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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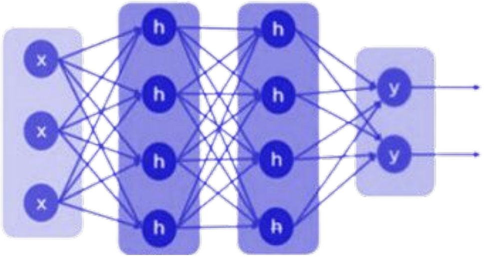
01 Introduction

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.
- Focus on daily closing prices for AAPL, MSFT, and GOOGL from 2015–2024.



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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.

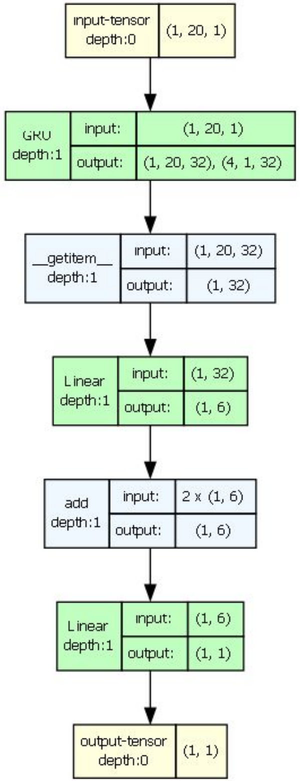
Dataset Composition:

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

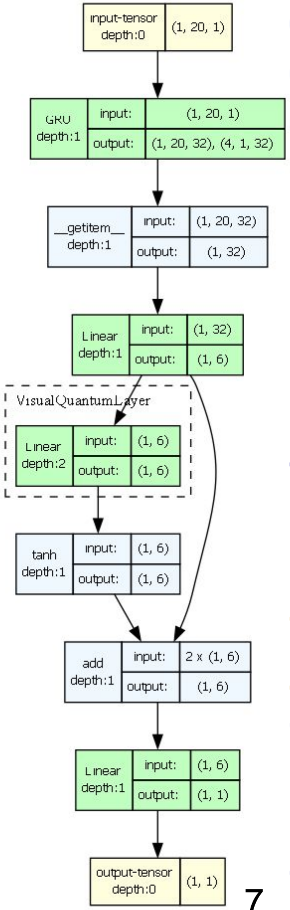
Model Architecture

- **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

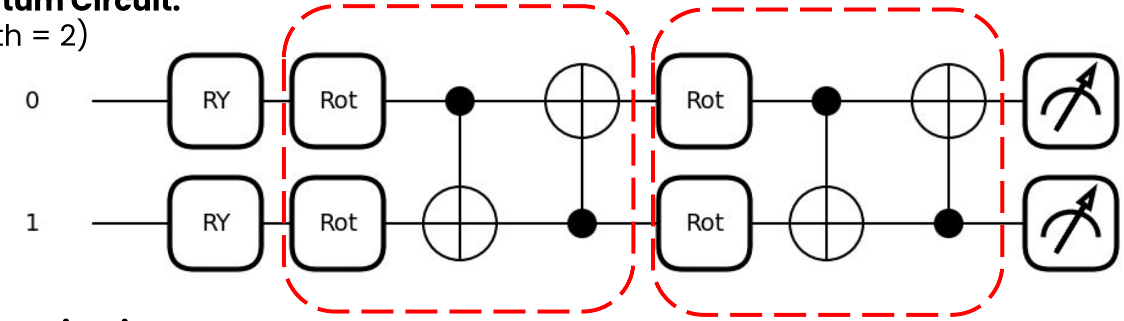


Quantum Hybrid Model

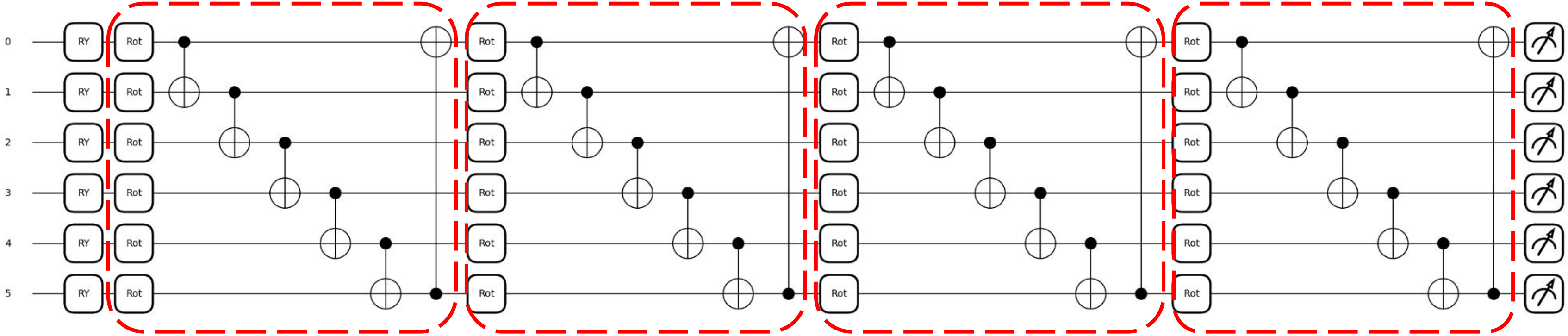


Quantum Layer - Variational Quantum Circuit

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



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



03

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

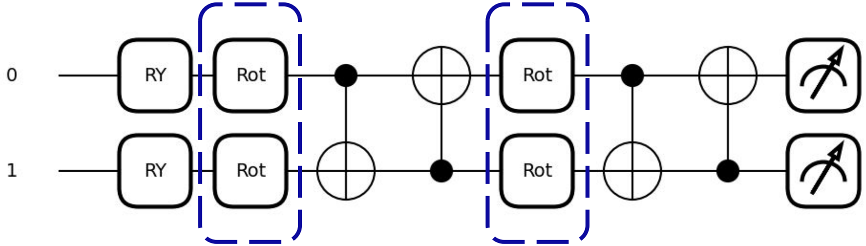
$$R_x(\theta) = \begin{pmatrix} \cos\left(\frac{\theta}{2}\right) & -i\sin\left(\frac{\theta}{2}\right) \\ -i\sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{pmatrix}$$

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

3 Parameters: R_z R_y R_z = Rot

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

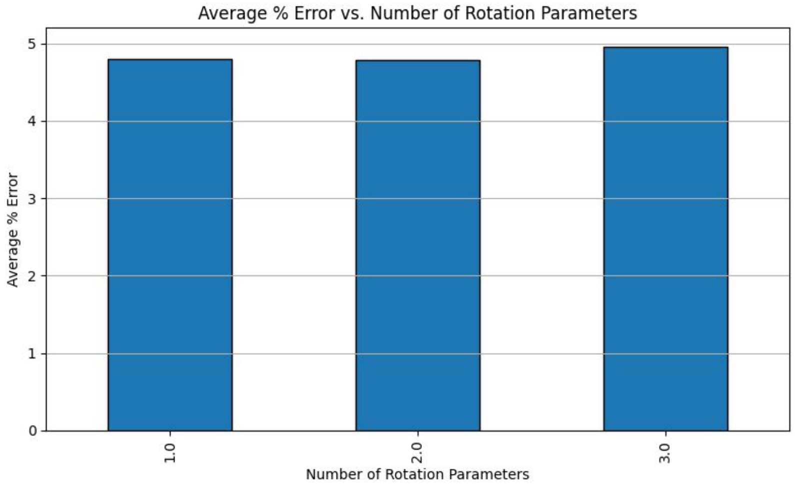
$$\mathrm{Rot}(\phi,\theta,\omega) = \begin{pmatrix} \cos\left(\frac{\theta}{2}\right) e^{-i\left(\frac{\phi+\omega}{2}\right)} & -\sin\left(\frac{\theta}{2}\right) e^{-i\left(\frac{\phi-\omega}{2}\right)} \\ \sin\left(\frac{\theta}{2}\right) e^{i\left(\frac{\phi-\omega}{2}\right)} & \cos\left(\frac{\theta}{2}\right)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

