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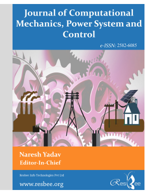

Improved Chicken Swarm Optimization Algorithm: Epileptic Seizure Detection by EEG Signal

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Abstract: To monitor epilepsy to regenerate a close-loop brain, the Electroencephalogram (EEG) signal is extensively used. Several existing approaches are formulated to identify the seizures, which are based upon the visually evaluating EEG signals which are exclusive as well as the complex procedure if there is an increase in amounts of the channel. A novel approach called Improved Chicken Swarm Optimization Algorithm (ICSOA) is developed and is exploited to train the deep-stacked autoencoder (Deep SAE) for identifying epileptic seizures. At first, using the bandpass filter, EEG signals are subjected to pre-processing phase in that noise is evaded. Subsequently, the noise-evaded signals are given as input whereas EEG is to train the Deep SAE that is partitioned into several channels and that channel carries out the feature extraction. Moreover, the features namely Holoentropy, relative energy, fluctuation index, Taylor-based delta AMS, spectral features, tonal power ratio, as well as Linear Prediction Coefficient (LPC) are obtained from each channel. To reduce the dimensionality of the feature, the Probabilistic Principal Component Analysis (PPCA) is used. For the recognition of epileptic seizures, the attained feature vectors are subjected to Deep SAE. Deep SAE training is done by exploiting ICSOA. Therefore, the outcome produced from adopted ICSOA -based Deep SAE is used to recognize the seizures from EEG. The adopted ICSOA -based deep SAE reveals the maximum accuracy, sensitivity, and specificity.

Keywords: Bandpass filter, Deep SAE, EEG, Epileptic seizure, LPC.

Nomenclature

Abbreviations	Descriptions
EEG	Electroencephalogram
FC	Fully Connected
SEEG	scalp EEG
DNN	Deep Neural Network
FPR	False Positive Rate
PPCA	probabilistic PCA
RF	Random Forest
LPC	Linear Prediction Coefficient
LSTM	Long-Short Term Memory
HPF	High Pass Filter
SVM	Support Vector Machine
MSE	Mean Square Error
RNN	Recurrent Neural Network
ICSOA	Improved Chicken Swarm optimization algorithm
PCA	Principal component analysis
CNN	Convolutional Neural Networks
PPCA	Probabilistic principal component analysis
ML	Machine Learning
DEEP SAE	deep-stacked autoencoder
LPF	Low Pass Filter
ANN	Artificial Neural Network
1D-CNN	one dimensional CNN
RS-DA	Random Selection and Data Augmentation
KNN	K-Nearest Neighbor

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1. Introduction

Generally, Epilepsy is considered chronic neurological anarchy of the brain which affects the public of all ages. About 70 million persons globally have epilepsy, creating it in general after the majority of general neurological disease subsequent to a migraine. The distinguishing epilepsy feature is recurring seizures that hit suddenly. Symptoms might run from small awareness suspension to aggressive convulsions and once eventually consciousness loss. EEG is the most important signal which is extensively exploited for an epilepsy diagnosis. As EEG visual inspection is time-utilizing as well as labor, EEG-based automatic recognition of epileptic seizures research is active [1].

By International League against Epilepsy, an epileptic seizure is explained that is an impermanent occurrence of indications because of the unusually extreme activities and synchronization of neurons in the brain. By epilepsy, it is calculated that about 65 million populace in humanity is affected. However, reviewing continuous EEGs is still a time-utilizing procedure for neurologists to monitor epileptic patients. Hence, various researchers were adopted various approaches that aid neurologists to recognize an epilepsy incidence. The complete procedure of automated epileptic seizure study mainly comprises feature extraction; signal pre-processing, channel selection or feature, classification as well as data acquisition [1].

