

QCNN for Object Detection and Classification

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Abstract—In order to efficiently discover and classify objects on the COCO and Pascal voc dataset, this investigation proposes a Quantum Convolutional Neural Network (QCNN) coupled with Grover's Algorithm. The suggested method seeks to improve the precision and computational effectiveness of object recognition by utilizing quantum feature extraction and quantum search techniques. We outline the experimental outcomes, quantum circuit implementation, and mathematical underpinnings of Qiskit.

Index Terms—Object Detection, quantum computing, QCNN, Two stage detectors.

I. INTRODUCTION

Object detection poses a significant challenge in the realm of computer vision. Traditional deep learning models like Faster R-CNN and YOLO demand considerable computational resources. Quantum computing presents an alternative framework where Quantum Convolutional Neural Networks (QCNNs) can extract features using a reduced number of parameters, and Grover's Algorithm can speed up the classification process. This article examines a combined QCNN-Grover method for classifying the COCO and Pascal VOC datasets. Classical computers struggle to match the computational speed and cost of quantum computers due to the vast number of bits available (exceeding the count of atoms in the observable universe) and the extended time frames needed (potentially thousands of years). Consequently, classical computation falls short in addressing scientific challenges due to computational complexity (outnumbering atoms in the observable universe) or the lengthy durations required (thousands of years); only quantum computation provides a feasible solution. Nevertheless, the currently accessible qubits lack the necessary capacity and fault tolerance for these applications. Other fields, such as finance, machine learning, and chemistry, also recognize the potential advantages of utilizing such computations on existing quantum devices. The purpose of this piece is to deliver a formal literature review that spans the years 2017 to 2023, outlining the various types of algorithms employed in quantum machine learning and their respective applications. The approach uses Systematic Literature Review (SLR) techniques as outlined by Kitchenham et al. in the software engineering domain. A total of 94 articles have been identified that discuss quantum machine learning algorithms or techniques implemented through computational quantum circuits or ansatzs [3][35].

II. OVERVIEW OF CLASSICAL NEURAL NETWORKS

Firstly, I will give a brief discussion of classical neural networks before we delve into how to build quantum neural networks. From a biological point of view, a neural network is made up of neurons that are synoptically connected.

Similarly, artificial intelligence based neural networks have nodes (artificial neurons) which can perform various functions.

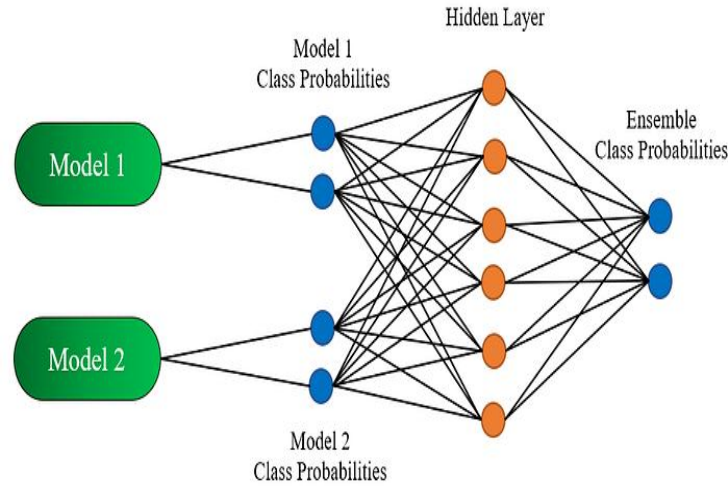


Figure 1: Classical Neural Networks

As shown above, the working principle of the neural networks is as follows: we submit a set of inputs and take them through a series of hidden layers and activation functions which result in a set of outputs. We base these neural nets on some cost function by training and adjusting parameters until they converge. Once you have built your own network, you help the computer learn how to process data so that it can give you what you desire from it. This has turned out to be quite amazing as it assists in translation services, image processing, handwritten text recognition among others.

