Forecasting US Stock Prices Through Sentiment Analysis and Machine Learning

–A Case Study of Tesla Inc.

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Abstract: The financial sector is characterized by high volatility, and the accurate forecasting of stock prices is an actively pursued area of research and analysis. This study extends the scope of machine learning techniques, such as Artificial Neural Networks and fuzzy-based techniques, to enhance the precision of stock price predictions. The central focus of this research is algorithmic trading, which combines various qualitative factors in stock buying and selling decisions. More specifically, this study delves into the unique relationship between Elon Musk's tweets and Tesla's stock value. To identify patterns in the pre-processed dataset, which has had stop words removed, exploratory data analysis is used as the primary research methodology. The study conclusively demonstrates that a positive correlation exists between the number of tweets/engagements and Tesla's closing price, and this correlation holds true in reverse: a decrease in tweets/engagements corresponds with a decrease in Tesla's closing price. This research has broader implications for macroeconomic analysis of the US stock market by highlighting the role of technology and innovation in financial markets, as well as the importance of data-driven approaches in economic research.

Keywords: stock market, Tesla stock , BP Neural Network Model, LSTM

1. Introduction

The stock market itself has a variety of attributes as a commodity, currency, and safe-haven asset, and it always plays an important role in international asset allocation. As a prominent player within the stock market, Tesla stock has become increasingly interdependent with the broader market in recent years. In addition, it is also suitable for hedging general uncertainty in post-pandemic markets. [1]. Therefore, in order to balance risk, earnings, and liquidity in a complex market environment, research and forecasting of both the stock market and Tesla stock price trends as hedges against the uncertainty of financial assets is highly meaningful, and this paper aims to explore this topic further. [2] . Thus, in order to balance risk, earnings and liquidity in a complex market environment, Research and forecasting as a hedge against the uncertainty of financial assets - Stock market and tesla stock price trends is very meaningful and is the direction of discussion in this paper.

In recent years, a growing number of experts and scholars have conducted extensive research based on Stock market and tesla stock predictions. The traditional model is flawed on the prediction of the price of Stock market. Liu Chengjun and others combined Markov theory and improved the grey one Markov composite model, better prediction of the price of Stock market over the next three years. [3] Stock market price forecasts based on WT-SVR and EMD-SVR models indicate empirical modal decomposition (EMD) has higher predictive accuracy than wavelet transform [4]. OG Darley and other studies have found a combination of significant coefficients and ARIMA values of volatility, red pool information quantity criterion and beth information quantity criterion Model accuracy up to 84.75%. Klein and others developed a BEKK-GARCH model [5] to estimate time-varying conditional correlation and showed that tesla stock has fundamentally different properties from Stock market when used as an asset [6]. Bouri and others tested the effectiveness of tesla stock as a hedge against Stock market based on a DCC model and showed that tesla stock is more suitable for diversification purposes in most cases [7]. Dyhrberg analyzed the relationship between tesla market and the U.S. dollar based on a GARCH model and showed that tesla stock is categorized between Stock market and the U.S. dollar [8]. Henriques and Sadorsky applied DCC, ADCC and GO-GARCH models to investigate the substitutability of tesla stock for Stock market in investment portfolios and found that it is possible to substitute tesla stock for Stock market in portfolios and obtain higher risk-adjusted returns [9]. Wuyi Ye et al. investigated the dynamic covariance between Stock market and tesla stock based on a semi-parametric MIDAS quantile point regression model [10].

With the above literature, we recognized the different properties of Stock market and tesla stock when used as assets. It is also because they have different properties that allow a portfolio of Stock market and tesla stock to balance risk, return and liquidity in a complex market environment and also as a financial asset to hedge against uncertainty in a complex environment. Therefore, as traditional investment assets and emerging investment assets, Stock market and tesla stock respectively, it seems very meaningful to study the portfolio problem between Stock market and tesla stock, which is exactly the direction of the research discussion in this paper.

In the process of analyzing the attachment data, we use Hermite interpolation to complete the daily price data of Stock market missing. Then map the trend of Stock market and tesla stock prices in recent years to have a preliminary understanding of the characteristics of the two currencies. At present, the GRU, RNN, and LSTM methods are considered to be the three best ways to get forecast tesla stock prices [11] , The nonlinear model established by BP neural network has higher prediction accuracy [11] . This paper selects BP neural networks and LSTM models for prediction, using data from 2009 to 2021, to compare which models perform better in this study. Our diagrams visually reflect the comparison of daily price forecasts and true daily price values with trends over the five-year trading period (2016-2021), the BP neural network model and the LSTM model. At the same time, the Spearman correlation coefficient is used to calculate the fitting degree of the data and the real values obtained by different model predictions.

