Application of Machine Learning and Deep Learning Algorithms on Stock Price Forecasting -The Case of Tesla

Siyu Yin[1,a,*]

[1]London of Political Science and Economics, London, WC2A 2AE, UK
a. yu5392020@163.com
**corresponding author*

Abstract: The application of mathematical models, such as ARIMA and the exponential smoothing model, has covered a wide range of financial analyses to meet the increasing demand for understanding financial assets. In spite of their efficiency, current works do face some cons due to poor fitness in dealing with a large amount of dataset pf high dimensionality. Also, accompanying the US presidential election, Tesla company has always become a hot spot. This paper collects the past 14 years historical data and proposes adoption of appropriate machine learning(Lasso, Random Forest and XgBoost) and deep learning models (RNN and LSTM) in the field of forecasting Tesla stock price and its volatility; adapt the parameters to achieve the best goodness of fit and incorporate the alternative factors, such as political indicators to better capture the complex shocks and jumps in realized volatility; and present how these models outperform traditional mathematical models. The evaluation of the model is done using the root mean squared error (RMSE) , Mean square error (MSE) and R square metrics.

Keywords: Machine learning application, Deep learning models, Stock volatility forecasting, LSTM.

1. Introduction

Tesla is the world's largest new energy vehicle company. From the perspective of business modules, Tesla's revenue mainly comes from five aspects: car sales, car leasing, policy subsidie, energy production and storage, services and others. At present, new energy vehicles are the development trend of the automobile industry, facing the deteriorating global environment. Moreover, through the recent US presidential election, the value of Tesla's stock has become a major focus for investors due to Elon Reeve Musk's big bet on the former president Donald Trump's candidacy.

The influence of macroeconomic and political policies on Tesla is enormous. The financial crisis of 2008 and Tesla's refusal to list its shares was certainly a huge shock to Tesla, which further led to financial problems. Tesla has since recovered from the crisis by taking strict cost-cutting measures and increasing marketing initiatives. However, it is worth noting that Tesla's car deliveries did not drop significantly during the COVID-19. After the announcement of the US new presidential election, Tesla stock price reached a 14.5%rise since the last market close.

In tradition, researchers often adopt fundamental and technical techniques to conduct the stock analysis. The fundamental analysis evaluates a company's stock by examining its intrinsic value (Financial Analysis), including tangible assets, financial statements, management effectiveness;

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essentially all the basics of a company. It relies on both historical and present data to measure revenues, assets, costs, liabilities, and so on. La Porta, Shleifer, and Vishny provide evidence in support of the value investing strategy, which relies heavily on fundamental analysis. [1]. The authors argue that stocks with low price-to-book ratios tend to outperform growth stocks, suggesting that fundamental indicators are valuable in identifying undervalued stocks. Piotroski introduces the Piotroski FScore for evaluating the financial health of companies[2]. The F-Score focuses on a set of fundamental indicators that can help investors identify companies with strong growth potential and low risk of financial distress. On the other hand, due to the efficient market hypothesis which claims that stock movements are not a stochastic process but reveal repeated patterns over time, the technical analysis study prices movements through analyzing historical data, such as the moving average. Lo, Mamaysky, and Wang offer a detailed exploration of technical analysis from a computational and statistical perspective, touching upon how technical indicators are combined with fundamental factors for stock price forecasting[3].

Businesses in the finance sector increasingly rely on data-driven decision-making. As the field of machine learning evolves, there will be new opportunities to apply machine learning skills in the finance sector.

This research highlights the promising results of specific machine learning methods for time-series forecasting in the case of Tesla. Here, this paper will primarily construct machine learning models and the deep learning machines to forecast the Tesla stock price and volatility from the past historical data, also, compare ML-based approaches and traditional ones in order to discuss which method could be more effective considering the arbitrage opportunity in Tesla.

2. Literature Review

Fama postulates the efficient market hypothesis, which states that the current price of an asset swiftly reflects all prior available information[4]. Additionally, the random walk hypothesis asserts that a stock price changes independently of its historical prices[5]. These two hypotheses indicate that reliable methods for predicting stock prices do not exist.

