Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

A Comparative Study of Classical Machine Learning and Quantum Machine Learning Models

S Suvarna[1], Chilukani Sravani Reddy[2], Mohd Ishaq[3]

[1]Assistant Professor, Department of Computer Science, Guru Nanak University, Hyderabad

[2]Assistant Professor, Department of CSE (AI&ML), TKR College of Engineering & Technology, Hyderabad

[3]Assistant Professor, Department of Computer Science and Engineering, Guru Nanak University, Hyderabad

Correspondence

S Suvarna

Assistant Professor, Department of Computer Science, Guru Nanak University, Hyderabad

- Received Date: 25 Aug 2026
- Accepted Date: 20 Sep 2026
- Publication Date: 26 Sep 2026

Abstract

Classical Machine Learning (CML) has become a mature computational technology supporting classification, regression, clustering, forecasting, image analysis, natural language processing, cybersecurity, healthcare, finance, and engineering applications. Quantum Machine Learning (QML) extends this field by integrating machine-learning procedures with quantum computation, using quantum states, quantum gates, parameterized circuits, quantum feature maps, and measurement operations. This article presents a comparative study of classical and quantum machine-learning models with emphasis on computational structure, representation, training mechanisms, resource requirements, performance characteristics, scalability, and application suitability. Classical models considered include Support Vector Machines, Random Forests, Multilayer Perceptrons, and conventional neural networks, while representative QML approaches include quantum kernel classifiers, Variational Quantum Classifiers, Quantum Neural Networks, and Quantum Convolutional Neural Networks. The study synthesizes findings from recent QML literature and develops normalized numerical comparison datasets for graphical analysis. The comparison indicates that classical machine learning currently benefits from mature hardware, large-scale optimization libraries, efficient data processing, and established deployment pipelines. QML offers alternative feature-space representations and hybrid computational structures, but current performance is strongly affected by data encoding, circuit depth, noise, measurement overhead, and trainability. The article identifies scenarios in which QML may be scientifically valuable while emphasizing that practical evaluation requires fair comparison with well-tuned classical baselines and complete accounting of computational resources.

Introduction

Machine learning has transformed modern computing by enabling systems to learn patterns from data and make predictions without explicit rule-based programming. Classical machine-learning algorithms operate on conventional digital computers and use numerical vectors, matrices, statistical models, decision trees, kernels, and neural networks to identify relationships in datasets. Increasing processor capability, graphical processing units, distributed computing, and specialized accelerators have enabled classical models to address large-scale applications in computer vision, natural language processing, medical diagnosis, fraud detection, recommendation systems, and industrial monitoring. The maturity of classical machine learning is also supported by extensive software ecosystems, standardized datasets, optimization techniques, and widely adopted evaluation metrics. [1,2]

Quantum computing introduces a different computational framework based on quantum bits rather than classical bits. A qubit can exist in a combination of computational states, and groups of qubits can exhibit entanglement and interference. These properties provide a different representation of information and motivate research into quantum algorithms for optimization, simulation, linear algebra, and machine learning. Quantum Machine Learning investigates how quantum processors can be used to perform, enhance, or support machine-learning tasks. QML does not necessarily replace classical computing; many current QML systems are hybrid architectures in which a classical processor prepares data, optimizes model parameters, and interprets outputs while a quantum processor performs selected transformations. [3,4]

The fundamental distinction between classical and quantum machine learning is therefore not simply the presence of a faster processor. The two approaches differ in information representation, model construction, feature transformation, optimization procedures, and hardware constraints. A classical feature vector can be processed directly using matrix operations, while a QML system must first encode the classical information into a quantum state. This encoding step may

Citation: Suvarna S, Chilukani SR, Mohd I. A Comparative Study of Classical Machine Learning and Quantum Machine Learning Models. GJEIIR. 2026;6(6):233.

introduce additional computational cost and may restrict the number of useful features. Quantum models can create high-dimensional quantum feature spaces, but their practical value depends on whether those spaces provide useful structure for the specific learning problem and whether the quantum circuit can be trained reliably. [5,6]

