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Paper Title:

**Optimizing Quantum Support Vector Machine (QSVM) Circuits Using
Hybrid Quantum Natural Gradient Descent (QNGD) and Whale
Optimization Algorithm (WOA)**

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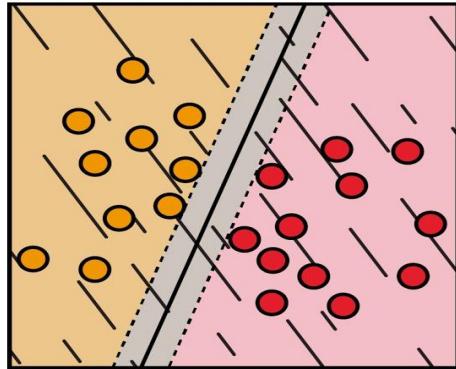
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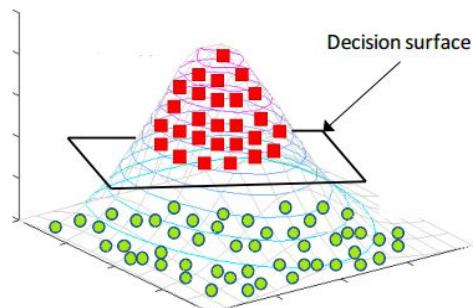


Introduction to Quantum Support Vector Machines



Support Vector Machines

A Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression tasks.



Quantum Support Vector Machines

A Quantum Support Vector Machine (QSVM) is a machine learning algorithm that combines the principles of quantum computing with the classical Support Vector Machine (SVM) framework.

- Quantum Support Vector Machines (QSVMs) use quantum kernels for high-dimensional data classification but suffer from noise and inefficiency. Our hybrid method merges QNGD's precision with WOA's global search to improve speed, accuracy, and circuit reliability in real-world quantum environments.
- Classical optimizers like SGD struggle in quantum models due to vanishing gradients and sensitivity. By combining WOA for exploration and QNGD for local tuning, we achieve faster convergence, better accuracy, and reduced gate complexity for scalable QSVM optimization.
- The proposed model reaches 96.8% accuracy in 38 iterations with just 44 quantum gates and a fidelity of 0.985. This hybrid optimization offers strong performance and robustness, making it ideal for practical quantum applications across industries.

Challenges in Existing Systems

🚫 High Quantum Noise and Decoherence:

QSVM circuits are prone to errors from environmental noise. Decoherence disrupts quantum states, lowering accuracy and making QSVMs unreliable on today's noisy intermediate-scale quantum (NISQ) devices.

⚡ Slow Training and Gradient Issues:

Gradient-based methods like SGD face vanishing gradients in deep circuits. This causes slow training and risks getting stuck in suboptimal solutions.

⚖️ Circuit Complexity and Scalability:

QSVMs often require many gates, increasing error rates and runtime. As circuits grow, scalability becomes a major obstacle for real-world deployment.



Objective of the Research

Improve Accuracy

Achieve better prediction by refining quantum kernel computations.

Faster Training

Accelerate convergence using hybrid quantum-classical optimization techniques.

Reduce Complexity

Simplify circuits by eliminating unnecessary quantum operations.



Boost Resilience

Increase fidelity through robust and optimized circuit design.

Enable Deployment

Make QSVMs viable on noisy intermediate-scale quantum hardware.

HYBRID OPTIMIZATION FRAMEWORK



Global and Local Optimization Synergy

Combines Whale Optimization Algorithm (WOA) for global parameter exploration with Quantum Natural Gradient Descent (QNGD) for precise local refinement.

Balanced Speed and Accuracy

WOA avoids poor local minima by exploring broadly, while QNGD ensures fast, accurate updates using quantum-aware gradients.

Improved Circuit Efficiency

The hybrid model reduces gate count, accelerates convergence, and enhances noise resilience—ideal for noisy intermediate-scale quantum (NISQ) devices.

Quantum Natural Gradient Descent (QNGD)



Parameter Optimization

QNGD updates parameters using the Fisher Information Matrix, adapting to the geometry of quantum space for smarter optimization.



