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Resource-Efficient Variational Quantum Classifier

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We introduce the unambiguous quantum classifier based on Hamming distance measurements combined with classical post-processing. The proposed approach improves classification performance through a more effective use of ansatz expressivity, while requiring significantly fewer circuit evaluations. Moreover, the method demonstrates enhanced robustness to noise, which is crucial for near-term quantum devices. We evaluate the proposed method on a breast cancer classification dataset. The unambiguous classifier achieves an average accuracy of 90%, corresponding to an improvement of 6.9 percentage points over the baseline, while requiring eight times fewer circuit executions per prediction. In the presence of noise, the improvement is reduced to approximately 3.1 percentage points, with the same reduction in execution cost. We substantiate our experimental results with theoretical evidence supporting the practical performance of the approach.

Background and Motivation

The Variational Quantum Classifier (VQC) is a hybrid quantum–classical model. In this approach, a quantum circuit is employed, consisting of three main components: first, classical data are encoded into a quantum state using a ***feature map***. The quantum state is processed by a parameterized ***ansatz***. This is followed by the ***measurement*** of the quantum state. Classical postprocessing of outcomes is needed to obtain predicted label. The quantum circuit is executed repeatedly, while the ansatz parameters are iteratively optimized using classical optimization algorithms.

While VQCs are promising candidates for the practical application of QML on current near-term quantum devices, they face a significant efficiency bottleneck.

- **Standard many-shot models**: Require thousands shots per prediction, leading to substantial computational overhead.
- **Novel single-shot models**: Require only one circuit execution per prediction, improving efficiency but making training challenging due to inherent measurement uncertainty. [1]

The unambiguous approach

To address the trade-off between many-shot and single-shot models, we propose the unambiguous model. Its key contribution is a specialized post-processing strategy that utilizes information from all qubits while discarding ambiguous measurement outcomes. A measurement outcome is deemed valid only if the absolute sum of measured eigenvalues satisfies a threshold defined relative to the number of qubits. This mechanism enhances the separation between quantum states while requiring significantly fewer circuit executions. Rejected invalid outcomes form a barrier between classes, and the model exhibits theoretically supported quadratic error suppression.

Quantum circuit architecture

The proposed unambiguous model consists of a quantum circuit comprising three components:

1. **Feature Map**: ZZ-entangling map U_{FM}
2. **Parametrized Ansatz**: l layered 2-local ansatz U_A with data re-uploading technique [2]
3. **Measurement**: All qubits measured in the Pauli-Z basis

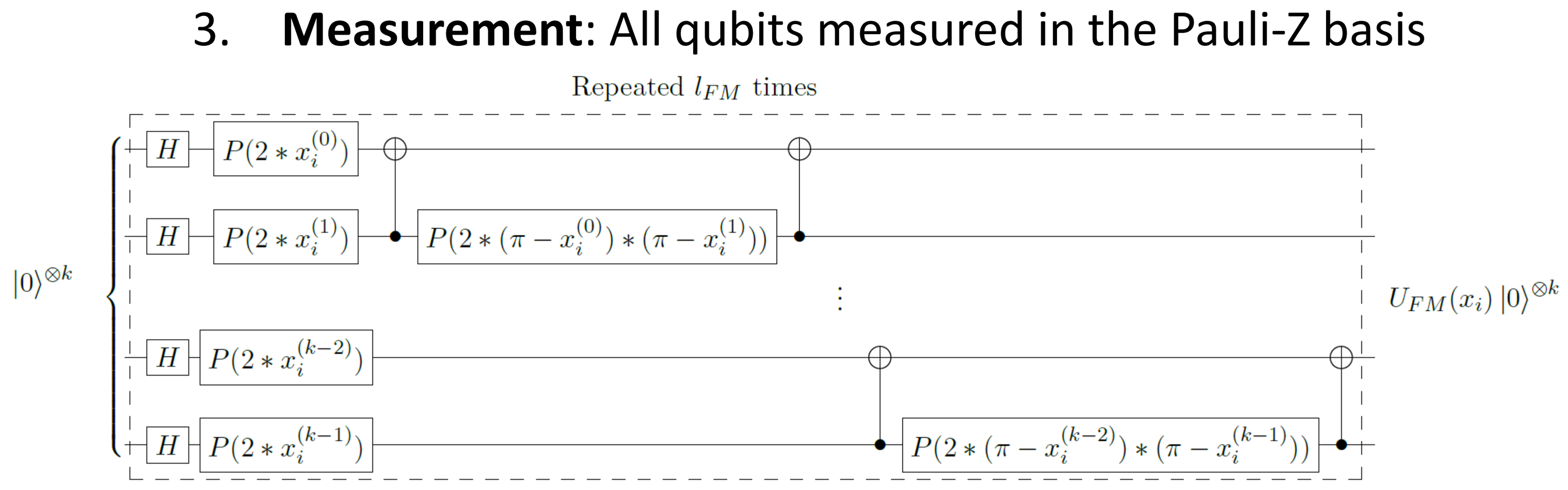

Figure 1: ZZ-entangling feature map $U_{FM}(x_i)$ encoding data point x_i of k data features into a quantum state. After initializing each qubit in an equal superposition state, we apply single-qubit phase rotations $P(\varphi)$, followed by two-qubit entangling gates.

