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RESEARCH ARTICLE

QUANTUM FEATURE ENCODING FOR ENHANCING CNN-BASED IMAGE CLASSIFICATION PERFORMANCE

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Abstract - Convolutional Neural Networks (CNNs) have exposed robust results for classifying images in data analytics. On the other hand, the effectiveness of these models is often limited by their substantial computational complexities, 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, which 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 representations and classification purposes. 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, precision, recall, and F1-score were 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 has been recognized as an upcoming technological breakthrough with considerable potential implications for daily life, markets, and industry. The McKinsey report mentioned, the world-wide 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 putting billions of dollars into the research-led development of quantum computing, making some of these quantum computers partially available to the public via cloud computing infrastructure.[1]. Governments have investments in the development of quantum technology. EU allocated more than EUR 1 billion budget, while the US government contributed USD 1 billion, and China has invested USD 10 billion in a quantum computing centre [2]. Quantum computers utilize the phenomena of quantum mechanics for storing and manipulating data.

Quantum Machine Learning (QML) combined the emerging fields of machine learning techniques and quantum computing to analyse data using the capabilities of quantum systems [3]. By utilizing concepts such as entanglement and superposition, quantum computing offers enhanced computational capability for handling complex data structures more efficiently than conventional techniques [4]. QML models can be broadly classified based on how they integrate quantum and conventional computing. One popular classification comprises four the concepts of 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 wholly classical to entirely quantum. The CQ technique, for example, comprises classical data being processed by quantum algorithms, with quantum speedups used for certain computational tasks [5]. One of the key advantages of QML is the possibility for exponential speedups in specific jobs. For instance, quantum forms of techniques like PCA and SVM are more capable at dealing with high dimensional data compared to their classical counterparts [6]. Quantum PCA, for example, can locate eigenvalues and eigenvectors of big matrices tenfold quicker than classical approaches, illustrating QML's promise in dealing with complicated data structures. Quantum computing, which is attached on principles of quantum mechanics, exhibits remarkable computational ability using properties like superposition and entanglement [7].

Despite these promising breakthroughs, the incorporation of quantum computing into daily machine learning tasks has several limitations. A significant proportion of existing research has focused on quantum computing speedups, with relatively little research on structured image data and deep learning architectures. In particular, the integration of quantum processing and convolution-based architectures for image classification has been an emerging research area that requires further investigation, particularly with regards to performance and implementation issues [8]. The growing reliance on CNNs for deep image processing has led to significant advancements for different tasks, such as the process of classification, detection, and recognition. However, despite the breakthrough and the significant use of CNNs for various applications, CNN models face persistent issues with high computational complexity and inefficient parameterization. As

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deep learning continues to significantly influence high-stakes domains like the diagnosis of various diseases, autonomous vehicles, and security, the major emphasis for the future needs to be on comprehending the underlying process for the acquisition of the final model predictions, as opposed to merely ensuring the accuracy of the model. This fundamental limitation for making the model transparent maintains ever-growing vulnerabilities for the model's integrity. As such, new age research for filling the gaps begins to focus on the prospective use of quantum computing.

Several recent studies have also investigated the efficacy of a hybrid quantum-classical model for improving deep learning architectures. The most common technique used is replacing a few layers of a neural network with a parameterized quantum circuit or quantum feature maps. However, several models remain at a conceptual level with small-scale datasets or lack a systematic analysis. Hence, a systematic and experimentally verified framework is essential to understand the efficacy of a quantum-classical framework for improving a convolutional neural network [9]. The key issue being addressed here is how to incorporate quantum feature encoding with a CNN architecture to achieve enhanced classification while maintaining computational efficiency and high classification performance. To solve this issue, a well-designed framework is essential that exploits both classical and quantum computation. Hence, a Quantum-Enhanced Convolutional Neural Network architecture is proposed that exploits both classical and quantum computation for image classification. The major implications of this work are as follows:

1. The 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 is 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 in improving nonlinear feature representations, while maintaining high classification accuracy and generalization stability in image processing tasks? To overcome this gap, this study developed an experimental Quantum-Enhanced Convolutional Neural Network model. The proposed model integrates Quantum feature encoding with the CNN architecture in improving nonlinear feature representations, while maintaining high classification accuracy and generalization stability in image processing tasks. Furthermore, hybrid models have also been proposed for practical applications in leveraging the benefits of Quantum Machine Learning, particularly in terms of Quantum-Classical models [10-11].

The structure of the rest of the paper starts by providing background information and discussions on the various concepts that are integral to the research work, the motivations for the study, and the importance of the research area, and provides an overview and background information regarding the necessary concepts for the rest of the research content. The second section delivers an overview of the experimental environment and the corresponding results analyses, and discussions for the research. The last section provides an overview and the corresponding discussions regarding the insights and the future directions for the research.

2. Related Works

QML is an emergent technology that applies the ideas of quantum computing and ML to tackle complicated problems with higher efficiency than traditional computers. The concepts of QML derived from quantum physics with its features. These concepts include entanglement, superposition, and quantum interference, which allow for revolutionary data processing and analysis approaches [12].

