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Research Article

Stock Price Forecasting with Deep Learning Techniques

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ABSTRACT

In this study, LSTM (Long-Short Term Memory) and GRU (Gated Recurrent Unit) techniques of deep learning, which are among the latest advanced technologies, were applied in the Google Colab software program for stock price forecasting. The dataset used in the study was obtained from Yahoo Finance and covers the dates between 02/01/2013 and 30/12/2022. Forecast models were created by considering 5 companies belonging to the XELKT (Electricity Market in Borsa Istanbul) index, which is part of BIST (Borsa Istanbul). Subsequently, the success of these forecast models was tested with the calculated model performance criteria, aiming to determine whether the techniques used were successful in stock price forecasting. Additionally, based on the results of MSE (Mean Squared Error) and MAPE (Mean Absolute Percentage Error) among the calculated model performance criteria, the techniques used were compared with each other, aiming to determine which of these techniques provided forecasts with less error. Then, through the analysis conducted on four different days, an attempt was made to identify the day that yielded the most successful forecasts. As a final step, the goal was to find a model with the least error based on techniques, epoch number, and the number of days forecasted, considering both MSE and MAPE for stocks. Since the model performance criteria outputs obtained from these analyses are below 1 for MSE and below 5% for MAPE, it can be concluded that both techniques demonstrate successful stock price forecasting. Consequently, in the comparison between these two techniques, it is observed that the LSTM technique is slightly more successful than the GRU technique.

Keywords: LSTM, GRU, Deep Learning, Forecasting Stock Price, BIST, XELKT

This paper is derived from first author's Master's thesis dissertation entitled "Forecasting stock prices using deep learning techniques: An application in BIST", conducted under the supervision of the second author.

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1. Introduction

Due to the increasing globalization of financial markets, forecasts in finance are becoming more complicated. For example, a decision taken by the Central Bank of America immediately affects the dollar exchange rate in Turkey, while in the same way, Russia's war with Ukraine, which are located in Turkey's geography, deeply affects energy market prices in Turkey. Therefore, the techniques and simple statistical calculations used in situations where many factors interact easily, such as in the examples, are insufficient. AI (Artificial Intelligence) algorithms and techniques, the foundations of which were laid about 80 years ago for the first time as a solution to these situations where simple techniques are insufficient, have emerged as a solution. One of the most advanced tools of AI is deep learning. The foundations of deep learning were also laid for the first time at the end of the 1990s. Deep learning techniques are very useful for understanding and modeling complex structures in large datasets. In addition to this advantage, it is gaining popularity in many areas of life, including finance, as it is one of the newest tools and gives more successful results than other old tools.

In this study, it is aimed to forecast stock prices using deep learning techniques based on the XELKT (Borsa İstanbul Electricity Index) index on Borsa İstanbul (BIST) and to determine the applicability of the techniques used in stock price forecasting. In addition, a comparison among the methods used is attempted to determine which one yields more successful results. The methods employed in the study are LSTM (Long Short Term Memory) and GRU (Gated Recurrent Unit) techniques. The application of these techniques was performed using the Google Colab software program, which provides a Python software environment, developed by Google. AKENR, AKSEN, AKSUE, AYEN and ZOREN companies were selected among the companies traded in XELKT for the study. The data set of these companies has been generated to cover 10 years between 02.01.2013 and 30.12.2022. The data of the companies are taken from Yahoo Finance. The data set generated for each company has 2511 observations and 17 variables. In these data sets, there are daily opening and closing highest and lowest values of BIST 100 (the most valuable 100 companies in BIST), USD/TL (Dollar to Turkish Lira Exchange Rate) and XELKT variables, which are thought to affect the stock price. Likewise, each stock is included in the data set with its opening, closing, highest and lowest values.

In Turkey, the first stock market activities date back to the 1850s, or in other words, to the period of the Ottoman Empire. After the establishment of the republic, legal regulations were introduced in the field of stock trading, and in 1929, the Exchange Law for foreign currency markets came into effect. In 1985, the first modern stock exchange in Turkey, the Istanbul Stock Exchange (İstanbul Menkul Kıymetler Borsası - İMKB), was established. The name of IMKB was changed in 2013 and its new name became Borsa Istanbul (BIST) and continues its activities under this name (Borsa Istanbul, 2023). According to the official gazette published on October 19, 2014, the activities of BİST are defined as follows: fulfilling obligations related to executed transactions, order transmission, trading on the stock exchange, suspension of trading, dispute resolution, and market making (T.C. Resmi Gazete, 2014).

In addition to the fixtures, machinery, real estate, money, debts and receivables of a commercial enterprise, the ownership certificate representing all tangible and intangible assets consisting of participation shares and patents in other enterprises is called “stock” (Bakkal et al, 2012). To determine the price of a stock, the company's production level, economic course and general economic situation in the relevant year are taken into account (Aytekin, 2018). The news in the media is also very effective on stock prices. For example, bad news about the economy and politics decreases the prices in the stock market, while good news increases the prices in the stock market (Özçalık & Özçalık, 2020).

The XELKT code is used to define the energy index in BIST, and there are a total of 55 indices including XELKT in BIST. XELKT has been actively traded on BIST since December 27, 1996 (Kamuyu Aydınlatma Platformu, 2023).

Energy sources are divided into two renewable energy and non-renewable energy. The characteristic of renewable energies is that they remain unchanged in a natural cycle and do not decrease or deplete when used. Solar, wind, hydroelectric, geothermal and biomass are known renewable energy sources (Montasham, 2015). Non-renewable energy resources are resources that are completely dependent on natural processes and are very slow to change shape. Non-renewable energy sources consist of coal, oil, nuclear energy and natural gas (Gosh & Prelas, 2009).

In 2022, Turkey's electrical energy consumption decreased by 1.2% compared to the previous year, 2021, and decreased to 328.9 TWh. Electricity production decreased by 2.5% compared to 2021 and reached the level of 326.2 TWh. In the study of the Turkish National Energy Plan for the future, Turkey's electricity consumption in the future will be 380.2 TWh for 2025, 455.3 TWh for 2030 and 510.5 TWh for 2035. As of the end of April 2023, the sources of Turkey's installed power are as follows: 30.2% hydraulic energy, 24.3% natural gas, 20.9% coal, 11% wind, 9.5% solar, 1.6% geothermal and 2.5% other energy sources. The power plants owned by Turkey are distributed as follows: 751 hydroelectric, 67 coal, 361 wind, 63 geothermal, 345 natural gas, 9864 solar and 491 other resources (T.C. Enerji ve Tabii Kaynaklar Bakanlığı, 2023).

