# Channel Selection Method Based on CNNSE for EEG Emotion Recognition

Zhongmin Wang
*School of Computer Science and Technology Xi'an University of Posts and Telecommunications*
*Shaanxi Key Laboratory of Network Data Analysis and Intelligent Processing Xi'an University of Posts and Telecommunications*
Xi'an, China
zmwang@xupt.edu.cn

Shuyuan Hu
*School of Computer Science and Technology Xi'an University of Posts and Telecommunications*
Xi'an, China
shuyuanhu01@gmail.com

Ge Liu
*School of Computer Science and Technology Xi'an University of Posts and Telecommunications*
Xi'an, China
bick1230@163.com

Hui Song
*School of Computer Science and Technology Xi'an University of Posts and Telecommunications*
*Shaanxi Key Laboratory of Network Data Analysis and Intelligent Processing Xi'an University of Posts and Telecommunications*
Xi'an, China
songhui@xupt.edu.cn

***Abstract*—Emotion recognition using electroencephalogram (EEG) signals has become a very important research direction in the field of artificial intelligence. However, traditional emotion recognition using all channels of EEG signals may cause computational complexity and interference information, thus it is not suitable for daily-life emotion recognition. This paper proposes a novel channel selection framework, called convolutional neural network with Squeeze-Excitation block (CNNSE), to select an optimal EEG channel set for emotion recognition. First, EEGLAB is used to obtain EEG time-frequency images. And the weights of all EEG channels are recalibrated by the CNNSE module. Finally, channel reduction is conducted by the analysis of obtained weight value. The experiments use publicly available dataset DEAP. It can be seen from the experimental results that the proposed method could maintain a higher recognition accuracy, and reduce EEG channels effectively.**

***Index Terms*—emotion recognition, channel selection, electroencephalogram (EEG), deep learning, data preprocessing**

## I. Introduction

Emotions can effectively reflect people's mental state [1], and emotions have an important impact on our lives. Researchers use various methods such as facial expressions and sounds to identify emotional states [2]. However, people can easily use these external physiological reactions to disguise their true emotions. Electroencephalogram (EGG) is an autonomous activity of the nervous system. Its objectivity determines that it is difficult for people to consciously control their emotional expression. This physiological response can more realistically and objectively reflect the emotional state of the people, so EEG signals have received more and more attention in the research of emotion recognition.

The EEG signals generally are multi-channel signals, we have two strategies to process signals: the first method is to perform channel selection, and another is to use all channels for research [3]. Using all channel signals will lead to high computational complexity and cause overfitting problems. Therefore, using an effective channel selection algorithm is helpful to solve the above problems, [4].

EEG channel selection have become more and more important in emotion recognition [5]. In recent years, a lot of channel selection method are proposed. For example, Rizon et al [6] proposed a novel channel selection method using asymmetric ratio for identifying human emotions from EEG signals. Lin et al [7] proposed F-score index based to select the optimal EEG channels for emotion recognition. He et al [8] adopted rayleigh coefficient (RC) for EEG channel selection. J Zhang et al [9] proposed a channel selection method based on the ReliefF. By weighting the extracted features and selecting features according to the weight of the features, the channel containing these selected features is the selected channel. On this basis, they also adjusted the weights based on the contribution of a single channel to the classification result, thereby optimizing the channel selection method. Zheng et al [10] presented a channel selection method using DNN. Hu J et al [11] proposed an architecture called Squeeze-and-Excitation Networks (SENet) to study the relationship between convolution neural network (CNN) channels. The method utilizes inter-channel interdependencies to adaptively recalibrate the feature's response on the channel.

