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Multidimensional CNN and LSTM for Predicting Epilepsy Seizure Activities

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Abstract - Epilepsy is a chronic neurological disease caused by sudden abnormal brain discharges, leading to temporary brain dysfunction. It can manifest in various ways, including paroxysmal movement, sensory, autonomic nerve, awareness, and mental abnormalities. It is now the second largest neurological disorder worldwide, affecting around 70 million people and increasing by approximately 2 million new cases each year. While about 70% of epilepsy patients can control their seizures with regular antiepileptic drugs, surgery, or nerve stimulation treatments, the remaining 30% suffer from intractable epilepsy without effective treatment, causing significant burden and potential danger to their lives. Early prediction and treatment are crucial to prevent harm to patients. Electroencephalogram (EEG) is a valuable tool for diagnosing epilepsy as it records the brain's electrical activity. EEG can be divided into scalp and intracranial types, and doctors typically analyze EEG signals of epileptic patients into four periods.

Keywords— Epilepsy, EEG, LSTM, seizure prediction, 3DCNN

I. INTRODUCTION (SIZE 10 &BOLD)

In epilepsy, seizures are defined as the time from the beginning to the end of abnormal brain activity, typically lasting for a few seconds to minutes. The preictal period refers to the time span from a few minutes to dozens of minutes before the seizure onset. Following a seizure, the postictal period is the time it takes for the patient to return to a normal state. In the interictal period, which occurs between the late onset of one seizure and the next pre-seizure phase, the patient's state is indistinguishable from normal. Identifying the preictal period accurately is crucial for predicting epilepsy and preventing seizures. The process of seizure prediction involves data collection, EEG signal preprocessing, feature extraction, classification, and evaluation of the results. Different characteristics of EEG signals during the preictal and interictal periods are utilized for seizure prediction. Seizure prediction research dates back to the early 1870s, with Viglione et al. [1] being among the first to use patient EEG data for epilepsy prediction. In the 1980s, Rogowski et al. [2] and Salant et al. [3] introduced an autoregressive model to analyze parameter changes within six seconds before seizure onset, incorporating physical-mathematical theories of nonlinear systems. Recent advancements in machine learning and deep learning have led to increased interest in seizure prediction. Mingkan Shen et al. [4] used an improved Lyapunov exponent algorithm to better capture subtle chaotic dynamics in epileptic signals using the fractional Fourier transform domain, achieving higher prediction accuracy than traditional methods.

Raghu et al. [14] introduced the successive decomposition index (SDI) feature, which demonstrated a significant increase during seizures, enabling prediction based on changes in SDI before seizure onset. In their research, Bandarabadi et al. employed the feature selection of amplitude distribution histograms (ADHs) to predict epileptic seizures [5]. They calculated ADHs of epileptic EEG sample features, ranked each feature, and selected features with the largest ADHs difference. Wang and Lyu proposed a feature selection approach based on elimination and combined it with Support Vector Machines (SVM) to select the optimal feature set for seizure prediction. Yuan and Wei introduced a Bayesian linear discriminant analysis (BLDA) algorithm as a classifier to determine the sample features for seizure prediction. BLDA employs a regularization method to prevent overfitting issues, which is different from conventional Fisher's linear discriminant analysis. Jyotismita Chaki et al. [6] presented an end-to-end one-dimensional convolutional neural network (CNN) architecture to directly input epileptic EEG signals into the CNN model for seizure prediction.

Zhang et al. [15] computed the Pearson correlation coefficient of the EEG signals to obtain the correlation matrix, which they used in a CNN model for seizure classification. Ozcan and Erturk introduced a 3D CNN model that utilizes temporal and spatial correlations of EEG signals for predicting epileptic seizures. Abdelhameed and Bayoumi used a deep convolutional auto-encoder to identify the best spatial features from EEG signals and a BiLSTM for temporal information classification in seizure prediction. Shahbazi and Aghajan [13] developed a CNN-LSTM model to extract temporal and spatial characteristics of multi-channel EEG signals, aiming to predict epileptic seizures.

