

goldpricemodel

April 9, 2024

1 Gold price prediction using regression techniques

1.1 importing essential libraries

```
[85]: 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.ensemble import RandomForestRegressor, AdaBoostRegressor ,
↳ GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
import pickle
```

1.2 Data Processing

```
[86]: gold_data = pd.read_csv('golddaily.csv') #reading data from
↳ dataset.csv
```

```
[3]: gold_data.head()
```

```
[3]:
```

	Date	Price	Open	High	Low	Chg%
0	01-Jan-24	63320	63225	63379	63181	0.19%
1	29-Dec-23	63203	63246	63385	63051	-0.29%
2	28-Dec-23	63389	63728	63821	63333	-0.45%
3	27-Dec-23	63678	63198	63710	63179	1.04%
4	26-Dec-23	63025	63149	63198	62903	0.11%

```
[87]: # gold_data['Price'] = gold_data['Price'].int.replace(',', '').astype(float)
# gold_data['Open'] = gold_data['Open'].int.replace(',', '').astype(float)
# gold_data['High'] = gold_data['High'].int.replace(',', '').astype(float)
```

```
# gold_data['Low'] = gold_data['Low'].int.replace(',', '').astype(float)
gold_data['Chg%'] = gold_data['Chg%'].str.rstrip('%').astype(float)
↳ #changing datatype of change from % object to float64
```

```
[88]: # Convert 'Date' column to datetime format with specified format
gold_data['Date'] = pd.to_datetime(gold_data['Date'], format='%d-%b-%y')
gold_data['Date'] = pd.to_datetime(gold_data['Date'], format='%b-%y')

# Extract Year, Month, and Day
gold_data['Year'] = gold_data['Date'].dt.year
gold_data['Month'] = gold_data['Date'].dt.month
gold_data['Day'] = gold_data['Date'].dt.day

# Drop the original 'Date' column
gold_data.drop('Date', axis=1, inplace=True)
```

```
[89]: ## Adding some noise for overcoming overfitting
synthetic_data = pd.DataFrame()

for column in gold_data.columns:
    # Generate synthetic data for each column
    synthetic_column = np.random.choice(gold_data[column], size=100)
    synthetic_data[column] = synthetic_column
```

```
[90]: merged_data = pd.concat([gold_data, synthetic_data])
```

```
[91]: merged_data
```

```
[91]:
```

	Price	Open	High	Low	Chg%	Year	Month	Day
0	63320	63225	63379	63181	0.19	2024	1	1
1	63203	63246	63385	63051	-0.29	2023	12	29
2	63389	63728	63821	63333	-0.45	2023	12	28
3	63678	63198	63710	63179	1.04	2023	12	27
4	63025	63149	63198	62903	0.11	2023	12	26
..
95	26892	50275	30036	29739	0.06	2022	10	16
96	28541	46851	27274	26350	-1.43	2022	1	18
97	29012	34465	51065	26911	-1.21	2019	7	7
98	27198	46766	32319	31875	-0.59	2021	9	11
99	29487	30930	29105	45479	0.82	2015	11	5

[2692 rows x 8 columns]

```
[9]: gold_data.describe()
```

```
[9]:
```

	Price	Open	High	Low	Chg%	\
count	2592.000000	2592.000000	2592.000000	2592.000000	2592.000000	

mean	38255.199460	38249.878472	38452.240355	38053.575617	0.034904
std	11337.916616	11337.067365	11403.420055	11272.424903	0.847437
min	24597.000000	24535.000000	24701.000000	24451.000000	-8.670000
25%	28788.750000	28796.500000	28910.250000	28667.750000	-0.410000
50%	31638.000000	31633.500000	31827.000000	31513.500000	0.040000
75%	48681.000000	48691.000000	48925.750000	48465.750000	0.480000
max	63678.000000	63728.000000	64460.000000	63333.000000	5.670000

	Year	Month	Day
count	2592.000000	2592.000000	2592.000000
mean	2018.475309	6.513889	15.719136
std	2.884796	3.447545	8.792376
min	2014.000000	1.000000	1.000000
25%	2016.000000	4.000000	8.000000
50%	2018.000000	7.000000	16.000000
75%	2021.000000	9.250000	23.000000
max	2024.000000	12.000000	31.000000

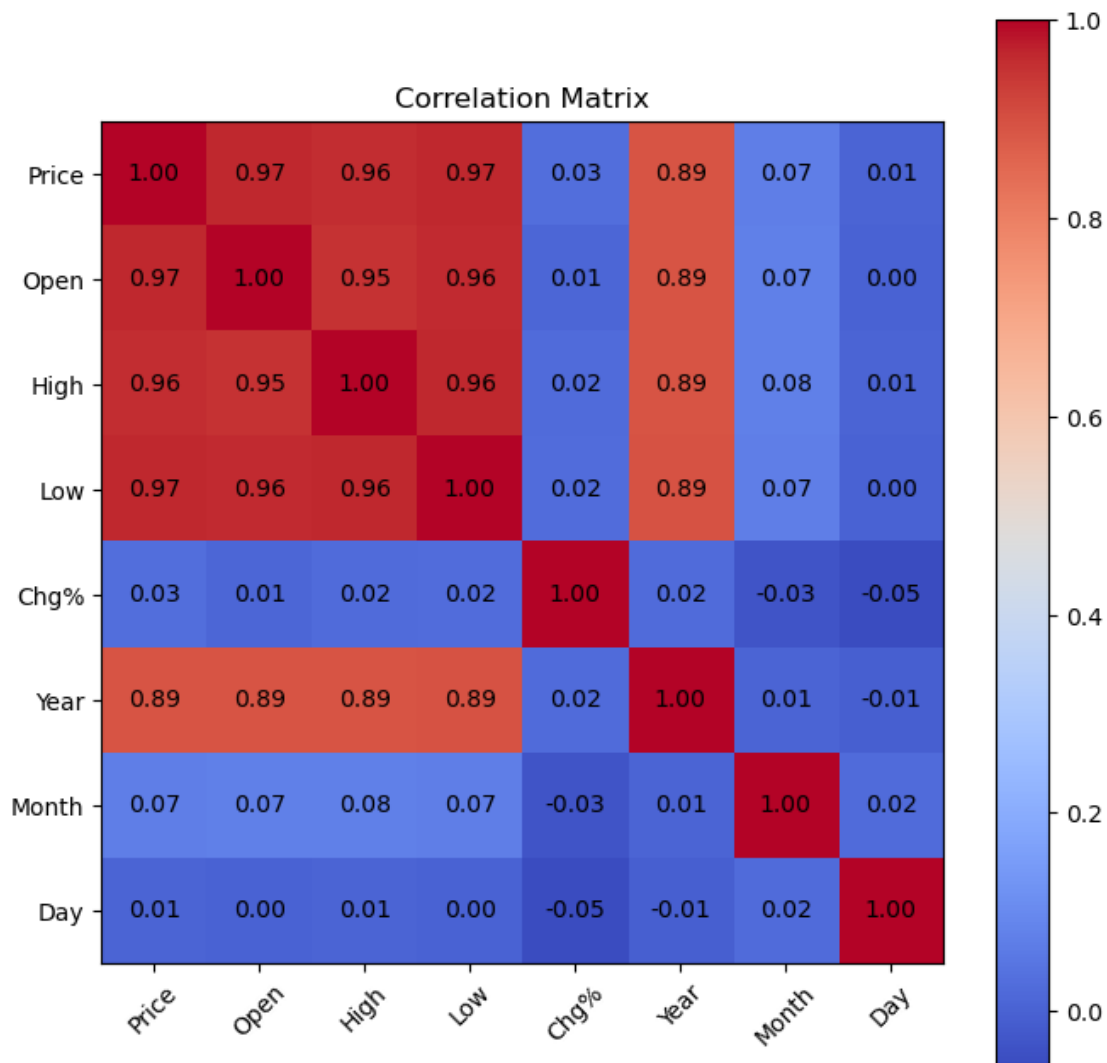
1.3 Data Extraction

```
[92]: correlation = merged_data.corr()

plt.figure(figsize=(8, 8))
plt.title('Correlation Matrix')
plt.imshow(correlation, cmap='coolwarm', interpolation='nearest')

# Add text annotations
for i in range(len(correlation)):
    for j in range(len(correlation)):
        plt.text(j, i, f'{correlation.iloc[i, j]:.2f}', ha='center',
        ↪va='center', color='black')

plt.colorbar()
plt.xticks(ticks=np.arange(len(correlation.columns)), labels=correlation.
↪columns, rotation=45)
plt.yticks(ticks=np.arange(len(correlation.columns)), labels=correlation.
↪columns)
plt.show()
```



```
[11]: print(correlation)
```

	Price	Open	High	Low	Chg%	Year	Month	\
Price	1.000000	0.965637	0.958791	0.961114	0.026571	0.891795	0.075933	
Open	0.965637	1.000000	0.959905	0.952252	0.002116	0.884415	0.072420	
High	0.958791	0.959905	1.000000	0.960012	0.021382	0.883587	0.069189	
Low	0.961114	0.952252	0.960012	1.000000	0.018365	0.887666	0.070271	
Chg%	0.026571	0.002116	0.021382	0.018365	1.000000	0.024354	-0.034528	
Year	0.891795	0.884415	0.883587	0.887666	0.024354	1.000000	0.003376	
Month	0.075933	0.072420	0.069189	0.070271	-0.034528	0.003376	1.000000	
Day	0.005627	0.009561	0.005068	0.001848	-0.054451	0.002105	0.017166	

	Day
Price	0.005627

```
Open    0.009561
High    0.005068
Low      0.001848
Chg%    -0.054451
Year     0.002105
Month    0.017166
Day      1.000000
```

```
[12]: gold_data.isnull().sum()
```

```
[12]: Price      0
      Open       0
      High       0
      Low        0
      Chg%       0
      Year       0
      Month      0
      Day        0
      dtype: int64
```

```
[13]: price_column = gold_data.pop('Price')
      gold_data['Price'] = price_column
```

```
[93]: merged_data.isnull().sum()
```

```
[93]: Price      0
      Open       0
      High       0
      Low        0
      Chg%       0
      Year       0
      Month      0
      Day        0
      dtype: int64
```

```
[15]: gold_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2592 entries, 0 to 2591
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype
---  -
 0   Open    2592 non-null   int64
 1   High    2592 non-null   int64
 2   Low     2592 non-null   int64
 3   Chg%    2592 non-null   float64
 4   Year    2592 non-null   int32
 5   Month   2592 non-null   int32
```

```

6   Day      2592 non-null   int32
7   Price    2592 non-null   int64
dtypes: float64(1), int32(3), int64(4)
memory usage: 131.8 KB

```

```
[94]: X = merged_data.drop('Price', axis=1)
      Y = merged_data['Price']
```

```
[95]: X.tail()
```

```
[95]:
```

	Open	High	Low	Chg%	Year	Month	Day
95	50275	30036	29739	0.06	2022	10	16
96	46851	27274	26350	-1.43	2022	1	18
97	34465	51065	26911	-1.21	2019	7	7
98	46766	32319	31875	-0.59	2021	9	11
99	30930	29105	45479	0.82	2015	11	5

```
[96]: from sklearn.model_selection import train_test_split
```

```
[97]: X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
      ↪random_state=42)
```

1.4 Standardisation

```
[20]: # Standardize the features
      scaler = StandardScaler()
      X_train_scaled = scaler.fit_transform(X_train)
      X_test_scaled = scaler.transform(X_test)
```

1.5 LINEAR REGRESSION

```
[21]: linear_regressor = LinearRegression()
      linear_regressor.fit(X_train_scaled, Y_train)
```

```
[21]: LinearRegression()
```

```
[22]: test_data_prediction = linear_regressor.predict(X_test_scaled)
```

```
[23]: test_data_prediction
```

```
[23]: array([28977.01380179, 26919.40070297, 51176.7656607 , 47194.70528544,
        28164.12487887, 30829.87416499, 37929.46833345, 27285.98801479,
        29581.99062323, 29271.17830187, 29684.6454153 , 29127.12685534,
        28011.25937088, 58321.69757268, 30944.27604551, 38565.88608774,
        28717.08114202, 28206.26733439, 51380.23354289, 26476.92027073,
        49949.88985957, 46577.46519137, 26813.85161442, 33820.74040148,
        47278.93004689, 49321.10689966, 46738.59537691, 28860.80959624,
```

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26302.75037376, 28968.05103122, 33562.65474021, 26534.22038549,
30248.12618661, 43354.41393013, 41325.82904874, 28888.96049638,
51533.81835687, 55704.98798754, 47309.33315245])

```

```

[24]: error_score = metrics.r2_score(Y_test, test_data_prediction)
mae_lr = mean_absolute_error(Y_test, test_data_prediction)
mse_lr = mean_squared_error(Y_test, test_data_prediction)
print("MAE (Linear Regression): {:.2f}".format(mae_lr))
print("MSE (Linear Regression): {:.2f}".format(mse_lr))
print("R squared error : ", error_score)

