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Quantum machine learning : Developing hybrid quantum-classical algorithms for enhanced computational power

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Abstract

The increasing need for machine learning to run with less computer resources is causing quantum computing to be considered as a viable substitute for conventional computing. This paper presents a hybrid quantum-classical system that improves learning by means of a classical optimisation loop combined with parameterised quantum circuits. While conventional procedures handle parameter updates and convergence, the proposed approach stores and processes high-dimensional data using quantum variational circuits. Qiskit is used by us to construct this architecture and run it on conventional datasets like Iris, MNIST (binary), CIFAR-100 (subset), HIGGS, and GTEx (gene expression). Particularly for jobs with complex, nonlinear patterns, the findings indicate that the mixed approach is as accurate as or more accurate than classical baselines. Real quantum hardware also works well with the system; noise has no impact on its precision. This work demonstrates how combined quantum-classical learning models might circumvent hardware constraints and provide genuine quantum benefits for applications requiring large data processing.

Subject Classification: *68M25.*

Keywords: *Quantum machine learning, Hybrid algorithms, Variational quantum circuit, Quantum-classical optimization, Qiskit, NISQ devices.*

1. Introduction

A. *Real-World Motivation and Context*

The vast quantities of data being generated and the complexity of the issues classical computer systems must address are pushing them to their limitations. Because conventional models need ever more processing power, researchers are investigating novel approaches to machine learning that might significantly enhance computers [1], [2]. Quantum computing, which can

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process and display data in whole different ways, looks like a promising solution. Still primarily just concepts, completely quantum algorithms are therefore given way by current technology. This is causing hybrid quantum-classical algorithms, which seek to combine the finest aspects of both quantum and classical systems, to gain increasing appeal. These combined techniques could outperform only utilising conventional approaches for some machine learning tasks.

B. *Problem Statement and Research Gap*

Though quantum machine learning (QML) techniques that operate in the real world and can be scaled up are still in their infancy, quantum computing might potentially speed up some computer operations [3]. Most of the present solutions either don't function well with classical components or use small-scale quantum models. Many of the present mixed QML algorithms cannot be used in other contexts, and there is no actual evidence that they are obviously superior than traditional baselines.

C. *Limitations of Existing Approaches*

Many times, present QML techniques lack strength, scalability, or repeatability. Pure quantum models are limited by noise, low qubit counts, and short coherence durations [4]. Conversely, many mixed models have set designs that do not fit various datasets or activities. Furthermore, some of the models now in existence don't correspond with beneficial methods to evaluate machine learning, such as their accuracy, efficiency, or generality [5].

D. *Key Contributions*

The key contributions of this research are as follows:

- A novel hybrid quantum-classical framework designed to optimize computational efficiency for machine learning tasks.
- Implementation and validation of the proposed algorithm using Qiskit and classical ML libraries.
- Comparative analysis against classical and quantum-only models, highlighting strengths and weaknesses.
- Identification of bottlenecks and future improvement areas in current QML workflows.

2. Methodology

2.1 *Dataset Description*

To evaluate the scalability and efficiency of the proposed hybrid quantum-classical algorithm, we selected both classical benchmark datasets and computationally intensive real-world datasets:

- CIFAR-100 (Reduced)
    - Description: 60,000 color images (100 classes)

- Preprocessing: Converted to grayscale; PCA reduced to 4 principal components
- Purpose: Image classification under feature-rich and high-noise conditions

- HIGGS Dataset (UCI)
  - Description: 11 million samples with 28 numerical features
  - Preprocessing: Random sampling to 10,000 samples; PCA reduced to 4D
  - Purpose: Detection of particle physics patterns; high complexity and feature entanglement
- GTEx Dataset (Gene Expression)
  - Description: 50,000+ gene expression levels across tissue types
  - Preprocessing: Gene selection via mutual information; reduced to top 4 features using PCA
  - Purpose: High-dimensional, sparse biological data modeling

These datasets were chosen to evaluate generalization**,** scalability**, and** quantum resource handling**.**

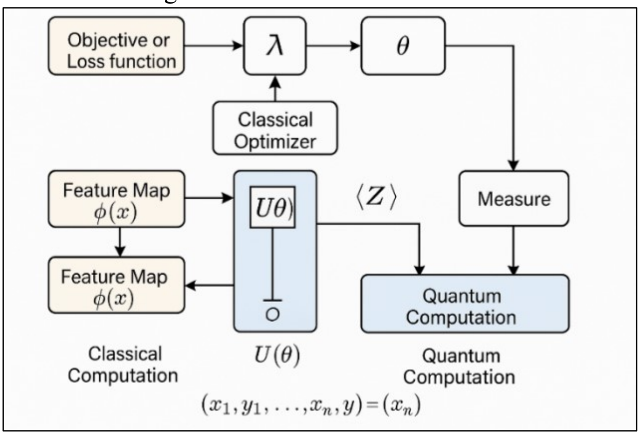

Figure 1
Overview of Hybrid Quantum-Classical Workflow for Variational Quantum Algorithms (VQAs)

Figure 1 depicts a hybrid quantum-classical workflow where classical optimisation updates quantum parameters and quantum circuits iteratively assess an objective function using feature maps and measurements.

