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Designing a hybrid model for stock marketing prediction based on LSTM and transfer learning

Tahereh Rameh[a], Rezvan Abbasi[b,*], Mohamadreza Sanaei[a]

[a]*Department of Information Technology Management, Faculty of Management and Accounting, Qazvin Branch, Islamic Azad University, Qazvin, Iran*
[b]*Faculty of Electrical, Biomedical and Mechatronics Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

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Abstract

One of the most complex and controversial issues in financial markets is the prediction of price and stock returns which is always a matter of interest to shareholders. The stock market is vulnerable to various factors that affect the price fluctuations in the stock market. The development of a strong stock market algorithm that can accurately predict stock behaviour is important to maximize profits and minimize the loss of investors. Although in addition to the history of each share, other psychological factors affect the value of each share, in this research, an artificial intelligence model is proposed based on long short-term memory and text embedding. In addition to being paid to the stock market in the form of time series data; In order to investigate the psychological force of the market, features are also extracted from news sites. And finally, based on the combination of features extracted from news sites and time-series data, predicts the future of the stock market. The results of the evaluations show the proposed model can predict the market future truly.

Keywords: Long Short-term Memory, Text Embedding, Stock Market
2010 MSC: 60G25, 91G15

1. Introduction

Price prediction and stock returns is one of the most complex and controversial issues in financial markets [13] that is always considered by investors and shareholders [12]. The stock exchange is one of the sources of collecting savings and securing investments [3]; The stock exchange and its

*Corresponding author
Email addresses: maharameh17@gmail.com (Tahereh Rameh), rezvanabbasi@yahoo.com (Rezvan Abbasi), mohamadrezasanaei@gmail.com (Mohamadreza Sanaei)

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performance can have a good place in the financial and economic structure of the country for the development and expansion of liquidity resources [15]. Predicting the stock market is a very difficult task due to the various uncertainties that affect the market price, which includes political, economic events and the feelings of investors [2]. The stock market is naturally dynamic and turbulent [1]. Advanced stock knowledge is required to predict the stock market. Investors prefer to buy stocks whose prices will rise in the future; and avoid stocks whose value decreases over time. However, developing a strong stock market algorithm that can accurately predict stock behavior is important to maximize profits and minimize investor losses [11].

Incomplete information about stock market data is a challenge to predict future stock prices. The stock market is vulnerable against various factors; that affects its fluctuations in the stock market. Investors in stocks rely on various technical indicators to predict the movement of stock prices. Although these indicators are used to evaluate stocks, but it is difficult to predict market trends; Because economic and non-economic factors affect the behavior of stock trends [4]. Therefore, stock market forecasting is considered as an important challenge for production growth.

A financial decision support system can greatly facilitate investors' decisions after disclosure of financial statements [5]. Such systems can help identify financially viable stocks and exercise ownership and whatever the algorithm is being powerful and complete; the predictions will be more accurate. So it is necessary to use efficient algorithms for this. Various algorithms have been proposed for this purpose over the years. Many classical algorithms, such as the ARIMA autoregressive moving average model, emerged [10]. However, they are linear models and have many functional problems, because stock market data have the nature of time series that reveal the time dimension. Linear models are used for prediction with traditional machine learning methods such as support vector machine [12].

It is proven that, Deep learning models are promising alternatives in stock price prediction research. Because they achieved great success [17]. Vargas et al [16], Liu et al [9] and Katayama et al [6] showed that the deep learning model works better than traditional machine learning models. Due to their complex nature, these algorithms have been able to provide promising results in stock price predicting. Although deep learning models lead to high accuracy in stock forecasting; but they generally suffer from a lack of generalizability. Econometric models cannot provide an accurate relationship to stock returns due to relatively low coefficients of determination, such as automatic regression and moving average in relation to highly volatile markets, or the markets in which they are applied [8]. Usually in such situations, the use of hybrid models that can modify the outputs in different situations; Will be on the agenda. The use of combined data mining models leads to increased accuracy and generalizability compared to each of the predictive models [14].

