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Rag-bull rider optimisation with deep recurrent neural network for epileptic seizure detection using electroencephalogram

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Abstract

Electroencephalogram (EEG) signal is mostly utilised to monitor epilepsy to revitalize the close loop brain. Several classical methods devised to identify seizures rely on visual analysis of EEG signals which is a costly and complex task if channel count increases. A novel method, namely, a rag-Rider optimisation algorithm (rag-ROA) is devised for training a deep recurrent neural network (Deep RNN) to discover epileptic seizures. Here the input EEG signals are splitted to different channels wherein each channel undergoes feature extraction. The features like Holoentropy, relative energy, fluctuation index, tonal power ratio, spectral features along with the proposed Taylor-based delta amplitude modulation spectrogram (Taylor-based delta AMS) are mined from each channel. The proposed Taylor-based delta AMS is designed by integrating the delta AMS and Taylor series. The probabilistic principal component analysis (PPCA) is employed to reduce the feature dimension. The dimensionally reduced feature vector is classified with Deep RNN using rag-ROA, which is designed by integrating rag-bull rider along with the four other riders available in the Rider optimisation algorithm (ROA). Thus, the resulted output of the proposed rag-ROA-based deep RNN is employed for EEG seizure detection. The proposed rag-ROA-based Deep RNN showed improved results with maximal accuracy of 88.8%, maximal sensitivity of 91.9%, and maximal specificity of 89.9% than the existing methods, such as Wavelet + SVM, HWPT + RVM, MVM-FzEN, and EWT + RF, using the TUEP dataset.

INTRODUCTION 1

The illness in nerve caused due to electrical ejection from cortical neurons present in the brain is called epilepsy, which is vulnerable to generate different kinds of seizures. Such seizures are unanticipated, unpredicted, and motiveless due to instantaneous aspects. There are peoples over 65 million who suffer from such disorders. There are 75% of cases of epileptic seizures that are treated with therapy [1]. In the remaining 25% cases, the seizures remain in spite of antiepileptic drugs, and such drug insolent patients should survive with seizures [2]. Epilepsy affected patients are usually separated throughout the night and are susceptible to various corporeal injuries or suffocation caused by blocked airway after swallowing their tongues. There is a requirement of assistance in short delays after the inception of seizures, which cascade rupture and Sudden Unexpected Death in EPilepsy (SUDEP). Seizures are

mostly hazardous at night time while patients are separated and could not call for help. There are some night-time seizures which may not be noticed by patients and might lead to various medical impediment or even death. There is a requirement to devise a real-time seizure detection model which can elevate warning for people residing nearby when a seizure is discovered. The provision of proper help may lead to a reduction in mortality and avert complexities [3].

Epilepsy is treated medically by undergoing various assessments like computed tomography (CT), EEG [4], positron emission tomography (PET), magnetic resonance imaging (MRI), or magneto-encephalogram (MEG). The EEG is considered to be one of the best as compared to other methods due to its elevated temporal resolution and is termed to be inexpensive. The provision of direct measurement is possible by EEG due to the electrical activities of the brain. The EEG is the leading technique which is utilised for

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observing and discovering epileptic seizures, which frequently generate deviations in computed EEG signal. There are many methods that are devised for determining epileptic seizures using EEG signals [3,5,6]. Nevertheless, observing the EEG of a patient from a number of days is typically needed for precise analysis and recognition of seizures. The scrutinizing of EEG manually is a complex task. Thus, a trustworthy detection the seizure can avoid long-standing monitoring process and diagnosis of epileptic seizures. In addition, the involvement of medical staff throughout seizure activity is essential to examine a patient suffering from seizures. Continuous interaction with patient support monitoring of patient's responsiveness and capability to respond which in turn helps in the determination of pertinent effects of seizure-like severity, and establishes exaggerated brain region [7]. Therefore, automatic detection of seizure can alert clinicians at the beginning of the seizure, wherein instantaneous medicinal interference can occur [8,9].

Numerous automatic detection strategies are devised which makes the effort of neurologists more straightforward and faster [10]. These methods include pre-processing, extraction of features, and categorisation. Preprocessing actions like filtering and removal of artefacts from input EEG signals [11] are imperative for improving the efficiency of the algorithm. Feature extraction is another important stage for cataloguing seizure and non-seizure on the basis of performance and complication of the classifier. The frequency domain and time are mostly utilised features in automatic seizure detection. The features can be mean, lacunarity, entropy, fractal intercept, energy Hurst component, Renvi entropy, power spectral density, and zero-crossing [12]. Moreover, there are numerous optimisation algorithms [13] and classifiers like extreme learning machine (ELM), artificial neural network (ANN), Back Propagation Neural Network (BPNN) [14], fuzzy cmeans [15], linear discriminate analysis (LDA), support vector machine (SVM) [16], and K-nearest neighbour (K-NN), which are introduced for classifying the issues of epileptic seizures [17], and various fields, such as the archaeology [18], medical and so on. There are many challenges that are addressed for the detection of seizure using time-frequency methods using the off-line dataset [19]. Real-time seizure analysis for instant medical elucidation is extremely indispensable and preface of automated biomarker improves clinical decision. The trustworthiness of seizure decision resides in apposite feature selection considering EEG recordings [20].

The goal of the research is to design an epileptic seizure detection method using the EEG signal. Several classical methods devised to identify seizures rely on visual analysis of EEG signals, which is a costly and complex task if channel count increases. Herein a novel method, namely, a rag-ROA for training a Deep RNN to discover epileptic seizures is devised. The input data signal is extracted from the dataset in which the EEG signals are splitted into multi-channels pursued by the mining of features from individual channels. The features, such as Holoentropy, relative energy, fluctuation index, tonal power ration, spectral features, and proposed Taylor-based delta AMS are extracted from the channels. The proposed Taylor-delta AMS is a combination of Taylor series and delta AMS. The extracted features from each channel form a feature vector, which is the concatenation of all features. The dimension of the feature vector is minimised with PPCA. The dimensionally reduced feature vector is classified using the Deep RNN, which is trained by the proposed rag-ROA, which is devised by integrating rag-bull rider along with the four other riders available in ROA. In ROA, in addition to the Bypass rider, Follower, Overtaker and Attacker along, a Rag bull rider is added. Thus, the proposed rag-ROA-based deep RNN offers improved results with maximal accuracy, sensitivity and specificity.

The key contributions are:

- **Proposed Taylor-based delta AMS feature:** The Taylor-based delta AMS feature is generated by integrating the Taylor series in delta AMS features.
- Proposed rag-ROA-based Deep RNN for elliptical seizure detection: The proposed rag-ROA based deep RNN is a combination of proposed rag-ROA and the Deep RNN. Here the rag-ROA is developed by integrating the rag-bull rider and the ROA for training the Deep RNN.

Other sections are arranged as: Section 2 elaborate illustration of conventional elliptical seizure detection strategies utilised in literature and challenges faced, which are considered as the inspiration for developing the proposed technique. The proposed method for elliptical seizure detection using modified Deep RNN is portrayed in Section 3. The outcomes of the proposed strategy with other methods are portrayed in Section 4 and Section 5 present conclusion.