2. Literature review

Before conducting a quantitative analysis of U.S. stock market trading, we examined the existed literature. In fact, researchers have been conducting studies related to the macro influences on stock

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market trading for decades. Eugene F. Fama examines the relationship between stock returns, real activity, inflation, and money, and explores how these macroeconomic factors affect the stock market [12]. Andrew Ang and Geert Bekaert examine the predictability of stock returns and analyze the relationship between macroeconomic variables and stock returns [13]. Cochrane argues that dividend growth must be predictable when returns are not, analyzes the relationships between a range of macroeconomic variables and stock market returns, and explores how these relationships can be used for stock market forecasting [14]. John Y. Campbell and Robert J. Shiller examine the relationship between dividend price ratios and expectations of future dividends and discount factors, and analyze how these factors affect stock market forecasts [15]. Pesaran and others examine the predictability of stock returns and explore their practical implications for the economy and the role of macroeconomic variables in forecasting stock markets [16]. Goyal and others examine the empirical performance of stock return forecasting from several perspectives and analyze the contribution of macroeconomic variables in predicting the stock market [17].

We found that changes in policy regimes and investor sentiment in credit markets can also affect stock market exchanges. Kritzman M. and others examines the impact of changes in policy regimes, including Fed rate hikes, on dynamic investment strategies and how these changes can be used to optimize stock portfolios [18]. López-Salido D. and others examines the relationship between credit market sentiment and business cycles and how this relationship affects the stock market [19].

3. Data Analysis

3.1. Data collection

We have gathered essential data for this analysis, including detailed information on Tesla's Opening, Closing, Day High, Day Low, and Adjusted Closing prices. The data spans from January 1, 2017, onwards. Additionally, we have incorporated an analysis of Elon Musk's tweets to evaluate their impact on TSLA stock prices. Using APIs, we extracted tweets from Elon Musk's Twitter account (@elonmusk) and conducted Sentiment Analysis on tweets starting from December 2, 2018. The main reason for selecting Tesla Inc. as the focus of this study is its high volatility, primarily driven by the tweeting patterns of its CEO, Elon Musk.

3.2. Data Preprocessing

In the case of 10 deletions in the given Stock market price data, we chose to use the segmented three-time Hermite interpolation polynomial based on the known Stock market price data (PCHIP) [20] and cubic spline interpolation . Processing and analysis, i.e. using some mathematical methods to simulate the generation of 10 new but more spectral values to achieve the need to reduce subsequent errors. Comparing the results of the two interpolation algorithms, we found that the values obtained by the two interpolation algorithms are similar. After the comparison, we chose the data obtained by the segmented three-time Hermite interpolation prediction as supplementary data for the missing Stock market price data.

3.3. Trend Analysis and Data Visualization

In order to better discover the market rules of Stock market and tesla stock on a long scale in order to make optimal decisions later, we will collect all the Stock market and tesla stock daily price data (Supplementary data obtained through interpolation algorithms) The drawing statistics were made and the following Figure 1 was obtained.

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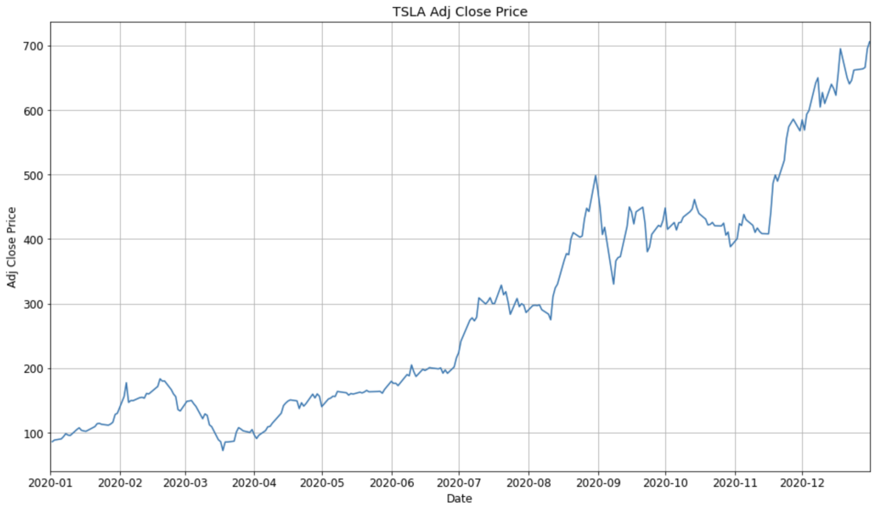

Figure 1: Trend analysis of Tesla stock

The Scikit-learn package in Python was used to categorize each tweet on Twitter into one of three categories: positive, neutral, or negative, based on its anticipated emotional language. The tweets were pre-processed and sourced from the CSV file's text column for machine learning purposes. This analysis enabled us to establish a connection between Musk's online sentiments and potential changes in Tesla's stock market, allowing us to further investigate our hypothesis.

Figure 2: sentiment analysis of the tesla stock model

By visualizing the data and analyzing the resulting graphs, We found that 2009 was too far from the current interval. Has a low reference value, and the standard deviation and fluctuations of previous tesla stock are relatively large. Adding this part of the data may affect the universality of the model, potentially reducing the accuracy of the forecast values. Choose from the later BP neural network prediction model and the LSTM model to discard the pre-2009 tesla stock daily price data.

