COLOURED IMAGE CLASSIFICATION WITH QUANTUM MACHINE LEARNING ALGORITHMS FOR INTELLIGENT TRANSPORTATION SYSTEMS

A Thesis submitted by

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ABSTRACT

Quantum computers have great potential to change the future of Artificial Intelligence (AI) applications for practical problems. There currently exist some algorithm design that takes exponential time on a classical computer can take polynomial time on a quantum computer. With high demand for fast and reliable AI applications, such as traffic sign recognition for Intelligent Transportation Systems, it is beneficial for society and smart infrastructure to develop and utilise the most suitable AI algorithms for Quantum Computers (QCs). This Ph.D research project aims to focus on the feasibility of QCs to implement the image multi class classification techniques used in various domains, including AI applications. Moreover, in this study new successful techniques such Quantum Neural Network algorithms will also be explored to improve the efficiency of quantum image processing algorithms on QCs based on the similarity of these techniques with the mechanics of the QCs. This PhD research is expected to contribute to the knowledge domains in areas of real-life road traffic signs. The objectives of the research are: (i) To develop a new image-based multiclass classification algorithm using the quantum entanglement approach in comparison with classical machine learning (CML). (ii) To design a new filter for image processing to determine efficiency of quantum machine learning over CML. (iii) To investigate proposed quantum filter for binary image classification of complex traffic signs on small sample data. Within the context of these goals, this project is a partnership between Commonwealth Scientific and Industrial Research Organization (CSIRO) and University of Southern Queensland, which aims to build cutting-edge algorithms and novel methods for future QCs. The designed algorithms will be implemented in the Python software interface on available online quantum simulators. The scientific contributions indicate remarkable improvement in our model's performance on black and white images. However, we did not observe Quantum Machine Learning (QML) performing better for complex traffic signs using multi-class classification. Nevertheless, we achieved good results with binary image classification. This research will contribute to the scientific foundation for future applications of AI in quantum computers.

CERTIFICATION OF THESIS

I, Farina Riaz, declare that the PhD thesis entitled ***Coloured Image Classification with Quantum Machine Learning Algorithms for Intelligent Transportation Systems*** is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

This thesis is the work of Farina Riaz except where otherwise acknowledged, with the contribution to the papers presented as a Thesis by Publication undertaken by the student. This research is collaborated, and Intellectual Property is owned by Commonwealth Scientific Industrial Research Organisation (CSIRO). The work is original and has not previously been submitted for any other award, except where acknowledged.

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STATEMENT OF AUTHORS CONTRIBUTION

This doctoral Thesis by Publications has produced five publications that comprise three journal articles as primary, two conference posters presented as presented as supplementary contributions to knowledge.

Field of Research: The focus of this doctoral thesis is in the national priority area of: '*Quantum Computing', 'Artificial Intelligence, and Image Processing'*.

Articles 1, 2, 3 are primary (core) contributions part of this thesis, Poster 1, and 2 are the secondary contributions placed in the Appendix section as additional research output completed during the PhD candidature.

The following presents the student contributions and the contributions of the co-authors of the publications.

Contribution 1: Article 1: Chapter 3

Farina Riaz, Shahab Abdulla, Hajime Suzuki, Srinjoy Ganguly, Ravinesh C. Deo, Susan Hopkins (2023). "Accurate Image Multi-Class Classification Neural Network Model with Quantum Entanglement Approach" *Sensors* 23.5 (2023): 2753 (2023) **(Published Q1)**

The percentage contribution of the paper are: Farina Riaz 70% , Shahab Abdulla 10% , Hajime Suzuki 7%, Srinjoy Ganguly 5%, Ravinesh C. Deo 5%, Susan Hopkins 3%.

Author	Task Performed
Farina Riaz *(Candidate)*	Exploring the methodology in literature, data collection, and analysis, programming, preparation of tables and figures, writing and revising of the manuscript.
Shahab Abdulla *(Principal Supervisor)*	Supervised and assisted in model concepts, provided detailed and beneficial comments on the manuscript, edited, and prepared for the submission. Guidance for the choice of journal.
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DEDICATION

This thesis is dedicated to my wonderful father Riaz Alam

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ABBREVIATIONS

QNN	Quantum Neural Network
CNN	Convolutional Neural Network
QC	Quantum Computer
CSIRO	Commonwealth Scientific and Industrial Research Organisation
AI	Artificial Intelligence
ITS	Intelligent Transportation System
QuanvNN	Quanvolutional Neural Network
CNOT	Controlled NOT

CHAPTER 1: INTRODUCTION

1.1. Quantum Computers

With the growing popularity of AI applications, even the most powerful traditional supercomputers are unable to process large amounts of data due to their processing limitations. Technology corporations, such as Google, Twitter, Facebook, and Amazon, have gathered this data in order to give their customers a tailored service [1]. These organisations use supercomputers and high-performance servers to process large amounts of data, however the processing power remains a constraint that can cause significant delays in the computation of such complex data related to text, image, or audio formats. Since traditional supercomputers have some degree of processing limits, such limitations have led to rethought and redesigned computer hardware using the quantum phenomena. These are relatively new and powerful computers, also known as Quantum Computers, which have demonstrated a polynomial speedup while solving logical explanations and mathematical tasks. Shors algorithms, which demonstrate the factoring of integers and deducing discrete logarithms, for example, are difficult tasks for classical computers, but the more efficient quantum randomised algorithms have shown the potential to solve this problem by designing robust algorithms that take several polynomial steps in the input size, or the number of digits of the integer to be factored [2]. This polynomial speed has enticed many researchers to construct QCs for any computations that traditional computers may not be able to complete efficiently [3].

To conduct various kinds of computations, quantum computers are able to exploit the properties of superposition and entanglement [4]. These often represent patterns in the data an AI algorithm aims to reveal. In classical computers, information (signal) is computed as a bit (0 or 1), with ‘0' indicating the absence of electric current and ‘1' indicating the presence of an electric current [5]. A qubit is a quantum bit that clusters both '0' and '1' and is used to demonstrate the quantum phenomena [5]. The ability of quantum computing to result in numerous states (superposition state) at the same time until it is measured is known as superposition [6]. A qubit can hold a superposition state with portions of 0 and 1 [7]. A single qubit can be in two quantum superposition states: 0 or 1, while two qubits can be in four quantum superposition states: “00,01,10,11” superposition states increase exponentially (2^n) when a single qubit is added to a multi-qubit system. [5]. The efficiency of computing improves as the number of superposition states of QC grows exponentially.

In general, quantum computing is known to display the entanglement characteristics in a multiqubit system. It appears that when two qubits are physically close to each other, they may stop acting independently [7]. When two (source and target) qubits become entangled, the target qubit is likely to display the same output state as the source qubit, even if separated for a long time. For example, if the source qubit is in state ‘1,' the target qubit can display the same output state as the source qubit upon measurement and vice versa [8]. It is impossible to untangle qubits once they have been entangled. This occurrence aids in the cutting, pasting, and repurposing of information. [9]. In terms of performance, quantum machines benefited from entanglement, especially in image processing (image segmentation—feature extraction for image processing/computer vision) [10].

To pursue this challenge, this Ph.D project has established a new partnership between the University of Southern Queensland and the Commonwealth Scientific and Industrial Research Organization (CSIRO). In particular, the expert researchers in the CSIRO are keen to offer new solutions to resolve the difficult scientific challenges faced by AI, by researching new problems in the image classification using Quantum Machine Learning. The findings of this collaborative project, through the proposed Ph.D program, is expected to have a major impact on the future AI methods developed for quantum computing research and practical applications like Intelligent Transportation Systems. To understand the basics of Quantum Machine learning, however, first we need to understand Quantum gates and operations.

1.2. Quantum Operations and Qubit Visualisation

We will first look at classical computing to better comprehend quantum operators. We offer a collection of frequently used gates, including AND, NOT, OR, NAND, XOR, and FANOUT[11]. Any classical computer operation can be carried out by combining these gates. A Turing-complete or universal computer is one that can operate these gates. In fact, we can demonstrate that all other classical operators can be built using only the NAND gate. With these fundamental building elements, we may create classic circuits like a half-adder circuit.

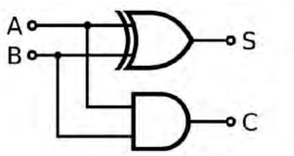

Figure 1 Half-adder in classical computing source [12]

Full adder can be built from those elements:

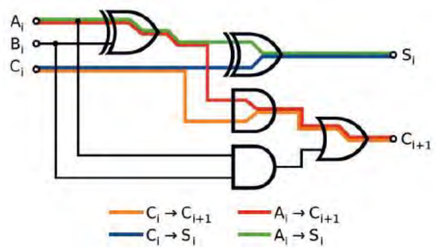

Figure 2 Full adder in classical computing source [13]

In quantum computing, neither classical gates like AND, OR, XOR, NAND, nor FANOUT are applicable. The gates AND, OR, XOR, and NAND cannot be reversed. Since the FANOUT gate requires the replication, or cloning, of a state and would go against the no-cloning theorem, it would not be permitted in quantum computing. Only the NOT operator, which is reversible and doesn't require cloning, can be employed in the quantum computing regime among the main classical gates. Two quantum operators that are used for entanglement are discussed in this study. Hadamard and CNOT gates was utilised in this study's quantum circuit construction.

1.2.1. H Gate

Hadamard operator is crucial in quantum computing since it enables a qubit to be taken from a definite computational basis state into a superposition of two states [14], as shown in equation (1-3).

$$H = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \tag{1}$$

If we apply H Gate to state |0), we get

$$\frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}\begin{pmatrix} 0 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1+0 \\ 1+0 \end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ 1 \end{pmatrix} = \frac{|0>+|1>}{\sqrt{2}} \tag{2}$$

If we apply H Gate to state |1), we get

$$\frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}\begin{pmatrix} 0 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1+0 \\ 1-0 \end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ -1 \end{pmatrix} = \frac{|0>-|1>}{\sqrt{2}} \tag{3}$$

H operator takes a computational basis state and projects it into a superposition of states $(|0> + |1>)/\sqrt{2}$ or $(|0> - |1>)/\sqrt{2}$, depending on the initial state. Thus, recalling the Born rule that the square of the modulus of the amplitudes of a quantum state is the probability of that state. Furthermore, for all amplitudes α, β, etc. of a state $|\alpha|^2+|\beta|^2 = 1$. That is, the probabilities must sum to one since one of the states will emerge from the measurement.

1.2.2. CNOT Gate

Critical operator for quantum computing: controlled- NOT (CNOT). In this binary operator, the first qubit is identified as the control qubit and the second as the target qubit [8]. If the control qubit is in state $|0>$ then we do nothing to the target qubit. If, however, the control qubit is in state $|1>$then we apply the NOT operator (X) to the target qubit. We use the CNOT gate to entangle two qubits in the QC. We can represent CNOT with the following matrix in equation 4 and 5.

$$CNOT := \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \tag{4}$$

Apply CNOT on state $|10>$ we get

$$CNOT := \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 0+0+0+0 \\ 0+0+0+0 \\ 0+0+0+0 \\ 0+0+1+0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} = |11> \tag{5}$$

There are several ways to represent the state of a qubit:

We can write out the state in Dirac notation. For example, if we have a qubit that is prepared in state $|0>$ and then apply the X operator, we will then find the qubit in state $|1>$ (assuming no outside noise) as shown in equation 6.

$$X\,|0> \rightarrow |1> \tag{6}$$

The Bloch sphere provides a way to visualize and represent the state of a single qubit in a quantum computation. A vector that begins at the origin and ends on the surface of the unit Bloch sphere can represent any state in a quantum computation. The application of unitary operators to the state vectors enables the movement of the state around the sphere. The convention is to consider the two antipodes of the sphere as representing the states $|0>$ and $|1>$, with $|0>$being represented at the top of the sphere and $|1>$at the bottom. This convention is widely adopted in quantum computing and allows for a clear and consistent representation of the qubit state. The Bloch sphere provides a valuable tool for understanding and visualizing the behaviour of qubits in quantum computations, and the convention of representing $|0>$ and $|1>$ at the top and bottom of the sphere respectively is an important aspect of this representation.

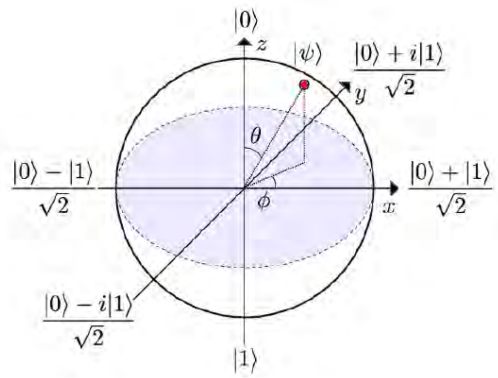

Figure 3 Bloch Sphere of Qubit visualisation[15]

As depicted in the Figure 3, the Bloch sphere offers the advantage of visualizing superposition states, such as $|0>$ + $|1>$ /√2, which can be represented along the X axis. Moreover, the Bloch sphere allows us to distinguish between states that have different phases, which are shown along the X and Y axes. Returning to the concept of computational universality, we can use the Bloch sphere to think about a set of gates that can achieve universal computation, as it enables us to reach any point on the sphere.

Interactive visualizations of qubits on the Bloch sphere can provide a more intuitive understanding of quantum computing, as it allows users to explore the effects of various gates and operations on the qubit state. By understanding the behaviour of qubits on the Bloch sphere, we can develop better intuition and insights into the behaviour of quantum algorithms and systems. Quantum phenomena that can be visualised from Bloch sphere led us to the exploration of the area of quantum artificial intelligence.

1.3. Quantum Artificial Intelligence

Quantum Computers have recently showed powerful computation speed and are assumed now to be used for solving optimization issues. Artificial Intelligence algorithms are too heavy to compute results on classical computers, so researchers are trying to solve AI Neural network using Quantum supremacy. Superposition and entanglement are two main properties that make quantum computers unique. These powerful computers are designed in a way that they can store and process more information compared to classical computers.

Images classification requires feature extraction as part of training. All images will have extremely regular structures. Because all nodes (pixels) are connected in a grid, images have a banded pattern in their adjacency matrix. To make the ansatz more amenable to training and avoid the barren plateaus (quantum parametric circuit no free lunch) problem [4], we need to add some constraints and specificity. To that end, more specialized architectures where parameters are tied spatially (convolutional) or tied over the sequential iterations of the exponential mapping (recurrent) can be used.

Machine learning methods are used in the artificial intelligence area to solve real-world problems. Quantum computers have been researched in terms of their potential to help improve the efficiency of AI [16-18]. The following section outlines some of the key applications of quantum AI, especially Intelligent Transportation Systems. In this Ph.D thesis, the focus has been on the image classification of real-life complex traffic sign images. AI algorithms train the model to learn image features. As Quantum hardware is noisy and can result in inaccurate results, we have used Penny lane quantum simulator to test our proposed design models.

We have developed three different image classification Neural network models that have been trained and tested on 3 benchmark datasets (MNIST, CIFAR-10 and GTSRB). The models have shown outstanding results, showing quantum better accuracy and performance over existing quantum and classical neural network models. In the next chapter, we will discuss how much work has been previously done in the literature for image classification, especially for real life complex AI applications.

1.3.1. Intelligent Transportation System

Intelligent Transportation System (ITS) refers to the system that uses advanced technologies and data analytics to improve transportation efficiency, safety, and sustainability. ITS includes various components such as vehicle-to-vehicle communication, vehicle-to-infrastructure communication, real-time traffic management systems, and advanced driver assistance systems.

Traffic sign identification is an essential component of ITS, especially for future driverless cars. Driverless cars rely on computer vision algorithms to identify and interpret traffic signs, which helps them make informed decisions about speed, lane changing, and stopping. By using traffic sign identification, driverless cars can detect and respond to markers such as stop signs, yield signs, and speed limit signs, ensuring safe and efficient driving [19].

The need to use traffic sign identification in driverless cars arises because it can significantly improve the vehicle decision making accuracy and reliability. Without this technology, driverless cars may miss important traffic signs, leading to accidents, traffic congestion, and delays. Moreover, traffic sign identification can help driverless cars navigate complex roadways and intersections, making them more efficient and safer.

Neural networks are an effective tool for identifying traffic signs because they can process large amounts of visual data quickly and accurately. Neural networks are a type of machine learning algorithm that are inspired by the structure and function of the human brain. Neural networks can be trained using large datasets of traffic sign images, which allows them to learn to recognize different types of traffic signs, even in varying lighting and weather conditions. The neural network is trained to recognize patterns and features in the images, such as colour, shape, and text, and use this information to classify the traffic sign. One of the advantages of using neural networks for traffic sign identification is their ability to adapt to new and unfamiliar situations. For example, if a new type of traffic sign is introduced, the neural network can be trained on new images of that sign to recognize it.

Deep learning neural network can be optimized for efficient performance on different hardware platforms, such as low-power embedded systems that might be used in driverless cars or traffic cameras. They offer a powerful and flexible approach to traffic sign identification, which is critical for improving the safety and efficiency of transportation systems.

In this research we will use Quantum feature extraction as it is a new and exciting area of research in quantum computing, which involves using quantum algorithms to extract features from data that can be used for machine learning applications such as neural networks. One of the key advantages of using quantum feature extraction in neural networks is the ability to process large amounts of data more efficiently. Quantum feature extraction algorithms can analyse multiple features simultaneously, which allows them to process more data in less time than classical algorithms. Another advantage is the ability to extract features that are difficult or impossible to extract using classical methods. Quantum feature extraction algorithms can identify patterns and relationships in data that are not apparent using classical methods, which can improve the accuracy and robustness of neural network models. The use of quantum feature extraction in neural networks is still an emerging area of research, but it holds great promise for improving the efficiency and accuracy of machine learning models. As quantum computing technology continues to advance, we can expect to see more applications of quantum feature extraction in a wide range of industries, including transportation, finance, healthcare, and more.

