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Research Article

Prediction of Financial Time Series with Deep Learning Algorithms

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Abstract: Stock market index data, foreign currency, and gold have an important place in financial time series. Therefore, value or direction of movement estimation studies on this subject attracts the attention of both investors and researchers. This study aims to estimate the daily value of the US Dollar, Gold, and Borsa Istanbul (XU) 100 index using deep learning methods: Recurrent Neural Networks and Long-Short-Term Memory. A data set consisting of 2280 business days between 2013-2022, which includes the date, US Dollar, Gold, and XU 100 closing data, was used in the study. Mean absolute error, mean square error, root mean square error, and coefficient of determination were used to evaluate the performance of the developed prediction models. When the results were examined, it was seen that the Long-Short-Term Memory algorithm performs better than the Recurrent Neural Network algorithm and achieved a determination coefficient value of over 95% for the US Dollar, Gold, and XU 100 index. Moreover, the findings obtained in the study indicate that deep learning algorithms can show high prediction performance on financial time series without using extra independent variables.

Finansal Zaman Serilerinin Derin Öğrenme Algoritmaları ile Tahminlenmesi

Makale Bilgileri

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Öz: Borsa endeks verileri, döviz ve altın finansal zaman serileri içerisinde önemli bir yere sahiptir. Bu konuda yapılacak değer ya da hareket yönü tahmini çalışmaları hem yatırımcıların hem de araştırmacıların ilgisini çekmektedir. Bu çalışmada, derin öğrenme yöntemlerinden Tekrarlayan Sinir Ağları ve Uzun-Kısa Süreli Bellek algoritmaları ile; Dolar, Altın ve BİST 100 endeksinin günlük değer tahmini amaçlanmıştır. Çalışmada tarih, dolar, altın ve BİST 100 günlük kapanış verileri içeren 2013-2022 yılları arasındaki 2280 iş gününden oluşan bir veri seti kullanılmıştır. Geliştirilen tahmin modellerinin performanslarını değerlendirmek için ortalama mutlak hata, ortalama karesel hata, hata kareler ortalamasının karekökü ve belirlilik katsayısı değerlendirme ölçütleri kullanılmıştır. Tahmin sonuçları incelendiğinde Uzun-Kısa Süreli Bellek algoritmasının Tekrarlayan Sinir Ağı algoritmasına göre daha iyi performans gösterdiği ve Dolar, Altın ve BİST 100 endeksi için belirlilik katsayısı değerinin %95'in üzerinde olduğu görülmüştür. Ayrıca çalışmada elde edilen bulgular, derin öğrenme algoritmalarının finansal zaman serileri üzerinde ekstra bağımsız değişkenlere ihtiyaç duymadan yüksek tahmin başarımı gösterebileceğini belirtmektedir.

1. Introduction

In today's global world, with constantly changing conditions and ambiguous data, making decisions is challenging for companies and individual investors. Accordingly, following the price movements of financial instruments and predicting the upcoming trends is essential for making an investment decision. Therefore, accurate estimation of financial data with statistical methods based on data mining and machine learning is crucial for investors.

While making an investment decision, investors can convert their savings into values such as gold, foreign currency, or stocks according to the risk and return expectations. The prediction studies of stock market index data, foreign exchange, and gold values attract the attention of both investors and researchers as they have an important place in financial time series. Stock markets, which consist of dynamic and chaotic stocks, can be affected by several factors, such as political events, general economic situation, preferences of institutional investors, investor expectations, and investor psychology. Hence, due to uncertainty, stock markets carry more risk than all other investment areas.

XU is a remarkably active stock market since it is very sensitive to adverse market conditions, reacting quickly, increasing the number of companies traded, and increasing the total transaction volume daily. These advantages make XU solid and attractive for domestic and foreign investors. Investors need to reach some critical information about the stock they will invest in and predict the stock's future price expectations. The market value, trading amount, and trading volume of the stock are some of the information that plays a critical role in predicting the future price expectations of the stock. However, although this information is easily accessible, it is difficult to make accurate estimations because stock prices are affected by many other factors. Thus, a robust prediction model should be chosen to make accurate estimations.

