Stocks Prices Prediction with Long Short-term Memory

Zinnet Duygu Akşehir[1][a], Erdal Kılıç[1][b], Sedat Akleylek[1][c], Mesut Döngül[2][d] and Burak Coşkun[2][e]

[1]*Department of Computer Engineering, Faculty of Engineering, Ondokuz Mayıs University, Samsun, Turkey*
[2]*Rönesans Holding, Ankara, Turkey*

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Abstract: It is a difficult problem to predict the one-day next closing price of stocks since there are many factors affecting stock prices. In this study, by using data from November 29, 2010 to November 27, 2019 and stocks for the closing price of the next day are predicted. The long short-term memory method, a type of recurrent neural networks, is preferred to develop the prediction model. The set of input variables created for the proposed model consists of stock price data, 29 technicals and four basic indicators. After the set of input variables is created, the one-day next closing prices of AKBNK and GARAN stocks are developed the model to predict. The model's prediction performance is evaluated with Root Mean Square Error(RMSE) metric. This value is calculated as 0.482 and 0.242 for GARAN and AKBNK stocks respectively. According to the results, the predictions realized with the set of input variables produced are sufficiently successful.

1 INTRODUCTION

While the predictability of stock returns is of great importance for investors, it has become the most researched and curious subject by researchers. Determining stock prices is a very difficult problem. This situation can be associated with high uncertainty and mobility in prices. Moreover, many variables such as political events, general economic situation, movements in other stock exchanges and investors' expectations affect price movements.

When the stock market and stock index forecasting studies are surveyed, it is seen that artificial intelligence and data mining techniques are at the forefront. It is observed that artificial neural network (ANN) methods are used more frequently than other methods. In addition to these methods, studies have shown that deep learning methods are also used. Studies are usually in the direction of estimating the value of the stock market index.

For example, Akel and Bayramoğlu using data from 4 January 1999 to 28 February 2001 date, estimated the IMKB 100 ındex by the ANN method. Input variables of the network; USD / TL exchange rate, ISE trading volume, central bank exchange reserves, central bank one-month deposit interest rate, and gold exchange are determined (Akel and Bayramoğlu, 2008).

Karaatlı et al. used regression and artificial neural network models to estimate the IMKB100 index value. They used data from January 1960 to December 2002 date and determined as the period of analysis and the data were dealt with monthly. In the study, input variables for forecasting models were treasury bill rate, gold price, inflation rate, industrial production index, savings deposit interest rate, exchange rate, and time variables. When the models were compared, the regression model has seen to be more successful than the artificial neural network model (Karaatlı et al., 2005).

Using data from 2 July 2001 to 13 July 2006 date, Kutlu and Badur, who using different input variables in their models, tried to estimate the IMKB 100 index with the artificial neural networks approach. In the study, the previous day's index, US dollar, overnight

[a] https://orcid.org/0000-0002-6834-6847
[b] https://orcid.org/0000-0003-1585-0991
[c] https://orcid.org/0000-0001-7005-6489
[d] https://orcid.org/0000-0002-2479-6475
[e] https://orcid.org/0000-0001-7175-1109

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interest rate values, and the previous day's stock market index values of France, Germany, UK, S&P500, Brazil, and Japan were used as input variables. Three different models were created using these variables.

The first model, which was composed of the previous day's index value, US dollar, and overnight interest rate variables, produced more successful results (Kutlu and Badur, 2009).

Diler attempted to predict the direction of the IMKB 100 index the next day with the Ann method in his study. Input variables of the model determine as 10-day simple moving average, 5 and 10-day weighted moving average, 10-day momentum, a stochastic indicator (K%), relative strength index (RSI), MACD (12 and 26-day exponential averages). The success rate of the model calculated as 60.81% (Diler, 2003).

Altay and Satman tried to estimate the IMKB 30 index with ANN and regression methods. They tackled the data they used in the model on a daily and monthly basis. When the models compared, it appeared that the regression model is more successful for both cases. It also stated that the ANN model generally correctly predicted the direction of the IMKB 30 index (Altay and Satman, 2005).

