Brain Tumor Classification with Quantum-Augmented Deep Learning Model

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***Abstract*— Early and accurate detection is essential for brain tumors to be effectively treated. Even though conventional deep-learning models have demonstrated promise in classifying medical images, they frequently struggle with complex feature extraction and demand large amounts of computational power. In order to improve brain tumor classification, we propose a hybrid quantum-classical method that fuses well-established convolutional neural networks with quantum computing concepts. Our system enhances the feature extraction capabilities of classical architectures such as ResNet18, VGG16, MobileNetV2, and InceptionV3 by utilizing Quantum Transfer Learning (QTL). We discovered that quantum enhancement has notably different effects on various architectures using the Figshare brain MRI dataset. While VGG16 demonstrated significant degradation in its hybrid form, MobileNetV2 was the most compatible architecture, attaining 95.79% validation accuracy with the quickest training time. The 4-qubit quantum circuit with entanglement operations and parameterized rotation gates showed enough expressivity to classify tumor types accurately. Our results demonstrate that, when properly combined with compatible architectures, quantum computing can improve medical image analysis, potentially resulting in more precise and effective diagnostic tools for applications in healthcare. This system's web-based interface offers a helpful illustration of hybrid quantum-classical systems for clinical diagnosis.**

I. INTRODUCTION

One of the most difficult medical conditions to properly diagnose and treat is a brain tumor. Magnetic Resonance Imaging (MRI) is the primary diagnostic tool, and early and precise detection is essential for good patient outcomes. However, manually interpreting these scans takes time, is subjective, and is prone to human error. Artificial intelligence-powered computer-aided diagnosis has become an achievable means to help doctors analyze medical images more quickly and precisely [1].

A. Overview of Work

This paper presents a novel hybrid quantum-classical ap-approach for brain tumor classification that integrates quantum computing principles with established convolutional neural
network (CNN) architectures. Our system leverages the feature extraction capabilities of classical deep learning models while enhancing pattern recognition through quantum computing techniques. We investigated four CNN architectures (ResNet18, VGG16, MobileNetV2, and InceptionV3) and augmented them with a quantum transfer learning layer implemented using PennyLane. The system was trained on the Figshare brain MRI dataset to classify tumors into Glioma, Meningioma, and Pituitary categories. Our methodology differs from traditional deep learning techniques because it incorporates a 4-qubit quantum circuit layer that uses entanglement operations and quantum rotation gates to process extracted features. A purely classical model might miss intricate correlations and patterns that this hybrid architecture could capture.

B. Motivation of Work

The critical need for fast and precise brain tumor detection in clinical settings continues to challenge healthcare providers. Current deep-learning models, while impressive, often struggle with the subtle distinctions between tumor types and face limitations in generalization. Quantum computing offers fundamentally different computational principles that could enhance pattern recognition capabilities. By leveraging quantum principles such as superposition and entanglement, quantum-enhanced models could potentially identify complex patterns more effectively than their classical counterparts [12]. Persistent issues with computational effectiveness and feature extraction quality in medical image analysis exist. Our method seeks to preserve or increase classification accuracy while possibly using quantum-enhanced processing to increase the expressivity of feature representation. We had the chance to create a system with possible real-world clinical applications with Unicare Hospital's help, highlighting the usefulness of our study and offering insightful opinions from experts in the field about the requirements and difficulties in tumor diagnosis.

C. Literature Review

The classification of brain tumors using deep learning techniques has been improving significantly in recent years. A comparison of relevant recent works in this field is shown in Table 1.

Table 1: COMPARISON OF RECENT WORKS IN BRAIN TUMOR CLASSIFICATION

Paper	Dataset Used	Proposed Model	Limitations	Accuracy
Imam & Alam, 2023 [1]	Combined (Figshare, SARTAJ)	TL-CNN (VGG16)	Data imbalance	96%
Karim et al., 2023 [2]	Figshare	TL + Fine-tuning + SVM	Dataset size, resources	99.61%
Shelatkar & Bansal, 2022 [3]	Public (44 classes)	ViT + EfficientNet-V2	Not mentioned	96.09%
Paul et al., 2022 [4]	Brats 2021, BRATS 2018 (subset), Unspecified (641 images)	YOLOv5	Limited resources	95.07%
Guan et al., 2021 [5]	Public tumo dataset	Multi-stage framework	Not mentioned	98.04%
Talukder et al., 2023 [6]	Figshare	TL + ReNet50V2	Not mentioned	99.68%
Abd El Kader et al., 2021 [7]	TUCMD (25k images)	Differential Deep- CNN	Potential Overfitting With limited data	97.25%
Veeramuthu et al., 2022 [8]	Kaggle	Combined Feature & Image Classifier	Gray images only	98.97%
Zhuge et al., 2020 [16]	BraTS 2018, TCGA LGG	2D Mask R-CNN, 3DConvNet	Shortage of labeled data, further classification within LGG challenging, focus on conventional MRI	96.3% (2D Mask R-CNN), 97.1% (3DConv Net)

