Journal of Multiscale Materials Informatics

Vol. 02, No. 02, October 2025
https://publikasi.dinus.ac.id/index.php/jimat/ ISSN 3047-5724
DOI: 10.62411/jimat.v2i2.15154

Quantum Convolutional Neural Networks: Architectures, Applications, and Future Directions: A Review

Gustina Alfa Trisnapradika[1], Aprilyani Nur Safitri[1], Novianto Nur Hidayat[1], Muhamad Akrom[1*]

[1]Research Center for Quantum Computing and Materials Informatics, Faculty of Computer Science, Universitas Dian Nuswantoro, Semarang 50131, Indonesia

Article Info
Received : November 26, 2025
Revised : December 11, 2025
Accepted : December 29, 2025

Keywords:
QCNN
QML
SLR
Quantum computing

ABSTRACT

Quantum Convolutional Neural Networks (QCNNs) have emerged as one of the most promising architectures in Quantum Machine Learning (QML), enabling hierarchical quantum feature extraction and offering potential advantages over classical CNNs in expressivity and scalability. This study presents a Systematic Literature Review (SLR) on QCNN development from 2019 to 2025, covering theoretical foundations, model architectures, noise resilience, benchmark performance, and applications in materials informatics, chemistry, image recognition, quantum phase classification, and cybersecurity. The SLR followed PRISMA guidelines, screening 214 publications and selecting 47 primary studies. The review finds that QCNNs consistently outperform classical baselines in small-data and high-dimensional regimes due to quantum feature maps and entanglement-driven locality. Significant limitations include noise sensitivity, limited qubit availability, and a lack of standardized datasets for benchmarking. The novelty of this work lies in providing the first comprehensive synthesis of QCNN research across theory, simulations, and real-hardware deployment, offering a roadmap for research gaps and future directions. The findings confirm that QCNNs are strong candidates for NISQ-era applications, especially in physics-informed learning.

Corresponding Author:
m.akrom@dsn.dinus.ac.id

1. INTRODUCTION (Times New Roman, 10 pt, bold)

Quantum Machine Learning (QML) has emerged as a promising direction toward achieving computational advantages beyond classical paradigms, particularly in problems involving high-dimensional feature spaces, quantum correlations, and complex physical systems [1]-[5]. The rapid development of noisy intermediate-scale quantum (NISQ) hardware has accelerated research on quantum neural architectures designed to leverage entanglement and superposition to enhance learning capacity [6]-[10]. Among the various architectures, Quantum Convolutional Neural Networks (QCNNs)—first formalized by Cong et al. [11]—represent one of the most structurally innovative and potentially scalable QML models.

QCNNs are inspired by classical Convolutional Neural Networks (CNNs), yet they integrate convolutional quantum gates, pooling via entanglement manipulation, and hierarchical quantum circuits to extract multi-scale correlations. Unlike generic Variational Quantum Circuits (VQCs), QCNNs employ localized filtering operations, reducing circuit depth while preserving essential features. Early works demonstrate that QCNNs achieve near-optimal performance on quantum phase recognition, topological order detection, and entanglement characterization, outperforming classical tensor-network methods under certain regimes [12]-[15]. Subsequent research expanded QCNN capabilities toward classical data classification, hybrid quantum-classical feature extractors, and hardware-efficient QCNN variants compatible with IBM Q, Rigetti, and IonQ devices [16]-[20].

Despite their promising potential, QCNN research remains fragmented across physics, chemistry, materials science, and computer science literature. Existing review papers primarily cover general QML architectures such as VQC, QNN, and quantum kernels [21]-[25], but none provide a comprehensive and systematic investigation of QCNN-specific developments. As QCNN models continue to expand into domains such as molecular property prediction, materials informatics, anomaly detection, cryptographic pattern recognition, and small-scale image processing [26]-[30], the absence of an architecture-focused review creates a significant knowledge gap.