Sui et al. attempted to predict the direction of the Shanghai stock market with support vector machines (SVM). In the forecast model, they tried to estimate the stock market direction of the day based on the previous day's price. Alexander filter, relative strength index, money flow index, Bollinger bands, Chaikin oscillator, moving average convergence/divergence, stochastic K%, accumulation/distribution oscillator, and Williams' R technical indicators used as input variables in the study. The prediction study with these technical indicators achieved a 54.25% success rate (Sui et al., 2007).

Inthachot et al. attempted to estimate the Thai stock exchange index with ANN and SVM methods. He used ten technical indicators for this forecast model. When the performance of the two models evaluated, it is seen that the model created by the ANN method was more successful (Inthachot et al., 2015).

Gündüz et al. attempted to estimate the daily movement directions of three shares in Borsa Istanbul with convolutional neural networks. In the model they created, data between January 2011 and December 2015 used. Two different sets of input variables used for the model created. There are daily opening, closing, highest and lowest values of stocks in the first input variable set. In the second input variable set, there are technical indicators calculated from gold and dollar price data. When the second dataset is added to the model created with the first dataset, it was seen to improve the classification performance of the model (Gündüz et al., 2017).

Parmar et al. attempted to predict the future value of stocks of a company with regression and long short term memory (LSTM) methods. The input variables of the models consist of the open, close, low, high and volume values of the stock. The input variables of the models consist of approximately nine lakh records consisting of the open, close, high, low, and volume values of the stock. When the models compared, the model created with the LSTM method was found to be more successful than regression-based model (Parmar et al., 2018).

Hossain et al. proposed a novel hybrid model based on deep learning for stock forecasting. The dataset used in the model consists of 66 years of S&P500 index values (date, open, close and volume). The proposed hybrid network has achieved 0.00098 MSE for this dataset (Hossain et al., 2018).

Pang et al. attempted to predict the Shanghai A-Share Composite index and price of the Sinopec stock via LSTM with embedded layer (ELSTM). This layer used to reduce the data dimension. The created model has achieved 0.017 MSE for Shanghai A-Share Composite index while achieved 0.0019 MSE for Sinopec stock (Pang et al., 2018).

Given the domestic and international stock market index studies examined above, we found that stock price data generally was chosen as the input dataset. We have created a slightly different set of data from these studies. This dataset we created; consists of stock price data (including the opening price, the highest price, the lowest price, the closing price and the volume), 29 technical indicators calculated from these price data, and 5 basic indicators. In this study, we tried to estimate the closing price of two stocks within the IMKB100 by using the LSTM method with this data set we created.

The rest of this study is organized as follows: In Section II, information about the dataset used in the developed model is given. The LSTM method used in the application is detailed in Section III. We describe our experimental results in Section IV. The last section consists of the conclusion and future works.

2 PREPARATION OF DATASET

This section provides information about how the dataset created for the prediction model.

2.1 Feature Selection

Determining the attributes to be used in the prediction model is one of the most important parts of the study. As a result of the researches, stock price values, basic and technical indicators were used to determine the closing next day price of two stocks within the IMKB 100. The stock price data includes the open, close, high, low, and volume values of these stocks. Also in the input dataset, there are 29 technical indicators calculated from these price data of the stock. In addition to these attributes, there are also 5 basic indicators: S&P 500, USD / TL parity, brent oil, MSCI Turkey ETF, and BIST100 closing values. The size of this dataset created as a matrix is 2265x39.

Technical analysis indicators use price and transaction data to determine trends and analyze formations. And with the help of some mathematical calculations, he tries to express price movements by a numerical value. Technical analysis indicators are examined in 4 sub-headings: momentum, volume, trend, and volatility indicators (Çetinyokuş, 2002). In this study, the technical indicators to be used in the model were determined as follows: 4 volume (Chaikin Money Flow, On Balance Volume, etc.), 7 volatility (Average True Range, Bollinger Band, Kelter Channel Central, etc.), 6 momentum (Relative Strength Index, Stochastic Oscillator, Money Flow Index, etc.), and 12 trend (Mass Index, Aroon Indicator, Commodity Channel Index, Exponential Moving Average, etc.) indicators.

2.2 Creation of the Dataset

The stock price data used in the study obtain from Borsa Istanbul. The values of basic indicators obtain from the stooq.com website.