Past research has generally focused on time series data related to stock prices. The purpose of this study is to provide a hybrid model for constructing stock market forecasts. It is this research that provides a hybrid model for constructing the target stock market forecast. In this research, a model based on deep learning for stock price forecasting is proposed. The proposed model predicts its future, using the capital market psychological forces and the history of each stock. The proposed hybrid model is based on long short-term memory and text embedding. Which, in addition to time series data, also extracts features from news sites; In order to examine the psychological force of the market predict the future of the stock market. The budget of the article is as follows: Section 2 shows the proposed model architecture. Section 3 presents the practical results of using the proposed model. Section 4 concludes the article with a summary and provides guidelines for the scope of future research.

2. The proposed model

The symbol chosen for this analysis; It is a symbol of kh bahman that belongs to the automotive group. In order to have more accurate predictions; The behavior of other symbols of this group has also been used. Considering that necessarily all of the symbols of the automotive group; do not have a high correlation with the good symbol, First, the correlation of the symbols of this group was calculated with the symbol of kh bahman and only symbols were used; that have a high correlation with this symbol.

Also, in order to consider the psychological aspect of the market, was used the news related to the stock market was used. First, news related to this field was converted into numerical vectors with the help of deep learning. Then, on the one hand these vectors and the short long-term memory network on the other were used in a deep neural network. The steps of the proposed model are shown in Figure 1.

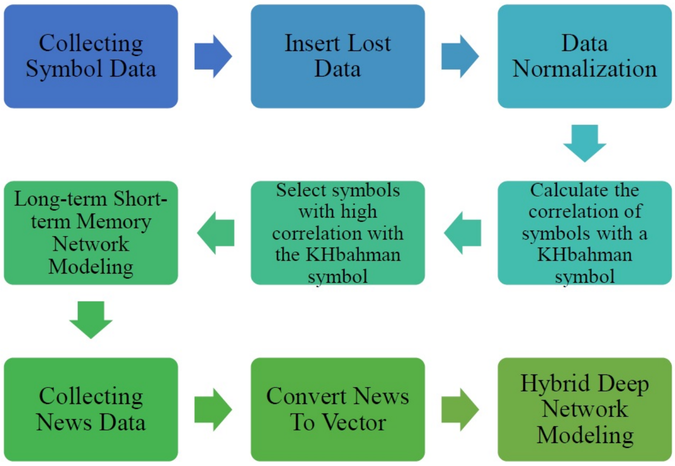

Figure 1: Steps of the proposed model

To obtain stock market news, news texts are received by reviewing the news archive of stock exchange sites and some virtual network channels. The first and last date of registration of daily symbol information; and the total number of data recorded in this interval, displayed, symbols with a very small number of records (most days the symbol is closed) are removed. Missing data is replaced by linear interpolation. Linear interpolation means estimating the amount lost by connecting points in a straight line with increasing order. In short, it estimates the unknown value in the same order of magnitude as the previous values.

The min-max normalization technique is used to normalize the features. In this normalization technique, a linear conversion is performed on the primary data. The minimum and maximum amount of data is reactive and each value is replaced according to Formula (2.1). Min-Max normalization maintains the relationships between the original data values.

$$A' = \frac{A - \text{min value of } A}{\text{max value of } A - \text{min value of } A} \tag{2.1}$$

Where A' contains the normalized max-min data and A is the original data range. Next, the correlation of the closing price column of all symbols is calculated. For this purpose, the use of Pearson correlation coefficient is proposed. The purpose of the correlation coefficient between two variables is the ability to predict the value of one in relation to the other. One of the most popular ways to measure the dependence between two quantitative variables is to calculate the Pearson correlation coefficient. Assume that X and Y are two random variables that they have Expected value $E(X)$ and $E(Y)$ and variance $V(X)$ and $V(Y)$. We show the correlation coefficient between X and Y with $\rho(X,Y)$ or $corr(X<Y)$ and we calculate with Formula (2.2).