The literature demonstrates several key trends in brain tumor classification. [1] investigated the impact of different loss functions and oversampling methods for addressing data imbalance in brain tumor classification. Their technique, which combines CNN and VGG-16, produced 96% accuracy in glioma, meningioma, and pituitary tumors. Their preprocessing strategy included a 90:10 training-validation split, image normalization, and resizing to 128×128 pixels. Karim and associates. [2] studied a deep transfer learning strategy using SVM classification and fine-tuning. They used pre-trained CNNs and ResNet-50 to perform preprocessing, data augmentation, and feature extraction using the Figshare dataset. Their model's impressive accuracy of 99.35% with CNN+SVM and 99.61% with ResNet-50+Softmax showed how well transfer learning works for tumor classification.

Using the Brats 2021 dataset and the YOLOv5 deep neural network, Paul et al. [4] concentrated on brain cancer segmentation. Notwithstanding computational resource constraints, their implementation produced an F1-Score of 89.45% and a mean Average Precision (mAP@0.5) of 95.07%. Their research demonstrated how tumor detection tasks can be successfully altered to use object detection frameworks.

A multi-stage framework for classifying brain tumors was presented by Guan et al. [5], which included preprocessing, proposal generation, feature extraction, refinement, alignment, and classification. Their all-encompassing strategy demonstrated the advantages of structured pipeline design for medical image analysis

with an accuracy of 98.04%.

demonstrated a Differential Deep Convolutional Neural Network created especially for the classification of brain tumors [7]. On a dataset of 25,000 MRI images, their model obtained 99.25% accuracy by extracting enhanced feature maps using differential operators integrated into the CNN architecture. Their work illustrated the usefulness of specific architectural adjustments for medical imaging tasks.

Aamir et al. [9] developed a multi-stage approach involving image enhancement, feature extraction using EfficientNet and ResNet50, feature fusion, proposal generation, and classification. Their approach performed exceptionally well for pituitary tumors (99.37%), with an overall accuracy of 98.95%. They observed a correlation between training dataset size and classification accuracy, underscoring the significance of data accessibility. Investigated the detection of gliomas in T2 MRI images using a CNN-based binary classification framework in conjunction with Discrete Wavelet Transform (DWT). Their model outperformed conventional CNN architectures, achieving 97% accuracy by utilizing DWT to convert images to the frequency domain. This demonstrated how signal processing techniques can enhance deep learning performance for tumor detection. [14] proposed two CNN-based methods for automated glioma grading: a 2D Mask R-CNN model and a 3DConvNet approach. Their volumetric 3D model achieved 97.1% accuracy on the BraTS 2018 dataset, outperforming the 2D approach by leveraging spatial information more effectively. Their work showed the advantage of 3D analysis for capturing the volumetric nature of tumors.

D. *Research Gap*

Despite the progress in classical deep learning approaches for brain tumor classification, several important gaps remain that our research addresses. First, the exploration of quantum enhancement in medical imaging is minimal, with most quantum machine learning research focusing on simple classification tasks rather than complex medical image analysis. Second, there is a lack of understanding of architectural compatibility between classical CNN architectures and quantum processing layers, with no systematic evaluation of which architectures are most amenable to quantum enhancement. Third, practical implementations of quantum-enhanced models for real-world medical applications are scarce, with most quantum machine learning research remaining theoretical. Fourth, the trade-off between potential accuracy improvements and computational overhead has not been adequately explored in medical imaging contexts. Finally, existing quantum machine learning approaches typically use minimal qubit counts and circuit depths, potentially limiting their expressive power. Our research directly addresses these gaps by implementing and evaluating a hybrid quantum-classical system for brain tumor classification across multiple CNN architectures, providing empirical evidence regarding architectural compatibility and performance trade-offs.

