

8_Predicting_Gold_Market_Trends_A_Random_Forest_Approach

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##Gold Price Prediction Using Random Forest: A Machine Learning Perspective -Vignesh Prabhu

Predicting gold prices is challenging due to various influencing factors. This project uses Random Forest Regression, a machine learning technique, to forecast gold prices. By analyzing historical data and economic indicators, we aim to create an accurate and reliable model to assist investors and analysts in making informed decisions.

Import Dependencies

```
[1]: import pandas as pd
import numpy as np
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 Preprocessing

```
[2]: #Load data into Dataframe
gold_data=pd.read_csv("/content/Gold_Price.csv")
```

```
[3]: #to print First 5 rows
gold_data.head()
```

```
[3]:
```

	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

```
[4]: #To check information
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

```
[5]: #to Check rows and columns
gold_data.shape
```

```
[5]: (2290, 6)
```

```
[6]: #To check statistical Values
gold_data.describe()
```

```
[6]:
```

	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

```
[7]: # To check Any Null values in dataset
gold_data.isnull().sum()
```

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

Correlation

```
[12]: # Assuming 'gold_data' is your DataFrame
# Convert the date column to datetime objects
gold_data['Date'] = pd.to_datetime(gold_data['Date']) # Replace 'Date' with
↳ the actual column name
```

```

# Extract numerical features from the datetime object if needed
gold_data['Year'] = gold_data['Date'].dt.year
gold_data['Month'] = gold_data['Date'].dt.month
gold_data['Day'] = gold_data['Date'].dt.day

# Now calculate the correlation
correlation = gold_data.corr()

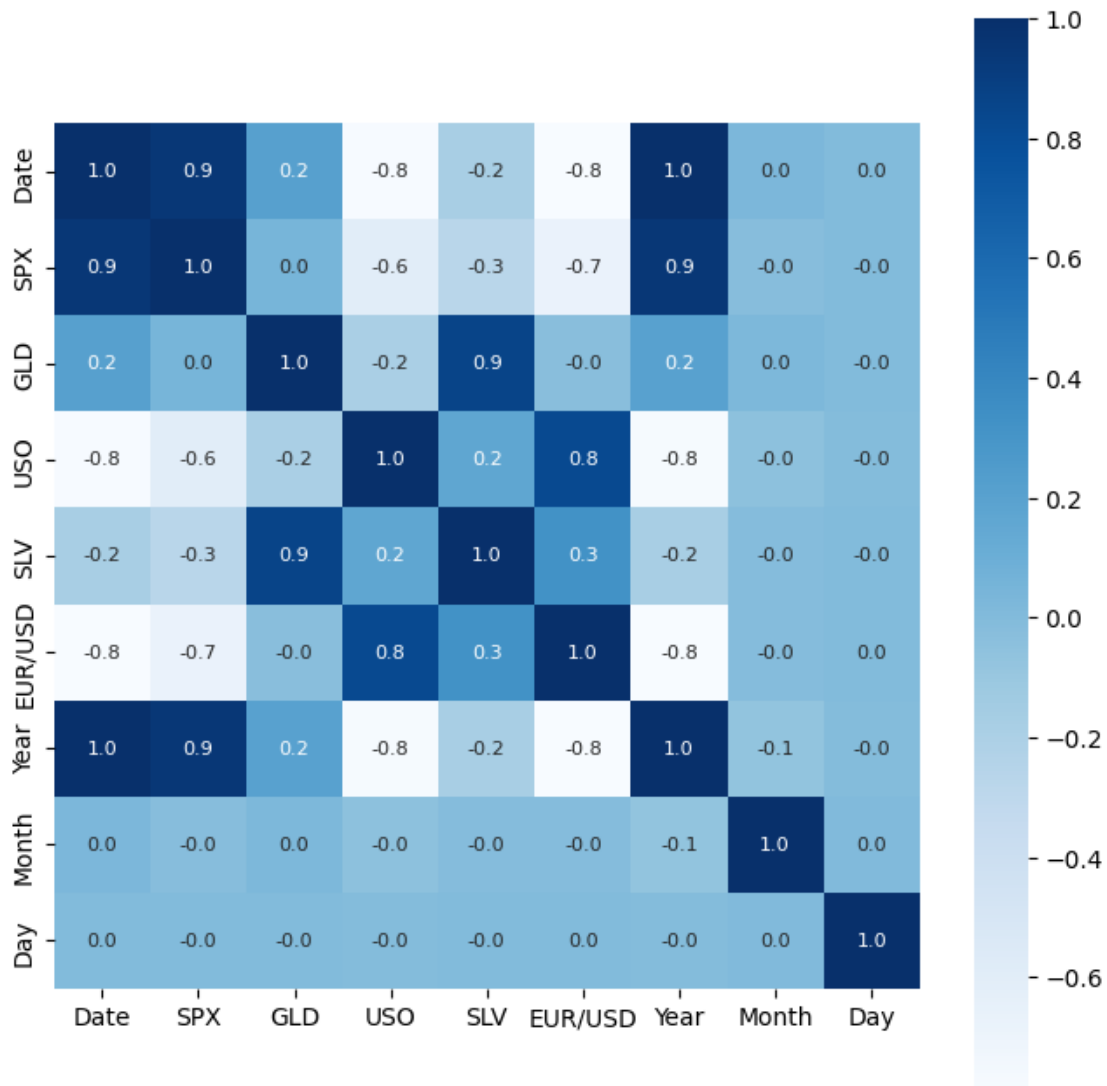
```

```

[13]: #HeatMap
plt.figure(figsize=(8,8))
sns.heatmap(correlation,cbar=True,square=True,fmt='.
↳1f',annot=True,annot_kws={'size':8},cmap='Blues')

