Quantum Machine Learning for Traffic Sign Recognition

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***Abstract*—This paper presents a comparative study of classical and quantum approaches to traffic sign recognition. We implemented and evaluated three distinct models: a classical Convolutional Neural Network (CNN), a quantum-classical hybrid model, and a quantum neural network (QNN). Using the German Traffic Sign Recognition Benchmark (GTSRB) dataset [1] supplemented with custom data, we achieved an accuracy of 85.6% with the classical CNN, 71.6% with the hybrid model, and 10.87% with the quantum model. Our findings highlight both the potential and current limitations of quantum machine learning in computer vision tasks.**

I. Introduction

Traffic sign recognition is a crucial component of autonomous driving systems and advanced driver assistance systems (ADAS). While classical deep learning approaches have shown significant success in computer vision tasks [2], recent developments in quantum neural networks [3] and quantum vision transformers [4] suggest promising applications. This study explores the application of quantum machine learning techniques to traffic sign recognition, comparing their performance with classical approaches.

When processing image using classical CNN for GTSRB, LeCun et al. resized images to 32x32 pixels and pre-processed them using YUV color space conversion [5] [6]. In their proposed model Neural Network with Quantum Entanglement (NNQE), Riaz et al. used the same scale [7] , and converted the images into grayscale, then normalized. Hu et al. also proposed reducing computational costs by encoding grayscale image [8].

Encoding classical data into quantum systems is a crucial aspect of building quantum machine learning models [9]. For efficiently converting classical data into quantum states, Grover et al. proposed a method to create quantum superpositions that approximate discrete versions of probability distributions, enabling efficient data encoding [10]. Soklakov et al. expanded on this by using Grover's search algorithm to prepare arbitrary pure states [11]. Havlicek et al. showed quantum states can map data into high-dimensional spaces, similar to classical kernel methods but with greater nonlinearity [12]. Schuld et al. explored data mapping in quantum Hilbert space [13], while Farhi et al. and Benedetti et al. focus on Parameterized Quantum Circuits (PQC) [14] [15] to enhance machine learning expressiveness. Wilson et al. presented Quantum Kitchen Sinks (QKS) [16] to encode classical data using random quantum gate operations. Henderson et al. introduced Quanvolutional Networks [17], later refined by Mari, integrating quantum circuits with neural networks [18] [19]. Cong et al. designed a QCNN structure [3] inspired by the multi-scale entanglement renormalization ansatz (MERA), and Riaz et al. developed NNQE, using strongly entangled circuits for image processing [7].

Kerenidis et al. [20] proposed a QCNN that effectively reproduces classical CNN functionalities while leveraging quantum principles to implement non-linearities and pooling operations, achieving efficiency in deep networks and demonstrating its potential in image recognition tasks such as MNIST classification. Similarly, Shiba et al. [21] addressed the qubit limitation issue by introducing a convolutional quantum autoencoder, which processes images in blocks using convolution filters to reduce dimensionality and noise. This approach was tested successfully on quantum simulators and IBM Q Melbourne, showcasing the potential of quantum methods in denoising and dimensionality reduction.

Recent advancements in quantum and quantum-inspired multi-class classification have led to innovative solutions addressing the challenges of computational complexity, hardware limitations, and classification accuracy. Bokhan et al. [22] proposed a hybrid quantum-classical QCNN framework that integrates quantum convolutional and pooling layers with classical optimization methods, demonstrating competitive performance on 4-class MNIST and Fashion-MNIST classification tasks. Silver et al. [23] introduced the QUILT framework, an ensemble-based quantum classification approach that effectively handles quantum noise and limited qubit availability, achieving up to 85% accuracy on datasets like MNIST when implemented on IBM quantum hardware. Mordacci et al. [24] further developed QCNNs with advanced encoding methods, surpassing classical CNNs in specific multi-class tasks with small datasets. Together, these works highlight the potential of quantum and hybrid quantum-classical approaches in advancing multi-class classification tasks, offering insights into scalable quantum machine learning methodologies for future applications.

II. Methodology

A. Dataset Preparation

Our study utilizes the GTSRB dataset [1], enhanced with additional custom data. The GTSRB (German Traffic Sign Recognition Benchmark) is a dataset containing 43 classes of German traffic signs with over 50,000 real-world traffic sign images, where each image is annotated with the traffic sign class label and its location information within the image. We collected 385 samples including UW logos, pedestrians, stop signs, etc. We labeled them using LabelMe [25], replaced UW logos with class 0, and reorganized the training and testing dataset. Representative samples from our dataset are shown in Fig. 1, with the complete class visualization provided in Appendix A.