2.1 Quantum Bits (Qubits)

In classical computing, the bit is the basic measuring unit used in computing tasks. The quantum bit, or qubit, operates as the foundation for quantum processing and information. A classical bit (chit) is an entity that has two clearly identifiable, or orthogonal, levels [13]. The difference between classical and quantum bits is shown in Figure 1. A classical bit exists in only one definite state at any given time, while the qubit can exist in a whole range of states between $|0\rangle$ and $|1\rangle$ due to the principle of superposition. It gives an ability to the qubit to encode several values at the same time till the moment when it is observed, and then it reduces 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

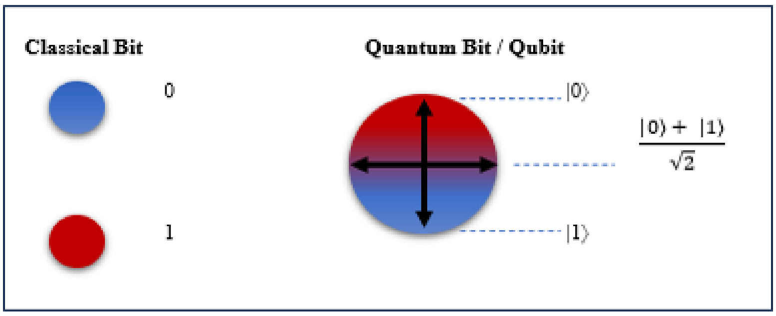

Figure 1. The comparison between classical bit and quantum bit

2.2 Classical Bit Encoding via One-Hot Vectors

The classical bit is stated as a system with exactly two distinguishable states. As an example, on-off switches and magnetization along the up & down direction. In mathematical expressions, the cbit is denoted by a binary digit, either 0 or 1. In another representation, the states of the cbit are also given by a "two-dimensional one-hot" amplitude vector, which has only one component equal to 1. In Table 1, it is shown how the component equal to 1 determines if the cbit is 0 or 1 [14-15].

As well as the status of a cbit can be expressed using a two-dimensional one-hot amplitude vector. The one-hot amplitude vector has one digit, which 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 is 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 the column vector. As show in Eq. (1), the column vector is represented by $|a\rangle$, where 'a' is the label of the vector. The ket vector, which is the one-hot vector associated with a cbit, serves as the label when it represents a cbit value of 0, as shown in the 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 considered the major characteristic in quantum mechanics that has a major influence on quantum computing and ML. It demonstrates the capability of quantum-based computing to handle several states at the same time. These phenomena represent one of the major distinctions between classical and quantum computing, and it underpin quantum systems' exceptional processing capability [16]. When considering traditional computing, a bit is considered the basic unit of measurement in information, which holds 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 stating the normalization condition $|\alpha|2+|\beta|2=1$. The equation shows the super positioned qubit is having the states $|0\rangle$ and $|1\rangle$, along with $|\alpha 2|$ and $|\beta 2|$ representing the probabilities of measuring the qubit in each respective state [17].

Figure 2 shows a bit and a qubit on the left and right sides. A bit can be either 0 or 1 with a probability of 100%. But the qubit, is possible to be in one of two states in similar 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%, $|1\rangle$. Even though they are physically apart, the characteristics of both qubits in an entangled state are connected to one another; one of them will expose the other [18].

2.4 Qubit related Concepts: Entanglement

The concept called Entanglement, in quantum mechanics, with inferences for QC as well as related to ML. It refers to the phenomena in which the quantum states of two or more qubits turn into entangled, so the state of one qubit directly influences the state of another qubit, regardless of their distance [19]. This feature distinguishes quantum systems from classical systems and provides the foundation for numerous quantum computing advantages [20]. The overall state of an entangled qubit system cannot be explained without reference to the states of each individual qubit.

This state is maximally entangled since it cannot be decomposed into a set of individual qubit states. The measurement of one qubit in this condition immediately identifies the state of the other qubit, demonstrating complete correlation regardless of the spatial space between the qubits [21]. Entanglement can be mathematically characterized using the Schmidt decomposition. For any pure state $|\psi\rangle|$ of a bipartite system, the Schmidt decomposition expresses $|\psi\rangle|$ as a sum of tensor products of orthonormal states of the subsystems. The number of non-zero terms in this total, known as the Schmidt rank, represents the degree of entanglement [22]. A Schmidt ranks greater than one indicates the subsystems are intertwined [1].

