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Research paper

Application of Deep-Learning-Based Models for Prediction of Stock Price in the Iranian Stock Market

Abdulrashid Jamnia[1], Mohammad Reza Sasouli[2], Emambakhsh Heidouzahi[3], Mohsen Dahmarde Ghaleno[4]

[1] Department of Economics, Higher Education Complex of Saravan, Saravan, Sistan and Baluchestan province, Iran

a.r.jamnia@gmail.com

[2] Department of Economics, Higher Education Complex of Saravan, Saravan, Sistan and Baluchestan province, Iran

sasouli.ageco@gmail.com

[3] Department of Economics, Higher Education Complex of Saravan, Saravan, Sistan and Baluchestan province, Iran

e.eiduzahi@gmail.com

[4] Department of Accounting, Higher Education Complex of Saravan, Saravan, Sistan and Baluchestan province, Iran

dahmarde.mohsen@yahoo.com

Abstract:
The capital or stock market along with the money market is one of the most important parts of financial sector of the nation's economy, providing long-term financing required for efficient production and service activities. The total stock price index as reflector of stock market fluctuation is important for finance practitioners and policy-makers. Therefore, in this research, a comparative investigation was presented on two superior deep-learning-based models, including long short-term memory (LSTM), and convolutional neural network long short-term memory (CNN)-LSTM, applied for analysing prediction of the total stock price index of Tehran stock exchange (TSE) market. The complete dataset utilized in the current analysis covered the period from September 23, 2011 to June 22, 2021 with a total of 3,739 trading days in the TSE market. Forecasting accuracy and performance of the two proposed models were appraised using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) criteria. Based on the results, the CNN-LSTM showed the lowest values of the aforementioned metrics compared to the LSTM model, and it was found that the CNN-LSTM model could be effective in providing the best prediction performance of the total stock price index on the TSE market. Eventually, graphically and numerically, various prediction results obtained from the proposed models were analysed for more comprehensive analysis.

Keywords: LSTM; CNN-LSTM; Stock Market; Prediction
JEL Classifications: B23, C52, E44, F37.

[1]Corresponding author
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1 Introduction

The capital or stock market along with the money market is one of the most important parts of financial sector of the nation's economy, providing long-term financing required for efficient production and service activities (Gao et al., 2020; Kim and Kim, 2019; Saud and Shakya, 2020; Thakkar and Chaudhari, 2021).

Prediction of the future movement of stock prices is one of the most important issues in financial markets that has always been a challenging duty for stakeholders in the financial field to allocate their assets well, and also for academic researchers to construct superior and more accurate assets' pricing models. Importance of this issue arises from the fact that fluctuation in financial market is one of important variables about investment decisions, such as stock pricing, risk management, regulation, and monetary policy. In addition, volatility of financial markets plays an important role in economies of countries by creating or reducing public confidence and trust. Therefore, the capital market's efficiency has a substantial effect on the national economy (Gao et al. 2020; Kim and Kim 2019; Saud and Shakya 2020; Thakkar and Chaudhari 2021).

The stock price index as an indicator has a noteworthy information on the stock market for finance practitioners, such as investors and speculators to make investment strategies. It is basically dynamic, non-linear, noisy, non-parametric, and deterministic chaotic system due to its complex nature influenced by many various internal and external factors, such as political events, economic conditions (e.g., economic trends, cycles, and structure), and other macro factors (Gao et al. 2020; Kim and Kim 2019; Saud and Shakya 2020; Thakkar and Chaudhari 2021).

Therefore, prediction and forecasting of random trends and fluctuations of stock price index, and hence analysis of the markets' behaviour is an extremely complicated and very challenging task. Knowing the market trends is essential for many people who are directly or indirectly associated with this sector of financial market (Gao et al. 2020; Hu et al. 2021; Thakkar and Chaudhari 2021).