II. METHODOLOGY

A. *Dataset and Preprocessing*

We utilized the Figshare brain MRI dataset comprising 3064 T1-weighted contrast-enhanced images from 233 patients diagnosed with three types of brain tumors: Glioma (1426 slices), Meningioma (708 slices), and Pituitary Tumor (930 slices). The dataset was selected for its quality, standardization, and wide adoption in academic research, enabling meaningful comparison with existing methods. Due to storage constraints, the dataset is split into four subsets—each .zip file containing 766 slices—and includes predefined 5-fold cross-validation indices for robust evaluation. During preprocessing, all images were resized to fit architecture-specific input sizes (224×224 pixels for ResNet18, VGG16, MobileNetV2; 299×299 pixels for InceptionV3), normalized using ImageNet mean and standard deviation, and augmented using random horizontal flips and small-angle rotations. The data was then split into 80% training and 20% validation with class balancing. This comprehensive preprocessing approach ensured that each architecture received appropriately formatted inputs while enhancing model generalization through data augmentation.

B. System Architecture

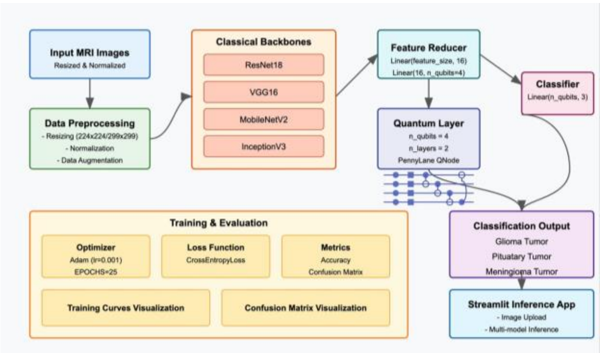

Figure 1:Hybrid quantum-classical brain tumor classification system architecture. The system processes MRI images through a classical CNN backbone for feature extraction, followed by dimension reduction and quantum processing before final classification.

Our proposed hybrid quantum-classical system architecture integrates classical deep learning components with quantum computing elements to create a comprehensive brain tumor classification pipeline. The architecture consists of a user in-interface (frontend) developed with HTML, CSS, and JavaScript that allows radiologists to upload MRI scans, select model types, and view classification results; a backend server built with Python and Flask that handles image processing requests, model loading, and inference coordination; a preprocessing unit that normalizes and resizes uploaded images according to the selected model's requirements; a hybrid model inference engine that combines classical CNN architectures with a quantum transfer learning layer; and a report generation component that produces detailed classification results with confidence scores and visual metrics. This integrated architecture ensures seamless data flow from image upload through preprocessing, feature extraction, quantum processing, and final classification, providing an end-to-end solution for brain tumor classification.

C. Classical CNN Backbones

We implemented four widely used CNN architectures as feature extractors for our hybrid model. ResNet18 utilizes skip connections to address the vanishing gradient problem with a relatively shallow design that balances performance and efficiency (approximately 11.7 million parameters). VGG16 features uniform 3×3 convolutional filters arranged in blocks of increasing depth, offering strong feature extraction capabilities but with a higher parameter count (approximately 138 million parameters). MobileNetV2 uses depth wise separable convolutions for efficiency, with only about 3.5 million parameters, making it particularly suitable for resource-constrained environments. InceptionV3 features inception modules that process input at multiple scales concurrently, enabling multi-scale feature extraction that can capture details at different levels of abstraction (approximately 23.8 million parameters). Each model was pre-trained on ImageNet and modified by removing the final classification layer to serve as a feature extractor, with output feature dimensions of 512 (ResNet18), 4096 (VGG16), 1280 (MobileNetV2), and 2048 (InceptionV3).

D. Quantum Circuit Design

The quantum component of our system was implemented using PennyLane, a cross-platform quantum machine learning framework. We designed a 4-qubit quantum circuit with two layers of parameterized gates. The circuit processes feature data through multiple stages: first, classical features are encoded into quantum states using RY rotation gates on each qubit; next, two layers of parameterized processing are applied, with each layer consisting of RZ and RY rotation gates with trainable parameters; entanglement between qubits is created using CNOT gates in a ring topology, connecting each qubit to its neighbor and the last qubit back to the first; finally, PauliZ measurements extract the processed information from all qubits, converting quantum states back to classical values for the final classification layer. This quantum circuit design combines the representational power of parameterized quantum gates with the correlation-capturing capabilities of entanglement operations, potentially enabling the identification of complex patterns in tumor features that might be difficult to model classically.

