Image Classification using Quantum Machine Learning Models, A Comparison Analysis

Report submitted to the SASTRA Deemed to be University

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INT430: ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

Submitted by

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Signature of Project Supervisor :

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Date :

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Date :

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ABSTRACT

Image classification is a foundational task across numerous industries, yet it faces significant computational challenges due to the rapid expansion of visual data. This project addresses these challenges by introducing two quantum machine learning models that harness the principles of quantum mechanics for more efficient computations. The first model, a hybrid quantum neural network (HQNN) with parallel quantum circuits, is specifically designed to operate effectively within the noisy intermediate-scale quantum (NISQ) era, where large-scale qubit circuits are not yet feasible. This HQNN achieved an unprecedented classification accuracy of 99.21% on the full MNIST dataset, surpassing known quantum–classical models and demonstrating eight times fewer parameters compared to its classical counterpart. Additionally, testing this model on Medical MNIST (achieving over 99% accuracy) and CIFAR-10 (achieving over 82% accuracy) supports its generalizability and highlights the efficiency of quantum layers in capturing common features in diverse input data.The second model introduces a novel Quanvolutional layer within a hybrid quantum neural network, applying a quantum-driven convolutional process to reduce image resolution while extracting critical features. This model matched the performance of a classical model while utilizing only a quarter of the trainable parameters, and it outperformed classical models with comparable parameter counts.

These findings underscore the advancements made in quantum machine learning (QML) for image classification, demonstrating that quantum-enhanced models can achieve superior accuracy with reduced parameter requirements. This research highlights the potential of quantum circuits to improve feature extraction efficiency, offering a promising pathway toward more accurate and scalable image classification systems in data-intensive fields.

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Key Words

Image Classification ,Quantum Machine Learning, Hybrid Quantum Neural Network, Classification Accuracy, Training Parameters, Feature Extraction, *Scalability.*

List of Figures

ABBREVIATIONS

HQNN	Hybrid Quantum Neural Network
MNIST	Modified National Institute of Standards and Technology
PQC	Parameterized Quantum Circuit

CHAPTER 1

INTRODUCTION & Literature Review

1.1. INTRODUCTION

Image classification is essential across various sectors, providing practical applications that significantly influence industries such as healthcare and autonomous vehicles. In the realm of medical imaging, classification algorithms improve both diagnostic accuracy and speed, while in autonomous driving, they are crucial for object detection and safe navigation. Deep learning techniques, particularly deep convolutional neural networks (CNNs), have achieved remarkable success in image classification tasks, establishing new performance benchmarks. However, the increasing volume of visual data poses considerable computational challenges for traditional neural networks.

Quantum technologies offer a promising avenue to address these challenges by utilizing quantum mechanics for parallel computations. Quantum machine learning (QML), an emerging field, merges quantum mechanics with classical machine learning techniques to tackle complex computational problems that are often intractable for classical computers. The unique properties of quantum computing, such as superposition and entanglement, provide the potential for exponential speedup in machine learning tasks, enhancing classification performance by enabling exploration of a larger search space. Although the application of QML in real-world scenarios is still nascent—primarily due to challenges like error correction and the sensitivity of quantum systems—it has shown significant potential for efficiently processing large image datasets.

Recent research has investigated hybrid quantum-classical models, such as hybrid quantum neural networks (HQNNs), which leverage the strengths of both classical and quantum computing. These hybrid models combine classical deep learning architectures with quantum algorithms, including parameterized quantum circuits (PQCs), to process large datasets more effectively. HQNNs have demonstrated promise across various industries, including healthcare, finance, and aerospace, but further research is necessary to fully realize their potential in image classification.

In this study, we propose two innovative approaches to integrate quantum computing into image recognition tasks. The first approach employs parallel PQCs following classical convolutional layers, while the second introduces an HQNN featuring a quanvolutional layer. We evaluate these hybrid models using the MNIST dataset of handwritten digits to assess their image classification performance. While much of the existing research has concentrated on purely quantum or various hybrid models, our work explores the integration of quantum circuits with classical neural networks, an area that remains relatively underexplored. Our novel HQNN architecture operates effectively within the noisy intermediate-scale quantum (NISQ) era, achieving record-breaking classification accuracy with fewer parameters than its classical equivalents, and without relying on pretrained models or transfer learning.