The Iranian stock market known as Tehran stock exchange (TSE) is in a state of youth and formation, which operates within a larger system called as the Iranian Social-Economic System, therefore, greatly influenced by environmental changes, and the associated assets can be valuable as well as vulnerable. Financial market on the TSE has an uncertain and vulnerable condition, due to political relations between Iran and the United States after withdrawal of the United States from the joint comprehensive plan of action (JCPOA) in early May 2018, and in 2020 because of the coronavirus disease 2019 (COVID-19) pandemic in Iran. Therefore, identifying fluctuations' pattern of price stock index in the TSE can be a good step to make investment and policy decisions. Considering that no comprehensive research has been conducted so far in the country on modelling volatility of price stock index in the TSE; therefore, due to importance of volatility in the TSE, in this research, it is tried to provide a suitable model for predicting fluctuations of price stock index in the TSE.

Since, the stock price index is a kind of financial time series, which has a noisy and chaotic nature, hence, constituting appropriate methodology leading to more accurate predictions of this kind of time series is a complicated and challenging problem. Based on the recent surveys, non-linear models, such as various machine learning approaches are able to extract inner complexity, superbly simulate volatile financial time series and enhance exploration of stock market trend than traditional econometric models, which usually involve assumptions, such as stationarity and linear correlation between records of dataset (Hassanien and Darwish 2020; Kelleher et al. 2020; Kim and Kim 2019; Ko and Chang 2021; Livieris et al. 2020; Thakkar and Chaudhari 2021).

In the recent years, deep neural networks (DNNs), such as long short-term memory (LSTM) networks and convolutional neural networks (CNNs) have been developed and used widely in various real world challenging fields, particularly in prediction issues, including time series forecasting (Hassanien and Darwish 2020; Lazzeri 2020; Livieris et al. 2020; Thakkar and Chaudhari 2021).

LSTM is a type of recurrent neural network (RNN) applied to solve the vanishing gradient problem in the basic RNN. LSTMs are proficient to learn long-term dependencies by substituting the hidden layers of RNN with memory cells (Hassanien and Darwish 2020; Lazzeri 2020; Thakkar and Chaudhari 2021; Yu et al. 2019).

CNNs can elicit numerous features via different filters in convolutional layers, pooling layers, followed by a few fully connected layers, thus boosting execution efficiency of different tasks. Nevertheless, CNNs cannot remember memory of preceding time series patterns and hence, it is challenging for CNNs to directly learn the most essential and descriptive features from time series fluctuations. Accordingly, CNNs have difficulty in extracting long temporal dependencies in dataset and may not provide accurate results. Based on various studies, CNN and LSTM models are combined simply known as CNN-LSTM model, which is used to overcome limitations of pure CNN model and proves effectiveness and superiority of the research problems solution (Hassanien and Darwish 2020; Jiang et al. 2019; Lazzeri 2020; Radenovic et al. 2019; Thakkar and Chaudhari 2021; Yu et al. 2019).

Accordingly, the current study contributes to expansion of prediction models for forecasting the total price index of the TSE. For achieving the aims, the two different deep-learning-based models, including LSTM, and CNN-LSTM were utilized, and the obtained results were compared with each other for discussion and achieving better conclusions about prediction of the applied models. Eventually, graphically and numerically, various prediction results obtained from the proposed models were analysed for more comprehensive analysis.

2 Materials and Methods

The Figure 1, as graphical abstract shows a schematic view of all studied stages in the current research, which could help to quickly gain an overview on the present study.

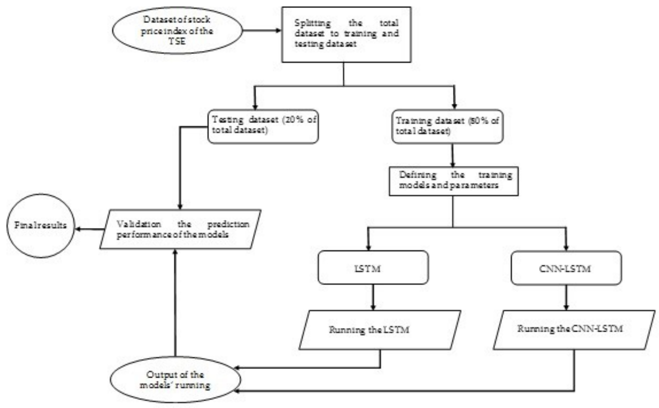

Figure 1: Graphical abstract
Source: Research finding

2.1 Data Description

Time series data of daily total stock price index of the TSE were derived from the website of Financial Information Processing of IRAN (FIPIran). The complete dataset covers the period from September 23, 2011 to June 22, 2021 with a total of 3,739 trading days. As shown in Figure 2, from May 8, 2018 distinguished by vertical red -dashed line, due to political relations between Iran and the United States after withdrawal of the United States from the JCPOA in early May 2018, and in 2020 because of the COVID-19 pandemic in Iran, the trend of the total price index is more chaotic and fluctuated than before.

