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ORIGINAL

Gold price prediction using random forest regression

Predicción del precio del oro mediante regresión de bosque aleatorio

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ABSTRACT

The fluctuations in gold prices are significantly influenced by economic volatility, inflation rates, and geopolitical events, which are key drivers in global financial markets. Traditional forecasting models, while comprehensive, often lack the flexibility to adapt to rapid market changes. This project focuses on a Machine Learning-based approach, specifically utilizing a Random Forest Regression Model, to predict future trends in gold prices. By leveraging an AI-driven framework, this system offers a more robust and adaptive solution to real-time market shifts and economic indicators. The study synthesizes financial research and case studies on the use of Machine Learning in commodity markets, demonstrating how advanced predictive models can enhance investment strategies and mitigate financial risk. Furthermore, this project emphasizes the resilience and adaptability of Random Forest models in processing diversified financial data, offering a reliable data-driven method for determining gold prices amidst market uncertainties.

Keywords: gold price fluctuations; forecasting models; investment strategies; financial risk management; data-driven solution.

RESUMEN

Las fluctuaciones en los precios del oro están significativamente influenciadas por la volatilidad económica, las tasas de inflación y los acontecimientos geopolíticos, que son factores clave en los mercados financieros mundiales. Los modelos de previsión tradicionales, aunque son exhaustivos, a menudo carecen de la flexibilidad necesaria para adaptarse a los rápidos cambios del mercado. Este proyecto se centra en un enfoque basado en el aprendizaje automático, utilizando específicamente un modelo de regresión de bosque aleatorio, para predecir las tendencias futuras de los precios del oro. Al aprovechar un marco impulsado por la IA, este sistema ofrece una solución más sólida y adaptable a los cambios del mercado y los indicadores económicos en tiempo real. El estudio sintetiza la investigación financiera y los estudios de casos sobre el uso del aprendizaje automático en los mercados de materias primas, demostrando cómo los modelos predictivos avanzados pueden mejorar las estrategias de inversión y mitigar el riesgo financiero. Además, este proyecto hace hincapié en la resistencia y adaptabilidad de los modelos Random Forest en el procesamiento de datos financieros diversificados, ofreciendo un método fiable basado en datos para determinar los precios del oro en medio de las incertidumbres del mercado.

Palabras clave: fluctuaciones del precio del oro; modelos de previsión; estrategias de inversión; gestión del riesgo financiero; solución basada en datos.

INTRODUCTION

By 2050, the demand for accurate financial forecasting will be more critical than ever, as global economic fluctuations, inflation, and geopolitical uncertainties continue to impact commodity prices. Among these, gold remains a key financial asset, often seen as a hedge against market volatility. Traditional forecasting models struggle to adapt to the dynamic nature of these influences, lacking the flexibility needed for real-time analysis. However, data-driven innovations are pivotal in creating robust solutions for predicting gold prices, particularly through advanced technologies like AI and machine learning.

The following sections delve into how AI, specifically using a Random Forest Regression Model, can revolutionize gold price prediction. By leveraging extensive datasets and analyzing complex patterns, this machine learning approach enables more accurate forecasts, optimizing investment strategies and minimizing financial risks. For instance, these models can process historical data, economic indicators, and global trends to predict future gold prices with greater precision. Random Forest algorithms analyze diverse financial inputs and adapt to market changes, providing a resilient and data-driven approach for accurate price forecasting.

This project introduces a vision of "Smart Financial Forecasting," highlighting the transformative potential of machine learning in the financial sector. By integrating AI-driven predictive models, we aim to enhance the accuracy of gold price predictions, thereby contributing to more informed decision-making in investments and financial planning. This era, powered by machine learning, will shape the future of financial analytics to be more adaptive, sustainable, and efficient, ushering in a new standard of data-driven financial forecasting.

