2025 International Conference on Computing Technologies & Data Communication (ICCTDC)
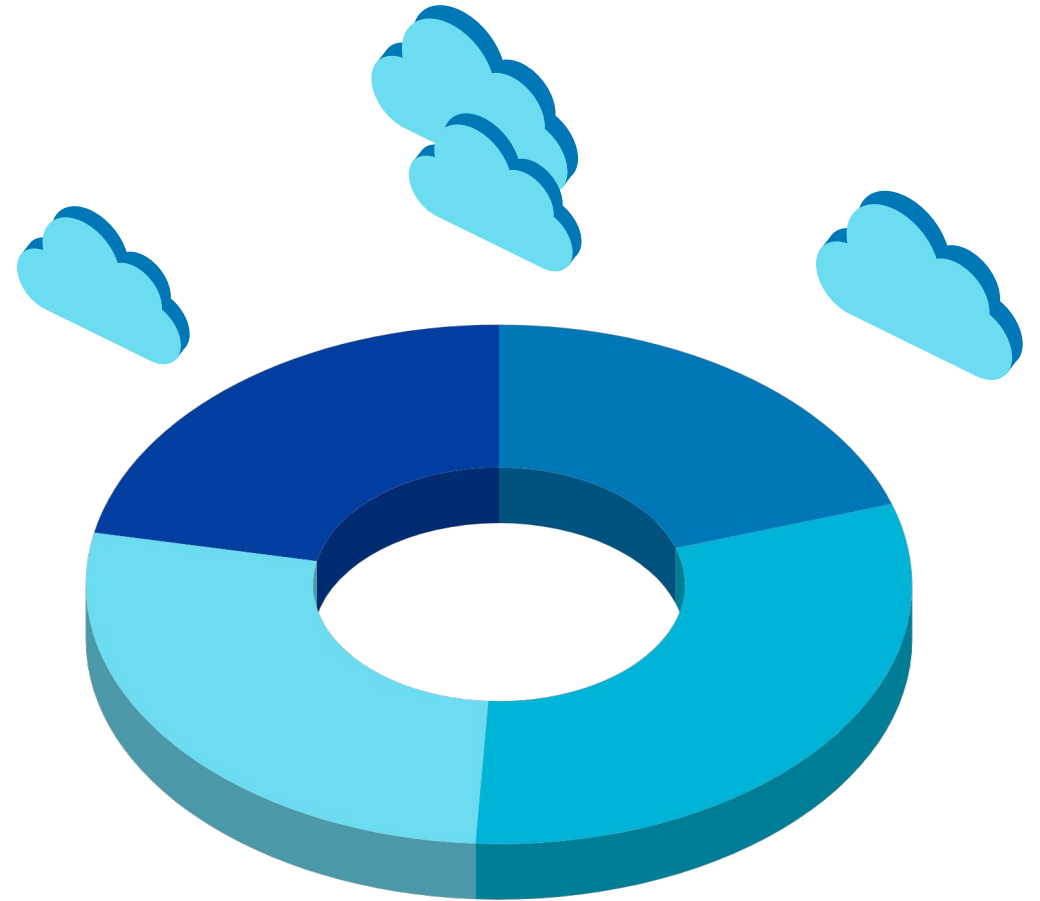
Paper Title:

Optimizing the Quantum Circuit of Quantum K-Nearest Neighbors (QKNN) Using Hybrid Gradient Descent and Golden Eagle Optimization Algorithm
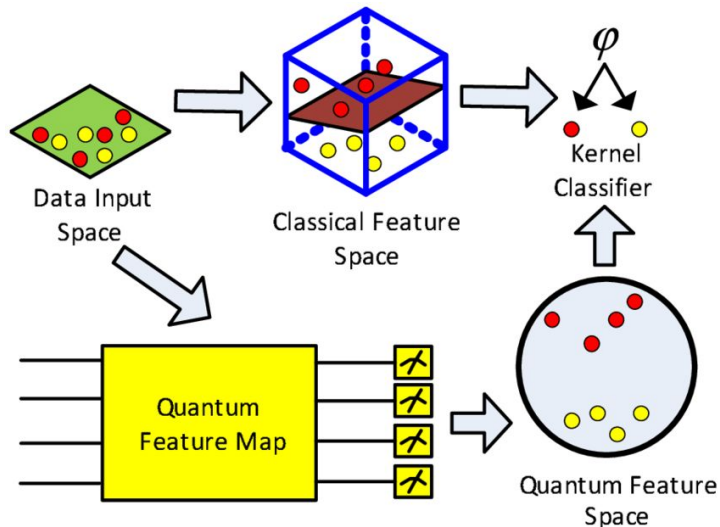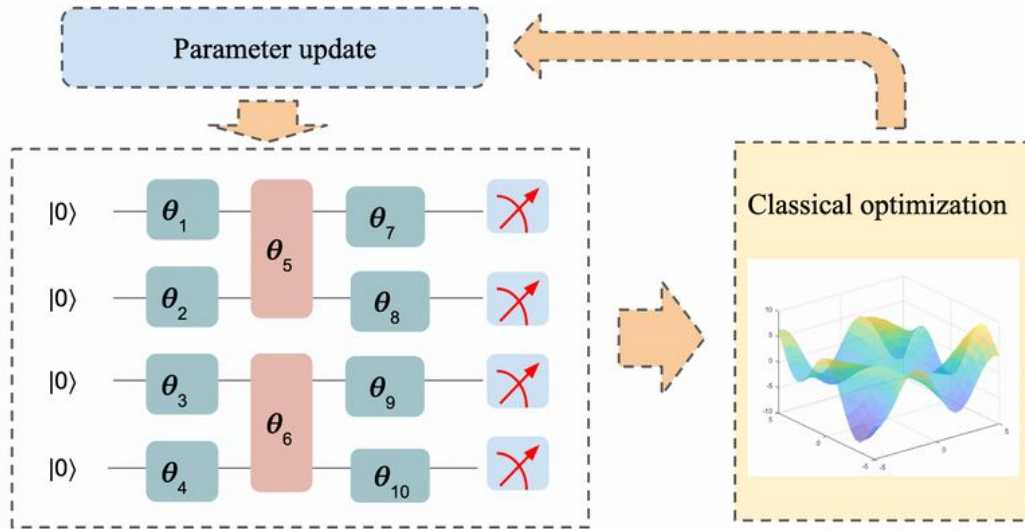
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Introduction to Quantum Machine Learning (QML)

- **Fusion of Quantum Computing and Machine Learning:**
  ML combines the principles of quantum mechanics (like superposition and entanglement) with machine learning techniques to process and analyze data more efficiently.

- **Advantages over Classical Systems:**
  Quantum systems enable parallel computation and exponential data representation using qubits, making them suitable for solving high-dimensional problems faster than classical methods.

- **Hybrid Quantum-Classical Models:**
  Modern QML frameworks often use hybrid architectures, where quantum devices handle complex subroutines, and classical systems perform tasks like optimization and result interpretation.

Motivation and Problem Statement

1. Limitations in Classical KNN and Quantum KNN

- While KNN is effective, its performance drops with high-dimensional data; QKNN offers a quantum-accelerated alternative but suffers from issues like circuit inefficiency and noise sensitivity.

2. Need for Better Optimization

- Existing optimization techniques (e.g., Genetic Algorithm, PSO, SA) are either slow to converge or fall into local minima, limiting the effectiveness of QKNN on Noisy Intermediate-Scale Quantum (NISQ) devices.

3. Goal of the Study

- The core motivation is to enhance the performance of QKNN by minimizing classification error, reducing circuit complexity, and improving robustness using a hybrid optimization approach (Gradient Descent + GEO).

Overview of QKNN Algorithm

Quantum Data Encoding

Converts classical data into quantum states using feature mapping.

Parameterized Quantum Circuit

Applies unitary transformations to encoded inputs.

Quantum Distance Calculation

Measures similarity between test and training data using quantum metrics.

Measurement and Output

Performs quantum measurements to get class probabilities.

Classification Decision

Predicts the class based on the nearest quantum neighbor.