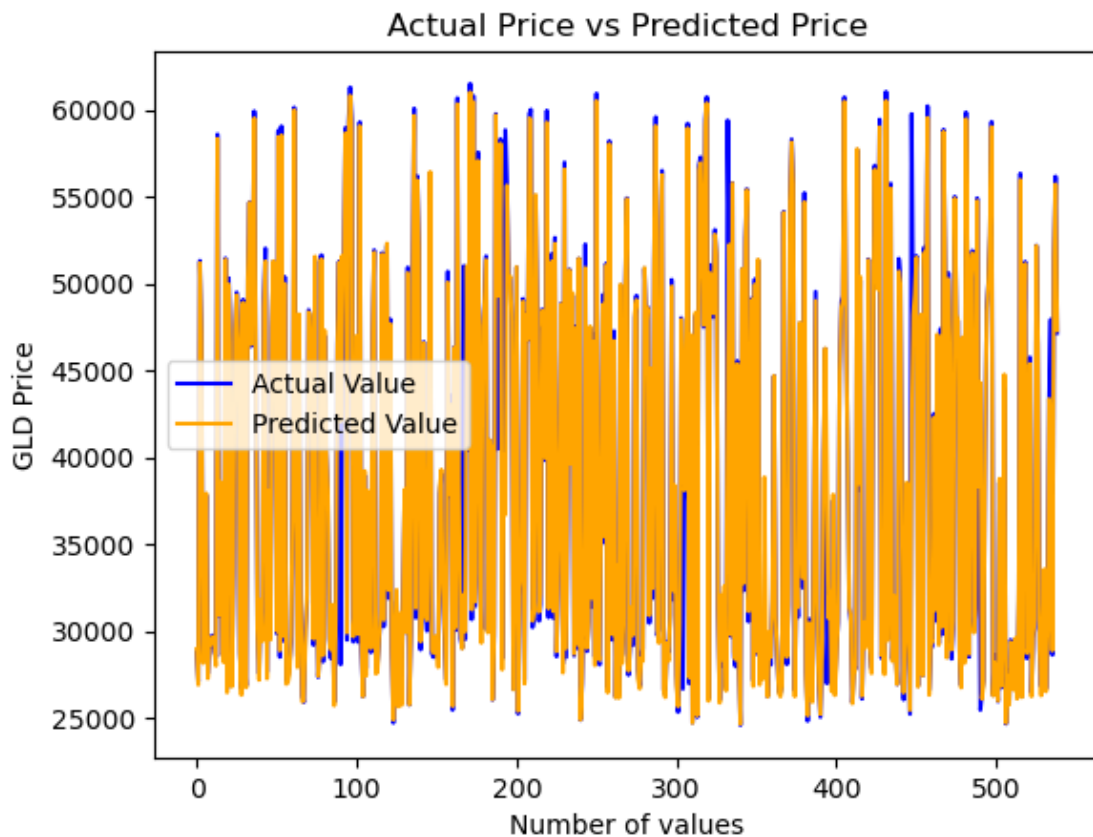
```

```

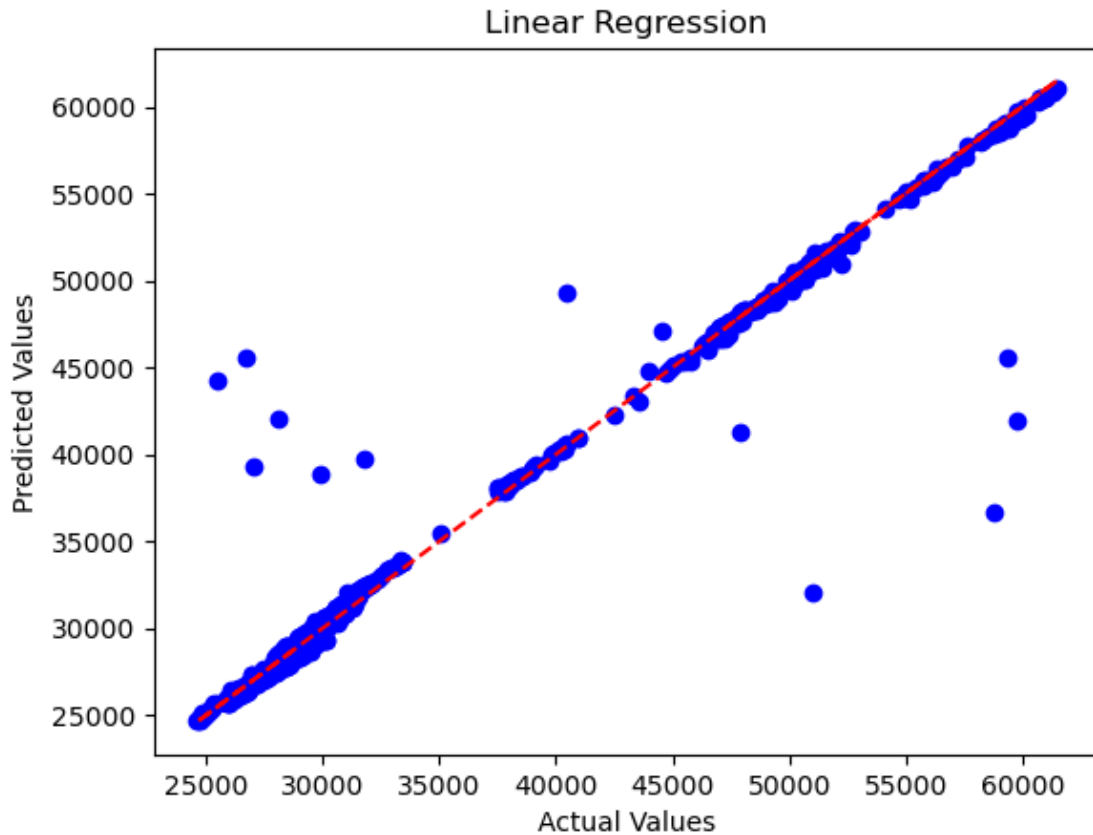
MAE (Linear Regression): 599.70
MSE (Linear Regression): 5098138.32
R squared error : 0.9601713615094156

```

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



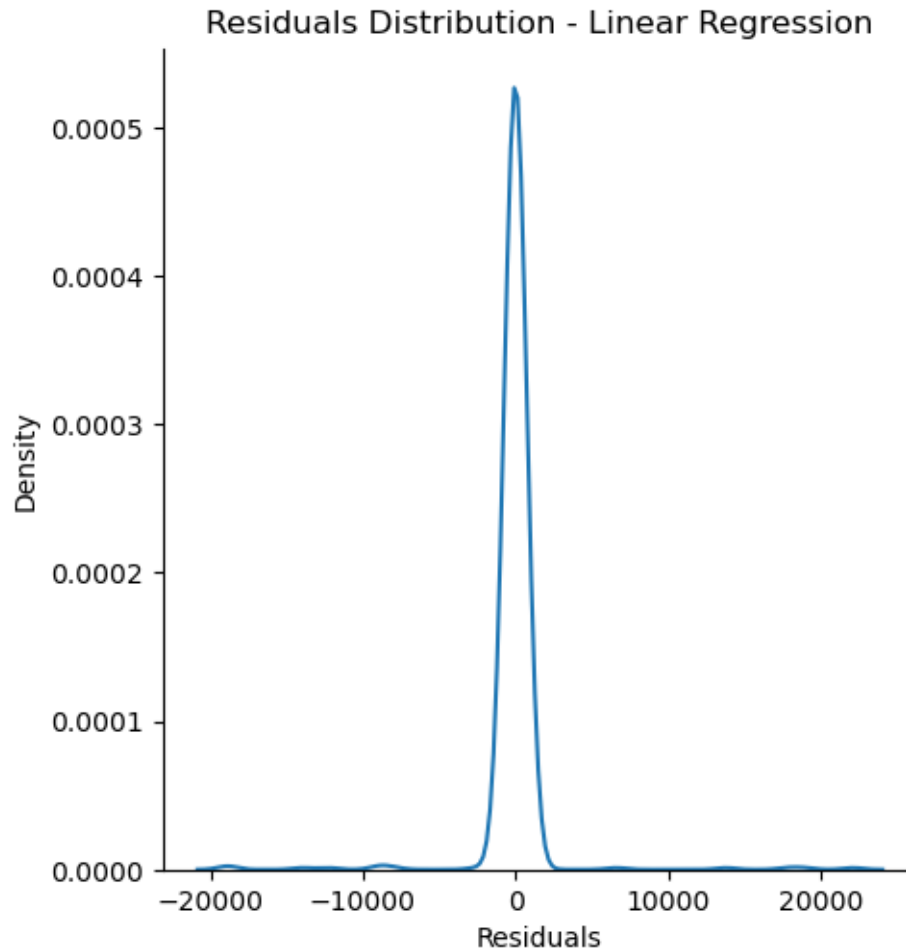
```
[26]: plt.scatter(Y_test, test_data_prediction, color='blue')
plt.plot(Y_test, Y_test, color='red', linestyle='--')
plt.title('Linear Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



```
[27]: sns.displot(Y_test - test_data_prediction, kind='kde')
plt.title('Residuals Distribution - Linear Regression')
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```

C:\Users\sarka\anaconda3\envs\Projects\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

```
with pd.option_context('mode.use_inf_as_na', True):
```



```
[28]: print("Accuracy of linear Regression model: {:.2f}%".format(error_score * 100))
```

Accuracy of linear Regression model: 96.02%

```
[29]: pickle.dump(linear_regressor, open('linear_regressor.pkl', 'wb'))
```

1.6 RANDOM REGRESSION

```
[30]: random_regressor = RandomForestRegressor(n_estimators=100)
```

```
[31]: random_regressor.fit(X_train_scaled, Y_train)
```

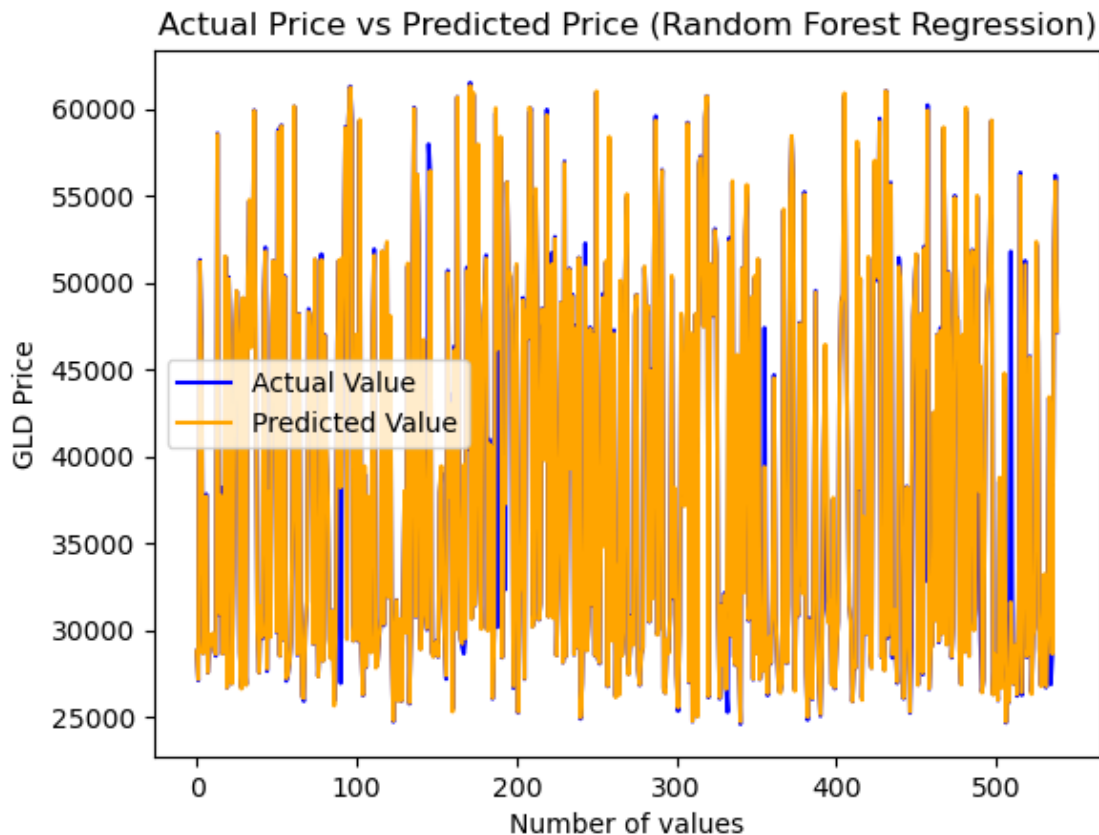
```
[31]: RandomForestRegressor()
```

```
[32]: test_data_predictionR = random_regressor.predict(X_test_scaled)
```

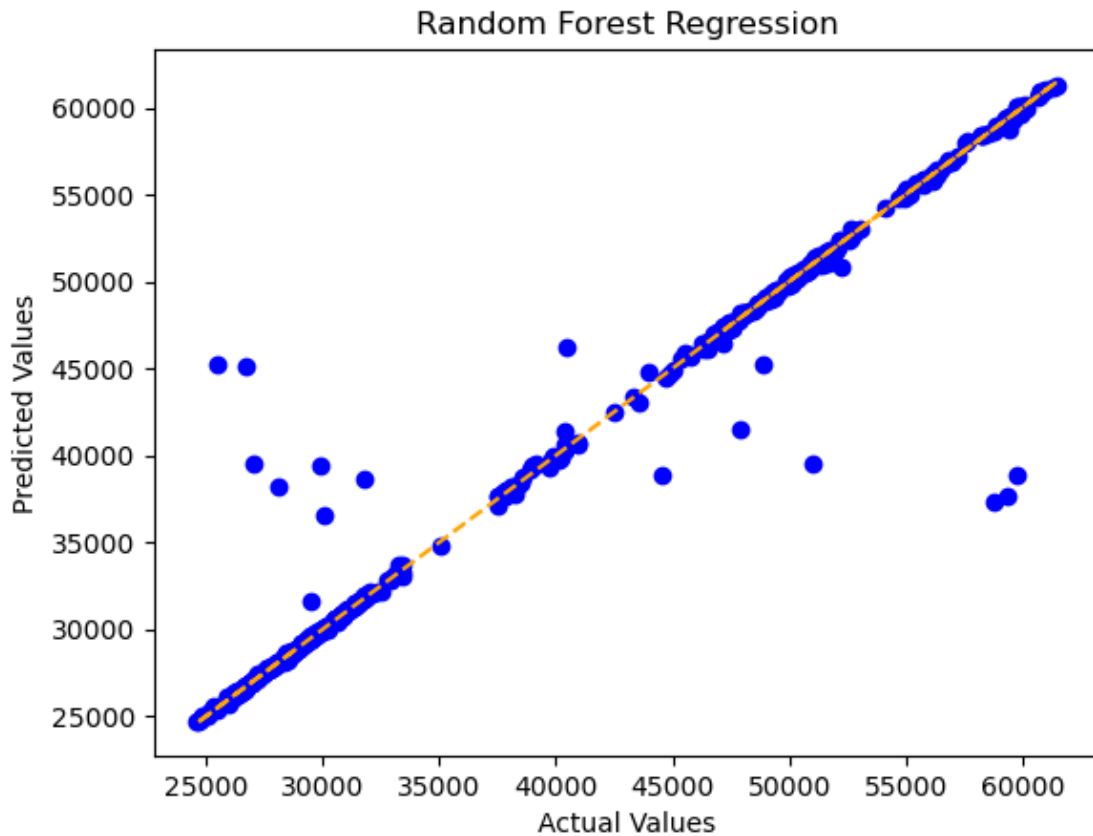
```
[33]: error_scoreR = metrics.r2_score(Y_test, test_data_predictionR) #add
      ↪test_data_prediction for random forest
mae_rf = mean_absolute_error(Y_test, test_data_predictionR)
mse_rf = mean_squared_error(Y_test, test_data_predictionR)
print("MAE (Random Forest Regression): {:.2f}".format(mae_rf))
print("MSE (Random Forest Regression): {:.2f}".format(mse_rf))
print("R squared error : ", error_scoreR)
```

MAE (Random Forest Regression): 440.98
MSE (Random Forest Regression): 5208386.08
R squared error : 0.9593100631769695

