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Developing a Stock Market Prediction Model by Deep Learning Algorithms

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Abstract

For investors, predicting stock market changes has always been attractive and challenging because it helps them accurately identify profits and reduce potential risks. Deep learning-based models, as a subset of machine learning, receive attention in the field of price prediction through the improvement of traditional neural network models. In this paper, we propose a model for predicting stock prices of Tehran Stock Exchange companies using a long-short-term memory (LSTM) deep neural network. The model consists of two LSTM layers, one Dense layer, and two DropOut layers. In this study, using our studies and evaluations, the adjusted stock price with 12 technical index variables was taken as an input for the model. In assessing the model's predictive outcomes, we considered RMSE, MAE, and MAPE as criteria. According to the results, integrating technical indicators increases the model's accuracy in predicting the stock price, with the LSTM model outperforming the RNN model in this task.

Keywords: Stock Price Prediction, Artificial Neural Networks, Deep Learning, Long Short-Term Memory, Recurrent Neural Networks.

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Introduction

Financial markets in the economy are investment institutions and intermediaries between investors and the economy. The stock market is one of the most important financial markets and can be considered an indicator of a country's economy (Gordon et al., 2009). The stock market is a snapshot of future growth expectations of companies as well as the economy. Many factors contribute to stock price fluctuations, including but not limited to macroeconomic factors, market anticipation, and confidence in the company's management and operations (Ramezanian et al., 2019). Forecasting stock price movements is an important, attractive, and extremely difficult topic for researchers, traders, and market analysts. The efficient market hypothesis posits that it is impossible to predict stock values and that stocks behave randomly, but recent technical analyses show that most stock values are reflected in previous records. Therefore, movement trends are vital for predicting values effectively (Nabipour et al., 2020).

Some studies aim to measure the different efficiency levels for mature and emerging markets, while others strive to build effective prediction models for stock markets. The effort starts with the stories of fundamental analysis and technical analysis. Fundamental analysis evaluates the stock price based on its intrinsic value, i.e., fair value, while technical analysis relies solely on charts and trends. With the development of machine learning techniques, it has proven useful for stock price prediction. Technical indicators from experience can be further used as hand-crafted input features for machine learning and deep learning models (Jiang, 2021). Subsequently, linear models like AR, ARMA, and ARIMA have been introduced as solutions for stock market prediction (Zhang, 2003; Menon et al., 2016). The most common machine learning algorithms applied for stock market prediction are artificial neural networks (ANN) and support vector machines (SVM) (Naeini et al., 2010; Guresen et al., 2011; Kara et al., 2011; Wang & Wang, 2015). Other tools and techniques like genetic algorithms (GA) (Atsalakis & Valavanis, 2009; Brown et al., 2013; Hu et al., 2015), linear discriminant analysis, quadratic discriminant analysis, logistic regression, and evolutionary computing algorithms are used for feature extraction from raw financial data and making predictions based on a set of variables.

In the past few years, both the basic tools for deep learning and the new prediction models have been undergoing rapid development. By inputting data from multiple factors and passing them through many layers, deep learning can extract useful features, increase representational power, enhance performance, and improve prediction accuracy for future stock markets. Deep learning methodologies have been applied to time-series predictions, focusing on popular real-world application domains such as the stock and cryptocurrency markets. Deep learning algorithms like deep multilayer perceptron (MLP) (Khare et al., 2017; Yong et al., 2017; Doaei et al., 2021), long short-term memory (LSTM) (Chen, 2015; Fischer & Krauss, 2018; Nikou et al., 2019; Nabipour et al., 2020; Moghar et al., 2020), autoencoder (AE) (Bao, 2017), and convolutional neural network (CNN) (Di Persio & Honchar, 2016; Gunduz et al., 2017; Mehtab et al., 2020; Chung & Shin, 2020) are prominent deep learning algorithms utilized to predict stock markets.

There is extensive research on predicting stock returns using past information, and researchers have identified several financial variables that can be used for making predictions. Various factors affecting prices have been identified, and different categories for price prediction variables have been presented. Company fundamentals, raw price data, technical indicators, macroeconomic factors, psychological behavioral factors, image data (e.g., candlestick charts), other markets with connections to the target market, exchange rates of currencies, oil prices, and many other variables can be useful for market prediction tasks (Jiang, 2021).

The Iranian stock market has become increasingly popular in recent years, due in part to the strong growth of the Tehran Stock Exchange Dividend and Price Index (TEDPIX) in recent decades. The Iranian stock market has some unique features compared to other stock markets around the world. One of these features is a price limitation of ±7% of the opening price of the day for each index. This limitation helps to prevent abnormal market fluctuations and spreads market shocks, political issues, etc., over a period, making the market smoother and more predictable. Trading on the Iranian stock market takes place through licensed registered private brokers of the exchange organization. The opening price of the next day is determined by the defined base volume of the companies and the transaction volume. Despite the growing popularity of the Iranian stock market, there is a lack of research using machine learning models to predict future values. This is a significant gap in the literature, as machine learning could be a valuable tool for investors in this market.

