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Hybrid Quantum-Classical Convolutional Neural Networks with Gradient Variance-Controlled Optimization for Medical Images Classification

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ABSTRACT: Medical image classification poses significant challenges due to the complex and nonlinear patterns present in imaging data. Traditional deep learning models often struggle to capture the intricate relationships inherent in such data, especially under conditions of noise and training instability. To address these limitations, this study proposes a novel Hybrid Quantum Convolutional Neural Network (HQCNN) integrated with a Gradient Variance-Controlled Optimizer (GVCO). The aim is to enhance diagnostic accuracy by combining classical convolutional layers for shallow feature extraction with a parameterized quantum circuit (PQC) that enables richer and more discriminative feature representations. The GVCO dynamically adjusts learning rates and momentum coefficients based on real-time gradient variance, improving convergence speed and generalization performance. The proposed HQCNN-GVCO model was evaluated on two public brain imaging datasets: the Kaggle Brain MRI dataset and the REMBRANDT dataset. It achieved classification accuracies of 99.2% and 98.2%, respectively. Compared to baseline HQCNN and other state-of-the-art models, HQCNN-GVCO demonstrated superior and more consistent performance. These findings highlight the potential of integrating quantum computing techniques with adaptive optimization strategies to advance reliable and accurate medical image analysis.

Keywords: Hybrid Quantum, Parameterized Quantum Circuits, Medical Image Classification, Gradient Variance Controlled Optimizer, Quantum Machine Learning.

1. INTRODUCTION

Analysis of medical images has become a cornerstone of modern healthcare, providing essential decision support in the diagnosis and treatment of conditions such as tumors, cardiovascular disease, and neurological disorders. With the rapid growth in both the volume and complexity of medical images, there is a pressing need for computational models that are not only accurate but also efficient and scalable. In recent years, deep learning methods—particularly Convolutional Neural Networks (CNNs)—have become the preferred approach for medical image classification because of their ability to automatically learn hierarchical features from image data. However, CNNs face several well-documented limitations: they are computationally intensive, often slow to converge when applied to high-dimensional datasets, and highly sensitive to hyperparameter tuning. These factors can hinder their usefulness in time-sensitive clinical settings [1–3].

The expansion of medical imaging technologies has amplified the demand for intelligent systems capable of handling complex visual data. While deep learning models have shown promise, they frequently struggle to capture the nonlinear relationships and fine-grained patterns present in medical images. To address these challenges, hybrid quantum–classical neural networks have emerged as a new frontier. By combining quantum computing principles with classical architectures, these models offer novel ways to process information and potentially overcome some of the limitations of purely classical methods [3]. Traditional approaches to medical image classification, including conventional machine learning algorithms and classical deep learning models, often fall short when applied to highly variable imaging data. These methods typically depend on handcrafted features or shallow architectures, which may fail to capture subtle patterns in high-resolution scans. They are also prone to overfitting, particularly when trained on limited datasets—a common reality in the medical domain. Furthermore, they frequently struggle to generalize across different imaging modalities or datasets from different institutions. Performance can also degrade when faced with noisy or imbalanced data, and the “black box” nature of many models limits transparency, making it difficult for clinicians to interpret or trust their outputs. These issues underscore the need for more robust, adaptive, and explainable systems tailored to the unique demands of medical image analysis [2,3].

Quantum computing has recently gained attention as a promising way to address some of these challenges. By exploiting quantum phenomena such as superposition and entanglement, quantum computers can represent and process information in ways that are unattainable for classical machines. In machine learning, Hybrid Quantum Neural Networks (HQNNs)—which combine classical neural network structures with quantum circuits—have shown potential to accelerate training, improve convergence, and enhance generalization [4,5].

The present study proposes a Hybrid Quantum Convolutional Neural Network (HQCNN) for medical image classification. The model incorporates Parameterized Quantum Circuits (PQCs) [6] as quantum convolutional layers within a classical CNN framework. To address the challenges of training hybrid models, particularly the issue of noisy and unstable gradients in quantum circuits, we introduce a novel optimization algorithm: the Gradient Variance-Controlled Optimizer (GVCO) [7,8]. Unlike conventional optimizers or adaptive gradient-based methods, GVCO explicitly regulates gradient variance during training and dynamically adjusts both the learning rate and momentum. This variance-aware strategy improves training stability and convergence efficiency, which is especially important for hybrid quantum–classical systems where gradient behavior can be unpredictable and prone to oscillations [9,10]. The proposed HQCNN architecture, combined with GVCO, is evaluated on multiple medical imaging datasets. Results demonstrate that the hybrid model achieves competitive or superior classification accuracy, faster convergence, and higher computational efficiency compared with traditional CNNs and standard quantum–classical models. These findings highlight the potential of integrating quantum computing with advanced optimization methods for medical image analysis. The main contributions of this work are:

1. To develop a Hybrid Quantum Convolutional Neural Network (HQCNN) based on classical convolutional layers and parametrized quantum circuits with quantum-enhanced feature learning capability.
2. To use a new Gradient-Variance-Controlled Optimizer (GVCO) that automatically calibrates and adapts learning parameters and gradients based on the gradient variance, to mitigate training instability and gradient noise problems with the hybrid models.
3. To show that HQCNN + GVCO are effective by achieving the state-of-the-art performance on two benchmark medical imaging datasets (Kaggle Brain MRI and REMBRANDT) with the 99.2% and 98.2\% classification accuracy.
4. To demonstrate that our method achieves better performance than those of well-established deep learning algorithms and classical HQCNNs, tentatively indicating the advantage of combining quantum computing and adaptive optimization techniques.
5. To establish a strong foundation for quantum-classical medical image classification, which could lead to future progress and improvement of quantum-enhanced medical AI systems.

