Hybrid Quantum-Classical Neural Networks for Stock Price Forecasting

A Comparative Study of Classical and Quantum-Enhanced Models for Stock Price Prediction

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For Terra Quantum

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01 Introduction

Financial time series forecasting is complex due to volatility, noise, and external factors.

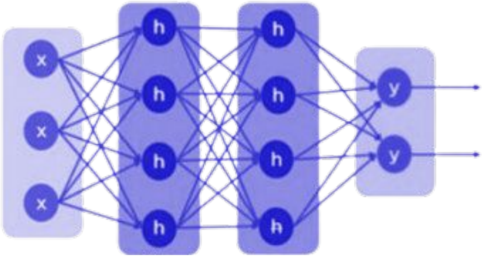
Traditional machine learning models often struggle to generalize across market conditions.

Problem Definition

- To predict stock values accurately, this project leverages classical Machine Learning (ML) and Hybrid Quantum ML.

- Specifically a modular hybrid model combining recurrent neural networks (RNNs) with a variational quantum layer.

- Goal to investigate whether quantum-classical hybrid architectures can improve stock price prediction accuracy.



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Methodology

Initial Model Design Including Data Source & Preprocessing

Data Source and Preprocessing

Data:

- Daily closing prices for AAPL, MSFT, and GOOGL (2015–2024) via yfinance API.

Data Cleaning:

- Forward-filled missing values to maintain continuity.
- Min-Max normalization applied per ticker to [0, 1] range.

Data Structuring:

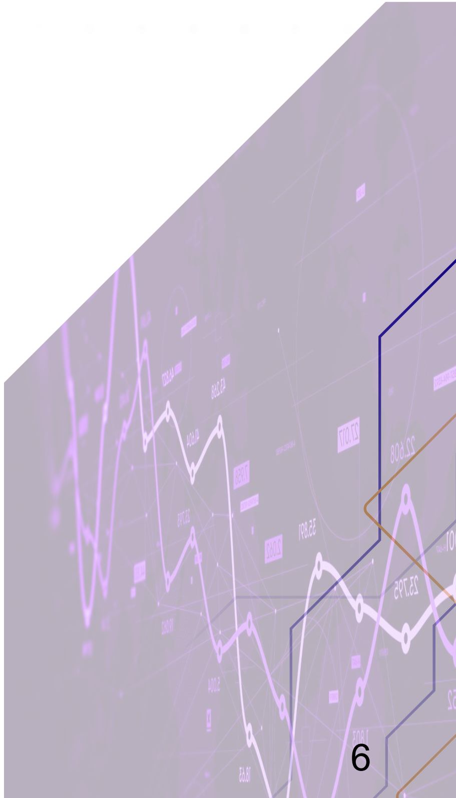
- Sliding window of 20 time steps mapped to the next price.
- Preserved short-term dependencies and momentum patterns.

Train/Test Split:

- 80/20 split without time leakage to maintain chronological order.

Dataset Composition:

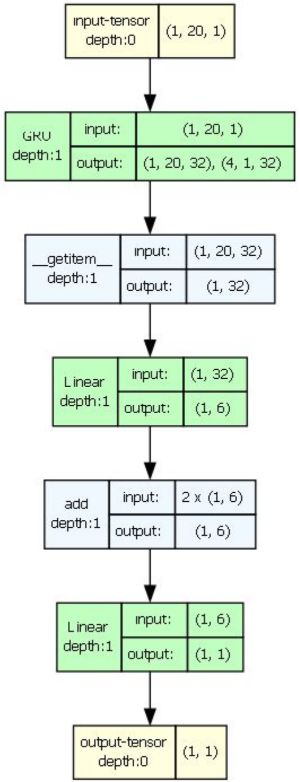
- Combined sequences across tickers to improve model diversity and generalization.



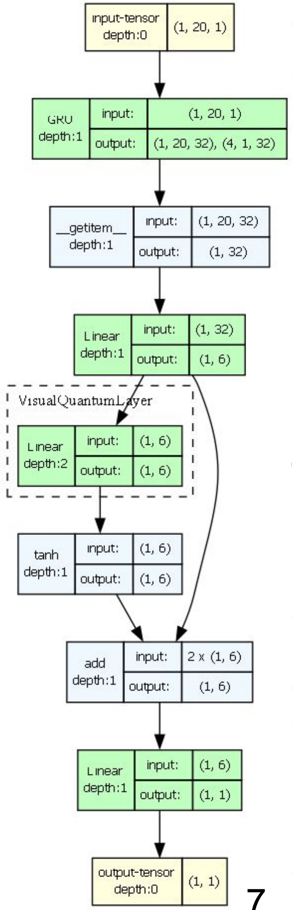
Modular Model Architecture

- **Input Tensor:** (batch size, 20, 1) — 20 time steps, 1 feature.
- **Recurrent Units:** (LSTM, GRU, RNN — single or mixed)
- **Hidden State Extraction**
- **Linear Layer (Classical Projection):**
- **Optional Quantum Layer:** Process n features through a variational quantum circuit.
- **Post-Quantum Activation:** (e.g., Tanh, Sigmoid, ReLU).
- **Skip Connection (Add or Concat):** Merge classical and quantum feature vectors.
- **Final Linear Layer:** Compress merged 6 features → 1 scalar output.
- **Final Activation:** (e.g., Tanh, Sigmoid, ReLU)
- **Output Tensor:** Shape (batch size, 1) — Predicted stock price.

