```python
import pandas as pd
df=pd.read_csv(r"/content/laptop_price.csv")
print(df.head())
```

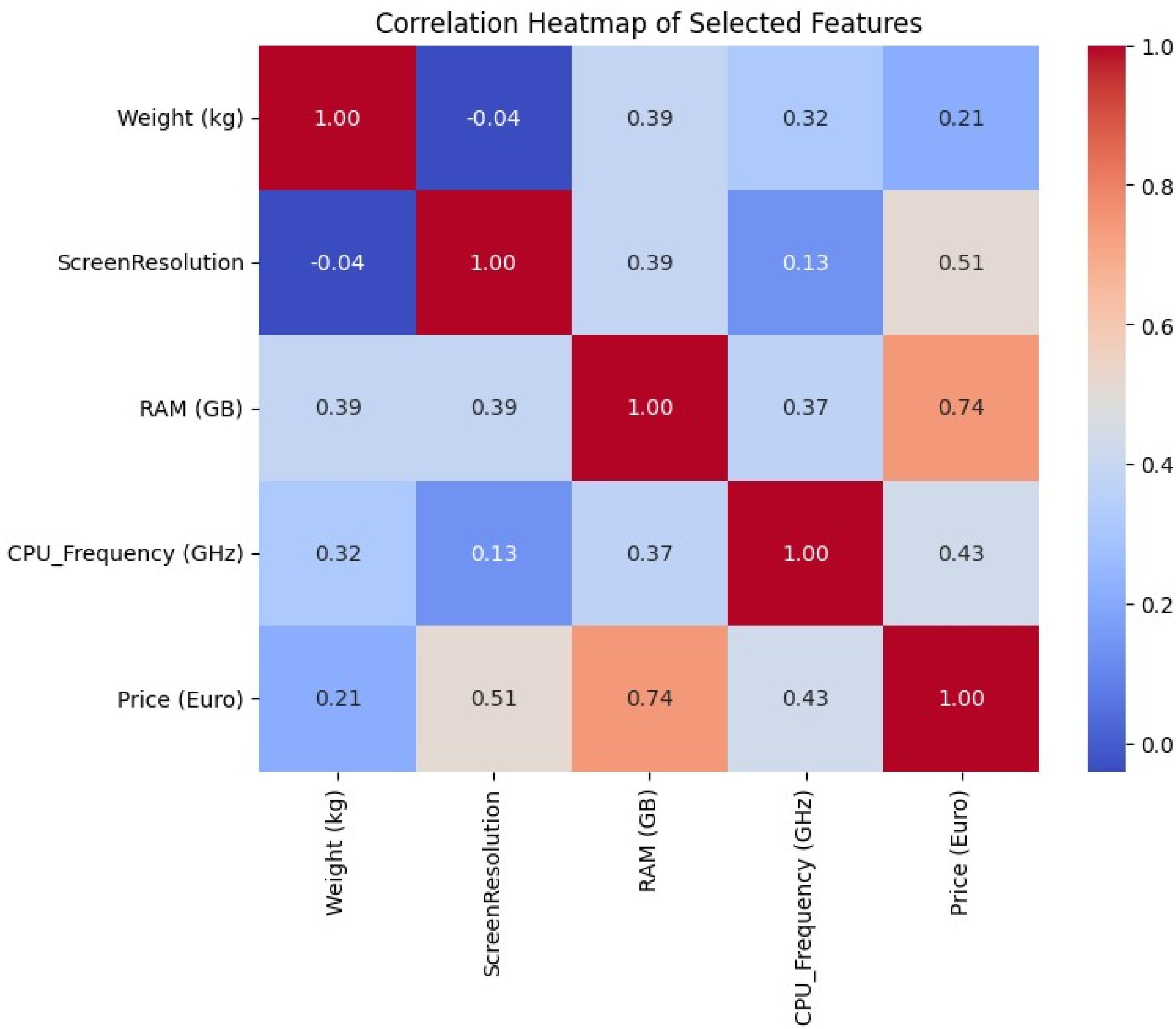
```
  Company      Product   TypeName  Inches  
ScreenResolution  \
0   Apple  MacBook Pro  Ultrabook    13.3  IPS Panel Retina Display 
2560x1600   
1   Apple  Macbook Air  Ultrabook    13.3                            
1440x900   
2      HP       250 G6   Notebook    15.6                    Full HD 
1920x1080   
3   Apple  MacBook Pro  Ultrabook    15.4  IPS Panel Retina Display 
2880x1800   
4   Apple  MacBook Pro  Ultrabook    13.3  IPS Panel Retina Display 
2560x1600   

  CPU_Company       CPU_Type  CPU_Frequency (GHz)  RAM (GB)  \
0       Intel        Core i5                  2.3         8   
1       Intel        Core i5                  1.8         8   
2       Intel  Core i5 7200U                  2.5         8   
3       Intel        Core i7                  2.7        16   
4       Intel        Core i5                  3.1         8   

                Memory GPU_Company               GPU_Type  OpSys  \
0            128GB SSD       Intel  Iris Plus Graphics 640  macOS   
1  128GB Flash Storage       Intel        HD Graphics 6000  macOS   
2            256GB SSD       Intel         HD Graphics 620  No OS   
3            512GB SSD         AMD          Radeon Pro 455  macOS   
4            256GB SSD       Intel  Iris Plus Graphics 650  macOS   

   Weight (kg)  Price (Euro)  
0         1.37       1339.69  
1         1.34        898.94  
2         1.86        575.00  
3         1.83       2537.45  
4         1.37       1803.60  
```

```python
# Check the first few rows
print(df.head())

# Get basic information about the dataset
print(df.info())

# Summary statistics for numerical columns
print(df.describe())

# Check for missing values
print(df.isnull().sum())
```

```
  Company      Product   TypeName  Inches
ScreenResolution  \
0   Apple  MacBook Pro  Ultrabook    13.3  IPS Panel Retina Display
2560x1600
1   Apple  Macbook Air  Ultrabook    13.3
1440x900
2      HP       250 G6   Notebook    15.6                   Full HD
1920x1080
3   Apple  MacBook Pro  Ultrabook    15.4  IPS Panel Retina Display
2880x1800
4   Apple  MacBook Pro  Ultrabook    13.3  IPS Panel Retina Display
2560x1600

  CPU_Company       CPU_Type  CPU_Frequency (GHz)  RAM (GB)  \
0       Intel        Core i5                  2.3         8
1       Intel        Core i5                  1.8         8
2       Intel  Core i5 7200U                  2.5         8
3       Intel        Core i7                  2.7        16
4       Intel        Core i5                  3.1         8

                Memory GPU_Company                GPU_Type  OpSys  \
0            128GB SSD       Intel  Iris Plus Graphics 640  macOS
1  128GB Flash Storage       Intel        HD Graphics 6000  macOS
2            256GB SSD       Intel         HD Graphics 620  No OS
3            512GB SSD         AMD          Radeon Pro 455  macOS
4            256GB SSD       Intel  Iris Plus Graphics 650  macOS

   Weight (kg)  Price (Euro)
0         1.37       1339.69
1         1.34        898.94
2         1.86        575.00
3         1.83       2537.45
4         1.37       1803.60
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1275 entries, 0 to 1274
Data columns (total 15 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Company              1275 non-null   object
 1   Product              1275 non-null   object
 2   TypeName             1275 non-null   object
 3   Inches               1275 non-null   float64
 4   ScreenResolution     1275 non-null   object
 5   CPU_Company          1275 non-null   object
 6   CPU_Type             1275 non-null   object
 7   CPU_Frequency (GHz)  1275 non-null   float64
 8   RAM (GB)             1275 non-null   int64
 9   Memory               1275 non-null   object
 10  GPU_Company          1275 non-null   object
 11  GPU_Type             1275 non-null   object
```

```
 12  OpSys                  1275 non-null   object 
 13  Weight (kg)            1275 non-null   float64
 14  Price (Euro)           1275 non-null   float64
dtypes: float64(4), int64(1), object(10)
memory usage: 149.5+ KB
None
            Inches  CPU_Frequency (GHz)      RAM (GB)  Weight (kg)  \
count  1275.000000          1275.000000  1275.000000  1275.000000   
mean     15.022902             2.302980     8.440784     2.040525   
std       1.429470             0.503846     5.097809     0.669196   
min      10.100000             0.900000     2.000000     0.690000   
25%      14.000000             2.000000     4.000000     1.500000   
50%      15.600000             2.500000     8.000000     2.040000   
75%      15.600000             2.700000     8.000000     2.310000   
max      18.400000             3.600000    64.000000     4.700000   

       Price (Euro)  
count   1275.000000  
mean    1134.969059  
std      700.752504  
min      174.000000  
25%      609.000000  
50%      989.000000  
75%     1496.500000  
max     6099.000000  
Company                0
Product                0
TypeName               0
Inches                 0
ScreenResolution       0
CPU_Company            0
CPU_Type               0
CPU_Frequency (GHz)    0
RAM (GB)               0
Memory                 0
GPU_Company            0
GPU_Type               0
OpSys                  0
Weight (kg)            0
Price (Euro)           0
dtype: int64

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load the dataset
file_path = 'laptop_price.csv'  # Replace with the correct path to 
your file
df = pd.read_csv(file_path)
```

```python
# Derive 'ScreenResolution' and 'Memory_Size' features if needed
df['ScreenResolution'] = df['ScreenResolution'].str.extract(r'(\d+)x(\
d+)').astype(float).prod(axis=1)  # Pixel count approximation
df['Memory_Size (GB)'] = df['Memory'].str.extract(r'(\
d+)').astype(int)  # Extract memory size in GB

# Selecting relevant features
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)", "Price (Euro)"]
df_selected = df[selected_features]

# Correlation matrix
correlation_matrix = df_selected.corr()

# Plotting the heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm",
fmt=".2f", cbar=True)
plt.title("Correlation Heatmap of Selected Features")
plt.show()
```



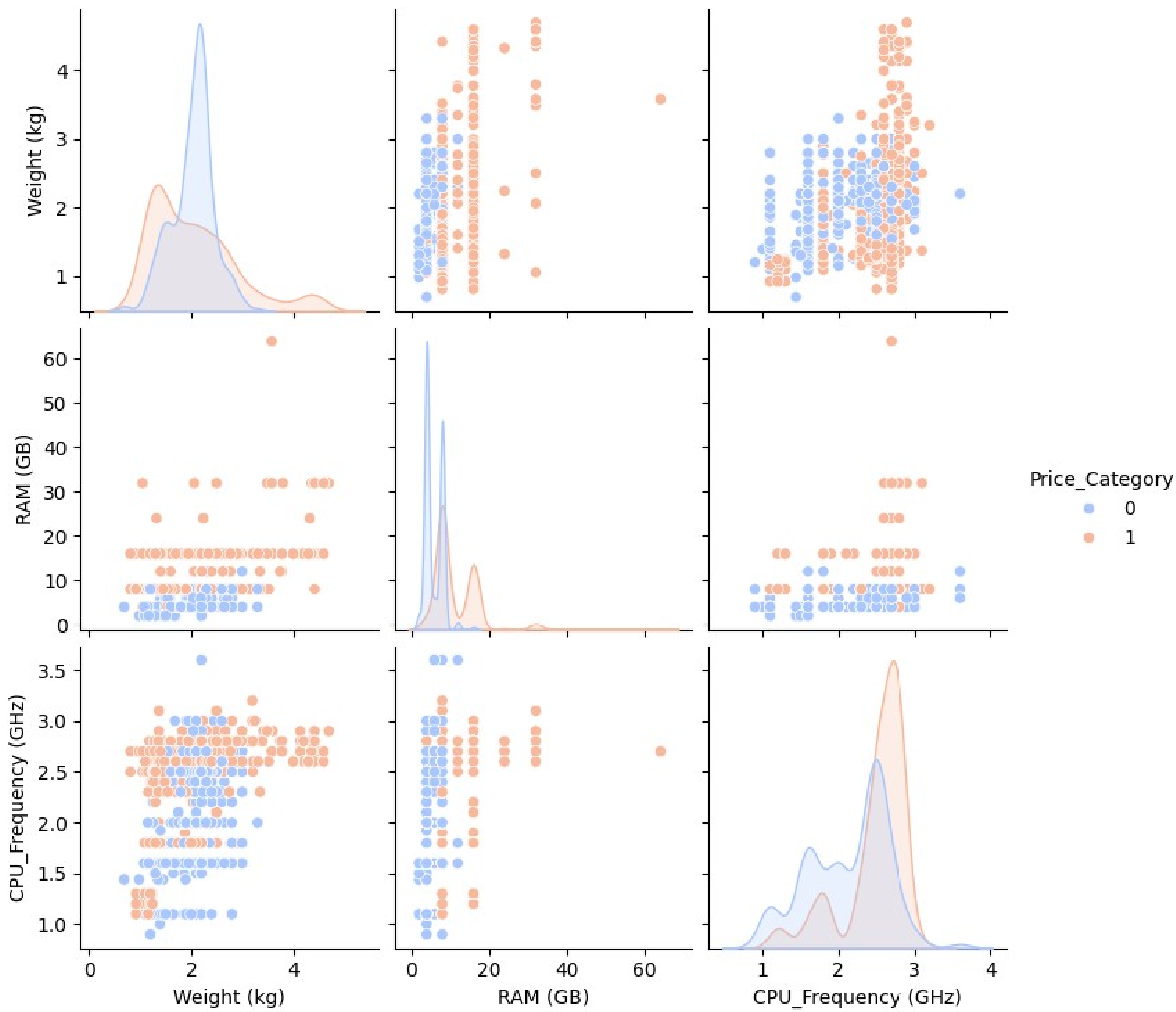

```
import pandas as pd

# Load the dataset
file_path = 'laptop_price.csv'  # Replace with the correct path to
your file
df = pd.read_csv(file_path)

# Derive 'ScreenResolution' and 'Memory_Size' features if needed
df['ScreenResolution'] = df['ScreenResolution'].str.extract(r'(\d+)x(\
d+)').astype(float).prod(axis=1)  # Pixel count approximation
df['Memory_Size (GB)'] = df['Memory'].str.extract(r'(\
d+)').astype(int)  # Extract memory size in GB

# Selecting relevant numerical features
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)", "Price (Euro)"]
```

```
df_selected = df[selected_features]

# Compute the correlation matrix
correlation_matrix = df_selected.corr()

# Display the correlation matrix
print("Correlation Matrix (Numerical):")
print(correlation_matrix)
```

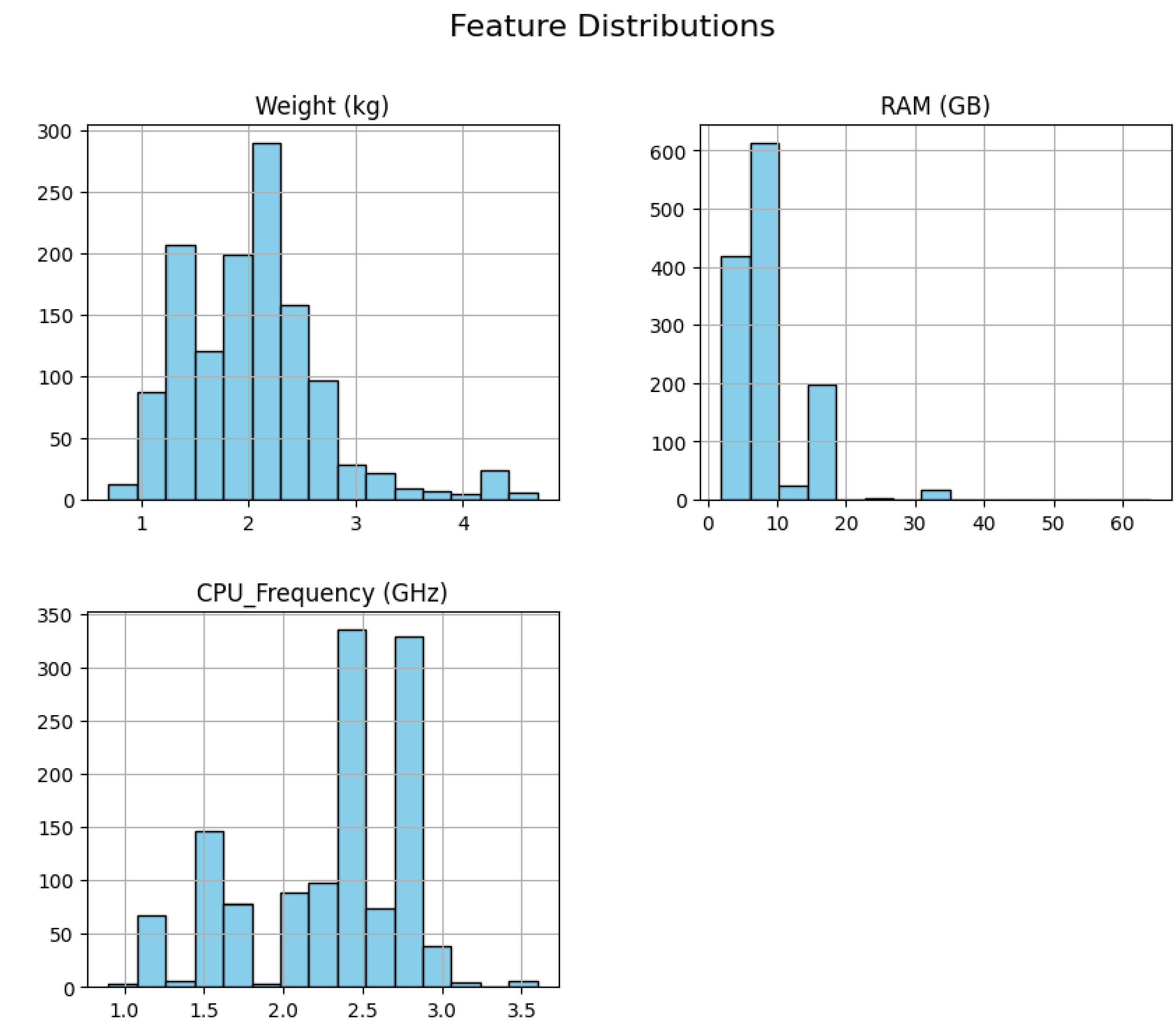
```
Correlation Matrix (Numerical):
                     Weight (kg)  ScreenResolution  RAM (GB)  \
Weight (kg)             1.000000         -0.040126  0.389370
ScreenResolution       -0.040126          1.000000  0.388002
RAM (GB)                0.389370          0.388002  1.000000
CPU_Frequency (GHz)     0.318649          0.130565  0.366254
Price (Euro)            0.211883          0.511753  0.740287

                     CPU_Frequency (GHz)  Price (Euro)
Weight (kg)                     0.318649      0.211883
ScreenResolution                0.130565      0.511753
RAM (GB)                        0.366254      0.740287
CPU_Frequency (GHz)             1.000000      0.428847
Price (Euro)                    0.428847      1.000000
```