```
[102]: plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(test_data_predictionR, color='orange', label='Predicted Value')
plt.title('Actual Price vs Predicted Price (Random Forest Regression)')
plt.xlabel('Number of values')
plt.ylabel('GLD Price')
plt.legend()
plt.show()
```

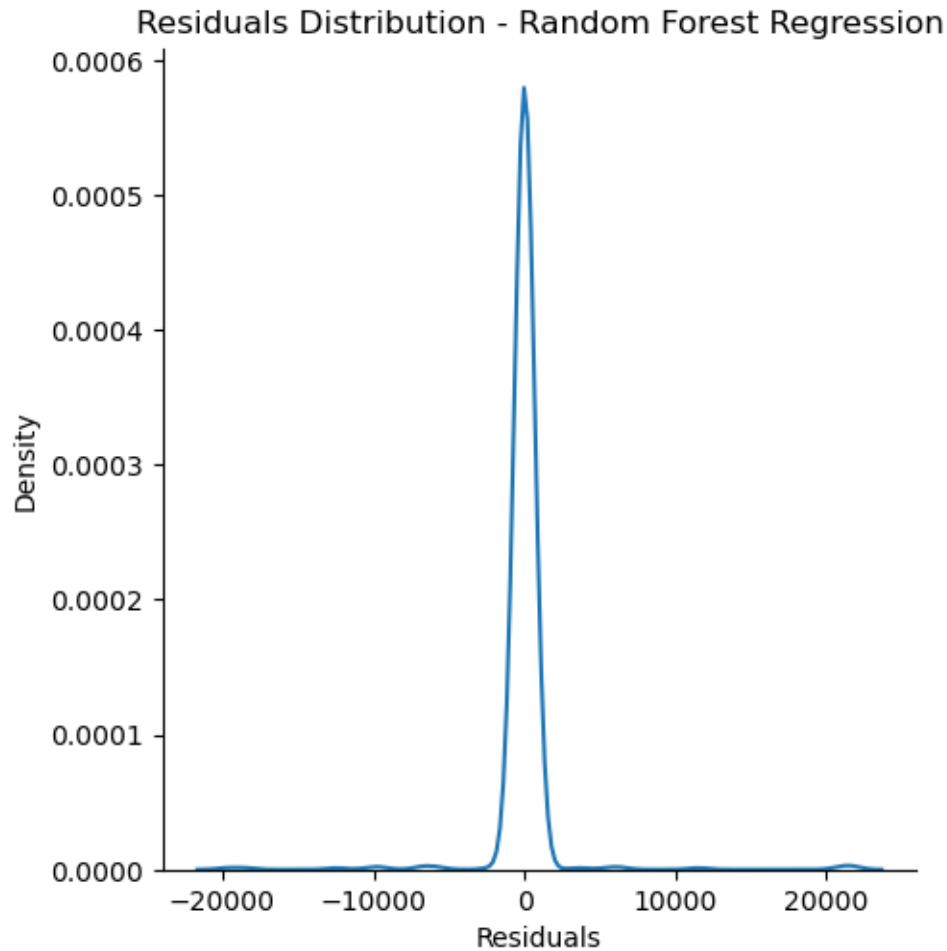


```
[36]: plt.scatter(Y_test, test_data_predictionR, color='blue')
plt.plot(Y_test, Y_test, color='orange', linestyle='--')
plt.title('Random Forest Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



```
[37]: sns.displot(Y_test - test_data_predictionR, kind='kde')
plt.title('Residuals Distribution - Random Forest Regression')
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```

```
C:\Users\sarka\anaconda3\envs\Projects\Lib\site-
packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



```
[38]: print("Accuracy of random forest Regression model: {:.2f}%".format(error_scoreR_
↪ * 100))
```

Accuracy of random forest Regression model: 95.93%

```
[39]: pickle.dump(random_regressor, open('random_regressor.pkl', 'wb'))
```

1.7 XGBOOST

```
[40]: import xgboost as xgb
from sklearn.metrics import r2_score
```

```
[41]: xgb_regressor = xgb.XGBRegressor()
xgb_regressor.fit(X_train_scaled, Y_train)
```

```
[41]: XGBRegressor(base_score=None, booster=None, callbacks=None,
colsample_bylevel=None, colsample_bynode=None,
```

```

colsample_bytree=None, device=None, early_stopping_rounds=None,
enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, grow_policy=None, importance_type=None,
interaction_constraints=None, learning_rate=None, max_bin=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=None,
multi_strategy=None, n_estimators=None, n_jobs=None,
num_parallel_tree=None, random_state=None, ...)

```

```
[42]: Y_pred_xgb = xgb_regressor.predict(X_test_scaled)
```

```
[43]: Y_pred_xgb
```

```

[43]: array([28841.941, 27170.264, 51470.887, 45909.82 , 28610.674, 30480.367,
37219.    , 27680.314, 29764.842, 29117.53 , 29723.436, 28853.213,
28564.691, 58520.49 , 30947.86 , 38471.51 , 28524.65 , 28817.498,
51331.39 , 26662.615, 50204.35 , 46489.844, 26903.797, 33044.574,
47357.566, 49651.062, 47435.918, 28703.87 , 26700.656, 49106.67 ,
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29599.13 , 50420.305, 27196.814, 27325.336, 28085.049, 29482.254,
35104.508, 60332.01 , 39083.656, 28571.986, 48130.812, 31538.01 ,
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51186.06 , 28315.5 , 46937.633, 40790.086, 37680.496, 29392.975,
28239.25 , 31086.803, 25954.299, 30117.627, 46179.082, 51399.89 ,
42413.71 , 51429.477, 50870.684, 58741.59 , 29470.258, 59427.996,
60926.504, 58837.688, 29463.133, 30419.258, 47061.81 , 29471.145,
59400.742, 28824.117, 26253.684, 38463.69 , 27880.715, 37942.91 ,
31446.703, 28686.059, 47086.008, 51125.812, 27921.277, 28035.268,
29179.62 , 30567.014, 52185.656, 30339.332, 48281.867, 52247.67 ,
31867.309, 48059.957, 29054.31 , 24818.342, 29613.625, 31617.598,
25850.082, 30512.115, 25960.395, 31158.75 , 37964.863, 29847.264,
51046.254, 25717.27 , 29971.44 , 50309.29 , 59742.027, 30760.023,
56034.62 , 51733.676, 28847.23 , 32085.9 , 46686.027, 30945.934,
30111.475, 40410.242, 56688.027, 28731.984, 28510.723, 29261.49 ,
29360.707, 28570.197, 38020.316, 38806.215, 32036.889, 29616.938,
27391.738, 50709.676, 37673.523, 43086.965, 25320.02 , 46268.062,
29932.996, 60823.953, 38325.65 , 29591.178, 29145.684, 40378.36 ,
29615.686, 50754.074, 40310.33 , 61324.2 , 30657.361, 60455.844,
31473.873, 48626.72 , 57447.26 , 32940.66 , 30107.006, 47749.984,
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29705.049, 60033.688, 52666.94 , 50531.484, 58526.81 , 28461.727,
39812.76 , 34024.348, 55774.715, 50631.074, 50528.03 , 47716.043,

```


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39000.395, 49153.793, 28600.598, 47365.098, 29128.225, 51394.152,
24950.875, 26958.588, 32043.521, 50700.383, 28823.332, 30478.307,
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29401.4 , 28587.402, 30918.98 , 50137.176, 31755.094, 38178.484,
27491.854, 25660.71 , 29886.094, 48047.73 , 45320.64 , 36930.676,
38720.902, 58996.36 , 27057.201, 47144.312, 24666.844, 26385.428,
48113.004, 25019.4 , 56915.156, 57238.598, 51607.445, 47413.344,
59541.277, 60543.04 , 26149.684, 51196.082, 49478.414, 48141.496,
53134.105, 51796.46 , 31274.553, 26189.258, 31459.861, 28030.607,
32164.424, 26713.84 , 35630.562, 52511.184, 29673.416, 55708.125,
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26930.992, 54185.676, 33459.6 , 28065.322, 31505.502, 54998.17 ,
58337.29 , 55656.785, 26447.34 , 32966.35 , 30844.396, 47710.332,
37762.223, 32278.885, 54904.16 , 27739.342, 24942.354, 30561.45 ,
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44827.387, 48518.69 , 48857.984, 60957.883, 47509.99 , 40624.914,
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38281.29 , 30852.248, 25302.854, 39312.57 , 47941.14 , 50245.082,
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```

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27202.8 , 40813.746, 48771.547, 50049.938, 53021.72 , 59368.508,
26246.496, 28549.145, 27949.838, 26163.564, 38285.555, 26762.826,
30833.727, 44759.78 , 24786.424, 27882.744, 26155.145, 34207.953,
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26411.168, 29617.94 , 30148.89 , 52546.004, 46279.14 , 28952.191,
26754.918, 28951.873, 33391.07 , 26787.83 , 29954.197, 43588.953,
40934.812, 28487.537, 51437.766, 55943.344, 47146.18 ],
dtype=float32)

```

```

[44]: r2_xgb = r2_score(Y_test, Y_pred_xgb)
mae_xgb = mean_absolute_error(Y_test, Y_pred_xgb)
mse_xgb = mean_squared_error(Y_test, Y_pred_xgb)
print("MAE (XGBoost Regression): {:.2f}".format(mae_xgb))
print("MSE (XGBoost Regression): {:.2f}".format(mse_xgb))
print("XGBoost Regression R squared error: ", r2_xgb)

```

```

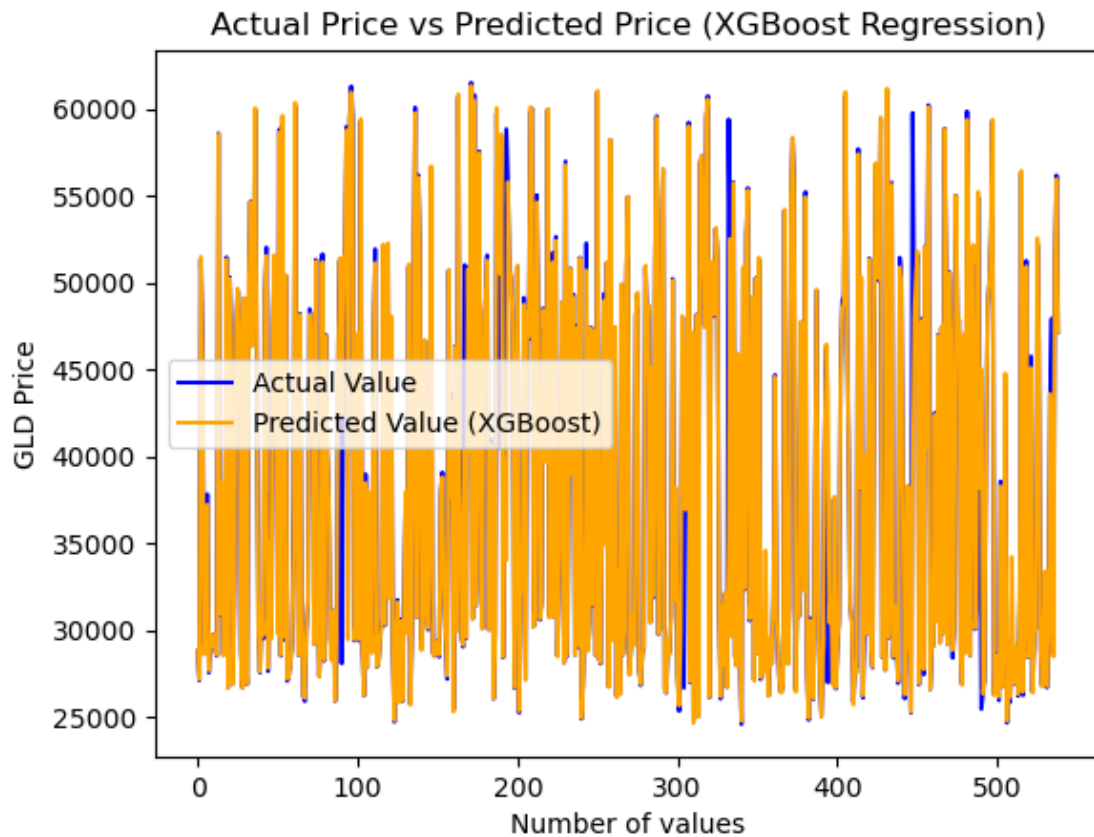
MAE (XGBoost Regression): 529.31
MSE (XGBoost Regression): 6631199.81
XGBoost Regression R squared error: 0.9481944891347766

```

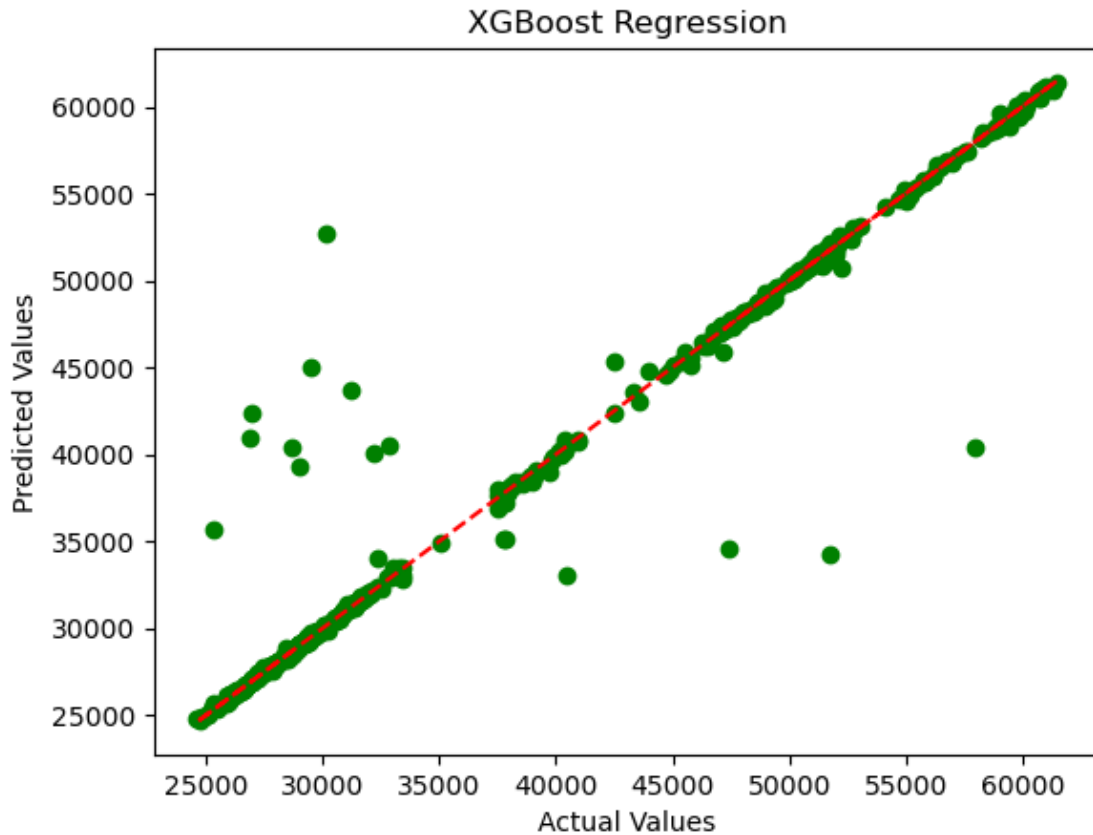
```

