Predictive Analysis of Tesla's Stock Closing Prices Utilizing LSTM and GRU Deep Learning Models

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Abstract: This study delves into advanced deep learning methods, namely Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), to predict Tesla's stock prices from 2013 to 2023, a period marked by notable market volatility. It aims to analyze these models' abilities in capturing complex financial trends, particularly in the rapidly evolving electric vehicle sector. The research employs a hybrid approach, combining LSTM and GRU layers to leverage their respective strengths in long-term and short-term forecasting. Methodologically, the study involves comprehensive data processing, model building, and validation using historical stock data from the Nasdaq platform. The models are evaluated through various statistical metrics, including RMSE, MSE, and MAE, to assess their predictive accuracy. The findings reveal that while GRU models excel in short-term forecasting, the hybrid model demonstrates stronger capabilities in long-term trend analysis. This suggests the need for tailored model selection based on specific forecasting timelines in financial markets. The study's implications extend to the practical application of LSTM and GRU models, recommending an integrated approach for more accurate and responsive market forecasting. It also highlights the potential for future research to incorporate real-time market data, enhancing the models' relevance and adaptability in a rapidly changing financial landscape.

1 INTRODUCTION

The pursuit of forecasting stock market trends has consistently intrigued numerous analysts and researchers (Shah et al 2019). Analyzing movements and price behaviors in the stock market is highly challenging due to its dynamic, nonlinear, nonstationary, nonparametric, and chaotic characteristics, coupled with inherent noise in the data (Abu-Mostafa and Atiya 1996). For investors, this predictive ability is crucial in planning investment portfolios and maximizing returns. For financial institutions and policymakers, accurate forecasts of stock prices are essential for a better understanding and management of market risks, as well as for formulating policies in line with economic trends. Throughout the years, both investors and researchers have shown keen interest in creating and evaluating models related to the behavior of stock prices (Fama 1970).

With increasing attention to climate change and the rapid evolution of electric vehicle technology, the new energy industry, led by electric vehicles, has rapidly developed and become a significant part of the stock market. As a leader in the electric vehicle and new energy industry, Tesla plays an important role in the global stock market. Particularly, the high volatility of Tesla's stock makes it an ideal case study for understanding and predicting dynamic market trends.

A notable characteristic of these new energy industries is the high volatility of their stock prices in recent years. As Pettinger pointed out, fluctuations in the stock market significantly influence both national economies and individual consumer finances, and a significant drop in stock prices can cause extensive economic disruptions (Pettinger 2023). Therefore, researching the prediction of Tesla's stock price is greatly beneficial for understanding the capital movements and investor sentiments in the clean energy market. The notable volatility of Tesla's stock prices in recent years underscores the importance of conducting a thorough analysis. This study aims to evaluate the effectiveness and adaptability of specific models in forecasting stock market trends, and hopes to provide a deeper understanding of future financial market trends by capturing the market dynamics and trends of Tesla's stock.

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Machine learning techniques have been extensively researched to automatically process a wealth of financial data, such as historical stock prices, thereby supporting investment decisions (Yoshihara et al 2014). In the realm of financial market prediction, especially in stock market forecasting, deep learning techniques such as LSTM and GRU have emerged as significant research tools. Touzani and Douzi, in the Journal of Big Data, demonstrate the application of LSTM and GRU in market forecasting, showcasing their potential in handling sequential data (Touzani and Douzi 2021). Moreover, a study by Gao et al. emphasized that traditional analysis methods fall short in addressing the complexities of stock market data, while LSTM and GRU exhibit superior predictive accuracy (Gao et al 2021). Soni et al. explored various techniques in stock price prediction, ranging from traditional machine learning and deep learning methods to neural networks and graph-based approaches (Soni et al 2022). Venkatarao et al. further contributed to this field by introducing a novel normalization approach in their study 'Stock Price Prediction by Normalizing LSTM and GRU Models,' underscoring the importance of optimizing these deep learning techniques for enhanced stock market prediction accuracy (Venkatarao et al 2023). Additionally, Mukherjee et al. employed deep learning algorithms for an in-depth prediction of stock market prices, achieving significant accuracy (Mukherjee et al 2023).

