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# Developing Financial Forecast Modeling With Deep Learning On Sil-ver/ Ounce Parity

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**Abstract** − In this study, financial prediction models have been developed over the silver / ounce parity using deep learning architectures. LSTM and ARIMA architectures, which are deep learning algorithms, are used. By loading the train-ing and test data into the established algorithms, the system was learned and a graphical estimation was requested on the silver / ounce parity for the next 10 days.

Written algorithms can produce different results each time they are run. However, in the graphs we have taken as an example, the graph created with the ARIMA architecture has produced a more real-istic result by specifying a range and making an upward forecast. The prediction chart we obtained with the LSTM architecture did not create a much decrease or upward forecast. However, as a feature of the LSTM algorithm, it clearly predicted the daily closing values, and did not specify an estimation as a range and direction as in the study with the ARIMA architec-ture. It should not be forgotten that these algorithms are dynamic and can give different results in predictions even when they are run with the same data.

According to the results obtained in the research, although the LSTM architecture clearly stated the daily closing values as numbers, the estimation study made with the ARIMA architecture produced a result closer to the graph in terms of both interval and direction.

***Keywords*** − *Artificial intelligence, deep learning, financial forecasting, machine learning, silver*

## 1. Introduction

With the introduction of computers into our lives, we have transferred many tasks from human power to machine power. From the simplest calculator to assembly line production systems managed by robots, machines and computers make our lives easier. With the foundations of artificial intelligence laid by Alan Turing during World War II, computers became much more functional and began to perform some activities similar to intelligent living things. There are many areas that artificial intelligence affects. recommender systems; They are systems used in social media and online sites that offer new content suggestions based on users' past behaviour. There are systems that allow translation from one language to another, which is called machine translation. Artificial intelligence is used in the field of signal processing, which performs tasks such as sound and image processing and interpretation. Finally, regression analysis; It enables the formation of predictive models for the future by evaluating the past data. In this regard, the consistency and sufficient number of numerical data in economic, financial or any other field increases the reliability of the analysis.

Machine learning and deep learning emerged after the idea of artificial intelligence. Machine learning is considered as a kind of artificial intelligence that can output even unprogrammed results. In 1959, Arthur Samuel defined machine learning as "the ability to learn outcomes for which machines are not specifically programmed". While machine learning processes in a single layer, deep learning processes in multiple lay-

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ers. In machine learning, you set the parameters so that an input can be defined. Deep learning, on the other hand, creates its own rules by determining its own parameters. In this case, deep learning algorithms can identify the differences in the entered data that cannot be perceived by human senses.

Deep learning started to make a name for itself in 2010 with the development of an artificial neural network model called "AlexNet" by Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton from the University of Toronto. Deep learning, to define simply, is the name we give to training multi-layer artificial neural networks with an algorithm called "backpropagation". (Krizhevsky, 2012) Deep learning models are based on the data on which they are trained. It shows great success in applications such as classification, regression analysis and estimation in time series. By using these models, it is possible to make future financial forecasts in many areas such as the stock market, precious metals and crypto markets. There are many deep learning models used for this purpose, and the success rates of each differ according to many variables such as the data set used, the time interval or the technique applied.

In today's economic world, people want to increase their existing capital by evaluating different investment areas. Metals such as gold, silver and platinum, which are accepted all over the world, experience fluctuations in their prices globally and investors want to earn profits by evaluating these products. Technical and fundamental analysis methods are used for graphical direction estimation of these products. In addition, with the widespread use of deep learning methods, different methods have been put into practice for graphical direction estimation.

Machine learning can be considered as a subset of artificial intelligence. Machine learning can be defined as a model that can make decisions or make predictions even though it is not fully programmed to perform a task using a sample dataset called "training data". Deep learning can be considered as a subset of machine learning. Although not very different from each other, the fields of study are the same, but artificial neural networks used in deep learning have a structure that mimics a biological nerve cell. A nerve cell makes an inference by comparing the information it has received with previous information. Deep learning algorithms analyze information by labeling and assigning elements such as a human brain to various categories (Jakhar & Kaur, 2009)..

