Human emotion recognition based on multi-channel EEG signals

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***Abstract*-EEG is a kind of sequential data. In order to learn the relationship of EEG in time series, this paper proposes to use long-term memory network to combine convolutional neural network and self-attention mechanism to extract features from EEG. In order to verify the superiority of this method, I design a complete experiment based on SEED data set, and the experimental strategy is an independent leave one method cross-validation experiment for subjects. The experimental results show that the proposed method can effectively learn the EEG temporal relationship, and can improve the convergence speed and have a high accuracy.**

Keywords-Emotion classification, EEG, physiological signals, signal processing, pattern classification, affective computing

I. INTRODUCTION

Emotion is a complex psychological and physiological expression, usually related to an individual's subjective feelings, temperament, personality, motivational tendencies, behavioral responses and physiological arousal. With the development of artificial intelligence and human interaction technology, affective computing has attracted more andmore researchers' attention for its purpose of establishing a harmonious human-computer environment by endowing computers with the ability to recognize, understand, express and adapt to human emotions. The basic problems of emotion computing include emotion recognition through physiological signals such as text, image, expression, language, action and EEG. Therefore, in the field of emotion recognition, both behavioral signals and physiological signals are used to recognize human emotions. Compared with the most commonly used behavioral signals, including speech, facial expressions, gestures and body movements, physiological signals have attracted more and more attention for their advantages of being difficult to disguise, more objective in identifying results and being a direct response to human emotions. Electroencephalography (EEG) is aphysiological signal with excellent temporal resolution that can be used directly for emotion recognition tasks by analyzing direct brain activity caused by emotional stimuli.

In recent years, with the development of brain science, EEG has influenced many fields.For medical diagnosis, the analysis of temporal relationships in EEG data provides real-time information about the functional state of the brain. For instance, doctors can use this analysis to determine if a patient is suffering from epilepsy[1-3], brain tumors, or other brain diseases. This temporal pattern analysis can reveal the electrical activity of the brain during seizure or other abnormal conditions, aiding in more accurate diagnosis and treatment planning.

In the field of brain-computer interfaces, temporal relationship analysis is equally essential. The goal of brain-computer interfaces is to understand the communication between the brain and external devices, which is often sequential in nature. By analyzing the temporal relationships in EEG data, we can gain insights into how the brain responds to specific tasks or stimuli, enabling direct communication and control between humans and machines[4-6].

Assistive technologies also benefit from temporal relationship analysis in EEG data. For instance, in wheelchairs or robotic arms controlled using brain-computer interfaces[7-9], temporal relationship analysis can enhance understanding of the user's intentions and movement sequences, optimizing device control and responsiveness. Additionally, in rehabilitation medicine, analyzing temporal relationships in EEG data can aid in neurorehabilitation efforts or improve quality of life for individuals with physical limitations.

With the development of emotion-labeling tools based on EEG, the emotion-recognition task based on EEG has achieved unprecedented development. At present, there are many researches on emotion recognition based on EEG, but how to design the most suitable algorithm for emotion recognition according to the characteristics of EEG data to extract the most favorable emotion features has always been the focus of attention. Time domain analysis, pattern recognition, deep learning, physiological mechanism research and other related algorithms can now be applied to emotion recognition. However, most of the existing EEG based emotion recognition methods can not effectively use the relationship of EEG in time dimension to learn more different EEG representations. Therefore, I propose to use the long term memory network to learn the characteristics of EEG in the time dimension and then use it for EEG emotion recognition.

At present, in the field of emotion recognition based on EEG, there have been some works to learn EEG features by using temporal models, such as long short-term memory network, convolutional neural network, recurrent neural network and so on. CNN can capture the local features of the input data through the local receptive field, and has a good processing ability for time series data with rich local information such as EEG signal. The convolutional layer of CNN can extract features, and the pooling layer can reduce the feature dimension. These operations can effectively reduce the calculation amount and improve the training speed and generalization ability of the model. But CNN time series data processing ability is weak and has no memory function. In LSTM networks, the long-term dependency problem is solved by using a gating mechanism to control the flow of information. However, this gating mechanism cannot fine-tune every part of

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the sequence because it treats all inputs equally. This makes LSTM perform well when dealing with long sequences, but may be less effective when dealing with short sequences.