III. QUANTUM CONVOLUTIONAL NEURAL NETWORK

Quantum Convolutional Neural Networks (QCNNs) have the potential to solve certain quantum problems which classical CNNs could not. The main obstacle in utilizing classical computing methods for solving quantum physics problems is that data size grows exponentially with system size. QCNNs address this problem by employing qubits to encode data in a quantum setting and applying CNN architectures on top of them. While building upon the foundations laid out by classic CNNs, QCNNs are different in that they adapt them for a realm of quantum systems. Qubits have been used under the concept of superposition which has made it possible for qubits. In order to accomplish this, QCNN encodes images into quantum circuits using a predefined feature map $Z\text{FeatureMap}[2]$ such as Qiskit's or $ZZ\text{FeatureMap}$. Next, we apply alternating convolutional and pooling layers to the encoded image such that we reduce the dimensionality of the circuit until we only have a single qubit remaining as shown in figure 3. Finally, the output of this last qubit is measured to give the input image classification. The Quantum Convolutional Layer consists of several two-qubit unitary operators that facilitate the recognition and establishment of interrelations among qubits within a circuit. The Quantum Pooling Layer minimizes the qubit count by executing operations on each qubit until a designated point, at which certain qubits are eliminated in a single layer. Each layer in QCNNs is composed of parameterized circuits, indicating that alterations to the parameters at each layer can result in changes to the output. Throughout the training process, adjustments are made to these parameters to minimize the loss function for the QCNN. This research aims to investigate the capabilities of QCNNs in physics. Parthasarathy and Bhowmik [12] conducted a study to investigate the potential of quantum computing in enhancing image recognition. They focused on the development and assessment of a novel machine learning algorithm termed the quantum optical convolutional neural network (QOCNN).

The Quantum photonics-based QOCNN architecture was evaluated against other models found in the literature, demonstrating comparable accuracy while surpassing them in terms of robustness. It is also possible that the suggested model could enhance computational speed to a great extent. Therefore, quantum computing has a huge potential for developing artificial intelligence and machine learning as this study indicates. For instance, other researchers such as [13] Tak Hur et al., Anirban Roychoudhury, Thomas F. George, and Maryam Rahmani have conducted studies on the use of quantum computers in machine learning. In another study by [13] Tak Hur et al.,

simulations of the VOC 2012 datasets were done using PennyLane with 8- qubit QCNN models for binary classification under various factor combinations determination. It was established from this study that QCNN performed well in terms of accuracy for classification, where it achieved 88% on VOC 2012 and 77 % on COCO.

IV. DATASETS

The VOC 2012 dataset was employed to train the model. The VOC 2012 dataset is a popular one for training and testing algorithms that recognize images. It comprises a Set of trains: 5,717 pictures, a Set of validation photos: 5,823, and a total of 10,991 photos (with annotations not publicly accessible) make up the test set with varying max sizes of 400*500. These photos have 20 object classes and a backdrop class for object detection. Bounding box annotations, segmentation masks, and object-level labels are all included in the dataset. The COCO dataset contains 330000 images with detailed annotations for 80 object classes with 5 captions per image.

