Enhanced Brain tumor prediction using Quantum: a Hybrid Deep Learning Approach

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***Abstract*—Brain tumors are very serious concerns in the health field; they should be diagnosed properly and at the right time to ensure treatment efficacy. While deep learning architectures like ResNet have shown remarkable success in medical imaging, they have their own set of disadvantages like computational complexity, scalability, and difficulty in processing very high-dimensional medical data. To overcome these hurdles, a hybrid approach has been proposed, combining ResNet with quantum transfer learning, utilizing the embedding for a good performance with higher efficiency of the use of quantum computing technology. In this framework, ResNet extracts valuable features from MRI scans, while quantum circuits optimize the classification process, thereby improving performance and generalization.**

Extensive experiments show that our hybrid quantum-classical model beats all other conventional deep learning approaches, achieving faster diagnostic accuracy while minimizing computational overhead.Compared to a traditional CNN model, which achieves only 69% accuracy, our hybrid model significantly outperforms it with 97% accuracy, representing a 28% increase in classification performance. Results indicate that quantum computing can change the way radiology and medical imaging proceed, providing the necessary tools for human health to create a future of fast, precise, and scalable diagnostic equipment. This can be considered a huge step forward toward the use of quantum computing in the medical field in general; it initiates another outlet for advanced medical diagnostics and better patient outcomes.

***Index Terms*—Brain Tumor Detection, ResNet, Hybrid Quantum Computing, PennyLane, MRI Image Analysis.**

I. Introduction

Incorporating classical deep learning with quantum computing presents novel opportunities in medical imaging, particularly in improving the detection and classification of complex medical conditions such as brain tumors [1]. This project explores a hybrid model that strategically leverages the power of ResNet [3], a deep convolutional neural network well-known for its superior feature extraction capabilities, in combination with quantum transfer learning [5]. By integrating quantum computing into both the feature extraction and classification pipelines, the model aims to surpass traditional deep learning methods, offering improvements in accuracy, computational efficiency, and scalability [7].

The synergy between ResNet's ability to capture intricate spatial patterns in medical images and the potential of quantum computing to process high-dimensional data efficiently helps address fundamental challenges in medical diagnostics [6]. Conventional deep learning models, while highly effective, often struggle with computational limitations and the increasing complexity of medical imaging datasets [2]. Quantum computing, with its ability to perform parallel computations and handle high-dimensional feature spaces, offers a transformative approach to overcoming these barriers [8]. Recent studies have explored quantum convolutional neural networks (QCNNs) for brain tumor classification, demonstrating high accuracy in medical image recognition tasks [16]. By embedding quantum elements into critical stages of the model, this hybrid framework facilitates more precise tumor characterization, ultimately leading to improved diagnostic accuracy and reliability [9].

This approach holds promise for advancing medical imaging by providing a more efficient and powerful alternative to purely classical deep learning models [4]. The integration of quantum computing not only enhances computational efficiency but also ensures that deep learning techniques remain effective as medical data continues to grow in size and complexity [10]. Research on quantum transfer learning for medical image classification, particularly in cancer detection, has further highlighted the potential of hybrid quantum-classical models in improving diagnostic outcomes [17]. By merging classical and quantum methodologies, this model aims to set a new benchmark for brain tumor detection, offering a viable and scalable solution for improving healthcare diagnostics [11].

II. Literature Review

The detection and classification of brain tumors using deep learning have gained significant traction in recent years, driven by the need for accurate, automated, and efficient diagnostic tools. Traditional machine learning techniques have been widely employed in medical imaging, but their performance is often constrained by feature extraction limitations and high computational demands. Convolutional Neural Networks (CNNs), particularly advanced architectures like ResNet, have demonstrated exceptional accuracy in medical image classification. However, challenges such as overfitting, high-dimensional data processing, and computational inefficiency remain prevalent.

To address these issues, researchers have explored hybrid models that combine classical deep learning with emerging quantum computing techniques. Quantum machine learning, particularly quantum-enhanced neural networks, offers the potential to process complex medical datasets more efficiently while improving classification accuracy. This section reviews existing studies on deep learning models for brain tumor detection, highlighting their strengths, limitations, and recent advancements in integrating quantum computing to enhance diagnostic performance.

