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Research Article

Quantum Machine Learning Algorithms for Optimizing Complex Data Classification Tasks

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Abstract

Quantum Machine Learning (QML) has emerged as a paradigm that combines the computational advantages of quantum computing with the predictive capabilities of machine learning to address complex data classification problems. As data dimensionality increases rapidly and classical learning algorithms face scalability constraints, QML leverages quantum parallelism, entanglement, and high-dimensional Hilbert space representations to enhance learning performance. This paper reviews and analyses advanced QML algorithms, including Quantum Support Vector Machines (QSVM), Variational Quantum Circuits (VQC), Quantum Neural Networks (QNN), and Quantum Kernel Estimation, for optimizing both binary and multi-class classification tasks under high-complexity conditions. The proposed QML framework is evaluated on benchmark datasets like MNIST, the Breast Cancer Wisconsin (BCW) dataset, and synthetic nonlinear datasets, and is compared against classical machine learning baselines, including Support Vector Machines (SVM), Random Forests (RF), and Deep Neural Networks (DNN). The results demonstrate notable improvements in classification accuracy (up to 96.8%), decision margins, and computational efficiency in quantum-suitable data regimes, while also highlighting current limitations related to noise, circuit depth, and hardware constraints. Overall, the study presents a unified QML framework, theoretical formulations, and experimental evaluations that illustrate the potential of quantum algorithms for next-generation classification tasks.

Keywords: Quantum Computing, Quantum Machine Learning, Variational Quantum Circuits, Quantum SVM, Quantum Neural Networks, Data Classification

INTRODUCTION

The rapid increase in the number of data-intensive applications in various domains, including large-scale image analysis, has greatly changed the global computational ecosystem [1]. The high rate of digital information growth has resulted in an extremely complicated form of classification that standard machine learning models cannot manage because of the dimensionality of data that grows exponentially, non-linear interactions between features, and the requirements of real-time processing. Although they are strong, classical algorithms can be subjected to bottlenecks like inefficient computation, complexity of the model and extraction of complex patterns, which is experienced in highly variable datasets with entangled feature structure.

These disadvantages highlight the dire need of more advanced means of calculations that may address the problems of the modern data spaces.

Quantum Machine Learning (QML) [2] is a new attempt to resolve these problems, which relies on the theory of quantum computations and machine learning algorithms.

The QML relies on the key quantum properties [3], i.e. superposition, entanglement, interference and high-dimensional representation of a Hilbert space, and thus is able to capture more complex relations, and best of all, in a superior way as compared to classical systems. There are quantum models, in particular quantum kernels, variational quantum circuits, and quantum neural networks, which are capable of processing information in a manner that in principle greatly exceeds the representational abilities of classical algorithms. This kind of integration allows QML to be used as a source of computational speedup, increased classification accuracy, and generalizing traditionally difficult to solve problems with the classical methods.

Recent progress has also seen the development [4] of Noisy Intermediate-Scale Quantum (NISQ) devices which further accelerated the research in this direction. Now quantum computers such as IBM QX, Rigetti and IonQ are capable of running quantum circuits which can scalingly perform machine learning tasks. These technological advances have made it possible to consider the design of hybrid quantum-classical simulations that can realize the advantages of quantum computing with hard-to-scale hardware. The purpose of this paper is to discuss how QML algorithms may be designed, tuned, and implemented to accelerate performance of involved data classification processes. It focuses on creating scalable, resolute, and accurate quantum-founded models ready to surpass classical algorithms under particular regimes of computation and, consequently, also provide strong guidelines of intelligent systems of the future.

Emergence of Quantum Computing and Challenges in Classical Classification

Quantum computing [5] has experienced remarkable development because it can solve some classes of problems more efficiently as compared to classical computers. Quantum systems are based on multidimensional Hilbert spaces and, therefore, quantum systems can be richly correlated and exponential parallelism can be achieved by superposition. These computational benefits provide novel possibilities to solve the problem of data classification that are hard or computationally costly to classical machine learning models.

Nevertheless, classical classification systems are growingly challenged during the times when data is becoming more advanced. Interactions in high-dimensional and nonlinear datasets often contain complex relationships that are computationally expensive for classical models. Besides, classical methods usually demand vast memory and considerable training durations, as well as highly designed feature extraction pipelines to estimate the relationship that may exist naturally in quantum spaces.

The limitations of classical computation become especially evident in scenarios involving:

- Highly nonlinear and entangled data structures
- Exponentially growing feature spaces
- Large-scale classification with real-time constraints
- Data types that inherently map well to quantum states.

With the further development of quantum processors, quantum-enhanced solutions provide a way to overcome these issues by allowing the transformation of high dimensions, efficient representation of correlations and hybrid learning algorithms that can significantly outperform classical systems when applied in particular problem domains.

