Quanvolutional Neural Networks: Powering Image Recognition with Quantum Circuits

Quantum Machine Learning Exam Project

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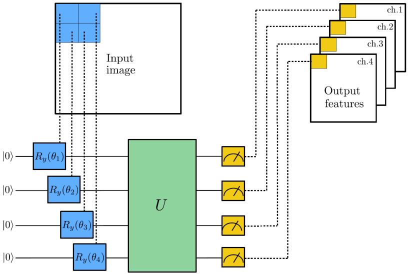
Introduction

Quanvolutional Neural Networks

Convolutional Neural Networks (CNNs) represent a core model architecture in computer vision, using learned filters to extract features from images. The paper by Henderson et al. asks a compelling question:

Central Idea

Can we replace a classical filter with a **quantum circuit** to generate more powerful, complex features that are difficult to replicate classically?



Henderson et al. Quanvolutional neural networks: Powering image Recognition with Quantum Circuits

Project Goals

Introduction

Our goal was not just to replicate the paper, but to perform a **rigorous analysis** to understand some of the practical trade-offs of the QNN approach.

- Does the QNN outperform a carefully designed classical baseline (CNN) on clean, full datasets?
- Is the QNN more **data-efficient**? Can it learn effectively from limited samples?
- Is the QNN more **robust** to perturbations of input data?
- Are the feature maps produced by quanvolutional layers actually useful without a deep neural network backend?

The Quanvolutional Layer

Implementation Details

We implemented the quantum feature extractor in PennyLane. It processes a 2×2 image patch in three stages:

1. **Encoding:** Pixel values $\phi \in [0, 1]$ are encoded into qubit states using angle encoding: $R_Y(\pi \cdot \phi)$.
2. **Transformation:** A fixed, non-trainable random quantum circuit is applied. The parameters are generated once with a fixed seed to act as a consistent filter.
3. **Measurement:** The expectation value $\langle \sigma_z \rangle$ of each qubit is measured to produce a classical feature vector.

Circuit Generation

Quanvolutional Neural Networks

```
dev = qml.device("lightning.qubit", wires=n_qubits)
rand_params = np.random.uniform(high=2 * np.pi, size
     =(n_layers, n_qubits))

@qml.qnode(dev)
def quanv_circuit(phi):
    # 1. Encoding
    for j in range(4):
        qml.RY(np.pi * phi[j], wires=j)
    # 2. Transformation (fixed params)
    RandomLayers(rand_params, wires=range(4))
    # 3. Measurement
    return [qml.expval(qml.PauliZ(j)) for j in range
         (4)]
```

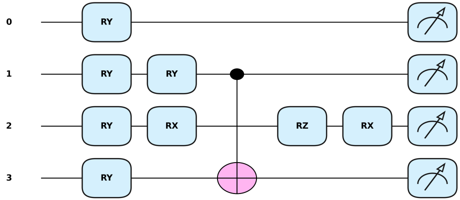


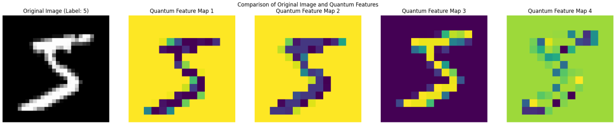
Figure: A random 1-layer quantum circuit

Patch Processing

Quanvolutional Neural Networks

```
def quanv_layer(image):
    out = torch.zeros((14, 14, 4))
    for j in range(0, 28, 2):
        for k in range(0, 28, 2):
            patch = torch.flatten(image
                 [0, 0, j : j + 2, k : k
                 + 2])
            q_results = quanv_circuit(
                 patch)
            for c in range(4):
                out[j // 2, k // 2, c] =
                     q_results[c]

    return out
```



Models

Experimental Setup

To isolate the effect of the feature extractor, we designed two models with nearly identical parameter counts.

1. **Quanvolutional CNN (QNN)**
   - **Input:** Quantum-processed feature maps $(14 \times 14 \times 4)$.
   - **Backend:** The backend is a deep classical CNN consisting of 2 convolutional blocks (Conv2D $\rightarrow$ ReLU $\rightarrow$ MaxPool2D) + 2 Linear layers with dropout
   - **Parameters:** 169,962
2. **Classical CNN Baseline**
   - **Input:** Original images $(28 \times 28 \times 1)$.
   - **First Layer:** A classical ‘Conv2D‘ layer that mimics the QNN’s transformation (2x2 kernel, stride 2). This ensures that the feature map sizes before the backend are the same as the QNN.
   - **Backend: Identical** to the QNN.
   - **Parameters:** 169,982

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Datasets & Workflow

Experimental Setup

Datasets Analyzed:

- MNIST, FMNIST, KMNIST (grayscale, 28x28)
- CIFAR10 (converted to grayscale, center-cropped to 28x28)

Preprocessing Workflow:

- Since the quantum circuit is not trained, we apply it as a **one-time preprocessing step**.
- The resulting quantum feature maps are saved to disk as *PyTorch* tensor files (.pt)
- **Practical Challenge:** This step is computationally expensive.
  - $\sim$**8 hours** to process one training set on a modern CPU.

