

# Medical Imaging Classification with Cold-Atom Reservoir Computing using Auto-Encoders and Surrogate-Driven Training

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**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.

A diagram of a typical reservoir computing architecture is shown in ‘Fig.-1’.

### 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

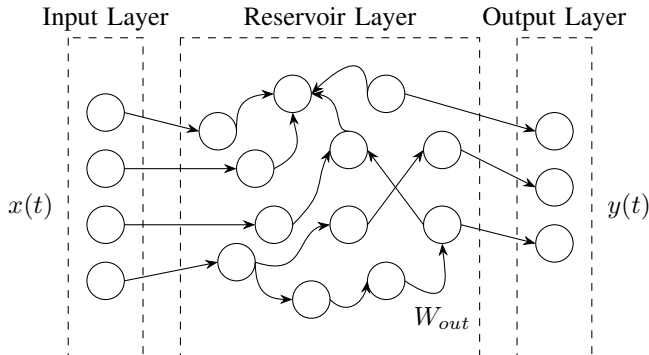


Fig. 1. Reservoir computing architecture showing input nodes, a recurrent reservoir network with internal dynamics, and an output layer.

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. Reservoir Computing with Neutral Atoms

As quantum Reservoir Computing (QRC) leverages the complex dynamics of quantum systems to process information, extending the classical reservoir computing paradigm into the quantum domain. Neutral atom platforms, particularly those utilizing Rydberg states, have emerged as promising candidates for implementing QRC due to their scalability and controllable interactions.

In the work by M. Kornjača et al. [6], a large-scale, gradient-free QRC algorithm was developed and experimentally implemented on a neutral-atom analog quantum computer. This system achieved competitive performance across various machine learning tasks, including classification and time-series prediction, demonstrating effective learning with increasing system sizes up to 108 qubits.

The dynamics of such neutral atom systems can be described by the Rydberg Hamiltonian, which captures the essential physics of laser-driven interactions among atoms in Rydberg states. Following Kornjača et al. [6] The Hamiltonian for a system of neutral-atoms is given by:

$$H(t) = \frac{\Omega(t)}{2} \sum_j (|g_j\rangle \langle r_j| + |r_j\rangle \langle g_j|) + \sum_{j < k} V_{jk} n_j n_k - \sum_j [\Delta_g(t) + \alpha_j \Delta_l(t)] n_j, \quad (5)$$

where  $\Omega(t)$  is the global Rabi drive amplitude between a ground state  $|g_j\rangle$  and a highly-excited Rydberg state  $|r_j\rangle$  of an atom,  $n_j = |r_j\rangle \langle r_j|$ ,  $V_{jk} = C/\|r_j - r_k\|^6$  describes the van der Waals interactions between atoms, and the detuning is split into a global term  $\Delta_g(t)$  and a site-dependent term  $\Delta_l(t)$ , with site modulation  $\alpha_j \in [0, 1]$ .

By initializing the system in a specific state and allowing it to evolve under this Hamiltonian, the resulting quantum state encodes information about the input data. Measurements of observables on this state yield outputs that can be used for tasks such as classification or prediction, with only the final readout layer requiring training.

#### D. Dimensionality Reduction for Image Data

Dimensionality reduction is a crucial preprocessing step in machine learning and data analysis, aiming to reduce the number of input variables in a dataset while preserving as much information as possible. This process enhances computational efficiency, mitigates the curse of dimensionality, and facilitates data visualization.

1) *Principal Component Analysis*: Principal Component Analysis (PCA) [8] is a linear dimensionality reduction technique that transforms a set of correlated variables into a set of uncorrelated variables called principal components. The goal is to capture the maximum variance in the data with the fewest number of components.

PCA is effective for datasets where the principal components align with the directions of maximum variance, but it may not capture complex, nonlinear relationships in the data [9].

2) *Autoencoder Architectures*: Autoencoders are a class of artificial neural networks designed to learn efficient codings of input data in an unsupervised manner. They consist of two main parts: an encoder that compresses the input into a latent-space representation, and a decoder that reconstructs the input from this representation.

Given an input  $x \in \mathbb{R}^d$ , the encoder maps  $x$  to a latent representation  $z \in \mathbb{R}^k$  (where  $k < d$ ):

$$z = f_{\theta}(x) \quad (6)$$

The decoder then reconstructs the input:

$$\hat{x} = g_{\phi}(z) \quad (7)$$

The network is trained to minimize the reconstruction loss:

$$\mathcal{L}(x, \hat{x}) = \|x - \hat{x}\|^2 \quad (8)$$

This typical architecture of an autoencoder is illustrated in ‘Fig.-2’.

Autoencoders can capture complex, nonlinear relationships in the data, making them suitable for tasks like image compression, denoising, and anomaly detection [1], [10].

3) *Quantum-Guided Autoencoding*: Quantum-Guided Autoencoders integrate quantum computing principles into the autoencoder framework to leverage quantum advantages in processing and representing data. These models aim to perform dimensionality reduction and classification within a single architecture, enhancing performance on complex datasets.

In the Quantum-Guided Autoencoder (QGAE) model, a classical encoder first reduced the dimensionality of the input data. The compressed data is then processed by a parametrized quantum circuit, which acts as the decoder and classifier. The quantum circuit transforms the input state  $|\psi_{\text{in}}\rangle$  into an output state  $|\psi_{\text{out}}\rangle$  using a unitary operation

$$|\psi_{\text{out}}\rangle = U(\theta)|\psi_{\text{in}}\rangle \quad (9)$$

Measurements on  $|\psi_{\text{out}}\rangle$  yield the final classification result. The parameters  $\theta$  are optimized to minimize a loss function that combines reconstruction error and classification accuracy.