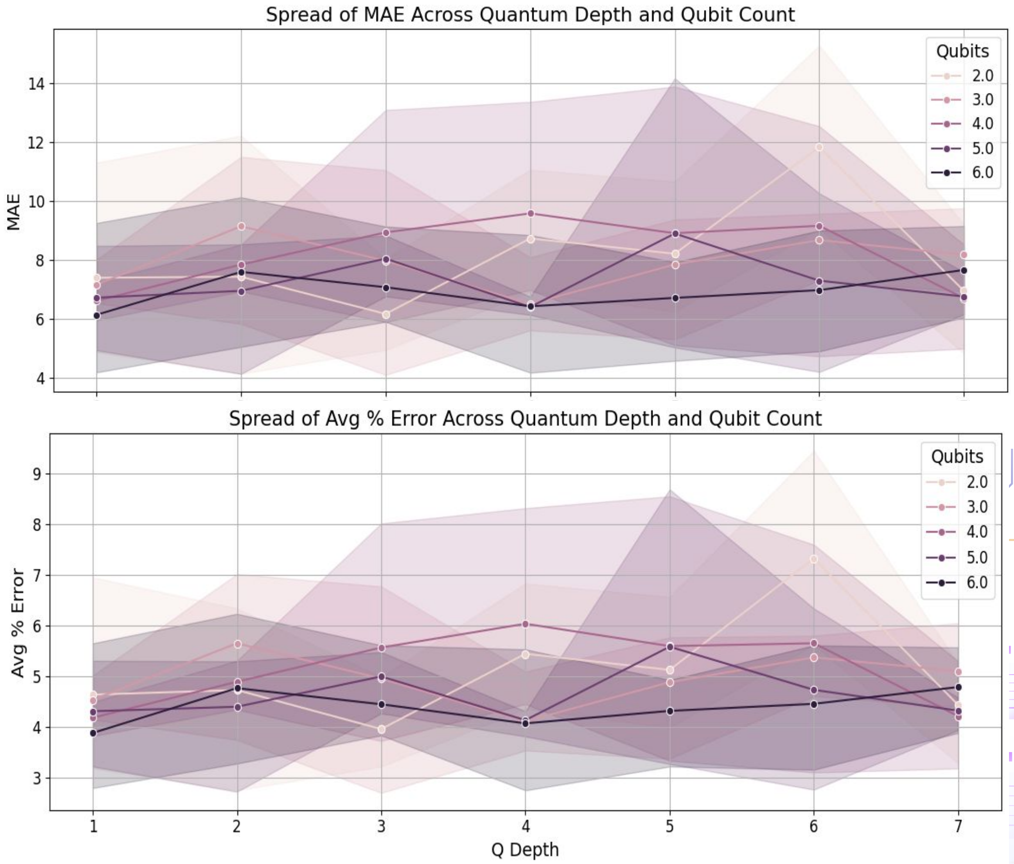


Quantum Circuit Optimization

Quantum Circuit Grid Search

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

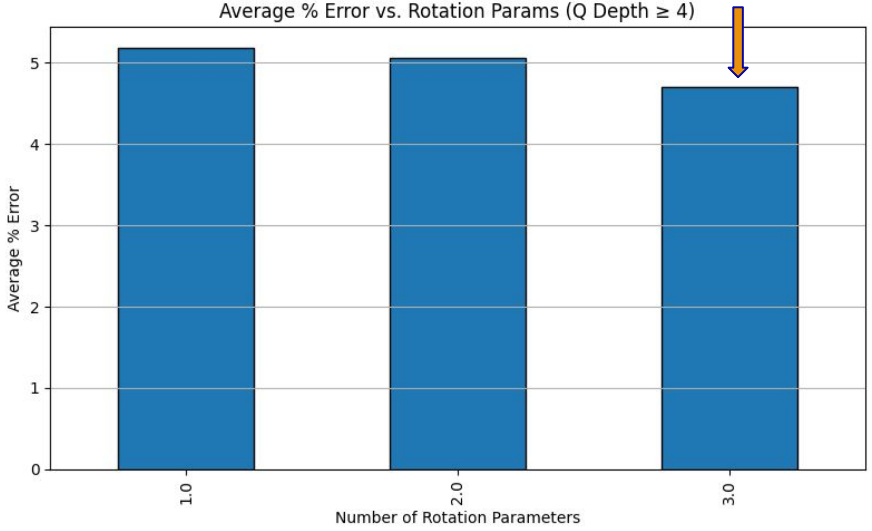


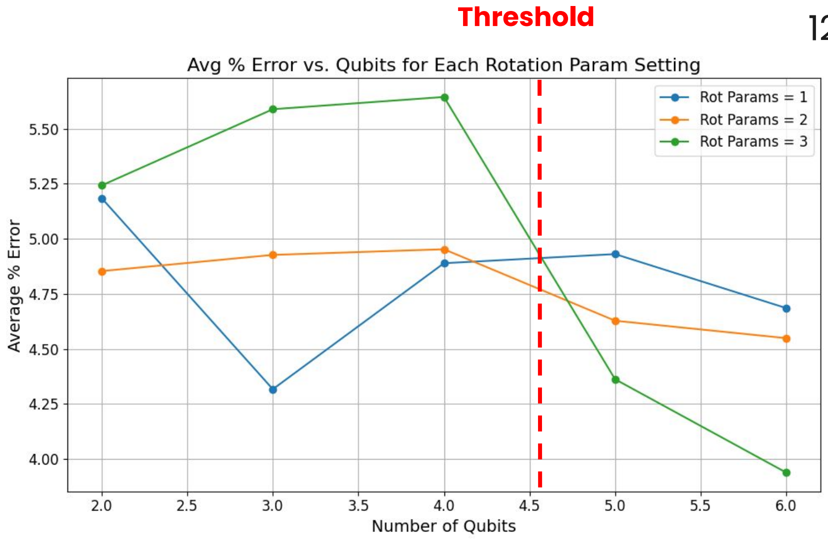


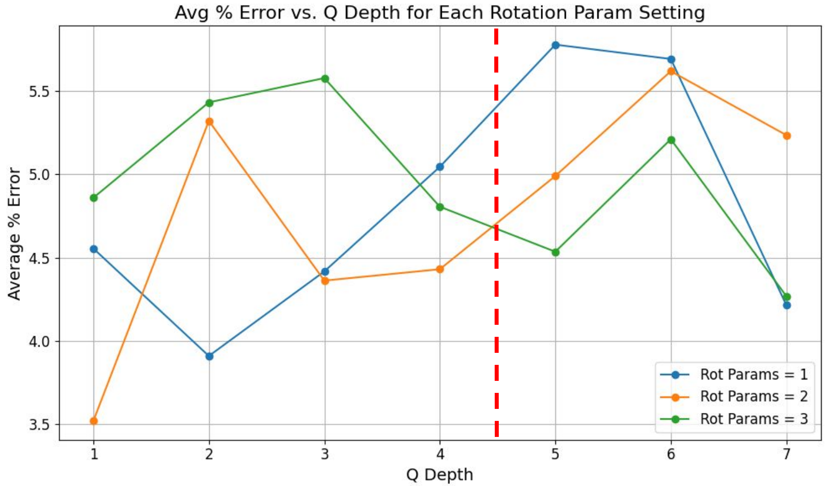
Quantum Circuit Optimization