The US dollar, which has become the universal currency, is used in the foreign trade of developing countries such as Turkey. Similar to stocks, forecasting studies for the US dollar attract the attention of both large and small-scale investors. Compared to other financial assets, gold is one of the investment instruments that attract the most attention as a traditional investment instrument in Turkey, as its transaction is simple, understandable, and reliable. Furthermore, it is observed that investors traditionally tend to invest in gold in times of crisis and uncertainty to protect themselves against the risk of a fall in the dollar or an increase in inflation. Therefore, prediction studies on XU, the US dollar, and gold have meaningful contributions to the literature.

Financial time series prediction is a popular research area for most researchers as it offers massive profit opportunities. With the developing computer technologies, deep learning algorithms allow the precise estimation of financial time series. Deep learning algorithms, which use hidden layers on the shallow structure consisting of input and output layers in traditional machine learning, are one of the most popular approaches for solving complex problems.

This study investigated the performances of deep learning algorithms on a financial time series containing US Dollar, Gold, and XU 100 values. The data set covers the period of 2013-2022 and consists of Dollar, Gold, and XU 100 values. To predict the daily values of Dollar, Gold, and XU 100 Long-Short Term Memory (LSTM) and Recurrent Neural Networks (RNN) algorithms, which are known to have high estimation performance on time series in the literature, were used. The main contribution of this study is that by using the optimized hyperparameters, deep learning algorithms such as RNN and LSTM can achieve high prediction performance in financial time series without multiple independent variables. The performances of the prediction models were evaluated by using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2).

The applied methodology in this study is generalized and explained in Figure 1 with a flowchart. First, the daily values of the US Dollar, Gold, and XU 100 are gathered from investing.com. Subsequently, data preprocessing is performed to convert the time series data into a supervised learning problem and reshape it into a suitable format for RNN or LSTM algorithms. Then, the prediction model architecture is defined, specifying the number of layers, memory cells, and additional layers like Dropout or Batch Normalization. In the next step, the model is trained using the training data. Evaluation of the trained model is carried out on the testing set, using performance metrics such as mean squared error, root mean squared error, or mean absolute error. The model's predictions are analyzed and compared with actual values. Model optimization involves fine-tuning the hyperparameters of the algorithms. Once the optimized hyperparameters are determined, the model is trained using the training data again, and final predictions are obtained.

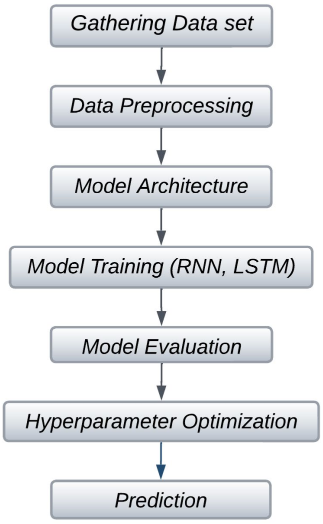


Figure 1. General overview of this study.

The remaining sections of the study are organized as follows; in the second section, a comprehensive literature review is presented. In the third section, deep learning algorithms applied in this study are introduced. Section 4 presents the prediction results. The last section gives general evaluations of the study and some remarks for future studies.

2. Literature

This section presents the prediction studies that used machine learning and deep learning methods on financial time series between 2011-2022 (in chronological order).

Akcan & Kartal (2011) predicted the stock prices of seven companies in the insurance sector using the Artificial Neural Networks model. Their data set consists of days between 05.01.2009-28.02.2011, and they used four macro and seven microeconomic variables as independent variables. It has been reported that the mean absolute percentage error in the 15-day estimation ranges from 0.85% to 2.36%, and the mean absolute error ranges from 2 cents to 27 cents.

Erdoğan & Özyürek (2012) aimed to predict the daily prices of white appliances companies in the Istanbul Stock Exchange (ISE) index using Artificial Neural Networks. They used Dollar Rate, ISE index, and stock closing values as independent variables in the data set consisting of 127 business days between 2011 and 2012. When the results from 5 different companies were examined, the mean percentage of errors was reported as the lowest at 0.43% and the highest at 2.56%.

