iJRASET
International Journal For Research in
Applied Science and Engineering Technology

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

**Volume:** 14 **Issue:** I **Month of publication:** January 2026

**DOI:** https://doi.org/10.22214/ijraset.2026.76869

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 14 Issue I Jan 2026- Available at www.ijraset.com*

# Quantum-Enhanced Classification and Clustering Through Hybrid Quantum–Classical Learning on Synthetic Data

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***Abstract: Quantum Machine Learning (QML) has emerged as a promising paradigm that combines principles of quantum computation with classical learning techniques to address challenges posed by complex, high-dimensional, and non-linear datasets. This work presents a systematic experimental study of quantum-enhanced classification and clustering using hybrid quantum–classical models evaluated on synthetically generated datasets. Quantum Support Vector Machines (QSVM) and Variational Quantum Classifiers (VQC) are implemented using the Qiskit framework and benchmarked against established classical algorithms. The synthetic datasets are carefully designed to control linearity, dimensionality, class overlap, and non-linear structure, enabling a detailed performance comparison under both ideal and noisy simulation conditions. The experimental results indicate that quantum feature representations can enhance class separability in non-linear scenarios, while also highlighting the practical limitations imposed by noise sensitivity and circuit depth constraints inherent to Noisy Intermediate-Scale Quantum (NISQ) devices .***

## I. INTRODUCTION

Classification and clustering constitute core tasks in machine learning and play a critical role in applications such as healthcare analytics, financial modeling, fraud detection, cybersecurity, and intelligent decision-support systems [1]. Although classical machine learning approaches have achieved considerable success in recent years, their performance often degrades when confronted with datasets exhibiting high dimensionality, strong non-linearity, and intricate feature relationships [1], [2].

To mitigate these challenges, kernel-based learning techniques and deep neural networks have been widely employed; however, these approaches often demand substantial computational resources and large volumes of labeled data [1]. Quantum computing introduces an alternative computational framework grounded in quantum mechanical phenomena, including superposition, entanglement, and interference, which enable information
processing in exponentially large Hilbert spaces [10], [11].

Quantum Machine Learning aims to exploit these quantum properties to enhance learning efficiency and representational capacity. In particular, quantum feature mappings and quantum kernel methods have gained attention as practical strategies for improving classification and clustering performance on near-term quantum devices [2], [4]. Hybrid quantum–classical models offer a realistic pathway for evaluating these approaches under current hardware and simulation constraints, especially within the limitations of Noisy Intermediate-Scale Quantum (NISQ) systems [9], [12].

## II. RELATED WORK

Early studies in quantum-enhanced machine learning demonstrated that embedding classical data into quantum feature spaces can significantly increase the expressive capacity of learning models. Havlíček et al. showed that quantum-enhanced feature maps can improve classification performance by exploiting the structure of high-dimensional Hilbert spaces [2]. Quantum kernel methods were subsequently introduced as a practical mechanism for leveraging such feature spaces without requiring full quantum optimization.

Further research established that several supervised quantum learning models, including Quantum Support Vector Machines and Variational Quantum Classifiers, can be formally interpreted as kernel-based methods. Schuld demonstrated that many quantum classifiers inherently operate as kernel machines, providing a theoretical bridge between classical and quantum learning paradigms [4]. The expressiveness of variational quantum models was further analyzed by Jäger and Krems, who highlighted their universality under appropriate circuit configurations [6].

In parallel, quantum-assisted clustering approaches have been explored through hybrid quantum autoencoders, quantum-enhanced k-means algorithms, and kernel-based clustering frameworks. Srikumar et al. proposed a hybrid quantum autoencoder architecture for improved clustering and classification performance [7]. Despite these advancements, most existing studies focus on isolated tasks or limited experimental setups. Unlike prior studies that evaluate classification or clustering independently, this work provides a unified experimental analysis of both tasks using consistent datasets. Comprehensive evaluations that jointly analyze classification and clustering within a unified quantum-enhanced framework remain limited, motivating the present study. Recent systematic reviews further emphasize the need for broader experimental validation of quantum machine learning techniques [8].

## III. PROBLEM STATEMENT

While quantum-enhanced machine learning models exhibit strong theoretical potential, their practical effectiveness under realistic quantum hardware constraints remains an open research challenge. Most currently available quantum devices operate in the Noisy Intermediate-Scale Quantum (NISQ) regime, where factors such as gate noise, decoherence, limited qubit connectivity, and measurement errors significantly affect computational reliability. These hardware imperfections can degrade the performance of quantum circuits, often offsetting the theoretical advantages predicted by idealized quantum models [10], [11]. In particular, the limited number of available qubits restricts the dimensionality of data that can be processed, while constraints on circuit depth impose limits on the expressiveness of quantum feature mappings.