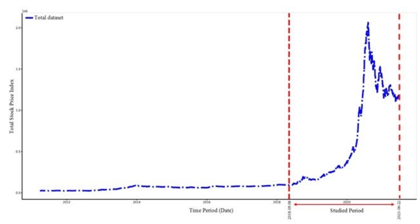

Figure 2: Trend presentation of the total dataset and studied period dataset
Source: Research finding

Hence, based on the above-demonstrated content, the studied period was selected from May 8, 2018 distinguished by vertical red -dashed line in Figure 1, to June 22, 2021, with 1,142 observations (trading days) for constituting appropriate prediction models to achieve more accurate simulations. The studied dataset was divided into two sections: The first one was training section with 80 percent of the dataset (914 observations) used to train the model and update the model parameters, the other one was testing section with remaining 20 percent of the dataset (228 observations) used to test them and compare their performance in order to optimize the model for data forecasting.

In addition to Figure 2 that presents the dataset, contents of Table 1 provide a more descriptive statistical information of the selective studied period dataset in numerical form.

Table 1: Descriptive statistics of the selective studied period dataset

Descriptive Statistic	Value
Number of records	1142
Mean	659467.8
Standard deviation	567658
Min	93165.9
Max	2078547
Number of train dataset records	914
Number of test dataset records	228

Source: Research finding.

2.2 Models

Long Short-Term Memory (LSTM)

LSTM is a special type of RNN, introduced by (Hochreiter and Schmidhuber 1997). LSTM is considered to solve long-term dependencies' problems of gradient explosion and gradient disappearance in RNN by replacing the usual hidden layers with memory cells. These models have inner procedure, including gates and cell state, which can adjust movement of information. In addition, because of making perfect predictions, the LSTMs are widely used in emotional and text analysis, and speech recognition, recently they have been also implemented in the field of stock market predictions (Hassanien and Darwish 2020; Kelleher et al. 2020; Lazzeri 2020; Sarkar and De Bruyn 2021; Thakkar and Chaudhari 2021; Yu et al. 2019).

In LSTM system, memory cells comprise three main gates, such as input gate, forget gate, and output gate, through which, they can regulate which information to hold and when to permit reading, writing, and forgetting. Figure 3 demonstrates the mechanism of LSTM model about the information flows through storage component adjusted by each gate along with activation function (Cura et al. 2020;

Hassanien and Darwish 2020; Kelleher et al. 2020; Lazzeri 2020; Sarkar and De Bruyn 2021; Thakkar and Chaudhari 2021; Yu et al. 2019).

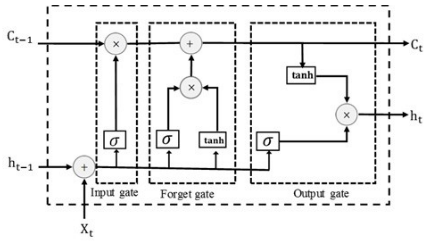

Figure 3: Mechanism of a single cell of the LSTM system
Source: Research finding

Figure 3 demonstrates working procedure of single cell of the LSTM system. Where, x_t denotes input vector at time step t; previous memory cell state vector is presented by C_{t-1}; also, h_{t-1} indicates the previous hidden state vector; besides σ and tanh are logistic sigmoid and the tanh activation function, respectively, $\bigotimes$ shows the elementwise vector product (i.e., the Hadamard product), and represents $\bigoplus$ an elementwise vector accumulation operation.

Operation of single cell of the LSTM system is graphically illustrated in Figure 3, mathematical definition of this process is presented in Equations (2.1) to (2.6) as below (Cura et al. 2020; Hassanien and Darwish 2020; Kelleher et al. 2020; Thakkar and Chaudhari 2021; Yu et al. 2019).

