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Research on the application potential and synergistic effects of quantum computing in the field of artificial intelligence: Integrative analysis centered on quantum machine learning (VQC/QNN)

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ABSTRACT

The rapid development of deep learning and large language models (LMs) has led to a "computing inflation" phenomenon in the demand for computing power, energy consumption, and training time for artificial intelligence (AI). As classical computing gradually approaches its scalability bottleneck due to the slowing of Moore's Law and limitations imposed by memory walls and energy consumption, quantum computing (QC), with its properties such as superposition, entanglement, and quantum interference, is considered a candidate computing paradigm that may provide acceleration for specific sub-problems and bring new inductive biases to representation learning.

This paper focuses on the application potential of quantum computing in artificial intelligence. It first establishes the theoretical foundation of quantum computing, then systematically outlines collaborative pathways that quantum computing can explore from three perspectives: AI training acceleration, data processing and representation learning, and neural networks and combinatorial optimization. Furthermore, this paper focuses on the most feasible quantum machine learning (QML) architectures for the Noisy Intermediate-Scale Quantum (NISQ) era, deeply comparing the design philosophy, data encoding strategies, parameter shift rule, shot complexity, and barren plateaus of Variational Quantum Circuits (VQC) and Quantum Neural Networks (QNN).

Finally, this paper analyzes potential application areas in finance, pharmaceuticals/materials, natural language processing, and recommendation systems, and discusses key obstacles such as input/output bottlenecks, noise and error mitigation, benchmarking and verifiability, and governance and security. The paper concludes that in the short to medium term, quantum computing is more likely to serve as a "co-processor" for classical AI, providing gains in specific subtasks through a hybrid quantum-classical workflow. In the long term, however, the development of fault-tolerant quantum computing and scalable quantum error correction is necessary to achieve reproducible and cost-effective quantum advantages across a wider range of AI tasks.

KEY WORDS: Quantum computing, quantum machine learning, variable quantum circuits, quantum neural networks, NISQ, quantum kernels, hybrid algorithms, Barren Plateaus

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1. Introduction

1.1 Research Background: Computing Power Inflation and AI in the Post-Moore's Law Era

Since the breakthrough of deep learning in image recognition tasks in 2012, AI has gradually formed an evolutionary path highly dependent on "scale": expanding data, increasing model parameters, and investing more computing power often bring predictable performance improvements. The success of LLM in recent years has made this path even clearer, but it also brings significant costs: training requires longer time, higher energy consumption, and more expensive hardware capital investment. From a system architecture perspective, the von Neumann architecture faces bottlenecks in data transfer, memory bandwidth, and energy efficiency; from an industry structure perspective, the high training cost may also lead to the centralization of computing power and model capabilities, raising the threshold for innovation.

Against this backdrop, academia and industry are once again focusing on computing paradigms that can provide novel acceleration or representation capabilities. Quantum computing, based on quantum mechanics, performs operations in high-dimensional Hilbert spaces through superposition and entanglement, and theoretically can exhibit computational complexity different from classical algorithms for certain types of problems (Biamonte et al., 2017; Harrow & Montanaro , 2017). Therefore, exploring the availability, entry points, and limitations of quantum computing in AI has dual value for both academia and industry.

1.2 Research Motivation: Quantum Computing as a Collaborative Engine for AI

The potential of quantum computing should not be understood merely as "faster computers," but rather as a new language for information representation and computation. For AI, this represents two potential values: (1) providing acceleration in certain subroutines (search, sampling, partial linear algebra, combinatorial optimization); and (2) providing different inductive biases and representational capabilities through quantum feature mapping and circuit structures, enabling models to characterize higher-order correlations of data in different ways. The motivation for this research is to establish an integrated framework to explain the possible synergistic modes of quantum computing and AI, and to point out the most feasible methodology under NISQ real-world conditions.

Figure1 The application potential of quantum computing in artificial intelligence

Source: Author's drawing

1.3 Research Objectives and Problem Statement

This paper focuses on the following research questions:

1. How do the core characteristics of quantum computing map to the training, representation, and optimization needs of AI?
2. What are feasible architectures for quantum machine learning under NISQ conditions? What are the differences and key limitations between VQC and QNN?
3. What are the key application points and risks of quantum computing in scenarios such as finance, pharmaceuticals/materials, NLP, and recommendation?
4. How should quantum advantage be defined and evaluated under a fair cost model and verifiable benchmarks?

