IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 6 February 2024, accepted 6 March 2024, date of publication 14 March 2024, date of current version 20 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3375393

RESEARCH ARTICLE

A Random Forest Weights and 4-Dimensional Convolutional Recurrent Neural Network for EEG Based Emotion Recognition

WENXU WANG[1], JIA YANG[2], SHENGJIA LI[2], BIN WANG[1,3], KUN YANG[1,4], SHENGBO SANG[1,4], QIANG ZHANG[1,4], AND BOYUAN LIU[1]

[1]Shanxi Key Laboratory of Micro Nano Sensor and Artificial Intelligence Perception, College of Electronic Information and Optical Engineering, Taiyuan University of Technology, Taiyuan 030024, China
[2]Centre of Research and Development, China Academy of Launch Vehicle Technology, Beijing 100076, China
[3]College of Computer Science and Technology, Taiyuan University of Technology, Taiyuan 030024, China
[4]Key Laboratory of Advanced Transducers and Intelligent Control System of the Ministry of Education, Taiyuan University of Technology, Taiyuan 030024, China

Corresponding author: Kun Yang (yangkun01@tyut.edu.cn)

This work was supported in part by the Innovation Fund of China Aerospace Science and Technology Corporation under Grant [2021]397, and in part by the Distinguished Young Scholars Development Program of Shanxi Province under Grant 202103021221006.

ABSTRACT Emotion recognition based on electroencephalography (EEG) signals has garnered substantial attention in recent years and finds extensive applications in the domains of medicine and psychology. However, individual differences in EEG signals pose a challenge to accurate emotion recognition and limit the widespread adoption of such techniques. To address this issue, this study proposes a model that combines random forest weights (RFWs) and four-dimensional convolutional recurrent neural network (4DCRNN) to minimize individual differences and captures emotion-relevant information. By integrating, the proposed model aims to improve the accuracy and generalization capability of emotion recognition. To evaluate the performance of the proposed model, experiments were conducted using the DEAP and SEED datasets. The results demonstrate the effectiveness of the RFW-4DCRNN in emotion recognition. Specifically, the proposed model achieves mean accuracy of 94.98% and 94.21% for Subject-dependent recognition using the DEAP and SEED datasets, respectively. For Subject-independent emotion recognition, the model achieved mean accuracy of 81.70% and 91.12% using two datasets, respectively. The result highlights the capability of the RFW-4DCRNN to effectively recognize emotions and improves generalization performance. Overall, this study presents an approach to addressing individual differences in EEG-based emotion recognition. The RFW-4DCRNN demonstrates promising results in terms of accuracy and generalization capability, offering potential for the advancement and application of emotion recognition techniques.

INDEX TERMS Emotion recognition, electroencephalography, individual differences, 4DCRNN.

I. INTRODUCTION

Research on emotion recognition has been characterized by continuous advancement, with researchers fervently striving to investigate effective emotion recognition algorithms that can be suitably implemented [1], [2], [3]. Certain researchers have been inclined toward recognizing emotions based on facial expressions and bodily movements [4], [5], [6], [7]. Nevertheless, these methods are susceptible to subjective manipulation. Consequently, the investigation of emotion recognition techniques based on physiological signals has garnered considerable attention. In particular, in recent times, emotion recognition based on electroencephalography (EEG) signals has witnessed a surge in interest. EEG-based emotion recognition technology is considered to improve human-computer interaction capabilities and provide wider commercial applications [8]. EEG captures electrical signals emanating from neuronal firing within the brain. Such firing activity of neurons undergoes alterations in response to diverse cognitive and emotional states. Consequently,

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

EEG signals serve as reflections of manifold cognitive and emotional conditions. Emotion represents a fundamental mental state intrinsic to human beings, encompassing subjective feelings and physiological responses to stimuli or events. Given the profound interdependence between emotion generation, expression, and brain activity, EEG signals can effectively mirror and discern several emotional states. However, a persistent challenge in the field is the intricate variability in EEG signals among individuals, which hinders the development of robust and universally applicable emotion recognition models. Individual differences pose a critical obstacle, necessitating innovative approaches to address this inherent complexity [9].

Adequately transforming raw EEG signals to extract meaningful features is imperative for classifying emotions based on EEG signals [10], [11], [12]. However, EEG signals inherently exhibit noise and variability [13], [14], with individual differences significantly affecting the reliability of emotion recognition. This issue assumes particular importance in cross-subject emotion recognition studies because individual variances in EEG signals have been widely acknowledged as a key obstacle in achieving a universal classifier [9], [15].

Various methods have been proposed to optimize the effectiveness of cross-subject emotion recognition in response to this limitation. Li et al. [16] conducted a systematic study on the emotional information recognition capabilities of different EEG features in diverse subjects. They extracted 18 linear and nonlinear EEG features, employed support vector machine (SVM) methods, and used "leave-one-out validation" to validate their strategies. Du et al. [17] introduced an attention-based long short-term memory (LSTM) emotion recognition model that incorporates a domain discriminator to ensure recognition efficiency in independent subject scenarios. Samavat et al. [18] proposed a multi-input deep model based on convolutional neural networks (CNNs) and LSTM, and applied adaptive regularization technology to improve generalization performance. Yildirim et al. [19] used the swarm intelligence algorithm to reduce the feature size by 87.17% and a random forest classifier to achieve average accuracy of 60.01%, providing an effective approach for analyzing and screening EEG features. Li et al. [20] proposed a method based on CNNs and contrastive learning (ECNN-C), which achieved remarkable results in the three dimensions of the Database for Emotion Analysis using Physiological (DEAP) and DERAMER datasets. Yang et al. [21] extracted multiple features to construct high-dimensional feature sets, and through the integration of significance test/sequential backward selection and SVM, the approach was validated using the DEAP and SEED datasets. Cimtay and Ekmekcioglu [22] employed a pre-trained state-of-the-art CNN architecture to enhance subject-independent recognition performance. Shen et al. [23] proposed a contrast learning method for intersubject alignment (CLISA) to address the challenge of intersubject sentiment recognition. There have also been significant advances in research on emotion recognition without cross-subject bias. Chen et al. [24] proposed the Personal-Zscore feature processing method, which was applied to the SEED dataset. The method effectively eliminated the aggregation of individuals in the feature space and improved the emotion representation of the dataset, demonstrating the importance of the feature processing method for cross-subject emotion recognition research. Shen et al. [25] improved the accuracy of EEG-based emotion recognition by manually extracting differential entropy features of EEG signals, followed by classification using a four-dimensional convolutional recurrent network. Despite the substantial progress achieved, individual differences continue to exert a significant impact on emotion recognition.

Prior research has predominantly steered toward two distinct paths: the conventional realm of feature engineering and the burgeoning landscape of deep learning models. The critical gap in the existing literature lies in the polarized nature of these two approaches. Conventional feature engineering offers transparency and interpretability but may fail to capture the full complexity of emotional states. Conversely, deep learning models excel in automatic feature extraction but may lack transparency, hindering their interpretability and potentially sacrificing the incorporation of domain-specific knowledge.

The primary objective of this study was to improve the accuracy and efficiency of EEG-based emotion recognition by addressing individual differences through a synergistic combination of conventional feature extraction and deep learning. EEG signals are inherently complex and nonlinear. Although deep learning models such as 4DCRNN are very powerful in learning hierarchical representations, the complexity of EEG signals causes significant interference for these models and significantly increases the number of calculations. Therefore, using a certain method to manually extract EEG features allows us to quickly identify and prioritize relevant features in the input space, remove noise, and improve recognition efficiency. Manual feature extraction can also analyze individual differences in EEG more clearly, extract features that are more closely related to emotions, and exclude features that are affected by individuals. Our contributions lie in the development of a novel model, termed RFW-4DCRNN, that strategically integrates the strengths of both methodologies. Through extensive experimentation and evaluation of established datasets, we demonstrate the efficacy of our approach in improving subject-dependent and subject-independent emotion recognition performance. This hybrid approach aims not only to address the challenge posed by individual differences but also to unlock new dimensions in understanding and improving emotion recognition. In particular, the proposed model integrates random forest weights (RFWs) with four-dimensional convolutional recurrent neural networks (4DCRNN). Initially, informative features are extracted from EEG signals using conventional feature engineering techniques. These features encompass a range of temporal, spectral, and spatial characteristics relevant to emotion recognition. Subsequently, RFW is used to train a model using these handcrafted features, which facilitates an initial understanding of the relationship between the features and emotions. To further enhance the performance of the model, the 4DCRNN model is introduced to learn more discriminative representations directly from the EEG data. The architecture of 4DCRNN is specifically designed to capture both spatial and temporal dependencies in EEG signals. By combining the strengths of random forests and 4DCRNN, the proposed model aims to leverage the interpretability of handcrafted features while benefiting from the powerful representation learning capabilities of deep learning.

This paper follows the following structure: In the introduction, related work on EEG-based emotion recognition is introduced. The second section of the article provides comprehensive details of the RFW-4DCRNN algorithm. Subsequently, in Section III, the focus shifts toward the experimental process, where the application of the RFW-4DCRNN network to the datasets is presented. Finally, this study concludes with a discussion in Section IV, followed by a presentation of the conclusions and future work in Section V.