This paper proposes a new channel selection method to classify valence emotion using convolutional neural network with Squeeze-Excitation block (CNNSE) to select EEG channels is proposed. Specifically, we first adopt EEGLAB as the preprocessing step to capture EEG spectrogram image containing time-frequency information. Each image can obtain a grayscale matrix, and all grayscale matrices are superimposed as input to the CNN, and each CNN channel corresponds to one EEG channel. Then the recalibration weight of all channels in the CNN by using SE block and sort them in descending order, and channel reduction are conducted by the

978-1-7281-2348-6/19/$31.00 ©2019 IEEE

weight analysis. Compared with other existing models, our contributions are as follows:

1) We use EEG spectrogram representation obtained by EEGLAB. The spectrogram representations are beneficial to extract features.

2) We develop a new channel selection framework use CNNSE-based to selection optimal channels for emotion recognition task. From experimental results, it can be derived that show that our proposed method works better

3) We propose a view that use Squeeze-Excitation block to recalibrate weights of all channels in the CNN, and sort them in descending order. Channel reduction are conducted by the weight analysis.

## II. Material And Method

### A. EEG Dataset

The experiment was performed on public database DEAP [12]. This dataset includes human physiological signals such as EEG signals, body temperature, and skin electricity. The EEG signals include 32 EEG channels, 12 peripheral channels, 3 unused channels, and 1 status channel. There is a total of 32 participants' EEG data. Each experimenter watched 40 music videos of 1s duration and recorded the EEG signal data during watching. Emotional state is described by liking, valence-arousal and other dimensions

### B. Data Processing

In this paper, we study the two-class emotion recognition in the valence dimension. In order to make the emotions easier to distinguish, we just select the data samples with the score on the valence dimension is large 7.5 and is small 3.5. In addition, the EEGLAB is used to convert the EEG data into a spectrogram image with time-frequency domain information. The image is shown in Fig.1. By this operation, we have a total of 15872 spectrogram images of size 400×200, and they will be used in EEG channel selection.

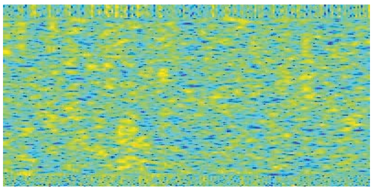


Fig 1. EEG spectrogram

### C. Feature Extraction

In EEG emotion recognition research, various features including statistical features, time domain features, frequency domain features and time-frequency domain features have been widely used in this field [13-15]. This paper uses power features, and SVM is also used in emotion recognition. To increase samples, each one-minute video is sliced into 15 four-second video clips, and 600 sample data can be obtained from each participant. The total number of samples is 19200, and we just select the data samples with score on the valence dimension is large 7.5 and is small 3.5. Thus, we obtain 7440 sample data in valence dimension, each sample contains 32 EEG channels. The feature extraction was performed on 7440 sample data. First, we use wavelet transform to decompose EEG signal into four bands including theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (30-45Hz). Then, the Fast Fourier Transform (FFT) is used in each frequency band of and the power spectrum is calculated. The formulation for calculating the power spectrum of each band is as follows:

$$\text{power} = \frac{1}{N}\sum_{k=1}^{N}|X_k|^2 \tag{1}$$

where $X_k$ is the EEG data obtained by FFT, $N$ is the length of $X$.

### D. Channel Selection Method

The framework of the proposed method is shown in Fig.2. Specifically, we first obtain the 32channel grayscale image, and the matrix of 32 grayscale images are combined into a matrix having a size of 400×200 ×32. The matrix can be obtained for each experimental sample in the dataset. The CNN input is sample data with a height of 200, a width of 400, and a channel of 32. Then, a separable convolution operation is performed to extract features. The data of each channel is separately convoluted, and the output is still 32 channels, representing 32 channels of EEG data. In addition, the 32-channel features are recalibrated using the Squeeze-Excitation module, and the obtained weights are used for channel selection. The Squeeze-Excitation block includes three operations: squeeze, excitation and reweight, and the input of the SE block is the feature U of the $Cth$ channel after convolution.

