A Scalable Quantum-enhanced Neural Network with Non-local Connections

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March 3, 2025

Contents

Introduction to Non-Local Operations in Neural Networks

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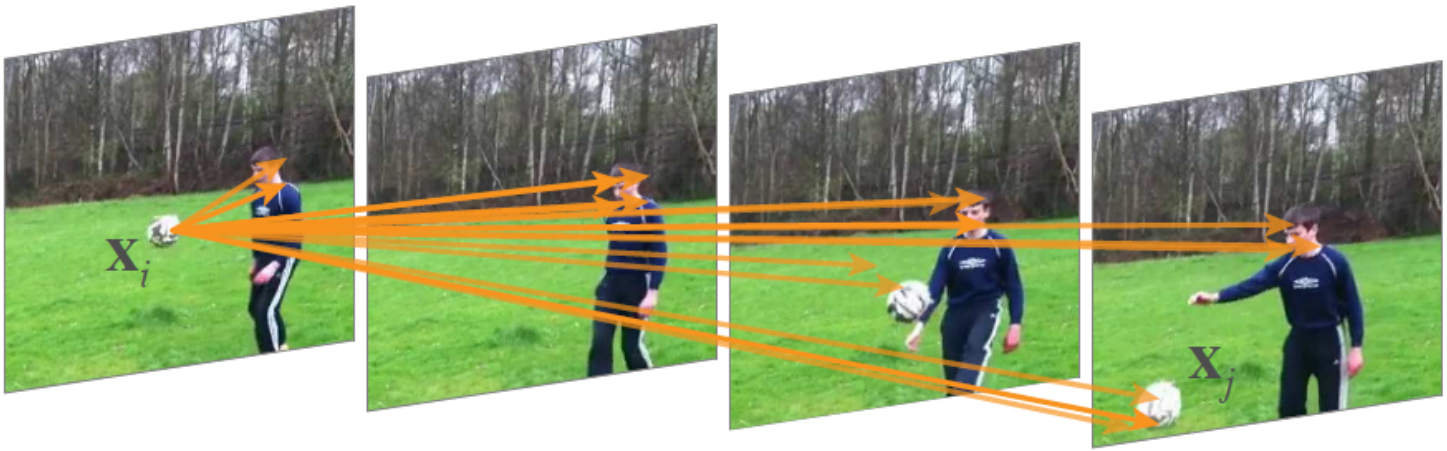

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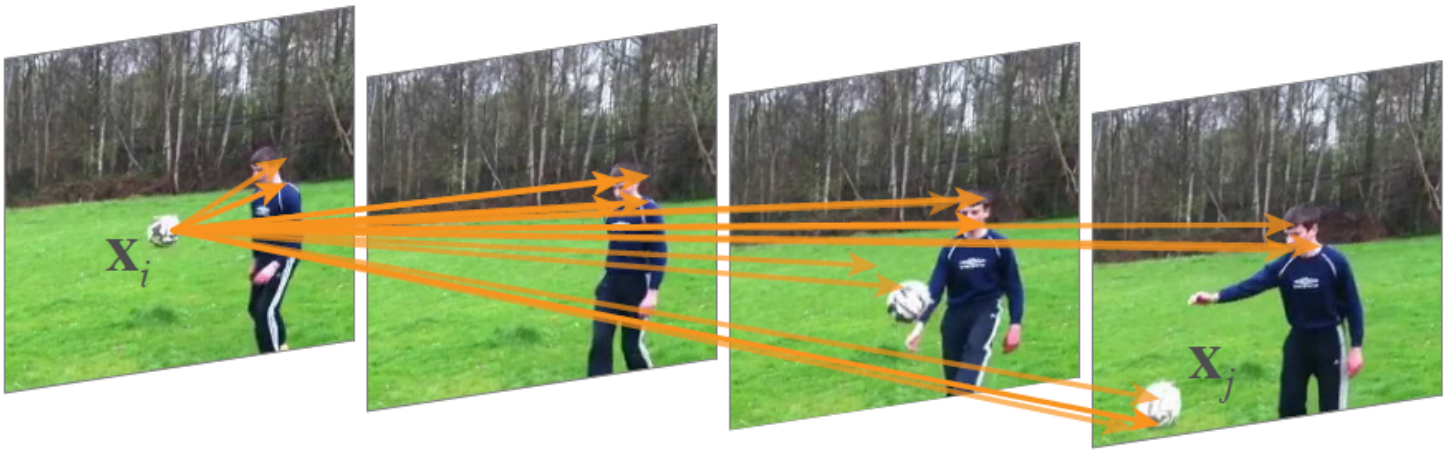

