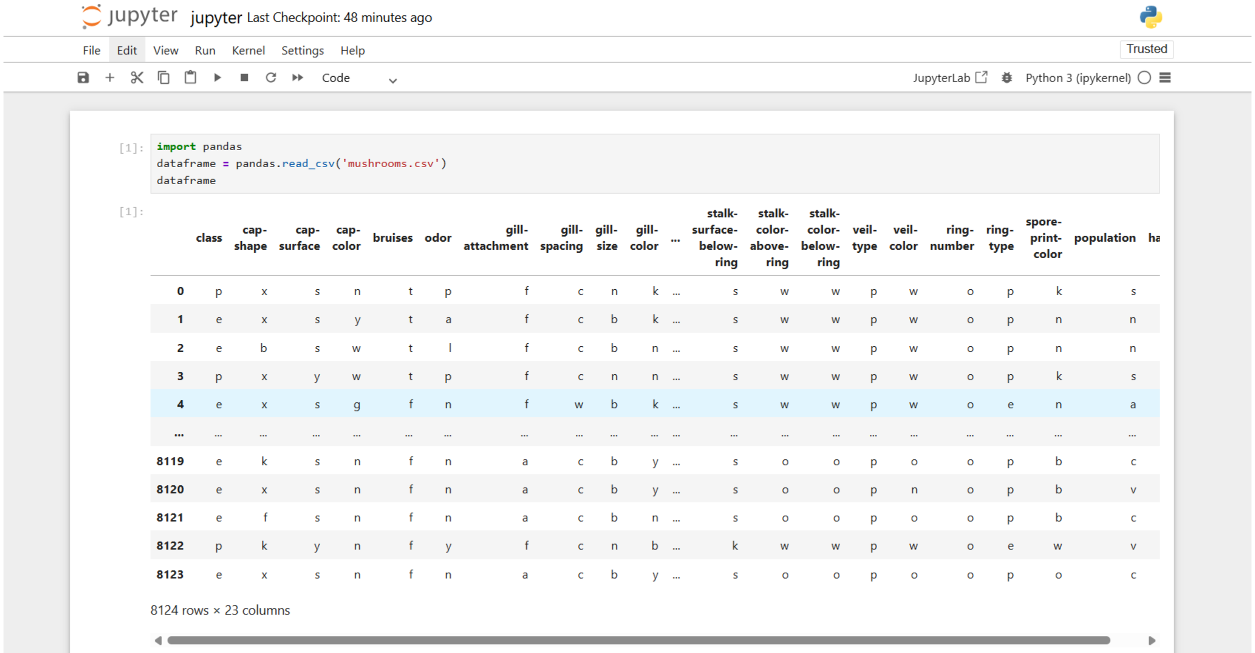
Name: Nour Mohamed Mahmoud

First we make importing required libraries, and make a classification of USA Cars dataset.



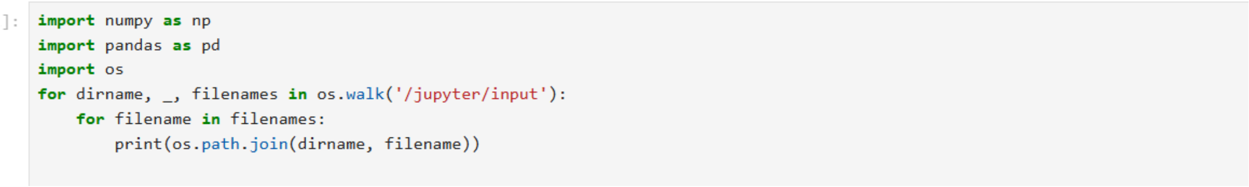
[1]:
```
import pandas
dataframe = pandas.read_csv('mushrooms.csv')
dataframe
```

[1]:

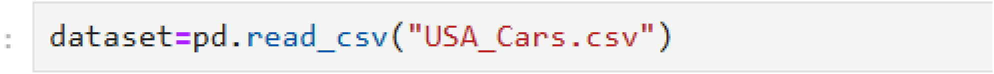
	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	...	stalk-surface-below-ring	stalk-color-above-ring	stalk-color-below-ring	veil-type	veil-color	ring-number	ring-type	spore-print-color	population	ha
0	p	x	s	n	t	p	f	c	n	k	...	s	w	w	p	w	o	p	k	s	
1	e	x	s	y	t	a	f	c	b	k	...	s	w	w	p	w	o	p	n	n	
2	e	b	s	w	t	l	f	c	b	n	...	s	w	w	p	w	o	p	n	n	
3	p	x	y	w	t	p	f	c	n	n	...	s	w	w	p	w	o	p	k	s	
4	e	x	s	g	f	n	f	w	b	k	...	s	w	w	p	w	o	e	n	a	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
8119	e	k	s	n	f	n	a	c	b	y	...	s	o	o	p	o	o	p	b	c	
8120	e	x	s	n	f	n	a	c	b	y	...	s	o	o	p	n	o	p	b	v	
8121	e	f	s	n	f	n	a	c	b	n	...	s	o	o	p	o	o	p	b	c	
8122	p	k	y	n	f	y	f	c	n	b	...	k	w	w	p	w	o	e	w	v	
8123	e	x	s	n	f	n	a	c	b	y	...	s	o	o	p	o	o	p	o	c	

8124 rows × 23 columns

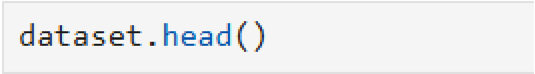
Importing the required libraries to show the dataset.



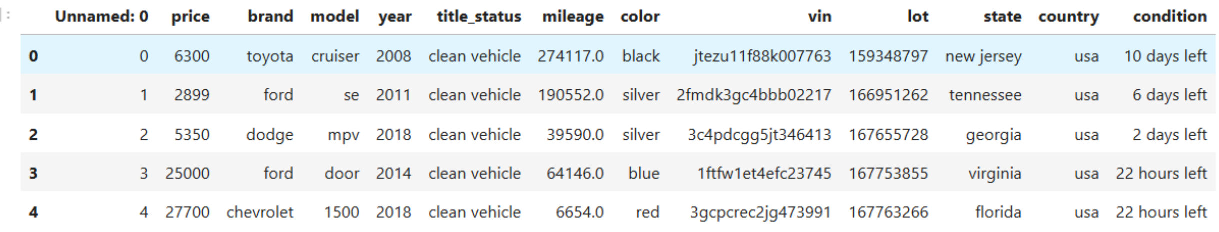
]:
```
import numpy as np
import pandas as pd
import os
for dirname, _, filenames in os.walk('/jupyter/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```



:
```
dataset=pd.read_csv("USA_Cars.csv")
```

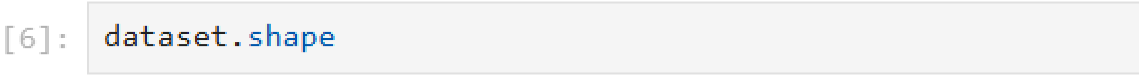


```
dataset.head()
```

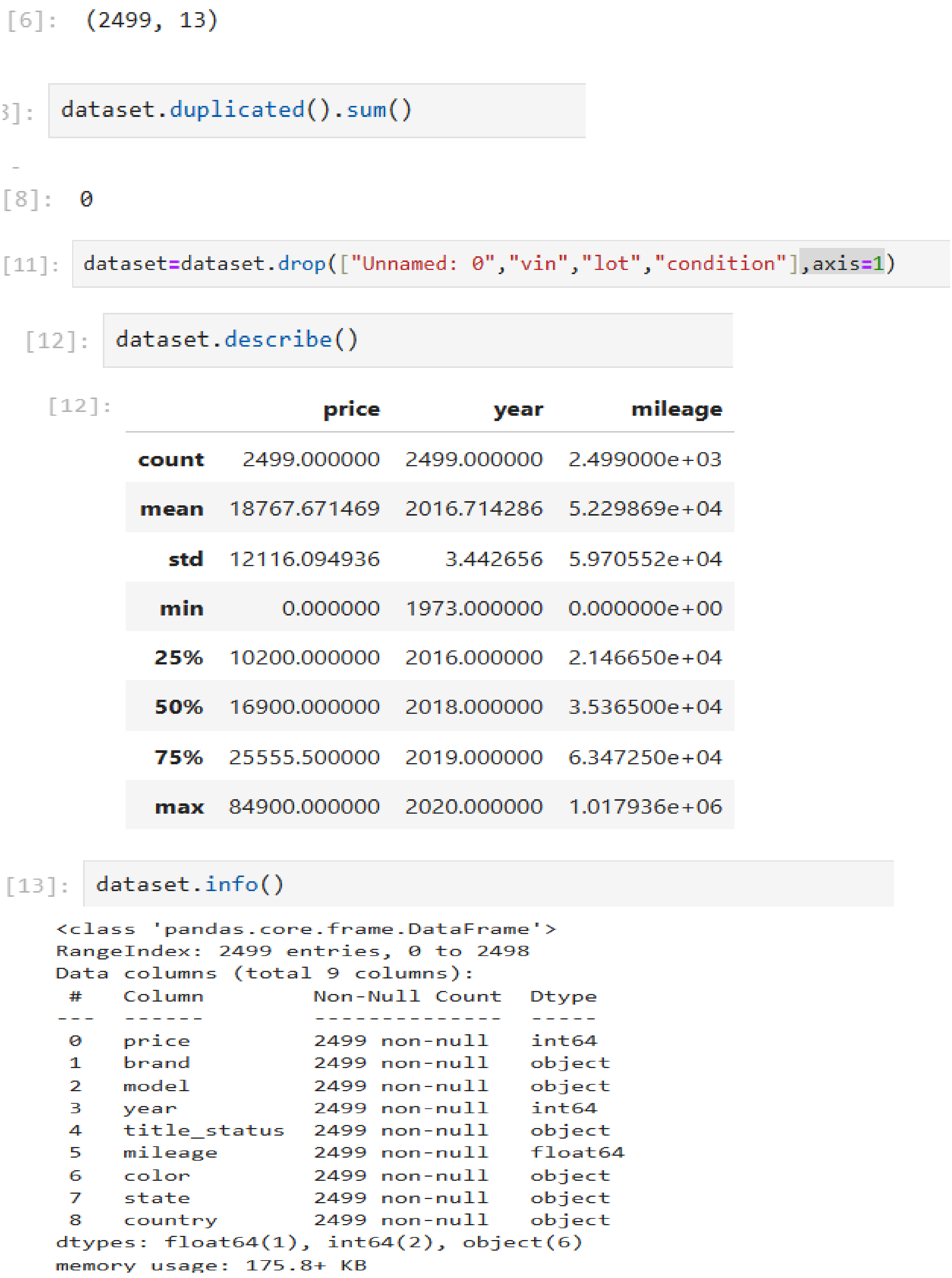


]:

	Unnamed: 0	price	brand	model	year	title_status	mileage	color	vin	lot	state	country	condition
0	0	6300	toyota	cruiser	2008	clean vehicle	274117.0	black	jtezu11f88k007763	159348797	new jersey	usa	10 days left
1	1	2899	ford	se	2011	clean vehicle	190552.0	silver	2fmdk3gc4bbb02217	166951262	tennessee	usa	6 days left
2	2	5350	dodge	mpv	2018	clean vehicle	39590.0	silver	3c4pdcgg5jt346413	167655728	georgia	usa	2 days left
3	3	25000	ford	door	2014	clean vehicle	64146.0	blue	1ftfw1et4efc23745	167753855	virginia	usa	22 hours left
4	4	27700	chevrolet	1500	2018	clean vehicle	6654.0	red	3gcpcrec2jg473991	167763266	florida	usa	22 hours left



[6]:
```
dataset.shape
```



