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# A personality-guided affective brain–computer interface for implementation of emotional intelligence in machines



**Key words:** Electroencephalogram (EEG); Emotion recognition; Attention mechanism; Personality traits

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# Motivation

1. Deep learning methods show great potential in emotion recognition based on electroencephalogram (EEG) signals, which is still a challenging and complex problem.

2. It would be better to incorporate the personality factor into EEG-based methods because many studies have found differences in electrodes' activities between people with different personalities.

3. Consequently, how to effectively incorporate the personality factor and EEG signals to construct more personalized and effective affective brain–computer interfaces (BCIs) is significant.

# Main idea

1. A convolutional recurrent neural network (CRNN) with personality-guided attention mechanism is designed to integrate personality information and EEG signals.

2. The information of personality is used to guide the attention mechanisms in convolutional neural network (CNN) and recurrent neural network (CRNN) to explore the correlations between activities of electrodes and people with different personalities.

3. Attention-based CNN can explore the complex relations of electrodes within distinct brain scalp regions. Attention-based RNN can extract discriminative representations.

# Method

1. A novel CRNN framework is proposed which consists mainly of three parts.

2. The first part of the model can simultaneously explore inter- and intra-regional correlations of electrodes. The second part can explore attentive regional and temporal dynamics by integrating the personality factor. The third part is used for emotion recognition.

# Method (Cont'd)

Personality-guided attention-based CRNN

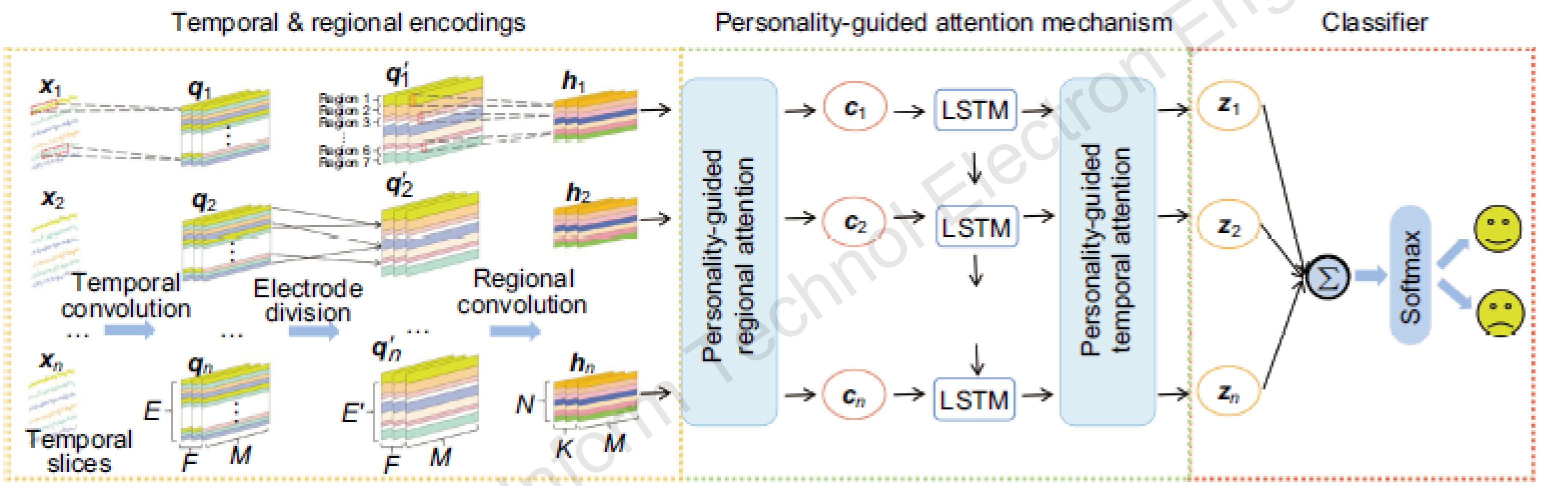


**Fig. 1 Flow diagram of our model**

(1) Temporal and regional encodings (yellow) first use temporal convolution to extract temporal representation $q_i$ from each EEG slice $x_i$. Then, electrode division is applied to organize electrodes into categories according to their locations. Next, regional convolution is used to extract regional representation $h_i$, which can simultaneously explore inter- and intra-regional correlations of electrodes. (2) Personality-guided attention mechanism (green) includes regional attention and temporal attention, which can explore attentive regional and temporal dynamics by integrating the personality factor. (3) Finally, feature vectors will be fed into one fully connected layer for emotion recognition (red). EEG: electroencephalogram; LSTM: long short-term memory. References to color refer to the online version of this figure

