Quantum Computing in Artificial Intelligence: a Review of Quantum Machine Learning Algorithms

Ololade Funke Olaitan [1]**, Samuel Oluwabukunmi Ayeni** [2]**, Adedapo Olosunde** [3]**, Francis Chukwudalu Okeke** [4]**, Ugochukwu Udonna Okonkwo** [5]**, Chukwuemeka George Ochieze** [6]**, Osinachi Victor Chukwujama** [7]**, Ogheneruemu Nathaniel Akatakpo** [8]

[1] *The University of Utah*
201 Presidents Circle, Salt Lake City, UT 84112, USA

[2] *Oregon State University*
1500 SW Jefferson Way, Corvallis, OR 97331, USA

[3] *The University of Toledo*
2801 Bancroft St, Toledo, OH 43606, USA

[4] *C. K. Tedam University of Technology and Applied Sciences*
Box 24 Kassena-Nankana Navrongo-Kolgo Road, Navrongo, Upper East, Ghana

[5] *Southern Illinois University, Edwardsville*
Campus Box 1015, Edwardsville, Illinois, 62026-1015, USA

[6] *The University of Virginia*
P.O. Box 400132, Charlottesville, VA 22904-4132, USA

[7] *Federal University of Technology Owerri*
P. M. B, 1526 Owerri, Ihiagwa, Nigeria

[8] *University of Benin*
P. M. B. 1154, Ugbowo, Benin City, Edo State, Nigeria

Abstract. Two of the most disruptive technologies of the 21st century are quantum computing and artificial intelligence. Their intersection has led to the emergence of a new discipline referred to as Quantum Machine Learning (QML), which aims to enhance the capabilities of classical machine learning by leveraging the computational advantages of quantum devices. This paper provides a survey of the most advanced Quantum Machine Learning (QML) algorithms, including Quantum Support Vector Machines (QSVMs), Quantum k-nearest Neighbours (QkNN), Quantum Principal Component Analysis (QPCA), Quantum Neural Networks (QNNs), and Quantum Reinforcement Learning (QRL). The theoretical and practical status, as well as the empirical performance, of these algorithms, were summarised using a structured review method. The findings reveal a potential for speed-ups in classification, clustering, and optimisation among a range of applications, particularly for perfect quantum systems. However, hardware constraints, software irregularities, and training issues, such as barren plateaus, have limited the practical utility of this approach. Applications of QML in areas such as disaster preparedness and management, environmental sustainability, urban planning methodology, drug discovery, NLP, and finance demonstrate both the potential and current limitations of QML, with most applications still at the proof-of-concept level. In this review, we conclude that QML could be revolutionary, but its feasibility ultimately relies on improvements in physical hardware, the robustness of algorithms, and the standardisation of benchmarks.

Keywords: Artificial Intelligence, Machine Learning, Quantum Algorithms, Quantum Computing, Quantum Machine Learning

INTRODUCTION

Artificial intelligence (AI) has become one of the most transformative technologies of the 21st century, essentially opening up new possibilities for machines to accomplish tasks that would previously require human intelligence. From speech recognition to self-driving cars and healthcare diagnosis, AI has a broad range of applications. At the heart of AI is the ability to use machine learning (ML) to recognise patterns in data, make predictions, and improve over time. However, with the explosive accumulation of data and increasing complexity, the use of classical ML models often presents high computational loads, necessitating the need for potent computational resources and extended training times [1].

With the progress made in AI, Quantum Computing (QC) is emerging as a new paradigm for information processing. Rather than the binary bits (0s and 1s) used in classical computers, quantum computers work with quantum bits (qubits) that leverage superposition and entanglement. Such a quantum nature allows for exponentially larger computational power, therefore leading to the possibility of solving significantly more problems than can be done on a classical computer [2].

This convergence of AI and QC has sparked a new field of research known as Quantum Machine Learning (QML). QML aims to enhance the performance of machine learning (ML) algorithms by leveraging the principles of quantum mechanics. The rationale behind this merge is to address some limitations of classical ML models, namely, speed, scalability, and management of high-dimensional data. Quantum-enhanced NISQ algorithms have demonstrated the potential to reduce computational overhead, optimise models more effectively, and even find previously unknown solutions for known problems [3].