This research focuses on the prediction of future values for the stock market, a vital aspect for investors. Despite the recent growth of Iran's stock market, there is a need for more research on using novel machine learning methods to predict stock prices and movements. In this research, we propose a model based on LSTM because it can learn long-term dependencies in sequential data, is robust to noise, and has proven capabilities in other domains, as well as successful past experiments reported in the market prediction domain. Our proposed model has 2 LSTM layers, a dense layer, and uses adjusted price and 12 technical indicators as its inputs. This paper aims to compare the performance of LSTM and RNN models and to find the optimal parameters for predicting the price of selected stocks. For this purpose, by tuning parameters, we try to reduce errors and increase the accuracy of models. The dataset consists of historical prices of the selected companies for prediction over a 5-year period from 2016 to 2021, collected from the Tehran Stock Exchange website.

The rest of the paper is organized as follows: Section 2 provides a literature review. Section 3 describes our proposed method in detail. Section 4 reports the experimental results and their analysis. Finally, Section 5 presents our conclusions.

Literature Review

Designing and developing models for predicting stock prices and stock price movements using deep learning has been a very active research area. Some researchers have used CNN deep neural networks (Hiransha et al., 2018; Hoseinzade & Haratizadeh, 2019), while others have used LSTM deep neural networks (Kim et al., 2019; Moghar & Hamiche, 2020; Nabipour et al., 2020; Mohanty et al., 2021). Additionally, some studies have employed hybrid algorithms such as CNN and LSTM (Liu et al., 2017; Mehtab et al., 2020; Vidal & Kristjanpoller, 2020).

Hiransha et al. (2018) applied four types of deep learning architectures, namely Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) to predict the stock price of a company. The research results indicated that CNN outperformed the other models. Mehtab et al. (2020) built two regression models on CNN and three prediction models based on LSTM networks. Their results indicated that the LSTM-based univariate model, which uses one-week prior data as input for predicting the next week's open value of the NIFTY 50 time series, is the most accurate.

Some studies compared different algorithms in stock market prediction. Nikou et al. (2019) performed the prediction process through four models of machine learning algorithms. The results indicate that the deep learning method is better in prediction than the other methods, with support vector regression ranking next, followed by neural network and random forest methods with less error. In another study, Nabipour et al. (2020) utilized various machine learning algorithms for predicting future values of stock market groups. They employed decision trees, bagging, random forests, adaptive boosting, gradient boosting, eXtreme gradient boosting (XGBoost), artificial neural networks (ANN), RNN, and LSTM. The results showed that among all the used algorithms, LSTM produced the most accurate results with the highest model fitting ability.

Vidal and Kristjanpoller (2020) combined LSTM and CNN to improve the forecast of gold volatility. The results showed improvement when this hybrid model was compared to the GARCH and LSTM models. Arévalo et al. (2016) used a deep ANN with five hidden layers to forecast Apple Inc.'s stock price, achieving up to about 65% directional accuracy. Nelson et al. (2017) utilized technical indicators as input for an LSTM to predict the direction of stock prices in the Brazilian stock market, reporting that LSTM outperformed MLP. Patel et al. (2020) proposed a hybrid cryptocurrency prediction approach focusing on Litecoin and

Monero cryptocurrencies. Their model, based on a recurrent neural network architecture utilizing LSTM and GRU layers, demonstrated that the proposed hybrid model outperforms traditional LSTM networks, exhibiting some promising results.

Doaei et al. (2021) proposed a hybrid MLP neural network combined with metaheuristic algorithms, including genetic algorithm (GA), particle swarm optimization (PSO), black hole (BH), grasshopper optimization algorithm (GOA), and grey wolf optimization (GWO), to predict the daily Tehran Exchange Dividend Price Index (TEDPIX). The experimental results showed that grey wolf optimization outperformed other metaheuristic algorithms in training MLPs for predicting the stock market.

Hoseinzade and Haratizadeh (2019) introduced a CNN-based framework applied to a diverse collection of data from various sources, including different markets, to extract features for predicting the future of those markets. The results demonstrated a significant improvement in prediction performance.

Yadav et al. (2020) optimized LSTM for time series prediction in the Indian stock market. The reported experiments showed that for time series prediction problems, a stateless LSTM model is preferable due to its higher stability.

Pokhrel et al. (2022) conducted a comparative analysis of three deep learning models—LSTM, Gated Recurrent Unit (GRU), and CNN—in predicting the next day's closing price of the Nepal Stock Exchange (NEPSE) index. Their experimental results indicated that the LSTM model architecture provides a superior fit with high prediction accuracy. Moreover, statistical evidence was presented to validate the models' reliability and robustness.

Ferdiansyah et al. (2019) proposed an LSTM-based method for bitcoin price prediction. They concluded that since stock markets are influenced by many uncertain factors such as political and economic issues at local or global levels, predicting bitcoin prices using LSTM alone may not suffice to make investment decisions.

Overall, stock price prediction and modeling are challenging problems due to noisy and non-stationary data. While researchers agree on this point, there is some disagreement about which indicators are most effective for modeling and predicting stock markets. Feature selection can be crucial for improving accuracy, but all studies concur that uncertainty is inherent in forecasting tasks due to fundamental variables. Many studies have compared different algorithms for stock market prediction, with deep learning algorithms such as CNNs, LSTM networks, and RNNs being the most common choices. Other algorithms used include support vector machines, random forests, and decision trees. Overall, the results of existing studies suggest that deep learning algorithms, particularly LSTM networks, have the potential to be highly effective for stock market prediction.

Methodology

The general workflow with four steps for stock price prediction using the proposed method is shown in Figure1 .

