Quantum Reservoir Learning with Rydberg Lattice

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***Abstract*—In this paper, we study a quantum reservoir learning (QRL) architecture based on a lattice of Rydberg atoms for the classification of handwritten digits from the MNIST dataset. Each image is first reduced to a 10-dimensional representation via principal component analysis (PCA), then encoded into the initial state of a reservoir comprising neutral atoms evolving under a fixed Rydberg Hamiltonian. Classical observables sampled from the reservoir's quantum state furnish high-dimensional feature embeddings, which are subsequently processed by simple linear or nonlinear classifiers. Our empirical evaluation reveals a 36% reduction in mean-squared error relative to PCA-only baselines. By eliminating gradient-based training and leveraging the intrinsic dynamics of the Rydberg system, this scheme not only simplifies implementation but also demonstrates inherent resilience to NISQ era. These results establish Rydberg reservoirs as efficient, high-expressivity feature mappers for scalable, noise-robust quantum learning.**

I. Introduction

Quantum Machine Learning (QML) techniques such as variational quantum circuits (VQCs) and quantum kernels promise expressive representations, yet they remain constrained by barren plateaus, kernel concentration effects, and sensitivity to NISQ-era noise. These issues limit generalization and scalability on near-term devices [1].

Quantum Reservoir Computing (QRC) addresses these limitations by leveraging untrained quantum dynamics governed by a fixed Hamiltonian to produce nonlinear, high-dimensional temporal embeddings. Unlike VQCs, QRC requires no gradient-based optimization, and unlike kernel methods, it captures temporal structure without computing pairwise overlaps, making it more resilient to circuit depth and measurement noise [2], [3].

In this work, we propose a Rydberg atom-based QRC framework for classification. Handwritten digit images are compressed via principal component analysis (PCA) to 10 dimensions, then encoded into the initial quantum state of a Rydberg reservoir. As the system evolves, task-relevant observables are sampled to construct expressive quantum embeddings for downstream classification. This hybrid architecture demonstrates strong performance on MNIST while preserving implementation simplicity and noise robustness, establishing QRC as a scalable alternative for quantum-enhanced learning.

II. Methodology

A. Quantum Reservoir Framework

Quantum Reservoir Learning (QRL) uses the dynamics of a fixed, untrained quantum system to encode classical inputs into expressive temporal embeddings. All trainable parameters are confined to a classical readout layer, avoiding gradient-based optimization in the quantum model.

In our setup, 10-dimensional feature vectors extracted via PCA from MNIST images are encoded into a quantum reservoir composed of N neutral Rydberg atoms. The system evolves under a time-dependent Hamiltonian:

$$H(t) = H_0 + H_{\text{int}} + H_{\text{drive}}(t), \tag{1}$$

where H_0 is the on-site energy, H_{int} encodes van der Waals interactions, and $H_{\text{drive}}(t)$ embeds input data via modulated detunings [3].

B. Rydberg Encoding and Quantum Evolution

We adopt a Constant Detuning (CD) scheme to map features $x = (x_1, \ldots, x_N)$ onto qubit frequencies. The reservoir evolves under:

$$H(t) = \sum_{i=1}^{N} \frac{\Omega}{2}\sigma_i^x - \sum_{i=1}^{N} \Delta_i n_i + \sum_{i<j} V_{ij} n_i n_j, \tag{2}$$

where $n_i = \frac{1}{2}(1 - \sigma_i^z)$ and V_{ij} captures inter-atomic interactions. Detunings Δ_i are linearly scaled:

$$\Delta_i = \Delta_{\min} + \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}(\Delta_{\max} - \Delta_{\min}). \tag{3}$$

The quantum state $|\psi(t)\rangle$ evolves via the Schrödinger equation:

$$\frac{d}{dt}|\psi(t)\rangle = -iH(t)|\psi(t)\rangle, \tag{4}$$

and is numerically integrated over time to capture the system's dynamics and produce time-dependent quantum states [4].

C. Measurement and Embedding Construction

At $M+1$ discrete times t_k over $[t_0, t_K]$, we measure local and pairwise Pauli observables:

$$\mathcal{O} = \{X_i, Y_i, Z_i\} \cup \{P_i P_j \mid P \in \{X, Y, Z\},\, i < j\}. \tag{5}$$

Each time step yields an embedding vector $E^{(k)} \in \mathbb{R}^{3N + \frac{9N(N-1)}{2}}$. The full embedding is:

$$E_{\text{full}} \in \mathbb{R}^{(M+1)\times\left(3N + \frac{9N(N-1)}{2}\right)}. \tag{6}$$

These embeddings serve as input to simple linear or nonlinear classifiers, enabling downstream digit classification without training the quantum model [5].