In order to solve this problem, I innovatively proposed CNN-LSTM-ATTENTION network to better handle sequences data. And the Leave-one-subject-out method is used to make full use of the data set, which makes the training process more comprehensive. CNN is able to better understand local patterns and trends in time series data,thereby improving the accuracy of predictions. The attention mechanism allows the network to process each time step with previous information in mind and focus on different parts of the sequence. In this way, the network can better understand and process the contextual information of the input sequence.

II. RELATED WORK

A. Emotion Model

At present, there are two kinds of emotion models incommon use, discrete emotion model and dimensional emotion model. Discrete emotion models are composed of basic emotions with limited space, such as the Ekman model of six basic emotions (happiness, sadness, surprise, fear,anger, and disgust), which is recognized by most researchers in the field of psychology, and from which other emotions can be combined. The dimensional emotion model generally has two dimensions of emotional space atmosphere, valence-arousal and VA, or valence-arousal-dominanceand VAD. At present, VA model is widely used in the field of emotion recognition. Compared with the VA model,the VAD model considers the emotional factors more comprehensively and can provide richer emotional information. However, due to the addition of one dimension, the VAD model is also relatively more complex to understand and calculate.Van Den et al. explored a rare combination of language, electrocardiograms, and an improved self-assessment model to assess people's emotions.[10] POSNER et al. proposed the circumplex model, the model offers fresh theoretical and empirical perspectives for examining the evolution of affective disorders, as well as the genetic and cognitive foundations of affective processing within the central nervous system.[11] According to PJ Lang, emotions are action dispositions -- states of watchful readiness that exhibit diverse reports of affect, physiology, and behavior.[12]

B. EEG-based Emotion Recognition

At present, emotion recognition based on EEG is mainly based on traditional methods and deep learning methods. Relevant researches on emotion recognition based on these two methods mainly include the following aspects:

Wei-Long Zheng et al. proposed a multi-module EmotionMeter, which can significantly improve recognition performance compared to a single mode. The average accuracy for happiness, sadness, fear, and neutral emotions reaches 85.11%.[13] Ziyu Jia et al. introduced a novel spatial spectrum time-based three-dimensional dense network of attention, named SST-EmotionNet, for EEG emotion recognition. The main feature of SST-EmotionNet is the simultaneous integration of spatial-spectrum-time features within a unified network framework. Additionally, a 3D attention mechanism is designed to adaptively explore differentiated local patterns.[14] Run Ning et al. proposed a single-source domain adaptive low-lens learning network (SDA-FSL) for cross-subject EEG emotion recognition. This is the first time that the domain adaptive method based on few-shot learning has been applied to the field of EEG emotion recognition. A CBAM-based feature mapping module is designed to extract common features of the two domains, and a domain adaptive module is used to align the data distribution of the two domains.[15]. Wai-Cheong Lincoln Lew et al. proposed a Regionally Operated Domain Adversarial Network that accounts for the spatial-temporal relationship between brain regions and time. This network combines attention mechanisms with cross-domain learning to capture the spatiotemporal relationship between EEG electrodes. By incorporating adversarial mechanisms, it mitigates domain drift in the EEG signal.[16] Suwicha Jirayucharoensak et al. suggests utilizing a deep learning network (DLN) to discover unknown feature correlations in input signals. The DLN incorporates a stacked autoencoder (SAE) using a hierarchical feature learning approach. The input features for the network consist of power spectral densities from 32-channel EEG signals obtained from 32 subjects. To address the issue of overfitting, principal component analysis (PCA) is applied to extract the most significant components of the initial input features.[17] Tenkedi et al. introduced an emotion EEG recognition model based on a fusion algorithm combining support vector machine (SVM) and K-nearest neighbors (KNN) (SVMKNN). In emotion classification, the spatial distance between the sample to be identified and the optimal classification hyperplane is first calculated. If this distance exceeds a preset threshold, the SVM classifier is used to classify the emotion sample; otherwise, the KNN classifier is employed.[18].

The traditional machine learning method has high classification accuracy and feature extraction ability in EEG emotion recognition, but it needs to manually extract features and a large number of labeled data. Deep learning model has strong ability of representation learning and small sample data set processing, but it needs a lot of labeled data and has poor model interpretation. Therefore, I proposed the CNN-LSTM-ATTENTION model based on the advantages and disadvantages of each model.

