

A QUANTUM FEDERATED LEARNING FRAMEWORK FOR PRIVACY PRESERVING BRAIN TUMOR CLASSIFICATION ACROSS DISTRIBUTED MEDICAL CENTERS

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ABSTRACT

Classification of brain tumor types based on Magnetic Resonance Imaging (MRI) images plays a crucial role in accurate diagnosis and developing appropriate strategies for treatment. Centralized Deep Learning models suffer from several shortcomings such as data privacy, security, and data-governance issues associated with transferring sensitive medical images from patients among different medical centers. For this purpose, a novel Quantum Federated Learning Framework (QFLF) is proposed for brain tumor classification of medical images of Glioma, Meningioma, Pituitary Tumor, and Normal Brain classes in this paper without sharing raw data from different institutions or hospitals. The proposed scheme utilizes the advantages of Quantum Computing and Federated Learning to enable privacy-preserving collaborative learning across distributed medical centers. In the suggested scheme, MRI images pass through stages such as CNN-based feature extraction, Quantum Feature Encoding, hybrid quantum-classical federated learning, Adaptive Weighted Federated Learning (AWFL), and secure exchange of encrypted model parameters. The performance evaluation of proposed QFLF was done by taking BraTS 2021 Dataset containing four classes of brain tumors. The proposed method attained accuracy, precision, recall, F1-score, and specificity values equal to 99.12%, 98.91%, 98.74%, 98.82%, and 99.28%, respectively. It has outperformed other conventional CNN models such as CNN, ResNet50, DenseNet121, and Vision Transformer. Additionally, federated training accuracy improved significantly from 90.25% to 99.12%, and federated training loss reduced from 0.452 to 0.082, indicating stable convergence during federated training. These findings demonstrate that the proposed framework can combine privacy-preserving collaborative learning with quantum-enhanced feature representation for accurate brain tumor classification. However, validation was limited to a simulated federated environment and the BraTS 2021 dataset. Future work should evaluate the framework using heterogeneous multi-center clinical datasets and practical quantum computing environments.

Keywords: *Quantum Federated Learning; Brain Tumor Classification; Magnetic Resonance Imaging (MRI); Privacy-Preserving Learning; Quantum Machine Learning; Distributed Medical Centers.*

1. INTRODUCTION

Brain tumors continue to be amongst the most lethal neurological diseases, which include gliomas, meningiomas, and pituitary tumors. Recent statistics on cancer cases worldwide have demonstrated that the death rate of brain and central nervous system (CNS) tumors remains relatively high as their diagnosis comes at a late stage. The accurate determination of brain tumor types in the early phase plays an important role in the treatment plan, increases chances of patients' survival, and reduces neurological complications [1], [2]. Magnetic Resonance Imaging (MRI) provides high-quality soft tissue contrast and the visualization of complex brain structures without ionizing radiation and thus remains a preferable modality for diagnostics. However, manual MRI scanning is rather time-consuming, dependent on radiologist experience and prone to inter-observer variability in multi-center healthcare facilities [3], [4].

This issue is especially important because accurate tumor classification directly influences subsequent patient assessment, treatment planning, and clinical care. MRI diagnoses are associated with a number of issues, such as complex tumor presentation, differences in the characteristics of lesions, and differences in interpreting images. For multi-center health care facilities, these issues are additionally affected by different imaging hardware, procedures used in obtaining MRIs, different patient populations, and institutional practices. On the other hand, MRI images contain highly sensitive data about patients, which makes the sharing of this information between institutions difficult due to privacy and security concerns. Thus, hospitals can have valuable yet geographically scattered data, which cannot be easily merged into AI training sets for developing robust artificial intelligence models. In this way, one faces a practical dilemma between the improvement of diagnostic models through access to diverse clinical data and the protection of patient privacy. Addressing this problem is therefore important for developing collaborative diagnostic systems that can learn from distributed medical data while reducing the need to transfer sensitive patient images.

The advances in Artificial Intelligence (AI) techniques, including Deep Learning (DL), allowed to significantly advance the automated brain tumor classification problem. The CNNs, ResNet, DenseNet, Vision Transformers (ViTs), and hybrid attention-based neural networks provide high-level classification due to the automatic extraction of

hierarchical MRI features [5], [6]. In this way, it is not required anymore to manually design features for brain MRI datasets while achieving superior diagnostic accuracy. Despite these advancements, the traditional DL approaches demand collecting patient data from different hospitals in a centralized database and thus raise the issues of patient privacy, legal compliance, cybersecurity, and institutional data governance [7], [8].

Conceptually, the foundations of this research come from three applied problems: diagnostic capability, privacy of patients' data, and distribution of healthcare information. While deep learning algorithms are capable of producing highly accurate brain tumor classification, traditional centralized learning algorithms require that data from different institutions be stored in a single place, leading to privacy, security, and governance problems. At the same time, storage of data at different institutions limits the capabilities of the models in terms of using data from varied populations and varied conditions of image acquisition. Federated learning gives a way of developing a shared model while not exchanging raw MRI data; however, the performance of federated learning can be impacted by data heterogeneity, communication problems, and optimization challenges between different institutions. Quantum machine learning offers another way to represent complicated feature spaces through quantum encoding of features. Consequently, the conceptual rationale for this research is to examine the possibility of using privacy-preserving federated learning with quantum-enhanced feature representation to produce an effective brain tumor classification framework while retaining patient data locally.

