# Quantum Convolutional Neural Networks for Multi-Channel Data

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## Abstract

**Abstract** — Quantum computing presents unique opportunities for advancing machine learning through Quantum Convolutional Neural Networks (QCNNs). This report explores the implementation of three methods: the Channel Overwrite (CO) method, the Weighted Expectation Value (WEV) method, and the Control QCNN. The CO method encodes classical data into quantum states, employing controlled phase operations to entangle inter-channel information. The WEV method combines quantum convolutions with classical weighting, creating a hybrid approach. The Control QCNN processes individual channels independently and aggregates results post-measurement. A modification to the CO method is also introduced, incorporating dynamic phase controls and deeper unitary blocks to improve feature extraction and hardware efficiency. These methods were evaluated on multi-channel datasets, showcasing distinct capabilities in quantum-classical hybrid learning and inter-channel feature analysis.

**Index Terms**— Quantum Computing, Quantum Convolutional Neural Networks, Multi-Channel Data, Machine Learning.

## I. INTRODUCTION

Quantum computers leverage quantum mechanical phenomena such as superposition and entanglement to solve computational problems that are infeasible for classical systems. QCNNs incorporate quantum circuits as convolutional filters in classical Convolutional Neural Networks (CNNs), aiming to exploit quantum advantage in tasks such as image and pattern recognition. Existing QCNN models often struggle with multi-channel data due to inefficient inter-channel feature extraction. Classical approaches typically measure individual channels and store results classically, losing valuable inter-channel information. Some methods, like the flat quantum convolutional Ansatz, require hardware resources beyond current capabilities, making practical implementations difficult. This study introduces an innovation to the COQCNN architecture by enhancing the entanglement and phase control mechanisms during channel overwrite operations. This approach improves the model's ability to learn inter-channel features while maintaining hardware compatibility.

## II. LITERATURE REVIEW

Quantum Convolutional Neural Networks (QCNNs) represent a significant milestone in integrating quantum computing with classical machine learning. The foundational work of Cong et al. (2019) introduced QCNNs as a means of leveraging quantum entanglement and superposition to perform convolutional operations on quantum data [1]. This approach has since been expanded to incorporate multi-channel data, which poses additional challenges due to the need for effective inter-channel learning mechanisms [2].

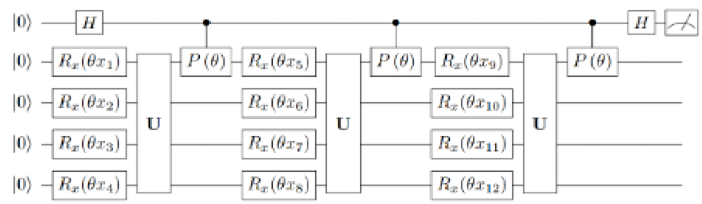
The Channel Overwrite (CO) method is one of the earliest approaches to address multi-channel quantum data. It encodes classical data into quantum states using rotation gates and employs controlled phase operations to entangle information across channels [3]. While effective for single-channel learning, its static phase configuration limits its ability to capture complex inter-channel relationships. The Weighted Expectation Value (WEV) method, on the other hand, combines quantum operations with classical post-processing, where channel outputs are weighted and aggregated. This hybrid approach reduces the quantum hardware requirements but sacrifices quantum-native inter-channel learning [2].

The Control QCNN model processes channels independently and aggregates results after measurement. While computationally straightforward, it does not exploit inter-channel dependencies, which are critical for many machine learning tasks [3]. These limitations have motivated researchers to explore innovative modifications, such as introducing dynamic phase controls and enhancing unitary operations, to improve the efficiency and performance of QCNNs for multi-channel data [4].

## III. METHODS

### A. Channel Overwrite (CO) Method

The CO method encodes classical data from a single channel into quantum states through angle rotations and applies learnable unitary operations to extract features. The quantum state is periodically collapsed into an ancilla qubit through controlled phase operations, enabling some level of inter-channel data exchange.




