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School of Computer Science and Engineering

Department of Computer Science and Engineering

Using AI to Build the Future of Quantum Computing

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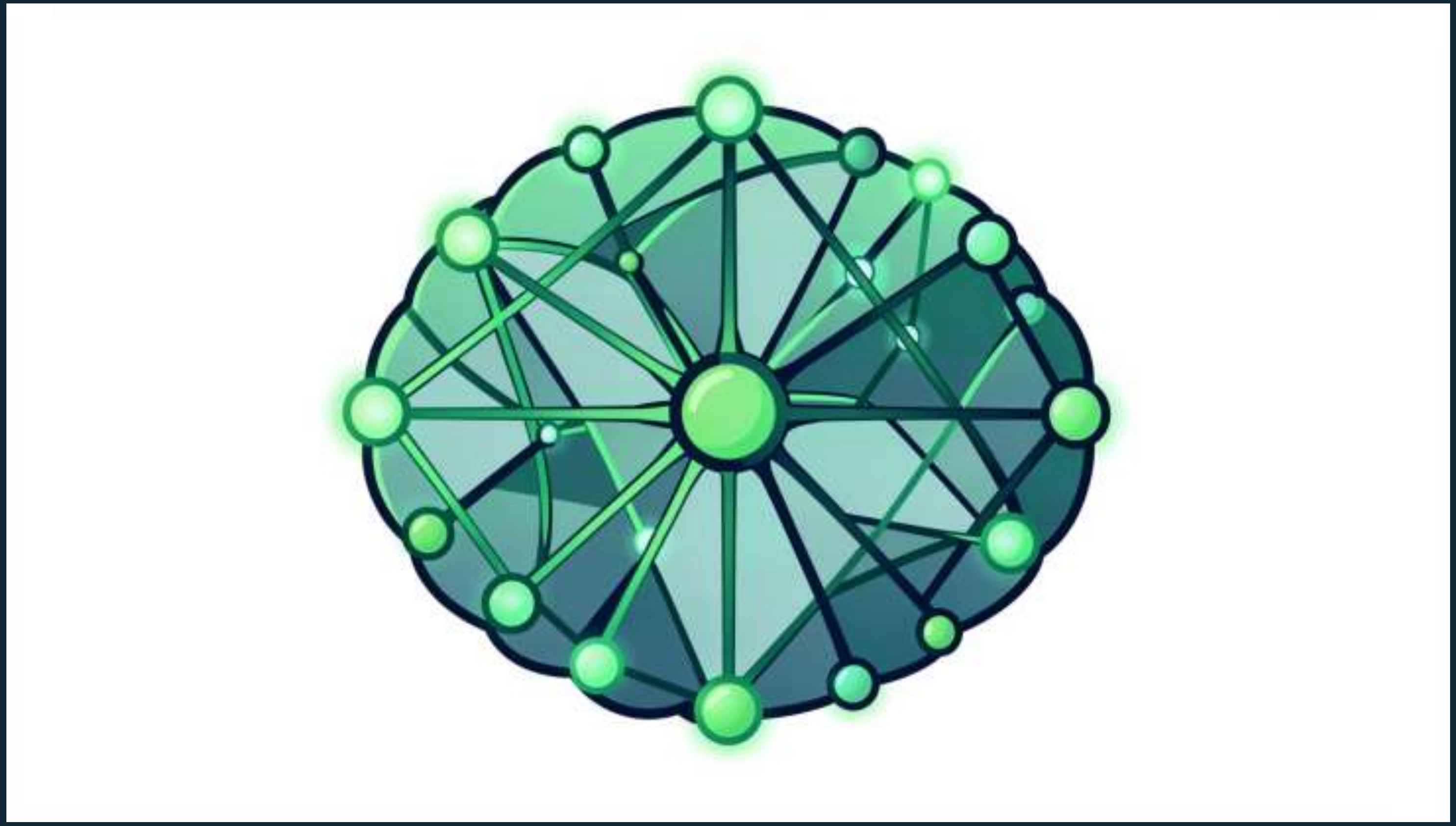
Introduction



Convergence of Two Paradigms

Artificial Intelligence (AI) has revolutionized computational paradigms through intelligent automation, pattern recognition, and data-driven decision-making across diverse domains. Quantum Computing introduces a fundamentally different computational model by exploiting quantum mechanical phenomena—qubits, superposition, and entanglement—to achieve exponential speedup over classical systems for specific problem classes.