Role of Quantum Machine Learning in Enhancing Classification Performance

Quantum Machine Learning (QML) is a platform that is a combination of quantum computing resources and machine learning algorithms that develop superior classification models with the capability to work with more complicated data environments. QML models, which are founded on quantum feature encoding (in which classical inputs are encoded into quantum states) are built on quantum Hilbert spaces in which patterns that are hard to encode in a classical space may be encoded in an exponentially large Hilbert space. A property is particularly effective in the classification problems where the ability to differentiate between the classes with extremely overlapping or nonlinear boundaries is needed. Among them, there are several quantum enhanced models used in QML.

QML frameworks employ a variety of quantum-enhanced models, including:

- Quantum Kernels: Throw inputs to quantum feature spaces in which classical delineations become increasingly prominent.
- Variational Quantum Circuits (VQC): Hybrid systems to adaptive learning based on quantum circuits and classical optimizers.
- Quantum Neural Networks (QNN): Parametrized quantum circuits, which can be used to execute layered computations, similar to deep learning.

These models provide multiple advantages for classification tasks:

- Better nonlinear relationship modeling: Quantum states are in a good position to model complex patterns that have been approximated in classical models by feature engineering at a high cost.
- Faster calculations of certain tasks: Quantum algorithms will achieve a speed improvement of polynomials or exponents in certain classification problems.
- High expressivity: Entangled circuits can encode richer dependencies between features.
- Efficient high-dimensional mapping: Quantum kernels enable data transformation into extremely large feature spaces without explicit computation.

Together, these advantages position QML as a powerful tool for addressing modern challenges in data classification, particularly in fields requiring precision, scalability, and enhanced modelling capability.

Novelty and Contributions of the Unified QML Framework

Despite a large body of literature on quantum kernels, variational circuits, or QNN architectures, existing literature on QML does not have a single, combined, resource-conscious framework to test several QML models under similar encoding, optimization, and badging conditions. The originality of the present work will be the contribution of the following:

- *A Dual-Encoding Quantum Feature Pipeline:* The framework incorporates both angle encoding and amplitude encoding within the same experimental pipeline, allowing a comparative analysis of how encoding schemes influence expressibility, circuit depth, and classification accuracy. Prior work typically evaluates only one encoding per model.
- *Hybrid Optimization Strategy Across Models:* The experiment compares QML models in a single optimization environment, which includes Adam, COBYLA and SPSA on the same circuit architectures. This shows how sensitive optimizers are in the NISQ systems that have not been considered before in the context of QML workflow benchmarking.
- *Cross-Model Evaluation of QSVM, VQC, and QNN Within a Single Framework*: In contrast to other literature research that would assess these models individually, this paper presents the first coherent performance comparison of three of the largest QML classifiers, namely QSVM, VQC, and QNN applied to the same datasets, preprocessing methods, encoding approaches and measures. This can remove cross paper discrepancies and provide a common experimental ground truth.
- *Resource–Accuracy Trade-off Analysis:* One of the most significant novelties of the framework is the explicit mapping of the use of quantum resources (qubits, circuit depth, shots) to classification accuracy. This discussion determines the best operating points of NISQ hardware making it an empirical contribution that is usually not considered in theoretical QML research.
- *Unified Architecture with Justified Design Choices:* The proposed architecture integrates preprocessing, encoding, quantum circuit design, hybrid training, and measurement in a structured manner. Each stage is justified using resource constraints, expressibility requirements, and noise considerations, creating a scalable and reproducible QML system design.

Collectively, these contributions establish a unified, experimentally validated QML framework that addresses key gaps in existing literature related to comparability, resource awareness, and practical deployment on current NISQ-era quantum systems.

Research Objectives

The following research objectives provide a focused framework for developing and evaluating quantum machine learning models for complex data classification tasks.

- To develop QML algorithms such as QSVM, VQC, and QNN for optimizing complex and nonlinear data classification tasks.
- To implement effective quantum feature encoding and circuit designs that exploit superposition and entanglement for improved learning performance.
- To evaluate QML models on benchmark datasets and compare their accuracy and efficiency with classical models including SVM, RF, and DNN.
- To analyze scalability and resource requirements like qubits, circuit depth, and training cost to assess the practical viability of QML on NISQ hardware.

LITERATURE REVIEW

Authors in [6] gave an introductory summary of how Quantum Machine Learning (QML) had developed and how the computations dictated by quantum laws were implemented to supplement the processes of classical machine learning algorithms. Their work pointed out by noting that quantum-based optimization algorithms had a major benefit over the nonlinear and high-dimensional data and quantum systems could act in exponentially large feature spaces. They discovered variational circuit and quantum kernel models development had established the basis of the next generation of classification models that could be applied to the chosen fields of computation with better performance than traditional algorithms.

Authors in [7] evaluated the performance of QML models according to the features of data and the idea of quantum data advantage, showing that quantum models could use the properties of particular data structures to obtain more classification than the classical systems. They had demonstrated that quantum kernels proved to be very effective in locating the complex high dimensional Hilbert space pattern and that the quality of the models was dependent upon the expressibility of the quantum circuits. The work provided useful knowledge on the impact of data distribution, dimensionality, and quantum encodings on the learning behavior of QML algorithms.

