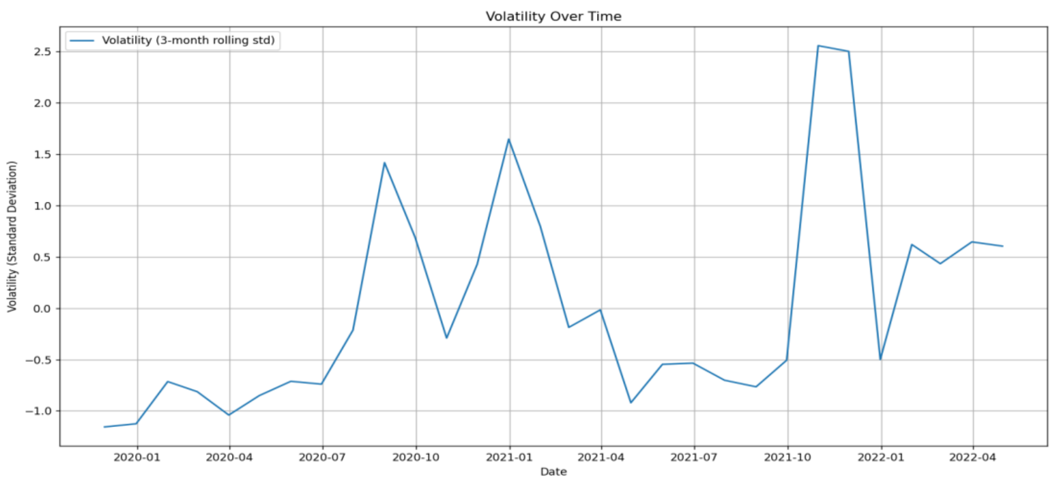
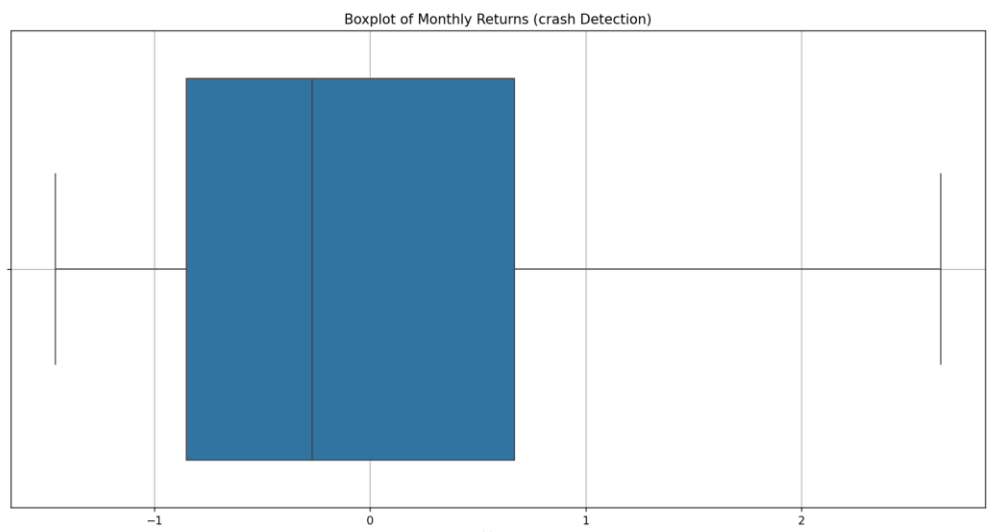
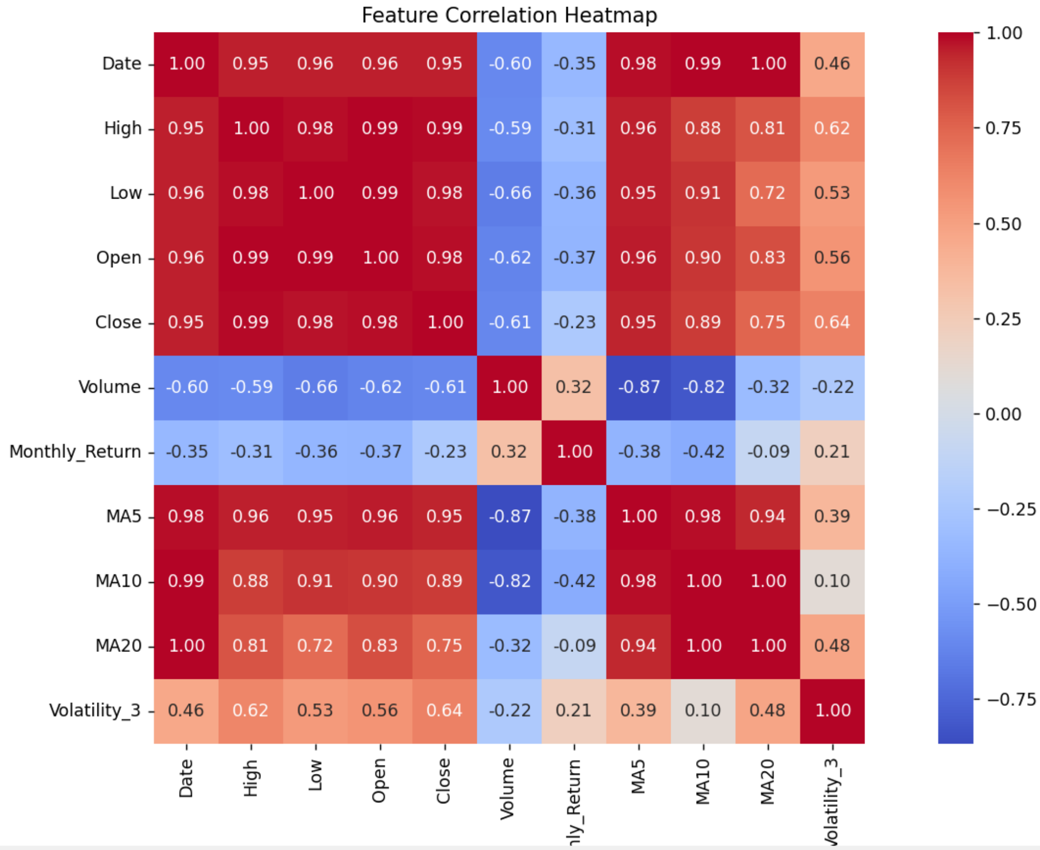
Comparative Analysis of Forecasting Models