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4. Methodology

BP neural network is a multi-layer feedforward network trained by error propagation algorithm. It has the advantages of simple network topology, high error accuracy and high maneuverability. At present, there are quite a few studies using and improving BP neural networks to model, such as forecasting stock market gains and losses, Predicting short-term gas loads using BP neural networks optimized by genetic algorithms [21] And accurate short-term load prediction based on RSBP (STLF) [22] . The BP neural network can learn and store a large number of input-output pattern mapping relationships (Figure 3) without prior disclosure of mathematical equations describing such mapping relationships. Its learning rule is to use the fastest descent method, through reverse propagation to continuously adjust the weights and thresholds of the network end, so that the error squares of the network and the minimum.

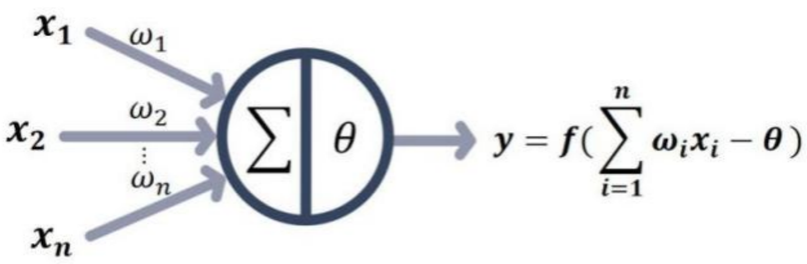

Figure 3: Mapping Relation of BP Neural Network

The topology of the BP neural network model includes input, hidden, and output layers corresponding to LayerL1, LayerL2, LayerL3 in Figure 3. In this model, neurons receive input signals from other n neurons, which are weighted during transmission. The total input received by the neuron is compared to the threshold of the neuron and then processed by the Excitation Function to produce the output of the neuron. Multiple neurons are interconnected to form a nested, specific network structure of several functions (e.g.y=f($\sum_1^n \omega_i - \theta$)).

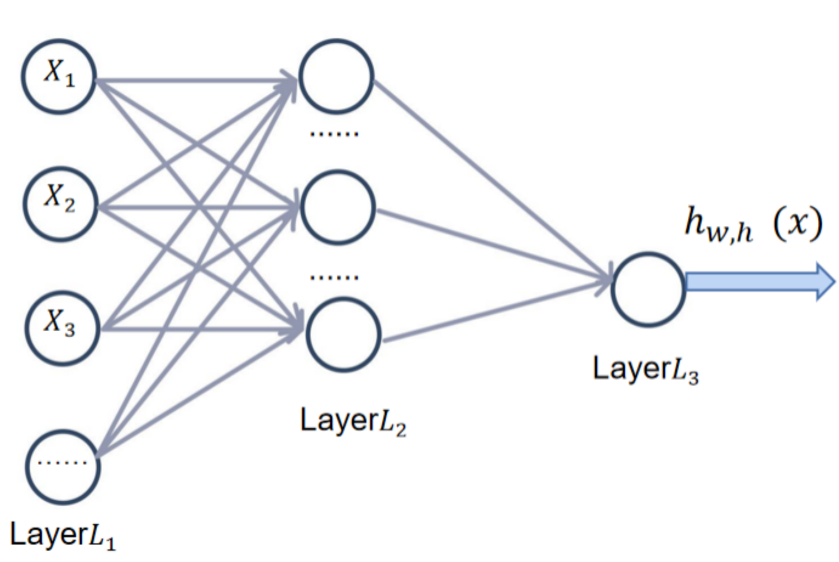

Figure 4: Topology of BP Neural Network Model

To summarize it from math perspective, it consists of the following process:
Forward pass process:

$$\text{Input layer:} \quad a^{(0)} = x$$
$$\text{Hidden layers:} \quad z^{(l)} = w^{(l)}a^{(l-1)} + b^{(l)}, \quad a^{(l)} = \sigma(z^{(l)})$$
$$\text{Output layer:} \quad z^{(L)} = w^{(L)}a^{(L-1)} + b^{(L)}, \quad \hat{y} = \sigma(z^{(L)})$$

Backward pass process:

$$\text{Output layer:} \quad \delta^{(L)} = \frac{\partial C}{\partial z^{(L)}} \odot \sigma'(z^{(L)})$$
$$\text{Hidden layers:} \quad \delta^{(l)} = ((w^{(l+1)})^T \delta^{(l+1)}) \odot \sigma'(z^{(l)})$$
$$\text{Compute gradients:} \quad \frac{\partial C}{\partial w^{(l)}} = \delta^{(l)}(a^{(l-1)})^T, \quad \frac{\partial C}{\partial b^{(l)}} = \delta^{(l)}$$

Weight update equations using gradient descent:

$$\text{Update hidden layers:} \quad w^{(l)} \rightarrow w^{(l)} - \eta\frac{\partial C}{\partial w^{(l)}},$$
$$b^{(l)} \rightarrow b^{(l)} - \eta\frac{\partial C}{\partial b^{(l)}}$$
$$\text{Update output layer:} \quad w^{(L)} \rightarrow w^{(L)} - \eta\frac{\partial C}{\partial w^{(L)}}$$
$$b^{(L)} \rightarrow b^{(L)} - \eta\frac{\partial C}{\partial b^{(L)}}$$