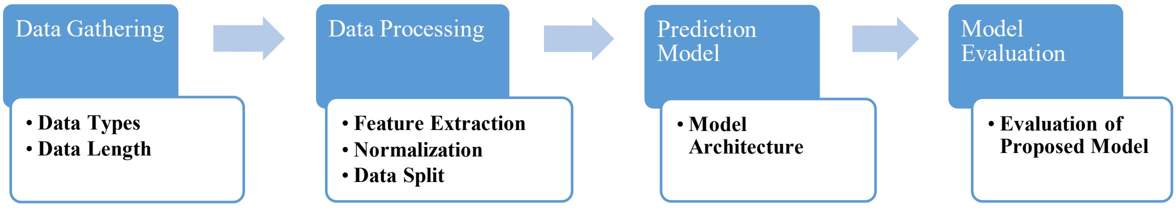

Figure *1* . General steps of the proposed method for stock price prediction

A. Data

The first step of stock price prediction involves collecting appropriate data as a basis for subsequent steps. Considering the factors affecting stock prices, this research utilizes two groups of data as input to the proposed deep learning model, comprising price data along with 12 technical indicators. The price data encompasses the open price, close price, lowest price, highest price, and adjusted price. Historical price data of the selected companies for prediction over 5 years from 2016 to 2021 were gathered from the Tehran Stock Exchange website. Table 1 illustrates all the technical indicators employed as input values, based on input from domain experts and previous studies.

Table 1. Selected technical indicators

Simple Moving Average (SMA)	$\frac{(C_t + C_{t-1} + \dots + C_{t-n+1})}{n}$
Exponential Moving Average (EMA)	$(C_t - EMA(n)_{t-1}) * (\frac{2}{n+1}) + EMA(n)_{t-1}$
Relative Strength Index (RSI)	$RSI = 100 - \frac{100}{1+RS} \quad RS = \frac{Avg(Gain)}{Avg(Loss)}$
Momentum	Ct - Ct-n+1
Stochastic K%	$\frac{C_t - LL_{t\_t-n+1}}{HH_{t\_t-n+1} - LL_{t\_t-n+1}} \times 100$
Stochastic D%	$\frac{K_t + K_{t-1} + \dots + K_{t-n+1}}{n} \times 100$
Larry William's R%	$\frac{HH_{t\_t-n+1} - C_t}{HH_{t\_t-n+1} - LL_{t\_t-n+1}} \times 100$
$MACD_t$	EMA(12)t - EMA(26)t
BolU	MA(TP,n)+m*σ[TP,n]
BolD	MA(TP,n)–m*σ[TP,n]
W	

While :
n is number of days
C_t is closing priceat time t
L_t and H_t is the low price and high price at time t, respectively
LL_{t_t-n+1} and HH_{t_t-n+1} is the lowest low and highest high prices in the last n days, respectively
MA = Moving Average
TP (Typical Price) = (H + L + C) / 3
σ[TP,n] : : standard deviation of the last n period TP

B. Data Processing

First, we checked the correlation of price data (open, close, highest, lowest, and adjusted price). Figure2 shows the correlation of price data. As we can see in the figure, open price, close price, highest price, lowest price, and the adjusted price are fully correlated with each other (the correlation value is equal to one). Therefore, to reduce the dimensions of the input and reduce the volume of calculations, we only considered the adjusted price variable (variable Adj_price) as the price input data for the evaluation of the proposed model. Figure3 shows the 13 input variables to the proposed model (adjusted price and technical indicators) and the correlation between them.

After the initial preparation of the data, we used the MinMaxScaler class to normalize the data, and all the data were scaled according to the minimum and maximum values in the [0,1] range.