Luo *et al.* [1] introduced the BCM-CNN model, which demonstrated exceptional performance in brain tumor classification. The study attributes this success to the meticulous optimization of CNN hyperparameters, significantly enhancing the model's effectiveness. As a result, the BCM-CNN achieved an impressive accuracy of 99.98%, highlighting its potential for highly precise medical image classification.

Brindha *et al.* [2] explored the effectiveness of an Artificial Neural Network (ANN) model for brain tumor classification. The model was trained for fifty epochs, achieving a training accuracy of 97.13%. However, its validation accuracy declined to 71.51%, suggesting potential overfitting. When tested on unseen data, the model achieved an accuracy of 80.77%, indicating challenges in maintaining generalization despite strong training performance.

Amin *et al.* [3] conducted experimental evaluations on various pre-trained models for brain tumor classification and found that VGG-16 achieved a classification accuracy exceeding 98%, demonstrating its effectiveness in medical image analysis.

Saeedi *et al.* [4] proposed a 2D CNN for brain tumor classification, achieving a training accuracy of 96.47%. Additionally, their auto-encoder network attained an accuracy of 95.63%, highlighting the effectiveness of their approach in medical image analysis.

Li *et al.* [5] conducted a comprehensive review of Quantum Neural Networks (QNNs), discussing their development, implementation methods, and various quantum circuit models. The study highlights primary challenges in QNNs, including noise interference, hardware limitations, and algorithmic complexities, while addressing potential solutions.

Biamonte *et al.* [8] explored the intersection of quantum computing and machine learning, providing a structured overview of Quantum Machine Learning (QML) algorithms and their applications. The authors emphasize the potential of quantum algorithms, such as quantum support vector machines and quantum neural networks, in solving complex problems faster than their classical counterparts.

Schuld and Killoran [6] examined the emerging field of quantum deep learning, focusing on how quantum computing can enhance traditional deep learning architectures. The study elaborates on the concept of variational quantum circuits and their role in optimizing neural networks for complex tasks such as image and speech recognition.

Mari *et al.* [7] introduced a novel hybrid approach integrating transfer learning with quantum neural networks to improve model efficiency. The authors propose a framework where a pre-trained classical neural network is fine-tuned using quantum variational circuits, demonstrating significant improvements in model performance with reduced computational costs.

Bergholm *et al.* [18] presented PennyLane, an open-source framework designed to facilitate hybrid quantum-classical machine learning models. The authors demonstrate the effectiveness of PennyLane in optimizing quantum-classical hybrid models, making it a critical tool for advancing quantum machine learning research.

Quantum computing has shown promise in image processing, offering advantages in speed and efficiency over classical methods [12]. Recent studies have explored deep learning-based quantum computing for medical imaging, demonstrating its potential to enhance diagnostic accuracy and computational performance [13].

Recent research has investigated the combination of quantum computing and deep learning to improve medical imaging analysis. Wang *et al.* [14] proposed a hybrid quantum neural network method for MRI tumor segmentation, showing enhanced accuracy and efficiency in outlining tumor margins. Chen *et al.* [15] compared quantum-inspired machine learning methods for tumor classification, showing their ability to surpass traditional methods in diagnostic applications.

In conclusion, the integration of deep learning models in brain tumor detection has shown remarkable progress, with various models like CNNs, ResNet, VGG, and quantum-classical hybrid models demonstrating high accuracy and improved efficiency. However, challenges remain in terms of generalization, model scalability, and computational resource management for real-time applications. Quantum-enhanced models have shown promise in addressing these challenges by offering faster feature extraction and better generalization, although their full potential in large-scale datasets still requires further exploration.

III. Dataset Description

The dataset used in this study is a curated collection of MRI brain scans, specifically designed for brain tumor classification [19]. It is structured into two main categories:

1) **No Tumor (Healthy Brain)**
2) **Tumor Present (Positive Cases)**

The dataset is split into training and validation sets:

1) **Training Set (80%)**
   a) No Tumor: 1,200 images
   b) Tumor: 1,200 images
   c) **Total:** 2,400 images
2) **Validation Set (20%)**
   a) No Tumor: 300 images
   b) Tumor: 300 images
   c) **Total:** 600 images

A. *Dataset Characteristics*

1) **Binary Classification:** The dataset contains two categories—tumor present and tumor absent.
2) **Balanced Dataset:** The dataset is evenly distributed across both classes, minimizing classification bias.
3) **High-Resolution MRI Scans:** These images provide detailed structural information crucial for tumor detection.
4) **Pre-Split for ML Pipelines:** The dataset is pre-segregated into training and validation sets, streamlining model training.