There are basically 3 types of machine learning algorithms: Supervised, semi supervised and unsupervised. For supervised learning, a training set with inputs and outputs is fed into the algorithm, accompanied by a supervisor, so that meaningful results are obtained. Based on machine-learned relationships, it can make assumptions for a sample that has never been introduced introduced (Mohri et al, 2012). Support vector machines, linear regression, logistic regression, naive bayesian classifiers, decision trees, k-nearest neighbor algorithms and artificial neural networks are examples of frequently used supervised learning algorithms (Russell ve Norvig, 2010). In the training set used in the semi-supervised learning method, there are labeled and unlabeled data as in both supervised and unsupervised learning methods. This method is used when labeling all data is difficult and costly. Semi-supervised learning method can be used to solve problems such as regression, classification and sequencing. Unsupervised learning is the algorithms in which only the inputs are given to the system as a training set, and the output and labeling information is not given. It is not necessary to have a supervisor during training to the system. The system using the data tries to perform operations such as classification and clustering by examining the input-output relations itself (Mohri et al, 2012).

Deep learning algorithms can be considered as a sub-branch of artificial intelligence and machine learning terms. Deep learning, inspired by the human brain structure and the working principle of nerve cells, is a kind of machine learning. As with biological nerve cells, artificial neurons receive input signals, collect and process them and transmit them to the outputs. (Şişmanoğlu et al., 2019) Deep learning uses many layers of nonlinear processing units for feature extraction and transformation. Each successive layer accepts the output of the previous layer as input (Şeker et al., 2017).

LSTM and ARIMA architectures are the most used algorithms to predict future of time series models. ARIMA architecture is a type of statistical models for forecasting time series data (Box and Jenkins, 1970). . Non-stationary time series is made stationary by using finite differencing of the data in ARIMA models. ARIMA is an acronym that represents AutoRegressive Integrated Moving Average. LSTM deep learning algorithm, developed by Hochreiter and Schmidhuber (1997) allows the preservation of the weights that are forward and back-propagated through layers. The network can continue to learn over many time steps by maintaining a more constant error. Thus, the network can be used to learn long term dependencies. An LSTM cell contains the forget and remember gates which allow the cell to determine what information to prevent or pass based on its strength and importance (Kingma and Ba, 2018)

Bingol et al. has made similar study on gold price prediction and has found that ARIMA architecture has better results among other future prediction models. Another research made a comparison between ARIMA and LSTM architectures and had an estimation on stock market graphs. The study has shown that LSTM architecture was superior to ARIMA (Namin and Namin, 2018). Alpay's research article has also used LSTM architecture to predict USD/TRY price for future. The study reveals that specific epoch and batch size values can make a successful prediction (Alpay, 2020).

Most of the recent studies focus on the forecasting of the gold prices ignoring the forecasts of other precious metals. For this reason, this study includes the forecasting of silver prices by using LSTM and ARIMA methods. Employing the prices of silver, predictive power of the model rises to provide better results for investors who aim to develop their portfolio and make more profitable investments.

In our study, first of all, silver/ounce parity data were obtained between 01.01.2018 and 12.04.2021. These data were used for testing. The obtained data were normalized. These data were taught to the LSTM and ARIMA deep learning algorithms used in the application. Then, the forecast values for the dates 13.04.2021 and 21.04.2021 were produced with two algorithms. Then, the performance of these estimations was evaluated using MSE and RMSE performance criteria.

## 2. Materials and Methods

In our study, firstly, data such as daily opening, closing, highest, lowest and silver/ounce parity values were obtained for the time period between 01.01.2018 and 12.04.2021. The source of the dataset is a website and the link is as follows: https://eatradingacademy.com/software/forex-historical-data/. You can use the following link to access the entire dataset: https://raw.githubusercontent.com/SnnUntz/Data/main/XAGUSD_D1.csv Only the 10-day portion of all data is shown in Table 1.

