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A Machine Learning Approach To Detecting Crosstalk-induced Fidelity Degradation

Background & Motivation

QPA Research Group

- Quantum multi-tenancy can enable qubit crosstalk (unintended inter-qubit perturbations) to function as a physical attack vector for fault injection or side-channel information leakage.
- Conventional detection via calibration-heavy routines (e.g., idle tomography) or hardware interventions often incurs high computational overhead, potentially limiting scalability for continuous, real-time cloud monitoring.
- Non-intrusive, classical machine learning techniques offers a hardware-agnostic pathway to quantify high-dimensional structural distortions in density matrices without requiring device modifications.

Proposed Solution: QRosetta

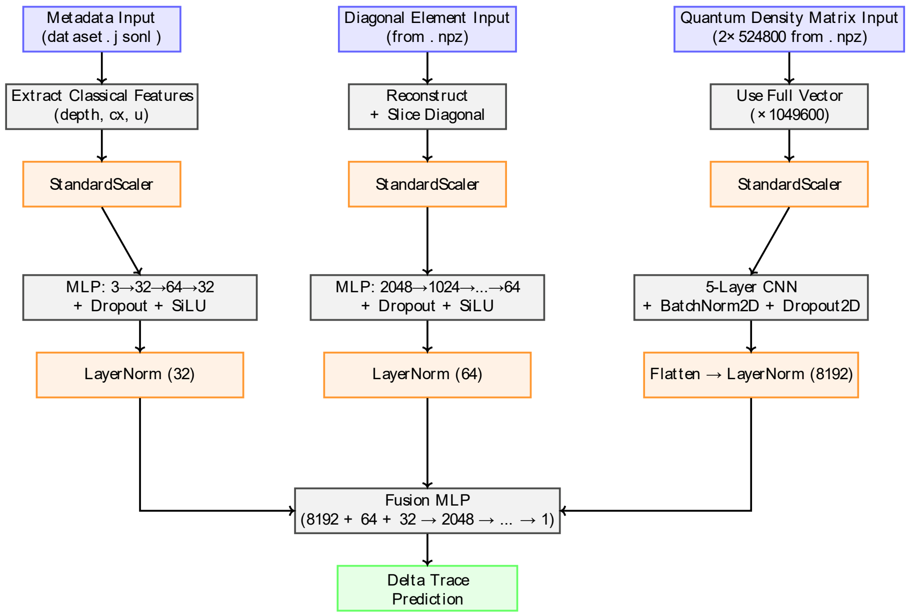

Figure: TripleBranchNet

Methods and Outcomes:

- TripleBranchNet integrates a five-layer CNN for density matrix coherence analysis with specialized MLP branches for diagonal populations and classical circuit metadata.
- The Simulation Pipeline leverages MNISQ-derived circuits to generate crosstalk-injected simulations modeled after the 127-qubit IBM Brisbane topology, isolating crosstalk from standard decoherence.
- The model predicted fidelity degradation with a Mean Absolute Error (MAE) of 0.0055 and an R2 score of 0.5131, confirming that crosstalk leaves a statistically learnable signature in the density matrix.
- Priorities include physical hardware validation, scaling via efficient state estimation (e.g., classical shadows), and incorporating explainability analysis to interpret specific noise signatures.

Publications:

- Shaswato Sarker *et al* 2026 *Phys. Scr.* 101 065102
- Master's Thesis: "Toward Secure Multi-Tenancy in Quantum Computing…"

▸ GOAL: Quantifying crosstalk-induced fidelity degradation via a non-intrusive, classical machine learning method ◂