Short-Term Price Trend Forecast Based on LSTM Neural Network

A Study Based on Chinese Stock Market Data on Liquor Stocks

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ABSTRACT
With the improvement and application of machine learning and enormous information innovation, securities market forecast has pulled in broad consideration within the business and the scholarly world. This ponders employments person stock information of listed liquor companies in China to investigate the impact of LSTM neural organize on liquor stock time arrangement forecast. The test takes every day exchanging information of Moutai and Wuliangye Yibin from March 31, 2002, to March 31, 2022, as the free variable to foresee the closing cost. The test comes about to appear that LSTM neural organize demonstrate has tall precision and steady forecast impact on cost drift forecast. It has superior prescient esteem for the stocks with little showcase esteem of Chinese liquor, which is helpful for speculators to create choices.

Keywords: *Liquor Industry, Deep Learning, Neural Networks, Price Trend Forecasting.*

1. INTRODUCTION

1.1. Background

China has a long history of liquor culture and is very famous in the world as one of the traditional industries in China. Meanwhile, liquor stocks reflect China's consumption level to a certain extent. Overall, the liquor industry entered a period of growth beginning in 2016. 2017 saw a rebound in the liquor industry, and 2018 saw a new round of gains. 2020 saw a slight drop in the index due to the impact of the beast epidemic, but signs of recovery soon emerged.

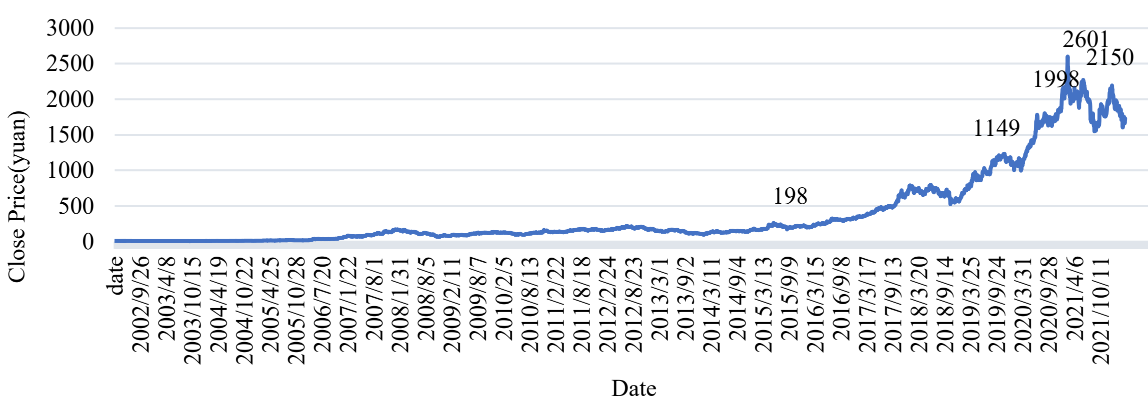

Figure 1 Kweichow Moutai Stock Close

Among them, the liquor industry's leading enterprise " Kweichow Moutai" for example, Moutai's stock price is from 100 yuan in 2010 up to about 1,100 yuan per share in 2019, up to 2,000 yuan in the first half of 2021, the second half of the year fell to 1,500 yuan after a small rebound. Listed liquor companies in China have better

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earnings, and investors have had high investment enthusiasm for the liquor industry in recent years, so it is worthwhile to study the stock development trend of the liquor industry and make predictions.

With the development of the globalized economy, along with the development and strong demand for financial markets, stock price trend forecasting has gained much attention. People's awareness of investment has increased and the demand for investment in stocks has risen. However, investing in stocks has both high returns and high risks. Factors affecting stock market fluctuations are complex, while accurately forecasting stock prices is challenging due to the complexity of factors. Stock data has the characteristics of high noise, dynamic, nonlinear, and non-parametric, so it is challenging to predict stock prices accurately [1]. Traditional forecasting methods are often ineffective in predicting stock prices. Therefore, it is important to explore the use of neural network techniques such as LSTM for stock prediction by mining the information in stocks using big data technology.