Convergence Speed

It speeds up training by reducing the number of required iterations, which is vital for limited-coherence quantum systems.



Gradient Stability

QNGD avoids vanishing gradients, ensuring consistent learning even in deep and complex quantum circuits.



Quantum Compatibility

Specifically tailored for quantum models, QNGD respects quantum mechanics, making it more effective than classical optimizers.



Whale Optimization Algorithm (WOA)



Global Exploration

WOA explores a wide solution space to find optimal quantum circuit parameters.



Exploration Balance

It balances discovering new solutions and refining current ones to avoid local optima.



Circuit Tuning

Helps identify efficient configurations for better quantum circuit performance.



Noise Handling

Enhances circuit robustness by reducing sensitivity to quantum noise.



Accuracy Gain

Improves classification accuracy by guiding better parameter selection.



Gate Minimization

Reduces unnecessary quantum gates, lowering circuit complexity and errors.



Hybrid QNGD-WOA Integration



01

QNGD fine-tunes parameters using quantum-aware gradients for precise optimization.

Local Refinement

02

WOA explores the broader search space to find promising regions for tuning.

Global Guidance

03

The hybrid approach merges QNGD's precision with WOA's exploration for better results.

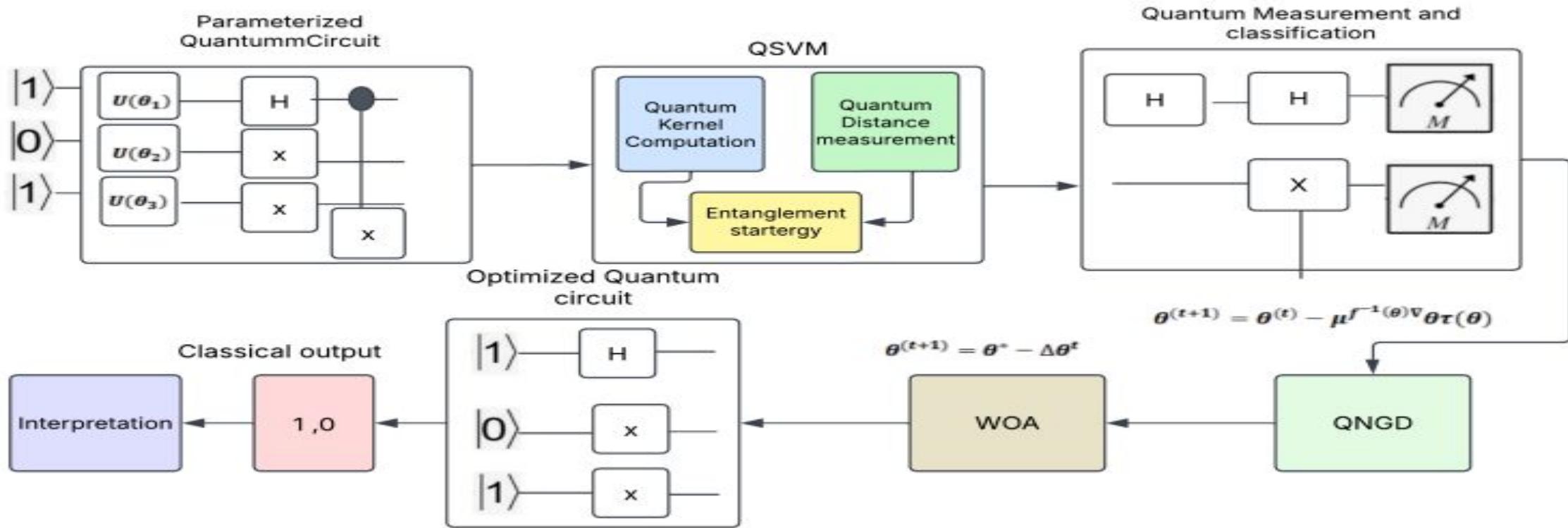
Combined Strength

04

Alternating updates lead to quicker optimization and reduced training time.

