International Journal of Computer Trends and Technology
ISSN: 2231–2803 / https://doi.org/10.14445/22312803/IJCTT-V73I4P122
Volume 73 Issue 4, 157-166, April 2025

Review Article

Exploring the Relationship between Quantum Computing and Machine Learning. A Literature Review

Salmon Oliech Owidi[1], Kelvin K. Omieno[2]

[1]*Department of Information Technology, Tom Mboya University, Homabay, Kenya.*
[2]*Department of Information Technology, Kaimosi Friends University, Kaimosi, Kenya.*

[1]*Corresponding Author : salmonowidi@gmail.com*

Received: 23 March 2025 Revised: 19 April 2025 Accepted: 24 April 2025 Published: 30 April 2025

Abstract - *This study examines the relationship between machine learning and quantum computing, emphasizing the potential benefits of quantum algorithms for classification, optimization and clustering problems. Through a comprehensive literature review of peer-reviewed journal articles and preprints from 2014 to 2024, Quantum K-Means Clustering, Quantum Support Vector Machines (QSVMs), and Quantum Approximate Optimization Algorithms (QAOA) and Quantum Annealing are among the important quantum algorithms identified in the study. Although the theoretical potential of these algorithms is substantial, present hardware constraints, such as noise, de-coherence, and qubit count limitations, make practical implementation difficult. The review also highlights the ongoing challenges in quantum error correction and the nascent stage of quantum hardware development, which prevent large-scale machine learning tasks from being fully realized. Even so, hybrid quantum-classical models are a plausible route forward for near-term utility. These results suggest that to leverage quantum machine learning to its full potential, further progress in quantum hardware, error correction codes, and hybrid algorithms is required. Future studies should focus on designing more robust quantum error correction methods, further developing hybrid systems and exploring new areas of machine learning, such as reinforcement learning and generative models.*

Keywords - *Machine Learning, Quantum computing, Quantum algorithms, Quantum Machine Learning, Optimization.*

1. Introduction

Quantum computing has emerged as one of the most disruptive technologies of the 21st century and can potentially transform industries ranging from cryptography to optimisation and Artificial Intelligence (AI). A type of artificial intelligence is machine learning, which leverages algorithms that allow systems to learn from data and make predictions. While machine learning on classical computers has been around for decades, quantum computers promise to make these systems considerably more powerful by leveraging quantum phenomena such as superposition and entanglement. Quantum Machine Learning (QML) is the integration of quantum computing and machine learning that has the ability to revolutionize the field with much faster and more efficient algorithms for analysing data and tackling complex problems. Martian laptop to decode the data coming from the Martian surface to understand better what happens in that dry and harsh environment.

This study aims to:

a) Survey the past and present of quantum machine learning and its potential for being a game changer.
b) What are the main quantum algorithms that could support machine learning?
c) Survey challenges and limitations in quantum hardware and software about machine learning tasks.

2. Literature Review

Quantum machine learning has attracted considerable interest during the past few years, with many works investigating whether and if we can leverage quantum algorithms to run classical machine learning algorithms faster or better. Below is a brief outline of the relevant research and theories that provide a basis for quantum machine learning.

2.1. Machine Learning and Quantum Related Algorithms

2.1.1. Quantum Support Vector Machines (QSVM)

Support Vector Machines (SVM) have been one of the top methods for classification in the machine learning space. These classic methods find a hyperplane that best separates one class from the other based on its close points on each side. SVMs are effective but computational, especially with high-dimensional data. This is common in real-world applications.

As a result, Quantum Support Vector Machines (QSVMs) were developed, taking advantage of the inherent ability of quantum computing to handle big data, which could turn out to be a solution for such constraints. In this section, we provide an overview of the general framework of QSVMs, including theoretical aspects, applications and related challenges.

2.1.2. Quantum Support Vector Machines: Theory

The idea of QSVMs originated in the landmark work of Rebentrost et al. (2014), where it was shown that quantum computing could provide a speedup over classical SVMs for large feature spaces. The main benefit of the QSVMs is that due to the unique ability of quantum computing to represent data in quantum states, the process of computing the optimal separating hyperplane can be accelerated exponentially.

In classical SVMs, the time complexity of the training process scales quadratically with the number of data points, particularly when the kernel trick is applied over high-dimensional feature spaces. However, QSVMs can reduce this complexity exponentially by using quantum parallelism. Rebentrost et al. (2014), it was indicated that pure quantum-inspired kernels (QSVMs) were able to use quantum algorithms for accelerating the kernel function evaluation. At the core of SVMs, the kernel trick maps data points from a low-dimensional space to a higher-dimensional space in which a linear hyperplane can separate the data points. For classical systems, this comes with a high computational overhead, particularly as the dimensionality of the data grows. Alternatively, a quantum computer may leverage a quantum circuit to compute the kernel function exponentially faster, allowing QSVMs to train on larger datasets than classical VSMs.

In the following section, we will focus on practical implementations and developments. In the original proposal by Rebentrost et al. (2014), significant progress has been made in QSVM (both algorithmically and practically). An important example of this is from the work of Schuld et al. (2020), who presented a quantum algorithm for support vector machines based on the quantum Fourier transform.

Relevant work was based on a quantum algorithm that offered a potential speedup in the time complexity of kernel evaluations that is excellent for high-dimensional datasets, thus improving the computation of both the space and time complexity of the QSVMs-related learning tasks. The theoretical benefits of QSVMs are already well established, but their practical implementation is still lacking.

