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Prediction of Seizure in the EEG Signal with Time Aware Recurrent Neural Network

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ABSTRACT

The human brain's actions are reflected by the significant physiological data relying on the Electroencephalogram (EEG), which is utilized in the detection of epileptic seizures and the diagnosis of epilepsy. The visual inspection process of a vast quantity of EEG data by any human expert is time-consuming and the judgemental process may vary or be inconsistent among the physician. Hence, an automated process in detection and diagnosis is initiated by utilizing deep learning approaches. The Convolutional Neural Network (CNN) is incorporated to correctly recognize the irregular inter-ictal discharges as non-seizures, but could not detect the ictal state and slower oscillations. To improve the performance of CNN for detecting seizures' ictal state and slower oscillations, Recurrent Neural Network (RNN) is combined with the CNN model. An RNN evokes every processed information via time and it assists in the prediction of time series data. The processed feature in RNN remembers the preceding input information which is Long Short Term Memory (LSTM). The investigational outcome of the proposed Time Aware CNN and Recurrent Neural Network (TA-CNN-RNN) attained effective classification accuracy. The experiments analysis exhibits that the TA-CNN-RNN achieves an accuracy of 89%, 88.6%, and 88.7% on CHB-MIT-EEG, Bonn-iEEG, and VIRGO-EEG databases, respectively compared to the Entropy+LSSVM, LBP+KNN and P-one-class SVM methods for epilepsy detection.

1. INTRODUCTION

An epileptic seizure is a transitory incidence of symptoms or signs due to the extreme or irregular synchronous actions of neurons in the brain [1]. Generally, the occurrence of epilepsy in the brain is confirmed by the visual examination of long-term recorded scalp electroencephalograms (EEGs) and spots the incidence of epileptic seizure that utilizes a huge time to process [2]. Thus, the process of automatic diagnosis to identify the epileptic seizure could be importantly minimized the diagnosis duration. Numerous features are included for the automatic identification of seizures in the brain [3, 4].

The values used in the automatic identification of seizure are the connectivity of functional network properties, autocorrelation, nearest neighbor and likelihood synchronization, and EEG morphology [5-9]. The early detection of seizures is necessary to cure the disease. The recurrent features in the domain are identified through rhythmic actions, which are observed frequently in seizures [10]. The incidence of seizure can be identified from the features that are easily detectable namely principal components, spectral, statistical, and nonlinear features [11-14].

The above-mentioned features have shown excellence in the identification of certain kinds of seizures. The diverse nature of seizures made numerous complications progress a global feature for automation in seizure detection. Additionally, seizures are rarely occurring events and it is suitable in training complicated supervised learning processes of seizure with linear type classifiers, artificial neural networks, support vector machine, and other computational algorithms [15-17].

The earlier approaches lack accuracy in detection and also it takes a long time to process the data [18-21]. Currently, the Kraskov entropy with Least Square Support Vector Machine (LSSVM) method [22] has been developed for classifying seizure and seizure-free EEG signals, which support an automated prognosis of epilepsy. Also, a mixture of entropy with a Logarithmic Band Power (LBP) and K-Nearest Neighbor (KNN) classifier [23] has been presented for classifying EEG features into either epilepsy or autism spectrum disorder. Meanwhile, a Pairwise one-class SVM [24] has been applied for epilepsy detection and diagnosis. Though these methods were robust to categorize normal and seizure EEGs, the labeled training with the manual preparation is taking longer time and is labor intensive whereas these issues increase the data quantity. CNN correctly recognized irregular inter-ictal discharges as non-seizures, but could not detect the ictal state and slower oscillations. To improve the performance of CNN for detecting seizures' ictal state and slower oscillations, Recurrent Neural Network (RNN) is combined with the CNN model. Seizure detection at the early stage is necessary and it is significant to detect with computational algorithms.

Seizure detection is attained through the diverse mechanism and the drawbacks in the mechanism are rectified in the proposed Time Aware Convolutional Neural Network with Recurrent Neural Network (TA-CNN-RNN). TA-CNN extract the EEG signals with time context. The time and the feature integration in TA-CNN helps to accurately find seizure. TA-CNN not only capture dynamic changes of feature over time but also the seizer time context to detect. The time context is then effectively utlized in LSTM. For the investigation of the approach, fifty non-focal and focal signals were randomly selected from the publicly accessible EEG database. The proposed TA-CNN-RNN is compared with the existing algorithms Entropy+LSSVM [22], LBP-KNN [23], and P-one-class SVM [24]. The existing and proposed approaches are applied to the different variants of datasets namely CHB-MIT-EG, Bonn-iEEG, and VIRGO-EEG. The numerical outcomes of the experiment are evaluated using the performance metrics namely accuracy, precision, f-measure, and recall.

The remainder of the paper is emphasized as follows: previous works and literature is described in Section 2, the detection and diagnosis of epilepsy in the EEG signal are attained by the proposed deep learning approach is detailed in Section 3, the numerical outcome of the experiment is given in Section 4 and the proposed deep learning approach is concluded with a future suggestion.