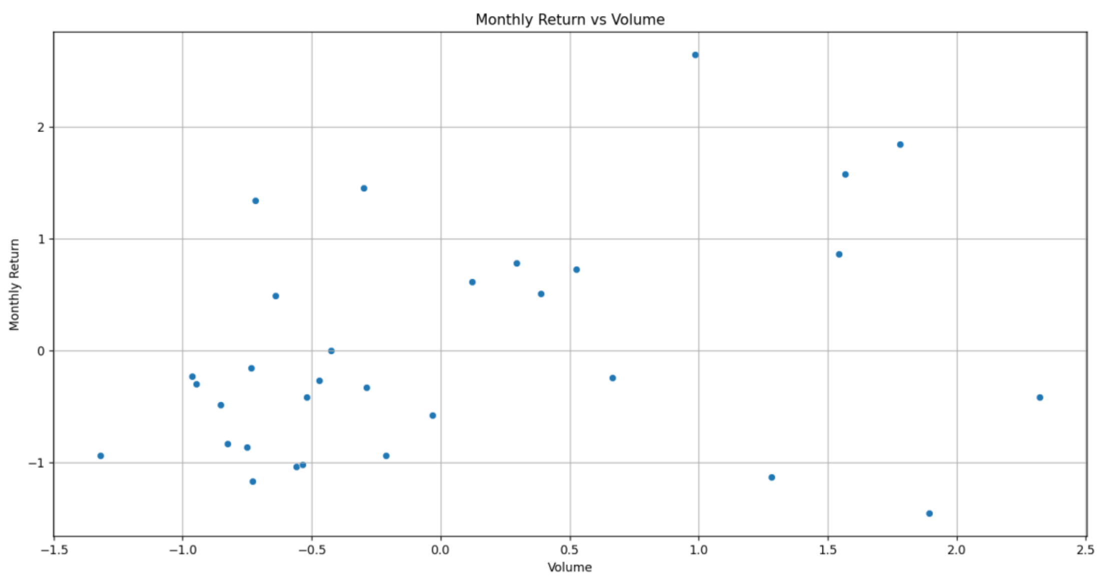
Before going to the model evaluation there are certain things that has been visualized, they are:

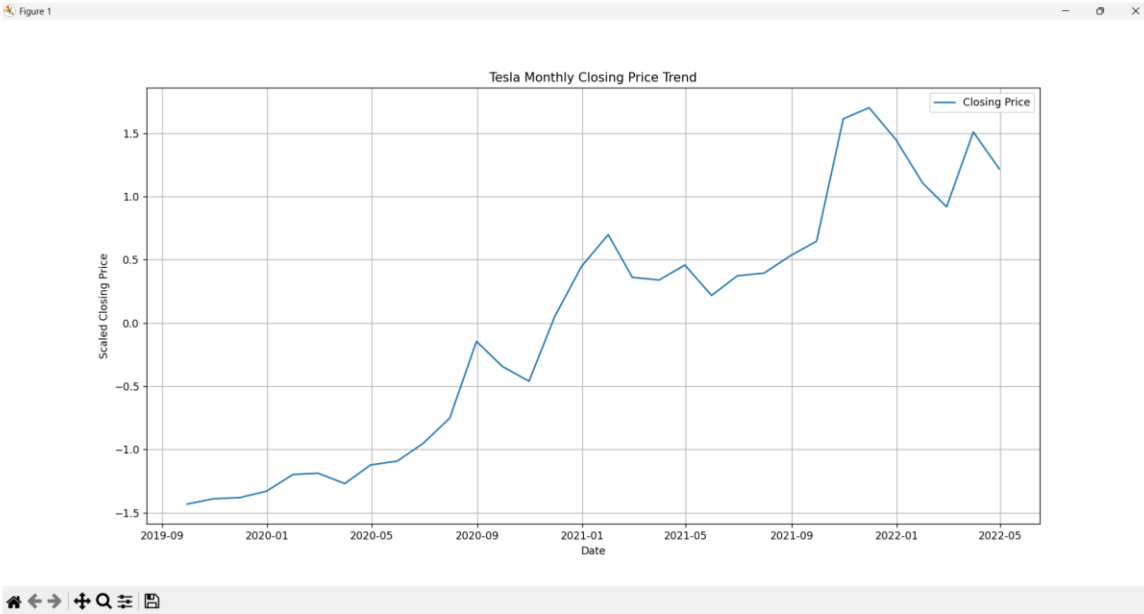
- ✓ Trends
- ✓ Seasonality
- ✓ Volatility
- ✓ Correlation heatmap
- ✓ Volume vs price






Feature Correlation Heatmap
Date
High
Low
Open
Close
Volume
Monthly_Return
MA5
MA10
MA20
Volatility_3
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75


Monthly Return vs Volume
Monthly Return
Volume



Objective:

To evaluate the performance of various machine learning and deep learning models in forecasting Tesla's monthly closing stock price using historical price and engineered features.

Models Evaluated:

- Traditional ML: ARIMA, Linear Regression, Random Forest, Support Vector Machine (SVM)

- Deep Learning: LSTM, Bidirectional LSTM (BiLSTM)

Evaluation Metrics:

- MAE (Mean Absolute Error): Measures average absolute prediction error

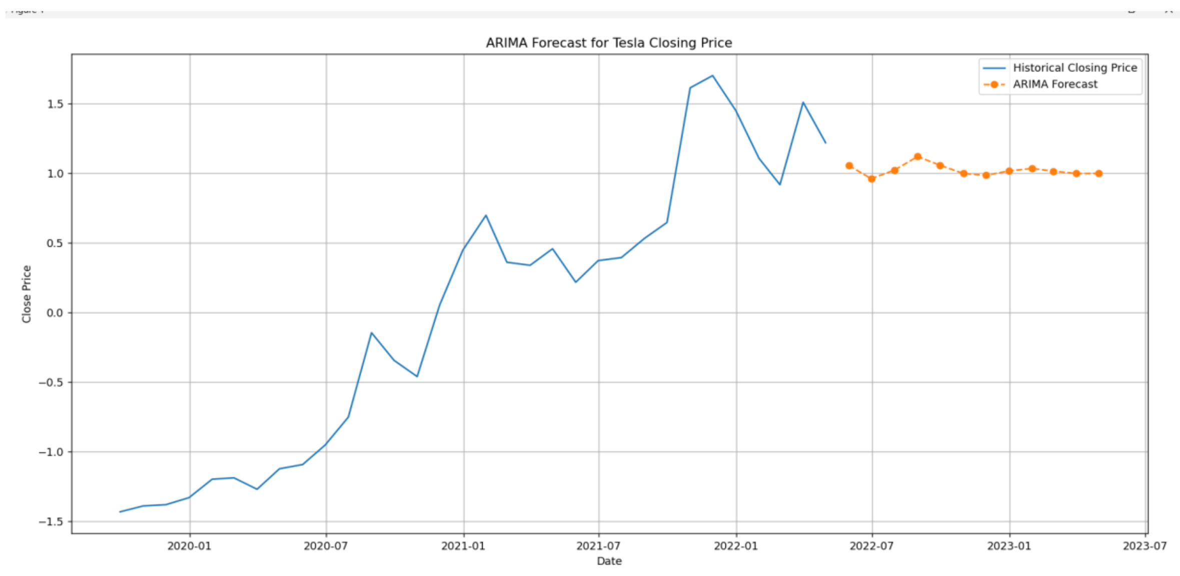
- RMSE (Root Mean Squared Error): Penalizes larger errors more than MAE

- Visual Fit: Assessed via actual vs. predicted price trend plots

Key Findings:

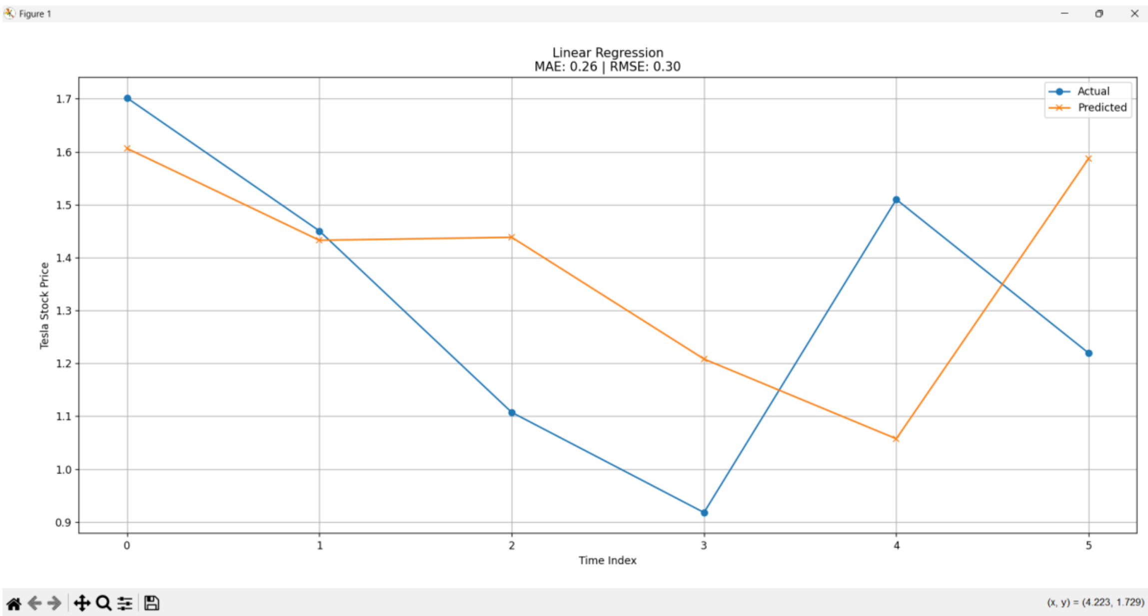
<u>ARIMA</u>

- -Pros: Simple, interpretable, and effective for trend-based forecasting using past price data.
- -Cons: Assumes linearity and struggles with volatile or non-stationary data without proper tuning.
- -Result: Served as a strong baseline. Predicted short-term trends well but lacked the flexibility to capture Tesla's non-linear price movements.