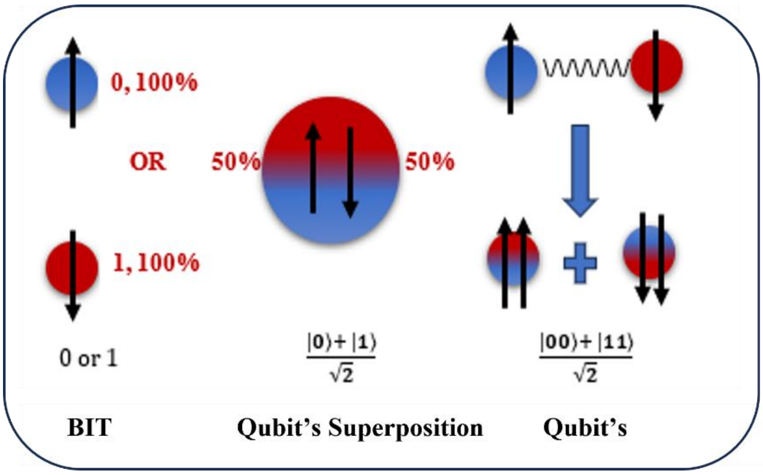

Figure 2. Superposition and entanglement of a qubit

2.5 Qubit related Concepts: Quantum Circuits

The quantum circuit is the fundamental structure for carrying out quantum computations, like classical circuits in classical computing. It is made up of qubits and quantum gates arranged in a certain order that allows for the manipulation and measurement of quantum states [23]. Quantum circuits are build-up of qubits and quantum gates, operations that change the state of qubits. The quantum circuits enable computations based on quantum physics concepts, including superposition and entanglement. The quantum circuits are created by assembling quantum enhances gates in a certain order to execute the needed computations [24]. Each of the qubits is represented by a horizontal line, combining with gates applied from left side to right side such as in Equ (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 the two qubits. Quantum circuits' distinguishing characteristics and capabilities provide significant computing advantages over classical systems.

2.6 Quantum Machine Learning Algorithms

Quantum-based ML can also be categorized into 03 different categories based on supervised, unsupervised, and deep learning, as illustrated in Table 2. Quantum algorithms refer to a set of algorithms that apply the principles of quantum mechanics in the processing of computations that could be many times more efficient than those executed by classical algorithms [25]. These algorithms exploit the parallelism of the past properties of quantum bits, better named qubits, with superposition and entanglement, that help them solve huge-class problems ranging from cryptography, through chemistry, to optimization. This permits an exponential increase in computational ability over classical machines while ensuring several orders of magnitude less power consumption [23].

Table 2. QML algorithms

Quantum Machine learning algorithms		
Supervised	Unsupervised	Deep Learning
Quantum Linear Regression	Quantum k-Means Clustering	Quantum Convolutional Neural Networks (QCNNs)
Quantum Support Vector Machine (QSVM)	Quantum Principal Component Analysis (QPCA)	Quantum Recurrent Neural Networks (QRNNs)
Quantum k-Nearest Neighbors (QkNN)	Quantum Boltzmann Machines (QBMs)	Quantum Neural Networks (QNNs)
Quantum Neural Networks (QNNs)	Quantum Autoencoders	Variational Quantum Circuits (VQCs)
Variational Quantum Classifier (VQC)		Hybrid Quantum-Classical Deep Networks

2.7 Analytical Comparison of Classical DL and Quantum-based DL

There is a necessity to conduct a comprehensive study between Classical and Quantum Deep Learning. This comparative study would emphasize the reasons that are compelling the development of QDL, as it appears to be an advanced version of classical deep learning. Table 3 shows the differences between deep learning and quantum-based deep learning in comparison. Table 3 summarizes the main differences between classical deep learning and quantum-based deep learning approaches. When it is comparing computational efficiency, the QDL outperform CDL with utilizing quantum features. In the aspect of extracting features from images, QDL is performing better as it is encoding the features to quantum features and in the end, those will be decoded after the dense layer. When considering the classification and generalization, QDL is outperforming while CDL is best for cost effective hardware utilization and better performance 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 the 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 the present noisy intermediate-scale quantum (NISQ) devices and real-world machine learning tasks, a new class of hybrid quantum-classical architectures has been developed, which replaces classical dense layers with quantum circuits. Ghasemian and Tavassoly [23] presented a hybrid classical-quantum classifier using two-qubit dissipative quantum channels, which provided enhanced feature separability for 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 (VQC) integrated with classical neural networks [26, 28]. However, despite these contributions, several research gaps remain. Most existing hybrid quantum–classical architectures have only been evaluated on limited datasets, which restricts the generalizability of their findings. In addition, the quantum components are often used as black-box replacements for classical dense layers, rather than being investigated for their direct influence on convolutional feature maps. Furthermore, while some quantum-based models claim improvements in classification performance, these improvements are commonly supported through classical post-hoc explanation methods, with limited attention given to intrinsic quantum feature mapping. Finally, there is still a lack of fair comparative studies between classical CNNs and quantum-enhanced CNN architectures under the same experimental settings.

2.9 QML Limitations on Simulator-Based Environments

The main bottlenecks in the current implementations of Quantum Machine Learning in Noisy Intermediate-Scale Quantum (NISQ) and simulator environments are limited qubit counts that require aggressive dimensionality reduction or classical preprocessing, as well as hardware noise such as decoherence and gate errors. Schaudt et al. (2025) have concentrated on hardware-specific encodings to process full-resolution images on 49-qubit systems, while the previous researches have examined noise robustness and discovered that hybrid architectures significantly deteriorate under depolarizing and amplitude damping noise [26-27]. Nevertheless, there is still a significant research gap: most of the literature now in publication suggests ad hoc, application-specific encoding methods (such as for medical imaging or MNIST) without offering a methodical, controlled evaluation of various quantum feature encoding techniques. Such as patch-based embeddings, amplitude, or angle under uniform noise profiles. The best design guidelines for quantum-enhanced feature extraction are therefore mainly unclear due to the lack of benchmarking that separates the incremental contribution of different encoding strategies to the classification performance of a traditional CNN backbone [28].