2. Literature Review

Aslan (2020) estimated the stock prices of three of the sports clubs traded in the BIST. Galatasaray (GSRAY), Fenerbahçe (FENER), and Beşiktaş (BJKAS) are the three clubs selected for the study. The date range to be used in the analysis has been determined as 10/11/2011 to 21/02/2020 for GSRAY, 21/09/2011 to 21/02/2020 for BJKAS, and 17/05/2010 to 21/02/2020 for FENER. In addition to the financial data of these three clubs in the study, sentiment analysis results obtained from the notification data in the Public Disclosure Platform (PDP) of the companies were also included. While the LSTM method, which is one of the deep learning methods, was used for estimation, RMSE was chosen as the model performance criterion. The analysis was carried out in Python. When the results of sentiment analysis are used as well as financial data, successful results are obtained in the analysis.

Jiang and Peng (2016) aimed to forecast stock prices using word embedding and deep learning methods. While word2vec was chosen from word embedding methods for forecasting, LSTM and GRU techniques were selected from deep learning methods. The dataset was obtained from the "Centre for Research in Security Prices" database and used to analyze the data between 2006 and 2013. The training set between 01/10/2006 and 31/12/2012 is divided into a validation set between 01/01/2013 and 15/06/2013, and the test set between 16/06/2013 and 31/12/2013. According to the authors, financial news positively affects the success of stock price forecasting. For this reason, they argue that using deep learning techniques together with financial news will yield successful results.

Moghar and Hamche (2020) aimed to successfully forecast future stock values using RNN and LSTM techniques. In the study, they used GOOGL (Google) and NKE (Nike) shares traded in the New York Stock Exchange. Two data sets were prepared for each stock, and all data were taken from Yahoo Finance. The date range of the dataset prepared for GOOGL is 19/08/2004 and 19/12/2019, while the dataset range prepared for NKE is between 04/01/2010 and 19/12/2019. 80% of the data sets created are reserved for training, and 20% for testing. In the analysis, 4 different epoch values, 12, 25, 50, and 100, were also considered. The performance of the models has been tested with MSE, one of the model performance criteria. As a result of the study, both techniques successfully provided forecasts for the future price of stocks.

In his study, Ozan (2021) made a daily price forecast based on the data between 31/12/2007 and 31/05/2021 of ISCTR, VAKBN, GARAN QNBFB and AKBNK stocks in BIST. Between 31/01/2007 and 28/02/2021, the training set is divided into a validation set between 01/03/2021 and 31/03/2021, and the test set between 01/04/2021 and 31/05/2021. In order to increase the success of the forecast, historical data of ISGYO, AKGRT, Dollar, BIST30 and BANKX indices are included in the study as well as stock data. The analysis was performed using LSTM and GRU techniques in Google Colab environment. In the study, 96 different models were created by using two different computers, two different deep learning models and different hypermeters, and as a result, it was observed that the LSTM technique was more successful than the GRU technique, based on the MSE performance criterion. Then, MSE, MAE and MRE criteria were calculated for five stocks using the LSTM technique. In the period of April 2021, the most successful performance among the 5 different stocks in the study belongs to ISCTR. For the period of May 2021, GARAN stock has the most successful performance.

Güney (2022) analyzed a 30, 60, 90 and 120-day price forecast of the GOLTS stock traded in the BIST by using RNN, LSTM, and GRU techniques, which are deep learning techniques. The data set includes the daily closing price values of the company between 02/01/2012 – 31/12/2020. For analysis, the data set is divided into 70% training and 30% test set. MAE, RMSE and MAPE were calculated as model performance criteria. According to the results, the most successful techniques were GRU, LSTM and RNN techniques, respectively.

In this study, Mehtab and Sen (2020) aimed to make a successful forecast about the future price of the NIFTY 50 index traded on the Indian National Stock Exchange using CNN and LSTM. For this, a dataset consisting of the index's daily opening, closing, highest, and lowest prices between December 2008 and July 2020 was created. In order to evaluate the performance of the model, MSE and MAE were calculated as part of the model performance criteria. According to the results, the model successfully forecasts the future price of the index.

Song and Choi (2023) aimed to test the use of hybrid models based on RNN-based models for forecasting single-step and multi-step closing prices of DAX, DOW, and S&P 500 indices. CNN – LSTM and GRU – CNN are two hybrid models used for this purpose. MSE and MAE performance criteria were calculated to measure the success of the models. According to the results, in the one-step case, the models are 48.1% more successful in terms of MSE value and 40.7% more successful in terms of MAE value compared to classical machine learning models. In multi-step forecasting, the success rate in terms of MSE and MAE is 81.5%.

Yussif (2020) conducted a study on the composite index from the Ghana Stock Exchange and aimed to forecast the price of the index using historical data. For this purpose, the deep learning techniques of Multi-Layer Perceptron, CNN, and LSTM were employed. The dataset was created from the daily values of the index between 02.01.2015 and 31.12.2019. In the dataset, the years between 2015 and 2019 were designated as the training set, while the remaining data for 2019 were set as the test set. According to the results of the study, the most successful technique was CNN, followed by LSTM, and the least successful technique was Multi-Layer Perceptrons.

