Adaptive Optimization of Transfer Learning in Cross-sample Electroencephalogram Depression Prediction Models

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Abstract: This paper focuses on the adaptive optimization problem of transfer learning in cross-sample electroencephalogram depression prediction models. This paper expounds the significance of electroencephalogram (EEG) signals in depression prediction and the challenges faced in cross-sample prediction, and analyzes the basic concepts and common methods of transfer learning and its preliminary application in the medical field. This paper explores the influence of factors such as data differences and individual differences on the model in cross-sample electroencephalogram (EEG) depression prediction, and elaborates in detail the adaptive optimization strategies of transfer learning in data preprocessing, feature extraction, model training and adjustment, etc. It points out the current challenges and looks forward to the future development direction, aiming to provide theoretical support for constructing a more accurate and universal cross-sample electroencephalogram depression prediction model.

Keywords: Transfer Learning; Cross-sample; Electroencephalogram (EEG) Depression Prediction Model; Adaptive Optimization

1. Introduction

1.1 Research Background and Significance

Depression, as a common mental disorder, seriously affects the physical and mental health and quality of life of patients [1]. Accurate and timely diagnosis of depression is of vital importance for the treatment and recovery of patients. Electroencephalogram (EEG) can record the electrical activity of brain neurons and reflect the functional state of the brain, which contains rich information related to depression. Therefore, using electroencephalogram (EEG) signals for depression prediction has become a hot research direction at present [2]. However, in practical applications, due to the differences among various sample groups in terms of age, gender, and severity of the disease, the performance of prediction models trained based on a single sample drops significantly when applied across samples [3]. Transfer learning, as a method that can transfer the knowledge learned in one field or task to other related fields or tasks, provides a new idea for solving the problem of cross-sample electroencephalogram depression prediction [4]. By adaptively optimizing the transfer learning strategy, the accuracy and generalization ability of the cross-sample electroencephalogram depression prediction model can be improved, which has important theoretical and practical application value.

1.2 Current Research Status at Home and Abroad

At present, certain research achievements have been made both at home and abroad in the fields of electroencephalogram (EEG) depression prediction and transfer learning. In the prediction of electroencephalogram (EEG) depression, early studies mainly relied on time-domain features (such as mean and variance) and frequency-domain features (such as power spectral density), but the recognition accuracy was relatively low [5]. With the development of deep learning, convolutional neural networks (CNNS) and recurrent neural networks (RNNS) have been introduced into EEG analysis, significantly enhancing the feature extraction capability [6]. For instance, Elnaggar et al. [7] extracted EEG spatio-temporal features through multi-scale CNN, achieving an accuracy rate of 92% in single-center validation, but the cross-center performance dropped to 75%. In the field of transfer learning, various transfer learning methods have been proposed, such as instance-based transfer, feature-based transfer, and model-based transfer, and have been widely applied in areas like image recognition and natural language processing [8]. However, there are still relatively few studies on cross-sample electroencephalogram (EEG) depression prediction, and the existing transfer learning methods face challenges such as complex data and large individual differences when applied to EEG data, which require adaptive optimization.

2. Theoretical Basis of Transfer Learning

2.1 Definition and Classification of Transfer Learning

Transfer learning aims to utilize the existing knowledge in the source domain to assist in the learning tasks of the target domain. According to different transfer methods, transfer learning can be classified into instance-based transfer, feature-based transfer and model-based transfer. Instance-based transfer improves the learning performance of the target domain by weighting instances similar to the target domain in the source domain. Feature-based transfer is dedicated to finding a common feature representation space, such that the data in the source domain and the target domain have similar distributions in this space. Model-based migration involves transferring and adjusting the parameters of the model trained in the source domain to adapt to the tasks in the target domain.

2.2 The Application Potential of Transfer Learning in the Medical Field

There exist problems such as data scarcity and uneven data distribution in the medical field. Transfer learning provides an effective way to solve these problems. For instance, in disease diagnosis, a large amount of data on known diseases can be utilized as the source domain, and the learned knowledge can be transferred to new target disease diagnoses with less data. In the prediction of electroencephalogram (EEG) depression, the EEG data of different sample populations can be regarded as different fields. Through transfer learning, the model knowledge trained on a certain sample population can be transferred to other sample populations, thereby improving the cross-sample prediction ability of the model.

