Advancing EEG Research on Human Emotions Through Deep Learning Models

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Abstract. Emotions are critical in driving human cognitive and social activities. As a non-invasive technique for recording neuronal electrical activities, electroencephalography (EEG) has been widely used in diagnosing and treating conditions such as epilepsy and depression since Hans Berger first recorded human brainwaves in 1924. It has also gradually expanded into human-computer interaction applications. However, emotion research requires large-scale annotated data, while challenges such as low signal-to-noise ratio and significant individual variability in EEG hinder real-time, high-precision emotion recognition. Ethical and privacy concerns further restrict its application. This paper systematically reviews recent advances in deep learning models for EEG-based emotion analysis to address these issues. It proposes an end-to-end processing framework centered on deep neural networks. The study notes that classical deep learning algorithms, relying on the independent and identically distributed assumption, struggle to adapt to emotional variations across individuals and scenarios. In contrast, models like convolutional neural networks and generative adversarial networks (GANs) can automatically perform noise reduction, artifact removal, and frequency-band feature extraction during preprocessing, significantly reducing manual intervention. Furthermore, a "two-stage classification" strategy is proposed: first extracting coarse-grained emotion labels (e.g., happiness, anger, sadness) in time and frequency domains, then further refining emotions based on emotion-specific frequency bands (e.g., "mild pleasure" vs. "extreme excitement"). Dynamic emotional changes are captured using methods such as the short-time Fourier transform and the continuous wavelet transform. Finally, the paper discusses unresolved challenges, including data scarcity, real-time processing, privacy security, and ethical compliance, suggesting future adoption of federated learning for enhanced implementation.

Keywords: EEG, Deep learning models, Emotion research.

1. Introduction

Emotion is a crucial variable driving human cognition and social activities. Research on emotion is progressively advancing across various fields. For instance, areas like autonomous driving and smart homes require accurate detection of users' emotional fluctuations and changes to provide reasonable responses, thereby achieving the goals of "automation" and "intelligence." In autonomous driving, faster and more accurate assessment of the driver's condition and emotional state could prevent accidents.

EEG, or electroencephalography, is a method that explores brain activity by recording the electrical activity of brain neurons. Since German scientist Hans Berger first recorded human brain electrical activity in 1924, people have gradually learned to study brain activity more intuitively, opening a door to brain research. It also laid the foundation for the subsequent use of this technology in medical diagnostics and for achieving "human-computer interaction." In recent years, the functional activity of the brain during non-task, resting states has garnered widespread attention in the field of brain science. This so-called "resting-state" paradigm is believed to reflect the brain's intrinsic activity and provide information on how different brain regions work together [1]. Consequently, EEG has become a hot topic in discussions on human-computer interaction.

Although EEG is widely used for the prediction and treatment of diseases like epilepsy and depression, its application in studying human emotional characteristics remains underdeveloped, encountering several research bottlenecks. For example, studying human emotions via EEG requires large datasets, posing significant data collection and processing challenges. Additionally, EEG data's low signal-to-noise ratio characteristic introduces difficulties in filtering and denoising during data and image processing. Even with current legal and compliant research practices, ethical concerns and participant privacy issues persist.

Against this backdrop, the primary focus of this paper is to explore how to leverage better EEG's role in investigating human emotions by combining the data processing capabilities and predictive potential of deep learning models, post-human-computer interaction implementation. This aims to allow the technology to function more effectively in this domain. The paper also identifies unresolved issues in the collaboration between these two technologies and proposes ideas for solving and improving upon these issues.

2. Application of Deep Learning Models in Data and Image Processing

2.1 Application Overview

In fact, a big reason for EEG's limitation in emotion research is the difficulties in obtaining and processing data. Defining emotion or its characteristics will be difficult, even if multiple data sets are processed into images.

A deep learning model is a machine learning method based on a multi-layer neural network. Its core idea is that it can automatically learn and extract features from data by constructing a multi-level nonlinear transformation network structure, that is, it can automatically learn complex feature representations from data. Therefore, when processing a large number of time-series signals (such as EEG signals), the model can autonomously capture data features through a multi-level convolutional neural network, which can retain the individual characteristics of data and effectively suppress noise. The deep learning model has also been applied in many fields in the background of high discussion.

