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Analyzing and Prediction of a Gold Price with ML Algorithms

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Abstract
Gold is a substance, shift element with an intense and metallic yellow appearance. By the above qualities of gold makes highly valued and versatile element. It has prominently played an important role in our economic area. It is one of the investment assets for the people. This paper analyses This document analyses gold price data from 2013 to 2023, showing daily prices, highs, lows, trading volumes, and daily changes. This rich data set is useful for anyone wanting to study or visualize gold market trends over the past decade. We started by cleaning the data, fixing missing values, and handling outliers. Then, we used various graphs and charts like trend lines, distribution plots, and pair plots to explore and understand the data. Next, we built prediction models using different techniques like Linear Regression, Support Vector Regression (SVR), Decision Tree, Random Forest, and Gradient Boosting. These models help us forecast future gold prices based on past data. The analysis reveals important trends and patterns in gold prices, providing insights that can help in financial analysis and market prediction.

Keywords: *Gold, Linear Regression, Decision Tree, Random Forest, Support Vector Regression, Gradient Boosting*

1. Introduction
Gold is a unique element which consists of beauty, purity, and power. It is a heat conductor, and it is a substance which is used as by the state of art like jewels, awards, medals, decorative items, medical and space exploration. Gold can also be used as the payment mode around the world for their transactions. Most people prefer Gold because of its purity and desirability. Gold is a good investment avenue for the investors to increase their creditworthiness [1]. The cost of gold is influenced by economy, currency, and areas [2]. By this gold's value is ought to be relied on offer and demand. The price started rapidly increasing after the traumatic COVID-19 crisis. Because of the various trends in the market the price of Gold is unpredictable. Before researchers used statistical models to predict gold but they have not produced accurate values [10]. Estimation of gold price depends on the different variables or factors [13] [31]. Machine Learning algorithms play an important role to predict and forecast of future value of gold by taking the chronological or old data [7] [12] [26] [33]. Now a days Advanced Machine Learning Methods are used to predict gold prices [16] [30].

1.1. About the Data Set
- Overview of the Dataset: The dataset includes daily gold price information from 2013 to 2023, covering opening and closing prices, highs and lows, trading volumes, and daily changes. [37] This primary data is enhanced by secondary data obtained from Kaggle; the shape of the data is (2583,7).
- Objective of the Analysis: The aim of this analysis is to predict future gold prices based on historical data from 2013 to 2023. By analyzing daily prices, highs, lows, trading volumes, and percentage changes, we seek to develop accurate forecasting models to support financial decision-making.
- Variables in the Dataset: Date: The specific day the data was recorded. High: The peak price of gold [3-6].

- Price: The closing price of gold (Target variable). Low: The lowest price of gold. Open: The opening price of gold. Vol.: The amount of gold traded. Change %: The percentage change in price. Rows are 2583.

1.2. Literature Review

Gold Price Prediction using Machine Learning (August 2022, International Journal of Environmental Engineering 6(6), DOI: 10.55041/IJSREM15027) Random Forest algorithm is the best one to predict gold price with respect to their dataset [8-9]. Forecasting gold price using machine learning methodologies. Author links open overlay panelGil Cohen, Avishay Aiche. Received 1 June 2023, Revised 30 August 2023, Accepted 18 September 2023, Available online 25 September 2023, Version of Record 25 September 2023. This paper predicts the price of gold using advanced Machine Learning (ML) methodologies and took the one day lagged data to predicate price of gold by using GBRT and XGBoost for gold investments [11]. Gold Price Prediction Using ML Algorithmshttps://ymerdigital.com/uploads/YMER210713.pdf Radhamani V*1, Manju D*2, Bobby Prathikshana M*3, Javagar M*4, Nivetha V*5, Rinubha P*6 This paper proved Random Forest algorithm is the best model. A few research papers on Price prediction are as follows. Car Price Prediction, House Price Prediction, Rank Predictions with marks, Bitcoin Price Prediction and Stock Closing Price Prediction.

