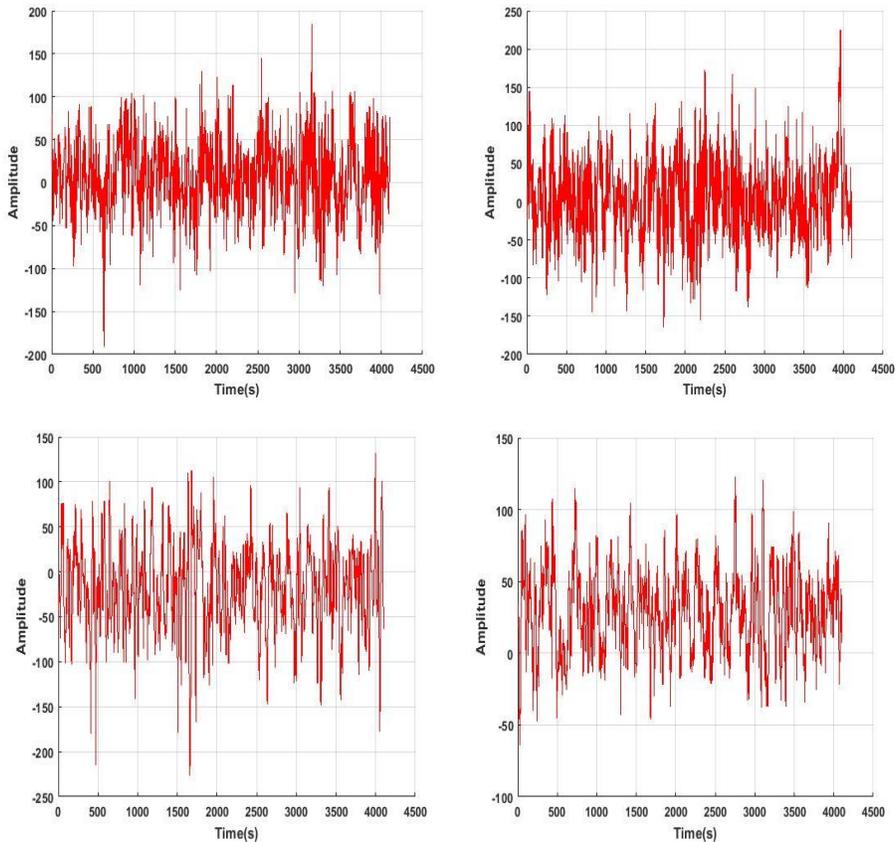
Figure 3: Experimental used sample signals

3.1 Evaluation metrics:

The proposed epileptic seizure detection is evaluated with the help of three efficient metrics namely, accuracy, sensitivity and specificity. The metrics are given below;

$$\text{Accuracy} = (TN + TP)/(TN + TP + FN + FP) \tag{27}$$

$$\text{Sensitivity} = TP \; / \; (TP + FN) \tag{28}$$

$$\text{Specificity} = TN \; / \; (TN + FP) \tag{29}$$

Where, TP, TN, FP, and FN denote a number of true positives, a number of true negatives, a number of false positives, and a number of false negatives, respectively.

3.2 Performance analysis:

In this section, the performance of the presented method that has used ANN and OCSA optimization algorithm along with its analysis has been given. The presented method's performance has been analyzed in terms of accuracy, sensitivity and specificity. Finally, the presented method has been compared with other existing methods such as ANN and GA+ANN methods.

Training and Testing	Sensitivity	Specificity	FAR	FRR	GAR	Accuracy
'90%-10%'	0.99387	0.750613	0.062347	0.001838	0.99954	0.937194
'80%-20%'	0.982542	0.715498	0.01586	0.002565	0.984565	0.925649
'70%-30%'	0.975146	0.648415	0.025495	0.001847	0.966542	0.912349

Table 1: Epileptic Seizure Detection using ANN

Training and Testing	Sensitivity	Specificity	FAR	FRR	GAR	Accuracy
'90%-10%'	0.95346	0.82451	0.049387	0.00246	0.998162	0.948775
'80%-20%	0.96358	0.81588	0.026875	0.002916	0.985469	0.937864
'70%-30%'	0.96234	0.857451	0.025656	0.002856	0.98945	0.927618

Table 2: Epileptic Seizure Detection using GA+ANN

Training and Testing	Sensitivity	Specificity	FAR	FRR	GAR	Accuracy

'90%-10%'	0.999549	0.8365	0.0352	0.0018	0.99763	0.964
'80%-20%	0.99125	0.82643	0.01634	0.0015	0.98524	0.955
'70%-30%'	0.985156	0.86241	0.02146	0.0022	0.98769	0.946

