import necessary libraries import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns from sklearn.model_selection import from sklearn.ensemble import Rando from sklearn.metrics import mean_a from sklearn.preprocessing import from sklearn.compose import Column	omForestRegressor absolute_error, mean_squared_error, r2_score OneHotEncoder
<pre>from sklearn.pipeline import Pipel from sklearn.preprocessing import  : #Load the Dataset data = pd.read_csv('https://raw.gd data.head()  : Unnamed: 0 carat cut color c</pre>	line
2 3 0.23 Good E 3 4 0.29 Premium I	SII         59.8         61.0         326         3.89         3.84         2.31           VSI         56.9         65.0         327         4.05         4.03         2.31           VSI         63.0         38.0         38.0         38.0         4.20         4.23         2.63           SII         8.0         38.0         38.0         4.20         4.20         4.20         4.20
<pre># Drop unnecessary columns data = data.drop(columns=['Unname  # Data Visualizations  # Distribution of the target vari plt.figure(figsize=(8, 6)) sns.histplot(data['price'], bins=5 plt.title('Distribution of Diamono)</pre>	<pre>iable (Price) 50, kde=True, color='blue')</pre>
<pre>plt.xlabel('Price') plt.ylabel('Frequency') plt.show()</pre> <pre>Distribution:</pre>	stribution of Diamond Prices
- 0000	
2000 -	
# 2. Correlation heatmap # Create a copy of the dataset to data_encoded = data.copy()  # Encode categorical columns	7500 10000 12500 15000 17500 Price  avoid modifying the original
<pre>label_encoders = {} for col in ['cut', 'color', 'clari     le = LabelEncoder()     data_encoded[col] = le.fit_tra     label_encoders[col] = le  # Correlation heatmap with encoded plt.figure(figsize=(10, 8)) corr = data_encoded.corr() sns.heatmap(corr, annot=True, cmap</pre>	ansform(data_encoded[col])  d categorical columns
Correlation Heatmap  1.00 0.02 0.29 -0.21	ith Encoded Categorical Columns) ')  (with Encoded Categorical Columns)  0.03 0.18 0.92 0.98 0.95 0.95  -0.19 0.15 0.04 0.02 0.03 0.00 -0.8
Note	0.05
<u>भू</u> - 0.18 0.15 0.03 -0.09 <u>भू</u> - 0.92 0.04 0.17 -0.07	-0.30       1.00       0.13       0.20       0.18       0.15         -0.01       0.13       1.00       0.88       0.87       0.86
> - 0.95 0.03 0.26 -0.22 N - 0.95 0.00 0.27 -0.22	-0.03
]: # 3. Pairplot for numerical featur	res h', 'table', 'x', 'y', 'z', 'price']])
2 - 2 - 2 - 1	
1	
90 -	
80 - 90 70 - 60 - 50 -	
10 - 8 - × 6 - 4 -	
2 - 0 -	
> 30 - 20 - 10 - 0 - 30 -	
25 - 20 - N 15 - 10 - 5 - 0 -	
15000 - 5000 -	
carat  # 4. Boxplot of price by cut plt.figure(figsize=(8, 6)) sns.boxplot(x='cut', y='price', da	ata=data, palette='viridis')
<pre>plt.title('Boxplot of Price by Cut plt.xlabel('Cut') plt.ylabel('Price') plt.show()  C:\Users\lsherpa\AppData\Local\Temp</pre>	p\ipykernel_1728\3423786036.py:3: FutureWarning: g `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.
17500 -	Boxplot of Price by Cut  Boxplot of Price by Cut  Boxplot of Price by Cut
12500 - <u>9</u> 10000 - 7500 -	
2500 -	ium Good Very Good Fair
<pre>plt.title('Scatter Plot of Carat v plt.xlabel('Carat') plt.ylabel('Price') plt.show()</pre>	<pre>ce', data=data, hue='cut', palette='viridis')</pre>
17500 - 15000 - 12500 -	
일 10000 - 7500 - 5000 -	cut
2500 - 0 1	ldeal Premium Good Very Good Fair  Carat
: #Data preprocessing #Handle categorical variables	= train_test_split(X, y, test_size=0.2, random_state=42)
<pre>categorical_features = ['cut', 'cot numerical_features = ['carat', 'de  preprocessor = ColumnTransformer(     transformers=[</pre>	epth', 'table', 'x', 'y', 'z']  merical_features),  categorical_features)
<pre>#create a data model model = Pipeline(steps=[</pre>	
preprocessor: ColumnTran  num  passthrough  NoneHot  RandomForestRegress	tEncoder 3
#make predictions y_pred = model.predict(X_test)  # Evaluate the model mae = mean_absolute_error(y_test, mse = mean_squared_error(y_test, r2 = r2_score(y_test, y_pred)  print(f"Mean Absolute Error: {mae}	y_pred) }")
<pre>print(f"Mean Squared Error: {mse}' print(f"R-squared: {r2}")  Mean Absolute Error: 270.1944588571 Mean Squared Error: 302594.57901389 R-squared: 0.9809650891568692  # Feature importance for Random For if isinstance(model.named_steps['importances = model.named_steps feature_names = numerical_feat</pre>	")  13696  9623  **oreset model  regressor'], RandomForestRegressor): ps['regressor'].feature_importances_ tures + list(model.named_steps['preprocessor'].named_transformers_['cat'].get_feature_names_out(categorical_features))
<pre>feature_importance_df = pd.Dat     print("\nFeature Importance:")     print(feature_importance_df.sc  Feature Importance:</pre>	taFrame({'Feature': feature_names, 'Importance': importances})
20 clarity_SI1 0.014462 17 color_J 0.010312 16 color_I 0.007273 23 clarity_VS2 0.007092 15 color_H 0.005649 22 clarity_VS1 0.005627 3 x 0.005504 5 z 0.005199 1 depth 0.003222 11 color_D 0.002837 14 color_G 0.002594	
2 table 0.002185  12 color_E 0.001639  13 color_F 0.001427  25 clarity_VVS2 0.001117  8 cut_Ideal 0.001001  19 clarity_IF 0.000697  24 clarity_VVS1 0.000492  9 cut_Premium 0.000359  10 cut_Very Good 0.000282  7 cut_Good 0.000246	
6 cut_Fair 0.000146  8 # Plot feature importance plt.figure(figsize=(10, 6))	ature',data=feature_importance_df.sort_values(by='Importance', ascending=False))

In [110... ##Project Objectives

#This project demonstrates the process of building a machine learning model

Importance