1.2. Related research

Recurrent Neural Network (RNN) incorporates the concept of temporal sequence into the network structure design, allowing for greater adaptability in the analysis of temporal data.

Hochreiter and Schmidhuber proposed Long Short-Term Memory (LSTM)model by improving the structure of the RNN network unit. By designing the control gate structure to account for gradient disappearance and explosion, as well as the lack of long-term memory capability, it is possible to make effective use of long-range temporal information [2].

In 2015, Chen et al. used the LSTM model to predict stock prices in China's stock market [3]. In 2016, Jia verified the effectiveness of the LSTM model in predicting stock price trends [4].In 2017, Nelso et al. used the LSTM model to predict future stock market trends based on historical stock data and technical indicators and compared it with other machine learning methods, showing that the LSTM prediction model has higher prediction accuracy [5]. In 2018, Fischer and Krauss applied the LSTM model to predict the volatility of the S&P 500 index [6]. Luyang Chen et al. use deep neural networks to estimate asset pricing models for individual stock returns [7]. Payal Soni et al. analyze in detail the techniques used to predict stock prices and discuss the challenges that will be faced in the future [8]. Sulandari et al. proposed that stock values are often considered as time series models, and therefore time series analysis is a popular model for predicting stock prices [9]. Xingzhou et al. focus on the role of indices in stock price prediction and use LSTM on the right-hand side of the S&P 500 [10]. Jeevan et al. represent stock prices in the form of time series, using normalized data and recursive neural network models yielded good results and concluded that machine learning algorithms are best suited to predict stock prices [11].

1.3. Objective

Machine learning algorithms are able to simulate the characteristics of objects to the maximum extent. At the same time, machine learning has greater advantages in handling large data volumes, more complex data, and making predictions. The closing price trend is an important basis for studying and judging the trend of stock price changes and an important indicator for analyzing microeconomics. Therefore, it is of great practical importance and use to study the prediction model of stock trends.

LSTM neural networks have some prediction ability for the trends of stocks, but there are fewer studies on short-term price trends. In the face of these problems, the study on the comparison of short-term trend prediction effects based on the LSTM neural network has some practical significance.

2. STOCK PRICE TREND FORECASTING FUNDAMENTALS

2.1. LSTM model structure and principle

The LSTM structure uses a control gate mechanism, consisting of a memory cell, an input gate, an output gate, and a forgetting gate. The computational principle of each control gate of the LSTM model is shown in Figure 2.

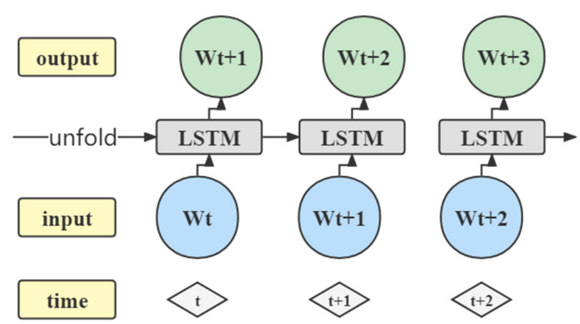

Figure2 LSTM model structure

2.2. LSTM Stock Price Trend Forecasting Model Construction

The article describes how to program the LSTM neural network's training and prediction processes using graph fitting and error evaluation. In this paper, PyTorch is used as a deep learning framework for the training model, and the Adam algorithm is used to optimize the training process. The experiments were conducted to determine the strength and weaknesses of the LSTM model prediction results by comparing the prediction results of the LSTM model with the true value of the stock.

