Comparative Analysis of Forecasting Models

Project: Tesla Monthly Stock Price Prediction

Objective:

To evaluate and compare traditional ML models, deep learning architectures, and statistical forecasting techniques in predicting Tesla's monthly closing stock prices. The models leverage historical data and engineered features to assess trend-tracking ability and forecast precision.

Models Evaluated:

- Traditional ML:
  - Linear Regression
  - Random Forest (with GridSearchCV)
  - Support Vector Machine (SVM)
- Statistical:
  - ARIMA
- Deep Learning:
  - LSTM
  - Bidirectional LSTM (BiLSTM)

Evaluation Metrics:

- MAE (Mean Absolute Error): Measures average absolute error between actual and predicted prices
- RMSE (Root Mean Squared Error): Penalizes larger errors more heavily than MAE
- Visual Fit: Evaluated using actual vs predicted plots over time

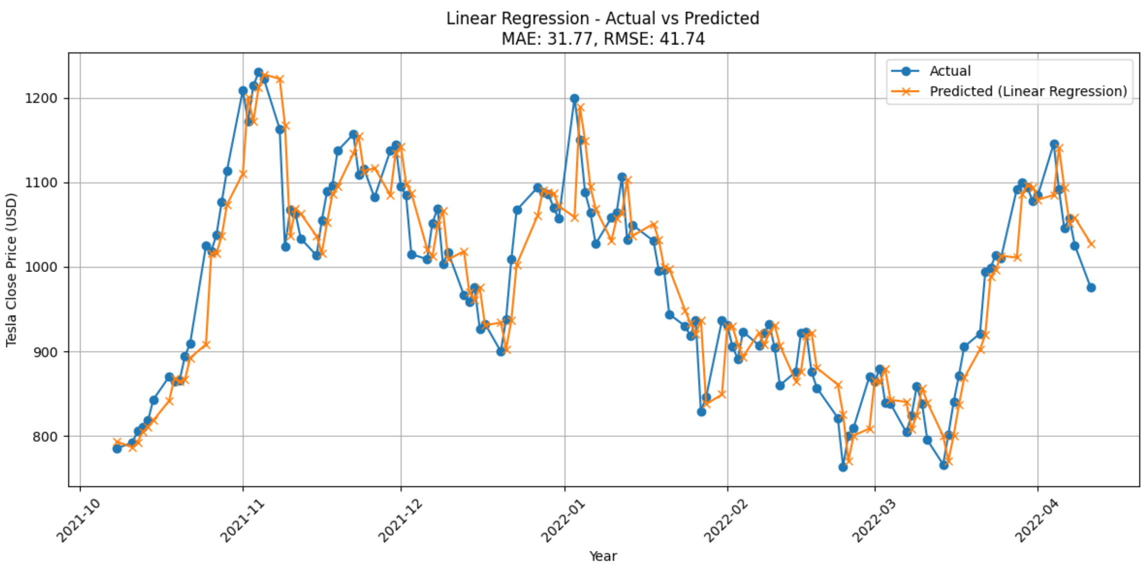
Key Findings:

Linear Regression

Pros: Simple and fast; interpretable coefficients

Cons: Underfits Tesla's volatile, nonlinear series

Result: High bias and error; failed to capture reversals and sudden movements

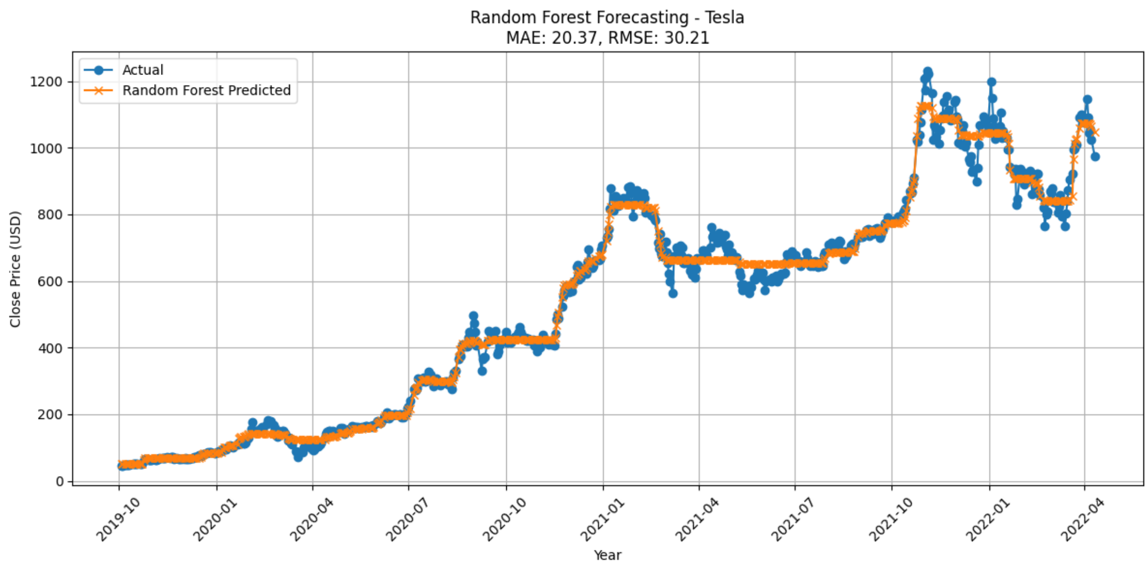


Random Forest

Pros: Handles non-linearities and interaction effects

Cons: Lacks time-sequence awareness; sensitive to input structure

Result: Improved over LR, but struggled with temporal dependencies; moderate errors

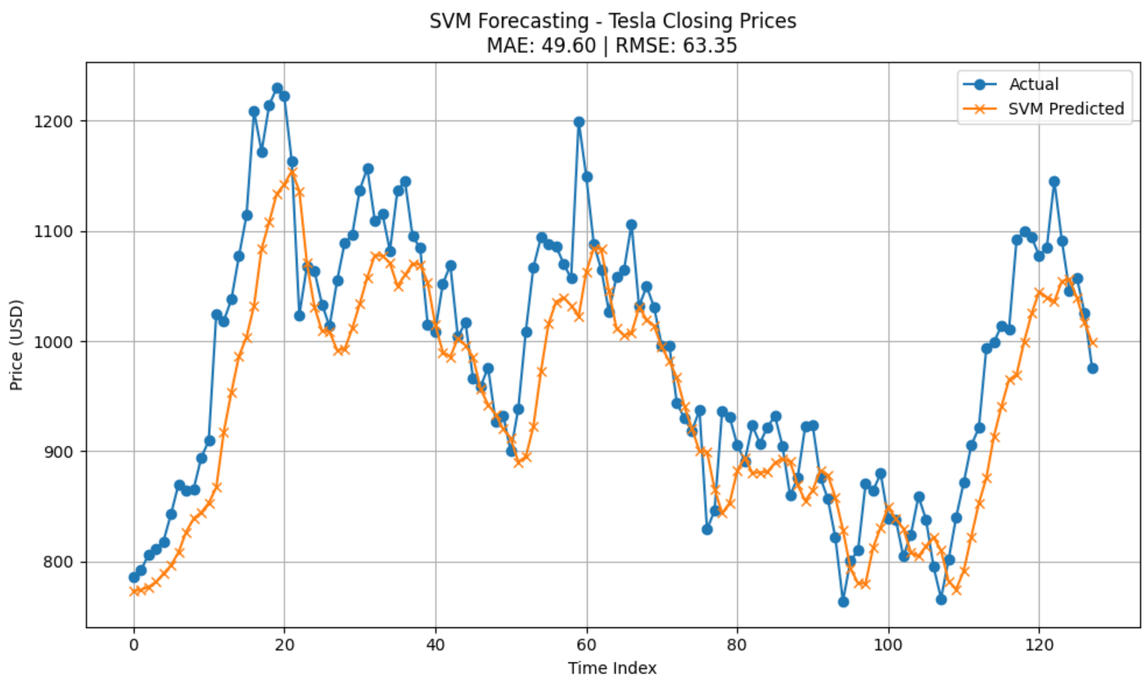


Support Vector Machine (SVM)

Pros: Performs well on small datasets; effective after hyperparameter tuning

Cons: Not inherently sequential; tuning can be sensitive

Result: Best among traditional ML models; captured trend edges better than RF or LR