Yakut et al. (2014) used Feed Forward Artificial Neural Networks and Support Vector Machines to predict the XU index. In the data set consisting of 1998 business days between 03.01.2005-31.12.2012, overnight interest rate, US dollar rate, and the stock market index values of the British Stock Exchange, the French Stock Exchange, the Japan Stock Exchange, the German Stock Exchange, and the Brazilian Stock Exchange were used as independent variables. It was reported that the R^2 values of the prediction models were 97% and 97.7%, respectively.

Özçalıcı (2016) predicted the price of 30 stocks listed in the Borsa Istanbul 30 index using Multilayer Artificial Neural Networks. The data set used in this study consists of 2760 working days between January 2010 and November 2015, and opening, closing, lowest, highest price, trading volume information, and fundamental and technical indicators are used as independent variables. As a result, it has been shown that stock price movements can be predicted with a success rate close to 72.88%.

Yüksel & Akkoç (2016) employed Artificial Neural Networks to predict gold prices. Seven independent variables were used in the data set of 2885 working days between 03.01.2002 and 31.10.2013. The results show that the artificial neural network algorithm could be used successfully for predicting gold prices. The R^2, RMSE, and MAE values of the developed prediction model have been reported as 99%, 16.61%, and 11.96%, respectively.

Onocak & Koç (2018) predicted monthly pension mutual fund stock prices using artificial neural networks. Five independent variables were used in the data set consisting of 154 monthly data between January 2003 and October 2017. As a result of the analysis, the R^2 value of the prediction model was reported as approximately 99%.

Çam & Kılıç (2018) used Markov chains and artificial neural network models together to estimate the daily returns of gold prices. They reported that their prediction model has a success of 70% in the gold price estimation.

Tuna (2019) conducted a gold price prediction study using artificial neural networks over 2608 working days between 01.07.2009 and 28.06.2019, and prediction performances were measured with two different approaches, in-sample and out-of-sample. The RMSE values of the artificial neural network model with 2 delayed 4 hidden neurons and 1 output neuron (2-4-1) were reported as 13.52% for in-sample estimation and 8.96% and 29.43% for out-of-sample estimation.

Akşehir & Kılıç (2019) employed Decision Tree, Multiple Regression, and Random Forest algorithms to predict the closing prices of some bank stocks. Two different sets of independent variables were used in the data set consisting of the data between 01.01.2016 and 09.05.2019. As a result, the highest R^2 value of 98% was obtained in the data set consisting of independent variables.

Şişmanoğlu et al. (2020) used three different deep learning algorithms, LSTM, Gated Recurrent Unit (GRU), and Bidirectional LSTM (BLSTM), to predict IBM stock. Five independent variables were used in the data set consisting of 12648 trading days between 02.01.1968 and 09.04.2018. It was reported that the prediction accuracy values for the 5-day input were 57.52%, 52.17%, and 63.54% for LSTM, GRU, and BLSTM, respectively.

Ustalı et al. (2020) aimed to predict the future prices of the stocks of the companies traded in the XU 30 index using Artificial Neural Networks, Random Forest Algorithm, and XGBoost Algorithm. The quarterly average of the monthly closing prices between 31.01.2010 and 31.12.2019 was used as the data set. As a result, the XGBoost algorithm (72.2%) showed better results than the Random Forest algorithm (69.5%), while the Artificial Neural Networks (68.6%) lagged behind these algorithms.

Söylemez (2020) estimated gold prices with multilayer artificial neural network using the independent variables of VIX index, Brent oil prices, US Dollar index, and Dow Jones index formed between 03.11.2014 and 31.10.2019. As a result, the R^2 of the developed model was reported as 98.44%.

Alpay (2020) used LSTM to predict the USD/TRY values on a data set between 01.01.2000 and 31.12.2017. As a result of the study, it was reported that the LSTM algorithm could make close estimations of the actual values.

Altunbaş (2021) used the Boruta algorithm and then the feed-forward deep neural network algorithm on the data set containing eight independent variables between 04.11.2015 and 04.11.2019. When the results were examined, the RMSE value was reported as 11203.49.

Ilgın & Sarı (2021) tried to predict the XU 100 index movements with Artificial Neural Networks. In the data set consisting of 143 monthly data between 2008-2019, the indicator indices of the BRICS countries were used as the independent variables. As a result, the RMSE and R^2 values of the prediction model were reported as 0.182% and 93%, respectively.

