Hybrid Quantum–Classical MNIST Classification: Phase 2 Progress Report

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Abstract

We present a hybrid MNIST classification pipeline that integrates classical downsampling with a quantum embedding layer based on photonic boson sampling (using Perceval). Our model maps 28×28 images to a 126-dimensional feature vector (matching a 12-mode interferometer) and uses variational quantum circuits to generate embedding features. We validate our proposal with larger-scale simulations and GPU runs while addressing QaaS challenges.

Methodology

Classical Downsampling: MNIST images are flattened and reduced via PCA (or bilinear interpolation) to 126 dimensions—the number of phase parameters required for a 12-mode interferometer.

Quantum Embedding: A `BosonSampler` (with variational parameters) constructs interferometer circuits (triangular, PDF-inspired, or convolutional) that encode the downsampled features as phase shifts.

Results

Our quantum-enhanced pipeline achieves a final validation loss of 0.1239 and a validation accuracy of 96.50%. The detailed classification report indicates robust performance (per-class F1-scores range from 0.942 to 0.984). For comparison, our classical PCA-based baseline attained around 93.8% accuracy. These results demonstrate that the quantum embedding provides a competitive representation.

Summary Metrics:

- **Validation Accuracy:** 96.50%
- **Final Loss:** 0.1239
- **Per-class F1:** 0.9636 (macro average)

Phase 2 Update

Validated proposals via larger-scale simulations and GPU-enabled emulation. Although remote execution using `sim:sampling:2l4` is slower than local SLOS, it offers more realistic performance.

Conclusion

Our hybrid pipeline combines classical feature reduction with a variational quantum embedding to achieve high MNIST classification accuracy. The strong performance (96.50% validation accuracy) and detailed evaluation metrics set a solid benchmark for further scaling in Phase 2. Future work will concentrate on optimizing sample counts, exploring alternative downsampling methods, and expanding circuit complexity to harness quantum advantages.