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Quantum-Enhanced Neural Architecture for Brain MRI Segmentation and Diagnosis

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ABSTRACT: Brain tumor detection using Magnetic Resonance Imaging (MRI) is an important task in medical diagnostics because early detection can significantly improve patient survival rates. However, manual examination of MRI scans by radiologists is time-consuming and may lead to diagnostic errors due to human limitations. In this paper, a hybrid quantum-enhanced neural architecture is proposed for automated brain tumor segmentation and diagnosis. The system combines a classical deep learning model based on the U-Net Convolutional Neural Network (CNN) with a Variational Quantum Circuit (VQC) to improve feature representation and segmentation accuracy. MRI images are first preprocessed through normalization, resizing, and slice extraction from 3D MRI volumes. The CNN extracts spatial features from the MRI slices, and these features are then processed using a quantum circuit to enhance high-level feature correlations. The model is trained and evaluated using the BraTS_2019 brain tumor MRI dataset. Performance is measured using metrics such as Dice Score, Accuracy, Precision, Recall, and Intersection-over-Union (IoU). Experimental results show that the hybrid CNN-VQC model improves tumor segmentation performance and provides reliable diagnostic predictions. The proposed system also includes a visualization interface for displaying segmentation results and tumor confidence scores.

KEYWORDS: Brain Tumor Segmentation, MRI, Quantum Machine Learning, Variational Quantum Circuit (VQC), U-Net, Convolutional Neural Network (CNN), Medical Image Analysis.

I. INTRODUCTION

Brain tumors are one of the most serious neurological disorders and require accurate and timely diagnosis for effective treatment planning. Magnetic Resonance Imaging (MRI) is widely used for brain tumor detection because it provides high-resolution images of brain tissues. However, manual analysis of MRI scans by medical experts is time-consuming and may produce inconsistent results depending on the experience of the radiologist.

In recent years, artificial intelligence and deep learning techniques have been widely applied to medical image analysis. Convolutional Neural Networks (CNN) and U-Net architectures have shown strong performance in image segmentation tasks. These models are capable of automatically identifying tumor regions from MRI scans. Despite their success, traditional deep learning models often require large datasets and high computational resources.

To address these limitations, this research proposes a hybrid quantum-enhanced neural architecture that integrates classical deep learning with quantum machine learning techniques. The proposed system uses a U-Net based CNN to extract spatial features from MRI images and a Variational Quantum Circuit (VQC) to enhance feature learning. By combining classical and quantum approaches, the system aims to improve segmentation accuracy and computational efficiency. The developed framework also includes a user-friendly interface that allows users to upload MRI scans and visualize tumor segmentation results.

II. LITERATURE SURVEY

Medical image segmentation has been extensively studied using deep learning techniques. Goodfellow et al. introduced deep neural networks that significantly improved automated disease detection and medical image analysis. U-Net architecture proposed by Ronneberger et al. became one of the most widely used models for biomedical image segmentation because of its encoder-decoder structure and skip connections that capture both global and local image features.

Several studies have focused on brain tumor detection using MRI images. The BraTS_2019_dataset introduced by Menze et al. provides a benchmark for evaluating brain tumor segmentation algorithms. Many researchers have applied convolutional neural networks to analyze this dataset and achieved high segmentation accuracy.

Recently, quantum machine learning has gained attention as a promising approach for enhancing classical machine learning models. Havlíček et al. demonstrated that quantum feature spaces can improve classification tasks using quantum circuits. Similarly, other studies have explored hybrid quantum-classical models for medical image classification. However, most existing works focus mainly on classification rather than tumor segmentation. Therefore, there is a need for a hybrid model that integrates deep learning segmentation with quantum feature enhancement. The proposed system aims to address this research gap by combining CNN-based segmentation with Variational Quantum Circuits.

III. PROPOSED METHODOLOGY AND DISCUSSION

System Overview

The proposed system is designed as a hybrid deep learning and quantum machine learning framework for automated brain tumor segmentation. The overall workflow includes dataset preparation, preprocessing, classical feature extraction, quantum feature enhancement, and segmentation prediction.

