International Journal of Computer Science and Information Technology Research (IJCSITR)
2025, Vol. 6, No.2, March - April, pp. 35-53
Journal ID: 9471-1297
website: www.ijcsitr.com
DOI: https://doi.org/10.5281/zenodo.15068399

AI and Quantum Computing: The Future of Data Analytics at Scale

Bhanu Raju Nida,
Independent Researcher, Philadelphia, United States.

Venkata Penumarthi,
Independent Researcher, Philadelphia, United States.

Abstract

The rapid growth of data driven applications has revealed the computational and scalability limitations of traditional computer systems in the delivery of AI and ML solutions. However, with artificial intelligence enhancing various sectors such as banking, healthcare and logistics, the need for improved and more efficient computing has led to the exploration of quantum computing as a possible solution. Quantum Computing (QC), that uses concepts such as superposition and entanglement of quantum bits or qubits is expected to improve AI based data analytics by reducing the time for training models, handling high dimensional problems and pattern recognition. This paper explores the integration of quantum computing with artificial intelligence, with the focus on Quantum Machine Learning (QML) and its effectiveness in enhancing AI data analysis. The potential of various quantum algorithms like Grover's search, Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolvers (VQE) in enhancing efficiency in optimization and AI model training is explored. The challenges of integrating quantum computing with the current AI frameworks are explored which include hardware issues, quantum error correction and scalability. Applications in practical scenarios such as banking, healthcare and supply chain management are also discussed, and quantum enhanced AI is found to bring revolutionary changes in these domains. Future directions in hybrid quantum classical computing, AI enhanced quantum algorithms and the gradual integration of quantum computing to the market are also discussed. The development of quantum technologies and its integration with AI is expected to redefine the ways of computing and provide better and faster solutions to data analytics problems.

ACADEMIA Google Scholar ELSEVIER SSRN ResearchGate SCOPE DATABASE INDEXED

Keywords

Quantum Computing, Artificial Intelligence, Quantum Machine Learning, Big Data Analytics, Optimization, Hybrid Quantum-Classical Computing, Quantum Algorithms, AI Acceleration, Quantum Error Correction, Quantum Hardware Scalability.

How to Cite: Bhanu Raju Nida, Venkata Penumarthi. (2025). AI and Quantum Computing: The Future of Data Analytics at Scale. *International Journal of Computer Science and Information Technology Research*, 6(2), 35–53.

Article ID: IJCSITR_2025_06_02_004

Copyright: © The Author(s), 2025. Published by IJCSITR Corporation. This is an **Open Access** article, distributed under the terms of the Creative Commons Attribution-Non-Commercial 4.0 International License (https://creativecommons.org/licenses/by-nc/4.0/deed.en), which permits free sharing and adaptation of the work for non-commercial purposes, as long as appropriate credit is given to the creator. Commercial use requires explicit permission from the creator.

1. INTRODUCTION

Artificial Intelligence (AI) has helped organizations to gain much insight from large and complex data sets. AI-based analytics, with the help of Machine Learning (ML) and Deep Learning (DL), can find patterns, make predictions, and support decision making in almost every industry including banking, healthcare and logistics among others. However, as the amount of data, the rate at which data is being generated and the type of data increase exponentially, the conventional computing systems are increasingly getting to their limits. Most conventional processors are inefficient in handling high-dimensional data, which requires a lot of computational power and energy. This bottleneck affects the performance of the AI models and limits their use in real-time and large-scale analytical applications.

Quantum computing (QC) is a new and improved computing system that is based on quantum mechanics, which is much better than classical theory. Unlike the classical computer that works based on sequential or parallel computing with the help of binary digits, quantum computers work on qubits to solve complex problems very efficiently. There are some quantum advantages, such as Grover’s search algorithm and Shor’s factorization, which are better than classical computing systems in solving certain problems. In the area of AI and data analytics, it is possible that quantum-enhanced machine learning (QML) will be able to accelerate the training of models, improve calculation of high dimensional problems, and discover patterns in a way that was not possible before.

This research aims to explore how quantum computing can outcompete classical data analysis through the integration of artificial intelligence.