2.2.1 Data acquisition and pre-processing

Based on experimental rigor, reasonableness, and accuracy considerations, the research object of the article is the stocks of listed Chinese liquor companies, and the stocks listed on the Shanghai Stock Exchange, and Shenzhen Stock Exchange with large market capitalization are selected. These include Kweichow Moutai, which has the highest market capitalization, and Wuliangye Yibin and Shanxi Xinghuacun Fen Wine Factory, which are the second and third largest listed companies in China in terms of market capitalization. The market capitalization of the selected companies is shown in Table 1. Kweichow Moutai (600519.SS), Wuliangye Yibin (000858.SZ), Shanxi Xinghuacun Fen Wine Factory(600809.SS), Luzhou Laojiao (000568.SZ), Anhui Gujing Distillery (000596.SZ), Shede Spirits (600702.SS), Jiugui Liquor (000799.SZ), Hebei Hengshui Laobaigan Liquor (600559.SS) was studied from March 31, 2002, to March 31, 2022, and the data was downloaded through Yahoo Finance. The stock attributes are date, opening price, closing price, high price, low price, and daily volume, and the data with invalid dates are excluded to obtain a CSV file with the above six attributes. To verify the validity of the model, the article selects several stocks' historical data for the experiment, and the sample data are shown in Table 2.

Table1. The market capitalization of the selected companies

Name of the company	Market capitalization (million yuan)
Kweichow Moutai	864279
Wuliangye Yibin	2575205
Shanxi Xinghuacun Fen Wine Factory	75480
Luzhou Laojiao	371857
Anhui Gujing Distillery	385288
Shede Spirits	110589
Jiugui Liquor	69047
Hebei Hengshui Laobaigan Liquor	25070

Table2. Example of historical stock sample data

Wuliangye Yibin (000858.SZ)						
Date	Open	High	Low	Close	Adj Close	Volume
2002/4/1	4.601648	4.647435	4.578754	4.613095	3.581307	3916261
2002/4/2	4.624542	4.640567	4.505494	4.510073	3.501328	6615008
2002/4/3	4.546703	4.562728	4.464285	4.496336	3.490663	5807024
…	…	…	…	…	…	…
2022/3/29	150.99001	153.77	149.11	149.17999	149.17999	23521130
2022/3/30	152.97	156.95	151.16	156.95	156.95	32367269

2.2.2 Data normalization

This article sorts the data, adds missing values, and removes useless variables. The data has varying magnitudes and orders of magnitude; for example, there is a large order of magnitude difference between volume and price. Therefore, the data needs to be standardized first.

$$\mathrm{X_{new}} = (\mathrm{X_{old}} - \min(\mathrm{X}))/(\max(\mathrm{X}) - \min(\mathrm{X})) \quad (1)$$

To ensure that the neural network's output data matches the input data in order of magnitude, results also needs to be de-normalized.

$$y(i) = y_i(\max(x_i) - \min(x_i)) + \min(x_i) \quad (2)$$

2.2.3 Data Classification

Before training the model, the data is divided. 90% of the data is considered as the training set and 10% of the data is considered as the test set.

2.2.4 Training model

The minimum price (low), maximum price (high), closing price(close), and volume are selected as feature data inputs to configure the training parameters of the LSTM model. In the LSTM model used in this paper, the number of input neurons is set to the number of input features and the output neurons correspond to the final predicted closing prices.

2.2.5 Stock prediction and parameter optimization

The model is trained several times and the prediction results are compared. Using the control variable method, the parameters are continuously adjusted according to the characteristics of the model and the prediction results, until the best prediction is achieved if the prediction cannot be enhanced by adjusting the parameters within a range.

After adjusting the parameters several times, the accuracy of the prediction results for different stocks is improved. The prediction resulting before and after the improvement of some stocks is shown in Fig3 and Fig 4.

