IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 March 2023, accepted 25 April 2023, date of publication 27 April 2023, date of current version 7 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3270977

RESEARCH ARTICLE

Domain-Adaptive Emotion Recognition Based on Horizontal Vertical Flow Representation of EEG Signals

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This work was supported in part by the National Natural Science Foundation of China under Grant 62103299, in part by the 2022 Tianjin Postgraduate Research and Innovation Project under Grant 2022SKYZ249, and in part by the Tianjin University of Technology Graduate Program under Grant YJ2226.

ABSTRACT With the development of cognitive science and brain science, brain-computer interface technology can use Electroencephalogram (EEG) signals to better represent the inner changes of emotions. In this paper, A video-induced emotional stimulation experimental paradigm was designed, and the EEG signals of 15 hearing-impaired subjects under three emotions (positive, neutral, and negative) were collected. Considering the flow diffusion properties of EEG signals, we used the diffusion effect based on horizontal representation and vertical representation forms to obtain the spatial domain features. After EEG preprocessing, the differential entropy feature (DE) in the frequency domain is extracted. The frequency domain features of 62 channels are delivered to two Bi-directional Long Short-Term Memory (BiLSTM) to obtain spatial domain features of horizontal and vertical representations respectively, and then two kinds of domain features are fused by the residual network. The attention mechanism is applied to effectively extract emotional representational information from the fused features. To solve the cross-subject problem of emotion recognition, the domain adaptation method is utilized, and a center alignment loss function is applied to increase the distance of inter-class and reduce the distance of intra-class. According to the experimental results, the average accuracies of 75.89% (subject- dependent) and 69.59% (cross-subject) are obtained. Moreover, the validation was also performed on the public dataset SEED, achieving average accuracies of 93.99% (subject-dependent) and 84.22% (cross-subject), respectively.

INDEX TERMS EEG signals, emotion recognition, domain adaptation, deep learning.

I. INTRODUCTION

Emotion is a complex psychological and physiological activity that occurs when people are confronted with objective things. It affects people's cognitive and decision-making abilities [1]. Emotion recognition is an interdisciplinary subject that integrates several types of disciplines such as computer science, psychology, cognitive science, and medicine. The main purpose of emotion recognition is to achieve a more comprehensive intelligent interaction by giving machines the ability to recognize and understand emotions, which in turn can lead to a better human-computer interaction (HCI) experience [2].

Psychologists have used two emotion models to characterize different affective states, namely the discrete model and the dimensional model [3]. The discrete emotion model

The associate editor coordinating the review of this manuscript and approving it for publication was Filbert Juwono.

focuses on assessing emotions by roughly classifying them into several common emotional states, while the continuous emotion model focuses on mapping emotions to different dimensions. In emotion recognition, researchers mainly use discrete models. Ekman et al. [4] proposed six basic emotion states, namely anger, fear, sadness, disgust, surprise, and joy. Based on this, Plutchik et al. [5] added anticipation, trust, and accepted for nine categories of basic emotion states.

Emotion recognition is a fundamental problem in affective computing, and its tasks are divided into two main types: emotion recognition based on non-physiological signals and emotion recognition based on physiological signals [6]. Non-physiological signals are mainly used for emotion recognition tasks using facial expression images [7], body poses [8], text [9], speech [10], etc. This type of approach is mainly used in the field of HCI, where it is hoped that the robot can determine the current emotional state by these common signals obtained in life to obtain a more intelligent and harmonious HCI environment. However, in practice, it has been found that such non-physiological signals are easily controlled by subjective subjects, and even the opposite emotion recognition results are obtained [11].

Related studies have shown that, compared to non-physiological signals, physiological signals such as EEG [12], Electromyogram (EMG) [13], Electrocardiogram (ECG) signals [14], etc., are spontaneously generated by multiple organs of the body after receiving relevant stimuli. These signals are not easily influenced by subjective will. Among them, EEG signals have been widely used in the field of emotion recognition because they are collected directly from the surface layer of the scalp, reflecting changes in the central nervous system, and having richer emotional information.

At this stage, there are two main steps for emotion recognition of EEG signals, feature extraction, and feature classification [15]. The feature extraction methods are mainly divided into the time domain, frequency domain, time-frequency domain, and spatial domain [16]. Yang et al. [17] used first-order difference and second-order difference for emotion recognition and found that the frontal, temporal, and occipital lobes have higher energy in emotional activities. Frequency domain information is mainly used to describe the details of the signal from the perspective of the frequency domain, where Power Spectral Density (PSD) is a widely used method for frequency domain features [18]. Lu et al. [19] proposed a time-frequency domain feature, which focuses on calculating the differential entropy (DE) feature at five different frequency band frequencies. Li et al. [20] proposed a space-time hypergraph convolutional network to explore spatial and temporal correlations in specific emotional states, and found that spatial domain information can effectively improve the accuracy of emotion recognition.

As the excellent performance of deep learning in the fields of image processing and natural language processing, it has attracted the attention of many emotion recognition researchers [21]. Researchers have started to use deep learning models for emotion classification tasks and achieved good results, such as convolutional neural networks [22], deep belief networks [19], graph convolutional neural networks [24], and domain adversarial networks [25]. Although the current research can classify emotions to a certain extent, EEG signals have the characteristics of circulation and inter-channel interaction, so the influence of these factors should be considered in the research.

For hearing-impaired subjects, the lack of hearing function may easily lead to problems such as emotional expression disorders and emotional cognition deviations [26]. In this paper, we collected the EEG signals of 15 hearing-impaired subjects when they were watching emotional movie clips. A domain-adapted emotion recognition model was proposed with horizontal and vertical flow. At the feature level, we combined original frequency domain features (DE) and the horizontal flow representation and vertical flow representation of frequency domain feature by attention mechanism, to obtain the EEG emotion representational information. For cross-subject emotion recognition, we construct the domain discriminator using the method of domain adaptation in transductive transfer learning where the main goal is to reduce the difference in distribution between the source and target domain.

The rest of the paper is organized as follows: in Section II, we present the related work. Section III presents the construction work of the dataset and the introduction of the public dataset. In Section IV, we describe the feature extraction methods and classifier construction in detail. Section V presents the experimental results. Section VI evaluates the performance of the proposed method. The VII section concludes.

II. RELATED WORK

In this section, we introduce the relevant content of EEG emotional representation feature extraction.

