The Research of NVIDIA Stock Price Prediction Based on LSTM And ARIMA Model

Zhenhao Yang [1], Zhiyang Wang [2, *]

[1] Department of Malvern Chengdu college, Chengdu, China

[2] School of Mathematical Sciences, University of Nottingham Ningbo China, Ningbo, China

* Corresponding Author Email: smyzw14@nottingham.edu.cn

Abstract. The paper explores stock forecasting methods using NVIDIA as the research object. It contrasts how well LSTM and ARIMA models forecast NVIDIA's stock return. According to the study, LSTM surpasses ARIMA in terms of prediction accuracy. However, both models capture the overall trend of the stock. The results suggest that LSTM is better suited for forecasting stock movements due to its ability to handle time series data. The non-stationary nature of the stock market adds complexity to predictions. The significance of stock forecasting is that informed investment decisions can be made to maximise financial returns. Stock forecasting aims to predict the future performance of individual stocks, market sectors or the market as a whole based on various factors such as historical data, market trends, company fundamentals and economic indicators. By analysing and forecasting stock movements, investors can identify opportunities to buy low and sell high, optimise their portfolios and potentially outperform the broader market. Successful stock forecasting can help investors make more informed decisions, reduce risk and improve their chances of achieving their financial goals.

Keywords: NVIDIA; stock price prediction; LSTM; ARIMA.

1. Introduction

The standard of living for individuals has greatly increased along with the economy's ongoing rise. As a result, more people are increasingly investing their spare money in stocks, viewing them as a tool for boosting wealth [1]. Forecasting stock prices is crucial for investors to make investment decisions since the stock market's volatility exposes them to more uncertainty. In this paper, NVIDIA will be used as the research object to explore the stock forecasting method. NVIDIA has shown a rising tendency when five-year stock index trends are considered. The stock price increases gradually between 2019 and 2021, then quickly declines to levels similar to 2020 in 2022 before surging to quadruple its prior peak in 2023. Because NVIDIA's high-performance AI chips and software represent the AI age's fuel and hard currency, the growth of ChatGPT and the arrival of the AI era have made chip giant NVIDIA and its CEO Jen-Hsun Huang the largest beneficiaries [2]. Through this essay, the research may give investors some reference material for forecasting the share price trend of NVIDIA.

Quantitative stock analysis, a revolutionary method that incorporates information from multiple academic subjects including economics, computer science, and mathematics, has evolved as a way to forecast future stock movements based on previous data [1]. Financial Time Series modelling during the pre-deep learning period mostly focused on the field of ARIMA and any variations on this, and the outcome has demonstrated that the conventional time series model does give respectable predictive power up to a point [3]. For instance, Lee et al. contrasted the accuracy of ARIMA with artificial neural networks in predicting the Korean stock price index. The outcomes demonstrated that back-propagation neural networks were less accurate in forecasting than ARIMA [4]. In comparison to conventional forecasting techniques, machine learning algorithms may learn from historical market trends and patterns to more accurately anticipate future stock values. To create more precise predictions over time, these algorithms continually update their expertise based on fresh information. Deep learning techniques have lately performed better because of increased computer power and the capacity to discover non-linear correlations included within a variety of financial data [3]. One study by Chen et al. that supports the effectiveness of SVMs in stock prediction is the research. In this study, the authors proposed an SVM regression-based model for predicting stock prices. They contrasted it with various machine learning models, including artificial neural networks, random forests, and decision trees. The outcomes demonstrated that, in terms of prediction accuracy and robustness, the SVM regression model performed better than the other models [5]. Another example is Jia-Qian et al. compared the performance of LSTM, SVM, and other machine learning models in predicting stock prices for 33 different companies listed on the Chinese stock market. They found that the LSTM model consistently outperformed SVM and other models in predicting stock prices. LSTM achieved higher accuracy, precision, recall, and F1-score values across most of the evaluated stocks compared to SVM and other models [6]. This advancement in machine learning has allowed people to utilize computers and algorithms to extract meaningful information from vast amounts of stock trading data, ultimately anticipating future prices and trends [1].

In this paper, LSTM and ARIMA models are taken to predict the stock return of NVIDIA, a stock in the sci-fi sector that has been in the heat of the moment recently. This study not only enriches the literature on stock price prediction from the theoretical aspect but also provides empirical evidence on the comparison of the accuracy of LSTM and ARIMA models.

The remainder of this essay is organised as follows: section II explains the information and methodology. Section III discusses the findings, and section IV draws a conclusion.

