Enhancing Image Classification in Quantum Computing: A Study on Preprocessing Techniques and Qubit Limitations

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Abstract. Quantum algorithms present unique advantages over classical methods but remain constrained by the limited number of qubits in current quantum computers. This limitation hinders their effectiveness in machine learning tasks, such as image classification. Despite its relevance, the impact of these constraints on quantum machine learning remains underexplored. This study addresses this gap by analyzing preprocessing techniques for preparing images on quantum processors. We evaluated 10 dimensionality reduction methods across four standard datasets using three distinct quantum neural network architectures. The results provide valuable insights into optimizing classification efficiency under qubit constraints, paving the way for broader applications of quantum machine learning.

1 Introduction

Quantum computing (QC) leverages principles such as superposition and entanglement, offering significant potential across domains like machine learning and image processing. Although early applications on Noisy Intermediate Scale Quantum Devices (NISQ) have not yet surpassed classical algorithms, their ability to handle complex tasks highlights a promising future for QC in data intensive areas [1].

Despite its potential, QC remains constrained by the fragile nature of qubits, which are highly susceptible to noise and environmental interactions [2]. These limitations, combined with the limited number of qubits available on NISQ devices, hinder their ability to process high dimensional input data, a common requirement in image classification tasks [1]. Consequently, dimensionality reduction has emerged as a critical preprocessing step for adapting image data to quantum systems. Despite its importance, the impact of different dimensionality reduction methods on quantum machine learning performance remains underexplored in the existing literature.

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This study systematically evaluates 10 dimensionality reduction techniques, including those proposed in [3], [4], and [5], across four datasets of varying complexity, using three distinct quantum neural networks (QNN) architectures to highlight the interaction between preprocessing techniques and quantum circuit design. By analyzing trade-offs in accuracy, computational efficiency, and adaptability, the findings provide practical recommendations for integrating classical and quantum methods, enhancing the feasibility of image classification in constrained quantum systems.

The paper is organized as follows: Section 2 reviews related works, Section 3 describes QNN architectures and dimensionality reduction methods, Section 4 presents experimental results and analysis, and Section 5 concludes with findings and future directions.

2 Related Works

In the context of image classification, recent methods address quantum computing limitations, such as those in [6], which leverage filters inspired by classical Convolutional Neural Networks (CNNs) [7] to enhance Quantum Convolutional Neural Networks (QCNNs) for high dimensional inputs. These methods improve accuracy despite hardware constraints. Other studies mitigate limitations by resizing images (e.g., 4x4), compatible with NISQ devices.

A comparative study [1] evaluated classical methods, including Support Vector Machines (SVMs) and CNNs, against quantum counterparts using the MNIST dataset. It employed NISQ devices with the PauliFeatureMap to encode data into quantum states within a 16 qubit circuit, demonstrating trade-offs in adapting classical preprocessing for quantum environments.

Input size remains a key challenge in quantum computing, with limited studies systematically exploring dimensionality reduction methods. Hybrid approaches combining classical techniques and QNNs are gaining traction, leveraging classical preprocessing to overcome qubit constraints.

Several resizing algorithms, such as top-hat filtering [8], bilinear interpolation [3], and Lanczos methods [4], offer diverse trade-offs between efficiency and image quality. More advanced methods, including bicubic interpolation [9], Gaussian smoothing [5], and Mitchell-Netravali filters [10], cater to specific scaling needs, balancing computational complexity with visual fidelity. Quantum Principal Component Analysis (QPCA) [11] represents a pioneering quantum data reduction method, but remains constrained by hardware limitations, further emphasizing the importance of hybrid classical-quantum strategies in preprocessing.

3 Quantum Neural Network Methods

QNNs are quantum circuits designed for classification and regression as their classical counterparts, but they rely on the use of quantum principles to increase their performance. In this study, all QNNs classify data into two classes, represented as +1 or −1. These classifications depend on unitary transformations parameterized by θ.

The first QNN model follows the approach in [12], encoding input data into a quantum state $|\psi, 1\rangle$ and applying unitary transformations $U_i(\theta_i)$ optimized through a loss function. The final qubit, measured via a Pauli operator Y_{n+1}, serves as the readout, producing results based on trained parameters. A 16 qubit circuit encodes preprocessed data, with unitary transformations enabling entanglement via Ising interactions between the components X and Z. The readout qubit is entangled with the circuit via a Hadamard and a NOT gate, ensuring that the measurement process is effectively integrated into the network's functionality.

The second QNN, a QCNN [13], features 3 pooling layers and 80 qubits. It applies CNOT gates to adjacent qubits in the convolutional layer, maintaining the same input size for comparability. The readout qubit uses Hadamard and NOT gates.

The third QNN extends the first, improving error mitigation and architecture efficiency. Incrementally, CNOT gates reduce the circuit to 8 qubits, followed by Controlled Z (CZ) gates, which further reduce the data to 4 qubits. The readout qubit remains consistent with that in the previous circuits.

4 Results

Experiments were conducted using the 10 filters described in Section 2 on four datasets: MNIST, Fashion MNIST, CIFAR-10, and CIFAR-100. These datasets, with varying geometric complexities, help evaluate the filters impact on shape preservation and classification performance.

The MNIST and Fashion MNIST datasets consist of 70,000 grayscale images (28x28 pixels), with Fashion MNIST being more complex due to greater variability in clothing and accessory categories. CIFAR-10 and CIFAR-100 contain 60,000 and 100,000 color images (32x32 pixels), respectively, with CIFAR-100 offering more granularity through 100 classes with 600 images each. Testing different QNN architectures on these datasets enables analysis of how filters preserve image information and enhance performance.

