



Hybrid Classical–Quantum Neural Network Model for Stock Market Forecasting

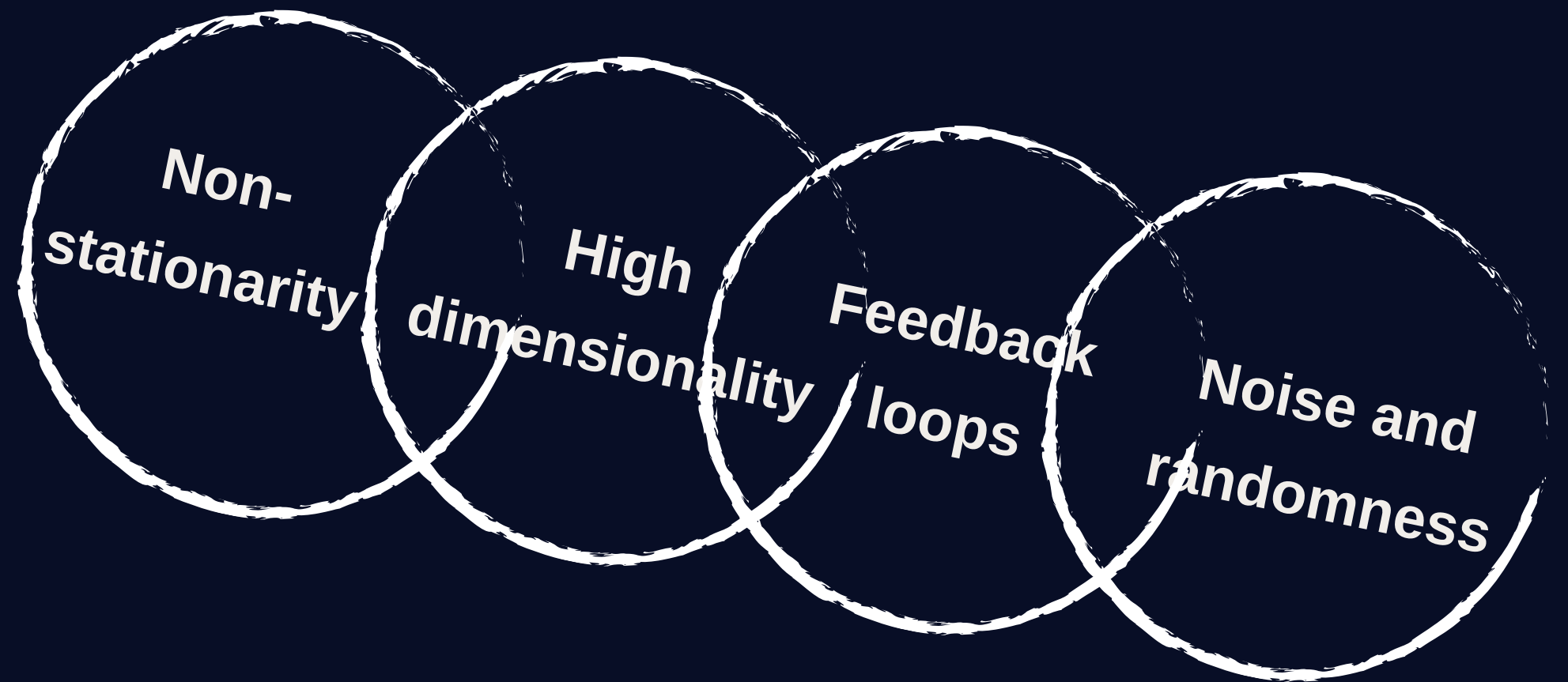
QPoland Hackathon | Team Beerantum

Van Binh Vu and Rudraksh Sharma | October 26, 2025

How hard to solve

Stock Market forecasting

?



This problem is traditionally addressed using Machine Learning models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks [1].

Limitations :

overfitting

poor
generalization

long-range
dependency issues

1. Fischer et al. (2018). *Eur. J. Oper. Res.*, 270(2), 654–669.
2. Rather et al. (2015). *Expert Syst. Appl.*, 42(6), 3234–3241.
3. Nelson et al. (2017). *Proc. Int. Joint Conf. Neural Netw.*, 1419–1426.