3. Materials and Method

In the 1600s, the idea of aristocratic class people to create automata with human and animal behaviors was seen as the first philosophical and concrete steps of AI. The development of the first calculator called "Difference Engine" by the English mathematician Charles Babbage in the 1820s, which aimed to imitate the mental characteristics of humans, is seen as a major development in the field of AI (Schultz et al., 2011). The foundations of AI in the modern sense were laid during and immediately after the Second World War. Warren McCulloch and Walter Pitts (1943) created a computational model for neural networks based on neural logic and mathematical algorithms to mimic the thought process of the human brain, which is considered as the first work in the field of AI. Later, Claude Shannon (1949), in his article "Programming a Computer for Playing Chess", was interested in giving computers functions beyond numerical calculations such as designing circuits, managing telephone calls, translating from foreign languages, performing non-numerical mathematical operations, orchestrating a melody, and programming a computer to play chess. Another British mathematician, Turing (1950), in his article "Computing Machinery and Intelligence", discussed the issue of whether machines could think, thus laying the foundations of AI in the intellectual sense. Although the intellectual foundations of AI were laid by Turing, the actual concept of "AI" was expressed by another British mathematician John McCarthy at the Dartmouth Conference in 1956 (Adaş & Erbay, 2022). In the late 1950s and 1960s, there were great developments as the speed of computers increased and it became easier to store information in computers. "General Problem Solver" developed by Newell, et.al (1959) and ELIZA developed by Weizenbaum (1966) at the Massachusetts Institute of Technology (MIT) are considered to be the pioneers of the developments in this period. The period between 1950 and 1975 was one of the most productive periods for AI. During this period, great progress was made in algorithms and semantic learning in the field of AI. Although there was a pause in the period until the 1980s, a new golden age in AI began in the 1980s, with significant leaps in both theory and practice (McCorduck, 2004). The 1980s also saw the introduction of machine learning, a sub-branch of AI. In 1997, a computer called "Deep Blue" developed by International Business Machines (IBM) defeated world champion Garry Kasparov in a chess match. In 2011, an AI program called IBM Watson defeated two contestants who became champions in the quiz show Jeopardy (Arslan, 2020). In the first decade of the 21st century, that is, in the 2010s, the difficulties and deficiencies experienced in machine learning were overcome by deep learning, a sub-branch of machine learning (Kayaalp & Süzen, 2020).

Deep learning is a type of machine learning that serves to teach computers abilities such as the ability to forecast and recognize the image that people see and the sound they hear (Aktürk & Talan, 2022). While in classical programming methods, learning is done with pre-coded rules, in deep learning, the forecasting process is carried out automatically. Thanks to their flexible structure, they can forecast from visual, numerical, and textual data, and their forecasting accuracy can increase depending on the size of the dataset (Yılmaz & Kaya, 2019). Deep learning is mostly used in image processing, voice recognition and intelligent robots, while machine learning is mostly used to extract information from data sets (Erden, 2021).

Deep learning is a subclass of machine learning and AI (Madan & Madhavan, 2020). Therefore, there are differences between deep learning and machine learning in feature extraction. While the model itself does the feature extraction in deep learning, human intervention is required for this step in machine learning. For this reason, machine learning requires human intervention more than deep learning (Asher et al., 2021).

There are two types of learning in deep learning: supervised learning and unsupervised learning. The type of learning that uses pre-labeled data to forecast features and thus classify similar but unlabeled data is called supervised forecasting (Vasilev et al., 2019). In unsupervised forecasting, the input data is not pre-labeled, and the aim is to forecast the relationship between data components (Mason et al., 2016).

The artificial neural networks are divided into two. These are feed-forward networks and feedback networks. In feed-forward networks, there is only a one-way signal flow from the input layer to the output layer (Krenker et al., 2011). Feedback networks are a type of artificial neural network that has been increasing in popularity since 1986 and is more successful than feed-forward networks. The feedback network has both forward and backward signal flow (Kuş, 2019).

Another important issue for making successful forecastings in deep learning applications is the selection of the correct activation function (Öztürk & Şahin, 2018). If no activation function is selected or a linear activation function is selected, the model will behave like a linear regression, so the input value and output value will be the same. The reason for this problem is that the linear model has deficiencies in learning non-linear situations in real life. For this reason, nonlinear activation functions are generally chosen (Athaiya et al., 2020). The main activation functions used are ReLU, sigmoid, tanh, signum, unit step and piecewise linear (Raschka & Mirjalili, 2017).

Deep learning and machine learning need optimization algorithms to learn the parameters of input data. Because optimization algorithms are very successful in solving real-world problems. However, there is no single general optimization algorithm suitable for solving problems. For this reason, the optimization algorithm that provides an appropriate solution to the problem should be selected (Zaheer & Shaziya, 2019).

There are six optimization algorithms used to minimize the error rate in machine learning and deep learning. These are listed chronologically based on their first use dates: Stochastic Gradient Descent in 1951, Momentum in 1964, AdaGrad in 2011, RMSProp (Root Mean Squared Propagation) and Adadelta algorithms in 2012, and finally the Adam algorithm in 2014 (Seyyarer et al., 2020).

Other parameters that need to be adjusted when establishing deep learning models are epoch and batch size values. Epoch indicates the number of repetitions in which the entire training set is used to update the weights of the model during the training of the created model (Amidi & Amidi, 2018). Batch size refers to the number of data points to be used at a time (Türk Ulusal Bilim e-Altyapısı, 2023).

Model performance criteria are used to measure the forecasting success of the created model. MSE, RMSE, MAE, and MAPE are the most commonly used model performance criteria (Durmuş, 2023).

The two most commonly used techniques of deep learning in stock forecasting are: LSTM and GRU.

3.1. Long Short Term Memory (LSTM)

LSTM emerged as a solution to the vanishing gradient problem, which is the biggest problem in the Recurrent Neural Network (RNN) (Metin & Karasulu, 2019). Another big advantage of LSTM over RNN is that it can keep longer-term information in memory. In LSTM, instead of the usual single entry and single secret state, three gates that can be adapted and reproduced according to the information entered: the entry gate, the forget gate and the exit gate. For this reason, compared to RNN, the single-time step cell of LSTMs has a more advanced structure. In LSTM, unlike RNN, the forget gate determines information about previous time steps and chooses to either keep or forget it (Persio & Honchar, 2017).

Three areas in LSTM is successful are (Brownlee, 2017): Automatic subtitle creation describing the image, Automatic text translation and Automatic handwriting creation.

3.2. Gated Recurrent Unit (GRU)

GRU, like LSTM, offers a solution to the explosion and vanishing gradient problem. Thanks to its update and reset gates, it both store and filter information (Karadağ, 2022). In addition to the update and reset gates, there is a repeat unit (Şişmanoğlu et al., 2020). GRU, a new type of recurrent neural network, has similarities to LSTM in its operating logic. However, its separation from the cell state and application of the hidden state make GRU different from LSTM (Güney, 2022).