The first model, HQNN-Parallel, integrates classical convolutional layers with parallel quantum layers, akin to a classical fully connected layer. This hybrid model surpasses its classical counterpart, achieving an accuracy of 99.21% with eight times fewer parameters. We also test the model on the Medical MNIST and CIFAR-10 datasets to demonstrate its generalizability. The second model, HQNN-Quanv, features a quanvolutional layer that reduces image resolution, achieving comparable accuracy (67%) to the classical model while utilizing fewer parameters. It also outperforms the classical model with an equivalent number of weights.

While quantum models typically incur higher training and operational costs compared to classical models, advancements in quantum hardware may help bridge this gap in the future. This study underscores the potential of quantum computing and QML in advancing image recognition and other fields, contributing to the expanding body of research in this area and paving the way for future breakthroughs.

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1.2. LITERATURE REVIEW

1.2.1.Image Classification using Convolutional Neural Network, IEEE 2022

This paper focuses on the use of Convolutional Neural Networks (CNNs) for image classification, emphasizing the importance of high-quality feature extraction for effective classification. It provides an explanation of the convolution and pooling operations utilized in the classification process. The study employs the Caltech101 dataset for training the classification model in MATLAB. An example is included to illustrate how to predict the category of an image.

1.2.2.CNN Model for Image Classification on MNIST and Fashion-MNIST Dataset

This paper explores the use of Convolutional Neural Networks (CNNs) for image classification, testing their performance on the MNIST and Fashion-MNIST datasets. It presents five different architectures with varying convolutional layers, filter sizes, and fully connected layers. The experiments involved adjusting hyperparameters such as activation functions, optimizers, learning rates, dropout rates, and batch sizes. Results show that the selection of these hyperparameters significantly affects accuracy, with all architectures achieving over 99% accuracy on the MNIST dataset. For the more complex Fashion-MNIST dataset, Architecture 3 performed the best. Overall, the findings confirm that CNNs are well-suited for classifying images in both datasets.

1.2.3. Quantum machine learning for image classification, Mar 2024

This research addresses computational challenges in image classification by introducing two quantum machine learning models that utilize quantum mechanics for efficiency. The first model, a hybrid quantum neural network with parallel quantum circuits, achieves 99.21% accuracy on MNIST with significantly fewer parameters than its classical counterpart, demonstrating its effectiveness even in the noisy intermediate-scale quantum (NISQ) era. Further testing on Medical MNIST and CIFAR-10 highlights the model's versatility. The second model uses a Quanvolutional layer for image resolution reduction, achieving comparable performance to classical models with fewer parameters. These advancements illustrate the potential of quantum models for more accurate and efficient image classification.

1.2.4.Image Classification Based on Quantum Machine Learning

Machine learning for image classification is common, but the increasing demand for data processing has led to the exploration of quantum machine learning (QML) as an enhancement. QML leverages quantum bits (qubits) that can represent both $|0\rangle$ and $|1\rangle$ states simultaneously, enabling faster and more efficient data processing compared to classical methods.In this study, we used Qiskit to simulate quantum circuits and developed a hybrid quantum-classical neural network model (VQNet) to classify the MNIST and CIFAR-10 datasets. Our experiments showed that QML outperforms classical machine learning in efficiency, accuracy, and security. This research advances quantum computing and offers a new approach to image classification, promoting faster and more accurate QML solutions.

CHAPTER 2

METHODOLOGY

2.1. Dataset

The Modified National Institute of Standards and Technology (MNIST) dataset is a well-known collection of grayscale images featuring handwritten digits from 0 to 9. Sample images from this dataset are shown in Figure 2.1.1. Each image has a resolution of 28x28 pixels, and the goal is to classify each digit by assigning it a label, effectively recognizing the digit displayed. This dataset is widely used as a foundational tool in machine learning, making it valuable for evaluating the performance of various neural network models, particularly those with parameterized quantum circuits (PQCs).