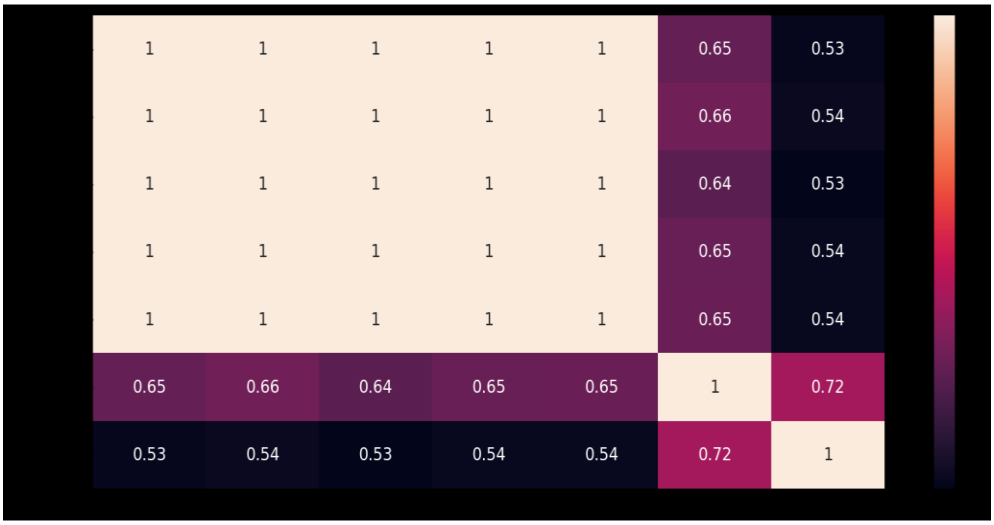

Figure*2* . Correlation of price data

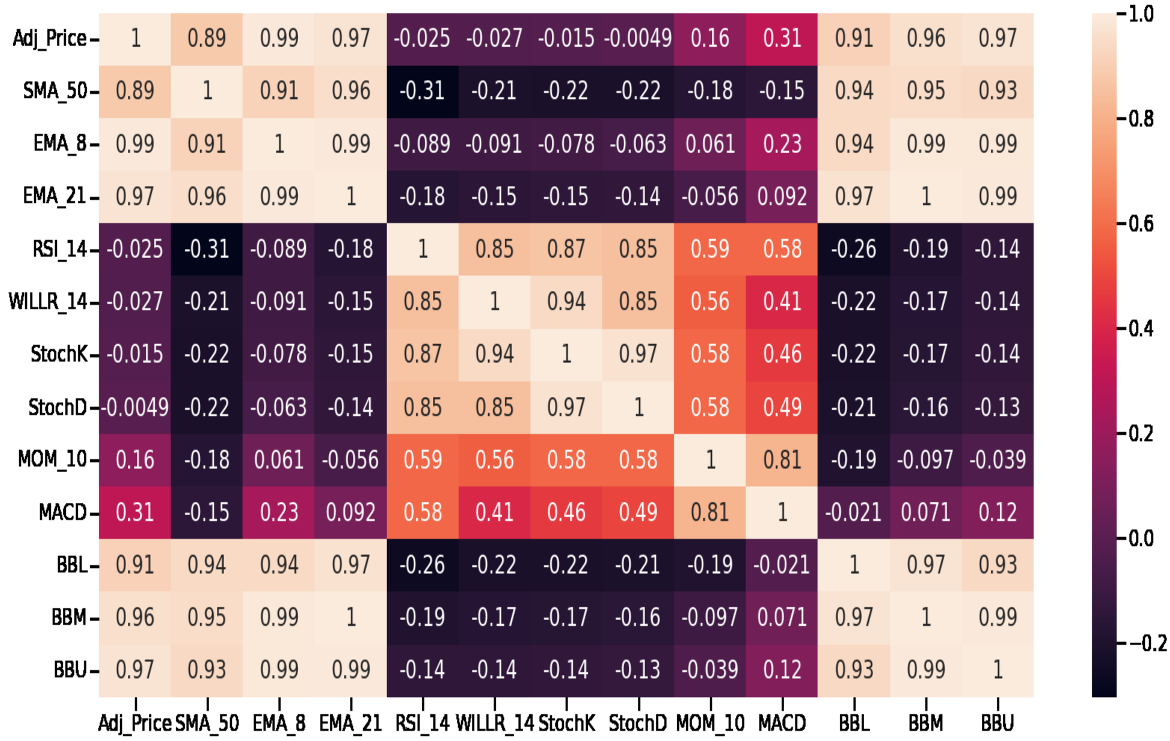

Figure3 . Correlation of the adjusted price and technical indicators

C. Proposed Model

Based on experiments with different architectures and checking the optimal number of layers for our data set and goals, the proposed model is a sequential model that has 2 LSTM layers, a Dense layer (output layer), and a DroupOut layer after each LSTM layer. The DropOut layer prevents the overfitting of neural networks by removing some neurons. The used parameters in the proposed model are listed in Table 2. Our model will be structured as shown in Table 3.

Table 2. The used parameters in the proposed model

Parameter	Value
Number of neurons in the first layer	128
Number of neurons in the first layer	64
Activation function	ReLU
Optimizer	Adam
Loss function	MSE
Epochs	1000
Batch size	64

