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Machine Learning-Based Comparative Analysis of the Determinants of Gold Prices

Abstract

In this study, various machine learning methods were compared to identify the economic factors influencing gold prices and to determine the most effective prediction model. The methods used include linear regression, multivariate adaptive regression splines (MARS), extreme gradient boosting (XGBoost), random forest, artificial neural networks (ANN), and the ensemble-based voting regressor. According to the test data results, the MARS model demonstrated the highest prediction accuracy, followed by the ANN model and the voting regressor model. The analysis of the three best-performing models revealed that the most influential factors on gold prices are silver prices, the BIST 100 Index, and the NASDAQ Index. Overall, machine learning approaches outperformed traditional models, with MARS providing the most reliable and accurate predictions for gold price forecasting.

Keywords: Gold prices, MARS, XGBoost, Machine learning

Altın Fiyatlarını Belirleyen Faktörlerin Makine Öğrenmesi Tabanlı Karşılaştırmalı Analizi

Öz

Bu çalışmada, altın fiyatlarını etkileyen ekonomik faktörleri belirlemek ve en etkili tahmin modelini ortaya koymak amacıyla çeşitli makine öğrenmesi yöntemleri karşılaştırılmıştır. Kullanılan yöntemler arasında doğrusal regresyon, çok değişkenli uyarlamalı regresyon eğrileri (MARS), aşırı gradyan artırma (XGBoost), rastgele orman, yapay sinir ağları (ANN) ve topluluk yaklaşımına dayalı voting regressor yer almaktadır. Test verisi sonuçlarına göre, en yüksek tahmin doğruluğunu MARS modeli göstermiş; MARS modelinden sonra yapay sinir ağları modeli ve voting regressor modeli güçlü performans sergilemiştir. En iyi performans gösteren üç modelin analizi, altın fiyatlarını en çok etkileyen faktörlerin gümüş fiyatı, BIST 100 Endeksi ve NASDAQ Endeksi olduğunu ortaya koymuştur. Genel olarak, makine öğrenmesi yaklaşımları geleneksel modellere göre daha üstün bir performans sergilemiş, MARS modeli ise altın fiyatı tahmininde en güvenilir ve en doğru sonuçları sağlamıştır.

Anahtar kelimeler: Altın fiyatları, MARS, XGBoost, Makine öğrenmesi

1. Introduction

Gold has an important place throughout history as a store of value, investment and exchange tools. Today, gold maintains this importance and is among the most important investment tools. It is considered a safe haven in times of economic and financial instability. Financial crises, wars, pandemics, inflation and exchange rate fluctuations cause investors to turn to gold. In this context, it is important for investors and policymakers to know the economic factors that may affect gold prices when making strategic decisions [1]. In global financial markets, gold prices are highly affected by various macroeconomic variables such as exchange rates, inflation rates, interest rates, stock market fluctuations and commodity prices. In recent years, fluctuations in global currencies such as the US dollar have directly affected the global price of gold. Similarly, when interest rates fall, demand for gold increases. In addition, sudden changes in stock and other commodity markets also direct investors to gold, which is considered a haven.

In recent years, alongside traditional econometric methods, the use of machine learning techniques to identify macroeconomic indicators affecting gold prices has increased significantly. Due to the volatile nature of financial markets, the relationships between macroeconomic variables and financial market indicators are often non-linear. Therefore, these relationships cannot be accurately analyzed using linear and traditional methods. In recent years, the methods such as MARS, XGBoost, and decision trees have become increasingly popular for analyzing non-linear relationships. These methods have also gained popularity in analyzing the factors affecting gold prices [2]. There are many studies in the literature examining the factors affecting gold prices. These studies mostly focus on macroeconomic and financial indicators. Since this study investigates the indicators affecting gold prices in Türkiye, more emphasis was placed on studies conducted with Turkey in the literature review. Details regarding the studies are provided below.

Özkan and Kolay [3] investigated the impact of basket exchange rate, the BIST 100 Index, deposit interest rate and inflation rate on gold prices. They found a statistically significant relationship between exchange rate, deposit interest rate, inflation rate and gold prices. However, they revealed that there is no relationship between the BIST 100 Index and gold prices. Elmas and Polat [1] examined the relationship between inflation, silver prices, oil prices, exchange rates, interest rates, the Dow Jones Index economic indicators and gold prices. As a result of the study, it was seen that inflation, silver and oil prices have a positive effect on gold prices, while exchange rates, interest rates and the Dow Jones index have a negative effect. Yüksel and Akkoç [4] examined whether there is a relationship between gold prices and silver prices, Brent oil prices, US dollar/EUR parity, the EuroNext100 Index, the Dow Jones Index, the 13-week US bond interest rate and the US CPI Index variables using artificial neural networks. As a result of the study, it was seen that the most important economic indicators affecting gold prices are silver and oil prices. Abar [2] investigated the relation between gold and silver prices, crude oil WTI futures prices, the US Dollar Index, the S&P500 Index, US federal funds compound interest rate, US CPI economic indicators using MARS and XGBoost methods. As a result of the analysis, he stated that MARS and XGBoost models can be preferred in gold price prediction. The results showed that the U.S. Consumer Price Index, Dollar Index, oil prices, and silver prices have an impact on gold prices.

Tursoy and Faisal [5] investigated the relation between stock, gold and crude oil prices using Türkiye data between 1986-2016. Cointegration and short and long term relationships were investigated with the ARDL model, and long-term relationships were investigated with FMOLS, DOLS and CCR methods. According to the analysis results, there was a negative correlation between gold and stock prices in the both short and long term, while positive correlation between crude oil and stock prices. Ojaghlou and Satvatı [6] analyzed the relationship between inflation and gold prices with the structural VAR model. According to the results of analysis, no long-term relationship between inflation and gold prices was found in Türkiye. In addition, they determined that inflation affected the gold price, but the gold price did not affect inflation according to causality analysis. The results of the structural VAR analysis showed that there was no statistically significant interaction between the variables except at the beginning of the period. Sui et al. [7] examined the potential of gold to protect against negative movements in inflation and exchange rates. They used the country data of Turkey, Peru and US utilizing the quantile-quantile regression and quantile-quantile correlation models. They showed that gold provides protection against currency movements and inflation fluctuations for Turkey and the US. It was understood that gold is seen as a safe haven against inflation or exchange rate volatility.