2.10 Quantum Feature Encoding Techniques

Quantum feature encoding techniques, including amplitude encoding, angle encoding, and basis encoding, map classical data into a high-dimensional space known as a Hilbert space. This approach theoretically enables more complex feature correlations and improves nonlinear separability [28]. Amplitude encoding allows exponential compression of classical data into quantum states, while angle encoding utilizes rotation gates to encode classical feature values into quantum representations. Recent studies have shown that quantum feature encoding can enhance the richness of feature representation. However, empirical studies on convolutional feature hierarchies, class-wise stability, and generalization patterns on structured image data remain limited. In addition, most existing studies have focused on evaluating each encoding technique independently, with limited attention given to the direct integration of quantum feature encoding with convolutional feature extraction layers. From the literature review, several critical research gaps have been identified. Existing QML studies utilized small datasets for experiments and there is a gap of research for multi class, complex dataset for measuring the classification accuracy and computational speedup. To overcome that issue the study utilized Google street view dataset with 10 classes.

Current studies have also not extensively explored quantum feature encoding as a mechanism for improving the transparency of convolutional feature representation. In addition, comparative studies between conventional CNNs and quantum-enhanced CNN architectures under controlled experimental conditions remain limited. The combined impact of angle and amplitude encoding on the separability of nonlinear features within convolutional networks has also not been thoroughly investigated. These research gaps highlight the importance of developing a structured and experimentally validated framework that integrates quantum feature encoding within convolutional neural network architectures while evaluating its impact on classification performance.

3. Materials and Methods

This study adopts a systematic experimental methodology starting from a literature review through assessing the present status and knowledge gap in classical machine learning and quantum machine learning, aiming to enhance data analysis tasks involving complex data. This section is followed by the amplification of model theory and an analysis of corresponding algorithms to establish a sharp foundation for integrating quantum-based technologies. As a more technological background of the research, quantitative and qualitative methodologies are less suitable for this study. Hence, the researcher is focused on using the experimental method as the methodology of the research. Figure 3 indicates the steps of the research methodology, with the start of the research phases until the completion of the research work. Table 4 shows the detailed plan of the tools and technologies required for each stage throughout the study.

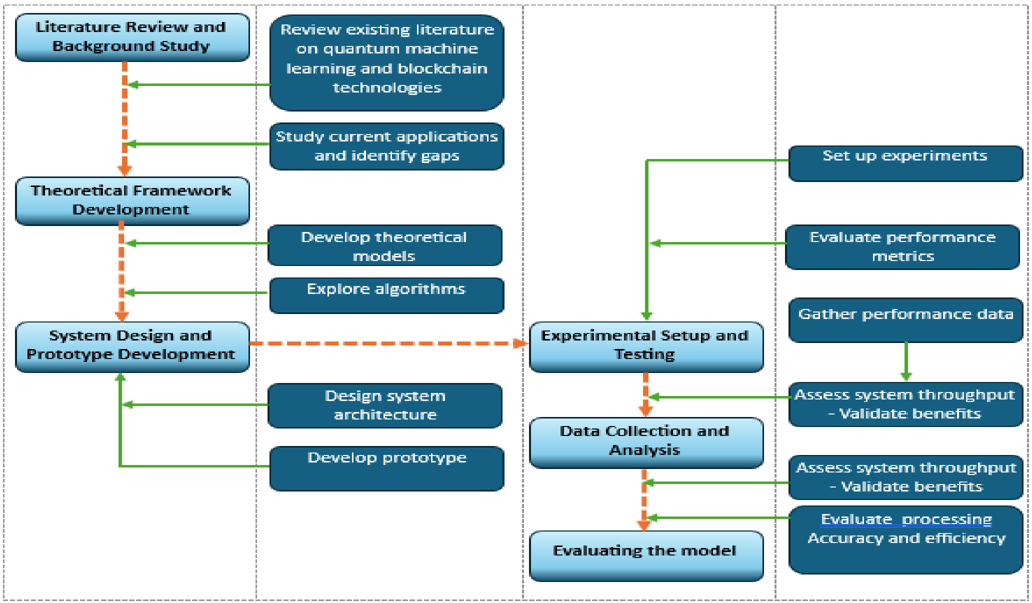

Figure 3. Proposed research methodology

3.1 Steps and Tools for Developing the Model

The IBM Quantum Simulator (Qiskit Aer Simulator) was mainly used as a quantum simulation environment to examine the integration of classical deep learning with quantum computing technology. The study was able to investigate quantum-enhanced feature processing without the constraints of existing quantum hardware because of the simulator's ability to execute and evaluate quantum circuits on classical computing infrastructure. TensorFlow and the Keras high-level API were then used to create the CNN model, while Scikit-learn was used for data preparation, performance assessment, and confusion matrix analysis. Convolutional layers, pooling layers, fully linked dense layers, and an output layer for digit classification made up the model architecture. To provide non-linearity and boost learning effectiveness, the Rectified Linear Unit (ReLU) activation function was employed.

Angle encoding was used in Quantum model 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 that corresponds to the feature vector. Angle encoding was chosen since it uses fewer qubits than amplitude encoding, is easy to implement using Qiskit, has a simpler circuit, and can be effectively implemented in NISQ devices. Figure 4 shows the technical implementation of the research using QCNN algorithm.