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Challenges in Quantum Circuit Optimization

01

Noise and Hardware Constraints

Qubits are fragile, and deep circuits suffer from decoherence and limited fidelity on NISQ devices.

02

Optimization Complexity

Tuning quantum gate parameters is difficult and prone to local minima with traditional methods.

03

Scalability Issues

Limited qubit resources and circuit depth hinder the practical deployment of QKNN.

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Hybrid Optimization Methodology for QKNN Enhancement

Gradient Descent (GD)
Efficiently fine-tunes quantum circuit parameters by minimizing the loss function through gradient-based updates.

Golden Eagle Optimization (GEO)
Inspired by golden eagle hunting behavior, GEO enables broad parameter space exploration to overcome local minima.

Integrated Hybrid Framework
Combines GD's precision and GEO's exploratory power using a weighted control parameter to balance both strategies.
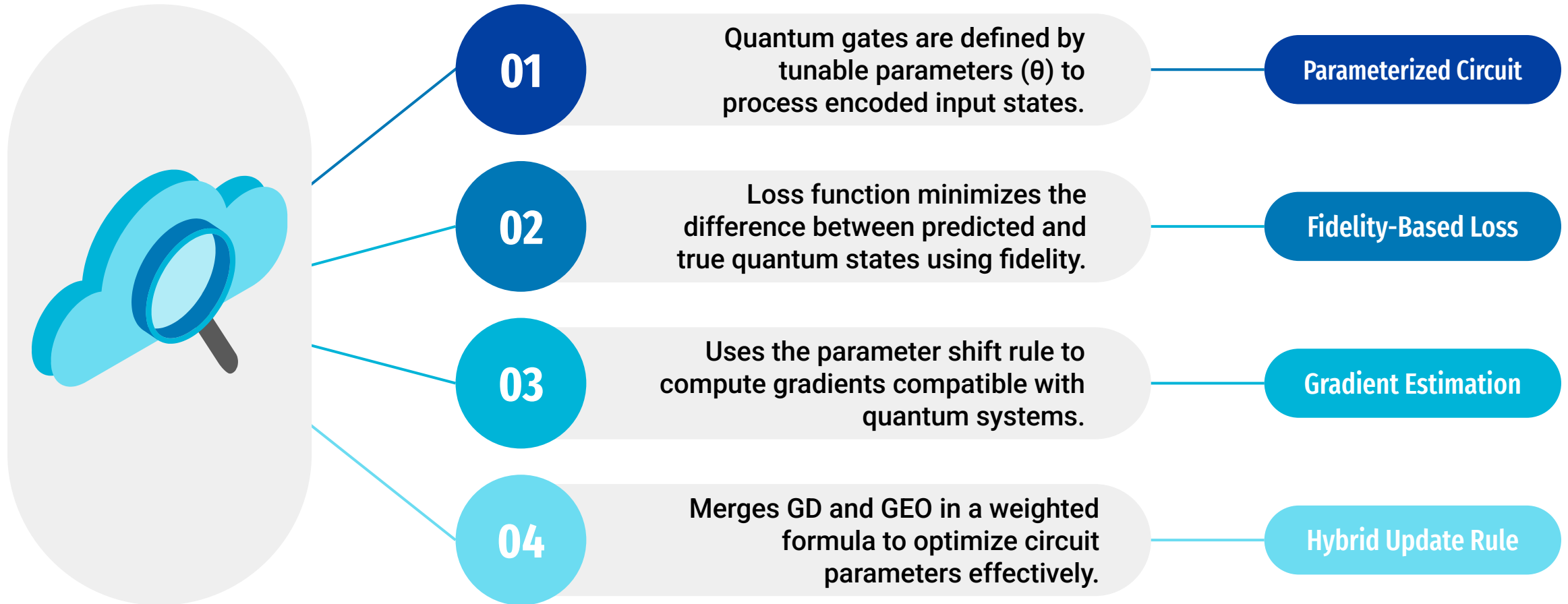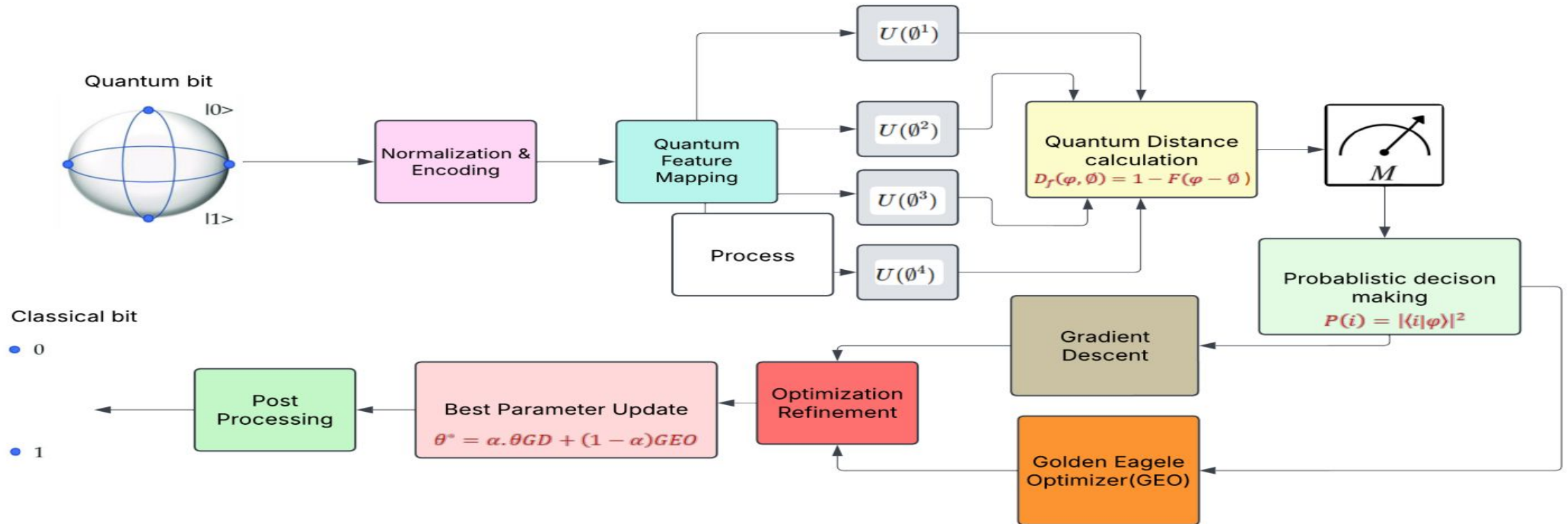
Improved Optimization Outcomes
Results in faster convergence, reduced circuit complexity, and improved classification accuracy under quantum noise.