Previous research in the field of ITS has not explored the potential of using quantum neural networks (QNNs) for developing quantum algorithms. This lack of exploration has motivated us to contribute to the field by developing QNN-based image classification algorithms for future AI applications in ITS. The potential benefits of using QNNs for image classification in ITS include the ability to process large amounts of data more efficiently and to extract features that are difficult to identify using classical methods. QNNs can also adapt to new and unfamiliar situations, which is particularly useful in the dynamic and complex environment of transportation systems. Our contribution to the field involves developing and testing QNN-based image classification algorithms for traffic sign recognition and other ITS applications. By doing so, we aim to improve the accuracy and efficiency of ITS algorithms, which can ultimately lead to safer and more sustainable transportation systems. The use of QNNs in ITS is an emerging area of research, and our contributions represent a significant step towards unlocking the potential of quantum computing for transportation systems.

1.4. Research Objectives

With the development of quantum computers and quantum internet [20], the Artificial Intelligence of the future is expected to change. Rich classical AI algorithms are performing in an outstanding manner already. Today's supercomputers are taking trillions of bits of data from the end-users and processing those using conventional image processing, machine learning [21], deep learning algorithms [22]. This PhD is to investigate how well quantum neural network can perform better than classical neural network on complex images for real life future AI applications. As a result, the goal of this study is to address the following research objectives:

Objective 1: Develop an image classification model that can use strongly entangling architecture for Quantum Machine Learning

1. To develop a new model architecture for Quantum image classification and compare it with existing models on quantum and classical. The model will be tested on all benchmark datasets (from black and white to complex coloured dataset).

Objective 2: Develop a new image classification model for feature extraction of images by using a smaller number of qubits and minimum entanglement.

2. Quantum machine learning is hybrid at the moment, so we need to investigate how well quantum neural networks behave in performance for feature extraction by using less number of qubits and gates.

Objective 3: Investigate proposed model using minimum entanglement for binary image classification.

3. The first two objectives have checked the quantum model to see how well quantum neural network performs with multiclass classification, but this objective will investigate towards using less training and testing samples and to check the accuracy with binary classification of multi-class dataset. That binary classification will be compared with the multi-class classification models to see how well the performance results.

Graphical representation for the research objective is as in figure 4.

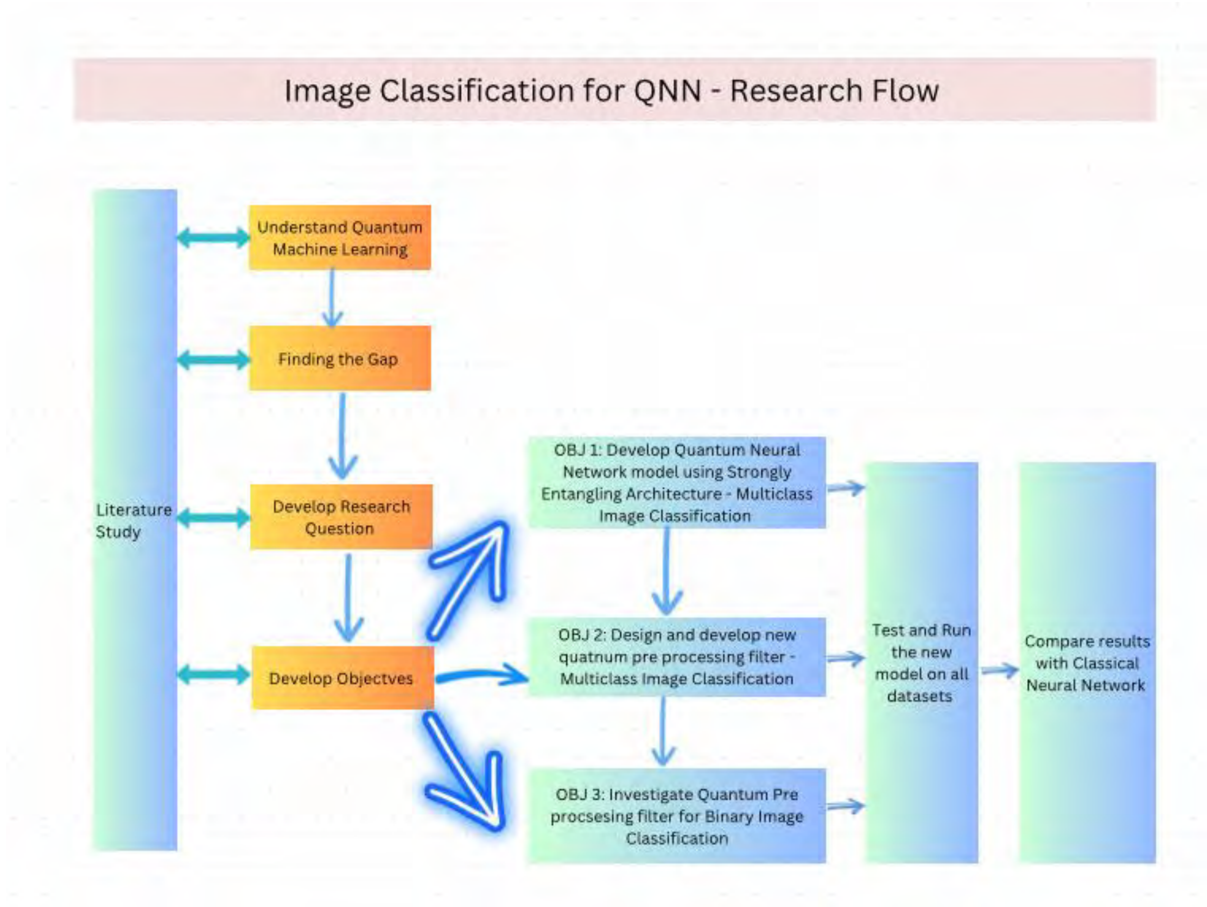

Figure 4 Research flow of doctoral research

1.5. Specific Contribution to the Research

In recent years, deep learning algorithms have achieved state-of-the-art results in many computer vision tasks, such as object recognition, segmentation, and detection. One of the key components of deep learning is feature extraction, which involves learning meaningful representations of the input data that can be used for subsequent classification or regression tasks. Traditional deep learning models use classical neural networks, which are good at processing data with high-dimensional features such as images. However, with the increasing complexity of data, such as high-resolution images and videos, classical neural networks face limitations in terms of computational efficiency and accuracy.

Quantum neural networks (QNNs) have emerged as a potential solution to overcome these limitations by leveraging the principles of quantum mechanics to process information. QNNs have shown promise in various machine learning tasks, including classification, regression, and clustering. In the context of image processing, QNNs can help improve feature extraction by exploiting quantum entanglement and superposition to simultaneously process multiple features in an image. This approach can potentially lead to more efficient and accurate feature extraction compared to classical neural networks. The approach will be evaluated through testing on both binary image classification (2 classes from the dataset) and multi-class image classification (more than 2 classes from the dataset).

Hence, the primary objective of this study is to explore the effectiveness of Quantum Neural Networks (QNNs) in enhancing feature extraction from images. By conducting a comprehensive comparison of QNNs and classical neural networks across multiple image datasets, this research aims to shed light on the advantages of leveraging QNNs for image processing tasks. The outcomes of this investigation have the potential to make significant contributions to the research domain, showcasing the capabilities of QNNs in improving accuracy and efficiency in image processing. Such advancements can find practical applications in diverse fields, including computer vision, robotics, and autonomous vehicles.

In the following chapter, we will explore the literature that has been studied in order to discuss the methods used in this research.

CHAPTER 2: LITERATURE REVIEW AND DATA DESCRIPTION

This chapter provides an overview of the literature study in developing the image classification models. The description of data used, length of data, and limitations, if any, are presented. This chapter also introduces a brief account of the methodology, while specific model development techniques have been described in respective chapters.

Many academics from all over the world are attracted to new research with quantum computers because of their remarkable computing speed. The research in quantum computers has progressed into areas of cryptography [23-25], health [26-28], education [29], finance [30, 31], location finding [32] and detecting materials [33]. The goal of this PhD research project is to improve image classification performance by using Quantum computer. This section will focus on a review of the relevant literature in the fields of AI and image classification processing.

Machine learning methods are used in the artificial intelligence area to solve real-world problems. Quantum computers have been researched in terms of their potential to help improve the efficiency of AI [16-18].

With the use of quantum algorithms, quantum computers have shown an increase in the speed of image processing [34-36]. The potential of a quantum computer's supremacy in image classification and recognition, as well as the challenges of such computers in dealing with noisy data [37, 38] have been investigated [39]. Image enhancement [40] has been demonstrated using Grover's quantum algorithm [34]. In the studies using a processing filter [41, 42], a denoising method [43], an image segmentation method [44], morphological image processing [45], image edge detection [46] and edge extraction [47, 48] has been well documented to demonstrate the power of quantum computers. In related areas, different image processing algorithms for quantum computers have been studied, *e.g.*, geometric transformation, image translation [49], image scaling [50-54], color transformation [55], image scrambling [56-62], feature extraction [63-66] and watermark [67]. In comparison with traditional computers, the adoption of quantum image processing has shown more accurate results [35, 44, 46, 47, 68].

Deep learning, as a subset of AI and machine learning, aims to mimic the workings of the human brain in order to handle relatively large and complex datasets to make quick decisions. Recently, deep learning on QCs has been researched for a range of AI applications. In 2019, deep AI solutions for finance and insurance had been proposed as a potential solution to the multitude of challenges experienced by industrialized countries like China and the United States in terms of data privacy, information distribution, and trusted authorities. [69]. Apart from data privacy, reinforcement learning (a training approach that learns from its surroundings) has been found to improve the computational speed of various applications such as autonomous vehicles and robots [70]. These learning techniques have benefited from the quantum supremacy as it has aided in the optimization of variational quantum circuit architecture [71] and quantum amplitude amplification, which is the foundation of the Quantum Grover algorithm [72]. Other learning techniques like self-supervised learning has been studied for classical neural networks [73]. Apart from self-supervised learning, function fitting, and data categorization, Liu and Ma simulated quantum artificial neural networks to demonstrate that quantum computers outperform classical computers when using quantum theory [74]. Because of the improved efficiency of neural networks, Mangini et al. developed a quantum artificial computing model to demonstrate the benefits of quantum machine learning [75].

Ramezeni et al., (2020) performed one of the most recent reviews of machine learning algorithms. The traditional viewpoint [76], as well as advancements in quantum machine learning, have been investigated [77, 78]. Advances in machine learning combined with quantum algorithms have the potential to transform clinical research, including medicine [79]. When combined with Grover's algorithm, these approaches can improve the classifiers and their feature spaces [65]. Machine learning algorithms to check quantum supremacy [80], event classification [81], and image classification are expected to aid the neural networks on IBM quantum simulators [82]. The pennylane quantum simulators will be used in this study because they have been tested and deployed for AI.

According to the preceding literature, it is evident that future quantum computers have been researched for various image processing and AI techniques. Purpose of this doctoral study is to address the concerns of investigating how quantum computers can be used for optimisation of machine learning. Quantum machine learning is hybrid and the use of quantum circuit is for the use of feature extraction. The images classification can be improved well if feature extraction can be completed accurately by reducing the speed of the process. With the speed limitation of classical computers, quantum computers have the potential to show enhanced processing of our future AI applications like traffic sign recognition.

2.1 Study Area: Image Classification models for Quantum Machine Learning

Among many proposals to combine classical machine learning methods with quantum computing, the method proposed by Henderson et. al. in [83] has the advantage of being implementable on quantum circuits with a smaller number of qubits with shallow gate depths and yet being able to be utilised for more practical applications. The method utilises quantum circuits as transformation layers to extract features for the purpose of image classification using convolutional neural networks (CNNs). These transformation layers are called quanvolutional layers, and the method is herein referred as quanvolutional neural network (QuanvNN) in this thesis.

An important question was raised whether the features produced by quanvolutional layers could increase the accuracy of machine learning models for classification purposes. Henderson et. al. attempted to address this question by applying randomly created quantum circuits and comparing the classification accuracy by QuanvNN with the results by a conventional CNN. The results did not show clear advantage in terms of classification accuracy over the classical model [83]. QuanvNN was further updated in [84], implemented on a quantum computer hardware (Rigetti's Aspen-7-25Q-B quantum processing unit) and was evaluated on a satellite imagery classification task. However, image classification accuracy by QuanvNN was not improved over that of conventional CNN.

An implementation of QuanvNN on a software quantum computing simulator, PennyLane [85], was provided by Mari [86]. Mari's implementation of QuanvNN differs from that of Henderson et. al. in that the output of the quantum circuit, which is a set of expectation values, is directly fed into the following neural network layer, while that of Henderson et. al. was made into a single scalar value by a classical method. The proposed method was applied to MNIST (handwritten 10-digit dataset,[87]) using 50 training and 30 test image set. No clear improvement in classification accuracy by QuanvNN over NN was observed in [86].

2.2 Data Description

Literature showed that image classification has been completed for black and white dataset MNIST. To apply our models, we have used CIFAR-10 and GTSRB explained below:

Table 1 Dataset description for research objectives

	Description	Training Images	Testing Images	Classes	Paper 1	Paper 2	Paper 3
MNIST ***[87]***	Images of handwritten digits of 0 to 9. The size of each image is 28 by 28 pixels. The original images are in greyscale within the values between 0 and 255, which are scaled by dividing them by 255.	***60,000***	10,000	10	YES	YES	YES
CIFAR-10 [88]	The original images are in RGB colour, which are converted into grayscale between 0 and 255, then scaled by dividing them by 255.	***50,000***	10,000	10	YES	NO	NO
GTSRB [10]	These are traffic signs images in-use in various conditions. The original dataset has various image sizes between 15 × 15 and 222 × 193 pixels. Those images were scaled to	***34,799***	12,630	43	YES	YES	YES

	a size of 32 × 32 pixels. The original images are in RGB colour, which are converted into grayscale between 0 and 255, then scaled by dividing them by 255.						

The benchmark datasets have been utilized to determine the testing accuracy of quantum neural network models in comparison to classical neural networks. This research aims to investigate the quantum neural networks' performance on complex image datasets, such as the German Traffic Sign Recognition Benchmark (GTSRB). The GTSRB dataset contains a vast array of images, with variations in shape, colour, and background, making it a challenging dataset for classification. This research endeavours to evaluate the ability of quantum neural networks to classify such complex images accurately.

To compare the performance of quantum neural networks with classical neural networks, the testing accuracy of both models is computed using the benchmark dataset. By analysing the results, we can determine whether quantum neural networks perform better or worse than classical neural networks in classifying complex images.

2.3 General Methodology

This research explores the design of a quantum neural network that utilizes a quantum circuit for feature extraction in image classification. Pre-processing is an essential step in image classification tasks. Converting the images into grayscale simplifies the data representation by reducing the colour channels from RGB (Red, Green, Blue) to a single channel. Grayscale images are easier to handle computationally and contain valuable information about the intensity variations in the image. This pre-processing step helps in improving the efficiency and accuracy of the subsequent classification algorithms applied to the images. All coloured images have undergone pre-processing, where they were converted into grayscale images before proceeding with the classification process.

The first paper referenced in this research employs a strongly entangled quantum circuit that includes four Hadamard gates, 20 three-axis rotations, and 20 CNOTs [83]. Following the encoding of the image, one Hadamard gate is applied to each qubit, and the gates are grouped into five layers, with each layer containing four three-axis rotations and four CNOTs. Within each layer, one three-axis rotation is applied to each qubit, with rotation angles randomly and uniformly chosen between 0 and 2π radians. Four CNOTs within each layer randomly connect the qubits without overlapping. The results show a significant improvement in testing accuracy compared to classical neural networks. This success prompted the development of another quantum circuit capable of using only four qubits and utilizing a single layer with two CNOTs. To summarize, this research introduces a hybrid quantum neural network that utilizes a quantum circuit for feature extraction in image classification. Concurrently, classical computers are employed for pre and post-image processing, as depicted in figure 5.

