Feature Representation and Parameter Efficiency in Hybrid Quantum-Classical Neural Networks

Wan Nursyafeeza Binti Wan Mohd Nasir, Taesoo Jun
Department of Software Engineering
Kumoh National Institute of Technology Gumi, South Korea
wsyafeeza@yahoo.com, taesoo.jun@kumoh.ac.kr

***Abstract*—This paper examines how feature representation and parameter efficiency in image classification are affected by quantum circuit layers. The MNIST dataset is used to compare three models: a classical Convolutional Neural Network (CNN), a Hybrid Quantum-Classical model that incorporates a variational quantum circuit and a Quantum-only model. Using feature space analysis, the study evaluates classification accuracy and analyzes feature transformation behavior. Results show that the hybrid model outperforms the CNN in terms of accuracy while reducing the number of parameters. In contrast, the quantum-only model performs poorly due to its small representational capacity. Results show that quantum layers can reduce model size and improve feature compactness, which makes hybrid quantum architectures a feasible option for near-term quantum computing.**

***Index Terms*—Hybrid quantum-classical learning, quantum computing, variational circuits, MNIST, feature learning**

I. Introduction

Deep learning models like Convolutional Neural Networks (CNNs) have achieved impressive performance in image classification tasks. However, their scalability in resource-constrained situations is limited by their frequent requirement for high computational resources and large parameter counts [1]. By utilizing quantum features like superposition and entanglement to improve learning efficiency and lower model complexity, quantum machine learning (QML) has emerged as a potential solution [2]. In comparison to classical models, recent research has demonstrated that hybrid quantum-classical designs can enhance feature learning while utilizing fewer parameters [3], [4].

This study evaluates the impact of quantum layers on learned feature representations and the possibility of parameter reduction without significant loss in accuracy. Unlike previous work that focuses only on the accuracy of hybrid models [5], this research compares classical, quantum and hybrid models using PCA-based visualization to analyze feature learning behavior and evaluates model complexity in terms of trainable parameters and classification performance.

Key research objectives include:

- Analyze how quantum layers change the feature space.
- Compare model-to-model parameter efficiency.
- Evaluate the consistency of classification performance.

II. Methodology

The experimental framework consists of three classification architectures trained on MNIST using PyTorch [6] and PennyLane [7]. The system design used in this study is presented in Fig 1.

A. Dataset and Preprocessing

The MNIST dataset [8] includes 70,000 handwritten digit images (28x28 pixels). Tensor conversion and data normalization were applied. The dataset was divided into 80% for training, 10% for validation and 10% for testing.

B. Classical CNN Model

Two convolutional layers with max-pooling and ReLU activation compose the reference model, which is followed by fully connected layers. It learns spatial features from pixel neighbourhoods.

C. Hybrid Quantum-Classical Model

A variational quantum circuit is used instead of a fully connected layer in the hybrid model, which has the same convolutional backbone as the CNN. AngleEmbedding is used to encode each input vector x into qubits, while StronglyEntanglingLayers is used for processing. The parameterized unitary transformation [9] is given by:

$$U(\theta) = \prod_{l=1}^{L} U_l(\theta_l)$$

Pauli-Z operator expectation values are used to determine the quantum circuit's output:

$${}_i = \langle \psi \mid Z_i \mid \psi \rangle$$

These quantum features are fed into the final softmax classifier.

D. Quantum-only Model

The input image is flattened and projected into four latent features, which are then stored into qubits for purely quantum learning. It has the fewest parameters but lacks convolutional extraction.

E. Training Setup

Cross-entropy loss was used:

$$L = -\sum_{k=1}^{K} y_k \log(\hat{y}_k)$$

AdamW was used for optimization across 30 epochs with a learning rate of 0.0005. Early stopping was used to avoid overfitting.

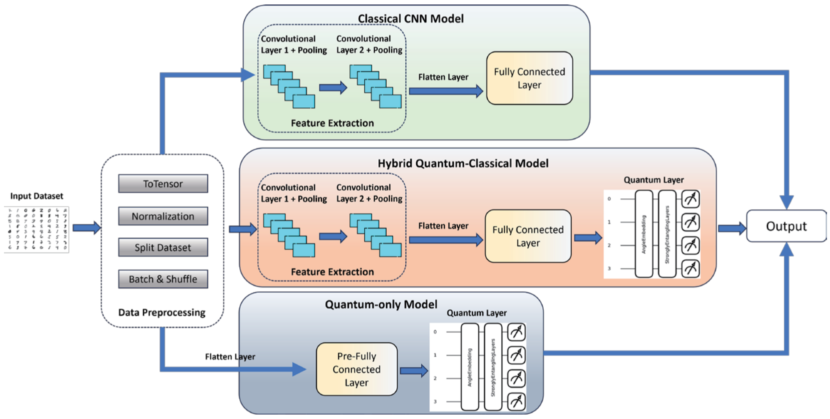

Fig. 1: Overview of classical, hybrid quantum-classical and quantum-only model architectures for image classification

III. Results and Discussion

The performance of each model is shown in Table I. The CNN achieved the highest accuracy due to effective spatial feature learning. The hybrid model was able to achieve comparable efficiency with fewer parameters by replacing a dense layer with a quantum layer. The poor performance of the quantum-only model suggests that convolutional priors are crucial for image learning.

TABLE I: Performance comparison of CNN, Hybrid and Quantum-only models on the MNIST dataset.

Model	Parameters	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	155,402	99.33	99.33	99.32	99.32
Hybrid Quantum-Classical	58,790	98.08	98.08	98.05	98.06
Quantum-only	3,238	78.54	78.24	77.76	76.62

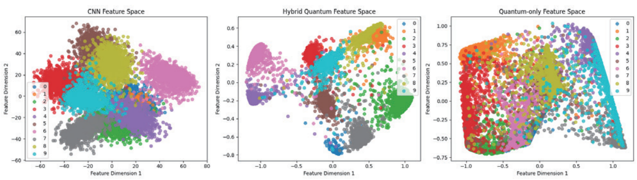

Fig. 2: PCA feature space comparison of CNN, Hybrid and Quantum-only models

As illustrated in Fig. 2, PCA feature space analysis showed different feature learning behaviors for each model. Although it showed clear overlap between similar digits like 3, 5 and 8, the CNN model formed class clusters. Particularly for digits 0, 1 and 6, the hybrid model achieved more compact and separable clusters, indicating that the quantum layer improved discriminative representation. In contrast, the quantum-only model showed a high degree of feature overlap, suggesting that feature learning was limited. These findings support the hybrid architecture by demonstrating that quantum entanglement only improves feature expressiveness when combined with classical convolutional learning.

IV. Conclusion & Future Work

This study demonstrates how dense classical layers can be replaced with quantum layers to increase parameter efficiency while maintaining a reasonable level of classification accuracy. Performance and efficiency are balanced in the hybrid approach, making it suitable for near-term quantum devices. Future research will explore adaptive embedding techniques, deeper quantum circuits and scalability to complex visual datasets like CIFAR-10.

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