4. Application

4.1. Datasets and Characteristics

The data was obtained from Yahoo Finance. Variables other than USD/TRY were exclusively traded in Turkey and, thus, did not trade on holidays in Turkey, while USD/TRY is global and traded on certain holidays in Turkey. Therefore, an examination was conducted to determine if there were missing data, and any excess data relative to the variable of each stock was removed from the dataset. Subsequently, the application phase was initiated. Five datasets in total were prepared, one for each company, and in addition to the company data, data for BIST 100, USD/TRY exchange rate, and XELKT were added to these datasets. In the analyses aimed at forecasting the closing price for each stock, two techniques, LSTM and GRU, were used. To assist other researchers and to answer a variety of questions, the analysis was diversified as much as possible. Four different numbers of epochs, (20, 50, 100, and 200) were used, along with four different batch size values corresponding to each epoch. Additionally, four different numbers of days, (30, 60, 90, and 120) were considered, and three different model performance criteria, (MSE, MAE, and MAPE) were calculated. In all the analyses applied to the datasets, the data was standardized, with 80% of the dataset used for training, 20% for testing, and another 20% for validation. The software used for the analysis in this study was Google Colab, which was developed by Google in 2017, is free to use and provides cloud-based Python programming, doesn't need installation.

4.2. GRU Analyze

In Python, libraries must be initially imported for analysis. Code Block 1 shows the libraries imported for analysis.

```
[1] #Importing Libraries
    import math
    import pandas_datareader as web
    import numpy as np
    import pandas as pd
    from sklearn.preprocessing import MinMaxScaler
    from keras.models import Sequential
    from tensorflow.keras.layers import Dense, Dropout, GRU
    import matplotlib.pyplot as plt
    plt.style.use("fivethirtyeight")
```

Code Block 1. Importing Python Libraries

Code Block 2 shows the row and column numbers in the data set.

```
[3] #Numbers of Row and Column
    df.shape

    (2511, 17)
```

Code Block 2. Numbers of Row and Column

Figure 1 shows the closing chart of the stock named AKSEN. The stock price, which remained stable move until 16th December 2020, the 2000th day, has shown a very high increase since this date.

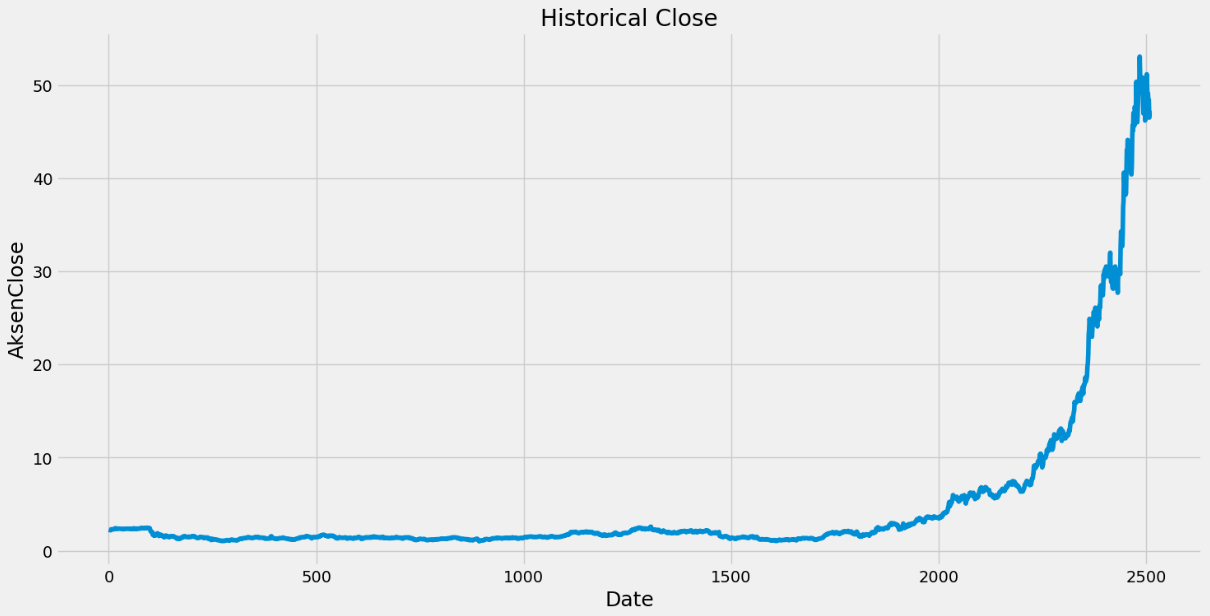

Figure 1. Historical Close Price Graph of AKSEN

80% of the data set is divided as the training set. The code for this operation is shown in Code Block 3.

```
[10] #Creating a new dataframe with only the "AKSENClose" column
     data=df.filter(["AKSENClose"])
     #Converting dataframe to a numpy array
     dataset=data.values
     #Determine the training set
     training_data_len=math.ceil(len(dataset)*.8)
     training_data_len

     2009
```

Code Block 3. Divide Training Set and Test Set

In Code Block 4, a sequential model was first generated to add layers sequentially. Then, the first GRU layer with 50 neurons is added to the model, and "return_sequences = True" indicates that the layer is in the input sequence. Then, another GRU layer with 50 neurons was added to the model, and the "return_sequences = False" entry indicates that there will be no other layers after this one. After this step, a dense layer with 25 neurons is added to the model. The role of this layer is to take the outputs from the previous GRU layers and connect them sequentially. As the final step, the last dense layer with only 1 neuron is added since only one value of the stock price is forecasted. This 1 neuron has an output value and provides the forecasted value as output.

```
[15] #Generating GRU model
     model=Sequential()
     model.add(GRU(50, return_sequences=True, input_shape=(x_train.shape[1],1)))
     model.add(GRU(50,return_sequences=False))
     model.add(Dense(25))
     model.add(Dense(1))
```