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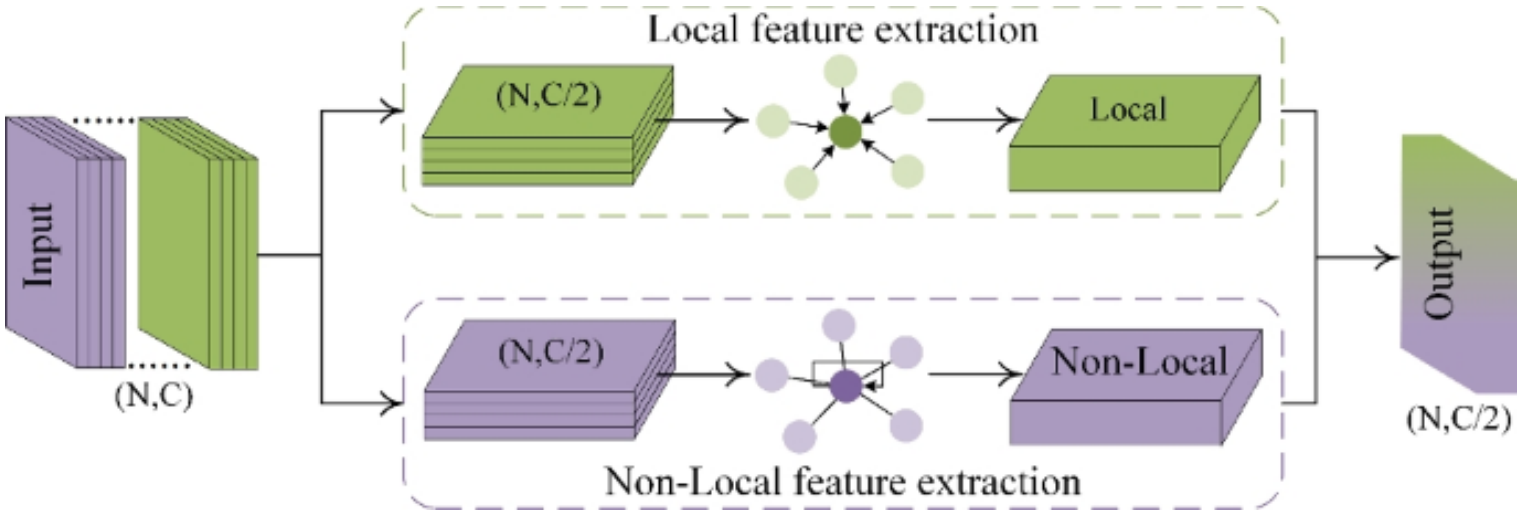

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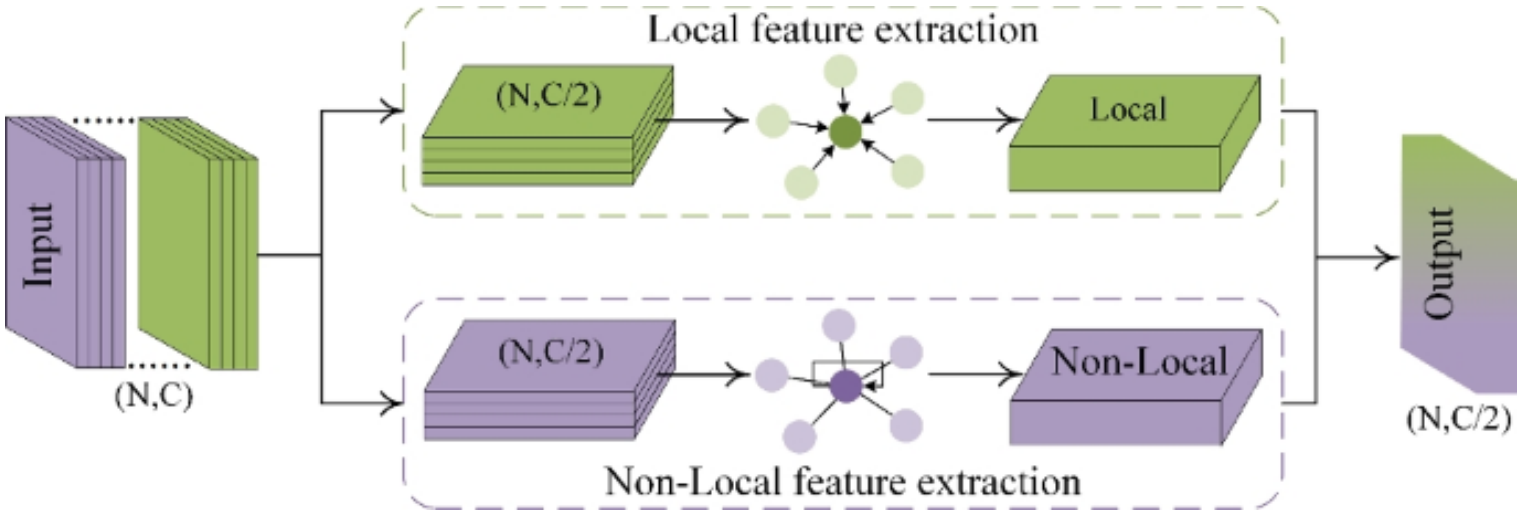

