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# An overview of the emotional brain-computer interface

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**Abstract.** This paper provides a comprehensive review of current research advances in emotional brain-computer interfaces. We introduce an approach to classifying emotions and highlight the two main datasets used for emotion recognition (DEAP and SEED). Subsequently, an extensive analysis of existing emotion recognition methods, both traditional and deep neural network methods, is presented. Finally, we explore the potential benefits of using transfer learning techniques to improve the performance of emotion recognition methods. Various deep neural network models exhibit redundant neural units and complexity, while facing challenges such as reduced computational power and reaction speed, increased storage requirements, and hardware dependency. The authors propose to integrate learned neural network pruning algorithms to simplify complex models, minimise hardware resource requirements without compromising accuracy, and improve operational capabilities with improved discriminants.

**Keywords:** emotion recognition, brain-computer interface, transfer learning, convolutional neural network.

## 1. Introduction

In the current era of rapid scientific and technological advancements, brain-computer interface (BCI) technology has become a focal point for both researchers and businesses due to its unique potential applications. BCI technology is a novel approach that enables direct communication between the brain and external devices, allowing individuals to use their thoughts to control machines for enhanced interaction and manipulation. The range of applications of BCI technology ranges from rehabilitative medicine to artificial intelligence, making it an incredibly versatile field with far-reaching prospects. As technology continues to advance, so does the capabilities of BCI technology in terms of real-time performance, reliability and adaptability. In recent years, the emergence of deep learning and artificial intelligence technologies has opened fresh opportunities for additional developments in the brain-computer interface domain.

The brain-computer interface technology consists of various components such as signal acquisition, processing and recognition, and control output. Signal acquisition is a crucial step in this technology, which involves extracting useful EEG signals from complex environments. Processing and identification involve analysing the collected signals to identify relevant information. Control output refers to the transmission of instructions obtained through analysis to an external device for execution of the corresponding operation. These technical features are closely related to specific application

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scenarios such as motor rehabilitation in healthcare, neurological disease diagnosis, intelligent control systems, and virtual reality in the AI domain.

Despite some advances in BCI technology, several obstacles and issues still hinder its practical application. These include signal acquisition stability, interference cancellation, optimization of signal processing algorithms, and real-time control accuracy, among others. To enhance the reliability and feasibility of brain-computer interface technologies, researchers must delve deeper into these challenges. In summary, brain-computer interface technology is a promising new area with significant potential to profoundly impact future scientific and technological societies. Despite ongoing research challenges, it is reasonable to believe that continued technological advances will enable brain-computer interfaces to play an increasingly vital role in the future by providing greater convenience and possibilities for humans.

In the following, this paper will review brain-computer interface techniques from three perspectives: the first one is on emotion classification methods and emotion recognition datasets, the second one is on EEG-based emotion recognition methods, and the third one is on performance improvement of emotion recognition methods. The second point will be divided into two modules, one of which is the traditional emotion recognition method. The other is a deep learning neural network-based approach for emotion recognition.

## 2. Emotion classification and recognition

### *2.1. Division of emotions*

Until now, there have been two main categories for recognized models of emotion. The first category is the discrete emotion model, which explains emotional states in a distinct manner and can be understood from a categorical perspective [1]. In 1980, psychologist Robert Plutchik created a wheel of emotions that consisted of eight primary emotions: happiness, trust, fear, surprise, sadness, disgust, anger, and anticipation [2], drawing inspiration from his "Ten Hypotheses." These specific emotions are clear-cut and easier to comprehend and have been extensively utilized in various studies on emotion recognition. The second category is the dimensional emotion models that define emotions within a coordinate system comprising multiple dimensions. Among these multidimensional models commonly used are the 2D emotion models that represent all human emotions on a 2D coordinate system based on valence and arousal. This allows for representing all emotions as single points on this 2D coordinate system. As a result, it becomes possible to assess and quantify more accurately the particular emotional response elicited by a stimulus.

