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Comparison of commodity prices by using machine learning models in the COVID-19 era

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Abstract

Commodity products such as gold, silver, and metal have been seen as safe havens in past economic crises. This situation increases the interest in commodity products. Due to the COVID-19 pandemic, quarantine decisions and precautions have caused an economic slowdown in stock markets and consumer activities. This inactivity in the economy has led to the COVID-19 recession that started in February 2020. Because of the increase in the number of COVID-19 cases, the difficulty of physical buying-selling transactions has shown that commodity products can be a safe investment tool. Based on the fact that machine learning approaches gained importance in commodity price prediction, the main goal of this study is to understand whether machine learning methods are meaningful for commodity price prediction even in extraordinary situations. To measure commodities' price volatility, a data set obtained from Borsa İstanbul is separated into pre-COVID-19 and COVID-19 periods. Daily prices for gold and silver commodities, from July 2018, which is before the ongoing COVID-19 recession, to October 2021 are used. The performances of the machine learning models were compared with MAE, MAPE, and RMSE metrics. The findings of this study point out that the LSTM model has more accurate predictions, especially in the pre-COVID-19 period. When considering the COVID-19 period only, SVR produces the best prediction results for the gold commodity and LSTM has the best prediction results for the silver commodity.

1. Introduction

The commodity market allows buying, selling, and exchanging of raw materials or primary products [1]. In the commodity market, everything can be changed suddenly because the market has large price fluctuations due to different types of players such as investors, brokers, and traders who anticipate each other's actions. Besides that, players or investors should prepare themselves for unexpected effects like COVID-19 [2]. Normally, when negative developments happen in the financial area such as interest rates, inflation, etc., commodities, especially gold and silver prices inevitably increase. However, the recent crisis is not related to the financial area but is stemmed from the health field. According to the risk and volatility indicators, the COVID-19 pandemic is considered the most substantial global phenomenon [3]. In such circumstances, gold and silver commodities come into prominence. Gold is already known as a safe harbor for investors, known for keeping its value. According to [4], the role of gold as a hedging tool consists of two theoretical mechanisms. One of them is, that when volatility increases, this provides the risk-averse investor to move away from other financial markets. This behavior creates a peak in demand for gold, then causes gold prices up and increases investors' wealth. The other mechanism is due to the biased behavior related to gold's history; gold becomes preferable to other assets. In addition to this, with the COVID-19 era, silver's demand increased. Both commodities are preferred by the concerned investors and other economic actors when market predictability diminishes.

Commodity prices, especially gold and silver have importance to investors, suppliers, governments, etc. If the prediction of commodity price is obtained with the best result, it will help people such as experts and other parties using and forecasting commodities prices while planning budgets or similar needs. This situation prompts academic research and agents of the market to

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start studies on predicting economic and financial crises and crashes such as Global Financial Crisis (2008), Eurozone Debt Crisis (2010–2012), and the novel COVID-19 pandemic [5].

From this point of view, machine learning methods have gained importance recently, and deep learning has become very popular, especially for commodity price prediction. In 2020, one of the black swan events took place during the COVID-19 pandemic in Turkey and around the world. During that period, commodity prices were more volatile, and it became more difficult to forecast. For this reason, measurement of the performance of prediction models gained great importance.

Machine learning is an application of artificial intelligence, which stems from the theory claiming that machines are capable of learning from data, pinpointing patterns, and making decisions with an insignificant amount of human interaction. It provides a wide variety of applications including portfolio optimization, image and speech recognition, weather forecasting, and many more. In today's data world, machine learning is of great importance due to its amount of learning potential [1].

In recent years, machine learning has been the first thing that comes to mind in solving many problems in computer science. It made analyses easier, more innovative, and more effective when working with an enormous amount of data. Machine learning can be categorized into three groups which are unsupervised, supervised, and reinforcement learning. For the price prediction of commodities or currencies based on historical data, existing machine learning systems generally use deep or supervised learning approaches to help investors with decision-making and risk calculation needs. Besides that, by using deep reinforcement learning, trading decisions can be made without human intervention [1].

In this study, data sets containing gold and silver commodity prices for the period before the COVID-19 pandemic and during the COVID-19 pandemic were analyzed. The analyzed data sets were obtained from Borsa İstanbul. Different prediction models were built using Long Short-Term Memory (LSTM), Random Forest (RF) and Support Vector Regression (SVR). To find the best prediction model, the performances of the models were compared using various evaluation metrics. The main goal is to find out whether machine learning methods are meaningful and useful for commodity price prediction even in unprecedented circumstances.

2. Literature review

There are many publications in the literature on the field of price prediction. In this study, a literature review process has been conducted based on the following steps:

a. The main research question of this study is stated as “How meaningful and accurate are machine learning methods for gold and silver commodity price prediction even in extreme situations?”.

b. Academic databases including ScienceDirect, IEEE Xplore, and Google Scholar were used.

c. 15 different search keywords were defined considering the study’s main research question. These keywords are “commodity market”, “commodity trading” “stock market”, “stock price”, “time series data”, “COVID-19”, “pandemics”, “machine learning”, “deep learning”, “SVR”, “LTSM”, “random forest”, “regression”, “price prediction”, and “predictive models”.

d. A time range covering the past five years was set to review recent studies.

e. The most relevant and most cited papers were selected during the literature review process.

f. Studies without any citations were excluded.

Based on this elimination and filtering methodology, the selected studies on price prediction are briefly mentioned below.

Ramakrishnan et al. [6] focused on predicting commodity prices and exchange rates in Malaysia. Gold commodities, rubber, palm oil, and crude oil were included in the study. For the predictions, Support Vector Machine (SVM), Neural Networks (NN), and RF machine learning algorithms were utilized. The following evaluation techniques were applied: Relative Absolute Error (RAE), Root Mean Squared Error (RMSE), Relative Squared Error (RSE), and Mean Absolute Error (MAE). The authors reached the conclusion that RF has better performance for accuracy and performance compared to the NN and SVM models.

