Proceedings of the 2nd International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/47/20230372

Investigation of LSTM Model in Stock Prices Prediction During the COVID-19 Based on Smartphone Brands

Jingming Li[1,a,*]

[1]*Department of Statistical Science, University College London, Gower Street, London, United Kingdom*
a. Jingming.li.20@ucl.ac.uk
**corresponding author*

Abstract: The unforeseen outbreak of the COVID-19 pandemic in early 2020 had a profound impact on the real economy and business sectors, leading to a period of heightened volatility. The stock price of smartphone brands had shown an abnormal trend of fluctuation and hard to be predicted by using the inchoate regression and machine learning models. In this paper, Long Short-Term Memory (LSTM) is adapted to predict the stock price of five top smartphone brands. Spanning the period from 2016 to 2021, the dataset for each brand contains 1258 data points, which are split into two groups, training set including 850 observations and test set including 408 observations after the pandemic in 2020. The model employed two prices as x and the next price as y to be predicted. The structure of the model in this work is composed of 3 layers, with 64 and 5 neurons in the first two LSTM layers respectively and a dense layer for dense equal to 1. The model is based on TensorFlow system with Adaptive Moment Estimation optimizer and Mean Absolute Error as the loss function. For the model checking, Root Mean Standard Error, Mean Absolute Error and R-square score are calculated to evaluate the precision of the prediction. Experimental results indicate that under an unexpected external condition, LSTM is effective in stock price prediction to a certain extent. Further investigations are still needed to improve LSTM applied in the stock market.

Keywords: machine learning, LSTM model, stock price prediction

1. Introduction

In the early of 2020, the world underwent a transformative shift with the rapid dissemination of the infectious disease known as COVID-19. In order to control the spread of pandemic, there was a trend of behavioral shifting such as working remotely, engaging social media and online contact, etc. [1]. Apart from fundamentally altering the way of life, the global economy has been disrupted by the breakout of COVID-19 pandemic and the business markets fluctuated under the unstable period. Many firms had faced demand shock and reported that their sales activities were disrupted significantly [2]. A statistic in California revealed that COVID-19 pandemic caused an extensive closure in business, and a 22% decrease in the number of active business owners in the second quarter of 2020 [3]. Compared with the value of the second quarter of 2019, the taxable sales average lost 17% in the second quarter of 2020 [3]. The impact on retail and brick-and -mortar businesses such as smartphones has been particularly significant. Especially in those great markets of smartphone industry such as China, India, the United States, and Europe, due to the unexpected spread of COVID-19, there was a severe impact on smartphone brands worldwide [4]. During the epidemic period, the stock prices are more volatile than usual. Therefore, it will be a significant task to forecast the companies' share prices accurately in this period. Precise predictions can provide advice to individuals, firms, and governments for reference in order to make better decisions and policies.

The algorithms in artificial intelligence and machine learning keep progressing from generation to generation and are constantly updated in recent years [5-7]. The machine learning algorithms for example, linear regression, Autoregressive Integrated Moving Average model (ARIMA), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) etc. are widely used in many areas like computer vision, medical statistics, etc. In particular, these methods took the financial development and stock prediction to a new stage. Numerous studies have been conducted to forecast stock prices during periods of relative stability and to discern the comparative efficacy of different predictive models. Since the stock market is highly nonlinear nature of the financial time series, the trend of the stock prices is hard to be observed. Some studies have tried to apply Artificial Neural Network (ANN) on the Japanese stock market in 2016 [8]. Also, a paper used random forest method to analyse Indian stock market in the early years [9]. For different models, there is a study which contrasted two methods and found that the neural network-based models like General Regression Neural Network method (GRNN) performed better than previous linear regression models in stock prediction [10]. Besides, research also compared nine machine learning models in reducing the risk of prediction [11]. The result indicated that two powerful deep learning, RNN and LSTM demonstrated outstanding performance in dealing with continuous data [11]. However, foreseeing daily behavior of stock markets is challenging for investors and corporate stockholders, especially taking risks and fluctuations into consideration [12]. There exist few previous studies referring to recent emerging algorithm like LSTM, particularly in unstable periods. Therefore, this paper aims to use the updated prediction model, LSTM, to test that it can still be effective when external condition is beyond expectation.

