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Efficient Brain Tumor Segmentation and Classification Using a Hybrid Qcq-Cnn Model with Quantum Neural Networks

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Abstract: Accurate detection and segmentation of brain tumors from magnetic resonance imaging (MRI) remain critical challenges in intelligent medical diagnosis due to the complexity of tumor structures and variability in imaging conditions. This study presents a novel hybrid quantum-classical deep learning framework, termed QCQ-CNN, for enhanced brain tumor segmentation and classification. The proposed approach integrates Gray Level Co-occurrence Matrix (GLCM)-based texture feature extraction with a convolutional neural network (CNN) to capture spatial and textural representations, followed by a U-Net architecture for precise tumor segmentation. To further improve classification performance, a Quantum Neural Network (QNN) is employed as a decision-making module, leveraging parameterized quantum circuits to model complex nonlinear feature relationships. The framework is evaluated on the BRISC 2025 MRI dataset, which includes multi-class tumor categories and expert-annotated segmentation masks. Performance is assessed using standard metrics such as accuracy, precision, recall, F1-score, and Intersection-over-Union (IoU). Experimental results demonstrate that the proposed model achieves superior segmentation accuracy and classification robustness compared to conventional deep learning methods. The integration of quantum computing enhances the model's generalization capability, particularly in limited and noisy data scenarios. Overall, the proposed hybrid framework provides an efficient and scalable solution for next-generation medical image analysis and intelligent diagnostic systems.

Keywords: Quantum-Classical Hybrid Learning, Quantum Neural Network (QNN), U-Net Architecture, Brain Tumor Detection, MRI Image Segmentation, Gray Level Co-occurrence Matrix (GLCM)

1. Introduction

The rapid advancement of medical imaging technologies, particularly Magnetic Resonance Imaging (MRI), has significantly enhanced the ability to detect and diagnose complex neurological disorders such as brain tumors [1]. However, the increasing volume and complexity of imaging data present substantial challenges for manual interpretation, often leading to variability in diagnosis and delayed clinical decisions [2]. Traditional image analysis methods rely heavily on handcrafted features and rule-based approaches, which are limited in capturing intricate spatial and textural patterns present in medical images [3]. Consequently, there is a growing demand for intelligent, automated systems that can accurately segment and classify tumor regions while maintaining high reliability and efficiency [4].

This figure 1 presents a comparative visualization of axial MRI brain scans, illustrating a normal brain image on the left and a malignant tumor case on the right. The normal MRI image exhibits uniform tissue intensity and well-defined anatomical structures without any visible abnormalities. In contrast, the malignant image shows a distinct hyperintense region, indicating the presence of a tumor with irregular shape and disrupted tissue patterns [5]. This visual distinction emphasizes the need for advanced automated detection and classification methods to accurately identify and analyze brain tumors in medical imaging [6].

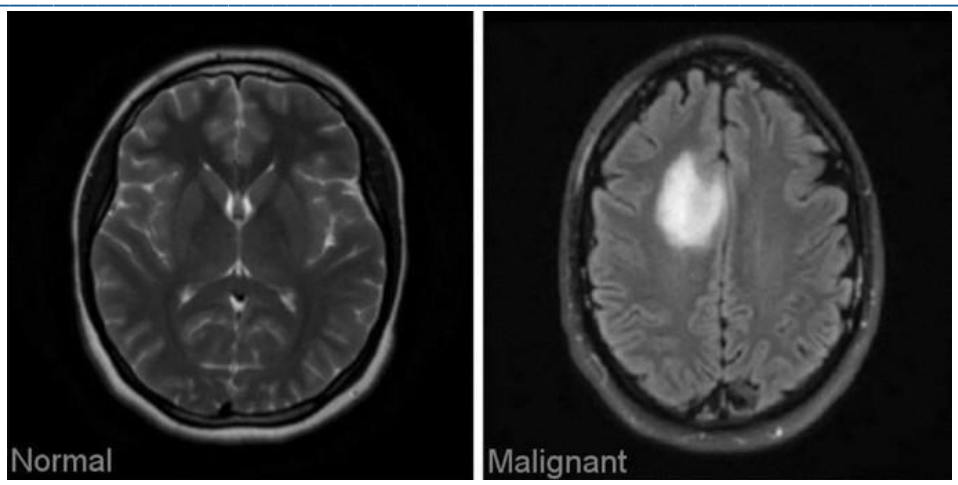

Figure 1 MRI Brain Images Showing Normal and Malignant Tumor Conditions

In recent years, deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in medical image analysis tasks due to their ability to learn hierarchical feature representations directly from raw data [7]. Architectures such as U-Net have become widely adopted for semantic segmentation, enabling precise localization of tumor regions through encoder–decoder structures and skip connections [8]. Despite these advancements, classical deep learning models often require large annotated datasets, are computationally intensive, and may struggle with generalization in noisy or limited-data environments [9]. Additionally, conventional models primarily rely on classical computation, which may limit their ability to model highly complex, nonlinear feature interactions [10].

To address these limitations, hybrid approaches that integrate classical deep learning with emerging quantum computing techniques have gained increasing attention [11]. Quantum Neural Networks (QNNs), leveraging principles such as superposition, entanglement, and parameterized quantum circuits, offer enhanced representational capacity for complex data distributions [12]. When combined with classical feature extraction methods such as Gray Level Co-occurrence Matrix (GLCM), which effectively captures second-order texture information [13], these hybrid models can significantly improve classification performance [14]. The integration of quantum models at the decision-making stage allows for more expressive nonlinear boundaries while reducing computational overhead through dimensionality reduction performed by classical networks.

Motivated by these developments, this study proposes a hybrid quantum-classical framework that combines GLCM-based texture feature extraction, CNN-based representation learning, U-Net-based segmentation, and QNN-based classification for brain tumor analysis. The proposed approach aims to enhance segmentation accuracy, improve classification robustness, and enable efficient learning in resource-constrained environments. By leveraging both classical and quantum paradigms, the framework addresses the limitations of existing methods and provides a scalable solution for next-generation medical image analysis systems [15]. The effectiveness of the proposed model is validated through extensive experimentation, demonstrating its potential for real-world clinical applications.