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load dataset
df = pd.read_csv("laptop_price.csv")

# Step 1: Convert 'Price (Euro)' to binary classification
threshold = df['Price (Euro)'].median()  # Define the threshold for
classification
df['Price_Category'] = (df['Price (Euro)'] > threshold).astype(int)  #
1 if price > threshold, 0 if price <= threshold

# Step 2: Selected features
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Adjust as needed

# Step 3: Pair plot
print("Pair Plot:")
sns.pairplot(df[selected_features + ["Price_Category"]],
hue="Price_Category", palette="coolwarm")
plt.show()

# Step 4: Histograms
print("Histograms:")
df[selected_features].hist(bins=15, figsize=(10, 8), color='skyblue',
```

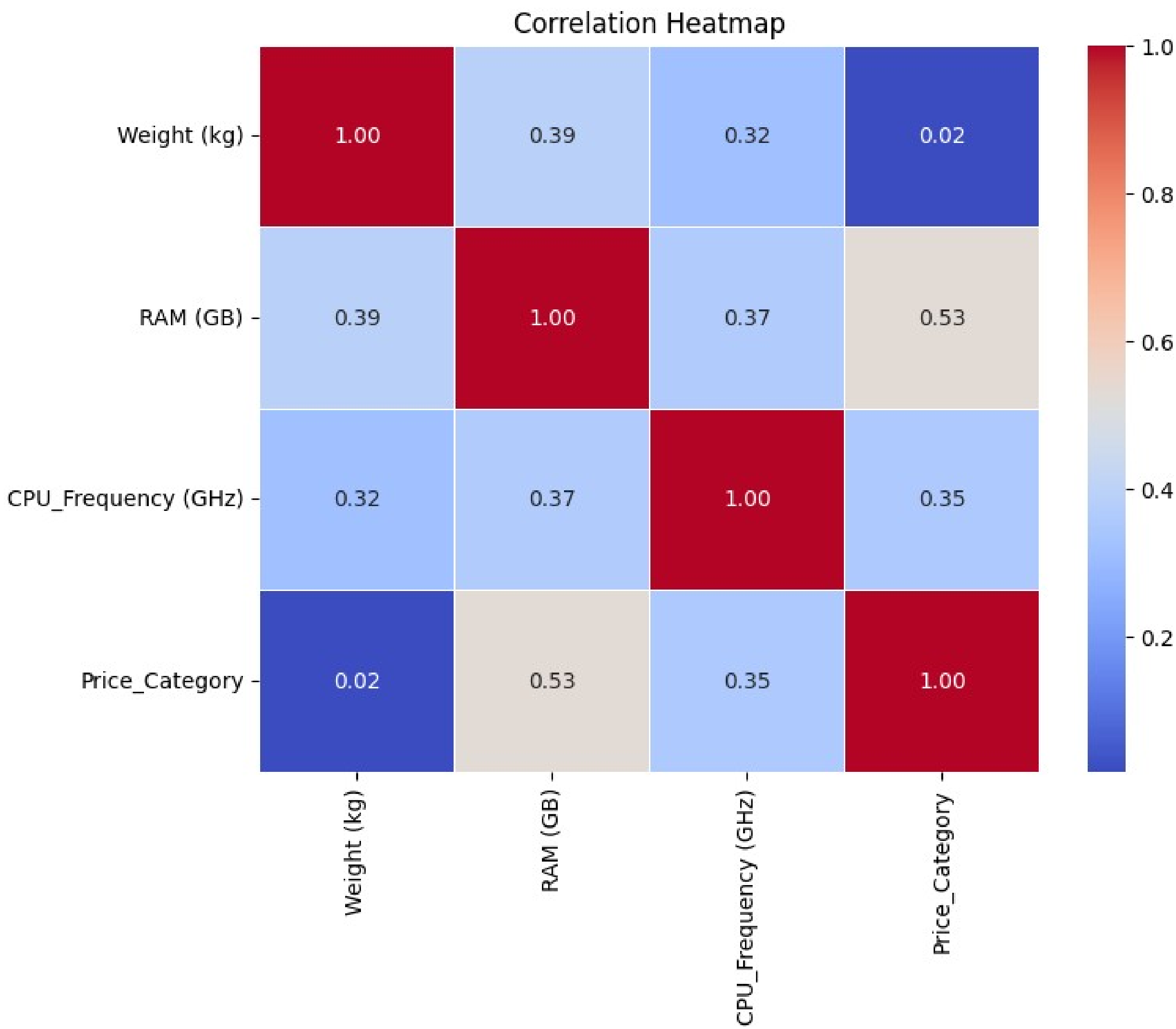
```
edgecolor='black')
plt.suptitle('Feature Distributions', size=16)
plt.show()

# Step 5: Correlation Heatmap
print("Correlation Heatmap:")
corr = df[selected_features + ["Price_Category"]].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f",
linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()

# Step 6: Scatter Plot (Weight vs CPU_Frequency, colored by
Price_Category)
print("Scatter Plot:")
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x="Weight (kg)", y="CPU_Frequency (GHz)",
hue="Price_Category", palette="coolwarm")
plt.title("Weight vs CPU Frequency (Colored by Price Category)")
plt.xlabel("Weight (kg)")
plt.ylabel("CPU Frequency (GHz)")
plt.show()

Pair Plot:
```



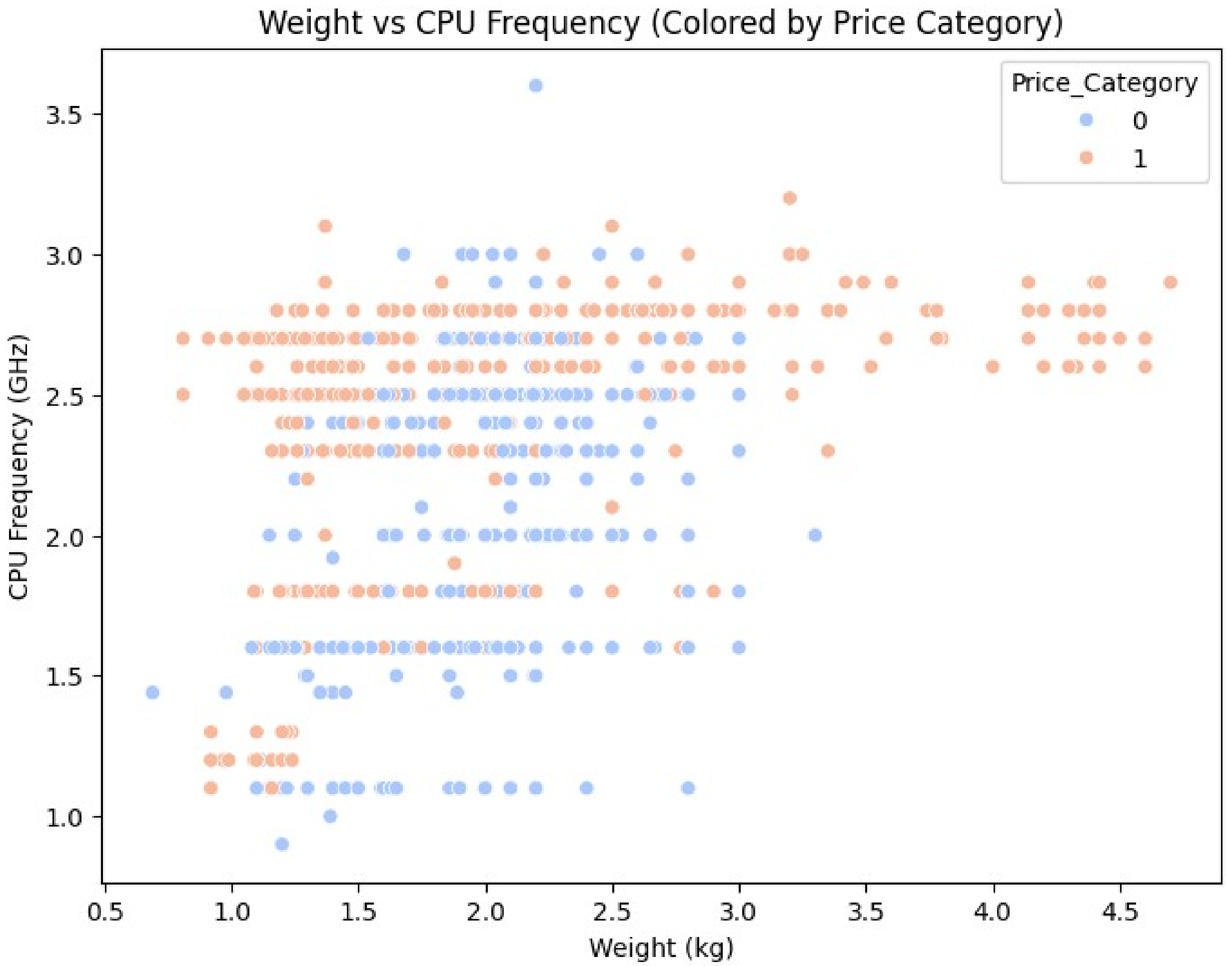

```
Histograms:
```




```
Correlation Heatmap:
```




```
Scatter Plot:
```




```
import pandas as pd



# Derive 'ScreenResolution' and 'Memory_Size' features if needed
df['ScreenResolution'] = df['ScreenResolution'].str.extract(r'(\d+)x(\
d+)').astype(float).prod(axis=1)  # Pixel count approximation
df['Memory_Size (GB)'] = df['Memory'].str.extract(r'(\
d+)').astype(int)  # Extract memory size in GB

# Define the selected features and target
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Based on correlation
X = df[selected_features]  # Features
y = df['Price (Euro)']  # Target

# Display the first few rows of X and y
print("Selected Features (X):")
print(X.head())
```

```
print("\nTarget (y):")
print(y.head())

Selected Features (X):
   Weight (kg)  ScreenResolution  RAM (GB)  CPU_Frequency (GHz)
0         1.37         4096000.0         8                  2.3
1         1.34         1296000.0         8                  1.8
2         1.86         2073600.0         8                  2.5
3         1.83         5184000.0        16                  2.7
4         1.37         4096000.0         8                  3.1

Target (y):
0    1339.69
1     898.94
2     575.00
3    2537.45
4    1803.60
Name: Price (Euro), dtype: float64

import pandas as pd
import numpy as np

# Load the dataset
file_path = 'laptop_price.csv'  # Replace with the correct path to
your file
df = pd.read_csv(file_path)

# Step 1: Check for missing values
print("Missing Values:\n", df.isnull().sum())

# Step 2: Handle missing values
# Assuming no missing values in key columns; fill any missing numeric
data with the mean
df.fillna(df.mean(numeric_only=True), inplace=True)

# Step 3: Convert categorical data to numeric
# Example: Encoding the 'OpSys' column using one-hot encoding
if 'OpSys' in df.columns:
    df = pd.get_dummies(df, columns=['OpSys'], prefix='OpSys',
drop_first=True)

# Step 4: Extract useful information from text columns
# Example 1: Extract screen resolution (if not already done)
if 'ScreenResolution' in df.columns:
    resolution_split = df['ScreenResolution'].str.extract(r'(\d+)x(\
d+)')
    df['ScreenResolution'] = resolution_split[0].astype(float) *
resolution_split[1].astype(float)

# Example 2: Extract numeric memory size from 'Memory' column
```

```
if 'Memory' in df.columns:
    df['Memory_Size (GB)'] = df['Memory'].str.extract(r'(\
d+)').astype(float)

# Step 5: Normalize or scale numerical columns (optional, depending on
the ML model)
from sklearn.preprocessing import StandardScaler

# List of numerical columns to scale
numerical_columns = ['Weight (kg)', 'ScreenResolution', 'RAM (GB)',
'CPU_Frequency (GHz)', 'Price (Euro)']
scaler = StandardScaler()
df[numerical_columns] = scaler.fit_transform(df[numerical_columns])

# Step 6: Drop redundant or irrelevant columns
# Example: Dropping the original 'Memory' column after extracting
numeric data
columns_to_drop = ['Memory']  # Add any other redundant columns here
df.drop(columns=columns_to_drop, inplace=True, errors='ignore')

# Step 7: Check the cleaned dataset
print("Cleaned DataFrame:")
print(df.head())

# Optional: Save the cleaned dataset
df.to_csv('laptop_price_cleaned.csv', index=False)
```

```
Missing Values:
 Company                0
Product                0
TypeName               0
Inches                 0
ScreenResolution       0
CPU_Company            0
CPU_Type               0
CPU_Frequency (GHz)    0
RAM (GB)               0
Memory                 0
GPU_Company            0
GPU_Type               0
OpSys                  0
Weight (kg)            0
Price (Euro)           0
dtype: int64
Cleaned DataFrame:
  Company      Product   TypeName  Inches  ScreenResolution
CPU_Company  \
0   Apple  MacBook Pro  Ultrabook    13.3          1.376413
Intel
1   Apple  Macbook Air  Ultrabook    13.3         -0.634604
```

```
Intel
2      HP       250 G6   Notebook    15.6         -0.076116
Intel
3   Apple  MacBook Pro  Ultrabook    15.4          2.157837
Intel
4   Apple  MacBook Pro  Ultrabook    13.3          1.376413
Intel

        CPU_Type  CPU_Frequency (GHz)  RAM (GB) GPU_Company  ... Price
(Euro)  \
0        Core i5            -0.005918 -0.086499       Intel  ...
0.292259
1        Core i5            -0.998674 -0.086499       Intel  ...    -
0.336954
2  Core i5 7200U             0.391185 -0.086499       Intel  ...    -
0.799410
3        Core i7             0.788288  1.483418         AMD  ...
2.002178
4        Core i5             1.582493 -0.086499       Intel  ...
0.954536

   OpSys_Chrome OS  OpSys_Linux  OpSys_Mac OS X  OpSys_No OS  \
0            False        False           False        False
1            False        False           False        False
2            False        False           False         True
3            False        False           False        False
4            False        False           False        False

   OpSys_Windows 10  OpSys_Windows 10 S  OpSys_Windows 7  OpSys_macOS
\
0             False               False            False         True

1             False               False            False         True

2             False               False            False        False

3             False               False            False         True

4             False               False            False         True


   Memory_Size (GB)
0             128.0
1             128.0
2             256.0
3             512.0
4             256.0

[5 rows x 22 columns]
```

```python
from sklearn.model_selection import train_test_split

# Define the features (X) and target variable (y)
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Based on analysis
X = df[selected_features]  # Features
y = df['Price (Euro)']  # Target

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Display the sizes of the splits
print(f"Training Set: {X_train.shape[0]} samples")
print(f"Testing Set: {X_test.shape[0]} samples")
```

```
Training Set: 1020 samples
Testing Set: 255 samples
```

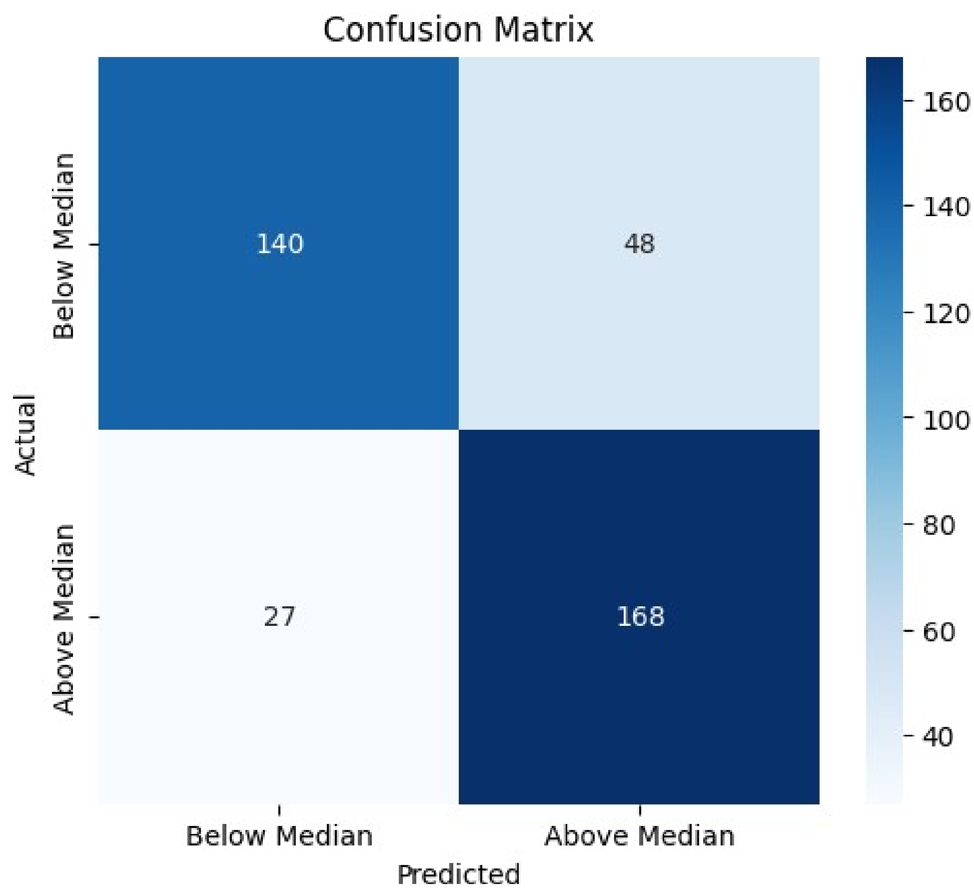
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Step 1: Convert target variable 'Price (Euro)' to binary
classification (e.g., high price vs low price)
# Define a threshold for binary classification (e.g., median price)
threshold = df['Price (Euro)'].median()
y_binary = (y > threshold).astype(int)  # 1 if price > threshold, 0 if
price <= threshold

# Step 2: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y_binary,
test_size=0.2, random_state=42)

# Step 3: Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 4: Initialize the Logistic Regression model
log_reg = LogisticRegression(random_state=42)

# Step 5: Train the model
log_reg.fit(X_train_scaled, y_train)

# Step 6: Predict on the test data
y_pred = log_reg.predict(X_test_scaled)

# Step 7: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
```