Depren et al. [8] examined the impact of global and national monetary policy measures and COVID-19 on gold prices using daily data between January and August 2020 using random forest, SVM and k-NN. According to the analysis result, the exchange rate before the pandemic is the most effective variable on gold prices. During the pandemic, the number of securities purchased by the central bank was effective on gold prices. During the pandemic, the number of cases and deaths had a moderate effect on gold prices. Alıcı and Köseoğlu [9], in their study covering the period from 2000 to 2019, employed the ARDL method to investigate the variables that influence gold prices in the long run. The results of the study indicate a long-term relationship between gold prices in Türkiye and various factors, including the London market gold ounce price, the U.S. inflation rate, the Dow Jones Industrial Index, the U.S. Federal Reserve interest rate, and the real effective exchange rate.

Kan and Serin [10] examined the correlation between gold prices and inflation rate, deposit interest rate, exchange rate and the BIST 100 Index for the period 2000-2019 in Türkiye using Fourier Toda-Yamamoto causality tests. The analysis revealed that positive significant relationship between inflation rate, the BIST 100 Index and gold prices in Türkiye. Moreover, there is a negative significant relationship between gold prices and interest rates. Kilimci [11] forecasted the gold index for the period between July 2019 and July 2020 using the opening, closing, lowest, and highest values of both the gold and dollar indices. The models employed include linear regression, polynomial regression, decision tree regression, random forest regression, support vector regression, as well as voting regressor and stacking regressor. The results of the study show that voting and stacking regressors provided better performance in predicting the gold index. Vargeloğlu and Özdemir [12] used hidden Markov models to estimate the percentage change in gold prices and its underlying causes for the 2013-2023 period. The effects of the dollar, interest rates, and inflation indicators on gold prices were investigated using Markov models. Unlike other methods, this approach provided estimates not only of the changes in gold prices but also of the underlying hidden states driving those changes.

Badshah et al. [13] examined the relationship between gold prices and inflation, the Turkish Lira/US Dollar exchange rate, interest rate, the BIST 100 Index closing price, the Brent oil price, platinum price, silver price and the 2010-based steel index in Türkiye using monthly data for the period 1997- 2021 using ARIMAX, GARCH and NARX models. The analysis shows that silver and platinum prices have a positive effect on gold prices. In addition, BIST 100 Index closing price and Brent oil prices also have an effect on gold prices; however, these relationships are negative. Qin et al. [14] investigated the Granger causal relationship between the geopolitical situation in Russia and the international gold market by applying the bootstrap subsample method. As a result of the study, it was proven that there are positive and negative effects from Russian geopolitical risk to gold price. Accordingly, while Russia's deteriorating geopolitical environment can stimulate the international gold market, it can be said that the gold price has a positive effect on Russian geopolitical risk and the gold market can be seen as a forward-looking indicator reflecting Russian geopolitical risk. Beladi et al. [15] investigated the effect of national culture on the demand for jewelry and gold, bars and coins using panel data analysis using 2010-2022 data from 24 countries. The analyses were examined in three cultural clusters: Confucian Asian economies, Western economies, and Middle Eastern and South Asian economies. It was revealed that the COVID-19 pandemic variable had a positive effect on the demand for gold in Confucian economies, jewelry in South Asian and Middle Eastern economies, and bars and coins in Confucian economies. When there are economic downturns, individuals in Confucian economies, South Asian and Middle Eastern economies may shift their assets to gold. Cohen and Aiche [16] used random forest, gradient boosted regression trees (GBRT) and extreme gradient boosting (XGBoost) methods to predict gold price fluctuations. In the study, they used data from leading global stock indices, S&P500 VIX volatility index, major commodity futures and 10-year bond yields from the US, Germany, France and Japan. They found that the most effective stock indices affecting the gold price forecast were one-day lagged data of ASX, S&P500, TA35, IBEX and AEX, US and Japanese bond yields and lagged data of gas and silver. Duman et al. [17] investigated the effects of the S&P 500 Index, crude oil prices, the dollar index, WTI, and the VIX Index on gold prices using machine learning methods, including random forest, decision tree, and k-nearest neighbor. According to the analysis results, the most significant variables influencing gold prices were the WTI, the VIX ındex, the S&P 500 Index, and the dollar index.

Since this study investigates the indicators affecting gold prices in Türkiye, a summary table of the studies conducted in this field in Türkiye in recent years is given in Table 1.

Table 1. Summary of literature findings related to Türkiye

Author	Method	Variables	Main Results
Ozkan and Kolay [3]	Multiple Linear regression	The basket exchange rate, the BIST 100 Index, deposit interest rate, inflation rate	Basket exchange rate, deposit interest rate, and inflation rate have a statistically significant impact on gold prices
Tursoy and Faisal [5]	ARDL, FMOLS, DOLS, CCR	Stock prices, gold prices, crude oil prices	Negative relationship between gold and stock prices in the short and long term, and a positive relationship between crude oil and stock prices.
Ojaghlou and Satvatı [6]	Structural VAR	Inflation, gold price	No long-term relationship or cointegration between inflation and gold prices
Depren et al. [8]	Random Forest, Support Vector Machines and k-NN	Global and national monetary policy measures, measures related to COVID-19, gold price	The exchange rate before the pandemic is the most effective variable on gold prices
Alıcı and Köseoğlu [9]	ARDL, VAR, Granger Causality	Inflation, interest rates, exchange rates, and indices	The relationship between gold prices, inflation, and exchange rates
Kan and Serin [10]	Fourier Toda-Yamamoto Causality	Gold prices, inflation rate, deposit interest rate, exchange rate, the BIST 100 Index	There is a positive and statistically significant relationship between inflation rate, the BIST 100 Index and gold prices
Vargeloğlu and Özdemir [12]	HMM, Viterbi Algorithm	Gold, exchange rates, interest rates, and inflation	The use of HMM enhanced predictability
Badshah et al. [13]	ARIMAX, GARCH and NARX	Gold prices, inflation, Turkish Lira/US Dollar exchange rate, interest rate, the BIST 100 Index closing price, the Brent oil price, platinum price, silver price, 2010-based steel index	Silver and platinum prices have a positive effect on gold prices. BIST 100 Index closing price and Brent oil prices also have a negative effect on gold prices

In the literature, the main macroeconomic variables that affect gold prices are generally inflation, exchange rates, interest rates, stock market indices, and energy and commodity prices. Previous studies have also shown that artificial intelligence and machine learning methods significantly improve prediction performance. In this context, the existing literature indicates that machine learning methods can be effectively used together with traditional econometric approaches to identify the factors affecting gold prices.