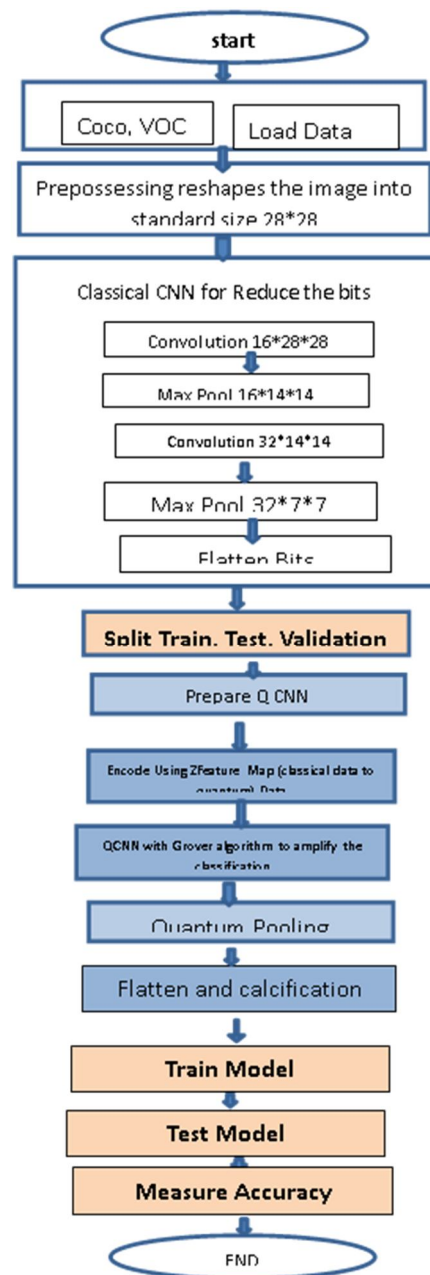


Figure 2: Work Flow

TABLE 1: ALGORITHM TYPES

Year of publication	Name of the Quantum Neural Methods	Description	Type	Key features
2016[6]	Quantum Boltzmann machines(QBM)	A quantum version of classical Boltzmann machines, using quantum superposition and entanglement for probabilistic modeling.	Quantum Model	Utilizes quantum properties like superposition for modeling complex distributions more efficiently.
2025[7]	Variable depth quantum circuits(vVQC)	Quantum circuits with variable depths that can adapt the complexity of quantum operations for specific tasks.	Quantum Model	Provides flexibility in circuit design, potentially offering a better approximation of quantum states.
2021[8]	Hybrid quantum auto encoders(HQA)	A combination of classical autoencoders and quantum circuits for dimensionality reduction and feature extraction.	Hybrid Model	Uses quantum resources for compression and feature extraction, while classical layers handle the encoding.
2021[9]	Quantum multiclass classifier (QMCC)	A quantum approach to classification tasks, extending quantum classifiers to multiple classes.	Quantum Model	Adapts quantum circuits for handling multi-class problems, potentially improving classification accuracy.
2021[10]	Quantum neural networks QNN	Quantum circuits designed to mimic neural network architectures, such as feedforward and recurrent networks.	Quantum Model	Leverages quantum entanglement and superposition to process information in ways classical networks cannot.
2020[11]	Orthogonal neural networks	Neural networks that use orthogonal activation functions to improve learning stability and convergence.	Classical / Hybrid Model	Enhances model stability by ensuring non-redundant activation functions, often used with quantum models.
2018[21]	Hybrid k-neighbors-nearby model (HKNN)	Combines classical k-nearest neighbors with quantum techniques to enhance the search for nearest neighbors.	Hybrid Model	Uses quantum state preparation to speed up nearest neighbor search and potentially improve classification.
2018[22]	CNOT neural networks(CMN)	A neural network architecture using controlled NOT gates to enable quantum parallelism and complex mappings.	Quantum Model	Makes use of quantum gates like CNOT to manipulate quantum bits and perform parallel computations efficiently.
2018[23]	Quantum convolutional deep convolutional neural networks (QD CNN)	A quantum version of CNNs that use quantum gates for convolutional operations and feature extraction.	Quantum Model	Enhances feature extraction in convolutional layers using quantum superposition, enabling more complex mapping.
2021[24]	Quantum back propagation neural networks (QBP)	Quantum adaptation of the classical backpropagation algorithm for neural network training.	Quantum Model	Uses quantum gates for efficient backpropagation, leveraging quantum properties to accelerate learning.
2020[25]	Feed forward neural networks(ffNN)	A classical neural network model where information moves in one direction, from input to output.	Classical Model	Simple and widely used architecture for many machine learning tasks; can be enhanced by quantum features.
2020[25]	Long short-term memory neural networks LSTM-QNN	Combines the capabilities of LSTMs for sequential learning with quantum enhancements for processing sequences.	Hybrid Model	Uses quantum gates to process sequential data, improving memory retention and sequence prediction over classical LSTMs.
[27]	Recurrent quantum neural networks (RQNN)	A quantum version of recurrent neural networks (RNNs) designed for handling sequential data using quantum computing principles.	Quantum Model	Integrates quantum mechanics into RNNs for improved sequential data processing, leveraging quantum superposition and entanglement for better temporal data handling.
2018[25]	Quantum generative adversarial networks (QGAN)	A quantum version of GANs, which consists of a quantum generator and a quantum discriminator, used for generating synthetic data and learning data distributions.	Quantum Model	Utilizes quantum circuits for both the generator and discriminator, aiming to improve data generation and model accuracy by exploiting quantum advantages.
[29]	Quantum Monte Carlo	A quantum adaptation of the classical Monte Carlo method, utilizing quantum states to perform probabilistic simulations more efficiently.	Quantum Model / Simulation	Quantum Monte Carlo methods are used for solving complex integrals and simulations, offering exponential speedup over classical Monte Carlo simulations by using quantum superposition and interference.

V. METHODOLOGY

In this study, we implement QCNN with Grover's diffusion operator to amplify correct classifications [35]. Apply Grover's search iteratively for enhanced recognition accuracy. Quantum Convolutional Neural Network (QCNN) for Feature Extraction: Construct a QCNN with quantum convolutional layers using parameterized quantum circuits (PQCs). Apply quantum pooling to reduce dimensionality while preserving key features. Extract quantum feature maps for classification. Preprocessing the COCO and VOC Dataset. Load the COCO and VOC dataset and preprocess images (resize, normalize). Encode images into a quantum-compatible format (amplitude encoding or binary encoding).

This method leverages the principles of quantum computation for identifying objects in visual data from the COCO dataset [30]. Initially, each image undergoes resizing and normalization, followed by a conversion of pixel values into a quantum state using an appropriate encoding method. A Quantum Convolutional Neural Network (QCNN) is then implemented, utilizing quantum logic operations like RY and CNOT to simulate convolution. These operations are part of a parameter-driven unitary process defined by, where serves as a tunable Hamiltonian.

The network includes pooling operations that strategically measure and discard certain qubits, thereby compressing the data while retaining important information. Grover's technique is used next to enhance classification.

