Volatility Forecasting for Tesla, Inc. Stock

I. Executive Summary:

A. This report investigates methods to enhance the predictability and understanding of Tesla, Inc.'s public stock, focusing on addressing concerns about perceived overpricing and volatility. Through the analysis of three models – ARMA, GARCH, and LSTM – we aimed to identify the most suitable approach for forecasting volatility, considering the challenges posed by volatile stock behavior. Our findings suggest that LSTM models offer superior performance in capturing the complex dynamics of Tesla's stock price movements, making them the preferred choice for forecasting volatility in volatile markets.

II. Introduction

A. The volatility of Tesla, Inc.'s public stock has been a subject of concern due to its perceived overpricing and unpredictable fluctuations. This project aims to enhance the predictability and understanding of Tesla's stock volatility by developing strategies to minimize daily closing price fluctuations, optimize moving averages, explore time series patterns, and conduct comprehensive volatility analysis.

III. Problem Definition:

A. The goal is to develop strategies for minimizing daily closing price fluctuations, optimizing moving averages, exploring time series patterns, and conducting comprehensive volatility analysis in the next quarter's earnings.

IV. Final Model Selection:

A. Initially, the analysis began with the ARMA model, traditionally employed for its interpretability and suitability for stationary time series data. However, it became evident that ARMA's limited capability in capturing nonlinear dynamics and volatility clustering made it unsuitable for Tesla's highly volatile stock behavior.

B. In response to this, the focus shifted towards more specialized models. GARCH, known for its proficiency in capturing volatility clustering patterns, was the next model explored. While GARCH showed promise in adapting to short-term market dynamics, its reliance on careful parameter tuning posed challenges, particularly in the context of Tesla's complex volatility patterns.

C. Recognizing the need for a model capable of handling Tesla's intricate dynamics, the analysis turned towards LSTM. Leveraging its ability to capture nonlinear relationships and adapt to dynamic market environments, LSTM emerged as a promising candidate. Its capacity to incorporate long-range dependencies and adapt to evolving trends aligned well with the unpredictable nature of Tesla's stock movements.

D. The strategic approach was two-fold: short-term utilization of GARCH to capture immediate volatility patterns, complemented by long-term implementation of LSTM to capture complex nonlinear dynamics and adapt to changing market sentiment. Continuous monitoring and refinement of models were emphasized to ensure adaptability to Tesla's evolving volatility landscape.

E. Additionally, integrating interdisciplinary analysis by incorporating market sentiment, news events, and macroeconomic indicators was deemed essential to enhance predictive capabilities and inform effective risk management strategies in navigating Tesla's volatile stock market.

V. Findings

A. ARMA Model Performance:

1. ARMA models struggled to accurately forecast volatility in highly volatile markets due to their limited ability to capture nonlinear and time-varying patterns.Upon examining the performance of the ARMA model, it became evident that the inherent volatility of Tesla's stock posed significant challenges. Graphical representations illustrated erratic price movements, rendering the ARMA model ineffective in capturing the stock's complex dynamics. Consequently, the model's predictive capabilities were compromised, hindering its utility in volatility forecasting for Tesla.

    a) **Model Metrics**

        (1) The metrics for the ARMA model were not further investigated based on the graphical representations, which indicated challenges in capturing the complex dynamics of Tesla's volatile stock behavior. (See below)