Classical Model

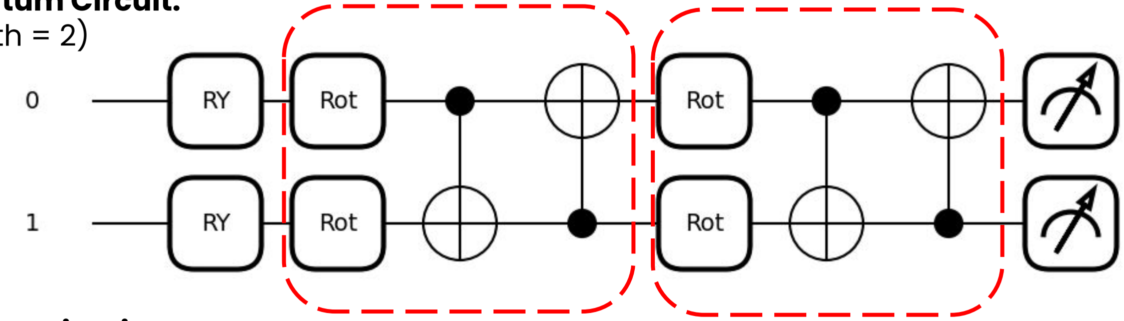


Quantum Hybrid Model

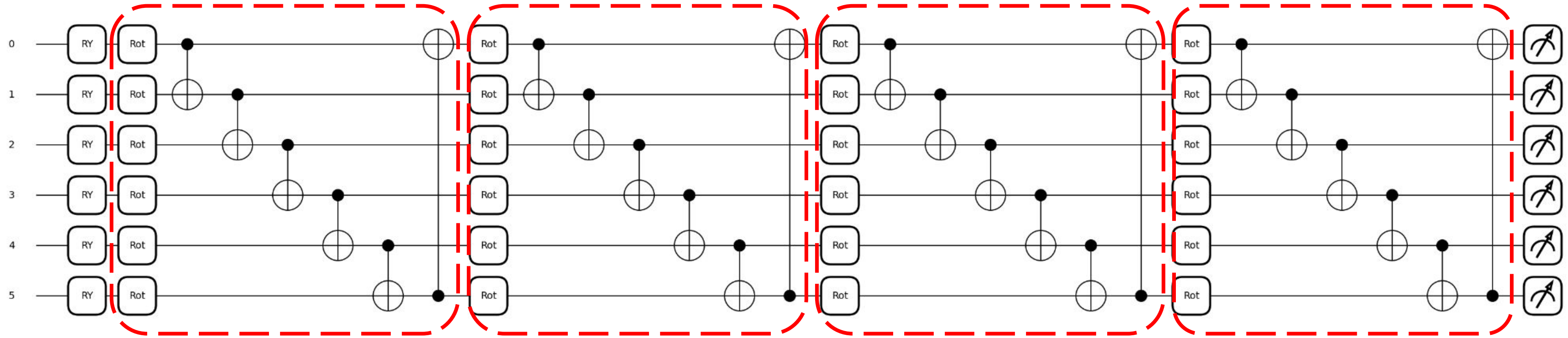


Quantum Layer - Variational Quantum Circuit

Simple Variational Quantum Circuit:
2 qubits, 2 layers (Q-depth = 2)



Final Variational Quantum Circuit:
6 qubits, 4 layers (Q-depth = 4)



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Optimization

Training Strategy, Hyper Parameter and Architecture Optimization

Quantum Circuit Optimization

Parameterized Rotation

1 Parameter: R_y

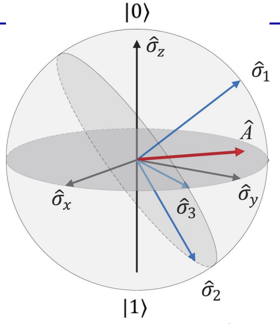
$$R_y(\theta) = \begin{pmatrix} \cos\left(\frac{\theta}{2}\right) & -\sin\left(\frac{\theta}{2}\right) \\ \sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{pmatrix}$$

2 Parameters: R_x — R_z

$$R_x(\theta) = \begin{pmatrix} \cos\left(\frac{\theta}{2}\right) & -i\sin\left(\frac{\theta}{2}\right) \\ -i\sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{pmatrix}$$

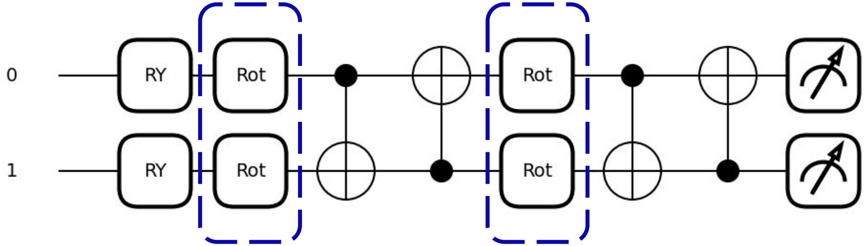
$$R_z(\theta) = \begin{pmatrix} e^{-i\frac{\theta}{2}} & 0 \\ 0 & e^{i\frac{\theta}{2}} \end{pmatrix}$$

