# Research Status and Development Trend of EEG Technology for Deep Learning in Emotion Recognition

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**Abstract.** EEG technology has made significant progress as people's attention to their emotions increases. This has also led to significant progress in various brain sciences, as well as their correlation with emotions. Nevertheless, based on the development of contemporary brain science, it is not possible to provide detailed cause analysis or draw accurate conclusions based on EEG information for a certain symptom or representation. The brain, as a complex organ of multiple entities, processes complex information by connecting multiple brain regions and clarifying the division of labor for each region. This creates a significant obstacle for the research method of brain computer interface, which uses computer algorithms to read information in the brain. Recently, many solutions and research methods have emerged to address this issue, such as electroencephalography (EEG), Positive Positron Emission Computed Tomography (PET) and Functional Magnetic Resolution Imaging (fMRI), etc. However, with such a large number of technologies, a method that can provide precise data from both temporal and spatial angles has not yet been derived. So in-depth research in biology, continuous exploration of computer algorithms can make outstanding contributions to the refinement of brain computer data. In summary, this article aims to provide an overview of the relationship between emotions and EEG analysis, as well as the principles of machine recognition and other applied technologies.

**Keywords:** EEG, emotion, algorithm, biology.

## 1. Introduction

As mentioned earlier, brain computer interface technology has not been able to derive universally applicable and effective technologies. Therefore, in this article, This work will start with the physiological structure of the brain, review the effective methods for implementing various brain computer interface technologies, and deeply explore the means required for processing information in these methods.Of course, this is also based on many issues related to EEG recognition technology. Firstly, the information filtering technology for EEG spectra has not yet made significant progress, and perfect solutions for low EEG noise ratio problems have not yet emerged. Secondly, there has not yet been a unified solution for the recognition technology of EEG spectra, and the clarity of these solutions in time-frequency domain, spatial frequency domain, or other fields is not satisfactory. No solution can achieve high-definition recognition in the entire domain. Once again, after obtaining EEG data, we still haven't found a method that can accurately identify programs.Based on this, this article will classify scholars who have made contributions to the development of brain computer interface technology in recent years in the following text, clarify the advantages and characteristics of scholars from various schools of thought, systematically summarize their advantages and disadvantages, and make prospects for their comprehensive utilization and new problem-solving methods. And this article will provide a detailed explanation of the various research methods used by scholars from various schools, and subdivide their steps, links, and specific operating methods as the information statement part of this article.

## 2. Research Works

### 2.1. Brain Structure

The brain is an important tool for processing information in our daily lives, consisting of the left and right brains, which are respectively composed of four brain regions: the frontal lobe, parietal lobe, temporal lobe, and occipital lobe like Figure 1 [1]. As a composite interconnection that generates complex reflections, on the one hand, the signals that EEG can express are infinitely vast, and on the other hand, the recognition of EEG signals will be extremely complex. We need to extract effective information through various filtering algorithms, which means that EEG signals have a low signal-to-noise ratio. So for such complex signal processing, it is necessary to classify them. From the perspective of amplitude, they can be divided into delta waves, theta waves, alpha waves, and beta waves [2]. The frequency of delta waves is usually lower than 4Hz, usually occurring during the period of infant development and extreme brain fatigue. The frequency of theta waves is 4-7Hz, mostly occurring during the period of adolescent brain development or adult relaxed rest. The frequency of alpha waves is generally 8-13Hz, mostly occurring during the resting state of the brain when it is awake. The frequency of beta waves is mostly above 14Hz, often appearing during the period when the brain is about to enter a dormant state.

