

QuEENet: Quantum-Enhanced Expressive Network for Image Classification

Supplementary Material

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1. Noise Integration

To evaluate performance under realistic hardware conditions, we conducted comprehensive noise ablation studies on both quantum circuits using PennyLane’s default.mixed simulator. We evaluated our model on simulated noise channels specifically amplitude damping and depolarization to all 12 qubits at error rates of 1% and 5%. Table 7 in main paper presents the resulting test accuracies on the CIFAR-10 dataset. The inclusion of noise simulation significantly increased computational overhead, extending training time to approximately 18 minutes per epoch. Notably, simulated depolarization noise demonstrated a pronounced degradation effect on qubit coherence, leading to substantial state information loss. Similarly when we applied amplitude damping in our proposed model. Amplitude damping noise is a quantum channel available in the default.mixed simulator it increased training time per epoch from 8 min to 16 min. For most noise values we observed slight decrement. In somecases, we observed minute increment after noise inclusion, the same pattern was observed and studied by [1] and [2].

2. t-SNE plots

We generated t-SNE plots to visualize both the input data and output features, providing insights into clustering efficiency across the CIFAR-10 and CIFAR-100 datasets for both CNOT+RZ and CNOT+RX quantum circuit topologies. These visualizations highlight the effectiveness of feature separation and class discrimination in the learned representations.

For the CIFAR-10 dataset, both quantum circuit variants exhibited clear data segregation, establishing distinct decision boundaries between classes while preserving coherent clustering of samples with similar features. The resulting plots showed well-defined class separations with minimal overlap across categories. On the CIFAR-100 dataset, the results varied with the number of classes. For experiments with 10-class subsets, both architectures achieved testing

accuracy above 83%, demonstrating effective clustering and classification. However, as the number of classes increased toward the full 100-class setting, the performance gap between CNOT+RZ and CNOT+RX circuits narrowed, and only marginal differences were observed. The greater class diversity and complexity in CIFAR-100 posed additional challenges, reducing the degree of improvement attainable by the quantum models.

3. Wall Clock Evaluation

In order visualize the effect of quantum circuit intergration on real time training overhead. We generated Wall clock graphs Figure 3 with and without quantum circuits. As result of increased evaluation of 164 parameters for phase shift, angle encoding, quantum measurement in probabilities resulted in increament in overall training time per epoch. But increased in training time was compensated by improvement classification accuracy on most datasets for same number of epochs.

4. Data Discription

The following Table 1 summarizes all the datasets used to evaluate our proposed model, including the total number of images, image dimensions, and the number of classes for each dataset.

Table 1. summarizes the datasets used in the study, detailing the number of images, image size, and the number of classes for each dataset.

Dataset	Images	Size	Classes
CIFAR-10	60,000	32 × 32	10
CIFAR-100	60,000	32 × 32	100
MNIST	70,000	28 × 28	10
F-MNIST	70,000	28 × 28	10
M-MNIST	58,954	64 × 64	6
FOG1	21,281	400 × 400	4
FOG2	6,225	256 × 256	6

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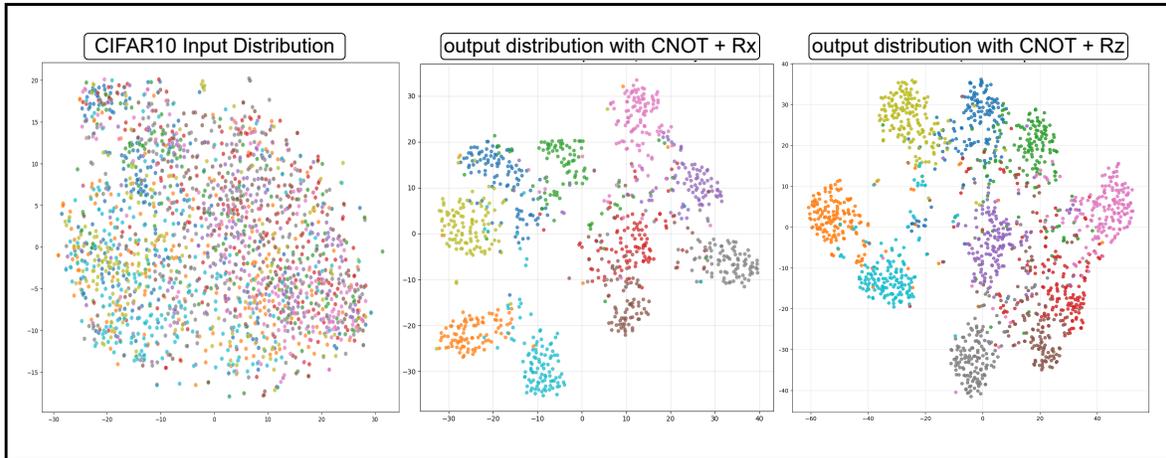


Figure 1. shows the t-SNE visualization of CIFAR-10, comparing the input distribution with output distributions from models trained using $CNOT + R_x$ and $CNOT + R_z$ circuits. The raw input features exhibit class overlap, whereas the trained models achieve clearer separation with compact clusters, highlighting the discriminative power of the proposed quantum layers.