3 Parameters: R_z — R_y — R_z = Rot



$$\mathrm{Rot}(\phi,\theta,\omega) = RZ(\omega)\cdot RY(\theta)\cdot RZ(\phi)$$

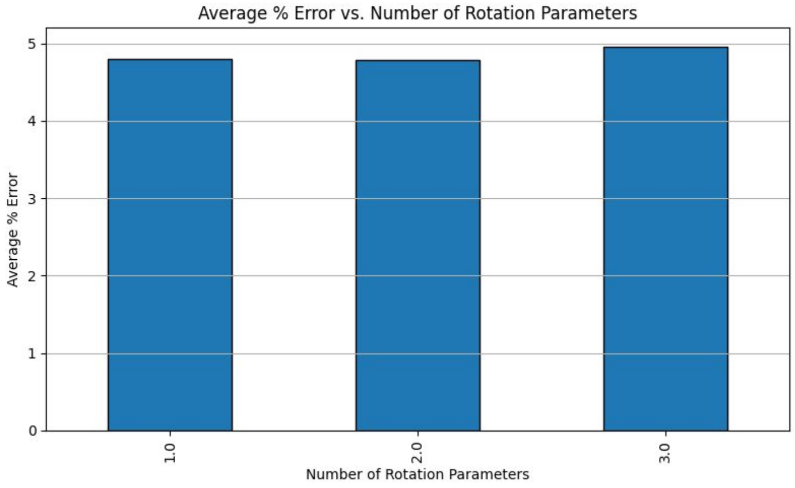
$$\mathrm{Rot}(\phi,\theta,\omega) = \begin{pmatrix} \cos\left(\frac{\theta}{2}\right)e^{-i\left(\frac{\phi+\omega}{2}\right)} & -\sin\left(\frac{\theta}{2}\right)e^{-i\left(\frac{\phi-\omega}{2}\right)} \\ \sin\left(\frac{\theta}{2}\right)e^{i\left(\frac{\phi-\omega}{2}\right)} & \cos\left(\frac{\theta}{2}\right)e^{i\left(\frac{\phi+\omega}{2}\right)} \end{pmatrix}$$

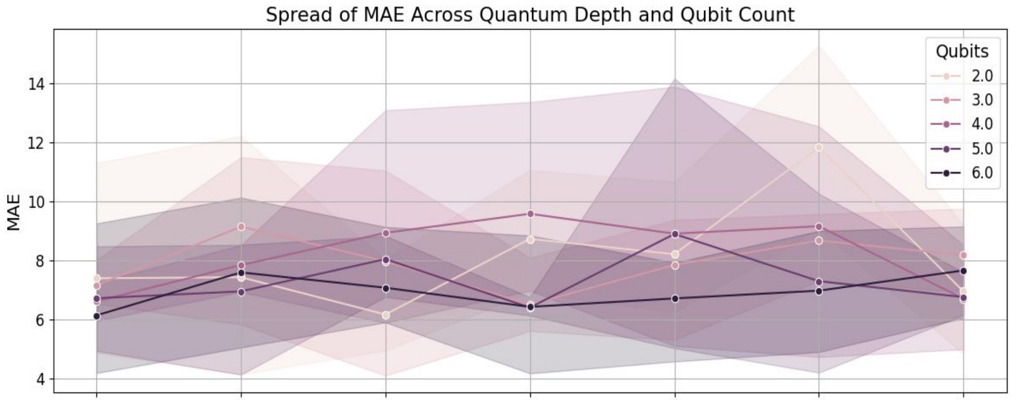


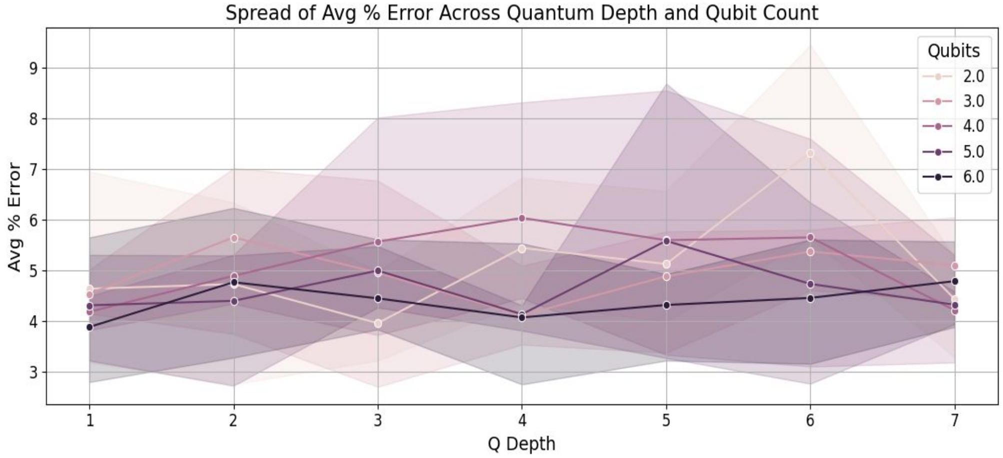
Quantum Circuit Optimization

Quantum Circuit Grid Search

Tested over 10 epochs
Number of Qubits (2–6), circuit depth (1–7), and gate complexity (1–3 parameters)



