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RESEARCH ARTICLE

Quantum feature encoding for enhancing CNN-based image classification performance

S. H. Niranjala*, Kazem Chamran, Mustafa Mowafak Alobaedy

Faculty of Information Technology, City University, 46100 Petaling Jaya, Selangor, Malaysia

Abstract - Convolutional Neural Networks (CNNs) have shown robust results for classifying images in data analytics. However, the effectiveness of these models is often limited by their substantial computational complexity, particularly when dealing with features represented in complex mathematical environments, multi-class image classification, and especially when dealing with complex nonlinear relationships between features, which need to be addressed for transparent decision-making processes. This study developed a Quantum-Enhanced Convolutional Neural Network (Q-CNN) model that incorporates traditional convolution-based feature extraction, Quantum Feature Encoding, and quantum processing. The developed model applies a quantum encoding mechanism to map classical features to quantum states for alternative feature representation and classification. The experimental results show that the Q-CNN outperformed the standard CNN, reaching 97% training and validation accuracy compared to 94% and lowering training and validation losses from 17% and 18% to 9% and 11%, respectively. Furthermore, the precision, recall, and F1-score increased from 90%, 88%, and 89% to 92%, 94%, and 93%, respectively. These findings demonstrate the potential effectiveness of quantum feature encoding for image classification tasks and provide a structured framework for enriched feature representation in convolution-based image-processing models.

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1. Introduction

Quantum-enhanced computing is an emerging technological breakthrough with significant potential implications for daily life, markets, and industry. According to a McKinsey report, the worldwide market value of quantum computing is expected to reach USD one trillion by 2035, primarily in the automotive, chemical, finance, and pharmaceutical industries. Major tech firms like Google, IBM, Microsoft, Amazon, and Alibaba are investing billions of dollars in research-led quantum computing development, making some of these quantum computers partially available to the public via cloud computing infrastructure [1]. Governments have also invested in quantum technology. The EU allocated more than EUR 1 billion in its budget, the US government contributed USD 1 billion, and China invested USD 10 billion in a quantum computing centre [2]. Quantum computers use quantum-mechanical phenomena to store and manipulate data.

Quantum Machine Learning (QML) combines machine learning and quantum computing to analyse data using the capabilities of quantum systems [3]. By utilising concepts such as entanglement and superposition, quantum computing offers enhanced computational capabilities for handling complex data structures more efficiently than conventional techniques [4]. QML models can be broadly classified by how they integrate quantum and conventional computing. One popular classification comprises four concepts: classical-classical (CC), quantum-classical (QC), classical-quantum (CQ), and quantum-quantum (QQ). Each paradigm reflects a different approach to data and computation, ranging from classical to quantum. The CQ technique, for example, involves processing classical data using quantum algorithms, leveraging quantum speedups for certain computational tasks [5]. One key advantage of QML is the potential for exponential speedups on specific tasks. For instance, quantum variants of techniques such as PCA and SVM are better suited to high-dimensional data than their classical counterparts [6]. Quantum PCA, for example, can compute the eigenvalues and eigenvectors of large matrices up to 10x faster than classical approaches, illustrating QML's promise for handling complex data structures. Quantum computing, which is based on the principles of quantum mechanics, exhibits remarkable computational power through properties such as superposition and entanglement [7].

Despite these breakthroughs, integrating quantum computing into everyday machine-learning tasks faces several limitations. Much of the existing research focuses on quantum computing speedups, with relatively little attention to structured image data and deep-learning architectures. In particular, integrating quantum processing with convolution-based architectures for image classification is an emerging research area that warrants further investigation, particularly regarding performance and implementation issues [8]. The growing reliance on CNNs for deep image processing has driven significant advances in tasks such as classification, detection, and recognition. Despite breakthroughs and the widespread use of CNNs across various applications, CNN models still face persistent issues with high computational complexity and inefficient parameterisation. As deep learning continues to influence high-stakes domains such as disease diagnosis, autonomous vehicles, and security, future emphasis must shift from merely ensuring model accuracy to understanding the underlying processes that produce final predictions. This fundamental lack of transparency leaves the model's integrity vulnerable to ever-growing risks. As such, new-age research aimed at filling these gaps is beginning to focus on the prospective use of quantum computing.

Several recent studies have investigated the efficacy of hybrid quantum-classical models for improving deep learning architectures. The most common technique is to replace a few layers of a neural network with parameterised quantum circuits or quantum feature maps. However, several models remain conceptual, use small-scale datasets, or lack systematic

***CORRESPONDING AUTHOR | S H Niranjala** | ✉ shyama@gwu.ac.lk
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analysis. Hence, a systematic, experimentally validated framework is essential to understand the efficacy of the quantum-classical approach in improving a convolutional neural network [9]. The key issue is how to incorporate quantum feature encoding into a CNN architecture to achieve enhanced classification while maintaining computational efficiency and high performance. To solve this issue, a well-designed framework that exploits both classical and quantum computations is essential. Therefore, we propose a Quantum-Enhanced Convolutional Neural Network architecture that exploits both classical and quantum computations for image classification. The major implications of this study are as follows:

1. A well-designed methodology is proposed that exploits both classical and quantum computation for image classification
2. An amplitude- and angle-encoding scheme is proposed to achieve efficient quantum feature representation.
3. A comprehensive set of experiments was conducted on standard image datasets to verify its efficacy.

This raises an important research question: How does quantum feature encoding integrate with the CNN architecture to improve nonlinear feature representations while maintaining high classification accuracy and generalisation stability in image processing tasks? To overcome this gap, we developed an experimental Quantum-Enhanced Convolutional Neural Network model. The proposed model integrates quantum feature encoding with the CNN architecture to improve nonlinear feature representations while maintaining high classification accuracy and generalisation stability in image processing tasks. Furthermore, hybrid models have been proposed for practical applications to leverage the benefits of Quantum Machine Learning, particularly quantum-classical models [10]-[11]. The remainder of the paper begins by providing background information and discussion of the concepts integral to the research, the study's motivations, and the importance of the research area, and provides an overview of the necessary concepts for the rest of the research. The second section provides an overview of the experimental environment and corresponding analyses and discussions of the research results. The last section provides an overview and corresponding discussion of the research insights and future directions of this study.