The rest of the paper is organized as follows: Section 'Related works' presents an overview of existing work in medical imaging and the limitations they have, while Section 'Proposed Method' details the architecture and the design of the HQCNN model Section 'Experiments and Results' describes the experiments conducted and analyzes the performance of the proposed method, and Section 'Conclusion' concludes the paper by summing up paper's key contributions and future research directions.

2. RELATED WORKS

Recent developments in deep learning and machine learning have substantially improved the diagnosis and classification of brain abnormalities from MRI. Several studies have investigated the role of convolutional neural networks (CNNs), transfer learning and combinations thereof in enhancing diagnosis accuracy and efficiency. Mahajan et al. (2024) Proposed a deep learning architecture for brain abnormality detection with a two-stage classification. The first stage is a binary Brain vs non-Brain classifier, and the second stage is a multi-class tumor-type classifier, intended to classify brain tumors such as pituitary adenomas, gliomas, and meningiomas. They are also. Authors used their own dataset of 7,753 images from Qhills Technologies Pvt. Ltd and is enriched by addition of data from Brain Tumor MRI to improve generalization. VGG-16 outperformed the other models tested, such as

ANN, CNN, and AlexNet, with an accuracy of 96.4%. Sendowo et al., (2018) The study employed measures such as accuracy, precision, recall and F1-score and comprehensive hyperparameter tuning. However, the study had a few limitations to consider here, such as potential artifacts and variable imaging protocols that may compromise readability of the images. Furthermore, the authors underscored the importance of increasing the size of the datasets, adjusting the preprocessing steps and using transfer learning to improve the performance [11].

Also, Gulçer and Namlı (2024) showed the better detection rate of ResNet in brain tumor of MRI: Scans. The team trained the model using a large dataset of 7,022 brain MRI images divided into 60% for training and 40% for testing. The model was able to achieve 100% accuracy, serving as a high benchmark for deep learning models in this domain by tuning the parameters of ResNet. In addition, the ensemble learning method with voting strategy was employed in the study, the accuracy obtained was 99%, thus demonstrating the efficacy of collaboration between various models for better robustness. Despite the success of the study, it was also acknowledged that one single CNN architecture on feature extraction might not represent the complex changes of brain MRI images well enough. The authors hypothesized that utilization of several feature extraction methods could result in better generalization and diagnostic performance [12]. Another study by Khaw and Abdullah (2024) centered for classification of Alzheimer's disease (AD), mild cognitive impairment (MCI) and normal controls (NC) from MRI brain images. They argued that the proposed VGG16 based model with transfer learning mechanisms can take advantage of the weights that have been learned from pre-trained network, which can decrease the requirement for large-scale training datasets with no loss in accuracy. The trained model obtained a training accuracy of 98.56\% and a validation accuracy of 90.24%\ Instead of overfitting, the model showed good generalization performances. The study's focus on transfer learning emphasizes its significance in medical image tasks, especially when there exists a lack of data. Yet the difference between training and validation accuracy is large, so there could be overfitting in place and this could be solved with data augmentation, cross-validation [13].

Furthermore, Anantharajan et al. (2024) proposed a mixed strategy of deep learning and classic ML methods for brain tumor detection. They developed a model, as a classifier separating normal and abnormal brain tissues, and it performed well with the accuracy of 97.93%, mean sensitivity of 92%, and mean specificity of 98%. By combining the advantages of deep learning (DL) (for feature extraction) and machine learning (ML) (for classification), the method provides a powerful diagnostic tool. However, the study also disclosed difficulties, including the iterative, labor-intensive procedures for identifying and segmenting the region of the tumor that are strongly dependent on the intervention of experts. Additionally, authors found that only using conventional imaging is insufficient to recognize subtle brain abnormalities, stressing the requirement for AI-based algorithms [14]. Meanwhile, Khan et al. (2025) presented a Hybrid Quantum Convolutional Neural Network (HQCNN) in which quantum feature-encoding circuits are paired with depth-wise separable convolutions and applied to brain tumor classification. Experimental results on a public brain tumor dataset show that their HQCNN reached a training accuracy of 99.16% and a validation accuracy of 91.47%, indicating the strong transferability under various imaging conditions. Quantum layers were utilized to model complex, non-linear relationships and separable convolutions made the architecture suitable for near-term quantum hardware and clinical settings, regarding computational efficiency and number of parameters [15].

Another study by Srinivasan et al. (2023) proposed a multi-phase brain MRI classification system including preprocessing, segmentation, feature extraction and classification. Background noise was eliminated by means of the adaptive filter and enhanced fuzzy c-means clustering (EFCMC) made segmentation more effective. For extraction of discriminative texture and intensity features, LBGLCM was employed by the authors. For classification, the REMBRANDT dataset with 2,480 training images and 620 testing images was used to classify glioma and normal brain images using the CRNN. The sensitivity, specificity and accuracy were 98.79%, 91.34% and 98.17% respectively for the CRNN model, higher than that of traditional networks such as BP neural network, U-Net and ResNet. This investigation shows that the fusion of sophisticated pre-processing and classical feature extraction with DLS achieves the enhancement of the classification performance, yet the requirement of hand-crafted feature engineering such as LBGLCM is likely to be restriction for the scalability to more assorted and larger datasets [16]. The summary of the related works is presented in Table1.