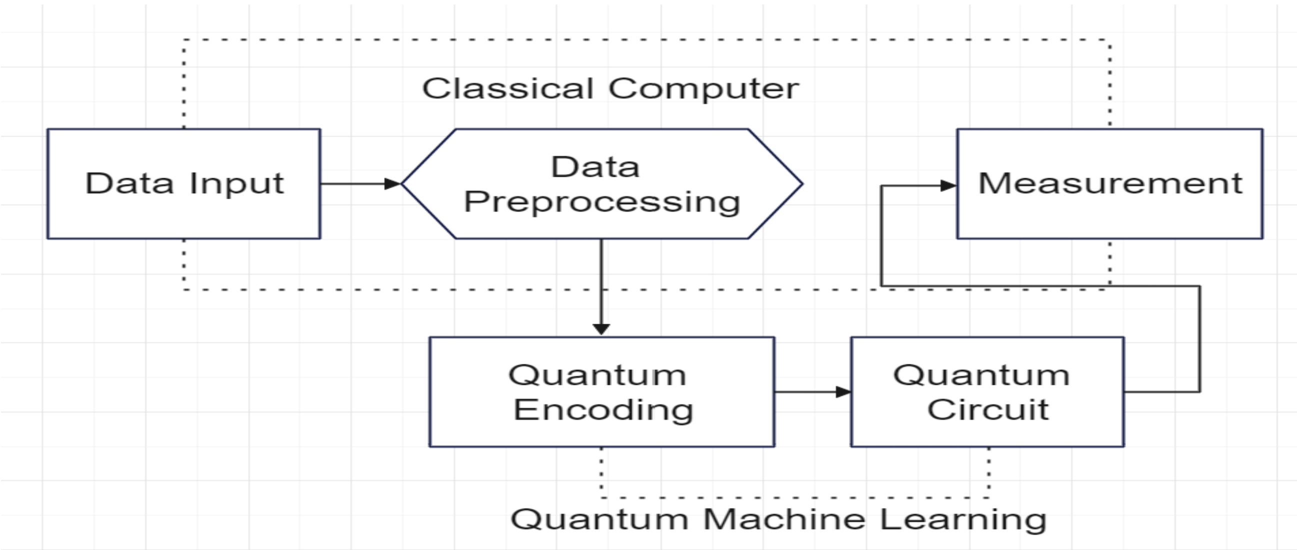

Figure 5 Hybrid Quantum- classical neural network

Through experimentation and comparison to classical neural networks, we demonstrate the effectiveness of the approach and the potential for further improvements. The development of a simplified quantum circuit showcases the potential for increased efficiency in quantum neural networks. The starting point for using quantum circuits for image classification is a two-dimensional matrix with dimensions m-by-m representing an input image. The pixel values in this matrix fall within the range of 0 and 1. To employ quantum circuits for both training and testing, we need to select n = 2 images per class, which leads to the utilization of 4 qubits.

The initialization of the qubits starts in the ground state. Then, we use an RY rotation to encode four-pixel values for each qubit. We accomplish this by using the pixel values x and setting the rotation angle θ to πx, as illustrated in equation (7).

$$RY = \begin{bmatrix} \cos\theta/2 & -i\sin\theta/2 \\ \sin\theta/2 & \cos\theta/2 \end{bmatrix} \tag{7}$$

To utilize the input image in a quantum circuit, we use the outputs of Y rotation gates as inputs. The Quantum circuit is used for feature extraction, and it consists of two CNOT gates that link four randomly chosen qubits.

To enhance the quantum circuit's performance, we apply four single-axis rotations that are chosen randomly from the X, Y, or Z axis rotations. The selected rotations are applied to the randomly chosen qubits with equal frequency, and the rotation angles are also chosen randomly and uniformly between 0 and 2 π radians.

To encode the image pixels into quantum states, we apply the Rotation Y gate to each qubit. It is noteworthy that four CNOT gates connect the qubits randomly but without overlapping. The CNOT gate can be described mathematically as shown in equation (8):

$$\text{CNOT}=\begin{bmatrix} \mathbf{1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{0} \end{bmatrix} \tag{8}$$

After the input image is processed through the quantum circuit, the measurement operations of the circuit produce output features as expectation values that fall within the range of -1 to 1. These output features are then flattened to form a one-dimensional vector.

It is important to note that the total number of parameters in the output features, which is 4 times the size of the input image's dimensions divided by 2, is equal to the number of parameters in the input image itself. The resulting one-dimensional vector of output features is then fed into a fully connected layer 1, where all the nodes are interconnected with one another. The output of this layer is then passed on to fully connected layer 2, which has several nodes equal to the number of classes for the classification task. To summarize, this research utilizes both quantum and classical models for binary image classification, with the quantum circuit serving as the feature extraction module. The circuit's measurement operations produce output features that are transformed into a one-dimensional vector and fed into fully connected layers for classification purposes. This methodology will be explained in more detail in the following chapters.

CHAPTER 3: ARTICLE 1 - ACCURATE IMAGE MULTI-CLASS CLASSIFICATION NEURAL NETWORK MODEL WITH QUANTUM ENTANGLEMENT APPROACH

The current paper presents a novel model for image classification in Quantum Machine Learning, which is called Neural Network with Quantum Entanglement (NNQE). The model takes images as input, which undergo a pre-processing stage before being fed into a strongly entangling circuit to extract relevant features. To evaluate the model's performance, it has been tested on three distinct datasets: MNIST, CIFAR-10, and GTSRB. The results obtained from these tests are used to assess the model's effectiveness and potential for future use in image classification tasks.

Highlights

1. To investigate a new Quantum Neural Network model using random circuits available on Penny lane.
2. To test the proposed model for all the classes of MNIST, CIFAR-10 and GTSRB datasets.
3. To redesign the proposed model of Quantum Neural Network by using strongly entangling circuit (or the NNQE).
4. To test the model for all the classes of MNIST, CIFAR-10 and GTSRB datasets and compare the results with a classical Neural Network model.
5. To investigate all results to deduce improvements by using the Quantum Neural Network approach and comparing the outcome with Classical Neural Network methods.

Graphical Representation

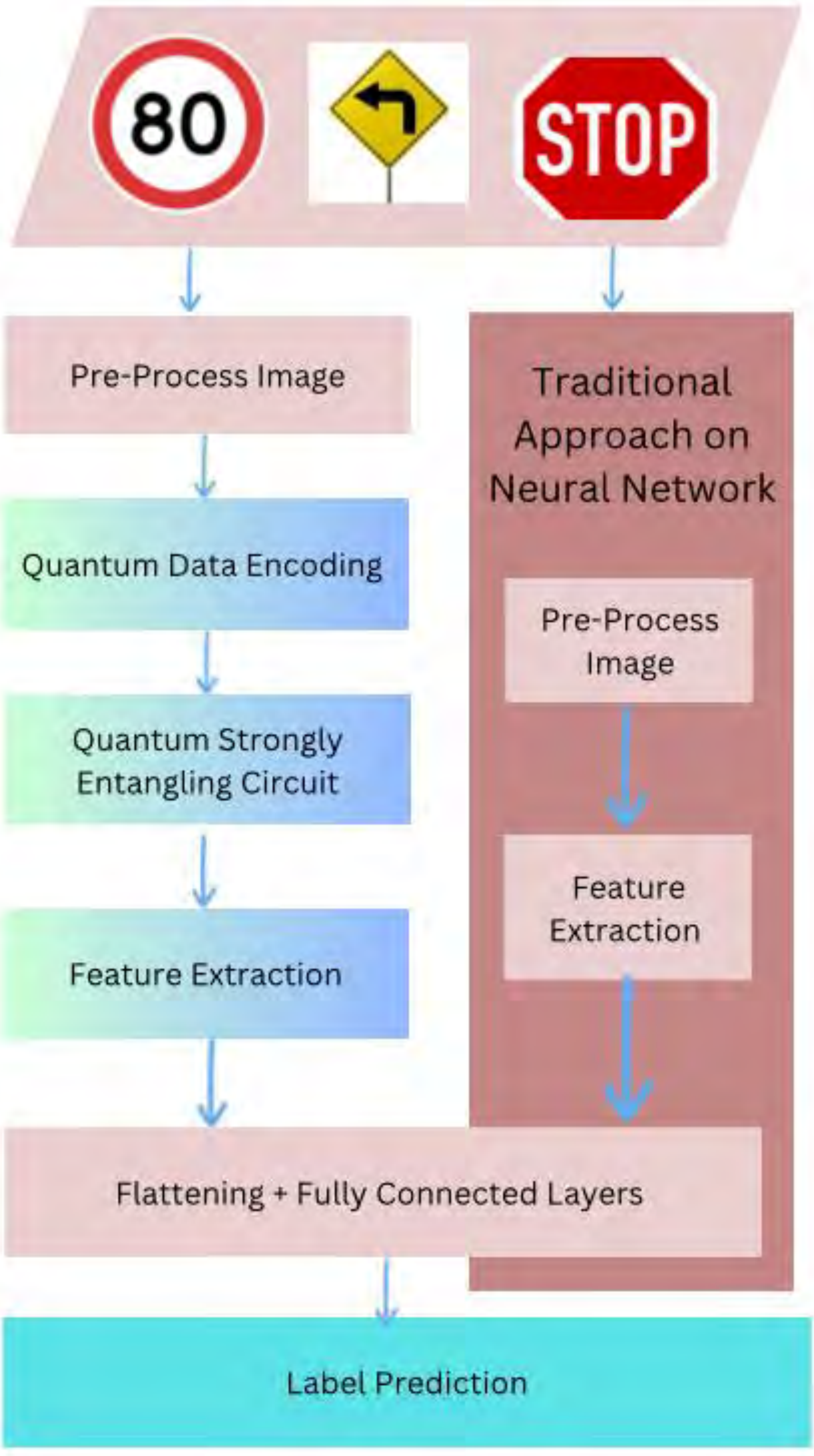

Figure 6 Graphical representation of the accurate image multi-class classification neural network model with quantum entanglement approach

sensors

MDPI

Communication

Accurate Image Multi-Class Classification Neural Network Model with Quantum Entanglement Approach

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Abstract: Quantum machine learning (QML) has attracted significant research attention over the last decade. Multiple models have been developed to demonstrate the practical applications of the quantum properties. In this study, we first demonstrate that the previously proposed quanvolutional neural network (QuanvNN) using a randomly generated quantum circuit improves the image classification accuracy of a fully connected neural network against the Modified National Institute of Standards and Technology (MNIST) dataset and the Canadian Institute for Advanced Research 10 class (CIFAR-10) dataset from 92.0% to 93.0% and from 30.5% to 34.9%, respectively. We then propose a new model referred to as a Neural Network with Quantum Entanglement (NNQE) using a strongly entangled quantum circuit combined with Hadamard gates. The new model further improves the image classification accuracy of MNIST and CIFAR-10 to 93.8% and 36.0%, respectively. Unlike other QML methods, the proposed method does not require optimization of the parameters inside the quantum circuits; hence, it requires only limited use of the quantum circuit. Given the small number of qubits and relatively shallow depth of the proposed quantum circuit, the proposed method is well suited for implementation in noisy intermediate-scale quantum computers. While promising results were obtained by the proposed method when applied to the MNIST and CIFAR-10 datasets, a test against a more complicated German Traffic Sign Recognition Benchmark (GTSRB) dataset degraded the image classification accuracy from 82.2% to 73.4%. The exact causes of the performance improvement and degradation are currently an open question, prompting further research on the understanding and design of suitable quantum circuits for image classification neural networks for colored and complex data.

Keywords: artificial intelligence; artificial neural network; intelligent transportation system; quantum computer; quantum computing; quantum machine learning; traffic signs

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1. Introduction

The theory of machine learning is an important subdiscipline in both artificial intelligence and statistics, with roots in artificial neural networks and artificial intelligence research since the 1950s [1]. Data processing using quantum devices is known as quantum computing. Because operations can be performed on numerous states simultaneously, the capacity of quantum states to be in a superposition can significantly speed up computation in terms of complexity in a broader machine learning context. Several quantum machine learning (QML) variations of classical models have recently been developed, including quantum reservoir computing (QRC) [2], quantum circuit learning (QCL) [3–5], continuous variable quantum neural networks (CVQNNs) [6], quantum kitchen sinks (QKSs) [7–9], quantum variational classifiers [10,11], and quantum kernel estimators [12,13]. Recent literature surveys on QML are available [14–16]. We note that the main approach taken by the community consists in formalizing problems of interest as variational optimization problems and using hybrid systems of quantum and classical hardware to find approximate solutions [15]. The intuition is that by implementing some subroutines on classical hardware, the requirement of quantum resources is significantly reduced, particularly the number of qubits, circuit depth, and coherence time, making the quantum algorithms suitable to be implemented on noisy, intermediate-scale quantum (NISQ) devices [15]. Recent examples in this direction include the work by Arthur and Date, who proposed a hybrid quantum-classical neural network architecture where each neuron is a variational quantum circuit [17], and the work by Sagingalieva et al., who proposed a combination of classical convolutional layers, graph convolutional layers, and quantum neural network layers to improve on drug–response prediction over a purely classical counterpart [18].

Among the many proposals to combine classical machine learning methods with quantum computing, the method proposed by Henderson et al. in [19] has the advantage of being implementable in quantum circuits with a smaller number of qubits with shallow gate depths and can be applied to more practical applications. This method utilizes quantum circuits as transformation layers to extract features for image classification using convolutional neural networks (CNNs). These transformation layers are called quanvolutional layers, and the method is herein referred to as the quanvolutional neural network (QuanvNN).

An important question raised was whether the features produced by the quanvolutional layers could increase the accuracy of the machine learning models for classification purposes. Henderson et al. attempted to address this question by applying randomly created quantum circuits and comparing the classification accuracy of the QuanvNN with the results obtained by a conventional CNN. The results did not show a clear advantage in terms of classification accuracy over the classical model [19]. The QuanvNN was further updated in [20], implemented on quantum computer hardware (Rigetti's Aspen-7-25Q-B quantum processing unit), and evaluated in a satellite imagery classification task. However, the image classification accuracy of the QuanvNN did not improve compared with that of the conventional CNN.

The implementation of the QuanvNN on a software quantum computing simulator, PennyLane [21], was provided by Mari [22]. Mari's implementation of QuanvNN differs from that of Henderson et al. in at least two aspects. Firstly, Mari's implementation combined a quanvolutional layer with a neural network (NN) instead of CNN. Secondly, the output of the quantum circuit (a set of expectation values) was directly fed into the following neural network layer, while the output of the quantum circuit was converted into a single scalar value using a classical method in the original QuanvNN proposal by Henderson et al. In Mari's implementation, 50 training and 30 test images from the Modified National Institute of Standards and Technology (MNIST) dataset (a handwritten 10 class 10-digit dataset [23]) were applied and tested. No clear improvement in the classification accuracy of QuanvNN over NN was observed in [22].

In this paper, we first show that a QuanvNN using a randomly generated quantum circuit (four qubits with 20 single-axis rotations and 10 controlled NOTs (CNOTs), extending Mari's implementation from using one random layer to five random layers) improves the image classification accuracy of a classical fully connected NN against MNIST and the Canadian Institute for Advanced Research 10 class (CIFAR-10) dataset (photographic 10 class image dataset [24]) from 92.0% to 93.0% and from 30.5% to 34.9%, respectively. We then propose a new model, termed Neural Network with Quantum Entanglement (NNQE), using a strongly entangled quantum circuit (four qubits with 20 three-axis rotations and 20 CNOTs) combined with Hadamard gates, instead of random quantum circuits. Our newly proposed NNQE further improves the image classification accuracy against MNIST and CIFAR-10 to 93.8% and 36.0%, respectively. These improvements were obtained using a quantum circuit consisting of only four qubits without introducing any additional parameters to the optimizing machine learning process. Unlike other QML methods, the proposed method does not require optimization of the parameters inside the quantum circuits; hence, it requires only limited use of the quantum circuit. Given the small number of qubits and relatively shallow depth of the proposed quantum circuit, the proposed method is well suited for implementation in noisy intermediate-scale quantum computers.

However, using QuanvNN or the proposed NNQE degrades the image classification performance when applied to a more complicated German Traffic Sign Recognition Benchmark (GTSRB) dataset (43 class real-life traffic sign images [25]) in comparison with the classical NN accuracy from 82.2% to 71.9% (QuanvNN) and to 73.4% (NNQE). Nevertheless, we note that NNQE produced improved image classification accuracy over QuanvNN from 71.9% to 73.4%. The exact causes of the performance improvement and degradation are currently an open question, prompting further research on the understanding and design of suitable quantum circuits for image classification neural networks for colored and complex data. We note that a similar result of QuanvNN not improving the image classification accuracy of NN when tested against GTSRB was also recently reported in [26], which is consistent with our findings.

The remainder of this paper is organized as follows: Section 2 presents the methodology for the proposed model. The details of our experiment are provided in Section 3. The results and discussion are presented in Section 4, followed by conclusions in Section 5.

2. Methods

For the implementation of QuanvNN, readers are referred to [22], noting that the number of random layers was increased from 1 to 5. This results in the use of a quantum circuit with 20 random single-axis rotations and 10 CNOTs with QuanvNN.

Figure 1 shows a flowchart of our proposed NNQE model. We assume that the input image is a two-dimensional matrix of size m-by-m and the pixel value x follows $0 \leq x \leq 1$. The extension to a multichannel pixel image is expected to be straightforward. A section of size n-by-n is extracted from the input image, where $n = 2$. An extension of $n > 2$ will be left for further study.

Given $n = 2$, we use a 4-qubit quantum circuit. The four qubits are initialized in the ground state, and the four-pixel values are then encoded using RY with $\theta = \pi x$ as in (1).

$$\mathrm{RY} = \begin{bmatrix} \cos\theta/2 & -\sin\theta/2 \\ \sin\theta/2 & \cos\theta/2 \end{bmatrix} \tag{1}$$

The outputs from RY gates are fed to the quantum circuit.

NNQE uses four Hadamard gates, 20 three-axis rotations, and 20 CNOTs. One Hadamard gate is applied to each qubit immediately after encoding. The gates are grouped into five layers, with each layer consisting of four three-axis rotations and four CNOTs. Three-axis rotation is applied to each qubit within the layer. The rotation angles were chosen randomly and uniformly between 0 rad and 2 π rad. The four CNOTs within each layer connect the qubits randomly, but without overlap. The Hadamard and CNOT gates can be described mathematically as in (2) and (3), respectively.

$$H = {}^{1}/_{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{2}$$

$$\mathrm{CNOT} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{3}$$

The outputs from the measurement operations are given as expectation values between -1 and 1 and form the output features.

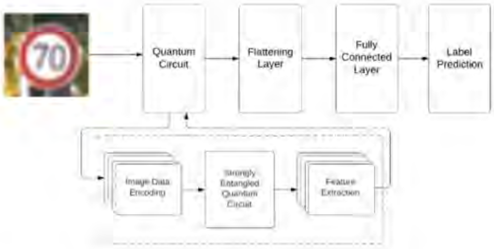

Figure 1. A flowchart of the proposed NNQE model.

