Final Report: A Quantum Approach to Financial Forecasting

QPoland Hackathon

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1. Executive Summary

This report documents the development of a high-performance, hybrid quantum-classical model for predicting stock index closing prices. The project's objective was to address the challenge of forecasting financial time-series data using quantum machine learning principles. After encountering significant performance issues with an initial, simple architecture, we pivoted to a more sophisticated **Quantum Residual Correction Model**. This final model, integrating a deep classical LSTM with a Qiskit-based quantum circuit, demonstrated strong predictive power, achieving an **R-squared (R^2) score of 0.7052** on unseen validation data. This document outlines our strategic evolution, the challenges we overcame, the final model's architecture, and a comprehensive analysis of its successful performance.

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2. The Initial Approach and Why It Changed

Our project began with a standard strategy for building a hybrid model: a **serial architecture** where a classical Long Short-Term Memory (LSTM) network would process the time-series data, and its output would be fed directly into a Variational Quantum Circuit (VQC) for the final prediction.

Challenges Faced

This initial approach failed decisively. The model was highly unstable and produced nonsensical predictions, resulting in large negative R^2 scores. The root cause was a critical design flaw known as an **information bottleneck**. The powerful LSTM distilled a rich summary of the input data, but by forcing this entire summary through a small quantum circuit that outputted only a single value, we were losing almost all the valuable information the classical component had captured. The quantum layer, instead of enhancing the model, was strangling it.

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3. Our Solution: The Quantum Residual Correction Model

To overcome these challenges, we engineered a superior, more sophisticated architecture.

Architecture and Workflow

The final model works in a complementary, parallel fashion:

1. **Classical Backbone:** A deep, two-layer **bidirectional LSTM** serves as the primary predictor. It processes the input data (a window of 20 days) and makes an initial, powerful prediction of the closing price.
2. **Quantum Corrector:** Simultaneously, the rich output vector from the LSTM is fed into a **4-qubit trainable quantum circuit** built with **Qiskit**. This circuit's sole purpose is not to predict the price, but to learn and predict the *error* (the residual) of the classical model's prediction.
3. **Final Prediction:** The ultimate forecast is the simple sum of the classical prediction and the quantum correction. This allows the robust classical model to capture the main trend, while the quantum circuit focuses on modeling the complex, noisy patterns in the errors that classical models often miss.

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4. Implementation and Project Phases

Our successful execution was broken down into four distinct phases:

- **Phase 1: Advanced Data Engineering:** We created a rich feature set including technical indicators like **RSI and Bollinger Bands**. To handle outliers common in financial data, we used a RobustScaler for normalization.
- **Phase 2: Hybrid Model Architecture:** The model was built in **PyTorch**, and we used **Qiskit's TorchConnector** to seamlessly integrate our VQC as a trainable layer. This allowed for a unified, end-to-end training process.
- **Phase 3: State-of-the-Art Training:** We employed a robust training protocol using the **AdamW optimizer**, a **CosineAnnealingWarmRestarts** learning rate scheduler, and **gradient clipping**. This combination was crucial for ensuring stable convergence to a high-performance solution.
- **Phase 4: Prediction and Evaluation:** The trained model was used in an iterative loop to forecast the 10 missing Close values, generating the final predictions.csv file for submission.

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5. Final Results and Performance Analysis

The Quantum Residual Correction Model demonstrated excellent performance on the unseen validation data, confirming the success of our architectural pivot.

Quantitative Metrics

- **R-squared (R^2) Score: 0.7052**. This is a strong result, indicating our model explains **70.52% of the price variance** in the validation set.
- **Mean Absolute Error (MAE): 28.24**. On average, the model's prediction was only about $28 off the true closing price.
- **Root Mean Squared Error (RMSE): 36.58**. This confirms the model does not make excessively large errors.

Visual Analysis

The performance graphs provided clear, visual proof of the model's effectiveness:

1. **Actual vs. Predicted Plot:** Showed the model's predictions tracking the true price movements with high fidelity.
2. **Residuals Plot:** The errors were randomly scattered around zero, indicating the model was unbiased and had captured the underlying predictable patterns.
3. **Error Distribution Histogram:** Formed a clean bell curve centered at zero, showing that small errors were common and large errors were rare—the ideal behavior for a forecasting model.

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6. Conclusion

By strategically evolving our approach in response to initial failures, we successfully developed a sophisticated hybrid quantum-classical model that meets all the requirements. The final architecture proved to be a robust and powerful solution for the complex task of financial time-series forecasting, delivering strong and verifiable results.