2. LITERATURE SURVEY

The incidence of epilepsy in the nerve tracts of the brain is considered a chronic neurological brain disorder. Electroencephalogram (EEG) signals are utilized to accessing the brain status. Automated diagnosis of the occurrence of epilepsy is carried out by analyzing and measuring the non-stationary and nonlinear signals of EEG. The features in the EEG signals attained by the tunable-Q wavelet transform (TQWT) and classified with the assistance of the Kraskov entropy based-LSSVM classifier [22]. It observed that the increased value of Kraskov entropy of seizure EEG signal might be because of the high variability of EEG signals for epileptic seizure subjects. It is analyzed by using the EEG data from the University of Bonn. Similarly, the LBP-based support vector machine (SVM) is used for seizure detection [23]. The mixture of LBP+SVM accomplished the highest accuracy for detecting epilepsy and autism spectrum disorder from the EEG signal datasets provided by Bonn University, Germany; MIT, USA; and King Abdulaziz University (KAU), Jeddah, Saudi Arabia.

The incidence of seizures and identification by these approaches are complicated and it couldn't identify all the seizures. The detection and diagnosis of seizures are attained by the p-one-class-SVM, which is accomplished proficiently [24]. It was analyzed by the Bern-Barcelona EEG database and CHB-MIT EEG database for epilepsy detection. It was highly stable and classified as normal, epilepsy, and other diseases that are not included in the training samples. But, it needs more characteristics for EEG signal representation to further increase the detection accuracy. The detection and diagnosis together in a single approach have made the limitations in the recognition of seizures. Seizure detection is attained by several approaches namely machine learning, deep learning, and temporal detection schemes [25-27].

The shortcomings in the existing systems are considered and rectified in this paper. The positional information retrieval complication is attained by the time-aware scheme that retrieves the position information effectively. The time-aware scheme is combined with CNN to retrieve the efficient features and the recurrent neural network is utilized as a classifier. It notices apprehensive segments of epilepsy segments in the identification of the seizure phase and then accomplishes the analysis of noticed segments to recognize the portions of epilepsy. It can deliver more reliable and accurate diagnosis outcomes with high computational effectiveness. This paper mainly focuses on epileptic seizure detection and epilepsy diagnosis with a TA-CNN-RNN approach.

3. SEIZURE PREDICTION USING TIME AWARE RECURRENT NEURAL NETWORK

In a deep learning-based system, EEG signal pre-processing commonly involves three steps: noise removal, normalization, and signal preparation for deep learning network applications. In the noise removal step, finite impulse response (FIR) or infinite impulse response (IIR) filters are usually used to eliminate extra signal noise. Normalization is then performed using various schemes such as the z-score technique. Finally, different time domain, frequency, and time-frequency methods are employed to prepare the signals for the deployment of deep networks. In this research work, Time-aware CNN (TA-CNN) is proposed which incorporates position information into CNN through an attention mechanism.

The suggested model accurately represents the time series dynamics present in EEG data. The temporal patterns of the signal vary greatly between the two time intervals, and even among the several time steps that make up the same interval. Therefore, the associated patterns require modelling at various time scales. So that the model may prioritise different scales at different time steps, we devised an efficient mechanism called TA-CNN that makes use of temporal context information to adjust the features of different scales. The proposed TA-CNN can capture important features for relation extraction effectively. To obtain more precise and fast detection of epileptic seizures TA-CNN is combined with RNN to correctly detect the ictal state and slower oscillations part of the EEG signal. RNN can learn temporal and context features, especially long-term dependency between features with a seizure while TA-CNN is capable of catching more capable features with positional information. Therefore, the combination of TA-CNN and RNN becomes necessary for a higher-quality epilepsy classification.

3.1 Signal pre-processing

In Figure 1, the overall illustration is the block diagram of the proposed TA-CNN-RNN. The signal pre-processing is intended to acquire the significant features with a greater probability of pre-ictal portion of correlation, the process of pre-processing is attained to the data before making the training and testing process with TA-CNN-RNN. The structure of TA-CNN-RNN is shown in Figure 2.

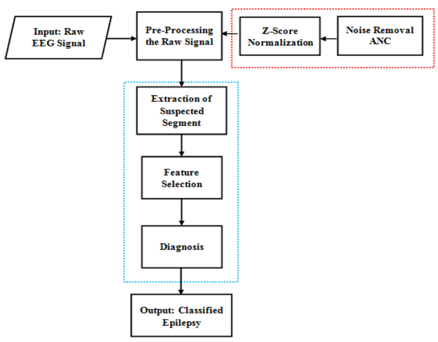


Figure 1. Overall process of epilepsy classification

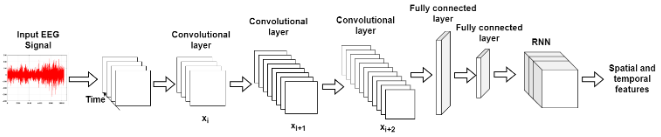


Figure 2. Structure of TA-CNN-RNN framework

3.1.1 Noise removal

The EEG's high quality is greatly influenced by the noise which is a huge enemy of the EEG signal. The incidence of noise is decisive for the accurate investigation of EEG. The incidence of noise in the EEG signal is removed by the Least Mean Square Adaptive Noise Cancellation (ANC). The unwanted information in the power line of the EEG signal is removed successfully by the ANC scheme.

