

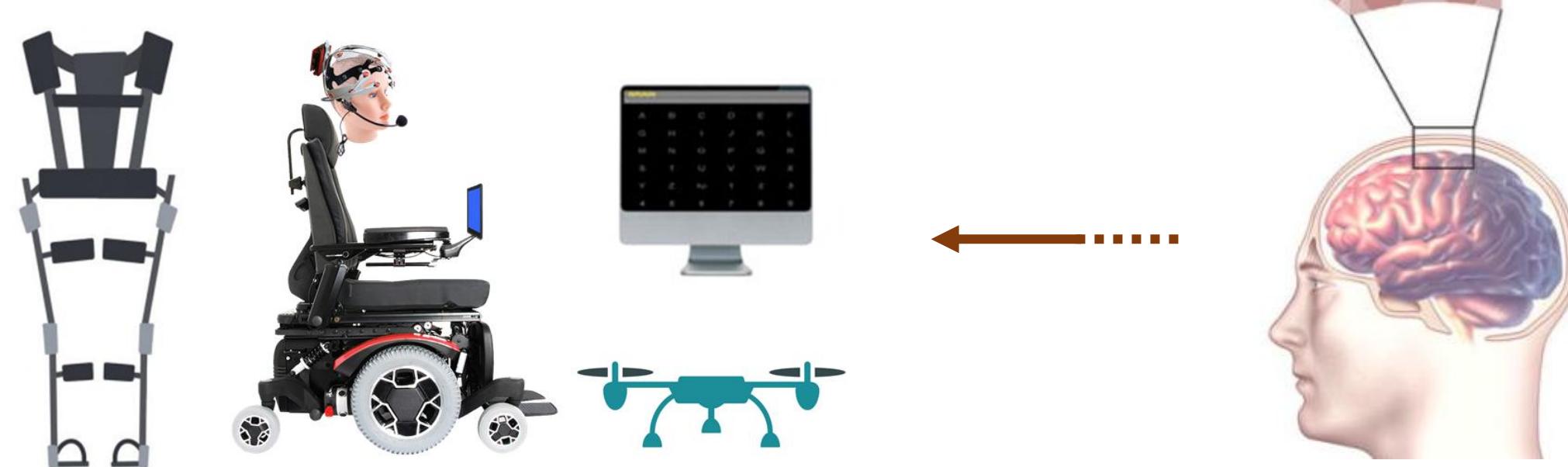
Dynamic convolution with multilevel attention for EEG-based motor imagery decoding

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Introduction

The brain-computer interface (BCI) is an emerging technology that has the potential to transform the world. EEG-based Motor imagery (MI) has been used in many BCI applications to assist disabled people and to augment human capabilities. EEG is a non-invasive, low cost, low risk, and portable method that records the electrical activities of the brain. MI is the activity of thinking about moving a human body part without physically moving it.



Recognizing human intention from EEG signal is challenging due to the low SNR and various sources of artifacts.

Aims

The goal is to develop a high-performance attention-based deep learning model to classify EEG-based MI brain signals.

Proposed Method

The proposed model consists of two main blocks:

Attention dynamic convolution (ADC) block: extracts low-level spatiotemporal features from the EEG data using three conv layers with multilevel attention at the kernel and features levels over the temporal, spatial, and spectral dimensions.

Attention temporal convolution (ATC) block: first highlights valuable temporal features via MSA and then extracts high-level temporal features from the via a TCN.

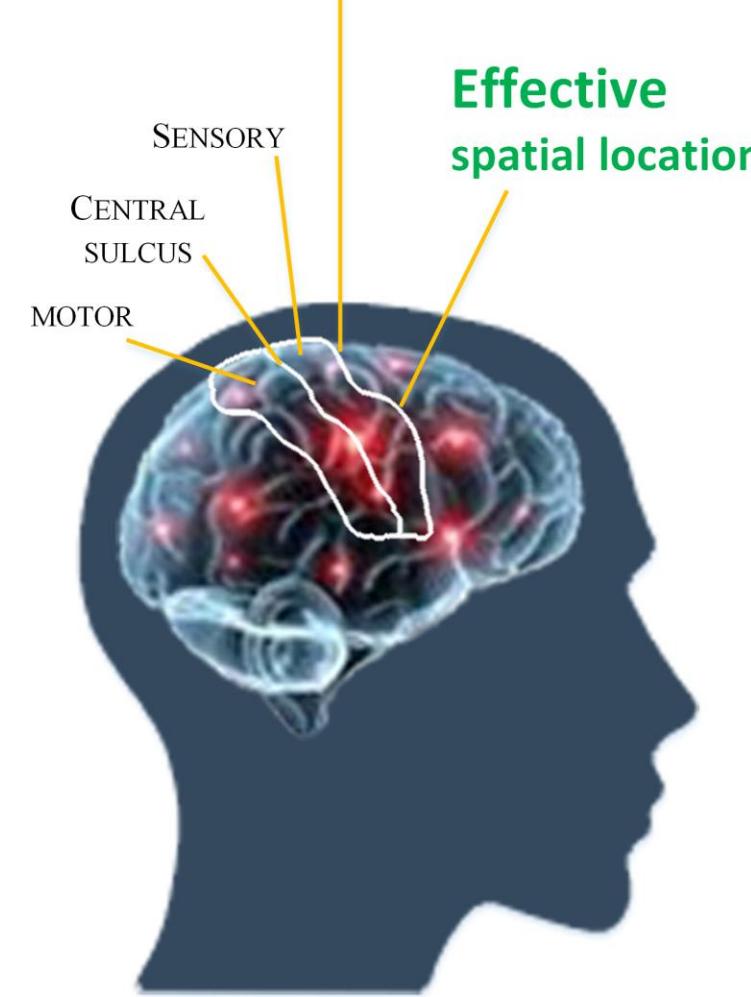
Main contributions of the proposed model:

- Performs attention at kernel and input levels
- Performs attention over three dimensions.
- Achieves state-of-the-art performance.
- Code is available at GitHub.



<https://github.com/Altaheri/EEG-ATCNet>

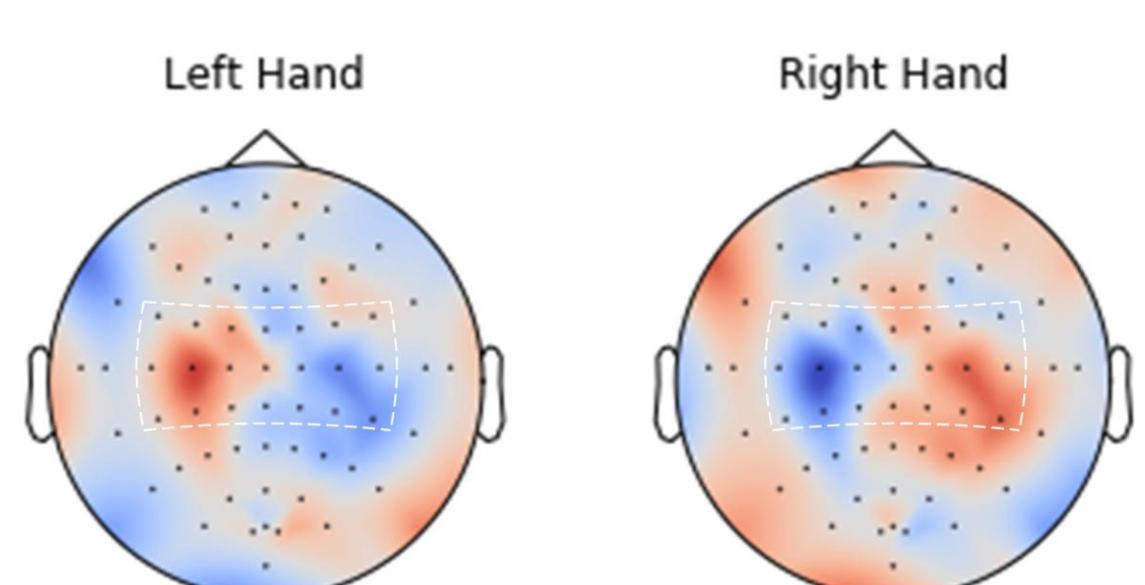
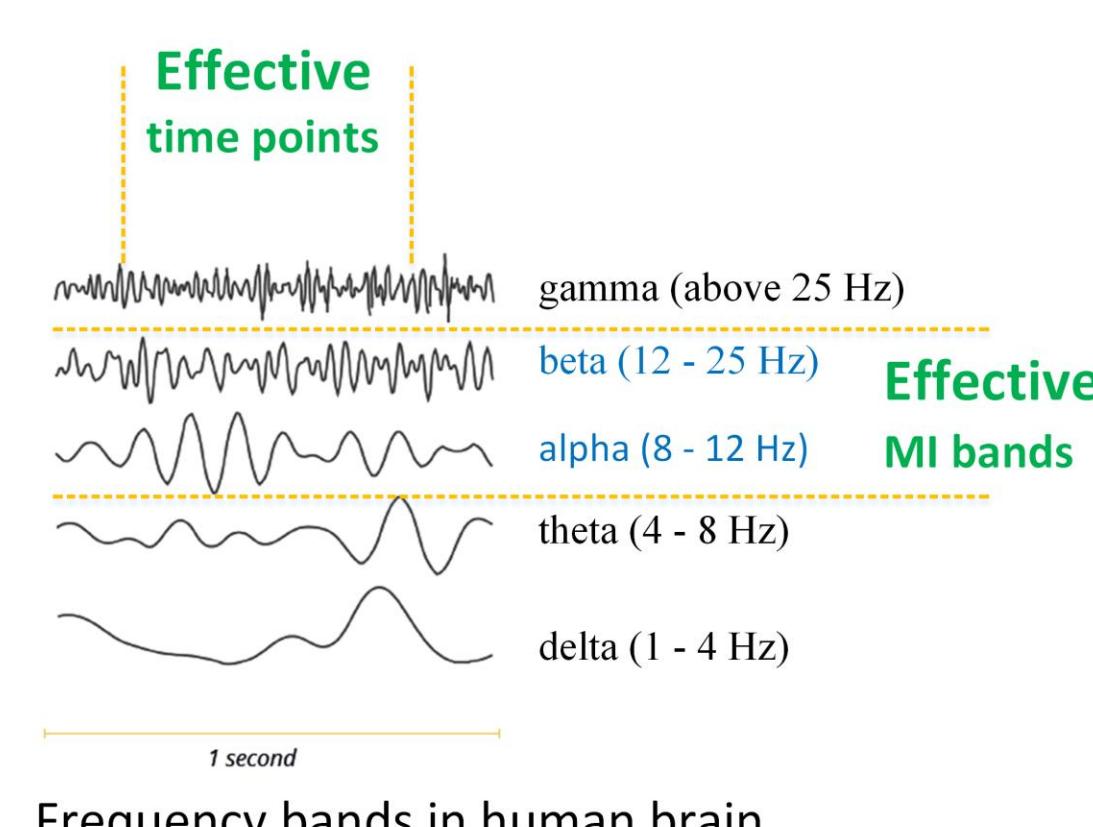
Sensorimotor Cortex shows distinct spatial patterns during MI tasks related to various human body parts, e.g., right hand, left hand, leg, and tongue.



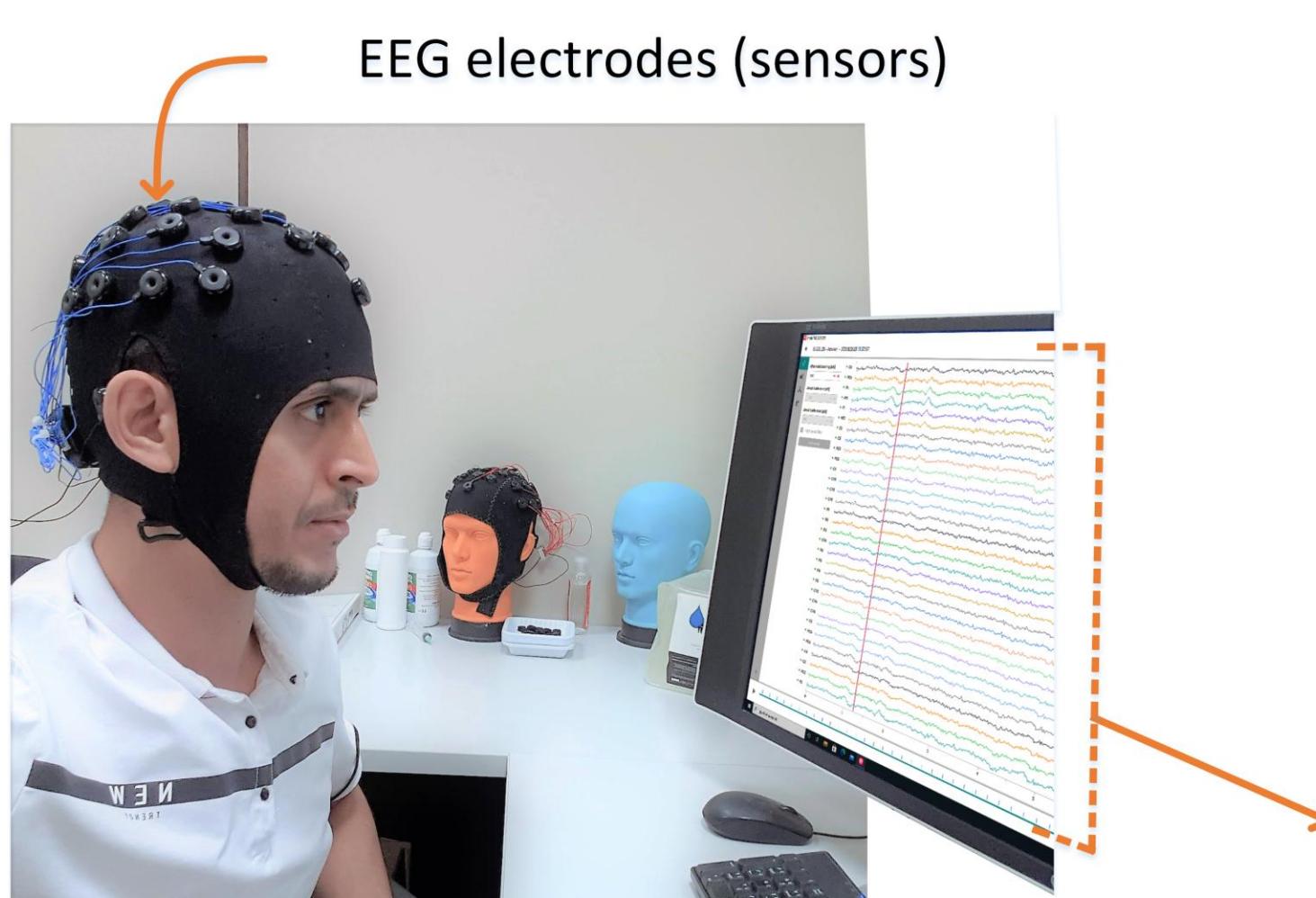
Why multilevel attention?

Effective MI information exists in different dimensions

MI-EEG signals are high-dimensional data. Effective information in such data occurs at specific channel locations, frequency bands, and time intervals.

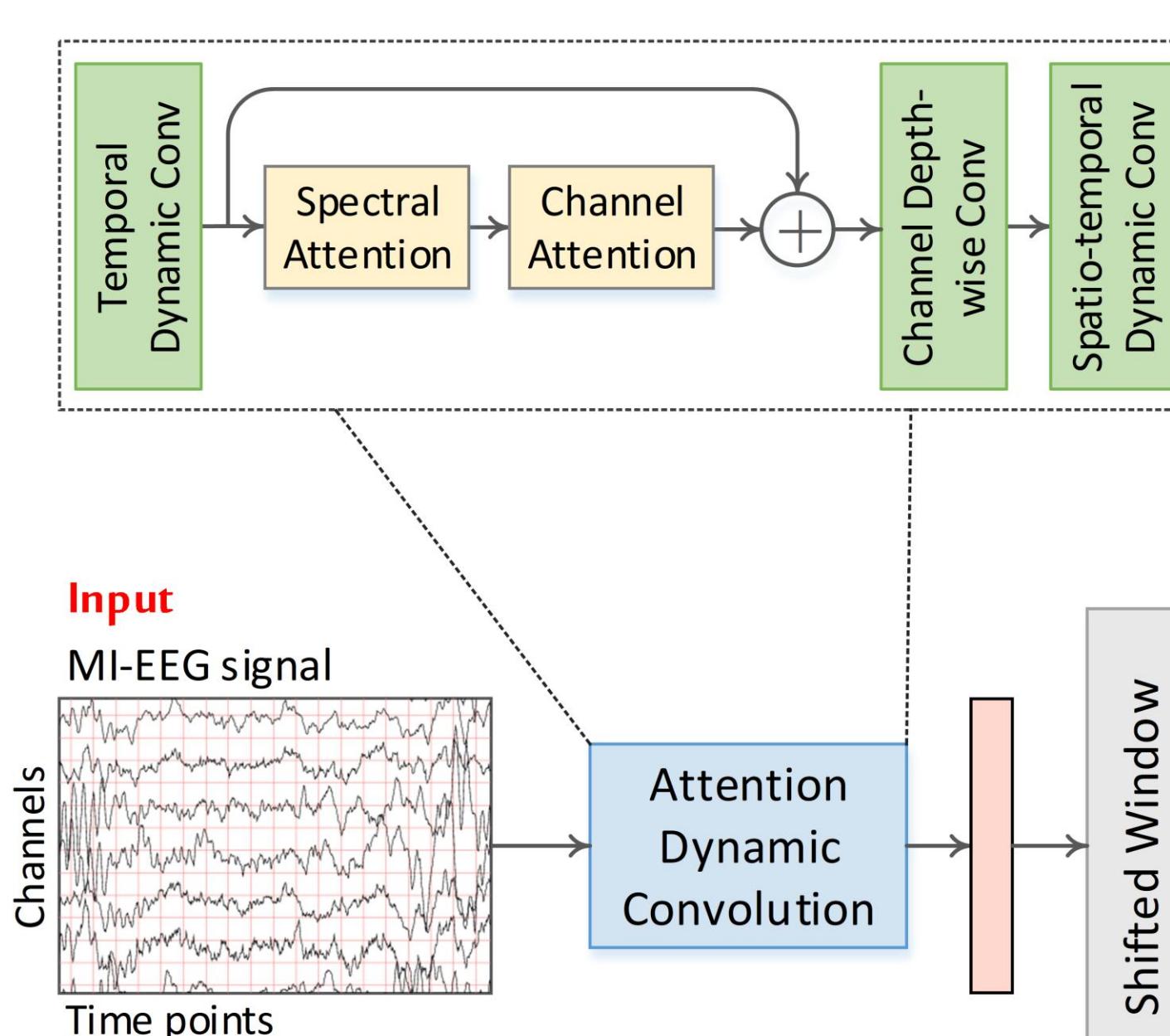
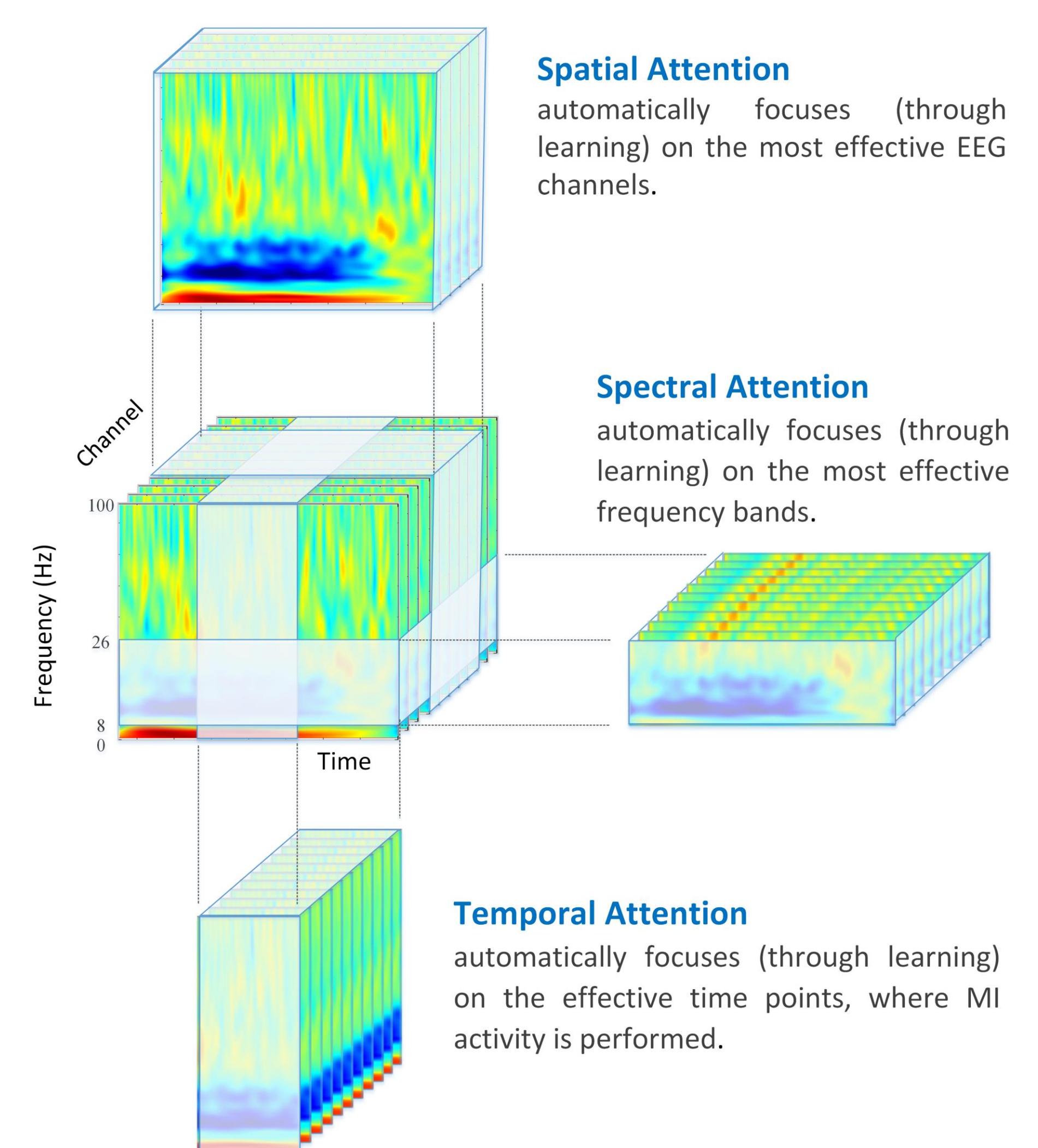


Different MI tasks have activities in different spatial locations or different frequency bands.

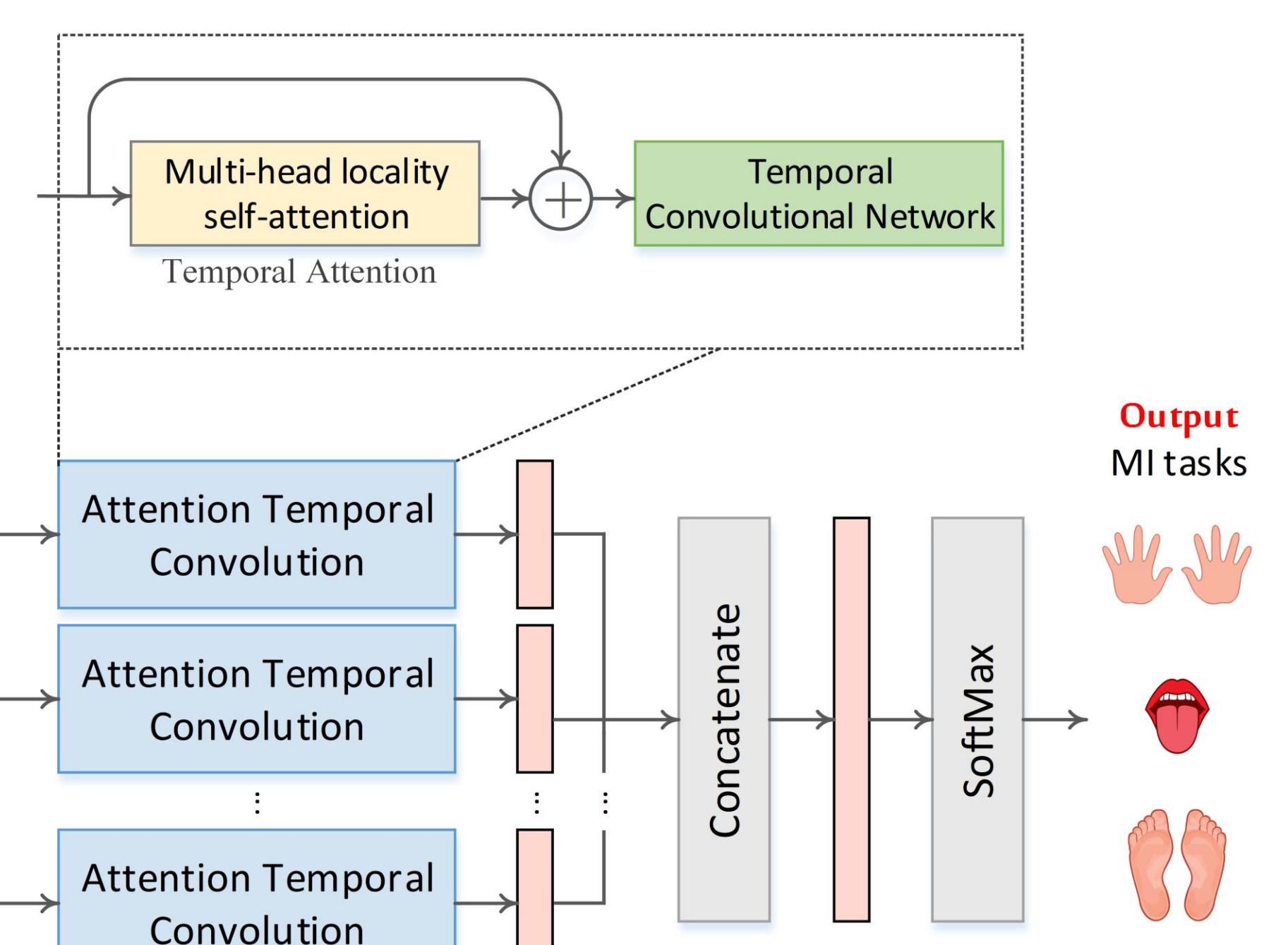


How is multilevel attention implemented?

The proposed model performs multilevel attention at the kernel level using dynamic convolution and at the features level using MLSA and SE. Features-level attention was investigated over the temporal, spatial, and spectral dimensions of the EEG signal.



Components of the proposed model



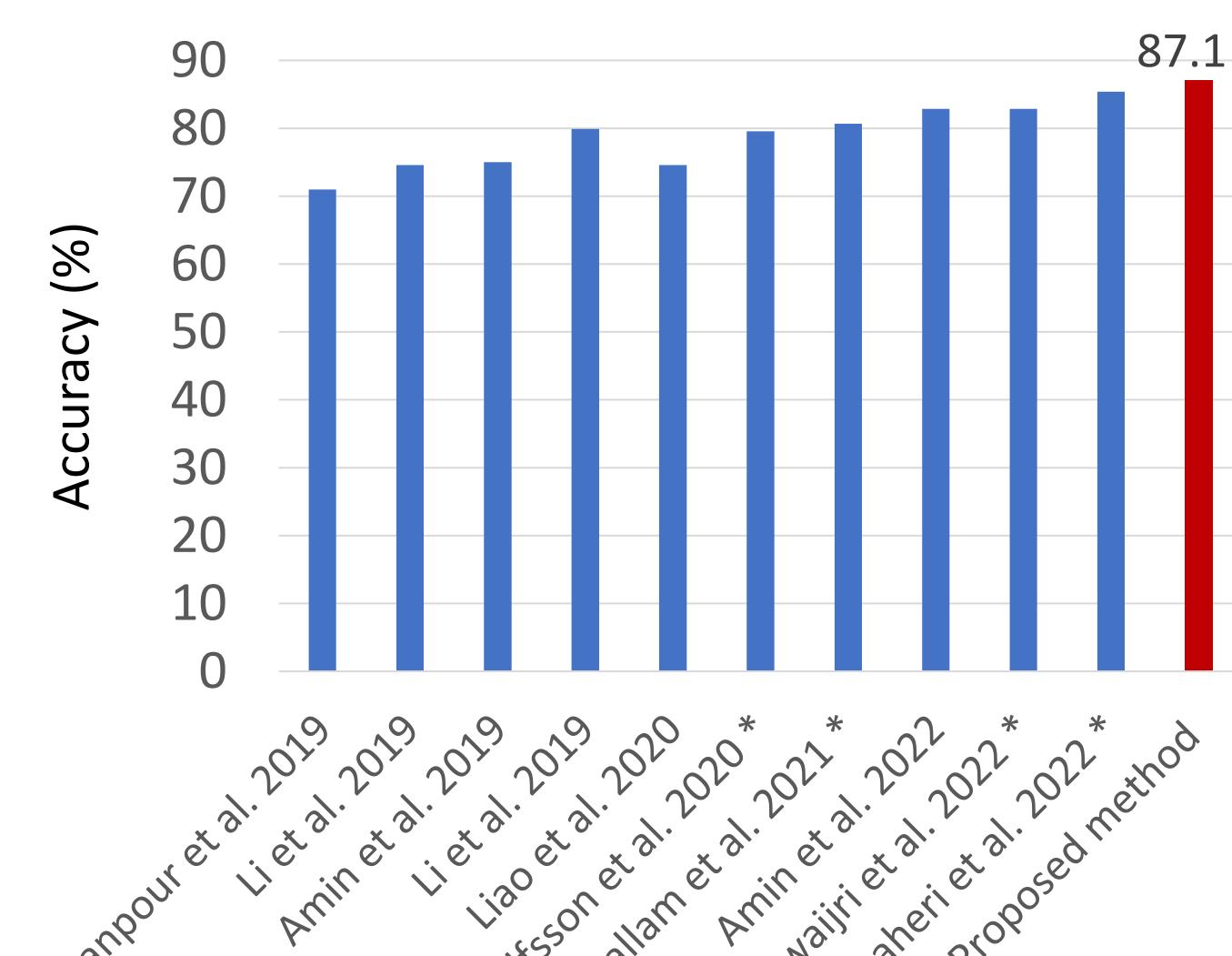
Results

- The proposed ATCNet model achieves a accuracy of 87.1% and a κ -score of 0.83, using the challenging and benchmark BCI Competition IV-2a dataset, which outperforms the state-of-the-art techniques by 1.7%.
- Ablation analysis showed the significant contributions made by dynamic convolution (0.97%) and multilevel attention (1.43%) to the overall network performance.

Removed attention	Accuracy %	κ -score
none (D-ATCNet)	87.08	0.828
kernel level attention	86.11	0.815
features level attention	85.65	0.809
multilevel attention	85.46	0.806
shifted window attention	85.72	0.809
Method	Accuracy %	κ -score
without Dy-conv	86.11	0.815
2D Dy-conv in the ADC block	87.08	0.828
1D Dy-conv in the ATC block	86.57	0.821
1D and 2D Dy-conv in both blocks	86.50	0.820

Ablation analysis of the multilevel in the proposed D-ATCNet model.

Ablation analysis of dynamic convolution in the proposed D-ATCNet model.



Performance comparison between the proposed method and recent studies.

* Reproduced Method
Proposed and reproduced methods are available at:
 <https://github.com/Altaheri/EEG-ATCNet>

Conclusions

This study proposed a novel attention-based dynamic convolutional network for EEG-based MI classification that outperformed state-of-the-art techniques using the BCI-2a dataset with an accuracy of 87.1% and a κ -score of 0.83. These high results came with a relatively small number of parameters (150 K), which is applicable to limited devices.

References

- Hassanpour et al., "A novel end-to-end deep learning scheme for classifying multi-class MI-EEG signals," 2019.
- Musallam et al., "EEG-based MI classification using TCN fusion," 2021.
- Amin, et al., "Attention-Inception and LSTM Classification for MI," 2022
- Altaheri et al., "Physics-Informed Attention Temporal Convolutional Network for EEG MI Classification," 2023.