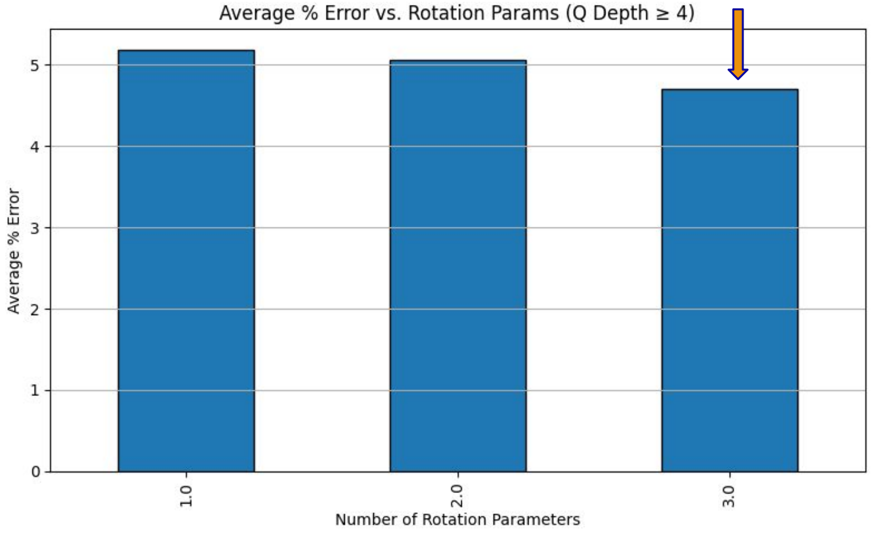




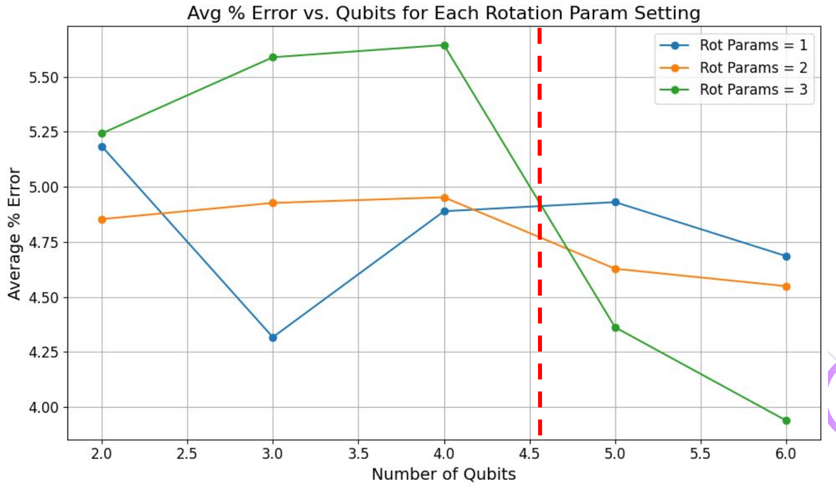
Quantum Circuit Optimization

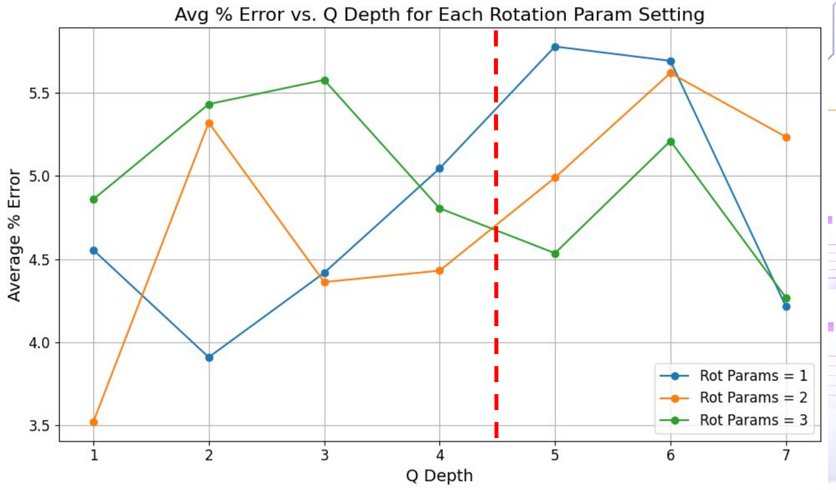
Quantum Circuit Grid Search

Focus on where a Full Rotation outperforms



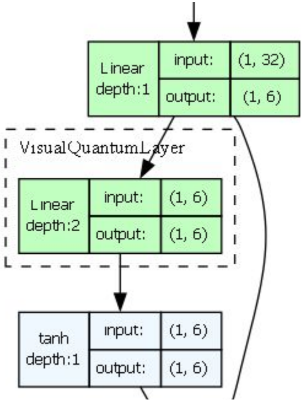
Threshold

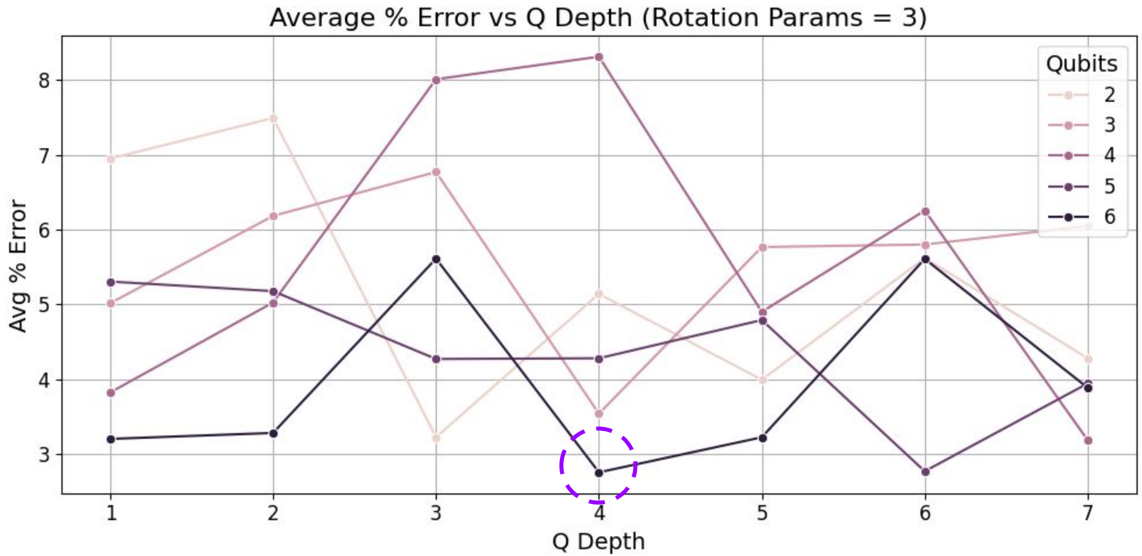




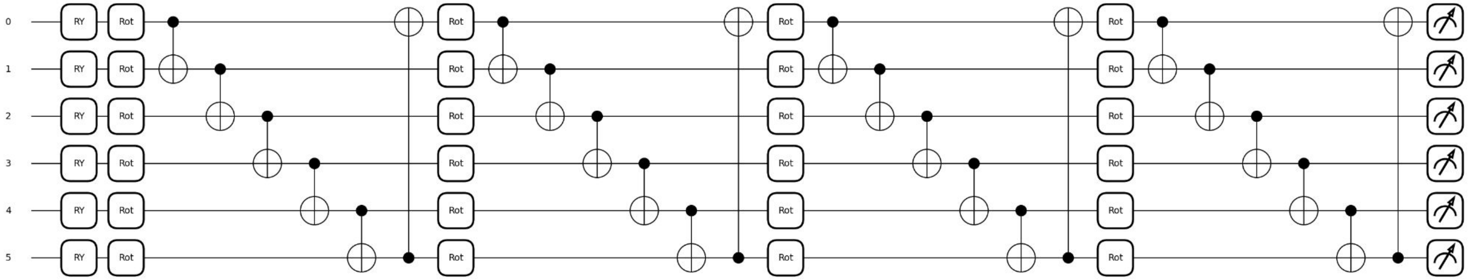
Quantum Circuit Optimization

Final Selection





Final Variational Quantum Circuit:
6 qubits, 4 layers (Q-depth = 4), Full Rotation Gate

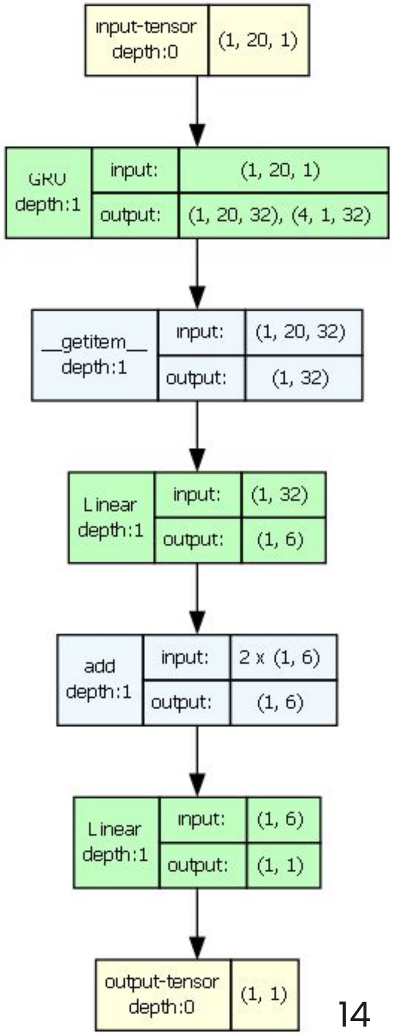


Classical Architecture Optimization

- Classical components optimized separately to reduce quantum training time over 10 epochs.
- Parameter sweeps with modular Python scripts; one parameter varied at a time. Results saved in Excel.
- Coarse-grained sweeps followed by fine-grained searches for refinement.
- Best configurations selected based on MAE, RMSE, and average percentage error.

Parameter	Sweep Range	Best Result(s)
Hidden Size	{8, 16, 32, 64}	32
Dropout Rate	{0.0 - 0.7}	0.16 / None
Recurrent Layers	{1–8}	4
Recurrent Units	LSTM, GRU, RNN, combinations	GRU
Input / Output Activations	None, ReLU, Tanh, Sigmoid	Tanh / None
Skip Connection	concat, add	add

Final Configuration: GRU units, 4 layers, hidden size = 32, add skip connection, Tanh post-quantum activation, no dropout.