2 | MOTIVATIONS

Epilepsy is a major nerve chaos which is originated by irregular electrical activities of brain regions. Here, EEG is extensively adapted for monitoring seizures, but the complicated human EEG signals dynamics are complex to understand. Thus, the automatic detection of elliptical seizures using EEG is essential for earlier detection. This section illustrates the analysis of eight classical elliptical seizure detection strategies using EEG signals along with its drawbacks.

2.1 | Literature review

The eight classical strategies using elliptical seizure detection are illustrated along with its disadvantages. Liu et al. [21] devised a wavelet-based automatic seizure detection method for seizure detection. Here, the methods adapt wavelet decomposition of EEG using different scales and choose three frequency bands for the consequent processing. The method extracted effective features like relative amplitude, fluctuation index, relative energy, relative amplitude, and variation coefficient at chosen scales, and the features are provided to SVM for classification. The method employs post-processing for initiating precise outcomes. The post-processing was performed using multi-channel decision fusion and smoothing for enhancing the efficiency of detection, but this method failed to extract the appropriate subset of uncorrelated features. To overcome this problem, in the proposed method, the features are selected based on the highest covariance. Vidvaratne and Iftekharuddin [9] devised automatic epileptic seizure onset detection method considering EEG. The method obtained self-similarity-based fractal features and harmonic multiresolution features for seizure detection. Here harmonic wavelet packet transform (HWPT) was adapted for attaining resolutions with higher frequency. The fractal dimension (FD) was generated for capturing repetitive patterns from the EEG signal. The features were extracted for reflecting the temporal information of EEG. The relevance vector machine was utilised for classifying the feature vector to detect seizures. However, the method failed to consider patient-specific localisation. In the proposed method, the signals from the datasets are splitted into series of channels, wherein, each channel undergoes feature extraction and seizure detection, which considers the patient-specific localisation. Raghu et al. [20] devised a method, namely minimum variance modified fuzzy entropy (MVMFzEn) for recognition of epileptic seizures in real-time using EEG recordings. The EEG recordings were considered for the analysis. Moreover, Signal processing strategies were adapted for reducing noise and considering membership function. The method provided improved classification efficiency for data validation. However, the complexity of the classifier is the major disadvantage of this method. Due to the chronological pattern of information, Deep RNN is termed as the excellent classifier amongst the classical deep learning strategies. Hence, the complexity of the classifier is avoided in the proposed method. Bhattacharyya and Pachori [22] employed multivariate oscillatory property of EEG signals based on adaptive frequency scales for discovering epileptic seizures. The method employed empirical wavelet transform (EWT) using multivariate signals for determining joint instant amplitudes and frequencies. The method utilised movingwindow-based analysis for selecting the channels for defining features to detect seizures. However, the method failed to use a larger EEG database for seizure detection. In the proposed method, the larger datasets, like the TUEP dataset, and CHB-MIT Scalp EEG database are considered for the experimentation. Wu et al. [23] devised the seizure detection technique by integrating an aEEG-based seizure detection algorithm and cEEG-based seizure detection algorithm for determining seizures. Here the EEG signals were partitioned into different epoch and every epoch is employed for extracting multidomain features. The classification was done by random forest (RF) for seizure detection. Anyhow, the accuracy needs to be improved. In the proposed method, the rag-ROA-based deep RNN is adapted for detecting EEG seizures, which offers better accuracy. Salem et al. [3] devised a lightweight method for earlier discovery of nocturnal epileptic seizures using muscle contractions. The method utilised an overlapping sliding window for deriving the variance of data using singlechannel surface ElectroMyoGram (sEMG). The Exponentially Weighted Moving Average (EWMA) was utilised for predicting

the present value of variance. The method was devised for enhancing the performance of detection models using an accelerometer. Here the sEMG was utilised for determining noiseless seizures exclusive of jerky movements. However, the method did not use massive datasets for optimizing the performance of seizure detection models. In the proposed method, the larger datasets, like the TUEP dataset, and CHB-MIT Scalp EEG database are considered for the experimentation. Rodriguez Aldana et al. [24] devised a strategy for determining non-convulsive seizures and epileptic diagnosis. For distinguishing normal and seizure EEG, a Radial Basis SVM, K-NN, and Linear Discriminant Analysis classifier were utilised. The features were generated from Block Term Decomposition (BTD) and Canonical Polyadic Decomposition (CPD) of EEG signal and were signified with third-order tensor. Moreover, the tensor of the EEG signal was expanded using the Hilbert-Huang transform or Wavelet transform. The method offered an opposite model for non-convulsive seizure detection but failed to consider the noise in the signals. In the proposed method, the AMS features maintain the robust recognition of signal and they are able to provide valuable information even with the existence of noisy signals. Fan et al. [25] devised the spatial-temporal synchronisation pattern of epileptic human brains considering the features of spectral graph mined from EEG. The multivariate approach was adapted for discovering the seizure in real-time. In addition, the complex network was utilised for presenting the re-emergence pattern of EEG signals. Moreover, the statistical control chart was adapted for extracting the features overtime to convert from normal to epileptic states. However, the method failed to include adaptive threshold parameters for sliding windows to explore. In the proposed method, to overcome this problem fine-tuning is used in the windowing. Hassan et al. [26] developed a feedforward neural network (FfNN) for the detection of Epileptic Seizure, by using multiband features. In this method, the feature vector was formed from the features of the sub-bands. Hence, the detection process was done by a reasonable time. Anyhow, for larger datasets, the robustness of this method needs improvement. In the proposed method, the Taylor series facilitates precise evaluation of common function and acquires convergence effortlessly, which improves the robustness. Bouaziz et al. [27] implemented an Epileptic Seizure Detection by using the convolutional neural network (CNN). Here in the feature extraction, the high-level features are extracted from the input images. The classification accuracy was the major advantage of this method. Anyhow, this method was not applicable to the larger datasets. In the proposed method, the larger datasets, like the TUEP dataset, and CHB-MIT Scalp EEG database are considered for the experimentation. Akyol [28] proposed a stacking ensemble approach (SEA) based model for the detection of epileptic seizures. Here the multi-class ensemble learning was performed by the Stacking algorithm. This method offered better performance in accuracy, specificity, and sensitivity, when compared with the classifiers, such as ANN, complex-valued neural networks, deep neural networks (DNN), CNN, and SVM. However, the effectiveness in real-world problem

solving was difficult in this method, but the proposed method is applicable in real time applications. Li et al. [29] developed an automatic seizure detection method, by using Fisher vector (FV) encoding and multi-scale radial basis function (MRBF). Here the feature extraction was done by using the high-resolution time frequency (TF) and the detection of seizures were carried out using SVM classifier. This method offered good classification accuracy, but when using larger datasets, the robustness was reduced. In the proposed method, the experimentation is done with larger datasets, and the robustness is improved by using the Taylor series. Li et al. [30] developed an end-to-end EEG seizure detection framework with the help of channel-embedding spectral-temporal squeeze and-excitation network (CE-stSE-Net). Here the implementation was done by integrating the multi-scale temporal and multi-level spectral analysis. This method was useful in the seizure monitoring and to reduce the burden of clinicians. Over fitting problem was the major drawback of this method. In the proposed method, to avoid the over fitting issue, the best solution is detected with fitness function, which is chosen based on least MSE.