Akın et al. [7] focused on forecasting the raisin commodity price index of Turkey using Decision Tree (DT), Artificial Neural Networks (ANN), and SVM methods. Researchers considered accuracy and f-measure scores to compare the model performances. Daily historical data for explanatory variables such as gold price, oil price, and political and social issues that occurred in Turkey were included. The results of the study showed that the accuracy performance of the SVM method performed better compared to other methods.

Yadav et al. [8] aimed on analyzing the forecasting models to predict the Bombay Stock Exchange (BSE) SENSEX, which is a parameter of the stock market of India. To find the best prediction model to forecast, the authors made a comparison of mean errors. R tool was used in the study. Research data was collected from BSE’s official website. The researchers converted the data set into time series. Following that, output from the time-series data was used as a newly created time-series object. It is stated that data is very volatile, therefore the authors transformed the data set for the Box-Jenkins approach to increase the accuracy of the forecast. Augmented Dickey-Fuller (ADF) Test and Ljung-Box Test were also applied. Autoregressive Integrated Moving Average (ARIMA) Model, Exponential Smoothing Forecast (ESF), BoxCox Transformation (BT), Mean Forecast (MF), Seasonal Naive Forecast (SNF) and NN were used and compared to find the best prediction result. For evaluation criteria, several metrics including MAE, MAPE (Mean Absolute Percentage Error), and RMSE were taken into account. According to the results of the study, NN and ESF methods gave the best outcomes.

Štifanić et al. [9] analyzed COVID-19’s impact on three stock indexes in the US: NASDAQ Composite, S&P 500, DJI, and also in crude oil prices. The authors proposed a system for predicting the integration of commodity and stock prices. Stationary Wavelet Transform (SWT) and Bidirectional Long Short-Term Memory (BDLSTM) networks were used in the prediction. To achieve low-performance measure values and high-quality regression, three main system configurations were examined. RMSE and MAE scores were taken as evaluation criteria. It was stated that the proposed system has successful results in forecasts of five-day crude oil prices.

Luo [10] conducted a study on forecasting Bitcoin price trends and return rates by comparing the performances of DT, RF, AdaBoost, and SVM algorithms. Prediction models used different historical data sets including Bitcoin exchange data, Bitcoin exchange & COVID-19 (recovery, confirmed, death) data, Bitcoin exchange & Twitter data, and Bitcoin exchange & COVID-19 (recovery, confirmed, death) & Twitter data. Researchers used RMSE and accuracy scores as evaluation criteria. Luo (2020) observed that the performance of the models is improved when Twitter data is included. On the other hand, SVM does not provide good performance in price trends or Bitcoin return predictions, and no improvement is achieved in the predictions with the usage of COVID-19 data.

Amin [11] aimed to predict commodity prices by using machine learning algorithms. Different kinds of daily commodities were included in the study which are wheat, avocado, and dairy foods. The data sets were gathered from Kaggle, Bangladesh Agricultural Research Council, and wheat prices were gathered from the Humanitarian Data Exchange. Researchers applied SVM, RF, Bagging, AdaBoost, GradientBoost, XGBoost, and LightGBM models. To evaluate the performance of the models, Mean Squared Error (MSE), MAE, and R2 evaluation metrics were used. The authors found that ensemble methods performed better for medium-to-large data sets compared to the base SVM model.

Ruan et al. [12] analyzed prediction models to estimate stock prices under unexpected circumstances like the COVID-19 pandemic situation. Stock prices were determined by using the top five stocks of each industry. The data set was collected from Yahoo Finance. 100 stocks from 20 industries were acquired. Researchers compared the methods which are parametric and non-parametric and forecasted stock prices under unpredicted conditions. Long Short-Term Memory (LSTM) and ARIMA models were applied at the single-stock level, industry level, and general market level respectively. It is observed that the LSTM model performed better than the ARIMA model in following the stock price trends and time complexity.

Ghosh [13] used a different approach to predict future prices. A novel hybrid granular ensemble of ensembles forecasting framework was studied. Crude oil, gold, copper, silver, and natural gas commodities' closing price values were taken into account. The framework included two separate methodologies on time series decomposition which are Singular Spectrum Analysis (SSA) and Ensemble Empirical Mode Decomposition (EEMD). The researchers concluded that their framework has high quality and had better results on all commodity forecasts compared with the other competitive five models.

Kamdem et al. [2] aimed to forecast the prices of exported commodities of African countries by using deep learning techniques. Researchers also explored the effect of COVID-19 on the market volatility of these commodities. The West Texas Intermediate crude oil, Brent oil, wheat, and silver were examined. Researchers applied the LSTM model for predicting commodity prices. For training, data was split into two parts. 80% of the data set was used for training and 20% was used for testing. Model scores including MAPE and RMSE were used as evaluation criteria. It was stated that the LSTM model has good accuracy scores for forecasting commodities prices.

Ly et al. [14] studied predicting cotton and oil prices by LSTM, ARIMA, and a combination of methods named the forecast averaging method. The authors gathered data from the World Bank commodity prices data set. The data set was split into 70% as training and 30% as testing. When the ARIMA and the LSTM model performances were compared, the ARIMA model performed better in predicting the prices for commodities. When comparing results with the proposed forecast averaging method, the authors stated that the new method gave better results in the prediction of commodity prices.

Mahdi et al. [15] focused on forecasting cryptocurrency returns. The authors considered the daily returns of Bitcoin, Ethereum, Ripple, Binance Coin, Cardano, and Dogecoin before and during the COVID-19 pandemic. SVM was used as the main predictor. The data set was split into 75% for training and 25% for testing. The best-performing model selection was based on the minimization of MAPE and RMSE. This study showed that the SVM model is a robust algorithm for the predictability of cryptocurrencies.

Vora et al. [16] studied predicting stock prices by historic prices of stock behavior. Researchers used the stock's closing price for further predictions and applied Google Colab for programming models. Authors utilized algorithms such as Linear Regression (LR), RF, DT, and LSTM. Model outputs were compared with the original closing values. It was founded that the Recurrent Neural Network (RNN) type of algorithm such as LSTM shows the best accuracy compared to other models.