Code Block 4. Generating GRU Model

As can be seen in Code Block 5, "mean squared error" was determined as the loss function of the model, while "adam", which was more successful than the others, was selected as the optimizer.

```
[16] #Selecting the Loss Function and Optimizer of the GRU Model
     model.compile(loss='mean_squared_error', optimizer='adam')
```

Code Block 5. Selecting the Loss Function and Optimizer of the GRU Model

Since the Batch Size number for this model was determined as 5, the training set was divided into 5 equal parts. Accordingly, the training set, which has 1889 observation values after the 80% division, is trained with 378 observation values as a result of dividing 1889 by 5. Since the number of epochs is determined as 20, the model reads the training set 20 times (Code Block 6).

```
[17] #Training the Model
     model.fit(x_train,y_train, batch_size=5, epochs=20)

     Epoch 1/20
     378/378 [==============================] - 45s 105ms/step - loss: 1.0543e-05
     Epoch 2/20
     378/378 [==============================] - 40s 105ms/step - loss: 4.8018e-06
     Epoch 3/20
     378/378 [==============================] - 40s 107ms/step - loss: 3.0155e-06
     Epoch 4/20
     378/378 [==============================] - 39s 104ms/step - loss: 3.1961e-06
     Epoch 5/20
     378/378 [==============================] - 40s 105ms/step - loss: 2.3542e-06
     Epoch 6/20
     378/378 [==============================] - 39s 104ms/step - loss: 1.9663e-06
     Epoch 7/20
     378/378 [==============================] - 40s 105ms/step - loss: 2.0727e-06
     Epoch 8/20
     378/378 [==============================] - 41s 107ms/step - loss: 2.0170e-06
     Epoch 9/20
     378/378 [==============================] - 40s 107ms/step - loss: 2.0791e-06
     Epoch 10/20
     378/378 [==============================] - 40s 106ms/step - loss: 1.4883e-06
```

Code Block 6. Training the Model

Model performance criteria that show the success of the created model are calculated with the codes in Code Block 7.

```
[31] #Calculation of mean square error (MSE)
     mse=np.mean(predicts - y_test)**2
     mse

     0.7162331326551202
```

```
[32] #Mean Absolute Error
     mae = np.mean(np.abs(y_test - predicts))
     print("MAE: ", mae)

     MAE:  0.9308499234226727
```

```
[33] #Mean Absolute Percentage Error
     mape = np.mean(np.abs((y_test - predicts) / y_test)) * 100
     print("MAPE: ", mape)

     MAPE:  3.439644044597646
```

Code Block 7. Results of MSE, MAE and MAPE

In Figure 2, where the blue line represents training, the red line represents validation, and the orange line represents forecasting, the more the orange and red lines overlap each other, the more successful the forecast is. According to the graph, the forecasting process, which was successful until the last 100 days, experienced disruptions, and forecast performance decreased in the last 100 days.

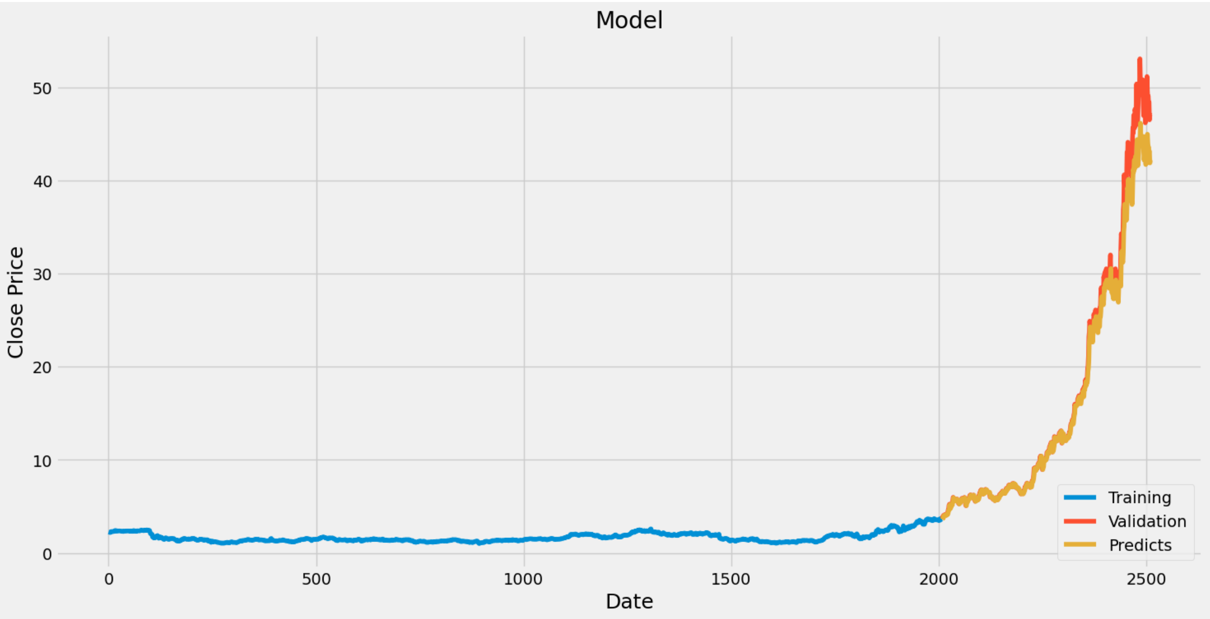

Figure 2. Forecast Graph

In Code Block 8, the first 5 and the last 5 values are given in order to compare the estimated values with the test set.

```
[28] ##Current prices and predicted prices
     valid
```

	AKSENClose	predicts
2009	3.720000	3.611125
2010	3.920000	3.691842
2011	3.850000	3.883260
2012	4.060000	3.815482
2013	4.080000	4.028182
...	...	...
2506	48.240002	43.580132
2507	48.400002	43.044334
2508	46.500000	43.124516
2509	47.060001	41.872528
2510	47.000000	42.179447

502 rows × 2 columns

Code Block 8. Closing Values and Model's Forecasted Values

As many performance criteria as possible were calculated so that the analysis could shed light on future researchers. However, in this study, MSE values will be interpreted because they are more prevalent in the general literature, and MAPE values will be interpreted because they are widely preferred in the field of finance. Since all MSE and MAE values were less than 1 and MAPE values were less than 5%, all model performance criteria gave successful results.

