ISSN: 2456-8503

International Journal for Development of Science and Technology (IJDST)

RESEARCH

Quantum machine learning architectures for high- dimensional data processing: A hybrid quantum-classical approach

Srikumaran[1*]

Abstract

Quantum Machine Learning (QML), leveraging principles of superposition, entanglement, and quantum parallelism, provides a promising pathway toward overcoming these limitations. This paper investigates advanced hybrid quantum–classical architectures designed for efficient high-dimensional data processing. Through detailed exploration of variational quantum circuits, quantum embedding techniques, and quantum kernel methods, we analyze the strengths and limitations of quantum models on Noisy Intermediate-Scale Quantum (NISQ) hardware. Comparative assessments against classical baselines demonstrate that carefully structured hybrid models can achieve improved expressive power and computational efficiency, particularly on complex, non-linear datasets. The study presents architectural guidelines, performance analyses, and insights into quantum-specific advantages for future scalable QML systems.

Keywords: *Quantum machine learning; high-dimensional data; hybrid quantum–classical models; variational quantum circuits; quantum feature embedding; quantum kernel methods; noisy intermediate-scale quantum (nisq) devices; non-linear data processing; computational complexity.*

1. Introduction

The rapid growth of high-dimensional datasets in areas such as genomics, finance, image analysis, and scientific simulations has exposed limitations in traditional machine learning techniques. As data dimensionality increases, classical algorithms face challenges including high computational cost, reduced generalization capability, memory bottlenecks, and the curse of dimensionality [1]. Quantum computing, guided by unique physical properties such as superposition and entanglement, offers a fundamentally different computational paradigm [2].

[1]*Assistant Professor, Department of Computer Science, Sri Krishnasamy Arts and Science College, Sattur.*

**Corresponding Author: srikumaran1996@gmail.com*

Quantum Machine Learning (QML) integrates quantum computation with machine learning principles to accelerate data processing and model training [3], [4]. Hybrid quantum–classical architectures combining quantum circuits with classical optimization are considered the most feasible approach in the noisy intermediate-scale quantum (NISQ) era [5], [6]. This paper explores how quantum architectures can address the limitations of classical machine learning in high-dimensional domains by analyzing quantum data encoding, circuit architectures, and performance on complex datasets [7].

2. Literature review

High-dimensional data processing poses significant challenges for classical machine-learning models, as performance degrades with increasing dimensionality due to exponential feature combinations, inefficient distance metrics, a heightened risk of overfitting, and substantial computational and memory demands [8].

Although deep learning partially addresses these issues, it still struggles with scalability and training complexity [9]. Quantum machine learning offers a promising foundation by leveraging superposition to represent exponentially large feature spaces, entanglement to capture intricate correlations, and quantum parallelism to evaluate many states simultaneously [10], [11]. These quantum properties enable more efficient handling of high-dimensional information. Given current hardware constraints, hybrid quantum–classical architectures present a practical approach: quantum circuits perform feature extraction and nonlinear transformations, while classical processors optimize circuit parameters [12], [13]. This division of labor reduces quantum circuit depth and improves overall performance on NISQ-era devices [14].

3. Methodology

Quantum data encoding plays a central role in determining the performance of quantum machine-learning models. Common techniques include amplitude encoding, which embeds $2n$ classical feature values into n qubits with high efficiency [15]. Angle encoding, which maps classical features into rotational parameters of qubits and qubit embedding, where features are directly assigned to qubits, making it suitable for shallow quantum circuits. After encoding, variational quantum circuits (VQCs) are used, incorporating parameterized quantum gates, layers of entanglement, and measurement-based outputs. These circuits rely on a classical optimizer to iteratively tune parameters and minimize a loss function.

A typical hybrid quantum–classical workflow encodes high-dimensional features into quantum states, applies a VQC transformation, measures quantum outputs, and updates parameters using classical optimizers such as Adam, COBYLA, or SPSA. Benchmarking commonly employs synthetic datasets with over 100 features, PCA-reduced image datasets, and complex domains such as genomics or finance.