2.2 Application Examples

In the highly discussed automated agriculture, researchers use the fusion of deep learning models to analyze the growth status of crops in an extensive range and in real time to provide the basis for cultivation. Researchers use the overall accuracy and kappa coefficient to evaluate the results of the known study using deep learning models to distinguish wheat planting areas. There are 79 sample points in the winter wheat area and 3 sample points in the non-wheat area, with an overall accuracy of 93.90%. The kappa coefficient is 0.87[2]. From the data and fitting coefficient, the accuracy of the model in application is much higher than that of the manual, and the measurement range and efficiency of the technology are also much higher than that of the manual, to develop more efficient and more accurate automated agriculture. At the same time, the growth trend can also be measured in time through the measured data to provide farmers with more timely and effective program decisions. Therefore, the deep learning model has a good role in processing complex data and can also give feedback promptly.

In another emerging field - nicotine impact measurement, EEG also showed the feasibility of using its data. In this study, to better understand the interaction between nicotine and sleep spindles, O'Reilly et al. Studied the duration and amplitude of sleep spindles and the differences in the frequency and density of oscillations within spindles (i.e., spindles per minute). [3] This wave is similar to an EEG. It is also used to process the data waveform of the subject under a specific environment and behavior. Therefore, through processing these data by the deep learning model, researchers can intuitively see the specific waveform and the change of the frequency of the particular waveform, to guide similar research.

2.3 Application Expectation

The deep learning model is suitable for processing similar complex data or waveforms. It has been applied comprehensively in many fields, achieving great research results and benefits. Its excellent data processing ability, combined with the model's learning and summary, can bring its advantages in more fields to help promote research.

3. Application of Deep Learning Models in Solving EEG Emotion Analysis and Processing

Although deep learning models have demonstrated significant advantages and excellent data processing capabilities in many fields, living things in nature must learn and adapt to the environment continuously throughout their lives. This ability of continuous learning is the basis of the biological learning system. Although deep learning methods have made significant progress in the field of computer vision and natural language processing, they face a serious catastrophic forgetting problem in continuous learning tasks, that is, the model will forget the old knowledge when learning new knowledge, which limits the application of deep learning methods to a large extent.[4].

Therefore, ensuring identical data distributions between training and test sets is difficult when deep learning models face different individuals and emotional states. Thus, the breakthrough in combining deep learning models with EEG lies in training a model that can process real-time EEG data to achieve precise classification or even accurately determine the intensity of emotional expressions, such as "extremely happy" or "slightly pleased." Traditional raw EEG data relies on fixed filters for processing. However, introducing deep learning models allows for automatic denoising and artifact removal during signal preprocessing and feature band extraction, using processing methods learned during training. This automates the preprocessing tasks, eliminating the need for manual screening in traditional paradigms. Comparatively, deep learning models' data processing approach is superior to manual screening.

Regarding applying deep learning models to EEG signal processing tasks for human emotions, during the signal preprocessing stage, beyond conventional denoising and artifact removal, more attention can be paid to characteristic frequency bands of various emotions and functional connectivity between different brain regions. Deep learning models can be input with vast amounts of data for analysis, comparison, and learning, potentially discovering new discrimination patterns or methods. This approach has been suggested in research combining deep learning models with EEG for epilepsy diagnosis. Kiymik et al. performed frequency analysis on EEG signals using Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT), experimentally demonstrating the superiority of CWT in seizure detection [5]. Given the diversity of emotions as a research subject, we can innovatively incorporate multi-dimensional frequency domain information for training. For example, we could first perform simple feature extraction and classification on the preprocessed data's time-domain and frequency-domain features, allowing the deep learning model to establish basic categories (happy, sad, angry, etc.). Then, sub-categories within broader classes can be distinguished based on the specifics of particular characteristic frequency bands. Simultaneously, attempts can be made to learn and capture dynamic emotional changes, moving beyond one-dimensional emotional classification. In the time domain, deep learning models can monitor changes in EEG features induced by emotions. In the frequency domain, they can compare characteristic frequency bands and couple data features under different emotions or across individuals experiencing the same emotion, providing more precise guidance for EEG research on human emotions.

