Stock Market Value Prediction using Deep Learning

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***Abstract*— The stock market is a key indicator of the economic conditions of a country. Stock exchange provides a neutral ground for brokers and companies to invest. Due to high investment return, people tend to invest in stock markets rather than traditional banks. However, there is high risk is investment in stock markets due to high fluctuations in exchange rates. Therefore, developing a highly robust stock prediction system can help investors to make a better decision about investment. In this study, a deep learning-based approach is applied on the stock historical data to predict the future market value. Specifically, we used Long-Short Term Memory (LSTM) for prediction of stock value of five well known Turkish companies in the stock market. The trained proposed model is later tested on corresponding data, and performance metrics such as accuracy, RMSE and MSE reveals that the proposed LSTM model successfully predicts stock prices.**

***Keywords*—Stock market prediction, machine learning, LSTM, deep learning**

I. INTRODUCTION

Stock market forecasting has been a difficult area to predict worldwide. There are many factors that affect the stock market locally and universally. For this reason, there is no precise method and theory in the studies conducted up to this time [1].

Generally, the stock prediction methods are grouped into three main categories, namely: technical analysis, basic analysis and evolutionary analysis. Technical analysis, based on statistical analysis, is the most commonly used method [1]. These statistics can be learned and analyzed directly from the input data. However, many external factors such as the condition of the company to which the shares belong, political order and universal events affect the stock market trend. For this reason, stock price prediction is generally a nonlinear and dynamic process. At the same time, the fluctuation in the stock market is quite severe. Therefore, it is very important to keep the risk low while forecasting a closing price of stock market.

Recently, deep learning-based approaches have shown better accuracies for classification of stock data. In particular, Recurrent Neural Networks (RNNs), have been widely used for time series data analysis [2]. For example, Xiao et al. used a deep convolutional neural network for event-based stock market prediction [3]. Bengio et al. used the LSTM model for stock price estimation [4].

LSTM is an advanced version of RNN. It has the ability to deal with sequential data and is highly suitable for training and testing the stock market value prediction. For stock forecasting, authors in [5] proposed a LSTM-based model on Chinese stock market data. They used historical price data of market indices and stocks. It is noted that LSTM attained promising results. LSTM can feed different types of sequential data to other networks to expand existing data. Likewise, Li, Bu and Wu [6] fed a network with historical market data using LSTM to estimate investor shares and CSI300 stock. Thus, they concluded that LSTM's support vector machines perform better than benchmark models and accomplished better results in price prediction. David M. Q. Nelson and his friends proposed LSTM model to predict whether a particular stock will rise in the near future [7]. They found that the model was more successful in predicting high variations. They achieved an average accuracy of 55.9%. Wei Bao and colleagues have created a three-stage deep learning framework by combining LSTM and autoencoders (SAEs) models for stock price estimation [8]. They created the LSTM model for the estimation of next day's closing price. The results show that the proposed model performs better than other similar models in both predictive accuracy and profitability performance. Pengfei Yu and Xuesong Yan have created a deep neural network model based on LSTM to estimate stock prices [9]. Their comparative analysis showed that the proposed prediction model achieved a higher prediction accuracy than other prior models. Thomas Fischer and Christopher Krauss used the LSTM, random forest (RAF), a deep neural net (DNN) and a logistic regression classifier (LOG) models to estimate S&P 500 stock movements from 1992 to 2015 [10]. Their comparison revealed that the LSTM model, which is spontaneously suitable for this area, overcomes a standard deep net and logistic regression by a clear margin. Most of the time (except for the global crisis) they have seen that models performed better than the RAF model.

In this study, a deep learning-based approach is applied on the stock historical data to predict the future market value. Specifically, we used Long-Short Term Memory (LSTM) for prediction of stock value of five well known

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Turkish companies in the stock market. These companies include Turkish Airlines (THYAO), Akbank (AKBNK), Arçelik (ARCLK), Aselsan (ASELS), and Garanti (GARAN). These are on the BIST30 list of Borsa Istanbul. The data spans over last 5 years between 2014-2019.

The rest of the paper is arranged as follows. In Section 2, we described the data set. Section 3 outlines the proposed methodology and the LSTM model. Section 4 presents the experimental results. Finally, the paper ends with concluding remarks and future perspective in section 5.

