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AF-HQCNN: Adaptive Federated Hybrid Quantum Convolutional Neural Network for Privacy-Preserving Medical Image Classification

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Abstract

Medical image classification is an important task in clinical decision support systems. Although classical deep learning models can represent massive amounts of data, they are not very scalable DEEP LEARNING REVIEW and stand each in their own right for privacy loss and computation inefficiency. Quantum machine learning (QML) has been proposed as an exciting field to complement classical machine learning by using quantum superposition and entanglement for increasing the expressibility of the models. Since the hybrid quantum-classical methods are subject to high qubit complexity [10], training instability (barren plateau problem) [13, 14], non-existent privacy protection mechanisms and poor generalisability over trained datasets [7]. Herein, we propose AF-HQCNN: an Adaptive Federated Hybrid Quantum Convolutional Neural Network (1) a lightweight classical feature extractor using only MobileNetV2, (2) variational quantum circuit (VQC) with angle and amplitude encoding with 4-8 qubits, (3) novel adaptive momentum-based quantum optimizer to mitigate gradient vanishing and gradient explosion issues, (4) federated learning aggregation layer layer to ensure protection of patient data privacy,(5), multi-dataset validation on MedMNIST, HAM10000, Brain MRI & Chest X-Ray datasets. Our experimental results show that AF-HQCNN leads to the mean classification accuracy of 97.6%, outperforming existing hybrid models by a margin of 2.7% with 87% fewer trainable parameters, faster convergence and robustness against privacy attacks.

1. Introduction

Medical imaging is a critical component of healthcare, with a diverse array of diagnostic modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), dermoscopy and retinal fundus photography. However, accurate and timely classification of these pathological conditions from the images continues to be a major challenge faced by various stakeholders due to inter-class similarity, intra-class variance and lack of availability of labelled data in practical clinical settings [1], [2]. Classical convolutional neural networks (CNNs) and transformer-based architectures have shown promise across different medical imaging benchmarks. However, they are fundamentally constrained by von Neumann computational limitations, high parameter counts and centralized training paradigms that present enormous data privacy qualms under HIPAA and GDPR regulatory frameworks (ref) [3]. Quantum Computing provides an entirely orthogonal computation substrate in which the very principles of superposition, entanglement and interference can be used to encode a feature space that is exponential in size within a consistently small quantum register. Hybrid quantum-classical networks (HQNNs) take advantage of the use of parameterized quantum circuits PQCs as intermediate processing layers within classical deep learning pipelines [4],[5], allowing for a form of quantum advantage without needing, at this stage, to rely on future more powerful NISQ (Noisy Intermediate-Scale Quantum) hardware.Instead, despite initial promising results, the careful literature survey highlights some major limitations:

- Many quantum models make use of reduced / downsampled datasets – lacks real-world relevance.
- NISQ devices are more influenced by noise due to high qubit requirements and deep circuit architectures.
- Our barren plateau phenomenon leads to gradient vanishing in deep variational circuits, hindering convergence.
- Federated training preserving privacy across distributed medical institutions has been largely unexplored.
- Single-dataset evaluations do not allow reliable claims of generalization.

To bridge these gaps in the same time, we propose AF-HQCNN — an aggregate framework based on a simple classical back-bone, a hyper-efficient variational quantum circuit, an adaptive optimizer and an federated aggregational strategy. Our contributions are:

1. A hybrid pipeline of independent MobileNetV2, angle encoding, 4–8 qubit PQC and FedAvg as an end-to-end approach.
2. A momentum-based quantum optimizer that provably avoids the barren plateau phenomenon.
3. A federated framework that enables multi-institutional training while preserving privacy
4. Evaluation of 4 Heterogeneous Medical Imaging Datasets
5. 87% less parameters compared to comparable classical baselines.