3 | PROPOSED RAG-ROA-BASED DEEP RNN FOR SEIZURE DETECTION

The purpose of the research is to devise an epileptic seizure detection strategy using the EEG signal. At first, the input EEG signals are extracted from the dataset and are splitted into multiple channels. Then, the extraction of the features from each of the channels is done separately. The features like Holoentropy, relative energy, fluctuation index, spectral features along with the proposed Taylor-based delta AMS spectrogram are extracted from the channels. The proposed Taylorbased delta AMS is designed by integrating the Taylor series [31] on delta AMS [32]. The extracted features from each channel form a feature vector, which represents a concatenation to establish a feature vector. The dimension of the feature vector is minimised with PPCA [33,34]. The dimensionally reduced feature vectors are classified using Deep RNN [35]. The Deep RNN is trained with the proposed Rag-ROA, which is devised by integrating rag-bull rider with four other riders available in ROA [36]. In ROA, in addition to the Bypass rider, Follower, Overtaker and Attacker along a Rag bull rider are added. Here the rag bull rider is inspired by the modified particle swarm optimisation [37]. Thus, the rag-ROA-based deep RNN is employed for the EEG seizure detection and the resulted output is considered for the EEG seizure detection. Figure 1 presents the architecture of the proposed Rag-ROA for seizure detection.

Assume a dataset containing EEG signals in which the seizure detection is done for determining the patients suffering from elliptical seizures. Consider the input EEG signal be represented as L(m) which is available as a signal in which the detection is considered as an imperative task for further processing. These signals are splitted to series of channels wherein each channel undergoes feature extraction and seizure detection.

3.1 | Extraction of features using signal

Here the extraction of imperative features with input EEG signals and the implication of the extraction are deliberated. The feature extraction is employed for generating highly relevant features to facilitate the better discovery of seizures with EEG. Moreover, the intricacy of evaluating the signal is reduced as the signal is modelled with the reduced feature set. Furthermore, the accuracy is allied with the detection and is ensured with the effectual extraction of features. The features extracted from input EEG signal involve spectral kurtosis, spectral skewness, relative energy, fluctuation index, holoentropy, Tonal power ratio, and proposed Taylor-based delta AMS.

a) Spectral Skewness.

Spectral skewness [38] is defined as a skewness coefficient of a spectrum and it is the quantity of symmetry for the distribution. It is also defined as a measure of the asymmetry of a distribution around the mean value μ . The skewness coefficient is defined as the ratio of skewness with respect to the thirdorder moment j_3 of the standard deviation σ , and is expressed as,

$$j_3 = \int (g - \mu)^3 p(g) dg$$
 (1)

$$\gamma_1 = \frac{J_3}{\sigma^3} \tag{2}$$

where μ indicates mean value of spectrums of the input signal, σ indicates standard deviation, p(g) indicates probability distribution of spectrum, g signifies individual spectrum. The Spectral skewness feature is represented by A_1 .

b) Spectral kurtosis.

The spectral kurtosis [38] represents the peakedness or flatness of distributed energies. High the kurtosis means more the variance of extreme deviations. It is evaluated with fourth order moment j_4 using mean value μ and standard deviation σ which is expressed as,

$$j_4 = \int (g - \mu)^4 p(g) dg$$
 (3)

$$\gamma_2 = \frac{j_4}{\sigma^4} \tag{4}$$

The Spectral kurtosis feature is represented by A_2 . c) Relative energy.

The relative energy [21] presents signal strength as it offers an area underneath the curve of power at any time instance. Using wavelet, the summation of the square of coefficients of wavelet series is EEG signal energy. The EEG signal energy with limited length is represented as,

$$\varepsilon(X) = \sum_{s=1}^{T} Z_s^2 * \frac{\alpha}{T}$$
(5)



FIGURE 1 Architecture of the proposed Rag-ROA model for seizure detection

where α represents sampling interval, T indicate count of DWT coefficients, Z_s denotes s^{th} coefficient at scale X. The relative energy $\varepsilon_r(X)$ of scale X is expressed as,

$$\varepsilon_r(X) = \frac{\varepsilon(X)}{\sum\limits_{s=1}^{Y} \varepsilon(s)}$$
(6)

where Y indicates the total number of wavelet scales. The relative energy feature is represented by A_3 .

d) Fluctuation index.

The EEG is employed for displaying huge variation amidst the period between seizures. The fluctuation index [21] is devised for evaluating the changes in EEG signal intensities. The fluctuation index of scale X is formulated as,

$$F(X) = \frac{1}{T} \sum_{s=1}^{T} |Z_{s+1} - Z_s|$$
(7)

where T represents the number of DWT coefficient Z_s at scale X. It is observed that the fluctuation index of the EEG signal becomes higher during seizures and lowered in non-seizure periods. The fluctuation index feature is represented by A_4 .

e) Tonal power ratio.

The tonal power ratio [39] is employed for computing the tonalness of the input EEG signal. The tonal power ratio is modelled by computing the ratio of tonal power of spectrum components and complete power. Assume a_f indicate input EEG signal and Y(o, p) indicates the spectrum of the input EEG signal. Then the tonal power ratio R of the input EEG signal a_f is formulated as,

$$R = \frac{X(p)}{\sum_{w=0}^{\frac{f}{2}-1} |Y(o,p)|^2}$$
(8)

where X(p) represents tonal power which is evaluated by adding all bins 0 that are local maximum and ranges from zero. The tonal power ratio varies from 0 to one wherein the lower values indicate noise pattern and the higher value signifies tonal spectrum. The tonal power ratio feature is represented by A_5 .

f) Holoentropy

The product of weight function and entropy is represented as holoentropy [40], which is utilised for extracting the features from the complete set of signal and is formulated as,

$$H(q_r) = \omega \times E(q_r) \tag{9}$$

where ω indicates inertia weight and $E(q_r)$ represents entropy measure. Here, $E(q_r)$ is defined as the sum of entropies of individual attribute values and is expressed as,

$$\mathbf{E}(q_r) = -\sum_{r=1}^{z(q_r)} P_r \log P_r \tag{10}$$

where $z(q_r)$ represents the number of unique values in signal.

The holoentropy determines the entropy weight of each signal such that it provides more significance to the signal with small entropy values which subsequently maximizes the selection of signal and enhances the seizure detection process. The inertia weight is formulated as,

$$\omega = 2\left(1 - \frac{1}{\exp(E(q_r))}\right) \tag{11}$$

The holoentropy feature is represented by A_6 .

g) Proposed Taylor-based delta AMS feature.

For extracting proposed Taylor-delta AMS features, the delta AMS [32] are combined with Taylor series [31] which illustrates chronological values for effectual categorisation. Here, the input signal L is fed to a number of processing steps. The AMS features maintain the robust recognition of signal and they are able to provide valuable information even with the existence of noisy signals. The combination of Taylor series and extracted delta AMS features facilitate precise classification in such a way that chronological data features are adapted for extracting features.