Quantum Machine Learning (QML) is gaining enthusiastic attention with the evolution of both quantum hardware and quantum software ecosystems. Academia and industry are both investing in quantum research, and IBM, Google, and D-Wave are among the companies that have developed quantum systems open for QML exploration. However, despite this recent surge, we are still in the early days, with a coherent picture of what algorithms exist and what they can and cannot do only beginning to emerge.

The objective of this review is to provide an understanding of Quantum Machine Learning algorithms, including their theoretical background, computational benefits, and applicability. We aim to:

1) Describe prominent quantum ML algorithms such as Q-SVM, QNN, and Qk-NN.

2) Provide some insight on the latest developments, deployed tools, and experimental outcomes.

3) Assess practical problems and future research directions in QML.

In this work, we aim to guide researchers, practitioners, and students to state-of-the-art quantum computing for artificial intelligence by surveying the current state of the field and presenting recent advances in the field.

Literature Review

Evolution of Quantum Computing in AI. The intersection of artificial intelligence and quantum computing is not new, dating back to a few decades on a purely theoretical basis. One of the earliest and most influential ideas was that of quantum information theory, developed by authors [4], which laid the groundwork for applying quantum concepts to encode and transmit data [5]. Shor's algorithm and Grover's algorithm revealed the potential for quantum computers to provide a computational advantage over classical computers in specific problems, prompting researchers to investigate quantum-enhanced AI models [6].

At the turn of the millennium, scientists began exploring the potential of quantum systems to assist with machine learning tasks, such as optimisation and pattern recognition [3]; this gave rise to the notion of Quantum Machine Learning (QML), in which a quantum system is treated as a data processor. Noisy Intermediate-Scale Quantum (NISQ) devices, such as those available from companies like IBM, Google, and Rigetti, have made applied experimentation with Quantum Machine Learning (QML) algorithms feasible in the 2010s. This shift marked the transition from theoretical promise to empirical exploration [7].

To provide a context for considering the emergence of QML, it is necessary to reflect on the history of the common tradition of quantum computing and AI. From the (very) early days of quan-

tum information theory to recent developments in NISQ and hybrid algorithms, the evolution of this field epitomises the passage from theoretical potentiality to empirical practice. These critical moments of progress are summarised in Figure 1.
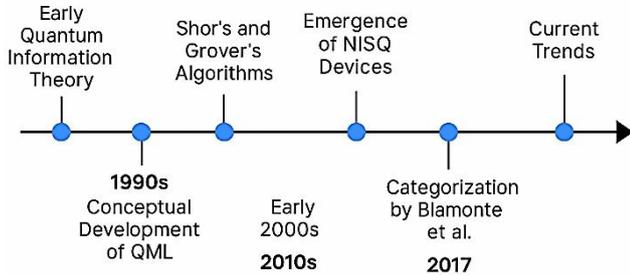

Figure 1 − Evolution of Quantum Computing in Artificial Intelligence

This timeline illustrates key milestones in the evolution of quantum computing and its integration with artificial intelligence, highlighting theoretical foundations, algorithmic breakthroughs, and the emergence of practical quantum platforms. Notably, authors [8] categorised QML research into four areas: quantum data with quantum algorithms, classical data with quantum algorithms, quantum data with classical algorithms, and hybrid systems. This classification remains a cornerstone for understanding how and where quantum computing enhances machine learning capabilities.

Review of Classical ML Limitations. Conventional machine learning (ML) models and deep learning (DL) models are typically computationally expensive. For example, training models (e.g., those handling high-dimensional, unstructured data) incur a high cost. Optimisation of millions of parameters, as in training neural networks, for example, can be time-consuming and costly in terms of energy. SVMs, such as the one in [9], have proven to be effective methods in the context of case-based reasoning; however, they scale poorly with the size of the dataset, as the complexity of such algorithms can be polynomial or exponential in the worst-case [10, 11].

Furthermore, classical ML cannot handle problems with vast search spaces (e.g., combinatorial optimisation) and may get stuck in local minima. Quantum approaches to optimise and transform data, exploiting quantum parallelism and entanglement, have been investigated [12].

Quantum mechanics offers a significant advantage in processing complex probability distributions and high-dimensional vector spaces over classical computers. Quantum Principal Component Analysis (QPCA) utilises quantum parallelism to compute principal components exponentially faster than classical PCA in the worst case [13]. These benefits place QML as a remedy against some of the most glaring bottlenecks of classical ML.