Feature extraction is an important part of emotion recognition, different features are applied to classification. Li et al. [27] verified the effectiveness of PSD features in emotion recognition using 11 classifiers. Delin et al. [28] explored the effect of different time window lengths on DE features in the frequency domain with short time windows. Cui et al. [29] used DE features to construct a four-dimensional network to obtain spatial features of the brain and used CNN-BiLSTM to deeply decode EEG signals to extract key features. Although the above studies obtained high accuracy, they did not consider the channel correlation of EEG. Therefore, this paper proposes horizontal and vertical flow features to fully characterize the EEG circulation characteristics. The EEG signals contain rich temporal and channel information which mainly includes the existence of certain connections between adjacent electrodes, and how to effectively characterize channel connections is a key factor considered by many researchers. Hao et al. [30] used a CNN approach to consider the connections between adjacent electrodes. Li et al. [31] introduced an attention mechanism to adaptively discriminate emotional information to obtain channels with strong emotional channels with high representational power. Li et al. [32] used a domain discriminator to induce the generation of emotionally relevant but invariant features to facilitate EEG emotion recognition and validated the model performance on three datasets.

The above studies increased certain accuracy of emotion recognition but did not consider the characteristics of EEG flow and diffusion. In this paper, based on the proposed feature extracted strategy, a combination of self-attention and domain adaptation is used to further capture representative features from the frequency domain and spatial domain for classification.

III. EXPERIMENTAL SETUP

This section describes the experimental setup for emotion elicitation in hearing-impaired people, including subject selection, elicitation video selection, and design of the experimental paradigm. To evaluate the proposed model, we also used the public dataset SEED.

A. SUBJECT SELECTION

The emotion elicitation experiment was approved by the Ethics Committee of Tianjin University of Technology. To validate the effect of the model among different subjects, 15 hearing-impaired sophomore college students (mean age: 22.0 years, 12 males and 3 females) from the School of Deaf Engineering of Tianjin University of Technology were recruited. Before participating in the experiment, basic information about each subject was collected, including personal information, auditory information, and family medical history, etc. Three of the subjects were born with congenital hearing impairment (two males and one female), and the rest had acquired hearing impairment due to disease. They all had normal vision or corrected vision, and were right-handed, could communicate normally with the sign language teacher.

The day before the experiment, the subjects were asked to get enough sleep, not to engage in strenuous physical activities, and not to eat or drink stimulating foods such as coffee and cola for a period before the experiment. Before the experiment, we invited a sign language teacher to participate in the experiment to ensure that the 15 subjects understood the purpose, procedure, and precautions of the experiment.

B. STIMULUS CLIPS SELECTION

The EEG signals of the hearing-impaired subjects were collected in three emotional states (positive, neutral, and negative). Our emotional movie clips selection and experimental procedure design refer to the SEED dataset [23]. The selection and experimental procedures of the movie clips in the SEED dataset have been shown to be effective in target emotion eliciting. There are 15 video clips as stimulus sources for positive (''Lost in Thailand'', ''Pandora's Box'', and ''Flirting Scholar''), negative (''Tangshan Earthquake'' and ''Back to 1942''), and neutral (''World Heritage in China'').

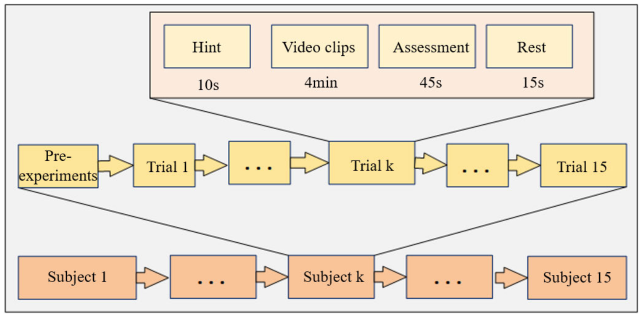

FIGURE 1. The schematic diagram of the experimental paradigm flow.

C. EXPERIMENTAL PARADIGM

To help the subjects understand the experimental process and to ensure that the subjects understand the purpose of the experiment, we added a pre-experiment. In the pre-experiment, the positive emotion clip, neutral emotion clip, and negative emotion clip were played sequentially, and the pre-experiment process was basically the same as the formal process. Figure 1 illustrates the basic experimental procedure. For each trial, a 5-s emotion hint was played to inform the subjects of the emotion induced by the clip to adjust their state. When the subject was calm and there was no obvious interference signal in the EEG signals, the EEG signals recording was started. A movie clip approaching 3-4 minutes was then played, and after the clip ended, the subject completed a self-assessment form to rate the current clip for preference and familiarity. If the subject was not induced with the corresponding emotion, the set of data was excluded. Finally, after a 15-s break, the next movie clip was moved to the next movie clip. The EEG signals acquisition device in this experiment was SymAmps2, a 64-lead EEG acquisition device manufactured by Neuroscan (Australia).

D. THE INTRODUCTION OF PUBLIC DATASET

The SEED emotion dataset is widely used for emotion recognition tasks of EEG signals and recognized by researchers [23]. The dataset contains 15 subjects (7 males and 8 females, a mean age of 23.27, and a standard deviation of 2.37), and each student collected data from three experiments, each separated by one week, so the experimental data contains a total of 15 subjects $\times$ 3 experiments $=$ 45 EEG subject data. There were 15 Chinese movie clips (5 positive, 5 neutral, and 5 negative clips) in one experiment, and each clip lasted approximately 4 minutes to induce the corresponding emotional state of the subjects. There was a 5-second cue before the start of each clip and a 15-second break at the end.

IV. METHODS

This section introduces the EEG signals pre-processing method, EEG emotion feature extraction method and the construction of classifier.

A. DATA PRE-PROCESSING

To obtain higher quality EEG signals, the pre-processing operation is needed to improve the signal-to-noise ratio of the signal. we downsampled the EEG signals to 200 Hz and used a band-pass filter (range 1-75 Hz) to remove low and high frequency noise, and a trap filter (49-51 Hz) to effectively avoid the influence of industrial frequency signals (50 Hz) on the EEG signals by EEGLAB. We used the mean value of the adjacent electrodes instead of the bad conductance, since some electrode shifts are inevitable in the acquisition process. Independent component analysis (ICA) is used to remove the sources of interference such as oscillogram and myoelectricity to improve the quality of the signal. Finally, the pre-processed signals were divided into five frequency bands, Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-16 Hz), Beta (16-32 Hz), and Gamma (32-50 Hz).

B. FEATURE EXTRACTION

Feature extraction is an important part of the emotion recognition task, we extracted the horizontal flow representation and vertical flow representation of EEG signals based on frequency domain features.