2. Related Works

QML is an emerging technology that applies quantum computing and ML principles to tackle complex problems more efficiently than traditional computers. QML concepts are derived from quantum physics. These concepts include entanglement, superposition, and quantum interference, which enable revolutionary approaches to data processing and analysis [12].

2.1 Quantum Bits (Qubits)

In classical computing, a bit is the basic unit of measurement. A quantum bit (qubit) is the foundation of quantum processing and information. A classical bit (chit) is an entity with two clearly identifiable or orthogonal levels [13]. The differences between classical and quantum bits are illustrated in Figure 1. A classical bit exists in only one definite state at any given time, whereas a qubit can exist in a whole range of states between $|0\rangle$ and $|1\rangle$ due to the principle of superposition. This lets the qubit encode several values simultaneously until it is measured, at which point it collapses to one of two basis states. It means that quantum systems have the possibility to process information in a completely new way compared with the classical one

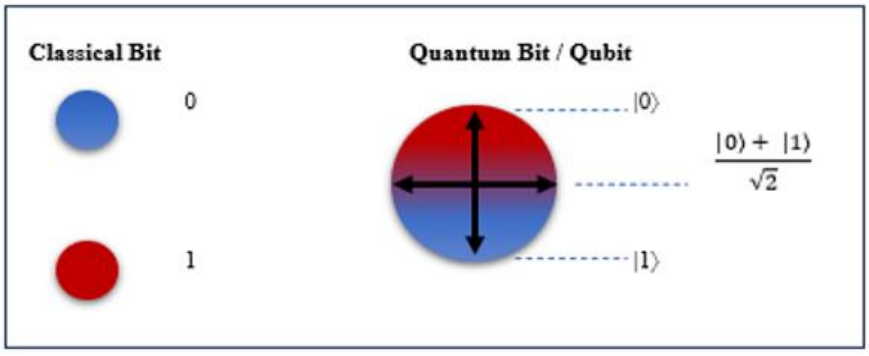


Figure 1. The comparison between classical bit and quantum bit

2.2 Classical Bit Encoding via One-Hot Vectors

A classical bit is defined as a system with exactly two distinguishable states. As an example, on-off switches and magnetisation along the up and down directions. In mathematical expressions, a cbit is denoted by a binary digit, either 0 or 1. In another representation, the cbit states are given by a "two-dimensional one-hot" amplitude vector with only one component equal to 1. In Table 1, a component equal to 1 determines whether the cbit is 0 or 1 [14]–[15].

The status of a cbit can also be expressed using a two-dimensional, one-hot amplitude vector. The one-hot amplitude vector has a single digit that specifies whether the cbit is 0 or 1. A one-hot vector with a 1 digit in the first position encodes a cbit with a value of 0, whereas a one-hot vector with a "1" digit in the second position encodes a cbit with a value 1. A cbit can also be represented as a binary digit or a two-dimensional one-hot vector, with the latter denoted using Dirac's ket notation. In quantum theory, the key notation described by Dirac is generally used to label column vectors. As shown

in Eq. (1), the column vector is represented by |a⟩, where 'a' is the label of the vector. The ket vector, which is a one-hot vector associated with a cbit, serves as the label when it represents a cbit value of 0, as shown in Table 1.

$$|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad |1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{1}$$

Table 1. One-hot amplitude vector

Cbit	Amplitude vector
0	$\|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$
1	$\|1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

2.3 Qubit-related Concepts: Superposition

Superposition is a defining characteristic of quantum mechanics and significantly influences quantum computing and ML. This demonstrates quantum computing's ability to handle multiple states simultaneously. These phenomena are major distinctions between classical and quantum computing and underpin the exceptional processing capability of quantum systems [16]. In traditional computing, a bit is the basic unit of information that represents 0 or 1. Mathematically, a qubit state can be expressed as $|\psi\rangle=\alpha|0\rangle+\beta|1\rangle$, where α and β are complex numbers that satisfy the normalisation condition $|\alpha|2+|\beta|2=1$. This equation shows the superposition of the qubit in the states $|0\rangle$ and $|1\rangle$, along with $|\alpha2|$ and $|\beta2|$, representing the probabilities of measuring the qubit in each respective state [17]. Figure 2 shows a bit and qubit on the left and right sides, respectively. A bit can be either 0 or 1 with equal probabilities. However, the qubit can be in one of two states at the same time: $|0\rangle$ or $|1\rangle$, or in a superposition of the two. This illustration depicts a qubit in a superposition condition, with 50% $|0\rangle$ and 50% $|1\rangle$ states. Even though they are physically apart, the characteristics of both qubits in an entangled state are connected to one another; one of them influences the other [18].

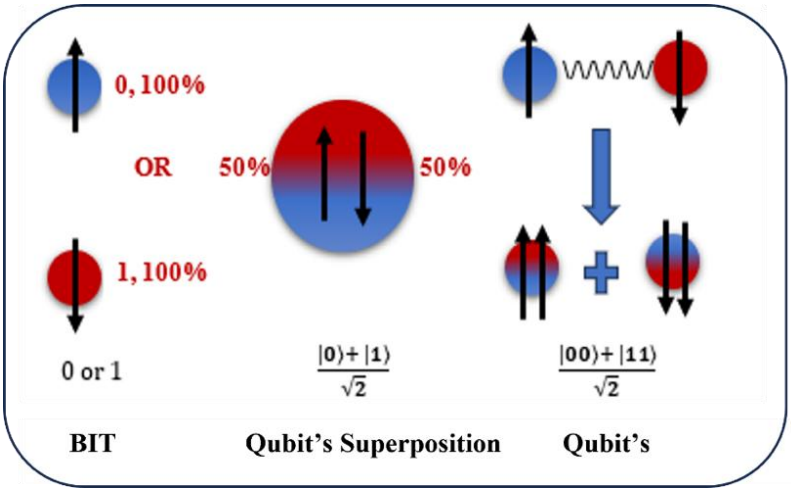


Figure 2. Superposition and entanglement of a qubit

2.4 Qubit-related Concepts: Entanglement

Entanglement in quantum mechanics has implications for both QC and ML applications. This refers to the phenomenon in which the quantum states of two or more qubits become entangled, such that the state of one qubit directly influences the state of another qubit, regardless of their distance [18]. This feature distinguishes quantum systems from classical systems and underpins numerous advantages in quantum computing [19]. The overall state of an entangled qubit system cannot be explained without reference to the states of each qubit. This state is maximally entangled because it cannot be decomposed into a set of individual qubit states. The measurement of one qubit under these conditions immediately identifies the state of the other qubit, demonstrating complete correlation regardless of the spatial space between the qubits [20]. Entanglement can be mathematically characterised using Schmidt decomposition. For any pure state $|\psi\rangle|$ of a bipartite system, the Schmidt decomposition expresses $|\psi\rangle$ as the sum of the tensor products of the orthonormal states of the subsystems. The number of nonzero terms in this sum, known as the Schmidt rank, represents the degree of entanglement [21]. A Schmidt ranks greater than one indicates that the subsystems are intertwined [1].

