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

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***Abstract*—This paper introduces a novel quantum-classical hybrid system for medical image classification using neutral atom quantum processors. We present the Quantum Guided Autoencoder with Reservoir Surrogate (QGARS), which addresses the gradient barrier problem in quantum-classical hybrid learning by introducing a differentiable surrogate model that enables end-to-end training. Our approach leverages quantum reservoir computing principles with Rydberg atom arrays while optimizing feature encoding through a specialized autoencoder that jointly minimizes reconstruction error and maximizes quantum classification performance. We evaluate our approach on polyp detection and classification tasks, demonstrating superior performance compared to traditional dimensionality reduction techniques and standard quantum reservoir computing implementations. We further present detailed ablation studies analyzing the impact of various quantum parameters, guided learning coefficients, and surrogate model architectures. Our results suggest that quantum guidance can significantly enhance feature encoding for quantum processing, pointing toward a practical pathway for quantum advantage in medical image analysis.**

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

I. Introduction

A. Background and Motivation

B. Challenges in Quantum-Classical Hybrid Systems

C. Contributions of This Work

II. Background

A. Quantum Computing with Neutral Atoms

B. Principles of Reservoir Computing

C. Quantum Reservoir Computing

D. Dimensionality Reduction for Image Data

1) Principal Component Analysis:

2) Autoencoder Architectures:

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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

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3) Three-atom Correlations:

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2) Classical Network Architectures:

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E. Parameter Sweep Strategy

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B. Ablation Studies

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2) Effect of Quantum Update Frequency:

3) Influence of Quantum Parameters:

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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