Our dataset includes:

- 42 classes of traffic signs plus 1 collected class
- 39,375 training images and 12,694 test images
- Image sizes ranging from 15×15 to 250×250 pixels

Fig. 1: Representative Samples from the Dataset

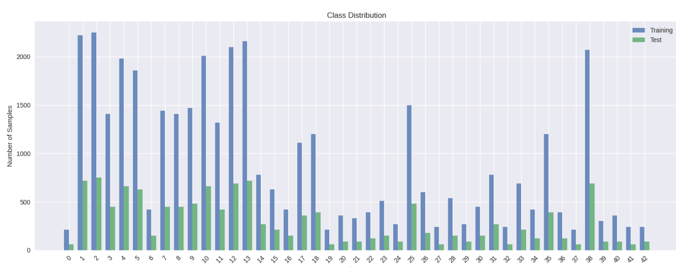

Fig. 2: Class Distribution of GTSRB Benchmark

The data distribution of GTSRB benchmark is shown in Fig.2. We can see that there is a severe imbalance between samples - the class with the highest number of samples is almost ten times larger than the class with the least number of samples. This significant data imbalance will largely affect the model's performance, as the model will tend to learn more from classes with large quantities and act lazy in studying the least represented ones as they contribute less to the loss. This can be improved by introducing data augmentation techniques to increase the number of undersampled classes. In the dataset generation phase, we developed a custom data preprocessing tool that implements features for class filtering, dataset size control, and distribution balancing to ensure optimal model training conditions.

B. Quantum Encoding

We explored several quantum encoding strategies, ranging from basic approaches to advanced implementations:

1) Basic Encoding Approaches
The three fundamental quantum encoding methods are: angle encoding, which maps classical data to rotation angles using RY gates; amplitude encoding, which represents data in quantum state amplitudes with higher information density; and Bloch sphere encoding, which provides maximum quantum expressivity through complete quantum state representation using RX, RY, and RZ gates.
2) Pennylane QCNN Encoding
The Pennylane QCNN [26] [17] implementation uses a specialized quantum encoding strategy:
    - Utilizes a 4-qubit quantum system to process 2×2 image patches
    - Applies RY rotation gates for initial data encoding
    - Implements random quantum layers to enhance non-linearity
    - Extracts features through PauliZ measurements
    - Functions similarly to classical CNN convolution operations but leverages quantum circuits for feature extraction
3) Neural Network with Quantum Entanglement (NNQE)
The NNQE represents an advanced quantum encoding approach with the following key features:
    - Implements a three-stage quantum encoding process:
        - RY encoding: Maps pixel values to rotation angles in the range $[0, \pi]$
        - Hadamard gates: Creates quantum superposition states
        - Strong entanglement: Applies 5 layers of quantum gates with three-axis rotations and CNOT gates
    - Provides full connectivity through adjacent qubit entanglement
    - Achieves high expressivity through three-axis rotations
    - Enhances non-linearity through multi-layer entanglement to capture complex data relationships
4) Implemented Methods
Our quantum encoding module utilizes a 4-qubit system to process 2×2 image blocks. The quantum encoding circuit diagram is shown in Fig. 3. For each image block, the quantum state preparation can be represented as:

$$|\psi\rangle = \left(\bigotimes_{i=0}^{3} R_Y(\pi x_i) \right) |\mathbf{0}\rangle \tag{1}$$

where x_i represents the normalized pixel values (0 to 1) from the 2×2 image block, and $R_Y(\theta)$ is the Y-rotation gate defined as:

$$R_Y(\theta) = \begin{pmatrix} \cos(\theta/2) & -\sin(\theta/2) \\ \sin(\theta/2) & \cos(\theta/2) \end{pmatrix} \tag{2}$$

The quantum convolution operation is implemented through a series of parameterized quantum circuits. For each 2×2 block, the quantum feature extraction process can be expressed as:

$$\mathbf{f}_{quantum} = [\langle\psi|Z_0|\psi\rangle, \langle\psi|Z_1|\psi\rangle, \langle\psi|Z_2|\psi\rangle, \langle\psi|Z_3|\psi\rangle] \quad (3)$$

where Z_i represents the Pauli-Z measurement on the i-th qubit. The output features are collected in a tensor of shape 14×14×4, where:

$$\text{Output}_{j,k,c} = \langle\psi_{j,k}|Z_c|\psi_{j,k}\rangle \quad (4)$$

For coordinates (j, k) in the output feature map and channel c, where $j \in [0, 13]$, $k \in [0, 13]$, and $c \in [0, 3]$. The quantum circuit includes random layers for enhanced non-linearity, implemented as:

$$U_{random} = \prod_{l=1}^{n_{layers}} \left(\prod_{i=0}^{3} R_Y(\theta_{l,i}) \right) \prod_{(i,j)\in E} \text{CNOT}_{i,j} \quad (5)$$

where $\theta_{l,i}$ are randomly initialized parameters, n_{layers} is the number of random layers (set to 1 in our implementation), and E represents the set of connected qubit pairs for entangling operations.