Table 1

Used silver/ounce data

| Date | Open | High | Low | Close | Volume |
|---|---|---|---|---|---|
| 2013-01-01 | 30.294 | 30.337 | 30.178 | 30.203 | 60 |
| 2013-01-02 | 30.197 | 31.490 | 30.193 | 31.033 | 1527 |
| 2013-01-03 | 31.042 | 31.183 | 29.981 | 30.102 | 1495 |
| 2013-01-04 | 30.100 | 30.264 | 29.208 | 30.205 | 1646 |
| 2013-01-06 | 30.193 | 30.237 | 30.139 | 30.170 | 64 |
| | | | | | |
| 2021-04-07 | 25.154 | 25.266 | 24.843 | 25.145 | 1596 |
| 2021-04-08 | 25.142 | 25.608 | 24.951 | 25.389 | 1641 |
| 2021-04-09 | 25.394 | 25.492 | 24.971 | 25.191 | 1453 |
| 2021-04-11 | 25.170 | 25.253 | 25.154 | 25.235 | 118 |
| 2021-04-12 | 25.235 | 25.264 | 24.694 | 24.795 | 1552 |

After downloading the data, it is prepared for use in deep learning with LSTM and ARIMA algorithms. During the preparation phase, the data were normalized to be between 0 and 1. After preprocessing, the algorithms to be used for estimation were selected.

With its ability to remember both long term and short-term values, the LSTM models have proved financially rewarding for the treatment of time series, thereby becoming the preferred Deep Learning tool for time series analysis (Sadefo Kamdem et. al., 2020). For this reason, the LSTM algorithm was used in our study.

The Autoregressive Integrated Moving Average (ARIMA) and its variants are the most used in the literature for forecasting stock price series (Aamir and Shabri, 2018). These have indicated that the ARIMA model has a strong predictive potential in the short term and has the ability to compete favorably with existing stock price prediction tools (Ariyo et. al., 2014). For this reason, the second algorithm used in our study was chosen as ARIMA.

### 2.1. Prediction Model Developed Using LSTM Architecture

Long and Short Term Memory is a variation of RNN and are known to learn problems with long-range temporal dependencies, so RNNs are sometimes replaced with LSTMs in MT networks (Hochreiter, S. and Schmidhuber, 1997). LSTMs also have this chain-like structure, but the structure of the repeating module is different from RNN. In place of a single neural network layer, there are four layers in a module. These layers interact within the same modules as well as with other modules for learning (Saini and Sahula, 2018) A typical structure of LSTM module is shown in Figure 1.

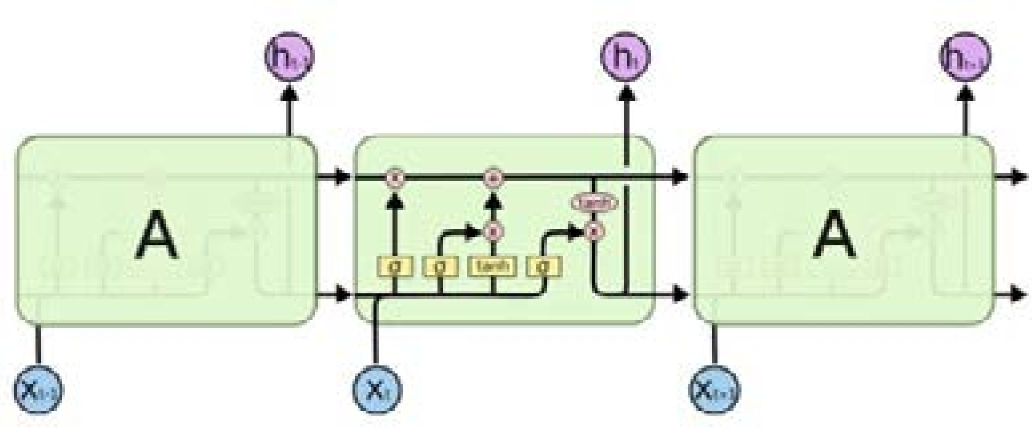


Figure 1. The repeating module in an LSTM contains four interacting layers (Saini and Sahula, 2018)