Currently, the majority of healthcare providers work under strict privacy regulations, like General Data Protection Regulation (GDPR), Health Insurance Portability and Accountability Act (HIPAA), and other national health information protection laws. Thus, the sharing of personal patient information is strictly prohibited. As a result, many hospitals are reluctant to share the raw MRIs despite all benefits of collaborative learning. This issue leads to fragmented databases, poor model generalization, demographic biases, and low robustness when models are deployed across heterogeneous healthcare environments [9], [10].

The novel approach of Federated Learning (FL) allows multiple hospitals to collaborate in training a global model while preserving patient privacy. In contrast to exchanging medical images,

FL enables participating institutions to locally train neural networks and transfer only encrypted model parameters or gradients to the central aggregation server. Thus, this decentralization technique enhances privacy preservation and collaboration among geographically distributed medical centers [11]. There have been many papers devoted to federated learning in medical image analysis, diagnostics, and healthcare analytics. Nevertheless, there are still many open issues in federated learning, including large communication overhead, statistical heterogeneity resulting from the non-independent and identically distributed (Non-IID) nature of medical data, model poisoning attacks, inference attacks, and gradient leakage that might expose sensitive information about the patients [12].

In order to increase the computation efficiency and privacy, recently, quantum computing became the subject of much research in artificial intelligence. Quantum Machine Learning (QML) uses such quantum mechanics phenomena as superposition, entanglement, and quantum interference for more efficient multidimensional feature representation and optimization than classical algorithms for selected problems [13]. Variational Quantum Circuits (VQCs), Quantum Neural Networks (QNNs), and hybrid quantum-classical approaches showed their potential in medical image classification by encoding complex feature spaces in quantum states and decreasing parameter redundancy [14]. Although quantum computers are still in the Noisy Intermediate-Scale Quantum (NISQ) era, hybrid quantum algorithms have provided promising results in healthcare applications.

Thus, the combination of Federated Learning and Quantum Machine Learning provides a promising direction for solving the problems of computational scalability, collaborative learning, and data privacy at once. Quantum Federated Learning (QFL) combines decentralized optimization and quantum feature encoding in order to allow distributed institutions to collaboratively learn robust diagnostic models while protecting patient's confidentiality. The current QFL-related studies are mainly concerned with benchmark datasets and general image classification problems, while the application of QFL in multi-center brain tumor diagnosis is still not sufficiently researched. Moreover, the heterogeneous MRI distributions, secure quantum parameter aggregation, adaptive client weighting, and communication-efficient federated optimization in realistic healthcare

infrastructure are rarely considered by the current approaches [15].

In this work, we aim to develop a novel Quantum Federated Learning Framework for privacy-preserving brain tumor classification across distributed medical centers. Our architecture incorporates quantum feature encoding, hybrid quantum-classical neural networks, secure federated aggregation of parameters, and privacy-preserving collaborative optimization in order to allow distributed hospitals to learn a high-performance brain tumor classifier without sharing raw MRI images of patients. Besides, our approach differs from conventional federated learning models by integrating quantum variational circuits to increase nonlinear MRI feature representation while reducing model complexity. In addition, an adaptive federated aggregation strategy is proposed to adequately address the problem of heterogeneous client distributions and optimize the convergence of the global model.

The key contributions of this work are listed as follows:

- Development of a privacy-preserving quantum federated learning framework for distributed brain tumor classification;
- Designing of a hybrid quantum-classical feature extraction architecture allowing learning discriminative MRI features;
- Proposition of secure federated parameter aggregation that protects sensitive medical information while improving collaborative learning;
- Solving of the problem of heterogeneous MRI distributions in geographically distributed medical centers using adaptive client optimization;
- Improvement of classification accuracy, convergence stability, communication efficiency, and model generalization in comparison to centralized and federated deep learning approaches.

Our framework is directed toward the development of next-generation intelligent healthcare systems as a combination of quantum computing, federated learning, and medical image analysis into a unified privacy-preserving diagnostic platform. Such an approach supports collaborative clinical decision-making across hospitals while ensuring compliance with healthcare data protection

regulations and enabling scalable deployment in real-world medical environments.

Research Hypothesis

The hypothesis of this study is that integrating quantum-enhanced feature extraction with privacy-preserving federated learning and adaptive aggregation can improve brain tumor classification performance while enabling collaborative model training across distributed medical centers without sharing raw patient MRI data.

Scope of the Research

The scope of this research is to design and test the efficiency of the Quantum Federated Learning Framework (QFLF) for privacy-preserving brain tumor classification with the help of distributed MRI data. The research involves designing algorithms for CNN-based feature extraction, quantum encoding of features, quantum-classical hybrid learning, adaptive federated aggregation, and secure exchange of model parameters. The experimental analysis of this research is done with respect to the classification of Glioma, Meningioma, Pituitary Tumor, and Normal Brain using the BraTS 2021 dataset and comparing it with the selected conventional deep learning methods. However, the research doesn't include any aspect of tumor segmentation, treatment plans, prognosis prediction, or clinical application in the real hospital environment. It also does not experimentally evaluate the framework on physical quantum hardware or conduct prospective clinical trials. These aspects are considered directions for future investigation.