Quantum Circuit Grid Search

Focus on where a Full Rotation outperforms

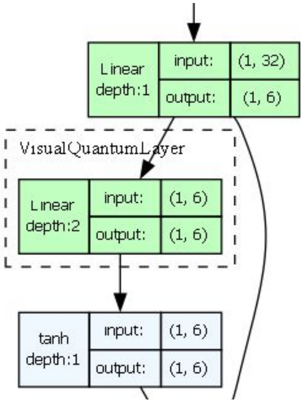


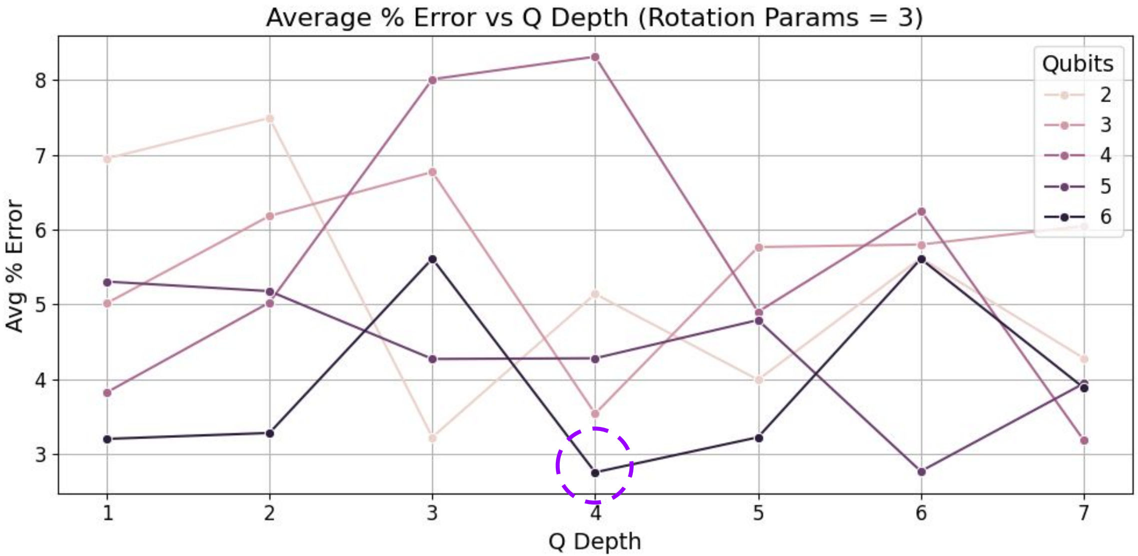




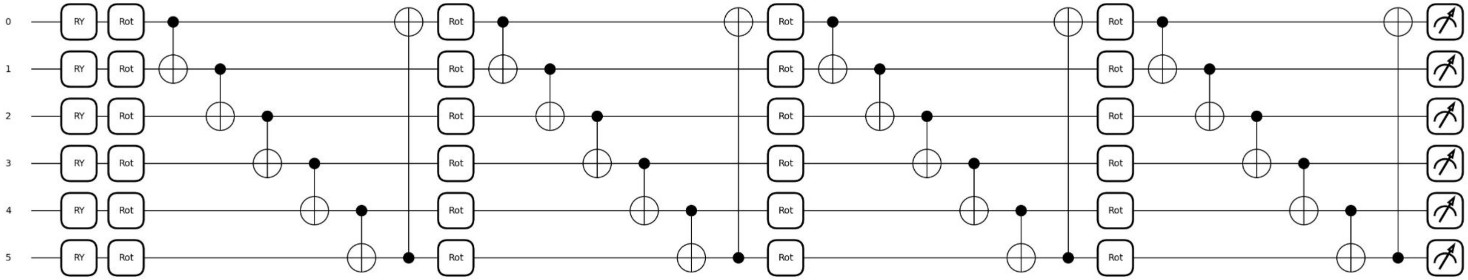
Quantum Circuit Optimization

Final Selection





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