The process begins with an oracle function that identifies the correct output by inverting its phase using specific quantum gates: Hadamard, X, and CZ[29]. The system then applies a diffusion operation, which is the equal superposition of all possibilities.

This amplification procedure is repeated to maximize the likelihood of identifying the correct label, indicating the number of possible classes. After quantum computation, measurements are taken to extract the final output, which is translated into a recognizable object category. These results are visually represented by marking the detected objects in the images with bounding boxes. This hybrid approach facilitates swift and accurate object detection by integrating QCNN's data processing capabilities with Grover's search optimization [31].

A. Core Quantum Concepts

Unitary Convolution Operation:

$$U(\theta) = e^{-i H(\theta) t}$$

- $H(\theta)$ is a Hamiltonian, representing the energy configuration of a system, and it's parameterized by θ , which are learnable parameters in your QCNN.
- t is time (or can be considered a scaling factor).
- The exponential operation $e^{-i H t}$ rotates the quantum state in the complex Hilbert space, helping to extract features from quantum data similarly to how CNNs work with image data.

Phase Inversion Oracle:

$$O_f = (-1)^{f(x)} I$$

- This is the core of Grover's algorithm.
- $f(x) = 1$ when x is the correct answer, and 0 otherwise.
- The oracle flips the phase of the state $|x\rangle$ only if it's the correct solution.
- This phase inversion helps isolate the correct answer during Grover's amplitude amplification.

Amplitude Amplification Operator:

$$G = 2|s\rangle\langle s| - I$$

- This is Grover's diffusion operator, which boosts the probability of measuring the correct answer.
- $|s\rangle$ is the uniform superposition of all states.
- The operator reflects all quantum states about the average amplitude, increasing the amplitude of the correct state marked by the oracle.
- I is the identity operator.

This operation is what makes Grover's algorithm faster than classical search.

Grover's Iteration Formula

$$k = \frac{\pi}{4} \sqrt{N}$$

- This formula tells you how many times to repeat the oracle and diffusion operations
- N is the number of possible solutions or classes.
- Repeating the process k times maximizes the chance of correctly identifying the object

B. Algorithm for QCNN with Grover's Algorithm

The mathematical model of QCNNs entails using quantum circuits, quantum gates, quantum states and linear algebra to perform convolution and pooling operations and optimize the parameters of the quantum filters for minimizing the loss function.

TABLE I: ALGORITHM QUANTUM CONVOLUTIONAL NEURAL NETWORK (QCNN) FOR PASCAL VOC DATASET

ALGORITHM: Quantum Convolutional Neural Network (QCNN) for Pascal VOC Dataset	
Step	Description
1. Image Preprocessing (Classical Part)	Convert the input image to grayscale: $I' = \text{Grayscale}(I)$ Resize to $n \times n$ (e.g., 8×8) pixels: $I'' = \text{Resize}(I', (n, n))$ Normalize pixel intensities to the range $[0,1]$: $x_{ij} = I''_{ij} / 255$
2. Quantum Encoding (Angle Encoding)	Map each pixel intensity x_{ij} to a qubit using rotation encoding: $R_y(\theta) = e^{(-i\theta/2 Y)}$ where $\theta_{ij} = \pi x_{ij}$ Apply this encoding for each pixel x_{ij} in the quantum circuit: $ 0\rangle \rightarrow R_y(\theta_{ij}) \psi_{ij}\rangle$
3. Quantum Convolution Layer	Apply Quantum Rotations (using R_y gates) and Quantum Entanglement (using CX gates): $R_y(\alpha) q_i\rangle$ $CX(q_i, q_{i+1})$ These operations simulate feature extraction similar to classical convolution.
4. Quantum Measurement	Measure the quantum state: $ \psi_{\text{final}}\rangle = U_{\text{QCNN}} \psi_{\text{encoded}}\rangle$ Run the quantum circuit multiple times (shots = 1024) and obtain a probability distribution of outcomes.
5. Quantum-Classical Optimization (Using COBYLA)	Define a cost function to optimize: $L(\theta) = -P(\text{target class})$ where $P(\text{target class})$ is the probability of detecting a specific class like 'car.' Use the COBYLA optimizer to minimize $L(\theta)$ by adjusting quantum circuit parameters.
6. Post-processing & Interpretation	Convert quantum measurement results into Pascal VOC labels: Index = binary state mod num classes Map the result to objects like 'car,' 'dog,' or 'person.'