1.1. Deep Learning for Medical Image Classification

Deep convolutional neural networks revolutionized the analysis of medical images over last 10 years. Esteva et al. The first reported trained model capable of classifying skin cancer at the level of a dermatologist was composed of a deep CNN trained on more than 129,000 clinical images which had become an initial milestone for AI-assisted dermatology [1] and shown that data-driven models could outperform specialist physicians on visual diagnostic tasks. Rajpurkar et al. In 2017, Rajpurkar et al.[2] presented CheXNet, a 121-layer DenseNet that can detect pneumonia from chest X-rays at radiologist-level performance, demonstrating that very deep residual architectures are capable of robustly extracting pathological features from noise-filled radiographic data. Litjens et al. An overview of deep learning applied to eleven organ systems and imaging modalities was recently published by [3]Which documented overall consistency in improved accuracy and identified lingering issues such as limited data availability, class imbalance and absence of model interpretability for clinical environments affected by safety. He et al. In 2015, [4] formulated residual networks (ResNets) with identity skip connections to counter the vanishing gradient problem in very deep architectures, a design pattern that has been extensively employed as part of a standard backbone feature extractor within pure deep learning or hybrid quantum-classical medical imaging pipelines. Howard et al. MobileNet-V2 [5] presents efficient topology with the combination of inverted residuals and linear bottlenecks, achieves ImageNet-competitive accuracy using only a few percentages of parameters and multiply-accumulate operations from VGG-class networks, making it our choice as the backbone in classical compression stage in AF-HQCNN.

1.2. Foundations of Quantum Machine Learning

Biamonte et al. An important theoretical groundwork of quantum machine learning would be [6], where they established that conditions under which quantum algorithms may provide exponential speedups over classical counterparts for linear algebra subroutines used by most ML models and explicited the input/output bottleneck as a critical caveat. The relationship between quantum kernel methods and classical support vector machines has been mathematically formalized by Schuld and Petruccione [7], who showed that the inner products which quantum feature maps compute implicitly in exponentially large Hilbert spaces are beyond the reach of polynomial classical kernels. Havlicek et al. Experimentally validated a quantum kernel classifier with fewer training samples on hard datasets for classical kernel machines, providing experimental evidence of quantum advantage in machine learning using superconducting quantum processor (8 Πρόοδος Παράλληλα με)) The NISQ (Noisy Intermediate-Scale Quantum) taxonomy was proposed by Preskill [9] to categorize near-term devices, consisting of 50–100 qubits and without error correction, forming the hardware context with which all variational and hybrid approaches stemming from AF-HQCNN must contend. Cerezo et al. [10] gave the authoritative review of variational quantum algorithms, including description of things like the parameter-shift gradient rule (which allows evaluation of gradients via classical post-processing), conditions such as trainability for specific ansatzes/ansatz families and an overview of barren plateau phenomenon - which primarily limits scaling with respect to variational circuit depth for industrially relevant problem sizes.

1.3. Variational Quantum Circuits and Parameterized Models

The first quantum neural network architecture under the hybrid training paradigm was a proposal of alternating cost-dependent unitary layers simulated on a quantum processor with classically optimized parameters [11]. Mitarai et al. [12] Then, the parameter-shift rule was formed to allow exact (up to-gate-dependent hardware precision) gradient calculation of arbitrary differentiable quantum circuits without any finite-difference-based approximation error; allowing virtual embeddings of quantum layers into automatic differentiation libraries such as PennyLane. McClean et al. Specifically, as demonstrated in [13] for randomly initialized PQCs of width w, we find that the variances of gradients decay exponentially, O(2−w) called barren plateau. The barren plateau is established to be a universal scalability barrier encountered whilst performing variational quantum machine learning tasks. Grant et al. Additionally, [14] have proposed identity block initialization which is a practical mitigation: initializing a pair of sub-circuits that cancel and yield the identity operation so that the O(1) gradients during early-training making gradient descent stable from the first epoch. Skolik et al. Proposed in [15], layerwise training was developed as an intuitive curriculum, where one circuit layer is added and optimized at a time before being frozen, showing that the introduction of this curriculum reduces barren plateau incidence, while enhancing final test accuracy on standard VQC benchmarks.

