

Research Article

Affective EEG-Based Person Identification Using Channel Attention Convolutional Neural Dense Connection Network

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In the biometric recognition mode, the use of electroencephalogram (EEG) for biometric recognition has many advantages such as anticounterfeiting and nonsteal ability. Compared with traditional biometrics, EEG biometric recognition is safer and more concealed. Generally, EEG-based biometric recognition is to perform person identification (PI) through EEG signals collected by performing motor imagination and visual evoked tasks. The aim of this paper is to improve the performance of different affective EEG-based PI using a channel attention mechanism of convolutional neural dense connection network (CADCNN net) approach. Channel attention mechanism (CA) is used to handle the channel information from the EEG, while convolutional neural dense connection network (DCNN net) extracts the unique biological characteristics information for PI. The proposed method is evaluated on the state-of-the-art affective data set HEADIT. The results indicate that CADCNN net can perform PI from different affective states and reach up to 95%-96% mean correct recognition rate. This significantly outperformed a random forest (RF) and multilayer perceptron (MLP). We compared our method with the state-of-the-art EEG classifiers and models of EEG biometrics. The results show that the further extraction of the feature matrix is more robust than the direct use of the feature matrix. Moreover, the CADCNN net can effectively and efficiently capture discriminative traits, thus generalizing better over diverse human states.

1. Introduction

Confirming that the identity of a person is becoming more critical in today's large data-driven society, which leads to an increasing demand for the reliability of user identification technology to meet the ever-increasing security. This is becoming particularly important in highly secure operations such as air traffic control and supervisory control of autonomous systems or remote operations such as remote operation of unmanned aerial vehicles. At present, identification based on EEG has shown high application value in security. For example, EEG signals are determined by a person's unique brain wave pattern. At the moment, EEG signals can be influenced by mood, stress, and mental state [1]. EEG-based PI system development has dramatically

increased in recent years. Motor tasks of EEG signals are eye closing [2], hands movement and foots movement [3], visual stimulation of EEG signals [4, 5], and multiple mental tasks of EEG signal such as mathematical calculation, writing text, and imagining movements [6, 7].

The methods of EEG-based PI are mainly divided into three categories: (1) EEG-based PI using motor tasks; (2) based on visually evoked EEG signals of PI; and (3) based on cognitive tasks induced EEG signals of PI. When using the first type of motor task EEG signal PI, the motor tasks are eyes open, eyes closed, left hand fist, right hand fist [8], etc. It is the potential signal generated by human behavior in the cerebral cortex, which is convenient for collecting EEG signal but lacks psychological response. The second type of EEG collected using visual evoked tasks occurs at a specific

time and part of the brain. It is easy to detect and is suitable for brain-computer interfaces to PI [9]. The requirements for the subjects are low. Only normal visual function is required, and the corresponding vision can be collected. However, visually induced EEG requires continuous display of pictures for visual stimulation, which is easy to cause visual fatigue and subjects are required to be very concentrated when performing visual stimulation. At the same time, visually evoked EEG signals for identification cannot be applied to subjects with visual dysfunction. The third type uses EEG signals collected by cognitive tasks, such as EEG signals induced by motor imaging tasks [10] and requires participants to imagine the brain electrical pattern of a certain limb movement. However, the brain regions activated by different imaging tasks are different. The motor imaging EEG of different tasks also have different characteristic frequency bands. Therefore, the EEG induced by cognitive tasks cannot be better applied to people with cognitive dysfunction. Because the EEG signals of the above three tasks (motor tasks, visual evoked, and cognitive tasks) PI did not explore the influence of the changes of mental state EEG signals on the performance of person identification. Emotions, feelings and attitudes are usually related to the individual's mental state affected by the environment. Emotion is always accompanied by a state of human psychology. However, emotion-induced EEG has rarely been studied to perform PI. Current research usually uses positive, neutral, and negative emotions for PI. While human emotions mainly include happiness, sadness, surprise, anger, disgust, fear, neutrality, pain, sadness, etc. Compared with the PI based on positive, neutral, and negative emotions of EEG signals, the identification of multiple different emotions [11] is more challenging because it needs to deal with extracting effective features for person identification under a variety of different emotional EEG. In recent years, in the literature on PI based on emotional EEG, 20 subjects were identified using the excitement state data in the public emotional DEAP EEG data set. The smaller emotional data set [11, 12] the average recognition accuracy can be up to 92%; in the literature [13], the average correct recognition rate (CRR) of DEAP data using wavelet feature extraction and deep neural network can reach 90%; in the literature [14], DelPozo-Banos et al. also use In the DEAP data set, the average CRR of the feature extraction algorithm using power spectral density reached 91.97%; in the literature [15], Li et al. used DEAP's emotional EEG signal data set, using the deep learning CNN + GRU algorithm for PI average CRR can reach 91%. Although a lot of research work has been proposed, it is basically based on the emotional EEG signal data set of DEAP. The emotional EEG in the DEAP data set uses the experimental paradigm of video stimulation to stimulate the corresponding emotional EEG and induce the emotional brain Electric emotions are very limited, and there is insufficient research on human emotional states for PI performance. Therefore, for overcomes the shortcomings of previous work to collect EEG signals of mental state changes for PI research, this paper proposes a PI method based on emotional EEG signals.