The two kinds of frequency domain features (PSD and DE) are extracted, respectively. The PSD feature mainly reflects the variation of signal power with frequency in unit frequency band. According to the energy conservation theorem, the time-domain energy is equal to the frequency-domain energy as shown in the following equation:

$$\int_{-\infty}^{\infty} |X(t)|^2 \, dt = \int_{-\infty}^{\infty} |f(t)|^2 \, df \tag{1}$$

The EEG signals is transformed from the time domain to the frequency domain for analysis, where the energy in the frequency domain is obtained using the discrete Fourier transform algorithm, for a discrete time series signal X in time, the transform equation is:

$$X(\omega) = \sum_{n=1}^{N} X(n) \, e^{-j\omega_k n} \tag{2}$$

The frequency domain energy values under each frequency band were averaged according to the EEG frequency division to the final power spectrum features.

The DE feature, as an extension of Shannon's entropy, demonstrates excellent performance in the characterization of EEG emotional features, which is defined as follows.

$$h(X) = -\int_X f(x) \log(f(x)) \, dx \tag{3}$$

where $f(x)$ is the probability density function of X. Assuming that the EEG signals time series X obeys a Gaussian distribution $N(\mu; \sigma^2)$, the differential entropy is calculated as:

$$\begin{aligned} h(X) &= -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}\right) dx \\ &= \frac{1}{2} log\left(2\pi e\sigma^2\right) \end{aligned} \tag{4}$$

The EEG signals contains rich spatial information, mainly because of the existence of certain connections among adjacent electrodes. Hence, we constructed two flow characterization matrix methods to represent the horizontal and vertical flow of the signal. Figure 2 shows the two flow characterization methods. The sequential signals of the two flows were obtained by arranging the PSD or DE of 62 channels which the position in order of horizontal and vertical directions.

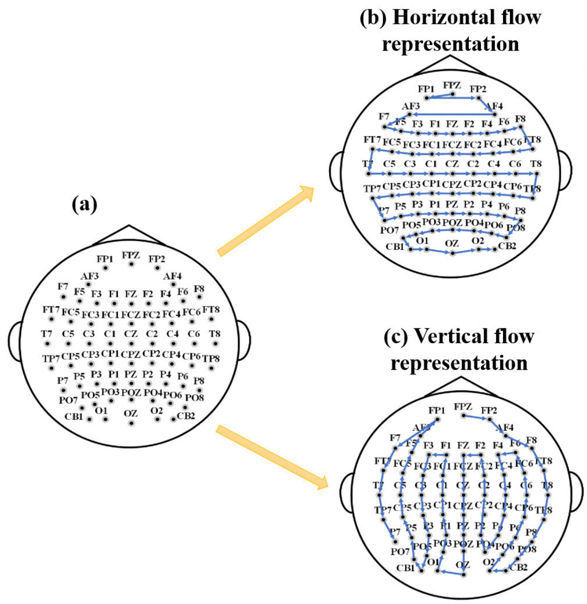

FIGURE 2. The horizontal and vertical flow characterization of EEG signals.

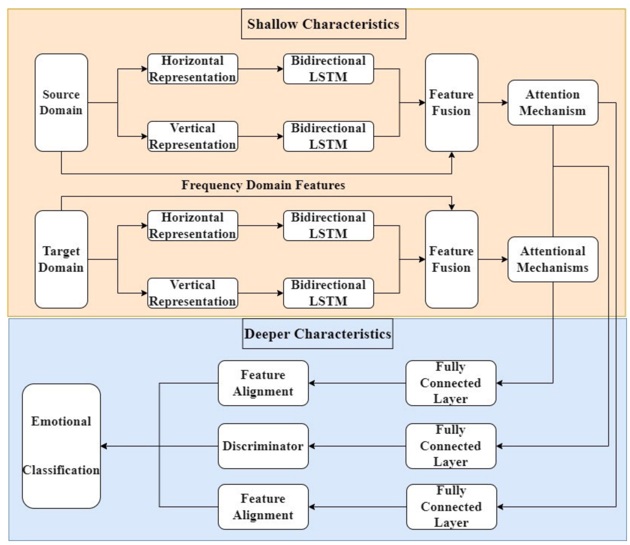

FIGURE 3. The schematic diagram of the structure of the domain adversarial emotion recognition network model based on the horizontal vertical flow of EEG signals.

C. EMOTION RECOGNITION NETWORK CONSTRUCTION

The structure of the domain adversarial emotion recognition network model based on horizontal vertical flow (HVF-DANN) of EEG signals can be divided into a shallow emotion feature extraction layer, and a deep emotion feature extraction layer. Figure 3 illustrates the network framework.

1) SHALLOW FEATURE EXTRACTION

A BiLSTM network was used to represent the bidirectional flow process of the EEG signals in the horizontal and vertical directions. The EEG features of the 62 electrode channels are fused according to the corresponding channel positions to extract the horizontal flow and vertical flow emotional representation features through BiLSTM to obtain the emotional feature f_s. The two-way emotional characteristics after the flow of EEG signals are $f_{h_1}, f_{h_2}, f_{v_1}, f_{v_2}$, the following equation is used to model the correlation action of the two types of signals.

$$f_s = \begin{cases} W_i f_{h_k}^i + M_i f_{v_j}^i \\ W_i f_{h_k}^i - M_i f_{v_j}^i \\ W_i f_{h_k}^i * M_i f_{v_j}^i \end{cases} \tag{5}$$

where the horizontal representation is h, the vertical representation is v, $i \in (1, 62)$ represents the 62 electrode serial numbers, and $k, j \in (1, 2)$ represents the BiLSTM networks in the forward and backward directions. W_i and M_i represent the weight vector of the horizontal flow signal and the weight vector of the vertical flow signal, respectively.

Hence, the frequency domain features (PSD or DE) and spatial domain features are fused by residual network, and obtain the fusion features as

$$F_{fusion} = \left[f, f_{h_1}, f_{h_2}, f_{v_1}, f_{v_2}, f_s\right] \tag{6}$$

Among them, f is the frequency-domain feature vector of the original input 62 channels and 5 frequency bands, f_{h_1}, f_{h_2} are the two-way emotional feature vectors after horizontal flow, f_{v_1}, f_{v_2} are the two-way emotional feature vectors after vertical flow Two-way emotional feature vector, f_s is the emotional feature vector after horizontal and vertical flow interaction, and the final emotional feature vector form is 62 channels × 421 neurons.