2. Data and Methodology

2.1. Data Description

The information of NVIDIA stock from 2013-8-12 to 2023-8-11 is obtained through the database on yahoo finance, and the data of daily closing price is collected to get Figure.1. The horizontal axis is the date/years, and the vertical axis is the stock's daily closing price /dollars. The horizontal axis is the date /Y, and the vertical axis is the daily closing price of the stock /$. Since 2013, the stock price has risen steadily through the second half of 2021. But share prices soon cooled. It was not until the second half of 2022 that stock prices began to recover to their all-time high in August 2023.

Fig 1. Stock close price.

2.2. Machine Learning

2.2.1. LSTM

LSTM is an RNN model proposed by Hochreiter and Schmidhuber (1997) and refined in the following years by Gers and Schmidhuber (2000) and Gers et al. (2000) [7, 8]. The LSTM unit uses a mechanism for adding or removing information called "thresholds" to create a new hidden state by copying the previous hidden state and adding or removing information as needed. The "threshold" mechanism determines how information is processed.

A typical LSTM unit consists of three gating units: input gate (i_t), the forget gate (f_t) and the output gate (o_t). LSTM can add and remove information from neurons through gated units. The gate can selectively let information through because the default activation function of the LSTM network is the sigmoid function (1). The sigmoid function, also called Logistic function, is used to hide the output of the layer, and the output is a real number between (0, 1), which can be used for binary classification, and the effect is better when the data features are similar. The real number between (0, 1) is the weight that allows the information to pass. The LSTM has a layer containing the tanh activation function (2), which is to update the state of the neurons.

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$\tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{2}$$

At t, each of the three gates receives the input $x_t$at the current time and the output h_{t-1} at the previous time.

Forget Gate:

The task of the forgetting gate is to accept c_{t-1} long-term memory A and decide which part of c_{t-1} to forget and retain, and the formula is (3).

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

Input gate:

The input gate is to process the discarded information. It determines how much input from the network is saved to the unit state at the current time, and the formula is (4)

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{4}$$

Out gate:

The output gate is a controlling gate which identifies the current output value of information and decides how much information could be outputted. The formula is (5).

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

WhereW_f, is the weight matrix of the forget gate; W_i is the weight matrix of input gate; and W_o stands for the weight matrices of the output gate. b_i, b_f and $b_o$are the bias vectors corresponding to the three gates; f_t, i_t and o_t are the activation value vectors of the forget gate, input gate and output gate respectively.

2.2.2. ARIMA

ARIMA model is a statistical model for time series analysis and is widely used in stock forecasting [9]. Autoregressive model, or AR (p) model, is a model that describes the effect of the first p values in a time series on the current value. Non-stationary time sequence is one in which the trend or periodicity of the data changes rapidly, which results in poor model prediction. Integrated model is a model used to deal with non-stationary time sequence, it can transform non-stationary time series into stationary series by D-order difference, so that the model is easier to describe. The MA (q) model is a model that describes the relationship between the error value of a certain point in a time series and the error value of q points in the past.

AR and MA combine to obtain ARMA (p, q) model, and the formula is (6).

$$y_t = c + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{6}$$

Where y_t is the t value of the time series, indicating the value of the current moment; c is the constant term; φ_i is the autoregressive coefficient, which is used to describe the influence of the values of the past p moments on the present moment. θ_i Is the moving average term coefficient, which is used to describe the influence of q error terms in the past on the current moment error term? εt is a random error term.

Akaike information criterion (AIC) this is an evaluation criterion used to measure the complexity of statistical models and the goodness of data fit of statistical models. In general, the formula of AIC can be expressed as the formula (7) [10].

$$AIC = 2k - 2ln(L) \tag{7}$$

3. Results

3.1. Prediction Results of LSTM

This study a0dopts LSTM neural network, build a model with 5 memory days, 1 LSTM layer, 2 dense layers and 3 fully connected layers. The number of LSTM neurons is 32. Each LSTM layer is followed by a layer of Dropout, the parameter is set to 0.1, and the neurons are randomly discarded in a ratio of 0.1. The number of neurons in the three fully connected layers was 32. Set the number of iterations to 50 and the Batch size to 32. Figure 1 is a fitting model, and the trend of the images is roughly the same because the prediction is made ten days in advance. From Figure 2, it can be observed that Tesla's stock price has a seasonal and obvious upward trend. The red polyline shows the real stock price, and the green polyline show the 10-day forecast.