EEG signal changes with time and cortical recording position, so researchers tend to use deep learning

architecture to capture features in EEG signal for classification task. Research shows, compared with traditional classifiers, deep learning models can extract deeper and more important feature information from the input raw data for classification tasks [16, 17]. Convolutional neural network (CNN) has been used in EEG identification [11, 16] and verification [11, 12]. In these studies, CNN is directly used to learn the characteristics of EEG signals from the amplitude changes of EEG time series. CNN algorithm uses filters for convolution operation, which can automatically learn the key features of EEG signal, and these filters can stack and combine the automatically learned features of multiple CNN layers into more complex local patterns. In the stack of convolution layer, pooling layer is usually the feature information placed intermittently. Then, the pooling layer samples the output of the convolution layer twice by only outputting the maximum value of each small area. The second sampling allows the convolution layer after the pooling layer to work in a different proportion to the layer before it. So the CNN model is adaptive.

In order to solve the above problems, this paper uses the EEG data set HEADIT [18], which is richer in emotion. HEADIT uses the experimental paradigm of audio stimulation to stimulate the emotions of each state. Be able to effectively PI based on emotional EEG signals, this paper proposes a deep learning method based on the channel attention mechanism (CA) [19] convolutional neural dense connection network (DCNN) [20] for emotional EEG of PI. The DCNN net used in this article can effectively shorten the number of neurons connected between the front layer and the back layer, reduce the problem of gradient disappearance, strengthen feature propagation and reduce network parameters, and more effectively use different emotional states EEG signals. The EEG signals characteristics of the EEG signal can effectively PI based on the emotional EEG signal, and solve the problem of insufficient research in the PI based on the emotional EEG signal. The EEG signals characteristics of the EEG signal can effectively implement PI based on the emotional EEG signal, and solve the problem of insufficient research in the PI based on the emotional EEG signal. Finally, the study found that as the time size of the EEG signal changes, the PI performance is not affected. It shows that the algorithm proposed in this paper has good stability. According to the existing literature, it has not been found that the combination of the channel attention mechanism algorithm combine the convolutional neural dense connection network algorithm is used in the PI of emotional EEG signals.

The main contributions of this investigation can be summarized as follows:

- (1) The deep learning method composed of CA and DCNN net can be applied to the PI of emotional state EEG. This method has not been studied in the existing literature.
- (2) The CADCNN net can retain all the feature information of the emotional EEG signal, and repeatedly learn the unique features, and the algorithm

proposed in this paper has the characteristics of high stability.

- (3) The experimental results on the public affective data set of HEADIT show that the method proposed in this paper can get the best results. At the same time, the method proposed in this paper overcomes the influence of the emotional EEG signal on the performance of PI.

The structure of this paper is as follows. Sections II and III present the deep learning approach to EEG and experiments design. The results are reported in Section 4. Section 5 discusses the results from the experimental studies. Finally, the conclusion is presented in Section 6.

2. Deep Learning Approach to EEG

2.1. Method Overview. This paper proposes a based on the emotional EEG signal PI method that is CADCNN net algorithm. Figure 1 demonstrates the 1s affective EEG data feeding into the CADCNN net the model for PI. It can be seen from Figure 1 that the method proposed in this paper includes a channel attention mechanism, two dense layers and a transition layer. Before performing PI, first use a band-pass filter method to filter the emotional EEG signal to obtain the target rhythm and remove the redundant information in the emotional EEG signal. Then use the CA method to calculate the channel weights from the channels that have been filtered affective EEG signal. Then set higher weights for the channels with rich emotional EEG signal feature information. Finally, add the assigned channel weights and the original emotional EEG data output to the DCNN net, the feature learning of the multi-emotion EEG signal is carried out in the DCNN net. The DCNN net contains dense layers and transition layers, respectively. The dense layer part is used for feature extraction of emotional EEG signals. However the transition layer performs a convolution operation on the feature matrix output by the dense layer to reduce the dimension of the feature and obtain a new feature matrix. Then the dense layer and the transition layer are combined to obtain a DCNN net to realize the task of PI. Next, this article will explain the three modules included in the model, namely the channel attention mechanism module, the dense layer and the transition layer network module.