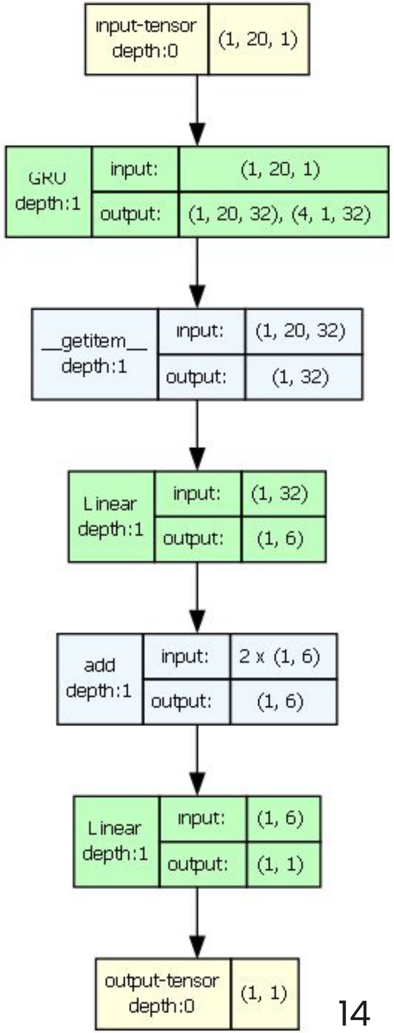


Classical Architecture Optimization

- Classical components optimized separately to reduce quantum training time.
- 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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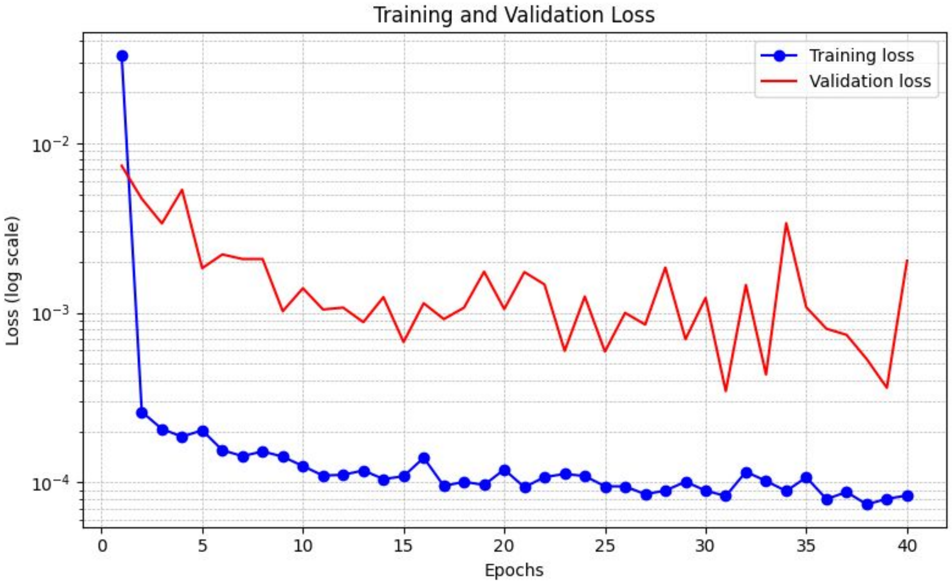
Results