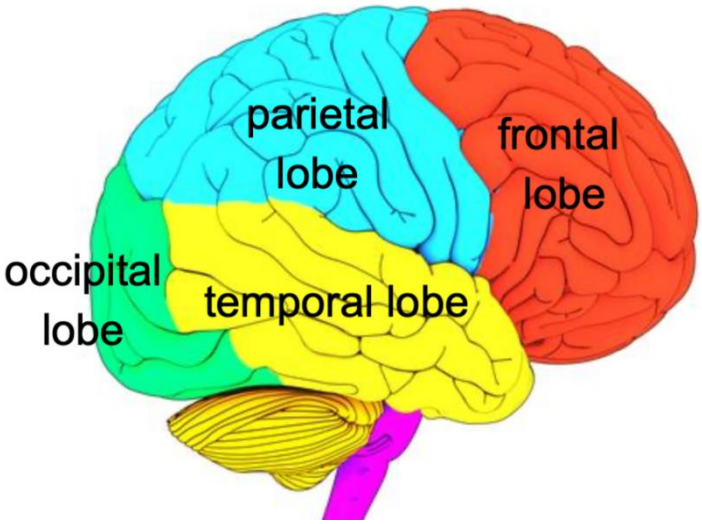



**Fig. 1**. Structure of brain regions [1]

#### 2.1.1 Overview of emotion

As a highly socialized animal, emotions play an extremely significant role in human daily life. Everyone in society is embedded in their corresponding social networks, and it is also because of the cooperative group life since ancient times that people express themselves and empathize with others through emotions in their daily lives. In modern society, with more developed productive forces, emotional issues have increasingly become the focus of people's daily lives. Based on this, the lives of people with emotional disorders have become increasingly difficult with the continuous development of modern society. Therefore, people crave solutions to emotional problems or emotional disorders, and research on causal logic requires quantifying the evaluation criteria for emotions, which has led to various so-called emotion calculation methods.The term 'emotional computing' was first proposed by Professor Picard of the MIT laboratory in 1995, and in the book 'Affective Computing' officially published in 1997, it was defined that emotional computing is about emotions, the calculation of emotions, their generation, and impact.

#### 2.1.2 Continuous Model and evaluation of Emotion

For the quantification of emotions, a two-dimensional emotion analysis model can be used as the blueprint, with arousal as the vertical axis and potency as the horizontal axis. Based on this emotion

discrete model, various emotions can be analyzed for brain stimulation, which originates from the structural idea of Wihelm Wundt, the father of psychology.

### 2.2. Processing of EEG waves

#### 2.2.1 Existing EEG signal dataset

So far, the datasets available for analysis include DEAP, eNTERFACE'06, HeadIT, SEED, SEED-IV, Mahnob-HCItagging, MPED, DREAMER, and more. When generating a dataset, participants are required to generate emotional changes through various means such as watching movies, videos, recalling emotions, and listening to music. Most of the data is collected through 32 or 62 channels, which provide raw training and testing parameters for analyzing EEG data.

#### 2.2.2 Deep data analysis and processing methods

In recent years, many scholars have proposed solutions for analyzing the complex data form of brainwave electrical signals, such as Duan et al. utilized Based on the differential entropy of each channel's EEG signal, the differential entropy asymmetric difference (Differential) is proposed Asymmetry (DASM) and Differential Entropy Asymmetry Quotient (RASM) as new Frequency domain features were experimented and explained the impact of left and right brains on emotion recognition.Of course, for non-stationary signals such as EEG signals, we need to use Short Term Fourier Transform (STFT), Wavelet Packet Transform (WPT), and Empirical Mode Decomposition information processing methods such as Empirical Mode Decomposition (EMD) make it easier for computers to understand. On the basis of understanding, due to the low signal-to-noise ratio of EEG, computers still need some algorithms for information filtering, which involves relatively classic computer learning methods, such as Support Vector Machine (SVM), K-Nearest Neighbor, KNN, Bagging Tree BT), etc. used SVM, KNN, linear discriminant analysis, naive Bayes, random forest, and deep learning and four integration methods (Bagging, Boosting, Stacking, and Voting) [3, 4]. Among them, deep learning also includes: Convolutional Neural Network CNN, Deep Neural Network (DNN), Long Short Term Memory Network Memory, LSTM, etc.In addition, algorithms that can contribute to emotional EEG processing include KNN, SVM, NB, multi-layer perceptual back propagation, logistic regression, gradient upgrading, linear discriminant analysis, quadratic discriminant analysis, random forests based on automatic encoders, decision trees, DNN, CNN, DBN, artificial neural networks, capsule networks, regional asymmetric convolutional neural networks, etc. [5].

