Cross-subject EEG Emotion Recognition based on Multitask Adversarial Domain Adaption

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Abstract

Emotion recognition is crucial for enhancing human-computer interaction. Due to considerable individual differences in emotion manifestation, traditional models do not adapt well to new individuals. Moreover, existing algorithms typically focus on identifying a single emotion, overlooking intrinsic connections among multiple emotions. Therefore, we propose a multi-task adversarial domain adaption (MADA) model for EEG-based emotion recognition. First, domain matching is employed to identify the most similar individual from the dataset as the source domain, alleviating individual differences and reducing training time. Subsequently, multi-task learning is utilized to simultaneously classify multiple emotions, capturing their intrinsic connections. Finally, adversarial domain adaption is applied to learn the individual differences between the source and target domains. Cross-subject experiments on the DEAP dataset indicate that our model achieves accuracies of 76.48%, 69.72%, and 68.14% on the valence, arousal, and dominance, respectively, surpassing state-of-the-art methods. This indicates the effectiveness of our model in recognizing multi-dimensional emotions.

Keywords: Electroencephalogram (EEG); Emotion recognition; Cross-subject; Domain adaption; Multi-task learning

Introduction

The field of human-computer interaction (HCI) is advancing toward greater intelligence and personalization. Human-computer interaction systems can create a more natural and effective interactive environment by analyzing users' emotional changes and adjusting their behavior and feedback in real time. The signals used for emotion recognition can be divided into physiological and non-physiological signals. Non-physiological signals include facial expressions, voice intonation, and others. Compared to non-physiological signals, physiological signals, such as electroencephalograms (EEGs), are less likely to be consciously controlled or disguised, making them more suitable for emotion recognition (Shu et al., 2018). EEG records the electrical signals produced by the activity of brain neurons, which are closely related to emotions (Y.-P. Lin et al., 2010). EEGs can capture rapidly changing dynamic emotions (Akhand, Maria, Kamal, & Murase, 2023) and are currently widely used in emotion recognition, demonstrating commendable performance.

However, due to individual differences and the non-stationarity of EEG signals (Kamrud, Borghetti, & Kabban, 2021), cross-subject EEG-based emotion recognition still faces challenges. With the continuous advancement of deep learning techniques, there have been extensive applications in the field of emotion recognition. However, deep learning methods often require a large amount of data to train the model for recognizing the emotions of a new individual, which is a time-consuming and complex process. Transfer learning proves to be an effective means to address this issue. Transfer learning aims to apply knowledge learned from one domain (source domain) to another different but related domain (target domain). Adversarial domain adaption is a branch of transfer learning that employs a concept similar to Generative Adversarial Networks (GANs). Through adversarial training, the model cannot distinguish between data from the source domain and the target domain. This reduces the distribution differences between the source and target domains, ensuring that the learned features are domain-invariant(Tzeng, Hoffman, Saenko, & Darrell, 2017). In recent years, domain adaption has been applied to emotion recognition with promising results. Zhang et al.(2019) combined transfer learning with AdaBoost, selecting appropriate source data by measuring the maximum mean discrepancy (MMD) between target and source instances, and then transferring knowledge from the source data to aid in training the target model. Li et al.(2020) applied style transfer mapping (STM) to EEG-based cross-subject emotion recognition, and achieved favorable test results. Zheng et al.(2015) identified common components shared between the source and target domains through transfer component analysis and kernel principal component analysis (PCA), thereby facilitating emotion recognition. Luo et al.(2018) utilized generative adversarial network domain adaption for emotion recognition, projecting features of the source and target domains into the same space, and then reducing the differences in the distribution of the data through adversarial learning to improve classification accuracy.