4.1. The Establishment of BP Neural Network Model

The essence of the problem is to find out the mapping of time indicator sets to Stock market and tesla stock daily value indicators, and to predict the mapping of future time to indicators Stock market and

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tesla stock daily price indicators. To do this, we consider using BP neural networks to achieve this mapping relationship. The basic process for establishing a BP neural network can be expressed by Figure 5 as :

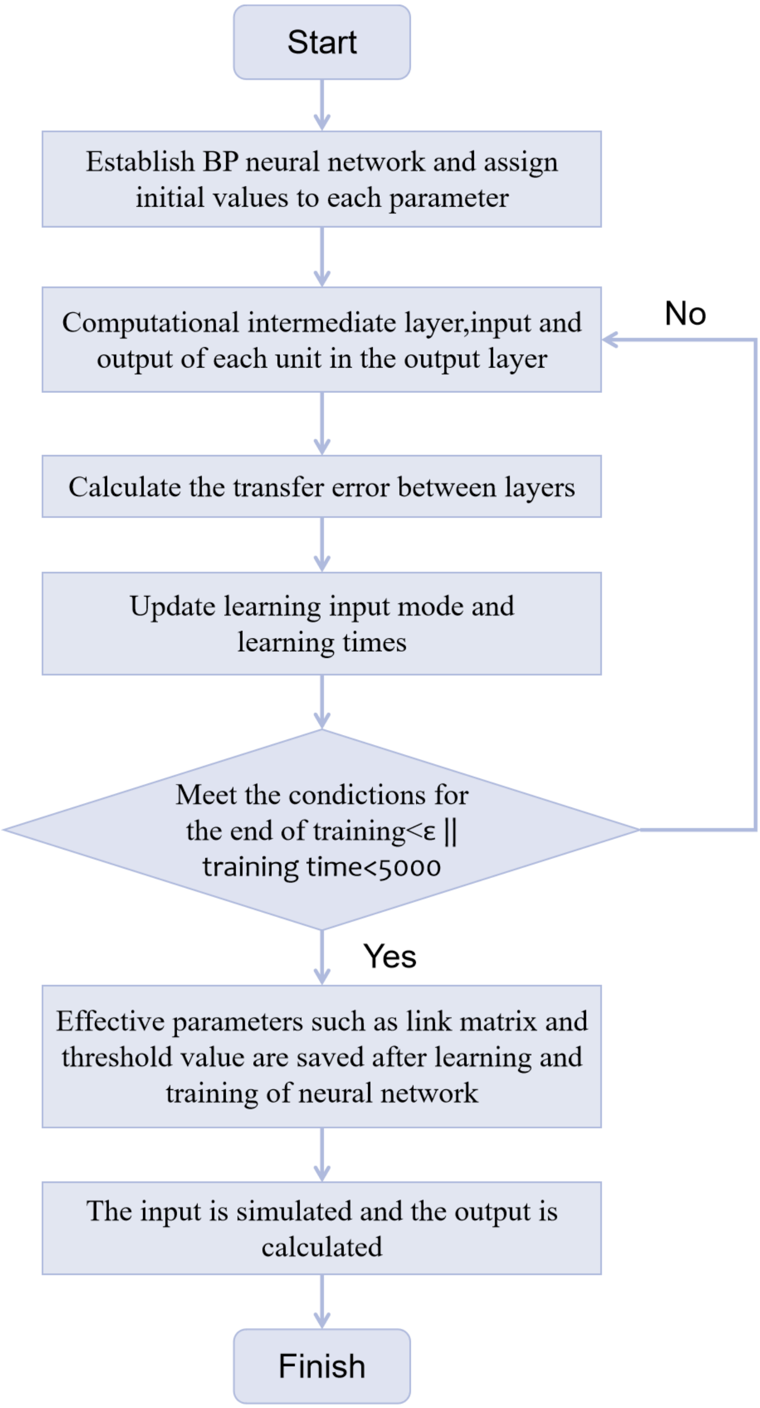

Figure 5: Basic process for the modeling of BP neural networks

Design of neural network When designing the input and output layers, you should minimize system size and reduce system learning time and complexity. Our model uses a single layer feed for the neural network, consisting of an input layer, a hidden layer, and an output layer. Because the metric used for training contains an indicator of the time variable, at the output layer we choose to set one neuron node. Two simulations predicted the output of Stock market and tesla stock, both as an indicator, so the output layer is composed of another neuron. For the hidden layer, we set the number of neurons in the hidden layer to 10, considering that there may be more hidden influence factors and correlations in the patterns of Stock market and tesla stock over time. Transfer function selection Different activation functions will affect the convergence speed of the BP network. Take the artificial neural network fault diagnosis of the power transformer as an example, select TTS (T for hyperbolic tangent function $\tan sig = \frac{1-e^{-2x}}{1+e^{-2x}}$ and S for Sigmoid function $\log sig = \frac{1}{1+e^{-x}}$) The combined activation function method has fast convergence and high fault diagnosis accuracy . In view of the nonlinear characteristics of the data sample, we use the S-type tangent activation function as the implied layer transfer function and the logarithmic activation function as the output layer transfer function. Additional statement When building the BP neural network prediction model, this study chose to use the year as the forecast time unit instead of a finer time unit such as day/week/month/quarter. Because of the volatility of the Stock market and tesla stock markets, if the model is solved in units of less time than the year, there may be inaccurate predictions due to the overlapping of regularity and periodicity.