Researchers have developed Classical CNN and Quantum CNN with the same dataset and the parameters to make a comparative analysis of the model classification.

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) Normalization - Pixel values normalized 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 advance model transparency by first passing input images through the usual CNN layers for the extraction of 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 final classification layers that ensure the model provides not only accurate but also visually explainable predictions with generated attention maps, effectively "opening the black box" of deep image processing.

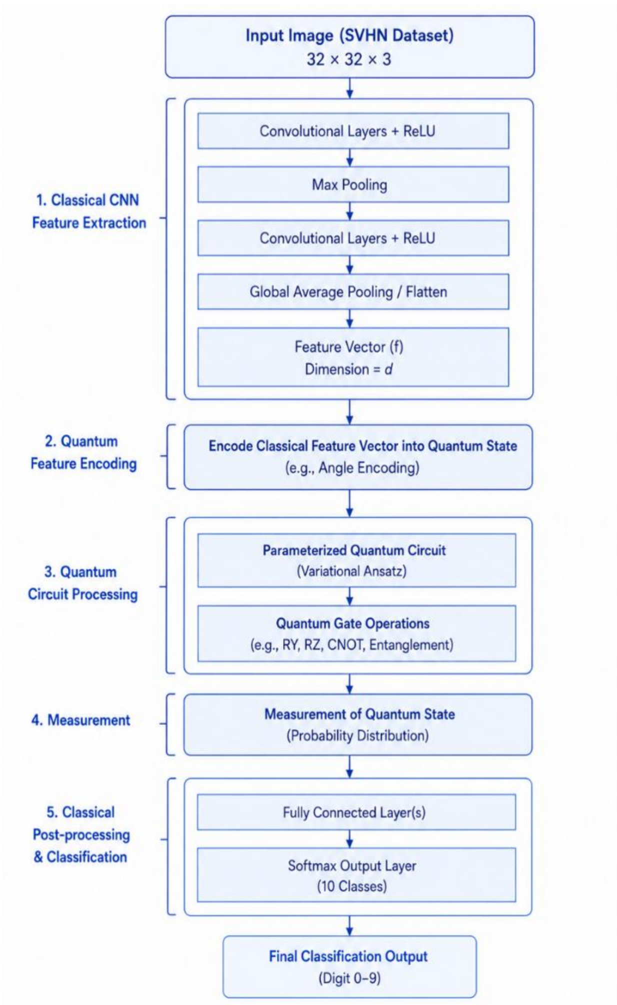

Figure 4. Technical framework

4. Results and Discussion

Initially, classical CNN model was developed in this study and then the quantum CNN model was developed. Both the classic CNN and the Q-CNN were trained and evaluated on the exact same data split, number of epochs, optimization algorithm, learning rate, batch size, preprocessing steps, and evaluation measures to make sure of fair comparison. Since this is a comparative study, all training parameters have been kept deliberately same to make sure that the differences, if any, in performance would only be due to the method of quantum feature encoding used. The model has achieved training accuracy of 94% and a validation accuracy of 94%. The experimental findings for the traditional CNN model showed a balanced learning performance, suggesting that the model could successfully generalize to new data without experiencing substantial overfitting. The learning process's stability is further supported by the comparable training loss of 17% and validation loss of 18%, as the slight variation between training and validation loss indicates consistent model behavior across both datasets. This baseline design was used as the basis for later optimization studies. for additional enhancement of convergence efficiency and feature extraction using sophisticated optimization methods.

Secondly, the quantum CNN model has developed. The models integrated variational quantum circuits (VQCs) within the CNN pipeline and utilize Aer simulators to simulate quantum behavior. The developed model was trained for 30 epochs using the SVHN dataset with the same pipelines for normalizing the images, one-hot encoding, and consistent data partitioning.

4.1 QCNN Circuit structure

The quantum circuit serves as an integral post-processing module within the setup of a Quantum Convolutional Neural Network (QCNN) framework. The circuit executes the inverse Quantum Fourier Transform (QFT), over four qubits and function as a feature decoding and transformation layer for quantum machine learning operations as shown in Figure 5. In the proposed circuit, four qubits quantum states, namely q0, q1, q2, q3 were processed through four layers for the generation of 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 reversely ordered to match with the QTF layout, which is important for restoring spatial or frequency structure post-convolution operations.

Each qubit subsequently undergoes the Hadamard (H) gate operation, which enables the fundamental process of superposition. During this process, Hadamard gates create quantum interference between qubits, which is an important step in non-local feature extraction. In addition, qubits went through the controlled phase rotations. Circuit includes a series of phase-controlled (CP) gates with increasingly smaller angles. These operations preserve relative phase information and build up pairwise entanglement among the qubits. In the perspective of QCNN framework, it helps convert localized features in an image (e.g., textures, edges) into overall frequency-domain descriptions, similar to the usage of FFT in conventional CNNs, hence providing improved invariance in translation while improving feature generalization. The circuit components and the description are shown in Table 5.

