MANTECH Publications

Journal of Converging Technologies in Intelligent Computing
Volume 1, Issue 3, September-December 2025

Quantum Machine Learning and Artificial Intelligence: Opportunities for Next-Generation Computational Intelligence – A Review of Algorithms, Trainability Limits, and Application Readiness

Ankit R. Sharma[1], Neha P. Verma[2], Rohit K. Tyagi[3], Pooja S. Gupta[4]

ABSTRACT

Quantum machine learning (QML) seeks to combine the representational power of quantum states with the adaptive learning capacity of modern artificial intelligence (AI), offering new routes to next-generation computational intelligence. The field, however, is marked by contrasting evidence: theoretical proofs of exponential advantage under restrictive assumptions, and empirical results on noisy intermediate-scale quantum (NISQ) devices that are limited by noise, shallow circuit depth, and trainability barriers. This review-based study critically synthesises 43 sources covering quantum linear algebra, quantum kernel methods, variational quantum circuits, quantum neural networks, and quantum generative models. A structured analytical framework is used to compare data-encoding strategies by qubit and circuit-depth cost, to examine gradient-variance scaling as an indicator of trainability, and to assign ordinal readiness scores across five AI application domains. The synthesis shows that data-encoding cost, rather than qubit count alone, is the dominant practical bottleneck; that global-cost circuits suffer gradient variance decaying as 2^{-n} whereas shallow local-cost circuits retain polynomial scaling; and that quantum chemistry and structured-data classification currently show the highest readiness (mean score 2.6 of 5), while large-scale language and generative AI is least mature (1.6 of 5). The paper concludes that near-term value lies in carefully benchmarked hybrid quantum–classical models rather than in wholesale replacement of classical AI.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

KEYWORDS: *Quantum machine learning, Artificial intelligence, Variational quantum circuits, Quantum kernels, NISQ, Barren plateaus, Hybrid quantum–classical computing, Computational intelligence*

INTRODUCTION

Artificial intelligence has become the dominant paradigm of modern computing, yet its progress is increasingly constrained by the energy, memory, and time needed to train large models on classical hardware. At the same time, quantum computing has moved from theoretical proposition to engineering reality. A programmable superconducting processor has been reported to complete a sampling task that its authors estimated to be infeasible for classical supercomputers within a practical time [1], and the noisy intermediate-scale quantum (NISQ) era, defined by devices of tens to hundreds of imperfect qubits, characterises the present hardware landscape [2]. Quantum machine learning (QML) lies at the intersection of these trends. It investigates how quantum systems can accelerate, enrich, or reformulate learning tasks such as classification, regression, clustering, generative modelling, and reinforcement learning [3, 4].

The scientific appeal of QML rests on three properties of quantum mechanics. First, an n-qubit register spans a 2^n-dimensional Hilbert space, so exponentially large feature spaces can be addressed with a linear number of physical resources [5]. Second, interference and entanglement generate correlations that are hard to reproduce classically, forming the basis for kernels that may be intractable to evaluate on classical machines [6]. Third, quantum linear-algebra subroutines such as the HHL algorithm suggest speed-ups for the matrix operations underlying many learning algorithms [7]. These advantages, however, depend on efficient data loading, readout, and trainability, assumptions that frequently fail in practice.

Problem statement. The central question addressed here is under what conditions QML can deliver a genuine, demonstrable benefit to AI systems, and what the evidence implies for the design of next-generation computational intelligence. Answering it requires reconciling theoretical promise with the engineering constraints of NISQ hardware. In the Indian context the question is timely, because the National Quantum Mission has committed substantial public investment to quantum technologies [8], creating demand for rigorous, evidence-based guidance for researchers and academic institutions entering the field.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

LITERATURE REVIEW

Early work established the conceptual basis of QML. Biamonte et al. surveyed how quantum algorithms could accelerate learning built on linear algebra and identified data input and output as fundamental bottlenecks [3], while Dunjko and Briegel provided a taxonomy that classifies QML by the nature of the data (classical or quantum) and of the processing device [4]. Quantum support vector machines and quantum principal component analysis were proposed with exponential speed-ups under the assumption of quantum random-access memory (QRAM) [9, 10], building on the HHL algorithm [7]. Quantum singular value transformation later recast many of these speed-ups within a single formalism [11].