Moreover, we use a multi-headed Self-attention mechanism to make the model learn the emotion representation information autonomously from frequency domain and spatial domain. The Self-attention mechanism maps the input sequences by Query-Key-Value. For each input information A, the input information is projected to the corresponding query space Q, key space K and value space V using W_Q, W_K, W_V.

$$Q = AW_Q \tag{7}$$

$$K = AW_K \tag{8}$$

$$V = AW_V \tag{9}$$

Using the operation of dot product to calculate the similarity of the Q, K, the Softmax function converts the similarity score to probability values, the specific formula as

$$S = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \tag{10}$$

Finally, by dotting the S and V, we can obtain

$$Attention\,(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{11}$$

2) DEEP FEATURE EXTRACTION

We construct the domain discriminator using the method of domain adaptation in transductive transfer learning where the main goal is to reduce the difference in distribution between the source and target domain. The center-based discriminative loss was used for feature alignment to reduce inter-target variability. So that the source domain data and the target domain data are in the same sample subspace, thus allowing the classifier to judge the information in the target domain by the knowledge in the source domain, which is calculated as follows.

$$\mathcal{L}_d^C = \beta \sum_{i=0}^{n_s} max\left(0, \left\|h_i^s - c_{y_i}\right\|_2 - m_1\right)^2 + \sum_{i,j=1, i\neq j}^{c} max\left(0, m_2 - \left\|c_i - c_j\right\|_2\right)^2 \tag{12}$$

where β is an empirical parameter, n_s represents the source domain samples, h_i^s represents the source domain training samples of the i-th deep fully connected layer, m_1 and m_2 are two parameters that limit the edge distribution, c_{y_i} denotes the center of the y_ith category feature, c is the number of categories, and c_i is the mean of the depth features of all samples under that batch. Since the updating is based on the smallest batch of samples, it is difficult to average over the depth features of the entire training set. Here, the necessary modifications are made, and for c_i and c_j in (12), the mean value used to measure sparsity between categories is the mean of the current batch used, while c_{y_i} is used to measure the compactness of features within categories, so that the formula for c_{y_i} during each iteration is

$$\Delta c_j = \frac{\sum_{i=1}^{b} \delta\left(y_i = j\right)\left(c_j - h_i^s\right)}{1 + \sum_{i=1}^{b} \delta\left(y_i = j\right)} \tag{13}$$

$$c_j^{t+1} = c_j^t - \gamma \cdot \Delta c_j^t \tag{14}$$

where γ is the learning rate, which is used to update the speed of the global class center, and finally Eq. (12) can be simplified as

$$\mathcal{L}_d^C = \beta \parallel \max\left(0, H_C - m_1\right) \parallel_{sum} + \parallel \max\left(0, m_2 - D_c\right) \parallel_{sum} \tag{15}$$

where $H_C = \left\|h_i^s - c_{y_i}\right\|_2^2$ represents the depth feature h_i^s of layer i and the corresponding center c_{y_i}, and $D_c = \left\|c_i - c_j\right\|_2^2$ represents the pairwise distance of batch class centers.

In the overall framework, we use the following minimization loss function for training.

$$\mathcal{L} = \mathcal{L}_s + \lambda_1 \mathcal{L}_c + \lambda_2 \mathcal{L}_d \tag{16}$$

$$\mathcal{L}_s = \frac{1}{n_s} \sum_{i=1}^{n_s} c(\Theta \left| x_i^s, y_i^s\right.) \tag{17}$$

$$\mathcal{L}_c = \mathcal{L}_{dis}\left(G_d\left(G_f\left(x_i; \theta_f\right); \theta_d\right), d_i\right) \tag{18}$$

$$\mathcal{L}_d = J_d(\Theta \left|X_s, Y_s\right.) \tag{19}$$

TABLE 1. The details of model parameters.

Classification	Model	Parameter
Machine learning	Support Vector Machines (SVM)	Linear kernel function, C=1
	K-Nearest Neighbor (KNN)	K: 5
	Random Forest (RF)	Estimators：1000
Deep learning	Deep Neural Networks (DNN)	Fully connected layer ：[256,64] Learning rate：0.01 Batch size：200
	Deep Belief Network (DBN)	Fully connected layer ：[256,64] Learning rate：0.01 Batch size：200
	Dynamic Graph Convolutional Neural Networks (DGCNN)	Learning rate：0.001 Batch size：200
	Domain Adaptation Neural Networks (DANN)	Learning rate：0.005 Batch size：200 L1：0.01
	HVF-DANN	Learning rate：0.005 Batch size：200 L1：0.01 Center Loss Parameters：10

where $\mathcal{L}_s$, $\mathcal{L}_c$ and $\mathcal{L}_d$ represent classification loss, domain variability loss and discriminative loss, respectively. λ_1 and λ_2 are empirical parameters to balance domain variability loss and discriminative loss. $\mathcal{L}_c$ is a domain discriminator method to determine the variability of source and target domains. $\mathcal{L}_d$ is a discriminative feature learning method to ensure that the data in the target domain have better inter-class and intra-class distances.

3) EXPERIMENTAL ENVIRONMENT

The experimental environment is configured with the following parameters: CPU: i5 8300H 2.4G, 16G, GPU: NVIDIA GeForce 1060 6G. python: 3.6, TensorFlow: 1.4. We used some classical networks for comparison experiments, and Table 1 shows the parameter settings used in all our experiments.

We selected 15 movie clips (3 emotions, 5 clips for each emotion), and each clip intercepted the end 180s data. For subject-dependent experiments, 9 movie clips (3 for each emotion) were selected for training and 6 movie clips (2 for each emotion) for testing. For cross-subject experiments, we used the leave-one-out method to test each subject individually, and the training set used all the data of the other 14 subjects.

V. RESULTS

This section introduces the discrete emotion classification experiments based on the hearing-impaired dataset, mainly including the feature extraction method, data length, and the effect of classifier selection on classification performance.

A. THE COMPARISON OF FEATURE EXTRACTION METHODS

To explore the effect of different emotion features on the discrete emotion classification performance of hearing-impaired subjects, we extracted two features here: PSD and DE, respectively. We use the non-overlapping sliding window method to slice the experimental data into data lengths of 1 s, and the obtained training set data are fed into the SVM classifier, the results as Figure 4. It shows that each subject has a large deviation in the classification effect, indicating that the EEG data has a large subject deviation, where subject 5, subject 6, and subject 12 have a better classification performance with 68.01%, 82.87% in PSD, DE, respectively, 76.05%, 80.24% and 85.64%, 82.30%, respectively, while subject 7 had poorer classification performance with an average classification accuracy of 45%. In the comparison of the two types of features, the DE feature has a better ability to characterize emotions in most subjects, significantly higher than the PSD feature with a smaller deviation.