$$p(X,Y) = corr(X,Y) = \frac{E[(X-E(X))(Y-E(Y))]}{[V(X)V(Y)]^{\frac{1}{2}}} \tag{2.2}$$

The face of this fraction is the covariance between the two variables X and Y. E also refers to the Expected value of two random variables, X and Y. The column for the final price of all the symbols was placed opposite each other according to the day. The correlation column of the closing price of all symbols was calculated and the symbols that have the highest correlation with the kh bahman symbol were determined.

After the symbols with the highest correlation with the kh bahman symbol are determined, the LSTM neural network is modeled in the next step. A recursive neural network is a network; that teaches sequential patterns through internal loops by receiving input sequences. Back propagation is done to learn the weights and the slope calculated by the chain law must be published. With the redistribution of values in the activation function, such as sigmoid and tanh functions, the slope becomes very small (or very large); and faces the problem of disappearing (or explosive slopes). Backward propagation is vulnerable to long-term dependence. LSTM models were developed to avoid these problems. (LSTM) is a type of RNN recursive neural network, that can take data from previous steps and use it for future predictions [**?**]. LSTM used memory cells and gateways to store information for long periods of time or to forget unnecessary information.

$$g_t = \sigma(U_g x_t + W_g h_{t-1} + b_f) \tag{2.3}$$

$$i_t = \sigma(U_i x_t + W_i h_{t-1} + b_i) \tag{2.4}$$

$$\widetilde{c_t} = \tanh(U_c x_t + W_c h_{t-1} + b_c) \tag{2.5}$$

$$c_t = g_t * c_{t-1} + i_t * \widetilde{c_t} \tag{2.6}$$

$$o_t = \sigma(U_0 x_t + W_0 h_{t-1} + b_0) \tag{2.7}$$

$$h_t = o_t * \tanh(c_t) \tag{2.8}$$

LSTMs are made up of memory blocks instead of neurons. As Figure 2 shows, LSTM consists of a memory cell (c_t) and three gates: An entrance gate (i_t), A gate of forgetfulness (g_t), And an output gate (o_t). At time t, x_t represents input and h_t represents hidden mode. The symbol $\otimes$ represents a point multiplication. C_t, also called the input module gate, It is a value that determines how much new information is received in cell state. The three gates, the cellular state (c_t) and the hidden state (h_t), are calculated as shown in Equations (2.3) to (2.8). In these equations, U and W are weight matrices, b A bias sentence, $\sigma(\bullet)$ is a sigmoid function, and the symbol $*$ represents the multiplication of the element. First, the gate of forgetfulness g_t, the equation. (2.3) Generates the sum of weights x_t, h_{t-1} and bias as values from 0 to 1 via the sigmoid function. A value of one passing through the gate means that all incoming information passes through the gate, and a value of zero means that no input information is sent. Thus, the forgetfulness gate controls the amount of information in the past cell state (c_{t-1}) in the cell state update at time t, as shown in the equation. Equations (2.6) and (2.4) are the formula for calculating the IT gateway and determines how much new information is stored in cell (c_t) mode. Equation (2.5) calculates new information at time t and its output through the tanh function has a value between -1 and 1. Past cell status information and new information, that is controlled by the gates of forgetfulness and the input, are calculated as variables. c_t time t, As mentioned in Equation (2.6). Finally, the output value h_t is determined by passing through the output gate o_t (Equation (2.5)) and filtering in c_t, While c_t is passed to the tanh function so that the value is between -1 and 1. Selected values are; Multiply them by o_t that converts to output. This process updates the status of the c_{t-1} cell, The required information is separated from the unnecessary information and the output is converted to h_t as mentioned in 6 equations. The LSTM model consisting of these memory blocks is learned using replication through a time algorithm [7].