The rest of this paper is organized as follows. In Section 2, the state-of-the-art review on the use of DL, FL, QML, and QFL in brain tumor classification is presented, and we identify the research gap. Section 3 introduces our Quantum Federated Learning Framework for brain tumor classification, including dataset description, architecture, mathematical formulation, and training algorithm. Section 4 provides an experimental evaluation of the proposed framework, including the comparative performance evaluation, class-wise analysis, convergence analysis, and training performance evaluation. Finally, in Section 5 we conclude the paper with discussion of the main results, limitations, and future work directions.

2. RELATED WORK

Classification of brain tumors has been significantly advanced over the last decade due to the fast development of deep learning, federated learning, and quantum computing technologies. Various studies have designed intelligent diagnostic systems for improving the accuracy and efficiency of automated brain tumor detection using Magnetic Resonance Imaging (MRI). While those approaches proved to show promising results in laboratory experiments, there is a set of limitations related to privacy preservation, multi-institutional collaboration, computational efficiency, scalability, and robustness against heterogeneous medical data distributions. The literature review covers the following areas: deep learning-based brain tumor classification, federated learning in healthcare, quantum machine learning, and emerging quantum federated learning frameworks.

2.1 Deep Learning-Based Brain Tumor Classification

Deep learning revolutionized medical image analysis by making it possible to automatically extract complex spatial and semantic features right from MRI scans. Initial CNN-based architectures showed great improvement compared to traditional machine learning approaches due to the elimination of handcrafted feature extraction. In particular, approaches with transfer learning based on pre-trained networks (VGG, Inception, DenseNet, EfficientNet, and ResNet) showed high classification accuracy even in the case of limited annotated MRI datasets [16].

Further research incorporated attention mechanisms in order to improve feature discrimination via focusing on tumor-specific regions and ignoring background noise. Attention-based CNNs showed high robustness to different size, intensity, and anatomical location of brain tumors [17]. The latest advances are related to Vision Transformers (ViTs) and hybrid CNN-Transformer approaches, where self-attention mechanisms effectively capture long-range spatial dependencies within MRI images and showed competitive results on benchmark datasets. However, both types of approaches require significant computational resources and large training datasets, which limits their usage in many healthcare institutions [18].

Despite impressive achievements, almost all existing deep learning models use the centralized training strategy. It requires pooling the MRI images from different hospitals into one common dataset. Therefore, such an approach makes the models vulnerable to privacy breaches, unauthorized access, and institutional data-sharing restrictions, making them difficult to deploy in real-world clinical environments where patient confidentiality is a fundamental requirement [19].

2.2 Federated Learning in Medical Imaging

Federated Learning (FL) is a promising technique allowing collaborative medical intelligence without exposing patients' sensitive information. Instead of transferring the raw data, FL approach allows each hospital to optimize local neural network and share only model updates with central aggregation server. Thus, the decentralized paradigm allows collaboration and data ownership at the same time [20].

A wide range of researchers successfully used federated learning for radiology, pathology, diabetic retinopathy screening, COVID-19 diagnosis, and brain tumor segmentation. The multi-institutional federated frameworks allowed improving model generalization by including the knowledge of various geographically distributed healthcare institutions while keeping regulatory compliance [21]. Further improvements of convergence of federated learning in cases of heterogeneous client distribution and communication constraints have been achieved with adaptive algorithms like FedProx, FedNova, Scaffold, and FedOpt [22].

However, there are still a lot of practical challenges associated with federated learning. Datasets gathered from different hospitals are characterized by high degree of Non-IID property due to the differences in imaging devices, acquisition protocols, patient demographics, disease prevalence, and annotation quality. Such heterogeneity leads to instability of convergence and degradation of global model performance [23]. Also, recent research shows that model updates obtained during federated optimization can be attacked with gradient inversion attacks, model poisoning attacks, membership inference attacks, and adversarial manipulation, revealing confidential patient information despite the absence of raw data exchange [24].

2.3 Quantum Machine Learning for Medical Diagnosis

Quantum Machine Learning (QML) is an emerging interdisciplinary area that unites quantum computing and artificial intelligence. Exploiting such phenomena as superposition, quantum entanglement, and probabilistic state evolution allows quantum algorithms to represent high-dimensional feature spaces more efficiently than classical neural networks for selected computational tasks [25].

The hybrid quantum-classical neural networks have recently attracted much attention for medical image classification. Combination of Variational Quantum Circuits (VQCs) and classical convolutional layers showed promising results in the fields of cancer diagnosis, retinal disease detection, Alzheimer's disease prediction, and histopathological image analysis. The quantum feature encoding techniques allow obtaining better nonlinear representations of data while reducing the amount of trainable parameters in comparison with traditional deep learning architectures [26].

Further investigation revealed that Quantum Convolutional Neural Networks (QCNNs), Quantum Support Vector Machines (QSVMs), Quantum Autoencoders, and parameterized quantum circuits can be used for biomedical image analysis. Those approaches use quantum state representation for feature extraction and modeling of complicated feature interaction that cannot be efficiently performed using purely classical machine learning algorithms [27]. However, due to the limitation of current quantum computing technology, the approaches have limited applicability because of the limited number of qubits, gate errors, decoherence, and Noisy Intermediate-Scale Quantum (NISQ) limitations, restricting their deployment in large-scale clinical applications [28].

