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# Redefining the Classical Limits of Data Analysis using Quantum Data Science - A Review

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**Abstract--** Quantum Data Science is an area of research that combines data science, machine learning, optimization theory and quantum computing. This field of Quantum Data Science is really exciting because it can change the way we look at complicated sets of data. Quantum Data Science does this by using effects that happen in the quantum world, which regular computers cannot do. Quantum Data Science is really powerful. Quantum Data Science has a lot of potential to make an impact, on how we analyze large and complex datasets, which is a big part of Quantum Data Science. Quantum computing is really good at solving problems with data. Quantum computing is especially good, with complicated data that is hard to understand. Quantum circuits and quantum optimization models can be useful alternatives to the machine learning models we use now for data analytics. This survey review of Quantum Data Science, providing an overview of its foundational principles, quantum computing paradigms, and quantum-enhanced data analysis algorithms.

**Keywords--** Quantum Data Science, Applied Quantum Computing, Quantum Machine Learning, Data Analytics.

## I. INTRODUCTION

Data science has emerged as one of the most influential and popular scientific practices both in the business community and the university setting due to its potential to extract useful patterns and make predictions based on the vast amount of complex data available. The conventional approaches used in data analysis incorporate various statistical approaches, machine learning techniques, optimization procedures, and problem-specific heuristics such that the solutions to diverse real-world problems can be achieved in the areas of finance, medicine, cyber security, weather modeling, and social media graphs. The exponential growth of the volume of the available data and the rate at which it is coming in with increasing variety, commonly referred to as Big Data, has presented various computational challenges that challenge the classical approaches of computing [1], [2].

Machine learning and optimization elements form the foundation of data science today and facilitate operations like classification, clustering, discovery of patterns, regression, and detection of anomalies.

Deep learning architectures and ensemble systems have proved to be effective in solving numerous data-intensive tasks with superior performance. However, such systems require substantial computational resources and considerable time for accomplishing the tasks, especially for large dimensions. Classical computers with the aid of distributed and high-performance computing may face difficulties in efficiently exploring very large problem spaces and providing timely solutions for specific problem types [3], [4].

Quantum computing is a new computing paradigm with promising capabilities to address many inherent limitations of the classical data analysis process. Quantum computing is based on the fundamental concepts of quantum physics, such as superposition, quantum entanglement, and quantum interference. Qubits are used as the basic unit of quantum computing to represent the quantum states of the system, which are otherwise difficult to express by classical computers [5], [6]. This basic gap allows quantum computers to simultaneously explore many computational paths and thereby achieve potential speedups for certain algorithms and optimizations problems. For specific problems, quantum advantage, when a quantum algorithm performs better than the best known classical algorithm for some task, has indeed been demonstrated and is being further extended due to active hardware and algorithmic improvements that keep increasing the range of tractable problems which may benefit from quantum enhancements [7].

Some advances in quantum hardware development and the introduction of Noisy Intermediate Scale Quantum computing have brought quantum computing within the grasp of experimentalists through cloud-based quantum computing platforms developed by leading information and communication technology organizations and research organizations around the globe [8], [9]. These platforms allow scholars to try out quantum circuit programming and simulation with the aim of executing a number of hybrid quantum-classical optimization strategies even as the current quantum computing capabilities remain in their infancy in terms of the number of qubits that they possess and the rate of decoherence that they exhibit.

In this changing environment, it is noticed that a new, emerging data science discipline, titled Quantum Data Science, can be considered as the intersection of the fundamental principles of data science and quantum paradigms of computation. It can also be viewed as a novel, emerging data science discipline that is not based merely on the principles of classical algorithms and systems, like the case of data science; instead, it utilizes the power of quantum resources to develop new algorithmic platforms, perform efficient optimization, and even transcend the boundaries of the limitations of data analysis in the era of classic technology [10], [11].

Definition of Quantum Data Science:

Quantum Data Science denotes the systematic development and application of data analysis techniques leveraging quantum computational models, like gate-based quantum computing and quantum annealing, either fully or partially, to realize performance improvements, improved scalability, or fundamentally new analytical capabilities that lie beyond classical limits.