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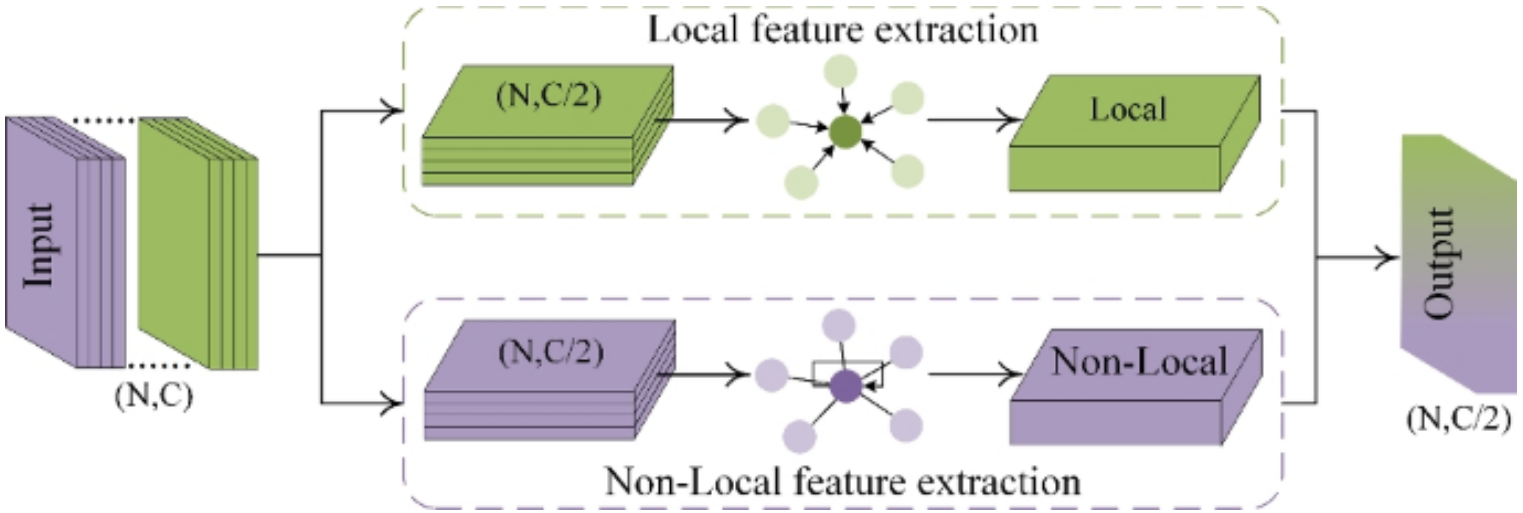