The Squeeze part uses a global average pooling to convert the input 32 channels with a size of 400×200 into 32 outputs with a size of 1×1, and z ∈ $R^C$ is generated by shrinking U through spatial dimensions $H \times W$, where the $c$-th element z can be defined as:

$$z_c = \mathrm{F_{sq}}(\mathrm{u_c}) = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} u_c(i,j) \tag{2}$$

The Excitation operation is used to capture the dependencies between channels. Use a simple gate mechanism and activate with sigmoid:

$$\mathrm{s} = F_{ex}(z,\mathrm{W}) = \sigma\big(g(z,\mathrm{W})\big) = \sigma\big(\mathrm{W_2}\delta(\mathrm{W_1}z)\big) \tag{3}$$

where $\delta$ refers to ReLU function, $\mathrm{W_1} \in R^{\frac{C}{r}\times C}$, $\mathrm{W_2} \in R^{C\times\frac{C}{r}}$. To limit model complexity and auxiliary generalization, two fully connected (FC) layers are introduced. The first is dimensionality-reduction layer with parameters $\mathrm{W_1}$ with reduction ration value is 16, a ReLU and then a dimensionality-increasing layer with parameters $\mathrm{W_2}$.

The weight $s$ output through the excitation operation can represent the importance of each channel. The selection of the EEG channel can be performed according to the weight $s$.

The final output of Squeeze-Excitation block is obtained by recalibrating U with the activations:

$$\widetilde{\mathrm{x_c}} = \mathrm{F_{scale}}(\mathrm{u_c}, \mathrm{s_c}) = s_c \times u_c \tag{4}$$

where $\widetilde{\mathrm{X}} = [\,\widetilde{\mathrm{x_1}}, \widetilde{\mathrm{x_2}} \dots, \widetilde{\mathrm{x_c}}]$ and $\mathrm{F_{scale}}(\mathrm{u_c}, \mathrm{s_c})$ refers to channel-wise multiplication between the feature map $u_c \in R^{H\times W}$ and the scalar $s_c$.

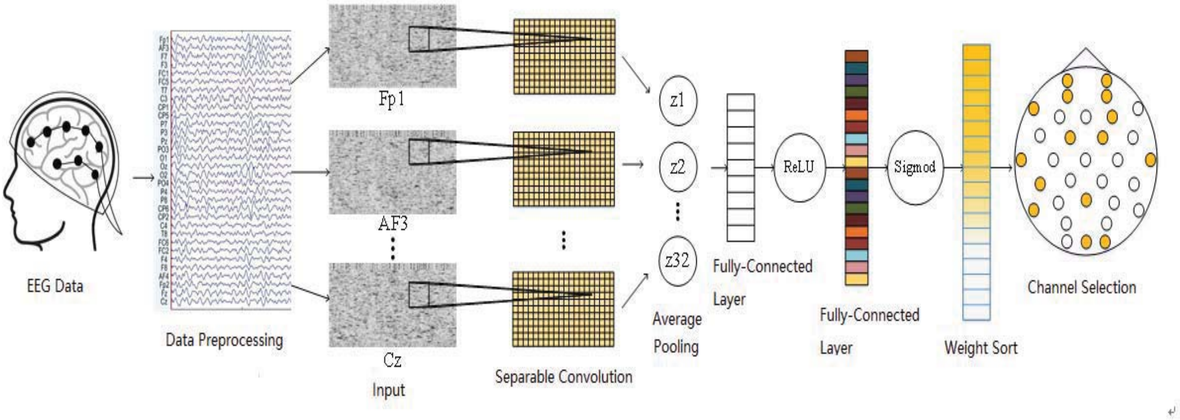



Fig.2 Flowchart of the over approach

## III. Experimental Results And Discussion

### A. Results of Channel Selection

In our work, we use 80% samples of dataset for channel selection experiment, and training iterations is 6205 times. Every 365 experimental trainings, we obtained a weight from the first SE module of CNN. After a lot of training, we finally obtain 32 recalibrated EEG channel weights.