Existing Surveys and Gaps. Several review papers and surveys have attempted to survey the QML landscape. For example, authors [14] investigated the fundamental mechanics of quantum-enhanced learners, with a particular focus on the reinforcement model for agents operating in a quantum environment. Authors [15] provided a practical introduction to QML algorithms, including learning with quantum data encoding and quantum circuit design, for novices. More recent works, such as authors [4], have explored variational quantum classifiers and hybrid models that utilise classical optimisers in conjunction with quantum feature maps.

Although such reviews were valuable in defining the research program, they are either theoretical or application-oriented. However, there is a lack of systematic studies on full-round comparison models of various QML algorithms and evaluations regarding their computational complexity and significance to human-centred practical AI processes. Moreover, existing reviews focus little to no attention on hardware-software integration challenges, especially as they relate to hybrid quantum-classical devices, which are becoming increasingly important in the context of NISQ-era devices.

Another under-investigated area is benchmarking QML algorithms on realistic datasets, as most of their performance claims are based on synthetic datasets. The scaling and robustness of QML models to noise and uncertainty have not yet been compared with state-of-the-art classical approaches in a longitudinal study.

To overcome these shortcomings, the objective of this review is to connect theoretical advances and practical applications of QML by conducting a comparative review of QML algorithms in terms of their theoretical promise and empirical performance. It highlights future research directions, in particular in benchmarking, quantum data preparation, and algorithmic robustness.

METHOD

Review Methodology. This review follows a structured narrative methodology aimed at synthesising the current landscape of Quantum Machine Learning (QML) algorithms. The objective is not only to summarise key quantum learning models but also to critically assess their theoretical underpinnings, computational potential, and empirical performance. To ensure comprehensive coverage, the researchers adopted a multi-step literature selection and analysis process. They identified relevant scholarly sources using academic databases, including IEEE Xplore, SpringerLink, ScienceDirect, arXiv, and Google Scholar. The primary keywords used were Quantum Machine Learning, Quantum Algorithms in AI, Quantum Neural Networks, Quantum Support Vector Machines (SVM), and Variational Quantum Circuits. The researchers limited the search to publications from 2014 to 2024, a period that captures the emergence of practical quantum computing platforms and experimental quantum machine learning (QML) implementations.

Inclusion criteria for selected articles included:

1) Peer-reviewed journal articles or well-cited preprints.

2) Explicit focus on machine learning techniques applied or adapted to quantum computation.

3) Clear description of algorithmic methodology, performance claims, or real-world applications.

4) Contributions to hardware-software integration or performance benchmarking.

Articles were excluded if they lacked technical detail, were purely conceptual without an implementation context, or focused solely on quantum physics without links to AI or machine learning (ML). After the initial filtering, approximately 60 papers were shortlisted and analysed. Each algorithm discussed in this review is examined across three core criteria: algorithmic structure, computational complexity, and implementation feasibility on current quantum systems.

Mathematical Foundations. The linear algebra of Quantum states and the manipulation of probability amplitudes in high-dimensional Hilbert spaces form the foundation of Quantum Machine Learning (QML) algorithms. For consistency and ease of understanding, the Dirac formalism ($|\psi\rangle$), quantum gates (such as the Hadamard and Pauli-X gates), and unitary operators (U) are employed throughout this review. When appropriate, classical mathematical counterparts – such as inner products, eigenvalue decompositions, and kernel functions – are provided in tandem with their quantum analogues for the sake of comparison [16].

For example, the Quantum Support Vector Machine (QSVM) makes use of the quantum kernel trick, where a pair of classical inner products is replaced by calculating quantum kernels using the fidelity between quantum states:

$$K(x_i, x_j) = |\langle \phi(x_i) | \phi(x_j) \rangle|^2$$

Similarly, Quantum Principal Component Analysis (QPCA) leverages the representation of data as density matrices. It utilises quantum phase estimation algorithms to approximate eigenvalues with exponential speed-ups under idealised quantum conditions:

$$\rho = i \sum \lambda_i |v_i\rangle\langle v_i|$$

The review also explores hybrid quantum-classical variational algorithms, where classical routines such as gradient descent optimise parameterised quantum circuits (PQCs). Researchers have made such hybrid models particularly relevant in the NISQ (Noisy Intermediate-Scale Quantum) era by training quantum circuits on noisy devices using classical optimisation loops.