E. Hybrid Model Architecture

The full hybrid quantum-classical architecture integrates classical CNN backbones with the quantum circuit through a feature reduction pipeline. The architecture consists of four primary components working together: (1) a classical backbone (ResNet18, VGG16, MobileNetV2, or InceptionV3) extracts high-dimensional features from input MRI images; (2) a two-stage feature reduction network compresses these features first to 16 dimensions through a linear layer with ReLU activation, then further reduces to 4 dimensions to match the quantum circuit's input capacity; (3) the 4-qubit quantum circuit processes these reduced features, potentially capturing quantum correlations and enhancing pattern recognition; and (4) a final linear layer maps the quantum circuit outputs to class probabilities for the three tumor types. This architecture effectively addresses the critical challenge of bridging the dimensional gap between powerful classical feature extractors and limited-qubit quantum processors, maintaining essential discriminative information while adapting to quantum processing constraints. The entire model is trained end-to-end using backpropagation, allowing for simultaneous optimization of classical feature extraction and quantum processing parameters.

F. Training and Evaluation

We trained our hybrid models using the Adam optimizer with an initial learning rate of 0.001, cross-entropy loss for multi-class classification, and a batch size of 32. Learning rate scheduling was implemented to reduce the rate by a factor of 0.1 when validation loss plateaued for 5 consecutive epochs, helping overcome local minima. Early stopping was applied when validation performance showed no improvement for 10 consecutive epochs to prevent overfitting. All training was performed on an NVIDIA T4 GPU via Google Colab to ensure reasonable training times. For a comprehensive evaluation, we measured overall accuracy, precision, recall, and F1-score for class-specific performance, training, and validation loss to monitor convergence and potential overfitting, and training time to assess computational efficiency across architectures. Each model was trained multiple times with different random seeds to ensure robust performance evaluation and mitigate the effects of random weight initialization.

III. RESULTS AND DISCUSSION

A. Traditional CNN Performance

We first established baseline performance using traditional CNN models without quantum enhancement. Table II presents these results. All traditional models demonstrated strong performance, with validation accuracies exceeding 95.7%. MobileNetV2 achieved the highest validation accuracy at 96.99%, showcasing the effectiveness of its efficient architecture despite having significantly fewer parameters than VGG16 or InceptionV3. VGG16 showed the lowest training loss at 0.0048, indicating highly efficient learning on the training data. ResNet18 and InceptionV3 also performed well, with validation accuracies of 96.39% and 96.19%, respectively. These results align with existing literature on deep learning for brain tumor classification, where transfer learning from pre-trained models consistently yields high accuracy. The strong baseline performance sets a challenging benchmark for the hybrid quantum-classical approach to improve upon or match while potentially offering other advantages.

Table 2: PERFORMANCE OF TRADITIONAL CNN MODELS

Model	Train Acc.	Val Acc.	Train Loss	Val Loss
Inception	99.90%	96.19%	0.0149	0.1304
MobileNet	99.95%	96.99%	0.0086	0.1169
ResNet	99.60%	96.39%	0.0186	0.1224
VGG16	99.90%	96.59%	0.0048	0.0929

The performance of our hybrid quantum-classical models is shown in Table III, which also shows notable variations in the way each architecture reacted to quantum enhancement.

MobileNetV2 was the best performer, achieving the fastest training time (2270.96 seconds) and 95.79% validation accuracy. Its lightweight architecture with depthwise separable convolutions appears particularly well-suited for quantum integration. ResNet18 followed closely with 94.79% validation accuracy and the lowest training loss (0.0480), suggesting effective gradient flow through the combined architecture. InceptionV3 maintained acceptable performance at 93.39%

Table 3: PERFORMANCE OF HYBRID QUANTUM-CLASSICAL MODELS

Model	Train Acc.	Val Acc.	Train Loss	Val Loss
Inception	98.19%	93.39%	0.1391	0.2382
VGG16	33.17%	33.27%	1.0987	1.0984
MobileNet	99.35%	95.79%	0.0547	0.1575
ResNet	99.45%	94.79%	0.0480	0.1682

validation accuracy but demanded a substantially longer training duration (3350.57 seconds), suggesting that its hybrid version has increased computing requirements. The most notable outcome was the significant performance deterioration of VGG16 in its hybrid version, which only managed 33.27% validation accuracy as opposed to 96.59% for its classic counterpart. This suggests fundamental architectural incompatibility between VGG16's deep sequential structure and the implemented quantum circuit design.