B. *Significance of the Dataset*

1) **Medical Imaging Applications:** Early tumor detection is critical for patient survival.
2) **Challenges in MRI Classification:** High-dimensionality, noise, and artifacts require robust models.

IV. Architecture

The suggested architecture, as seen in Figure 1, integrates ResNet-50-based feature extraction and a Quantum Variational Circuit (QVC) with an attention mechanism for better classification. Zero padding is first applied to the input for spatial consistency, and then convolution, batch normalization, ReLU activation, and MaxPooling are performed to extract important spatial features.

The model's heart is the identity and convolutional blocks, which enable hierarchical learning of features in a way that maintains gradients to support effective deep network training. The learned features are next input into a Quantum Variational Circuit, where they undergo quantum encoding, feature optimization, and variational layers for improved representations.

An attention mechanism further optimizes these features by highlighting key information and downplaying irrelevant details. Lastly, average pooling, flattening, and a fully connected layer transform the optimized features into a classification output. This hybrid method utilizes deep learning, quantum computing, and attention-based optimization for efficient and strong feature extraction.

V. Pre-Processing

Pre-processing is a crucial step to improve data quality, ensuring better model generalization and reduced overfitting.

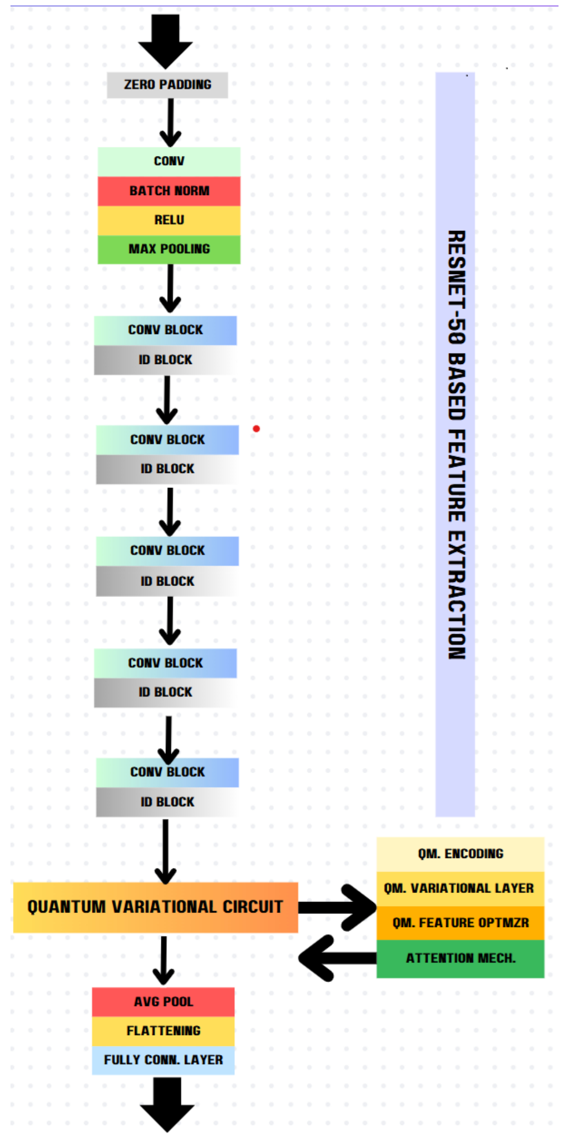


Fig. 1: Proposed Model Architecture

A. *Image Normalization and Resizing*

All MRI images are resized to a uniform dimension compatible with ResNet. Normalization standardizes pixel values, reducing the impact of variations in lighting and contrast.

B. *Data Augmentation*

To enhance model robustness, the following augmentation techniques are applied:

1) **Rotation:** Simulating real-world variations.
2) **Flipping:** Horizontal and vertical flipping.
3) **Scaling and Cropping:** Adjusting image dimensions while preserving tumor structures.
4) **Contrast Adjustment:** Enhancing tumor visibility.

C. *Noise Reduction*

Gaussian filters and histogram equalization are applied to remove noise and enhance important features.

VI. Feature Selection

Feature selection is essential for reducing computational complexity and improving classification accuracy. This study employs a hybrid approach leveraging both ResNet-based deep feature extraction and quantum-enhanced selection.