The complete quantum encoding process transforms the original 28×28×1 grayscale image into a 14×14×4 quantum feature map, where each 2×2 block of the original image is encoded into 4 quantum measurements. This dimensionality reduction preserves essential spatial relationships while introducing quantum correlations through the circuit operations.

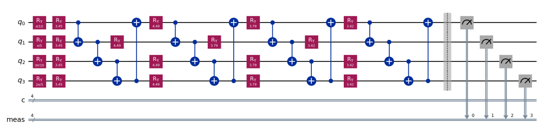

Fig. 3: Diagram of Quantum Encoding Circuit

C. Model Architectures

Our network architecture for image classification comprises three key components: backbone, neck, and head. The backbone extracts features, the optional neck processes these features further, and the head performs final classification. We explore multiple architectural configurations varying in their classical and quantum components:

- Classical CNN Model: Employs classical components throughout
- Classical-Quantum Hybrid Model: Classical backbone with quantum head
- Quantum-Classical Hybrid Model: Quantum backbone with classical head
- Quantum Model: Quantum components in all parts

These configurations allow us to systematically evaluate the effectiveness of quantum computing at different stages of the classification pipeline.

1) Classical CNN Model: The classical CNN model serves as our baseline architecture, implementing a deep convolutional neural network optimized for traffic sign recognition. The overall structure of our CNN model is shown in Fig. 4. The model accepts input images of size 28×28×1 and processes them through multiple stages. The first stage consists of a Conv2D layer with 32 filters and a 3×3 kernel, applying ReLU activation, followed by a max pooling layer that reduces spatial dimensions to 14×14×32. The second convolutional stage implements 64 filters with the same kernel size, followed by max pooling that further reduces dimensions to 7×7×64. After the convolutional stages, the features are flattened into a 3,136-dimensional vector. The network then employs two dense layers: the first with 128 neurons and ReLU activation, incorporating batch normalization and dropout (0.5) for regularization, and the second producing 43 outputs corresponding to the traffic sign classes. The model concludes with a softmax activation function for final classification probabilities.

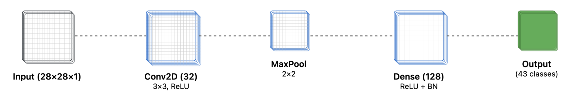

Fig. 4: Architecture of Classical CNN Model

2) Classical-Quantum Hybrid Model: The Quantum-Classical Hybrid Model (Hybrid-C) combines classical and quantum approaches by replacing the initial convolutional layer with a quantum feature extractor. This hybrid architecture (Fig. 5) employs a 4-qubit quantum circuit to process 2×2 image blocks, where each block undergoes RY/RZ rotations and random quantum layer operations. The quantum-encoded features (14×14×4) are then processed by classical layers, including max pooling and dense layers with batch normalization, maintaining the same classification structure as the classical CNN. This approach aims to leverage quantum advantages in feature extraction while utilizing classical methods for final classification.

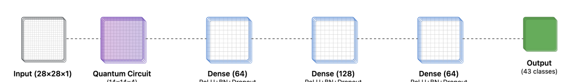

Fig. 5: Architecture of Classical-Quantum Hybrid Model

3) Quantum-Classical Hybrid Model: The Quantum-Classical Hybrid Model takes a different approach by maintaining classical feature extraction but implementing quantum classification. However, this model faces significant challenges as current Qiskit classifiers are not readily equipped for direct multi-class classification. The model explores two quantum classifier approaches: SamplerQNN, which requires an additional fully connected layer for 43-class output, and EstimatorQNN, which offers customizable output but is limited by observable design on few qubits. To address the multi-class challenge, a one-vs-all approach was considered, creating individual binary classifiers for each class. However, this solution introduces complications with computational cost, class imbalance, and increasing model complexity as the number of classes grows.