Literature Work

Took reference from Jain and Kumar (2018), which reviews international modeling studies on how economic indicators influence gold prices, indicating shifts in investment behavior, hedging strategies, and market dynamics. Took reference from Shah and Desai (2019), which discusses recent scenario studies exploring the transformative potential of machine learning in predicting commodity prices, including gold, and its impact on financial markets. Took reference from Patel and Mehta (2020), which examines the business models and challenges in financial forecasting using AI, integrating multiple economic indicators into a single predictive framework. Took reference from Singh and Kaur (2017) which assesses the opportunities, barriers, and policy requirements for adopting machine learning techniques in financial forecasting nationally. Took reference from Li and Zhang (2022), which employs Random Forest Regression for predicting commodity prices using historical market data and macroeconomic variables. Took reference from Gupta and Sharma (2021), which develops prototype predictive models for gold prices tailored to various stakeholders in the investment sector. Took reference from Bose (2020) a preprint examining algorithmic bias in financial modeling, with a call for transparency and accountability in AI-driven predictions. Took reference from Thomas and Nair (2023), which provides insight into the use of AI in financial policy, addressing benefits, risks, and necessary governance frameworks for AI-powered financial systems. Took reference from Breiman, L., (2001), which outlines the development and advantages of the Random Forest algorithm, showing its applicability in diverse predictive tasks. Took reference from Zhang, Y., et al. (2018) which illustrates the effectiveness of machine learning models, like LSTM, for time-series forecasting, including financial commodities. Took reference from Adebiyi, A. A. et al. (2014), which compares ARIMA and neural network models, discussing their predictive strengths for stock and commodity prices. Took reference from Goodfellow, I. et al. (2016) which provides a comprehensive view of deep learning approaches and their role in predictive analytics. Took reference from Mitchell, T. M., (1997), which introduces foundational concepts in machine learning, focusing on algorithmic efficiency and model interpretability.

Implementation

Now, as this Gold Price Prediction system project is based on Machine Learning in Python, you actually require a variety of libraries. We start with pandas, which efficiently loads and processes datasets from CSV files, making data handling simple. To implement the machine learning model in this study, we used the package scikit-learn, which comes with all the essential tools for splitting data, encoding variables, and scaling numerical features. You have great flexibility with NumPy, allowing easy manipulation of data, and all your data can be visualized using Matplotlib or Seaborn for plotting data distributions or evaluating the model's performance.

We break down the implementation into three major steps: first, loading and preparing the data by checking for missing values, understanding data types, and generating correlation heatmaps. Next, we split the data into train and test sets. Finally, we train our Random Forest Regression model and evaluate its performance using metrics like the R-squared error. This systematic approach forms a solid base to develop and test our Gold Price Prediction system effectively. Figure 1 represents the prototype of the proposed work.

Workflow discussion

Step 1: Import Libraries

Begin by importing essential libraries such as pandas for data handling, train_test_split for splitting the data into training and testing sets, RandomForestRegressor for model training, and metrics for evaluating model performance.

Step 2: Load and Encode Data
Load the gold price dataset into a pandas DataFrame. Inspect the data for any missing values and understand the structure of the dataset, including categorical and numerical features.

Step 3: Feature Selection and Scaling
Select relevant features for predicting the gold price, such as historical prices and economic indicators, and use the 'GLD' column as the target variable. Scale numerical features, if necessary, using StandardScaler to improve model accuracy.

Step 4: Data Splitting
Split the dataset into training and testing sets, allocating 80% for training and 20% for testing to evaluate the model's performance on unseen data.