II. MATERIALS AND METHODS

A. EMOTION MODEL

Emotions, inherently intricate and abstract, necessitate a preliminary understanding of the intended emotion model before embarking upon the study. Currently, the prevailing emotion models can be classified into two types: discrete and continuous. Initially, the discrete emotion model enjoyed popularity in the nascent stages of emotion recognition research because of its simplicity and comprehensibility. However, in recent years, the continuous emotion model has gained prominence as a widely adopted approach in emotion recognition research. The psychologist Russell introduced the two-dimensional representation model of emotions in 1980 [26]. The continuum model of emotion has several advantages because it portrays the intricate nature of emotions more accurately. Drawing upon arousal and valence dimensions, the two-dimensional spatial representation visually depicts a diverse range of complex emotional states.

B. DATASETS

The DEAP is a public emotion analysis dataset containing physiological signals, mental questionnaires, and electrode placement images from 32 participants [27]. The dataset was created in collaboration between researchers at McGill University, Canada, and École Polytechnique Fédérale de Lausanne, Switzerland. The dataset contains rich information from 32 participants who each watched 40 different 1-min videos. Simultaneously, the researchers recorded the participants' physiological signals. Furthermore, the researchers simultaneously recorded 32 channels of brain electrophysiological signals and 8 channels of peripheral physiological signals of the participants. After watching the video, the subjects scored the video on the four dimensions: valence, arousal, dominance, and liking. The emotion in each dimension can be divided according to different score thresholds to represent different levels of emotion. This study primarily investigates the 32-channel EEG data of the participants.

Another publicly available emotion-related EEG dataset is SEED from Shanghai Jiao Tong University [11], [12]. It includes 15 subjects (7 males and 8 females). During the experiment, an EEG recording device with 64 electrode channels was used. Reference electrodes were used on two channels. For approximately 4 min each, the subjects watched Chinese movie clips of three different emotion types (negative, neutral, and positive). Each subject viewed 15 different movie clips. All had five sets of negative, neutral, and positive movie clips. All subjects participated in three experiments, and 45 sets of EEG data were collected for each subject.

C. EVALUATING EMOTION RECOGNITION MODEL METHODS

Researchers have devised various strategies for evaluating the efficacy of emotion recognition models in different scenarios, aiming to assess their performance from diverse perspectives and cater to specific evaluation criteria. These strategies vary in terms of application scenarios and recognition difficulty. For instance, certain deep learning frameworks may excel in one strategy while under-performing in another. Consequently, such specialized emotion recognition models may lack the versatility required for application in diverse scenarios.

The subject-dependent strategy is extensively employed as the primary approach in emotion recognition research. This strategy uses the EEG data of a specific subject for both training and testing purposes. The EEG data of each subject are treated as an individual dataset and subsequently partitioned into training and test subsets. One-tenth of the subjects' data were selected as the validation set during training and the other nine-tenths of the data were used for training [28], [29]. The overall classification performance of the emotion recognition model was then determined by computing the average accuracy across all test subsets.

The subject-independent strategy presents a greater challenge than the subject-dependent strategy, however, it holds significant practical value. In the subject-independent strategy, distinct subjects are used to construct the training and test sets. The primary objective of this study was to assess the ability of the model to generalize across independent individuals. The expectation is that the model will exhibit strong performance even when applied to an unknown individual, thereby facilitating its practical application. Leave-one-out cross-validation is a widely employed approach within this strategy. To avoid the phenomenon of overfitting, in each cycle, the data of one subject were reserved for testing purposes, whereas the data of all other subjects were used for training. The data of a subject were selected as the validation set during training [30]. The evaluation criterion for the recognition model is the average accuracy rate computed across all cycles.

Adhering to the recommended guidelines for validating deep learning models based on EEG [31], this study examines the two recognition strategies individually and improves the model to ensure effective recognition under both approaches. Figure 1 illustrates subject-dependent and subject-independent strategies as examples.

D. RFW-4DCRNN

The RFW-4DCRNN model harnesses the strengths of random forests and deep learning techniques to improve the accuracy and efficiency of emotion recognition using EEG signals. On the one hand, the RFW component of the model incorporates the use of random forests, a well-known machine learning algorithm renowned for its capacity to handle high-dimensional feature spaces and capture intricate relationships between features and labels. On the other hand, the 4DCRNN component is specifically designed to extract spatio-temporal features from EEG signals. This type of neural network can effectively capture both spatial and temporal dependencies within data, enabling the model to learn intricate patterns and representations. A flowchart illustrating the RFW-4DCRNN model is shown in Figure 2. The entire RFW-4DCRNN model can be divided into three distinct parts: feature extraction, RFW, and 4DCRNN.

1) EEG FEATURES FOR EMOTION RECOGNITION

When analyzing EEG signals, it is crucial to acknowledge that brainwave data constitute a multidimensional time series. Furthermore, EEG waves exhibit distinct patterns of signal activity, depending on the specific cognitive or emotional activities being observed. Therefore, to quantify the different emotional states of the subjects, some researchers have performed mean square error analysis on the EEG signal [8], whereas others have used the principal component analysis [32]. The purpose of this study is to extract features that are more relevant to emotions. Electrodes in the prefrontal cortex have been widely studied and demonstrated to be associated with emotional processes [33], [34] [35]. In this section, each feature value is computed, incorporating both linear and nonlinear kinetic features.

The characteristics of the EEG signal are primarily divided into four basic waveforms: δ, θ, α, and β waves, with frequencies of 0.5-3, 4-7, 8-13, and 14-30 Hz, respectively. The signal was divided into four frequency bands for each channel. The first 3 s of data were used as the base band, and the remaining data were resegmented every 0.5s. Linear and nonlinear analyses were performed on each data segment, and 16 features were extracted.

The linear analysis method, which is mainly used in the time, frequency, and time-frequency domains, is the most basic

TABLE 1. Description of extracted EEG feature.

Feature	Description
Hjorth activity	Provides insights into brain activity, signals shifts in arousal, alertness, or engagement
Fractal dimension	Math measure quantifies EEG signal complexity and self-similarity across the scales
Hurst exponent	EEG measurement for long-term memory and self-similarity assessment of the time series
Logarithmic power spectrum	Power distribution of EEG signal across frequencies components on logarithmic scale
Band energy	Energy distribution within specific frequency bands
Differential, Approximate, Sample, Permutation, Transfer entropy	Measures EEG signal value distribution complexity or irregularity

method for processing EEG signals. Time-domain features capture the temporal statistics of EEG signals. Frequency-domain features capture emotional information from a frequency-domain perspective. Time-frequency-domain features are obtained from the Hilbert-Huang transform [36], [37], [38]. Based on previous studies, the features extracted by linear analysis are Hjorth activity [39], [40], [41], [42], fractal dimension [43], [44], Hurst exponent [45], [46], [47], differential entropy [48], [49], [50], [51], logarithmic power spectrum [52], and band energy [53]. Specific information can be found in Table 1.

With the widespread use and development of nonlinear dynamics techniques, researchers have discovered many nonlinear properties that reflect the characteristics of EEG signals. Building on previous work [8], [54], [55], [56], [57], [58], this study uses approximate entropy, sample entropy, permutation entropy and transfer entropy for feature extraction and analysis of EEG signals to investigate emotion classification and recognition.

2) RFW FEATURE SELECTION METHOD

After extracting each feature parameter of the raw EEG signal, the specific process of the RFW method proposed in this study is explained below. First, the Pearson correlation coefficient p_1 was obtained for each trait and emotion. The calculation method of the p value of the Pearson correlation coefficient is shown in Formula 1. This was done by testing all subjects' data for correlation with emotion. Second, each person's data were tested individually for correlation with emotion to obtain the Pearson correlation coefficient p_{1i} (i = 1, 2, …, N) for each person's features and emotion. Third, the number of individuals n_1 with each feature strongly correlated ($|p_{1i}| \geq 0.95$) with the subjects' emotions was calculated. Correlation tests were then conducted on all subjects' data with individuals to obtain the Pearson correlation coefficient p_2 values for each feature with individuals. Fifth, the feature data were fed into a random forest and trained with emotion as the label to obtain the importance value i_1. Finally, the feature data were fed into a random forest and trained with an individual as the label to

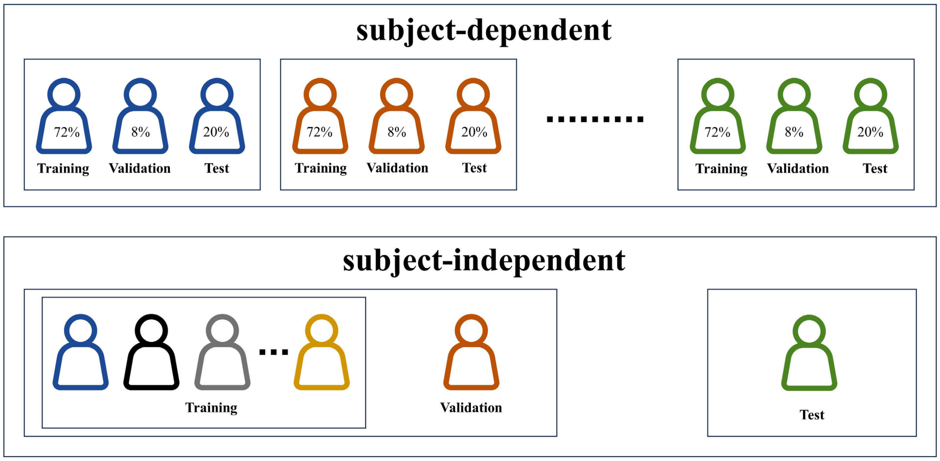

FIGURE 1. Two examples of model validation using subject-dependent and subject-independent methods. The top illustrates the topic-related division, where 72% of an individual's data are selected for training at a time, 8% of an individual's data are selected as the validation set during training, and the remaining 20% are used for testing. The bottom illustrates the topic-independent division, where data from one individual are used as the test set, data from another individual are used as the validation set during training, and data from the remaining portion are used as the training set.