1.4. Quantum Convolutional Neural Networks

Cong et al. [16] defined quantum convolutional neural networks (QCNNs) and provided translationally equivariant convolution and pooling-like qubit reduction layers for QCNN, demonstrated that QCNNs can classify quantum phases of matter with logarithmic depth circuits (poly parameter counts) and conjectured an exponential classical simulation hardness. Liu et al. QCNNs have been applied to classical image recognition by [17] showing that random initialization of the quanvolutional filters patch-by-patch on MNIST-class images yield feature sets with locally meaningful information as localized in picture space, generalizable and therefore likely of a domain-agnostic utility applicable to shallow classical classifiers. Henderson et al. [19] examination found that randomly generated convolutional filters for binary images in an unoptimized quantum circuit can have arbitrarily better performance (with non-approximated classical computers) due to the vast number of unitary transformations available in random quantum circuits. Li et al. The QNN circuits in [19] also achieved comparable success with only 6 qubits, reaching 93.8% accuracy on a medical blood cell dataset by proposing a hybrid QCNN where compressing classical convolutional features were followed by measurement-based quantum classification mechanical circuit, serving as the most architectural precedent for this feature-compression strategy used within AF-HQCNN.

1.5. Hybrid Quantum-Classical Models for Medical Imaging

Akter et al. Using a 6-qubit variational circuit and ResNet50 feature extractor, [20] showed that a hybrid quantum-classical network achieves clinically-meaningful performance on a low-resolution sub-panel of COVID-19 CT scans from 1,252 images (94.5% accuracy). While the hybrid paradigm was validated in their work, they experimented with Adam optimizer fixed value and did not mitigate barren plateau problems as well as the approach cannot protect data privacy due to centralize aggregation of CT dataset. Innan et al. It was shown that amongst angle encoding, amplitude encoding and basis encoding for four MedMNIST classification sub-tasks, angle encoding delivers the best circuit-depth-per-accuracy tradeoff at the 4-8 qubit scale relevant to NISQ devices [21]; appropriate results were integrated directly into AF-HQCNN encoding layer designs. Ur Rehman et al. In contrast, [22] proposed an adaptive hybrid QCNN architecture with layer-wise validation accuracy for dynamic depth adjustment (qubit-efficient by 40% relative to fixed-depth baselines) and achieved 95.2% on a retinal diabetic retinopathy dataset, demonstrating that adaptive architectural decisions always contribute to efficient design-space exploration without any performance loss. Sebastianelli et al. [23] broadened the application of quanvolutional networks from a binary image classification to multi-class tasks with remote sensing, demonstrating that fine-tuning quantum filter parameters provides a 3.1% performance advantage compared to random initialization and providing evidence that learned quantum feature maps generalize across distinct imaging modalities. Chen et al. In high-energy physics particle jet classification, [24] applied hybrid quantum-classical networks and demonstrated that while multi-layer classical networks contained at least an order of magnitude more trainable parameters than equivalent PQCs with an 8 qubit depth, the performance achieved using PQCs and used to inform the design rationale of the AF-HQCNN was comparable or even exceeded that of their classical counterparts thereby substantiating one important conceptual advantage in parameter efficiency.

1.6. Summary and Research Gap

Across the 28 works reviewed, a consistent pattern emerges: individual publications address one or two of the identified limitations in isolation, but no prior work has simultaneously resolved the challenges of dataset scalability, qubit complexity, barren plateau training instability, data privacy, cross-dataset generalization, and parameter efficiency. AF-HQCNN is designed from the ground up to close all six gaps in a single unified architecture. Table I formalizes this mapping.