Long Short-Term Memory networks (LSTMs) and Gated Recurrent Units (GRUs) have garnered considerable attention due to their exceptional ability to handle sequential data, a crucial aspect in the complex field of stock price prediction. This study is dedicated to employing LSTM and GRU, two advanced deep learning techniques, to analyze and predict the stock prices of Tesla, Inc.

This study employs cutting-edge deep learning techniques, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), to analyze and forecast the stock prices of Tesla, Inc. Utilizing historical stock price data from November 29, 2013, to November 27, 2023, sourced from the Nasdaq platform, our approach innovatively combines both LSTM and GRU models. This methodology aims to leverage the unique strengths of each model for more accurate and robust predictions. The data selection focuses on recent years to capture the significant fluctuations in Tesla's stock, reflecting the evolving dynamics of the electric vehicle and clean energy sectors.

2 METHODS

2.1 Data Acquisition

The historical daily stock data of Tesla from November 29, 2013, to November 27, 2023, were downloaded from the Nasdaq platform. The data's scientific rigor and accuracy were validated against actual stock prices. The dataset comprises Date, Open, Close, Volume, High, and Low. Initial data visualization was conducted to check for consistency and outliers.

2.2 Data Visualization

The complete statistics of Tesla's stock prices over the period are crucial for our research on time series analysis. Therefore, understanding the changes in Tesla's stock prices from November 29, 2013, to November 27, 2023, is essential.

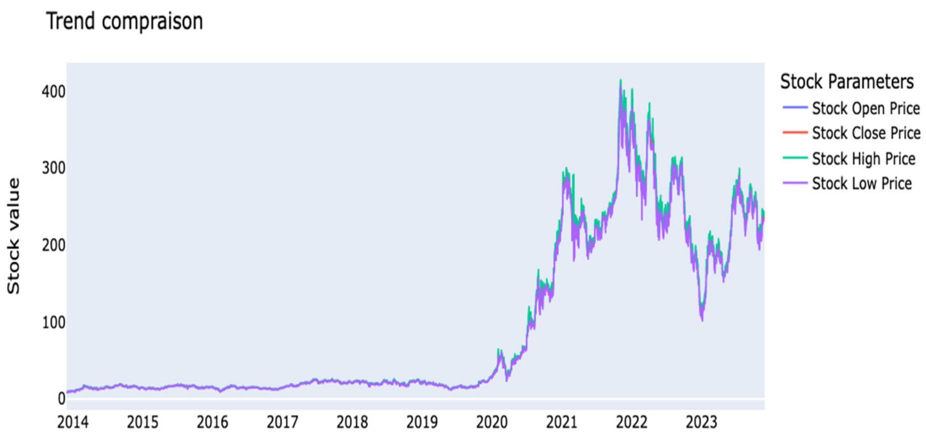

Figure 1: Stock Prices of TSLA (Picture credit: Original).

Fig. 1 illustrates the time series plot of Tesla's daily stock values, comprising Date, Open, Close, Volume, High, and Low. Observations from the monthly time series plot of Tesla's stock prices reveal key insights. Between 2013 and 2020, the stock price remained relatively stable, demonstrating a degree of steadiness. However, starting in 2020, a significant shift occurred as the stock price began to exhibit extreme volatility. Notably, from 2022 to 2023, there was an overall upward trend, with the stock reaching its peak in early 2022. Subsequently, a continuous decline was observed until the beginning of 2023. From early 2023 to the present, Tesla's stock price has gradually recovered but has shown strong fluctuations. Furthermore, no apparent seasonality or cyclical pattern was demonstrated in this time series plot. These observations not only highlight the dynamic changes in Tesla's stock price but also provide valuable perspectives for our time series analysis.

2.3 Data Cleaning and Selection

Data cleaning involved converting data types in the Date column, setting it as an index, and checking for null values. Given the continuity in stock closing prices, missing values were filled using the mean of adjacent days. Due to significant fluctuations in Tesla's stock price since 2020, only data post-January 1, 2022, were selected for model training and testing (Fig 2).

This subset of 478 data points was normalized to a range of 0-1. The data was then split into training (65%) and testing (35%) sets, and both sets were visualized (Fig 3).