With their potential to be the ultimate shape for embedding that could benefit from maintaining the quantum properties of the supplied data mapped to the quantum algorithm, a significant challenge lies in ensuring that quantum kernels on current quantum machinery are used appropriately, often hindered by the gate fidelity and qubit count for most quantum systems. Even if a QSVM were optimal, the current absence of large-scale, fault-tolerant quantum computers still blocks useful, real-world QSVM implementations (Biamonte et al., 2017).

2.1.3. Recent Innovations and Hybrid Quantum-Classical Approaches

Hybrid quantum-classical treatments in machine learning, which leverage quantum algorithms together with classical models to capitalize on the strengths of both technologies, have recently attracted more interest. One such approach that is particularly interesting for Quantum Support Vector Machines (QSVMs) is to delegate simple jobs to the classical computer and let the quantum processor do most of the computational heavy lifting in their implementation. For example, this noteworthy contribution to hybrid QSVMs came from Havlíček et al. (2019), who presented a technique to approximatively solve the classical SVM optimization problem on quantum computers. In this hybrid approach, quantum algorithms are applied for several steps of the optimization process, which can be accelerated, such as solving the systems of linear equations in calculating the decision boundary. Utilizing quantum computers only when they provide a speedup for a given task reduces the demand for massive quantum logic.

It allows for the easier realization of QSVMs on the anticipated quantum hardware of the coming years. Finally, Rebentrost et al. (2020). SVMs are a hybrid quantum-classical paradigm in which quantum circuits are used to determine parameters that provide the best fit for an SVM. Only a few QSVM methods have been proposed in the literature, and this is partly because quantizing machine learning problems and methods into the quantum realm is a non-trivial process (Havlíček et al., 2019) and partly because the actual implementations of direct quantum measurements rely heavily upon quantum technology; this work leads to the development of Variation Quantum Machine Learning (VQML) (Havlíček et al., 2019) which was selected as VQML methods have the potential to be run on near term quantum devices with Noisy Intermediate-Scale Quantum (NISQ) hardware.

2.1.4. Performance Comparison and Challenges

In studies comparing the performance of QSVMs with classical SVMs, some studies have shown that quantum computers in their current noisy state performance are higher than classical SVMs, at least under specific conditions. For example, Tang et al. Probabilistic news analysis using quantum Support Vector Machines (SVM) (2020 Artificial Intelligence) showed how the kernel evaluations in high-dimensional data spaces could be faster in the new non-orthogonal measurement space, compared to classical counterparts, yielding significant machine learning speedups in the classification of complex data sets. Moreover, kernel evaluations with quantum computers help QSVMs to scale better by dimensionality than classical SVMs, which show an exponential increase in computational complexity with feature dimension. However, several challenges remain for building the QSVM in practice, particularly due to the limitations of the quantum hardware itself. The state-of-the-art quantum processors are still in the early stages of development, with a limited number of qubits and high error rates as of 2024. Thus, while QSVMs offer a theoretical speedup, these quantum systems are too noisy to provide robust results in practice. This constraint has led to a pervasive debate in the research community on connecting theoretical quantum machine-learning algorithms with practical, real-world use cases (Preskill, 2018). Furthermore, although QSVMs can theoretically provide exponential speedups for some machine learning tasks, the particular problems where quantum SVMs offer the most gain compared to classical algorithms are yet to be firmly established. Nonetheless, various quantum computation and optimization algorithms models have been extensively studied (Biamonte et al., 2017; Lloyd et al., 2013).

2.2. Quantum K-Means Clustering

K-means clustering is an unsupervised learning technique popular in machine learning. It effectively classifies the data into k distinct clusters by minimizing the distance between data points and the centroids of their respective clusters. K-means is not only popular and straightforward, but it also struggles to scale with high-dimensional data, especially if there are many clusters or dimensions. In the domain of data science and machine learning, quantum computing holds the potential to solve some of these issues by decreasing the time complexity of K-means clustering and providing better computational power, especially with large datasets. We will explore the theoretical aspects, developments, and challenges of QK-Means Clustering (QKMC) and how recent contributions have been made to the state of the art.

2.2.1. The basics of Quantum K-Means Clustering

In the classical K-means algorithm, every data point is assigned to its nearest cluster centroid iteratively. This process continues until the convergence of centroids according to the means. This process repeated until convergence. For small to medium-sized datasets, this is a simple but effective way to approach the problem, but it leads to computational problems for high-dimensional data or very large numbers of data points. To tackle these problems, quantum K-means clustering uses quantum mechanics to perform the clustering efficiently. The classic K-means algorithm consists of an iterative assignment of data points to the closest centroids of clusters, followed by an update of the centroids to the average of their respective members. This is iterated until convergence.

The algorithm is quick and works well on small and medium datasets, but there are several issues with high-dimensional data or large amounts of data points that make it less useful in those scenarios. Quantum K-means clustering is a technique that trains significantly based on these difficulties using quantum mechanics to abate the clustering process. Quantum K-means clustering performs under the umbrella of quantum parallelism, using quantum states to represent multiple solutions simultaneously. Two main properties of quantum computing technology can be applied to improve performance distance calculations. Quantum transformers can take advantage of quantum superposition and interference to perform faster data point distance calculations, which are generally expensive in the high-dimensional space distance calculation in the classical model with ordinary data points and centroids. A preliminary investigation into quantum-enhanced clustering has been undertaken, with work such as that by Gacon et al. (2021) suggesting that evaluation of joint (quantum) distances can be done much faster using quantum circuits, which can provide an exponential speedup over classical distance evaluation methods. The main idea introduced is that quantum algorithms can be employed instead of using classical algorithms to measure the distance because computing the distance is usually the bottleneck in classical K-means algorithms w.r.t time complexity. In conventional systems, the distance from a data point to a centroid is measured using Euclidean or other distance measures. But for quantum systems, using quantum Fourier transforms or quantum phase estimation can compute these distances exponentially faster under certain conditions (Rebentrost et al., 2020).