Arslankaya & Toprak (2021) predicted the closing values of Ereğli Demir ve Çelik Fabrikaları T.A.Ş.'s stock prices by using Polynomial Regression, Random Forest Regression, Recurrent Neural Networks and Long-Short-Term Memory algorithms. The data set used in this study consists of 1619 business days between 01.01.2014 and 01.06.2020. When the results were examined, it was seen that the Random Forest Regression model gave the best result, while the Polynomial Regression model gave the worst result. The MSE, MAE, and RMSE values were reported as 0.14%, 2.4%, and 3.7% for Random Forest and 44%, 46%, and 66% for Polynomial Regression, respectively.

Gavcar & Metin (2021) aimed to predict the opening prices of Vestel's stocks with the LSTM algorithm. Four independent variables were used in the data set consisting of 1527 trading days between January 2016 and December 2021. As a result, a 95% accuracy rate was reported for the LSTM algorithm.

Taş et al. (2021) used the data from the S&P 500 index to predict the US dollar values. Estimations were made on the daily price data between 12.08.2000 and 13.8.2020 with LSTM and

Multi-Layer Perceptron. Training, testing, and all data RMSE values are $17.3, $65.3, and $22 for the LSTM and $16.1, $61.2, and $20.6 for multi-layer perceptron, respectively.

Aytekin (2021) tried to predict the closing prices of the stocks of 12 randomly selected companies in the XU 30 index with Artificial Neural Networks, Panel Regression Analysis, and Regression Analysis. The Market Value/Book Value ratio, Leverage Ratio, Return on Equity, Earnings Per Share, and Price/Earnings Ratio are used as independent variables in the data set consisting of quarterly data set for the years 2019-2020. As a result, it was reported that artificial neural networks gave more successful results than classical methods, with an R^2 value of 91.7%.

Sarıkoç & Çelik (2022) aimed to estimate the XU 100 index with LSTM. In the data set consisting of 4422 business days between 20.09.2002 and 24.07.2020, 49 different attributes were used as independent variables. As a result, R^2 and RMSE values were 88.2% and 2.7% for the PCA+LSTM hybrid prediction model and 92.6% and 2.1% for the LSTM.

When the literature is examined, it is seen that the studies for the estimation of financial data artificial neural network-based approaches have higher prediction accuracy. Due to these results and their compatibility with time series, it was preferred to employ RNN and LSTM algorithms on daily data sets in this study.

3. Material and Methods

In this section, the concept of deep learning is briefly mentioned, and the applied algorithms are explained.

3.1. Deep learning algorithms

Deep Learning, a subclass of Machine Learning, is inspired by layers of neural networks modeled according to the working logic of the human brain. As with biological neurons, artificial neurons receive their input, process it, and then deliver its output. This way, predictions can be made on the outputs of any data set. Information is gathered from multiple data sources in deep learning. By learning the distinctive features or their representations in these collected data, analysis can be performed without the need for human intervention. Sufficient training must be applied for the system to result in successful feature learning. Here, the feature learning phase consists of a hierarchical structure. While the distinctiveness of the features at the lower level of the structure is less, the features at the upper level derived from the features at this level are more distinctive. Low-level features play a significant role in generating meaningful features.

In this study, the RNN algorithm and the LSTM algorithm, which have been widely used in recent years, were preferred for the analysis of the data set because it has a structure that can remember essential information, can learn, and generalize through examples, and contains fewer assumptions compared to statistical methods.

3.1.1. Recurrent neural networks

In 1986, a study named “Learning representations by backpropagating errors” was presented by Rumelhart et al. (1986). RNNs are a class of artificial neural networks in which the interconnections of units form a directional loop. This loop creates an internal network state that allows it to behave dynamically. RNNs can use their own input memory to process random sequences of inputs. In other words, an RNN is an artificial neural network that transmits the output from the previous unit as the input of the next unit and creates a cyclic structure with new information from the outside. The main idea of this class is the sequential use of information. The RNN algorithm uses a hidden layer to calculate the activation value, taking the output from the previous step and the output from the lower layers as input. It uses self-renewal by combining new data with previous data to make decisions about the outputs. After the output is generated, it is copied and sent back to the input part of the RNN. The RNN uses this memory to process new inputs, but this memory is short-term. The most critical parameters of the RNN algorithm are epoch, batch size, embedding size, and learning rate.