Figure 2: Stock Prices of TSLA after 2022 (Picture credit: Original).

2.4 Model Building and Evaluation

Three models were built, trained, and evaluated: LSTM, GRU, and an innovative model combining LSTM and GRU layers. The models were assessed using RMSE, MSE, MAE, MGD, MPD, and regression R-squared coefficients for both training and testing sets. This analysis aimed to comparatively analyze the strengths and weaknesses of each model. The predictive performance of each model was visualized by plotting the predicted stock price trends.

2.5 Parameters Selection

LSTM, GRU and a combined models were selected. Parameters of these models were carefully chosen to ensure comparability across models (Table 1). All models were trained with 200 epochs, using MSE as the loss function, a batch size of 5, 32 nodes, and 'adam' optimizer. The LSTM model consisted of three LSTM layers, the GRU model of four GRU layers, and the innovative model of two LSTM layers followed by two GRU layers.

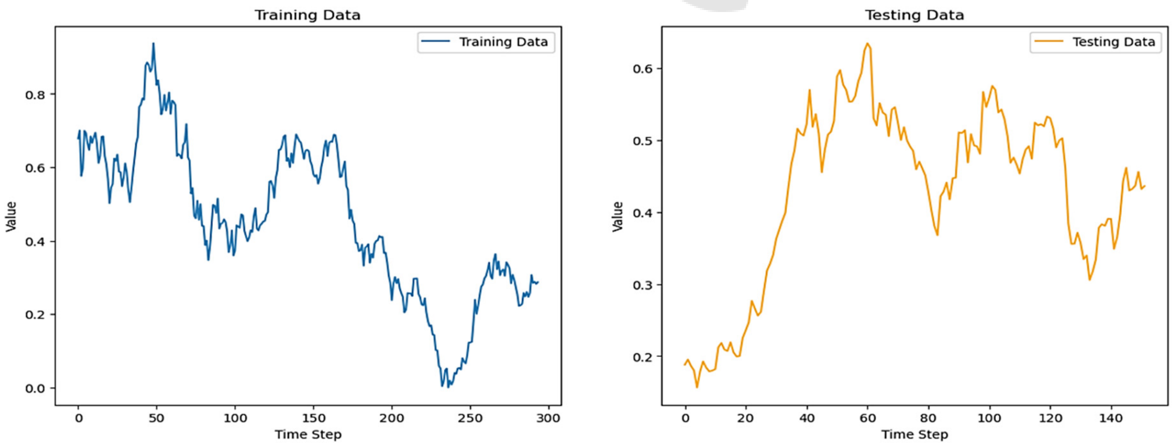

Figure 3: Normalized Training set and Testing Set (Picture credit: Original).

Table 1: Parameter Selection for Models.

Model	Parameter Selection
LSTM Epochs = 200 Batch = 5	loss = 'MSE' optimizer = 'adam' 3 LSTM layers with 32 nodes
GRU Epochs = 200 Batch = 5	loss = 'MSE' optimizer = 'adam' 4 GRU layers with 32 nodes
LSTM & GRU Epochs = 200 Batch = 5	loss = 'MSE' optimizer = 'adam' 2 LSTM and 2 GRU layers with 32 nodes

2.6 Assumption and Limitation

As shown in Table 2, the model is based on the following five assumptions to ensure its rigor.

Table 2: Assumption for Models.

Assumption	Contents
Market Efficiency Hypothesis	The stock market is semi-strong efficient, meaning all publicly available information is already reflected in the current stock prices.
Historical Trend Repetition Hypothesis	Historical price trends and patterns are assumed to recur to some extent in the future.
Locality of Market Influence Hypothesis	The primary factors influencing stock prices are assumed to be local and co
Ignoring Macro-Economic and Non-Structural Changes	Macro-economic factors and policy changes are not quantified in the model.
Non-Extreme Event Hypothesis	The prediction period is assumed not to include extreme market events like financial crises or significant political events.

The study primarily aimed to compare the regression and predictive performance of LSTM, GRU, and their combined model on a one-to-two-year time series of tesla stock. The study's limitations include a lack of consideration for various external factors affecting the stock market, making real-world applicability challenging. However, the approach is viable for comparing LSTM and GRU through statistical analysis and visualization, thereby supporting the research's conclusions.