For automatic seizure detection systems, various feature extraction models were exploited. Numerous models exploit hand-wrought features extracted in the integration of two domains [2]. Nevertheless, these domain-based techniques come upon 3 important confronts. Initially, they are responsive to sharp deviations in seizure patterns. It is due to EEG data being non-stationary as well as its statistical features modify athwart diverse subjects as well as overtime for similar subjects [4]. Next, data acquisition systems of EEG are vulnerable to a different range of artifacts like white environmental noise eye-blinks, as well as muscle activities. All these noise sources can change the real EEG features and therefore critically concern the seizure detection system's performance. At last, the majority of conventional seizure recognition systems were trained on small-scale EEG datasets gathered from a small number of precise patients, creation them minimum sensible in clinical applications.

For automated seizure detection, the EEG-based analysis was extensively explored over the past 2 decades. In preceding research regarding EEG-based seizure detection, the long-term CHB-MIT sEEG dataset and short-term Bonn EG dataset were the two most generally exploited datasets. For the “short-term Bonn EEG dataset”, numerous existing Deep Learning as well as ML approaches, such as RF, SVM, KNN, CNN, ANN, and LSTM, was developed to evaluate this dataset for seizure detection. Nonetheless, EEG recordings of the populace with epilepsy typically last from various hours to numerous weeks in the real world. Hence, continuous, as well as long-term EEG data analysis may have more sensible consequences for seizure detection [3].

The main aim of this research is to develop an Improved Chicken Swarm Optimization Algorithm (ICSOA) -based Deep SAE to identify the elliptical seizure: The adopted ICSOA-based deep SAE is used and it is exploited to train the deep SAE. Moreover, the ICSOA is carried out for seizure detection.

2. Literature Review

In 2019, D K Thara et al [1], developed an endeavor a seizure recognition as well as prediction technique by exploiting the stacked bidirectional LSTM approach. It was the majority appropriate method for time series datasets evaluation as it surmounts the disappearance gradient issue recognized in RNN. In 2019, Ramy Hussein et al [2], worked on a DNN model for robust recognition of epileptic seizures. Initially, to learn the maximum-level indications of diverse EEG patterns, a deep LSTM network was exploited. Subsequently, to extract the main robust EEG features appropriate to epileptic seizures, an FC layer was developed. At last, these features were transformed to a softmax layer to outcome the predicted labels. In 2020, Poomipat Boonyakitanont et al [3], worked on the widely reviewed feature interpretations and their descriptions to characterize the epileptic seizures by exploiting the EEG signals, and to summarize the performance of classification measures. Finally, they had carried out experimentation to inspect each featuring quality independently to present the significant information of feature selection. To ascertain the consequence of the individual features, the non-parametric probability distribution estimation, as well as Bayesian error, was exploited. In 2019, Syed Muhammad Usman et al [4], studied a few general steps, such as EEG signals recording, feature extraction, preprocessing, classification, as well as post-processing. Nevertheless, epileptic seizures online prediction remnants confront as all these steps require furthermore modification to attain high sensitivity and minimum FPR. Here, an evaluation of up-to-date techniques was presented, which was exploited to predict seizures by both scalp and intracranial EEG signals as well as propose enhancements to conventional techniques. In 2021, Xiaoshuang Wang et al [5], worked on a stacked 1D-CNN approach that integrated with an RS-DA scheme for seizure onset recognition. Initially, the long-term EEG signals were segmented by exploiting the 2-s sliding windows. Subsequently, using the stacked 1D-CNN technique was classified. An RS-DA scheme was developed to resolve the issue of sample imbalance at the time of model training to detect all seizures of each patient.

3. Adopted ICSOA -based Deep SAE for Seizure Detection

The main objective is to propose a technique for epileptic seizures by taking into consideration of EEG. At first, from the dataset, the "input EEG signal" attained is used for the pre-processing stage to remove artifacts subsequently; the "pre-processed signal" is presented to diverse channels. After that, features mining taking into consideration each channel is carried out. Hence, features like Holoentropyspectral features, fluctuation index, relative energy, Taylor-based delta AMS, and LPC are attained with channels. Moreover, by combining the Taylor series [6] as well as delta AMS [7], Taylor-based delta AMS is attained. To set up a feature vector, the attained features taking into consideration each channel are exploited. By exploiting the PPCA [8] [9], the feature vector size is minimized. The feature vectors with minimized dimensionality are classified with Deep SAE [10]. By exploiting the adopted ICSOA, the Deep SAE is trained and is attained by ICSOA. Therefore, to discover the EEG seizure, the ICSOA -based deep SAE is proposed. Fig. 1 demonstrates a block diagram of the adopted ICSOA to detect seizures.