Chandra and He [17] studied stock price predictor models' performances during the COVID-19 pandemic. Researchers also investigated if the pre-COVID-19 pandemic data sets would be useful for stock price forecasting during the COVID-19 pandemic. It was found that it is more challenging to provide forecasting because of the high volatility of stock prices during the pandemic. It was also stated that Bayesian NN could provide reasonable predictions in uncertain conditions.

Niu and Zhau [18] aimed to forecast daily prices and seven-day volatility of WTI crude oil and Brent oil. The data set contained 2000 daily observations for Brent oil and WTI oil gathered from the Energy Information Administration (EIA). The data set was divided into two subsets which are 80% training and 20% testing set. To forecast the volatility, researchers proposed a hybrid decomposition-ensemble forecasting model which is based on variational mode decomposition (VMD) and Kernel Extreme Learning Machine (KELM). In the proposed model, the VMD method was employed to separate the series into subseries with several frequencies, followed by forecasting subseries by KELM. The VMD-KELM model showed better prediction ability and performance with low evaluation criteria values when compared to other models. The authors stated that the decomposition-ensemble strategy is demonstrated by the point that hybrid models have significantly higher prediction accuracies compared to those of single models.

Depren et al. [3] analyzed the influential factors on the gold prices in Turkey during the COVID-19 pandemic by employing machine learning algorithms. Data that belong to the year 2020 were collected from the Ministry of Health of Turkey, Bloomberg, and the Central Bank of the Republic of Turkey. The collected data was split into pre-pandemic and pandemic periods. The researchers analyzed data by using Box and Whisker Plot, RF, K-Nearest Neighbors (KNN), and SVM algorithms. The model performances were assessed with R2, RMSE, and MAE evaluation criteria. It was found that the RF algorithm generated higher prediction accuracy.

Olubusoye et al. [19] focused on energy prices. Researchers analyzed how energy prices are affected during the COVID-19 pandemic under uncertainties. For the uncertainty measurements, the authors preferred to use Economic Policy Uncertainty (EPU), Volatility Index (VIX), Global Fear Index (GFI), COVID-Induced Uncertainty (CIU), and Misinformation Index of Uncertainty (MIU). The Multivariate Adaptive Regression Spline (MARS) algorithm was used. Eight energy price values which are for gasoline, diesel, kerosene, heating oil, natural gas, Brent oil, WTI oil, and propane was included. The study showed that EPU affects most types of energy prices during the COVID-19 pandemic within all examined uncertainty measurements. It was also emphasized that CIU, VIX, and MIU have forecast potential for global energy sources.

In this study, the gold and silver commodity price data set that was obtained from Borsa İstanbul was used for building price-prediction models. The data set was analyzed considering both before and during the COVID-19 pandemic period.

The main research question of this study is "How meaningful and accurate are machine learning methods for gold and silver commodity price prediction even in extreme situations?". To address this research question, our study uses and analyzes a novel data set obtained from Borsa Istanbul for gold and silver commodities. This data set is not used or analyzed in any other previous studies.

The main contribution of this study is to provide guidance to future machine learning studies by showing which prediction models are more accurate for price predictions in unprecedented circumstances such as the COVID-19 era. The result of this study will help investors, decision-makers, and other related stakeholders to make quicker decisions in unexpected situations.

3. Method

This section provides a detailed explanation of the data set and methods used in this study. Python is used as the primary implementation language in collaboration with Google Colab. Scikit-learn library is used for building machine learning models [20]. NumPy is used for scientific calculations [21]. Pandas is used for analyzing the data set [22]. For deep learning and additional machine learning processes, TensorFlow is included in the implementation [23].

3.1. Data set

Price values of gold and silver commodities from a past time period are used in this study. Since gold and silver are the most preferred commodities with the highest trading volume, the data used in this study only includes these commodities. Others were excluded from the data set.

Precious Metals and Diamond Market's historical data set covering a time frame between July 2018 and October 2021 is acquired from Borsa İstanbul DataStore. The attributes and their data types are given in Table 1.

The obtained data set is divided into two sets: pre-COVID-19 and COVID-19 pandemic data. The pre-COVID-19 data set covers instances until February 2021. The other set, which is the COVID-19 pandemic data covers values from March 2021 to November 2021.

Both sets are split into testing and training subsets. The COVID-19 period includes 333 silver and 409 gold observations whereas the pre-COVID-19 period includes 272 silver and 413 gold observations. Testing and training set sizes are given in the following Table 2.

Table 1. Attributes of the data set

#	Name	Type
1	Date	Alphanumeric
2	Instrument Code	Alphanumeric
3	Market	Alphabetical
4	Market Segment	Alphabetical
5	Instrument Group	Alphabetical
6	Instrument Type	Alphabetical
7	Instrument Class	Alphabetical
8	Metal Type	Alphabetical
9	Metal Bar Type	Alphabetical
10	Price Unit/Weight	Decimal, Numerical
11	Fineness	Decimal, Numerical
12	Weight	Decimal, Numerical
13	Vault Location	Alphanumeric
14	Settlement Date	Alphanumeric
15	Previous Close Price	Decimal, Numerical
16	Opening Price	Decimal, Numerical
17	Minimum Price	Decimal, Numerical
18	Maximum Price	Decimal, Numerical
19	Close Price	Decimal, Numerical
20	Weighted Average Price	Decimal, Numerical
21	Total Gross Weight	Decimal, Numerical
22	Total Traded Value	Decimal, Numerical
23	Total Traded Quantity	Decimal, Numerical
24	Total Number of Deals	Decimal, Numerical

Table 2. Testing and training set sizes

Commodity Name	Subsets of Data	# of instances (Pre-COVID-19)	# of instances (COVID-19)
Gold	Train	250	300
Gold	Test	22	33
Silver	Train	350	350
Silver	Test	63	59

3.2. The Data processing

The prediction process includes six phases. Figure 1 depicts each of these steps.

The first phase of the prediction process begins with data collection. Data sets containing gold and silver commodity prices are acquired using the source described in the previous section. The second phase is data preprocessing. The entire data preprocessing consists of the following steps:

Data discretization: Continuous quantitative data is converted into intervals.

Data transformation: Min-max normalization method is applied.