III. PROPOSED FRAMEWORK

A. Pre-processing

Because of the instability and irregularity of EEG signal, the processing of EEG signal is also complicated, and it is difficult to directly analyze the internal relationship from it. Under normal circumstances, the signal will be preprocessed to a certain extent. Through this rough processing, the signal with a certain regularity can be obtained, which is convenient for subsequent research.

EEG pre-processing mainly includes the following steps: data import, electrode positioning, removing useless electrodes, data filtering, noise removal, segmentation and baseline correction, bad segment and interpolation bad lead removal, independent component analysis, artifact component removal, automatic removal of extreme values, re-reference processing.

EEG feature extraction encompasses various types, including:

Time-domain features: Event-related potentials, energy, power, etc.;

Frequency-domain features: Power spectral density, high-order spectrum, differential entropy, etc.;

Time-frequency domain features: Short-time Fourier transform, wavelet packet transform, etc.

The Seed[19] dataset has been utilized to extract EEG segments that correspond to specific movie scenes. In total, 45 files with the .mat extension (MATLAB files) were utilized, with each file representing a distinct experiment. Every participant in the study completed the experiment three times, with a one-week interval between each session. Each participant's data is stored in a file containing 16 arrays. Fifteen of these arrays hold preprocessed and segmented EEG data from 15 different trials conducted during a single experiment (labeled as eeg_1 through eeg_15, organized by channel and data points). Notably, the array names also include corresponding emotional labels, with -1 indicating negative emotions, 0 representing neutral emotions, and +1 signifying positive emotions.

B. Feature Extractor

DE feature extraction: The frequency of brain waves in the human electroencephalogram can range from 0.5 to10 of Hertz, and it is usually classified by frequency to represent various components: delta waves (0.5-4Hz), theta waves (4-8Hz), alpha waves (8-13Hz), beta waves (13-32Hz), gamma waves (32-50Hz), the frequency range written by many people in this place is not the same but there is no great difference. We use a band pass filter to extract the frequency band here.

DE feature: Differential entropy is actually a generalization of Shannon entropy on a continuous signal, and Shannon entropy quantifies the total amount of uncertainty in the probability distribution, as follows:

$$H(x) = \sum_{i=0}^{k} P(x_i) log(P(x_i)) \quad (1)$$

Differential entropy: Quantifies the total amount of uncertainty in the probability distribution of a continuous random variable by the following formula:

$$H(x) = \int P(x) log(P(x)) dx \quad (2)$$

P(x) in formulas (1) and (2) represents the probability density function of continuous information.

C. Proposed Model

The whole network model is divided into five parts, namely input layer, convolutional layer, LSTM layer, attention layer and output layer. As shown in Figure 1.

The first layer of the model is the input layer. Specifies the format of the input data (batch size, time steps, feature dimension).

The second layer is the convolutional neural network layer (CNN layer). The CNN layer can extract the spatial relationship between different feature values in the data. For sequence data, one-dimensional convolution is adopted in this model, and convolution kernels are convolved in a single time domain direction.

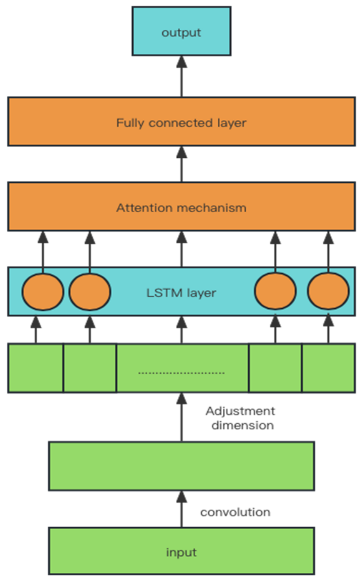

Fig.1. CNN-LSTM-ATTENTION network structure

The third layer is a LSTM layer. LSTM has the memory function and can extract the time series change information of the nonlinear data. It introduces input gate, forget gate and output gate, and also adds candidate state, cell state and hidden state. Cell states store long-term memory, which can mitigate gradient disappearance, and hidden states store short-term memory. This model employs an LSTM network, where the output of the upper LSTM layer serves as the input for the next layer. The output of the last LSTM hidden layer feeds into the attention layer for further processing.