2. Literature Review

Bhimavarapu et al [16] suggested a better Fuzzy C-Means (FCM) segmentation method for MRI images that would make things less complicated by choosing the most important form, texture, and color features. The improved Extreme Learning Machine (ELM) classifier did very well, with an accuracy of 98.56%, a precision of 99.14%, and a recall of 99.25%. This classifier consistently did better than other models for all tumor types, with accuracy gains of 1.21% to 6.23%. The suggested model performed exceptionally well on the Figshare dataset, attaining 98.47% accuracy, 98.59% precision, and 98.74% recall, and on the Kaggle dataset, obtaining 99.42% accuracy, 99.75% precision, and 99.28% recall. These results were better than those of other algorithms, especially when it came to finding glioma grades. When compared to other approaches, the model was about 5.39% more

accurate on the Figshare dataset and 6.22% more accurate on the Kaggle dataset. The study's enhancements to the FCM algorithm, despite limitations such artifacts and computing complexity, underscored its promise for more precise and dependable brain tumor classification, marking it as a notable advancement in the domain of brain tumor identification.

JS [17] suggested a new way to segment brain tumors by merging the Multiscale Attention U-Net with the EfficientNetB4 encoder. The model uses EfficientNetB4's compound scaling to get the best features from different resolutions without using too much processing power. The Multi-Scale Attention Mechanism improves the representation of tumor boundaries and hides areas that aren't important by using attention-based skip connections. We did a lot of tests on the Figshare brain tumor dataset, and EfficientNetB4 did better than other versions with an accuracy of 99.79%, an MCR of 0.21%, a Dice Coefficient of 0.9339, and an IoU of 0.8795. The suggested method also did better than the best models in all important areas, showing that it could be a useful tool for accurately segmenting brain tumors in both clinical and research settings.

Khan et al [18] suggested a Region-based Convolutional Neural Network (RCNN) method for automatically finding and separating brain tumors in MRI images, which solves the problems of finding brain tumors quickly and correctly. The methodology emphasized the precise and effective identification of tumorous regions, hence minimizing computational complexity and processing duration. We tested the experimental setup using the BraTS 2020 dataset and used binary evaluation measures based on Dice Similarity Coefficient (DSC) and Mean Average Precision (mAP) to measure its performance. To show how well the suggested method works, the segmentation results were compared to the best methods available. The approach got an average DSC of 0.92 and mAP of 0.92 for 10 patients. The whole dataset had a DSC of 0.89 and mAP of 0.90. These data clearly showed how well the proposed strategy worked.

Hossain et al [19] suggested a new lightweight segmentation model called MicrowaveSegNet (MSegNet) to separate brain malignancies and a new classifier called BrainImageNet (BINet) to sort RMW pictures. The original dataset was produced by taking 300 brain image samples from the sensor-based Microwave Brain Imaging (SMBI) system. We used picture preprocessing and augmentation methods to create 6000 training images for each fold of a 5-fold cross-validation. We compared MSegNet and BINet to the best models for segmentation and classification. For tumor segmentation, the MSegNet got an Intersection-over-Union (IoU) score of 86.92% and a Dice score of 93.10%. For three-class classification using raw RMW pictures, the BINet classifier got 89.33% accuracy, 88.74% precision, 88.67% recall, 88.61% F1-score, and 94.33% specificity. When working with segmented RMW pictures, BINet did better, with 98.33% accuracy, 98.35% precision, 98.33% recall, 98.33% F1-score, and 99.17% specificity. These results show that the suggested cascaded model, which combines MSegNet and BINet, may be successfully added to the SMBI system for precise and quick brain tumor segmentation and classification.

Ullah et al [20] developed a new hybrid method that blends hand-crafted features with Convolutional Neural Networks (CNNs) to make brain tumor segmentation better. This method involved extracting handmade elements from MRI scans, such as those based on intensity, texture, and shape. At the same time, a new CNN architecture was created and trained to find features in the data on its own. The hybrid technique combined the handcrafted features with the features found by the CNN through several pathways to make a new CNN model. The performance was tested using the Brain Tumor Segmentation (BraTS) challenge dataset and other assessment tools as segmentation accuracy, Dice score, sensitivity, and specificity. The results showed that the suggested hybrid method worked better than traditional methods that only used hand-crafted features or CNN-based segmentation. Adding custom features also made the CNN work better, making it a stronger and more generalizable solution. This research has substantial promise for therapeutic applications, wherein precise and efficient brain tumor segmentation is essential. Subsequent study will investigate alternate feature fusion methodologies and the use of supplementary imaging modalities to augment the performance of the suggested strategy.

Mostafa et al [21] proposed a novel and robust automated brain tumor detection method based on segmentation and feature fusion. To enhance localization accuracy, the images were pre-processed using a Gaussian Filter (GF)

and SynthStrip, a tool for brain skull stripping. The methodology was trained and tested on two well-known benchmarks, Figshare and Harvard datasets. The proposed approach achieved impressive results with 99.8% accuracy, 99.3% recall, 99.4% precision, 99.5% F1 score, and an AUC of 0.989. A comparative analysis was conducted against existing deep learning, classical, and segmentation-based approaches, demonstrating superior performance. Additionally, cross-validation on the Harvard dataset yielded 99.3% identification accuracy, further confirming the method's effectiveness. The results indicate that the proposed approach outperforms current methods, offering significant improvements in brain tumor detection and segmentation.