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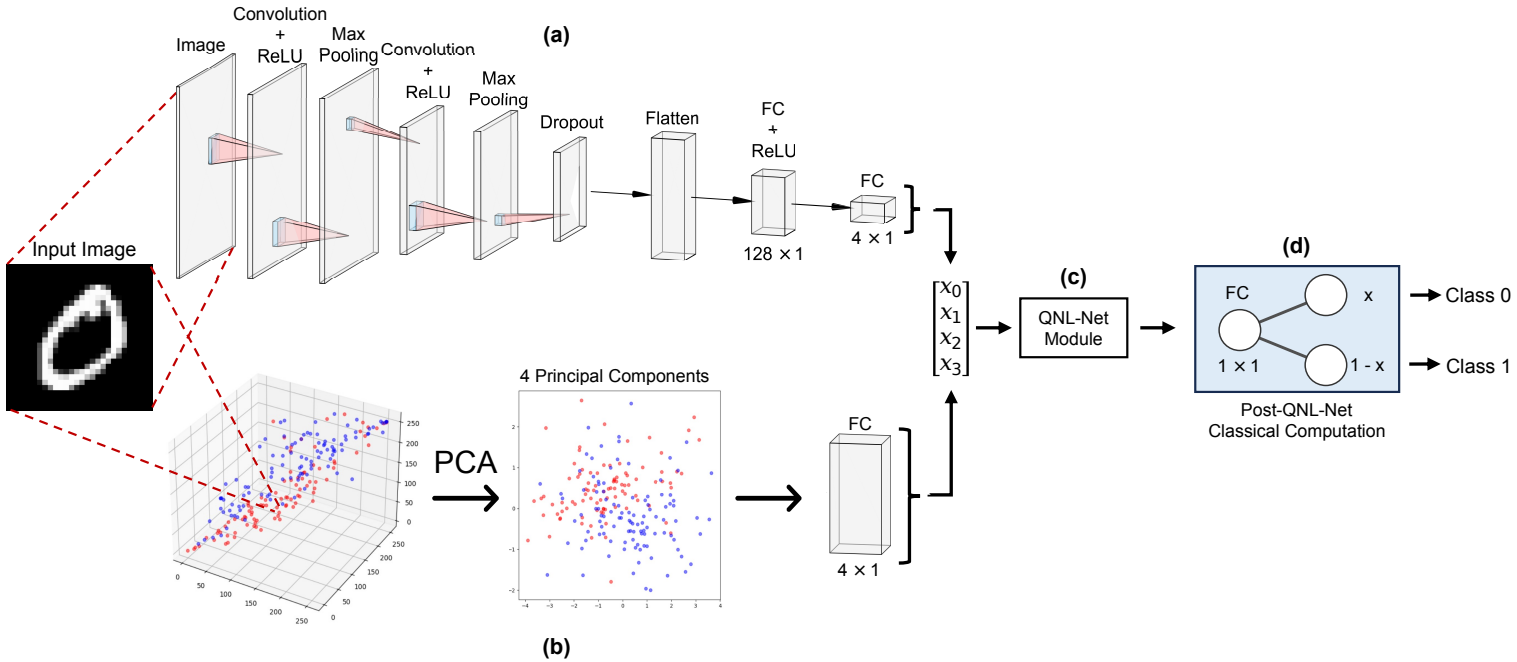