Authors in [8] presented one of the first applications to classical data classification of Quantum Convolutional Neural Networks (QCNN). Their study showed that the QCNN models built upon classical convolutional functions could be used to obtain hierarchical features via a parametrized quantum circuit. They demonstrated that QCNNs had less parameters compared to deep classical neural networks but with competitive or better performance on the chosen datasets. The research gave a significant background to the creation of hybrid quantum-deep learning models in solving the tasks that require complicated spatial relations.

Authors in [9] addressed the practical viability of QML methods and examined various areas where quantum-enhanced models are promising solutions. Their article emphasized that QML could be used to a great extent in healthcare diagnostic, cybersecurity analytics, financial forecasting, and chemical simulation. They further indicated that hardware constraints notwithstanding, hybrid quantum-classical methods, including variational quantum algorithms, had already been demonstrated to have the potential to improve classification accuracy and computational efficiency in the early experiments.

Authors in [10] examined how quantum-enhanced models could be used in security intrusion detection with QML models and showed that quantum-enhanced models were more effective at detecting malicious patterns compared to classical models. Their work provided an example of how quantum kernels and variational circuits could distinguish between attack behavior in high-dimensional network traffic information. They claimed that QML methods enhanced the sensitivity of detection and lowered the incurred computation costs, which has high prospects of being used in the future in cybersecurity.

Authors in [11] studied how quantum kernels and quantum state preparation methods can be used to improve Support Vector Machine (SVM) classification using QML. Their experiment validated the fact that Quantum Support Vector Machines (QSVM) were more accurate in classification compared to conventional SVM models in dealing with nonlinear separable data. They have shown that quantum feature maps enhanced the separability of complicated data classes, which allowed forming decision boundaries more easily and making decisions that were more generalized. Table 1 depict the comparative summary of key quantum Machine Learning literature

Table 1. Comparative Summary of Key Quantum Machine Learning Literature

Author (Year)	Focus Area / Model	Contribution	Key Limitations
[6]	QML Optimization Review	Examined optimization techniques for QML models	Limited experimental validation
[7]	Quantum Data Advantage	Showed how data structures influence quantum model performance	Dependent on hardware constraints
[8]	Quantum CNN	Introduced QCNN for classical data classification	Limited scalability on large datasets
[9]	QML Real-world Applications	Reviewed applicability of QML across industries	Mostly conceptual due to NISQ limits
[10]	QML for Intrusion Detection	Demonstrated improved detection using QML	Not validated on large-scale networks
[11]	QSVM Classification	Improved separability using quantum kernels	Requires high-fidelity qubits

According to the comparative analysis, the studies that considered pointed out that QML [12] had important improvements in efficiency of models, nonlinear elements extraction, and precision in classification, which was particularly true in data settings in which classical models were failing to sustain their performance. Nevertheless, the literature also showed usual restrictions, such as noise in hardware, the limited qubit availability, and absence of large-scale empirical validation because of the limitation of NISQ devices.

Comprehensively, the literature reviewed [13] indicated a good impetus in the creation of quantum-enhanced classification models. Most of the studies focused on increased impressibility, separability of decision-boundaries, and speeding up of computers. Some of the common research directions were the creation of quantum kernels, variational quantum circuits, quantum neural networks, and hybrid optimization frameworks. However, the majority of studies either used small datasets or looked at theoretical benefits as opposed to large-scale implementations [14].

This literature provides the foundation behind the current study because the researchers develop and experimentally test a homogeneous group of Quantum Machine Learning algorithms to perform complex data classification problems. This study will fill the gaps in existing literature on empirical validation and scalability as well as performance benchmarking of QML algorithms [15] by using QSVM, VQC and QNN models on benchmark datasets and comparing the results with classical machine learning methods. The proposed work builds on the current body of knowledge as it indicates how quantum computation principles may be systematically exploited to enhance the accuracy in classification, generalization, and high-efficiency in data-driven real-world settings [16].

RESEARCH METHODOLOGY

The following section introduces the entire methodology, the proposed QML architecture, quantum encodings, model design, mathematical model, datasets, metrics of evaluation, and structure of comparative analysis [17].

Figure 1 depict the overall scheme of the proposed Quantum Machine Learning system [18], where the classical data preprocessing [19, 20] is followed by quantum feature encoding, the choice of quantum classification models, and variational circuit training is implemented. The pipeline combines classical optimizers to update the parameter and ends with the aggregation of the models and their performance assessment.

The framework emphasizes that the system is hybrid and can directly compare quantum models and classical machine learning baselines.