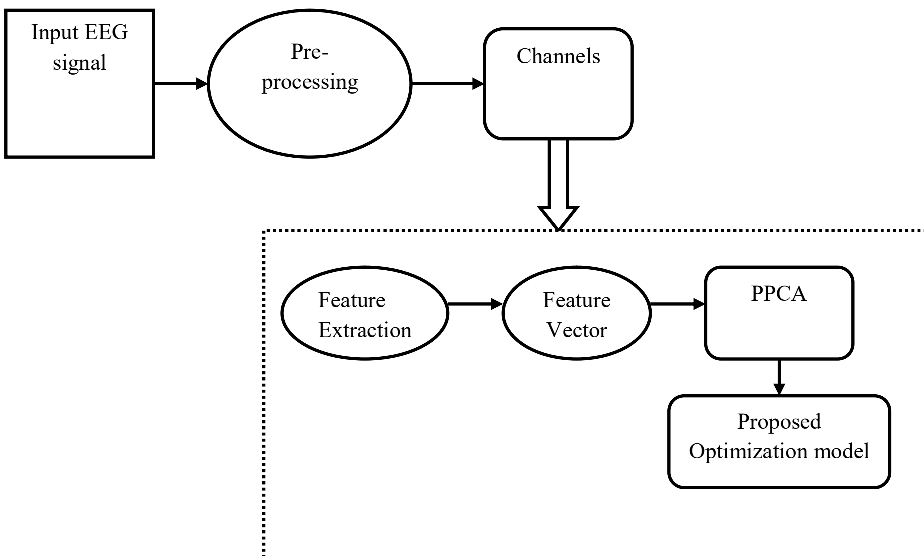

Fig. 1. *Architectural model of adopted ICSOA for elliptical seizure recognition*

Let database consists of EEG signals where seizure detection is carried out to recognize the patients possessing elliptical seizures. Presume $S(j)$ as an input signal, which is referred to as a signal where detection is considered a significant technique for the following processing. The signals are partitioned into diverse channels in that every channel carries out the features extraction as well as seizure detection.

3.1 Pre-processing

EEG signal is biased with various artifacts, namely eye movement, 50 Hz line noise, muscle activity, eye blink, etc. Therefore, these artifacts have to be evaded previous to processing the EEG signal. Moreover, from EEG signal to evade artifacts, the bandpass filter is exploited. Initially, the original signal $S(j)$ is transmitted into a bandpass filter that comprises a group of HPF as well as LPF. The LPF approximates signal as well as HPF presents missing information in approximation. It comprises minimum frequency and maximum scale components when details comprise high frequency-low scale elements.

3.2 Attainment of Features with Signal

In this technique, the acquisition of important features by exploiting input EEG as well as extraction inference is subjected. Moreover, to facilitate enhanced seizure discovery, feature extraction is used to produce pertinent features by exploiting the EEG. Additionally, precision is attained by exploiting detection and guaranteed with effective feature extraction. From input EEG signals, the features attained comprise "fluctuation index, spectral skewness, spectral kurtosis, relative energy, Taylor-based delta AMS, holoentropy, Tonal power ratio, as well as LPC".

i) Spectral Skewness

It [28] is explained as the coefficient of skewness as well as its symmetry quantity. Additionally, it is defined as an asymmetry metric about M mean value. The coefficient of skewness is referred to as a skewness proportion, devised as below:

$$h_3 = \int (f - M)^3 . P(f) df \tag{1}$$

$$\alpha_1 = \frac{h_3}{S^3} \tag{2}$$

where, $P(f)$ indicate probability distribution of spectrum, S indicate standard deviation, M indicate mean of spectrums by exploiting the input signal, f indicate every spectrum.