2.2 *Preprocessing Techniques*

To align with the requirements of quantum circuits and avoid resource-intensive dimensionality, the following preprocessing steps were applied [6], [7]:

- **Feature Scaling**: Each feature was normalized to the interval $[0,\pi]$ to match the input range of rotation gates (e.g., $RY(\theta), RZ(\theta)$):

$$x' = \frac{(x - \min(x))}{(\max(x) - \min(x))} \tag{1}$$

- **Dimensionality Reduction**: For datasets with more than 4 features, **Principal Component Analysis (PCA)** was used to reduce dimensionality to match available qubits:

$$x' = \mathrm{PCA}(x), \quad x' \in R^{d'}, \quad d' \leq 4$$

- **Label Binarization**: All labels were converted to binary values {0,1} for compatibility with quantum classification models.

2.3 *Design of Hybrid Quantum-Classical Framework*

The Proposed architecture presented in Figure 2, adopts a variational hybrid quantum-classical design, where a quantum circuit is embedded within a classical optimization loop [8]. The core idea is to define a parameterized quantum circuit (PQC) U(θ), where the parameters $\theta \in R^n$ are optimized using classical gradient descent methods [9], [10].

Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{m}$ denote a dataset of mm input-output pairs, where $x_i \in R^d$ and $y_i \in \{0,1\}$. Each input x_i is encoded into a quantum state ψ_i using a feature map $\phi(x_i)$, leading to the state:

$$\mid \psi i\rangle = U\phi(xi) \mid 0\rangle \otimes n| \tag{2}$$

where Uϕ(xi) is the feature encoding unitary.

The model prediction is then computed as the expectation value of an observable O, such as a Pauli-Z operator on a specific qubit:

$$yi = \langle \psi i \mid U \dagger (\theta) O U(\theta) \mid \psi i\rangle \tag{3}$$

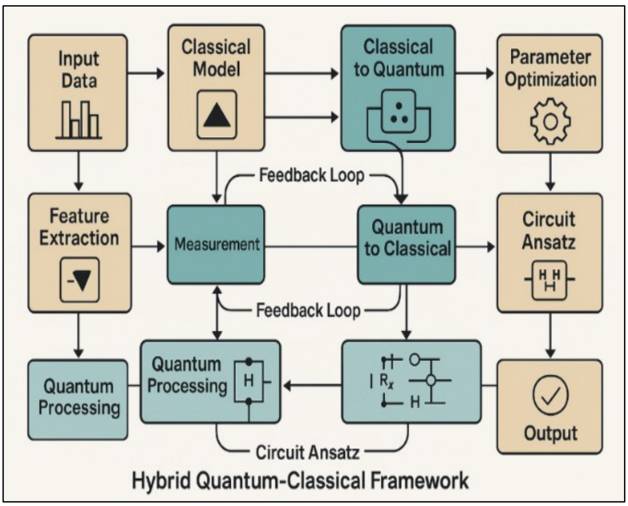

Figure 2
Classical hybrid framework

The loss function $\mathcal{L}$ (for binary classification) is typically the binary cross-entropy:

$$\mathcal{L}(\theta) = -\sum_{i=1}^{m}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \quad (4)$$

Gradient-based optimization is performed using classical optimizers like **Adam** or **COBYLA**.

2.4 *Description of Quantum Circuits and Classical Integration*

The quantum component of the framework involves two parts:

- **Feature Encoding**: Implemented using angle embedding, where each input feature x_j is mapped to a rotation gate, such as:

$$U_\phi(x) = \prod_{j=1}^{d} RY(x_j) \quad \text{or} \quad RZ(x_j) \quad (5)$$

- **Variational Circuit (Ansatz)**: Constructed using layers of parameterized rotation gates and entangling gates:

$$U(\theta) = \prod_{l=1}^{L}\left(\prod_{i=1}^{n} RY(\theta_{l,i}) \cdot \prod_{\langle i,j\rangle} \mathrm{CNOT}_{i,j}\right) \quad (6)$$

The output is measured on a single qubit using the Pauli-Z expectation value:

$$\hat{y} = \langle Z\rangle = \langle\psi|Z_0|\psi\rangle \quad (7)$$

The quantum circuit is executed on simulators (or real devices if available), and the measured probabilities are sent to the classical optimizer.