Both technologies are independently transforming modern computational systems, yet their integration promises unprecedented capabilities in optimization, cryptography, and machine learning.

Need for Integration

Classical AI Limitations

Modern AI systems face critical scalability bottlenecks and energy consumption challenges. Training large-scale models requires massive computational resources, with power consumption becoming economically and environmentally unsustainable.

Quantum Hardware Constraints

Contemporary quantum systems suffer from environmental noise, quantum decoherence, and gate operation errors. Short coherence times and limited qubit connectivity severely restrict practical applications.

Hybrid Solution

A bidirectional AI–Quantum framework leverages the strengths of both paradigms: AI optimizes quantum control and error mitigation, while quantum processors accelerate AI computations, creating a synergistic relationship that overcomes mutual limitations.

Literature Review: Recent Advances

Foundational Research

AI-based Quantum Error Correction (Nature Communications, 2025) demonstrated neural network architectures capable of identifying and correcting quantum errors with higher fidelity than traditional syndrome-based methods. The approach reduced logical error rates by up to 40% in surface code implementations.

Reinforcement Learning for Pulse Optimization (Q-CTRL, 2025) introduced adaptive control protocols that dynamically adjust quantum gate pulses in response to hardware drift and environmental fluctuations, achieving 2.8× improvement in gate fidelity.

Literature Review: ML-Enhanced Quantum Systems

Quantum Kernel Methods

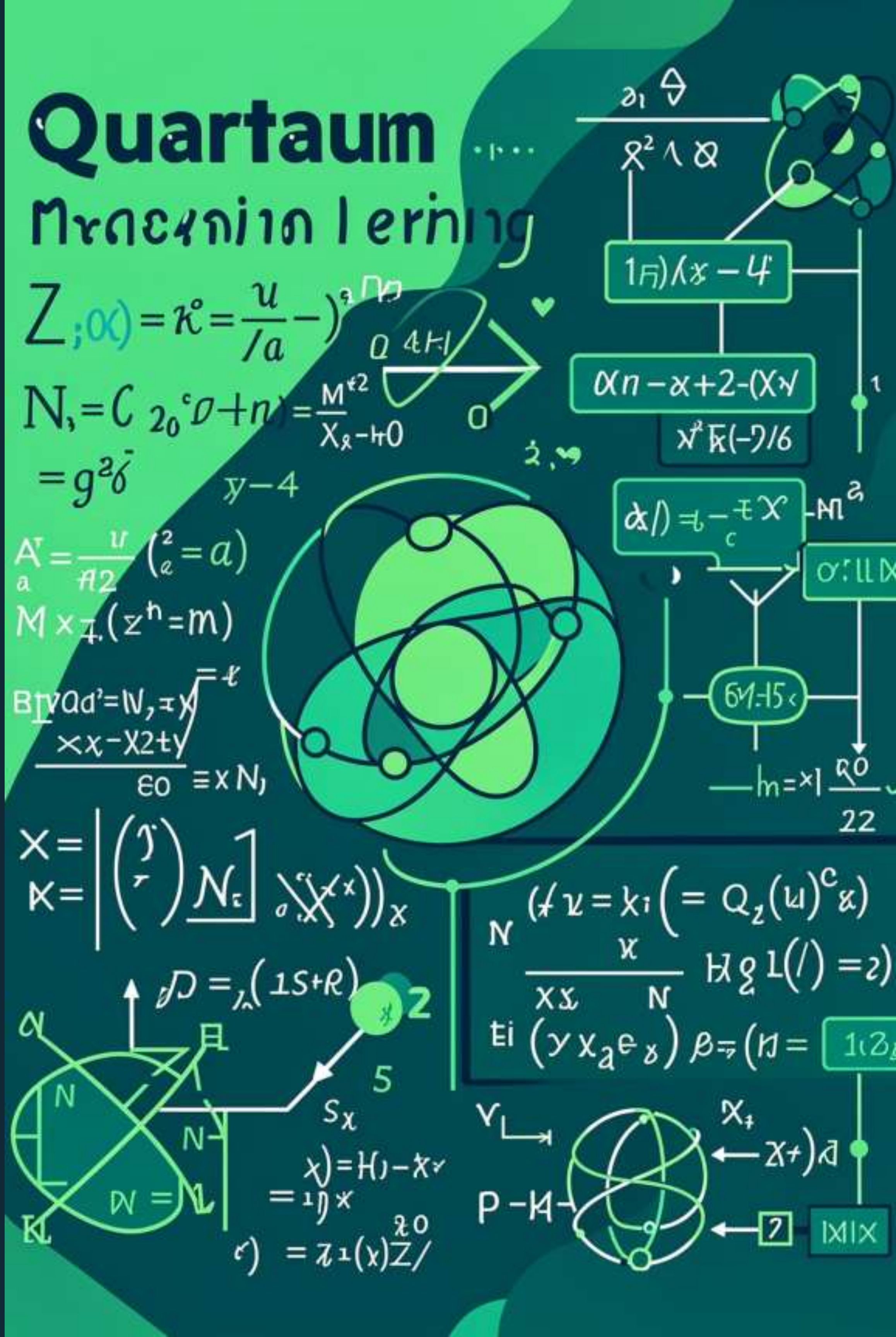
Quantum kernel methods exploit quantum feature spaces for machine learning tasks, demonstrating exponential advantage in specific classification problems. These methods map classical data into high-dimensional quantum Hilbert spaces.