Moreover, currently, most of the EEG emotion recognition studies based on transfer learning are predominantly single-task learning, focusing independently on the dimensions of valence, arousal, or dominance. Single-task learning necessitates training for each emotional dimension separately, which not only consumes a considerable amount of time but also overlooks the potential connections between different emotions (C. Li et al., 2022). To address this issue, we introduce multi-task learning into emotion recognition. In multi-task learning, multiple tasks share knowledge, and learning one task can help improve the performance of other tasks

In L. K. Samuelson, S. L. Frank, M. Toneva, A. Mackey, & E. Hazeltine (Eds.), *Proceedings of the 46th Annual Conference of the Cognitive Science Society.*

(Caruana, 1997). Multi-task learning enhances the model's generalization ability by learning multiple related tasks simultaneously. It also allows for the acquisition of additional data from other related tasks, which is beneficial for addressing data scarcity issues (Chen et al., 2022). For example, Priyasad et al.(2022) proposed an encoder network based on SincNet that combines deep learning and multi-task learning to classify three emotional dimensions, exploring the feasibility of multi-task learning in emotion classification.

To address these two aforementioned issues, this study proposes a cross-subject EEG emotion recognition method based on multi-task adversarial domain adaption, named as MADA model. This model, on one hand, flexibly matches the most similar source domains (i.e., all subjects in the training set) for target domain emotion recognition, significantly reducing training costs. On the other hand, it employs multi-task learning for multiple emotional dimensions, effectively leveraging the intrinsic connections between different emotional dimensions.

The remainder of this paper is organized as follows. The next section provides a detailed introduction to the framework of the MADA model. The experimental details and results on the DEAP dataset are presented. The final section is dedicated to the discussion.

Methods

As illustrated in Figure 1, the framework of the proposed MADA model consists of three main parts, namely domain matching, multi-task emotion classification and adversarial domain adaption.

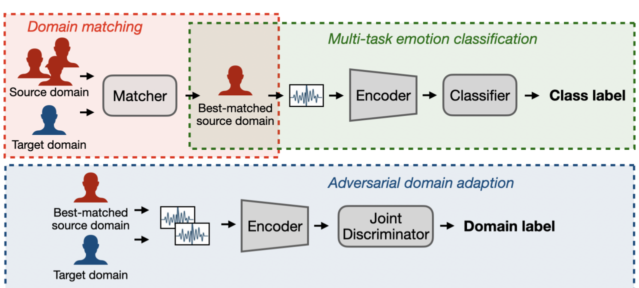

Figure 1: The framework of the proposed MADA model.

The domain matching is employed to assess the similarity between the training data and the target domain, marking the data most similar to the target domain as the source domain. In the multi-task emotion classification, the encoder transforms data from a high-dimensional feature space to a low-dimensional feature space, while the classifier simultaneously categorizes multiple emotion labels. In adversarial domain adaption, the encoder generates features that are challenging for the domain discriminator to differentiate, and the domain discriminator attempts to identify the domain of these features.

Domain matching

In the field of EEG-based emotion recognition, the data collection is costly and there are significant individual differences in the collected data (G. Li et al., 2022). Traditional deep learning-based emotion recognition algorithms often require the use of as many samples as possible for model training, including those with substantial individual differences. This can increase computational costs and lead to a decrease in algorithm accuracy. Therefore, we propose a domain matching method to reduce the impact of individual differences. Since EEG data are temporally correlated and brain activity is highly nonlinear, traditional clustering methods struggle to directly cluster EEG data. We use the accuracy of subject-independent classification as a metric to measure the similarity between the source and target domains. Specifically, for each source domain, a classification model is pre-trained using its own data. During domain matching, the data from the target domain are used to test each classification model. For a training set containing N subjects, the target domain obtains N subject-independent classification accuracies. The subject with the highest accuracy is then marked as the best-matched source domain.

Multi-task emotion classification

The proposed multi-task emotion classification module first extracts features from the raw input through an encoder; these features are subsequently utilized for emotion classification. The structure of this module is depicted in Figure 2. The encoder extracts domain-invariant features, transforming source domain data into higher-level, more compact features. The encoder consists of two convolutional layers (Conv1, Conv2) and two fully connected layers (FC1, FC2). After the FC2 layer, the high-level features are flattened to form a one-dimensional input vector for the classifier. A MaxPooling layer is added after the second convolutional layer to reduce the dimensionality of the features. The rectified linear unit (ReLU) activation function is employed to address the vanishing or exploding gradient issues. All the convolutional layers undergo batch normalization to reduce the risk of overfitting and accelerate the training process.