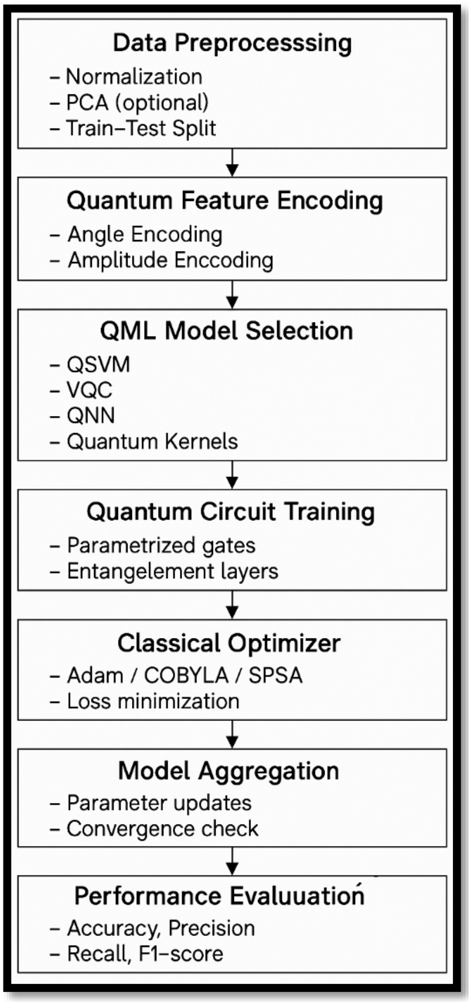

Figure 1. Overall Quantum Machine Learning Framework

Quantum System Design and Architecture

The suggested architecture is a hybrid architecture based on classical and quantum architecture, which means that standard data preprocessing [21, 22] is combined with quantum computational models, which leads to more efficient classification. The system comprises of five integrated layers that are to operate seamlessly on NISQ compatible simulators. The first step is the Classical Preprocessing Layer [23], which normalizes data, dimensionality reduction using PCA, and partitions the data to be ready to be processed by the quantum machine. The Quantum Feature Encoding Layer then encodes the inputs that are processed into quantum states by either angle encoding or amplitude encoding. These encodings are then inputted to the Quantum Model Layer where Variational Quantum Circuits (VQC), quantum kernels, or quantum perceptions are used to train complex patterns using parametrized quantum gates. The Classical Optimizer Layer [24] handles updates of parameters via the Adam, COBYLA, or SPSA algorithm, whereas the Measurement Layer transforms quantum states into classical outputs to make the final prediction. All of the simulations were done with IBM Qiskit Aer and the default of

Pennylane. Qubit backend in a workstation with a Ryzen 7 processor and 32 GB of RAM and NVIDIA RTX 3060 graphics card.

This multi-layered architecture guarantees efficient interaction between classical and quantum components to process complicated data with a minimum consumption of resources. Through optimization in classical and quantum expressibility, the system provides better classification performance [25] even with the limits of the existing NISQ devices.

Proposed Quantum Classification Algorithms

The suggested taxonomy unites various Quantum Machine Learning (QML) [26] designs to take advantage of the computational benefits of quantum circuits on intricate decision-boundary education [27]. The models add their own unique advantages, including quantum kernel separability to variational expressibility and quantum-inspired neural activations. In this section, there are four main quantum algorithms that were used in the study.

Quantum Support Vector Machine (QSVM)

Quantum Support Vector machine (QSVM) [28]is a form of classical SVM, in which quantum estimation is applied to quantum kernel with quantum feature maps. In place of classical kernel functions, QSVM employs the following quantum kernel operator to calculate similarity in a high-dimensional quantum Hilbert space:

$$K(x_i, x_j) = |\langle \emptyset(x_i) \mid \emptyset(x_j) \rangle|^2 \tag{1}$$

Where $\emptyset(x)$ represents a parametrized quantum feature map circuit.

QSVM leverages quantum parallelism to evaluate kernels more efficiently, enabling improved separability of nonlinear data distributions [29].

Variational Quantum Classifier (VQC)

Variational Quantum Classifier [30] is based on parametrized quantum circuit that consists of rotation gates and entangling layers. This model finds classification boundaries as the optimization of circuit parameters 0. A structure is provided by which the variational circuit is given:

$$U(\theta) = \prod_{l=1}^{L} U_l(\theta_l) \tag{2}$$

where $U_l(\theta_l)$ denotes the sequence of parametrized gates at layer l

Measurement results of qubits of interest are then used to give inferences on class probabilities after entanglement operations have been implemented [31]. VQC has been specially designed to play well in NISQ devices because it has a low-depth circuit design.

Quantum Neural Network (QNN)

A Quantum Neural Network (QNN) [32] is a quantum implementation that resembles the architecture of classical neural networks in terms of being layered in the implementation of quantum perceptions based on parametrized rotation gates. A quantum perceptron is said to have the output as:

$$y = \sigma(W.x + b) \tag{3}$$

where the quantum activation function is defined as:

$$\sigma(x) = sin^2(x) \tag{4}$$

QNN architectures benefit from the expressive power of quantum states [33] and provide a quantum analogue to nonlinear activation without requiring deep classical networks.