1.4 Research Level and Scope

This paper primarily employs literature review and conceptual analysis, adopting a structure of "theoretical foundation—methodological architecture—application scenarios—challenges and prospects." Instead of conducting engineering performance evaluations of single hardware platforms, this paper focuses on the algorithm and system levels: data encoding, circuit design, training and measurement costs, noise impact, and workflow integration.

2. Literature Review and Current Research Status

2.1 The Context of Quantum Computing and Quantum Algorithms

The concept of quantum computing can be traced back to the insight into the need to simulate quantum systems. Subsequent classical quantum algorithms (such as integer factorization and search) have provided representative examples of how quantum computing can outperform classical computing on specific problems. However, most of these algorithms assume fault-tolerant quantum computing and scalable error correction, while real-world hardware has long been subject to significant noise interference. Since Preskill (2018) introduced the concept of NISQ, research has gradually shifted its focus to how to design usable quantum-classical hybrid algorithms with finite qubits , finite circuit depth, and non-zero error rates.

2.2 Research Classification of Quantum Machine Learning (QML)

QML can be summarized into four categories: (1) Quantum-enhanced classical algorithms: accelerating classical ML subtasks with quantum subroutines; (2) Parametric quantum circuit learning: using VQC/PQC directly as a trainable model; (3) Hybrid quantum-classical learning: using quantum circuits as a layer or module of a classical model; (4) Quantum generative models: using quantum measurement distributions for sampling and distribution learning (Biamonte et al., 2017; Dunjko & Briegel, 2018). Among them, (2) and (3) were the most common in the NISQ era because they could be trained with short circuits in conjunction with classical optimizers.

2.3 The Debate and Assessment Challenges of Quantum Advantage

The definition of "quantum advantage" is often controversial in the field of QML. Some theoretical results rely on efficient state preparation and readout; if these costs are included, theoretical speedups may disappear. Harrow and Montanaro (2017) pointed out that comparisons of claimed advantages must be based on consistent cost models and control groups (state-of-the-art classical baselines). Current research trends have therefore shifted towards seeking reproducible gains from "task structure + quantum circuit inductive bias" under verifiable settings, rather than simply pursuing claims of asymptotic complexity.

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2.4 Variable Quantum Algorithm as the Core Path of NISQ

Cerezo et al. (2021) systematically organized Variational Quantum Algorithms (VQAs), pointing out that they can operate under NISQ in a "quantum estimation expectation + classical parameter update" manner, including VQE, QAOA, and various variational circuit learning methods. This approach also exposes problems such as training difficulties (e.g., Barren plateaus), measurement costs, and noise sensitivity, which constitute the main challenges for the practical application of QML.

3. Foundations of Quantum Theory

This chapter outlines the quantum computing foundations required for QML from the perspectives of linear algebra and probability, covering quantum states, entanglement, unitary evolution, measurement, noise, and cost models.

3.1 Quantum states and Hilbert space

A single qubit can be represented as: [|\psi\ rangle =\alpha|0\ rangle +\beta|1\ rangle ,\quad |\alpha| 2+|\beta| 2=1] The joint state of n qubits in (2 n)-dimensional space is: [|\psi\ rangle =\sum_{z\in{0,1} n} c_z|z \ rangle ,\quad \ sum_z|c_z |^2=1] This "exponential dimension" provides the core source of quantum representation capabilities and explains why classical complete simulation is quickly infeasible. For machine learning, if data can be effectively embedded into quantum states, similarity, kernel functions, or feature maps can be defined in high-dimensional space; however, this also introduces the bottleneck of data loading cost.

3.2 Entanglement and Correlation

If a joint state cannot be decomposed into a tensor product, it is an entangled state. Taking a Bell state as an example: [|\Phi^+\ rangle =\ frac {1}{\ sqrt {2}}(|00\ rangle +|11\ rangle)] Entanglement can be regarded as a kind of "indivisible dependency structure" resource, which can potentially help characterize higher-order associations; however, excessively random or deep entanglement of circuits may also cause training landscape flattening (barren plateaus) and noise accumulation problems.

