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Prediction of Epileptic Seizures Based on CNN-LSTM Network

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Abstract—Epilepsy is a common neurological disease, incidence of a disease is higher, it is mainly caused by excessive discharge of brain neurons, attack, the characteristics of transient, repeatability and consistency, in recent years the rise in the number of global disease, epilepsy, serious damage to human disease, so the research of epileptic seizure prediction is very necessary.In the traditional epilepsy prediction framework, due to the traditional convolutional neural network (CNN) network model and long and short-term memory network LSTM network hidden layer units and learning rate will be set up improper overfit and instability, will lead to poor network prediction effect.Therefore, the combination with CNN network and LSTM network is selected as the classification model in seizure prediction to form the epilepsy prediction model.The main research content of this paper are as follows: before extracting the seizure EEG data, using wavelet transform to preprocess EEG signals, and select sample entropy as a feature extraction method to predict the processed data using CNN-LSTM, the prediction accuracy reached 87.8%, 4.3% over CNN and 5.0% over LSTM.It shows that the present method can solve the classification problem of existing epilepsy datasets well.

Keywords-Prediction of epilepsy, wavelet transform, sample entropy, CNN-LSTM

I. FOREWORD

In recent years, epilepsy has become one of the most common neurological diseases in the world, and even become a refractory disease troubled by people and even the medical community.Epilepsy is a recurrent local brain disease that has a prevalence second only to stroke due to the abnormal discharge of local neurons in the brain and spreading to the surrounding normal parts.Roughly 50 million people currently have epilepsy worldwide, and about 4 to 10 people per 1,000 people have active epilepsy, and nearly 80% of them live in LMICs countries.People with epilepsy and their families are humiliated and discriminated against in many parts of the world.Epilepsy is also often a cause of the prohibition or cancellation of marriages.

In recent years, there has been great progress in the automatic epilepsy detection algorithm, which provides great help for doctors and patients in clinical medicine, and greatly reduces the prediction time.The classification of signals is a very important part of epilepsy prediction. The following paper introduces the current situation of research

on epilepsy prediction classification at home and abroad.In 2009, DerongLiu adopted the method of combining particle filtering and neural network to calculate the energy of the 4 to 12Hz frequency band after wavelet transformation, and used the optimal parameters of the minimum squared error algorithm to achieve the classification prediction of epilepsy.In 2013, Chungsoo L used data prefetch to improve the classification speed of SVM by reducing the gap between the processor and the main memory, and achieved to improve the accuracy of epilepsy classification.With the wide application of support vector in epilepsy signal analysis, more and more scholars are no longer limited to this classifier, and propose more aspect methods as classification networks.In 2014, Harikumar R proposed to compare singular value decomposition (SVD) and expectation maximization (EM performance, with improved Expectation Maximization (MEM) as the classifier, to classify the seizure risk of features extracted after wavelet transformation and morphological filtering of EEG signals.In the same year, YangZheng proposed a novel epilepsy prediction classification method based on neuronal electrical activity phase synchronization information, combining two-dimensional empirical mode decomposition (BEMD) and Hilbert transformation to detect the instantaneous phase of intracranial EEG recording, using phase information to calculate the average phase coherence (MPC) as a measure of the phase coupling strength between different channels of EEG recording, and finally using the preseizure MPC changes as the basis for prediction classification.In 2016, NamaziHamidreza et al. proposed a new method to study EEG signals by calculating the Hurst exponent and the fractal dimension.To verify the effectiveness of the method, the method was applied to the EEG signals in epilepsy patients and compared with the reference data to achieve the classification of different states of epilepsy.In 2017, P.Ramina proposed an efficient classifier to identify epileptic EEG signals in two periods and to reduce the amount of EEG data to accommodate the processing model.