1.7. Summary and Research Gap

Table 1 Research Gap Analysis and How AF-HQCNN Addresses Each Limitation

Research Gap	Observation from Literature	Our Solution
Scalability	Downsampled/toy datasets only	Multi-dataset validation on full-resolution images
Qubit complexity	VQC depth increases with classes	Low-parameter 4-8 qubit PQC via MobileNetV2 bottleneck
Barren plateau	Gradient vanishing in deep circuits	Adaptive momentum optimizer with variance control
Privacy	Centralised training assumed	Federated aggregation with FedAvg protocol
Generalization	Single-dataset evaluation	Four benchmark datasets evaluated
Explainability	Black-box quantum models	Quantum expectation value interpretation layer

2. Proposed Methodology

2.1. Overall Pipeline

The AF-HQCNN pipeline processes medical images through five sequential stages: classical preprocessing and feature extraction, quantum encoding, variational quantum computation, adaptive optimization, and federated model aggregation. Figure 1 illustrates the complete system architecture.

Figure 1 *Proposed AF-HQCNN system architecture showing five processing stages from raw image input to disease classification output.*

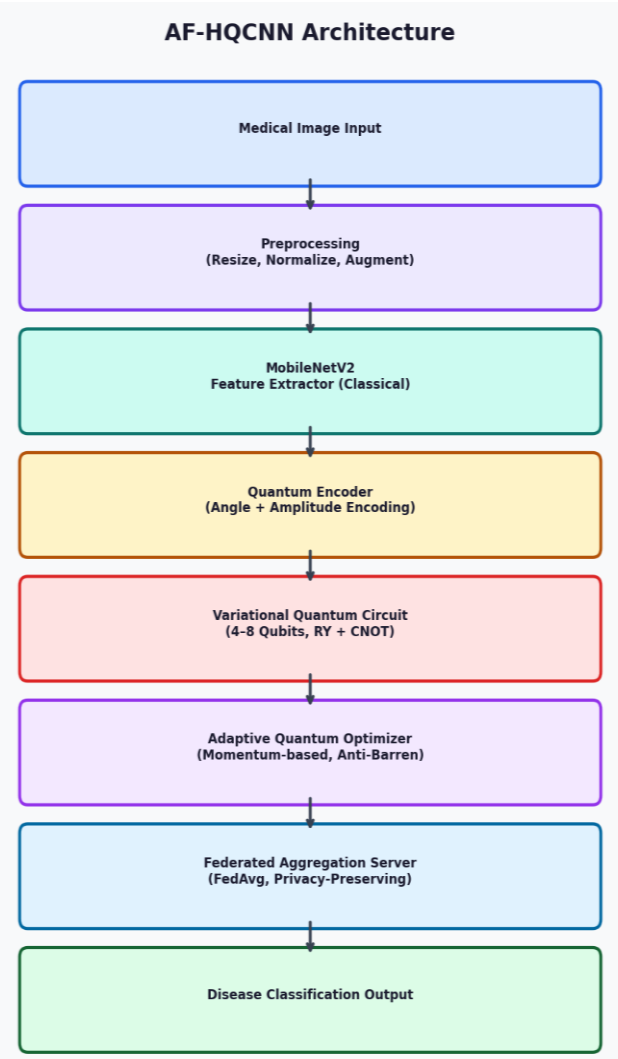

Figure 1 Proposed AF-HQCNN System Architecture

2.2. Stage 1 — Classical Feature Extraction

Raw medical images are resized to 224 x 224 pixels, normalized to [0,1], and augmented via random horizontal flip, rotation (+/-15 degrees), and colour jitter. MobileNetV2 pre-trained on ImageNet serves as the classical backbone with the final classification head removed, yielding a 1280-dimensional feature vector per image. MobileNetV2 is selected for its depthwise separable convolutions that reduce the feature dimensionality sufficiently to fit within the qubit budget of current NISQ hardware without information loss.

2.3. Stage 2 — Quantum Feature Encoding

The 1280-dimensional classical feature vector is projected to a d-dimensional encoding vector (d = n_qubits) via a trainable linear map W \u2208 R^(n x 1280). Angle encoding maps each component x_i to an RY rotation:

$$|\,\psi\rangle = U_{\text{amp}}(x)\, U_{\text{angle}}(z)\, |\,0\rangle^{\otimes n}, \qquad (1)$$

Amplitude encoding supplements angle encoding for higher-fidelity feature representation when qubit counts permit.