Data cleaning: Other commodities such as palladium and platinum are eliminated. Then, duplicated rows are dropped. Rows with missing values are deleted.

Data imputation: Duplicate records for each day are removed.

Data integration: The monthly data sets are combined.

After applying the preprocessing steps, the data set is split into training and testing sets.

The third phase of the process includes building prediction models. The data set is again split into two subsets, one containing values for the pre-COVID-19 pandemic period and the other one including values about the COVID-19 pandemic period observations. SVM, RF, and LSTM prediction models are built based on these two data sets.

The fourth phase includes the execution of SVM, RF, and LSTM models for forecasting commodity price values. To obtain the forecast of the next day's price, the last input window length (w) is fed into the model. The next day's forecasted price was used as an input, and it is re-fed into the model. This process is repeated up until reaching the prediction window length.

After completing the forecasting phase, the fifth phase includes evaluating model performances. MAPE, MAE, and RMSE scores are computed for each model to compare prediction performances.

In the final phase, gathered results obtained from the models using both pre-COVID-19 pandemic and COVID-19 pandemic data were compiled.

In the data preprocessing phase of this study, the Moving Average (MA) method is implemented. MA is a basic technical analysis tool used to smooth out the price data by establishing a continuously updated average price value. The average is taken for a specific period such as one month, one week, and so on. Strategies based on the MA tool are used widely and have the capability to be adapted to any time frame, which makes it appropriate both for long and short-term traders [24]. In this study, moving average prices and closing prices of gold and silver commodities are compared in time series. The results are shown in Figure 2 and Figure 3.

3.3. Model building

To analyze time series data set, machine learning methods are increasingly being preferred recently. Especially in the case of complex and non-linear data structures, machine learning methods can determine the relationship between the dependent and independent variables more precisely [3]. In accordance with the literature review, LSTM, RF and SVR are used as the most preferred algorithms for price forecast problems.

Considering such information, the following machine learning methods were used in this study for gold and silver price prediction.