The fourth layer is the attention layer. Attention enhances the impact of crucial time steps in the LSTM, thereby reducing prediction errors. Essentially, attention computes the weighted average sum of the LSTM output vectors from the last layer. The output vector of the LSTM hidden layer is trained through a fully connected layer as the input to the attention layer. Subsequently, the output of the fully connected layer undergoes normalization using the softmax function to determine the weight assigned to each hidden layer vector. The weight size indicates the significance of each time step's hidden state to the prediction outcome.

At the end of the model are the full connection layerand the output layer, the output dimension of the full connection layer can be adjusted to a specific dimension.

IV. SYSTEM IMPLEMENTATION DETAILS

A. Temporal Feature Extractor

For sequence data processing, this model incorporates a CNN module that employs one-dimensional convolution. The convolutional kernel performs convolution exclusively in the time domain direction. Given that the number of convolutional kernels is r with a kernel size of k, the subsequence $x_{i:i+k-1}$ represents the real matrix spanning from time step i to i+k-1 within the $R_{t\times n}$ space. The sliding window moves with a step size of 1. The weight matrix, denoted as W_1, is a real matrix of dimensions k×n. Feature extraction is conducted on every k-time step segment of the sequence vector, yielding a feature represented by o_i. The mathematical expression for this operation is as follows:

$$o_i = f(W_1 * x_{i:i+k-1} + b_1) \tag{3}$$

f is a nonlinear activation function and b1 ∈R is a bias. When a convolution kernel extracts the sequence dataof a sample, it will get a feature graph o with the shapeof (t-k+1) ×1. The calculation formula is as follows:

$$o = [o_1, o_2, \dots, o_{t-k+1}]\mathrm{T} \tag{4}$$

These r feature maps are the features extracted from the CNN layer, which are dimensionally reduced into a real vector of length r*(t-k+1)/2, in which the spatial relations between different feature values in the sample data are stored, and then input into the LSTM layer for further processing.

Since LSTM built-in functions can be called directly, the specific formulas of LSTM will not be described again. Attention is essentially finding the weighted average sum of the LSTM output vectors of the last layer. The weight training process formula is as follows:

$$S_i = tanh(WH_i + b_1) \tag{5}$$

$$a_i = softmax(S_i) \tag{6}$$

Using the trained weights to calculate the weighted average sum of the hidden layer output vector, that is, the LSTM+ATTEENTION principle is shown in Fig 2, the calculation results are as follows:

$$C_i = \sum_{i=0}^{k} a_i H_i \tag{7}$$

Where H_i is the output of the last LSTM hidden layer, S_i is the score of the output of each hidden layer, α_i is the weight coefficient, C_i is the result of weighted summation, and softmax is the activation function. The fifth layer is the output layer. This layer specifies the prediction time step o_t, and finally outputs the prediction result of the o_t step.

B. Classifier

After the model extracts the features, the classification layer classifies the emotions based on the features. We use the cross-entropy loss function and L1 regularization method to calculate the loss value. The Cross Entropy Loss function is a loss function commonly used in classification problems. It is mainly used to measure the difference between the predicted probability distribution of the model and the true distribution. The concept of cross entropy is derived from the axiom of cross entropy in information theory and is used to measure the difference between two probability distributions. In machine learning and deep learning, the cross-entropy loss function is often used to solve classification problems, especially multi-classification problems. The calculation process of the cross entropyloss function is as follows:

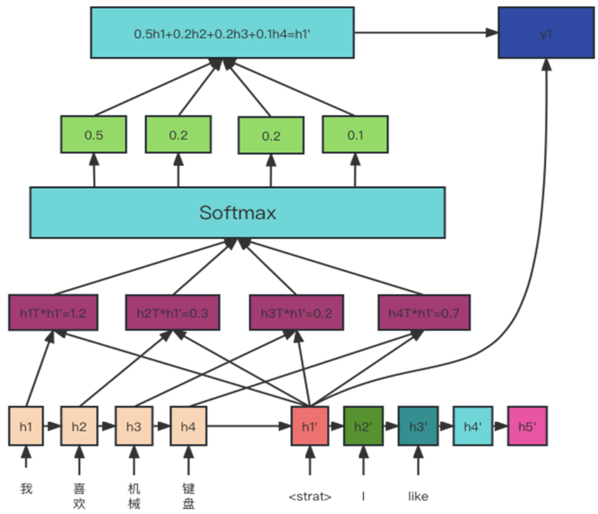

Fig.2. Schematic diagram of LSTM+Attention in machine translation

The original probability distribution of the model output is converted to the probability distribution in the logarithmic domain by LogSoftmax function. The LogSoftmax function is calculated as follows:

$$\sigma_{log}(x) = log\sum_{i=0}^{n} e^x \tag{8}$$

Then, the negative log likelihood is calculated based on the real label, that is, the cross entropy loss. For binary classification problems, if the true label is 1, then calculate$\sigma - \sigma\sigma_{\log}(x_i)$. If the true label is 0, then calculate$\sigma - \sigma_{\log}(1 - x_i)$. For multiple classification problems, calculate the logarithm of the maximum probability for all classes, and then subtract the logarithm of all predicted probabilities from this value.