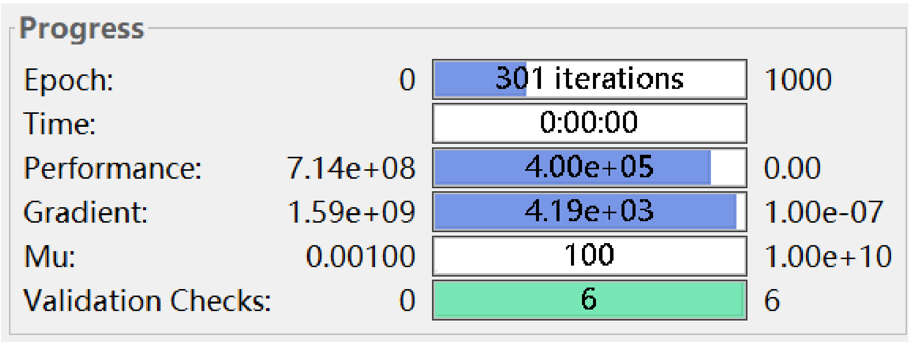

Figure 6: Progress of the model

4.2. The daily price forecast of Stock market and tesla stock for five years

In a simulation with 301 iterations (Figure 8), this study get a simulation with the smallest mean square error (MSE). According to the mean square error $S = \frac{1}{n}\sum_1^n (U_{iReal} - U_{iForecast})^2$, the mean square error of the model is 6.6738e-05. Because the correlation is good and the mean square error is small, this study can think that the data predicted by the BP neural network model is in good agreement with the true value.

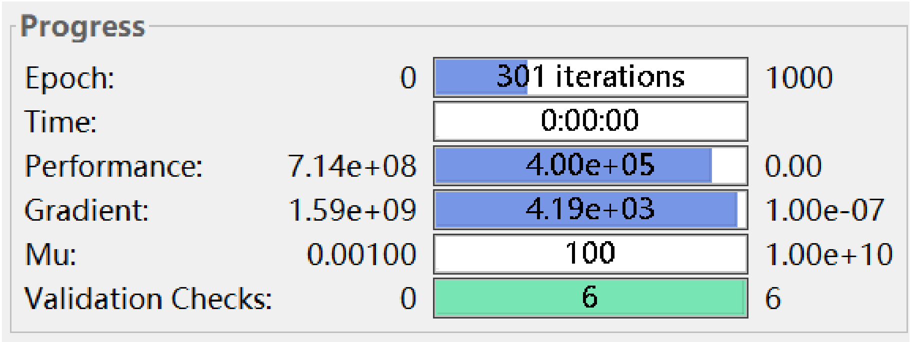

Figure 7: Progress of the model

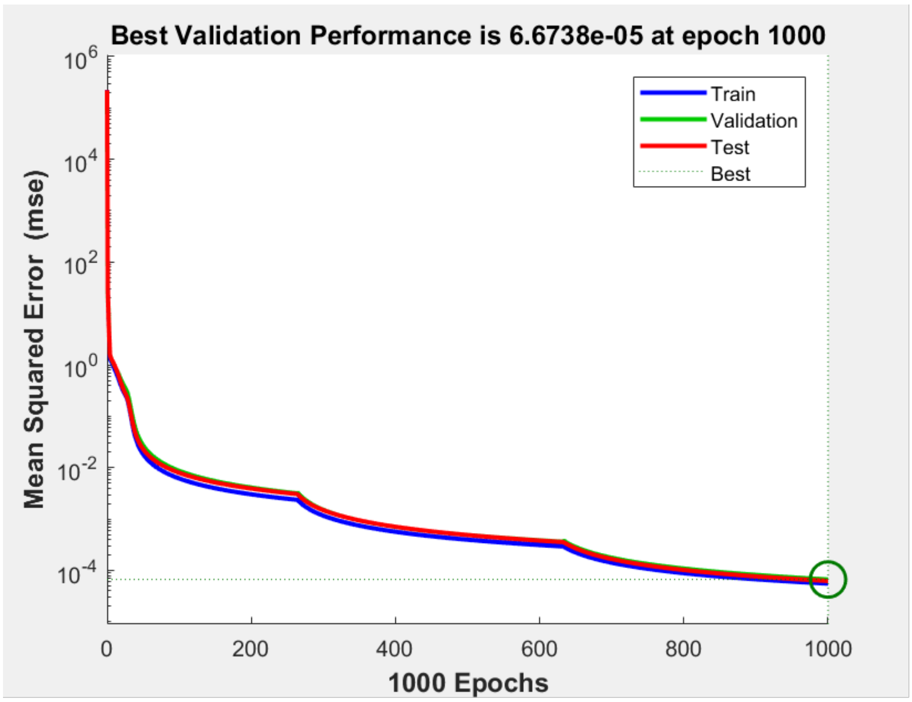

Figure 8: Correlation of BP neural network model (left) and mean square error of fit result (right)