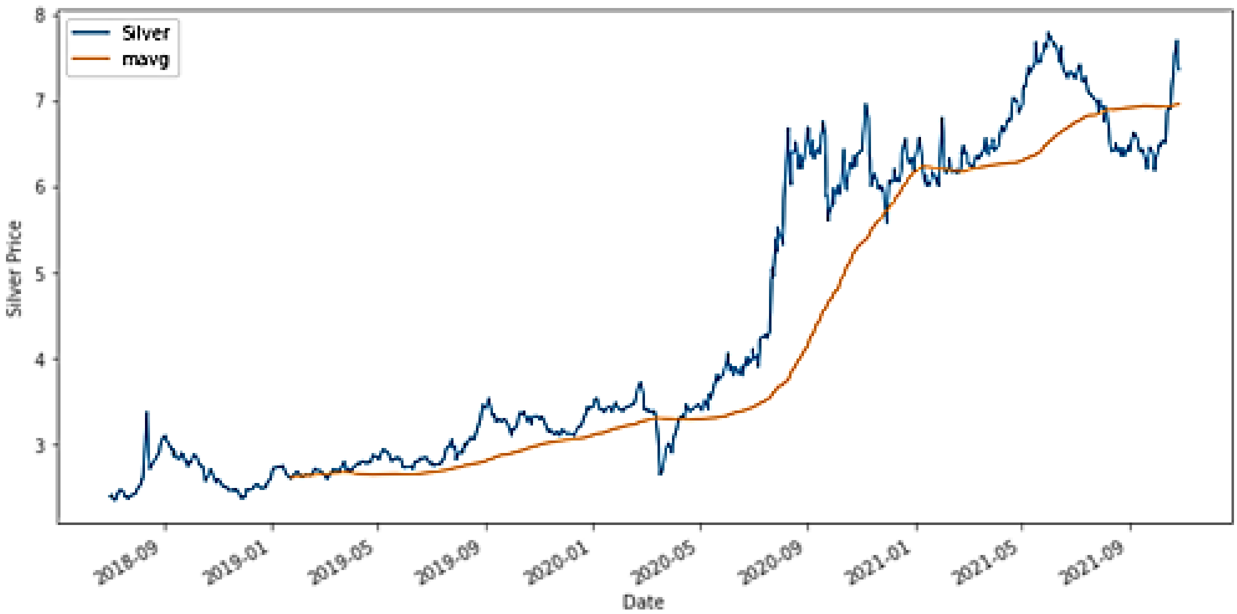

Figure 2. Silver closing prices with moving average prices

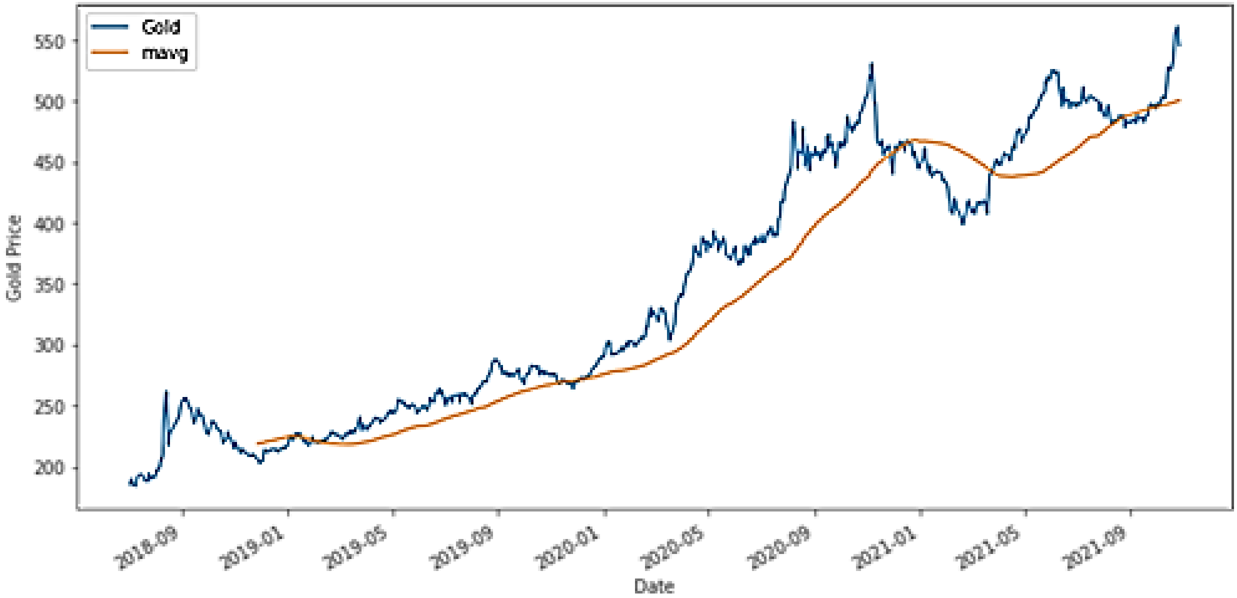

Figure 3. Gold closing prices with moving average prices

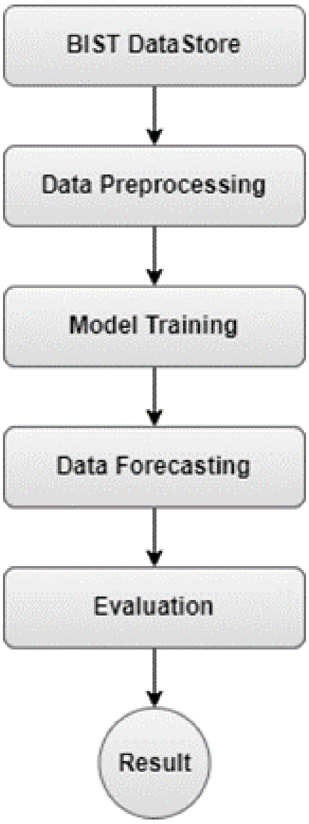

Figure 1. The prediction processes

3.3.1. Random Forest (RF)

RF model is introduced by Breiman [25]. Although it can be used in different areas, it is known as one of the most successful classification methods. In this algorithm, the decision trees examine randomly selected subsets at each node and are divided into branches.

RF is an ensemble method that is a combination of multiple models to create an optimal predictive model. RF works by building multiple decision trees during the training phase. Ensemble methods using slightly different data while building each tree increases the variety of models. Taking an average of the outcomes of several trees together diminishes the overfitting risk. Moreover, more accurate predictions are provided by multiple trees compared to a single tree [11].

The RF model used in this study is based on the TensorFlow machine learning framework [26]. The six parameters in Table 3 are crucial when building the model. The selected values are n_estimators = 300, max_depth = 5, min_samples_split = 2, min_samples_leaf = 1, bootstrap = True, random_state = 0. These selected values are picked by using the grid search method. Grid search is a brute-force approach for hyperparameter tuning. The model is trained and evaluated for each combination. The hyperparameters that result in the best performance are then selected.

Table 3. RF model parameters

Parameter	Description
n_estimators	refers to the number of trees in the forest
max_depth	refers to the maximum depth in a tree
min_samples_split	refers to the minimum number of data points prior to the splitting of the sample
min_samples_leaf	refers to the minimum number of leaf nodes that are required to be sampled
bootstrap	sampling for data points, true or false
random_state	generated random numbers for the random forest.

3.3.2. Long Short-Term Memory (LSTM)

Long-term short-term memory is considered one of the most successful RNN architectures. Long-term short-term memory is a memory cell, which is a processing unit that replaces conventional artificial neurons in the hidden layer of the network. These memory cells allow networks to efficiently allocate and remotely insert memory over time to dynamically record the data structure over time with high predictable capacity.

The main goal of RNN is to handle data sets whose inputs and outputs are sequences. The architecture of RNNs is adopted from artificial neural networks. The primary variance is that RNNs can reach both current and historical sequences to predict the results in the same step or current time sequence. This gives RNNs a substantial advantage while predicting time series data which can be categorized under time-sensitive sequential data [14].

An important shortcoming of RNN is its deficient ability to contend with long-term dependencies. This commonly occurs with a problem of vanishing gradients [14].

It is apparent that lots of complex financial indicators exist, and the fluctuation of the stock markets is overly aggressive. On the other hand, with the advances in technology, the chance to achieve a steady income in stock markets is expanded. This can also help experts to discover the best indicators to make better predictions.

At this phase, our data is inputted into the neural network and is trained for forecasts by assigning random weights and biases. Our LSTM model is built with 50 neurons and 4 hidden layers based on our previous experience. Lastly, one neuron was assigned to the output layer for predicting the normalized commodity close price. We also utilize the Adam stochastic gradient descent optimizer and the mean squared error. This model is based on Keras deep learning framework [26].

3.3.3. Support Vector Regression (SVR):

To be used in the Support Vector Machine (SVM) model, sub-algorithms of Support Vector Classification (SVC) and SVR algorithms should be used together. To implement the SVC model, the model needed to be separated in terms of kernel parameters as linear, sigmoid, and polynomial. The most suitable parameters are determined by changing the cache size and cost parameters of these three linear, sigmoid, and polynomial sub-models for the sub-algorithms.

Nu Support Vector Regression (NuSVR) is one of the sub-algorithms determined for SVR. To reach the best model, nu (upper limit of the training error rate and lower limit of the support vectors) value, cost, cache size, and other parameters such as degree is constantly tried during the performing of NuSVR. In addition to that, a radial basis function (RBF) kernel is applied to implement NuSVR.

Like the NuSVR, degree parameters, cache size, and cost are applied and tried to find the best model in the EpsilonSVR algorithm. Moreover, a linear kernel model is implemented in this algorithm.

The SVR model is based on the Scikit-learn machine learning framework [20].

SVR Scikit-learn library is defined as a class of the Support Vector Machine module. While training the model, it is applied for three different kernel parameters, and it is seen that the radial basis function kernel gives the best result.

3.4. Model accuracy assessment

The best-fit model is assessed based on higher accuracy and the least error scores. Regarding the measurement of performance results, the root mean square error measures the error between two data sets, the mean absolute error stands for the average of absolute values of all the differences in a set, and the mean absolute percentage error is considered in forecasting to compare the predicted results with LSTM, RF and SVR models.