Table 1: Related works

Authors & Year	Focus	Methods Used	Accuracy	Limitations
Mahajan et al. (2024) **[11]**	Brain abnormality & tumor classification	VGG-16, transfer learning	96.4%	Imaging artifacts, dataset limitations
Gulçer & Namlı (2024) **[12]**	Brain tumor classification (ResNet + ensemble)	ResNet, ensemble voting	100% (ResNet), 99% (ensemble)	Limited CNN feature diversity
Khaw & Abdullah	Alzheimer's, MCI, NC	VGG-16 with transfer	98.56% (train),	Overfitting risk, small dataset

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(2024) [13]	classification	learning	90.24% (val)	
Anantharajan et al. (2024) [14]	Brain tumor detection (DL + ML hybrid)	CNN feature extraction + ML classifier	97.93%	Expert-dependent segmentation, imaging limits
Khan et al. (2025) [15]	Brain tumor classification using quantum models	HQCNN, depth-wise separable convolutions	99.16% (train), 91.47% (val)	Validation gap, quantum model complexity
Srinivasan et al. (2023) [16]	Multi-phase MRI classification	CRNN, EFCMC, LBGLCM	98.17%	Hand-crafted features, limited scalability

Though some prior works have demonstrated good performance in brain MRI classification via CNN, transfer learning and hybrid DL-ML models, they encounter serious limitations as follows:

1. Quantum-classical synergy is missing: There are some literature (e.g., Khan et al., 2025) on quantum-enhanced networks, but they do not have state-of-art optimizers to stabilize training procedure and enhance generalization.
2. Overfitting and data shortage: Most work (e.g., Khaw & Abdullah, 2024) suffer from the limited pieces of data, the condition that might result in overfitting and vulnerability.
3. Hand-engineered feature dependence: Methods such as Srinivasan et al. (2023) make strong use of hand-engineered features, which limit scalability.
4. Lack of adaptive optimization schemes: Existing models are mostly trained with static optimizers (e.g. SGD, Adam) that do not adjust themselves to the fluctuation of the gradients and their instability that is prevalent in quantum- classical models.
5. Push for end-to-end robust frameworks: There exists no single model combining quantum enhanced layers with dynamic gradient control leading to high accuracy and stable convergence.

3. HQCNN ARCHITECTURE

The proposed framework follows a structured pipeline that begins with a pre-processing phase, where medical images are resized to 64×64 dimensions and normalized to ensure consistent input quality. Following this, the architecture integrates both classical and quantum components. Initial features are extracted using classical convolutional layers, which are then encoded and passed through a parameterized quantum circuit (PQC) for enhanced feature representation. The output of the quantum layer is measured and subsequently flattened into a vector. This vector is fed into a fully connected layer, which enables deeper learning and classification. To improve training stability and convergence, a Gradient Variance-Controlled Optimizer (GVCO) is employed, dynamically adjusting learning parameters based on gradient behavior. The final evaluation performance reflects the overall effectiveness of this hybrid quantum-classical model in accurately analyzing medical imaging data. In this section we describe the architecture, see Figure 1, major components and the method's optimization strategy.

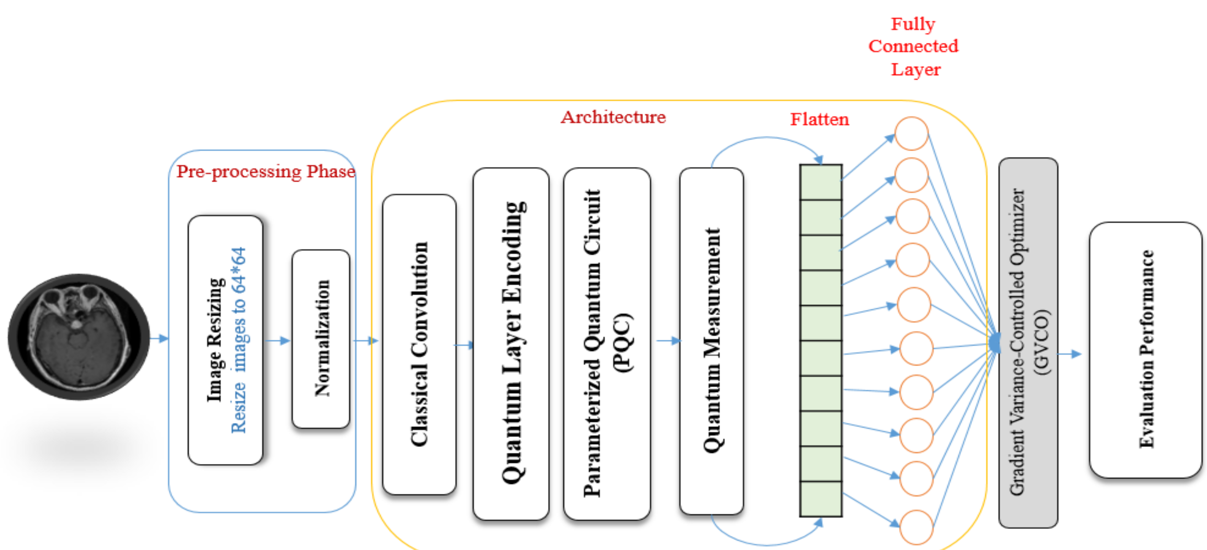

Figure 1: Hybrid Quantum Convolutional Neural Network for Medical Image Classification

