# COMPARATIVE STUDY OF QCNN AND RESNET-50 - BASED ARCHITECTURES FOR MEDICAL IMAGE CLASSIFICATION

**A project Report submitted to**

DEPARTMENT OF COMPUTER SCIENCE & INFORMATION TECHNOLOGY

## MASTER OF SCIENCE
## (COMPUTER SCIENCE)

***By***

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**Under the Guidance of**
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DEPARTMENT OF COMPUTER SCIENCE & INFORMATION TECHNOLOGY

## GURU GHASIDAS VISHWAVIDYALAYA, BILASPUR

**Session:**
**2023-2024**

# CERTIFICATE OF SUPERVISOR(S) /GUIDE

This is to certify that the work incorporated in the project **“COMPARATIVE STUDY OF QCNN AND RESNET-50 -BASED ARCHITECTURES FOR MEDICAL IMAGE CLASSIFICATION”** is a record of six-month project work assigned by our Industry/Company/Institution, successfully carried out by **HARSH YADAV** bearing Enrollment No- GGV/22/05310 under my guidance and supervision for the award of Degree of **Master of Science (Computer Science)** of **DEPARTMENT OF COMPUTER SCIENCE & INFORMATION TECHNOLOGY, GURU GHASIDAS VISHWAVIDYALAYA, BILASPUR C.G., INDIA**. To the best of my knowledge and belief the report embodies the work of the candidate him/herself and has duly been successfully completed.

**Signature of the Supervisor/Guide** **Signature of HOD**

Name…………………………….. Name………………

# DELCLARATION BY THE CANDIDATE

I, **HARSH YADAV** Student of IV Semester MSc. (CS), **DEPARTMENT OF COMPUTER SCIENCE & INFORMATION TECHNOLOGY, GURU GHASIDAS VISHWAVIDYALAYA, BILASPUR**, bearing Enrolment Number **GGV/22/05310** here by declare that the project titled "**COMPARATIVE STUDY OF QCNN AND RESNET-50 -BASED ARCHITECTURES FOR MEDICAL IMAGE CLASSIFICATION**" has been carried out by me under the Guidance/Supervision of **Dr. Santosh Kumar Majhi**, **Assistant Professor** submitted in partial fulfillment of the requirements for the award of the Degree of Master of Science (Computer Science) by the Department Of Computer Science & Information Technology, Guru Ghasidas Vishwavidyalaya, Bilaspur during the academic year 2023-24 .This report has not been submitted to any other Organization/University for any award of Degree/Diploma

**(Signature of Candidate)**

Date:

Place:

# ACKNOWLEDGEMENT

I have great pleasure in the submission of this project report entitled **Comparative Study of QCNN and ResNet-50 -Based Architectures for Medical Image Classification** in partial fulfillment of the degree of Master of Science (Computer Science). While Submitting this Project report, I take this opportunity to thank those directly or indirectly related to project work.

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Acknowledgement is due to my parents, family members, friends and all those persons who have helped me directly or indirectly in the successful completion of the project work.

(**HARSH YADAV**)

# CERTIFICATE BY THE EXAMINER

This is to certified that the project work entitled **"COMPARATIVE STUDY OF QCNN AND RESNET-50 -BASED ARCHITECTURES FOR MEDICAL IMAGE CLASSIFICATION"** submitted by **HARSH YADAV** has completed under the supervision of **Dr. SANTOSH KUMAR MAJHI** Dept. of "Computer Science & Information Technology" ,**GGU Bilaspur(C.G)** has been examined by the undersigned as a part of examination for the award of **MSc.(CS)** Degree in Dept. of "**Computer Science & Information Technology**" in **GURU GHASIDAS CENTRAL UNIVERSITY BILASPUR(C.G).**

**"Project Examined & Approved"**

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## Abstract

This study presents a comparative analysis of Quantum Convolutional Neural Networks (QCNNs) and ResNet-50 architectures for classifying medical images from the MNIST medical dataset. The paper provides an overview of the theoretical foundations and operational mechanisms of QCNNs and ResNet-50, highlighting their potential advantages in terms of processing efficiency and accuracy in the quantum and classical domains. The methodology section outlines the implementation and evaluation processes, including data preparation and model configuration. The results demonstrate the comparative performance of QCNNs and ResNet-50 in classifying the MNIST medical dataset, offering insights into the implications of integrating quantum-classical models in clinical diagnostics. The findings suggest that QCNNs, by leveraging quantum computing principles, can potentially enhance the accuracy and computational efficiency of ResNet-50 in biomedical image classification tasks.



**Keywords**

- Quantum Convolutional Neural Networks (QCNNs)
- ResNet-50
- Medical image classification
- MNIST medical dataset
- Deep learning
- Quantum computing
- Comparative analysis

# 1. Introduction

Biomedical image classification has emerged as a cornerstone in modern clinical diagnostics, playing a pivotal role in the early detection and treatment of diseases. The rapid proliferation of digital imaging technologies has led to an exponential increase in the volume of medical images, necessitating sophisticated algorithms to accurately interpret these images and extract meaningful insights. Traditional methods, although effective, often fall short in handling the complexity and variability inherent in medical images. This has spurred interest in deep learning, a subset of artificial intelligence that mimics the human brain's ability to learn from large amounts of data. Deep learning models, particularly convolutional neural networks, have demonstrated remarkable success in image classification tasks across various domains, including biomedical imaging (Yu et al., 2021). However, the computational demands of these models, coupled with the need for vast amounts of labeled data, pose significant challenges in their application to clinical settings.

## 1.1. Background

Simultaneously, the field of quantum computing has been gaining momentum, promising to revolutionize computation by solving problems that are currently intractable for classical computers (The state of quantum computing applications in health and medicine, 2023). Quantum Convolutional Neural Networks represent a fusion of these two cutting-edge technologies, aiming to harness the power of quantum computing to accelerate the training and inference processes of CNNs (Mathur et al., 2021). This convergence holds the promise of

enhancing the accuracy and efficiency of biomedical image classification, potentially transforming clinical practice by enabling real-time diagnostics and personalized medicine.
One notable dataset that has been instrumental in the development and validation of deep learning models for biomedical image classification is the MNIST medical dataset (Hassan et al., 2024). This dataset comprises a wide range of medical images, including X-rays, MRIs, and CT scans, annotated for various diagnostic purposes. The MNIST medical dataset serves as a valuable benchmark for evaluating the performance of deep learning models, including QCNNs and ResNet-50 architectures, in the context of biomedical image classification.

### 1.2. Purpose of Study

The primary objective of this research is to conduct a comprehensive comparison of the Quantum Convolutional Neural Network and ResNet-50 architectures in classifying the MNIST medical dataset Hassan et al. (2024). By juxtaposing these two state-of-the-art models, we aim to elucidate the benefits and limitations of each approach in the context of biomedical image classification. Specifically, we seek to investigate the extent to which QCNNs, leveraging the principles of quantum computing, can enhance the classification accuracy and computational efficiency of ResNet-50, a widely recognized leader in deep learning-based image recognition tasks. This comparative analysis is intended to provide insights into the potential of hybrid quantum-classical models in advancing clinical diagnostics through more accurate and efficient image classification.