3.4.1. Mean Absolute Percentage Error (MAPE)

MAPE is a type of measurement in statistics, used to predict the accuracy of a forecasting method, such as trend estimation. Another term used for MAPE is mean absolute percentage deviation (MAPD) [27].

3.4.2. Mean Absolute Error (MAE)

MAE is an expression referring to the average of absolute values of differences between measured values and actual values in a set. It measures the accuracy of the magnitude of errors and continuous variables without considering their direction [28].

3.4.3. Root Mean Square Error (RMSE)

RMSE compares a predicted value that is predicted by a model with the observed value. RMSE measures the magnitude of errors between two data sets [29].

4. Results

The prediction results of the models are visualized in Figures 4, 5, 6, 7, 8, and 9.

After the time series object is plotted with the information from the data set, it was seen that it can be analyzed on different components such as seasonality, trend, heteroskedasticity, and stationarity. To test the stationarity of the data set, the Augmented Dickey-Fuller Test and Kwiatkowski-Phillips-Schmidt-Shin Test are executed. The results of the tests are included and shown in Tables 4, 5, 6, and 7. According to these results of the applied tests, it is observed that the values of close price variables do not change over time.

LSTM, RF, and SVR methods are used to predict commodity prices and measure the effectiveness of using machine learning models during the COVID-19 recession. Table 8 lists the evaluated model results for gold and silver commodities. Results are given based on MAPE, MAE, and RMSE scores. The obtained findings are discussed in detail in the following section.

5. Discussion and Conclusion

This study compares LSTM, RF, and SVR methods to predict commodity prices and measure the effect of the economic crisis factor caused by the COVID-19 recession. The findings of this study point out that the LSTM model has more accurate predictions, especially in the pre-COVID-19 period. The reason for better LSTM model performance in predicting COVID-19 outcomes is likely due to the sequential nature of the data, which is well-suited for LSTMs. LSTMs are a type of RNN that can capture patterns in sequential data by processing information through hidden states that are passed from one-time step to the next. However, during the COVID-19 period, it could not give the most effective result for the gold commodity. Time series data typically exhibit temporal dependencies, where the value at a given time step is influenced by past values. Due to the fact that the bagging ensemble of decision trees used by RF could not capture the temporal relationships between observations for time series data, it could not provide efficient model performance in the pre-COVID-19 period for the gold commodity.

When considering the COVID-19 period only, SVR produces the best prediction results for the gold commodity and LSTM has the best prediction results for the silver commodity. With the COVID-19 recession, it is observed that uncertainties such as changes in market trends and prices caused by uncertainty and fear among investors, increased volatility and unpredictability in the financial markets, widespread job losses, reduced consumer spending, supply chain disruptions, and similar factors in the markets reflected a negative impact on the prediction models. It should also be highlighted that using a hybrid prediction model such as combining LSTM and SVR for commodity price prediction could provide better results even in extraordinary situations. For this reason, this study can provide a foundation to make emergency decisions even more precise and pragmatic for future machine learning studies. On the other hand, the main limitation of the study is the scope being narrowed down to Borsa Istanbul dataset for gold and silver commodities. Therefore, the obtained results depend on this cluster only. To eliminate this limitation, a future study may include testing LSTM, RF, and SVR methods with different datasets other than Borsa Istanbul.

Table 4. Stationarity test results for gold (COVID-19)

Augmented Dickey-Fuller Test		Kwiatkowski-Phillips-Schmidt-Shin Test	
Dickey-Fuller:	-1.8285878399555700	X-squared:	1.3232240371964543
Lag order:	0	Df:	17
p-value:	0.366363806384533	p-value:	0.01
Alternative hypothesis:	10%: -2.5714292194077513 5%: -2.8702852297358983 1%: -3.4502011472639724	Alternative hypothesis:	10% : 0.347 5% : 0.463 1% : 0.739

Table 5. Stationarity test results for gold (Pre-COVID-19)

Augmented Dickey-Fuller Test		Kwiatkowski-Phillips-Schmidt-Shin Test	
Dickey-Fuller:	-1.3903018258267308	X-squared:	1.3580822772797543
Lag order:	1	Df:	16
p-value:	0.5869166127306464	p-value:	0.01
Alternative hypothesis:	10%: -2.572506310013717 5%: -2.872304928618605 1%: -3.4548039258751206	Alternative hypothesis:	10% : 0.347 5% : 0.463 1% : 0.739

Table 6. Stationarity test results for silver (COVID-19)

Augmented Dickey-Fuller Test		Kwiatkowski-Phillips-Schmidt-Shin Test	
Dickey-Fuller:	-1.5465256906310958	X-squared:	1.5050727639465018
Lag order:	0	Df:	18
p-value:	0.5103831897872779	p-value:	0.01
Alternative hypothesis:	10%: -2.5705574627547096 5%: -2.8686500930967354 1%: -3.446479704252724	Alternative hypothesis:	10% : 0.347 5% : 0.463 1% : 0.739

Table 7. Stationarity test results for silver (Pre-COVID-19)

Augmented Dickey-Fuller Test		Kwiatkowski-Phillips-Schmidt-Shin Test	
Dickey-Fuller:	-0.5549123365711701	X-squared:	2.0040231470182444
Lag order:	2	Df:	18
p-value:	0.8808480575502857	p-value:	0.01
Alternative hypothesis:	10% : -2.5705 5% : -2.8686 1% : -3.4464	Alternative hypothesis:	10% : 0.347 5% : 0.463 1% : 0.739

Table 8. Evaluated model results

Commodity Name	Evaluating Indicators	LSTM (Pre-COVID-19)	LSTM (COVID-19)	RF (Pre-COVID-19)	RF (COVID-19)	SVR (Pre-COVID-19)	SVR (COVID-19)
Gold	MAPE	0.0182	0.0387	0.0608	0.0148	0.0386	0.0149
Gold	MAE	0.0647	0.2694	0.2123	0.1021	0.1350	0.1025
Gold	RMSE	0.0979	0.3620	0.2293	0.1434	0.1488	0.1180
Silver	MAPE	0.0216	0.0173	0.0361	0.0677	0.1718	0.0922
Silver	MAE	6.5359	8.9148	18.6405	20.6489	52.1202	46.7167
Silver	RMSE	8.4863	12.9622	27.9628	24.7679	55.1280	51.4302