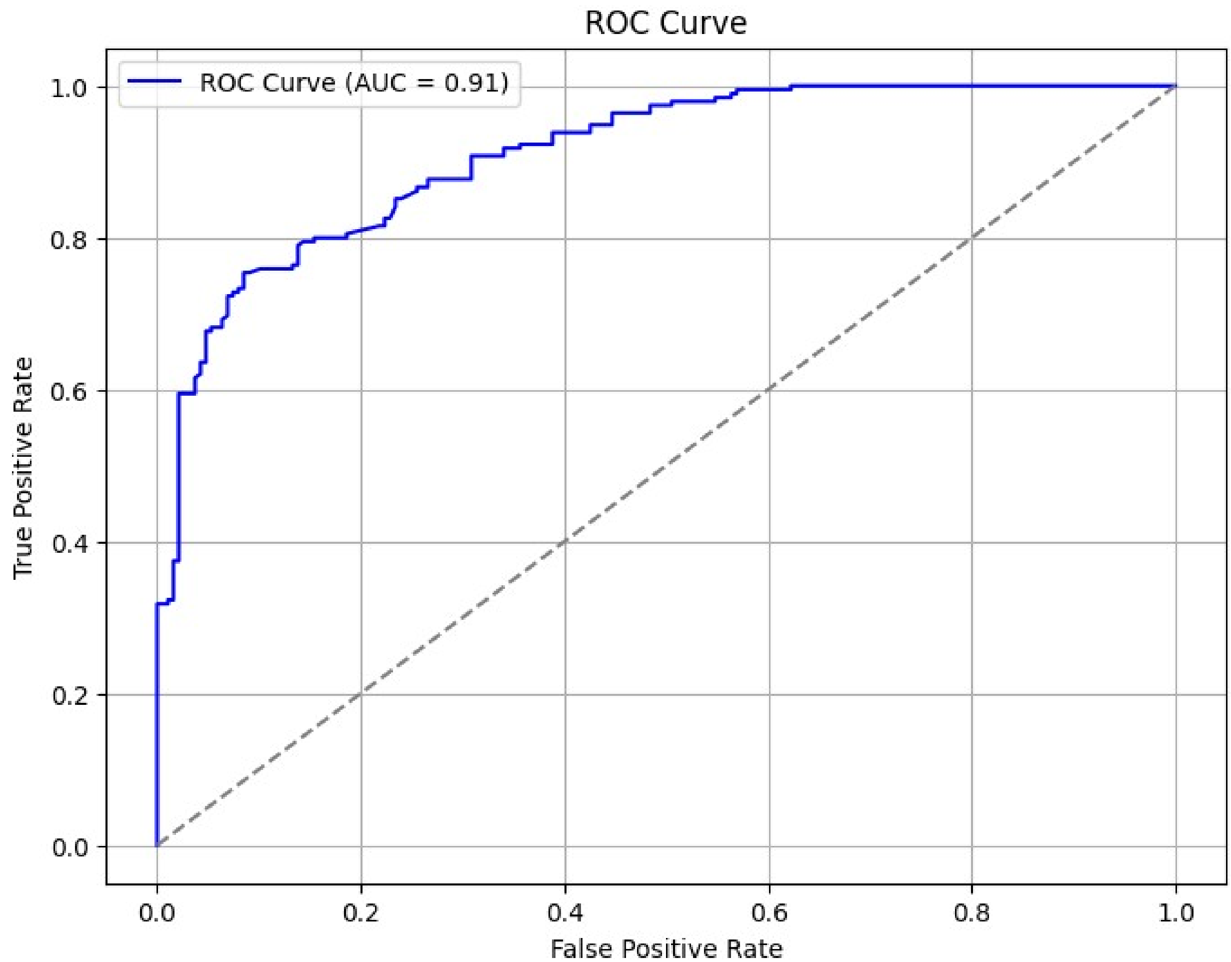
```python
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

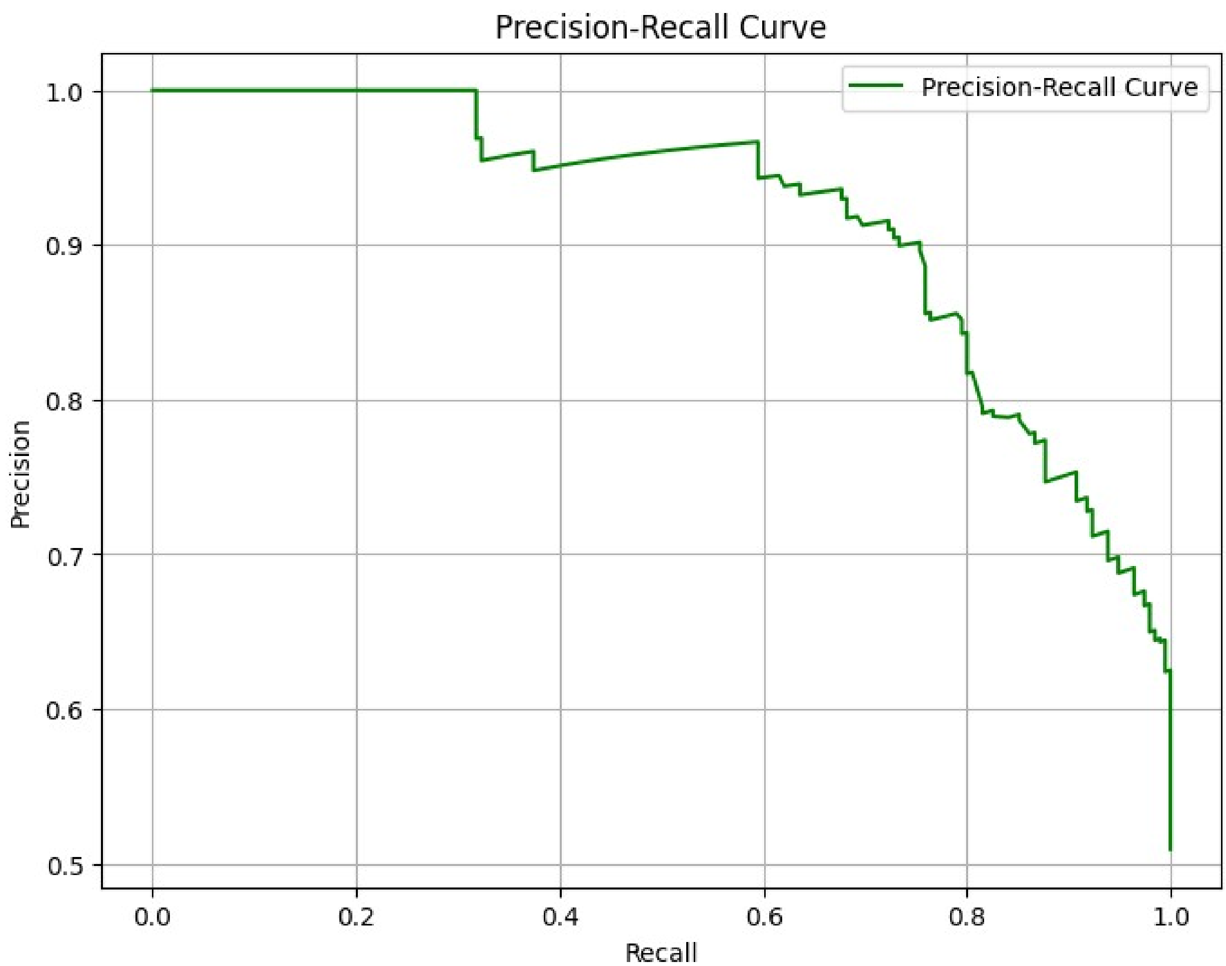
```
Accuracy: 0.7961
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.72      0.77       118
           1       0.78      0.86      0.82       137

    accuracy                           0.80       255
   macro avg       0.80      0.79      0.79       255
weighted avg       0.80      0.80      0.79       255
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report,
roc_curve, auc, precision_recall_curve
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

# Assuming 'df' is already loaded, cleaned, and preprocessed
# Define features and target
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Example features
X = df[selected_features]
y = (df['Price (Euro)'] > df['Price (Euro)'].median()).astype(int)  #
Binary classification

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Train Logistic Regression model
log_reg = LogisticRegression(max_iter=1000, random_state=42)
log_reg.fit(X_train, y_train)

# Predictions
y_pred = log_reg.predict(X_test)
y_pred_proba = log_reg.predict_proba(X_test)[:, 1]

# Step 1: Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
xticklabels=["Below Median", "Above Median"],
            yticklabels=["Below Median", "Above Median"])
plt.title("Confusion Matrix")
```

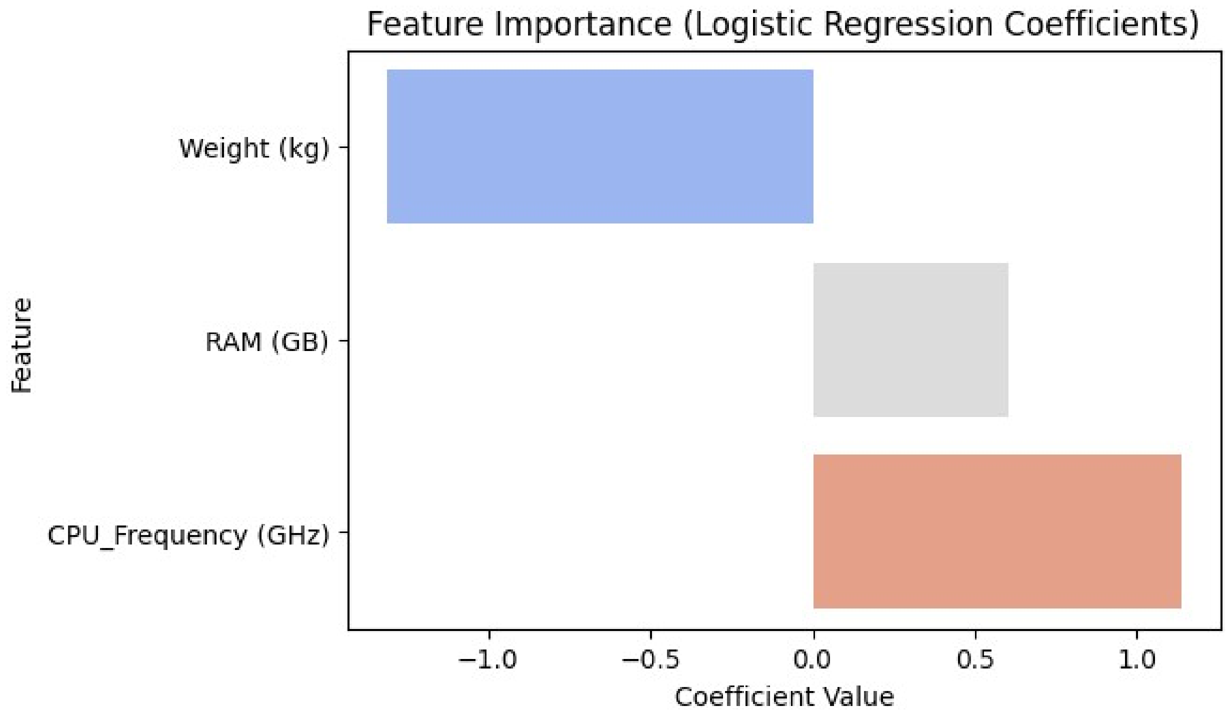
```
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Step 2: ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (AUC =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='grey', linestyle='--')
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid()
plt.show()

# Step 3: Precision-Recall Curve
precision, recall, thresholds = precision_recall_curve(y_test,
y_pred_proba)
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, color='green', label="Precision-Recall
Curve")
plt.title("Precision-Recall Curve")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.legend()
plt.grid()
plt.show()

# Step 4: Feature Importance
coefficients = pd.DataFrame(log_reg.coef_[0], index=selected_features,
columns=['Importance']).sort_values(by='Importance')
plt.figure(figsize=(6, 4))
sns.barplot(x=coefficients['Importance'], y=coefficients.index,
palette="coolwarm")
plt.title("Feature Importance (Logistic Regression Coefficients)")
plt.xlabel("Coefficient Value")
plt.ylabel("Feature")
plt.show()
```


Confusion Matrix
Actual
Below Median
Above Median
140
48
27
168
Below Median
Above Median
Predicted
160
140
120
100
80
60
40


ROC Curve
ROC Curve (AUC = 0.91)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0




```
<ipython-input-6-ec32ee96fb35>:61: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=coefficients['Importance'], y=coefficients.index,
palette="coolwarm")
```



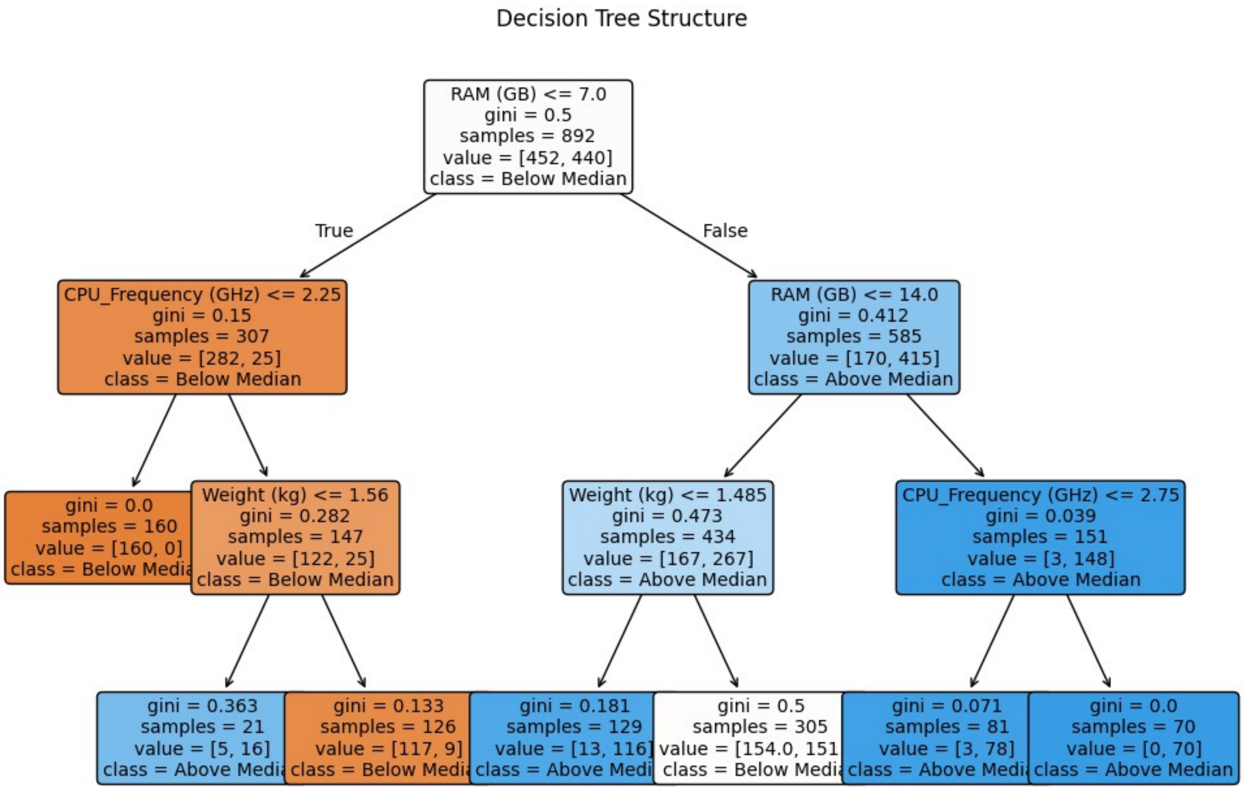

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Step 1: Convert target variable 'Price (Euro)' to binary
classification (e.g., high price vs low price)
# Define a threshold for binary classification (e.g., median price)
threshold = df['Price (Euro)'].median()
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Standardize the features (optional)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```python
# Step 5: Initialize the Decision Tree Classifier
dt_classifier = DecisionTreeClassifier(random_state=42)

# Step 6: Train the model
dt_classifier.fit(X_train_scaled, y_train)

# Step 7: Make predictions on the test set
y_pred = dt_classifier.predict(X_test_scaled)

# Step 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

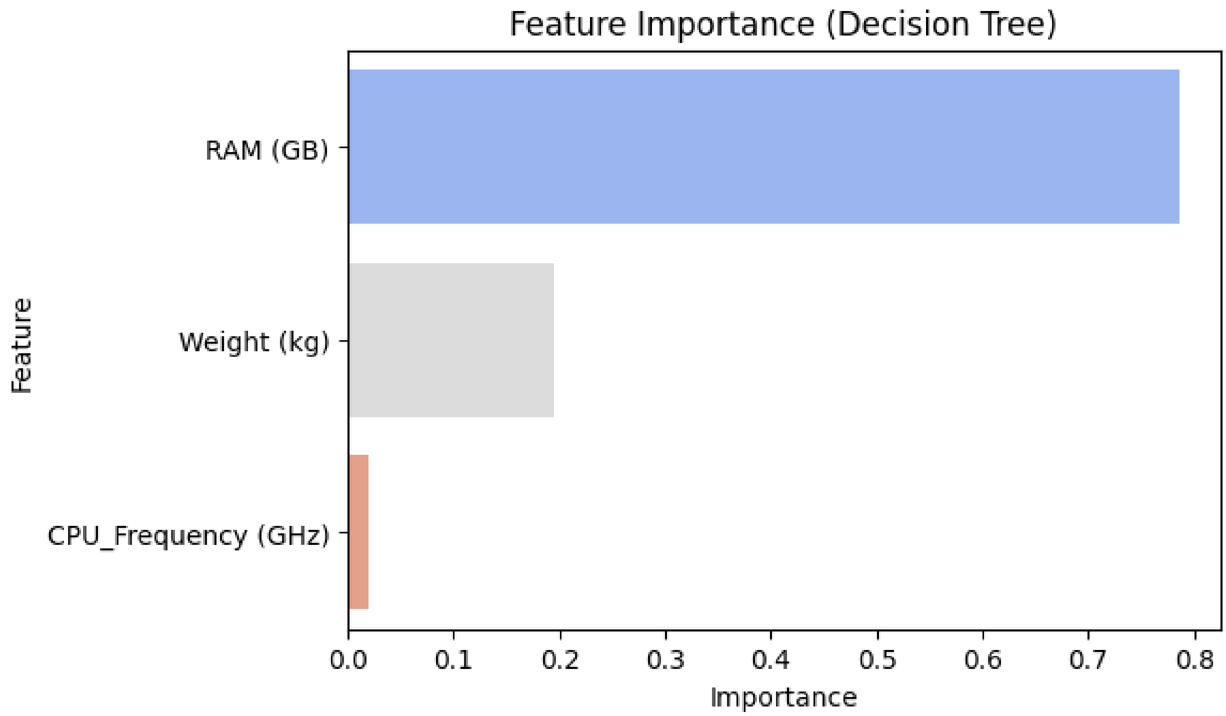
```
Accuracy: 0.8471
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.86      0.84       118
           1       0.88      0.83      0.85       137

