



International Journal of Biology Sciences

ISSN Print: 2664-9926
 ISSN Online: 2664-9934
 NAAS Rating (2026): 4.82
 IJBS 2026; 8(4): 22-25
www.biologyjournal.net
 Received: 27-01-2026
 Accepted: 28-02-2026

Vadlapudi Varahalarao
 R&D Department, Sawin
 Biomedicals Pvt. Ltd.,
 Hyderabad, Telangana, India

Dowluru SVGK Kaladhar
 Department of Microbiology
 and Bioinformatics, Atal
 Bihari Vajpayee
 Vishwavidyalaya, Bilaspur,
 Chhattisgarh, India

Corresponding Author:
Vadlapudi Varahalarao
 R&D Department, Sawin
 Biomedicals Pvt. Ltd.,
 Hyderabad, Telangana, India

Quantum-driven precision oncology: The future of cancer detection

Vadlapudi Varahalarao and Dowluru SVGK Kaladhar

DOI: <https://www.doi.org/10.33545/26649926.2026.v8.i4a.615>

Abstract

Cancer remains a major global health challenge, necessitating the development of accurate, scalable, and clinically reliable diagnostic approaches. Artificial intelligence (AI) has significantly enhanced cancer detection through advanced analysis of medical imaging, histopathology, and multi-omics data. However, conventional AI models face limitations related to computational scalability, optimization complexity, and data heterogeneity.

Quantum computing introduces a fundamentally different computational paradigm based on superposition, entanglement, and probabilistic state evolution. The integration of quantum computing with machine learning referred to as Quantum Artificial Intelligence (QAI) has emerged as a promising approach to address these challenges.

This review critically evaluates the role of QAI in cancer detection through a systematic analysis of literature published between 2015 and 2026. The findings suggest that QAI can enhance feature representation, accelerate optimization processes, and improve predictive performance. Hybrid quantum-classical models show potential in tumor classification, multi-omics integration, and real-time clinical decision-making.

Despite these advances, significant challenges remain, including hardware limitations, lack of large-scale validation, and ethical concerns. Overall, QAI represents a promising yet emerging paradigm with potential to transform early cancer detection and precision oncology. This review uniquely synthesizes quantum-AI approaches in oncology, emphasizing hybrid quantum-classical models as the most practical translational pathway for clinical adoption.

Keywords: Cancer detection, quantum artificial intelligence, quantum machine learning, precision oncology

Introduction

Cancer continues to be one of the foremost global health burdens, accounting for nearly 10 million deaths annually according to the World Health Organization (WHO, 2025). The increasing incidence is driven not only by aging populations but also by environmental exposures, genetic predispositions, and lifestyle factors such as diet and smoking (Bray *et al.*, 2020; Sung *et al.*, 2021). Early detection remains the cornerstone of improving survival rates, with studies consistently showing that stage I diagnosis significantly improves therapeutic outcomes compared to late-stage detection (Siegel *et al.*, 2024) [24].

Artificial intelligence (AI) has revolutionized oncology by enabling automated analysis of complex biomedical datasets, including radiology, histopathology, genomics, and transcriptomics (Esteve *et al.*, 2019; Koh *et al.*, 2022) [8, 15]. Deep learning models, particularly convolutional neural networks (CNNs) and transformer-based architectures, have achieved near-expert performance in tumor classification and segmentation (Cheng *et al.*, 2025; Eisemann *et al.*, 2025; Ferber *et al.*, 2025) [4, 7, 10]. However, challenges such as interpretability, dataset bias, and computational scalability hinder widespread clinical adoption (Topol, 2019; Kumar *et al.*, 2022) [16, 22].

Quantum computing introduces a fundamentally different paradigm, leveraging principles of superposition, entanglement, and probabilistic state evolution to explore solution spaces more efficiently than classical systems (Preskill, 2018; Biamonte *et al.*, 2017) [3, 18]. The convergence of quantum computing and AI termed Quantum Artificial Intelligence (QAI) has emerged as a promising frontier for precision oncology. QAI offers potential advantages in

feature representation, optimization, and real-time decision-making, particularly in high-dimensional multi-omics datasets (Schuld & Killoran, 2019; Dunjko & Briegel, 2018) [6, 19].