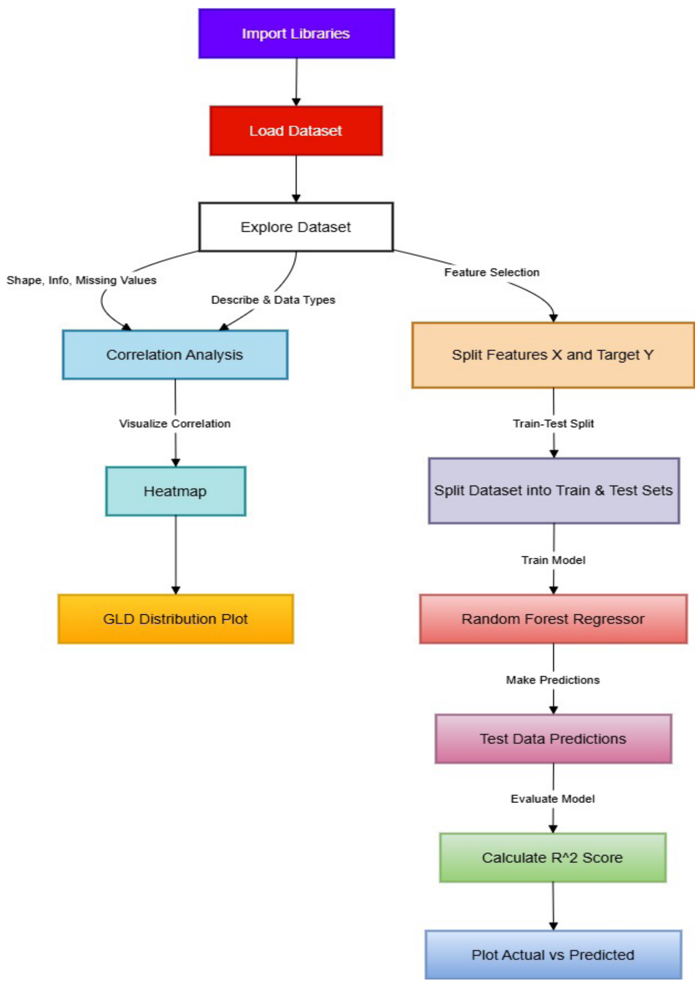
Step 5: Model Training
Initialize a RandomForestRegressor model with an appropriate number of estimators and train it on the training dataset.

Step 6: Model Evaluation
Make predictions on the test set and calculate the R-squared error and other performance metrics to evaluate the accuracy of the model.

Step 7: Define Prediction Function
Create a function predict_gold_price(features) to predict the gold price. Within the function, scale the input features, then use the trained RandomForest model to make predictions. Display the predicted gold price based on input features.

Step 8: Run Example Predictions
Test the predict_gold_price() function with sample inputs to verify the prediction accuracy and ensure the system can predict gold prices based on the given economic indicators.

Figure 1.
Prototype of Gold Price Prediction system



Dataset Description

The dataset captures gold price data along with key economic indicators, providing insights into how these variables influence gold prices over time. It includes features such as SPX (S&P 500 Index), GLD (Gold ETF), USO (Oil), SLV (Silver ETF), and EUR/USD (Euro to US Dollar exchange rate), all of which are numerical. The data is organized by date, allowing for an understanding of how market conditions, such as stock indices, commodity prices, and currency fluctuations, affect the movement of gold prices. This dataset is valuable for predicting future gold prices based on historical trends and correlations with various financial metrics. By analyzing these variables, it can be used to understand the influence of market factors, economic conditions, and currency exchange rates on gold pricing trends over time. Figure 2 refers dataset details

Figure 2.

Dataset Visualization

Data Preprocessing

The initial phase involves preparing data to be fed into the machine learning model, RandomForestRegressor. The dataset is transformed and standardized to ensure optimal performance. The following steps outline the detailed process:

Encode Categorical Features

In this project, the dataset primarily consists of numerical features, except for the 'Date' column which needs conversion. Since machine learning models like RandomForestRegressor require numerical input, we drop the 'Date' column to focus on purely numerical data. This step simplifies the dataset, ensuring that no categorical encoding is necessary, and allows the model to interpret all input features directly as numerical values during training.

Numerical Features Standardization

The dataset includes various economic indicators such as 'SPX', 'USO', 'SLV', and 'EUR/USD' that differ in scale. For instance, stock indices and currency exchange rates may have different magnitudes compared to the 'GLD' prices. To address this, we use feature scaling techniques like StandardScaler, which adjusts these values so that they have a mean of 0 and a standard deviation of 1. This normalization process ensures that no single feature dominates the model training due to its scale, enabling better model performance.

Division of Data

Once the dataset is preprocessed with the necessary transformations, it is split into features (X) and the target variable (Y). The features (X) include columns such as 'SPX', 'USO', 'SLV', and 'EUR/USD', while the target variable (Y) is the 'GLD' price. The dataset is then divided using train_test_split with an 80% allocation for the training set and 20% for the test set. This division helps in evaluating the model's accuracy on unseen data, ensuring that it generalizes well beyond the training dataset.

Model Description

This model is designed to forecast gold prices based on historical financial data, including stock indices, commodity prices, and currency exchange rates. Since predicting gold prices involves continuous values, a regression model is the most suitable approach. The chosen model, Random Forest Regressor, is known for its robustness, versatility, and ability to handle complex datasets with a mix of correlated features. By leveraging an ensemble technique, it enhances generalization and minimizes overfitting, making it ideal for financial forecasting where data may be noisy or imbalanced.

