PO-1

# Predicting emotions using channel attention mechanism on fMRI signal data

Hong-kun Lin [1] Chia-Yen-Lee[2*]

[1]Department of Biomedical Engineering National Yang Ming Chiao Tung University, Taiwan

[2]Department of Electrical Engineering, National United University, Taiwan

Corresponding Email:leecyya@gmail.com

## I. Introduction

### *Emotion recognition*

- Emotion recognition can assist doctors in diagnosing mental illnesses related to depression, anxiety, post-traumatic stress disorder, and emotional regulation abnormalities.
- fMRI has high spatial resolution and whole-brain coverage, which allows it to identify different regions of the brain and their activity patterns during various emotional states. Its non-invasive nature makes it more acceptable to the public.

### *Goal*

- In this work, we propose a deep learning model that applies automatic focus to signals from 246 brain regions measured by fMRI, classifying them into three categories: positive valence, negative valence, or neutral valence, as well as into nine levels of emotional classification.

## II. Methods and material

### *Data acquisition*

- Data sourced from the 2024 International Conference on Biomedical and Health Informatics, Mind-Reading Emotions Challenge .
- Data from 20 participants, each consisting of 30 preprocessed fMRI sessions of 25 seconds (including signals from 246 brain regions).
- Each trial was collected while participants watched emotion-evoking video clips from three predefined categories (positive, negative, or neutral valence).
- Each trial was rated by participants on a 9-point valence scale, ranging from -4 (maximum negative valence) to 4 (maximum positive valence).

### *Methods*

This study used emotion-related brain regions (EBR) proposed by Lee et al. [1] as input for the emotion classification model, comparing it with the use of Squeeze-and-Excitation blocks (SE blocks) to allow the model to automatically focus on emotion-related brain regions. The dataset was split in an 8:1:1 ratio for training, validation, and testing.

- ***Data Preprocessing***

Since the brain signals measured by fMRI have different value ranges, they were normalized to a range of 0 to 1.

- ***Baseline CNN model***

The baseline CNN model in this study combines residual connections, batch normalization, and SE blocks to enhance model performance and stability. Residual connections are used to alleviate the vanishing gradient problem in deep networks, batch normalization helps accelerate convergence and improve the model's generalization ability, and SE blocks enhance the model's focus on important features by adaptively adjusting the weights of the channels.

- ***Deep learning model architecture focusing on signals from emotion-related brain regions.***

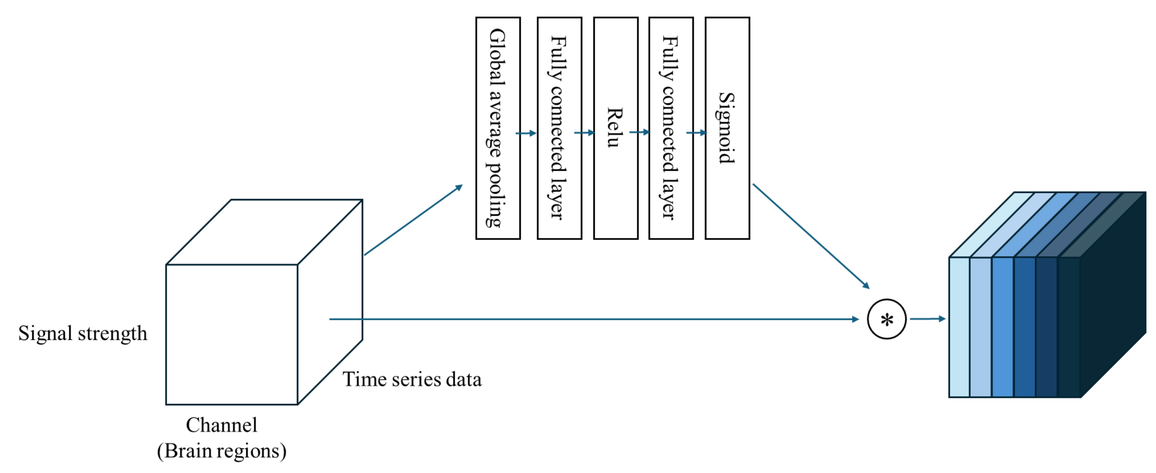


Figure1:Focusing on emotion-related brain region signals through the SE block.

