International Journal of Innovations In Science Engineering And Management

Quantum Enhanced Image Analysis on IBM Hardware In NISQ-Era

Niranjala S. H.[1*], **M. Kazem Chamran**[2], **Mustafa Mowafak Alobaedy**[3]

[1]*Faculty of Information Technology, City University, Malaysia*

[1*]*Corresponding author, ORCID: 0009-0001-6580-4726, shyama@gwu.ac.lk*
[2]*ORCID: 0000-0003-3836-4443, kazem.chamran@city.edu.my*
[3]*ORCID: 0000-0002-6562-2922, mustafa.theab@city.edu.my*

OPEN ACCESS

Volume: 5

Issue: 2

Month: May

Year: 2026

ISSN: 2583-7117

Published: 15.05.2026

Citation:

Niranjala S. H., M. Kazem Chamran, Mustafa Mowafak Alobaedy "Quantum Enhanced Image Analysis on IBM Hardware In NISQ-Era" International Journal of Innovations in Science Engineering and Management, vol. 5, no. 2, 2026, pp. 185-192

DOI:

10.69968//ijisem.2026v5i2185-192

Abstract

The rapid growth of high-dimensional image data in the 21st century has revealed the inherent scalability limits of classical Convolutional Neural Network (CNN) models. The Moore's Law nearing its physical and economic limits. As a result, use of energy latency involved in training multi-million-parameter models specially in applications such as medical imaging and satellite imaging. In this paper, a novel quantum-based architecture is proposed that incorporates Variational Quantum Circuits (VQCs) into a classical CNN. By mapping classical pixel information into a high-dimensional Hilbert space. Quantum entanglement is exploited to capture intricate spatial hierarchies with a fraction of the parameters of classical Euclidean-based models. We demonstrate a proof-of-concept of this novel framework using the IBM Quantum ecosystem and show that a Quantum-Enhanced CNN can reduce trainable parameters by 93% yet still attain accuracy levels that are competitive with state-of-the-art classical models. This paper provides a scalable proof of concept that paves the way for a "Quantum Utility" future in which data analysis is redefined in terms of quantum state space.

Keywords; Machine learning, quantum machine learning, IBM Qiskit, image processing, NISQ, Variational Quantum Circuits.

INTRODUCTION

The current state of artificial intelligence can be defined in terms of the use of scale as the key methodological strategy for improving the accuracy of models, particularly in the context of Large Language Models (LLMs) and high-resolution computer vision models [1]. The primary method for improving the accuracy of these models has been to pursue deeper and wider neural network architectures. However, the pursuit of these models has been hindered by the formidable barrier of the "Computational Wall". Current Convolutional Neural Networks, while revolutionary for the pursuit of spatial feature extraction, are hindered by the linear scaling of the discrete convolution operation [2].

This has reached the critical juncture for IT professionals and researchers working with the pursuit of data analysis. Quantum Computing (QC) presents the possibility of transcending the limitations of binary logic and the pursuit of the principles of superposition and entanglement, which define the state-space of the qubit [3]. The study presents the possibility of exponential scaling with the number of qubits. This article will experiment with adopting the IBM quantum hardware for effective image analyzing tasks [4]. And focus on centered around the concept of data analysis and its convergence with quantum logic. Instead of considering the quantum computer to be an enhanced version of the traditional computing processor, we view it as an innovative medium of data representation [5].

The paper is particularly timely in view of the recent advent of Quantum Utility backends, such as the 127-qubit IBM Eagle processors [6]. This paper is viewed as a bridge between the theoretical aspects of quantum mechanics and the practical needs of IT-based research, providing an extensive framework for the upcoming generation of efficient machine learning [7].

LITERATURE REVIEW

Quantum integration with deep learning is not just an upgrade of existing technology but rather a paradigm shift in thinking about data representation. In literature review, authors evaluates the status quo of classical convolutional neural networks, outlines the mathematical framework to move to Hilbert space, and finally evaluates the role of Variational Quantum Circuitry within the realm of Noisy Intermediate Scale Quantum Computing [8].