The study focuses on these key questions:

- How can quantum computing improve AI-based data analysis?
- What are the primary quantum algorithms for machine learning and big data analysis?
- What are the issues in integrating quantum computing with the current AI frameworks?

This paper offers the vision of the future of big data analysis and discusses how quantum computing can change the approach to AI.

2. BACKGROUND AND THEORETICAL FOUNDATIONS

2.1. AI in Large-Scale Data Analysis:

2.1.1. Machine Learning (ML) and Deep Learning (DL) in Data Analytics

Artificial Intelligence (AI) is one of the major enablers of extensive data analytics and ML and DL are integral to it. Supervised, unsupervised and reinforcement learning are types of machine learning that enable the discovery of patterns and relationships in complex data sets. Deep learning is a version of machine learning that uses many layers of neural networks for features and representation learning from large datasets. Other approaches, such as CNNs and transformers, have shown a high level of effectiveness in image recognition, natural language processing, and time series forecasting.

As the availability of big data increases, AI models are being adopted in areas such as banking, healthcare, and supply chain management to enhance performance and decision making. AI-based analytics can work with both structured and unstructured data to develop predictive models, detect anomalies and provide real time decision support. The effectiveness of these approaches is often hampered by computational complexities and the challenges associated with scaling up the AI models.

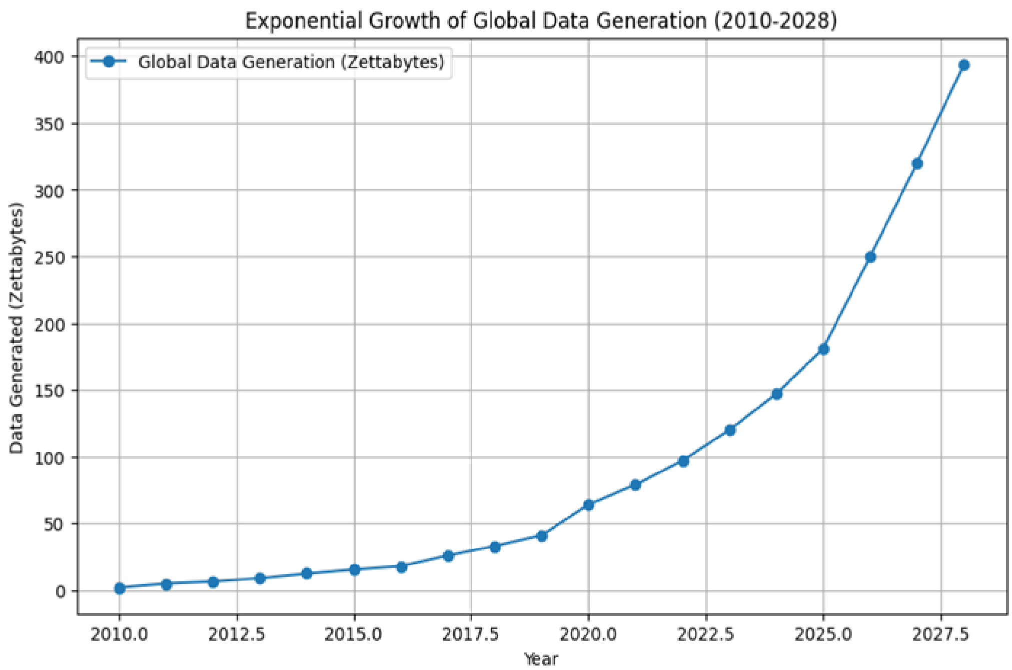

Figure 1: Growth of Global Data Generation

2.1.2. Challenges in Managing Large Datasets

This paper aims at contributing to the understanding of the following topic that has emerged because of the exponential growth of data in the last few years:

1. Computational Cost —Training a deep learning model is a computational expensive process that often requires powerful GPUs or TPUs. The size of the models has been increasing rapidly, making them costly and resource demanding entities, and thereby making AI systems expensive.

2. Energy Consumption — Deep neural network-based AI computations are energy intensive and, therefore, unsustainable. The training of the state-of-the-art language models such as GPT-4 requires the amount of energy that is used in a small metropolis.