    accuracy                           0.85       255
   macro avg       0.85      0.85      0.85       255
weighted avg       0.85      0.85      0.85       255
```

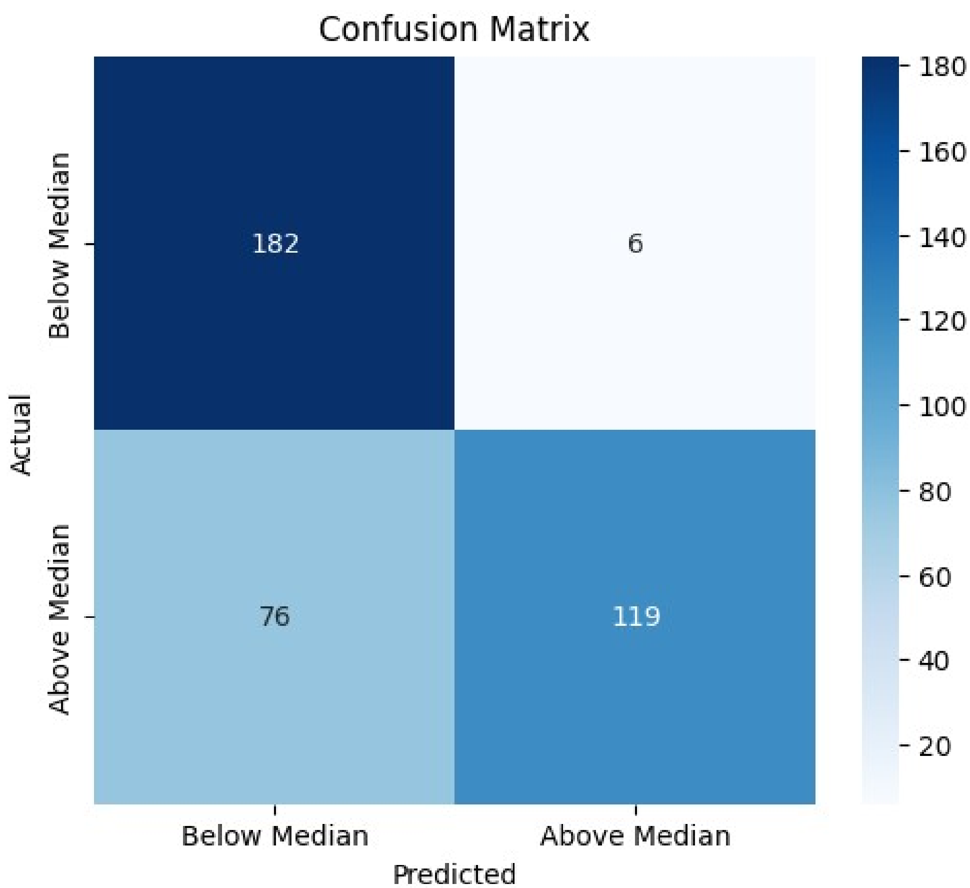
```python
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

# Define features and target
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Example features
X = df[selected_features]
y = (df['Price (Euro)'] > df['Price (Euro)'].median()).astype(int)  #
Binary classification

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Train Decision Tree model
tree_clf = DecisionTreeClassifier(max_depth=3, random_state=42)  #
Adjust max_depth as needed
tree_clf.fit(X_train, y_train)

# Step 1: Decision Tree Structure Visualization
plt.figure(figsize=(12, 8))
```

```
plot_tree(tree_clf, feature_names=selected_features,
class_names=["Below Median", "Above Median"],
          filled=True, rounded=True, fontsize=10)
plt.title("Decision Tree Structure")
plt.show()

# Step 2: Feature Importance
feature_importances = pd.DataFrame(tree_clf.feature_importances_,
index=selected_features,

columns=["Importance"]).sort_values(by="Importance", ascending=False)
plt.figure(figsize=(6, 4))
sns.barplot(x=feature_importances["Importance"],
y=feature_importances.index, palette="coolwarm")
plt.title("Feature Importance (Decision Tree)")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()

# Step 3: Confusion Matrix
y_pred = tree_clf.predict(X_test)
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
xticklabels=["Below Median", "Above Median"],
            yticklabels=["Below Median", "Above Median"])
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```




```
<ipython-input-7-174f91e135b3>:30: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=feature_importances["Importance"],
y=feature_importances.index, palette="coolwarm")
```


Feature Importance (Decision Tree)
RAM (GB)
Weight (kg)
CPU_Frequency (GHz)
Feature
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Importance


Confusion Matrix
Below Median
Above Median
Actual
182
6
76
119
Below Median
Above Median
Predicted
180
160
140
120
100
80
60
40
20

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import pandas as pd

# Step 1: Convert target variable 'Price (Euro)' to binary
classification (e.g., high price vs low price)
# Define a threshold for binary classification (e.g., median price)
threshold = df['Price (Euro)'].median()
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features and handle the categorical
'ScreenResolution' feature
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Convert 'ScreenResolution' (categorical) to numerical format
using LabelEncoder
label_encoder = LabelEncoder()
X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))

# Step 4: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 5: Standardize the features (optional)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 6: Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100,
random_state=42)

# Step 7: Train the model
rf_classifier.fit(X_train_scaled, y_train)

# Step 8: Make predictions on the test set
y_pred = rf_classifier.predict(X_test_scaled)

# Step 9: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

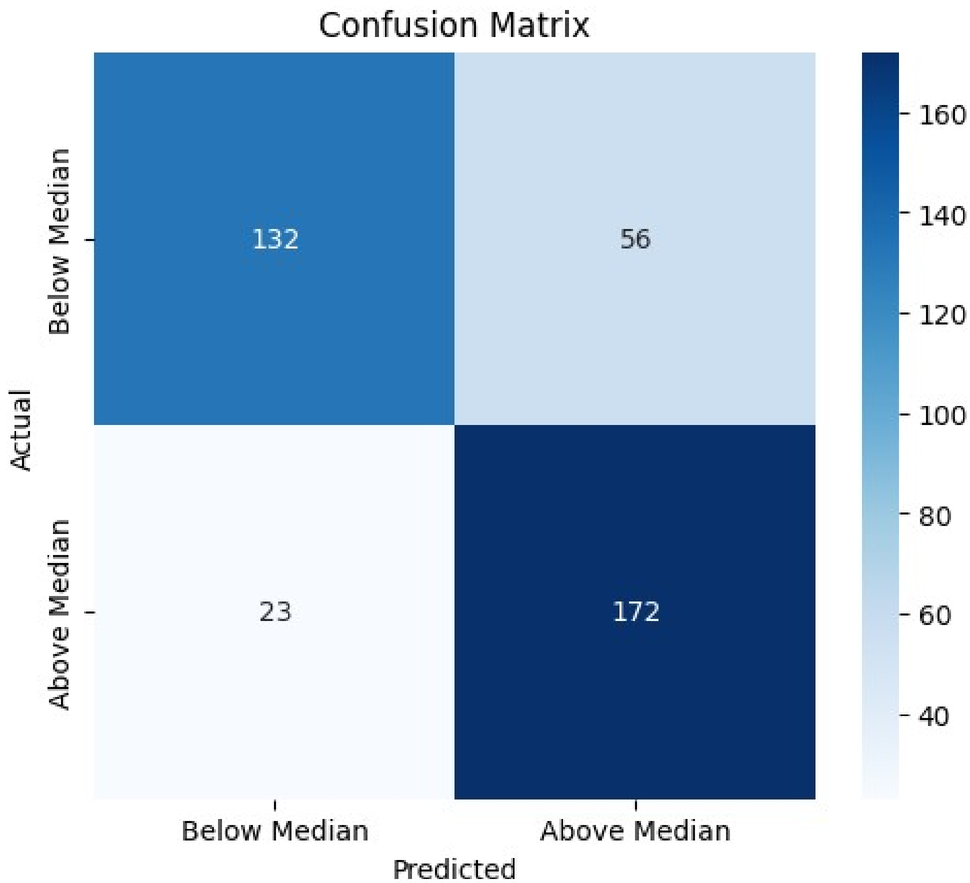
```
<ipython-input-23-69a697354206>:19: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))

Accuracy: 0.8392
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.83      0.83       118
           1       0.85      0.85      0.85       137

    accuracy                           0.84       255
   macro avg       0.84      0.84      0.84       255
weighted avg       0.84      0.84      0.84       255


from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Step 1: Convert target variable 'Price (Euro)' to binary
classification (e.g., high price vs low price)
# Define a threshold for binary classification (e.g., median price)
threshold = df['Price (Euro)'].median()
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Standardize the features (SVM models are sensitive to
feature scaling)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Initialize the SVM model
```

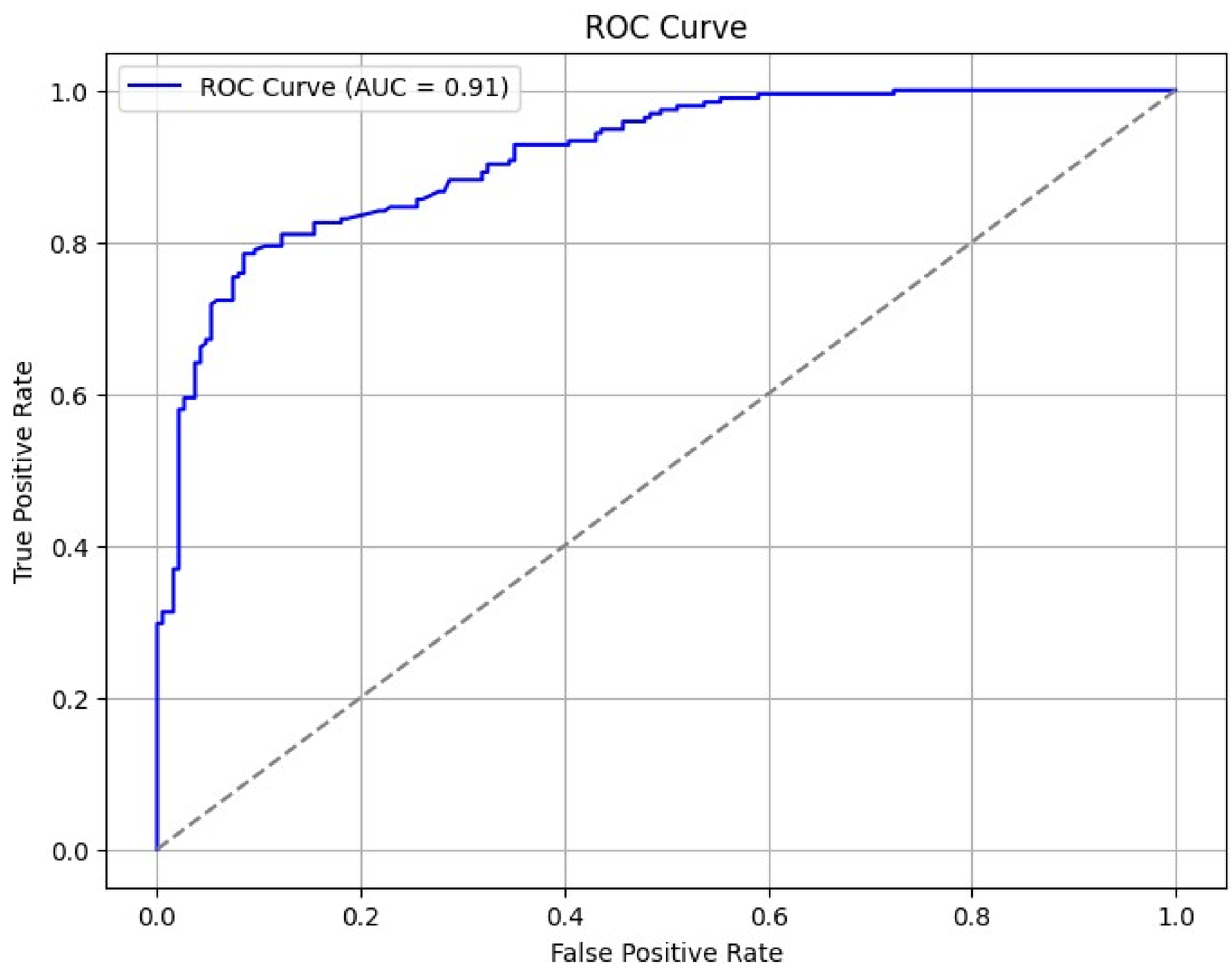
```
svm_classifier = SVC(kernel='linear', random_state=42)  # You can use
'linear', 'rbf', or 'poly'

# Step 6: Train the model
svm_classifier.fit(X_train_scaled, y_train)

# Step 7: Make predictions on the test set
y_pred = svm_classifier.predict(X_test_scaled)

# Step 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.7882
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.69      0.75       118
           1       0.77      0.87      0.82       137

    accuracy                           0.79       255
   macro avg       0.79      0.78      0.78       255
weighted avg       0.79      0.79      0.79       255
```

```
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, roc_curve, auc
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA  # For dimensionality reduction
(if necessary)

# Define features and target
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Example features
X = df[selected_features]
y = (df['Price (Euro)'] > df['Price (Euro)'].median()).astype(int)  #
Binary classification

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Train SVM model
svm_clf = SVC(kernel='linear', probability=True, random_state=42)  #
Change kernel to 'rbf', 'poly', etc., as needed
svm_clf.fit(X_train, y_train)
```

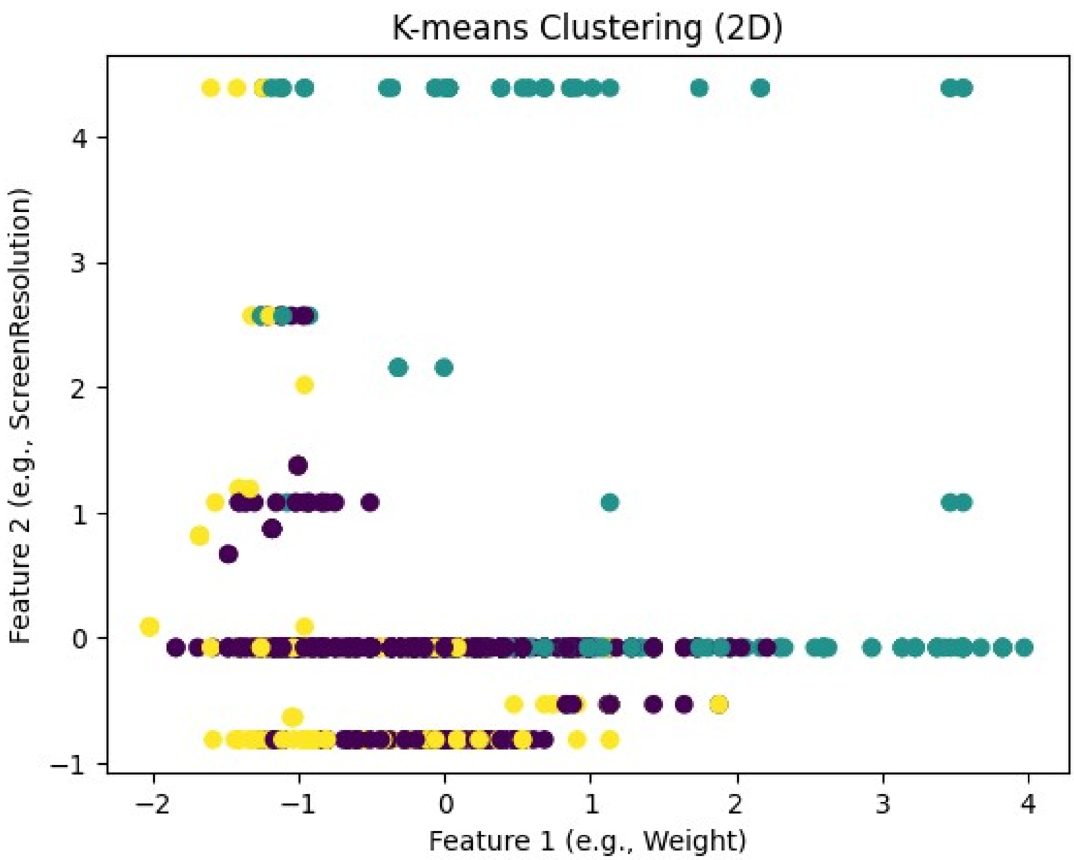
```
# Step 1: Confusion Matrix
y_pred = svm_clf.predict(X_test)
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
xticklabels=["Below Median", "Above Median"],
            yticklabels=["Below Median", "Above Median"])
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Step 2: Decision Boundary (if reduced to 2 features)
if len(selected_features) == 2:
    import numpy as np
    x_min, x_max = X_train[selected_features[0]].min() - 1,
X_train[selected_features[0]].max() + 1
    y_min, y_max = X_train[selected_features[1]].min() - 1,
X_train[selected_features[1]].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                         np.arange(y_min, y_max, 0.01))
    Z = svm_clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    plt.figure(figsize=(8, 6))
    plt.contourf(xx, yy, Z, alpha=0.8, cmap="coolwarm")
    sns.scatterplot(x=X_train[selected_features[0]],
y=X_train[selected_features[1]],
                    hue=y_train, palette="coolwarm", edgecolor="k")
    plt.title("Decision Boundary (SVM)")
    plt.xlabel(selected_features[0])
    plt.ylabel(selected_features[1])
    plt.show()

# Step 3: ROC Curve
y_pred_proba = svm_clf.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (AUC =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='grey', linestyle='--')
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid()
plt.show()
```