Algorithm Description

The Random Forest Regressor algorithm operates as follows:

Dataset Bootstrapping

The algorithm begins by creating multiple bootstrapped subsets from the training dataset. Each subset is generated through random sampling with replacement, meaning some data points may appear multiple times, while others may be excluded. This ensures that every decision tree in the forest is trained on a slightly different dataset, adding diversity to the model.

Building Decision Trees
For each bootstrapped subset, a decision tree is constructed. Unlike traditional decision trees, Random Forest introduces randomness by selecting a random subset of features at each split. This feature randomness ensures that the model does not become overly dependent on any single dominant predictor, thereby capturing a wider range of patterns within the data that might otherwise be overlooked.

Averaging Predictions
Once all the decision trees are trained, they make predictions on the test set. For regression tasks like gold price prediction, the Random Forest model averages the predictions from all the trees to generate the final output. This averaging process adds stability to the predictions, reducing variance and improving overall model accuracy.

Prediction and Evaluation
The model's performance is evaluated using metrics such as R-squared and Mean Squared Error (MSE). These metrics provide insights into how well the model predicts the gold prices on unseen data, allowing for a clear assessment of its accuracy and reliability in financial forecasting.

Model Selection and Training
Choosing and training the right model for gold price prediction is crucial to accurately forecasting future gold prices based on historical data and financial indicators. The primary goal of the system is to provide clear interpretations of various financial metrics such as stock indices, commodity prices, and exchange rates, which influence gold prices. This enables the development of a robust prediction framework.

Model Selection
For the regression task involving gold price prediction, two strong contenders are the Random Forest Regressor and Gradient Boosting Regressor. Both models excel in handling datasets with a mix of categorical and continuous variables, thanks to their ensemble learning approach. While Random Forest is known for its robustness against overfitting, Gradient Boosting often achieves superior accuracy by minimizing prediction errors through an iterative model-building process. However, for this project, the Random Forest Regressor was selected due to its ability to handle noisy data effectively and generalize well across various financial scenarios.

Feature Extraction
To prepare the data for modeling, several preprocessing techniques were applied, such as OneHot Encoding for categorical features and StandardScaler for numerical features. OneHot Encoding converts categorical variables into a binary format, while StandardScaler normalizes numerical variables to ensure that all features are on the same scale, thereby enhancing the model's performance.

Input Error Handling and Variability
Gold price prediction data can include inconsistencies, missing values, and variability, especially in financial indicators. Thus, the dataset underwent thorough preprocessing to handle missing values, encode categorical variables, and standardize numerical data. This ensures that the model is trained on clean and consistent data, making it more robust against real-world financial fluctuations.

Training Process
The dataset was split into 70% training and 30% test sets to ensure that the model generalizes well to unseen data. The training process involved fitting the Random Forest Regressor on the training data, where it learns patterns related to various financial metrics. Cross-validation was employed to prevent overfitting and to fine-tune the model's hyperparameters, ensuring optimal performance.

Evaluation Metrics
The model's performance was evaluated using Mean Squared Error (MSE) and R-squared (R^2) metrics. These metrics provide insights into the model's accuracy in predicting gold prices and the reduction of prediction errors. Additionally, scatter plots comparing actual vs. predicted values were used to visualize the model's effectiveness. The Random Forest Regressor's performance was benchmarked against other models, confirming its suitability for gold price forecasting.

Continuous Improvement
Gold price prediction is a dynamic task, influenced by evolving market conditions and financial trends. Therefore, the

model is designed for continuous improvement, with periodic updates based on new financial data and feedback loops. By incorporating recent data from financial markets, the model can adapt to changing patterns, ensuring ongoing accuracy in gold price predictions.