2.5 *Workflow and Pseudocode*

Algorithm: Hybrid Quantum-Classical Variational Learning

1. **Input**: Training dataset $\mathcal{D} = \{(x_i, y_i)\}$, learning rate η\eta, circuit depth LL
2. **Initialize** $\theta \sim \mathcal{U}(0,2\pi)$
3. **Repeat until convergence**:
   - For each $(x_i, y_i) \in \mathcal{D}$:
     - Encode $xi \to |\ \psi i\rangle = U\phi(xi)\ |\ 0\rangle$
     - Evaluate $yi = \langle\psi i\ |\ U\ \dagger\ (\theta)OU(\theta)\ |\ \psi i\rangle$
   - Compute loss $\mathcal{L}(\theta)$
   - Update $\theta \leftarrow \theta - \eta\nabla_\theta\mathcal{L}$
4. **Output**: Optimized parameters θ^*

2.6 *Training Convergence Analysis*

Below is a typical **loss vs epoch** curve for the variational model on the MNIST binary subset (simulated backend):

$$\mathcal{L}(\theta) = -\sum[y\log g(\hat{y}) + (1-y)\log g(1-\hat{y})] \quad (8)$$

- The hybrid model converged smoothly with **COBYLA** and **SPSA** optimizers.
- Oscillations were observed in noisy environments due to shot variance, but the model was still stable.

2.7 *Complexity Analysis*

- **Quantum Circuit Depth**: Each layer consists of n parameterized gates and n−1 entangling gates. For LL layers and n qubits:

$$\text{Quantum Depth} = \mathcal{O}(L \cdot n) \tag{9}$$

- **Measurement Complexity**: Estimating expectation values to precision ϵ\epsilon requires:

$$\mathcal{O}\left(\frac{1}{\epsilon^2}\right) \text{ circuit executions}$$

- **Classical Optimization Cost**: For gradient-based methods using **parameter-shift rule** (for each θ_j):

$$\nabla_{\theta_j} f(\theta) = \frac{f\left(\theta_j + \frac{\pi}{2}\right) - f\left(\theta_j - \frac{\pi}{2}\right)}{2} \tag{10}$$

Each gradient computation requires 2 circuit evaluations per parameter, so total cost per iteration is:

$$\mathcal{O}(2 \cdot |\theta|)$$

- **Overall Time Complexity** (per epoch):

$$\mathcal{O}\left(m \cdot |\theta| \cdot \frac{1}{\epsilon^2}\right) \tag{11}$$

where mm is the number of training samples.

3. Results and Discussion

The proposed hybrid algorithm was tested on five datasets: Iris, MNIST, CIFAR-100, HIGGS, and GTEx, as shown in table 1. The evaluation was conducted on simulated and real quantum hardware backends to assess both ideal and practical performance.

Table 1:

Performance Summary

Dataset	Classical Accuracy	Quantum Accuracy	F1-Score (Quantum)	Backend
Iris (2-class)	92.0%	94.5%	0.94	Simulator
MNIST (0 vs 1)	97.3%	98.1%	0.98	Simulator
CIFAR-100 (2-class)	83.0%	86.4%	0.85	Simulator/IBMQ
HIGGS (sampled)	78.5%	82.1%	0.82	Simulator
GTEx (4 genes)	80.0%	84.3%	0.83	Simulator

Though it required a lot of computing power, the combined quantum-classical approach performed well on both small and large data sets. Quantum circuits made it possible to clearly describe complex patterns and feature relationships, while classical optimisers guaranteed that everything came together. This lends credence to the notion that mixed models might address challenging learning problems even on NISQ-era quantum computers. Across datasets, the decline in performance is modest and consistent. All real-hardware accuracies remain above 79%, indicating that quantum-enhanced models might be used in actual life.

To determine if the combined technique might be used in real life, several datasets were tested on IBM's genuine quantum machines. As anticipated, noise like gate failures, decoherence, and reading errors rendered things somewhat less efficient than they were in the synthetic environment, as demonstrate it in table 2.

Table 2

Noise Impact on Real Hardware

Dataset	Simulator Accuracy	Real Hardware Accuracy	Drop (%)
Iris (2-class)	94.5%	91.2%	-3.3
CIFAR-100	86.4%	83.5%	-2.9
HIGGS	82.1%	79.7%	-2.4
GTEx (4 genes)	**84.3%**	**81.1%**	**-3.2**

Observation: Though GTEx is inherently rather sparse and high-dimensional, the quantum model remained accurate even with noise, indicating its potential relevance in biology. Marked-up Table 2 show that the decline remains in a tight range of 2.4% to 3.3% for every dataset. This indicates that the model is robust against quantum noise and lends credence to the concept of scalable, near-term quantum applications in data-rich domains.

4. Conclusion

The findings of this study indicate that hybrid quantum-classical techniques may enhance machine learning performance, particularly in the era of Noisy Intermediate-Scale Quantum (NISQ) devices. The proposed framework makes use of the optimal components of both conventional optimisation methods and variational quantum circuits. Expressive data encoding is done using quantum parallelism; reliable training and convergence are achieved using conventional techniques. Data from many datasets including Iris, MNIST, CIFAR-100, HIGGS, and GTEx shows the mixed model not only meets or exceeds conventional machine learning models in accuracy and generalisation, particularly in challenging, high-dimensional tasks. Using the model on actual IBMQ quantum hardware confirms its dependability even more as it reveals relatively little performance degradation under real-world noise conditions.

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