A. Dataset Preparation

The MRI data used in this research is obtained from the BraTS (Brain Tumor Segmentation) dataset, which is widely used as a benchmark dataset for brain tumor segmentation research. The dataset contains multi-modal MRI scans including FLAIR, T1, T1CE, and T2 sequences along with ground truth tumor segmentation masks provided by medical experts. These MRI scans are stored in NIfTI (.nii) format and represent 3D volumetric brain images. For training and evaluation purposes, the dataset is divided into training, validation, and testing sets. Typically, 70% of the data is used for training the model, 15% for validation, and the remaining 15% for testing. This split ensures that the model is evaluated on unseen data and avoids overfitting during training.

B. Data Preprocessing

MRI images often contain noise, intensity variations, and scanner-dependent artifacts that may affect the performance of deep learning models. Therefore, several preprocessing operations are applied before feeding the images into the neural network. First, intensity normalization is applied to standardize pixel intensity values across different MRI scans. This reduces variations caused by different imaging devices and improves model generalization. Next, the MRI images are resized to a fixed resolution so that all input images have the same dimensions for the neural network.

Since the MRI scans are provided as 3D volumes, slice extraction is performed to convert the volumetric images into 2D slices. These slices are easier to process using convolutional neural networks. Additional preprocessing operations such as noise reduction, contrast normalization, and image augmentation (including rotation and flipping) are also applied to improve model robustness.

C. Classical Feature Extraction Using U-Net

The core segmentation model used in this research is based on the U-Net architecture. U-Net is a widely used convolutional neural network designed specifically for biomedical image segmentation tasks. It consists of an encoder-decoder structure connected through skip connections that allow the model to capture both local and global image features.

The encoder part of the network performs feature extraction using multiple convolutional layers followed by pooling operations. These layers capture important spatial patterns such as edges, textures, and tumor boundaries. As the network depth increases, higher-level features representing complex tumor structures are learned.

The decoder part of the network reconstructs the segmentation mask using up-sampling and convolutional layers. Skip connections are used to combine high-resolution features from the encoder with the decoder layers. This helps the model retain fine-grained spatial information required for accurate tumor boundary detection.

The output of the U-Net model is a pixel-wise tumor segmentation mask that highlights the tumor region within the MRI slice.

D. Variational Quantum Circuit (VQC) Integration

To improve the feature learning capability of the proposed system, a Variational Quantum Circuit (VQC) module is integrated with the classical U-Net architecture. Instead of processing raw MRI images directly, the quantum module operates on high-level features extracted from the bottleneck layer of the U-Net network. These features represent compressed spatial information learned by the convolutional encoder during segmentation.

In the proposed architecture, a **4-qubit quantum circuit** is used to encode the feature vector obtained from the CNN. The classical feature vector $x = [x_1, x_2, x_3, x_4]$ is mapped to quantum states using **angle embedding**, where each feature controls the rotation of a qubit through rotation gates. The initial quantum state can be expressed as

$$|\Psi(x)\rangle = \otimes_{i=1}^4 R_y(x_i) |0\rangle$$

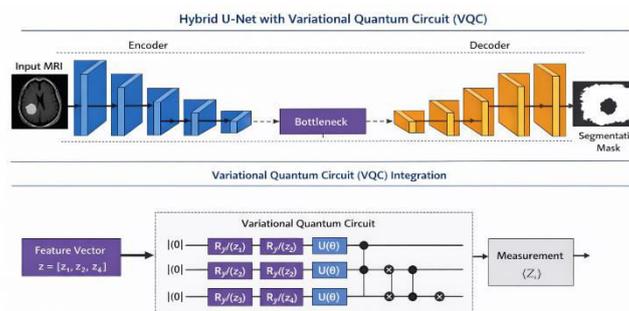
where $R_y(x_i)$ represents a rotation gate applied to the i^{th} qubit. After encoding, parameterized quantum gates with trainable parameters θ are applied to form the variational circuit, represented as