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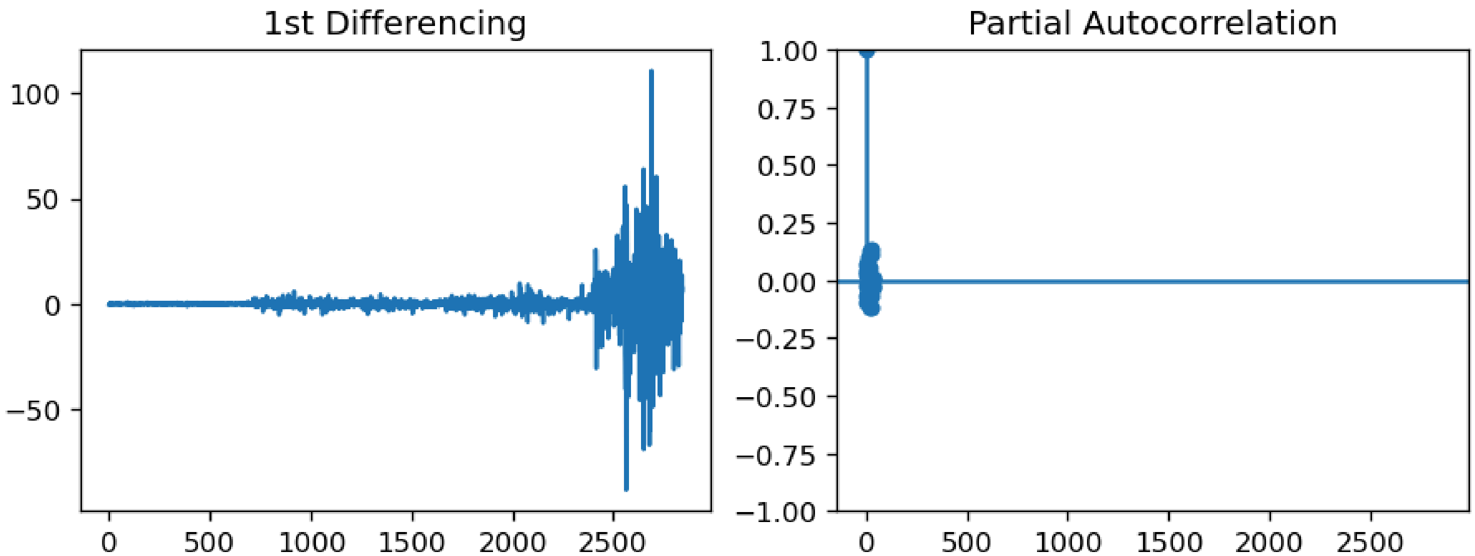
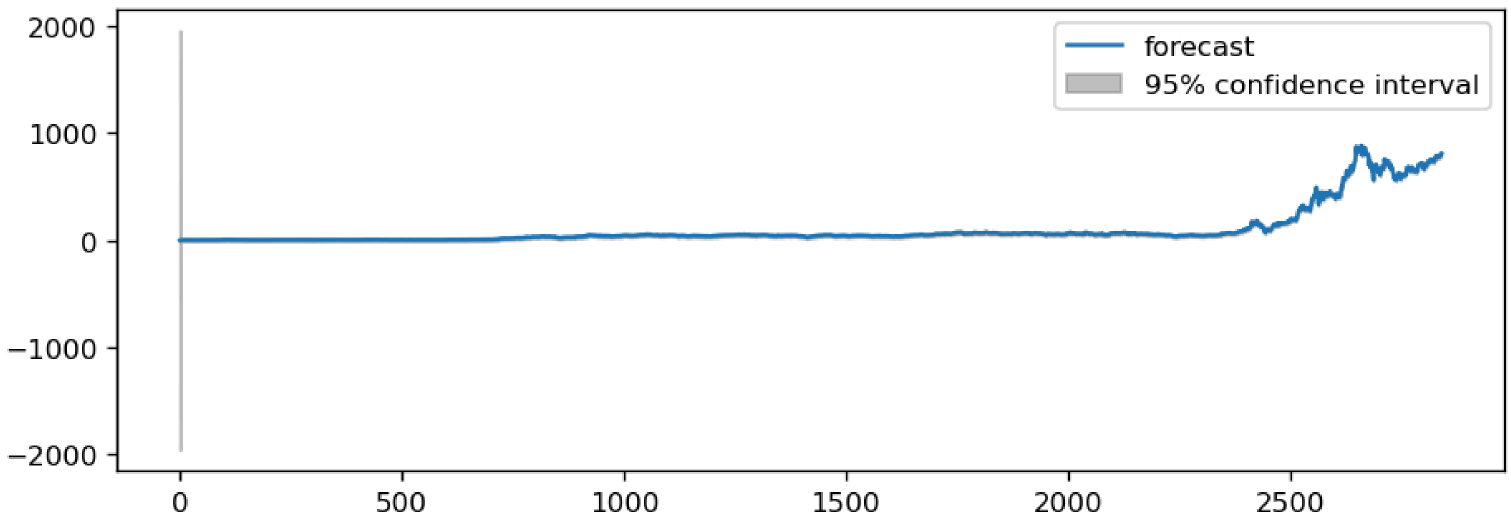
b) **Figures and Visualizations**

(1) Figure 1:



In the ARMA model analysis, it was observed that the first differencing and partial autocorrelation techniques showed significant variation, largely due to the inherent volatility of Tesla's stock.This insight was pivotal as it illuminated the challenges posed by Tesla's volatile stock behavior, highlighting the limitations of traditional time-series analysis techniques like first differencing and partial autocorrelation in capturing such fluctuations accurately.