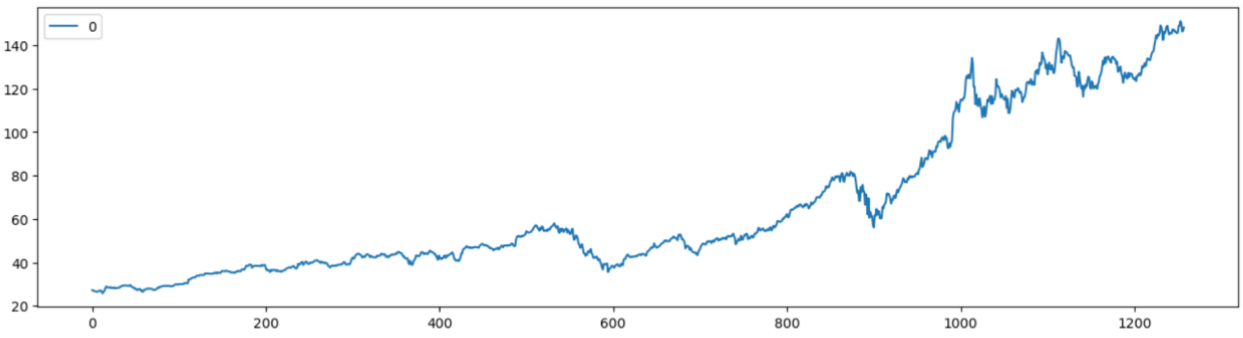
In order to accomplish the purpose, this paper adopts the stock prices of five leading smartphone companies, Apple, Google pixel, Lenovo, Nokia, and VIVO, in a period from 2016 to 2021. Utilizing the data from 2016 to 2019 before the pandemic as training set to build LSTM models and data after the outbreak of COVID-19 as test set to make prediction. The results indicate that the values of Root Mean Squared Error are in the range from 0.03 to 0.07, the values of Mean Absolute Error are between 0.02 and 0.05, and the R-square scores are in the interval from 0.89 to 0.99. The LSTM model is mostly precise in stock price prediction during the COVID-19 pandemic.

2. Method

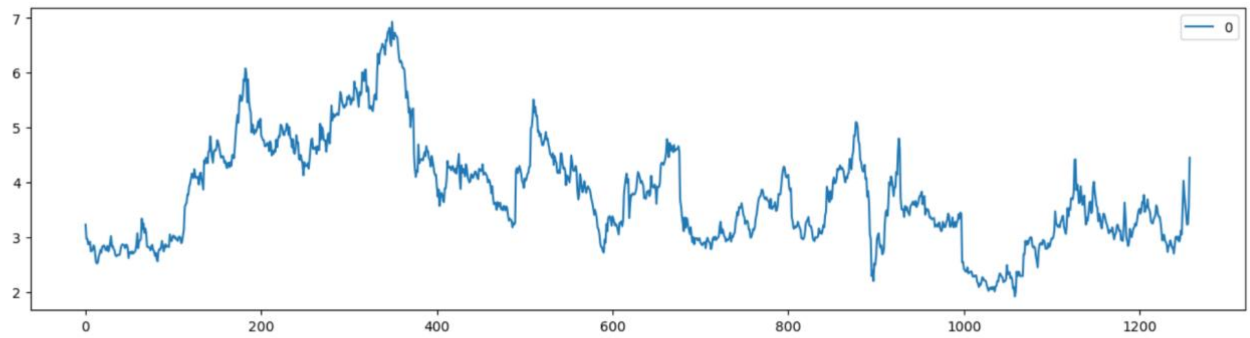
2.1. Data Description and Preprocessing

The source of the dataset is from Kaggle [13]. The data used in this study contains stock prices of five top brands of smartphone market, namely Apple, Google pixel, Lenovo, Nokia, and VIVO. Spanning the period from 2016 to 2021, the dataset comprises seven variables for each brand, with a total of 1258 data points. The primary aim of employing this dataset is to complete the regression task and use LSTM model to predict the close price. Figure 1 illustrates the curves of the close price for each brand.