The output features are transformed into a one-dimensional vector using a flattening layer, as shown in Figure 1. The output of the flattening layer is connected to the fully connected layer to classify and predict the image labels for testing model learning. The dotted box in Figure 1 is expanded in detail in Figure 2. The circuit is expanded into multiple rotations and CNOTs in the expectation it will achieve better feature extraction than that of the random circuit. In particular, the design of the quantum circuit was inspired by the Circuit 15 in [27] which was found to retain high expressibility with a strong entangling capability. In addition, an extra layer of the Hadamard gates was added by us by trial, which showed further performance improvements.

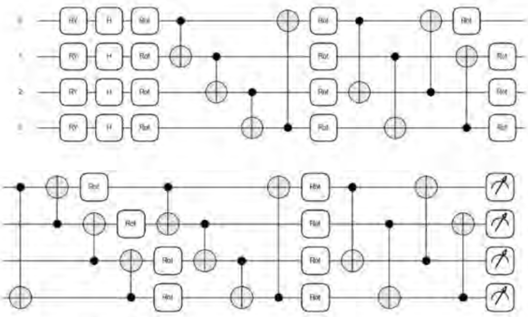

Figure 2. The quantum circuit architecture of the proposed NNQE Circuit model with 5 layers.

3. Experiment

The method proposed in this study was implemented on a quantum computing simulator using Python (version 3.7.0) and PennyLane libraries (release 0.27.0) [21]. The random quantum circuit and strongly entangled quantum circuit were implemented using PennyLane's built-in RandomLayers and StronglyEntanglingLayers functions. Unless otherwise stated, the Adam optimizer and a batch size of 128 were used to train the network. Table 1 summarizes the parameters of the three image datasets used in this experiment. The method was implemented on a MacBook Pro (Intel Core i7 2.5 GHz CPU). Processing data for MNIST for NNQE, for example, took approximately two days each.

Table 1. Parameters of image datasets used in experiment.

	MNIST	CIFAR-10	GTSRB
Image Size	28 × 28	32 × 32	32 × 32
Number of color channel	1	3	3
Number of classes	10	10	43
Number of training set images	60,000	50,000	34,799
Number of testing set images	10,000	10,000	12,630

3.1. *Testing Dataset MNIST*

The MNIST dataset [23] consists of 60,000 training and 10,000 testing images of handwritten digits from 0 to 9. Each image measures 28 × 28 pixels. The original images are grayscale with values between 0 and 255, which were scaled by dividing them by 255. Figure 3 shows an example of the MNIST dataset images and the corresponding output features obtained using NNQE circuit.

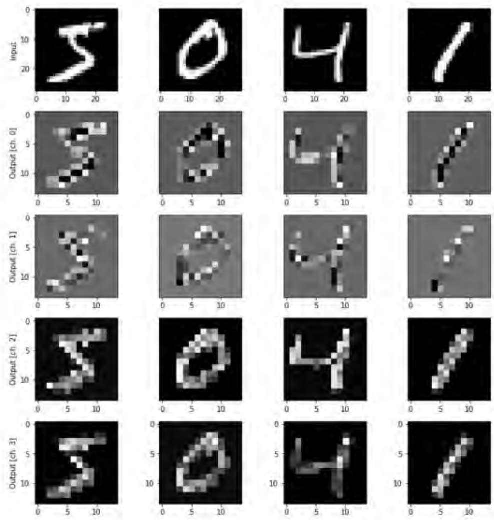

Figure 3. Example MNIST dataset images and corresponding output features using NNQE circuit model.

3.2. *Testing Dataset CIFAR-10*

The CIFAR-10 dataset [24] consists of 50,000 training images and 10,000 testing images. Photographic images are colored and consist of ten classes. The original images are in RGB color, which were converted into grayscale between 0 and 255 and then scaled by dividing them by 255. Examples of CIFAR-10 dataset images are shown in Figure 4. Figure 5 shows an example of the original CIFAR-10 dataset images and the corresponding output features obtained using an NNQE circuit.

Figure 4. Example visualization of CIFAR-10 colored dataset images.

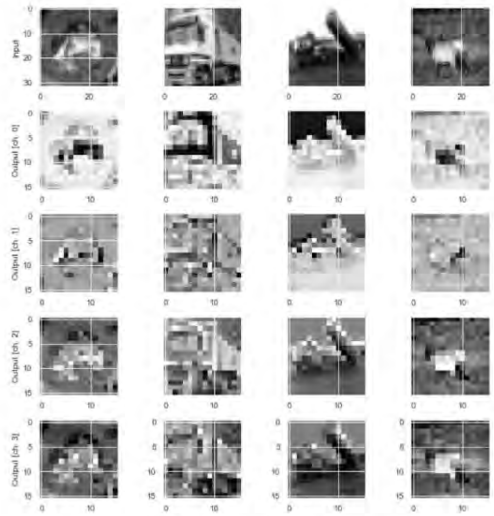

Figure 5. Example CIFAR-10 dataset images and corresponding output features using NNQE circuit.

3.3. Testing Dataset GTSRB

The GTSRB dataset [25] consists of 34,799 training and 12,630 test images of 43 classes of traffic signs captured from actual use under various conditions. These images were captured at night, during rainy weather, and in fog-based atmospheric environments under various illumination conditions, which could make it challenging for any machine to learn concealed features from dark and relatively unclear images. The original dataset has image sizes varying between 15 × 15 pixels and 222 × 193 pixels. As suggested by Sermanet and LeCun in [28], the images were scaled to 32 × 32 pixels. The original images are in RGB color, which were converted into grayscale between 0 and 255 and then scaled by dividing them by 255. Examples of the GTSRB dataset images are shown in Figure 6, whereas the original and corresponding output features using the NNQE circuit are shown in Figure 7.

Figure 6. Example GTSRB dataset images. (Digits indicate class labels.)

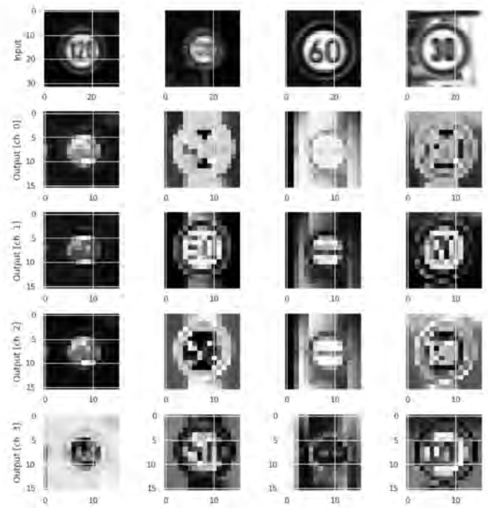

Figure 7. Example GTSRB dataset images and corresponding output features using NNQE circuit.

4. Results and Discussion

Figure 8 shows the variation in the classification accuracy of the test set as a function of the training epoch using the MNIST dataset. As shown in Figure 8, QuanvNN improves the accuracy of the test set over the classical NN. The performance was further improved by the NNQE circuit. Again, we emphasize that this improvement was obtained without introducing any additional optimizing parameters in the machine learning process.

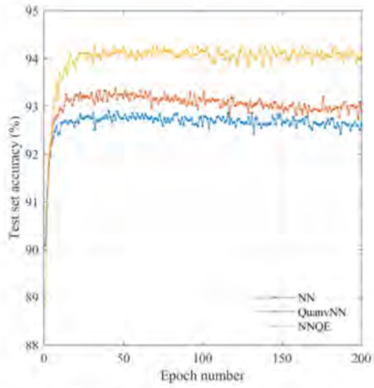

Figure 8. Test set accuracy against MNIST dataset images.

Figure 9 shows the variation in the accuracy of the test set as a function of the training epoch using the CIFAR-10 dataset. A large improvement was obtained by the application of the QuanvNN over the classical NN, with a further improvement obtained by the application of the NNQE circuit.

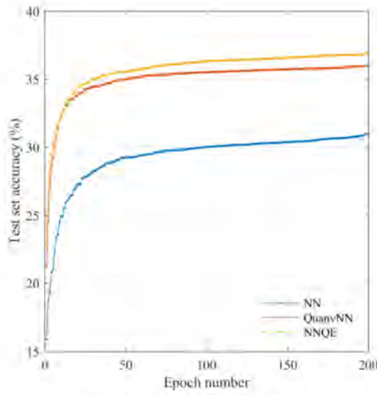

Figure 9. Test set accuracy against CIFAR-10 dataset images.

Figure 10 shows the variation in the accuracy of the test set using the GTSRB dataset. Unlike the cases using the MNIST and CIFAR-10 datasets, the test set accuracy obtained using the QuanvNN was reduced compared with that of the classical NN. However, the proposed NNQE circuit outperforms the QuanvNN, as shown in Figure 10.

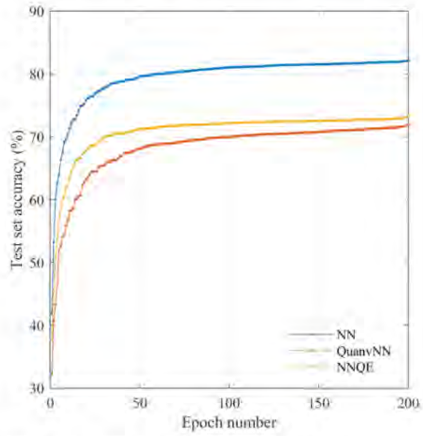

Figure 10. Test set accuracy against GTSRB dataset images.

We note that in each case of the MNIST, CIFAR-10, and GTSRB datasets, other classical methods, such as CNNs, which are algorithmically more complex but can be implemented efficiently on modern processors, can in practice produce a higher image classification accuracy than that by our proposed NNQE method. However, the benefit of our proposed NNQE method is to observe that the application of the quantum circuit can improve the image classification accuracy over a classical method. Understanding the exact causes of this observation is expected to lead a better design of the quantum circuit that is more beneficial in practice in the future. However, the exact cause of this phenomenon is currently unknown and requires further investigation. We believe one plausible reason could be the better correlations between the image pixels that may be enhanced owing to the strong entanglement between the qubits, thereby leading to an overall improvement in accuracy. A summary of the results is presented in Table 2.

Table 2. Converged training and testing accuracy.

	Classical NN	QuanvNN	NNQE
Training Accuracy against MNIST	93.5%	94.2%	95.1%
Testing Accuracy against MNIST	92.0%	93.0%	93.8%
Training Accuracy against CIFAR-10	34.1%	41.2%	42.0%
Testing Accuracy against CIFAR-10	30.5%	34.9%	36.0%
Training Accuracy against GTSRB	96.2%	94.8%	97.5%
Testing Accuracy against GTSRB	82.2%	71.9%	73.4%

To investigate the characteristics of the proposed NNQE, eight optimizers and five batch sizes were tested using the GTSRB dataset. These optimizers were used to run the model and have different effects on the model execution and training. The following are the models used to check the performance efficiency of our proposed NNQE circuit: Adam, AdaDelta, RMSProp, Adagrad, AdaMax, SGD, Nadam and FTRL. Figure 11 shows test set accuracy using the different optimizers and batch sizes against GTSRB.

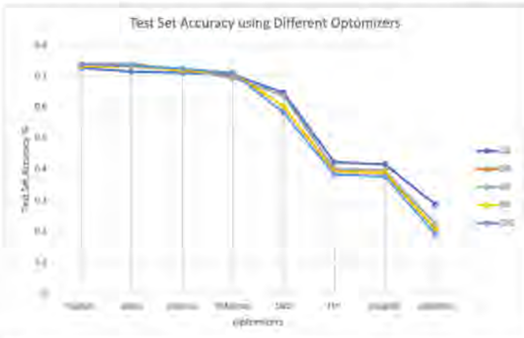

Figure 11. Test set accuracy using different optimizers and batch sizes against GTSRB. The batch size is listed in the legend.

It is evident from Figure 11 that the Nadam-based optimizer algorithm performs better than all other optimizers used in this study. For the different batch sizes tested in Figure 11, the results show only a small difference among the best-performing optimizers using a wide range of batch sizes (10, 30, 60, 90, and 120).

5. Conclusions and Future Directions

In this study, we developed a new NNQE method and investigated the image classification performance using three different well-known image datasets. As shown in Table 2, the testing accuracy against MNIST (handwritten digits) was improved from 92.0% by the classical NN to 93.0% by the previously proposed QuanvNN, and further to 93.8% by our proposed NNQE. Similarly, the testing accuracy against CIFAR-10 (colored images) was improved from 30.5% by the classical NN to 34.9% by QuanvNN, and further to 36.0% by NNQE. Both MNIST and CIFAR-10 had 10 distinct classes. While the exact cause of this is not yet clear and requires further investigation, one plausible reason could be the better correlations between the image pixels that may be enhanced owing to the strong entanglement between the qubits, thereby leading to an overall improvement in accuracy. However, the performance of the proposed model was degraded when applied to real-life, complex, colored images of traffic signs (GTSRBs), which have 43 classes in comparison with the classical NN. This is shown in Table 2 as follows: The testing accuracy against GTSRBs by the classical NN was found to be 82.2%, which was reduced to 71.9% by the previously proposed QuanvNN. The testing accuracy against GTSRBs was improved from 71.9% to 73.4% by our proposed NNQE. However, this is still a reduction in the testing accuracy against GTSRB from 82.2% achieved by the classical NN. This indicates that further development of the NNQE model may be necessary for relatively larger classes in more complex datasets, such as real-life traffic signs and GTSRBs. We also tested different optimizers for the proposed model to demonstrate the efficacy of NNQE model further. The results showed that Nadam-based optimizers produced the most optimal results. This is perhaps attributable to the Nadam algorithm being an extension of Adam optimizers, which add Nesterov's Accelerated Gradient (NAG), or Nesterov momentum, to provide an improved type of momentum for the search procedure. Future research could also include increasing the number of qubit sizes from four, as well as investigating the indicators of performance improvements, or their relative degradation, in comparison with classical NN. These studies could involve proposing new methodologies for designing quantum circuits to build on the present study and tests with more complex datasets with larger classes or concealed data features.

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Synthesis of Outcomes

To address real world traffic sign classification, we used a penny-lane template module built into this paper. Based on results obtained on MNIST and CIFAR-10 datasets, the proposed NNQE model outperformed both existing quantum and classical neural networks. Nevertheless, in the following chapter, we have introduced a quantum filter model with higher performance and lower computational complexity than the NNQE. To improve the quality of extracted features, this new model reduces the number of parameters for the filter weights. In summary, the paper provides insight into quantum neural network models` potential for real-word applications, especially in the field of image classification.

In the next chapter, we propose a promising new approach for feature extraction by comparing the performance of a variety of entangling arrangements for quantum neural network model.

CHAPTER 4: ARTICLE 2 - DEVELOPMENT OF A NOVEL QUANTUM PRE-PROCESSING FILTER TO IMPROVE IMAGE CLASSIFICATION ACCURACY OF NEURAL NETWORK MODELS

The paper proposes a novel approach to improve the accuracy of image classification in neural networks (NNs) through a quantum pre-processing filter (QPF). The QPF employs a four-qubit quantum circuit using Y-rotation for encoding and two controlled NOT gates to create correlation among the qubits as a feature extraction filter before the fully connected NN. The QPF was tested using MNIST and EMNIST datasets, and results showed significant improvements in accuracy without the need for additional parameter optimization in the machine learning process. The QPF performed poorly when tested on a more complex GTSRB dataset, indicating the need for further research into designing suitable quantum circuits for image classification NNs.

Highlights

1. To propose a novel approach to improve image classification accuracy in neural networks using a quantum pre-processing filter (QPF).
2. The proposed QPF uses a four-qubit quantum circuit with Y-rotation for encoding and two controlled NOT gates to create correlation among the qubits as a feature extraction filter.
3. The proposed QPF is tested on MNIST and EMNIST datasets, showing significant improvements in accuracy without additional parameter optimization in the machine learning process.
4. The proposed QPF performed poorly on a more complex GTSRB dataset, indicating the need for further research into suitable quantum circuits for image classification NNs.