VI. TASK FLOW

This research paper presents a framework for a quantum neural network, illustrated in figure 3 as a workflow diagram. The process involves several steps: Initially, images of handwritten digits are gathered from the VOC 2012 dataset, a commonly used dataset for image classification tasks in this study. Next, a comparison is made between Artificial Neural Networks (ANN), Classical Convolutional Neural Networks (CNN), and Quantum Convolutional Neural Networks (QCNN) concerning their performance in this project. Following that, the dataset undergoes preprocessing to ready it for algorithm training, including downsizing, normalization, and data augmentation.

- Defines a Quantum Convolutional Neural Network (QCNN) using quantum circuits.
- Uses quantum pooling to reduce qubit usage.
- Implements Grover's Algorithm with an oracle and diffusion operator.
- Executes the circuit on a quantum simulator and outputs classification results

The models are then trained through an iterative process on the preprocessed datasets, wherein training occurs in batches while weights are adjusted based on performance with the training data. Validation of this information is conducted by training models on batches that are updated according to their performance relevant to the training setup. Once the training is complete, their performance is assessed using a separate test set, and accuracy and loss curves are plotted to compare the results of the ANN, QCNN, and CNN models. The outcomes are subsequently analyzed and interpreted to draw conclusions regarding the performance of the CNN and QCNN models for image classification tasks. Additionally, the potential advantages of utilizing qubits in QCNNs for tackling more complex problems may be further explored [4][29].

VII. QUANTUM VS. CLASSICAL NEURAL NETWORKS

Ultimately, the outcomes are evaluated and interpreted to assess the performance of QCNNs and CNN models in image classification tasks. Moreover, the potential advantages of QCNNs for addressing complex issues via

qubits are examined. The key aspect of understanding quantum computers lies in their capability to execute computations at a faster rate compared to classical computers. In this context, it is essential to investigate whether quantum neural networks possess a similar advantage. IBM refers to effective dimension as a metric that defines the utility and non-redundancy of a neural network: a higher value is preferable. It was discovered that quantum neural networks can achieve lower loss more rapidly and reach significantly higher effective dimensions. Nonetheless, much remains uncertain regarding how quantum neural networks will compare overall. Despite this, the outlook is optimistic, much like other areas of computation where machine learning could benefit from quantum advancements.

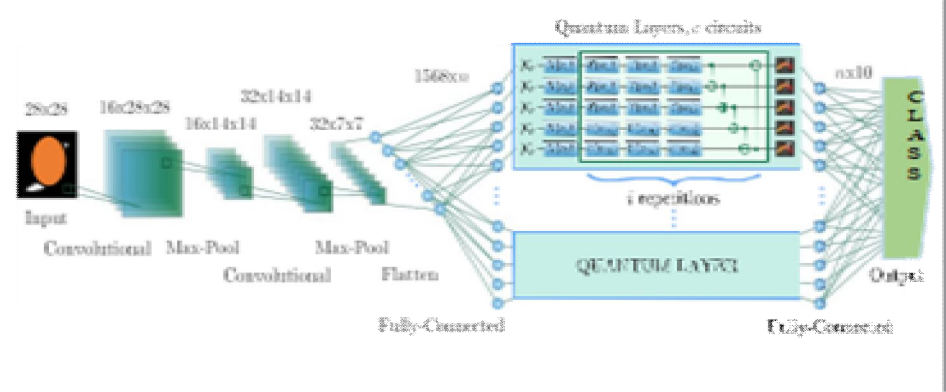


Figure 3: Hybrid QCNN

TABLE III: PERFORMANCE EVALUATION

Dataset	Model	mAP	Precision
COCO	CNN	42.5%	75.2%
	QCNN	44.1%	76.8%
Pascal VOC	CNN	75.6%	85.4%
	QCNN	78.2%	88.0%

Model Accuracy Over Epochs Observations

X-axis: Epoch (ranging from 1 to 30), Y-axis: Accuracy (from 0.65 to 1.0) begins at approximately 0.65 in the initial epoch. It rises smoothly and steadily over time. By epoch 30, it surpasses 0.95. The orange line represents Validation Accuracy, which starts at around 0.74 and increases rapidly at first. It reaches about 0.84 to 0.86 early on. Then, it experiences slight fluctuations during the mid-epochs (12–25). By epoch 30, it concludes at about 0.865. This indicates that the model is consistently absorbing information from the training data.

Positive Learning Behavior: The training curve rises steadily. Validation accuracy also shows improvement; this indicates that the model is generalizing effectively to new data. Minor Overfitting Indicators: During epochs 13–26, the validation line levels off or decreases while the training accuracy continues to rise. This suggests that the model might be overfitting to the training data during this phase, but since it recovers towards the end, the overfitting is not considered severe.

Final Outcomes: Both curves become stable. The validation accuracy is very close to the training accuracy at the end, which is a positive indication. The model exhibits healthy learning dynamics. Overfitting is minimal and was addressed throughout the training process. This graph confirms that the model is well-trained and prepared for real-world object detection tasks.