2.5 Qubit-related Concepts: Quantum Circuits

The quantum circuit is the fundamental structure for performing quantum computations, similar to classical circuits in classical computing. It consists of qubits and quantum gates arranged in a specific order that enables manipulation and measurement of quantum states. [22]. Quantum circuits are built from qubits and quantum gates, operations that change qubit states. Quantum circuits enable computations based on quantum physics concepts such as superposition and entanglement. Quantum circuits are created by assembling quantum gates in a specific order to execute the required

computations [23]. Each qubit is represented by a horizontal line combined with gates applied from left to right, as in Eqs. (2)-(4).

$$|a, b\rangle \rightarrow |a, a \oplus b\rangle \tag{2}$$

$$\rightarrow |a \oplus (a \oplus b), a \oplus b\rangle = |b, a \oplus b\rangle \tag{3}$$

$$\rightarrow b, (a \oplus b) \oplus b)\ \rangle = |b, a\rangle \tag{4}$$

This sequence efficiently switches the states of two qubits. The distinguishing characteristics and capabilities of quantum circuits provide significant computing advantages over classical systems.

2.6 Quantum Machine Learning Algorithms

Quantum-based ML can also be categorised into three different categories based on supervised, unsupervised, and deep learning, as illustrated in Table 2. Quantum algorithms apply the principles of quantum mechanics to computation, potentially making them many times more efficient than classical algorithms [24]. These algorithms exploit the parallelism inherent in quantum bits (qubits), including superposition and entanglement, which help them solve large-scale problems ranging from cryptography and chemistry to optimisation. This permits an exponential increase in computational ability over classical machines while ensuring several orders of magnitude lower power consumption [22].

Table 2. QML algorithms

Quantum Machine learning algorithms		
Supervised	Unsupervised	Deep Learning
Quantum Linear Regression	Quantum k-Means Clustering	Quantum Convolutional Neural Networks
Quantum Support Vector Machine	Quantum Principal Component Analysis	Quantum Recurrent Neural Networks
Quantum k-Nearest Neighbors	Quantum Boltzmann Machines	Quantum Neural Networks
Quantum Neural Networks	Quantum Autoencoders	Variational Quantum Circuits
Variational Quantum Classifier		Hybrid Quantum-Classical Deep Networks

2.7 Analytical Comparison of Classical DL and Quantum-based DL

A comprehensive study of classical and quantum Deep Learning. This comparative study emphasises the reasons driving the development of QDL, as it appears to be an advanced version of classical deep learning. Table 3 compares the deep learning and quantum-based deep learning models. Table 3 summarises the main differences between classical and quantum-based deep learning approaches. In terms of computational efficiency, QDL outperformed CDL by using quantum features. In terms of extracting features from images, QDL performs better because it encodes features into quantum representations and ultimately decodes them after the dense layer. For classification and generalisation, QDL outperformed CDL, whereas CDL was better for cost-effective hardware utilisation and performed better in noisy environments.

Table 3. Comparison of classical DL and quantum-based DL

Aspect	Classical DL	Quantum DL
Computational Efficiency	Computationally expensive, scalability problems for larger models and larger volumes of data	Speedup possibilities by leveraging parallelism and entanglement for computation
Feature Representation	Traditional sets of features, inability to represent global relationship complexities	The encoding of features into high-dimensional Hilbert spaces makes it possible to model much richer correlations.
Generalization & Overfitting	It needs regularization techniques	Minimizing the parameter dependence as well as inherent randomness improves generalization
Hardware requirement	Widely accessible hardware requirement	Limited hardware availability, GPUs/TPUs have limited availability
Sensitivity for Noise	Stable and deterministic computation environment	Affected by the presence of quantum noise and decoherence

2.8 Hybrid Quantum-Classical Deep Learning Architectures

To bridge the gap between current noisy intermediate-scale quantum (NISQ) devices and real-world machine learning tasks, researchers have developed a new class of hybrid quantum-classical architectures that replace classical dense layers with quantum circuits. Ghasemian and Tavassoly [22] presented a hybrid classical-quantum classifier that uses two-qubit dissipative quantum channels, thereby enhancing feature separability on benchmark datasets. Abdulsalam et al. [4] introduced a new ensemble quantum machine learning model for heart disease prediction with integrated explainability mechanisms. Other related studies have explored Variational Quantum Classifiers integrated with classical neural networks [25], [27]. However, despite these contributions, several research gaps remain. Most existing hybrid quantum–classical architectures have been evaluated only on limited datasets, which restricts the generalisability of their findings. In addition, researchers often use quantum components as black-box replacements for classical dense layers rather than investigating their direct influence on convolutional feature maps. Furthermore, while some quantum-based models claim improvements in classification performance, these improvements are often supported by classical post hoc explanation methods, with limited attention to intrinsic quantum-feature mapping. Finally, fair comparative studies between classical CNNs and quantum-enhanced CNN architectures under identical experimental settings remain lacking.