2.2. Channel Attention Mechanism (CA). The channel selection for the PI of emotional EEG signals is done by using the channel attention module. Specifically, the channel attention mechanism consists of a convolutional neural network and a LeakRelu activation function. The emotional features of the prepared emotional EEG signal are extracted through the convolution operation, and then the LeakyRelu activation function is used to calculate the weight of each channel. With the calculated the channel weight is added to the original emotional EEG data, and finally the result of the channel weighted calculation is output. The structure is shown in Figure 1. The attention network takes the output features of the DCNN net as input. There we define the filter

data sequence as $F = (F_1, F_2, \dots, F_N) \in R^{N \times \text{inch} \times \text{time} \times \text{sample}}$, where N represents batch size, inch represents the number of channels, and time and sample represent time length and data sampling point, respectively. For each sample, we use one scale CNN to obtain one dimensional feature representation $F_c = (F'_1, F'_2, \dots, F'_N) \in R^{N \times \text{inch} \times 1 \times 1}$. Where C_F represent the one scale convolution results. In addition, The 1×1 convolution is be used for activation function. The purpose of activation function is to computing channel weight. The activation process can be expressed by:

$$F_A = \text{LeakyRelu}(F_c) \in R^{N \times \text{inch} \times 1 \times 1}. \quad (1)$$

Subsequently, the channel attention value can be calculated as

$$F_{CA} = \text{ADD}(F, F_A) \in R^{N \times \text{inch} \times \text{time} \times \text{sample}}. \quad (2)$$

2.3. Dense Layer. In order to better retain the biological characteristics of the emotional EEG signal and make the PI efficient and stable. This paper proposes a different data connection method that is to combine the input of the matrix and the output of the dense layer to form a new the feature matrix. The structure diagram is shown in Figure 2. The output of the model result is that x_l has obtained the feature maps of all layers before it. x_0, \dots, x_{l-1} as input:

$$Xl = h\ell([X_0, X_2, X_3]), \quad (3)$$

where $[x_0, x_1, \dots, x_{l-1}]$ refers to the series of feature maps generated in the 0th, \dots , $l-1$ th layer and $h\ell(\cdot)$ is the feature splicing function. Due to the dense connectivity of its feature maps, this paper refers to this network structure as a convolutional neural dense connection network (DCNN net).

2.4. Transition Layer. To reduce the dimension of emotional EEG signal features and reduce redundant information, this paper adds a transition layer to extract higher-level feature information after dense layer splicing. And perform the following four operations on the feature matrix of the $H_l(\cdot)$ function: BatchNormalization (BN), nonlinear activation function (LeakyReLU) and 3×3 convolution (Conv) and the four steps of maximizing the pooling layer. The feature stitching in the dense layer network completes the output feature matrix for input into the transition layer. First, it is normalized to speed up the training process. After convolution operation, LeakyRelu is used to add nonlinear factors to improve the expression ability of the model. Finally, we use maximize the pooling layer reduces the dimension of the salient features, finally outputs the feature matrix. The structure diagram is shown in Figure 3.

When training the model, the loss function used is the iterative cross-entropy loss function [21] to train the network, and the initial learning rate is 0.001. The loss function formula is as follows:

