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FCTA-CSTM: A Hybrid Optimized Deep Convolutional Neural Network and Long Short-Term Memory for Epileptic Seizure Prediction

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Abstract: Epileptic seizure is a nerve-wracking chronicle disease that occurs in older patients as well as middle-aged people, which is necessary to predict the disease sometimes it may cause serious health issues and lead to death in rare cases. Even though there are more methods for Epileptic seizure prediction, the computational efficiency and accurate results for prediction are very low. Hence a feasible deep learning (DL) based Felidae Canis tracking algorithm with a deep convolutional neural network and long short-term memory (FCTA-CSTM) model for predicting epileptic seizure is proposed. The electroencephalography (EEG) signals are used in this research for effective prediction. The FCTA-CSTM model employed with optimization mechanism, FACTA is the combination of three nature-inspired optimizers that intend to select the most suitable feature to train the model and improve the convergence speed as well as increase the potential of the model. Besides the model, CSTM trains effectively and accurately predict the disease which avails patients for early diagnosis. The performance of the model can be analyzed using accuracy, sensitivity, and specificity metrics and achieved 95.35%, 94.76%, and 95.94% respectively compared to other state-of-the-art methods.

Keywords: *Epileptic seizure, electroencephalography signals, Felidae Canis tracking algorithm, deep convolutional neural network and long short-term memory,deep learning.*

1. Introduction

Epilepsy is a kind of chronic nerve disorder that is characterized by the phenomenal evolution of spontaneous seizures [1] [2]. Seizures are also determined as sudden uncontrollable electrical disruption in human brain cells that changes the behavior, action, and emotional state of humans [3]. Moreover, this disease affects all age groups people, and more probably middle-aged and old people were affected by this disease also reduced their eternity life span of humans [4]. So the early detection of this disease is very important to reduce the mortality rate, thus emerging an advanced prediction process for epileptic seizure and thus improving human life. The seizures were normally classified into three primary types namely generalized, focal, and unidentified seizures. The epileptic seizures were predicted using EEG signals, which were composed of certain significant physiological and pathological information, for better analysis and prediction [5-11] [12]. According to the dependencies of the several methods, the EEG signals are divided into two types namely, intracranial EEG (iEEG) and scalp EEG (sEEG). Due to the continuous increment of signal processing and other convenient AI methods, recent predicting researchers have chosen EEG signals for effective prediction performance [13].

In general, the EEG is used to measure the electrical impulse from the brain by placing multiple metal electrodes on the scalp [14] [4]. EEG signals are considered an important diagnostic tool as well as used for predicting epileptic seizures [15, 16]. It is noted that the patterns in EEG signals are normal when a seizure is not diagnosed and change when a seizure is diagnosed [4]. Significantly, the EEG patterns are highly classified into four states such as ictal, pre-ictal, post-ictal, and inter-ictal state [17]. The ictal state is known for initial onsets and ends with an epileptic seizure on the other hand, the post-ictal starts while the seizure has ended and continues for a short period of time. Also, the pre-ictal occurs more or less 60 to 90 minutes before the inter-ictal state [3]. Moreover, it is important to classify the two states of EEG patterns which include ictal and pre-ictal for advanced prediction [15, 17, 18] [8]. However, the EEG signals vary from patient to patient, and quite difficult to forecast the disease also requires more time, some of the techniques employ a supervised learning model for prediction.

This era highly utilized deep learning (DL) and machine learning (ML) techniques to solve complex problems. Usually, these techniques collaborate with pre-processing techniques and feature extraction processes, and the selection process plays a vital role in solving anticipating problems with great efficiency. Using ML and DL techniques, the EEG signals were efficiently decomposed

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into several frequency bands and extracts common spatial patterns (CSP) therefore the type of seizures was classified using some of the techniques like CNN, LSTM, DNN, and so on. The generative adversarial networks (GAN) model highly reduces the impacts on imbalanced issues that occur during the prediction process [19] [20]. The neural network (NN) model was mostly utilized in prediction, detection, classification, and other problems [24-29], in which the hidden layers are quite feasible to undergo different processes for different problems. One-dimensional CNN (1D-CNN) is another DL-based method that effectively detects epileptic seizures using EEG signal-based data. The BiLSTM is the other model for predicting the disease, later binary single-dimensional convolutional neural network (BSDCNN) model was established and achieved minimum accuracy [12]. However, these models literally gone through some limitations during the prediction like over-fitting issues, not a robust prediction, time-consuming, and so on.

This research overcame several existing drawbacks and developed a hybrid-based model, FCTA-CSTM for epileptic seizure prediction. Here, EEG signals are taken as an input which is decomposed into alpha, beta, delta, theta, and gamma frequency sub-bands, therefore predicting the disease effectively using the FCTA-CSTM model. The proposed FCTA-CSTM model holds the FCTA optimizer and CSTA method that drives effective disease prediction. Moreover, the FACTA optimizer was developed to select the suitable parameter to train the model. Using this optimizer increases the efficiency as well as convergence speed of the model that highly determined for accurate prediction. Besides, the CSTM model predicts epileptic seizures with higher accuracy which avail patients for early diagnosis. The contribution is discussed briefly in the below context.

- Felidae Canis tracking algorithm (FCTA) optimizer for feature selection and training the model: The FCTA optimizer holds the behaviour of three significant optimizers, which optimally selects beneficial features to train the mode. Hence reduce local optimal issues and increase its convergence efficiency for accurate prediction.

- Convolutional neural network and long short-term memory (CSTM) model: The hybrid model is embedded with deep CNN and LSTM model, in which, the deep CNN model extract the important features where, the LSTM model captures long-term dependencies for prediction. Therefore decrease the overall loss and provides high accuracy for better prediction.

- Felidae Canis tracking algorithm with deep convolutional neural network and long short-term memory (FCTA-CSTM) for epileptic seizure prediction: The FCTA-CSTM model further reduce over-fitting issues, time complexity and cost effective during training. Hence the FCTA-CSTM model efficiently predicts epileptic seizure and provides significant results.