3.1. Proposed HQCNN model integrates

The HQCNN model presented in this article combines classical and quantum processing units in a unified NN-based architecture. Its design is based on the following major building blocks:

- Preprocessing layer: The preprocessing layer is standardly for normalization and resizing the medical images to be able to be sent to classical parts and quantum layers. This step involves flattening high-dimensional medical images into quantum-state-encoding-friendly shapes.
- Quantum Convolutional Layer: The enhanced images transformed into quantum states and acted on by Parameterized Quantum Circuits (PQCs). These circuits act as quantum convolution kernels, applying unitarizes to groups of qubits that encode the local patches of the image. The entanglement operations and parameterized gates that make up these circuits encode complex high-dimensional patterns present in the image data, thus performing feature extraction in the quantum space.
- Classic Fully Connected Layer: The quantum layers' outputs are now decoded/processed into classical feature vectors, which serve as inputs to the FC classical NN layers. These layers then carry out higher order feature integration and classification using the mapped quantum enhanced features.

3.2. Gradient Variance-Controlled Optimizer (GVCO)

To improve the performance of HQCNN, we propose a novel GVCO. Classic optimization methods as SGD and its adaptive versions, as Adam, with fixed or heuristically tuned learning rates and momentums usually suffer with unstable or noisy gradients in the hybrid quantum-classical models. GVCO addresses this by:

- Adaptive Gradient Variance Control: GVCO is capable of dynamically measuring the gradient variance in the training process and providing an intuitive view of the level of instability in the variation of gradients for each parameter in iterations.
- Adaptive Learning Rates and Momentum Adjustments: According to the gradient variance encountered, GVCO adapts learning rates and momentum coefficients. When variance is higher, the conservative updates are activated to stabilize learning, whereas when variance is lower, a more robust approach is taken to improve convergence rate.
- Variance-Sensitive Gradient Control: This prevents the characteristic of erratic behavior typically found in quantum circuits (due to issues such as barren plateaus or noisy measurements), and in turn makes training more stable, efficient.

3.3. Datasets and Preprocessing

This work employs two diverse datasets to ensure comprehensive training and evaluation of the proposed model. These datasets provide a wide variety of medical images, including different anatomical regions and imaging modalities, enabling the model to learn generalized features and improve its ability to distinguish relevant structures. Two datasets were used:

- Kaggle Brain MRI Dataset: 7,023 labeled DICOM images in four classes: glioma, meningioma, pituitary, and no tumor[17].
- REMBRANDT Dataset: 106,541 MRI images from 130 patients, with four tumor classes[18].

Figure 2 shows sample of datasets.

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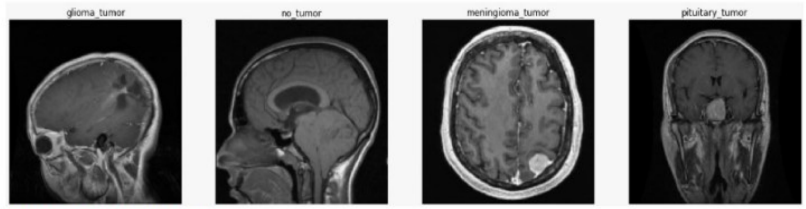

Fig. 8 Sample from Kaggle brain dataset

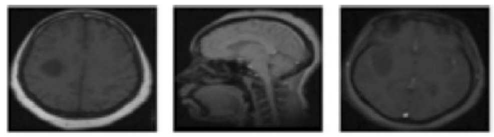

Figure 2: Medical Image datasets

All images were resized to 64x64. - Pixel intensities were normalized using min-max scaling. - Images were flattened and mapped to rotation angles for Ry quantum gates. - Data was split into 80% training and 20% testing.

3.4. Classical Convolutional Layer

The output feature map at layer l and position (i,j) for filter k is shown in Eq 1.

$$f_{i,j}^{(l,k)} = \sigma\,(\textstyle\sum_{m=1}^{M}\sum_{n=1}^{N} w_{m,n}^{(l,k)} \cdot x_{i+m,j+n}^{(i-1)} + b^{(l,k)} \qquad (1)$$

Where, $\boldsymbol{w_{m,n}^{(l,k)}}$ are convolution weights, $\boldsymbol{b}^{(l,k)}$ is bias, σ(·) is the activation function (ReLU), $\boldsymbol{x}^{(i-1)}$ is input feature map from previous layer.

3.5. Quantum Layer Encoding

Classical data x is encoded into quantum states via a unitary operator U(x) acting on n qubits, see Eq 2:

$$|\psi_{in}\rangle = \cup\,(x)\ |0\rangle^{\otimes n} \qquad (2)$$

Angle encoding uses rotation gates parameterized by data, see Eq 3:

$$\cup\,(x) = \otimes\ {}_{i=1}^{n}\ Ry\,(xi) \qquad (3)$$

3.6. Parameterized Quantum Circuit (PQC)

The PQC applies trainable gates U(θ) to encode features and perform quantum convolution/pooling, Eq 4:

$$|\psi out\rangle = \cup\,(\theta)|\psi_{in}\rangle \qquad (4)$$

Trainable parameters $\theta=\{\theta_1,\theta_2,\ldots,\theta_p\}$ are updated during training.