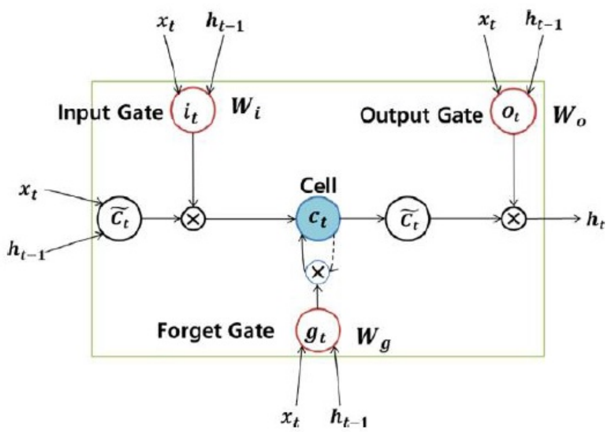

Figure 2: An LSTM memory block

In the proposed method, the activation functions commonly found in MLP architectures use the sigmoid function:

$$f(x) = \frac{1}{1 - e^{-x}} \tag{2.9}$$

The network is configured with the parameters optimizer=Adam and loss=MAE and activation_function=sigmoid and is performed on modeling training data. The parameters examined include the number of EPOCHs, the number of LSTM cells, the addition of a DENSE layer to the network architecture and BATCH SIZE, which are the results and other parameters evaluated the number of days before for network input. The DENSE layer was added after the LSTM layer. The DENSE layer or fully connected layer is a layer in which each neuron connects to all the neurons in the next layer.

To better understand the impact of market sentiment and the impact of news on symbols, using the news texts of stock exchange sites, a more complete analysis is performed. To do this, stock news is received by reviewing the news archive of stock sites such as Tejarat News, Bourse Press, Senate and some channels of virtual networks.

By placing the obtained news data in front of the desired symbol and other related symbols of the same group with this symbol based on the date, a new data set is obtained. As before, the turbulent days of the stock market, when the increase in prices was unrealistic, will be removed from this data set.

In the next stage, the text must be converted into a comprehensible numerical vector for the neural network. FastText was used for this purpose. In this study the FastText was used to convert text into an understandable numerical vector for neural network. FastText is an open source, free and lightweight library that allows users to learn how to represent and categorize text. Works on standard and general hardware. FastText is an extension for Word2Vec that created by Facebook in 2016 to learn how to effectively represent words and categorize sentences. FastText breaks words into several n-gram instead of putting them separately on a neural network. After training the neural network, according to the training data set, we will have word embedding for all n-grams that can show rare words correctly, because there are most probably some sub-words in other words as well. FastText allows unattended and supervised learning of words and sentences. These embedings can be used for multiple applications of data compression, as features in additional models, for candidate selection, or as a regulator for learning transfer.

As shown in Figure 3, After vectors are extracted from news data by Fast Text and features from time series data by Long Short-Term Memory and two layers of DENSE, they are linked and the results are issued according to the proposed combination model after a DENSE stage. In the following, we will evaluate the proposed model.

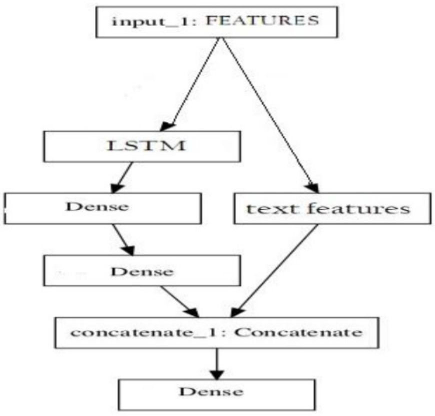

Figure 3: The proposed model

3. Evaluate the proposed model

In this modeling, once in a single variable, that is, the target variable, which is the closing price of the symbol, the modeling is done using Long Short-Term Memory, and in the second stage, modeling is done with the help of closing price of other symbols with high correlation with this symbol. In the third stage, in addition to stock market data, news network data is added to the results. The performance of the proposed model is evaluated using criteria such as Root Mean Squared Error (RMSE).