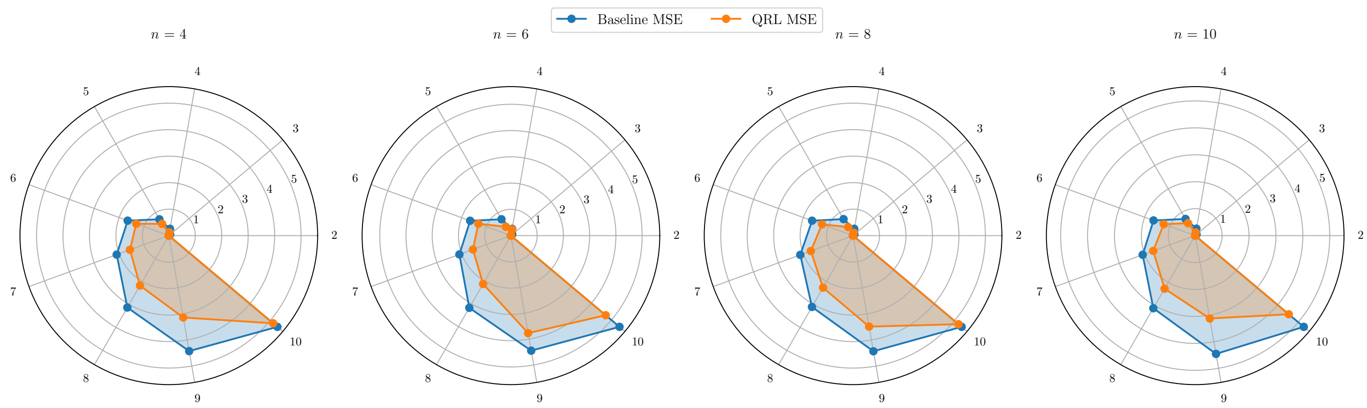

Fig. 1. QRC achieves a 36% reduction in mean squared error over PCA-only baselines, with the best performance observed at $N = 6$ atoms and 6-class digit classification.

III. Simulation and Results

We evaluated the proposed Rydberg-based QRC framework on MNIST digits, each reduced to a 10-dimensional vector via PCA. These vectors are encoded into the initial quantum state of a reservoir comprising $N = 4$ to $N = 10$ Rydberg atoms. The system evolves under a fixed Hamiltonian over a time window of $0\,\mu$s to $3\,\mu$s in $0.5\,\mu$s steps.

At each time step, single- and two-qubit Pauli observables are sampled to construct temporal embeddings that capture the reservoir's evolving quantum correlations. These embeddings are processed by a classical gradient boosting model for downstream digit classification.

At $N = 6$ and six digit classes, the QRC model achieves a 36% reduction in mean squared error relative to PCA-only baselines. These results confirm the framework's effectiveness as a gradient-free, noise-resilient approach for scalable quantum learning with untrained dynamics.

TABLE I
Rydberg Reservoir Parameters

Parameter	Value	Description
d	$10\,\mu$m	Spacing between atoms
N_{sites}	4	Atoms in the chain
Ω	2π	Rabi frequency
t_{start}	$0.0\,\mu$s	Start time for the evolution
t_{end}	$3.0\,\mu$s	End time for the evolution
t_{step}	$0.5\,\mu$s	Time step for the evolution
t_{rate}	1.0	Measurement rate per step
$\boldsymbol{\alpha}$	$\alpha_i \sim \mathcal{U}(0, 1)$	Site-specific modulation
V	Symmetric, $V_{ii} = 0.1$, $V_{ij} \sim \mathcal{U}(0, 1)$	Interaction matrix capturing pairwise interactions.

IV. Conclusion

This work demonstrates the effectiveness of Rydberg-based Quantum Reservoir Computing for scalable and noise-resilient feature embedding in classification tasks. By encoding PCA-reduced inputs into a fixed Rydberg Hamiltonian and sampling quantum observables over time, the proposed framework generates expressive embeddings without circuit training or variational optimization. Applied to MNIST digit classification, our model achieves significant improvement over classical baselines, validating QRC's utility under limited data and hardware constraints. The results underscore the potential of quantum reservoirs as efficient, high-expressivity mappers for near-term quantum learning. Future directions include evaluating QRC on more complex datasets, investigating adaptive encoding strategies, exploring implementation on real quantum hardware, and integrating with variational and privacy-preserving quantum sensing frameworks [6].

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