Yuan et al [22] developed an improved instance segmentation method based on the Mask Region-based Convolutional Neural Network (Mask R-CNN). This method uses various new techniques to make the segmentation performance for brain tumors better. The model may better focus on important areas and finer tumor features by using squeeze-and-excitation networks, a channel attention mechanism, and a concatenated attention neural network. The backbone network is made up of Residual Network-50, an attention module, and Feature Pyramid Network (FPN). This lets the model successfully capture the multi-scale features of brain tumors. It also used a Region Proposal Network (RPN) and Region of Interest (RoI) alignment technology to make sure that the area that was segmented matched the shape of the tumor exactly. This research is novel because it combines the deep residual network with the attention mechanism and FPN, replacing the Mask R-CNN's typical backbone. This makes it easier to extract features from brain tumors. The proposed model's experimental findings reveal that it had a 90.72% accuracy rate, which is 0.76% better than the previous model, and a 91.68% recall rate, which is 0.95% better. The Mean Intersection over Union (IoU) was 94.56%, which is a 1.39% improvement. This technology accurately divides MRI scans of brain tumors into sections, making it easy for doctors to find the tumor area, measure its diameter, area, and other features. This gives doctors all the information they need to make a diagnosis.

Aggarwal et al [23] proposed an efficient method for brain tumor segmentation based on an Improved Residual Network (ResNet). The existing ResNet architecture is enhanced by preserving the details of all available connection links and improving the projection shortcuts, allowing these details to be passed through to later phases of the network. This improvement results in higher precision and a faster learning process. The proposed Improved ResNet addresses key components of the original ResNet: the flow of information through network layers, the residual building block, and the projection shortcut. This modification minimizes computational costs and accelerates the overall process. Experimental analysis on the BRATS 2020 MRI dataset demonstrates that the proposed methodology outperforms traditional methods, such as CNN and Fully Convolutional Networks (FCN), showing more than a 10% improvement in accuracy, recall, and F-measure. These results highlight the effectiveness of the improved ResNet in brain tumor segmentation tasks.

Ali et al [24] suggested using two segmentation networks, a 3D CNN and a U-Net, in a simple but effective way to make segmentation predictions better. Both models were trained independently on the BraTS-19 challenge dataset and assessed to generate segmentation maps. The segmentation of tumor sub-regions was very different on these maps, and they were then combined in different ways to make the final prognosis. The proposed ensemble got Dice scores of 0.750 for augmenting tumor, 0.906 for total tumor, and 0.846 for tumor core on the validation set. These results showed that the ensemble worked better than the best current architectures for tumor segmentation accuracy.

Bagyaraj et al [25] presented two automated deep learning networks: a U-Net with dense network and a U-Net-based deep convolution network. A bespoke brain tumor image library of 300 high-grade brain tumor cases and 200 normal instances was used to assess the suggested approach. Data augmentation was used in both the training and validation stages to improve the network's overall performance. When the suggested U-Net-based Dense Convolutional Network (DenseNet) architecture was compared to the conventional U-Net architecture, it was discovered that the DenseNet produced a higher Dice value. The DenseNet design offered superior segmentation efficiency, according to the validation results. Furthermore, the suggested DenseNet performed better than the most advanced algorithms currently in use. The segmented output categorization of tumor risk and normal regions achieved a sensitivity of 88.7%, Jaccard index of 0.839, Dice score of 0.911, F1 score of 0.906, and 100% specificity utilizing the U-Net-based DenseNet architecture, according to validation of test pictures.

Research Gap

The study discovered a substantial gap in current brain tumor segmentation approaches, particularly in their capacity to blend handcrafted data with automated deep learning models for greater accuracy and efficiency. While existing methods such as Fuzzy C-Means (FCM), U-Net, and ResNet have produced promising results, there is still space for improvement in terms of computing complexity and generalization across different datasets. Many techniques struggle to segment tumors in noisy or limited-data environments, or they fail to capture multi-scale characteristics. The proposed models, such as 3D CNN, U-Net with DenseNet, and Improved ResNet, improve precision; however, additional improvement in feature extraction and model fusion is required to provide more robust and accurate segmentation across diverse brain tumor datasets. Furthermore, while some systems rely on accuracy measurements, many fail to successfully combine feature fusion techniques such as squeeze-and-excitation networks and attention processes, which could lead to improved identification, particularly in difficult-to-diagnose tumor kinds. There is also a potential to investigate hybrid models that combine classical and quantum computing, which could lead to new possibilities for future study in medical image segmentation. Future methods should address these constraints by merging cutting-edge segmentation structures with advanced feature fusion techniques, with the goal of improving precision, speed, and generalization across numerous tumor types and imaging modalities.

3. Proposed Methodology

The proposed methodology presents a hybrid quantum-classical framework, QCQ-CNN, for enhanced brain tumor detection and classification from MRI scans. The framework integrates Gray Level Co-occurrence Matrix (GLCM)-based texture feature extraction, Convolutional Neural Networks (CNN) for spatial feature learning, U-Net for precise tumor segmentation, and a Quantum Neural Network (QNN) for classification.

3.1. GRAY LEVEL CO-OCCURRENCE COEFFICIENTS (GLCMS) FOR FEATURE EXTRACTION

The first step of the methodology involves using GLCM to extract second-order texture features from the MRI images. These features capture the spatial arrangement of pixel intensities and help to enhance tumor discrimination, especially in complex regions. After texture extraction, a CNN is employed for hierarchical learning, capturing essential patterns from the raw MRI data. The CNN model, equipped with multiple convolutional layers, learns both local and global features from the image.

Gray level co-occurrence coefficients (GLCMs) have been used in this study. The GLCM coefficients prepare a second-order approach for generating the texture features of images [26]. These coefficients show the conditional joint probabilities of all pairs with combinations of gray levels in the spatial window of interest given two parameters: Interpixel distance (δ) and orientation (θ). The probability measure is stated as the equation (1):

$$P_r(x) = \{C_{ij}|(\delta, \theta)\} \quad (1)$$

Where C_{ij} (the co-occurrence probability between gray levels i and j) is determined as the equation (2):

$$C_{ij} = \frac{P_{ij}}{\sum_{i,j=1}^{G} P_{ij}} \quad (2)$$

where P_{ij} indicates the number of occurrences of gray levels $i\ and\ j$ within the given window, given a certain (δ, θ) pair; and G is the quantized number of gray levels. The sum in the denominator illustrates the total number of gray level pairs (i, j) within the window.