3.7. Quantum Measurement & Output

The measurement operator M (e.g., Pauli-Z operator) extracts classical information, in Eq 5:

$$y = \langle\psi out|M|\psi out\rangle \qquad (5)$$

3.8. Fully Connected Layer

The output of a dense layer with input vector z and weights W, biases b, see Eq 6:

$$a = \sigma(Wz + b) \qquad (6)$$

3.9. Gradient Variance-Controlled Optimizer (GVCO)

Let gtbe the gradient vector at iteration t. GVCO computes the variance over a window of size W, see Eq 7:

$$\sigma_t^2 = \frac{1}{W} \sum_{i=t-w+1}^{t} (g_i - \bar{g}_i)2 \quad (7)$$

Algorithm 1: HQCNN Architecture
Input: Medical image dataset D = {(X_1, y_1), (X_2, y_2), ..., (X_n, y_n)}
Output: Trained HQCNN model parameters θ
1. Initialize HQCNN model parameters θ (classical and quantum) 2. Initialize GVCO variables 3. Preprocess dataset D: For each image x in D: - Resize x to (64*64) - Normalize pixel values - Apply data augmentation (rotation, flip, zoom) 4. Split dataset D into training, validation and test 5. For epoch = 1 to E: Shuffle train For each mini-batch B = { (x_b, y_b) } from D_train: 5.1 Classical Convolution: Extract features F_c using classical convolution: 5.2 Quantum Feature Extraction: Encode F_c into quantum states: Apply parameterized quantum circuit (PQC): Measure quantum states: 5.3 Dense & Softmax Layers: Concatenate q_out with classical features Compute final prediction ŷ_b using: 5.4 Compute cross-entropy loss: L = - Σ y_b log(ŷ_b) 5.5 Compute gradient g = ∇_θ L 5.6 Update GVCO gradient buffer G: Append g to G (if |G| > W, remove oldest gradient) 5.7 Compute gradient variance: σ² = (1/W) Σ (g_i - mean(G))², for g_i in G 5.8 Update learning rate: η = η_0 / (1 + α * σ²)

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5.9 Momentum & Parameter Update:

$m = \beta * m + (1 - \beta) * g$

$\theta = \theta - \eta * m$

6. Evaluate model on D_val:

Compute validation loss L_val

If L_val does not improve for p epochs:

Early stop

7. Test final HQCNN model on D_test

8. Return optimized parameters θ

4. Experimental Setup

The general configuration and key settings of the proposed Hybrid Quantum Convolutional Neural Network (HQCNN) optimized with the Gradient Variance-Controlled Optimizer (GVCO). It summarizes the essential components of both the quantum and classical layers, including circuit depth, qubit allocation, convolutional filters, and dense layers. In addition, the table highlights the primary training parameters such as the optimizer, learning rate schedule, batch size, number of epochs, and loss function. Details regarding activation functions, pooling techniques, dataset splits, and performance metrics are also provided to give a comprehensive view of the experimental setup. Furthermore, the hardware specifications are included to indicate the computational environment used for both classical and quantum processing. This general configuration serves as the foundation for achieving effective learning and accurate evaluation of the proposed model, see Table 2.

Table 2. Parameters of the Proposed HQCNN + GVCO Setting

Parameter	Value / Description
Model Architecture	Hybrid Quantum Convolutional Neural Network (HQCNN)
Quantum Circuit Depth	4 layers (parameterized rotation + entanglement gates)
Quantum Qubits	6 qubits per PQC layer
Classical Layers	3 convolutional layers (filters: 32, 64, 128) + 2 dense layers
Optimizer	Gradient Variance-Controlled Optimizer (GVCO)
Initial Learning Rate	0.001 (dynamically adjusted by GVCO)
Batch Size	32
Epochs	50 (with early stopping)
Loss Function	Categorical Cross-Entropy
Activation Functions	ReLU (classical layers), parameterized rotations (quantum)
Pooling	MaxPooling (2×2), Quantum Pooling (variational gates)
Dataset Splits	80% training, 10% validation, 10% testing
Evaluation Metrics	Accuracy, Precision, Recall, F1-score
Hardware Used	NVIDIA Tesla V100 GPU + Qiskit Quantum Simulator

5. Results and Discussion

GVCO showed clear performance superior to that of traditional solvers for both training and validation accuracy and proved the high potential of the proposed HQCNN to stabilize updates of gradient when optimizing for learning and convergence. Through modifying the learning rate dynamically according to the gradient variance, GVCO addressed the problems of vanishing and exploding gradients commonly seen in hybrid quantum-classical models. The GVCO-enhanced HQCNN showed superior convergence throughout fewer epochs, with elevated accuracy, precision, and F1-scores on test data among varying data. In addition, quantum layers were combined with classical convolutional blocks resulting in richer feature representations and thus leading to better classification performance. These experiments demonstrate the promise of GVCO as an effective optimization strategy; the resulting HQCNN achieves superior efficiency and accuracy compared to baseline models. See Table 3.