Although results may not rival state-of-the-art quantum neural networks, as shown in [1], this was expected due to the circuit's simplicity and was not the main goal. The true findings emphasize the achieved results of classical dimensionality reduction techniques, even in basic quantum architectures as shown in Table 1, as viable alternatives or complements to advanced quantum embedding methods [14].

In the second circuit, the QCNN demonstrated superior overall performance, as shown in Table 2. Even in a more complex circuit, the choice of filters not only contributed to more consistent results across different configurations but also led to a significant improvement in performance, underscoring the critical impact of appropriate filter selection.

The results in Table 3 demonstrate a trade-off between accuracy and reli-

Filter/Dataset	**MNIST**	**CIFAR-10**	**CIFAR-100**	**Fashion MNIST**
Hat/Tent	0.67	0.57	0.63	0.79
Bilinear	0.86	0.56	0.53	0.56
Bicubic	0.91	0.62	0.64	0.69
Lanczos (radius 3)	0.87	0.57	0.66	0.69
Lanczos (radius 5)	0.85	0.60	0.62	0.69
Gaussian	0.86	0.62	0.63	0.68
Nearest	**0.91**	**0.63**	0.61	0.69
Area	0.77	0.60	0.66	**0.80**
Mitchell-Netravali	0.86	0.62	**0.67**	0.69

Table 1: Accuracy of filters on the base circuit.

Filter/Dataset	**MNIST**	**CIFAR-10**	**Fashion MNIST**	**CIFAR-100**
Hat/Tent	0.73	0.66	0.78	0.72
Bilinear	**0.90**	0.61	0.61	0.55
Bicubic	0.88	0.68	0.70	0.67
Lanczos (radius 3)	0.87	0.66	0.68	0.63
Lanczos (radius 5)	0.87	0.67	0.69	0.64
Gaussian	0.88	0.68	0.68	0.67
Nearest	0.87	0.67	0.69	0.70
Area	0.84	**0.68**	**0.80**	**0.79**
Mitchell-Netravali	0.88	0.67	0.68	0.77

Table 2: Accuracy of filters on the QCNN circuit.

ability in the error correction circuit. Error correction stabilizes performance across datasets and filters but slightly reduces overall accuracy by mitigating noise, which diminishes filter specific optimizations. In complex datasets like CIFAR-10 and CIFAR-100, the circuit prioritizes stability over peak accuracy, highlighting its practicality for quantum applications where consistency and predictability are crucial.

Considering the results across all networks and datasets, it is important to evaluate the trade-offs inherent to the different resizing techniques used, such as variations in sharpness, preservation of similarity, computational cost, and area covered. Interestingly, simpler filters like the Hat filter still managed to enhance accuracy in specific scenarios, proving viable depending on dataset and configuration.

The results also reveal that the differences in mean accuracy across datasets are influenced by the complexity of the dataset and the network architecture. In simpler datasets like MNIST and Fashion MNIST, the choice of filter significantly impacted performance. However, in more complex datasets like CIFAR-10 and CIFAR-100, the differences across filters were less pronounced, particularly in architectures with error correction mechanisms.

Filter/Dataset	MNIST	CIFAR-10	Fashion MNIST	CIFAR-100
Hat/Tent	0.67	0.58	0.78	0.62
Bilinear	**0.86**	0.58	0.58	0.62
Bicubic	0.86	0.58	0.70	0.64
Lanczos (radius 3)	0.86	0.57	0.69	0.62
Lanczos (radius 5)	0.86	0.58	0.69	0.63
Gaussian	0.86	0.58	0.68	0.64
Nearest	0.86	0.57	0.69	0.61
Area	0.77	**0.58**	**0.80**	0.65
Mitchell-Netravali	0.86	0.57	0.69	**0.68**

Table 3: Accuracy of filters on the error mitigating circuit.

Furthermore, the QCNN architecture demonstrated improvements in overall accuracy and stability across filters, showing the value of convolutional layers in handling geometric complexities in image data, highlighting the importance in using filters that preserve such geometry. On the other hand, the error correcting circuit lowered peak accuracy due to its qubits aggregating information, having more stable results. These findings emphasize the dual importance of aligning the right filter with the circuit design to address dataset specific challenges and ensure reliable performance.

5 Conclusion

The investigation into the impact of classical dimensionality reduction algorithms on QNNs has yielded valuable insights. Despite the limitations in qubit capacity and noise sensitivity of quantum devices, this study highlights the critical role classical preprocessing algorithms play in hybrid setups, achieving high accuracy and efficient execution.

Among the evaluated techniques, Nearest Neighbor interpolation consistently performed well across datasets, while Area and Bicubic also showed competitive results depending on the dataset and circuit architecture. These findings reinforce the importance of selecting dimensionality reduction techniques that minimize information loss and maximize efficiency, particularly in constrained NISQ environments.

The study also emphasizes the interplay between preprocessing choices and quantum circuit architecture. Simpler circuits exhibited greater variability across filters, while advanced architectures like QCNNs and error-correcting QNNs achieved enhanced stability and consistent performance. This demonstrates the need to integrate preprocessing strategies with architectural design, ensuring critical image features are preserved, making hybrid approaches increasingly viable.

Future research should explore integrating error mitigation techniques with classical preprocessing to further stabilize performance while maintaining high accuracy. Investigating the scalability of these methods for larger datasets and their execution in distributed and cloud environments would offer valuable insights. Additionally, expanding research to include emerging quantum error correction protocols could further unlock the potential of NISQ.

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