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Optimisation of Real-time EEG Signal Classification Accuracy

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Abstract:

This study proposes a hybrid model based on the combination of a convolutional neural network (CNN) and a long short-term memory network (LSTM) for the classification of electroencephalographic (EEG) signals, with a particular focus on the motor imagery task in the BCI Competition IV Dataset 2a. The usability of the data is enhanced by band-pass filtering and independent component analysis (ICA), which effectively removes artefacts and noise from the signal, thus improving the quality of the data. In the process of feature extraction, time-domain statistical features are employed, while high-dimensional features are reduced in dimension through principal component analysis (PCA), thus enhancing the computational efficiency and classification performance of the model. This paper experimental results show that the CNN-LSTM model achieves 100% accuracy on the training set, but only 72.41% on the test set. These findings suggest that the model demonstrates robust classification capabilities when processing training data, but exhibits some limitations in its ability to generalise to previously unseen data. This paper also discusses the limitations of the model and makes suggestions for improvements to further optimise its generalisation performance and enhance the results of its applications.

Keywords: EEG; CNN; LSTM.

1. Introduction

Brain-computer interface (BCI) technology provides a novel method of information exchange through the acquisition and decoding of electroencephalogram (EEG) signals. These signals are generated by changes in the electric field triggered by neuronal activity in the brain and represent a valuable tool for studying brain function and its activity [1]. BCI systems employ EEG signals to decode brain activity, thereby enabling the control of external devices. This technology is widely utilized in the fields of medicine, neuroscience, and human-computer interaction [2]. In numerous BCI applications, the real-time classification of EEG signals represents a pivotal technology, with its performance directly influencing the system's response speed and accuracy [3].

EEG signals are characterized by high time variability, nonlinearity, and low signal-to-noise ratio. These characteristics pose significant challenges for

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real-time processing and classification [4]. The current mainstream classification algorithms include traditional machine learning methods such as Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Random Forest (RF), and Multi-Layer Perceptron (MLP). Meanwhile, deep learning methods such as convolutional neural networks (CNNs), recurrent neural networks (RNNs) and long short-term memory (LSTM) are also widely used. LSTMs have also been widely used in EEG signal classification studies [5]. These methods have shown efficacy in offline classification. However, numerous technical challenges still need to be addressed for real-time applications [6].

To enhance the real-time classification accuracy of EEG signals, it is essential to optimize several key aspects: data preprocessing, feature extraction and selection, classification algorithm optimization, and system architecture design. Data preprocessing forms the foundation of classification. It involves employing filtering and artifact removal techniques, which can markedly enhance signal quality and system robustness [7]. Secondly, feature extraction and selection represents a crucial step in optimising classification performance. The selection of appropriate features will significantly enhance the accuracy and efficiency of the classification algorithm [8]. Furthermore, optimising the classification algorithm and combining parallel processing and hardware acceleration techniques is essential for achieving efficient real-time classification [9]. Finally, a well-designed system architecture, encompassing appropriate hardware selection and optimal software integration, is crucial for ensuring efficient real-time processing [10].

The objective of this study is to investigate the most effective methods for enhancing the real-time classification accuracy of electroencephalogram (EEG) signals and to develop an efficient real-time classification system. Specifically, the objective is to enhance the real-time performance and classification accuracy of the system by optimising data preprocessing techniques, refining feature extraction and selection methods, investigating and implementing advanced classification algorithms, and integrating hardware acceleration techniques. The results of the experimental verification and performance evaluation of the system will provide reliable technical support and a theoretical basis for the practical application of BCI systems.

T This paper is organized as follows: Section 2 provides a comprehensive literature review, covering the fundamental characteristics of EEG signals, current real-time classification methods, and strategies for improving real-time performance. The third part outlines the research methodology, which encompasses data acquisition and pre-processing, feature extraction and selection, optimisation of classification algorithms, and the experimental design. The fourth part presents the experimental results and analyses, offering a detailed evaluation of the system performance. The fifth part discusses the research findings, limitations, and potential avenues for future research. Finally, the sixth part summarises the primary contributions and research outcomes of this study. This paper aims to advance real-time EEG signal classification technology and provide a solid foundation for the widespread use of BCI systems.