- This paper is organized in the following manner: A review of multiple literature and its challenges are occupied in section 2. The next section 3 is established with the proposed methodology and the result placed in section 4. At last, the conclusion is deployed in section 5.

2. Literature Review

B. Jaishankar, et al [27] introduced an optimal model for predicting epileptic seizure, an Adaptive Genetic auto-encoder (aADGA) embedded with a genetic algorithm (GA) which highly optimizes the hyperparameters from the model and comprises the time for computation. Even though the model was highly challenged with complex datasets and required maximum computational cost to achieve the prediction process. Imene jemal, et al [28] utilized a DL model, a deep neural network (DNN) for epileptic seizure prediction which corresponds to providing pertinent features using layer-wise propagation and thus leads to accurate prediction. However, the model cannot be deployed in real-world applications and also dealt with over-fitting problems due to many number of deep networks.

Bhaskar Kapoor, et al [3] introduced the hybrid model, AdaBoost, random forest (RF), and the decision tree (DT) model for prediction, in which the hybrid seek optimizer fuses the hybrid models to appropriate predicted values. This model was highly feasible and reliable for the practical approach. However, the prediction performance of this model required more time, and was also quite challenging to pay attention to every single hybrid model. Kuldeep Singh, et al [2] came up with a spectral feature-based two-layer LSTM model for high prediction using the EEG signals. More or less, the time taken for prediction required 30 sec and achieved better accuracy, which was capable of solving the vanishing gradient problem. Nevertheless, the model has computational complexity due to multiple hidden layers.

Xin Xu, et al [13] deployed a gradient boosting decision tree (GBDT) model, which is one of the ML-based models that highly avoids class imbalance issues and the EEG signals were de-noised using CEEMD and wavelet that aid for effective prediction. However, the model cannot handle the annotation that relies upon the seizures and thus provides an impact on the model. Fatma E. Ibrahim, et al [29] focused on developing a CNN model, which utilized thirteen layers and several residual learning blocks for effortless prediction of an epileptic seizure. Meanwhile, the developed model performed using spectrogram images limits some processes during prediction and also requires high computational expenses.

Rowan Ihab Halawa, et al [14] developed a modern DL method, 1D CNN for epileptic seizure prediction. In addition, the model demanded a wavelet-based pre-processing approach that highly reduces unwanted background noises for effective prediction. Somehow, the wavelet approach has shift sensitivity and sometimes lacks important information during noise reduction. Ranjan Jana, et al [4] deployed a CNN model for prediction, in which the features are extracted automatically and determine high prediction with maximum accuracy. However, the EEG signal patterns varied at independent seizure prediction, so the process of prediction was quite challenging.

2.1 Challenges of Existing Methods

The limitations and the challenges of the existing methods are summarized below;

- The aADGA model was not efficient enough to perform using complex datasets and required maximum computational cost to achieve the prediction process [27]
- The DNN model cannot be deployed in real-world applications and also dealt with over-fitting problems due to many number of deep neural layers [28]
- The hybrid model of AdaBoost, random forest (RF), and the decision tree (DT) for prediction required more time and also quite challenging to pay attention to every single hybrid model [3]
- The GBDT model cannot handle the annotation relies upon the seizures and thus provides impacts on predicting the seizures using the deployed model [13]
- In the CNN model, the EEG signal patterns varied at independent seizure prediction, so the process of prediction was quite challenging for many researchers [4].

3. Methodology for epileptic seizure prediction

The research focused on to develop an ensemble model to overcome the limitations of previous methods such as computational complexity, over-fitting issues and other challenges for predicting epileptic seizure disease. The proposed ensemble deep learning based FCTA-CSTM model is contributed to predict epileptic seizure and provides better performances. In this work adopts two datasets namely the CHB-MIT scalp EEG database [30] and the UCI dataset [31] that are deployed to train the model effectively for epileptic seizure prediction. The input EEG signals are prone to noises and lower amplitude hence the input signals are subjected to pre-processing for eliminating the unwanted noises present in the signal. The processed signals are decomposed into alpha, beta, delta, theta, and gamma frequency bands, which are then subjected to the feature extraction using (a) Time domain (b) Frequency/Spectral domain (c) Time-Frequency domain (d) Decomposition domain, and (e) Deep features. The extracted features establish the feature vector which is then subjected to the optimized feature selection procedure for selecting the optimized frequency sub-bands. Thus, established feature vector that avails training CSTM classifier, which is designed for predicting epileptic seizures. The prediction model is developed through hybridizing the deep CNN and LSTM models where the model is trained using hybridizing the behaviour of three nature inspired optimizers thus providing high prediction accuracy with low computational expenses and the framework of the proposed model is given in Figure 1.

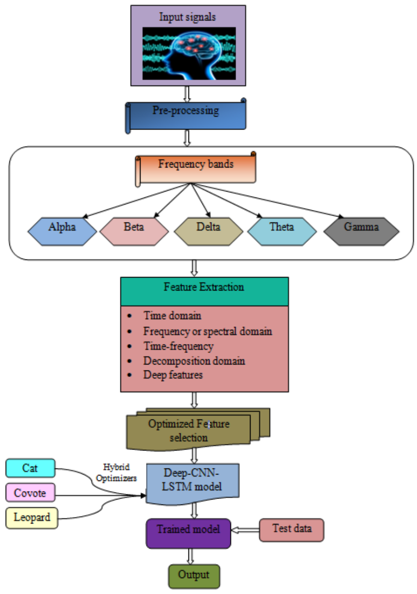


Fig. 1: Framework of proposed model

3.1 Input signals

The electrical impulse of the brain cells congregates using the EEG signals, which involves high-level prediction with the help of several informatics representations from the signals, and very particular, it holds relevant data of the nerve disorder, epileptic seizure disease. Here, two available datasets namely the CHB-MIT scalp EEG database and the UCI dataset are utilized. The input signals are represented as,

$$Z_d = \{N_{d_1}, N_{d_2}, ..., N_{d_i}, ..., N_{d_n}\} \tag{1}$$

where Z_d represents the datasets with many signals N_{d_n}, which undergo effective training in the model.