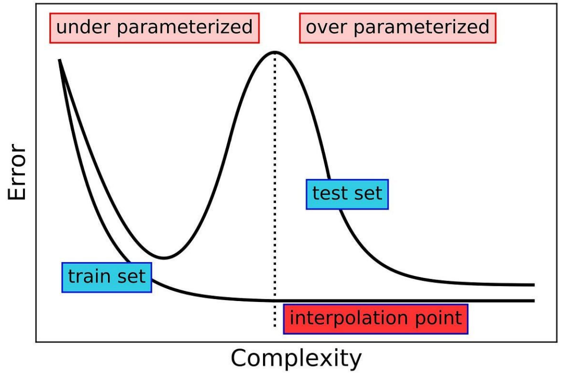
Evaluation of Hybrid Model and Comparison to Classical Model

Training & Validation

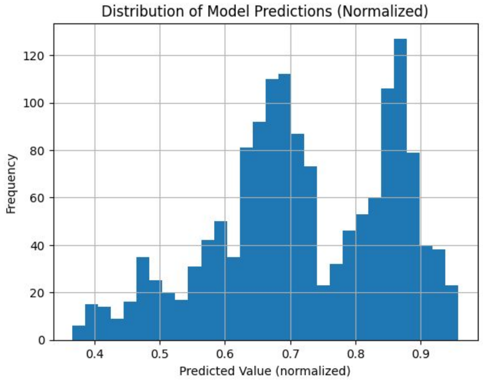


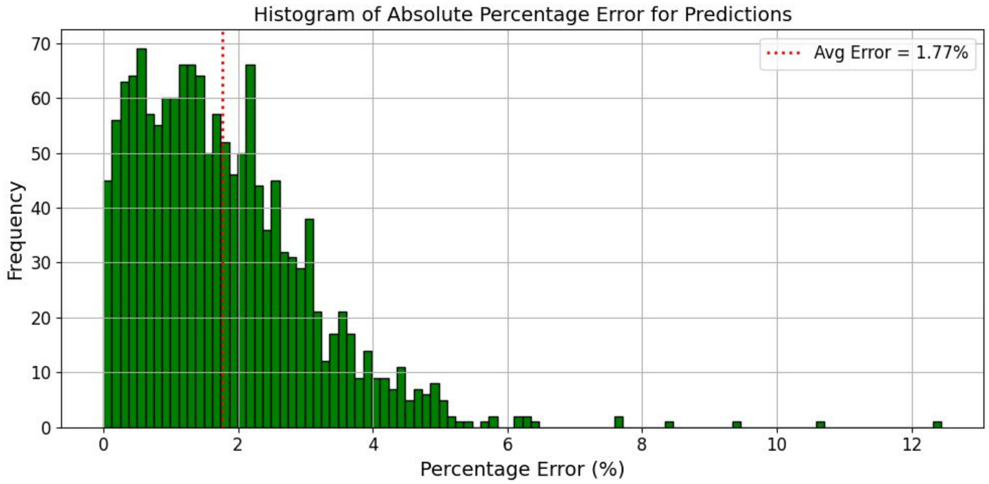
Hybrid models trained for 40 epochs, achieving a best training loss of **0.000083** and validation loss of **0.000346**.

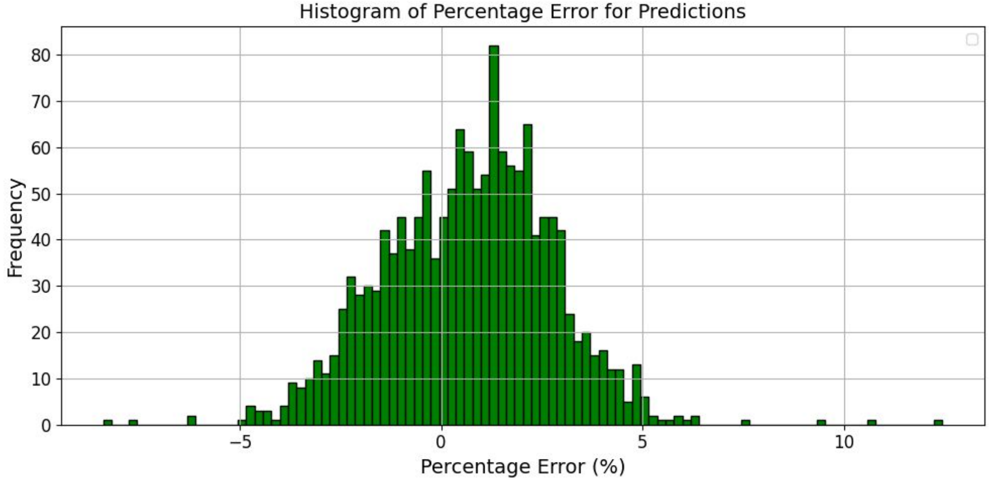
Overfitting and Model Complexity:
Higher validation loss suggests overfitting or possible double descent behavior; further tuning of model depth, quantum circuit size, and training duration is required.



