Quantum-Enhanced Feature Bottlenecks for Hybrid CNN-Based Image Classification

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***Abstract*—This paper extends our previous work on hybrid quantum-classical neural networks by redefining the role of quantum circuits in image classification. A variational quantum circuit is used as a feature enhancement module operating on compact representations obtained through a learned bottleneck, rather than replacing classical dense layers. The proposed hybrid model demonstrates competitive performance compared to classical CNN and quantum-only baselines while achieving parameter efficiency on MNIST, Fashion-MNIST and CIFAR-10. PCA-based feature analysis highlights the effectiveness of quantum-enhanced feature representations and further illustrates the scalability of the proposed architecture across all datasets.**

***Index Terms*—Hybrid quantum-classical learning, quantum machine learning, variational quantum circuits, feature bottleneck, image classification**

I. Introduction

Hybrid quantum-classical neural networks have emerged as a practical approach for utilizing near-term quantum devices in machine learning applications [1], [2]. Most prior work has focused on improving expressivity or reducing model parameters by replacing classical neural components with quantum circuits [3], [4]. However, replacement-based quantum architectures often suffer from limited scalability on complex visual datasets [3], [4].

To address these limitations, we extend our previous work by redefining quantum circuits as feature enhancement modules operating on compact classical representations rather than as direct replacements for classical layers [5], [6]. The proposed approach is evaluated on MNIST, Fashion-MNIST and CIFAR-10 datasets [7] to assess scalability and performance against classical and quantum-only baselines.

The main contributions of this paper are summarized as follows:

- A hybrid quantum-classical image classification architecture that employs quantum circuits as feature enhancement modules with a learned bottleneck.
- Experimental validation on MNIST, Fashion-MNIST and CIFAR-10 demonstrating competitive performance with improved parameter efficiency.

II. Proposed Methodology

A. Overall Architecture

The proposed hybrid architecture consists of four main stages:

1) Classical feature extraction,

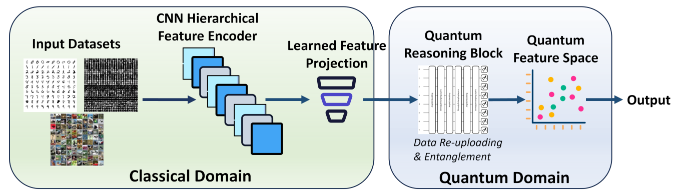

Fig. 1: CNN–quantum hybrid architecture for image classification

2) Feature bottleneck projection,
3) Quantum feature transformation and
4) Classification

Unlike our previous architecture, where quantum layers directly replaced classical dense layers, the proposed approach maintains classical feature hierarchies and applies quantum processing only after dimensionality reduction. An overview of the architecture is illustrated in Fig. 1.

B. Classical Feature Extraction

Given an input image $\mathbf{x} \in \mathbb{R}^{H\times W\times C}$, a lightweight convolutional neural network extracts intermediate representations:

$$\mathbf{h} = f_{\text{CNN}}(\mathbf{x}), \quad \mathbf{h} \in \mathbb{R}^d$$

The CNN captures spatial and local patterns essential for image classification, particularly for complex datasets such as CIFAR-10.

C. Feature Bottleneck Projection

To interface with a limited number of qubits, the extracted features are compressed through a learned bottleneck:

$$\mathbf{z} = \phi(\mathbf{W}_b\mathbf{h} + \mathbf{b}_b), \quad \mathbf{z} \in \mathbb{R}^{n_q}$$

Here, n_q denotes the number of qubits and $\phi(\cdot)$ represents a nonlinear activation function. This bottleneck reduces the feature dimensionality while preserving discriminative information.