Daoud and Bayoumi [16] utilized convolutional neural networks to extract significant spatial features from different scalp locations and recurrent neural networks for seizure prediction. They also introduced a semi-supervised method based on transfer learning techniques to improve optimization problems in their approach [7][8]. In this study, the main objective is to develop an accurate seizure prediction model by automatically extracting features from epileptic EEG data using deep learning techniques. To leverage both the temporal and spatial characteristics of the EEG signals, the researchers propose a CBAM-3D CNN-LSTM model for predicting seizures.

The process involves several steps. First, the EEG signals are preprocessed using Short-Time Fourier Transform (STFT) to enhance their representation [9][10]. Then, a 3D CNN model is used to extract features from both the interictal stage (the period between seizures) and the preictal stage (shortly before seizure onset) from the preprocessed signals [11][12]. To classify the extracted features effectively, a Bidirectional Long Short-Term Memory (Bi-LSTM) network is integrated with the 3D CNN.

To further improve the model's learning ability and robustness, the researchers introduce a Channel and Spatial Attention Module (CBAM) into the model. CBAM selectively focuses on important information from both the channel and spatial dimensions of the data, enabling accurate extraction of interictal and pre-ictal features. The proposed approach was evaluated on a public CHB-MIT scalp EEG dataset, achieving impressive results with 97.95% accuracy, 98.40% sensitivity (true positive rate), and a false alarm rate of 0.017 h−1 on 11 patients. The structure of the article is divided into sections as follows, Section II: Describes the materials and methods used in the study, including details about the dataset, data preprocessing, the 3D CNN, Bi-LSTM, CBAM, and training and testing procedures, Section III: Presents the experimental results and compares them with other existing models and Section IV: Discusses the findings from the experiments and the models used, providing insights and implications of the results. Overall, this study focuses on leveraging deep learning techniques and attention mechanisms to develop an accurate and robust seizure prediction model, and it provides comprehensive analyses of the proposed approach and experimental results.

II. METHODOLOGY

In epilepsy prediction, EEG signals exhibit both temporal and spatial correlations. While the 2D Convolutional Neural Network (CNN) model excels at extracting spatial features, it disregards the temporal information of EEG signals. On the other hand, the Long Short-Term Memory (LSTM) model is more suitable for handling timing information, but it does not fully leverage the spatial correlations [17]. As a result, neither model effectively captures the combined temporal and spatial characteristics of epileptic EEG signals. To address this limitation, the researchers propose a novel CBAM-3D CNN-BiLSTM seizure prediction model [18][19]. This model is inspired by successful applications of deep learning in video processing, human behavior recognition, and surface electromyography (sEMG) noise recognition. The process begins by collecting and preprocessing the dataset [20]. The preprocessed data is then extracted using a 3D CNN model, which allows for the incorporation of both temporal and spatial information. To enhance the learning capability and robustness of the model, a Channel and Spatial Attention Module (CBAM) is introduced. The CBAM module selectively attends to important information in both the channel and spatial dimensions of the data, ensuring that the model accurately captures the relevant features. Finally, a Bidirectional LSTM (BiLSTM) is utilized to classify the interictal and preictal stages of the EEG signals.

II. DATASET

In this study, we used CHB-MIT dataset, which is a widely used public dataset for seizure detection and prediction. The dataset was co-created and recorded by scientists from MIT and Boston Children's Hospital. It consists of EEG data from 22 pediatric patients, totaling 23 incidents and 844 hours of continuous scalp EEG recordings [21][22]. The EEG data were collected from 22 electrodes using the international 10-20 system at a sampling rate of 256 Hz with the bipolar montage technique. For seizure prediction, the researchers utilized specific time periods from the dataset. The pre-seizure period was defined as continuous EEG signals from 35 minutes to 5 minutes before a seizure, while the post-seizure period was taken as the 10 minutes after the end of seizures. The interictal period, representing the non-seizure state, was defined as the time between 4 hours after the end of a seizure and 4 hours before the start of the next seizure. Additionally, for intervention purposes, the EEG signal 5 minutes before a seizure was used as the intervention period and excluded from the data. To ensure sufficient data for model training and testing, the researchers-imposed constraints on the number of seizures per patient, choosing between 3 and 10 seizures. Therefore, 11 patients, with a total of 55 seizures and 235 hours of continuous EEG data, were selected from the CHB-MIT dataset for this study. These carefully selected samples were then used for the development and evaluation of the proposed CBAM-3D CNN-LSTM seizure prediction model.