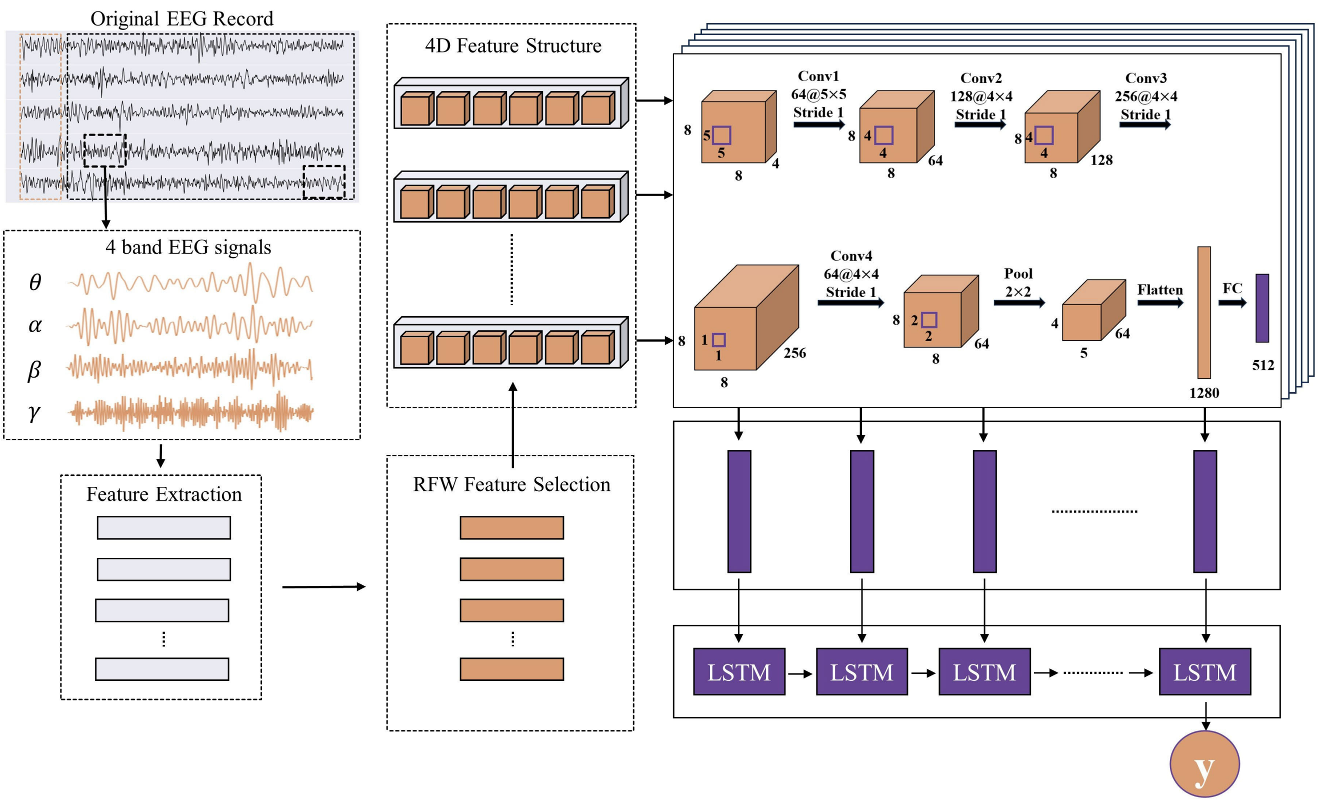

FIGURE 2. The RFW-4DCRNN emotion recognition model comprises three components: feature extraction, feature selection, and 4DCRNN. The model takes as input a feature matrix that contains distinct representations of signals extracted from each channel of the EEG signals. The RFW method is used to select the most informative features, followed by the transformation of the feature structure into four dimensions. The resulting features are then passed through the 4DCRNN network structure for emotion identification.

obtain the importance value i_2.

$$p = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{1}$$

where x_i represents the value of an eigenvalue in the ith sample; y_i represents the label represented by the ith sample; $\overline{x}$ represents the mean of the eigenvalues of all samples; $\overline{y}$ represents the mean of label values of all samples.

For each feature, the final score is calculated as a combination of the scores obtained. After this step, the final score of each feature can be calculated on the basis of the following equation:

$$\text{Score} = \frac{n_1}{N}\left[W \cdot \frac{p_1^2 - p_2^2}{p_2^2 + \varepsilon} + (100 - W) \cdot \frac{i_1 - i_2}{i_2 + \varepsilon}\right] \quad (2)$$

where W represents the weight, and ε denotes a minuscule value used to prevent division by zero.

The best formula for finding feature scores is obtained by searching for W. The process involves assigning a value to W and then using the random forest algorithm to perform sentiment recognition on the high-scoring features and calculate the recognition accuracy between individuals. The value of W with the highest accuracy is obtained as the best.

Algorithm 1 describes the specific process for optimizing W.

Algorithm 1 Optimization of W

Require: S: original subject sample data set.

Accuracy = One-dimensional array of length 101
for W in range(0, 101): # Assign values to W from 0 to 100 respectively **do**
  Score = Put W into the Formula 1 to calculate the score of each feature in S
  S' = Selecting the characteristics of the top 256 in the score ranking
  for i in range(0, N): # Iterate over the data of N individuals **do**
    trainingSet = Exclude the i-th person's data S_i' from S'
    testingSet = S_i'
    accuracy$_i$ = Accuracy of Random Forest identification testing set
  end for
  Accuracy$[W]$ = $\sum_{i=0}^{N-1}$ accuracy$_i$ /N
end for
W = Index of the maximum value in the Accuracy array
return W

2: W= Index of the maximum value in the Accuracy array return W

After finding the best value of W, the validity scores of all EEG features are ranked, and the top 256 features are used in the next step of model training and emotion recognition.

3) 4DCRNN EMOTION RECOGNITION MODEL

The 4DCRNN model is a neural network model for processing spatiotemporal data. It combines the advantages of CNNs and recurrent neural networks (RNNs) for effective modeling and prediction of spatiotemporal data. Unlike conventional three-dimensional CNNs, 4DCRNN introduces an additional temporal dimension. This allows the network to process four-dimensional spatiotemporal data. The core idea of 4DCRNN is to use CNNs to extract features while processing spatiotemporal data, and RNNs are then used for modeling and prediction. Specifically, 4DCRNN extracts features from input data through multiple convolutional layers. The feature sequences are then fed into the RNN, which combines the previously extracted features for modelling and prediction. Compared with conventional three-dimensional CNN and RNN models, 4DCRNN can better handle spatiotemporal data and can automatically learn spatiotemporal relationships and long-term dependencies. Consequently, it has demonstrated excellent performance in the field of EEG signal processing and classification.

The 4DCRNN network framework can be summarized in the following steps:

a: INPUT DATA PREPROCESSING

The input data are converted into a four-dimensional tensor. The specific operation is to filter out 256 features with strong relevance to emotions using the RFW method sorting calculation, then four-dimensional processing of these features to generate a new dataset, and finally feeding this dataset into the 4DCRNN network for training classification. The detailed process of four-dimensional feature processing is to convert 256 features into a 4×8×8 data format, and then combine the features of 6 adjacent periods as a new dimension. The tensor structure of 6×4×8×8 is obtained after the previous part of the operation.

b: FEATURE EXTRACTION

Feature extraction from the input data is performed using convolutional layers, each of which contains operations such as convolution, batch normalization, and nonlinear activation functions. Unlike conventional CNNs, where each convolutional layer is typically followed by a pooling layer, this study adds a pooling layer only after the last convolutional layer. Pooling reduces the data size in which significant information may be buried. In this study, the data size is significantly reduced by manually extracting the EEG features. Therefore, for data manipulation, it is not necessary to reduce the parameters in exchange for processing speed. As shown in Figure 2, it contains four convolutional layers, a maximum pooling layer, and a fully connected layer. The fourth convolutional layer contains 64 feature maps with a filter size of 1×1, which is used to fuse the feature maps of the previous convolutional layer. The zero fill and rectified linear unit activation functions are applied to all convolution layers. After convolution, a max-pooling layer of size 2×2 with a step size of 2 is applied. This reduces overfitting and increases the robustness of the network. The output of the final pooling layer is flattened to a fully connected 512-cell layer.

c: SEQUENCE MODELING

By feeding the sequence of features extracted from the convolutional layer into a recurrent layer, the RNN can combine the previously extracted features for modeling and prediction. Because the EEG signal contains dynamic