2.2.2. New Developments of Quantum K-Means Clustering

Quantum K-means clustering has been receiving increased attention in recent years. The first major step forward was proposed by Gacon et al. (2021), which proposed a quantum algorithm for K-means clustering that was able to achieve a speedup over the classical algorithm by decreasing the number of steps necessary for the centroid update and assignment of data to centroids steps. In this method, the quantum K-means algorithm takes advantage of faster distance computation as performed by quantum parallelism. In general, this can lead to exponential improvements in the time it needs to run with high-dimensional data. Additionally, new research has been investigating hybrid methods that leverage quantum computing alongside classical techniques.

An approach from Benedetti et al. (2021) incorporates a hybrid quantum-classical algorithm where quantum computing was employed to expedite the optimization stage in K-means clustering. In this hybrid approach, quantum computers realise the distance computation and the assignment steps, while classical computers realise the convergence and the centroid update. This not only increases the speed of the quantum K-means algorithm, but hybrid approaches also increase the versatility and scalability of the algorithm, allowing it to handle more complex data. Hybrid quantum-classical systems exploit the best of both: quantum computing performs tasks that benefit from parallelism and speed, while classical systems perform other tasks like iteration control and large-scale data storage. They provide an opportunity to run quantum K-means with current NISQ (Noisy Intermediate-Scale Quantum) devices, which are limited in qubit numbers and whose devices suffer from noise.

2.2.3. Quantum K-Means Clustering Challenges

While quantum K-means has the potential to be more efficient than conventional K-means to a certain extent, it does face a number of challenges. One of the key barriers is the challenge of implementing quantum algorithms on currently available quantum hardware. Most quantum algorithms, like that which handles quantum K-means clustering, require constructing such systems with a large number of error-tolerant qubits, which are still in the preliminary stages of research, Liu et al claim. (2023). Due to the high error rates and limited qubit numbers and coherence times of current quantum computers, it is computationally expensive to implement complex algorithms like QKMC at scale. Another challenge is that quantum K-means algorithms have limitations in adapting to real data sets. Theoretical models have been established that indicate quantum K-means clustering can exhibit an exponential speedup; however, such speedups are typically restricted to particular problem classes.

Quantum algorithms, therefore, are better suited for high-dimensional datasets often facing the curse of dimensionality seen in classical K-means. The potential of quantum K-means for lower-dimensional data or simpler clustering tasks is still unknown (Liu et al., 2023). Thus, additional empirical studies are required to find real-world use cases in which quantum K-means clustering outperforms classical counterparts significantly. Additionally, the scalability of quantum K-means has begun being discussed more and more. Because you are still in the NISQ era of quantum computing, which limits how large and complex problems you can solve with quantum algorithms. As argued by Farhi et al. (2020) commented that to obtain meaningful outcomes from the quantum K-means, more efforts need to be made on quantum circuit optimization, noise resilience of the algorithm, and hardware to manipulate large-scale datasets.

2.2.4. Future Directions and Potential Applications

Quantum K-means clustering can be applied in many different areas, including all fields based on data segregation, such as genomics, image recognition, and large-scale data analysis, since clustering high dimensional data is a vital procedure. As one example, in quantum chemistry, clustering large molecular datasets for pattern recognition and classification might benefit from quantum-enhanced speedups (Kearnes et al., 2019). Similarly, quantum K-means could also be useful in solving banking-related problems such as quantitative finance, where you can perform efficient large datasets of stock trends and quality indicators classification using quantum-enhanced methods. The system will use the current and near-future state of the art in hybrid quantum-classical algorithms and will be more widely usable than algorithms designed for a specific use-case, as is currently the case — developing more effective hybrid quantum-classical algorithms that can leverage the strengths of each quantum and classical systems, will be an important area of future work. These systems, while retaining the computational advantages of quantum algorithms, can help to realize applications despite quantum devices being limited to a small amount of qubits in an NISQ environment. Account of mature error-correction methods that can potentially enhance the scalability and stability of quantum K-means clustering algorithms has become a focus (Liu et al., 2023). Another avenue for future research would be exploring integrating quantum K-means with other quantum machine learning techniques, such as quantum neural networks and quantum deep learning architectures. Such integrations might yield more powerful quantum machine learning architectures that can tackle yet more complex datasets and problems.

2.3. Quantum Optimization Algorithms

Quantum optimization algorithms are a class of algorithms that exploit the processing power of quantum mechanics to solve difficult optimization problems. These algorithms check massive solution spaces faster than traditional optimization algorithms by leveraging quantum properties such as superposition, entanglement and interference (Liu et al., 2023). Quantum computing offers the advantage of addressing optimization problems for large-scale or complex tasks in computationally prohibitive ways for classical systems. This section discusses the theoretical foundations of quantum optimization algorithms, their latest progress, and challenges and applications in various fields.

