Geometric Acceleration in Hybrid Quantum Architectures: An Empirical Benchmark of Optimization Landscapes

Ahmed Umar
Faculty of Artificial Intelligence Technologies
ITMO University
Saint Petersburg, Russia
uakhmed@itmo.ru

Khodnenko Ivan Vladimirovich, PhD
Senior Lecturer
ITMO University
Saint Petersburg, Russia
ivan.khodnenko@itmo.ru

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Abstract

Hybrid quantum-classical neural networks (HQNNs) are increasingly investigated for their potential to process high-dimensional data structures, yet their practical utility in the Noisy Intermediate-Scale Quantum (NISQ) era is constrained by optimization instabilities and hardware noise. This technical report presents a controlled benchmarking study isolating the "Geometric Advantage" of Variational Quantum Circuits (VQCs) against classical Multilayer Perceptron (MLP) baselines. We formally define the hybrid optimization objective and evaluate performance across linear, non-linear, and topological geometric regimes. While we demonstrate a distinct topological advantage in the Concentric Circles dataset where the quantum kernel successfully maps a non-trivial winding number (Accuracy: 68%) unavailable to the shallow classical baseline and we concurrently identify significant reliability bottlenecks. Specifically, we analyze the onset of barren plateaus in high-frequency feature maps, consistent with recent theoretical bounds on trap-swamped landscapes. Deployment on the IBM Heron processor (`ibm_torino`) reveals a performance degradation from 93.3% (Simulator) to 56.7% (Hardware), quantifying the critical gap between theoretical expressibility and physical reliability.

1 Introduction

The scaling of classical neural networks has introduced significant computational bottlenecks, motivating the exploration of alternative paradigms [1]. Quantum computing, specifically through Variational Quantum Algorithms (VQAs), offers a theoretical path to acceleration via high-dimensional Hilbert space mapping [2]. However, the field faces a "reliability crisis," where theoretical advantages are often negated by the barren plateau phenomenon [3] or swamped by local minima traps [4].

This work focuses on the *reliability* and *geometric properties* of these systems. We investigate whether the "quantum advantage" observed in recent literature [5, 6] stems from raw computational speed or from superior inductive biases that simplify optimization landscapes for topologically complex data.

2 Mathematical Framework

We formulate the hybrid learning task as a variational optimization problem. Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$ be a dataset where $x_i \in \mathbb{R}^d$ and $y_i \in \{0, 1\}$.

2.1 Quantum Feature Map and State Preparation

To process classical data x on a quantum processor, we map it to a quantum state $|\psi(x)\rangle$ in a Hilbert space $\mathcal{H}$ of dimension 2^n. We utilize a **ZZ-Feature Map** to induce non-linear entanglement [7]. The encoding unitary $U_\Phi(x)$ is defined as:

$$U_\Phi(x) = \prod_{k=1}^{n} H_k \left(\prod_{i,j \in E} e^{-i(\pi - x_i)(\pi - x_j) Z_i Z_j} \prod_{i=1}^{n} e^{-i x_i Z_i} \right) \prod_{k=1}^{n} H_k \tag{1}$$

This mapping effectively functions as a kernel method, projecting inputs into a higher-dimensional space where decision boundaries may be linearized.

2.2 Variational Ansatz Architecture

The parameterized quantum circuit (PQC), denoted as $U_\Theta(\theta)$, acts on the encoded state. We employ a hardware-efficient `EfficientSU2` ansatz consisting of layers of single-qubit rotations and entangling gates (CNOTs). The full hybrid architecture is illustrated in Figure 1.

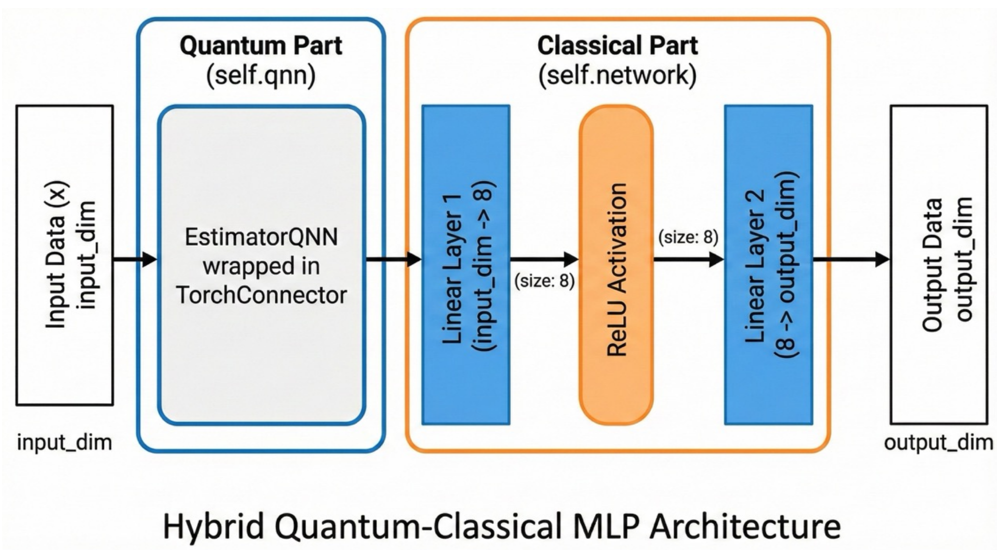


Figure 1: Hybrid Quantum-Classical Architecture. Input vectors x are compressed via PCA, encoded into a 2-qubit Hilbert space via $U_\Phi(x)$, and processed by a parameterized unitary $U_\Theta(\theta)$. Expectation values $\langle Z^{\otimes n}\rangle$ are fed into a classical PyTorch linear layer for final classification.