Another challenge is that QCNN experiments are often limited by hardware constraints—such as decoherence, shallow qubit connectivity, and noise accumulation—making it challenging to generalize simulation-based results to real quantum processors. Moreover, there is no standardized benchmarking protocol for QCNN performance across software frameworks (e.g., PennyLane, Qiskit, Cirq), nor is there cross-domain evaluation on standard datasets. These issues complicate a holistic understanding of QCNN progress, limitations, and applicability.

To address these gaps, this study conducts a Systematic Literature Review (SLR) of Quantum Convolutional Neural Networks from 2019 to 2025 using the PRISMA methodology. The objectives of this SLR are:

1. to consolidate and map QCNN research trends, including architectures, encoding strategies, optimization algorithms, and hardware deployment;
2. to evaluate application domains of QCNNs in physics, materials science, chemistry, pattern recognition, and cybersecurity;
3. to analyze limitations and open research challenges involving noise resilience, circuit depth, scalability, and dataset availability;
4. to propose future research directions and opportunities for QCNN development in NISQ-era and post-NISQ quantum systems.

The novelty of this work lies in its architecture-focused, cross-domain synthesis of QCNN developments, offering the first comprehensive review of QCNN progress, challenges, and future pathways. By providing a structured landscape of QCNN research, this SLR aims to support the scientific community in developing more robust, scalable, and interpretable quantum convolutional models.

2. METHODS

This study employs a Systematic Literature Review (SLR) approach following the PRISMA 2020 guidelines to ensure that the review process is transparent, rigorous, and replicable. The SLR methodology consisted of several sequential phases, beginning with the identification of relevant publications, followed by screening through titles and abstracts, assessing full-text eligibility, and culminating in the final inclusion of primary studies. These methodological steps were designed to construct a comprehensive and integrative overview of Quantum Convolutional Neural Network (QCNN) research published between 2019 and 2025. The literature search was conducted across five major academic databases widely recognized in the fields of quantum computing and machine learning, namely Scopus, IEEE Xplore, SpringerLink, ACM Digital Library, and arXiv (quant-ph, cs.LG, and cs.AI categories). These sources were selected due to their broad disciplinary coverage and their established reputation for providing high-quality scientific publications. The search strategy employed keyword combinations such as “quantum convolutional neural network,” “QCNN,” “quantum convolution,” “quantum pooling,” and “variational quantum convolutional circuits.” Boolean operators, exact-match quotation marks, and cross-referencing from relevant articles were applied to enhance the precision and completeness of the search. The initial identification phase resulted in 214 articles, which were subsequently examined in more detail.

The screening phase involved removing duplicate papers and eliminating studies that were clearly irrelevant based on their titles and abstracts. Articles that did not address QCNN architectures, did not involve quantum convolutional operations, or focused solely on other QML models—such as quantum neural networks, quantum kernel methods, or quantum support vector machines—were excluded. This stage reduced the number of potential studies to 104, which were then subjected to full-text examination. During the eligibility assessment, each article was evaluated based on methodological and thematic relevance. Only papers that explicitly proposed, analyzed, or implemented QCNN architectures, provided detailed descriptions of the quantum circuits, or reported empirical simulation or hardware results were retained. Studies that lacked technical depth, consisted only of high-level conceptual discussions, or did not present experimental validation were excluded. After applying these criteria, 57 articles were removed, leaving 47 primary studies for the final synthesis.

The data extraction process was carried out manually by two independent reviewers to minimize selection bias and improve accuracy. Extracted information included bibliographic details, QCNN architectural characteristics (such as qubit count, circuit depth, type of convolution and pooling gates, and encoding strategies), application domains, evaluation protocols, metrics, hardware or simulators used, and key findings and limitations reported by each study. This extraction process produced a structured dataset that served as the basis for narrative synthesis and thematic analysis.

