Advancements and Applications of Using Federated Learning in Diagnosing and Analyzing Brain Tumor Images

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Abstract: Brain tumors represent a major health concern, and conventional diagnostic approaches can be intricate and prone to errors, especially given the diversity of tumor types. The swift progress in Artificial Intelligence (AI) has emerged as a promising avenue for enhancing brain tumor diagnosis. Federated Learning (FL), which is a distributed machine learning approach, facilitates collaborative model training among various institutions, improving diagnostic precision while safeguarding data privacy. This study introduces a federated learning framework for classifying brain tumors using Convolutional Neural Networks (CNNs), specifically leveraging an optimized Visual Geometry Group 16 (VGG16) architecture alongside transfer learning methods. The model was trained across several clients, achieving an outstanding classification accuracy of 98%. Furthermore, U-Net was utilized for segmenting brain tumors, demonstrating notable performance enhancements with an increasing number of participating clients. Despite the evident advantages of FL regarding privacy preservation and model efficacy, challenges such as differences in institutional equipment and the Non-independent and Identically Distributed (non-IID) characteristics of data impede generalization and convergence of models. To address these challenges, this paper suggests employing adaptive algorithms and data augmentation strategies to improve model flexibility and effectiveness. Additionally, effectively merging multimodal data remains a significant technical challenge that needs resolution in future work.

1 INTRODUCTION

A brain tumor is characterized as an abnormal proliferation or mass of cells located in or around the human brain (DeAngelis et al., 2001). In this country, both the incidence and mortality rates associated with brain tumors are notably high, with an annual occurrence rate of 7 per 100,000 individuals. Brain tumors can impact people of all ages, and genetic conditions such as neurofibromatosis and Turner syndrome may elevate the risk. Patients often present symptoms including paralysis and psychological disturbances. The five-year relative survival rate for those diagnosed with malignant brain tumors is approximately 36%, while glioblastoma—the most common primary malignant type—has a significantly lower five-year survival rate of just 7.2% (International Neurosurgery Group, INC., 2021). Traditional diagnostic methods for brain tumors tend to be complex and inefficient; due to the variety of tumor types, there exists a notable misdiagnosis frequency. Consequently, there is a pressing need for improved diagnostic approaches and adjunct treatments.

Artificial Intelligence (AI), known for its robust feature extraction capabilities and predictive power, presents a potential solution to enhance diagnosis rates. AI has been utilized across various fields—including chemical biology—and particularly within medicine where numerous studies have emerged. Reham noted that processing large volumes of images can be time-consuming and labor-intensive; thus, automated segmentation and classification techniques are essential to expedite the diagnosis process for brain tumors. Imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) facilitate rapid detection.

For instance, Akmalbek et al. developed a model aimed at automating the detection of brain tumors effectively from MRI scans by leveraging advanced object detection features inherent in You Only Look Once Version 5 (YOLOv5) architecture; their model demonstrates exceptional accuracy in identifying tumor regions critical for early diagnosis and timely

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medical intervention (Abdusalomov et al., 2024). Furthermore, Liu et al. indicated that while AI systems in medical imaging show significant promise in aiding diagnoses and treatment processes, challenges like data silos related to medical images, privacy concerns regarding data security, along with inconsistent industry standards severely limit their effectiveness. By integrating federated learning principles alongside FAIR scientific data management guidelines, these issues could be addressed technically, maximizing multi-center data utility to develop more efficient disease diagnosis systems while guiding AI technology implementation within clinical settings (Liu et al., 2022).

Given the significance surrounding brain tumors coupled with recent advancements in artificial intelligence necessitates a thorough review on how AI applications can aid in diagnosing these conditions effectively. The subsequent sections will outline previous research efforts focused on techniques designed to improve recognition of brain tumor images before discussing existing challenges faced when employing AI methodologies within this domain. Finally, the paper will conclude by summarizing key findings derived from investigations into using artificial intelligence for diagnosing brain tumors.