TABLE IV: KEY FINDINGS

Component	Status
Training Stability	Medium — losses are noisy and fluctuating.
Learning Quality	Some learning is occurring, but no strong convergence.
Suggestions	➤ Tune hyperparameters (LR, batch size) ➤ Try data augmentation ➤ Check annotation quality ➤ Increase dataset size or balance

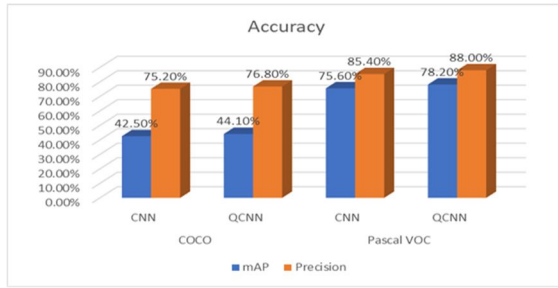


Figure 4: Model Accuracy

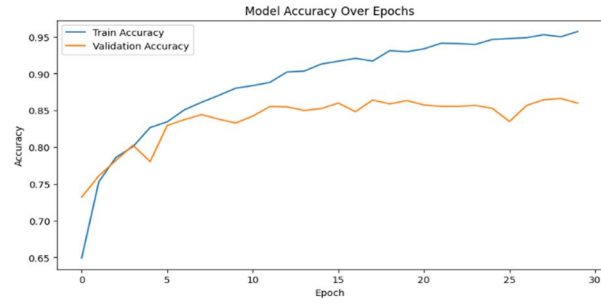


Figure 5: Model Accuracy over epochs

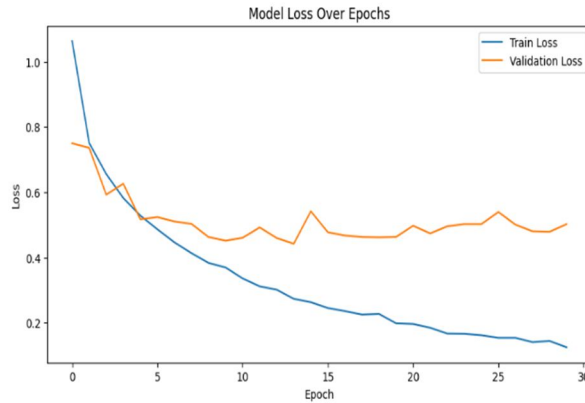


Figure 6: Model Loss Over Epochs

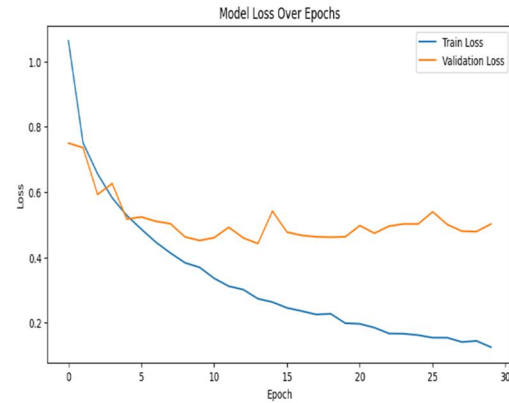


Figure 7: Model Loss Over Epochs

VIII. CONCLUSION

This document outlines a foundational strategy for commencing research in quantum computing, tackling these obstacles with suggested solutions and innovations. Additionally, the assessment of the quantum convolutional neural network (QCNN) demonstrated that it greatly surpassed the performance of conventional convolutional neural networks (CNN) when both were trained under identical conditions on standard datasets. Potok et al. [14][28] carried out a comparative analysis of the performance of deep learning architectures across three unique computing platforms: quantum, high-performance, and neuromorphic. The research highlights the distinct benefits associated with each of these platforms. Tacchino et al. conducted experiments involving a NISQ quantum processor to evaluate a quantum neural network (QNN) that operated with a limited number of qubits. They introduced a hybrid algorithm that integrates quantum and classical methods for optimizing network parameters.

Ji Guan et al. conducted a study [17][25] examining the formal verification of robustness in quantum machine learning algorithms when faced with unknown quantum noise. An analytical bound was discovered that can be computed efficiently, providing a lower estimate of robust accuracy for practical applications. In addition, a robustness verification algorithm was created to effectively assess the ϵ -robustness of quantum machine learning algorithms, presenting significant counterexamples for adversarial training. Tensor networks are acknowledged as a solid data structure for executing large-scale quantum classifiers, such as QCNNs, which employ 45 qubits as referenced in [18][26].