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Experiment 1: Performance on Full Datasets

Dataset	Classical CNN	QNN (1-Layer)	QNN (2-Layer)
MNIST	**99.05**	98.98	97.48
FMNIST	**90.56**	90.13	88.43
KMNIST	**95.16**	94.68	94.93
CIFAR-10	61.63	**62.21**	61.12

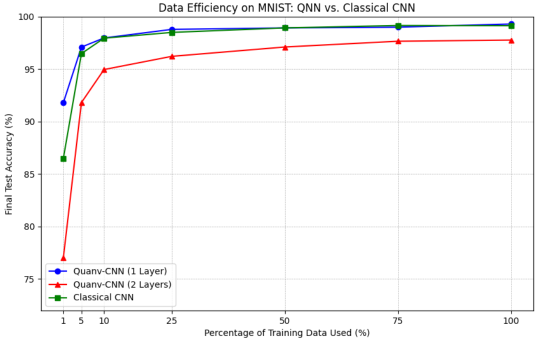
- On MNIST-like datasets, the trainable classical model achieves slightly higher accuracy.
- Considering the **8-hour quantum preprocessing time**, the classical approach is more practical for these tasks.
- The 1-layer QNN wins on the more complex CIFAR-10 dataset.
- Increasing quantum layers (2 vs 1) consistently degrades performance.

Experiment 2: Data Efficiency

Experiments

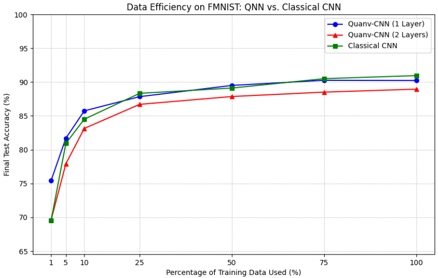
Goal: To determine whether the quantum features are ”good enough” to yield a performance advantage over classical feature maps in the low-data regime

- $\rightarrow$ Trained each model on random subsets of the training data: [1,5,10,25,50,75,100 %]
- Reported the final test accuracy for each training run

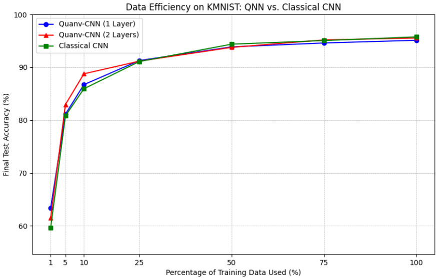


Data Efficiency on MNIST-like Datasets

Experiments



(a) Data efficiency on FMNIST

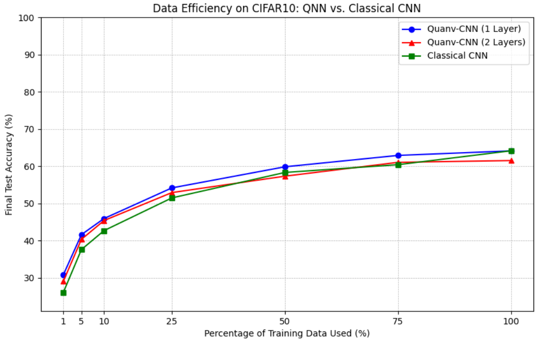


(b) Data efficiency on KMNIST

Experiment 2: Data Efficiency

Experiments

- The QNN (blue) consistently outperforms the classical CNN (green) in low-data regimes (1-25% of data) across all datasets.
- On CIFAR-10, this advantage is sustained across the **entire** data range.



Experiment 3: Robustness to Input Noise

Goal:

- To determine whether the quantum features confer any degree of resilience to input noise compared to the classical baseline.

Method:

- Evaluate pre-trained models on test sets corrupted with two distinct types of noise at varying levels of intensity.

Gaussian Noise (Continuous Perturbation)

Perturbs **every** pixel I_p by adding random noise n, where:

$$n \sim \mathcal{N}(0, \sigma^2)$$

The standard deviation σ controls the noise intensity.

Salt & Pepper Noise (Sparse Errors)

Corrupts a random **fraction** p of pixels, setting them to the extreme values of 0 (pepper) or 1 (salt).