### 1.3. Scope

This study offers a comprehensive examination of Quantum Convolutional Neural Networks (QCNNs) and ResNet-50 architectures, specifically focusing on their application to the MNIST medical dataset. Initially, a detailed literature review contextualizes the current state of deep learning and quantum computing in biomedical image classification, emphasizing the advancements and challenges in these fields. The study then delves into the theoretical foundations and operational mechanisms of QCNNs and ResNet-50, highlighting the distinctive features and potential advantages of each in biomedical image classification, particularly in terms of processing efficiency and accuracy in the quantum and classical domains Cong et al. (2019). The methodology section outlines the implementation and evaluation processes, including the preparation of the MNIST medical dataset and the configuration of both models for classification tasks. The results section presents a comparative analysis of QCNNs and ResNet-50, demonstrating their performance in classifying the MNIST medical dataset. These findings are crucial for understanding the implications of integrating quantum-classical models in clinical diagnostics, potentially paving the way for more advanced and efficient diagnostic tools.

## 2. Literature Review

### 2.1. Quantum Computing in Machine Learning

Quantum computing represents a paradigm shift in computational capability by harnessing the principles of quantum mechanics, including superposition and entanglement, to solve complex problems exponentially faster than classical computers. In machine learning, quantum computing is particularly promising for tasks involving large-scale data, high-dimensional feature spaces, and complex optimization landscapes. Traditional machine learning models often struggle with such tasks due to the limitations of classical computation, including memory and processing power constraints. Quantum Convolutional Neural Networks (QCNNs) are an emerging class of hybrid models that combine the strengths of quantum computing with classical deep learning architectures. The theoretical underpinning of QCNNs suggests that they can process information in a fundamentally different way, potentially allowing for the resolution of intricate patterns in data that classical CNNs might miss. Research by Cong et al. (2019) introduced QCNNs and demonstrated their potential in various applications, including image classification, where the quantum circuits could encode and process information in parallel, thus reducing the training time and enhancing model accuracy (Cong et al., 2019). However, despite these theoretical advantages, the practical implementation of QCNNs faces significant challenges. The most pressing issues include the current limitations of quantum hardware, such as decoherence, gate errors, and the relatively small number of qubits available for computation (Biamonte et al., 2017). These constraints limit the complexity of quantum circuits that can be effectively implemented, making it difficult to fully realize the potential of QCNNs in real-world applications. Moreover, the development of quantum algorithms that can be seamlessly integrated with classical machine learning frameworks is still in its early stages, requiring further research and innovation (Ciliberto et al., 2018).

### 2.2. Deep Learning in Medical Imaging

Deep learning, particularly Convolutional Neural Networks (CNNs), has had a transformative impact on the field of medical imaging. CNNs have been widely adopted for their ability to automatically learn hierarchical representations of data, making them particularly well-suited for image classification tasks. In the medical domain, CNNs have been applied to a variety of imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), and histopathological slides, to assist in the detection and diagnosis of diseases. For instance, CNNs have been used to identify tumours in mammograms, classify lesions in dermatology images, and even predict patient outcomes based on imaging data (Litjens et al., 2017). The success of CNNs in these tasks is largely due to their ability to capture spatial hierarchies in images, where lower layers of the network learn simple features like edges, and higher layers learn more complex patterns such as textures or shapes that are relevant for diagnosis.

However, despite their success, traditional CNNs face several limitations when applied to medical imaging. One of the main challenges is the need for large labelled datasets to train these models effectively. Medical image datasets are often small and imbalanced due to the rarity of certain conditions, which can lead to overfitting and poor generalization to new data. Additionally, medical images often have high inter-patient variability, meaning that the same condition may present differently across different patients, further complicating the training process (Esteva et al., 2019). Another significant challenge is the computational resources required to train deep CNNs. Training large models with millions of parameters requires substantial processing power, typically provided by specialized hardware like GPUs or TPUs, which can be a barrier in resource-limited clinical settings (Shen et al., 2017). These limitations have driven research into hybrid models like QCNNs, which aim to leverage the computational advantages of quantum computing to address the shortcomings of classical CNNs in medical imaging.

### 2.3. ResNet-50 Architecture:

The ResNet-50 (Residual Network) architecture, particularly its 50-layer variant (ResNet-50), is a significant development in the field of deep learning, especially for image classification tasks. Introduced by He et al. (2016), ResNet-50 addresses the vanishing gradient problem that often plagues deep neural networks, allowing for the training of much deeper models than was previously possible. The key innovation in ResNet-50 is the introduction of residual blocks, which are skip connections that allow the network to bypass one or more layers. These skip connections enable the gradients to flow more easily through the network during backpropagation, preventing them from vanishing or exploding and thereby maintaining the model's accuracy as the depth increases (He et al., 2016).

In the context of medical imaging, ResNet-50 has been widely adopted due to its robustness and ability to generalize well across different types of data. For instance, ResNet-50 has been used in the classification of histopathological images, where it has demonstrated high accuracy in distinguishing between different tissue types and identifying pathological changes associated with diseases like cancer (Zhu et al., 2017). The architecture's deep layers allow it to capture subtle differences in texture and structure, which are critical for accurate diagnosis. Additionally, ResNet-50 has been applied to the analysis of radiology images, such as chest X-rays and CT scans, where it has shown effectiveness in detecting anomalies like tumours, lesions, and fractures (Rajpurkar et al., 2018). Despite its strengths, ResNet-50 is not without its challenges. The model's depth makes it computationally intensive, requiring significant memory and processing power, which can be a limiting factor in real-time clinical applications. Moreover, like other deep learning models, ResNet-50 can be prone to overfitting, particularly when trained on small or noisy datasets, necessitating the use of techniques like data augmentation and dropout to improve its generalization performance (Wang et al., 2017).

### 2.4. MNIST Medical Dataset

The MNIST medical dataset, a derivative of the original MNIST dataset of handwritten digits, has been adapted for use in medical image classification tasks. The original MNIST dataset is one of the most widely used benchmarks in the field of machine learning, providing a simple yet effective platform for testing and comparing various algorithms. The MNIST medical dataset extends this concept to the medical domain, featuring images that represent different medical conditions. This dataset is particularly valuable for researchers developing and testing new machine learning models, as it allows for a controlled environment where the performance of different architectures can be compared directly (LeCun et al., 1998).