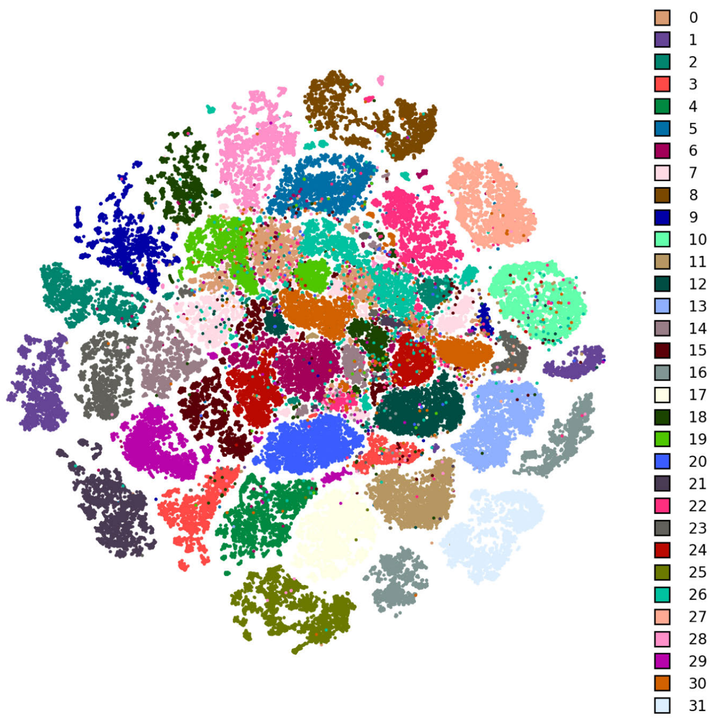

FIGURE 3. Visualization of the original feature t-SNE dimensionality reduction based on the DEAP dataset. Before applying RFW, showcase the results of dimensionality reduction in the EEG characteristics of 32 subjects. In this representation, the EEG data are clustered according to individual identity, highlighting the strong individual differences in each person's EEG patterns.

content, the variation between time slices in the four-dimensional structure may hide additional information that makes it possible to classify emotions more accurately. Therefore, LSTM units are used to extract temporal information from the CNN output. In this study, an LSTM layer with 128 memory units is used to mine the temporal dependence of features, as shown in Figure 2. 128 outputs of the last LSTM node are obtained after LSTM processing, which inherits the frequency, spatial and temporal features of the EEG segments every 3s.

Finally, the softmax layer is used to classify the 128 outputs of the LSTM. Two outputs can be obtained, which are the probabilities of the two outcomes.

III. RESULTS

The main experiments included feature selection using RFW. The effectiveness of this approach in reducing individual variability is demonstrated through t-distribution random neighbor embedding (t-SNE) data visualization. Finally, the performance of the 4DCRNN model in emotion identification is evaluated using the DEAP and SEED datasets.

A. ELIMINATION OF INDIVIDUAL DIFFERENCES

Based on the subjects' EEG features obtained from the preprocessing data, it is expected that the features strongly associated with emotions can be identified and used. To understand the influence of individual differences in EEG features, this study uses data mining methods to investigate individual differences in EEG features from different perspectives, especially data visualization methods. Direct observation of the two- or three-dimensional spatial distribution of the data can reveal some potential patterns. These patterns can be translated into hypotheses for further investigation. t-SNE was used to reduce the dimensionality of the data. The data can be visualized for each individual. Chen et al. [24] have analyzed individual variability in SEED in detail; therefore, this study presents the phenomenon of individual differences in DEAP in more detail. Figure 3 shows the visualization of the EEG features of each person in the DEAP dataset after dimensionality reduction. All feature data are aggregated on an individual basis. Thus, this study considers individual differences an important barrier to the effective transfer of emotion recognition techniques. To reduce individual differences in EEG features, an RFW method is proposed. After processing the above RFW steps, 256 effective features can be obtained for identifying emotions. Figure 4 depicts the variation of the mean with W for the random forest, and the classification results of three random forest classifiers with different numbers of nodes (100, 1000, and 10,000).

The top 256 features of the ranking were subjected to a new t-SNE data dimensionality reduction operation and

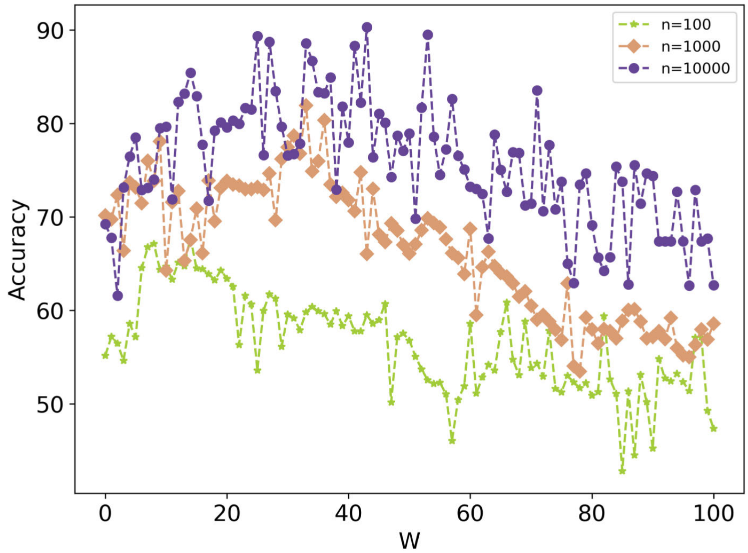

FIGURE 4. Variation in the mean with W for the random forest for all subjects using the leave-one-out cross-validation method.

visualized. The results are shown in Figure 5, where individual differences are significantly reduced. There is also a slight tendency to aggregate data for the same emotion. Therefore, the RFW method can effectively reduce individual differences in EEG, which is beneficial for expanding the application of emotion recognition technology.

The classification of these features showed that emotions can be well distinguished. Figure 6 shows the results of the two classifications of emotions in the valence dimension in the subject-dependent scenario of the features screened using the RFW method. This method ensures the effectiveness of emotion recognition without destroying the correlation between EEG and emotion.

TABLE 2. Average accuracy of the RFW-4DCRNN model in subject-dependent evaluation using the DEAP dataset.

Method	Classifier	Accuracy	
		Valence	Arousal
Yang and Liu(2019) [59]	TCN	74.40	71.40
Liu et al. (2020) [60]	CNN, SAE, and DNN	89.49	92.86
Yang et al.(2018) [61]	CRNN	90.80	91.03
Luo et al. (2023) [62]	SNNs	78.00	74.00
Singh et al. (2023) [63]	LSTM	92.50	81.25
Li et al. (2022) [20]	ECNN-C	98.35	98.51
This Work	**RFW-4DCRNN**	**94.82**	**94.98**

B. EMOTION RECOGNITION EFFECT

This section presents the experimental results for both databases and compares them with those obtained using various methods. The results are effectively visualized using line plots, where two lines represent the recognition accuracy of the subject-dependent and subject-independent methods. The x-axis corresponds to different participants, and the y-axis represents recognition accuracy.

1) EVALUATION ON THE DEAP DATABASE

In this study, the emotion labels in the DEAP database are classified as high/low arousal and positive/negative potency. We then performed a binary classification task for evaluation. Two separate line plots were created to illustrate the effect of the valence and arousal dimensions on emotion recognition. The results of the RFW-4DCRNN model on DEAP are shown in Figure 7.

Subject-dependent Evaluation: In the subject-dependent treatment, data from each participant are used individually to train and evaluate the emotion recognition models. This approach allows the models to capture the specific patterns and characteristics of each individual's EEG signals and their corresponding emotions. Specifically, 32 subjects, each with 40 trial data, used the data from 39 trials as a training set and 1 trial as a test set. The cycle was repeated 40 times until each subject used every dataset as a test set. The average of the 40 times was taken as the effectiveness of the model in recognizing the subject's emotions. Various methods have been applied to the subject-dependent treatment of the DEAP dataset, and their accuracies in emotion recognition have been compared in Table 2. In comparison, the proposed 4DCRNN method achieved higher accuracies for subject-dependent emotion recognition. These results indicate the competence of the model in capturing individual-specific EEG patterns and recognizing emotions within the same subject, demonstrating its suitability for personalized emotion recognition.

Subject-independent Evaluation: The leave-one-subject-out cross-validation strategy is applied to evaluate the

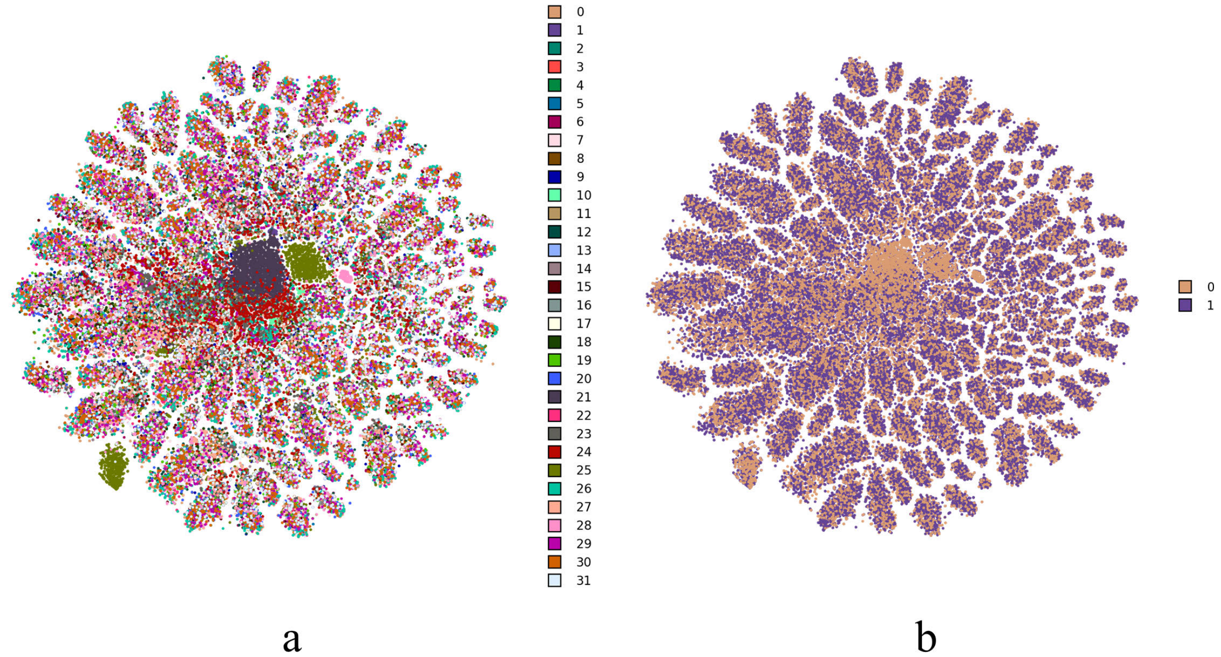

FIGURE 5. Results of the top 256 features for the new t-SNE visualization: (a) individual and (b) emotion as labels. In this case, the data of all individuals were evenly distributed, indicating that the proposed method successfully eliminated individual differences in EEG characteristics. This accomplishment is crucial in improving the capability of the model for emotion recognition across subjects and enhancing the generalization capability of the proposed model.