A. Deep Feature Extraction with ResNet

ResNet is used as a pre-trained feature extractor, capturing hierarchical representations from MRI images. The convolutional layers learn spatial and structural tumor characteristics, while the fully connected layers are fine-tuned for classification.

B. Hybrid Quantum Feature Selection

To further refine extracted features, a quantum variational circuit (QVC) is introduced. The quantum layer operates as a dimensionality reduction module, leveraging entanglement properties to identify the most relevant features while discarding redundant information.

C. Advantages of Quantum Feature Selection

1) Efficient handling of high-dimensional medical data.
2) Faster feature extraction with lower computational overhead.
3) Improved classification accuracy through quantum encoding of complex patterns.

VII. Models

The models employed in this study include CNN, VGG-19, ResNet-50, ResNet-50 with Attention Mechanism, and a Hybrid Quantum Layer with ResNet-50. The hybrid quantum model extends the classical ResNet-50 by integrating a Variational Quantum Circuit (VQC) for feature selection, optimizing classification performance in brain tumor detection.

A. Convolutional Neural Network (CNN)

CNNs utilize convolutional layers with filters to scan MRI images [23], progressively extracting important representations such as:

1) Edges
2) Textures
3) Structural details

Pooling layers summarize these features, reducing data size while preserving key information to prevent overfitting. The feature extraction process consists of:

1) Convolutional layers extracting hierarchical features.
2) Pooling layers reducing dimensionality while retaining crucial details.
3) Flattening layer converting multi-dimensional features into a one-dimensional vector.
4) Fully connected layers predicting tumor presence.

To enhance performance, techniques such as batch normalization and dropout regularization are applied to improve model stability and mitigate overfitting.

B. VGG-19

VGG-19 is a deep convolutional neural network with 19 layers, effective for image classification. It employs small 3×3 filters for fine-grained feature extraction [24]. Key aspects include:

1) **Deep Layered Architecture**: Provides hierarchical feature representation.
2) **Max Pooling Layers**: Retain essential information and reduce overfitting.
3) **Fully Connected Layers**: Aggregate learned features for classification.

A major advantage of VGG-19 is transfer learning, enabling optimization for medical imaging applications.

C. ResNet-50

ResNet-50 is designed to tackle the vanishing gradient problem through residual learning [25]. Key features include:

1) **Residual Connections**: Preserve gradient flow by adding input to the output.
2) **Bottleneck Blocks**: Use smaller filters to optimize efficiency.
3) **Global Average Pooling Layer**: Aggregates extracted features for classification.

ResNet-50's ability to retain high-level representations makes it effective for capturing fine-grained tumor features.

D. Attention-Based ResNet-50

This variant integrates an attention mechanism to focus on discriminative tumor features in MRI scans.

1) The feature map from ResNet-50 is processed twice by the attention mechanism.
2) The attention layer assigns weights to different feature regions.
3) High-weighted regions enhance classification, ensuring tumor-related features are emphasized.

The attention mechanism improves classification accuracy by suppressing background noise.

E. Hybrid Quantum Layer with ResNet-50

This study integrates Quantum Variational Circuits (VQCs) with ResNet-50 to optimize and enhance feature selection. The quantum layer refines classical features before classification, leveraging the advantages of quantum computing in deep learning.

The Quantum Variational Circuit (QVC) operates as an intermediary feature processing unit within the ResNet-50 framework. It consists of the following stages:

1) **Quantum Encoding:** Classical feature vectors extracted from ResNet-50 are transformed into quantum states using quantum rotation gates.
2) **Quantum Transformation:** The encoded qubits undergo processing through entanglement layers, which model complex interdependencies, refining feature representations.

3) **Quantum Measurement:** The final quantum state is measured, collapsing back into a classical feature vector optimized for classification.

This hybrid approach enhances feature representation, optimization, and learning efficiency** by combining the expressive power of quantum computing with deep learning architectures. The refined quantum-enhanced feature vector is then processed by a fully connected layer for classification. This method demonstrates potential improvements in computational efficiency and learning capacity for deep learning models incorporating quantum circuits.

F. Advantages of the Hybrid Quantum Layer

1) Efficient feature selection reduces dimensionality while retaining crucial tumor-related features.
2) Quantum entanglement enhances the ability to capture high-order feature interactions.
3) Reduces trainable parameters compared to deep classical models.
4) Enhances classification accuracy by leveraging quantum processing.