3.1.2 Normalization

Generally, normalization is utilized in carrying the two signals to a similar or predefined series. A distinctive example of a predefined series is the statistical discernment of the normalization that is converting the signal where the mean value is 0 and the standard deviation value is 1. In this proposed scheme, the z-score technique is utilized for the normalization and this technique unveils the performance by flattening the signal. The value of the z-score is equated in Eq. (1):

$$z - score = \frac{score - mean}{standard\ deviation} \tag{1}$$

This normalization preserves the correlation between the normalized and original EEG signal whereas it considerably minimizes the selection bias. After completing the normalization process deep learning approaches are incorporated and the normalization makes the learning approach easier.

3.2 Significant feature extraction and signal preparation for the categorization of signal

The raw EEG signal is suspicious for redundancy and hence it is necessary to mine the explanatory parameters. The significant tool for investigating the non-stationary signal is accomplished by the Time Aware Convolutional Neural Network. Diverse time fields, frequencies, and time-frequency are incorporated to formulate the signals for the disposition of the deep neural network. The information about the location is taken into the CNN via an attention mechanism. The proposed TA-CNN can acquire the significant features in the extraction relation proficiently. The time intervals are deployed to acquire the short and long-term interest. The TA-CNN is utilized for the feature selection and suspected portions in the signal are acquired. Every attribute is a rate of discrete coincidence and utilizes the data among the measurement of similarity in the attributes $S(a, b)$ as:

$$S(a,b) = \sum_{b \in B} \sum_{a \in A} (a,b) log \left(\frac{p(a,b)}{p_1(a) p_2(b)} \right) \tag{2}$$

In Eq. (2), $p(a, b)$ is the probability of combined a and b attributes in the function distribution. The $p_1(a)$ and $p_2(b)$ illustrated the marginal probability. The combination of probability in the equation is acquired from the neural network. The proposed scheme identifies the significant features that signify the component's magnitude and every signal represents a diverse spectrum of components in original data that is adequate and informative for diverse EEG patterns. The acquired features are fed to the classification and diagnosing part.

The Long Short Term Memory network is a special kind of recurrent neural network and it is an order sequence of data. The main intent of the proposed scheme is to classify the sequence of data among the pre-ictal and inter-ictal states that indicate the probability range of high or low in every class. This process is attained by the Recurrent Neural Network (RNN) to accept the sequence of temporal information and preserve the appropriate information. The network is formulated to estimate the data batches that create an output. It is elected to utilize the data with high-size processed data. This approach has three networks and one output layer.

The acquired features are passed to the first two layers whereas the values are elected randomly that minimize the error. This process returns the output after processing the data in the preceding layers and probability is estimated by the softmax activation function. The RNN selects the data that is remembered or forgotten. In this study, the LSTM [28] is adopted as the RNN, which is made up of a cell and 3 gates (input, forget, and output). At time t_i, the learning network is updated from Eqns. (3-8):

$$i_{ti} = \sigma(W_{ai} a_{ti} + W_{hi} h_{ti-1} + y_i) \tag{3}$$

$$f_{ti} = \sigma(W_{af} a_{ti} + W_{hf} h_{ti-1} + y_f) \tag{4}$$

$$g_{ti} = tanh\ (W_{ac} a_{ti} + W_{hc} h_{ti-1} + y_c) \tag{5}$$

$$c_{ti} = i_{ti} \odot g_{ti} + f_{ti} \odot c_{ti-1} \tag{6}$$

$$o_{ti} = \sigma(W_{ao} a_{ti} + W_{hi} h_{to-1} + y_o) \tag{7}$$

$$h_{ti} = o_{ti} \odot tanh\ (c_{ti}) \tag{8}$$

In Eqns. (3) – (8), i_{ti} is the input gate, f_{ti} is the forget gate, g_{ti} is the memory cell candidate, c_{ti} is the memory gate, o_{ti} is the output gate, h_{ti} is the hidden states in the LSTM, σ is the activation function, $\odot$ is the element-wise multiplication, a_{ti} is the input vector value at the time ti, W_{ai}, W_{af}, W_{ac}, W_{ao} are the weight matrix of a_{ti}'s input, forget, memory, and output gates, respectively. Also, W_{hi}, W_{hf}, W_{hc}, W_{ho} are the weight matrix of h_{ti}'s input, forget, memory, and output gates, respectively. As well, y_i, y_f, y_c, y_o are the bias offset of every gate.