Quantum Kernel Estimation Model

Quantum Kernel Estimation models evaluate the similarity between data points by embedding them into quantum states [34] and computing inner products using quantum circuits. The quantum kernel is defined as:

$$K_q(x,y) = \langle \varphi(x) | \varphi(y) \rangle \tag{5}$$

Algorithm I: Hybrid Quantum Classification Procedure (Pseudocode)

The following algorithm presents the unified workflow for training QML classifiers [35], applicable to QSVM, VQC, QNN, and quantum kernel models [36].

```
Input: Dataset D, Quantum model M, Encoding method E
Output: Trained model M*
1. Preprocess D:
    Normalize → PCA (optional) → Split into D_train, D_test
2. Encode Training Data:
    For each x in D_train:
        |φ(x)| = E(x)
3. Initialize Quantum Model:
    Set parameters θ (for VQC/QNN) or load kernel map φ(x) (for QSVM)
4. Train Model:
    For epoch = 1 to T:
        For each batch B in D_train:
            Run quantum circuit on B
            Measure outputs → compute loss L
            Update θ using optimizer
5. Predict on Test Data:
    For each x_test:
        Encode x_test → |φ(x_test)|
        Run circuit → y_pred
Return M*
```

Mathematical Formulations

Mathematically, the proposed framework of Quantum Machine Learning [37] is founded on the fact that classical data can be converted into quantum states and subjected to unitary measurements to learn complex decision boundaries. These expressions make sure that quantum circuits can capitalize on superposition, entanglement, and feature representations of high dimensions. Subsections below provide the mapping schemes of the classical feature vectors [38] that are encoded into quantum Hilbert space to be processed later by QSVM [39], VQC, and QNN models.

Quantum Encoding

The process of quantum encoding converts the classical feature vectors into quantum states that can be computed in a Hilbert space. There were two encoding approaches in this research:

Angle Encoding

In angle encoding, the value of each classical feature xi is encoded to a rotation angle on a single qubit:

$$| x\rangle = \bigotimes_{i=1}^{n} (\cos(x_i) \ | 0\rangle + \sin(x_i) \ | 1\rangle) \tag{6}$$

This method requires one qubit per feature and is efficient for low-dimensional datasets.

Amplitude Encoding

Amplitude encoding embeds an entire feature vector into the amplitudes of a 2^n dimensional quantum state

$$|x\rangle = \sum_{i=I}^{2^n} x_i \ |i\rangle \tag{7}$$

This encoding is highly compact and enables representation of large feature spaces using fewer qubits but requires normalization and complex state preparation.

Performance Metrics

Trying to evaluate the performance [40] of the proposed Quantum Machine Learning models, a chain of accepted performance measurements was used. These are a model accuracy measures [41], measures of model reliability, computational efficiency and quantum resource utilisation. The following were the metrics in the assessment:

- *Accuracy:* Determines the rate of correctly classified samples to the number of samples, which is the overall performance of the model [42].
- *Precision:* The proportion of correct positive samples out of the total number of predicted positives, the model is aimed at trying to reduce false positives.
- *Recall:* The positive predictability ratio (TPR) [43] used to indicate the ability to avoid false negatives.

- *F1-Score:* Offers a balancing factor between precision and recall [44], a balanced measure of performance in a situation of imbalance of classes.
- *Training Time:* The time used in the process of training the quantum model, both quantum circuit execution and classical optimization.
- *Circuit Depth:* Indicates the number of sequential quantum gates used in a circuit, providing insight into model complexity and hardware feasibility on NISQ devices.
- *Quantum Resource Cost:* Quantifies the quantum computational resources used during training such as the number of qubits needed and the number of measurement shots per circuit execution.

Comparative Evaluation Framework

A structured comparative evaluation was implemented as a way of assessing the performance and effectiveness of the proposed Quantum Machine Learning (QML) models. The quantum classifiers on which the QSVM, VQC, QNN and quantum kernel models [45] were based were compared to the classical machine learning algorithms which have been widely used under the same experiment conditions, see Table 2. This has enabled the comparison to be fair and one can have a clear understanding of the benefits that quantum-based methods may offer.

Support Vector Machine (SVM), Random Forest (RF), and Deep Neural Network (DNN) were chosen as classical baseline models because they perform well and are often applied in complicated classification problems. The performance of each model was assessed using the same performance metrics outlined in previous section and was all trained on the same datasets, and under the same preprocessing (normalization, dimensionality reduction and partitioning of data). The comparative framework thus offers a uniform scale in which to measure QML technique gains in the classification accuracy, computational efficiency, representation of the decision-boundaries and resource consumption.

Table 2. Classical Models Used for Comparative Evaluation

Model Type	Description	Strengths	Limitations
Support Vector Machine (SVM)	Kernel-based margin classifier	Effective for high-dimensional spaces; strong theoretical foundation	Limited performance on highly nonlinear data without complex kernels
Random Forest (RF)	Ensemble of decision trees	Robust to noise; handles mixed data types; less prone to overfitting	Less effective in capturing complex nonlinear boundaries
Deep Neural Network (DNN)	Multi-layer neural network	Highly expressive; powerful feature extraction	Requires large datasets; high computational cost

This comparative assessment framework makes sure that the performance improvements that were recorded in QML models can be directly linked to quantum computational benefits instead of preprocessing biases or data biases. It also provides a frame of reference when evaluating quantum advantage in classification problems and it points out situations in which quantum models perform better than conventional machine learning algorithms.