RESULT AND DISCUSSION

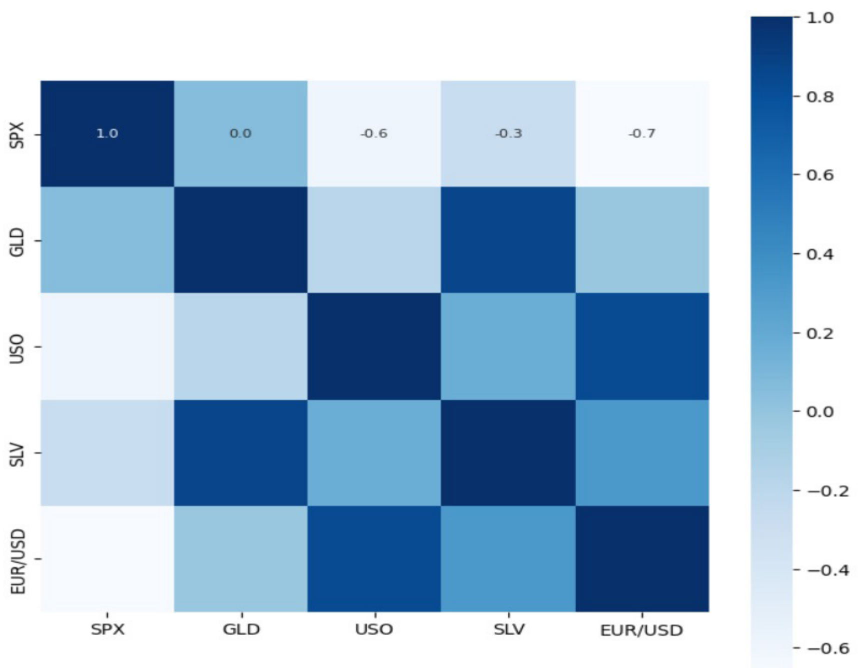
This figure represents the correlation matrix for different financial indicators relevant to predicting gold prices. The dataset includes columns like SPX (S&P 500 index), GLD (Gold ETF), USO (Oil ETF), SLV (Silver ETF), and EUR/USD (currency exchange rate). The matrix highlights the correlation between these variables, with values ranging from -1 to 1, indicating negative to positive correlations respectively. For example, there is a strong positive correlation between GLD and SLV (0,866632), suggesting that silver prices might influence gold prices. Conversely, a strong negative correlation is seen between SPX and EUR/USD (-0,672017), which could indicate an inverse relationship between stock market performance and currency exchange rates. These insights are crucial for building a robust gold price prediction system using a Random Forest Regression model by considering how various financial indicators interplay. Figure 3 represents dataset details.

Figure 3.
Dataset Details

```
Date          object
SPX          float64
GLD          float64
USO          float64
SLV          float64
EUR/USD      float64
dtype: object
                SPX       GLD       USO       SLV   EUR/USD
SPX       1.000000  0.049345 -0.591573 -0.274055 -0.672017
GLD       0.049345  1.000000 -0.186360  0.866632 -0.024375
USO      -0.591573 -0.186360  1.000000  0.167547  0.829317
SLV      -0.274055  0.866632  0.167547  1.000000  0.321631
EUR/USD -0.672017 -0.024375  0.829317  0.321631  1.000000
```

Figure 4.
Heatmap

<Axes: >



This heatmap visualizes the correlation between various features used in the gold price prediction model. The matrix displays correlations ranging from -1 to 1, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 signifies no correlation. Here, we observe that features like SPX (S&P 500 Index), GLD (Gold ETF), USO (Oil Fund), SLV (Silver ETF), and EUR/USD (currency exchange rate) have varying degrees of correlation with each other. Notably, GLD shows minimal to moderate correlation with other indices, suggesting that the features are relatively independent. This independence can enhance the robustness of the Random Forest Regression model by reducing the chances of multicollinearity, thereby improving the predictive performance of the model on gold prices. Figure 4 represents heatmap visualization.

This figure shows the correlation of various financial indicators with the GLD (Gold ETF), which serves as a proxy for gold prices. A strong positive correlation is observed between GLD and SLV (0,866632), suggesting that changes in silver prices tend to align closely with gold prices. On the other hand, the correlation between GLD and other indicators like SPX (0.049345) and EUR/USD (-0,024375) is relatively weak, indicating minimal direct influence on gold prices. The negative correlation with USO (-0,186360) implies that oil prices might have an inverse impact on gold prices to some extent. These correlations are instrumental in designing a Random Forest Regression model for gold price prediction, as they help in selecting relevant features for better model accuracy. Figure 5 represents correlation of GLD.