Variational And Kernel-Based Models

The arrival of NISQ hardware shifted attention to variational quantum algorithms, in which a parameterised circuit is optimised by a classical routine [12, 13]. Mitarai et al. introduced quantum circuit learning, showing that low-depth parameterised circuits can fit nonlinear functions [14], and Schuld et al. formulated circuit-centric classifiers that treat the circuit itself as a trainable model [15]. Parameter-shift rules allow analytic gradients to be evaluated on hardware [16], and expressibility metrics help compare circuit designs [17]. In parallel, Havlíček et al. demonstrated a variational classifier and a kernel estimator on a superconducting processor, using a feature map conjectured to be hard to simulate classically [6], while Schuld and Killoran showed that quantum encodings act as feature maps into Hilbert space, linking QML to kernel theory [18]. Cong et al. proposed quantum convolutional neural networks of logarithmic depth for recognising quantum phases of matter [19], and Abbas et al. argued that well-designed quantum neural networks can attain higher effective dimension than comparable classical networks [20]. Data re-uploading architectures show that even a single qubit can act as a universal classifier [21].

Trainability, Dequantization, And Benchmarking

Critical studies have tempered early optimism. McClean et al. demonstrated that gradients of randomly initialised deep circuits vanish exponentially with qubit number, the so-called barren plateau [22], and Cerezo et al. showed that shallow circuits with local cost functions avoid this decay [23]. Training variational algorithms is also NP-hard in the worst case [24]. Tang's quantum-inspired classical algorithm removed the exponential advantage claimed for an earlier quantum recommendation algorithm [25, 26], launching a wave of dequantization results [27].

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

Huang et al. showed that access to data can allow classical models to rival quantum ones, so advantage requires carefully identified problem structure [28], whereas Liu et al. proved a rigorous quantum speed-up for a classification task built on the discrete logarithm problem [29]. More recently, exponential concentration of quantum kernels has been identified as a further obstacle [30], and Bowles et al. found that simple classical baselines often match or outperform quantum classifiers under careful benchmarking [31].

Applications Linking QML And AI

Reported applications include molecular energy estimation with hardware-efficient variational eigensolvers [32, 33], financial modelling [34], quantum generative adversarial networks [35], quantum Boltzmann machines [36], and quantum-enhanced reinforcement learning [37]. Error-mitigation techniques improve the accuracy of expectation values obtained from noisy short-depth circuits [38], and differentiable-programming libraries now allow quantum circuits to be trained within standard AI workflows [39].

RESEARCH GAP

Existing surveys either emphasise algorithmic speed-ups under idealised fault-tolerant assumptions or catalogue variational models without quantifying their practical resource costs [40]. Three gaps remain. First, data-encoding cost is rarely compared quantitatively alongside model expressivity. Second, trainability analyses are seldom translated into concrete design guidance for cost-function and circuit selection. Third, no consolidated, application-oriented assessment connects the theoretical literature to the AI domains that practitioners care about. This paper addresses these gaps through a unified analytical review.

OBJECTIVES

- To review and classify the principal QML paradigms and their relationship with established AI methods.
- To compare data-encoding strategies in terms of qubit requirements, circuit depth, and suitability for NISQ devices.
- To analyse the scaling of gradient variance and the associated trainability limits of variational models.
- To assess the readiness of QML across major AI application domains using a transparent ordinal rubric.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

- To identify limitations and formulate a research agenda for hybrid quantum–classical intelligence.

METHODOLOGY

Review Design And Corpus

This study adopts a structured narrative review design guided by the transparency principles of the PRISMA 2020 statement [41] and the systematic-review guidelines of Kitchenham and Charters [42]. The corpus comprises the 43 peer-reviewed articles, recognised preprints, and monographs cited in this paper, published between 2009 and 2024. Sources were selected for foundational importance, rigorous theoretical or experimental contribution, and direct relevance to AI tasks. Each source was coded along four dimensions: learning paradigm, data-encoding strategy, hardware or resource assumptions, and evidential status (proof, simulation, or hardware demonstration). Table 1 summarises the five paradigms that emerged. No new hardware experiments were performed; the research type is therefore review-based, with analytical scaling components.

