Turning Quantum Noise on its Head:
Using the Noise for Diffusion Models to Generate Images

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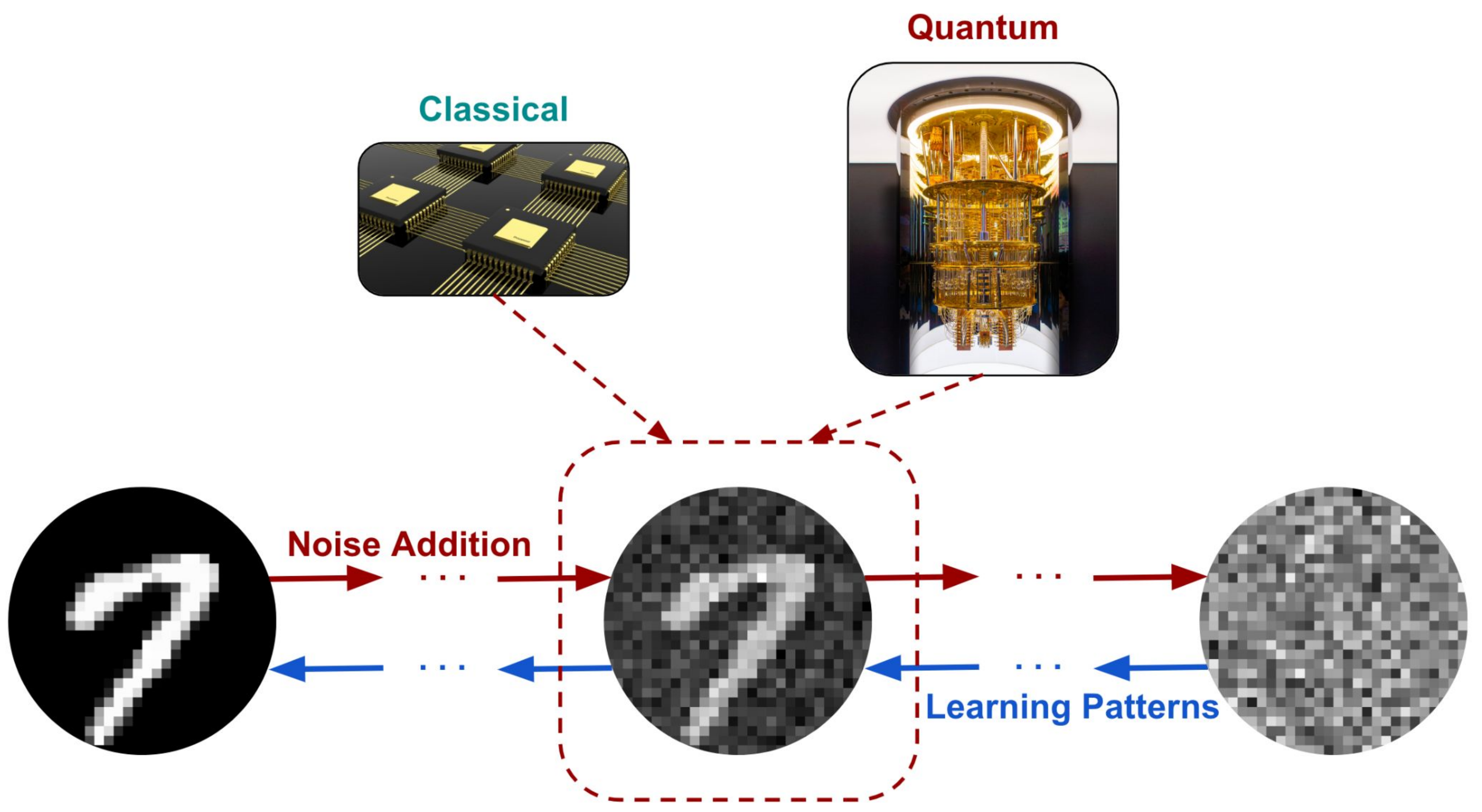
Introduction

Background and Motivation
- Generative image models have dramatically grown in use and popularity in the recent years for various applications
- Noise schedule significantly impacts training process

Problem Formulation
- Improving the speed and quality of image generation for diffusion models