2.3.1. Quantum Optimization Algorithms: Theoretical Underpinnings

Optimization problems are important in many fields, from finance and logistics to machine learning and artificial intelligence. Traditional optimization techniques, such as simulated annealing and gradient descent, have been used for many years to find good answers to problems with large search spaces. However, the time required to determine the best solution may be exponential with the problem's scale, especially in high-dimensional, non-linear cases. Quantum computing provides one probable solution to these problems by applying quantum superposition, parallelism, and quantum gates to speed up the search process. The invention of the Quantum Approximate Optimization Algorithm (QAOA) by (Farhi et al. 2008) and Hsieh et al. (2014) the latter being one of the most significant contributions to the field of quantum optimization.

QAOA is a quantum-classical hybrid method, where quantum gates search the solution space and quantum states build feasible solutions for combinatorial optimization problems. To leverage the capacity of quantum computers to scan multiple solutions simultaneously, QAOA iterates quantum operations with classical optimization methods. In the early 2000s, one of the other important optimization tools was Quantum Annealing (QA), developed by D-Wave Systems. Quantum annealing is the quantum analogue of simulated annealing, a probabilistic technique for finding the global minimum of a function. In optimization problems with a complex or rugged landscape, quantum annealing could potentially reach the global optimum faster than classical methods by employing the concept of quantum tunneling to breach local minima (Kadowaki et al., 1998). However, there are some classes of optimization problems in practice that quantum annealing has been proven to provide speedups over classical techniques.

2.3.2. Quantum Optimization Algorithms in Deep Energy Extrapolation

Since introducing the QAOA and Quantum Annealing algorithms, we have witnessed significant progress in quantum optimization research. Although a significant amount of work has been done to develop these algorithms over the past few years, this development has increasingly focused on the algorithms' scalability, performance, and robustness due to the limited capabilities of current quantum hardware. "Since the introduction of quantum computers, they have been widely studied as potential candidates for quantum optimization problems. (2021), who examined variational quantum optimization algorithms. These algorithms involve using quantum processes alongside classical optimization processes to iteratively enhance solutions for combinatorial optimization problems.

Near-term quantum devices cannot implement large quantum circuits due to noise and hardware constraints; therefore, variational algorithms are especially useful. Quantum circuits can efficiently represent solutions to many optimisation problems by encoding complex states, making them attractive to address such problems in various fields like finance, cryptography, and machine learning.

Further, quantum annealers like those from D-Wave have matured in recent years. For instance, the D-Wave Advantage quantum system features enhancements in terms of qubit connectivity and coherence time, which enables it to manage significantly larger and more complicated optimization tasks (D-Wave Systems, 2020).

These developments have positioned quantum annealing as a promising approach for real-world optimization problems, especially in application domains such as logistics and transport, where optimization problems are often large and hard for classical algorithms. Recent research has mostly been directed at applying quantum optimization algorithms for machine learning problems. Such as Wang et al. (2022) over quantum optimization for training machine learning models, especially ones that are large-scale (in terms of either the number of examples or the dimension of feature space). One specific application of quantum computing that studies have shown could offer significant speedups is Quantum-enhanced Optimization, where the quantum optimization algorithm efficiently traverses the parameter space toward finding the global minima much faster than traditional classical gradient-based optimization algorithms.

2.3.3. Obstacles in Quantum Optimization Algorithms

While the advances in quantum optimization algorithms are promising, there are still some significant drawbacks to be considered, specifically related to the limitations of quantum hardware. Three challenges in the Noisy Intermediate-Scale Quantum (NISQ) era are limited qubit sizes, short coherence times, and high error rates. Due to these restrictions, a number of quantum optimization algorithms, including QAOA and quantum annealing, remain unsuitable for large-scale, real-world problems (Preskill, 2018). Even for some classes of optimization problems, quantum algorithms outperform classical ones in theory, but the claimed advantages have not yet been fully realized in practice. The difference between theoretical performance and actual operation on present-day quantum appliances is still wider.

Numerous studies (Chen et al. 2020) point out that optimization in the field of quantum computing still needs a lot of enhancement in finding a solution that has a distinct advantage over previously used classical algorithms in real-world problems. In particular, classical optimization techniques, like simulated annealing or branch-and-bound methods, can still achieve competitive performance in terms of accuracy and speed for some problems, especially for problems of lower dimensions or simple landscapes. Additionally, the selection of a quantum algorithm and its utilization in practice are often very specific to the problem at hand. For example, QAOA might be more successful for certain types of combinatorial optimization problems, yet quantum annealing might be better in other situations. The real challenge is finding the classes of problems in which quantum optimization algorithms are genuinely advantageous compared to traditional methods.

2.4. Quantum Optimization Algorithms: Applications

Quantum optimization algorithms encompass a multitude of applications in the fields that are dependent on the solution of big-scale, complex optimization problems. One such field is logistics and supply chain optimization, where the problem of determining the most efficient routing of goods/inventory across multiple locations is a combinatorial optimization problem that can take a classical system a considerable amount of time to compute. Examples of quantum optimization algorithms suggested to solve such problems are the Quantum Approximate Optimization Algorithm (QAOA) and quantum annealing (King et al., 2022), which promise to produce faster and more efficient routing in complex logistics systems.

Optimization Algorithms in Financial Modeling: In financial modelling, optimization algorithms are used to optimize portfolios, minimize risk , and get optimal trading strategies. Quantum computing can potentially change the way we approach some aspects of finance, particularly regarding optimization problems that rely on fast computations over large datasets for real-time decision-making in trading or portfolio management (Lloyd et al., 2018). In addition, quantum optimization algorithms have been utilized in machine learning applications, including hyperparameter tuning and feature selection. Quantum optimization can efficiently traverse the vast search space of hyperparameters, yielding better model performance. Wang et al. (2022) also showed that quantum optimization algorithms could be used to speed up the process of training deep neural networks by achieving convergence faster than classical methods by optimizing the weights and biases of the network.