[45]: plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_xgb, color='orange', label='Predicted Value (XGBoost)')
plt.title('Actual Price vs Predicted Price (XGBoost Regression)')
plt.xlabel('Number of values')
plt.ylabel('GLD Price')
plt.legend()
plt.show()

```

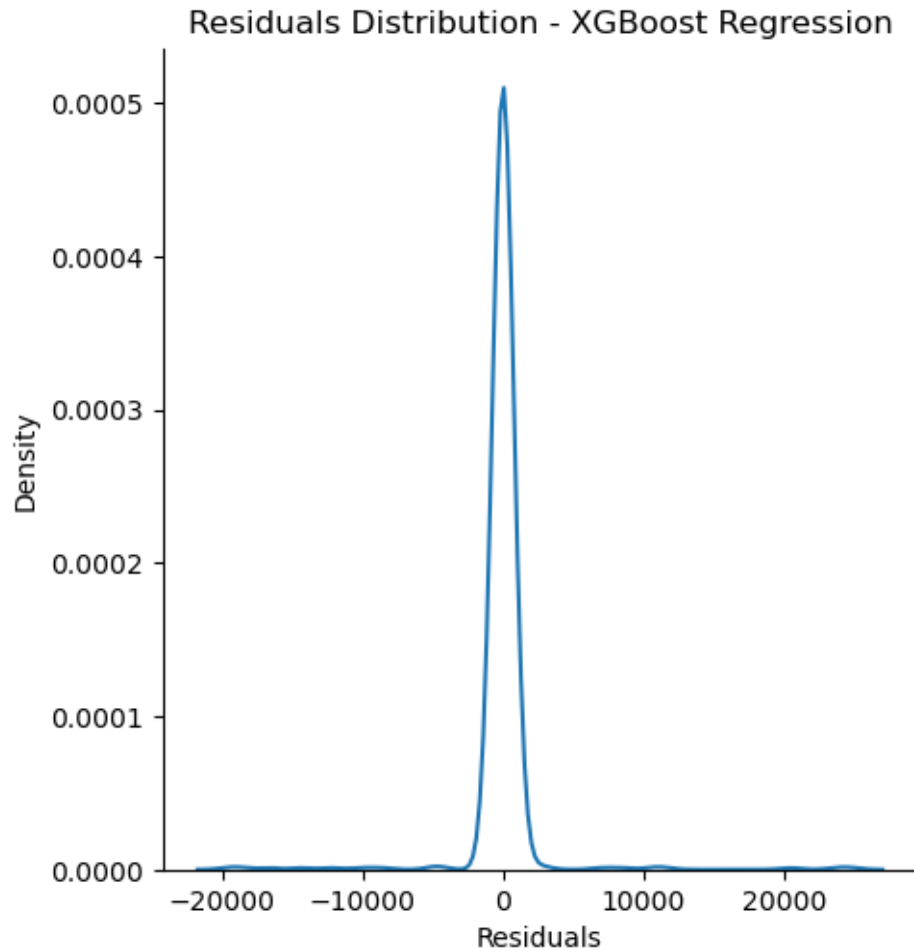


```
[101]: plt.scatter(Y_test, Y_pred_xgb, color='green')
plt.plot(Y_test, Y_test, color='red', linestyle='--')
plt.title('XGBoost Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



```
[47]: sns.displot(Y_test - Y_pred_xgb, kind='kde')
plt.title('Residuals Distribution - XGBoost Regression')
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```

```
C:\Users\sarka\anaconda3\envs\Projects\Lib\site-
packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



```
[48]: print("Accuracy of XGBoost Regression model: {:.2f}%".format(r2_xgb * 100))
```

Accuracy of XGBoost Regression model: 94.82%

```
[49]: pickle.dump(xgb_regressor, open('xgb_regressor.pkl', 'wb'))
```

1.8 ADA BOOST Regression

```
[50]: adaboost_regressor = AdaBoostRegressor()
```

```
[51]: adaboost_regressor.fit(X_train_scaled, Y_train)
```

```
[51]: AdaBoostRegressor()
```

```
[52]: Y_pred_adaboost = adaboost_regressor.predict(X_test_scaled)
```

```
[53]: Y_pred_adaboost
```

```
[53]: array([30713.88687783, 30380.91340782, 48718.67172676, 43991.74691865,
        28658.74385511, 30713.88687783, 40563.46759639, 28658.74385511,
        30412.94402421, 30713.88687783, 30713.88687783, 30713.88687783,
        30380.91340782, 57359.91428571, 32814.89508197, 39729.40931373,
        28762.53266332, 30713.88687783, 48718.67172676, 28443.88975155,
        50683.62162162, 43955.58040665, 28524.7877095 , 35304.01846154,
        43955.58040665, 44093.07635468, 43991.74691865, 30545.12987013,
        28268.52873563, 44093.07635468, 29182.94979079, 28443.88975155,
        43955.58040665, 50683.62162162, 42378.88400703, 43955.58040665,
        59415.46315789, 42005.50229885, 30713.88687783, 29182.94979079,
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        28658.74385511, 39729.40931373, 30713.88687783, 43955.58040665,
        48718.67172676, 43955.58040665, 30713.88687783, 57359.91428571,
        28658.74385511, 57359.91428571, 30713.88687783, 48718.67172676,
        29342.52219873, 28658.74385511, 28762.53266332, 30399.40298507,
        40563.46759639, 59415.46315789, 40563.46759639, 30380.91340782,
        44092.33023796, 32814.89508197, 28437.38770053, 28268.52873563,
        30713.88687783, 33864.73134328, 44092.33023796, 46210.80573951,
        42005.50229885, 30399.40298507, 48718.67172676, 39729.40931373,
        30412.94402421, 30713.88687783, 50477.55339806, 28658.74385511,
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        48718.67172676, 30399.40298507, 43991.74691865, 50683.62162162,
        32814.89508197, 44092.33023796, 30412.94402421, 28268.52873563,
        30412.94402421, 32814.89508197, 28268.52873563, 32814.89508197,
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```

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43955.58040665, 29182.94979079, 43991.74691865, 43991.74691865,
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28762.53266332, 43955.58040665, 30412.94402421, 48718.67172676,
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30412.94402421, 28443.88975155, 29182.94979079, 30713.88687783,
48718.67172676, 43955.58040665, 45904.28235294, 30713.88687783,
42378.88400703, 32814.89508197, 48718.67172676, 58671.52884615,
30399.40298507, 30713.88687783, 50683.62162162, 57059.08888889,
28437.38770053, 28437.38770053, 30713.88687783, 29182.94979079,
32814.89508197, 44093.07635468, 34238.88043478, 40563.46759639,
30412.94402421, 28151.89889026, 30399.40298507, 44092.33023796,
42342.04470588, 40563.46759639, 40563.46759639, 58671.52884615,
28658.74385511, 43991.74691865, 28268.52873563, 28268.52873563,
46210.80573951, 28151.89889026, 57059.08888889, 57059.08888889,
48718.67172676, 43955.58040665, 58671.52884615, 59415.46315789,
28443.88975155, 48718.67172676, 44093.07635468, 46210.80573951,
48718.67172676, 48718.67172676, 32814.89508197, 28443.88975155,
32814.89508197, 29342.52219873, 35304.01846154, 28443.88975155,
37474.95778612, 48718.67172676, 30380.91340782, 52909.0625,
30412.94402421, 29342.52219873, 42005.50229885, 29342.52219873,
28151.89889026, 48718.67172676, 35304.01846154, 48718.67172676,
50683.62162162, 32814.89508197, 34589.74659401, 43955.58040665,
30380.91340782, 48718.67172676, 29342.52219873, 48718.67172676,
28658.74385511, 32814.89508197, 29182.94979079, 38240.98188751,
29182.94979079, 28437.38770053, 30412.94402421, 29342.52219873,
34238.88043478, 42378.88400703, 32814.89508197, 30412.94402421,
28443.88975155, 28437.38770053, 28443.88975155, 50683.62162162,

39729.40931373, 29342.52219873, 32814.89508197, 50477.55339806,
57359.91428571, 52336.755, 28437.38770053, 35304.01846154,
32814.89508197, 43955.58040665, 40622.22585227, 35304.01846154,
48718.67172676, 28658.74385511, 28151.89889026, 30713.88687783,
29342.52219873, 28268.52873563, 39729.40931373, 43955.58040665,
32814.89508197, 28437.38770053, 28151.89889026, 30380.91340782,
40917.08280255, 43955.58040665, 35304.01846154, 30713.88687783,
35304.01846154, 28443.88975155, 39729.40931373, 28443.88975155,
30713.88687783, 34589.74659401, 42378.88400703, 44093.07635468,
44093.07635468, 59415.46315789, 43955.58040665, 40917.08280255,
32814.89508197, 30713.88687783, 28151.89889026, 28658.74385511,
30380.91340782, 57059.08888889, 40622.22585227, 48718.67172676,
28443.88975155, 30991.3255814, 30412.94402421, 32814.89508197,
48718.67172676, 30713.88687783, 28762.53266332, 45112.97333333,
57059.08888889, 48718.67172676, 43955.58040665, 58671.52884615,
29342.52219873, 30399.40298507, 30412.94402421, 59415.46315789,
30713.88687783, 40563.46759639, 50477.55339806, 30380.91340782,
30713.88687783, 30713.88687783, 28443.88975155, 48718.67172676,
44093.07635468, 39729.40931373, 28151.89889026, 30380.91340782,
40563.46759639, 34589.74659401, 28151.89889026, 40917.08280255,
43991.74691865, 43955.58040665, 48718.67172676, 28443.88975155,
43991.74691865, 44093.07635468, 29182.94979079, 48718.67172676,
43991.74691865, 59415.46315789, 28443.88975155, 30545.12987013,
30713.88687783, 40917.08280255, 30713.88687783, 43955.58040665,
30713.88687783, 43955.58040665, 30380.91340782, 58671.52884615,
48718.67172676, 30713.88687783, 50477.55339806, 43955.58040665,
30412.94402421, 30713.88687783, 50477.55339806, 43991.74691865,
43955.58040665, 30713.88687783, 28443.88975155, 43955.58040665,
30545.12987013, 59415.46315789, 48718.67172676, 30412.94402421,
48718.67172676, 48718.67172676, 30412.94402421, 32814.89508197,
50477.55339806, 40563.46759639, 48718.67172676, 28268.52873563,
28658.74385511, 42342.04470588, 43955.58040665, 43955.58040665,
50683.62162162, 58671.52884615, 28268.52873563, 29182.94979079,
28658.74385511, 28268.52873563, 40563.46759639, 28658.74385511,
30991.3255814, 42378.88400703, 28151.89889026, 28658.74385511,
28268.52873563, 37474.95778612, 30380.91340782, 28437.38770053,
30412.94402421, 28443.88975155, 34238.88043478, 57059.08888889,
28437.38770053, 39729.40931373, 48718.67172676, 30380.91340782,
30713.88687783, 42005.50229885, 28151.89889026, 30380.91340782,
30399.40298507, 48718.67172676, 42378.88400703, 30545.12987013,
28443.88975155, 30713.88687783, 33864.73134328, 28443.88975155,
30399.40298507, 42342.04470588, 42828.89940828, 29342.52219873,
48718.67172676, 50477.55339806, 43955.58040665])

```
[54]: r2_adaboost = r2_score(Y_test, Y_pred_adaboost)
mae_adaboost = mean_absolute_error(Y_test, Y_pred_adaboost)
mse_adaboost = mean_squared_error(Y_test, Y_pred_adaboost)
```



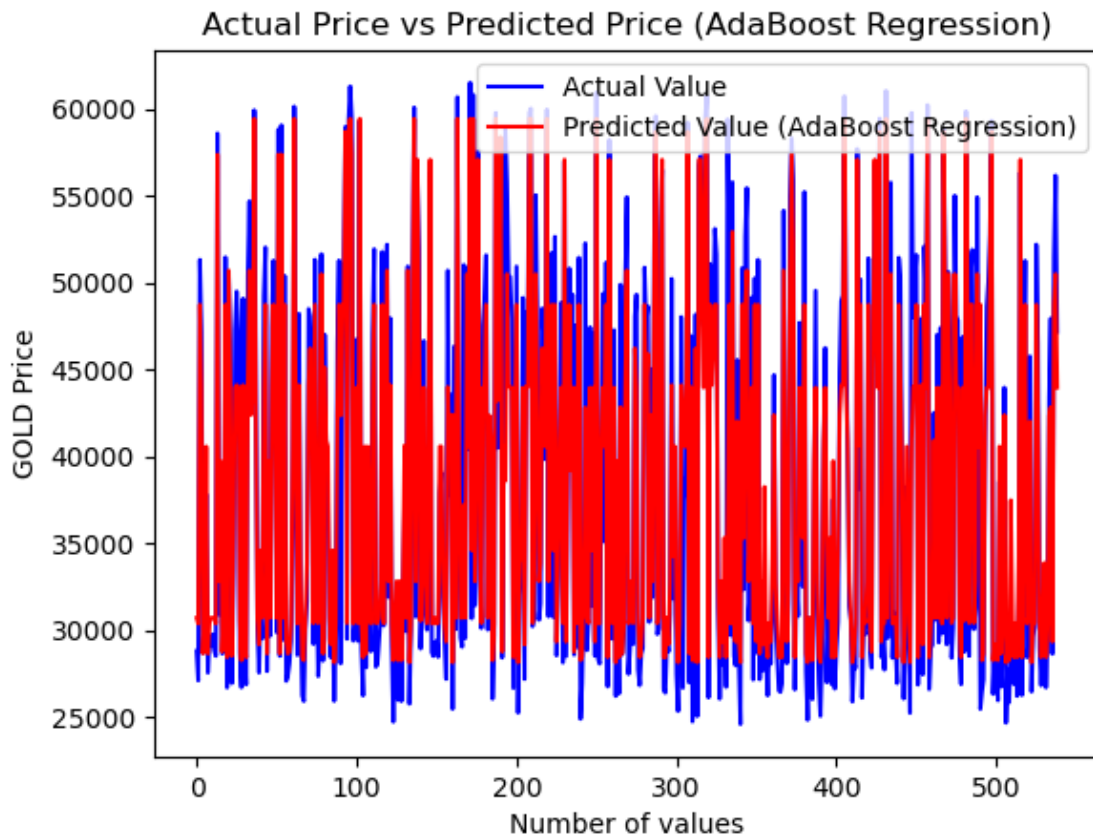
```
print("MAE (AdaBoost Regression): {:.2f}".format(mae_adaboost))
print("MSE (AdaBoost Regression): {:.2f}".format(mse_adaboost))
print("R squared error (AdaBoost Regression):", r2_adaboost)
```

MAE (AdaBoost Regression): 2457.56

MSE (AdaBoost Regression): 11990808.47

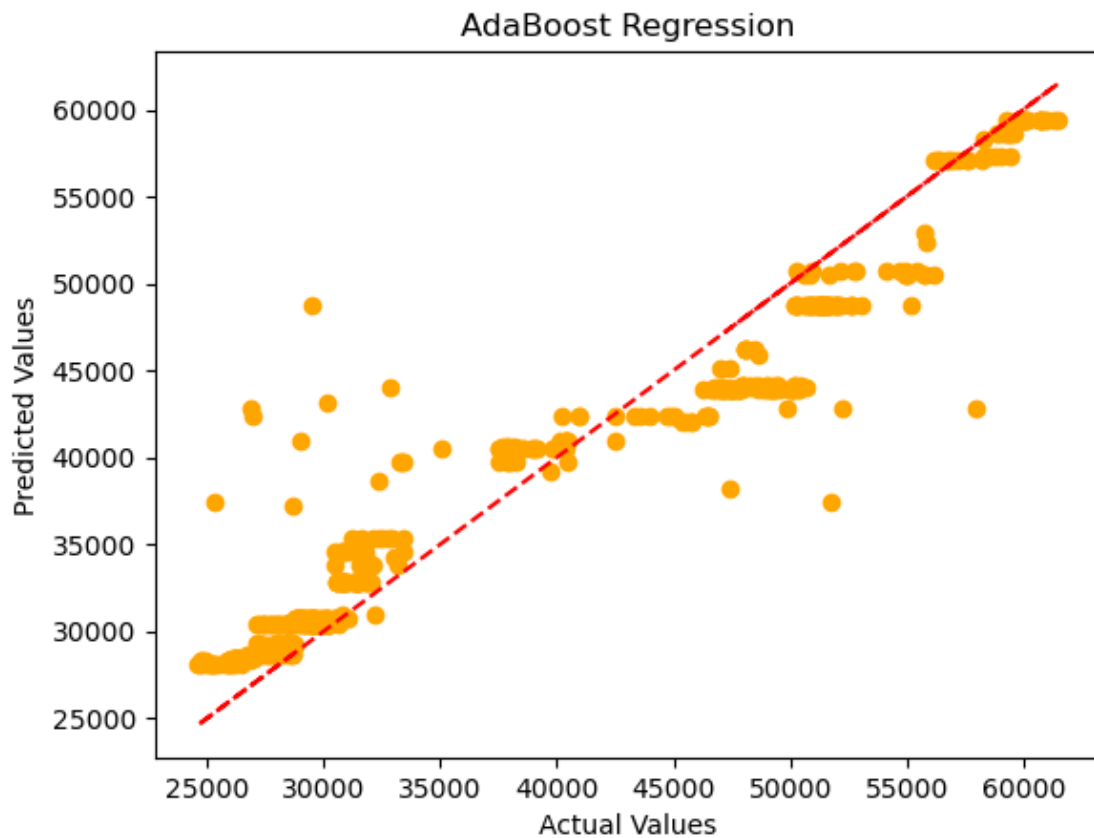
R squared error (AdaBoost Regression): 0.9063231427262854

