GOLD PRICE PREDICTION USING RANDOM FOREST REGRESSOR

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<u>Section 1</u>: Introduction to Gold Price Prediction

<u>Understanding the Dataset</u>

- **<u>Historical Data:</u>** The dataset comprises historical data from January 2008 to May 2018, including various financial indicators such as SPX, USO, SLV, and EUR/USD. This data forms the foundation for our gold price prediction model.
- **<u>Data Exploration</u>**: With 2290 rows and 6 columns, the dataset provides a comprehensive view of the factors influencing gold prices. There are no missing values, ensuring the integrity of our analysis.
- **<u>Statistical Measures</u>**: Basic statistical measures reveal key insights into the distribution and variability of the data, setting the stage for our predictive model.

Correlation Analysis

- **Feature Correlation**: A heatmap visualizes the correlation between different features, indicating a moderate positive correlation between GLD and SLV. This insight is crucial for understanding the relationships between gold prices and other financial indicators.
- **Insights for Prediction**: The correlation analysis provides valuable insights into the interplay of factors affecting gold prices, laying the groundwork for our predictive model.

Model Training and Evaluation

- **Random Forest Regressor**: Leveraging the Random Forest Regressor model, we aim to accurately predict gold prices based on the historical dataset. The model's performance is evaluated using the R-squared score, demonstrating a high accuracy in predicting gold prices.
- **Predictive Power**: The model's R-squared score of 0.9884 indicates a strong fit between the predicted and actual gold prices, showcasing the potential of machine learning in forecasting financial markets.

Section 2: Methodology and Findings

Data Preprocessing and Training

- **Data Manipulation**: Python libraries are utilized for data manipulation, visualization, and machine learning, ensuring the integrity and usability of the dataset for predictive modeling.
- **Model Training:** The Random Forest Regressor is trained on the dataset, with a 20% test size for model evaluation, setting the stage for accurate predictions.

Predictive Insights

- **Prediction Results**: The model's predictions provide valuable insights into the future movements of gold prices, empowering investors and analysts with actionable information.
- **Visual Representation**: Visualizations of actual versus predicted gold prices offer a clear understanding of the model's predictive power, enabling informed decision-making in the financial markets.

Implications for Stakeholders

- **Investment Opportunities**: The accurate prediction of gold prices has significant implications for investors, providing insights into potential investment opportunities and risk management strategies.
- **Analytical Tools**: The model's performance suggests that it can be a valuable tool for students and analysts in understanding and forecasting gold price movements, enhancing their analytical capabilities.

Section 3: Conclusion and Implications

Key Takeaways

- **Model Accuracy**: The Random Forest Regressor demonstrates high accuracy in predicting gold prices, offering a reliable tool for financial analysis and decision-making.
- **Investment Insights**: The predictive insights generated by the model have implications for investment strategies and risk management, providing valuable guidance for stakeholders.

Future Research and Applications

- **urther Exploration**: Future research can delve into the application of machine learning models in predicting other financial indicators and market trends, expanding the scope of predictive analytics.
- **Educational Significance**: The implications of this study extend to educational settings, where students can leverage predictive models to enhance their understanding of financial markets and data analysis.

Conclusion

- **Value of Predictive Modeling**: The study successfully demonstrates the potential of Random Forest Regressor in predicting gold prices with high accuracy, highlighting the value of predictive modeling in financial analysis.
- **Call to Action**: The implications of this study call for further exploration and application of predictive analytics in financial markets, offering valuable insights for students and stakeholders alike.