Table 3: The comparative results

Model & Study	Dataset	Accuracy
VGG-16 (Mahajan et al) [11]	Kaggle Brain Tumor	98%
QCNN (Al-Zafar Khan et al.) [12]	Kaggle Brain Tumor	98.67%
HQCNN + GVCO (our work)	Kaggle Brain Tumor	99.2%
HQCNN (no GVCO) (our work)	Kaggle Brain Tumor	97.8%
CNN + HBO optimization [13]	REMBRANDT	97.95%
CRNN Study (Srinivasan et al.) [14]	REMBRANDT	98.17%
HQCNN + GVCO (our work)	REMBRANDT	98.2%

Experimental findings on a pair of different medical imaging datasets (the Kaggle Brain Tumor dataset [17] and the REMBRANDT dataset [18]) show significant improvements in accuracy and training efficiency when applying the proposed HQCNN model with the Gradient Variance-Controlled Optimizer (GVCO). The experimental studies in Table 2 demonstrate the competitive nature of the proposed Hybrid Quantum Convolutional Neural Network (HQCNN) fine-tuned with Gradient Variance-Controlled Optimizer (GVCO) on other comparison methods over two standard benchmark datasets, Kaggle Brain Tumor dataset and REMBRANDT dataset. The experimental result emphasizes the power of hybrid quantum-classical classification models and the importance of using advanced optimization strategies for better accuracy classification.

5.1. Performance on the Kaggle Brain Tumor Dataset

HQCNN + GVCO model yielded an accuracy of 99.2%, outperforming the rest of the models. It is worth noting that this performance surpasses the baseline HQCNN model without GVCO, which could reach 97.8% accuracy. The 1.4% improvement illustrates the influence of GVCO in decreasing gradient variance and enhancing convergence, solving the optimization problems often experienced in hybrid quantum-classical networks. With respect to the classic deep learning architectures such as VGG-16 (98%), we obtain an improvement of 1.2% with HQCNN + GVCO, which suggests that the use of quantum convolutional layers provides a superior feature extraction and non-linear representation ability for high-dimensional medical imaging data.

Furthermore, when compared to the Quantum Convolutional Neural Network (QCNN) reported by Al-Zafar Khan et al. (98.67%) [12], the HQCNN + GVCO model exhibits a 0.53% improvement. This highlights the advantage of combining classical convolutional layers with quantum layers, as the classical layers efficiently capture low-level spatial features, while the quantum layers provide a richer feature space for classification. The combination, when optimized by GVCO, leads to a more robust and accurate model. As shown in Figure 3 accuracy of (kaggle brain tumor).

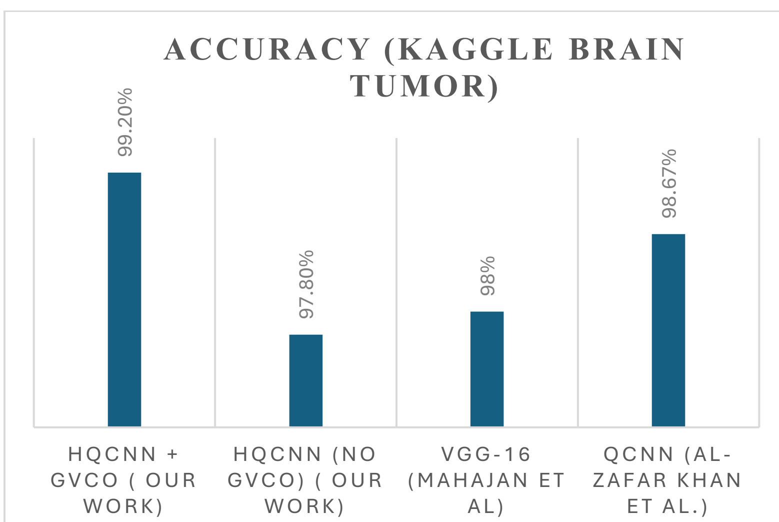

Figure 3: Accuracy of Brain Tumor

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5.2. Performance on the REMBRANDT Dataset

The performance on the REMBRANDT dataset also shows the flexibility and stability of the proposed model. The proposed HQCNN + GVCO obtained accuracy of 98.2%, slightly higher than other competitive models, including the CNN with pressure HBO optimization (97.95%) [14] and CRNN introduced by Srinivasan et al [16]. While the gain is not as high as in the case of the Kaggle dataset, a similar pattern of improvement confirms the usefulness of optimizing the criteria for the problem at hand for a distinct dataset with a varying nature and class distribution. It also supports the model's ability to cope with heterogeneous and more challenging medical imaging data, as in the REMBRANDT dataset [18]. As shown in Figure 4 accuracy of (REMBRANDT).