The input gate layer i_t takes output value of the last moment, and the input value of time step t then, the results include the output value and new cell state C_t , which remembering the information over time is achieved after computation by the formulas as shown in the following equations:

$$i_t = \sigma\left(W_i X_t + U_i h_{t-1} + b_i\right) \tag{1}$$

$$\widetilde{C_t} = tanh\left(W_C X_t + U_C h_{t-1} + b_c\right) \tag{2}$$

After the process in input gate layer, the current cell state is updated by the following equation:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \tag{3}$$

The forget gate layer f_t receives the obtained value of the previous moment and the input value of time step t, then it decides what values are needed to be saved in cell state or be rejected by the sigmoid activation function. The final output of this layer is calculated by the formula as shown in the following equation:

$$f_t = \sigma\left(W_f X_t + U_f h_{t-1} + b_f\right) \tag{4}$$

The output gate layer O_t obtains value of the previous hidden state h_{t-1}, and the input value of time step t, X_t, as input values, then output of this layer is determined by the formula as indicated in the following equation:

$$O_t = \sigma \left(W_O X_t + U_O h_{t-1} + b_O \right) \tag{5}$$

The output of the memory cell value is calculated by the formula as shown in the following equation:

$$h_t = O_t * \tanh \left(C_t \right) \tag{6}$$

Where, i_t , f_t , and O_t denote the input, forget, and output gates at time step t with a value range of $(0, 1)$, respectively; W_i , W_f, W_O , and W_C indicate weights mapping the hidden layer input to the three above-mentioned gates, and new cell state, whereas U_i , U_f , U_O , and U_C present the weights' matrices mapping the hidden layer output to gates, and new cell state; b_i , b_f , b_O , and b_C show bias term vectors. Moreover, C_t and h_t are the output of the current cell state vector and the output of the current hidden cell state vector, respectively. In addition, C_{t-1} and h_{t-1} , are the previous cell state vector, and the past hidden state, respectively.

Based on the above-demonstrated LSTM calculation process presented graphically and mathematically, it can be said that, by activation of input gate layer i_t , at every time the information of new input will be stored to the cell. Besides this process, the previous cell state, C_{t-1} could be forgotten through activation of forget gate layer f_t. Whether the updated current cell state value C_t will be propagated to the final state operation h_t is further regulated by the output gate layer O_t.

Convolutional Neural Network (CNN)

CNN is a network system proposed by (Lecun et al. 1998). CNN model is a type of feed forward neural network, which has good performance in forecasting of time series. The local perception and weight sharing characteristics of CNN model can importantly diminish the number of parameters, to improve efficiency of model learning. CNN consists of two sections, such as convolution layer, which includes a plurality of convolution kernels, and its calculation procedure is considered by the Equation (2.7), and another one is max pooling layer. The max pooling layer is added after convolution layer to reduce feature dimension for solving the problem of high dimensions in the extracted features derived from convolution operation, hence shrinking cost of training the network (Hassanien and Darwish 2020; Kelleher et al. 2020; Lazzeri 2020; Lecun et al. 1998; Lu et al. 2020; Radenovic et al. 2019; Thakkar and Chaudhari 2021).

$$L_t = tanh \left(x_t {*} k_t + b_t \right) \tag{7}$$

Where, L_t denotes the output value after convolution process, tanh is the activation function, x_t is the input vector, k_t is the weight of convolution kernel, and

b_t is the bias of convolution kernel.

Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM)

The CNN-LSTM model consists of CNN layers for feature extraction on input data joint with LSTM to support sequence forecasting. The CNN-LSTM system procedure is presented in Figure 4.