The rapid development of integrated circuit and progress by leaps and bounds, the use of computer processing of various signal processing theory applications to promote the development of the whole epileptic EEG signal in the detection and identification, seizure prediction and other technologies.In 2018, Jakub Jirka et al. introduced a new classification method of automatic seizures: after digital filtering and adaptive segmentation of EEG signals analysis, using genetic planning method combined with support vector machine confusion matrix as a fitness function weight, extract the feature vector compressed to low dimensional space, finally realize the classification of seizure signal seizure period and interseizure period.In 2019, Laura Gagliano et al. proposed a method for EEG state classification based on bispectral analysis and recursive long and short-term

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memory (LSTM) neural networks to identify EEG signals in different states of patients.In the same year, Xiaoyan Wei et al. converted EEG time series into two-dimensional images for multi-channel fusion, proposing a feasible method to build spatio-temporal deep learning models for seizure prediction, using convolutional network blocks to automatically extract deep features from the data to identify pre-onset segments.

The study divided the extracted EEG signals into two states: pre-seizure and seizure period, and realized the seizure prediction when the system detects the pre-seizure state.The established predictive structure of seizures is divided into pre-processing of epileptic EEG signals, feature extraction and achieving classification prediction using trained algorithms.The network framework for epilepsy prediction is shown in Figure 1.

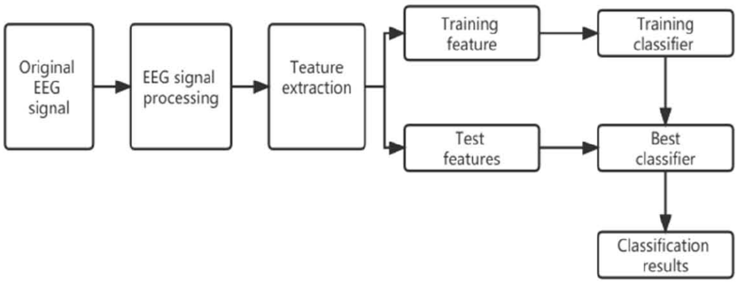

Figure 1. The epilepsy prediction framework

The research significance of this paper is to solve the problem of epilepsy prediction in the existing data sets in the hospital, while the present method integrates the advantages of the existing framework and has certain general applicability.

II. Experimental Materials and Methods

A. EEG signal preprocessing and feature extraction

The collected 16-channel EEG dataset was first preprocessed using wavelet transform and feature extracted on processed EEG signals using sample entropy, and 10-minute EEG signals into 15 sequences, each containing 3200.The EEG data before episodes were labeled as label=0, those during episodes as label=1, and finally the processed data were saved as.mat form.The software used for the pretreatment of EEG signals is MATLAB and EEGLAB.

TABLE I. Time Domain and Frequency Domain Feature Extraction Methods and Their Characteristics

Feature extraction method	relevant feature
time domain feature （Time-domain features）	Mean, standard deviation, skewness, kurtosis, amplitude, and absolute face Product, root mean square, and zero times
Frequency domain features （Frequency-domain features）	Wavelet transform coefficient, power spectrum and band distribution (Wave 0.5-3HZ, Wave 4-7HZ, Wave 8-13HZ, wave 14-30HZ, Wave 31-50HZ,> 50 components)

B. CNN network and LSTM network

Deep learning technology has achieved great success in recognition tasks such as computer vision, automatic speech recognition, natural language processing and bioinformatics due to its powerful end-to-end self-learning capability of complex feature representation, which avoids a large number of manual feature extraction.convolutional neural network (CNN), as shown in Figure 2, CNN has the most obvious features, so it has been widely used in feature engineering.The CNN is a network model proposed by Lecun et al.In 1998,.CNN is a feedforward neural network with good performance in natural language processing in image processing and image processing.The prediction of the time series can be effectively applied.Local perception and weight sharing of CNN can greatly reduce the number of networks and thus improve the efficiency of model learning.CNN is mainly composed of two parts: convolutional layer and pooling layer, each with a complex convolution kernel and its calculation formula.

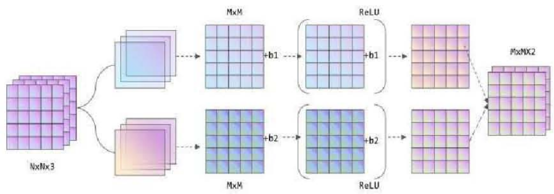

Figure 2. The prototype framework of the convolutional neural network

$$f_t = \delta(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

As shown in Equation (1). After the convolution operation, the convolution layer extracts data features, but the dimensions of extracted features are very high. Therefore, in order to solve this problem and reduce the cost of network training, the pool layer is increased after convolution to reduce the size of features.