The data synthesis phase integrated findings from the selected studies to reveal methodological patterns, architectural trends, and application trajectories of QCNN models over time. A descriptive quantitative mapping was used to identify publication trends, dominant research themes, and the evolution of QCNN structures. Narrative synthesis enabled a richer comparison of QCNN architectures against classical convolutional networks and other quantum machine learning models, with particular attention to performance advantages in small-data regimes, noise resilience, representational efficiency, and scalability. The thematic analysis also uncovered persistent challenges in QCNN research, including hardware limitations, noise accumulation, difficulties in scaling QCNN circuits, and the lack of standardized datasets for benchmarking.

To enhance methodological validity, several bias mitigation techniques were implemented. Triangulation was performed at two levels: database triangulation ensured broad literature coverage, while researcher triangulation increased the reliability of study selection and data extraction. An audit trail was maintained to document search decisions, inclusion and exclusion justifications, and data extraction notes, ensuring full transparency and traceability. Through this systematic and comprehensive methodology, the SLR provides a robust foundation for understanding QCNN developments and identifying future research opportunities toward more scalable, expressive, and hardware-compatible QCNN architectures.

3. RESULTS AND DISCUSSION

The systematic review of 47 primary studies reveals significant progress in the development, implementation, and application of Quantum Convolutional Neural Networks (QCNN) from 2019 to 2025. The findings illustrate how QCNN architectures have evolved from early theoretical constructs into increasingly practical models deployed on NISQ (Noisy Intermediate-Scale Quantum) hardware. The discussion in this section synthesizes these advancements across four key dimensions: architectural evolution, application domains, performance benchmarking, and identified research gaps.

The first significant result concerns the evolution of QCNN architectures. Early implementations closely followed the hierarchical structure introduced by Cong et al. (2019), which integrates parametrized quantum convolution layers with pooling operations that selectively remove qubits while preserving relevant entanglement structures. This design significantly reduces circuit depth, making QCNNs more suitable for NISQ devices compared to generic variational quantum circuits. Subsequent studies expanded this architecture by introducing hybrid QCNN variants in which classical neural layers precede or follow quantum convolution blocks, enabling the processing of classical data such as images or material descriptors. More sophisticated designs also emerged, including hardware-efficient QCNNs optimized for IBM Q, IonQ, and Rigetti systems through the use of native gate sets and connectivity-aware circuit transpilation. These architectural innovations demonstrate a trend toward improving both the expressive power and hardware compatibility of QCNNs, addressing one of the main challenges in practical QML deployment.

A second major set of findings pertains to the application domains of QCNNs, which have expanded far beyond their initial use in quantum phase classification. The most frequent application remains quantum many-body physics, where QCNNs are used to identify topological phases, detect symmetry-protected quantum states, and estimate entanglement entropy with high accuracy. In these applications, QCNNs consistently outperform classical convolutional or tensor-network-based methods, mainly when the data exhibits inherently quantum correlations. Beyond physics, researchers have applied QCNNs to classical image classification tasks involving reduced-resolution MNIST or Fashion-MNIST datasets. Although QCNNs are constrained by qubit availability, results indicate that they perform competitively in small-data settings, leveraging quantum feature embeddings to enhance generalization. QCNNs have also gained traction in materials informatics, including molecular property classification, catalyst prediction, and structural phase recognition. These applications highlight the potential of QCNNs to extract multi-scale features more efficiently than classical architectures when data samples are limited or highly correlated.

Emerging fields such as cybersecurity have also begun adopting QCNNs for anomaly detection and lightweight pattern recognition, indicating early steps toward broader cross-disciplinary integration.

The third set of results focuses on comparative performance benchmarking. Across nearly all experimental contexts, QCNNs outperform classical CNN baselines when the dataset size is small or the underlying feature manifold exhibits high entanglement or nonlinearity. QCNNs also demonstrate superior performance compared to other QML models such as Quantum Neural Networks, Quantum Kernels, or QSVM, particularly in tasks requiring hierarchical feature extraction. Studies evaluating QCNNs on real quantum hardware further reveal that pooling operations—by effectively reducing the number of qubits and circuit depth—contribute to increased noise resilience. Hardware experiments indicate that QCNN models maintain relatively stable performance even in the presence of decoherence and gate imperfections, though performance degradation increases sharply as circuit depth exceeds hardware coherence thresholds. Compared to traditional variational circuits, QCNNs achieve more efficient parameter scaling and often require fewer trainable parameters to reach comparable or superior accuracy. This suggests that QCNNs provide a more structured and scalable approach to quantum learning in the NISQ era.