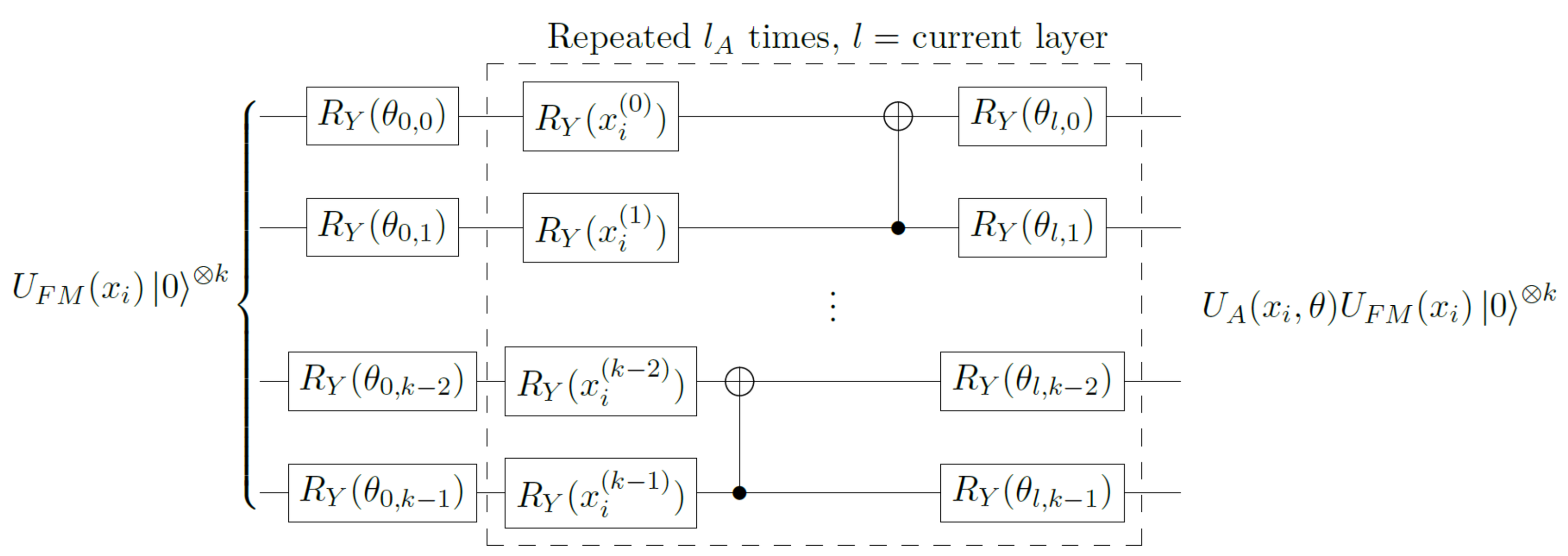

Figure 2: Parametrized layered ansatz $U_A(x_i,\theta)$ using data re-uploading technique [2] with trainable parameters $\theta_{l,j}$ for layer l on j-th qubit.

Experimental results

Unambiguous model (M3) was evaluated using a Breast Cancer dataset [3] and was compared against two many-shot models (M1, M2):

Metric	Many-shot M1	Many-shot M2	Unambiguous M3
Peak Avg. Accuracy	75.16%	83.93%	**90.0%**
Accuracy gain vs M1	-	+8.77%	**+14.84%**
Circuit Executions	8x shots	8x shots	**1x shots**

In noisy simulations, the improvement relative to M1 remains positive at approximately 3.3%, while maintaining the same reduction in computational cost. However, the overall performance of all models decreases significantly under noise.

