Random Neural Network-Based Epilepsy Prediction Using Statistical Features

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***Abstract*—Epilepsy is a neurological disorder characterized by recurring episodes of seizures caused by abnormal electrical activity in the brain. Predicting seizures can allow early intervention by caregivers and improve patient outcomes. This paper proposes a novel Random Neural Network (RNN)-based method for prediction of epileptic seizures using feature vector extracted from each segment of EEG data. The proposed model is trained and tested using the CHB-MIT EEG database, employing a 10-fold cross-validation technique. The proposed RNN-based model, achieved an accuracy of 95.66%, sensitivity of 93.84%, and specificity of 96.17% in predicting seizure states.**

***Index Terms*—Epilepsy Prediction, Remote Healthcare, Random Neural Network**

I. Introduction

Epilepsy is a neurological disorder in which patients suffer from recurring seizures caused by abnormal electrical activity in the brain. Approximately two-thirds of patients with epilepsy can be treated using medication and surgery. However, there is no treatment currently available for the remaining 30% epilepsy patients [1]. Therefore, it is imperative to predict and manage subsequent seizures in a timely manner once a patient is diagnosed with epilepsy [2]. Seizure detection is a process of identifying a seizure after it has occurred which can help neurologists with the diagnosis of epilepsy. In contrast, seizure prediction provides an alert prior to the onset of a seizure which is critical for pre-emptive treatment, especially for patients who suffer from recurrent seizures [3]. Epileptic seizures can be predicted by identifying EEG segments preceding seizure events. The segments of EEG data are categorised in multiple states depending upon its time proximity with the seizure. The 'ictal' state represents segment that starts with the onset of a seizure. The segments corresponding to the time before the seizure onset is known as 'pre-ictal' state while the normal EEG data segments are identified as 'inter-ictal' state [4]. The EEG signal in the three states is displayed in Figure 1, covering a duration of 10 seconds. Epilepsy detection involves the classification of ictal and inter-ictal EEG data which is relatively straightforward due to the presence of characteristic abnormalities such as spikes and sharp waves in the ictal signal. Epilepsy prediction involves the classification of inter-ictal and pre-ictal signals which is a challenging task due to the similarity between the two signal types, as they may exhibit similar patterns and features in the EEG signal.

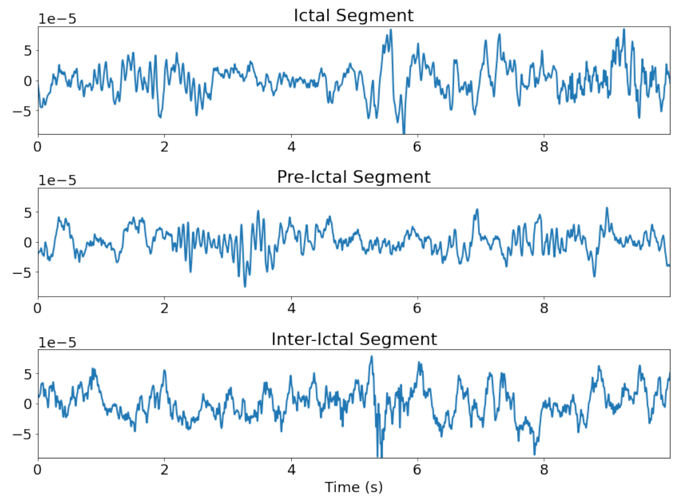

Fig. 1. EEG signal in Ictal, Pre-Ictal, and Inter-Ictal States

Most of the research found in the literature is focused on the detection of epileptic seizures [5]–[7]. Automatic seizure detection can help in treatment and management of epilepsy. However, early prediction of seizures can allow prompt intervention and timely adjustment in medication, thereby reducing the severity and frequency of seizures [8]. Gao. et. al [9] considers detecting different states of epileptic seizures using CNN and transfer learning. The four different classes include inter-ictal, pre-ictal (duration to 30 min), pre-ictal (duration to 10 min), and seizures. Initially, the EEG signal is transformed to power spectrum density energy before using it to train and test the proposed model.