### B. Weighted Expectation Value (WEV) Method

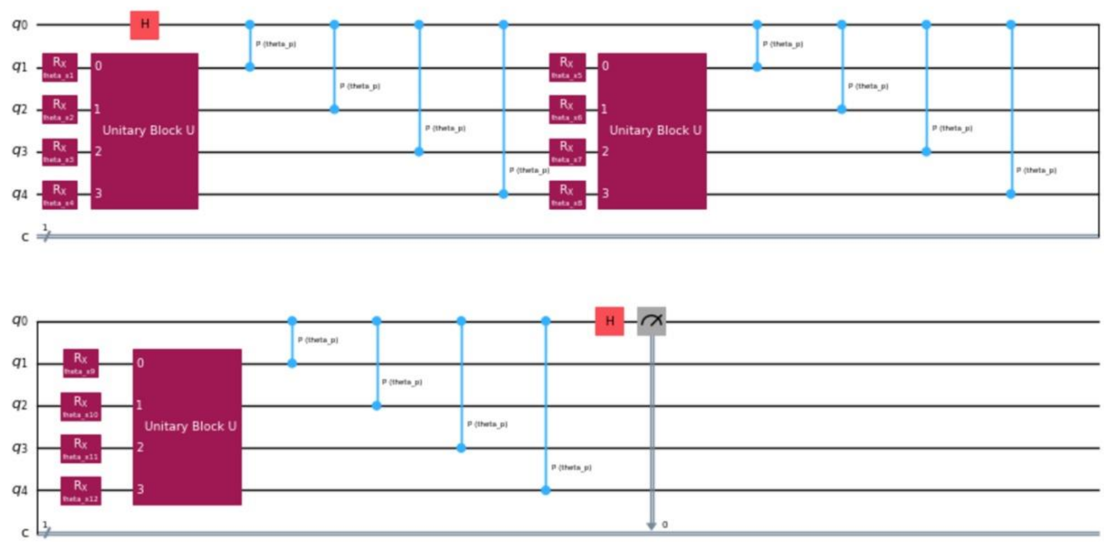
The Weighted Expectation Value (WEV) method offers an alternative by classically weighting the outputs of individual quantum convolutions performed on separate channels. While this hybrid approach minimizes quantum resource requirements, it sacrifices quantum-native inter-channel learning, making it suboptimal for datasets with strong inter-channel dependencies. This method is ideal for few qubits few gates and shallow circuit depth.

### C. Control QCNN Model

The Control QCNN model, a common benchmark, processes channels independently, extracting features with quantum circuits and aggregating results post-measurement. While computationally simple, it fails to capture inter-channel relationships, leading to suboptimal accuracy for multi-channel datasets. Despite this, it serves as a baseline for evaluating advanced models like the Modified CO and WEV methods.

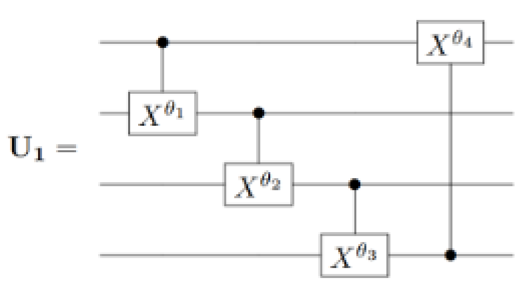
## D. Modified CO Method

We made a key modification to the original Channel Overwrite (CO) method by increasing phase entanglements. This change helps the system retain and make better use of inter-channel information, allowing it to extract features more effectively while staying efficient for use on today's quantum hardware.




## E. CONVOLUTIONAL UNITARY BLOCKS

The unitary blocks used to perform the convolutions are designed to demonstrate the functionality of the proposed methods. Unitary block U is shown below.