The algorithm, which obtains the data that needs to be processed through the link we have added, has only used the data since 2018 and has been deemed sufficient. The loaded and processed data is shown at Figure 2.

| Date | Close |
|---|---|
| 2018-01-01 | 17.004 |
| 2018-01-02 | 17.191 |
| 2018-01-03 | 17.090 |
| 2018-01-04 | 17.166 |
| 2018-01-05 | 17.187 |
| ... | ... |
| 2021-04-07 | 25.145 |
| 2021-04-08 | 25.389 |
| 2021-04-09 | 25.191 |
| 2021-04-11 | 25.235 |
| 2021-04-12 | 24.785 |

1020 rows × 1 columns

Figure 2. Loaded data for the LSTM algorithm

As can be seen, the closing value was taken from the data and 1020 rows of data were loaded as of 1.1.2018. Our normalized graph is as shown at Figure 3.

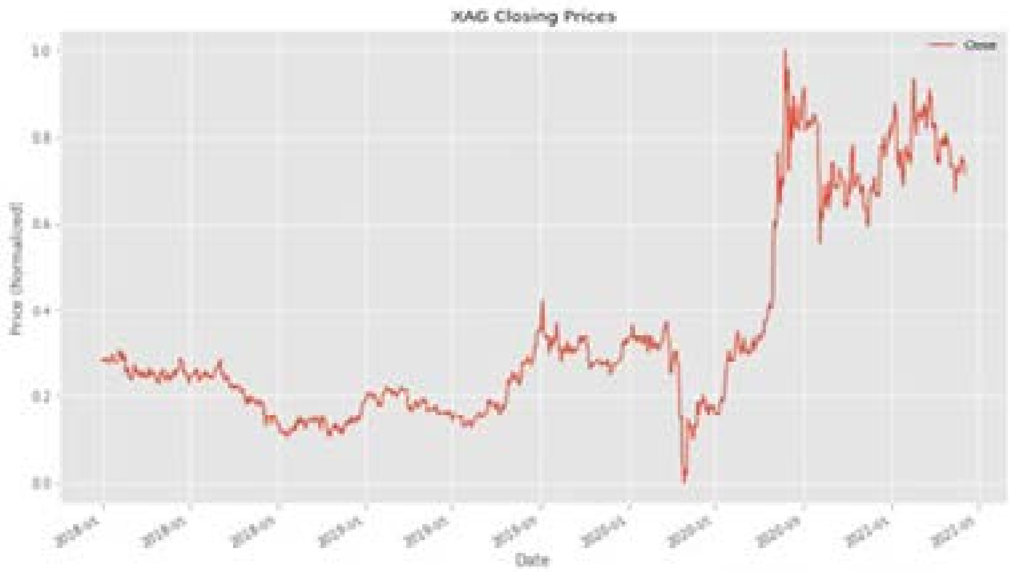


Figure 3. Normalized silver/ounce graph for LSTM architecture

As training data, the last 30 days of data were processed for every 10-day chart. It is programmed to make a 10-day forecast for the future.

In the algorithm we use, it is stated that the closer the loss values are to each other, the better the result will be. In the model we applied, the loss and accuracy values are given as Figure 4.