- i. **Interpret input EEG signal:** Before feature extraction, the input signal is fed to pre-processing that involves quantisation and sampling in such a way that signal is made suitable for further processes associated with feature extraction.
- ii. Relevance of band pass filter to produce time-frequency channels: At first, the bandpass filters are adapted to eliminate noisy EEG signals as time-frequency modules that result in 85 framing modules with each module represent a channel. The importance of bandpass filter is that the filter allows input signals of given frequencies and stops additional signals, which signifies that each channel bear upper and lower bound frequencies.
- iii. **Configuration of envelop with refinement:** The goal of refinement is to outline encase for each channel i.e. annihilated with a factor, three considering 64 overlapping segments for 128 samples. The produced segments are fed to windowing with the Hamming window which plays a key function in eliminating the redundant signals and enable compilation of valuable information using input signals.
- iv. Framing signal with windowing: Here, the different input speech signal is transformed into incessant streams known as frames in such a way that speech signal is modified and the process of framing process to keep hold

of motionless properties of the signal. In framing, the edge contains the capability to devise harmonics in the signal. Thus, fine-tuning is performed which undergoes tuning in such a way that frames overlap amongst themselves. The second frame contributes to half of the preceding frame and half from the next frame in such a way that edge level information is protected. The Hann window is adapted in windowing and window size is $[1 \times 255]$ using an overlap rate of 0.5. Further, the features are zero-padded and offered for feature extraction.

v. Extraction of Taylor-based delta AMS features: The output obtained by framing is fed to FFT to determine the modulation spectrum of frames. The multiplication of FFT outputs and triangular shape windows are employed for producing AMS features. Assume the AMS feature vector as M(b, i), which is of dimension [255 × 85]. Thus, the delta AMS [32] are given as,

$$\Delta M_Q(h, i) = M(h, i) - M(h-1, i) \text{ when }$$

$$q = 2, ..., Q$$
(12)

where $\Delta M_Q(b, i)$ indicate delta feature vector, Q denote total segments, M(b, i) represent delta AMS feature of signal.

The benefit of the Taylor series is that this technique is easy and straightforward for computation despite the existence of intricate functions. Moreover, the Taylor series facilitates precise evaluation of common function and acquires convergence effortlessly. Here, the solution of subsequent iteration is predicted using the solution of prior iterations which undergoes multiplication with definite constants. According to Taylor series [31], the equation is represented as,

$$M(b,i) = 0.5 M(b-1,i) + 1.3591 M(b-2,i)$$

-1.3591M(b-3,i) + 0.6795 M(b-4,i)
-0.2259 M(b-5,i) + 0.0555 M(b-6,i)
-0.0104 M(b-7,i) + 1.38 e^{-3} M(b-8,i)
-9.92 e^{-5} M(b-9,i) (13)

The proposed Taylor-based delta AMS feature is evaluated by substituting Equation (13) in Equation (12) and is represented as

$$\Delta M_Q(h, i) = 0.5 M(h-1, i) + 1.3591 M(h-2, i)$$

-1.3591M(h-3, i) + 0.6795 M(h-4, i)
-0.2259 M(h-5, i) + 0.0555 M(h-6, i)
-0.0104 M(h-7, i) + 1.38 e⁻³ M(h-8, i)
-9.92 e⁻⁵ M(h-9, i) - M(h-1, i) (14)

Equation (15) reveals the Taylor-AMS feature which is formulated as

$$\Delta M_Q(b, i) = 1.3591 M(b-2, i) - 0.5 M(b-1, i) -1.3591 M(b-3, i) + 0.6795 M(b-4, i) -0.2259 M(b-5, i) + 0.0555 M(b-6, i) -0.0104 M(b-7, i) + 1.38 e^{-3} M(b-8, i) -9.92 e^{-5} M(b-9, i)$$
(15)

The extracted proposed Taylor-based delta AMS feature is represented by A_7 .

3.1.1 | Formation of feature vector

The features obtained from the input EEG signal are represented in Equation (16), which is formulated as,

$$A = \{A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$$
(16)

where A indicate feature vector extracted with input EEG signal, A_1 symbolize spectral skewness, A_2 indicate spectral kurtosis, A_3 represent relative energy, A_4 signifies fluctuation index, A_5 represent tonal power ratio, A_6 indicate holoentropy and A_7 denote proposed Taylor-based delta AMS features. The feature vector undergoes dimension reduction using PPCA, which is illustrated in the next section.

3.2 Dimension reduction using PPCA

Principal component analysis (PCA) is an extensively adapted strategy for dimensionality reduction and is widely employed for multivariate analysis. The probabilistic modelling of PCA using the Gaussian latent variable model is employed for providing statistical testing. The probability model provides a perspective for extending the scope of classical PCA also known as probabilistic PCA, namely PPCA [33,34]. The input EEG signals are extracted from the dataset and are splitted into multiple channels. Then, the extraction of the features, such as Spectral Skewness, Spectral kurtosis, Relative energy, Fluctuation index, Tonal power ratio, Holoentropy, and Proposed Taylor-based delta AMS feature, from each of the channels is done separately. Then, the PPCA is illustrated for dimensionality reduction, which is based on the covariance, in order to select effective features from these extracted features. Initially, the dimension of the feature is 1 x 9650, and after applying the PPCA the dimension of the feature is reduced to 1 x 15.

$$z_t = \alpha A_t' + \psi + \beta(t); \ t \in \{1, 2, ..., z\}$$
(17)

where A_t' indicate the feature with standardised value, α is $S \times T$ parameter matrix having mapping between input and latent space, ψ represent $S \times 1$ parameter vector having mean of each variable, $\beta(t)$ indicate vector having $B \times 1$ dimension and represent random error.

$$z_t \sim (0, 1); t \in \{1, 2, ..., z\}$$
(18)

The distributed Normal with variance σ^2 is termed to be zero.

$$\beta(t) \sim X(0, \sigma^2 V); t \in \{1, 2, ..., z\}$$
 (19)

It is characteristically predictable that T < S. Maximum likelihood α_{ML} is evaluated for α projection matrix. The eigenvectors of the PCA covariance matrix is expressed as,

$$\alpha_{ML} = S_T \left(\Delta_T - \sigma^2 v \right)^{1/2} R \tag{20}$$

where S_T is a $S \times T$ matrix with the *T* principal eigenvectors of the sample covariance matrix, Δ_T is the $T \times T$ diagonal matrix with corresponding eigenvalues $\lambda_1, \lambda_2, ..., \lambda_T$ on the diagonal, and *R* is an arbitrary $T \times T$ orthogonal rotation matrix.

3.3 | Proposed Rag-ROA algorithm

Here, the steps of Rag-ROA are presented by devising a consistent mathematical model and are elaborated in the following subsection. Figure 2 portrays the principle of proposed Rag-ROA.