## IV. RESULTS AND DISCUSSION

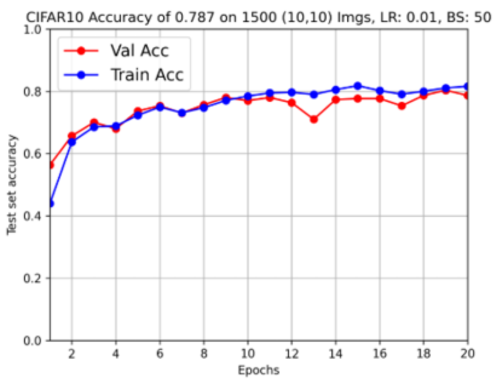
The comparative analysis highlights the strengths and weaknesses of each method when applied to multi-channel datasets. The Modified CO method consistently demonstrated superior performance, particularly in achieving higher accuracy and lower loss on both CIFAR-10 and COLORS datasets. These results emphasize the benefits of incorporating dynamic phase controls and deeper unitary blocks for inter-channel learning. While the WEV method showed moderate performance, its reliance on classical weighting limited its ability to fully leverage quantum-native properties. Similarly, the Control QCNN faced challenges in effectively integrating inter-channel information, resulting in suboptimal accuracy. These findings underscore the potential of the Modified CO method as a more efficient and adaptable approach for multi-channel quantum data processing.

## A. CIFAR-10 Dataset

The provided graphs illustrate the accuracy performance across different datasets and methods. For the CIFAR-10 dataset, the Modified CO method demonstrates the highest validation accuracy (81.6%), indicating better convergence and generalization compared to the WEV method (75.6%) and the original CO method (80.03%). The Control QCCN performed the worst (64.6%). The Modified CO method also exhibits a more consistent and stable trend in validation accuracy across epochs, reflecting its capability to effectively capture inter-channel relationships.

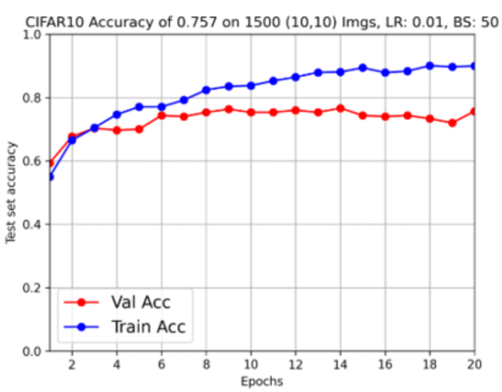
In contrast, the COLORS dataset shows significantly higher accuracy for the Modified CO method, achieving 0.985 validation accuracy, far surpassing its performance on CIFAR-10. This suggests that the Modified CO method excels on simpler datasets like COLORS, where inter-channel relationships are easier to model. The tighter alignment between training and validation curves in the COLORS dataset also indicates reduced overfitting, highlighting the robustness of the Modified CO method across varying datasets and complexities.

### 1. CO Method

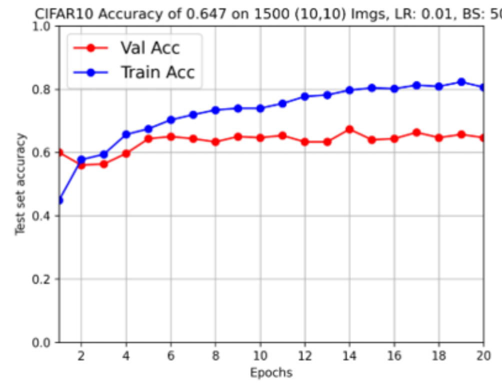



2.