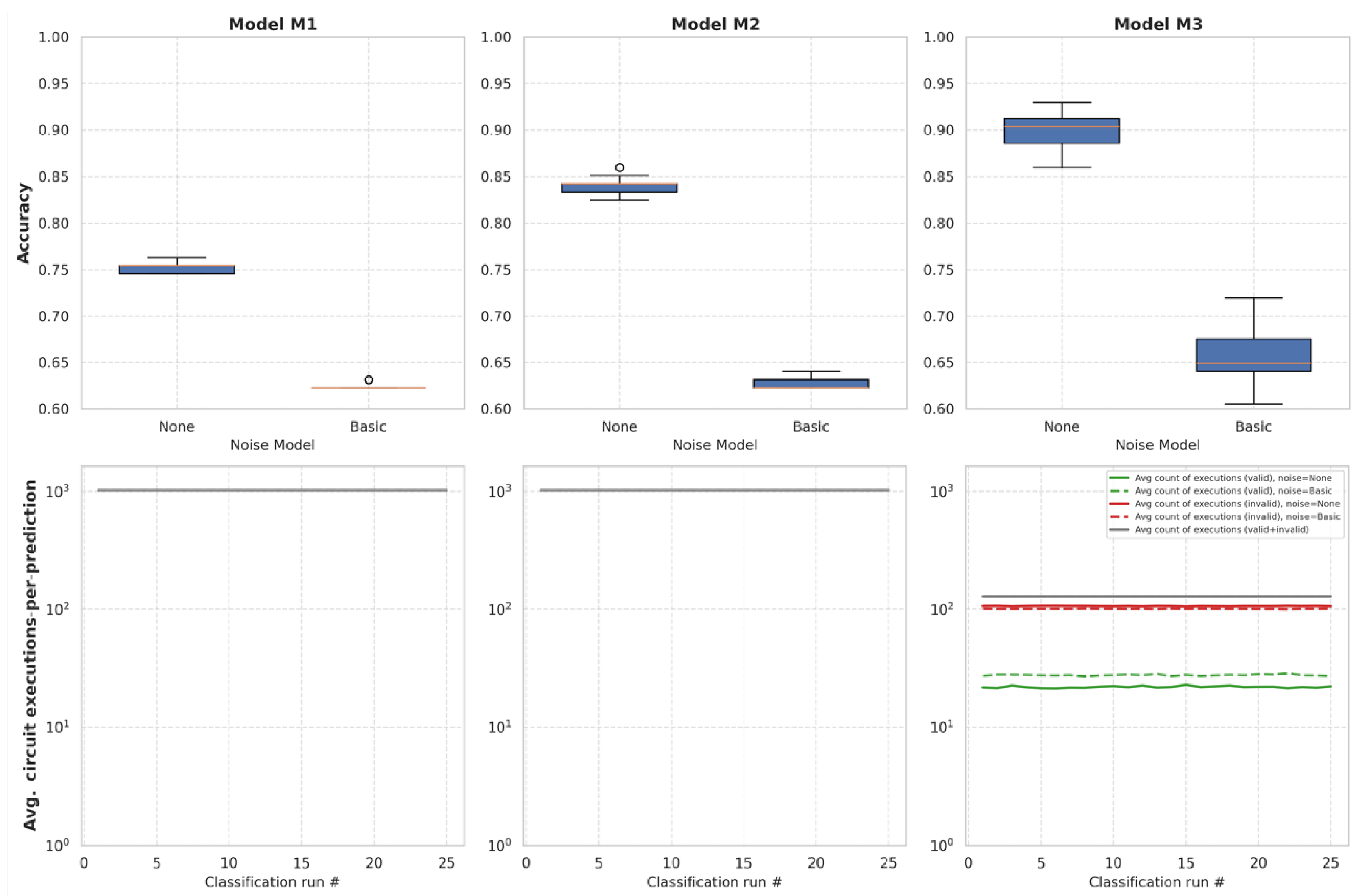

Figure 3: Comparison of classification performance (first row subfigures; linear y-axis) and the number of circuit executions per prediction (second row subfigures; logarithmic y-axis) across 25 classification runs for each model, using a circuit with 3 qubits and 2 ansatz layers. The unambiguous model is denoted as M3, while M1 and M2 represent many-shot models.