# Major results

**Table 2** **Performance comparison among different EEG modeling methodologies**

| Model | | Accuracy (%) | | Precision (%) | | F1 score (%) | |
|---|---|---|---|---|---|---|---|
| | | Arousal | Valence | Arousal | Valence | Arousal | Valence |
| SVM | Mean | 50.8** | 55.2** | 53.7** | 44.6** | 53.0** | 41.8** |
| | Std | 6.5 | 6.5 | 13.3 | 10.8 | 9.7 | 10.3 |
| DT | Mean | 50.0** | 52.1** | 53.7** | 41.8** | 51.0** | 41.2** |
| | Std | 7.5 | 6.3 | 13.2 | 13.0 | 8.5 | 10.5 |
| DeepConvNet | Mean | 51.9** | 50.6** | 54.0** | 54.1* | 58.4* | 49.9** |
| | Std | 11.6 | 6.7 | 20.1 | 18.9 | 19.1 | 18.9 |
| EEGNet | Mean | 55.1** | 50.1** | 57.2* | 41.4** | 58.6* | 43.3** |
| | Std | 12.6 | 10.3 | 15.6 | 17.3 | 16.1 | 16.8 |
| CRAM | Mean | 50.5** | 50.2** | 51.0** | 40.7** | 53.2** | 43.1** |
| | Std | 10.0 | 10.7 | 16.3 | 14.2 | 15.8 | 13.9 |
| PA-CRNN | Mean | **66.2** | **65.4** | **64.0** | **59.5** | **65.6** | **56.9** |
| | Std | **8.5** | **8.8** | **8.7** | **7.7** | **16.0** | **13.4** |

* for paired-sample $t$-test at significance level $\alpha = 0.05$ and ** for paired-sample $t$-test at significance level $\alpha = 0.01$. Best results are in bold