2. Literature Review

Electroencephalographic signals, weak electrical signals generated by neuronal activity in the cerebral cortex, are acquired by placing electrodes on the scalp surface. The properties of EEG signals include time-varying, nonlinear, and low signal-to-noise ratios, which present a significant challenge in terms of processing and analysis [4]. Nunez and Srinivasan provided a comprehensive description of the physical background of the EEG signals in their work, including an explanation of the basic properties, the mechanism of electric field propagation in the brain, and a detailed account of how EEG signals in different frequency bands correspond to different functional states of the brain [1]. Such knowledge is essential for understanding the complexity of EEG signals and their application in brain-computer interfaces.

Real-time classification represents a pivotal technology in the domain of brain-computer interface systems, with its performance directly influencing the system's response speed and user experience. In the current research landscape, real-time classification methods are primarily classified into two categories: traditional machine learning methods and deep learning methods. Traditional machine learning methods, such as support vector machines (SVM), k-nearest neighbour (kNN) and random forest (RF), have been extensively employed in EEG signal classification. These methods possess relatively straightforward implementations and low computational complexity. However, their performance may be compromised when confronted with large-scale data and high-dimensional features [3].

Improvements in computational power have facilitated a gradual increase in the application of deep learning methods for EEG signal classification in recent years. Schirrmeister et al. demonstrated the potential of deep learning in improving classification accuracy by decoding and classifying EEG signals through convolutional neural networks (CNNs) [4]. In comparison to traditional methodologies, deep learning techniques are capable of automatically extracting high-level features, thereby reducing the necessity for manual feature engineering. They are particularly well-suited to the classification of complex

EEG signals. However, deep learning models typically necessitate longer training periods and greater computational resources, which present challenges in real-time applications.

In order to achieve real-time classification of EEG signals, it is necessary to select appropriate classification algorithms and to implement improvements in terms of data preprocessing, feature extraction and algorithm optimisation. The study conducted by Makeig and Onton demonstrated that Independent Component Analysis (ICA) has a significant effect in removing artefacts and noise from the EEG signals, which significantly improves the quality of the signals and thus enhances the accuracy of the classification [5]. Roy et al. conducted a comprehensive review of deep learning-based EEG analysis techniques. Their study highlighted that parallel processing and hardware acceleration methods can significantly improve the model's real-time performance [6].

In the realm of real-time classification, feature extraction and selection play a pivotal role. Commonly used methods include the wavelet transform, power spectrum analysis, principal component analysis (PCA) and linear discriminant analysis (LDA). These methods are able to extract representative features that simplify the classification model and improve its efficiency [7]. Furthermore, parallelisation of algorithms and hardware acceleration (e.g. using GPUs or FPGAs) are important technical strategies to improve real-time performance [8].

The rationality of the experimental design and system architecture has a decisive impact on the performance of a real-time EEG classification system. In his book, Cohen provides theoretical and practical guidance on the analysis of neural time-series data, including aspects of data acquisition, preprocessing, and feature extraction. This guidance is crucial for designing rigorous experimental protocols [7]. Furthermore, the EEGLAB toolbox, developed by Delorme and Makeig, offers a comprehensive range of functions for processing and analysing EEG data. It supports a variety of commonly used EEG processing methods, including independent component analysis, which is of significant practical value in the development of real-time systems [8].

In terms of practical system implementation, Wolpaw et al. undertook a comprehensive review of the fundamentals and applications of brain-computer interface (BCI) systems, and proposed a general framework, specifically designed for real-time communication and control [9]. Mason and Birch further proposed a general framework for BCI design, which provided guiding suggestions for real-time processing and system implementation. These studies provide a robust theoretical foundation and practical guidance for the design and optimisation of real-time BCI systems [10].

While existing research has made significant strides in real-time classification of EEG signals, several challenges persist. These challenges primarily revolve around improving real-time classification accuracy and developing more robust classification systems. Despite the considerable promise of deep learning techniques, there are inherent constraints to their deployment in real-time scenarios. Furthermore, the advancement of feature extraction and algorithm optimisation techniques is of paramount importance to enhance the real-time performance and accuracy of the system. It is therefore recommended that future research should continue to focus on how to improve classification accuracy while ensuring real-time performance. In addition, new optimisation strategies and acceleration techniques should be explored in order to promote the development and application of EEG signal classification techniques.