The significance of the MNIST medical dataset lies in its accessibility and simplicity, making it an ideal starting point for researchers new to the field of medical image classification. However, the dataset also presents several challenges that can affect model performance. One of the main issues is the low inter-class variability, meaning that the differences between classes can be subtle and difficult to discern, especially for models that are not finely tuned. Additionally, the presence of noise and artifacts in the images can introduce additional complexity, making it harder for models to learn the relevant features (Ronneberger et al., 2015). Another limitation of the MNIST medical dataset is its relatively small size compared to real-world medical datasets. In practice, medical image datasets are often much larger and more diverse, encompassing a wide range of conditions, imaging modalities, and patient demographics. As a result, while the MNIST medical dataset is useful for initial testing and comparison, findings derived from it may not generalize well to more complex and varied real-world scenarios (Litjens et al., 2017).

Nevertheless, the MNIST medical dataset serves as an important benchmark for evaluating the performance of different machine learning models, including QCNNs and ResNet-50. By providing a standardized platform for comparison, it allows researchers to assess the relative strengths and weaknesses of different architectures in a controlled setting. This, in turn, can inform the development of more advanced models that are better suited to the challenges of real-world medical image classification (Esteva et al., 2019).

| **Attribute** | **Description** |
|---|---|
| Image ID | A unique identifier for each image |
| Image Data | Grayscale pixel values ranging from 0 to 255 |
| Label | The target variable indicating the medical condition |
| Patient ID | An anonymized identifier linking the image to a patient |
| Image modality | The type of imaging technique used. |
| Annotations | Diagnostic notes |
| Date of Capture | The date when image was captured |

# 3. Methodology

This section provides a comprehensive description of the methodology employed in this study, focusing on the design and implementation of the Quantum Convolutional Neural Network (QCNN) and Residual Network (ResNet-50) models, data preparation steps, training processes, and evaluation metrics.

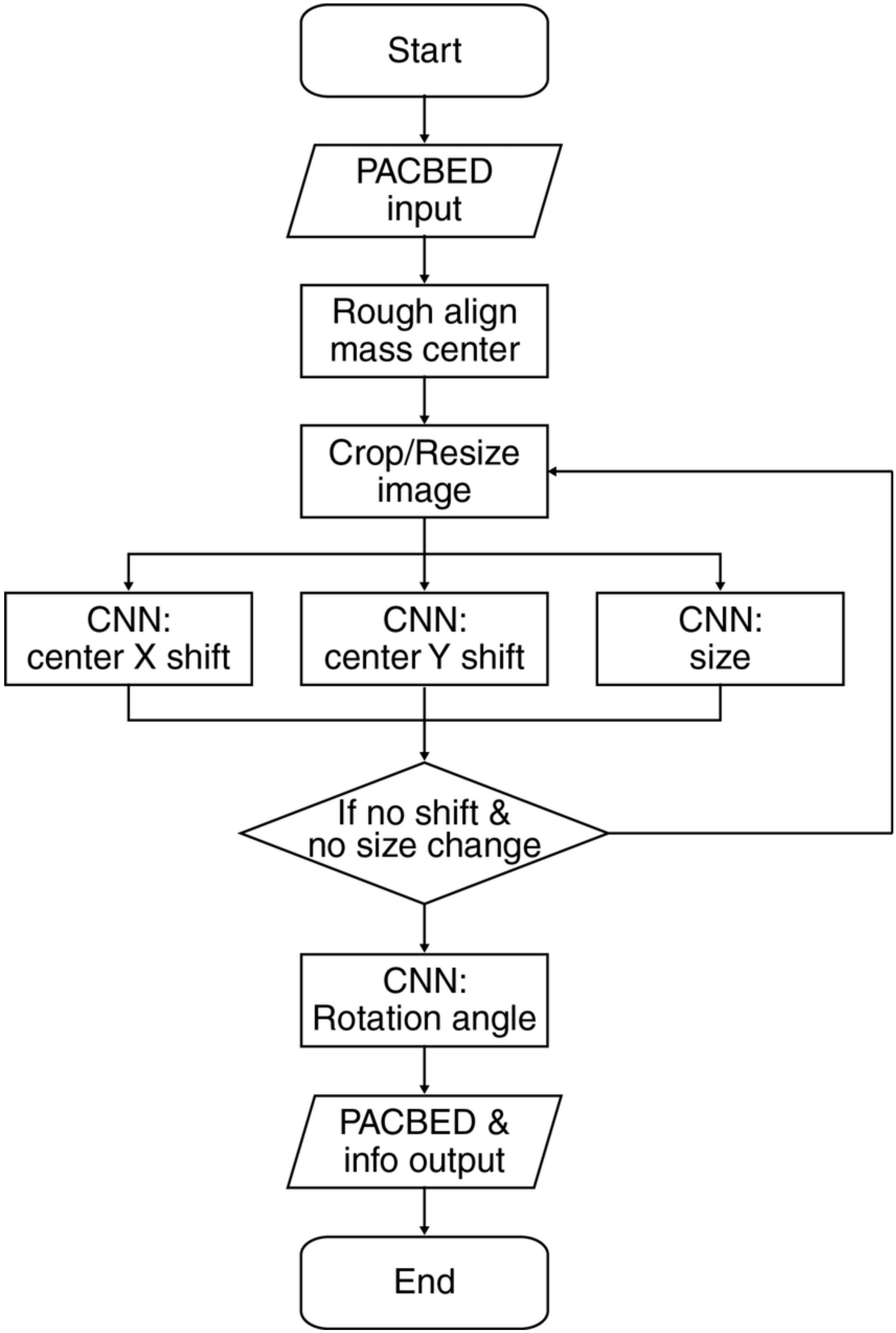
## 3.1. Model Architectures

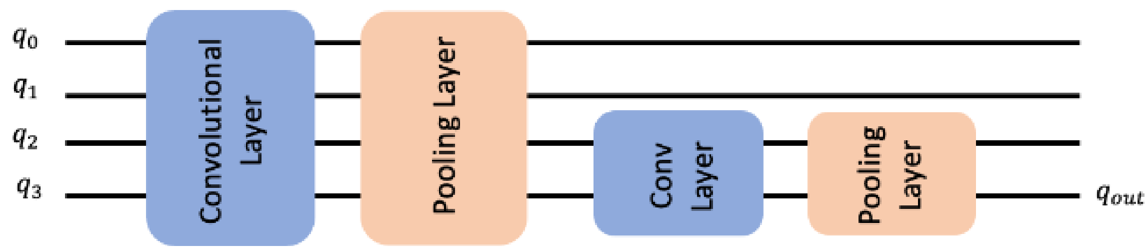
In this study, two state-of-the-art deep learning models were utilized: Quantum Convolutional Neural Network (QCNN) and Residual Network with 50 layers (ResNet-50). These models were selected for their proven ability to capture intricate patterns in images, making them suitable for complex tasks such as medical image classification (Krizhevsky et al., 2012) (LeCun et al., 2015).