2. Methods

2.1.Data Preprocessing

- Handling Missing Values: Fill in or fix any gaps where data is missing by median Imputation. Since there exists outliers (Figure 3).
- Converting Data Types: Change the format of data for consistency and ease of use [14-18].
- Removing Duplicates: Remove any repeated entries to ensure each data point is unique.
- Removing Outliers: Identify and address any unusual data points that differ significantly from the rest.
- This method takes the input from Table 4 and converts that one into other tables like 2 and 3. The total process has been explained in Figure 1.
- Normality Tests: QQ plots are graphical tools used to assess if a dataset follows a theoretical distribution by comparing quantiles of the data against quantiles of the expected distribution. (Figure 2)

2.2. Exploratory Data Analysis (EDA)

2.2.1.Descriptive Statistics

Descriptive statistics summarize and describe the main features of a dataset, providing insights into its central tendency, dispersion, and overall distribution.

2.2.2.Central Tendency

Mean, median, and mode give an idea of the average values in the dataset. If the mean is significantly higher than the median, it indicates skewness due to high value outliers [19-23].

2.2.3.Spread and Variability

Standard deviation, variance, range, and interquartile range (IQR) provide insights into how spread out the data is. An extreme standard deviation or variance indicates that the data points are more widened over the values.

2.3. Shape of Data Distribution

Skewness indicates the asymmetry of the data, showing if the data leans towards the left or right. • Kurtosis measures the heaviness of the tails or the sharpness of the data distribution.

2.4. Distribution Analysis

- Histograms: Represents frequency distribution of data, point out how often each value occurs.
- Density Plots (KDE): Visualize data distribution using smoothed curves, providing a continuous estimate of the distribution.
- Unimodal Distribution: The histogram has one peak, showing that most data points are grouped around a central value, indicating a single main pattern in the dataset. If the peak is symmetric and bell-shaped, it suggests that the data might follow a normal distribution (Figure 4) [24-25].

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- Bimodal Distribution: The histogram reveals two distinct peaks, indicating the presence of two different subgroups or clusters within the dataset (Figure 5).
- Pair Plot: A pair plot shows how different pairs of variables relate to each other in a dataset. It includes scatter plots for pairs of variables and histograms or density plots for individual variables. This helps in identifying correlations, patterns, and potential outliers among multiple variables (Figure 6). [27-29]

According to Table 1, Volume and Change % have very low correlations with the other variables, indicating that changes in volume and percentage change do not have strong linear relationships with price-related variables. The high correlations among price-related variables suggest that they are good predictors of each other, while Volume and Change % might not be as useful in predicting these values directly [31-32].

- Line Plot for Price Over Time: A line plot for price versus date displays the gold price trend over time (Figure 7) [34-35].
- Trend Analysis: If you observe an increase in the trend after 2019, it indicates that gold prices have been rising significantly in recent years. (Figure 8)
- Rapid Increase: A steep upward slope or sharp rise in the line after 2019 suggests a fast increase in gold prices during this period. (Figure 8)

2.5. Tables

Table 1 Dataset Description

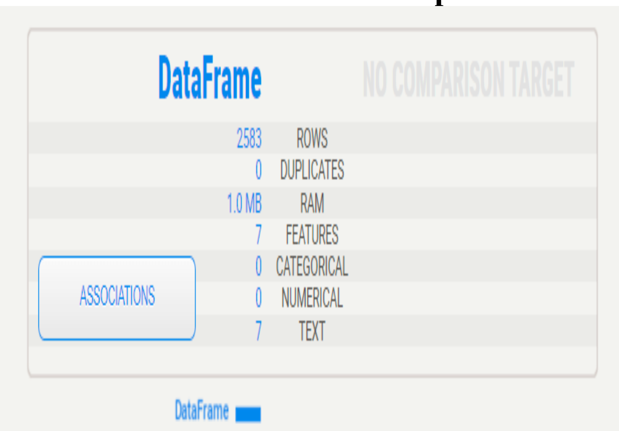

Table 2 Datatypes of Columns

Date	objecttype
Price	object
Open	objecttype
High	object
Low	object
Vol.	object
Change %	object

Table 3 Converting Datatypes of Columns

Date	datetime64[ns]type
Price	float64
Open	float64type
High	float64
Low	float64
Vol.	float64
Change %	float64