3. Results

The objective of this study is to develop and validate a deep learning model that employs a combination of convolutional neural networks (CNNs) and long-short-term memory networks (LSTMs) for the classification of electroencephalogram (EEG) signals associated with motor imagery tasks within the BCI Competition IV Dataset 2a. The research methodology encompasses data preprocessing, feature extraction and dimensionality reduction, model design and optimisation, and performance evaluation.

3.1 Data set description and pre-processing

The dataset employed in this study is derived from the BCI Competition IV Dataset 2a and encompasses electroencephalogram (EEG) data obtained from nine subjects while engaged in a four-category motor imagery task. In order to enhance the quality of the data and the validity of the model, the preprocessing stage initially employs band-pass filtering of the raw EEG signals at a frequency range of 1-30 Hz, with the objective of removing noise such as work frequency interference and low frequency drift. Subsequently, an independent component analysis (ICA) method was employed to further remove artefactual signals, such as ocular and cardiac interference, thus ensuring the purity of the data. The processed EEG signals were constructed in the form of time series, providing a foundation for subsequent feature extraction.

3.2 Feature Extraction and Dimension Reduction

To extract effective time-domain features from EEG signals, this paper focused on six key metrics. These include the mean, standard deviation, skewness, kurtosis, root-mean-square, and extreme deviation of each subject's

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EEG data. These features provide insights into the statistical properties and temporal trends of the EEG signals. To mitigate the risk of model overfitting due to high-dimensional feature space, this paper employed principal component analysis (PCA) for dimensionality reduction. This paper selected the top 10 principal components as this paper final feature vectors based on their cumulative variance contribution ratio. This approach reduced feature dimensionality while retaining most of the original data's information, thereby enhancing the model's generalization ability.

3.3 Design of the CNN-LSTM model

To address both spatial and temporal dependencies of EEG signals, this paper propose a hybrid CNN-LSTM model. This model aims to comprehensively capture the spatio-temporal features of EEG signals. The spatial characteristics of EEG signals are initially extracted through the utilisation of a convolutional neural network (CNN) layer.

Specifically, the convolutional operation extracts high-dimensional local features using multiple convolutional kernels within a specified time window. This processing technique can effectively capture signal variations at varying spatial locations. To circumvent feature overfitting and simultaneously refine the global information, the model incorporates Global Average Pooling (GAP) and Global Maximum Pooling (GMP) operations to reduce the data dimensionality and maintain the representativeness of the features.

This paper also incorporated a spatial attention mechanism into the model design. This mechanism aims to enhance the recognition of important spatial features. This mechanism serves to ensure that critical information is retained during feature fusion by combining the pooled features with the output of the convolutional layer, thus improving the effectiveness of classification. Based on the high-dimensional features extracted by the CNN, the LSTM layer is trained to learn the temporal dependencies of the EEG signals. The LSTM layer is capable of effectively capturing the dynamic changes and temporal structure of the signals through the gating mechanism, and is particularly adept at handling the long- and short-term dependence observed in EEG signals.

In order to further enhance the performance of the model in processing long time series data, the model also incorporates the self-attention mechanism, which enhances the LSTM's ability to perceive signals over long time spans. Subsequently, the LSTM-processed features are fed into the fully-connected layer for further feature integration, and a softmax classifier is employed for the classification of the two-class motion imagery task. The incorporation of a convolutional neural network (CNN) for the extraction of spatial features, a long short-term memory (LSTM) unit for the capture of temporal dependence, and an attention mechanism enables the model to analyse electroencephalogram (EEG) signals in a more comprehensive manner, resulting in enhanced classification outcomes.

The model demonstrates efficacy in classification accuracy, time-dependent modelling, and the handling of spatial and temporal features of EEG signals, thereby substantiating its effectiveness in the classification of motor imagery tasks. The model's design not only enhances classification accuracy but also demonstrates high computational efficiency and real-time performance, rendering it well-suited for practical EEG signal classification applications.

3.4 Model Training and Optimisation

This paper employs the Adam optimization algorithm to optimize the model parameters during training. This algorithm combines the features of momentum and adaptive learning rate tuning, thereby improving the convergence speed of the model during the training process while maintaining stability. In order to enhance the model's generalisation capacity and prevent overfitting, key parameters such as the initial learning rate, learning rate decay and L2 regularisation were set. The aforementioned hyperparameters are set with the objective of optimising the training efficiency and stability of the model. In particular, the initial learning rate during training is set to 0.004, thereby ensuring that the model is able to converge rapidly in the initial phase. In subsequent training phases, the learning rate is gradually decreased in order to enhance the model's capacity for precise parameter calibration. The application of L2 regularisation enables the control of model weights, preventing their excessive expansion and thus reducing the likelihood of overfitting while enhancing the model's generalisation performance.