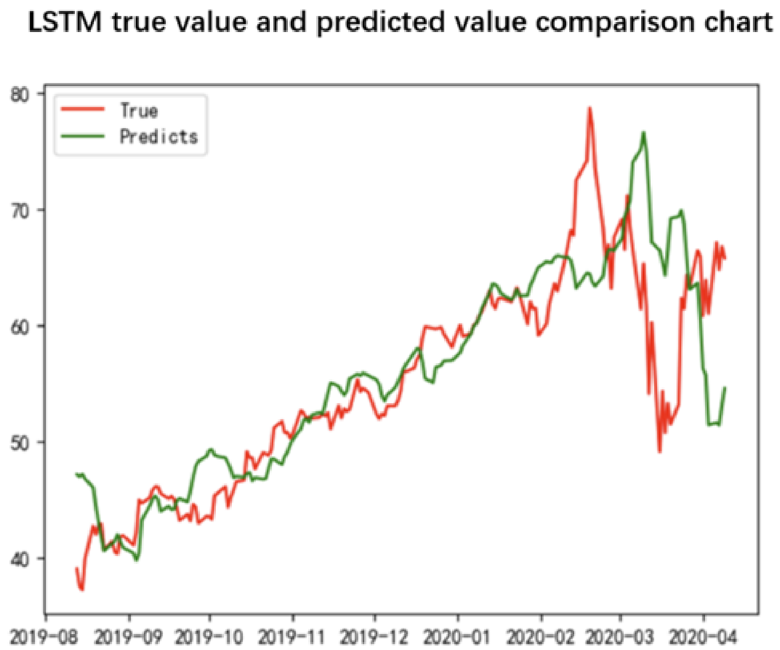

Fig 2. LSTM true value and predicted value comparison chart.

3.2. Prediction Results of ARIMA Model

The difference method is then used to make the whole curve more stable, and then the ARIMA model is used to make predictions. Figure 3 shows the first-order difference. So d is equal to 1.

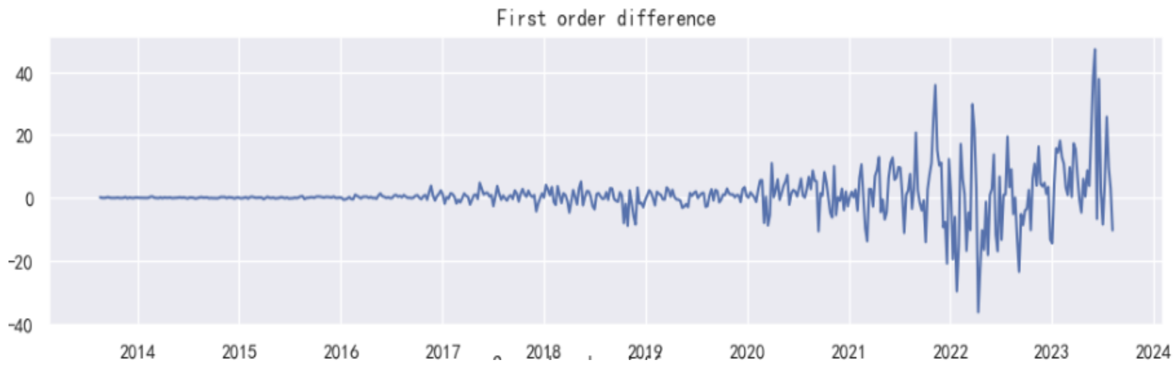

Fig 3. First order difference.

The optimal model can be selected through AIC, and the values of p and q are 4, 2 respectively. From this, we can construct the ARIMA model Figure 4 and obtain the effect index of the model fitting Table 1. As can be seen from the test results in Table 1, the P-values of the statistics are all greater than 0.05, so their significance level was less than 0.05. It can be concluded that the fitting effect of SARIMAX (4, 1, and 2) model is very good, which means this result can help researchers understand the original time series data and use it as a basis to make predictions about future values.

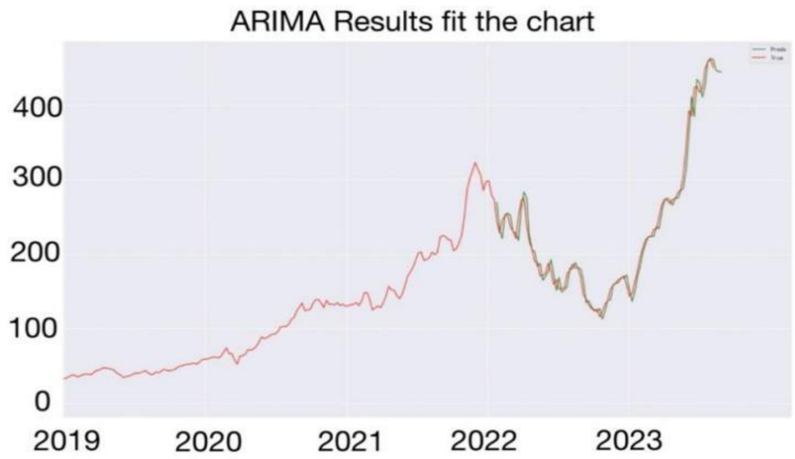

Fig 4. ARIMA result.