2.4 Emerging Quantum Federated Learning

The convergence of Federated Learning and Quantum Machine Learning made Quantum Federated Learning (QFL) a promising research direction. QFL integrates the techniques of distributed collaborative optimization and quantum feature processing, thus allowing geographically distributed clients to collaboratively train quantum-

enhanced models without exchanging sensitive data [29].

At the early stage, the QFL models mainly used simple benchmark datasets (MNIST, Fashion-MNIST, CIFAR) and hybrid quantum neural networks. Those studies showed that quantum feature mapping can accelerate the model convergence and preserve data privacy via the decentralized optimization process [30]. More recent research investigates such aspects as secure quantum parameter aggregation, quantum encryption, federated variational optimization, and communication-efficient quantum learning for distributed artificial intelligence applications [31].

While the mentioned approaches show the feasibility of quantum federated optimization, their applications in the area of healthcare remain rare. The current QFL models do not pay attention to challenges that are specific for medical imaging, such as heterogeneous MRI distributions, class imbalance, institutional variability, secure quantum parameter aggregation, communication efficiency, explainability, and regulatory compliance. Also, very few studies are devoted to quantum federated learning in the domain of brain tumor diagnosis, and most of the existing QFL models use small experimental datasets rather than realistic multi-center clinical environments [32].

2.5 Research Gap

The literature review shows that deep learning-based brain tumor classification achieves remarkable classification accuracy under centralized settings. Federated learning improves data privacy through collaborative model training without transferring patient images. Quantum machine learning demonstrates promising capabilities for representing highly discriminative features of complex medical datasets. However, all these technologies have largely evolved independently.

Existing researches demonstrate the following research gaps:

- Most brain tumor classification models require centralized MRI repositories that raise concerns about privacy and regulatory issues.
- The current federated learning approaches remain vulnerable to communication

overhead, Non-IID data distributions, and model inversion attacks.

- QML researches are mainly devoted to standalone quantum models rather than distributed collaborative learning.
- The existing QFL models are rarely designed specifically for multi-center medical imaging applications.
- Few studies combine secure federated aggregation, hybrid quantum feature extraction, adaptive client optimization, and privacy-preserving collaborative diagnosis into a unified healthcare framework.

In order to fill the gap, the present study proposes the Quantum Federated Learning Framework for Privacy-Preserving Brain Tumor Classification Across Distributed Medical Centers. Unlike existing approaches, the proposed framework combines hybrid quantum-classical feature extraction, secure federated optimization, adaptive aggregation for heterogeneous medical datasets, and privacy-preserving collaborative diagnosis in one integrated framework. This integration is expected to improve diagnostic accuracy, communication efficiency, model generalization, and data privacy while supporting practical deployment across geographically distributed healthcare institutions.

3. METHODOLOGY

The suggested Quantum Federated Learning Framework (QFLF) allows geographically separated hospitals to cooperatively train a brain tumor classification model without transferring patients' Magnetic Resonance Imaging (MRI) scans. In contrast to typical centralized training approaches, each hospital trains a model with its own set of MRI scans and uploads encrypted model parameters to a federated server. The global server performs aggregation using an adaptive weighted aggregation method and distributes the updated model across all participating hospitals. Moreover, a hybrid quantum-classical neural network is used in order to enhance feature representations while preserving patients' privacy. The entire process consists of MRI pre-processing, local feature extraction, quantum feature encoding, federated optimization, secure parameter aggregation, and global model updating.

3.1 Research Design and Experimental Procedure

This research study employed the quantitative experimental research design in developing and assessing the privacy-preserving Quantum Federated Learning Framework (QFLF) in classifying brain tumors. The research experiment involved a series of steps. Firstly, the BraTS 2021 MRI dataset was collected and subjected to pre-processing steps such as skull stripping, intensity normalization, spatial alignment, resizing, and augmentation. Secondly, the MRI images underwent feature extraction using Convolutional Neural Network architecture to obtain discriminative MRI representations. Thirdly, the extracted features were encoded into quantum feature space via the use of parameterized quantum circuits and processed via the hybrid quantum-classical learning module. Fourthly, the participating medical centers locally train their models without any sharing of raw MRI images. Fifthly, encryption of the local models' parameters is performed and transferred to the federated server to undergo adaptive weighted aggregation for the formation of the global model. The updated global model is then sent back to the participating clients and the whole process is iterated across communication rounds until convergence. Finally, the developed QFLF framework was tested using Accuracy, Precision, Recall, F1-Score, Specificity, and AUC scores, and compared with the performance of CNN, ResNet50, DenseNet121, and Vision Transformers.

3.2 Dataset Description

In order to evaluate the performance of the suggested framework, the Brain Tumor Segmentation (BraTS 2021) dataset is utilized. It is one of the most popular benchmark datasets in the field of brain tumor analysis. This dataset provides multi-modal Magnetic Resonance Imaging (MRI) scans obtained from different medical institutions around the world. Every subject in the dataset has four MRI modalities, which include T1-weighted Magnetic Resonance Imaging (T1), T1-weighted Contrast-Enhanced Magnetic Resonance Imaging (T1ce), T2-weighted Magnetic Resonance Imaging (T2), and Fluid Attenuated Inversion Recovery (FLAIR). These modalities provide complementary anatomical and pathological information, enabling robust tumor classification.