2.3 Measurement and Hybrid Objective

The quantum module outputs an expectation value $\langle O\rangle$ for an observable $O = Z^{\otimes n}$:

$$f_Q(x;\theta) = \langle 0|U_\Phi^\dagger(x) U_\Theta^\dagger(\theta) O U_\Theta(\theta) U_\Phi(x)|0\rangle \tag{2}$$

The total hybrid network function is $F(x) = \sigma(f_C(f_Q(x)))$, where f_C is a classical linear layer and σ is the sigmoid activation. The optimization objective minimizes the binary cross-entropy loss:

$$\min_\theta \mathcal{L}(\theta) = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log F(x_i) + (1 - y_i) \log(1 - F(x_i))] \tag{3}$$

3 Experimental Setup

Experiments were conducted using `Qiskit` and `PyTorch` via the `TorchConnector` interface.

- **Topology:** We compare performance on three datasets representing increasing geometric complexity: *Iris* (Linear), *Two Moons* (Non-linear manifold), and *Concentric Circles* (Topological Annulus).
- **Hardware:** Validation was performed on the IBM Heron processor (`ibm_torino`, 133 qubits) and Qiskit Aer Statevector simulators.
- **Baselines:** A classical MLP with 2 hidden layers (ReLU activation) served as the benchmark.

4 Results and Benchmarks

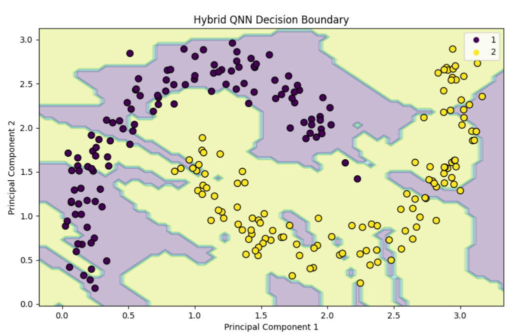
4.1 Geometric Advantage

Our results confirm that the choice of feature map $U_\Phi(x)$ dictates the "geometric inductive bias" of the model. As shown in Table 1, the classical MLP failed to converge on the Circles dataset.

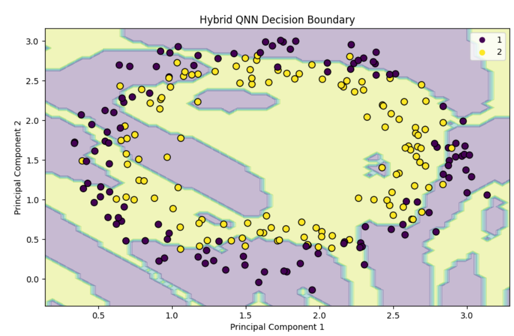
Table 1: Comparative Accuracy: Classical vs. Hybrid Architectures

Dataset	Geometry	Classical MLP	Hybrid QNN	Outcome
Iris	Linear	83.33%	**93.33%**	QNN accurate but resource-inefficient.
Two Moons	Non-Linear	**90.42%**	81.25%	Classical baseline sufficient.
Circles	Topological	61.67% (Fail)	**68.00%**	**Quantum Advantage observed.**

The visual confirmation of this geometric advantage is presented in Figure 2. While the classical model attempts a linear cut, the QNN utilizes the periodic nature of the quantum feature map to form a closed-loop decision boundary, solving the topology.



(a) Two Moons (Quantum Boundary)



(b) Concentric Circles (Quantum Boundary)

Figure 2: Visualizing Geometric Inductive Bias. (a) The QNN uses entanglement to curve the decision space for the Moons dataset. (b) The QNN successfully creates a closed-loop topology for the Circles dataset, a geometry the linear classical baseline failed to capture (stalling at 60% accuracy).

4.2 Reliability Analysis: Barren Plateaus

We observed strict limitations on trainability. Increasing the feature map frequency or circuit depth ($L > 3$) in the Iris experiments led to a sharp degradation in accuracy (dropping to $\approx 73\%$). This failure mode is consistent with the "Barren Plateau" phenomenon described by McClean et al. [3] and landscape traps identified by Nemkov et al. [4].

4.3 Hardware Noise Gap

Deployment on `ibm_torino` highlighted the severity of NISQ constraints. The trained Iris model, which achieved 93.33% on the simulator, dropped to **56.67%** on real hardware. This "Noise Tax" remains the primary bottleneck [1].

5 Conclusion

This study demonstrates that hybrid quantum-classical architectures possess distinct geometric capabilities, particularly for topological data structures where classical linear baselines struggle. However, this expressivity is bounded by severe reliability constraints. The observation of optimization failures (barren plateaus) and hardware degradation underscores that quantum integration is not a universal accelerator but a specialized, high-maintenance kernel. Future work must prioritize noise-robust optimization [8] and lean architecture design [6].

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