Faster Convergence

System Architecture and Workflow



Data Preparation

Classical data is normalized and encoded into quantum states using feature mapping.



Quantum Execution

Parameterized circuits perform kernel computation, entanglement, and classification.



Hybrid Optimization

QNGD refines parameters locally while WOA explores globally for optimal circuit tuning.

Convergence Speed & Classification Accuracy

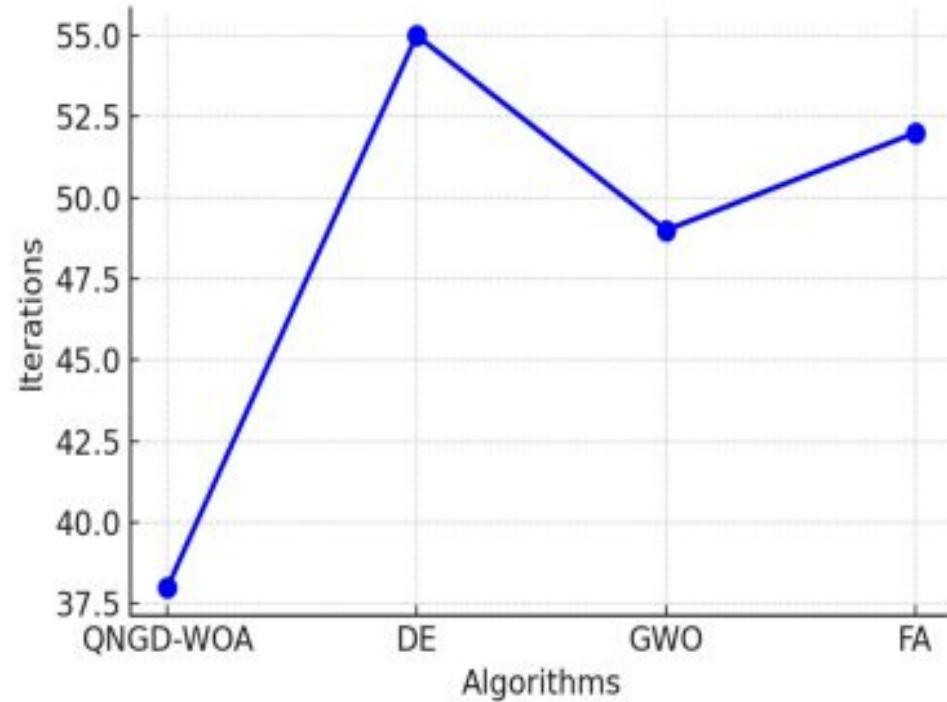