II. Data Set

The data set used in this study belongs to THYAO, AKBNK, ARCLK, ASELS, and GARAN companies, which spans over a period of 5 years (2014-2019). The data for each share in our data set consists of one-minute bar data. Table 1 shows the state before processing.

We made some adjustments to our dataset before applying the LSTM model. The correct preparation of the data set, the use of the correct data and the removal of noise increases the accuracy of the model to be applied.

TABLE I. 5 MINUTES DATA

Symbol	Signal_Time	Date_Time	Close	High	Low	Open	Total Quantity	Volume	Weighted Average
THYAO	1412145300000	2014-10-01T09:35:00+03:00	6.51	6.52	6.49	6.49	533009	3.464895	6.50063
THYAO	1412145360000	2014-10-01T09:36:00+03:00	6.53	6.53	6.51	6.51	267332	1.742998	6.51998
THYAO	1412145420000	2014-10-01T09:37:00+03:00	6.52	6.53	6.52	6.52	165859	1.082718	6.52794
THYAO	1412145480000	2014-10-01T09:38:00+03:00	6.52	6.53	6.52	6.53	90008	5.869022	6.52056

A. Data Pre-processing

In the data set, we first indexed the date column in the data because it is a time series. The data set consisted of one-minute bars. Since the one-minute data is very noisy data, therefore, we removed the GMT value and divided it into five-minute periods (Table II).

TABLE II. 5 MINUTES DATA

Date Time	Symbol
2014-10-01 09:35:00	THYAO
2014-10-01 09:40:00	THYAO
2014-10-01 09:45:00	THYAO

Looking at past price movements in financial markets, forecasting methods for future price movements are called technical analysis. The main methods when using technical analysis are formations and indicators.

Indicators are called technical analysis indicators. It helps investors by presenting buy or sell signals about stocks. Indicators are calculated using stock price and volume data. We used the Weighted Moving Average (WMA) indicator, one of the most used indicator types in our study. WMA shows the average of the past period, reflecting how far the current price is on the train. We have added the WMA indicator to the data set by taking the average of the 15-period time period using the close value in the data.

After adding the indicator values to our data set, we determined the direction (trend) by taking the difference of the close values of the previous line with the previous line in 5-minute periods. We added this trend value to 1 if it is positive and 0 if it is negative. The final version of our data set is shown in Table 3. The closing values of AKBNK, ARCLK, ASELS, GARAN, and THYAO are shown in Fig. 1, Fig. 2, Fig. 3, Fig. 4, and Fig. 5, respectively.

TABLE III. DATA SET AFTER PRE-PROCESSING

DATE_TIME	SYMBOL	SIGNAL_TIME	CLOSE	HIGH	LOW	OPEN	QUANTITY	VOLUME	WA	INDICATOR	TRENDS
2014-10-01 10:50:00	THYAO	1412149800000	6.51	6.53	6.51	6.53	75214	490394.29859	6.51999	6.518750	0
2014-10-01 10:50:00	THYAO	1412150100000	6.52	6.52	6.51	6.51	3140	20441.46072	6.51002	6.519083	1
2014-10-01 10:50:00	THYAO	1412150400000	6.50	6.50	6.50	6.50	1334	8671.00000	6.50000	6.517000	0
2014-10-01 10:50:00	THYAO	1412150700000	6.52	6.52	6.51	6.51	93352	607804.83930	6.51089	6.517500	1