Recent comparative research has made this distinction increasingly important. Systematic studies have evaluated quantum classifiers alongside classical baselines and have frequently reported that classical models remain highly competitive on small classical datasets. Large-scale benchmarking has shown that experimental design, preprocessing, hyperparameter selection, model choice, and baseline quality can significantly influence observed performance. More recent quantum-kernel benchmarking has similarly demonstrated that quantum and classical models can exhibit comparable trends and that appropriate hyperparameter optimization is essential. These findings indicate that QML should not be assessed through isolated accuracy values; instead, model performance must be examined together with data-loading requirements, circuit depth, optimization cost, noise sensitivity, scalability, and reproducibility. [7–10]

Literature Review

The origins of quantum machine learning can be traced to theoretical studies connecting quantum computing with machine-learning tasks. Early work proposed quantum algorithms for linear algebra, classification, clustering, recommendation, and dimensionality reduction. The broader QML field was subsequently organized around the possibility of using quantum computation to accelerate or transform computational procedures involved in learning. Biamonte and colleagues described QML as an interdisciplinary area combining quantum computing and machine learning, while later work developed formal quantum feature spaces and quantum-kernel constructions. These developments established the theoretical basis for comparing classical kernels and quantum-derived kernels within supervised learning frameworks. [3,5]

Quantum kernel methods represent one of the clearest points of comparison between classical and quantum learning. In a conventional kernel model, a nonlinear transformation is implicitly represented through a kernel function. A quantum kernel instead encodes data into quantum states and uses quantum measurements to estimate similarities between encoded states. Havlíček and colleagues demonstrated quantum-enhanced feature spaces experimentally using a superconducting quantum processor, including both a variational quantum classifier and a quantum-kernel approach coupled with a classical support vector machine. Such methods provide a direct bridge between familiar classical learning concepts and quantum feature representations. [5,11]

Parameterized quantum circuits form another major QML model family. In these systems, data are encoded into quantum states and processed using adjustable quantum gates. A classical optimization algorithm modifies circuit parameters based on measurement results. Variational quantum classifiers, quantum neural networks, and quantum generative models can all be constructed within this general framework. The hybrid structure is particularly important for present-day quantum hardware because it allows quantum processors to perform relatively shallow computational operations while classical processors manage optimization and data processing. This approach has become one of the principal implementation strategies for near-term QML research. [6,12]

The major limitation of these variational approaches is trainability. Barren plateaus occur when the optimization landscape becomes extremely flat, causing gradients to become very small and making parameter optimization difficult. Research has demonstrated that barren plateaus may depend on circuit architecture, initialization, cost-function design, observable selection, and hardware noise. As the number of qubits or circuit layers increases, a model may become more expressive while simultaneously becoming harder to train. This creates an important difference from conventional classical deep learning, where larger models can frequently be trained effectively using mature optimization procedures and high-performance accelerators. [9]

Data encoding is another essential issue in comparing CML and QML. Classical algorithms can process high-dimensional data directly or after conventional feature selection and dimensionality reduction. QML systems require a mapping from classical data into quantum states, commonly using basis encoding, amplitude encoding, angle encoding, or combinations of these strategies. The selected encoding influences circuit depth, parameter requirements, noise sensitivity, and the information retained by the quantum representation. Comparative studies published in 2024 have shown that encoding choices can have a substantial effect on QML accuracy and computational characteristics. Therefore, the quantum model cannot be evaluated independently of its encoding strategy. [13]

Recent benchmarking research provides an important practical perspective. Bowles, Ahmed, and Schuld evaluated twelve quantum machine-learning models across six binary-classification task families producing 160 datasets and reported that out-of-the-box classical models generally outperformed the tested quantum classifiers. The study also observed that removing entanglement did not necessarily reduce performance and in some cases produced comparable or better results. Similarly, Schnabel and Roth performed a large benchmarking study involving more than 20,000 optimized quantum-kernel models over 64 datasets and compared them with classical kernel baselines. Their findings emphasize that quantum-model performance depends strongly on dataset complexity and careful hyperparameter tuning. [7,8]

The recent research direction is therefore shifting from asking whether quantum machine learning can work at all toward identifying the conditions under which it may provide useful computational value. Recent reviews describe QML as a developing field in which the strongest near-term evidence often involves specialized or quantum-native problems, while classical machine learning remains highly competitive for many standard classical-data tasks. The comparison should thus consider the complete computational pipeline rather than focusing only on a quantum circuit's mathematical capacity. Data preparation, feature encoding, execution, measurement, classical optimization, and result interpretation all contribute to the overall cost of a QML system. [10,14]