Long and short memory network (LongShortTerm memory, LSTM), as shown in Figure 3, in many applications involving time series dynamics showed the most advanced performance, such as text and speech recognition, information extraction and semantic analysis of LSTM has a time sequential expansion characteristics, widely used in time series, because it has its own memory and can be a relatively accurate predictor. The 1997 LSTM is a model designed by Schmidhuber et al. to solve the long-term gradient problem of RNN during explosion and gradient disappearance. In recent years, it has also been applied to the field of stock market prediction. The LSTM memory unit consists of three parts: input gate, forget gate, and output gate.

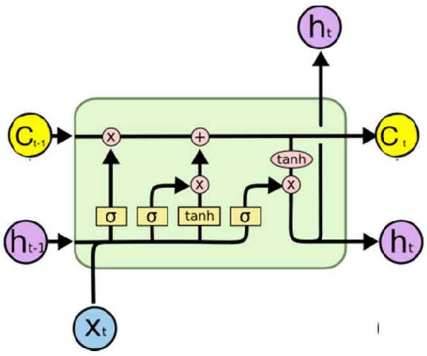

Figure 3. The prototype framework of the convolutional neural network

Recently, CNN-LSTM binding has become a hot topic.Convolutional neural networks consists of alternating superposition of convolutional and pooling layers, Between each convolution and pooling layers there are relu activation function actions to accelerate the convergence of the model, In the model, the data are processed by a convolutional neural network, The feature description of the convolutional neural network is obtained, The data is then passed to the LSTM, Normally, the data entered at this time requires reshape into the type of LSTM processing, After the LSTM gets the new input, Identify what needs to be maintained and discarded, Where holding and discarding is done with the sigmoid activation function, Any data multiplied by 1 is for itself, Whereas any function multiplied by 0 is 0, Choose you to forget and save important data.When the data multiply by 1, it is retained, and the data obtained from the input gate updates our state.Finally, the output gate is used to determine the carried information, and the new state and the hidden state are transferred to the next time step.

III. EXPERIMENTAL PROCEDURE

A. CNN-LSTM Network classifier

The processing method in this paper is to use CNN-LSTM network data after the first convolution kernel of the data, the purpose of the model is to be able to better get the predicted data value, after trying the standard method, after several adjustment parameters, the data loss is not reduced to 0.5, in order to output data more accurate, adjust the data standardization, still normal distribution, but the expected value is not 0.

The module part of CNN adopts four layers of convolution, two layers of maximum pooling, including the activation function in the middle. At this time, the data obtained by CNN is input into the LSTM, processed through the LSTM layer and Dropout layer, and finally output the data in the fully connected layer.

The CNN-LSTM network model presented in this paper is shown in Figure 4.

Layer (type)	Output Shape	Param #
Conv1 (TimeDistributed)	(None, 15, 8, 1600, 16)	416
batch_normalization_1 (Batch	(None, 15, 8, 1600, 16)	64
activation (Activation)	(None, 15, 8, 1600, 16)	0
time_distributed (TimeDistri	(None, 15, 4, 800, 32)	12832
activation_1 (Activation)	(None, 15, 4, 800, 32)	0
time_distributed_1 (TimeDist	(None, 15, 2, 400, 32)	0
time_distributed_2 (TimeDist	(None, 15, 2, 400, 32)	25632
activation_2 (Activation)	(None, 15, 2, 400, 32)	0
time_distributed_3 (TimeDist	(None, 15, 2, 400, 32)	25632
activation_3 (Activation)	(None, 15, 2, 400, 32)	0
time_distributed_4 (TimeDist	(None, 15, 1, 200, 32)	0
FC1 (TimeDistributed)	(None, 15, 6400)	0
activation_4 (Activation)	(None, 15, 6400)	0
time_distributed_5 (TimeDist	(None, 15, 6400)	0
FC2 (TimeDistributed)	(None, 15, 256)	1638656
activation_5 (Activation)	(None, 15, 256)	0
time_distributed_6 (TimeDist	(None, 15, 256)	0
cu_dnnlstm (CuDNNLSTM)	(None, 64)	82432
dropout_2 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 2)	130