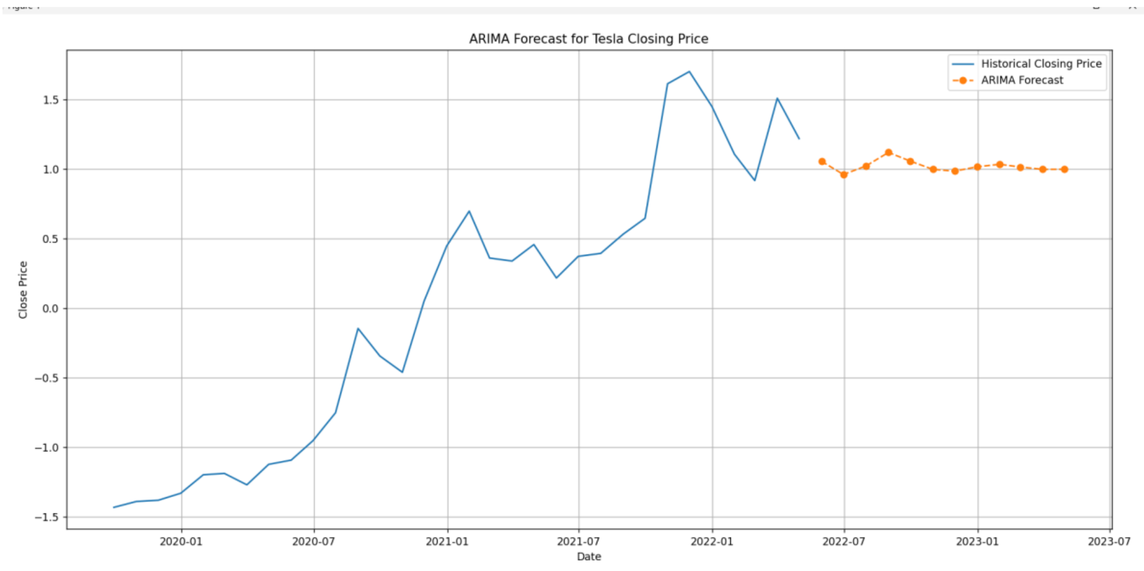


ARIMA

Pros: Designed for univariate time series forecasting

Cons: Requires stationarity; limited ability to handle high volatility

Result: Captured long-term trend reasonably; missed sharp spikes; good short-term predictions