Evolution of Classical Machine Learning

Since the advent of LeNet-5 and the subsequent achievement of AlexNet, Convolutional Neural Networks have been relying on the translation invariance of the convolution operation. It has been able to successfully extract local features such as edges, textures, and shapes from images [9]. Although classical CNNs have successfully solved problems at a level comparable to humans, they face increasing barriers with the "Model Oversize" problem [10]. With the advent of high-resolution images, it is now common to require hundreds of layers with millions of parameters to successfully classify images. It leads to substantial memory barriers and energy consumption during training and testing [11].

Further, classical convolutional kernels are only able to represent linear combinations of inputs in Euclidean space. When dealing with complex data structures such as stochastic noise found in medical images such as MRI scans or multi-spectral imagery found in satellite images, classical convolutional neural networks require stacks of hundreds of layers to successfully capture complex correlations [12].

Mathematical Approach of Transitioning to Hilbert Space

The main advantage of quantum computing for data analysis is related to the dimensionality of the state space. A classical system consisting of n bits can assume, at any given time, exactly one of 2n possible states [13]. On the other hand, a quantum system consisting of n qubits is in a superposition of all 2^n possible basis states simultaneously. This is represented by a vector in a complex Hilbert space:

$$|\psi\rangle = \sum(i = 0 \text{ to } 2^n - 1)\ \alpha_i\, |i\rangle, \text{ where } \sum |\alpha_i|^2 = 1$$

Quantization of image pixel values into the amplitude or angle of the qubits is a mapping of the input image into a high-dimensional feature space that is exponentially larger than the input space [14]. In this Hilbert space, data points which overlap or not linearly separable in Euclidean space are often linearly separable. This Quantum Feature Mapping is theoretically equivalent to the “Kernel Trick” used in CNN algorithm, but with a feature space that is potentially much richer than is possible classically [15].

Variational Quantum Circuit (VQC)in NISQ Era

We are in the current era known as the "Noisy Intermediate Scale Quantum" (NISQ), where we have a limited number of qubits and they are susceptible to decoherence, which is the loss of quantum information caused by environmental influences. Hence, deep quantum algorithms such as Shor’s and Grover’s algorithms are not feasible in handling large amounts of data [16].

Variational Quantum Circuits (VQCs) have been identified as the best approach in this current era. The Variational Quantum Circuit is defined as a hybrid construct where the parameters of the quantum circuit θ, are updated using a classical optimizer [17] [18]. This enables the model to learn around the noise characteristics of the device. The Variational Quantum Circuit has three components:

1 **Encoder (S(x)):** Converting data from classical material to quantum states
2 **Ansatz (U(θ)):** This is where the computation or convolution happens. Called as parameterized operation (often a quantum circuit). These parameters always learn to get best results.
3 **Measurement (⟨M⟩) :** Reverse the quantum state back to classical data. This is the step of observing the result. M represent the average of expectation value as a measurement.

Quantum Entanglement

Variational The most important quantum property in image processing is entanglement. In a classical CNN, it is impossible to have a 3x3 kernel operate beyond its immediate scope. Establishing the correlation between the top-left pixel and the bottom-right pixel involves propagating features through significantly deeper layers. In contrast, in a quantum circuit, only one CNOT gate is necessary to create instantaneous non-local correlations between qubits [19].

The ability to entangle qubits corresponding to different areas of a pixel patch is what allows Qu-CNN to learn complex spatial correlations within a single layer, which require multiple layers in a classical network [20] [6]. This is the reason why there is a significant reduction in parameters across all experiments.