$$\text{loss} = - \sum_{o=1}^B \sum_{c=1}^C y_{o,c} \log(p_{o,c}). \quad (4)$$

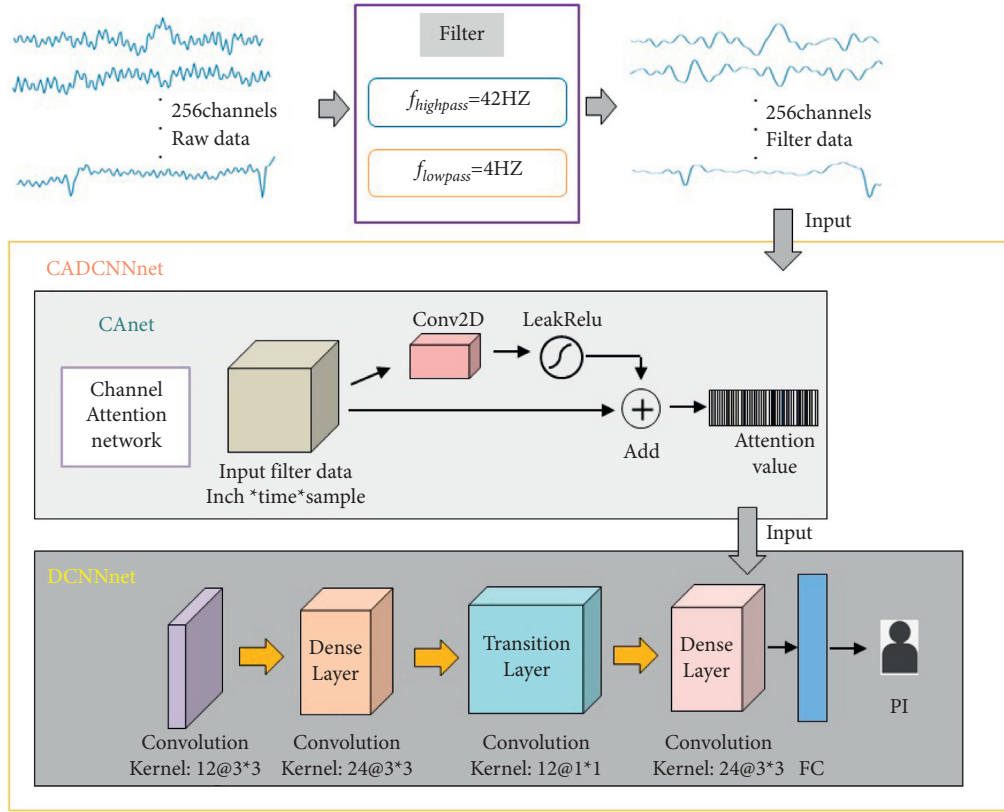


FIGURE 1: Overview of the proposed network architecture. There are three parts in the model: channel attention model, dense layer, and transition layer. The channel attention model is formed by a convolutional layer and a LeakyRelu activation function layer with one channel scales. The dense layer comprises of a convoluted and a concrete layer. The transition layer consists of a convolutional module and a max pooling layer which models can reduce the dimension of the concrete feature matrix.

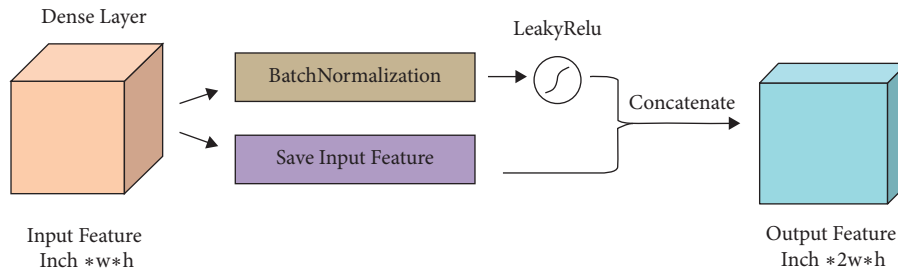


FIGURE 2: Dense layer model structure. Inch represents the number of channels, w and h represent the width and height of the feature.

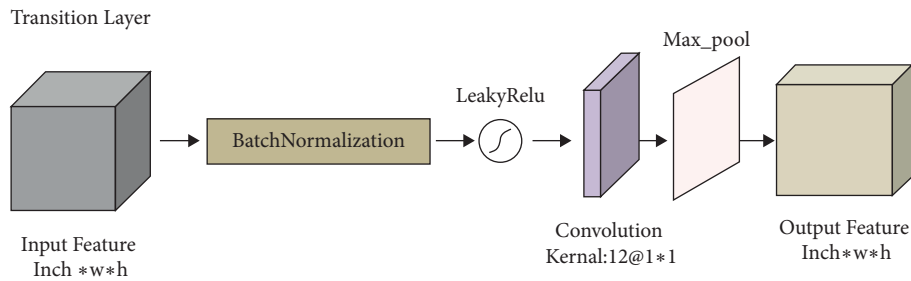


FIGURE 3: Transition layer model structure. Inch represents the number of channels, w and h represent the width and height of the feature.

Among them, $C = 32$ represents the number of categories, $B = 32$ represents the batch training size, and y represents the correct hot coding. When the class label c is consistent with the predicted class label, $y_{(o, c)} = 1$, otherwise $y_{(o, c)} = 0$. Dropout is set to 0.5 to reduce model over fitting.

3. Experimental

In this section, we first illustrate the HEADIT affective EEG data set that we used to conduct experiments studies and also described the preprocessing step of our solution. Since HEADIT was created for mental state classification purposes, we described our data partition methodology used to accommodate the performance of the PI task. Finally, we explained the proposed CADCNN net approach and its implementation.

3.1. Affective EEG Data Set. In this experiment, we performed experiments using HEADIT data set which is considered as a standard data set to perform emotion recognition tasks. The emotional EEG data contains positive and negative emotional tasks. Thirty healthy volunteers participated in the experiment. A realistic emotional state is induced through oriented language narration. There are 15 guiding image, narrative, each narrative describes a different emotion and situation. The subjects are asked to image target emotion by a voice-guided.

The representation of the data set is shown in Table 1; the steps used in the preprocessing of EEG data are as follows:

- (1) The sampling frequency of the data is 256 Hz
- (2) A band-pass filter from 4.0 to 42.0 Hz was applied the original EEG signal. The signal was further separate into the different frequency band of EEG signal as follows: theta (4–8 Hz), alpha (8–15 Hz), beta (15–32 Hz), gamma (32–40 Hz) and EEG signals of all bands (4–42 Hz)
- (3) The data was divided into 1 s, 3 s and 5 s from short length of EEG data set.