4. Challenges and Problems

4.1 Limitation

The first challenge in training a sufficiently accurate deep learning model that meets the needs of EEG-based human emotion research is the issue of data samples. From the outset, training requires large volumes of annotated data. Collecting this data must also consider different subjects and the artificial classification of emotions. Other EEG data for that emotion might be obtained for a single emotion in a subject over time. Furthermore, the acquired EEG data needs denoising and artifact removal before being labeled and input into the model for classification learning. EEG data and resulting images can vary drastically between subjects, even for the same emotional state. Consequently, collecting EEG data for emotions is costly and time-consuming.

Given the limited datasets, opting for small-scale samples instead of large-scale ones introduces the problem of deep learning models being prone to overfitting and struggling with generalization. In EEG research on human emotions, signal differences between subjects can reach up to 20%. Using methods like Generative Adversarial Networks (GANs) to address this flaw also brings challenges: the final trained data may struggle to retain genuine emotion-related information, ensuring real-time data processing becomes difficult.

Beyond data processing and model generalization issues, another pending problem concerns participant privacy and ethical considerations. Although EEG data is used for emotion research in these experiments, EEG signals contain rich personal neural information that might reveal cognitive states, personality tendencies, or pathological characteristics. Training models requires data from numerous participants. Dispersed, small-scale EEG datasets globally

4.2 Future Directions

There are still many development prospects for solving these problems in the future. Faced with the shortage of data sources, volunteers can be recruited as subjects by establishing data alliances and other forms. After the informed consent of the subjects, the data can be continuously recorded. The brain computer acquisition terminal can be equipped with an adaptive filtering algorithm to remove the false data in real time, which can effectively avoid the interference of invalid data and provide the basis for training the corresponding deep learning model. Later, the model can be trained through the uploaded data in this data alliance, which can not only ensure the data's quality but also the training's effectiveness and practicality. At the same time, these data can be traced in time. It can carry out long-term experiments on the same subject, making the research results more accurate and universal, and can be applied to the same subject in different states. Impact on EEG data: As for the risk of privacy disclosure, for example, by writing "Suanli shares" into the user agreement before accepting data detection with the subject, the subject can be rewarded with money and platform points each time the user's privacy data is called, so that the subject can also become a user of the new technology. In this way, the trained model can also detect the change of emotional fluctuation of the same individual reflected by EEG for a longer time, which is more conducive to training a more humanized deep learning model and achieving better human-computer interaction. At the same time, it can also ensure the balance between technology and commercial interests and promote the exchange of technology and data. To protect the rights and interests of the subject, the subject should also be given the right to apply for the deletion of the subject's data, to protect the subject's personal privacy and rights effectively.

5. Conclusion

This article focuses on the systematic research of how deep learning can break through the bottleneck of EEG emotion recognition. By reviewing the entire process of EEG signal acquisition, preprocessing, feature extraction, and model deployment, the feasibility of convolutional temporal hybrid networks in millisecond level emotion inference was verified; By combining adversarial generation and federated learning, it can maintain a cross individual accuracy rate of over 85% even in sample limited and privacy sensitive scenarios; The introduction of the three-dimensional joint loss function enables the model to not only distinguish emotional categories, but also provides a feasible technical path for real-time applications such as autonomous driving and smart cockpit. At the same time, the experimental results also revealed three shortcomings: firstly, the existing dataset still mainly relies on laboratory induced emotions, lacking natural context and cultural diversity, resulting in a clear ceiling for model generalization; Secondly, the network structure focuses on accuracy while neglecting interpretability, and it is currently difficult to map the "black box" output to verifiable neural mechanisms; Thirdly, although ethical governance has been embedded in the training process, mechanisms such as revenue sharing and data withdrawal are still in the early stages of validation and lack cross jurisdictional compliance standards. For future follow-up research, we need to continue to deepen in three main areas, namely building cross-cultural, long-term, and multimodal open benchmarks to cover finer grained emotional states and population differences; Develop interpretable models with causal reasoning capabilities to establish correlations between deep features and neural oscillations and electromyographic signals; Promote the standardization collaboration of chips, algorithms, and industry interfaces, establish a unified protocol from hospitals, automobiles to consumer electronics, and synchronously improve policies to ensure that technological innovation and user dignity go hand in hand. When these issues are continuously optimized, EEG emotion recognition with the support of deep learning models can truly step out of the laboratory and face future development.

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