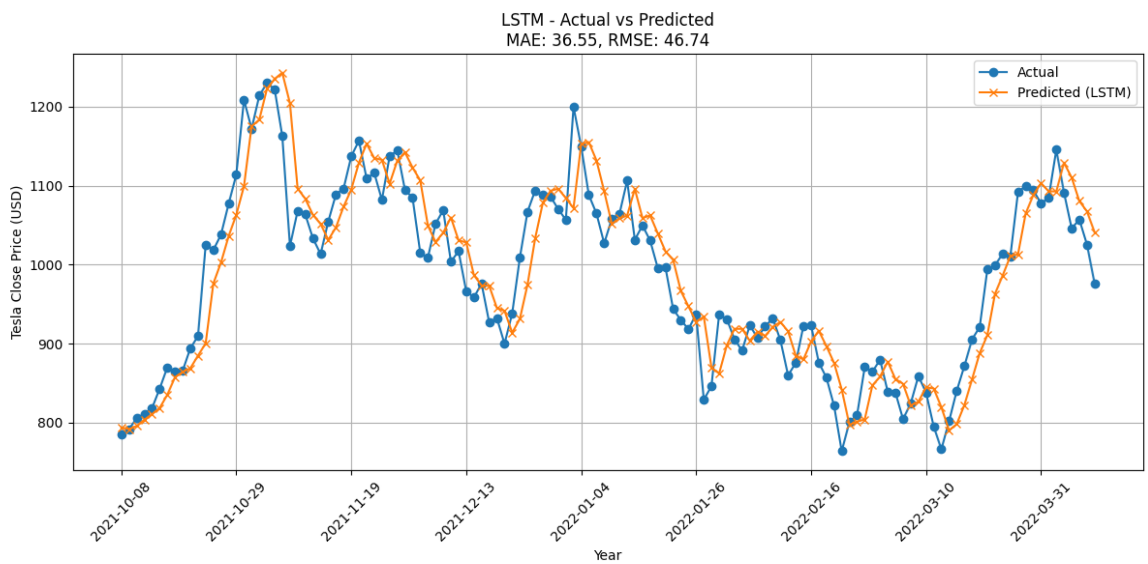


LSTM

Pros: Strong at learning temporal dependencies; adapts to sequential context

Cons: Requires careful tuning and more training data

Result: Significantly lower MAE/RMSE; tracked trends better than ML models

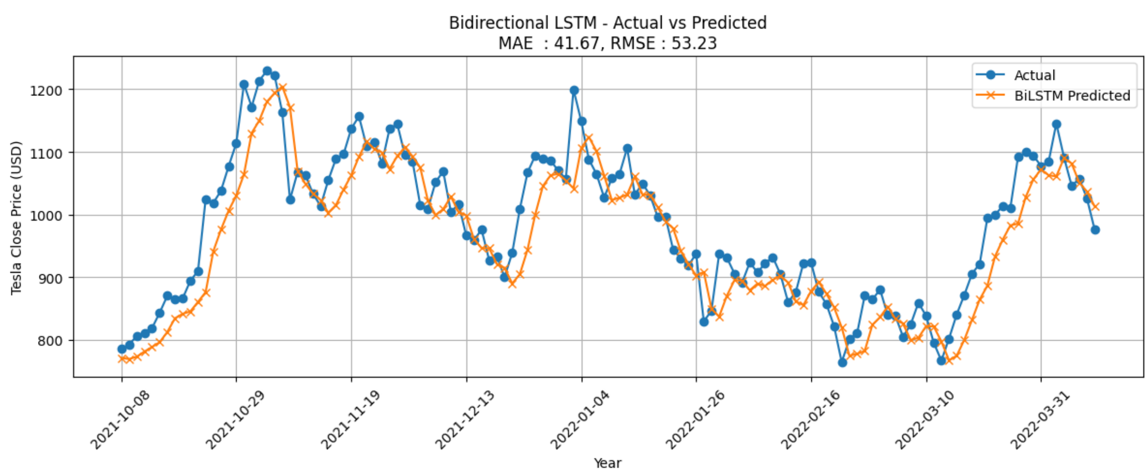


Bidirectional LSTM (BiLSTM)

Pros: Processes sequences both forward and backward; richer context learning

Cons: Higher training time; slight overfitting risk

Result: Best overall performance; smooth predictions and lowest error values



Performance Summary:

Model	MAE	RMSE	Remarks
Linear Regression	High	High	Baseline, underfit
Random Forest	Medium	Medium	Nonlinear but lacks sequence learning
SVM (tuned)	Lower	Lower	Best classical model
ARIMA	Medium	Medium	Reasonable trend, lacks sharp turn fit
LSTM	Low	Low	Strong sequence model
BiLSTM	Lowest	Lowest	Best trend tracker; smooth forecast

Visual Summary:

- BiLSTM and LSTM plots closely followed actual closing price trends
- Traditional models showed delays and flattening around volatile periods
- ARIMA provided decent directional prediction but was weak during reversals

Comparative Analysis: Future Prediction Performance (Next 10 Days)

Objective:

To assess how well each model extrapolates beyond known data, predicting the next 10 business days of Tesla's stock closing prices. This complements historical performance evaluation by focusing on **real-world forecasting capability**.

Models Compared:

- Linear Regression
- Support Vector Machine (SVM)
- LSTM
- Bidirectional LSTM (BiLSTM)