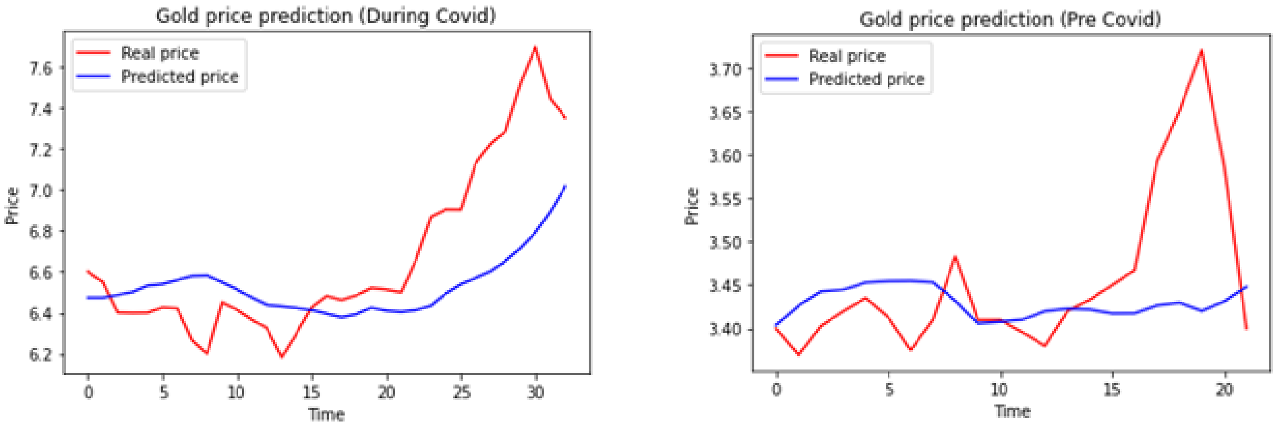

Figure 4. Gold price predictions using LSTM (left: COVID-19, right: Pre-COVID-19)

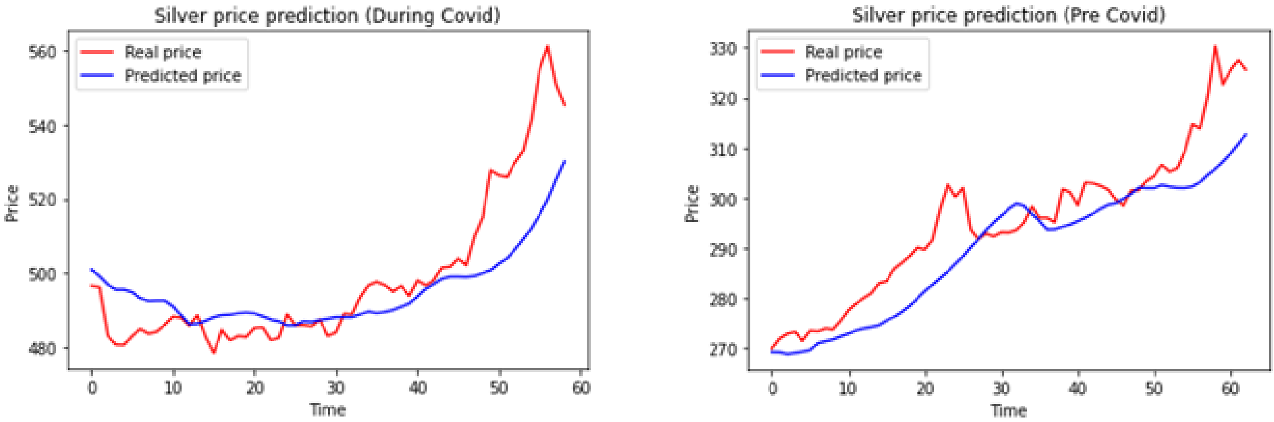

Figure 5. Silver price predictions using LSTM (left: COVID-19, right: Pre-COVID-19)

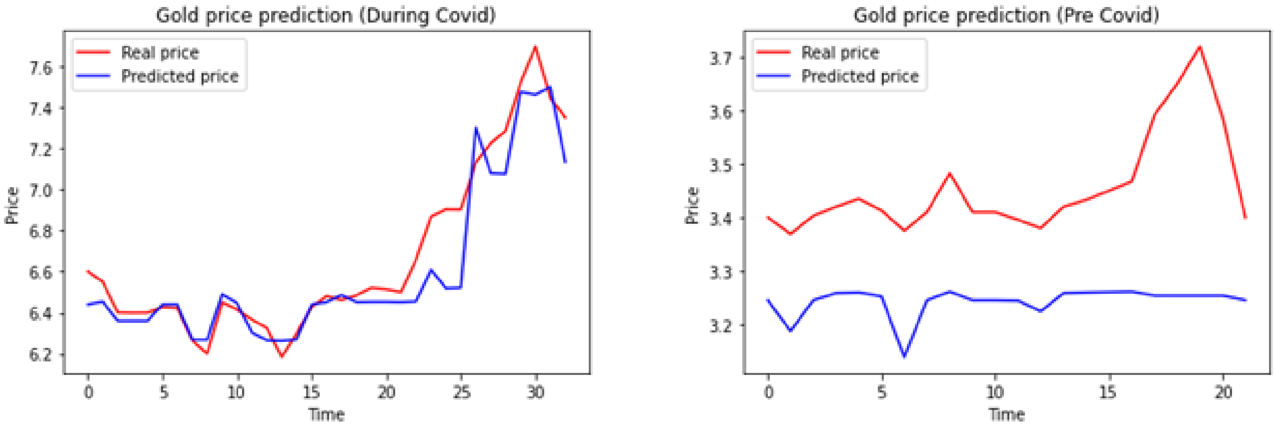

Figure 6. Gold price predictions using RF (left: COVID-19, right: Pre-COVID-19)

