Leveraging Quantum Contrastive Learning and Federated Averaging for Robust Out-of-Distribution Generalization

Abstract

In this work, we propose a hybrid quantum-classical framework that combines Quantum Contrastive Learning (QCL) with Vertical Federated Learning (VFL) to address significant challenges in distributed machine learning, such as data scarcity, adversarial robustness, and scalability. Our framework leverages quantum-enhanced representations using parameterized quantum circuits, a Quantum Autoencoder, and a Projection Head to produce secure and robust embeddings optimized for contrastive learning.

The integration of Enhanced Federated Averaging ensures dynamic aggregation of contributions from both quantum and classical clients, prioritizing nodes with richer feature representations to maintain fairness and robustness. We provide theoretical guarantees for the convergence of the framework under standard assumptions, achieving a convergence rate of $\mathcal{O}(1/t)$. This framework sets a new benchmark for scalable and secure federated learning systems, with potential applications in privacy-sensitive domains by addressing critical issues related to heterogeneity and adversarial vulnerabilities.