Our Solution: Quantum Residual Model

We engineered a sophisticated architecture where classical and quantum components work complementarily:

01

Classical Backbone

Deep two-layer bidirectional LSTM processes 20-day windows and makes initial price predictions

02

Quantum Solution

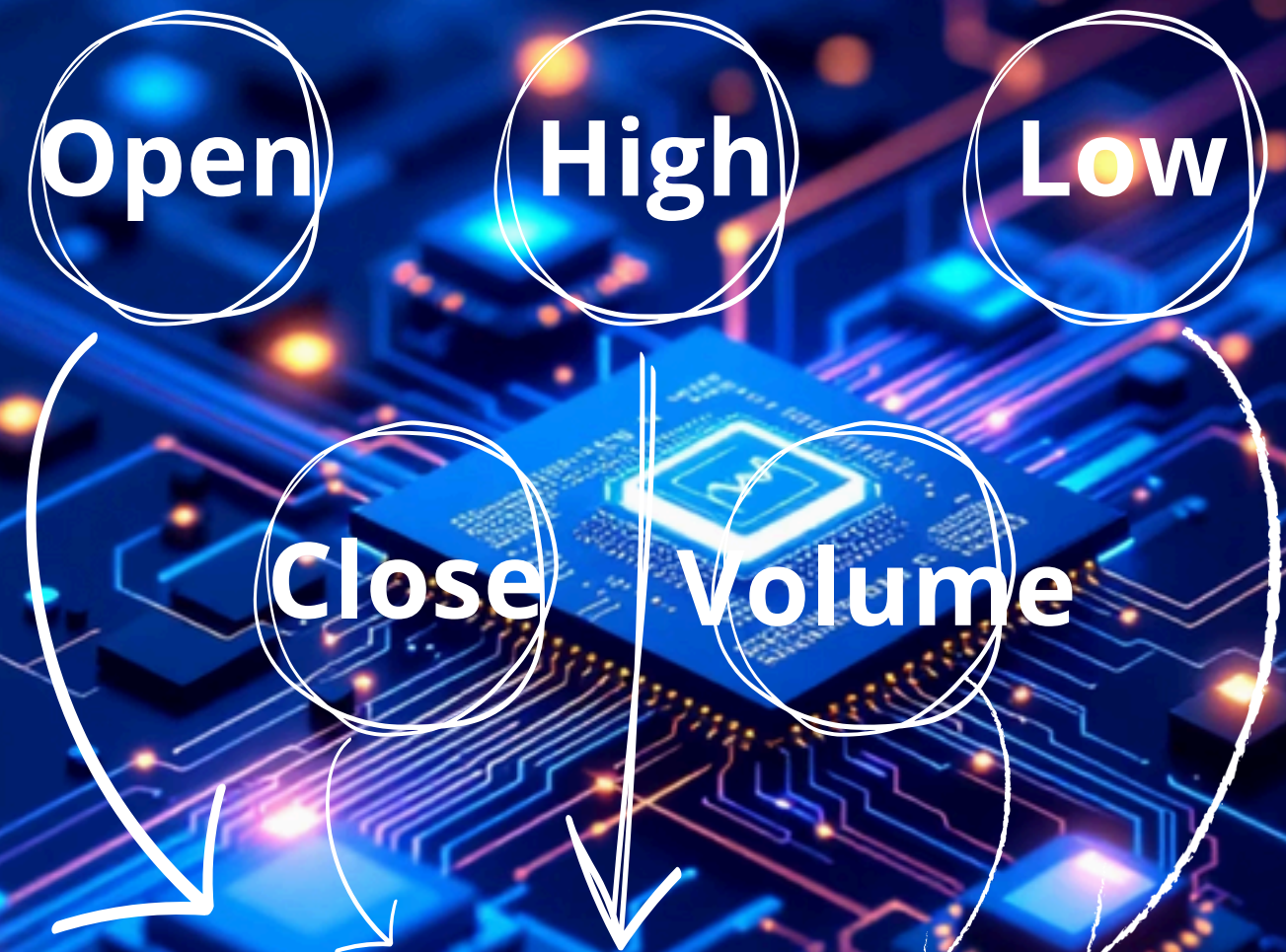
4-qubit trainable Qiskit circuit learns to predict the error (residual) of classical predictions