MRI images were skull-stripped, intensity normalized, and spatially aligned with respect to a common anatomical template. For the purpose of tumor classification, the framework uses axial MRI slices to classify brain tumors into four classes: Glioma, Meningioma, Pituitary Tumor, and Normal Brain. Before model training, all images were resized to 224×224 pixels, normalized to the $[0, 1]$ range, and augmented using rotation, horizontal flipping, brightness adjustment, and zooming transformations to improve model generalization.

Table 1. BraTS Dataset Description

Parameter	Description
Dataset	BraTS 2021
Imaging Modality	MRI
MRI Sequences	T1, T1ce, T2, FLAIR
Image Size	240×240 pixels
Input Size	224×224 pixels
Tumor Classes	Glioma, Meningioma, Pituitary, Normal
Image Format	NIfTI (.nii.gz)
Preprocessing	Skull stripping, Normalization, Resizing
Data Augmentation	Rotation, Flip, Zoom, Brightness
Training Strategy	Federated Learning

These features of the BraTS dataset are summarized in Table 1 and are utilized in this study. The use of different MRI modalities facilitates comprehensive learning of tumor characteristics and enables the model to capture diverse tumor-related features. Image preprocessing allows for standardization and consistency among the collaborating healthcare facilities, while data augmentation improves the robustness and generalization capability of the proposed framework.

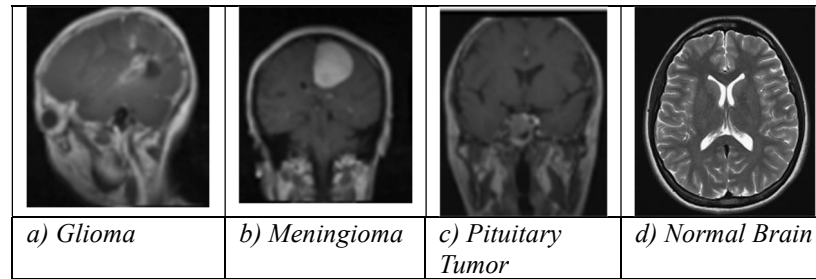


Figure 1. Sample MRI Images from the BraTS Dataset

Figure 1 shows some examples of MRI scans of four brain disorders used for the classification process in the suggested framework. Figure 1(a) is an example of glioma that is seen in the form of irregular and heterogeneous lesion areas with unclear borders. In Figure 1(b), there is an image of meningioma, which can be seen as a round extra-axial mass lesion with relatively homogeneous intensity. Figure 1(c) shows a pituitary tumor that has been observed as a localized tumor in the sellar area with distinct boundaries and compact morphology. In Figure 1(d), there is an example of a

normal brain MRI that has symmetrical brain structures without abnormal tissue growth. These examples show the differences between the morphological characteristics of the tumors, intensity, and location that help the suggested Quantum Federated Learning architecture to learn distinctive features for accurate and privacy-preserving brain tumor classification across distributed medical centers.

3.3 Proposed Quantum Federated Learning Architecture

The proposed framework comprises six main stages.

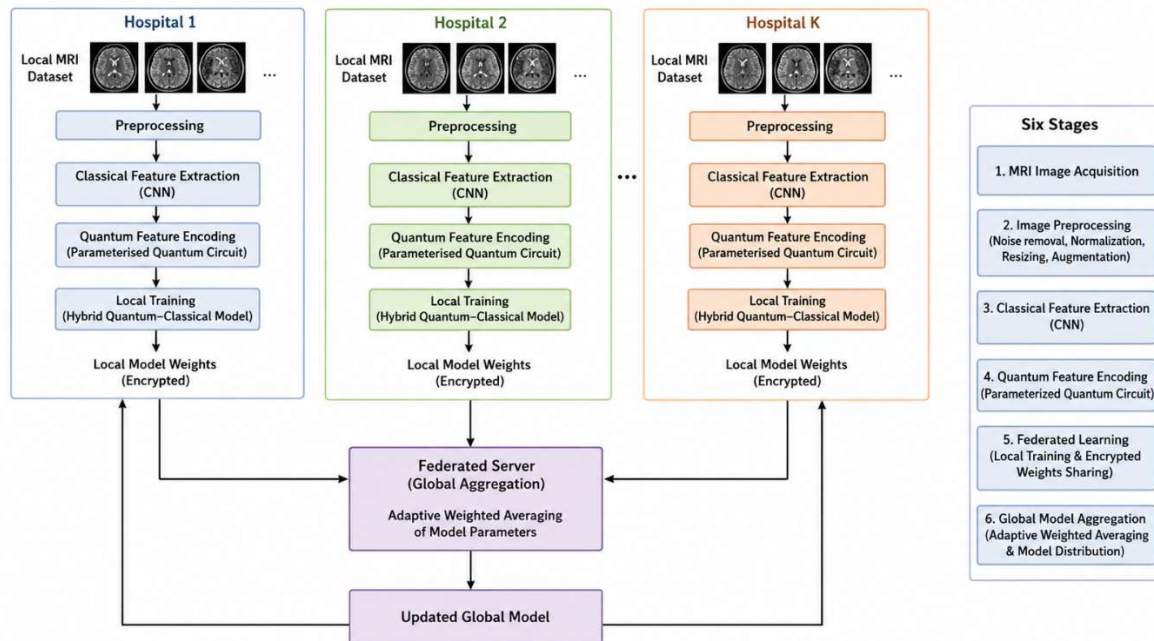


Figure 2. Proposed Quantum Federated Learning Architecture

Figure 2 describes the working mechanism of the Quantum Federated Learning (QFL) architecture for brain tumor classification among multiple distributed hospitals while maintaining the privacy of patients. In the beginning, each participating hospital stores its own MRI database