Confusion Matrix
132
56
23
172
Below Median
Above Median
Actual
Below Median
Above Median
Predicted
160
140
120
100
80
60
40




```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Step 1: Select the features for clustering
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features to use for clustering
X = df[selected_features]

# Step 2: Standardize the features (K-means is sensitive to feature
scaling)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 3: Apply K-means clustering (let's assume 3 clusters, you can
tune this)
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(X_scaled)

# Step 4: Add cluster labels to the dataframe
```

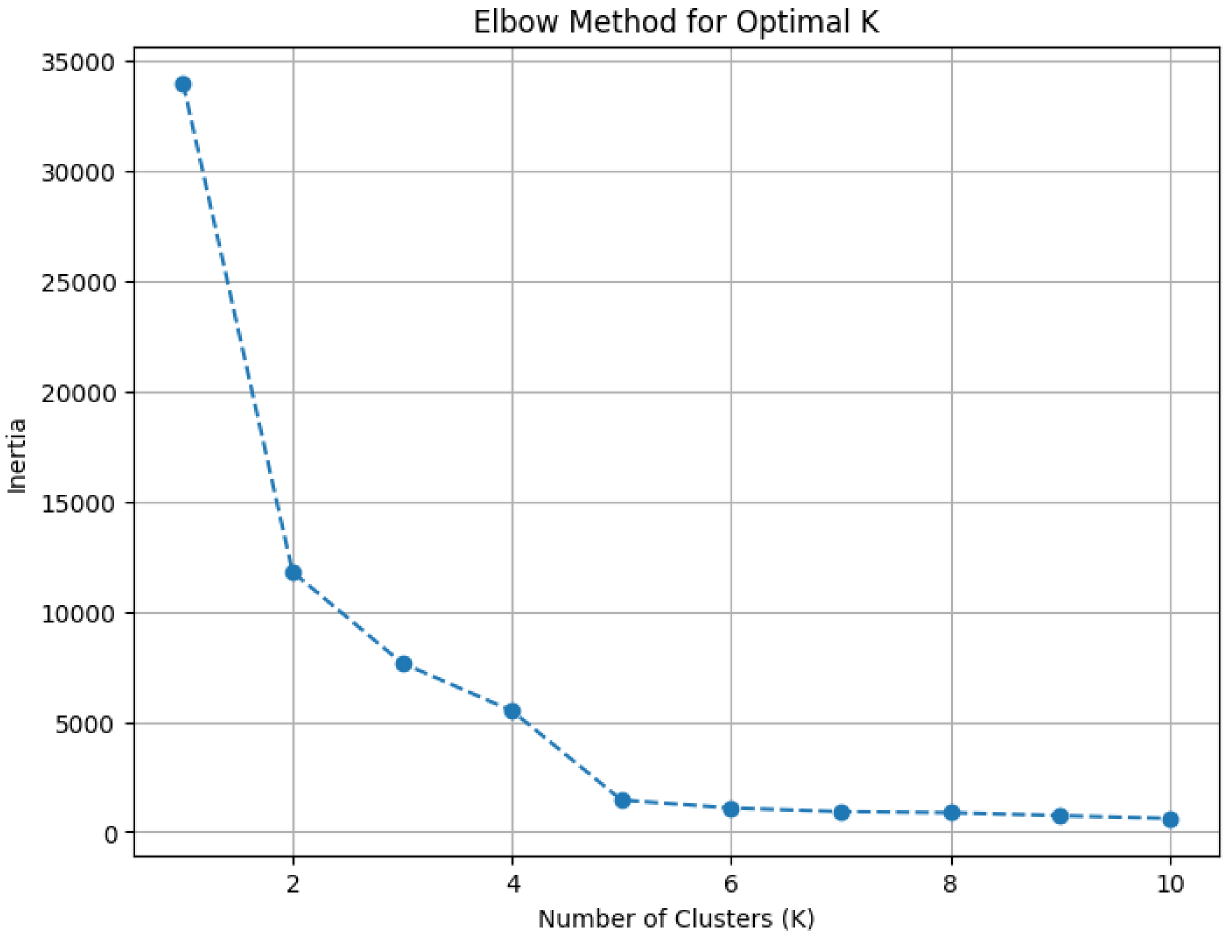
```
df['Cluster'] = kmeans.labels_

# Step 5: Evaluate clustering - inertia (sum of squared distances of
samples to their closest cluster center)
print(f"Inertia: {kmeans.inertia_:.4f}")

# Step 6: Optional - Visualize the clusters (2D visualization for
simplicity)
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=kmeans.labels_,
cmap='viridis')
plt.title('K-means Clustering (2D)')
plt.xlabel('Feature 1 (e.g., Weight)')
plt.ylabel('Feature 2 (e.g., ScreenResolution)')
plt.show()

Inertia: 2891.4306
```



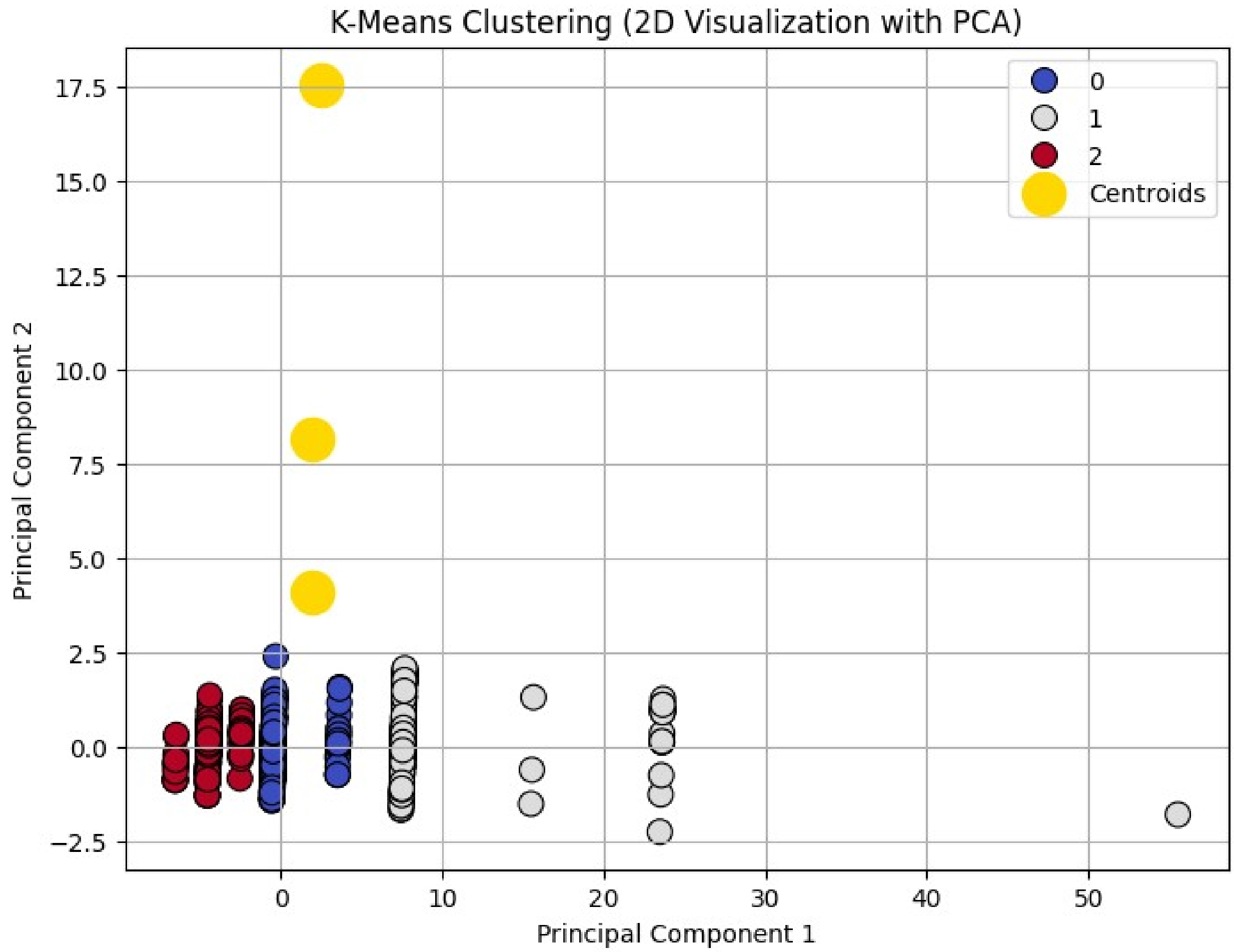

```
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

```python
# Define features for clustering
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Example features
X = df[selected_features]

# Step 1: Elbow Method for Optimal Number of Clusters
inertia = []
k_values = range(1, 11)  # Try 1 to 10 clusters
for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(8, 6))
plt.plot(k_values, inertia, marker='o', linestyle='--')
plt.title("Elbow Method for Optimal K")
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Inertia")
plt.grid()
plt.show()

# Step 2: K-Means Clustering
optimal_k = 3  # Based on elbow method (adjust as needed)
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
clusters = kmeans.fit_predict(X)
df["Cluster"] = clusters  # Add cluster labels to the dataset

# Step 3: Silhouette Score
sil_score = silhouette_score(X, clusters)
print(f"Silhouette Score: {sil_score:.2f}")

# Step 4: PCA for Visualization (Reduce to 2D)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

plt.figure(figsize=(8, 6))
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=clusters,
palette="coolwarm", s=100, edgecolor="k")
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,
1], s=300, c='gold', label='Centroids')
plt.title("K-Means Clustering (2D Visualization with PCA)")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend()
plt.grid()
plt.show()

# Optional: Distribution of Clusters
plt.figure(figsize=(6, 4))
```

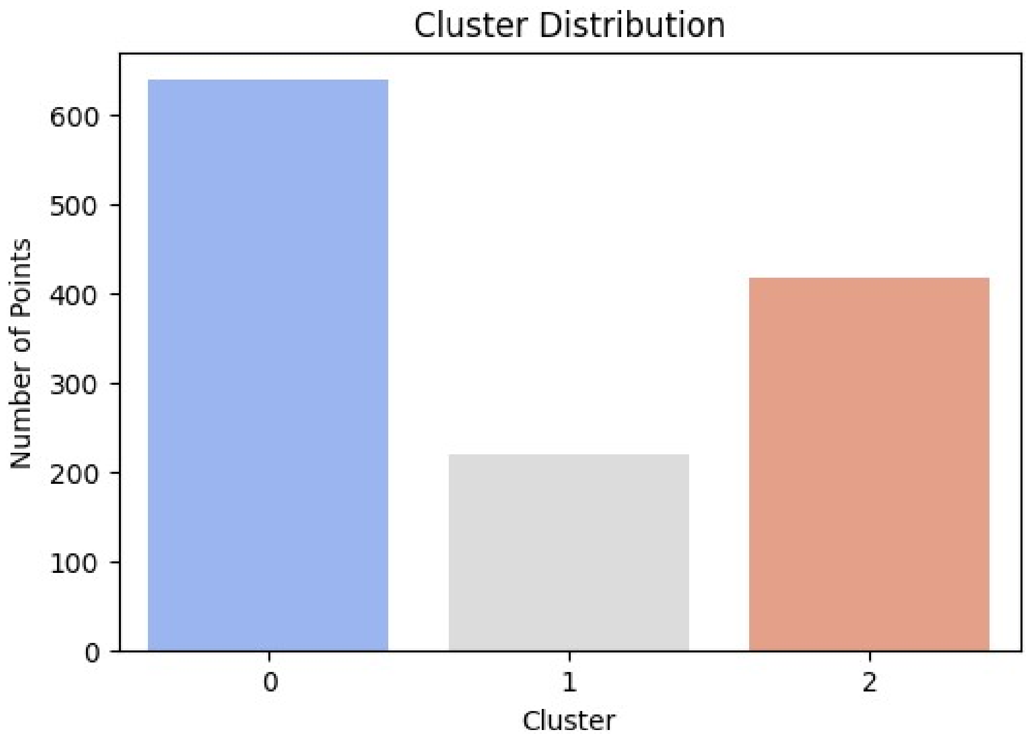
```
sns.countplot(x="Cluster", data=df, palette="coolwarm")
plt.title("Cluster Distribution")
plt.xlabel("Cluster")
plt.ylabel("Number of Points")
plt.show()
```



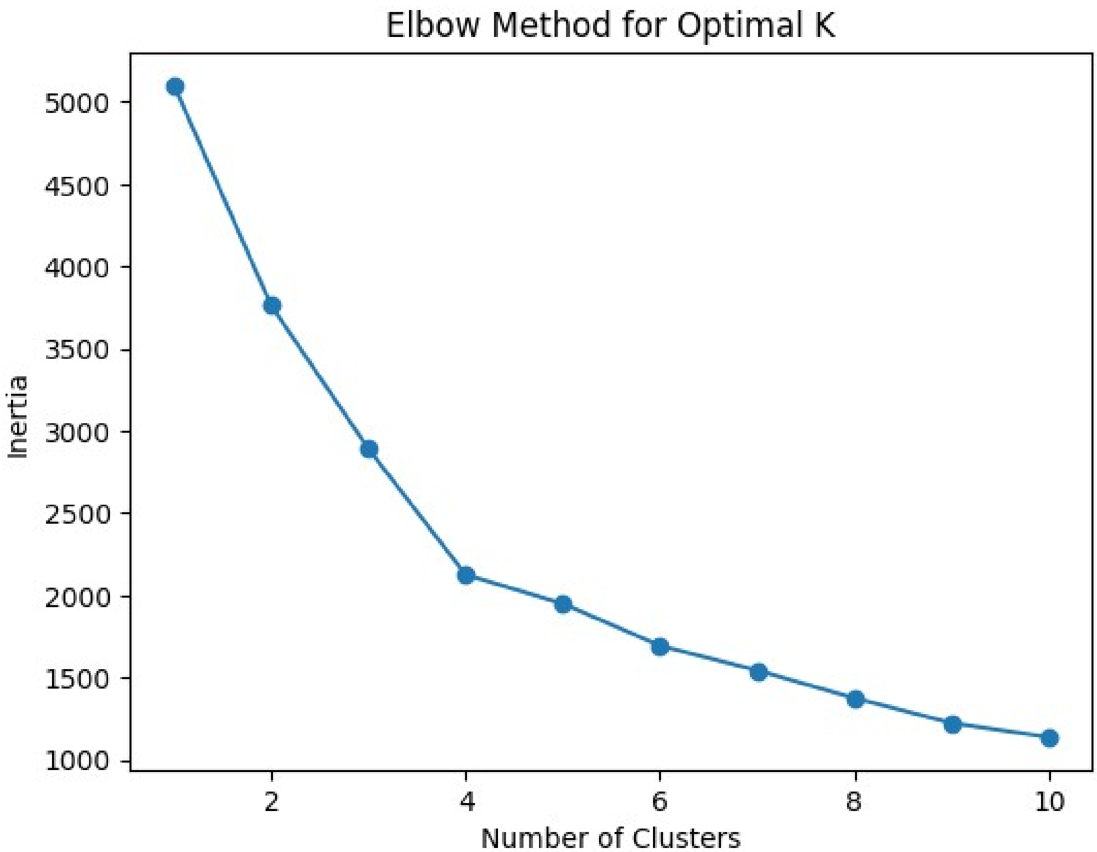

```
Silhouette Score: 0.71
```




```
<ipython-input-11-f60b85c4fe27>:54: FutureWarning:

Passing `palette` without assigning `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.

  sns.countplot(x="Cluster", data=df, palette="coolwarm")
```




```
inertia_values = []
for k in range(1, 11):  # Testing clusters from 1 to 10
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia_values.append(kmeans.inertia_)

# Plotting the elbow curve
plt.plot(range(1, 11), inertia_values, marker='o')
plt.title('Elbow Method for Optimal K')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show()
```