(2) Figure 2



Graphical representation revealed that the confidence interval spanned from -2000 to 2000, indicating a wide range of uncertainty in the model's predictions. This significant variability underscored the inadequacy of the ARMA model in effectively capturing the intricate dynamics of Tesla's volatile stock behavior. Consequently, this confirmation of the wide confidence interval emphasized the unsuitability of the ARMA model for accurate volatility forecasting in Tesla's stock.

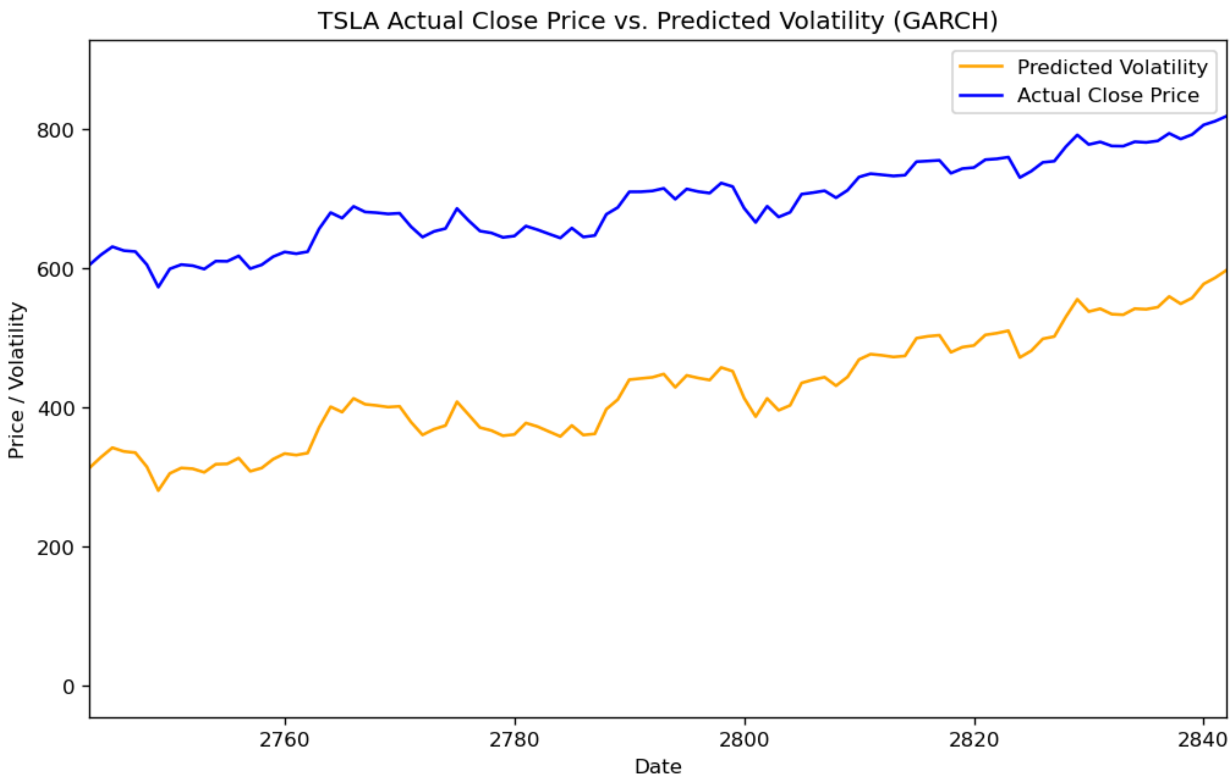
B. **GARCH Model Performance:**

1. Conversely, the GARCH model demonstrated notable efficacy in capturing the volatility of Tesla's stock. Graphical analyses showcased the model's ability to track and predict fluctuations in conditional variance, aligning closely with observed market volatility. Despite exhibiting promise, the model's performance metric, with an RMSE of 1725.26, suggested room for improvement. This metric highlighted potential discrepancies between predicted and actual conditional variances, indicating the need for refinement in model specification or parameter estimation.

    a) **Model Metrics**

        (1) The **root mean square error (RMSE)** for the GARCH model was calculated to be **1725.26**, indicating the average magnitude of errors between predicted and actual conditional variances.

2. **Figures and Visualizations**
   a) **Figure 1:**



The representation of the GARCH model exhibited a linear pattern similar to the actual data. However, a notable discrepancy was observed in the values predicted by the model compared to the actual data points. This discrepancy resulted in a deviation between the predicted and observed conditional variances, consequently affecting the overall accuracy of the model.