Later, Elman proposed a Recurrent Neural Network (RNN)[6]. The Long Short-Term Memory (LSTM) algorithm, introduced by Hochreiter and Schmidhuber, aims to enhance performance by addressing the gradient vanishing problem that recurrent networks face when dealing with long sequences of data. Huang and Yang explore the utilization of machine learning models, particularly support vector machines (SVM), for forecasting stock price volatility, and compare traditional econometric models with machine learning approaches, demonstrating the effectiveness of the latter in predicting volatility more precisely.[7]. Krauss and Huck investigate application of deep neural networks (DNNs), gradient-boosted trees, and random forests in predicting stock price movements and volatility [8]. The authors find that deep learning models can provide better results for forecasting compared to traditional models. Dai adopted the Random Forest model to forecast the Tesla stock price compared to linear regression, which demonstrates that the linear regression outperforms well[9]. A previous study has also tested the LSTM accuracy in predicting the trend in the stock market[10]; Rigamonti investigates that the machine learning model shows predictive power and that its performance greatly increases when feature selection is performed[11].

3. Data

This paper collects the Tesla data from Wind, the dataset includes 14 years of data from 2010/06/07-2024/09/01 containing 9 features: open, high, low volume, GDP, unemployment rate, Musk's Twitter retweets, Twitter comments, US presidential election votes as shown in Table 2, and over 30 thousand instances. The dataset is split into both training and testing samples as shown in Table 1 and set The

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sliding window is 10 days. Then, this paper merges the dataset to fill the gap and scale the target data. Target data are primarily Tesla daily stock close price, and its daily realized volatility as shown in equation 1.

Table 1: Data Splitting

Dataset	Training Dataset	Testing Dataset
2010/06/07-2024/08/23	2016/06/07-2024/12/31	2024/01/01-2024/09/01

Table 2: Input Variables

Technical and Macroeconomic Indicators	Political Indicators
Open/High/Low/Volume	Musk's Twitter retweets/comments
GDP/Unemployment Rate	Election Votes

According to Hansen and Lunde (2005), the realized Volatility is:

$$RV_t = \frac{N^{-1}\sum_{t=1}^{N} R_t^2}{N^{-1}\sum_{t=1}^{N} RV_t}\sum_{d=1}^{n} R_{t,d}^2 \tag{1}$$

4. Models and Methodology

Enlightened by previous studies, the supervised models appear to be massively adopted in stock forecasting. In this study, the Lasso, Random Forest and XgBoost models come into use. Besides, this paper adopts Recurrent Neural Network and Long Short-Term Memory to further capture the shocks in volatility. Last, this research combines the Geometric Brownian Motion with the Heston model to relatively test the stochastic process of Tesla stock close price and realized volatility.

4.1. Supervised Models

LASSO model:

$$L(\omega) = \left||X\omega - Y|\right|^2 + \alpha\sum_{j=0}^{m}\left|\omega_j\right| \tag{2}$$

$$\omega = \left(X^T X\right)^{-1}\left(X^T Y - \frac{\alpha}{2}C\right) \tag{3}$$

Lasso improves the OLS regression by adding the L1 regularization term, here, the X and Y are relatively our input variables and target features as previously stated. ch features could be input to this model.

Random Forest-Bagging:

$$f(x) = \frac{1}{M}\sum_{m=1}^{M} f_m(x) \tag{4}$$

This model draws random sample and features from the assigned forest based on our parameters.

XgBoost model:

$$Obj^{(t)} = \sum_{i=1}^{n} L\left(y_i, y^{(t)}\right) + \sum_{i=1}^{t}\omega(f_i) \tag{5}$$

$$= \sum_{i=1}^{n}\left(L\left(y_i, y^{(t-1)}\right) + f_t(x_i)\right) + \sum_{i=1}^{t}\omega(f_i)$$

$$= \sum_{i=1}^{n}\left(L\left(y_i, y^{(t-1)}\right) + f_t(x_i)\right) + \sum_{i=1}^{t}\omega(f_i) + C \tag{6}$$

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As an optimized gradient boosting model, here the grid search is utilized to optimize hyper parameters for better model performance.