3 METHODOLOGY

A Recurrent Neural Network (RNN) is a type of neural network whose inputs are sequences of data ranges from text, image to time series. RNN architectures provide successful results in time-based problems due to their ability to connect with the past and interpret. But in the case of establishing a connection with the distant past, it's hard to keep that much information in its memory and use it (Elman, 1990). As a solution to this memory problem of RNN and the 'vanishing gradient problem,' Hochreiter and Schmidhuber proposed the Long Short Term Memory (LSTM) units in 1997 (Hochreiter and Schmidhuber, 1997). LSTM is a variant of RNNs and can learn long-term dependencies. In this way, it produces new outputs based on what it has learned in the past.

While traditional RNNs have a single tangent layer (see Fig. 1), the LSTM has four different layers: input gate, output gate, forget gate, and the memory cell.

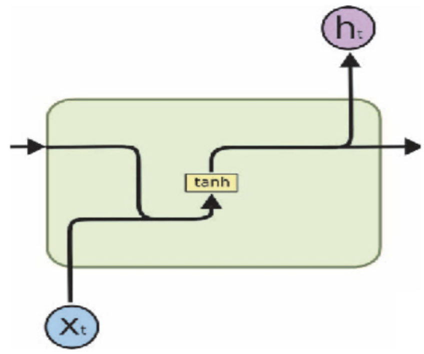

Figure 1: The traditional RNN unit.

The LSTM transaction equations are given as fallow (Hochreiter and Schmidhuber, 1997):

$$f_t = \sigma\left(W_f.[h_{t-1}, X_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i.[h_{t-1}, X_t] + b_i) \tag{2}$$

$$o_t = \sigma(W_o.[h_{t-1}, X_t] + b_o) \tag{3}$$

$$\check{C}_t = \tanh(W_c.[h_{t-1}, X_t] + b_c) \tag{4}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \check{C}_t \tag{5}$$

$$h_t = o_t \odot \tanh(C_t) \tag{6}$$

From the above equations, for an input vector (X) the LSTM unit at time step t: i_t is an input gate, f_t is a forget gate, o_t is an output gate, C_t is a memory cell, h_t is hidden state, W is weight matris, b is bias vector, and σ activation function. The default conections among these units are presented Figure 2.

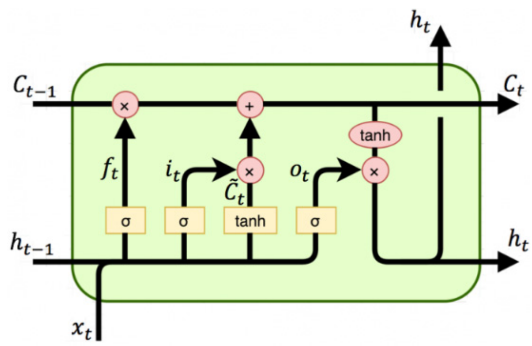

Figure 2: LSTM unit.

4 EXPERIMENTAL RESULTS

With the LSTM model we created within the scope of the study, we evaluated closing price of AKBNK and GARAN stocks of the next day. In this study, we determined the analysis period from November 29, 2010 - November 27, 2019, and we handled the data daily.

We used the AKBNK and GARAN stocks price data (open, high, low, and close), 29 technicals, and 5 basic indicators as the input variable of the model we developed.

The details of the model we developed are as follows:

- For the training set, we take the first 75% of the data, and for testing, we chose the rest of the data.
- Input data segmentation is made by 9 width sliding window. That is, each input variable having 9 days of observation.
- Our model consists of five LSTM layers and one dense layer. The output sizes of the LSTM layers are 256, 128, 64, 32, and 16, respectively.
- We added a dropout layer between the LSTM layers to prevent the model from over-fitting.
- The activation function of the LSTM layers is 'hard sigmoid' while the activation function of the dense layer is 'hyperbolic tangent'.
- We've set the number of epochs to 150, the batch size is 32.

We also benefited from the Root Mean Square Error (RMSE) metric indicated with (7) when evaluating the performance of the model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Qp_i - Qa_i)^2} \qquad (7)$$

In the above equation, n shows the number of data, Qp is predicted value, and Qa is actual value. According to this metric, the RMSE value's close to zero shows that the created prediction model is successful.

After all these model parameters were set, we went through to the training stage of the model. After the training of the model was completed, we performed the prediction on the test data. The graphs of the actual closing prices of GARAN and AKBNK stocks and the values predict during the test is given in Figure 3 and Figure 4 respectively.