Purely mathematical formulations are extracted from the literature during the analysis, as we do not wish to make any initial assumptions about them, seeking clarity, reproducibility, and compliance with standard quantum computing formalism.

RESULTS AND DISCUSSION

Overview of Key Quantum Machine Learning Algorithms. Comparing the most essential features of different Quantum Machine Learning (QML) algorithms can provide a clearer understanding of these algorithms. In Figure 2, we present the main QML models, considering their task domains, introductory quantum mechanics, theoretical speed-up prospects, and implementation maturity levels. This "side-by-side" perspective reinforces the flexibility and applicability of QML approaches while also pointing out the realisation gap. Quantum Machine Learning (QML) algorithms are generally grouped according to the

type of learning paradigm that they tackle, namely supervised, unsupervised, and quantum reinforcement learning. Several promising algorithms have been developed, aiming to leverage quantum features (such as superposition and entanglement) to achieve faster learning and improved scalability [17, 18].
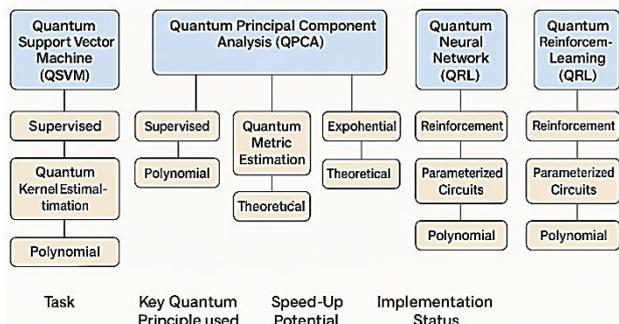

Figure 2 – Comparative Overview of Key Quantum Machine Learning Algorithms

This flowchart presents a comparative overview of prominent Quantum Machine Learning (QML) algorithms, detailing their learning paradigms, key quantum principles, potential computational speed-ups, and current implementation status. The diagram emphasises the diverse approaches and challenges associated with each algorithm in the context of AI tasks.

Quantum Support Vector Machines (QSVM). Researchers know that QSVMs rely on quantum-enhanced kernel methods to perform classification. Quantum kernel estimation offers a significant advantage by utilising a fidelity-based similarity measure between two quantum states; this approach enables researchers to potentially achieve exponential speed-ups in high-dimensional feature spaces [19]. Implemented a hybrid QSVM on a physical quantum computer, where data were encoded into quantum circuits via a feature map and classified with little difference in performance compared to classical models.

Quantum k-Nearest Neighbors (QKNN). The QkNN procedure for distance computation. The QkNN algorithm computes distances between quantum states using inner products between qubit code vectors. We use quantum state fidelity instead of Euclidean distance. Machine learning algorithms, such as those developed by Wiebe and others, demonstrate substantial computational ad-

vantages, particularly in terms of memory accesses from quantum random-access memory (qRAM). However, qRAM technology is currently essentially a theoretical concept [20].

Quantum Principal Component Analysis (QPCA). QPCA is designed to extract the most significant eigenvectors from a density matrix representation of quantum data. Introduced by authors [21], the method utilises quantum phase estimation to retrieve principal components exponentially faster than classical principal component analysis (PCA) under certain constraints. Although promising, current QPCA implementations are limited by decoherence and require precise control of quantum systems [22].

Quantum neural networks (QNNS). QNNs aim to replicate the layered structure of classical neural networks using quantum gates and circuits. They typically involve parametrised quantum circuits (PQCs) that are optimised via classical gradient descent. Notable architectures include the Quantum Perceptron and Variational Quantum Classifiers (VQCs), which have demonstrated feasibility for small-scale classification tasks on IBM Q and other platforms [15]. However, training is sensitive to vanishing gradients – a problem known as the barren plateau effect – which limits scalability.

Quantum Reinforcement Learning (QRL). Quantum reinforcement learning explores the use of quantum systems as decision-making agents. Author [23] proposed quantum agents that can outperform classical strategies in Markov decision processes through entanglement-assisted learning. QRL remains theoretical mainly due to the complexity of quantum feedback loops and the lack of interactive quantum environments.