B. THE COMPARISON OF DATA LENGTH

In feature extraction, different data lengths have an important effect on classification performance. In the data length comparison experiments, in order to keep the training and test sets with the same data samples under different data lengths, different sliding window strategies are used, a sliding window with no overlap for 1 s, a sliding window with 50% overlap for 2 s, a sliding window with 66% overlap for 3 s, and a sliding window with 75% for 4 s, followed by DE extraction of the obtained data, input to the SVM classifier.

Figure 5 shows the classification performance results of EEG emotions for 15 hearing-impaired subjects under different data length divisions. We found that the increase in data length can enhance the classification performance, but the effect is not significant, and the average accuracies are 67.33%, 70.09%, 70.94%, and 70.97%, respectively. The best classification performance is for data length, which improves the performance by 3.64% compared to 1 s data length, and after the paired t-test, the results of 4 s and other time lengths are all less than 0.05. However, the required data length is four times more than the 1 s data length. Therefore, we choose 1 s data length for all experiments in the following sections.

C. THE COMPARSION OF CLASSIFICATION METHODS

To demonstrate the effectiveness of our proposed model, we compare it with commonly used methods, including machine learning methods: SVM, KNN, RF, and deep learning methods: DNN, DBN [19], DANN, DGCNN [24], respectively. For better correlation and comparison, the experiments all choose 1s data length for DE feature extraction, and finally extract the data format of 5 (EEG frequency band) × 62 (EEG electrode channel). The results in Table 2 show that the HVF-DANN method has the best classification performance and is significantly better than the other classification methods with an average accuracy of 75.89%, and has the

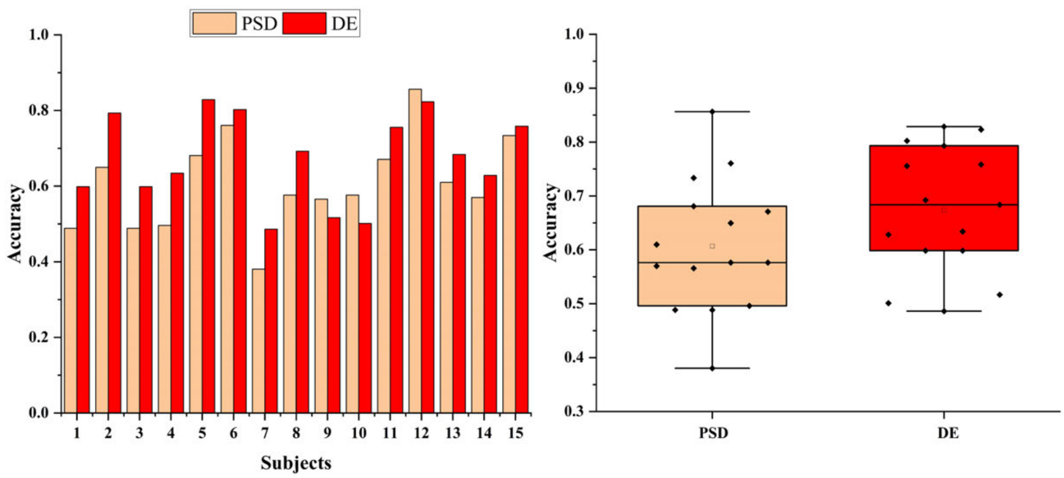

FIGURE 4. The subject-dependent classification results with different frequency domain features.

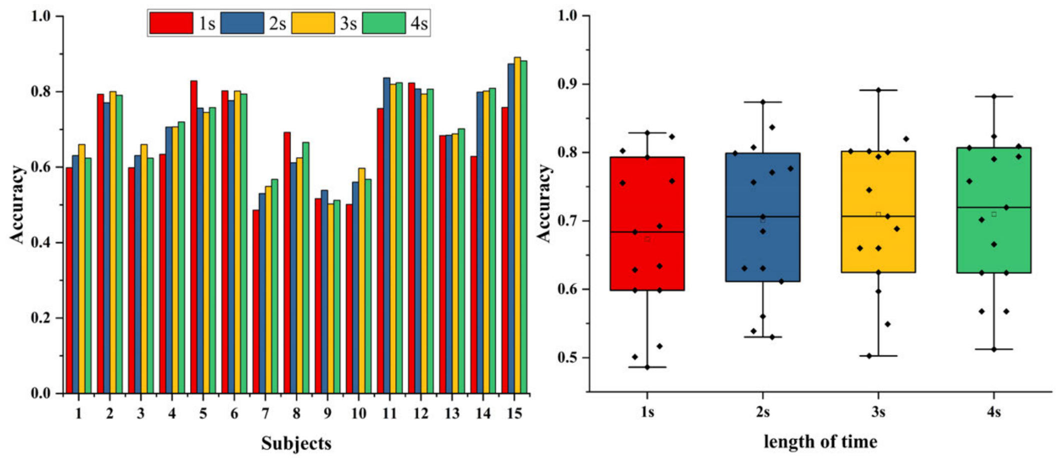

FIGURE 5. The subject-dependent classification results with different data lengths of DE features.

TABLE 2. The experimental results for subject-dependent with hearing-impaired subject.

Method	SVM	KNN	RF	DNN	DBN	DGCNN	DANN	**HVF-DANN**
ACC (%)	67.33	61.05	59.21	58.72	68.05	72.87	72.00	**75.89**
STD (%)	11.43	12.71	16.35	12.97	12.99	11.15	11.90	**10.75**
F1 score (%)	65.23	57.45	55.29	55.17	64.95	68.12	69.32	**72.95**
STD (%)	12.92	14.24	19.09	15.29	13.54	14.23	13.54	**12.01**

smallest standard deviation. The F1 score is higher than other classifiers, and the paired t-test is less than 0.05.

The performance of 15 subjects with different classifiers is shown in figure 6. From the results, subject 7 has the worst classification performance, with only about 40% classification accuracy, and each classifier cannot effectively improve the classification performance, probably due to the presence of too many interference signals that make it difficult to extract the corresponding emotional features. In comparison, subject 12 has a better classification performance, and has good classification results in each classifier, with an average classification accuracy of about 80%. Also, the mean and variance of the box plot data show that our proposed HVF-DANN has significantly higher classification performance and less bias than the other methods, indicating that our method has better emotion classification performance and can effectively classify three different emotions.