Basic of GLCM surface considers the connection between two neighbouring pixels in one balanced, as the moment arrange surface that represented in Figure 2. The gray esteem connections in a target are changed into the co-occurrence network space by a given bit veil such as 33, 55, 77 and so forward. Within the change from the picture space into the co -occurrence lattice space, the neighbouring pixels in one or a few of the eight characterized bearings can be utilized; regularly, four course such as 0°, 45°, 90°, and 135° is at first respected, and its switch heading (negative heading) can be moreover numbered under consideration.

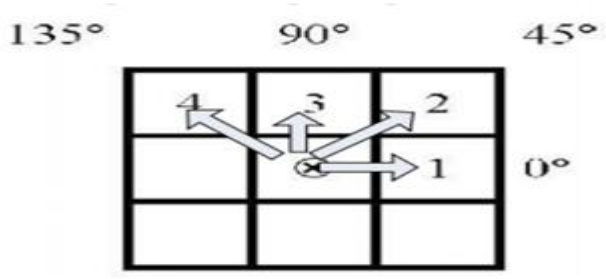

Figure 2. GLCM Direction

3.2. U-Net Architecture

The next stage incorporates U-Net for semantic segmentation. U-Net**'s** encoder-decoder architecture, along with its skip connections, ensures that tumor regions are accurately localized, even with limited data. The segmented regions help isolate the tumor from the surrounding healthy tissue, ensuring that subsequent classification steps are focused only on the relevant tumor areas.

U-Net is a fully connected CNN used for efficient semantic seg mentation of images. Such U-Net deep neural network fits in various analytical tasks of wide-ranging application. This is particularly useful where the input data is the form of images. This architecture has several applications ranging from consumer videos, earth observations and medical imaging [27]. The U-Net architecture is based on an autoencoder network where the network will copy its inputs to its outputs [28]. An autoencoder network functions by compressing the input image into a latent-space representation which is simply a compressed representation of the images indicating which data points are closest together [29]. The compressed data is later reconstructed to produce an output. An autoencoder network contains two paths, an encoder and a decoder. The encoder compresses the data into a latent space representation while the decoder is used for the reconstruction of the input data from its latent-space representation. U-Net uses a convolutional autoencoder architecture where the convolutional layers are used to encode and decode the input images.

Similarly, to an autoencoder network, U-Net contains two paths, a contraction path (encoder) and a symmetric expanding path (decoder). The encoder path of U-Net captures the context of the input image, this path is simply a pipeline of convolutional and pooling layers. The decoder path uses transposed convolutions enabling precise localization. There is no fully connected feedforward layer (or dense layer) in the U-Net, and it only contains the stacks of convolutional layers and max-pooling layers. Although U-Net was originally designed for 572 × 572 images, it can be easily modified to work with any image dimension. Several stacked convolutional layers can enable the network to learn more precise features from the compressed input images, see Figure.3.

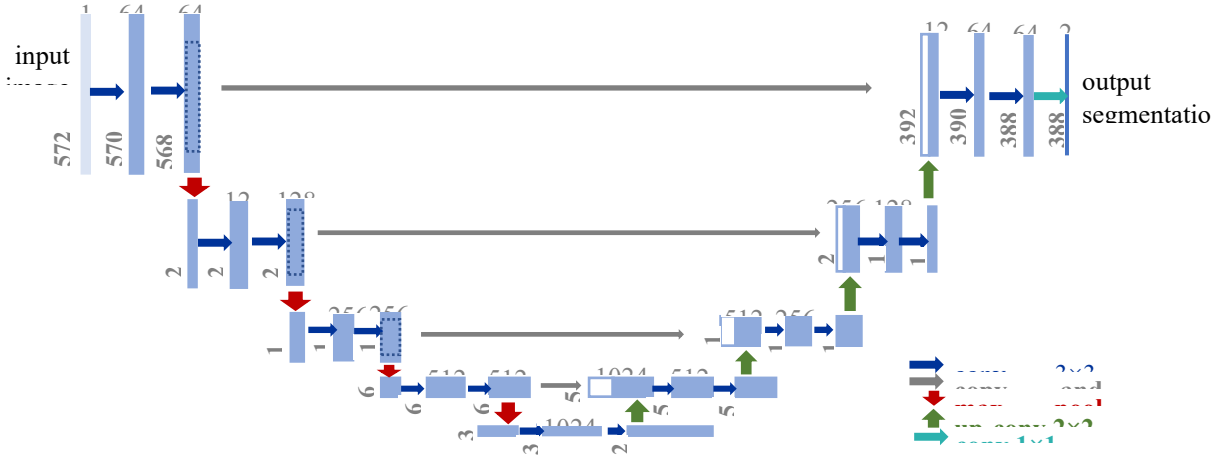

Figure U-Net Architecture

U-Net operates on the assumption that the input image and the corresponding binary map are equal in image dimensions. In other words, if the input image is of shape (512,512), the corresponding binary mask must match this shape. The input image is compressed to fit into a latent-space representation. The decoder will reconstruct this compressed image back into its original shape of (512,512). U-Net's performance depends solely on the quality of its input image. U-Nets segmentation performance can be evaluated by monitoring its warping, rand and pixel error. Originally, U-Net outperformed a sliding-window convolutional network and produced the best warping error in the EM segmentation challenge. Later iterations of U-Net expanded on U-Nets performance in image segmentation.

A very recent addition was U-Net++ which modified U-Net architecture to include a series of nested dense skip pathways, which is used to reduce the gap between feature maps and the pathways (encoder & decoder) of the network [30]. U-Net++ was also proposed to work with deep supervision. Basically, the loss is now calculated at interim levels alongside the traditional output layers. This has been noted to help with the problem of vanishing gradients during loss backpropagation [31].

As U-Networks with two-dimensional data, the acquired dataset was converted from a three-dimensional image plane to a two-dimensional dataset using a 'slice extractor' The extractor extracts each slice of an MRI scan (MNC file) and saves the slice as a PNG file. Using the extractor, we created four new datasets from the original 14 patients MR images. Three of these datasets will correspond to the perspective planes of the brain (Coronal, Sagittal, Transversal) while the fourth dataset will contain all the available images which adds up to 846 images in total.