The next step is to calculatethe L1 regular term and add the result to the loss value to get the final loss value. L1 regularization is a regularization strategy used to prevent overfitting. The L1 regularization term is the sum of the absolute values of the model's parameters, which encourages the model to use fewer parameters, thereby reducing the risk of overfitting. L1 regularization is a regularization strategy used to prevent overfitting. The L1 regularization term is the sum of the absolute values of the model's parameters, which encourages the model to use fewer parameters, thereby reducing the risk of over fitting. The process is to first traverse all the parameters of the model, calculate the absolute value of each parameter, and then add all the absolute values to get the regular term.

V. EXPERIMENTS

A. EEG Dataset

The SEED dataset contains EEG and eye movement data from a total of 15 Chinese subjects, including 7 males and 8 females with a mean age of 23.27 and a standard deviation of 2.37. The dataset was collected while the subjects watched carefully selected film clips designed to induce different emotional responses: positive, negative, and neutral.

To ensure the protection of personal privacy, the subjects' names have been withheld, and each subject is identified by a unique number from 1 to 15. EEG and eye movement data were collected for subjects 1 through 5, 8 through 14 (totaling 12 subjects), while subjects 6, 7, and 15 only provided EEG data.

The film clips chosen for the experiments were selected based on specific criteria:

(a) The overall length of the experiment needed to be brief to prevent subject fatigue.

(b) The videos needed to be self-explanatory to avoid the need for additional explanations.

(c) Each video was intended to evoke a single desired target emotion.

Each film clip had a duration of approximately 4 minutes and was meticulously edited to ensure coherent emotional elicitation and to maximize emotional impact. Detailed information about the specific film clips used in the experiments can be found in Table 1

Table.1. The Details of the Film Clips

No.	Emotion label	Film clips sources
1	negative	Tangshan Earthquake
2	negative	Back to 1942
3	positive	Lost in Thailand
4	positive	Flirting Scholar
5	positive	Just Another Pandora's Box
6	neutral	World Heritage in China

There were a total of 15 trials for each experiment. A 5-second hint was provided before each clip, followed by a 45-second self-assessment period and a 15-second rest period after each clip in one session. The order of presentation was carefully arranged to ensure that two film clips targeting the same emotion were not shown consecutively.For feedback, participants were instructed to report their emotional reactions to each film clip by completing a questionnaire immediately after watching each clip. The detailed protocol is shown in Figure 3.

Fig.3. The detailed of protocol

EEG signals and eye movements were collected using the 62-channel ESI NeuroScan System and SMI eye-tracking glasses. The experimental setup and the placement of EEG electrodes are depicted in Figure 4.

B. *Evaluation on SEED*

For the design of the experiment, I used the Leave-one-subject-out cross validation method, which is a technique for designing experiments and is commonly used in thefields of machine learning and statistics. The main idea of this technique is to treat each subject in the original data set as a separate test set, and the remaining subjects as a training set. During training, the model uses all the data except the current topic to predict the outcome of the current topic. The performance of the model is then evaluated by comparing the actual results with the predicted results.

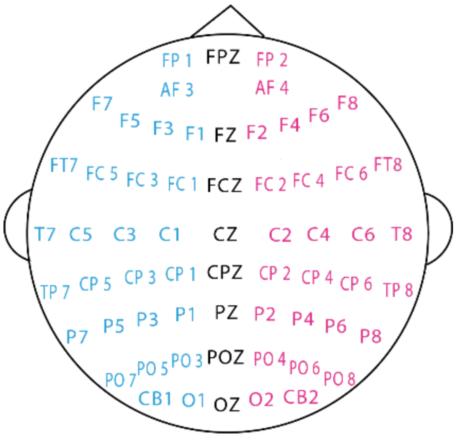

Fig.4. The EEG cap according to the international 10 - 20 system for 6 2 channels

This process is repeated until each topic is treated as a separate test set once. Finally, all the test results are combined and used to evaluate the overall performance ofthe model. The advantage of this method is that all raw data can be fully utilized, and an independent predictive model can be generated for each topic, which improves the generalization ability of the model.