Table 1. Principal QML Paradigms Identified in the Reviewed Literature

Paradigm	Representative Method	Hardware Need	Theoretical Status	Ref.
Quantum linear algebra	HHL, qPCA, qSVM	Fault-tolerant, QRAM	Exponential speed-up under data-access assumptions; partly dequantized	[7, 9, 10]
Quantum kernels	Kernel estimator	NISQ, shallow	Advantage possible for structured data; concentration risk	[6, 18, 30]
Variational circuits	Circuit learning, circuit-centric classifiers	NISQ, hybrid loop	Expressive but barren-plateau limited	[14, 15, 22]
Quantum neural networks	QCNN, re-uploading models	NISQ	Favourable trainability for structured architectures	[19, 20, 21]
Generative models	QGAN, quantum Boltzmann machine	NISQ	Early stage; limited evidence	[35, 36]

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

Analytical Framework

Three analyses were performed. First, encoding cost was derived for basis, angle, amplitude, instantaneous quantum polynomial (IQP)-type feature maps, and data re-uploading circuits as functions of the feature dimension d, using published circuit constructions [5, 6, 15, 21]. Second, trainability was examined through the scaling of the gradient variance Var[$\partial C/\partial\theta$] with qubit number n, using the exponential decay established for random deep circuits [22] and the polynomial scaling for shallow local-cost circuits [23]; these trends are plotted as normalised analytical curves, not simulation outputs. Third, readiness was scored on an ordinal scale from 1 (conceptual) to 5 (practically competitive) for each paradigm–domain pair, using four criteria: availability of rigorous advantage arguments, demonstrated hardware results, robustness to noise, and competitiveness against classical baselines [31]. The scores are judgement-based syntheses of the cited evidence and should be read as relative rather than absolute measures. Fig. 1 shows the generic hybrid workflow assumed throughout.

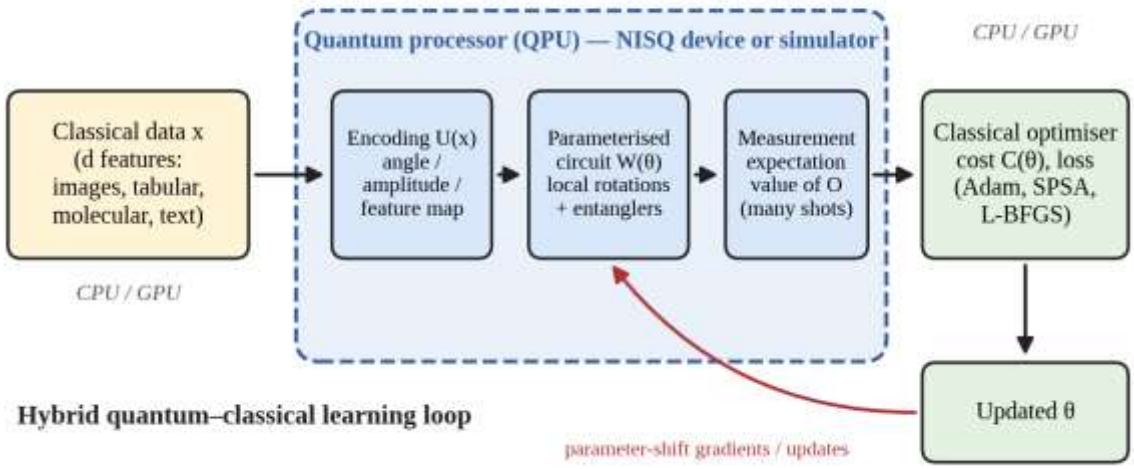


Figure 1. Generic hybrid quantum–classical learning workflow: classical data are encoded into a quantum state, processed by a parameterised circuit, measured, and used by a classical optimiser to update the circuit parameters.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

RESULTS AND FINDINGS

Data-Encoding Cost

Table 2 summarises the resources needed to load a d-dimensional feature vector. Amplitude encoding compresses d features into $\lceil \log_2 d \rceil$ qubits, an apparent exponential saving, but preparing an arbitrary state generally requires a circuit whose size grows linearly with d [5], which cancels the saving unless the data have exploitable structure or reside in QRAM [3]. Angle encoding is the opposite: it needs d qubits but only constant depth, which suits NISQ devices at the cost of a less rich feature space. IQP-type feature maps used for quantum kernels need d qubits and a gate count that grows quadratically with d when all feature pairs interact [6], while data re-uploading trades qubit count for depth by reusing a small register L times [21]. Because the encoding fixes the family of functions a variational model can represent [43], encoding is a modelling decision, not a preprocessing detail.