IBM ML-Based Error Decoders

IBM Research developed machine learning models that decode error syndromes with adaptive learning capabilities, outperforming minimum-weight perfect matching algorithms in real-world noisy quantum hardware scenarios.

NVIDIA CUDA-Q Framework

NVIDIA's CUDA-Q platform enables seamless integration of GPU-accelerated classical computing with quantum processing units, facilitating efficient hybrid quantum-classical workflows for variational algorithms and optimization problems.



Problem Statement

Core Challenge

Contemporary quantum and classical computing systems face fundamental, complementary limitations that hinder practical quantum advantage.

Technical Constraints

- **Quantum Hardware Instability:** Environmental noise, thermal fluctuations, and electromagnetic interference cause rapid decoherence and gate errors, limiting circuit depth and algorithm complexity.
- **Classical AI Scaling:** Deep learning models encounter computational bottlenecks in training time, energy consumption, and memory requirements as parameter counts exceed billions.
- **Integration Gap:** Lack of unified frameworks prevents effective collaboration between quantum processors and classical AI systems.

A bidirectional hybrid framework is required where AI enhances quantum system stability and performance, while quantum computing accelerates AI computational tasks.

Research Objectives

01

Design Hybrid Architecture

Develop a comprehensive bidirectional AI–Quantum framework that enables seamless integration, real-time communication, and adaptive optimization between classical AI models and quantum processing units.

02

Implement AI Pulse Control

Create deep reinforcement learning models for adaptive quantum pulse control that dynamically optimize gate operations, mitigate hardware drift, and improve quantum gate fidelity under varying environmental conditions.