Table3 . The LSTM model summery

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 20, 128)           72704

 dropout (Dropout)           (None, 20, 128)           0

 lstm_1 (LSTM)               (None, 64)                49408

 dropout_1 (Dropout)         (None, 64)                0

 dense (Dense)               (None, 1)                 65

=================================================================
Total params: 122,177
Trainable params: 122,177
Non-trainable params: 0
_________________________________________________________________
```

Results

In this section, we describe the settings that are used to evaluate the model, including evaluation methodology and datasets. Then, the evaluation results are reported.

A. Evaluation methodology

To evaluate the efficiency of the proposed model and compare it with other models, we use the criteria of MSE, RMSE, MAE, and MAPE, which we will introduce below. In the following relationships, At is the actual value, Ft is the predicted value, and n is the number of samples.

The Mean Squared Error (MSE) measures the quality of a predictor, and its value is always non-negative (values closer to zero are better). This criterion is dimensional and gives more weight to larger errors. The formula is shown in Equation (1) [30]:

$$MSE = \frac{1}{n}\sum_{1}^{n}(A_t - F_t)^2 \tag{1}$$

The Root Mean Square Error (RMSE) is calculated using Equation (2) [30]:

$$RMSE = \sqrt{MSE} \tag{2}$$

The reason for using the RMSE is its dimension and scale are the same as the target feature.

The Mean Absolute Error (MAE) is a measure of the difference between the predicted values from the actual values. The formula is shown in Equation (3) [30]:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} | A_t - F_t | \quad (3)$$

The Mean Absolute Percentage Error (MAPE) is like MAE but uses relative error instead of error. MAPE is often employed to assess the performance of the prediction methods. The formula is shown in Equation (4) [30]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| * 100 \quad (4)$$

B. Data gathering and preparation

The proposed model is implemented with Python language and the Keras library (Chollet et al., 2015) is used to develop the LSTM model. The selected companies from the Tehran Stock Exchange for this research, along with the number of collected data for each, are shown in Table 4. The data collected for the study is from the Tehran Stock Exchange website (http:///www.tsetmc.com). The data for all listed companies except "BSDR1" are from Mar. 2017 Mar. 2022. The data of "BSDR1" is from May 2018 to May 2022.

Table 4. Selected companies of the Tehran Stock Exchange to evaluate the proposed model

Symbol	Co. Name	Group	Number of data records
PTEH1	Tehran Oil Refining Co.	Petroleum	1125
PNES1	Isfahan Oil Refinery Co.	Petroleum	1130
BSDR1	Saderat Bank	Banks	920
MSMI1	National Iranian Copper Industries Co.	Basic Metals	1140
FOLD1	Mobarakeh Steel Co.	Basic Metals	1160

In the first step of evaluation, we compared the efficiency of RRN and LSTM deep neural network models. In this regard, the LSTM model is like the proposed model (including two LSTM layers, one output layer (Dense), and two DropOut layers) and the RNN model is also like the LSTM model in terms of architecture, with a difference that the SimpleRNN layer is used instead of the LSTM layer. In this step, the number of Epochs is equal to 100, the batch size is 200, and our model uses 80% of the data for training and the other 20% of the data for testing data.

To evaluate the models, price data including the adjusted price and technical indicators were given as input to both LSTM and RNN models. The results of comparing the efficiency of the two models are illustrated in Table 5. As the results show, the values of MSE, RMSE, and MAE criteria are close to each other in both models, but the results of MAPE criteria in the LSTM model are better than the RNN model and the price prediction has been done more accurately.

Table 5. Comparing the performance results of LSTM and RNN models on normalized training and test dataset

Symbol	LSTM Model				RNN Model			
	MSE	RMSE	MAE	MAPE	MSE	RMSE	MAE	MAPE
PTEH1	0.000812	0.028498	0.014473	0.1206	0.000797	0.028244	0.018356	0.37382
FOLD1	0.000224	0.014997	0.00921	0.064062	0.000271	0.016475	0.010288	0.104706
BSDR1	0.000434	0.02084	0.014061	0.061718	0.000533	0.023107	0.018952	0.15947

In the second step of the current research, to optimize the proposed model, a basic model was considered and then to achieve a more optimal model, it was evaluated with different parameters. In the basic model, for all stock market symbols, the window size is 20, batch size is 32, Epochs is 100, training data is 80% and test data is 20% of the total data. Also, price data including adjusted price and technical indicators were given as input to the model. Finally, by comparing the results of executions with different parameters, the parameter values of Table 6 were obtained for the optimal model.