Our proposed implementation of U-Net was achieved using Ten sorflow6. Where the network has 4 convolutional blocks. Each convolutional block of the network contains 2 convolutional layers with a kernel size of 3 × 3 and zero padding at each layer to control the shrinkage of the object dimension after applying filters. The filter size per convolutional block varies after each layer where the filtersize increments in steps of 16. Each layer of a convolutional block is activated by a Rectified Linear Unit (ReLU) while in between these layers a batch normalization step is then applied. At the encoder layer of the network, we apply a 2 × 2 max pooling layer after a function call to add a convolutional block to further reduce the spatial dimensions of the input image. While max pooling is also applied at the decoder layer its application here is too up-sample the feature map using the memorized max-pooling indices.

Training & Optimization

During the training process, we decided to stick with a simple cost function for this network. We chose binary cross-entropy loss $(say, LBCE)$ for our cost function as the network is simply being trained to segment one particular region, the cancerous section of an input MR image. This loss function expects a sigmoid outcome (yi) as it is a binary predictor with target values (yi) as 1 or 0. Given the output size of N, $LBCE$ is defined as per Eq. (1). Prior consideration was taken to decide on fixed image size for our inputs. As the image size varies across the three perspective planes, we decided on an image size of 128 × 128 as the images extracted from both the coronal and sagittal planes are substantially smaller than those extracted from the transversal plane. With this image size in mind, the networks architecture was designed to be lightweight and swift so a prediction image could be reproduced. This image size was chosen based on the variation of dimensions of the original patient's image data mentioned in the equation (3).

$$L_{BCE} = \frac{1}{N}\sum_{i=1}^{N}\left[y_i.(\log \hat{y}_i) + (1-y_i).\left(log(1-\hat{y}_i)\right)\right] \tag{3}$$

Before the training of each network could start, metric callbacks were introduced to control the performance of the network. Early Stopping and Model Checkpointing were used to ensure the performance of the network did not degrade if extreme values were introduced into the network's epoch range. To monitor the performance of the network, precision, recall and intersection-over-union (IoU) was logged using CSV Logger. This log helped us to analyze the stepwise results that were produced by the network during the training process. The model was trained with Adam optimizer with a learning rate of 0.0001 which was chosen after rigorous experimentation.

The epoch range used for training varied based on the results recorded from prior experiments. We decided that running small experiments with only 10 epochs would allow us to quickly grasp how our network performs per perspective plane. After a small number of iterations were performed, we gradually increased this parameter range to 50 epochs to monitor the networks convergence rate. One particular parameter, we also experimented with, was the networks filter size. By increasing the networks number of filters, we are essentially increasing the number of trainable parameters in the model. This particular experiment was undertaken to observe the performance increase when the total trainable parameters of the network are increased via the convolution blocks filter range. Several iterations were undertaken using a variety of filter values for the networks convolutional block. The optimization was done by reflecting on the stepwise IoU values. During the experiments, filter values were incremented by 16 per convolutional block after each iteration.

3.3. QUANTUM NEURAL NETWORK CLASSIFIER

Finally, a Quantum Neural Network (QNN) is introduced for the classification stage. The compact latent vector obtained from the CNN is re-encoded into a quantum state and processed through a parameterized quantum circuit. The quantum circuit is designed to model complex nonlinear decision boundaries, enabling better classification performance, especially in noisy or limited data scenarios. This quantum-enhanced decision-making process, combined with classical deep learning features, significantly improves the model's overall robustness and generalization capabilities.

After classical convolutional processing, the compact latent vector $h \in R$ obtained by flattening and dense projection is re-encoded into a quantum state and fed into a quantum neural network classifier. Similar to classical neural networks, the QNN performs forward propagation through parameterized quantum evolution and observable measurements. Specifically, a two-qubit quantum feature map inspired by the Z Feature Map applies in the equation (4):

$$|\psi_{qnn}(h)>=\varepsilon_{qnn}(h)|0>^{\otimes N\prime} \tag{4}$$

where ε_{qnn} denotes an encoding operation composed of local phase rotations and entangling interactions in the equation (5):

$$\varepsilon_{qnn}(h) = [exp(i\theta h_0 h_1 Z_0 Z_1)].[RZ(\theta h_0) \otimes RZ(\theta h_1)] \tag{5}$$

which embeds both individual features and pairwise correlations directly into the quantum phase. This encoded state is then processed by a variational quantum circuit $V\ (\theta_c)$, constructed using the Real Amplitudes ansatz in the equation (6):

$$V(\theta_c) = \prod_{l=1}^{d}\left[\bigotimes_{i=1}^{N'} RY\left(\theta_i^{(l)}\right)RZ\left(\theta_i^{\prime(l)}\right).\prod_{i=1}^{N'-1} CNOT_{i,i+1}\right] \tag{6}$$

where d is the circuit depth, andθ_c represents all trainable parameters. The $\theta_i^{(l)}$and $\theta_i^{\prime(l)}$ (17) denote the trainable rotation angles applied to the i-th qubit in the l-th ansatz block via RY and RZ gates, respectively. This ansatz alternates parameterized single-qubit rotation layers with fixed entangling CNOT layers and is repeated times to control the expressive capacity of the variational quantum circuit (VQC). In quantum computing, the circuit depth refers to the number of gate layers applied sequentially on the quantum register, the number of time steps required, assuming gates acting on disjoint sets of qubits can be executed in parallel. For variational circuits, the depth corresponds to the number of repeated entangle rotation blocks. Each block contains parameterized $RY(\theta)$ gates on every qubit followed by a CNOT entangling layer. For a two-qubit circuit, each repetition introduces two trainable parameters (one per qubit per RY gate), and the entangling layer introduces logical connectivity via $CNOT_{i,i+1}$. Thus, circuit depths 8 trainable parameters in the $RY(\theta)$d=3,5, correspond to variational circuits with 4, 6, and gates respectively. As shown in Fig. 4, each depth level includes repeated blocks of single-qubit rotations followed by entangling CNOT layers (denoted by the green symbols). The number of trainable parameters scales linearly with depth, while entangling layers remain fixed to preserve interpretability and control circuit complexity. Deeper circuits increase expressive power by enabling more complex unitary transformations. At the