To evaluate the model's performance across different datasets and assess its robustness, this paper employs a cross-validation methodology. The application of cross-validation, whereby the training dataset is split multiple times and the training is repeated, enables the performance of the model to be effectively measured under different data distributions, thus further reducing the risk of overfitting. Furthermore, to enhance the training efficiency and circumvent overfitting, this study incorporates an early-stop strategy. This entails the automated termination of the training process when the model's performance on the validation set ceases to improve, thus averting the decline in performance that can result from over-training.

In order to further optimise the model performance in the classification task, a hyperparameter search and tuning was carried out, and the impact of different hyperparameter combinations on the model effect was explored. Ultimately, a hybrid model integrating a Convolutional Neural Network (CNN) and a Long Short-Term Memory Network (LSTM) was selected. The convolutional neural network (CNN) is employed to extract spatial features from the data, while the long short-term memory (LSTM) network is responsible for capturing temporal information. Through this combination, the model is able to efficiently process the time-dependent electroencephalogram (EEG) signals.

To improve the model's classification proficiency, this paper employed data augmentation techniques. These techniques increase data diversity through appropriate transformations, enhancing the model's adaptability to various data distributions. Furthermore, this study introduces a model fusion technique, which weights and averages the outputs of the CNN and LSTM, thus enhancing the final classification performance.

The optimisation strategies employed have resulted in a model that demonstrates satisfactory performance in the classification of EEG signals, thereby substantiating its efficacy and potential utility in the context of motor imagery tasks.

4. Experimental results and analyses

This study have devised and implemented a hybrid convolutional neural network (CNN) with long short-term memory (LSTM) model based on the BCI Competition IV Dataset 2a. The objective is to evaluate its classification performance in a motor imagery task. This section presents a detailed analysis of the experimental results, demonstrating the effectiveness and limitations of the model through the use of various visualizations, and suggests potential improvements.

4.1 Effectiveness of Data Preprocessing and Feature Extraction

The preprocessing of data represents a pivotal stage in the classification of electroencephalogram (EEG) signals. In the present study, the raw EEG signals were subjected to a 1-30 Hz bandpass filtering process and an independent component analysis (ICA) denoising procedure. Fig. 1 illustrates the contrast between the original signal and the pre-processed signal. The implementation of these preprocessing techniques significantly reduced signal artifacts, thereby enhancing overall signal quality.

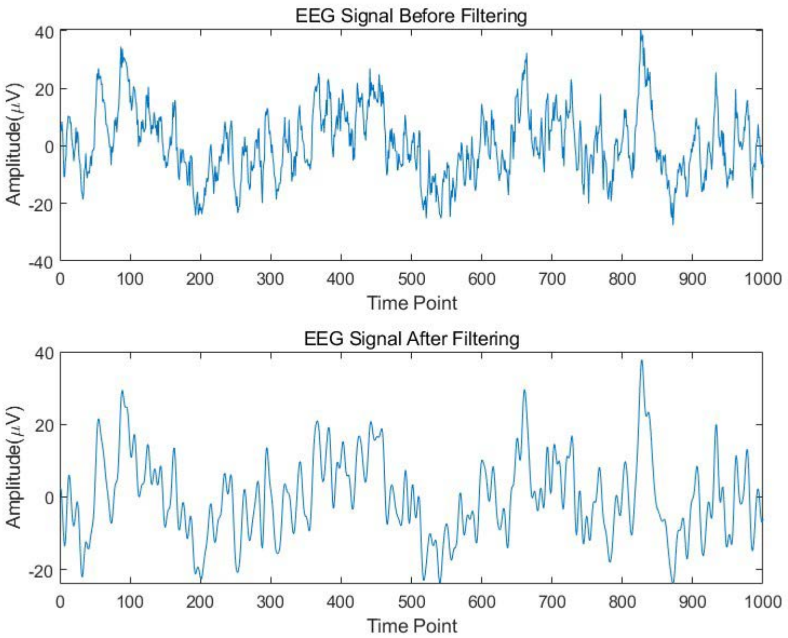

Fig. 1 Comparison of raw EEG signal and pre-processed signal (Photo/Picture credit: Original)