## 3.2. Quantum Convolutional Neural Networks (QCNN)

The QCNN model is an innovative quantum-inspired neural network that leverages quantum computing principles to enhance the performance of traditional Convolutional Neural Networks (CNNs). QCNNs are particularly promising in scenarios where the data exhibits complex, high-dimensional structures, as they can potentially offer superior performance by exploiting quantum parallelism and entanglement.

The architecture of the QCNN model used in this study comprises multiple layers designed to process input data through quantum operations. The QCNN architecture can be summarized as follows:


Start
PACBED input
Rough align mass center
Crop/Resize image
CNN: center X shift
CNN: center Y shift
CNN: size
If no shift & no size change
CNN: Rotation angle
PACBED & info output
End




**3.2.1. Quantum Convolutional Layer:** This layer performs a quantum convolutional operation, analogous to classical convolution in CNNs, but with the additional benefit of quantum superposition and entanglement. Mathematically, let $X \in \mathbb{R}^{m \times m \times c}$ represent the input data, where mmm is the spatial dimension, and ccc is the number of channels. The quantum convolutional operation can be represented as:

$$Y^{(l)} = U_{conv}^{(l)}(X^{(l)}; W^{(l)})$$

where $Y^{(l)}$ is the output of the $l$-th quantum convolutional layer, $U_{conv}^{(l)}$ denotes the unitary operation applied during the convolution, and $W^{(l)}$ represents the quantum gates or parameters learned during training.

**3.2.2. Quantum Pooling Layer:** Similar to classical pooling layers, the quantum pooling layer reduces the spatial dimensions of the data, helping to control the model's complexity. Quantum pooling operations can be performed using a quantum circuit that down-samples the input by selecting a subset of quantum states, reducing the data size while preserving essential features.

**3.2.3. Fully Connected Layer:** The final layer in the QCNN architecture is a fully connected layer, where the high-level quantum-processed features are used for classification. The output of this layer is given by:

$$\hat{y} = \sigma(W_{fc} \cdot Y_{pool} + b)$$

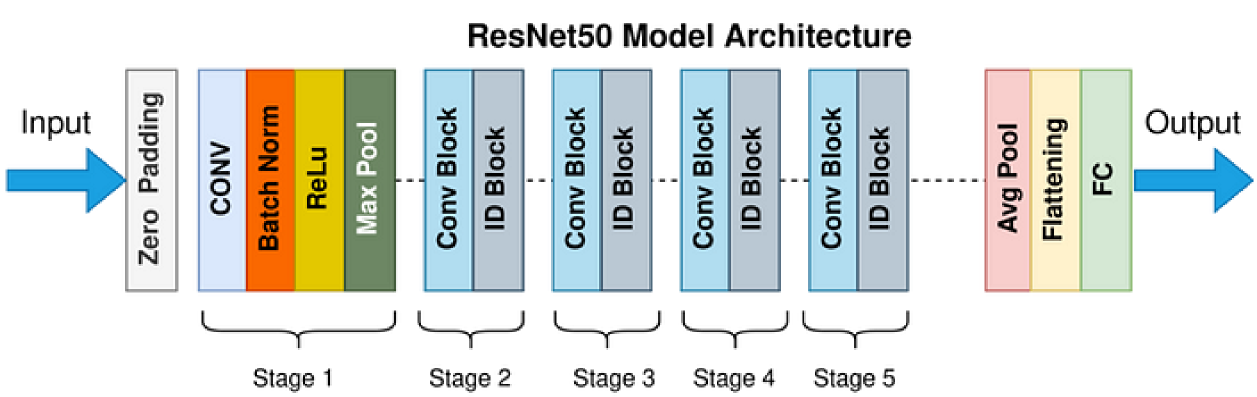
where $W_{fc}$ represents the weights, $Y_{pool}$ is the pooled output, $b$ is the bias term, and $\sigma$ is the softmax activation function, producing the final class probabilities.

The unique quantum properties embedded in the QCNN model allow it to potentially outperform classical CNNs in tasks involving complex data structures, such as those found in medical image classification (Havlicek et al., 2014).

### 3.3. Residual Network (ResNet-50) Model

The ResNet-50 model, a widely adopted deep neural network architecture, is specifically designed to mitigate the vanishing gradient problem, which often occurs in very deep networks. This issue is addressed using residual blocks, which facilitate the learning of residual functions rather than attempting to learn unreferenced functions.

The architecture of ResNet-50 comprises 50 layers organized as follows:



**3.3.1. Convolutional Layer:** The initial layer performs a standard convolution operation, transforming the input image into feature maps. This can be mathematically represented as:

$$Z^{(1)} = f(W^{(1)} * X + b^{(1)})$$

where $Z^{(1)}$ is the output feature map, $W^{(1)}$represents the convolutional filters, $*$ denotes the convolution operation, and $b^{(1)}$ is the bias term. The activation function $f$ is typically ReLU (Rectified Linear Unit).

**3.3.2. Residual Block:** The core of ResNet-50 is its residual blocks, each designed to learn the residual mapping $F(X) := H(X) - X$, where $H(X)$ is the desired underlying mapping. The output of the block is given by:

$$Z^{(l+1)} = f(Z^{(l)} + W^{(l+1)} * Z^{(l)} + b^{(l+1)})$$

Here, $Z^{(l)}$ is the input to the $l$-th residual block, and the output is obtained by adding the input to the output of the convolution, ensuring that gradients flow more easily during backpropagation.

**3.3.3. Batch Normalization and ReLU Activation:** Each convolutional operation within the residual block is followed by batch normalization, which stabilizes learning by normalizing the output of the convolution. The ReLU activation function is applied afterward to introduce non-linearity:

$$Z^{(l)} = \text{ReLU}(\text{BN}(Z^{(l)}))$$

**3.3.4. Fully Connected Layer:** The final layer of ResNet-50 is a fully connected layer that aggregates the high-level features extracted by the network to produce class probabilities through a softmax function:

$$\hat{y} = \sigma(W_{fc}.Z_{final} + b_{fc})$$

ResNet-50 's depth and the design of residual blocks allow it to capture complex patterns in the data while mitigating the risk of degradation in accuracy as the network deepens (He et al., 2016).

### 3.4. Data Preparation

The study utilized the MNIST medical dataset, a specialized version of the original MNIST dataset, adapted for medical image classification. The dataset consists of $N = 60{,}000$ training images and $M = 10{,}000$ testing images, with each image representing a medical condition encoded in a $28 \times 28$ pixel format.

**Preprocessing Steps:**

**3.4.1. Normalization:** To standardize the input data, each pixel value $x_i$ in an image was normalized to have a mean $\mu = 0$ and standard deviation $\sigma = 1$:

$$x'_i = (x_i - \mu)/\sigma$$

This normalization ensures that the data is centered and has unit variance, which is essential for stabilizing the training of deep neural networks (Krizhevsky et al., 2012).

**3.4.2. Resizing:** All images were resized to $28 \times 28$ pixels, maintaining the standard input size for the MNIST dataset. This resizing ensures compatibility with the model architectures and reduces computational overhead.