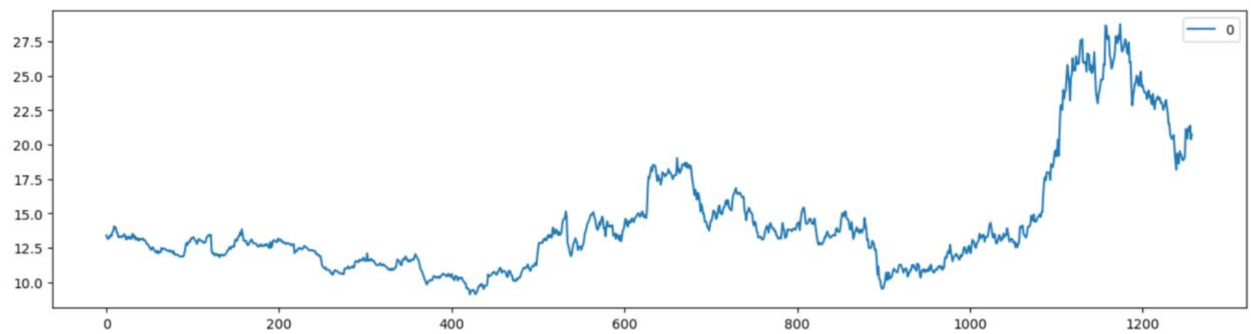
DOI: 10.54254/2754-1169/47/20230372



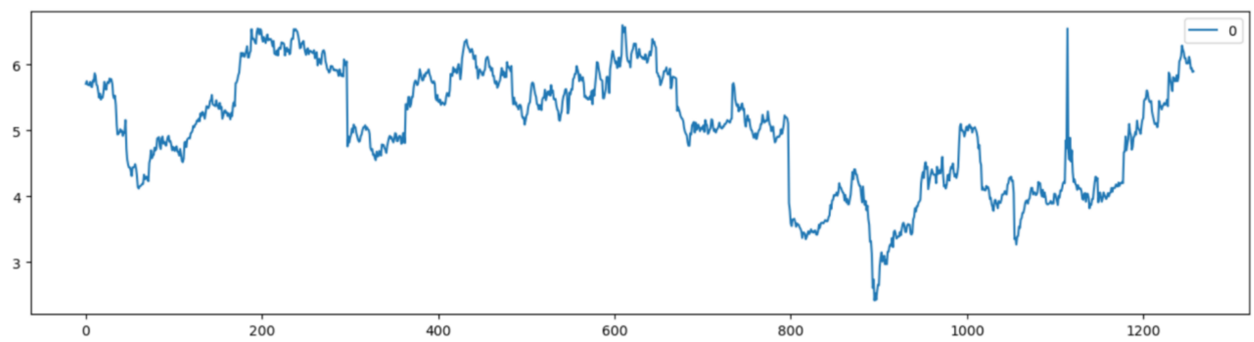
(a)