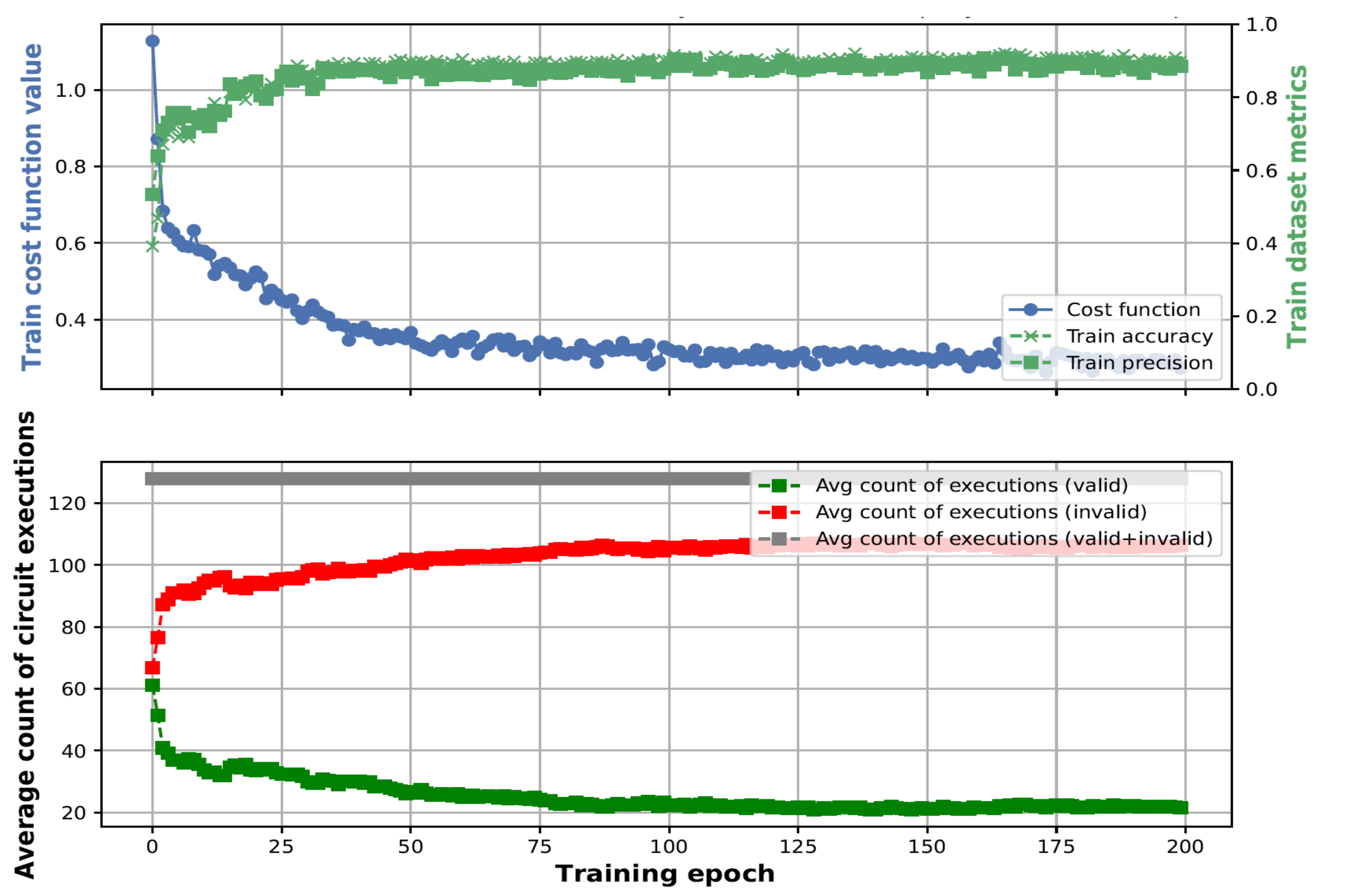

Figure 4: Training history and average counts of valid and invalid shots per prediction per training epoch for the unambiguous model (3 qubits, 2 ansatz layers, up to 128 shots).

References

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- [3] Dataset breast cancer. https://archive.ics.uci.edu/dataset/17/breast+cancer+wisconsin+diagnostic. Accessed on 2026-03-06

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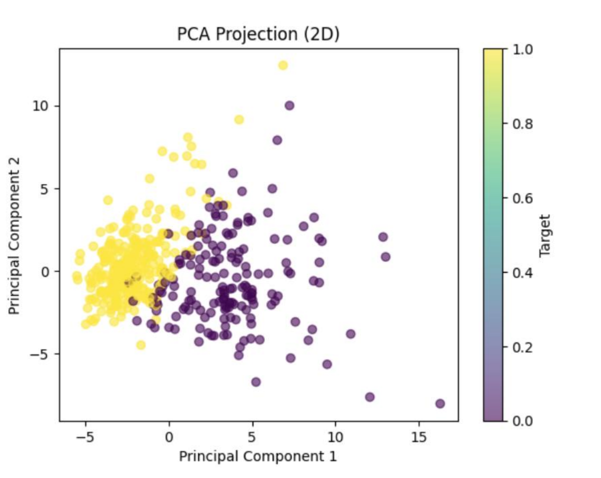

Figure 5: Distribution of input data in the first two principal components.

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