3.3 Unitary Evolution and Quantum Gates

The evolution of a closed system is described by a unitary matrix: [|\psi'\ rangle =U|\psi\ rangle ,\quad U^\dagger U=I] Common rotation gates include: [R_z (\theta)=\ exp (-i\theta Z/2)] Multi-bit entangled gates (such as CNOT) combined with single-bit rotations can form general-purpose circuits. For QML, circuit design typically involves repeatedly stacking "parameterized rotation layers + fixed entanglement layers" to achieve sufficient expressiveness at a controllable depth.

3.4 Measurement and Expected Value Estimation

The probability of obtaining a bit string (z) from a basis measurement is (P(z) = | c_z |^2). In QML, the expected value of the observable (M) is often used as the output: [\ langle M\ rangle =\ langle \ psi|M |\psi\ rangle]. Since the output of quantum hardware is a random sample, estimating the expected value requires multiple repetitions (shots), and its error is approximately (O (1/\ sqrt {S})). This directly causes cost pressure for training and inference.

3.5 Density Matrix, Quantum Channels, and Noise

In NISQ systems, the state is often mixed, represented by a density matrix: [\rho=\ sum_k The evolution of noise can be expressed using quantum channels: [\rho'=\ sum_jK_j \ rho K_j \ dagger , \ quad \ sum_jK_j \ dagger K_j =I] Noise not only reduces accuracy, but also interferes with gradient estimation, increases shot requirements, and destroys trainability, making the "theoretical quantum speedup" not necessarily visible in practice.

3.6 Cost Boundary of Quantum Advantage

Assessing quantum advantage requires considering data loading, circuit depth, measurement shots, error mitigation costs, and classical end-to-end optimization iterations simultaneously. Ignoring any of these factors can lead to unfair comparisons. Therefore, the feasibility of QML often depends on end-to-end cost rather than the asymptotic complexity of a single subroutine.

4. Detailed Explanation of Quantum Machine Learning Architecture: VQC, QNN, and Quantum Kernel Methods

4.1 Hybrid Training Loop in QML

A typical NISQ-QML workflow is as follows: Data encoding → Parameterization → Measurement → Classical loss calculation → Classical optimization and parameter update. The quantum end is responsible for generating the expected value or sampling distribution, while the classical end is responsible for gradient-based or gradient-free updates, forming a collaborative process.

4.2 Variable Quantum Circuits (VQC/PQC)

4.2.1Formalization

Define the data feature mapping circuit (U_\phi(x)) and the trainable ansatz (U_\theta): [|\psi(x;\theta)\ rangle =U_\theta U_\phi(x)|0\ rangle ^{\ otimes n}] Output expected value: [E(x;\theta)=\ langle \psi(x;\theta)|M|\psi(x;\theta)\ rangle] Then map (E) to the classification or regression output and minimize the loss function (\ mathcal {L}).

4.2.2Ansatz Design

A common structure is a stack of "single-bit rotation + entangled layers": [U_\theta {(l)}=\left(\prod_{j=1} n R_z(\theta_{l,j,1})R_y(\theta_{l,j,2})R_z(\theta_{l,j,3})\right)\cdot U_\text{entangle}] The larger the depth (L), the better the expressive power usually is, but the noise and training difficulty will also be aggravated.

4.2.3Advantages and limitations of VQC

Advantages: Controllable circuitry, NISQ-friendly, and easy to modularize and integrate with classic processes.

Limitations: shot complexity, noise sensitivity, input/output bottlenecks and barren plateaus.

4.3 Quantum Neural Networks (QNN): Layered Representation and Repeated Data Injection

QNNs emphasize a "layered architecture like neural networks," often using data re-uploading to enhance expressive power: [|\psi(x;\theta)\ rangle =\left(\prod_{l=1} {L}U_\theta {(l)}U_\phi {(l)}(x)\right)|0\ rangle {\ otimes n}] Quantum circuits are inherently linear, but nonlinearity can be introduced by measurement (Born rule) and classical post-processing. The risk of QNNs is that increasing depth can lead to noise accumulation and more severe Barren plateaus.

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4.4 Data Encoding Strategies: Basis, Angle, Amplitude, and Feature Mapping Circuits

Data encoding is the key to the success or failure of QML.

