A Hybrid Quantum-Classical Deep Learning Framework for Efficient Brain Tumor Classification Using MRI Images

Sayali Nale[1], Tejashree Jena2, Anita Atiwadkar[3]
[1,2,3]*Department of Science and Computer Science, MAEER's MIT ACSC, Alandi (D), Pune, India*
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Abstract—Accurate and computationally efficient classification of brain tumors from MRI scans is critical for deployment in resource-constrained clinical settings, where conventional deep CNN architectures—despite achieving strong accuracy—often require large parameter counts that limit scalability. This work proposes a hybrid quantum-classical deep learning framework that combines a classical convolutional feature extractor with a variational quantum circuit (VQC) for multi-class tumor classification. Spatial features extracted by the CNN backbone will be dimensionality-reduced and encoded into quantum states using angle encoding; a parameterized quantum circuit will then process these features in a higher-dimensional Hilbert space, leveraging superposition and entanglement to capture non-linear feature correlations. Measurement outputs from the quantum layer will be passed to a classical fully connected layer for classification into glioma, meningioma, pituitary tumor, and no-tumor categories. The proposed framework will be evaluated on a publicly available benchmark MRI dataset and benchmarked against state-of-the-art classical CNN architectures in terms of accuracy, precision, recall, F1-score, and parameter efficiency. This study aims to demonstrate that quantum-enhanced layers can achieve competitive classification performance while substantially reducing trainable parameters, offering a practical direction for efficient, quantum-assisted medical image analysis.

Index Terms—Quantum Machine Learning; Variational Quantum Circuit; Convolutional Neural Network; Brain Tumor Classification; MRI Image Analysis; Hybrid Deep Learning

I. INTRODUCTION

Brain tumors are the second most common category of cancer and represent one of the most challenging neurological diseases. Early and accurate detection of brain tumors plays an indispensable role in guiding treatment strategies. The most common non-invasive imaging modality employed by radiologists for brain tumor detection, localization, and classification is MRI, owing to its capability to provide high contrast between various soft tissues in the brain. Nevertheless, the interpretation of MRI slices by humans requires time, a substantial level of expertise, and is sensitive to inter-observer variations. Therefore, the utilization of automated, computer-aided diagnosis (CAD) systems for the classification of brain tumors into different categories remains an active area of research. In recent years, deep learning, with a particular focus on Convolutional Neural Networks (CNNs), has become the prevalent methodology for medical image classification, achieving unprecedented accuracy on brain tumor datasets. However, most state-of-the-art deep learning models rely on millions of learnable parameters and require large volumes of labeled data and immense computational power for both training and inference. These requirements pose a challenge for deployment on edge devices and in low-resource clinical settings, fostering research into more compact and efficient alternative architectures.

Quantum computing has recently emerged as a potential solution for advancing machine learning performance. Quantum Machine Learning (QML) leverages quantum phenomena, such as superposition and entanglement, for efficiently processing information in high-dimensional Hilbert spaces with a modest number of qubits and trainable parameters. Variational Quantum Circuits (VQCs) are trainable quantum circuits that can be optimized using conventional gradient-based methods, and they have shown to be effective, compact components for classical neural networks. When combined with a classical neural network architecture, these VQCs create what are known as Hybrid Quantum-Classical Neural Networks. By integrating the well-established feature-extraction capabilities of CNNs with the dense feature representation power of quantum circuits, these models aim to benefit from both worlds. This paper introduces a novel Hybrid Quantum-Classical Deep Learning Framework that leverages MRI images to classify brain tumors.

Our contributions include:

- We propose a novel Hybrid Quantum-Classical Architecture that combines a lightweight classical CNN feature extractor with a Variational Quantum Circuit to classify different types of brain tumors.
- We develop a dimensional reduction and encoding method for efficiently mapping high-dimensional CNN features to a small number of qubits without significant loss of information.
- We evaluate the performance of our proposed model against pure classical CNN benchmarks in terms of accuracy and efficiency (parameter count and training time).
- We perform a detailed analysis of the impact of the circuit depth, number of qubits, and encoding scheme on classification performance.

The subsequent sections of this paper are organized as follows: Section II provides an overview of previous work on classical and quantum-assisted brain tumor classification. Section III details our proposed hybrid quantum-classical approach. Section IV presents the experimental setup, including the dataset and evaluation metrics. Section V discusses the obtained results. Finally, Section VI summarizes our contributions and outlines future research directions.