II. PRE-PROCESSING

We encountered a data imbalance problem, where the number of interictal data samples vastly exceeded the number of preictal data samples. To address this issue, they employed overlapping sampling techniques to generate more training datasets and balance the interictal and preictal datasets [23][24]. The overlapping sampling technique involved selecting 8-second-long overlapping activity windows from continuous scalp EEG signals. A sliding length of 4 seconds was used for the overlap, as illustrated in Figure 4. For the interictal period, N fragments (where N is the number of preictal datasets) were randomly selected from the interictal data to serve as the training set. Since the researchers needed to use a 3D CNN model to extract features from the dataset, they converted the EEG signals into spectrograms. To achieve this, they employed Fourier transform and wavelet transform methods, which are commonly used for converting EEG signals into spectrograms in epilepsy detection and prediction studies. The EEG signals captured by the CHB-MIT dataset were affected by 60 Hz power line noise. To remove this noise interference, the researchers utilized band-stop and high-pass filters to eliminate the frequency components within the 57-63Hz and 117-123Hz ranges. Additionally, they removed the 0Hz DC component from the signals. The resulting 8-second EEG signal spectrogram was then used for denoising, and Short Time Fourier Transform was applied to accomplish this task. This approach aimed to enhance the quality and reliability of the EEG signal data, which would subsequently be used for the training and evaluation of the proposed CBAM-3D CNN-LSTM seizure prediction model.

BI-LSTM

RNN is a type of neural network that is specifically designed to handle sequential data as input. It is based on the concept of recursion, where each recurrent unit in the network is connected in a chain, allowing it to process sequences of data by considering the previous elements in the sequence. RNNs are commonly used for time series data prediction tasks, natural language processing, and other sequential data analysis tasks.

3D CNN

A Convolutional Neural Network (CNN) is a type of feedforward neural network with a deep structure that incorporates convolution calculations. It is a fundamental and widely used deep learning method, finding applications in image classification, speech recognition, machine vision, and various other domains. The key strength of CNN lies in its ability to learn hierarchical representations, making it capable of translation-invariant classification, which has led to it being referred to as a "translation-invariant artificial neural network. The core component of CNN is the convolution operation. In this study, a CNN is utilized to process the input data, generating a feature vector. To further process the time series data and classify it, the researchers employ a Bidirectional Long Short-Term Memory (Bi-LSTM) classifier. The Bi-LSTM processes the time series in two opposing orientations and substitutes two blocks for each LSTM block. By integrating both CNN and Bi-LSTM, the study leverages the advantages of both approaches: the hierarchical feature learning capabilities of CNN and the ability of Bi-LSTM to effectively handle sequential data. The combination of these techniques is expected to improve the model's performance in predicting epileptic seizures.

Model is input into the forward transfer block of Bi-LSTM from the beginning to the end of its first instance, and then the same fragment is processed in the opposite order. Each time step's combined output from its two blocks is what is known as the network output for that step. Compared to LSTM, Bi-LSTM can handle both previous and future contexts, thus enhancing prediction results. In the Bi-LSTM classification process, to prevent overfitting, we employ the Dropout regularization technique. Dropout is applied with a 50% factor to the input and loop states. As the cost function, the cross-entropy loss function is employed and Adma is selected as the optimizer for optimization.

TRAINING & TESTING METHODS

To ensure the model's performance reflects real-world scenarios and to address concerns related to overfitting and model robustness, the researchers employed the leave-one-out cross-validation approach (LOOCV) for each patient. This approach involves selecting one seizure from a patient's total of N seizures as the test set, while the model is trained using the remaining N-1 seizures. This process is repeated N times, with each seizure serving as the test set once. In this study, to create balanced training and test sets, 25% of the data from both the pre-ictal and interictal samples were randomly chosen as the test set, while the remaining 75% were used for training. During the training process, the researchers aimed to achieve higher accuracy by increasing the number of iterations. However, this could lead to overfitting. To mitigate this issue, they implemented the early-stop method. This method involves stopping the training process immediately when either the validation set accuracy reaches 99% or when the validation set loss function starts to increase. This ensures that the model is trained sufficiently without overfitting to the training data. By using LOOCV and early-stop, the researchers aimed to rigorously evaluate the model's performance, validate its generalization capability, and ensure it can accurately predict epileptic seizures in real-world scenarios.