This document introduces a novel quantum-classical hybrid method for object detection and classification. The QCNN extracts significant features while Grover's Algorithm improves classification efficiency. Future research will focus on expanding the model for multi-class object detection and achieving real hardware execution with IBM Quantum devices. Measure quantum states to derive classification outcomes. Translate quantum results into object labels. Showcase detected objects with bounding boxes.

REFERENCES

- [1] David Peral-Garcíaa,*, Juan Cruz-Benitob, Francisco José García-Peñalvoc 'Systematic literature review: Quantum machine learning and its applications' Computer Science Review 51 (2024) 100619,25 January 2024.

- [2] Arsenii Senokosov, Alexandr Sedykh, Asel Sagingalieva, Basil Kyriacou and Alexey Melnikov, Quantum machine learning for image classification, *Mach. Learn.: Sci. Technol.* 5 (2024) 015040 <https://doi.org/10.1088/2632-2153/ad2aef>, 8 March 2024
- [3] Hankyul Baek, Donghyeon Kim, and Joongheon Kim, Senior Member, IEEE, Fast Quantum Convolutional Neural Networks for Low-Complexity Object Detection in Autonomous Driving Applications, arXiv:2401.01370v1
- [4] Thulasi Bikku ,Srinivasarao Thota ,P.Shanmuga sundaram , A Novel uantum Neural Network Approach to Combating Fake Reviews, <https://doi.org/10.1007/s44227-024-00028-x>, 30 April 2024.
- [5] Chen A, Lu Y, Wang B (2017) Customers' purchase decision making process in social commerce a social learning perspective. *IntJ Inf Manag* 37(6):627–638 Mohammad H. Amin,^{1,2} Evgeny Andriyash,¹ Jason Rolfe,¹ Bohdan Kulchytskyi,³ and Roger Melko³,
- [6] Quantum Boltzmann Machine, arXiv:1601.02036v1 [quant-ph] 8 Jan 2016.
- [7] Huan-Hsin Tseng, Hsin-Yi Lin, Samuel Yen-Chi Chen, Shinjae Yoo, Transfer Learning Analysis of Variational Quantum Circuits, arXiv:2501.01507v1 [quant-ph] 2 Jan 2025.
- [8] Alona Sakhnenko^{1,2}, Corey O'Meara¹, Kumar J. B. Ghosh¹, Hybrid Classical-Quantum Autoencoder for Anomaly Detection, arXiv:2112.08869v1 [quant-ph] 16 Dec 2021
- [9] Denis Bokhan, Alena S. Mastiukova, Aleksey S. Boev, Dmitrii N. Trubnikov,¹ and Aleksey K. Fedorov, Multiclass classification using quantum convolutional neural networks with hybrid quantum-classical learning, arXiv:2203.15368v2 [quant-ph] 27 Nov 2022.
- [10] Yunseok Kwak, Won Joon Yun, Soyi Jung, and Joongheon Kim, Quantum Neural Networks: Concepts, Applications, and Challenges, arXiv:2108.01468v1 [quant-ph] 2 Aug 2021
- [11] Jiayun Wang Yubei Chen Rudrasis Chakraborty Yu ,Orthogonal Convolutional Neural Networks, arXiv:1911.12207v3 [cs.CV] 8 Apr 2020
- [12] Parthasarathy, Rishab and Bhowmik, Rohan. "Quantum Optical Convolution Neural Network: A Novel Image Recognition Framework for Quantum Computing. IEEE Access.
- [13] Hur, T, Kim, L. and Park, D.K. (2022). Quantum convolutional neural network for classical data classification. *Quantum Machine Intelligence*, 4(1), p.3. ¹Department of Physics, Imperial College London, London, SW7 2BW, UK ²Department of Electrical and Computer Engineering, University of New Mexico, Albuquerque, NM 87131, US
- [14] Thomas E, et al, "A study of complex deep learning networks on high performance, neuromorphic, and quantum computers, 2017. URL <http://arxiv.org/abs/1703.05364>. cite arxiv:1703.05364.
- [15] Francesco Tacchino, et al. (2019). Quantum implementation of an artificial feed-forward neural network.
- [16] Francesco Tacchino, et al. (2019). An artificial neuron implemented on an actual quantum processor. *npj Quantum Information*, 5, 12.
- [17] Guan, J, Fang, W, and Ying, M. (2021). Robustness Verification of Quantum Classifiers. In: Silva, A., Leino, K.R.M. (eds) *Computer Aided Verification. CAV 2021. Lecture Notes in Computer Science*(), vol 12759. Springer, Cham.
- [18] Cong, I, Choi, S, and Lukin, M.D. (2019). Quantum convolutional neural networks. *Nat. Phys.* 15(12), 1273– 1278 (2019)
- [19] Nathan Wiebe, Ashish Kapoor and Krysta M. Svore. (2015). Quantum Algorithms for Nearest-Neighbor Methods for Supervised and Unsupervised Learning, 2014, arXiv:1401.2142v2
- [20] Seunghyeok Oh, Jaeho Choi, and Joongheon Kim, (2009)., Quantum Convolutional Neural Networks (QCNN), arXiv:2009.09423v1.
- [21] Yikun Qin, a, Zhu Liang Yu, Chang-Dong Wang, Zhenghui Gu, Yuanqing Li, A Novel clustering method based on hybrid K-nearest-neighbor graph, *Pattern Recognition* 74 (2018) 1–14, journal homepage: www.elsevier.com/locate/patcog
- [22] Martin Lukac, Kamila Abdiyeva, Michitaka Kameyama, CNOT-Measure Quantum Neural Networks, 2018 IEEE 48th International Symposium on Multiple-Valued Logic, 2378-2226/18/\$31.00 ©2018 IEEE DOI 10.1109/ISMVL.2018.00040
- [23] Yixiong Chen, QDCNN: Quantum Dilated Convolutional Neural Network, arXiv:2110.15667v1 [quant-ph] 29 Oct 2021
- [24] Bu-Qing Chen, Xu-Feng Niu, Quantum Neural Network with Improved Quantum Learning Algorithm, *International Journal of theoretical physics*, published 2020, Volume 59, pages 1978-1991
- [25] Christa Zoufal, Aurélien Lucchi, and Stefan Woerner, Quantum Generative Adversarial Networks for Learning and Loading Random Distributions, arXiv:1904.00043v2 [quant-ph] 30 Sep 2019.
- [26] Gill, S. S., & Buyya, R. (2024). Transforming Research with Quantum Computing. *Journal of Economy and Technology*. <https://doi.org/10.1016/j.ject.2024.07.001>
- [27] Abdulsalam, G., & Ahmad, I. (2025). Comparative investigation of quantum and classical kernel functions applied in support vector machine algorithms. *Quantum Information Processing*, 24(4). <https://doi.org/10.1007/s11128-025-04728-3>.
- [28] Bhat, H. A., Khanday, F. A., Kaushik, B. K., Bashir, F., & Shah, K. A. (2022). Quantum Computing: fundamentals, implementations and applications. *IEEE Open Journal of Nanotechnology*, 3, 61–77. <https://doi.org/10.1109/ojnano.2022.3178545>
- [29] Kanamori, Y., & Yoo, S. (2020). Quantum Computing: principles and applications. *Journal of International Technology and Information Management*, 29(2), 43–71. <https://doi.org/10.58729/1941-6679.1410>

