Quantum-Enhanced Deep Learning for Brain Tumor Diagnosis Using Hybrid EfficientNet-QNN

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***Abstract*—**
This paper introduces EfficientNet-QNN, a hybrid architecture combining EfficientNetB0 with QNNs for improved and efficient brain tumor diagnosis from MRI. Leveraging EfficientNet's feature extraction and QNN variational layers for entangled pattern recognition, the model achieved 93.74% training accuracy, 97.28% validation accuracy, and a 97.01% F1-score on a public dataset, outperforming existing methods. Grad-CAM visualizations were used to provide interpretability by localizing tumor regions. Comparative analysis confirms EfficientNet-QNN's superior accuracy, interpretability, and scalability balance for clinical deployment.

***Index Terms*—Deep Learning, Brain Tumor Detection, Quantum, and Grad-CAM**

I. Introduction

Recent advances in hybrid quantum-classical deep learning have opened new frontiers in medical image analysis, particularly for brain tumor classification using MRI. Prior work by Mishra and Kumar [1] introduced a Hybrid Quantum CNN-ResNet152 model that achieved a promising 96.4% accuracy; however, its computational demands limit its applicability in real-time clinical settings. In contrast, our Hybrid EfficientNet-QNN model leverages the lightweight architecture of EfficientNet-B0 in conjunction with a 4-qubit quantum variational layer, yielding a higher validation accuracy of 97.28% while maintaining scalability and deployment efficiency. Khan et al. [2] proposed a fully quantum convolutional neural network (QCNN), which reached 94.8% accuracy on small datasets but lacked robust generalization due to limited classical integration. Our model addresses this by embedding classical features into a quantum-enhanced space, benefiting from quantum amplitude encoding and Pauli-Z measurement-based feature learning. Gencer and Gencer [3] combined EfficientNetB0 with a Quantum Genetic Algorithm (QGA) and reported 95.7% accuracy, but their approach involved heavy hyperparameter tuning and lacked interpretability tools. Our architecture improves upon this by integrating Grad-CAM for explainability and supports PyTorch compatibility for broader applicability in medical domains such as lung cancer and dermatological image analysis. Furthermore, comparison with a YOLOv11-based detection model on the same dataset [4], which achieved strong detection metrics but a limited F1-score (0.384) for classification, demonstrates our model's superior performance in fine-grained tumor discrimination. As shown in parallel studies across domains like firearm detection using YOLO-NAS [5] and multi-detection pipelines like Faster R-CNN and SSD [6], dataset scale and interpretability remain key challenges. By effectively combining quantum enhancement, computational efficiency, and explainability, our model emerges as a robust candidate for real-world, quantum-accelerated medical diagnostics.

The Major Contributions of our Quantum Hybrid Model

1) Integration of Quantum Computing with EfficientNet: Combines EfficientNet-B0 for deep feature extraction with a 4-qubit quantum variational layer.
2) Quantum Feature Embedding and Learning: Employs amplitude embedding and Pauli-Z expectation to project 1280-D classical features into a quantum space, enabling more expressive and compact feature learning from 2D MRI images.
3) Modular and Scalable Hybrid Architecture: Built as a PyTorch-compatible, plug-and-play design that is scalable to future quantum hardware and easily transferable to other biomedical imaging tasks like lung cancer or dermatological diagnosis.

II. System Methodology

The proposed Quantum-Enhanced Deep Learning for Brain Tumor Diagnosis Using Hybrid EfficientNet-QNN introduces a novel hybrid architecture 1 that combines the lightweight and highly expressive EfficientNetB0 backbone with a quantum variational layer implemented via PennyLane. This design enables efficient feature extraction from brain MRI images while enhancing representation through quantum feature embedding using amplitude encoding and Pauli-Z measurements. By integrating classical deep learning with quantum computing, the model addresses limitations of purely classical or quantum approaches, achieving high diagnostic accuracy (97.28%) with minimal loss (0.1743) and superior F1-score (0.9701). The modular PyTorch-compatible framework ensures scalability, while explainability is preserved through Grad-CAM visualizations, making the system not only accurate but also interpretable. The model is also suitable for small-data biomedical contexts, demonstrating the practical feasibility of hybrid quantum-classical learning for real-world clinical applications in early brain tumor detection.