Figure 5.
Correlation of GLD

```
SPX        0.049345
GLD        1.000000
USO       -0.186360
SLV        0.866632
EUR/USD   -0.024375
Name: GLD, dtype: float64
```

The density plot demonstrates the distribution of gold prices (GLD). The distribution appears to be unimodal with some skewness, highlighting peaks around certain price ranges. The smoothed curve overlay indicates the probability density, showing that the majority of gold prices cluster around the central value, approximately between 120 and 140 units. This visualization helps in understanding the spread and central tendency of gold prices, which are crucial for training the Random Forest Regression model. Identifying such patterns can aid in the model's ability to capture price fluctuations and provide accurate predictions. Figure 6 represents density plot.

Figure 6.
Density Plot

```
<Axes: xlabel='GLD', ylabel='Density'>
```

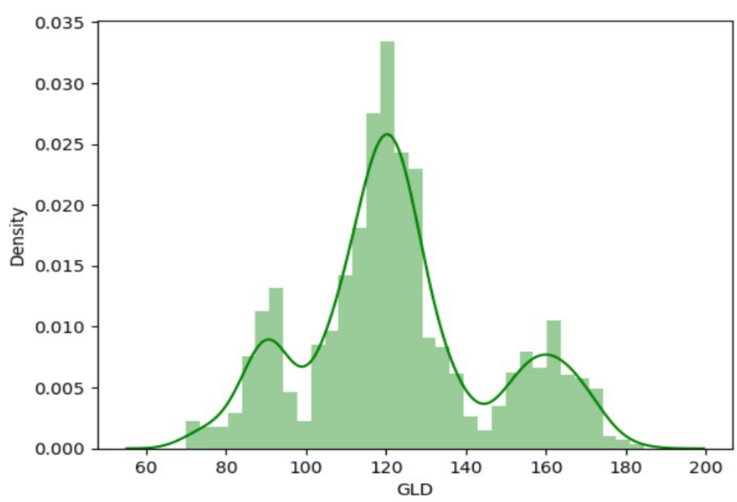


Figure 7 displays a portion of the dataset used for the gold price prediction system, focusing on key financial indicators that may impact gold prices. The dataset includes 2290 rows and 4 columns, featuring variables like SPX (S&P

500 Index), USO (United States Oil Fund), SLV (Silver ETF), and EUR/USD (Euro to US Dollar exchange rate). These indicators are crucial in building a predictive model as they provide insights into various market trends that influence gold prices. By leveraging this data in a Random Forest Regression model, we can enhance the accuracy of gold price forecasts, helping to capture the underlying patterns and dependencies effectively.

Figure 7.
Gold Data after dropping 'Date, GLD'

```
              SPX        USO      SLV   EUR/USD
0     1447.160034  78.470001  15.1800  1.471692
1     1447.160034  78.370003  15.2850  1.474491
2     1411.630005  77.309998  15.1670  1.475492
3     1416.180054  75.500000  15.0530  1.468299
4     1390.189941  76.059998  15.5900  1.557099
...           ...        ...      ...       ...
2285  2671.919922  14.060000  15.5100  1.186789
2286  2697.790039  14.370000  15.5300  1.184722
2287  2723.070068  14.410000  15.7400  1.191753
2288  2730.129883  14.380000  15.5600  1.193118
2289  2725.780029  14.405800  15.4542  1.182033

[2290 rows x 4 columns]
```

Figure 8 displays a portion of the dataset used for the gold price prediction system, focusing on key financial indicators relevant to predicting gold prices. The dataset comprises 2290 rows and several columns, including variables like SPX (S&P 500 Index), USO (United States Oil Fund), SLV (Silver ETF), and EUR/USD (Euro to US Dollar exchange rate). These financial indicators are essential for building a predictive model as they offer insights into broader market trends affecting gold prices. By applying a Random Forest Regression model, we aim to capture the complex relationships and patterns in the data, ultimately enhancing the precision of gold price forecasts.