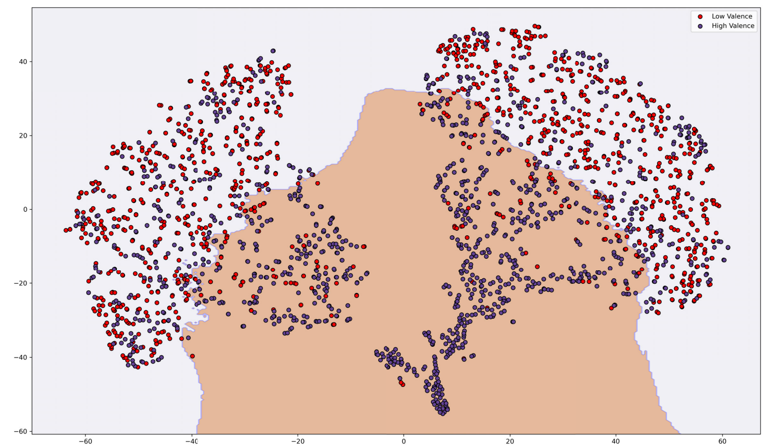

FIGURE 6. Emotion classification effect of the first 256 features using the random forest algorithm in a subject-dependent scenario.

subject-independent emotion recognition. In the subject-independent treatment, the experimental data of 31 subjects were used for training, and the data of the remaining 1 subject were used for testing. The cycle was repeated 32 times until all subjects were used for testing. The average of the 32 trials was taken to show the effect of the model. Here, accuracy of 78.6% was achieved in the valence dimension and 84.8% in the arousal dimension. For a better comparison, average accuracy of 81.7% was taken for both dimensions. Compared with the other methods shown in Table 3, the proposed method achieved an effective improvement. These results are particularly impressive as they demonstrate the ability of the model to generalize well across different individuals, despite their unique EEG characteristics. The significant improvement in subject-independent accuracy with the RFW-4DCRNN model compared with conventional approaches highlights its effectiveness in minimizing individual differences and improving cross-subject emotion recognition.

2) EVALUATION ON THE SEED DATABASE

The EEG data in the SEED database are associated with three mood labels: positive, neutral, and negative. Therefore, we perform a three-category classification task for

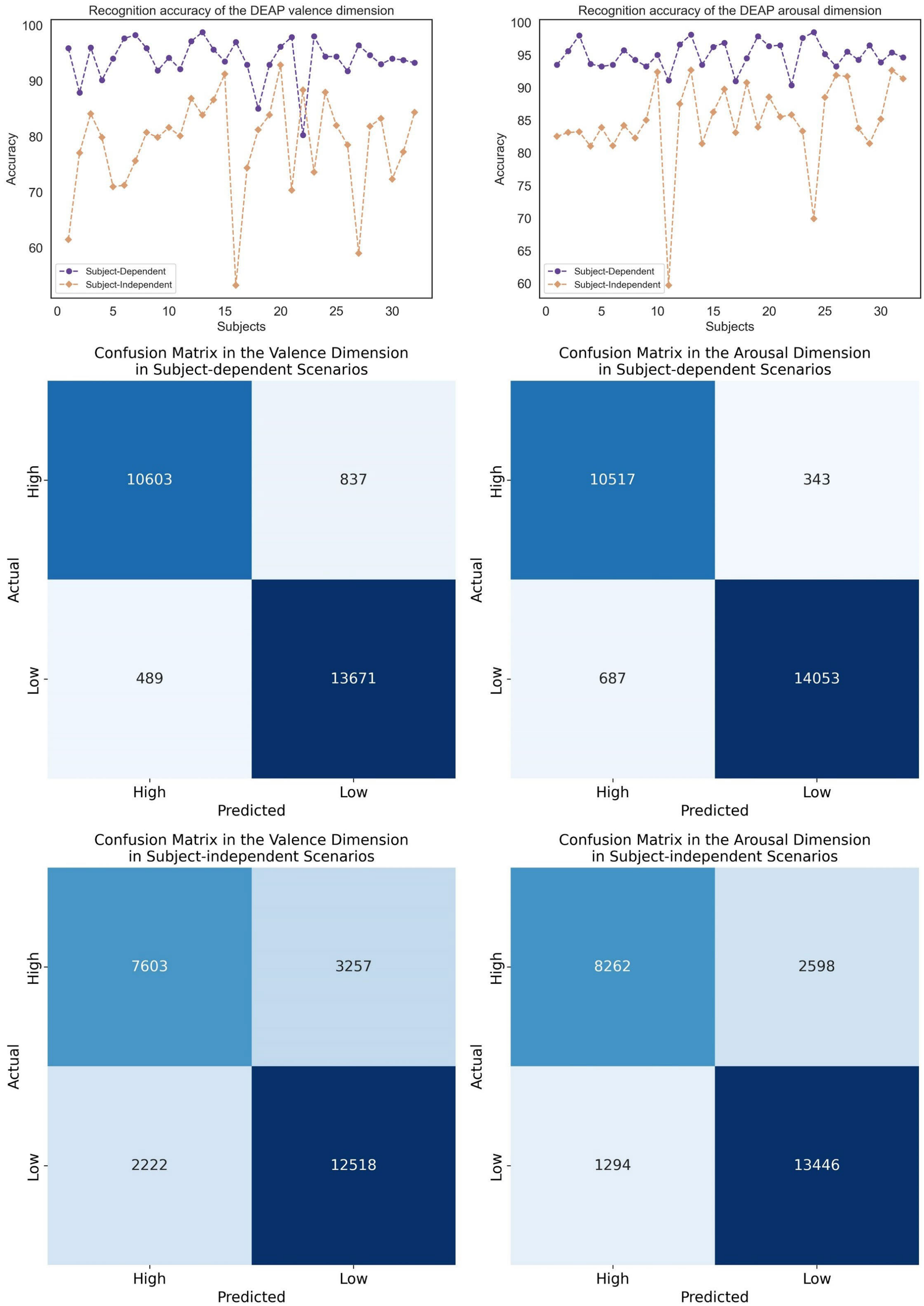

FIGURE 7. Results of 4DCRNN on DEAP: The left picture of the first line shows the classification effect of the valence label. The right picture of the first line shows the classification effect of the arousal label. The pictures in the second row show the classification confusion matrix in the subject-dependent scenario. The pictures in the third row show the classification confusion matrix in the subject-independent scenario.

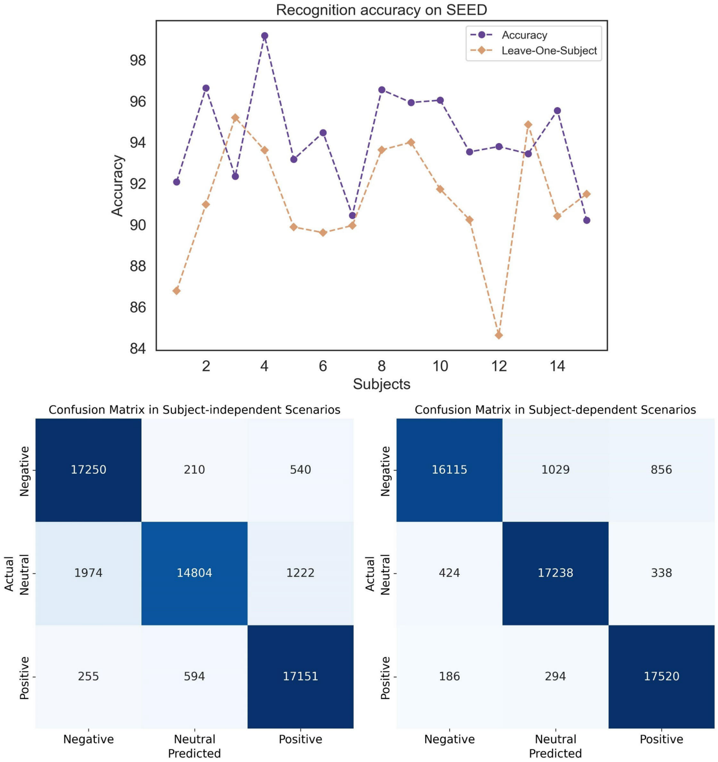

FIGURE 8. Performance of RFW-4DCRNN on the SEED dataset. The picture in the first row shows the classification accuracy for each subject in both scenarios. The picture on the left of the second row shows the classification confusion matrix in a subject-dependent scenario. The picture to the right of the third row shows the classification confusion matrix in a subject-independent scenario.

TABLE 3. Average accuracy of the RFW-4DCRNN model in subject-independent evaluation using DEAP.