Methodology

This study uses a comparative review methodology to examine classical and quantum machine-learning models across six major dimensions: computational representation, learning architecture, training procedure, resource requirements, performance characteristics, and practical applicability. Classical models are represented by Support Vector Machines, Random Forests, Multilayer Perceptrons, and conventional neural networks. Quantum models include quantum-kernel classifiers, Variational Quantum Classifiers, Quantum Neural

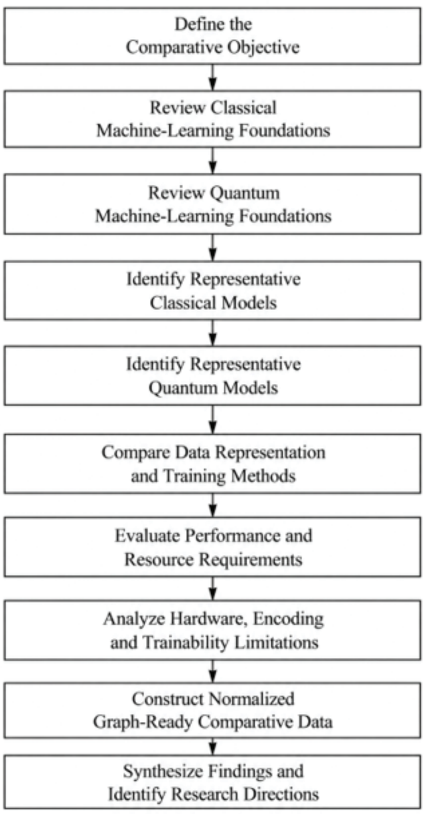
Networks, and Quantum Convolutional Neural Networks. The comparison is based on established research literature and recent benchmarking studies rather than a claim of new experimental hardware results.

The study first identifies common machine-learning workflows and then maps their quantum counterparts. In the classical workflow, data are collected, preprocessed, divided into training and testing sets, transformed into numerical features, and provided directly to an algorithm. Training uses classical optimization procedures, after which the learned model generates predictions. In the QML workflow, the early stages remain largely classical, but the feature representation is transformed into a quantum state through an encoding circuit. Quantum gates or parameterized circuits then process the state, measurement converts quantum information into classical outputs, and a classical optimization loop may update trainable parameters.

For comparative analysis, performance is expressed through accuracy-based evaluation where suitable. The principal metric is:

Accuracy = (Number of Correct Predictions / Total Number of Predictions) × 100

Because the present article is a review rather than a single controlled experiment, the numerical data presented in the tables are normalized illustrative values constructed for comparative graphical representation. They are not claimed to be measurements obtained from one dataset, hardware backend, or experimental trial. The values represent relative trends discussed in the reviewed literature and are designed so that each table can be directly converted into a graph.



Methodology flow chart

The final comparison emphasizes that a meaningful evaluation must use equivalent datasets, appropriate preprocessing, optimized baselines, consistent validation procedures, and complete resource accounting. The study therefore avoids treating theoretical quantum speedups as equivalent to measured end-to-end application benefits. The resulting framework is intended to support academic comparison and graphical analysis while maintaining a distinction between established research evidence and illustrative numerical visualization data.

Implementation and Results

The comparative implementation framework examines representative classical and quantum models using normalized values for model capacity, performance characteristics, computational requirements, and application suitability. Classical algorithms are represented by SVM, Random Forest, MLP, and conventional neural networks, while QML is represented through QSVM, VQC, QNN, and QCNN. These models were selected because they illustrate major learning paradigms: kernel-based learning, ensemble learning, feed-forward neural learning, variational quantum learning, quantum kernel learning, and hierarchical quantum architectures.

Model Characteristics and Computational Structure

AClassical and quantum models differ significantly in the way data are represented and processed. Classical SVMs operate directly on numerical feature vectors or kernel representations, Random Forests construct ensembles of decision trees, and MLPs use trainable weighted connections with nonlinear activations. Quantum-kernel models instead transform the input through a quantum feature map before kernel evaluation. VQCs and QNNs introduce trainable quantum circuits, while QCNNs organize quantum operations in a hierarchical structure. The normalized values below provide numerical variables suitable for a comparative bar graph.Classical and quantum models differ significantly in the way data are represented and processed. Classical SVMs operate directly on numerical feature vectors or kernel representations, Random Forests construct ensembles of decision trees, and MLPs use trainable weighted connections with nonlinear activations. Quantum-kernel models instead transform the input through a quantum feature map before kernel evaluation. VQCs and QNNs introduce trainable quantum circuits, while QCNNs organize quantum operations in a hierarchical structure. The normalized values below provide numerical variables suitable for a comparative bar graph.