3. Cognition and Delay Bottlenecks — The realization of real time data processing necessitates high memory bandwidth and proper data location. Most classical architectures are inhibited by the Von Neumann bottleneck, which causes problems because data is moved back and forth between memory and processor units.

4. Scalability and Optimization — Many gradient descent-based machine learning algorithms require iterative computations that become infeasible for very large datasets. These challenges however continue to present limitations in performance scalability in parallelization approaches and distributed computing frameworks such as Apache Spark and TensorFlow.

2.1.3. Current State-of-the-Art in AI-Driven Analytics

To address these challenges, researchers have developed techniques such as model pruning, quantization, and federated learning to optimize AI computations. Moreover, AI hardware accelerators, including neuromorphic chips and AI-specific processors like Google's Tensor Processing Units (TPUs), have improved computational efficiency. Despite these advancements, AI's ability to scale for truly massive datasets remains constrained by classical computing architectures. This limitation has led to the exploration of alternative computing paradigms, with quantum computing emerging as a potential breakthrough.

2.2. The Basics of Quantum Computing

Core Principles: Superposition, Entanglement, and Quantum Parallelism

Quantum computing is an application of quantum mechanics to solve problems that are impossible or unfeasible to solve with classical computers. Classical bits are either in the 0 or 1 state, but quantum bits (qubits) can be in both states at once, by virtue of superposition. This is because quantum computers work with qubits, which can represent several values at the same time, which makes some computational tasks solve them exponentially faster.

Entanglement is another crucial concept that sees qubits linked such that one qubit can influence the state of the other qubit instantly regardless of the distance between the two. This phenomenon enhances the computational efficiency and the security of quantum communication.

The concepts of superposition and entanglement make quantum parallelism possible, and thus quantum algorithms outperform conventional algorithms for search, optimization, and simulation.

2.2.1. Quantum Algorithms Focused on Data Analytics

There are several quantum algorithms that have been proposed for extensive data analytics:

1. Grover's search algorithm — It gives quadratic speedup for all search-based tasks, which can lead to faster data recovery and pattern recognition in intelligent systems.
2. Quantum Approximate Optimization Algorithm (QAOA): Utilized for solving combinatorial optimization problems in clustering, feature selection, and AI model optimization.
3. Variational Quantum Eigensolver (VQE): VQE was originally proposed for quantum chemistry; VQE can be used in machine learning to solve the optimization problems related to neural network training.
4. QSVMs enhance the classification tasks by using quantum kernels to process the high-dimensional data faster than the classical SVMs.

2.2.2. Hardware Overview: Superconducting Qubits, Trapped Ions and Photonic Quantum Computing Systems

Quantum hardware development is a rapidly evolving field, with several competing architectures being explored:

1. Superconducting Qubits: These qubits that are used by IBM, Google and Rigetti have Johson junctions and are one of the most popular quantum computing systems that are being researched currently.

2. Trapped Ions: IonQ and Honeywell are implementing trapped ion technology where ions are controlled by electromagnetic fields to perform quantum operations with high accuracy.

3. Photonic Quantum Computers – Companies including Xanadu and PsiQuantum are building photonic quantum computers that use photons as the basis of computation, and which may have an advantage in terms of scalability and robustness to errors.

Even though significant progress has been made in the development of quantum hardware, major challenges remain, including qubit coherence, error correction, and scalability. In their increasing sophistication, quantum computers are expected to combine with AI-based data analysis to fundamentally change computational potential and present new opportunities for extensive analytics beyond the limits of classical computing.

