



Jye Sawtell-Rickson

m1361019@cgu.edu.tw

Chang Gung University

April 30, 2026

QML for Image Classification

*Quantum Machine Learning for Image Classification,
Terra Quantum*

- **Paper's Goal:** Evaluate hybrid QNNs for image classification.
- **Quantum Machine Learning (QML):** Potential to enhance machine learning.

Quantum machine learning for image classification

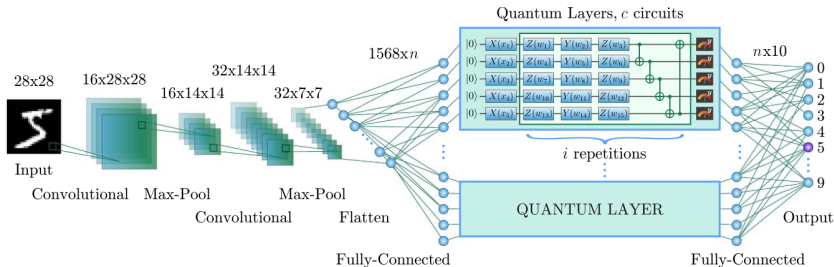
Arsenii Senokosov, Alexandr Sedykh, Asel Sagingalieva, Basil Kyriacou, and Alexey Melnikov*
Terra Quantum AG, Kornhausstrasse 25, 9000 St. Gallen, Switzerland

Image classification, a pivotal task in multiple industries, faces computational challenges due to the burgeoning volume of visual data. This research addresses these challenges by introducing two quantum machine learning models that leverage the principles of quantum mechanics for effective computations. Our first model, a hybrid quantum neural network with parallel quantum circuits, enables the execution of computations even in the noisy intermediate-scale quantum era, where circuits with a large number of qubits are currently infeasible. This model demonstrated a record-breaking classification accuracy of 99.21% on the full MNIST dataset, surpassing the performance of known quantum-classical models, while having eight times fewer parameters than its classical counterpart. Also, the results of testing this hybrid model on a Medical MNIST (classification accuracy over 90%)

- **Classical Methods:** Convolutional Neural Networks (CNNs).
 - **Convolutional layers:** Feature extraction and classification.
 - **Limitations:** Computational cost, large data requirements.
- **Quantum Computing Concepts:**
 - Qubits: Superposition, entanglement.
 - Quantum gates and circuits.
- **Quantum Neural Networks (QNNs):** Quantum principles in neural networks.

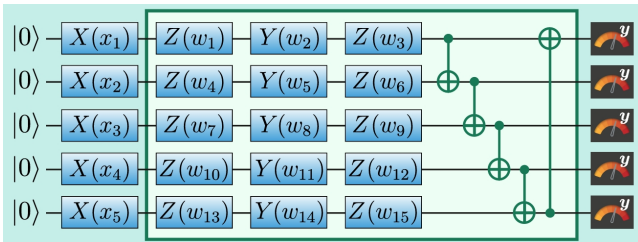
- **Hybrid Architectures:** Focus of the paper.
 - **HQNN-Parallel:** Parallel quantum circuits after classical layers.
 - **HQNN-Quanv:** Quanevolutional layers for quantum feature extraction
- **Quantum optimisation:** Standard loss, but calculate gradients with the parameter shift rule (c.f. finite difference approximation).
- **Classical Components:** Classical neural network parts.

- Parallel quantum circuits after classical layers.
- Analogous to classical fully connected layers
- c circuits with i repetitions (ci blocks), best architecture found to be $i=3$ with 5 qubit layers.

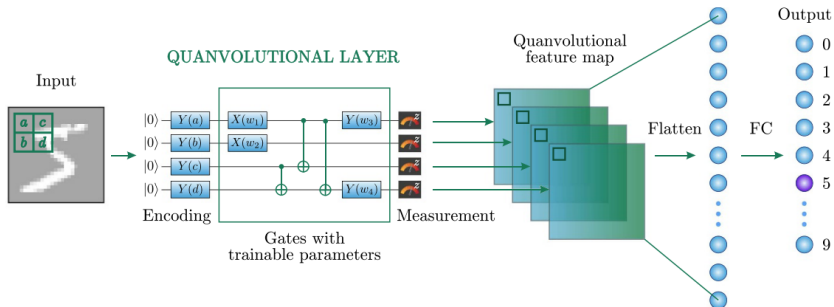


Parameterised Quantum Circuit

- Similar to a regular neural network.
- Inputs: n features, divided into c parts of length q ($n = cq$)
- Three parts
 - **Embedding:** c.f. tokens
 - **Angle-embedding method:** rotate each qubit in ground state around X-axis (RX) proportional to values in the input vector.
 - **Variational Gates:** rotations based on trainable parameters plus CNOT (entanglement).
 - **Measurement:** c.f. map back to tokens (Pauli basis).

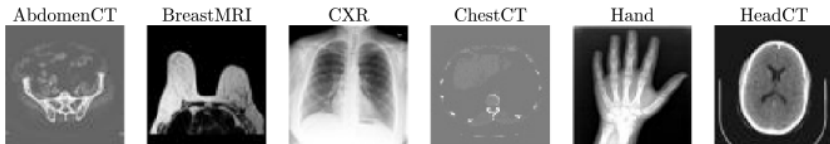


- A quantum take on convolutional layers.
- Apply to $2 \times 2 \times 1$ kernel, outputs for channels.
- Similar to PQC: embedding, variational gates, quantum measurement.



Datasets and Experimental Setup

- **Datasets:** MNIST, CIFAR-10, MedicalMNIST.
- **Experimental Setup:** Quantum simulators (not real!).
- **Evaluation Metrics:** Accuracy, loss.

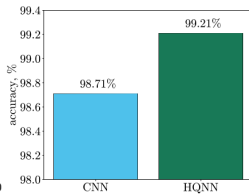
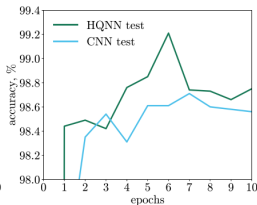
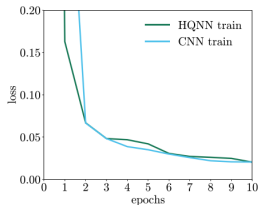


➤ HQNN-Parallel:

- Accuracy on full MNIST: 99.21%.
- Outperforms classical model with fewer parameters.
- Generalizes to MedicalMNIST and CIFAR-10.

➤ HQNN-Quanv:

- Matches classical counterpart performance.
- Outperforms classical model with equal weights.
- The HQNN-Quanv achieved an accuracy of $67\pm 1\%$ on the test data, outperforming the CNN1 with an accuracy of $53\pm 2\%$ and matching CNN4 with an accuracy of $66\pm 2\%$.



- Potential of QML for image classification.
- To obtain a practical advantage with the fewer number of weights, more efficient quantum computers or simulators of quantum computers are required.
- Future Research: Exploring different architectures, scalability, noise resilience.



Questions?