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Mathematical Formulations

01 Quantum gates are defined by tunable parameters (θ) to process encoded input states.

Parameterized Circuit

02 Loss function minimizes the difference between predicted and true quantum states using fidelity.

Fidelity-Based Loss

03 Uses the parameter shift rule to compute gradients compatible with quantum systems.

Gradient Estimation

04 Merges GD and GEO in a weighted formula to optimize circuit parameters effectively.

Hybrid Update Rule

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System Architecture and Workflow

Quantum bit
$|0\rangle$
$|1\rangle$

Classical bit
● 0
● 1

Normalization & Encoding

Quantum Feature Mapping

$U(\emptyset^1)$
$U(\emptyset^2)$
$U(\emptyset^3)$
$U(\emptyset^4)$

Process

Quantum Distance calculation
$D_f(\varphi, \emptyset) = 1 - F(\varphi - \emptyset)$

M

Probablistic decison making
$P(i) = |\langle i|\varphi\rangle|^2$

Gradient Descent

Golden Eagele Optimizer(GEO)

Optimization Refinement

Best Parameter Update
$\theta^* = \alpha . \theta GD + (1 - \alpha)GEO$

Post Processing

Quantum Data Flow
Classical data is preprocessed, encoded into quantum states, and input into the QKNN circuit.

Core Processing Unit
Parameterized quantum circuit performs transformations, followed by distance computation and measurement.