### *2.2. Emotion recognition dataset*

In the field of brain-computer interfaces, there are two commonly used emotion recognition datasets, namely the DEAP dataset and the SEED dataset. This section explains them in different dimensions to make it easier to understand and use the two datasets and then compare them.

The DEAP dataset is a collection of data used to study human emotional states. This dataset consists of multiple physiological signals recorded while participants watched a music video as a stimulus. The study involved 32 subjects and measured psychological measures such as video salience, arousal, dominance and liking. Facial expressions were also captured for the first 22 participants. This dataset is valuable for investigating physiological signals across different modalities and conducting EEG studies of emotions. In total, there are 40 channels available for physiological signals in this dataset. The initial 32 channels are dedicated to recording depth data for EEG signals based on a standardised international system called '10-20'. For our research purposes, we selected 32 individuals from the DEAP database who were school staff members aged between 19 and 37 years (with an average age of 26.9 years), including an equal number of males and females. All participants met criteria to ensure their physical and mental well-being and did not have any history of mental illness or brain damage; in addition, they are both right-handed.

The process of EEG acquisition involves the following steps: (1) The current sequence number of the video position is displayed for a duration of two seconds. (2) Baseline recording acquisition is conducted by displaying a cross on the screen for five seconds, during which participants are instructed to remain calm and record the onset of the EEG signal. Music videos are then played, with each video transitioning after three seconds and playing for 60 seconds. Participants were instructed to maintain body balance and minimise movement throughout the session. (4) Participants provide self-assessment scores using the Self-Assessment Manikins (SAM) questionnaire to rate their authentic emotional experience while watching each music video. The whole process takes approximately 15 seconds. (5) The next experiment begins, repeating the aforementioned steps until all 40 music videos have been played.

The SEED dataset, provided by the BCMI lab under the direction of Professor Baoliang Lv, consists of EEG datasets that capture the emotional responses of individuals while watching carefully selected film clips. The film clips were chosen to elicit various emotions such as positive, negative and neutral. To ensure optimal experimental conditions, 15 Chinese film clips (representing positive, neutral, and negative emotions) were selected from a material library consisting of six movies. The selection criteria included avoiding excessively prolonged durations to prevent participant fatigue, selecting films that were easy to understand without special instructions, and ensuring that each clip effectively evoked a specific target emotion within approximately four minutes. Meticulous editing was applied to each segment to maintain emotional coherence and maximise impact.

In each trial, participants were instructed to observe a set of fifteen film clips, resulting in a total of fifteen trajectories per trial. Before viewing each clip, a brief five-second cue was presented and participants were asked to assess their emotional state after viewing the video. The duration of each clip is forty five seconds, followed by a fifteen second break. To ensure variety, the experimenter carefully arranged the sequence of clips so that consecutive clips evoking the same emotion were avoided. Following each segment, participants provided immediate feedback by completing a questionnaire detailing their emotional responses. See Fig. 1 for a comprehensive protocol.

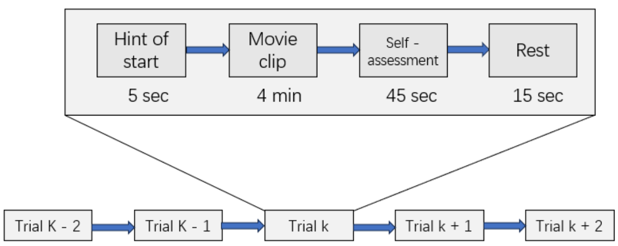


**Figure 1:** detailed protocol

There are a total of fifteen Chinese participants in the SEED dataset, consisting of seven males and eight females. The mean age of the subjects was 23.27 years, with a standard deviation of 2.37 years. The SEED dataset consists of disabled EEG data in MATLAB, divided into two versions: preprocessing and segmentation. The data was downsampled to two hundreds HZ and subjected to a bandpass filter ranging from zero to seventy-five Hz. Simultaneously, EEG segments corresponding to each slice duration are extracted. Each participant completed three repetitions of the experiment.