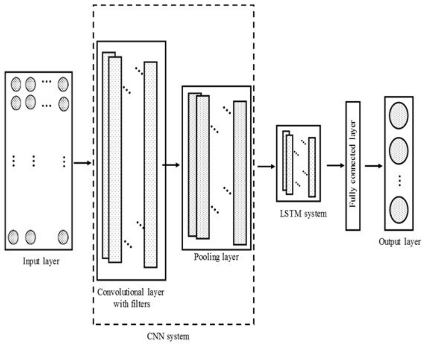

Figure 4: $CNN - LSTM$ system architecture
Source: Research finding

According to the literature (Cura et al. 2020; Hassanien and Darwish 2020; Jiang et al. 2019; Lazzeri 2020; Lu et al. 2020; Thakkar and Chaudhari 2021; Wu et al. 2021) and considering the process presented in Figure 4, as the acquired input dataset is fed into the CNN-LSTM network, firstly the imported data are properly approved through one- dimensional convolution layers and pooling layers with suitable filters, where feature extraction of the input data is conducted, and output values are attained. After dimensionality reduction and obtaining output data from the CNN previous process, fed into the LSTM layer, it will go to dense layer where all the outputs of the prior layer come into the neurons and then, the activation function modifies the kernels, bias, and supplementary inner features for training and forecasting, which this happens after performing all procedures in this stage, such as exploration of internal features and pattern. Finally, the proper output values will be obtained (Hassanien and Darwish 2020; Jiang et al. 2019; Kelleher et al. 2020; Lazzeri 2020; Livieris et al. 2020; Lu et al. 2020; Thakkar and Chaudhari 2021; Wu et al. 2021; Xu et al. 2020)

2.3 Performance Criteria

The two applied models are evaluated based on the prediction results. During training of the models, root mean square error (RMSE) is used as a loss function, which is a proper criterion for determining relatively big prediction errors. The mean absolute error (MAE) is suitable for defining systematic bias of the model, and mean absolute percentage error (MAPE) is a metric of validity of predictions in statistics. The models with smaller and closer value of RMSE, MAE, and MAPE to 0 indicate high forecasting accuracy. Calculating formulas of above-mentioned predictive performance criteria are shown in the following equation (Hassanien and Darwish 2020; Kelleher et al. 2020; Lazzeri 2020; Lu et al. 2020):

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}(x_i - y_i)^2} \quad (8)$$

$$MAE = \frac{1}{N}\sum\nolimits_{i=1}^{N}|y_i - x_i| \quad (9)$$

$$MAPE = \frac{100}{N}\sum\nolimits_{i=1}^{N}\left|\frac{y_i - x_i}{x_i}\right| \quad (10)$$

Where, N denotes the total number of data records, y_i represents the predicted value, and x_i shows the real value.

All the experiments of models in the current research were performed based on Anaconda Navigator 2.0.3 software (Anaconda 2021), by open-source Python programming language 3.7.9 (Python 2021) using Spyder application 4.1.4 (Spyder 2021), with open source libraries, like TensorFlow 2.1.0 (Tensorflow 2021), Keras 2.3.1 (Keras 2021), Pandas, NumPy, Scikit-Learn, Matplotlib ,and all other sub-libraries. The experimental setup was based on working environment involving Intel(R) Core (TM) i7-4720HG CPU @ 2.60GHz with 12 GB RAM under 64-bit Windows 8.1 pro Operating system.

3 Results and Discussion

The consequences of the total stock price index time series forecasting based on LSTM and CNN-LSTM models are compared regarding graphs and varied evaluation criteria.

Table 2 represents the results of performance comparison measurements of the two implemented forecasting models.

Table 2: Performance comparison of the two implemented forecasting models

Models	Criteria		
	RMSE	MAE	MAPE
LSTM	0.012	0.0129	2.333
CNN-LSTM	0.0011	0.0075	1.37

Source: Research finding.

Based on the results presented in Table 2, the RMSE, MAE, and MAPE scores of CNN-LSTM were smaller than the LSTM ones by 90, 41.8, and 41.2 percent, respectively. Hence, the CNN-LSTM proposed model in the current research was superior to the LSTM model in terms of the smallest values of above-mentioned performance criteria, as confirmed by the literature (Livieris et al. 2020; Lu et al. 2020; Thakkar and Chaudhari 2021). Therefore, prediction results of the total price index of TSE obtained by the CNN-LSTM proposed model can be more trusted and credible, and they can well predict the next day total stock price index and provide a reference for finance practitioners, such as investors and speculators to make investment strategies in financial market of the TSE.