Table 2. Resource Scaling of Common Data-Encoding Strategies for d Features

Encoding	Qubits	Circuit Depth	Main Trade-off
Basis	≈ d·b (b bits)	O(d)	Exact but qubit-hungry
Angle	d	O(1)	NISQ-friendly; limited richness
Amplitude	$\lceil \log_2 d \rceil$	O(d) generic	Compact; costly state preparation
IQP / ZZ map	d	O(d) to $O(d^2)$	Kernel-oriented; entanglement overhead
Re-uploading	1 to few	O(L·d)	Few qubits; deeper circuits

Scaling And Trainability

Fig. 2(a) illustrates why quantum state spaces attract interest: storing a 30-qubit state vector at double precision requires 16 GiB of classical memory, whereas a 50-qubit state requires 16 PiB. Fig. 2(b) shows the complementary difficulty. For deep, random circuits the gradient variance falls as 2^{-n} [22], and the same exponential behaviour affects global cost functions even in shallow circuits [23]. Resolving a gradient of magnitude $2^{-n/2}$ to fixed relative precision then requires on the order of 2^n measurement shots, roughly 10^6 per component at n = 20. By contrast, local cost functions in circuits of logarithmic depth decay only polynomially [23], and

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

structured architectures such as quantum convolutional networks are designed to remain trainable [19].

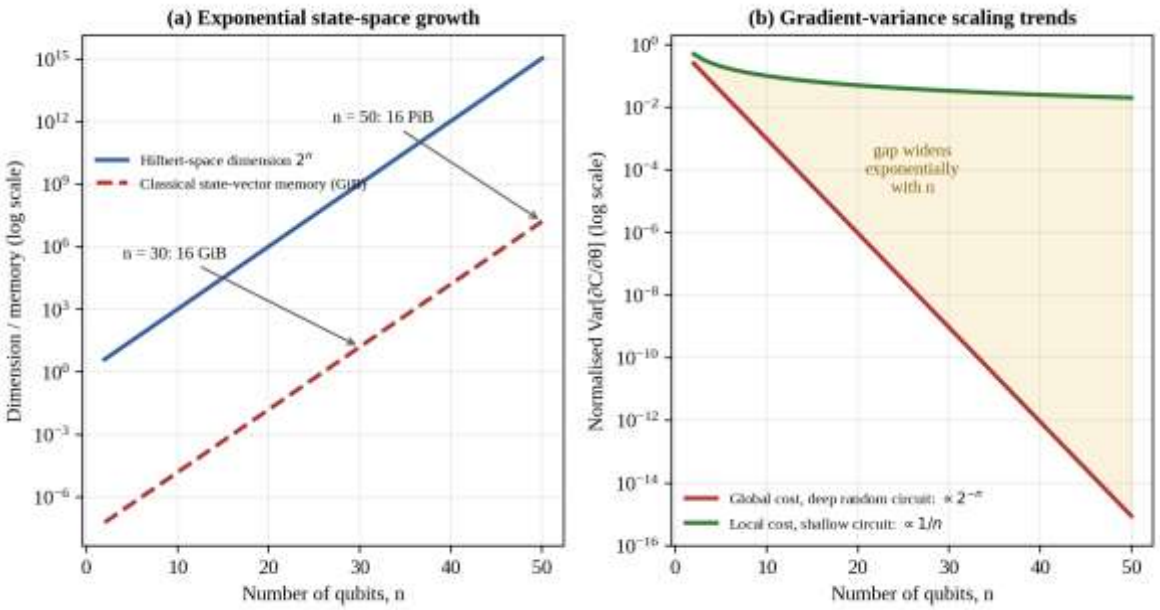


Figure 2. Analytical scaling trends: (a) Hilbert-space dimension and classical state-vector memory versus qubit number; (b) normalised gradient variance for global-cost deep circuits (2^{-n}) and local-cost shallow circuits (1/n).