3 RESULTS AND DISCUSSION

3.1 Performance Metrics

In this study, a comprehensive analysis was conducted on LSTM and GRU models for predicting Tesla's stock prices. Key findings include (table 3):

Table 3: Evaluation Metrics of Models.

	LSTM		GRU		LSTM and GRU	
Metrics	Train	Test	Train	Test	Train	Test
RMSE	9.8563	8.3645	9.5030	7.4402	9.0924	7.5828
MSE	97.1460	69.9655	90.3066	55.3569	82.6720	57.4990
MAE	7.5581	6.3781	7.4933	5.6884	7.1255	5.6682
MGD	0.0017	0.0012	0.0016	0.0010	0.0015	0.0010
MPD	0.3942	0.2899	0.3662	0.2342	0.3412	0.2396
R^2	0.9740	0.9447	0.9759	0.9563	0.9779	0.9546
EVR Score	0.9764	0.9481	0.9765	0.9574	0.9781	0.9560

In comparing the performance of LSTM, GRU, and the combined models, all displayed robust regression. GRU and the combined models demonstrated superior precision in predicting stock price fluctuations. Despite higher MSE and MAE in training, GRU showed more effective forecasting in testing.

3.2 Major Findings

Comparing the performance of LSTM, GRU, and the combined model, they all displayed robust regression. GRU and the combined model demonstrated superior precision in predicting stock price fluctuations. Despite higher MSE and MAE in training, GRU showed more effective forecasting in testing.

3.3 Minor Findings

The regression R-squared coefficients and explained variance analysis indicate that LSTM underperformed compared to GRU and the combined model in both training and testing phases. Overall, GRU excelled in forecasting Tesla's stock prices, particularly in testing, whereas the combined model showcased a robust predictive capacity.

3.4 Visual Comparison Results

As illustrated in Fig. 4, the closing stock prices of Tesla, exhibit significant fluctuations and lack clear patterns, indicating the challenging nature of accurately forecasting its stock prices.

Figure 4: Stock Close Price for Training and Testing (Picture credit: Original).

Following this, we visualized the regression results from three distinct models-LSTM, GRU, and a combined approach, and also depicted their predictions for the closing stock prices over the next ten trading days following November 27, 2023.

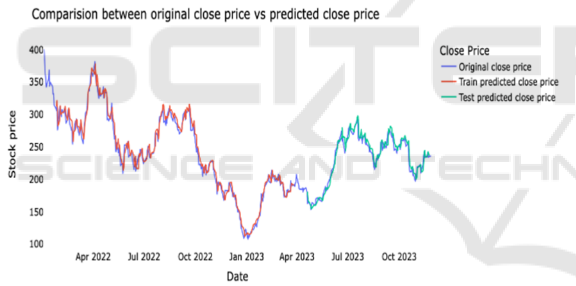

Figure 5: Comparison Between Original Close Price and Predicted Close Price for LSTM (Picture credit: Original).

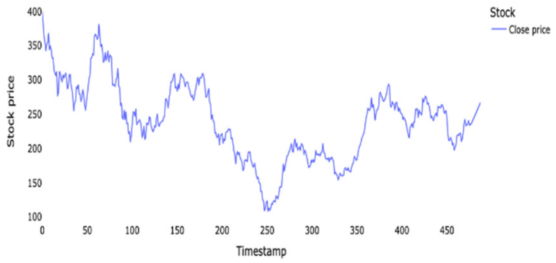

Figure 6: Whole Close Stock Price Chart with Ten-Day Predictions for LSTM (Picture credit: Original)

From Figure 5 and 6, it can be seen that the LSTM predicts an upward trend for the next ten days.

Figure 7: Comparison Between Original Close Price and Predicted Close Price for GRU (Picture credit: Original).

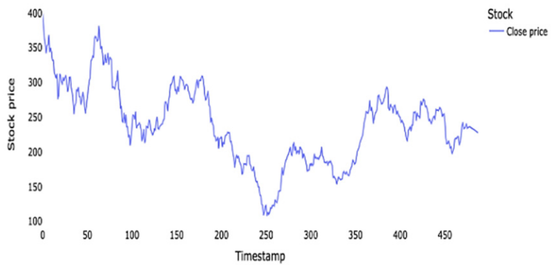

Figure 8: Whole Close Stock Price Chart with Ten-Day Predictions for GRU (Picture credit: Original).