4.2. Deep-learning Models

Recurrent Neural Network:

$$\begin{gathered} a^{(0)} = 0 \\ a^{(1)} = g_1\left(W_{aa}a^{(0)} + W_{ax}X^{(1)} + b_a\right) \\ \vdots \\ a^{(t)} = g_t\left(W_{aa}a^{(t)} + W_{ax}X^{(t)} + b_a\right) \\ y^{(t)} = g_t\left(W_{ya}a^{(t)} + b^y\right) \end{gathered} \tag{7}$$

After integrating the parameter matrices, the equation concludes to:

$$\left[a^{(t-1)}, x^{(t)}\right] = [W_{aa}, W_{ax}][\begin{matrix} a^{(t-1)} \\ x^{(t)} \end{matrix}] \tag{8}$$

Long Short-Term Memory:

$$c^{(t)} = \tanh\left(W_c\left[a^{(t-1)}, x^{(t)}\right] + b_c\right) \tag{9}$$

$$g_u = \sigma\left(W_u\left[a^{(t-1)}, x^{(t)}\right] + b_u\right) \tag{10}$$

$$g_f = \sigma\left(W_f\left[a^{(t-1)}, x^{(t)}\right] + b_f\right) \tag{11}$$

$$c^{(t)} = g_u \cdot c_c^{(t)} + g_f \cdot c^{(t-1)} \tag{12}$$

4.3. Traditional Mathematical Models

Geometric Brownian Motion: the principle of GBM satisfies the standard differential equation,

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{13}$$

Applying Itô's Calculus,

$$d(\ln S_t) = (\ln S_t)' dS_t + \frac{1}{2}(\ln S_t)'' dS_t \tag{14}$$

$$\ln\frac{S_t}{S_0} = \left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t \tag{15}$$

To improve the precision of stochastic volatility forecasting, the Heston Model is introduced to GBM:

$$d\sqrt{\sigma_t} = -\theta\sqrt{\sigma_t}dt + \delta dW_t^{\sigma} \tag{16}$$

(W_T^S) and (W_t^{σ}) are correlated with (ρ).

5. Result and Analysis

To Forecast the Tesla stock price and realized volatility, first, this project conducts a basic descriptive analysis and an auto-correlation test.

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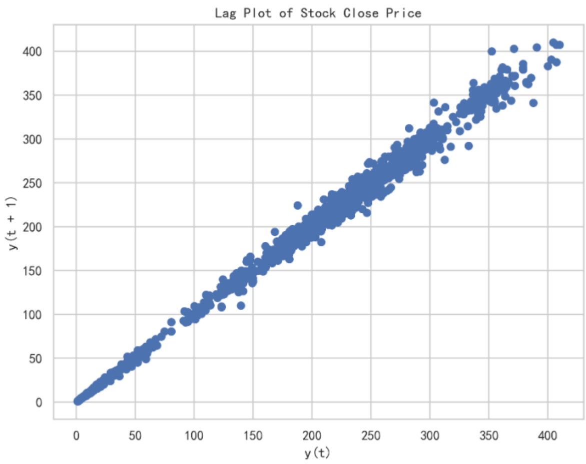

Figure 1: lag plot

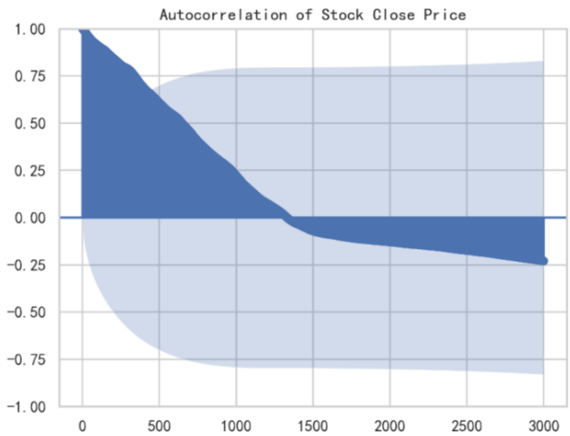

Figure 2: auto correlation plot

From the graphs below, the result demonstrates that the historical Tesla stock close price is highly autocorrelated which do not follow the stochastic process. The residual shows high volatility after COVID-19 and 2024 US presidential election; and the stock return follows standard normal distribution.