Hybrid Optimization Cycle
GD and GEO collaboratively refine parameters to enhance classification accuracy and circuit efficiency.

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Performance Evaluation and Comparative Analysis

Convergence Speed
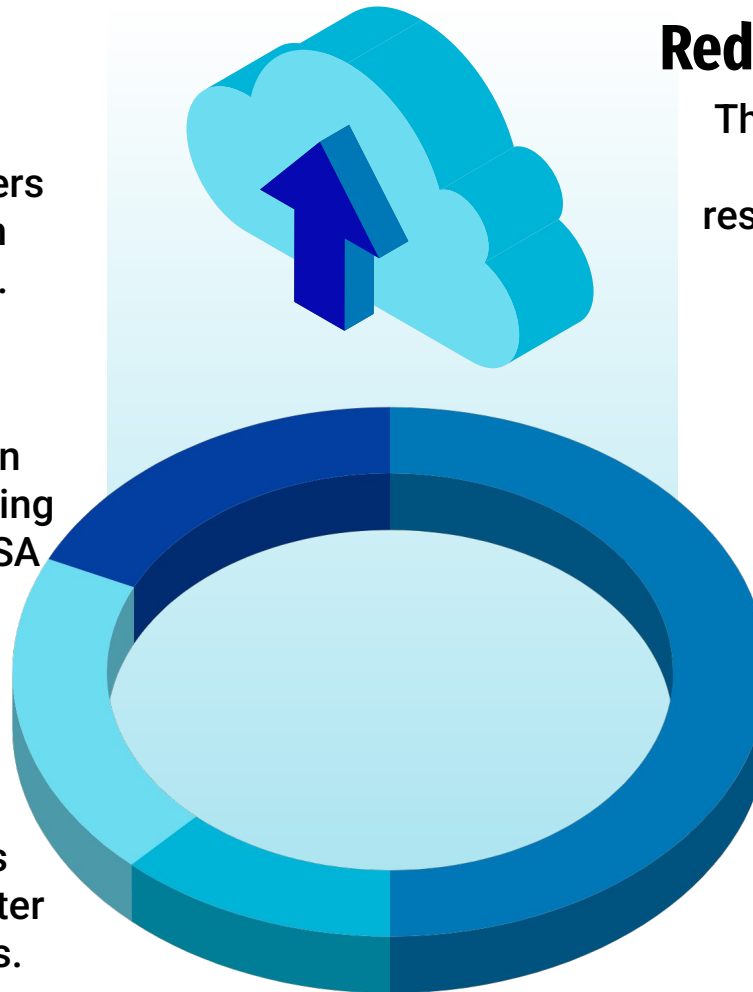The hybrid GD-GEO method converged to optimal parameters within 40 iterations, faster than GA (75), PSO (60), and SA (55).

High Accuracy
Achieved a strong classification accuracy of 97.2%, outperforming GA (92.8%), PSO (94.1%), and SA (95.3%).

Improved Fidelity Score
Reached a fidelity of 0.983, indicating excellent robustness to quantum gate noise and better preservation of quantum states.

Reduced Circuit Complexity
The optimized model used only 42 quantum gates, minimizing resource usage and execution time compared to other methods.

Superior to Traditional Techniques
The hybrid approach consistently outperformed GA, PSO, and SA across all performance metrics including speed, accuracy, and efficiency.