2.9 QML Limitations on Simulator-Based Environments

The main bottlenecks in current Quantum Machine Learning implementations in Noisy Intermediate-Scale Quantum (NISQ) and simulator environments are limited qubit counts, which require aggressive dimensionality reduction or classical preprocessing, and hardware noise, such as decoherence and gate errors. Hardware-specific encodings for processing full-resolution images on 49-qubit systems, while previous research has examined noise robustness and found that hybrid architectures are significantly degraded under depolarising and amplitude-damping noise [25]-[26]. Nevertheless, a significant research gap remains: most of the literature currently in print proposes ad hoc, application-specific encoding methods (such as those for medical imaging or MNIST) without providing a systematic, controlled evaluation of various quantum feature-encoding techniques. These include patch-based embeddings, amplitude, or angle encodings, under uniform noise profiles. The best design guidelines for quantum-enhanced feature extraction remain unclear because benchmarking has not separated the incremental contributions of different encoding strategies to the classification performance of a traditional CNN backbone [27].

2.10 Quantum Feature Encoding Techniques

Quantum feature encoding techniques, including amplitude, angle, and basis encoding, map classical data into a high-dimensional Hilbert space. This approach theoretically enables more complex feature correlations and improves the nonlinear separability [27]. Amplitude encoding exponentially compresses classical data into quantum states, whereas angle encoding uses rotation gates to map classical feature values into quantum representations. Recent studies show that quantum feature encoding can enrich feature representations. However, empirical studies on convolutional feature hierarchies, class-wise stability, and generalisation patterns of structured image data remain limited. In addition, most existing studies evaluate each encoding technique in isolation, with limited attention to directly integrating quantum feature encoding with convolutional feature extraction layers. Several critical research gaps have been identified in the literature. Existing QML studies have used small datasets, leaving a gap in research on multi-class, complex datasets for measuring classification accuracy and computational speedup. To overcome this issue, this study used the Google Street View dataset with 10 classes. Current studies have not extensively explored quantum feature encoding to improve the transparency of convolutional feature representations. In addition, comparative studies between conventional CNNs and quantum-enhanced CNN architectures under controlled experimental conditions are limited. The combined impact of angle and amplitude encoding on the separability of nonlinear features within convolutional networks has not been thoroughly investigated. These gaps highlight the need for a structured, experimentally validated framework that integrates quantum feature encoding into convolutional neural network architectures and evaluates its impact on classification performance.

3. Materials and Methods

This study adopts a systematic experimental methodology, beginning with a literature review to assess the current state and knowledge gaps in classical and quantum machine learning, with the aim of enhancing the analysis of complex data. This section is followed by an expansion of the model theory and an analysis of the corresponding algorithms, establishing a solid foundation for integrating quantum-based technologies. Given the technological focus of this research, quantitative and qualitative methodologies are less suitable. Hence, the researcher focused on using the experimental method as the research methodology. Figure 3 shows the steps of the research methodology from the start of the research phases to the completion of the research work. Table 4 presents a detailed plan of the tools and technologies required at each stage of the study.

