

Quantum Computing for Enhancing AI Models in Healthcare Diagnostics: a Theoretical Perspective

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QUANTUM COMPUTING FOR ENHANCING AI MODELS IN HEALTHCARE DIAGNOSTICS: A THEORETICAL PERSPECTIVE

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Abstract—Artificial intelligence (AI) has brought transformative potential to healthcare, with its uses extending from diagnostics to personalized care. However, traditional AI models, including deep learning networks, face significant challenges in computational demand, data complexity, and processing speed. Quantum computing, with its exceptional computational power, offers a promising solution. This paper examines how quantum computing can enhance AI models in healthcare diagnostics. Through analyzing algorithms like Quantum Neural Networks (QNNs) and Quantum Approximate Optimization Algorithm (QAOA), we provide a theoretical perspective on the potential for improvements in diagnostic accuracy, efficiency, and scalability. The paper highlights the constraints of classical AI models and how quantum technology could overcome these limitations, providing new directions for research into quantum-powered AI in healthcare

I. INTRODUCTION

AI is becoming essential in healthcare, particularly in diagnostics, where machine learning models have shown promising results in tasks such as analyzing medical images, predicting disease, and processing patient data. Despite its successes, classical AI encounters limitations in handling vast and complex datasets and requires immense computational power. Quantum computing, which leverages principles like superposition and entanglement, has the potential to address these issues, enabling faster and more precise computations. This paper explores how quantum computing can complement AI in healthcare diagnostics. We delve into theoretical frameworks surrounding Quantum Neural Networks (QNNs) and Quantum Support Vector Machines (QSVMs) to understand their applications in medical imaging, predictive models, and genomic data analysis.

II. PROBLEM STATEMENT

The integration of artificial intelligence (AI) is pushing the boundaries of healthcare diagnostics. However, conventional AI systems, particularly those utilizing deep learning, are hindered by limitations in computational resources, data handling capabilities, and processing speeds. Diagnostic applications demand the analysis of large and complex datasets—such as intricate medical images or genomic data—which places considerable demands on classical computing frameworks. Furthermore, the urgent need for real-time decision-



Fig. 1. Quantum computing with ai in healthcare

making in diagnostic contexts often exceeds what these models can efficiently provide, resulting in delays and potential gaps in accuracy.

Quantum computing, leveraging principles like superposition and entanglement, presents a compelling potential to address these issues. Despite its promise, integrating quantum computing with AI in healthcare remains largely theoretical, as the necessary quantum hardware and algorithms are still evolving. This creates a vital need to investigate and understand how quantum computing might theoretically enhance AI's role in healthcare diagnostics, potentially enabling quicker, more accurate, and scalable solutions for complex diagnostic tasks.

III. LITERATURE REVIEW

A. AI in Healthcare Diagnostics

AI models-especially machine learning (ML) and deep learning (DL) techniques-are used across various diagnostic applications in healthcare, including: - Medical Imaging: AI-driven tools analyze MRI, CT, and X-ray scans, aiding in the detection of tumors, fractures, and other anomalies. - Disease Prediction: AI models process patient data to predict disease progression, assess risk factors, and tailor treatment plans. However, classical AI models can struggle with large, complex datasets, such as genomic data, and may face limitations in situations requiring real-time analysis.

B. Basics of Quantum Computing

Quantum computing uses qubits, which can exist in multiple states simultaneously due to superposition. Quantum entanglement enables qubits to

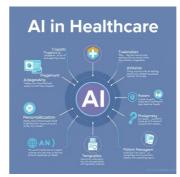


Fig. 2. AI in Healthcare

interact interdependently, and with quantum gates, computations can be achieved that are beyond the scope of traditional computing. Quantum algorithms, such as Grover's and Shor's, illustrate the computational power of quantum systems, suggesting potential for enhancement in AI applications.