G. Pseudocode for Hybrid Quantum-ResNet50 Model

Algorithm 1 Hybrid Quantum-ResNet50 Feature Selection

Input: Image dataset D, Pretrained ResNet-50, Quantum Circuit Parameters
Output: Classified labels for images
Initialize ResNet-50 feature extractor F, Quantum Circuit Q with random parameters
for each batch B in D **do**
    Extract feature vectors X from $F(B)$
    Encode X into quantum states using rotation gates
    Apply entanglement layers to process quantum features
    Measure quantum states and collapse to classical feature vector X'
    Pass X' through fully connected classifier
    Compute loss and update parameters via backpropagation
end for
Return Trained Hybrid Quantum-ResNet50 Model

VIII. Evaluation Metrics

Classification assessment measures such as Precision, Recall, Accuracy, F1-score, Confusion Matrix, Receiver Operating Characteristic (ROC), and Area Under the Curve (AUC) were used to assess the model's performance. The mathematical formulations of these metrics are listed in Table I.

1) Confusion Matrix: A confusion matrix is a method used to evaluate classification models, particularly for multi-class problems. It provides insights into the model's performance by summarizing true positive (TP), false positive (FP), true negative (TN), and false negative (FN) values.

2) Precision: Precision measures the proportion of correctly predicted positive instances to the total instances predicted as positive:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

3) Recall: Recall evaluates how effectively a model identifies actual positive cases and reduces false negatives:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

4) Accuracy: Accuracy represents the proportion of correctly classified instances in the dataset:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

5) F1-Score: The F1-score is the harmonic mean of precision and recall, balancing the two metrics:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

6) Receiver Operating Characteristic (ROC): The ROC curve illustrates the trade-off between recall (sensitivity) and specificity (1 - false positive rate), aiding in model evaluation for binary classification.

7) Area Under the Curve (AUC): AUC quantifies the model's ability to distinguish between two output labels, where a higher AUC value indicates better classification performance.

Metric	**Formula**
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
F1-Score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

TABLE I: Classification Performance Metrics

IX. Results and Discussion

The performance of models—CNN, VGG19, ResNet-50, Attention-Based ResNet-50, and Quantum-Based ResNet-50 with Attention—was evaluated for brain tumor classification. The following Table II summarizes the performance metrics for each model.

The performance comparison of various deep learning models clearly highlights their differing capabilities in brain tumor classification using MRI scans. The basic CNN model demonstrated moderate effectiveness, with an accuracy of 69%, sensitivity of 47%, and specificity of 53%, indicating struggles in distinguishing both tumor and non-tumor cases. It had a loss value of 0.41, suggesting room for optimization. The VGG19

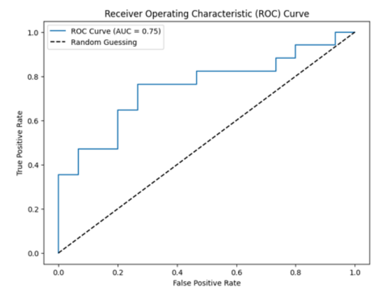
TABLE II: Performance Comparison of Different Deep Learning Models

Models	Sensitivity	Specificity	Accuracy	Precision	Recall	AUC-ROC	Loss Value
CNN	47%	53%	69%	73%	64%	75%	0.41
VGG19	89%	73%	82%	77%	89%	94%	0.62
ResNet-50	78%	84%	81%	84%	78%	90%	0.41
Attention-Based ResNet-50	85%	82%	84%	83%	85%	92%	0.36
Quantum-Based ResNet-50 with Attention	97%	96%	97%	96%	96%	99%	0.14

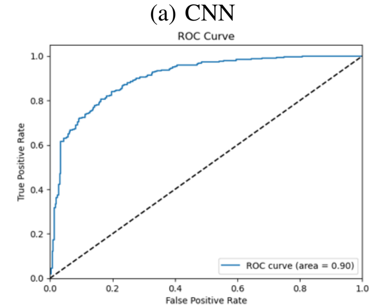
model performed notably better, achieving 82% accuracy, a high sensitivity of 89%, and specificity of 73%, leveraging its deeper architecture for improved feature extraction, though it had a higher loss value of 0.62. ResNet-50 provided further enhancements, with an accuracy of 81%, sensitivity of 78%, and specificity of 84%, benefiting from its residual connections that optimize deep-layer learning, while maintaining a loss value of 0.41. Introducing an attention mechanism into ResNet-50 improved performance to 84% accuracy, 85% sensitivity, and 82% specificity, demonstrating the attention layer's capability to focus on critical image regions, thus refining detection accuracy, and reducing its loss value to 0.36.