In [10], the authors designed a semi-supervised domain adaptive seizure prediction model (SSDA-SPM) to predict seizures. The idea is to utilize unlabelled data along with available labelled data for adaptation. A feature alignment (FA) transfers existing knowledge to the new model using the data distribution. The consistency regularization (CR) module presents additional capability of enhancing the discrimination power. Similarly, Ouichka et. al., [11] examined the performance of standard CNN model, and the fusions multiple CNNs including fusions of 2, 3 and 4 CNNs, and transfer learning with ResNet50. Additionally in [2], the authors proposed a seizure prediction method based on Multi-Layer Perceptrons (MLP). A weighted layer was introduced to assign weight to the layers that contain more relevant information about the seizures. The experiments are conducts on two datasets including the CHB-MIT. The proposed model achieved a sensitivity of 93.80% with 80.03% specificity.

A. Aims and Objectives

This research is aimed to develop a novel RNN-based method for classification EEG signal for prediction of epileptic seizures. The main contributions of this research are given below:

- A novel RNN-based machine learning model is presented for the prediction of seizures.
- The proposed model involves extracting six statistical features from the EEG data that includes SD, Mean, Kurtosis, Skewness, Min, Max.
- The performance of the proposed RNN based model is evaluated by comparing the results with other state-of-the-art epilepsy prediction models.
- The analysing the results conclude that the proposed model outperforms the traditional classification algorithms of accuracy, sensitivity, and specificity.

II. Experimental Analysis

In this section, the experimental setup for evaluating the performance of the proposed epilepsy prediction model based on RNN is described. The model utilizes the CHB-MIT EEG database, which contains multi-channel surface EEG recordings. The proposed RNN-based model aims to predict seizures by computing statistical features for each channel of the EEG data capturing vital characteristics of the EEG signals. The proposed RNN-based model has been trained and tested using k-fold cross-validation technique to validate the model's effectiveness in accurately classifying EEG signals for the prediction of epileptic seizures. The proposed model is trained and validated ten times. In each iteration, the dataset is divided into ten subsets, with nine of the subsets used for training while one is used for validation. The model that demonstrates the highest validation accuracy that indicates superior generalization capabilities is selected for further testing.

The experiment has been conducted using a computer running the Microsoft Windows 11 operating system equipped with an AMD Ryzen 7 3700X 8-Core Processor and 48 GB of RAM. The implementation of data preparation, frequency analysis, and feature extraction was performed in Python while the data normalization and classification process using RNN were carried out using MATLAB.

A. The Dataset

In this study, the CHB-MIT dataset is utilized which is available publicly online [12]. The dataset is composed of 24 folders, each of which contains surface EEG recordings in EDF format. Additionally, each folder has a corresponding text file that contains a summary of the EEG recordings and seizure information. We have selectively chosen to utilize only the files that include seizure activity, as shown in Table I

TABLE I
SEIZURE INFORMATION IN CHB-MIT DATASET

Folder	Number of Seizures	Average Seizure Time (sec)
chb01	7	63.14
chb02	3	57.33
chb03	7	57.43
chb04	4	94.50
chb05	5	111.60
chb06	10	15.30
chb07	3	108.33
chb08	4	196.25
chb09	4	69.00
chb10	7	63.86
chb11	3	268.67
chb12	40	36.88
chb13	12	44.58
chb14	8	21.13
chb15	20	99.60
chb16	10	8.40
chb17	3	97.67
chb18	6	52.83
chb19	3	78.67
chb20	8	36.75
chb21	4	49.75
chb22	3	68.00
chb23	7	60.57

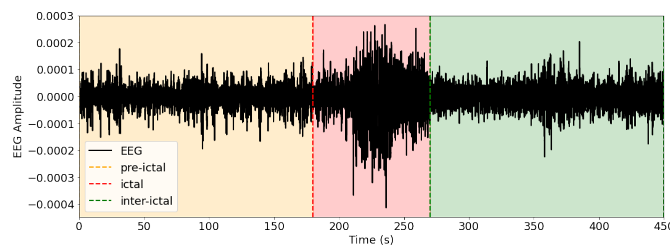

Fig. 2. EEG signal in Ictal, Pre-Ictal, and Inter-Ictal States

B. Data Preparation

Before training the proposed model, the raw data extracted from the CHB-MIT database is pre-processed by dividing it into segments using a sliding window approach. The data segments are 10 seconds long, with a 3-second overlap between consecutive segments. The purpose of this segmentation is to capture specific temporal patterns within the signal.