Table 4 Dataset with variables and Values

2583 / 7	Date	Price	Open	High	Low	Vol.	Change %
0	12/30/2022	1,826.20	1,821.80	1,832.40	1,819.80	107.50K	0.01%
1	12/29/2022	1,826.00	1,812.30	1,827.30	1,811.20	105.99K	0.56%
2	12/28/2022	1,815.80	1,822.40	1,822.80	1,804.20	118.08K	-0.40%
3	12/27/2022	1,823.10	1,808.20	1,841.90	1,808.00	159.62K	0.74%
4	12/26/2022	1,809.70	1,805.80	1,811.95	1,805.55	nan	0.30%
5	12/23/2022	1,804.20	1,801.00	1,812.20	1,798.90	105.46K	0.50%
6	12/22/2022	1,795.30	1,823.80	1,829.30	1,792.70	175.77K	-1.65%
7	12/21/2022	1,825.40	1,827.90	1,833.80	1,821.30	110.18K	0.00%
8	12/20/2022	1,825.40	1,796.80	1,832.40	1,793.70	197.50K	1.54%
9	12/19/2022	1,797.70	1,801.60	1,808.60	1,793.20	86.09K	-0.14%
10	12/16/2022	1,800.20	1,786.90	1,804.20	1,783.90	128.75K	0.69%
11	12/15/2022	1,787.80	1,818.70	1,819.70	1,782.00	185.32K	-1.70%
12	12/14/2022	1,818.70	1,822.60	1,825.40	1,806.20	143.80K	-0.37%
13	12/13/2022	1,825.50	1,792.30	1,836.90	1,791.80	230.91K	1.85%
14	12/12/2022	1,792.30	1,808.00	1,809.30	1,789.00	107.78K	-1.02%
15	12/09/2022	1,810.70	1,801.90	1,819.00	1,800.10	150.94K	0.51%
16	12/08/2022	1,801.50	1,799.50	1,806.90	1,793.20	116.27K	0.19%
17	12/07/2022	1,798.00	1,783.30	1,803.20	1,780.50	155.57K	0.88%
18	12/06/2022	1,782.40	1,780.80	1,793.20	1,779.10	127.86K	0.06%
19	12/05/2022	1,781.30	1,810.50	1,822.90	1,778.10	179.82K	-1.56%
20	12/02/2022	1,809.60	1,817.00	1,818.70	1,791.80	183.72K	-0.31%
21	12/01/2022	1,815.20	1,783.10	1,818.40	1,782.90	226.15K	3.14%
22	11/30/2022	1,759.90	1,763.40	1,784.20	1,758.20	192.24K	-0.22%
23	11/29/2022	1,763.70	1,754.60	1,773.40	1,752.90	127.32K	0.48%
24	11/28/2022	1,755.30	1,771.10	1,778.50	1,753.30	128.55K	0.07%
25	11/25/2022	1,754.00	1,751.00	1,761.20	1,745.90	134.30K	-0.08%
26	11/24/2022	1,755.35	1,753.05	1,758.95	1,752.55	nan	0.56%
27	11/23/2022	1,745.60	1,740.80	1,754.90	1,719.00	167.77K	0.33%

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2.6. Figures

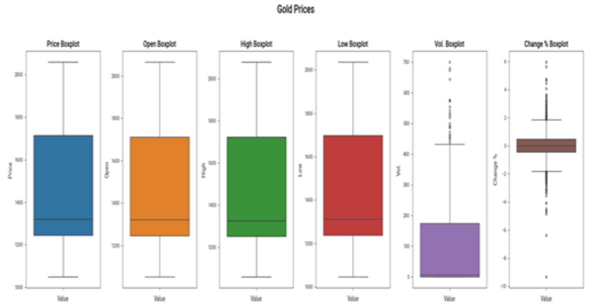

Figure 1 Box Plots of Individual Columns [Table 4]

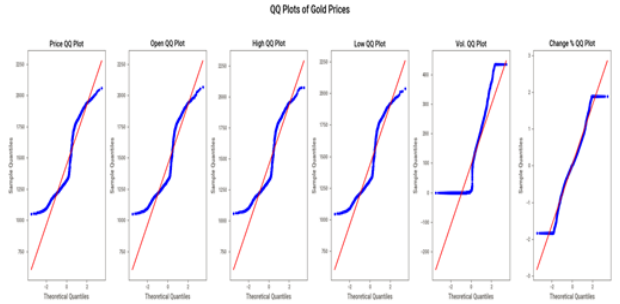

Figure 2 QQ Plots for Each Column

Index	Price	Open	High	Low	Vol.	Change %
count	2583	2583	2583	2583	2578	2583
mean	1440.33	1440.65	1449.64	1430.89	94.0468	0.00812234
std	257.338	257.503	259.634	254.753	117.354	0.975231
min	1049.6	1051.5	1060.1	1045.4	0	-9.34
25%	1244.2	1244.35	1251.6	1236.45	0.29	-0.44
50%	1320.5	1320.7	1326.5	1313.2	7.215	0.01
75%	1713.95	1711.95	1723	1699.45	174.343	0.49
max	2058.4	2065.1	2078.7	2037.2	700.34	5.97