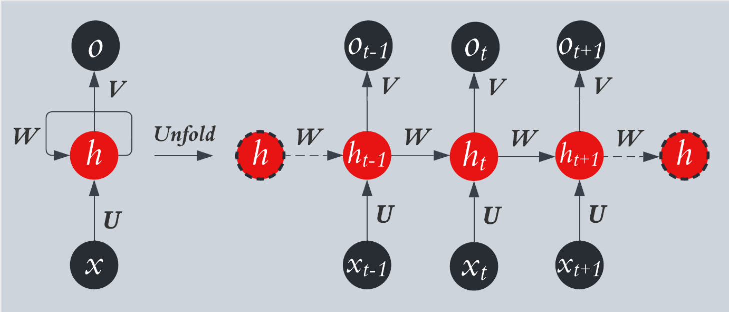


Figure 2. The structure of recurrent neural networks.

Figure 2 shows the RNN structure. In this figure, x and o represent the input and output vectors, respectively. The part defined as h represents the internal structure of the RNN algorithm. When the recurrent part of this structure is broken and opened, the structure in the direction of the unfold arrow is revealed. The structure with length $t+1$ in the form of $x_{t-1} \ldots x_{t+1}$ is distributed in the RNN, as shown in the figure, and an output h_i is obtained for each x_i.

3.1.2. Long-short term memory

LSTM, a sub-branch of RNNs, is a feedback neural network. LSTM networks were introduced by Hochreiter and Schmidhuber in 1997 (Hochreiter & Schmidhuber, 1997). It was created to solve the recall problem of RNNs. It is a type of neural network suitable for classifying, processing, and predicting time series. LSTMs are a special type of RNN that adds a cell state in addition to a hidden state to protect valuable information throughout the time series. It is also controlled by a special gate system that can handle many challenging situations much better than the ordinary RNN algorithm. Here, the gates are the structures where the decision is made whether the signal will pass or not.

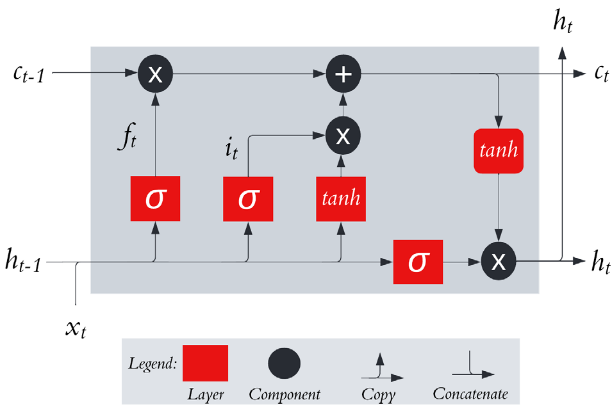


Figure 3. The structure of long-short term memory.

In the LSTM structure, the input, output, and forget gates serve the functions of reading, writing, and resetting, respectively. Changes in the cell's state are controlled through these gates. Thus, the control of the information added to the memory is the task of the input gate. It is the task of the forget gate to control how much of the old information is transferred to the new data. Controlling how much of the information in the memory will be used in the output stage is a task of the output gate. Parameters such as the number of hidden units, batch size, and previous data length in the LSTM algorithm have a major impact on prediction accuracy. In the last sigmoid layer, the output gate layer, what to send as output is obtained because of filtering (Figure 3).

A more detailed explanation of the working principle of LSTM can be given through its formulas. The LSTM equations can be summarized as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

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

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

$$\widetilde{C_t} = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

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

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

The forget gate output (f_t), input gate output (i_t), and output gate output (o_t) are determined by applying sigmoid activation functions to linear combinations of the previous hidden state (h_{t-1}) and the current input (x_t), along with corresponding weight matrices (W_f, W_i, W_o) and bias vectors (b_f, b_i, b_o). The new candidate values ($\widetilde{C_t}$) are computed by applying the hyperbolic tangent activation function to a linear combination of h_{t-1}, x_t, and a bias vector (b_C). The memory cell state (C_t) is updated by combining the previous state (C_{t-1}) with the candidate values (scaled by f_t and i_t). Finally, the hidden state (h_t) is calculated by applying the output gate values (o_t) to the hyperbolic tangent of the updated memory cell state (C_t). These equations demonstrate the intricate interplay between gates, memory cells, and hidden states, enabling LSTMs to effectively capture long-term dependencies in sequential data.