Graphics shown in blue in Figure 3 and Figure 4 shows the actual closing price, while the graph in red indicates the predicted values.

When the figures are examined, the two curves generally overlap. However, successful forecasts could not be produced in cases where the stock price dipped or peaked.

Also, the RMSE values of the model created for GARAN and AKBNK stocks calculated as 0.282 and 0.482 respectively. These values indicates that the created prediction model is successful.

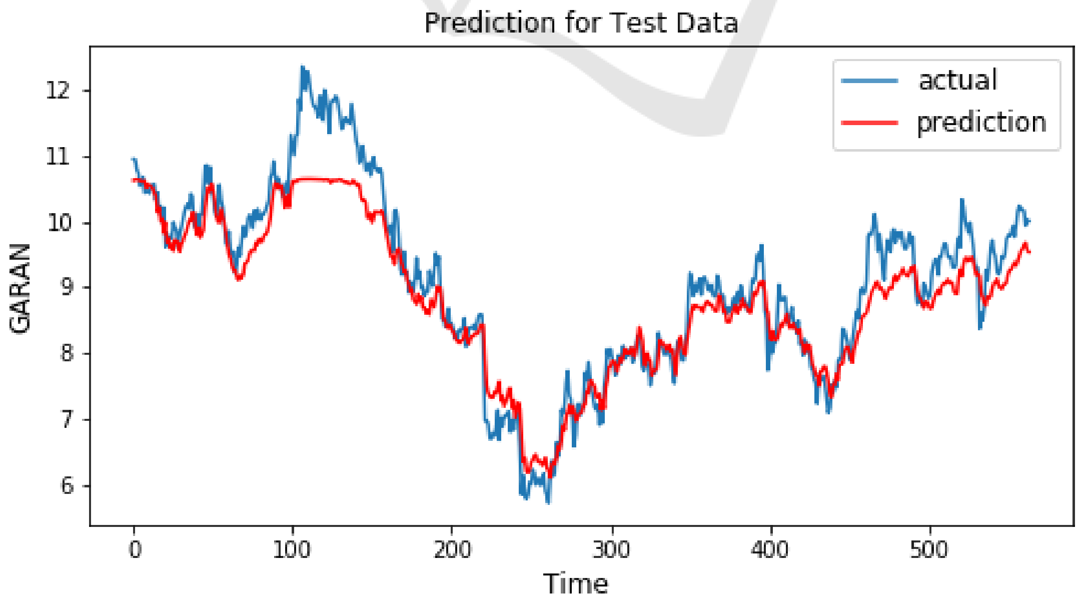

Figure 3: GARAN stock prediction and actual closing price during the test.

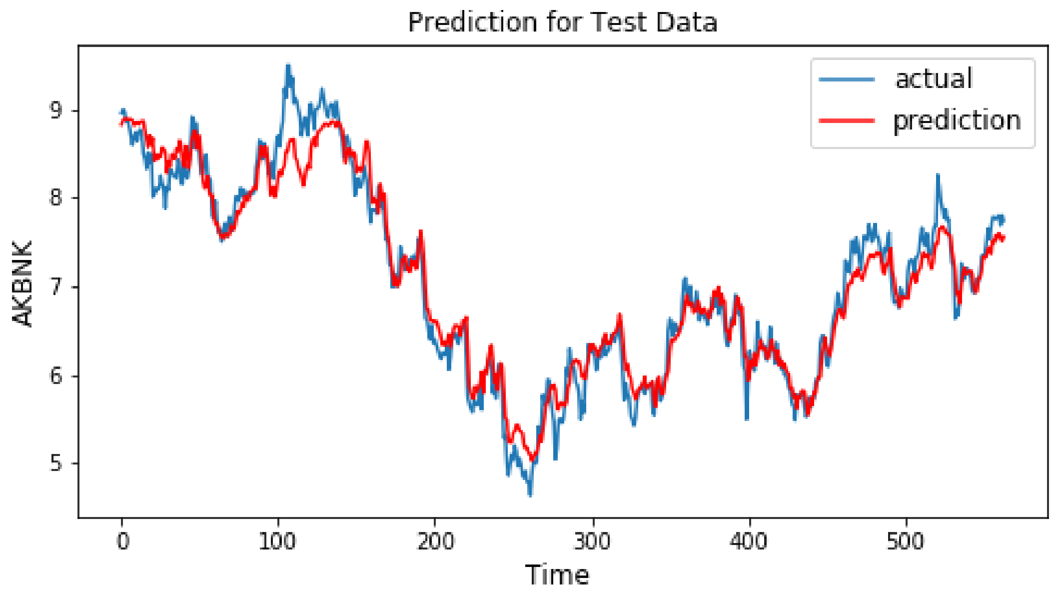

Figure 4: AKBNK stock prediction and actual closing price during the test.