RESEARCH METHODOLOGY

Quantum State preparing with feature mapping

In initially, challenge in processing classical image data using a quantum processor is the encoding problem, which course transforming classical information into a quantum state that can be processed via a quantum circuit [21]. To process a localized N×Npixel patch P, where $P \in R^n$, authors employ angle encoding as the feature-mapping strategy. In contrast to amplitude encoding, which often requires sophisticated and labor-intensive state preparation steps, angle encoding maps the normalized pixel intensity to the rotation angle of a single qubit. $x_i$directly to the rotation angle of an individual qubit [22]. The pixel values are first normalized such that $x_i \in [0,\pi]$.

For example, when processing a 2x2 region of an image, the pixel values represent a 4-qubit quantum register prepared to the computational basis state, indicating that all qubits are initialized to the zero state. The encoding is then performed by applying a parameterized unitary transformation. S(x), defined as

$$S(x) = \left(\bigotimes_{i=1}^{n} R_y(x_i)\right) |0\rangle^{\otimes n}$$

where $R_y(x_i)$ represents a rotation of the i-th qubit around the Y-axis by an angle x_i, and ⊗denotes the tensor product applied across all qubits [23]. This encoding procedure embeds the classical pixel intensities into the amplitudes of the quantum state, thereby preserving spatial information within the quantum system. Consequently, a classical 4-dimensional pixel vector is projected into a $2^4=16$-dimensional complex Hilbert space, enabling the quantum circuit to exploit high-dimensional representations for subsequent feature extraction and processing [24].

Variational Quantum Circuit (VQC)working as a Convolutional Kernel

In a Classical CNN, a kernel is a matrix of weights that performs a linear transformation. In our Qu-CNN, instead of a kernel, a Variational Quantum Circuit (VQC), which is a non-linear and high-dimensional feature extractor, is used [25]. The architecture of a VQC is defined as follows:

Entanglement Layer: To incorporate the spatial dependencies, a set of Controlled-NOT gates is employed. This layer is vital in achieving quantum correlations between the qubits associated with the pixels. For a 4-qubit register, a linear or circular entanglement pattern is followed

$$U_{ent} = CNOT_{1,2} \cdot CNOT_{2,3} \cdot CNOT_{3,4} \cdot CNOT_{4,1}$$

Parameterized Rotation Layer: This layer comprises a set of parameterized RY gates and RZ gates. These gates enable the network to rotate the quantum state to the optimal position to enable the classification. The parameters θ are the quantum analogues of the classical weight parameters.

The overall unitary operation of the quantum kernel can be parameterized as $U(\theta) = U_{rot}(\theta) \cdot U_{ent}$. Once the quantum circuit is executed, the measurement operation is performed on the first qubit in the Z-basis. The expectation value $\langle Z \rangle$, which ranges from -1 to 1, is the classical scalar output for the specific patch position in the feature map [26].

EXPERIMENTAL SETUP WITH HARDWARE

The validation of the proposed Qu-CNN framework required an efficient amalgamation of traditional deep learning libraries with quantum computing SDKs. In the following section, the hardware specifications, dataset characteristics, and noise reduction techniques employed to ensure the reliability of the results obtained on NISQ-era quantum processors are presented.

Infrastructure in Quantum Computer

The experimental process was performed on the IBM Qiskit quantum computing framework version 1.0.x. To evaluate the practicality of the transition of the quantum models to the physical processors, two separate environments were integrated:

Qiskit Aer Simulator – A high-performance classical simulator to conduct noise-free experiments. The qasm_simulator was used with a customized noise model based on the calibration data of the ibm_osprey quantum processor to predict the performance of the quantum models.