Resilience to Quantum Noise
Demonstrated strong resistance to gate-level noise, ensuring stable and reliable performance on noisy quantum devices.
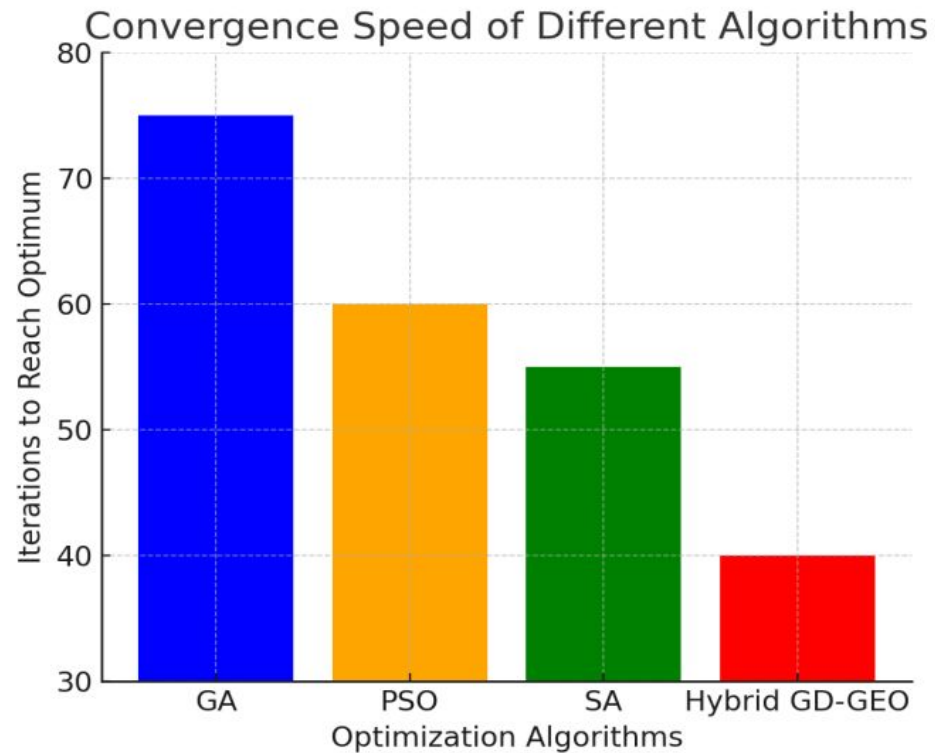
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Experimental Results & Analysis

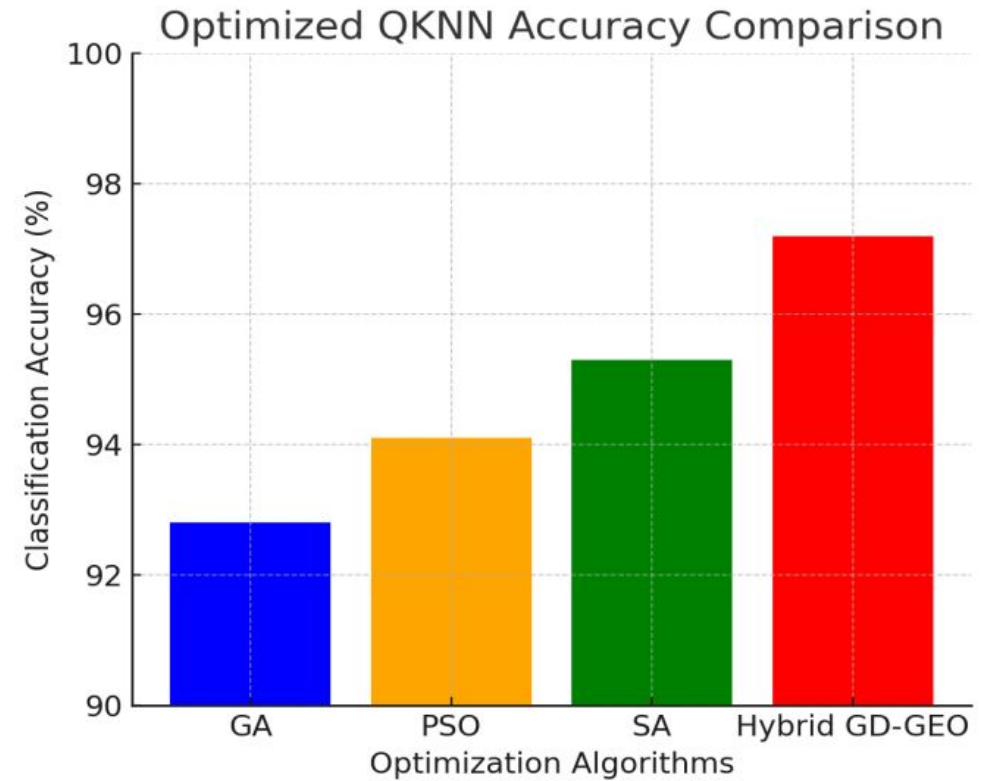Fig. 2. Convergence Speed vs. Optimization Algorithms