3. LITERATURE REVIEW

Recent research highlights the growing intersection of AI, ML, and quantum computing in addressing big data challenges. AI and ML techniques are transforming data analytics, enhancing scalability, accuracy, and decision-making capabilities [2]. Quantum computing offers significant potential for accelerating AI and big data processing, with quantum algorithms demonstrating improved computational speed and efficiency [1][3]. Quantum machine learning (QML) is emerging as a promising field, exploring how quantum computing can enhance ML algorithms and vice versa [8]. However, challenges remain in scalability, error correction, and integration with existing systems [3]. Researchers are also investigating quantum-inspired algorithms and hybrid quantum-classical models for optimization and analytics [5][6] As these fields evolve, ethical considerations, data privacy, and model interpretability become increasingly important [4][7]. In particular, the ethical implications of AI-driven IoT systems highlight critical concerns regarding algorithmic bias, transparency, and data governance, which also extend to quantum AI applications where ethical oversight is necessary to ensure responsible deployment and prevent unintended biases [9]. Additionally, AI-driven automation and digital workforce management are gaining prominence, particularly in dynamic operational environments such as hospitality and customer service. The integration of AI-powered oversight mechanisms demonstrates how AI is being leveraged to optimize workforce efficiency, task allocation, and operational monitoring. These advancements suggest a broader shift toward intelligent automation, where AI not only enhances performance but also ensures adaptability in high-complexity environments [10]. As AI-driven fault tolerance mechanisms continue to evolve, the integration of quantum computing promises to revolutionize data analytics at scale by enhancing computational efficiency and overcoming the constraints of traditional deep learning models in distributed systems [11].

- The paper reviews the potential of quantum computing to accelerate and enhance artificial intelligence, including for handling big data challenges.
- The paper discusses how AI and ML can enhance big data analytics for scalable, accurate, and real-time decision-making.
- Quantum computing offers significant improvements in computational speed and efficiency for big data analytics, but faces challenges in scalability, error correction, and integration.
- The paper reviews challenges in using data for AI, including quality, volume, privacy, bias, and interpretability, and offers recommendations to address them.
- Quantum computing can address the challenges of big data analytics by enabling faster data processing and analysis compared to traditional computing.
- Quantum computing offers promises for accelerating big data analytics and machine learning but faces challenges.
- This paper reviews the use of ML and DL methods for big data analytics, including challenges and applications.
- The paper reviews the mutual benefits and challenges of integrating quantum computing and ML/AI.

4. METHODOLOGY

4.1. Comparative Analysis Framework: Classic Artificial Intelligence versus Quantum Artificial Intelligence Enhanced.

This paper uses a comparison approach to compare the benefits of quantum-enhanced AI over classical AI in terms of efficiency, scalability, and accuracy in various data analysis tasks. The comparison focuses on:

1. Computational Complexity – Comparing the time and resource consumption of classical AI algorithms with those of QML.
2. Scalability - Comparing the effectiveness of each approach as the amount of data and its complexity increase.
3. Optimization Capabilities – Checking how quantum algorithms (e.g. QAOA, VQE) perform in solving optimization issues that are typical in AI applications such as feature selection and hyperparameter tuning.
4. Error Tolerance and Stability - Discusses the impact of quantum noise and errors on the performance of AI models compared to classical models.
5. Energy Efficiency - Comparing the power consumption of conventional hardware (such as GPUs, TPUs) to quantum processors.

Table 1: Comparison of Classic AI vs. Quantum AI

Aspect	**Classical AI**	**Quantum AI**
Data Processing	Traditional methods, structured pre-processing	Quantum data encoding, superposition, entanglement
Feature Engineering	Manual & automated feature extraction	Quantum feature mapping, enhanced representations
Model Training	Neural Networks, SVMs	QML algorithms, quantum circuits

Computational Complexity	High time & resource consumption	Exponential speedups using quantum computation
Scalability	Struggles with large datasets	Improved scalability via quantum parallelism
Optimization	Gradient Descent, Bayesian Optimization	QAOA, VQE, Quantum-enhanced tuning
Error Tolerance	Sensitive to noise, needs regularization	Affected by quantum noise, requires error mitigation
Energy Efficiency	High power consumption (GPUs, TPUs)	Potential for lower power consumption
Model Evaluation	Accuracy, stability, generalization	Quantum-enhanced accuracy and robustness

The framework of the analysis uses a benchmark approach where conventional and quantum AI systems are compared under equal conditions with real world datasets and performance metrics.

