Efficient Quantum Convolutional Neural Networks for Image Classification: Overcoming Hardware Constraints

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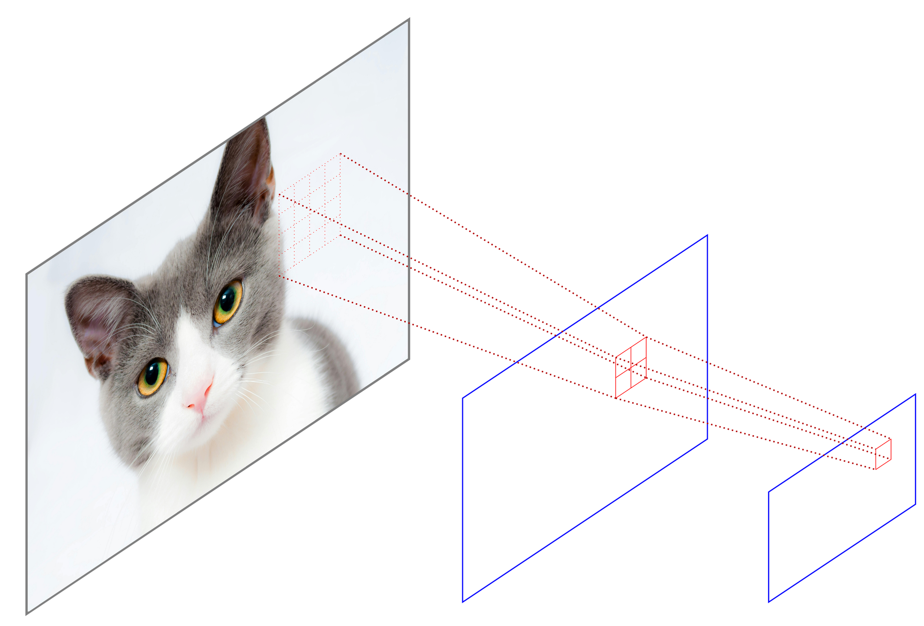
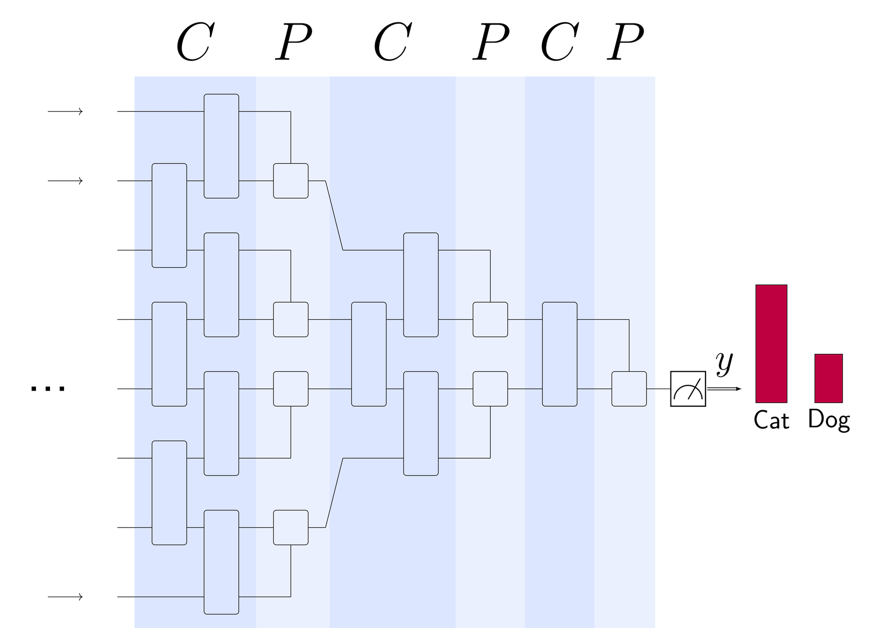
Background

Quantum convolutional neural networks (QCNNs) extend classical CNN concepts to parameterized quantum circuits (PQCs), but their deployment on NISQ devices is challenging [1, 2]. To fit QCNNs on current hardware, often dimensionality-reduction techniques (e.g. PCA, autoencoders) are applied, which can lead to:

- Loss of fine details
- Disrupt spatial structure that CNNs exploit
- Obscuring whether the QCNN or the pre-processing do the classification
- Limiting generalization to more complex architectures





Fragment encoding

We encode image fragments into a compact quantum representation, where each qubit sequentially processes a fragment analogous to multiple convolutional layers.