- **Basis encoding** is suitable for discrete features, but it is not natural for continuous data.
- **Angle encoding:** Features are carried by rotation angle; the circuit is shallow and it is the most commonly used.
- **Amplitude encoding: Theoretically,** a d-dimensional vector can be represented as (\log d) qubits, but state preparation can be expensive.
- **Feature mapping circuits (such as IQPs):** form quantum nuclei or quantum feature spaces using structures that are difficult to simulate classically, but the advantage may be unstable under noise.

4.5 Quantum Nucleus Approach: Constructing Nuclei from the Inner Product of Quantum States

Define a quantum eigenstate (|\phi(x)\ rangle), and a kernel function: [k(x,x ')=|\ langle \phi(x)|\phi(x')\ rangle | 2] . Then train it using classical SVM or other methods. The advantage is that it transforms training into classical convex optimization; the disadvantage is that kernel matrix calculation usually requires O(N 2) cost, and noise will distort the kernel value.

4.6 Gradient Estimation: Parameter Shift Rule and Measurement Cost

For a gate that can be represented as (U(\theta)=e^{-i\theta G/2}), the gradient can be estimated by the parameter offset: [\ frac {\partial E}{\partial \theta}=\ frac {E(\theta+\pi/2)-E(\theta-\pi/2)}{2}] If the number of parameters (P) is large, the number of quantum executions for each update is approximately (O(P)) (multiplied by the number of shots and the observability decomposition). Therefore, deep QNNs are often limited by training costs under NISQ.

4.7 Trainability Issues: Barren Plateaus

Barren plateaus refer to gradients concentrating near zero in the parameter space, causing training stagnation. Causes include excessive depth, overly random ansatz patterns, or global cost. Possible mitigation strategies include structured circuits, local costing, hierarchical training, and better initialization. This issue is one of the core obstacles to the transition of QML from concept to engineering (McLean et al., 2018).

4.8 Quantum Generative Models: The Possibilities of Sampling and Distribution Learning

Quantum circuit measurements naturally yield probability distributions, thus providing a conceptual fit for generative tasks (learning distributions, sampling generation). Although still limited by noise and training difficulties, generative tasks may be more tolerant of some noise than those requiring high-precision numerical outputs, making them a worthwhile area to explore (Dunjko & Briegel, 2018).

5. Industry Application Case Analysis: Key Application Points of Quantum Computing in AI

This chapter emphasizes that most feasible applications at present belong to hybrid workflows, and quantum modules are mostly used for sub-problems (optimization, sampling, feature mapping) rather than completely replacing deep learning training.

5.1 Finance: Portfolio Optimization and Risk Assessment

Financial problems often exhibit combinatorial optimization characteristics, making them suitable for QUBO/Ising models. Quantum annealing or QAOA-like methods can search for near-optimal solutions under multiple constraints (risk, cost, and correlation), serving as candidate solution generators for asset allocation decisions. On the other hand, quantum kernel methods can be used as feature mappers for nonlinear classifiers in credit risk, fraud detection, etc., but their gains compared to mature classical methods need to be verified using fair benchmarks.

5.2 Drug Discovery and Materials: Synergy of Quantum Chemistry and AI

Quantum computing possesses a native fit in simulating the electronic structure of molecules and materials. Methods such as Variable Quantum Eigenvalue Estimation (VQE) can be used to estimate the ground-state energy of molecules, and the generated quantum chemical features can serve as training data or annotation sources for AI models (such as neural networks and generative models), assisting in more reliable inferences and generation in data-scarce chemical spaces. This direction is often considered one of the most promising areas to demonstrate practical value first.

5.3 NLP and Recommendation: High-Dimensional Vectors, Similarity, and Search

The core of NLP and recommender systems largely involves high-dimensional vector operations, similarity calculations, and large-scale ranking/searching. Quantum feature mapping or quantum kernel methods can be seen as alternative similarity metric learning methods; furthermore, if certain ranking or search subroutines can provide advantages through quantum search/amplitude amplification, latency may be reduced in specific scenarios. However, due to the high cost of data loading and unloading, and the extremely mature nature of existing GPU solutions, they are more likely to be introduced in the short term as research prototypes or small-scale sub-modules.