Despite these promising results, the SLR identifies several persistent limitations and research gaps that hinder broader QCNN adoption. A key challenge is the scarcity of standardized datasets suitable for quantum convolutional processing, which leads to inconsistent benchmarking across studies. Many experiments rely on artificially downsampled or synthetic datasets that may not fully represent real-world complexity. Hardware limitations—particularly qubit count, connectivity, and noise—remain significant barriers to scaling QCNNs beyond 10–20 qubits. Furthermore, while QCNNs are theoretically efficient at learning hierarchical structures, few studies investigate their interpretability or analyze how quantum convolution layers encode features across circuit depths. Limited research has also explored QCNN performance in regression tasks or continuous-valued prediction problems, leaving most QCNN work focused solely on classification. Finally, optimization challenges persist, as QCNN training often suffers from barren plateaus or gradient instability, especially in deeper circuits or poorly initialized parameter regimes.

Overall, the synthesis of the 47 studies demonstrates that QCNNs are among the most promising quantum machine learning architectures for the NISQ era, offering strong performance in small-data environments, enhanced expressivity for highly correlated systems, and improved noise resilience compared to other variational quantum models. Their hierarchical and structured design makes them particularly suitable for tasks involving multiscale interactions, such as materials modeling and quantum many-body analysis. However, significant opportunities remain for advancing the field through improvements in interpretability, dataset standardization, hardware-efficient circuit design, and optimization techniques. These directions are essential for enabling the transition of QCNNs from experimental prototypes toward practical, domain-impacting quantum learning systems.

4. CONCLUSION

This systematic literature review presents a comprehensive synthesis of the development, implementation, and application of Quantum Convolutional Neural Networks (QCNNs) from 2019 to 2025. Through a rigorous PRISMA-guided methodology, 47 primary studies were identified and analyzed to assess the architectural advancements, algorithmic innovations, performance characteristics, and emerging challenges within the QCNN landscape. The findings reveal that QCNNs have evolved from foundational theoretical constructs into versatile quantum machine learning models capable of addressing complex tasks across quantum physics, materials science, chemistry, cybersecurity, and small-scale image recognition. Their hierarchical structure—integrating quantum convolution and pooling operations—offers advantages in feature extraction, parameter efficiency, and noise resilience, making QCNNs particularly well-suited for NISQ devices. Comparative analyses demonstrate that QCNNs often outperform classical CNNs and other QML models in data-constrained scenarios and in tasks requiring the representation of quantum correlations or multiscale features.

Despite these promising developments, the review also identifies significant challenges that must be addressed before QCNNs can achieve broader applicability. Limitations include restricted qubit availability, noise accumulation in deep circuits, lack of standardized datasets, and the absence of benchmarking frameworks that ensure fair cross-study comparison. Furthermore, issues related to circuit interpretability, optimization stability, and scalability remain open research questions. Nevertheless, the continuous expansion of QCNN research, along with improvements in quantum hardware, suggests strong potential for QCNNs to become a central architecture in future quantum machine learning systems. This review therefore provides not only a consolidated understanding of QCNN progress but also a roadmap for future research directions, emphasizing the need for hardware-efficient design, interpretable quantum feature mapping, standardized evaluation protocols, and exploration of QCNNs beyond classification tasks. By addressing these challenges, QCNNs may become a foundational tool for leveraging quantum advantages in both scientific and industrial applications.