```
[6]:  (2499, 13)
```

```
3]:  dataset.duplicated().sum()
```

```
[8]:  0
```

```
[11]:  dataset=dataset.drop(["Unnamed: 0","vin","lot","condition"],axis=1)
```

```
[12]:  dataset.describe()
```

[12]:

	price	year	mileage
count	2499.000000	2499.000000	2.499000e+03
mean	18767.671469	2016.714286	5.229869e+04
std	12116.094936	3.442656	5.970552e+04
min	0.000000	1973.000000	0.000000e+00
25%	10200.000000	2016.000000	2.146650e+04
50%	16900.000000	2018.000000	3.536500e+04
75%	25555.500000	2019.000000	6.347250e+04
max	84900.000000	2020.000000	1.017936e+06

```
[13]:  dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2499 entries, 0 to 2498
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   price         2499 non-null   int64  
 1   brand         2499 non-null   object 
 2   model         2499 non-null   object 
 3   year          2499 non-null   int64  
 4   title_status  2499 non-null   object 
 5   mileage       2499 non-null   float64
 6   color         2499 non-null   object 
 7   state         2499 non-null   object 
 8   country       2499 non-null   object 
dtypes: float64(1), int64(2), object(6)
memory usage: 175.8+ KB
```

[14]:

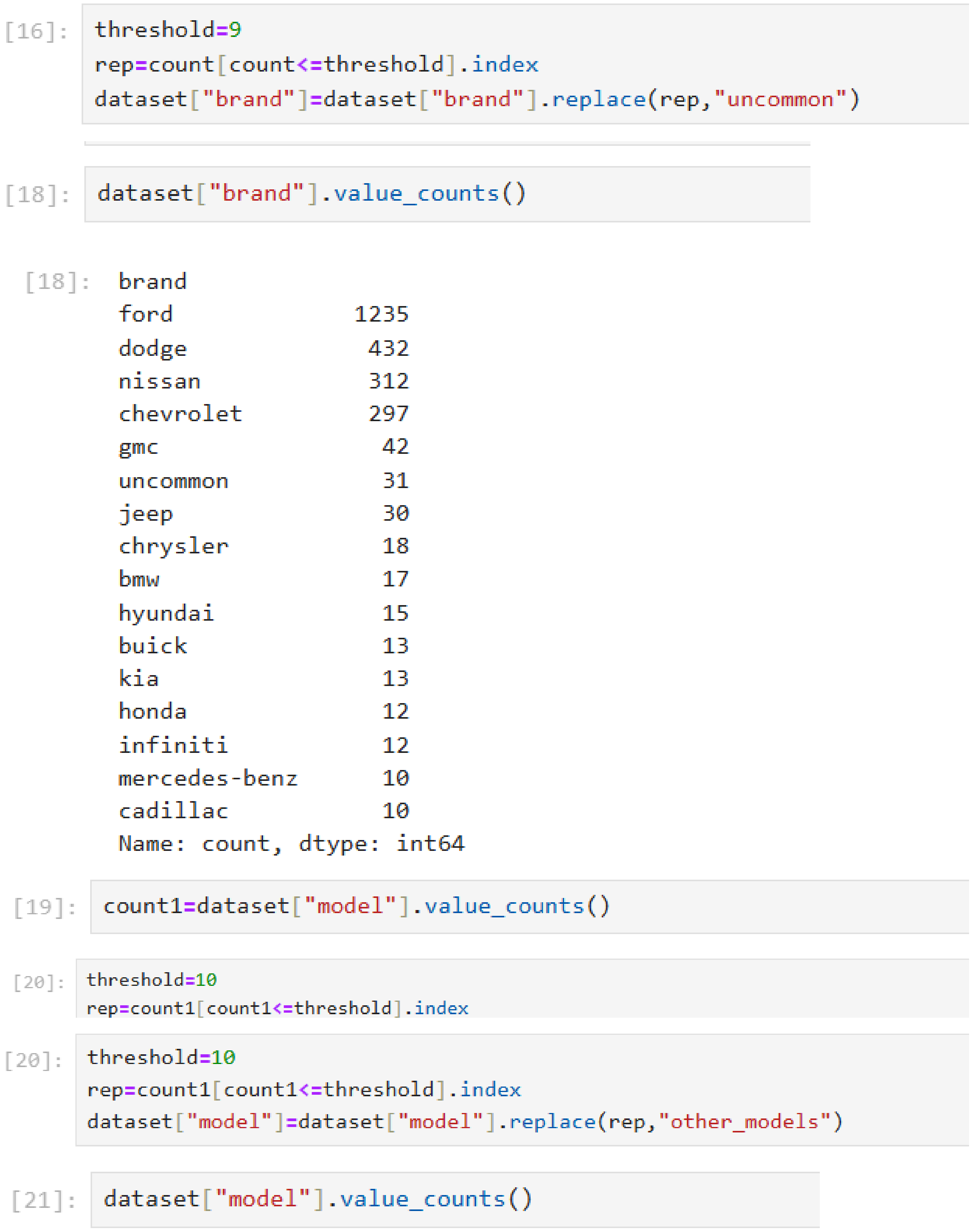
```
col1=["brand","model","title_status","color","state","country"]
for col in col1:
    dataset[col]=dataset[col].str.strip()
```

[15]:

```
count=dataset["brand"].value_counts()
count
```

[15]:

```
brand
ford               1235
dodge               432
nissan              312
chevrolet           297
gmc                  42
jeep                 30
chrysler             18
bmw                  17
hyundai              15
buick                13
kia                  13
infiniti             12
honda                12
mercedes-benz        10
cadillac             10
heartland             5
audi                  4
land                  4
peterbilt             4
acura                 3
mazda                 2
lexus                 2
lincoln               2
toyota                1
harley-davidson       1
jaguar                1
maserati              1
ram                   1
Name: count, dtype: int64
```



```
[16]: threshold=9
      rep=count[count<=threshold].index
      dataset["brand"]=dataset["brand"].replace(rep,"uncommon")
```