# Major results (Cont'd)

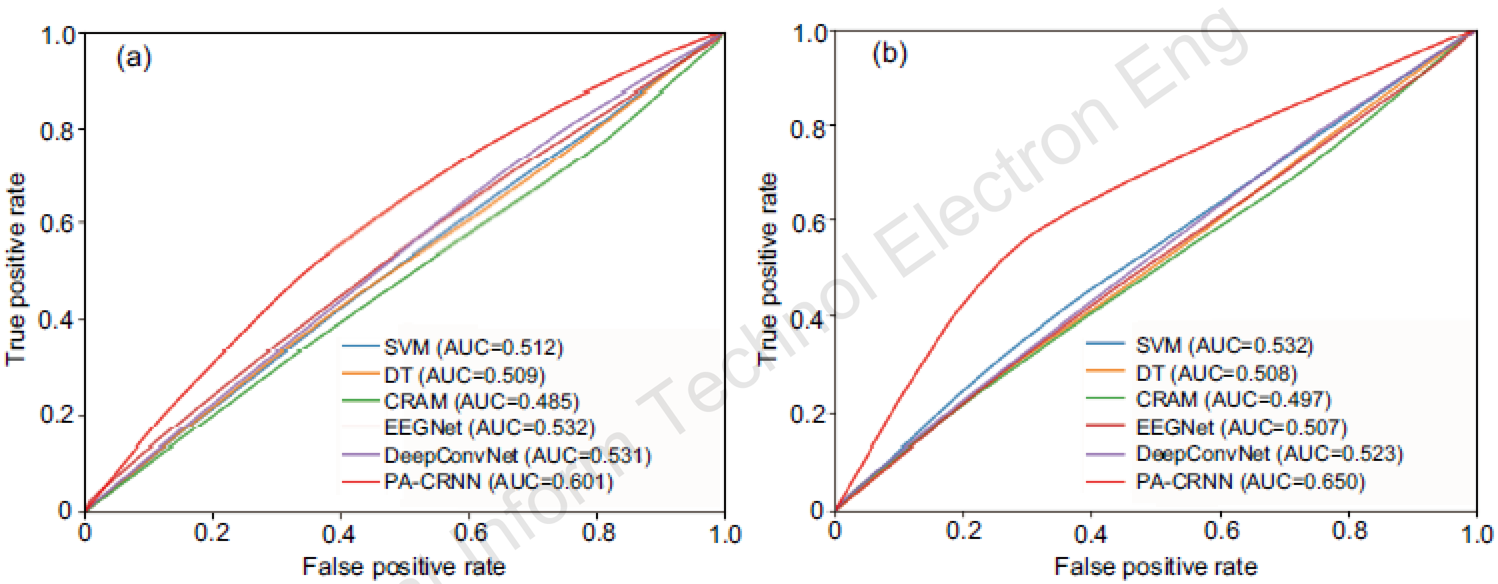


**Fig. 4** Comparison of the ROC curves among different EEG modeling methodologies: (a) arousal; (b) valence

# Major results (Cont'd)

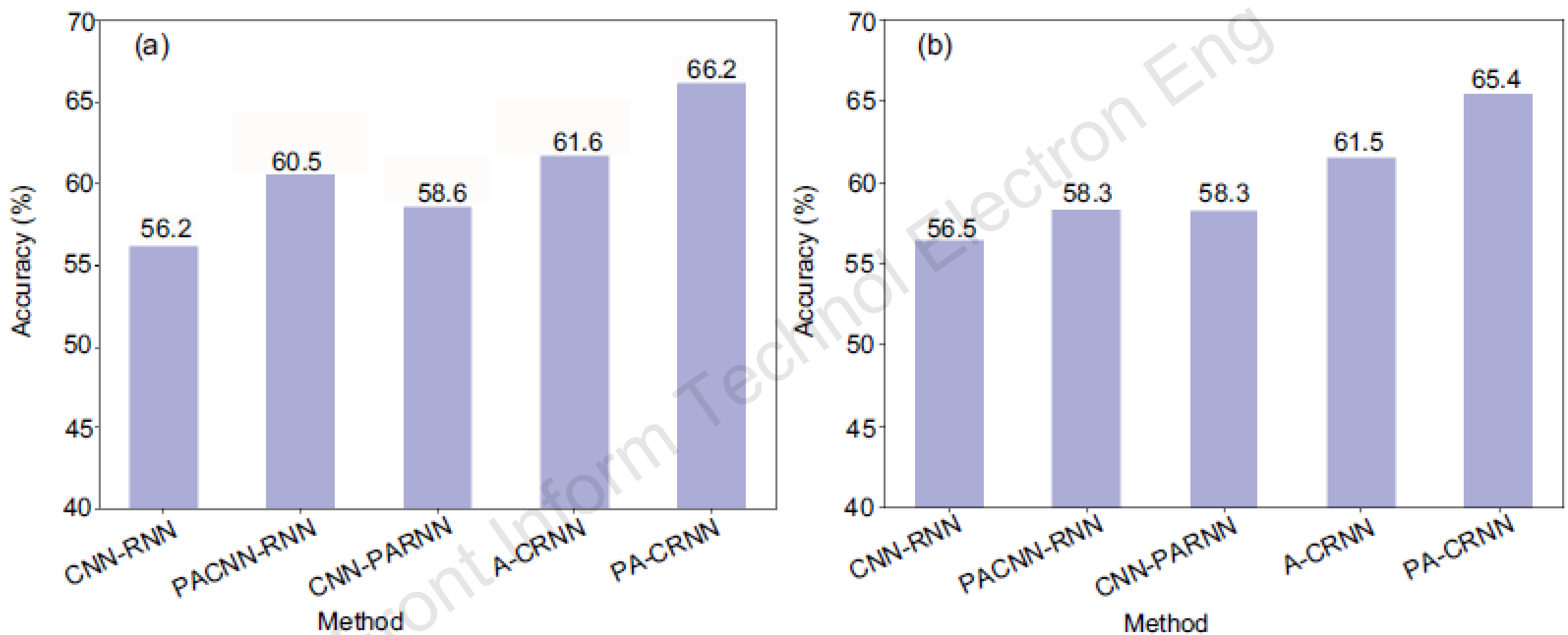




**Fig. 5** Average classification accuracy of our model after ablation of different modules: (a) arousal; (b) valence

# Major results (Cont'd)

**Table 3 Performance comparison among different incorporating strategies for the personality factor**

| Model | | Accuracy (%) | | Precision (%) | | F1 score (%) | |
|---|---|---|---|---|---|---|---|
| | | Arousal | Valence | Arousal | Valence | Arousal | Valence |
| SVM-P | Mean | 50.3** | 55.4** | 53.6** | 44.8** | 51.9** | 41.9** |
| | Std | 7.5 | 6.1 | 14.0 | 9.9 | 10.3 | 10.0 |
| DT-P | Mean | 51.0** | 51.8** | 54.5** | 42.0** | 50.2** | 42.0** |
| | Std | 7.0 | 6.0 | 14.2 | 10.9 | 10.6 | 8.7 |
| Fiterau et al. (2017)'s | Mean | 50.4** | 52.7** | 50.9** | 45.2** | 50.5** | 44.8** |