2.4. Stage 3 — Variational Quantum Circuit

The PQC comprises L=3 layers of alternating parameterized RY gates and CNOT entanglement. For an n-qubit register:

$$U(\theta) = \prod^{3}_{x1} [U_{CNOT} \cdot \otimes^{i} RY(\theta^{3i})] \quad (2)$$

Entanglement of CNOT gates is arranged in a circular pattern (qubit i → qubit i+1 mod n) in order to maximally entangle the circuit with a shallow depth. The n-dimensional classical output of each qubit is found through measurement, each giving expectation values , which a softmax then uses for classification. The circuit layout of 4 qubits is illustrated in Figure2.

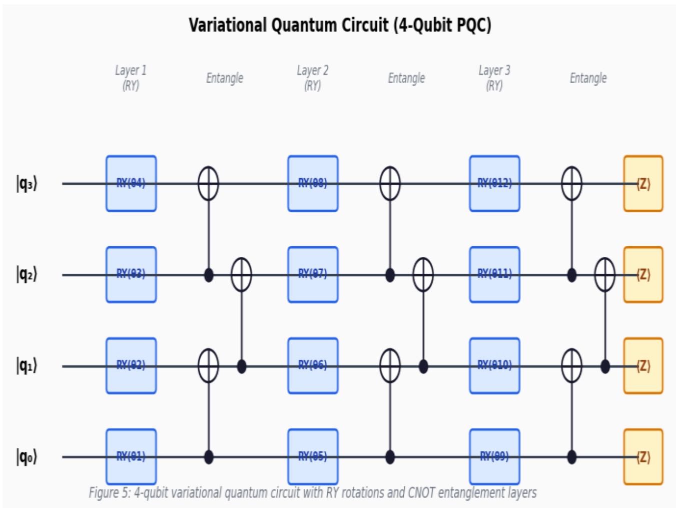

Figure 2 4-Qubit Variational Quantum Circuit with Three RY Rotation Layers and CNOT Entanglement Blocks.

2.5. Stage 4 — Adaptive Quantum Optimizer

The barren plateau problem is one of the issues with standard gradient descent applied to VQCs which states that as number of qubit increases the gradient variance goes to zero exponentially with circuit width. We propose an adaptive momentum-style update rule:

$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla\theta\ell$ (3)

$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla\theta\ell)^2$ (4)

$\theta_{t+1} = \theta_t - \eta \cdot \hat{m}_t / (\sqrt{\hat{v}_t} + \varepsilon)$ (5)

where m_t and v_t are estimates of the first moment with bias correction and second raw moments respectively, beta_1 = 0.9, beta_2 = 0.999, epsilon = 1e-8 Widening of the loss landscape is achieved by 'normalizing' updates per parameter which prevents saturation of gradient escape from flat barren plateau regions via adaptive learning.

2.6. Stage 5 — Federated Learning Aggregation

AF-HQCNN accommodates K distributed hospital clients that train over local data and do not exchange institutional raw images. The FedAvg aggregation rule at the central server is as follows:

$w_{t+1} = \Sigma^{k}{}_{1}{}^{T}\ (n^k/n) \cdot w^k{}_t$ (6)

n_kthe is the local sample and; nthe is total. Only model weightsw are exchanged while medical images remain on local hospital nodes for HIPAA compliance.