Figure 2 illustrates the segmentation where the segments containing seizure activity are labeled as 'ictal'. In addition to the 'ictal' segments, two more classes have been defined based on their temporal proximity to the seizure events. The period preceding a seizure is represented by the segments that occur less than 90 seconds before the onset of a seizure event and are labeled as 'pre-ictal'. Similarly, the segments of data that occur between seizures are identified as 'inter-ictal' and are marked at least 100 seconds after the end of a seizure. By dividing the data into 'ictal', 'pre-ictal', and 'inter-ictal' segments, we enable the RNN-based machine learning model to capture the distinctive features associated with different seizure states.

III. Data pre-processing

This section describes the pre-processing steps taken to the raw EEG data from the CHB-MIT dataset before feeding it

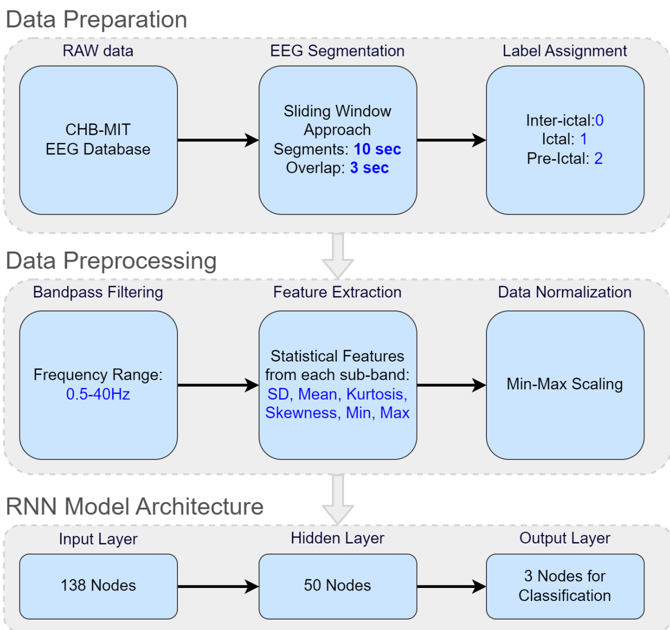

Fig. 3. Data pre-processing and RNN Model Architecture

into the RNN-based model. The pre-processing steps consist of data normalization, segmentation, and label assignment. Figure 3 illustrates each step involved in data preparation, pre-processing and the RNN model architecture.

A. *band-pass Filtering*

A band-pass filter is with a frequency range of 0-40Hz applied to each channel of the raw EEG data to focus on the frequency range associated with seizure activity. The purpose of band-pass filter is to attenuate frequencies outside the specified range and retain the relevant frequencies necessary for epilepsy prediction. This step is to ensure that unwanted noise and artefacts are removed from the EEG signal.

B. *Segmentation and Label Assignment*

To facilitate the classification process and capture temporal patterns, the raw EEG data is divided into multiple segments using a sliding window approach, where a window of fixed-length slides over the data with a specified overlap. The overlap segment length parameters need to be determined based on the desired temporal resolution and the characteristics of the seizures. In this study, a segment length of 10 seconds is used, which has been determined using trial and error method as optimal duration for capturing relevant information in EEG signals. The overlap between consecutive segments is set to 3 seconds to ensure sufficient coverage of the temporal dynamics.

After data segmentation, each segment is assigned a label based on the seizure states: ictal, pre-ictal, and inter-ictal. The process of labeling involves associating each segment with the corresponding label based on its temporal proximity to seizure events. The segments falling during a seizure are labeled as ictal, while the segments preceding a seizure event within a 90 seconds time window are labeled as pre-ictal. The rest of the segments occurring between seizures and at least 100 seconds after a seizure event are labeled as inter-ictal.

C. *Feature Extraction*

The feature extraction step is crucial for reducing the dimensionality of the data and improving computational efficiency by removing redundant and irrelevant information. Six statistical features (standard deviation, mean, kurtosis, skewness, minimum, and maximum) are extracted from each EEG channel to capture the discriminating characteristics of the EEG signals. These features represent quantitative information about the distribution, shape, and range of the EEG signals in each channel. The resulting feature vector for each segment combines the relevant features from all channels, resulting in a comprehensive representation of the signal characteristics.

D. *Data Normalization*

Data normalization is performed to ensure that the EEG data is consistent and comparable across different statistical features and channels. In this research, min-max scaling is employed to normalize the data between 0 and 1. Min-max scaling transforms the data to the specified range while preserving the relative characteristics of the data. The data is scaled using the following min-max formula:

$$\text{Normalized Value} = \frac{\text{Max Value} - \text{Min Value}}{\text{Original Value} - \text{Min Value}}$$

E. *RNN Model Architecture*

The proposed RNN model architecture consists of three layers, including the input layer, hidden layers, and the output layer. The input layer receives the pre-processed EEG data containing a feature vector of 138 values, which is then fed into the RNN. The hidden layer in the proposed RNN-based model consists of 50 nodes.