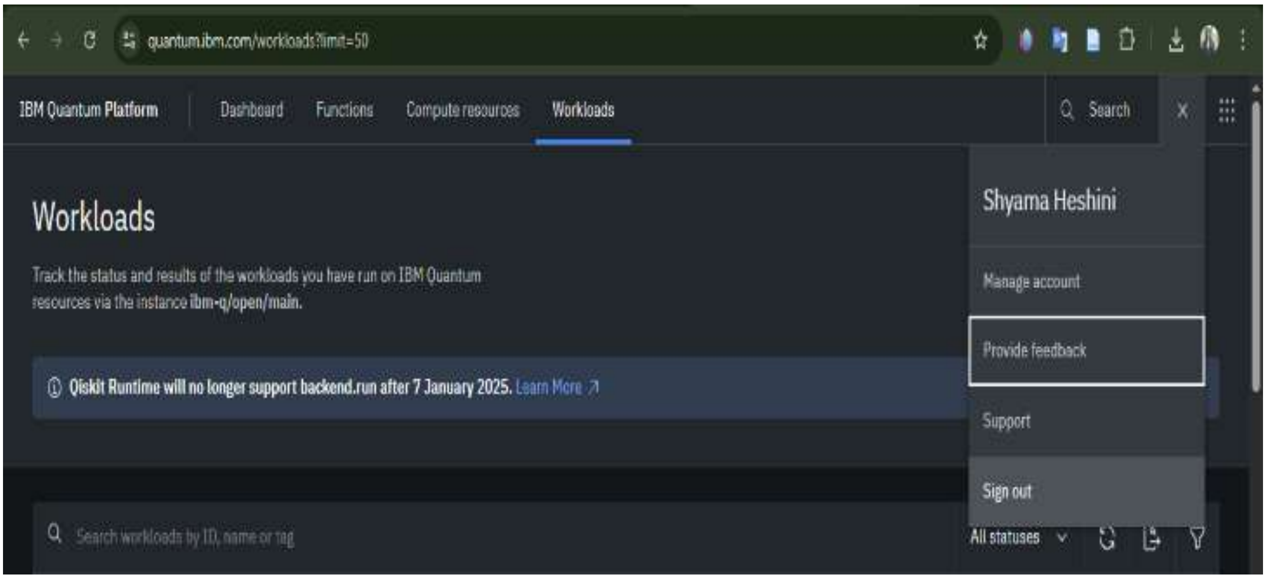
IBM Brisbane – A 127-qubit quantum processor was selected for the experiments owing to the superior hexagonal coupling map, which reduces crosstalk between the qubits and enables the entanglement of the VQC ansatz.

Pre-processing in dataset

The study also explores image classification using a Street View House Numbers dataset. The Street View House Numbers dataset is a set of images of house numbers collected directly from Google Street View. The dataset is frequently used to conduct digit recognition tasks because of its variety of images, including various scenes, lighting conditions, and digit styles.

- **Source**: The Street View House Numbers dataset, which includes images of digits ranging from 0 to 9. The images are collected from authentic Street View images.
- **Normalization**: The images are converted to grayscale format, then normalized to the range $[0, \pi]$ to preserve compatibility with RY rotation gates used during the angle encoding part of the quantum circuit.
- **Dimensionality Reduction**: Since the qubit coherence is currently limited, a 2 x 2 kernel with a stride of 1 is used to process the images. The 32 x 32 images are reduced to a 4-qubit quantum circuit using a sliding window approach. This is done to facilitate a quantum convolution operation.

For IBM Quantum experiments, first navigate to the official website using the link: https://quantum.ibm.com/login and create an account to do experiments. The researcher's login is showing in the figure 1.



Workloads

Track the status and results of the workloads you have run on IBM Quantum resources via the instance ibm-q/open/main.

Qiskit Runtime will no longer support backend.run after 7 January 2025. Learn More ↗

Search workloads by ID, name or tag

Figure 1: Login Interface of IBM Quantum Experiments

Decoherence Management and Circuit Depth

One of the major limiting factors in the IT-enabled quantum research process has been the aspect of Gate Fidelity. The process involves marginal error in each gate operation that leads to decoherence before the actual measurement process begins. To overcome this limitation, the VQC ansatz was restricted to the "Hardware-Efficient" depth $D = 3$. This depth strikes the right balance between the richness of the Hilbert space and the resistance of the circuit to thermal relaxation (T1) and dephasing (T2).