Application Readiness

Fig. 3 presents the ordinal readiness assessment. No paradigm–domain pair reached the top score of 5. Variational circuits obtained the highest paradigm mean (2.8), followed by quantum neural networks (2.6), quantum kernels (2.0), generative models (1.8), and quantum linear algebra (1.4), the last being penalised by its reliance on QRAM and fault tolerance [11]. By domain, quantum chemistry and structured-data classification scored highest (2.6 each), reflecting hardware demonstrations of molecular energy estimation [33] and kernel classification [6]. Image tasks (2.0) and reinforcement learning and optimisation (1.8) occupy the middle, while language and large-scale generative AI scored lowest (1.6) because data volumes far exceed present encoding and qubit capacity.

A second cross-cutting pattern is that proofs of advantage and hardware demonstrations rarely coincide. Rigorous separations rely on cryptographically structured tasks [29] or on fault-tolerant resources such as QRAM and deep circuits [7, 11], whereas hardware demonstrations

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

involve registers of only a few qubits and no proven advantage [6, 33]. Closing this gap between provable and demonstrable benefit is the central scientific challenge of the field, and it explains why no paradigm earned a score above 4 in any domain.

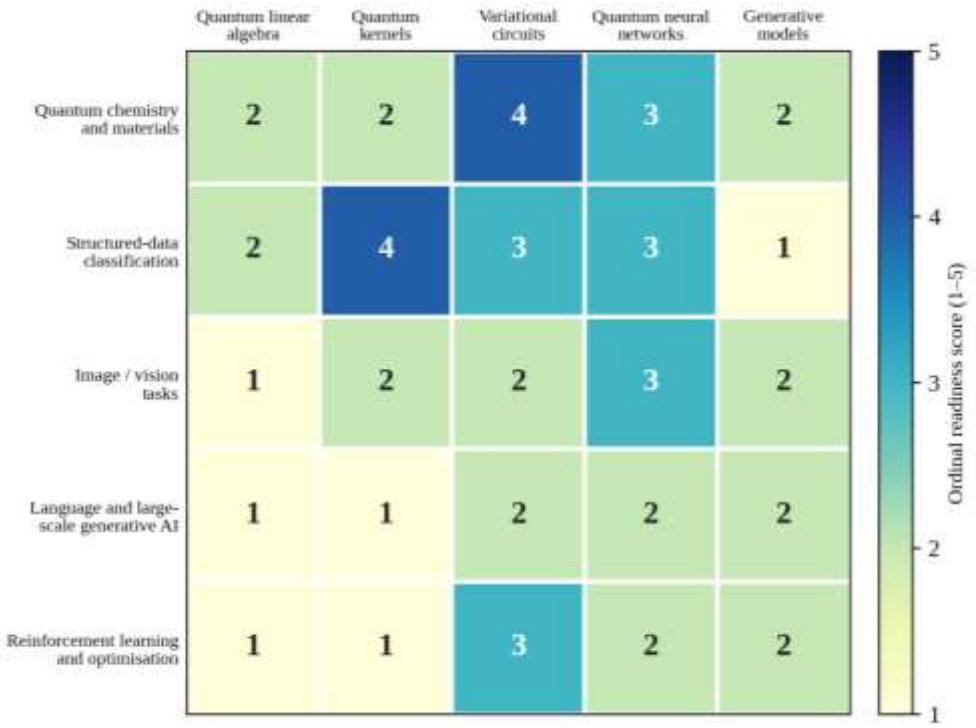


Figure 3. Ordinal readiness of QML paradigms across five AI application domains (1 = conceptual, 5 = practically competitive), derived from the review-based rubric.