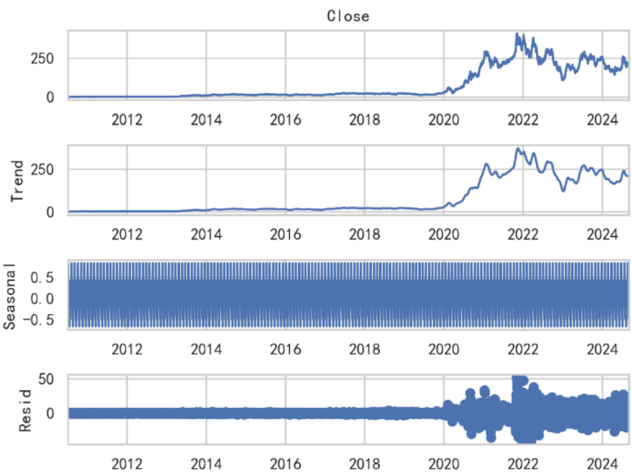

Figure 3: decomposition plot FIG

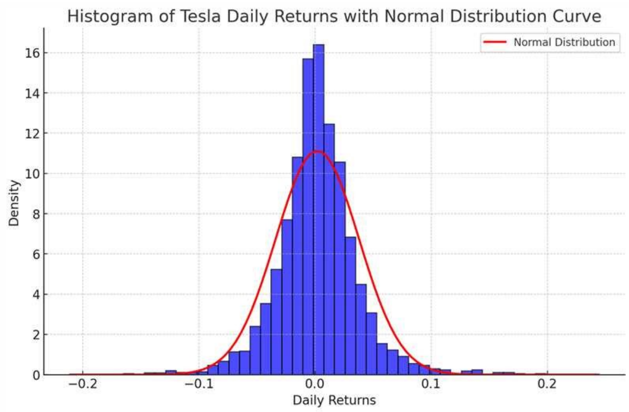

Figure 4: histogram of Tesla daily return

The forecasting findings on testing samples indicate that both supervised models and deep learning methods generally align well with stock prices. LSTM and RNN models reflect higher residuals in volatility forecasting. Lasso, RF and XGboost model couldn't capture the shocks and jumps in volatility.