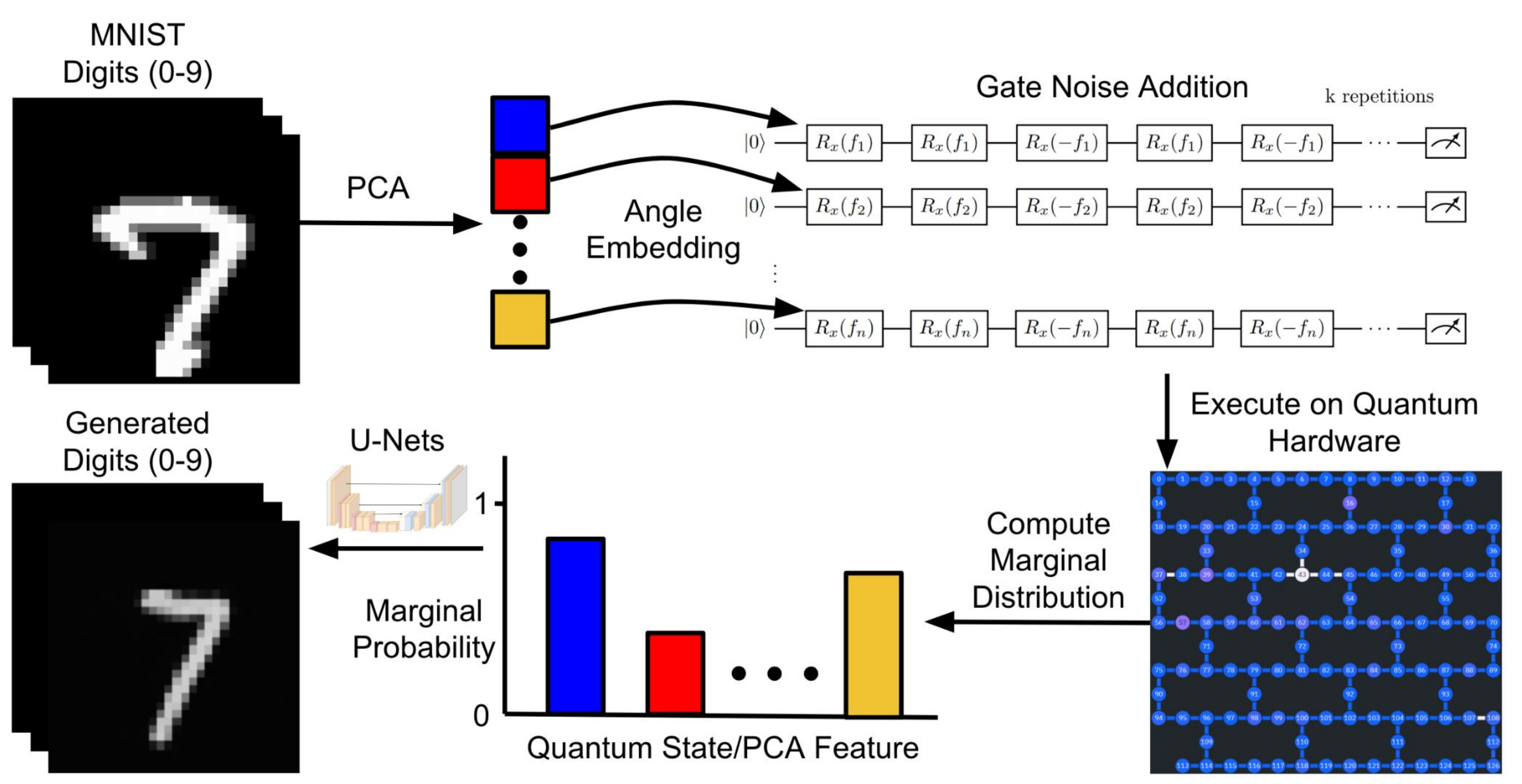
Our Solution
- Using noise from superconducting quantum computers as noise added to images in diffusion models
- Allows for parallel and 'true random' noise generation



Our Approach: Instead of sampling random noise using pseudo-random algorithms on classical computers, we propose adding noise to images generated from quantum decoherence and environmental factors using quantum computers.

Design & Implementation

Workflow: Using Superconducting Quantum Computers for Noise



Quantum Noise Addition: To represent the image in a quantum circuit, we first perform Principal Component Analysis (PCA) and use angle embedding. We then run the circuit on IBM's superconducting quantum hardware, and compute the marginal probability for each qubit to extract the noisy image. To generate new images, we train a time-based diffusion model using U-Net autoencoders.

