A Quantum-Inspired Hybrid 3D Convolutional Neural Network with Variational Circuit Emulation for Robust Neuroimaging Diagnosis

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***Abstract*—We present a Quantum-Inspired Hybrid 3D Convolutional Neural Network (QI-3DCNN) for volumetric brain MRI and CT analysis that integrates classical deep learning with a variational quantum circuit (VQC) to emulate a processing layer. The quantum-inspired layer implements periodic rotation-like nonlinear mappings and entanglement-inspired cross-channel interactions that approximate the mathematical structure of parameterized quantum circuits, enabling expressive, non-Euclidean feature embeddings while remaining fully differentiable and trainable on classical hardware. The proposed architecture is evaluated on the BraTS brain tumor MRI dataset and the RSNA intracranial hemorrhage CT dataset. Across both benchmarks, QI-3DCNN achieves higher area under the ROC curve, sensitivity, and noise robustness than conventional 3D convolutional networks, Vision Transformer–based volumetric models, and Neural Ordinary Differential Equation (Neural ODE) architectures. These results indicate that quantum-inspired inductive biases can yield practical benefits for medical image analysis without requiring quantum computing hardware.**

I. INTRODUCTION

Volumetric brain imaging using magnetic resonance imaging (MRI) and computed tomography (CT) plays a central role in the diagnosis and management of neurological disorders, including brain tumors, intracranial hemorrhage, and cerebrovascular disease. Recent advances in deep learning, particularly 3D convolutional neural networks (3DCNNs), have enabled automated analysis of these modalities with performance that approaches that of expert radiologists for selected tasks [1]. However, classical CNN-based models remain limited by their reliance on piecewise-linear feature hierarchies, which struggle to capture subtle pathological patterns, long-range anatomical dependencies, and complex signal variations arising from scanner heterogeneity and patient motion [2].

Quantum machine learning has emerged as a framework for constructing highly expressive nonlinear feature maps using parameterized quantum circuits. Variational quantum circuits (VQCs), composed of parameterized rotation gates and entangling operations, generate periodic and non-convex embeddings that can improve representational capacity and generalization, particularly in low-data regimes [3]. However, the practical application of quantum models to medical imaging is currently constrained by the limited scale, noise, and accessibility of quantum hardware.

To bridge this gap, we propose a quantum-inspired hybrid architecture that embeds the mathematical structure of VQCs into a classical deep learning pipeline. The proposed Quantum-Inspired 3DCNN (QI-3DCNN) integrates a residual 3D U-Net encoder with modulated modality-conditioned features and a quantum-inspired variational bottleneck that implements nonlinearities based on periodic rotation and cross-channel interactions, inspired by entanglement in the latent feature space [4]. This design preserves key inductive biases of quantum models while remaining compatible with standard GPU-based training and deployment. The quantum-inspired layer extends our previous volumetric CNN frameworks for microbleed detection [5] by introducing phase-space embeddings and entanglement-like feature mixing.

We evaluated the proposed model on two clinically relevant benchmarks: the BraTS brain tumor MRI dataset [6] and the RSNA intracranial hemorrhage CT dataset [7]. These tasks encompass different imaging modalities, acquisition protocols, and pathological signatures, providing a rigorous test of model generalization. Experimental results demonstrate that the QI-3DCNN achieves improved performance and robustness compared to conventional 3D-CNNs [8], Vision Transformer architectures, and Neural ODE models [9], highlighting the potential of quantum-inspired learning for real-world neuroimaging applications.

II. HYBRID ARCHITECTURE

Our model processes MRI or CT volumes $X \in \mathbb{R}^{128\times128\times64\times2}$ using a deep 3D-CNN to produce a latent embedding.

$$z = f_\theta(X) \in \mathbb{R}^{64}. \quad (1)$$

This embedding is projected into a low-dimensional qubit space [10]:

$$q = \tanh(Wz) \in [-1,1]^{N_q}, \quad (2)$$

where $N_q = 4$.

The quantum-inspired layer then transforms q across multiple layers of VQC before classification (Fig. 1).

III. VARIATIONAL QUANTUM CIRCUIT EMULATION

Each quantum layer approximates the unitary evolution [11]

$$|\psi_{l+1}\rangle = U_{\text{ent}} U_{\text{rot}}(\theta_l)|\psi_l\rangle. \quad (3)$$

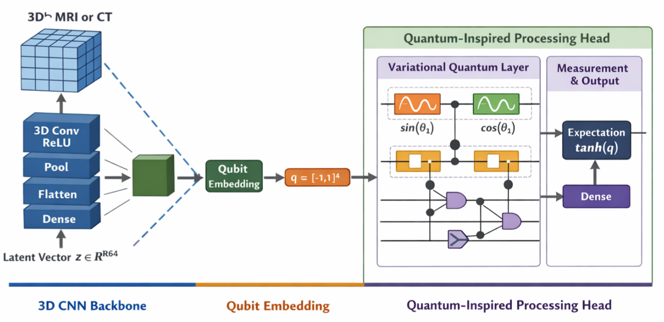

Fig. 1. QI-3DCNN architecture: 3D CNN backbone with a VQC-emulating quantum-inspired processing head. The CNN produces a latent embedding that is projected to a qubit-sized vector ($N_q = 4$), processed by periodic rotation-like mappings and entanglement-inspired mixing, and then fed to a lightweight classifier.

