Sosyoekonomi

2025, Vol. 33(63), 103-113

RESEARCH ARTICLE

ISSN: 1305-5577
DOI: 10.17233/sosyoekonomi.2025.01.05
Date Submitted: 26.03.2024
Date Revised: 11.06.2024
Date Accepted: 26.11.2024

The Role of International Variables in Predicting Gold Prices: Analysis with Machine Learning Algorithms

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Uluslararası Değişkenlerin Altın Fiyatlarını Tahmin Etmedeki Rolü: Makine Öğrenmesi Algoritmaları ile Analiz

Abstract

This study predicted gold prices using the S&P 500, crude oil prices, dollar index and volatility index variables and various machine learning methods. Research results show that gold prices are predicted successfully with existing methods. According to analysis, the most successful gold price forecasters are the WTI, VIX, S&P 500 and US dollar indexes. The machine learning method that best predicts gold prices is the random forest method, with an R-square of 0.96 and a MAPE value of 3.5%. This study is expected to contribute to the literature in measuring the success of machine learning algorithms in price prediction and the predictability of gold prices within the framework of the efficient markets hypothesis.

Keywords : Gold Price, Financial Market, Machine Learning, Regression, Random Forest, Decision Tree, K Nearest Neighbour.

JEL Classification Codes : C45, G12, G17.

Öz

Bu çalışmada S&P 500, ham petrol fiyatları, dolar endeksi ve volatilite endeksi değişkenleri aracılığıyla makine öğrenmesi yöntemleri kullanılarak altın fiyatları tahmin edilmeye çalışılmıştır. Araştırma sonuçları, altın fiyatlarının makine öğrenme yöntemleriyle başarılı bir şekilde tahmin edildiğini göstermiştir. Analiz sonuçlarına göre en başarılı altın fiyatı tahmincileri sırasıyla WTI, VIX endeksi, S&P 500 ve dolar endeksidir. Altın fiyatlarını en iyi tahmin eden makine öğrenmesi yönteminin ise R-kare değeri 0,96 ve MAPE değeri %3,5 olan rastgele orman yöntemi olduğu belirlenmiştir. Bu çalışmanın makine öğrenmesi algoritmalarının fiyat tahmininde başarısını ve etkin piyasalar hipotezi çerçevesinde altın fiyatlarının tahmin edilebilirliğini ölçmede literatüre katkı sunması beklenmektedir.

Anahtar Sözcükler : Altın Fiyatları, Finansal Piyasa, Makine Öğrenmesi, Regresyon Rastgele Orman, Karar Ağacı, K-En Yakın Komşu.

1. Introduction

Investment is the purchase of assets from which earnings are expected today with savings. There are many investment alternatives for investors, such as stocks, bonds, real estate, investment funds and precious metals, each with different risk and return performance. Among these, gold is an investment instrument generally seen as a safe haven and especially preferred among risk-averse investors. Some other properties make gold superior to other metals. For example, although the use of gold varies according to geographical regions in the world, its production is limited. Only certain areas and countries have limited gold reserves. For this reason, it is difficult for the gold supply to respond to changes in gold prices in the short term; in other words, the supply has an inelastic structure in the short term. Gold is an important metal due to its physical and chemical properties, such as its resistance to chemicals and oxidation, ability to be easily shaped, and high thermal and electrical conductivity. No other material can replace gold, and no precious metal has the same or similar properties. In addition, gold is a reserve tool. This is because this metal is used as a reserve instrument by many countries worldwide (Atay, 2013: 12-13). In addition to these features, the fact that it is accepted worldwide as a savings tool further increases the value of gold.

Many global variables affect the gold price. These factors increase its volatility, cause irregularity, and make it difficult to predict it accurately (Alameer et al., 2019: 250-260).

Figure: 1
Gold Prices (USD/Ounce)

Source: Prepared by the authors with data taken from <tr.investing.com>, 12.11.2023.