Furthermore, quantum machine learning algorithms are highly sensitive to circuit depth and noise accumulation. Deeper circuits, although theoretically more expressive, are more susceptible to decoherence and gate errors, leading to unstable training and reduced classification accuracy in practice [12]. As a result, achieving a balance between circuit expressiveness and hardware feasibility remains a critical challenge for near-term quantum-enhanced learning models. These limitations highlight the importance of empirical evaluation under realistic noise models rather than relying solely on ideal quantum simulations.

In addition to hardware-related challenges, existing research in quantum-enhanced learning is often fragmented, with many studies focusing exclusively on either supervised learning tasks such as classification or unsupervised learning tasks such as clustering. Relatively few works attempt to evaluate both classification and clustering within a unified experimental framework using consistent datasets, evaluation metrics, and hardware assumptions. This lack of integrated analysis makes it difficult to draw general conclusions regarding the practical advantages and limitations of quantum-enhanced learning across different learning paradigms [4], [9]. Consequently, systematic experimental studies that jointly analyze classification and clustering under realistic NISQ constraints are necessary to better assess the real-world applicability of quantum-enhanced machine learning.

## IV. RESEARCH OBJECTIVES

The primary objective of this research is to systematically investigate the effectiveness and practical feasibility of quantum-enhanced learning models for both supervised and unsupervised machine learning tasks under realistic quantum hardware constraints. In particular, the study aims to bridge the gap between theoretical advances in quantum machine learning and their empirical validation on near-term quantum platforms.

The specific objectives of this research are as follows.

First, to design and generate synthetic datasets with controlled complexity, including linear separability, non-linear decision boundaries, and high-dimensional feature overlap, in order to ensure fair, reproducible, and unbiased evaluation of learning models [1], [2]. Synthetic datasets enable precise control over data characteristics and are commonly used in benchmarking learning algorithms.

Second, to implement Quantum Support Vector Machines (QSVM) and Variational Quantum Classifiers (VQC) using hybrid quantum–classical architectures, following established formulations of quantum kernel learning and variational optimization [3]–[7]. These models are selected due to their suitability for execution on Noisy Intermediate-Scale Quantum (NISQ) devices.

Third, to perform a comparative analysis between quantum-enhanced models and classical machine learning baselines, such as classical Support Vector Machines and k-means clustering, in order to quantify any performance gains attributable to quantum feature representations [1], [2], [5].

Fourth, to analyze the robustness of quantum-enhanced models under noisy simulation environments, examining the impact of quantum noise, circuit depth, and limited qubit availability on learning performance [10]–[12]. This objective directly addresses the challenges posed by current quantum hardware limitations.

Finally, to identify and characterize specific scenarios in which quantum feature spaces provide measurable advantages over classical feature mappings, particularly for datasets exhibiting strong non-linearity and complex feature interactions [3], [4], [9]. The outcomes of this objective aim to contribute practical insights into when and where quantum-enhanced learning is most beneficial.

## V. RESEARCH METHODOLOGY

This research adopts an experimental and comparative methodology that integrates classical machine learning techniques with quantum-enhanced learning models within a unified evaluation framework. The methodology is designed to ensure reproducibility, controlled experimentation, and fair comparison across learning paradigms.

### A. *Synthetic Dataset Design*

Three synthetic datasets are generated to evaluate learning behavior under increasing levels of complexity.

The first dataset is linearly separable, consisting of two classes generated from Gaussian distributions, and serves as a baseline for evaluating both classical and quantum models under ideal conditions [1], [2].

The second dataset is non-linearly separable, composed of concentric class structures that require non-linear decision boundaries, making it suitable for assessing the expressive power of quantum feature spaces [3], [4].

The third dataset is a high-dimensional overlapping dataset with multiple features and partial class overlap, designed to test model scalability and robustness in more challenging learning scenarios.

All datasets are normalized to ensure numerical stability and consistent feature scaling across classical and quantum implementations.

### B. *Classical Baseline Models*

Classical machine learning baselines include Support Vector Machines (SVM) for classification and k-means clustering for unsupervised learning. These algorithms are selected due to their widespread use, strong theoretical foundations, and established performance on synthetic datasets [1], [2]. The results obtained from these models serve as reference benchmarks against which quantum-enhanced approaches are evaluated.