In order to extract the relevant features, six statistical properties were calculated based on the time domain. These were the mean, standard deviation, skewness, kurtosis, root mean square value and extreme deviation. Following this, a principal component analysis was conducted in order to reduce the dimensionality of the

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data set. Table 1 presents the statistical outcomes of the time-domain features for a selected cohort of subjects. The experiment demonstrates that selecting the initial 10 principal components is an effective method for retaining the primary information of the original data set while reducing the redundancy of feature dimensions.

Table 1. Statistics of Time Domain Characteristics of Selected Subjects

	Subject 1	Subject 2	Subject 3
Mean	0.2238	0.1349	0.5241
Standard deviation	8.8854	8.8807	8.7213
Skewness	0.0331	0.0307	0.0304
Kurtosis	3.1351	3.1778	3.1683
Root Mean Square	9.0365	9.0433	8.8641
Polar deviation	50.7361	50.7708	50.0008

4.2 CNN-LSTM model training and testing results

In the course of training the model, the Adam optimiser was employed for the CNN-LSTM hybrid model. The model rapidly achieved 100% accuracy on the training set, reaching this milestone after approximately 1,000 iterations. This was accompanied by a notable reduction in the loss function. This suggests that the model is adequately fitting to the training set. The model demonstrated a satisfactory performance on the test set, attaining an accuracy of 72.41% and an average test time of 0.2372 seconds per test sample. However, a decline in accuracy on the test set in comparison to the training set indicates that, while the model exhibits proficiency in handling the training data, there is scope for enhancement in its capacity for generalisation when confronted with unseen test data.

4.3 Comparison and analysis of different models

To further validate this paper CNN-LSTM model's effectiveness, this paper compared its classification performance with that of Support Vector Machine (SVM) and Random Forest models on the same dataset. Table 2 presents the classification accuracy, F1-score, and AUC values for the various models. Although the CNN-LSTM model exhibits marginal superiority over the traditional machine learning model on the test set, its classification performance nevertheless fails to meet expectations.

Table 2. Performance of SVM and Random Forest Model on the Test Set

Models	Accuracy
SVM	22.09%
Random Forest	18.60%
CNN-LSTM	72.41%

The experimental analysis conducted in this section revealed that the optimised CNN-LSTM model exhibited superior training set performance when confronted with the EEG signal classification task. However, it became evident that the model's generalisation ability on the test set still necessitates enhancement. Further work will be conducted to optimise the structure and training strategy of the model with a view to enhancing its performance in practical applications. It is anticipated that the optimisation of the model structure will result in enhanced performance and stability in the future.

5. Discussion

5.1 Discussion of findings

This study has developed a classification model for electroencephalographic signals (EEG) based on a convolutional neural network with long short-term memory (CNN-LSTM) architecture, which has been optimized for this purpose. The experimental results demonstrate that the model achieves 100% accuracy on the training set, thereby exhibiting excellent performance on known data. Nevertheless, the model exhibits a relatively low level of accuracy on the test set, suggesting that it may have limited generalisation capabilities when confronted with previously unseen data. Further analysis revealed that the model may be prone to severe overfitting on the training set. Despite demonstrating proficiency in learning the patterns within the training data, the model exhibited suboptimal performance on new data samples.

Furthermore, the statistical analysis of the features indicates significant differences in the time-domain features between different subjects, which provide valuable information for the classification of EEG signals. However, the existing models do not fully utilise these differentiated features in the generalisation process, resulting in their suboptimal performance on the test set.

5.2 Research limitations

Despite the advancements in EEG signal classification, this paper study has several limitations.

1. A notable limitation is the small dataset size. The limited and unevenly distributed data may have contributed to the model's poor performance on unseen data. The smaller dataset is inadequate for fully representing the distribution characteristics of the various types of EEG signals, which consequently affects the model's generalisation ability.
2. The higher model complexity CNN-LSTM models have a more intricate structure and a lower dimensionality of the input data, which may impede the models' capacity to effectively utilise all the feature information. Complex models are susceptible to overfitting during the training phase, which subsequently results in suboptimal performance on the test set.
3. Feature Selection and Processing: Despite the application of data reduction and normalisation techniques, the current feature extraction methods may not fully capture the essential information present in the EEG signal. It is therefore evident that further research into the improvement of feature selection and processing methods represents an important avenue for enhancing classification performance.