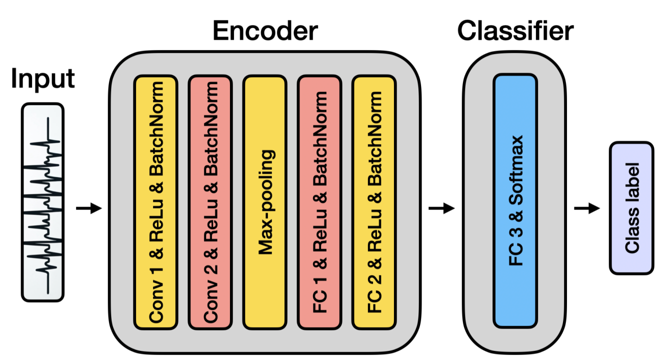

Figure 2: Network architecture of the multi-task emotion classification module

There are certain correlations between different dimensions of emotions, and simultaneously engaging in various emotion-related tasks may be advantageous for enhancing the precision of emotion recognition. The shared mechanism in multi-task learning allows for the acquisition of more information from different tasks. Therefore, in emotion prediction, we classify the arousal, valence, and dominance of emotions simultaneously, allowing for the sharing of complementary information that is beneficial to each other. The classifier receives the feature vector outputted by the encoder and simultaneously predicts multiple emotional labels. However, due to the imbalance in the ratio of positive to negative labels for some individuals, binary classification may be biased (He & Garcia, 2009). Here, we employ focal loss (T.-Y. Lin, Goyal, Girshick, He, & Dollár, 2020) to address the issue of sample inequality. This loss function is designed to reduce the weight of a large number of easy negative samples during training. The formula for the focal point is stated below:

$$L_f = \begin{cases} -(1-y)^{\lambda}\log(y), & y=1 \\ -y^{\lambda}\log(1-y), & y=0 \end{cases} \tag{1}$$

The weight coefficient λ is a hyperparameter. When $\lambda > 0$, the model reduces the loss of easily classified samples, thereby focusing more on those samples that are difficult to classify or misclassified. Lin et al.(2020) validated that the optimal value for λ is 2; hence, in the experiments of this work, we also set λ to 2.

In multi-task learning, a common challenge is that the model may exhibit a preference for a specific task, resulting in good performance on that task but underperformance on others. To address this issue, we construct a dynamic weighting mechanism to balance the learning of multiple tasks. The formula for calculating dynamic weights can be expressed as follows:

$$\begin{aligned} W_{\mathrm{new}} = \max(&W_{\min}, \\ &\min(W_{\max}, W_{\mathrm{old}} \times (1+\beta\times(1-\mathrm{Acc})))) \end{aligned} \tag{2}$$

$$L = \sum_{i=1}^{n} W_i \cdot L_i \tag{3}$$

where β is a hyperparameter related to the scale of adjustment. W_{new} is the previous weight, and $W_{\max}$ and $W_{\min}$ control the range of weight adjustment.

This dynamic weighting strategy dynamically adjusts the weight of each emotion in multi-task learning based on its predictive performance, thereby ensuring that the model pays balanced attention to each task.

Adversarial domain adaption

In the proposed method, to learn which category the features belong to while distinguishing between the source and target domains, we divided the sample pairs into four groups, as shown in Figure 3. This includes two positive sample pairs and two negative sample pairs. The positive sample pairs in Pair 1 and Pair 3 share the same label, where Pair 1 consists of samples from the same domain, while Pair 3 is composed of different domains. On the other hand, negative sample pairs in Pair 2 and Pair 4 have different labels. Pair 2 consists of samples from the same domain, while Pair 4 is composed of subjects from different domains.