In the RNN, the information is propagated from the front layer to the back layer and the drawback in the one-way approach in the learning scheme is rectified by this approach. The RNN has an inverted and positive LSTM that captures the significant feature and also combines the features in the forward and backward by utilizing the element-wise sum equated in Eq. (9):

$$h_i = \overrightarrow{h_i} \odot \overleftarrow{h_i} \tag{9}$$

The main intention of the attention strategy is identified and the input information is significant in the process of training where the attention is close to the data. From the RNN layer the h_i and TI is assigned to the matrix M.

$$M = [m_1, m_2, \ldots \ldots, m_L] \tag{10}$$

In Eq. (10), the length is signified as L of the input signal and the M_{tr} is acquired by the weighted alpha for every m_i as shown in Eqns. (11) - (13):

$$M_{tr} = tanh(M) \tag{11}$$

$$\alpha = softmax(\omega^L M_{tr}) \tag{12}$$

$$M_{tr} = M \odot \alpha^L \tag{13}$$

The dimension unit of hidden value in the learning unit is given as M belongs to $d(h*L)$, the parameter of trained vector and transpose vector are ω and ω^L respectively. The signals are acquired that is assigned as d_h*L. The process of convolution is carried by the kernel W:

$$A_j = f(X_j \odot \mathrm{W} + \mathrm{b}) \tag{14}$$

In Eq. (14), the convolution operator is signified as $\odot$, the effect of bias is signified as b, the activation function for non-linear data is signified as f and the ReLU activation is equated in Eq. (15):

$$f(a) = \max(0.1a, a) \tag{15}$$

The dropout layer in the learning process is equated as:

$$h_n = \omega_n^L (r \odot b) + b_n \tag{16}$$

In Eq. (16) the same signal shared among the values is signified as r and each element of r has the probability value 0 for p and 1 for 1-p. The dropout layer is assigned with the subsequent layers and the rates of probability are 0.3, 0.3, 0.3 and 0.5.

The overfitting issue in the signal processing is rectified by the enhanced generalization capability and the cost function for the regulation is added as:

$$J(\theta) = \sum_{i=1}^{m} ti_i \log(b_i) + \boldsymbol{\lambda} \|\boldsymbol{\theta}\|_F^2 \tag{17}$$

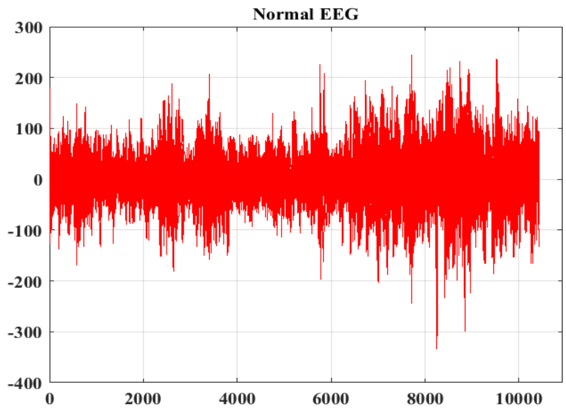
In Eq. (17), the hyperparameter utilized for regularization is given as λ.

The RNN attains the classification that relies on the sequence of signals that are analyzed and the categorical cross-entropy is utilized as a loss function. The overlay performance in the RNN in the input segment of the initial layer is altered to acquire the batches of signals whereas the length of the signal is longer in the process of training and simple in the testing. Additionally, the internal values are estimated in the preceding batch that is no longer to pass every substantial batch of data due to alterations in the architecture of the network to acquire the efficient signal batches count. The utilized training epoch in the RNN considerably minimizes the incidence of error during the process of training which eventually increases the rate of accuracy.

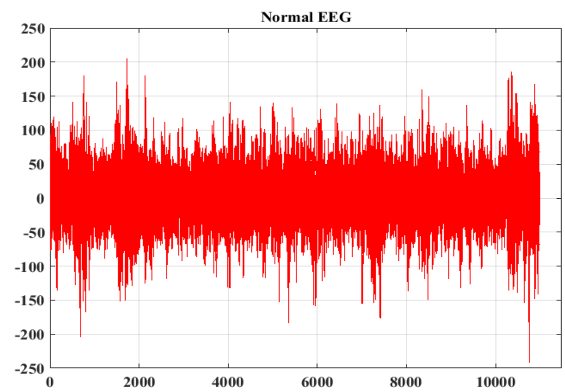
4. EXPERIMENTAL RESULTS

In this section, the outcome of the epilepsy classification by the proposed and existing approach is discussed. The data in the Bern-Barcelona EEG database is collected from patients with the incidence of epilepsy that comprises non-focal and focal channels with 1024Hz. The database holds 3750 pairs of signals recorded from the channels of EEG and the recorded samples are divided into slots of windows with an interval of ten seconds, which results in a sample of 10240. For this experiment, the publicly accessible EEG databases which are already used in many published articles are used. CHB-MIT Scalp EEG Database [29], Bonn iEEG dataset [30], and VIRGO EEG dataset [31] are used in this paper. CHB-MIT Scalp EEG Database is collected at the Children's Hospital Boston, and consists of EEG recordings from pediatric subjects with intractable seizures. The bonniEEG dataset is collected at the Department of Epileptology, University of Bonn, Germany. VIRGO EEG dataset consists of EEG data for 40 epileptic seizure patients (both male and female) in the age group ranging from 4 to 80 years. The raw data was collected from the Allengers VIRGO EEG machine at Medisys Hospitals, Hyderabad, India.