In this experiment, in addition to testing the CNN-LSTM-ATTNENTION model, we also tested three models as a comparison, namely LSTM, CNN-LSTM and LSTM-ATTENTION. Their losses in the training process are shown in Fig 5,6,7 and 8 and the corresponding training set accuracy is shown in Fig 9.After preliminary experiments,we confirmed that CNN-LSTM-ATTENTION had the best performance, and the fastest rate of accuracy improvement and loss reduction. After 1400 iterations of training, we found that the loss and accuracy curves of CNN-LSTM model did not converge completely, so we conducted another experiment. Change the number of iteations to 2800.The accuracy curve obtained is shown in Figure 10, and The accuracy of all models in various situations is summarized in Table 1.It can be seen that the CNN-LSTM model has converged after 2800 iterations, and the accuracy of the training set has reached 99.81%, which is still lower than the CNN-LSTM-ATTENTION model's 99.94%, and the condition of the test set is the same.

With the addition of attention mechanisms, the model needs to be able to recognize and focus on key information when processing EEG data. The attention mechanism allows the model to assign different weights when processing data, giving greater attention to the parts that matter. This means that models can be more focused on important features and patterns and less focused on irrelevant or redundant information. In this way, models are able to learn and process data more efficiently, resulting in faster convergence.

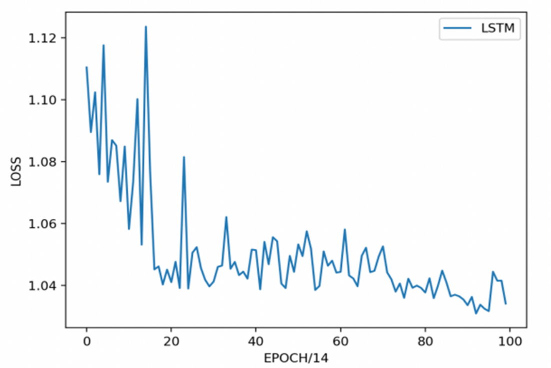

Fig.5. The loss change curve of LSTM

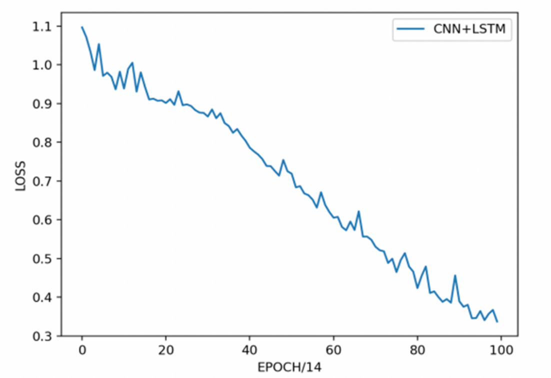

Fig.6. The loss change curve of CNN-LSTM

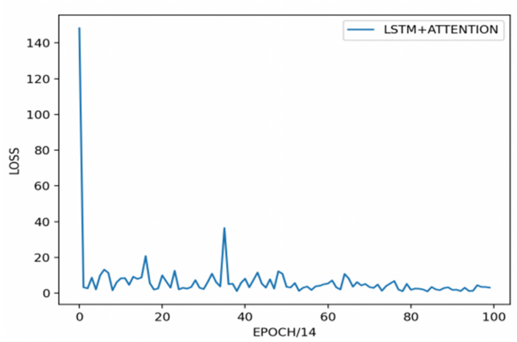

Fig.7. the loss change curve of LSTM-ATTN

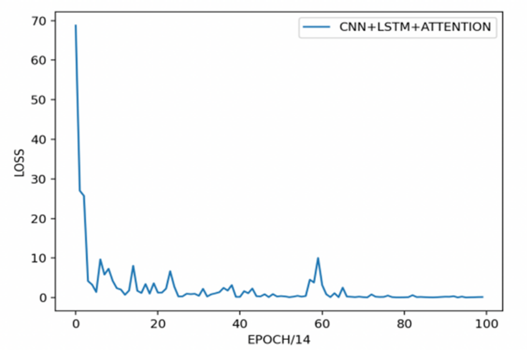

Fig.8. the loss change curve of CNN-LSTM-ATTENTION

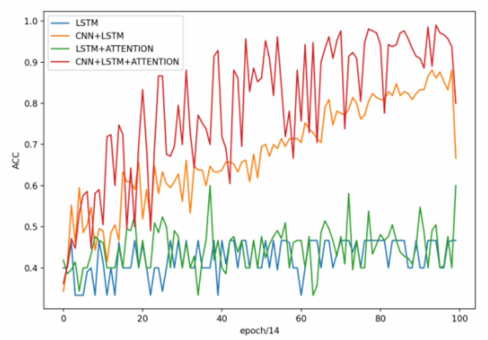

Fig.9.The change curve of training set accuracy of four modelsunder 14 00 iterations

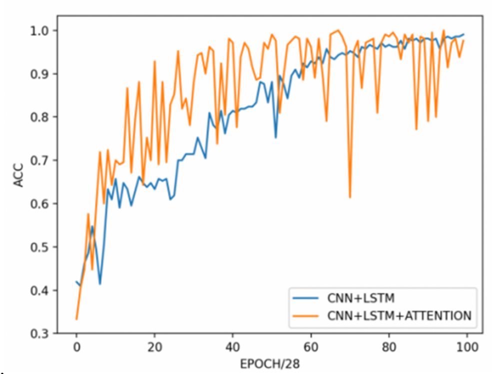

Fig.10.The change curve of training set accuracy of two models under 2800 iterations.

C. Results Analysis

According to the experimental results, the best model is CNN-LSTM-ATTENTION, followed by CNN-LSTM, the third best is LSTM-ATTENTION, and the worst performance is LSTM.The reason is that adding attention mechanism to LSTM can make the model pay more attention to task-related information when processing time series data, thus improving the model's attention and processing efficiency. And there may be some redundant information in the time series data, which will