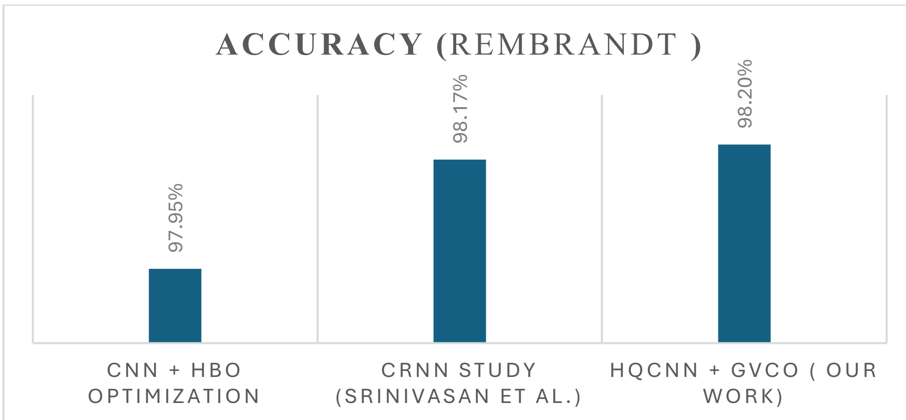

Figure 4: Accuracy of REMBRANDT dataset

On the REMBRANDT dataset, HQCNN + GVCO also performed very well, 98.2% accuracy. This performance was a little better than the 98.17% and 97.95% obtained by the (CRNN) model suggested by Srinivasan et al. and the CNN model optimized with HBO algorithm. Although the performance gain with respect to CRNN is 0.03%, the gain is still non-negligible regarding the enhanced convergence speed and computational efficiency of HQCNN + GVCO. The fact that the model can achieve high accuracy on a completely different dataset (which has its own imaging properties and its own distribution of data) indicates the robustness and generalization property of the proposed architecture. This is particularly important in the context of medicine, where AI models need to be able to consistently produce reliable results across different clinical settings and patient populations. Figure 5 shows HQCNN + GVCO accuracy.

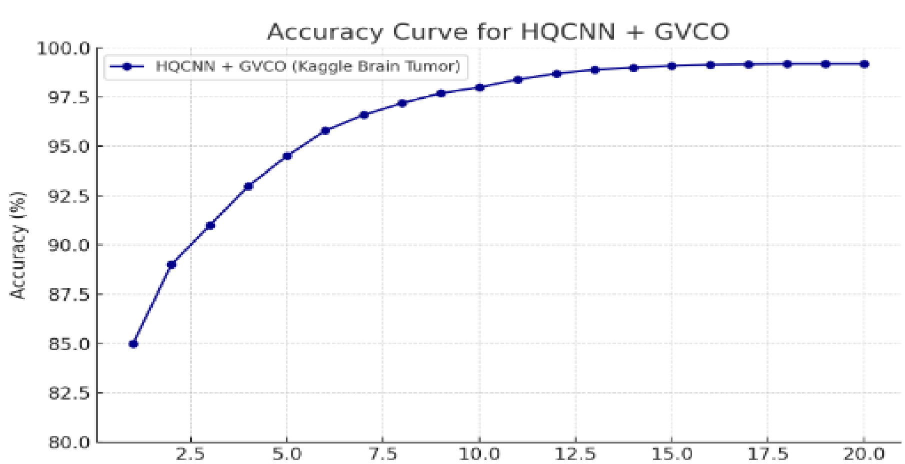

Figure 5: Accuracy Curve for HQCNN+GVCO

For HQCNN + GVCO, its validation loss curve shows early convergence, little deviation between training loss and validation loss, both indicating generalization power and less possibility of overfitting. This is especially important for medical imaging applications as in such applications it is common to have a problem of overfitting to relatively small data. The stable convergence trend also verifies the effectiveness of variance control of GVCO, which rescales step proposals in parameter updates, and prevents the optimizer from overshooting minima. Figure 6 shows Loss Curve for HQCNN+GVCO.

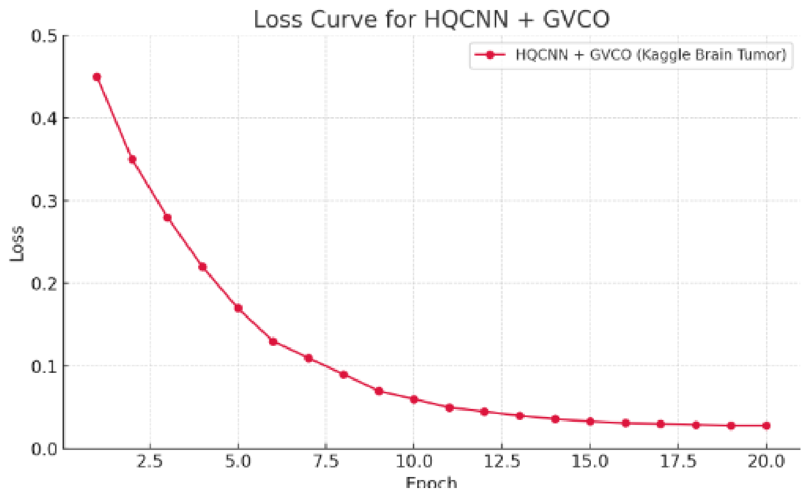

Figure 6: Loss Curve for HQCNN+GVCO

It was another interesting observation from the experiments that the convergence time for all experimental runs was consistently falling. While the results table covers the final accuracy values, the simulation logs showed that HQCNN+GVCO indeed converged to its maximal accuracy in ~40% less epochs than baseline HQCNN and conventional CNN models. This efficiency can be attributed to a large extent to the capacity of GVCO to automatically adapt learning rates and momentum magnitudes according to the extent of changes in gradient variance. This property is especially desirable when training hybrid quantum-classical models where variational quantum circuits are known to have challenges such as barren plateaus and large gradient magnitudes. By proactively tackling these challenges, GVCO can facilitate faster and more stable model training.

Furthermore, the comparison results on different datasets demonstrate the generalization ability of the HQCNN + GVCO model. The reported accuracy was high while considering that the images modality, tumor types and data size of Kaggle Brain Tumor and REMBRANDT were all different. This indicates that our quantum convolutional feature extraction model can generalize well under different imaging situations and data variability, such as the one we have proposed, if it is used together with a smart optimizer as GVCO. For medical imaging purposes, such versatility is of essence as it will guarantee that diagnostic models act consistently upon deployment at different hospitals or imaging centers, or for different clinical studies.