CODE AND OUTPUTS

IMPORTING THE LIBRARIES

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.ensemble import RandomForestRegressor
        from sklearn import metrics
```

DATA COLLECTION AND PRE PROCESSING

In [5]:
```
# loading the csv data to a Pandas DataFrame
gold_data = pd.read_csv('/Users/divyanshsahai/Desktop/gld_price_data.csv')
```

In [6]:
```
# print first 5 rows in the dataframe
gold_data.head()
```

Out[6]:

	Date	SPX	GLD	USO	SLV	EUR/USD
0	1/2/2008	1447.160034	84.860001	78.470001	15.180	1.471692
1	1/3/2008	1447.160034	85.570000	78.370003	15.285	1.474491
2	1/4/2008	1411.630005	85.129997	77.309998	15.167	1.475492
3	1/7/2008	1416.180054	84.769997	75.500000	15.053	1.468299
4	1/8/2008	1390.189941	86.779999	76.059998	15.590	1.557099

In [7]:
```
# print last 5 rows of the dataframe
gold_data.tail()
```

Out[7]:

	Date	SPX	GLD	USO	SLV	EUR/USD
2285	5/8/2018	2671.919922	124.589996	14.0600	15.5100	1.186789
2286	5/9/2018	2697.790039	124.330002	14.3700	15.5300	1.184722
2287	5/10/2018	2723.070068	125.180000	14.4100	15.7400	1.191753
2288	5/14/2018	2730.129883	124.489998	14.3800	15.5600	1.193118
2289	5/16/2018	2725.780029	122.543800	14.4058	15.4542	1.182033

In [29]:
```python
# number of rows and columns
gold_data.shape
```

Out[29]:
```
(2290, 6)
```

In [9]:
```python
# getting some basic informations about the data
gold_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2290 entries, 0 to 2289
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Date     2290 non-null   object
 1   SPX      2290 non-null   float64
 2   GLD      2290 non-null   float64
 3   USO      2290 non-null   float64
 4   SLV      2290 non-null   float64
 5   EUR/USD  2290 non-null   float64
dtypes: float64(5), object(1)
memory usage: 107.5+ KB
```

In [10]:
```python
# checking the number of missing values
gold_data.isnull().sum()
```

Out[10]:
```
Date       0
SPX        0
GLD        0
USO        0
SLV        0
EUR/USD    0
dtype: int64
```

In [22]:
```
# getting the statistical measures of the data
gold_data.describe()
```

Out[22]:

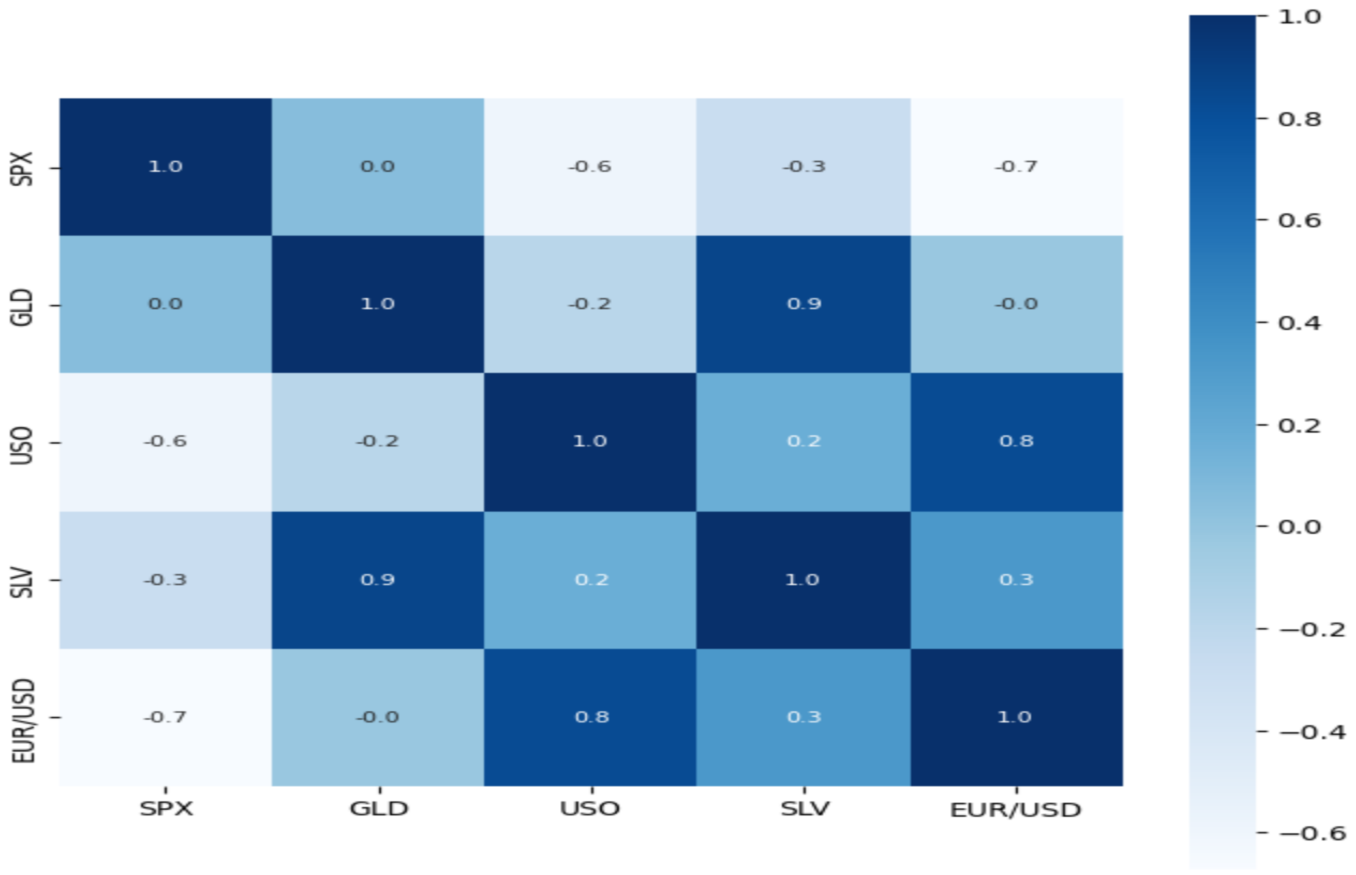
	SPX	GLD	USO	SLV	EUR/USD
count	2290.000000	2290.000000	2290.000000	2290.000000	2290.000000
mean	1654.315776	122.732875	31.842221	20.084997	1.283653
std	519.111540	23.283346	19.523517	7.092566	0.131547
min	676.530029	70.000000	7.960000	8.850000	1.039047
25%	1239.874969	109.725000	14.380000	15.570000	1.171313
50%	1551.434998	120.580002	33.869999	17.268500	1.303297
75%	2073.010070	132.840004	37.827501	22.882500	1.369971
max	2872.870117	184.589996	117.480003	47.259998	1.598798

CORRELATION

1. Positive Correlation
2. Negative Correlation