DISCUSSION

The most significant result is that the practical frontier of QML is set by input–output costs and trainability rather than by qubit counts alone. Quantum advantage is a property of the pairing between an algorithm and a dataset, not of the hardware in isolation, a conclusion consistent with the finding that classical models given access to data can match quantum ones [28] and with the dequantization of earlier speed-ups [26, 27]. The rigorous separation established for a cryptographically structured task [29] shows that advantage is possible, but such structure is rarely present in everyday AI data.

From an engineering perspective, the scaling analysis converts into design rules: prefer local cost functions and shallow, structure-aware circuits; choose encodings whose depth scales gently with d; tune kernel bandwidth to avoid concentration [28, 30]; and benchmark against

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

tuned classical baselines [31]. Table 3 links the principal challenges to their origin and the mitigation strategies reported in the literature.

Table 3. Principal Challenges in QML and Reported Mitigation Strategies

Challenge	Origin	Mitigation Strategy	Ref.
Barren plateaus	Deep random circuits; global costs	Local costs, shallow structured ansätze	[22, 23]
Hardware noise	Decoherence, gate errors	Error mitigation, noise-aware design	[2, 38]
Data loading	State-preparation overhead	Angle or re-uploading encodings; QRAM research	[3, 21]
Dequantization	Quantum-inspired classical algorithms	Rigorous benchmarking against classical baselines	[26, 31]
Kernel concentration	High expressivity, wide features	Bandwidth tuning, projected kernels	[28, 30]

Practical applications are most credible where the data are themselves quantum or low-dimensional and structured. Molecular and materials simulation through variational eigensolvers is the clearest case [32, 33], and risk and portfolio problems in finance are another candidate [34]. For Indian institutions, the National Quantum Mission [8] together with open-source differentiable simulators [39] means that meaningful QML research can be conducted on classical hardware, building algorithmic expertise ahead of large-scale fault-tolerant devices.

The relationship between QML and AI is also bidirectional. Classical machine learning is increasingly used to assist quantum technology itself, for example in device calibration, circuit compilation, and error decoding, and such 'AI for quantum' uses may deliver practical value sooner than 'quantum for AI'. Researchers should therefore evaluate both directions of the partnership. Finally, because quantum models are hard to inspect and noisy hardware makes results stochastic, reproducibility practices, such as reporting shot counts, random seeds, and device calibration data, must become standard in future QML studies.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

LIMITATIONS

- The review is based on a curated corpus rather than an exhaustive search, so selection bias toward prominent venues is possible, and the literature evolves rapidly.
- Readiness scores are ordinal judgements; their sensitivity to independent raters or alternative criteria was not tested.
- The scaling curves assume idealised, noiseless random circuits; real behaviour depends on the ansatz, initialisation, and device noise.
- No new hardware experiments were performed, and hardware results from different studies use different devices and benchmarks, limiting direct comparability.

FUTURE SCOPE

- End-to-end benchmarking of hybrid models against tuned classical baselines on shared datasets, accounting for time, energy, and measurement shots [31].
- Trainability-aware ansätze and initialisation strategies, including symmetry-informed architectures, to avoid barren plateaus [23, 40].
- Resource estimation for QRAM and quantum linear-algebra subroutines in the fault-tolerant era [11].
- Application studies aligned with national priorities in materials, healthcare, and energy under the National Quantum Mission [8].

CONCLUSION

This review synthesised 43 sources to assess how quantum machine learning can contribute to next-generation computational intelligence. Three conclusions follow. First, data-encoding cost, not qubit count alone, governs whether a quantum model is practical. Second, trainability depends strongly on cost-function locality and circuit depth, with global-cost deep circuits facing exponentially vanishing gradients. Third, readiness is uneven: variational circuits and quantum neural networks lead, quantum chemistry and structured-data classification are the most promising domains, and large-scale language and generative AI remain distant. The most defensible near-term strategy is therefore hybrid quantum–classical modelling, evaluated rigorously against strong classical baselines, rather than wholesale replacement of classical AI.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