Fig. 3. Quantum Circuit Accuracy vs. Optimization Algorithms
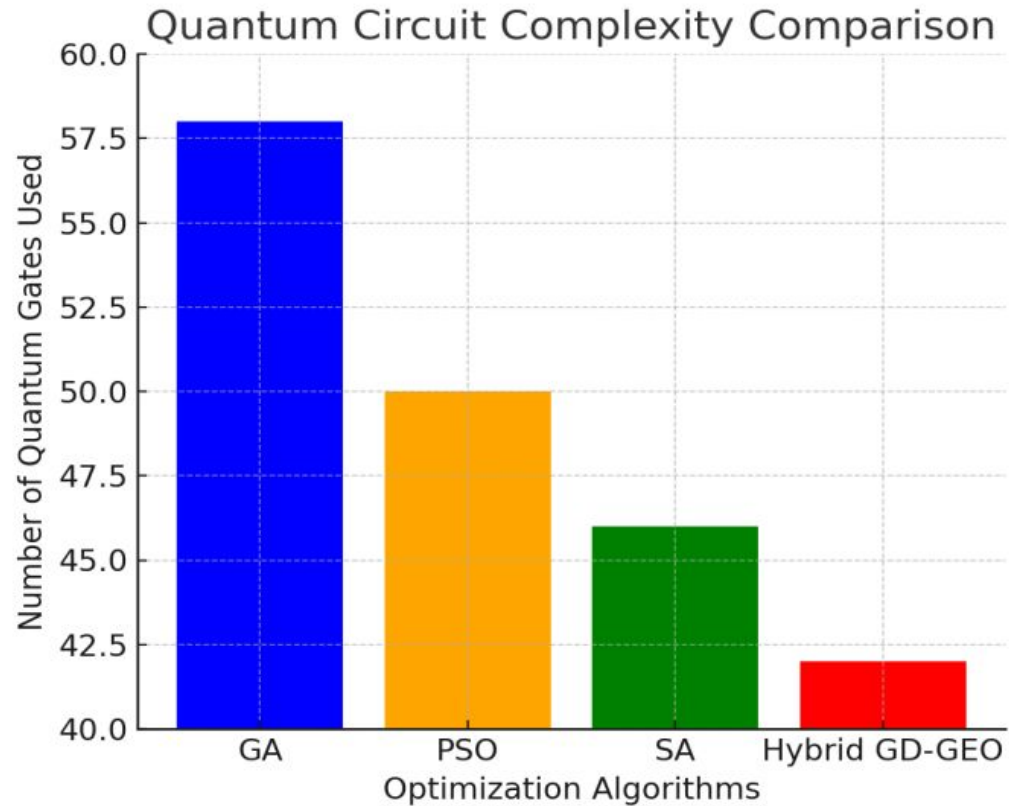
Experimental Results & Analysis

