Abstract

Introduction: Quantum computing promises revolutionary advancements in fields ranging from cryptography to drug discovery. Among its potential applications, quantum machine learning (QML) stands out, especially for tasks involving generative models. Quantum Generative Adversarial Networks (QGANs) have been theorized to offer exponential advantages over their classical counterparts for generating high-fidelity images, a claim that has sparked considerable interest. However, the practicality of QGANs on near-term quantum devices for real-world tasks remains an open question.

Problem Statement: Despite theoretical advancements, the feasibility and effectiveness of implementing QGANs on contemporary noisy intermediate-scale quantum (NISQ) devices for practical image generation tasks have not been adequately explored. This gap between theory and practice limits our understanding of the potential advantages and applications of quantum computing in machine learning, specifically in the domain of generative models for complex tasks like image generation.

Methodology: We propose a flexible QGAN scheme that leverages the quantum superposition principle to process multiple training examples in parallel, aiming to harness the computational capabilities of NISQ devices efficiently. Our experimental setup involves a superconducting quantum processor to generate real-world handwritten digit images, employing a quantum generator and a classical discriminator. The performance of the proposed QGAN is compared with classical GANs through the Fréchet Distance score, using a gray-scale bar dataset to evaluate the generative capabilities of both models. If we get time, we can try training the model in Quaternion domain and test it further on different datasets CelebA-HQ and Oxford Flowers Dataset.

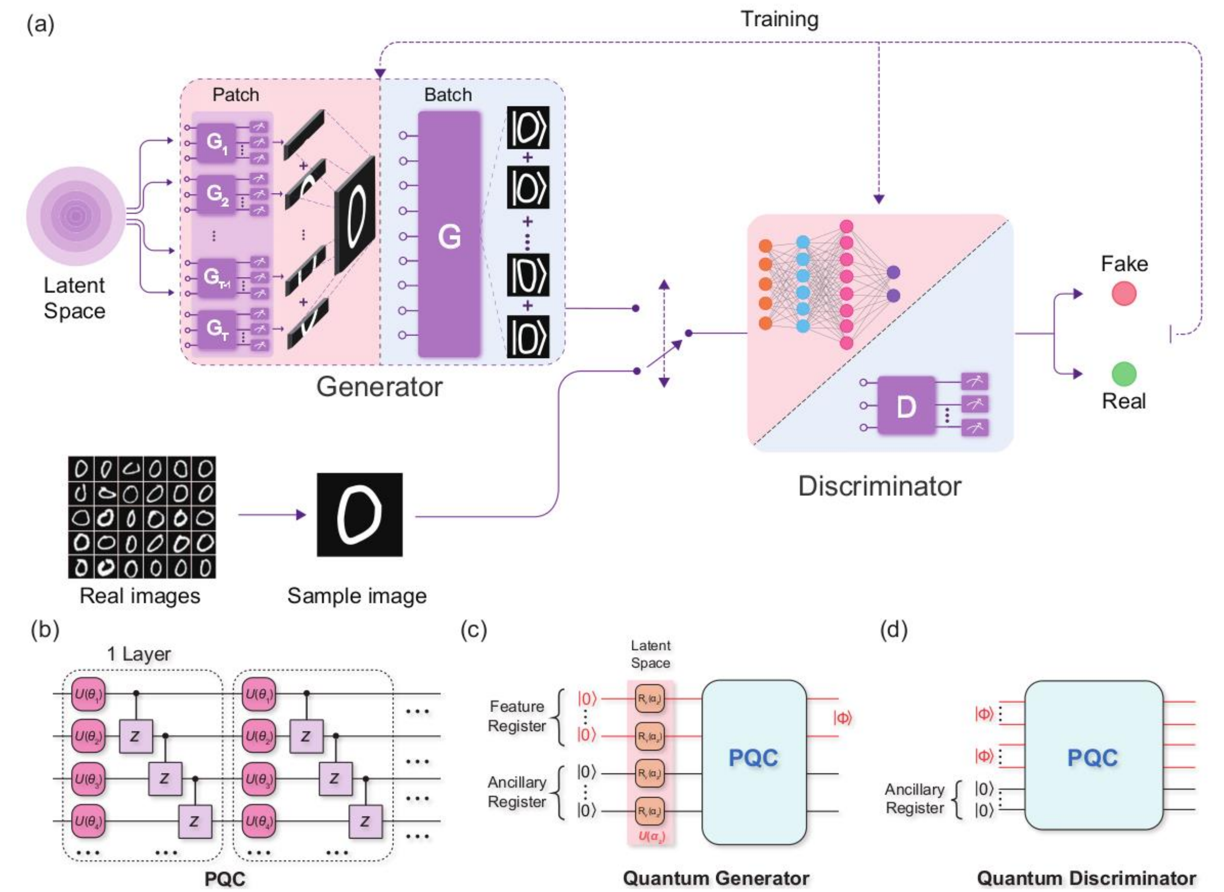

FIG. 1: **The resource-efficient quantum GAN scheme.** (a) The proposed quantum GANs scheme contains a quantum generator G and a discriminator D, which can either be classical or quantum. The mechanism of quantum patch GAN is as follows. First, the latent state $|\boldsymbol{z}\rangle$ sampled from the latent space is input into quantum generator G formed by T sub-generators (highlighted in pink region), where each G_t is built by a PQC $U_{G_t}(\boldsymbol{\theta}_t)$. Next, the generated image is acquired by measuring the generated states $\{U_{G_t}(\boldsymbol{\theta}_t)\,|\boldsymbol{z}\rangle\}_{t=1}^{T}$ along the computation basis. Subsequently, the patched generated image and the real image are input into the classical discriminator D (highlighted in pink region) in sequence. Finally, a classical optimizer uses the classified results as the output of D to update trainable parameters for G and D. This completes one iteration. The mechanism of quantum batch GAN is almost identical to the quantum patch GAN, except for three modifications: 1) we set $T = 1$ and introduce the quantum index register into G (highlighted in blue region); 2) the generated state $U_G(\boldsymbol{\theta})\,|\boldsymbol{z}\rangle$ directly operates with quantum discriminator D implemented by PQC (highlighted in blue region), where the output is acquired by a simple measurement; and 3) the real image is encoded into the quantum state to operate with D. (b) The implementation of PQC used in the quantum generator and quantum discriminator. (c) The machinery of quantum generators employed in quantum patch and batch GANs. For quantum batch GAN, an index register with extra operations should be involved when the batch size is larger than one. (d) The quantum discriminator employed in the quantum batch GAN. To attain nonlinear property, two generated states are fed into the quantum discriminator simultaneously.

{Images taken from the paper in reference**}**

Expected Outcome: The experiment demonstrates that our QGAN can generate hand-written digit images with competitive fidelity to classical GANs, showcasing the potential of quantum computing in enhancing machine learning tasks. This work narrows the knowledge gap regarding the practical application of QGANs and provides insights into developing advanced quantum generative models on NISQ devices. It also opens up avenues for exploring quantum advantages in broader generative learning tasks, potentially leading to the discovery of efficient, scalable solutions for image generation and beyond. We will try training it on different Datasets and try to take it in Quaternion domain if we get time.

References:

- He-Liang Huang et al., "Experimental Quantum Generative Adversarial Networks for Image Generation," arXiv:2010.06201v3 [quant-ph], 2021.
- Eleonora Grassucci, Edoardo Cicero and Danilo Comminiello, “Quaternion Generative Adversarial Networks”, https://arxiv.org/abs/2104.09630