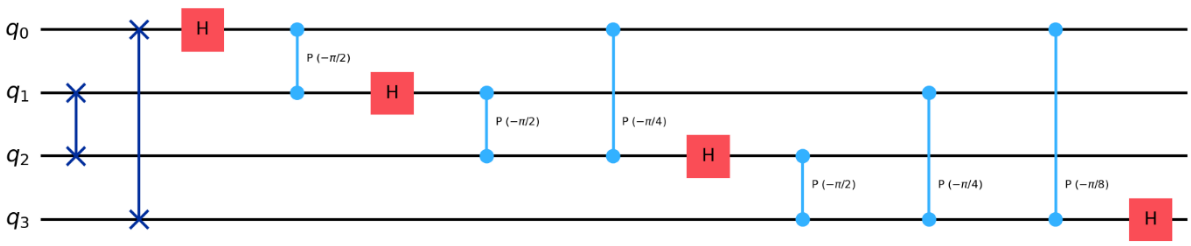

Figure 5. Developed quantum circuit

Table 5. Components of the circuit

Component	QCNN Role	Description
Inverse QFT in the circuit	Post-convolutional decoding or transformation layer	Enables efficient compression of features, adding towards 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	Optimizes the depth of circuits and 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 input images of dimensions 32 × 32 × 3 RGB from the SVHN data set, and then uses three convolutional layers, which have 64, 32, and 16 filters respectively. The kernel size is 3 × 3. Used ReLU activation function, same padding, and MaxPooling of 2 × 2. The extracted features are compressed with a Global Average Pooling layer and are fed into a Dense Softmax output layer with 10 neurons for classification of digits. In

Quantum-Classical CNN architecture, the classical network is used to extract the features in the similar manner, and then the extracted features are mapped onto 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 in the order of 12–15 (before transpiration), having four trainable quantum parameters representing the angles of RX rotation. The quantum layer is added between the CNN feature extraction layer and the classical classifier. The output of the quantum layer, which is provided in the form of a probability vector from the Qiskit Aer Simulator, is used to train the classical Dense Softmax classifier for end-to-end hybrid learning and final digit classification.

4.2 Performance of Training and Validation

Based on the developed circuit, quantum CNN models were evaluated using accuracy and loss metrics. Table 5 shows the results obtained using the classical and quantum CNN model, which is a standard measure to compare the performance of the Quantum-Enhanced Convolutional Neural Network. The four most important results shown are Accuracy - Training, Accuracy - Validation, Loss - Training, and Loss - Validation. These metrics provide a standard benchmark for evaluating the effectiveness of the proposed CNN model.

In classical CNN model, training accuracy achieved 94% and a validation accuracy of 94%, the model demonstrated efficient generalization to new data without substantial overfitting. The learning process's stability is further supported by the comparable training loss of 17% and validation loss of 18%, as the slight variation between training and validation losses indicates consistent model behaviour across the dataset. The curves of classical CNN accuracies and loss is shown in Figure 6.

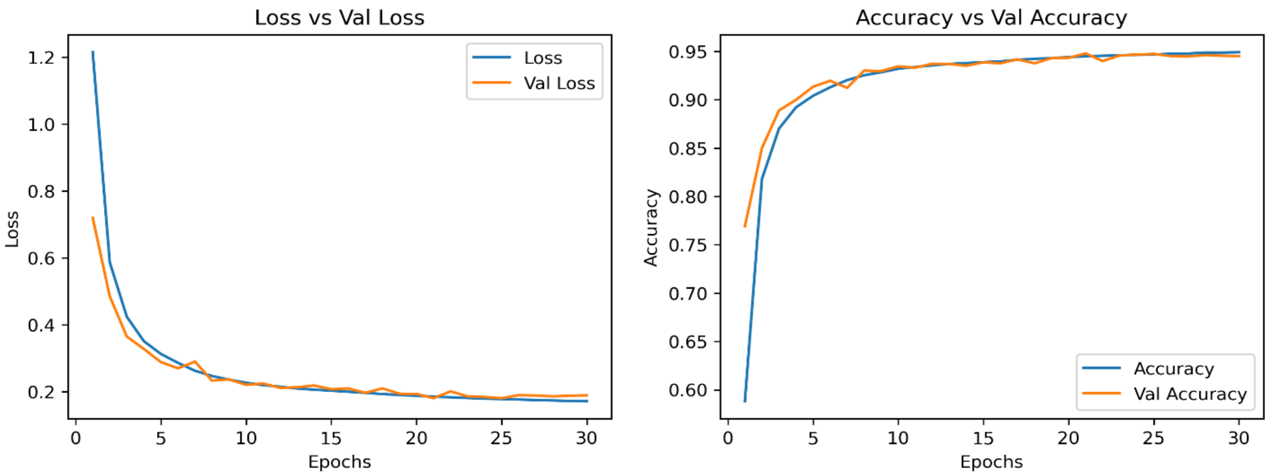

Figure 6. Accuracy and loss of Classical CNN Model

As shown in Table 6, When considering the Quantum CNN model, the model reached an accuracy of 97% during training, which implies that the model is indeed capable of mastering the underlying patterns within the training dataset. The validation results indicate an accuracy level of 97%, which implies that there is no degradation during evaluation. In terms of loss functions, a training loss of 9% is shown to be achieved by the model, which converges effectively during training. The validation loss is 11%, which is slightly higher, but this is to be expected and signifies a small amount of overfitting on a relatively acceptable level for a conventional CNN model.