The trends of testing dataset values as actual data (solid blue line) and predicted time series data set values (solid red line) using LSTM, and CNN-LSTM models are graphically visualized in Figure 5 and 6, respectively.

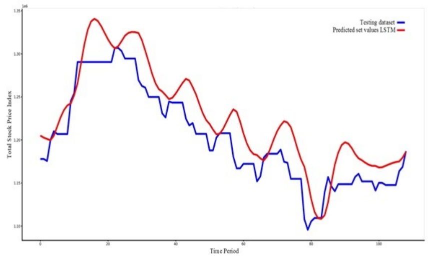

Figure 5: Graphic display of the predicted set values of the test set values by LSTM
Source: Research finding

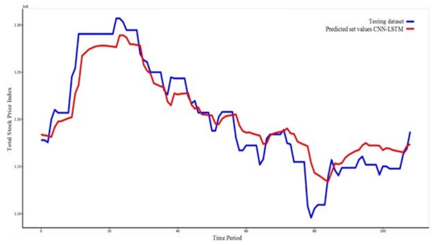

Figure 6: Graphic display of the predicted set values of the test set values by CNN-LSTM
Source: Research finding

Comparing the Figure 5, and 6, it can be concluded that the predicted values by the CNN-LSTM closely follow actual values than the LSTM model ones, confirming the previously-mentioned results of performance comparison, where the CNN-LSTM proposed model is superior to the LSTM model, and its results are more trusted and credible about prediction of the next day total stock price index.

Table 3 provides numerical comparison of the four last actual dataset values with the predicted corresponding values obtained using the two studied prediction models. In addition, the next day predicted total stock price index value is considerable in Table 3.

Table 3: Actual and predicted values for last four day of dataset

Actual values	Predicted values	
	LSTM	CNN-LSTM
1147675	1174338.1	1165783.3
1163757	1175034.2	1165052.1
1168664.7	1179458.1	1171455.1
1186921.5	1186188.5	1173772.6
Next day predicted value	1197309.96	1176943.06

Source: Research finding.

Figure 7 graphically shows the trend of training (solid blue line) and testing (solid red line) datasets together with prediction values' time series set obtained using LSTM (dashed green line), and CNN-LSTM (solid block line) models. In addition, the next day predicted total stock price index value in June 23, 2021, obtained by the LSTM, and CNN-LSTM models is presented in the above-mentioned figure, which is equal to 1197309.96 and 1176943.06, respectively. Also, besides performance comparison measurements in the beginning of the results section, visual comparing of the predicted values of testing dataset values confirmed superior prediction performance of the CNN-LSTM proposed model in comparison with the LSTM model, as confirmed by the various previous findings (Kim and Kim 2019; Livieris et al. 2020; Lu et al. 2020; Thakkar and Chaudhari 2021; Wu et al. 2021).

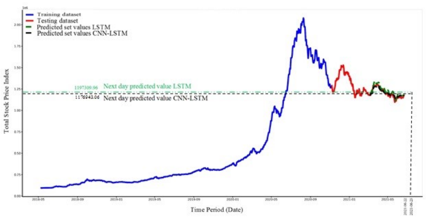

Figure 7: Graphic display of the train set values, test set values , and predicted set values related to both studied models
Source: Research finding

4 Conclusion

In the current research, due to complicated conditions in TSE market influenced by various internal and external factors, such as political events, economic conditions, and other macro factors, two comprehensive forecasting methods, such as LSTM, and hybrid model CNN-LSTM were used to predict fluctuations and stock price index values. Forecasting accuracy and the best performance of the two proposed models were evaluated by the standard statistical criteria, such as RMSE, MAE, and MAPE. Based on the results, the CNN-LSTM model showed the lowest values of the aforementioned criteria compared to the LSTM model, and thus, it can be concluded that the CNN-LSTM model could provide a best forecasting performance for stock price index. Therefore, as a practical experiment, finance practitioners can apply the final CNN-LSTM model to predict various prices in the stock price market. Eventually, due to high complexity of the proposed CNN-LSTM architecture, it can possibly improve accuracy of prediction results by further monitoring and optimized configuration.

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