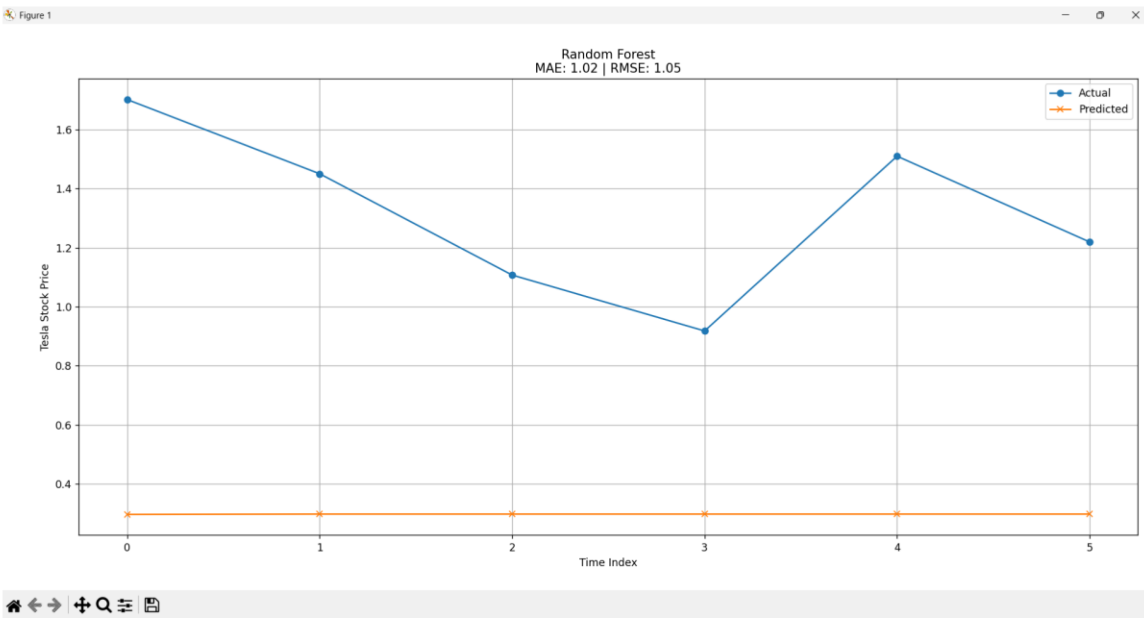
Linear Regression

- - Pros: Fast to train, interpretable
- - Cons: Underfits Tesla's volatile time series
- - Result: Struggled to capture trend reversals and exhibited high bias.