REFERENCES

1. Arute F, Arya K, Babbush R, et al. Quantum supremacy using a programmable superconducting processor. *Nature.* 2019; 574(7779): 505–510.
2. Preskill J. Quantum computing in the NISQ era and beyond. *Quantum.* 2018; 2: 79.
3. Biamonte J, Wittek P, Pancotti N, Rebentrost P, Wiebe N, Lloyd S. Quantum machine learning. *Nature.* 2017; 549(7671): 195–202.
4. Dunjko V, Briegel HJ. Machine learning & artificial intelligence in the quantum domain: a review of recent progress. *Reports on Progress in Physics.* 2018; 81(7): 074001.
5. Schuld M, Petruccione F. *Machine Learning with Quantum Computers.* 2nd ed. Springer, Cham. 2021.
6. Havlíček V, Córcoles AD, Temme K, et al. Supervised learning with quantum-enhanced feature spaces. *Nature.* 2019; 567(7747): 209–212.
7. Harrow AW, Hassidim A, Lloyd S. Quantum algorithm for linear systems of equations. *Physical Review Letters.* 2009; 103(15): 150502.
8. Department of Science and Technology, Government of India. *National Quantum Mission (NQM).* New Delhi. 2023. Available at: https://dst.gov.in
9. Rebentrost P, Mohseni M, Lloyd S. Quantum support vector machine for big data classification. *Physical Review Letters.* 2014; 113(13): 130503.
10. Lloyd S, Mohseni M, Rebentrost P. Quantum principal component analysis. *Nature Physics.* 2014; 10(9): 631–633.
11. Gilyén A, Su Y, Low GH, Wiebe N. Quantum singular value transformation and beyond: exponential improvements for quantum matrix arithmetics. *Proceedings of the 51st ACM Symposium on Theory of Computing (STOC).* 2019: 193–204.
12. Cerezo M, Arrasmith A, Babbush R, et al. Variational quantum algorithms. *Nature Reviews Physics.* 2021; 3(9): 625–644.
13. Bharti K, Cervera-Lierta A, Kyaw TH, et al. Noisy intermediate-scale quantum algorithms. *Reviews of Modern Physics.* 2022; 94(1): 015004.
14. Mitarai K, Negoro M, Kitagawa M, Fujii K. Quantum circuit learning. *Physical Review A.* 2018; 98(3): 032309.
15. Schuld M, Bocharov A, Svore KM, Wiebe N. Circuit-centric quantum classifiers. *Physical Review A.* 2020; 101(3): 032308.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

16. Schuld M, Bergholm V, Gogolin C, Izaac J, Killoran N. Evaluating analytic gradients on quantum hardware. *Physical Review A.* 2019; 99(3): 032331.
17. Sim S, Johnson PD, Aspuru-Guzik A. Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms. *Advanced Quantum Technologies.* 2019; 2(12): 1900070.
18. Schuld M, Killoran N. Quantum machine learning in feature Hilbert spaces. *Physical Review Letters.* 2019; 122(4): 040504.
19. Cong I, Choi S, Lukin MD. Quantum convolutional neural networks. *Nature Physics.* 2019; 15(12): 1273–1278.
20. Abbas A, Sutter D, Zoufal C, Lucchi A, Figalli A, Woerner S. The power of quantum neural networks. *Nature Computational Science.* 2021; 1(6): 403–409.
21. Pérez-Salinas A, Cervera-Lierta A, Gil-Fuster E, Latorre JI. Data re-uploading for a universal quantum classifier. *Quantum.* 2020; 4: 226.
22. McClean JR, Boixo S, Smelyanskiy VN, Babbush R, Neven H. Barren plateaus in quantum neural network training landscapes. *Nature Communications.* 2018; 9: 4812.
23. Cerezo M, Sone A, Volkoff T, Cincio L, Coles PJ. Cost function dependent barren plateaus in shallow parametrized quantum circuits. *Nature Communications.* 2021; 12: 1791.
24. Bittel L, Kliesch M. Training variational quantum algorithms is NP-hard. *Physical Review Letters.* 2021; 127(12): 120502.
25. Kerenidis I, Prakash A. Quantum recommendation systems. *Proceedings of the 8th Innovations in Theoretical Computer Science Conference (ITCS).* 2017; 67: 49:1–49:21.
26. Tang E. A quantum-inspired classical algorithm for recommendation systems. *Proceedings of the 51st ACM Symposium on Theory of Computing (STOC).* 2019: 217–228.
27. Chia NH, Gilyén A, Li T, Lin HH, Tang E, Wang C. Sampling-based sublinear low-rank matrix arithmetic framework for dequantizing quantum machine learning. *Proceedings of the 52nd ACM Symposium on Theory of Computing (STOC).* 2020: 387–400.
28. Huang HY, Broughton M, Mohseni M, et al. Power of data in quantum machine learning. *Nature Communications.* 2021; 12: 2631.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