The purpose of recalibrate the weights is to select these channels that are useful for emotion recognition task while suppress unrelated channels. Therefore, according to the experimental results, the weights of the channels are arranged in descending order. After channel weight sorting, the top 15 channels are shown in Table I.

TABLE I. WEIGHT SORT OF TOP 15 CHANNELS

| Weight sort | Channel name | Brain region |
|---|---|---|
| 1 | O2 | Occipital lobe |
| 2 | Fp1 | Frontal lobe |
| 3 | AF3 | Frontal lobe |
| 4 | Fp2 | Frontal lobe |
| 5 | FC2 | Frontal lobe |
| 6 | F4 | Frontal lobe |
| 7 | Pz | Parietal lobe |
| 8 | F7 | Frontal lobe |
| 9 | FC1 | Frontal lobe |
| 10 | Oz | Occipital lobe |
| 11 | AF4 | Frontal lobe |
| 12 | CP5 | central |
| 13 | T7 | Temporal lobe |
| 14 | P7 | Parietal lobe |
| 15 | T8 | Temporal lobe |

### B. Channel Combination Performance Analysis

In the channel selection process, 80% of the samples are used to channel selection experiments, and 20% of the samples are not used. This 80 % of the samples are denoted as dataset A, and 20% of the samples are denoted as dataset B. A and B are used in the selected channel to verify the validity for emotion recognition, respectively. Specifically, dataset A firstly is used to the channel selection experiment, and then it is applied to the selected channel to verify classification rate in the original data. Dataset B is used to verify the recognition rate of the selected channel in an unknown sample. Both datasets use LIBSVM [16] for emotion classification.

We have obtained four bands, and by computing the power of each band, four features are available in each channel. Then, using SVM classifier to recognizing emotion. According to the order of the selected channels, the EEG channel data in the SVM is continuously increased. The valence emotion recognition accuracy of dataset A and dataset B under different channel numbers is shown in Table II.

TABLE II. EMOTION RACOGNITION RATE OF TOP N CHANNELS

| Top-N | Dataset A | Dataset B | Top-N | Dataset A | Dataset B |
|---|---|---|---|---|---|
| 1 | 59.88 | 59.88 | 17 | 73.19 | 74.66 |
| 2 | 60.45 | 60.95 | 18 | 73.74 | 72.58 |
| 3 | 62.68 | 62.5 | 19 | 73.71 | 72.72 |
| 4 | 65.84 | 67.34 | 20 | 73.03 | 75.07 |
| 5 | 68.08 | 67.74 | 21 | 74.14 | 73.52 |
| 6 | 69.35 | 68.88 | 22 | 73.1 | 74.8 |
| 7 | 69.59 | 70.36 | 23 | 73.69 | 75 |
| 8 | 68.95 | 69.02 | 24 | 73.79 | 73.52 |
| 9 | 69.15 | 70.36 | 25 | 73.69 | 74.04 |
| 10 | 70.90 | 71.77 | 26 | 73.56 | 72.78 |
| 11 | 70.53 | 70.7 | 27 | 74.02 | 73.79 |
| 12 | 71.54 | 74.53 | 28 | 74.19 | 75.07 |
| 13 | 71.34 | 72.71 | 29 | 73.62 | 73.39 |
| 14 | 72.16 | 73.12 | 30 | 73.94 | 74.8 |
| 15 | 72.66 | 73.05 | 31 | 73.24 | 74.66 |
| 16 | 72.78 | 72.85 | 32 | 74.63 | 74.53 |

Fig.3 shows the change in the recognition accuracy of the number of channels in dataset A from 1 to 32. It can be found that the emotion recognition accuracy rate is 69.59% when using 7 channels. And 18 channels are enough to obtain 73.74% of classification accuracy. In addition, from 1 channel to 7 channels, the rate of emotion recognition increased rapidly while from 7 channels to 18 channels, the rate of increase in emotion recognition accuracy was relatively slow. Increasing the number of channels, the recognition rate remains basically stable and does not change significantly.