3.2. Statistical analysis

To evaluate the prediction performance of the models, mean squared error, mean absolute error, root mean squared error (RMSE), and coefficient of determination evaluation criteria were used in equations (7)-(10), respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\bar{y}_i - y_i)^2 \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\bar{y}_i - y_i| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{y}_i - y_i)^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y})^2} \tag{10}$$

where, $\bar{y}_i$ is the i-th predicted value; y_i is the actual value of the ith sample, and $\hat{y}$ is the mean of the y values; n represents the total number of samples.

4. Application

This section gives the prediction results of applied algorithms on real-life data. To perform algorithms, Python 3.9.7 programming language and packages were preferred since it facilitates the implementation of the necessary steps for solving artificial intelligence problems with the packages it contains. In addition, Microsoft Excel (Microsoft 365) was used as the database because it provides convenience in terms of operations and controllability that can be applied to the data.

4.1. Data set

The data set used in the study includes the observed values for the years between 2013-2022, which contains 2280 rows in total (consisting of only working days as the stock market is closed on weekends and holidays). The data set was obtained from the address *investing.com*. The minimum, maximum, mean, and standard deviation values of the data are given in Table 1.

Table 1. Variables used in the study

Variables	Minimum	Maximum	Mean	Standard Deviation
US Dollar	1.75	16.41	4.51	2.49
Gold	74.05	950.1	217.76	159.04
XU 100	611.89	2 278.55	983.31	267.1

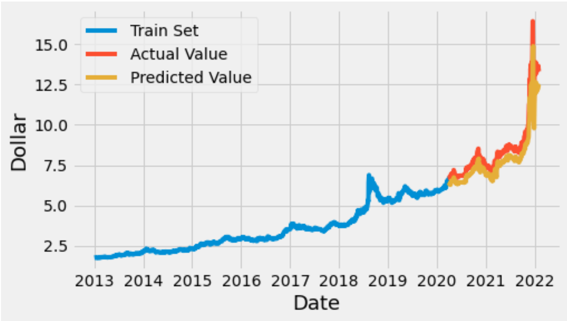
4.2. Prediction performance analysis of deep learning algorithms

The data set was divided into 80% training and 20% test data to examine the success of the algorithms. Training and test data did not shuffle in time series because the data is based on all previous days. Thus, the first 1824 rows were used as training data, and the remaining 456 rows were used as test data. The first and last 5 rows of the data set are given in Table 2. To obtain better performance from the algorithms, scaling was also performed on the data. Therefore, the variables in the data set were brought to the same metric by taking values between 0 and 1.

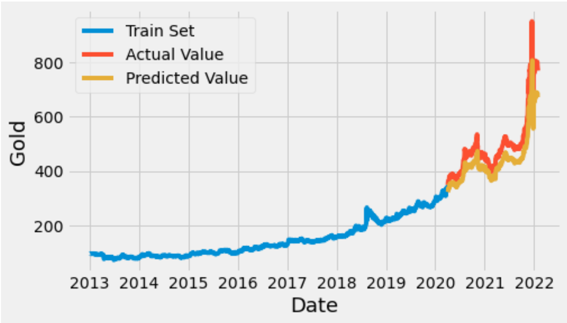
Table 2. The data set used in the study

	Date	Dollar	Gold	XU 100
0	02.01.2013	1.7787	98	796.4208
1	03.01.2013	1.7847	98.5	800.3333
2	04.01.2013	1.7818	98.5	795.6395
3	07.01.2013	1.7798	97	802.2441
4	08.01.2013	1.7783	96.5	801.6171
…	…	…	…	…
2275	25.01.2022	13.4769	801.87	1 945.07
2276	26.01.2022	13.5561	794.408	1 951.17
2277	27.01.2022	13.6470	786.936	1 997.69
2278	28.01.2022	13.5507	781.148	1 983.18
2279	31.01.2022	13.3074	769.081	2 003.20