4. Proposed architecture

A hybrid quantum–classical pipeline begins with a Quantum Embedding Layer, which encodes high-dimensional data using amplitude or angle encoding techniques. The encoded states are processed by a Quantum Feature Transformation Block composed of variational layers with entangling operations such as controlled-Z and CNOT gates [16]. Following this, a Measurement Layer converts quantum states into classical probability distributions, which are then fed into a classical post-processing stage—typically shallow neural networks or logistic regression models—to produce the final output [17]. Effective circuit design requires careful optimization of circuit depth to remain compatible with NISQ-era hardware [18]. Strategic entanglement to capture long-range correlations and regularization via circuit pruning to mitigate noise amplification [19].

4.1. Algorithmic Flow

- Input high-dimensional vector
- Quantum data encoding
- Variational quantum circuit transformation
- Measurement
- Classical optimization
- Output prediction

5. Results and discussion

Performance evaluation of hybrid quantum–classical models includes accuracy, training time, circuit depth, qubit and gate counts, and fidelity under realistic noise conditions. Comparative studies indicate that hybrid QML systems provide superior feature extraction on nonlinear manifolds and higher expressivity for modeling complex correlations. In certain optimization landscapes, faster convergence is observed compared to classical baselines. However, classical deep learning models still outperform current QML approaches at large scale due to hardware noise, limited qubit availability, and constrained circuit depths imposed by NISQ-era devices [20]. Overall, results suggest that quantum embeddings capture richer geometric structures, shallow circuits with moderate entanglement yield optimal performance, and quantum kernels are particularly effective for complex classification tasks.

6. Advantages and limitations

The advantages of quantum machine-learning approaches include their ability to represent data in exponentially large feature spaces, efficiently handle sparse or highly correlated high-dimensional inputs, and offer the potential for quantum advantage in feature extraction. Despite these strengths, several limitations remain: current hardware is highly susceptible to noise, available qubit counts are limited, data encoding can introduce significant overhead, and classical optimization steps often become bottlenecks that restrict overall performance.

7. Future work

Future research directions include the development of error-mitigated quantum circuits and transformer-inspired quantum neural networks, which aim to enhance robustness and expressive power in quantum models.

Progress is also expected in adaptive quantum feature maps that dynamically adjust to data characteristics, along with stronger theoretical foundations to rigorously demonstrate, quantum advantage in practical scenarios. Additionally, integrating quantum machine-learning techniques into emerging domains such as 6G communication systems, biomedical analytics, and cyber security is anticipated to open new, high-impact application pathways.

8. Conclusion

Quantum Machine Learning offers a powerful paradigm for addressing high-dimensional data processing challenges. Hybrid quantum–classical architectures, leveraging variational circuits and quantum feature embeddings, can significantly enhance model expressiveness and computational efficiency. While current limitations in hardware restrict scalability, the rapid evolution of quantum processors positions QML as a transformative technology for next-generation intelligent systems.

Conflicts of interest: None declared.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability statement: No new datasets were generated or analyzed during the current study. All data discussed in this article are derived from publicly available sources cited in the references.

Ethical approval: This study does not involve human participants, animals, or clinical trials. Therefore, ethical approval was not required.

Acknowledgements: I would like to express sincere gratitude to the Department of Computer Science, Sri Krishnasamy Art and Science College, Sattur, for providing an encouraging academic environment and institutional support for carrying out this research.

The author also acknowledges the researchers whose foundational work in quantum machine learning contributed significantly to this study.