a) CHB-MIT scalp EEG database description [30]: The CHB-MIT scalp EEG database consists of a collection of multiple EEG signal-based data, which is proclaimed with twenty-two pediatric subjects and intractable seizures are accompanied. Also, the onset and ends of 182 seizures are interpreted.

b) UCI dataset [31]: The UCI dataset, epileptic seizure recognition was sorted by pre-processing and reshaping the commonly used dataset featured for epileptic seizure detection

3.2 Pre-processing of input signals

The pre-processing step is the initial step to predict the epileptic seizure in which, the EEG signals are headed to the pre-processing filter to evacuate some unwanted artifacts from the EEG signals, therefore providing high accuracy to the FCTA-CSTM model. In this work, a band-pass filter is taken for the noise reduction process. Significantly, the frequency bands of the EEG signals range from 0.25 to 25 Hz where the rest is removed to make high progress for the prediction model. The pre-processed time series data can be represented as $S(j)$.

3.2.1 Frequency bands

The frequency bands of EEG signals produce multiple sub-bands for evaluating the inner nodal data, which involves delta, theta, alpha, beta, and gamma for high prediction. The significant characteristics of each sub-band vary according to the epileptic seizures that highly represent the alterations in both functional and behavioral features of complex epileptic patients [32] [2]. However, the frequency of respective sub-bands of delta ranges from 0.5 to 4 Hz, theta ranges from 4 to 8 Hz, alpha ranges from 8 to 12 Hz, beta ranges from 12 to 30 Hz, whereas gamma ranges from 30 to 100 Hz.

3.3 Feature Extraction Process

The feature extraction process is highly known for extracting distinct features from the input. Here, each sub-band of EEG signals from the pre-processed phase is deployed to aid in designating various stages of epileptic seizure and therefore acts as a descriptor for prediction. In this research, the extraction of beneficial features from each sub-band takes place with five different methods such as time domain, frequency or spectral domain, time-frequency domain, decomposition domain, and finally deep features to extract the key features from each sub-band that is subjected to develop and train the FCTA-CSTM model.

3.3.1 Time domain-based feature extraction

The time domain technique is determined to extract features from different aspects of time and henceforth separate extraneous signals from each sub-band of EEG signals, which is necessary for predicting epileptic seizures. Moreover, the extraction of features using the time domain technique employed several constrained techniques that include Correlation Dimension Feature, Detrended Fluctuation Analysis, Hjorth Features, and Hurst Exponent Feature which are explained below.

a) Correlation Dimension Feature

Correlation dimension (CD) is one of the geometric measures that evaluate dynamic complexity also approximates the dimensional phase space and is more often enumerated from the time series data from the single vector. The CD can be defined in the following equation [33], where, the time series data $S(j)$ is taken as an input. The below-mentioned equation (2), $c(q)$ represents the correlation integral with the radial distance q around every reference point.

$$c_d = \lim_{q \to 0} \left[\ln c(q) / \ln q \right] \tag{2}$$

b) Detrended Fluctuation Analysis

Detrended fluctuation analysis [34] is one of the time domain methods prioritized for extracting the features of sub-bands of EEG signals. Here, the sub-bands are computed with the help of scaling components that highly index the long-range power-law correlation placed in non-stationary signals. At first, the sequence of the time series data $S(j)$ is computed as follows,

$$k(l) = \sum_{j=1}^{l} S_j - \langle S \rangle, \ l = \{1, \ldots, n\} \tag{3}$$

The next step is to divide $k(l)$ into $n_{ts} \equiv [n / ts]$, where n represents the length of time series data and ts is the considered time scale. However, the series length is not a multiple of the time scale, whereas the small part of the sum sequences remains at the end. Thereby repeating the process from one end to the other end, produce $2n_{ts}$ segments. The third step is to eliminate the local trends from the segments, which can be defined in the below equation.

$$k_{st}(l) = k(l) - f_e(l) \tag{4}$$

Here, f_e represents the fitting polynomial in segment e, the linear, cubic, quadratic, and other polynomials are used in the fitting process. However, the fourth step is to take an overall average of each segment thereby taking the square root to produce a fluctuation function, which is determined as follows.

$$X(ts) = \left[\frac{1}{2n_{ts}} \sum_{e=1}^{2n_{ts}} X_{ts}^2(e) \right]^{1/2} \tag{5}$$

From the above equation, $X(ts)$ is the fluctuation function, which $X_{ts}^2(e)$ can be evaluated using the below equation.

$$X_{ts}^2(e) = \left\langle k_{st}^2(l) \right\rangle = \frac{1}{ts} \sum_{l=1}^{ts} k_{ts}^2 [(e-1)ts + l] \tag{6}$$

c) Hjorth Feature

Hijorth features or parameters are the important features, which represent the statistical features of the indicators and are more probably used in various signal processing tasks in time series data. Also quite necessary for EEG signal analysis and there were three features involved in Hijorth are complexity, activity, and mobility. The activity feature of Hjroth (A_{hj}) can be defined as the signal power of the function, which is evaluated using the below equation.

$$A_{hj} = \varphi_S^2(S(j)) \tag{7}$$

Whereas, the mobility feature of the Hjroth (M_{hj}) is the square root ratio of the first derivative variance to that of signal variance, which is represented as follows,

$$M_{hj} = \sqrt{\frac{\varphi_S^2\left(\frac{dS(j)}{dj}\right)}{\varphi_S^2(S(j))}} \tag{8}$$

The complexity feature (C_{hj}) can be expressed by the switch state of frequency in the EEG signals and can be evaluated as follows

$$C_{hj} = \frac{M_{hj}\left(\frac{dS(j)}{dj}\right)}{M_{hj}(S(j))} \tag{9}$$

d) Hurst Exponent Feature

The Hurst exponent feature is meant to evaluate the existence of extinct long-range dependence in the time series data and can be computed as follows.

$$G_{hu} = v_{ex}\left[\frac{d_{cun}(x)}{u_{ser}(x)}\right] = Yx^{H_{cmp}} \tag{10}$$

where, v_{ex} indicated the contemplated value, $d_{cun}(x)$ denotes the cumulative derivative from mean value (x) whereas, $u_{ser}(x)$ denotes the first time series with SD φ and Y is the constant value with the hurst component H_{cmp} . The feature extraction performance of the time domain feature can be denoted as D_{tm} .

