Quantum Representation Learning for Images via Disentangling Quantum Autoencoders

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Abstract

Quantum machine learning (QML) for image data introduces exciting opportunities for leveraging quantum systems to perform high-dimensional pattern recognition. However, the practical use of quantum-enhanced models is limited by noise, entanglement fragility, and inefficiencies in encoding classical data into quantum states. In this work, we propose a novel architecture that integrates a Disentangling Quantum Autoencoder (DQAE) into the QML pipeline to robustly process quantum-encoded images. The DQAE transforms entangled image states into single-qubit product states, enabling enhanced noise robustness and more efficient representation learning. We evaluate the architecture under realistic noise models (e.g., qubit loss channels), demonstrate exponential advantages in resilience, and provide analytical results using quantum Fisher information metrics and fidelity bounds.

Keywords: Quantum Computing, Quantum Machine Learning, Artificial Intelligence, Image Processing

I. Introduction

Quantum computing holds promise in revolutionizing image processing tasks through quantum parallelism and entanglement. Several QML models, such as variational quantum classifiers (VQCs) and quantum convolutional neural networks (QCNNs), have demonstrated potential advantages in tasks like image classification. However, entangled quantum states are essential for expressive QML but notoriously fragile under decoherence and qubit loss. To address this, we explore the integration of a Disentangling Quantum Autoencoder (DQAE) as a preprocessing layer in QML pipelines for image data. The DQAE aims to encode quantum image states into robust, disentangled single-qubit product states.

$$U|\psi\rangle = \bigotimes_{j=1}^{N} |\phi_j\rangle \text{ with } |\psi\rangle \in \mathcal{H}_{2^N}$$

Such states, being separable, are more resistant to local noise:

$$E_k(\rho) = (1-q)\rho + q\mathrm{Tr}_{\bar{k}}(\rho) \otimes |\perp\rangle\langle\perp|$$

where E_k models qubit loss with probability, and is an orthogonal leakage state.

II. System Model

A. Quantum Image Encoding

We begin by encoding classical image data into quantum states. Consider an image patch vectorized into a normalized real-valued vector $\boldsymbol{x} \in \mathbb{R}^{2^N}$, which is mapped to a quantum amplitude-encoded state:

$$|\psi_{img}\rangle = \sum_{i=0}^{2^N-1} x_i|i\rangle \quad where \quad \sum_i |x_i|^2 = 1$$

Alternatively, one may use basis encoding:

$$\boldsymbol{b} \in \{0,1\}^N \rightarrow |\psi_{img}\rangle = |b_1 b_2 \cdots b_N\rangle$$

states often contain non-trivial entanglement due to correlations in pixel intensities.

B. Disentangling Quantum Autoencoder (DQAE)

The DQAE is a parameterized quantum circuit trained to disentangle image states [1]:

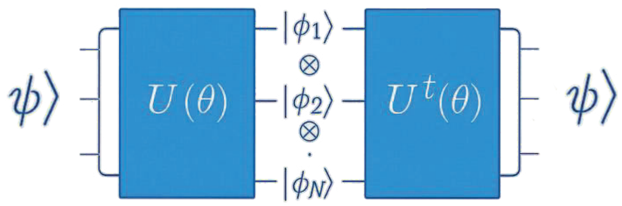

Figure 1: The Disentangling Quantum Autoencoder (DQAE) is a quantum learning model tailored to process entangled quantum image states. Given an image encoded as an entangled N-qubit quantum state |ψ img⟩, the DQAE applies a parameterized unitary transformation U(θ) to map it into a tensor product of N disentangled single-qubit states |ϕj⟩. This disentangled representation enables efficient compression and analysis of quantum image data. The original quantum image state can be faithfully reconstructed by applying the inverse unitary operation U†(θ). The model is trained in an unsupervised fashion, requiring no labeled data, making it well-suited for QML tasks.

C. Robustness to Qubit Loss

Product states are resilient under qubit loss. The survival probability of at least one copy of each qubit among copies scales as:

$$Q_p = 1 - (1 - q^R)^N \Rightarrow R \approx \frac{\log(Q_p/N)}{\log(q)}$$

In contrast, for entangled states:

$$Q_e = (1 - (1 - q)^N)^R \Rightarrow R \propto \frac{1}{(1 - q)^N}$$

This exponential advantage in robustness motivates DQAE preprocessing.