ii) Spectral Kurtosis

The spectral kurtosis [15] states the evenness or peakedness of dispersed energies. Higher kurtosis indicates a large intense divergence variance. It is calculated by exploiting the fourth-order moment h_4 represents M mean value, as well as standard deviation, which is devised as:

$$h_4 = \int (f - M)^4 . P(f) df \tag{3}$$

$$\alpha_2 = \frac{h_4}{S^4} \tag{4}$$

B_2. refers the spectral kurtosis.

iii) Relative Energy

It [11] is called signal strength as it presents area in the power curve at all time instant. The energy of EEG by exploiting length is devised as,

$$E(K') = \sum_{m=1}^{L} G_m^2 * \frac{\vartheta}{L} \tag{5}$$

wherein, L denotes the number of DWT coefficients, ϑ denotes sampling interval, G_m denotes m^{th} coefficient at scale K'. The $E_p(K')$ relative energy with scale K' is indicated as,

$$E_p(K') = \frac{E(K')}{\sum_{m=1}^{N} E(m)} \tag{6}$$

iv) Fluctuation Index

EEG is considered to exhibit enormous changes among seizures period. The fluctuation index [11] is used to assess intensities altres allowing for EEG. The X fluctuation index is indicated as,

$$D(K) = \frac{1}{L} \sum_{m=1}^{L} | G_{m+1} - G_m | \tag{7}$$

Where in, L implies a number of DWT coefficients G_m. It is illustrious EEG signal fluctuation index represents turn out to be minimum during non-seizure maximum and during seizures periods.

v) Tonal Power Ratio

It [12] is represented as assessing input EEG signal tonalness. It is devised by calculating tonal power spectrum unit's ratio as well as complete power. Let k_1 imply $F(d,e)$ as well as EEG implies EEG spectrum. Hence, the ratio of "tonal power H of EEG signal" k_1 is represented as,

$$H = \frac{K(e)}{\sum_{w=0}^{\frac{f}{2}-1} | F(d,e) |^2} \tag{8}$$

wherein, $K(e)$ implies the tonal power calculated by summation of all bins 0 that are limited maximum range from "0". It changes from zero to one in that minimum values indicate the noise pattern, as well as a maximum value, indicates the tonal spectrum. B_5. represents the tonal power ratio feature.

vi) Holoentropy

The entropy, as well as weight function multiplication, is stated as holoentropy [13] that is exploited to extract features from a complete signal set it is formulated as,

$$A(n_p) = Wi \times \varepsilon(n_p) \tag{9}$$

wherein, $\varepsilon(n_p)$ represents entropy and Wi represents inertia weight. The $\varepsilon(n_p)$ is stated as the sum of entropies of every attribute value which is devised as,

$$\varepsilon(n_p) = -\sum_{p=1}^{z(n_p)} P_p \log P_p \tag{10}$$

wherein, $z(n_p)$ implies the number of characteristic signal values.

The holoentropy identifies entropy weight by taking into consideration each signal so that it presents more connotations to the signal by exploiting the lesser values of entropy as a result increases the signal choice and improves seizure detection. Eq. (11) indicates the inertia weight and S_6. indicates the holoentropy feature.

$$Wi = 2\left(1 - \frac{1}{\exp(\varepsilon(n_p))}\right) \tag{11}$$

vii) Taylor-based delta AMS feature

By combining delta AMS [7] as well as the Taylor series [6], the Taylor-delta AMS features are attained that states the chronology values for effective classification. Moreover, L input signal is given in definite steps. The AMS features hold the energetic signal recognition they are the capability to present valuable data by means of noisy signals. The integration of AMS [7], as well as the Taylor series [6], are used to offer precise classification so that features of sequential data are used for the extraction of features.

a) Infer input EEG signal: Ahead of feature mining, the input signal is fed into pre-processing that comprises quantization as well as sampling so that the signal is appropriate to process connected to features extraction.

b) Bandpass filter: Initially, “bandpass filters are considered to evade noisy EEG as time-frequency models which outcome in eighty-five framing modules with every module represented as a channel”.

c) Association of an envelope with modification: The principle of an enhancement is to define enclose of every channel that is destroyed by exploiting a factor, three using 128 samples with 64 overlapping segments. By exploiting Hamming window, produced segments are fed into windowing which acts as a function to remove the extra signals and make a possible collection of exclusive information with input signals.