5. LSTM model predicts the daily price of Stock market and tesla stock

The LSTM algorithm is one of the most important time series algorithms currently used for bidirectional LSTM using TIMIT database (BLSTM) and several other network structures on the baseline task of frame phoneme classification, it is not difficult to find LSTM than standard regression neural networks (RNN) and time window multi-layer sensing (MLP) faster and more accurate [23] . LSTM solves the problem of gradient disappearance and gradient explosion during long sequence training, Better performance in processing and predicting longer time series. Often applied to language modeling tasks [24] , naming entity identification [25] . and Human Activity Recognition (HAR) [26] . The value data for Stock market and tesla stock in this paper have a large time span and a long time interval, which is the type that LSTM is suitable for solving.

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5.1. Principles of LSTM Model Algorithm

The core part of the LSTM is the unit state, similar to the portion of the conveyor belt, as shown in Figure 9, which is present throughout the chain system of the LSTM (Figure 10). where, denotes the unit state of the t-moment, indicates the candidate value, indicates the input gate. There is no way to delete or add information to the cellular state. This needs to be achieved through the door, which is simply a combination of a sigmoid layer and a dot multiplication operation. The specific calculation process can be divided into three steps according to the type of door, with dotted lines in the diagram:

5.1.1. The Door of Obli

As time grows, the reference value of some Stock market and tesla stock prices, which are larger than the current interval, decreases. In order to improve the accuracy of forecasts, it is necessary to discard prices with large intervals. Forgot the door by looking at t-1 moments of hidden state $h_t - 1$ and t moments of input, representing the weights that let the corresponding information pass (0 means no retention, 1 means all retention).

5.1.2. The Door of Input

The next step consists of two main steps: first, using and) respectively, to decide which information to update and which to obtain new candidate cell information. Then forget part of the old state of the door selection, add part of the candidate cell information of the input door selection to update the old cell state, that is, get the new cell state by.

5.1.3. The Door of Output

Finally, the input and pass through the sigmoid layer to get the output gate judgment conditions. Then the cell state passes through the tanh layer to get a vector between -1 and 1. The vector is multiplied by the judgment condition obtained by the output gate by the final output, which is expressed as.

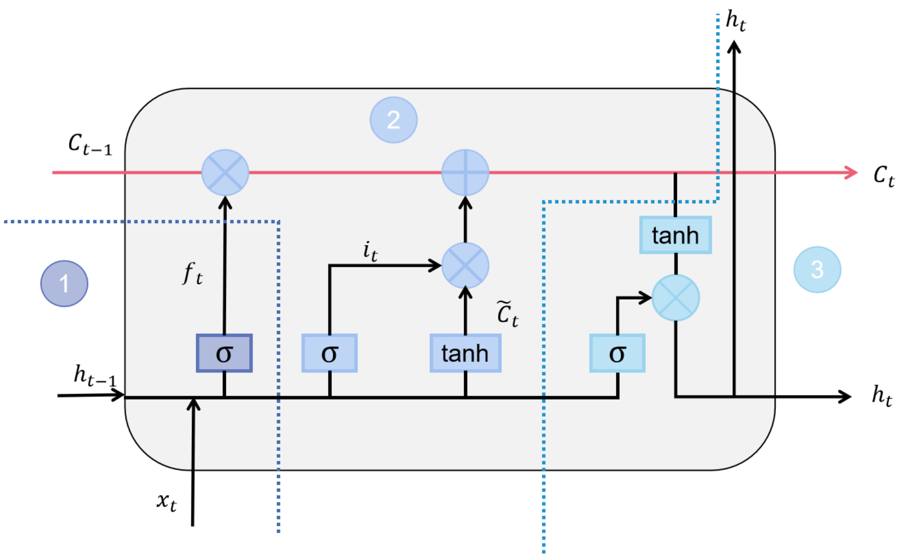

Figure 9: Unit structure of the LSTM model

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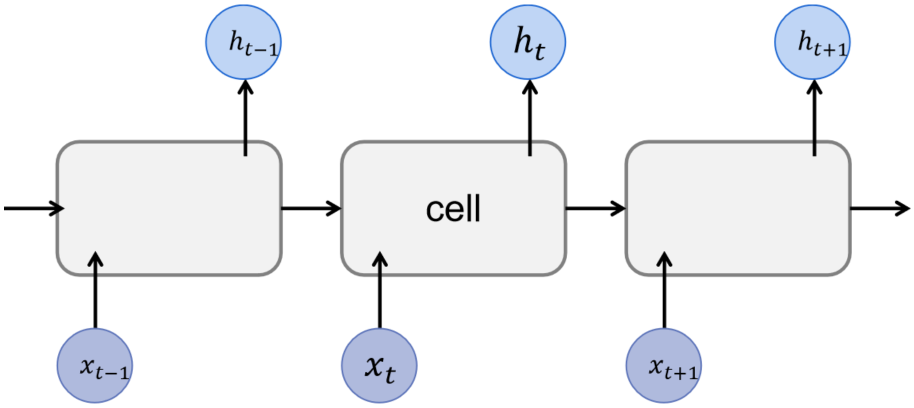

Figure 10: Unit structure of the LSTM model

5.2. Model establishment

5.2.1. The selection of dropout layer

When the training model is large and the training data is scarce, it is easy to cause the fitting, and then this study need to add a dropout layer to the model. Dropout is training when randomly dropping some neural units, the effect is to reduce overfitting, enhance the network's generalization ability. The introduction of the Dropout layer has brought significant improvements to many benchmarking tasks. and created new records for speech and target recognition [27] .