#### 2.2.3 Automatic time-frequency feature extraction module

Solving the need for traditional manual feature extraction and processing of EEG signals using deep neural networks. The problem of time-frequency modeling can be automatically extracted by a scaling convolutional neural network layer (SL). The time-frequency characteristics of multi-channel EEG emotional signals are purely data-driven automatic features, and the scaled convolutional neural network layer can input any length of EEG emotional signals [6]. The processing process includes setting the upper and lower bounds of the convolutional kernel size, initializing the convolutional kernel, calculating the correlation between the convolutional kernel and the input signal, determining whether the convolutional kernel size is greater than the lower bound of the convolutional kernel size, and determining whether the convolutional kernel size is odd when it is true. If it is, the convolutional kernel is downsampled. If it is not, the convolutional kernel is filled with size and downsampled, and then the signal is filled with a size of 1/2 of the current convolutional kernel size, Perform cross correlation calculation with the convolutional kernel, add bias, and record the current result. If the size of the convolutional kernel is not greater than the lower bound of the convolutional kernel size, stack multiple cross correlation results into a two-dimensional tensor form and end the program [7].

#### 2.2.4 Emotion recognition based on multiple physiological signals

Due to the various difficulties in EEG extraction, algorithm requirements, and requirements for highly domesticated computer deep learning models mentioned earlier, blindly improving the

accuracy and efficiency of algorithms can be considered as a solution. However, verifying the accuracy of EEG in emotion recognition through various physiological phenomena is more effective. For the effectiveness of emotion recognition, we usually use methods such as facial expression recognition, speech intonation recognition, behavior recognition, text recognition, etc. as auxiliary research tools to further confirm the accuracy of EEG in emotion recognition. At the same time, it can also be used to assist experimenters in making judgments about the subtle differences in participants' specific emotions, For example, pity and sympathy are two emotions that are almost indistinguishable in EEG recognition, but we can use the above methods to classify them, which is partly attributed to the low accuracy of EEG recognition in the spatiotemporal and frequency domain. For example established an emotional and physiological database, recording 30 participants in four types of induced emotions (neutral ECG, GSR, and Photoplethysmography (PPG) in sadness, fear, and pleasure An individual response specific model based on population was proposed to identify physiological signals Response Specificity (IRS) to improve the performance of emotion recognition based on multiple physiological signals will combining EEG with PPG and using Convolutional Long Short Term Memory (convLSTM) model for emotion recognition [8].

## 3. Discussion

### 3.1. Classification

Based on all the research on EEG recognition technology and emotion correlation mentioned above, this article believes that it can be roughly divided into several schools: modeling digital training school, multi-angle emotion assistance analysis school [9], and generative adversarial network algorithm analysis school (see Figure 2) [10]. Scholars of the modeling digital training school focus on improving the data model and formula derivation of EEG analysis, so that it can better reflect the composite linear function displayed by EEG neural stimulation signals. It can refine accuracy and provide a more comprehensive description of the data, but it cannot completely solve the problem of high-density noise in EEG. Scholars in the field of generative adversarial network analysis focus on training AI algorithms, enabling them to simulate and generate realistic EEG datasets, which can be used as raw training data when continuing EEG models. However, the reason why this algorithm is widely used is actually due to the limitations on the collection of EEG raw data and the ethical issues involved, The data generated by simulation algorithms will always have some deviations from the actual data. Secondly, it still fails to propose solutions to the problem of low signal-to-noise ratio in EEG. Scholars of the multi-angle emotion assistance analysis school use various physical representations that occur when people generate emotions and algorithms that comprehensively analyze their valence to conduct multi-angle analysis of emotions, thereby improving accuracy. But its data volume is relatively large, requiring more time, computational power, and financial costs, and it can only provide relatively rough emotional classification. In summary, there are some difficulties in overcoming the research methods and directions of these schools. Based on this, This work will provide a detailed summary of the three schools and point out their shortcomings in the following text.This work will also propose improvement suggestions based on my personal perspective for their research direction.