Table 6. Optimal parameter values of the model for each of the selected companies

Symbol	Parameters				
	Window Size	Batch Size	Epochs	Train Data	Test Data
PTEH1	20	32	1000	0.8	0.2
FOLD1	20	32	1000	0.8	0.2
BSDR1	20	32	1000	0.85	0.15
PNES1	20	64	500	0.8	0.2
MSMI1	20	32	1000	0.85	0.15

The performance evaluation results between the basic model and the optimal model of the proposed method on the training and test data sets are given in Table 7. Also, the evaluation results for each of the training and test data are given separately in

Table 8Table 8 and Table 9, respectively. As we can see, the optimal model has better accuracy than the basic model in price prediction and has provided better performance.

Table 7. Comparing the performance results of the optimal model and the basic model on the normalized training and test dataset

Symbol	Optimal model of proposed method				Basic model			
	MSE	RMSE	MAE	MAPE	MSE	RMSE	MAE	MAPE
PTEH1	0.000146	0.012091	0.00691	0.0518	0.000812	0.028498	0.014473	0.120607
FOLD1	0.000176	0.0133	0.008508	0.05174	0.000224	0.014997	0.00921	0.06406
BSDR1	0.000403	0.02009	0.013911	0.0488	0.000434	0.02084	0.014061	0.061718
PNES1	0.00016	0.01266	0.007313	0.08374	0.001372	0.03704	0.026245	0.41554
MSMI1	0.000205	0.014318	0.0081	0.06258	0.000427	0.02067	0.012548	0.13506

Table 8. Comparing the performance results of the optimal model and the basic model on the normalized training dataset

Symbol	Optimal model of proposed method				Basic model			
	MSE	RMSE	MAE	MAPE	MSE	RMSE	MAE	MAPE
PTEH1	0.0000609	0.0078	0.00382	0.04967	0.000855	0.029253	0.012723	0.133669
FOLD1	0.0000804	0.00897	0.00589	0.05741	0.000158	0.012607	0.007041	0.073291
BSDR1	0.000261	0.01616	0.01125	0.05623	0.000342	0.018505	0.011755	0.06229
PNES1	0.0001121	0.01059	0.05197	0.09367	0.00098	0.031307	0.020177	0.485811
MSMI1	0.0000992	0.00996	0.00538	0.06806	0.000347	0.01864	0.010284	0.161555

Table 9. Comparing the performance results of the optimal model and the basic model on the normalized test dataset

Symbol	Optimal model of proposed method				Basic model			
	MSE	RMSE	MAE	MAPE	MSE	RMSE	MAE	MAPE
PTEH1	0.00048	0.0219	0.019	0.06014	0.000641	0.025324	0.021324	0.068292
FOLD1	0.000555	0.0235	0.0187	0.02948	0.000483	0.021994	0.017749	0.027854
BSDR1	0.000856	0.02925	0.02514	0.06954	0.000342	0.028129	0.02302	0.059459
PNES1	0.000349	0.01869	0.01562	0.04477	0.002912	0.053971	0.050067	0.139714
MSMI1	0.000793	0.02816	0.02321	0.03212	0.00074	0.027212	0.021437	0.031052

Figure 4. to Figure 6. show the graph of the actual price and the price predicted by the optimal model for the normalized training and test data for “PTEH1”, “FOLD1” and “BSDR1” stocks.

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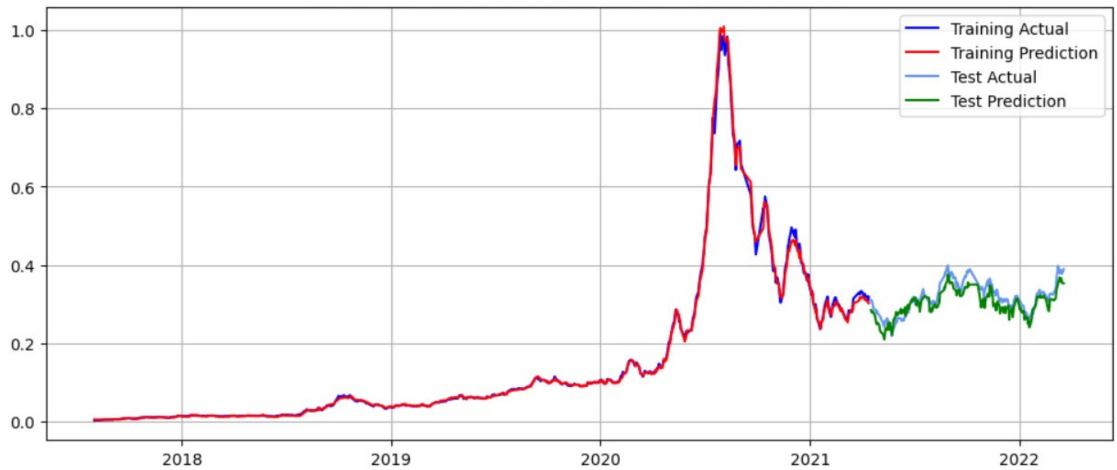

Figure 4. “PTEH1” stock price prediction chart

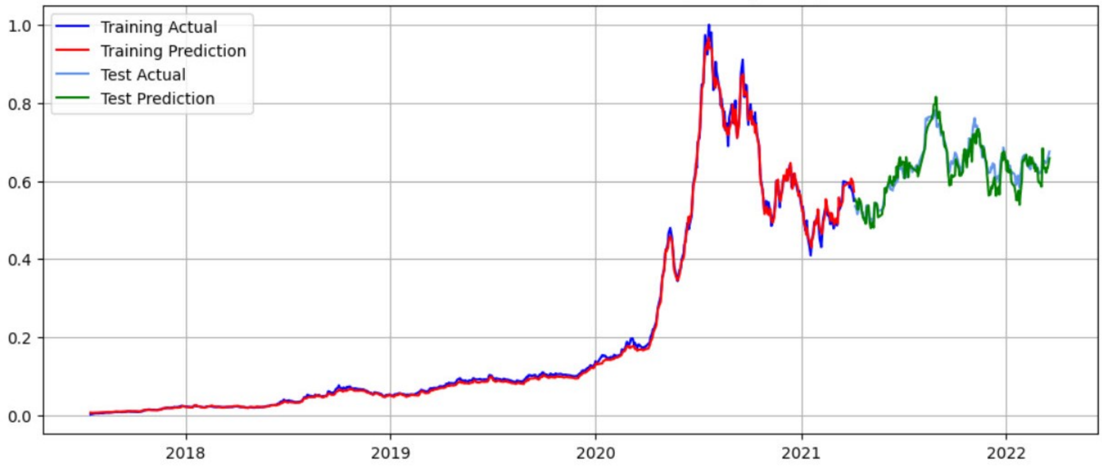

Figure 5. "FOLD1" stock price prediction chart

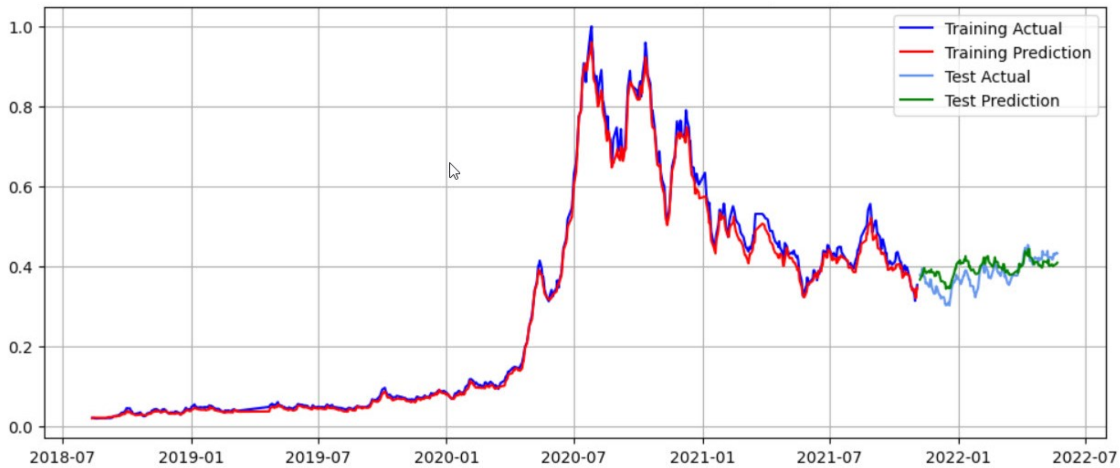

Figure 6. "BSDR1" stock price prediction chart

Discussion and Conclusion

For investors, it is always necessary to predict stock market changes to accurately identify profits and mitigate potential risks. Financial time series predicting, especially with machine learning techniques, is a vast field of study. Recently, deep learning methods (especially time series analysis) have shown better prediction than machine learning methods.

In this paper, we proposed a model based on LSTM deep neural networks for stock price prediction. The presented model has two LSTM layers and one Dense layer. Also, the proposed model includes two dropout layers. The input data to the model include the adjusted price and technical indicators. To be more detailed, since price variables are fully correlated, to reduce the dimensions of the input and reduce the volume of calculations, we only considered the adjusted price variable. The presented model was implemented by combining the values of different parameters (such as the number of neurons, batch size, Epochs, etc.) and finally the parameters of the optimal model were determined by different evaluations. The suggested model was tested to make predictions in five companies active in the Tehran Stock Exchange. Results showed that adding technical indicators in addition to price data as input variables to the model increases predicting accuracy. Also, the evaluation results indicate that the LSTM model has a better performance than the RNN model. Furthermore, the research results indicate that it is preferable to fine-tune price prediction parameters (such as the number of neurons, batch size, Epochs, etc.) for each stock separately to achieve more accurate forecasting.