C. LSTM Model Performance:

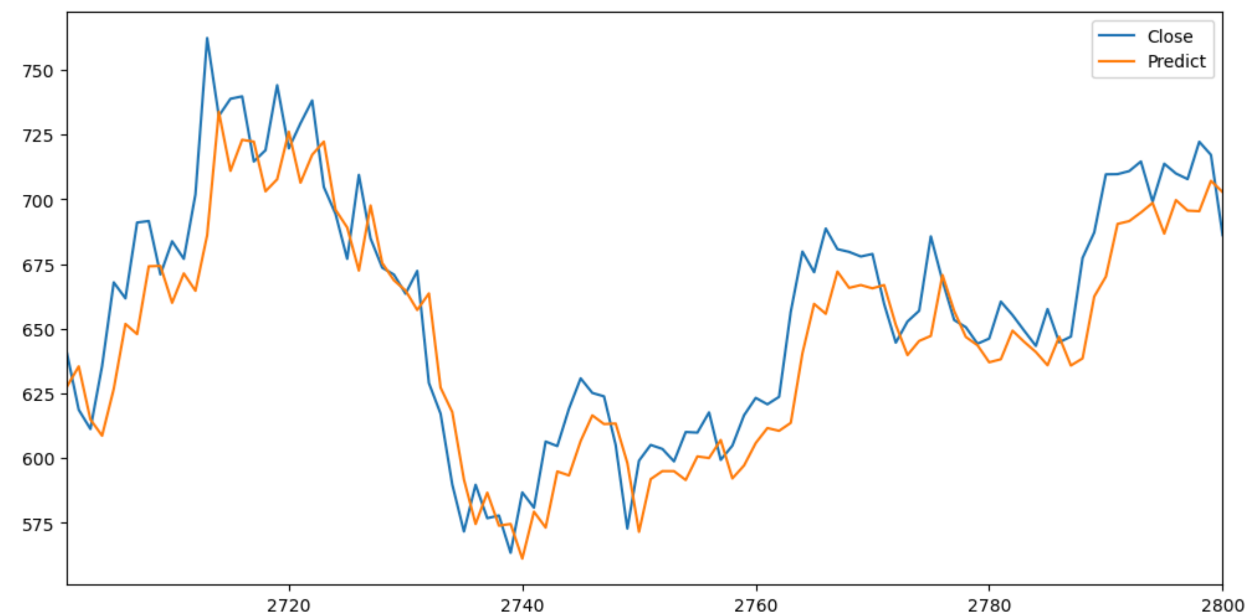
1. In contrast, the LSTM model emerged as a standout performer, marked by its remarkable alignment with actual stock price movements. Graphical representations depicted a close correspondence between LSTM predictions and observed data, underscoring the model's aptitude in capturing Tesla's volatile behavior. Furthermore, with an RMSE of 17.78, significantly lower than that of the GARCH model, LSTM demonstrated superior predictive accuracy. This metric affirmed the model's ability to effectively forecast conditional variance, offering valuable insights for volatility analysis and strategic decision-making.

   (1) Model Metrics

   (a) The **root mean square error (RMSE)** for the GARCH model was calculated to be **17.78**, indicating the average magnitude of errors between predicted and actual conditional variances.