4) Quantum Model: The Quantum Model (QNN) represents our attempt at a more purely quantum approach, though true "pure" quantum models remain challenging due to current hardware limitations. The diagram of quantum model circuit is shown in Fig.6. The model begins with dimensionality reduction to extract 8 key features, followed by ZFeatureMap encoding. The quantum circuit architecture consists of three layers: the first using 8 qubits with four convolutional circuits and four pooling circuits, the second using 4 qubits with two convolutional circuits and one pooling circuit, and the final layer using 2 qubits with a single convolutional circuit.

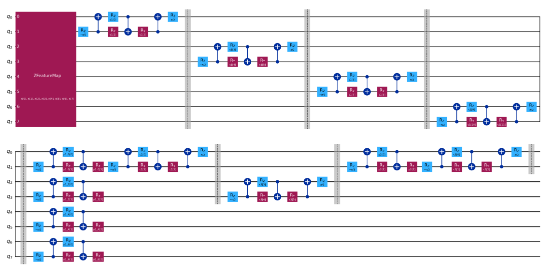

Fig. 6: Diagram of Quantum Model Circuit

III. Results and Analysis

We trained and tested our models on 60,525 training samples (upsampled from the original dataset) and 12,694 test samples. Our experimental results show varying levels of performance across the three approaches. The key metric we use here is accuracy, which is evaluated at two levels: overall and class-wise. For each level, accuracy is defined as the ratio of correctly predicted samples to the total number of samples:

$$\text{Accuracy}_{\text{overall}} = \frac{\text{Number of correctly predicted samples}}{\text{Total number of samples}}$$

$$\text{Accuracy}_{\text{class}_k} = \frac{\text{Number of correctly predicted samples in class k}}{\text{Total number of samples in class k}}$$

A. Classical CNN Performance

The classical CNN model is trained using categorical cross-entropy loss and the Adam optimizer, achieving convergence in approximately 80 epochs. The performance metrics of the CNN model are listed in Table I and Table II.

The CNN model demonstrates strong overall performance with an average accuracy of 85.63% and a median accuracy of 89.72%. The standard deviation of 13.52% indicates relatively stable performance across different classes. For the best-performing classes, it achieves perfect accuracy (100%) on Class 19 despite its small training data proportion (0.53%), suggesting the model's strong feature extraction capability for this class. Other top-performing classes (15, 33, 31, 13) also achieve high accuracies (>98%), with varying data proportions from 1.60% to 5.49%. However, the model struggles with certain classes, particularly Class 40 (44.44% accuracy) and Class 0 (50.00% accuracy), both having relatively small training data proportions (0.91%). This indicates that while the model can handle some small-data classes well, performance on others might be limited by data scarcity.

Overall Accuracy(%)	
Average Accuracy	85.63
Median Accuracy	89.72
Std Accuracy	13.52

Table I: Overall Performance Metrics of the CNN Model

Top 5 Best Classes			
Class	Accuracy(%)	% of Training Data	% of Test Data
19	100.00	0.53	0.47
15	99.52	1.60	1.65
33	98.57	1.75	1.65
31	98.52	1.98	2.13
13	98.33	5.49	5.67
Top 5 Worst Classes			
Class	Accuracy(%)	% of Training Data	% of Test Data
40	44.44	0.91	0.71
0	50.00	0.91	0.95
30	58.67	1.14	1.18
41	60.00	0.61	0.47
24	61.11	0.69	0.71

Table II: Class-wise Metrics of the CNN Model

B. Hybrid Model Performance

Tables III and IV show the detailed performance analysis of the CNN model. The hybrid model shows moderate performance with an average accuracy of 71.60% and a median accuracy of 75.83%. The larger standard deviation of 16.94% suggests more variable performance across classes compared to the CNN model. The best performance is achieved on Class 13 (98.61% accuracy) with a relatively large training data proportion (5.49%), followed by Class 31 (95.19%) and Class 34 (95.00%). Notably, two of the top-performing classes (13 and 10) have larger training data proportions (>5%), indicating the model might benefit more from abundant training data. The model particularly struggles with Classes 32 and 24, achieving only 38.33% and 38.89% accuracy respectively, both having small training data proportions (<0.7%). Interestingly, Class 18, despite having a relatively larger training data proportion (3.05%), shows poor performance (43.08%), suggesting that data quantity alone doesn't guarantee good performance for this model.