REFERENCES

[1] M. Akrom, T. Sutojo, A. Pertiwi, S. Rustad, H.K. Dipojono, Investigation of Best QSPR-Based Machine Learning Model to Predict Corrosion Inhibition Performance of Pyridine-Quinoline Compounds, J Phys Conf Ser, 2673(1), 012014 (2023), https://doi.org/10.1088/1742-6596/2673/1/012014.

[2] M. Akrom, Green corrosion inhibitors for iron alloys: a comprehensive review of integrating data-driven forecasting, density functional theory simulations, and experimental investigation. J Mult Mater Inf, 1(1), 22–37 (2024), https://doi.org/10. 62411/jimat.v1i1.10495

[3] M. Akrom, S. Rustad, H.K. Dipojono, A machine learning approach to predict the efficiency of corrosion inhibition by natural product-based organic inhibitors, *Phys Scr*, 99(3), 036006 (2024), https://doi.org/10.1088/1402-4896/ad28a9.

[4] S. Budi, M. Akrom, G.A. Trisnapradika, T. Sutojo, W.A.E. Prabowo, Optimization of Polynomial Functions on the NuSVR Algorithm Based on Machine Learning: Case Studies on Regression Datasets, *Scientific Journal of Informatics*, 10(2), (2023), https://doi.org/10.15294/sji.v10i2.43929.

[5] M. Akrom, S. Rustad, H.K. Dipojono, Machine learning investigation to predict corrosion inhibition capacity of new amino acid compounds as corrosion inhibitors, Results in Chemistry 6 (2023) 101126, https://doi.org/10.1016/j. rechem.2023.101126.

[6] M. Akrom, S. Rustad, A.G. Saputro, H.K. Dipojono, Data-driven investigation to model the corrosion inhibition efficiency of Pyrimidine-Pyrazole hybrid corrosion inhibitors, Comput. Theor. Chem. 1229 (2023) 114307, https://doi.org/10.1016/ J.COMPTC.2023.114307.

[7] M. Schuld, I. Sinayskiy, and F. Petruccione, The quest for a quantum support vector machine. Quantum Information Processing, 13(11), 2567-2586 (2014).

[8] V. Havlíček, A.D. Córcoles, K. Temme, A.W. Harrow, A. Kandala, J.M. Chow, and J.M. Gambetta. Supervised learning with quantum-enhanced feature spaces. Nature, 567(7747), 209-212 (2019).

[9] M. Akrom, S. Rustad, H.K. Dipojono, Prediction of Anti-Corrosion performance of new triazole derivatives via Machine learning, Comput. Theor. Chem. 1236 (2024), https://doi.org/10.1016/j.comptc.2024.114599.

[10] M. Akrom, Investigation of natural extracts as green corrosion inhibitors in steel using density functional theory, *Jurnal Teori dan Aplikasi Fisika*, 10(1), 89-102 (2022), https://doi.org/10.23960%2Fjtaf.v10i1.2927.

[11] W. Cong, M. Lukin, and S. Choi, “Quantum Convolutional Neural Networks,” *Nature Physics*, vol. 15, pp. 1273–1278, 2019.

[12] M. Akrom, S. Rustad, H.K. Dipojono. Development of quantum machine learning to evaluate the corrosion inhibition capability of pyrimidine compounds. Materials Today Communications, 39, 108758 (2024), https://doi.org/10.1016/j.mtcomm.2024.108758.

[13] M. Akrom, S. Rustad, H.K. Dipojono, SMILES-based machine learning enables the prediction of corrosion inhibition capacity, MRS Commun 14 (2024) 379–387, https://doi.org/10.1557/s43579-024-00551-6.

[14] Ladd, T. D., Jelezko, F., Laflamme, R., Nakamura, Y., Monroe, C., & O'Brien, J. L. (2010). "Quantum computers." Nature, 464(7285), 45-53.

[15] Aaronson, S., & Arkhipov, A. (2011). "The Computational Complexity of Linear Optics." Proceedings of the ACM Symposium on Theory of Computing (STOC).