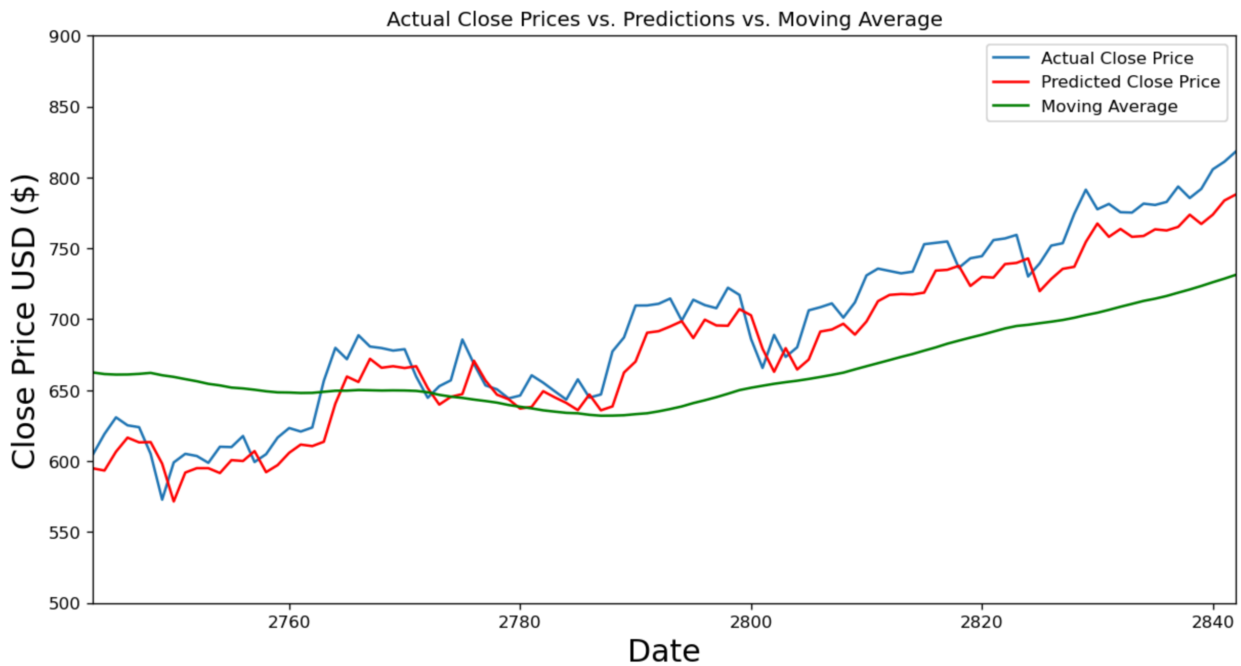
(2) Figures and Visualizations

(a) Figure 1:



Based on the graphical representation of the fitted predicted values overlaid on the actual values, it is evident that the LSTM model closely aligns with the actual data points, exhibiting the best fit among the models considered.

(b) Figure 2:



In the final step before selecting the model, we referred to the dummy variable model, represented by the moving average. Despite this reference, a visual confirmation was sought to ascertain the most suitable model fitting with the actual data. Upon careful examination, it became evident that the LSTM model outperformed the moving average and other models, demonstrating the closest alignment with the actual data points.

VI. Recommendations

A. Utilize LSTM Model:

1. In our analysis, we observed that while the GARCH model and moving average approach showed some predictive performance in forecasting volatility, the LSTM model emerged as the most suitable model for predicting the volatility of volatile stocks. The LSTM model's ability to capture complex patterns, nonlinear relationships, and temporal dynamics allowed it to outperform traditional econometric models like ARMA and GARCH in volatile market conditions. Therefore, for forecasting volatility in volatile stocks, the LSTM model is recommended due to its superior performance and ability to adapt to the intricate dynamics of volatile markets.

B. Explore External Factors:

1. To enhance predictive accuracy in volatility forecasting for Tesla's stock, one recommendation is to consider incorporating external factors such as market sentiment, news events, and macroeconomic indicators into the LSTM model. By integrating these variables, the predictive framework can be enriched, providing a more holistic understanding of the factors influencing Tesla's stock volatility. This augmentation of the model with additional data sources enables the capture of nuanced market dynamics, leading to improved predictive accuracy and more informed decision-making processes.

C. Continuous Model Evaluation:

1. Another crucial recommendation is the continuous evaluation and refinement of the LSTM model. Given the dynamic nature of Tesla's stock market behavior, ongoing assessment of the model's performance is essential. Regular monitoring of model outputs and

incorporation of new data allow for adjustments to be made, ensuring that the model remains adaptable to changing market conditions. This iterative approach facilitates the improvement of forecasting accuracy over time, empowering stakeholders to make strategic decisions based on reliable and up-to-date information.

VII. Further Research

A. **Model Ensembling:** Explore the possibility of ensembling multiple models, including LSTM, ARMA, and GARCH, to further enhance predictive performance.

B. **Feature Engineering:** Investigate additional features and data sources that could improve the LSTM model's ability to capture the underlying drivers of Tesla's stock volatility.

C. **Advanced Deep Learning Techniques:** Investigate advanced deep learning techniques beyond LSTM, such as attention mechanisms or transformer models, for volatility forecasting in financial markets.

VIII. Conclusion

A. The LSTM model demonstrates significant promise in accurately forecasting the volatility of Tesla's stock, offering valuable insights for risk management and strategic decision-making. By incorporating LSTM models into Tesla's stock analysis toolkit and continuously refining them, the company can better navigate the challenges posed by its volatile stock behavior.

	Close	Predict
2701	640.390015	627.708313
2702	618.710022	635.492310
2703	611.289978	614.966736
2704	635.619995	608.693298
2705	667.929993	626.781982
...	...	...
2838	785.489990	773.709961
2839	791.940002	767.195007
2840	805.719971	773.771484