$$|\Psi(\theta, x)\rangle = U(\theta) |\Psi(x)\rangle.$$

To capture correlations between different features, **entanglement operations** are introduced using controlled gates such as CNOT. Finally, the quantum state is measured using the expectation value of the Pauli-Z operator,

$$y_i = \langle \Psi(\theta, x) | Z_i | \Psi(\theta, x) \rangle.$$

The measured outputs form a **quantum-enhanced feature vector**, which is combined with the classical CNN output to improve tumor confidence estimation and segmentation accuracy. This hybrid approach enables the model to learn complex feature relationships within MRI data more effectively.



E. Hybrid Model Training

The hybrid CNN-VQC model is trained using a combination of classical backpropagation and quantum gradient optimization methods. During training, the model learns both convolutional parameters and quantum circuit parameters simultaneously.

Dice loss and Binary Cross Entropy loss functions are used to measure the difference between predicted tumor masks and ground truth segmentation masks. These loss functions help the model learn accurate tumor boundaries while minimizing segmentation errors.

The Adam optimizer is used for updating the model parameters during training. Training is performed over multiple epochs until the model converges and achieves stable performance on the validation dataset.

F. Evaluation Metrics

To evaluate the performance of the proposed system, several standard medical image segmentation metrics are used. Accuracy measures the overall correctness of predictions, while Precision and Recall evaluate the model's ability to correctly detect tumor pixels.

The Dice Score and Intersection-over-Union (IoU) metrics are particularly important for segmentation tasks because they measure the overlap between the predicted tumor region and the ground truth mask. Higher Dice and IoU values indicate better segmentation performance.

G. Visualization and Diagnostic Output

After segmentation is completed, the system generates visual outputs that help users interpret the prediction results. The system displays the original MRI slice, the predicted tumor mask, and an overlay image showing the tumor region highlighted on the MRI scan.

In addition, the model provides a tumor confidence score indicating the probability of tumor presence. These visualization and diagnostic outputs improve the interpretability of the model and assist researchers or clinicians in analyzing tumor detection results.

System Architecture

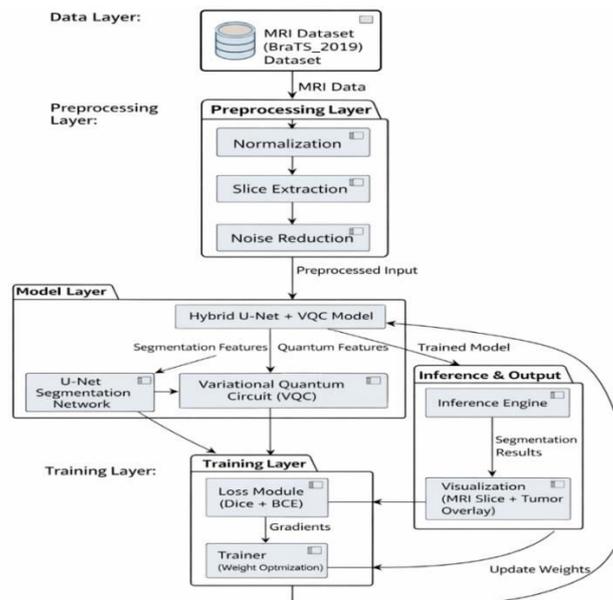


Fig 1 System Architecture

The overall architecture of the proposed hybrid CNN-VQC model is illustrated in Fig. 1. The architecture consists of five major components: data layer, preprocessing layer, model layer, training layer, and inference output layer. Each component performs a specific task in the brain tumor segmentation pipeline. The data layer contains MRI scans obtained from the BraTS_2019_dataset. These images are first processed in the preprocessing layer where

normalization, slice extraction, and noise reduction are applied. The processed MRI slices are then passed to the hybrid deep learning model.