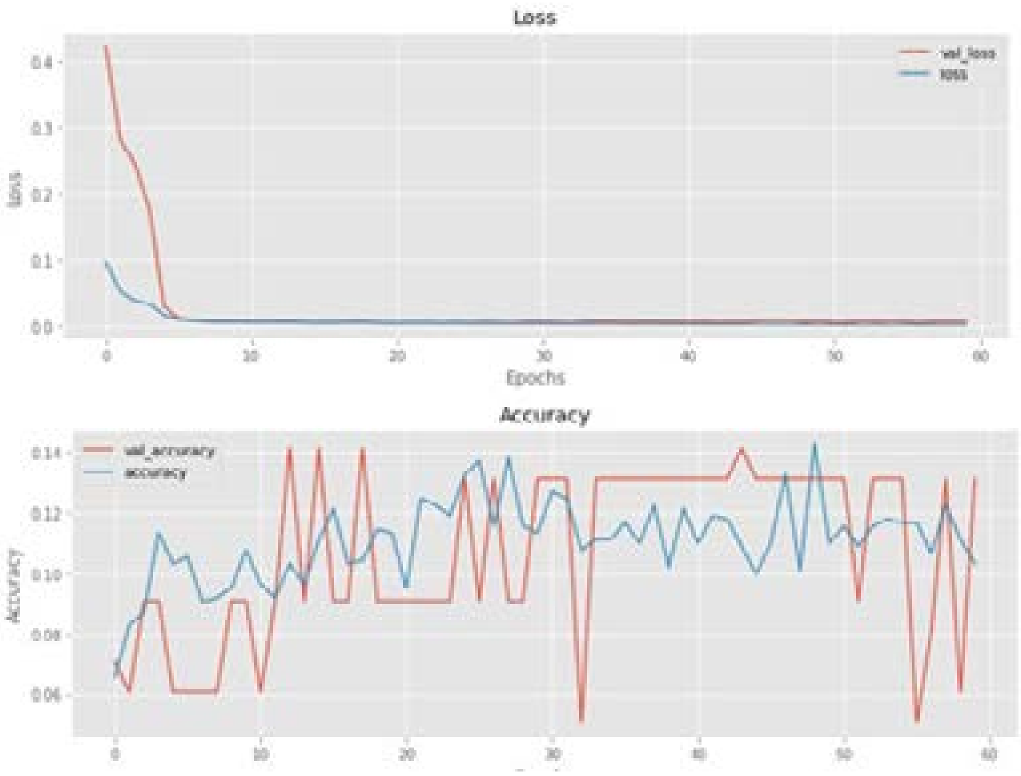


Figure 4. Loss and accuracy values for the LSTM algorithm

The forecast made from the test data and the actual data graph for the last 10 days are as Figure 5 It is seen that mostly consistent results are given. After the test estimation, the algorithm is run for the actual estimation.


Figure 5. Test prediction graph for LSTM algorithm

We want to create a forecast graph for 10 days ahead from the last day on the data fed into the system. The daily closing values for the forecast graph made by the algorithm and the entire graph are as Figure 6 and Table 2.

Table 2.

Daily closing values in the forecast made with the LSTM algorithm

| Date | Closing Price |
|---|---|
| 2021-04-12 | 25.102 |
| 2021-04-13 | 24.966 |
| 2021-04-14 | 24.995 |
| 2021-04-15 | 24.859 |
| 2021-04-16 | 25.066 |
| 2021-04-17 | 24.874 |
| 2021-04-18 | 24.879 |
| 2021-04-19 | 24.804 |
| 2021-04-20 | 25.188 |
| 2021-04-21 | 24.782 |

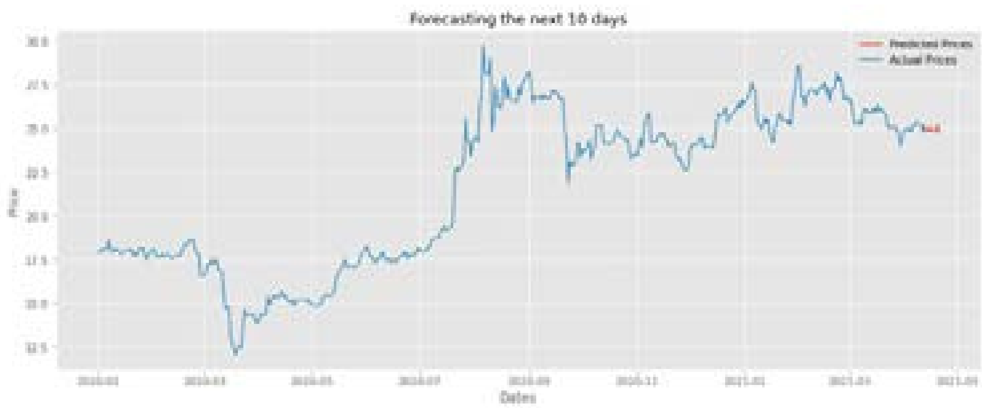


Figure 6. 10-day forecast model graph with LSTM algorithm

The details are not clear as the chart we obtained represents a long period of time. Figure 7 is the graphic where we can see the details more closely.