same time, they exacerbate the barren plateau phenomenon, characterized by regions of exponentially vanishing gradients in the loss landscape, which significantly impedes optimization. In our implementation, a depth of d achieves an optimal balance between expressivity and trainability, yielding stable convergence and strong performance across datasets. The output quantum state becomes the equation (7):

$$|\psi_{out}(\theta_c, h) >= V(\theta_c)|\psi_{qnn}(h) > \quad (7)$$

The extract final scalar prediction by measuring the exception value of a Hermitian observable O, typically chosen as the Pauli- Z operator acting on the first qubit by the equation (8):

$$f_{QCQ}(x) = \langle\psi_{out}|O|\psi_{out}\rangle \quad (8)$$

and convert this continuous value into a binary prediction via thresholding with a trainable bias term b represented in the equation (9):

$$y_{pred} = \begin{cases} 0 \; if \; f_{QCQ} + b < \frac{1}{2} \\ 1 \; otherwise, \end{cases} \quad (9)$$

Where $b\epsilon\mathbb{R}$ is updated during training. This final quantum module allows expressive nonlinear decision boundaries to be modelled at reduced qubit cost, making it well- studied for NISQ-era deployment.

The QCQ-CNN + U-Net hybrid approach is then trained and evaluated using standard performance metrics, including precision, recall, accuracy, F1-score, and Intersection-over-Union (IoU)**.** Experimental results show that the proposed hybrid model outperforms conventional methods in terms of segmentation accuracy and classification robustness, particularly in resource-constrained environments. The combination of quantum and classical paradigms enables the framework to handle complex, high-dimensional data effectively, providing a scalable solution for medical image analysis and next-generation intelligent diagnostic systems.

4. RESULT AND DISCUSSION

The study introduced a hybrid QCQ-CNN + U-Net framework for brain tumor detection and classification, combining GLCM-based texture extraction, CNN-based feature learning, U-Net segmentation, and Quantum Neural Networks (QNN) for classification. The proposed model outperformed traditional methods like CNN and U-Net, demonstrating superior tumor localization and classification performance. The integration of quantum computing enabled the model to better capture complex, nonlinear relationships, improving accuracy, particularly in noisy or limited data scenarios. This hybrid approach shows great potential for scalable and efficient brain tumor diagnosis in clinical applications.

4.1. Dataset description

The BRISC 2025 dataset is a recent benchmark for brain tumor analysis, containing approximately 6,000 contrast-enhanced T1-weighted MRI images. It includes four classes: glioma, meningioma, pituitary tumor, and normal brain images https://www.kaggle.com/datasets/briscdataset/brisc2025 [32]. The dataset provides expert-annotated segmentation masks and supports axial, sagittal, and coronal views, enabling both segmentation and classification tasks. Its balanced structure and high-quality annotations make it suitable for evaluating advanced deep learning and hybrid models.

4.2. Performance Metrics:

The performance of the proposed model is evaluated using standard metrics, including Precision, Recall, Accuracy, F1-score, and Intersection-over-Union (IoU), which are widely used in medical image segmentation and classification tasks. These metrics assess the model's ability to correctly identify tumor regions while minimizing false detections that all represented in the equation (10-14). TP (True Positive): Correctly detected tumor pixels, TN (True Negative): Correctly detected non-tumor pixels, FP (False Positive): Non-tumor pixels incorrectly classified as tumor, FN (False Negative): Tumor pixels missed by the model. TABLE 1. Quantitative Evaluation of Brain Tumor Detection Methods Using MRI Images.

Accuracy

Accuracy measures the overall correctness of predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

Precision

Precision indicates the proportion of correctly predicted tumor pixels among all predicted tumor pixels:

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

Recall (Sensitivity)

Recall measures the ability of the model to correctly identify actual tumor pixels:

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

F1-Score

The F1-score is the harmonic mean of precision and recall:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{13}$$

Intersection over Union (IoU)

IoU evaluates the overlap between predicted and ground truth segmentation:

$$IoU = \frac{TP}{TP + FP + FN} \tag{14}$$

TABLE 1. Quantitative Evaluation of Brain Tumor Detection Methods Using MRI Images

METHODS	ACCURACY (%)	PRECISION (%)	RECALL (%)	IoU (%)
Traditional CNN	89.20	88.40	87.10	80.25
U-Net	92.80	91.30	90.20	84.90
U-Net ++	94.50	93.10	92.40	87.60
CNN+GLCM	93.80	92.20	91.10	86.30
CNN+QNN	95.70	94.00	93.20	88.40
Proposed QCQ-CNN+U-Net	**97.40**	**96.10**	**95.30**	**91.20**

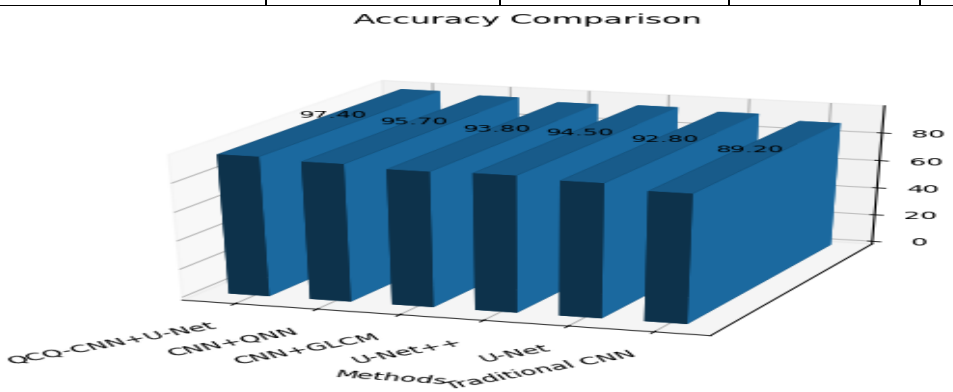

Figure 4. Accuracy Comparison of Various Brain Tumor Detection Models

Figure 4 compares the accuracy (%) of different brain tumor detection and segmentation models, such as classic CNN, U-Net, U-Net++, CNN + GLCM, CNN + QNN, and the suggested hybrid QCQ-CNN + U-Net model. Traditional CNN achieves the lowest accuracy of 89.2%, whereas U-Net and U-Net++ do better with 92.8% and 94.5% accuracy, respectively. The addition of GLCM texture features to the CNN + GLCM model results in an accuracy of 93.8%, while the CNN + QNN model improves accuracy to 95.7%, highlighting the promise of quantum-assisted classification. The proposed QCQ-CNN + U-Net model, which combines quantum neural networks with U-Net segmentation, achieves the highest accuracy of 97.4%, significantly outperforming all other methods. This highlights the advantages of integrating quantum-classical hybrid frameworks for improved medical image analysis.