d) Frame signal: The several “input speech signal” is transformed into determined streams called frames so that the speech signal is improved as well as the framing process is regarded as signal motionless properties. The edge consists ability to develop signal harmonics in framing. Therefore, fine-tuning is done that carries out to tune so that those frames overlap between themselves.

e) Taylor-based delta AMS features extraction: By framing output produced is fed to FFT to identify spectrum frames modulation. The multiplication of triangular shape windows, as well as FFT outputs, is considered to create AMS features [7]. Let AMS feature vector as $D(y,z)$ is indicated as

$$\Delta D_Z(y,z) = D(y,z) - D(y-1,z) \text{ when } \ell = 2,\ldots,Z \tag{12}$$

wherein, Z indicates total segments, $\Delta D_Z(y,z)$ indicates delta feature vector, and $D(y,z)$ represents delta AMS feature [6].

f) Linear Prediction Coefficient

From Levinson-Durbins's recursive approach, the LPC [32] model was formulated which aids to get rid of redundant patterns from the signal. The method predicts data $y(q)$ with prior values linear grouping $y(q-r)$. Hence, B_8 indicates LPC and is stated as,

$$y(q) = \sum_{j=1}^{r} a(r) y(q-r) \tag{13}$$

3.3. Feature Vector Model

Eq. (14) states features produced by input EEG, wherein, S implies extracted feature vector by exploiting the input EEG, S_1 implies spectral skewness, S_2 implies spectral kurtosis, S_3 implies relative energy, S_4 implies fluctuation index, S_5 implies tonal power ratio, S_6 implies holoentropy, S_7 implies Taylor-based delta AMS features, as well as S_8 implies LPC feature. By exploiting the PPCA, the feature vector undergoes dimension minimization.

$$S = \{S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8\} \tag{14}$$

3.4 PPCA for Dimension Reduction

PCA is an extensively approved technique to reduce the size and is broadly used to perform a multivariate estimation. With PCA probabilistic approach employing the "Gaussian latent variable" technique is used to present the statistical examination. The probability technique presents a probable to develop the possibility of existing PCA is referred to as PPCA [9], [8].

Moreover, a probabilistic combination of PCA is described to minimize the dimensionality for choosing the effective features. The most important maximal-likelihood calculates the attribute taking into consideration of covariance matrix is competently estimated with data principal units, wherein, α implies $S \times T$ parameter "matrix with a mapping amid latent as well as input space, J'_u implies feature by exploiting the consistent value, ψ implies $S \times 1$ parameter vector with variable mean, $\beta(u)$ implies a vector with $B \times 1$ dimension".

$$s_u = \alpha J'_u + \psi + \beta(u);\ u \in \{1,2,\ldots,s\} \tag{15}$$

$$s_u \sim (0,1);\ u \in \{1,2,,,s\} \tag{16}$$

Variance σ^2 is represented as "0". It is normally predictable that $D < B$. The utmost likelihood α_{ML} is calculated for α projection matrix. The PCA covariance matrix eigenvectors as eq. (20), wherein B_D indicate a $B \times D$ matrix by exploiting the D eigenvectors with a sample covariance matrix, R indicate arbitrary $D \times D$ orthogonal rotation matrix as well as Δ_B indicates $D \times D$ diagonal matrix by exploiting the equivalent eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_T$ on the diagonal.

$$\beta(u) \sim X(0, \sigma^2 V);\ u \in \{1,2,\ldots,s\} \tag{17}$$

$$\alpha_{ML} = B_D(\Delta_T - \sigma^2 v)^{1/2} R \tag{18}$$

3.5 Proposed ICSOA -based Deep SAE to Discover Epileptic Seizure

The epileptic seizures recognition by exploiting the adopted ICSOA model is presented and detection is performed by exploiting a feature vector. By exploiting the deep SAE [10], the produced features are presented to classification, and training is done by exploiting ICSOA.

a) Proposed ICSOA model:

The CSO approach [16] is a stochastic search algorithm on the basis of the chicken swarm search behavior; here the complete chicken swarm is partitioned into various groups, which comprise a rooster, a combination of hens as well as various chicks.