29. Liu Y, Arunachalam S, Temme K. A rigorous and robust quantum speed-up in supervised machine learning. *Nature Physics.* 2021; 17(9): 1013–1017.
30. Thanasilp S, Wang S, Cerezo M, Holmes Z. Exponential concentration in quantum kernel methods. *Nature Communications.* 2024; 15: 5200.
31. Bowles J, Ahmed S, Schuld M. Better than classical? The subtle art of benchmarking quantum machine learning models. *arXiv preprint* arXiv:2403.07059. 2024.
32. Peruzzo A, McClean J, Shadbolt P, et al. A variational eigenvalue solver on a photonic quantum processor. *Nature Communications.* 2014; 5: 4213.
33. Kandala A, Mezzacapo A, Temme K, et al. Hardware-efficient variational quantum eigensolver for small molecules and quantum magnets. *Nature.* 2017; 549(7671): 242–246.
34. Orús R, Mugel S, Lizaso E. Quantum computing for finance: overview and prospects. *Reviews in Physics.* 2019; 4: 100028.
35. Dallaire-Demers PL, Killoran N. Quantum generative adversarial networks. *Physical Review A.* 2018; 98(1): 012324.
36. Amin MH, Andriyash E, Rolfe J, Kulchytskyy B, Melko R. Quantum Boltzmann machine. *Physical Review X.* 2018; 8(2): 021050.
37. Dunjko V, Taylor JM, Briegel HJ. Quantum-enhanced machine learning. *Physical Review Letters.* 2016; 117(13): 130502.
38. Temme K, Bravyi S, Gambetta JM. Error mitigation for short-depth quantum circuits. *Physical Review Letters.* 2017; 119(18): 180509.
39. Bergholm V, Izaac J, Schuld M, et al. PennyLane: automatic differentiation of hybrid quantum-classical computations. *arXiv preprint* arXiv:1811.04968. 2018.
40. Cerezo M, Verdon G, Huang HY, Cincio L, Coles PJ. Challenges and opportunities in quantum machine learning. *Nature Computational Science.* 2022; 2(9): 567–576.
41. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ.* 2021; 372: n71.
42. Kitchenham B, Charters S. *Guidelines for performing Systematic Literature Reviews in Software Engineering (EBSE Technical Report).* Keele University and University of Durham. 2007.
43. Schuld M, Sweke R, Meyer JJ. Effect of data encoding on the expressive power of variational quantum-machine-learning models. *Physical Review A.* 2021; 103(3): 032430.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved

***Author for Correspondence:**
Ankit R. Sharma
E-mail: ankit.sharma.qml@yahoo.com

[1]Assistant Professor, Department of Computer Science and Engineering, Raj Kumar Goel Institute of Technology, Ghaziabad, Uttar Pradesh
[2]Associate Professor, Department of Computer Science and Engineering, Raj Kumar Goel Institute of Technology, Ghaziabad, Uttar Pradesh
[3]Assistant Professor, Department of Computer Science and Engineering, Raj Kumar Goel Institute of Technology, Ghaziabad, Uttar Pradesh
[4]Research Scholar, Department of Computer Science and Engineering, Raj Kumar Goel Institute of Technology, Ghaziabad, Uttar Pradesh

Received Date: September 21, 2025
Accepted Date: October 04, 2025
Published Date: October 13, 2025

Citation: Ankit R. Sharma, Neha P. Verma, Rohit K. Tyagi, Pooja S. Gupta. Quantum Machine Learning and Artificial Intelligence: Opportunities for Next-Generation Computational Intelligence – A Review of Algorithms, Trainability Limits, and Application Readiness. Journal of Converging Technologies in Intelligent Computing. 2025; 1(3): 189-203p.

Page 189-203 © MANTECH PUBLICATIONS 2025. All Rights Reserved