```
[18]: dataset["brand"].value_counts()
```

```
[18]: brand
      ford             1235
      dodge             432
      nissan            312
      chevrolet         297
      gmc                42
      uncommon           31
      jeep               30
      chrysler           18
      bmw                17
      hyundai            15
      buick              13
      kia                13
      honda              12
      infiniti           12
      mercedes-benz      10
      cadillac           10
      Name: count, dtype: int64
```

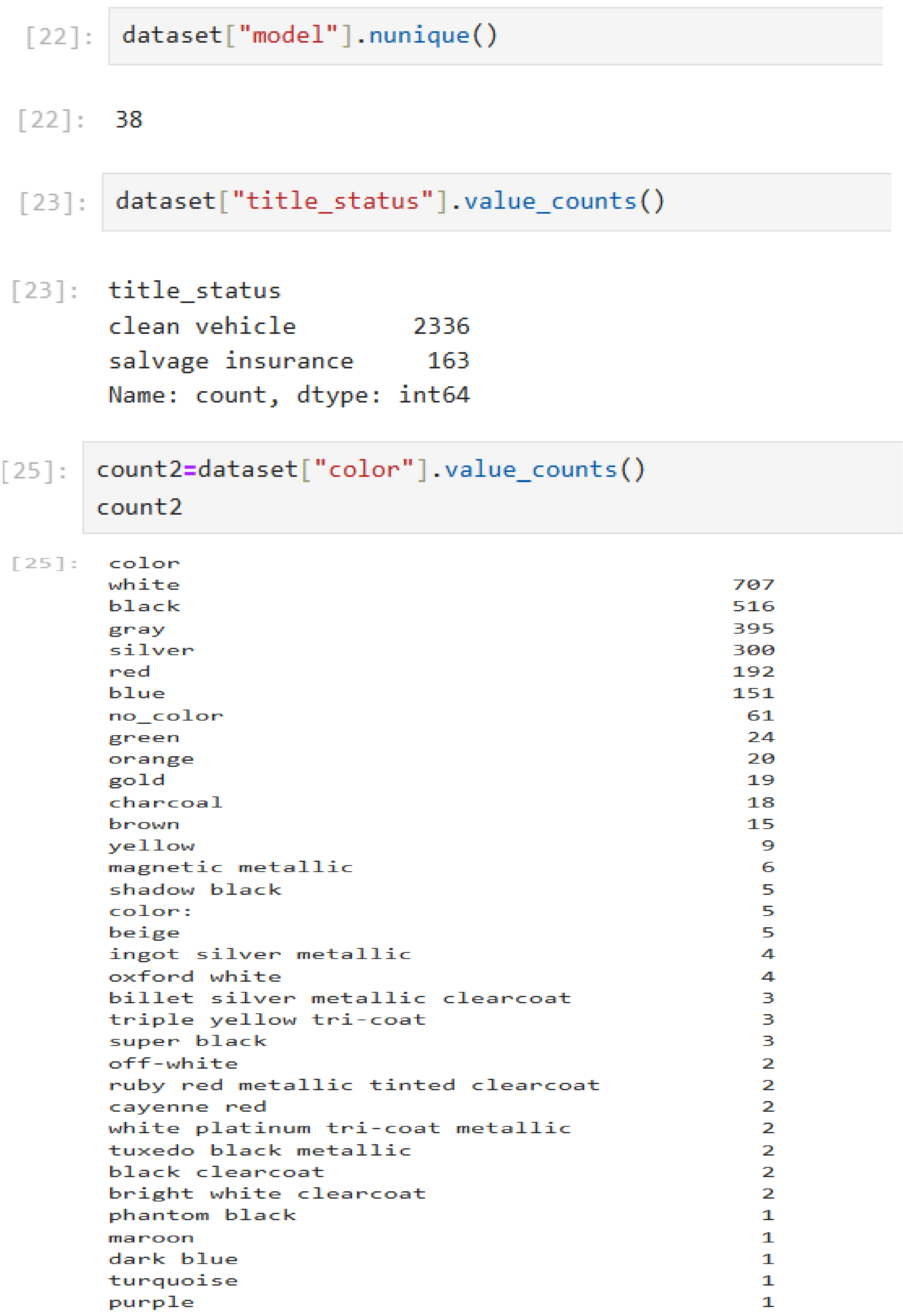
```
[19]: count1=dataset["model"].value_counts()
```

```
[20]: threshold=10
      rep=count1[count1<=threshold].index
```

```
[20]: threshold=10
      rep=count1[count1<=threshold].index
      dataset["model"]=dataset["model"].replace(rep,"other_models")
```

```
[21]: dataset["model"].value_counts()
```

```
[21]:  model
       door              651
       other_models      255
       f-150             219
       doors             148
       caravan           102
       mpv                87
       fusion             65
       durango            64
       journey            61
       rogue              54
       van                46
       challenger         44
       charger            42
       transit            41
       max                41
       sport              40
       1500               39
       escape             39
       explorer           39
       srw                38
       versa              34
       edge               34
       flex               33
       wagon              30
       mustang            29
       sentra             28
       expedition         28
       pathfinder         22
       altima             21
       equinox            18
       suburban           16
       pickup             15
       frontier           14
fiesta            14
malibu            12
colorado          12
cutaway           12
impala            12
Name: count, dtype: int64
```



```
[22]: dataset["model"].nunique()
```

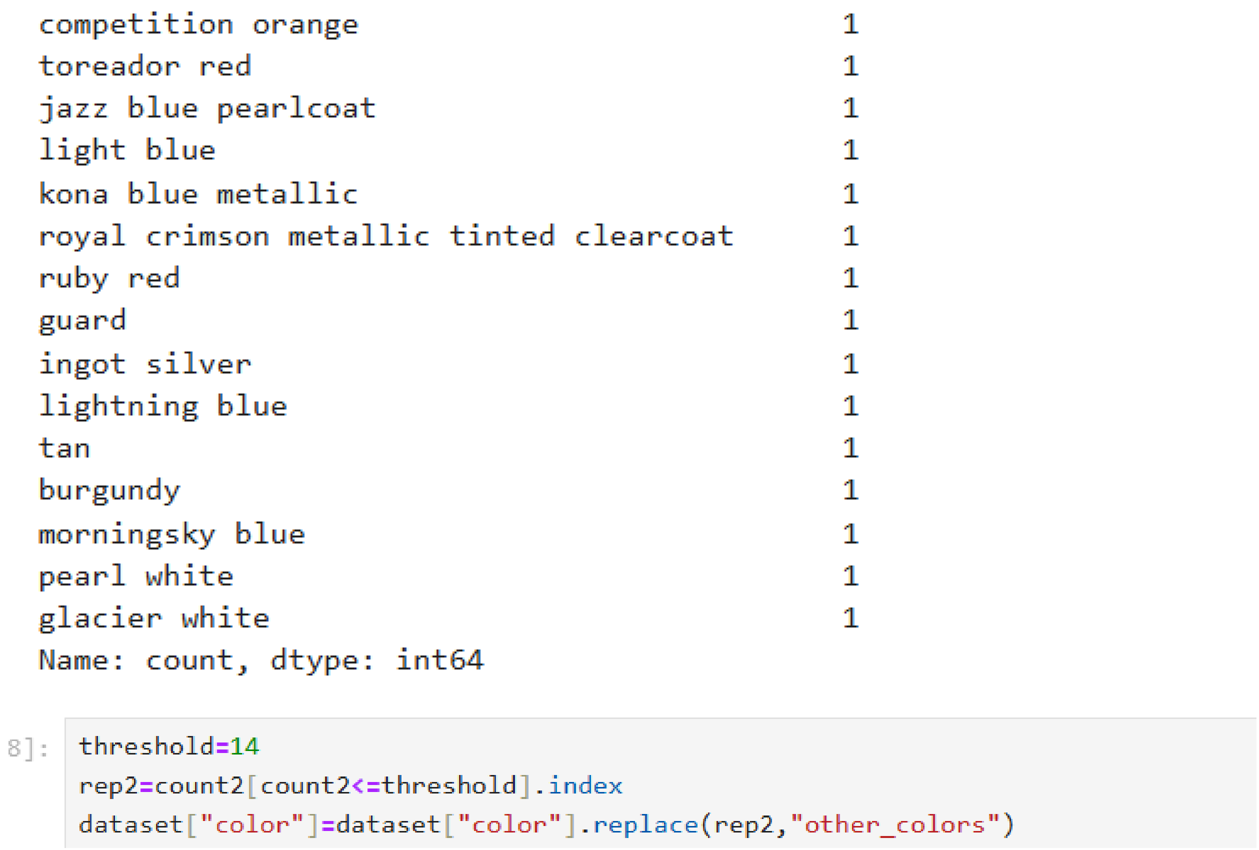
```
[22]: 38
```

```
[23]: dataset["title_status"].value_counts()
```

```
[23]: title_status
      clean vehicle        2336
      salvage insurance     163
      Name: count, dtype: int64
```

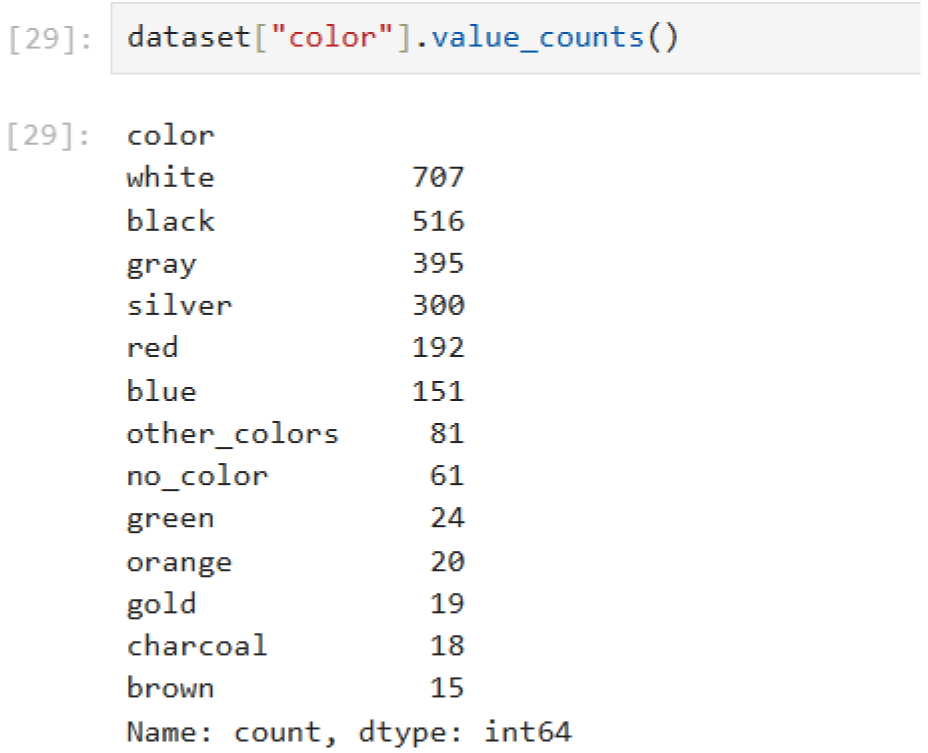
```
[25]: count2=dataset["color"].value_counts()
      count2
```