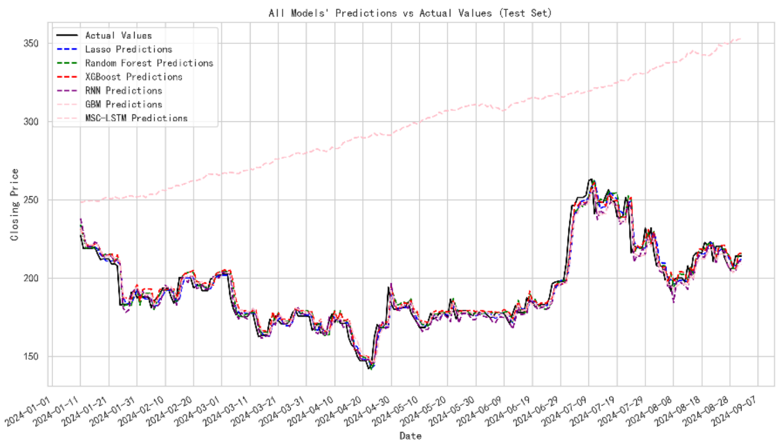

Figure 5: Models prediction on close price

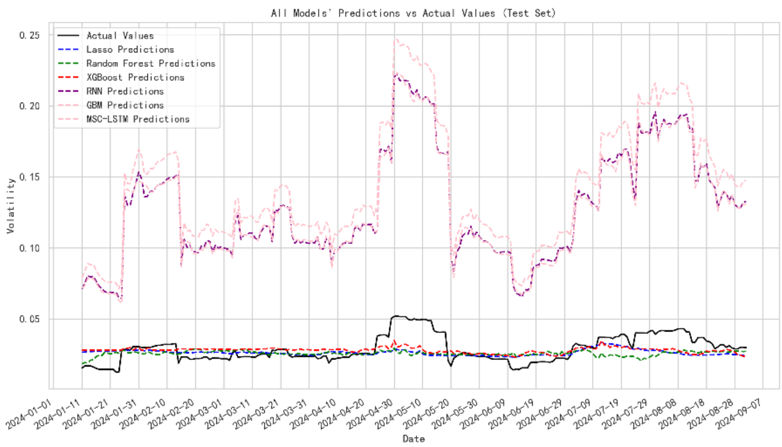

Figure 6: Models prediction on volatility

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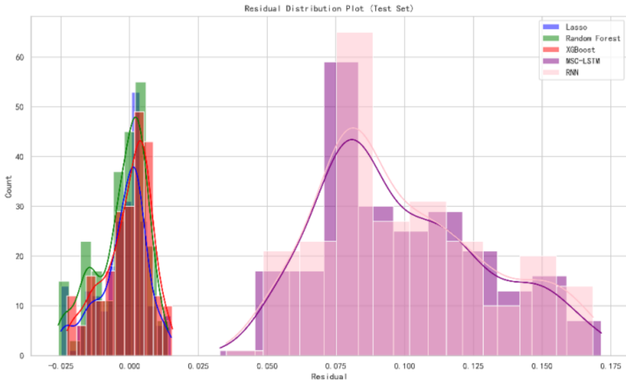

Figure 7: residual distribution on testing sample

In contrast, the Geometric Brownian Motion based on Monte Carlo simulations in which this project simulates 100 paths tends to overestimate the predicted stock price, which shows poor goodness of fit on the stock price. Despite introducing Heston model on realized volatility forecasting, the volatility reverts to its mean and reflects no fluctuation as shown in figure 9.