Table 3: Epileptic Seizure Detection using OCSA+ANN

Table 1 shows the ANN based Epileptic Seizure Detection performance. When analyzing table 1, ANN based Epileptic Seizure Detection approach attains the maximum accuracy of 93.7%, 92.5% and 91.2% for training and testing data of 90:10, 80:20 and 70:20, respectively. In table 2, GA+ANN based Epileptic Seizure Detection performance are analyzed. Here, the method attains the maximum accuracy of 94.87%, sensitivity of 96.35% and specificity of 85.77%. The performance of proposed Epileptic Seizure Detection is given in table 3.when analyzing table 3, our proposed method attain the maximum accuracy of 96.4%, 95.5% and 94.6% for training and testing data of 90:10, 80:20 and 70:20, respectively. Compared to other two methods, our proposed approach attains the better result. The reason for this is the use of the OCSA algorithm in the proposed method.
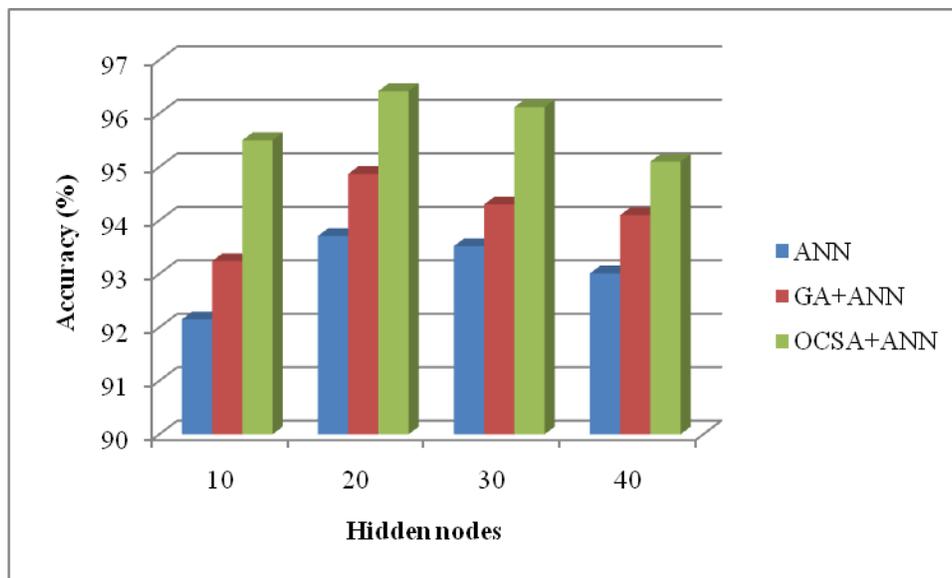

Figure 3: Performance analysis of ANN, OCSA+ANN and GA+ANN based on accuracy

The performance analysis of the proposed OCSA+ANN approach along with ANN and GA+ANN approaches is shown in Figure 3. The performance has been analyzed for various quantities of nodes. When the hidden node is 10, the accuracy of the proposed OCSA+AANN

method is 95.5%, the accuracy of ANN is 92.15% and the accuracy of GA+ANN is 93.24%. The proposed method has higher accuracy than ANN and GA+ANN. The accuracy of the proposed OCSA+AANN method is 96.42%, the accuracy of ANN is 93.71% and the accuracy of GA+ANN is 94.87% when the hidden node is 20. The accuracy of proposed OCSA+AANN method is higher than ANN and GA+ANN.
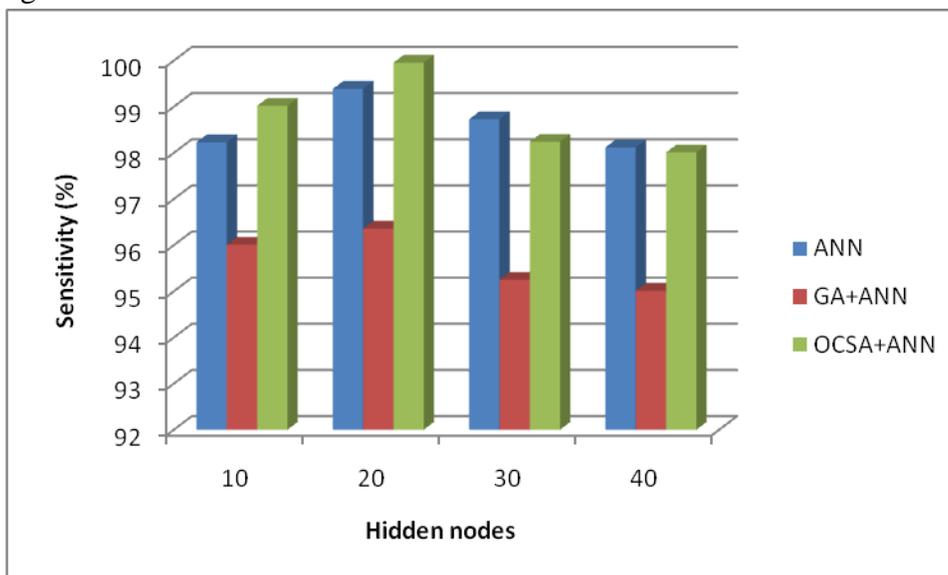