## 3. EEG-based methods for emotion recognition

EEG-based emotion recognition is a technique that uses EEG signals to identify and classify emotions. EEG signals are weak electrical signals generated by the brain and can reflect the state of brain activity, including emotional states. Currently, there are numerous variants of EEG-based emotion recognition methods, but they can be classified into two categories. One category is the traditional machine learning approach, which is currently a simple and versatile procedure for EEG emotion recognition. Another approach involves using a Convolutional Neural Network (CNN) for sentiment feature recognition.

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EEG-based emotion recognition techniques have certain advantages, such as being non-intrusive and having strong temporal and spatial resolution.

### *3.1. Traditional methods*

In general, there are five basic steps in traditional EEG emotion detection methods: data acquisition, data preprocessing, feature extraction, feature selection/dimensionality reduction, and classification.

Data acquisition refers to the utilization of EEG signal detection equipment for gathering EEG signals from subjects. Data preprocessing involves refining the collected raw EEG signals to extract their inherent characteristics. Preprocessing steps encompass filtering, denoising, downsampling, and other operations aimed at enhancing signal quality and minimizing noise. Conversely, feature extraction entails isolating emotion-related features from preprocessed EEG signals. Frequently employed properties include time domain properties, frequency domain properties, as well as time and frequency domain properties. The objective of feature extraction is to reduce data size while preserving sentiment information. On another note, feature selection/reduction encompasses choosing or reducing the size of extracted features in order to eliminate redundant information and prevent overfitting. Commonly utilized methods comprise PCA, LDA, and various feature selection algorithms.

Finally, according to this paper, the most important step is classification, which has wildly different approaches such as Bayesian, SVMS, Decision Trees, and Deep Learning Classifiers. EEG emotion detection can also be divided into user-dependent and user-independent tasks, depending on whether the classifier is trained on user-dependent data or not. Substitution and cross-validation techniques can be used to evaluate the performance of the model and adjust the parameters during model training.

Of the five steps above, the classification method is the most relevant. However, several methods have been proposed to classify emotions based on EEG data. These methods include Support Vector Machine (SVM), Spectral Power Density (PSD), Fast Fourier Transform (FFT), K-Nearest Neighbour (kNN), Multilayer Perceptron (MLP), Short-Term Fourier Transform (STFT), and Linear Discriminant Analysis Transformation (LDA), Convolutional Neural Network (CNN), Wavelet Transform (WT), Discrete Wavelet Transform (DWT), Least Squares Support Vector Machine (MC-LS-SVM), Empirical Mode Decomposition (EMD), Mode Function intrinsic (FMI), correlation-based filtering (CIF); variational Mode Decomposition (VMD); tuneable Q-wavelet transform (TQWT); Extreme Learning Machine (ELM); flexible analytic wavelet transforms (FAWT). However, the choice of philtre, FFT and wavelet methods is based on empirical considerations such as philtre type, sequence type, window type and wavelet type.

### *3.2. Convolutional neural networks*

EEG signal extraction involves a variety of different neural network models. In this paper, we will focus on four neural network models including EGGNet, EEGResNet, Deep ConvNet, and FBCNet. For a particular BCI pattern, the feature extractor and classifier are personalised to the unique properties of the EEG signal and applied to the corresponding signal type in the intended context. Convolutional neural networks (CNN) have been successfully applied to Brain-Computer Interface (BCI) systems based on EEG signals. It is also widely used in automatic feature extraction and classification tasks such as computer vision and speech recognition.