The model layer consists of two main modules: the U-Net segmentation network and the Variational Quantum Circuit (VQC). The U-Net architecture extracts spatial features from MRI slices using encoder and decoder blocks. These extracted features are then passed to the VQC module, which enhances feature representation using quantum operations. During the training stage, the loss module computes segmentation errors using Dice loss and Binary Cross-Entropy loss functions. The trainer updates model weights using gradient-based optimization techniques. After training, the inference engine generates segmentation results that highlight tumor regions in MRI images.

H. Algorithm: Hybrid U-Net+VQC Brain Tumor Segmentation

- Step 1: Load MRI dataset from BraTS database
- Step 2: Apply preprocessing techniques such as normalization and slice extraction
- Step 3: Convert 3D MRI volume into 2D slices
- Step 4: Feed MRI slices into U-Net encoder for feature extraction
- Step 5: Generate feature representation at the bottleneck layer
- Step 6: Encode extracted features into quantum states using angle embedding
- Step 7: Apply parameterized quantum gates and entanglement operations in VQC
- Step 8: Measure quantum states to obtain enhanced feature representation
- Step 9: Decode features using U-Net decoder to generate tumor segmentation mask
- Step 10: Compare predicted mask with ground truth using Dice and BCE loss
- Step 11: Update model weights using Adam optimizer
- Step 12: Generate final segmentation results and tumor visualization

IV. ADVANTAGES OF THE PROPOSED SYSTEM

The proposed hybrid U-Net–VQC architecture offers several advantages over traditional medical image segmentation methods. By integrating a Variational Quantum Circuit with a classical deep learning model, the system can capture complex feature relationships present in MRI images. This hybrid approach enhances feature representation and improves the model’s ability to detect subtle tumor patterns that may not be easily identified using only classical neural networks. Additionally, the use of the U-Net architecture ensures accurate tumor localization through its encoder–decoder structure and skip connections, which help preserve spatial information while reconstructing precise segmentation masks.

Another advantage of the proposed system is its ability to provide clear visualization and interpretation of segmentation results. The system allows users to analyze MRI scans and view predicted tumor masks along with overlay visualizations, which helps in understanding the detected tumor regions more effectively. Furthermore, the hybrid architecture offers flexibility for future improvements, as more advanced quantum circuits and hybrid learning techniques can be integrated with deep learning models. This makes the proposed framework a promising solution for future research and development in AI-assisted medical image analysis and brain tumor diagnosis.

V. RESULTS

The proposed hybrid CNN–VQC model was evaluated using MRI images from the BraTS brain tumor dataset. The dataset contains multi-modal MRI scans with annotated tumor regions, which makes it suitable for evaluating segmentation algorithms. The trained model was tested on unseen MRI slices to evaluate its ability to identify tumor regions accurately.

The segmentation results demonstrate that the proposed hybrid model can successfully detect tumor regions and generate accurate segmentation masks. The predicted tumor mask highlights abnormal tissue areas within the MRI image while preserving normal brain structures. Additionally, the generated segmentation outputs closely match the ground truth annotations provided in the dataset, indicating reliable tumor localization. The visualization of tumor regions through overlay images further assists in verifying the accuracy of the segmentation results and improves interpretability for medical analysis.

Figures below shows an example MRI slice used as input for tumor detection, and the manually annotated tumor region provided in the BraTS dataset.

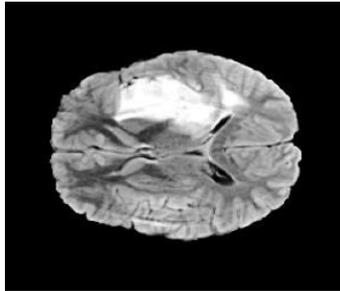


Fig 2 Brain Slice



Fig 3 Actual Tumor at that slice



Fig 4 Predicted Tumor Segmentation



Fig 5 Tumor Overlay on MRI Image

The overlay visualization combines the predicted tumor mask with the original MRI image, making it easier to identify the tumor location.

The results indicate that the hybrid CNN-VQC architecture can effectively detect tumor regions in MRI images. The segmentation masks generated by the model closely match the ground truth annotations, demonstrating the ability of the proposed system to identify abnormal brain tissue accurately.