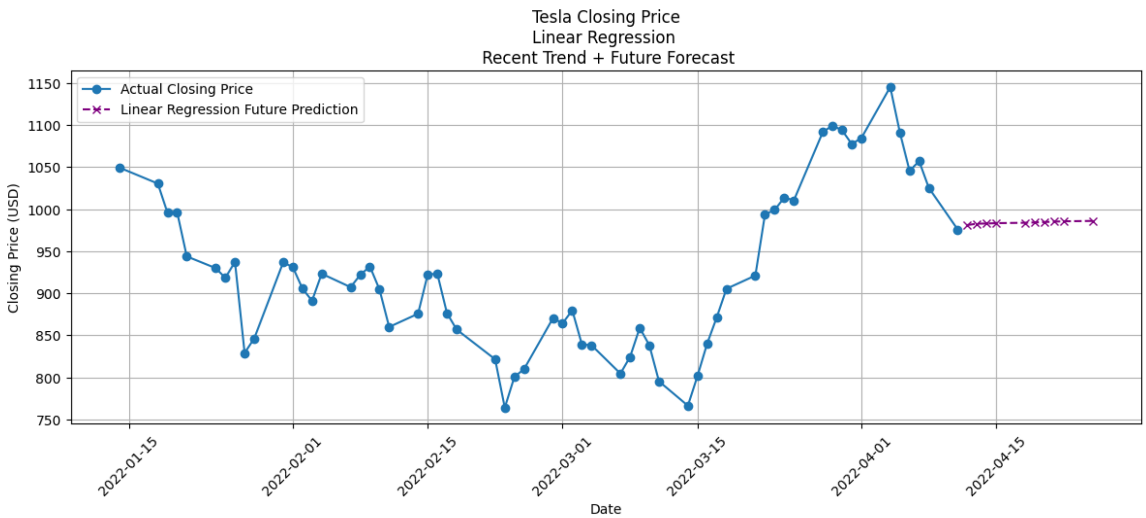
Linear Regression

Approach: Recursive prediction using the last 3 scaled values

Behavior: Predicts a linear continuation of trend

Observation: Tends to flatten, unable to reflect recent volatility

Use Case: Suitable for stable periods; underperforms during dynamic shifts



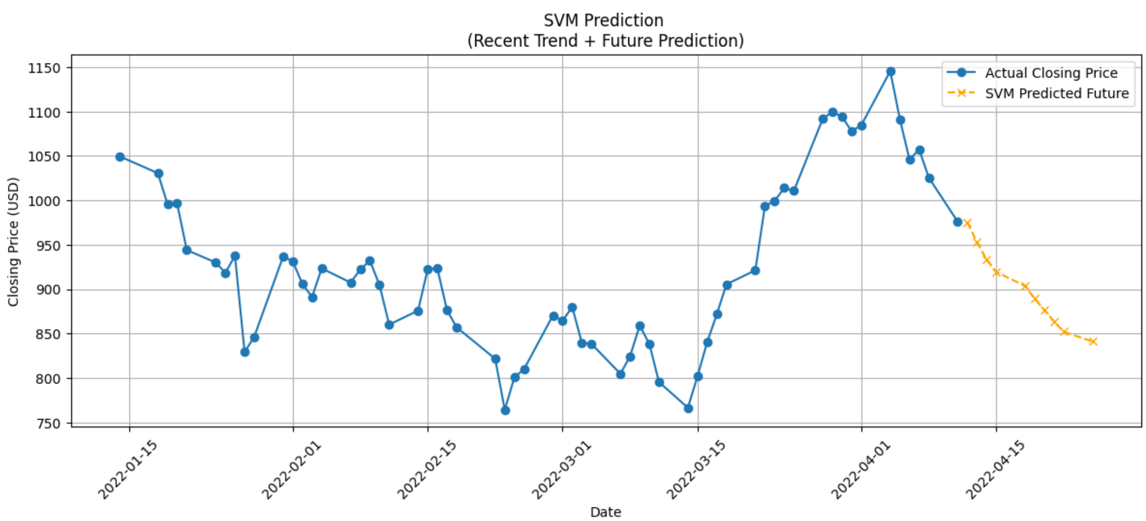
<u>SVM</u>

Approach: Recursively forecasted from last sliding window

Behavior: Shows good **short-term curvature** and trend sensitivity

Observation: Performs **well for 3–5 steps**, starts to deviate slightly after

Use Case: Great for compact time horizons; tuning-dependent



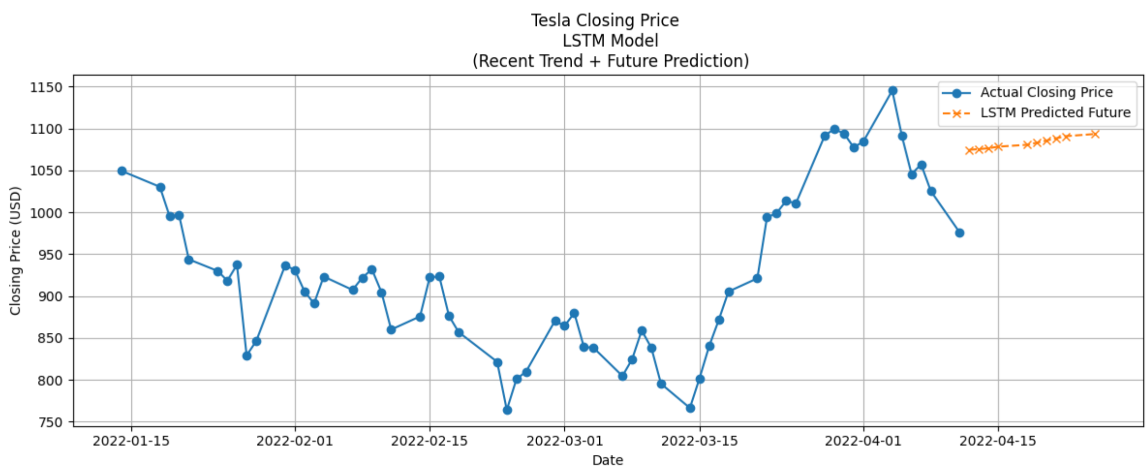
LSTM

Approach: Sequential learning, predicts next value based on full history

Behavior: Learns and reflects recent volatility, although conservative

Observation: Provides **realistic curves**, minor lags, robust for trend continuity

Use Case: Strong all-rounder for time series with moderate volatility