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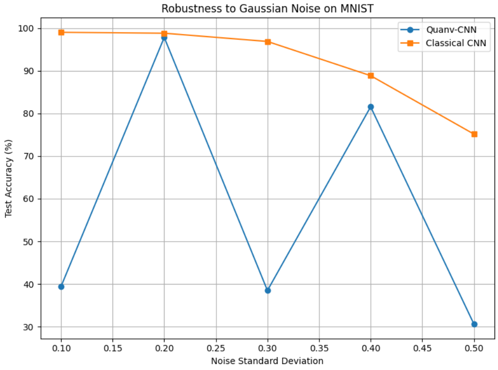
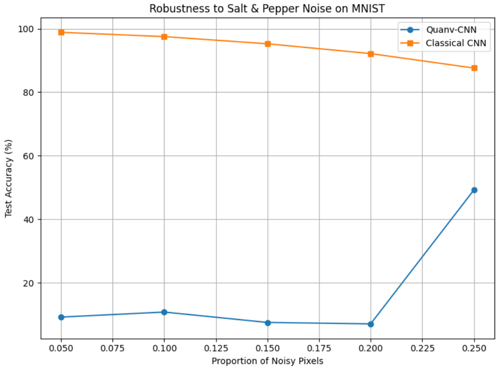
Experiment 3: Robustness to Input Noise (MNIST)

Experiments



(a) Gaussian Noise on MNIST



(b) Salt & Pepper Noise on MNIST

The classical model (orange) shows a graceful decline, while the QNN (blue) is highly erratic and brittle. This trend was consistent across all datasets.

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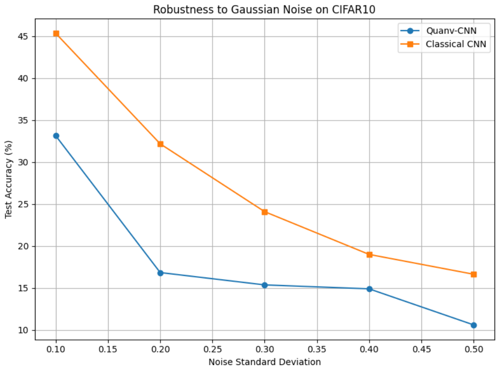
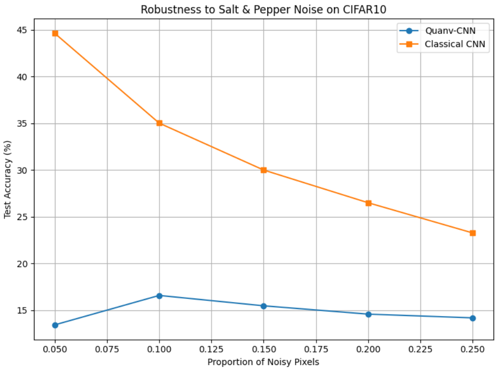
Experiment 3: Robustness to Input Noise (CIFAR10)

Experiments



(a) Gaussian Noise on CIFAR10



(b) Salt & Pepper Noise on CIFAR10

Experiment 4: Architectural Ablation

Goal:

- To isolate the "raw power" of the features themselves, without the influence of a deep CNN backend.

Method:

- We designed a **Minimal Classifier**: a *Flatten* layer followed by a single *Linear* layer.
- This minimal model was trained directly on the feature maps produced by the quantum and the classical feature extractors

Table: Test Accuracy (%) with a Minimal Classifier.

Dataset	Classical Features	Quantum Features
MNIST	92.57	**93.62**
FMNIST	84.29	**85.08**
KMNIST	70.30	**73.60**
CIFAR-10	29.64	**33.19**

Key Finding

The quantum features are consistently and significantly better for direct, shallow classification across all tested datasets.

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QNN vs CNN

Conclusions

Quanvolutional CNN (QNN)

✓ **Strengths:**

- Performs well in the low data regime
- Powerful features for shallow classification

✗ **Weaknesses:**

- Sensitive to input noise
- High computational cost

Classical CNN (Baseline)

✓ **Strengths:**

- More robust to input noise
- Lower computational cost
- Performs better on most full, clean datasets

✗ **Weaknesses:**

- Lower performances in the low data regime
- Weaker features for shallow classification

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Future Work

Conclusions

- **Trainable Quantum Kernels:** The most promising direction is to explore **variational quantum circuits**. A learnable kernel could potentially adapt to the data statistics to become robust to noise while retaining its powerful feature extraction capabilities.

- **Robust Encoding Schemes:** Investigating alternative, more resilient methods for encoding classical data into quantum states is crucial to mitigate the input sensitivity we observed.

- **Real Hardware Analysis:** Testing this architecture on NISQ-era devices to verify the paper's hypothesis that a random kernel may be inherently resilient to *quantum hardware noise*.

Thank You
Conclusions

Questions?

The complete project, including all code and experimental logs, is available on GitHub (code) and Weights and Biases (logs & plots):

github.com/jaysenoner99/quanv_nn

wandb.ai/jaysenoner/quanvolutional-nn-mnist?nw=nwuserjaysenoner1999