Performance and Benchmarks. Comparisons of QML algorithms are still challenging due to the emergence of quantum hardware, and most importantly, there are no publicly available standard datasets. However, there are some early signals in several studies about performance.

For instance, the QSVM on IBM superconducting qubits yielded competitive classification accuracy compared to classical SVMs for small datasets. At the same time, the kernel computation on a quantum device exhibited impressive speed-ups. Simulator and 5–7 qubit devices have also been trained with QNNs on binary classification tasks, but as the number of qubits increases, the noise degrades performance [3].

The theoretical analysis predicts that using a combination of QPCA (or QFT) can achieve a speed-up in the exponential scaling dimension of a data space, thereby facilitating the learning of latent structures in extensive datasets. Despite this, the performance of experiments is often well below the theoretical limit, and a gap is observed between idealised and practical performance. A summary of algorithm performance characteristics is provided in Table 1.

Table 1 – Summary of performance and implementation status of key QML algorithms

Algorithm	Task Type	Speed-up Potential	Implementation Status	Key Limitation
QSVM [24]	Supervised	Polynomial to Exponential	Early-stage hardware	Quantum kernel estimation noise
QkNN [25]	Supervised	Polynomial	Mostly theoretical	qRAM impracticality
QPCA [26]	Unsupervised	Exponential (idealised)	Simulated/early-stage	Requires pure state input
QNN/VQC [26]	Supervised	Moderate (hybrid)	Implemented on NISQ	Barren plateaus in training
QRL [20]	Reinforcement	Unknown	Theoretical	Lack of quantum feedback systems

Practical Applications. QML algorithms are slowly gaining practical applications in fields where classical ML struggles with dimensionality or optimisation scale.

a) Quantum-enhanced natural language processing (QNLP) is being explored using tensor networks and quantum circuits to represent grammatical structure and semantic relationships [27].

b) Drug discovery and molecular simulation are aided by incorporating quantum chemistry with QML methods to predict molecular properties or results of quantum simulations.

c) Quantum optimisation routines (e.g., Quantum Approximate Optimisation Algorithm, QAOA) are being used to model finance and risk, including portfolio optimisation and the detection of fraud, waste, and abuse.

d) There are also recent results showing that some recommendation systems (similar to those considered by authors [28] can be computed much faster in the high-dimensional user-item matrix setting compared to classical settings. However, the majority of the applications are still in the proof-of-concept phase and have been tested only with relatively small datasets and under controlled environments.

Limitations and Challenges. Although QML is highly promising from a theoretical perspective, there are many challenges to confront:

a) The lack of hardware is still the most significant issue. NISQ processors are high-noise, coherently limited gates with short T1 times and low T2 times. Scaling beyond 100 qubits remains a challenge for the majority of quantum hardware.

b) The software and tooling landscape is fragmented, with frameworks such as Qiskit, Pennylane, and Cirq providing a variety of capabilities but no consistent user experience. There are no standard APIs and benchmarking tools.

c) Data encoding (through quantum feature maps) is not trivial and often mitigates speed-ups when the classical-to-quantum transformation of the data is costly.

d) Barren plateaus – regions of the optimisation landscape where gradients are incredibly close to zero – hamper the training of deep quantum neural networks [29, 30].

The absence of large quantum datasets also hinders experimentation. Simulations of classical systems are computationally costly and inconclusive when compared to quantum behaviour.

In summary, while theoretical results continue to reach new frontiers, the practical implementation of QML is as much constrained by engineering considerations as by algorithmic foundations.

CONCLUSIONS

In this paper, we have discussed the emerging research area of Quantum Machine Learning (QML), where we utilise quantum techniques to enhance classical artificial intelligence algorithms. The synergy of qubit-type computation with machine learning algorithms suggests some interesting possibilities for going beyond the lim-

itations of classical models in terms of computational complexity and effectiveness.

The fundamental algorithms such as QSVMs, QkNN, QPCA, and QNNs have different levels of theoretical and practical prospects. Although some quantum models offer exponential or polynomial acceleration in kernel estimation, classification, and unsupervised learning, hardware constraints imposed by NISQ (Noisy Intermediate-Scale Quantum) technologies often limit their performance. Experimental works and early applications demonstrate the feasibility of small quantum devices. In contrast, deployment in practical applications remains challenging due to decoherence, low qubit numbers, and intricate training behaviour, such as barren plateaus.