In an unpredictable environment, the complete flock searches for food, Levy flight explore approach is differentiated using short-range deep local search as well as infrequent longer distance walks [16], which can aid to enhance the search effectiveness as well as raises the disturbance to construct chickens deal out more consistently.

The count of hens is the highest; therefore hens act as a significant role in the whole groups in the CSO approach [19]. Enthused by this the proposed model adopts the "Levy flight search scheme into hen's location" update formulation, which can improve the global searchability of the proposed model. The enhanced hen's position update formulation is stated as follows:

$$x_i^j(t+1) = x_i^j(t) + S_1 * ran = *\left(x_{r1}^j(t) - x_i^j(t)\right) + S_2 * ran * \mathrm{Levy}(\lambda) \otimes \left(x_{r2}^j(t) - x_i^j(t)\right) \tag{19}$$

wherein, λ indicates a "scaling parameter in the range [1, 3]", $Levy(\lambda)$ indicates jump path of an arbitrary search that step size follows Levy distribution, $\otimes$ indicates a vector operator indicating the point multiplication.

"The nonlinear schemes of minimizing the inertia weight are used to update, chick's location that aids the chicks not only learn from their mother, however, learns from themselves in the adopted model". It would examine using the numerical analysis where coupling nonlinear minimizing "inertia weight in chick's" location formulation can evade the Improved CSO approach. "The nonlinear decreasing inertia weights updating" as stated below:

$$\omega = \omega_{min}\left(\omega_{max} / \omega_{min}\right)^{(1+ct/M)} \tag{20}$$

$$x_i^j(t+1) = \omega * x_i^j(t) + FL * \left(x_m^j(t) - x_i^j(t)\right) \tag{21}$$

Wherein, ω_{max} indicates the maximum inertial weight, ω_{min} indicates the least "inertia weight, $\omega_{min} = 0{:}4$, $\omega_{max} = 0{:}95$," *c indicates* an acceleration factor.

b) Architecture Model of Deep SAE Model

It is a very important module in DNN. The auto encoder uses pertinent features of the input. "The single-layer Auto Encoder does not consist of directed loops and this auto-encoder comprises Y hidden units, X input visible units, as well as Z output visible units. The auto-encoder is developed by encoding the input vector into a complicated stage hidden adaptation represented as K". Deterministic mapping T_θ changes the input vector X into a hidden vector in the encoder. Eq. (33), R_1 implies the bias vector, ω_1 implies weight matrix and U implies reconstruction. Subsequent to the decoding hidden model K back to reconstruction T and in eq. (34), R_2 implies bias vectors, ω_2 implies weight matrix, and Y implies hidden units. The Auto Encoder is trained using the ICSOA rather than reconstruction error as well as back-propagation is used to minimize cost function as well as squared reconstruction error and it is stated as follows:

$$\vartheta = fun\left(\omega_1 U + R_1 U\right) \tag{22}$$

$$\hat{U} = fun\left(\omega_2 Y + R_2 Y\right) \tag{23}$$

$$Jac(\omega, R) = \frac{1}{2z}\sum_{x=1}^{z} ||\,\hat{U}_x^z - U_x^X\,||^2 \tag{24}$$

Wherein, R implies bias vectors set, ω implies weight set, z implies complete layers, wherein, U_x^X implies output reconstruction on x^{th} layer and $1 \le x \le z$, U_x^z implies reconstruction of input on x^{th} layer.