4.2. Simulation and Modeling Methodologies

Since there are currently limitations on the availability of quantum hardware, a combined approach is used, which includes classical modelling of quantum algorithms and actual application on real quantum hardware whenever available. The research employs:

1. Quantum Circuit Simulators — Applications including IBM Qiskit Aer, Google Cirq, and PennyLane are used to model quantum AI designs before they are applied to real hardware.

2. Quantum Classical Intermediary — It uses VQCs to design quantum enhanced learning models and classical optimizers to tune them.

3. Monte Carlo Simulations — Used to model the stochastic nature of quantum algorithms in solving high dimensional optimization problems.

4. Tensor Network Methods — Used to describe the quantum states in classical simulations to understand the possible benefits of scale up.

4.3. Sources of Data and Selection of Case Studies

The study applies AI and QML models to concrete data sets across different industries to ensure the findings are practical. Chosen datasets comprise:

1. Finance — Historical trading data of S&P 500 and cryptocurrency prices for stock market forecasting and risk assessment.
2. Healthcare — Medical image classification and genetic data analysis using publicly available datasets such as the NIH Chest X-ray dataset or the Cancer Genome Atlas.
3. Supply Chain Optimization – Route optimization and logistics management using data sets from OpenStreetMap and commercial supply chain networks.
4. Quantum Computing Benchmarks — Standardized datasets like MNIST for classification tasks and specific datasets for quantizing models to test quantum models.

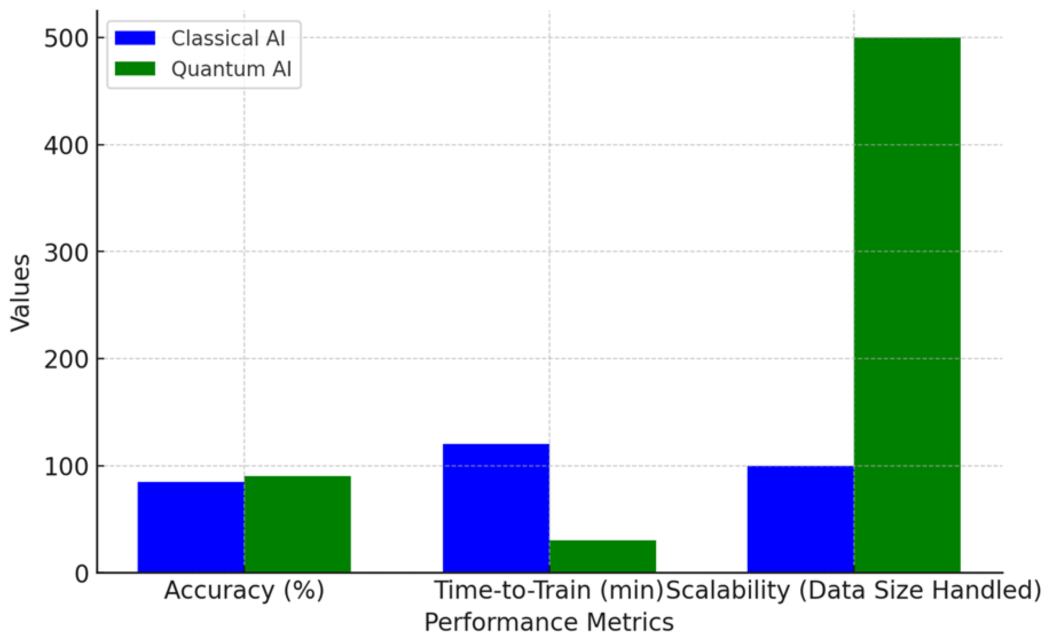

Figure 2: Benchmark Results: Classical vs. Quantum AI

The case studies aim to illustrate how the integration of quantum technology into AI may outperform conventional approaches in certain applications, particularly in combinatorial optimization and complex pattern recognition.

5. AI-QUANTUM SYNERGIES: POTENTIAL AND CHALLENGES

5.1. Quantum Machine Learning (QML) for Large-Scale Analytics

Enhancing Feature Selection and Clustering

Quantum Machine Learning (QML) is a new field that combines the principles of quantum computing with conventional machine learning techniques to develop new strategies for data analysis. In feature selection and clustering, QML is better in dealing with high dimensional data than conventional methods. Some quantum techniques like the Quantum Approximate Optimization Algorithm (QAOA) have been proposed to solve combinatorial optimization problems in feature selection to identify good features while keeping computational cost minimal [12].