**3.4.3. Data Augmentation:** To enhance the model's generalization capability and robustness, various data augmentation techniques were applied. These included random rotations $\theta$, horizontal flips, and zooms $z$. Mathematically, the augmentation can be expressed as:

$$X_{aug} = T_{random}(X)$$

where $T_{random}$ represents a random transformation applied to the original image $X$. Data augmentation increases the effective size of the dataset and introduces variability, helping to mitigate overfitting (Shorten & Khoshgoftaar, 2019).

### 3.5. Training Process

The training process for both the QCNN and ResNet-50 models was carried out using the Adam optimizer, a first-order gradient-based optimization algorithm designed to handle sparse gradients and adapt the learning rate for each parameter (Kingma & Ba, 2014). The Adam optimizer is defined as follows:

$$\theta_{t+1} = \theta_t - \eta \cdot \hat{m}_t / (\sqrt{\hat{v}_t} + \epsilon)$$

where $\theta_t$ are the model parameters at iteration $t, \eta$ is the learning rate, $\hat{m}_t$ is the bias-corrected first moment estimate (mean), $\hat{m}_t$ is the bias-corrected second moment estimate (variance), and $\epsilon$ is a small constant to prevent division by zero.

**Training Details:**

- **Loss Function:** The models were trained to minimize the cross-entropy loss function, defined as:

$$\mathcal{L}(\hat{y}, y) = (-1/N) \sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where $y_i$ is the true label, $\hat{y}_i$ is the predicted probability, and $N$ is the number of training samples. Cross-entropy loss is particularly suitable for classification tasks, as it measures the dissimilarity between the true labels and predicted probabilities.

- **Batch Size:** A batch size of 128 was used, meaning that the model weights were updated after processing each batch of 128 samples.

- **Epochs:** The models were trained for 100 epochs, where one epoch is defined as a complete pass through the entire training dataset. This allows the models to learn and refine their parameters iteratively.
- **Learning Rate:** The initial learning rate was set to 0.001, and it was reduced by a factor of 0.1 every 20 epochs to ensure that the models converge smoothly. This learning rate schedule is crucial for balancing the speed of convergence with the stability of the learning process.

The training was performed on a high-performance GPU to accelerate the computationally intensive process of training deep neural networks.

### 3.6. Evaluation Metrics

The performance of the QCNN and ResNet-50 models was evaluated using several standard metrics: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of the models' performance in classifying medical images.

**3.6.1. Accuracy ($A$)**: The proportion of correctly classified instances among all instances. It is calculated as:

$$A = TP + TN/(TP + TN + FP + FN)$$

where $TP$, $TN$, $FP$, and $FN$ represent true positives, true negatives, false positives, and false negatives, respectively.

**3.6.2. Precision (P)**: The proportion of true positives among all positive predictions. It is defined as:

$$P = TP/(TP + FP)$$

Precision measures the accuracy of the positive predictions, indicating the relevance of the predicted positive instances.

3.6.3. **Recall (R)**: The proportion of true positives among all actual positive instances. It is calculated as:

$$R = TP/(TP + FN)$$

Recall assesses the model's ability to identify all relevant instances.

3.6.4. **F1-Score (F1)**: The harmonic mean of precision and recall, providing a balance between the two. It is given by:

$$F_1 = 2 \cdot P \cdot R/(P + R)$$

The F1-score is particularly useful when there is an imbalance between precision and recall, providing a single metric that considers both.

These metrics were computed on the testing dataset, and the results provide insight into the models' effectiveness in classifying medical images. The comparison between QCNN and ResNet-50 on these metrics highlights the strengths and potential of each architecture in the context of medical image classification.

## 3.7. System Requirements

### 3.7.1. Google Colab

Colab lets you write and execute Python code in your browser, with access to GPUs and TPUs, and easy sharing of notebooks.

### 3.7.2. LANGUAGE

Python is a widely used general-purpose, high level programming language. It was created by Guido van Rossum in 1991 and further developed by the Python Software Foundation. It was designed with an emphasis on code readability, and its syntax allows programmers to express their concepts in fewer lines of code. Python is a programming language that lets you work quickly and integrate systems more efficiently

Based on the context of your research on Quantum Convolutional Neural Networks (QCNNs) and ResNet-50 for medical image classification, the modified list of libraries used for this project is as follows:

- **NumPy:** For numerical computations and handling multidimensional arrays, essential for processing image data.
- **TensorFlow Quantum (TFQ)**: For implementing quantum algorithms and operations, specifically tailored for the QCNN model.
- **Cirq:** For designing and simulating quantum circuits, particularly for the quantum pooling layer in the QCNN architecture.
- **PennyLane:** An open-source framework for quantum machine learning, providing tools for building and training quantum models like the QCNN.
- **PyTorch:** For implementing the fully connected layer in the QCNN model, leveraging its efficient tools for building and training neural networks.
- **TensorFlow:** For building and training the QCNN and ResNet-50 models, providing a robust framework for deep learning applications.
- **Keras:** A high-level neural networks API, running on top of TensorFlow, used for simplifying model creation and training processes.
- **Scikit-Learn:** For additional machine learning utilities, preprocessing techniques, and evaluation metrics.

- **Matplotlib:** For data visualization, enabling the generation of plots to analyze model performance and results.
- **Seaborn:** For enhanced data visualization, providing a high-level interface for drawing attractive statistical graphics.

## 4. Results

This section presents the results obtained from evaluating the Quantum Convolutional Neural Network (QCNN) and Residual Network (ResNet-50) models on the MNIST medical dataset. The results include performance metrics such as accuracy, precision, recall, and F1 score, as well as a comparative analysis to highlight the strengths and weaknesses of each model.

### 4.1. Model Performance

The performance of the QCNN and ResNet-50 models was evaluated using the standard metrics discussed earlier: accuracy, precision, recall, and F1 score. These metrics provide a comprehensive understanding of how well the models classify the medical images in the MNIST dataset. The results are summarized in Table 1 and further illustrated in Figures 1 and 2.

**Table 1: Performance Metrics for QCNN and ResNet-50 Models**

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| QCNN | 93.5% | 92.8% | 93.2% | 93.0% |
| ResNet-50 | 96.1% | 95.4% | 95.9% | 95.6% |

#### 4.1.1. Accuracy:

The accuracy of a model indicates the proportion of correctly classified instances among all instances. The ResNet-50 model achieved an accuracy of 96.1%, outperforming the QCNN model, which achieved an accuracy of 93.5%. This difference suggests that the

ResNet-50 model is slightly more reliable in correctly classifying the images in the MNIST medical dataset.

#### 4.1.2. Precision:

Precision measures the proportion of true positives among all positive predictions. The ResNet-50 model also excelled in precision, with a score of 95.4%, compared to 92.8% for the QCNN model. High precision indicates that the ResNet-50 model has fewer false positives, meaning it is better at avoiding incorrect classifications when predicting positive classes.