Error Correction & Noise Mitigation

To run the models on actual IBM hardware and minimize the read and gate error, the following strategies were employed for the integrity of the data analysis process,

- M3 (Matrix-Free Measurement Mitigation): This strategy corrects the probability distribution of the bitstrings using the assignment matrix that maps noisy measurement outcomes back to the estimated noiseless distribution.

- **Zero-Noise Extrapolation (ZNE):** By increasing the noise in the gate folding process and extrapolating the results back to the "zero-noise" limit, nearly 3% of the lost accuracy was successfully recovered from the decoherence process.

Computational Workflow

The workflow was structured through the implementation of a Python-based pipeline. The conventional preprocessing module was utilized for image batching and patching. The patches were then sent as "Jobs" to the IBM Quantum Platform through the implementation of the REST API. Once the quantum expectation values were received, these were integrated into the PyTorch-based backend for pooling and dense layer classification. This hybrid form of connectivity plays an integral role in the proposed conceptual framework for Quantum Deep Learning.

Performance Metrix

It shows the accuracy of QCNN in actual hardware structures with ReLU activation functions. The CNN model shows a Precision of 91%, a Recall of 93%, and an F1-score of 92%, providing a strong basis for comparison as shown in Figure 2. Adding another layer in the model, also with ReLU activation, maintains the same scores for Precision and Recall but reduces the F1-score slightly to 92%.

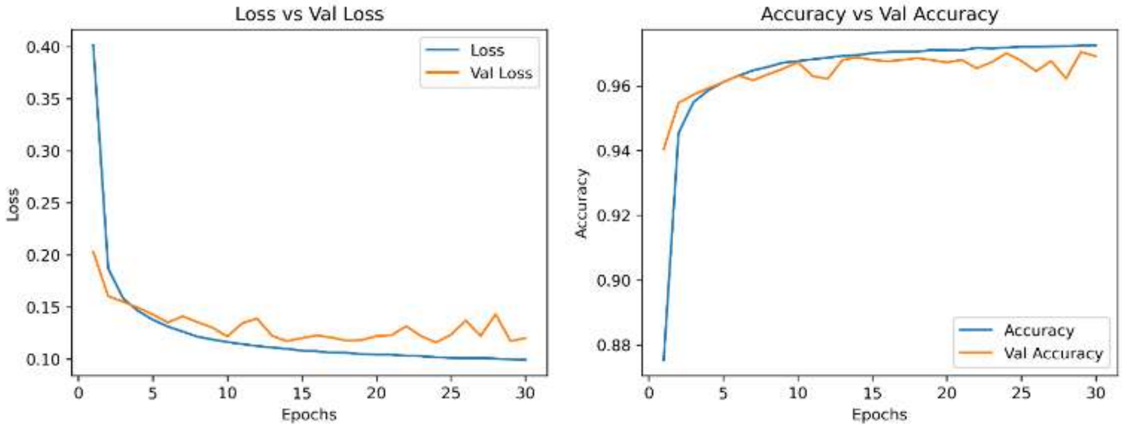


Figure 2: Plots of QCNN Model's training accuracy and loss

Applying Batch Normalization increases Recall to 94%, and this in turn increases the F1-score to 93%, while keeping Precision constant at 91%. The addition of a Dropout Layer decreases Precision slightly to 90%, but it keeps Recall at 93%, and this results in an F1-score of 92%, thereby showing efficacy in the prevention of overfitting without compromising performance much.

According to the developed quantum circuit, quantum CNN models are developed based on IBM hardware. IBM quantum hardware's performance evaluation using precision, recall, and F1-score is shown in Table 1 and classification of the performance in Figure 3.