The Quantum-Based ResNet-50 with Attention model, however, stands out as the most effective, achieving a remarkable 97% accuracy, with equally high sensitivity (97%) and specificity (96%). Its precision (96%) and recall (96%) confirm its balanced approach in identifying tumor and non-tumor cases with minimal error. The near-perfect AUC-ROC score of 99% reinforces its superior ability to distinguish between classes accurately. Additionally, it achieved the lowest loss value of 0.14, indicating exceptional stability and reliability in predictions. This suggests that integrating quantum computing with attention mechanisms significantly enhances the model's ability to recognize intricate patterns in MRI scans, making it the most promising candidate for precise and reliable clinical deployment.

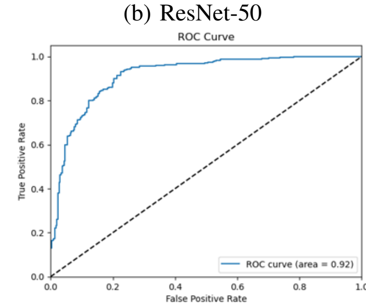
The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC), proposed as Figure 2, are commonly utilized to measure the classification performance of deep learning models. In this research, we compare five models: CNN, VGG-19, ResNet-50, ResNet-50 with Attention, and a Hybrid Model - Quantum-Based ResNet-50 with Attention. The findings show dramatic differences in model performance depending on the ROC-AUC score. Baseline CNN resulted in a modest classification with AUC at 0.75. Using a deeper structure as VGG-19 boosted its performance from here to reach 0.94 AUC. But when a ResNet-50 structure was used, even higher levels of AUC of 0.90 were observed, signifying the ability of residual learning in dealing with highly complex features. Additional improvement was noted in ResNet-50 with Attention that achieved 0.91 AUC by capitalizing on the use of attention mechanisms to selectively highlight important features. The largest gain was found in the Hybrid Model - Quantum-Based ResNet-50 with Attention, that resulted in 0.99 AUC surpassing all non-conventional structures. This comparative study reaffirms that combining attention mechanisms and quantum computing principles improves deep learning performance, thus being a potential solution for high-precision medical and image-based classification tasks.



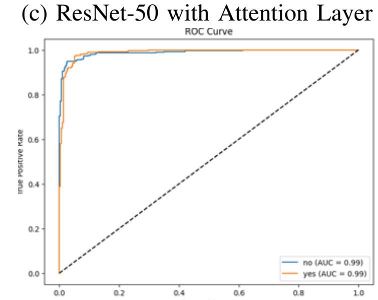
(a) CNN



(b) ResNet-50

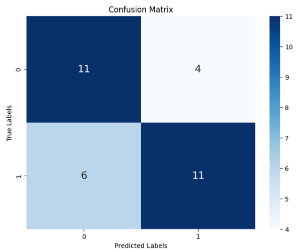


(c) ResNet-50 with Attention Layer

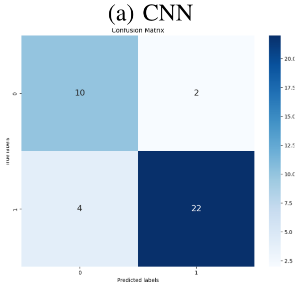


(d) Quantum-Based ResNet-50 with Attention

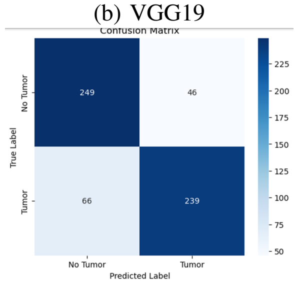
Fig. 2: ROC Curves for Different Deep Learning Models