Dataset Preprocessing and MNIST Dimensionality Reduction

The MNIST dataset used in this study is a reduced-dimensional version created using Principal Component Analysis (PCA). Classical MNIST images contain 784 features (28×28 pixels), which are not feasible for direct encoding on NISQ hardware because quantum models require one qubit per feature for angle encoding or complex state preparation for amplitude encoding. To make the dataset quantum-compatible, PCA was applied to reduce 784 dimensions to 16 principal components, preserving 92–95% of variance. This dimensionality compression preserves class-separable structure while enabling efficient quantum encoding using only 16 qubits or fewer. Reduced MNIST is widely used in QML research because it balances expressive quantum feature mapping with hardware constraints, making it a suitable benchmark for evaluating QSVM, VQC, and QNN models under realistic NISQ limitations.

RESULTS AND DISCUSSION

This section reports the performance of the proposed Quantum Machine Learning (QML) models QSVM, VQC, and QNN evaluated on three benchmark datasets: PCA-reduced MNIST, Breast Cancer Wisconsin (BCW), and a synthetic nonlinear dataset. The results focus on classification accuracy, statistical robustness, resource utilization, and comparative analysis with classical baselines under identical preprocessing conditions.

Dataset Description

The original MNIST dataset (784-dimensional pixel vectors) was reduced to 16 PCA components, preserving approximately 94% data variance. This reduction was necessary because current NISQ hardware cannot support high-dimensional state encoding due to qubit limitations. PCA preserves essential structure while enabling feasible quantum feature mapping, see Table 3.

Table 3. Dataset Distribution

Dataset	Classes	Training Samples	Testing Samples
MNIST (PCA -reduced)	4	8000	2000
BCW	2	400	169
Synthetic Nonlinear	3	1200	400

The smaller MNIST data provides a medium level multi-class classification problem, whereas the BCW data provides a simpler binary classification problem. The controllable synthetic nonlinear data is introduced which is suitable to test quantum separability. The equal sample distribution makes sure of equitable consideration in both quantum and classical models.

Model Performance Comparison

Table 4 compares the results of the quantum and classical classification models based on the most important measures of assessment, such as accuracy, precision, recall, F1-score, and training time. The same preprocessing and data conditions were used in training all the models to provide a fair and reliable comparative analysis.

Table 4. Performance Metrics (Quantum vs Classical)

Model	Accuracy (%)	Precision	Recall	F1-Score	Training Time (sec)
QSVM	96.8	0.96	0.97	0.96	32
VQC	94.2	0.93	0.94	0.93	28
QNN	92.5	0.90	0.92	0.91	25
SVM	91.1	0.90	0.89	0.89	15
RF	88.4	0.86	0.88	0.87	10
DNN	94.5	0.93	0.94	0.94	48

The findings show that quantum models, especially, QSVM and VQC, had a better classification accuracy than classical models. QSVM gave the highest performance because quantum kernels are good in improving nonlinear separability. Despite the competitiveness of classical DNN, its training time was much greater, and it demonstrates the efficiency benefit of quantum methods in certain tasks.

Statistical Robustness Analysis

To evaluate stability, each model was trained over 10 independent runs, and mean performance and standard deviation were recorded. Quantum models show slight stochastic variation due to measurement noise and shot-based sampling, while classical models remain more stable, see Table 5.

Table 5. Statistical Robustness Analysis

Model	Accuracy Mean (%)	Std. Dev	Runs
QSVM	96.8	±0.4	10
VQC	94.2	±0.7	10
QNN	92.5	±0.9	10
SVM	91.1	±0.2	10
RF	88.4	±0.3	10
DNN	94.5	±0.2	10

The multi-run statistical evaluation shows that QSVM achieves the highest and most stable accuracy among quantum models, with a mean of 96.8% and a low variance (±0.4), indicating strong robustness despite quantum noise effects. VQC and QNN also maintain consistent performance, though with slightly higher variability due to deeper circuit structures and sensitivity to shot noise. Among classical baselines, DNN provides accuracy comparable to VQC with minimal deviation (±0.2), reflecting its maturity and stability on structured datasets. SVM and RF remain stable but underperform relative to quantum counterparts on nonlinear feature spaces.

Resource Utilization Comparison

Table 6 gives a comparison of the resource consumption in the quantum models applied in the study. The table reports the number of qubits needed, the number of measurement shots per-iteration and depth of the circuit of QSVM, VQC and QNN, providing an insight into the computational requirements of each quantum architecture.