The originality of this study lies in using a broader and more up-to-date dataset that includes not only macroeconomic indicators but also sectoral and financial indicators, unlike the limited variable sets commonly used in the literature. This data structure is analyzed using methods that can better capture nonlinear relationships. As a result, both prediction accuracy is improved, and the factors affecting gold prices are evaluated in a more comprehensive framework. This approach allows comparing methods by considering not only training performance but also testing and validation results. Therefore, the study adds further depth to the existing literature in terms of data scope and methodological design.

2. Methods

In this study, different modeling approaches were applied and compared to determine the factors affecting gold prices. In the first stage, linear regression (LR) was used as the reference model. However, since nonlinear relationships and interactions between variables were observed in the dataset, more flexible methods were applied. In this context, Multivariate Adaptive Regression Splines (MARS), Random Forests (RF), Artificial Neural Networks (ANN), XGBoost and Voting Regression (VR) methods were used.

The LR model was estimated using the standard OLS approach. The MARS model created piecewise linear basis functions through knot points; the RF model built many decision trees using the bagging method, XGBoost used the gradient boosting technique. In addition, a Voting Regressor was constructed by combining the predictions of the RF and XGBoost models to leverage their complementary strengths and improve predictive performance. Five-fold cross-validation was applied to the training set to assess model validity and reduce overfitting. In the MARS model, cross-validation was employed to determine the optimal number of basis functions; in the RF model, to select hyperparameters and determine the number of trees using an early stopping strategy; in the XGBoost model, to tune hyperparameters and stop the model at the optimal boosting iteration through early stopping; and in the ANN model, to assess whether the selected network architecture produces consistent and stable results across different data splits and to reduce overfitting by means of early stopping. Model performances were compared based on the following criteria: Root Mean Square Error (RMSE), Relative Root Mean Square Error (RRMSE), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (CAIC), Coefficient of Determination (R^2), and Adjusted R^2.

2.1. Linear Regression Model (LR)

Multiple linear regression expressed as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} + \varepsilon_i$$

where y is the dependent variable, $x_{i1}, x_{i2}, \ldots, x_{ik}$ are the independent variables, $\beta_0, \beta_1, \ldots, \beta_k$ are unknown regression parameters and ε_i is the error term. The matrix form of multiple LR is as follows:

$$y = X\beta + \varepsilon$$

where **X** is an (nxp) matrix of predictors, **y** is an (nx1) vector of observed values, β is a (px1) vector of unknown parameters and ε is an (nx1) vector of error. The least squares estimation of β is given by

$$\sum_{i=1}^{n} (y_i - x_i'\beta)^2 = (y - X\beta)'(y - X\beta)$$

By taking the derivative of the sum of squared errors concerning β and setting it equal to zero, we obtain

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

For the multiple linear regression model to be valid, several assumptions must be satisfied: the error terms should be normally distributed, uncorrelated with each other, and exhibit homoscedasticity (constant variance); there should be no multicollinearity among the independent variables; and the relationship between the dependent and independent variables should be linear. If any of these assumptions are violated, the results of the multiple linear regression model may not be reliable.

2.2. Multivariate Adaptive Regression Splines (MARS)

Nonparametric regression models are used when the functional form of the relationship between the dependent and independent variables is unknown. MARS (Multivariate Adaptive Regression Splines) is one such nonparametric model. In MARS, the relationship between the dependent and independent variables is estimated using piecewise linear and cubic spline functions [18]. MARS was proposed by Friedman [19] to overcome certain limitations of traditional regression trees. It constructs a simplified decision tree structure by combining piecewise basis functions and applying both forward and backward stepwise algorithms, commonly used in regression analysis. Via MARS, flexible regression models are constructed by applying different basis functions over distinct ranges of independent variables. The MARS model is expressed as follows:

$$y_i = \alpha_0 + \sum_{k=1}^{K} \alpha_k \, \beta_k(x_t) + \varepsilon_i$$

where k denotes the number of knots, K denotes the number of basis functions, α_0 represents the intercept term, α_k is the coefficient of the kth basis function, $\beta_k(x_t)$ is the kth basis function for the tth independent variable [20]. A piecewise curve as a basis function is defined using a truncated power function, also known as a hinge function, which for a knot at point t is expressed as

$$(x-t)_+ = \begin{cases} x-t, & x > t \\ 0, & otherwise \end{cases}$$

$$(t-x)_+ = \begin{cases} t-x, & t > x \\ 0, & otherwise \end{cases}$$

The relationships between the dependent and independent variables can be linear, curvilinear, or cubic in nature. The value of an independent variable at which the form of the relationship changes is referred to as a "knot." At the knot, the sum of squared errors reaches its minimum value [21].

2.3. Random Forest (RF)

The Random Forest algorithm was introduced by Ho [22] and later improved by Breiman [23]. As an advanced ensemble learning method, random forest is based on decision trees. By combining the results of individual decision trees, it delivers higher performance compared to a single decision tree model. The random forest algorithm relies on the bagging (bootstrap aggregating) strategy. According to this strategy, multiple subsets are generated from the original training set through bootstrap sampling. A decision tree is trained using these samples. This process is repeated B times. When predicting a new observation, random forest aggregates the decisions of all trained trees; the final prediction is obtained by averaging the outputs of the B trees.

The model can be described as follows:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(x)$$

where $T_b(x)$, is the prediction of the b-th decision tree represented, and B indicates the total number of trees.

2.4. Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) was developed by Tianqi Chen [24]. This method is an ensemble learning algorithm based on the boosting method. XGBoost is built on decision trees, and the gain function optimizes the selection of the best splitting points within the trees. This approach adjusts the model complexity and prevents overfitting by adding a term to the loss function. The loss function of the model is given below

$$L(\Phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Here, l is the loss function that measures the prediction error, $\Omega(f_k)$ controls the complexity of the model.