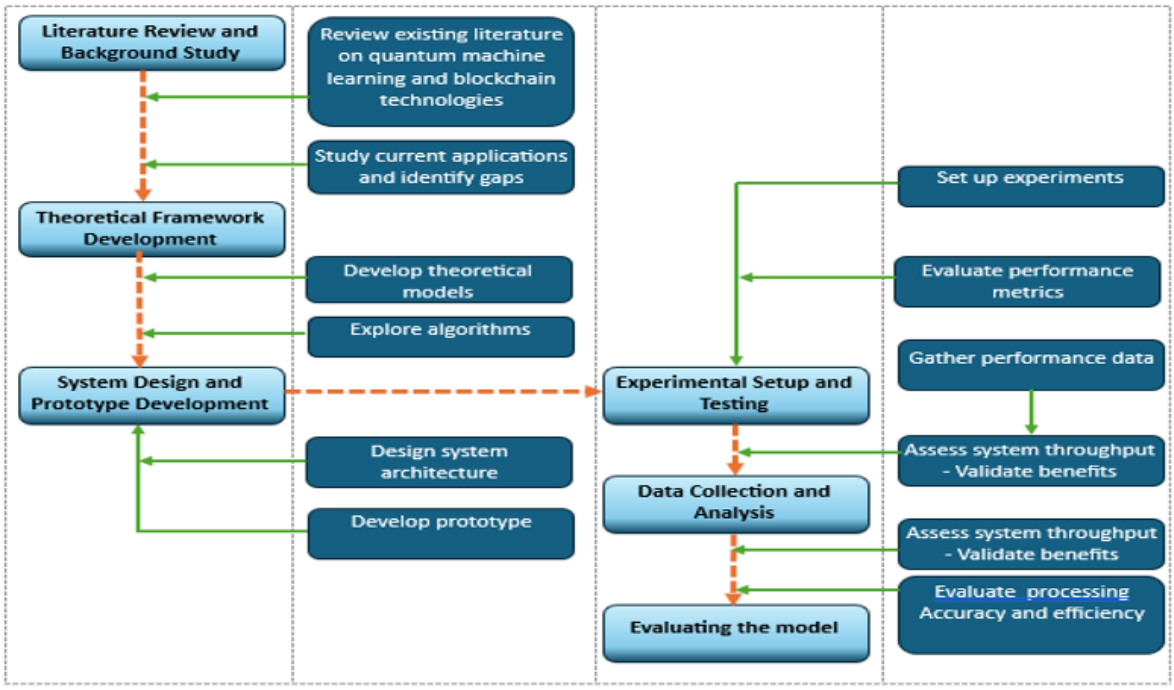


Figure 3. Proposed research methodology

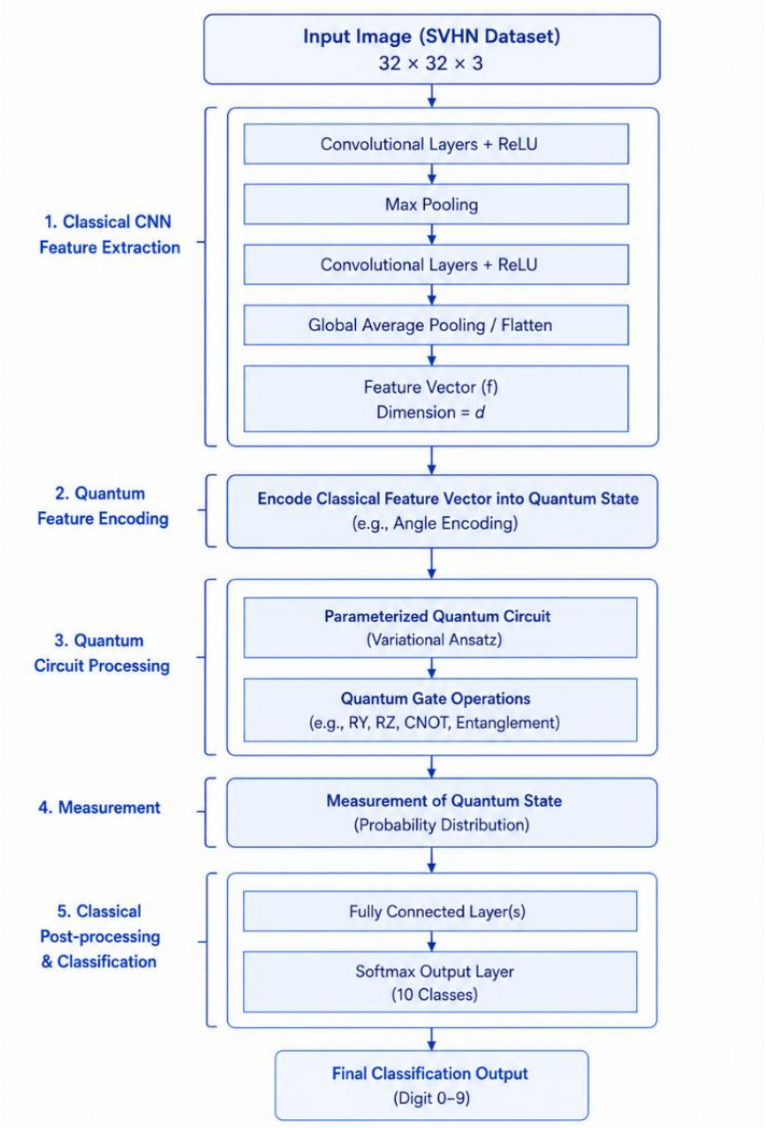


Figure 4. Technical framework

3.1 Steps and Tools for Developing the Model

The IBM Quantum Simulator (Qiskit Aer Simulator) served as the primary quantum simulation environment to examine the integration of classical deep learning with quantum computing. This study investigated quantum-enhanced feature processing without the constraints of existing quantum hardware, owing to the simulator's ability to execute and evaluate quantum circuits on a classical computing infrastructure. TensorFlow and the Keras high-level API were used to create the CNN model, whereas Scikit-learn was used for data preparation, performance assessment, and confusion matrix analysis. The model architecture comprised convolutional, pooling, fully connected dense, and output layers for digit classification. To introduce nonlinearity and improve learning, the Rectified Linear Unit (ReLU) activation function was used. The quantum model used angle encoding to map the classical latent feature vector to quantum states. Under angle encoding, the classical feature vector is encoded in the angle of the RX gate operation performed on the qubit corresponding to the feature vector. Angle encoding was chosen because it uses fewer qubits than amplitude encoding, is easy to implement in Qiskit, has a simpler circuit, and works well on NISQ devices. Figure 4 shows the technical implementation of this study using the QCNN algorithm. Researchers developed a classical CNN and a quantum CNN using the same dataset and parameters to compare the models' classification performance.

Table 4. Steps and tools for research

Steps	Tools and technologies
Literature review	Google Scholar, IEEE Xplore, Scopus, EndNote
Data preparation	Online databases, public image datasets from Kegalle and other data repositories
Data set	Over 600,000-digit instances in multi-digit images Training Set - 73,257 Validation Set - 26,032 Extra Dataset - 531,131 Split ration – 70% to 30%
Pre-Processing	Reshaped to TensorFlow format (N × 32 × 32 × 3) Normalisation: Pixel values were normalised by dividing each pixel value by 255. Label Encoding - one-hot encoded vectors using LabelBinarizer Digit Classes - All ten digit classes (0–9)
Model Development	CNN, Python, TensorFlow, Keras
Quantum Hardware	IBM Quantum simulator (Air simulator)
Optimization and Refinement	Scikit-learn, Optimization tools
Reporting and Documentation	Microsoft Word

This hybrid architecture combines classical deep learning with quantum computing to enhance model transparency by first passing the input images through standard CNN layers to extract basic features. These features are then mapped to a higher-dimensional Hilbert space via a Quantum Feature Encoding Layer, using amplitude or angle encoding, and subsequently processed by a Quantum Processing Unit that captures complex, non-linear correlations. The work product is then fed into a module, along with the final classification layers, that ensures the model provides accurate and visually explainable predictions with generated attention maps, effectively "opening the black box" of deep image processing.

4. Results and Discussion

We first developed a classical CNN model, followed by a quantum CNN model. Both the classical CNN and Q-CNN were trained and evaluated on the exact same data split, number of epochs, optimisation algorithm, learning rate, batch size, preprocessing steps, and evaluation measures to ensure a fair comparison. Because this is a comparative study, we deliberately kept all training parameters the same to ensure that any performance differences were due solely to the quantum feature-encoding method used. The model achieved training and validation accuracies of 94%. The experimental findings for the traditional CNN model showed balanced learning performance, suggesting that the model could generalise to new data without substantial overfitting. The stability of the learning process is further supported by comparable training loss (17%) and validation loss (18%), as the slight variation between them indicates consistent model behaviour across the two datasets. This baseline design served as the basis for subsequent optimisation studies. To further improve convergence efficiency and feature extraction, we used advanced optimisation methods. Second, we developed a quantum CNN model. The models integrate variational quantum circuits into the CNN pipeline and utilise Aer simulators to model quantum behaviour. The developed model was trained for 30 epochs on the SVHN dataset using the same pipelines for image normalisation, one-hot encoding, and consistent data partitioning.