Streamlit-Based Visualization Interface

To facilitate interactive visualization and analysis of segmentation results, a lightweight web-based interface was developed using the Streamlit framework. Streamlit allows the proposed hybrid U-Net-VQC model to be deployed as an interactive application where users can upload MRI images and observe the segmentation results in real time. The interface processes the uploaded MRI slice, sends it to the trained segmentation model, and displays the predicted tumor mask along with an overlay visualization highlighting the detected tumor region. This interface simplifies the interaction between the user and the underlying machine learning model, enabling researchers or clinicians to easily analyze tumor localization results without directly interacting with the code. Streamlit also enables dynamic visualization features such as changing MRI slices, adjusting display parameters, and re-running segmentation on selected images.

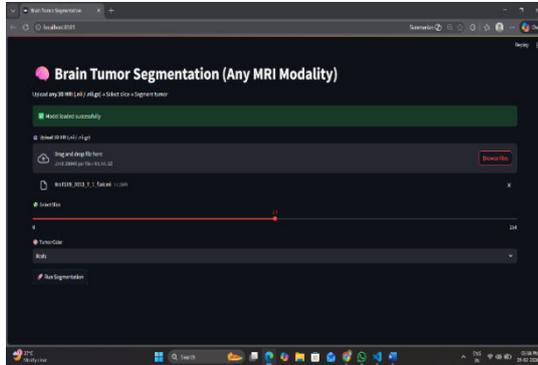


Fig 6 UserInterface using Streamlit

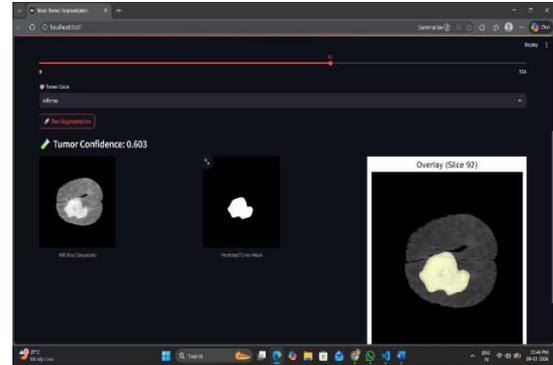


Fig 7 Tumor Overlay on MRI Image Visualization

VI. CONCLUSION

In this paper, a hybrid U-Net–VQC architecture for brain MRI tumor segmentation and diagnosis was proposed. The system integrates a classical deep learning model with a Variational Quantum Circuit to enhance feature representation and improve segmentation performance. MRI images from the BraTS dataset were used to train and evaluate the model. The proposed approach performs preprocessing, feature extraction using U-Net, and quantum feature enhancement through the VQC module to generate tumor segmentation masks.

Experimental results demonstrate that the hybrid model can effectively detect tumor regions and produce accurate segmentation outputs. The integration of quantum feature processing allows the system to capture complex patterns in MRI data that may not be easily modeled by classical neural networks alone. Visualization of the predicted tumor mask and overlay images further helps in understanding the location and shape of the detected tumor. Overall, the proposed hybrid architecture shows promising potential for improving automated brain tumor detection and medical image analysis.

VII. FUTURE SCOPE

Although the proposed hybrid U-Net–VQC model shows promising results for brain tumor segmentation, there are several directions for future improvements. One possible extension is the integration of real quantum hardware instead of quantum simulators. As quantum computing technology advances, using actual quantum processors may improve computational efficiency and enable more complex quantum models.

Another potential improvement is the use of multi-modal MRI data simultaneously, such as T1, T2, and FLAIR images. Combining multiple MRI modalities could provide richer information about brain tissue structures and improve tumor detection accuracy. Additionally, more advanced quantum neural network architectures can be explored to enhance feature representation and learning capability.

Future research can also focus on optimizing the hybrid architecture for faster inference and real-time clinical applications. Integrating the proposed system with hospital imaging systems could assist radiologists in early tumor detection and treatment planning.

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