The latter belongs to several paradigms of quantum computing. Quantum computing in its gate version uses sequences of quantum gates on qubit registers to implement parameterized quantum circuits, which can be leveraged for learning and optimization problems. On the other hand, quantum annealing relies on adiabatic evolution to solve optimization problems for QUBO or Ising models, which naturally appear in many data science applications [12]. Some techniques for encoding quantum data include amplitude, angle, or basis encoding, which are essential to transform classical information into quantum states directly consumable by quantum processors and thus play an important role in algorithm development and performance [13].

However, Quantum Data Science remains at the early, exploratory stage despite its promise. Practical deployment is severely limited due to hardware limitations, noise effects, and efficient encoding of large classical datasets into their quantum analogs without losing potential quantum advantages. Besides, thorough benchmarking against classical baselines and strict performance analysis are crucial in correctly estimating actual benefits of quantum-enhanced approaches for real data science applications [14].

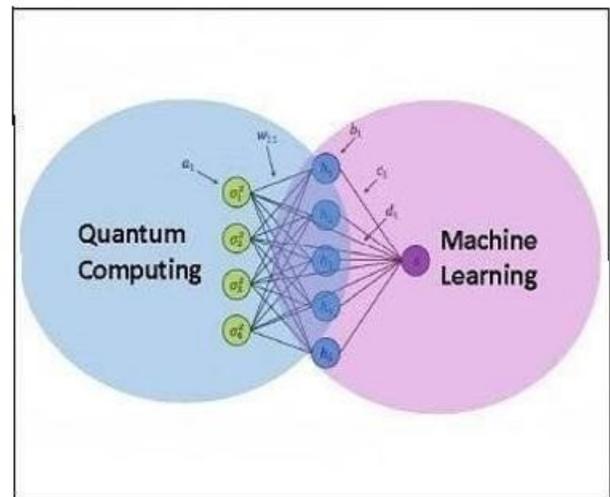
## II. LITERATURE REVIEW

Quantum Data Science (QDS) has grown into a collaborative interdisciplinary area that uses classical data science techniques combined with the efficiency brought by quantum computing.

In recent years, there has been extensive interest in applying quantum resources for solving challenging problems associated with high-dimensional data analysis, optimization, and machine learning, which are difficult or even impossible to handle by classical approaches themselves [1–14].

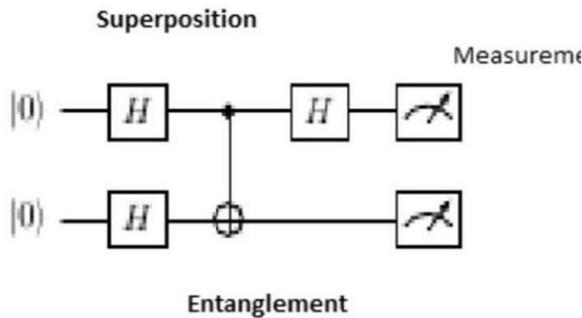
### 2.1 Quantum Machine Learning (QML)

Quantum Machine Learning (QML) is perhaps the most popular field to be studied within the domain of QDS, with researchers such as Zegundry et al. in their paper [1] giving the first comprehensive overview of QML techniques and techniques for how the power of quantum circuits can be used to improve the traditional data analysis techniques commonly used in classical computing. While Thanasilp et al. in their paper [2] sought to elucidate the intricacies in learning quantum models, other researchers such as Tomar et al. attempted a broader overview of the field of QML. Another factor that has promoted this domain is regional development. Li et al. published a paper that reviewed the development of QML research studies carried out in China. This showed how this domain has rapidly grown. Another paper by Ivanova et al. covered quantum computing and classical machine learning workflows.



### 2.2 Data Encoding for Quantum Systems

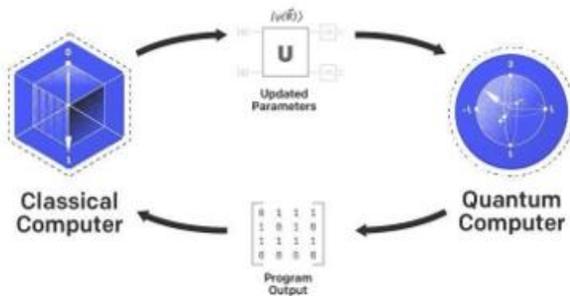
An important part of QDS is the effective encoding of classical data in a quantum state. Rath and Date in their work [6] compared different encoding methods, namely amplitude encoding, angle encoding, and basis encoding, and analyzed their influence on the complexity of quantum circuits. In a work on big data processing using quantum computing, namely, QDS, by Ilyas and Ilyas in [7], the encoding is stated to have a major impact in QD.