Figure 1 shows the value of gold prices in dollars for the twenty years between 2003 and 2023. Gold prices fluctuate over the years and are prone to ups and downs. Many studies examine the relationships between gold prices and alternative investment instruments. In predicting gold prices, country indices (Mombeini & Chamzini, 2015; Manjula & Karthikeyan, 2019; Patalay & Rao Rao, 2021; Yüksel & Akkoç; 2016), exchange rates (Mombeini & Chamzini, 2015; Gülhan, 2020; Yüksel & Akkoç, 2016), interest and inflation rates (Mombeini & Chamzini, 2015; Toraman et al., 2011; Yüksel & Akkoç, 2016; Gültekin & Hayat, 2016), crude oil prices (Patalay & Rao Rao, 2021; Gülhan, 2020; Patalay & Rao Rao, 2021) were used in many research. Predicting gold prices allows testing a market for weak-form efficiency and helps portfolio managers, investors, and the government treasury department make better investment decisions.

This study used machine learning algorithms Random Forest, Hist Gradient Boosting Regressor, K-Nearest Neighbor, and Multilayer Perceptron to predict gold prices. It used famous and neglected variables in the literature to determine the factors affecting gold prices. This study distinguishes itself from other studies by ranking the importance of variables in predicting gold prices, operating with a wide sample window, and measuring the success of different machine learning algorithms.

2. Literature Review

This study evaluated the literature from two perspectives. It included studies on predicting gold prices or the factors affecting gold prices. It also included studies using machine learning algorithms and measuring the method's success.

Mombeini and Chamzini (2015) predicted gold prices with ARIMA and artificial neural networks, and it was determined that the artificial neural network model was superior to ARIMA. Yüksel and Akkoç (2016) predicted gold prices with an artificial neural network model and concluded that oil and silver prices successfully predicted gold prices. Manjula and Karthikeyan (2019) predicted gold prices with stock market, crude oil, interest and inflation variables. Among the methods used in prediction, Random Forest regression showed the best performance. Hansun and Suryadibrata (2021) used the Long Short-Term Memory (LSTM) model, a deep learning method, to predict gold prices during the Covid-19 period and achieved successful results with a 97% R^2 value. Patalay and Rao Rao (2021) used the M5P machine learning algorithm to predict gold prices using S&P 500 and crude oil variables. In the study, the algorithm was successful with 85% accuracy. Madziwa et al. (2022) estimated the gold demand and used the lagged gold price and bond interest rates. As a result of the study, the primary determinant of gold demand is gold demand, not bond interest rates. Swamy and Lagesh (2023) showed in their research that the mood on Twitter can be used to predict gold prices with the Granger causality test. Vrontos et al. (2021) used a variety of machine learning algorithms to evaluate the VIX index, which measures investor fear. This research shows that discriminant analysis techniques, the rigit model, adaptive boosting, and Naive Bayes produced the best results. Pfahler (2021) estimated the monthly foreign exchange data used in OECD countries between 1973 and 2014 with artificial neural networks and random walk models. Uncovered Interest Rate Parity (UIP), Purchasing Power Parity (PPP), Monetary Model (MM) and Artificial Neural Networks (ANN) model were used in the study. As a result of the study, it was determined that ANN models were the method with the best predictive power. Söylemez (2020) used artificial neural networks to predict the price of gold using data from 2014 to 2019 on Brent oil prices, the VIX index, the Dow Jones index, and the US Dollar index. An analysis was performed by creating a 4-layer artificial neural network using different neuron counts. The investigation revealed that the model with 20 neurons had the highest prediction accuracy of gold prices, ending at 98.44%. In the study, Cohen and Achie (2023) used advanced machine learning (ML) techniques to forecast the price of gold. The analysis used the S&P 500, the VIX volatility index, and the yields on 10-year bonds issued by the USA, Germany, France, and Japan as inputs. Three machine learning methods were selected to predict gold prices: Random Forest, Extreme Gradient Boosting (XGBoost), and Gradient Boosted Regression Trees (GBRT). The findings demonstrate that, with varying levels of accuracy, these machine-learning algorithms can be helpful to instruments for anticipating changes in the price of gold. According to the models analysed, gold's three-day Moving Average (MA) accounts for most of the daily price variation. In addition, the testing relative mean square error (RSE) of 0.43635 and the testing mean square error (MSE) of 0.00004892 were obtained from the random forest (Rf) model. The RSE value indicates that the model's predictions are near the actual values. Gbadomisi et al. (2024), monthly estimated US market gold prices from 1978 to March 2023, based on the Multilayer Perceptron (MLP) regression model and the Autoregressive Integrated Moving Average (ARIMA) model. When compared to the ARIMA model, it has been found that the multilayer perceptron (MLP) model from artificial neural networks provides the most accurate results. Özkan (2011) used an artificial neural network model to forecast the foreign currency rates for 2020 and 2021. Decision Tree, Support Vector, Gaussian, and Linear Step analyses were employed in the study. The investigation revealed that the Decision tree method was the best machine learning model, with a 99.84% predictive power. In addition, it was found that, at 86.83%, the linear step analysis performed worse than the others.

