Evaluating the Computational Efficiency of Hybrid Quantum Neural Networks

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1 Thesis Statement

As deep learning models grow increasingly complex, Hybrid Quantum Neural Networks (HQNNs) have emerged as a potential solution, combining quantum variational circuits with classical architectures to improve feature extraction, reduce parameter overhead, and enhance computational efficiency. However, their true computational efficiency remains an open question—*do HQNNs provide meaningful speedups, or do quantum-classical interactions introduce new bottlenecks?*

This study critically evaluates HQNN efficiency by benchmarking training time, floating-point operations (FLOPs), parameter efficiency, and scalability. Theoretical analysis will be supplemented with empirical evaluation using real datasets, measuring HQNN performance against classical deep learning models on quantum simulators such as IBM's Qiskit and PennyLane.

While many studies focus on theoretical projections of HQNN performance, this research expands on prior experimental benchmarks by providing an in-depth analysis of execution time, model convergence, and quantum-classical communication latency, offering a practical evaluation of HQNN feasibility. The results will contribute to the broader discourse on quantum machine learning scalability, outlining key areas for optimization and future research.