Hybrid Model Predictions







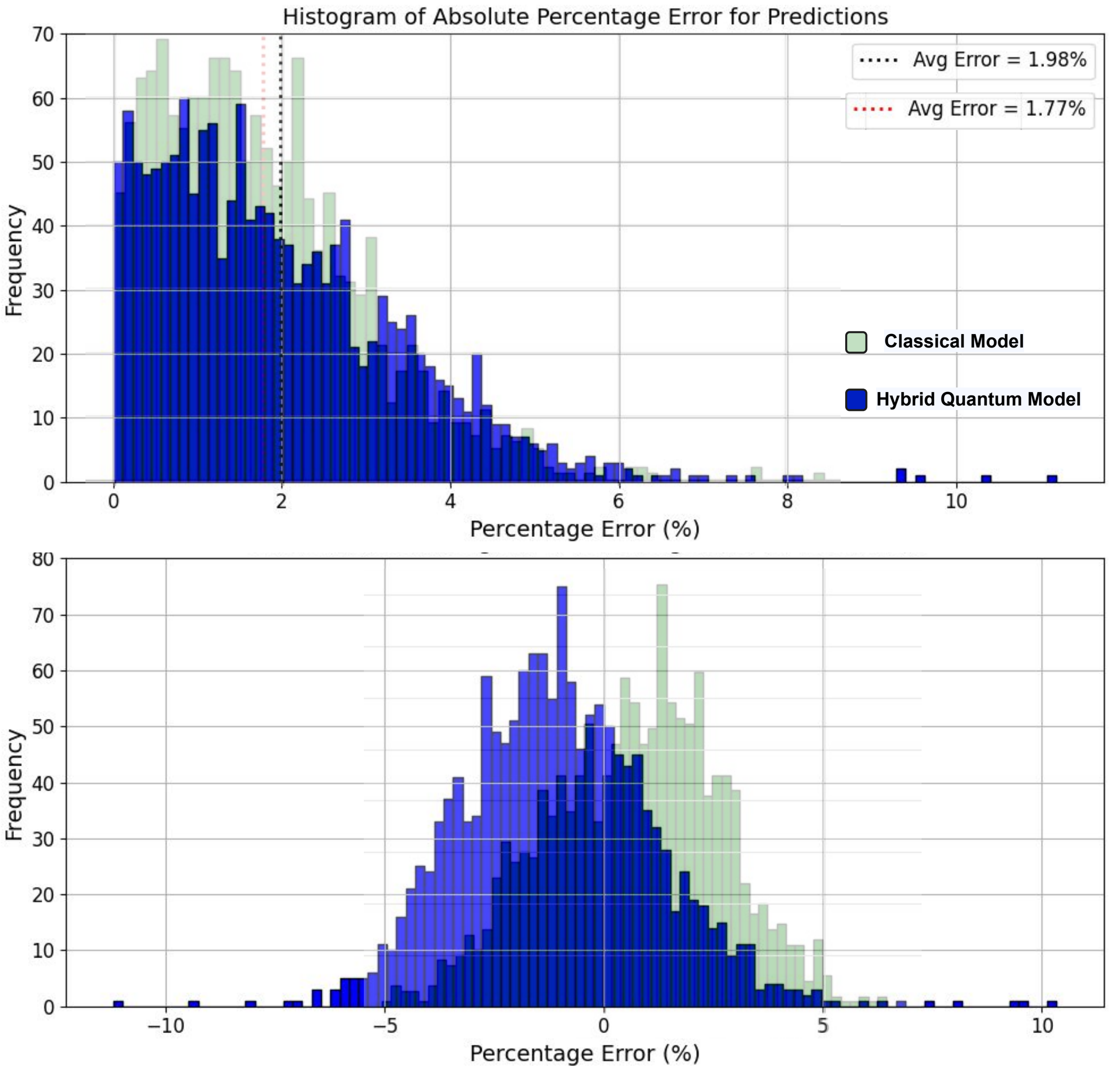
Predictions Distribution:
Ranges over full 0 to 1 with two distinct peaks