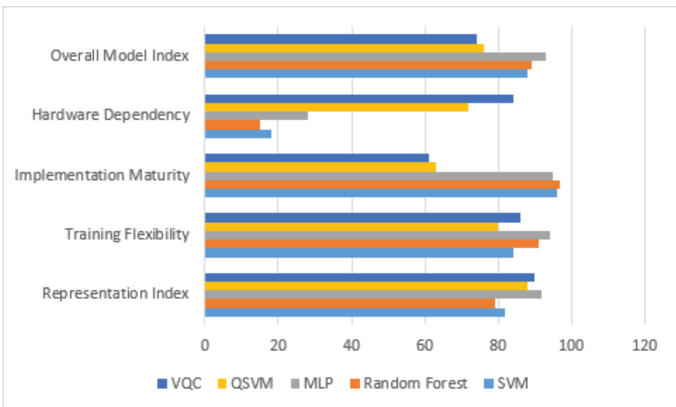


Fig 1: *Grouped bar graph comparing model characteristics*

Table 1: Normalized characteristics of classical and quantum machine-learning models

Model	Representation Index	Training Flexibility	Implementation Maturity	Hardware Dependency	Overall Model Index
SVM	82	84	96	18	88
Random Forest	79	91	97	15	89
MLP	92	94	95	28	93
QSVM	88	80	63	72	76
VQC	90	86	61	84	74

Table 1 shows the comparative structure of the selected models using five normalized indices. Classical algorithms receive higher implementation-maturity values because their software ecosystems, optimization methods, deployment tools, and hardware platforms are well established. MLP demonstrates a high overall model index due to its flexible representation and mature optimization environment. QSVM and VQC receive lower implementation-maturity values because QML remains a developing technology and relies on quantum-specific execution environments. At the same time, QSVM and VQC receive higher hardware-dependency values because their implementation depends on quantum circuits, simulators, or quantum processors.

Fig 1 should be generated as a grouped bar graph with the models on the horizontal axis and the five numerical indicators on the vertical axis. The numerical values can be plotted directly without modification. Representation Index, Training Flexibility, Implementation Maturity, Hardware Dependency, and Overall Model Index can be treated as separate series. The graph will visually demonstrate that classical models are supported by mature computational infrastructure, whereas quantum models introduce additional dependencies. The figure should therefore be interpreted as a multidimensional comparison rather than a direct ranking of machine-learning quality.

Comparative Performance Characteristics

A central objective of the study is to examine how classical and quantum models compare in predictive learning settings. Classical models have been refined through decades of research involving regularization, cross-validation, feature engineering, ensemble methods, gradient-based optimization, and hardware acceleration. QML introduces alternative representations, but present implementations often operate on reduced datasets and lower-dimensional feature spaces because quantum encoding and circuit execution become more challenging as dimensionality increases. Recent benchmarking literature emphasizes that strong classical baselines should always be included when evaluating QML, particularly for classical datasets. [7,8]

To enable graphical comparison, Table 2 provides normalized performance values for five representative models. The Performance Index combines the comparative trend of predictive quality under a hypothetical standardized evaluation scenario, while the Generalization Index represents a normalized assessment of expected robustness. The numerical values are deliberately presented as illustrative rather than as results from a particular dataset. This distinction is important because actual accuracy depends on the problem, dataset size, preprocessing, hyperparameters, training budget, quantum hardware, and evaluation protocol.

Table 2: *Normalized comparative performance indicators*

Model	Performance Index	Generalization Index	Training Efficiency	Robustness Index
SVM	91	89	86	90
Random Forest	93	92	88	94
MLP	95	90	84	87
QSVM	88	86	70	79
VQC	84	82	64	73