In cases where the epoch value is 20, in table 1 MSE, MAPE and MAPE results were obtained for each company. Moreover, the days when the most successful MSE and MAPE results were obtained for companies were determined.

The most successful forecast for AKENR stock in terms of MSE and MAPE was the 30-day forecasting. For AKSEN stock, the 120-day forecast had a more successful MSE, and the 30-day forecast had a more successful MAPE. While this MSE result indicates that the model generally makes accurate forecasts, the MAPE result suggests that the model better reduces percentage errors. AKSUE stock achieved its most successful forecast in terms of MSE with the 60-day forecast. The most successful forecast in terms of MAPE is the 120-day forecast, similar to AKSEN. Like AKSUE, AYEN stock had the lowest MSE value with the 60-day forecast. The most successful MAPE value was obtained as a result of the 30-day forecasting. The most successful MSE and MAPE performance of ZOREN stock is its 90-day forecast.

Number of Days	Batch Size	Measure of Errors	AKENR	AKSEN	AKSUE	AYEN	ZOREN
30	5	MSE	0.0019	0.0349	0.0139	0.2201	0.0048
		MAE	0.0589	0.4423	0.4735	0.5986	0.0847
		MAPE%	2.4720	2.5511	2.2502	3.5587	2.5588
60	5	MSE	0.0068	0.8231	0.0090	0.2185	0.0076
		MAE	0.0886	0.9242	0.4907	0.6200	0.0985
		MAPE%	3.4317	4.6474	2.3793	3.6497	3.0365
90	5	MSE	0.0027	0.3011	0.3714	0.3836	0.0012
		MAE	0.0641	0.7472	0.7102	0.7429	0.0703
		MAPE%	2.6585	3.0160	2.7298	4.0676	2.1104
120	5	MSE	0.0032	0.0215	0.0375	0.7388	0.0087
		MAE	0.0665	0.5626	0.4341	0.9177	0.1065
		MAPE%	2.7432	3.6807	1.9528	5.0021	2.9127

Table 1. Results of GRU with 20 Epoch and 5 Batch Size

Since the study was analyzed with four different epoch values, the above table and results were performed four times in total.

4.3. LSTM Analyze

As can be seen in Code Block 9, unlike GRU, the "from keras.layers import Dense, LSTM" code was written for the LSTM technique instead of the "from tensorflow.keras.layers import Dense, Dropout, GRU" code.

```
[1] #Importing Libraries
    import math
    import pandas_datareader as web
    import numpy as np
    import pandas as pd
    from sklearn.preprocessing import MinMaxScaler
    from keras.models import Sequential
    from tensorflow.keras.layers import Dense, LSTM
    import matplotlib.pyplot as plt
    plt.style.use("fivethirtyeight")
```

Code Block 9. Import Python Libraries for LSTM

Another difference is that in the model creation step, GRU entry is written in the places where LSTM is located and it is stated that the GRU technique will be used. This difference can be seen in Code Block 10.

```
#Generating LSTM model
model=Sequential()
model.add(LSTM(50, return_sequences=True, input_shape=(x_train.shape[1],1)))
model.add(LSTM(50,return_sequences=False))
model.add(Dense(25))
model.add(Dense(1))
```

Code Block 10. Generating LSTM Model

In LSTM, just like GRU, only MSE and MAPE model performance criteria will be interpreted. In LSTM, as in GRU, all model performance criteria gave successful results since all MSE and MAE values are less than 1 and MAPE values are less than 5%.

AKENR stock achieved its most successful forecast in terms of MSE and MAPE as a result of 30-day forecasts. For AKSEN stock, MSE's 60-day forecast is more successful, while MAPE's 120-day forecast is more successful. Similar to AKENR stock, AKSUE stock achieved its most successful forecast in terms of MSE and MAPE as a result of 30-day forecasts. AYEN stock also achieved its most successful forecast in terms of MSE and MAPE as a result of 30-day forecasts. For ZOREN stock, MSE's 60-day forecast is more successful, while MAPE's 30-day forecast is more successful.

Number of Days	Batch Size	Measure of Errors	AKENR	AKSEN	AKSUE	AYEN	ZOREN
30	128	MSE	0.0001	0.0927	0.2221	0.2959	0.0008
		MAE	0.0512	0.4930	0.6130	0.7175	0.0636
		MAPE%	2.1405	2.9676	2.5011	3.8397	2.0686
60	128	MSE	0.0015	0.0001	0.3804	0.8127	0.0006
		MAE	0.0567	0.4432	0.7293	0.9791	0.0718
		MAPE%	2.3253	2.4402	2.8590	4.9415	2.5756
90	128	MSE	0.0007	0.0083	0.4401	0.4853	0.0020
		MAE	0.0520	0.4218	0.7668	0.8653	0.0689
		MAPE%	2.2171	2.3367	3.0358	4.4359	2.2472
120	128	MSE	0.0003	0.1221	0.5574	0.8155	0.0064
		MAE	0.0566	0.4214	0.8418	0.9728	0.0908
		MAPE%	2.5153	2.3169	3.1556	4.9735	3.0298

Table 2. Results of LSTM with 200 Epoch and 128 Batch

In the LSTM analysis, models were established with four different epoch values, such as GRU, and both MSE, MAE and MAPE values were calculated as above. In addition, as in GRU, the days when the best model performance criterion results were achieved were determined on a company basis. The most successful forecast results will be compared with each other to understand which technique is better among the two techniques. Table 10 shows the best results of the companies in the relevant epoch number, row by row. In this table, in the relevant row where the GRU and LSTM results will be compared if the result of the LSTM technique is less than the result of the GRU technique, a value of 1 will be assigned to the relevant row cell in the rightmost column named "Result". There are 40 rows in total. Therefore, if the score of the LSTM technique is 19 and below as a result of the calculation, it means that the GRU technique is more successful than the LSTM technique, if it is 20, both techniques are not superior to each other, and if it is 21 and above, it means that the LSTM technique is more successful than GRU.