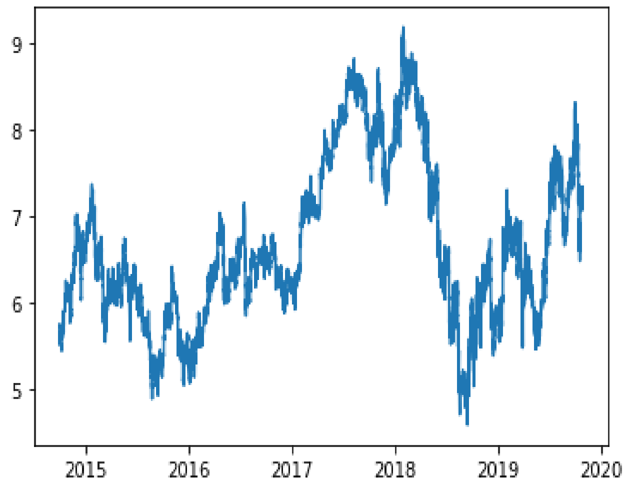

Fig. 1. Close Price of AKBNK Stock

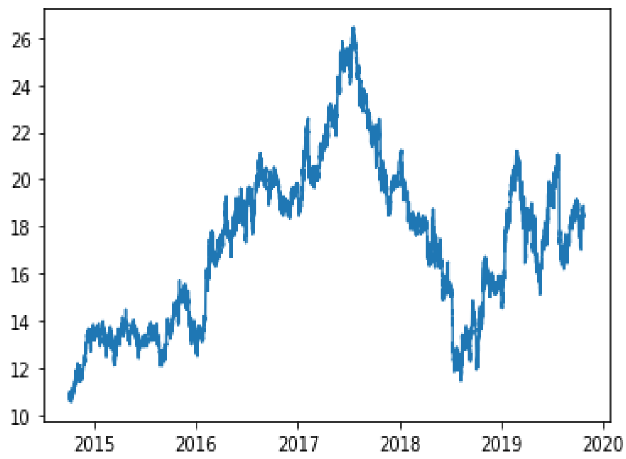

Fig. 2. Close Price of ARCLK Stock

Fig. 3. Close Price of ASELS Stock

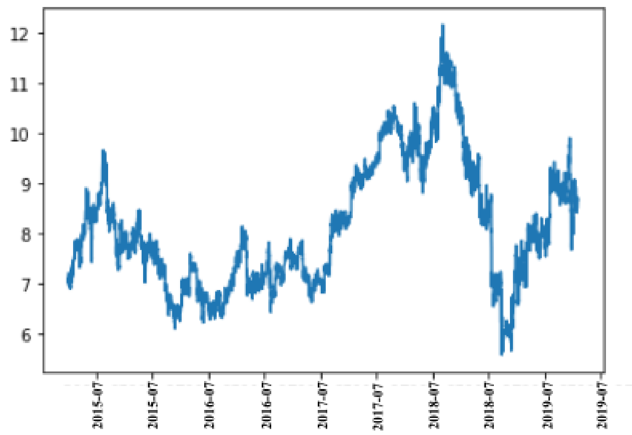

Fig. 4. Close Price of GARAN Stock

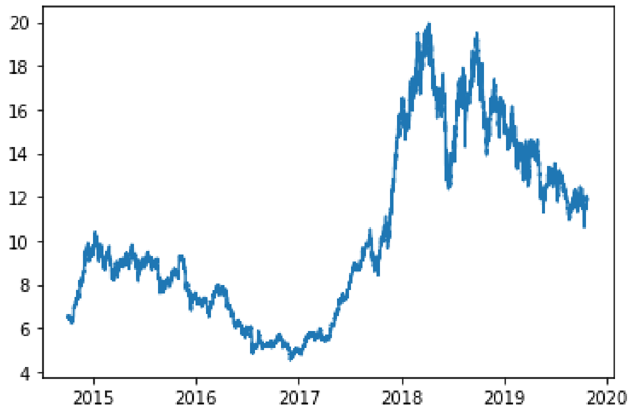

Fig. 5. Close Price of THYAO Stock

III. PROPOSED METHODOLOGY

This section explains the LSTM model that is employed to the pre-processed data set. First, it presents an overview of the LSTM structure and its advantages and later describes the proposed model created for experimental work.

A. LSTM Basics

LSTM is a special type of RNN with ability to remember longer historical data. It presents the memory cell, a computation unit that replaces artificial neurons of the hidden layer in the network. This memory cell allows the network to be effectively associated with the past. For this reason, it can dynamically grasp and predict the structure of the data over time, thanks to its high estimation capability. LSTM is naturally suitable for this area. When the data is given, it can automatically grasp the models depending on the appropriate data. The memory cells can prevent the extinction tendency by keeping the information for a while. It is more advantageous than RNN because it can learn long-term dependencies. LSTM can keep error for reverse transition through time and layer, thus keeps the error at a more stable level.