D. CROSS-SUBJECTS AFFECTIVE CATEGORIZATION PERFORMANCE

In the cross-subjects emotion classification task, we also compare the proposed model with a series of cross-subjects emotion recognition models. The results in Table 3 show the cross-subjects average emotion classification results for 15 hearing-impaired subjects, from which it can be seen that the proposed HVF-DANN has the best classification performance and significantly outperforms the other classification methods with an average accuracy of 69.59% and a standard

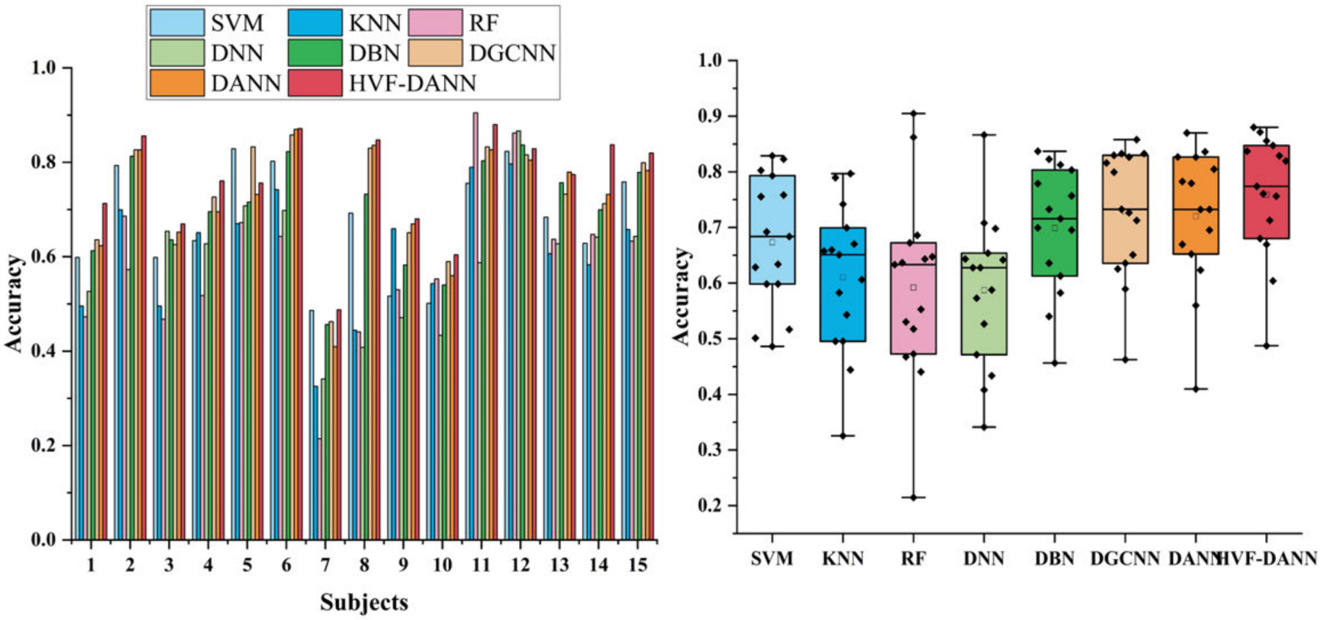

FIGURE 6. The classification results of subject-dependent under different classifiers.

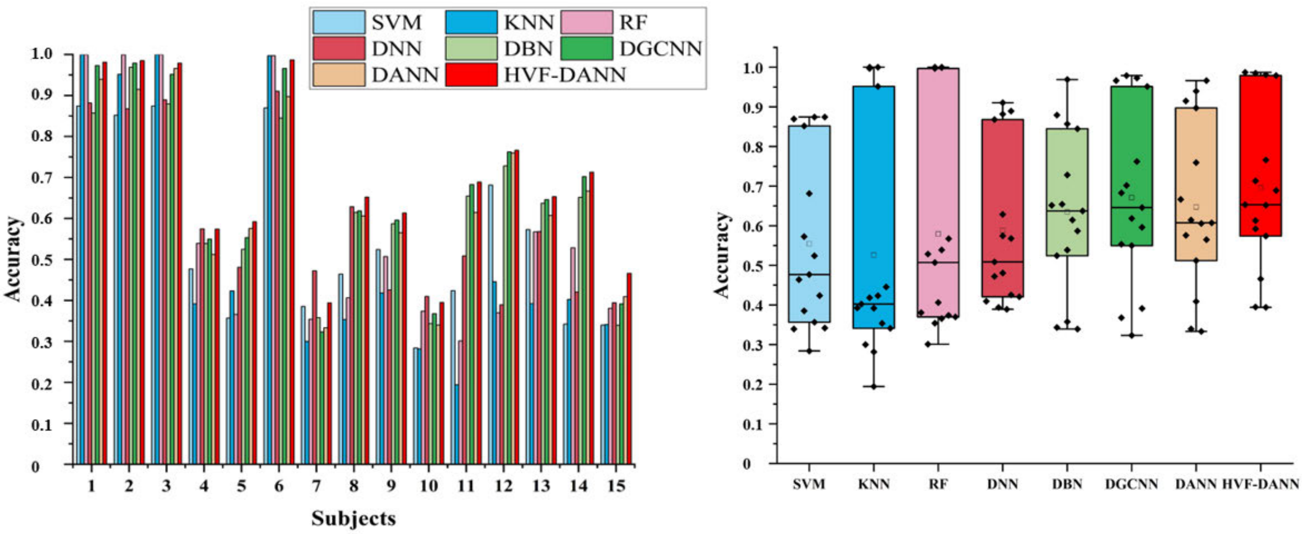

FIGURE 7. The classification results of cross-subject under different classifiers.

TABLE 3. The experimental results for cross-subjects with hearing-impaired subject.

Method	SVM	KNN	RF	DNN	DBN	DGCNN	DANN	**HVF-DANN**
ACC (%)	55.46	52.62	57.93	58.80	63.50	67.07	64.71	**69.59**
STD (%)	21.19	28.48	26.37	19.25	19.10	21.45	20.31	**20.09**
F1-SCORE (%)	52.60	50.38	54.39	56.21	65.21	66.51	62.51	**73.21**
STD (%)	23.51	30.17	29.31	23.51	19.31	23.84	24.56	**17.42**

deviation of 20.09% At the same time, we conducted F1 score and paired t-test, the F1 score of HVF-DANN is the highest, and the paired t-test with other classifiers is less than 0.05.