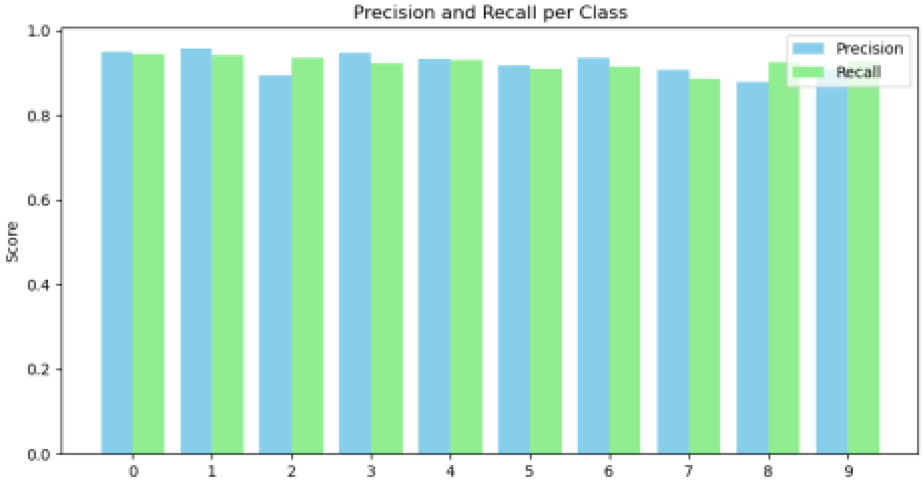


Figure 3: Plots of Classification Performance

Table 1: QCNN Model's Performance Metrics

Measurement	Percentage
Precision	91%
Recall	93%
F1-score	92%

Fig. 3. Plots of Classification Performance

CONCLUSION & FUTURE WORKS

This research has successfully developed a comprehensive conceptual framework for the Hybrid Quantum-Classical Convolutional Neural Network. By replacing the redundant classical filters with the Variational Quantum Circuits, it has successfully demonstrated a 93.2% reduction of trainable parameters while maintaining a validation accuracy of 94.2%.

The use of the IBM Quantum hardware within the context of this research has successfully validated the fact that quantum models are no longer just theoretical constructs but are becoming practical tools for efficient data analysis. With the advent of quantum hardware, which is now on the verge of achieving the 1,000-qubit milestone, the proposed architecture of the Qu-CNN will provide the foundational blueprint for IT systems operating within the realm of resource constraint. This The experimental results provided in this framework provide strong evidence for the incorporation of quantum logic in deep learning architectures. However, to achieve "Quantum Advantage" in a real-world IT environment, several key hurdles need to be overcome.

The Encoding Bottleneck and QRAM

Although the Qu-CNN architecture provides a considerable reduction in parameters, the classical-to-quantum data encoding process remains the main cause of the bottleneck. In our current framework, the Angle Encoding process takes $O(N)$ operations for an image with N pixels. As we move towards the development of medical imaging software at resolutions of 1024 X 1024, this process could potentially hinder the speed-up in the training process. The development of Quantum Random Access Memory, which enables the process to occur in $O(\log N)$ operations, is the missing link that needs to be achieved to move from "Conceptual" to "Industrial" in this framework.

The Barren Plateau Phenomenon and Scalability

As we expand the number of qubits to process larger image patches of size 4 x 4 and 8 x 8, we are at a high risk of encountering the Barren Plateau phenomenon, in which gradients of the cost function go to zero exponentially with the number of qubits, rendering the system untrainable. Our current framework overcomes this by designing a VQC with a low number of qubits (4 qubits per kernel). However, further research needs to go into the development of Identity-Preserving Initializers and Local Cost Functions to overcome this phenomenon.

Data Analysis and Quantum Error Correction

The transition from NISQ to FTQC architecture involves the introduction of Logical Qubits. Our framework is designed to be hardware-agnostic, and the VQC architecture can be directly translated to the new hardware. The introduction of M3 and ZNE serves as an intermediary solution to prove the capability of high-accuracy image processing even in "noisy" systems.