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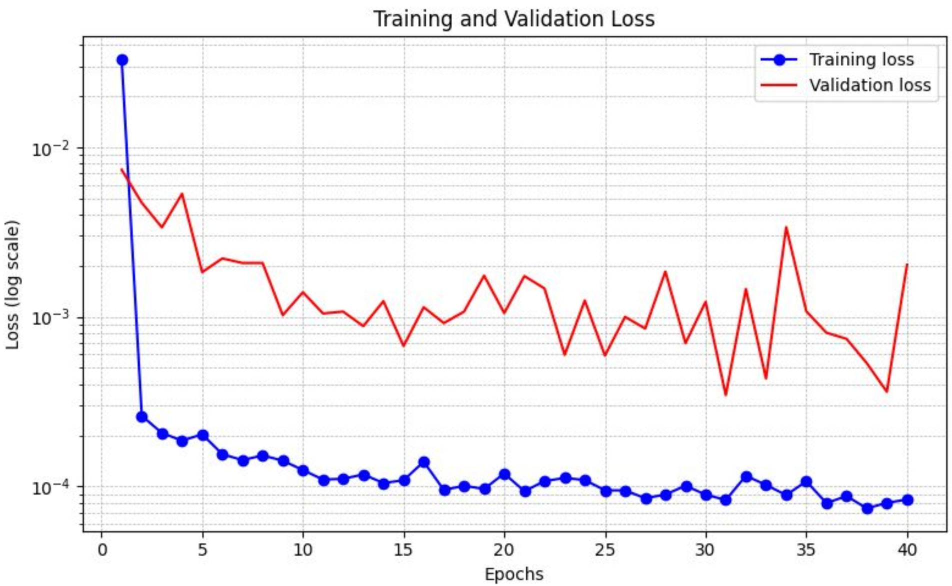
Results

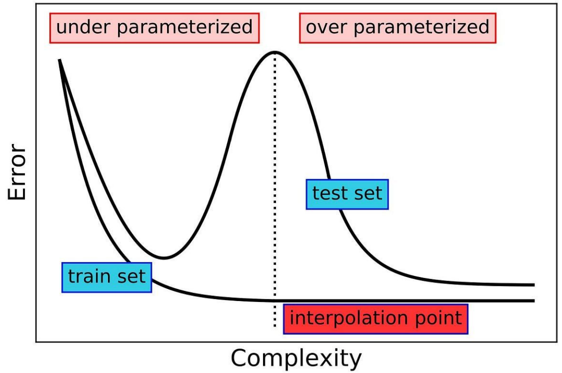
Evaluation of Hybrid Model and Comparison to Classical Model

Training & Validation

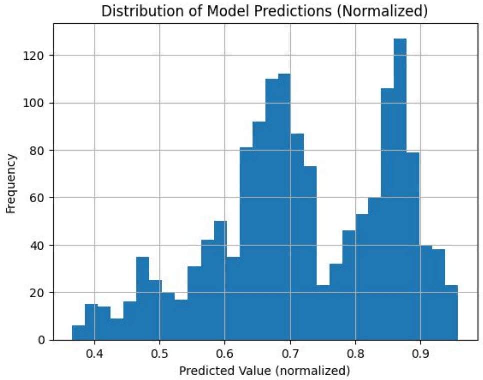


Hybrid models trained for 40 epochs, achieving a best training loss of **0.000083** and validation loss of **0.000346**.

Overfitting and Model Complexity:
Higher validation loss suggests overfitting or possible double descent behavior; further tuning of model depth, quantum circuit size, and training duration is required.



