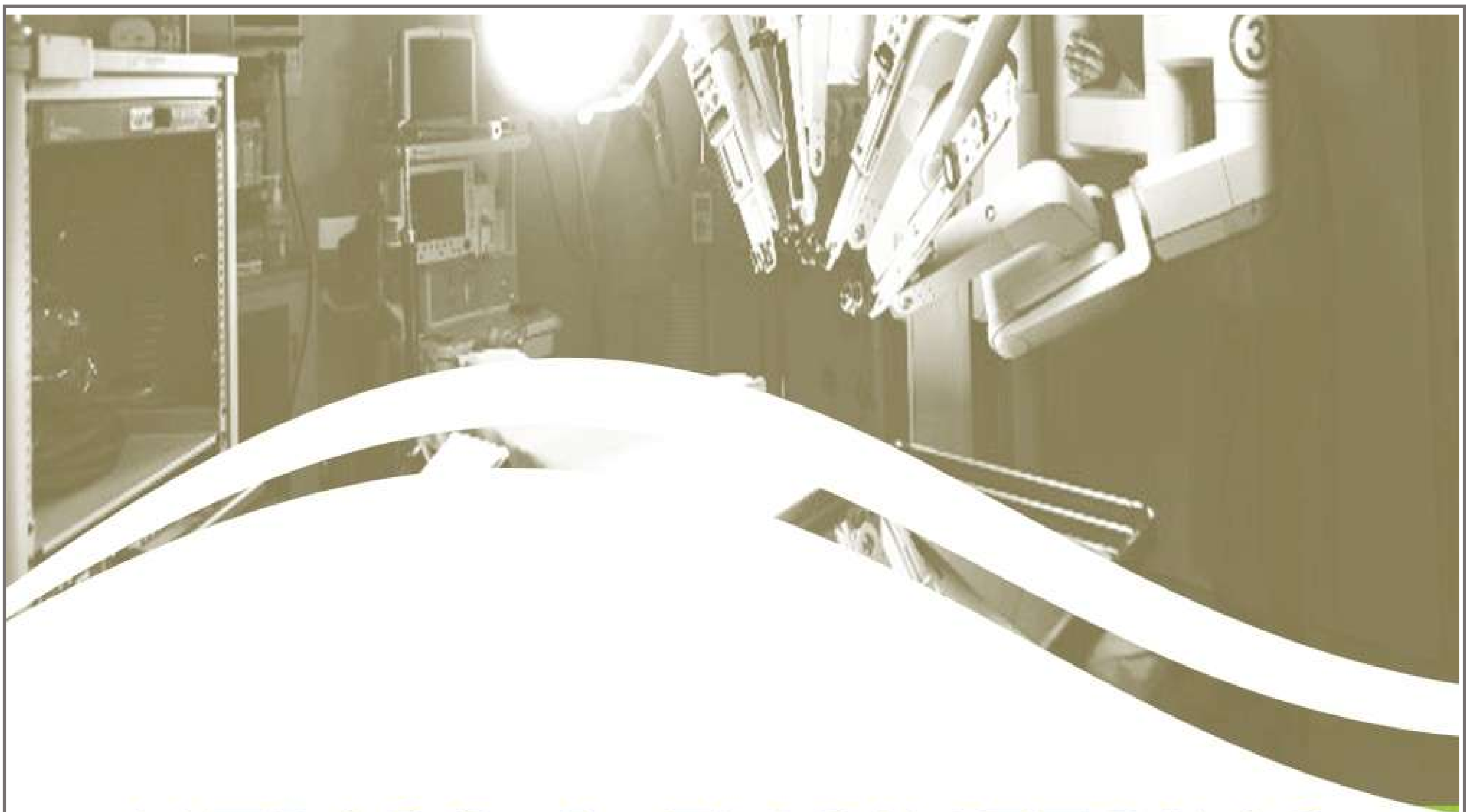

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Federated Learning in Brain-Computer Interfaces: A Systematic Review on Aggregating Intrinsic Data for Enhanced Performance

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Abstract

The development of brain-computer interfaces (BCIs) that leverage deep learning models is often hindered by the challenge of data scarcity. Despite the extensive efforts of numerous research groups and institutions in compiling EEG datasets, the variability in device usage across different sites creates significant obstacles for data sharing. In response to these challenges, this paper introduces FLEEG (Federated Learning EEG), a novel model designed to integrate data from diverse formats during the training process. FLEEG assigns each client a specific dataset and utilizes a hierarchical, personalized approach to manage these varying data formats, thereby enhancing the exchange of information. The training process is centrally coordinated by a server that aggregates knowledge from all participating datasets, ultimately improving overall performance. Experimental results demonstrate that this framework can boost classification performance by up to 84%.