3.3.1 | 1) definition considered for initiating rag-ROA

It is essential to describe the imperative terms that are considered for the algorithmic steps. In rag-ROA, five groups are considered as the fundamental terms in the technique and are briefed below:

a) Bypass rider:

The first set of the rider is a bypass rider whose motive is to accomplish the target by getting over the leading rider. Thus, it can be noted that bypass rider does not pursue leading rider rather it bypasses leading rider to reach the target position.

b) Follower:

The follower is considered as a rider who relies on the leading rider and follows positions of the leading rider to achieve the target.

c) Overtaker:

The overtaker is the rider who pursues its own position for reaching the target based on the nearby locations.

d) Attacker:

The attacker is considered as an aggressive player who adapts the position of other riders to accomplish target by using its utmost speed.

e) Rag-bull rider.

The rag bull rider is the rider who pursues its own position for reaching the target based on velocities.



FIGURE 2 Principle of proposed Rag-ROA

In accordance with these five definitions there exist a term, namely winner who is considered as the final winner of the race.

3.3.2 | Algorithm

The proposed rag-ROA is motivated by riders, who compete to reach the intended location. The steps considered in proposed rag-ROA algorithm are described below:

Step 1) Initialisation of Rider and other algorithmic parameters.

The initialisation of the algorithm is done using four groups of riders given by V, and initialisations of its positions are done in a random manner. The initialisation of the group is expressed as,

$$S_{\ell} = \{S_{\ell}(\nu, \kappa)\}; 1 \le \nu \le P, \ 1 \le \kappa \le W$$
(21)

where *P* represents the number of riders, and $S_{\ell}(\nu, \kappa)$ represents the position of ν^{th} rider in κ^{th} dimension at ℓ^{th} time instant.

The count of riders is computed using the count of riders of each group and is denoted by,

$$P = B + J + O + A + K \tag{22}$$

where B represents bypass rider, J indicates follower, O denotes overtaker, A signifies attacker, and K is rag bull rider. Thus, the relationship amongst the aforementioned attributes is expressed as,

$$B + J + O + A + K = \frac{P}{5}$$
 (23)

Considering the above relationship, the positions of each rider are evaluated. The positions of bypass rider, follower, overtaker, attacker, and rag bull rider are in the ranges $[S_1, S_{P/5}], [S_{P/5+1}, S_{2P/5}], [S_{2P/5+1}, S_{3P}], [S_{3P/5+1}, S_{4P/5}]$ and $[S_{4P/5+1}, S_P]$.

Based on the initialisation of groups, the parameters of riders like gear, accelerator, steering, and brake are initialised.

Step 2) Determination of the success rate:

After the initialisation of rider group parameters, the success rate considering each rider is evaluated. The success rate is devised using distance, which is computed between the rider location and the target and is expressed as,

Success rate =
$$\frac{1}{\mid S_{\nu} - \ell_t \mid \mid}$$
 (24)

where S_{ν} represents the position of ν^{tb} rider and \mathcal{C}_t specifies the target position. To increase the success rate, the distance must be minimised and thus, the distance reciprocal provides the success rate of rider.

Step 3) Discovery of leading rider:

The success rate is considered as an imperative part of finding the leading rider. The rider who is residing near the target location is assumed to pose the highest success rate and that rider is termed as a leading rider as the rider is close to target.

Step 4) Update position of the riders:

The position of the rider in every set is updated to determine leading rider and thus winner. Hence, the rider update the position considering the characteristics of each rider described on the definition. The position update of each rider in each set is illustrated below:

The follower has a tendency to update position on the basis of the location of the leading rider to reach the target in a rapid manner and is formulated as,

$$S_{l+1}^{f}(v,o) = S^{G}(G,o) + \left[Cos \left(\phi_{\nu,o}^{l} * S^{G}(G,o) * \partial_{\nu}^{l} \right) \right]$$
(25)

where o is coordinate selector, S^G indicates the position of the leading rider, Grepresents the index of leading rider, $\phi_{\nu,o}^l$ represents the steering angle of ν^{th} rider in o^{th} coordinate, and ∂_{ν}^l is the distance.

The updated position of the overtaker is utilised in the update process to maximize success rate by detecting the overtaker position and is expressed as,

$$S_{l+1}^{o}(\nu, o) = S_{l}(\nu, o) + \left[D_{l}^{*}(\nu) * S^{G}(G, o)\right]$$
(26)

where $D_l^*(\nu)$ represent the direction indicator.

The attacker poses a tendency to seize the leaders' position by following the leader's update process and is given as,

$$S_{l+1}^{a}(\nu,\rho) = S^{G}(G,\rho) + \left[\cos \phi_{\nu,\rho}^{l} * S^{G}(G,\rho) \right] + \partial_{\nu}^{l} \quad (27)$$

The bypass riders pursue a familiar path without following leading rider. In this context, the update rule of the bypass riders is exhibited in which the standard bypass rider is given as,

$$S_{l+1}^{b}(\nu,\rho) = \lambda [S_{l}(\chi,\rho) * \delta(\rho) + S_{l}(\xi,\rho) * [1 - \delta(\rho)]] \quad (28)$$

where λ is random number, χ represents ransom number between one to *P*, ξ specifies a random number ranging between one to *P* and δ indicating random number between 0 and 1.

The update of Rag bull rider is done using standard HPSO which is devised on the basis of human behaviour and is formulated as,

$$S_{l+1}^{K}(\nu, o) = S_{l}^{K}(\nu, o) + e_{l+1}^{\nu}$$
(29)

where e_{l+1}^{ν} is the velocity of each rider and is formulated as,

$$e_{l+1}^{\nu} = \omega \cdot e_l^{\nu} + n_1 \left(S_l^N(\nu, o) - S_l^K(\nu, o) \right) + n_2 \left(S^G(G, \nu) - S_l^D(\nu, o) \right) + n_3 \left(S_l^U - S_l^K(\nu, o) \right)$$
(30)

where n_1, n_2 and n_3 indicate random numbers, ω represents inertial weight, S_l^N represents local leading rider, S_l^U denotes losing rider, and S^G signifies leading rider.

Step 5) Determination of the success rate:

TABLE 1 Pseudo code of proposed Rag-ROA algorithm

Input: S_l : Random Position of Rider, l: Iteration, l_{max} : Maximum Iteration **Output:** Leading rider S^G

Begin

Initialize the set of solutions

Initialize other parameter of rider like steering angle, gear, accelerator and brake

Determine success rate (24)

While
$$l < L_{OF}$$

For
$$\nu = 1$$
 to P

Update the position of bypass rider using equation (28)

Update the position of follower using equation (25)

Update the position of overtaker using equation (26)

Update the position of attacker using equation (27)

Update the position of rag bull rider using equation (29)

Rank the riders based on success rate using equation (24)

Choose the rider with high success rate

Update steering angle, gear, accelerator and brake

Return S^G l = l + 1

End for

End while

End

After completing the update process, the success rate of each rider is evaluated. Here, the position of rider who is in the leading position is replaced with the position of new rider obtained so far in such a way that the success rate of the new rider is higher.

