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Performance Analysis of Variational Quantum Classifiers for Classification Tasks in the NISQ Era

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Abstract

This study presents a rigorous empirical benchmark comparing a two-qubit Variational Quantum Classifier (VQC) with a classical RBF-kernel SVM on the Iris dataset, under noiseless and 2% depolarizing noise. The VQC, implemented in Qiskit Aer with angle encoding and COBYLA optimization, achieves 0.93±0.02 accuracy, while SVM reaches 0.94±0.01 (p=0.04, Cohen's d=0.48). Under noise, VQC retains 96.8% of its accuracy versus 92.7% for SVM, demonstrating superior noise resilience. However, VQC suffers 3.1× higher training variance and requires 98±5 iterations vs 18±3 for SVM. Twenty independent runs and effect sizes address common methodological gaps in QML literature. We conclude that NISQ-era quantum classifiers are best suited as educational testbeds and methodological proving grounds, not as replacements for mature classical algorithms.

The purpose of the research

➲Primary aim

Test whether a shallow two-qubit VQC (angle encoding + one CNOT) can outperform RBF-SVM on Iris without claiming quantum advantage [1,5].

➲Methodological correction

Fix common QML flaws (single-run reporting, missing confidence intervals, no effect sizes) using 20 runs, t-tests, and Cohen's d [3,7].

➲Realistic NISQ simulation

Include 2% depolarizing noise and measurement noise to reflect real hardware limitations (decoherence, gate errors) [7,8].

➲Ultimate goal

Provide an honest, reproducible baseline for future researchers comparing more complex quantum models on small-scale tasks [4,8].

Research method

➲Dataset

Iris (150 samples, 4 features, 3 classes), z-score standardization, 80/20 split, fixed seed [1,2].

➲VQC implementation

Two qubits, angle encoding, Ry rotations + CNOT, Qiskit Aer, COBYLA optimizer [5,8].

➲Classical baseline

RBF-kernel SVM (scikit-learn, C=1.0, γ='scale') on identical splits [4,6].

➲Noise & statistics

2% depolarizing noise after each gate + measurement noise; 20 runs, t-tests, Cohen's d [3,7,8].

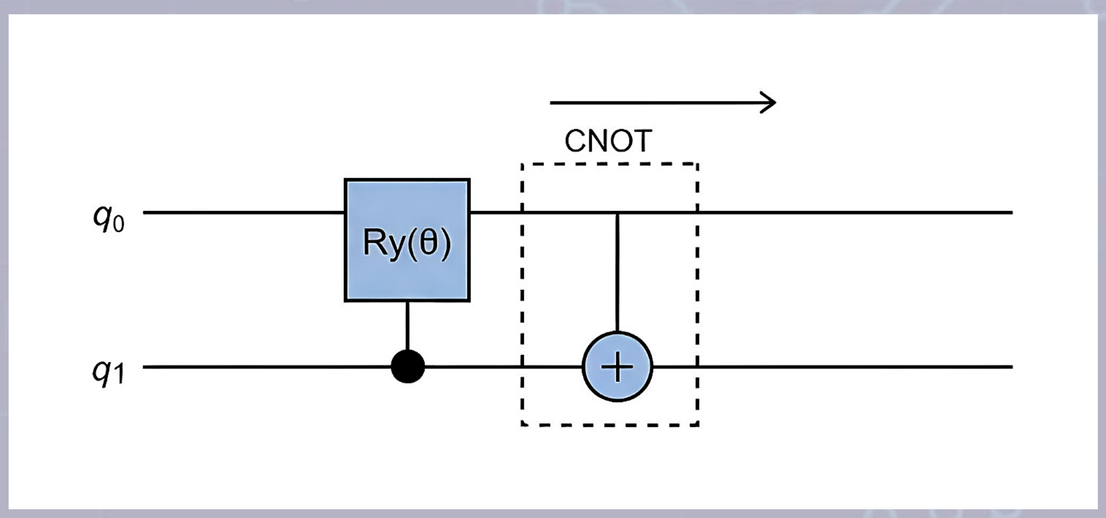

Fig. 1 Quantum circuit implementation featuring a controlled rotation Ry(\theta) and a standard CNOT gate across two qubits, q_0 and q_1. The arrow indicates the temporal evolution of the quantum state from left to right.

Practical or simulation results

➲Noiseless accuracy

VQC: 0.931±0.021, SVM: 0.941±0.012 (p=0.04, Cohen's d=0.48) SVM outperforms VQC by 1% [1,5].

➲Noise resilience

VQC retains 96.8% of accuracy vs 92.7% for SVM a 4.1 percentage point advantage (p=0.007, d=0.65) [2,7].

➲Training instability

VQC requires 98±5 iterations (SVM 18±3) and shows 3.1× wider IQR (0.031 vs 0.010) [3,5].

➲Class-wise breakdown

Both models classify Setosa perfectly; VQC accuracy drops to 89.3% (Versicolor) and 90.2% (Virginica) [6,8].