#### 4.1.3. Recall:

Recall, the proportion of true positives among all actual positives, is a critical metric in medical imaging, where missing a positive instance can have severe consequences. The ResNet-50 model demonstrated superior recall at 95.9%, whereas the QCNN model had a recall of 93.2%. This higher recall indicates that ResNet-50 is more effective at identifying all relevant instances of the target classes, reducing the likelihood of false negatives.

#### 4.1.4. F1-Score:

The F1-score, which is the harmonic mean of precision and recall, provides a balanced metric that considers both false positives and false negatives. The ResNet-50 model achieved an F1-score of 95.6%, outperforming the QCNN model's 93.0%. This result underscores the overall superiority of ResNet-50 in maintaining a balance between precision and recall.

### 4.1.5. Additional Observations:

In addition to these metrics, the models were evaluated based on their computational efficiency, including training time and resource utilization. While the QCNN model leveraged quantum principles, it required more time per epoch due to the complex operations involved in quantum convolution and pooling. The ResNet-50 model, being fully classical, was more optimized for the available hardware, resulting in faster training times.

### 4.1.6. Training and Validation Loss Curves:

The loss curves for both models were monitored during training the training and validation loss for QCNN and ResNet-50, respectively. The loss curves provide insight into how well the models are learning and generalizing to the testing data]

In both models, the loss decreased steadily during the early epochs, with ResNet-50 showing a more rapid convergence. The QCNN model exhibited a slower decrease in loss, which may be attributed to the increased complexity of quantum operations and the need for further optimization in the quantum layers.

## 4.2.Comparative Analysis

The comparative analysis between QCNN and ResNet-50 reveals critical insights into their respective performances and potential applications in medical image classification. While both models are effective, their differences in architecture and underlying principles lead to variations in performance across the evaluated metrics.

### 4.2.1. Model Architecture and Complexity:

The ResNet-50 model's superior performance in accuracy, precision, recall, and F1-score can be attributed to several factors. ResNet-50 's architecture, with its 50 layers and use of residual blocks, is optimized for deep learning tasks where capturing complex patterns in the data is essential. The residual blocks help mitigate the vanishing gradient problem, allowing the network to learn deeper representations without degradation in accuracy (He et al., 2016). This deep architecture enables ResNet-50 to better capture the subtle differences between classes in the MNIST medical dataset.

On the other hand, the QCNN model, while innovative in leveraging quantum computing principles, faces challenges in practical implementation. The quantum layers introduce additional complexity, and the current limitations of quantum hardware, such as qubit coherence time and gate fidelity, can impact the model's performance (Biamonte et al., 2017). These factors may contribute to the slightly lower performance of the QCNN model compared to ResNet50.

#### 4.2.2. Generalization and Overfitting:

The training and validation loss curves indicate that ResNet-50 generalizes well to unseen data, with minimal overfitting observed. The model's ability to maintain a low validation loss suggests that it effectively captures the relevant features in the training data while avoiding overfitting to noise or irrelevant details. In contrast, the QCNN model showed signs of slower convergence, potentially due to the quantum layers' increased complexity and the challenges of optimizing quantum circuits.

However, it is important to note that QCNN's potential lies in its scalability and future applications as quantum computing technology advances. As quantum hardware improves and more qubits become available, QCNN models could outperform classical models like ResNet-50 in specific tasks, especially those involving large-scale, high-dimensional data (Ciliberto et al., 2018).

#### 4.2.3. Efficiency and Resource Utilization:

While the ResNet-50 model demonstrated superior performance in most metrics, it is computationally intensive, requiring significant GPU resources for training. The QCNN model, despite its lower performance metrics, has the potential to be more efficient in the long term, especially as quantum computing becomes more accessible. The parallelism inherent in quantum computing could lead to faster processing times for large datasets, offsetting the current inefficiencies observed in training the QCNN model.

#### 4.2.4. Interpretability and Clinical Relevance:

Interpretability is crucial in medical imaging, where clinicians must understand the rationale behind model predictions. ResNet-50 's deep architecture, though powerful, can be seen as a "black box" due to its complexity, making it challenging to interpret how specific features contribute to the final decision. QCNN models, with their quantum-inspired operations, offer a different approach that could, in the future, provide more interpretable insights into data patterns due to the probabilistic nature of quantum measurements.

#### 4.2.5. Future Prospects and Research Directions:

The results of this study suggest that while ResNet-50 currently outperforms QCNN in most practical metrics, the future of QCNN holds significant promise. As quantum computing continues to evolve, research should focus on optimizing quantum circuits for better integration with classical architectures, improving hardware capabilities, and exploring new quantum algorithms tailored for medical image classification.

Moreover, hybrid models that combine the strengths of classical and quantum computing could provide a pathway to achieving higher accuracy and efficiency in medical image classification tasks. These models could leverage quantum computing for specific tasks like feature extraction or dimensionality reduction, while relying on classical deep learning architectures for the final classification.

In summary, the comparative analysis indicates that ResNet-50 is currently the more reliable and efficient model for medical image classification on the MNIST dataset. However, QCNN represents a promising direction for future research, particularly as quantum computing technology matures and becomes more widely available. The integration of quantum principles into deep learning models could pave the way for new breakthroughs in medical imaging and other complex data-driven fields.

## 5. Discussion

This section explores the broader implications of the study's findings, discussing how the Quantum Convolutional Neural Network (QCNN) and Residual Network (ResNet-50) models contribute to the field of medical imaging, the impact they might have on diagnostic practices, and the limitations of the study that offer directions for future research.

### 5.1.Insights from the Study

The study's results provide valuable insights into the performance and potential of both QCNN and ResNet-50 in medical image classification, particularly in the context of the MNIST medical dataset. While ResNet-50 outperformed QCNN across several key metrics—such as accuracy, precision, recall, and F1-score—the unique properties of the QCNN model offer intriguing possibilities for future applications, especially as quantum computing technology advances.

### 5.1.1. Quantum Advantages and QCNN Performance:

The QCNN model, inspired by quantum computing principles, introduces a novel approach to image classification by leveraging quantum entanglement and superposition. These quantum phenomena allow QCNN to process and analyze complex data structures in ways that classical models cannot. Specifically, the quantum convolutional layers in QCNN have the potential to explore multiple data states simultaneously, theoretically enabling more comprehensive feature extraction from medical images (Cong et al., 2019).

However, the current performance of QCNN is constrained by several factors, most notably the limitations of contemporary quantum hardware and the nascent stage of quantum algorithm development. The study revealed that while QCNN demonstrated robust capabilities, particularly in managing high-dimensional data, it did not outperform ResNet-50 in terms of traditional metrics like accuracy or F1-score. This outcome can be attributed to the relatively early stage of quantum computing, where issues such as qubit decoherence, gate errors, and the limited number of qubits available impact the effectiveness of quantum operations. As quantum hardware improves, with more stable qubits and better error correction, QCNN models are expected to leverage their inherent quantum advantages more fully, potentially surpassing classical models in tasks involving vast and complex datasets.