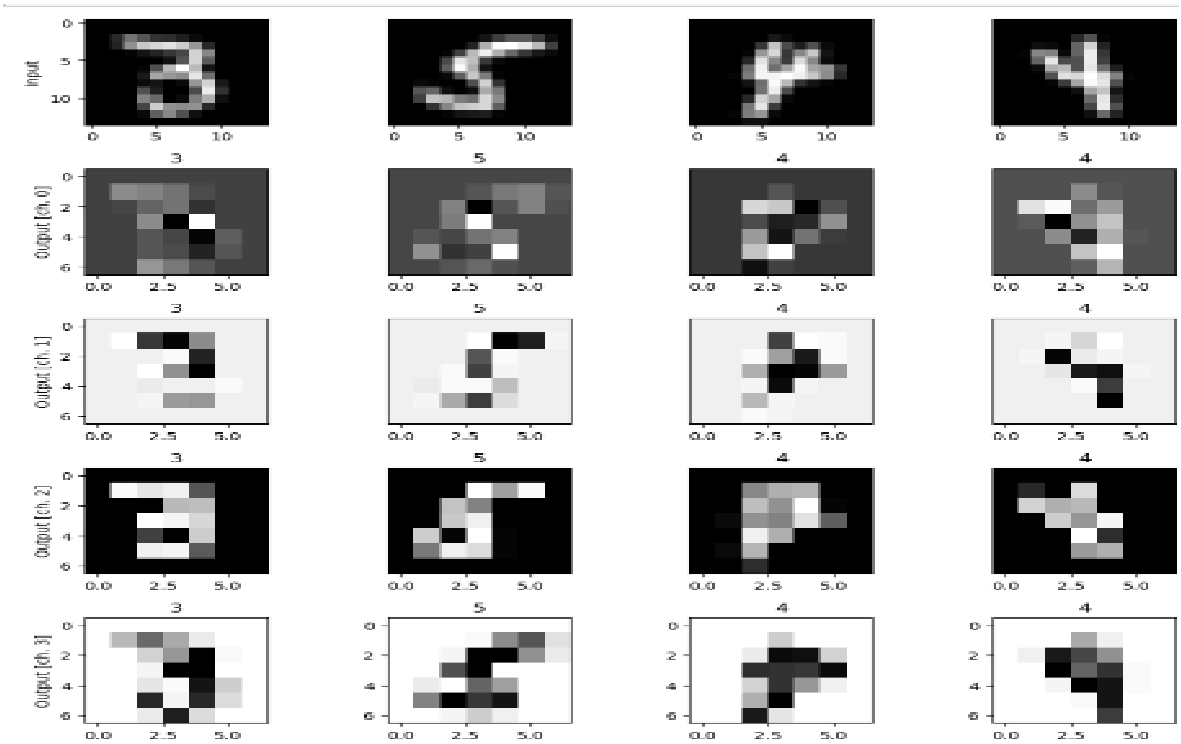


Fig 2.1.1.MNIST Dataset

In this study, we use the MNIST dataset with a total of 70,000 images, split into 60,000 for training and 10,000 for testing. In some cases, it can be advantageous to reduce the dataset size to speed up training and quickly evaluate model performance. Although popular, the MNIST dataset includes a few images that are unclear or ambiguous, posing challenges even for human interpretation.Despite this, our hybrid model achieves over 99% accuracy in accurately classifying such images.

2.2.Methodology

2.2.1.HQNN with Parallel Quantum Dense Layers (HQNN-Parallel)

This section introduces the HQNN with parallel quantum dense layers, each acting as a parameterized quantum circuit (PQC).We compare this hybrid model to its classical counterpart, the CNN. The HQNN-Parallel consists of two key components: a classical convolutional block that reduces input dimensionality, and a combination of classical fully connected layers and parallel quantum layers responsible for predictions. Additional details on the architecture and implementation will follow in the subsequent sections.