EEGNet is a compact convolutional neural network proposed by Lawhern et al.. It is specifically designed for routine tasks involving the analysis of EEG signals and can be applied to a variety of BCI paradigms. In comparison to Shallow ConvNet, EEGNet utilises deep convolution and separable convolution techniques to reduce the number of training parameters. Moreover, it employs the ELU activation function instead of the square activation function. The structure of EEGNet includes Conv2D layers, DepthwiseConv2D layers, Average Pool2D layers, SeparableConv2D layers, and totally connected layers. The final output is a one-dimensional array of size four. Moreover, EEGNet also has neurophysiologically interpretable features and the ability to be trained with limited data.

FBCNet introduces a new method called the current VArIance layer to efficiently synthesize time domain information from EEG signals. This design allows researchers to compare FBCNet with

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additional advanced BCI algorithms using four different MI datasets: BCIC-IV-2a, the OpenBMI dataset, as well as two datasets from patients with chronic stroke. The results demonstrate that FBCNet outperforms previous methods on the BCIC-IV-2a dataset and achieves an 8% improvement in the accuracy of the binary classifier on the other three datasets. The main goal of FBCNet is to efficiently extract spatially and spectrally discriminant information specific to MI-EEG while minimizing the crowding problem when dealing with modest sample sizes. The architecture of FBCNet consists of four steps: multi-view data representation, spatial information learning, temporal feature extraction, and feature classification.

The Residual Network (ResNet) is a convolutional neural network architecture proposed by He et al. [6] and achieved first place in the 2015 ImageNet Large-scale visual Recognition competition. The main objective of applying ResNet to EEG decoding is to explore whether a deeper network can demonstrate superior performance in decoding EEG signals. In the structure of a residual block, we represent the input as x and aim to learn the hidden mapping H(x), while the learned residual F(x) = H(x) - x captures any remaining information that cannot be directly mapped by H(x). If the residual F(x) equals zero, it indicates that the residual block can effectively perform identity mapping.

The Deep Convolutional Neural Network (ConvNet) architecture draws inspiration from a successful computer vision architecture proposed by Krizhevsky et al. [7]. Its purpose is to design a versatile architecture [8] capable of achieving competitive accuracy with minimal expertise required for neural network models. This architecture consists of four regular Max pooling blocks, where the initial ad-hoc block processes the input EEG signal and three additional standard convolutional Max pooling blocks are equipped with a Softmax classification layer.

## 4. Transfer learning

Transfer learning is a powerful technique in the field of machine learning that has gained significant attention and popularity due to its ability to address data scarcity or imbalances in the target domain. By leveraging the knowledge learned from a source domain, transfer learning aims to improve the performance and generalization capabilities of the model in the target domain.

A key assumption behind transfer learning is the existence of similar or shared features between source and target domains. These similarities can be observed at different levels, such as low-level visual features, high-level semantic concepts, or even abstract representations. By identifying these commonalities, transfer learning enables the efficient utilization of pre-trained models or knowledge from related tasks to enhance performance on new tasks with limited labelled data.

The benefits of transfer learning are manifold. First, it reduces the need for large amounts of labelled data in the target domain by leveraging information already captured during training on a different but related task. This not only saves time and resources, but also allows the model to generalize better when faced with limited samples.

Second, transfer learning helps overcome the challenges caused by the uneven distribution of data across classes or categories within the target domain. In scenarios where certain classes have significantly fewer examples than others, traditional machine learning approaches may struggle to learn accurate representations for these underrepresented classes. Transfer learning addresses this issue by leveraging knowledge from well-represented classes in the source domain and efficiently transferring it to improve classification accuracy for all classes in the target domain.

So far, EEG-based emotion recognition has encountered two major challenges. One challenge is to develop a model that can effectively handle individual differences, enabling it to generalize across different individuals while taking into account their unique characteristics. Another challenge involves learning from noisy labels and constructing a stable model that is not affected by the subject's abnormal responses. Recently, researchers have explored the use of transfer learning methods to address individual differences in EEG signals. This approach aims to minimize the discrepancy between the source and target domains while taking into account the independence and distributional assumptions in the minimization process. By increasing the similarity between these domains, it can leverage data from the target domain or achieve better recognition compared to the commonly used previous methods. This approach identifies invariant features across different domains through a domain transformation strategy and establishes relationships among features, data distributions, and labels.