### 2.3 Hybrid Quantum–Classical Approaches

In this context, hybrid methods that fuse quantum computing and classical optimization methodologies have started receiving significant attention with respect to QDS. Nida & Penumarthy emphasize[d] the capability of hybrid systems in facilitating faster execution of data analytics using quantum computing. This allows for efficient exploration of large solution spaces. López- Meneses et al. demonstrate[d] how quantum computing in the cloud helps facilitate practical applications in education and research scenarios that teach quantum- enhanced data analytics.

Owidi and Omieno offered a comprehensive review on hybrid approaches to QML, concluding that using a combination of quantum circuits and classical algorithms could enhance convergence, optimization, and prediction. In turn, Purohit and Vyas also discussed alternative applications, such as quantum key distribution, using QDS techniques.



### 2.4 Domain-Specific Applications

The areas of QDS's practical use are very diverse. In Khan's work [12], the author used QML to propose a predictive application for financial risk analysis. The accuracy and efficiency of the predictive results were significantly higher with QML than with conventional approaches.

In the paper by Y. et al. [13], the authors reviewed different hybrid quantum-classical approaches to solving problems in the health sector, finance, and scientific simulations. The available approaches efficiently solved problems in complex description spaces. X. et al.'s paper [14] focused on the practical implementation of QML and hybrid approaches using noisy intermediate-scale quantum computing. Challenges include noise, decoherence, and the number of qubits available for the computations.

### 2.5 Challenges in Quantum Data Science

Despite these promises, several challenges remain. Current quantum hardware is limited by the number of qubits, noise, and coherence times. Algorithmic constraints such as circuit depth and efficient data encoding also restrict performance further [2, 6, 14]. Furthermore, proper benchmarking of quantum algorithms against classical baselines is required to demonstrate real advantage in practical settings [3, 7]. Overcoming this demands effective hybrid designs and error mitigation strategies [10, 13].

### 2.6 Research Gap

Although the field of QDS has experienced a surge in the number of research studies carried out, there still exist additional needs to be filled in exploiting the computational power available using quantum computing for the betterment of data science in real- world applications. The existing literature mainly focuses on experimental, algorithmic, and theoretical work, while the need for the development of a complete picture in which quantum-enhanced learning, optimization, and analytics can be integrated in a practical way remains to be filled [1–14].

## III. APPLICATION

### 3.1 Intelligent Robotics

For example, there are quantum algorithmic processes that can better handle sensor and actuator data. This allows robots to adapt to changing environments through real-time updates, resulting in precise actions.

### 3.2 Autonomous Vehicles

Quantum-optimized systems for optimization enable self-driving vehicles to enhance their ability to navigate through the road. Such systems will enable self-driving cars to make real-time adjustments to their control systems, including perception systems.



### 3.3 Industrial Automation

Quantum Data Science enables predictive maintenance, process optimization, and even scheduling in smart factories by rapidly analyzing large volumes of sensor and operational data-building down the possibility of downtime and driving high production efficiency.

### 3.4 Smart Energy Systems

Quantum algorithms optimize power grid operations, energy storage, and renewable integration. This enhances the stability and resilience in the energy system, enabling it to adapt in real time to any fluctuations in supply and demand.

### 3.5 Aerospace and UAVs

Quantum-enhanced data analytics enhances the control systems of drones and aircraft by allowing for adaptive flight-path optimization, load balancing, and compensation for wind gusts and environmental disturbances.

## IV. FINDINGS

### 4.1 Quantum Advantage and Adaptive Analysis

- QDS reveals improved power in analyzing complex high-dimensional data sets that conventional methods find particularly difficult to handle.
- The fusion of various components of quantum computing, like superposition and entanglement, with traditional machine learning will create more adaptive learning with faster convergence.
- Hybrid models of quantum-classical computing have the capacity to continuously adapt to changes in data while it is being processed.

### 4.2 Performance Impro

- Quantum-enriched methodologies result in substantial reductions of the time taken to solve optimization-intensive problems, as seen when comparing the outcome of classical
- They offer higher predictive accuracy and efficiency when utilized for operations like financial risk analysis, healthcare predictions, and data analytics.