Number of Epoch	Stock	Measure of Errors	GRU	LSTM	Result
20	AKENR	MSE	0.0006	0.0001	1
		MAPE	2.1966	2.0391	1
20	AKSEN	MSE	0.0215	0.0021	1
		MAPE	2.5511	2.3575	1
20	AKSUE	MSE	0.0090	0.0066	1
		MAPE	1.9528	1.8419	1
20	AYEN	MSE	0.2185	0.0011	1
		MAPE	3.5587	2.9811	1
20	ZOREN	MSE	0.0048	0.0017	1
		MAPE	2.1104	2.3507	0
50	AKENR	MSE	0.0008	0.0001	1
		MAPE	2.0979	2.0947	1
50	AKSEN	MSE	0.0590	0.0005	1
		MAPE	2.5101	2.2211	1
50	AKSUE	MSE	0.1279	0.0083	1
		MAPE	2.3339	1.9773	1
50	AYEN	MSE	0.0481	0.1365	0
		MAPE	3.0519	3.4050	0
50	ZOREN	MSE	0.0014	0.5384	0
		MAPE	2.1052	4.0285	0
100	AKENR	MSE	0.0001	0.0002	0
		MAPE	2.1613	2.1093	1
100	AKSEN	MSE	0.0061	0.0073	0
		MAPE	2.2802	2.3508	0

Number of Epoch	Stock	Measure of Errors	GRU	LSTM	Result
100	AKSUE	MSE	0.1024	0.2301	0
		MAPE	2.0958	2.5188	0
100	AYEN	MSE	0.0581	0.3308	0
		MAPE	3.0949	3.8444	0
100	ZOREN	MSE	0.0003	0.0001	1
		MAPE	2.0872	1.9985	1
200	AKENR	MSE	0.0002	0.0001	1
		MAPE	2.0569	2.1405	0
200	AKSEN	MSE	0.0781	0.0001	1
		MAPE	2.3880	3.1556	0
200	AKSUE	MSE	0.0015	0.2221	0
		MAPE	1.8512	2.5011	0
200	AYEN	MSE	0.0745	0.2959	0
		MAPE	3.3533	3.8397	0
200	ZOREN	MSE	0.0009	0.0006	1
		MAPE	2.0636	2.0686	0

Tablo 3. Comparison of Results

As a result of the calculation, the LSTM technique obtained the value 1 on 21 times. This explains that since subtracting 21 from 40 gives the number 19, the GRU technique also received a score of 19. Thus, it means that the LSTM technique was more successful than the GRU technique with slight success. In addition, the days with the lowest error values are as follows: 30-day forecasts and 120-day forecasts were the forecasts with the lowest error criteria, with 21 each. These days were followed by 60-day forecasts and 90-day forecasts, each with 19 error criteria. Taking into account the technique used for companies, the number of epoch and the number of days, it was checked which parameter combination obtained the minimum MSE or MAPE value. Thus: The most accurate forecast in terms of MSE for AKENR stock was achieved with 0.0001 as a result of both LSTM and GRU techniques. The models that produced this result had forecast parameters of 20 epochs - 120 days and 200 epochs - 30 days for LSTM, and GRU had 100 epochs - 60 days forecast parameters. When evaluating the model performance of AKENR stock based on MAPE, the most accurate result was obtained with the model that made a 20-epoch and 120-day forecast using the LSTM technique. The MAPE value obtained as a result of this model is 2.0391. Among the analyzes performed on AKSEN stock, the analysis that gave the least erroneous MSE value was the 200-epoch and 60-day forecast model performed with LSTM. As a result of this estimation, an error value of 0.0002 was obtained. The least erroneous estimation for MAPE is the LSTM with 50 epochs and 30 days with an error value of 2.2211. From the analyzes within AKSUE stock, the minimum error value for MSE was obtained with a 200-epoch and 120-day forecast model applying the GRU technique. The result of this estimate was 0.0015. According to MAPE, the minimum error value is 1.8419. This output was found with 20 epochs and 90-day forecasts made with the LSTM technique. The least erroneous MSE estimation for AYEN stock is the LSTM with 20 epochs and 30 days estimation. This estimation gave an output of 0.0011 as an error value. When MAPE was taken into account in terms of model performance, the LSTM technique was applied, and the 20-epoch and 60-day forecast gave the least error value. As a result of this estimation, the value of 2.9811 was obtained. For ZOREN stock, based on the MSE, the least erroneous estimate was 0.0001. This forecast consists of 100 epochs and 90-day forecasts with the LSTM technique. Considering MAPE, the least error value is the 100-epoch and 90-day forecast applied with LSTM.

According to these results; If an investor based on MSE values wants to invest in AKENR shares, it would be better to act according to the 20-epoch 120-day and/or 200-epoch 30-day forecast using the LSTM technique or the 100-epoch 60-day forecast using the GRU technique. If it acts according to the MAPE value, it should consider the 120-day forecast result with 20 epochs by applying the LSTM technique. An AKSEN share investor who takes the MSE value into consideration should apply the LSTM technique and make a 60-day forecast with 200 epochs. It would be better for an investor based on the MAPE output to use the LSTM technique and make a 30-day forecast with a 50-epoch model. An investor who is considering investing in AKSUE shares will make a more successful investment with a 200-epoch 120-day forecast using the GRU technique, taking into account the MSE outputs. Investors who take MAPE into account should consider estimating a 90-day forecast model with 20 epochs using the LSTM technique. When an investor bases the MSE values for the investment he wants to make in AYEN shares, he must act according to the 20-epoch 30-day forecast model with the LSTM technique applied. An investor who uses the MAPE value as a criterion should consider the 20-epoch 60-day forecast estimated with the LSTM technique. In order to get the best results from the investment in ZOREN shares, the LSTM technique output should be taken into account in the 100-epoch 90-day forecast model for both MSE and MAPE.

5. Conclusion and Suggestions

In this study, the effectiveness of deep learning in the field of finance was examined by applying it to BIST. Deep learning was used to attempt the forecasting of daily stock prices for 5 energy companies listed in XELKT, one of the energy indexes of BIST. The selected stocks for stock price forecasting were AKENR, AKSEN, AKSUE, AYEN, and ZOREN. This analysis employed deep learning methods, specifically LSTM and GRU techniques. The dataset was collected from Yahoo Finance and covered the period from 02/01/2013, to 30/12/2022. In addition to the daily opening, closing, highest, and lowest stock price variables for each company, variables such as "BIST 100," "USD/TL" exchange rate, and "XELKT" were included in the datasets, as they were believed to have an impact on stock prices. Thus, a separate dataset was prepared for each company, resulting in a total of 5 datasets with 2511 observations and 17 variables.