Graphical Representation

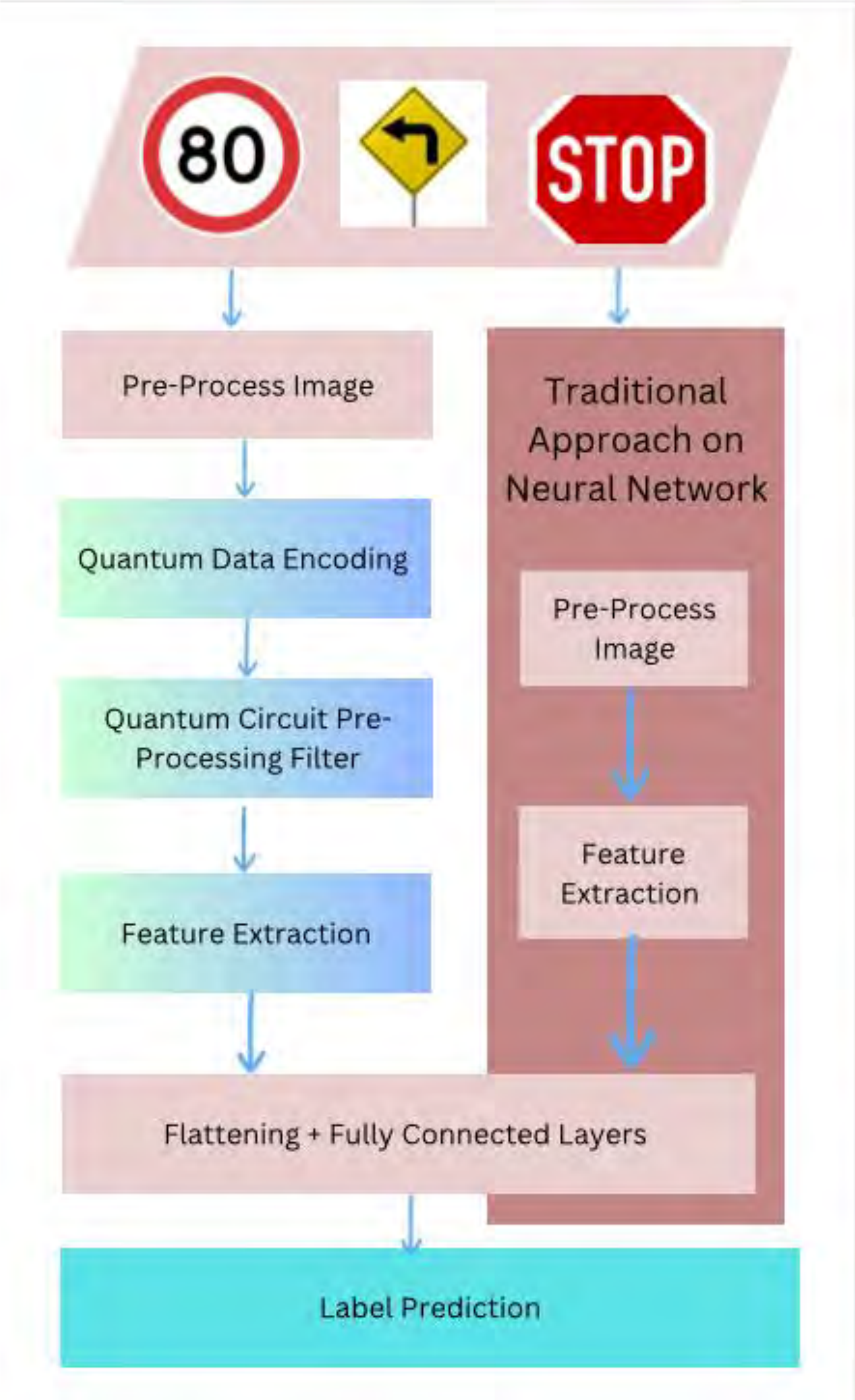

Figure 7 Graphical representation of the development of a novel quantum pre-processing filter to improve image classification accuracy of neural network models

Development of a Novel Quantum Pre-processing Filter to Improve Image Classification Accuracy of Neural Network Models

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Keywords: *Quantum Computing, Machine Learning, Image Classification, Neural Network*

A novel quantum pre-processing filter (QPF) to improve the image classification accuracy of neural networks (NNs) is proposed in this paper. A simple four qubit quantum circuit that uses Y rotation for encoding and two controlled NOT gates for creating corre- lation among the qubits is applied as a feature extraction filter prior to the fully connected NN. By the application of QPF, image classification accuracy using MNIST (handwritten 10 digits) and EMNIST (handwritten 47 class digits and letters) datasets is improved from 92.5% to 95.0% and from 68.9% to 75.8%, respectively. These improvements were obtained without introducing any extra parameters to optimize in machine learning process. However, a test against a more complicated GTSRB dataset (43 class real-life traffic sign images) shows degradation in classification accuracy by the application of QPF, which calls for further research into understanding and design of suitable quantum circuits for image classification neural networks.

1 Introduction

The application of quantum computing to the tasks of machine learning, herein referred to as quantum machine learning, has attracted much research efforts in recent years. Literature surveys on quantum machine learning can be found in [1, 2, 3]. Among many proposals to combine classical machine learning methods with quantum computing, quanvolutional neural network (QNN) proposed by Henderson et. al. [4] has an advantage of being implementable on quantum circuits with a smaller number of qubits with shallow gate depths and yet being applicable to practical applications. QNN utilizes quantum circuits as transformation layers, called quanvolutional layer, to extract features for the purpose of image classification using convolutional neural networks (CNNs). In [4], MNIST handwritten 10-digit dataset [5] was applied to QNN using 9 qubits. The results showed classification accuracy improvement using QNN over CNN. However, when the quanvolutional layer of QNN was replaced by a conventional layer, no improvement in classification accuracy was observed. Henderson et. al. later updated QNN and implemented on Rigetti Computing's Aspen-7-25Q-B quantum processing unit which has 25 qubits with 24 programmable two-qubit gate interactions [6]. The proposed method was applied to 4 class low resolution satellite image dataset. However, no improvement in classification accuracy by QNN over CNN was observed in [6].

An implementation of QNN on a software quantum computing simulator, PennyLane [7], was provided by Mari [8]. Mari's implementation of QNN differs from that of Henderson in that the output of the quantum circuit, which is a set of expectation values, is directly fed into the following neural network layer, while that of Henderson was made into a single scalar value by a classical method. The proposed method was applied to MNIST dataset using 50 training and 30 test image set. No clear improvement in classification accuracy by QNN over NN was observed in [8].Inspired by Henderson's and Mari's QNNs, we have proposed a novel model by proposing a new model NNQE by using strong entanglement for QNN and have shown improvement for MNIST and CIFAR-10 datasets on Quantum over classical neural network but applying the same model on GTSRB results in degradation [12]. This led us to investigate a new model for Quantum NN that can perform better by using a smaller number of computational gates. we propose a new method, herein called quantum pre-processing filter (QPF), that shows clear improvements in image classification accuracy over conventional neural networks. QPF uses a quantum circuit with four qubits, four Y rotations, two controlled NOTs (CNOTs), and four measurements. When QPF is applied as a pre-processing unit of an image classification neural network, i.e. as a feature extraction filter, the image classification accuracy of fully connected neural net- work against MNIST and EMNIST (handwritten 47 class digits and letters, [9]) improves from 92.5% to 95.0% and from 68.9% to 75.8%, respectively. These improvements were obtained without introducing any extra parameters to optimize in machine learning process. Unlike other quantum machine learning methods, the use of QPF does not require optimization of the parameters inside the quantum circuits,and hence requires only a limited use of the quantum circuit. Given the small number of qubits and relatively shallow depth of the quantum circuit, QPF is well suited to be implemented on noisy intermediate- scale quantum computers. While the proposed method is promising, a test against a more complicated dataset, GTSRB (43 class real-life traffic sign images, [10]), showed degradation in classification accuracy by the application of QPF. This prompts further research into understanding and design of suitable quantum circuits for image classification neural networks.This paper is organized as follows: The new QPF unit combined with the classical image classification neural network is proposed in Section 2. Section 3 describes the experiment conducted using software simulation. Results and discussion are presented in Section 4, followed by conclusions in Section 5.

2 Methodology

Figure 1 shows the architecture of the proposed model. We assume that the input image is a two-dimensional matrix with size m-by-m and the pixel value, x, follows $0 \leq x \leq 1$. An extension to multi-channel pixel image is considered as straightforward. Similar to QNN models, a section of size n-by-n is extracted from the input image. While $1 < n \leq m$ in the case of QNN, the proposed QPF uses $n = 2$. This 2×2 section of the input image is referred as QPF window. An extension of QPF using $n > 2$ is left for further studies. Given $n = 2$, we use 4 qubit quantum circuit as shown in Figure 1. The four qubits are initialized in the ground state. The four-pixel values are then encoded using Y rotation with $\theta = \pi x$ according to (1).

$$R_y(\theta) = \begin{pmatrix} \cos\frac{\theta}{2} & -i\sin\frac{\theta}{2} \\ \sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{pmatrix} \quad (1)$$

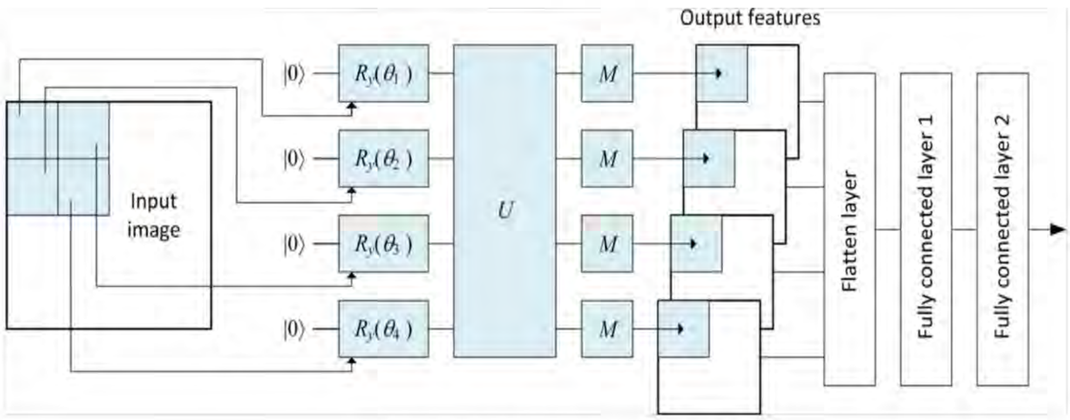

Figure 1: Architecture of proposed model.

The outputs from the Y rotation gates are fed to the quantum circuit referred as U in Figure 1. Measurements, referred as M in Figure 1, are performed on the output of the quantum circuit U. Three different quantum circuits are examined in this paper. The first circuit, referred as Encoding only and shown in Figure 2, performs measurement straight after the encoding. The second circuit, referred as One CNOT

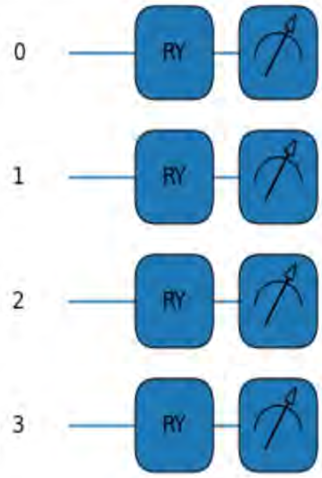

Figure 2: Quantum pre-processing filter, encoding only.

and shown in Figure 3, performs controlled NOT operation with the first qubit as the control and the4th qubit as the target as shown in Figure 3. The third circuit, referred as Two CNOTs, performs two controlled NOT operations as shown in Figure 4.The outputs from the measurement operations are given as expectation values between -1 and 1, and form output features. We note that the total number of parameters in the input image ($n \times n$) is the same as the total number of parameters in the output features ($4 \times (n/2) \times (n/2)$). The output features are made into one dimensional vector by the flatten layer. The number of the nodes of the output of the flatten layer is $n \times n$. The nodes are fully connected by the first fully connected layer 1. The output of the fully connected layer 2 has the number of nodes equal to the number of classes.

3 Experiment

As was performed by many, we first apply the proposed method to the MNIST dataset [5] to obtain bench-mark results. The MNIST dataset consists of 60,000 training and 10,000 test images of handwritten digits of 0 to 9. The size of each image is 28 by 28 pixels. The original images are in greyscale within the values between 0 and 255, which are scaled by dividing them by 255. We then chose the EMNIST dataset [9] to extend the number of image class. The EMNIST dataset (Balanced and By_Merge [9]) contains 112,800 training and 18,800 test images of handwritten digits and letters making up 47 classes. Note that some of upper- and lower-case letters are merged due to their similarity (e.g. C is similar to c) in this dataset. Original EMNIST dataset is divided by 255 to create dataset with pixel values between 0 and 1. The GTSRB dataset [10] consists of 34,799 training and 12,630 test images of 43 class traffic signs captured from actual traffic signs in-use in various conditions. The original dataset has various image sizes between 15×15 and 222×193 pixels. Those images were scaled to a size of 32×32 pixels. The original images were in RGB color, which were converted into grayscale between 0 and 255. Unlike MNIST and EMNIST dataset, to normalize the dynamic range of each image, the normalization is applied to each image according to the following formula:

$$\tilde{c}_{x,y} = \frac{c_{x,y} - \min(I)}{\max(I) - \min(I)} \tag{2}$$

where $c_{x,y}$ and $\tilde{c}_{x,y}$ represent the original and normalized pixel values in the position (x,y), and max(I)

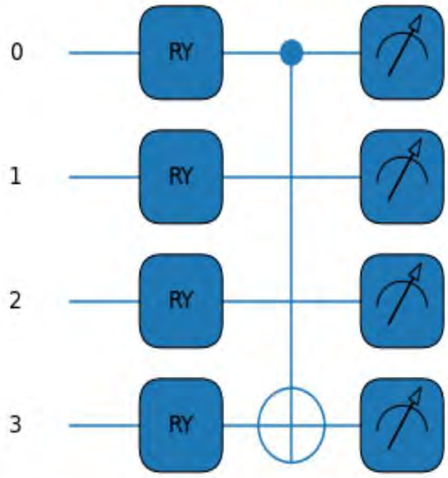

Figure 3: Quantum pre-processing filter, one CNOT.

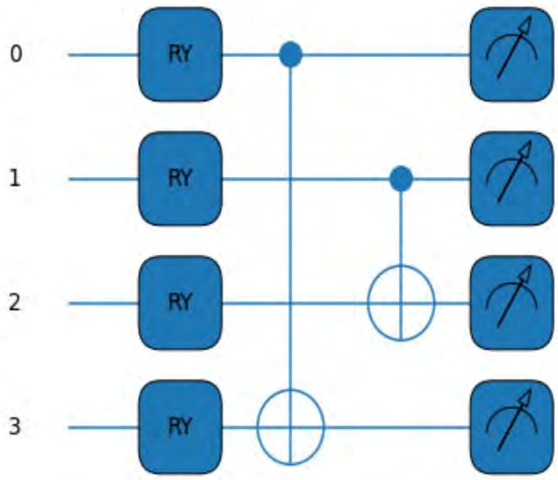

Figure 4: Quantum pre-processing filter, two CNOTs.

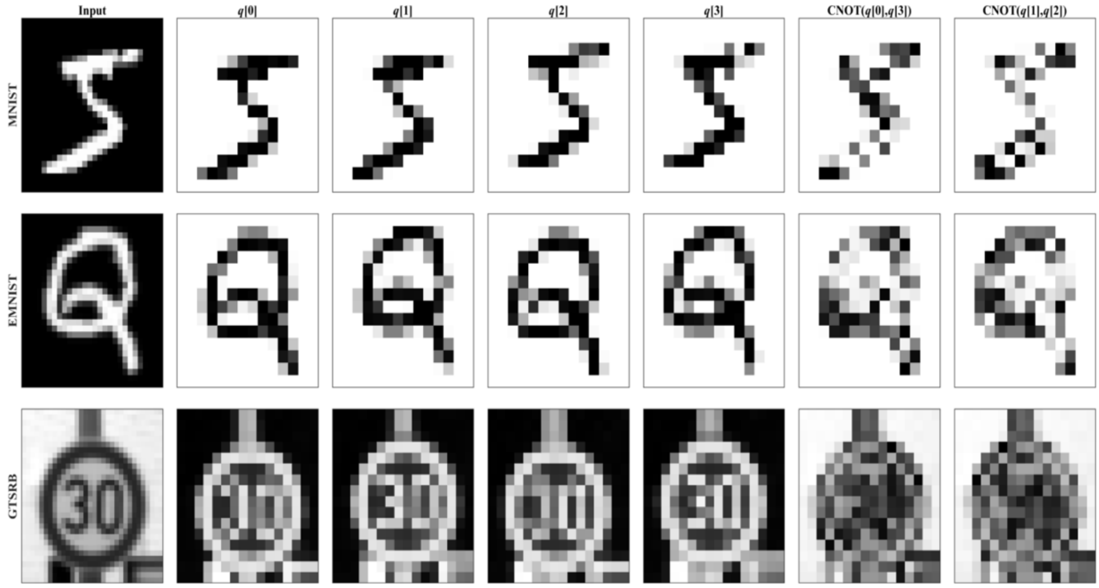

Figure 5: Example input image and output features.

and min(I) denote the maximum and the minimum element in the two dimensional image matrix I, respectively.
The experiment was performed by Penny Lane quantum simulator using custom codes to describe the operation of the quantum circuit and Statistical and Machine Learning Toolbox for the training of the neural network. Adam optimizer [11] was used as the solver for the training network. Default mini-batch size of 128 was used for all three datasets.
Figure 5 shows example input images from MNIST, EMNIST, and GTSRB, and corresponding output features using encoding only (labelled as $q[0]$ to $q[3]$), and two CNOTs (CNOT($q[0]$, $q[3]$) and CNOT($q[1]$, $q[2]$)).

4 Results and Discussion

Figure 6 shows the variation of test set accuracy as a function of training iterations using MNIST dataset. As can be seen in Figure 6, the test set accuracy using QPF Encoding only converges faster than that of NN. The phenomenon of faster convergence was also observed in Henderson's QNN [4]. However, the converged test set accuracy of the QPF Encoding only model does not improve that of NN. The application of QPF One CNOT improves the test set accuracy from 92.2% to 93.7%. The test set accuracy is further improved to 95.1% by the application of QPF Two CNOTs.
Similarly, small but clearly faster convergence is observed by the application of QPF Encoding only in the case of EMNIST dataset as shown in Figure 7. However, in the case of EMNIST, the converged test set accuracy of the QPF Encoding only is reduced from that of NN. Nonetheless, the test set accuracy is improved from 68.1% to 71.4% by the application of QPF One CNOT, and to 75.6% by the application of QPF Two CNOTs.
Figure 8 shows the variation of test set accuracy using GTSRB dataset. Unlike the cases using MNIST and EMNIST datasets, the converged test set accuracy by the application of QPF is reduced from that of NN in the case of GTSRB dataset. We see improvement in accuracy as entanglement increases the correlation between the image pixel, which results in improved accuracy in MNIST [12] and EMNIST. We can increase the complex image accuracy in GTSRB by increasing more qubits as future work.