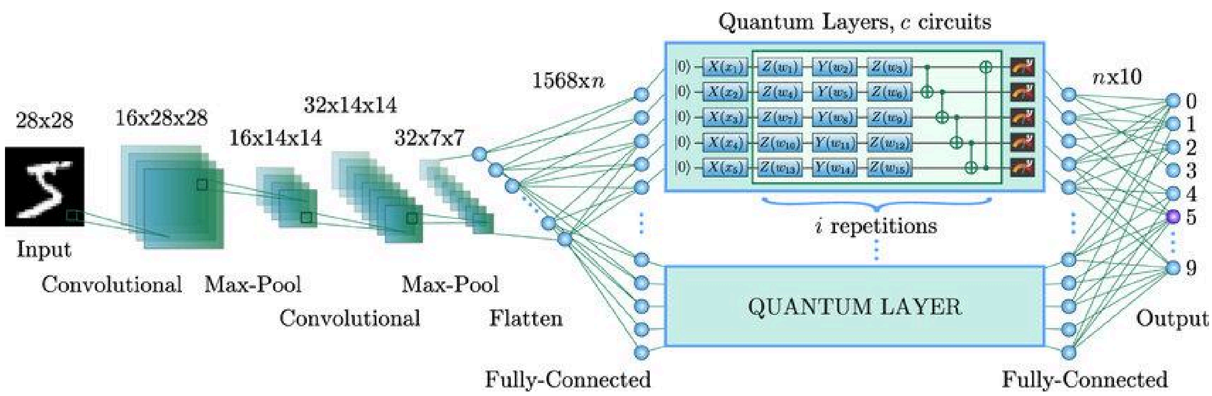


Figure 2.2.1. This figure depicts the architecture of the proposed HQNN-Parallel. The input data undergoes processing through a series of convolutional layers designed to extract essential features while reducing the dimensionality of the input. The output from these layers is flattened into a single vector before being directed into the dense section of the HQNN-Parallel. This dense section features a combination of classical and quantum layers. The quantum layers, illustrated as blue rectangles, employ parallel parameterized quantum circuits (PQCs) to allow for simultaneous execution, which helps to decrease computation time. The upper rectangle provides a closer look at the subsequent

quantum layers and their respective circuit counts. The final output from the last classical fully connected layer results in a predicted digit ranging from 0 to 9.

2.2.1.1. Classical Convolutional Layers

Figure 2.2.1.1 shows the structure of the classical convolutional component of the HQNN-Parallel, which includes two main blocks followed by fully connected layers. We utilize the Rectified Linear Unit (ReLU) as the activation function and apply Batch Normalization to enhance training stability and model accuracy.The first block features a convolutional layer with one input channel and 16 output channels, using a 5×5 kernel with a stride of one pixel and two-pixel padding. This design maintains the input image's spatial dimensions of 28×28 while allowing for the extraction of complex features. After convolution, Batch Normalization, ReLU activation, and 2×2 MaxPooling are applied, resulting in a feature map of 16×14×14 pixels.The second block consists of a convolutional layer with 16 input channels and 32 output channels, maintaining the same kernel size and padding. This block also uses MaxPooling, producing a feature map of 32×7×7 pixels, which feeds into the fully connected layers.

2.2.1.2. Structure of Quantum Layer

The quantum component of the HQNN-Parallel, illustrated in Figure 2.2.1, consists of (c) parallel quantum layers, each a Parameterized Quantum Circuit (PQC) with three main parts: embedding, variational gates, and measurement. The input to these quantum layers comprises (n) features from the preceding classical fully connected layer, divided into (c) segments, each containing (q) values, represented as (x = $\phi_1, \phi_2, ..., \phi_q$) ϵR^q. To encode classical features into quantum Hilbert space, we use the angle embedding method. Each qubit is rotated around the X-axis on the Bloch sphere by an angle proportional to the corresponding input value: $|\varphi \succ = R_x^{emb}(x)|\varphi_0 \succ$, where $|\varphi_0 \succ = |0 \succ^{\otimes q}$. This operation encodes the input vector into quantum space. It is essential that (n) is divisible by (q) so that the input vector can be evenly divided into (c = n/q) parts for each PQC.Following the encoding, the variational part consists of rotations with trainable parameters and CNOT operations, which entangle the qubits. The depth of this variational component, denoted as (i), is a hyperparameter determining the number of iterations of rotations and CNOT operations. Each PQC has unique variational parameters for each of the (i) iterations and for each of the (c) circuits, resulting in a total of (q.3i.c) weights in the quantum section.After these operations, measurement in the Pauli basis is performed, yielding

$$v^{(j)} = \langle 0 | R_x^{\text{emb}}\left(\phi_j\right)^{\dagger} U(\theta)^{\dagger} Y_j U(\theta) R_x^{\text{emb}}\left(\phi_j\right) | 0 \rangle$$

where (Y_j) is the Pauli-Y matrix for the j th qubit, ($R_x^{emb}(\phi_j)$) and ($U(\theta)$) are operations from the embedding and variational parts, respectively, and θ represents the trainable parameters. This results in a vector ($v \in R^q$).The outputs from all PQCs are concatenated to form a new vector ($\hat{v} \in R^n$), which serves as input to a subsequent classical fully connected layer. This final layer produces a probability distribution over ten possible digit classes (0 to 9), with the neuron having the highest output probability being selected as the predicted class for the image. Further theoretical analysis, including ZX-calculus reduction and Fourier expressivity, is provided in the appendix.