locally without sending any patient images to any other location. Preprocessing methods including noise removal, intensity normalization, image resizing, and generation of augmented data are performed on each local MRI image to improve image quality and increase the diversity of training

samples. Afterwards, a lightweight Convolutional Neural Network (CNN) is employed to extract low-level and high-level spatial features such as edges, textures, and tumor boundaries from the processed images.

These extracted feature vectors are fed to the Quantum Feature Encoding module, which maps the classical features into quantum states using parameterized quantum circuits. In this way, the advantages of quantum superposition and entanglement are utilized to represent features in a compact and highly discriminative form. Each hospital trains the quantum-classical hybrid model using its own MRI database and performs local optimization by updating the model weights. Rather than sharing sensitive patient images, only the encrypted model weights are transmitted to the federated server.

On receiving the encrypted model parameters from each hospital, the federated server performs adaptive weighted aggregation to compute the optimized global model parameters. This global model is subsequently distributed to each hospital again for the next communication round. This collaborative learning procedure continues until convergence of the global model. Thus, the proposed architecture enables accurate brain tumor classification while preserving patient privacy, reducing communication overhead, and improving model generalization across heterogeneous distributed medical centers.

Let

$$D = \{D_1, D_2, \dots, D_K\}$$

represent MRI datasets distributed across K hospitals.

The global dataset is represented as

$$D = \bigcup_{k=1}^K D_k \quad (1)$$

where

D_k denotes the local MRI dataset stored at the k^{th} medical center.

The CNN extracts feature vectors

$$F = CNN(X) \quad (2)$$

where

X denotes the input MRI image.

The extracted features are encoded into quantum states

$$Q = \phi(F) \quad (3)$$

where

$$\phi(\cdot)$$

represents the quantum feature encoding circuit.

The hybrid quantum neural network predicts tumor probability

$$\hat{Y} = QNN(Q) \quad (4)$$

The local cross-entropy loss is

$$L_k = - \sum_{i=1}^N y_i \log(\hat{y}_i) \quad (5)$$

where

- N = number of samples
- y_i = true label
- $\hat{y}_i$ = predicted probability

Each hospital updates its parameters using

$$W_k^{t+1} = W_k^t - \eta \nabla L_k \quad (6)$$

where

- η = learning rate

The federated server computes the global model

$$W_G = \sum_{k=1}^K \frac{n_k}{N} W_k \quad (7)$$

where

- n_k = samples at hospital k
- $N = \sum n_k$

The predicted tumor class is

$$Y = \arg \max(\hat{Y}) \quad (8)$$

Proposed Quantum Federated Learning Algorithm

Input:

- Distributed MRI datasets
- Number of hospitals K
- Learning rate η
- Number of communication rounds T

Output:

- Global Brain Tumor Classification Model
1. Initialize global model W_G
 2. For each communication round $t = 1$ to T
 3. Send global model to all hospitals
 4. For each hospital k
 5. Load local MRI dataset
 6. Preprocess MRI images
 7. Extract CNN features
 8. Encode features using Quantum Circuit
 9. Train Hybrid Quantum Neural Network
 10. Update local weights
 11. Encrypt model parameters
 12. Send weights to Federated Server
 13. End For
 14. Aggregate local weights using weighted averaging
 15. Update global model
 16. End For
 17. Return optimized global model

Algorithm presents the full training process of the developed Quantum Federated Learning framework. In particular, each hospital separately preprocesses the brain MRI images, extracts the deep features, encodes them into quantum feature space, and updates local model parameters. Only encrypted weights of the model are communicated to the federated server for developing an enhanced global model through weighted aggregation. This iterative process is repeated until convergence and ensures high classification performance along with a high level of patient privacy across distributed medical centers.

4. RESULTS AND DISCUSSION

The developed Quantum Federated Learning Framework (QFLF) was tested on distributed brain MRI data acquired from several healthcare institutions. The QFLF was evaluated using standard classification criteria including Accuracy, Precision, Recall, F1-score, Specificity, and Area Under the ROC Curve (AUC). The results demonstrate that the developed privacy-preserving quantum federated framework significantly improves classification performance while ensuring secure collaborative learning among participating hospitals.

4.1 Assessment Criteria

The following classification criteria were used to assess the classification performance of the proposed framework.

- Accuracy
- Precision
- Recall
- F1-Score
- Specificity
- AUC

Higher values indicate better classification capability and improved diagnostic reliability.