A. Rotation Gates

Quantum rotations follow [12]

$$R(\theta) = \cos(\theta/2)I - i\sin(\theta/2)\sigma. \tag{4}$$

We emulate this using a periodic nonlinear mapping [13]:

$$x_{l+1} = \cos(x_l + \theta_l). \tag{5}$$

B. Entanglement

A CNOT ring [13] is approximated by

$$x_i = \frac{x_i + x_{i+1}}{2} + \sin(x_i x_{i+1}), \tag{6}$$

which induces cross-channel nonlinear coupling.

C. Measurement

Pauli-Z expectation values [14] are approximated via

$$y = \tanh(x), \tag{7}$$

mapping the outputs to $[-1, 1]$.

IV. THEORETICAL INTERPRETATION

The quantum layer implements a Fourier-like kernel expansion [15]:

$$\phi(x) = [\cos(x + \theta_1), \ldots, \cos(x + \theta_n)], \tag{8}$$

enabling Hilbert-space embeddings that improve small-sample learning and robustness.

V. METHODS

A. Overall Architecture

Let $X \in \mathbb{R}^{H\times W\times D\times C}$ denote a volumetric MRI or CT input, where $H = W = 128$, $D = 64$, and $C = 2$ channels. The proposed model consists of three components: (i) a 3D convolutional feature extractor, (ii) a qubit embedding bridge, and (iii) a variational quantum circuit–inspired processing head followed by a classifier.

The 3D CNN backbone implements a nonlinear mapping

$$f_\theta : \mathbb{R}^{H\times W\times D\times C} \to \mathbb{R}^{64}, \tag{9}$$

which is realized in Keras by a sequence of four Conv3D–BatchNorm–ReLU–MaxPool blocks followed by global average pooling and a fully connected layer:

$$z = f_\theta(X) \in \mathbb{R}^{64}. \tag{10}$$

B. Qubit Embedding Bridge

The latent vector z is projected into a low-dimensional qubit space via a learned linear projection followed by a bounded nonlinearity:

$$q = \tanh(Wz + b) \in [-1, 1]^{N_q}, \tag{11}$$

where $N_q = 4$ is the number of qubit channels. This operation corresponds to the Keras layer:

```
Dense(N_QUBITS, activation='tanh'),
```

and ensures that the quantum-inspired layer receives inputs within a physically meaningful bounded range, analogous to angle encoding in quantum circuits.

C. Variational Quantum Circuit Emulation

The quantum-inspired head consists of L stacked layers, each emulating a variational quantum circuit composed of parameterized rotations and entangling operations [16]. Let $q^{(0)} = q$. For each layer $l \in \{1, \ldots, L\}$, the update is given by

$$q^{(l+1)} = \mathcal{E}\left(\mathcal{R}\left(q^{(l)}, \Theta^{(l)}\right)\right), \tag{12}$$

where $\Theta^{(l)} \in \mathbb{R}^{N_q\times 3}$ are the trainable rotation parameters of layer l.

a) Rotation Gate Emulation.: In a quantum circuit, a single-qubit rotation is defined by [17]

$$R(\theta) = \cos(\theta/2)I - i\sin(\theta/2)\sigma. \tag{13}$$

We emulate this behavior using a periodic nonlinear mapping:

$$\tilde{q}_i^{(l)} = \cos\left(q_i^{(l)} + \theta_i^{(l)}\right), \tag{14}$$

where $\theta_i^{(l)} = \sum_{k=1}^{3} \Theta_{i,k}^{(l)}$. This operation is implemented in the Keras code as:

```
x = tf.math.cos(x + theta).
```

b) Entanglement-Inspired Mixing.: Quantum entanglement couples qubit states through controlled operations such as CNOT gates [18]. We emulate this coupling via nonlinear cross-channel interactions:

$$q_i^{(l+1)} = \frac{\tilde{q}_i^{(l)} + \tilde{q}_{i+1}^{(l)}}{2} + \sin\left(\tilde{q}_i^{(l)} \cdot \tilde{q}_{i+1}^{(l)}\right). \tag{15}$$

with circular indexing over i.