Method	Classifier	Accuracy
Li et al. (2018) [16]	SVM	59.06
Yang et al. (2019) [21]	ST-SBSSVM	72.00
Cimtay and Ekmekcioglu (2020) [22]	InceptionResnetV2	72.81
Luo et al. (2018) [64]	WGANDA	66.92
Du et al. (2020) [17]	ATDD-LSTM	71.01
She et al. (2023) [65]	Multi-Source Transfer Learning	64.40
This Work	**RFW-4DCRNN**	**81.70**

assessment. Similarly, for the SEED dataset, a line graph was created to demonstrate the effect of emotion recognition. The graph is shown in Figure 8.

Subject-dependent Evaluation: There were 15 subjects with data from 15 EEG trials each. Data from 14 trials were used for model training and the remaining 1 trial was used for testing. The average of the 15 cycles was taken as the subject's accuracy. The average of the 15 subjects was taken and compared with the other methods, as shown in Table 4. According to the table, the proposed method achieves the best results.

TABLE 4. Average accuracy of the RFW-4DCRNN model in subject-dependent evaluation using SEED.

Method	Classifier	Accuracy
Song et al. (2018) [66]	DGCNN	90.40
Wang et al. (2020) [67]	CNN	90.59
Li et al. (2018) [50]	BiDANN	92.38
Zhu et al. (2023) [68]	MWACN	92.08
Zhang et al. (2023) [69]	TANN	93.34
This Work	**RFW-4DCRNN**	**94.21**

TABLE 5. Average accuracy of the RFW-4DCRNN model in subject-independent evaluation using SEED.

Method	Classifier	Accuracy
Li et al. (2018) [16]	SVM	83.33
Cimtay and Ekmekcioglu (2020) [22]	InceptionResnetV2	78.34
Yang et al. (2019) [21]	ST-SBSSVM	89.00
Luo et al. (2018) [64]	WGANDA	87.07
Du et al. (2020) [17]	ATDD-LSTM	90.92
She et al. (2023) [65]	Multi-Source Transfer Learning	86.59
Zhu et al. (2023) [68]	MWACN	87.59
This Work	**RFW-4DCRNN**	**91.12**

Subject-independent Evaluation: The same treatment for the DEAP dataset was applied to the SEED dataset. The average

TABLE 6. Analysis of the complexity of the framework.

Parameter Quantities	GPU use	Flops	Model Size	Dataset	Method	Training Time
1,531,906	45%	527.33M	17.6M	DEAP	dependent	1'17
					independent	2'13
				SEED	dependent	1'06
					independent	1'47

was obtained by cycling 15 times. The results are shown in Table 5, indicating that our method is based on other methods.

3) ANALYSIS OF THE COMPLEXITY OF THE FRAMEWORK

Analysis of the complexity of the framework is crucial. Our analysis of the framework and training model is presented in Table 6. This comprehensive analysis includes a detailed elaboration of the framework parameter quantities, providing nuanced insights into the architectural complexity that governs model representation. In addition, the investigation is extended to GPU use metrics, elucidating how efficiently our framework uses computing resources on the RTX3090-24G GPU. To quantitatively assess computational requirements, explicit reporting of floating point operations per second (Flops) and model size is introduced, allowing for a comprehensive assessment of computational complexity. Regarding training efficiency, we carefully recorded and reported the training time of four different classification scenarios, capturing the performance changes of the framework in different tasks. The experimental setup was based on an AMD Ryzen 9 5950X CPU and an NVIDIA RTX 3,090 GPU with 24 GB of VRAM.

IV. DISCUSSION

This study introduces the RFW-4DCRNN model for EEG-based emotion recognition. Experiments were conducted in both subject-dependent and subject-independent scenarios using the DEAP and SEED datasets. The experimental results demonstrate significant improvements in the model performance. Furthermore, this study investigates the impact of individual differences in EEG features and suggests that reducing such variability enhances the effectiveness of cross-subject emotion recognition.

In this study, we conducted extensive analysis of EEG features and their correlation with emotions, considering individual differences. To address the challenge of individual aggregation, we introduced the RFW method. By applying t-SNE dimensionality reduction, we demonstrate that the RFW method effectively minimizes individual variations in EEG data. One of the significant advantages of this method is that it not only ensures efficient emotion recognition within individuals, but also effectively mitigates the effect of individual differences in EEG signals and improves the efficiency of emotion recognition between individuals. By comparing the accuracy of subject-independent emotion recognition with and without the RFW method, as shown in Figure 9, the inclusion of RFW significantly improved the performance of the model in cross-subject emotion recognition. We then captured the interconnections among features and their temporal dynamics using the 4DCRNN model. Through extensive experiments on the DEAP and SEED datasets, we demonstrated the effectiveness of the RFW-4DCRNN method in achieving cross-subject emotion recognition. Our proposed approach achieved accuracy of 81.7% on the DEAP dataset and 90.12% on the SEED dataset. Nevertheless, this study has some limitations. One of the disadvantages of the algorithm is its computational complexity, particularly during the training phase of the 4DCRNN network. The integration of feature extraction from the random forest and subsequent deep learning training may require significant computational resources, limiting the efficiency of the algorithm in resource-constrained environments. In addition, the complexity of the hybrid model introduces the risk of overfitting, especially when dealing with smaller datasets. Regularization techniques and careful tuning of model parameters are essential to mitigate this risk and ensure the reliability of the algorithm in real-world applications. Specifically, our approach has only been applied to the aforementioned datasets, which restricts the generalizability of our findings. Furthermore, although our model successfully reduces the influence of individual differences on cross-thematic emotion recognition, further research is required to gain deeper insights into the nature of individual variations in EEG signals.

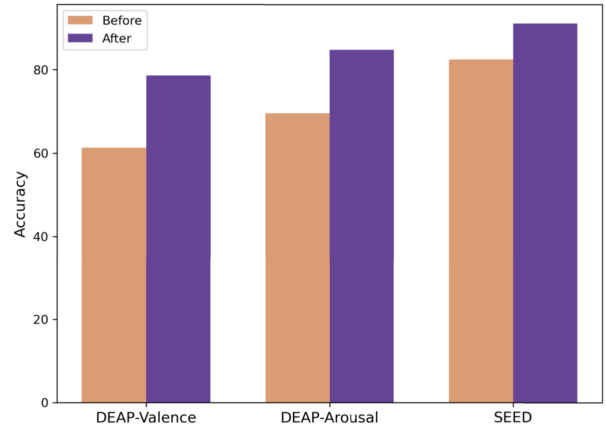

FIGURE 9. Comparison of the accuracy of emotion recognition before and after using the RFW method.

V. CONCLUSION

In conclusion, the proposed RFW-4DCRNN model offers a promising approach for EEG-based emotion recognition. By integrating the strengths of RFW and 4DCRNN, the model effectively addresses individual differences and captures spatiotemporal dependencies in EEG signals. Experimental results on the DEAP and SEED datasets demonstrate the advanced performance of the RFW-4DCRNN model in emotion recognition tasks, under both subject-dependent and subject-independent scenarios. These findings highlight the significance of feature processing methods and deep learning techniques in achieving robust and accurate cross-subject emotion recognition. Further research can explore the generalizability of the model to additional datasets and investigate individual differences in EEG in greater depth. Overall, the RFW-4DCRNN model holds promise for enhancing emotion recognition applications and advancing our understanding of the interplay between EEG signals and emotions. Future investigations will explore additional domains and delve into a more comprehensive study of individual differences in EEG signals. In future research, performing more detailed analyses and specifically targeting factors that potentially contribute to individual differences could improve the effectiveness of emotion recognition. Furthermore, applying the proposed approach to a larger dataset for validation would further validate its applicability.

REFERENCES

[1] D. O. Bos, ‘‘EEG-based emotion recognition,’’ *Influence Vis. Auditory Stimuli*, vol. 56, no. 3, pp. 1–17, 2006.

[2] R. Jenke, A. Peer, and M. Buss, ‘‘Feature extraction and selection for emotion recognition from EEG,’’ *IEEE Trans. Affect. Comput.*, vol. 5, no. 3, pp. 327–339, Jul. 2014.

[3] Y.-P. Lin, C.-H. Wang, T.-P. Jung, T.-L. Wu, S.-K. Jeng, J.-R. Duann, and J.-H. Chen, ‘‘EEG-based emotion recognition in music listening,’’ *IEEE Trans. Biomed. Eng.*, vol. 57, no. 7, pp. 1798–1806, Jul. 2010.

[4] N. Jain, S. Kumar, A. Kumar, P. Shamsolmoali, and M. Zareapoor, ‘‘Hybrid deep neural networks for face emotion recognition,’’ *Pattern Recognit. Lett.*, vol. 115, pp. 101–106, Nov. 2018.

[5] S. A. Hussain and A. S. A. A. Balushi, ‘‘A real time face emotion classification and recognition using deep learning model,’’ *J. Phys. Conf. Ser.*, vol. 1432, no. 1, Jan. 2020, Art. no. 012087.

[6] F. Ahmed, A. S. M. H. Bari, and M. L. Gavrilova, ‘‘Emotion recognition from body movement,’’ *IEEE Access*, vol. 8, pp. 11761–11781, 2020.

[7] J. Zhao, W. Zhong, D. Zhang, Y. Wang, M. Song, and Q. Li, ‘‘EVAI: An approach for real-time video-based emotion recognition,’’ in *Proc. 4th Int. Conf. Electron. Eng. Informat.*, Jun. 2022, pp. 1–8.