III. RESULTS

To assess how well seizure prediction algorithm's function, two important time parameters were defined during the study: seizure occurrence period (SOP) and seizure prediction hori- zon (SPH). SPH refers to the period between the time point when the predictive alarm is issued. In this study, we also used three parameters: accuracy, sensitivity and false prediction rate (FPR) as the evaluation indexes of epileptic seizure prediction model. Among them, sensitivity and FPR are two key evaluation indicators that researchers are most interested. Sensitivity is the prediction model's capacity to recognize the pre-epileptic phase of the EEG with accuracy., and FPR is a measure of how many incorrect predictions the model makes each hour [6].

Seizures occur within the SOP range, and the specific time point of the attack can be different. All other things are wrong. Therefore, to assess the effectiveness of seizure prediction models, different ranges of SPH and SOP need to be defined. For example, the smaller the SOP, the more accurate the prediction of the upcoming epileptic seizure time point. Theideal situation is that the SOP is reduced to a time point, which means that the epileptic seizure is accurately generated at this time point. However, it is particularly difficult to design such a prediction model. There is no perfect prediction modelthat can accurately predict a certain time point of epileptic seizures in patients. Therefore, SOP is not the smaller the better. As the SOP range decreases, the number of false predictions increases. In addition, the researchers believe that although the scope of the SPH definition of the larger the number of false positives, but the SPH range will increase the patient 's anxiety, to bring a heavy psychological burdenon patients [21]. Therefore, SOP was set at 30 minutes and SPH to 3 minutes for this study.

Model	ACC	SEN	FPR/h^{-1}
3DCNN-BiGRU	93.21%	90.11%	0.09
3DCNN-BiLSTM	94.86%	91.87%	0.06
This Work	97.95%	98.40%	0.017

Among them, TP was true positive, FP was false positive, TN was true negative, and FN was false negative. Table 2 shows the accuracy, sensitivity and FPR prediction results of our model for 11 patients. We can see that the average performance of the proposed model reaches 97.95 % accuracy, 98.40 % sensitivity and 0.017 h^{-1} FPR on the CHB-MIT dataset. Among all patients, Pt01 and Pt08 achieved very good results, reaching more than 99 % accuracy, 100 % zero sensitivity and 0 false prediction rate, and achieved good results in other patients. Table 3 shows the comparison results of 3DCNN model and time prediction model. We can see that the model combining 3DCNN with BiLSTM has better accuracy, sensitivity and FPR than the model combining 3DCNN with BiGRU. Therefore, we use the 3DCNN-BiLSTM model to predict seizures. At the same time, we introduce CBAM into 3DCNN-BiLSTM. It can be seen from Table 3 that the CBAM-3DCNN-BiLSTM model achieves better results thanthe other two models. The CHB-MIT dataset is usedto assess all methodologies. The table shows that, in com- parison to other models, our model achieves high accuracy, high sensitivity, and a low false prediction rate. Therefore, our proposed CBAM-3DCNN-BiLSTM model is significantly superior to other CNN-based methods.

CONCLUSION

The study proposes a model called CBAM-3DCNN-BiLSTM for predicting seizures. It uses EEG signals transformed into three-dimensional feature vectors using the STFT algorithm. The model employs 3DCNN to extract features from time, frequency, and channel data. CBAM is integrated to enhance the model's learning ability, filter important information, and avoid redundant features. BiLSTM is used for classifying the extracted features. The proposed method achieves high accuracy of 97.95%, sensitivity of 98.40%, and a low false positive rate of 0.017 h^ (-1). Compared to previous approaches, the model demonstrates better performance in predicting epileptic seizures. However, to ensure wider applicability, the method needs to be tested on more subjects of different age groups, clinical conditions, and disease characteristics in future work. Additionally, continuous improvement of the prediction accuracy is essential to reduce risks for epilepsy patients and protect their life and health.

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