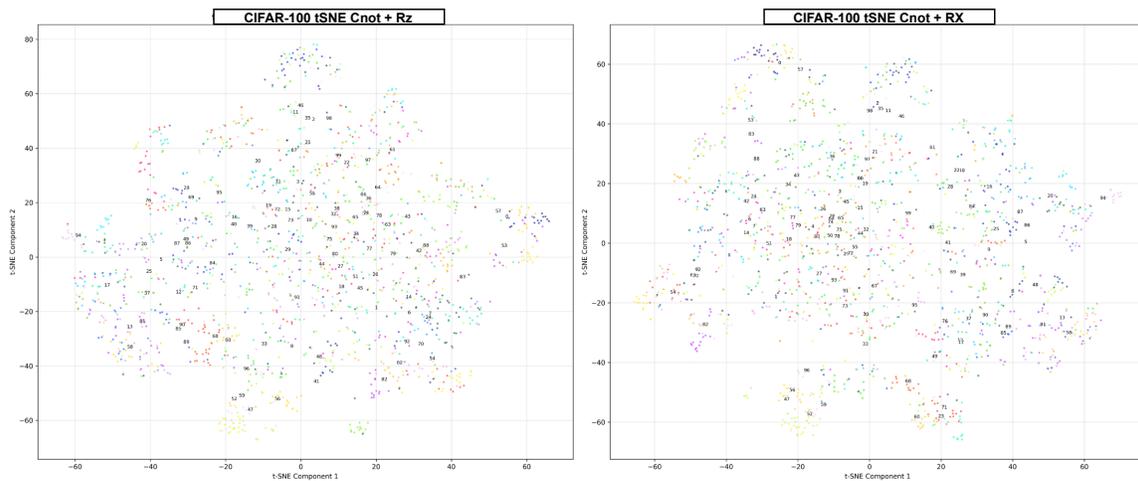


Figure 2. shows the t-SNE visualization of CIFAR-100 on QuEENet with $CNOT+R_z$ gates, and QuEENet with $CNOT+R_x$ gate on 100 classes

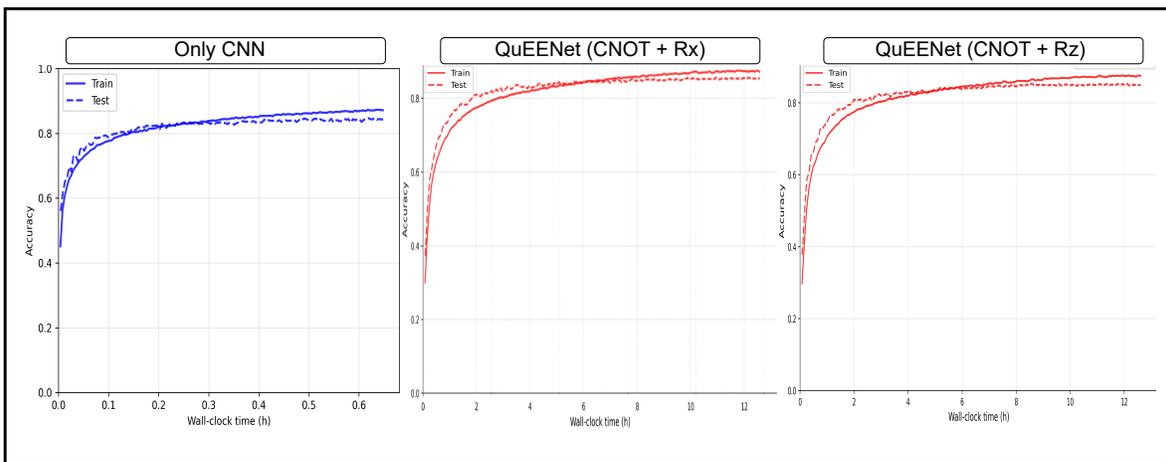


Figure 3. shows the training and testing accuracy over wall-clock time for three models: (a) a baseline CNN, (b) QuEENet with $CNOT+R_x$ gates, and (c) QuEENet with $CNOT+R_z$ gates. model QuEENet.

References

- [1] Yuxuan Du, Min-Hsiu Hsieh, Tongliang Liu, Dacheng Tao, and Nana Liu. Quantum noise protects quantum classifiers against adversaries. *Phys. Rev. Res.*, 3:023153, 2021. [1](#)
- [2] Wilfrid Somogyi, Ekaterina Pankovets, Viacheslav Kuzmin, and Alexey Melnikov. Method for noise-induced regularization in quantum neural networks, 2024. [1](#)