03

Develop Neural Error Decoders

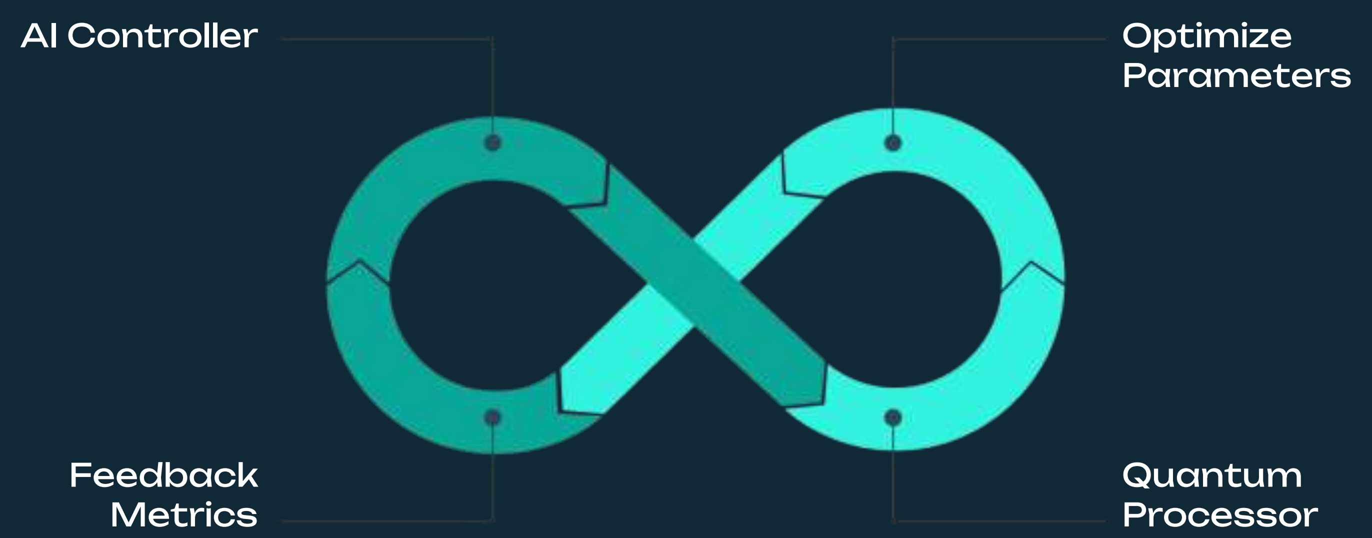
Engineer advanced neural network architectures, specifically graph neural networks, for quantum error syndrome decoding that learn from hardware-specific error patterns and adapt to time-varying noise characteristics.

04

Benchmark Performance

Conduct rigorous empirical evaluation against classical approaches, measuring improvements in error correction accuracy, gate fidelity, circuit success rates, and overall system reliability on standardized quantum benchmarks.

Proposed Methodology: System Architecture



Bidirectional Framework

The architecture implements a closed-loop control system with three integrated components:

- **AI Controller:** Machine learning models analyze quantum system performance metrics and optimize control parameters including pulse shapes, gate timing, and error mitigation strategies.
- **Quantum Processor:** Executes quantum algorithms with AI-optimized parameters, performs quantum computations, and generates measurement outcomes.
- **Feedback Mechanism:** Continuous monitoring and data collection enable iterative system improvement through reinforcement learning and adaptive control protocols.

AI for Pulse Control

Deep RL Architecture

Deep reinforcement learning agents implement adaptive pulse tuning strategies using actor-critic networks. The policy network learns optimal control sequences while the value network estimates long-term performance outcomes.