3.2. Subsampling and Cross-Validation. Emotional EEG's emotional type label division is to induce the subject to spend time to recall or imagine a scene by playing audio cause the real experience of the suggested emotion. Table 2 lists the emotional EEG emotional categories induced EEG by audio in detail. In order to imitate the real emotions of identity recognition in actual application scenarios, this paper combines all the emotion categories of the induced emotional EEG signals inputs it into the model for learning. At the same time, we explore the influence of EEG signals with different time window sizes on the performance of identification. Then we divided the induced EEG into three kinds of different time window sizes: 1 s, 3 s and 5 s EEG data for PI. Each subject performed 265 emotional EEG trails, with a total of 8480 samples (265 sub-samples \times 32 subjects); each participant's ID number was used as a label in the PI. The description of the data and labels is as follows:

TABLE 1: Emotional EEG data format with tags.

Array name	Array shape
Data	$30 \times 265 \times 256 \times 256$ participate \times trial \times channel \times data
Labels	30×265 participate \times trail

TABLE 2: Emotional categories of EEG signals induced by audio stimulation.

Positive	Negative
Love	Disgust
Joy	Jealousy
Happy	Grief
Compassion	Frustration
Content	Anger
Relief	Sad
Excite	Fear
Awe	

- (1) Data: number of participants \times 265 sub-sample \times 256 EEG data points (1 s, 256 Hz adoption rate)
- (2) Label: identification number \times 265 sub-sample \times 1 (ID)

In all experiments, the training and test sets are divided into samples using 5-fold cross-validation. 80% of the sub-samples are used as training data and 20% of the sub-samples are used as the test set. In each compromise, we ensure that the sub-samples of each trial are not allocated to multiple sets. Therefore, the sub-samples in the training and test sets are completely independent.

3.3. Comparison of Affective EEG-Based PI among EEGs from Different Frequency Bands. The acquisition of EEG signals is usually a change in the potential activity of the human cerebral cortex. Electrical activity is the EEG signal formed by billions of cells forming the neurons of the human brain. The potential difference between the inside and outside of the neuron cell membrane is the EEG signal. Most researchers usually divide EEG signals into multiple frequency bands for analysis. Here, this paper also divides the EEG signal into four frequency bands: theta (4–8 Hz), alpha (8–15 Hz), beta (15–32 Hz), gamma (32–40 Hz) and all frequency bands (4–40 Hz). First, we used classic Butterworth band-pass filter to obtain EEG signal data for each frequency band, and then use CNN dense net algorithms to extract effective features of the affective EEG signal from different frequency bands for PI. This article is to verify whether the rhythm of different frequency bands has an impact on the performance of PI. This paper uses the proposed DCNN net method, CNN-LSTM [13] and EEG-net [19, 22] for comparison experiments. We used the average of fivefold cross-validation CRR accuracy rate is compared and analyzed. The EEG rhythm with the most significant biological characteristics is selected as the rhythm for PI.

3.4. Comparison of Affective EEG-Based PI among EEGs from Sets of Sparse EEG Electrodes. Evaluation of electrode recording factors in EEG-based personal identification: A vital step in real implementations[23]. In order to simplify the PI device, it is more convenient in actual application scenarios. In this experiment, this paper assumes whether it is possible to reduce the number of electrodes from 256 to 32 while maintaining the same high CRR accuracy. The fewer the number of electrodes needed in PI, it's the easier the system is to use and practical. For study this problem, this paper defines 8 groups of EEG electrode groups respectively: right frontal lobe (A), parietal lobe (B), left temporal lobe (C), right brain Lobe (D), left cerebral lobe (E), left frontal lobe, left temporal lobe, left cerebral lobe (F), left frontal area (G) and right temporal lobe (H). In this research, this paper also uses the DCNN net method proposed in this paper and CNNLSTM and EEG net for comparison experiments. We used the average CRR accuracy of five-fold cross-validation for comparison and analysis. Select the electrode group with the most obvious and stable biological characteristics as the electrode group for PI.

In the case of reducing the number of electrodes, in order to further improve the performance of the model, channels with more emotional EEG information are further selected from the screened 32-channel electrodes. This paper proposes a channel attention mechanism algorithm for automatic channel selection. Make the DCNN net focus on the channels with strong EEG signal characteristics when learning the biological characteristics of the emotional EEG signal. So this paper adds the channel attention mechanism method before the DCNN net performs biological feature learning to makes the performance of DCNN net better. Through the channel attention mechanism method, each sample (including training samples and test samples) has its own unique set of weights, which are used for the weighting of its own feature channels. Therefore the model can efficiently perform PI.