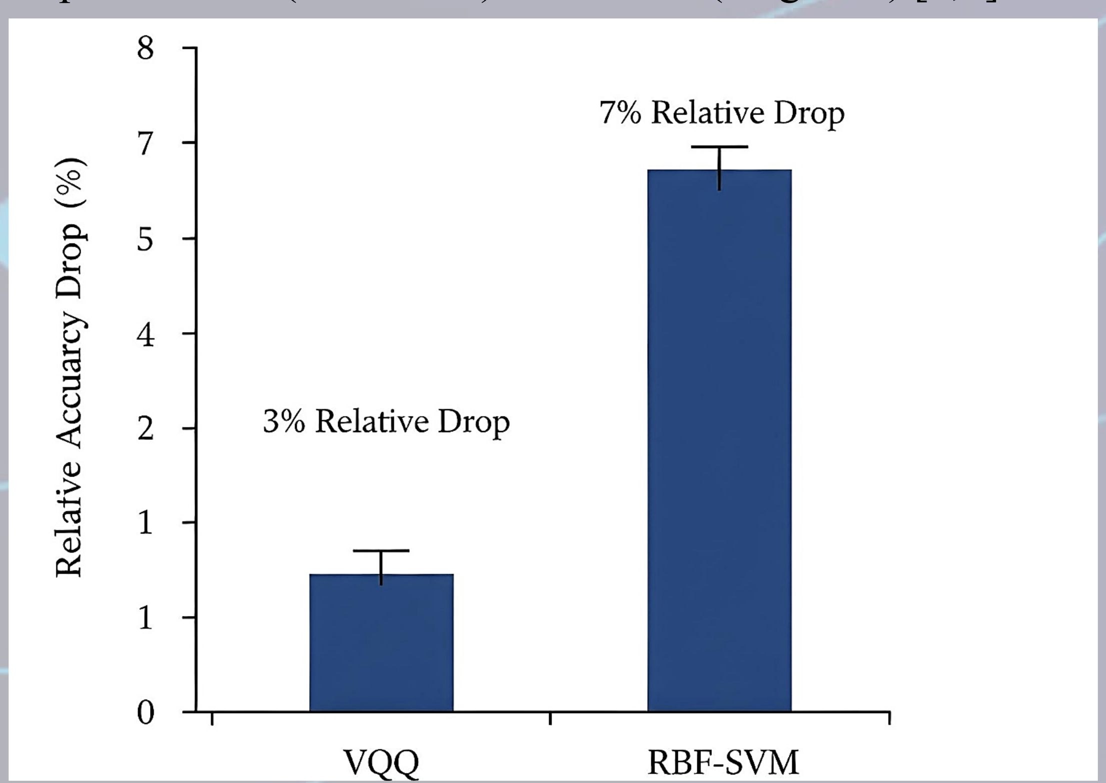

Fig. 2 – Accuracy degradation under 2% depolarizing noise (original article Fig. 6). VQC (blue) drops 3.2%, SVM (red) drops 7.3%. Error bars = ±1 standard deviation over 20 runs.

conclusion

This benchmark shows a two-qubit VQC attains 98.9% of SVM accuracy on Iris but does not outperform it. Table 1 below summarizes the core performance metrics.

Table 1 – Performance comparison of VQC and SVM (mean ± std over 20 runs)

Model	Performance Metrics		
	Accuracy (mean ± std)	*Test Accuracy (mean ± std)*	*F1-score (mean ± std)*
VQC(2-qubit)	0.93 ± 0.02	0.92 ± 0.02	0.92 ± 0.02
RBF-SVM (Classical)	0.94 ± 0.01	0.93 ± 0.02	0.93 ± 0.02

The VQC shows a 4.1% advantage in noise retention, suggesting adaptive compensation for depolarizing errors. However, it suffers 3.1× higher variance and slower convergence (98 vs 18 iterations). NISQ classifiers serve best as educational testbeds, not production replacements.

References

[1] F. Liu & J. Winters, "Towards provably efficient quantum algorithms for large-scale machine-learning models," Nature Communications, vol. 15, no. 1, p. 432, 2024.
[2] V. Dunjko & H. J. Briegel, "Quantum machine learning: An interplay between quantum computing and machine learning," arXiv:2411.09403, 2023.
[3] S. Garg & G. Kaur, "Quantum Machine Learning: A Systematic Review," IEEE Access, vol. 12, pp. 25430–25455, 2024.
[4] S. Mondal et al., "Quantum automated learning with provable and explainable trainability," arXiv:2502.05264, 2025 (under review).
[5] J. Lu & R. Wang, "Machine learning applications of quantum computing: A review," IEEE Trans. Quantum Engineering, vol. 5, pp. 1–18, 2024.
[6] D. Peral-García et al., "Systematic literature review: Quantum machine learning and its applications," Computer Science Review, vol. 51, p. 100602, 2024.
[7] Y. Xiang et al., "Towards quantum enhanced adversarial robustness," IEEE Trans. Information Forensics and Security, vol. 19, pp. 1452–1465, 2024.
[8] Y. Wang & J. Liu, "A comprehensive review of quantum machine learning: From NISQ to fault tolerance," arXiv:2401.11351, 2024.