[8] M. Fraiwan, M. Alafeef, and F. Almomani, ‘‘Gauging human visual interest using multiscale entropy analysis of EEG signals,’’ *J. Ambient Intell. Hum. Comput.*, vol. 12, no. 2, pp. 2435–2447, Feb. 2021.

[9] J. A. Meltzer, M. Negishi, L. C. Mayes, and R. T. Constable, ‘‘Individual differences in EEG theta and alpha dynamics during working memory correlate with fMRI responses across subjects,’’ *Clin. Neurophysiol.*, vol. 118, no. 11, pp. 2419–2436, Nov. 2007.

[10] L.-C. Shi, Y.-Y. Jiao, and B.-L. Lu, ‘‘Differential entropy feature for EEG-based vigilance estimation,’’ in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 6627–6630.

[11] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, ‘‘Differential entropy feature for EEG-based emotion classification,’’ in *Proc. 6th Int. IEEE/EMBS Conf. Neural Eng. (NER)*, Nov. 2013, pp. 81–84.

[12] W.-L. Zheng and B.-L. Lu, ‘‘Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks,’’ *IEEE Trans. Auto. Mental Develop.*, vol. 7, no. 3, pp. 162–175, Sep. 2015.

[13] E. Habibzadeh Tonekabony Shad, M. Molinas, and T. Ytterdal, ‘‘Impedance and noise of passive and active dry EEG electrodes: A review,’’ *IEEE Sensors J.*, vol. 20, no. 24, pp. 14565–14577, Dec. 2020.

[14] C. Q. Lai, H. Ibrahim, M. Z. Abdullah, J. M. Abdullah, S. A. Suandi, and A. Azman, ‘‘Artifacts and noise removal for electroencephalogram (EEG): A literature review,’’ in *Proc. IEEE Symp. Comput. Appl. Ind. Electron. (ISCAIE)*, Apr. 2018, pp. 326–332.

[15] X. Zhang, J. Liu, J. Shen, S. Li, K. Hou, B. Hu, J. Gao, T. Zhang, and B. Hu, ‘‘Emotion recognition from multimodal physiological signals using a regularized deep fusion of kernel machine,’’ *IEEE Trans. Cybern.*, vol. 51, no. 9, pp. 4386–4399, Sep. 2021.

[16] X. Li, D. Song, P. Zhang, Y. Zhang, Y. Hou, and B. Hu, ‘‘Exploring EEG features in cross-subject emotion recognition,’’ *Frontiers Neurosci.*, vol. 12, p. 162, Mar. 2018.

[17] X. Du, C. Ma, G. Zhang, J. Li, Y.-K. Lai, G. Zhao, X. Deng, Y.-J. Liu, and H. Wang, ‘‘An efficient LSTM network for emotion recognition from multichannel EEG signals,’’ *IEEE Trans. Affect. Comput.*, vol. 13, no. 3, pp. 1528–1540, Jul. 2022.

[18] A. Samavat, E. Khalili, B. Ayati, and M. Ayati, ‘‘Deep learning model with adaptive regularization for EEG-based emotion recognition using temporal and frequency features,’’ *IEEE Access*, vol. 10, pp. 24520–24527, 2022.

[19] E. Yildirim, Y. Kaya, and F. Kiliç, ‘‘A channel selection method for emotion recognition from EEG based on swarm-intelligence algorithms,’’ *IEEE Access*, vol. 9, pp. 109889–109902, 2021.

[20] C. Li, X. Lin, Y. Liu, R. Song, J. Cheng, and X. Chen, ‘‘EEG-based emotion recognition via efficient convolutional neural network and contrastive learning,’’ *IEEE Sensors J.*, vol. 22, no. 20, pp. 19608–19619, Oct. 2022.

[21] F. Yang, X. Zhao, W. Jiang, P. Gao, and G. Liu, ‘‘Multi-method fusion of cross-subject emotion recognition based on high-dimensional EEG features,’’ *Frontiers Comput. Neurosci.*, vol. 13, p. 53, Aug. 2019.

[22] Y. Cimtay and E. Ekmekcioglu, ‘‘Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset EEG emotion recognition,’’ *Sensors*, vol. 20, no. 7, p. 2034, Apr. 2020.

[23] X. Shen, X. Liu, X. Hu, D. Zhang, and S. Song, ‘‘Contrastive learning of subject-invariant EEG representations for cross-subject emotion recognition,’’ *IEEE Trans. Affect. Comput.*, vol. 14, no. 3, pp. 2496–2511, Jul./Sep. 2023, doi: 10.1109/TAFFC.2022.3164516.

[24] H. Chen, S. Sun, J. Li, R. Yu, N. Li, X. Li, and B. Hu, ‘‘Personal-Zscore: Eliminating individual difference for EEG-based cross-subject emotion recognition,’’ *IEEE Trans. Affect. Comput.*, vol. 14, no. 3, pp. 2077–2088, Jul./Sep. 2023, doi: 10.1109/TAFFC.2021.3137857.

[25] F. Shen, G. Dai, G. Lin, J. Zhang, W. Kong, and H. Zeng, ‘‘EEG-based emotion recognition using 4D convolutional recurrent neural network,’’ *Cognit. Neurodynamics*, vol. 14, no. 6, pp. 815–828, Dec. 2020.

[26] J. A. Russell, ‘‘A circumplex model of affect,’’ *J. Personality Social Psychol.*, vol. 39, no. 6, p. 1161, Dec. 1980.

[27] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, ‘‘DEAP: A database for emotion analysis; Using physiological signals,’’ *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 18–31, Jan. 2012.

[28] J. Shen, Y. Zhang, H. Liang, Z. Zhao, K. Zhu, K. Qian, Q. Dong, X. Zhang, and B. Hu, ‘‘Depression recognition from EEG signals using an adaptive channel fusion method via improved focal loss,’’ *IEEE J. Biomed. Health Informat.*, vol. 27, no. 7, pp. 1–12, Apr. 2023.

[29] J. Shen, Y. Zhang, H. Liang, Z. Zhao, Q. Dong, K. Qian, X. Zhang, and B. Hu, ‘‘Exploring the intrinsic features of EEG signals via empirical mode decomposition for depression recognition,’’ *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 356–365, 2023.

[30] J. Shen, S. Zhao, Y. Yao, Y. Wang, and L. Feng, ‘‘A novel depression detection method based on pervasive EEG and EEG splitting criterion,’’ in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Nov. 2017, pp. 1879–1886.

[31] A. Kamrud, B. Borghetti, and C. S. Kabban, ‘‘The effects of individual differences, non-stationarity, and the importance of data partitioning decisions for training and testing of EEG cross-participant models,’’ *Sensors*, vol. 21, no. 9, p. 3225, May 2021.

[32] M. A. Rahman, M. F. Hossain, M. Hossain, and R. Ahmmed, ‘‘Employing PCA and T-statistical approach for feature extraction and classification of emotion from multichannel EEG signal,’’ *Egyptian Informat. J.*, vol. 21, no. 1, pp. 23–35, Mar. 2020.

[33] E. Harmon-Jones, ‘‘Contributions from research on anger and cognitive dissonance to understanding the motivational functions of asymmetrical frontal brain activity,’’ *Biol. Psychol.*, vol. 67, nos. 1–2, pp. 51–76, Oct. 2004.

[34] G. Zhao, Y. Zhang, and Y. Ge, "Frontal EEG asymmetry and middle line power difference in discrete emotions," *Frontiers Behav. Neurosci.*, vol. 12, p. 225, Nov. 2018.

[35] M. K. Ahirwal and M. R. Kose, "Audio-visual stimulation based emotion classification by correlated EEG channels," *Health Technol.*, vol. 10, no. 1, pp. 7–23, Jan. 2020.

[36] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N.-C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. Roy. Soc. London. Ser. A, Math., Phys. Eng. Sci.*, vol. 454, no. 1971, pp. 903–995, Mar. 1998.

[37] N. E. Huang, "Introduction to the Hilbert–Huang transform and its related mathematical problems," in *Hilbert–Huang Transform and Its Appl.*, Singapore: World Scientific, 2005, pp. 1–26.

[38] A. Pigorini, A. G. Casali, S. Casarotto, F. Ferrarelli, G. Baselli, M. Mariotti, M. Massimini, and M. Rosanova, "Time–frequency spectral analysis of TMS-evoked EEG oscillations by means of Hilbert–Huang transform," *J. Neurosci. Methods*, vol. 198, no. 2, pp. 236–245, Jun. 2011.

[39] B. Hjorth, "EEG analysis based on time domain properties," *Electroencephalogr. Clin. Neurophysiol.*, vol. 29, no. 3, pp. 306–310, Sep. 1970.

[40] B. Hjorth, "The physical significance of time domain descriptors in EEG analysis," *Electroencephalogr. Clin. Neurophysiol.*, vol. 34, no. 3, pp. 321–325, Mar. 1973.

[41] R. M. Mehmood, R. Du, and H. J. Lee, "Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors," *IEEE Access*, vol. 5, pp. 14797–14806, 2017.

[42] A. Patil, C. Deshmukh, and A. R. Panat, "Feature extraction of EEG for emotion recognition using Hjorth features and higher order crossings," in *Proc. Conf. Adv. Signal Process. (CASP)*, Jun. 2016, pp. 429–434.

[43] M. J. Katz, "Fractals and the analysis of waveforms," *Comput. Biol. Med.*, vol. 18, no. 3, pp. 145–156, Jan. 1988.

