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

Abstract

In the era of advanced data privacy regulations and stringent ethical guidelines, the acquisition of extensive labeled datasets for training robust deep learning models has become increasingly challenging, and processing large datasets is difficult due to high computational demands. However, a model running on quantum hardware with limited resources and small, simple datasets can be a game changer. This quantum module can be easily incorporated as an effective feature extractor, capable of running on minimal data while generalizing to larger datasets. This capability helps powerful classical models work more effectively. This is particularly pertinent in various domains, including medical imaging, where data scarcity is a critical concern, and sensor networks, where the demand for large data is significant and challenging to process.

Traditional machine learning models heavily depend on extensive datasets for effective generalization. However, they encounter difficulties when confronted with limited labeled data. Compounding this challenge is the current stagnation of classical computer performance, diverging from Moore's Law, coupled with the increasing data hunger of deep learning algorithms. Additionally, existing quantum machine learning (QML) models demand a large number of qubits, which is impractical with today's quantum hardware limitations. To address these challenges, we propose a novel approach that leverages the principles of quantum contrastive learning combined with a modified Federated Averaging (FedAvg) algorithm. Our research focuses on developing a machine learning model capable of generalizing to out-of-distribution data using simple and minimal datasets while maintaining accuracy comparable to powerful classical models. Therefore, the primary research question addressed in this study is: “How can we effectively generalize a machine learning model for out-of-distribution data using simple and minimal classical data, enhanced by quantum contrastive learning and a modified FedAvg algorithm?”

Classical approaches to address data scarcity include representation learning techniques, such as Supervised Contrastive Learning (SCL), and semi-supervised learning methods. These techniques aim to improve feature learning from limited data but are still bound by the need for a substantial amount of labeled data to achieve high accuracy. In the realm of quantum machine learning, methods like Quantum Convolutional Neural Networks (QCNNs) and Quantum Autoencoders (QAEs) have shown promise but are constrained by the need for a large number of qubits and are not yet fully optimized for multi-class classification problems. Our proposed system integrates quantum computing principles with classical learning methods to overcome these limitations. The model incorporates a Quantum Data Augmentation Module, which enhances the diversity of the training data through quantum operations, and a Quantum Encoder that extracts meaningful representations from the augmented data. The Quantum Projection Head then projects the encoded data into a space suitable for contrastive learning, where the contrastive loss (L) is defined as:

$$[L = -\sum_{i \in I} \log \frac{\exp(z_i \cdot z_{j(i)} / \tau)}{\sum_{a \in A(i)} \exp(z_i \cdot z_a / \tau)}]$$

To address the qubit demand issue, we incorporate Quantum Autoencoders (QAEs) to efficiently compress and encode the data, reducing the number of qubits required. The Qubit Efficiency is a significant factor, as the QAEs help manage the large data requirements by compressing the input state $(|\psi\rangle)$ into a lower-dimensional latent space. Additionally, a modified Federated Averaging (FedAvg) algorithm is employed to aggregate the model updates from different nodes, ensuring effective learning from limited data across distributed systems.

$$[Fe\bar{d}Avg = \sum_{k=1}^{K} \frac{N_k}{N} w_k]$$

The uniqueness of the proposed system lies in several key innovations. First, it utilizes the power of quantum contrastive learning to enhance feature learning with minimal data, leveraging quantum computing to achieve superior performance. Second, it addresses the high qubit demand of current quantum machine learning (QML) models by incorporating Quantum Autoencoders (QAEs) for efficient data compression. Third, the system employs a modified Federated Averaging (FedAvg) algorithm, which ensures robust model aggregation and learning in a federated setup, even with limited data availability. Finally, the model is specifically designed to generalize well to unseen, out-of-distribution data, marking a significant advancement over traditional models.