### C. *Quantum-Enhanced Learning Models*

Quantum-enhanced classification is performed using Quantum Support Vector Machines (QSVM) and Variational Quantum Classifiers (VQC) implemented through the Qiskit framework. QSVM utilizes quantum kernel estimation, where similarity between data points is computed using quantum circuits that embed classical data into quantum feature spaces [3], [5].

VQC employs parameterized quantum circuits optimized via classical algorithms, following the hybrid learning paradigm proposed for NISQ devices [6], [7].

### D. *Quantum Data Encoding*

Classical feature vectors are mapped to quantum states using angle encoding, where individual features are encoded as rotation angles of quantum gates. This encoding strategy is selected due to its low circuit depth and compatibility with limited qubit resources, making it suitable for near-term quantum devices [4], [6].

### E. *Experimental Setup and Noise Modeling*

Experiments are conducted using shot-based quantum simulators, which emulate the probabilistic measurement behavior of real quantum hardware. Both ideal (noise-free) and noisy simulation environments are considered. Noise models incorporate depolarizing errors and measurement noise to reflect realistic NISQ conditions [10], [11].

Key experimental parameters such as circuit depth, number of qubits, and noise levels are systematically varied to analyze their impact on learning performance. This approach enables evaluation of the trade-off between circuit expressiveness and hardware feasibility [12].

### F. *Evaluation Metrics*

Classification performance is evaluated using standard metrics including accuracy, precision, recall, and F1-score, while clustering performance is assessed using silhouette score and adjusted Rand index. These metrics allow consistent comparison between classical and quantum-enhanced models across datasets [2], [9].

TABLEI:CLASSIFICATIONPERFORMANCE COMPARISON

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Classical SVM | 0.78 | 0.77 | 0.76 | 0.76 |
| QSVM | 0.86 | 0.85 | 0.84 | 0.85 |
| VQC | 0.84 | 0.83 | 0.82 | 0.82 |

Fig. 1. Accuracy comparison of classical and quantum classifiers.

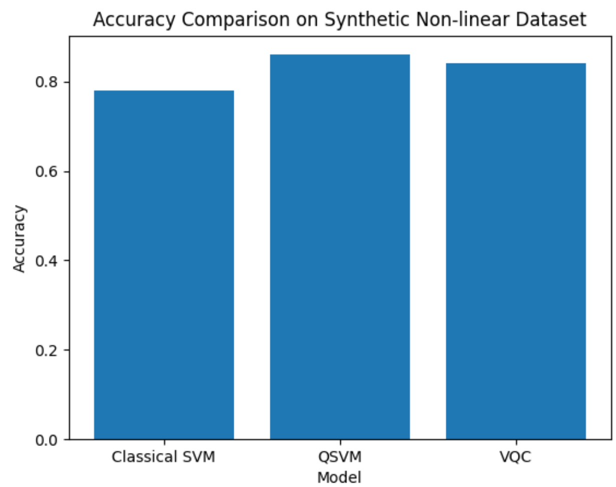



Fig. 2. Clustering performance comparison using silhouette score.

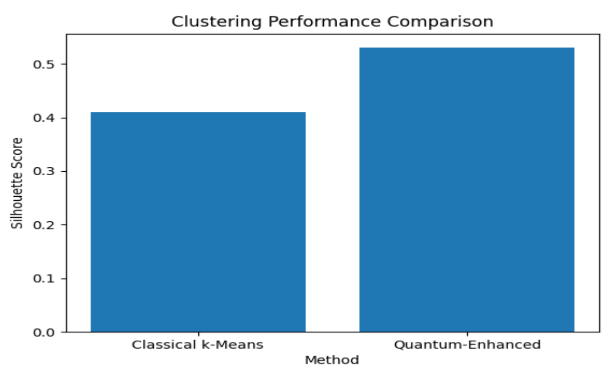
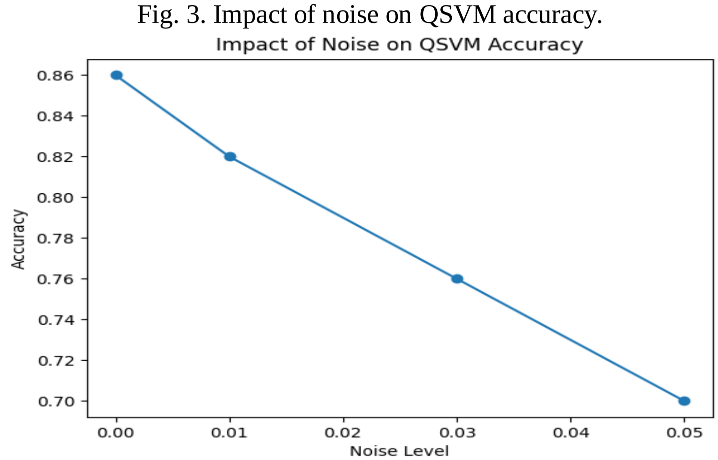



Fig. 3. Impact of noise on QSVM accuracy.