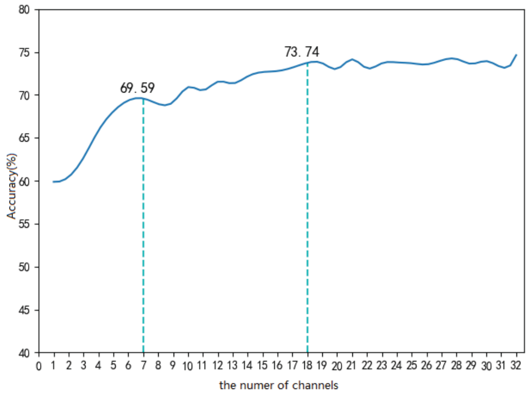



Fig.3 Emotion recognition accuracy in dataset A

The recognition accuracy of dataset B is shown in Fig. 4. When using 7 channels， the rate of emotion recognition reaches 70.36%. When the number of channels reaches 12, its accuracy is 74.53%. The overall trend of recognition accuracy is similar to dataset A. it can be seen that the channels exceed 12, the accuracy does not increase anymore.

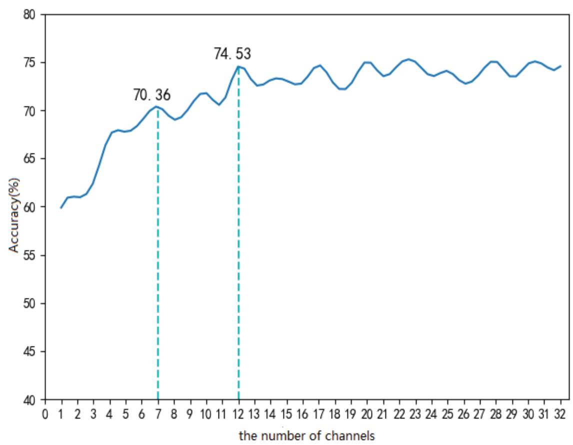



Fig.4 Emotion recognition accuracy in dataset B

Experimental results show that when the number of EEG channels is small, the accuracy of emotion recognition is low. Increasing channel numbers, the emotional information becomes richer, so the accuracy of emotion recognition is also improved. At the same time, when there are too many EEG channels, some unrelated channels will introduce interference, which will adversely affect the recognition rate.

The time-consuming in the emotion recognition task for different channels is illustrated in Fig.5. With the number of channels increases, the time spent on emotional recognition increases dramatically. The selected channels exceeds 12, the accuracy of emotion recognition is basically no longer changed, and the consumption time is still increasing. Using 32-channel takes a total of 0.93s, and the time to use 12 channels is 0.39s. The former takes 2.38 times longer than the latter, but the recognition accuracy differs by no more than 4%. It can be seen that the selected channel can effectively improve emotion recognition accuracy and reduce computational complexity.

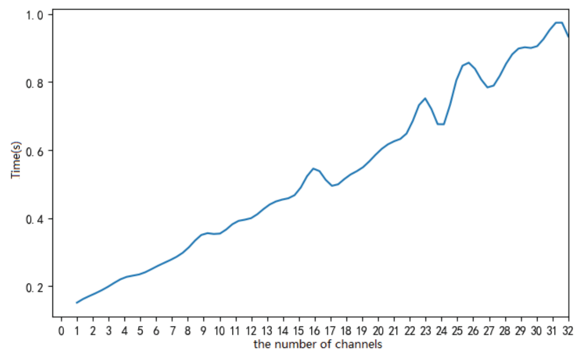



Fig.5 Time-consuming relationship with the number of channels

Based on the above experimental results, two channel subsets are finally obtained, which respectively include 7 channels and 12 channels. The distribution of these two channel subsets is shown in Fig.6, mostly in the frontal and parietal, and the distribution is symmetrical. This result is consistent with other literature [17-18].