After the preparation of the data sets, as a first step, models were established for application. The models created for both LSTM and GRU have 4 layers. The first layer has 50 neurons and is designed to process sequences sequentially. The second layer, like the first layer, has 50 neurons, but instead of producing sequential data like the first layer, the code is entered to produce results in the last time step. The third layer is the relative layer with 25 neurons, so it will enable learning more complex structures in the model. The fourth layer, which is the last layer, has 1 neuron and gives the final result with this neuron.

Once the models were created, they were trained. 4 different epoch values, standard batch size values for each epoch, 4 different numbers of days, and 3 different model performance criteria were used for training. The epoch values used are 20, 50, 100, and 200, respectively. Batch values are set to 5 when the epoch is 20, 32 when the epoch is 50, 64 when the epoch is 100, and 128 when the epoch is 200. The number of days is 30, 60, 90, and 120 days. MSE, MAE, and MAPE, among the model performance criteria that will measure the success of the created models, were selected for analysis. 80% of the data set is divided into the training set, 20% as the validation set and 20% as the test set.

In the analysis, first of all, the model performance criteria MAE, MSE and MAPE were calculated for both techniques. Then, in order to understand which technique is more successful in forecasting stock price, the MSE and MAPE values obtained as a result of the LSTM technique and the MSE and MAPE values obtained as a result of the GRU technique, based on the companies' epoch values, were compared between the two techniques. According to the comparison results, based on the relevant epoch value for the relevant company, it was said that whichever technique had less error value was more successful than the other. In addition, since the forecast was made for 4 different days, it was calculated how many days the forecast was more successful.

After calculating the model performance criteria, a total of 8 result tables were created for each technique and each epoch value. However, the analyses in the table were interpreted based only on MSE and MAPE. Since all calculated values are below the limits accepted in the literature, the techniques used can be considered successful in stock forecasting. Based on this, it can be said that correct models can be established. As a result of comparing the two techniques used in the analysis, it was seen that the LSTM technique had lower error values than GRU in 21 of the 40 comparisons made. Thus, it can be concluded that the LSTM technique is more successful than the GRU technique. Daily, 30-day and 120-day forecasts were more successful than 60-day and 90-day forecasts. Combinations of technique, epoch number, and daily forecasts that yield the least MSE and MAPE values for companies were investigated.

Stock	Number of Epoch	Days of Forecast	Technique	Measure of Errors	
AKENR	20	120	LSTM	MSE	0.0001
	200	30	LSTM	MSE	0.0001
	100	60	GRU	MSE	0.0001
	20	120	LSTM	MAPE	2.,0391
AKSEN	200	60	LSTM	MSE	0.0002
	50	30	LSTM	MAPE	2.2211
AKSUE	200	120	GRU	MSE	0.0015
	20	90	LSTM	MAPE	1.8419
AYEN	20	30	LSTM	MSE	0.0011
	20	60	LSTM	MAPE	2.9811
ZOREN	100	90	LSTM	MSE	0.0001
	100	90	LSTM	MAPE	1.9985

Table 4. Models That Provide the Least Error Model Performance Criteria for Companies

For AKENR, both LSTM and GRU usage on an MSE basis and LSTM usage on a MAPE basis were more successful. In the estimations of AKSEN, the least erroneous estimations were obtained with the LSTM technique in terms of both MSE and MAPE. For AKSUE, it made the least incorrect estimation with the GRU technique for MSE and LSTM for MAPE. The least erroneous MSE and MAPE values in the estimations for the AYEN were obtained by the LSTM technique. ZOREN, like AKSEN, made the least erroneous forecasts for both MSE and MAPE using the LSTM technique.

With this study, the use of LSTM and GRU techniques, which are deep learning techniques in stock price forecasting, is successful. Among these two techniques, the performance of LSTM is better than GRU. When considering daily success in forecasting, 30 and 120-day forecasts are more accurate than 60 and 90-day forecasts. Additionally, the study has provided clarity on which technique, epoch value, and the number of days for forecasting will yield the most successful results specifically for the companies.

The economic reason why the 120-day forecast, which is the longest-term forecast and one of the most successful daily forecasts in the study, is more successful than the shorter-term forecasts of 60 days and 90 days can be stated as follows;

- Nobel Prize-winning economist Fama (1970), with his Efficient Market Hypothesis, argued that stock prices reflect all available information and follow a random walk pattern, which makes short-term price forecasts difficult, and that long-term forecasts can include fundamental analysis that takes into account economic and financial factors.
- Stock markets are generally subject to volatility and variability. As a result, while markets are stable in the long run, they are more volatile and uncertain in the short run (Malkiel, 2003).

The 30-day forecast, which is one of the other most successful daily forecasts in the study, is the shortest-term forecast in the study. Lo et al., (1999) argue that short-term forecasts may be more successful than long-term forecasts for the following reasons;

- Important news in the markets usually has a quick impact on the market in the short-term.
- In short-term forecasts, high liquidity and the ability to trade quickly are of great importance. fast trading has an impact on short-term forecasts and this ability to trade quickly is important for capturing short-term opportunities.

Recommendations have been offered to investors. In conclusion, individuals contemplating investment in the related stocks whose price is estimated in this study can increase the success of their investment by considering the findings. If investors want to conduct a forecasting study on a company or index other than the ones mentioned in this study, making adjustments to parameters such as epoch, batch, activation function, number of layers, and number of neurons by the objectives of their study can result in more accurate results (Saracık, 2023).

The current model can be hybridized with the sentiment analysis method in the future to increase model performance. In this way, issues such as whether the periodic forecast differences are caused by people or whether the news affects on stocks can be clarified more easily. Additionally, if the effects of other factors on the model are wondered, the data set can be expanded and the analysis diversified with variables such as inflation, unit price of electricity, and Brent Crude Oil. In addition, mathematical techniques such as the Heston model and Fourier Transforms can be used with artificial neural networks to test whether model performance is increased.

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