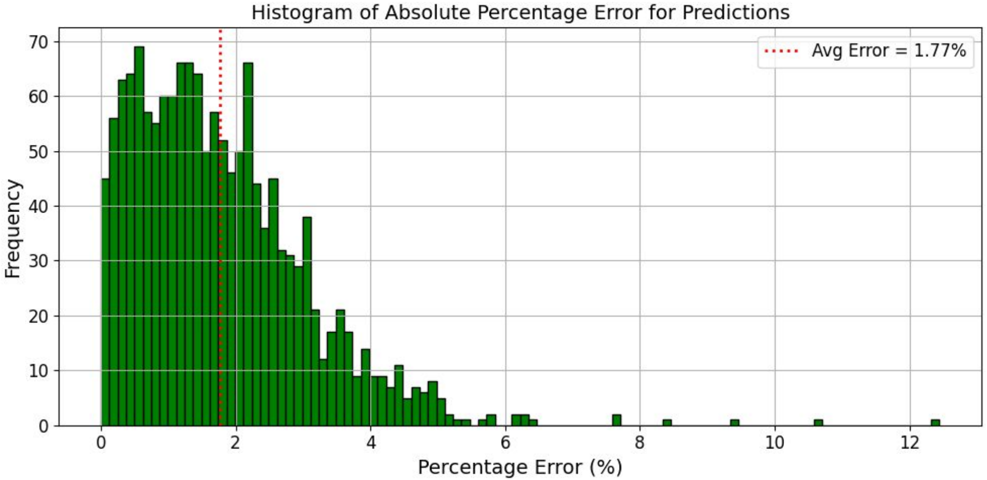
Hybrid Model Predictions

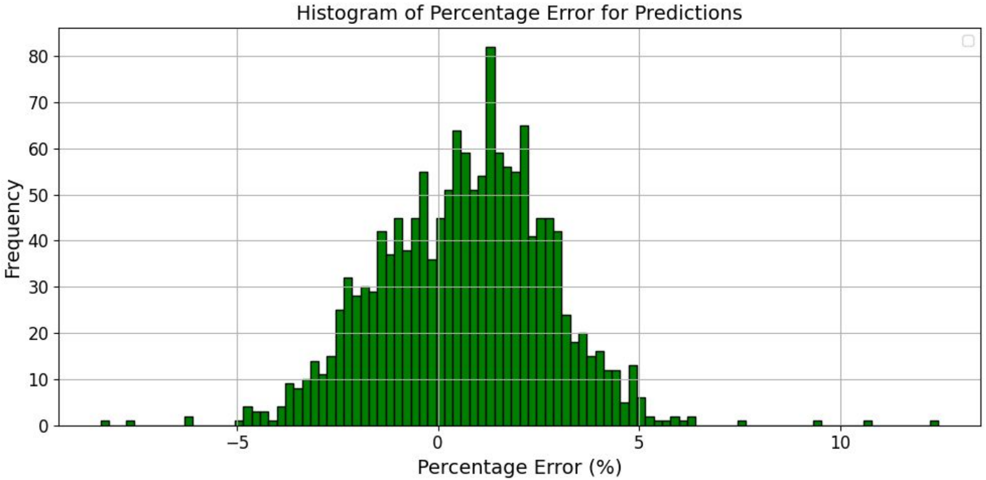


Predictions Distribution:
Ranges over full 0 to 1 with two distinct peaks

Model Evaluation Metrics:
Test MAE = 2.5660, **Test RMSE = 3.1719**, and **Average Absolute Percentage Error = 1.77%.**

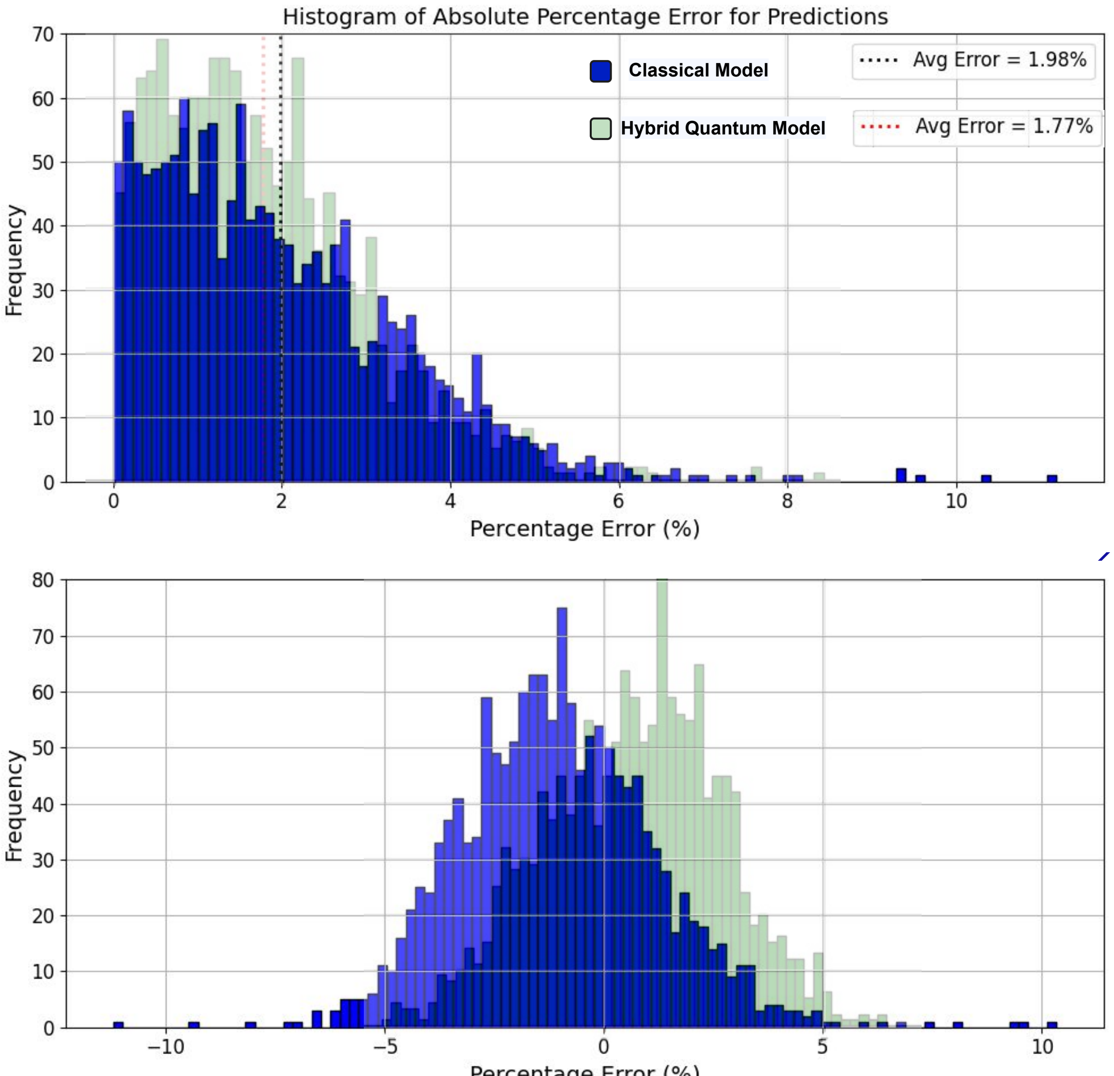
Error Distribution Analysis:
Most prediction errors fall within 0–2%, centered near 0%, indicating high accuracy and minimal bias.