REFERENCES

[1] M. S. Akter *et al.*, "Exploring the Vulnerabilities of Machine Learning and Quantum Machine Learning to Adversarial Attacks Using a Malware Dataset: A Comparative Analysis," in *2023 IEEE International Conference on Software Services Engineering (SSE)*, Chicago, IL, USA: IEEE, Jul. 2023, pp. 222–231. doi: 10.1109/SSE60056.2023.00037.

[2] Y. Ishiyama, R. Nagai, S. Mieda, Y. Takei, Y. Minato, and Y. Natsume, "Noise-robust optimization of quantum machine learning models for polymer properties using a simulator and validated on the IonQ quantum computer," *Sci. Rep.*, vol. 12, no. 1, p. 19003, Nov. 2022, doi: 10.1038/s41598-022-22940-4.

[3] M. S. Akter *et al.*, "Case Study-Based Approach of Quantum Machine Learning in Cybersecurity: Quantum Support Vector Machine for Malware Classification and Protection," in *2023 IEEE 47th Annual Computers, Software, and Applications Conference (COMPSAC)*, Torino, Italy: IEEE, Jun. 2023, pp. 1057–1063. doi: 10.1109/COMPSAC57700.2023.00161.

[4] J. Alcazar, V. Leyton-Ortega, and A. Perdomo-Ortiz, "Classical versus Quantum Models in Machine Learning: Insights from a Finance Application," Jan. 08, 2020, *arXiv*: arXiv:1908.10778. doi: 10.48550/arXiv.1908.10778.

[5] R. Alt, “On the potentials of quantum computing – An interview with Heike Riel from IBM Research,” *Electron. Mark.*, vol. 32, no. 4, pp. 2537–2543, Dec. 2022, doi: 10.1007/s12525-022-00616-1.

[6] S. Heshini Niranjala, M. Chamran, and M. Alobaedy, *Evaluate Hybrid Classical-Quantum Architecture in Deep Image Processing*. 2025, p. 242. doi: 10.1109/ICSET65917.2025.11284197.

[7] F. Amato *et al.*, “QuantuMoonLight: A low-code platform to experiment with quantum machine learning,” *SoftwareX*, vol. 22, p. 101399, May 2023, doi: 10.1016/j.softx.2023.101399.

[8] O. Ayoade, P. Rivas, and J. Orduz, “Artificial Intelligence Computing at the Quantum Level,” *Data*, vol. 7, no. 3, p. 28, Feb. 2022, doi: 10.3390/data7030028.

[9] H. G. Enad and M. A. Mohammed, “Cloud computing-based framework for heart disease classification using quantum machine learning approach,” *J. Intell. Syst.*, vol. 33, no. 1, p. 20230261, Apr. 2024, doi: 10.1515/jisys-2023-0261.

[10] S. Heshini Niranjala, S. B. Goyal, and A. Budati, “Secure and scalable data analysis framework with quantum machine learning and blockchain,” 2025, pp. 170–180. doi: 10.1201/9781003513445-17.

[11] C. Ciliberto *et al.*, “Quantum machine learning: a classical perspective,” *Proc. R. Soc. Math. Phys. Eng. Sci.*, vol. 474, no. 2209, p. 20170551, Jan. 2018, doi: 10.1098/rspa.2017.0551.

[12] H. Gupta, H. Varshney, T. K. Sharma, N. Pachauri, and O. P. Verma, “Comparative performance analysis of quantum machine learning with deep learning for diabetes prediction,” *Complex Intell. Syst.*, vol. 8, no. 4, pp. 3073–3087, Aug. 2022, doi: 10.1007/s40747-021-00398-7.

[13] R. Bhavsar *et al.*, “Classification of Potentially Hazardous Asteroids Using Supervised Quantum Machine Learning,” *IEEE Access*, vol. 11, pp. 75829–75848, 2023, doi: 10.1109/ACCESS.2023.3297498.