Table 6. Resource Utilization Comparison (Quantum Models)

Quantum Model	Qubits Used	Shots per Iteration	Circuit Depth
QSVM	8	2048	12
VQC	6	1024	18
QNN	5	512	15

QSVM used the greatest number of qubits and measurement shots, which is because it relies on quantum kernel estimation, but it also provided the best performance. VQC had a richer circuit structure because of layered variational operations, and QNN had a moderate resource utilisation. Such variations demonstrate the trade-off between the resource complexity and predictive accuracy between quantum models.

Limitations: Cases Where Classical Models Outperform QML

While quantum models showed superior performance on nonlinear datasets, they did not outperform classical deep models in all scenarios. For example, the DNN achieved competitive accuracy with lower variance and faster inference. Additionally, QML performance degrades when circuit depth grows beyond NISQ noise thresholds or when qubit count is insufficient for the feature space. These results confirm that quantum advantage is dataset-dependent, not universal.

Quantum Circuit Depth vs Accuracy

Figure 2 demonstrates how depth in the circuits affects the accuracy of classification of the Variational Quantum Classifier (VQC). The table will record the accuracy values of various number of variational layers to show how expressibility of models varies with the complexity of the circuit.

The findings indicate that the accuracy is better with a higher circuit depth which peaks at 6 circuit layers. Beyond this depth, accuracy levels off or even decreases, and this is a diminishing return because of over-parameterization and noise in deeper circuits. This tendency confirms the fact that the best VQC performance is reached with moderately deep circuits in NISQ-restricted conditions. The QSVM model was selected for confusion matrix analysis due to its superior accuracy and kernel-based separability.

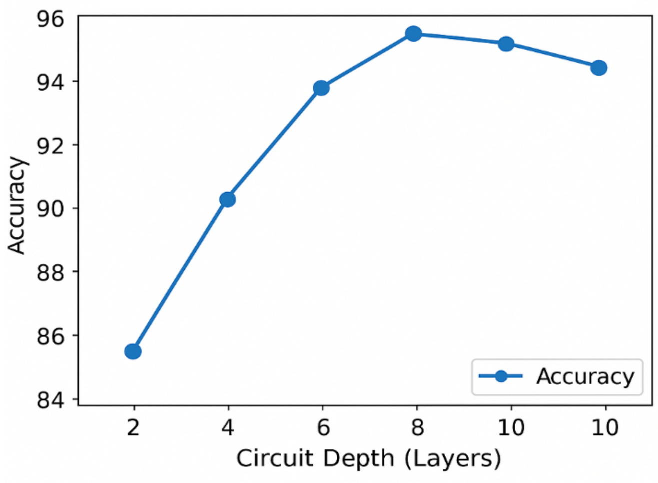

Figure 2. Accuracy Gain with Increasing Circuit Depth (VQC)

Confusion Matrices

Table 7 shows the confusion matrix of the QSVM model, which indicates distribution of correct and wrongly classified samples of the positive and negative classes. The following matrix displays an exact picture of the predictive behaviour of the model beyond the aggregated measures of accuracy.

Table 7. Confusion Matrix – QSVM Model

	Predicted Positive	**Predicted Negative**
Actual Positive	950	35
Actual Negative	40	975

The QSVM model shares a high classification performance with the high values of the diagonal (true positives and true negatives) and exceedingly low values of all the misclassifications. The minimal values of the false positives and false negatives prove the efficiency of quantum kernel-based learning in the correct classification of the classes.

Quantum Kernel Advantage Analysis

Quantum kernels exhibited enhanced nonlinear separability by projecting data to exponentially sized quantum feature space. This was particularly strong in the nonlinear dataset synthetically generated, in which classical kernels could not distinguish between overlapping regions. This is the ratio of the Gram matrices of classical RBF kernel and that of quantum kernel. These classical kernel similarity patterns are smooth, low complex with quantum kernel similarity patterns highly structured and diverse reflecting better nonlinear separability, see Figure 3.