Furthermore, QAOA has been shown to be efficient in solving graph partitioning problems such as Max-Cut that is useful in network design and data clustering [13].

Accelerating AI Model Training with Quantum Optimization

Training of artificial intelligence models, especially deep neural networks is computationally expensive and time consuming. Some optimization algorithms in quantum such as the Variational Quantum Eigensolver (VQE) can speed up this process by finding the optimal parameters more efficiently. These algorithms explore many parameter configurations concurrently through quantum parallelism, which reduces the time to convergence and allows the training of more complex models on larger datasets.

5.2. Quantum Assisted Decision Making in Finance and Healthcare

Risk Modeling and Portfolio Optimization

In the financial domain, risk management and portfolio management require the evaluation of a large amount of data to make the right investment decisions. Quantums computing can solve complex probabilistic models faster than the classical computer, thus providing better risk assessment and better portfolio management. Companies such as Terra Quantum are using quantum algorithms to enhance financial modeling and collateral management, which are some of the real applications of quantum computing in the financial services industry.

Drug Discovery and Genomic Data Analysis

There are many applications of quantum computing in drug discovery and genomic data analysis. Quantum computing can precisely simulate the molecular dynamics and may determine the properties of new drugs and may even reduce the time and cost of introducing new drugs to the market. Schrödinger Inc. has developed computational systems that predict the properties of chemicals and thereby aid in the design of new drugs [14].

Also, the collaboration between Schrödinger and Novartis, which may reach $2.5 billion, demonstrates the willingness of the industry to integrate quantum computing into the drug discovery process [15].

The integration of quantum computing with AI-driven predictive analytics in healthcare finance has the potential to exponentially enhance data processing capabilities, enabling more accurate forecasting, optimizing resource allocation, and driving cost-effective, patient-centric decision-making at scale [16].

5.3. Integration Challenges

Hardware Demands and Quantum Error Correction Demands

Although there are many prospects for integrating quantum computing with AI systems, there are major difficulties. The current quantum hardware has qubit coherence times and error rates that are poor and require the development of good quantum error correction codes. These constraints are a major impediment to the real-world application of large-scale quantum algorithms and require ongoing research into the stability and robustness of the hardware.

Lack of Standard Quantum Programming Frameworks

The absence of standard quantum programming frameworks poses a significant challenge. Different quantum hardware platforms require varied programming approaches, limiting the development of universally applicable quantum applications. Developing standard frameworks is essential for integrating and embedding quantum computing into current AI architectures effectively.

Scalability Concerns Regarding Practical Implementation

Scalability is a major problem when it comes to the application of quantum enhanced AI. Although the small-scale experiments are promising, translating these systems to manage the large real-world data analytics tasks is difficult due to the limitations of the hardware and the complexity of quantum algorithms. Therefore, the ongoing development of quantum hardware and algorithms is crucial to address the scaling problem and realize the potential of AI-Quantum convergence.

6. FUTURE DIRECTIONS AND EMERGING TRENDS

Progress in Hybrid Quantum-Classical Computing

Hybrid quantum-classical computing integrates the advantages of quantum and classical systems to address intricate computational challenges more efficiently. This method utilizes the recognized strengths of classical computing in conjunction with the potential of quantum computing to address jobs more effectively. For example, businesses like Quantinuum have created platforms like TKET, an open-source quantum software development kit, to enhance quantum algorithms and enable their integration with classical computer systems [17].

Likewise, Multiverse Computing's Singularity platform allows individuals lacking prior quantum computing expertise to utilize quantum algorithms using familiar applications such as Microsoft Excel, thereby connecting classical and quantum computing [18].

The Function of AI in Enhancing Quantum Algorithms

AI significantly enhances quantum computing by optimizing quantum algorithms and alleviating current hardware constraints. Collaborations between AI and quantum computing organizations have resulted in substantial progress. Quantinuum partnered with Google DeepMind to employ AI (Alpha-Tensor) for optimizing the T-gate count, with the objective of reducing the computational expenses linked to one of the most resource-demanding quantum logic gates [19]. AI will also facilitate progress in Internet of Things (IoT) and Edge Computing technologies [20].