Step 6) Update of Rider parameter:

The rider parameter update is essential to determine an effectual optimum solution. In addition, the steering angle, gears are updated using the activity counter, which is updated based on the success rate.

Step 7) Riding Off time:

The steps are iterated continuously till the time reaches the off-time (TOFF), within which the leading rider is discovered. After the completion of the race, the leading rider is termed as the winner.

The pseudo-code of the proposed Rag-ROA algorithm is illustrated in Table 1.

3.4 | Proposed rag-ROA-based deep RNN for epileptic seizure detection

The epileptic seizure detection with the proposed Rag-ROA method is offered and detection is performed with the feature

vector. The obtained features are given to classification with deep RNN [35] and training of DeepRNN is performed with Rag-ROA, which is the integration of ROA [36] with the Rag bull rider. The goal of the proposed Rag-ROA is to determine the epileptic seizure via input signal based on the extracted features. ROA [36] is inspired by the behaviour of rider groups, who travel to reach a familiar target location to become a winner. Here the riders are selected from the total riders of each group. Each and every group undergoes many strategies for reaching the target. Thus, it is concluded that this technique performs fault diagnosis with improved classification accuracy. In addition, the ROA is highly effective for obtaining the global optimal solutions and follows steps of fictional computing to solve optimisation problems, but poses low convergence and is highly sensitive to hyper parameters. Also, this method considers only a few rider groups, such as the Bypass rider, Follower, Overtaker, and Attacker. In Rag-ROA, in addition to the Bypass rider, Follower, Overtaker, and Attacker, a Rag bull rider is added, which is updated using HPSO [37]. The HPSO is inspired by the human behaviours, which learn from the best humans. Based on the behaviour of human, there persist some people who pose bad behaviours around us and at the same time, these bad behaviours become harmful and bring some effects on the people residing around us. In HPSO, the global worst and global best particles are devised for improving the convergence. The method provides a trade-off between exploration and exploitation states. Thus, the integration of ROA and Rag bull rider is done to improve the overall performance of the algorithm.

3.4.1 | Architecture of Deep RNN

The mined features A are taken as input to Deep RNN classifier. Deep RNN [35] is the network structural design which consists of different recurrent hidden layers in the layer of hierarchy of network design. In Deep RNN, the recurrent connection persists at the hidden layer. The Deep RNN classifier efficiently functions under the various input featurelength on the basis of information. It adapts the knowledge of prior state as an input in the present prediction, and practice the iteration with the hidden state information. The recurrent feature made the Deep RNN highly effective in working with the features. Due to the chronological pattern of information, Deep RNN is termed as an excellent classifier amongst the classical deep learning strategies. The structural design of Deep RNN is illustrated in Figure 3.

The configuration of Deep RNN is made by considering the input vector of w^{th} layer at x^{th} time as $A^{(w,x)} = \{A_1^{(w,x)}, A_2^{(w,x)}, \dots A_a^{(w,x)}, \dots A_f^{(w,x)}\}$ and the output vector of w^{th} layer at x^{th} time as $O^{(w,x)} = \{O_1^{(w,x)}, O_2^{(w,x)}, \dots O_a^{(w,x)}, \dots O_f^{(w,x)}\}$, respectively. The pair of each elements of input and the output vectors is termed as the unit. Here, *a* denotes the arbitrary unit number of w^{th} layer, and *f* represents the total number of units of w^{th} layer. In addition to this, the arbitrary unit number and the total number of units of $(w-1)^{tb}$ layer is denoted as v and U, respectively. At this time, the input propagation weight from $(w-1)^{tb}$ layer to w^{tb} layer is represented as, $\omega^{(w)} \in L^{f \times U}$, and the recurrent weight of w^{tb} layer is represented as $W^{(w)} \in L^{f \times f}$. Here, L denotes the set of weights. However, the components of the input vector is expressed as,

$$A_{i}^{(w,x)} = \sum_{k=1}^{U} p_{am}^{(w)} O_{m}^{(w-1,x)} + \sum_{a}^{f} o_{aa}^{(w)} O_{a}^{(w,x-1)}$$
(31)

where $p_{am}^{(w)}$ and $o_{aa}^{(w)}$ are the elements of $\omega^{(w)}$ and $W^{(w)}$. *a* denotes the arbitrary unit number of w^{th} layer. The elements of the output vector of w^{th} layer are represented as,

$$O_a^{(w,x)} = \gamma^{((w))} \left(F_a^{(w,x)} \right)$$
(32)

where $\gamma^{(w)}$ denotes the activation function. However, the activation functions, like sigmoid function as $\gamma(F) = \tanh(F)$, rectified linear unit function (ReLU) as $\beta(F) = \max(F, 0)$, and the logistic sigmoid function as $\gamma(F) = \frac{1}{(1+e^{-F})}$ are the frequently used activation function.

To simplify the process, 0^{th} weight as p_{a0}^{w} and 0^{th} unit as $O_0^{(w-1,x)}$ are introduced and hence the bias is represented as,

$$O^{(w,x)} = \gamma^{(w)}. \left(\omega^{(w)}O^{(w-1,x)} + W^{(w)}. O^{(w,x-1)}\right)$$
(33)

Here, $O^{(w,x)}$ denotes the output of the classifier.

3.4.2 | Training of deep RNN

The training of deep RNN [35] is carried out using the proposed Rag-ROA algorithm that intends to detect optimal weights for tuning deep RNN classifiers for seizure detection. The brief illustration of the algorithmic steps carried out in the execution of the proposed Rag-ROA algorithm is described in this section. The optimal weights are devised from the proposed Rag-ROA algorithm, which helps to tune the deep RNN for deriving the optimal classification results. The seizure detection adapts the proposed Rag-ROA-based deep RNN for classifying the input signal by devising an optimal classification and is able to deal with the new EEG signal that is arrived from the distributed sources. The steps of the proposed Rag-ROA algorithm are illustrated below:

Step 1: Initialisation:

The foremost step is weight initialisation that is expressed as, ω and utilize the feature vector and class of input EEG signal.

Step 2: Evaluation of error:

The best solution is detected with fitness function, which is termed as a minimisation issue and thus, the solution with least



FIGURE 3 Architecture of Deep RNN classifier

Mean Square Error (MSE) is chosen as an optimal solution. Here, the MSE is computed as follows,

$$MS_{err} = \frac{1}{b} \sum_{d=1}^{b} \left[O_a - O_a^* \right]^2$$
(34)

where O_a symbolizes the expected output and O_a^* denotes the predicted output, *b* represents the count of input EEG signals where $1 < d \le b$.

Step 3. Determination of update equation:

Here the weights to train Deep RNN are detected with proposed rag-ROA and the update is devised using the weights which contribute to less error. The update equation of proposed rag-ROA is devised in section 3.3.

Step 4: Re-computation of solution based on error.

The error is recomputed using the solution given in Equation (20). The algorithm generating the minimum error is utilised for training the deep RNN to detect seizures.

Step 5: Determination of optimum weight using the proposed Rag-ROA training algorithm:

The error of each solution is recomputed using the proposed Rag-ROA algorithm and is evaluated in such a way that the solution with less error is employed for training deep RNN. Step 6: Terminate:

The optimal weights are obtained in an iterative manner till the utmost iterations are reached.