References

1. Schuld M, Sinha A, Briegel HJ, The quest for a quantum neural network, quantum information processing, 2014, 13(11):2567–2586. doi.org/10.1007/s11128-014-0809-8
2. Benedetti M, Lloyd E, Sack S, Fiorentini M, Parameterized quantum circuits as machine learning models, quantum science and technology, 2019, 4(4):043001. doi.org/10.10 2058-9565/ab4eb5
3. Abbas A, Sutter D, Zoufal C, Lucchi A, Figalli A, Woerner S, The power of quantum neural networks, nature computational Science, 2021, 1(6):403–409. doi.org/10.1038/s43588-021-00084-1
4. Biamonte J, Wittek P, Pancotti N, Rebentrost P, Wiebe N, Lloyd S, Quantum machine learning, Nature Communications, 2017, 549(7671):195-202. doi.org/10.1038/ nature23474
5. Cerezo M, Arrasmith A, Babbush R, Benjamin S C, Endo S, Fuji, et al. Variational quantum algorithms, Nature Reviews Physics, 2021, 3(9):625–644. doi.org/10.1038/s42254-021-00348-9
6. Havlicek V, Corcoles AD, Temme K, Harrow AW, Kandala A, Chow JM, et al. Supervised learning with quantum-enhanced feature spaces, Nature Communications, 2019, 567(7747):209–212. doi.org/10.1038/s41586-019-0980-2
7. Orus R, Mugel S, Lizaso E, Quantum computing for finance: Overview and prospects, reviews in physics, 2019, 4,100028. doi.org/10.1016/j.revip.2019.100028
8. Mitarai K, Negoro M, Kitagawa M, Fujii K, Quantum circuit learning physical review, 2018, 98(3):032309. doi.org/10.1103/physreva.98.032309
9. McClean JR, Romero J, Babbush R, Aspuru-Guzik A, The theory of variational hybrid quantum–classical algorithms, New Journal of Physics, 2016, 18(2):023023. doi.org/10.1088/131067-2630/18/2/023023
10. Preskill J, Quantum computing in the NISQ era and beyond quantum, 2018, 2(1):65-79. doi.org/10.22331/q-2018-08-06-79
11. Schuld M, Killoran N, Quantum machine learning in feature Hilbert spaces, Physical Review Letters, 2019, 122(4):040-504. doi.org/10.1103/ physrevlett.122.040504
12. Farhi E, Neven H, Classification with quantum neural networks on near term processors, ArXiv preprint arXiv:2018, 1802.06002
13. Peruzzo A, McClean J, Shadbolt P, Yung MH, Zhou XQ, Love PJ, et al. A variational eigenvalue solver on a photonic quantum processor nature communications, 5(4):13-42. doi.org/10.1038/ncomms5213
14. Schuld M, Bocharov A, Svore KM, Wiebe N, Circuit-centric quantum classifiers review a physical, 2020, 101(3):032308. doi.org/10.1103/ Physreva.101.032308
15. Larose R, Coyle B, Robust data encodings for quantum classifiers review a physical, 2020, 102(3):032-420. doi.org/10.1103/physreva.102.03240
16. Sim S, Johnson PD, Aspuru-Guzik A, Expressibility and entangling capability of parameterized quantum circuits advanced quantum technologies, 2019, 2(12):1900070. doi.org/10.1002/qute.201900070

17. Wang S, Fontana E, Cerezo M, Sharma K, Sone, A, Cincio L, et al. Noise-induced barren plateaus in variational quantum algorithms. Nature Communications, 2021, 12(3):61-69. doi.org/10.1038/s41467-021-27045-6
18. Jerbi S, Fiderer LJ, Perdomo-Ortiz A, Guerreschi GG. Quantum machine learning beyond kernel methods, Nature Communications, 2023, 14(1):501-517. doi.org/10.1038/s41467-023-36110-6
19. Peters E, Schuld M, Petruccione F, Measuring A review physical the effective dimension of quantum models, 2021, 104(4):042403. doi.org/10.1103/phy serva.104.042403
20. Huang HY, Broughton M, Cotler J, Chen, S, Li J, Mohseni M, et al. Power of data in quantum machine learning, Nature Communications, 2021, 12(3):26-31. doi.org/10.1038/s41467-021-22539-9