Overall Accuracy(%)	
Average Accuracy	71.60
Median Accuracy	75.83
Std Accuracy	16.94

Table III: Overall Performance Metrics of the Hybrid Model

C. Quantum Model Performance

The quantum model, despite its theoretical potential, demonstrates significant limitations in handling complex image classification tasks. When evaluated on a simplified version of the problem with only 10 classes (reduced from

Top 5 Best Classes			
Class	Accuracy(%)	% of Training Data	% of Test Data
13	98.61	5.49	5.67
31	95.19	1.98	2.13
34	95.00	1.07	0.95
37	91.67	0.53	0.47
10	90.00	5.10	5.20
Top 5 Worst Classes			
Class	Accuracy(%)	% of Training Data	% of Test Data
32	38.33	0.61	0.47
24	38.89	0.69	0.71
18	43.08	3.05	3.07
27	43.75	0.65	0.50
19	45.00	0.53	0.47

Table IV: Class-wise Metrics of the Hybrid Model

the original 43 classes due to quantum resource constraints), the model achieves an accuracy of merely 10.87%. This performance level, which is notably close to random guessing in a 10-class scenario, underscores the current practical challenges in implementing pure quantum approaches for image classification. The difficulty in scaling the quantum model to accommodate the full 43-class problem further highlights the existing technological constraints in quantum computing applications for complex pattern recognition tasks. These results suggest that while quantum computing shows promise in theoretical frameworks, substantial advances in both quantum hardware and algorithmic design are necessary before such approaches can effectively compete with classical methods in real-world image classification scenarios.

D. Model Comparison

Comparing the three approaches — classical CNN, hybrid, and quantum models — reveals distinct patterns in their capabilities and limitations. The classical CNN demonstrates superior performance with an average accuracy of 85.63% across all 43 classes, showcasing robust feature extraction capabilities even for classes with limited training data. This is evidenced by its ability to achieve perfect accuracy (100%) on Class 19 despite having only 0.53% of the training data. The hybrid model shows moderate performance with an average accuracy of 71.60%, exhibiting stronger dependence on training data volume, as demonstrated by its best performance in classes with larger training proportions (e.g., Class 13 with 5.49% training data achieving 98.61% accuracy). In stark contrast, the quantum model, limited by current hardware constraints to a simplified 10-class version of the problem, achieves only 10.87% accuracy, highlighting the significant challenges in implementing quantum approaches for complex image classification tasks.

These results suggest a clear hierarchy in current image classification capabilities: classical CNN approaches remain the most practical and effective, hybrid models show promise but require further refinement, particularly in handling data-scarce classes, while pure quantum approaches, despite their theoretical potential, require substantial technological advancement before becoming competitive in real-world applications.

IV. Challenges and Future Directions

Our experimental results highlight several significant challenges in implementing quantum approaches for traffic sign recognition. The fundamental challenge lies in data processing, specifically the quantum encoding of high-dimensional image data. The current necessity to reduce 32×32 RGB images to accommodate quantum circuit constraints leads to substantial information loss during dimensionality reduction, potentially compromising the model's ability to capture subtle visual features critical for accurate classification.

In terms of algorithm development, we encounter limitations inherent to current quantum computing paradigms. While quantum models have shown promise in binary and small-scale classification tasks, scaling them to handle 43 distinct classes presents considerable technical challenges. The requirement for additional fully connected layers at quantum circuit outputs introduces noise propagation issues, adversely affecting model accuracy. This suggests the need for more sophisticated quantum circuit architectures that can maintain information fidelity across larger classification spaces.

The challenge of model generalization becomes particularly evident when considering different traffic sign datasets. The variations between different regional standards (such as Canadian versus German traffic signs) emphasize the importance of developing more robust data augmentation strategies. This cross-dataset variability not only affects model performance but also raises questions about the broader applicability of quantum-based approaches in real-world scenarios where environmental and regional variations are common.

V. Conclusion

Our comprehensive study of quantum approaches to traffic sign recognition has revealed both promising potential and significant challenges in the current state of quantum machine learning. The classical CNN model achieved the highest accuracy at 85.6%, while the hybrid quantum-classical model demonstrated moderate performance at 71.6%. The pure quantum approach, achieving only 10.87% accuracy on a reduced classification task, highlights the current technological gap in quantum computing applications for complex image recognition.

The challenges identified in this study, from quantum data encoding to algorithm scalability and model generalization, suggest that significant advancements in both quantum hardware and algorithmic design are necessary before quantum approaches can effectively compete with classical methods. However, the moderate success of our hybrid model indicates that quantum-classical integration might offer a promising intermediate path forward, potentially combining the advantages of both paradigms while mitigating their respective limitations.

These findings contribute to the broader understanding of quantum machine learning's current capabilities and limitations in real-world applications, while also highlighting critical areas for future research and development in quantum computing for computer vision tasks.

APPENDIX

Fig. 7: Complete Visualization of All Classes in the Dataset

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