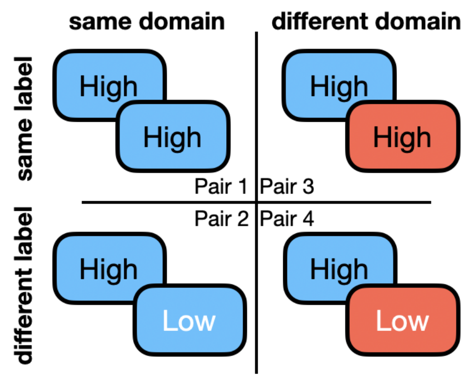

Figure 3: Sample pairs in the adversarial domain adaption module

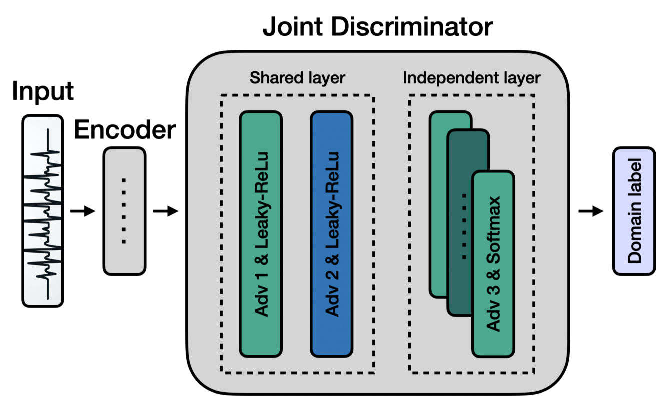

Figure 4: Network architecture of the adversarial domain adaption module

This study uses a joint discriminator to align the source and target domains. The joint discriminator needs to identify not only whether the data come from the source or the target domain but also consider the category information, thereby ensuring content alignment between the source and target domains. As shown in Figure 4, the domain mapping layers Adv 1 and Adv 2 use the leaky-ReLU activation function, and Adv 3 uses the Softmax activation function; Adv 1-Adv 3 layers are all fully connected layers. The adversarial domain adaption process for each label shares the first two layers. The loss of the joint discriminator can be expressed as follows:

$$L_{\mathrm{DCD}} = -\sum_{i=1}^{4}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right] - \lambda \sum_{i=1}^{4}\left[z_i \log(\hat{z}_i) + (1-z_i)\log(1-\hat{z}_i)\right] \quad (4)$$

where λ is a hyperparameter used to balance the class loss and domain loss. For the ith sample pair, y_i and z_i represent the true class and domain labels, respectively,, while $\hat{y}_i$ and $\hat{z}_i$ denote the model's predicted probabilities for class and domain, respectively.

Training process

The training process can be divided into four steps. The first step is to identify the source domain most compatible with the target domain, referred to as the best-matched source domain. It is crucial to note that each source domain dataset undergoes preliminary training with a straightforward classification model. These models are instrumental in the domain matching process. The target domain data are evaluated through classifiers trained on each source domain separately. The source domain exhibiting the highest accuracy is then selected as the best-matched source domain. The second step trains the encoder and classifier utilizing the best-matched source domain data. The third step employs a joint discriminator to facilitate adversarial domain adaption training, determining the domain of origin for the samples and the category labels to which they belong. Sample pairs are created by combining the source domain and target domain, and each sample pair is annotated with domain labels, reflecting whether they originate from the same domain and whether their labels are consistent. These annotated sample pairs are subsequently used to train the discriminator. Finally, a training session is performed to integrate the trained encoder, classifier, and discriminator until the model converges. It should be noted that all training data and testing data are strictly separated.