Weight regularization is used, the constraints are obtained to produce a cost function to mitigate over-fitting and it is stated in eq. (25), wherein, P_x^X implies output reconstruction on x^{th} layer, P_x^z implies input reconstruction on x^{th} layer α implies regulation circumstance weight, and β implies sparse circumstance weight, and $|\omega_1||^2 + ||\omega_2||^2$ implies parametric circumstances, P implies sparse parameter, and P_y implies hidden unit average activation y, and $V(P\,||\,Y_y)$ implies KullbackLeibler divergence, as well as Y implies "count of hidden units so that" $1 \le y \le Y$.

$$Jac(\theta) = \frac{1}{z}\sum_{x=1}^{z} ||\,P_x^z - P_x^X\,||^2 + \alpha\left(||\,\omega_1\,||^2 + ||\,\omega_2\,||^2\right) + \beta\sum_{y=1}^{Y} V\left(P\,||\,P_y\right) \tag{25}$$

The average hidden unit is stated in eq. (26), wherein, z implies whole layers wherein $1 \le x \le z$ and $l_{2,x}^y$ implies y^{th} entry hidden layer activation function.

$$\hat{U}_y = \frac{1}{z}\sum_{x=1}^{z} l_{2,x}^y \tag{26}$$

Eq. (27) states the KullbackLeibler divergence, wherein, P_y implies hidden unit average activation y, P indicates a sparse parameter.

$$V\left(P\,||\,P_y\right) = P\log\frac{P}{P_y} + (1-P)\log\frac{1-P}{1-P_y} \tag{27}$$

Eq. (28) indicates z^{th} layer activation output, wherein $l_{1,x} = u_x$. By evaluating $p_{\omega,O}\left(u_x^X\right) = l_{o,x}$,

$$l_{qx}^X = wq\left(l_{q-1}^X \omega_{q-1} + s_{q-1}^X\right) \tag{28}$$

The cost function is expressed as follows: γ^q as well as U^q implies hyper-parameters in q^{th} layer, i_q implies complete layers in the network.

$$jac(\omega, O) = \frac{1}{2z}\sum_{x=1}^{z} ||\,p_{\omega,O}\left(u_x^X\right) - u_x\,||^2 \tag{29}$$

$$jac(\theta) = jac(\omega, O) + \frac{\alpha}{2} \sum_{q=1}^{i_z - 1} \sum_{n=1}^{j_z} \sum_{o=1}^{j_{z+1}} \left(\omega_q^{n,o}\right)^2 + \sum_{q=z}^{i_z - 1} \sum_{y=1}^{j_z} \gamma^q V\left(U^q \,||\, \hat{U}_y^q\right) \tag{30}$$

c) Deep SAE Training

Training of Deep SAE [10] is done by exploiting the adopted ICSOA which is inclined to tune the deep SAE classifier for identification of optimum weights as well as seizures. From the adopted ICSOA, "to tune deep SAE, optimal weights" are exploited that help to obtain optimum results of classification. The seizure detection uses the ICSOA -based deep SAE for the classification of the input signal using an optimal classification that can hold a novel EEG signal that is attained by means of distributed sources.

By exploiting fitness, the optimal solution is identified that is referred to as a reduction issue, and therefore, a solution with minimum MSE is elected as an optimum solution. Moreover, MSE is expressed as,

$$MS_{err} = \frac{1}{\kappa} \sum_{o=1}^{\kappa} \left[O_o - O_o^* \right]^2 \tag{31}$$

wherein, O_o^* implies output predicted, O_o implies output expected as well as κ implies the count of input EEG signals in that $1 < o \le \kappa$.

4. Result and Discussion

The experimentation analysis of schemes with the existing techniques with dataset concerning the accuracy, specificity as well as sensitivity discussed in this section. Here, the analysis was done by varying the training data. Additionally, the adopted model ICSOA +Deep SAE efficiency was calculated using two datasets. "The TUEP was a rift of TUEG that comprises 100 subjects' epilepsy and 100 subjects without epilepsy, as determined by specific neurologists. The data is attained in association with diverse partners which comprises NIH. CHB-MIT Scalp EEG Database gathered from the Children's Hospital Boston, has EEG recordings from pediatric subjects with intractable seizures. It comprises of recordings that were gathered from 22 subjects involving 17 females with ages 1.5–19 as well as 5 males with ages 3–22;" Here, the proposed model was compared with the Support Vector Machine (SVM), Relevance Vector Machine (RVM), FzEN [17], RF [18], and Deep RNN.

Fig 2 demonstrates and 3 the evaluation of models with TUEP and CHB-MIT Scalp EEG dataset datasets by exploiting specificity, sensitivity, and accuracy. Here, the maximum accuracy specificity, and sensitivity are obtained by using the adopted model.