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Introcdution

Brain-computer interfaces (BCIs) facilitate direct communication between the human brain and external devices, with applications spanning motor function recovery, cognitive health, and entertainment. Electroencephalography (EEG) signals are commonly utilized in BCIs and are decoded using deep learning algorithms. However, the collection of EEG data is often limited by high costs and logistical challenges, resulting in smaller, less diverse datasets. Additionally, the heterogeneity of devices employed to collect EEG data complicates the sharing and integration of these datasets, thereby impeding effective knowledge transfer between research groups. This paper proposes a federated learning framework aimed at overcoming these challenges, thereby enhancing BCI performance through collaborative learning.

The majority of existing studies have concentrated on transferring knowledge within a single dataset. However, only a limited number have tackled the challenges presented by device heterogeneity across multiple datasets. Techniques such as channel deletion or zero-padding have been employed to standardize data formats, yet these methods may lead to data loss or introduce noise. More advanced techniques, such as channel mapping, have been explored, but they often lack the flexibility required to adapt to various datasets.

Federated Learning (FL) is an innovative machine learning approach that allows multiple data owners to collaboratively train models while keeping their data decentralized. This method enables local models to benefit from each other's insights without the need to share raw data, thus preserving privacy. Personalized Federated Learning (PFL) has been developed to address the issue of data heterogeneity across clients, inspiring the proposed framework for EEG decoding presented in this paper.

Methodology Overview

Problem Description

The primary challenge addressed in this research is the heterogeneity of devices used to collect EEG data, which results in a limited amount of usable data and a reduction in model testing accuracy. The objective is to leverage data from various devices to train more robust models