```
[25]: color
      white                                               707
      black                                               516
      gray                                                395
      silver                                              300
      red                                                 192
      blue                                                151
      no_color                                             61
      green                                                24
      orange                                               20
      gold                                                 19
      charcoal                                             18
      brown                                                15
      yellow                                                9
      magnetic metallic                                     6
      shadow black                                          5
      color:                                                5
      beige                                                 5
      ingot silver metallic                                 4
      oxford white                                          4
      billet silver metallic clearcoat                      3
      triple yellow tri-coat                                3
      super black                                           3
      off-white                                             2
      ruby red metallic tinted clearcoat                    2
      cayenne red                                           2
      white platinum tri-coat metallic                      2
      tuxedo black metallic                                 2
      black clearcoat                                       2
      bright white clearcoat                                2
      phantom black                                         1
      maroon                                                1
      dark blue                                             1
      turquoise                                             1
      purple                                                1
```



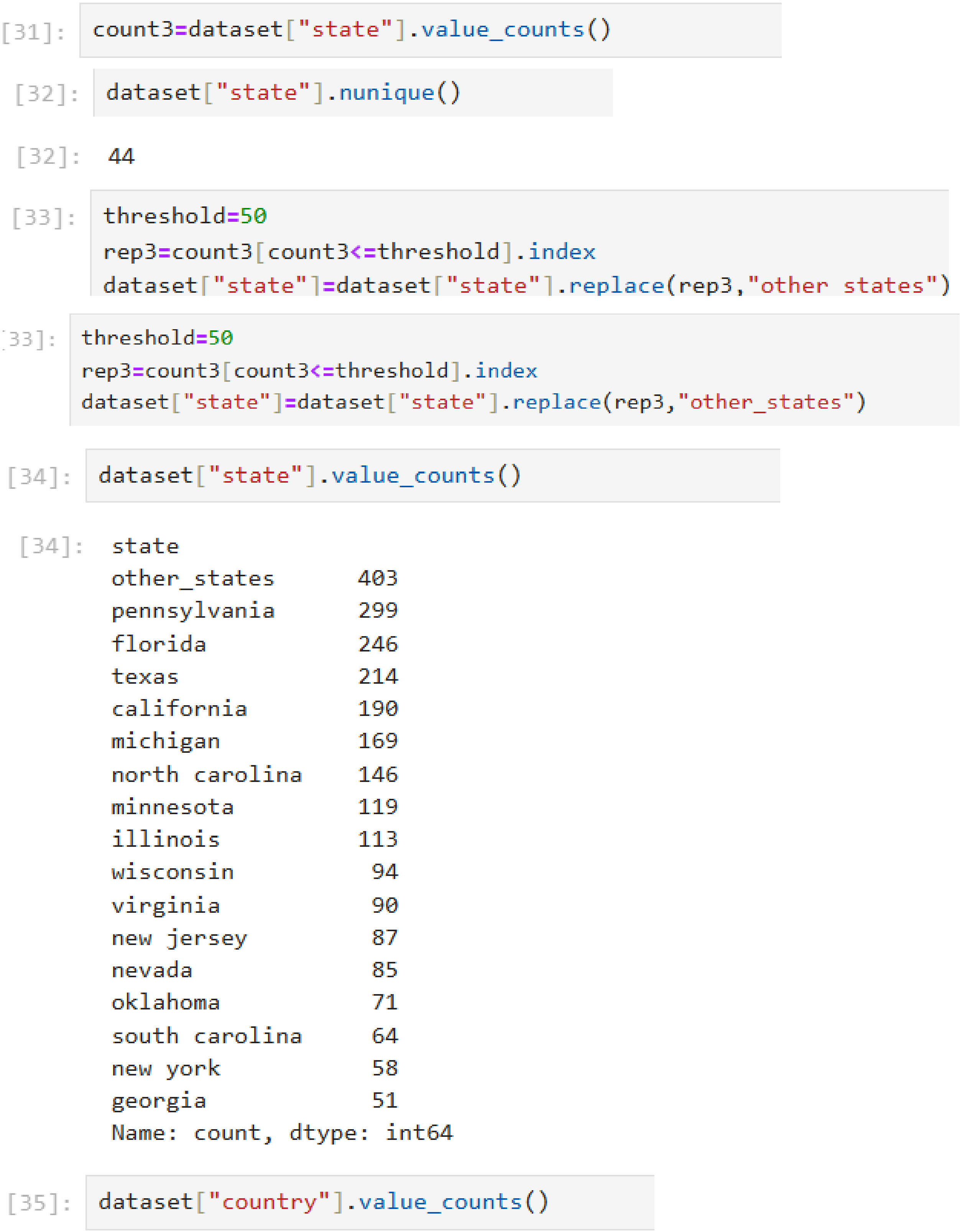
```
competition orange                           1
toreador red                                 1
jazz blue pearlcoat                          1
light blue                                   1
kona blue metallic                           1
royal crimson metallic tinted clearcoat      1
ruby red                                     1
guard                                        1
ingot silver                                 1
lightning blue                               1
tan                                          1
burgundy                                     1
morningsky blue                              1
pearl white                                  1
glacier white                                1
Name: count, dtype: int64
```

```
8]: threshold=14
    rep2=count2[count2<=threshold].index
    dataset["color"]=dataset["color"].replace(rep2,"other_colors")
```



```
[29]: dataset["color"].value_counts()
```

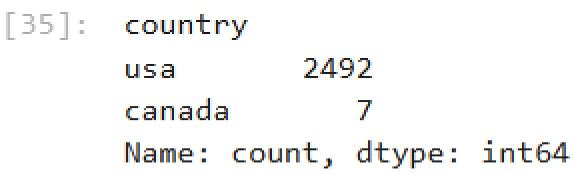
```
[29]: color
      white           707
      black           516
      gray            395
      silver          300
      red             192
      blue            151
      other_colors     81
      no_color         61
      green            24
      orange           20
      gold             19
      charcoal         18
      brown            15
      Name: count, dtype: int64
```



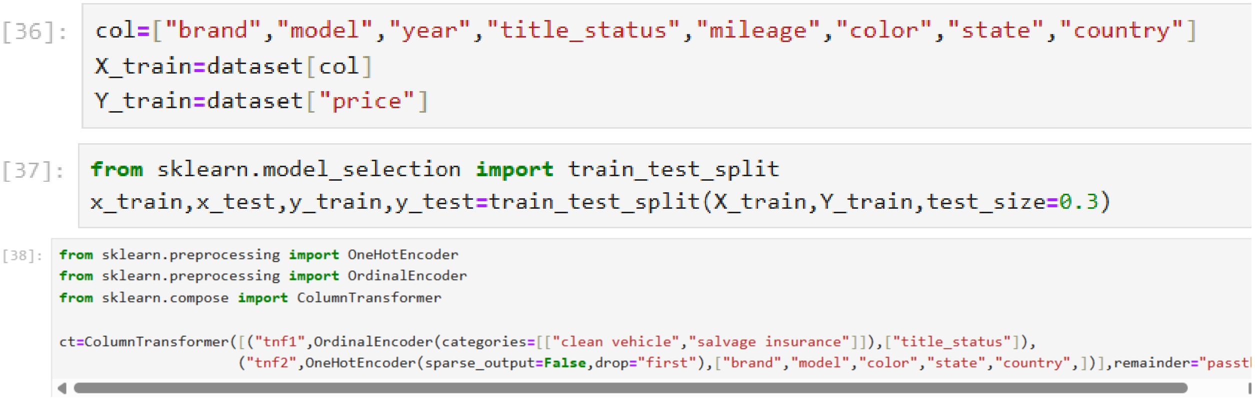
```
[31]: count3=dataset["state"].value_counts()

[32]: dataset["state"].nunique()

[32]: 44

[33]: threshold=50
      rep3=count3[count3<=threshold].index
      dataset["state"]=dataset["state"].replace(rep3,"other states")
```

```
[33]: threshold=50
      rep3=count3[count3<=threshold].index
      dataset["state"]=dataset["state"].replace(rep3,"other_states")
```

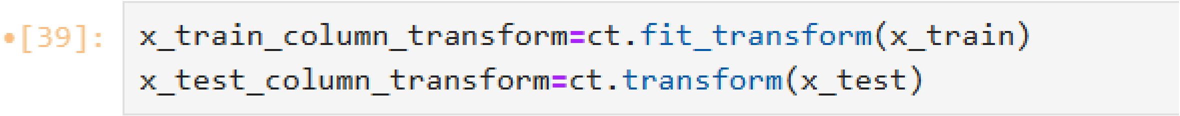
```
[34]: dataset["state"].value_counts()

[34]: state
      other_states      403
      pennsylvania      299
      florida           246
      texas             214
      california        190
      michigan          169
      north carolina    146
      minnesota         119
      illinois          113
      wisconsin          94
      virginia           90
      new jersey         87
      nevada             85
      oklahoma           71
      south carolina     64
      new york           58
      georgia            51
      Name: count, dtype: int64

[35]: dataset["country"].value_counts()
```



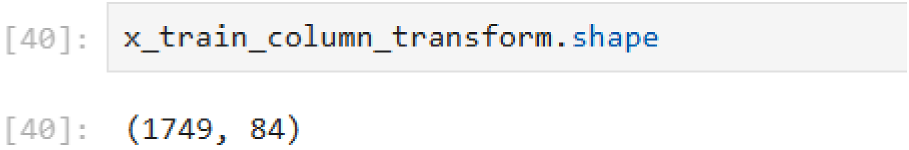
```
[35]:  country
       usa       2492
       canada       7
       Name: count, dtype: int64
```



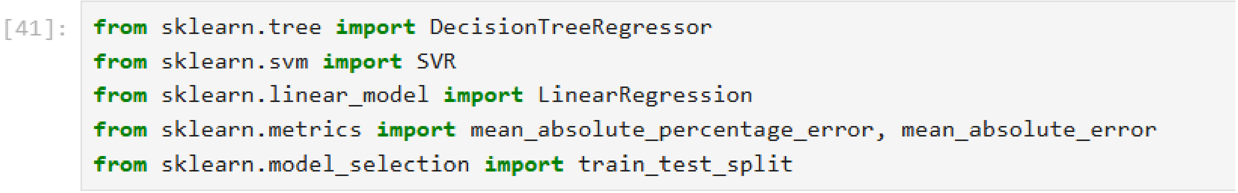
```
[36]:  col=["brand","model","year","title_status","mileage","color","state","country"]
       X_train=dataset[col]
       Y_train=dataset["price"]