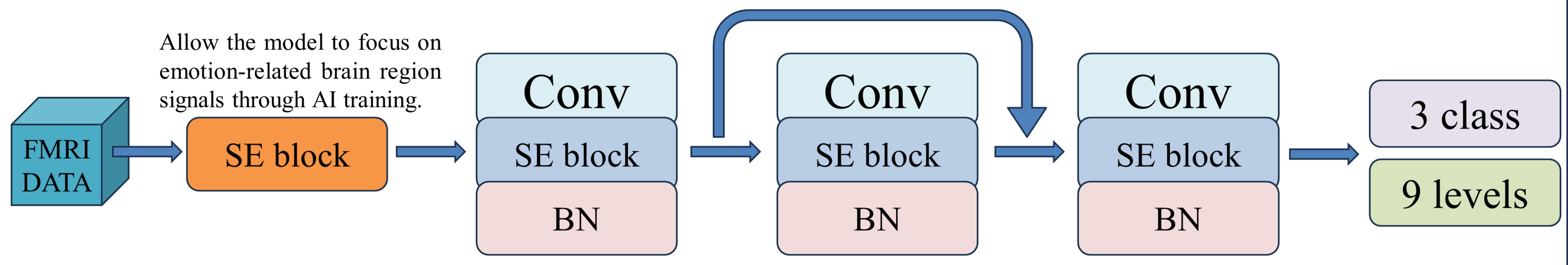


Figure2:Propose model(ASB)

## III. Results & Discussion

- By incorporating SE-block for automatic selection of emotion-related brain regions(ASB), the precision, sensitivity, and F1-score for the class classification task are 0.73, 0.73, and 0.73, respectively, while for the level classification task, they are 0.23, 0.33, and 0.26, respectively.
- The ASB prediction results submitted for the competition achieved a score of 0.5132 in the first phase and 0.4213 in the second phase.
- Vanilla: Baseline CNN model, ASB: Using SE block in the first layer of the CNN model to select brain regions, EBR: Using emotion-related brain regions as inputs to the CNN model

Table 1. Class classification task inner test performance

| Class task | Precision | Sensitivity | F1 score |
|---|---|---|---|
| **ASB** | 0.73 | 0.73 | 0.73 |
| **EBR** | 0.49 | 0.48 | 0.47 |
| **Vanilla** | 0.59 | 0.54 | 0.52 |

Table 2. Level classification task inner test performance

| Level task | Precision | Sensitivity | F1 score |
|---|---|---|---|
| **ASB** | 0.23 | 0.32 | 0.26 |
| **EBR** | 0.04 | 0.07 | 0.05 |
| **Vanilla** | 0.19 | 0.25 | 0.21 |

Table 3. SE method Submit Score

| ASB | Score |
|---|---|
| **First Stage** | 0.5132 |
| **Second Stage** | 0.4213 |

- The comparison between the ASB and Vanilla methods shows that adding the SE-block to the first layer of the baseline CNN model, allowing for automatic attention to brain regions, improve the model's performance.
- When comparing ASB with the EBR method, ASB demonstrates a clear advantage in precision, sensitivity, and F1-score for both class and level classification tasks. Furthermore, EBR underperforms compared to the Vanilla method, with lower precision, sensitivity, and F1-score in both class and level classification tasks.
- The experimental results indicate that using the ASB, which allows the model to adaptively focus on brain regions, is more effective for emotion recognition tasks compared to directly using emotion-related brain regions as input for the baseline CNN model.

## IV. Conclusion

- This study compares the ASB and EBR methods, and the results show that the ASB method outperforms the EBR method in terms of precision, sensitivity, and F1-score for both class and level classification tasks. The ASB method automatically adjusts channel weights, enabling the model to focus more effectively on important features related to emotion classification, thereby improving classification performance.

## IV. References

1. Lee, Y., Seo, Y., Lee, Y., & Lee, D. (2023). Dimensional emotions are represented by distinct topographical brain networks. International Journal of Clinical and Health Psy-chology, 23(4), 100408.