To evaluate the proposed model, the Pandas Python library was used to read the files. Symbols with a lower record are deleted after reading the automotive group file. The correlation of the closing price column of all symbols was obtained. And the symbols (kh bahman, kh charkhesh, kh komak, kh shargh, kh kar, verna, kh mehvar, kh pouyesh, khodro) that have the most correlation with each other were preserved. To predict the kh bahman symbol, all daily information of 8 other symbols was placed in front of this symbol.

For the variables of kh bahman symbol, the linear graph of the total lifespan of the symbol from 2000 to 2021 is drawn in Figure 4. As can be seen, on many days the closing price is equal to the

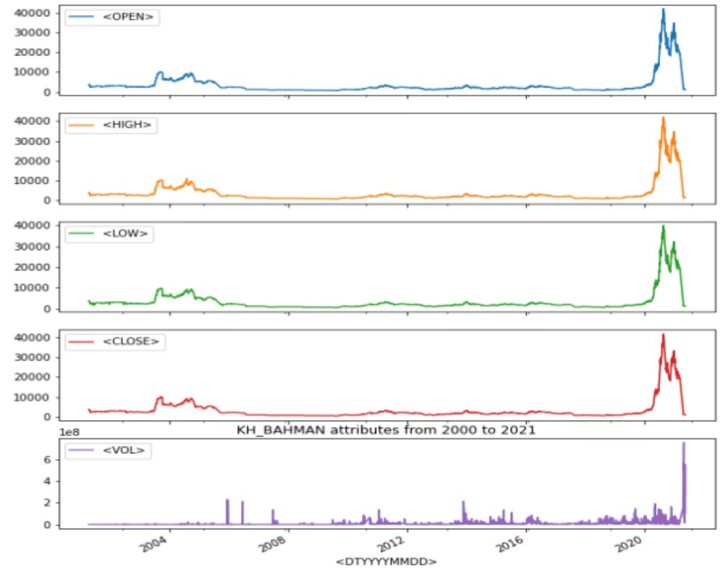

Figure 4: Lifespan of kh bahman symbol from 2000 to 2021

opening price and the minimum and maximum daily prices are equal. This indicates that the symbol price is fixed in one day. For symbols with high correlation with the symbol of kh bahman such as charkhesh, komak, verna, khodro, etc. for the closing price, a linear graph of the total lifespan of the symbols was drawn together. As can be seen, the closing price changes of these automotive group symbols are interdependent.

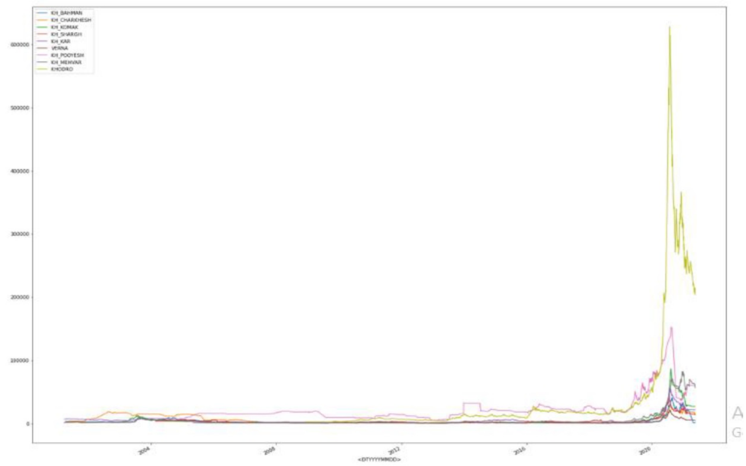

Figure 5: Linear chart of closing price of lifetime of symbols related to kh bahman.