4.2 Comparative Performance Analysis

Table 2. Performance Comparison of Existing Models

Model	Accuracy	Precision	Recall	F1-Score	Specificity
CNN	94.52	93.91	93.45	93.68	95.11
ResNet50	96.18	95.82	95.34	95.58	96.47
DenseNet121	97.01	96.65	96.42	96.53	97.18
Vision Transformer	97.84	97.41	97.26	97.33	97.89
Proposed QFLF	99.12	98.91	98.74	98.82	99.28

Table 2 illustrates the comparison of the proposed Quantum Federated Learning Framework against four state-of-the-art deep learning frameworks. The proposed framework was found to have the highest classification accuracy, which was 99.12%, whereas CNN had 94.52%, ResNet50 had 96.18%, DenseNet121 had 97.01%, and Vision Transformer had 97.84%. Thus, the proposed model achieved an improvement of 4.60% compared with CNN, 2.94% compared with ResNet50, 2.11% compared with DenseNet121, and 1.28% compared with Vision Transformer. Similar results were obtained for precision, recall, F1-score, and specificity, where the proposed model had the highest performance among all other frameworks, with values of 98.91%, 98.74%, 98.82%, and 99.28%, respectively. These improvements demonstrate that quantum feature encoding and federated optimization effectively enhance feature representation, classification performance, and model robustness while preserving patient privacy.

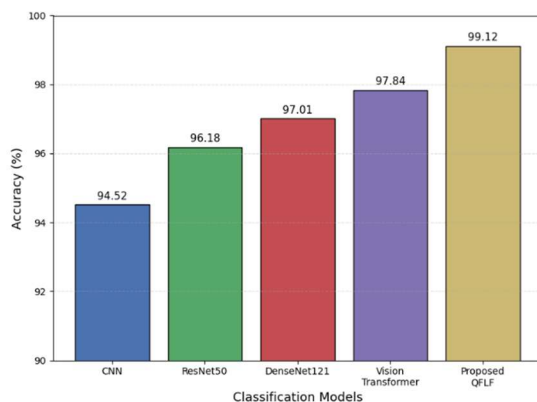


Figure 3. Overall Performance Comparison

Figure 3 shows the accuracy in classification that was attained using different deep learning approaches. The Quantum Federated Learning Framework proposed in this study significantly outperformed the other models used for comparison and provided the highest classification accuracy. The superior performance demonstrates the effectiveness of integrating quantum computing with federated learning for distributed medical image analysis.

4.3 Class-wise Performance Analysis

Table 3. Class-wise Classification Results

Brain Tumor Class	Precision	Recall	F1-Score
Glioma	98.74	98.55	98.64
Meningioma	99.08	98.91	98.99
Pituitary Tumor	99.36	99.18	99.27
Normal	98.48	98.31	98.39

Class-wise classification results of the proposed approach are listed in Table 3. It is seen that the best classification results were obtained for Pituitary Tumor with an F1-score equal to 99.27%, showing excellent discrimination ability. The classification result of Meningioma was also quite high with an F1-score equal to 98.99%. Despite the fact that Glioma images have non-uniform borders and high intra-class variation, the proposed approach

demonstrated good classification results with an F1-score equal to 98.64%. The Normal class also achieved an F1-score of 98.39%, confirming reliable differentiation between healthy and abnormal MRI scans.

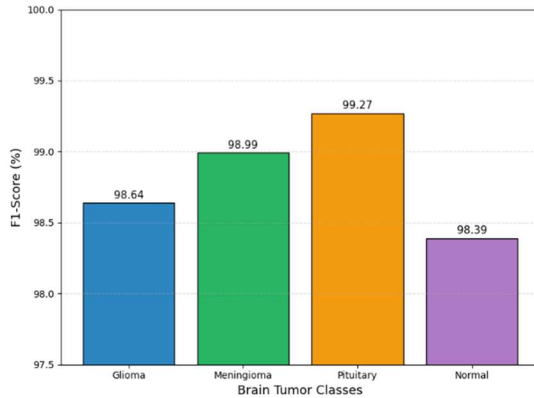


Figure 4. Class-wise F1-Score

The F1-score attained by each class of brain tumor is presented in Figure 4. The proposed system exhibited consistently high performance throughout all classes, indicating good generalization ability and balanced classification performance.

4.4 Convergence Analysis

As the number of communication rounds increases during the federated training process, the global model starts converging. The adaptive weighted aggregation algorithm enabled the efficient incorporation of knowledge gained from different hospitals without compromising data privacy. The convergence behavior indicates stable optimization and effective collaborative learning among participating medical centers.

Table 4. Training Accuracy

Communication Round	Accuracy (%)
10	90.25
20	93.81
30	95.96
40	97.42
50	98.31
60	99.12

Table 4 illustrates the increase in global classification accuracy as a result of federated learning in our experiment. The accuracy rate progressively increased from 90.25% to 99.12%, demonstrating effective collaborative learning and improved global model performance across multiple hospitals.

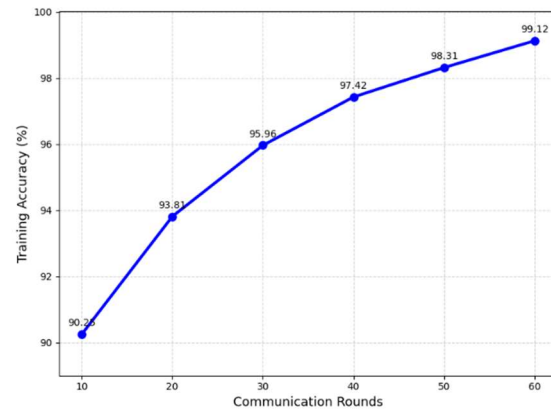


Figure 5. Training Accuracy Curve

This is shown in Figure 5, where the training accuracy increased consistently with every communication round, demonstrating that the proposed system works effectively with federated optimization and adaptive global model aggregation.