The RNN layers capture the spiking behavior and temporal dependencies in the data. In the RNN model, each neuron has a potential state indicating its accumulated signals represented by a non-negative integer. The neurons in RNN transition between an idle state ($k_i(t) \leq 0$) and an excited state ($k_i(t) > 0$) depending on whether the received input is excitatory or inhibitory.

In each neuron in the RNN layers , the activation function f_i is calculated as shown in Equations 1 and 2 of the RNN description. The excitatory and inhibitory inputs of a neuron i are represented by λ_i^+ and λ_i^-. These inputs are computed based on the firing rates r_j, activation functions f_j , and probabilities $p_{j,i}^+$ and $p_{j,i}^-$ of the neurons in the preceding layer. The weights in RNN are similar to those in classical neural networks and are adjusted through a learning process employing gradient descent algorithm to minimize the network's loss.

$$f_i = \frac{\lambda_i^+}{r_i + \lambda_i^-} \tag{1}$$

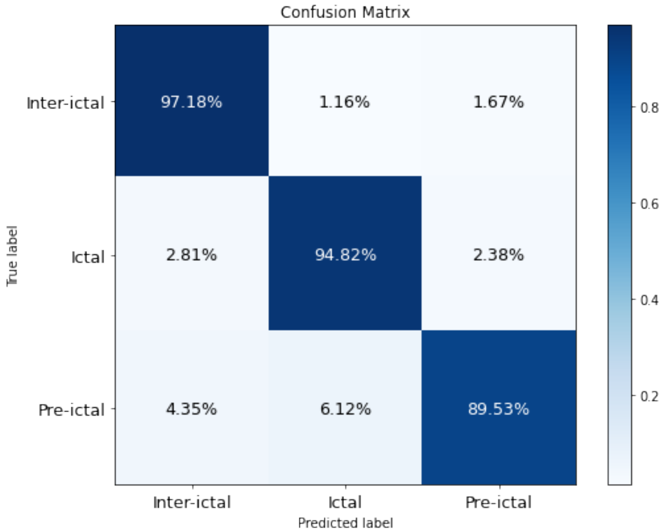

Fig. 4. Confusion Matrix for RNN-based epilepsy prediction

$$f_i = \frac{\sum_{j=1}^{N} f_j r_j p_{j,i}^{+}}{r_i + \sum_{j=1}^{N} f_j r_j p_{j,i}^{-}} \tag{2}$$

Finally, the output layer produces the final prediction based on the learned representation from the hidden layer in the RNN architecture. In our case, the output layer contains 3 nodes corresponding to the 3 classes in the classification problem.

F. Training and Evaluation

The RNN-based model is trained using the feature vector obtained after pre-processing the EEG data. The model learns to predict seizures based on the feature vector and associated labels through iterative parameter updates using optimization method namely gradient descent to minimize the loss.

Figure 4 illustrates the results of proposed RNN-based epilepsy prediction scheme in terms of confusion matrix. The vertical axis represents the true classes (aka actual classes or ground truth) including inter-ictal, ictal, and pre-ictal. The predicted outcomes by proposed scheme, in terms of the same classes as given on vertical axis, are illustrated on horizontal axis. The numbers in diagonal cells of the confusion matrix, for example, at positions (1,1), (2,2), and (3,3) illustrate how accurately the given true class has been predicted by the model under consideration. The additional row-wise cells demonstrate the wrong predictions of the true class into the predicted class, given on horizontal axis. The confusion matrix of an ideal algorithm will put all the classifications in the diagonal cells illustrating that all the predictions have been achieved with a 100% accuracy. Lower values in the diagonal cells and higher values in other cells of a confusion matrix means more miss-predictions as compared to correct predictions.

The confusion matrix in Figure 4 represents the prediction results in terms of percentage. For example, the cell (1,1) represents the percent of correctly predicted inter-ictal samples to the total number of true inter-ictal samples. Similarly, the results in diagonal cells (2,2), and (3,3) represent the percentage of predictions for ictal and pre-ictal classes. The results show that the proposed algorithm was able to achieve satisfactory results by correctly predicting inter-ictal, ictal, and pre-ictal classes with an accuracy of 97.18%, 94.82%, and 89.53%, respectively. However, it was more challenging to predict pre-ictal as compared to other two classes due to the complex nature of the EEG signal in this case. The similar trend can be found in various works proposed in the literature. Moreover, the most miss-predictions (more than 6%) of pre-ictal samples were made in the ictal class as compared to the inter-ictal class. These results show large similarity between the signals of the two classes, as shown in Figure 1.