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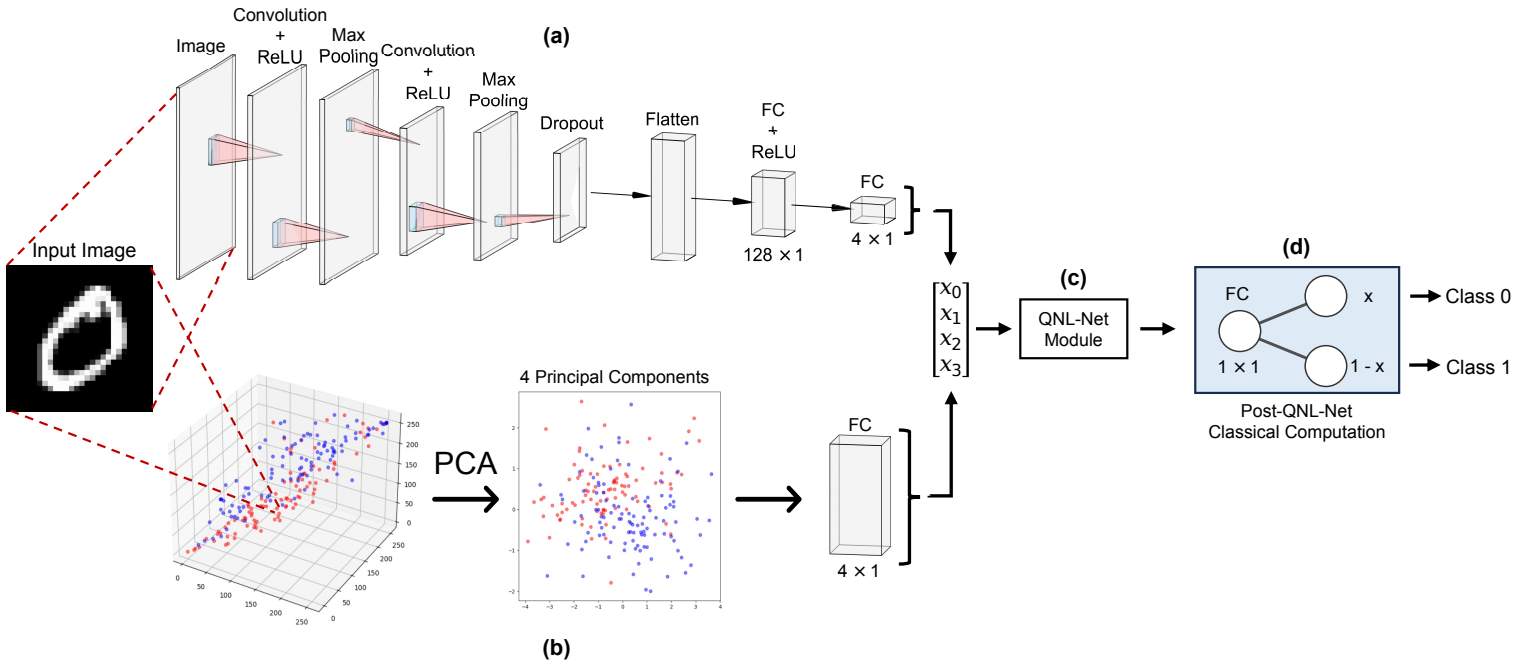

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- How can quantum entanglement be leveraged to perform non-local operations more efficiently than classical methods?

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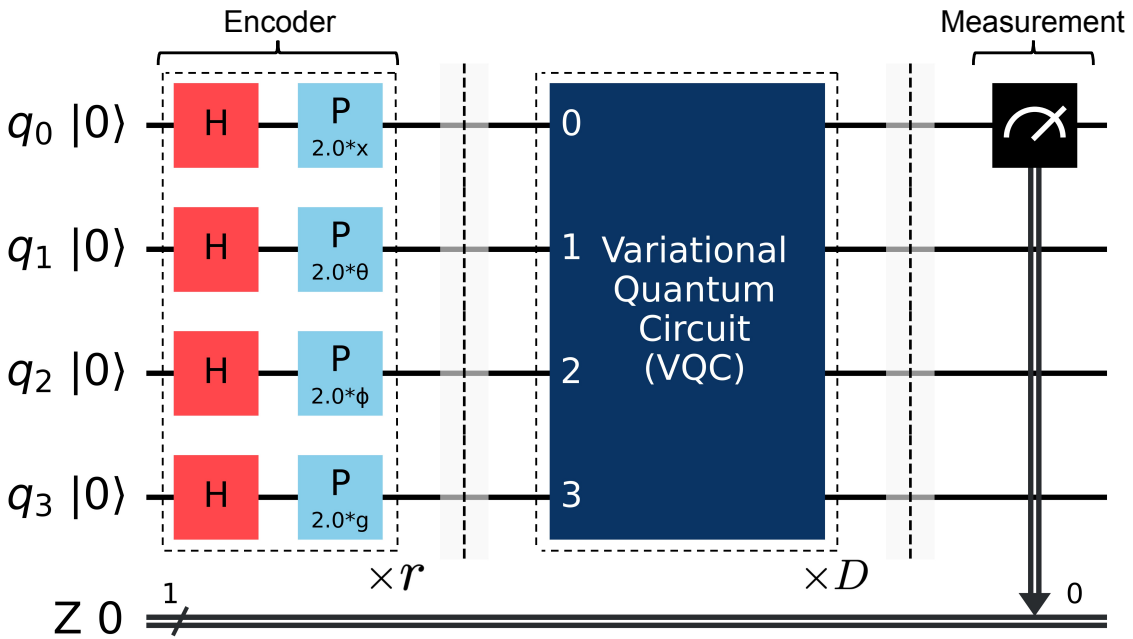