Experiments

Dataset

To evaluate the effectiveness of the proposed model, this study utilized the publicly available international dataset DEAP (Koelstra et al., 2012), for EEG-based emotion recognition. The DEAP dataset consists of data from 32 healthy individuals (50% female) with ages ranging from 19 to 37 years and an average age of 26.9 years. During the experiment, each subject was asked to watch 40 music video clips, each lasting one minute, while their EEG signals were recorded. The EEG signals underwent artifact removal processing, resulting in data from 32 channels with a sampling frequency of 128 Hz. After the experiment, the subjects rated each video on multiple dimensions, including overall valence, arousal, dominance, and liking, using an integer scale from 1 to 9. For instance, in the valence dimension, 1.0 represents extreme sadness, while 9.0 represents extreme happiness. The data collected in this study included 40 EEG recordings from each subject and their corresponding emotional labels. Each data segment consisted of 60 seconds of experimental signals and 3 seconds of baseline signals (recorded in a relaxed state). Table 1 shows a summary of the DEAP dataset.

Table 1: The summary of key features of the DEAP dataset.

Features	
Number of subjects	32
Number of video clips	40
Recorded signals	32-channel EEG(128Hz)
Labels	Valence, Arousal, Dominance

Experimental design

Data segmentation For data segmentation, within the context of the DEAP dataset, participants were presented with 40 video clips, each consisting of EEG data for 60 seconds across 32 channels, sampled at a frequency of 128 Hz. In this study, a 1-second segment of EEG data was designated as the fundamental unit for emotion analysis. Consequently, the data from a single participant can be segmented into 2400 samples of dimensions 32×128 using a non-overlapping window technique. These samples are labeled across three dimensions, valence, arousal, and dominance, with each dimension being rated on a scale of 1 to 9. As shown in Figure 3, each dimension is further categorized into two binary classification problems, using 5 as the threshold: high/low valence, high/low arousal, and high/low dominance (ratings ≤ 5 are considered low, and ratings > 5 are considered high). Thus, the task of emotion recognition in this study is formulated as a binary classification framework.

Feature extraction The differential entropy (DE) feature was used for emotion recognition in this study, as expressed as follows:

$$DE = -\int_{-\infty}^{+\infty} p(x)\log p(x)\,dx = -\frac{1}{2}\log(2\pi e\sigma^2) \quad (5)$$

where p(x) denotes the probability density function of the random variable x, and x is the value of the random variable. The DE feature is one of the most commonly used features in EEG analysis and is a critical feature for EEG-based emotion classification (J. Li, Qiu, Du, Wang, & He, 2020).

Results

To validate the effectiveness of our proposed MADA model in emotion recognition, we conducted classification experiments on 32 subjects from the DEAP dataset across three emotional dimensions: valence, arousal, and dominance. The classification accuracy for each subject and the average accuracy across all subjects are depicted in Figure 5. Our model achieves commendable cross- subject classification performance in these three emotional dimensions. Specifically, an