3.5. Comparison of Proposed CADCNN Net and Other Traditional Machine Learning Approaches toward Affective EEG-Based PI Application. In the previous experiments, this paper conducted experiments on the CADCNN net and DCNN net. At the same time, to prove that the deep learning algorithm proposed in this paper is better than the traditional machine learning algorithm. In this experiment, this paper chose the traditional and commonly used machine learning algorithms: Random Forest (RF) [21, 24] and Multilayer Perceptron (MLP) [1]. The above two traditional machine learning classifiers and the latest deep learning methods EEG net, CNNLSTM, CADCNN net and DCNN net are respectively compared. The EEG data used in this experiment is the optimal rhythm and optimal electrode group selected in the previous two experiments.

4. Results

The experimental results are reported separately for each experiment in this section. The analysis based on the various frequency bands of emotional EEG signals, the sparsity of

EEG electrodes and the performance of existing methods is compared.

4.1. Comparison of Affective EEG-Based PI among Different Affective States. Collecting EEG signals in real time and preprocessing the signals and selecting the appropriate rhythm are very important to improve the performance of PI. Therefore, we firstly evaluated our proposed method (DCNN net) using EEG signals in the five canonical bands to identify the critical ones. In addition to DCNN net, latest deep learning methods EEG net, CNNLSTM was used on the same input bands to confirm the finding. When experimenting with different frequency bands on the emotional EEG data set, it spanned 15 different emotional states (love, joy, happy, relief, compassion, content, excite, awe, anger, jealousy, disgust, frustration, fear, sad, grief) EEG signal. As shown in Figure 4, the experimental results showed that alpha and beta frequency bands provide significantly higher CRR than gamma, theta and all bands. As the calculated variance of the alpha rhythm is lower than that of the beta rhythm, the alpha rhythm has a higher stability than the beta rhythm. Therefore, this article chooses the alpha rhythm as the main rhythm for PI. The comparison of the mean CRR (with standard error bar) among different affective EEG frequency bands and different recognized approaches had been shown in Figure 4.

4.2. Comparison of Affective EEG-Based PI among EEGs from Different Frequency Bands. In order to evaluate the impact of reducing the number of electrodes on the PI performance of the method proposed in this paper, we divides the 256 electrodes into brain functional areas, and divides the electrode groups into 8 groups with 32 electrodes in each group. The brain functional areas of each electrode group are respectively Right frontal lobe (A), parietal lobe (B), left temporal lobe (C), right cerebral lobe (D), left cerebral lobe (E), left frontal lobe, left temporal lobe, left cerebral lobe (F), Left frontal area (G) and right temporal lobe (H). From the results, we can see that the reduction in the number of electrodes does not reduce the PI performance of the algorithm proposed maintains a fairly high accuracy rate, while the EEG net and CNNLSTM algorithms have reduced the number of electrodes PI performance drops. According to Table 3, the mean CRR reported that brain function area in the B area (parietal lobe) shows the best performance. CADCNN net reached up to 96.24% mean CRR. After the reduction of the number of EEG electrodes from 256 to 32 for more practical application , B area was the best 32 electrodes for application in similar scenarios to this experiment.

Furthermore, to get more informative electrodes from the 32 selected electrodes, this experiment adds the channel attention mechanism algorithm. Before the data is input to the DCNN net, first use the channel attention mechanism algorithm to quickly filter out the channels of high-value information from the limited electrodes information and then input it into the DCNN net algorithm proposed in this article to PI.

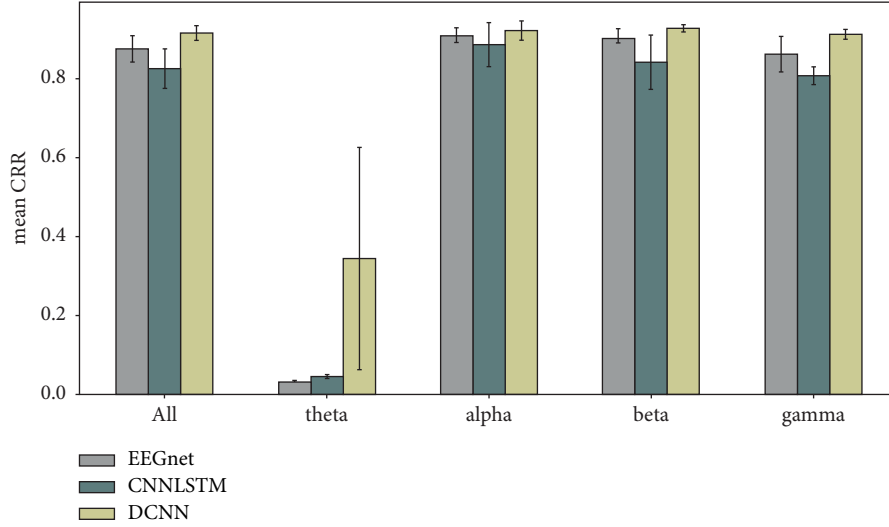


FIGURE 4: Comparison of CRR among five sets of EEG frequency bands.

TABLE 3: The average correct recognition accuracy of 8 brain functional areas and all electrode groups in EEG-net, CNN, CNNLSTM and CADCNN net experiments.