[37]:  from sklearn.model_selection import train_test_split
       x_train,x_test,y_train,y_test=train_test_split(X_train,Y_train,test_size=0.3)

[38]:  from sklearn.preprocessing import OneHotEncoder
       from sklearn.preprocessing import OrdinalEncoder
       from sklearn.compose import ColumnTransformer

       ct=ColumnTransformer([("tnf1",OrdinalEncoder(categories=[["clean vehicle","salvage insurance"]]),["title_status"]),
                            ("tnf2",OneHotEncoder(sparse_output=False,drop="first"),["brand","model","color","state","country",])],remainder="passt
```



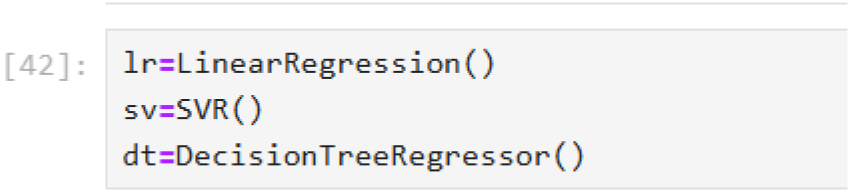
```
•[39]:  x_train_column_transform=ct.fit_transform(x_train)
        x_test_column_transform=ct.transform(x_test)
```



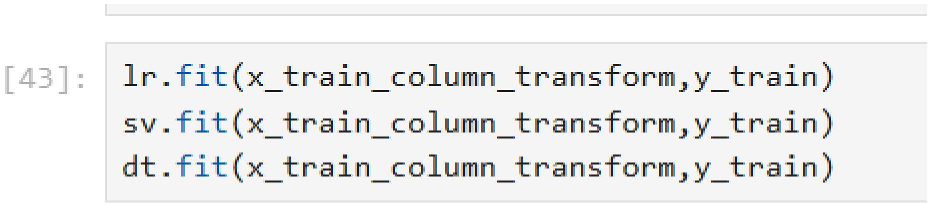
```
[40]:  x_train_column_transform.shape

[40]:  (1749, 84)
```



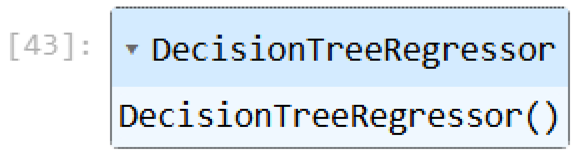
```
[41]:  from sklearn.tree import DecisionTreeRegressor
       from sklearn.svm import SVR
       from sklearn.linear_model import LinearRegression
       from sklearn.metrics import mean_absolute_percentage_error, mean_absolute_error
       from sklearn.model_selection import train_test_split
```



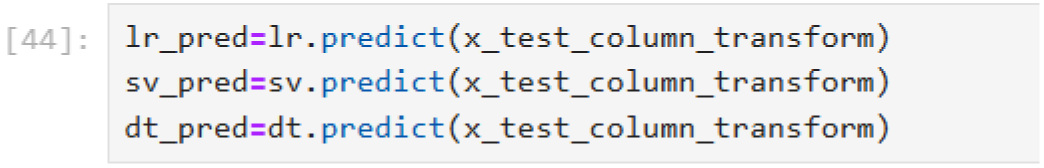
```
[42]:  lr=LinearRegression()
       sv=SVR()
       dt=DecisionTreeRegressor()
```



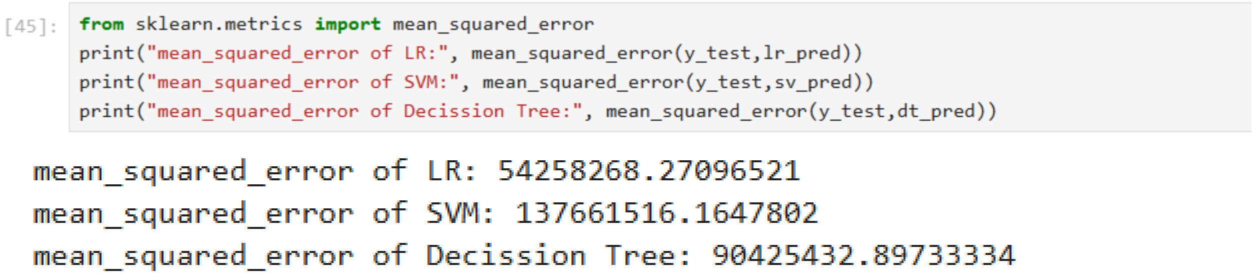
```
[43]:  lr.fit(x_train_column_transform,y_train)
       sv.fit(x_train_column_transform,y_train)
       dt.fit(x_train_column_transform,y_train)
```



```
[43]:
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

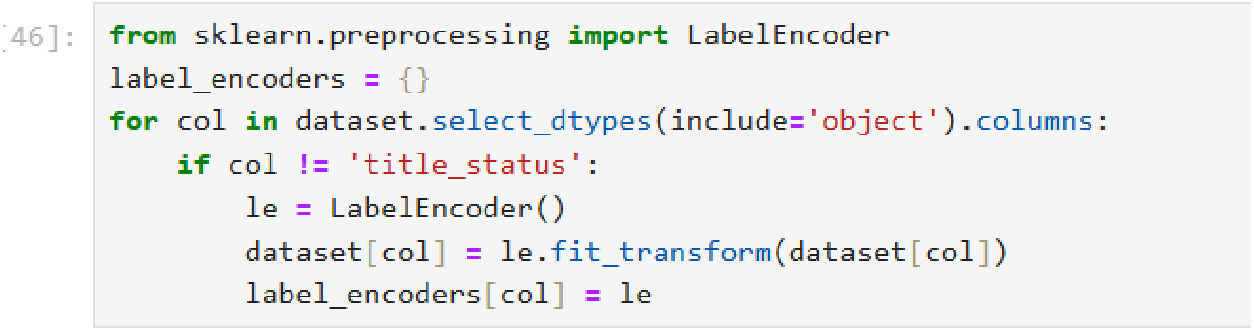


```
[44]: lr_pred=lr.predict(x_test_column_transform)
      sv_pred=sv.predict(x_test_column_transform)
      dt_pred=dt.predict(x_test_column_transform)
```

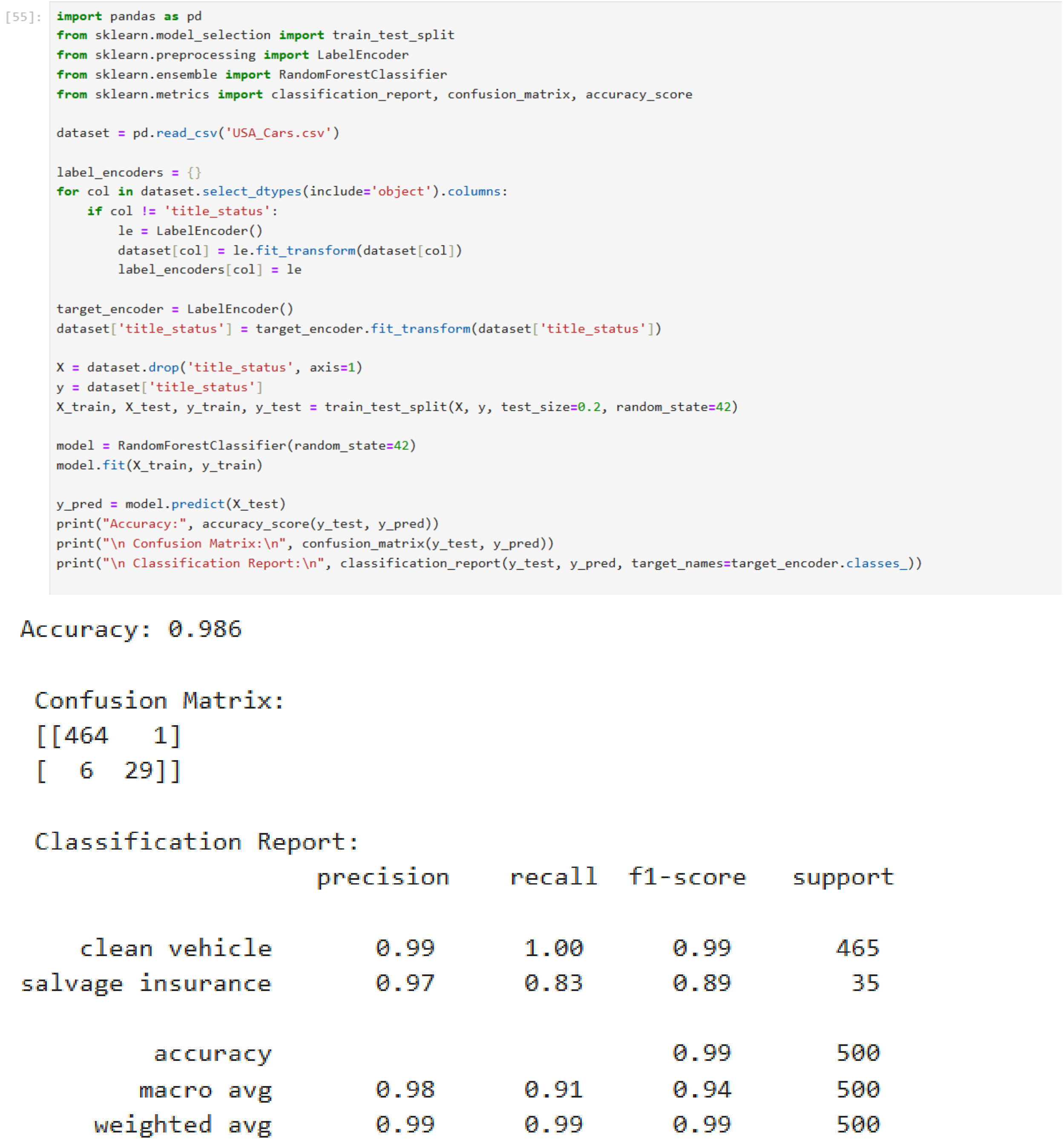


```
[45]: from sklearn.metrics import mean_squared_error
      print("mean_squared_error of LR:", mean_squared_error(y_test,lr_pred))
      print("mean_squared_error of SVM:", mean_squared_error(y_test,sv_pred))
      print("mean_squared_error of Decission Tree:", mean_squared_error(y_test,dt_pred))
```

```
mean_squared_error of LR: 54258268.27096521
mean_squared_error of SVM: 137661516.1647802
mean_squared_error of Decission Tree: 90425432.89733334
```