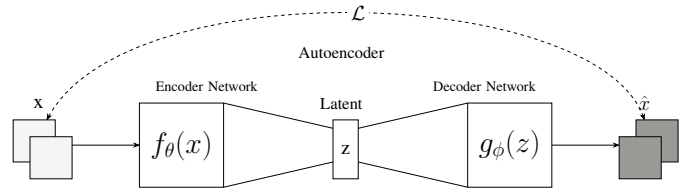


Fig. 2. Autoencoder architecture. The encoder network  $f_{\theta}(x)$  compresses the input  $x$  into a latent representation  $z$ , while the decoder network  $g_{\phi}(z)$  reconstructs the input from the latent representation, producing  $\hat{x}$ . The reconstruction loss  $\mathcal{L}$  measures the difference between the input  $x$  and the reconstructed input  $\hat{x}$ .

This approach has demonstrated improved performance over traditional methods in tasks such as identifying the Higgs boson in particle collision data, showcasing the potential of quantum-guided models in handling high-dimensional, com-

plex datasets [11].

### III. METHODOLOGY

#### A. System Architecture Overview

Our proposed pipeline integrates classical and quantum components to perform dimensionality reduction and classification. A classical autoencoder compresses high-dimensional image data into a lower-dimensional latent space. This compressed representation is encoded into a Rydberg Atom chain, which serves as the input to a quantum reservoir. The reservoir will then produce quantum embeddings by measuring quantum observables, which capture the dynamics of the quantum system in response to the input data.

These quantum embeddings will be used to train a surrogate model that aims to approximate the quantum reservoir's behaviour.

The surrogate model's outputs will then pass through a linear classifier, which is trained to map the approximated quantum embeddings to class labels.

The autoencoder is trained to minimize in interpolation between the data reconstruction's loss function as well as the classification task loss function.

Our approach, allows the model to learn representations that are not only compact and informative for the reconstruction of the input data, but also well-suited for quantum reservoir computing.

When autoencoder model is trained, we can use the trained encoder to compress the train data into the latent space, and then pass the compressed data through the real quantum reservoir. The obtained embeddings are then used to train a linear classifier that maps the quantum embeddings to class labels.

The overall architecture is illustrated in 'Fig.-III-A'.

#### B. Quantum Guided Autoencoder

The Quantum Guided Autoencoder (QGA) combines classical preprocessing with quantum processing to leverage the strengths of both paradigms. The classical encoder reduces the dimensionality of the input data, facilitating efficient quantum processing. The quantum circuit then processes the compressed data, aiming to reconstruct the original input and perform classification simultaneously.

1) *Loss Function Design:* The QGA is trained to minimize a composite loss function that balances reconstruction fidelity and classification accuracy:

$$\mathcal{L} = (1 - \lambda) \cdot \mathcal{L}_R + \lambda \cdot \mathcal{L}_C, \quad (10)$$

where:

- $\mathcal{L}_R = \|x - \hat{x}\|^2$  is the reconstruction loss, measuring the mean squared error between the input  $x$  and its reconstruction  $\hat{x}$ .
- $\mathcal{L}_C = -\sum_i y_i \log(\hat{y}_i)$  is the classification loss, computed as the cross-entropy between the true labels  $y_i$  and the predicted probabilities  $\hat{y}_i$ .
- $0 < \lambda < 1$  is a hyperparameter that controls the trade-off between reconstruction and classification objectives.

#### 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

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- 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:*

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#### 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

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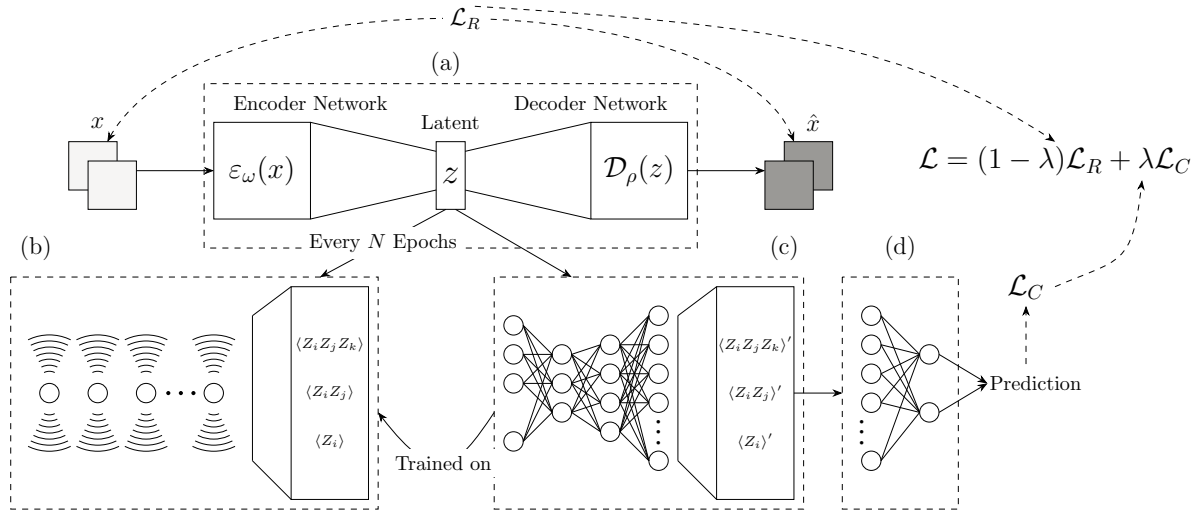


Fig. 3. Overview of the Quantum-Guided Autoencoder Reservoir Computing System.