```

[13]: <Axes: >



```
[14]: #correlation Of GLD
print(correlation['GLD'])
```

```
Date      0.209118
SPX       0.049345
GLD       1.000000
USO      -0.186360
SLV       0.866632
EUR/USD   -0.024375
Year      0.206654
Month     0.020494
Day       -0.000198
Name: GLD, dtype: float64
```

```
[16]: #distribution of gold price
sns.distplot(gold_data['GLD'], color='red')
```

<ipython-input-16-7518d28b8e5b>:2: UserWarning:

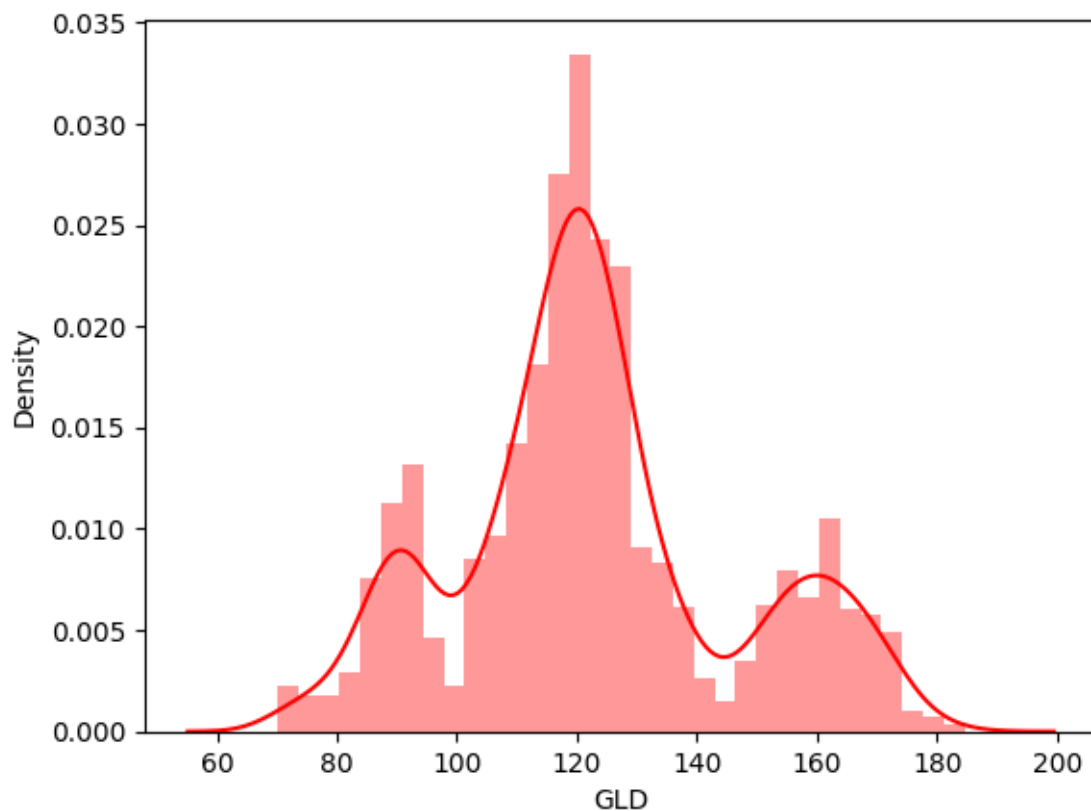
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(gold_data['GLD'], color='red')
```

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



Splitting Features and Target

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

