Quantum-Guided Autoencoding for Enhanced Neutral Atom Reservoir Computing in Medical Image Classification

*Note: Sub-titles are not captured for https://ieeexplore.ieee.org and should not be used

Nuno Batista
Department of Informatics Engineering
Faculty of Sciences and Technology, University of Coimbra
Coimbra, Portugal
nunomarquesbatista@gmail.com

2nd Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

***Abstract*—We introduce a quantum-classical hybrid architecture for medical image classification based on neutral atom quantum processors. This approach is designed to address the challenges of medical imaging, with a particular focus on tasks such as polyp detection and classification. By integrating an autoencoder guided by a quantum reservoir, the pipeline learns compact and discriminative representations of image data that are also well-suited for quantum reservoir computing. To overcome the non-differentiability of quantum measurements, we circumvent this 'gradient barrier' by incorporating a differentiable surrogate model that simulates the behaviour of the quantum layer, enabling end-to-end backpropagation. The guided training process jointly optimizes for both image reconstruction and classification accuracy, ensuring that the latent representations are both meaningful and effective for quantum processing. In our implementation, image data is encoded as atom detuning parameters in a Rydberg Hamiltonian, and quantum embeddings are obtained through expectation values. These embeddings are then passed to a linear classifier, enabling faster training and inference compared to deep classical networks. Our experiments show that this method outperforms traditional approaches using PCA or unguided autoencoders. We also conduct ablation studies to evaluate the impact of quantum and training parameters, demonstrating the robustness and flexibility of the proposed pipeline for real-world medical imaging applications, even in the NISQ era.**

***Index Terms*—Reservoir Computing, Quantum-Guided Autoencoding, Neutral Atoms, Autoencoder, Dimensionality Reduction, Quantum Machine Learning, Hybrid Quantum-Classical Algorithms, Medical Image Classification, Quantum Surrogate Models**

I. Introduction

A. Background and Motivation

Advances in medical imaging have significantly improved disease diagnosis and treatment planning. For conditions like colorectal cancer, early detection of polyps through colonoscopy image analysis is critical for reducing mortality [1]. Deep learning techniques, especially autoencoders, are widely used to extract compressed, informative features from high-dimensional images for classification and segmentation tasks [2]. However, classical neural networks may struggle to capture intricate correlations in complex medical data.

Quantum computing offers novel opportunities for machine learning, particularly through quantum reservoir computing (QRC), where a physical quantum system processes classical inputs into high-dimensional nonlinear embeddings [3], [4]. Recent works show that analog quantum systems, such as neutral-atom platforms, can serve as untrained reservoirs with rich dynamics for temporal and pattern recognition tasks [5], [6]. In hybrid approaches, a classical encoder compresses image data, and a quantum reservoir expands the encoded features into a higher-dimensional space, potentially boosting classification performance.

A major challenge in such hybrid quantum-classical models is the non-differentiability of quantum measurements, which obstructs gradient-based optimization. Additionally, tuning quantum parameters can suffer from barren plateaus, where gradients vanish in high-dimensional Hilbert spaces [7]. To address this, we introduce a classical neural surrogate that emulates the quantum reservoir's input-output behavior. This surrogate enables end-to-end training via backpropagation, while the quantum system remains fixed and non-trainable.

B. Contributions of This Work

We propose a quantum-guided autoencoder architecture that integrates a classical image encoder with a neutral-atom quantum reservoir.

A classical surrogate network of the reservoir itself enables gradient flow through the whole model during training.

The model is evaluated and compared to classical benchmarks on three different datasets:

1) A synthetic dataset of polyp images, generated to simulate realistic medical imaging scenarios.
2) Real image patches extracted from the CVC-ClinicDB dataset, a well-known benchmark for polyp detection.

3) A reduced version of the MNIST dataset, containing only the digits 0 and 1, suitable for binary classification tasks.

Our results illustrate the viability of QRC for real-world medical tasks and offer a scalable path to hybrid quantum-classical learning, even in the noisy intermediate-scale quantum (NISQ) era.

II. Background

A. Principles of Reservoir Computing

Reservoir computing is a computational framework derived from recurrent neural networks (RNNs). It involves a fixed, high-dimensional dynamical system—the reservoir—that projects input data into a rich feature space. Only the output layer is trained, simplifying the learning process and reducing computational overhead. This approach is particularly effective for time-series prediction and pattern recognition tasks.

Mathematically, let $u(t) \in \mathbb{R}^m$ be the input at time t, $x(t) \in \mathbb{R}^n$ the reservoir state, and $y(t) \in \mathbb{R}^k$ the output. The reservoir dynamics and output are given by:

$$x(t) = f(W_{in}u(t) + W_{res}x(t-1)) \quad (1)$$

$$y(t) = W_{out}x(t) \quad (2)$$

Where f is a nonlinear activation function, W_{in} and W_{res} are fixed input and reservoir weight matrices, and W_{out} is the trained output weight matrix.