To address these difficulties, Li et al. introduced a novel approach for tackling multiple sources in transfer learning using dual transfer learning [9]. Initially, suitable samples are carefully chosen from the source domain during the first stage. Subsequently, a transfer mapping technique is employed in the second stage to minimize differences between these selected samples and unfamiliar target samples. Inspired by neuroscience's understanding that distinct brain responses are elicited by different emotions, Li et al. introduced R2G-STNN model which incorporates a regional attention layer to learn weights that enhance or weaken contributions from specific brain regions [10]. In addition, the proposed approach integrates spatio-temporal dynamics of EEG within local and global brain regions, while incorporating techniques for efficient emotion performance despite shifts in data distribution across domains.

However, in video-induced EEG emotion experiments, subjects are inconsistently able to accurately generate the corresponding emotions, which results in noisy labels that affect the model performance. To address this issue, Zhong et al. developed a distributed learning method called Emotion-Aware, which is an RGNN neural network. Instead of one-hot encoding (1,0,0), the method uses $(1-\frac{2\varepsilon}{3},\frac{2\varepsilon}{3},1+\frac{2\varepsilon}{3})$ to fuzzy label information. This approach makes the trained model fewer affected by noisy labels.[11]

The optimal ε value can be influenced by various databases and individuals. However, prevailing models for emotion recognition based on EEG predominantly rely on pointwise learning techniques that exhibit a strong dependence on annotated data.

Today, existing EEG-based transfer learning models for emotion recognition can be broadly classified into two categories:

### *4.1. Non-deep transfer learning models*

The algorithm proposed by Pan et al. utilizes TCA to minimize the discrepancy in marginal distributions between the source and target domains, aiming to learn transfer information within a RKHS by maximizing variance [12]. Similarly, Zheng and Lu proposed two techniques for handling individual variations in EEG signal processing across different subjects. One method involves exploring the shared feature space in the source domain using Pan's TCA algorithm and KPCA algorithm. Another approach entails constructing multiple personalized classifiers in the source domain, with parameters from these classifiers being transferred to the target domain through the application of Conduction Parameter Transfer (TPT) algorithm [13]. These conventional transfer learning techniques can somewhat mitigate the disparity between the source and target domains, thereby enhancing performance on the target domain. Nevertheless, given their constrained capabilities and relatively simple nature, this approach does not adequately cater to present practical requirements of emotional brain-computer interfaces.

### *4.2. Deep handover models*

A large number of sentiment models rely on the DANN method originally proposed [14], which aims to find a general feature representation that can accommodate slightly different distributions between source and target domains, while maintaining predictive power for specific classification tasks based on features of source samples. Lee et al. were among the first to apply DANN to the study of aBCI systems. [15] Because DANN can effectively capture deep network features and utilise adversarial learning for distributed adaptation, the aBCI system built based on this method performs better than other alternative methods. By using DANN, sentiment models can completely exploit the information provided by the minor differences between source and target domains, thereby improving their accuracy and robustness on cross-domain capability recognition tasks. This technique has significant implications for our understanding and treatment of mood changes in different domains and contexts. Moreover, in real-world applications, DANN-based aBCI systems also have strong generalisation capabilities and can achieve great results when faced with unknown domains or datasets. As a result, this technique has been widely adopted in various emotion-related tasks. In summary, domain capacity transfer with the help of DANN has become an influential and effective approach in current research on sentiment modelling.