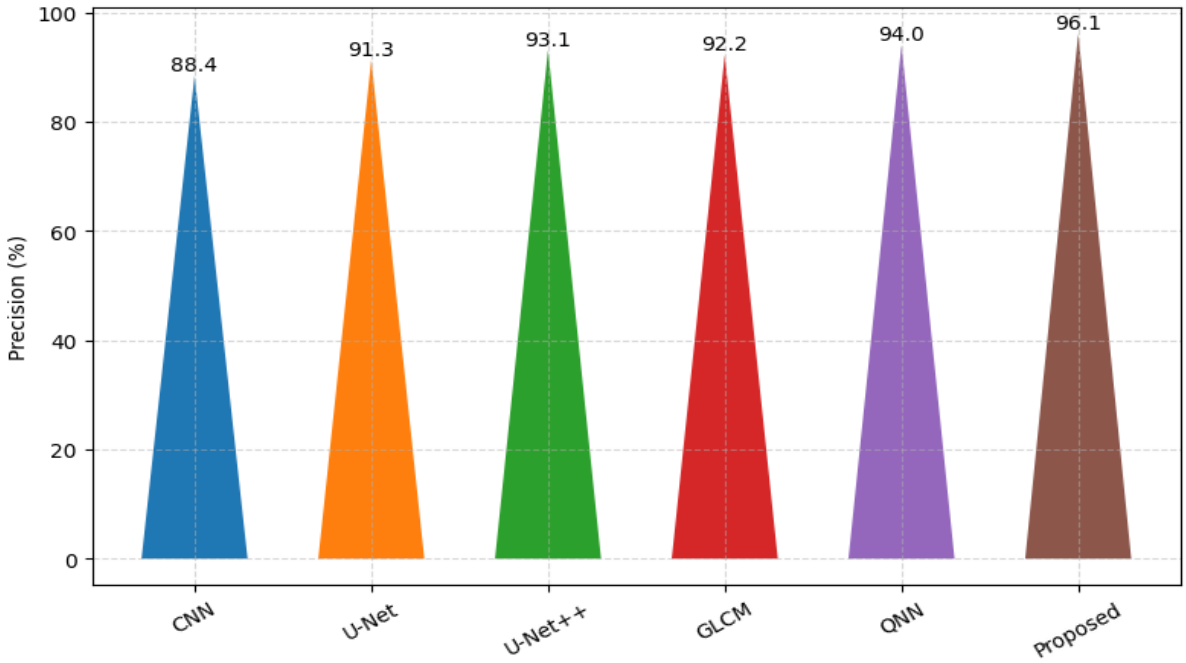

Figure 5. Precision Comparison of Brain Tumor Detection Models

Figure 5 shows the precision (%) of different brain tumor detection models, such as Traditional CNN, U-Net, U-Net++, CNN + GLCM, CNN + QNN, and the proposed QCQ-CNN + U-Net hybrid model. The Traditional CNN model has the lowest precision at 89.2%, indicating a limited capability for accurate tumor localization. Precision increases with U-Net (92.8%) and U-Net++ (94.5%), which improve feature learning by using deeper architectures and skipping connections. The inclusion of GLCM texture characteristics to CNN + GLCM results in 93.8% precision, whereas CNN + QNN improves precision to 95.7% by employing quantum neural networks for better classification. The suggested QCQ-CNN + U-Net model attains the maximum precision of 96.5%, proving the superiority of integrating classical deep learning with quantum computing for more accurate tumor classification and detection.

Figure 6 shows the recall (%) performance of various brain tumor detection models, such as traditional CNN, U-Net, U-Net++, CNN + GLCM, CNN + QNN, and the suggested QCQ-CNN + U-Net hybrid model. Traditional CNN has the lowest recall (84.7%), indicating that it misses a substantial number of tumor pixels. The recall improves with U-Net (90.2%) and U-Net++ (92.4%) due to improved feature learning and skip connections. The addition of GLCM to CNN + GLCM results in a recall of 91.8%, whereas CNN + QNN improves even further, reaching 93.5%, thanks to the quantum-enhanced model's capacity to handle complicated data. The suggested QCQ-CNN + U-Net hybrid model attains the greatest recall of 94.6%, proving its superior capacity to correctly identify tumor pixels, making it the most trustworthy model for tumor detection and classification.