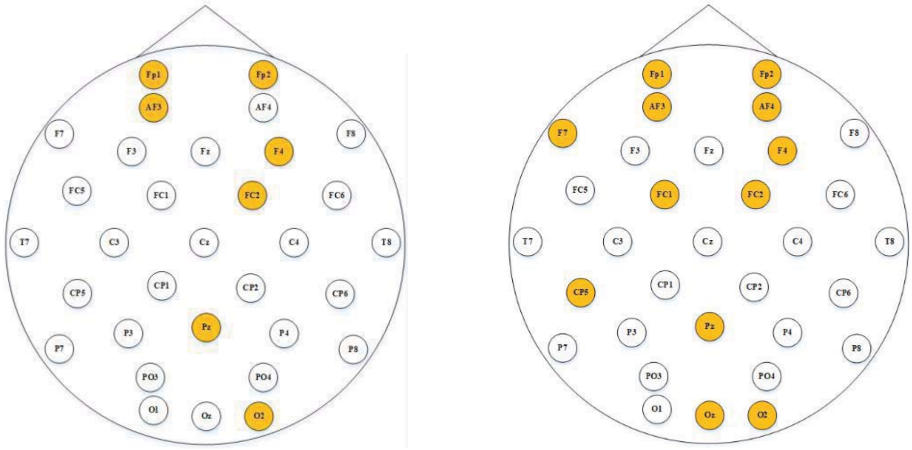
### *C. Comparisons And Discussions*

We compared the experimental results with other existing models using the DEAP database shown in [19]. The comparison results are shown in Table III.

TABLE III. VALENCE：COMPARISON WITH EXISTING MODELS

| Method | Channel Subset | Accuracy |
|---|---|---|
| Relief | Fp1,AF3,F7,F3,FC1,FC5,T7,CP5, P3,Pz,O2,P4,P8,CP6,CP2,C4,T8, FC6,FC2,F4,F8,Fp2,Fz | 64.21% |
| mRMR | Fp1,AF3,Oz,O2,P4,P8, CP2,C4, FC6,FC2,F4,F8, AF4,Fp2,Fz,Cz | 62.89% |
| Our method | O2,Fp1,AF3,Fp2,FC2,F4,Pz (top-7) | 70.36% |
| | O2,Fp1,AF3,Fp2,FC2,F4,Pz, F7,FC1,Oz,AF4,CP5 ( top-12) | 74.53% |

As shown in Table III, the method listed in[19] need to use a host of channels to obtain a high recognition rate. However, our method greatly reduce the number of channels, and obtain a high recognition rate. We select 7 or 12 channels can be utilized in the design of wearable EEG devices.



7 channels 12 channels

Fig.6 Top-7 and Top12 channel distribution

## IV. CONLUSIONS

This paper proposes a channel selection method based on SENet for emotion recognition task. SVM is used to classify different emotion. We select 7 channels and 12 channels for valence emotion recognition, respectively. The experimental results show that the channel combination obtained by this method can greatly reduce the number of channels, effectively reduce the computational complexity, and improve the recognition efficiency. Therefore, the proposed method can be effectively applied to the EEG channel selection study. In addition, it can provide new ideas for simplifying the design of wearable devices. In future work, we will apply the proposed method to multimodal emotion recognition task.


## ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (No.61373116), the Special Scientific Research Program of Education Department of Shaanxi Province (No.16JK1706), Shaanxi Science and Technology Coordination Innovation Project (No.2016KTZDGY04-01).


## REFERENCES


[1] S. Poria, E. Cambria, R. Bajpai, and A. Hussain, “A review of affective computing: From unimodal analysis to multimodal fusion,” Information Fusion, vol. 37, pp. 98–125, 2017.