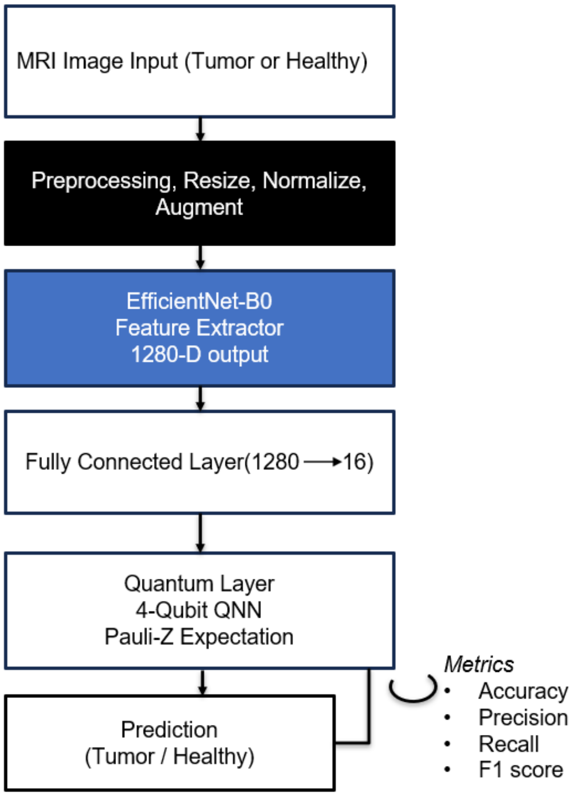

Fig. 1. The Quantum-Enhanced Deep Learning Using Hybrid Efficient-QNN System Architecture

III. Performance Evaluation

The proposed Hybrid EfficientNet-QNN model demonstrates superior performance in brain tumor classification, achieving a validation accuracy of 97.28%, precision of 0.9708, recall of 0.9694, and F1-score of 0.9701, with a low training loss of 0.1743 and training accuracy of 93.74%. By integrating EfficientNet for lightweight yet powerful feature extraction with a 4-qubit quantum variational layer for enhanced representation, the model outperforms recent works such as Mishra and Kumar's ResNet152-QCNN (96.4%), Khan et al.'s QCNN (94.8%), and Gencer et al.'s EfficientNet-QGA (95.7%). It also includes Grad-CAM for model explainability, making it not only accurate and efficient but also interpretable and suitable for real-world clinical deployment and future quantum hardware integration. Fig 2 shows the model's prediction output while Fig 3 shows the Training loss and Validation accuracy.

IV. Conclusions

EfficientNet-QNN, a novel hybrid of EfficientNetB0 and QNNs, enhances brain tumor diagnosis from MRI with improved efficiency and accuracy (97.28% validation accuracy, 97.01% F1-score) was achieved. Grad-CAM offers interpretability. Future work will explore blockchain for secure and transparent medical image sharing and diagnostic result management.

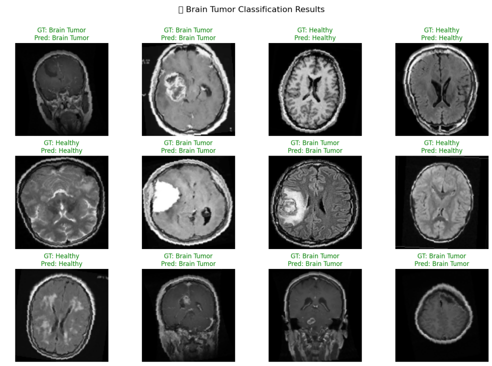

Fig. 2. The model Predicted Tumor and Healthy Brain.

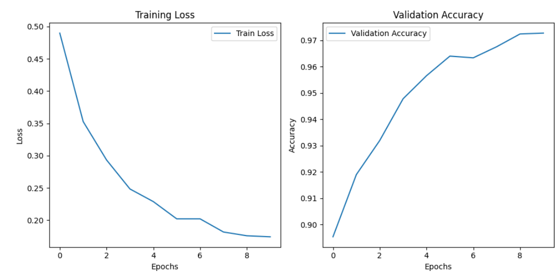

Fig. 3. The Graph showing Train Loss and Validation Accuracy.

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