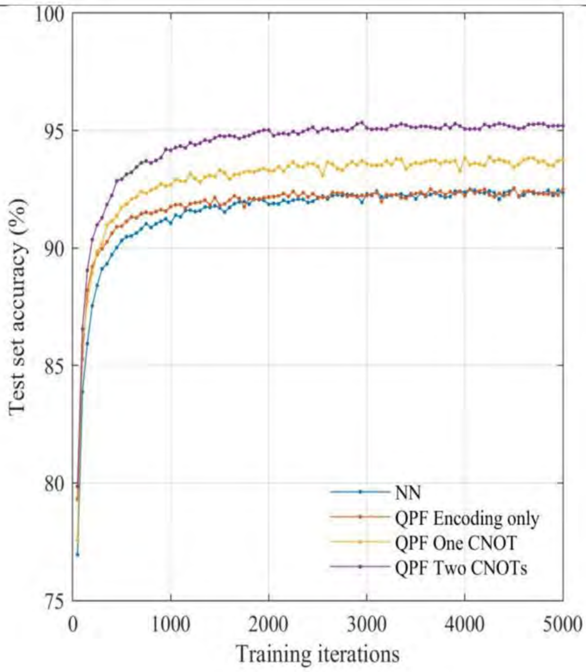

Figure 6: Test set accuracy using MNIST dataset.

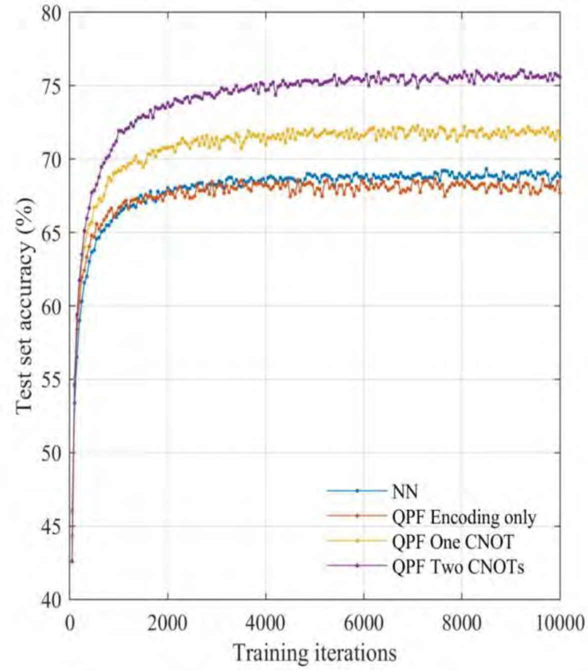

Figure 7: Test set accuracy using EMNIST dataset.

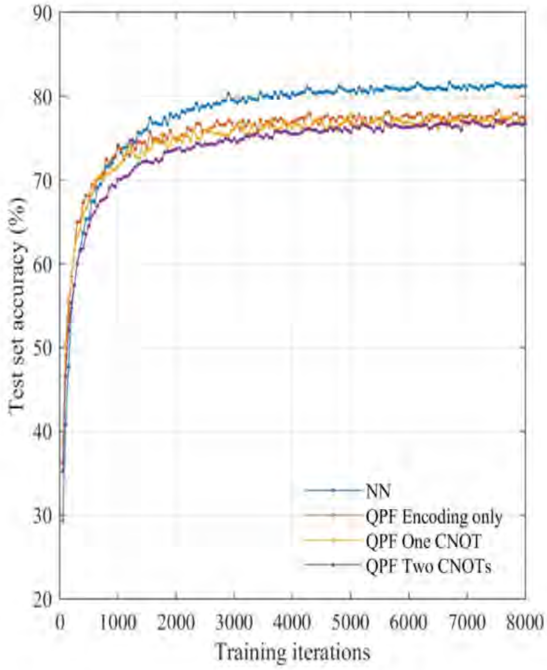

Figure 8: Test set accuracy using GTSRB dataset.

Referring back to Figure 3, there are 12 different ways to create a CNOT circuit from four qubits. In order to investigate if different CNOT arrangement would make the difference in classification accuracy, the training of the network and the classification of the images were performed for MNIST dataset using the 12 different CNOT arrangements. Figure 9 shows the results. The x axis of Figure 9 denotes the arrangement of the CNOT where the lower number refers to the control qubit and the upper number refers to the target qubit. For example, "0 3" refers to the arrangement as shown in Figure 3. As can be seen from Figure 9, the variation of test set accuracy for different CNOT arrangement is considered to be small, within less than 0.6%.Similarly, there are 24 different ways to arrange the two CNOTs using four qubits. The test set accuracy was derived for 24 different two CNOTs arrangement using MNIST dataset, and the results are shown in Figure 10. In Figure 10, the x axis label refers to the arrangement of the two CNOTs in the order of the control and target qubits of the first CNOT, then the control and target qubits of the second CNOT. For example, "0 3 1 2" refers to the arrangement as shown in Figure 4. As can be seen in Figure 10, the CNOT arrangements pairing the 1st and the 4th qubits and pairing the 2nd and 3rd qubits achieve a higher test set accuracy, irrespective to which qubit is assigned as target or control. Referring back to Figure 1, the pairing of the 1st and 4th qubits and the pairing of the 2nd and 3rd qubits correspond to the pairing the diagonal elements of the 2 x 2 QPF window. The exact reason for the improved classification accuracy in the case of MNIST and EMNIST dataset when correlating the diagonal elements of the QPF window will be addressed in future research.

5 Conclusion

A novel QPF that can improve the image classification accuracy of NN for MNIST and EMNIST datasets is proposed. While clear improvements are observed, it has been proven that the model we proposed has improved accuracy while using fewer computations for quantum NN. The model only required 4 qubits and 2 entanglements for feature extraction, and outperformed all other QNN models in terms of test accuracy. Our model requires to be scalable further as a future work, since complex images like the GTSRB traffic sign contain multiple tiny details on the image pixels. Also, further investigation is needed in order to improve the classification accuracy of NNs against complex images such as those from GTSRB dataset.

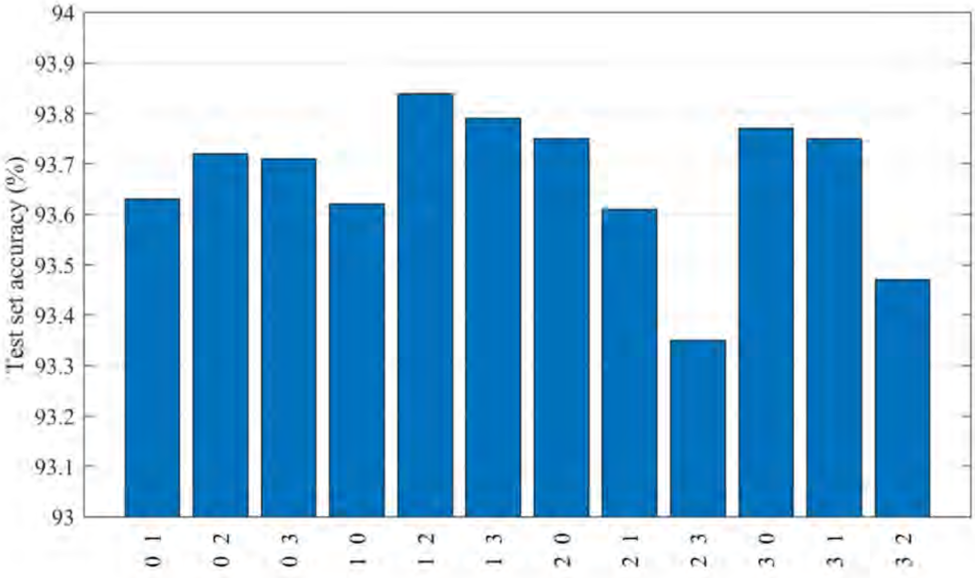

Figure 9: Test set accuracy on MNIST dataset using different CNOT arrangements.

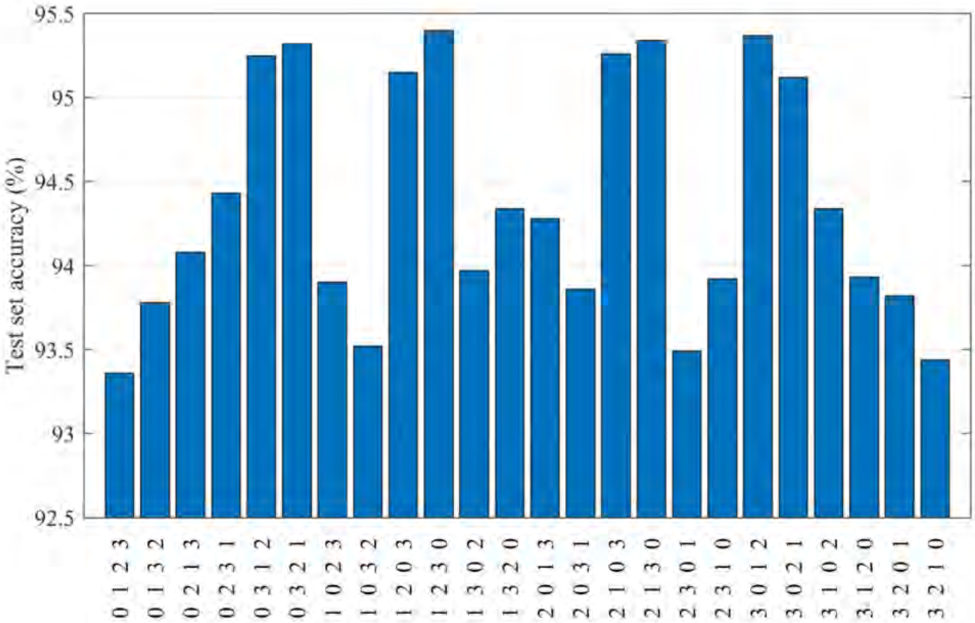

Figure 10: Test set accuracy on MNIST dataset using different two CNOTs arrangements.

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Synthesis of Outcomes

This paper presents a new approach to image classification using quantum neural networks (QNNs) called the quantum filter model (QPF). The QPF was applied to the MNIST and EMNIST datasets and achieved higher accuracy with fewer computations, utilizing only 4 qubits and 2 entanglements for feature extraction. The model outperformed all other QNN models in terms of test accuracy. However, the QPF needs further development to be scalable for complex images such as those found in the GTSRB traffic sign dataset. The exact reasons for the improvements seen in the QPF are not yet known and require further investigation. The authors suggest that improving the accuracy of NNs on complex images remains an area for future research.

The model has demonstrated success but exhibited a decline in performance when applied to complex images, such as traffic signs, for multi-class classification. This prompted further exploration of the model for binary classification in the subsequent chapter.

CHAPTER 5: ARTICLE 3 -
APPLICATION OF QUANTUM PRE-PROCESSING FILTER FOR BINARY IMAGE CLASSIFICATION WITH SMALL SAMPLES

The paper has completed an investigation on our proposed novel approach in Chapter 4 (Article 2) to improve the accuracy of image classification in neural networks (NNs) through a quantum pre-processing filter (QPF) with use of binary classification. We evaluated the QPF on two datasets: 14 MNIST, which consists of handwritten digits, and GTSRB, which includes 43 class real-life traffic sign images. Similar to our previous multi-class classification results, the application of QPF 16 improved the binary image classification accuracy using neural network against MNIST but degraded it against GTSRB. We then applied QPF in cases using 18 smaller number of training and testing samples, i.e. 80 and 20 samples per class, respectively. In 19 order to derive statistically stable results, we conducted the experiment with 100 trials choosing 20 randomly different training and testing samples and averaged the results. Further research is required to investigate the potential of QPF in other machine learning applications and to assess the scalability of the proposed approach to larger datasets and more complex models.

Highlights

1. The paper presents a new technique proposed in Chapter 4 (Article 2) to enhance image classification accuracy in neural networks (NNs) by utilizing a quantum pre-processing filter (QPF) with binary classification.
2. The experiment used a smaller number of training and testing samples (80 and 20 samples per class, respectively), and was repeated 100 times with different sample selections to obtain statistically stable results.
3. The application of QPF improved the binary image classification accuracy using neural network.

Graphical Representation:

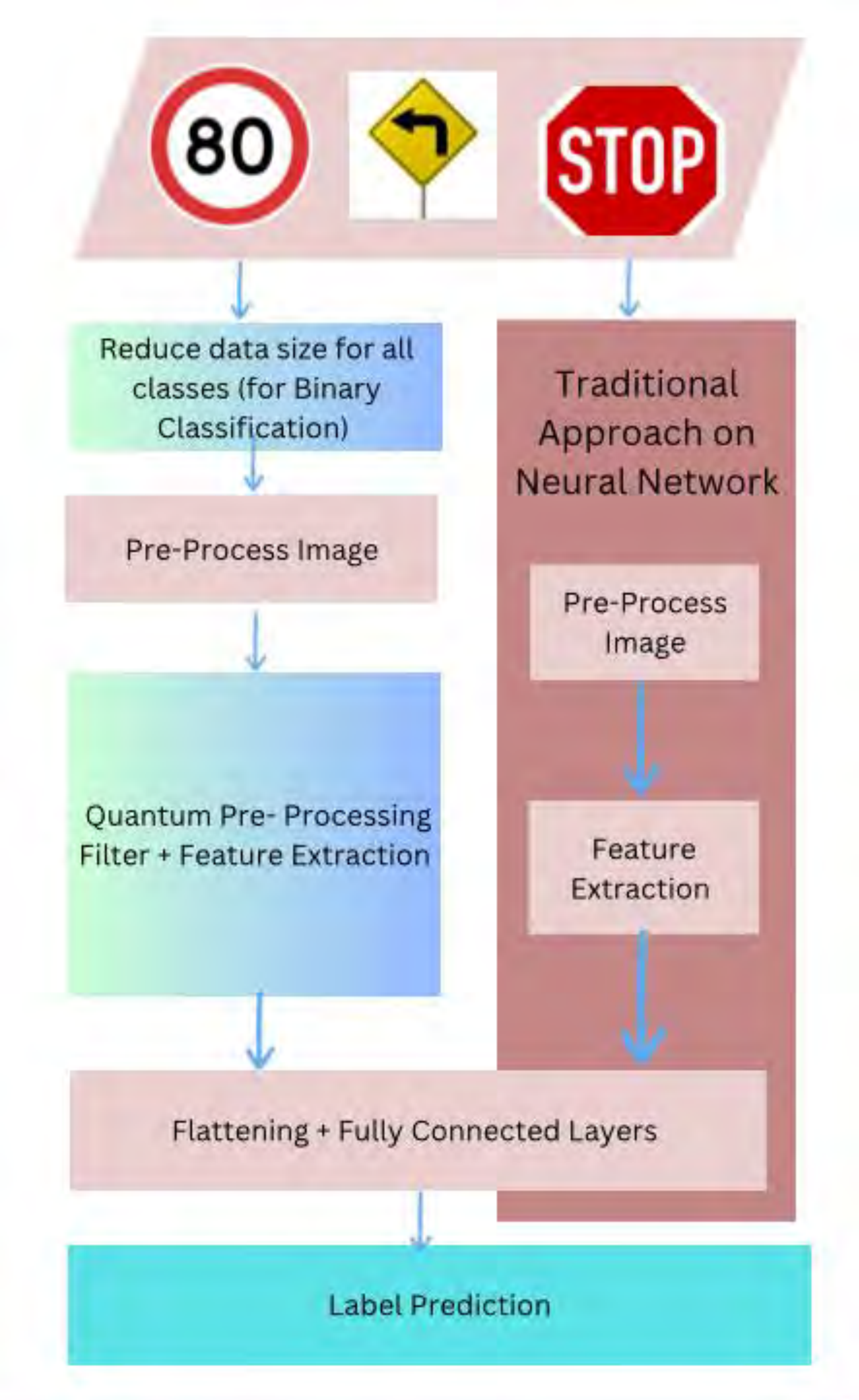

Figure 8 Graphical representation of the application of quantum pre-processing filter for binary image classification with small samples

sensors MDPI

Article

Application of Quantum Pre-Processing Filter for Binary Image Classification with Small Samples

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Abstract: Over the past few years, there has been significant interest in Quantum Machine Learning (QML) among researchers, as it has the potential to transform the field of machine learning. Several models that exploit the properties of quantum mechanics have been developed for practical applications. In this study, we aim to extensively investigate the application of our previously proposed quantum pre-processing filter (QPF) to binary image classification for smaller number of samples. of the dataset to improve the accuracy for complex images further which is inspired from the recent advancement in quantum machine learning. We evaluated the QPF on two datasets: MNIST, which consists of handwritten digits, and GTSRB, which includes 43 class real-life traffic sign images. Similar to our previous multi-class classification results, the application of QPF improved the binary image classification accuracy using neural network against MNIST from 98.9% to 99.2% but degraded it against GTSRB from 93.5% to 92.0%. We then applied QPF in cases using smaller number of training and testing samples, i.e. 80 and 20 samples per class, respectively. In order to derive statistically stable results, we conducted the experiment with 100 trials choosing randomly different training and testing samples and averaged the results. The result showed that the application of QPF did not improve the image classification accuracy against MNIST from 94.7% to 94.5% but improved it against GTSRB from 90.5% to 91.8%. Further research will be conducted as part of future work to investigate the potential of QPF to assess the scalability of the proposed approach to larger and complex datasets.