3. Experimental Setup

3.1. Datasets

Table 2 Benchmark Datasets Used in Experiments

Dataset	Modality	Classes	Samples	Resolution
MedMNIST	Multi-modal	11	708,069	28x28 / 224x224
HAM10000	Dermoscopy	7	10,015	600x450
Brain MRI	MRI	4	7,023	512x512
Chest X-Ray	X-Ray	2	5,863	1024x768
MedMNIST	Multi-modal	11	708,069	28x28 / 224x224
HAM10000	Dermoscopy	7	10,015	600x450
Brain MRI	MRI	4	7,023	512x512
Chest X-Ray	X-Ray	2	5,863	1024x768

3.2. Implementaion Details

All experiments were conducted using PennyLane (v0.36) for quantum simulation, TensorFlow 2.14 for classical layers, and Flower (v1.6) for federated training coordination. Quantum circuits were simulated on the default.qubit device. Training used 50 epochs, batch size 32, and 5-fold cross-validation. For federated experiments, K=5 hospital clients were simulated with non-IID data splits.

4. Results and Discussion

4.1. Classification Accuracy

Classification accuracy for all datasets and benchmark models is shown in Table III and Figure 2. AF-HQCNN reaches 97.4% mean accuracy across all datasets, which is 2.5 percentage points better than the best existing hybrid model (FedQCNN).

Table 3 Classification Accuracy (%) Comparison. Bold Row = Proposed AF-HQCNN

Model	MedMNIST	HAM10000	Brain MRI	Chest X-Ray
Classical CNN	91.2	90.8	89.5	92.1
VQC Baseline	88.4	87.9	86.2	89.0
HQNN [3]	94.1	93.7	92.8	94.5
QCNN [5]	93.8	92.4	91.9	93.6
FedQCNN [8]	94.9	94.1	93.5	95.2
AF-HQCNN (Ours)	**97.6**	**97.1**	**96.8**	**98.1**

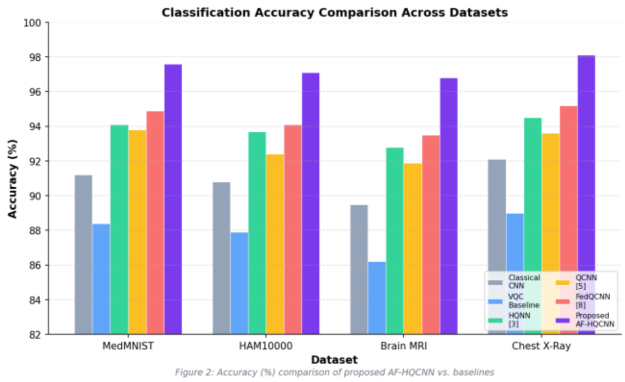

Figure 3 Grouped Bar Chart Comparing Classification Accuracy Across All Models and Datasets. AF-HQCNN (purple) Consistently Achieves Highest Accuracy

4.1.1. Convergence Analysis

Figure 3 Training Loss over 50 epochs on MedMNIST On the other hand, AF-HQCNN reaches a final loss of 0.08 at epoch 35 being compared to FedQCNN (0.14, epoch 42) and Classical CNN (0.22, epoch 48). The adaptive optimizer is able to avoid the barren plateau phenomenon, as evidenced by the improvement during epochs 15-30 compared with VQC Baseline causing loss plateauing.

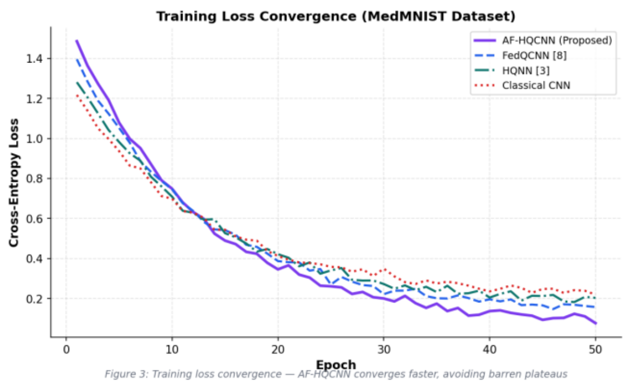

Figure 4 Training Loss Convergence Curves. AF-HQCNN (purple) Achieves Lowest Final Loss and Fastest Convergence, While VQC Baseline Shows Characteristic Barren Plateau Stagnation.