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

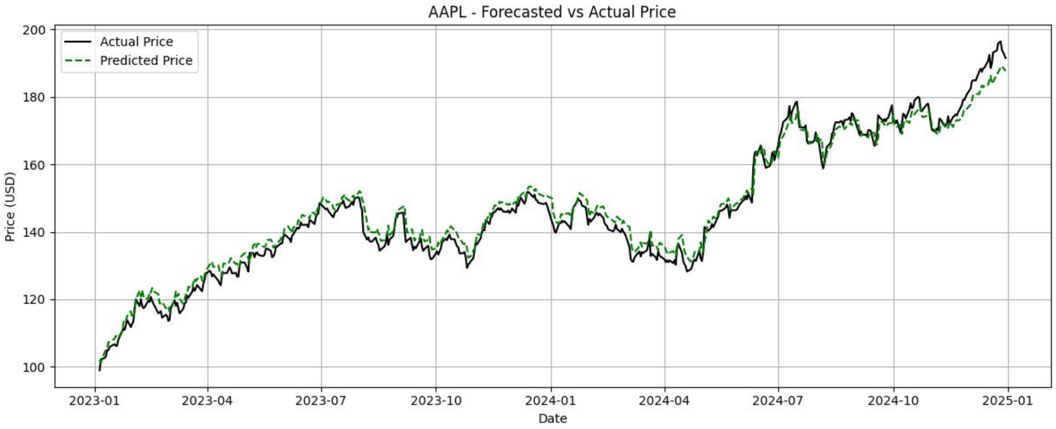
Error Distribution Analysis:
Most prediction errors fall within 0–2%, centered near 0%, indicating high accuracy and minimal bias.

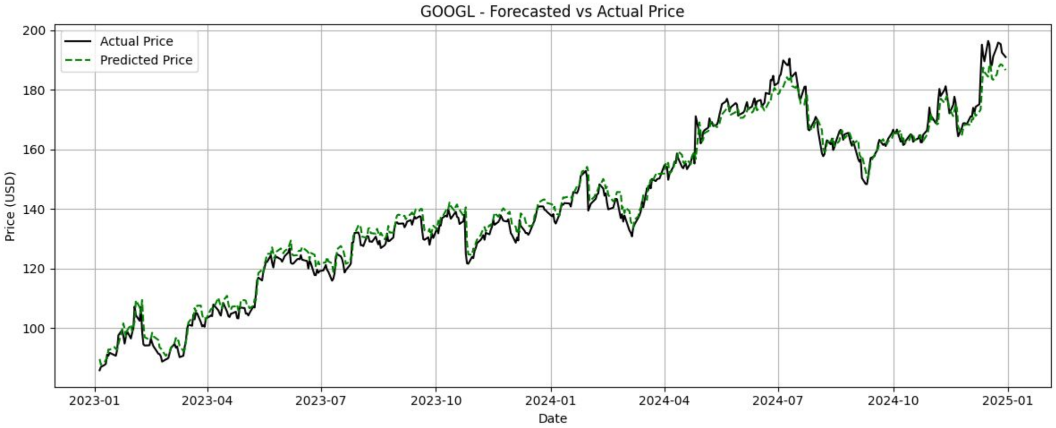
Predictions Comparison

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



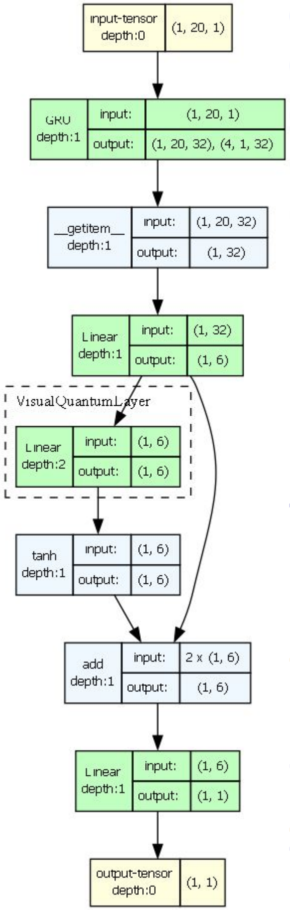


Conclusions & Future Work

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 for real-world validation.

Thank you!

Do you have any questions?