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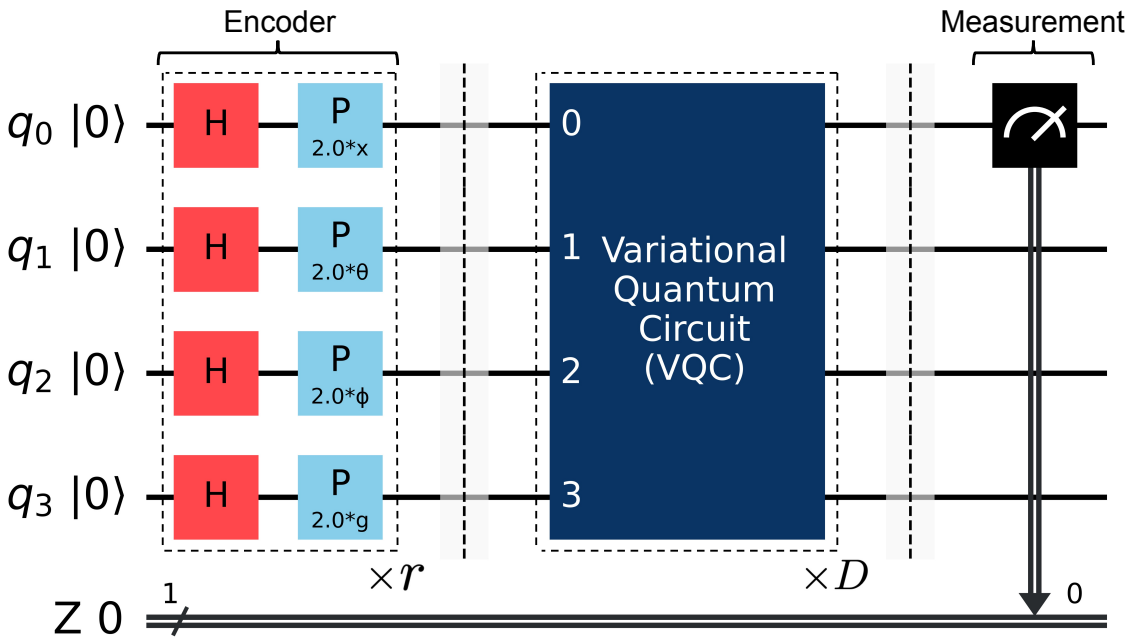

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- Encoding classical data, $X = [y_0, y_1, \cdots, y_{n-1}] \in \mathbb{R}^n$ into quantum space: $|\psi_\Phi\rangle = (\bigotimes_{k=1}^{n} P(\lambda_k) H^{\otimes n})^r |X\rangle$

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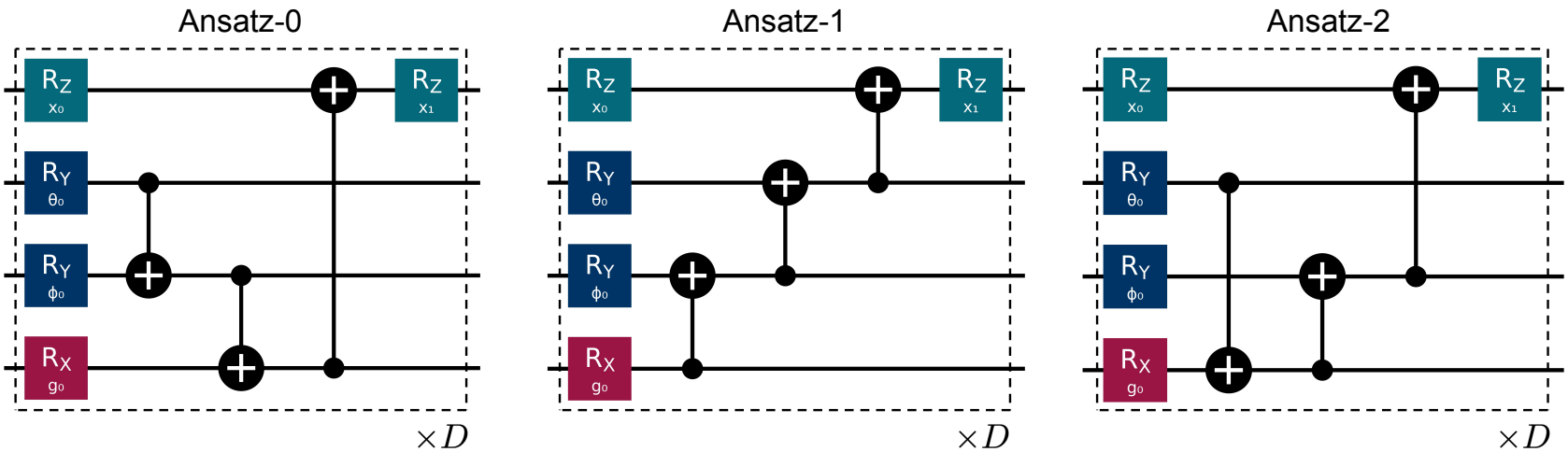