Due to unrealistic fluctuations, the last 300 days of data were set aside for analysis and modeling of this part of the data. Modeling with the Prophet algorithm was once examined only as a single-variable self-variable target of the same final price, once with the help of other variables including the highest daily price, the lowest daily price, the daily opening price and the trading volume of the symbol and the closing price of high correlation symbols were performed by creating lag variables and once by rolling variables that results can be seen in Table 1. It is worth noting that 400 days from the end of the data were used as experimental data and 3600 days of the initial data were used as training data, and the evaluation criterion was the Root Mean Squared Error or RMSE.

Table 1: Modeling with Prophet algorithm

Model	**RMSE**
Proof algorithm without auxiliary variables of other symbols	843.368
Proof algorithm by making seven-day rolling of variables with the help of variables of other symbols	143.48
Proof algorithm by making a one-day lag of variables with the help of variables of other symbols	114.966

In the following modeling is done with neural network and Long Short-Term Memory. Once this modeling was done univariate; that's mean, the target variable was modeled at the same closing price as the kh bahman symbol, and once were modeled with the help of closing price, other symbols with high correlation with this symbol in the automotive group.

The network was configured with the parameters optimizer=Adam, loss= MAE and activation_function = sigmoid, and modeling was performed on the training data. The studied parameters include the number of epochs, the number of Long Short-Term Memory cells, the addition of DENSE layer to the network architecture, and the batch size, the results of which can be seen in Table 2. Another evaluated parameter was the number of days before for network input for which the numbers 1, 2, 3 and 7 were tested.

Table 2: Univariate modeling with neural network and Long Short-Term Memory

Number of long-term short-term memory cells	**EPOCH**	**Batch size**	**DANS**	**Number of days viewed in advance**	**RMSE**
50	100	72	None	1	91.416
50	1000	72	None	1	93.497
50	1000	80	None	1	95.361
50	1000	64	None	1	88.849
50	1000	56	None	1	98.388
50	1000	88	None	1	90.311
100	1000	88	None	1	91.066
50	1000	88	50,30,20	1	90.647
50	1000	88	None	2	84.477
50	1000	88	None	3	88.267
100	100	72	20,40	1	111.23
100	100	72	20,40	2	158.73
100	100	72	20,40	3	196.35
100	100	72	20,40	7	220.64
50,100	1000	80	30,20,10	2	180.36
50,100	1000	80	30,20,10	3	240.11
50,100	1000	80	30,20,10	7	270.36
200	300	72	None	1	161.35
200	300	72	None	2	143.12
200	300	72	None	3	196.18
200	300	72	None	7	231.86

As shown in Table 4, the best solution was a model using a neural network algorithm and Long

Table 3: Multivariate modeling with neural network and Long Short-Term Memory

Number of long-term short-term memory cells	**EPOCH**	**Batch size**	**DANS**	**Number of days viewed in advance**	**RMSE**
100	100	72	20,40	1	140.32
100	100	72	20,40	2	111.26
100	100	72	20,40	3	105.12
100	100	72	20,40	7	170.66
50,100	1000	80	30,20,10	2	180.32
50,100	1000	80	30,20,10	3	200.02
50,100	1000	80	30,20,10	7	220.65
200	300	72	None	1	160.32
200	300	72	None	2	110.64
200	300	72	None	3	180.65
200	300	72	None	7	200.5
50	100	72	None	1	119.399
50	1000	72	None	1	112.496
50	1000	80	None	1	66.324
50	1000	64	None	1	123
50	1000	56	None	1	106.772
50	1000	88	None	1	71.169
100	1000	88	None	1	84.88
50	1000	88	30,20,10	1	89.882
50	1000	88	None	2	64.914
50	1000	88	None	3	139.373
50	1000	88	None	7	185.092

Table 4: Compare the best results of different models

Model	**RMSE**
Multivariate modeling table with neural network and short-term memory	64.914
Proof algorithm by making a one-day lag of variables with the help of variables of other symbols	114.966
Univariate modeling table with neural network and short-term memory	90.647

Short-Term Memory layer with the parameters of 50 cell counts, making a two-day lag variable, and the number of epochs equal to 1000 times which had the lowest error in predicting the closing price of the kh bahman symbol. Also, the use of closing prices of other symbols with high correlation with this symbol had a positive effect on increasing the accuracy of the model.