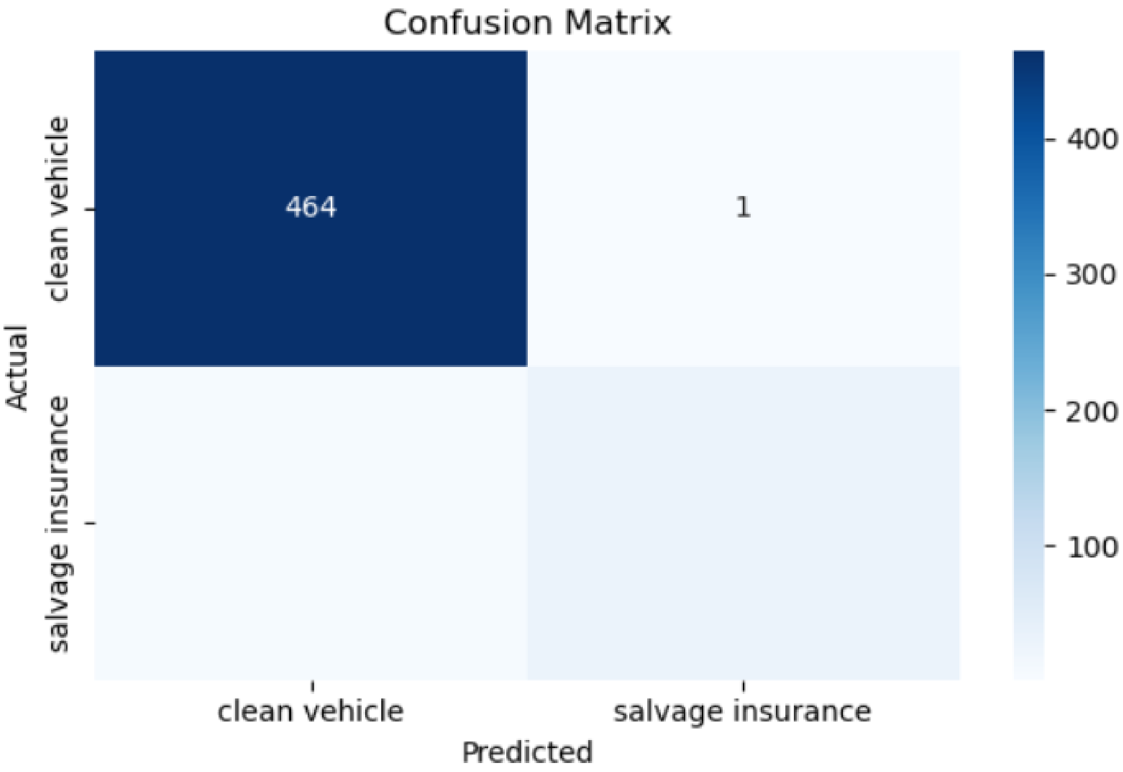
```
[46]: from sklearn.preprocessing import LabelEncoder
      label_encoders = {}
      for col in dataset.select_dtypes(include='object').columns:
          if col != 'title_status':
              le = LabelEncoder()
              dataset[col] = le.fit_transform(dataset[col])
              label_encoders[col] = le
```



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

dataset = pd.read_csv('USA_Cars.csv')

label_encoders = {}
for col in dataset.select_dtypes(include='object').columns:
    if col != 'title_status':
        le = LabelEncoder()
        dataset[col] = le.fit_transform(dataset[col])
        label_encoders[col] = le

target_encoder = LabelEncoder()
dataset['title_status'] = target_encoder.fit_transform(dataset['title_status'])

X = dataset.drop('title_status', axis=1)
y = dataset['title_status']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\n Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\n Classification Report:\n", classification_report(y_test, y_pred, target_names=target_encoder.classes_))
```

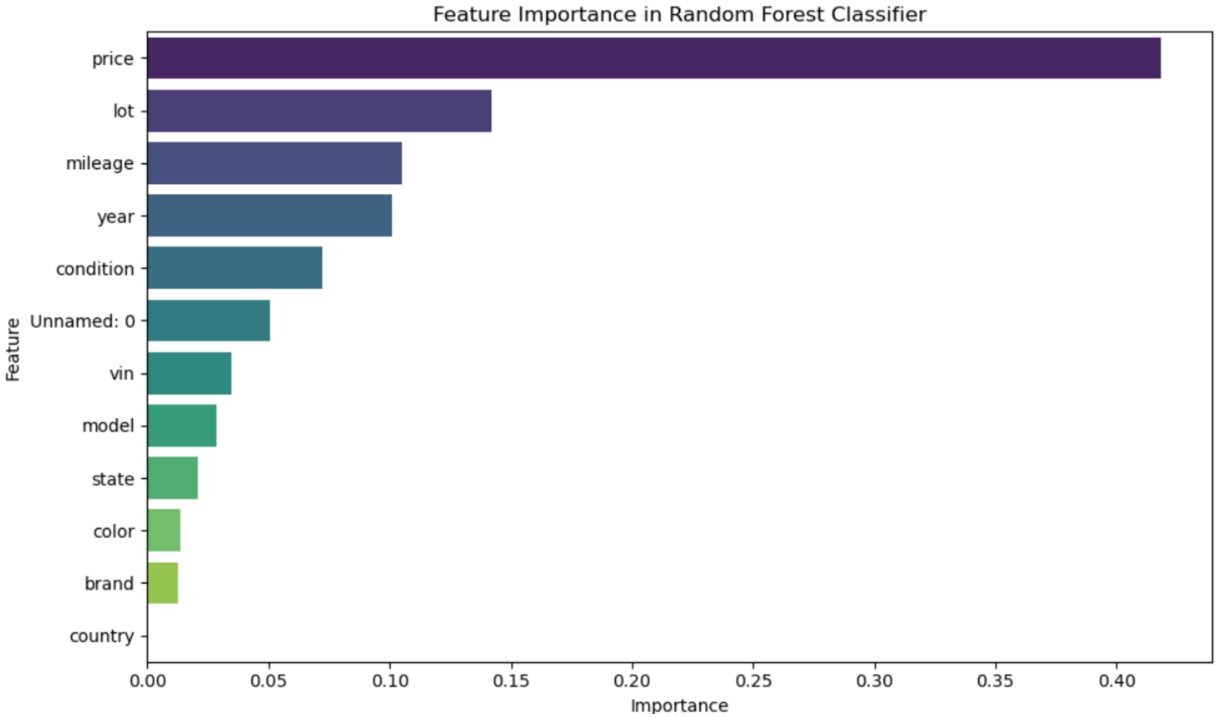
```
Accuracy: 0.986

 Confusion Matrix:
 [[464   1]
 [  6  29]]

 Classification Report:
                    precision    recall  f1-score   support

    clean vehicle       0.99      1.00      0.99       465
salvage insurance       0.97      0.83      0.89        35

         accuracy                           0.99       500
        macro avg       0.98      0.91      0.94       500
     weighted avg       0.99      0.99      0.99       500
```

```
[56]: import matplotlib.pyplot as plt
      import seaborn as sns
      from sklearn.metrics import confusion_matrix