```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report

# Step 1: Convert 'Price (Euro)' to binary classification (e.g., high
price vs low price)
threshold = df['Price (Euro)'].median()
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features for KNN
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Standardize the features (KNN is sensitive to feature
scaling)
```

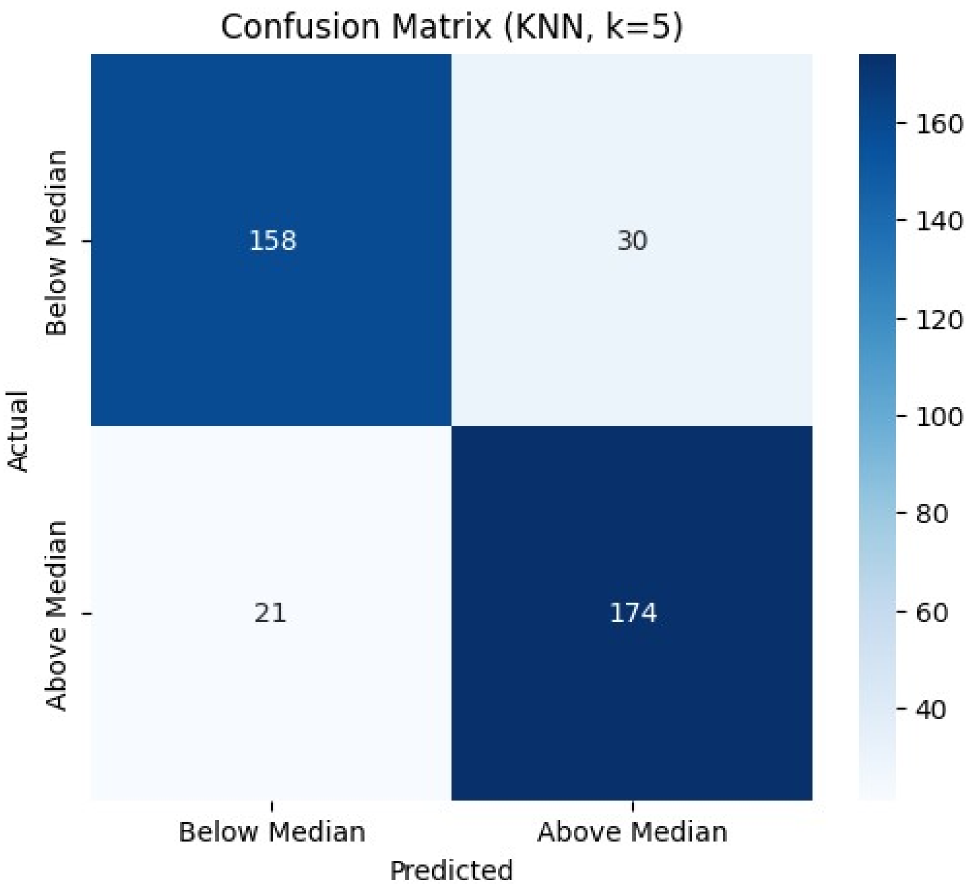
```python
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Initialize the KNN classifier
knn_classifier = KNeighborsClassifier(n_neighbors=5)  # You can tune
the number of neighbors (k)

# Step 6: Train the KNN model
knn_classifier.fit(X_train_scaled, y_train)

# Step 7: Make predictions on the test set
y_pred = knn_classifier.predict(X_test_scaled)

# Step 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

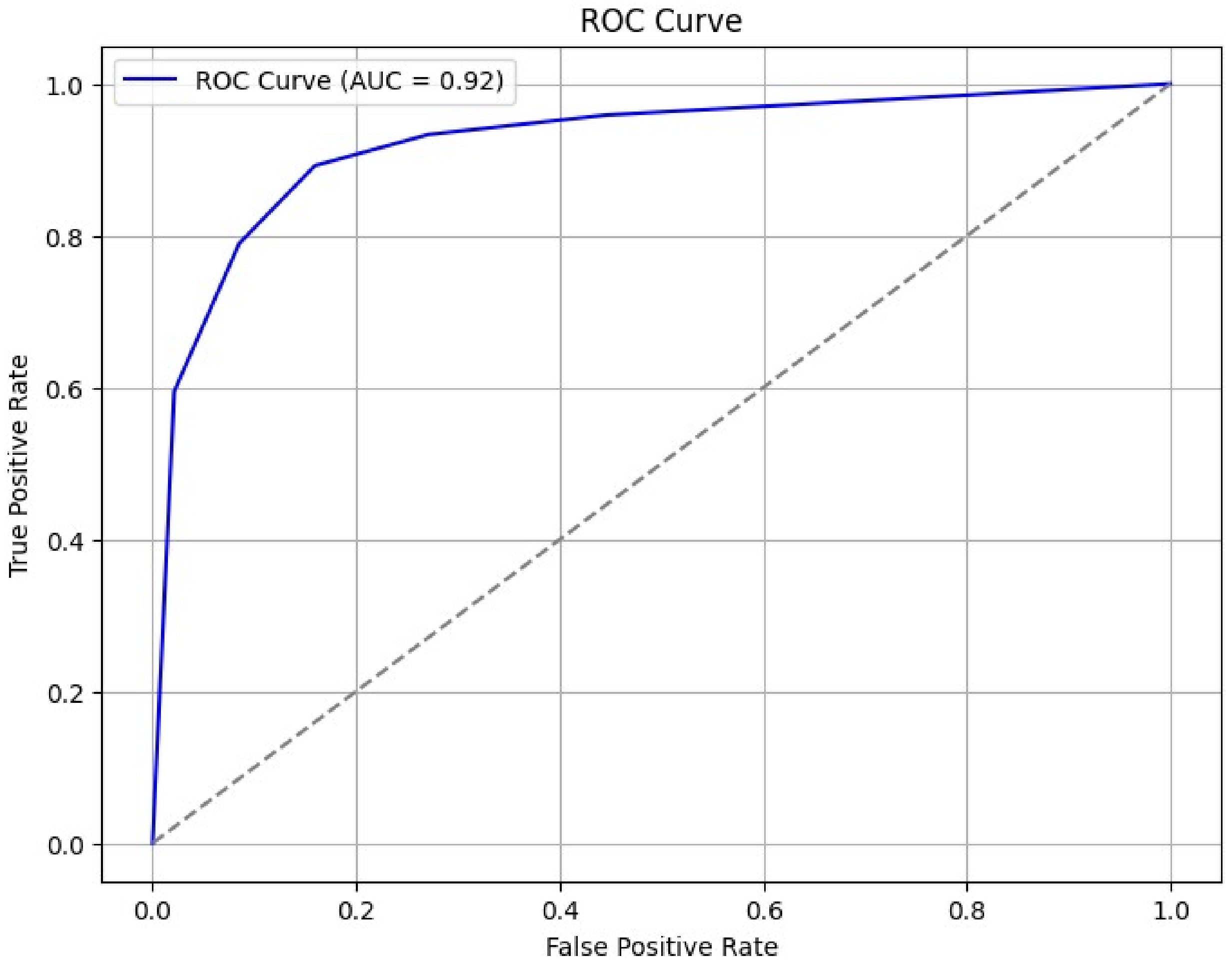
```
Accuracy: 0.8706
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.86      0.86       118
           1       0.88      0.88      0.88       137

    accuracy                           0.87       255
   macro avg       0.87      0.87      0.87       255
weighted avg       0.87      0.87      0.87       255
```

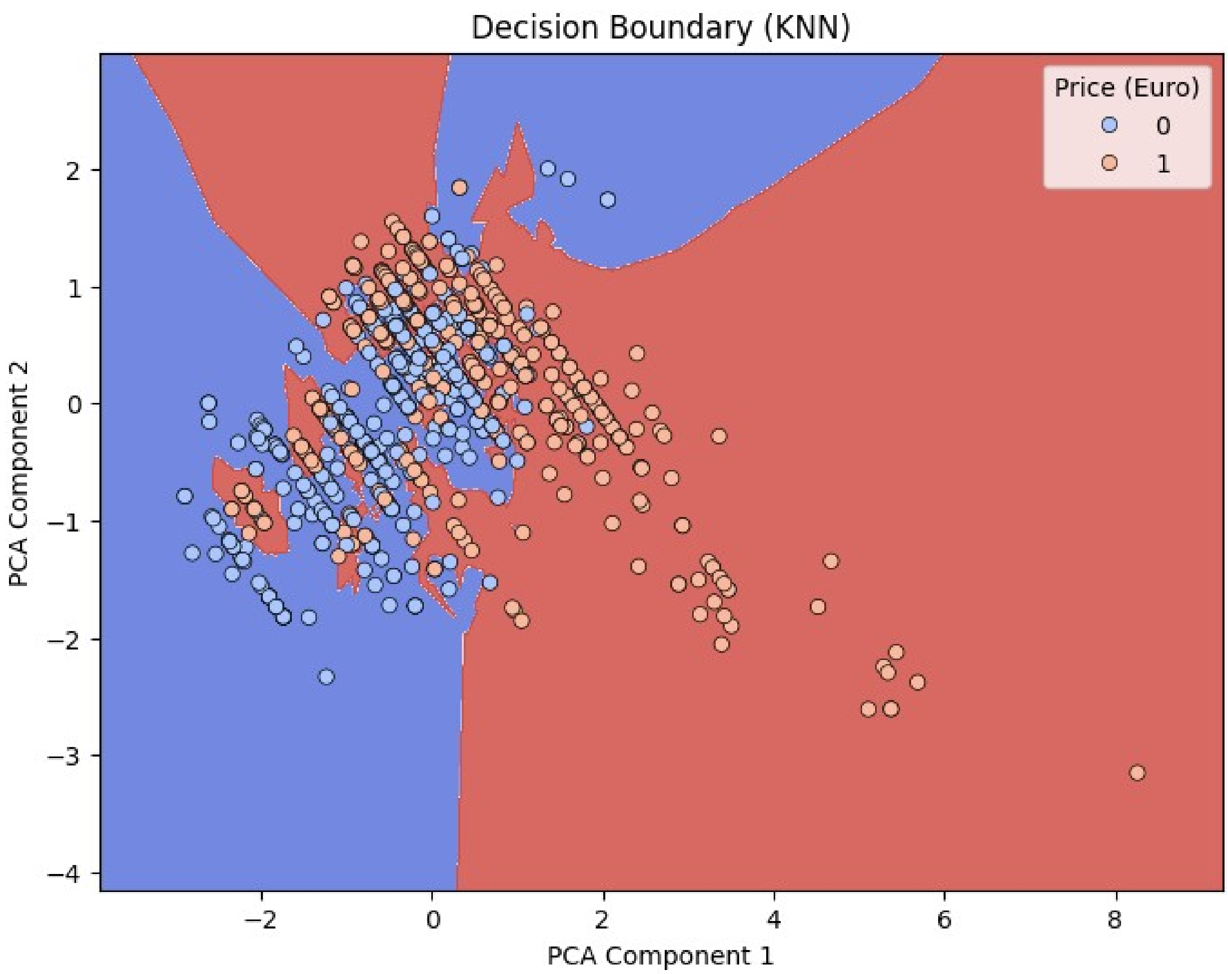
```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Step 1: Define features and target
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Example features
X = df[selected_features]
y = (df['Price (Euro)'] > df['Price (Euro)'].median()).astype(int)  #
Binary classification: Above/Below Median Price

# Step 2: Standardize features for KNN
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
# Step 3: Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.3, random_state=42)

# Step 4: Train KNN model
k = 5  # You can tune this parameter
knn_clf = KNeighborsClassifier(n_neighbors=k)
knn_clf.fit(X_train, y_train)

# Step 5: Confusion Matrix Visualization
y_pred = knn_clf.predict(X_test)
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
xticklabels=["Below Median", "Above Median"],
            yticklabels=["Below Median", "Above Median"])
plt.title(f"Confusion Matrix (KNN, k={k})")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Step 6: ROC Curve
y_pred_proba = knn_clf.predict_proba(X_test)[:, 1]  # Probability for
the positive class
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (AUC =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='grey', linestyle='--')
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid()
plt.show()

# Step 7: Decision Boundary (if reduced to 2D)
if len(selected_features) > 2:  # Reduce features to 2D for
visualization
    pca = PCA(n_components=2)
    X_train_2d = pca.fit_transform(X_train)
    X_test_2d = pca.transform(X_test)
    knn_clf.fit(X_train_2d, y_train)
    x_min, x_max = X_train_2d[:, 0].min() - 1, X_train_2d[:, 0].max()
+ 1
    y_min, y_max = X_train_2d[:, 1].min() - 1, X_train_2d[:, 1].max()
+ 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
```

```
                            np.arange(y_min, y_max, 0.01))  # Fixed
closing parenthesis here
    Z = knn_clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    plt.figure(figsize=(8, 6))
    plt.contourf(xx, yy, Z, alpha=0.8, cmap="coolwarm")
    sns.scatterplot(x=X_train_2d[:, 0], y=X_train_2d[:, 1],
hue=y_train, palette="coolwarm", edgecolor="k")
    plt.title("Decision Boundary (KNN)")
    plt.xlabel("PCA Component 1")
    plt.ylabel("PCA Component 2")
    plt.show()
```




ROC Curve
ROC Curve (AUC = 0.92)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0