All recursive neural networks are a chain of recursive modules of the neural network. In standard RNNs, this recursive module has a very simple structure like a single tanh layer. LSTMs also have this chain-like structure, but the recursive module has a different structure. Instead of having a single neural network layer, there are four and they interact in a very special way.

B. LSTM Model

For this study, the data is divided into train and test sets before creating the LSTM model. Since it is a time series data, so shuffle is set to false. As the amount of data is high, so 0.3% of it is reserved as test data. Two separate files were created; test and train, and then applied the min-max scaler normalization method to these files. For learning to be efficient in the time series, a time-step algorithm is applied. The working logic of the algorithm is that it groups the number of data, as per specification of a user, and then tries to estimate the next value from the number determined by the previous values. For experimental work, this grouping value is set to 50. After grouping it as 50 each, it tries to guess the 51st compared to the previous 50 values. This is particularly suitable for the LSTM model that stores this grouping in long-term memory.

LSTM is an advanced version of RNN. It has the ability to deal with sequential data, which makes it highly suitable for training and testing the stock market value prediction. In the experimental setup, we used four LSTM layers with 50 units in each layer, having hyperbolic tangent function as activation. The hyperbolic tangent function is used because of the hidden layers fitting the LSTM model. The advantage of the tangent function derivative is that it approaches slowly to zero, thus offers longer learning opportunities.

The biggest problem of Deep Learning is undoubtedly overfitting. While memorizing the data brings low loss and high accuracy in the train phase, it turns into a complete disaster in the test phase. To prevent this, 2% dropout is set to each of the LSTM layers. Dropout randomly removes some nodes; hence, the problem of memorizing the same values is prevented. The last layer of the network is a dense layer containing one unit for regression output. Adam is employed as the default optimizer while mean squared error is used as loss function, as it offers a better learning process because it decreases the learning rate. In the loss evaluation, we used the mean squared error function. The total number of epochs were set to 100 and the batch size was set to 32 to speed up the training process.

IV. EXPERIMENTAL RESULTS

A number of experiments were carried out to test the efficiency of the proposed method. The results presented below are the accuracy rates for each stock. The performance of the proposed system is evaluated by comparing the actual value and the predicted values. We evaluated the accuracy of our results with overall accuracy, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics. RMSE determines the average magnitude of estimation error in stock market trends which can be calculated as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(forecast(t) - actual(t))^2}{n}} \tag{1}$$

While MAE determines the average measure of errors in the prediction of stock market indices, which can be calculated as:

$$MAE = \frac{\sum_{t=1}^{n}|forecast(t) - actual\ (t)|}{n} \tag{2}$$

Table IV summarizes the results obtained for the proposed method on the utilized dataset. As can be seen from the table, the RMSE and MAE values show that the LSTM model achieved a high success while predicting the stock values. Based on these values, the model attained a high accuracy.

The predicted closing stock prices for AKBNK, ASELS, GARAN, THYAO, and ARCLK are shown in Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, respectively. It is evident from the predictions depicted in these graphs that predicted price values are close to real values.

TABLE IV. PREDICTION ACCURACY OBTAINED FOR ON OUR DATASET

Company	Accuracy (%)	RMSE	MAE
THY	97.52	0.0068	0.034
AKBANK	98.91	0.0078	0.016
ASELSAN	98.02	0.0050	0.047
GARANTI	98.35	0.024	0.033
ARCELIK	97.55	0.0048	0.043