4.1 QCNN Circuit structure

The quantum circuit serves as an integral post-processing module in the Quantum Convolutional Neural Network (QCNN) framework. The circuit performs the inverse Quantum Fourier Transform (QFT) on four qubits and serves as a feature-decoding and transformation layer for quantum machine learning operations, as shown in Figure 5. In the proposed circuit, four-qubit quantum states (q0, q1, q2, and q3) pass through four layers to generate quantum-encoded image patches from the SVHN digit dataset. The circuit consists of a series of SWAP gates, including q0 <–> q3 and q1 <–> q2. The qubits

are ordered in reverse to match the QTF layout, which is important for restoring the spatial or frequency structure after convolution operations. Each qubit subsequently undergoes a Hadamard (H) gate operation, which enables the fundamental process of superposition. During this process, the Hadamard gates create quantum interference between the qubits, which is an important step in non-local feature extraction. In addition, the qubits undergo controlled phase rotations. The circuit includes a series of phase-controlled (CP) gates with increasingly smaller angles. These operations preserve the relative phase information and build pairwise entanglement among the qubits. From the perspective of the QCNN framework, this helps convert localised image features (e.g., textures and edges) into overall frequency-domain descriptions, similar to the use of the FFT in conventional CNNs, thereby improving translation invariance and feature generalisation. Table 5 lists the circuit components and their descriptions.

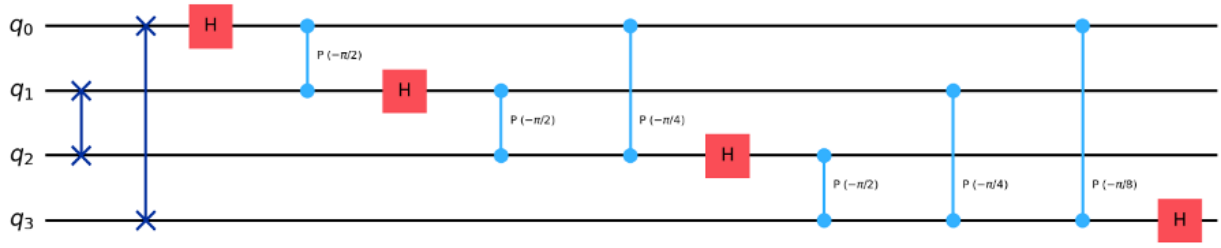


Figure 5. Developed quantum circuit

Table 5. Components of the circuit

Component	QCNN Role	Description
Inverse QFT in the circuit	Post-convolutional decoding or transformation layer	It enables the efficient compression of features, adding to the measurement of computational precision.
Hadamard + CP Gates	Implement Fourier decoding of the encoded image patches	Enhances representation of the image via quantum-native transformations
SWAP Layer	Do Prepares qubit layout for the Fourier decoding	Optimises the depth of circuits and the implementation fidelity of quantum hardware.
Entire Module	Interpreted as a frequency-domain decoder in QCNN	Integrates with dataset's patch-wise encoding and it helps to compare classical vs QML models

The CNN architecture for the classical model takes 32 × 32 × 3 RGB input images from the SVHN dataset and uses three convolutional layers with 64, 32, and 16 filters, respectively. The kernel size was 3 × 3. The model used ReLU activation, same padding, and 2 × 2 MaxPooling. The extracted features were compressed using a Global Average Pooling layer and then fed into a Dense Softmax layer with 10 neurones for digit classification. In the Quantum-Classical CNN architecture, the classical network extracts features similarly, and the resulting features are mapped to a 4-dimensional latent space and then into a 4-qubit quantum circuit using RX-angle encoding. The quantum layer performs the Quantum Fourier Transform and its inverse with an approximate number of gates on the order of 12–15 (before transpiration), using four trainable quantum parameters representing the RX rotation angles. We add a quantum layer between the CNN feature extraction and classical classifier layers. The quantum layer output, provided as a probability vector by the Qiskit Aer Simulator, was used to train the classical Dense Softmax classifier for end-to-end hybrid learning and final digit classification.

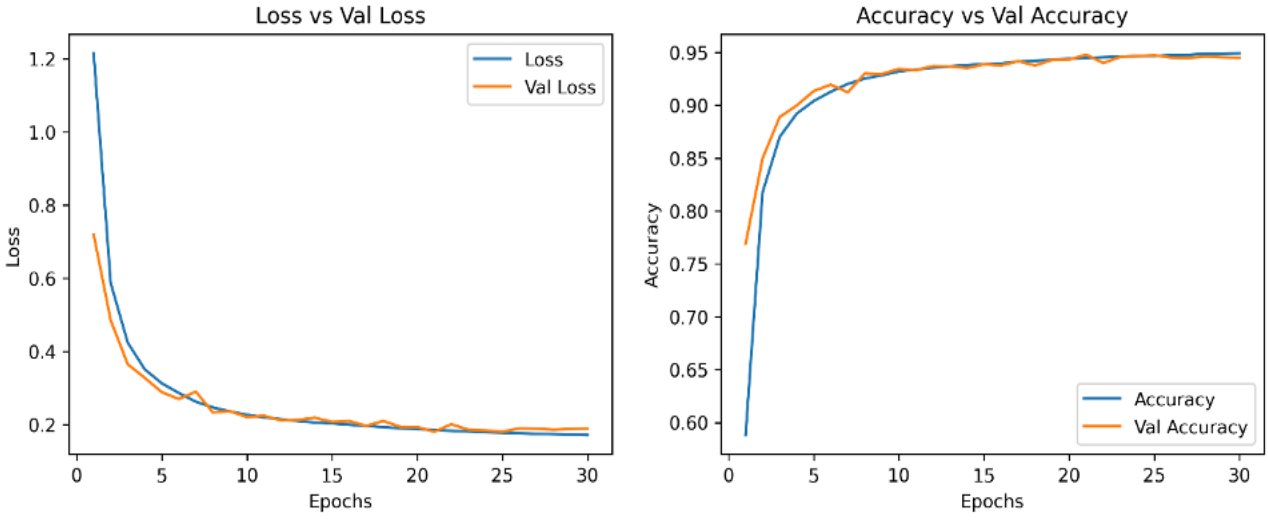


Figure 6. Accuracy and loss of classical CNN Model

4.2 Performance of Training and Validation

Based on the developed circuit, we evaluated the quantum CNN models using accuracy and loss metrics. Table 6 shows the results for the classical and quantum CNN models, standard measures for comparing the performance of the quantum-enhanced Convolutional Neural Network. The four most important results are training accuracy, validation accuracy, training loss, and validation loss. These metrics provided a standard benchmark for evaluating the effectiveness of the proposed CNN model. In the classical CNN model, training and validation accuracies were 94% and 94%, respectively; the model generalised efficiently to new data without substantial overfitting. The stability of the learning process is further supported by comparable training and validation losses of 17% and 18%, respectively, as the slight variation indicates consistent model behaviour across the dataset. Figure 6 shows the classical CNN accuracy and loss curves.