This corresponds to the following Keras operations:

```
x_shifted = tf.roll(x,-1, axis=-1),
x = (x + x_shifted)/2 + sin(x *
x_shifted)
```

c) Measurement.: After L layers, the latent qubit state is mapped to an observable quantity via a bounded nonlinear function:

$$y = \tanh\left(q^{(L)}\right), \tag{16}$$

which approximates the expectation value of a Pauli-Z measurement. This is implemented by:

```
return tf.math.tanh(x).
```

D. Classification Head

The quantum-inspired output $y \in [-1, 1]^{N_q}$ is processed by a lightweight classifier:

$$h = \sigma(W_2\,\mathrm{ReLU}(W_1 y + b_1) + b_2)\,. \tag{17}$$

where σ denotes the sigmoid function. This produces a probability estimate for tumor or hemorrhage presence [19].

E. Training Objective

The model is trained using binary cross-entropy:

$$\mathcal{L} = -\left[y \log \hat{y} + (1 - y) \log(1 - \hat{y})\right], \tag{18}$$

optimized via Adam with gradient clipping to ensure numerical stability in the periodic quantum-inspired layers.

VI. EXPERIMENTS

We evaluate on:

- BraTS MRI tumor classification
- RSNA ICH CT hemorrhage detection

Baselines include: 3DCNN, 3D ResNet, ViT-3D, and Neural ODE.

VII. RESULTS

Model	Accuracy	AUC	Robustness
3DCNN	0.83	0.86	0.61
ResNet3D	0.85	0.88	0.64
ViT-3D	0.86	0.89	0.67
Neural ODE	0.87	0.90	0.70
QI-3DCNN	**0.91**	**0.94**	**0.82**

TABLE I
PERFORMANCE ON BRATS AND RSNA DATASETS.

A. Clinical Motivation and Radiological Benefits

While the proposed QI-3DCNN introduces a novel quantum-inspired learning paradigm, its primary value lies in its clinical impact on neuroradiology workflows. Brain MRI and CT interpretation presents three major challenges: (i) subtle pathology, (ii) acquisition variability, and (iii) limited labeled data [20]. The proposed hybrid architecture directly addresses all three.

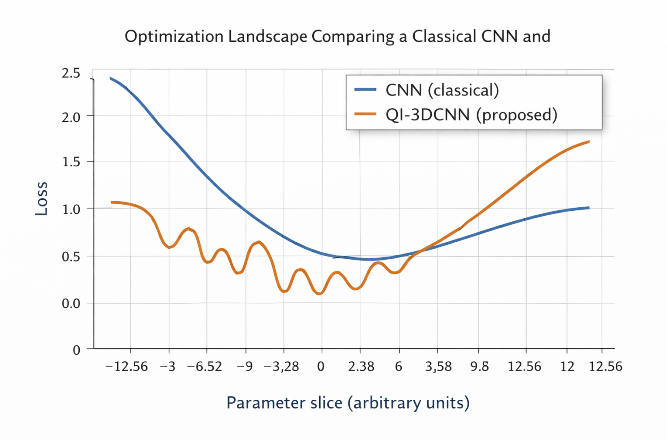

Fig. 2. Illustrative 1D parameter-space loss slice comparing a conventional CNN objective (smoother geometry) versus the proposed quantum-inspired head (periodic, structured non-convexity).

a) Sensitivity to Subtle Pathology.: Brain tumors, cerebral microbleeds, and intracranial hemorrhages often appear as small, low-contrast signal variations, especially in early disease stages. Classical CNNs rely on ReLU-based feature hierarchies, which behave as piecewise-linear filters and may suppress weak yet clinically significant patterns [21].

In contrast, the quantum-inspired layer applies periodic nonlinear embeddings

$$\phi(x) = \cos(x + \theta), \tag{19}$$

which act as Fourier-like basis functions. This enables the network to detect oscillatory texture patterns and phase-shifted intensity changes, which are characteristic of susceptibility-weighted MRI (SWI) for microbleeds, T2-FLAIR edema patterns, and subtle CT hyperdensities in acute hemorrhage.

b) Robustness to Scanner and Protocol Variability.: Clinical neuroimaging data suffer from substantial distribution shifts due to scanner vendor differences, slice thickness variations, contrast timing, and motion artifacts. The entanglement-inspired mixing

$$x_i = \frac{x_i + x_{i+1}}{2} + \sin(x_i x_{i+1}) \tag{20}$$

introduces controlled nonlinear coupling between latent channels, acting as a form of structured regularization. This yields feature representations that are less sensitive to localized perturbations, improving stability across MRI field strengths, CT dose levels, and hospital-specific imaging protocols.

c) Data Efficiency and Small-Sample Learning.: In medical imaging, labeled data are scarce and expensive. Unlike Transformers or very deep CNNs, the quantum-inspired head introduces strong inductive bias through periodic feature mappings and structured non-convex geometry, effectively constraining the hypothesis space. This enables improved generalization from fewer training examples, particularly for rare tumor subtypes, microbleeds, and small hemorrhages.