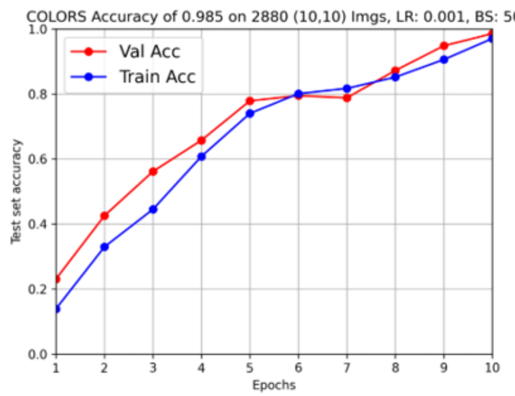
### 2.WEV Method




### 3. Control QCNN




### *4. Modified CO Method*

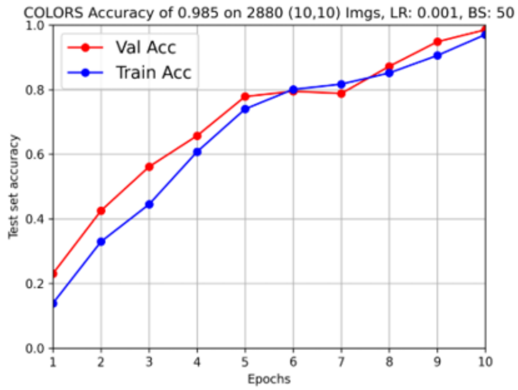



## B. COLORS Dataset

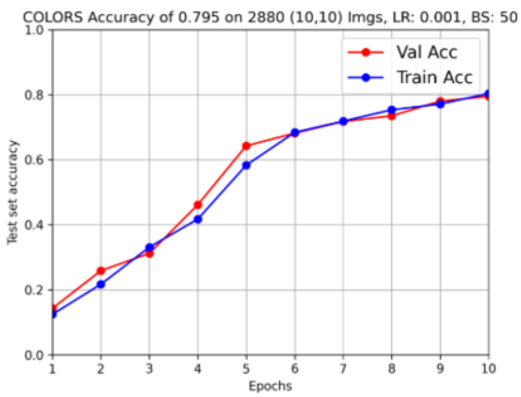
The provided graphs compare the performance of various methods on the COLORS dataset. The Modified CO method achieves the highest validation accuracy at 0.985, indicating its ability to capture inter-channel relationships effectively. This is closely followed by the WEV method, which reaches a validation accuracy of 0.795. However, the WEV method shows slightly slower convergence and a wider gap between training and validation accuracies in earlier epochs.

The Control QCNN method performs poorly with a validation accuracy of only 0.236, reflecting its inability to capture inter-channel dependencies due to independent channel processing. On the other hand, the graph with 1.0 accuracy demonstrates the robustness of the Modified CO method with a higher learning rate, achieving perfect validation accuracy in just a few epochs, showcasing faster convergence and excellent generalization. This analysis underscores the effectiveness of the Modified CO method in handling multi-channel data compared to other approaches.

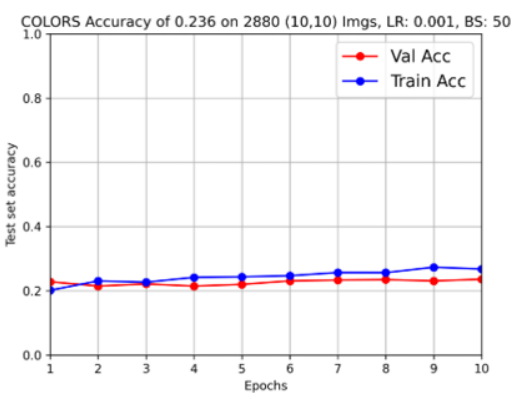
### 1. CO Method



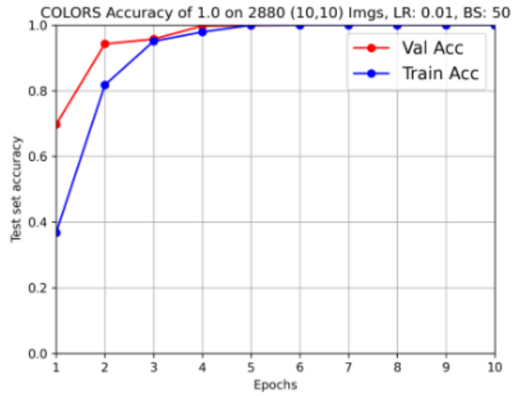

### 2. WEV Method




### 3. Control QCNN




### 4. Modified CO Method




## V. CONCLUSION

The proposed modification to the COQCNN architecture addresses limitations in inter-channel learning for multi-channel quantum data. By integrating dynamic phase control and deeper unitary operations, the model achieves a more robust capability for processing complex datasets. In comparison to the WEV method and Control QCNN, the modified CO method demonstrates enhanced quantum-native learning and hardware efficiency. Each method brings unique strengths, making them valuable for different applications within quantum machine learning. Future work will explore extending these innovations to larger datasets and real quantum hardware implementations.

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