Figure 3 Handling Missing Values and Fill the Gap by median Imputation

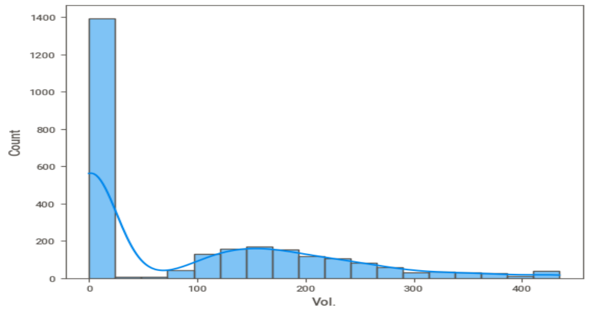

Figure 4 Unimodal Distribution

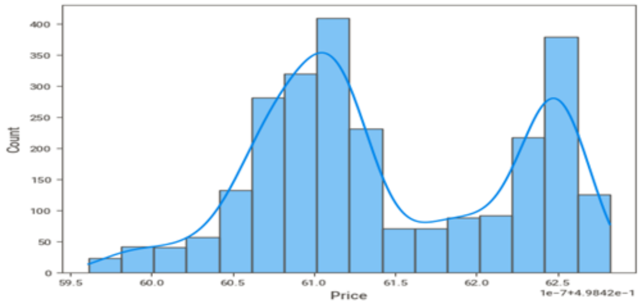

Figure 5 Bimodal Distribution

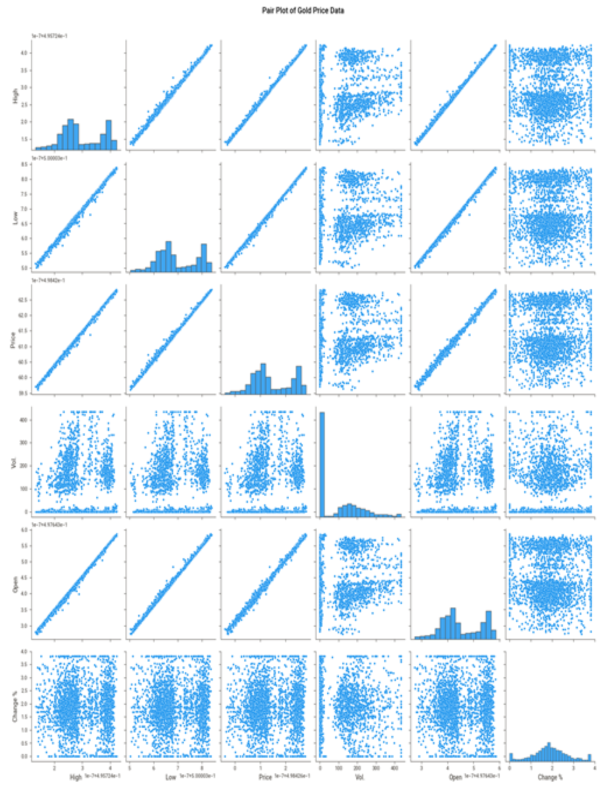

Figure 6 Pair Plot of a Dataset

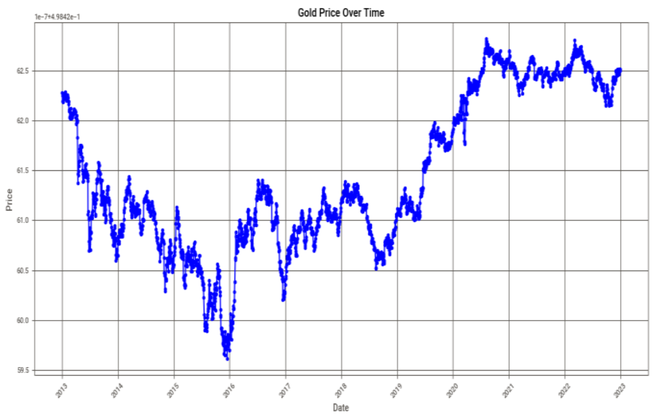

Figure 7 Line Plot Between Date and Price

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Figure 8 **Trend Analysis and Rapid Increase of 2022**