Figure 8.
Gold Data for 'GLD'

```
0        84.860001
1        85.570000
2        85.129997
3        84.769997
4        86.779999
           ...
2285    124.589996
2286    124.330002
2287    125.180000
2288    124.489998
2289    122.543800
Name: GLD, Length: 2290, dtype: float64
```

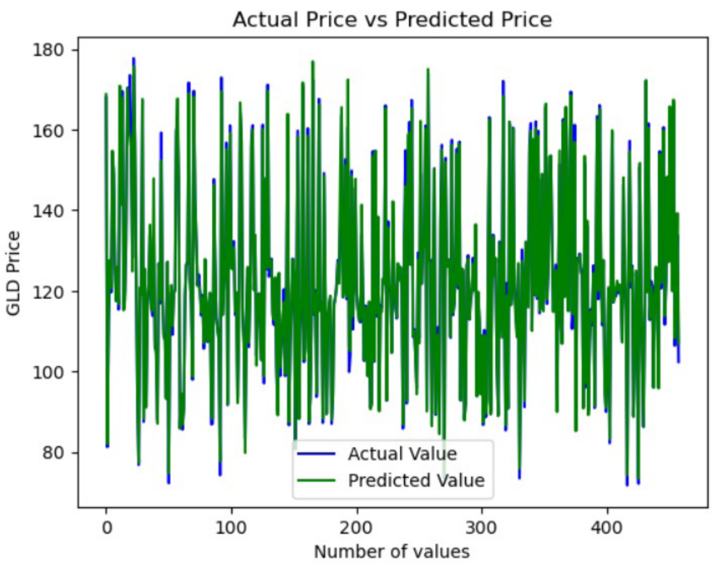
Figure 9 demonstrates the evaluation metric for the gold price prediction system utilizing the Random Forest Regression model. The model's R squared error is 0,98975, indicating an excellent fit with the actual data. An R squared value close to 1 suggests that the model can explain most of the variance in the dependent variable (gold price). Such a high score signifies that the model has effectively captured the patterns and relationships in the dataset, leading to reliable and accurate predictions.

Figure 9.
R squared error

```
R squared error :  0.9897506669412209
```

Figure 10 line graph compares the actual gold prices with the predicted values generated by the Random Forest Regression model. The x-axis represents the index of data points, while the y-axis represents the gold price values. The plot shows two lines: the blue line indicates actual gold prices, and the green line represents the model's predictions. The close alignment between the two lines suggests that the model is able to capture the underlying trends and fluctuations in gold prices with a reasonable degree of accuracy. However, some deviations are still visible, indicating areas for potential model optimization to reduce prediction errors further.

Figure 10.
Actual Price vs Predicted Price



CONCLUSIONS

Through the project on Gold Price Prediction, advanced machine learning technologies like the Random Forest Regression model have been leveraged to enhance the accuracy of gold price forecasting. This approach emphasizes the capability of data-driven models to handle the complexities associated with financial markets, particularly in predicting the fluctuations of gold prices. By utilizing ensemble learning techniques, this system offers a robust predictive framework that can analyze historical trends, capture patterns, and deliver reliable forecasts.

The implementation of such a system not only optimizes investment strategies but also assists stakeholders, including traders and analysts, in making informed decisions. This project provides an integrative platform that uses historical data, market indicators, and economic variables to predict gold prices in near real-time. It enhances the traditional methods of financial analysis by addressing typical challenges such as market volatility, external economic shocks, and the unpredictability of commodity prices.

This machine learning-based gold price prediction system supports the financial industry in achieving better foresight, reducing uncertainties, and optimizing portfolio management. Additionally, continuous model refinement using new data ensures that the prediction system stays adaptive to evolving market conditions, thus delivering consistent performance in forecasting. This project demonstrates a significant step towards leveraging AI technologies to transform the way financial predictions are approached, ultimately contributing to more efficient and data-driven decision-making in the investment landscape.

Future improvements for the Gold Price Prediction System using Random Forest Regression could incorporate additional economic factors to enrich the input dataset. This may include incorporating real-time commodity prices (e.g., silver, crude oil), exchange rate fluctuations, and broader financial indicators such as stock market indices. Another potential enhancement is the inclusion of social media sentiment analysis to gauge public perception and investor confidence, which can influence short-term market trends. Moreover, macroeconomic events like interest rate changes, inflation announcements, and geopolitical developments could be factored in as predictors, providing a more comprehensive understanding of the variables that drive gold prices.

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CONFLICT OF INTEREST
Authors declare that there is no conflict of interest.

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