Quantum Convolutional Neural Networks for Jet Images Classification

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Abstract

Recently, interest in quantum computing (QC) has significantly increased, driven by its potential advantages over classical techniques. Quantum machine learning (QML) exemplifies QC applications, where the task involves calculating a loss function with trainable parameters optimized classically. However, determining the type of data that can be efficiently leveraged in QML to surpass classical machine learning remains an open question. Additionally, there is no established systematic approach to constructing QML models tailored for specific problems. We focus on addressing these issues within the realm of experimental high-energy physics (HEP), particularly in classifying QCD jet images for top quark jet tagging. Our goal is to identify a suitable architecture for this task, quantify its accuracy and scaling, and compare its performance with classical machine learning methods. While classical convolutional neural networks (CNNs) have been effective for top-quark tagging, they often fall short in accuracy when dealing with highly energetic jet images, such as those encountered in supersymmetric models. This project aims to construct a quantum convolutional neural network (QCNN) and compare its performance with a CNN. We utilized publicly available JetNet library datasets, preprocessing the data to form images and applying principal component analysis (PCA) to reduce dimensionality. This reduction enables the use of a simple quantum circuit where each qubit takes a single pixel value from the image as an input. The quantum model was implemented on a PennyLane simulator, while the classical counterpart was built using the TensorFlow framework. Given that we are working with a classical dataset, incorporating an appropriate encoding in our quantum circuit model is essential. We tested four encoding methods: angle encoding, a variational quantum circuit (VQC)-like encoding, a two-layer VQC-like encoding, and Classically Hard Embedding (CHE). We compared various setups for the QCNN, varying the convolutional circuit, type of encoding, loss function, and batch sizes. For every quantum setup, we designed a similar setup to the corresponding classical model for a fair comparison. Our findings indicate that most QCNN setups performed better than their CNN counterparts, particularly in the low number of parameters regime. Angle encoding and the VQC-like encoding with one layer yielded the best accuracy results. This suggests that quantum models, especially with appropriate encodings, hold promise for enhancing performance in HEP tasks like top quark jet tagging.