```
[55]: plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_adaboost, color='red', label='Predicted Value (AdaBoost_
Regression)')
plt.title('Actual Price vs Predicted Price (AdaBoost Regression)')
plt.xlabel('Number of values')
plt.ylabel('GOLD Price')
plt.legend()
plt.show()
```



```
[103]: plt.scatter(Y_test, Y_pred_adaboost, color='orange')
plt.plot(Y_test, Y_test, color='red', linestyle='--')
plt.title('AdaBoost Regression')
```

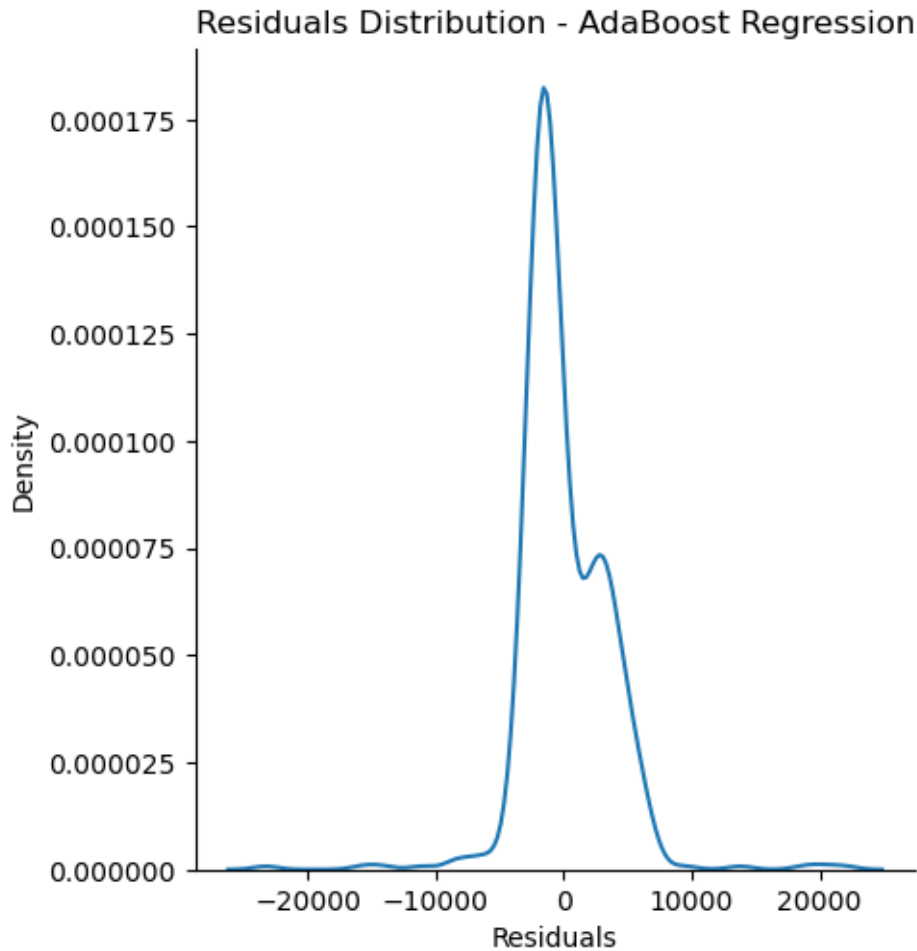
```
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



```
[57]: sns.displot(Y_test - Y_pred_adaboost, kind='kde')
plt.title('Residuals Distribution - AdaBoost Regression')
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```

C:\Users\sarka\anaconda3\envs\Projects\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

```
with pd.option_context('mode.use_inf_as_na', True):
```



```
[58]: print("Accuracy of AdaBoost Regression model: {:.2f}%".format(r2_adaboost * 100))
```

Accuracy of AdaBoost Regression model: 90.63%

```
[59]: pickle.dump(adaboost_regressor, open('adaboost_regressor.pkl', 'wb'))
```

1.9 Support Vector Machine

```
[60]: pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in
c:\users\sarka\anaconda3\envs\projects\lib\site-packages (0.12.0)
Requirement already satisfied: numpy>=1.17.3 in
c:\users\sarka\anaconda3\envs\projects\lib\site-packages (from imbalanced-learn)
(1.26.4)
Requirement already satisfied: scipy>=1.5.0 in
```

```
c:\users\sarka\anaconda3\envs\projects\lib\site-packages (from imbalanced-learn)
(1.12.0)
Requirement already satisfied: scikit-learn>=1.0.2 in
c:\users\sarka\anaconda3\envs\projects\lib\site-packages (from imbalanced-learn)
(1.3.0)
Requirement already satisfied: joblib>=1.1.1 in
c:\users\sarka\anaconda3\envs\projects\lib\site-packages (from imbalanced-learn)
(1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
c:\users\sarka\anaconda3\envs\projects\lib\site-packages (from imbalanced-learn)
(2.2.0)
Note: you may need to restart the kernel to use updated packages.
```

```
[61]: from sklearn.model_selection import GridSearchCV
      from sklearn.feature_selection import SelectKBest, f_regression
      from imblearn.over_sampling import RandomOverSampler
```

```
[62]: svm_regressor = SVR()
```

```
[63]: svm_regressor.fit(X_train_scaled, Y_train)
```

```
[63]: SVR()
```

```
[64]: # # Making predictions on the test data
      Y_pred_svm = svm_regressor.predict(X_test_scaled)
```

```
[65]: # SVM Hyperparameter Tuning
      param_grid = {'C': [0.1, 1, 10, 100], 'gamma': [1, 0.1, 0.01, 0.001], 'kernel': ['linear', 'rbf', 'poly']}
      svm_regressor = SVR()
      grid_search = GridSearchCV(svm_regressor, param_grid, scoring='r2', cv=5)
      grid_search.fit(X_train_scaled, Y_train)
      best_params = grid_search.best_params_
      print("Best Parameters for SVM:", best_params)

      # Feature Selection
      selector = SelectKBest(score_func=f_regression, k=7)
      X_train_selected = selector.fit_transform(X_train_scaled, Y_train)
      X_test_selected = selector.transform(X_test_scaled)

      # SVM with best parameters
      svm_regressor = SVR(**best_params)
      svm_regressor.fit(X_train_selected, Y_train)
      Y_pred_svm = svm_regressor.predict(X_test_selected)
      r2_svm = metrics.r2_score(Y_test, Y_pred_svm)
      print("Accuracy of SVM Regression model after rectifications: {:.2f}%".
            format(r2_svm * 100))
```

```

# Handle Data Imbalance
oversampler = RandomOverSampler(random_state=42)
X_train_resampled, Y_train_resampled = oversampler.
    ↪fit_resample(X_train_selected, Y_train)

# SVM after handling data imbalance
svm_regressor = SVR(**best_params)
svm_regressor.fit(X_train_resampled, Y_train_resampled)
Y_pred_svm = svm_regressor.predict(X_test_selected)
r2_svm = metrics.r2_score(Y_test, Y_pred_svm)
print("Accuracy of SVM Regression model after handling data imbalance: {:.2f}%".
    ↪format(r2_svm * 100))

```

Best Parameters for SVM: {'C': 10, 'gamma': 1, 'kernel': 'linear'}

Accuracy of SVM Regression model after rectifications: 95.63%

Accuracy of SVM Regression model after handling data imbalance: 95.63%

```

[66]: r2_svm = r2_score(Y_test, Y_pred_svm)
mae_svm = mean_absolute_error(Y_test, Y_pred_svm)
mse_svm = mean_squared_error(Y_test, Y_pred_svm)
print("MAE (SVM Regression): {:.2f}".format(mae_svm))
print("MSE (SVM Regression): {:.2f}".format(mse_svm))
print("R squared error (SVM Regression):", r2_svm)

```

MAE (SVM Regression): 411.91

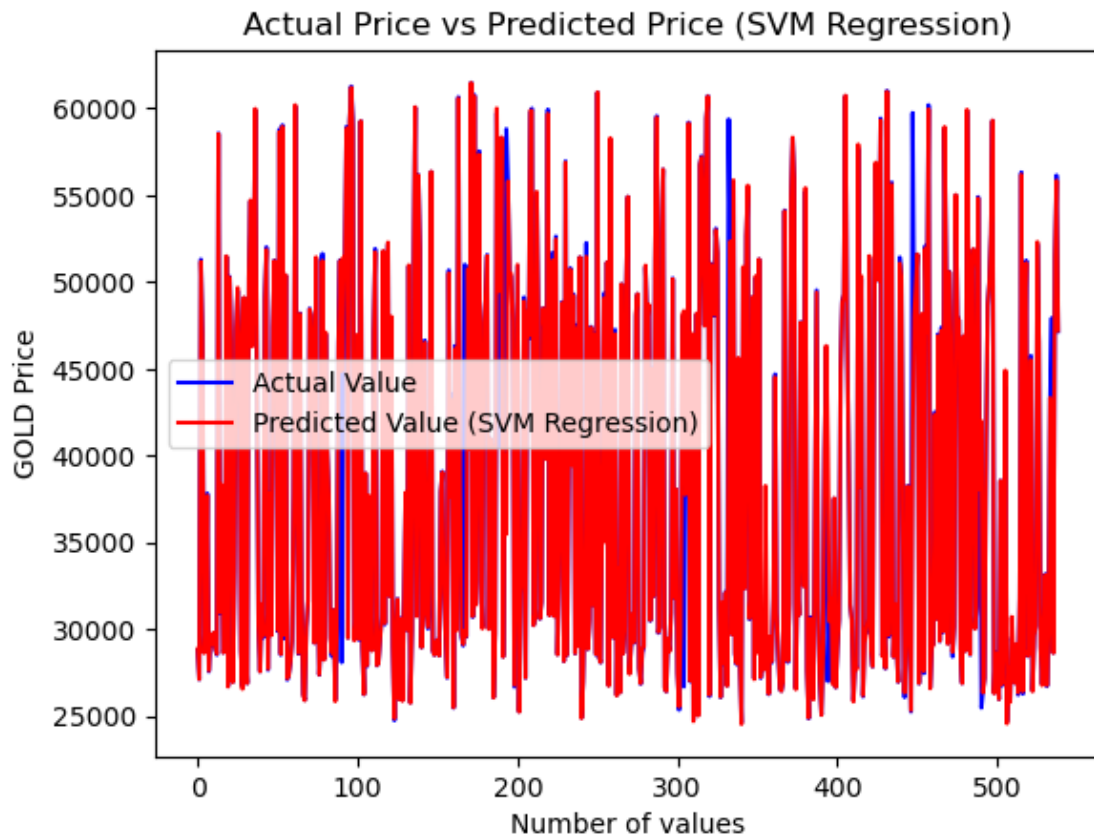
MSE (SVM Regression): 5594331.29

R squared error (SVM Regression): 0.9562949091107288

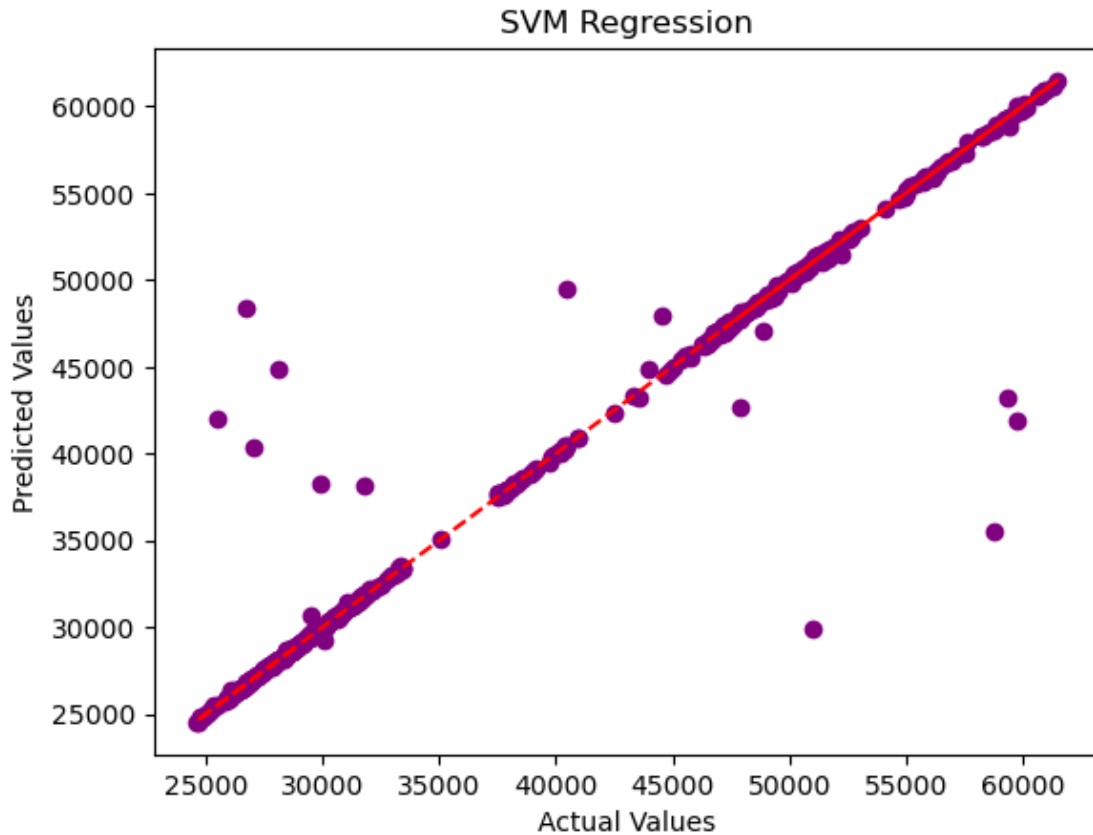
```