2.5. Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are learning models inspired by the human brain's nervous system, featuring a multilayered, feedforward structure. They are primarily known for their effectiveness in modeling complex and non-linear relationships [25]. ANN model consists of an input layer, one or more hidden layers, and an output layer. Each neuron multiplies the input values by specific weights, adds a bias term, and then transforms the result using an activation function:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Here, f is the activation function; w represents the weight coefficients; x denotes the input variables; and b is the bias term. The model uses the backpropagation algorithm to minimize error, and the weights are updated during this process.

2.6. Voting Regressor (VR)

The voting regressor is an ensemble model that makes predictions by averaging the outputs of different regression models. In this method, various independent regression algorithms are run together, and each of their predictions is considered with equal weight to produce the final prediction. The general structure of the model is defined as follows:

$$\hat{y} = \frac{1}{M} \sum_{m=1}^{M} \hat{y}^m$$

Here, M represents the number of models used, and each model's prediction contributes equally to the final averaged output. $\hat{y}^m$, m-th denotes the prediction made by the m-th model.

3. Results

In recent years, determining macroeconomic indicators that may affect gold prices has become quite important. These indicators help investors better interpret market conditions and develop strategies. Gold is seen as both a store of value and a hedge against inflation. It is becoming a popular investment tool during periods of economic uncertainty. Therefore, determining the main indicators affecting gold prices is very important for making the right investment decisions. Commodity prices such as gold, silver and oil are directly affected by global economic expectations and investor risk perception. For example, investors often turn gold and silver during periods of financial crisis or global recession. Similarly, changes in oil prices can indirectly affect investor behavior in the precious metals market. The US Dollar Index (DXY), which measures the value of the US dollar against other currencies, and the US real interest rate have a significant impact on gold prices. When the dollar appreciates, gold prices tend to fall. On the other hand, when the inflation-adjusted real interest rate increases, interest-bearing assets become more attractive, and demand for gold decreases. When major stock indices, such as the BIST 100, NASDAQ, DAX, the S&P 500 Indexes, the Dow Jones Index, and the Nikkei 225, perform well, investors may prefer stocks with higher returns and reduce their gold holdings. However, during stock market declines or periods of high volatility, investors often turn to gold. When the U.S. Consumer Price Index (CPI) rises, the value of money decreases, and investors tend to buy gold. In this context, gold prices usually move in the same direction as inflation, making inflation one of the most essential variables in gold pricing models. The variables used in this analysis are directly or indirectly related to gold prices given in Table 2. Taken together, these indicators provide a comprehensive framework for understanding both short-term price movements and long-term trends in the gold market.

Table 2. Abbreviations, descriptions and sources of variables

Abbreviation of Variables	Variables	Source
Gold	Gold Price (USD)	www.investing.com
Silver	Silver Price (USD)	www.investing.com
DXY	U.S. Dollar Index (USD)	www.investing.com
Oil	Crude Oil WTI Futures (USD)	www.investing.com
BIST	BIST 100 – Borsa Istanbul (TRY)	www.investing.com
NASDAQ	Nasdaq Index (USD)	www.investing.com
DAX	DAX – German Composite Stock Index (EUR)	www.investing.com
SP500	S&P 500 Stock Index (USD)	www.investing.com
DJ	Dow Jones Industrial Average (USD)	www.investing.com
Nikkei	Nikkei 225 – Tokyo Stock Exchange Index (JPY)	www.investing.com
CPI	U.S. Consumer Price Index (All Items – Total for the United States)	www.bls.gov
IR	United States Real Interest Rate	fred.stlouisfed.org

In this study, a data preprocessing process was applied before combining the different financial indicator datasets used in the analysis. This process was carried out to obtain a comparable and suitable data structure for analysis.

The date formats in all datasets were standardized. Date columns from different sources were converted from the text format “Month/Day/Year” to the “Date” type. This ensured time alignment between the time series. Missing or incorrect observations were identified, and data cleaning was performed when necessary. Non-numeric columns were excluded from the analysis, keeping only numeric variables representing economic and financial indicators. Since the time series had different frequencies (daily, weekly, or monthly), all data were converted to a monthly level. For each variable, the arithmetic mean of the observations within each month was calculated to obtain monthly average values. This step reduced short-term fluctuations and made the overall trend of the data clearer. After preprocessing, the datasets were merged. The dataset covers the period from 01.2004 to 03.2024, consists of monthly observations, and contains no missing values. The data were split into 80% training and 20% testing sets, corresponding to the period 01.2004–02.2020 for training and 03.2020–03.2024 for testing. The alternative values tested for the model parameters and the selected optimal values used in the study are presented in Table 3:

Table 3. Alternative and optimal parameter values for the models

Method	Parametre	Alternative values	Optimal value
MARS	degree	1; 2; 3	3
	penalty	0; 1; 2; 3; 4; 5	0
	nk	20; 40; 60; 80; 100	40
	nprune	[2 ,100]	15
	pmethod	-	forward
RF			
	n_estimators	50; 100; 200	200
	max_depth	10; 20; None	10
	max_features	sqrt; "log2"; None	sqrt
	min_samples_split	2; 5; 10	2
	min_samples_leaf	1; 2; 4	1

XGBoost			
	learning_rate	0.01; 0.1; 0.2	0.1
	max_depth	3; 5; 7	3
	colsample_bytree	0.8; 1.0	0.8
	subsample	0.8; 1.0	0.8
	n_estimators	50; 100; 200	200
	early stopping	-	20 (CV), 30 (final model)
ANN			
	hidden_sizes	(64,32); (128,64); (128,64,32)	(128, 64, 32)
	dropout	0.0; 0.2; 0.5	0
	learning_rate	0.001; 0.005; 0.01	0.01
	optimizer	Adam; rmsprop; sgd	Adam
	batch_size	32; 64	32
	weight_decay	0.0; 0.0001; 0.001	0.0001
	epochs	800	800
	early_stopping	patience=50; min_delta=1e-6	Applied using validation loss
	selection criteria	Validation RMSE (val_RMSE)	Smallest val_RMSE
VR			
	RF_n_estimators	50; 100	100
	RF_max_depth	10; None	None
	RF_min_samples_split	2; 5	2
	RF_min_samples_leaf	1; 2	1
	XGB_n_estimators	50; 100	100
	XGB_learning_rate	0.1; 0.2	0.2
	XGB_max_depth	3; 5	3
	LR_model	LinearRegression (no tuning applied)	Default
	Voting_estimators	[('rf', RF); ('xgb', XGB); ('lr', LR)]	An equal-weighted ensemble of three models