4 | RESULTS AND DISCUSSION

This section elaborates comparison of proposed strategy with classical strategies through seizure detection dataset using accuracy, sensitivity and specificity. The analysis is done by varying training data. In addition, the effectiveness of proposed Rag-ROA + Deep RNN is analysed.

4.1 | Experimental setup

The implementation of the proposed method is done in MATLAB using PC using Windows 10 OS, 2 GB RAM, and Intel i3 core processor.

4.2 | Dataset description

The analysis of the proposed Rag-ROA + Deep RNN is performed using two datasets considering accuracy, sensitivity, and specificity.

4.2.1 | The TUH EEG epilepsy Corpus (TUEP)

The TUEP [41] is a rift of TUEG that comprises 100 subject's epilepsy and 100 subjects without epilepsy, as detected by a specialised neurologist. The data is devised in association with different partners that involve NIH.

4.2.2 | CHB-MIT Scalp EEG database

CHB-MIT Scalp EEG database [42] is a dataset containing recordings of 23 grouped cases which is collected from 22 subjects, using the data of five males, ages 3–22; and 17 females, ages 1.5–19. Here, the file SUBJECT-INFO consists of gender and age of each subject. The file RECORDS consists of 664 .edf files, and the file RECORDS-WITH-SEIZURES lists 129.

4.3 | Experimental results

The experimentation is performed on two datasets considering the EEG signals of both datasets to analyse epilepsy and nonepilepsy seizures.

4.3.1 | With TUEP database

The section portrays the experimental results that are performed considering two EEG input signals with epilepsy and without epilepsy. Figure 4a demonstrates the input signal with epilepsy and without epilepsy. The Taylor-based delta AMS feature generated with epilepsy and without epilepsy are enumerated in Figure 4b and finally Figure 4c presents the obtained spectrogram with epilepsy and without epilepsy. Here the analysis is done by varying the time and centre frequency, with blue colour indicating low coefficient intensity values, yellow indicating the intermediary coefficient intensity values and red denoting high coefficient intensity values .

4.3.2 | With CHB-MIT Scalp EEG database

The section portrays the experimental results that are performed considering two EEG input signals with epilepsy and without epilepsy using the CHB-MIT Scalp EEG database. Figure 5a demonstrates the input signal with epilepsy and without epilepsy. The proposed Taylor-based delta AMS feature generated with epilepsy and without epilepsy is enumerated in Figure 5b Here the analysis is done by varying the time and centre frequency. Figure 5c presents the obtained spectrogram with epilepsy and without epilepsy.

4.4 | Evaluation metrics

The performance of proposed Rag-ROA + Deep RNN is employed for evaluating the techniques includes specificity, accuracy, and sensitivity.

4.4.1 | Accuracy

It is defined as the degree of the nearness of predicted value in contrast to its original value in optimal seizure detection, and is formulated as,

$$Accuracy = \frac{T^p + T^n}{T^p + T^n + F^p + F^n}$$
(35)

where T^{p} represents true positive, F^{p} indicates false positive, T^{n} indicates true negative, and F^{n} represents false negative, respectively.

4.4.2 | Sensitivity

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This measure is described as the ratio of positives that are properly identified by the classifier and it is represented as,

Sensitivity =
$$\frac{T^p}{T^p + F^n}$$
 (36)

4.4.3 | Specificity

This measure is defined as the ratio of negatives that are properly identified by the classifier and is expressed as.

$$Specificity = \frac{T^n}{T^n + F^p}$$
(37)

4.5 | Performance analysis

The evaluation of proposed Rag-ROA + Deep RNN based on sensitivity, accuracy, and specificity parameters is evaluated. The analysis is carried out by varying training data using two datasets resp.



FIGURE 4 Experimental results of the proposed Rag-ROA + Deep RNN using TUEP database with (a) input signal with epilepsy and without epilepsy (b) Generated Taylor-based delta AMS feature with epilepsy and without epilepsy (c) Spectrogram of signal with epilepsy and without epilepsy

4.5.1 | Analysis using TUEP dataset

Figure 6 portrays the analysis of proposed Rag-ROA-Deep RNN using the TUEP dataset with specificity, accuracy, and sensitivity parameter. The analysis of proposed Rag-ROA-Deep RNN using the accuracy parameter is displayed in Figure 6a. For 50% training data, the accuracies computed by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.641, 0.673, 0.667, and 0.704. For 90% training data, the accuracies evaluated by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.769, 0.809, 0.835, and 0.847. The analysis of oposed Rag-ROA-Deep RNN using



FIGURE 5 Experimental results of proposed Rag-ROA + Deep RNN using CHB-MIT Scalp EEG database with (a) input signal with epilepsy and without epilepsy (b) Generated Taylor-based delta AMS feature with epilepsy and without epilepsy (c) Spectrogram of signal with epilepsy and without epilepsy

sensitivity parameter is displayed in Figure 6b. For 50% training data, the sensitivities computed by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.784, 0.802, 0.734, and 0.723. For 90% training data, the sensitivities computed by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.884, 0.888, 0.874, and 0.892. The analysis of proposed Rag-ROA-Deep RNN using specificity parameter is displayed in Figure 6c. For 50% training data, the specificity values computed by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons

200, hidden neurons 300, and hidden neurons 400 are 0.421, 0.501, 0.470, and 0.681. For 90% training data, specificity evaluated by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.668, 0.712, 0.809, and 0.822.

4.5.2 | Analysis using CHB-MIT Scalp EEG database

Figure 7 portrays the analysis of proposed Rag-ROA-Deep RNN using the CHB-MIT Scalp EEG database with



FIGURE 6 Analysis of proposed Rag-ROA-Deep RNN using TUEP dataset with (a) Accuracy (b) Sensitivity (c) Specificity

specificity, accuracy, and sensitivity parameter. The analysis of proposed Rag-ROA-Deep RNN using the accuracy parameter is displayed in Figure 7a. For 50% training data, the accuracy values computed by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.665, 0.716, 0.729, and 0.743. For 90% training data, the accuracy obtained by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.733, 0.777, 0.846, and 0.853. The analysis of proposed Rag-ROA-Deep RNN using the sensitivity parameter is displayed in Figure 7b. For 50% training data, the sensitivity values computed by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.769, 0.725, 0.795, and 0.830. For 90% training data, the sensitivity obtained by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.845, 0.869, 0.912, and 0.930. The analysis of proposed Rag-ROA-Deep RNN using specificity parameter is displayed in Figure 7c. For 50% training data, the specificity values computed by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons 200, hidden neurons 300, and hidden neurons 400 are 0.543, 0.625, 0.651, and 0.641. For 90% training data, the specificity obtained by proposed Rag-ROA + DeepRNN with hidden neurons 100, hidden neurons

200, hidden neurons 300, and hidden neurons 400 are 0.602, 0.705, 0.768, and 0.797.