3. Challenges in Cross-sample Electroencephalogram (EEG) Depression Prediction

3.1 Data Discrepancy Issues

The electroencephalogram (EEG) data of different sample groups vary in multiple aspects. Firstly, factors such as the collection equipment and the collection environment can lead to differences in data in terms of noise level, signal quality, and other aspects. Secondly, there are also differences in physiological and pathological characteristics among different sample groups. For instance, factors such as age, gender, and the severity of the disease can affect the patterns of electroencephalogram (EEG) signals. These data differences will cause the model trained on a single sample to fail to accurately capture the features of the target sample when applied across samples, thereby leading to a decline in prediction performance.

3.2 Issues of Individual Differences

Even within the same sample population, there are significant differences among individuals. Everyone's brain structure and function are unique, which leads to differences in the characteristic patterns of electroencephalogram (EEG) signals among different individuals. In addition, an individual's psychological state, living habits and other factors can also have an impact on electroencephalogram (EEG) signals. The existence of individual differences increases the difficulty of cross-sample electroencephalogram (EEG) depression prediction, requiring the model to have strong adaptability and generalization ability.

3.3 Requirements for Model Generalization Ability

A cross-sample electroencephalogram (EEG) depression prediction model needs to have the ability to make accurate predictions on unknown samples, that is, it should have good generalization ability. However, traditional machine learning models are often trained and optimized on specific samples and have strong assumptions about the distribution and features of the data. When applied to cross-sample prediction, these assumptions may no longer hold true, resulting in insufficient generalization ability of the model. Therefore, how to improve the generalization ability of the model is an important challenge faced by cross-sample electroencephalogram (EEG) depression prediction.

4. Adaptive Optimization Strategies for Transfer Learning in Cross-Sample EEG

Depression Prediction

4.1 Adaptive Optimization in the Data Preprocessing Phase

During the data preprocessing phase, targeted optimization is required to adapt to the characteristics of cross-sample EEG data. First, to address data discrepancies caused by different acquisition devices and environments, methods such as data normalization and standardization can be used to convert the data to a unified scale, reducing the impact of these factors. Second, to address noise in EEG data, algorithms such as filtering and denoising can be used for preprocessing. Furthermore, considering the differences in physiological and pathological characteristics across sample groups, data can be stratified, for example, grouped by factors such as age and gender, and preprocessed separately to improve data quality and consistency.

4.2 Adaptive Optimization in the Feature Extraction Phase

Feature extraction is a key step in EEG depression prediction. In cross-sample scenarios, it is necessary to extract features that are both universal and discriminative. Traditional EEG feature extraction methods, such as mean and variance in the time domain and power spectral density in the frequency domain, can be employed, combined with transfer learning techniques to select and optimize these features. For example, feature selection algorithms can be used to identify features that are stable across different sample groups, reducing feature dimensionality and improving model efficiency. Alternatively, new feature extraction methods, such as those based on deep learning, can be explored. Deep learning models can automatically learn deep-level features of data. By jointly training in both the source and target domains, they can learn feature representations with greater generalizability.

4.3 Adaptive Optimization in the Model Training and Tuning Phase

During the model training and tuning phase, appropriate transfer learning methods and model architectures should be selected based on cross-sample characteristics. For instance-based transfer, instance weights can be adjusted to ensure that instances in the source domain that are more similar to the target domain play a greater role in model training. For feature-based transfer, feature mapping can be used to map features from the source and target domains into the same feature space, ensuring that they have similar distributions within that space. For model-based transfer, parameters of models trained in the source domain can be fine-tuned to adapt them to tasks in the target domain. Furthermore, ensemble learning methods can be used to integrate multiple transfer learning models to improve model stability and generalization.

4.4 Adaptive Optimization of Evaluation Metrics and Validation Methods

For cross-sample EEG depression prediction, it is necessary to establish appropriate evaluation metrics and validation methods to assess model performance. Traditional evaluation metrics such as precision, recall, and F1 score may not fully reflect model performance in cross-sample scenarios. Therefore, it is possible to consider introducing new evaluation metrics, such as cross-sample generalization error and model stability indicators. Regarding validation methods, cross-validation can be used to divide the data into multiple subsets and perform multiple training and validation runs to reduce bias introduced by data partitioning. Furthermore, an independent test set approach can be used to test on samples completely different from the training set to more accurately assess the model's cross-sample prediction capabilities.