Linear Regression (LR), Random Forest (RF), Artificial Neural Network (ANN) and Voting Regressor (VR) models were developed using Python libraries. ANN models were implemented using the PyTorch library (torch, torch.nn, torch.optim, torch.utils.data), while LR, RF, and VR models were constructed using the scikit-learn library. Gradient-boosting–based models were implemented using the xgboost package. Data preprocessing and preparation were carried out using pandas and numpy, and visualizations were produced using the matplotlib library. The MARS model was estimated in the R environment using the earth package. The modeling process, including dataset construction and training–testing split procedures, was conducted using the caret package. All models employed the StandardScaler method for data normalization to ensure comparability across predictors.

Table 4. Descriptive statistics of variables

Variables	Min.	Mean	Median	Std. Dev.	Max	Kurtosis	Skewness
Gold	388.90	1249.29	1277.80	461.40	2072.70	2.16	-0.23
Silver	5830.00	18695.64	17240.00	7441.09	48000.00	3.82	0.72
DXY	72.23	89.01	89.00	9.02	112.15	2.10	1.06
Oil	19.04	70.34	70.60	22.27	140.18	2.48	0.29
BIST	213.72	1176.22	854.96	192.65	2520.44	13.90	2.34
NASDAQ	1356.13	5610.17	4121.25	4101.90	18066.19	2.86	1.07
DAX	3794.17	9363.51	7934.70	3676.35	17795.15	1.91	0.27
SP500	729.60	2165.34	1845.90	1118.07	5098.51	2.64	0.92
DJ	7056.48	18646.85	16278.63	8578.39	39899.51	2.22	0.74
Nikkei	7454.28	17472.09	16566.06	6871.40	39254.69	2.65	0.63
CPI	-1.92	0.22	0.13	0.40	1.37	6.17	-0.62
IR	-0.41	0.94	0.95	0.73	2.50	2.09	0.28

When examining the descriptive statistics of the indicators thought to affect gold prices, it is observed that the standard deviations of silver, NASDAQ, and DJ are quite high. This indicates that these assets have exhibited significant volatility over time. Additionally, an analysis of kurtosis values related to the data distribution shows that the BIST Index and CPI exhibit sharper peaks compared to a normal distribution, indicating leptokurtic characteristics. When skewness values are examined, the NASDAQ, BIST, DXY, SP500, DJ, Silver, and Nikkei indicators show a right-skewed distribution since the skewness coefficient is greater than 0.5, while the CPI exhibits a left-skewed distribution since the skewness coefficient is less than -0.5.

When comparing the models, performance metrics such as RMSE, RRMSE, MAD, MAPE, AIC, CAIC, R^2, and Adjusted R^2 are used. In this context, lower values of RMSE, RRMSE, MAD, MAPE, AIC, and CAIC, and higher values of R^2 and Adjusted R^2 indicate better model performance. The model comparison criteria for the training and test datasets are presented in Tables 5 and 6, respectively.

Table 5. Model comparison for train data

Criteria	LR	MARS	RF	XGBoost	ANN	VR
RRMSE	83.4163	41.4288	31.3490	**10.3480**	33.0267	34.3684
RRMSE	0.0670	0.0332	0.0251	**0.0083**	0.0265	0.0276
MAD	76.2846	40.5463	20.1455	**7.9583**	24.8466	26.8842
MAPE	6.6973	3.0852	1.7122	**0.7292**	1.9647	2.6807
R2	0.9675	0.9920	0.9954	**0.9995**	0.9949	0.9944
Adj.R2	0.9656	0.9915	0.9951	**0.9994**	0.9946	0.9941
AIC	2304.6850	2011.7372	1365.6211	**933.3528**	1387.9540	1401.4850
CAIC	2347.2340	2021.5562	1412.6241	**980.3558**	1439.2300	1448.4880

Boldfaced values indicate the “best” performances.

The results of the training dataset presented in Table 5 reveal notable performance differences among the models. The baseline LR method produced the highest error values with RRMSE = 83.42, RMSE = 0.0670, and MAPE = 6.69%. In contrast, the MARS model significantly reduced the error rates (RRMSE = 41.43, MAPE = 3.09%) and achieved a marked improvement in accuracy. The XGBoost model demonstrated the best predictive performance among all methods, reaching RRMSE = 10.35, MAPE = 0.73%, R^2 = 0.9995, and Adjusted R^2 = 0.9994. Similarly, the RF and ANN models achieved high accuracy with low error rates, while the VR model, despite its ensemble structure, performed slightly below XGBoost. Furthermore, the XGBoost model exhibited the lowest AIC (933.35) and CAIC (980.36) values. These results clearly indicate that nonlinear and flexible approaches outperform linear models and that XGBoost stands out as the most powerful model for predicting gold prices.

Table 6. Model comparison for test data

Criteria	LR	MARS	RF	XGBoost	ANN	VR
MSE	81.1589	**54.1308**	64.6431	60.2856	57.7370	58.5941
RRMSE	0.0638	**0.0426**	0.0508	0.0474	0.0454	0.0461
MAD	101.4085	**38.2797**	45.2220	45.6375	42.7343	43.8646
MAPE	6.6412	3.4014	3.6116	3.7883	**3.2662**	3.5812
R2	0.9682	**0.9867**	0.9791	0.9818	0.9833	0.9829
AdjR2	0.9585	**0.9827**	0.9728	0.9763	0.9783	0.9776
AIC	2304.6850	520.6437	422.2127	415.5130	413.3663	412.7810
CAIC	2329.0107	526.2573	453.7959	447.0963	447.8207	444.3642

Boldfaced values indicate the “best” performances.

