FISQ: A Few-Shot, Interpretable, and Self-Supervised Quantum Machine Learning Approach to Automated Real-Time Prediction Over Multiple Domains

Agarwal, Shobhit (School: Rick Reedy High School)

To ascertain complex relationships between inputs and outputs and function at high accuracies, Machine Learning algorithms require vast amounts of high-quality data. In many instances, the quantity of data needed is unobtainable and even if present, the resulting model is unable to effectively capture granularities between multimodal data, adapt its learnings to other problem domains, or explain its predictions. Therefore, a novel end-to-end self-supervised quantum machine learning approach to provide interpretable predictions on fewer data is proposed. In a procedural flow, data can be sourced from virtually any data modality including images, text, video, and signal-based data. Images are encoded using a Quantum Convolutional Neural Network, text-based data is encoded using a Bidirectional Encoder Representation model; videos and signals are encoded manually. Each of the encoded representations are passed into a contrastive self-supervised embedder, which learns relationships between the data simultaneously and encapsulates its learnings in a feature vector output. Using the vector as input, a Quantum Neural Network outputs a final prediction for any specified task. The proposed approach was tested on 27 benchmark datasets and the downstream task of identifying diagnoses, prognoses, and treatments for thousands of diseases. On benchmark datasets, the model outperformed all previous state-of-the-art approaches in visual classification when only trained on 2 data samples, achieving 99.3% and 96.32% accuracy on the STL10 and ImageNet datasets respectively. For the task of disease prediction, the model predicted diagnoses with a 98.53% accuracy, achieved a Concordance-Index of 0.98 in predicting prognoses, and a 99.32% accuracy for treatment prediction.