The experiment is accomplished in Matlab with the computation atmosphere's RAM of 8.00 GB and CPU2.30 GHz. The proposed TA-CNN-RNN is compared with the existing algorithms Entropy+LSSVM [22], LBP-KNN [23], and P-one-class SVM [24]. The numerical outcomes of the experiment are evaluated using the performance metrics namely accuracy, precision, f-measure, and recall. The EEG signal and the EEG with the incidence of epilepsy are displayed in Figure 3 and Figure 4 respectively.

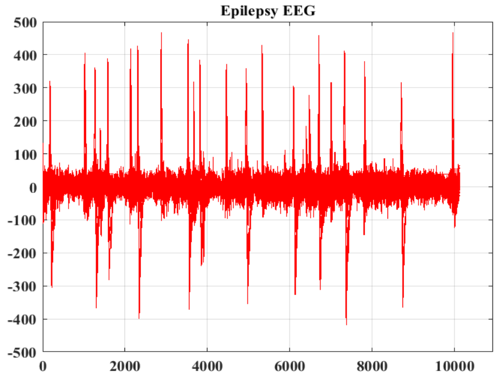


(a)

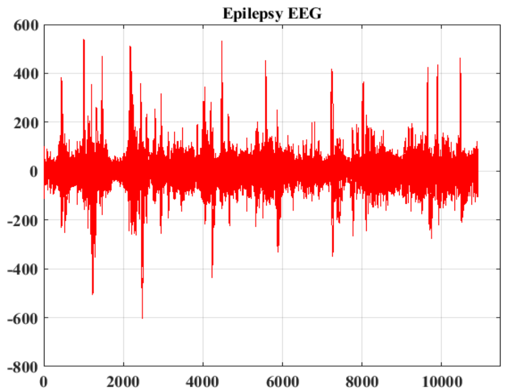


(b)

Figure 3. Representation of Normal EEG



(a)



(b)

Figure 4. Representation of EEG with epilepsy

4.1 Accuracy

Accuracy indicates the closeness of the value determined from the classified EEG signals and it is the illustration of systematic errors or statistical bias. Accuracy is the near value of calculated true positive and true negative values from the investigated signal classes. The incidence of minimal accuracy arises from differences among the investigational outcome of true values. It is the ratio of incidence of epilepsy in the EEG signal is the total count of signal investigated. The value of accuracy is equated in Eq. (18) as:

$$Acc = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (18)$$

In Figure 5 and Table 1, the accuracy acquired from the proposed TA-CNN-RNN is compared with the existing algorithms Entropy+LSSVM, LBP-KNN and P-one-class SVM algorithm. The rate of accuracy is {8.6%, 10.5%, 13.1%} higher than the Entropy+LSSVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively, {6.3%, 3.3%, 7.5%} higher than the LBP-KNN for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively and {2.7%, 3.4%, 2.5%} higher than the P-one-class SVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively. The acquired high accuracy illustrates the effectiveness of the proposed TA-CNN-RNN.

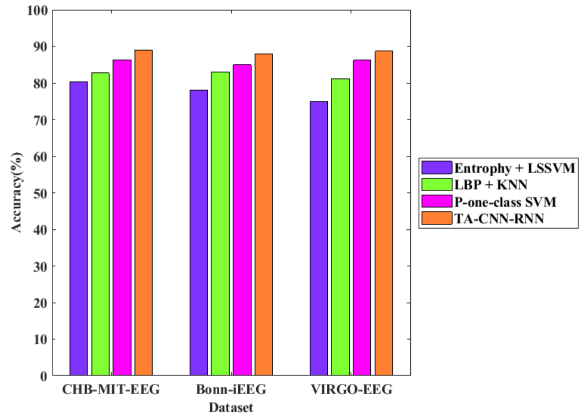


Figure 5. Comparison of accuracy (%)

4.2 Precision

The analytical rate with positive values or precision indicates the closeness of the measurement and the significance of the signals identified. The occurrence of random errors is indicated as precision that is stated with the statistical variables. The acquired signal values of accuracy and precision are identical terms. Typically, binary or decimal digits are utilized in denoting the signal's value of precision. It is estimated based on True Positive (TP) and False Positive (FP) rates. The value of precision directly relies on the percent of positive values in the total EEG signal. In the process of classification, the precision value for a definite issue is the count of the true positive values (i.e. the count of the item appropriately labeled as positive classes of EEG signals). The algorithm acquired high precision indicates a resultant value that accomplishes more desired data than inappropriate information. It is equated in Eq. (19) as:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (19)$$

In Figure 6 and Table 2, the precision acquired from the proposed TA-CNN-RNN is compared with the existing algorithms Entropy+LSSVM, LBP-KNN, and P-one-class SVM algorithm. The rate of precision is {9.62%, 11.6%, 11.9%} higher than the Entropy+LSSVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively, {7.2%, 5.3%, 7.2%} higher than the LBP-KNN for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively and {11.9%, 7.1%, 3%} higher than the P-one-class SVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively. The acquired high precision illustrates the effectiveness of the proposed TA-CNN-RNN.