II. RELATED WORK

A. Classical Deep Learning for Brain Tumor Classification

Several works in the literature have explored different CNN architectures (custom shallow CNNs or transfer learning from large models like VGG, ResNet, DenseNet, and EfficientNet) for brain tumor classification based on MRI. While these studies generally achieve high classification accuracy, they utilize architectures with millions of trainable parameters, driving research into more lightweight or efficient architectures, such as those using attention mechanisms, pruning, or knowledge distillation.

B. Quantum and Hybrid Quantum-Classical Machine Learning

Various quantum and hybrid quantum-classical machine learning methods have been applied to image classification, including Variational Quantum Circuits (VQCs), Quantum Convolutional Neural Networks (QCNNs), and hybrid quantum-classical pipelines. These methods have been implemented on quantum simulators and on near-term noisy intermediate-scale quantum (NISQ) hardware, and have shown promise as efficient and compact non-linear feature extractors when integrated into classical neural network architectures, particularly on small-scale datasets like MNIST or subsampled medical imaging datasets.

C. Research Gap

Although classical deep learning models have achieved impressive results in brain tumor classification, and quantum-enhanced learning approaches have demonstrated potential on simpler benchmark datasets, there is a limited body of research that systematically investigates hybrid quantum-classical models for multi-class brain tumor classification on MRI images, specifically addressing the accuracy-efficiency trade-offs. Our paper fills this gap by proposing and empirically evaluating such a framework.

III. PROPOSED METHODOLOGY

Our proposed Hybrid Quantum-Classical framework for brain tumor classification comprises four stages: (1) MRI image pre-processing, (2) feature extraction using a classical convolutional neural network, (3) encoding and processing of extracted features using a Variational Quantum Circuit, and (4) classification using a classical output layer.

The overall architecture is illustrated in Figure 1 (illustration to be added).

A. Pre-processing

The input MRI images are resized to a fixed resolution, converted to grayscale (if applicable), normalized to a [0, 1] range, and augmented with random rotations, horizontal flips, and intensity variations to enhance generalization and mitigate class imbalance issues.

B. Classical Convolutional Feature Extractor

We employ a lightweight CNN consisting of several convolutional blocks. Each block includes a convolution layer, batch normalization, a ReLU activation function, and a max-pooling layer to extract hierarchical spatial features from the input MRI images. A global average pooling layer followed by a fully connected bottleneck layer then reduces these extracted features to a low-dimensional vector of size n, where n is the number of qubits in the subsequent quantum circuit.

C. Quantum Encoding

The n-dimensional bottleneck feature vector is mapped onto the quantum circuit using an angle encoding scheme. In this method, each classical feature value is used to define the rotation angle of a single-qubit rotation gate (e.g., RY or RX), applied to each corresponding qubit. This encoding strategy offers scalability with the number of qubits, making it suitable for near-term quantum hardware.

D. Variational Quantum Circuit (VQC)

The encoded quantum state undergoes processing by a trainable quantum circuit. This circuit consists of layers of single-qubit rotation gates with learnable parameters interspersed with entangling gates (such as CNOTs arranged linearly or circularly). The circuit depth, representing the number of such layers, is treated as a hyperparameter. Finally, expectation values of Pauli-Z observables are measured on each qubit, yielding an n-dimensional real-valued vector which serves as the quantum-derived feature representation.

E. Classification Head

The measured expectation values are fed into a small, fully connected classical layer followed by a softmax activation function, which outputs the probabilities for each of the four target classes: glioma, meningioma, pituitary tumor, and no-tumor. The entire hybrid model, including the classical and quantum circuit parameters, is trained end-to-end using a hybrid gradient-based optimization technique. Gradients for the quantum circuit parameters are computed via the parameter-shift rule, while those for the classical parameters are calculated through standard backpropagation. The categorical cross-entropy loss is minimized using the Adam optimizer.

IV. EXPERIMENTAL SETUP

A. Dataset

Our proposed framework is validated using a publicly available dataset of brain tumor MRI scans that includes T1-weighted contrast-enhanced axial MRI images. The data is categorized into four classes: glioma, meningioma, pituitary tumor, and no-tumor. [Insert exact dataset name, source, and citation, e.g., Figshare Brain Tumor Dataset / Kaggle Brain Tumor MRI Dataset, along with the total number of images per class and the train/validation/test split used.]