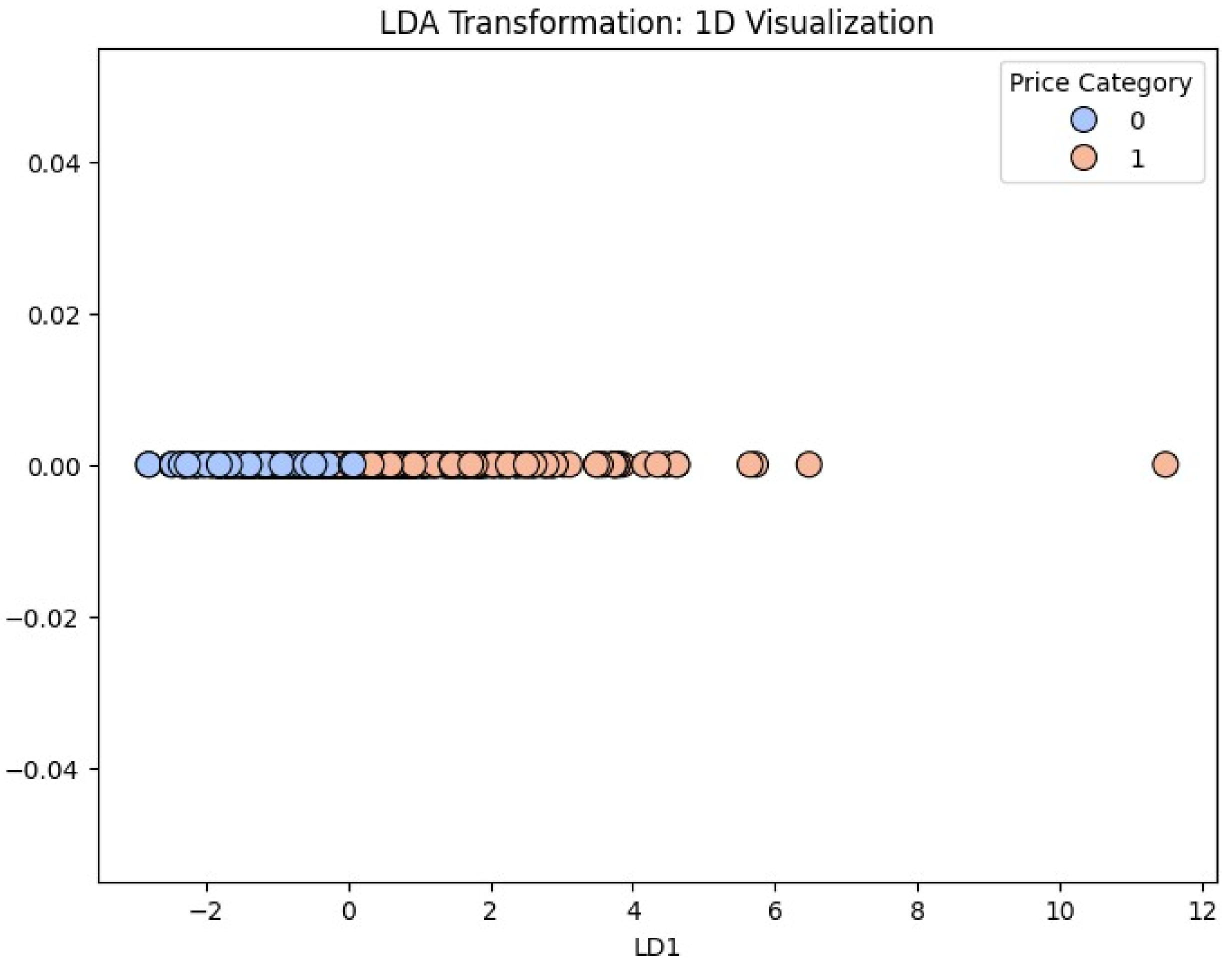

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report

# Step 1: Convert 'Price (Euro)' to binary classification (e.g., high
price vs low price)
threshold = df['Price (Euro)'].median()
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features for LDA
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

```python
# Step 4: Standardize the features (LDA is sensitive to feature scaling)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Initialize the LDA model
lda_classifier = LinearDiscriminantAnalysis()

# Step 6: Train the LDA model
lda_classifier.fit(X_train_scaled, y_train)

# Step 7: Make predictions on the test set
y_pred = lda_classifier.predict(X_test_scaled)

# Step 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.7765
Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.81      0.77       118
           1       0.82      0.74      0.78       137

    accuracy                           0.78       255
   macro avg       0.78      0.78      0.78       255
weighted avg       0.78      0.78      0.78       255
```

```python
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Step 1: Define features and target
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Example features
X = df[selected_features]
y = (df['Price (Euro)'] > df['Price (Euro)'].median()).astype(int)  # Binary classification: Above/Below Median Price

# Step 2: Standardize features for LDA
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
# Step 3: Apply LDA with n_components=1
lda = LinearDiscriminantAnalysis(n_components=1)  # Reduce to 1D since
we have only 2 classes
X_lda = lda.fit_transform(X_scaled, y)

# Step 4: Split data into training and testing sets (not necessary for
visualization but common practice)
X_train, X_test, y_train, y_test = train_test_split(X_lda, y,
test_size=0.3, random_state=42)

# Step 5: Visualization of LDA transformation in 1D (since only 1
component is chosen)
plt.figure(figsize=(8, 6))
sns.scatterplot(x=X_lda[:, 0], y=np.zeros_like(X_lda[:, 0]), hue=y,
palette='coolwarm', edgecolor='k', s=100)
plt.title("LDA Transformation: 1D Visualization")
plt.xlabel('LD1')  # First Linear Discriminant Component
plt.ylabel('')
plt.legend(title="Price Category", loc='best')
plt.show()

# Optionally, visualize decision boundaries for LDA if needed (for 1D
it may not be meaningful)
```




```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report
from sklearn.tree import DecisionTreeClassifier

# Step 1: Convert 'Price (Euro)' to binary classification (e.g., high
price vs low price)
threshold = df['Price (Euro)'].median()  # Define the threshold for
classification
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features for AdaBoost
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Split the data into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Standardize the features (AdaBoost works better when
features are scaled)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Initialize the AdaBoost model (using default decision stump
base estimator)
ada_boost_classifier = AdaBoostClassifier(n_estimators=50,
random_state=42)

# Step 6: Train the AdaBoost model
ada_boost_classifier.fit(X_train_scaled, y_train)

# Step 7: Make predictions on the test set
y_pred = ada_boost_classifier.predict(X_test_scaled)

# Step 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

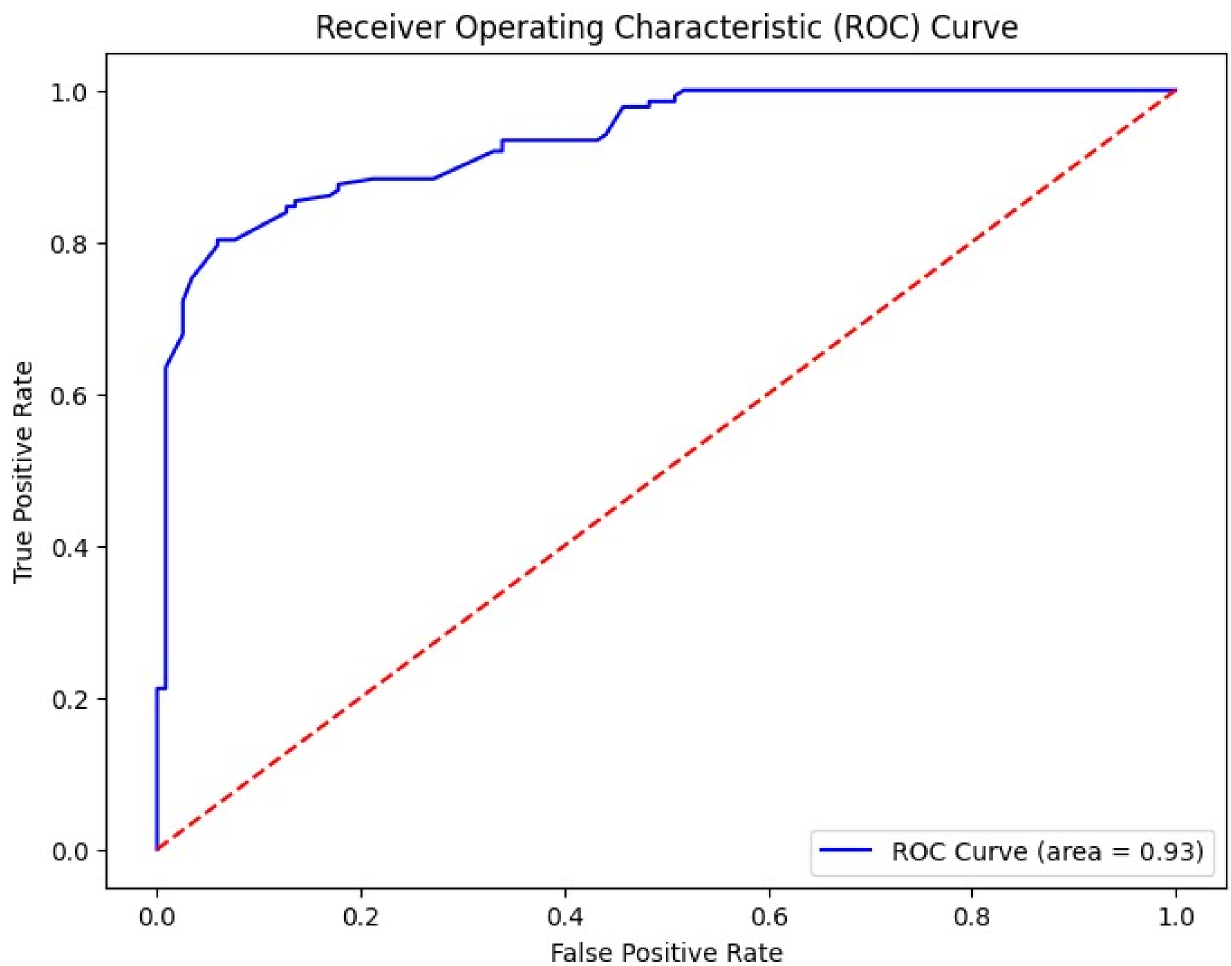
```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/
_weight_boosting.py:527: FutureWarning: The SAMME.R algorithm (the
default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(

Accuracy: 0.8510
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.85      0.84       118
           1       0.87      0.85      0.86       137

    accuracy                           0.85       255
   macro avg       0.85      0.85      0.85       255
weighted avg       0.85      0.85      0.85       255
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score, roc_curve, auc,
confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import AdaBoostClassifier
```

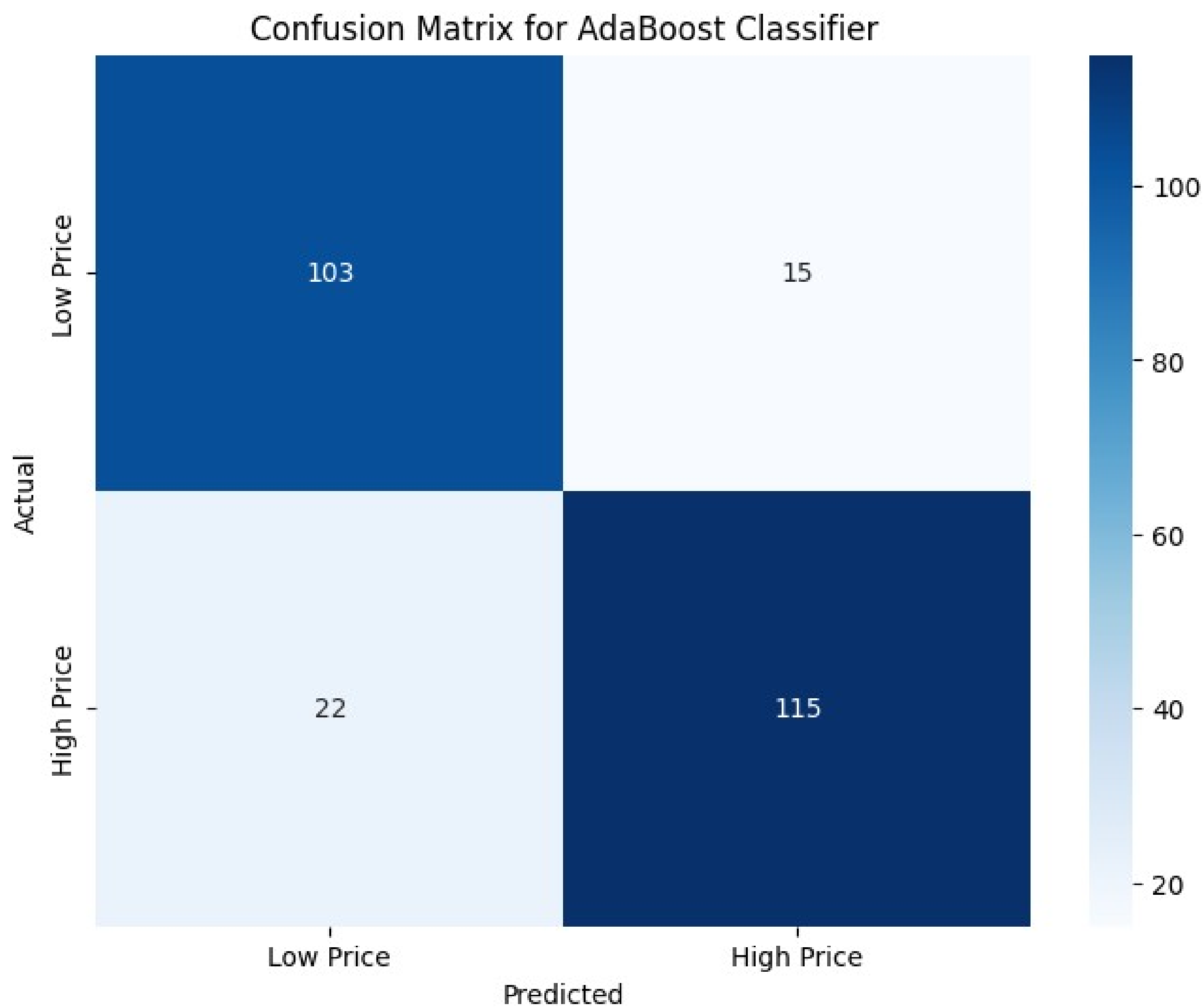
```python
import pandas as pd

# Step 1: Convert target variable 'Price (Euro)' to binary classification (e.g., high price vs low price)
threshold = df['Price (Euro)'].median()  # Define a threshold for binary classification (e.g., median price)
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price > threshold, 0 if price <= threshold

# Step 2: Select features and handle the categorical 'ScreenResolution' feature
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)", "CPU_Frequency (GHz)"]  # Features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Convert 'ScreenResolution' (categorical) to numerical format using LabelEncoder
label_encoder = LabelEncoder()
X['ScreenResolution'] = label_encoder.fit_transform(X['ScreenResolution'].astype(str))

# Step 4: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 5: Standardize the features (optional but recommended for AdaBoost)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 6: Initialize AdaBoost Classifier (no base estimator specified)
ada_boost_classifier = AdaBoostClassifier(n_estimators=50, random_state=42)

# Step 7: Train the model
ada_boost_classifier.fit(X_train_scaled, y_train)

# Step 8: Make predictions on the test set
y_pred = ada_boost_classifier.predict(X_test_scaled)
y_pred_prob = ada_boost_classifier.predict_proba(X_test_scaled)[:, 1]  # Probabilities for the positive class

# Step 9: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")

# Visualizations
```

```
## 1. Accuracy of AdaBoost Classifier
print("Accuracy of AdaBoost Classifier: ", accuracy)

## 2. ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (area =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='red', linestyle='--')  # Diagonal line
(Random classifier)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()

## 3. Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Low Price', 'High Price'], yticklabels=['Low Price',
'High Price'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for AdaBoost Classifier')
plt.show()
```

```
<ipython-input-28-0e8ca5f63704>:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_weight_boost
ing.py:527: FutureWarning: The SAMME.R algorithm (the default) is
deprecated and will be removed in 1.6. Use the SAMME algorithm to
circumvent this warning.
  warnings.warn(

Accuracy: 0.8549
Accuracy of AdaBoost Classifier:  0.8549019607843137
```



Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
ROC Curve (area = 0.93)
0.0
0.2
0.4
0.6
0.8
1.0




```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report

# Step 1: Convert 'Price (Euro)' to binary classification (e.g., high
price vs low price)
threshold = df['Price (Euro)'].median()  # Define the threshold for
classification
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features for the model
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Example features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)
```

```python
# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Standardize the features (though Gradient Boosting is less
sensitive to this)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Initialize the Gradient Boosting model
gradient_boosting_classifier =
GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,
random_state=42)

# Step 6: Train the Gradient Boosting model
gradient_boosting_classifier.fit(X_train_scaled, y_train)

# Step 7: Make predictions on the test set
y_pred = gradient_boosting_classifier.predict(X_test_scaled)

# Step 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

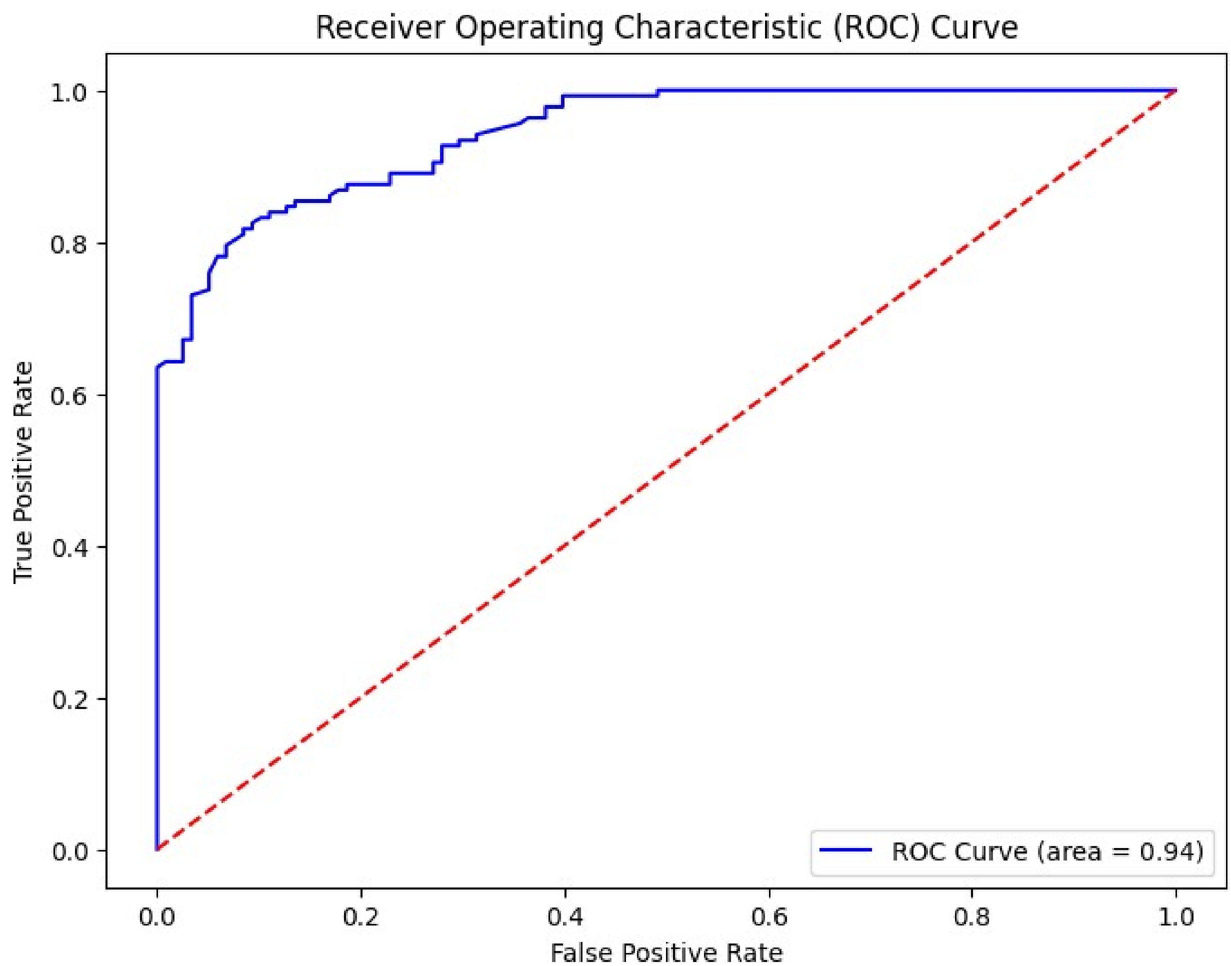
```
Accuracy: 0.8588
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.88      0.85       118
           1       0.89      0.84      0.86       137

    accuracy                           0.86       255
   macro avg       0.86      0.86      0.86       255
weighted avg       0.86      0.86      0.86       255
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import pandas as pd

# Step 1: Convert target variable 'Price (Euro)' to binary
classification (e.g., high price vs low price)
threshold = df['Price (Euro)'].median()  # Define a threshold for
binary classification (e.g., median price)
```