5.2.2. The selection of dropout layer

For the convenience of subsequent data processing, the data needs to be normalized before training the model. this study used (μ mean, σ standard deviation) to obtain new data that met the standard normal distribution with a mean of 0 and a standard deviation of 1. This unifies the evaluation criteria for sample data and converges faster when the gradient drops are solved.

5.2.3. Additional statement

When predicting the price of Stock market using the LSTM model, this study still use the year as our predicted time unit. Because tesla stock prices fluctuate much more than Stock market, taking into account the convenience and feasibility of the model and the inaccuracy of predictions resulting from the prevention of regular and periodic overlapping, this study chose half a year as the time unit for predicting the value of tesla stock.

5.3. The daily price forecast of Stock market and tesla stock for five years and the comparison of the two models

With multiple experiments and parameter tuning, this study finally performed best in models with 80 memory configured LSTM layers, dropout layers with Dense layer and 0.2. At the same time, this study mapped the comparison between the Stock market price and the true price predicted by the BP neural network and the LSTM model for five years and tesla stock's forecast price is compared to the true price and is analyzed as follows: Stock market Daily Price Curve Forecast Using BP Neural Network (Stock market Forecast BP) Volatility is significantly weaker than the daily true price curve (Stock market Real), but the approximate trend of the curve is consistent. tesla stock market has a lot

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of uncertainty, fluctuations of the regularity is not obvious, the prediction is more difficult. Overall, the daily price curve for tesla stock using LSTM forecasts (tesla stock Forecast LSTM) Volatility Closer to tesla stock's Daily True Price Curve (tesla stock Real) and the fitting effect and accuracy are higher than the daily tesla stock price curve predicted using the BP neural network (tesla stock Forecast BP). As the number of iterations continues to increase and the data continue to update, our knowledge of tesla stock price trends is gradually increasing, and the model can more accurately predict tesla stock daily price trends.

In order to quantitatively analyze the difference between the data obtained by BP neural network prediction and the data obtained by LSTM prediction and real data, this study calculated the direct correlation of Stock market and tesla stock with their predictions and real values respectively. Because there is no linear relationship between our data and this study do not obey the normal distribution, So this study decided to use the Spearman correlation coefficient [28] calculate . The Spearman correlation coefficients of Stock market and tesla stock for BP neural networks and LSTM are shown below. The darker the color, the closer the correlation coefficient, the better the prediction and true value fit.

Table 1: Performance comparison of prediction ability of our models

Methods	BP neural network	LSTM
Twitter	0.7264	0.7842
Tesla Price	0.7181	0.7183
Overall US stock	0.5131	0.4131

By analysis the above table, both models have generally performed well, but LSTM's predictions are better than those of BP neural networks. At the same time, both Stock market forecasts are more accurate than tesla stock forecasts, which may be associated with greater market impact and greater volatility and uncertainty. In summary, in order for investors to better understand the financial market situation and maximize their own interests, choosing the LSTM model for forecasting is a better strategy.

The analysis of the correlation between Tesla stock and Elon Musk's Twitter shows a positive relationship between the two variables. Specifically, an increase in the number of tweets or engagements on Elon Musk's Twitter account correlates with an increase in Tesla's stock price, and vice versa. This indicates that the sentiments expressed in Musk's tweets may influence the perceptions and expectations of Tesla's investors and, in turn, impact the stock's performance. However, it is important to note that correlation does not necessarily imply causation and further research is needed to establish a causal relationship between Musk's tweets and Tesla's stock performance. Additionally, the correlation may be influenced by other factors such as market trends, news releases, and company performance.

6. Model Evaluation and Further Discussion

6.1. Error Analysis

The market economy as a self-generated open system, its source is non-design, so the future of any market is full of uncertainty, its development trend is naturally difficult to fully predict and navigate [22]. No matter how precise the model is, error always exists. Based on the above, this study analyze the error source of BP neural network model and LSTM and summarize the following three reasons: (1) the traditional BP neural network is an optimization method for local search. It's going to solve a complex nonlinearization problem, The weights of the network are gradually adjusted in the direction of local improvement. This causes the algorithm to fall into local extremes and the weights to converge to local minimums, causing network training to fail.

