Quantum Machine Learning Frameworks for Improved SiD Calorimetry and Higgs Boson Analysis

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Quantum neural networks (QNNs) provide efficient data analysis through large feature Hilbert spaces and could solve classically-intractable particle physics problems. However, current research on QNN applications at future Higgs factories is limited. The performance of several essential QNN frameworks at particle physics tasks has also not been evaluated. This research examined the usability of deep and convolutional QNNs in calorimetry and event tagging at the SiD detector for the International Linear Collider (ILC). QNNs with different input sizes, circuit depths, and connectivity patterns were trained to correct electron energy measurements and identify Higgs to two taus events to determine optimal QNN designs for current and future quantum computers. Quantum and statistical noise was applied to assess robustness and current implementability. Optimal QNNs were compared with similarly-trained classical NNs. Both energy correction and event selection tasks were readily solved by QNNs. Eight-qubit QNNs with ~150 trainable variables and moderate circuit depth (~3 hidden layers) performed optimally regardless of connectivity, allowing for versatile implementation. Deep QNNs performed better than deep convolutional QNNs for few qubits but were less scalable. Low-connectivity, short-depth QNNs helped mitigate low-level quantum noise, improving performance under realistic conditions. All QNNs trained quickly, and data compression minimally impacted performance. The results indicate that low-connectivity deep QNNs provide flexible, noise-mitigating frameworks for solving diverse particle physics problems at the ILC on current and future quantum computers. These results can guide future QNN research as quantum technologies and ILC data analysis continue to grow.