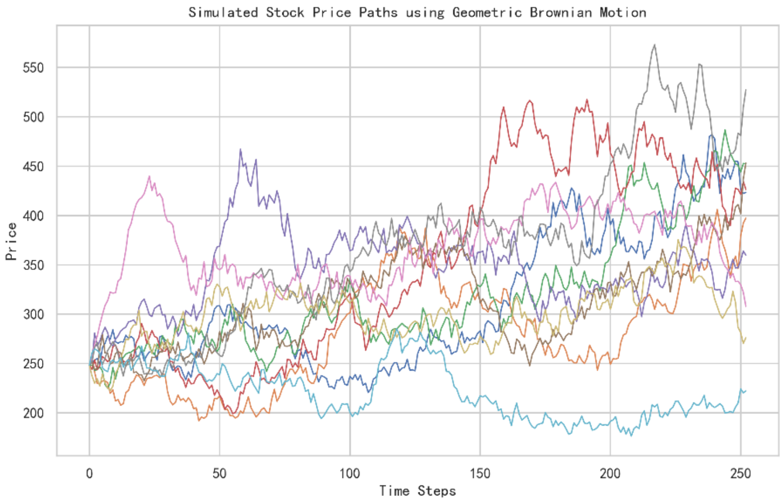

Figure 8: GBM simulation paths

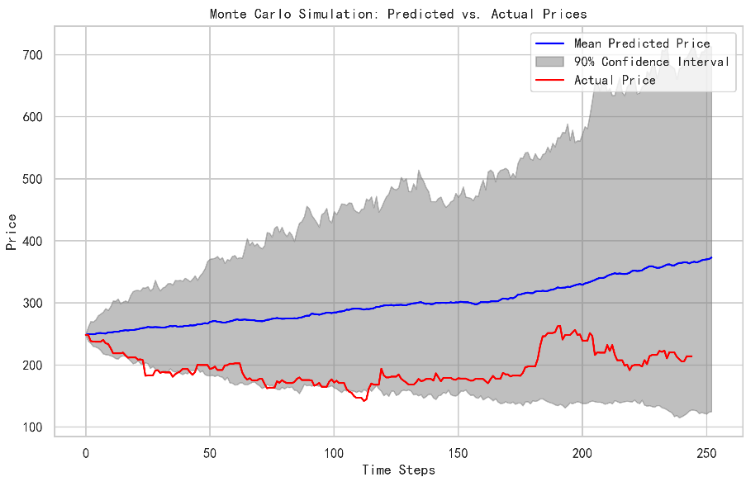

Figure 9: GBM prediction vs actual price

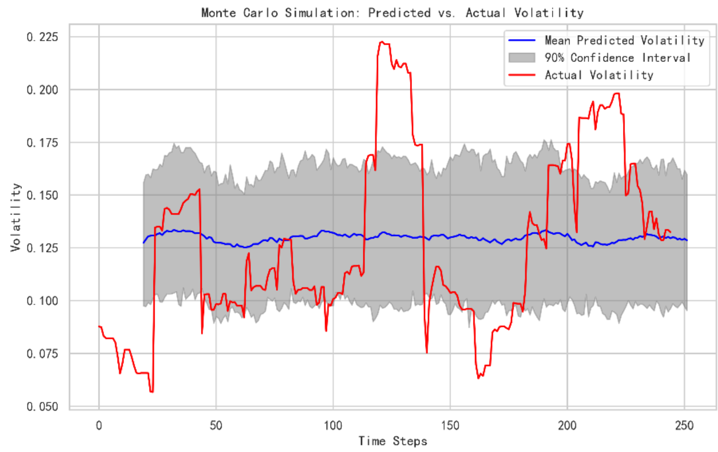

Figure 10: GBM prediction on volatility vs actual price

Table 3: Model Evaluation Metrics on Stock Price

Model	MAE	MSE	RMSE	R square
Lasso	4.15	41.08	6.41	0.94
Random Forest	4.43	42.35	6.51	0.93
XGBoost	4.61	43.39	6.59	0.93
MSC-LSTM	4.81	46.17	6.8	0.927
RNN	4.58	43.43	6.6	0.93

Table 4: Evaluation Metrics on Volatility

Model	MAE	MSE	RMSE	R square
Lasso	0.006	0.000086	0.0095	0.02
Random Forest	0.0073	0.000096	0.0098	-0.10
XGBoost	0.007	0.000078	0.0088	0.107
MSC-LSTM	0.098	0.010	0.103	-121
RNN	0.099	0.010	0.104	-123

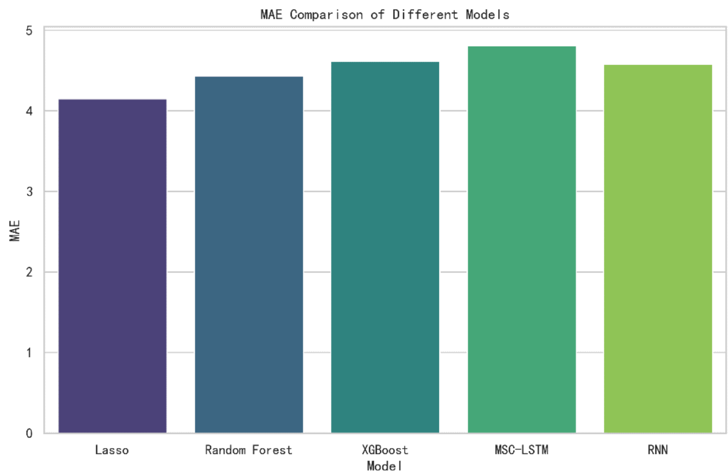

Figure 11: MAE comparison of machine and deep learning models

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6. Evaluation

Based on Evaluation metrics on close price fore- casting the results support that the Lasso model performs the best due to the smallest residuals in each metrics. The R square of LSTM indicates the slightest error compared to other model. In terms of forecasting realized volatility, all models demonstrate underfit-ting since they are not capable of capturing the short-term shocks and jumps driven by events and news.

7. Conclusion and Future Outlook

In conclusion, the Lasso model achieves the best goodness of fit. To improve the fitness of Deep Learning models, this paper can introduce a new scale parameter to adapt the realized volatility which can be digged further in my future research.

$$\mathrm{RV}_t^* = \lambda_0^* \mathrm{RV}_t^*$$

$$\lambda^0 = \frac{N^{-1}\sum_{t=1}^{N} R_t^2}{N^{-1}\sum_{t=1}^{N} \mathrm{RV}_t} \tag{17}$$

Also, future research could incorporate the Jump diffusion model in volatility forecasting to effectively capture the fluctuations in the stochastic process of the stock price. Moreover, the features applied in the models are far from sufficient. Any more unstructured data, such as text, audio, and images about Tesla and the company's events, could demonstrate the feasibility of analytical applications on the stock price.

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