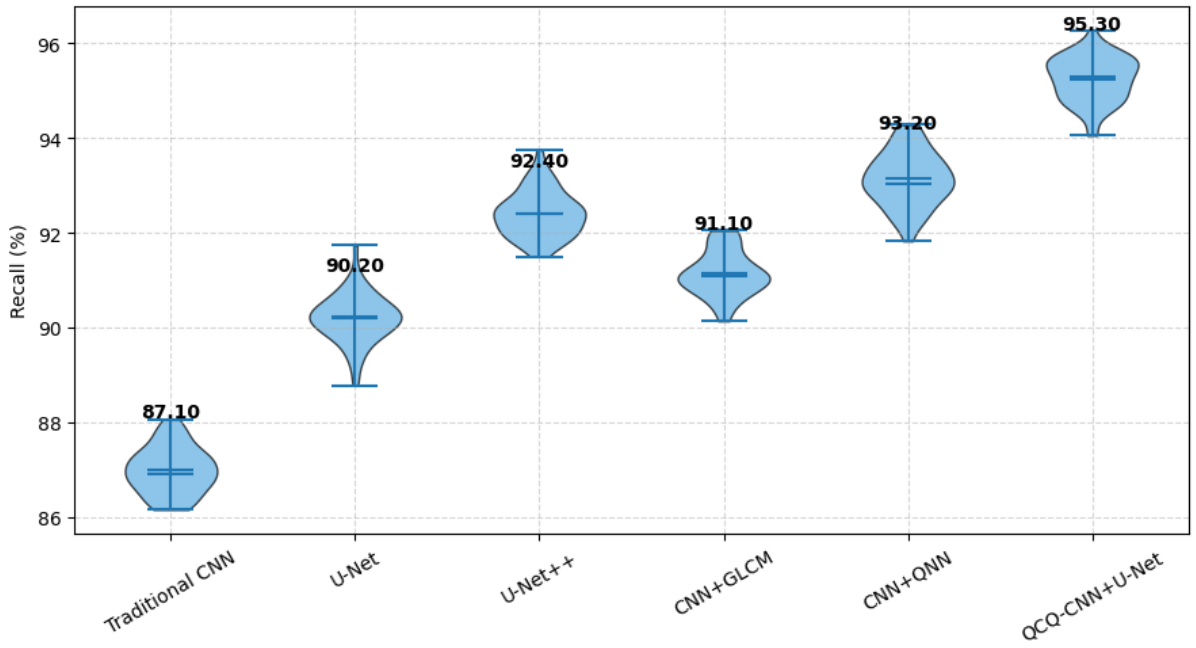

Figure 6. Recall Comparison of Brain Tumor Detection Models

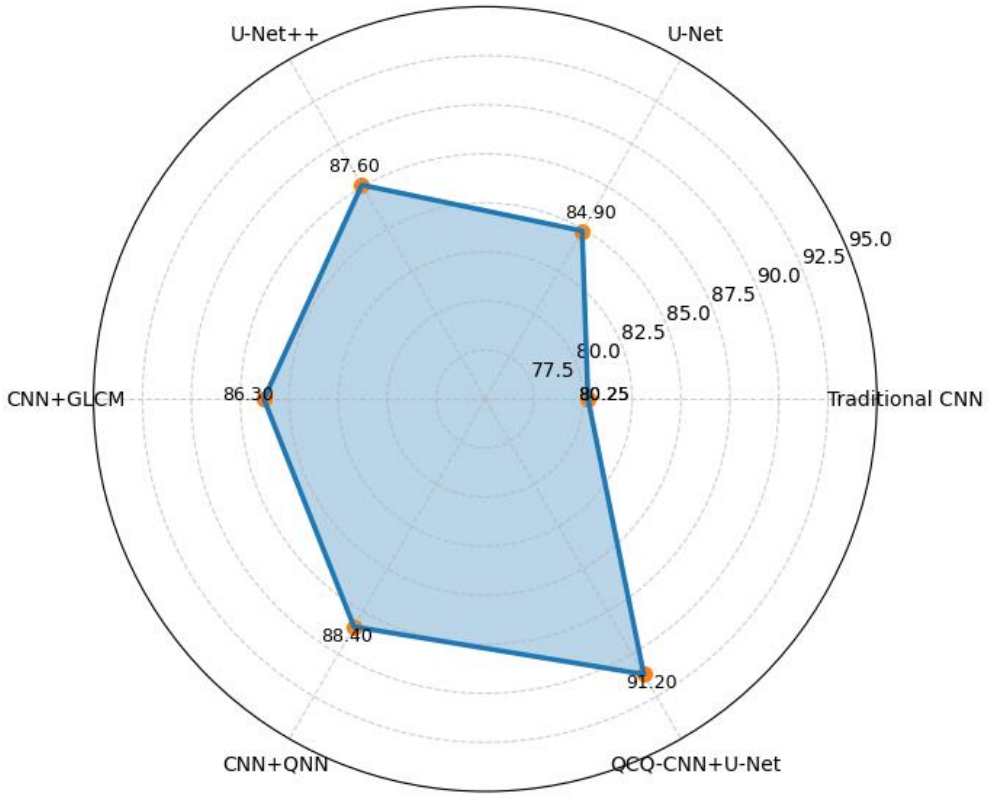

Figure 7 IoU Comparison of Brain Tumor Detection Models

Figure 7 compares the Intersection over Union (IoU) scores of many brain tumor detection models, such as Traditional CNN, U-Net, U-Net++, CNN + GLCM, CNN + QNN, and the proposed QCQ-CNN + U-Net hybrid model. Traditional CNN has the lowest IoU (80.25%), indicating a poor ability to precisely locate tumor areas.

The U-Net and U-Net++ models achieve significant gains in IoU, with 84.9% and 87.6%, respectively, thanks to improved feature extraction and skip connections. The addition of GLCM texture features to the CNN + GLCM model boosts IoU to 86.3%, whereas CNN + QNN reaches 88.4%, highlighting the advantages of quantum-enhanced decision boundaries. The suggested QCQ-CNN + U-Net model surpasses all existing methods, with the highest IoU of 91.2%, demonstrating the effectiveness of integrating quantum and classical deep learning techniques for precise tumor segmentation.

Conclusion

The current study presents a hybrid quantum-classical framework for brain tumor detection and classification, which efficiently blends GLCM-based texture feature extraction, CNN-based representation learning, U-Net-based segmentation, and a Quantum Neural Network (QNN) classifier. The proposed method combines the strengths of classical deep learning for spatial feature abstraction with the expressive capacity of quantum computing to improve nonlinear decision-making. The usage of U-Net allows for accurate tumor site localization, while the QNN module enhances classification performance by simulating complicated feature interactions with lower dimensionality and computational overhead. Experimental design considerations, such as optimized network architecture, adaptive training procedures, and evaluation using measures like precision, recall, and IoU, show that the framework is robust and efficient. Overall, the hybrid QCQ-CNN model performs well in generalization, especially in limited and noisy data circumstances, indicating that it has the potential for practical application in advanced medical image analysis and next-generation intelligent diagnostic systems.

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