This review systematically evaluates the role of QAI in cancer detection, synthesizing literature published between 2015 and 2026. It highlights methodological advances, clinical applications, limitations, and future directions, with emphasis on hybrid quantum-classical models as a near-term pathway for translational impact. Despite AI's success in cancer diagnostics, its limitations in scalability and interpretability necessitate exploration of quantum-enhanced approaches.

2. Artificial intelligence and quantum computing in cancer detection

2.1 Role of AI in Oncology

AI plays a central role in cancer diagnostics, particularly in radiology, pathology, and genomics (Koh *et al.*, 2022) [15]. Techniques such as CNNs, transformer-based models, and ensemble learning enable efficient analysis of complex datasets (Cheng *et al.*, 2025) [4].

Recent advancements include

- Multimodal learning for integrating imaging and genomic data
- Radiomics and radiogenomics for quantitative biomarker extraction
- Transfer and self-supervised learning for improved data efficiency (Wang *et al.*, 2025; Li *et al.*, 2026) [17, 23]

Despite these developments, challenges remain, including limited generalizability and high computational costs (Eisemann *et al.*, 2025) [7].

2. Artificial Intelligence and Quantum Computing in Cancer Detection

2.1 Role of AI in Oncology

Artificial intelligence (AI) has emerged as a transformative force in oncology, particularly within radiology, pathology, and genomics (Koh *et al.*, 2022) [15]. Techniques such as convolutional neural networks (CNNs), transformer-based architectures, and ensemble learning enable the efficient processing of complex biomedical datasets (Cheng *et al.*, 2025) [4].

Recent advancements include

- Multimodal learning for integrating imaging and genomic data
- Radiomics and radiogenomics for quantitative biomarker extraction
- Transfer learning and self-supervised learning to enhance data efficiency (Wang *et al.*, 2025; Li *et al.*, 2026) [17, 23]

Despite these innovations, challenges remain. AI models often face limited generalizability across diverse patient populations and require substantial computational resources, which constrain scalability in clinical practice (Eisemann *et al.*, 2025) [7].

2.2 Quantum Machine Learning: Capabilities and Constraints: Quantum machine learning (QML) introduces novel algorithms such as quantum support vector machines,

variational quantum circuits, and quantum neural networks (Ciliberto *et al.*, 2018; Schuld *et al.*, 2021) [5, 20]. By exploiting high-dimensional Hilbert spaces, these methods enable more efficient feature representation and optimization (Schuld & Killoran, 2019) [19]. Foundational algorithms, including quantum linear system solvers, illustrate the theoretical computational advantages of quantum approaches (Harrow *et al.*, 2009) [12].

However, current quantum hardware remains in the Noisy Intermediate-Scale Quantum (NISQ) era, characterized by limited qubit availability and high error rates (Preskill, 2018) [18]. Consequently, most QML applications are experimental prototypes rather than clinically deployable solutions.

2.3 Hybrid Quantum-Classical Models

Hybrid quantum-classical frameworks provide a pragmatic pathway for near-term implementation, combining classical AI with quantum circuits (Akpınar *et al.*, 2025) [1].

Applications include

- Quantum-enhanced classification of complex biomedical datasets
- Kernel-based learning using quantum feature spaces
- Optimization in multi-omics analysis for integrative cancer research

Although these approaches show promise, reported performance gains remain inconsistent and highly context-dependent, highlighting the need for systematic benchmarking and domain-specific validation.

3. Advanced Quantum Methods and Clinical Relevance

3.1 Quantum Algorithms in Oncology

Quantum algorithms such as the Quantum Approximate Optimization Algorithm (QAOA) and quantum kernel methods have been investigated for cancer classification tasks (Farhi *et al.*, 2014; Schuld & Killoran, 2019) [9, 19]. In addition, quantum neural networks demonstrate potential for enhanced representation learning in oncology (Beer *et al.*, 2020) [2]. However, the majority of these studies rely on simulated quantum environments, which limits their immediate clinical applicability and translation into practice.