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This opens new ideas to explore capacity sharing and transfer mechanisms across multiple domains, and improves the solution to the cross-domain capacity identification problem, showing great potential in practical applications. The aBCI system consists of DANN models that enhance performance in two ways. Firstly, it incorporates knowledge from neuroscience and brain anatomy to create a bipolar domain adversarial network (BiDANN) that utilises global and local domain discriminators to distinguish the unique characteristics of each hemisphere related to emotional consciousness. Secondly, an R2G-STNN combines spatial-temporal information of brain regions by orientation for improved function stability across domain differences. Additionally, ATDD-LSTM optimises channel selection for sentiment correlation by utilising an attention mechanism, LSTM and DANN while considering the nonlinear correlations between different EEG channels in a data-driven manner.

The following two aBCI systems can be considered as DANN-based models that improve performance in two directions. The study is the first to combine previous knowledge of neuroscience and brain anatomy to show that the left and right hemispheres of the brain exhibit a marked asymmetry in neural responses. Yang and his associates propose an adversarial network model in two hemispheres. According to this approach, a tripartite discriminator was designed to learn separable traits related to emotional perception in both hemispheres of the brain, which improves the stability of the traits for each other with difference.[16] Furthermore, considering the different emotional responses generated by different brain regions, Yang and his associates proposed a method that combines indications of importance and hierarchical features, represented by R2G-STNN. [10] The second direction is probability distribution matching. The formation of unstable DANN, LUO and his associates proposed WGAN-GP to solve this problem by reducing the distance of the boundary probability distribution of different objects.[17] However, current DANN-based methods consider only the distributional differences of different domains and ignore the general distribution differences. To address this issue, Li and his associates proposed a network named JLNN [18], which uses generic adaptive allocation to combine demand-invariant and task-specific features. However, there are still three technical challenges, one is noise, the other is that the current model ignores the separability of features of the target domain, and overfitting the source domain data will reduce the separation ability. separation of features of the target domain. target domain. data type of the target domain, and third, the current algorithm relies so much on the data labels of the source domain that we ignore that in real applications we cannot collect exact labels for every test.

Transfer learning has revolutionised various fields as a powerful technique and continues to gain momentum. In the realm of natural language processing, transfer learning has proven instrumental in improving tasks such as sentiment analysis, machine translation, and text classification. By leveraging pre-trained models on large-scale datasets like, remarkable results have been achieved with reduced computational cost.

Similarly, in computer vision applications, transfer learning has played a pivotal role in advancing object detection, image recognition, and even autonomous driving systems. By transferring knowledge from pre-trained models such as ResNet or VGGNet to fresh datasets with limited labelled samples, practitioners can effectively overcome the data scarcity problem and achieve superior performance.

Moreover, speech recognition systems have also benefited considerably from transfer learning techniques. By utilising pre-trained acoustic models trained on vast amounts of multilingual data or specific domains (e.g., medical or legal), researchers have been able to enhance speech-to-text accuracy significantly. This not only improves transcription services, but also facilitates the capabilities of voice-controlled devices and virtual assistants.

Looking ahead to the future of transfer learning research across these domains and beyond, there is enormous potential for additional exploration. Researchers are actively investigating the theoretical mechanisms underlying successful knowledge transfer between different tasks and domains. Understanding how representations learned from one task generalise to different tasks will unlock new avenues for more efficient model training.

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## 5. Conclusion

The BCI technique establishes a direct communication channel between the brain and external devices, with signals originating from the central nervous system and not relying on peripheral nervous and muscular systems for propagation. The technology is widely used in medical, educational, entertainment and other fields. Currently, brain-computer interface datasets are complex. In general, brain-computer interfaces are only suitable for some simple application scenarios, and technical issues are the key factors limiting their industrial development. Despite significant advances in brain-computer interface technology, its functionality still needs to be improved. Accurate and reliable acquisition and interpretation of EEG signals is an extremely complex task. However, the introduction of deep learning neural network techniques is expected to promote the wider application of BCI techniques. However, most deep neural network models have redundant neural units, which leads to reduced computational power and reaction speed, as well as increased storage space and hardware requirements. Therefore, the use of neural network pruning algorithms to simplify complex network structures, reduce hardware requirements, and improve computational and discriminative capabilities has become a direction worth exploring.

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