5.3 Recommendations for improvement

In order to address the aforementioned limitations, a series of improvements have been proposed with the aim of further enhancing the classification performance of the model.

1. To improve the model's generalization ability, future studies should focus on expanding the dataset. This could involve collecting more EEG samples and employing data augmentation techniques. The incorporation of additional samples and a more diverse subject population will serve to mitigate the risk of model overfitting.
2. Optimizing the model structure could be beneficial. This might involve simplifying the CNN-LSTM model or adopting a more suitable alternative for the current dataset. Potential alternatives could include a lightweight deep learning model or a model based on integrated learning. Furthermore, regularisation techniques, such as dropout, or early stopping strategies may be employed to prevent overfitting of the model during training.
3. Improved feature engineering With regard to feature selection, the introduction of more sophisticated feature extraction techniques, such as frequency domain features or wavelet transform features, may prove beneficial in capturing more useful information from the EEG signal. Concurrently, feature selection algorithms, such as LASSO regression or the mutual information method, can be employed to automatically identify the most discriminative features, thereby enhancing the classification performance of the model.
4. The issue of category imbalance must be addressed. To address the issue of category imbalance, techniques such as oversampling, undersampling, or Generative Adversarial Networks (GANs) can be employed to equalise the distribution of the diverse categories within the training set, thereby enhancing the model's capacity to recognise samples belonging to a limited number of categories.

It is anticipated that the aforementioned enhancements will yield more pronounced outcomes in the domain of EEG signal processing and classification, thereby offering more pragmatic solutions for real-world applications.

6. Conclusion

6.1 Summary of research

This study proposes and implements a hybrid CNN-LSTM model for EEG signal classification, exploring the potential of deep learning in this field. After preprocessing and feature extraction of the original EEG signals, this paper used principal component analysis (PCA) to reduce data dimensionality. The reduced features were then classified using a convolutional neural network (CNN) with long short-term memory (LSTM) units. The experimental results demonstrate that the proposed model exhibits an exceptionally high level of classification accuracy on the training set, thereby validating the effectiveness of the method in a specific data environment. However, the relatively poor performance on the test set indicates that the model has limitations in terms of generalisation ability, which provides a key direction for improvement in future research.

During the course of the study, statistical analyses of the time-domain features of different subjects revealed significant differences in EEG features across subjects. These differences provide a basis for further optimisation of the

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classification algorithm; however, the existing model still appears to be insufficient in dealing with complex and diverse features, especially in coping with unseen data, and thus shows obvious limitations.

6.2 Practical applications

After preprocessing and feature extraction of the original EEG signals, this paper used principal component analysis (PCA) to reduce data dimensionality. The capacity to accurately classify EEG signals can markedly enhance the decoding accuracy of BCI systems, thereby facilitating more natural and intuitive human-computer interaction. Concurrently, in the domain of neurological rehabilitation, the monitoring and analysis of real-time EEG signals can facilitate the optimisation of rehabilitation plans and enhance the efficacy of patient rehabilitation. Furthermore, the implementation of precise EEG classification techniques can facilitate the expedient identification of anomalous EEG patterns, thereby enhancing the precision and timeliness of diagnosis.

However, to apply these results in practice, this paper need to improve the model's generalization ability for large-scale and diverse data. Furthermore, it is essential to strike a balance between real-time data processing and computational efficiency to guarantee the responsiveness and user experience of the system in practical applications.

6.3 Outlook for future work

Future research should concentrate on the following areas: firstly, in order to address the issue of the model's generalisation ability, it is necessary to expand the size of the dataset and investigate more efficient model architectures and regularisation strategies in order to enhance the model's performance for practical applications. Secondly, efforts could be made to incorporate multimodal data (for example, a joint analysis of EEG and magnetoencephalography) into the model, with the aim of enhancing the feature information and further improving the classification accuracy.

As computing technology advances, future research should focus on real-time EEG signal analysis methods using cloud and edge computing. The combination of cloud computing and edge computing, which offers real-time processing capabilities, can facilitate the development of an efficient and low-latency EEG signal analysis system. This system would be better suited to meeting user needs in practical application scenarios.

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