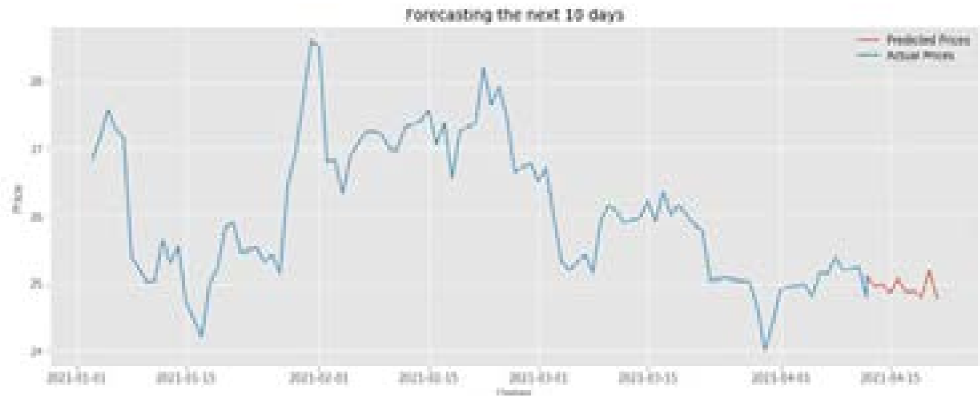


Figure 7. LSTM algorithm detail graph

### 2.2. Prediction Model Developed Using ARIMA Architecture

The time series model using the Box-Jenkins method was proposed by Box and Jenkins (1970). This approach is widely used in the literature due to its simplicity and good results. Often this method is referred to as the ARIMA method. The ARIMA method is quite different from other methods as the prediction series does not contain explanatory independent variables. When creating an ARIMA model, the current series must be stationary. If the series is not stationary, the difference of the series should be taken before using the method (Gahirwal, 2013).

In order to construct the best ARIMA model for exchange rate time series, the autoregressive ($p$) and moving average ($q$) parameters are need to be identified for an effective model. We decided to determine the best model based on Bayesian Information Criterion (BIC) for various orders of autoregressive ($p$) and moving average ($q$) terms keeping integrated term ($d$) as order 1 (Babu and Reddy, 2015). Since silver/ounce parity time series was used in this study, the parameters in ARIMA were determined in the same way.

The data source we used for the LSTM architecture was also used for the ARIMA architecture over the same link. Table 3. showing the last 5 days of the data fed into the system is as follows. It also extends from 01.01.2018 to 12.04.2021.

Table 3.

Data table fed into the system for ARIMA architecture

| | Date | Open | High | Low | Close | Volume |
|---|---|---|---|---|---|---|
| **2566** | 2021-04-07 | 25.154 | 25.266 | 24.843 | 25.145 | 1596 |
| **2567** | 2021-04-08 | 25.142 | 25.608 | 24.951 | 25.389 | 1641 |
| **2568** | 2021-04-09 | 25.394 | 25.492 | 24.971 | 25.191 | 1453 |
| **2569** | 2021-04-11 | 25.170 | 25.253 | 25.154 | 25.235 | 118 |
| **2570** | 2021-04-12 | 25.235 | 25.264 | 24.694 | 24.795 | 1552 |

The algorithm will perform training and testing operations on this table based only on the closing values. The silver/ounce chart created according to the closing values of the system is as Table 4. Our graph that expresses the daily change in price on the silver/ounce chart is as Figure 8.


Figure 8. Silver/ounce daily price change chart for ARIMA architecture

Table 4.