| schools | focus | advantages | disadventages |
|---|---|---|---|
| modeling digital training school | Improving the data model derivation of EEG analysis | refine accuracy and data | cannot deal with high-density noise in EEG |
| multi-angle emotion assistance analysis school | Improving EEG recognition accuracy through emotional multi-angle analysis | high accuracy | time&money consuming |
| generative adversarial network algorithm analysis school | Training AI algorithms enabling them to generate realistic EEG datasets | provide raw training data | deviations |

**Fig. 2** Schools' classification of generative adversarial network algorithm

### 3.1.1 Modeling digital training

As mentioned earlier, this type of school has made outstanding contributions to data summarization, such as using algorithms such as Fourier transform to unify the wave forms of brainwave stimuli, and has made outstanding contributions to data collection and processing. It has also demonstrated high accuracy in predicting trends and numerical evaluations of specific data. Especially, it can provide good analysis, classification, data statistics, and visualization for time-domain, frequency-domain, time-frequency domain, nonlinear, and brain network features. Specifically, it can analyze sample entropy, process and calculate data dispersion, and split EEG waves into multi frequency band signals for reception and processing, greatly improving the efficiency of EEG information processing. However, its filtering of information validity is not sufficient, and it cannot accurately determine the difference between information and noise and filter information based on this feature. However, this is a very serious problem in EEG popularization

### 3.1.2 Multi-angle emotion assistance

The performance of scholars from this school is even more commendable. They conduct comprehensive research through multiple data collection methods to ensure the accuracy of the results. The advantages of this research method are obvious, with extremely high data accuracy. Based on the confirmation of the original high-precision data collection, it can also produce more detailed data curves, which is more conducive to analysis. In addition, It can also provide a solution to the problem of low signal-to-noise ratio of EEG signals, which is due to its high recognition of effective information, which can be used for highly refining data. Of course, the drawbacks of this genre are also evident. It has high requirements for various data collection devices and includes an extremely wide range of data input sources, which determines its high cost of single data collection. At the same time, its diverse data sources also increase its time cost. The reason is that it requires multiple data processing and aggregation to find consistency at each node, in order to draw conclusions, The processing of various types of data requires a significant amount of time to compare algorithm accuracy and efficiency, or to find algorithms that can be comprehensively calculated. Even so, a large amount of data will consume a lot of computing power and thus time cost

### 3.1.3 Generative adversarial network algorithm

Scholars of this genre have innovatively proposed the generation of datasets based on generative adversarial network algorithms to address the issue of data scarcity, in order to serve as reference data. It uses multi view input to extract images of items, imports them into a database, and after passing through convolutional layers, extracts them as output results that express features. Through this process, it is converted into EEG like data and stored. This method can also be combined with School 2 to improve the accuracy of EEG recognition and emotional perception by combining the complementary information generated by this method with other physiological preference features. But it also has certain problems, such as not being able to fully bridge the differences between it and real data when used alone. It can only provide basic data and cannot solve various problems related

to EEG signal processing, such as data organization and feature point analysis. It has not been able to provide specific solutions for EEG and emotional relationships.

## 4. Conclusion

Based on the description of each school in the previous text and the introduction to the correlation between emotion and EEG recognition, it is not difficult to summarize the current development direction and potential future prospects of EEG recognition technology. Most EEG recognition technologies use emotion discrete models to quantify emotions and collect data such as potency and arousal based on the indicators of this model. However, this model itself cannot segment emotions, which is a so-called issue of emotional accuracy. This article proposes some future development directions that may be able to solve these problems. The scholars of the generative adversarial network school mentioned earlier have used AI technology to assist in generating simulated EEG data, indicating that they have also noticed the rapid development trend of AI technology and utilized it. Based on this, this article proposes prospects for its possible future applications. The general idea of this processing method in this article is to import the raw data into the computer and hand it over to the AI algorithm for processing. With the emergence of the generative adversarial network school, we can use sufficient raw data and allow AI to seek the optimal performance algorithm in the input large amount of EEG data, which can solve the data processing problems related to EEG signals. We can also establish a reward and punishment mechanism while inputting EEG data, establish a standard answer set by collecting personal descriptions of the protagonist and the subjects, as well as the reactions of the subjects after being stimulated, and transmit their corresponding EEG waves to AI, so that they can approach the correct answer through continuous trial and error and explore the connection between EEG recognition and emotions.

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