Hybrid Quantum Neural Networks in Practice: Evaluating Algorithms, Architecture, and Efficiency

Andrew Nerud

April 1, 2025

1 Thesis Statement

As deep learning models scale in complexity, the design of computationally efficient hybrid software architectures has become increasingly important. This project explores Hybrid Quantum Neural Networks (HQNNs), which integrate variational quantum circuits (VQCs) with classical architectures to enhance feature extraction, reduce parameter overhead, and improve computational performance. A key focus lies in the software and algorithmic design of VQCs—parameterized quantum layers trained via classical optimization—highlighting the engineering challenges of quantum-classical integration, including latency, data measurement, and communication bottlenecks.

To evaluate the feasibility of HQNNs, this study benchmarks hybrid models against classical neural networks using metrics such as parameter count, FLOPs, and convergence speed. The work includes a prototype HQNN pipeline implemented in a simulated quantum environment, providing empirical data on runtime, training stability, and system-level bottlenecks. Unlike prior work that emphasizes theoretical promise, this project offers a computer science-centered evaluation of HQNN viability. The findings contribute a reproducible benchmarking framework and outline future directions for software-driven quantum machine learning systems.