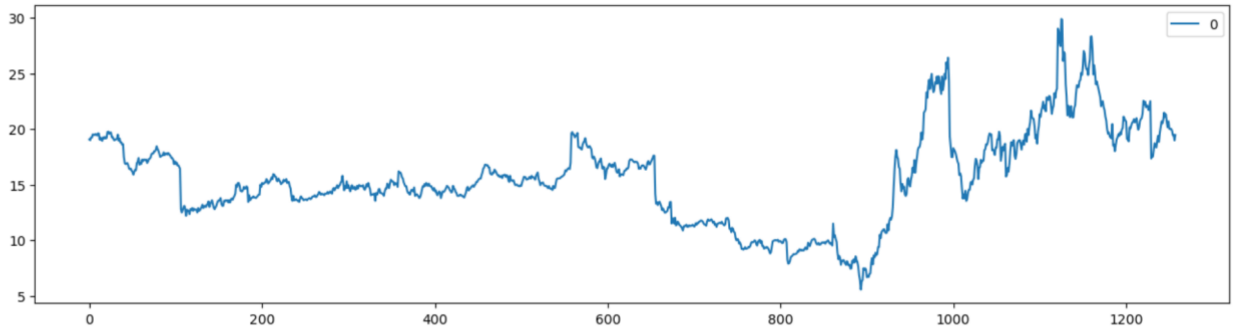
(b)



(c)



(d)



(e)

Figure 1: Close price curves of each brand related to (a) Apple (b) Google pixel (c) Lenovo (d) Nokia and (e) VIVO.

The preprocessing of the data consists of two parts. Firstly, splitting the data into train set and test set. Each train set has 850 observations, whereas the test set contains 408. From the close price curves in Figure 1, there exists dramatic fluctuation after the outbreak of COVID-19 about 850. Hence, the main standard of this division is that most data in train set is collected before the COVID-19 while most data in test set is recorded after the widespread of the COVID-19, in order to investigate whether the LSTM model can predict the stock price well even under an unexpected condition. Secondly, normalizing the values in the data to the numerical interval between 0 and 1, in order to eliminate the effects on the accuracy of the prediction caused by different dimensions for different features and variables.

2.2. LSTM Model

LSTM as a specific type of RNN architecture, had been created to address the challenge of collecting long-term dependencies in sequential data. Different from RNN, LSTM introduces a concept of gate, in order to solve the problem of long-term dependence, which can help the system extract the value in t_i at the time t_n. Comparing to the hidden state in RNN, LSTM also increases a cell state. The cell state is the core of LSTM. It runs through the whole cell, in order to make sure information can go through the cell remaining unchanged. There are three gates controlling the cell state. The forget gate is in charge of ascertaining the selective removal of information, whereas the input gate and output gate govern the selective incorporation and transmission of information, respectively, within the cell. Each gate encompasses a sigmoid layer, which generates values within the range of [0,1], in conjunction with a dot product operation, collectively functioning as a screening mechanism. There are three input values for the cell: the remain state C_{t-1} from the last hidden neuron, the output value for information transforms h_{t-1} from the last hidden neuron and the sample x at this time t. As gates add or delete information, cells process data and finally get new C_t and h_t outputs.

For the auto-regression process, the model employed two prices as x and the next price as y which will be predicted. The structure of the LSTM model in this study is composed of 3 layers. The first LSTM layer has 64 neurons, while the second LSTM layer contains 5 neurons. The third layer is a dense layer where the value of dense is equal to 1, representing the close price predicted.

2.3. Implementation Details

The study is based on Tensorflow, which is an Artificial Intelligence (AI) system that can transmit complex data structure to AI neural network in order to analyze and process data. Tensorflow is

DOI: 10.54254/2754-1169/47/20230372

widely used in machine learning and deep learning. ADAM is chosen as the optimizer in the model to optimize the loss function. It consists of two parts, adaptive and momentum. Mean Absolute Error (MAE) is the loss function used in the model, which aims to measure the absolute errors between the values. Besides, the value of epochs equals 20, representing the iterations for model training is 20 times. The research uses the three following values to evaluate the efficiency of the prediction.

2.3.1. Root Mean Squared Error (RMSE)

RMS measures the deviation between the predicted values and real observations. The model will be better if RMSE closes to 0.

$$\mathrm{RMSE} = \sqrt{[\textstyle\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 / n]} \tag{1}$$

y_i in the formula above represents the predicted value, while $\bar{y}_i$ is the real observations, and n is the sample size.