Daily closing values in the forecast made with the ARIMA algorithm

| Date | Closing price |
|---|---|
| 2021-04-12 | 25.121 |
| 2021-04-13 | 24.829 |
| 2021-04-14 | 24.815 |
| 2021-04-15 | 24.840 |
| 2021-04-16 | 24.834 |
| 2021-04-17 | 24.852 |
| 2021-04-18 | 24.851 |
| 2021-04-19 | 24.866 |
| 2021-04-20 | 24.867 |
| 2021-04-21 | 24.880 |

### 3. Results and Discussion

Many architectures and algorithms are used for financial forecasting and they are developing day by day. Based on the literature research, LSTM and ARIMA architectures, which are two of the architectures that give the best results today, have been the main subject of our study and they were asked to make a 10-day forecast by processing the training and test data on the silver / ounce graph. In this context, starting from 01.01.2018, daily opening, closing, low, high and volume values for the silver/ounce chart were obtained and fed into the algorithms written for both architectures and the desired graphics were created.

Forecast values were produced by LSTM and ARIMA algorithms for the dates 12.04.2021 - 21.04.2021. The relationship between the estimated values produced and the actual values was examined. It is known that the algorithm that produces values close to the real values performs better. Many criteria can be used as performance criteria.

Performance measure is forecast accuracy. The measures are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The MAE is a measure of the difference between two continuous variables. The MAE is the average vertical distance between each actual value and the line that best fits the data. MAE is also the average horizontal distance between each data point and the best-fit line. Since the MAE value is easily interpretable, it is frequently used in regression and time series problems. The formula expression of MAE is as shown at 3.1 and 3.2.

$$\mathrm{MAE} = \frac{1}{n} \sum_{j=1}^{n} |e_j| \tag{3.1}$$

$$e_j^2 = (Actual_j - Predicted_j)^2 \tag{3.2}$$

It is a quadratic metric that measures the magnitude of error of a machine learning model, which is often used to find the distance between the predicted values of the estimator and the true values. The RMSE is the standard deviation of the estimation errors (residues). That is, residuals are a measure of how far the regression line is from the data points; The RMSE is a measure of how widespread these residues are. The formula expression of RMSE is as shown at 3.3.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{n} e_j^2}{n}} \tag{3.3}$$

Table 4.

MAE and RMSE values for LSTM and ARIMA algorithms

| | MAE | RMSE |
|---|---|---|
| LSTM | 733 | 870 |
| ARIMA | 811 | 920 |

As can be seen from the MAE and RMSE performance criteria, LSTM outperforms the ARIMA algorithm. The LSTM algorithm is relatively 5.74% and 10.64% better than the ARIMA algorithm in terms of RMSE and MAE, respectively.

**4. Conclusion**

Today, both financial markets and artificial intelligence gain importance day by day and both are affected by the world's economic situation and technological developments and meet at a common point. In the study we have done, it is aimed to predict which direction the graph will go by creating a forecasting model on silver, which is the most popular commodity along with gold. In this study, we created a prediction model based on the silver/ounce graph using two deep learning architectures that are used for continuous time series and that we see give the best results. In our study, the MAE and RMSE performance criteria are used to compare LSTM and ARIMA algorithms. According to the performance criteria, LSTM outperforms the ARIMA algorithm. The LSTM algorithm better than the ARIMA algorithm in terms of RMSE and MAE. It is possible to obtain different results by making changes in the written coding. Again, the results will change when we change deep learning layers or want to generate predictions for different time periods. Since no artificial intelligence or deep learning algorithm can know the future one hundred percent, trying to make predictions with high consistency has been the main subject of deep learning and financial forecasting studies. Our study shows that it is possible to make financial forecasts for the future with appropriate deep learning architectures as the main idea. In the future, it will be possible to make financial forecasts with higher consistency by using more advanced programming languages or algorithms.

**Author Contributions**

Adem Üntez: Analized the study, gathered the data, run algorithms and evaluated the conclusions.

Mümtaz İpek: Checked the steps of the study.

**Conflicts of Interest**

The authors declared no conflict of interest.

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