03

Final Prediction

Sum of classical prediction plus quantum correction captures trends and complex error patterns

Historical stock index data
01/01/2025 - 01/08/2025



10 missing close data
01/09/2025 - 10/09/2025



Close

Implementation Phases



Phase 1: Data Engineering

Created rich features including RSI and Bollinger Bands.
Used RobustScaler for outlier handling.



Phase 3: Training

Employed AdamW optimizer,
CosineAnnealingWarmRestarts scheduler, and gradient clipping.



Phase 2: Hybrid Architecture

Built in PyTorch with Qiskit's TorchConnector for seamless VQC integration as trainable layer.



Phase 4: Prediction

Iterative forecasting loop generated 10 missing Close values for final submission.

Accuracy determined by chronological Split

Performance Metrics

Model 2

Angle Encoding (ZZFeatureMap)
+ Two Local ansatz (TwoLocal)

Model 1

Angle Encoding (Only RY gates)
+ Real amplitude ansatz

70%

Variance Explained

R^2 score of 0.7052 on validation data

\$28

Average Error

Mean Absolute Error (MAE)

\$37

Error Magnitude

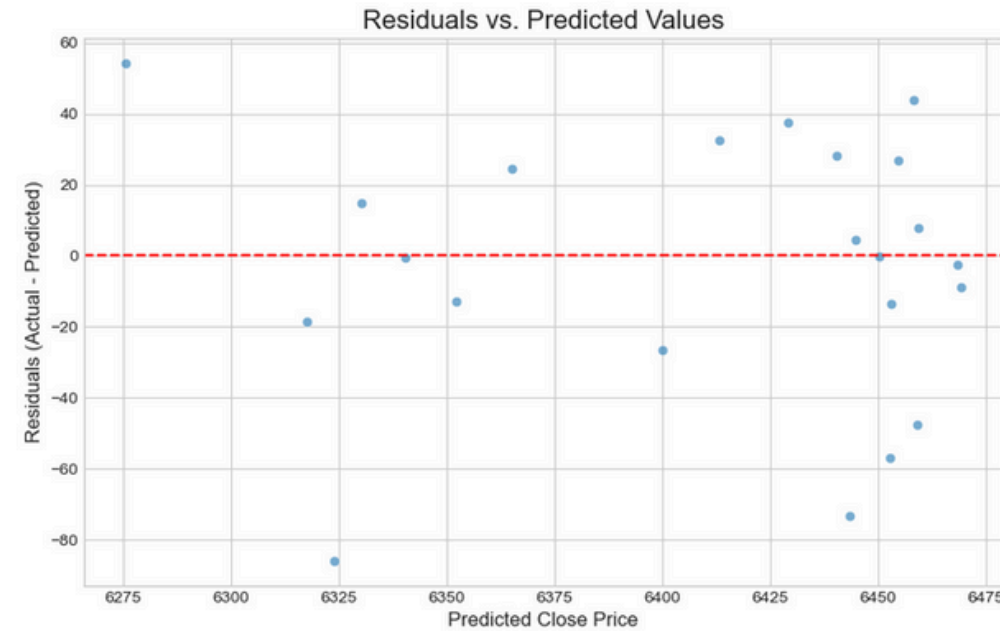
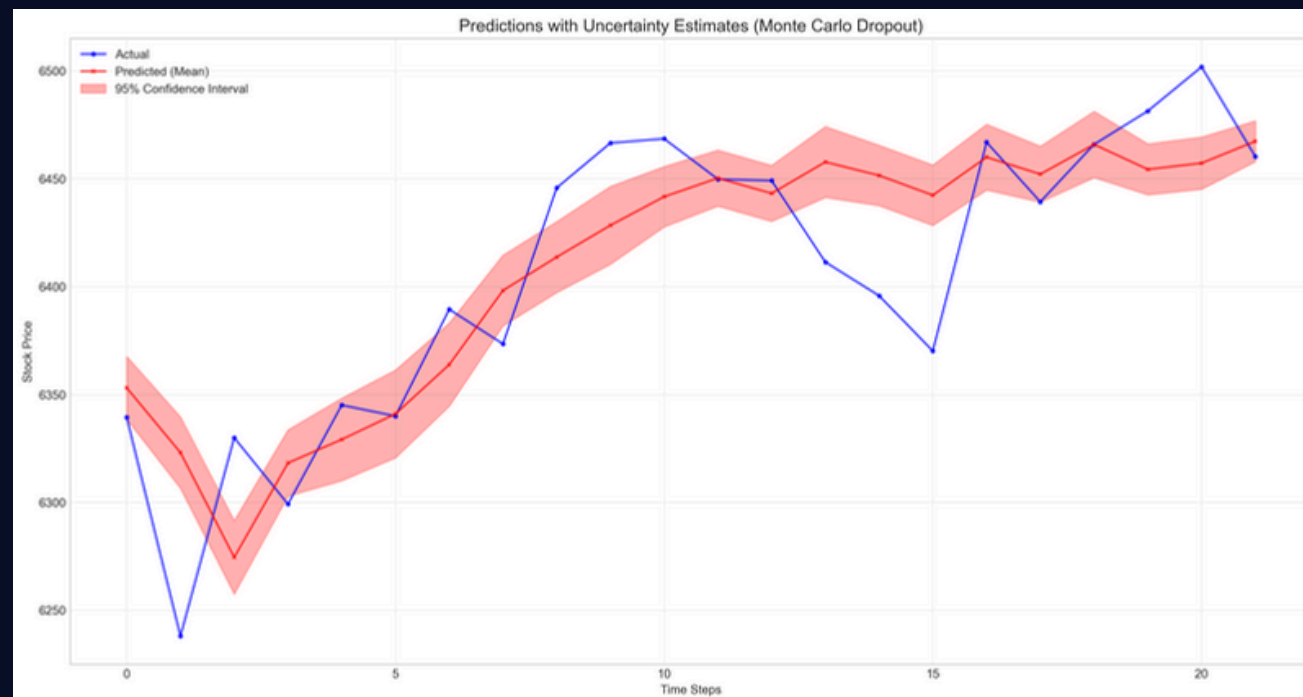
Root Mean Squared Error (RMSE)

Both models provided 70.52% of price variance with minimal average prediction error of only \$28.