```
[19]: print(X)
```

	SPX	USO	SLV	EUR/USD	Year	Month	Day
0	1447.160034	78.470001	15.1800	1.471692	2008	1	2
1	1447.160034	78.370003	15.2850	1.474491	2008	1	3
2	1411.630005	77.309998	15.1670	1.475492	2008	1	4
3	1416.180054	75.500000	15.0530	1.468299	2008	1	7
4	1390.189941	76.059998	15.5900	1.557099	2008	1	8
...
2285	2671.919922	14.060000	15.5100	1.186789	2018	5	8
2286	2697.790039	14.370000	15.5300	1.184722	2018	5	9
2287	2723.070068	14.410000	15.7400	1.191753	2018	5	10
2288	2730.129883	14.380000	15.5600	1.193118	2018	5	14
2289	2725.780029	14.405800	15.4542	1.182033	2018	5	16

[2290 rows x 7 columns]

```
[20]: 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 And Test data

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

```
[23]: print(X.shape,X_train.shape,X_test.shape)
```

```
(2290, 7) (1832, 7) (458, 7)
```

Model training

```
[25]: regressor=RandomForestRegressor(n_estimators=100) #default Number
```

```
[26]: regressor.fit(X_train,Y_train)
```

```
[26]: RandomForestRegressor()
```

Model Evaluation

```
[27]: #prediction on test Data
test_data_prediction=regressor.predict(X_test)
```

```
[ ]: print(test_data_prediction)
```

```
[29]: #R squarred Error
Error_score=metrics.r2_score(Y_test,test_data_prediction)
print("R squarred Error : ",Error_score)
```

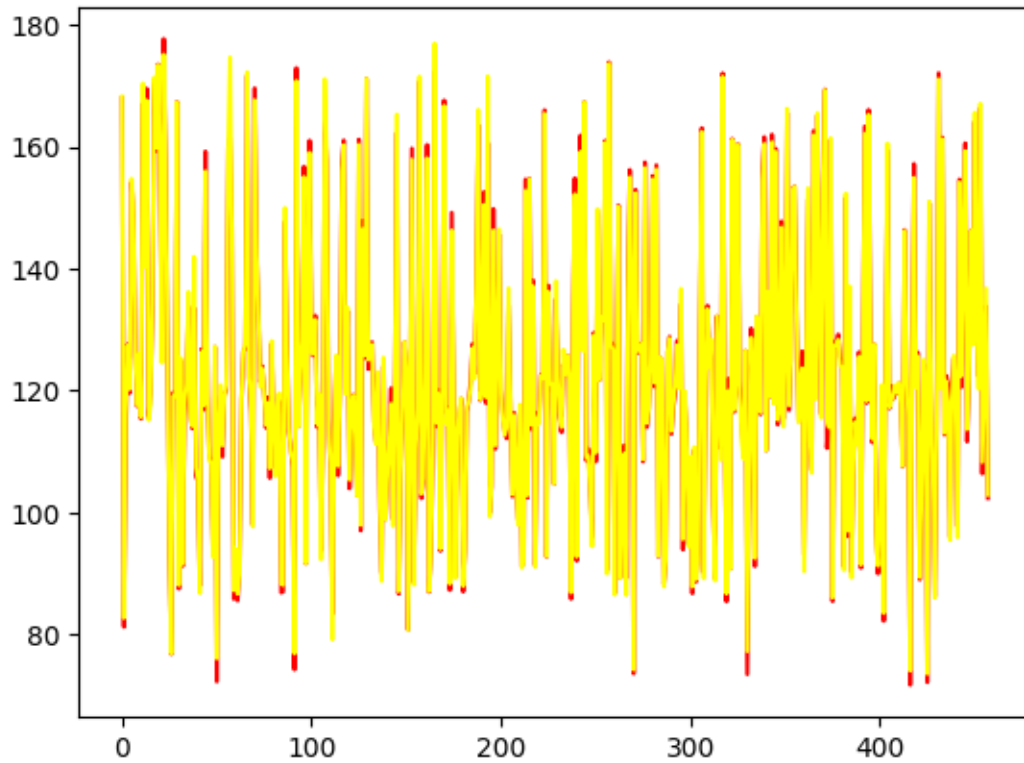
```
R squarred Error : 0.9954394762121126
```

Compare Actual values and Predicted values

```
[30]: Y_test=list(Y_test)
```

```
[33]: plt.plot(Y_test,color='red',label='Actual Value')
plt.plot(test_data_prediction,color='yellow',label='Predicted Value')
```

[33]: [



This project used Random Forest Regression to predict gold prices, achieving high accuracy by leveraging historical data and economic indicators. The model's effectiveness highlights the potential of machine learning in financial forecasting, offering valuable insights for investors and analysts.

1 Thank You!