5 CONCLUSIONS AND FUTURE WORK

When we examined the results, we found that the LSTM model, created with the selected basic and technical indicators, realized successful predictions.

Also, we found that the price direction correctly predicted even though the price value could not be predicted correctly when the stock price reached the bottom and peak.

We have identified future studies as make improvements for these situations where the stock price is not closely predicted.

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REFERENCES

Akel, V., Bayramoğlu, M. F., 2008. Kriz Dönemlerinde Yapay Sinir Ağları ile Finansal Öngörüde bulunma: İMKB 100 Endeksi Örneği. *International Symposium on International Capital Flows and Emerging Markets*, pp. 24-28.

Altay, E., Satman, M. H., 2005. Stock Market Forecasting: Artificial Neural Network and Linear Regression Comparison in An Emerging Market. *Journal of Financial Management and Analysis*, 18(2), pp. 18-33.

Çetinyokuş, T., Gökçen, H., 2002. Borsada Göstergelerle Teknik Analiz için Bir Karar Destek Sistemi. *Gazi Üniversitesi Mühendislik-Mimarlık Fakültesi Dergisi*, 17(1).

Diler, A. İ., 2003. İMKB Ulusal-100 Endeksinin Yönünün Yapay Sinir Ağları Hatayı Geriye Yayma Yöntemi ile Tahmin Edilmesi. *İMKB Dergisi*, 7(25- 26), pp. 66-82.

Elman, J. L., 1990. Finding structure in time. *Cognitive science*, *14*(2), pp. 179-211.

Gunduz, H., Cataltepe, Z., Yaslan, Y., 2017. Stock Market Direction Prediction Using Deep Neural Networks. In *2017 25th Signal Processing and Communications Applications Conference (SIU),* pp. 1-4. IEEE.

Hochreiter, S., Schmidhuber, J., 1997. Long Short-Term Memory. *Neural computation*, *9*(8), pp. 1735-1780.

Hossain, M. A., Karim, R., Thulasiram, R., Bruce, N. D., Wang, Y., 2018. Hybrid Deep Learning Model for Stock Price Prediction. In *2018 IEEE Symposium Series on Computational Intelligence (SSCI),* (pp. 1837-1844. IEEE.

Inthachot, M., Boonjing, V., Intakosum, S, 2015. Predicting SET50 Index Trend Using Artificial Neural Network and Support Vector Machine. *In International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, pp. 404-414. Springer.

Karaatlı, M., Güngör, İ., Demir, Y., Kalaycı, Ş., 2005. Hisse Senedi Fiyat Hareketlerinin Yapay Sinir Ağları Yöntemi ile Tahmin Edilmesi. *Yönetim ve Ekonomi Araştırmaları Dergisi*, 3(3), pp. 38-48.

Kutlu, B., Badur, B., 2009. Yapay Sinir Ağları ile Borsa Endeksi Tahmini. *Yönetim*, 20(63), pp. 25-40.

Pang, X., Zhou, Y., Wang, P., Lin, W., Chang, V., 2018. Stock Market Prediction based on Deep Long Short Term Memory Neural Network. *In Proceedings of the*

3rd International Conference on Complexity, Future Information Systems and Risk (COMPLEXIS 2018), pp. 102-108.

Parmar, I., Agarwal, N., Saxena, S., Arora, R., Gupta, S., Dhiman, H., Chouhan, L., 2018. Stock Market Prediction Using Machine Learning. In *2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)*, pp. 574-576. IEEE.

Sui, X., Hu, Q., Yu, D., Xie, Z., Qi, Z. *A., 2007.* Hybrid Method for Forecasting Stock Market Trend Using Soft-Thresholding De-noise Model and SVM. *Springer Verlag Berlin Heidelberg*, pp. 387-394.