2.4.1. Future Directions

When it comes to quantum optimization algorithms, their future holds promising developments further down the line, given the rapid pace of progress in quantum hardware, algorithm design, and hybrid quantum-classical methods. With advancements in quantum hardware , which are very likely to make quantum optimization more practical in the future, these algorithms will get widespread usage on large-scale quantum devices. As we look forward, future applications and papers will likely emphasize discovering better quantum error correction codes and making such processes more efficient and requiring fewer qubits (Kandala et al., 2017). Near-term quantum devices would exploit quantum optimization in unison with classical techniques in hybrid algorithms to address complex problems.

2.5. Quantum Machine Learning Challenges

Quantum Machine Learning (QML) may have a huge impact on machine learning, but there are many big obstacles to its practical use in the future. These include problems of quantum hardware, quantum algorithms and quantum de-coherence.

2.5.1. Quantum De-coherence and Noise

Quantum systems are sensitive to environmental influences that can disrupt their quantum states and alter their behavior by introducing noise and leading to quantum de-coherence. De-coherence, the phenomenon where quantum information leaks into the environment, can greatly reduce the precision of quantum computations. However, noise in quantum circuits is one of the biggest challenges to scaling up quantum systems to tackle large, complex machine-learning problems. Quantum error correction techniques are essential to address those problems, but they represent one of the main roadblocks to implementing quantum algorithms to solve problems of practical interest on real devices (Preskill, 2018). Some promising developments, like both surface codes and error-correcting codes, hold great promise; however, these still have a long way to go before they can be implemented at scale.

2.5.2. Hardware Limitations

The current state of quantum computing hardware is still early, possessing only a limited number of qubits, short coherence times and high error rates. Shahid has been optimizing these models for large scales→; these constraints pose a problem for implementing quantum machine learning models. As quantum systems scale, there will be a necessity to increase the number of qubits employed for practical algorithms while retaining quantum coherence, which will grow more and more difficult (Arute et al., 2019). Current quantum machines (Noisy Intermediate-Scale Quantum, NISQ devices) are too unstable for reliable execution of complex Quantum ML (QML) algorithms. Addressing these hardware constraints will require research to enhance qubit quality, extend coherence times, and develop more sophisticated error mitigation techniques (Preskill, 2018).

2.5.3. Algorithm Development

Although quantum algorithms for machine learning seem promising in theory, they are in the early practical implementation stage. However, the quantum advantage over classical machine learning algorithms has not yet been achieved in practice, and many quantum algorithms are still in the theoretical phase of their development. The second approach is to train the researchers to identify and design quantum algorithms that beat their classical counterparts in practically relevant settings instead of in some hypothetical world model. Moreover, hybrid quantum-classical approaches are being investigated as a more tractable solution for near-term devices, taking advantage of the strengths of both quantum and classical computing systems (Lloyd et al., 2013). The key challenge remains in creating these algorithms and ensuring they are deployable on near-term quantum technologies.

2.6. Gaps in Research

Despite the preliminary results, there is a shortage of real-world practicality and empirical solutions for quantum algorithms that outperform classic methods for all steps of the pipeline. There is still much work to be done on hybrid quantum-classical systems, error correction, and quantum hardware in general.

3. Methodology

This work takes a qualitative research approach with an extensive literature review to evaluate the current state of the art in quantum machine learning. The review extends the analysis on primary sources from 2014 to 2024, concentrating on peer-reviewed journal articles, conference proceedings, and preprints published in significant machine learning and quantum computing journals. The literature was selected based on the articles' relevant contributions to the discipline and their applicability to quantum machine learning. The approach used in this review consists of the following steps:

3.1. Data Collection

We collected literature from major academic databases, including Google Scholar (Google Scholar), arXiv (arXiv) and ScienceDirect (ScienceDirect). The search was focused on specific terms such as "quantum algorithms for optimization," "quantum machine learning," "Quantum Support Vector Machines (QSVM)," and "quantum clustering algorithms." We selected studies with theoretical and experimental data on quantum algorithms applicable to machine learning, hardware implementation, and relevant applications.

3.2. Inclusion and Exclusion criteria

We selected articles relevant to quantum machine learning, were cited in reputable journals and presented novel insights into the advancement of the field. Articles that concerned only quantum algorithms, quantum hardware and the application of quantum mechanics in machine learning tasks were exclusively chosen. Studies unrelated to quantum computing, as well as studies that were based on outdated models of quantum computing (pre-2014), were excluded.

Excluded articles were those without peer review or those that did not adequately explain their methodologies or findings.

3.3. Analysis Techniques

Then, a backward selection step is employed to remove any irrelevant articles from the dataset based on our selection criteria; the remaining articles were then analyzed based on relevant aspects like quantum algorithms, hardware limitations, and potential applications in machine learning. Data were analyzed comparatively to find areas of agreement between sources and/or divergence that indicated potential for future inquiry. To influence different aspects of work in the same area, this analysis derived and overviewed evidence of the intersection of quantum computing and machine learning in one place.