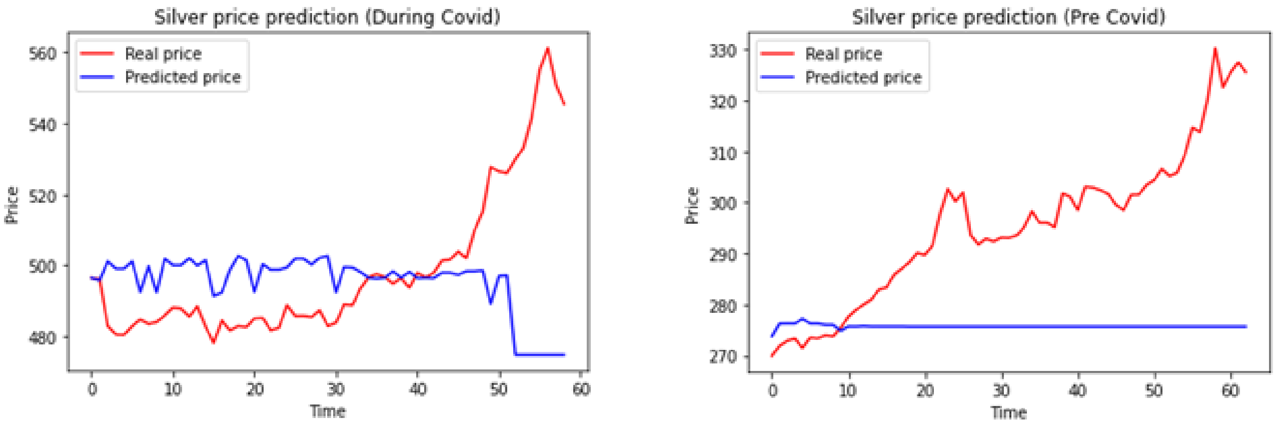

Figure 7. Silver price predictions using RF (left: COVID-19, right: Pre-COVID-19)

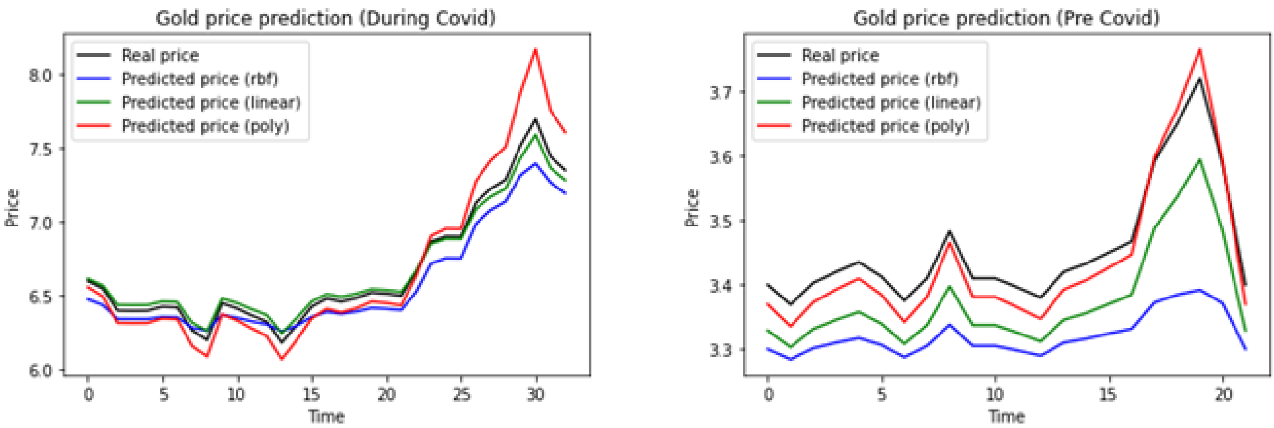

Figure 8. Gold price predictions using SVR (left: COVID-19, right: Pre-COVID-19)

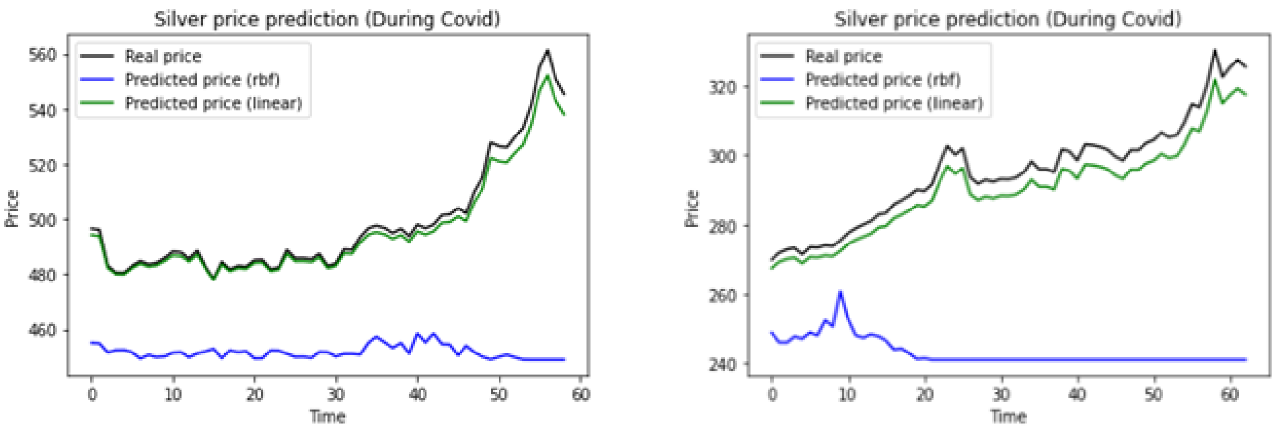

Figure 9. Silver price predictions using SVR (left: COVID-19, right: Pre-COVID-19)

Author contributions

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Tamer Uçar: Methodology, Reviewing, Editing

Conflicts of interest

The authors declare no conflicts of interest.

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