| | Std | 11.6 | 10.6 | 20.5 | 12.7 | 19.4 | 15.6 |
| van Leeuwen et al. (2019)'s | Mean | 51.5** | 50.6** | 54.6** | 43.3** | 56.2** | 48.0** |
| | Std | 10.8 | 9.2 | 15.2 | 11.0 | 14.4 | 16.8 |
| Zhang XW et al. (2020)'s | Mean | 50.8** | 52.3** | 53.8** | 43.7** | 52.7** | 47.2** |
| | Std | 12.7 | 9.7 | 15.3 | 11.4 | 14.4 | 11.2 |
| PA-CRNN | Mean | **66.2** | **65.4** | **64.0** | **59.5** | **65.6** | **56.9** |
| | Std | **8.5** | **8.8** | **8.7** | **7.7** | **16.0** | **13.4** |

SVM-P: support vector machine with personality factor; DT-P: decision tree with personality factor. ** for paired-sample $t$-test at significance level $\alpha = 0.01$. Best results are in bold

# Major results (Cont'd)

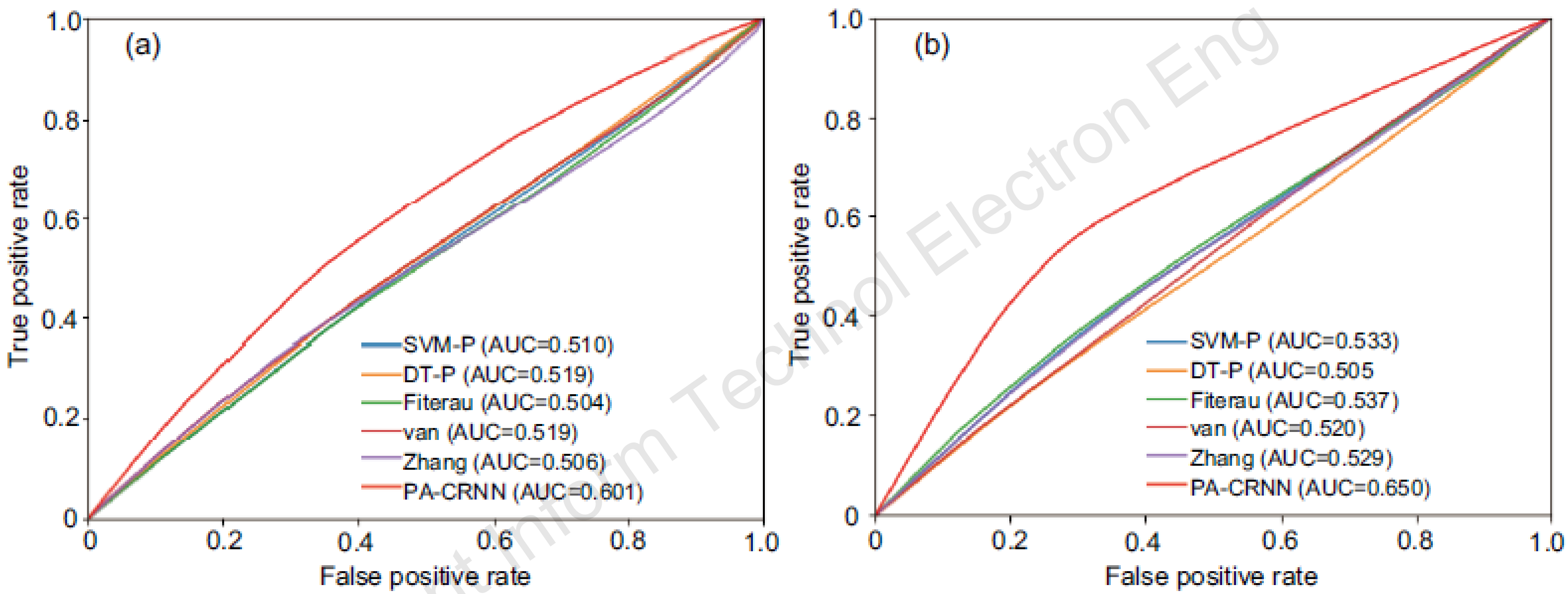




**Fig. 6** Comparison of the ROC curves among different incorporating strategies for the personality factor: (a) arousal; (b) valence (Fiterau: Fiterau et al. (2017); van: van Leeuwen et al. (2019); Zhang: Zhang XW et al. (2020))