[67]: # Plotting Actual vs Predicted values
plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_svm, color='red', label='Predicted Value (SVM Regression)')
plt.title('Actual Price vs Predicted Price (SVM Regression)')
plt.xlabel('Number of values')
plt.ylabel('GOLD Price')
plt.legend()
plt.show()

```



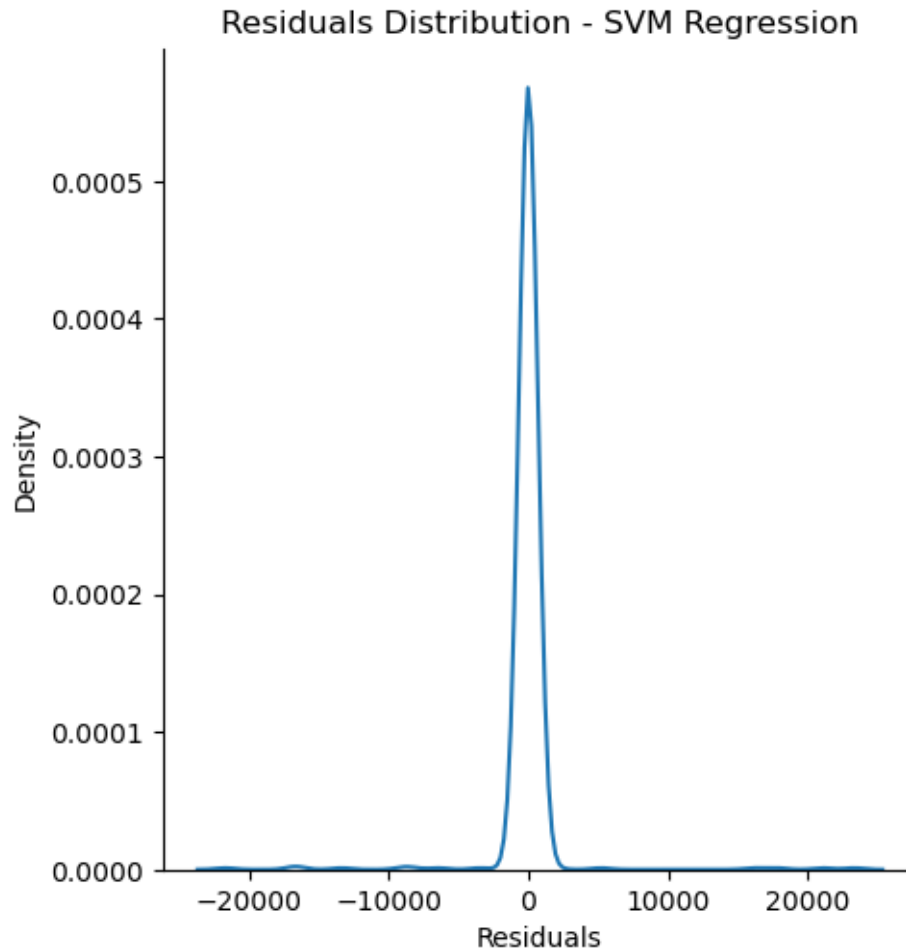
```
[68]: plt.scatter(Y_test, Y_pred_svm, color='purple')
plt.plot(Y_test, Y_test, color='red', linestyle='--')
plt.title('SVM Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



```
[69]: sns.displot(Y_test - Y_pred_svm, kind='kde')
plt.title('Residuals Distribution - SVM Regression')
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```

C:\Users\sarka\anaconda3\envs\Projects\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

```
with pd.option_context('mode.use_inf_as_na', True):
```



```
[70]: print("Accuracy of AdaBoost Regression model: {:.2f}%".format(r2_svm * 100))
```

Accuracy of AdaBoost Regression model: 95.63%

```
[71]: pickle.dump(svm_regressor, open('svm_regressor.pkl', 'wb'))
```

1.10 GRADIENT BOOST REGRESSION

```
[ ]:
```

```
[72]: # Instantiating the Gradient Boosting Regression model
gradient_boost_regressor = GradientBoostingRegressor()
```

```
[73]: gradient_boost_regressor.fit(X_train, Y_train)
```

```
[73]: GradientBoostingRegressor()
```



```
[74]: Y_pred_gradient_boost = gradient_boost_regressor.predict(X_test)
```

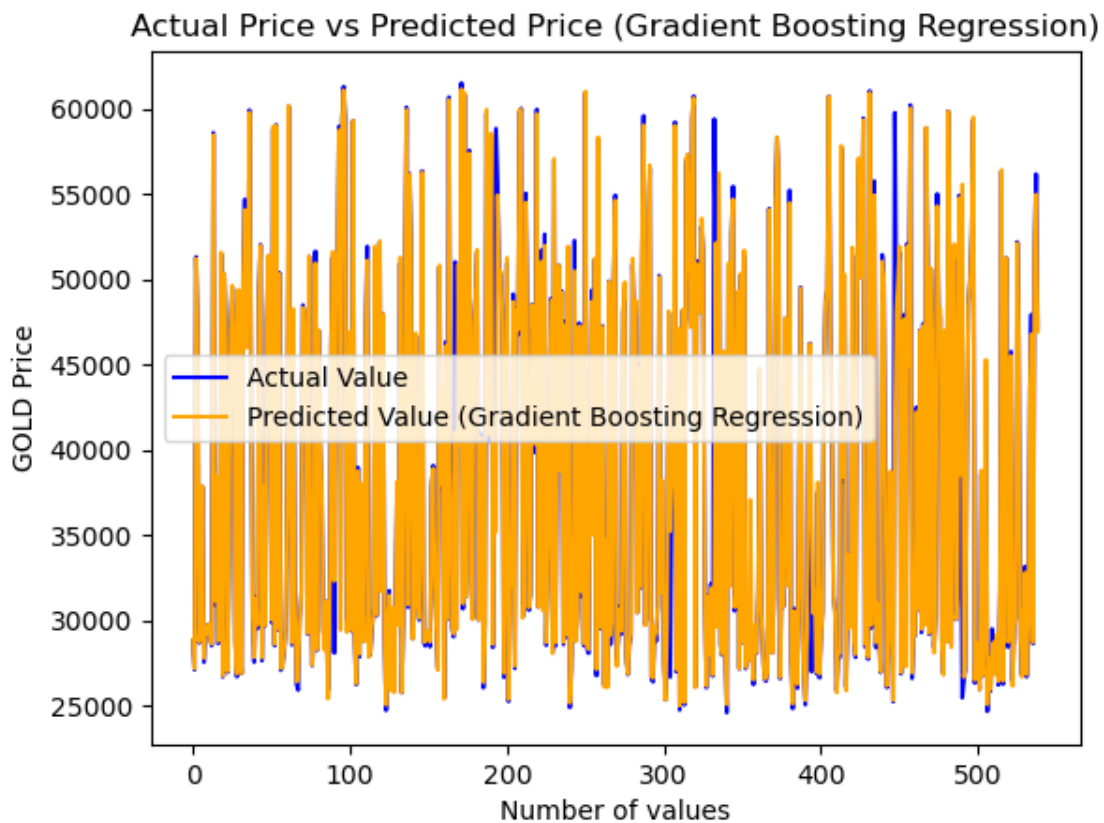
```
[75]: r2_gradient_boost = metrics.r2_score(Y_test, Y_pred_gradient_boost)
Y_pred_gradient_boost = gradient_boost_regressor.predict(X_test)
mae_gradient_boost = mean_absolute_error(Y_test, Y_pred_gradient_boost)
mse_gradient_boost = mean_squared_error(Y_test, Y_pred_gradient_boost)
print("MAE (Gradient Boosting Regression): {:.2f}".format(mae_gradient_boost))
print("MSE (Gradient Boosting Regression): {:.2f}".format(mse_gradient_boost))
print("R squared error (Gradient Boosting Regression):", r2_gradient_boost)
```

MAE (Gradient Boosting Regression): 490.27

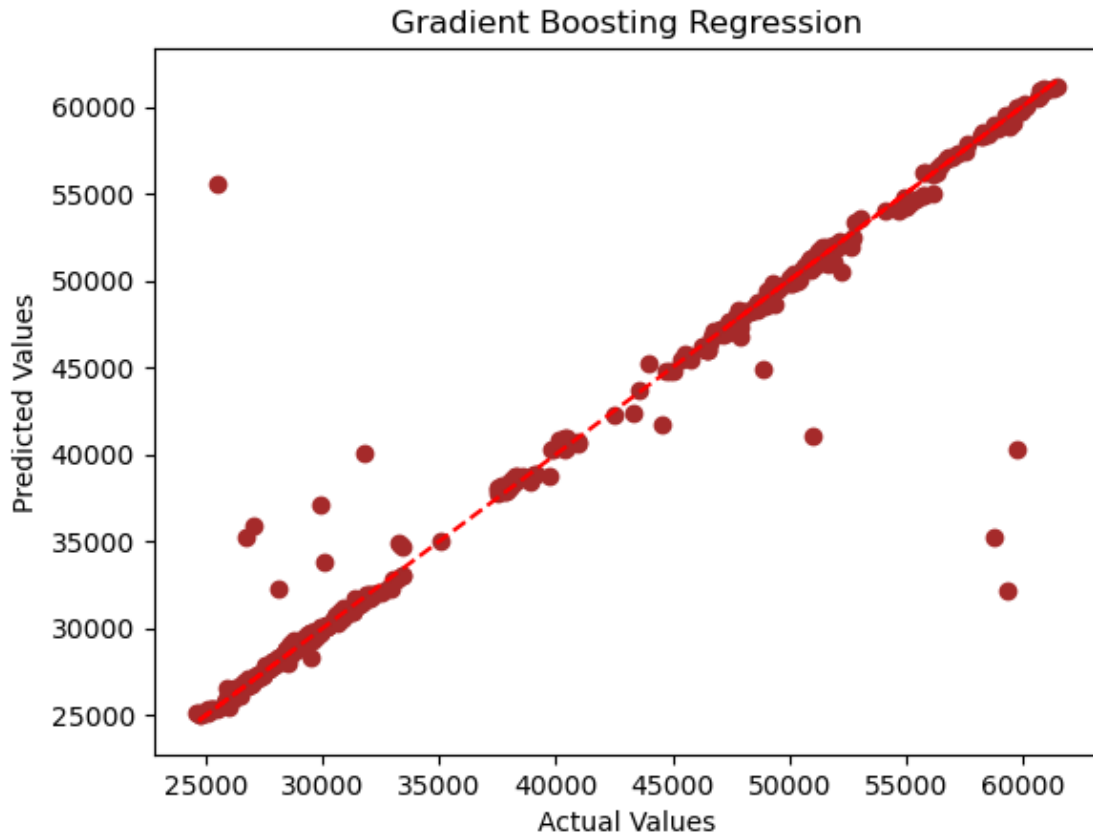
MSE (Gradient Boosting Regression): 5674536.85

R squared error (Gradient Boosting Regression): 0.9556683121389324

```
[76]: plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_gradient_boost, color='orange', label='Predicted Value_
↪(Gradient Boosting Regression)')
plt.title('Actual Price vs Predicted Price (Gradient Boosting Regression)')
plt.xlabel('Number of values')
plt.ylabel('GOLD Price')
plt.legend()
plt.show()
```



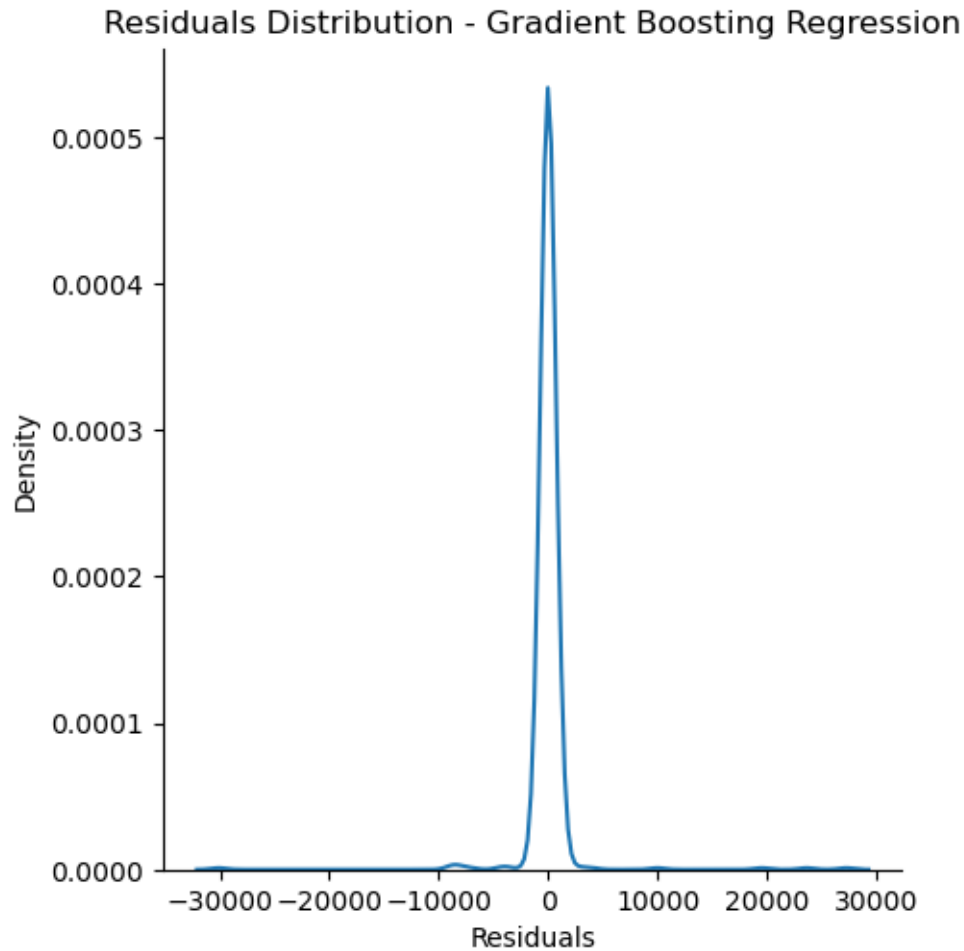
```
[77]: plt.scatter(Y_test, Y_pred_gradient_boost, color='brown')
plt.plot(Y_test, Y_test, color='red', linestyle='--')
plt.title('Gradient Boosting Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



```
[78]: sns.displot(Y_test - Y_pred_gradient_boost, kind='kde')
plt.title('Residuals Distribution - Gradient Boosting Regression')
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```

C:\Users\sarka\anaconda3\envs\Projects\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