      cm = confusion_matrix(y_test, y_pred)
      labels = target_encoder.classes_
      plt.figure(figsize=(6, 4))
      sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=labels, yticklabels=labels)
      plt.xlabel('Predicted')
      plt.ylabel('Actual')
      plt.title('Confusion Matrix')
      plt.tight_layout()
      plt.show()
```



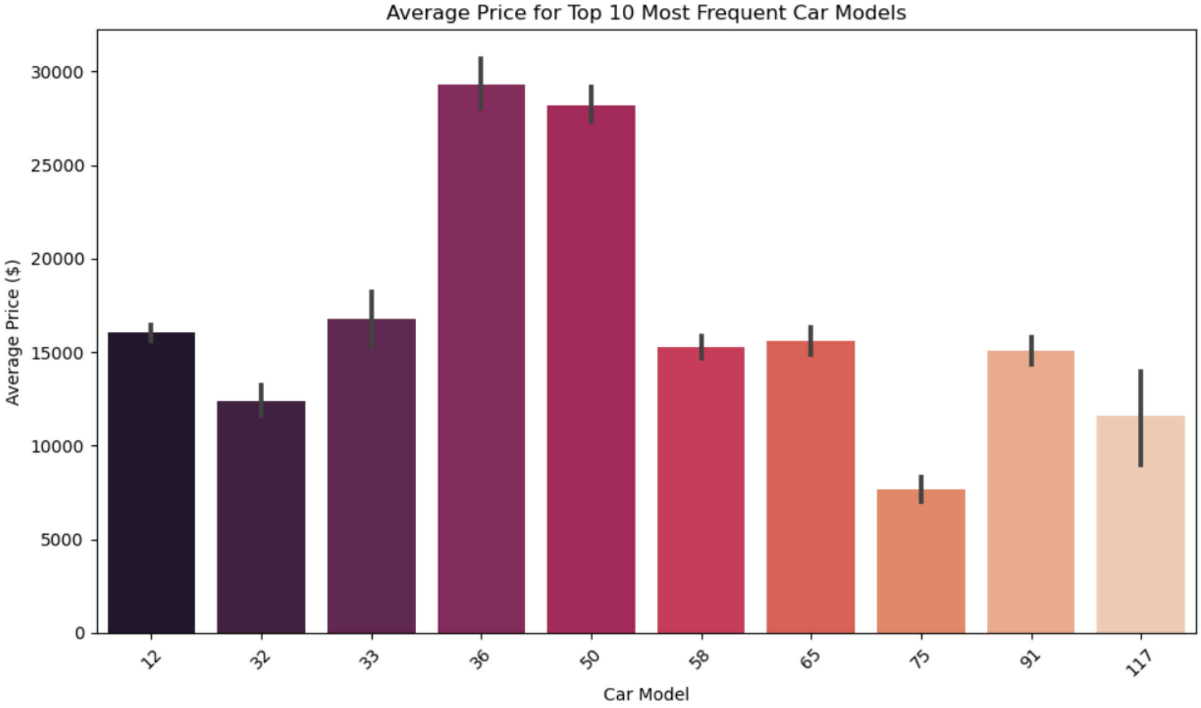
[58]:

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

importances = model.feature_importances_
feature_names = X.columns

feat_dataset = pd.DataFrame({
    'Feature': feature_names,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feat_dataset, palette='viridis')
plt.title('Feature Importance in Random Forest Classifier')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```



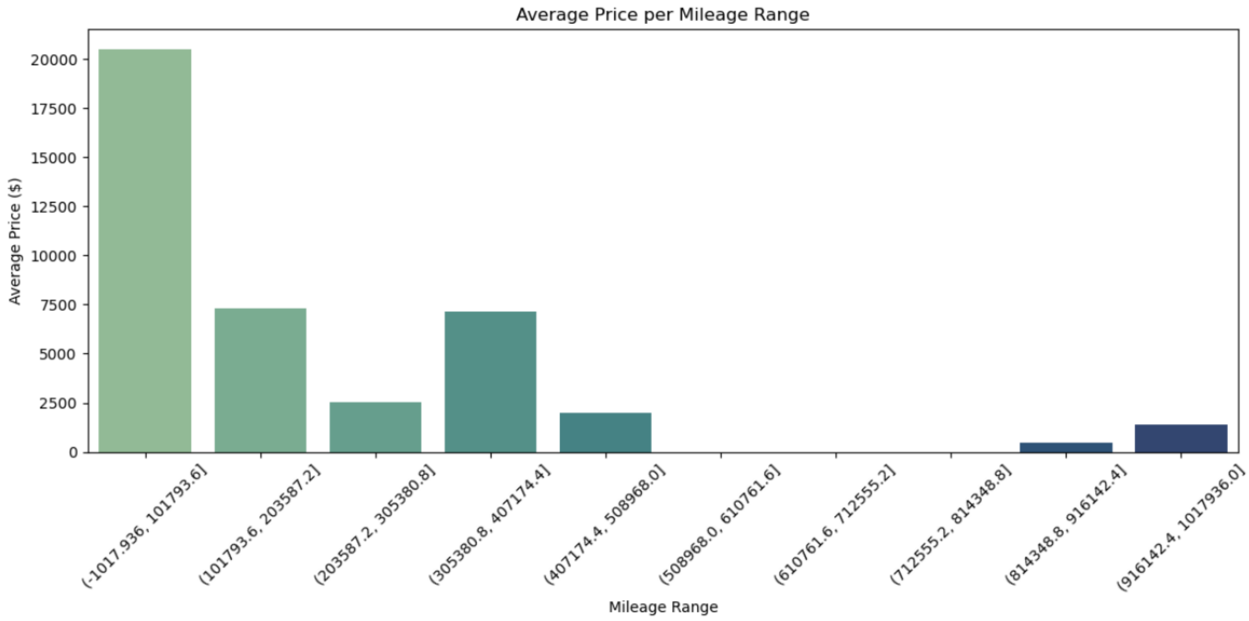
[61]:

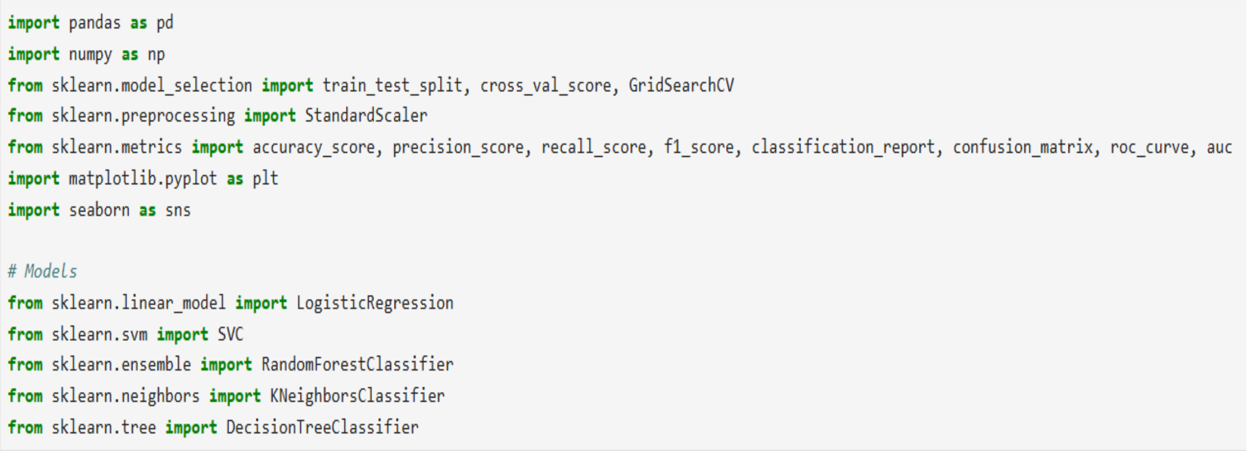
```
top_models = dataset['model'].value_counts().head(10).index
filtered_dataset = dataset[dataset['model'].isin(top_models)]

plt.figure(figsize=(10, 6))
sns.barplot(data=filtered_dataset, x='model', y='price', estimator='mean', palette='rocket')

plt.title('Average Price for Top 10 Most Frequent Car Models')
plt.xlabel('Car Model')
plt.ylabel('Average Price ($)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



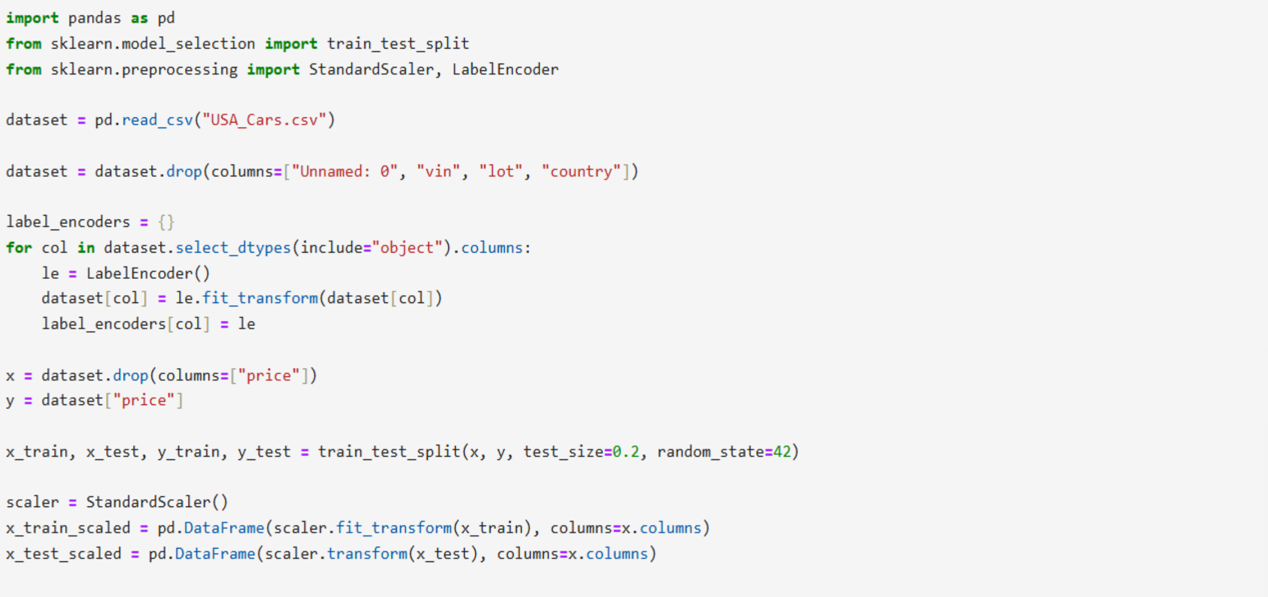
[66]:

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

dataset['mileage_bin'] = pd.cut(dataset['mileage'], bins=10)

grouped = dataset.groupby('mileage_bin')['price'].mean().reset_index()

plt.figure(figsize=(12, 6))
sns.barplot(data=grouped, x='mileage_bin', y='price', palette='crest')

plt.title('Average Price per Mileage Range')
plt.xlabel('Mileage Range')
plt.ylabel('Average Price ($)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