Table 1. Comparison of accuracy

Dataset	Existing Algorithm			Proposed Algorithm
	Entropy+ LSSVM	LBP+KNN	P-one-class SVM	TA-CNN-RNN
CHB-MIT-EEG	80.4	82.7	86.3	89.0
Bonn-iEEG	78.1	83.3	85.2	88.6
VIRGO-EEG	75.6	81.2	86.2	88.7

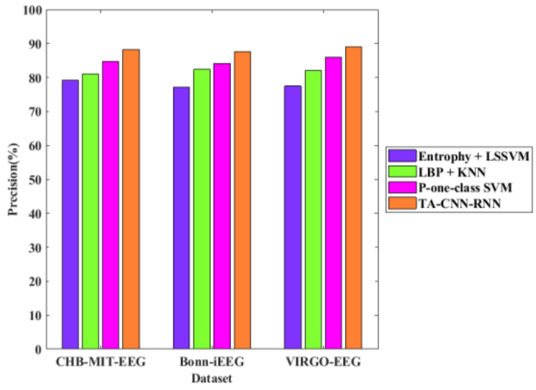


Figure 6. Comparison of precision (%)

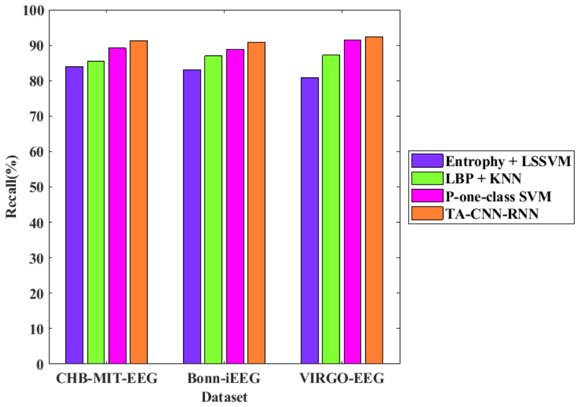


Figure 7. Comparison of recall (%)

4.3 Recall

The rate of recall is the correlated EEG signals between the essentially reclaimed instances. The successful forecasting rate is the estimation measure of recall and the count of correlated outcomes is stated as recall. A recall is determined as a count of appropriately spotted values over the count of TP and FP values in the EEG signals. Precision is estimated based on epilepsy in the EEG signal identification at TP and False Negative (FN) rates. It is calculated in Eq. (20) as:

$$Recall = \frac{TP}{TP + FN} \tag{20}$$

In Figure 7 and Table 3, the recall acquired from the proposed TA-CNN-RNN is compared with the existing algorithms Entropy+LSSVM, LBP-KNN, and P-one-class SVM algorithm. The rate of recall is {7%, 5.8%, 2.1%} higher than the Entropy+LSSVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively, {7.7%, 3.7%, 2.1%} higher than the LBP-KNN for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively and {11.6%, 5.2%, 1%} higher than the P-one-class SVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively. The acquired high recall illustrates the effectiveness of the proposed TA-CNN-RNN.

4.4 F-measure

F-measure or F-score is determined as an accuracy of investigation of the classification problem. The algorithm attains the highest precision and recall value, which gives the best f-measure value. The F-measure value results in a better retrieval of needed information from the EEG and offers a realistic portion of the performance of the algorithm. It is computed in Eq. (21) as:

$$F - measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{21}$$

In Figure 8 and Table 4, the F-Measure acquired from the proposed TA-CNN-RNN is compared with the existing algorithms Entropy+LSSVM, LBP-KNN and P-one-class SVM algorithm. The rate of F-Measure e is {8.3%, 8.9%, 11.6%} higher than the Entropy+LSSVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively, {6.5%, 4.6%, 6.2%} higher than the LBP-KNN for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively and {11.6%, 6.2%, 2.1%} higher than the P-one-class SVM for {CHB-MIT-EG, Bonn-iEEG, VIRGO-EEG} respectively. The acquired high F-Measure illustrates the effectiveness of the proposed TA-CNN-RNN.

Table 2. Comparison of precision

Dataset	Existing Algorithm			Proposed Algorithm
	Entropy+LSSVM	LBP+KNN	P-one-class SVM	TA-CNN-RNN
CHB-MIT-EEG	79.1	81.1	84.7	88.3
Bonn-iEEG	77.1	82.4	84.2	87.7
VIRGO-EEG	77.5	82.3	86.4	89.4

Table 3. Comparison of recall

Dataset	Existing Algorithm			Proposed Algorithm
	Entropy+LSSVM	LBP+KNN	P-one-class SVM	TA-CNN-RNN
CHB-MIT-EEG	84.3	85.5	89.2	91.3
Bonn-iEEG	83.2	87.2	88.8	90.9
VIRGO-EEG	80.8	87.2	91.4	92.4

Table 4. Comparison of F-measure

Dataset	Existing Algorithm			Proposed Algorithm
	Entropy+LSSVM	LBP+KNN	P-one-class SVM	TA-CNN-RNN
CHB-MIT-EEG	81.5	83.3	86.9	89.8
Bonn-iEEG	80.3	84.6	86.4	89.2
VIRGO-EEG	79.1	84.5	88.6	90.7