The RNN network used in the study includes 4 layers in total. It has been observed that the prediction values of RNN are close to the actual values when the number of blocks in the first 3 layers is given as 128. Giving the number of blocks more than 128 extended the processing time and did not make a significant difference in the results. The *relu* function, which can take 0 for negative and x for positive inputs, is used as the activation function. To avoid the overfitting problem, the Dropout layer, which is connected to the RNN layers, has been added. Since an output will be taken from the last layer, the number of blocks has been determined as 1. "*adam*" is used as the optimization function of the RNN network. For the RNN algorithm, Mean Squared Error was chosen as the loss function. The best results were obtained when the epoch was 100, and the number of data in a group (batch_size) was 20. The number of data in a group indicates how much data the forward and backward propagation algorithm will be applied to simultaneously. Figure 4a, Figure 4b, and Figure 4c show the actual and predicted values of the RNN algorithm for the US Dollar, Gold, and XU 100, respectively.



(a)



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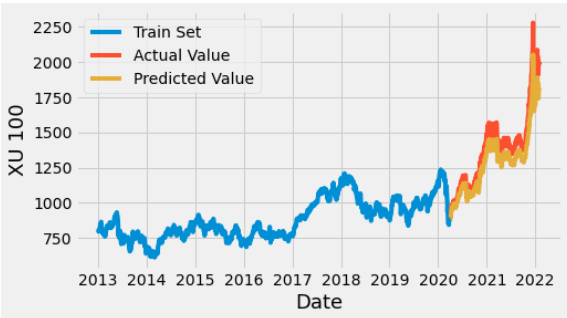
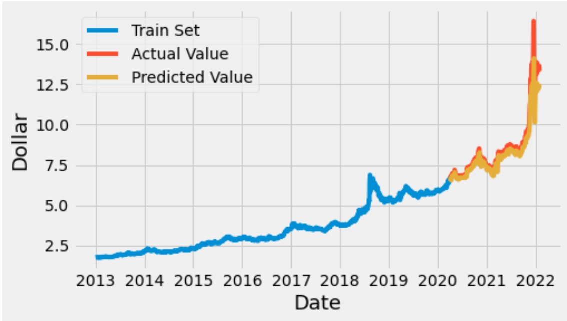
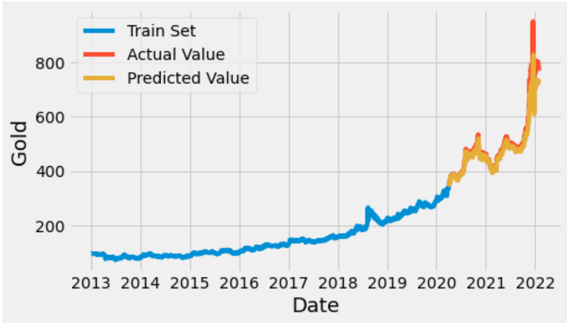


(c)

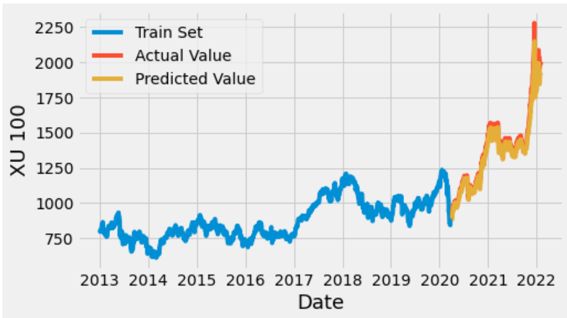
Figure 4. a) US Dollar b) Gold and c) XU 100 prediction results of RNN algorithm.



(a)



(b)



(c)

Figure 5. a) US Dollar b) Gold and c) XU 100 prediction results of LSTM algorithm.