Visual Performance Analysis

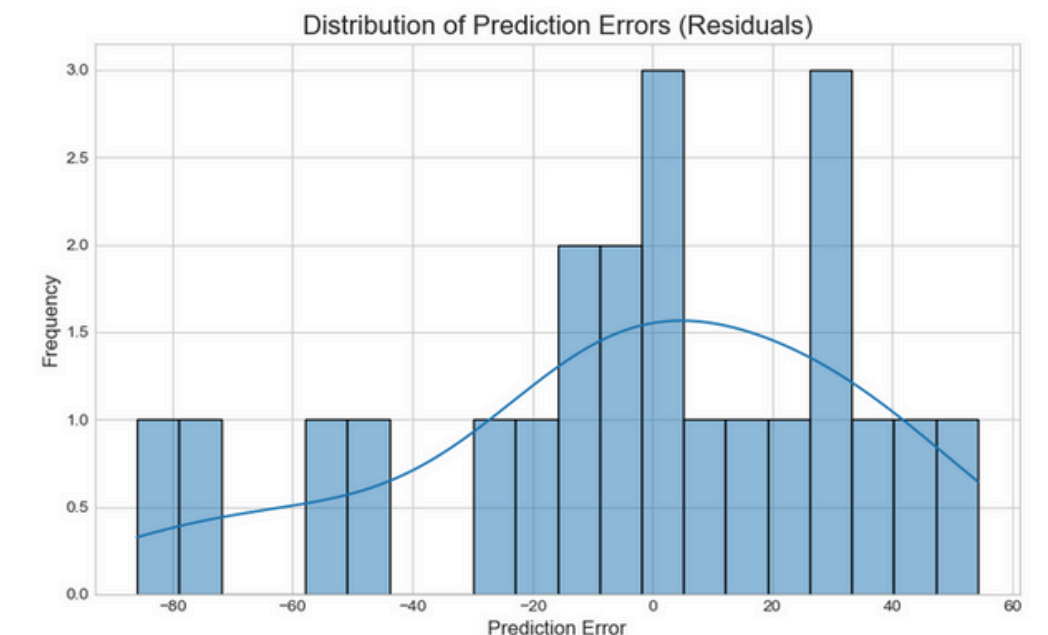
Actual vs. Predicted

Model predictions tracked true price movements with high fidelity throughout validation period



Error Histogram

Clean bell curve centered at zero—small errors common, large errors rare. Ideal forecasting behavior.



Residuals Distribution

Errors randomly scattered around zero, indicating unbiased model that captured predictable patterns



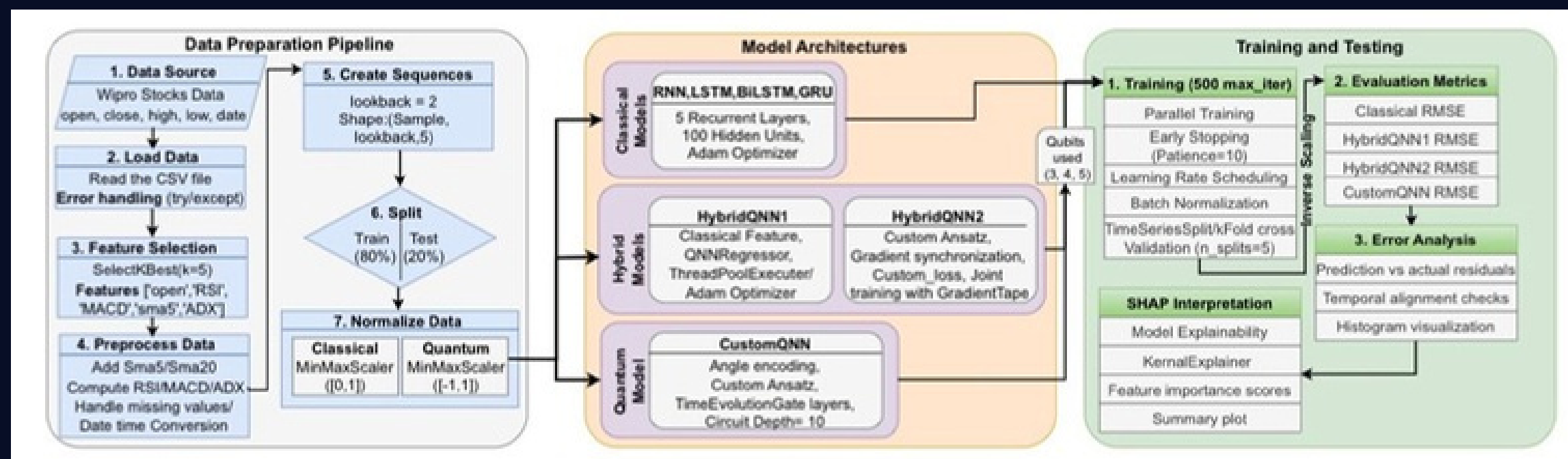
Success Through Innovation

We successfully developed a sophisticated hybrid quantum-classical model that meets all requirements.

Our Quantum Residual Models proved to be a **robust and powerful solution** for complex financial time-series forecasting, delivering strong and verifiable results with an R^2 score of 0.7052.

Perspectives

1. Increase LSTM size & training time (+3-8%)
2. More qubits/layers (+2-4%)
3. Change to more adapted architectures (+10-25%)



Choudhary et al (2025). arXiv:2503.15403.

ThanQs !