Keywords: Artificial Intelligence, Binary classification, Intelligent Transportation System, Quantum Computer, Quantum Computing, Quantum Machine learning, Traffic Signs

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1. Introduction

Over the past few years, there has been significant interest in Quantum Machine Learning (QML), with various algorithms proposed for image processing [1]. Quantum machine learning is a hot topic recently [2], especially since quantum hardware development has gradually accelerated [3]. The application of quantum technology in image processing is crucial for efficiently extracting valuable information from real-world scenarios. Numerous approaches have been developed for quantum image classification, such as quantum neural networks [4] quantum convolutional neural network [5], Hybrid quantum classical convolutional neural network [6], quantum generative adversarial network [7] [8] and quantum support vector machines [9]. The goal of using QML in images is to extract essential features from the image. To achieve this, a classical kernel approach can first be used to estimate unsolvable quantum kernels on a quantum device.

Secondly, different models can be created that process the feature vectors using quantum models based on variational circuits. These models gain their strengths by outsourcing nonlinearity into the process of encoding inputs into a quantum state or the quantum feature map. This combination of quantum computing with kernel theory will help in developing QML algorithms that offer potential quantum speedup on near-term quantum devices [10].

Of the various suggested ways to merge classical machine learning techniques with quantum computing, the method introduced by Henderson *et al.* in [11] offers several advantages. It can be implemented on quantum circuits with fewer qubits and shallow gate depths, yet it can be applied to more practical use cases. This method employs quantum circuits as transformation layers to extract features for image classification using convolutional neural networks (CNNs). The transformation layers are referred to as quanvolutional layers, and the method is referred as a quanvolutional neural network (QuanvNN) in this research article.

A crucial query arose regarding whether the features generated by quanvolutional layers could enhance the classification accuracy of machine learning models. To investigate this, Henderson *et al.* have conducted a study where randomly generated quantum circuits were used to compare the classification accuracy of QuanvNN with a standard CNN. However, the findings did not demonstrate a clear advantage in classification accuracy over the classical model [11]. In a subsequent study [12], QuanvNN was updated, implemented on quantum hardware (Rigetti's Aspen-7-25Q-B quantum processing unit), and evaluated on a satellite imagery classification task. Nevertheless, the image classification accuracy of QuanvNN was not improved in comparison to that of a traditional CNN algorithm.

The work of Mari [13] provided an implementation of QuanvNN on a software quantum computing simulator called PennyLane [14]. Their approach differs from that of Henderson *et al.* in that the output of the quantum circuit, which is a set of expectation values, is directly fed into the subsequent neural network (NN) layer, whereas Henderson *et al.* [11] transformed it into a single scalar value using a classical method. The proposed method was tested on the MNIST dataset [15], which consists of handwritten digits, using 50 training and 30 test images. However, the study of [13] shows that no clear improvement in classification accuracy by QuanvNN over NN was observed in Mari's study.

In our previous research [16], we extended Mari's QuanvNN by utilizing a randomly generated quantum circuit with four qubits, 20 single axis rotations, and 10 controlled NOTs (CNOTs), to enhance image classification accuracy when compared to a classical fully connected NN. Specifically, the extended QuanvNN approach improved the accuracy of MNIST and CIFAR-10 datasets (photographic 10 class image dataset [17]) from 92.0% to 93.0% and from 30.5% to 34.9%, respectively [16]. We also proposed a new model, neural network with quantum entanglement (NNQE), that incorporates a strongly entangled quantum circuit with four qubits, 20 three axis rotations, 20 CNOTs, and Hadamard gates. This model further increased image classification accuracy against MNIST and CIFAR-10 to 93.8% and 36.0%, respectively [16]. However, using QuanvNN or NNQE was found to degrade the image classification accuracy when applied to a more complicated German Traffic Sign Recognition Benchmark (GTSRB) dataset (43 class real-life traffic sign images [18]) in comparison with the classical NN accuracy from 82.2% to 71.9% (QuanvNN) and to 73.4% (NNQE) [16].

The concept of using a quantum circuit as a pre-processing filter for image classification tasks has been extended by the introduction of quantum pre-processing filter (QPF) by the authors in [19]. In [19], a much simplified quantum circuit, i.e. a four qubit quantum circuit with Y rotations for encoding and two CNOTs, was introduced. By applying the QPF approach, the results showed that the image classification accuracy based on MNIST and EMNIST (handwritten 47 class digits and letters [20]) datasets was improved against classical NN from 92.0% to 95.0% and from 68.9% to 75.8%, respectively.

However, tests using the proposed QPF approach against GTSRB showed again a degradation in the classification accuracy from 81.4% to 77.1% [19].

In this study, we first extend the application of QPF using two CNOTs from multi-class classification to binary classification against all possible different pairs of image classes. For 10 classes, e.g. MNIST, the total number of pairs is 10 × 9 = 90. For 43 classes, .e.g. GTSRB, the total number of pairs is 43 × 42 = 1,806. The proposed method achieves a higher image classification accuracy of 98.9% compared to 92.5% against MNIST using NN. The image classification accuracy was further improved to 99.2% by the application of QPF. While the image classification against GTSRB was improved from 81.4% to 93.5% by the use of the proposed binary image classification method, the application of QPF degraded the image classification accuracy from 93.5% to 92.0%, similar to our previous results. We note that practical application of the proposed binary classification approach requires an additional categorization method to extract training and testing images corresponding to the chosen classes from larger samples. This additional categorization method is outside of the scope of the current study and is left for a further study.

Secondly, we apply QPF to cases using a smaller number of training and testing samples, i.e. 80 training samples and 20 testing samples per class. The use of a smaller number of samples is considered in application where faster training and testing is required. In order to derive statistically stable results, we conducted the experiment with 100 trials choosing randomly different training and testing samples and averaged the results. The result showed that the application of QPF did not improve the image classification accuracy against MNIST from 94.7% to 94.5% but improved it against GTSRB from 90.5% to 91.8%. While the exact cause of this phenomenon is currently under investigation, this result is significant in understanding of the effects of QPF in machine learning methods.

The structure of this research paper is as follows: Section 2 outlines the methodology of our proposed model. Section 3 provides a detailed account of our experimental setup. Section 4 contains the results and discussion. Finally, in Section 5, we present our conclusions.

2. Methodology

The architecture of QPF was first proposed in [19]. For the sake of completeness, we reproduce the description of QPF in this section. Figure 1 shows the architecture of the proposed QPF. The method assumes that the input image is a two-dimensional matrix with size m-by-m and the pixel value x, follows $0 \le x \le 1$. An extension to multi-channel pixel image is considered as straightforward. A section of size n-by-n is extracted from the input image. The proposed QPF uses $n = 2$. This 2 × 2 section of the input image is referred as QPF window.

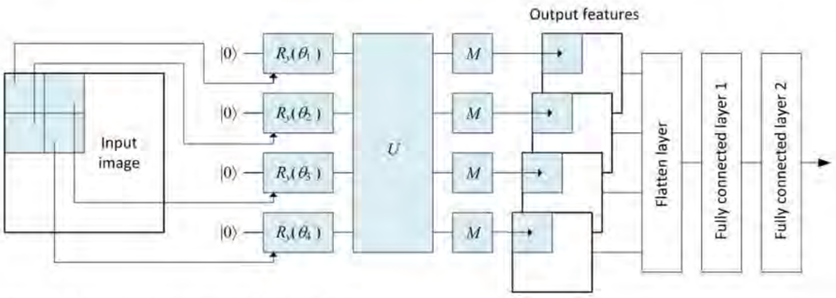


Figure 1. The architecture of QPF model.

Given $n = 2$, we use 4 qubit quantum circuit as shown in Figure 1. The four qubits are initialized in the ground state. The four pixel values are then encoded using Y rotation with $\theta = \pi x$ according to

$$R_y(\theta) = \begin{bmatrix} \cos\frac{\theta}{2} & -i\sin\frac{\theta}{2} \\ \sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{bmatrix}, \tag{1}$$

The outputs from the Y rotation gates are fed to the quantum circuit referred as U in Figure 1. Measurements, referred as M in Figure 1, are performed on the output of the quantum circuit U. The structure of the quantum circuit U is further detailed in Figure 2. In [19], we conducted experiments with different CNOTs arrangement (quantum entanglement property of quantum mechanics) and found that the arrangement as given in Figure 2 showed superior improvements in image classification accuracy.

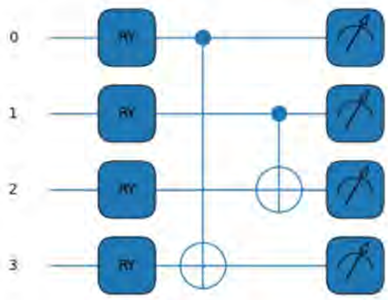


Figure 2. QPF with two CNOTs.

The outputs from the measurement operations are given as expectation values between −1 and 1, and form output features. We note that the total number of parameters in the input image ($m \times m$) is the same as the total number of parameters in the output features ($4 \times (m/2) \times (m/2)$). The output features are made into a one-dimensional vector by the fatten layer. The number of the nodes of the output of the flatten layer is $m \times m$. The nodes are fully connected by the first fully connected layer 1. The output of the fully connected layer 2 has the number of nodes equal to the number of classes.

3. Experiment

The method proposed has been implemented using python. The Adam optimizer and a batch size of 128 have been used for training the network. Two datasets were utilized: MNIST and GTSRB.

The MNIST dataset comprises of 60,000 training and 10,000 testing images of handwritten digits ranging from 0 to 9 [15]. Each image is of size 28 by 28 pixels. The original images are represented in grayscale with pixel values between 0 and 255, which are normalized by dividing them by 255. Figure 3 shows some examples of images from the MNIST dataset.

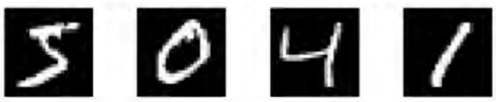


Figure 3. Example MNIST dataset images.

The GTSRB dataset [18] comprises 34,799 training and 12,630 test images of 43 different classes of traffic signs. These images are actual pictures of traffic signs captured under different conditions. The size of the original images varies between 15 × 15 and 222 × 193 pixels. However, in this experiment, all images have been scaled to a size of 32 × 32 pixels. The images in the dataset are initially in RGB color format, but they were converted into grayscale, with pixel values ranging between 0 and 255. Then, the pixel values were scaled down by dividing them by 255 to normalize the data. Figure 4 provides some examples of images from the GTSRB dataset.

Figure 4. Example GTSRB dataset images.

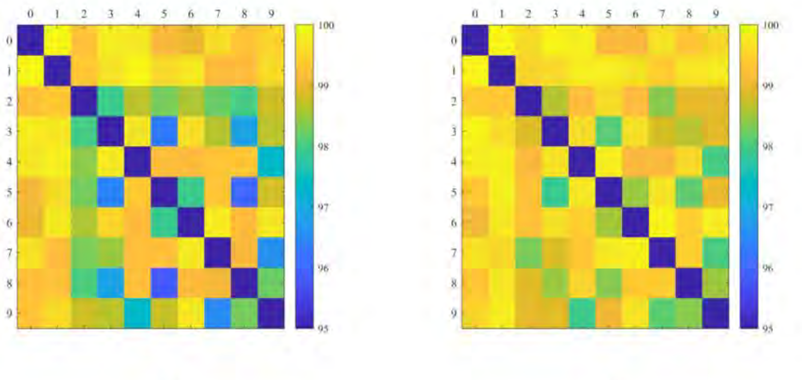
Table 1 summarizes the parameters of the three image datasets used in the experiment.

Table 1. Parameters of image datasets used in experiment.

	MNIST	GTSRB
Image size	28 × 28	32 × 32
Number of color channel	1	3
Number of classes	10	43
Number of class pairs	90	1,806

4. Results and Discussion

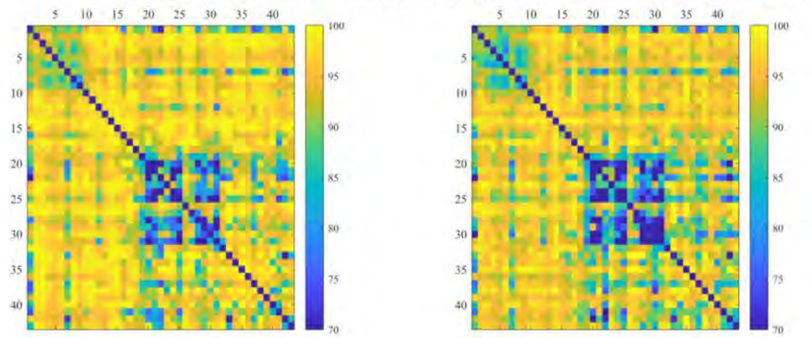
First, we use all available training and testing samples to perform binary image classification against all different pairs of classes using NN. The results are shown in Figure 5 (a). In this graph, the testing accuracy for the given pair is shown by different color. For example, classifying the number 0 against 1 achieves close to 100% accuracy as shown in light yellow. In comparison, we can observe that the testing accuracy for number 5 against 8 is poor about 96% accuracy. This is due to the similarity in the shapes of the handwritten numbers 5 and 8. Additionally, other class pairs such as 3 and 5, 3 and 8, 4 and 9, and 7 and 9 also have similar shapes, leading to lower testing accuracy for those pairs. In average, the binary image classification using classical NN against MNIST achieved 98.9% testing accuracy using all data. Figure 5 (b) shows the results for QPF-NN against MNIST using all data. A similar result is obtained with an improvement in average image classification accuracy of 99.2%.



(**a**) (**b**)

Figure 5. Testing accuracy against MNIST using all data. (**a**) Using NN. (**b**) Using QPF-NN.

Figure 6 (a) shows the NN results against GTSRB using all data. We can identify pairs of classes that produce high testing accuracy and those that do not. For example, the class 7 shows lower testing accuracy against many of the classes between 20 to 43, compared to class 6 or 8, as indicated by the red oval. Referring to [18], Fig. 1, class 7 corresponds to 80 km/h sign with a diagonal strip. This class also has smaller number of samples (Approx.. 1/3) compared to class 6 or 8. Detailed examination of this graph may provide further insights, however, we focus on the effects of the application of QPF, and hence this is left for a future study. The average testing accuracy over all different pairs is 93.5%. In comparison, Figure 6 (b) shows the QPF-NN results against GTSRB using all data. Similar results were obtained with a reduced average testing accuracy of 92.0%.



(**a**) (**b**)

Figure 6. Testing accuracy against GTSRB using all data. (**a**) Using NN. (**b**) Using QPF-NN.

Secondly, we performed 100 trials with each trial extracting 80 training samples and 20 testing samples per class randomly to perform training and testing. Figure 7 shows the variation of testing accuracy as a function of trial index when NN and QPF-NN are used against MNIST. We observe that variation is relatively large (approximately 3%) which shows the importance of performing multiple trials and average the results to obtain statistically stable results. In average the testing accuracy of 94.7% and 94.5% was obtained for NN and QPF-NN, respectively. In this case, the application of QPF shows minimal effects.

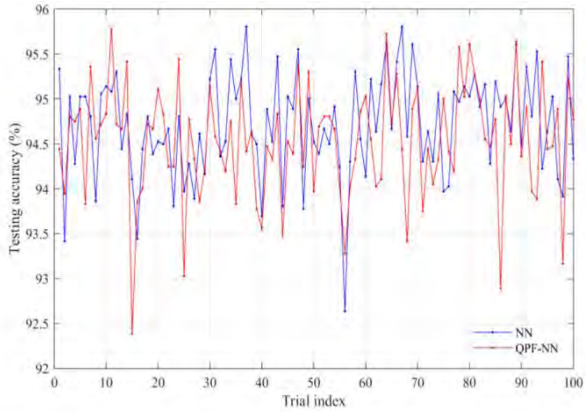


Figure 7. Testing accuracy against MNIST using 100 samples, 100 trials.

Figure 8 shows the results against GTSRB. We observe that the variation is relatively small (approximately 1%) which may be due to a larger number of class pairs (1,806 for GTSRB compared to 90 for MNIST) over which the testing accuracy is averaged for each trial. Importantly, the application of QPF shows improvement over NN against GTSRB, which was not observed in any of our previous experiments. It is also notable that QPF-NN always improved the testing accuracy over NN in any of the 100 trials. We note that the same set of training and testing samples was used for NN and QPF-NN for each trial.

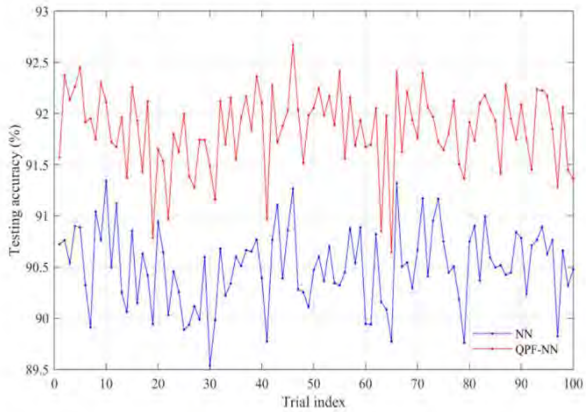


Figure 8. Testing accuracy against GTSRB using 100 samples, 100 trials.

The reason behind slight decrease and fluctuation in QPF models can be explained in detail here. It can be difficult to train a quantum machine learning model. Like classical machine learning, the objective is to modify the model's parameters to reduce the loss function, which measures the gap between the model's predictions and actual values. It is challenging to choose the best settings for quantum machine learning because, in contrast to classical machine learning, the loss function is frequently non-convex and may have numerous local minima. Additionally, the optimisation procedure must deal with the phenomena known as "barren plateaus" because of the problem's quantum nature. The cost function's topography tends to flatten out in most directions in high-dimensional quantum issues, leading to large areas (plateaus) where the gradient is almost zero [21].