[2] M. Soleymani, S. Asghari-Esfeden, Y. Fu, and M. Pantic, “Analysis of eeg signals and facial expressions for continuous emotion detection,” IEEE Transactions on Affective Computing, vol. 7, no. 1, pp. 17–28, 2016.

[3] D. Garrett, D. A. Peterson, C. W. Anderson, and M. H. Thaut, “Comparison of linear, nonlinear, and feature selection methods for eeg signal classification,” IEEE Transactions on neural systems and rehabilitation engineering, vol. 11, no. 2, pp. 141–144, 2003.

[4] T.Alotaiby,F.E.A.El-Samie,S.A.Alshebeili,andI.Ahmad,“A review of channel selection algorithms for eeg signal processing,” EURASIP Journal on Advances in Signal Processing, vol. 2015, no. 1, p. 66, 2015.

[5] K. Ansari-Asl, G. Chanel, and T. Pun, “A channel selection method for eeg classification in emotion assessment based on synchronization likelihood,” in 2007 15th European Signal Processing Conference. IEEE, 2007, pp. 1241–1245.

[6] M Rizon, M. Murugappan and S. Yaacob, “Asymmetric ratio and fcm based salient channel selection for human emotion detection using eeg,” 2008.

[7] Y.-P.Lin, C.-H.Wang, T.-P.Jung, T.-L. Wu, S.-K. Jeng,J.-R. Duann,and J.-H. Chen, “Eeg-based emotion recognition in music listening,” IEEE Transactions on Biomedical Engineering, vol. 57, no. 7, pp. 1798–1806, 2010.

[8] L. He, Y. Hu, Y. Li, and D. Li, “Channel selection by rayleigh coefficient maximization based genetic algorithm for classifying single-trial motor imagery eeg,” Neurocomputing, vol. 121, pp. 423–433, 2013.

[9] J. Zhang, M. Chen, S. Zhao, S. Hu, Z. Shi, and Y. Cao, “Relieff-based eeg sensor selection methods for emotion recognition,” Sensors, vol. 16, no. 10, p. 1558, 2016.

[10] W.-L. Zheng and B.-L. Lu, “Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks,” IEEE Transactions on Autonomous Mental Development, vol. 7, no. 3, pp. 162–175, 2015.

[11] Hu J, Shen L, Sun G. Squeeze-and-excitation networks[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2018: 7132-7141.

[12] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, “Deap: A database for emotion analysis; using physiological signals,” IEEE transactions on affective computing, vol. 3, no. 1, pp. 18–31, 2012.

[13] Zheng W L, Zhu J Y, Lu B L. Identifying stable patterns over time for emotion recognition from EEG[J]. IEEE Transactions on Affective Computing, 2017, 1(Jun)1-1

[14] Abdossalehi M, NASRABADI A M, Firoozabadi M. Combining independent component analysis with chaotic quantifiers for the recognition of positive, negative and neutral emotions using EEG signals[J]. Indian J. Sci. Res, 2014, 5(1): 432-437.

[15] Yin Z, Zhao M, Wang Y, et al. Recognition of emotions using multimodal physiological signals and an ensemble deep learning model[J]. Computer methods and programs in biomedicine, 2017, 140(Mar): 93-110.

[16] Chang C C, Lin C J. LIBSVM: a library for support vector machines[J]. ACM transactions on intelligent systems and technology (TIST), 2011, 2(3): 27.

[17] Srinivas M V, Rama M V, Rao C B R. Wavelet Based Emotion Recognition Using RBF Algorithm[J]. brain, 2016, 4(5):29-34.

[18] Kwon Y H, Shin S B, Kim S D. Electroencephalography Based Fusion Two-Dimensional (2D)-Convolution Neural Networks (CNN) Model for Emotion Recognition System[J]. Sensors (Basel, Switzerland), 2018, 18(5):1383-1396.

[19] R. Jenke, A. Peer, and M. Buss, “Feature extraction and selection for emotion recognition from eeg,” IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 327–339, 2014.