Quantum RNN Report 3

1. Objective

This report presents the findings from our third phase of quantum recurrent neural network (QRNN) experimentation, building upon the foundational improvements established in Quantum Report 2. The primary objective was to overcome the 50% accuracy ceiling observed in previous iterations through architectural enhancements, specifically exploring multi-layer QRNN configurations with various interaction layer designs. Additionally, this phase involved critical debugging of optimizer parameter tracking issues that had been limiting model performance.

2. Critical Bug Resolution

Optimizer Parameter Tracking Issue

A significant breakthrough was achieved when we identified and resolved a fundamental issue with parameter optimization:

Problem Identified:

- Optimizer parameters were not being updated during training due to incorrect parameter tracking across QNodes
- Parameters required definition using `qml.numpy` instead of standard numpy arrays for compatibility with quantum machine learning optimizers
- The optimizer required flattened parameter arrays and could not handle nested list structures

Resolution Impact:

- Fixing this issue revealed that our models had significantly more potential than previously measured
- This correction enabled meaningful training progress beyond the 50% accuracy barrier
- Subsequent experiments showed consistent improvement patterns rather than stagnant performance

3. Architectural Evolution and Experimental Results

Model Variants and Performance Analysis

Model Configuration	Architecture Details	Test Accuracy	Key Observations
2-QRNN + Final Interaction (Rot)	• 2 QRNN layers • Intermediate interaction layers • Final layer: `qml.Rot`	**58.5%**	First successful model post-optimizer fix. Demonstrated consistent and reproducible results.
3-QRNN + Final Interaction (Rot)	• 3 QRNN layers • 2 intermediate interaction layers • Final `qml.Rot` layer	**~52%**	Performance degradation attributed to overparameterization effects. Model complexity exceeded optimal threshold.
3-QRNN + Enhanced Final Layer	• 3 QRNN layers • CNOT ring topology • RX, RY, RZ rotations	**~55%**	Marginal improvement over base 3-layer configuration but exhibited training instability.
3-QRNN + Minimal Interactions	• 3 QRNN layers • **No intermediate entanglement** • Strong final interaction layer • CNOT ring + composite rotations	**61.0%**	**Best performing configuration.** Consistently outperformed other variants with stable training dynamics.

Architecture Component Analysis

QRNN Layer Structure

- **Qubit Configuration:** 4 qubits per layer
- **Encoding Method:** Dense angle embedding with 3 rotations (RX, RY, RZ) per wire
- **Hidden State Management:** 1 qubit dedicated as hidden state, propagated across timesteps
- **State Persistence:** Hidden state reused at every timestep without re-encoding

Interaction Layer Variants

1. **Intermediate Interactions:** `qml.Rot` entanglements between QRNN layers (showed limited effectiveness)
2. **Final Interaction Layer:**
   - **Option A:** Simple `qml.Rot` operations
   - **Option B:** Ring topology `qml.CNOT` + composite rotation blocks (**optimal performance**)

4. Barren Plateau Mitigation Analysis

Attempted Solution: Layerwise Training

Before proceeding with architectural modifications, we attempted to address the barren plateau phenomenon affecting the 2-layer QRNN:

Methodology:

- Implemented iterative layer-wise training approach
- Sequential training and freezing of previously trained layers
- Aimed to create meaningful gradient landscapes for subsequent layers

Results:

- **Maximum Accuracy Achieved:** 43.5%
- **Outcome:** Unsuccessful - performance remained below baseline
- **Conclusion:** Layerwise training insufficient for overcoming fundamental architectural limitations

This failure motivated our transition to exploring multi-layer architectural variants rather than training methodology modifications.

5. Performance-Consistency Paradox

Quantitative vs. Qualitative Performance

Despite achieving **61% accuracy on the test set**, manual inference testing revealed critical model limitations:

Test Set Performance

- **Accuracy:** 61.0% (best achieved)
- **Training Accuracy:** ~60% (indicating good generalization)
- **Statistical Significance:** Consistent across multiple training runs

Manual Inference Issues

- **Consistency Problem:** Results vary randomly across runs despite fixed shot parameters
- **Classification Instability:** Positive sentences frequently misclassified as negative and vice versa
- **Sensitivity to Input Variations:** Minor sentence rewording causes classification flips
- **Practical Usability:** Poor real-world applicability despite statistical success

Analysis of Discrepancy

This paradox suggests that while the model captures statistical patterns in the test distribution, it lacks robust feature extraction capabilities necessary for consistent real-world inference. The model may be exploiting dataset-specific artifacts rather than learning generalizable sentiment representations.

6. Current Best Architecture Configuration

Optimal Model Specification

Architecture: 3-layer QRNN without intermediate interactions + final CNOT-based entangled layer

Key Design Principles:

- **Minimal Entanglement:** Removal of intermediate interaction layers to reduce noise and overparameterization
- **Strong Final Processing:** Concentrated computational complexity in final interaction layer
- **Ring Topology:** CNOT gates arranged in ring structure for maximum qubit connectivity
- **Composite Rotations:** Multiple rotation gates (RX, RY, RZ) for enhanced expressivity

Performance Metrics

- **Test Accuracy:** 61.0%
- **Training Accuracy:** ~60%
- **Generalization Gap:** Minimal (1%)
- **Inference Consistency:** Poor (critical limitation)

7. Conclusions and Future Directions

Key Findings

1. **Optimizer Fix Impact:** Resolving parameter tracking issues was crucial for meaningful progress
2. **Architecture Optimization:** Simpler interaction schemes outperformed complex multi-layer entanglement
3. **Performance Ceiling:** 61% represents current architectural limit under present configuration
4. **Consistency Challenge:** Statistical performance does not guarantee practical reliability

Immediate Research Priorities

1. **Inference Stability:** Investigate sources of prediction inconsistency and develop stabilization techniques
2. **Feature Representation:** Analyze learned quantum states to understand what features the model captures
3. **Robustness Enhancement:** Implement techniques to improve model consistency across input variations
4. **Alternative Architectures:** Explore quantum attention mechanisms or hybrid classical-quantum approaches

Long-term Directions

- Integration of error mitigation techniques for improved quantum circuit reliability
- Investigation of variational quantum algorithms specifically designed for sequential data
- Development of quantum-classical hybrid models that leverage strengths of both paradigms

The current work establishes a foundation for quantum sentiment analysis while highlighting the critical need to bridge the gap between statistical performance and practical inference reliability.

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Complete implementation details and experimental code are available in the accompanying Jupyter notebooks.