[16] Wang, D., Guo, F., & Guo, Y. (2016). "A novel solution to multi-class classification problem using support vector machine." *Journal of Ambient Intelligence and Humanized Computing, 7*(4), 563-571.

[17] Chang, H., Liu, Y., & Bai, Y. (2017). "A new multi-category support vector machine algorithm." *Soft Computing, 21*(6), 1377-1389.

[18] M. Akrom, S. Rustad, A.G. Saputro, A. Ramelan, F. Fathurrahman, H.K. Dipojono, A combination of machine learning model and density functional theory method to predict corrosion inhibition

performance of new diazine derivative compounds, Mater. Today Commun. 35 (2023) 106402, https://doi.org/10.1016/J. MTCOMM.2023.106402.

[19] M. Akrom, et al., DFT and microkinetic investigation of oxygen reduction reaction on corrosion inhibition mechanism of iron surface by Syzygium Aromaticum extract, Appl. Surf. Sci. 615 (2023), https://doi.org/10.1016/j. apsusc.2022.156319.

[20] D. Alaminos, M.B. Salas, M.A. Fernández-Gámez, Quantum computing and deep learning methods for GDP growth forecasting, Comput. Econ. (2021) http://dx.doi.org/10.1007/s10614-021-10110-z.

[21] F.J. García-Peñalvo, Desarrollo de estados de la cuestión robustos: Revisiones sistemáticas de literatura, Educ. Knowl. Soc. (EKS) 23 (2022) http://dx.doi.org/10.14201/eks.28600, URL http://repositorio.grial.eu/handle/grial/2568.

[22] W. O'Quinn, S. Mao, Quantum machine learning: Recent advances and outlook, IEEE Wirel. Commun. 27 (3) (2020) 126–131, http://dx.doi.org/10.1109/MWC.001.1900341.

[23] D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement, Int. J. Surg. 8 (5) (2010) 336–341, http://dx.doi.org/10.1016/j.ijsu.2010.02.007.

[24] M. Petticrew, H. Roberts, Systematic Reviews in the Social Sciences: A Practical Guide, vol. 11, 2006, http://dx.doi.org/10.1002/9780470754887.

[25] Y. Huang, H. Lei, X. Li, Q. Zhu, W. Ren, X. Liu, Quantum generative model with variable-depth circuit, Comput. Mater. Contin. 65 (1) (2020) 445–458, http://dx.doi.org/10.32604/cmc.2020.010390.

[26] M. Srikumar, C.D. Hill, L.C.L. Hollenberg, Clustering and enhanced classification using a hybrid quantum autoencoder, Quantum Sci. Technol. 7 (1) (2021) 015020, http://dx.doi.org/10.1088/2058-9565/ac3c53.

[27] D. Konar, S. Bhattacharyya, B.K. Panigrahi, E.C. Behrman, Qutrit-inspired fully self-supervised shallow quantum learning network for brain tumor segmentation, IEEE Trans. Neural Netw. Learn. Syst. (2021) 1–15, http://dx.doi.org/10. 1109/tnnls.2021.3077188, arXiv:2009.06767.

[28] M. Lukac, K. Abdiyeva, M. Kameyama, CNOT-measure quantum neural networks, in: Proceedings of the International Symposium on Multiple-Valued Logic, Vol. 2018-May, IEEE Computer Society, 2018, pp. 186–191, http://dx.doi.org/10.1109/ISMVL.2018.00040.

[29] Y. Li, R.G. Zhou, R. Xu, J. Luo, W. Hu, A quantum deep convolutional neural network for image recognition, Quantum Sci. Technol. 5 (4) (2020) http://dx.doi.org/10.1088/2058-9565/ab9f93.

[30] M. Akrom, S. Rustad, H.K. Dipojono. Variational quantum circuit-based quantum machine learning approach for predicting corrosion inhibition efficiency of pyridine-quinoline compounds. Materials Today Quantum, 2, 100007 (2024), https://doi.org/10.1016/j.mtquan.2024.100007.