Our focus on LSTM deep neural networks aligns with many contemporary approaches in the field, emphasizing the significance of recurrent architectures for stock price prediction. However, while our model incorporates adjusted price and technical indicators as input features, variations exist in the selection and combination of input variables across different studies. Despite these differences, our study, like others, underscores the importance of leveraging deep learning techniques to enhance predictive accuracy in financial markets. Our research demonstrates improved prediction accuracy through the inclusion of technical indicators alongside price data, a finding consistent with certain prior studies. However, variations in evaluation criteria and achieved accuracy levels highlight the complexity of model assessment in stock price prediction.

For future works, information from other markets (such as exchange rates, gold, etc.) can be added as variables to the input of the proposed model. In addition, as an input variable to the model, sentiment analysis of social networks and monitoring news related to a share can be used as input to the model.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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References

Aali-Bujari, A., Venegas-Martínez, F., & Pérez-Lechuga, G. (2017). Impact of the stock market capitalization and the banking spread on growth and development in Latin America: A panel data estimation with System GMM. *Contaduría y Administración, 62*(5), 1427-1441.

Arévalo, A., Niño, J., Hernández, G., & Sandoval, J. (2016). High-frequency trading strategy based on deep neural networks. In S. Fujita, D. Slezak, & M. Paprzycki (Eds.), *Intelligent Computing Methodologies: 12th International Conference, ICIC 2016, Lanzhou, China, August 2-5, 2016, Proceedings, Part III* (pp. 424-436). Springer International Publishing.

Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques–Part II: Soft computing methods. *Expert Systems with Applications, 36*(3), 5932-5941.

Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. *PloS One, 12*(7), e0180944.

Brown, M. S., Pelosi, M. J., & Dirska, H. (2013). Dynamic-radius species-conserving genetic algorithm for the financial forecasting of Dow Jones index stocks. In P. Perner (Ed.), *Machine Learning and Data Mining in Pattern Recognition: 9th International Conference, MLDM 2013, New York, NY, USA, July 19-25, 2013. Proceedings 9* (pp. 27-41). Springer Berlin Heidelberg.

Chen, K., Zhou, Y., & Dai, F. (2015, October). A LSTM-based method for stock returns prediction: A case study of China stock market. In *2015 IEEE International Conference on Big Data (Big Data)* (pp. 2823-2824). IEEE.

Chollet, F. et al. (2015). Keras. Retrieved from https://keras.io.

Chung, H., & Shin, K. S. (2020). Genetic algorithm-optimized multi-channel convolutional neural network for stock market prediction. *Neural Computing and Applications, 32*, 7897-7914.

Deng, L., & Yu, D. (2014). Deep learning: Methods and applications. *Foundations and Trends® in Signal Processing, 7*(3–4), 197-387.

Di Persio, L., & Honchar, O. (2016). Artificial neural networks architectures for stock price prediction: Comparisons and applications. *International Journal of Circuits, Systems and Signal Processing, 10*(2016), 403-413.

Doaei, M., Mirzaei, S. A., & Rafigh, M. (2021). Hybrid multilayer perceptron neural network with grey wolf optimization for predicting stock market index. *Advances in Mathematical Finance and Applications, 6*(4), 883-894.

Ferdiansyah, F., Othman, S. H., Radzi, R. Z. R. M., Stiawan, D., Sazaki, Y., & Ependi, U. (2019, October). A LSTM-method for bitcoin price prediction: A case study yahoo finance stock market. In *2019 International Conference on Electrical Engineering and Computer Science (ICECOS)* (pp. 206-210). IEEE.

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 270*(2), 654-669.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press.

Gordon, E., & Natarajan, K. (2009). *Financial markets and services*. Mumbai: Himalaya Publishing House.

Gunduz, H., Yaslan, Y., & Cataltepe, Z. (2017). Intraday prediction of Borsa Istanbul using convolutional neural networks and feature correlations. *Knowledge-Based Systems, 137*, 138-148.

Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications, 38*(8), 10389-10397.

Heidari, A. A., Faris, H., Aljarah, I., & Mirjalili, S. (2019). An efficient hybrid multilayer perceptron neural network with grasshopper optimization. *Soft Computing, 23*, 7941-7958.

Hiransha, M., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2018). NSE stock market prediction using deep-learning models. *Procedia Computer Science, 132*, 1351-1362.