As shown in Table 6, the Quantum CNN achieved 97% accuracy during training, indicating that it can capture the underlying patterns in the training dataset. The validation results showed 97% accuracy, indicating no degradation during evaluation. In terms of loss, the model achieved a training loss of 9% and converged effectively. The validation loss was 11%, slightly higher, as expected and indicating a small amount of overfitting, which is acceptable for a conventional CNN model. This establishes an ideal baseline for comparing the developed Q-CNN. Future improvements in accuracy and decreases in loss will provide insight into how adding quantum layers to this convolutional structure can be useful. Figure 7 shows the training and validation accuracy and loss. They show the proposed model's training and validation results after 30 epochs. Training and validation losses declined rapidly in the early stages, then stabilised, indicating successful learning and convergence. Additionally, training and validation accuracies steadily increased to approximately 97% with no noticeable deviation.

Table 6. Results of performance metrics

Variant	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
Classical CNN Model	94%	94%	17%	18%
Quantum CNN Model	97%	97%	9%	11%

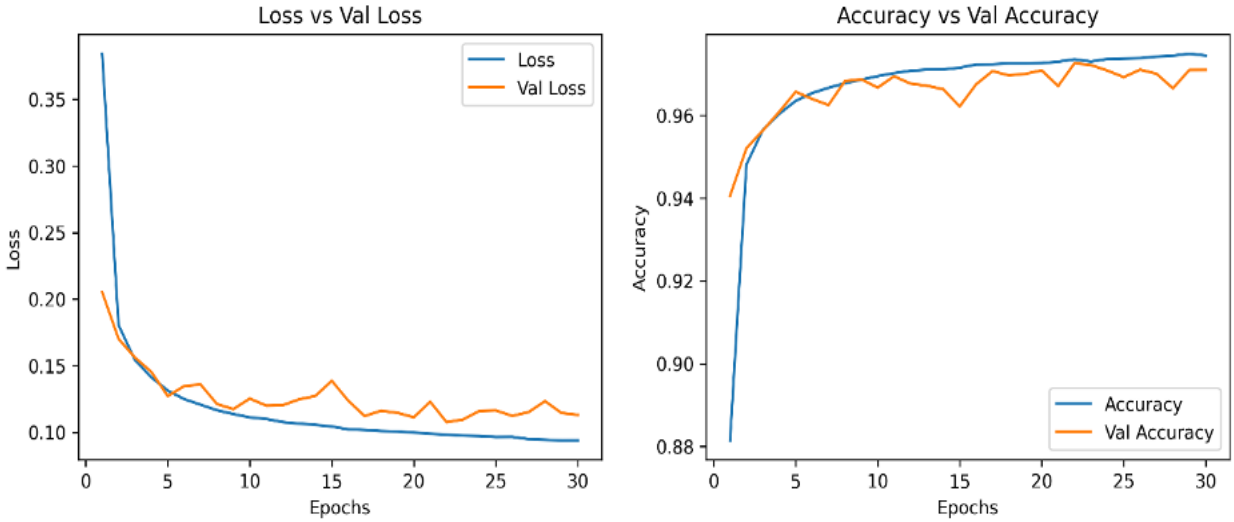


Figure 7. Accuracy and loss of Quantum CNN model

4.3 Classification Performance

The Q-CNN consistently outperformed the Classical CNN across all evaluation measures in the comparative assessment of classification performance. With 92% precision compared to 90% for the Classical CNN, the Q-CNN showed a greater ability to accurately detect positive predictions while reducing false positives. Similarly, recall increased from 88% in the Classical CNN to 94% in the Q-CNN, indicating that the quantum-enhanced model better identifies and accurately classifies pertinent events. The F1-score showed the largest improvement, increasing from 89% for the Classical CNN to 93% for the Q-CNN. This result confirms that the Q-CNN achieves a superior balance between classification accuracy and detection performance, as the F1-score is the harmonic mean of precision and recall. Table 7 presents the Precision, Recall, and F1-score for the CNN model, which are standard measures used to assess the improvements achieved by the Quantum-Enhanced CNN in image classification. Figure 8 graphically illustrates the Precision and Recall values for the ten image classes (digits 0–9). Figure 8 demonstrates the Q-CNN architecture's effectiveness and robustness, with both Precision and Recall consistently exceeding 0.88 and reaching approximately 0.97 across several classes. The results also show low variability across all image classes, indicating a balanced and stable classification performance. Although almost every image class shows an identical ratio between these two values, meaning they both represent balanced results to establish reliable classifications, minute trade-offs specific to each image class, such as the slightly diverged Precision and Recall in image classification.

Table 7. Results of Classification Performance

Evaluation Metrics	Classical CNN	Q-CNN
Precision	90%	92%
Recall	88%	94%

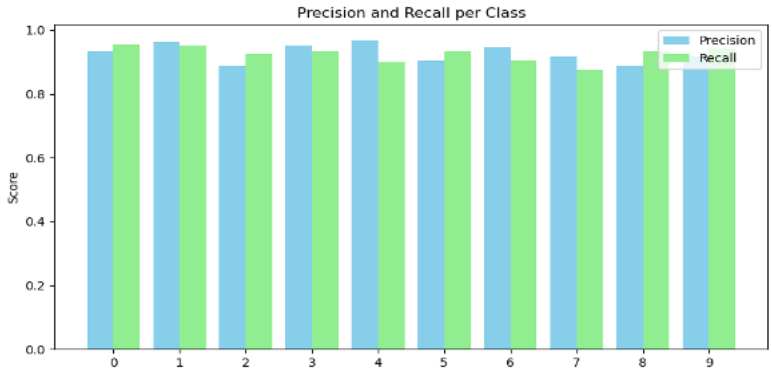


Figure 8. Graph of precision and recall among 10 classes

Figures 9 and 10 present the confusion matrices of the Classical CNN and Q-CNN, respectively, enabling a direct comparison of their classification performances. We used Q-CNN to compare the performance of the two CNNs for each digit class. Overall, the Q-CNN achieved higher classification accuracy for most digit classes, particularly 0, 3, 4, 5, 6, 8, and 9, as shown by more correct diagonal entries and fewer off-diagonal errors. Digits 1, 2, and 7 remain more difficult to classify because their images are similar to other classes, but the Q-CNN reduces several classification errors made by the classical CNN.