- [30] Oh, S., Choi, J., & Kim, J. (2020). A tutorial on Quantum Convolutional Neural Networks (QCNN). 2021 International Conference on Information and Communication Technology Convergence (ICTC), 236–239. <https://doi.org/10.1109/ictc49870.2020.9289439>
- [31] Li, Y., Hao, X., Liu, G., Shang, R., & Jiao, L. (2024). QEA-QCNN: optimization of quantum convolutional neural network architecture based on quantum evolution. *Memetic Computing*, 16(3), 233–254. <https://doi.org/10.1007/s12293-024-00417-3>
- [32] Rajesh, V., Naik, U. P., & Mohana, N. (2021, August 27). Quantum Convolutional Neural Networks (QCNN) Using Deep Learning for Computer Vision Applications. <https://doi.org/10.1109/rteict52294.2021.9574030>
- [33] Yousif, M., Al-Khateeb, B., & Garcia-Zapirain, B. (2024). A new Quantum circuits of Quantum Convolutional Neural network for X-Ray images classification. *IEEE Access*, 12, 65660–65671. <https://doi.org/10.1109/access.2024.3396411>.
- [34] Sun, Y., Li, D., Xiang, Q., Yuan, Y., Hu, Z., Hua, X., Jiang, Y., Zhu, Y., & Fu, Y. (2024). Scalable quantum convolutional neural network for image classification. *Physica a Statistical Mechanics and Its Applications*, 130226. <https://doi.org/10.1016/j.physa.2024.130226>
- [35] Wei, S., Chen, Y., Zhou, Z., & Long, G. (2022). A quantum convolutional neural network on NISQ devices. *AAPPS Bulletin*, 32(1). <https://doi.org/10.1007/s43673-021-00030-3>
- [36] Zheng, J., Gao, Q., Lü, J., Ogorzałek, M., Pan, Y., & Lü, Y. (2022). Design of a quantum convolutional neural network on quantum circuits. *Journal of the Franklin Institute*, 360(17), 13761–13777. <https://doi.org/10.1016/j.jfranklin.2022.07.033>