Gradient-based optimisation techniques, which are frequently employed in machine learning, may struggle to identify a solution that results in a reduction in the cost function, which can cause poor training progress as we have seen for GTSRB in multi class classification and MNIST in Binary image classification.

Quantum computations and classical computations are frequently used together in quantum machine learning models. A quantum computer performs the quantum component that is signal processing of the computation, whereas a classical computer performs the results processing/measurement. The performance of QML models may fluctuate and be inaccurate due to this interface between the quantum and classical elements of the calculation. The "readout" phase, in which the outcomes of the quantum computation are measured and transformed into classical information, is one significant challenges [22]. Even if the quantum state being measured is the same, quantum measurements are probabilistic, which means that they may yield different results each time they are carried out. The outputs of the quantum computer may contain some degree of uncertainty due to this intrinsic unpredictability, which may reduce the precision of the QML model. Additionally, mistakes may be introduced during the information transmission process between the quantum and classical components of the calculation. For instance, the existing quantum hardware may not allow for flawless measurement or manipulation of the quantum state, which could result in errors in the quantum computation. Additionally, errors may be introduced during the process of converting the quantum results into a format that can be accepted by a classical computer. The problem of "quantum data loading" is the last one [23]. To use quantum machine learning, one must convert classical data into a quantum state, which is a difficult and potentially costly operation. The performance of QML models may be impacted by the challenges this method presents. The similar phenomena is the reason of the slight degradation in the results we have observed in MNIST and GTSRB for small sample size using Binary image classification and our previous work for multi-class classification. This will enable us to conduct more investigations as future research work.

5. Conclusions

This study aimed to evaluate the performance of a proposed binary image classification method using a QPF model with 4 qubits and 2 CNOTs. In our previous research we have shown that QPF is used for efficient image feature extraction while existing quantum circuits demand high computation and multiple layers to extract image features Similar to the previously reported multi-class classification case, the proposed QPF model improved binary image classification accuracy against MNIST but we observe slight decrease in the performance against GTSRB using all training and testing samples. It might be because of 2 reasons- inherent quantum model training difficulties and interface between quantum and classical model. However, when applied to the cases with smaller number of training and testing samples, QPF improved image classification performance against GTSRB, which shows better generalization of our model QPF for smaller number of samples compare to previous classical NN models which mostly requires larger number of sample to generalize [24]. The results presented in this article provide further insights into the effects QPF on machine learning algorithms. Further research will be conducted as part of future work to investigate the potential of QPF to assess the scalability of the proposed approach to larger and complex datasets.

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Synthesis of Outcomes

This paper presents a new approach to image classification using quantum neural networks (QNNs) called the quantum filter model (QPF). The QPF was applied to the study, a binary image classification method using a quantum pre-processing filter (QPF) with 4 qubits and 2 CNOTs was evaluated. The proposed QPF model improved binary image classification accuracy on MNIST but degraded the performance on GTSRB using all training and testing samples. However, when applied to cases with smaller numbers of samples, QPF improved image classification performance against GTSRB. The results suggest the potential of QPF on machine learning algorithms, but further research is required to investigate its effectiveness in other applications and on larger datasets.

The upcoming chapter will cover the results and discussion obtained from the objectives.

CHAPTER 6: CONCLUSION AND DISCUSSION

The field of quantum machine learning is an emerging technology that combines the principles of quantum computing with the field of machine learning. In this thesis, we have contributed to the advancement of quantum machine learning in three significant ways.

Firstly, a significant achievement of this research is the design and development of a quantum neural network model capable of effectively classifying real-life traffic sign images. This advancement represents a crucial step towards the practical implementation of quantum machine learning in real-world applications. Secondly, to enhance the model's accuracy in processing complex images, we investigated a strongly entangled architecture for feature extraction. This particular architecture has shown potential in achieving high accuracy levels. To assess its performance, we conducted experiments using 4 qubits to measure the model's accuracy in classifying traffic sign images. Lastly, to demonstrate the feasibility of quantum machine learning in practical settings, we implemented a hybrid model. In this approach, all image pre-processing and post-processing tasks were executed on a classical computer, while the quantum simulator exclusively handled feature extraction during model training. This resource-efficient approach showcases the practicality of employing quantum machine learning techniques in real-world applications.

The accuracy degradation may be attributed to several factors, including the complexity of real-life traffic sign images and the challenges posed by the quantum circuit's limited qubit resources. Additionally, the selection of an appropriate entangled architecture for feature extraction plays a crucial role in the model's accuracy. The trade-off between quantum resources and computational power may also impact the model's performance. Addressing these factors and optimizing the model's design are critical areas for future research to further improve accuracy and efficiency in quantum-based image classification tasks.

To evaluate the performance of the model, we used three different datasets, including MNIST, EEMNIST, CIFAR-10, and GTSRB. By testing the model on a variety of datasets, we can ensure that the model is generalizable and can be used in a range of real-world scenarios. Overall, our contributions represent an important step forward in the field of quantum machine learning and have significant potential for practical applications in a variety of fields.

Existing literature on quantum neural networks has shown that all the models developed in this field have utilized a random layer architecture. However, through our investigation, we discovered that the strongly entangling layer architecture could yield amazing results. In our first model, called NNQE, we used five layers of architecture, which involved 20 three-axis rotations and 20 CNOTs with Hadamard gates to create a maximally entangled model. This model demonstrated excellent performance not only over classical neural networks for MNIST and CIFAR-10 but also outperformed all other quantum neural network models in the literature.

However, when we applied this model to complex traffic sign images, we observed a degradation in accuracy compared to classical neural networks. These traffic sign images were captured in various climates, including night, day, fog, and rain. This observation led us to design a model that could reduce computation while still outperforming our proposed model NNQE.

To accomplish this, we designed a new model that incorporates a hybrid architecture, combining a quantum neural network with a classical neural network. The quantum neural network is used exclusively for feature extraction, while the classical neural network is responsible for classification. This approach reduces computation while maintaining high accuracy levels. We tested this hybrid model on complex traffic sign images and achieved improved accuracy compared to the proposed model NNQE. Overall, our research demonstrates that the strongly entangling layer architecture has the potential to significantly improve the performance of quantum neural networks. In addition, by utilizing a hybrid architecture, we can reduce computation while maintaining high accuracy levels, making quantum machine learning more practical for real-world applications.

Following our investigation of the NNQE model, we developed a new model called the Quantum Filter. This model utilized only four qubits and applied two CNOTs, yet demonstrated amazing results. Not only did it outperform classical neural networks, but it also outperformed all other quantum neural networks, including NNQE. The Quantum Filter model is extremely simple in computation, requiring only two CNOTs compared to NNQE's 20 CNOTs, yet it achieved better accuracy levels. We tested this model on the same datasets as NNQE, including MNIST, CIFAR-10, and GTSRB, and like NNQE, we evaluated the model on all classes and the full dataset.

Our results showed an increase in MNIST and CIFAR-10 testing accuracy, indicating the potential of the Quantum Filter model to improve upon existing quantum neural network models. However, we observed that for GTSRB, the classical neural network still performed better. Despite this, the Quantum Filter model has proven to be a significant contribution to quantum machine learning research.

Based on the promising results of the Quantum Filter model, we explored binary classification for the same datasets, leading us to make our third contribution. We designed a binary classification model using a hybrid architecture that combines a quantum neural network with a classical neural network. The quantum neural network is used for feature extraction, while the classical neural network is responsible for classification. This model was trained and tested on the same datasets as the previous models, and the results showed a significant improvement in binary classification accuracy compared to previous models.

Our research demonstrates that a simple model such as the Quantum Filter can yield impressive results, and the hybrid architecture approach can significantly improve the accuracy of quantum machine learning models. Our contributions open new avenues for future research in quantum machine learning and bring us closer to practical quantum machine learning applications.

We have investigated from research aimed to explore binary classification using the Quantum Filter model, and our findings demonstrated its superior performance compared to classical neural networks. We observed that our model outperformed not only the MNIST dataset but also the GTSRB dataset, which contains real-life traffic sign images, suggesting its potential for practical applications using complex real-time images.

For our third objective, we trained the model on a limited sample size of only 100 samples per class. This revealed that the Quantum Filter model not only reduces computation requirements but also outperforms other quantum neural network models. aimed to assess a QPF model with 4 qubits and 2 CNOTs in a binary image classification method. The results showed that the QPF model improved binary image classification accuracy on the MNIST dataset, consistent with previous multi-classification experiments. However, the QPF model degraded performance when applied to the GTSRB dataset using all training and testing samples. Interestingly, when the QPF model was applied to cases with smaller numbers of training and testing samples, it improved image classification performance on GTSRB. These findings provide further understanding of the impact of QPF on machine learning algorithms. Future research should explore the potential of QPF in other machine learning applications and assess whether the approach can be scaled up to larger datasets and more complex models.

This is a significant breakthrough in quantum machine learning as it presents a promising solution for future AI applications that require the processing of complex images in real-time. Overall, our research highlights the potential of the Quantum Filter model for improving the accuracy of binary classification tasks in quantum machine learning. With further development, this model has the potential to revolutionize the field of AI and contribute to the development of practical applications in various industries, such as autonomous driving, medical imaging, and security surveillance.

Previous research in the field of quantum machine learning has mostly focused on black and white or grayscale images. However, our research aims to explore and develop new models that can not only train grayscale images but also perform better for more complex images, such as real-life traffic signs that are captured in different weather conditions including day, night, fog, and rain. Our research has significant implications for the future of quantum AI, particularly in the development of Intelligent Transportation Systems (ITS). ITS is an emerging field that utilizes advanced technologies to improve the safety, efficiency, and sustainability of transportation systems. By leveraging the power of quantum machine learning, we can develop more sophisticated ITS systems that can process complex images in real-time and enhance the overall performance of transportation networks. In summary, our research represents a crucial step forward in the development of quantum machine learning models that can process complex images and improve the accuracy and efficiency of AI applications in various industries, including transportation, healthcare, and security.

The future work for colour image classification of traffic signs in Intelligent Transportation Systems (ITS) outlines several research directions to enhance the performance and applicability of the classification system. The key areas of focus include expanding the model to handle a broader range of traffic signs with various shapes and colours, improving robustness and accuracy in classification. Dataset augmentation techniques are proposed to increase the diversity and size of the training dataset, leading to better generalization in real-world scenarios. Fine-tuning the colour image classification model for specific environmental conditions, such as different weather and lighting conditions, aims to ensure reliable performance in challenging situations. Additionally, optimizing the model for real-time processing and exploring hardware accelerators like GPUs for efficient inference on edge devices and ITS infrastructure are essential for real-world deployment. The research emphasizes incremental learning techniques to continually adapt the model with new traffic sign data, enabling the recognition of previously unseen signs. Leveraging transfer learning from pre-trained models and developing model explain ability methods further improve the system's performance and build trust in its classifications. The future work also calls for extensive field tests and evaluations in real-world ITS environments to assess accuracy, reliability, and usability under various traffic conditions and road types. Furthermore, addressing privacy and security concerns is crucial to safeguard sensitive data and ensure the system's resilience against potential attacks. By pursuing these research directions, the capabilities of colour image classification for traffic signs in ITS can be significantly enhanced, leading to safer and more efficient transportation systems. The proposed advancements hold promising implications for the future of intelligent transportation management.

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APPENDIX A

This conference poster has been submitted in Quantum Australia 2022. Title of the poster is "Quantum Artificial Intelligence Prediction Enhancement by Improving Signal Processing". Poster have been presented in a YouTube video: https://www.youtube.com/watch?v=5mO92kUsQwI

Quantum Artificial Intelligence Predictions Enhancement by Improving Signal Processing

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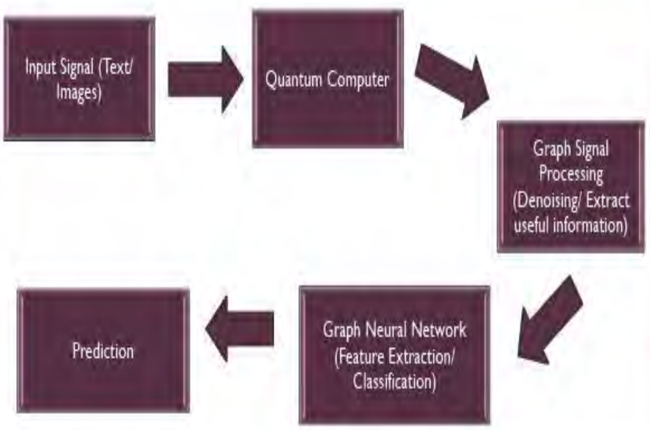
INTRODUCTION

- Quantum Computers have shown exponential computational speed
- Graph Signal Processing can refine the signal by compressing, denoising or extracting useful information
- Graph Neural Network perform feature extraction and classification to perform predictions

Artificial Intelligence (AI) applications are in high demand but with limitations of classical computer processing speed it is difficult to take reliable and timely decisions

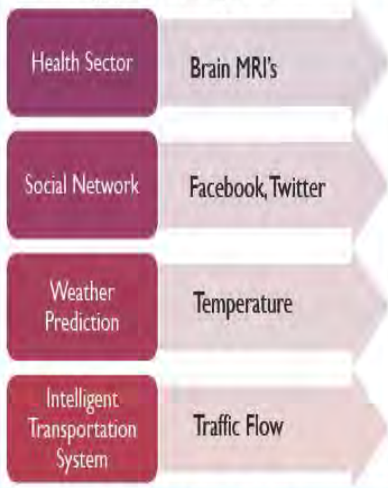
METHOD



- Input signal will be converted into graph from signals observed. to fed in quantum computer. . The graph signal will be processed for removing noise from the signal and extract useful information. This refined signal will fed into Graph Neural Networks for feature extraction and classification.
- With refined signal, deep learning will require less layers and can perform accurate predictions. Quantum Computer with fast computational efficiency will make this computation in timely manner for real time series data

APPLICATIONS

All Artificial Intelligence applications can get benefit from this research. Whose underlying domain is graph. Few examples are:



CONCLUSION

This research will impact all AI applications that have graph domains Many AI applications can be designed which are imaginable in current times

Acknowledgment: This research is supported by an Australian Government Research Training Program (RTP) Scholarship

APPENDIX B

This conference poster has been submitted in Quantum Australia 2023 and have been presented in-person. Title of the poster is "*Performance comparison of Quantum Machine Learning Models- Image Classification for Future AI applications*" This poster won runners up people choice award by the conference.

Performance Comparison of Quantum Machine Learning Models – Image Classification for Future AI Applications

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INTRODUCTION

Quantum technology has fundamentally changed how image classification is thought of. Previously, we have shown that our proposed quantum pre-processing filter (QPF) improved neural network (NN) based image classification accuracy for handwritten 10-class digit dataset MNIST but not for real-life 43-class traffic sign dataset GTSRB using all image samples [1]. In this work, we investigate the performance of QPF with support vector machine (SVM) based image classification accuracy when using a small number of samples (100 samples per class) for faster training.

Future AI Applications such as Intelligent Transportation System: Which Quantum Machine Learning Model is the Best in Training Accuracy?

METHOD

Figure 1 shows the flow chart of our model. We use a quantum circuit with four qubits. Quantum data encoding is performed by Y rotations. The quantum filter circuit consists of two controlled NOTs. Quantum measurement produces expectation values between −1 and 1, which are fed into classical machine learning models (NN or SVM).

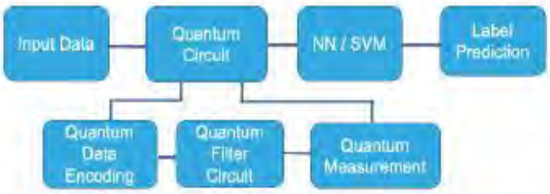

Fig. 1: Quantum Pre-Processing Filter + Machine Learning.

Figure 2 show example MNIST and GTSRB dataset images. For SVM, principal component analysis (PCA) is performed to reduce the dimension of samples to 4.

Fig. 2: Example of MNIST and GTSRB dataset images.

RESULTS & CONCLUSION

We randomly select 80 samples for training and 20 samples for testing per class to perform binary classification for each pair of classes. Performance is evaluated on mean accuracy over all pair of classes. Figure 3 shows the model test accuracy results. Contrary to our previous result [1], QPF-NN improves image classification accuracy over classical NN for both MNIST and GTSRB when trained with a smaller number of samples for binary classification. In contrast, QPF-SVM degrades the image classification accuracy over classical SVM for both MNIST and GTSRB. We will further investigate the exact causes of the performance improvement and degradation.

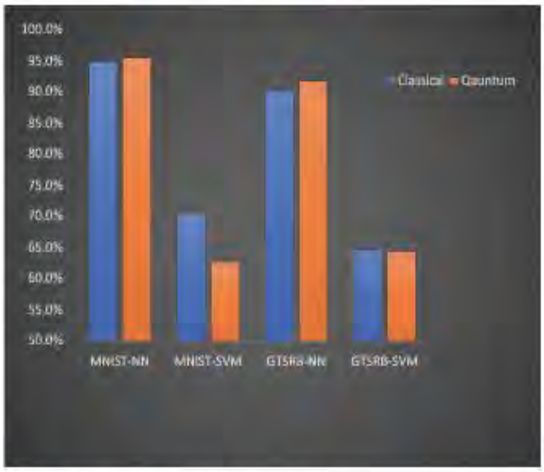

Fig. 3: Average model test accuracy.

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