negatively affect the performance of the model. The attention mechanism can reduce the model's dependence on redundant information and improve the model's performance. In addition, the LSTM model itself can handle long sequences, but with the increase of sequence length, the computational complexity of the model will increase. The attention mechanismcan reduce the dependence of the model on long sequences, thus reducing the computational complexity and improving the processing efficiency of the model. This is why models with attention converge faster than models without attention.

Adding CNN before the LSTM model can effectively capture local features of the input sequence, while the LSTM part can capture long-term dependencies. By combining these two mechanisms, the CNN-LSTM model is able to better understand patterns and trends in time series data,thereby improving prediction accuracy . Table 2 provides a comparison of accuracy indicators between our model and some existing models

Table.2. Accuracy Tables For Each Case of the Four Models

	Iterations	Accuracy of the training set	Accuracy of the testing set
LSTM	1400	48.03%	49.78%
LSTM-attn	1400	55.11%	65.78%
CNN-LSTM	1400	91.37%	77.33%
	2800	99.81%	75.56%
CNN-LSTM-attn	1400	98.86%	82.22%
	2800	99.94%	82.22%
SVM	-	-	56.73%
TCA[20]	-	-	63.64%
SA[21]	-	-	69.00%
T-SVM[22]	-	-	72.53%
DGCNN[23]	-	-	79.95%

VI. Conclusion

In this paper, we propose a model CNN-LSTM-ATTENTION model to solve the problem of emotion recognition based on EEG signals. None of the existing EEG based emotion recognition methods can effectively use the relationship of EEG in time dimension to learn more distinctive EEG representations. Therefore, we propose to use long term memory network to learn EEG features in time dimension. In addition, The CNN can extract the spatial relationship between different feature values in the data, so as to make up for the shortcoming that LSTM cannot capture the spatial components of the data, thus improving the accuracy of the prediction. Adding attention mechanism to the CNN-LSTM model can further improve the accuracy and speed of convergence.

In the experiment, we used the Leave-one-subject-out method to conduct 15 experiments. Different subjects were selected in each experiment, so that all subjects were selected. Finally, the results of these 15 experiments were comprehensively evaluated to obtain the final results. Our model achieved an average accuracy of 99.94% in the training set and 82.22% in the test set Both have better performance than LSTM, CNN-LSTM, and LSTM-ATTENTION.

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