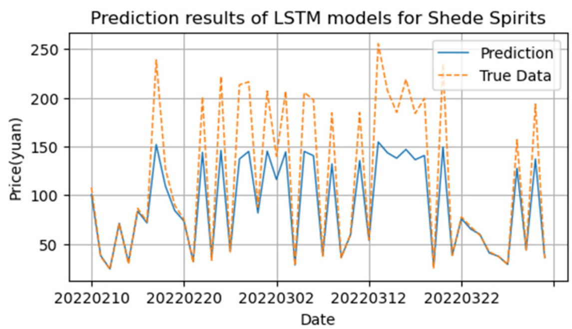

Figure 3 Prediction results before model improvement

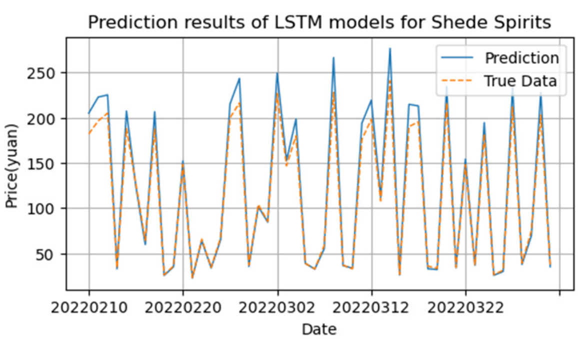

Figure 4 Prediction results after model improvement

The final model parameters obtained are shown in Table 3.

Table 3. LSTM Model parameter presets

Parameters	Value
sequence_length	10
batch_size	64
train_test_split	0.9
loss	MSE
optimizer	Adam
learning rate	0.0001
input_size	5
hidden_size	32

3. RESULTS

Plot the predicted value of the LSTM model against the actual stock closing price. Compare the prediction results with the real values and explore the prediction effectiveness of the LSTM model, as shown in Figure 5 to Figure 12 (2022.02.10-2022.03.31)