3.3.2 Frequency domain-based feature extraction

The frequency domain is mostly utilized to analyze the spectral features from each sub-band of the EEG signals and extracted using some important parameters that include band power and spectral entropy are discussed below.

a) Band power

The power band of EEG signals is highly demonstrated by the mean power metric in the signals with specific band frequency. This technique highly reduces the computation complexity and provides further improvements in prediction, the band power can be represented as O_{bd} .

b) Spectral Entropy

The term entropy means disorder, however, spectral entropy is the method to calculate the quantity of irregularity in the EEG spectrum as well as disorder, which is expressed in the below equation.

$$z_{sf} = \sum_{f_0} B_{psd}(f_0)\ln\frac{1}{B_{psd}(f_0)} \tag{11}$$

here, B_{psd} is the power spectral density and f_0 denotes the frequency component of each sub-bands. The output of frequency domain extraction can be denoted as $D_{fd} = \|O_{bd}\|\|z_{sf}\|$

3.3.3. Time-frequency domain-based feature extraction

In the time-frequency domain, the discrete wavelet transform (DWT) technique is deployed to extract features from the EEG signals. More frequently, the DWT utilized time series signals, in which the signals are decomposed or separated as a discrete wavelet form and can be denoted as follows [35],

$$P_{DWT_s} = \int S(j)\vartheta_{i,j}^*(j)dj \tag{12}$$

here, ϑ represents the wavelet function, where $i \in Z, j \in Z$. The overall results

3.3.4 Decomposition domain-based feature extraction

In the decomposition domain features carry three different functions required to extract the EEG signals such as mean, phase frequency detector (PFD), and standard deviation.

a) Mean: The ratio of total average time instances to the total number of instances I_t of EEG signals that are expressed as follows.

$$\tau_m = \frac{1}{I_t \sum_{j=1}^{I_t} S_j} \tag{13}$$

b) Phase frequency detector (PFD): The PFD can be evaluated by transforming the fractal dimension of EEG signals into multiple binary sequences with the length l_s and the resulting binary sequence provides a number of sign changes S_Δ , the FD can be denoted as follows.

$$\tau_{PFD} = \frac{\log_{10} l_s}{\log_{10} l_s + \log_{10}\left(\frac{l_s}{l_s + 0.4S_\Delta}\right)} \tag{14}$$

c) Standard deviation (SD): The variation in each time series of EEG signals concerning the mean. The SD is defined as,

$$\varphi_S = \sqrt{\frac{1}{I_s - 1}\sum_{j=1}^{I_s}\left(S_j - \tau_m\right)^2} \tag{15}$$

The extracted features of the decomposition domain can be denoted as $D_{xg} = \|\tau_m\|\|\tau_{PFD}\|\|\varphi_S\|$.

3.3.5 Deep features based feature extraction

Using statistical features such as mean, SD, variance, medium, Skewness, kurtosis, geometric mean, sum-minimum, and sum-maximum are determined to extract the features from the signals. Here mean τ_m is defined for taking an average of time instances in EEG signals whereas, the SD φ_S measures each time instance in the EEG signals. Variance is the square of SD, which is denoted as φ_S^2. The median is utilized to find the center value of the EEG signals which is denoted as τ_{med}. On the other hand, skewness is implemented to find the total disproportion among the random variables in the probability distribution that is denoted as τ_{skw} and Kurtosis can be expressed in terms of peaked distribution of random variables with the sub-bands of the EEG signals which is denoted as τ_{kru}. The geometric mean is the other statistical feature, that can be defined as the average value that specifies the central tendency by evaluating the product of the values and can be denoted as τ_{geo}. The minimum and the maximum functions find the max and min values where the sum of both min and max functions are subtracted to have significant signals which are denoted as $\min_{sum}$ and $\max_{sum}$. The above-mentioned statistical features are an aid for high improvement in speed training and effective visualization that will help to reduce over-fitting issues. The deep features-based feature extraction can be represented as $D_f = \|\tau_m\|\|\varphi_S\|\|\varphi_S^2\|\|\tau_{med}\|\|\tau_{skw}\|\|\tau_{kru}\|\|\tau_{geo}\|\|\min_{sum}\|\|\max_{sum}\|$.

The overall extraction of semantic features from each sub-band of the EEG signals for epileptic seizure prediction is denoted as E_{xf} highly symbolizing the model prediction accuracy, further developed for better performance.

3.4 Felidae Canis Tracking Algorithm

The FCTA optimization technique contributes to feature selection and CSTM training process in which, the characteristics of three optimization algorithms such as seeking and tracking character, community group, and path-finding behaviors are taken from cat swarm optimizer [36, 37], coyote optimizer [38], and leopard optimizer [39] that indicates Felis Catus, Canis Latrans, and Panthera Pardus for this experiment. In this FCTA optimizer, the community group behavior depends on the social organization condition effectively denotes number of solution among the group. However, the seeking and tracking behavior is one of the important character plays a role of finding the best suitable solutions by memorizing the position and move further to track other global solution from the search space that aids to select the best solution among the group. At last, the behavior, path-finding employed to determine the path which is modelled with zig-zag patterns for finding the missing community group and thus provides an effective solution to select the best feature from the search space and highly trains the model's parameter to achieve better prediction for epileptic seizure. Using the FCTA optimizer provides speed computational efficiency and also reduces over-fitting issues and thus remains a resilient model for prediction.