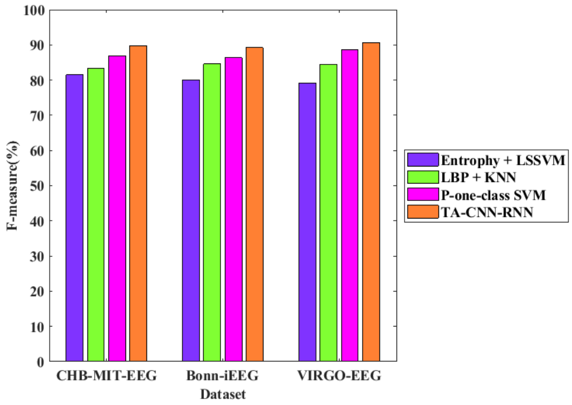


Figure 8. Comparison of F-measure

The major goal of this study is to train the TA-CNN-RNN using the EEG signals having seizures. The trained TA-CNN-RNN is later applied to test the newly observed EEG signals and identify patients having epilepsy in the early stage for proper diagnosis. Thus, these experimental analyses indicate that the TA-CNN-RNN can efficiently detect patients with epileptic seizures from their EEG signals compared to the other methods. Also, it supports physicians to early identify epileptic patients and diagnosing them properly.

5. CONCLUSIONS

In this study, a new deep-learning method was designed for seizure detection from EEG signals. Initially, the raw EEG signals were collected and pre-processed by the noise removal and Z-score normalization methods. Then, those pre-processed EEG signals were fed to the TA-CNN-RNN, which extracts spatial and temporal characteristics from the EEG signals for detecting the pre-ictal durations of the EEG signals. Thus, the patients having epilepsy were identified and diagnosed timely. Finally, the experimental results proved that the TA-CNN-RNN method on CHB-MIT-EEG, Bonn-iEEG, and VIRGO-EEG databases has 89%, 88.6%, and 88.7% accuracy, respectively compared to the Entropy+LSSVM, LBP+KNN and P-one-class SVM methods. But, the creation and annotation of large-scale databases were time-consuming. So, future work will focus on reducing the complexity of generating large-scale databases using adversarial networks.

REFERENCES

[1] Fisher, R.S., Boas, W.V.E., Blume, W., Elger, C., Genton, P., Lee, P., Engel Jr, J. (2005). Epileptic seizures and epilepsy: Definitions proposed by the international league against epilepsy (ILAE) and the international bureau for epilepsy (IBE). Epilepsia, 46(4): 470-472. https://doi.org/10.1111/j.0013-9580.2005.66104.x

[2] Tzallas, A.T., Tsipouras, M.G., Tsalikakis, D.G., Karvounis, E.C., Astrakas, L., Konitsiotis, S., Tzaphlidou, M. (2012). Automated epileptic seizure detection methods: a review study. Epilepsy-Histological, Electroencephalographic and Psychological Aspects, 75-98. https://doi.org/10.5772/31597

[3] Ocak, H. (2009). Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. Expert Systems with Applications, 36(2): 2027-2036. https://doi.org/10.1016/j.eswa.2007.12.065

[4] Takahashi, H., Takahashi, S., Kanzaki, R., Kawai, K. (2012). State-dependent precursors of seizures in correlation-based functional networks of electrocorticograms of patients with temporal lobe epilepsy. Neurological Sciences, 33(6): 1355-1364. https://doi.org/10.1007/s10072-012-0949-5

[5] Iscan, Z., Dokur, Z., Demiralp, T. (2011). Classification of electroencephalogram signals with combined time and frequency features. Expert Systems with Applications, 38(8): 10499-10505. https://doi.org/10.1016/j.eswa.2011.02.110

[6] Polat, K., Güneş, S. (2008). Artificial immune recognition system with fuzzy resource allocation mechanism classifier, principal component analysis and FFT method based new hybrid automated identification system for classification of EEG signals. Expert Systems with Applications, 34(3): 2039-2048. https://doi.org/10.1016/j.eswa.2007.02.009

[7] Alickovic, E., Kevric, J., Subasi, A. (2018). Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction. Biomedical Signal Processing and Control, 39: 94-102. https://doi.org/10.1016/j.bspc.2017.07.022.

[8] Hassan, A.R., Subasi, A. (2016). Automatic identification of epileptic seizures from EEG signals using linear programming boosting. Computer Methods and Programs in Biomedicine, 136: 65-77. https://doi.org/ 10.1016/j.cmpb.2016.08.013

[9] Übeyli, E.D. (2010). Lyapunov exponents/probabilistic neural networks for analysis of EEG signals. Expert Systems with Applications, 37(2): 985-992. https://doi.org/10.1016/j.eswa.2009.05.078

[10] Altaf, M.A.B., Zhang, C., Yoo, J. (2015). A 16-channel patient-specific seizure onset and termination detection SoC with impedance-adaptive transcranial electrical stimulator. IEEE Journal of Solid-State Circuits, 50(11): 2728-2740. https://doi.org/ 10.1109/JSSC.2015.2482498