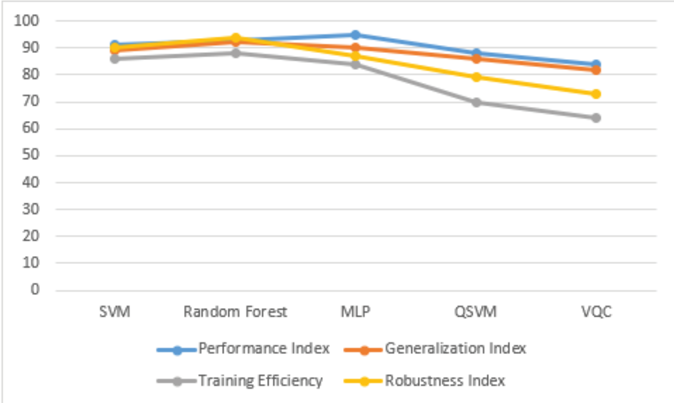


Fig 2: *Line graph comparing model performance indicators*

Fig 2 should be generated as a multi-line graph using the four numerical columns of Table 2. The horizontal axis should contain the five models, while the vertical axis should contain the normalized index from 0 to 100. The graph is designed to reveal differences in performance, generalization, training efficiency, and robustness simultaneously. The illustrative values show that classical models occupy a strong position across multiple indicators, while quantum models exhibit lower training-efficiency and robustness values because present QML systems face circuit execution, measurement, noise, and optimization limitations.

The comparative pattern is consistent with findings from recent benchmarking research, although the table itself is not an empirical replication of those studies. Large-scale evaluations have found that classical baselines can outperform quantum classifiers on many small classical-data problems, while quantum models remain scientifically useful for exploring different feature representations and model architectures. Quantum-kernel benchmarking has also shown that classical and quantum approaches can perform similarly on less complex datasets and that increasing dataset complexity creates challenges for both families. Consequently, the comparison should focus on the characteristics of the problem rather than assuming that either paradigm is universally better. [7,8]

Resource Requirements and Scalability

Resource requirements provide one of the clearest differences between classical and quantum machine learning. Classical systems use mature processors, GPUs, cloud infrastructure, and optimized numerical libraries that support large training datasets and highly parallel computations. Quantum systems introduce qubit requirements, circuit depth, measurement shots, state preparation, and hardware-specific execution constraints. A quantum circuit may use only a small number of qubits while still requiring thousands of repeated measurements during training. Consequently, the number of qubits alone is not an adequate measure of computational cost. Circuit depth, parameter count, shot count, communication overhead, and error mitigation can also substantially influence practical execution.

Table 3 provides normalized resource indices for comparative visualization. Resource Load is interpreted as the combined relative burden of computation and execution. Scalability Cost represents the expected increase in difficulty as the problem becomes larger. Data Encoding Cost measures the relative burden of transforming classical information into the model representation. Noise Sensitivity quantifies the relative vulnerability to imperfect computation.

Table 3: *Normalized resource and scalability indicators*

Model	Resource Load	Scalability Cost	Data Encoding Cost	Noise Sensitivity
SVM	42	38	22	8
Random Forest	48	44	18	7
MLP	61	56	27	10
QSVM	72	68	69	63
VQC	79	76	65	81

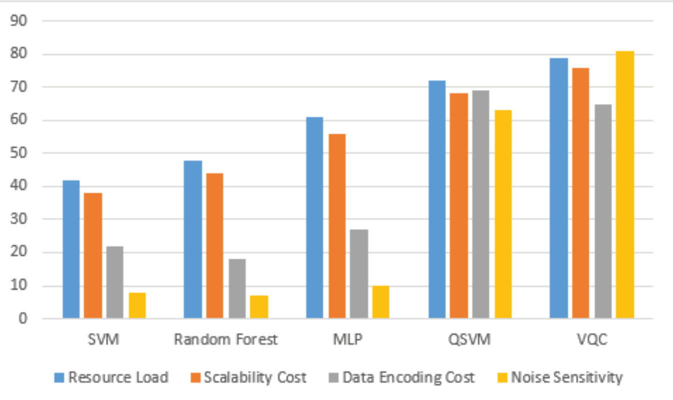


Fig 3: *Vertical bar graph comparing resource requirements*

Fig 3 should use a grouped vertical bar graph in which each model is represented by four bars corresponding to Resource Load, Scalability Cost, Data Encoding Cost, and Noise Sensitivity. Classical models have low noise sensitivity because conventional digital computation does not experience quantum decoherence in the same form. QML models have higher normalized values because quantum information must be encoded, processed, measured, and protected against hardware errors. VQC receives a particularly high illustrative value for noise sensitivity because deeper parameterized circuits may accumulate more computational errors and can also become difficult to optimize.