Table 1. SARIMAX Results.

Dep.variable		Close		**No.Observations**		522
Model		ARIMA(4,1,2)		**Log Likelihood**		-1706.39
Date		Sat.12 Aug 2023		**AIC**		3426.769
Sample		08-12-2013 -08-07-2023		**BIC** / **HQIC**		3456.559 / 3438.44
Covariance Type		opg				
	coef	**std err**	**z**	**P>IzI**	**0.025**	**0.975**
ar.L1	0.1740	7.853	0.022	0.982	-15.217	15.565
ar.L2	0.1870	0.436	0.429	0.668	-0.668	1.043
ar.L3	-0.0735	1.752	-0.042	0.967	-3.508	3.361
ar.L4	0.0128	0.332	0.038	0.969	-0.638	0.663
ma.L1	0.2000	7.850	0.025	0.980	-15.186	15.586
ma.L2	-0.0413	3.212	-0.013	0.990	-6.337	6.254
sigma2	40.9426	1.139	35.939	0.000	38.71	43.175
Ljung-Box (L1) (Q):			0.02	**Jarque-Bera (JB):**		2216.49
Prob(Q):			0.89	**Prob(JB):**		0.00
Heteroskedasticity (H)			671.56	**Skew**		0.65
Prob(H) (two-sided)			0.00	**Kurtosis**		13.02

3.3. Model Comparison

In this experiment, Mean Absolute Error (MAE), R square (R^2) and Root Mean Squared Error (RMSE), were used as evaluation indexes.

RMSE is used to measure the deviation between the measured value and the true value. The calculation formula is formula (8).

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i-\bar{y}_i)^2} \tag{8}$$

In this formula y_i represents real data; the inverse $\hat{y}_i$ represents forecast data; n is the number of samples and $\bar{y}$ is the mean of the real data. The smaller the root-mean-square-error is, the more exact the prediction effect of the model would be.

MAE is a method used to calculate the deviation between the forecast value and the real value, and the formula is (9)

$$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i-\bar{y}| \tag{9}$$

R^2stands for the degree of correlation between the forecast data and the real data. The calculation formula is (10).

$$R^2=\frac{\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{10}$$

Then, the prediction data of the two models were compared and analyzed, and the comparison results were shown in Table 2. Table 2 shows that the prediction results of ARIMA model and LSTM model have a certain lag. RMSE and MAE of ARIMA model are greater than LSTM model, but R^2 of LSTM is smaller than ARIMA. The numerical fitting accuracy of the two models is not very high in the short term, but they also have good results in the long-term trend prediction. The R^2 values of both models are close to 1, indicating that both models have strong predictive ability, and ARIMA is better than LSTM.

Table 2. Comparison results of evaluation indexes.

models	MAE	RMSE	R^2
LSTM	3.5043	5.451	0.6368
ARIMA	3.2698	6.3945	0.9953

To better grasp the trend of individual stocks, ARIMA and LSTM models are used to forecast and compare the Shanghai Composite Index. The results show that the two models have a certain lag in the prediction results. The RMSE and MAE of ARIMA are greater than that of LSTM, but the R2 of LSTM is smaller than that of ARIMA. Although the two models have a large deviation in predicting the daily index, the prediction results can basically reflect the development trend of the index.

4. Conclusion

In this study, the NVIDIA stock was predicted using ARIMA and LSTM models. The results demonstrate a discrepancy between the two models' forecasting abilities: the RMSE and MAE of ARIMA are higher than those of LSTM, but LSTM's R^2 is lower than ARIMA's. Despite the significant differences between the two models' daily index forecasts, the forecasts for both models essentially capture the index's trend. The results have shown ARIMA model modelling requires stable time series, but the stock data is an unstable series, so there may be prediction bias when dealing with stabilisation into a stable series. When the fluctuation of the real value is not very violent, the prediction with ARIMA may be more applicable, while the stock data is more changeable, in comparison, the prediction of ARIMA is not as good as that of the LSTM. The LSTM model works well with the market data and can forecast stock movements more accurately than other models since it is ideally suited for dealing with issues that are heavily associated with time series.

The non-stationary nature of the stock market makes predictions challenging. With just one model, it can be challenging to precisely anticipate its trend. More optimal models have therefore been suggested, which should be further discussed in future study.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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