In applications, QML has demonstrated early successes in natural language processing, drug design, financial modelling, and recommendation systems. Yet, such applications are primarily experimental and heavily based on simulations or limited datasets. Moreover, standard benchmarks and datasets for rigorous performance evaluation do not exist for comparison with classical counterparts.

While the review of the experimental status below shows encouraging progress, the road ahead for QML requires and is, in turn, premised on further strides in quantum hardware, on the construction of scalable but fault-tolerant quantum algorithms (typically hybrid in nature and quantum/classical in execution), and highly integrated quantum-classical software stacks. It is also necessary to pay attention to the interpretability of the algorithms and to analyse domain-specific quantum advantages. Although challenges persist, quantum computing and machine learning appear poised to reshape the computational underpinnings of artificial intelligence over the coming decades.

REFERENCES

1. Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management, 60*, 102383. doi: 10.1016/j.ijinfomgt.2021.102383

2. Memon, Q. A., Ahmad, M. A., & Pecht, M. (2024). Quantum Computing: Navigating the future of computation, challenges, and technological breakthroughs. *Quantum Reports, 6*(4), 627–663. doi: 10.3390/quantum6040039

3. Devadas, R. M., & T, S. (2025). Quantum Machine Learning: A Comprehensive Review of Integrating AI with Quantum Computing for Computational Advancements. *MethodsX, 14*, 103318. doi: 10.1016/j.mex.2025.103318

4. Benedetti, M., Lloyd, E., Sack, S., & Fiorentini, M. (2019). Parameterised quantum circuits as machine learning models. *Quantum Science and Technology, 4*(4), 043001. doi: 10.1088/2058-9565/ab4eb5

5. Barnett, S. M. (n.d.). *Introduction to Quantum Information.* Oxford University Press.

6. Valle, C. (2011). Shor's Algorithm and Grover's Algorithm in Quantum Computing. (Thesis; University of Kansas).

7. Bharti, K., Cervera-Lierta, A., Kyaw, T. H., Haug, T., Alperin-Lea, S., Anand, A., Degroote, M., Heimonen, H., Kottmann, J. S., Menke, T., Mok, W., Sim, S., Kwek, L., & Aspuru-Guzik, A. (2022). Noisy intermediate-scale quantum algorithms. *Reviews of Modern Physics, 94*(1). doi: 10.1103/revmodphys.94.015004

8. Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., & Lloyd, S. (2017). Quantum machine learning. *Nature, 549*(7671), 195–202. doi: 10.1038/nature23474

9. Baudat, G., & Anouar, F. (2000). Generalised discriminant analysis using a kernel approach. *Neural Computation, 12*(10), 2385–2404. doi: 10.1162/089976600300014980

10. Safonova, A., Ghazaryan, G., Stiller, S., Main-Knorn, M., Nendel, C., & Ryo, M. (2023). Ten deep learning techniques to address small data problems with remote sensing. *International Journal of Applied Earth Observation and Geoinformation, 125*, 103569. doi: 10.1016/j.jag.2023.103569

11. Taye, M. M. (2023). Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. *Computers, 12*(5), 91. doi: 10.3390/computers12050091

12. Ranga, D., Rana, A., Prajapat, S., Kumar, P., Kumar, K., & Vasilakos, A. V. (2024). Quantum Machine Learning: Exploring the role of data encoding techniques, challenges, and future directions. *Mathematics, 12*(21), 3318. doi: 10.3390/math12213318

13. Bellante, A., Luongo, A., & Zanero, S. (2022). Quantum algorithms for SVD-based data representation and analysis. *Quantum Machine Intelligence, 4*(2). doi: 10.1007/s42484-022-00076-y

14. Dunjko, V., Taylor, J. M., & Briegel, H. J. (2017). Advances in quantum reinforcement learning. *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 282–287. doi: 10.1109/smc.2017.8122616

15. Schuld, M., Sinayskiy, I., & Petruccione, F. (2014). An introduction to quantum machine learning. *Contemporary Physics, 56*(2), 172–185. doi: 10.1080/00107514.2014.964942