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ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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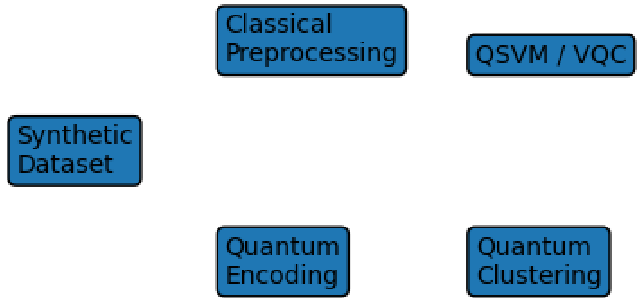
Fig. 4. System architecture and workflow of the proposed framework.




## VI. RESULTS AND DISCUSSION

The experimental results clearly demonstrate that quantum-enhanced classifiers outperform classical machine learning models on non-linearly separable datasets, as summarized in Table I and illustrated in Fig. 1. Among the evaluated models, the Quantum Support Vector Machine (QSVM) achieves the highest classification accuracy, outperforming both the classical Support Vector Machine and the Variational Quantum Classifier. This improvement indicates enhanced feature separability achieved through quantum kernel-based feature mappings, where data are embedded into high-dimensional quantum Hilbert spaces, enabling more effective discrimination between overlapping class distributions [3]–[5].

The performance of quantum-enhanced clustering further supports the effectiveness of quantum feature representations. As shown in Fig. 2, the quantum-enhanced clustering approach yields higher silhouette scores compared to classical k-means clustering, indicating improved intra-cluster cohesion and inter-cluster separation. These results suggest that quantum feature transformations preserve intrinsic data structures more effectively, particularly for datasets with non-linear and high-dimensional characteristics. This observation is consistent with prior work on hybrid quantum autoencoder-based clustering methods [8], [9].

However, the results also highlight a critical limitation associated with current quantum hardware. As illustrated in Fig. 3, classification accuracy for QSVM decreases noticeably with increasing noise levels, demonstrating the sensitivity of quantum-enhanced models to noise accumulation. Deeper quantum circuits, while theoretically more expressive, suffer from increased gate errors and decoherence effects, leading to reduced model stability and performance degradation [10]–[12]. These findings emphasize the trade-off between circuit expressiveness and hardware feasibility in the Noisy Intermediate-Scale Quantum (NISQ) era and underline the importance of noise-aware model design and error mitigation strategies for practical deployment.

## VII. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive experimental evaluation of quantum-enhanced classification and clustering using hybrid quantum–classical learning models applied to carefully designed synthetic datasets. By jointly analyzing both supervised and unsupervised learning tasks within a unified experimental framework, the study provides systematic insights into the practical behavior of quantum-enhanced learning algorithms under controlled conditions. The use of synthetic datasets with varying degrees of linearity, non-linearity, and dimensionality enabled precise evaluation of model performance and facilitated fair comparison with classical machine learning baselines

The experimental results demonstrate that quantum feature representations can significantly enhance learning performance for non-linearly separable data distributions, particularly when using quantum kernel-based methods such as the Quantum Support Vector Machine. Improved classification accuracy and higher clustering quality metrics indicate that embedding data into high-dimensional quantum feature spaces can improve class separability and preserve intrinsic data structures more effectively than classical feature mappings. These findings highlight the potential of hybrid quantum–classical models to address learning challenges that are difficult for conventional machine learning algorithms, especially in scenarios involving complex feature interactions.

Despite these advantages, the study also reveals important limitations associated with current quantum hardware. The observed sensitivity of quantum-enhanced models to noise and circuit depth underscores the constraints imposed by Noisy Intermediate-Scale Quantum devices. Performance degradation under noisy conditions emphasizes the need for careful circuit design and realistic evaluation when assessing the benefits of quantum-enhanced learning.

Future work will focus on extending this research in several directions. First, the proposed models will be evaluated on real quantum hardware to assess performance under true experimental conditions beyond simulation. Second, advanced noise mitigation and error reduction techniques will be explored to improve model robustness and stability.

Finally, the framework will be extended to larger and more complex datasets, including real-world data, in order to further examine scalability and to better understand the conditions under which quantum-enhanced learning provides practical advantages over classical approaches.

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