The classification performance of 15 subjects in the cross-subject emotion classification task under different classifiers is shown in Figure 7. From the results, it can be seen that the classification performances of subject 7, subject 10, and subject 15 are poor, with only about 40% classification accuracy. Our proposed HVF-DANN model improves the classification performance somewhat compared to other

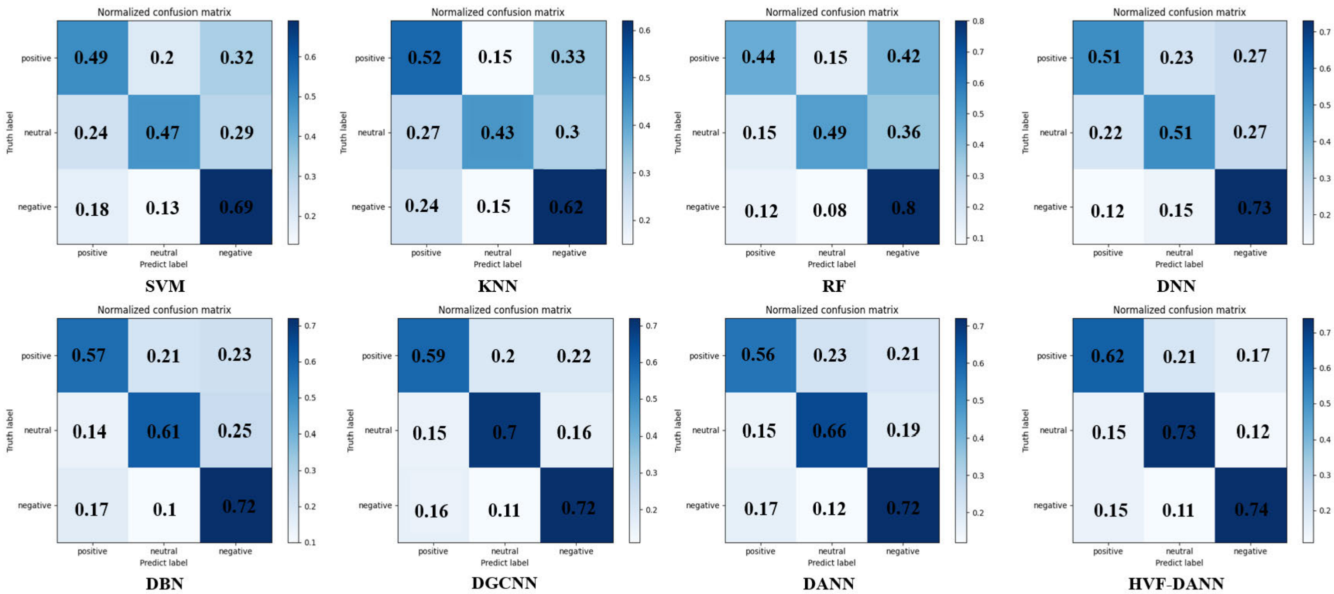

FIGURE 8. The average subject confusion matrix based on different classifiers.

TABLE 4. The results of subject-dependent with different frequency bands.

Method	ACC/STD (%) Delta	Theta	Alpha	Beta	Gamma
SVM	56.20 (13.43)	59.84 (14.07)	60.66 (12.29)	62.58 (12.54)	63.08 (11.98)
KNN	46.23 (13.37)	53.94 (13.65)	55.34 (12.00)	55.95 (13.32)	57.20 (13.12)
RF	49.96 (17.05)	51.44(15.81)	53.89 (17.44)	54.43 (16.59)	55.21 (16.41)
DNN	47.33 (16.03)	51.92 (12.65)	53.06 (13.12)	52.43 (12.24)	54.77 (13.05)
DBN	58.59 (12.50)	63.90 (11.75)	63.06 (12.23)	64.99 (11.25)	66.23 (10.33)
DGCNN	61.08 (12.78)	65.50 (9.34)	66.99 (13.65)	67.68 (11.91)	68.39 (10.15)
DANN	63.63 (11.01)	65.45(13.82)	65.01 (13.70)	66.41 (12.07)	68.56 (11.60)
HVF-DANN	**66.85 (14.67)**	**67.27 (12.15)**	**69.19(10.75)**	**69.94 (12.41)**	**72.39 (10.35)**

TABLE 5. The results of subject-dependent based on the SEED dataset.

Method	SVM	RF	DBN	DGCNN	DANN	GCNN	CCA	GSCCA	R2G-STNN	**HVF-DANN**
ACC (%)	83.99	78.46	86.08	90.40	91.36	87.40	77.63	82.96	93.38	**93.99**
STD (%)	9.72	11.77	8.34	8.49	8.30	9.20	13.21	9.95	5.96	**4.59**

TABLE 6. The results of subject-dependent based on the SEED dataset at different frequency bands.

Method	ACC/STD（%） Delta	Theta	Alpha	Beta	Gamma
SVM	60.50 (14.14)	60.95 (10.20)	66.64 (14.41)	80.76 (11.56)	79.56 (11.38)
RF	64.56 (8.32)	65.27 (11.64)	65.67 (13.94)	73.35 (14.35)	74.48 (12.80)
CCA	55.30 (12.02)	55.75 (10.99)	64.96 (12.05)	69.16 (11.45)	70.67 (14.06)
GSCCA	63.92 (11.16)	64.64 (10.33)	70.10 (14.76)	76.93 (11.00)	77.98 (10.72)
DBN	64.32 (12.45)	60.77 (10.42)	64.01 (15.97)	78.92 (12.48)	79.19 (14.58)
GCNN	72.75 (10.85)	74.40 (8.23)	73.46 (12.17)	83.24 (9.93)	83.36 (9.43)
DGCNN	74.25 (11.42)	71.25 (5.99)	74.43 (12.16)	83.65 (10.17)	85.73 (10.64)
DANN	72.13 (11.22)	68.75 (7.40)	70.27 (10.84)	83.35 (11.46)	87.89 (11.35)
R2G-STNN	77.76 (9.92)	76.17 (7.43)	82.30 (10.21)	88.35 (10.52)	88.90 (9.97)
HVF-DANN	**78.16 (8.32)**	**77.07 (8.59)**	**84.11 (12.22)**	**89.42 (11.32)**	**89.51 (12.14)**

models, but the results are still not satisfactory, probably because there are too many noisy signals in the subjects' EEG signals that affect the overall signal quality. The comparison shows that Subject 1, Subject 2, Subject 3, and Subject 6 have better classification performance in the cross-subject emotion classification task, with an average classification accuracy of about 90%. Meanwhile, the box plots show the distribution, mean, and variance of the emotion classification accuracies

TABLE 7. The results of cross-subject experiments based on the SEED dataset.

Method	DGCNN	DANN	Bi-DANN	R2G-STNN	**HVF-DANN**
ACC (%)	79.95	75.08	83.28	84.16	**84.22**
STD (%)	9.02	11.18	9.60	7.63	**8.77**

TABLE 8. The results of ablation experiments.