Inspiration

The combination of existing behaviors such as seeking and tracking character, community group, and path-finding are taken to find the best solution to train the model. However, the community group is the population-based algorithm that depends on maintaining the group to search for the best suitable solution. The seeking and tracking are inspired by the resting and tracing behavior, which is quite spontaneous to seek the best solution in the search space whereas, the path-finding character is taken from the snow leopard behavior that simultaneously finds the missing community group and thus enhances the performance for better prediction.

a) Initialization: At first, the population of solutions is specified in the form of a matrix, which is the initial step to identify the best solution among the community group and represented as,

$$b = \begin{bmatrix} b_1 \\ \vdots \\ b_i \\ \vdots \\ b_N \end{bmatrix} \tag{16}$$

In the above equation, b represents the population of the solution, b_i denotes the i^{th} position of the solution, and b_N represents the total number of solutions in the community group.

b) Fitness evaluation: The fitness of the solution can be determined by the accuracy metric in which, the random solutions and the corresponding solution of the maximal classifier, the accuracy of the solution is declared as the best suitable solution at each iteration that is defined as,

$$fit(b^t) = \max(J_{acc}(b^t)) \tag{17}$$

c) Condition strategy: To define a problem, several conditions are evolved to evaluate and identify the best suitable solution and therefore train the model and provide high accuracy. In this section, two cases are implemented to find a suitable solution which is described in the below context.

Case 1: Following Phase: $F(b^t) > F(b^{t-1})$: Here, $F(b^t)$ represents the fitness of the solution at t iteration and $F(b^{t-1})$ denotes the fitness of the solution at $t-1$ iteration. Considering the solutions are found inside the community group, where the whole group instinct to search for the suitable solution. In this case, the solution among the community group should be to update its current state or position in order to remain in the community group. Now, the behavior of seeking and tracking plays an important role in updating the position of each solution from the group. However, the behavior intended to seek the best suitable solution simultaneously traces the leading one among the group. Therefore, the combination aids in overcoming the local optimal issues and thus updates its position to increase the converging ability. The updated position of the solution can be represented as

$$b^{t+1} = \frac{[b_t + W_t]}{2} + \left[b_t + a_1(b_g - b_t) + \frac{a_2(b_{cult} - b_t)}{2}\right] \tag{18}$$

In the above equation, b_{cult} represented as the medium social condition of all solutions in the community group, a_1 denoted as the seeking factor that belongs to $(0,1)$ whereas, a_2 indicates the seeking range of the solution and b_g represents the global best position. In addition, W_t indicated as velocity at iteration t, which can be evaluated as follows

$$W_t = W_{t-1} + a_3 U_1 (b_g - b_t) \tag{19}$$

where, W_{t-1} is the velocity at iteration $t-1$, a_3 denotes the influence factor with respect to the circumference U_1 covered by the solution.

Case 2: Path-finding phase: $If\ F(b^t) \leq F(b^{t-1})$: This condition shows that the position of the solution is not greater than or equal to its precious iterated value. During iteration, the solution has a probability of being struck at any point of unoptimal position, and therefore the position of the solution must be updated on the basis of the cultural tendency of the community group. Sometimes, this condition leads to obtaining a worse solution, hence the solution utilized its experience in finding the position by exchanging the information and identifying the path to console with the community group. Moreover, this behavior improves the quality of the solution, develops its exploration ability, and more probably increases the cultural tendency of the community group. The improved equation is,

$$b^{t+1} = \frac{\left|b^t + U_2(b_t - Lb_t)\sin(F(b_t) - F(b_{rand}))\right| + \left[b_t + a_1(b_g - b_t) + a_2(b_{cult} - b_t)\right]}{2} \tag{20}$$

where, U_2 represents the memory factor of the solution, L denotes the path-finding character of the solution with the fitness function of the current solution $F(b_t)$ and a random solution $F(b_{rand})$. Here, the condition for terminating this procedure is $t < t_{max}$, that the total iteration ends with its best suitable solution. The FCTA optimizer is necessary for identifying the best suitable solution that exaggerates the model training process with the best-selected features. In addition, the FCTA optimizer reduces over-fitting and local optimal issues thus providing better accuracy performance for prediction. The flow chart of the FCTA optimizer is shown in Figure 2.

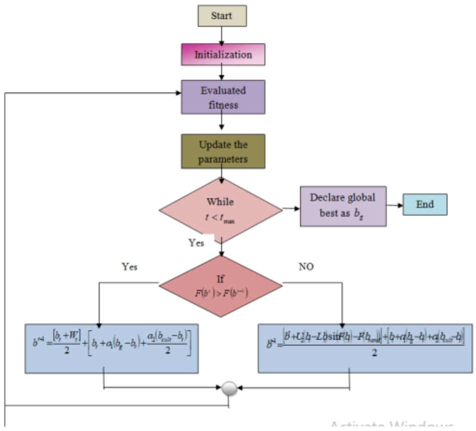


Fig. 2: Flowchart of FCTA optimizer

3.5 Feature selection

The selection procedures involved in choosing the significant feature for effective training of the FCTA-CSTM model. Here, FCTA is employed to select the optimal feature from various parameters, highly exploited with two conditional phases, which include the following and path-finding phase of optimization. Therefore, select significant feature to train the model and reduced computational complexity as well as improves the exploration ability of the model. The selected feature can be denoted as p_{sf} .

3.6 Hybrid CSTM model for epileptic seizure prediction

The CSTM is the hybrid of the deep CNN and LSTM model which contains multiple hidden layers that usually predict the occurrence of epileptic seizures using EEG signals [40]. Here, two-dimensional (2D) convolution, rectified linear unit (ReLU), and max-pooling layers are comprised in the CSTM model. However, in this experiment, three 2D convolutional layers, three ReLU layers, and two max-pooling layers are implemented which is shown in Figure 3. The selected features of the EEG signals are the feature vectors of 2D convolution with the size $(7015,1,1)$. The 2D convolution subsequently contains kernels to train the model with the size $(7015,1,32)$ and thus generate a feature map. The further process includes the ReLU function which concentrates on securing the growth of high exponential and therefore minimizes the computational expenses that can be expressed as,

$$f(P_{sf})_{ReLU} = \max(0, P_{sf}) \tag{21}$$

The max-pooling layer evaluates the maximum pooled features from the map and certainly increases the accuracy percentage by means of reducing its dimensionality and therefore increases the learning speed, and the size of the max-pool $(7015,1,32)$. Following this, the reshaped features with size $(7015,64)$ are fed into the LSTM [41] layer that captures global and local information from long and short terms of feature vectors which is composed of significant gate features such as input gate, output gate, memory state, and forget gate. These gate features avail better prediction with low computational expenses, where the size of the LSTM layer is (100). The flatten layer of this model effectively reduces the dimensionality of the features to enhance the prediction. On the other hand, the dense layer captures complex patterns from the previous layer and provides further improvements in prediction. The output of the CSTM is taken from the softmax layer that highly predicts the presence of epileptic seizures. The complete architecture of the CSTM model is depicted in Figure 3.