Figure 6 shows the error of model in the training and testing phase at 1000 epochs. Figure 7 shows the predicted amount by the model and the actual value of the closing price of the kh bahman symbol in the last 400 days of the data.

Till here, market analysis and forecasting have been done without considering the impact of news related to the stock market, to better understanding the impact of market sentiment and the impact of news on symbols, a more complete analysis is performed by using the news texts of stock exchange sites.

To do this, first to obtain stock market news, by examining the news archives of stock exchange

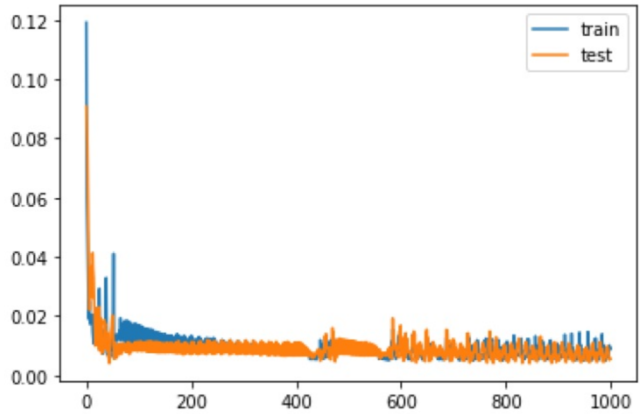

Figure 6: Error of model in the training and testing phase at 1000 epochs

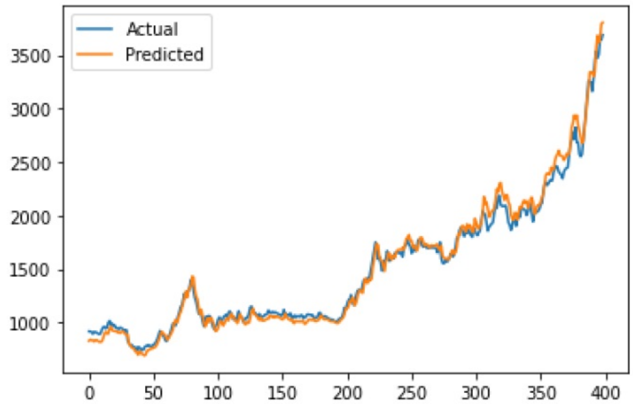

Figure 7: The predicted amount by the model and the actual value of the closing price of the kh bahman symbol in the last 400 days of the data

sites such as Tejarat News, Bourse Press, Senate and some channels of virtual networks, considering that the history of Tejarat News site was more than other sites by using of web mining techniques and selenium library, news texts were received from Tejarat News site from 15/05/2017 (the first day that the news was available in the site archive) until 05/09/2021. By placing the obtained news data in front of the kh bahman symbol and 8 related symbols of the same group with this symbol, based on the date of the new data set with 897 days for analysis, it was obtained that as before, the turbulent days of the stock market, when price increases were unrealistic, were removed from this data set and finally, this analysis and forecast was performed with 500 days of data that 400 days as training data and 100 days as experimental data were used to evaluate the combination model.

In the combination model, the features related to the symbol itself were first normalized as a one-day lag to the Long Short-Term Memory layer and the output of this layer, after two fully connected layers, was combined with the obtained features related to news texts and the combination of these properties was given to a fully connected layer with the Sigmoid activity function. Given that the stock news vector was used in this modeling with its symbol features and the characteristics of kh bahman group symbols.

To compare the analysis without considering news texts and with news texts, the prediction of this data set was performed in two cases without news text features and using the features obtained from Fast Text for news texts about the stock market that for both cases, different parameters and architectures were compared, the results of which can be seen in Table 5.