2 METHOD

2.1 Introduction of Federated Learning

Federated Learning (FL) is a novel method in distributed machine learning that allows various devices or organizations to collaboratively develop a model while maintaining the confidentiality of their raw data. In this approach, each participant performs training on their local datasets and subsequently transmits only the updated model parameters to a central server. The server then integrates these parameters to create an overarching global model. This strategy is especially beneficial in sensitive fields such as healthcare and finance, where privacy and security are paramount.

The primary characteristics of federated learning include: protecting data privacy (since data remains stored on local devices), accommodating heterogeneity (recognizing that different nodes may possess varying data distributions and processing capabilities), improving communication efficiency (by sending only model parameters), and ensuring fault tolerance (considering potential node instability or dropout). Essential elements of this framework involve local model training, aggregation of the global model, effective communication strategies, and privacy-preserving techniques like differential privacy and secure multiparty computation.

2.2 Federated Learning-based CNN

MRI imaging plays a crucial role in identifying brain tumors, a task essential for developing targeted treatment strategies. The complexity of tumor shapes and the differences in imaging make accurate diagnosis challenging. Typically, this process depends on manually analyzing MRI scans and using basic machine learning methods. Yet, these traditional techniques often fall short in consistently and automatically categorizing tumors due to several drawbacks. These include the need for extensive manual input, the risk of human mistakes, difficulties in managing vast amounts of data, and limited flexibility in accommodating different kinds of tumors and imaging scenarios.

The authors introduced a deep learning model that combines federated learning with advanced Convolutional Neural Networks (CNNs) to achieve precise and automated classification of brain tumors. This model improves upon the Visual Geometry Group 16 (VGG16) architecture, tailoring it specifically for brain MRI images. It emphasizes the dual benefits of federated learning and transfer learning in medical imaging. Federated learning allows for the decentralized training of models across various clients while maintaining the privacy of medical data, which is vital in handling sensitive health information.

The architecture utilizes transfer learning by employing pre-trained CNNs, greatly enhancing its accuracy in brain tumor classification by leveraging knowledge from diverse datasets. The model underwent training with a mixed dataset that included Figshare, SARTAJ, and Br35H, using federated learning to facilitate decentralized training while maintaining privacy. Additionally, the application of transfer learning improved the model's ability to handle the complex variations in MRI images associated with different types of brain tumors, boosting its overall performance.

The model achieved high precision rates (glioma: 0.99; meningioma: 0.95; no tumor: 1.00; pituitary: 0.98), along with impressive recall rates and F1 scores during classification—outperforming existing methodologies overall with an accuracy rate reaching 98%. This demonstrates the model’s ability to accurately classify various tumor types while emphasizing how federated learning combined with transfer learning can transform brain tumor classification using MRI imagery (Albalawi et al., 2024).

2.3 Federated Learning-based U-net

Segmenting brain tumors in medical imaging is essential for precise diagnosis and treatment planning, but it presents notable challenges in maintaining patient data privacy and security. Traditional centralized approaches struggle with data sharing constraints imposed by privacy laws and security risks, which can stymie the progress of advanced AI technologies in this area. This study addresses these challenges by introducing a federated learning framework that supports collaborative training of models on distributed datasets across multiple medical institutions, without needing direct access to the original data. This method ensures privacy and enhances security while advancing AI applications in brain tumor segmentation.

The research utilizes the Universal Network (U-Net) architecture, known for its effectiveness in semantic segmentation tasks, emphasizing its scalability for applications within medical imaging. Experimental findings indicate that federated learning significantly enhances performance metrics: specificity improved from 0.92 to 0.96, while the Dice coefficient rose from 0.84 to 0.89 as the number of participating clients increased from 50 to 100. Furthermore, this proposed method outperforms existing techniques based on CNNs and Recurrent Neural Networks (RNNs), achieving greater accuracy and efficiency overall. This work contributes to advancing segmentation techniques in medical imaging while maintaining essential standards of data privacy and security (Ullah et al., 2023).