2.2.1.3. Training and Results

The HQNN-Parallel model was trained on the MNIST dataset without preprocessing, using all 60,000 training images and 10,000 test images. The goal was to minimize the cross-entropy loss function defined as

$$l = - \sum_{c=1}^{k} y_c \log p_c$$

where p_c is the predicted probability, y_c indicates if the image belongs to the class (0 or 1), and k is the number of classes. Classical layers were optimized with backpropagation in PyTorch, while quantum layer optimization used PennyLane's parameter-shift rule, enabling gradient calculations through small shifts in quantum parameters.The optimal HQNN-Parallel architecture included a quantum layer with 5 qubits and 3 repetitions of strongly entangling layers, achieving 99.21% accuracy on MNIST. A classical CNN variant with equivalent convolution layers but a classical dense layer in place of the quantum layer was also tested for comparison, yielding lower accuracy and requiring eight times more parameters.

Dataset	Model	train loss	test loss	test acc	param num
MNIST	CNN	0.0205	0.0449	98.71	372 234
	HQNN	0.0204	0.0274	99.21	45 194

Fig 2.2.1.4.Summary of the results for the HQNN-Parallel and its classical analog,CNN

Model structures remained similar across datasets, with minor variations in convolution layers and output neurons based on input size and classification requirements, while qubit count and quantum layers stayed constant.

2.2.2.HQNN with quanvolutional layer,HQNN-Quanv

This section provides a detailed description of our second hybrid quantum approach for recognizing numbers in the MNIST dataset, utilizing a combination of a quanvolutional layer and classical fully connected layers, as shown in Figure 2.2.2. We also compare the performance of this hybrid model with its classical CNN counterpart, examining the relationship between quanvolutional and convolutional layers and how it depends on the number of output channels.

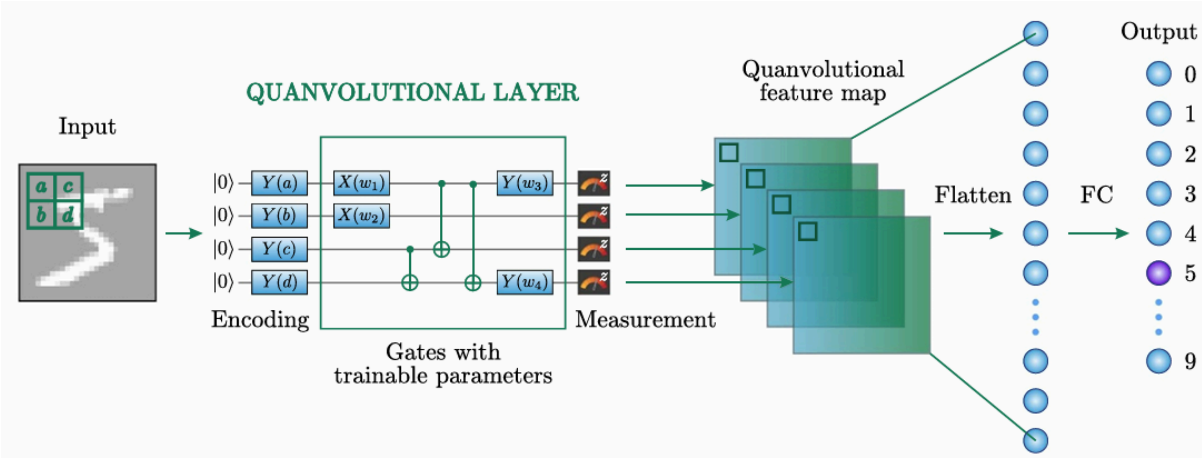


Fig- 2.2.2.The HQNN-Quanv architecture transforms the input image into four quanvolutional feature maps. These maps are concatenated and flattened, then fed into a fully connected classical layer that produces 10 probability scores, corresponding to each class.

2.2.2.1. Quanvolutional Layer

The general architecture of a quanvolutional layer, as illustrated in Figure 2.2.2, shares similarities with classical convolutional layers. It features a kernel of size ($n \times n$) pixels that convolves the input image, resulting in a lower-resolution output image. However, the quanvolutional layer is distinct in that its kernel is realized through a quantum circuit comprising (n_q) qubits. This circuit can be divided into three main components: classical-to-quantum data encoding, variational gates, and quantum measurement. Together, these components define how the kernel interacts with the input image.There are various methods for encoding classical data into quantum states. In this section, as in the previous one, we utilize the "angle embedding" technique. This technique involves rotating the qubits from their initial state |0> using the $R_y(\varphi)$ unitaries, where φ is determined by the value of the corresponding pixel. Once the classical data is encoded, the quantum states undergo unitary transformations defined by the variational component.The variational part of the quanvolutional layer typically includes arbitrary single-qubit rotations and CNOT gates, organized in a specific manner determined by the researcher. The unitaries in the parameterized quantum circuit (PQC) are governed by a set of variational parameters that are adjusted during the training of the neural network. The primary objective of model training is to identify a measurement basis (by fine-tuning the variational gate parameters) that conveys the most information about a portion of the image affected by the quantum kernel.Finally, for each qubit, the expectation value of an arbitrary operator is computed to produce the classical output. Since this output is a real number, it represents the pixel value of the kernel's output, with each qubit corresponding to a different image channel. For example, a quanvolutional kernel of size (2×2) utilizes a 4-qubit circuit, transforming a single input image into four smaller images.