Çam and Kılıç (2018) predicted daily returns of gold prices in Turkiye by using artificial neural networks algorithm and Markov chains models together. They found that gold price returns provided 70% success in future prediction. Gülhan (2020) investigated the effect of oil prices, the BIST100 Index, the exchange rate (US Dollar) and the VIX Index on gold prices. It was concluded that there is a Granger causality relationship between gold prices, BIST 100 Index, oil prices and exchange rate. Küçükaksoy and Yalçın (2017), the effects of oil prices, silver prices, Dow Jones Industrial Index, Dollar Sterling parity and FED fund interest rate on gold prices were examined, and the power of past price data to explain the spot price of gold was found to be 97%. Toraman, Basarir and Bayramoğlu (2011) investigated the effects of oil prices, the US Dollar exchange rate, the US inflation rate, and US real interest rates on gold prices and found a high negative correlation with the US dollar exchange rate and a high positive correlation with oil prices. Gültekin and Hayat (2016) explained the relationship between the gold prices of the Istanbul Gold Exchange and the exchange rate, interest rate, CPI and BIST 100 index, ounce price of gold, and oil price. As a result, the variables with the largest share in the future forecast error variance for the gold price were the ounce price and the oil price.

When the studies are evaluated in general, it can be concluded that machine learning algorithms are quite successful in price predictions. In addition, some international variables have also yielded positive results in predicting gold prices.

3. Data and Methodology

This study utilised a dataset spanning 1200 days, covering the time frame from January 2, 2000, to December 18, 2022, to evaluate the predictive capabilities of machine learning in estimating gold prices using three distinct algorithms. The analysis period was determined by considering the continuity of the data. Table 1 shows this research's variables, symbols, and data sources.

Table: 1
Variables

Variable	Symbol/Unit	Source
Ounce Gold	XAU/USD	<https://tr.investing.com>
S&P 500 Index	SPX/USD	<https://tr.investing.com>
US Dollar Index	DXY/USD	<https://tr.investing.com>
WTI	WTI/USD	<https://tr.investing.com>
VIX	VIX	<https://tr.investing.com>

WTI, one of the variables shown in Table 1, represents the spot price of American WTI (West Texas Intermediate) crude oil, an important economic component. The VIX index reflects fear and anxiety about the markets. This index was created by CBOT (Chicago Board of Trade) in 1993 to measure the level of risk perception in the market.