From Figure 7 and 8, it can be seen that the GRU predicts a downward trend for the next ten days.

Figure 9: Comparison Between Original and Predicted Close Price for LSTM and GRU (Picture credit: Original).

Figure 10: Whole Close Stock Price Chart with Ten-Day Predictions for the Combined Model (Picture credit: Original).

From Figure 9 and 10, it can be seen that the combined model predicts an upward trend for the next ten days.

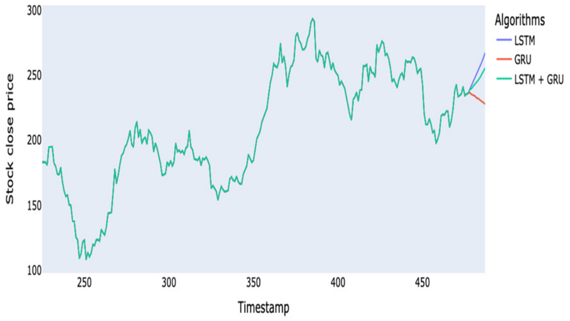

Figure 11: Comparison Chart of Ten-Day Future Stock Price Predictions (Picture credit: Original).

As illustrated in Figure 11, the LSTM and combined models predict an upward trend in Tesla's stock prices over the next ten days. Conversely, the GRU model anticipates a decline.

3.5 Discussion

Through the calculation of multiple statistical metrics, this study has proven the GRU model's high precision in short-term stock market forecasting. This aligns with the findings of Touzani and Douzi, who also emphasized the effectiveness of GRU in volatile market conditions. Additionally, the combined model has shown strong predictive power in long-term trend analysis, which is an innovative aspect of this study. The effectiveness of GRU in short-term predictions provides a strategic tool for navigating rapid market changes, while LSTM supports more extended-term investment. This offers insights for practical stock market applications based on the data range used in training models: the shorter the time, the more layers of GRU should be chosen; conversely, the longer the time, the more layers of LSTM should be selected. Firstly, a limitation is its reliance on historical data without real-time insertion of new data, which may hinder capturing real-time market dynamics. Secondly, the study's focus solely on Tesla's stock with a single data pattern might limit the model's general applicability across different market conditions. This study implies that when researching highly volatile time-series data, an appropriate ratio of GRU to LSTM should be chosen according to the time range. In the future, first, more market factor constraints should be added to enhance the model's predictive ability. Second, research could explore the combined model's capability in handling other stock data, such as fluctuation ranges, differences between closing and opening prices, etc., to help improve overall fitting accuracy.

4 CONCLUSION

In the comparative analysis of predicting Tesla's stock prices using LSTM and GRU models, this study has garnered profound insights. Not only did it affirm the effectiveness of these deep learning models in processing complex financial time series data, but it also explored their unique strengths in forecasting the highly volatile Tesla stock market.

The findings indicate that while both models demonstrated capability in capturing the essential trends and fluctuations of stock prices, they exhibited differences in specific areas. Notably, the GRU model showed enhanced performance in the testing phase, illustrating its superiority in real-world forecasting applications. Additionally, the innovative model combining LSTM and GRU layers, although not excelling in every performance metrics, showed robust predictive capacity overall. These discoveries highlight the potential of GRU and the combined models in volatile financial time series contexts.

In terms of visual comparison, the study presented regression results of past Tesla stock prices for all three models and predicted their closing stock prices over the next ten trading days. The outcomes revealed that both the LSTM and the combined LSTM & GRU models predict an upward trend for the next ten days, while the GRU model forecasts a downturn. This further confirms the distinct characteristics and advantages of different models in handling specific financial data.

In conclusion, this research not only demonstrates the significance of LSTM and GRU in stock market prediction but also offers new perspectives and methodological guidance for deep learning technology in financial time series forecasting. Furthermore, the study suggests that a combination of LSTM and GRU models might be particularly effective in predicting stock prices in highly volatile markets like Tesla's.

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