2.3.2. Mean Absolute Error (MAE)

MAE reflects the actual prediction error, avoiding the counteraction of the errors. The model will be better if MAE closes to 0.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\bar{y}_i - y_i| \tag{2}$$

y_i in the formula above represents the predict value, while $\bar{y}_i$ is the real observation, and n is the sample size.

2.3.3. R-square Score

R-square score evaluates the degree of fitting for a regression model. The model fits well if R-square closes to 1.

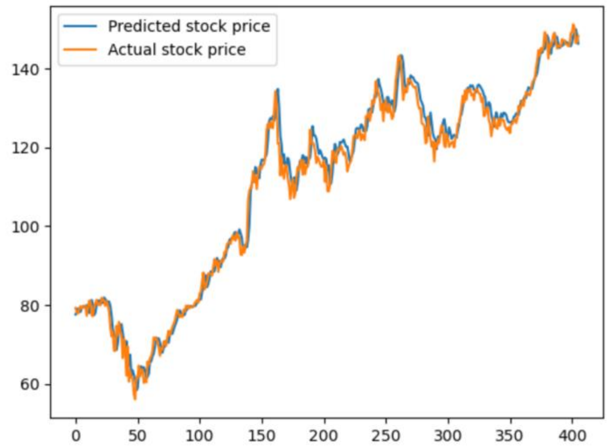
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}{\sum_{i=1}^{n}(\bar{y}_i - \bar{y})^2} \tag{3}$$

y_i in the formula above presents the predicted value, $\bar{y}_i$ is the real observation, $\bar{y}$ is the mean value of these real samples, and n is the sample size.

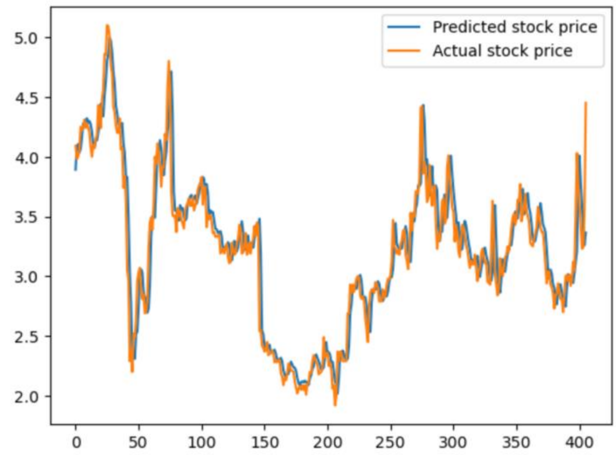
3. Results and Discussion

From Table 1, the LSTM model demonstrates the capability to predict stock prices accurately for most of the companies, even in the face of unforeseen circumstances such as the outbreak of the COVID-19. Comparing five top smartphone brands, the LSTM model used in this research predicts Apple and Lenovo best with the smallest errors RMSE and MAE around 0.03 and 0.02 respectively, and with the largest R-square score about 0.98. Conversely, the LSTM model exhibits comparatively poorer performance in forecasting the stock price of Google pixel since it achieves largest RMSE and MAE around 0.07 and 0.04, also the smallest R-square score around 0.89.