# Major results (Cont’d)

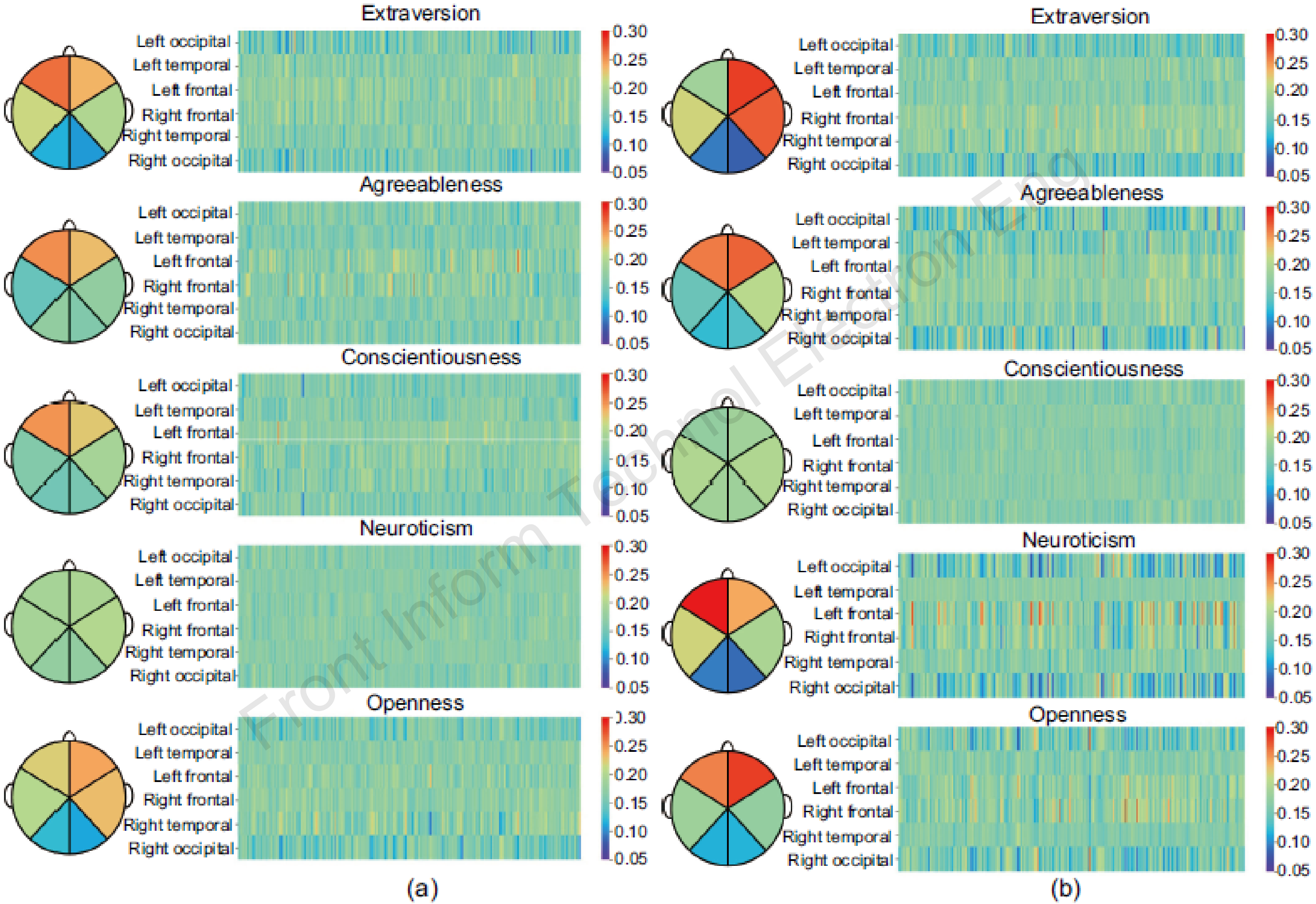




**Fig. 7 Visualization of the regional-attention weights for each Big-Five personality dimension on the arousal (a) and valence (b) labels**

For each matrix, the rows represent different brain scalp regions and the columns correspond to different dimensions of the regional-attention weight vectors. References to color refer to the online version of this figure

# Conclusions

1. A deep neural network for emotion recognition has been proposed which uses the personality-guided attention mechanism to combine EEG signals and personality traits and learn the regional and temporal information of EEG signals.

2. The personality-guided attention mechanism can effectively capture the relationships between EEG signals and personality traits.

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