2.4 FL-PedBrain

Lee et al. introduced an FL system named FL-PedBrain, specifically aimed at addressing pediatric pilocytic astrocytomas (PF tumors) in children. While brain tumors are the most common solid tumors found in childhood, they remain relatively rare and scattered across various pediatric and subspecialty centers. Thus, creating a collaborative platform that enables large-scale AI training among different institutions can greatly benefit this patient demographic.

In their research, the authors utilized an extensive and diverse dataset of brain MRI scans gathered from 19 institutions globally, concentrating on pediatric PF tumors. They designed and assessed an FL framework for joint tumor pathology prediction and segmentation tailored to this data-limited population. The results revealed that FL-PedBrain exhibited strong generalization capabilities across all participating sites, including three external validation cohorts.

When comparing federated learning with Centralized Data Sharing (CDS), which pooled data from all locations, FL showed a classification bias of less than 1.5% and only a 3% bias in segmentation performance. Although there was no statistically significant difference in classification outcomes between CDS and FL, the latter demonstrated slightly lower segmentation performance for two out of four tumor categories. In contrast, models trained exclusively on local datasets—referred to as isolated training—performed approximately 20% worse than both FL and CDS approaches. This finding highlights the challenges associated with AI generalization as well as the vulnerabilities of models developed in isolation (Lee et al., 2024).

2.5 MQTT

Intelligent healthcare utilizes AI to analyze and learn from patient data. Due to the rarity of large and diverse datasets for training Machine Learning (ML) models within a single medical facility, traditional centralized AI methods necessitate the transfer of privacy-sensitive information from healthcare institutions to data centers for processing and integration. This movement of data not only requires substantial communication resources and energy but also raises significant privacy concerns, creating challenges for international clinical research collaborations.

FL has emerged as a distributed AI strategy that enables collaborative training of ML models without requiring the sharing of patient information. This paper provides an in-depth analysis of various federated learning techniques and introduces a real-time distributed network framework utilizing the Message Queuing Telemetry Transport (MQTT) protocol. The authors specifically developed several network-based ML solutions using FL tools, which depend on parameter servers (PS) as well as fully decentralized paradigms driven by consensus mechanisms.

The proposed approach was tested on brain tumor segmentation tasks using a modified U-Net model, which incorporated a clinical dataset typical of routine clinical workflows. The FL process was executed on physically separate machines situated in various countries, with these machines communicating over the Internet. This setup allowed for effective validation while adhering to the requirements of data privacy and security in a distributed computing environment. A real-time testbed was utilized to evaluate the balance between training accuracy and latency, emphasizing critical operational conditions that influence performance during actual deployment (Tedeschini et al., 2022).

2.6 LEAF

FL presents an opportunity to create customized AI services for hospital networks, aiding in the reduction of overfitting and improving the robustness of models. However, integrating FL introduces significant challenges, particularly regarding user privacy, which remains a major barrier to its practical implementation. Many current solutions utilize blockchain technology to mitigate these privacy issues. While blockchain can prevent external systems from interfering with decision-making processes, it still permits network devices to access shared data. Additionally, adopting blockchain requires a new framework and infrastructure, resulting in further indirect costs.

To tackle these challenges, a Limited Access Encryption Algorithm Framework (LEAF) framework has been proposed that merges Federated Learning with a limited access encryption algorithm. This cryptographic approach employs edge AI models to effectively address privacy concerns while aiming to safeguard user confidentiality and reduce indirect expenses. The authors assessed the performance of the LEAF framework through comprehensive simulations and obtained encouraging results. Notably, the precision achieved by this framework is 3% higher than that of traditional centralized systems as well as FL-based approaches without compromising user privacy. In optimal conditions, the encryption process within this proposed framework can decrease data size by four to five times (Patel et al., 2024).