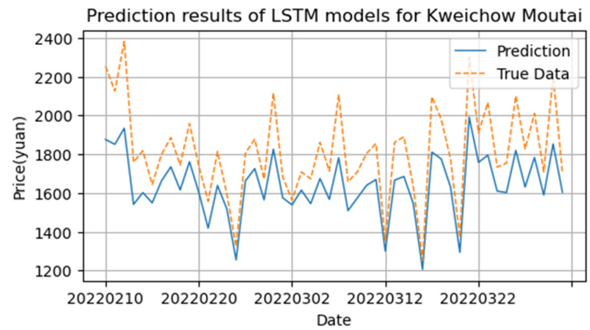

Figure 5 Kweichow Moutai

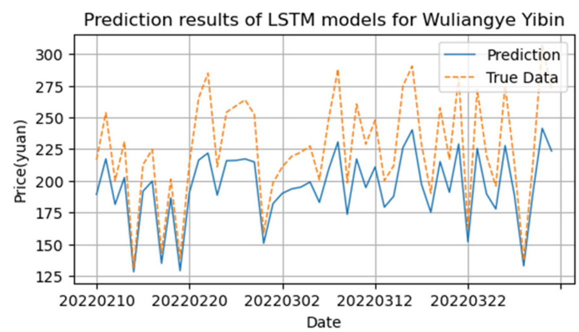

Figure 6 Wuliangye Yibin

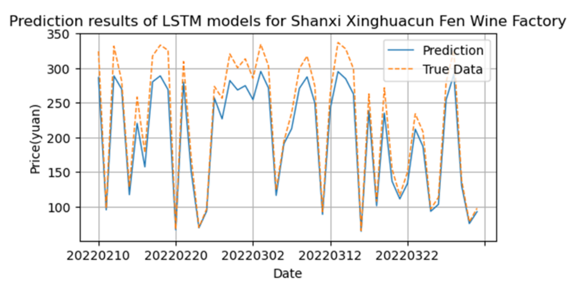

Figure 7 Shanxi Xinghuacun Fen Wine Factory

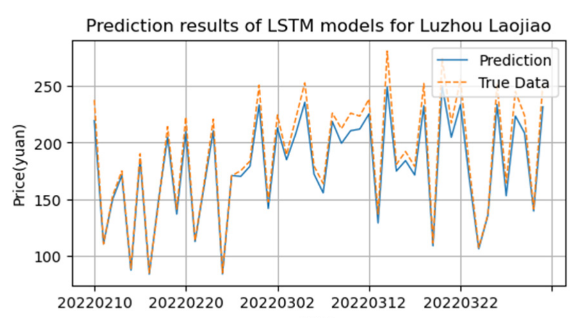

Figure 8 Luzhou Laojiao

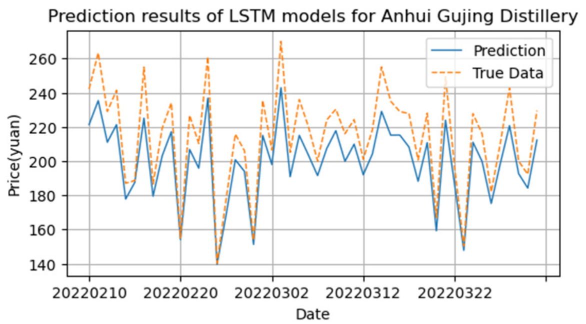

Figure 9 Anhui Gujing Distillery

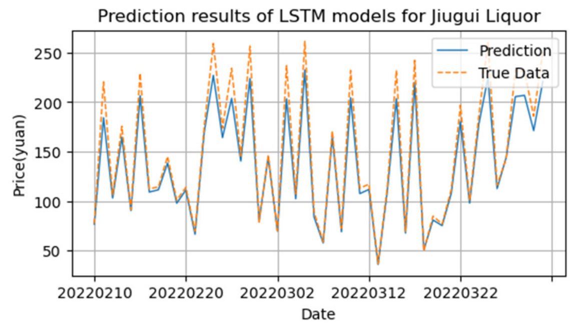

Figure 11 Jiugui Liquor

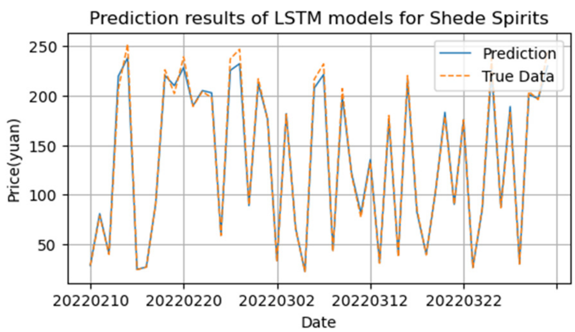

Figure 10 Shede Spirits

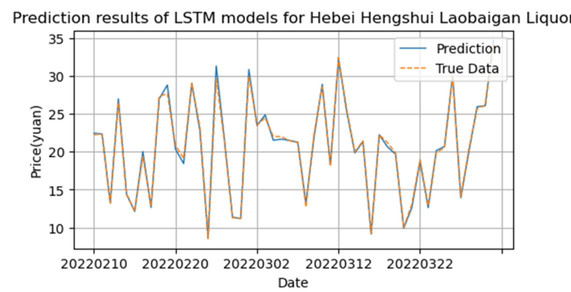

Figure 12 Hebei Hengshui Laobaigan Liquor

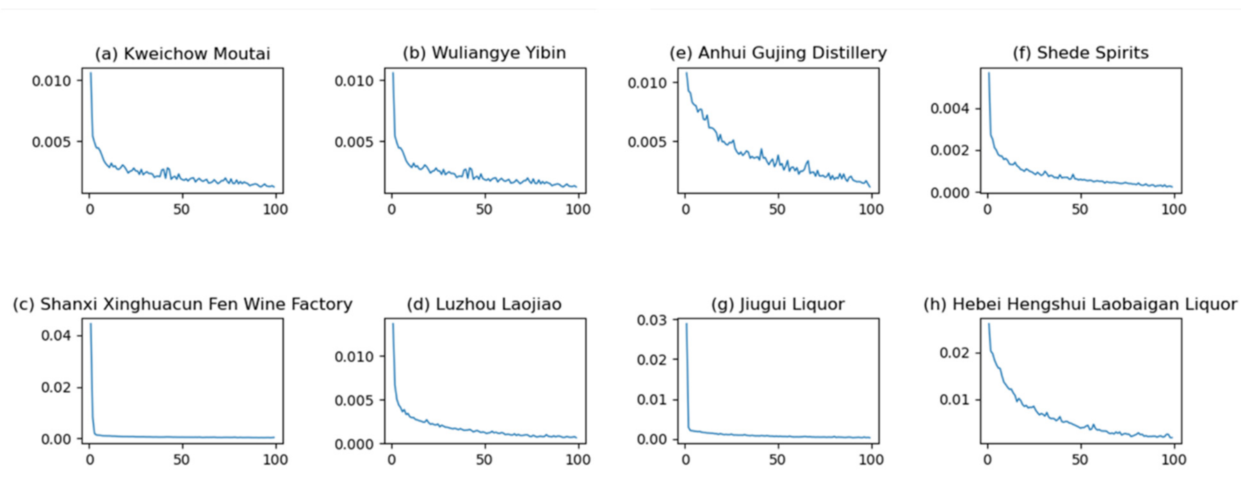

Figure 13 Trend of training error of LSTM neural network

The model's parameters are adjusted, and the training set data for the model all cause the neural network's prediction error to converge rapidly, indicating that the constructed network is lightweight. The model's error is stable at a low level following training, indicating that the model is stable. The prediction process involves some time lag, and the predicted values are more accurate and stable for data-intensive or obvious trend areas. The prediction effect is limited to fluctuating peak and trough regions and turning points.

4. DISCUSSION

From the comparison of predicted and true prices of individual stocks, Luzhou Laojiao's prediction is the best among all models, while Wuliangye and Fen Wine's predicted and true values deviate to a greater extent, making the prediction slightly less effective. The fitted curves of the model prediction results show that the LSTM neural network is relatively accurate in predicting the price trends of most stocks.

Table 4. Comparison of the MSE of the model for individual stock price prediction