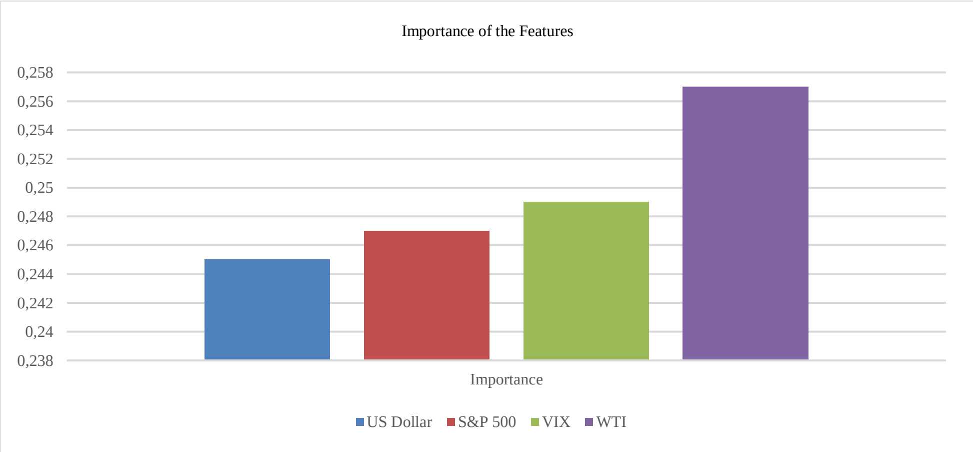
3.1. Feature Selection

In this study, the importance and requirements of the features were analysed using the tree-based feature selection algorithm before analysing the data set. Tree-based feature selection is a crucial technique in finance studies, as it allows for the identification of relevant variables for modelling financial phenomena. The use of tree-based models for feature selection in finance has been highlighted in various studies. For instance, it emphasised the interpretability of tree-structured regression models and the impact of variable selection bias on model interpretability (Hothorn et al., 2006: 651-674). Additionally, it pointed out the absence of a standard feature selection or regularisation procedure in tree-based methods, unlike in linear regression and LASSO models (Wundervald et al., 2020). Furthermore, it highlighted the effectiveness of tree regularisation frameworks in providing efficient feature selection solutions for practical problems, given the natural ability of tree models to handle various data complexities (Deng & Runger, 2012).

The dataset used in the study includes four features: the US dollar index, the S&P 500 index, VIX, and WTI, to estimate ounce gold prices. According to the feature importance array given by the tree-based feature selection algorithm, the S&P 500 index, WTI, US dollar, and VIX are more critical, respectively. The importance value array is given in Equation 1, and the importance graph is shown in Figure 2.

$$[0.2470 \quad 0.2577 \quad 0.2456 \quad 0.2495] \tag{1}$$

Figure: 2
Importance of the Features of Classification



The algorithm did not eliminate a feature because no feature was significantly less critical according to the importance array. In this context, all features (US dollar index, S&P 500 index, VIX and WTI) have been used to estimate ounce gold prices.

3.2. Data Analyses

Machine learning is a broad field encompassing diverse techniques to construct predictive models based on data. These algorithms play a crucial role in transforming raw datasets into meaningful models that can be used for various purposes. The selection of the most appropriate algorithm type, whether supervised, unsupervised, classification, regression, or others, is contingent upon several factors. These factors include the characteristics of the data under analysis, the computational resources available for model training, and the modelling process's specific objectives and desired outcomes. In this study, the focus is on applying regression algorithms. The regression algorithms are used when the goal is to predict a continuous numerical value based on input features. Three distinct regression algorithms have been employed in this study to train and evaluate the model using a specific dataset. The choice of regression algorithms may vary depending on the complexity of the data, the presence of outliers or noise, and the underlying relationships between the variables in the dataset (Bishop, 2006).

The study used four different regression algorithms to predict ounce gold prices: Hist Gradient Boosting Regression, Random Forest, K-nearest neighbour, and Multilayer Perceptron.

Hist Gradient Boosting Regressor is a machine learning algorithm implemented in the scikit-learn library, designed explicitly for regression tasks. It belongs to the family of gradient boosting machines (GBM), which are ensemble learning methods that build a series of decision trees sequentially, each one correcting the errors of its predecessor (Sharma et al., 2023).

Random Forest (RF) is a supervised learning algorithm known for its versatility in handling classification and regression tasks. RF is distinguished by its user-friendly interface and adaptability across various domains. This algorithm operates by creating an ensemble of decision trees, each trained on randomly selected subsets of the data. By leveraging these individual trees, RF can make predictions based on each tree's output. RF combines these predictions through aggregation to arrive at an optimal solution, improving its overall predictive accuracy (Louppe, 2015: 58-60).

The K-Nearest Neighbor (KNN) regressor is a machine learning algorithm categorised as a density-based or distance-based learner. It is extensively applied for prediction tasks by utilising the knowledge from the k-nearest samples to the input sample. This methodology entails computing the distances between the k and input samples through diverse distance metrics. Among these metrics, the Euclidean metric is frequently utilised, quantifying the direct distance between two points in space. Throughout its experimental phase, the KNN regressor employs the Euclidean metric and analogous methodologies to enhance its predictive capabilities (Zou & Li, 2022: 1-12).

Multilayer Perceptron (MLP) regressors are a popular choice in machine learning for implementing neural network-supervised regression models. MLPs are structured with neurons arranged in multiple layers, interconnected by weighted connections, allowing complex nonlinear relationships to be captured (Ramchoun et al., 2016: 26-30).