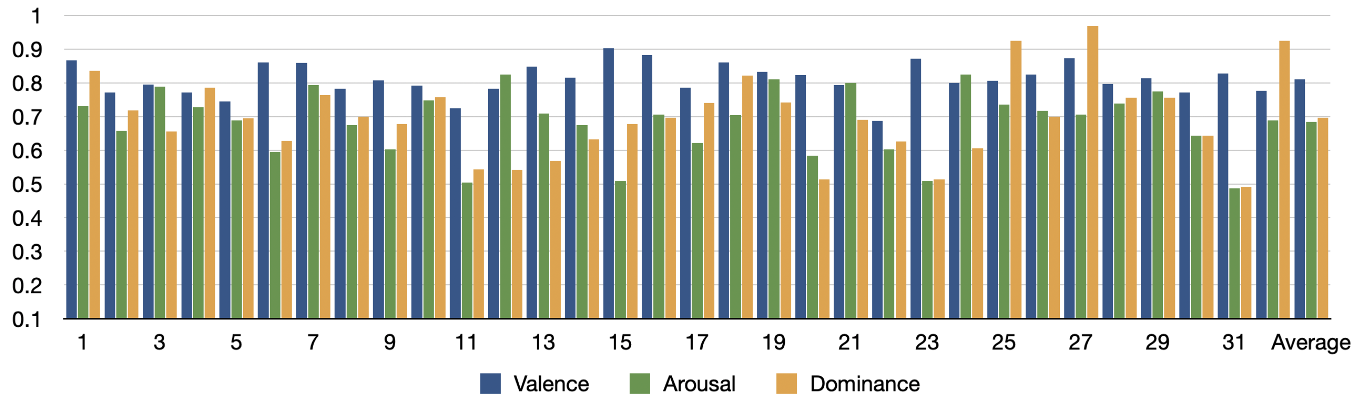

Figure 5: Accuracy of valence, arousal and dominance in DEAP dataset.

average classification accuracy of 76.48% was achieved for valence, 69.72% for arousal, and 68.14% for dominance.

Table 2: Comparison of emotion recognition results with other domain adaption or multi-task learning methods in the DEAP dataset.

Method	Valence	Arousal	Dominance
MT-MKL	60.00	56.00	/
PLRSA	61.84	62.07	/
WGANDA	66.85	67.99	/
TS-DATL	71.89	60.42	/
Proposed method	**76.48**	**69.72**	**68.14**

Furthermore, we compared our results with other emotion recognition methods based on domain adaption or multi-task learning approaches. As shown in Table 2, Kandemir et al.(2014) proposed the MT-MKL method, which combines multi-task learning with multiple kernel learning strategies to simultaneously classify multiple emotions. On the DEAP dataset, it achieved accuracies of 60.00% for valence and 56.00% for arousal. Luo et al.(2021) introduced the progressive low-rank subspace alignment (PLRSA) framework, unifying a semi-supervised instance-transfer paradigm and an unsupervised mapping-transfer learning paradigm in a single optimization framework. It achieved accuracies of 61.84% for valence and 62.07% for arousal on DEAP. The Wasserstein generative adversarial network domain adaption (WGANDA) framework proposed by Luo et al.(2018) achieved an accuracy of 66.85% for valence and 67.99% for arousal on DEAP. Pei et al.(2023) proposed the two-step domain adversarial transfer learning (TS-DATL) framework based on typical subjects, achieving accuracies of 71.89% for valence and 60.42% for arousal on DEAP. Compared to these models, our model demonstrated superior classification performance in the valence and arousal emotional dimensions on the DEAP dataset. Specifically, our model achieved accuracies 4.59%-16.48% higher for valence and 1.73%-13.72% higher for arousal compared to these four models. While PLRSA, WGANDA, and TS-DATL utilized domain adaption methods, they were based on single-task learning. Although MT-MKL employed multi-task learning, its accuracy was relatively lower, possibly due to the limitation of traditional multi-task learning in effectively handling inter-subject variability. None of the compared models classified emotions on the dominance dimension.

To further validate the effectiveness of the proposed MADA model, we conducted extensive ablation experiments and compared the classification results in the cases of the complete MADA model (i.e., complete model), no domain adaption, and no domain matching. In the no-domain adaption experiment, we utilized the domain matching module without employing the domain adaption module. The model trained with the best-matched source domain was directly applied to predict the target domain. In the no-domain matching experiment, we did not select the best-matched source domain; rather, the data for each subject in the dataset were independently treated as a source domain for training, and the average accuracy of all subject models was computed.

Table 3: Average accuracies(%) of ablation study on the DEAP dataset.

Method	Valence	Arousal	Dominance
No Domain adaption	54.36	53.90	55.12
No Domain matching	73.08	60.24	62.02
Complete model	76.48	69.72	68.14

The comparative results of no domain adaption, no domain matching, and the complete model across three emotional dimensions (valence, arousal, and dominance) are presented in Table 3 and Figures 6-8. It is evident that both domain adaption and domain matching modules, particularly the domain adaption module, play crucial roles in enhancing prediction accuracy. In the absence of domain adaption, even when selecting the best-matched source domain for the target domain, the average accuracies on valence, arousal, and dominance are only 54.36%, 53.90%, and 55.12%, respectively, which are notably lower than the results of the no-domain matching and the complete model. This indicates the necessity of addressing inter-subject variations in model training to enhance model performance. Moreover, training the model with the best-matched source domain for the target domain contributes to improved model performance, especially in the arousal and dominance dimensions, with average accuracies increasing by 9.48% and 6.12%, respectively.