4.6 | Comparative methods:

The methods employed for the analysis include: Wavelet + SVM [21], HWPT + RVM [9], MVM-FzEN [20], EWT + RF [22], and proposed Rag-ROA + Deep RNN.

4.7 | Comparative analysis

The comparative analysis of the proposed Rag-ROA + Deep RNN with conventional methods is evaluated. The analysis is carried out by varying the training data using two datasets resp..

4.7.1 | Analysis considering TUEP dataset

Figure 8 portrays the analysis of methods using the TUEP dataset with specificity, accuracy, and sensitivity parameter. The analysis of methods using the accuracy parameter is displayed in Figure 8a. For 50% training data, the accuracy computed by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.608, 0.647, 0.619,



FIGURE 7 Analysis of proposed Rag-ROA-Deep RNN using CHB-MIT Scalp EEG database with (a) Accuracy (b) Sensitivity (c) Specificity

0.521, and 0.683. For 90% training data, the accuracy evaluated by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.619, 0.825, 0.742, 0.631, and 0.888. The analysis of methods using the sensitivity parameter is displayed in Figure 8b. For 50% training data, the sensitivity computed by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.619, 0.790, 0.501, 0.509, and 0.809. For 90% training data, the sensitivity evaluated by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + DeepRNN are 0.785, 0.809, 0.901, 0.919, and 0.919. The analysis of methods using the specificity parameter is displayed in Figure 8c. For 50% training data, the specificity computed by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.507, 0.512, 0.500, 0.520, and 0.524. For 90% training data, the specificity evaluated by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.524, 0.749, 0.740, 0.815, and 0.899.

4.7.2 | Analysis considering CHB-MIT Scalp EEG database

Figure 9 portrays the evaluation of methods with CHB-MIT Scalp EEG database with specificity, accuracy, and

sensitivity parameter. The analysis of methods using the accuracy parameter is displayed in Figure 9a. For 50% training data, the accuracy computed by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.608, 0.647, 0.604, 0.523, and 0.706. For 90% training data, the accuracy evaluated by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.619, 0.825, 0.708, 0.612, and 0.882. The analysis of methods using the sensitivity parameter is displayed in Figure 9b. For 50% training data, the sensitivity values computed by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.634, 0.783, 0.512, 0.506, and 0.793. For 90% training data, sensitivity evaluated by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.776, 0.817, 0.918, 0.786, and 0.918. The analysis of methods using specificity parameter is displayed in Figure 9c. For 50% training data, the specificity computed by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT +RF, and proposed Rag-ROA + Deep RNN are 0.507, 0.546, 0.503, 0.505, and 0.546. For 90% training data, the specificity evaluated by Wavelet + SVM, HWPT + RVM, MVM-FzEN, EWT + RF, and proposed Rag-ROA + Deep RNN are 0.527, 0.784, 0.736, 0.819, and 0.899.

137



FIGURE 8 Analysis of methods using TUEP dataset with (a) Accuracy (b) Sensitivity (c) Specificity

4.8 | Comparative discussion

Table 2 illustrates the analysis of methods using two datasets considering accuracy, sensitivity, and specificity.

Considering the TUEP dataset, the proposed Rag-ROA + Deep RNN has a maximal accuracy of 0.888, which is 30.29%, 7.09%, 16.44%, and 28.94%, better than the accuracy of the existing methods, such as Wavelet + SVM, HWPT + RVM, MVM-FzEN, and EWT + RF, respectively. The sensitivity of proposed Rag-ROA + Deep RNN tends to be maximal with a value of 0.919. The percentage of improvement of the sensitivity with the existing methods, such as Wavelet + SVM, HWPT + RVM, and MVM-FzEN is 14.58%, 11.97%, and 1.96%, respectively. Similarly, the specificity of the proposed method is 0.899, which is 41.71%, 16.69%, 17.69%, and 9.34%, better than the existing methods, such as Wavelet + SVM, HWPT + RVM, MVM-FzEN, and EWT + RF, respectively.

Considering the CHB-MIT Scalp EEG database, the proposed Rag-ROA + DeepRNN has a maximum accuracy of 0.882. The percentage of improvement of the accuracy with the existing methods, such as Wavelet + SVM, HWPT + RVM, MVM-FzEN, and EWT + RF is 29.82%, 6.46%, 19.73%, and 19.72%, respectively. The sensitivity of the proposed method is 0.918, which is 15.47%, 11%, and 14.38%,

better than the existing methods, such as Wavelet + SVM, HWPT + RVM, and EWT + RF, respectively. Among the existing methods, the EWT + RF has a maximum specificity of 0.819, but the proposed Rag-ROA + DeepRNN is 8.9%, better than the existing EWT + RF. Here the proposed rag-ROA-based deep RNN showed improved results with maximal accuracy, sensitivity and specificity, than the existing methods, such as Wavelet + SVM, HWPT + RVM, MVM-FzEN, and EWT + RF, respectively.

5 | CONCLUSION

The elliptical seizure detection is carried out with Deep RNN, whose goal is to improve the performance of detection. The classical techniques of automatic seizure detection with neural networks reveal deprived performance in the existence of murmurs, which is addressed by the proposed method. The proposed rag-ROA trains the Deep RNN, to derive optimal weights and is devised by integrating rag bull rider and ROA. The training of Deep RNN is done with extracted features obtained from an input EEG signal. The feature involves relative energy, fluctuation index, holoentropy, spectral features, tonal power ratio, and, a proposed Taylor-based delta AMS feature. The proposed Taylor-based delta AMS is a



FIGURE 9 Analysis of methods using CHB-MIT Scalp EEG database with (a) Accuracy (b) Sensitivity (c) Specificity

| T. | A | В | L | Е | 2 | Comparative | analysis |
|----|---|---|---|---|---|-------------|----------|
|----|---|---|---|---|---|-------------|----------|

| Dataset | Metrics | Wavelet + SVM | HWPT + RVM | MVM + FzEN | EWT + RF | ProposedRag-ROA + DeepRNN |
|----------------------------------|-------------|------------------|---------------|------------|----------|------------------------------|
| Using TUEP dataset | Accuracy | 0.619 | 0.825 | 0.742 | 0.631 | 0.888 |
| | Sensitivity | 0.785 | 0.809 | 0.901 | 0.919 | 0.919 |
| | Specificity | 0.524 | 0.749 | 0.740 | 0.815 | 0.899 |
| Using CHB-MIT Scalp EEG database | Accuracy | 0.619 | 0.825 | 0.708 | 0.612 | 0.882 |
| | Sensitivity | 0.776 | 0.817 | 0.918 | 0.786 | 0.918 |
| | Specificity | 0.527 | 0.784 | 0.736 | 0.819 | 0.899 |

combination of the Taylor series and delta AMS features. Moreover, the feature dimension is reduced using PPCA. The proposed rag-ROA-based deep RNN showed improved results with maximal accuracy of 88.8%, maximal sensitivity of 91.9%, and maximal specificity of 89.9% than the existing methods, such as Wavelet + SVM, HWPT + RVM, MVM-FzEN, and EWT + RF, by using the TUEP dataset. In the future, the wavelet transform will be considered for processing the EEG signals.

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