2.2.2.2.Structure of HQNN

The HQNN-Quanv architecture, shown in Figure 2.2.2, begins with angle embedding, where classical data is encoded through $R_y(\varphi)$ single-qubit rotations on each wire, scaling pixel values [0,1] to ψ in [0,Π]. This is followed by a variational circuit with four single-qubit rotations, each parameterized by trainable weights, and three CNOT gates. The circuit ends with measuring the expectation value (σ_z) of the Pauli-Z operator on each qubit, producing 4×4-pixel images per channel. These four channels are then flattened and passed into a fully connected layer, outputting probabilities for each digit.

2.2.2.3. Training and Results

In this section, we outline the training process for the HQNN-Quanv. To expedite the training time, we utilized only 600 images from the MNIST dataset , with 500 images designated for training and 100 for testing. We applied PyTorch’s resize transform with bilinear interpolation to downscale the images from 28×28 to 14×14 pixels. A cross-entropy loss function was employed for the training.While classical models rely solely on backpropagation for weight training, the HQNN offers multiple training options, including the parameter-shift rule, adjoint differentiation, and backpropagation (the latter being infeasible on a real quantum computer). Among these methods, adjoint differentiation appears to scale favorably with both layers and wires. However, for this particular circuit (as shown in Figure 2.2.2), backpropagation demonstrated a quicker training process.With these considerations in mind, we present the results of the training. We trained two CNNs with varying numbers of output channels, alongside one HQNN, for a total of 20 epochs (illustrated in Figures 2.2.2.3 (a) and (b)). The models were intentionally kept simple, with a limited number of parameters to mitigate the risk of overfitting on the relatively small dataset. The test accuracies for these models are displayed in Figure 2.2.2.3(c). For each epoch, the accuracy was averaged across 10 models with randomly initialized weights, and the error bars represent one standard deviation.