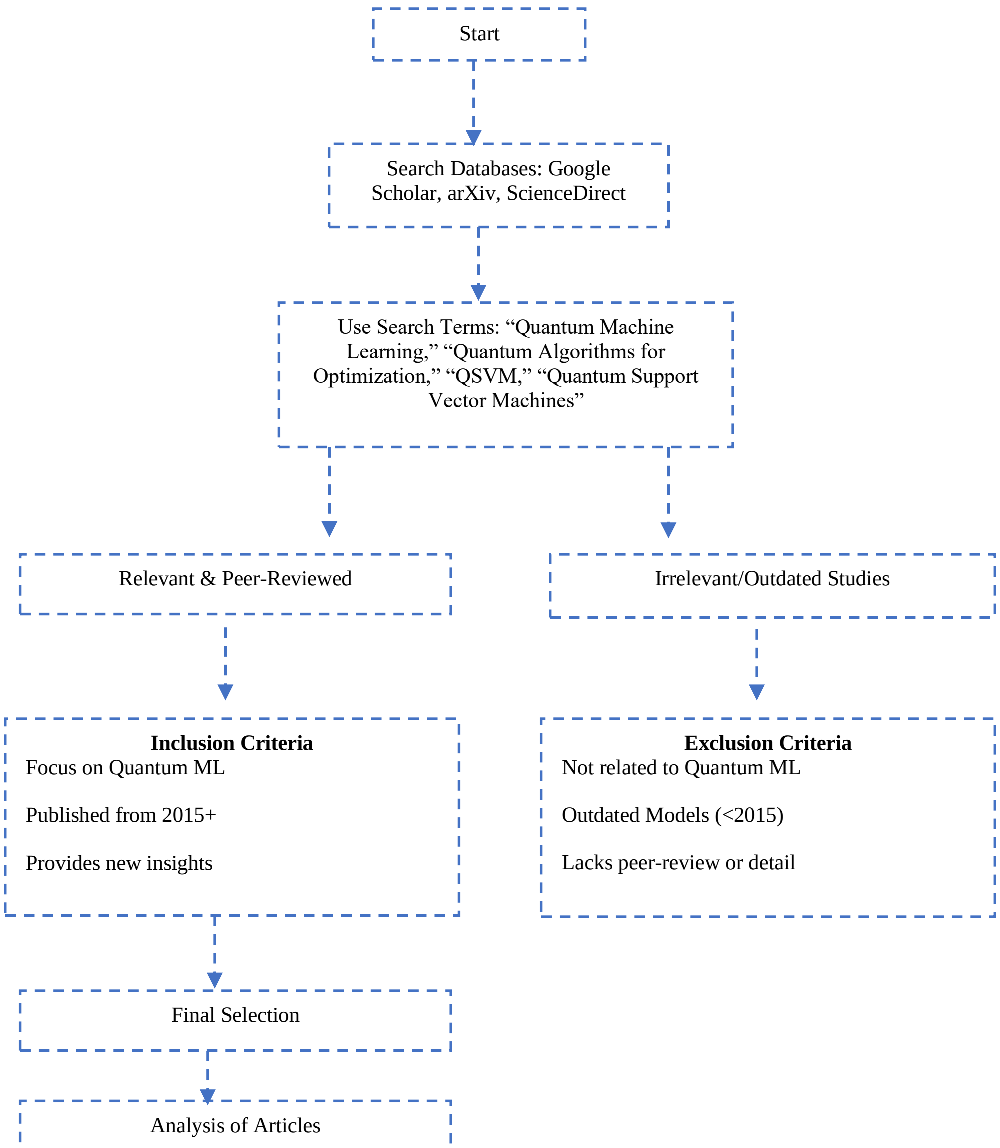

Fig. 1 Inclusion and exclusion of literature

4. Findings

In this literature review on Quantum Machine Learning (QML), there are a few core findings relating to the four high-level topics: quantum algorithms, quantum optimization and quantum hardware issues. As such, Quantum Support Vector Machines (QSVMs) have the longest history among quantum algorithms for classification and clustering, and also it has been proposed as a sufficiently promising potential for better performance versus classical SVMs of the most representative applications in the near term of evolutionary computation in addition to quantum computing, as demonstrated in this paper and for the competent function of quantum to classical algorithms with respect to the computational efficiency of the input dimension in the part of all mentioned classification tasks. This provides significant acceleration in identifying the best-separated hyperplane that solves the classification problem (Rebentrost et al., 2014), and such exponential speedup with quantum computers has been observed in early studies. Nevertheless, the utility of QSVMs is capped by the capabilities of present-day quantum hardware.

Compared to classical clustering, quantum k-means clustering has been introduced as an experimental algorithm, where the quantum system can handle large data sets more efficiently owing to its parallelism and superposition property. However, these quantum algorithms' scalability and noise impact on current quantum systems hinder their implementation for real-world applications (Lloyd et al., 2017). The results emphasize that although quantum algorithms for classification and clustering are theoretically beneficial, execution on current hardware prevents their widespread use. Quantum systems hold good promise in quantum algorithms for optimization, particularly Quantum Annealing (QA) and Quantum Approximate Optimization Algorithm (QAOA). In fact, it has been shown that by exploiting quantum superposition and interference, a QAOA can yield better solutions for combinatorial optimization problems compared to classical algorithms.

