Exploring Quantum Generative Models: A Benchmark Analysis

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INTRODUCTION

In recent years, numerous contributions have been made to the field of quantum machine learning, driven by its promising potential. One prominent area within this discipline is the development of **quantum generative models**.

However, in the domain of **image generation**, most proposed projects have focused on generating images with **simple distributions, limited resolution, or substantial downscaling.**

These constraints make it difficult to fully **evaluate the potential** of quantum generative models, especially when applied to more complex and realistic datasets.

CONTRIBUTIONS

* **Benchmark analysis** to assess the performance of quantum generative models at various image resolutions and parameter settings. This includes evaluating model behavior using metrics such as Fréchet Inception Distance and Peak Signal-to-Noise Ratio.

* **Open-source repository** with quantum generative models (including Quantum GANs and Quantum Diffusion models) for training and evaluation on two biomedical datasets.

* Evaluation of the **Contribution of the Quantum Component** in a Hybrid GAN with a hybrid Generator

MATERIALS & DATABASE

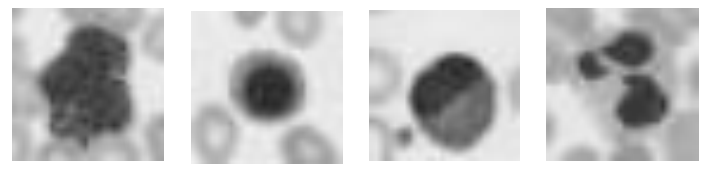

Figure 1. Example of images from the BloodMNIST dataset [1,2].

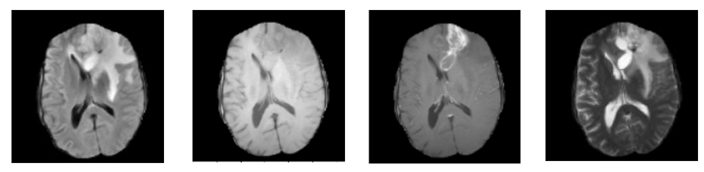

Figure 2. Example of images from the BraTS dataset [3,4,5].

PROPOSED METHODOLOGY

MODELS

Quantum GANs:

- Patch GAN [6]: This hybrid architecture applies the patch method to the generator and uses a classical discriminator.
- PQWGAN [7]: This hybrid model features a quantum generator and employs the patch method, similar to the previous model, while also incorporating a Wasserstein distance gradient penalty.
- QC-GAN [8]: This architecture combines a classical discriminator with a hybrid generator, where the classical component handles the mapping and nonlinear transformation.

Quantum Denoising Diffusion Models:

- Q-Dense [9]: This architecture trains dense quantum circuits to perform the denoising step.
- Q-Dense Directed [9]: Building on the previous model, this one incorporates the image class to guide the training process.

REPOSITORY

The code for all the models, except for the QC-GAN, was extracted from the literature and modified to generate the repository.

QUANTUM CONTRIBUTION

Since QC-GAN features a **hybrid generator**, the **contribution** of the quantum component was analyzed by generating images using only the classical part.