- Classical convolution:

$$x_{i,j}^{(l+1)} = \sum_{a=1}^{k}\sum_{b=1}^{k} w_{a,b} x_{i+a,j+b}^{(l)}. \tag{1}$$

- Fragment encoding:

$$U(\phi_0)E(x_0)\dots U(\phi_{k^2})E(x_{k^2}) = (U(\phi_0)E(x_0))\dots(U(\phi_{k^2})E(x_{k^2})), \tag{2}$$

$$E(x_{i,j}^{(l+1)}) = \prod_{a=1}^{k}\prod_{b=1}^{k} U(\phi_{a,b}^{(l)})E(x_{i+a,j+b}^{(l)}). \tag{3}$$

Proposition

The depth of fragment encoding scales as $O(1)$.

Scaling

We evaluate QCNN architectures across different qubit counts. In the Best Model column, the sequence before '$\rightarrow$' denotes the fragment-encoding gates, and the sequence after '$\rightarrow$' refers to the QCNN circuit blocks from [3]. Models are read left to right in layer order.

Number of Qubits	Best Model	Accuracy
1	$R_x - R_y - R_z - R_x - R_y \rightarrow U3$	51.35
4	$U3 - U3 - U3 - U3 \rightarrow C5$	61.37
16	$U3 - U3 - U3 \rightarrow Pool - C2$	71.79

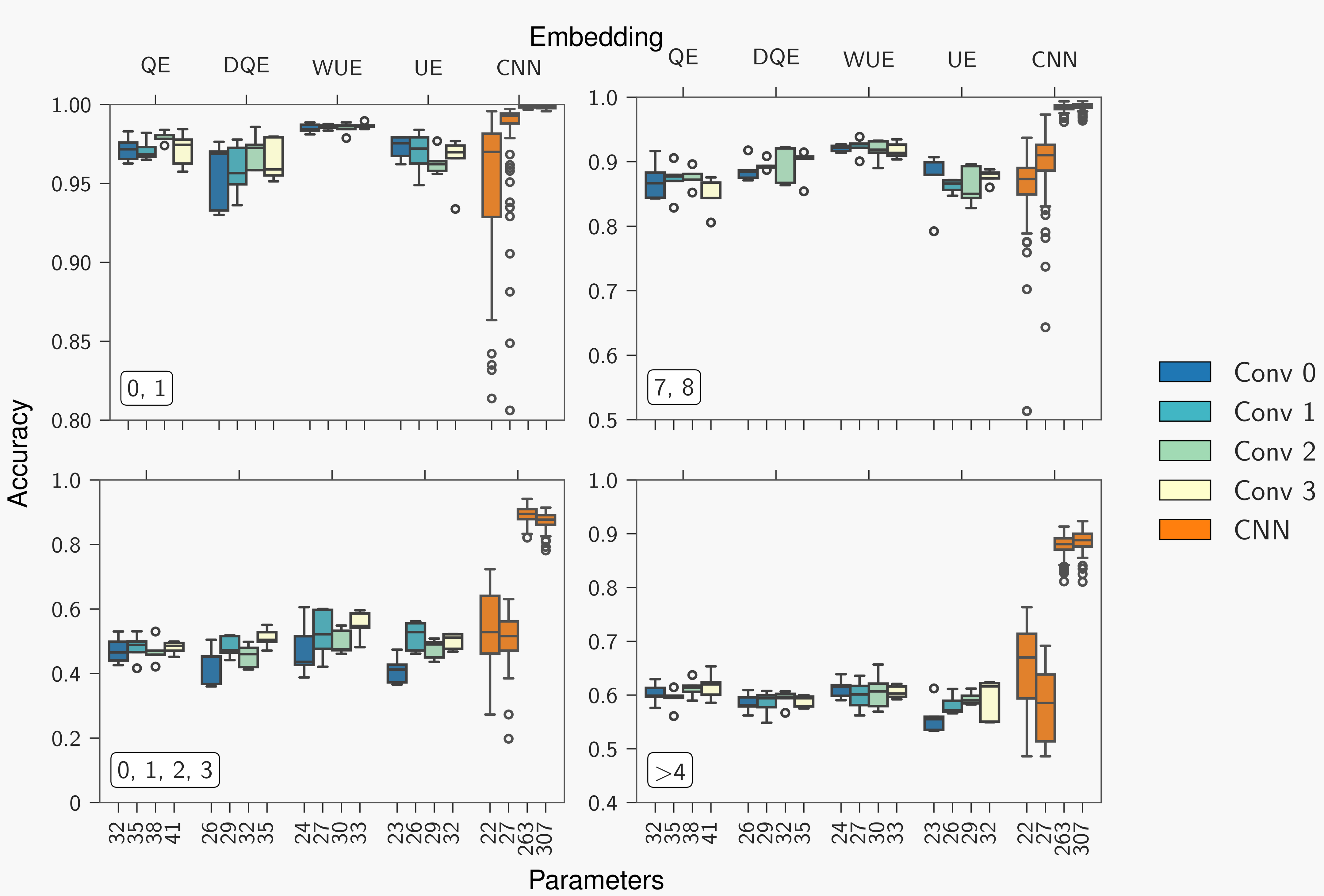
CNN baseline

To ensure a fair comparison, we optimize the classical CNN baseline using Bayesian optimization [4, 5] over 50,000 sampled architectures (100-run averaged performance). The objective encourages high accuracy while penalizing overly large models:

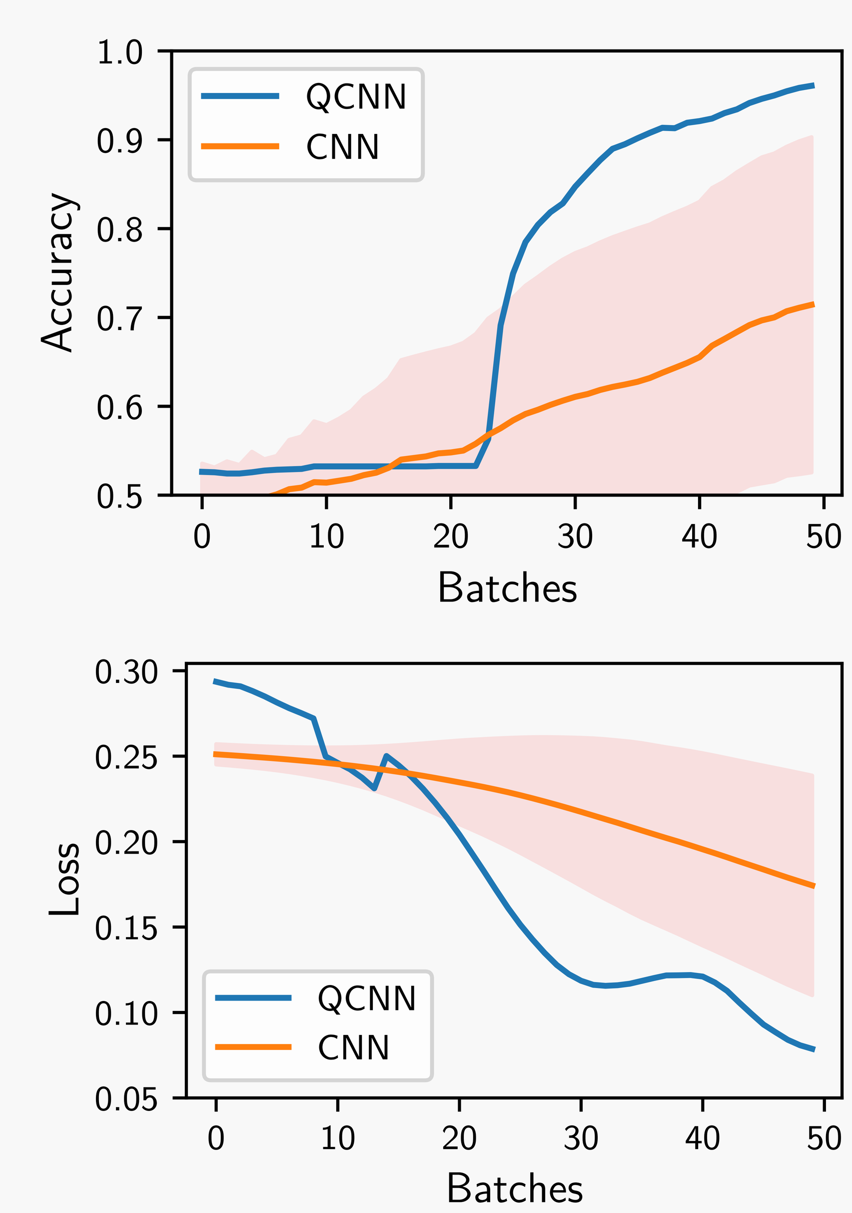
$$\mathcal{L}_{CNN} = \begin{cases} 1.9 - \text{acc}, & \text{if acc} \leq 0.9 \\ \frac{\text{params}}{100{,}000}, & \text{otherwise} \end{cases}. \tag{4}$$

Subset MNIST 49 qubit classification

Simulation



IBM Heron r2 (0 vs. 1)



Conclusion & limitations

- QCNN accuracy improves with more qubits
- QCNNs converge faster than classical models
- Trainable encoding sequences hint at efficient quantum feature maps
- Tasks were simple (subsets MNIST)
- QCNNs are classically simulatable if not carefully designed [6]

References

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