D. Quantum Feature Transformation

The bottleneck features are encoded into a variational quantum circuit using a data re-uploading strategy [6], [8]. In this work, the circuit consists of n_q qubits and L layers of parameterized entangling operations.

$$|\psi(\mathbf{z},\boldsymbol{\theta})\rangle = \prod_{l=1}^{L} U_{\text{ent}}(\boldsymbol{\theta}_l)\, U_{\text{enc}}(\mathbf{z})\, |0\rangle\,,$$

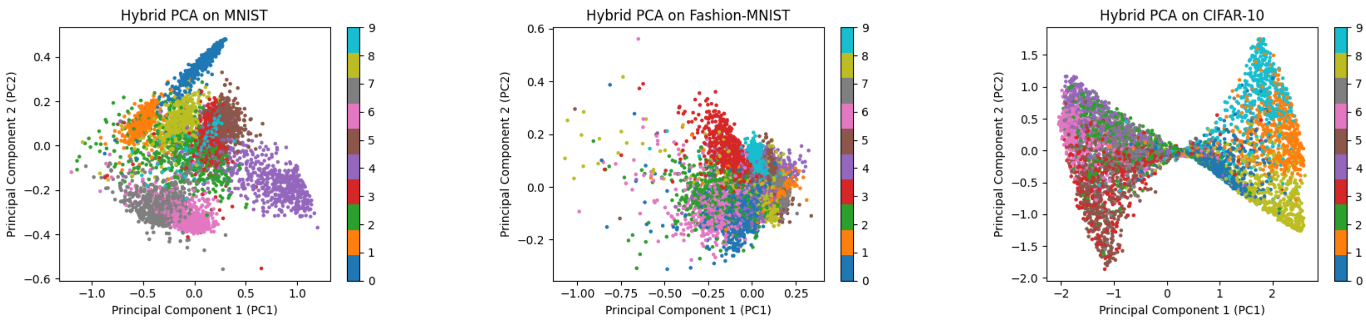

Fig. 2: PCA visualization of learned feature representations for (a) MNIST, (b) Fashion-MNIST, and (c) CIFAR-10.

where $U_{\text{enc}}(\cdot)$ denotes angle encoding of the classical features and $U_{\text{ent}}(\boldsymbol{\theta}_l)$ represents parameterized entangling operations at layer l [9]. The circuit outputs expectation values given by:

$$q_i = \langle \psi | Z_i | \psi \rangle,$$

which together form the quantum-enhanced feature vector $\mathbf{q}$.

E. Classification

The quantum-transformed features are passed to a classical classifier:

$$\hat{\mathbf{y}} = \mathrm{softmax}(\mathbf{W}_c \mathbf{q} + \mathbf{b}_c)$$

This separation of responsibilities enables the quantum circuit to act as a feature enhancement module rather than a full classifier replacement.

III. Result Analysis and Performance Evaluation

A. Experimental Setup

Experiments are conducted on MNIST, Fashion-MNIST and CIFAR-10 using the same training settings for all models. Performance is evaluated using test accuracy, which is suitable given the balanced datasets. The number of trainable parameters is also reported to assess model efficiency.

B. Quantitative Results

TABLE I: Test Accuracy (%) and Model Size.

Model	#Params (MNIST/Fashion-MNIST)	#Params (CIFAR-10)	MNIST	Fashion-MNIST	CIFAR-10
CNN	105.9K	38.6K	98.78%	91.53%	66.70%
Hybrid	**55.4K**	**21.9K**	**98.10%**	**90.72%**	**57.68%**
Quantum-only	6.4K	–	76.85%	77.45%	–

Table I summarizes the test accuracy and parameter size of the evaluated models. The proposed hybrid architecture achieves competitive accuracy with fewer parameters than the classical CNN. As dataset complexity increases, the advantages of the hybrid approach become more apparent. Quantum-only models are excluded from the CIFAR-10 evaluation due to limited qubit capacity.

C. Feature Space Analysis

PCA is applied to visualize the learned feature representations of the hybrid model, as shown in Fig. 2. MNIST and Fashion-MNIST show distinct class separation while CIFAR-10 shows more complex yet structured distributions, indicating the scalability of the proposed approach.

IV. Conclusion & Future Work

This paper proposes a hybrid quantum-classical image classification framework that uses quantum circuits as feature enhancement modules operating on compact classical representations. Experimental results show that the proposed approach achieves competitive performance while improving parameter efficiency across several benchmark datasets. These results highlight how hybrid architectures balance scalability and expressiveness under near-term quantum constraints. Future work will explore deeper quantum circuits, alternative encoding strategies and deployment on real quantum hardware.

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