```
with pd.option_context('mode.use_inf_as_na', True):
```



```
[79]: print("Accuracy of Gradient Boost Regression model: {:.2f}%".
        ↪format(r2_gradient_boost * 100))
```

Accuracy of Gradient Boost Regression model: 95.57%

```
[80]: pickle.dump(gradient_boost_regressor,open('gradient_boost_regressor.pkl','wb'))
```

2 —————RESULT SUMMARY—————

```
[81]: import pandas as pd

# Create a dictionary to store the metrics of each regression model
metrics_data = {
    'Regression': ['Linear', 'Random Forest', 'XGBoost', 'AdaBoost', 'SVM',
        ↪'Gradient Boost'],
    'MAE': [mae_lr, mae_rf, mae_xgb, mae_adaboost, mae_svm, mae_gradient_boost],
```

```

    'MSE': [mse_lr, mse_rf, mse_xgb, mse_adaboost, mse_svm, mse_gradient_boost],
    'R2': [error_score, error_scoreR, r2_xgb, r2_adaboost, r2_svm,
↪r2_gradient_boost],
    'Accuracy': [error_score * 100, error_scoreR * 100, r2_xgb * 100,
↪r2_adaboost * 100, r2_svm * 100, r2_gradient_boost * 100]
}

# Create a DataFrame from the dictionary
metrics_df = pd.DataFrame(metrics_data)

# Display the DataFrame
print(metrics_df)

```

	Regression	MAE	MSE	R2	Accuracy
0	Linear	599.701140	5.098138e+06	0.960171	96.017136
1	Random Forest	440.977551	5.208386e+06	0.959310	95.931006
2	XGBoost	529.312616	6.631200e+06	0.948194	94.819449
3	AdaBoost	2457.561945	1.199081e+07	0.906323	90.632314
4	SVM	411.913631	5.594331e+06	0.956295	95.629491
5	Gradient Boost	490.268889	5.674537e+06	0.955668	95.566831

2.1 PLOT

```

[82]: plt.figure(figsize=(18, 12))

plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(test_data_prediction, color='orange', label='Predicted Value (Linear
↪Regression)')
plt.title('Actual Price vs Predicted Price (Linear Regression)')
plt.xlabel('Number of values')
plt.ylabel('GLD Price')
plt.legend()
plt.show()

plt.figure(figsize=(18, 12))
plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(test_data_prediction, color='orange', label='Predicted Value (Random
↪Forest Regression)')
plt.title('Actual Price vs Predicted Price (Random Forest Regression)')
plt.xlabel('Number of values')
plt.ylabel('GLD Price')
plt.legend()
plt.show()

```

```

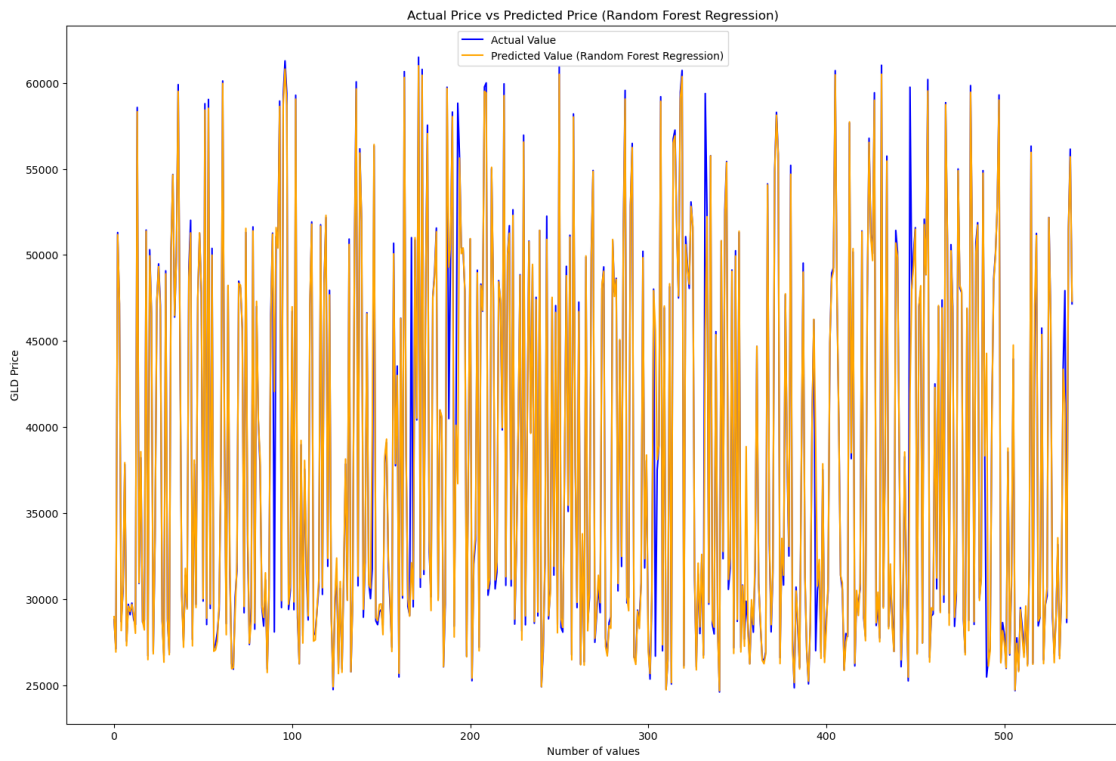
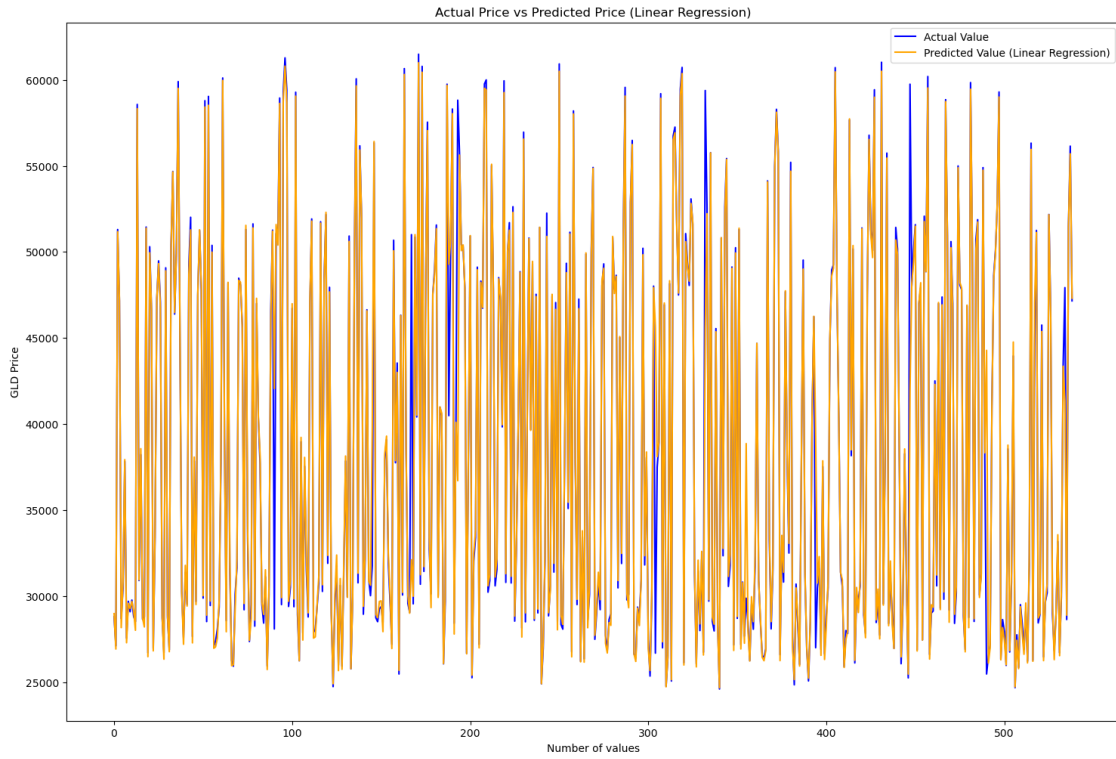
plt.figure(figsize=(18, 12))
plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_xgb, color='orange', label='Predicted Value (XGBoost)')
plt.title('Actual Price vs Predicted Price (XGBoost Regression)')
plt.xlabel('Number of values')
plt.ylabel('GLD Price')
plt.legend()
plt.show()

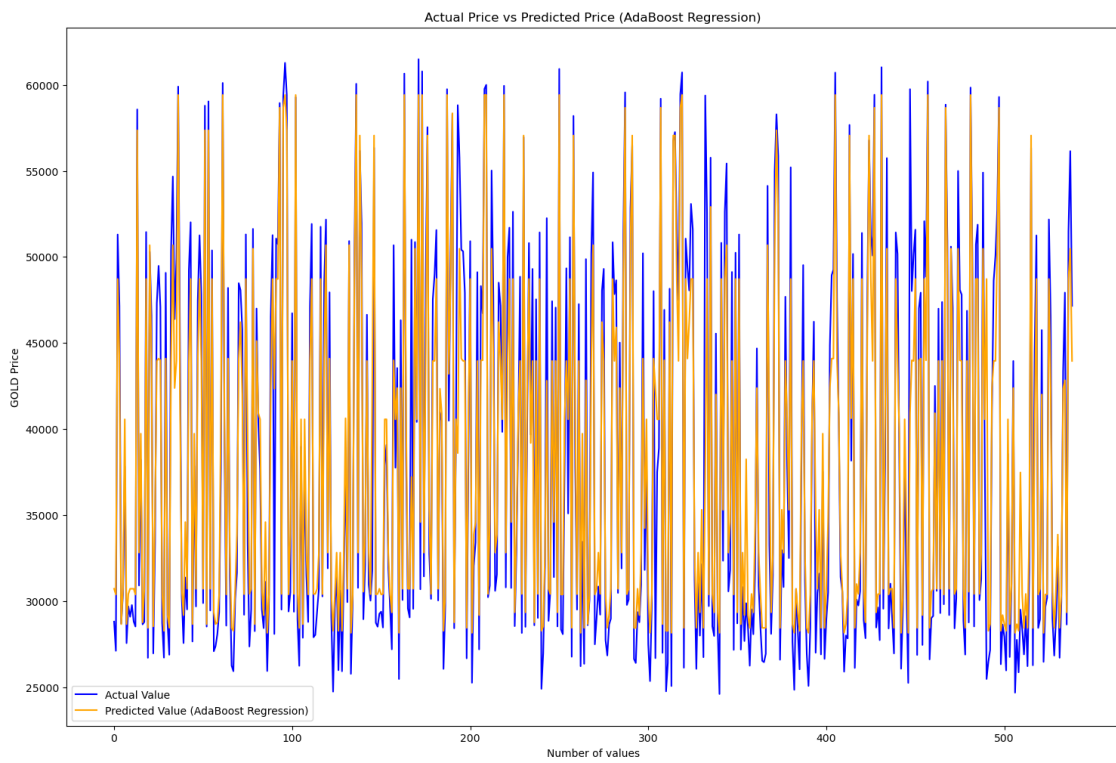
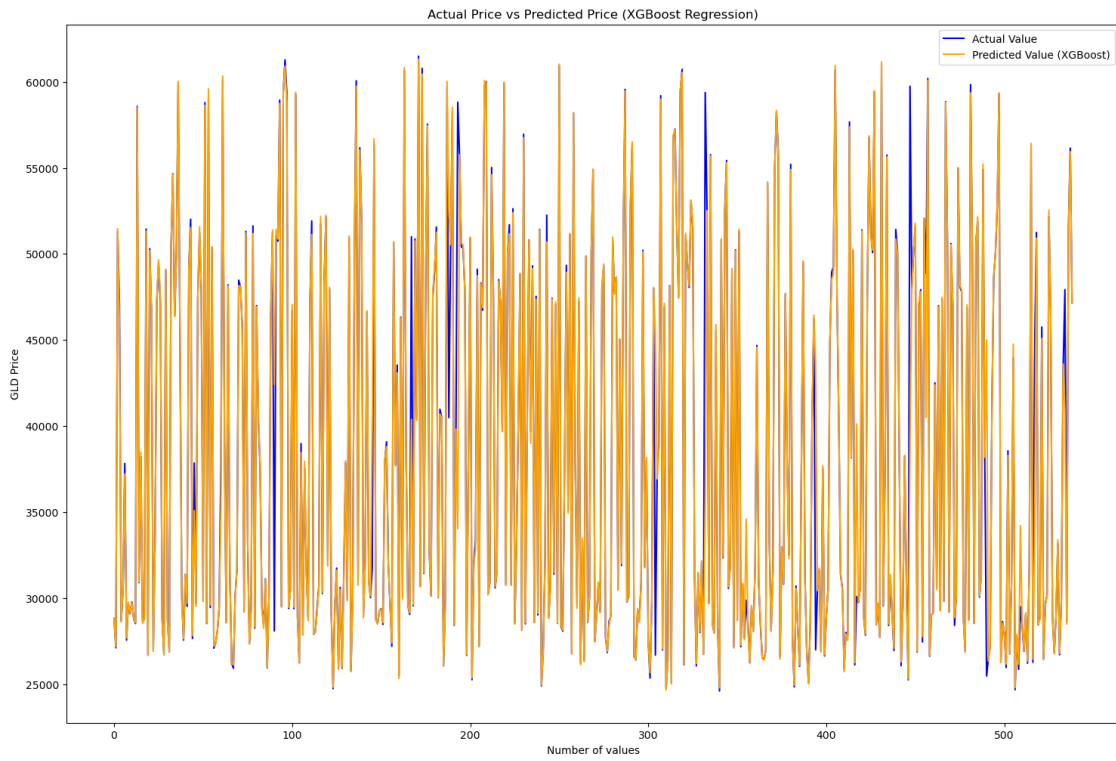
plt.figure(figsize=(18, 12))
plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_adaboost, color='orange', label='Predicted Value (AdaBoost_
↳Regression)')
plt.title('Actual Price vs Predicted Price (AdaBoost Regression)')
plt.xlabel('Number of values')
plt.ylabel('GOLD Price')
plt.legend()
plt.show()