- Parametrized quantum circuits facilitate the exploration of vast solution space much more efficiently with better performance in problems for which classical approaches are struggling due to combinatorial explosion.

### 4.3 Computational and Implementation Aspects

- Although quantum calculations involve algorithmic complexity, hybrid approaches guarantee practicality using current Noisy Intermediate-Scale Quantum (NISQ) technology.
- Cloud-based quantum platforms and simulation tools facilitate experimentation and integration with classical pipelines, making it accessible in research and industrial applications.
- The modularity of the approaches in the QDS paradigm makes it possible for them to be used in conjunction with existing classical analytical systems without the need to replace the respective hardware.

### 4.4 Robustness

- Quantum Data Science demonstrates robustness with noisy and uncertain data that are characteristic of large and complex data sets, especially those where strategies involving error mitigation and data encoding are adopted.
- Hybrid quantum classical approach is also capable of making reliable predictions even in actual scenarios where classical approach may not work due to dimensionality and non-linearity.
- The flexibility of QDS ensures its consistency of performance across various problem domains.

### 4.5 Applicability and Practical Importance

- QDS is appropriate for high-impact domains like finance, healthcare, cybersecurity, climate modeling, and autonomous systems.
- In real-time data analysis, prediction, and optimization, quantum computing brings speed and precision enhancements.
- This process helps to overcome the limitations found in classical data science methods and establish a pathway toward energy-efficient analytics frameworks.

*COMPARISON STUDY:*

Method	Processing Strategy	Adaptation / Learning	Handling Complex Data	Computational Complexity	Suitability for Real- Time Use
<b>Classical Machine Learning (SVM, Decision Trees, Neural Networks)</b>	Traditional CPU/GPU-based algorithms	Offline or incremental online learning	Moderate – struggles with very high-dimensional or strongly correlated data	Moderate–High	Moderate
<b>Classical Deep Learning</b>	GPU/CPU training of large models	Batch or online learning	High – can handle complex data but requires long training times	High	Low–Moderate
<b>Bio-Inspired Optimization (GA, PSO, ACO)</b>	Evolutionary algorithms for parameter tuning	Rule-based adaptation	Low–Moderate – works well offline	Moderate–High	Low
<b>Quantum Machine Learning (QML)</b>	Parametrized quantum circuits and quantum optimization	Continuous online learning	Very High – exploits superposition to encode many features	Moderate	High (NISQ devices)
<b>Hybrid Quantum–Classical ML</b>	Quantum feature encoding + classical optimization	Adaptive via quantum-classical feedback loops	High – captures complex correlations efficiently	Moderate–High	Moderate–High
<b>Quantum Annealing</b>	Adiabatic evolution / QUBO optimization	Limited – problem-specific adaptation	Moderate – optimized for combinatorial problems	Moderate–High	Low
<b>Quantum Data Encoding (Amplitude / Angle / Basis)</b>	Mapping classical data into quantum states	None (encoding step only)	Moderate – preserves correlations for downstream algorithms	Low–Moderate	Moderate
<b>Noisy Intermediate- Scale Quantum (NISQ) Devices</b>	Experimental quantum circuits with limited qubits	Partial adaptation via hybrid algorithms	Moderate – constrained by qubit count	High	Moderate
<b>Parametrized Quantum Circuits (PQC)</b>	Variational quantum circuits	Continuous adaptation via variational parameters	High – encodes many features efficiently	High	Moderate

**V. CONCLUSION**

The Quantum Data Science, which is a paradigm that needs to be understood in reference to its combination of both quantum computing and classical data science/machine learning methods. Unlike others that depend on the capacities of computers in processing information, QDS follows phenomena like superposition, entanglement, and interference in quantum mechanics to provide effective computation in very high-dimensional spaces. The need to develop QDS resulted from the growing demand for quicker, precise, and scalable data analysis methods that conventional data analysis algorithms can no longer provide.

QDS needs to be considered and understood as a harmonic mix of hybrid classical/quantum methods, parametrized quantum circuits, and optimal quantum encodings to ensure versatile, resilient, and top-performance data analysis. Thus, even though the present research deals with theory principles, new emerging methods and approaches, and potential applications, its conclusions indicate that QDS can make a huge impact in relation to computational efficiency, accuracy, and reliability regarding data analysis.



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