3.3. Evaluation Metrics

The assessment of regression models involves the utilisation of various metrics, including the Mean Absolute Percentage Error (MAPE), R-squared (R^2) coefficient, MSE (Mean Squared Error) and MAE (Mean Absolute Error). The Mean Absolute Percentage Error (MAPE) is a metric that quantifies the average accuracy in percentage terms relative to the original values, as defined in Equation 2 (Kim & Kim, 2016: 669-679).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - f(x_i)|}{y_i} \tag{2}$$

The coefficient of determination, denoted as R-squared (R^2), is a statistical metric that signifies the proportion of the variance in the dependent variable that is predictable from the independent variables (Miles, 2014). It is calculated using Equation 3.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - f(x_i))^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

MSE (Mean Squared Error) is the squared difference average between predicted and actual values. By squaring the differences, MSE penalises more significant errors than smaller ones, making it sensitive to outliers (Allen, 1971). It is calculated using Equation 4.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}((y_i - \hat{y}_i)^2 \tag{4}$$

MAE is the average of the absolute differences between predicted and actual values. It is calculated using Equation 5 and gives a straightforward measure of the average magnitude of errors without considering their direction (Willmott, 2005).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{5}$$

4. Findings

The study split the dataset into 80% for training and 20% for testing. Among the regression algorithms used, the random forest algorithm showed the best performance with an R^2 value of 0.96, MAE-MSE 0.13 and a MAPE value of 3.5%. The algorithm that showed the second-best prediction success was the Hist Gradient Boosting algorithm with 0.15 MAE, 0.16 MSE, 0.94 R^2 and 5.01% MAPE value. After these two algorithms, the other algorithm that ranks third is KNN with 0.21 MAE, 0.2 MSE, 0.94 R^2 and 5.57% MAPE. The MLP algorithm, based on artificial neural networks, showed the worst success, with an R^2 value of 0.73, 0.36 MAE, 0.27 MSE and a MAPE value of 29.1%. Table 2 and Figure 3 show the performance of the regression algorithms.

Table: 2
Performance of the Algorithms

Algorithm	MAPE	R^2	MAE	MSE
RF	**3.5%**	**0.96**	**0.13**	**0.13**
HGB	5.01%	0.94	0.15	0.16
KNN	5.57%	0.94	0.21	0.20
MLP	29.1%	0.73	0.36	0.27

The adaptability of random forest and histogram gradient boosting methodologies enables them to perform better even in constrained sample sizes. These techniques can discern significant patterns and provide precise predictions despite limited data points. This flexibility guarantees the extraction of valuable insights and the generation of dependable outcomes from relatively small datasets. On the contrary, artificial neural network-based algorithms perform less in datasets with few data and features. Additionally, the WTI and

VIX features have increased the models' success, and it can be said that these two values are important for predicting gold prices, as seen in the importance array.

5. Conclusions

Throughout history, gold has gained a seat in the monetary system first as a medium of exchange and then as a means of storage and investment. In addition to the physical and chemical properties that make gold valuable, the fact that it symbolises wealth in the world is a reserve tool. It has the feature of a safe haven in traditional investment and, in times of financial instability, makes it strategically important. Predicting and interpreting gold prices is vital for investors, who have investors almost all over the world. A wide variety of factors affect gold prices in international markets. Various variables and methods have been used in the literature to predict gold prices. The most important are stock market indices, crude oil, Brent oil, exchange rates and fear index.

In this study, the factors that are successful in predicting the ounce gold price were examined. This research used the S&P 500 index, VIX, WTI and the US dollar index as input variables to estimate gold prices. Considering the variables, both frequently used and less used factors in the literature were discussed in this study. Three different algorithms, Random Forest, K-Nearest Neighbor, and Decision Tree, were used to test gold pricing. The machine learning algorithms used are statistically successful in predicting gold prices. The random forest method, with an R-square value of 89.77%, achieved the best result among the techniques used. The study also included the importance of the variables and demonstrated the models' predictive success. According to the study results, the variable that has the highest impact in predicting gold prices is the WTI index. This is followed by the fear, S&P 500, and US dollar indexes.

The findings of this study show two issues that can support and contribute to the finance literature. First of all, those who invest in gold can predict the price of gold with the help of some variables, which can undoubtedly benefit the investor. In addition, this result contradicts Fama's popular random walk and efficient markets hypothesis (1965). In these hypotheses, Fama argues that asset prices occur randomly and cannot be predicted. However, machine learning algorithms offered by developing technology to researchers have successfully predicted prices. Future studies can test different asset prices with different prediction algorithms.

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