Table 5: Comparison of results without considering news data and using news data

Number of long-term short-term memory cells	EPOCH	Number of dans layers neurons	Batch size	RMSE
No use of news data				
100,50	500	20,50	16	250.968
100	400	20	64	220.451
50	1000	—	8	206,427
50	200	—	64	85,128
50	400	20,30	32	170,322
Using news data				
100,50	400	—	128	98,158
100,50	600	20,30	64	95,624
100	600	50,30,10	32	78,412
50	500	50,30,10	64	72,426
50	400	—	128	76,145

The result is that considering stock market news helps predict. As shown in the table 5 above, when we used news data for analysis, the error rate decreased and the predictions were performed better and the results of the best parameters and neural network architecture which resulted in the lowest error rate are shown below.

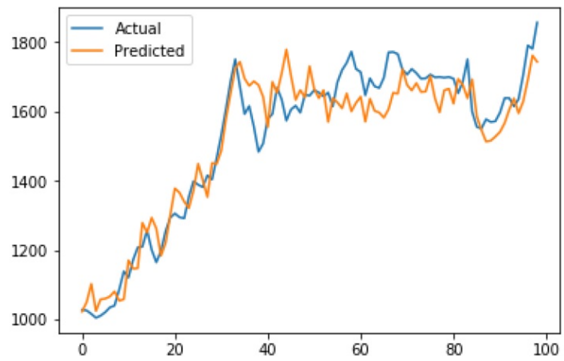

Figure 8: Actual movement of market and predicted values by the combination model

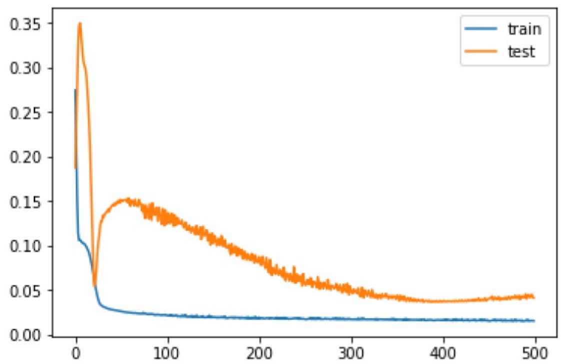

Figure 9: The amount of error in the training phase on the training data

In Figure 8, as shown, the blue line is the actual movement of market and the red line is the predicted values by the combination model. Figure 9 shows the error rate in the training phase on the training data. As can be seen, in the training phase, convergence occurred in the early epochs, but convergence of the experimental phase occurred in the epoch 400.

4. Conclusion and suggestion of future works

Predicting the stock market, due to the various uncertainties that affect the market price, which include political, economic events and the feelings of investors, is a very difficult task. The stock market in nature is dynamic and noisy, and stock market price fluctuations lead to random fluctuations. A financial decision support algorithm can greatly facilitate investors' decisions after disclosure of financial statements and can help identify financially beneficial stocks and exercise ownership. Whatever the more powerful and complete the algorithm used, the predictions will be more accurate. So it is necessary to use efficient algorithms for this work. Past research has generally focused on time series data on stock prices. With the breadth of data used, it is virtually impossible to achieve a robust and efficient approach to predicting the majority stock price in different capital markets. As regards in addition to the history of each share, other political and psychological factors affect the value of each share, in this research, a combination model based on Long Short-Term Memory and text embedding is proposed that in addition to time series data, in order to examine the psychological force of the market, it also extracts features from news sites and based on a combination of news data and time series data, predicts the future of the stock market. The evaluation results showed that by combining the data extracted from news networks and adding it to the time series data of the stock market, the proposed model could well predict the future of the market.

As regards configuring deep neural networks is a challenging task, it is recommended for future work to train the Long Short-Term Memory network more accurately with more details and parameters and examine the gains of predictive performance resulted from deep learning for daily (including possible delay effects) and long-term data.

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