Quantum Transfer Learning with Adversarial Robustness for Classification of High-Resolution Image Datasets

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The integration of quantum computing and machine learning is an emerging area of research and development in the field of quantum technologies. However, the application of quantum machine learning to large-scale high-resolution image datasets is not yet possible due to the limited number of qubits and relatively high level of noise in the current generation of quantum devices. Moreover, dealing with high-resolution images on quantum computers requires a large number of qubits [1, 2] which leads to inefficient training. In this work, we address these challenges by proposing a quantum transfer learning (QTL) approach that integrates quantum variational circuits with a classical machine learning network pre-trained on a large, and diverse ImageNet [3] dataset. By transferring the learned knowledge from the pre-trained classical convolutional neural networks, which possess a comprehensive understanding of the target domain, to the small-scale quantum neural network, remarkable classification accuracy and significant speedup are achieved for the proposed QTL method. This hybrid model enables the extraction of meaningful features from raw image data, bridging the gap between classical and quantum paradigms. Through a systematic set of simulations over a variety of image datasets such as Ants & Bees [4], CIFAR-10 [5], and Road Sign Detection [6], we demonstrate the superior performance of our QTL approach over classical approach and quantum machine learning without involving transfer learning. Furthermore, we evaluate the adversarial robustness of QTL architecture with and without adversarial training [7], confirming that our QTL method is adversarially robust against data manipulation attacks and outperforms classical methods.

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