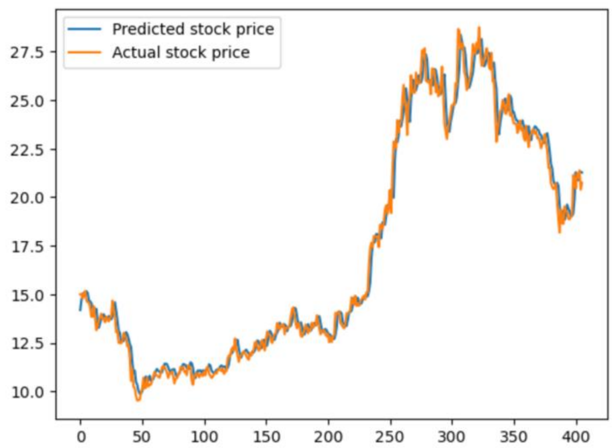
DOI: 10.54254/2754-1169/47/20230372



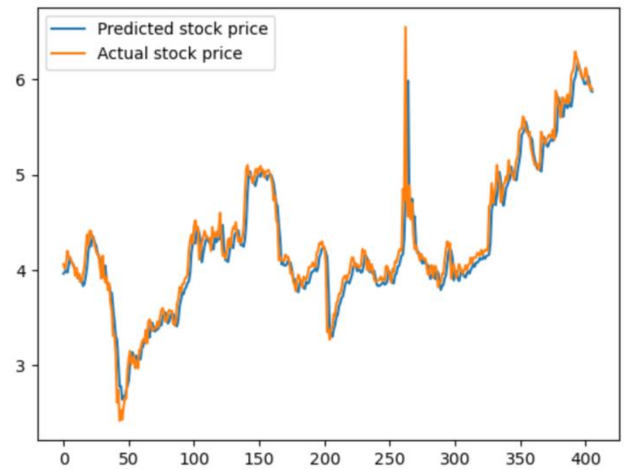
(a)



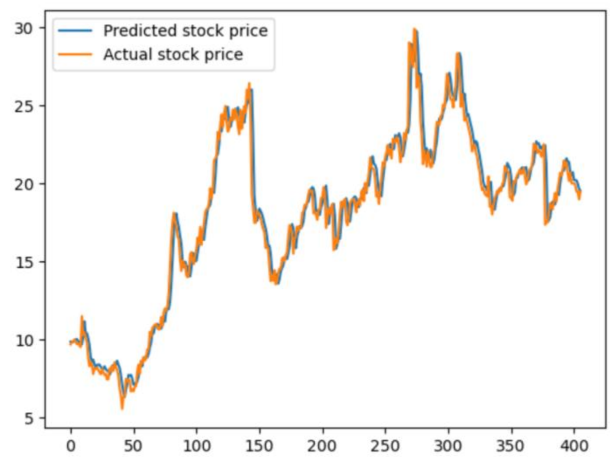
(b)



(c)



(d)



(e)

Figure 2: Predicted stock price versus actual stock price for brands (a) Apple (b) Google pixel (c) Lenovo (d) Nokia and (e) VIVO.

Table 1: The prediction results for five stocks evaluated by various metrics.

	RMSE	MAE	R-square score
Apple	0.03134	0.02345	0.98649
Google pixel	0.06620	0.04437	0.89157
Lenovo	0.03266	0.02348	0.98857
Nokia	0.04649	0.02861	0.92881
VIVO	0.04325	0.02882	0.96282

Based on the observations depicted in Figure 2, (a) and (c) demonstrate consistent upward trend of the stock prices with little fluctuation while (b) for Google pixel shows a volatile variation with irregular trend. The presence of such volatility may have implications for the accuracy of stock price predictions, specifically for Google pixel. Besides, a notable disparity emerges between the blue predicted line and the orange actual line in (b) after the number of 400 test observations, potentially resulting in significant prediction errors. From the figures and results illustrated above, the LSTM model can predict the stock price accurately to a certain extent, it still exhibits occasional inaccuracies at specific value and when confronted with pronounced market fluctuations. For example, it shows a huge difference between the predicted value and the actual one at peak point about the number at 270 observations in (c) that the predicted value is much lower than the actual one.