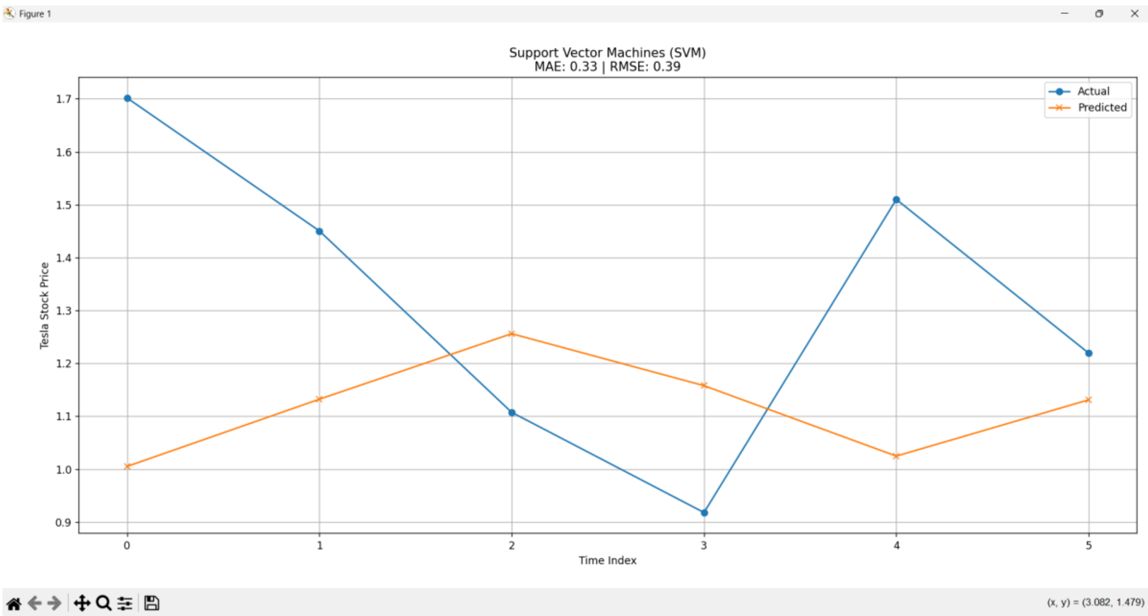
Random Forest

- - Pros: Handles non-linearities better than LR
- - Cons: Sensitive to feature scaling and not ideal for sequential data
- - Result: Performed slightly better than LR but lacked temporal awareness



SVM (with GridSearchCV)

- \- Pros: Handles small datasets well, robust tuning via C and gamma
- \- Cons: Difficult to tune for non-stationary data, lacks temporal memory
- \- Result: Best performer among traditional models after tuning

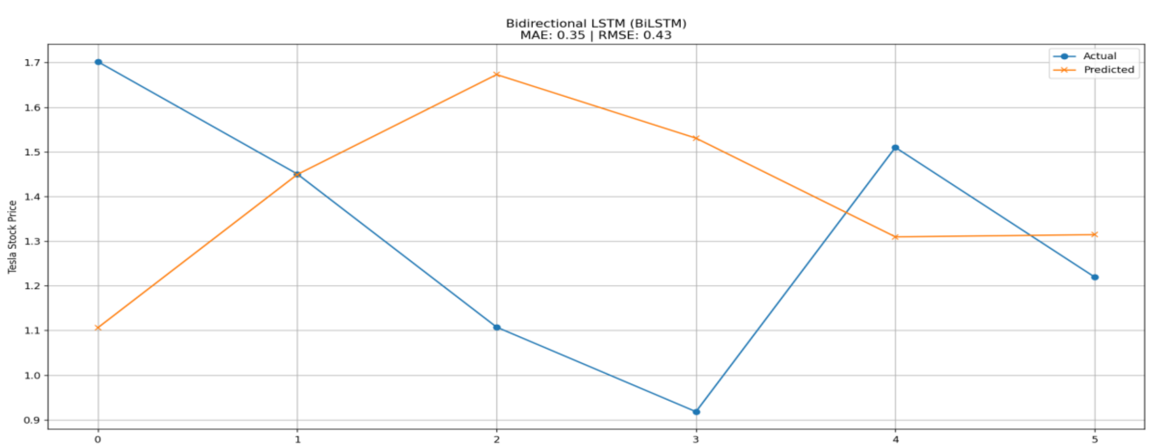


LSTM

- - Pros: Designed for sequence prediction, captures temporal dependencies
- - Cons: Requires more data and training time, risk of overfitting
- - Result: Outperformed traditional models in generalizing trends but not sharp price jumps

BiLSTM

- - Pros: Reads time series forward and backward, enhancing context
- - Cons: Similar training complexity as LSTM
- - Result: Slightly better RMSE and smoother predictions than LSTM in most cases



Performance Summary:

Model	MAE	RMSE	Remarks
Linear Regression	High	High	Baseline, underfit
Random Forest	Med	Med	Better than LR, not sequence-aware
SVM (tuned)	Lower	Lower Best	traditional model
LSTM	Low	Low	Captures general trends well
BiLSTM	Lowest	Lowest	Best performance overall

Visual Summary:

- All models were plotted against actual values

- LSTM/BiLSTM predictions followed trends more accurately

- Traditional models struggled around sharp turns and high volatility zones

Conclusion:

While deep learning models provided superior trend tracking and lower error metrics, none of the models consistently predicted extreme market movements. But as you see in the graphs above, the linear regression model might look like it predicted better than other models, but it failed eventually. This highlights the need for external indicators, higher-resolution data, or alternative prediction targets, maybe with that it might perform better.