5. Application Prospects and Challenges of Adaptive Optimization in Transfer Learning

5.1 Application Prospects

Adaptive optimization in transfer learning for cross-sample EEG depression prediction has broad application prospects. On the one hand, it can improve the accuracy and timeliness of depression diagnosis, providing clinicians with more reliable diagnostic evidence. By building a model with strong cross-sample predictive capabilities, it can be widely applied across different medical institutions and populations, enabling early screening and intervention for depression. On the other hand, it can provide new methods and insights for depression research. By analyzing the model's feature changes and knowledge transfer during transfer learning, we can gain a deeper understanding of the pathogenesis and EEG characteristics of depression, providing theoretical support for its treatment and prevention.

5.2 Challenges

Although transfer learning has great potential for cross-sample EEG depression prediction, it also faces several challenges. First, the complexity and individual variability of EEG data make transfer learning difficult to ensure effectiveness. EEG data from different sample groups may have significant distribution differences, and finding effective transfer strategies to overcome these differences is a key issue. Second, transfer learning suffers from poor interpretability. Transfer learning methods like deep learning are often viewed as "black box" models, making it difficult to explain how the models transfer knowledge and make predictions. This can hinder their application in the medical field. Furthermore, data privacy and security are important considerations in transfer learning applications. EEG data contains sensitive personal information, and protecting data privacy and security during transfer learning is a pressing issue.

6. Conclusion

This paper explores the adaptive optimization of transfer learning in cross-sample EEG depression prediction models. By analyzing the challenges of cross-sample EEG depression prediction, such as data variability, individual differences, and model generalization requirements, adaptive optimization strategies are proposed in areas such as data preprocessing, feature extraction, model training and tuning, and evaluation metrics and validation methods. These strategies can improve the accuracy and generalization of cross-sample EEG depression prediction models, providing new methods and technical support for the diagnosis and research of depression.

Future research can further explore the application of transfer learning in cross-sample EEG depression prediction. On the one hand, more effective transfer learning algorithms and model structures can be developed to improve model performance and adaptability. For example, adaptive transfer learning can be achieved by combining methods such as reinforcement learning. On the other hand, research on multimodal data fusion can be strengthened, combining EEG data with other physiological data (such as electrocardiograms and eye movement data) or psychological data to improve the accuracy and reliability of depression prediction. Furthermore, attention should be paid to the interpretability and data privacy issues of transfer learning to promote its practical application in the medical field. In summary, optimizing the adaptability of transfer learning in cross-sample EEG depression prediction models is a challenging and significant research direction. Through continued research and exploration, we hope to build more accurate and universal cross-sample EEG depression prediction models, contributing to the prevention and treatment of depression.

References

[1] Kandhakatla, R., Yarra, R., Pallepati, A., & Patra, S. (2018). Depression-A common cold of mental disorders. Alzheimers Dement. Cogn. Neurol, 2, 1-3.

[2] Liu, W., Jia, K., Wang, Z., & Ma, Z. (2022). A depression prediction algorithm based on spatiotemporal feature of EEG signal. Brain Sciences, 12(5), 630.

[3] Kumar, S. D., & Subha, D. P. (2019, April). Prediction of depression from EEG signal using long short term memory (LSTM). In 2019 3rd international conference on trends in electronics and informatics (ICOEI) (pp. 1248-1253). IEEE.

[4] Lanzino, R. (2025). Sparking Light on Deep Learning in EEG Research.

[5] Dev, A., Roy, N., Islam, M. K., Biswas, C., Ahmed, H. U., Amin, M. A., ... & Mamun, K. A. (2022). Exploration of EEG-based depression biomarkers identification techniques and their applications: a systematic review. IEEe Access, 10, 16756-16781.

[6] Bai, R., Guo, Y., Tan, X., Feng, L., & Xie, H. (2021). An EEG-based depression detection method using machine learning model. Int J Pharma Med Biol Sci, 10(1), 17-22.

[7] Elnaggar, K., El-Gayar, M. M., & Elmogy, M. (2025). Depression detection and diagnosis based on electroencephalogram (EEG) analysis: A systematic review. Diagnostics, 15(2), 210.

[8] Kora, P., Ooi, C. P., Faust, O., Raghavendra, U., Gudigar, A., Chan, W. Y., ... & Acharya, U. R. (2022). Transfer learning techniques for medical image analysis: A review. Biocybernetics and biomedical engineering, 42(1), 79-107.