Predictions on Commercialization and Industrial Adoption

The path toward the commercialization and industrial deployment of quantum computing evokes both optimism and caution. Prominent technological companies, including Google, Microsoft, and Amazon, have introduced new quantum computing prototypes, indicating substantial investments in this field. Nevertheless, academics and industry specialists assert that significant advancements, especially in error correction and scalability, may remain many years distant, with operational and usable quantum computers likely 10 to 20 years ahead [21].

Despite these hurdles, the increasing interest and investment in quantum computing persist in propelling research and development, facilitating the field's incremental progress. As technology advances, its incorporation into diverse sectors is expected to transform businesses including finance, healthcare, and transportation by significantly enhancing optimization, pattern recognition, and simulation capacities [22].

7. CONCLUSION

It is an evolutionary change in computational efficiency that has been brought about by the integration of quantum computing and artificial intelligence to solve the challenges in AI driven big data analytics. This paper has highlighted the advantages of quantum computing in improving the training of AI models, optimizing complex tasks and improving the performance of high dimensional data analysis. The various quantum machine learning techniques that include Grover's search, QAOA and VQE have been applied effectively in solving challenging AI problems that are typically hard for classical systems to solve accurately.

However, there are several major challenges that stand in the way of fully integrating quantum-enhanced AI in practice. Quantum hardware is still under development and has its issues including qubit coherence, quantum error correction, and insufficient scalability that limit the practical use. The lack of standard quantum programming paradigms makes it difficult to integrate quantum computing into the current AI infrastructure without complications.

Nevertheless, the research and development processes are still active and granted by large technology companies to sustain the development of hybrid quantum-classical computing and quantum smart AI. The future of AI quantum synergy will be defined by the development of quantum hardware, quantum algorithms, and the development of real quantum computing applications in such areas as banking, healthcare, and supply chain. Although we may not see fully fledged commercial quantum computing in the next few years, the ongoing quantum AI research shows that these technologies will one way change the way we look at computation, large data analysis and decision making.

REFERENCES

[1] Fernández Pérez, I., Prieta, F. de la, Rodríguez-González, S., Corchado, J. M., & Prieto, J. (2023). Quantum AI: Achievements and Challenges in the Interplay of Quantum Computing and Artificial Intelligence. In Lecture Notes in Networks and Systems (pp. 155–166). Springer International Publishing. https://doi.org/10.1007/978-3-031-22356-3_15

[2] Malaga, M. (2021). Next-Generation Big Data Analytics: Integrating AI and Machine Learning for Scalable Decision-Making Frameworks. In International Journal of Innovative Research in Science, Engineering and Technology (Vol. 10, Issue 03, pp. 267–282). Ess & Ess Research Publications. https://doi.org/10.15680/ijirset.2021.1003214

[3] Akoh Atadoga, Ogugua Chimezie Obi, Femi Osasona, Shedrack Onwusinkwue,

Shedrack Onwusinkwue, Andrew Ifesinachi Daraojimba, & Samuel Onimisi Dawodu. (2024). QUANTUM COMPUTING IN BIG DATA ANALYTICS: A COMPREHENSIVE REVIEW: ASSESSING THE ADVANCEMENTS, CHALLENGES, AND POTENTIAL IMPLICATIONS OF QUANTUM APPROACHES IN HANDLING MASSIVE DATA SETS. In Computer Science & IT Research Journal (Vol. 5, Issue 2, pp. 498–517). Fair East Publishers. https://doi.org/10.51594/csitrj.v5i2.794

[4] Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2023). Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges. In Applied Sciences (Vol. 13, Issue 12, p. 7082). MDPI AG. https://doi.org/10.3390/app13127082

[5] Sharma, A. (2022). QUANTUM COMPUTING: A REVIEW ON BIG DATA ANALYTICS AND DATA SECURITY. In International Research Journal of Computer Science (Vol. 9, Issue 4, pp. 96–100). AM Publications. https://doi.org/10.26562/irjcs.2021.v0904.005