Figure 4. C N N-LSTM network structure

B. A 50% off cross-validation method

In this paper, 80 of the epileptic EEG data were used to train the model, and the remaining 20 percent of the data were used to test the evaluation model.The loss function of the binary classification model generally chooses the cross-entropy loss function (bi nary_crossentropy), and the calculation formula is:

$$Loss =-\sum_{i=1}^{n} Y_i log y_i + (1 - Y_i) log(1 - Y_i) \quad (2)$$

$$\frac{\partial loss}{\partial y} = -\sum_{i=1}^{n} \frac{Y_i}{y_i} - \frac{1-Y_i}{1-y_i} \quad (3)$$

The flow of finally selecting the optimal classifier is shown in Figure 5.

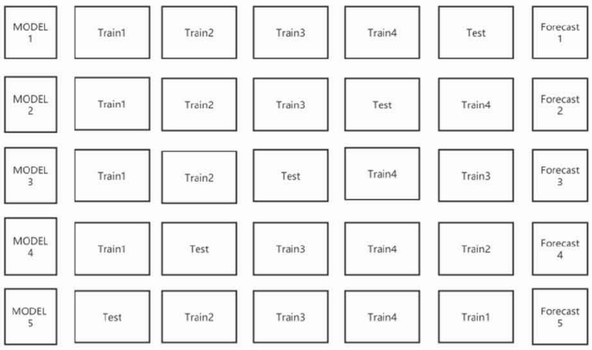

Figure 5. A 50% off cross-validation process

IV. EXPERIMENTAL RESULT

The final training set table obtained after cross-validation of the data at 50% discount is shown in Table 2.

TABLE II. ACCURACY OF CNN-LSTM MODEL TRAINING SET

unit:%

CNN-LSTM	model 1	model2	model 3	model 4	model 5
precision	87.5	86.3	87.6	86.8	87.3
Average accuracy			87.1		

The five models obtained from the training set were 87.5%, 86.3%, 87.6%, 86.8%, 87.3%, with an average accuracy of 87.1%.Finally, model 3 with the highest classification accuracy was selected as the model of the test set, and the classification accuracy of 87.8%, recall of 84.18% .Finally, this paper performed epilepsy prediction using CNN and LSTM networks, respectively, as shown in Tables 3 and 4.

TABLE III. ACCURACY OF CNN MODEL TRAINING SET

unit:%

CNN	model 1	model 2	model 3	model 4	model 5
precision	85.1	84.3	85.6	84.5	85.7
Average accuracy			85.0		

TABLE IV. ACCURACY OF LSTM MODEL TRAINING SET

unit:%

LSTM	model 1	model 2	model 3	model 4	model 5
precision	83.2	83.4	84.1	83.7	84.3
Average accuracy			83.7		

The five models obtained from the C NN network training set were 85.1%, 84.3%, 85.6%, 84.5%, 85.7%, respectively, with an average accuracy of 85.0%.Finally, the model 5 with the highest classification accuracy was selected as the model of the test set, which obtained the classification accuracy of 84.2%.

The five models obtained in the LSTM network training set were 83.2%, 83.4%, 84.1%, 83.7%, and 84.3%, respectively, with an average accuracy of 83.7%.Finally, the model 3 with the highest classification accuracy was selected as the test set, which obtained the classification accuracy of 83.7%.

V. CONCLUSION

Combined with the existing research results of seizure prediction, we select the time and frequency domain features of epilepsy data set, fuse the statistically related inter-channel data, use CNN-LSTM as the classifier, and obtain the classification accuracy of test set of 87.8%, recall of 84.18% and false alarm rate of 0.62 / h.4.3% improvement over CNN prediction accuracy and 5.0% over LSTM prediction accuracy.It shows that the present method can solve the classification problem of existing epilepsy datasets well.However, this paper only models each patient alone and requires at least 1 to 2 recorded seizures, and there is still much work to be done before the actual hospital application, that is, finding a uniform seizure pattern of patients.

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