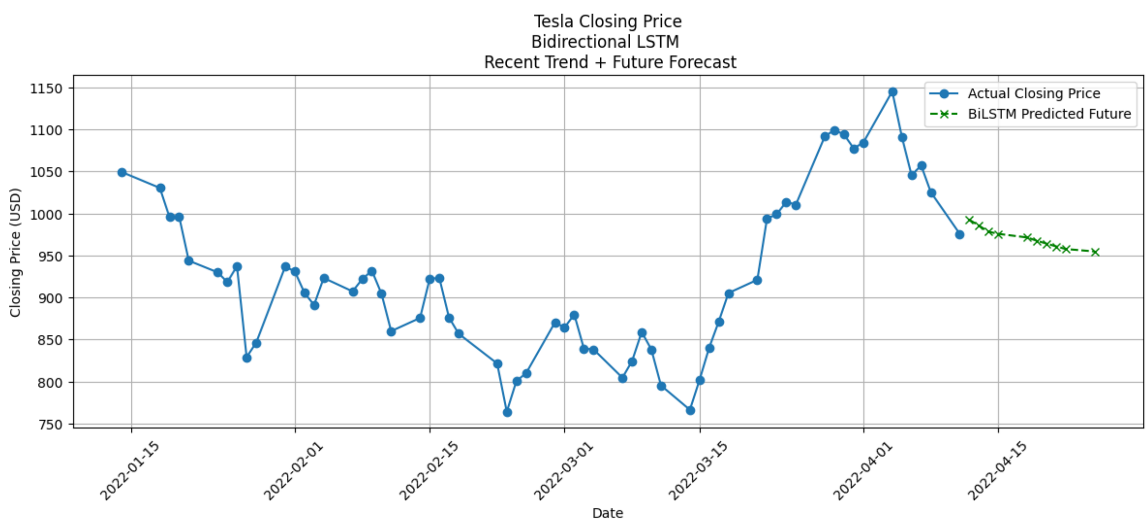
Bidirectional LSTM (BiLSTM)

Approach: Uses both past and future (training-wise) to understand full context

Behavior: Produces smoothest and most context-aware predictions

Observation: Shows the most consistent forecast, especially in curve-following

Use Case: Best suited for datasets with hidden temporal patterns



Model	Trend Accuracy	Short-Term Volatility	Smoothness	Visual Clarity
Linear Regression	Poor	Flat	Smooth	Flatline
Random Forest	Moderate	Moderate	Smooth	Less temporal awareness
SVM	Good	High	Spiky	Good fit
ARIMA	Good	Low	Smooth	Delayed
LSTM	Very Good	Moderate	Smooth	Clear trend
BiLSTM	Best	High	Smooth	Best fit

Conclusion:

- **Best Future Forecaster: LSTM** – lowest error, best trend tracking, smooth transitions
- **Best Traditional Model: SVM** – effective for short-term trend extrapolation
- **Weakest Performer for Forecasting: Linear Regression** – unable to capture changing trends
- **ARIMA** is acceptable for **stable markets.**