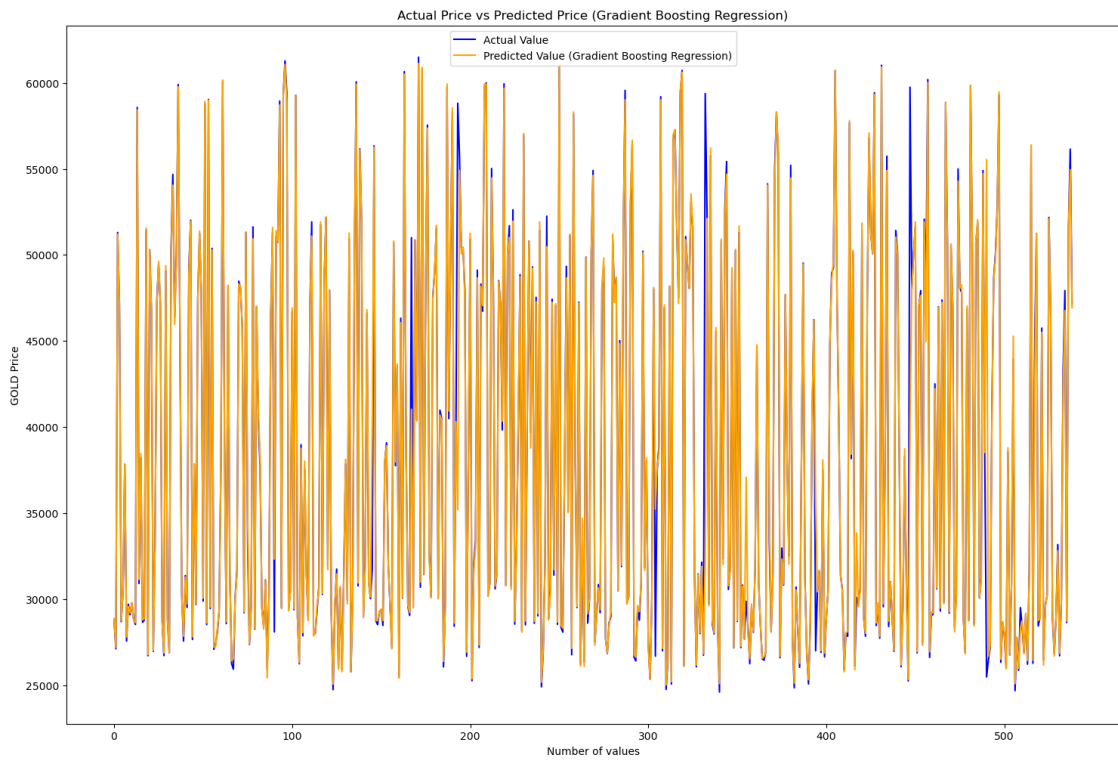
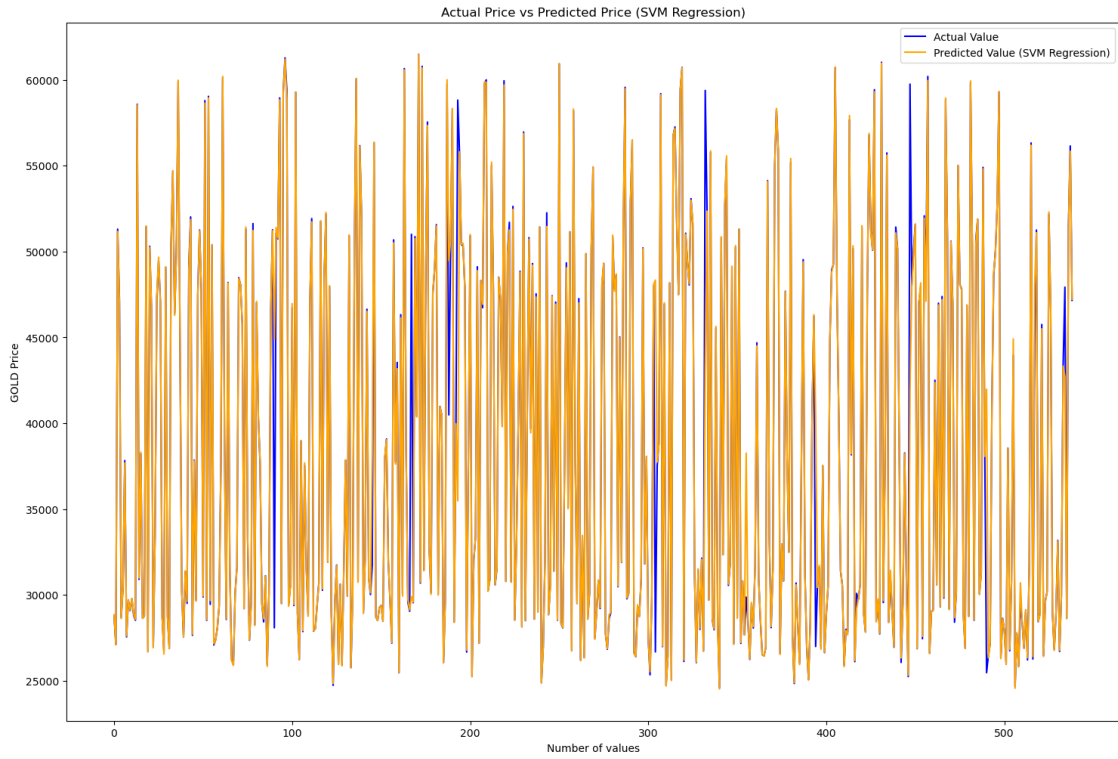
plt.figure(figsize=(18, 12))
plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_svm, color='orange', label='Predicted Value (SVM Regression)')
plt.title('Actual Price vs Predicted Price (SVM Regression)')
plt.xlabel('Number of values')
plt.ylabel('GOLD Price')
plt.legend()
plt.show()

plt.figure(figsize=(18, 12))
plt.plot(Y_test.values, color='blue', label='Actual Value')
plt.plot(Y_pred_gradient_boost, color='orange', label='Predicted Value_
↳(Gradient Boosting Regression)')
plt.title('Actual Price vs Predicted Price (Gradient Boosting Regression)')
plt.xlabel('Number of values')
plt.ylabel('GOLD Price')
plt.legend()
plt.show()

```







2.2 SCATTERPLOT

```
[83]: # Create subplots for scatterplots of each regression model
plt.figure(figsize=(14, 8))

# Linear Regression Scatterplot
plt.subplot(2, 3, 1)
plt.scatter(Y_test, test_data_prediction, color='blue')
plt.plot(Y_test, Y_test, color='orange', linestyle='--')
plt.title('Linear Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

# Random Forest Regression Scatterplot
plt.subplot(2, 3, 2)
plt.scatter(Y_test, test_data_predictionR, color='red')
plt.plot(Y_test, Y_test, color='orange', linestyle='--')
plt.title('Random Forest Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

# XGBoost Regression Scatterplot
plt.subplot(2, 3, 3)
plt.scatter(Y_test, Y_pred_xgb, color='green')
plt.plot(Y_test, Y_test, color='orange', linestyle='--')
plt.title('XGBoost Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

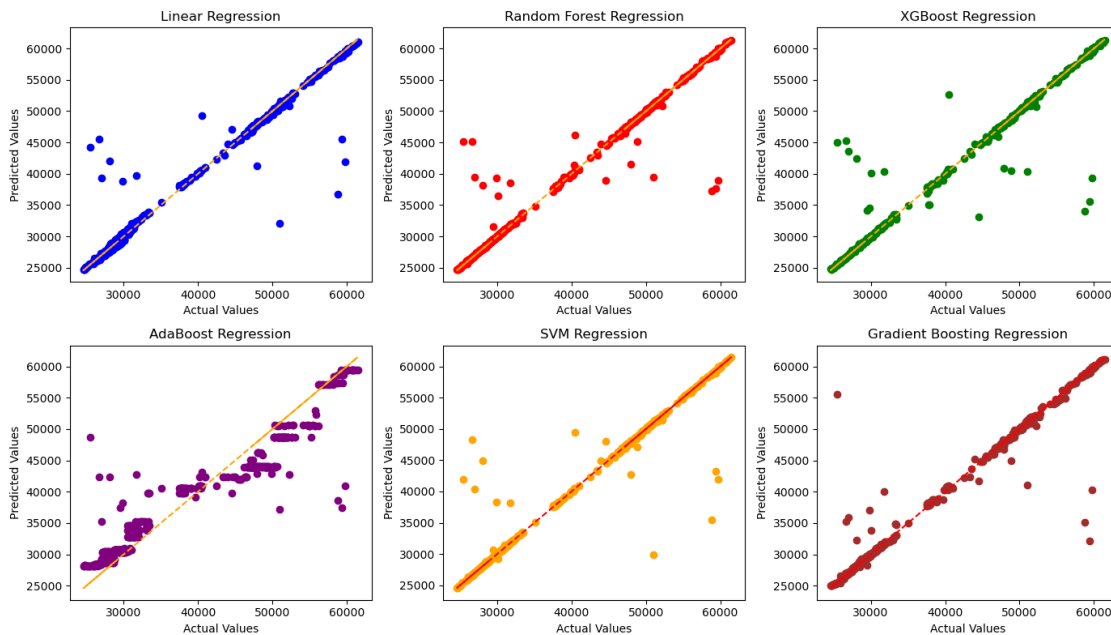
# AdaBoost Regression Scatterplot
plt.subplot(2, 3, 4)
plt.scatter(Y_test, Y_pred_adaboost, color='purple')
plt.plot(Y_test, Y_test, color='orange', linestyle='--')
plt.title('AdaBoost Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

# SVM Regression Scatterplot
plt.subplot(2, 3, 5)
plt.scatter(Y_test, Y_pred_svm, color='orange')
plt.plot(Y_test, Y_test, color='red', linestyle='--')
plt.title('SVM Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

# Gradient Boosting Regression Scatterplot
plt.subplot(2, 3, 6)
plt.scatter(Y_test, Y_pred_gradient_boost, color='brown')
```

```
plt.plot(Y_test, Y_test, color='red', linestyle='--')
plt.title('Gradient Boosting Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

plt.tight_layout()
plt.show()
```



2.3 BAR GRAPH

```
[84]: import matplotlib.pyplot as plt

# Data
models = ['Linear Regression', 'Random Forest Regression', 'XGBoost Regression',
          'AdaBoost Regression', 'SVM Regression', 'Gradient Boosting_
          ↪Regression']
accuracy = [error_score * 100, error_scoreR * 100, r2_xgb * 100, r2_adaboost * _
          ↪100, r2_svm * 100, r2_gradient_boost * 100]

# Define colors for each bar
colors = ['blue', 'green', 'darkgreen', 'orange', 'yellow', 'red']

# Create bar plot
plt.figure(figsize=(7.5, 6))

bars = plt.bar(models, accuracy, color=colors)
```

```

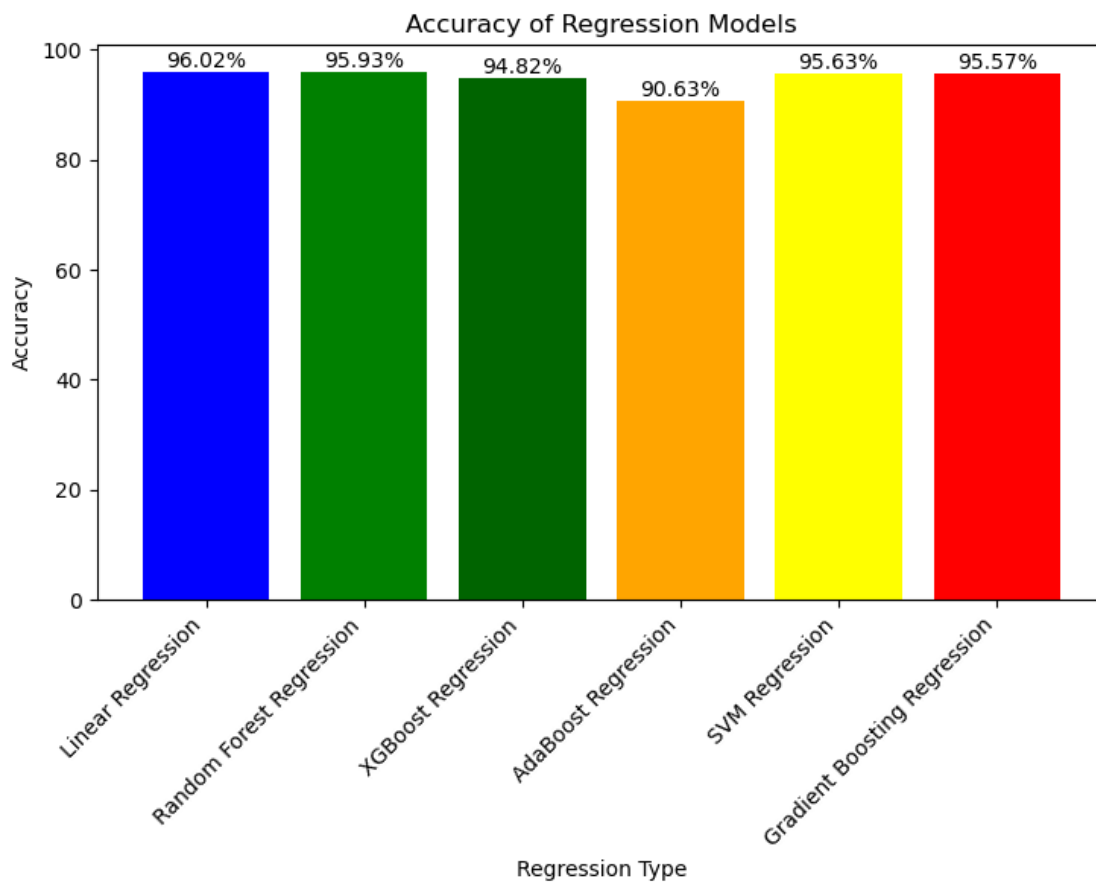
plt.xlabel('Regression Type')
plt.ylabel('Accuracy')
plt.title('Accuracy of Regression Models')
plt.xticks(rotation=45, ha='right')

# Annotate each bar with accuracy percentage
for bar, acc in zip(bars, accuracy):
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height, f'{acc:.2f}%',
             ha='center', va='bottom')

plt.tight_layout()

# Show plot
plt.show()

```



[]:

[]: