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A Spatial-Temporal Transformer based on Domain Generalization for Motor Imagery Classification

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Introduction

Motor Imagery Classification Using EEG signals

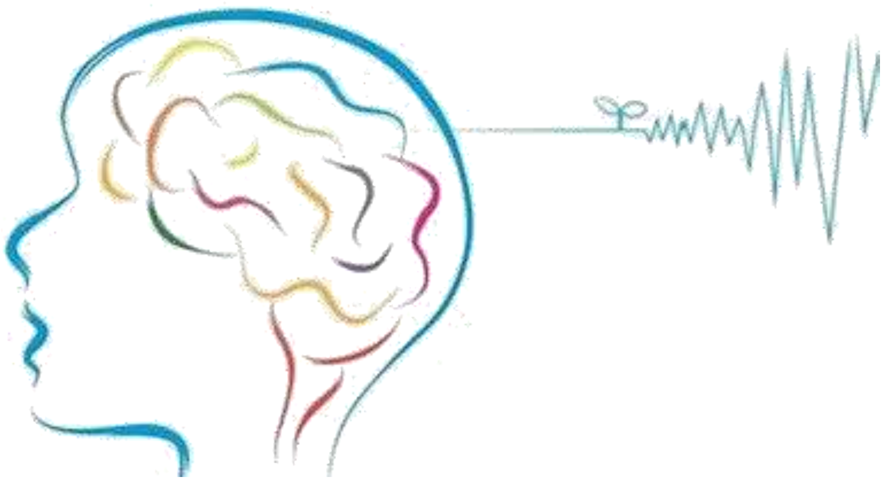
- Goal : Accurately identify and classify an individual's motor imagery activities.
- Utilization :
  - Better understanding of the neural mechanisms and brain activity patterns.
  - Apply in rehabilitation training and skill enhancement.

Related Work

Motor Imagery Classification

Traditional methods:

- Need to extract hand-crafted features, which requires a lot of prior knowledge.
- Feature extraction methods.

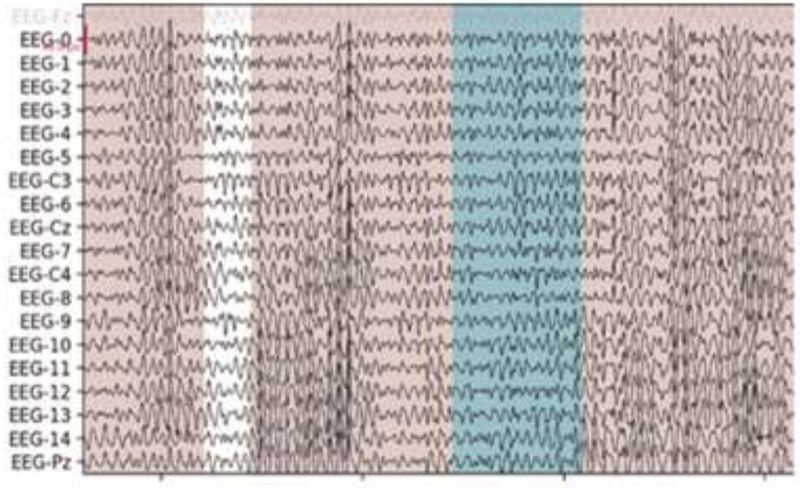


Deep Learning methods:

- End-to-end learning of raw data.
- EEGNet, ShallowNet, DeepConvNet, etc.

Motivation & Challenges

Challenge1: How to Extract Spatial and Temporal Features from EEG signals in Motor Imagery Classification?

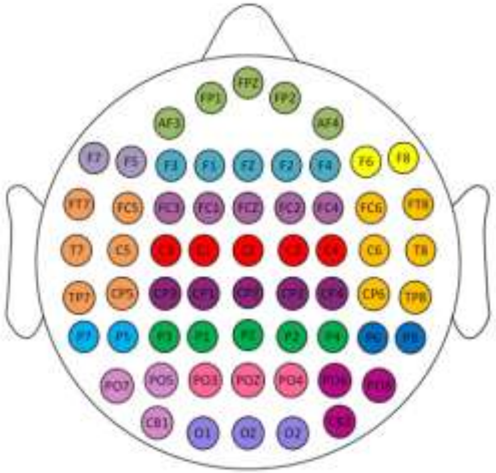


Temporal perspective:

- Activity pattern of the brain changes over time.
- EEG signals exhibit different characteristics at different time points.

Spatial perspective:

- Different functional regions of the brain exhibit different activation patterns.

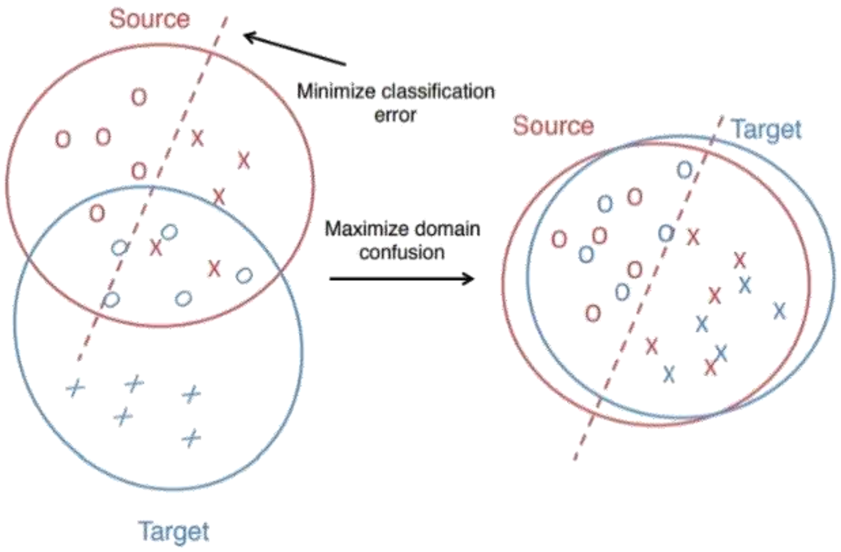


Motivation & Challenges

Challenge2: How to solve the cross-subject accuracy decline problem?

Individual differences:

- Physiological structures & Functional characteristics.
- EEG signals exhibit different characteristics at different time points.

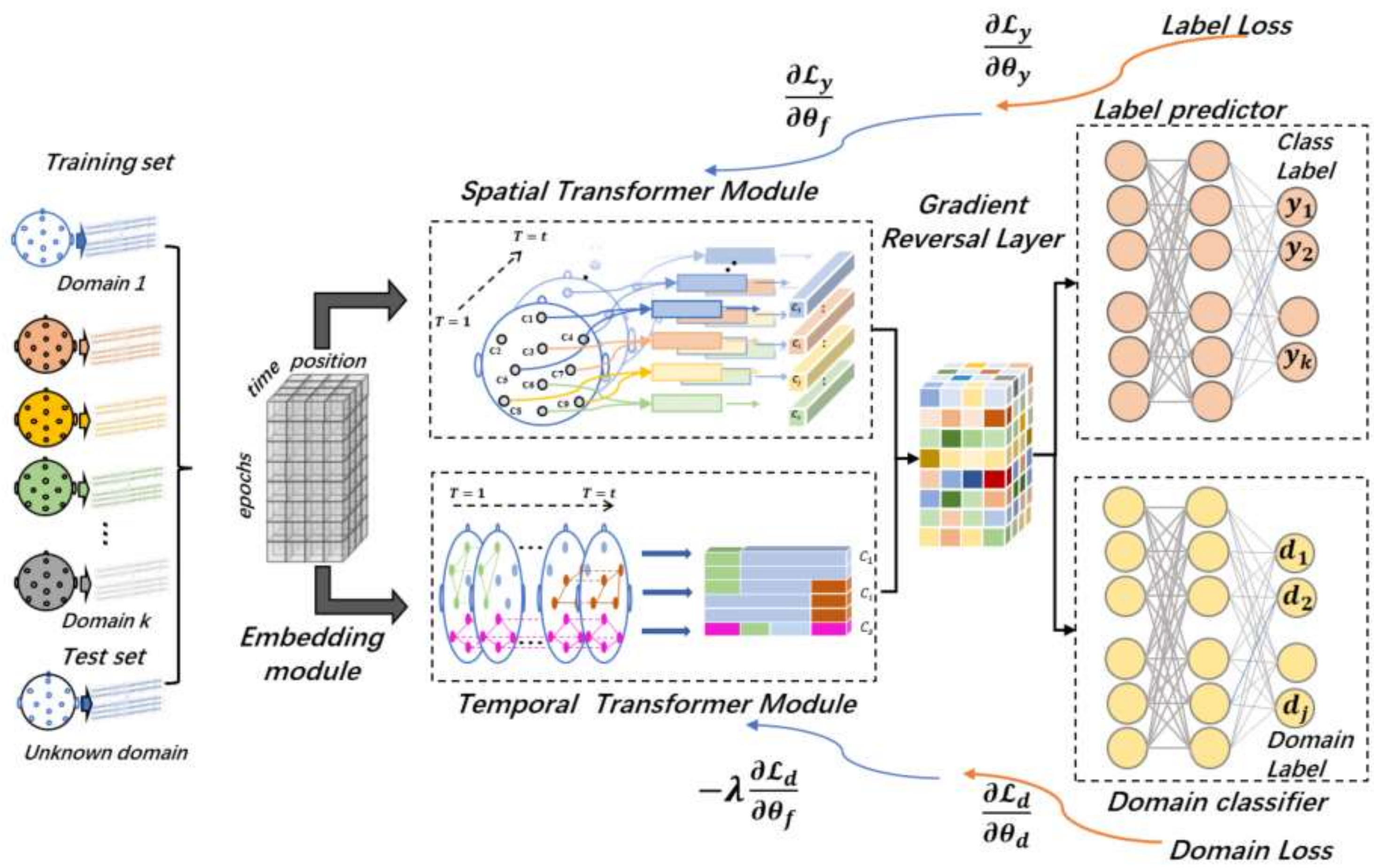


Noise and interference:

- These noise and interference vary among different subjects.

Methods

ST-DG: Spatial-Temporal Transformer with Domain Generalization



Contribution:

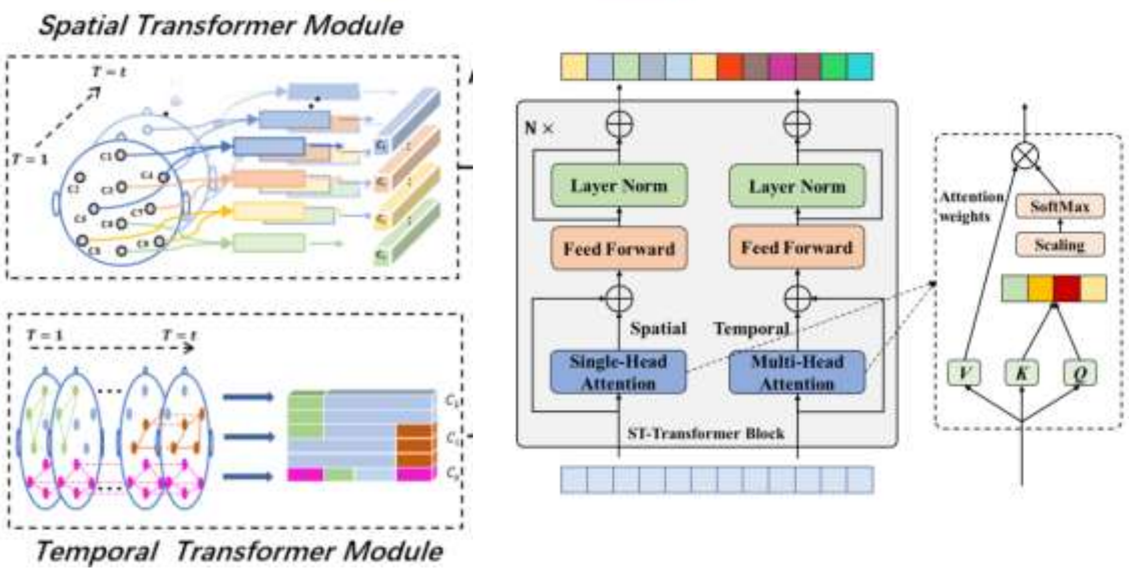
- The *first attempt* to apply *ST-DG* for MI classification.
- We design a spatial-temporal Transformer.
- We apply DG to extract subject-invariant features.
- Achieve SOTA performance on BCI-2A and 2B dataset.

Methods

***C1:* How to Extract Spatial and Temporal Features?**

***S1:* We propose ST-Transformer architecture to encode Spatial and Temporal information.**

- Depict the correlation between the individual EEG channels.
- Encodes the temporal correlations of EEG sequences into Sequence.



$$Q, K, V = Linear(X), X \in R^{C \times T}$$

$$Attention_s(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_s}})V$$

$$Attention_t = softmax(\frac{Q^T K}{\sqrt{d_t}})V^T$$

$$head_t = Attention_t(QW_i^Q, KW_i^K, VW_i^V)$$

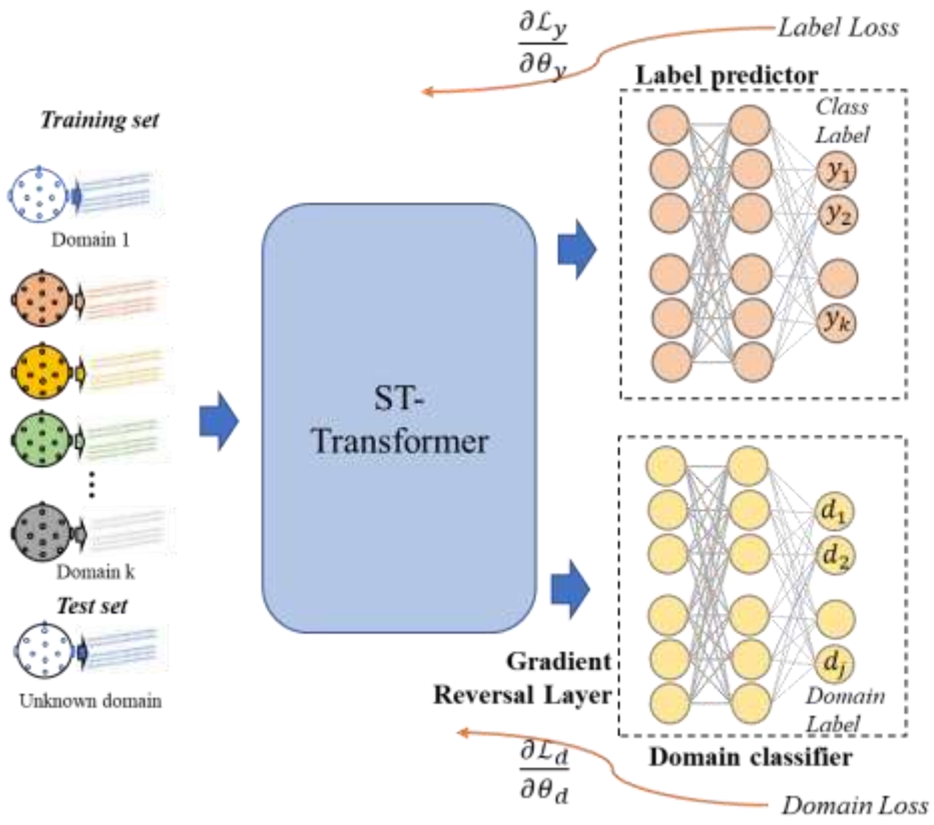
$$MultiHead = Concat(head_1, \ldots head_h)W^o$$

Methods

***C2:* How to solve the cross-subject accuracy decline problem?**

***S2:* We apply DG to extract subject-invariant features.**

- We incorporate a Gradient Reversal Layer (GRL).
- Domain generalization includes three parts:
  - Feature extractor $\mathcal{G}_f$
  - Domain classifier $\mathcal{G}_d$
  - Label predictor $\mathcal{G}_y$



Experiments

Datasets

BCIIV-2A

- EEG data from 9 subjects.
- Consists four different motor imagery tasks.

BCIIV-2B

- EEG data from 9 subjects.
- Consists two different motor imagery tasks.

Baselines

- **EEGNet**: A classical compact fully convolutional network with depth-wise and separable convolutions for EEG classification using CNN.
- **ConvNet**: Four convolutional pooling blocks that give it a strong ability to extract features from raw EEG signals.
- **MMCNN**: An end-to-end deep learning model consists of 5 parallel EEG Inception Networks. Each EIN consists of an EEG Inception block, a Residual block, and a Squeeze and Excitation block.

Experiments

Comparison with the state-of-the-art models

TABLE I

THE PERFORMANCE COMPARISON ON DATASETS 2A AND 2B

Dataset	Methods	Accuracy(%)	AUC
BCI-2A	EEGNet	51.639±0.017	0.777±0.013
	ConvNet	53.003±0.017	0.799±0.014
	MMCNN	52.135±0.015	0.789±0.013
	ST-DG	57.705±0.014	0.823±0.014
BCI-2B	EEGNet	70.441±0.017	0.785±0.013
	ConvNet	69.134±0.018	0.765±0.014
	MMCNN	70.613±0.015	0.782±0.013
	ST-DG	75.089±0.014	0.834±0.013

TABLE II

CLASSIFICATION ACCURACY(%) ON DIFFERENT SUBJECT

Model	Subject									Avg.
	1	2	3	4	5	6	7	8	9	
ConvNet	65.2	66.0	63.0	81.1	65.9	65.7	75.5	71.8	67.7	69.1
EEGNet	66.7	71.2	64.5	83.8	68.3	70.0	75.7	71.3	68.5	71.1
MMCNN	72.0	71.0	64.5	81.9	70.4	76.7	76.0	75.2	68.0	72.8
ST-DG	75.0	71.7	67.0	85.4	70.7	79.7	77.7	73.8	74.5	75.0

Experiments

Ablation Experiments

- S-DG: The Temporal Transformer module is removed.
- T-DG: The Spatial Transformer module is removed.
- ST: The DG architecture is removed.

Modeling spatial-temporal and subject invariant features with ST-DG for MI classification is important.

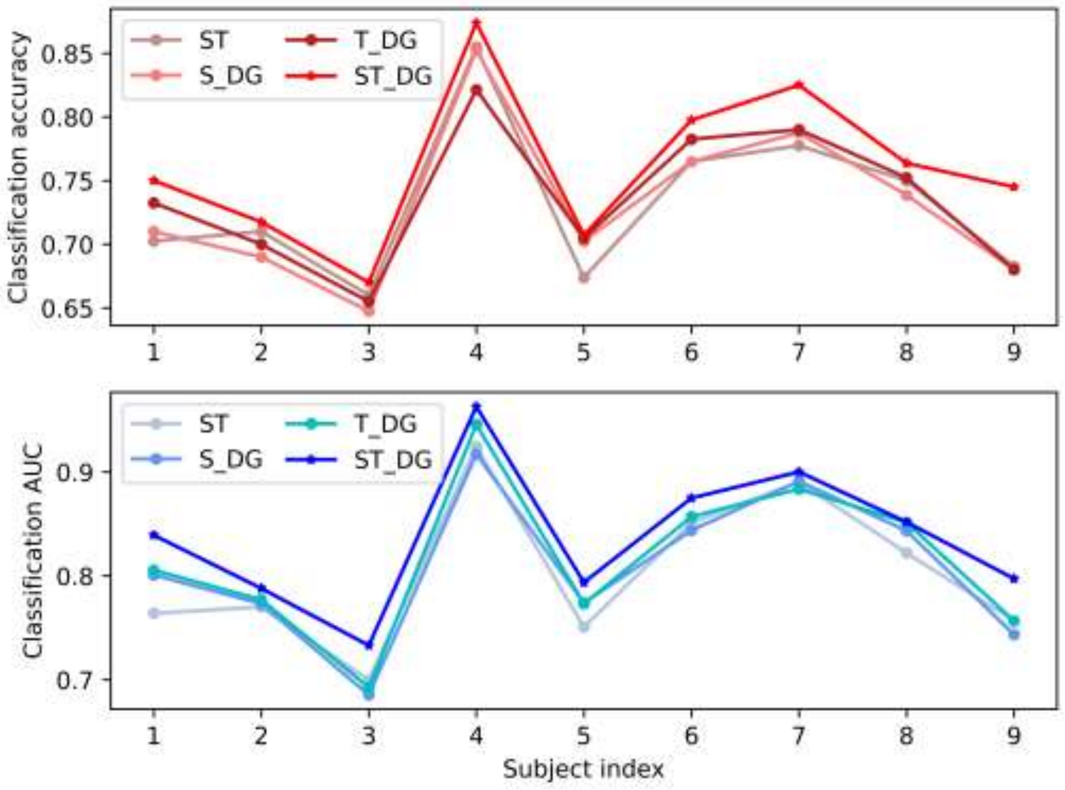
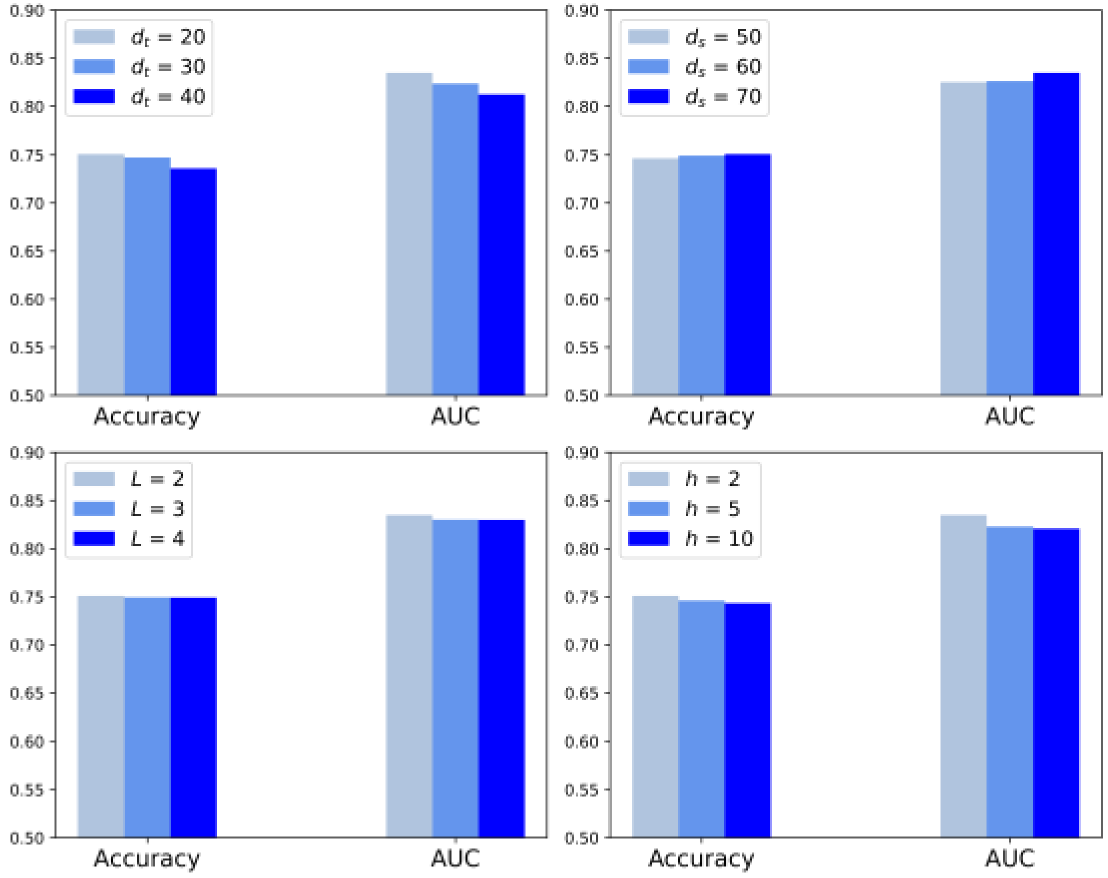


Fig. 4. Ablation experiments results in each subject on BCI-2B dataset.

Experiments

Sensitivity test results

- Temporal model dimension (d_t)
- Spatial model dimension (d_s)
- Number of encoder layers (L)
- Number of attention heads (h).



Conclusion

Contribution

- It is the first attempt to integrate the Spatial-Temporal Transformer and Domain Generalization techniques within a cohesive framework to enhance MI classification.
  - We devise the ST-Transformer to proficiently capture the spatial and temporal characteristics of the EEG signals.
  - We employ the technique of Domain Generalization to extract subject-invariant features, thereby enhancing the generalization capabilities of the proposed model.
- The proposed ST-DG achieves the state-of-the-art performance on BCI-2A and 2B datasets in leave-one-subject-out (LOSO) validation.

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Thanks for Listening !

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