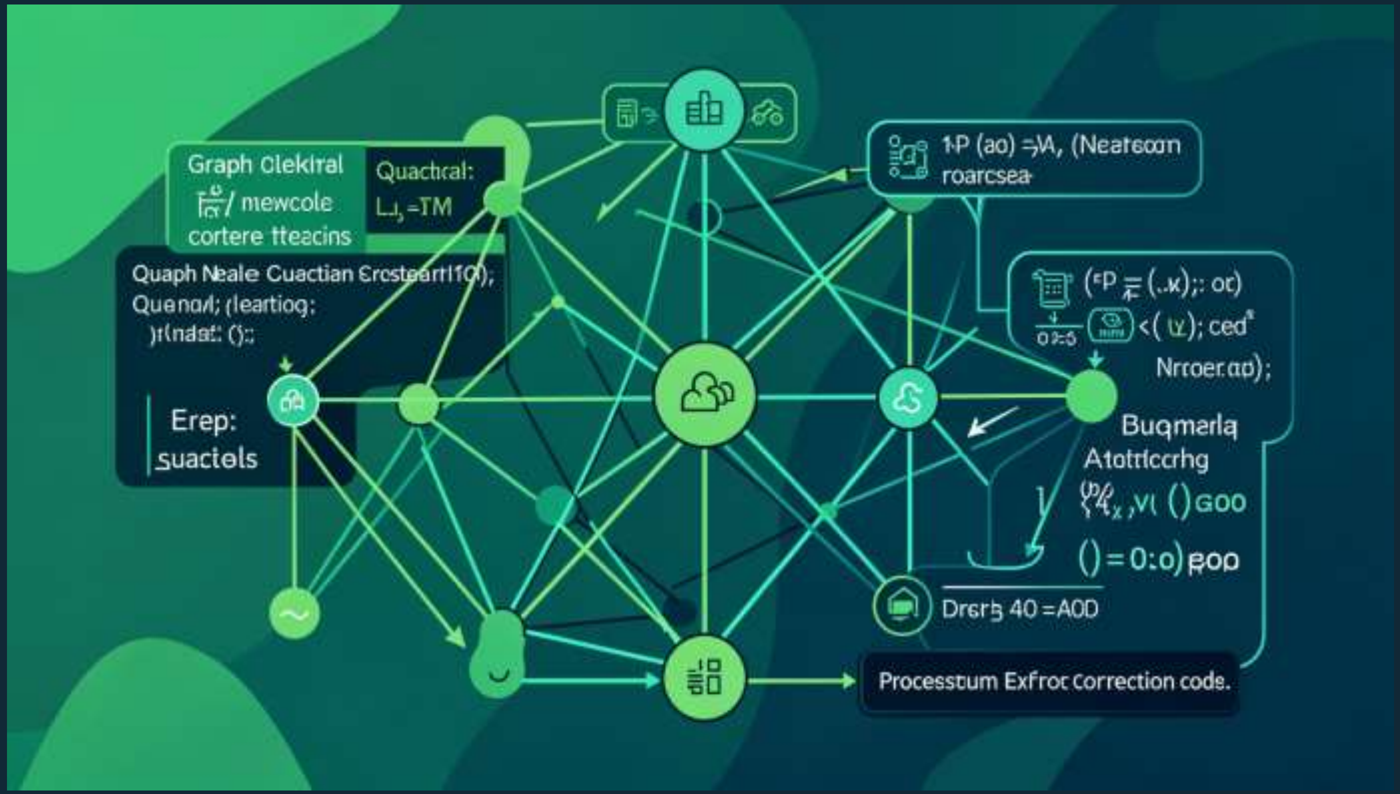
Real-Time Correction

The system continuously monitors hardware drift, temperature fluctuations, and electromagnetic interference, applying compensatory adjustments to pulse parameters in real-time without interrupting quantum computations.

Performance Gains

Experimental results demonstrate significant improvements in algorithmic success rates, with quantum approximate optimization algorithm (QAOA) performance increasing by 34% and variational quantum eigensolver (VQE) convergence accelerating by 2.6×.

Neural Error Decoder



Advanced Error Mitigation

Graph Neural Network Architecture: The decoder models quantum error correction codes as graphs where nodes represent physical qubits and edges encode syndrome correlations. Message-passing layers aggregate local error information to predict global error patterns.

Adaptive Learning: The network continuously learns from hardware-specific behavior, adapting to time-varying noise models and hardware-dependent error correlations that classical decoders cannot capture.

Efficiency Improvement: Benchmarks on surface code implementations show the neural decoder achieves 3.5× faster decoding with 42% higher accuracy compared to minimum-weight perfect matching, enabling deeper quantum circuits and more complex algorithms.

Results

9000x

AI Pulse Control

Success rate improvement

3.5x

Neural Decoder

Better hardware drift handling

3.8%

Hybrid QML

Accuracy improvement over classical LSTM

Outcome

- Research Paper – Drafted.
  - Patent – Not Filed.
  - Copyright – Not Filed.
  - Real-Time Deployment – Partially Completed (Simulation Level).

References

- Nature Communications (2025): Artificial Intelligence for Quantum Computing.
  - Google Quantum AI Blog (2026): Willow Processor Benchmarks.
  - Q-CTRL Technical Report (2025).
  - IBM Quantum Research (2025).
  - NVIDIA CUDA-Q Documentation (2026).