This sets up an ideal baseline to compare the developed Q-CNN against. Going ahead, an enhancement in accuracy values and a decrease in loss values will provide insight into how adding quantum layers to this convolutional structure can prove to be useful. Plots of the training accuracy and loss as well as validation accuracy and loss are illustrated in Figure 7. It shows the training and validation results for the proposed model after 30 epochs. There is a rapid decline in training and validation loss in the early stages followed by stabilization, which signifies successful learning and convergence. Additionally, there is a steady rise in training and validation accuracy up to around 97% without any 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%

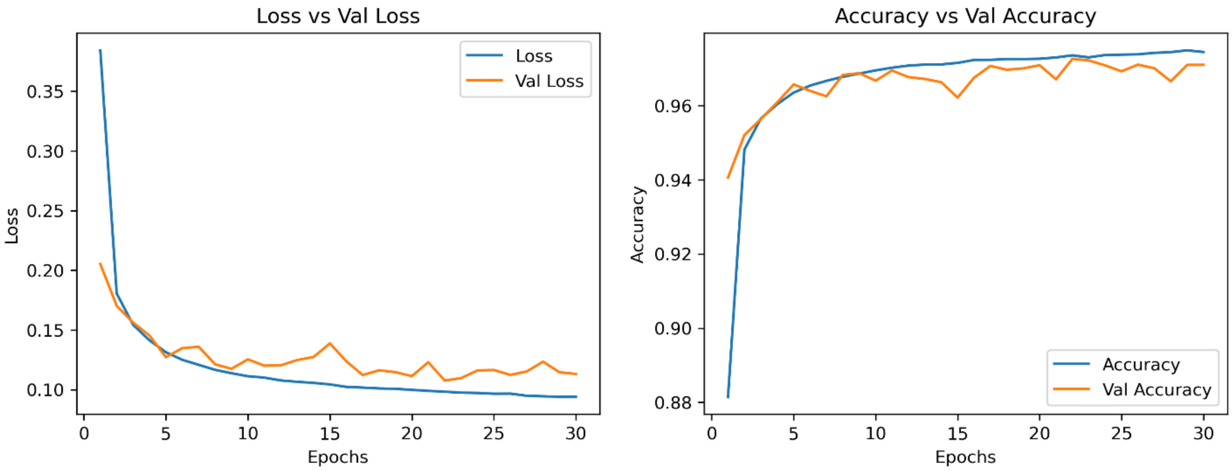

Figure 7. Accuracy and loss of Quantum CNN Model

4.3 Classification Performance

The Q-CNN continuously performed better than the Classical CNN in all evaluation measures for the comparative assessment of classification performance. With a precision of 92% as opposed to 90% for the Classical CNN, the Q-CNN demonstrated a greater capacity to accurately detect positive predictions while lowering false positives. In a similar vein, the recall increased from 88% in the Classical CNN to 94% in the Q-CNN, indicating that the quantum-enhanced model is better at identifying and accurately classifying pertinent events. The F1-score showed the biggest improvement, rising from 89% for the Classical CNN to 93% for the Q-CNN. This result validates that the Q-CNN attained a superior balance between classification accuracy and detection capabilities because the F1-score is the harmonic mean of precision and recall. Table 7 presents the Precision, Recall, and F1-score values for the CNN model, which is essentially the standard measure that is currently being used to assess improvements incurred by the Quantum-Enhanced CNN (Q-CNN) on image classification.

Figure 8 graphically illustrates the Precision and Recall values for the ten image classes (digits 0–9). The figure demonstrates the effectiveness and robustness of the Q-CNN architecture, where both Precision and Recall values consistently exceeded 0.88 and reached approximately 0.97 for several classes. The results also show low variability across all image classes, indicating 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%

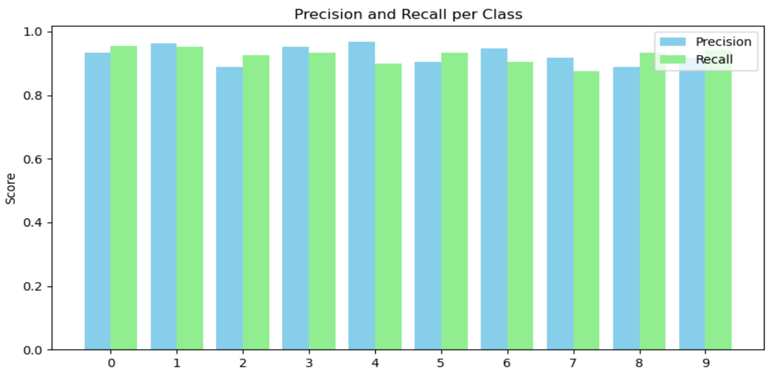

Figure 8. Graph of precision and recall among 10 classes

Figures 9 and 10 present the confusion matrices of the Classical CNN and Q-CNN, respectively, enabling a direct comparison of their classification performance. Q-CNN provided to compare the performances of the two CNNs based on each digit class. Overall, the Q-CNN shows better accuracy of classification for most digit classes especially 0, 3, 4, 5, 6, 8, and 9, which is evident from the higher number of correctly classified values on the diagonal and lesser off-diagonal errors. Digits 1, 2, and 7, however, continue to be more difficult for classification because of the similarity of their images to other classes, but Q-CNN manages to decrease several error types of classification that the classical CNN makes.