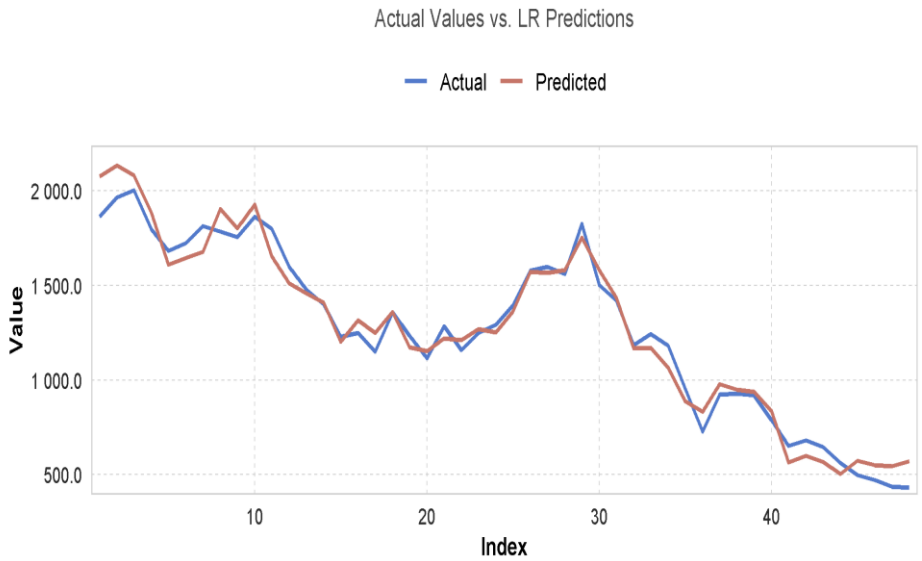
The test dataset results (Table 6) provide a clearer picture of the actual predictive power of the models. The MARS model demonstrated the best performance on the test data, achieving both low error rates and high explanatory power with RMSE = 0.0426, MAPE = 3.40%, and R^2 = 0.9867. Similarly, the ANN model produced strong results with low error values (RMSE = 0.0454, MAPE = 3.27%) and high explanatory power (R^2 = 0.9833). These two models stood out for their ability to capture nonlinear relationships and their high generalizability. Although the XGBoost and VR models also yielded satisfactory results, they did not achieve the same level of accuracy as the MARS and ANN models.

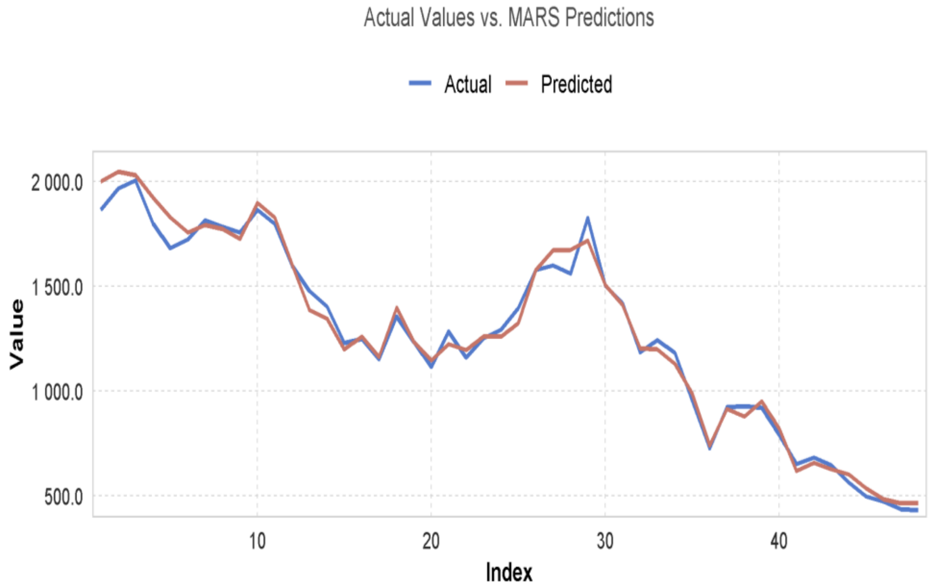
The findings indicate that the models’ performances on the training and test datasets are consistent with each other. On the training data, the lowest error and highest explanatory power were observed in the XGBoost model (R^2 = 0.9995, MAPE = 0.73%), confirming its strong ability to handle complex data structures. However, when evaluated on the test dataset, the MARS and ANN models outperformed others. The MARS model achieved the lowest error rates and the highest explanatory power on the test data, exhibiting a generalized performance without overfitting. The ANN model also performed strongly, achieving high accuracy and balanced error values, making it a robust second-best model. The RF and VR models demonstrated moderate performance but were not as effective in generalization as the MARS and ANN models. Considering both training and test results together:

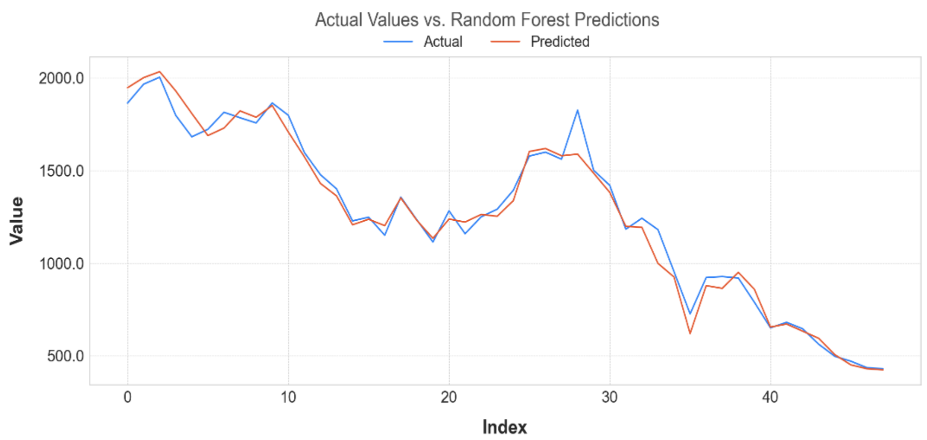
- XGBoost achieved the highest accuracy during training.
- MARS demonstrated the best generalizable performance on the test data, standing out in terms of overall balance and stability.

Therefore, in this study, the MARS model was identified as the most successful and reliable overall. With its ability to capture complex and nonlinear relationships, low error rates, and high generalizability, the MARS model stands out as the most suitable method for predicting gold prices. The ANN model follows as the second most powerful alternative.

Figure 1 provides a visual comparison of the actual and predicted values, highlighting the performance differences among the machine learning models.