Fig. 2. Convergence Speed vs. Optimization Algorithms

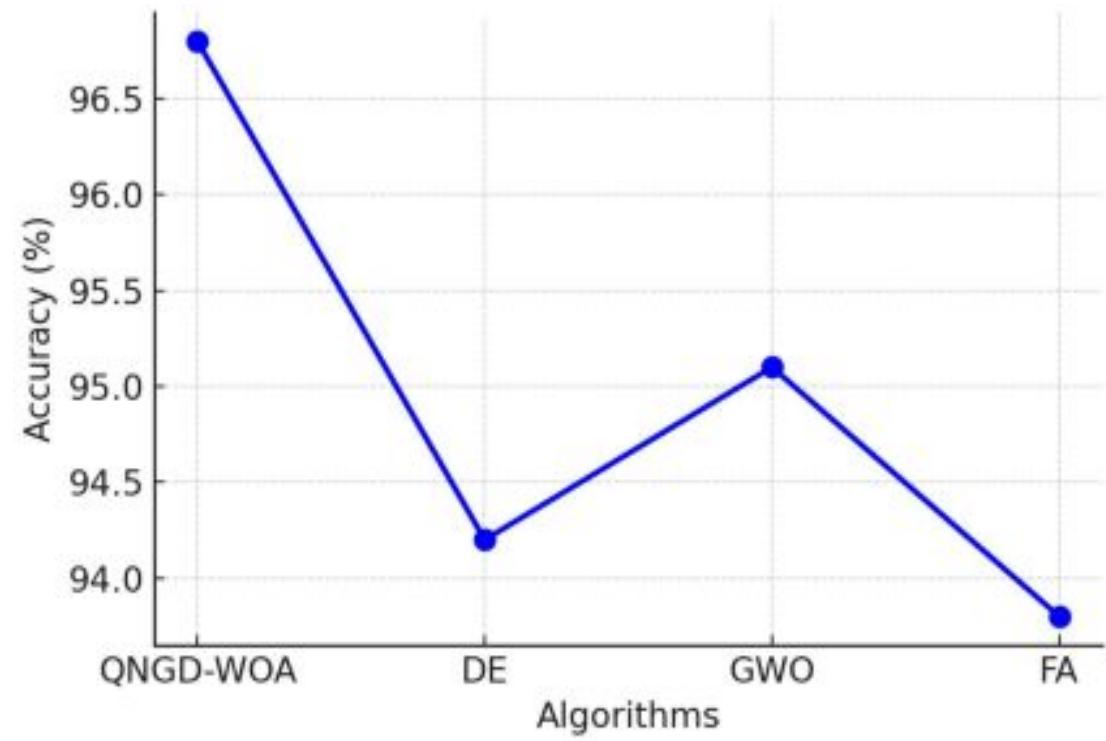


Fig. 3. Classification accuracy of hybrid QNGD-WOA

Circuit Complexity & Fidelity Score

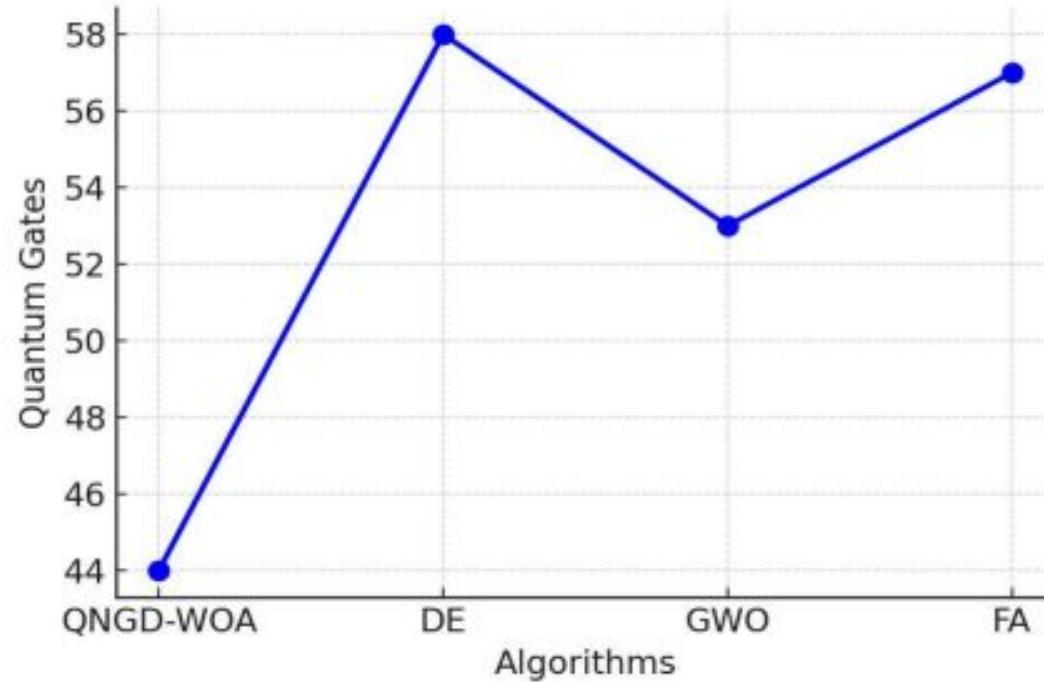


Fig. 4. Quantum circuit complexity of hybrid QNGD-WOA

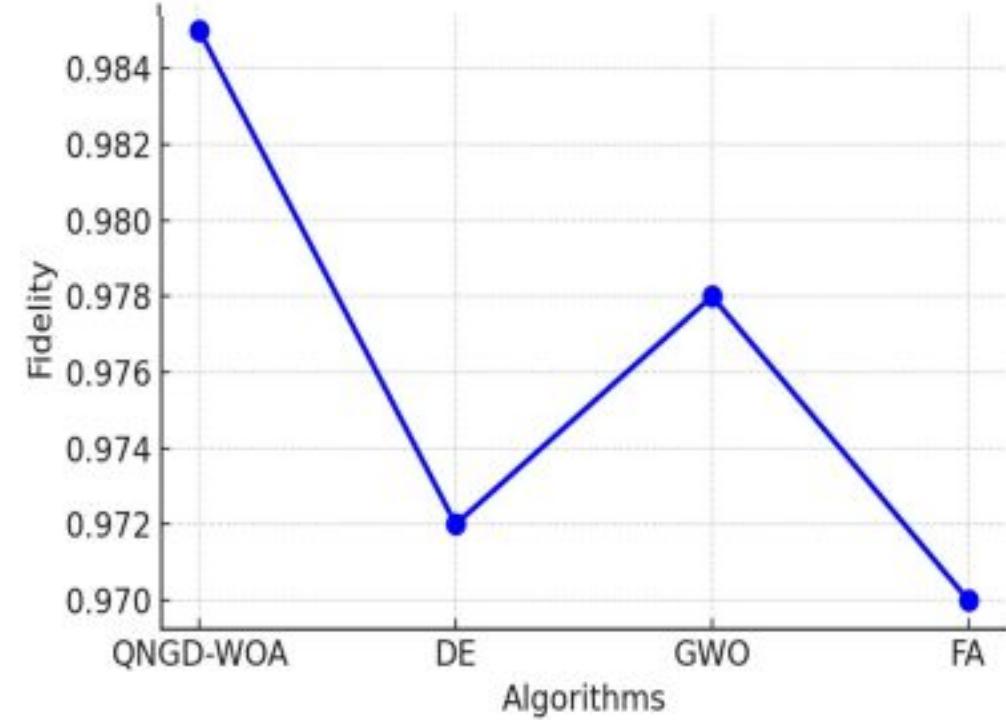


Fig. 5. Fidelity Score Comparison

Experimental Results and Discussion



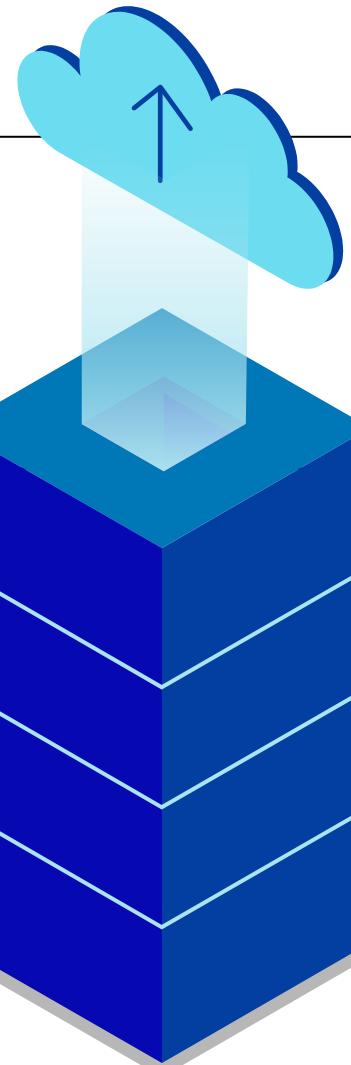
Quick Convergence

The hybrid method required only 38 iterations, outperforming other algorithms in speed.



Low Complexity

Reduced circuit to just 44 gates, enhancing efficiency and reducing execution errors.



High Accuracy

Achieved a classification accuracy of 96.8%, better than traditional optimization.



Strong Fidelity

Maintained high noise resilience with a fidelity score of 0.985 in quantum operations.



Conclusion and Future Work



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