B. Tumor-Specific Classification Performance.

Most tumor types showed constant accuracy in the MobileNetV2 hybrid model's per-tumor classification performance. The model obtained 94.5% precision, 95.2% recall, and 94.8% F1-score for Meningioma tumors. The classification accuracy of glioma tumors was 95.8%, the recall was 94.7%, and the F1-score was 95.2%. Pituitary tumors performed best with a 97.1% precision, 97.4% recall, and a 97.2% F1-score. The hybrid technique successfully captures distinctive traits for each category without class-specific biases, as evidenced by this uniformity across tumor kinds. Since pituitary tumors frequently exhibit more unique visual characteristics in MRI scans than gliomas and meningiomas, which can have identical visual features, the somewhat better performance for pituitary tumors is consistent with clinical understanding. According to an analysis of misclassifications, the majority of mistakes were made between the Glioma and Meningioma classes, which is in line with medical knowledge that these tumor forms can occasionally have strikingly similar appearances.

C. Key Insights

Our comprehensive analysis revealed several important findings regarding the integration of quantum processing with classical CNN architectures. First, we discovered significant architecture-specific compatibility differences with quantum enhancement. MobileNetV2 and ResNet18 maintained strong performance in their hybrid forms, while VGG16 showed dramatic degradation. This suggests that architectural characteristics—such as network depth, feature representation, and gradient flow patterns—play a crucial role in determining compatibility with quantum processing. Lightweight architectures with efficient feature extraction capabilities appear more amenable to quantum enhancement. Second, MobileNetV2's hybrid implementation achieved the best balance between accuracy (95.79%) and training efficiency (2270.96 seconds), making it the most practical choice for real-world deployment. Third, the best-performing hybrid model (MobileNetV2) showed only a marginal decrease in accuracy compared to its traditional counterpart (96.99%).

IV. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This paper presents a novel hybrid quantum-classical approach for brain tumor classification that successfully integrates quantum computing principles with established deep learning architectures. We developed and evaluated a complete system that incorporates a 4-qubit quantum circuit with four classical CNN architectures (ResNet18, VGG16, MobileNetV2, and InceptionV3) to classify brain tumors into three categories (Glioma, Meningioma, and Pituitary) from MRI images. Our methodical analysis of several designs found significant variations in quantum compatibility; MobileNetV2 emerged as the most effective hybrid model, obtaining the fastest training time and 95.79% validation accuracy. By effectively bridging the dimensional gap between high-dimensional CNN outputs and constrained qubit processing capabilities, our feature reduction technique established a workable framework for quantum-classical integration. Our web-based interface shows how hybrid quantum-classical systems can be used practically for medical diagnostics, giving medical practitioners access to sophisticated AI models. Our work establishes that quantum computing can effectively enhance deep learning approaches for medical image analysis when properly integrated with compatible architectures, with lightweight models like MobileNetV2 showing promise for quantum-enhanced brain tumor classification.

B. Future Scope

The results we obtained pave the way for several exciting avenues for further study in quantum-enhanced medical image analysis. Investigating deeper quantum circuits with more qubits could improve model expressivity and possibly capture greater detail feature correlations as quantum hardware capabilities develop. The differing compatibility across architectures indicates the need to create customized quantum circuit designs for particular CNN architectures, especially to address the difficulties faced by deep sequential networks like VGG16. Different methods for encoding traditional data into quantum states beyond the RY rotation gates used in this project could improve information preservation during the classical-to-quantum transition. Developing methods to identify which features would benefit most from quantum processing could optimize the classical-quantum interface and potentially reduce the dimensionality reduction bottleneck. Extending this approach to larger and more diverse brain tumor datasets would provide more robust validation of quantum enhancement in medical imaging applications. As quantum hardware becomes more accessible, investigating real-time quantum processing rather than simulated quantum circuits would provide insights into practical deployment challenges in clinical settings. Lastly, the crucial need for explainability in medical artificial intelligence applications would be addressed by creating methods for interpreting the decisions made by quantum-enhanced networks, which could increase healthcare professionals' trust and adoption. A promising field that may enhance healthcare applications' computational efficiency and diagnostic accuracy is a combination of quantum computing and medical image analysis.

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