Quantum Neural Network Benchmarking with MNIST Dataset

SenSIP Algorithms and Devices REU

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ABSTRACT

- Leverage inherent parallelization of quantum computers for machine learning applications.
- Compare quantum computer simulations against classical neural networks on the MNIST dataset.

MOTIVATION

Quantum computing is a pillar of future-leaning research in computation. Phenomena from quantum mechanics principles such as superposition and entanglement are leveraged for greater parallel computation power than classical Boolean computing. In theory certain application areas could see computation speed increases in the order of thousands.

PROBLEM STATEMENT

Current hardware is still early, so we test the majority of our quantum algorithms in simulators. These don't vet fully encompass the speed advantages vet, but are able to provide a relatively robust simulation of how the algorithm will operate on actual quantum hardware.



systems

Figure 1: Legacy IBM Quantum Computer

DESIGN: HYBRID QUANTUM NEURAL NETWORK

- Developed hybrid quantum-classical neural network (QNN) framework
- Tested capabilities on 2, 3 and 4 qubit quantum systems
- Designed two separate algorithm architectures for training on 2 classes of MNIST and full 10 class MNIST dataset.



Figure 2: QNN Architecture



concept

CHALLENGES

 Early nature of quantum computing led to challenges in design Prime difficulty in runtime of quantum simulated programs



Figure 4: Time cost of increasing number of qubits in design

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