Figure 4: Performance analysis of ANN, OCSA+AANN and GA+ANN based on sensitivity
The performance analysis of the proposed OCSA+AANN method with ANN method and GA+ANN method based on their sensitivity has been shown in Figure 4. When the hidden node is 40, the sensitivity of the proposed OCSA+AANN method is 95.1%, the sensitivity of ANN is 93.01% and the sensitivity of GA+ANN is 94.1%. The proposed OCSA+AANN method has the highest sensitivity when compared with ANN and GA+ANN. The case is same for all the values of hidden nodes. The presented approach can be considered as the efficient one in terms of sensitivity.
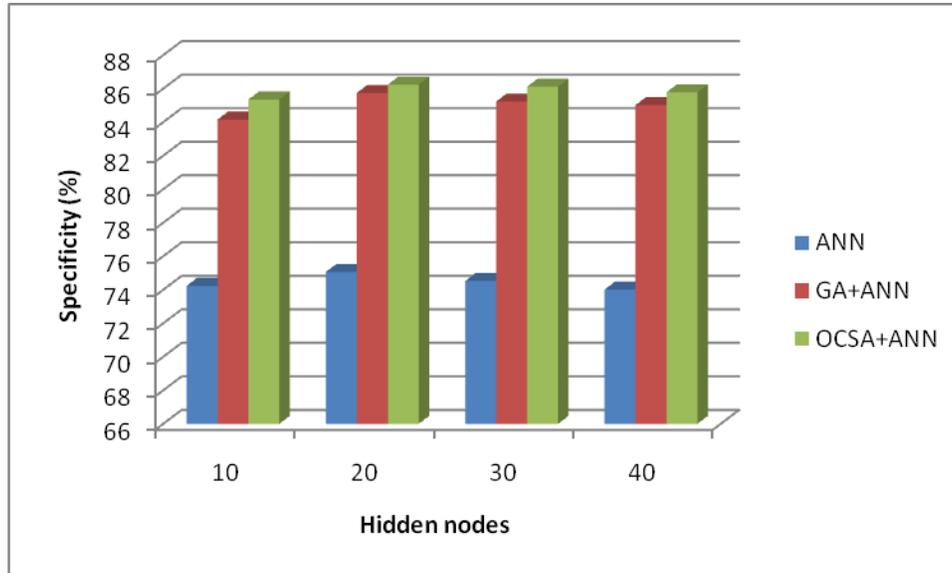
Figure 5: Performance analysis of ANN, GOA+AANN and GA+ANN based on specificity

In Figure 5, the performance analysis of the proposed OCSA+AANN method with ANN method and GA+ANN method based on their specificity has been presented. The specificity value of ANN is 74.23%, the specificity value of OCSA+AANN is 85.35 and the specificity value of GA+ANN is 84.12 when the hidden node is 10. The proposed OCSA+AANN method has higher specificity than compared ANN method and GA+ANN method. The order of values is same for 20, 30 and 40 hidden nodes. From the results, we clearly understand our proposed method effectively detects the normal signals and epileptic signals.

4. Conclusion

An efficient epileptic seizure detection method using entropy features with optimal neural network has been presented. Initially, the features have been extracted and for classifying a signal as normal or epileptic, the extracted features have been provided to the input of ANN. For optimally selecting the weights during the training of network, the Oppositional Crow Search Algorithm has been utilized. This has enhanced the overall effectiveness of the approach. The presented method has been analyzed for its performance based on sensitivity, specificity and accuracy. Also, the existing approaches such as ANN based epileptic seizure detection and GA+AANN based epileptic seizure detection have been compared with the presented OCSA+AANN based epileptic seizure detection approach so as for calculating its efficiency over them. The simulation results have shown that the proposed OCSA+AANN method has outperformed the other compared methods.

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