3 DISCUSSIONS

3.1 Limitations and Challenges

3.1.1 Generalizability

Model adaptability: Different hospitals or research centers may use different types of equipment, imaging techniques, and data formats. Even if federated learning can share models across locations, these device or imaging differences can cause the model to perform poorly in certain scenarios. For example, the quality, resolution, or imaging conditions of MRI scans may affect the model's generalizability, leading to some hospitals' models performing better than others.

Data heterogeneity: Brain tumor types, sizes, and shapes vary, and different patient populations may have significant differences. This heterogeneity presents a challenge to the model's generalization, and the federated learning global model may have difficulty simultaneously adapting to all different brain tumor features.

3.1.2 Data Discrepancies

Non-IID data: One of the major challenges of federated learning is that the data contributed by participants is often not Independent and Identically Distributed (Non-IID). In brain tumor prediction, some hospitals may receive more rare case types, leading to differences in data distribution. These differences can affect the convergence of the global model, causing it to overfit certain datasets or perform poorly on certain datasets.

Data quality and annotation: Medical imaging data typically requires professional annotation, and the accuracy and consistency of annotation may vary between hospitals. Federated learning relies on local annotation quality, and if certain institutions' annotations are incorrect or inconsistent, it may affect the performance of the global model.

3.1.3 Multimodal Learning

Complexity of Fusing Information from Different Data Modalities: Brain tumor prediction may not only depend on MRI or CT images, but also requires combining patient's clinical information (such as age, genetic data, etc.). In federated learning of multi-modal data, how to effectively fuse information from different modalities is a critical issue. The feature dimensions and distribution of data from different modalities are quite different, how to fully utilize this information without exchanging data remains a technical challenge.

Synchronization Problem of Multi-modal Data: The data sources, storage systems, and collection frequencies in different hospitals may all differ. To achieve multi-modal federated learning, it is necessary to ensure that the data from each hospital can be synchronized in time and content, which will face considerable technical difficulties in practice.

3.2 Future Prospects

3.2.1 Improving Scalability

To improve the scalability of federated learning models and address the challenge of data heterogeneity, strategies such as multi-center collaboration and transfer learning can be employed. By promoting collaboration among multiple medical centers, the diversity and scale of the data increase, enhancing model robustness and generalizability across different populations. In domains with limited labeled data, transfer learning can transfer knowledge from data-rich areas to improve model performance in new environments. Additionally, personalized models can be developed to adapt to the data characteristics of individual users, with ensemble learning methods combining predictions from multiple models to boost overall performance. Aligning data distributions through augmentation and preprocessing techniques is also crucial for reducing bias caused by non-IID data, thus improving the model's generalization and fairness.

3.2.2 Addressing Data Heterogeneity (non-IID) Issues

Adaptive algorithms: Develop adaptive algorithms that dynamically adjust model parameters based on the distribution of data, improving the model's ability to adapt to non-IID data.

Label balancing and sampling strategies: Introduce label balancing and effective sampling strategies to ensure that the model has access to data samples from different categories during training, thereby improving overall performance.

3.2.3 Integration of Multimodal Learning

Multimodal Data Fusion: Establish cross-modal learning frameworks to utilize complementary information from different modalities (such as imaging and genomic data) to improve prediction accuracy.

Cross-modal Knowledge Distillation: Extract knowledge from one modality and transfer it to another modality to enhance the model's generalization ability.

4 CONCLUSIONS

This article provides a comprehensive overview of how federated learning can be used in the field of brain tumor detection and analysis. It describes how methods such as CNN and U-NET can be used to detect and analyze brain tumors, as well as the accuracy and adaptability of these methods. The article also highlights the limitations of federated learning in terms of its lack of scientific rigor and limited applicability, and suggests that efforts should be made in the future to improve its generalizability and scientific validity in order to better integrate it into the detection, analysis, and treatment of brain tumors.

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