Subject-dependent Experiment		
Cross-subject experiments	ACC/STD (%)	
	Hearing-impaired	SEED
HVF-DANN（w/o hvflow）	72.33/11.69	91.52/6.52
HVF-DANN（w/o attention mechanism）	73.59/10.88	90.22/8.26
HVF-DANN（w/o domain adaptation）	70.55/11.38	88.21/7.21
HVF-DANN	**75.90/10.75**	**93.99/4.59**
Cross-subject experiments	ACC/STD (%)	
	Hearing-impaired	SEED
HVF-DANN（w/o hvflow）	65.56/21.33	82.55/10.11
HVF-DANN（w/o attention mechanism）	66.52/21.65	82.78/11.22
HVF-DANN（w/o domain adaptation）	61.33/21.55	80.62/10.96
HVF-DANN	**69.59/20.10**	**84.22/8.77**

of the 15 subjects. From the above results, it can be seen that the HVF-DANN has significantly higher classification performance and less bias than the other methods, indicating that our method has better cross-subject emotion classification performance and can effectively classify three different emotions in the cross-subject emotion classification task.

VI. DISCUSSION

In this section, we analyze the effect of specific emotion recognition in hearing-impaired subjects and validate the model on a public SEED dataset. The classification performance of specific frequency bands is also investigated, and finally, the model is subjected to ablation experiments.

To explore the classification performance of each classifier on the emotional categories, we obtained the confusion matrix for each subject in the emotion classification. Here, to analyze the performance of different classifiers for emotional categories, we obtained confusion matrices for 15 subjects under each of the three emotions, as shown in Figure 8. We found that among the three categories of emotions, negative emotions have the highest classification accuracy among the eight classifiers, and it may indicate that negative emotions are easily distinguished. While neutral emotions have the lowest classification accuracy, and it may indicate that neutral emotions are difficult to be distinguished by the classifiers. The neutral emotions were easily misclassified into positive emotions and positive emotions were also easily misclassified into neutral emotions, which may indicate that it was more difficult to distinguish positive emotions from neutral emotions in our dataset. Moreover, we found that negative emotion was more easily misclassified into positive emotions.

To investigate the contribution of different frequency bands in EEG emotion recognition, we also extracted DE features from five frequency bands, and the experimental results are shown in Table 4. We found that higher classification performance was achieved in the high-frequency band (Beta, Gamma) and the highest classification performance in the Gamma band, indicating that the emotional activity of the hearing-impaired subjects was mainly concentrated in the high-frequency bands. Instead, the lower-frequency bands (Delta, Theta, Alpha) have poorer classification performance, possibly indicating that emotions had less display in these three frequency bands.

To demonstrate the classification performance of HVF-DANN, we will conduct experiments under the public dataset SEED dataset, which mainly consists of subject-dependent emotion classification experiments and cross-subject emotion classification experiments. According to Table 5, it can be seen that among the machine learning methods, SVM significantly outperforms RF, CCA [34], and GSCCA [35] with 4.76%, 6.36%, and 1.03% higher classification accuracy, respectively. Among the deep learning methods our proposed method significantly outperforms DBN, GCNN, DGCNN [36], DANN, and R2G-STNN [37] with 13.91%, 6.59%, 3.59%, 2.63%, and 0.61%, respectively. This result demonstrates that domain adaptation methods can significantly improve emotion classification performance. In addition, the proposed method significantly outperforms the other methods, obtaining the highest recognition rate of emotion classification and the smallest standard deviation of 93.99% and 4.59%, respectively.

We also studied the effect of different frequency bands for emotion classification on the SEED dataset, and the results are shown in Table 6. The high-frequency bands (Beta, Gamma) have higher emotion recognition performance compared to the low-frequency bands (Delta, Theta, Alpha), and the recognition performance of the Gamma band is about 10% higher than the classification results of Delta and Theta bands, indicating that emotions have more obvious changes in the high-frequency bands. This result is generally consistent with previous findings that part of the research indicates that emotional information is mainly concentrated in the high-frequency bands (Beta, Gamma) [33].

In the cross-subject emotion classification task, the relevant experimental results compared with a series of cross-subject emotion recognition models are shown in Table 7. The experimental results show that the proposed HVF-DANN model improves by 4.27%, 9.14%, 0.94%, and 0.06% over DGCNN, DANN, Bi-DANN, and R2G-STNN models, respectively. In addition, we found that the use of domain adaptation can effectively improve the experimental performance of cross-subjects emotion classification, and this may be because the data of the target subjects is used to train the model so that the model learns the data distribution information of the target subjects and therefore has better generalization ability on the target subjects.

We conducted a series of ablation experiments to demonstrate the effectiveness of the model structure, verifying the information flow integration layer, the attention mechanism layer, and the domain adaptation method layer of the model, respectively. The HVF-DANN (w/o hvflow) is without horizontal flow representation and vertical flow representation. HVF-DANN (w/o attention mechanism) is without an attention mechanism for feature fusion. HVF-DANN (w/o domain adaptation) is without domain adaptation, and the subsequent domain discriminator and alignment loss function are removed. Table 8 shows the ablation performance in both subject-dependent experiments and cross-subject experiments. We can see that the information flow integration layer, the attention mechanism layer, and the domain adaptation approach layer, all help to improve the classification performance of emotions in two datasets. Moreover, the domain adaptation approach layer has the greatest effect on classification performance. The results prove that the domain adaptation approach can indeed effectively improve the generalization ability of the model by considering the data distribution of the target domain.

VII. CONCLUSION

This paper focuses on proposing an HVF-DANN emotion recognition model to improve the performance of emotion recognition tasks under EEG signals for the hearing impaired. The model mainly considers the interconnections between channels and uses the horizontal flow representation and vertical flow representation of EEG signals to obtain the spatial domain features. We fused the frequency domain features and spatial domain features and utilized an attention mechanism to obtain the emotional representational information. A domain discriminator is constructed using the domain adaptation method in transduction transfer learning is used to realize cross-subject emotion recognition, with the emotion recognition accuracy (75.89% for subject-dependent) and 69.59% for cross-subject). Moreover, to evaluate the generalization ability and effectiveness of the model, we validate the proposed model on the SEED dataset and use ablation experiments. The quantitative evaluation results demonstrate that the proposed HVF-DANN model has an excellent performance.

In our future work, we will systematically investigate cross-subject emotion recognition using deep learning and reinforcement learning methods. At the same time, we will further explore the emotional representation capabilities of different brain regions of the hearing-impaired population, as well as the characteristics suitable for this population.

ACKNOWLEDGMENT

(Zhongli Bai and Zeyu Li are co-first authors.)

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