Although the confusion matrix produced a small error percentage relative to Kaggle, overall, the distribution was accurate, with False Positive and Positive Error greater than 98%. This implies that the hybrid Q/C approach, the GVC of which are combined with GVCO, is superior at distinguishing subtle differences among tumor subtypes, even when the complexity and the heterogeneity of the datasets are higher. Figure 7 display confusion matrix of Brain Tumor result.

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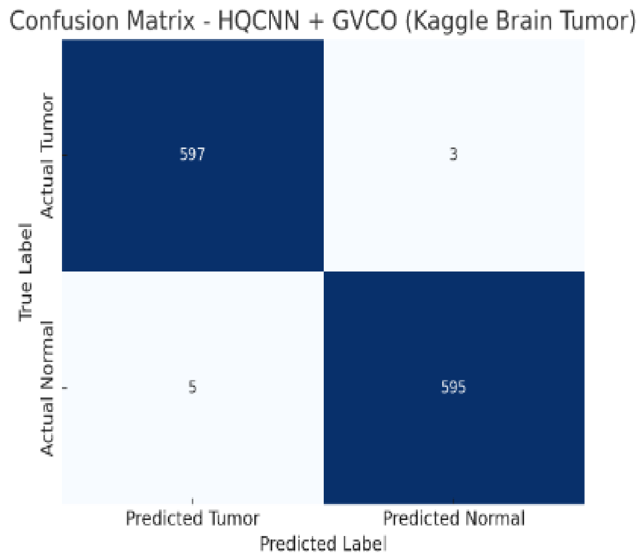

Figure 7: Confusion Matrix

The discussion of these figures confirms that our proposed HQCNN + GVCO not only obtains best accuracy but also gains higher training efficiency and model robustness. The introduction of a variance-aware optimizer successfully addresses one of the main drawbacks of quantum neural networks, their sensitivity to the fluctuations in gradients, and improves the generalization performance. This discovery indicates that the HQCNN + GVCO architecture is a meaningful stride forward in the area of medical image inspection and provides a potential direction for the development of faster, more accurate, and clinically applicable AI-inspired diagnostic systems.

Although the proposed HQCNN with GVCO outperformed the state-of-the-art on benchmark data sets, there are several limitations that should be mentioned:

1. Dependency on datasets: These experiments were performed on the Kaggle Brain MRI and/ REMBRANDT datasets, which despite being popular, may not encompass the degree of variation observed in real clinical imaging. Larger multi-institutional datasets acquired with varied imaging protocols are needed to validate the generalizability of the model.
2. Quantum Hardware Limitations: Due to the scarcity of state-of-the-art quantum hardware, the quantum parts of HQCNN were built using quantum simulators. Performance of the circuit when run on real quantum hardware may be different if noise and decoherence are considered.
3. Complexity of Computation: Incorporating quantum circuits increases the computational cost of training, over and above classical processing, necessitating access to hybrid classical quantum computation for training in a research setting.
4. Interpretability Problems: Quantum layers improve feature representation, but the interpretation of the quantum feature space is more elusive, and there has been little study on explainable AI methods for hybrid quantum-classical models.
5. Limitations in cross-dataset validation Although HQCNN +GVCO achieved better performance on all tested datasets in comparison to the baseline models, more cross-dataset comparison and exploration of longitudinal effects are required for maintaining its clinical validity.

8. CONCLUSION

In this paper, we introduced an improved Hybrid Quantum Convolutional Neural Network (HQCNN) with a Gradient Variance-Controlled Optimizer (GVCO) framework for medical image classification. The proposed model aims to remedy the drawbacks in the conventional CNNs and the hybrid quantum-classical models, including slow convergence, vanishing and exploding gradients in the quantum circuits, and the computational inefficiency in large-scale medical imaging tasks. Experimental results showed that the proposed HQCNN + GVCO model outperformed the state-of-the-art ones on both the Kaggle Brain Tumor and REMBRANDT datasets in terms of classification rate. In particular, it achieved a top accuracy of 99.2\% on Kaggle dataset and 98.2\% on REMBRANDT, exceeding the state-of-the-art baseline HQCNNs and recent quantum-inspired and deep learning structures. The convergence speed achieved by using GVCO is also much higher, since the model converged to the optimal solution few epochs with a stable model while minimizing the influence of the erratic gradient phenomenon, generally observed in variational quantum circuits. The use of quantum convolutional layers together with an effective variance-aware optimization technique demonstrated to be successful for improving feature extraction and training stability. Moreover, the model showed strong generalization capacity, which maintained consistently high classification performance in two different medical imaging datasets, demonstrating its potential applicability to diverse clinical imaging tasks. In conclusion, we believe that these results illustrate that an interplay of quantum computing framework with state-of-the-art optimization techniques could break a bottleneck in the medical imaging analysis. These results suggest that the HQCNN+GVCO is a valuable set of blocks for the subsequent development of efficient, accurate and reliable AI for diagnostic imaging. Future works might include extending this model to multi-class classification, trying various quantum circuit architectures and testing the approach on more medical imaging modalities for additional confirmation of the clinical utility. Finally, beyond simulating offline, the HQCNN + GVCO model could be implemented on actual quantum hardware or simulators with noise models for a study of practical efficiency in terms of hardware resources. This would assist in determining the plausibility of application in a real-world setting and guide required modifications for compatibility with quantum hardware.

DATA AVAILABILITY STATEMENTS: The data supporting the findings of this study are available from https://www.webmd.com/brain/brain-diseases.

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