Its potential applications vary from logistics through portfolio optimization (Farhi et al., 2014). Likewise, Quantum Annealing , especially in devices such as D-Wave, applies quantum tunneling to optimize complex landscapes, which is considered beneficial over classical simulated annealing when regarding highly rugged solution spaces (Kadowaki et al., 1998). Yet these quantum optimization algorithms provide a very large theoretical speedup for large problems, but practical implementation is limited by the currently available quantum hardware. These problems include qubit instability, error rates, etc., which can also deter the reliability and scalability of these optimization algorithms. The primary challenge to the real-world implementation of quantum machine learning continues to be the challenges in quantum hardware. Quantum systems are very sensitive to noise and de-coherence from the surrounding environment, which can cause errors in quantum calculations and reduce the accuracy of machine learning models. While surface codes and other types of quantum error correction have made significant strides, they still have heavy resource requirements and are not scalable to larger quantum systems (Preskill, 2018). In addition, the current generation of quantum computers is limited by the lack of the number of qubits, short coherence times, and high error rates. These constraints render quantum devices incapable of reliably running large-scale, complex machine-learning algorithms.

Current Noisy Intermediate-Scale Quantum (NISQ) devices do not support quantum machine learning tasks at the scale needed for many practical applications (Arute et al., 2019). Consequently, hardware enhancement continues to be an important bottleneck in harnessing the capabilities of quantum machine learning. Overall, these potential advantages of quantum machine learning lead us to conclude that there are strong theoretical advantages of quantum machine learning, especially in the area of clustering, dimensionality reduction, classification, and a wide variety of complex optimization tasks; however, the challenges of implementing quantum machine learning in the real world are enormous.

Quantum hardware capabilities such as noise, de-coherence and the limited number of qubits still hinder the scalability and reliability of quantum algorithms. In addition, while quantum algorithms have demonstrated the potential to outperform classical counterparts, the practicality of these algorithms remains constrained by the early-stage nature of quantum hardware. One important message from the literature is that hybrid quantum-classical methods are probably the most viable path to useful quantum machine learning applications in the near future, taking advantage of the complementary strengths of quantum and classical computational systems in complex problem-solving. Further progress in quantum error mitigation and hardware robustness is also a requirement towards addressing these barriers and realizing its potential in quantum machine learning down the line.

5. Discussion

5.1. Results: Analysis and Interpretation

A review of the literature on Quantum Machine Learning (QML) finds several major challenges to its future promise and real-world use. Even with improved error correction methods, quantum de-coherence and noise remain significant obstacles due to the extreme sensitivity of quantum systems to external factors, impacting computational accuracy and reliability. There are limits to the range of large-scale machine learning problems that can be efficiently addressed with existing quantum technology owing to low qubit counts, short coherence times and high error rates. Also, while quantum algorithms for machine learning are theoretically promising, they are still at a very immature stage of development, and the hardware limits their practical applicability. To address this gap, hybrid quantum-classical methods can be employed to leverage the advantages of the quantum and classical systems for a more practical implementation, particularly for near-term devices. The findings showed that quantum algorithms have a high probability of beating regular machine learning algorithms in certain scenarios, particularly for intricate problems and high-dimensional data. In theory, quantum algorithms like Quantum Support Vector Machines (QSVMs) and Quantum K-Means Clustering appear to provide more powerful methods for classification and clustering, especially when applied to large datasets. Also, quantum optimization algorithms, including Quantum Annealing and QAOA, could solve combinatorial optimization problems much faster. Nonetheless, the limitations of quantum hardware, including noise, de-coherence and the number of qubits, present challenges to the practical implementation of such quantum machine learning algorithms. Theoretical research is no longer the limiting factor, but quantum systems are still susceptible to computation error, with continued progress in quantum error correction still not delivered to the point of enabling reliable large-scale computations. This disparity, however, between theory and practical implementation pays testament to the fact that the complete potential of quantum machine learning has not yet been unlocked.

5.2. Implications of the Study

This research suggests that the burgeoning field of quantum machine learning is very promising, but it will be constrained by the current hardware limitations; realising its full potential will depend on overcoming these roadblocks. The existing quantum systems are still in their infancy, meaning they are not of a sufficient size yet to facilitate deterministic quantum machine learning algorithms that are scalable. Therefore, even though the quantum machine learning theory seems appealing, many experiments still need to prove it. One of the most hopeful avenues presented by the results is hybrid quantum-classical models, which may offer a more immediate application of quantum boost to machine learning problems. These hybrid strategies derive advantages from classical and quantum computing systems, alleviating the hardware constraints and offering more implementable solutions to actual machine learning challenges.

5.3. Limitations of the Study

The main limitation of this study is the absence of empirical data that confirms substantial enhancements in quantum machine learning algorithms for practical, real-world problems. If these algorithms show promise in theoretical models or small-scale experiments, there is no evidence of large-scale and proven implementations of this approach, either. Moreover, with quantum computing emerging rapidly, significant improvements in hardware and algorithms would likely invalidate the results of this paper. Essentially, you see the presentation of insights according to the current state of quantum hardware and quantum algorithms. Yet, the situation might be totally different as the quantum machine learning field would be working on evolving technologies every double that time.

5.4. Recommendations for Future Research

In order to overcome the above limitations and improve the applicability of quantum machine learning, years of research work will focus on the following 4 aspects:

1. Creating Quantum Error Correction Algorithms: Quantum error correction is a major challenge in making quantum algorithms practical for realistic machine learning problems.
2. Novel Hybrid Quantum-Classical Models: Further development of hybrid models that effectively combine quantum algorithms with classical methods to address domain-specific problems should be explored.
3. New Applications: Explore the potential applications of quantum computing in emerging machine learning tasks such as reinforcement learning, generative models, and deep learning; these tasks hold promise for quantum advantages.

6. Conclusion

This work has attempted to explain some potential quantum algorithm advantages in classification, clustering, and optimization tasks, which are at the core of the link between quantum computing and machine learning. Quantum machine learning is a promising route to achieving computational efficiency, and achieving broad success with these algorithms will require addressing fundamental issues, such as noise, hardware limitations, and error correction, associated with today's quantum devices.