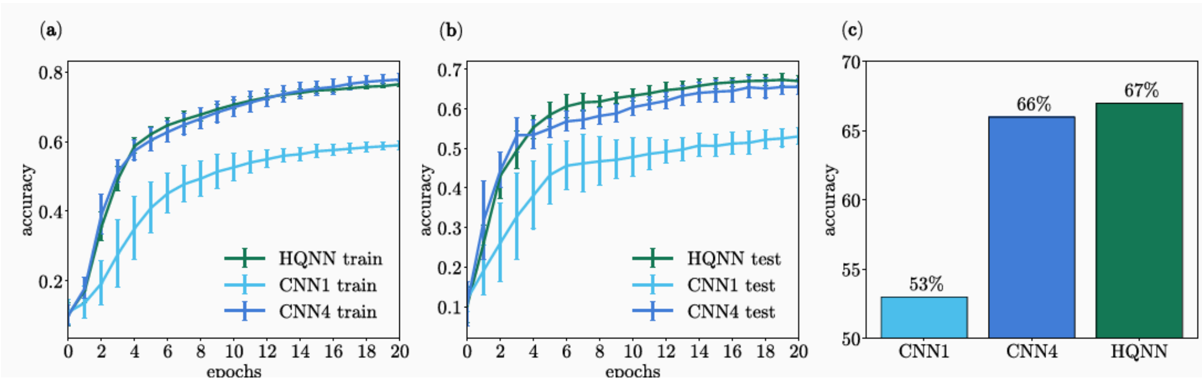


Figure 2.2.2.3(a) and (b) illustrate the training and test accuracies for the CNN and HQNN-Quanv models, with the stride set to 4. The models differ solely in the kernel configuration and the number of output channels:1.HQNN: Utilizes a quanvolutional kernel with 1 input channel and 4 output channels.2.CNN1: Employs a convolutional kernel with 1 input channel and 1 output channel.3.CNN4: Features a convolutional kernel with 1 input channel and 4 output channels.The results indicate that the HQNN-Quanv achieved a test accuracy of ($67 \pm 1\%$), surpassing CNN1, which recorded an accuracy of ($53 \pm 2\%$), and CNN4, which attained an accuracy of ($66 \pm 2\%$). Notably, CNN1 has the same number of weights in its kernel as the HQNN model, while CNN4 contains four times more weights than the HQNN. Figure 2.2.2.3.(c) summarizes the test accuracies for the models: HQNN-Quanv (67%), CNN1 (53%), and CNN4 (66%). The HQNN outperforms CNN1, which has an identical number of variational parameters. Furthermore, the accuracy score of the HQNN is comparable to that of CNN4, despite the latter having four times as many weights in its kernel.At the conclusion of the training, the HQNN-Quanv achieved a test accuracy of (0.67 \pm 0.01), which is comparable to the CNN4 result of (0.66 ± 0.02), while CNN1 achieved (0.53 ± 0.02). Notably, the HQNN model contains only four trainable weights in its quanvolutional kernel, which parameterizes the rotation gates in the PQC. In contrast, CNN1 and CNN4 have four and sixteen trainable

parameters in their convolutional kernels, respectively. Thus, the HQNN's performance, as indicated by the accuracy score, is equivalent to that of CNN4, despite having four times fewer weights in its kernel.

CHAPTER 3

METRICS

3.1.Accuracy & Confusion Matrix:

In image classification, accuracy is calculated in the same way as general classification tasks, but it specifically involves comparing the predicted labels of images with the true labels. The formula for accuracy in image classification is:

$$\text{Accuracy} = \frac{Number\ of\ Correctly\ Classified\ Images}{Total\ Number\ of\ Images} \times 100$$

Where:

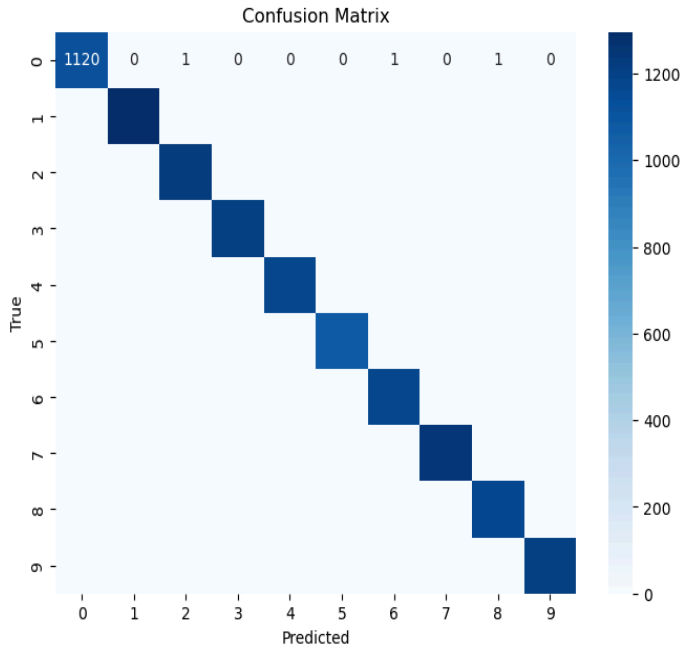
Number of Correctly Classified Images refers to how many images the model predicted correctly.

Total Number of Images refers to the total number of images in the dataset (test or validation set).

The accuracy for the model1- HQNN Classic is 99.21%

The accuracy obtained for the model 2 - HQNN Hybrid is 98.97%

For multi-class classification (such as recognizing multiple objects in an image), the accuracy can be calculated over all classes, but the overall process remains the same.



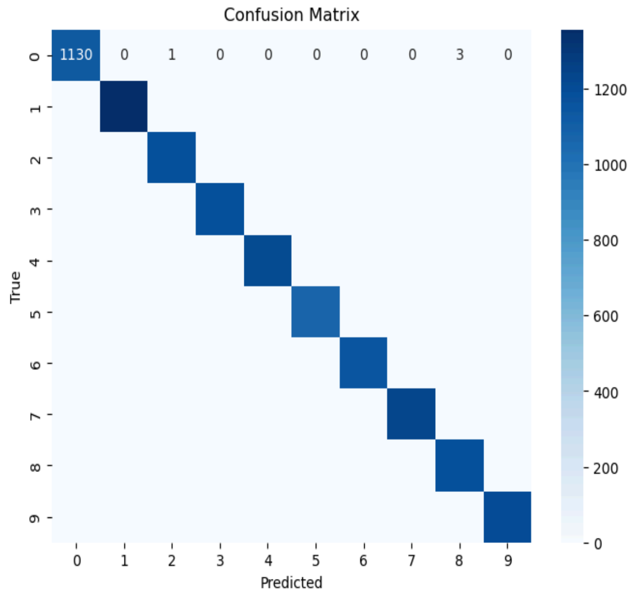


Fig-3.1.Confusion Matrix of model 1 & 2

In terms of confusion matrix elements:

TP (True Positive): The model correctly classifies an image in the correct category.