Stock	Kweichow Moutai	Wuliangye Yibin	Shanxi Xinghuacun Fen Wine Factory	Luzhou Laojiao
MSE	192.271	23.994	44.181	9.699
Stock	Anhui Gujing Distillery	Shede Spirits	Jiugui Liquor	Hebei Hengshui Laobaigan Liquor
MSE	10.815	2.809	3.870	0.610

The model's predicted MSE for Kweichow Moutai is 192.271, which is larger than the predicted MSE for the other 7 stocks, and its predicted value has a greater dispersion from the true value fit graph, while the model's predicted MSE for Hebei Hengshui Laobaigan Liquor is 0.610, which is smaller than the predicted MSE for the other 7 stocks, and its predicted value has a smaller dispersion from the true value fit graph and the highest prediction accuracy.

In 2020, as the virus coming back, the consumption scenario will be affected under zero Covid-19 strategy. Consumption of Chinese Baijiu rose during the Spring Festival in 2022 though, overseas investors were pessimistic for the conflict between Russia and Ukraine. Moreover, with growing epidemic at the beginning of the year, investors were not optimistic about its consumption in China. The fact that Chinese Baijiu shares retreated earlier this year was obvious. Moutai, the leading Chinese Baijiu, with the highest market value and higher efficiency of making money, was easy to be influenced by public sentiment, and its stock price volatility is more obvious. The LSTM model has a limited prediction effect on areas with large fluctuations and turning points, so its prediction of stocks with large market value is barely satisfactory. Overall, high-end Chinese Baijiu has social attributes and needs long-term stability, thus there is still room for growth. With repeated pandemics, the model is more meaningful for small and medium-sized shares of Chinese Baijiu.