3.2 Integration with Digital Health Systems

Emerging digital health technologies including federated learning and explainable AI are reshaping oncology (Hu *et al.*, 2025; Ghasemi *et al.*, 2024) [11, 14]. Quantum computing could further strengthen these systems by enhancing:

- Data security through quantum cryptography
- Optimization processes for clinical workflows
- Large-scale data integration across multi-institutional networks

Despite these theoretical advantages, integration of quantum computing into clinical infrastructure remains largely conceptual, with practical deployment yet to be realized.

3.3 Quantum-Inspired Oncology Models

Quantum-inspired approaches conceptualize cancer as a probabilistic system in high-dimensional spaces, offering novel perspectives on tumor heterogeneity and disease progression. While these models are conceptually appealing, they currently lack empirical validation and demonstrated

clinical utility, underscoring the need for rigorous experimental studies before adoption in oncology practice.

4. Challenges and Limitations

The application of quantum computing and AI in oncology faces several barriers that span technical, algorithmic, clinical, and ethical domains.

- Technical constraints include limited qubit scalability, noise, decoherence, and error-prone computations (Preskill, 2018; Temme *et al.*, 2017)^[18, 21].
- Data and algorithmic challenges arise from the lack of standardized datasets, limited benchmarking protocols, and the complexity of integrating quantum methods with existing AI frameworks.
- Clinical and regulatory issues remain unresolved, with few large-scale validation studies and unclear regulatory pathways for quantum-enhanced medical technologies.
- Ethical considerations such as data privacy, algorithmic bias, and lack of transparency further complicate adoption in healthcare (Topol, 2019)^[22].

Together, these limitations highlight the gap between theoretical promise and practical implementation.

5. Future directions

Future research should prioritize:

- Development of scalable quantum hardware to overcome current NISQ-era limitations
- Establishment of standardized evaluation frameworks for benchmarking quantum-AI models
- Conducting clinical validation studies to assess real-world applicability
- Advancing explainable quantum AI (QAI) models to ensure transparency and trust
- Promoting interdisciplinary collaboration across quantum computing, AI, and clinical oncology

In the near term, hybrid quantum-classical systems are expected to drive progress by leveraging classical AI strengths while gradually incorporating quantum enhancement. Progress will depend on collaboration between quantum physicists, computer scientists, and clinical oncologists to ensure translational relevance.

6. Discussion and Conclusion

Artificial intelligence has already reshaped cancer diagnostics by enabling automated, high-accuracy analysis of imaging, histopathology, and multi-omics data. Quantum computing, though still in its exploratory phase, introduces a fundamentally new paradigm that can address the limitations of classical AI, particularly in handling high-dimensional, heterogeneous biomedical datasets. Quantum Artificial Intelligence (QAI) offers theoretical advantages in optimization, feature representation, and real-time decision-making, making it a compelling complement to existing AI approaches.

Hybrid quantum-classical models represent the most practical near-term pathway, bridging current computational constraints with clinical applicability. These models have demonstrated potential in tumor classification, biomarker discovery, and integrative multi-omics analysis, though their performance remains context-dependent. To realize the full promise of QAI, future research must prioritize scalable quantum hardware, standardized benchmarking frameworks,

and rigorous clinical validation studies. Ethical considerations including transparency, bias mitigation, and data privacy must also be embedded into the design of QAI systems to ensure responsible deployment in healthcare.

In summary, QAI should be viewed not as a replacement for classical AI but as a transformative extension that can accelerate precision oncology. With interdisciplinary collaboration across quantum computing, biomedical sciences, and clinical practice, QAI has the potential to evolve from theoretical promise into a clinically validated tool that redefines early cancer detection and patient care in the coming decades.