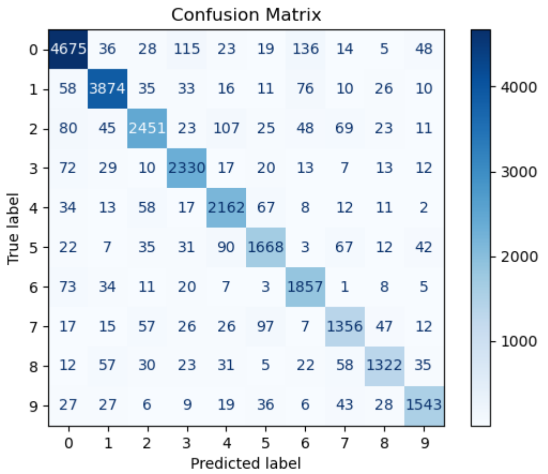

Figure 9. Classical model's confusion matrix

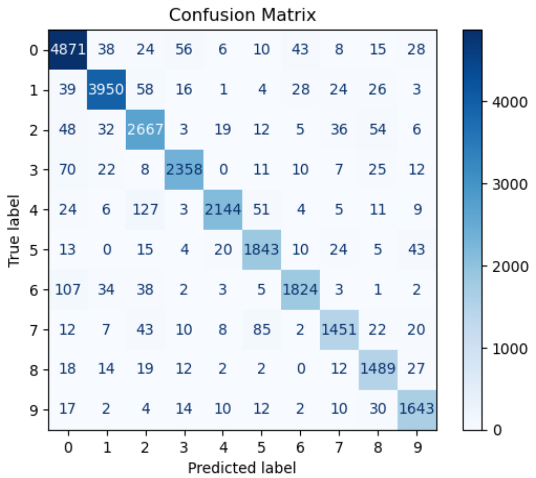

Figure 10. Quantum model's confusion matrix

4.4 Discussion of the Results

The comparison between the conventional CNN and the developed Quantum-Enhanced CNN shows not only the superiority in the quantum feature encoding but also highlights the benefits of quantum computing. The comparison of the Classical CNN Model to the Quantum CNN Model highlights the efficacy of incorporating quantum computing concepts into deep learning architecture. The Quantum CNN outperformed the Classical CNN in terms of learning capacity and generalization on unknown data, achieving greater training and validation accuracies of 97% as opposed to 94%. Additionally, compared to the Classical CNN, which showed losses of 17% and 18%, respectively, the Quantum CNN recorded significantly lower training loss (9%) and validation loss (11%).

These findings imply that during training, the quantum-enhanced architecture was able to converge more successfully and learn more discriminative feature representations. The Quantum CNN's lower loss values validate its improved predictive confidence and classification performance, but the equal training and validation accuracies seen in both models show steady learning behaviour without severe overfitting. Overall, the results show how quantum-assisted learning techniques can improve image classification tasks beyond what traditional CNN structures can accomplish. Taken together, the above points indicate the validity of the proposed hybrid technique, which not only maintains competitive accuracy but also enables improvements regarding explainability and decision support robustness.

There are some drawbacks to this study. 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, only the SVHN dataset was used in the studies, which limited the findings' applicability to other image classification tasks. Due to growing computing demands, the suggested method's scalability for bigger datasets and more intricate quantum circuits is still problematic. Decoherence, gate faults, and quantum noise may also have an impact on deployment on actual quantum hardware, which could lower model performance in comparison to simulator-based outcomes.

5. Conclusions

In this study, a Quantum-Enhanced Convolutional Neural Network has been developed by combining classical CNN along with Variational Quantum Circuits for achieving efficient image classification performance. This paper has been focused on multi-class image classification, and the performance has been evaluated based on traditional evaluation criteria, such as accuracy, precision, recall, and loss. Based on the experiment, Q-CNN has obtained satisfactory classification performance in all ten categories of images with precision and recall greater than 0.88. Another major insight is using quantum features for encoding and dimensionality reduction can obtain better classification results with higher stability.

In this study, the key innovation involves integrating classical neural networks with quantum computing for the purpose of image classification. However, there are certain limitations to this research, Although the suggested Q-CNN gave encouraging results, its performance has been tested using a quantum simulator and one benchmark dataset. This may be considered an insufficient test for real-life application of quantum computing, since it does not cover the whole range of possible benchmarks. Further research will concentrate on testing the proposed model in real-life conditions using several benchmark sets. As well as the future investigations related to this research should focus on optimizing the Variational Quantum Classifier to allow for more precise adjustments within the classification areas, especially by finetuning quantum circuit parameters to diminish any disparities between Precision and Recall values. Additionally, an important avenue for further research is the enhancement of quantum encoding methods to bolster the robustness of quantum feature representations and decrease sensitivity to slight variations in input data.

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S. H. Niranjala: Methodology; Data Analysis; Writing - Original Draft
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Mustafa Mowafak Alobaedy: Conceptualization; Visualization

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. Ethical approval was therefore not required for this research.

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No generative artificial intelligence tools were used in the preparation of this manuscript. All intellectual content is original and solely attributable to the authors.

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