EXPERIMENTS: BENCHMARK ANALYSIS

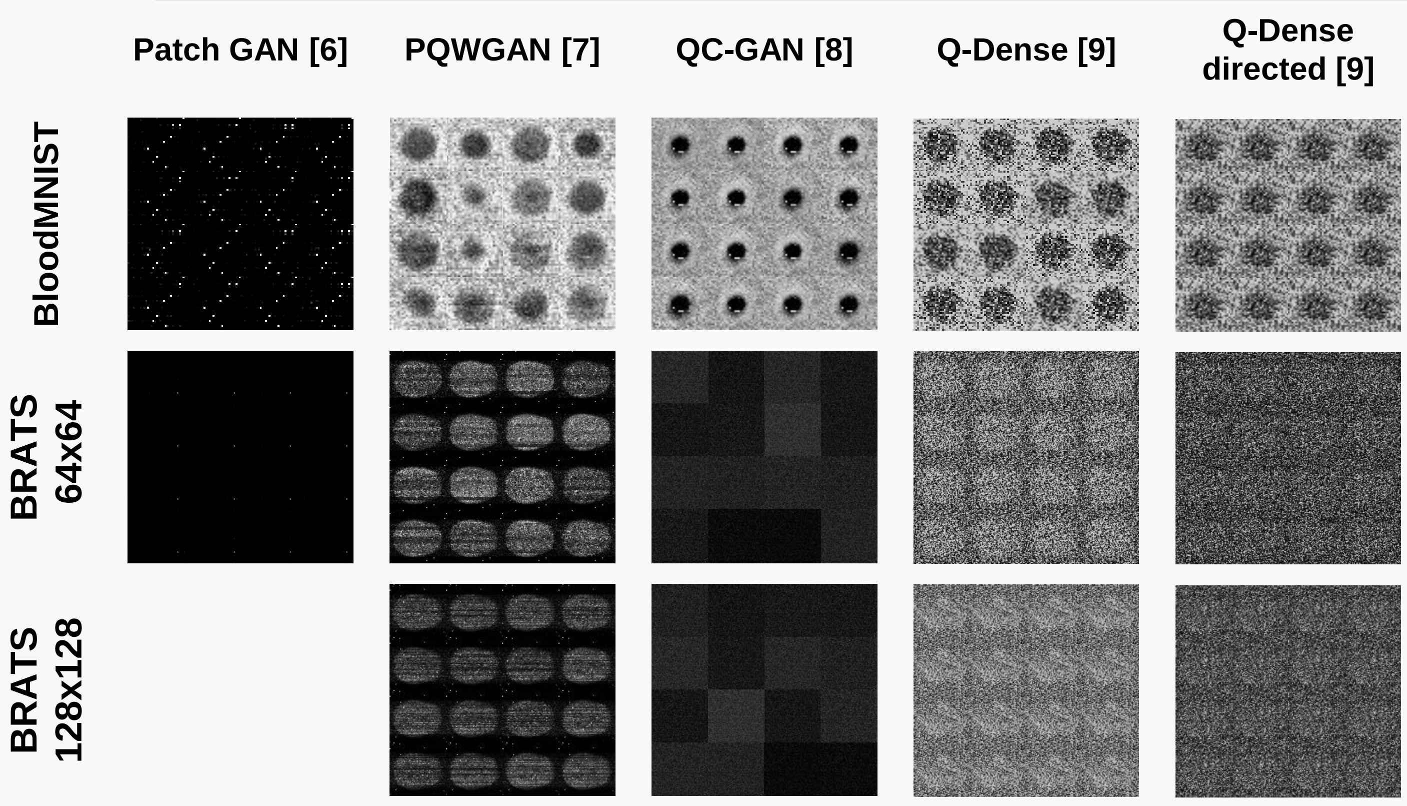

Figure 3. Some of the images generated with the different datasets.

		Patch GAN	PQWGAN	QC-GAN	Q-Dense	Q-Dense di
BloodMINST	FID	465.66	348.64	436.78	403.84	504.29
	PSNR	2.44	12.36	11.71	9.58	9.29
BraTS 64x65	FID	341.99	318.78	407.63	390.88	396.53
	PSNR	9.93	14.46	11.43	7.30	9.46
BraTS 128x128	FID	-	354.16	494.02	440.05	490.9
	PSNR	-	16.11	8.93	6.62	9.45

EXPERIMENTS: OPEN SOURCE REPOSITORY

Open-Source-Repository-for-Evaluating-Quantum-Image-Generative-Models

https://github.com/nmunoz317/Open-Source-Repository-for-Evaluating-Quantum-Image-Generative-Models.git

EXPERIMENTS: QUANTUM CONTRIBUTION QC-GAN

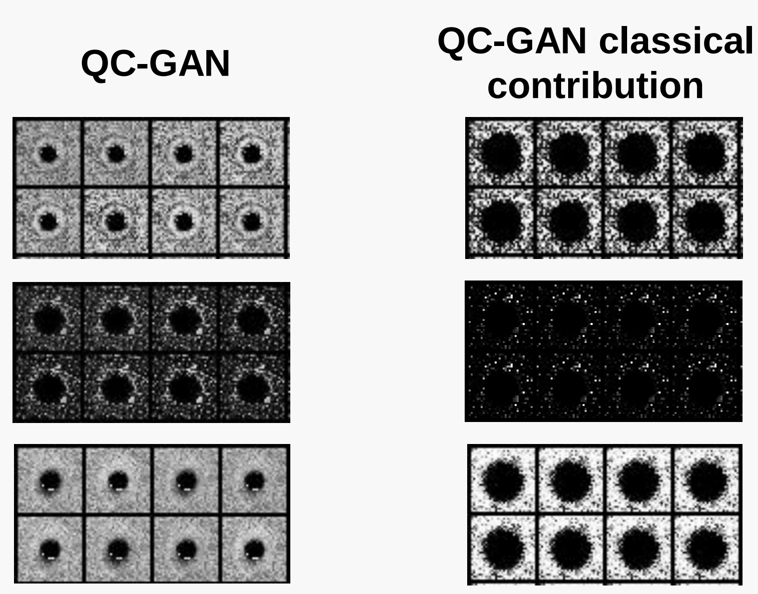

Figure 4. Analysis of Quantum and Classical Contributions in the QC-GAN Generator.

CONCLUSIONS

Increasing image resolution and using more complex distributions present **challenges for quantum generative models**. However, it is important to emphasize that benchmarking requires **complex and extensive analysis**. Therefore, expanding the range of explored parameters is recommended to further the understanding of the current state of the art. An **open-source repository** has been provided to encourage community involvement and enhance the benchmarking process.

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