Actual Values vs. LR Predictions
Actual
Predicted
2 000.0
1 500.0
1 000.0
500.0
Value
10
20
30
40
Index


Actual Values vs. MARS Predictions
Actual
Predicted
2 000.0
1 500.0
1 000.0
500.0
Value
10
20
30
40
Index


Actual Values vs. Random Forest Predictions
Actual
Predicted
2000.0
1500.0
1000.0
500.0
Value
0
10
20
30
40
Index

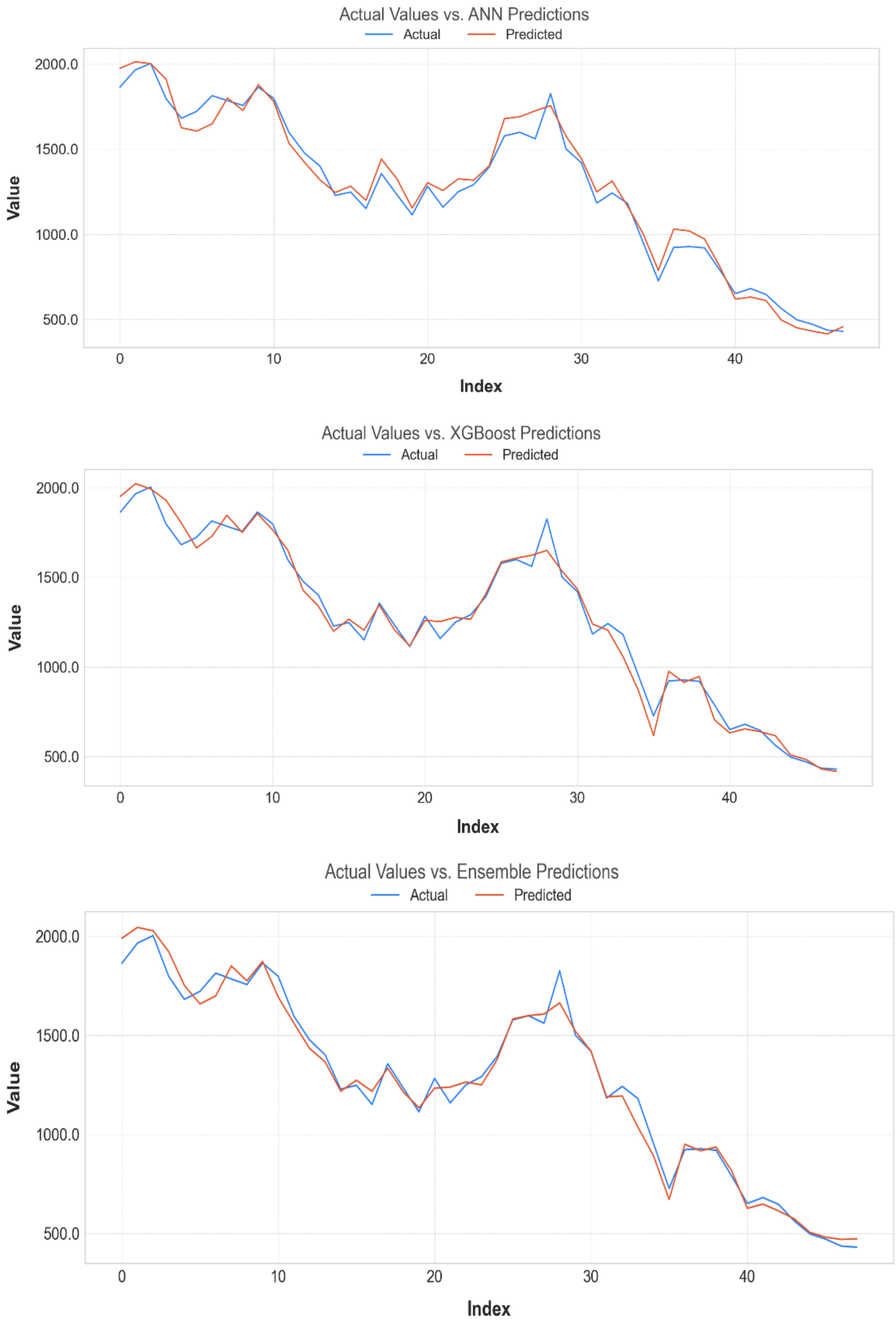


Figure 1. Time series graphs of actual and predicted values for LR, MARS, RF, ANN, XGBoost and VR (Ensemble method)

According to the model results, some indicators were found to have a much stronger influence on gold prices than others. In this context, variable importance analyses derived from the models were examined to identify the most significant indicators in gold price prediction. This analysis enhances the interpretability of the model by visualizing the relative effects of macroeconomic and financial variables. However, a variable importance plot could not be directly obtained for the ANN model. Figure 2 presents the top five most influential indicators on gold prices according to the variable importance analysis.