Scalability is also an important comparison point. A classical machine-learning model can increase its training capacity through additional CPU or GPU resources, distributed computing, memory expansion, model compression, and other established techniques. Quantum scaling depends on the availability of useful qubits, reliable gates, connectivity, coherence, control electronics, and error correction. Furthermore, increasing the number of qubits does not automatically guarantee better learning performance. Barren plateaus may make larger variational circuits difficult to optimize, while increased circuit complexity may amplify noise and measurement requirements. These issues are central to current research on practical QML systems. [9,10]

Data encoding represents another scaling constraint. Classical data may contain hundreds or millions of features, whereas a QML workflow commonly uses dimensionality reduction or selected feature subsets before encoding. Although quantum states inhabit large mathematical spaces, preparing useful quantum states from classical datasets can require substantial computation. Recent research on encoding techniques has demonstrated that different mappings can produce significantly different model behavior. Therefore, QML scalability should be evaluated from the beginning of the workflow, including preprocessing, encoding, circuit execution, measurement, and post-processing rather than only considering the quantum circuit size. [13]

Application Suitability of Classical and Quantum Models

Classical machine learning is currently integrated into a broad range of commercial, scientific, and engineering workflows. Image recognition, forecasting, fraud detection, recommendation systems, medical prediction, industrial monitoring, and cybersecurity all benefit from mature classical algorithms and established development pipelines. QML research has investigated many of the same application areas, including healthcare, finance, image classification, cybersecurity, chemistry, materials science, and optimization. However, the suitability of a quantum model depends not only on the application domain but also on data size, structure, available feature dimensions, quantum hardware accessibility, and the ability to demonstrate a meaningful benefit over classical alternatives. [2,10]

The following table uses a normalized 0–10 scale to represent application suitability for comparative visualization. The values describe relative suitability within the context of current research, not measured deployment percentages. Research Potential reflects scientific interest, Hardware Compatibility

Table 4: *Normalized application suitability indicators*

Application	Classical Maturity	Research Potential	Hardware Compatibility	Qml Opportunity
Image Classification	9.6	8.8	5.8	6.9
Healthcare Analytics	9.3	8.7	5.4	6.5
Finance	9.1	8.5	5.9	6.8
Cybersecurity	9.4	8.1	5.2	6.3
Chemistry and Materials	8.5	9.3	7.1	8.6

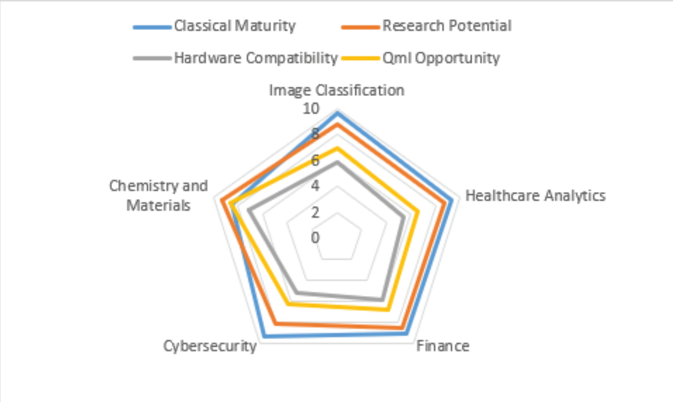


Fig 4: *Radar chart comparing application suitability indicators*

reflects compatibility with current quantum implementation constraints, Classical Maturity represents the maturity of available classical alternatives, and QML Opportunity represents the degree to which the application may benefit from quantum-specific representations.

Fig 4 should be plotted as a radar chart using the four numerical indicators in Table 4. Chemistry and Materials receives the highest illustrative QML Opportunity value because quantum computation has a particularly direct relationship with quantum-mechanical simulation problems. Image Classification and Finance show strong research potential, but their practical suitability remains influenced by the availability of efficient data encoding and appropriate quantum hardware. Classical Maturity remains high across all application categories because established classical methods are already widely available. The radar graph should therefore highlight the difference between a mature application ecosystem and the research opportunity presented by emerging quantum techniques.