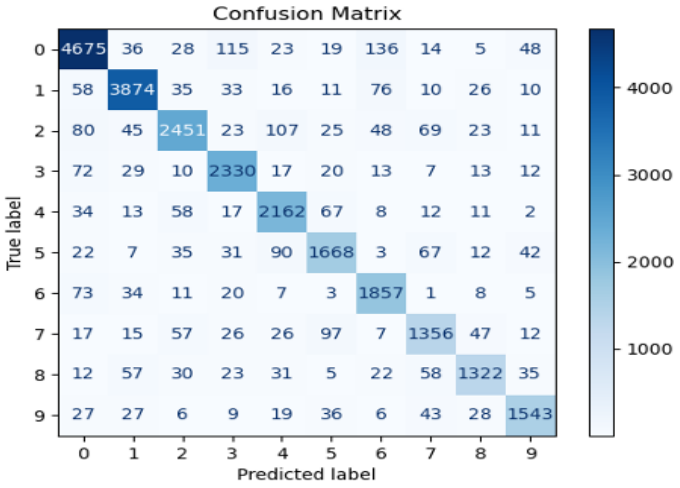


Figure 9. Confusion matrix

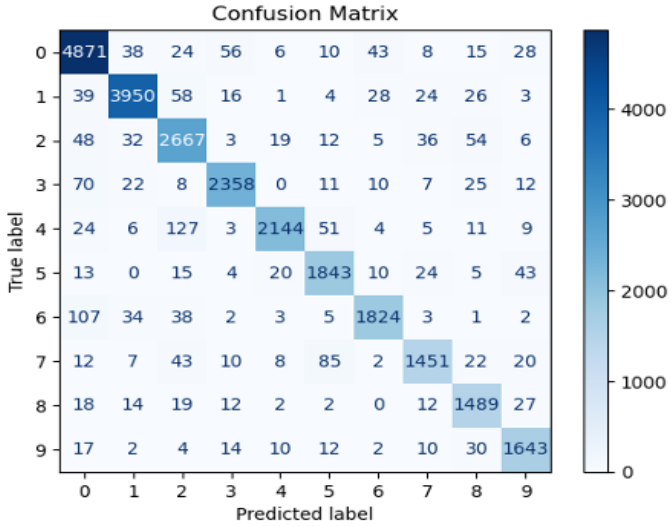


Figure 10. Quantum model's confusion matrix

4.4 Discussion

The comparison between the conventional CNN and the developed Quantum-Enhanced CNN shows not only the superiority of quantum feature encoding but also highlights the benefits of quantum computing. Comparing the classical CNN and quantum CNN models highlights the efficacy of incorporating quantum computing concepts into deep learning architectures. The Quantum CNN outperformed the Classical CNN in learning capacity and generalisation on unseen data, achieving higher training and validation accuracies of 97% versus 94%. Additionally, compared to the Classical CNN, which showed training losses of 17% and 18%, respectively, the Quantum CNN recorded significantly lower training (9%) and validation (11%) losses. These findings imply that during training, the quantum-enhanced architecture converged more successfully and learned more discriminative feature representations than the classical architecture. The lower loss values of the Quantum CNN indicate improved predictive confidence and classification performance, whereas the equal training and validation accuracies across both models suggest steady learning behaviour without severe overfitting. Overall, the results show that quantum-assisted learning techniques can improve image classification beyond the capabilities of traditional CNNs. Taken together, these points support the validity of the proposed hybrid technique, which not only maintains competitive accuracy but also improves the explainability and robustness of decision support. This study has some drawbacks. The main tool used to assess the Quantum CNN was a quantum simulator, which does not account for the noise and hardware limitations found in actual quantum systems. Furthermore, the study used only the SVHN dataset, which limits the applicability of the findings to other image classification tasks. Because computational demands are growing, the scalability of the proposed method to larger datasets and more complex quantum circuits remains problematic. Decoherence, gate faults, and quantum noise may also affect deployment on actual quantum hardware, potentially reducing model performance compared to simulator-based results.

5. Conclusions

In this study, we developed a Quantum-Enhanced Convolutional Neural Network by combining a classical CNN with Variational Quantum Circuits to achieve efficient image classification performance. This study focuses on multi-class image classification and evaluates performance using traditional criteria such as accuracy, precision, recall, and loss. Based on the experiment, Q-CNN achieved satisfactory classification performance across all ten image categories, with precision and recall exceeding 0.88. Another major insight is that using quantum features for encoding and dimensionality reduction can yield better, more stable classification results. The key innovation is integrating classical neural networks with quantum computing for image classification. However, this study has certain limitations. Although the proposed Q-CNN yielded encouraging results, we tested its performance only on a quantum simulator and a single benchmark dataset. This may be an insufficient test for real-world applications because it does not cover the full range of possible benchmarks. Further research will test the proposed model under real-world conditions using several benchmark datasets. Future investigations should focus on optimising the Variational Quantum Classifier to enable more precise adjustments within the classification regions, particularly by fine-tuning quantum circuit parameters to reduce disparities between Precision and Recall. Another important avenue for further research is improving quantum encoding methods to strengthen the robustness of quantum feature representations and reduce sensitivity to small variations in input data.

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CRediT Author Contribution Statement

S. H. Niranjala: Methodology; Analysis; Writing – original draft
Kazem Chamran: Supervision; Methodology; Writing- review & revise
Mustafa Mowafak Alobaedy: Conceptualisation; Visualisation; Writing- review & revise

Availability of Data and Materials

Data sharing is not applicable to this article, as no new datasets were generated or analysed in this study.

Ethics Statement

This study did not involve human participants or animal subjects. Therefore, ethical approval was not required for this study.

Generative Artificial Intelligence Disclosure

The authors declare that artificial intelligence-assisted technologies, such as generative AI, were not used to generate content, ideas, or theories. We have utilised AI to enhance readability and refine the language. We used it under strict human control and supervision. The authors take full responsibility for reviewing and approving the manuscript content.

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