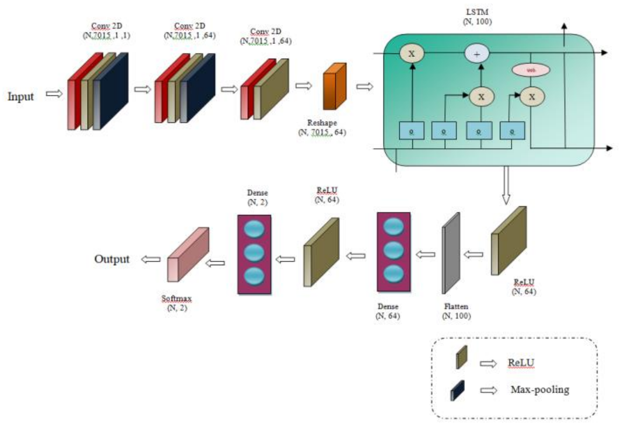


Fig. 3: Architecture of CSTM model

4. Results

The performance and the comparative results of epileptic seizure prediction using the FCTA-CSTM model is provided in this section. At the same time, the discussion of existing methods is also detailed to prove the efficiency of the FCTA-CSTM model.

4.1 Experimental setup

The developed model is implemented using Python tool in Windows version 11 OS with RAM 16 GB, ROM 100 GB and CPU-1.7 Ghz.

4.2 Performance Metrics

To validate the performance of the proposed FCTA-CSTM model, several metrics such as accuracy, sensitivity, and specificity are measured to demonstrate the performance as well as the comparison between the proposed and the existing models.

a) Accuracy: This metric can stated as the ratio of correct predicted value with total predicted value, which is denoted as,

$$J_{acc} = \frac{T_e P_i + T_e N_a}{T_e P_i + T_e N_a + F_s P_i + F_s N_a} \tag{22}$$

b) Sensitivity: Sensitivity results demonstrate the correct positive outcome and can be expressed as,

$$J_{sen} = \frac{T_e P_i}{number of\ F_s N_a} \tag{23}$$

c) Specificity: Specificity is to identify the number of incorrect test results occurred and can be determined as,

$$J_{spc} = \frac{T_e N_a}{number of\ F_s N_a} \tag{24}$$

Here, $T_e P_i, T_e N_a, F_s P_i, and\ F_s N$ represents true positive, true negative, false positive, and false negative respectively.

4.3 Performance Analysis

The prediction performance of the FCTA –CSTM model is analyzed using the above-mentioned metrics with a constant training percentage of 90 and provides reasonable and accurate performance values, therefore proving the proposed model is highly efficient and effective in predicting epileptic seizures. Moreover, the model reduces the computational cost and increases computation speed for effective prediction.

4.3.1 Performance analysis using TP

The prediction performance of the FCTA –CSTM model can be analyzed using varying epochs 100, 200, 300, 400, and 500 with constant TP 90. Here, the average accuracy performance of the FCTA –CSTM model with epoch 100 is 86.64%, and with maximum epoch 500, the accuracy is 95.35%. However, the sensitivity value with minimum epoch 100 is 86.33% whereas with maximum epoch, the sensitivity is 94.76%. Along with this, the specificity value with min epoch is 86.94% and with max epoch is 95.94%

respectively, which is depicted in Table 1. This analysis shows high prediction performance accompanied by several metric measurements and thus carries the advantage of reducing computational complexity and other computational expenses therefore improving the potential of the FCTA –CSTM model.

Table 1: Performance analysis using TP-90

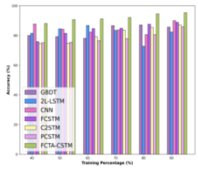
TP-90			
	Accuracy %	**Sensitivity %**	**Specificity %**
FCTA-CSTM at Epoch = 100	86.64	86.33	86.94
FCTA-CSTM at Epoch = 200	88.60	88.38	88.83
FCTA-CSTM at Epoch = 300	91.82	90.87	92.77
FCTA-CSTM at Epoch = 400	93.17	92.77	93.57
FCTA-CSTM at Epoch = 500	95.35	94.76	95.94

4.4 Comparative Analysis

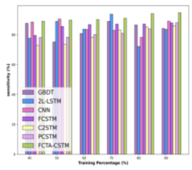
The comparative measures with the FCTA-CSTM model and the existing models such as GBDT [8], 2L-LSTM [2], CNN [29], Felis Catus CSTM (FCSTM), Canis Latrans CSTM (C2STM), and Panthera Pardus CSTM (PCSTM) models are compared using the above-mentioned metrics with the constant training percentage 90. This analysis exaggerates that the proposed FCTA-CSTM model is suitable for predicting epileptic seizure

4.4.1 Comparative Analysis using TP

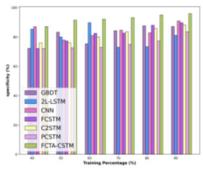
The comparison of the FCTA-CSTM model with above mentioned existing models plays a role in this analysis, which is shown in Figure 4. This section shows the improved performance of the FCTA-CSTM model with the above-mentioned metrics. The improved accuracy percentage of the FCTA-CSTM model with the existing methods is 10.11%, 13.60%, 5.57%, 6.81%, 8.67%, and 9.95%. The improved sensitivity is 11.08%, 11.77%, 5.97%, 7.18%, 9.25%, and 7.03% whereas, the improved specificity is 9.14%, 15.40%, 5.17%, 6.46%, 8.09%, and 12.84% respectively. The performance of the proposed model is highly increased than the other existing models hence the FCTA-CSTM model achieved a high success rate of epileptic seizure prediction with increased accuracy. In addition to its accuracy, the model effectively learns from the previous stage of the entire process and thus decreases the computation expenses as well as does not require high memory.