Why PCA and Angle Embedding?
- PCA retains features capturing the most variance for the image
- Angle embedding keeps circuit depth shallow for controlled noise

Circuit Architecture Used for Noise Addition?
- Rx gates followed by the inverse allow for feature-specific noise
- More gates added increases circuit depth, increasing decoherence

Experimental Details

Specific Experimental Choices Made

500 Images → **PCA + Scaling** → **Gate Repetition Noise** → **Superconducting Hardware** → **Image Extraction** → **Neural Networks**

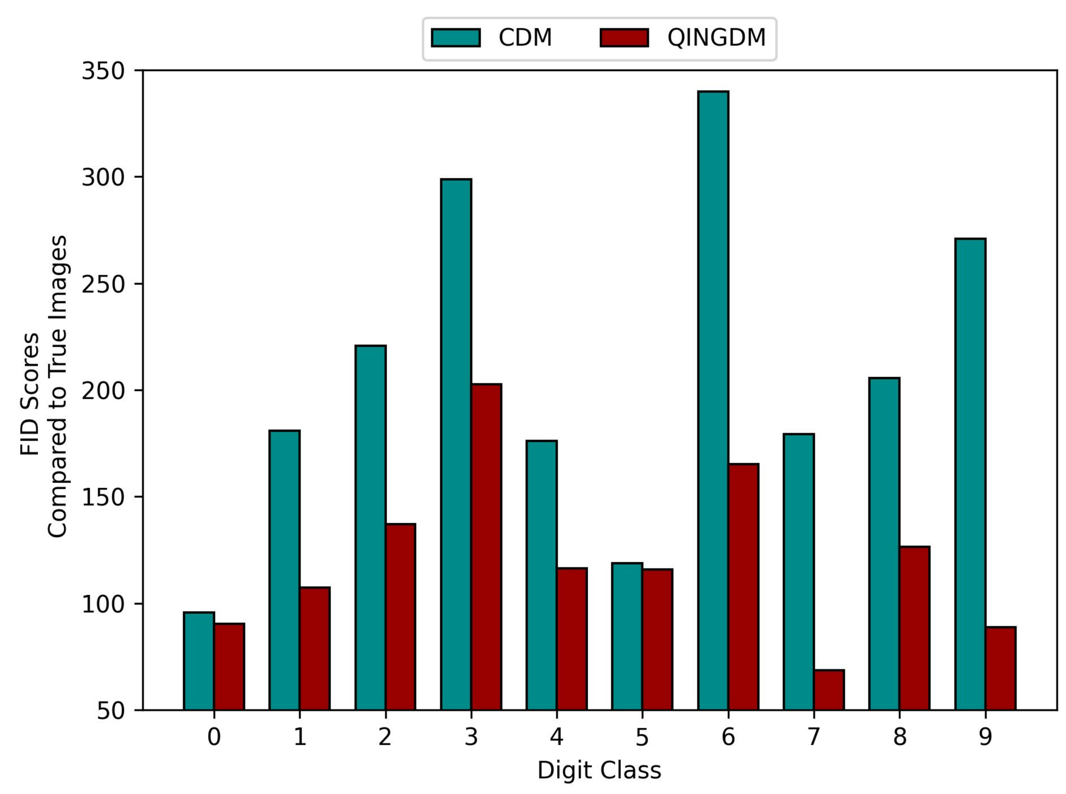
- **500 Images**: Randomly sampled images for each digit
- **PCA + Scaling**: PCA reduction to 127 features; scaled from 0 to π
- **Gate Repetition Noise**: 0, 2, 4, 8, 16, and 32 repetitions
- **Superconducting Hardware**: IBM Nazca, a 127-qubit quantum computer
- **Image Extraction**: Marginal Probabilities => Angle Values => Inverse PCA
- **Neural Networks**: Time-based with U-Net architecture