Figure 9 **Analysis on Price Prediction on Gold in 2019**

Figure 10 **Analysis on Price Prediction on Gold in 2020 (COVID – 19)**

2.7. Models Used

In the context of gold price prediction, this dataset consists of continuous data, making it suitable for supervised learning. This dataset includes daily records of opening and closing prices, highs and lows, trading volume, and percentage change. By training supervised learning models on this continuous data, we aim to predict future gold prices accurately, shown in figure 9, figure 10, figure 11 & figure 12.

- Linear Regression: Linear Regression is a method used to find the relationship between two variables by fitting a straight line to the data. The formula for this line is y=mx+by = mx + by=mx+b, where yyy is the dependent variable (what we want to predict), xxx is the independent variable (what we use to make the prediction), mmm is the slope (how much yyy changes for a unit change in xxx), and bbb is the intercept (the value of yyy when xxx is 0). By minimizing the differences between the actual data points and the predicted values, we find the best-fitting line.
- Decision Tree: A Decision Tree works by splitting the data into branches based on certain conditions. At each branch, a question is asked (e.g., "Is the price greater than $1500?"), by the answer the data is divided. This continues until a prediction can be made. The process uses algorithms like Gini impurity or entropy to decide where to split the data to make the best decisions.
- Random Forest: It is a combination of many trees (a "forest") and linking their predictions. For each tree prediction can be trained. The resultant prediction is the average of all the subtrees' predictions. This method decreases errors and increases accuracy by averaging out the noise and overfitting of individual trees.
- Gradient Boosting: Gradient Boosting builds trees one at a time, where each new tree tries to correct the errors of the previous ones. It uses a method called "boosting" to improve accuracy. The trees are added in a sequence, with each tree focusing on the areas where the previous ones made mistakes. The final model is a combination of all these trees, which gives a more accurate prediction by learning from its mistakes iteratively.
- Support Vector Regression (SVR) Support Vector Regression (SVR) aims to find the best line (or curve) that fits the data, allowing for some errors. It uses a technique called the "kernel trick" to handle nonlinear data by

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- transforming it into a higher-dimensional space where it becomes easier to fit a linear model. The goal is to ensure that the errors are minimized while maintaining a balance, which is controlled by parameters that determine the width of the margin around the line.

3. Results and Discussion

3.1. Results

The performance of various regression models used in predicting gold prices has been evaluated based on key metrics such as the R^2 score, Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These metrics provide a comprehensive understanding of how well each model fits the data and its predictive accuracy. The Table 5 results are as follows:

Table 5 Results of The Models

MODEL	R SQUARE	MEAN SQUARE ERROR
Linear Regression	0.9546708930215699	2842.5495510248893
Support Vector Regression (SVR)	0.8687759840738416	8228.94586765369
Decision Tree Regression	-0.21239645186630307	76028.34513277868
Random Forest Regression	0.40359244941568284	37400.207684391935
Gradient Boosting Regression	0.03369908536643762	60595.904356854444

3.2.Discussion

The Linear Regression has the highest R^2 score, indicating that it explains approximately 95.47% of the variance in gold prices. This model suits the data with high R^2 score. The low MSE value further supports this, indicating that the predictions made by the model are close to the actual values. Overall, Linear Regression is the most effective model among those evaluated. SVR also performs well, with an R^2 score of 86.88%, meaning it explains a significant portion of the variance in gold prices. However, its MSE is much higher than that of Linear Regression, indicating that while the model captures the trend, its predictions are less accurate. SVR is a good alternative but not as precise as Linear Regression. Decision Tree Regression performs poorly, with a negative R^2 score indicating that the model does not fit the data well at all. The high MSE value further confirms this, showing that the predictions are far from the actual values. This model is not suitable for predicting gold prices in this context. Random Forest Regression shows moderate performance with an R^2 score of 40.36%. This indicates that it explains some of the variance in gold prices but not enough to be considered highly effective. The high MSE suggests that the model's predictions are not very accurate. While better than Decision Tree Regression, it still falls short compared to Linear Regression and SVR. Gradient Boosting Regression has a very low R^2 score of 3.37%, indicating that it explains very little of the variance in gold prices. The high MSE value also points to poor predictive accuracy. This model is not effective for this task.