The LSTM network used in the study consists of 4 layers in total. The LSTM algorithm gave the best results when the number of blocks in the first 3 layers is set to 64. Giving the number of blocks more than 64 extended the processing time and did not make a significant difference in the results. The *tanh* function, which can take values in the range of [-1,1], is used as the activation function. The number of values in this range also contributes to learning. The Dropout layer, which depends on the LSTM layers, has been added to avoid the overfitting problem. Similarly, since there is an output to be taken from the last layer, the number of blocks is determined to be 1. "*adam*" is used as the optimization function of the LSTM network. In addition, momentum value and learning rate can be given in this function. For the LSTM model, Mean Squared Error was chosen as the loss function. The best results were obtained when the batch_size was 20 and the epoch was 100. Figure 5a, Figure 5b, and Figure 5c show the actual and predicted values of the LSTM for the US Dollar, Gold, and XU 100, respectively. To compare the prediction performance of the algorithms, MSE, MAE, RMSE, and R^2 measures were used. A low value of MSE, MAE, and RMSE and a high value of R^2 indicate the success of the prediction model. Accordingly, the results of the RNN and LSTM algorithms are reported in Table 3.

Table 3. Test data error values of deep learning algorithms

	Dollar		Gold		XU 100	
Error metrics	RNN	LSTM	RNN	LSTM	RNN	LSTM
MSE	0.43	0.17	2 387.75	655.29	7 098.79	1 884.84
MAE	0.57	0.24	46.55	14.26	75.37	32.80
RMSE	0.66	0.41	48.86	25.60	84.25	43.41
R^2	0.88	0.95	0.81	0.95	0.90	0.97

When Table 3 is examined, it is seen that the RNN algorithm has higher error values than the LSTM algorithm. When predicting US Dollar, MSE and MAE values of the LSTM algorithm are approximately 60% better than the RNN. Besides, the R^2 value of LSTM is 7% higher than the RNN. For predicting the Gold prices, the LSTM algorithm has approximately 70% better values of MSE and MAE than the RNN algorithm. In addition, the R^2 value of the RNN is 81%, while this value equals 95% for LSTM. When the error metrics of XU 100 index prediction are compared, the LSTM shows approximately four- and two-times better performance for MSE, MAE, and RMSE, respectively, than the RNN. The R^2 values of the RNN 7% lower than the LSTM.

Table 4. Error metric values of LSTM and RNN algorithms for the Price prediction in test data of THYAO, TUPRS, and MAVI data sets

	THYAO		TUPRS		MAVI	
Error metrics	RNN	LSTM	RNN	LSTM	RNN	LSTM
MSE	0.62	0.24	0.44	0.23	0.67	0.12
MAE	0.48	0.30	0.49	0.29	0.71	0.25
RMSE	0.78	0.49	0.66	0.48	0.82	0.35
R^2	0.95	0.98	0.96	0.98	0.89	0.97

In addition to the Dollar, Gold, and XU 100 analyses, the performance of the developed prediction model is tested on some different financial time series stocks from different work areas, such as THYAO, TUPRS, and MAVI. To create data sets for these stock prices, the same time period for US Dollar, Gold, and XU 100 datasets is selected. Thus, each data set consists of 2280 business days between 2013 and 2022. The THYAO data set is a collection of data related to the aviation industry, while the TUPRS data set focuses on the energy sector. Lastly, the MAVI data set is tailored for textile production analysis. THYAO, TUPRS, and MAVI stock prices were obtained from the address investing.com. Table 4 shows the values of the error metrics for RNN and LSTM algorithms using THYAO, TUPRS, and MAVI data sets. When the results are examined, it is seen that RNN and LSTM algorithms have R^2 values above 89% and 97%, respectively. Thus, these results indicate that the developed prediction model can achieve high accuracy for different time series from different work areas.

5. Conclusion

Making accurate predictions in financial time series benefits investors in terms of risk and return when making decisions. This study aims to predict financial time series with deep learning algorithms. In this context, first, a comprehensive literature review was conducted. Then, daily prediction performances of RNN and LSTM algorithms on financial time series containing US Dollar, Gold, and XU 100 values were examined. The data used for each application consists of the date and the considered value (Dollar/Gold/XU 100). Statistical analysis of the results was performed using the error metrics MSE, MAE, RMSE, and R^2. The R^2 values for the test data of the RNN algorithm are 88%, 81%, and 90% for US Dollar, Gold, and XU 100, respectively. These values are 95%, 95%, and 97% for the LSTM algorithm. The error metrics of the algorithms show that the LSTM algorithm has a higher prediction performance than the RNN algorithm. In addition, showing that the prediction on time series with deep learning algorithms can provide high accuracy without using extra independent variables is another contribution of this study to the literature.

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