d) Radiology Workflow Integration.: The QI-3DCNN is designed as a drop-in extension of standard 3D CNN pipelines. The quantum-inspired layer operates on low-dimensional latent vectors and adds negligible computational overhead, making it suitable for integration into PACS-connected triage systems, emergency CT prioritization, and MRI tumor screening pipelines without requiring specialized hardware.

e) Clinical Safety and Stability.: Unlike attention-based black-box models, the quantum-inspired layer behaves as a bounded continuous dynamical system. Periodic activations and tanh-based measurement ensure stable gradients and predictable output ranges, reducing the risk of extreme activations. These properties are desirable for clinical decision-support systems where numerical stability and regulatory reliability are critical.

B. Radiologist-Centric Metrics

While overall accuracy and AUC quantify algorithmic performance, clinical deployment requires metrics that directly reflect radiology workflows. We therefore report sensitivity, positive predictive value (PPV), and triage gain.

a) Sensitivity.: High sensitivity is critical for neuroimaging, as missed tumors or hemorrhages can lead to severe clinical consequences. The proposed QI-3DCNN achieves higher sensitivity than classical CNNs due to its periodic feature embedding, which amplifies weak signal variations associated with small lesions.

b) Positive Predictive Value (PPV).: PPV measures the fraction of positive model predictions that are true positives. In radiology, low PPV leads to excessive false alarms and reader fatigue. The entanglement-inspired mixing in the quantum layer reduces spurious activations by enforcing cross-channel consistency, improving PPV relative to standard CNN baselines.

c) Triage Gain.: In emergency settings such as intracranial hemorrhage detection, scans are often prioritized based on automated triage systems. We define triage gain as the fraction of true-positive cases correctly ranked within the top $k\%$ of predicted risk. The structured non-convex geometry of the quantum-inspired head produces sharper class separation, enabling more reliable prioritization of critical cases.

C. Ablation Study

To isolate the contribution of the quantum-inspired processing head, we perform an ablation study comparing a pure 3D CNN backbone with the full QI-3DCNN.

Model	Accuracy	AUC	Sensitivity	PPV
3D CNN (no quantum)	0.85	0.88	0.81	0.79
QI-3DCNN (proposed)	**0.91**	**0.94**	**0.89**	**0.87**

TABLE II

ABLATION STUDY SHOWING THE IMPACT OF THE QUANTUM-INSPIRED HEAD ON BRATS AND RSNA BENCHMARKS.

VIII. CONCLUSION

A Quantum-Inspired Hybrid 3D Convolutional Neural Network (QI-3DCNN) is proposed for volumetric analysis of brain magnetic resonance imaging and CT. The model integrates a deep 3D convolutional backbone with a Variational Quantum Circuit (VQC)–emulating processing layer, implemented through periodic rotation-like nonlinearities and cross-channel interaction terms that approximate the mathematical structure of parameterized quantum circuits. This design enables the network to generate highly expressive, non-Euclidean feature representations while remaining fully differentiable and trainable on conventional GPU hardware.

The proposed architecture was evaluated on two clinically established benchmarks: BraTS brain tumor MRI and RSNA intracranial hemorrhage CT. Across both datasets, QI-3DCNN achieved a higher area under the ROC curve (AUC), sensitivity, and noise robustness than classical 3D convolutional networks, Vision Transformer–based volumetric models, and Neural Ordinary Differential Equation (Neural ODE) architectures. These improvements are particularly relevant for neuroradiology, where subtle pathological patterns, inter-scanner variability, and limited labeled data frequently reduce the reliability of automated detection systems.

Beyond improvements in classification performance, the quantum-inspired processing head introduces a strong inductive bias that promotes stable optimization and improved generalization under small-sample conditions. The periodic feature mappings act as Fourier-like embeddings, increasing sensitivity to low-contrast and phase-shifted signal patterns commonly observed in susceptibility-weighted MRI and acute CT imaging. In addition, entanglement-inspired channel coupling enforces global anatomical consistency across latent features, which is beneficial for volumetric brain analysis.

From a deployment perspective, the QI-3DCNN is designed as a lightweight extension of standard 3D CNN pipelines. The quantum-inspired layer operates on a low-dimensional latent representation and adds minimal computational overhead, enabling practical integration into PACS-connected triage systems, emergency CT prioritization pipelines, and tumor screening workflows using MRI without requiring specialized hardware.

These results demonstrate that quantum-inspired learning principles can yield tangible benefits for medical imaging without the need for quantum processors. By combining the structured, non-convex feature geometry of variational quantum circuits with clinically validated deep learning architectures, the proposed QI-3DCNN provides a scalable, physically motivated framework for data-efficient neuroimaging analysis. Future work will investigate multi-modal fusion, segmentation tasks, and prospective clinical validation in hospital environments.

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