B. Implementation Details

The classical CNN is implemented using [PyTorch / TensorFlow specify]. The Variational Quantum Circuit is simulated using [PennyLane / Qiskit specify] on a classical quantum-circuit simulator. [Insert hyperparameters: number of qubits, circuit depth, learning rate, batch size, number of training epochs, optimizer settings, and hardware specifications used for training.]

C. Baseline Models

Our Hybrid Quantum-Classical model is compared against the following purely classical baseline architectures trained on the same dataset splits with identical pre-processing: (i) a CNN of similar depth to the classical component of our hybrid model, (ii) a transfer-learning model utilizing a pre-trained backbone like VGG16 or ResNet-18, and (iii) a lightweight MobileNet-style architecture, selected to represent both accuracy-oriented and efficiency-oriented classical baselines.

D. Evaluation Metrics

Model performance is evaluated using classification accuracy, precision, recall, and F1-score (macro-averaged across the four classes), along with a confusion matrix for qualitative error analysis. Computational efficiency is assessed via the total number of trainable parameters and average training time per epoch, in order to characterize the accuracy-efficiency trade-off between the hybrid and classical models.

V. RESULTS AND DISCUSSION

Table I summarizes the classification performance of the proposed hybrid quantum-classical model against the classical baselines. Table II reports the corresponding computational efficiency comparison. The values reported below are placeholders and must be replaced with the actual results obtained from experiments conducted on the chosen dataset.

Table I. Classification Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Classical CNN (baseline)	95.96	95.76	95.63	95.67
VGG16 (transfer learning)	95.04	94.77	94.70	94.70
MobileNet (lightweight)	94.51	94.26	94.04	94.11
Proposed Hybrid Quantum-Classical Model	95.58	95.58	95.58	95.58

Table II. Computational Efficiency Comparison

Model	Trainable Parameters	Training Time / Epoch (s)
Classical CNN (baseline)	10,700,000	29.6
VGG16 (transfer learning)	165,700,000	31.0
MobileNet (lightweight)	3,200,000	23.7
Proposed Hybrid Quantum-Classical Model	3,200,000	48.0

Discuss the actual trends once results are obtained for example: whether the hybrid model achieves comparable accuracy to the classical CNN baselines while using substantially fewer parameters due to the compact quantum layer; how classification performance varies with circuit depth and qubit count; which tumor classes are most frequently confused, based on the confusion matrix; and how these findings compare with prior quantum machine learning studies discussed in Section II.]

Overall, the discussion should emphasize the accuracy-efficiency trade-off, the sensitivity of the model to quantum circuit hyperparameters, and the practical implications for deployment in resource-constrained clinical settings.

A. Ablation Study

An ablation study is conducted to analyze the effect of key design choices, including the number of qubits, the number of variational layers (circuit depth), and the choice of quantum encoding strategy (angle vs. amplitude encoding), on overall classification accuracy and training stability. [Insert ablation results and analysis.]

B. Limitations

The proposed framework is evaluated on a classical quantum-circuit simulator rather than physical quantum hardware; consequently, the effects of hardware noise, decoherence, and limited qubit connectivity present on near-term quantum devices are not captured in the current evaluation. Additionally, the quantum layer's dimensionality is constrained by the number of qubits that can be efficiently simulated, which may limit the amount of information that can be encoded from the classical feature extractor.

VI. CONCLUSION AND FUTURE WORK

This paper presented a Hybrid Quantum-Classical Deep Learning Framework for efficient brain tumor classification using MRI images, combining a classical CNN feature extractor with a Variational Quantum Circuit to achieve a compact yet expressive classification model. Experimental evaluation on a benchmark brain tumor MRI dataset demonstrates the trade-offs between classification accuracy and computational efficiency relative to purely classical CNN architectures. The results suggest that quantum-enhanced layers hold promise for developing lightweight diagnostic tools suitable for resource-constrained clinical environments and near-term quantum hardware.

Future work will focus on validating the proposed framework on physical quantum hardware to assess the impact of hardware noise, extending the approach to additional MRI modalities and tumor grading tasks, exploring alternative quantum encoding and ansatz designs, and investigating quantum transfer learning strategies to further improve scalability to larger and more diverse clinical datasets.

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