5.4 Manufacturing, Logistics, and Scheduling: Quantum-Assisted Combinatorial Optimization

Problems such as manufacturing scheduling, path planning, and supply chain configuration are often NP-hard and form a closed loop with AI (demand prediction and dynamic scheduling). Quantum annealing and QAOA-like methods can be used to generate high-quality candidate scheduling solutions, which are then checked and fine-tuned by classical systems, forming a collaborative model of "quantum proposing candidates, classical verification and execution".

6. Technical Challenges and Practical Obstacles: The Gap between Theory and Deployment

6.1 Input/output bottleneck: Data loading and measurement costs

A common pitfall in QML is calculating only the computational cost within the quantum circuit while ignoring data loading and readout. If loading N-dimensional data into a quantum state requires O(N) gate operations, the speedup may be negated. On the other hand, expectation estimation requires a large number of shots, increasing

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training costs; if parameter offsets are also required for multiple circuit evaluations, the cost can explode rapidly.

6.2 The Cost of Noise, Decoherence, and Error Mitigation

The gate error rate and readout error limit the effective circuit depth of NISQ devices. While error mitigation methods (such as zero-noise extrapolation and probabilistic error elimination) can improve the reliability of results, they usually come at the cost of increased circuit execution times and sampling costs, essentially "trading more time for lower noise." Therefore, the cost of error mitigation must be included in the end-to-end evaluation.

6.3 Trainability: Barren Plateaus and Engineered Training Strategies

Barren plateaus make gradient training difficult, especially with deep circuits and high-expression ansatz . In engineering practice, it may be necessary to adopt: shallower circuits, layered training, local costing, or problem-heuristic circuit design, and to accept the design philosophy that "quantum circuits do not have to be extremely deep to be useful".

6.4 Benchmarking and Verifiability: Avoiding Unfair Comparisons

To claim quantum advantage, cost models and benchmarks must be aligned: the comparison should be with the strongest classical method under equivalent resources, not a simplified baseline. Evaluation metrics should include: training time, energy consumption, hardware cost, accuracy/generalization, stability, and reproducibility, and reproducible experimental settings should be made public.

6.5 Safety, Governance and Social Impact

Quantum resources are expensive and scarce, potentially exacerbating the concentration of computing power. Meanwhile, the black-box nature of quantum enhancement models and potential new adversarial attacks (such as perturbations targeting quantum states or quantum feature maps) also raise security concerns. Future efforts need to lower barriers to entry in standardization, open-source toolchains, and cross-platform portability, and establish a framework for responsible innovation and governance.

7. Conclusion and Outlook

7.1 Research Conclusions

This paper integrates interdisciplinary research on quantum computing and AI, pointing out that the value of quantum computing lies not only in its speed improvement but also in providing new representation and computation mechanisms. Analysis of VQC and QNN reveals that in the NISQ era, the most feasible path is typically a hybrid quantum-classical workflow, allowing quantum modules to provide gains on specific sub-problems (combinatorial optimization, sampling, eigenmapping/kernel estimation). This paper also identifies the main obstacles to the implementation of QML, including data loading and measurement costs, noise and error mitigation costs, trainability difficulties such as Barren plateaus, and the lack of a consistent benchmarking and cost-benefit evaluation framework.

7.2 Future Research Directions

Future QML research can focus on three directions:

5. **Hardware-aware algorithm:** Designing circuits based on specific hardware coupling diagrams and noise characteristics.
6. **Hybrid workflow standardization:** Establish reproducible benchmarks, end-to-end cost models, and engineering toolchains so that quantum modules can be invoked like GPU kernels.
7. **Explainability and security:** Researching the verifiability, robustness, and governance issues of quantum models to ensure their responsible deployment in high-risk areas (healthcare, finance).

7.3 Conclusion

The integration of quantum computing and AI is more likely to present "synergy and complementarity" rather than "complete replacement." In the short term, quantum modules as coprocessors are a more pragmatic approach; in the long term, if fault-tolerant quantum computing matures, quantum eigenmapping, quantum sampling, and quantum optimization may bring reproducible paradigm shifts to some AI tasks. The integrative analytical framework established in this paper can serve as the basis for subsequent research and practical evaluation of the synergistic benefits of quantum-AI.

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