Figure 5: The three ansatzes used as the Variational Quantum Circuits (VQC) in our QNL-Net using C_X gates (CNOT) are: cyclic pattern (Ansatz-0), reverse linear chain (Ansatz-1), and a mixed pattern (Ansatz-2)[3].

QNL-Net: Simulation Results

- Our QNL-Net has been implemented using the *EstimatorQNN* module of Qiskit ML 0.7.2 and Qiskit 1.1.0.

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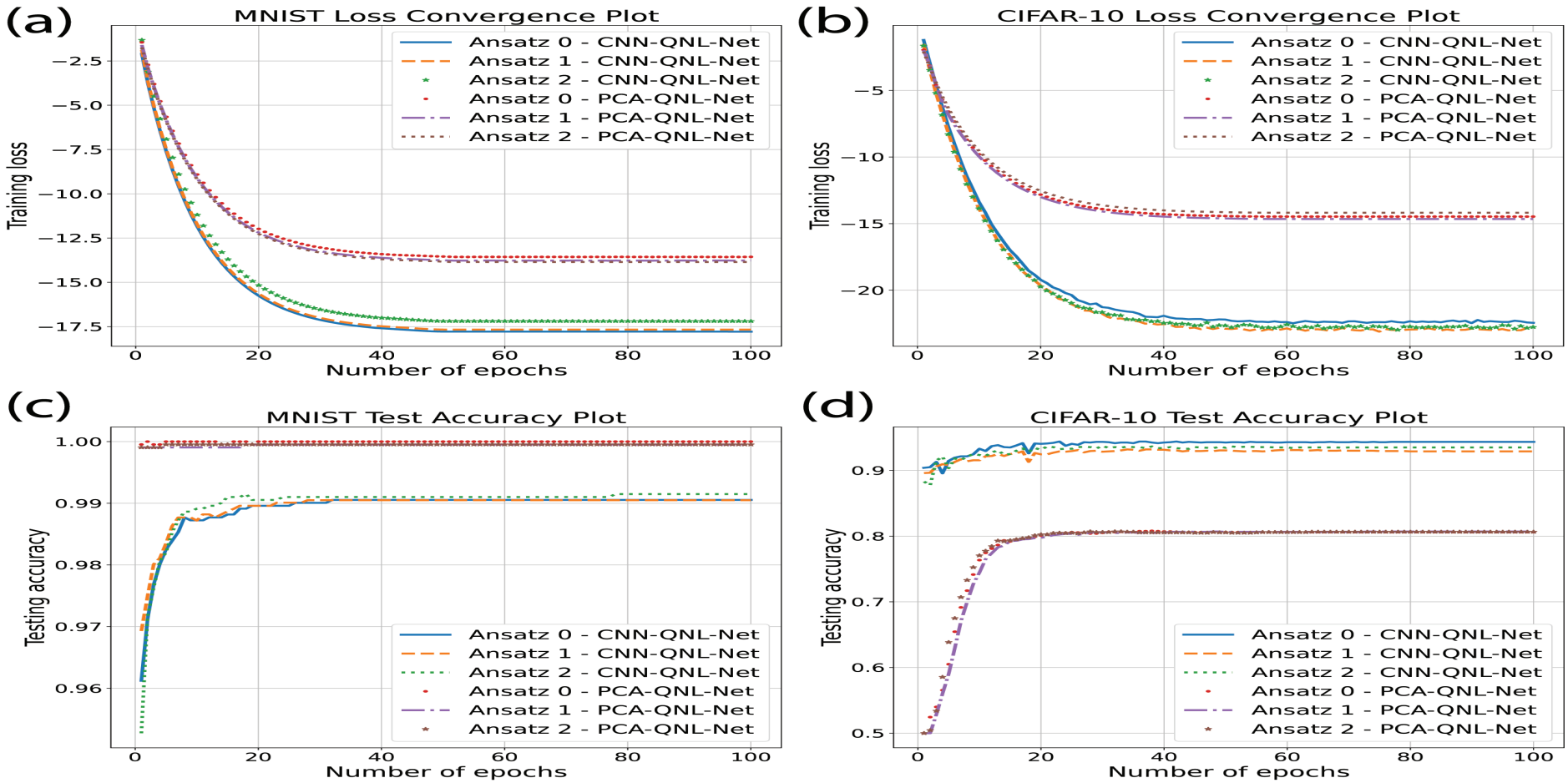