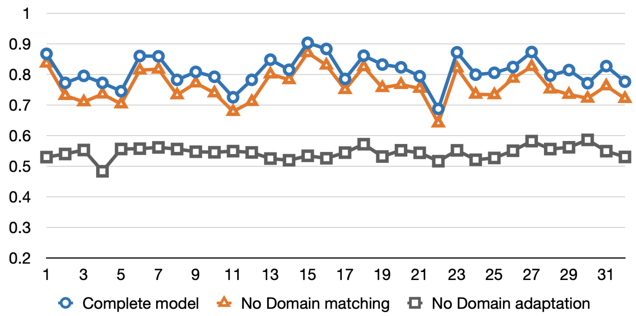

Figure 6: Accuracy of valence in ablation study

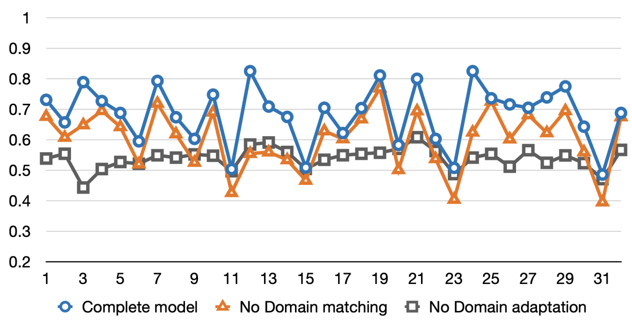

Figure 7: Accuracy of arousal in ablation study

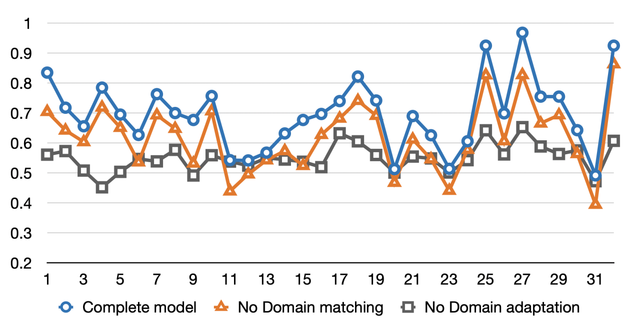

Figure 8: Accuracy of dominance in ablation study.

Discussion

In this study, we proposed a novel multi-task adversarial domain adaption (MADA) model for cross-subject EEG-based emotion recognition. The main challenges in the field of emotion recognition are significant individual differences and the scarcity of data. By introducing multi-task learning, our approach captures the intrinsic connections between various emotions, effectively mitigating the issue of data scarcity. Additionally, we employ domain matching to identify the most similar individuals in the source domain for model training, greatly reducing training time. The use of adversarial domain adaption techniques allows for the transfer of the optimally trained model from the best-matched source domain to the target domain, effectively alleviating the problem of individual differences. Extensive comparative experiments and ablation studies are conducted to validate the effectiveness of our model. The results affirm that our model enhances the performance of EEG-based emotion classification in user-dependent scenarios. In real applications, there is a need to achieve real-time emotion prediction. Traditional emotion classification models require extensive training when predicting new individuals. Our proposed MADA model can rapidly match and accurately predict emotions. However, current research still faces limitations, particularly in the imbalanced accuracy of predicting three different emotions, likely due to data imbalance and feature diversity issues. In future studies, we aim to improve the feature extraction method of the model to more effectively capture key information across different emotional dimensions. Additionally, we aim to further enhance the generalizability of the framework through cross-dataset emotion classification, addressing the challenge of sample scarcity in EEG-based emotion recognition research.

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