GLASE: Gradient-free Light-based Adaptive Surrogate Ensemble for MNIST Classification

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I. Introduction

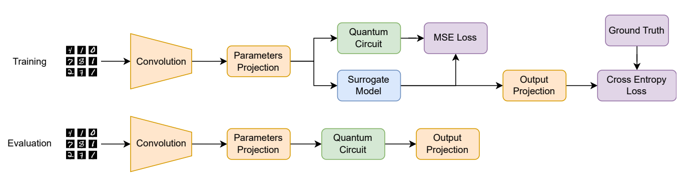
In QNN MNIST [1] classification, many photonic quantum neural network (QNN) approaches rely on either quantum embedding of the raw image or calculating gradients using the parameter-shift rule (in discrete systems), but these methods often incur training instabilities or the barren plateaus [2] phenomenon. We propose a surrogate-based strategy that circumvents all of these issues, achieves robust performance and exhibits a better result over classical baselines.

II. Method

CNN Feature Extraction. We first employ a lightweight Convolutional Neural Network (CNN), to compress each 28×28 image $\mathbf{x}$ into a 256-dimensional feature vector $\mathbf{z} = f_\theta(\mathbf{x})$.

Photonic Quantum Encoding. We map the classical feature vector $\mathbf{z}$ to phase parameters $\boldsymbol{\phi} = \Pi(\mathbf{z})$ in a boson sampling interferometer with N photons distributed over M modes via the Perceval [3] platform. The interferometer produces multi-photon detection probabilities $\mathbf{p}(\boldsymbol{\phi}) = (p_1, p_2, \ldots, p_M)$, which we then computes the *expectation value of the number of photons in each mode*: $\langle \hat{n}_i \rangle = \sum_{\mathbf{n}} n_i \mathbf{p}(\mathbf{n})$, where $\mathbf{n} = (n_1, n_2, \ldots, n_m)$ represents a specific photon number state across all modes.

Surrogate-Assisted Training. Since photonic optical gates are non-differentiable, our completely novel method leverages a surrogate-based approach to calculate the gradients for modules before the QNN (thus "gradient-free"). We introduce a surrogate neural network $g_\alpha(\boldsymbol{\phi})$ that approximates the photon number expectation value $\mathbf{p}(\boldsymbol{\phi})$. The surrogate is updated periodically by minimizing $\|\mathbf{p}(\boldsymbol{\phi}) - g_\alpha(\boldsymbol{\phi})\|^2$, and is then used during backpropagation. The overall loss function for QNN during training is given by $\mathcal{L} = \ell_{\mathrm{CE}}(\hat{y}, y) + \lambda \|\mathbf{p}(\boldsymbol{\phi}) - g_\alpha(\boldsymbol{\phi})\|^2$, where ℓ_{CE} is the cross-entropy loss for classification and λ controls the regularization of the surrogate network (we chose $\lambda = 0.5$). The overall architecture during training and evaluation is:



III. Experiments

Setup. We train on the provided subset of MNIST for 50 epochs, $N = 3$ photons and $M = 20$ qumodes.

Simulation Results. The table below summarizes the training outcomes based on the "CliffordClifford2017" simulator backend. For reference, we compare Our two QNN models' (with 380k and 517k parameters each) performance against a mini ResNet [4] baseline, which is known to achieve state-of-the-art accuracy on MNIST with relatively few parameters. Our QNN models achieved higher validation accuracies with fewer parameters than the classical baseline.

Model	Params	Train Acc	Val Acc	Val Loss
Mini ResNet (baseline)	716k	100.00%	98.17%	0.1405
QNN (380k)	380k	100.00%	**99.00%**	**0.1044**
QNN (517k)	517k	100.00%	**99.33%**	**0.0961**

Real QPU Validation. Since the available Ascella QPU only supports 16 qumodes, we trained a smaller version of the QNN with 16 qumodes (the accuracies are lower than the 24-qumodes QNN) and tested on 4 backends with 1000 shots on 150 images. The result is less accurate on the real QPU test due to the presence of noise and hardware error, but since there are currently no software-side noise-mitigation strategies, the overall results are still very promising:

Backend	Val Acc (%)	Val Loss
CliffordClifford2017	91.00	0.3780
sim:sampling:h100	94.17	0.3125
qpu:ascella	76.79	0.8070

IV. Conclusion

GLASE demonstrates a promising gradient-free approach by integrating photonic quantum encoding with surrogate neural networks, leading to barren plateaus-free[1] training. GLASE outperforms the mini ResNet baseline in both accuracy and parameter efficiency. Preliminary tests on a real 16-qumode QPU yield promising results, motivating future experiments on the new 24-qumode QPU. Additionally, GLASE can in principle scale to larger photonic circuits with improved results due to more gate parameters and a large state size. In the future, GLASE can even become a general training framework for photonic QNNs that allows backpropagating through the photonic circuit during training without differentiating it.

References

[1] Y. LeCun *et al.*, "Gradient-based learning applied to document recognition," *Proc. IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

[2] J. R. McClean *et al.*, "Barren plateaus in quantum neural network training landscapes," *Nat. Commun.*, vol. 9, no. 1, pp. 4812, 2018.

[3] N. Heurtel *et al.*, "Perceval: A software platform for discrete variable photonic quantum computing," *Quantum*, vol. 7, pp. 931, 2023.

[4] K. He *et al.*, "Deep Residual Learning for Image Recognition," *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[1] Barren Plateaus in photonic QNNs has not been formally studied, but difficulties with optimization and local minima in some of the photonic algorithms have been noticed.