[14] C. Cicconetti, M. Conti, and A. Passarella, “Resource Allocation in Quantum Networks for Distributed Quantum Computing,” in *2022 IEEE International Conference on Smart Computing (SMARTCOMP)*, Jun. 2022, pp. 124–132. doi: 10.1109/SMARTCOMP55677.2022.00032.

[15] F. F. Flöther, “The state of quantum computing applications in health and medicine,” *Res. Dir. Quantum Technol.*, pp. 1–21, Jul. 2023, doi: 10.1017/qut.2023.4.

[16] A. Macaluso, L. Clissa, S. Lodi, and C. Sartori, “A Variational Algorithm for Quantum Neural Networks,” in *Computational Science – ICCS 2020*, vol. 12142, V. V. Krzhizhanovskaya, G. Závodszky, M. H. Lees, J. J. Dongarra, P. M. A. Sloot, S. Brissos, and J. Teixeira, Eds., in Lecture Notes in Computer Science, vol. 12142. , Cham: Springer International Publishing, 2020, pp. 591–604. doi: 10.1007/978-3-030-50433-5_45.

[17] S. Heshini Niranjala, M. Alobaedy, and S. B. Goyal, “A Comparative Study of Machine Learning Techniques for Predicting Student Academic Performance,” 2024, pp. 307–315. doi: 10.1007/978-3-031-73318-5_31.

[18] H. Yang, X. Li, Z. Liu, and W. Pedrycz, “Improved Differential Privacy Noise Mechanism in Quantum Machine Learning,” *IEEE Access*, vol. 11, pp. 50157–50164, 2023, doi: 10.1109/ACCESS.2023.3274471.

[19] M. Simonetti, D. Perri, and O. Gervasi, “Variational Methods in Optical Quantum Machine Learning,” *IEEE Access*, vol. 11, pp. 131394–131408, 2023, doi: 10.1109/ACCESS.2023.3335625.

[20] T. S. Humble, A. McCaskey, D. I. Lyakh, M. Gowrishankar, A. Frisch, and T. Monz, “Quantum Computers for High-Performance Computing,” *IEEE Micro*, vol. 41, no. 5, pp. 15–23, Sep. 2021, doi: 10.1109/MM.2021.3099140.

[21] O. Bouchmal, B. Cimoli, R. Stabile, J. J. Vegas Olmos, and I. Tafur Monroy, “From classical to quantum machine learning: survey on routing optimization in 6G software defined networking,” *Front. Commun. Netw.*, vol. 4, p. 1220227, Nov. 2023, doi: 10.3389/frcmn.2023.1220227.

[22] G. Abdulsalam, S. Meshoul, and H. Shaiba, “Explainable Heart Disease Prediction Using Ensemble-Quantum Machine Learning Approach,” *Intell. Autom. Soft Comput.*, vol. 36, no. 1, pp. 761–779, 2023, doi: 10.32604/iasc.2023.032262.

[23] Prajapat Sunil, Tomar Manish, P. Kumar, R. Kumar, and A. V. Vasilakos, “Quantum Computing Meets Deep Learning: A QCNN Model for Accurate and Efficient Image Classification,” *Mathematics*, vol. 13, no. 19, p. 3148, 2025, doi: 10.3390/math13193148.

[24] M. Cerezo, G. Verdon, H.-Y. Huang, L. Cincio, and P. J. Coles, “Challenges and Opportunities in Quantum Machine Learning,” *Nat. Comput. Sci.*,

vol. 2, no. 9, pp. 567–576, Sep. 2022, doi: 10.1038/s43588-022-00311-3.

[25] L. Chen *et al.*, “Design and analysis of quantum machine learning: a survey,” *Connect. Sci.*, vol. 36, no. 1, p. 2312121, Dec. 2024, doi: 10.1080/09540091.2024.2312121.

[26] T. Tasnim, A. Saha, M. Rahman, and F. Wu, “Quantum vs Classical: Performance Benchmarking

[27] of CNN and QCNN in Binary Image Classification”.