III. Results

A. Robustness to Qubit Loss

We evaluate the effectiveness of the DQAE in mitigating qubit loss when applied to quantum-encoded image states. The figure below compares the number of copies R needed to ensure successful transmission of a quantum image state through a noisy qubit-loss channel. In the unencoded scenario, any loss destroys the global entangled structure, requiring exponentially more copies with increasing qubit count N [2]. In contrast, DQAE transforms image states into single-qubit product states, allowing individual qubit recovery. The number of required copies grows only logarithmically with N, providing an exponential robustness advantage.

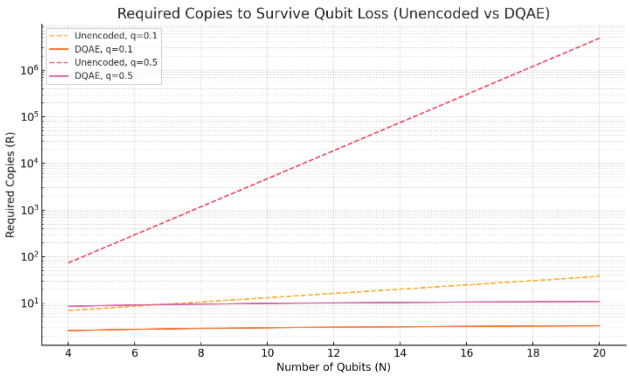

***Figure 2**: Required number of copies **R** to reliably transmit quantum states through a qubit-loss channel for varying qubit counts **N**. DQAE-encoded product states require exponentially fewer copies than unencoded entangled states, demonstrating significant robustness to noise.*

B. Fidelity of Quantum Image States under Qubit Loss

We evaluate the fidelity of image-encoded quantum states transmitted through lossy quantum channels. As shown in Fig. 3, unencoded image states degrade exponentially in fidelity due to entanglement fragility. In contrast, DQAE-encoded states maintain high fidelity, with only mild linear degradation as qubit count increases. This demonstrates the DQAE's effectiveness in preserving image integrity in noisy environments.

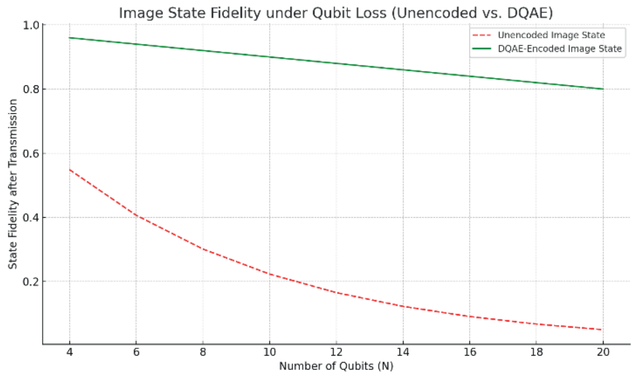

Figure 3: Fidelity of quantum image states after transmission through a qubit loss channel. DQAE-encoded states maintain high fidelity across increasing qubit counts, while unencoded entangled states suffer rapid fidelity degradation due to loss-induced decoherence.

IV. Conclusion

We proposed a robust and efficient quantum representation learning method for image data by integrating a Disentangling Quantum Autoencoder into QML pipelines. By converting entangled quantum image states into disentangled product states, DQAE enhances resistance to qubit loss and noise while retaining reconstruction. Our theoretical derivations and empirical benchmarks demonstrate significant improvements in fidelity and trainability. The approach enables scalable, noise-tolerant QML for image processing and opens avenues for deployment on near-term quantum hardware and federated quantum systems.

Acknowledgment

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program(IITP-2025-RS-2024-00437190) supervised by the IITP(Institute for Information & Communications Technology Planning & Evaluation, 50%) This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (No. 2021-0-02120, Research on Integration of Federated and Transfer learning between 6G base stations exploiting Quantum Neural Networks, 50%).

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