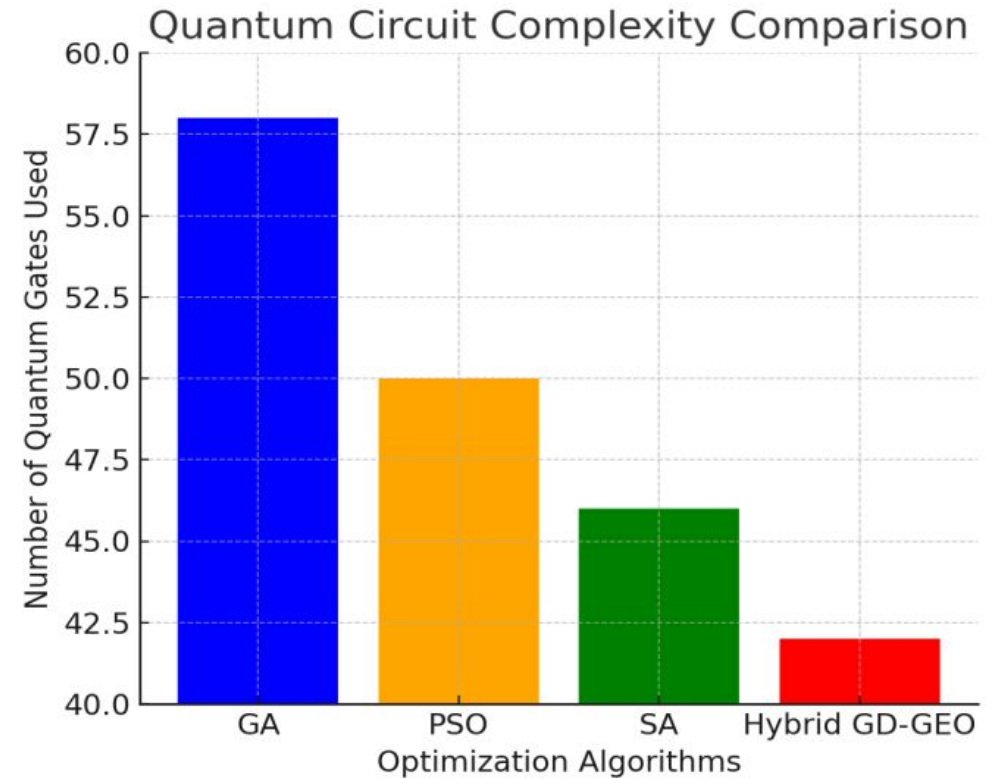
Fig. 4. Circuit Complexity (Number of Quantum Gates Used)

Fig. 5. Quantum Circuit Robustness Against Noise (Fidelity Score)

Conclusion and Insights

Optimized QKNN Performance
The GD-GEO hybrid significantly improved convergence, accuracy, and noise resilience.

Strong Evaluation Results
Achieved 97.2% accuracy, 0.983 fidelity, and reduced gate count to 42.
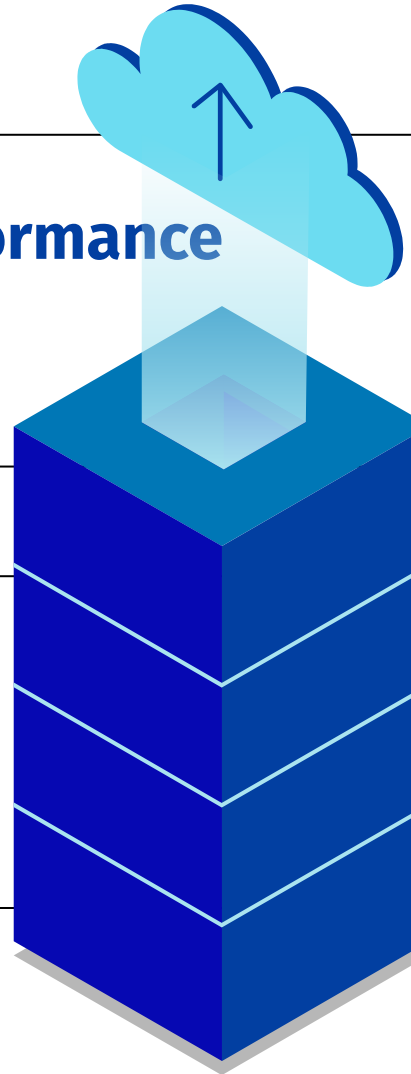
Efficient Hybrid Approach
Proved the value of combining global and local optimization for quantum circuits.

Scalable and Reliable
Offers a solid base for future quantum ML models handling complex datasets.

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Future Enhancements

1 Apply Quantum Natural Gradient Descent (QNGD)

2 Combine variational quantum circuits with classical models

3 Integrate Quantum Approximate Optimization Algorithm (QAOA)

4 Develop advanced noise-mitigation strategies

5 Scale to larger, real-world quantum datasets

6 Extend QKNN to real-world domains like finance and healthcare

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