16. Fiveable. (n. d.). Linear algebra for quantum computing – Quantum Computing. Retrieved from https://library.fiveable.me/quantum-computing/unit-9/linear-algebra-quantum-computing/study-guide/Cc4WgWVUYDq4oZjr

17. Ajibosin, S. S., & Cetinkaya, D. (2024). Implementation and performance evaluation of quantum machine learning algorithms for binary classification. *Software, 3*(4), 498–513. doi: 10.3390/software3040024

18. Ghobadi, M. Z., & Afsaneh, E. (2024). The potential of quantum machine learning for solving the real-world problem of cancer classification. *Deleted Journal, 6*(10). doi: 10.1007/s42452-024-06220-6

19. Schnabel, J., & Roth, M. (2025). Quantum kernel methods under scrutiny: a benchmarking study. *Quantum Machine Intelligence, 7*(1). doi: 10.1007/s42484-025-00273-5

20. Gao, L., Lu, C., Guo, G., Zhang, X., & Lin, S. (2022). Quantum K-nearest neighbours classification algorithm based on Mahalanobis distance. *Frontiers in Physics, 10*. doi: 10.3389/fphy.2022.1047466

21. Lloyd, S., Mohseni, M., & Rebentrost, P. (2014). Quantum principal component analysis. *Nature Physics, 10*(9), 631–633. doi: 10.1038/nphys3029

22. Li, Z., Chai, Z., Guo, Y., Ji, W., Wang, M., Shi, F., Wang, Y., Lloyd, S., & Du, J. (2021). Resonant quantum principal component analysis. *Science Advances, 7*(34). doi: 10.1126/sciadv.abg2589

23. Hu, W. (2018). Empirical analysis of decision making of an AI agent on IBM's 5Q quantum computer. *Natural Science, 10*(01), 45–58. doi: 10.4236/ns.2018.101004

24. Montalbano, G., & Banchi, L. (2025). Quantum adversarial learning for kernel methods. *Quantum Machine Intelligence, 7*(1). doi: 10.1007/s42484-025-00238-8

25. Lawal, O. P., Egwuatu, E. C., Akanbi, K. O., Orobator, E. T., Eweje, O. Z., Omotayo, E. O., Igbokwe, C., Ogundeko-Olugbami, O., Awuah, S. B., & Chibueze, E. S. (2025). Fighting Resistance with Data: Leveraging digital surveillance to address antibiotic misuse in Nigeria. *Path of Science, 11*(3), 1009. doi: 10.22178/pos.115-25

26. Chaudhry, M., Shafi, I., Mahnoor, M., Vargas, D. L. R., Thompson, E. B., & Ashraf, I. (2023). A Systematic Literature Review on Identifying Patterns using Unsupervised Clustering Algorithms: A Data Mining Perspective. *Symmetry, 15*(9), 1679. doi: 10.3390/sym15091679

27. Coecke, B., Giovanni, D. F., Meichanetzidis, K., & Toumi, A. (2020). Foundations for Near-Term Quantum Natural Language Processing. *arXiv (Cornell University).* doi: 10.48550/arxiv.2012.03755

28. J. G., Ambafi, Onuche, O.P., Onuche P U, Babatunde E.T., Abdullahi A. O., Osazuwa P., Ogunnaike, O., and Okonkwo U. U. 2025. "Development of a Novel IoT-Based Smart Firefighting Robot for Real-

Time Fire Detection and Suppression". Current Journal of Applied Science and Technology 44 (5):88-97. https://doi.org/10.9734/cjast/2025/v44i54539

29. Kerenidis, I., & Prakash, A. (2017). Quantum recommendation systems. *Conference on Innovations in Theoretical Computer Science, 67*, 21. doi: 10.4230/lipics.itcs.2017.49

30. Karuppasamy, K., Puram, V., Johnson, S., & Thomas, J. P. (2025). A comprehensive review of Quantum Circuit Optimisation: current trends and future directions. *Quantum Reports, 7*(1), 2. doi: 10.3390/quantum7010002

31. Pfaendler, S. M.-., Konson, K., & Greinert, F. (2024). Advancements in Quantum Computing—ViewPoint: Building adoption and competency in industry. *Datenbank-Spektrum, 24*(1), 5–20. doi: 10.1007/s13222-024-00467-4