TN (True Negative): The model correctly classifies an image as not belonging to a particular category.

FP (False Positive): The model incorrectly classifies an image as belonging to a category.

FN (False Negative): The model incorrectly classifies an image as not belonging to a category.

Thus, accuracy is a general measure of how well the model is performing in terms of correct classifications across all images.

3.2.Precision,Recall & F1 Score

1. Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It measures how many of the predicted positive labels were actually correct.

$$\text{Precision} = \frac{TP}{TP+FP}$$

2. Recall (Sensitivity or True Positive Rate)

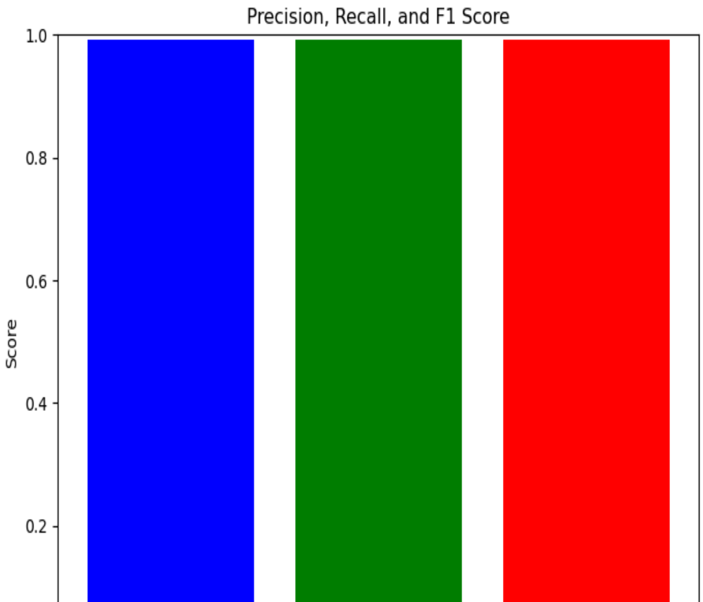
Recall is the ratio of correctly predicted positive observations to all observations in the actual class. It shows how many of the actual positives were correctly identified.

$$\text{Recall}=\frac{TP}{TP+FN}$$

3. F1 Score

The F1 score is the harmonic mean of Precision and Recall. It balances the two metrics, especially when you need to consider both false positives and false negatives. It is useful when the dataset is imbalanced, as it combines both metrics into one number.

$$\text{F1 Score}=2\times\frac{Precision \times Recall}{Precision + Recall}$$



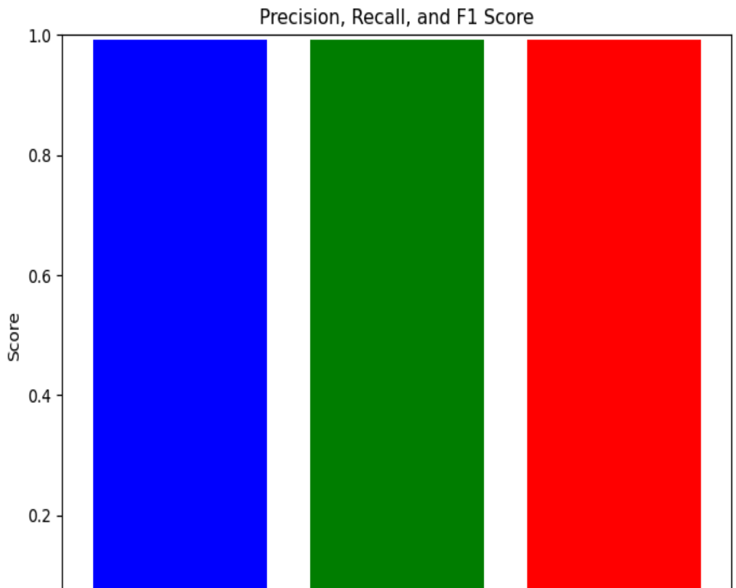


Fig 3.2 Precision,Recall,F1 Score

CHAPTER 4

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