```
In [30]: if 'Date' in gold_data.columns:
             gold_data['Date'] = pd.to_datetime(gold_data['Date'])

In [31]: numeric_data = gold_data.select_dtypes(include=[np.number])

In [32]: correlation = numeric_data.corr()
         print(correlation)

                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
```

```
In [33]: # constructing a heatmap to understand the correlatiom
         plt.figure(figsize = (8,8))
         sns.heatmap(correlation, cbar=True, square=True, fmt='.1f',annot=True, annot_kws={'size':8}, cmap='Blues')

Out[33]: <Axes: >
```

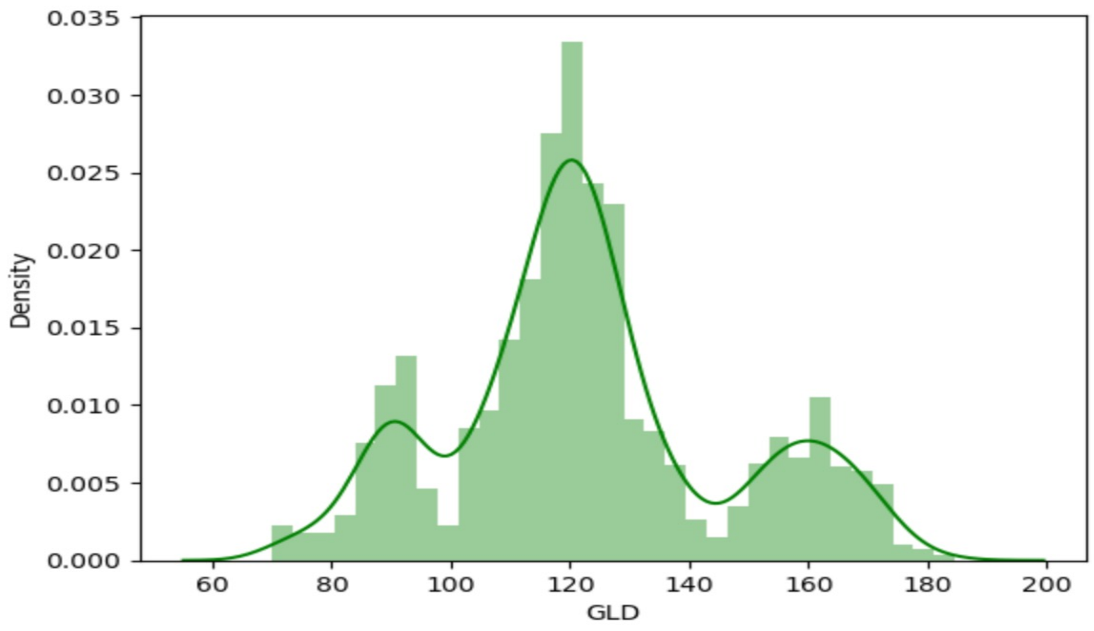


In [34]:
```
# correlation values of GLD
print(correlation['GLD'])
```

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

In [36]:
```
# checking the distribution of the GLD Price
sns.distplot(gold_data['GLD'],color='green')
```

Out[36]: <Axes: xlabel='GLD', ylabel='Density'>



Splitting the Features and Target