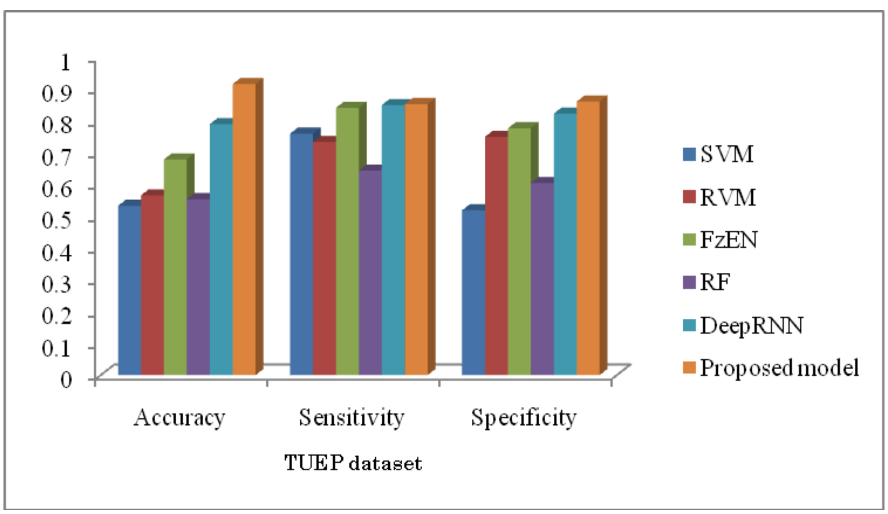

Fig. 2. *Analysis of adopted model regarding TUEP dataset*

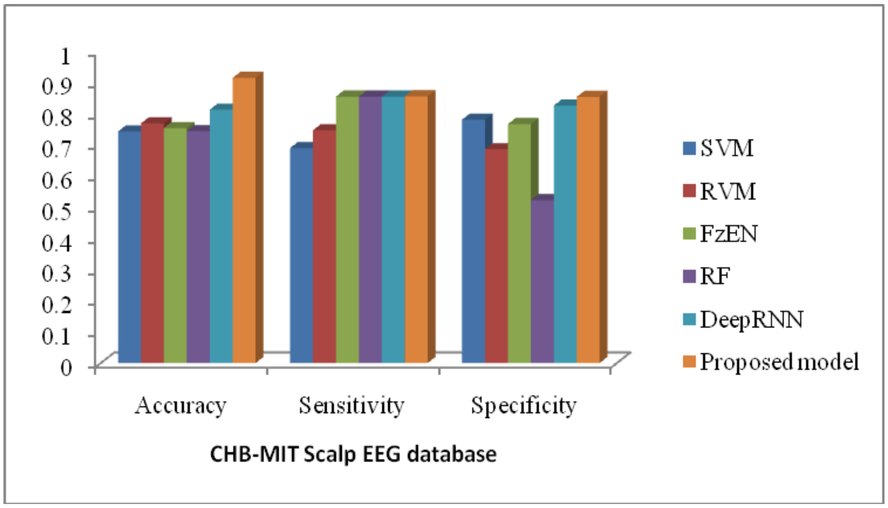

Fig.3. *Analysis of adopted model regarding CHB-MIT Scalp dataset*

5. Conclusion

The elliptical seizure recognition was done by exploiting the Deep SAE; the main objective of this Deep SAE was to improve the recognition effectuality. The existing technique of automated seize recognition by exploiting the Neural Networks reveals the bad performance because of the noise presence and was resolved using the adopted technique. The Deep SAE was trained by the adopted optimization model to obtain the optimum weights and attained an optimization algorithm. Moreover, from input EEG "Deep SAE training" was done by exploiting the extracted features generated. The feature comprises the Taylor-based delta AMS feature, the ratio of tonal power, relative energy, fluctuation index, holoentropy, spectral features, as well as LPC. In addition, the dimensionality of the feature was considerably reduced with PPCA. The adopted ICSOA-based Deep SAE obtained maximum accuracy, sensitivity, and specificity.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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