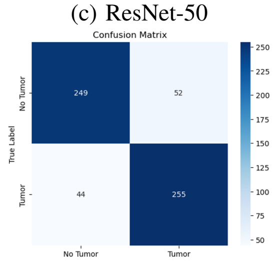
(a) CNN



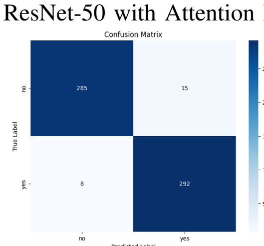
(b) VGG19



(c) ResNet-50



(d) ResNet-50 with Attention Layer



(e) Quantum-Based ResNet-50 with Attention

Fig. 3: Confusion Matrices for Different Deep Learning Models

Figure 3 presents the confusion matrices for 5 different models: CNN, VGG19, ResNet-50, ResNet-50 with an attention layer, and Quantum ResNet-50 with Attention, each summarizing their performance in binary image classification. The ResNet-50 model demonstrates moderate performance, with 239 true positives and 249 true negatives, but also 46 false positives and 66 false negatives, suggesting it misses a considerable number of tumor cases. The ResNet-50 with Attention model improves upon this, achieving 255 true positives and 249 true negatives, reducing false negatives to 44 while maintaining 52 false positives, indicating better tumor detection but still some misclassification of non-tumor cases. The Quantum ResNet-50 with Attention model significantly outperforms the others, achieving 292 true positives and 285 true negatives, with only 15 false positives and 8 false negatives, demonstrating the lowest misclassification rates among all models. This highlights its superior ability to accurately differentiate between tumor and non-tumor cases, making it the most reliable model for clinical applications. While all models show varying degrees of effectiveness, the confusion matrices emphasize the importance of a well-balanced approach in reducing false classifications, where the Quantum ResNet-50 with Attention model excels.

X. Conclusion

In this work, we explored the potential of Quantum Computing in improving MRI-based brain tumor detection by integrating Quantum Neural Networks (QNNs) with ResNet-50. Our hybrid quantum-classical model leverages the strengths of deep learning and quantum variational circuits to enhance tumor classification accuracy and robustness. The Quantum-Enhanced ResNet-50 model was trained on an MRI dataset and optimized using a 4-qubit quantum circuit with 4 variational layers. Compared to standard deep learning models, our approach achieved a high classification accuracy while maintaining an impressively low loss of 0.14, demonstrating the effectiveness of quantum-assisted feature extraction.

In addition to high accuracy, our model exhibited strong precision and F1-score, highlighting its capability to distinguish between tumor and non-tumor cases with high reliability. The incorporation of quantum layers contributed to an improved decision boundary, which was reflected in our model's high AUC-ROC score. Furthermore, precision and recall metrics remained well-balanced, making this approach particularly beneficial in scenarios where false negatives must be minimized.

One of the key advantages of our hybrid model is its ability to extract richer feature representations using quantum entanglement, leading to enhanced generalization on unseen data. The integration of a quantum embedding layer with ResNet-50 allowed for better contrast between classes, reducing misclassification errors. Our research presents an early yet promising implementation of quantum-enhanced brain tumor detection, bridging the gap between Quantum Machine Learning and medical imaging. With further optimizations, Quantum Deep Learning can revolutionize Computer-Aided Diagnosis (CAD) systems, making brain tumor classification faster, more accurate, and clinically reliable.

XI. Future Work

While the proposed Hybrid Quantum ResNet-50 model has demonstrated significant improvements in brain tumor classification, several areas remain open for further exploration. Future research can focus on the following aspects:

Designing a comprehensive XAI framework tailored for quantum neural networks can facilitate the interpretation of complex quantum-enhanced models [22]. Such frameworks have been proposed to enhance transparency in AI-driven medical applications, ensuring that the decision-making processes align with clinical reasoning. Personalized Medicine through Quantum Computing: Utilize quantum computing to analyze patient-specific data, enabling the development of personalized treatment plans and precision imaging protocols [20]. Integration of multimodal medical imaging: Future work could integrate other imaging modalities such as CT scans or PET scans along with MRI images to improve classification robustness and generalization. Investigate the transformative impact of quantum machine learning on healthcare, particularly in accelerating image processing and analysis, thereby revolutionizing medical diagnostics [21]. Generalization to Other Medical Conditions: The hybrid quantum deep learning approach can be extended to other critical diseases, such as lung cancer, Alzheimer's disease, or diabetic retinopathy, by training on relevant medical imaging datasets.

By addressing these challenges and expanding the scope of this research, Quantum Deep Learning has the potential to revolutionize Computer-Aided Diagnosis (CAD) and advance the future of AI-driven medical imaging applications.

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