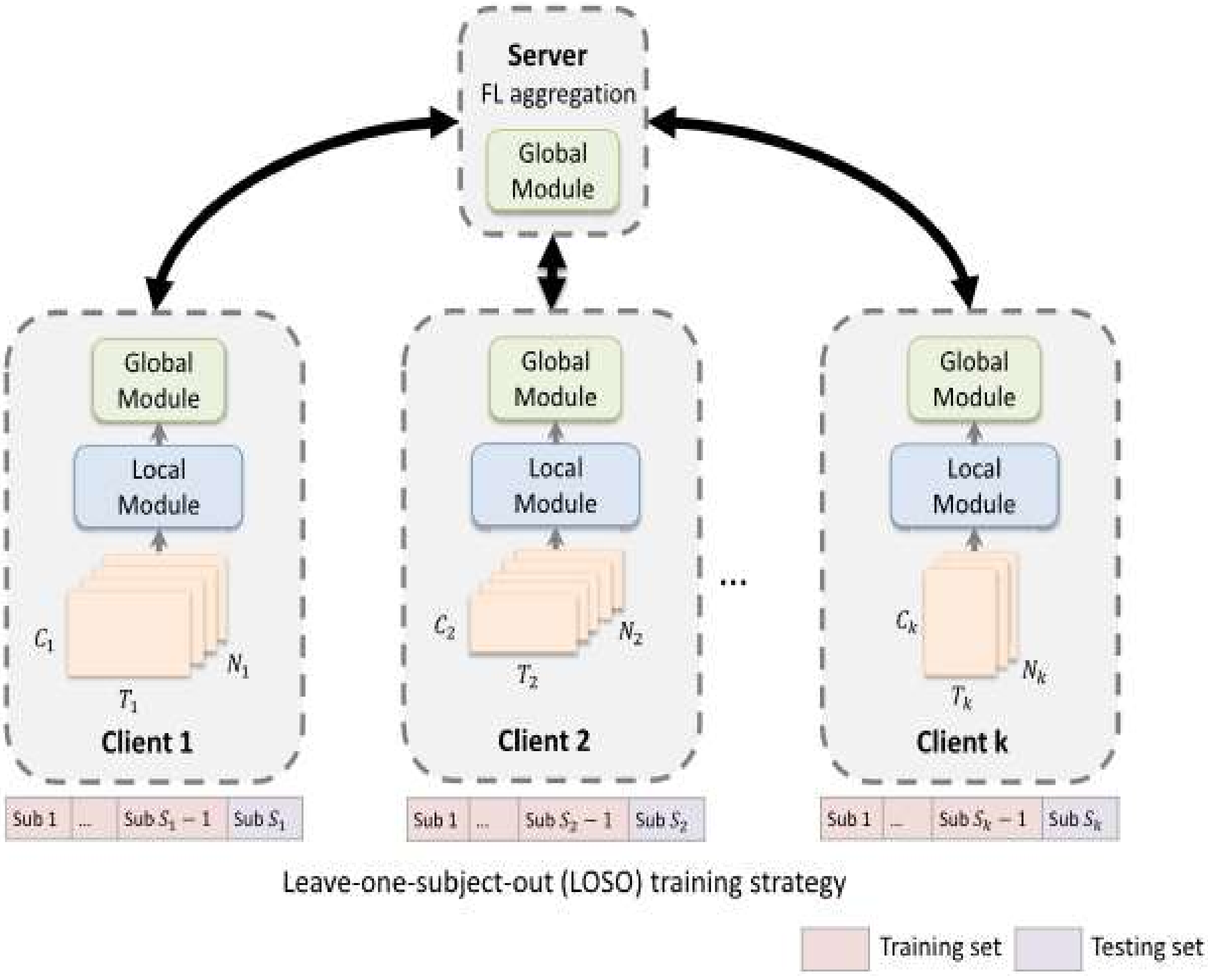

Figure 4: The overview of the proposed hierarchical personalized federated learning framework. Each client is assigned one dataset with various formats defined by , T_k, and N_k, $k \in \{1, 2, \ldots, K\}$. Clients train their local personalized model, including a local module and a global module, for the classification task. The server manages the cooperation between clients. Each dataset applies the LOSO strategy simultaneously[3]

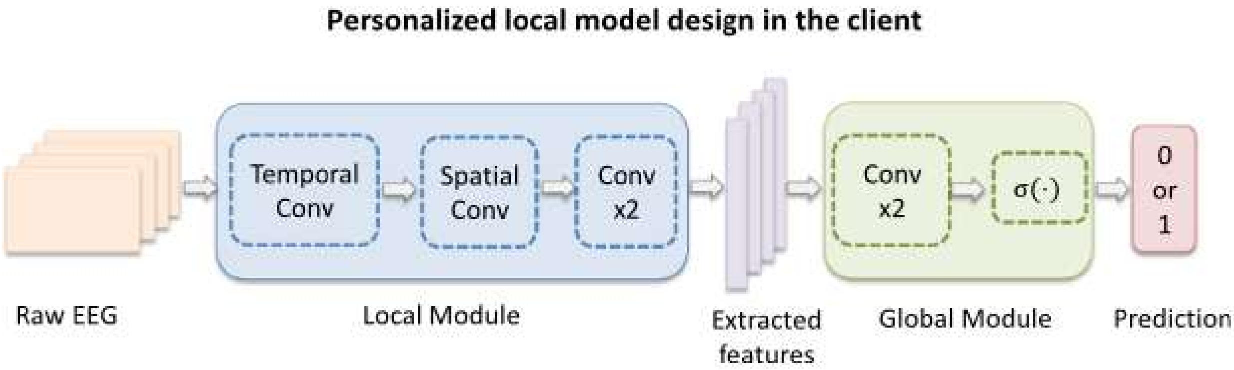

Figure 5: . A local personalized model with local and global modules in one client

FL Aggregation in the Server

Following local training, the server aggregates the global model weights from all clients. The server then redistributes the updated model parameters to the clients, allowing for continued local training.The training process is iterative, involving multiple rounds of local training, weight aggregation by the server, and parameter redistribution to the clients. The model with the lowest validation loss is selected for final testing.

The FLEEG framework was evaluated using nine publicly available EEG motor imagery (MI) datasets. A leave-one-subject-out strategy was implemented to ensure subject independence during the evaluation process. Various network architectures, evaluation strategies, and baseline models were employed to assess the framework's performance.

Result

The results indicate that the FLEEG framework significantly enhances classification accuracy compared to baseline models, particularly for smaller datasets. Visualization of the results further supports the framework's ability to effectively harness information from diverse datasets.

Discussion

The number of trials per subject plays a crucial role in determining the effectiveness of the FLEEG framework. Datasets with fewer trials exhibited the greatest improvements. Additionally, a sensitivity analysis of hyperparameters revealed that learning rates must be meticulously tuned for each dataset to achieve optimal performance.

Saliency maps were utilized to identify the most informative regions within the EEG data. The FLEEG framework consistently focused on motor cortex regions, even in smaller datasets, suggesting its ability to extract neurophysiologically meaningful features.

Th1 cytokines (e.g., IFN-γ) enhance cytotoxic T lymphocyte (CTL) activity against tumor cells

They inhibit regulatory T cell (Treg) function

They promote DC maturation and antigen presentation

This immunogenic profile contrasts sharply with many conventional chemotherapies that inadvertently suppress anti-tumor immunity through myelosuppression or T-cell exhaustion. Capsaicin's dual functionality (direct cytotoxicity + immune activation) could therefore address two key limitations in current osteosarcoma treatment:

Conclusion

This study presents an innovative approach for enhancing BCI performance through federated learning. The FLEEG framework addresses the challenge of data scarcity by enabling smaller datasets to benefit from knowledge transfer across multiple sources. Future research will explore the application of this framework in more complex scenarios and the development of more robust feature extraction methods.

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