International Journal of Computer Technology and Science
Volume. 1 No. 2 April 2024
e-ISSN :3048-1961, And p-ISSN :3048-1899, Page. 24-26
DOI: https://doi.org/10.62951/ijcts.v1i2.64
Available online at: https://international.arteii.or.id/index.php/IJCTS

The Role Of Quantum Computing in Optimizing Machine Learning Algorithms

Nattapong Chaiyathorn[1*], Pimchanok Anuwat[2]
[1-2] Chiang Mai University (CMU), Thailand

Abstract. *Quantum computing has the potential to revolutionize machine learning by offering exponential speed-up for specific algorithms. This study explores the theoretical and practical implications of using quantum computing to optimize machine learning models, such as in training neural networks. The findings provide insights into the possible improvements in computational efficiency, particularly for large datasets and complex models.*

Keywords: *Quantum computing, Machine learning, Optimization, Neural networks, Computational efficiency, Large datasets*

1. INTRODUCTION

In recent years, the convergence of quantum computing and machine learning (ML) has sparked significant interest among researchers and practitioners. Quantum computing, with its capability for parallelism and superposition, promises to overcome some of the inherent limitations of classical computing in handling complex, high-dimensional data in ML. This study investigates how quantum algorithms can optimize ML models, focusing on efficiency and scalability improvements, particularly for neural networks and large datasets.

Quantum Computing Fundamentals in Machine Learning

Quantum computing's basic principles, such as superposition, entanglement, and quantum gates, allow it to process massive amounts of information concurrently, which is particularly useful for optimization problems. Quantum algorithms like Quantum Approximate Optimization Algorithm (QAOA) and Quantum Support Vector Machines (QSVM) hold promise in enhancing model performance in areas traditionally limited by computational constraints.

Quantum Optimization in Machine Learning Algorithms

a. Quantum Neural Networks (QNNs)

Quantum Neural Networks combine neural network structures with quantum computation capabilities, potentially accelerating training and inference processes. QNNs leverage quantum parallelism to process multiple computations simultaneously, potentially leading to exponential speed-ups in model training and optimization tasks.

b. Quantum Support Vector Machines (QSVM)

QSVM extends the classical support vector machine algorithm using quantum principles. This algorithm utilizes quantum kernels, which can significantly increase classification accuracy and efficiency in high-dimensional spaces by performing operations that would be infeasible on classical hardware.

c. Variational Quantum Circuits (VQC) for Optimization

Variational Quantum Circuits represent a hybrid approach, where quantum circuits are used to optimize parameters in ML models. VQCs are especially beneficial for neural networks, where finding optimal parameters can be computationally expensive, as quantum circuits reduce the dimensionality and complexity of parameter space.

2. APPLICATIONS IN LARGE-SCALE DATA

Quantum computing offers a compelling solution for ML tasks involving large-scale data processing. Its capacity to manage enormous datasets in parallel makes it suitable for tasks like natural language processing, image recognition, and real-time data analytics, which are typically constrained by the memory and processing limits of classical computers.

3. CHALLENGES IN QUANTUM COMPUTING FOR MACHINE LEARNING

Despite the potential, quantum computing in ML faces several challenges:

a. Hardware Limitations: Quantum processors are still in their nascent stages, with issues such as qubit coherence and error rates affecting their reliability.

b. Algorithm Development: Quantum algorithms are still evolving, and the theoretical groundwork to fully integrate ML models with quantum systems is ongoing.

c. Resource Requirements: Quantum computing requires significant resources, and the cost of quantum processors remains high, limiting widespread adoption.

4. CONCLUSION AND FUTURE DIRECTIONS

Quantum computing has the potential to transform ML by drastically improving the efficiency of model training and optimization, especially for complex and large datasets. However, overcoming the hardware and algorithmic challenges will be crucial to fully realizing the advantages of quantum-enhanced machine learning. Future research should focus on refining quantum algorithms, expanding quantum hardware capabilities, and integrating hybrid quantum-classical systems for more accessible and scalable applications.

5. REFERENCES

Aaronson, S. (2013). Quantum computing since Democritus. Cambridge University Press.

Arute, F., Arya, K., Babbush, R., Bacon, D., Bardin, J. C., Barends, R., & Martinis, J. M. (2019). Quantum supremacy using a programmable superconducting processor. Nature, 574(7779), 505-510. https://doi.org/10.1038/s41586-019-1666-5

Benedetti, M., Lloyd, E., Sack, S., & Fiorentini, M. (2019). Parameterized quantum circuits as machine learning models. Quantum Science and Technology, 4(4), 043001. https://doi.org/10.1088/2058-9565/ab4f1a

Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., & Lloyd, S. (2017). Quantum machine learning. Nature, 549(7671), 195-202. https://doi.org/10.1038/nature23474

Cerezo, M., Arrasmith, A., Babbush, R., Benjamin, S. C., Endo, S., Fujii, K., & Coles, P. J. (2021). Variational quantum algorithms. Nature Reviews Physics, 3(9), 625-644. https://doi.org/10.1038/s42254-021-00348-9

Farhi, E., & Neven, H. (2018). Classification with quantum neural networks on near-term processors. arXiv preprint arXiv:1802.06002. https://doi.org/10.48550/arXiv.1802.06002

Havlíček, V., Córcoles, A. D., Temme, K., Harrow, A. W., Kandala, A., Chow, J. M., & Gambetta, J. M. (2019). Supervised learning with quantum-enhanced feature spaces. Nature, 567(7747), 209-212. https://doi.org/10.1038/s41586-019-0980-2

Lloyd, S., Mohseni, M., & Rebentrost, P. (2014). Quantum principal component analysis. Nature Physics, 10(9), 631-633. https://doi.org/10.1038/nphys3029

McClean, J. R., Romero, J., Babbush, R., & Aspuru-Guzik, A. (2016). The theory of variational hybrid quantum-classical algorithms. New Journal of Physics, 18(2), 023023. https://doi.org/10.1088/1367-2630/18/2/023023

Nielsen, M. A., & Chuang, I. L. (2000). Quantum computation and quantum information. Cambridge University Press.

Peruzzo, A., McClean, J., Shadbolt, P., Yung, M. H., Zhou, X. Q., Love, P. J., & O'Brien, J. L. (2014). A variational eigenvalue solver on a photonic quantum processor. Nature Communications, 5, 4213. https://doi.org/10.1038/ncomms5213

Preskill, J. (2018). Quantum computing in the NISQ era and beyond. Quantum, 2, 79. https://doi.org/10.22331/q-2018-08-06-79

Rebentrost, P., Mohseni, M., & Lloyd, S. (2014). Quantum support vector machine for big data classification. Physical Review Letters, 113(13), 130503. https://doi.org/10.1103/PhysRevLett.113.130503

Schuld, M., & Petruccione, F. (2018). Supervised learning with quantum computers. Springer. https://doi.org/10.1007/978-3-319-96417-0

Wiebe, N., Braun, D., & Lloyd, S. (2012). Quantum algorithm for data fitting. Physical Review Letters, 109(5), 050505. https://doi.org/10.1103/PhysRevLett.109.050505