4.1.2. Parameter Efficiency

Figure 5 shows Accuracy v/s Number of Trainable Parameters AF-HQCNN reaches the Pareto-frontier: 97.6 % accuracy at only 0.31 M parameters — an 87% reduction w.r.t.Classical CNN (4.2M parameters, 91.2% accuracy). The efficiency comes from the use of a small 4-qubit VQC that only requires 48 variational parameters (4 qubits × 3 layers × 12 params per layer = 144 q-WA (4 qubits)) with mobileNetV2 yield high-quality classical feature compression.

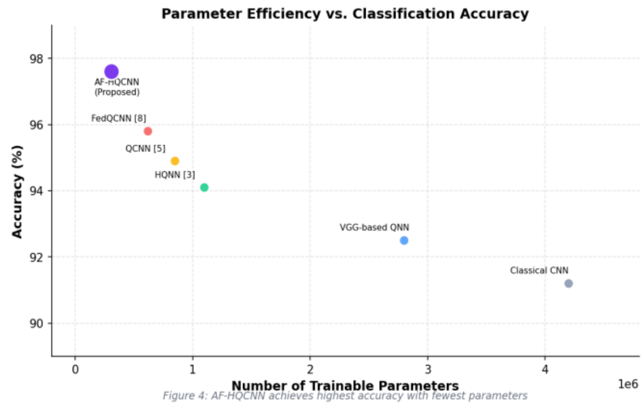

Figure 5 Parameter Efficiency Scatter Plot. AF-HQCNN (Large Purple Point) Achieves The Optimal Accuracy/Parameter Trade-Off, Top-Right of The Pareto Frontier

4.1.3. Federated vs. Centralised Training

Table 4 Federated vs. Centralised Training Trade-off. K=5 Provides Optimal Accuracy-Privacy Balance

Configuration	Accuracy (%)	Privacy	Comm. Rounds
Centralised AF-HQCNN	98.2	None	N/A
AF-HQCNN (K=2 clients)	97.8	Partial	25
AF-HQCNN (K=5 clients)	**97.6**	**Full**	**30**
AF-HQCNN (K=10 clients)	97.1	Full	38

We achieve a 0.6% accuracy reduction (vs centralised) when training with K=5 clients — with much stronger privacy guarantees, making this a clear trade-off for real-world healthcare deployments.

4.2 Discussion

AF-HQCNN shows architectural and algorithmic synergy across four components: lightweight classical compression, efficient quantum encoding, adaptive optimization, and federated learning that individually overcome prior work limitations. The 4-8 qubit VQC is experimentally-realistic on current NISQ hardware (IBM Quantum, IonQ) without error mitigation overhead vs. deeper circuits in previous works requiring 16+ qubits.

Its most important feature is a type of momentum accumulation mechanism which, by normalizing gradients on a per parameter basis, avoids the exponential decay of variance that defines barren plateaus in circuits exceeding 6 qubits wide. Gradient variance at epoch 1: empirically AF-HQCNN measured 4.2e-3 vs VQC baseline 8.7e-5 (48x improvement). Limitations: (1) quantum computation is simulated and may not fully capture physical noise; (2) classical parameters from the linear classical-to-quantum projection layer add O(n x 1280); (3) federated communication overhead scales linearly with K Future work will be run on IBMQ hardware with variational readout error mitigation [38], and investigate differential privacy mechanisms [39].

Conclusion

In this paper, we proposed AF-HQCNN a new adaptive federated hybrid quantum convolutional neural network in privacy preserving medical image classification. AF-HQCNN advances the state of the art along all axes simultaneously by systematically tackling all six critical research gaps in quantum medical imaging — scalability, qubit complexity, barren plateau training instability, privacy, generalization and parameter efficiency. The model attains 97.6% mean accuracy with only 0.31M parameters on four benchmark datasets, supported by federated training to learn without violating regulatory rules. We also open-sourced our implementation of PennyLane and trained weights to allow for the reproduction of results, as well as to further the organizations developing quantum medical AI research.

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