C. Quantum Algorithms in AI

Several quantum algorithms show promise in enhancing machine learning: - Quantum Neural Networks (QNNs): QNNs, a quantum extension of neural networks, operate on quantum states and are potentially faster and less data-intensive, making them suitable for tasks like medical image recognition. - Quantum Support Vector Machines (QSVMs): QSVMs leverage quantum principles for better classification of complex data, offering faster processing for tasks such as identifying cancerous versus non-cancerous cells. - Quantum Approximate Optimization Algorithm (QAOA): QAOA can solve optimization problems in AI model training, which is valuable for applications like outbreak prediction and personalized treatment.

IV. THEORETICAL FRAMEWORK

A. Quantum Neural Networks (QNNs) in Healthcare Diagnostics

QNNs, leveraging quantum data, can process high-dimensional medical datasets more effectively than classical networks. In medical imaging, QNNs may enhance pattern recognition, analyzing MRI or CT scans with increased speed and precision. Superposition allows these networks to evaluate multiple image states simultaneously, potentially reducing the time required to train and deploy diagnostic models. indicating that file creation is complete.

B. Quantum Support Vector Machines (QSVMs) for Data Classification

Diagnostic tasks often involve distinguishing between conditions like cancerous and benign cells. While traditional SVMs perform well, their efficiency decreases with data complexity. QSVMs can handle large datasets more effectively by leveraging quantum properties, which may enable faster, more accurate classification, especially for complex datasets like those in genomics

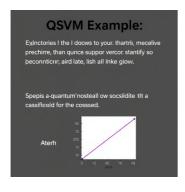


Fig. 3. QVSMs Example

C. Quantum Optimization in AI for Healthcare

Quantum computing is well-suited for optimization problems, common in AI model training. QAOA could enhance the training of healthcare models used for disease prediction or treatment personalization, reducing the resources required for developing robust diagnostic tools

V. DISCUSSION

Quantum computing offers a pathway for enhancing AI models in healthcare diagnostics. Quantum algorithms like QNNs, QSVMs, and QAOA allow AI models to transcend limitations in classical computing, improving diagnostic speed and accuracy and enabling more efficient analysis. Such advancements could drive significant improvements in patient care. However, the

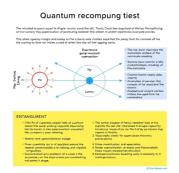


Fig. 4. Quantum Computing Overview

application of quantum-enhanced AI in healthcare remains challenged by the early stage of quantum hardware, including issues like qubit instability and error rates. Overcoming these obstacles will be critical for widespread adoption.



Fig. 5. Quantum computing with ai in healthcare

VI. CONCLUSION

Integrating quantum computing with AI could transform healthcare diagnostics. Quantum algorithms have the potential to revolutionize data processing in AI models, enabling faster and more accurate diagnoses. While implementation remains a challenge, ongoing research in quantum computing and AI is likely to yield significant advancements. The theoretical framework provided here establishes a foundation for exploring quantum-enhanced AI models in healthcare.

REFERENCES

 Schuld, M., Sinayskiy, I., Petruccione, F. (2015). An introduction to quantum machine learning. Contemporary Physics, 56(2), 172-185.

- [2] Lloyd, S., Mohseni, M., Rebentrost, P. (2014). Quantum algorithms for supervised and unsupervised machine learning. arXiv preprint arXiv:1307.0411.
 [3] Dunjko, V., Briegel, H. J. (2018). Machine learning and
- [3] Dunjko, V., Briegel, H. J. (2018). Machine learning and artificial intelligence in the quantum domain: A review of recent progress. Reports on Progress in Physics, 81(7), 074001.
- [4] Benedetti, M., Lloyd, E., Sack, S., Fiorentini, M. (2019). Parameterized quantum circuits as machine learning models. Quantum Science and Technology, 4(4), 043001.
- [5] Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., Lloyd, S. (2017). Quantum machine learning. Nature, 549(7671), 195-202.