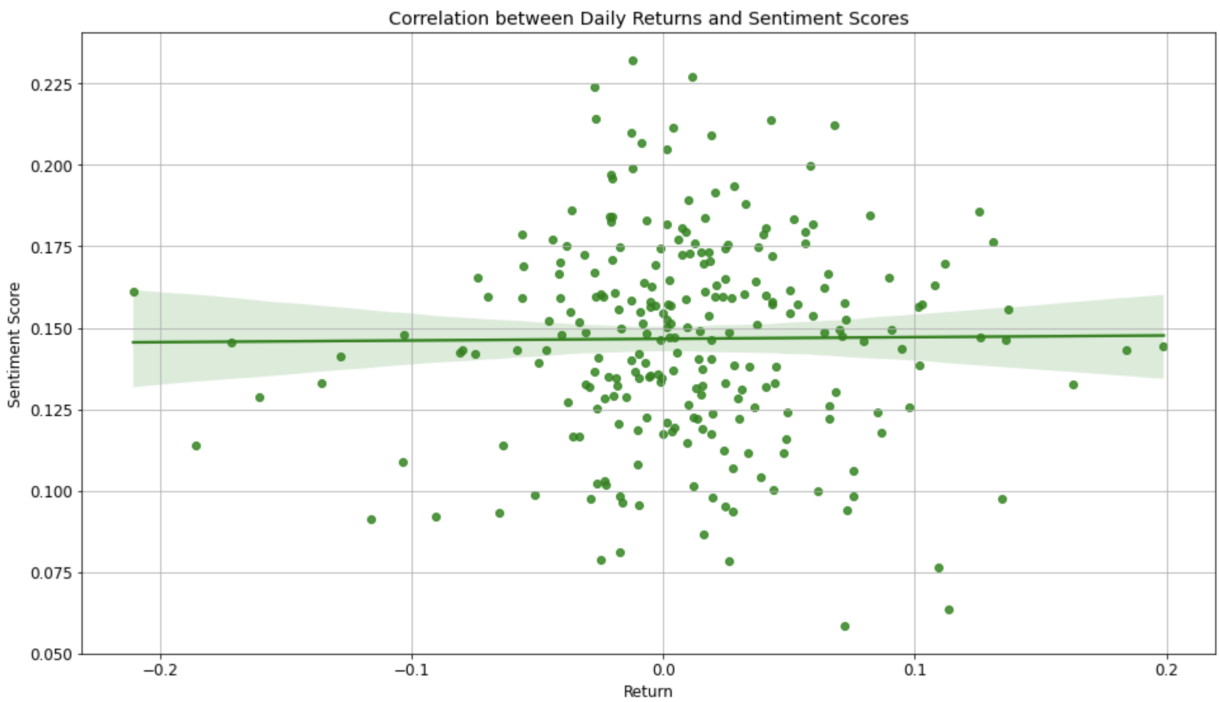

Figure 11: Correlation analysis of Tesla stock and elon musk's twitter

6.2. Strengths

(1) Because the daily prices of tesla stock and Stock market are more volatile, There are no linear features, so use the S-type tangent activation function to transfer data as an implied layer of the BP neural network. This kind of nonlinear data can be well solved with slow convergence and large errors. (2)The door structure of the LSTM is able to control the flow and loss of features and effectively mitigate the gradient disappearing problems that may occur in long sequence problems.

6.3. Weaknesses

(1) Because the BP neural network adopts gradient method, it may encounter problems such as slow convergence rate and easy convergence to local minima, resulting in poor operation efficiency and poor prediction. (2) The LSTM network does not explicitly mark the end of a sequence when processing a continuous input stream. If it is not reset, the internal state value may grow infinitely, eventually causing the network to crash.

6.4. Further Discussion

this study can try the following improvement directions:

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- Adding training data and hidden units or building a controlled feedforward neural network model [29] to avoid local minimums.
- Utilize adaptive "doors of oblivion" to enable LSTM cells to reset themselves in due course, thus releasing internal resources [30] .

7. Conclusion and Social impact

this study built two models, BP Neural Network and LSTM, to predict the daily price of Stock market and tesla stock for 2016-2021. The accuracy of the two prediction models is compared by drawing and calculating correlation coefficient. The LSTM model was found to be better predicted. This study have analyzed the advantages and disadvantages of the model, the resulting model convergence speed, can alleviate the gradient disappearing and explosion to some extent, has a strong practicality, but there are still some shortcomings, there is room for improvement.

To achieve our goal of identifying a clear association between Elon Musk's Twitter activity and Tesla's stock price, this study utilized various tools and techniques. Our research found that in the short run, there is a marginal correlation between the number of tweets and interactions by Elon Musk and the stock price of Tesla. By examining the frequency of replies or tweets and the stock value over time, we found that there is a weak correlation in the short term.

However, in the long run, the association between Elon Musk's Twitter activity and Tesla's stock price becomes more evident. When this study analyzed the tweets over a longer period, such as months or years, this study found a strong correlation between Musk's engagement and Tesla's closing price changes. Our research suggests that Elon Musk's Twitter activity is a good predictor of stock price rise, which is valuable information for investors.

Our findings have broader implications for predicting the trend of the US stock market. By leveraging social media and machine learning techniques, analysts can gain insights into market trends and predict future stock prices. This approach can help investors make informed decisions and manage their portfolios effectively. Moreover, it highlights the importance of data-driven approaches in financial analysis and underscores the potential of social media as a valuable source of financial information.

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