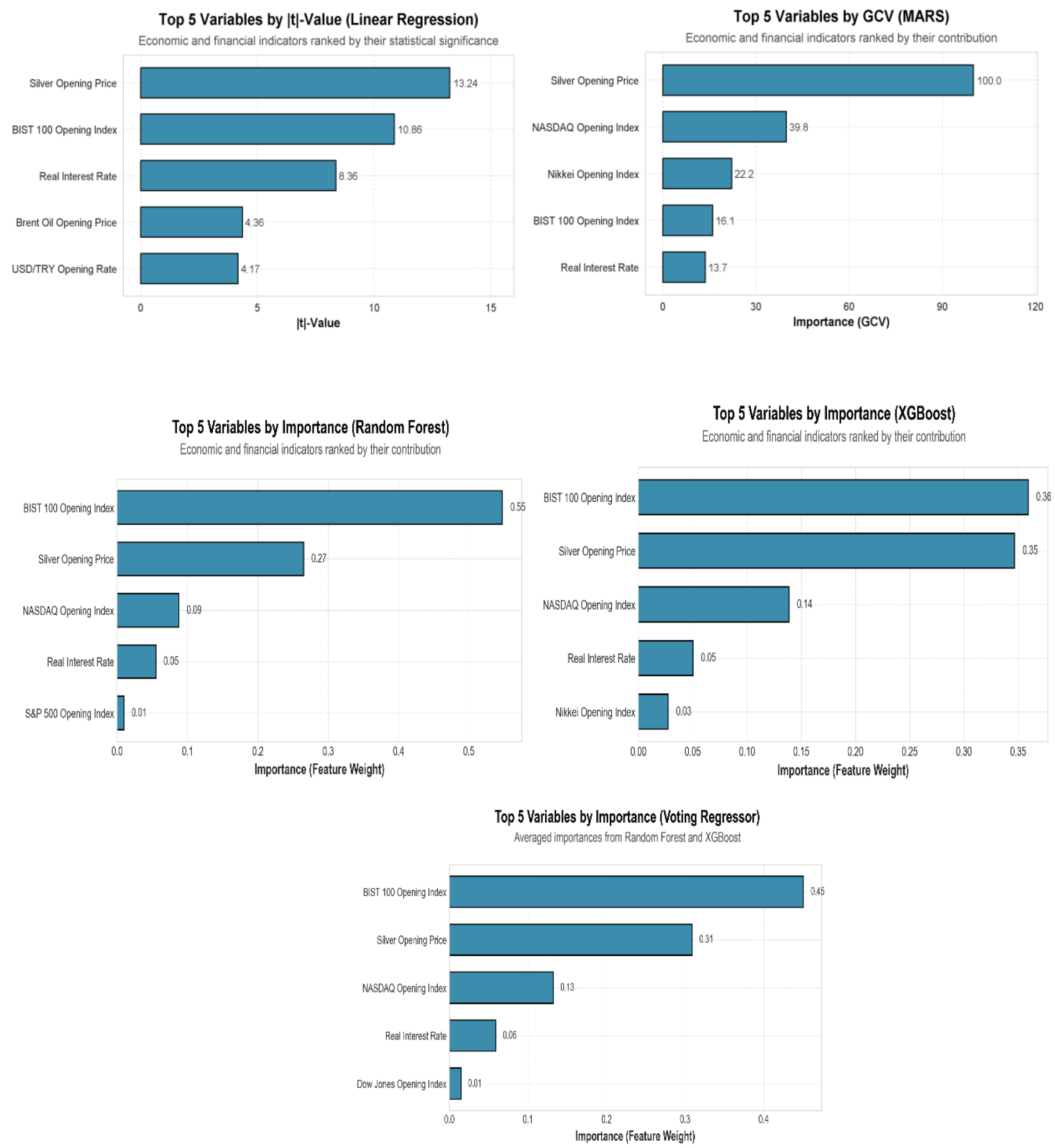


Figure 2. The top five indicators that most affect gold prices

When the variable importance graphs, training and test results, and model performance criteria are evaluated together, the MARS model stands out as the best overall model. It is followed by the ANN, VR, and XGBoost models, respectively. Except for the ANN model, variable importance graphs were obtained for the others, and they show similar patterns. The graphs clearly indicate that the BIST 100 Index and silver price have the strongest effects on gold prices. In addition, the NASDAQ Index, Nikkei Index, and U.S. real interest rate also play important roles, showing that gold prices are influenced not only by commodity market dynamics but also by major financial indicators and global market connections.

4. Conclusion

This study presents a detailed analysis using advanced machine learning methods to predict gold prices and to examine the macroeconomic and financial factors that influence gold prices. The monthly dataset covers the period 2010–2023 and includes commodity prices such as gold, silver, and oil; major stock market indices like BIST 100, NASDAQ, DAX, S&P 500, Dow Jones, and Nikkei; as well as the U.S. Dollar Index (DXY), Consumer Price Index (CPI), and real interest rates. The results show that the MARS model gives the best prediction performance on the test data. It has the lowest RMSE and MAPE values and high R^2 and adjusted R^2 values, meaning it explains most of the variation in gold prices. The ANN model performs similarly well, ranking second. The XGBoost model shows very strong performance on the training data but slightly lower accuracy on the test data.

Overall, the results indicate that the main factors affecting gold prices are similar across models. The BIST 100 Index, silver prices, NASDAQ Index, real interest rates, and oil prices are the most important predictors. The BIST 100 Index and silver prices have the highest weights in predicting gold prices. These results support the dynamic relationship between risk perception in financial markets and the preference for safe-haven assets. Stock indices like BIST 100 and NASDAQ reflect investor risk appetite and capital flows, while silver prices represent movement toward safe assets such as gold. Therefore, when stock markets fall, investors tend to move toward gold and silver, pushing gold prices upward. Real interest rates also affect gold demand indirectly by influencing investors' search for alternative returns. Low real interest rates usually increase gold demand. Likewise, higher oil prices can affect gold prices through production costs and inflation expectations.

From an economic perspective, the BIST 100 Index and silver prices are the two strongest variables influencing gold prices in all models. Silver prices move closely with gold, reflecting investors' safe-haven preferences, while stock market indices like BIST 100 and NASDAQ reflect changes in global financial conditions and investor behavior. Evaluating these indicators together is important for both investment strategies and financial stability. For policymakers, understanding the interactions between interest rates, stock indices, and commodity prices is crucial for managing capital flows, balancing inflation expectations, and ensuring stability in foreign exchange markets.

For future research, it is planned to improve prediction accuracy by using daily or hourly data with deep learning–based models such as LSTM, GRU, and Transformer. These models offer important advantages over classical methods in capturing long-term dependencies, nonlinear relationships, and complex patterns in time series. LSTM (Long Short-Term Memory) models are strong in learning the long-term effects of past information, so they perform well when gold prices are affected by past shocks or long-term trends. GRU (Gated Recurrent Unit) models work similarly to LSTM but have fewer parameters, making them faster and more efficient for smaller datasets or situations where quick computation is needed. Transformer-based models can consider global dependencies across the entire time series at once, which allows them to achieve the best performance for multivariate and high-frequency financial data such as daily or hourly gold prices.

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Declarations:

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This work is original.

2. Author Contributions:

Concept: AYS,ST; ***Conceptualization:*** AYS,ST; ***Literature Search:*** AYS,ST; ***Data Collection:*** AYS,ST; ***Data Processing:*** AYS,ST; ***Analysis:*** AYS,ST; ***Writing – original draft:*** AYS,ST; ***Writing – review & editing:*** AYS,ST.

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No GenAI tools were used at any stage of the study.

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