Figure 6: Training loss convergence and test accuracy plots for the CNN-QNL-Net and PCA-QNL-Net models for the three ansatzes with one feature map repetition ($r = 1$) and one ansatz repetition ($D = 1$) on MNIST and CIFAR-10 datasets.

QNL-Net: Simulation Results

Table 1: Performance of the proposed QNL-Net model on binary classification tasks across datasets: MNIST digits 0 and 1 and CIFAR-10 classes 2 (bird) and 8 (ship).

Dataset	Ansatz	Model	Learning Rate	Train Accuracy	Test Accuracy
MNIST (0, 1)	0	CNN-QNL-Net	1×10^{-4}	99.97 ± 0.02	99.96 ± 0.03
	1	CNN-QNL-Net	1×10^{-4}	99.96 ± 0.02	99.95 ± 0.02
	2	CNN-QNL-Net	1×10^{-4}	99.96 ± 0.03	99.95 ± 0.04
	0	PCA-QNL-Net	1.5×10^{-4}	99.65 ± 0.17	99.54 ± 0.16
	1	PCA-QNL-Net	1.5×10^{-4}	99.24 ± 0.19	99.18 ± 0.34
	2	PCA-QNL-Net	1.5×10^{-4}	99.67 ± 0.23	99.59 ± 0.21
CIFAR-10 (2, 8)	0	CNN-QNL-Net	3×10^{-4}	94.20 ± 0.77	93.54 ± 0.66
	1	CNN-QNL-Net	3×10^{-4}	94.13 ± 0.45	93.98 ± 0.37
	2	CNN-QNL-Net	3×10^{-4}	94.21 ± 0.32	93.76 ± 0.14
	0	PCA-QNL-Net	4×10^{-4}	81.94 ± 1.51	81.16 ± 1.09
	1	PCA-QNL-Net	4×10^{-4}	81.79 ± 0.34	80.95 ± 0.35
	2	PCA-QNL-Net	4×10^{-4}	81.67 ± 0.73	80.86 ± 0.74

Table 2: Performance of the QNL-Net model compared with QTN-VQC [4], Hybrid TTN-MERA [5], Tensor Ring VQC [6], SQNN [7], and QF-hNet-BN [8] on binary classification tasks using the MNIST dataset.

Model	Classes	Qubits	Test Accuracy
QTN-VQC	0, 1	12	98.60
Hybrid TTN-MERA	0, 1	8	99.87 ± 0.02
Tensor Ring VQC	0, 1	4	99.30
CNN-QNL-Net [Ours]	0, 1	**4**	$\mathbf{99.96 \pm 0.03}$
SQNN	3, 6	64	97.47
QF-hNet-BN	3, 6	12	98.27
CNN-QNL-Net [Ours]	3, 6	**4**	$\mathbf{99.94 \pm 0.02}$

Discussions and Future Works

- Our proposed QNL-Net shows promise in advancing accuracy and efficiency for image classification tasks.
- The proposed QN-Net leverages quantum entanglement as a key advantage.
- However, our QNL-Net faces limitations in multi-class classification and efficiency with larger, complex datasets.
- Investigating the integration of more efficient quantum encoding strategies may further enhance performance..

Funding Organizations

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