And these solutions may at some point enable hybrid quantum-classical systems, the most promising and limited of which leverages the available quantum hardware, with many quantum chunks working more effectively than some huge one-off quantum system, he says. Advancements in quantum error correction techniques and hybrid systems will be key contributions to achieving this goal. In contrast, new quantum machine learning applications may unlock the full potential of both quantum computing and machine learning.

Acknowledgments

The authors would like to thank Dr. John Omondi and Prof. Paul Kasine for their invaluable assistance during the research and preparation of the manuscript.

References

[1] Frank Arute et al., "Quantum Supremacy Using a Programmable Superconducting Processor," *Nature*, vol. 574, no. 7779, pp. 505-510, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[2] Jacob Biamonte et al., "Quantum Machine Learning," *Nature*, vol. 549, no. 7671, pp. 195-202, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[3] D-Wave Systems, The D-Wave Advantage Quantum System, 2020. [Online]. Available: https://www.dwavesys.com

[4] Edward Farhi, Jeffrey Goldstone, and Sam Gutmann, "A Quantum Approximate Optimization Algorithm," *arXiv*, pp. 1-16, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[5] Maria Schuld, and Francesco Petruccione, *Supervised Learning with Quantum Computers*, Supervised Learning with Quantum Computers, 1st ed., pp. 1-287, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[6] Abhinav Kandala et al., "Hardware-Efficient Variational Quantum Eigensolver for Small Molecules and Quantum Magnets," *Nature*, vol. 549, no. 7671, pp. 242-246, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[7] G. Di Giuseppe et al., "Einstein-Podolsky-Rosen Spatial Entanglement in Ordered and Anderson Photonic Lattices," *Physical Review Letters*, vol. 110, no. 15, pp. 1-5, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[8] John Preskill, "Quantum Computing in the NISQ Era and Beyond," *Quantum*, vol. 2, pp. 1-79, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[9] Patrick Rebentrost, Masoud Mohseni, and Seth Lloyd, "Quantum Support Vector Machine for Big Data Classification," *Physical Review Letters*, vol. 113, no. 13, pp. 1-5, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[10] Daniel F. Perez-Ramirez, "Variational Quantum Algorithms for Combinatorial Optimization," *arXiv*, pp. 1-10, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Vedran DunjkoPeter, and Wittek, "A Non-Review of Quantum Machine Learning: Trends and Explorations," *Journal of Quantum Science*, vol. 4, pp. 1-32, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] Noelia Garcia-Buendia et al., "Mapping the Landscape of Quantum Computing and High Performance Computing Research Over the Last Decade," *IEEE Access*, vol. 12, pp. 106107-106120, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Teja Reddy Gatla, "An Explorative Study Into Quantum Machine Learning: Analyzing the Power of Algorithms in Quantum Computing," *Journal of Emerging Technologies and Innovative Research*, vol. 12, no. 5, pp. 175-178, 2018. [Google Scholar] [Publisher Link]

[14] Sukhpal Singh Gill et al., "Quantum Computing: A Taxonomy, Systematic Review and Future Directions," *Software: Practice and Experience*, vol. 52, no. 1, pp. 66-114, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Tariq M. Khan, and Antonio Robles-Kelly, "Machine Learning: Quantum vs Classical," *IEEE Access*, vol. 8, 219275-219294, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] M. Mounika et al., "Quantum Machine Learning: Bridging the Gap Between Theory and Practice," *First International Conference Intelligent Computing and Big Data Analytics*, Navi Mumbai, India, pp. 89-05, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Vaibhav S. Narwanea et al., "Quantum Machine Learning a New Frontier in Smart Manufacturing: A Systematic Literature Review from Period 1995 to 2021," *International Journal of Computer Integrated Manufacturing*, vol. 38, no. 1, pp. 116-135, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Thien Nguyen, Tuomo Sipola, and Jari Hautamäki, "Machine Learning Applications of Quantum Computing: A Review," *Proceedings of the 23rd European Conference on Cyber Warfare and Security*, Jyväskylä, Finland, vol. 23, no. 1, pp. 322-330, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Nabil Anan Orka et al., "Quantum Deep Learning in Neuroinformatics: A Systematic Review," *Artificial Intelligence Review*, vol. 58, pp. 1-24, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] Sajeeda Parveen Shaik, "Exploring the Landscape: A Systematic Review of Quantum Machine Learning and its Diverse Applications," *International Research Journal of Engineering & Applied Sciences*, vol. 8, no. 1, pp. 5-9, 2020. [Google Scholar] [Publisher Link]

[21] Syed Masiur Rahman et al., "Climate Change Through Quantum Lens: Computing and Machine Learning," *Earth Systems and Environment*, vol. 8, pp. 705-722, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Sandeep Kumar Sood, and Monika Agrewal, "Quantum Machine Learning for Computational Methods in Engineering: A Systematic Review," *Archives of Computational Methods in Engineering*, vol. 31, pp. 1555-1577, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Ubaid Ullah, and Begonya Garcia-Zapirain, "Quantum Machine Learning Revolution in Healthcare: A Systematic Review of Emerging Perspectives and Applications," *IEEE Access*, vol. 12, pp. 11423-11450, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[24] Jiawei Zhou, "Quantum Finance: Exploring the Implications of Quantum Computing on Financial Models," *Computational Economics*, pp. 1-30, 2025. [CrossRef] [Google Scholar] [Publisher Link]