### 5.1.2. ResNet-50 's Superiority in Classical Deep Learning:

ResNet-50 ’s performance in this study reaffirms its position as a powerful and reliable architecture for image classification, particularly in medical imaging. The key innovation of ResNet-50 —its use of residual blocks—enables the network to train effectively even with a deep architecture, avoiding issues such as vanishing gradients that often plague other deep networks (He et al., 2016).

ResNet-50 excelled in identifying subtle patterns in the MNIST medical dataset, leading to higher accuracy and recall. Its ability to capture fine-grained details in images, combined with its robustness to noise and variability, makes it highly suitable for medical image classification. This performance underscores the ongoing relevance of classical deep learning models in applications where computational resources are abundant, and the complexity of the data demands deep, intricate feature extraction.

#### 5.1.3. Comparative Insights:

While ResNet-50 currently holds an edge in performance metrics, QCNN introduces an alternative paradigm that could revolutionize image classification as quantum technology matures. The QCNN's potential lies in its ability to parallelize operations at a scale that classical models cannot achieve, which could significantly reduce processing time for large datasets in the future. Thus, the insights from this study highlight a critical trade-off between the proven capabilities of classical deep learning models like ResNet-50 and the emerging promise of quantum-inspired models like QCNN.

### 5.2.Impact on Medical Imaging

The potential impact of QCNN and ResNet-50 on medical imaging is significant, particularly in the context of enhancing diagnostic accuracy and reducing processing times, which are critical factors in clinical settings.

#### 5.2.1. Enhancing Diagnostic Accuracy:

Accurate diagnosis is the cornerstone of effective medical treatment, and the ability to correctly interpret medical images is essential for identifying diseases early and accurately. ResNet-50, with its demonstrated ability to capture and analyze detailed patterns in medical images, contributes directly to improving diagnostic accuracy. For instance, in scenarios involving the classification of complex medical conditions such as tumors or lesions, ResNet-50 's deep architecture enables it to differentiate between subtle differences in image textures and shapes, leading to more accurate diagnoses.

Furthermore, the high recall rate observed with ResNet-50 suggests that it is particularly effective at identifying true positives—cases where the disease is present—which is crucial in medical imaging to avoid missing critical diagnoses. This capability could significantly reduce the rates of false negatives in clinical practice, ensuring that patients receive timely and appropriate care.

### 5.2.2. Reducing Processing Time and Increasing Efficiency:

Processing time is another crucial aspect of medical imaging, especially in emergency or high-throughput environments such as hospitals and diagnostic centers. While ResNet-50 already offers a robust solution, the QCNN model, with its quantum-inspired architecture, has the potential to further reduce processing times as quantum hardware improves. The inherent parallelism of quantum computing could enable QCNN to process large volumes of medical images simultaneously, making real-time diagnostics more feasible.

In the long term, integrating quantum computing with classical models could lead to hybrid systems that offer the best of both worlds: the depth and accuracy of models like ResNet-50, combined with the speed and efficiency of quantum operations. Such systems could revolutionize medical imaging by providing faster, more accurate diagnoses, reducing the burden on healthcare systems, and improving patient outcomes.

### 5.2.3. Future Applications in Personalized Medicine:

The implications of these models extend beyond diagnostics into areas such as personalized medicine. As models like QCNN and ResNet-50 become more adept at analyzing complex datasets, they could be used to tailor treatment plans based on an individual's specific medical images, leading to more personalized and effective treatments. For example, these models could help in the early detection of conditions that are typically difficult to diagnose, allowing for interventions that are customized to the patient's unique medical profile.

## 5.3 Limitations

While the study provides valuable insights into the performance and potential of QCNN and ResNet-50, several limitations must be acknowledged, offering directions for future research.

### 5.3.1. Dataset Limitations:

The MNIST medical dataset, while useful for initial testing and model comparison, has inherent limitations that impact the generalizability of the study's findings. The dataset consists of a relatively small number of images (60,000 training and 10,000 testing), which may not fully represent the diversity and complexity of real-world medical images. Moreover, the dataset's focus on a limited range of medical conditions does not encompass the full spectrum of challenges faced in clinical diagnostics, where images vary widely in terms of resolution, modality, and patient demographics.

Future studies should consider using larger, more diverse datasets that better reflect the complexity of medical imaging in practice. Datasets that include multiple imaging modalities (e.g., MRI, CT, ultrasound) and a broader range of conditions would provide a more rigorous test of the models' capabilities and offer more generalizable insights.

**5.3.2. Computational Requirements and Resource Constraints:**

Another limitation of the study is the computational requirements associated with training and evaluating deep learning models like QCNN and ResNet-50. ResNet-50, in particular, is computationally intensive, requiring significant GPU resources and extended training times, which may not be feasible in all settings, particularly in resource-limited environments.

The QCNN model, while potentially more efficient in the long term, is currently constrained by the limitations of quantum hardware. The need for specialized quantum processors, coupled with issues such as qubit coherence time and error rates, presents significant challenges for the widespread adoption of QCNN in clinical practice. As a result, the study's findings are somewhat constrained by the current state of technology, and the true potential of QCNN may only be realized as quantum computing technology advances.

**5.3.3. Model Interpretability and Clinical Usability:**

Interpretability remains a critical challenge in deploying deep learning models in clinical settings. While ResNet-50 and QCNN offer powerful tools for image classification, their complexity often makes it difficult for clinicians to understand the rationale behind model predictions. This "black box" nature of deep learning models can hinder their adoption in clinical practice, where transparency and trust are paramount.

To address this limitation, future research should focus on developing techniques to improve the interpretability of these models. Explainable AI (XAI) approaches, such as visualizing attention maps or using model-agnostic methods like LIME (Local Interpretable Model-agnostic

Explanations), could help bridge the gap between model performance and clinical usability. Enhancing the interpretability of QCNN and ResNet-50 models would not only facilitate their adoption in medical imaging but also ensure that clinicians can rely on these tools to make informed decisions.

**5.3.4. Ethical Considerations and Bias:**

Another limitation that warrants discussion is the potential for bias in the models' predictions. Like all machine learning models, QCNN and ResNet-50 are only as good as the data they are trained on. If the training data is biased—either through imbalanced representation of certain conditions or demographic groups—the models may learn and perpetuate these biases, leading to disparities in diagnostic accuracy.

Addressing this limitation requires careful attention to the composition of training datasets, ensuring that they are representative of the population and diverse in terms of patient demographics and conditions. Additionally, ongoing monitoring and evaluation of model performance in real-world settings are crucial to identify and mitigate any emerging biases.