Cortical regions	CADCNN	EEG net	CNN	CNNLSTM
Right frontal lobe	0.8649	0.8569	0.9198	0.8612
Parietal lobe	0.9624	0.8442	0.9299	0.8718
Left temporal lobe	0.9217	0.7756	0.9249	0.8535
Right cerebral lobe	0.9228	0.7716	0.9211	0.8620
Left cerebral lobe	0.9222	0.7925	0.9226	0.8544
Right cerebral lobe	0.8971	0.7756	0.9247	0.8503
Left frontal area	0.9179	0.6750	0.9205	0.8705
Right temporal lobe	0.9151	0.7037	0.9163	0.8666
All electrodes	0.9107	0.8873	0.9162	0.9236

According to experiment results, it shows that the algorithm proposed in this paper has learned the main biological characteristics of emotional EEG signals well, and the reduction of the number of electrodes can effectively reduce the noise and redundant EEG signal biometric information generated by the environmental impact of EEG signals. And after the channel attention mechanism is added, the loss value of training in each epoch drops the fastest. The training loss value is shown in Figure 5. It shows that after adding channel attention mechanism, CADCNN net model can strengthen the learning of important features while learning individual EEG features, reduce the learning of unimportant features, and then carry out effective identification.

4.3. Comparison of Proposed CA-DCNN Net and Other Traditional Machine Learning Approaches toward Affective EEG-Based PI Application. In the previous two band screening and channel selection experiments, we found that there are two people's data sets are pathological EEG data. Therefore, in this experiment, we will eliminate the EEG signals of these two people, and then carry out the algorithm comparison experiment. A comparison between the latest deep learning methods and traditional machine learning classifiers used in

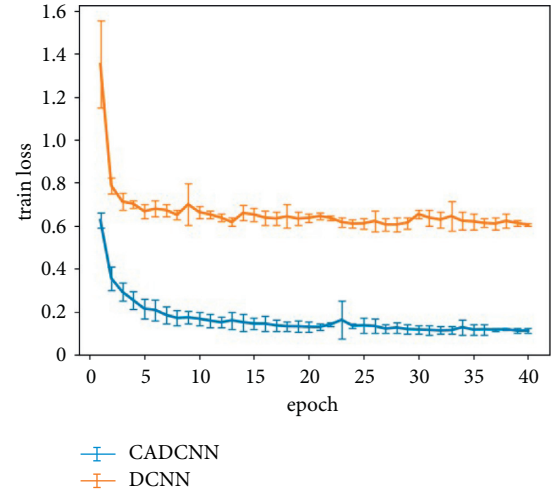


FIGURE 5: CADCNN net and DCNN net algorithm loss value per epoch.

the PI based on different emotional state EEG. To evaluate the effectiveness of the algorithm, we compared our CADCNN net model with classical EEG-net and CNNLSTM two conventional classifiers, MLP and random forest (RF) using to PI. Results show that the CADCNN net and CNN models are able to generalize over different states. However, the conventional classifiers can hardly handle EEG signals of different states other than those used in the training phase. In this experiment, CADCNN net achieved a mean CRR of 96.24%. In comparison, MLP and RF only achieved a mean CRR of 92.12% and 80.54% using signals in the 15 different affective states. The comparative results in Table 4 also indicated that CACNN dense net was potentially a better solution to use the different states affective EEG than CNN and traditional machine learning classifiers. Since the feature matrix actually represents the feature splicing between each layer of convolution operation and the previous layer of convolution operation. Compared with the traditional convolution operation, CADCNN net can provide a more

TABLE 4: Experimental results of the average correct recognition accuracy of each algorithm.

Algorithm	Accuracy
CADCNN net	0.9624
DCNN net	0.9588
CNNLSTM	0.9000
EEG-net	0.8539
MLP	0.9212
RF	0.8054

effective method to learn biology the uniqueness of EEG signals. In summary, the proposed learning model based on affective EEG and CADCNN net is demonstrated to be able to learn unique biometric traits from EEG signals for PI in diverse affective states.

4.4. Comparison of the Time Window Size of Emotional EEG Signals. In this analysis, we investigate whether different window sizes will affect the PI performance. In this experiment, this article used 15 kinds of emotional EEG signal of alpha band and B area brain function electrodes for training and testing. We used the forward steps for all the moving windows, despite the three window sizes. Specifically, the three moving windows in comparison are, 1 second, 3 seconds, and 5 seconds. The PI results of emotional EEG signals with different time window sizes are shown in Figure 6. As the time window size of emotional EEG signals changes, it does not bring higher PI performance. Results in Figure 6 indicate that larger window sizes do not bring improved performance. Contrarily, a slight degradation of the correct recognition rate is observed with larger window sizes.

