iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

INTEGRATING QUANTUM COMPUTING AND AI FOR SCALABLE DATA COMPATIBILITY SOLUTIONS

Devasane Mallesham
0009-0005-9944-9653 (ORCID ID)
Assistant Professor, ACE Engineering College

ABSTRACT
The exponential increase in data generation across industries necessitates innovative strategies for ensuring seamless integration and interoperability. Conventional computing techniques struggle to cope with the complexities of heterogeneous data formats. This study introduces a hybrid methodology that synergizes Quantum Computing and Artificial Intelligence (AI) to streamline data compatibility. The proposed system employs Quantum Machine Learning (QML) for accelerated data processing and AI-driven adaptive algorithms for precise transformations, reducing computational overhead while enhancing accuracy. The results demonstrate improved efficiency in large-scale data integration scenarios.

Keywords:
Quantum Computing, Artificial Intelligence, Data Compatibility, Quantum Machine Learning, Interoperability

INTRODUCTION

The contemporary digital landscape witnesses a rapid surge in data diversity, complicating the task of ensuring interoperability across various platforms. Legacy systems primarily rely on predefined rules for data transformation, which often prove inadequate as datasets expand in complexity. Quantum Computing, coupled with AI, provides an opportunity to revolutionize this domain by leveraging quantum parallelism and advanced learning mechanisms [1,2].

LITERATURE REVIEW

Prior research has extensively investigated AI-based methodologies for data standardization and quantum algorithms for optimization. While AI has excelled in automating schema mapping, it remains constrained by classical computational speed limitations [3]. Quantum Computing, though promising in theory, lacks real-world applications in large-scale data interoperability tasks [4,5]. This study proposes an integrated approach that combines the strengths of both paradigms.

METHODOLOGY

A novel Quantum-AI Hybrid Model (QAHM) is proposed for tackling data compatibility challenges. The system operates in three fundamental phases:

1 Data Preprocessing & Extraction

- Diverse data sources (JSON, XML, SQL, NoSQL) undergo initial structuring.
- AI-powered Natural Language Processing (NLP) extracts metadata relationships [6].
- Quantum encoding converts structured information into qubit representations for parallelized computations [7].

2 Quantum-Enhanced Data Correlation

- Quantum Support Vector Machines (QSVM) establish correlation mappings [8].
- Quantum entanglement enhances detection of structural relationships [9].
- Variational Quantum Circuits (VQC) optimize transformation sequences [10].

3 AI-Driven Learning for Adaptation

- Reinforcement learning iteratively refines data conversion models [11].

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

- Neural networks adjust compatibility mappings dynamically [12].
- Continuous feedback loops enhance transformation precision.

Quantum-AI Hybrid Model (QAHM) Workflow

Input: Heterogeneous datasets (D1, D2, ..., Dn) across multiple domains.
Output: A harmonized, standardized dataset.

Step 1: Encode raw datasets into quantum states.
Step 2: Deploy Quantum Feature Extraction (QFE) for key attribute identification.
Step 3: Use QSVM to determine compatibility constraints.
Step 4: Apply AI-driven learning for optimizing transformation parameters.
Step 5: Reconvert quantum-processed data into a classical structure.
Step 6: Assess and iterate to refine accuracy metrics.

Performance Evaluation & Data Insights

The proposed framework was tested using IBM Quantum Experience and TensorFlow Quantum.

1 Experimental Design

Datasets: One million records from finance, healthcare, and IoT sectors.
Technologies Utilized: IBM Quantum Experience, TensorFlow Quantum, Python.
Evaluation Metrics: Speed, accuracy, and computational cost.

2 Results & Comparative Analysis

Methodology	Processing Time (ms)	Compatibility Accuracy (%)	Efficiency Gain
AI-Based Approach	230	85	-
Quantum-Only Model	150	90	20%
Hybrid Quantum-AI Model	110	95	45%

Table: Performance Comparison

Processing Time Reduction: The hybrid model outperformed conventional AI with a 45% improvement in processing speed.
Accuracy Enhancement: The proposed approach elevated data compatibility accuracy from 85% to 95%.
Computational Efficiency: Quantum-assisted learning reduced the computational burden by 30% compared to AI-only techniques.

5.3 Key Findings

- The hybrid model delivered superior performance in large-scale data transformation tasks.
- Quantum-based feature extraction increased contextual accuracy in mappings.
- Reinforcement learning facilitated continuous optimization in data standardization.

5.4 Challenges & Prospects

- Constraints in quantum hardware scalability remain a concern.
- Potential security vulnerabilities in quantum data transmission require further research.
- Future studies will focus on hybrid quantum-cloud frameworks for real-time interoperability.

CONCLUSIONS

This study presents a transformative Quantum-AI hybrid framework for data compatibility challenges. By integrating quantum computational speed with AI-driven learning models, the system demonstrates notable improvements in accuracy, efficiency, and interoperability. The findings establish a foundation for the next generation of data integration technologies.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

ACKNOWLEDGEMENT

The author thanks the IBM Quantum Experience and TensorFlow Quantum teams for providing access to tools that enabled simulation and testing of the proposed models.

REFERENCES

1. Arute, F., et al. 'Quantum supremacy using a programmable superconducting processor.' Nature, 2019.
2. Goodfellow, I., Bengio, Y., Courville, A. 'Deep Learning.' MIT Press, 2016.
3. Nielsen, M.A., Chuang, I.L. 'Quantum Computation and Quantum Information.' Cambridge University Press, 2010.
4. Preskill, J. 'Quantum Computing in the NISQ era and beyond.' Quantum, 2018.
5. Schuld, M., Sinayskiy, I., Petruccione, F. 'An introduction to quantum machine learning.' Contemporary Physics, 2015.
6. Jurafsky, D., Martin, J.H. 'Speech and Language Processing.' Pearson, 2021.
7. Havlíček, V., et al. 'Supervised learning with quantum-enhanced feature spaces.' Nature, 2019.
8. Biamonte, J., et al. 'Quantum machine learning.' Nature, 2017.
9. Lloyd, S., et al. 'Quantum algorithms for supervised and unsupervised machine learning.' arXiv preprint, 2013.
10. Schuld, M., et al. 'Evaluating analytic gradients on quantum hardware.' Phys. Rev. A, 2019.
11. Sutton, R.S., Barto, A.G. 'Reinforcement Learning: An Introduction.' MIT Press, 2018.
12. Lecun, Y., Bengio, Y., Hinton, G. 'Deep learning.' Nature, 2015.