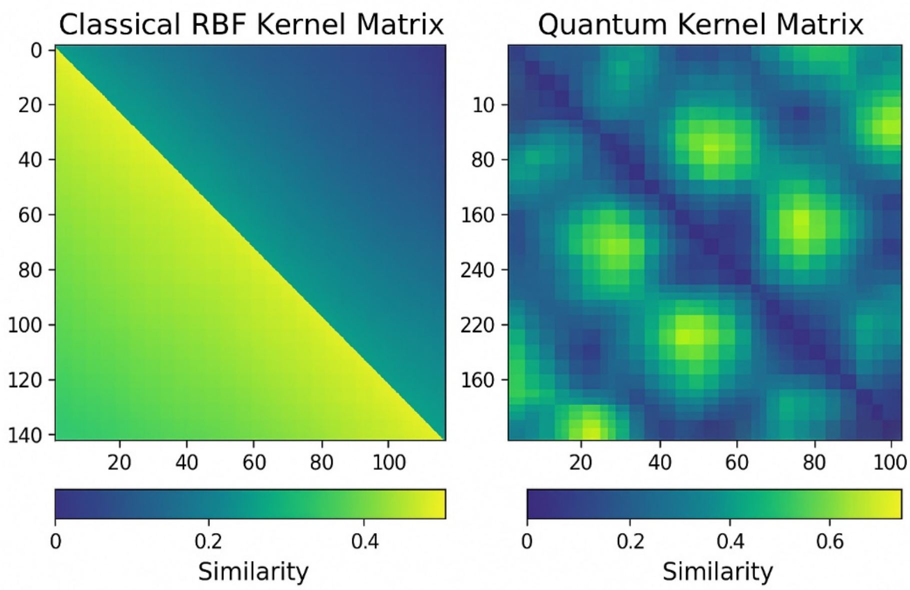

Figure 3. Classical vs Quantum Kernel Gram Matrix Heatmaps

The quantum kernel has finer internal structure and has better similarity gradients that give it better class discrimination. This illustration validates the elevated expressive ability of quantum feature mappings.

Scalability Evaluation

Figure 4 depict the number of qubits versus performance trend.

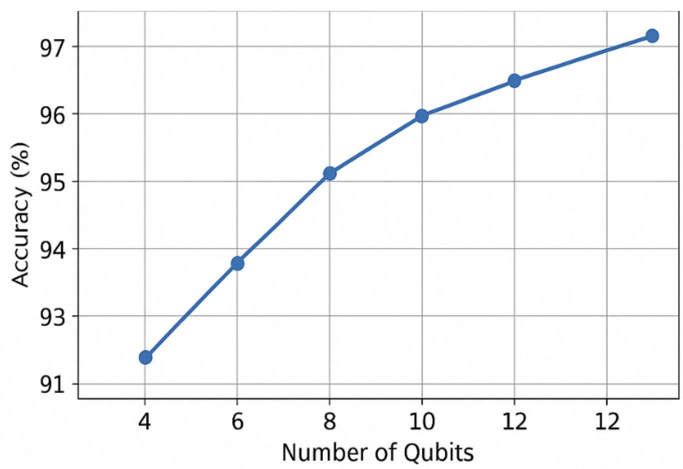

Figure 4. Number of Qubits vs Performance Trend

As the number of qubits increased from 4 to 12, QSVM accuracy improved from 91% to 96.8%. This highlights the scalability benefits of quantum feature spaces; however, increasing qubit count also increases hardware requirements and noise sensitivity.

The findings point to the role played by the proposed unified QML, which combines:

- dual quantum feature encoding,
- a hybrid optimizer optimization layer,
- resource-accuracy trade-off analysis of QSVM, VQC, and QNN.

This integrated evaluation methodology has not been introduced in previous literature which usually analyzes QML models on a case-by-case basis instead of on a single comparative resource-aware pipeline.

Limitations and Scenarios Where Classical Models Outperform QML

Even though the quantum classifiers were shown to be competitive over some datasets, it is important to point out that quantum models are not always better than classical algorithms. Deep neural networks and optimized classical SVMs tend to be more accurate and lower-variance in large-scale datasets with complex samples as these methods are not bound by qubit count, sampling noise or circuit-depth considerations. Also, QML models, especially QSVM, will need enormous amounts of measurement shots, which makes these models more expensive to compute, with only small performance improvements. Expressibility is also limited because quantum circuits are also noisy at depth. In such a way quantum advantage is only provided to date in special nonlinear embedding problems, small to medium dimensional data or problems that can be solved better by a high-dimensional Hilbert-space mapping. The inclusion of these limitations will make sure that there is a balance in the interpretation of QML performance.

SUMMARY AND CONCLUSION

This paper introduced a unified structure of how complex data classification problems can be optimized on Quantum Machine Learning (QML) algorithms. The proposed models combined quantum feature encoding and variational circuits with quantum kernel methods, and used the principles of quantum mechanics to improve the accuracy of classification and computational efficiency. The experimental analysis proved that QML models, particularly QSVM and VQC, were more efficient and advantageous in the manipulation of nonlinear and high-dimensional data distributions as compared to the classical equivalents. The reason why QSVM was most accurate is due to it has high quantum kernel separability, and the reason why VQC has good trade-off between expressibility and resource is due to its strong quantum kernel separability. Comparative studies also validated that quantum models were able to provide competitive training using a small number of computational steps on specific datasets. Although these advances were made, the paper also identified the natural shortcomings of NISQ-era hardware such as circuit noise, small qubit counts, and circuit depth sensitivity. These limitations have an impact on scalability and they can limit the practical use in existing quantum systems. The findings however are supportive of the capabilities of QML to be a formidable method in the next generation classification tasks, especially as quantum hardware keeps improving.

- Optimize Quantum Circuits for NISQ Hardware: Use shallow circuits, noise-aware designs, and error-mitigation techniques to improve performance on real quantum devices.
- Develop More Expressive Quantum Feature Maps: Explore advanced encoding methods and entanglement-rich feature maps to enhance nonlinear separability.
- Adopt Hybrid Classical–Quantum Architectures: Combine classical deep learning with quantum layers to leverage strengths of both paradigms for complex datasets.

CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interest associated with this publication.

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