5. Discussion

In this paper, we mainly focus on two issues, namely, the physical and algorithmic issues of EEG-based PI applications. The physical issues referred to the EEG capturing such as the different affective states, the different frequency bands, and the electrode positions on the scalp. The algorithmic issues exhibited the operation of the proposed CADCNN net approach on EEG in an effective way for PI applications. We also considered the advantages of CADCNN net over the other relevant traditional machine learning approaches (MLP and RF).

Regarding physical issues, the experimental results indicated that CADCNN net approaches could deal with different affective states EEG signals, reaching up to 93.34% mean CRR. On the other hand, a traditional machine learning approach such as RF and MLP to PI did not reach 85% mean CRR. The performance of PI in each frequency band is uneven. Finally, this paper selects the alpha rhythm of the emotional EEG signal with the highest mean CRR of PI. Then this article also explores the impact of reducing the number of electrodes on the performance of PI. We divide the electrodes of emotional EEG signals into 8 groups of 32-lead electrodes according to the brain function area. It is found that the algorithm proposed in this paper does not

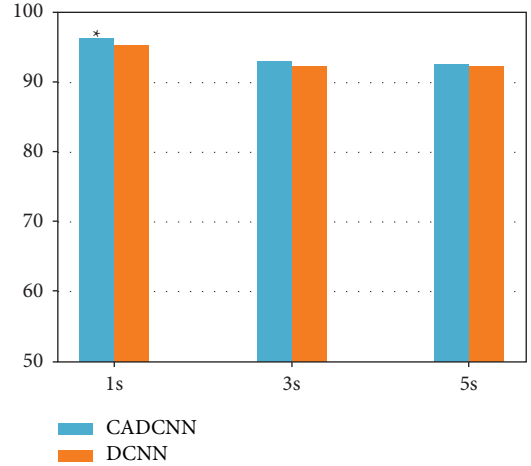


FIGURE 6: The PI results of different time window sizes in the average correct recognition accuracy of CADCNN net and DCNN net algorithms.

affect the PI performance and still maintains equivalent high CRR when the number of electrodes is reduced. It shows that the reduction of the number of electrodes is helpful to design EEG signal acquisition equipment, which is convenient for practical application. For further explore the feasibility of PI in practical applications, this paper also further explores the impact of different time windows on the performance of PI. We use different emotional EEG signal data with time windows of 1 s, 3 s, and 5 s, respectively. The experimental results of the proposed algorithm show that with the change of the time window of the affective EEG signal, the PI performance is not affected. It shows that the algorithm proposed in this paper can effectively learn the unique biological characteristics that promote PI. With the extension of the EEG signal time, the noise in the acquisition process also increases. Therefore, it is also very important to effectively learn the unique characteristics of PI from the emotional EEG signal containing noise. However, the CADCNN net proposed in this paper does not affect the performance of PI as the time window of the EEG signal changes. It can be determined that the algorithm proposed in this paper has effectively learned the unique characteristics to PI.

Concerning algorithmic issues, the CADCNN net proposed based on emotional EEG signal PI can be seen from the experimental results to be superior to the latest deep learning algorithms and related traditional machine learning algorithms (CNNLSTM, EEG-net, MLP and RBF). For example, in the comparison between the CADCNN net and the CNN, CNNLSTM, EEG net, MLP and RBF algorithms, the CADCNN net is significantly faster in the training model convergence speed while having a slightly higher mean CRR, especially when a small number of electrodes are used. In addition, the CADCNN net overcomes the influence of feature engineering on the performance of PI. The algorithm proposed in this paper does not use specially designed feature extraction methods such as PSD, which avoids the influence of emotional state when extracting biometrics for

PI. On the contrary, the CADCNN net algorithm proposed in this paper is a data-driven algorithm, which builds a model based on training data, and is an uncertainty algorithm. The minimizing of loss guided the models to overcome the influence of affective states. Therefore, CADCNN net can outperform machine learning algorithms. The algorithm model proposed in this paper also overcomes the influence of different emotional states and the influence of different time window sizes on the performance of PI. Therefore, the CADCNN net algorithm proposed in this paper can outperform the machine learning algorithm and the latest deep learning algorithm. In addition, recent research on the PI of emotional EEG signal data sets has shown that deep learning methods have higher accuracy than traditional classifiers.

6. Conclusion

This paper proposes a novel CADCNN net algorithm for the PI of emotional state EEG. The algorithm proposed in this paper has better PI performance than conventional machine learning algorithms in the mean CRR of PI. CADCNN net can learn the unique biological characteristics for PI better than the current relatively new deep learning methods and machine learning methods. The mean CRR of extracting the alpha rhythm from the emotional EEG and selecting 32 electrodes for PI can reach 96.24%. Therefore, the CADCNN net overcomes the influence of emotional state in EEG-based PI reported in previous studies and complements the research on affective EEG signal PI.

Data Availability

The data are available at <https://headit.ucsd.edu/studies/3316f70e-35ff-11e3-a2a9-0050563f2612>.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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