Analysis of Photonic Transfer learning for MNIST Classification

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1 Introduction

The MNIST dataset has long served as a benchmark for machine learning models. While classical models achieve near-perfect accuracy, quantum machine learning (QML) approaches aim to explore novel computational advantages. This study investigates the performance of a photonic quantum embeddings (boson sampler) implemented using the Perceval framework in combination with transfer learning (TL) from pre-trained classical models.

2 Experimental Setup

Several TL strategies were tested using ResNet18 and a vanilla CNN:

1. **ResNet18 (ImageNet) → MNIST (Reproduction of Paper Maria Schuld et al. 2019)**
2. **ResNet18 (ImageNet) → MNIST (10-Class TL)**
3. **ResNet18 (ImageNet) → MNIST (2-Class TL, Distant Classes)**
4. **ResNet18 (ImageNet) → MNIST (2-Class TL, Similar Classes)**
5. **ResNet18 (Full MNIST) → MNIST (2-Class TL)**
6. **ResNet18 (CIFAR-10) → MNIST**
7. **Vanilla CNN (2Conv + fc & 1Conv + fc) [CIFAR-10] → MNIST**

Despite varying the dataset size and source of pre-training, none of these strategies led to meaningful improvements beyond random guessing.

3 Results and Discussion

The observed performance degradation suggests a fundamental limitation in the interaction between classical feature extraction and photonic quantum kernels. Key hypotheses include:
Quantum Kernel Limitations: Photonic quantum models rely on linear optical transformations and boson sampling, which may not be optimal for classical feature space embeddings. Unlike gate-based quantum models, which allow flexible unitary transformations, photonic models use Gaussian and non-Gaussian states that might restrict the nonlinearity needed for effective classification.
Feature Representation Mismatch: The embeddings produced by pre-trained classical networks may not align well with the Hilbert space used by photonic quantum kernels, limiting the ability of the quantum model to extract meaningful information.

4 Encoding Conjecture

The encoding circuit applies beamsplitters (BS) and phase shifters (PS) to encode classical features into the quantum photonic system. However, the current encoding scheme may not optimally preserve class-separability in the feature space due to:
Linear Interference Structure: The BS arrangement primarily mixes modes linearly, limiting expressivity. The transformation might not effectively embed high-dimensional nonlinear features. **Mode Redundancy and Loss of Information:** Since features are encoded via phase shifts at specific modes, there might be redundancy in encoding, leading to loss of discriminative information after multiple interferometric layers.

5 Conclusion

This study demonstrates that photonic quantum models struggle to benefit from classical feature extraction in MNIST classification tasks. The limitations of photonic quantum architectures, particularly in expressivity and feature representation alignment, likely contribute to this issue. Future work should explore alternative hybridization techniques and investigate encoding schemes that better match photonic quantum computing capabilities. For example, instead of applying BS in a fixed pattern, design encoding adaptively based on data structure.

6 Appendix

Some of the architecture we used for the transfer learning model. Note for all the classical models, with or without the transfer learning implementation, the accuracy normally reached at least up to 87%. While for the quantum TL models, the accuracy is either around 12% for the 10-class dataset or 53% for a binary classification dataset.

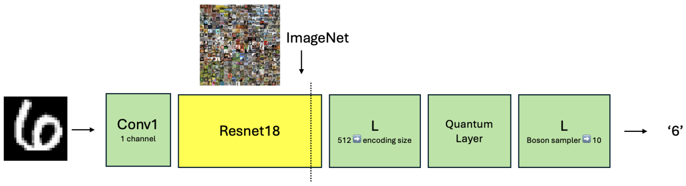

Figure 1: TL model with pretrained ImageNet dataset.

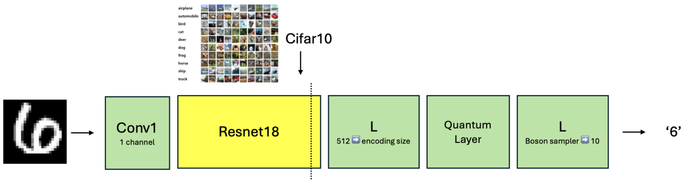

Figure 2: TL model with pretrained Cifar-10 dataset.

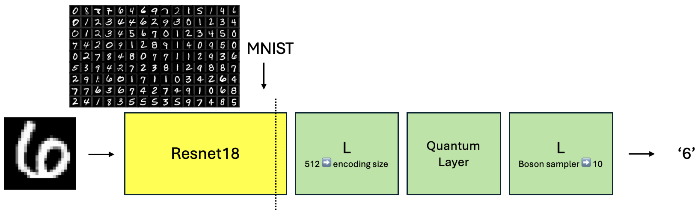

Figure 3: TL model with pretrained MNIST dataset.

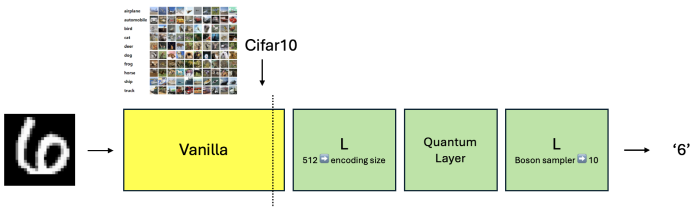

Figure 4: Vanilla TL model with pretrained Cifar-10 dataset.

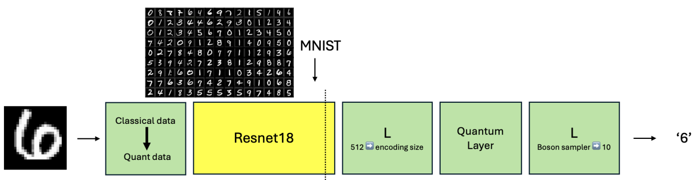

Figure 5: MNIST data classification with quantum data input.