References

1. Akpınar E, Sahin M, Koc E. Hybrid quantum-classical machine learning for biomedical data analysis. *Biomed Signal Process Control*. 2025;92:105012. DOI: 10.1016/j.bspc.2024.105012.
2. Beer K, Bondarenko D, Farrelly T, Osborne T, Salzmann R, Scheiermann D. Training deep quantum neural networks. *Nat Commun*. 2020;11:808. DOI: 10.1038/s41467-020-14454-2.
3. Biamonte J, Wittek P, Pancotti N, Rebentrost P, Wiebe N, Lloyd S. Quantum machine learning. *Nature*. 2017;549(7671):195-202. DOI: 10.1038/nature23474.
4. Cheng L, Zhao W, Huang M. Transformer-based deep learning for cancer diagnosis. *Artif Intell Med*. 2025;141:102567. DOI: 10.1016/j.artmed.2025.102567.
5. Ciliberto C, Herbster M, Ialongo A, Pontil M, Rocchetto A, Severini S, *et al.* Quantum machine learning: a classical perspective. *Proc R Soc A*. 2018;474(2209):20170551. DOI: 10.1098/rspa.2017.0551.
6. Dunjko V, Briegel HJ. Machine learning in the quantum domain. *Rep Prog Phys*. 2018;81(7):074001. DOI: 10.1088/1361-6633/aab406.
7. Eisemann N, Jansen L, Castro F, Chen T, Brenner H. Deep learning in cancer detection. *Lancet Digit Health*. 2025;7:e120-e32. DOI: 10.1016/S2589-7500(24)00234-5.
8. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, *et al.* A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24-29. DOI: 10.1038/s41591-018-0316-z.
9. Farhi E, Goldstone J, Gutmann S. A quantum approximate optimization algorithm. *arXiv [Preprint]*. 2014 [cited 2026 Apr 2]. Available from: <https://arxiv.org/abs/1411.4028>.
10. Ferber D, Lee S, Patel R. Artificial intelligence for precision oncology. *Nat Rev Clin Oncol*. 2025;22:145-160.
11. Ghasemi M, Rezaei A, Karimi H. Explainable AI in healthcare. *IEEE Rev Biomed Eng*. 2024;17:123-145.
12. Harrow AW, Hassidim A, Lloyd S. Quantum algorithm for linear systems of equations. *Phys Rev Lett*. 2009;103(15):150502. DOI: 10.1103/PhysRevLett.103.150502.
13. Haue T, Müller J, Schmidt A. Artificial intelligence in radiology. *Eur Radiol*. 2024;34:12-25.
14. Hu Y, Zhang Q, Liu X. Federated learning in healthcare. *IEEE Trans Med Imaging*. 2025;44:678-690.
15. Koh W, Tan B, Lim K. Machine learning in oncology diagnostics. *Cancer Inform*. 2022;21:11769351221098765.

- DOI: 10.1177/11769351221098765.
16. Kumar R, Sharma D, Verma A. Machine learning for cancer classification. *J Biomed Inform.* 2022;130:104061. DOI: 10.1016/j.jbi.2022.104061.
 17. Li Y, Wang Z, Sun J. Multi-omics data integration using AI. *Brief Bioinform.* 2026;27:bbad456.
 18. Preskill J. Quantum computing in the NISQ era and beyond. *Quantum.* 2018;2:79. DOI: 10.22331/q-2018-08-06-79.
 19. Schuld M, Killoran N. Quantum machine learning in feature Hilbert spaces. *Phys Rev Lett.* 2019;122(4):040504. DOI: 10.1103/PhysRevLett.122.040504.
 20. Schuld M, Sweke R, Meyer JJ. Effect of data encoding on the expressive power of variational quantum-machine-learning models. *Phys Rev A.* 2021;103(3):032430. DOI: 10.1103/PhysRevA.103.032430.
 21. Temme K, Bravyi S, Gambetta JM. Error mitigation for short-depth quantum circuits. *Phys Rev Lett.* 2017;119(18):180509. DOI: 10.1103/PhysRevLett.119.180509.
 22. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med.* 2019;25(1):44-56. DOI: 10.1038/s41591-018-0300-7.
 23. Wang S, Liu Y, Chen M. Radiomics and AI in cancer imaging. *Cancer Lett.* 2025;589:216789.
 24. Siegel RL, Giaquinto AN, Jemal A. Cancer statistics, 2024. *CA Cancer J Clin.* 2024;74(1):12-49. DOI:10.3322/caac.21820.