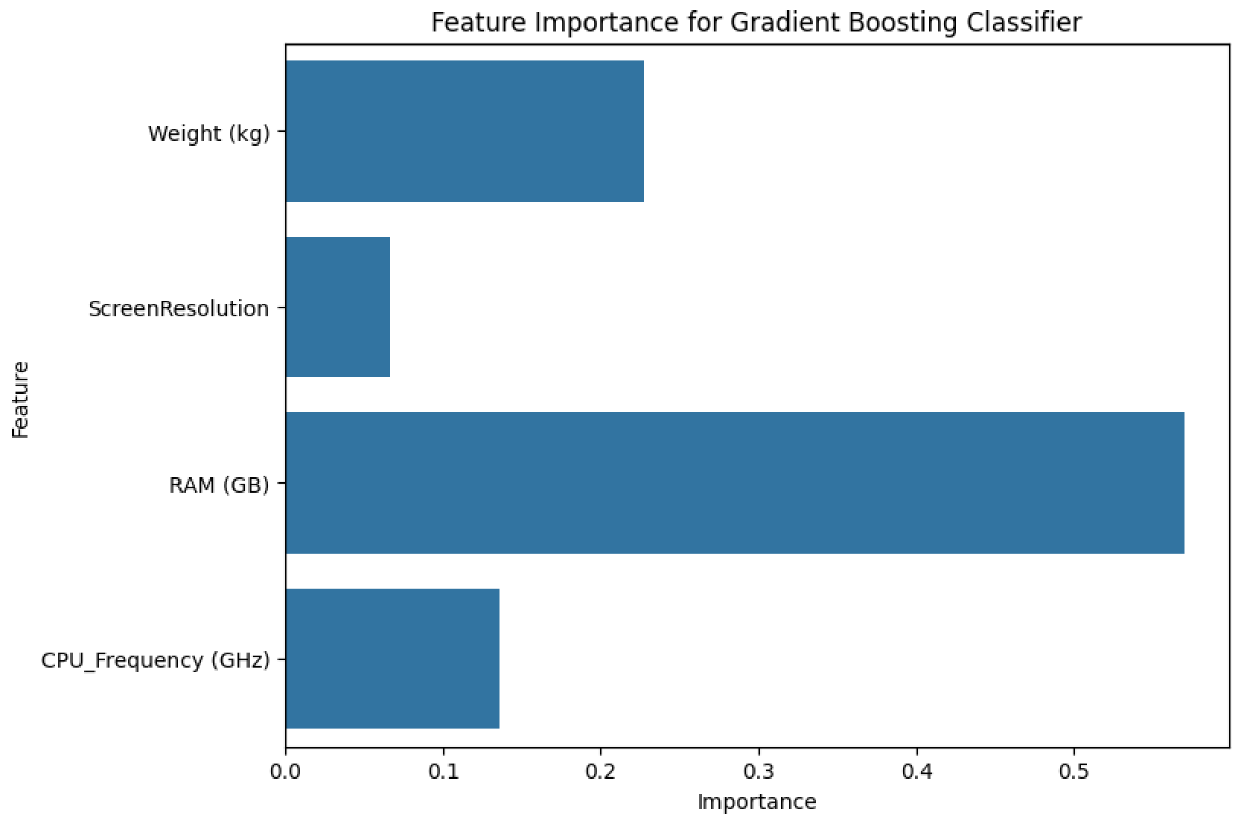
```
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features and handle the categorical
'ScreenResolution' feature
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Convert 'ScreenResolution' (categorical) to numerical format
using LabelEncoder
label_encoder = LabelEncoder()
X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))

# Step 4: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 5: Standardize the features (optional)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 6: Initialize Gradient Boosting Classifier
gb_classifier = GradientBoostingClassifier(n_estimators=100,
random_state=42)

# Step 7: Train the model
gb_classifier.fit(X_train_scaled, y_train)

# Step 8: Make predictions on the test set
y_pred = gb_classifier.predict(X_test_scaled)
y_pred_prob = gb_classifier.predict_proba(X_test_scaled)[:, 1]  #
Probabilities for the positive class

# Step 9: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")

# Visualizations

## 1. Accuracy of Gradient Boosting Classifier
print("Accuracy of Gradient Boosting Classifier: ", accuracy)

## 2. ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)
```

```
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (area =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='red', linestyle='--')  # Diagonal line
(Random classifier)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()

## 3. Feature Importance Plot
importances = gb_classifier.feature_importances_
feature_names = X.columns

plt.figure(figsize=(8, 6))
sns.barplot(x=importances, y=feature_names)
plt.title('Feature Importance for Gradient Boosting Classifier')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```

```
<ipython-input-25-9440e78996d2>:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))

Accuracy: 0.8588
Accuracy of Gradient Boosting Classifier:  0.8588235294117647
```



Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC Curve (area = 0.94)




```
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report

# Step 1: Convert 'Price (Euro)' to binary classification (e.g., high
price vs low price)
threshold = df['Price (Euro)'].median()  # Define the threshold for
classification
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features for the model
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Example features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Standardize the features (Gaussian Naive Bayes assumes
normally distributed features)
scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Initialize the Naive Bayes model
naive_bayes_classifier = GaussianNB()

# Step 6: Train the Naive Bayes model
naive_bayes_classifier.fit(X_train_scaled, y_train)

# Step 7: Make predictions on the test set
y_pred = naive_bayes_classifier.predict(X_test_scaled)

# Step 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

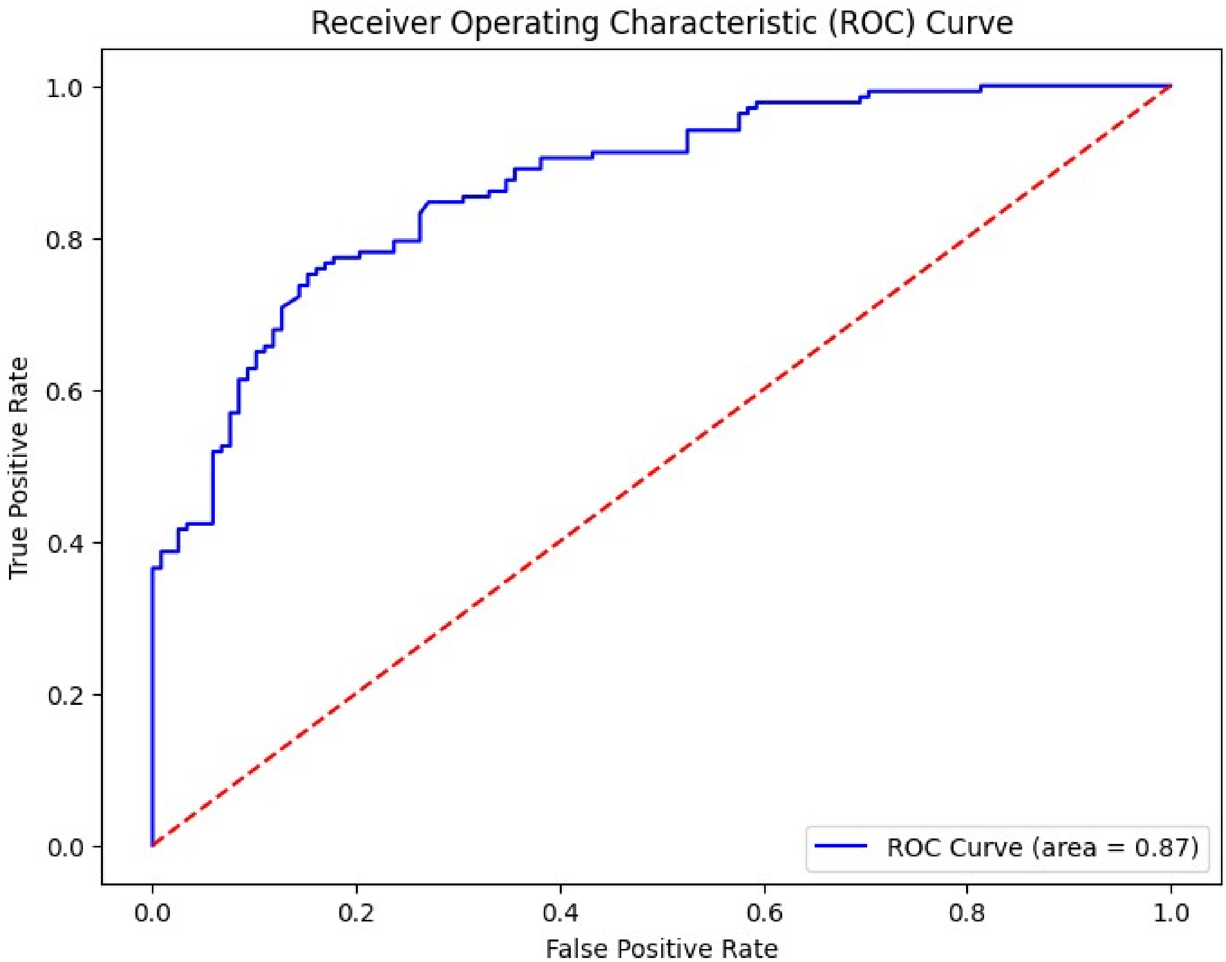
```
Accuracy: 0.7098
Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.97      0.75       118
           1       0.94      0.49      0.64       137

    accuracy                           0.71       255
   macro avg       0.78      0.73      0.70       255
weighted avg       0.79      0.71      0.70       255
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score, roc_curve, auc,
confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.naive_bayes import GaussianNB
import pandas as pd

# Step 1: Convert target variable 'Price (Euro)' to binary
classification (e.g., high price vs low price)
threshold = df['Price (Euro)'].median()  # Define a threshold for
binary classification (e.g., median price)
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features and handle the categorical
'ScreenResolution' feature
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features
X = df[selected_features]  # Features
```

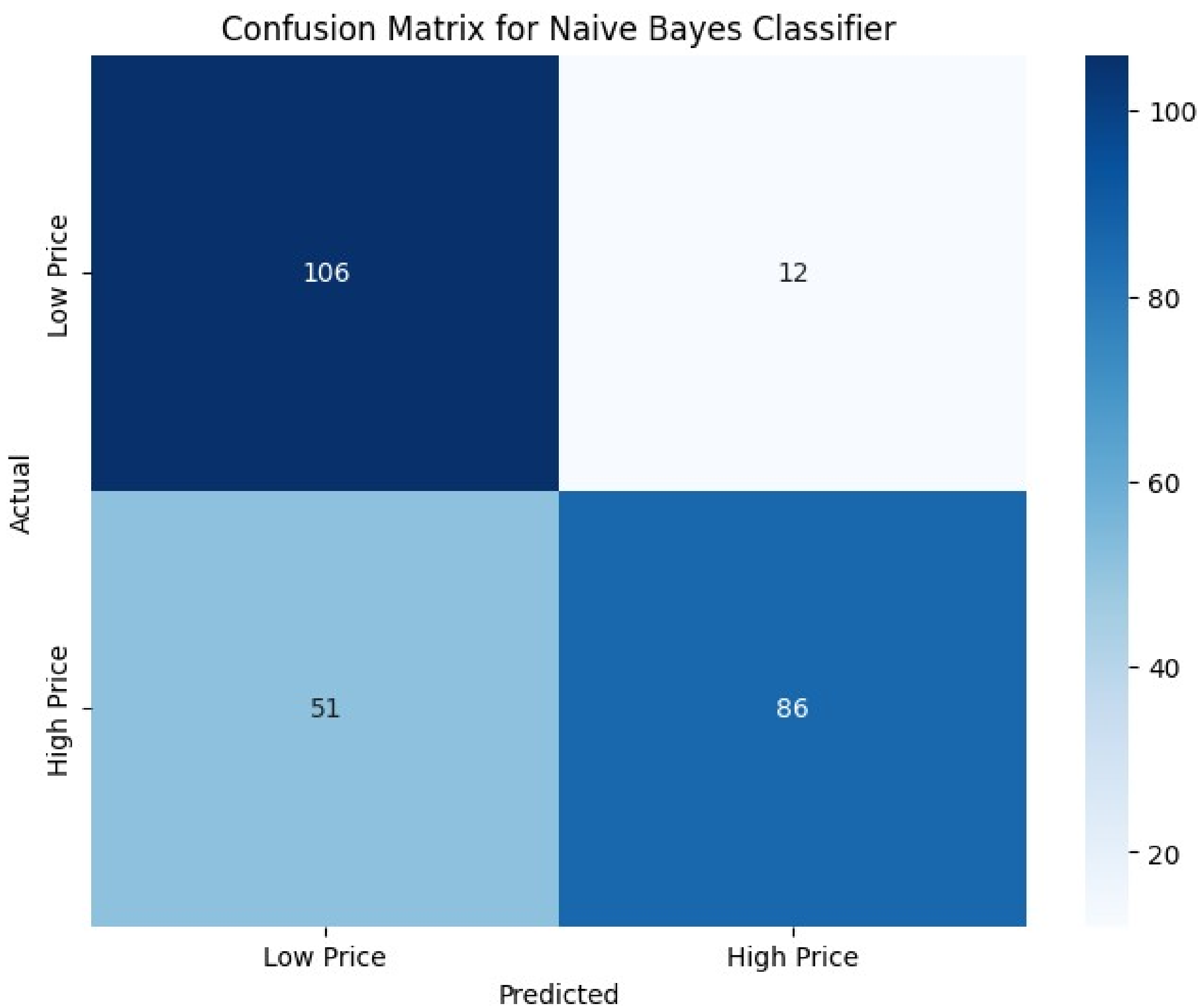
```
y = y_binary  # Target (binary classification)

# Step 3: Convert 'ScreenResolution' (categorical) to numerical format
using LabelEncoder
label_encoder = LabelEncoder()
X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))

# Step 4: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 5: Standardize the features (optional but recommended for Naive
Bayes)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 6: Initialize Naive Bayes Classifier
nb_classifier = GaussianNB()

# Step 7: Train the model
nb_classifier.fit(X_train_scaled, y_train)

# Step 8: Make predictions on the test set
y_pred = nb_classifier.predict(X_test_scaled)
y_pred_prob = nb_classifier.predict_proba(X_test_scaled)[:, 1]  #
Probabilities for the positive class

# Step 9: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")

# Visualizations

## 1. Accuracy of Naive Bayes Classifier
print("Accuracy of Naive Bayes Classifier: ", accuracy)

## 2. ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (area =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='red', linestyle='--')  # Diagonal line
(Random classifier)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
```

```
plt.legend(loc='lower right')
plt.show()

## 3. Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Low Price', 'High Price'], yticklabels=['Low Price',
'High Price'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Naive Bayes Classifier')
plt.show()
```

```
<ipython-input-26-2df5ca840585>:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))

Accuracy: 0.7529
Accuracy of Naive Bayes Classifier:  0.7529411764705882
```



Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC Curve (area = 0.87)




```
from sklearn.metrics import accuracy_score, f1_score, precision_score,
recall_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB

# Step 1: Define features and target
selected_features = ["Weight (kg)", "RAM (GB)", "CPU_Frequency (GHz)"]
# Example features
X = df[selected_features]
y = (df['Price (Euro)'] > df['Price (Euro)'].median()).astype(int)  #
```

```
Binary classification: Above/Below Median Price

# Step 2: Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.3, random_state=42)

# Step 4: Initialize models
models = {
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier(),
    'SVM': SVC(),
    'KNN': KNeighborsClassifier(),
    'LDA': LinearDiscriminantAnalysis(),
    'AdaBoost': AdaBoostClassifier(),
    'Gradient Boosting': GradientBoostingClassifier(),
    'Naive Bayes': GaussianNB()
}

# Step 5: Train and evaluate each model
results = {}
for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Calculate performance metrics
    accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)

    results[model_name] = {
        'Accuracy': accuracy,
        'F1 Score': f1,
        'Precision': precision,
        'Recall': recall
    }

# Step 6: Display results
results_df = pd.DataFrame(results).T
print(results_df.sort_values(by='F1 Score', ascending=False))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/
_weight_boosting.py:527: FutureWarning: The SAMME.R algorithm (the
default) is deprecated and will be removed in 1.6. Use the SAMME
```

```
algorithm to circumvent this warning.
  warnings.warn(

                     Accuracy  F1 Score  Precision    Recall
AdaBoost             0.877285  0.877922   0.889474  0.866667
KNN                  0.866841  0.872180   0.852941  0.892308
Random Forest        0.861619  0.862338   0.873684  0.851282
SVM                  0.859008  0.862245   0.857868  0.866667
Gradient Boosting    0.856397  0.857143   0.868421  0.846154
Decision Tree        0.838120  0.836842   0.859459  0.815385
Logistic Regression  0.801567  0.814634   0.776744  0.856410
LDA                  0.798956  0.798956   0.813830  0.784615
Naive Bayes          0.767624  0.722741   0.920635  0.594872
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Step 1: Convert target variable 'Price (Euro)' to binary
classification
threshold = df['Price (Euro)'].median()  # Define a threshold for
binary classification
y_binary = (df['Price (Euro)'] > threshold).astype(int)  # 1 if price
> threshold, 0 if price <= threshold

# Step 2: Select features and handle the categorical
'ScreenResolution' feature
selected_features = ["Weight (kg)", "ScreenResolution", "RAM (GB)",
"CPU_Frequency (GHz)"]  # Features
X = df[selected_features]  # Features
y = y_binary  # Target (binary classification)

# Convert 'ScreenResolution' (categorical) to numerical format using
LabelEncoder
label_encoder = LabelEncoder()
X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
```

```
test_size=0.2, random_state=42)

# Step 4: Standardize the features (optional but recommended for some
models)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Initialize all classifiers
models = {
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier(n_estimators=100,
random_state=42),
    'SVM': SVC(probability=True),
    'KNN': KNeighborsClassifier(),
    'Naive Bayes': GaussianNB(),
    'AdaBoost': AdaBoostClassifier(n_estimators=50, random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(),
    'LDA': LinearDiscriminantAnalysis(),
}

# Step 6: Train each model, make predictions, and store accuracy
scores
accuracy_scores = []
model_names = []

for model_name, model in models.items():
    # Train model
    model.fit(X_train_scaled, y_train)
    # Make predictions
    y_pred = model.predict(X_test_scaled)
    # Calculate accuracy score
    accuracy = accuracy_score(y_test, y_pred)
    accuracy_scores.append(accuracy)
    model_names.append(model_name)

# Step 7: Create a DataFrame for visualization
model_comparison = pd.DataFrame({
    'Model': model_names,
    'Accuracy': accuracy_scores
})

# Step 8: Visualize the model comparison (Bar chart)
plt.figure(figsize=(10, 6))
sns.barplot(x='Accuracy', y='Model', data=model_comparison,
palette='viridis')
plt.title('Comparison of Model Performance')
plt.xlabel('Accuracy')
```

```
plt.ylabel('Model')
plt.show()

<ipython-input-29-450d9891bf53>:25: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X['ScreenResolution'] =
label_encoder.fit_transform(X['ScreenResolution'].astype(str))
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_weight_boost
ing.py:527: FutureWarning: The SAMME.R algorithm (the default) is
deprecated and will be removed in 1.6. Use the SAMME algorithm to
circumvent this warning.
  warnings.warn(
<ipython-input-29-450d9891bf53>:70: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='Accuracy', y='Model', data=model_comparison,
palette='viridis')
```