Hoseinzade, E., & Haratizadeh, S. (2019). CNNpred: CNN-based stock market prediction using a diverse set of variables. *Expert Systems with Applications, 129*, 273-285.

Hu, Y., Feng, B., Zhang, X., Ngai, E. W. T., & Liu, M. (2015). Stock trading rule discovery with an evolutionary trend following model. *Expert Systems with Applications, 42*(1), 212-222.

Jiang, W. (2021). Applications of deep learning in stock market prediction: Recent progress. *Expert Systems with Applications, 184*, 115537.

Kara, Y., Boyacioglu, M. A., & Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. *Expert Systems with Applications, 38*(5), 5311-5319.

Khare, K., Darekar, O., Gupta, P., & Attar, V. Z. (2017, May). Short term stock price prediction using deep learning. In *2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)* (pp. 482-486). IEEE.

Liu, S., Zhang, C., & Ma, J. (2017). CNN-LSTM neural network model for quantitative strategy analysis in stock markets. In *Neural Information Processing: 24th International Conference, ICONIP 2017, Guangzhou, China, November 14-18, 2017, Proceedings, Part II 24* (pp. 198-206). Springer International Publishing.

Livieris, I. E., Kiriakidou, N., Stavroyiannis, S., & Pintelas, P. (2021). An advanced CNN-LSTM model for cryptocurrency forecasting. *Electronics, 10*(3), 287.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91.

Mehtab, S., & Sen, J. (2020, November). Stock price prediction using CNN and LSTM-based deep learning models. In *2020 International Conference on Decision Aid Sciences and Application (DASA)* (pp. 447-453). IEEE.

Menon, V. K., Chekravarthi Vasireddy, N., Jami, S. A., Pedamallu, V. T. N., Sureshkumar, V., & Soman, K. P. (2016). Bulk price forecasting using spark over nse data set. In *Data Mining and Big Data: First International Conference, DMBD 2016, Bali, Indonesia, June 25-30, 2016. Proceedings 1* (pp. 137-146). Springer International Publishing.

Moghar, A., & Hamiche, M. (2020). Stock market prediction using LSTM recurrent neural network. *Procedia Computer Science, 170*, 1168-1173.

Mohanty, D. K., Parida, A. K., & Khuntia, S. S. (2021). Financial market prediction under deep learning framework using auto encoder and kernel extreme learning machine. *Applied Soft Computing, 99*, 106898.

Nabipour, M., Nayyeri, P., Jabani, H., Mosavi, A., & Salwana, E. (2020). Deep learning for stock market prediction. *Entropy, 22*(8), 840.

Naeini, M. P., Taremian, H., & Hashemi, H. B. (2010, October). Stock market value prediction using neural networks. In *2010 International Conference on Computer Information Systems and Industrial Management Applications (CISIM)* (pp. 132-136). IEEE.

Nelson, D. M., Pereira, A. C., & De Oliveira, R. A. (2017, May). Stock market's price movement prediction with LSTM neural networks. In *2017 International Joint Conference on Neural Networks (IJCNN)* (pp. 1419-1426). IEEE.

Nikou, M., Mansourfar, G., & Bagherzadeh, J. (2019). Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms. *Intelligent Systems in Accounting, Finance and Management, 26*(4), 164-174.

Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Systems with Applications, 42*(1), 259-268.

Patel, M. M., Tanwar, S., Gupta, R., & Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions. *Journal of Information Security and Applications, 55*, 102583.

Pokhrel, N. R., Dahal, K. R., Rimal, R., Bhandari, H. N., Khatri, R. K., Rimal, B., & Hahn, W. E. (2022). Predicting nepse index price using deep learning models. *Machine Learning with Applications, 9*, 100385.

Ramezanian, R., Peymanfar, A., & Ebrahimi, S. B. (2019). An integrated framework of genetic network programming and multi-layer perceptron neural network for prediction of daily stock return: An application in Tehran stock exchange market. *Applied Soft Computing, 82*, 105551.

Tsai, C. F., & Hsiao, Y. C. (2010). Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches. *Decision Support Systems, 50*(1), 258-269.

Vidal, A., & Kristjanpoller, W. (2020). Gold volatility prediction using a CNN-LSTM approach. *Expert Systems with Applications, 157*, 113481.

Wang, J., & Wang, J. (2015). Forecasting stock market indexes using principle component analysis and stochastic time effective neural networks. *Neurocomputing, 156*, 68-78.

Yadav, A., Jha, C. K., & Sharan, A. (2020). Optimizing LSTM for time series prediction in Indian stock market. *Procedia Computer Science, 167*, 2091-2100.

Yong, B. X., Abdul Rahim, M. R., & Abdullah, A. S. (2017). A stock market trading system using deep neural network. In *Modeling, Design and Simulation of Systems: 17th Asia Simulation Conference, AsiaSim 2017, Melaka, Malaysia, August 27–29, 2017, Proceedings, Part I 17* (pp. 356-364). Springer Singapore.

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing, 50*, 159-175.

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