a) Accuracy



b) Sensitivity



c) Specificity

Fig. 4: Comparative Analysis using TP-90

4.5 Comparative Discussion

The complete analysis of the existing versus the proposed illustrates that the FCTA-CSTM model is quite manifest for predicting epileptic seizures using EEG signals. The accuracy percentage of the existing is 85.71%, 82.39%, 90.04%, 88.85%, 87.09%, and 85.86% but the FCTA-CSTM model is 95.35% which is quite high comparatively. Although, the sensitivity is 84.25%, 83.60%, 89.10%, 87.96%, 85.99%, and 88.09% and specificity is 87.17%, 81.17%, 90.98%, 89.75%, 88.18%, and 83.63%. But for the proposed FCTA-CSTM model 94.76% and 95.94% respectively. Besides, the FCTA-CSTM model is more viable for predicting epileptic seizure disease and therefore rescues people from dangerous life threads due to this disease. Moreover, the model has a high tendency to solve complex problems using its adaptable techniques used in pre-processing, feature extraction, and optimization which highly increase the convergence speed as well as reduce the local optimal issues. Therefore the model can effectively increase its performance accuracy, be more reliable, provide robust prediction, and gain more attention than the existing models.

Table 2: Comparative discussion table

TP-90			
	Accuracy %	**Sensitivity %**	**Specificity %**
GBDT	85.71	84.25	87.17
2L-LSTM	82.39	83.60	81.17
CNN	90.04	89.10	90.98
FCSTM	88.85	87.96	89.75

C2STM	87.09	85.99	88.18
PCSTM	85.86	88.09	83.63
FCTA-CSTM	95.35	94.76	95.94

5. Conclusion

The chronicle disease of epileptic seizure is highly predicted using the proposed FCTA-CSTM model, which intends to lower the mortality rate by predicting its presence. The previous methods are highly complicated also require more computational efficiencies as well and the accurate results for prediction are very low. However, the FCTA-CSTM overcomes several limitations by using multiple techniques to pre-process, feature extract, and select the features, therefore providing great prediction. Here, EEG signals are utilized, which undergo certain processes, where, the features are selected using a newly developed optimizer, FCTA is the combination of three nature-inspired optimizers that intend to select the best suitable feature to train the model and improve the convergence speed as well as increase the potential of the model. Besides, the CSTM model ensemble with CNN and LSTM trains effectively and efficiently for accurate prediction of epileptic seizure, which avails for early diagnosis. Moreover, the performance of the FCTA-CSTM model can be analyzed using accuracy, sensitivity, and specificity metrics and achieved 95.35%, 94.76%, and 95.94% respectively compared to other state-of-the-art methods. In the future, this method will be implemented in real-time applications and various domains.

Reference

[1] NINDS (2021) Focus on Epilepsy Resarch: National Institute of Neurological Disorders and Stroke. https://www.ninds.nih.gov/ Current-Research/Focus-Research/Focus-Epilepsy. Accessed 23 Feb 2021.

[2] K, Singh, J. and Malhotra, "Two-layer LSTM network-based prediction of epileptic seizures using EEG spectral features." Complex & Intelligent Systems. 2022, 8(3), 2405-18.

[3] B, Kapoor, B, Nagpal, PK, Jain, A, Abraham, and LA. Gabralla, "Epileptic seizure prediction based on hybrid seek optimization tuned ensemble classifier using EEG signals." Sensors. 2022, 23(1):423.

[4] R, Jana, and I. Mukherjee, "Deep learning based efficient epileptic seizure prediction with EEG channel optimization." Biomedical Signal Processing and Control. 2021, 68,102767.

[5] Y. Jiang, W. Li, M. Chen, "Symplectic geometry decomposition-based features for automatic epileptic seizure detection." Comput.Biol. Med. 2020, 116, 103549.

[6] Y. Yuan, G. Xun, K. Jia, A. Zhang, "A Multi-View Deep Learning Framework for EEG Seizure Detection." IEEE J. Biomed. Health Inform. 2018, 23, 83–94.

[7] R.J. Racine, "Modification of seizure activity by electrical stimulation: II. Motor seizure." Electroencephalogr. Clin. Neurophysiol. 1972, 32, 281–294.

[8] World Health Organization, Epilepsy. Available online: https://www.who.int/en/news-room/fact-sheets/detail/epilepsy (accessed on 15 April 2022).

[9] P. Mirowski, D. Madhavan, Y. LeCun, R. Kuzniecky, "Classification of patterns of EEG synchronization for seizure prediction." Clin. Neurophysiol. 2009, 120, 1927–1940.

[10] L.S. Vidyaratne, K.M. Iftekharuddin, "Real-Time Epileptic Seizure Detection Using EEG. IEEE Trans. Neural Syst." Rehabil. Eng. 2017, 25, 2146–2156.

[11] M. Sharma, S. Shah, P.V. Achuth, "A novel approach for epilepsy detection using time–frequency localized bi-orthogonal wavelet filter." J. Mech. Med. Biol. 2019, 19, 1940007.

[12] RI, Halawa, SM, Youssef, MN. Elagamy, "An efficient hybrid model for patient-independent seizure prediction using Deep Learning." Applied Sciences. 2022, 12(11):5516.

[13] X, Xu, M, Lin, T. Xu, "Epilepsy seizures prediction based on nonlinear features of EEG signal and gradient boosting decision tree." International Journal of Environmental Research and Public Health. 2022, 19(18);11326.

[14] N. Paul, P. Kenneth, "The spline-laplacian in clinical neurophysiology," J. Clin. Neurophysiol. 1991, 8, 397–413.