[44] S. A. Akar, S. Kara, S. Agambayev, and V. Bilgiç, "Nonlinear analysis of EEGs of patients with major depression during different emotional states," *Comput. Biol. Med.*, vol. 67, pp. 49–60, Dec. 2015.

[45] C. W. Yean, W. Khairunizam, M. I. Omar, M. Murugappan, Z. Ibrahim, B. S. Zheng, S. A. Bakar, Z. M. Razlan, and W. A. Mustafa, "Emotional states analyze from scaling properties of EEG signals using Hurst exponent for stroke and normal groups," in *Proc. 2nd Symp. Intell. Manuf. Mechatronics–(SympoSIMM)*, 2019, pp. 526–534.

[46] Z. Jamaludin and M. N. A. Mokhtar, *Intelligent Manufacturing and Mechatronics: Proceedings of the 2nd Symposium on Intelligent Manufacturing and Mechatronics—SympoSIMM*. Cham, Switzerland: Springer, 2019.

[47] J. Selvaraj, M. Murugappan, K. Wan, and S. Yaacob, "Classification of emotional states from electrocardiogram signals: A non-linear approach based on Hurst," *Biomed. Eng. OnLine*, vol. 12, no. 1, p. 44, 2013.

[48] X.-H. Wang, T. Zhang, X.-M. Xu, L. Chen, X.-F. Xing, and C. L. P. Chen, "EEG emotion recognition using dynamical graph convolutional neural networks and broad learning system," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2018, pp. 1240–1244.

[49] Z. Gao, X. Wang, Y. Yang, Y. Li, K. Ma, and G. Chen, "A channel-fused dense convolutional network for EEG-based emotion recognition," *IEEE Trans. Cognit. Develop. Syst.*, vol. 13, no. 4, pp. 945–954, Dec. 2021.

[50] Y. Li, W. Zheng, Z. Cui, T. Zhang, and Y. Zong, "A novel neural network model based on cerebral hemispheric asymmetry for EEG emotion recognition," in *Proc. 27th Int. Joint Conf. Artif. Intell.*, Jul. 2018, pp. 1561–1567.

[51] Y. Li, L. Wang, W. Zheng, Y. Zong, L. Qi, Z. Cui, T. Zhang, and T. Song, "A novel bi-hemispheric discrepancy model for EEG emotion recognition," *IEEE Trans. Cognit. Develop. Syst.*, vol. 13, no. 2, pp. 354–367, Jun. 2021.

[52] X.-W. Wang, D. Nie, and B.-L. Lu, "EEG-based emotion recognition using frequency domain features and support vector machines," in *Proc. Int. Conf. Neural Inf. Process.* Springer, 2011, pp. 734–743.

[53] N. Jatupaiboon, S. Pan-ngum, and P. Israsena, "Emotion classification using minimal EEG channels and frequency bands," in *Proc. 10th Int. Joint Conf. Comput. Sci. Softw. Eng. (JCSSE)*, May 2013, pp. 21–24.

[54] X. Jie, R. Cao, and L. Li, "Emotion recognition based on the sample entropy of EEG," *Bio-Medical Mater. Eng.*, vol. 24, no. 1, pp. 1185–1192, 2014.

[55] J. Shen, X. Zhang, G. Wang, Z. Ding, and B. Hu, "An improved empirical mode decomposition of electroencephalogram signals for depression detection," *IEEE Trans. Affect. Comput.*, vol. 13, no. 1, pp. 262–271, Jan. 2022.

[56] J. Shen, X. Zhang, X. Huang, M. Wu, J. Gao, D. Lu, Z. Ding, and B. Hu, "An optimal channel selection for EEG-based depression detection via kernel-target alignment," *IEEE J. Biomed. Health Informat.*, vol. 25, no. 7, pp. 2545–2556, Jul. 2021.

[57] C.-S. Huang, N. R. Pal, C.-H. Chuang, and C.-T. Lin, "Identifying changes in EEG information transfer during drowsy driving by transfer entropy," *Frontiers Hum. Neurosci.*, vol. 9, p. 570, Oct. 2015.

[58] W. Yao and J. Wang, "Multi-scale symbolic transfer entropy analysis of EEG," *Phys. A, Stat. Mech. Appl.*, vol. 484, pp. 276–281, Oct. 2017.

[59] L. Yang and J. Liu, "EEG-based emotion recognition using temporal convolutional network," in *Proc. IEEE 8th Data Driven Control Learn. Syst. Conf. (DDCLS)*, May 2019, pp. 437–442.

[60] J. Liu, G. Wu, Y. Luo, S. Qiu, S. Yang, W. Li, and Y. Bi, "EEG-based emotion classification using a deep neural network and sparse autoencoder," *Frontiers Syst. Neurosci.*, vol. 14, p. 43, Sep. 2020.

[61] Y. Yang, Q. Wu, M. Qiu, Y. Wang, and X. Chen, "Emotion recognition from multi-channel EEG through parallel convolutional recurrent neural network," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2018, pp. 1–7.

[62] Y. Luo, Q. Fu, J. Xie, Y. Qin, G. Wu, J. Liu, F. Jiang, Y. Cao, and X. Ding, "EEG-based emotion classification using spiking neural networks," *IEEE Access*, vol. 8, pp. 46007–46016, 2020.

[63] U. Singh, R. Shaw, and B. K. Patra, "A data augmentation and channel selection technique for grading human emotions on DEAP dataset," *Biomed. Signal Process. Control*, vol. 79, Jan. 2023, Art. no. 104060.

[64] Y. Luo, S.-Y. Zhang, W.-L. Zheng, and B.-L. Lu, "WGAN domain adaptation for EEG-based emotion recognition," in *Neural Information Processing*. Cham, Switzerland: Springer, 2018, pp. 275–286.

[65] Q. She, X. Shi, F. Fang, Y. Ma, and Y. Zhang, "Cross-subject EEG emotion recognition using multi-source domain manifold feature selection," *Comput. Biol. Med.*, vol. 159, Jun. 2023, Art. no. 106860.

[66] T. Song, W. Zheng, P. Song, and Z. Cui, "EEG emotion recognition using dynamical graph convolutional neural networks," *IEEE Trans. Affect. Comput.*, vol. 11, no. 3, pp. 532–541, Jul. 2020.

[67] F. Wang, S. Wu, W. Zhang, Z. Xu, Y. Zhang, C. Wu, and S. Coleman, "Emotion recognition with convolutional neural network and EEG-based EFDMs," *Neuropsychologia*, vol. 146, Sep. 2020, Art. no. 107506.

[68] L. Zhu, W. Ding, J. Zhu, P. Xu, Y. Liu, M. Yan, and J. Zhang, "Multisource Wasserstein adaptation coding network for EEG emotion recognition," *Biomed. Signal Process. Control*, vol. 76, Jul. 2022, Art. no. 103687.

[69] X. Zhang, D. Huang, H. Li, Y. Zhang, Y. Xia, and J. Liu, "Self-training maximum classifier discrepancy for EEG emotion recognition," *CAAI Trans. Intell. Technol.*, vol. 8, no. 4, pp. 1480–1491, Dec. 2023.

WENXU WANG received the B.S. degree from Henan University, China. He is currently pursuing the master's degree with the College of Electronic Information and Optical Engineering, Taiyuan University of Technology. His current research interest includes emotion recognition.

JIA YANG received the B.S. degree in metallurgy material and engineering from Wuhan University of Technology, Wuhan, China, in 1989, the M.S. and Ph.D. degrees in mechanical science and engineering from the Huazhong University of Science and Technology, Wuhan, in 1998 and 2003, respectively, and the Ph.D. degree in sustainable energy engineering and design from The University of Warwick, Coventry, U.K., in 2013. Her current research interests include human–computer interaction, brain–computer interface, and emotion recognition-based human physiological signals.

SHENGJIA LI received the B.S. degree in electronic information engineering from Heilongjiang University, Harbin, China, in 2017, and the M.S. degree in information and communication engineering from Tianjin University, Tianjin, China, in 2020. He is currently studying signal processing on artificial intelligence with China Academy of Launch Vehicle Technology, Beijing, China. His research interests include deep learning, reinforcement learning, and cross modality.

BIN WANG received the Ph.D. degree from Okayama University, Japan, in 2013. He is currently a Professor with the College of Computer Science and Technology, Taiyuan University of Technology. He is mainly engaged in the study of brain cognitive function, brain–computer interface, and the diagnosis of brain diseases.

KUN YANG received the Ph.D. degree from Shandong University, in 2019. He is currently an Associate Professor with the College of Electronic Information and Optical Engineering, Taiyuan University of Technology. His current research interests include the integration physiological signs monitoring systems and emotion recognition-based human physiological signals.

SHENGBO SANG received the B.Eng. degree in communication engineering and the M.Eng. degree in electronic science and technology from the North University of China, Taiyuan, China, in 2000 and 2006, respectively, and the Ph.D. degree from the School of Mechanical Engineering, Ilmenau University of Technology, Ilmenau, Germany, in 2010. His current research interests include MEMS/NEMS, optical devices, biosensors, signal processing, and deep learning.

QIANG ZHANG received the bachelor's degree in detection guidance and control technology and the master's and Ph.D. degrees in test measurement technology and instrumentation from the North China University of China, in 2010, 2013, and 2015, respectively. Her current research interests include the preparation method and performance research of new flexible sensors and deep learning.

BOYUAN LIU is currently pursuing the bachelor's degree with the College of Electronic Information and Optical Engineering, Taiyuan University of Technology. His current research interest includes deep learning algorithms for physiological signal processing.