```
In [37]: X = gold_data.drop(['Date','GLD'],axis=1)
         Y = gold_data['GLD']
```

```
In [38]: print(X)
```

```
               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]
```

```
In [39]: print(Y)
```

```
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
```

Splitting into Training data and Test Data

```
In [40]: X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state=2)
```

Model Training: Random Forest Regressor

```
In [41]: regressor = RandomForestRegressor(n_estimators=100)
```

```
In [42]: # training the model
         regressor.fit(X_train,Y_train)
```

```
Out[42]: ▸ RandomForestRegressor
```

MODEL EVALUATION

```
In [43]: # prediction on Test Data
         test_data_prediction = regressor.predict(X_test)

In [44]: print(test_data_prediction)

[168.76829971  82.18829959 116.23410027 127.5674008  120.62270108
 154.71719784 150.04719887 126.16890035 117.66989876 126.06290049
 116.73160075 172.27110078 141.83419834 167.76609874 115.22450001
 117.50600051 138.24400331 170.43690097 159.44380243 159.35360011
 155.00559987 125.07500044 175.29609979 157.42990403 125.15680053
  93.7665996   78.52829999 120.3315998  119.13719967 167.46479965
  88.14750083 125.56270024  91.13840088 117.60690032 121.03429896
 135.75240091 115.35360115 115.20890059 146.93200024 107.28520116
 104.21120231  87.21809814 126.55120089 117.77010013 152.16679857
 119.47440021 108.43369996 108.11349845  93.16320066 126.93079794
  74.99960049 113.66059923 121.55940049 111.4665992  118.94509913
 121.06329933 159.37650092 167.73280074 147.07139661  85.78759859
  94.37560042  86.77779895  90.62120029 119.01440081 126.31670088
 127.32839977 168.85600031 122.28969894 117.24229909  98.53520055
 167.38750157 142.82689856 132.07460331 121.07910221 121.11059944
 119.49270029 114.57210167 118.45810047 107.2110013  127.85710028
 114.03889951 107.64999997 116.59100088 119.73919877  89.02940102
  88.32229857 146.02410214 127.24129991 113.40510009 110.13299841
 108.06209908  77.77509894 169.22650192 114.03349909 121.72629889
 127.95050204 154.96979768  91.66889952 136.41830156 158.64060388
 125.19920075 125.53520052 130.86430227 114.80760136 119.93300008
  92.06619963 110.38969867 166.63459928 157.69169879 114.14229947
 106.57850129  79.56849964 113.03140032 125.89620076 107.29549897
 119.28880093 155.71030333 159.78199868 120.13549986 134.83220365
 100.9523     117.4757981  119.28400026 113.02250073 102.75959892
 159.99869706  99.22050022 146.93249929 125.49020097 170.16899939
 125.76389855 127.49479673 127.42570164 113.65619936 112.81140055
 123.68629896 102.15189912  89.03199994 124.48209956 102.19799948
 107.17229942 113.78620041 117.0614007   99.53309969 121.69260048
 163.39999899  87.36439868 106.86199979 117.23340072 127.66520092
 124.10780054  80.68509901 120.33230059 157.49299811  87.8069993
 110.33009942 118.93989903 172.42019888 102.90619899 105.32000062
 122.90260034 157.8503978   87.85599817  92.85140048 112.56010026
 176.59000005 114.31519999 119.31880008  94.64340093 125.76210012
 166.36260125 114.82360081 116.90950129  88.32869856 148.71810071
 120.40929917  89.68779989 112.30680003 117.29140024 118.73890125
  88.04859918  94.14340014 116.88480017 118.69490152 120.40890049
 126.78439809 122.03819964 150.37990052 165.07900039 118.54099964
 120.61500153 150.92920043 118.29679902 173.41409921 105.63489942
 104.89170174 149.15490065 113.77410081 124.78420134 147.00900042
 119.6824009  115.49290054 112.59730003 113.57670187 140.65130147
 117.89769785 102.94360028 115.8441012  103.20730149  99.00540049