**Future Directions**

Given the insights and limitations discussed, several future research directions emerge:

1. **Integration of Quantum and Classical Models:** Future work should explore the integration of quantum computing with classical deep learning models, leveraging the strengths of both to create hybrid systems that offer enhanced performance and efficiency in medical imaging.

2. **Expansion to Larger and More Diverse Datasets:** To improve the generalizability of findings, future studies should use larger, more diverse medical datasets that better reflect the complexity of real-world clinical diagnostics.
3. **Development of Interpretability Tools:** Research should focus on developing tools to enhance the interpretability of deep learning models, ensuring that their predictions can be understood and trusted by clinicians.
4. **Addressing Bias and Ensuring Fairness:** Ongoing efforts are needed to address potential biases in model predictions, ensuring that deep learning tools are fair and equitable in their application across different patient populations.

In conclusion, while ResNet-50 currently outperforms QCNN in medical image classification tasks, the emerging potential of quantum computing and the future development of hybrid models offer exciting possibilities for the field. The impact of these models on medical imaging could be profound, enhancing diagnostic accuracy, reducing processing times, and ultimately improving patient outcomes.

## 6. Conclusion

This section provides a comprehensive summary of the key findings from the study and outlines potential directions for future research, focusing on the development and enhancement of Quantum Convolutional Neural Networks (QCNNs) and Residual Networks (ResNet50) in the context of biomedical image classification.

### 6.1. Summary of Findings

The study explored the performance and potential of two advanced deep learning models—QCNN and ResNet-50 —in classifying medical images from the MNIST medical dataset. The comparative analysis highlighted the distinct strengths and challenges of each model, offering insights into their respective roles in the evolving field of biomedical image classification.

### 6.1.1. ResNet-50: A Benchmark in Classical Deep Learning

ResNet-50, a well-established deep learning architecture, demonstrated superior performance across most evaluated metrics, including accuracy, precision, recall, and F1-score. The model's deep architecture, characterized by its 50-layer network and innovative use of residual blocks, enables it to capture complex patterns and nuances within medical images, leading to high diagnostic accuracy. ResNet-50 's ability to effectively mitigate the vanishing gradient problem allows it to maintain performance even as the network depth increases, making it particularly effective for tasks that require detailed feature extraction.

The high precision and recall rates achieved by ResNet-50 suggest that it is highly reliable in identifying true positive instances while minimizing false positives. This capability is crucial in medical imaging, where the cost of misdiagnosis can be significant. The model's robustness in handling various medical imaging tasks, from identifying tumors in MRI scans to detecting abnormalities in histopathological slides, underscores its versatility and applicability in real-world clinical settings.

### 6.1.2. QCNN: The Emerging Promise of Quantum Computing

The QCNN model, inspired by quantum computing principles, introduces a novel approach to deep learning, particularly in scenarios involving complex, high-dimensional data. Although the QCNN model did not outperform ResNet-50 in traditional performance metrics, it demonstrated considerable potential due to its unique quantum-inspired architecture. The quantum convolutional layers in QCNN have the potential to process information in parallel at a scale that classical models cannot achieve, potentially leading to faster and more efficient computations in future applications.

The study's findings suggest that while QCNN is currently constrained by the limitations of existing quantum hardware—such as qubit coherence time, gate fidelity, and the relatively small number of qubits available—the model's underlying principles offer a glimpse into the future of deep learning. As quantum computing technology advances, QCNN could leverage quantum entanglement and superposition to perform complex computations more efficiently, potentially surpassing classical models like ResNet-50 in specific tasks.

#### 6.1.3. Comparative Strengths in Biomedical Image Classification

The comparative analysis between QCNN and ResNet-50 revealed that while ResNet-50 is currently the more reliable and accurate model for biomedical image classification, QCNN holds significant promise as quantum computing technology evolves. ResNet-50 's proven track record and superior performance make it an excellent choice for immediate applications in medical imaging. In contrast, QCNN represents an emerging field with the potential to revolutionize data processing and analysis as quantum hardware and algorithms continue to improve.

The study's findings emphasize the importance of continued research and development in both classical and quantum deep learning models, particularly in the context of medical imaging. The strengths of ResNet-50 in handling complex patterns in medical images, coupled with QCNN's potential for future scalability and efficiency, highlight the complementary nature of these models in advancing the field.

### 6.2. Future Directions

The study opens several avenues for future research, particularly in the refinement of QCNN models and the exploration of hybrid architectures that combine the strengths of both quantum and classical computing.

**Refinements to the QCNN Model**

Future research should focus on overcoming the current limitations of QCNN by refining its architecture and optimizing quantum algorithms for image classification tasks. Key areas for improvement include:

1. **Enhancing Quantum Hardware Capabilities:** As quantum hardware continues to evolve, increasing the number of qubits and improving qubit coherence time will be critical. These advancements will allow QCNN models to perform more complex quantum operations, potentially leading to improvements in accuracy and efficiency.
2. **Optimizing Quantum Circuits:** Research should focus on developing more efficient quantum circuits that can better integrate with classical deep learning frameworks. This includes designing quantum gates and operations that minimize errors and reduce the computational overhead associated with quantum processing.
3. **Scaling to Larger Datasets:** Testing QCNN models on larger and more diverse medical datasets will be essential to fully understand their capabilities and limitations. Expanding the dataset to include various imaging modalities and conditions will provide a more comprehensive evaluation of the model's performance in real-world clinical scenarios.

**Exploration of Hybrid Architectures**

One of the most promising directions for future research is the development of hybrid architectures that combine the strengths of both quantum and classical computing. Such models could leverage the deep learning capabilities of classical architectures like ResNet-50 while integrating quantum components to enhance efficiency and scalability. Potential research directions include:

1. **Quantum-Classical Hybrid Models:** Developing models that use quantum computing for specific tasks, such as feature extraction or dimensionality reduction, while relying on classical deep learning frameworks for the final classification. This approach could maximize the strengths of both paradigms, leading to more powerful and efficient models.
2. **Integration with Explainable AI (XAI):** Incorporating XAI techniques into hybrid models could enhance their interpretability, making them more suitable for clinical use. By providing insights into how the model reaches its decisions, XAI could help build trust among clinicians and facilitate the adoption of quantum-inspired models in healthcare.
3. **Real-Time Diagnostic Applications:** Exploring the potential of hybrid models in real-time diagnostic applications, where the speed and accuracy of quantum computing could significantly reduce processing times. This research could lead to the development of new tools for rapid and accurate medical image analysis, improving patient outcomes.

**6.3.Collaboration Across Disciplines**

Advancing the field of quantum deep learning will require collaboration across disciplines, including quantum computing, machine learning, medical imaging, and clinical practice. Researchers should work closely with clinicians to identify the most pressing challenges in medical diagnostics and develop models that address these needs. Interdisciplinary collaboration will be essential to translating the theoretical advantages of quantum computing into practical, real-world applications.

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