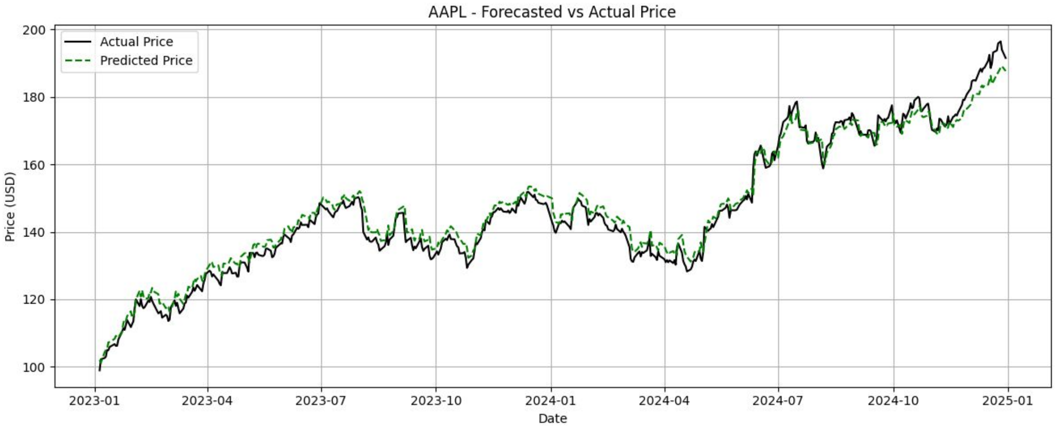


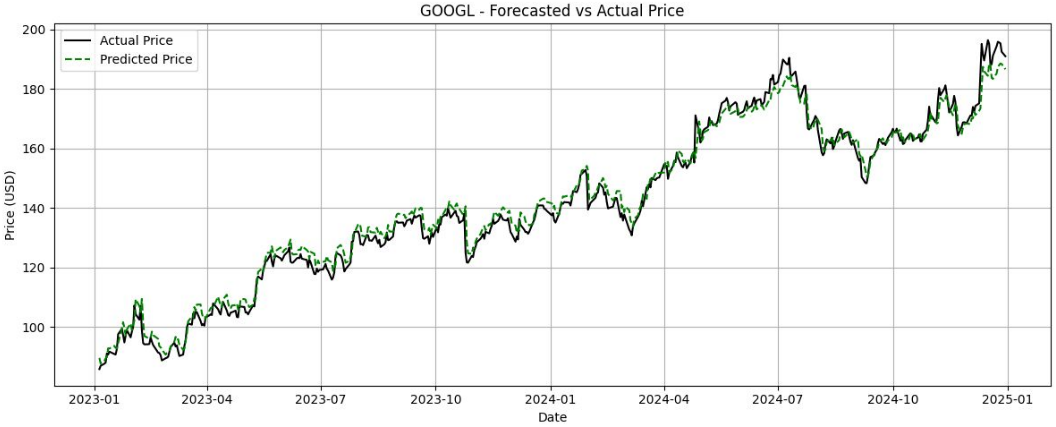
Predictions Comparison

Metric	Hybrid Model	Classical Model
Test MAE	2.566	3.0522
Test RMSE	3.1719	3.9727
Average Absolute Percentage Error	1.77%	1.98%



Hybrid Model Price Predictions



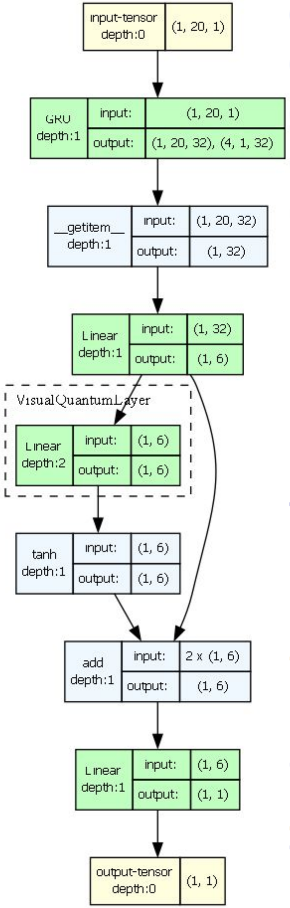


Conclusions & Future Work

Metric	Hybrid Model	Classical Model
Test MAE	2.566	3.0522
Test RMSE	3.1719	3.9727
Average Absolute Percentage Error	1.77%	1.98%

Conclusion

- Hybrid model showed slight improvement over classical, but within typical uncertainty ranges.
- No definitive advantage of the quantum layer yet; further validation needed across more datasets.



Future Work

- Accelerate training using parallelization, GPU support, or cloud quantum platforms.
- Optimize additional hyperparameters (e.g., learning rate) and explore alternative quantum circuit designs.
- Expand dataset to include more stock tickers and additional features.
- Test hybrid models on real quantum hardware and different quantum platforms (e.g., Qiskit).
- Evaluate model performance on live or unseen financial data or new stock To see overparameterized or under-parameterized.

Thank you!

Do you have any questions?