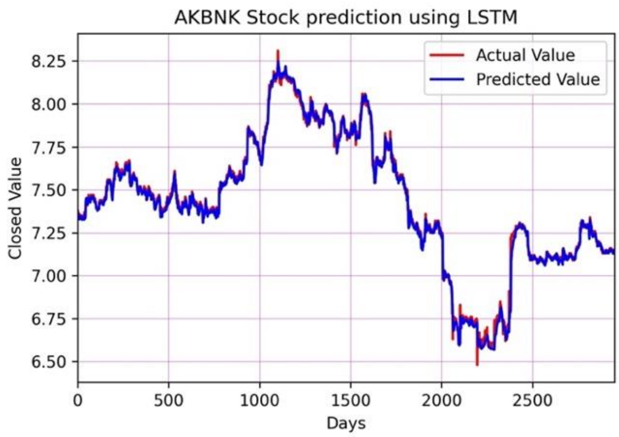

Fig. 6. AKBNK Stock Prediction using LSTM

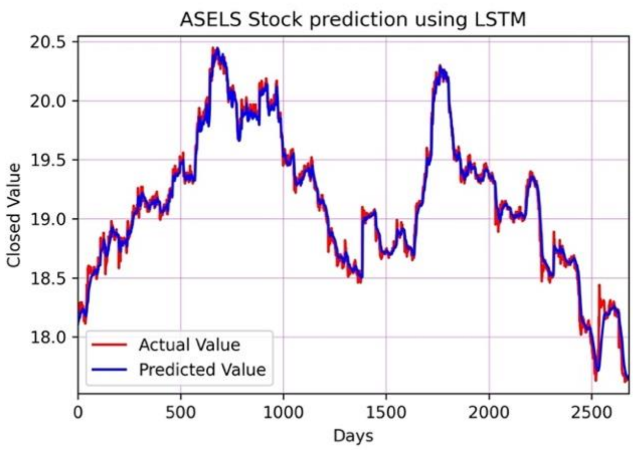

Fig. 7. ASELS Stock Prediction using LSTM

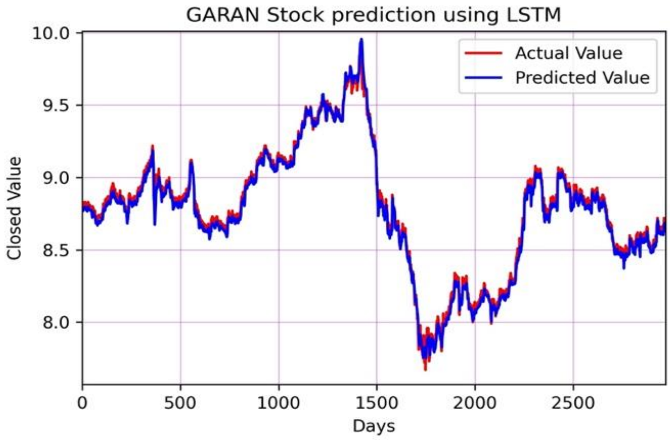

Fig. 8. GARAN Stock Prediction using LSTM

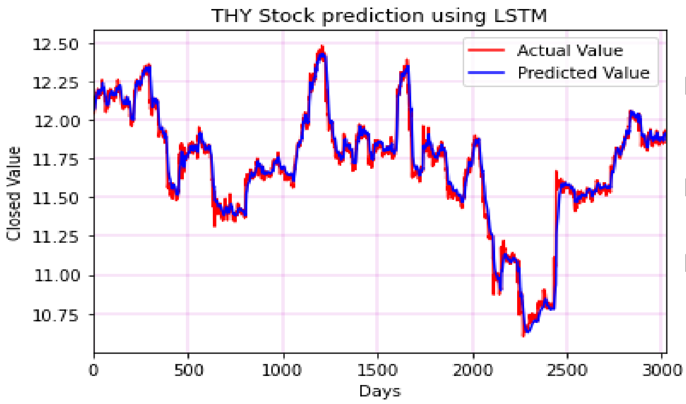

Fig. 9. THYAO Stock Prediction using LSTM

V. CONCLUSION

In recent years, it has been observed that methods based on deep learning have been adopted because they can solve complex problems. Sufficient data is more likely to increase the accuracy rate, as deep learning networks are larger and deeper. This article provides a proposal to estimate the closing price of five popular stocks traded on Borsa Istanbul. First of all, the WMA index, calculated according to the close value, was added to the data set. Then the trend value was calculated by subtracting the previous close value from the close value in the current bar and then added to the set as input. After the created data set was separated as train and test sets, min-max scaler normalization process was applied separately and made suitable for LSTM model. Estimation was made by creating the model structure suggested above. It is seen that LSTM gives successful results in line with the RMSE and MAE values stated in Table 4. It is possible to conclude that the LSTM-based model offers less risk.

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