```

117.09020045	90.84119981	91.43770049	153.93619924	102.64239983
155.08690073	114.46180143	139.45430088	90.14519827	115.52499953
114.72109993	122.68900026	121.89180011	165.29420179	92.82759962
135.60660098	121.35249932	120.5186009	104.71969999	141.19590304
121.62279951	116.58960032	113.52520049	127.03829728	122.39659957
125.79169926	121.25340035	86.90429909	132.7075016	144.04590242
92.66679998	160.31379921	157.98170281	126.40809863	165.62089997
108.72619927	110.34820106	103.61409825	94.36070065	127.6160028
107.08530045	162.20589988	121.83370021	132.12089978	130.97760242
160.63280025	90.04709833	174.73430216	128.10750013	126.77749803
86.54569935	124.66639961	150.14199748	89.68800009	106.93329967
109.02689969	84.56069911	136.06219932	154.8288023	139.088604
73.79670045	152.13230116	126.30539976	126.83829983	127.49099877
108.64109961	156.0903999	114.48390105	117.09570107	125.1347995
154.0024018	121.30209997	156.44909909	92.9162005	125.46510144
125.65800017	88.06620098	92.0583991	126.40279933	128.62030397
113.18700058	117.6246973	120.68320033	127.1277975	119.67520108
136.10650165	93.88539931	119.75480042	113.12400093	94.22299919
108.97669968	87.68509918	109.09419943	89.59539957	92.43740036
131.41210341	162.29870023	89.17760022	119.47550093	133.26340188
123.971	128.71540204	101.91679841	88.95409901	131.60600069
119.92569995	108.56150012	168.3552013	115.25880041	86.65519882
118.97720059	91.03509982	161.84330064	116.55680044	121.60850011
160.1049977	120.00539935	112.86239938	108.44539871	126.67209979
75.78290035	103.03459987	127.65950237	121.89919927	92.61340025
132.09020057	118.1096014	116.04949954	154.44130299	159.38760084
110.21039933	157.69499813	119.27440082	160.2606009	118.50980065
157.26660075	115.13729921	116.57600019	149.34569903	114.68170085
125.78089879	167.29229996	117.98700029	124.8028993	153.29100377
153.51920237	132.12510088	114.74210067	121.15840197	125.2400005
89.89210059	123.18149958	154.89610151	111.82430038	106.88409962
162.16680101	118.5193995	165.67049967	133.92430073	114.91729957
153.02879861	168.52260006	114.61520012	113.98620136	158.34109893
85.48089859	126.97430085	127.87730046	128.7544002	124.37360085
123.84980061	90.5399006	153.12749948	97.06169988	137.61030046
89.07619948	107.59559994	115.02510059	112.43670069	123.88599937
91.51799891	125.47220149	162.37499818	119.79869924	165.08550179
126.79689784	112.28110026	127.48189938	94.6366988	90.93560009
103.85459921	120.7429998	82.67939952	126.38529987	160.59110439
117.32700079	118.34679992	119.98109984	122.56849959	120.06590117
121.54219995	118.06790094	107.28489998	147.89899909	126.18709791
115.81800072	73.98550005	127.78900097	154.17810067	123.12140006
125.56950055	88.95590011	103.16809869	124.25970047	120.29720021
73.47450088	151.89300019	121.25960077	104.46180029	86.84789774
115.18059908	172.27199897	119.89320035	159.63209812	113.28109951
121.20990029	118.80010117	95.94119973	118.78900028	125.96950057
118.69279937	95.65790051	153.91100209	122.06140012	147.83389998

```
In [45]: # R squared error
         error_score = metrics.r2_score(Y_test, test_data_prediction)
         print("R squared error : ", error_score)

         R squared error :  0.9884013301809286

In [46]: Y_test = list(Y_test)
```

Compare the Actual Values and Predicted Values in a Plot

In [47]:
```
plt.plot(Y_test, color='blue', label = 'Actual Value')
plt.plot(test_data_prediction, color='green', label='Predicted Value')
plt.title('Actual Price vs Predicted Price')
plt.xlabel('Number of values')
plt.ylabel('GLD Price')
plt.legend()
plt.show()
```