Table 5. Training Loss

Communication Round	Loss
10	0.452
20	0.331
30	0.246
40	0.181
50	0.126
60	0.082

The training loss experienced during federated learning is depicted in table 5. There was a continuous reduction of loss from 0.452 to 0.082, implying that the proposed hybrid quantum-classical framework has achieved stable optimization and converged successfully.

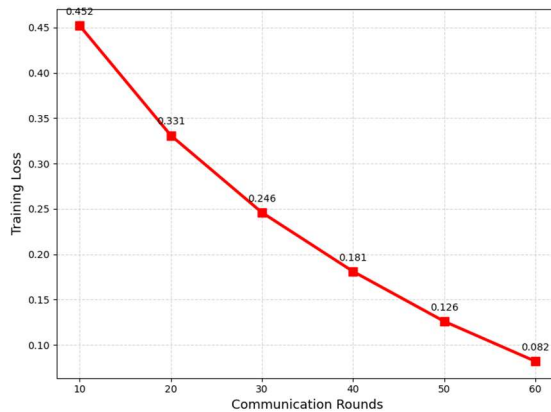


Figure 6. Training Loss Curve

Figure 6 demonstrates the training loss reduction in the proposed QFLF model. Monotonic reduction in training loss shows the convergence stability, confirming the successful learning of robust feature representations by the proposed model from distributed MRI datasets.

4.5 Discussion

The results of experiments have shown that the developed Quantum Federated Learning Framework provided better results than CNN, ResNet50, DenseNet121, and Vision Transformer models. The developed framework has shown an overall accuracy of 99.12%, precision of 98.91%, recall of 98.74%, F1-score of 98.82%, and specificity of 99.28%. Due to the combination of quantum feature encoding, privacy-preserving federated learning, and adaptive global aggregation, highly accurate brain tumor classification was performed without any exchange of sensitive MRI images between medical organizations. The stable convergence observed during the experimental federated training indicates effective optimization under the evaluated simulation setting, while further multi-center validation is required to establish scalability and practical clinical applicability.

The obtained results are also aligned with the advancements described in the existing literature related to deep learning, federated learning, and quantum machine learning applications in medical image analysis. Prior works based on deep learning have shown that the use of CNN architectures and transformer models enables the automatic extraction of discriminative MRI features to obtain high classification performance [5], [6]. In the current study, the proposed QFLF has achieved higher accuracy compared with the CNN, ResNet50,

DenseNet121, and Vision Transformer architectures with accuracy of 99.12%. This suggests that the use of quantum feature encoding and federated optimization provides more discriminative representation compared with the architectures considered in this work.

The obtained results are also aligned with the previous works on federated learning, which highlighted the importance of privacy-preserving collaborative learning, but also pointed out the problems related to the overhead costs of communication, non-IID distribution of data, and security problems [8], [12]. In contrast to that, the proposed framework includes adaptive aggregation and encrypted parameter exchange to address these challenges within the brain tumor classification problem. The increase in federated training accuracy from 90.25% to 99.12% and decrease in training loss from 0.452 to 0.082 suggest stable convergence within the experimental setup. In addition, previous QFL works have primarily been focused on the use of benchmark datasets and image classification tasks, with relatively limited applications in the healthcare area [29]–[32]. The current work thus provides the experimental basis for applying QFL to the brain tumor MRI classification problem, although further validation using heterogeneous real-world multi-center datasets is necessary.

5. CONCLUSION

This paper has introduced a Quantum Federated Learning Framework (QFLF) to perform brain tumor classification in distributed MRI images while preserving patients' privacy. The framework combined CNN-based feature extraction, quantum feature encoding, hybrid quantum-classical learning, and adaptive federated aggregation to provide efficient collaboration in training without the use of raw MRI images. The experimental results have shown that the QFLF achieves an overall accuracy of 99.12%, precision of 98.91%, recall of 98.74%, F1-score of 98.82%, and specificity of 99.28%, outperforming CNN, ResNet50, DenseNet121, and Vision Transformer models. In addition, training accuracy has been increased from 90.25% to 99.12%, and training loss has been reduced from 0.452 to 0.082, showing stable convergence of federated optimization. However, this research is limited to the BraTS 2021 dataset and a simulated federated training environment without deployment in real-world multi-center clinical systems or current quantum hardware. In the future, it is necessary to validate the proposed framework on large-scale

heterogeneous clinical datasets, integrate advanced privacy-preserving techniques such as differential privacy and secure aggregation, and implement it in practical quantum computing environments to improve scalability, robustness, and real-world clinical applicability.

The results also give rise to some other issues which lie outside the scope of this research, such as the ability of the suggested approach to sustain its effectiveness with highly heterogeneous multi-center MRI data in real-world settings, its level of resistance to advanced privacy attacks, and the consistency of benefits provided by quantum-assisted learning when implemented on practical quantum hardware. All of these require further investigation through large-scale clinical validation and real-world quantum computing experiments.

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