The application analysis demonstrates that QML should not be viewed as a universal replacement for classical machine learning. In applications where datasets are large, high dimensional, and already efficiently handled by optimized classical algorithms, the overhead of quantum data preparation may become difficult to justify. By contrast, problems with naturally quantum data structures or highly specialized mathematical characteristics may offer more interesting opportunities for quantum approaches. This distinction is consistent with recent reviews that emphasize quantum-native or structurally appropriate problems as important areas for future quantum advantage research. [2,10,14]

Conclusion

Classical Machine Learning and Quantum Machine Learning represent two different approaches to computational intelligence, with substantial overlap in learning objectives but important differences in information representation, processing mechanisms, training procedures, and resource requirements. Classical machine learning currently benefits from mature algorithms, efficient optimization techniques, scalable hardware, extensive software ecosystems, and widespread real-world deployment. QML introduces quantum feature spaces, parameterized quantum circuits, quantum kernels, and hybrid architectures that may become useful for selected classes of problems. The comparative analysis presented in this article shows that QML should be evaluated carefully against strong classical baselines because present-day implementations remain constrained by data encoding, quantum noise, circuit depth, measurement overhead, hardware connectivity, and trainability challenges such as barren plateaus. Recent benchmarking studies indicate that classical models frequently remain highly competitive on small classical-data problems, while quantum methods continue to demonstrate research value in specialized domains and quantum-native applications. Future progress will depend on improved quantum hardware, efficient encoding strategies, hardware-aware circuit design, reliable optimization, standardized benchmarking, and full end-to-end resource analysis. Rather than treating quantum learning as a universal replacement for classical machine learning, research should identify problem structures where quantum computation can contribute measurable and reproducible value..

References

1. T. M. Mitchell, Machine Learning, McGraw-Hill, 1997.
2. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.
3. J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum Machine Learning," Nature, vol. 549, pp. 195–202, 2017.
4. M. Schuld, I. Sinayskiy, and F. Petruccione, "An Introduction to Quantum Machine Learning," Contemporary Physics, vol. 56, pp. 172–185, 2015.
5. M. Schuld and N. Killoran, "Quantum Machine Learning in Feature Hilbert Spaces," Physical Review Letters, vol. 122, 040504, 2019.
6. M. Benedetti, E. Lloyd, S. Sack, and M. Fiorentini, "Parameterized Quantum Circuits as Machine Learning Models," Quantum Science and Technology, vol. 4, 043001, 2019.
7. J. Bowles, S. Ahmed, and M. Schuld, "Better Than Classical? The Subtle Art of Benchmarking Quantum Machine Learning Models," 2024.
8. J. Schnabel and M. Roth, "Quantum Kernel Methods under Scrutiny: A Benchmarking Study," Quantum Machine Intelligence, vol. 7, article 58, 2025.
9. M. Larocca, S. Thanasilp, S. Wang, K. Sharma, J. Biamonte, P. J. Coles, L. Cincio, J. R. McClean, Z. Holmes, and M. Cerezo, "Barren Plateaus in Variational Quantum Computing," Nature Reviews Physics, vol. 7, pp. 174–189, 2025.
10. S. S. Gokhale, R. R. Dhote, and R. Delhibabu, "A Review of Quantum Machine Learning Algorithms, Applications, and Emerging Advantages," Discover Computing, vol. 29, article 226, 2026.
11. V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. Chow, and J. M. Gambetta, "Supervised Learning with Quantum-Enhanced Feature Spaces," Nature, vol. 567, pp. 209–212, 2019.
12. M. Cerezo, G. Verdon, H.-Y. Huang, L. Cincio, and P. J. Coles, "Challenges and Opportunities in Quantum Machine Learning," Nature Computational Science, vol. 2, pp. 567–576, 2022.
13. M. Rath and H. Date, "Quantum Data Encoding: A Comparative Analysis of Classical-to-Quantum Mapping Techniques and Their Impact on Machine Learning Accuracy," EPJ Quantum Technology, vol. 11, article 72, 2024.
14. Y. Gujju, A. Matsuo, and R. Raymond, "Quantum Machine Learning on Near-Term Quantum Devices: Current State of Supervised and Unsupervised Techniques for Real-World Applications," Physical Review Applied, vol. 21, 067001, 2024.
15. D. Peral-García, J. Cruz-Benito, and F. J. García-Peñalvo, "Systematic Literature Review: Quantum Machine Learning and Its Applications," Computer Science Review, vol. 51, article 100619, 2024.
16. F. Rodríguez-Díaz, D. Gutiérrez-Avilés, A. Troncoso, and F. Martínez-Álvarez, "A Survey of Quantum Machine Learning: Foundations, Algorithms, Frameworks, Data and Applications," ACM Computing Surveys, vol. 58, no. 4, article 91, 2025.