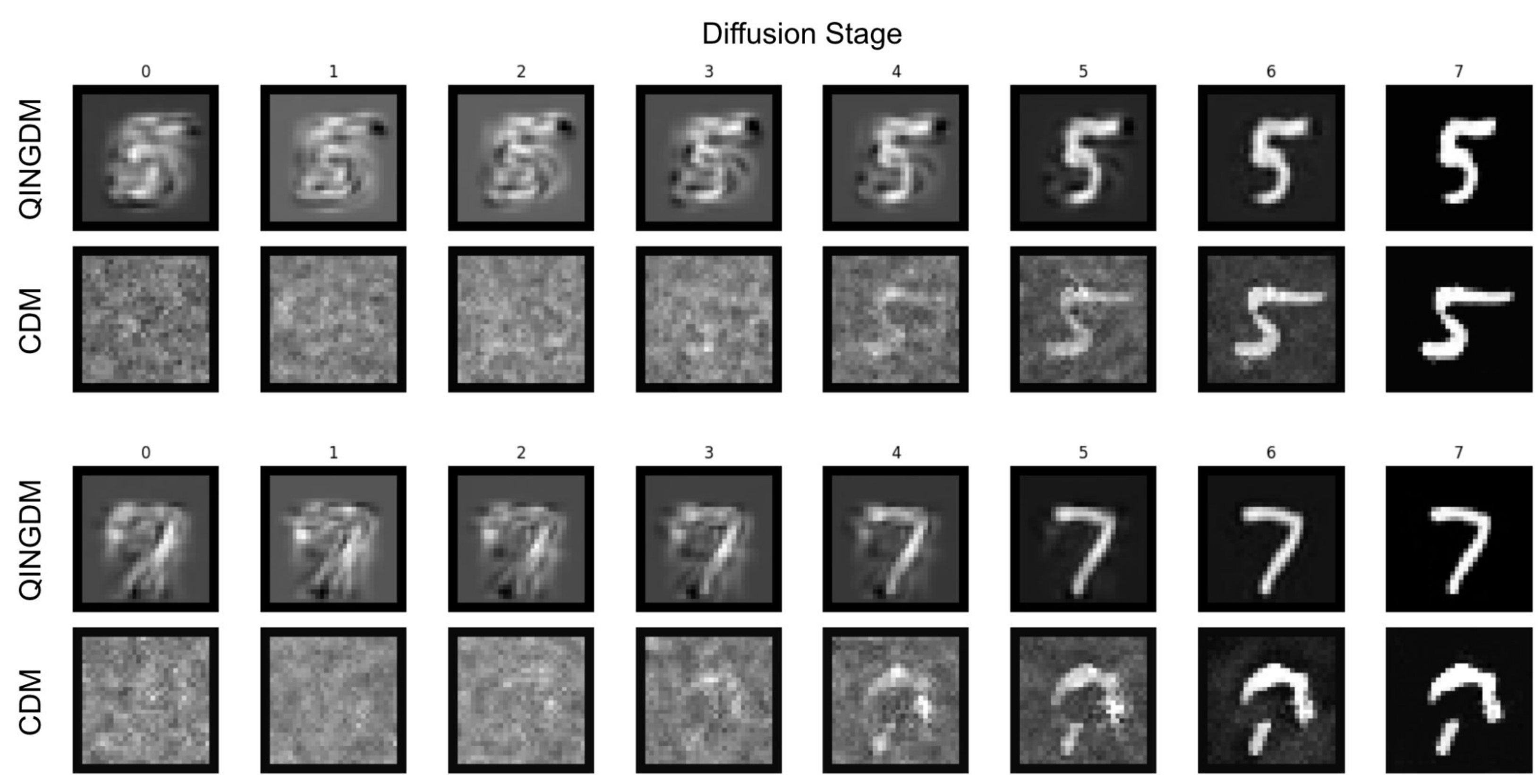
Hyperparameter Choices: The following choices performed well:
- ***Batch size:*** 10 Images
- ***Diffusion Steps:*** 8 (6 noisy quantum, 1 PCA, and 1 original image)
- ***Learning Rate:*** 0.0008
- ***Learning Rate Step Size:*** 100 Epochs

Results & Analysis

QINGDM (Quantum Image Noise-based Generative Diffusion Models) achieves a lower FID score compared to classical methods (CDM) for all 10 digit classes.

We use a pre-trained InceptionV3 model to calculate FID between 5000 real and generated images. The average FID score is 121.9 *(lower is better)*.





Comparative Analysis of Quantum and Classical Reverse Diffusion
We plot the reverse diffusion process for our approach (QINGDM) and a classical approach (CDM) for digit 5 and digit 7, where QINGDM has the worst and best improvements in FID score, respectively.
- For digit 5, QINGDM and CDM both generate realistic images
- For digit 7, QINGDM yields a realistic digit, but CDM is disjointed

Discussion and Contributions
- Limited training data and random noise addition was employed by QINGDM, but still yields improved FID
- Our methodology can be applied to larger models for faster and higher quality image generation