[11] Zhang, C., Altaf, M.A.B., Yoo, J. (2016). Design and implementation of an on-chip patient-specific closed-loop seizure onset and termination detection system. IEEE Journal of Biomedical and Health Informatics, 20(4): 996-1007. https://doi.org/10.1109/JBHI.2016.2553368

[12] Subasi, A., Kevric, J., Canbaz, M.A. (2019). Epileptic seizure detection using hybrid machine learning methods. Neural Computing and Applications, 31(1): 317-325. https://doi.org/10.1007/s00521-017-3003-y

[13] Emami, A., Kunii, N., Matsuo, T., Shinozaki, T., Kawai, K., Takahashi, H. (2019). Seizure detection by convolutional neural network-based analysis of scalp electroencephalography plot images. NeuroImage: Clinical, 22: 101684. https://doi.org/10.1016/j.nicl.2019.101684

[14] Wen, T., Zhang, Z. (2018). Deep convolution neural network and autoencoders-based unsupervised feature learning of EEG signals. IEEE Access, 6: 25399-25410. https://doi.org/10.1109/access.2018.2833746

[15] Li, M., Chen, W. (2021). FFT-based deep feature learning method for EEG classification. Biomedical Signal Processing and Control, 66: 102492. https://doi.org/10.1016/j.bspc.2021.102492

[16] Ahmad, I., Wang, X., Zhu, M., Wang, C., Pi, Y., Khan, J.A., Li, G. (2022). EEG-based epileptic seizure detection via machine/deep learning approaches: A systematic review. Computational Intelligence and Neuroscience, 2022: 6486570. https://doi.org/10.1155/2022/6486570

[17] Socher, R., Huang, E.H., Pennington, J., Ng, A.Y., Manning, C.D. (2011). Dynamic pooling and unfolding recursive autoencoders for paraphrase detection. In NIPS, 24: 801-809.

[18] Ishii, T., Komiyama, H., Shinozaki, T., Horiuchi, Y., Kuroiwa, S. (2013). Reverberant speech recognition based on denoising autoencoder. In Interspeech, 3512-3516.

[19] Wilson, S.B. (2004). U.S. Patent No. 6,735,467. Washington, DC: U.S. Patent and Trademark Office.

[20] Hallett, M. (2007). Volitional control of movement: The physiology of free will. Clinical Neurophysiology, 118(6): 1179-1192. https://doi.org/10.1016/j.clinph.2007.03.019

[21] Khan, Y.U., Farooq, O., Sharma, P. (2012). Automatic detection of seizure onset in pediatric EEG. International Journal of Embedded Systems and Applications, 2(3): 81-89. https://doi.org/10.5121/ijesa.2012.2309

[22] Patidar, S., Panigrahi, T. (2017). Detection of epileptic seizure using Kraskov entropy applied on tunable-Q wavelet transform of EEG signals. Biomedical Signal Processing and Control, 34: 74-80. https://doi.org/10.1016/j.bspc.2017.01.001

[23] Alturki, F.A., AlSharabi, K., Abdurraqeeb, A.M., Aljalal, M. (2020). EEG signal analysis for diagnosing neurological disorders using discrete wavelet transform and intelligent techniques. Sensors, 20(9): 2505. https://doi.org/10.3390/s20092505

[24] Chen, Z., Lu, G., Xie, Z., Shang, W. (2020). A unified framework and method for EEG-based early epileptic seizure detection and epilepsy diagnosis. IEEE Access, 8: 20080-20092. https://doi.org/10.1109/access.2020.2969055

[25] Siddiqui, M.K., Morales-Menendez, R., Huang, X., Hussain, N. (2020). A review of epileptic seizure detection using machine learning classifiers. Brain Informatics, 7: 1-18. https://doi.org/10.1186/s40708-020-00105-1

[26] Jaoude, M.A., Jing, J., Sun, H., Jacobs, C.S., Pellerin, K.R., Westover, M.B., Lam, A.D. (2020). Detection of mesial temporal lobe epileptiform discharges on intracranial electrodes using deep learning. Clinical Neurophysiology, 131(1): 133-141. https://doi.org/10.1016/j.clinph.2019.09.031

[27] Hossain, M.S., Amin, S.U., Alsulaiman, M., Muhammad, G. (2019). Applying deep learning for epilepsy seizure detection and brain mapping visualization. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 15(1s): 1-17. https://doi.org/10.1145/3241056

[28] Coto-Jiménez, M., Goddard-Close, J. (2018). LSTM deep neural networks postfiltering for enhancing synthetic voices. International Journal of Pattern Recognition and Artificial Intelligence, 32(1): 1860008. https://doi.org/10.1142/S021800141860008X

[29] Andrzejak, R.G., Schindler, K., Rummel, C. (2012). Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. Physical Review E, 86(4): 046206. https://doi.org/10.1103/PhysRevE.86.046206

[30] http://epileptologie-bonn.de/cms/upload/workgroup/lehnertz/eegdata.html.

[31] https://ieee-dataport.org/documents/eeg-dataset-epileptic-seizure-patients#files.