B. Quantum Reservoir Computing

Quantum Reservoir Computing (QRC) extends the reservoir computing paradigm into the quantum domain. By leveraging quantum systems' inherent properties, such as superposition and entanglement, QRC aims to enhance computational capabilities. Implementations using quantum oscillators have shown promise in solving complex learning tasks, offering advantages over classical counterparts. Notably, large-scale experiments utilizing neutral-atom analog quantum computers have demonstrated the scalability and effectiveness of QRC in various machine learning applications [6]

In QRC, classical input data $u(t)$ is encoded into quantum states $|\psi(t)\rangle$, which evolve under a fixed Hamiltonian H:

$$|\psi(t+1)\rangle = U|\psi(t)\rangle = e^{-iH\Delta t}|\psi(t)\rangle, \quad (3)$$

where U is the unitary evolution operator. Measurements of observables $\hat{O}$ yield outputs:

$$y(t) = \langle\psi(t)|\hat{O}|\psi(t)\rangle. \quad (4)$$

The output weights are trained classically, while the quantum reservoir remains fixed.

C. Quantum Computing with Neutral Atoms

D. Dimensionality Reduction for Image Data

1) Principal Component Analysis:

2) Autoencoder Architectures:

E. Quantum-Guided Autoencoding

III. Methodology

A. System Architecture Overview

B. Quantum Guided Autoencoder

1) Loss Function Design:

2) Balancing Reconstruction and Classification:

C. The Gradient Barrier Problem

D. Surrogate Modeling for Quantum Layers

1) Architecture and Training:

2) Gradient Flow Through Surrogate Models:

E. Rydberg Hamiltonian and Quantum Dynamics

F. Data Encoding Schemes

G. Quantum Readout Methods

1) Single-atom Measurements:

2) Two-atom Correlations:

3) Three-atom Correlations:

IV. Experimental Setup

A. Datasets

B. Implementation Details

1) Quantum Simulation Parameters:

2) Classical Network Architectures:

C. Comparison Methods

D. Performance Metrics

E. Parameter Sweep Strategy

V. Results and Discussion

A. Classification Performance Comparison

B. Ablation Studies

1) Impact of Guided Lambda Parameter:

2) Effect of Quantum Update Frequency:

3) Influence of Quantum Parameters:

C. Dimensionality Reduction Comparison

D. Surrogate Model Fidelity Analysis

E. Generalization to Unseen Data

VI. Theoretical Analysis

A. Information Encoding in Quantum Reservoirs

B. Gradient Flow in Quantum-Classical Hybrid Systems

C. Computational Complexity

D. Quantum Resource Requirements

VII. Limitations and Future Work

A. Current Limitations

B. Potential Extensions

C. Hardware Implementation Considerations

VIII. Conclusion

References

[1] A. Esteva, A. Robicquet, B. Ramsundar, V. Kuleshov, M. DePristo, K. Chou, C. Cui, G. Corrado, S. Thrun, and J. Dean, "A guide to deep learning in healthcare," *Nature Medicine*, vol. 25, no. 1, pp. 24–29, Jan. 2019.

[2] Y. Bengio, "Learning Deep Architectures for AI."

[3] G. Tanaka, T. Yamane, J. B. Héroux, R. Nakane, N. Kanazawa, S. Takeda, H. Numata, D. Nakano, and A. Hirose, "Recent advances in physical reservoir computing: A review," *Neural Networks*, vol. 115, pp. 100–123, Jul. 2019.

[4] K. Fujii and K. Nakajima, "Harnessing disordered quantum dynamics for machine learning," *Physical Review Applied*, vol. 8, no. 2, p. 024030, Aug. 2017.

[5] L. Domingo, G. Carlo, and F. Borondo, "Optimal quantum reservoir computing for the NISQ era," May 2022.

[6] M. Kornjavca, H.-Y. Hu, C. Zhao, J. Wurtz, P. Weinberg, M. Hamdan, A. Zhdanov, S. Cantu, H. Zhou, R. A. Bravo, K. Bagnall, J. Basham, J. Campo, A. Choukri, R. DeAngelo, P. Frederick, D. Haines, J. Hammett, N. Hsu, M.-G. Hu, F. Huber, P. N. Jepsen, N. Jia, T. Karolyshyn, M. Kwon, J. Long, J. Lopatin, A. Lukin, T. Macri, O. Markovi'c, L. A. Mart'inez-Mart'inez, X. Meng, E. Ostroumov, D. Paquette, J. M. Robinson, P. S. Rodriguez, A. Singh, N. Sinha, H. Thoreen, N. Wan, D. Waxman-Lenz, T. Wong, K.-H. Wu, P. L. S. Lopes, Y. Boger, N. Gemelke, T. Kitagawa, A. Keesling, X. Gao, A. Bylinskii, S. Yelin, F. Liu, and S.-T. Wang, "Large-scale quantum reservoir learning with an analog quantum computer," Jul. 2024.

[7] J. R. McClean, S. Boixo, V. N. Smelyanskiy, R. Babbush, and H. Neven, "Barren plateaus in quantum neural network training landscapes," *Nature Communications*, vol. 9, no. 1, p. 4812, Nov. 2018.