However, the research and the model still have some limitations and deficiencies. In this paper, the same LSTM model is used to predict all five brands' stock prices. Improvements in prediction accuracy, particularly for Google pixel, may be achieved by adjusting certain parameters within the LSTM model, such as the number of layers, neurons, or training epochs. Moreover, the number of observations in training set before the pandemic is 850, while test set contains 408 observations. Therefore, the prediction may be more precise and credible if there is a larger size of sample in the training set. In the future, the study can still be improved by testing large scales of brands, in other ranges of time under different unexpected conditions, or changing some parameters in LSTM models to check the efficiency of using LSTM to predict the stock price even under the unstable time periods.

4. Conclusion

In this work, the research takes the stock prices from five top smartphone brands as dataset to examine the effectiveness of employing the LSTM model for stock price prediction, even amid unexpected external conditions. The LSTM model is developed and the RMSE, MAE, and R-square score are used as standards to evaluate the accuracy of the results of the prediction. The results demonstrate that the LSTM performed mostly well in the stock price prediction during the spread of the COVID-19 pandemic with a few values have considerable discrepancy between predicted and actual values. In the future, the research can still be improved and adapted to be applied in other business areas when facing external fluctuations for stock price predictions and provide references for individuals, firms, investors, and governments on decision making in stock markets.

References

[1] *Ayush, G.K., & Gowda, R. (2020) A Study on Impact of COVID-19 on Digital Marketing. Vidyabharati International Interdisciplinary Research Journal, 225-228, https://www.researchgate.net/publication/346647663*

[2] *Meyer, B.H., Prescott, B. and Sheng, X.S. (2022) The Impact of the COVID-19 Pandemic on Business Expectations. International Journal of Forecasting, 38, 529-544.*

[3] *Fairlie, R., & Fossen, F.M. (2022) The Early Impacts of the COVID-19 Pandemic on Business Sales. Small Bus Econ, 58, 1853-1864.*

DOI: 10.54254/2754-1169/47/20230372

[4] Alam, S. (2021) Reviewing the Global Smartphone Industry Strategic Implication in Response to COVID-19 Situation. International Journal of Interactive Mobile Technologies (jJIM), 15, 169-192.

[5] Li, X., Li, M., Yan, P., et al. (2023) Deep learning attention mechanism in medical image analysis: Basics and beyonds. International Journal of Network Dynamics and Intelligence, 93-116.

[6] Qiu, Y., Yang, Y., Lin, Z., et al. (2020) Improved denoising autoencoder for maritime image denoising and semantic segmentation of USV. China Communications, 17(3): 46-57.

[7] Gunasekaran, K. P., Tiwari, K., Acharya, R. (2023) Deep learning based Auto Tuning for Database Management System. arXiv preprint arXiv:2304.12747.

[8] Qiu, M., Song, Y. and Akagi, F. (2016) Application of Artificial Neural Network for the Prediction of Stock Market Returns: The Case of the Japanese Stock Market. Chaos, Solitons and Fractals, 85, 1-7.

[9] Patel, J., Shah, S., Thakkar, P. and Kotecha, K. (2015) Predicting Stock and Stock Price Index Movement Using Trend Deterministic Data Preparation and Machine Learning Techniques. Expert Systems with Applications, 42, 259-268.

[10] Ahangar, R.G., Yahyazadehfar, M. and Pournaghshband, H. (2010) The Comparison of Methods Artificial Neural Network with Linear Regression Using Specific Variables for Prediction Stock Price in Tehran Stock Exchange. International Journal of Computer Science and Information Security (IJCSIS), 7, 38-46.

[11] Nabipour, M., Nayyeri, P. and Jabani, H. (2020) Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis. IEEE Access, 8, 150199-150212.

[12] Gharehchopogh, F. S., Bonab, T. H., Khaze, S. R. (2013) A linear regression approach to prediction of stock market trading volume: a case study. International Journal of Managing Value and Supply Chains, 4(3): 25.

[13] Nagadia, M. (2021) Stock Price of Top 10 Smartphone Company 2016-2021. Kaggle, https://www.kaggle.com/datasets/meetnagadia/stock-price-of-top-10-smartphone-company-20162021