The prediction results of proposed RNN-based scheme are illustrated in Table II. The percent of prediction accuracy, sensitivity, and specificity are given for inter-ictal, ictal, and pre-ictal classes obtained from testing the proposed model using the test set. These results follow the same argument concluded from the confusion matrix, i.e., the model can predict the inter-ictal class with higher accuracy as compared to predicting ictal and pre-ictal classes. Similarly, the Ictal class can be identified easier than the pre-ictal. Furthermore, the sensitivity follows a similar trend to that of accuracy for all the classes. However, the specificity for pre-ictal class is the highest among the three classes followed by inter-ictal in the list and then the ictal with the least specificity of all. A reason can be higher miss-predictions of the ictal class into the pre-ictal class due high similarity among the characteristics of the samples.

TABLE II
ACCURACY, SENSITIVITY AND SPECIFICITY FOR RNN-BASED SEIZURE PREDICTION

Class	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Inter-ictal	96.56	97.18	96.19
Ictal	95.74	94.82	94.26
Pre-Ictal	94.6	89.53	98.07

A comparative analysis of the proposed RNN-based model with the state-of-the-art techniques in literature is given in Table III. The three algorithms in the analysis include EESC [9], SSDA [10], and 4D-CNN [11]. These algorithms have been primarily selected among because they have been published in the last three years (2020 to 2023). Moreover, these algorithms focused on the prediction of seizures which makes them perfectly aligned with scope of current work.

In [13], the authors used performed epilepsy prediction using CNN. In feature extraction phase, a featured Stability Index has been added to the feature set which is calculated using multivariate autoregressive model. The model achieved an overall accuracy of 94.5% and sensitivity of 90.1%. Similarly, Kapoor et al. [14] extracted 8 statistical features from the raw EEG data for epilepsy prediction. The classification was performed using ensemble classifier combining AdaBoost, random forest and decision trees. The proposed model achieved a sensitivity of 90.18% with an accuracy of 92.31%. In comparative analysis given here, the best results reported by

TABLE III
COMPARISON OF RNN-BASED EPILEPSY PREDICTION MODEL WITH OTHER METHODS

Ref	Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Gao et al. [9]	EESC	92.6	92.3	97
Liang et al. [10]	SSDA	88.80		
Ouichka et al. [11]	4D CNN	95.00		
Chang et al. [2]	MLP		93.80	80.03
Assali et al. [13]	CNN	94.5	90.10	88.60
Kapoor et al. [14]	AdaBoost+DT+RF	93.91	91.67	88.56
This work	RNN	95.66	93.84	96.17

these studies have been added to prove the efficiency of proposed RNN-based epileptic seizure prediction.

Table III shows that the proposed model was able to beat the other algorithms in terms of achieving higher accuracy, and sensitivity. The results of proposed algorithm presented here are averaged across the accuracies, sensitivities, and specificities across all the classes, i.e., inter-ictal, ictal, and pre-ictal. The proposed RNN-based seizure prediction model achieved highest accuracy of 95.66% among all the given set of models. In addition, the EESC [9] algorithm was able to achieve higher specificity of 97% as compared to the proposed algorithm with specificity of 96.17%.

IV. CONCLUSION

In this study, we presented a novel RNN-based epilepsy prediction scheme. The proposed model was trained and test on the CHB-MIT dataset, which is widely used among researchers for training and testing AI-based epilepsy prediction models. The data was divided into 3 classes. The EEG segments corresponding to the seizure events were labelled as ictal, while those segments that fell just before the seizure were labelled as pre-ictal and the segments falling after the seizure events were labelled as inter-ictal. The EEG segments of 100 second duration after the seizure events were ignored to account for the post-ictal data. Statistical features were extracted from each EEG channel to form feature vector for training the RNN model. A 10-fold cross-validation method was followed to ensure reliability of the results. The proposed RNN-based model achieved an overall accuracy of 95.66% with 93.84% sensitivity and 96.17% specificity. The RNN-based model achieved superior performance as compared to state-of-the-art methods found in literature.

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