[15] M.Z. Parvez, M. Paul, "Epileptic seizure detection by analyzing EEG signals using different transformation techniques," Neurocomputing, 2014, 145, 190–200.

[16] Mayo Clinic [Online]. Available: https://www.mayoclinic.org/tests-procedures/eeg/about/pac-20393875.

[17] S. Elgohary, S. Eldawlatly, M.I. "Khalil, Epileptic seizure prediction using zero crossings analysis of EEG wavelet detail coefficients, in:" IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology, Chiang Mai, Thailand, 2016, 1–6.

[18] J. Liang, R. Lu, C. Zhang, F. Wang, "Predicting seizures from electroencephalography recordings: a knowledge transfer strategy, in:" IEEE International

Conference on Healthcare Informatics, Chicago, USA, 2016, 184–191.

[19] S.M. Usman, S. Khalid, S. Bashir, "A deep learning based hybrid learning method for epileptic seizure prediction." Comput. Biol. Med. 2021; 136, 12

[20] S. Yan, Q. Yu, H. Wang, "Meg classification based on band power and statistical characteristics." In2015 12th Web Information System and Application Conference (WISA) 2015, 255-258.

[21] S.R. Ashokkumar, S. Anupallavi, M. Premkumar, V. Jeevanantham, "Implementation of deep neural networks for classifying electroencephalogram signal using fractional S-transform for epileptic seizure detection." Int. J. Imaging Syst. Technol. 2021, 31, 895–908.

[22] Y. Gao, B. Gao, Q. Chen, J. Liu, Y. Zhang, "Deep Convolutional Neural Network-Based Epileptic Electroencephalogram (EEG) Signal Classification." Front. Neurol. 2020, 11, 375.

[23] A. Salamatian, A. Khadem, "Automatic Sleep Stage Classification Using 1D Convolutional Neural Network." Front. Biomed. Technol. 2020, 7, 142–150.

[24] M.L. Giudice, G. Varone, C. Ieracitano, N. Mammone, A.R. Bruna, V. Tomaselli, F.C. Morabito, "1D Convolutional Neural Network approach to classify voluntary eye blinks in EEG signals for BCI applications." In Proceedings of the 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 2020, 19–24.

[25] R.A. Osman, S.N. Saleh, Y.N.M. Saleh, M.N. Elagamy, "A Reliable and Efficient Tracking System Based on Deep Learning for Monitoring the Spread of COVID-19 in Closed Areas." Int. J. Environ. Res. Public Health. 2021, 18,12941.

[26] R.A. Osman, S.N. Saleh, Y.N.M. Saleh, M.N. Elagamy, "Enhancing the Reliability of Communication between Vehicle and Everything (V2X) Based on Deep Learning for Providing Efficient Road Traffic Information." Appl. Sci. 2021, 11,11382.

[27] B, Jaishankar, AM, Ashwini, D, Vidyabharathi, L. Raja, "A novel epilepsy seizure prediction model using deep learning and classification." Healthcare Analytics. 2023, 4,100222.

[28] I, Jemal, N, Mezghani, L, Abou-Abbas, A. Mitiche, "An interpretable deep learning classifier for epileptic seizure prediction using EEG data." IEEE Access. 2022, 10, 60141-50.

[29] FE, Ibrahim, HM, Emara, W, El-Shafai, M, Elwekeil, M, Rihan, IM, Eldokany, TE, Taha, AS, El-Fishawy, ES, El-Rabaie, E, Abdellatef, FE. Abd El-Samie, "Deep-learning-based seizure detection and prediction from electroencephalography signals." International Journal for Numerical Methods in Biomedical Engineering. 2022, 38(6), 3573.

[30] CHB-MIT Scalp EEG Database. Available online: https://physionet.org/content/chbmit/1.0.0/ (accessed on 03 April 2024).

[31] UCI dataset: https://data.world/uci/epileptic-seizure-recognition (accessed on 03 April 2024).

[32] MG. sipouras, "Spectral information of EEG signals with respect to epilepsy classification." EURASIP J Adv Signal Process. 2019, 1,10.

[33] S. Geng, W. Zhou, Q. Yuan, D. Cai, Y. Zeng, "EEG non-linear feature extraction using correlation dimension and Hurst exponent." Neurological research. 2011; 33(9), 908-12.

[34] Z. Jiang, Y. Ning, B. An, A. Li, H. Feng, "Detecting mental EEG properties using detrended fluctuation analysis." In2005 IEEE Engineering in Medicine and Biology 27th Annual Conference. 2006.

[35] N. Ji, L. Ma, H. Dong, X. Zhang, "EEG signals feature extraction based on DWT and EMD combined with approximate entropy." Brain sciences. 2019; 9(8):201.

[36] AM. Ahmed, TA. Rashid, M.S. Soran Ab, "Cat swarm optimization algorithm: a survey and performance evaluation." Computational intelligence and neuroscience. 2020.

[37] SC. Chu, PW. Tsai, JS. Pan, "Cat swarm optimization. InPRICAI 2006: Trends in Artificial Intelligence:" 9th Pacific Rim International Conference on Artificial Intelligence Guilin, China, August 7-11, 2006 Proceedings, 2006, 854-858.

[38] MI, Abdelwanis, A, Abaza, RA, El-Sehiemy, MN, Ibrahim, H. Rezk, "Parameter estimation of electric power transformers using coyote optimization algorithm with experimental verification." IEEE Access. 2020, 8, 50036-44.

[39] P. Coufal, Š. Hubálovský, M. Hubálovská, Z. Balogh, "Snow leopard optimization algorithm: A new nature-based optimization algorithm for solving optimization problems." Mathematics. 2021, 9(21), 2832.

[40] SK, Pandey, RR, Janghel, PK, Mishra, MK. Ahirwal, "Automated epilepsy seizure detection from EEG signal based on hybrid CNN and LSTM model." Signal, Image and Video Processing. 2023,

17(4),1113-22.

[41] H, Daoud, MA. Bayoumi, “Efficient epileptic seizure prediction based on deep learning.’ IEEE transactions on biomedical circuits and systems. 2019, 13(5),804-13