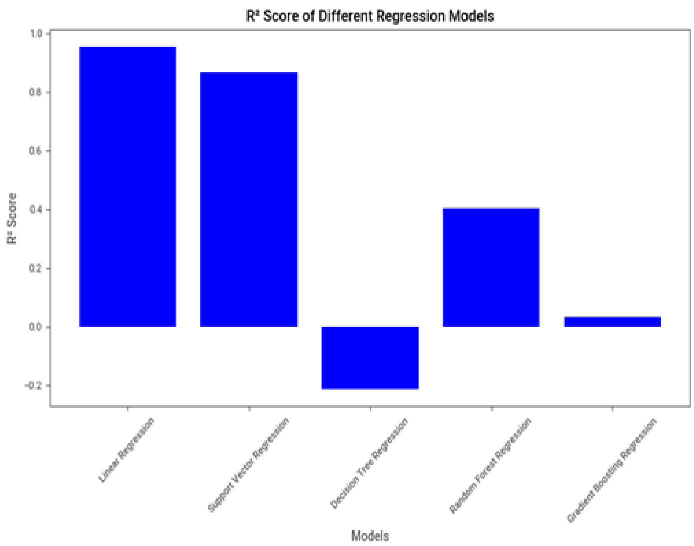

Figure 11 Results of the R^2 Score of Different Regression Models

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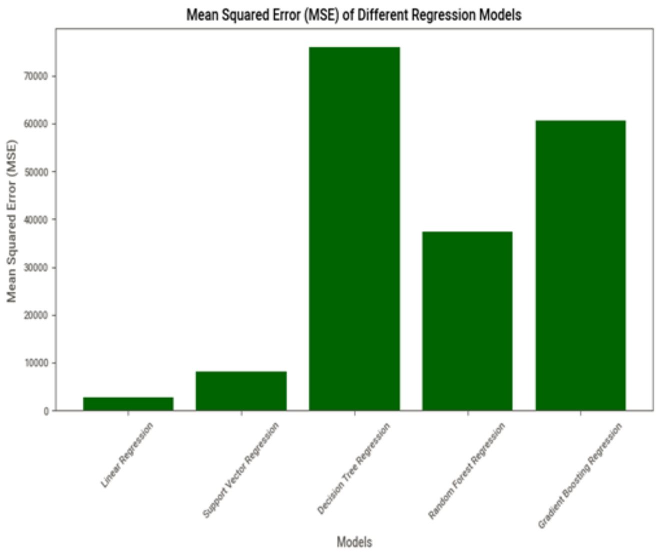

Figure 12 P Results of the R^2 score of different Regression Models

Conclusion

In evaluating the performance of various regression models for predicting gold prices, Linear Regression stands out as the most effective model. It achieved an impressive R² score of 0.9547, indicating that it explains approximately 95% of the variability in the target variable. Additionally, it recorded the lowest Mean Absolute Error (41.87), Mean Squared Error (2842.55), and Root Mean Squared Error (53.32), suggesting that it provides the most accurate predictions with minimal error. In comparison, Support Vector Regression (SVR) also performed well with a high R² score of 0.8688, but its Mean Squared Error was significantly higher, indicating less accuracy than Linear Regression. Decision Tree Regression showed poor performance with a negative R² score (-0.2124) and a high Mean Squared Error (76028.35), suggesting that it is not a suitable model for this dataset. Random Forest Regression displayed moderate performance with a lower R² score (0.4036) and a high Mean Squared Error (37400.21), falling short of Linear Regression's effectiveness. Lastly, Gradient Boosting Regression had the lowest R² score (0.0337) and a high Mean Squared Error (60595.90), making it the least effective model among those tested. Overall, Linear Regression is the preferred model due to its superior accuracy and reliability in predicting gold prices.

- Best Model: Linear Regression, with the highest R² score and the lowest MSE, making it the most accurate and reliable model for predicting gold prices.
- Good Alternative: Support Vector Regression, which performs reasonably well but with less accuracy than Linear Regression.
- Poor Performers: Decision Tree Regression, Random Forest Regression, and Gradient Boosting Regression, all of which have high MSE values and low or negative R² scores, indicating poor predictive performance.

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