Quantum Neural Network (QNN) Evaluation on IEEE and SECOM Datasets

Overview

This document presents the implementation and evaluation of a Quantum Neural Network (QNN) trained on the IEEE and SECOM datasets for 20 epochs. The model discussed here is a newer, more complex architecture compared to a previously used simpler one. The performance and stability of the newer model are assessed based on test loss and accuracy.

Model Architecture Description

The newer QNN architecture integrates both classical and quantum components into a hybrid neural network. The primary architectural highlights are:

- **Hybrid Input Encoding**: Classical data is normalized and encoded into quantum states using angle encoding (also known as rotation encoding). This technique ensures the input is suitable for quantum circuit processing.
- **Parameterized Quantum Circuit (PQC)**:
    - The PQC comprises multiple layers of quantum gates including Hadamard, CNOT, and parameterized rotation gates (e.g., RX, RY).
    - The circuit is built with entanglement between qubits, enhancing the expressiveness and non-linearity of the model.
    - The quantum layer is wrapped within a `qml.qnode` (from PennyLane) and interfaced via a custom `TorchLayer` to integrate with PyTorch's autograd engine.
- **Classical Layers**:
    - The model begins with one or more fully connected (dense) classical layers to preprocess the input.
    - After the quantum processing stage, the output is passed through additional classical layers, including ReLU activation functions, batch normalization, and dropout for regularization.
    - A final dense layer with a Softmax activation is used for classification.
- **Hybrid Design Purpose**:
    - The combination allows the model to harness the strengths of quantum computation (like entanglement and superposition) while leveraging the scalability and established training routines of classical deep learning.

Performance Comparison

The new architecture is evaluated on two datasets and compared against a simpler previous architecture.

Dataset	Metric	Previous Architecture	New Architecture
IEEE	Test Loss	0.1521	**0.1491**
	Test Acc	0.9649	**0.9649**
SECOM	Test Loss	0.2489	**0.2452**
	Test Acc	0.9351	**0.9351**

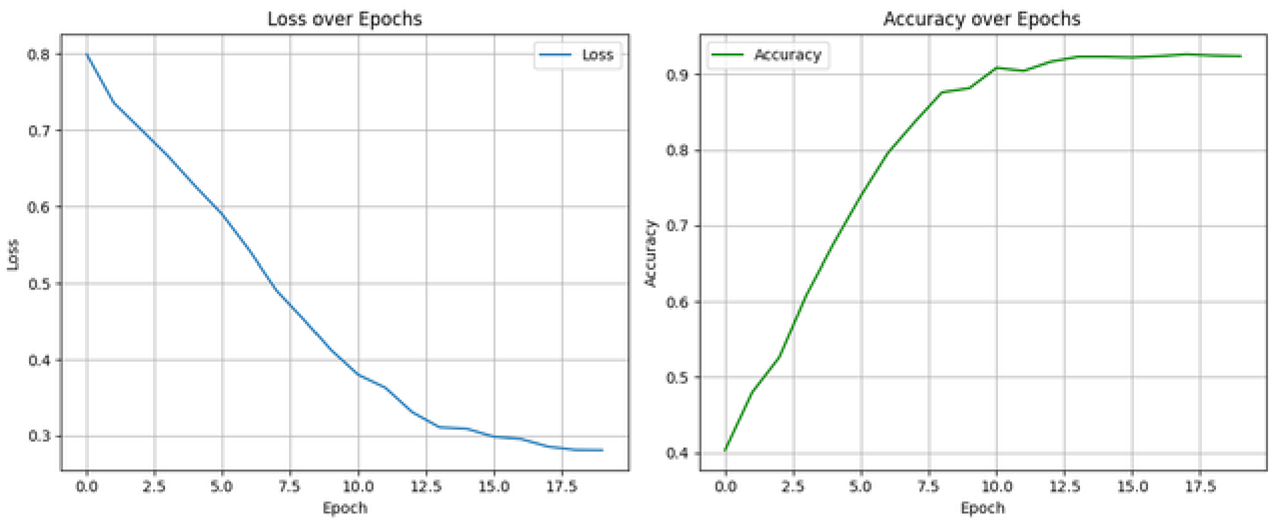
Interpretation

- While the performance gains in test loss are modest, they are consistently lower in the new model.
- Accuracy remains the same across architectures; however, this does not account for model behavior during training.

Stability & Training Behavior

Despite similar accuracy values, the newer architecture demonstrates improved **training stability**:

- The **training and validation loss curves** are smoother and converge more steadily in the newer model.



- This indicates **better generalization** and **resilience to overfitting**, especially important in quantum models where vanishing gradients and noisy updates can lead to erratic behavior.
- Batch normalization and dropout contribute to this enhanced training robustness, while the richer quantum circuit enables the model to capture more nuanced patterns in the data.

This makes the newer model more **reliable** and **suitable for scaling or transfer learning**, particularly in quantum-classical hybrid environments where stability can significantly impact reproducibility and inference quality.

Conclusion

The newer QNN architecture outperforms the previous version in terms of training stability and slightly better loss metrics. Its hybrid design effectively combines classical preprocessing, expressive quantum computations, and regularized classical post-processing. These enhancements ensure smoother training and improved consistency across multiple datasets, making it a strong candidate for quantum-enhanced classification tasks.