5. CONCLUSION

The explore employments LSTM to show Chinese securities market forecast and employments preparing to demonstrate to foresee stock. In this paper, the stock information of a few listed liquor companies with expansive showcase esteem are chosen as cases to move forward with the show structure and optimize the parameters based on THE LSTM demonstrate. It is demonstrated that LSTM neural arrangement can accomplish superior comes about in-stock showcase forecast through learning and preparing. LSTM show is a great variation demonstrate of RNN, which employments its memory capacity to associate the relationship between the current information and the past information, spare the state data sometime recently input to the arrange, and foresee the improvement drift. In this stock cost slant expectation show, distinctive stock information will have diverse impacts on the forecast comes about. Stock information is associated with degree unstable statistics, whereas for alcohol recorded corporations with little showcase capitalization. Because of the tiny vacillation of stock information, LSTM encompasses a way better forecast on the stock of firms.

In this paper, only five features: the opening price, closing price, high price, low price, and volume are employed for prediction, while the features affecting the stock market are more complex. The characteristic information of stock forecast may moreover include content examination, stock opinion correction so on, that's anticipated to extra progress the precision of stock expectation.

REFERENCES

[1] Y. W. Si, & J. Yin, OBST-based segmentation approach to financial time series. Engineering Applications of Artificial Intelligence, vol.26, no.10, 2013, pp. 2581-2596. DOI: https://doi.org/10.1016/j.engappai.2013.08.015

[2] S. Hochreiter, & J. Schmidhuber, Long short-term memory, Neural computation, vol.9, no. 8, 1997, pp. 1735-1780. DOI : https://doi.org/10.1162/neco.1997.9.8.1735

[3] K. Chen, Y. Zhou, & F. Dai, A LSTM-based method for stock returns prediction: A case study of China stock market, international conference on big data (big data), vol. 9, no.8, 2015, pp. 2823-2824. DOI: https://doi.org/10.1162/neco.1997.9.8.1735

[4] H. Jia, Investigation into the effectiveness of long short term memory networks for stock price prediction, arXiv preprint arXiv:1603.07893, 2016,DOI: https://doi.org/10.48550/arXiv.1603.07893

[5] D. M. Q. Nelson, A. C. M. Pereira & R. A. de Oliveira, Stock market's price movement prediction with LSTM neural networks, International Joint Conference on Neural Networks, 2017, pp. 1419-1426, DOI: 10.1109/IJCNN.2017.7966019.

[6] T. Fischer & C. Krauss, Deep learning with long short-term memory networks for financial market predictions, European Journal of Operational

Research, vol.270, no.2, 2018, pp. 654-669. DOI: https://doi.org/10.1016/j.ejor.2017.11.054.

[7] L. Chen, M. Pelger, & J. Zhu, Deep learning in asset pricing, arXiv preprint arXiv:1904.00745, 2019. DOI: https://doi.org/10.48550/arXiv.1904.00745

[8] P. Soni, Y. Tewari, & D. Krishnan, Machine Learning Approaches in Stock Price Prediction: A Systematic Review, In Journal of Physics: Conference Series, vol. 2161, no.1, 2022, pp. 012065. DOI: https://doi.org/10.1088/1742-6596/2161/1/012065.

[9] W. Sulandari, Suhartono, Subanar, & P. C. Rodrigues, Exponential Smoothing on Modeling and Forecasting Multiple Seasonal Time Series: An Overview, Fluctuation and Noise Letters, vol. 20, no. 04, 2021, pp. 2130003. DOI: https://doi.org/10.1142/s0219477521300032.

[10] L. Xingzhou, R. Hong, & Z. Yujun, Predictive Modeling of Stock Indexes Using Machine Learning and Information Theory, Proceedings of the 2019 10th International Conference on E-business, Management and Economics, 2019, pp. 175-179. DOI: https://doi.org/10.1145/3345035.3345087.

[11] B. Jeevan, E. Naresh, B. P. V. kumar and P. Kambli, Share Price Prediction using Machine Learning Technique, 2018 3rd International Conference on Circuits, Control, Communication and Computing, 2018, pp. 1-4. DOI: 10.1109/CIMCA.2018.8739647.