[6] Shaikh, T. A., & Ali, R. (2016). Quantum Computing in Big Data Analytics: A Survey. In 2016 IEEE International Conference on Computer and Information Technology (CIT) (pp. 112–115). 2016 IEEE International Conference on Computer and Information Technology (CIT). IEEE. https://doi.org/10.1109/cit.2016.79

[7] Rane, N., Paramesha, M., Choudhary, S., & Rane, J. (2024). Machine Learning and Deep Learning for Big Data Analytics: a Review of Methods and Applications. In SSRN Electronic Journal. Elsevier BV. https://doi.org/10.2139/ssrn.4835655

[8] Dunjko, V., & Briegel, H.J. (2017). Machine learning \& artificial intelligence in the quantum domain. ArXiv, abs/1709.02779.

[9] Rahaman, S. U., & Patchipulusu, S. (2022). Ethical implications of AI-Driven IoT systems: Perspectives from data Practitioners. Journal of Mathematical & Computer Applications, 1–6. https://doi.org/10.47363/jmca/2022(2)e135

[10] Shaik, M. (2024). Robot Manager: AI-Powered Oversight of digital workers in

Hospitality. Zenodo. https://doi.org/10.5281/zenodo.14471669

[11] Gogineni, A. (2023). Artificial Intelligence-Driven Fault Tolerance Mechanisms for Distributed Systems Using Deep Learning Model. Journal of Artificial Intelligence, Machine Learning and Data Science, 1(4), 2401–2406. https://doi.org/10.51219/jaimld/anila-gogineni/519

[12] Farhi, E., Goldstone, J., Gutmann, S., & Zhou, L. (2022). The Quantum Approximate Optimization Algorithm and the Sherrington-Kirkpatrick model at infinite size. Quantum, 6, 759. https://doi.org/10.22331/q-2022-07-07-759

[13] Quantum Approximate Optimization Algorithm (QAOA). (2024, February 22). https://www.classiq.io/insights/quantum-approximate-optimization-algorithm-qaoa

[14] Schrödinger. (2025, February 10). Schrödinger - Physics-based Software Platform for Molecular Discovery & Design. https://www.schrodinger.com/

[15] Philippidis, A. (2024, December 13). Schrödinger, Novartis Ink Up-to-$2.3B Collaboration, Software Agreement. GEN - Genetic Engineering and Biotechnology News. https://www.genengnews.com/topics/drug-discovery/schrodinger-novartis-ink-up-to-2-3b-collaboration-software-agreement/

[16] Veernapu, K. (2021b). The role of Artificial Intelligence in healthcare finance: Improving financial forecasts and operational effectiveness. International Journal of Multidisciplinary Research and Growth Evaluation, 2(4), 873–876. https://doi.org/10.54660/.ijmrge.2021.2.4-873-876

[17] Wikipedia contributors. (2025c, February 25). Quantinuum. Wikipedia. https://en.wikipedia.org/wiki/Quantinuum?

[18] Wikipedia contributors. (2025d, February 25). Multiverse computing. Wikipedia. https://en.wikipedia.org/wiki/Multiverse_Computing

[19] Wikipedia contributors. (2025f, February 25). Quantinuum. Wikipedia. https://en.wikipedia.org/wiki/Quantinuum

[20] Swathi, S. (2024). Cloud-Native Data Science for Edge Computing and IoT Applications. International Journal of Current Science Research and Review, 07(10), 8011–8016. https://doi.org/10.5281/zenodo.13994966

[21] Tangalakis-Lippert, K. (2025, March 4). Big Tech is starry-eyed over quantum computers, but scientists say major breakthroughs are years away. Business Insider. https://www.businessinsider.com/scientists-say-major-quantum-computing-breakthroughs-are-years-away-2025-2

[22] Spencer, B. (2024, September 27). What is quantum computing? Our science editor tries to explain. The Sunday Times. https://www.thetimes.com/magazines/the-sunday-times-magazine/article/what-is-quantum-computing-explained-science-editor-hn8ks0blj.