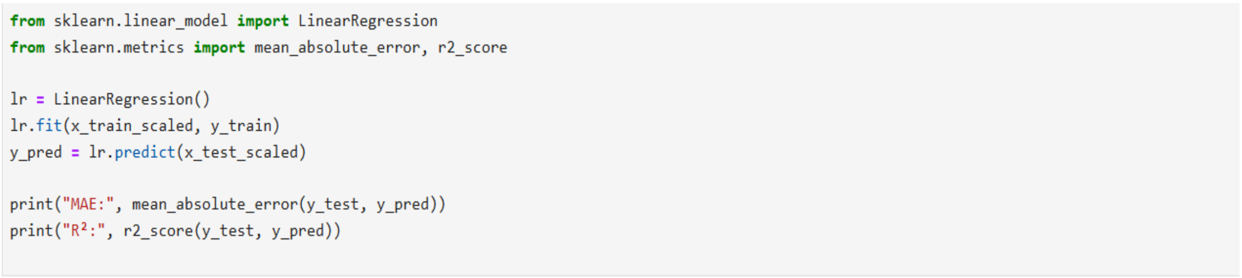




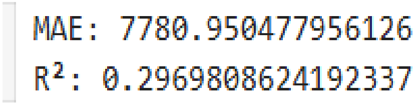
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report, confusion_matrix, roc_curve, auc
import matplotlib.pyplot as plt
import seaborn as sns

# Models
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
```



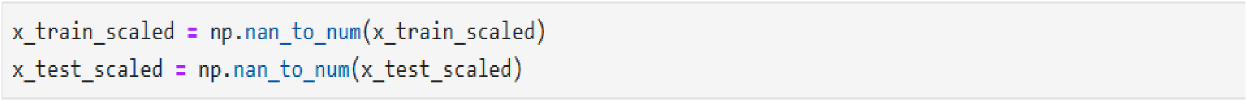
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder

dataset = pd.read_csv("USA_Cars.csv")

dataset = dataset.drop(columns=["Unnamed: 0", "vin", "lot", "country"])

label_encoders = {}
for col in dataset.select_dtypes(include="object").columns:
    le = LabelEncoder()
    dataset[col] = le.fit_transform(dataset[col])
    label_encoders[col] = le

x = dataset.drop(columns=["price"])
y = dataset["price"]

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

scaler = StandardScaler()
x_train_scaled = pd.DataFrame(scaler.fit_transform(x_train), columns=x.columns)
x_test_scaled = pd.DataFrame(scaler.transform(x_test), columns=x.columns)
```



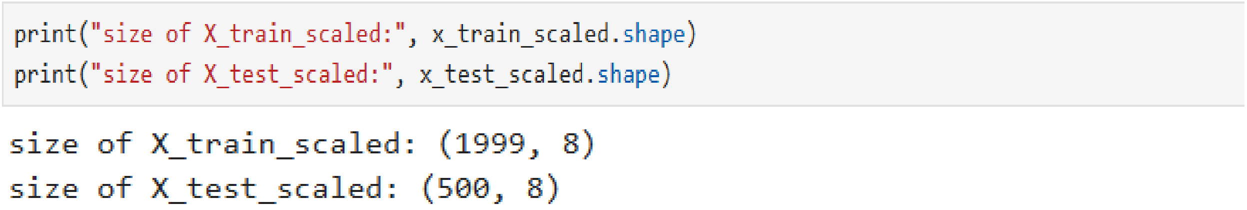
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score

lr = LinearRegression()
lr.fit(x_train_scaled, y_train)
y_pred = lr.predict(x_test_scaled)

print("MAE:", mean_absolute_error(y_test, y_pred))
print("R²:", r2_score(y_test, y_pred))
```



```
MAE: 7780.950477956126
R²: 0.2969808624192337
```

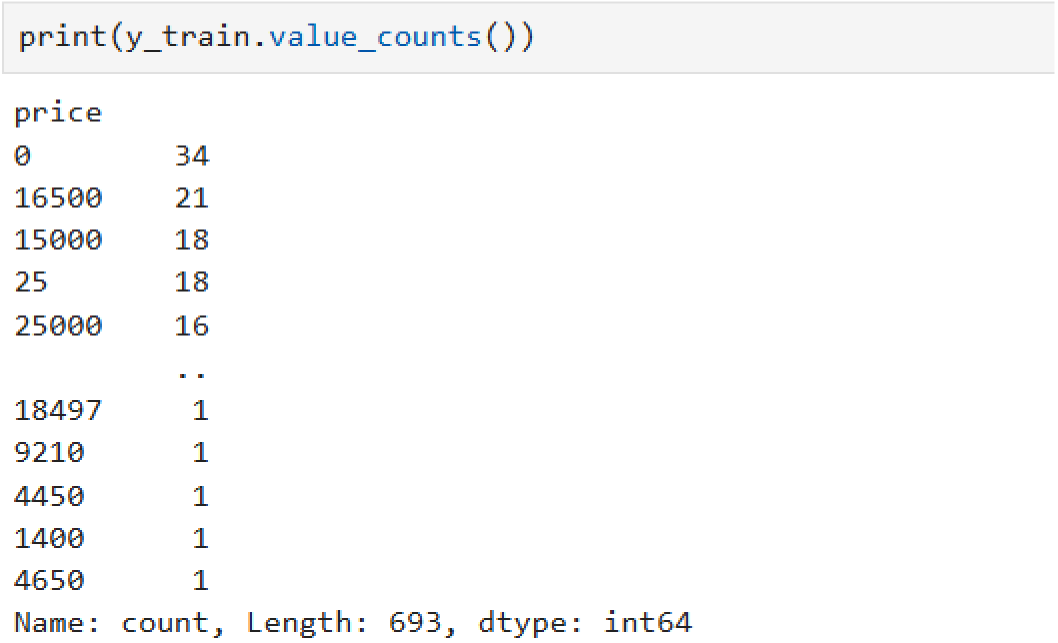


```
x_train_scaled = np.nan_to_num(x_train_scaled)
x_test_scaled = np.nan_to_num(x_test_scaled)
```



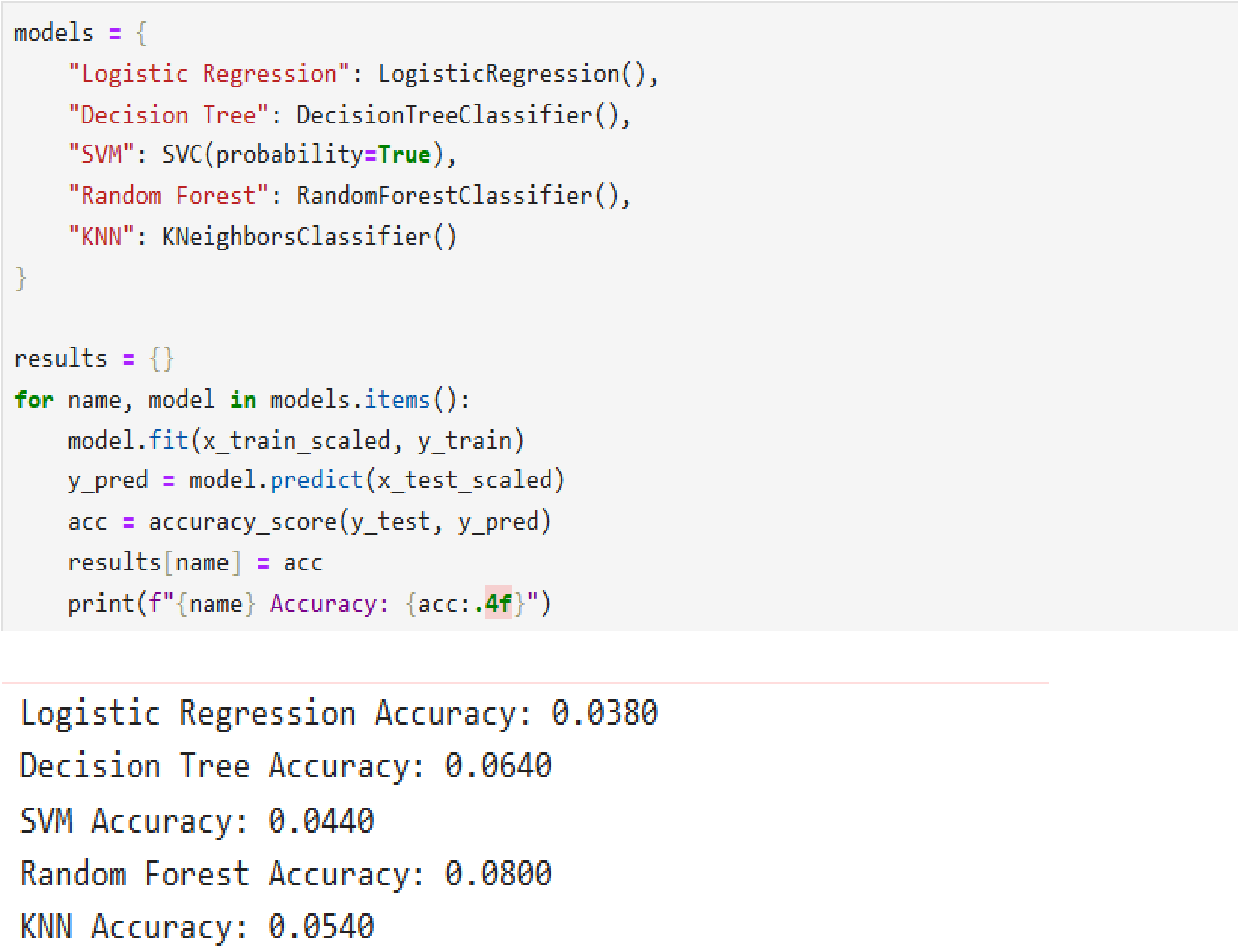
```
print("size of X_train_scaled:", x_train_scaled.shape)
print("size of X_test_scaled:", x_test_scaled.shape)
```

```
size of X_train_scaled: (1999, 8)
size of X_test_scaled: (500, 8)
```



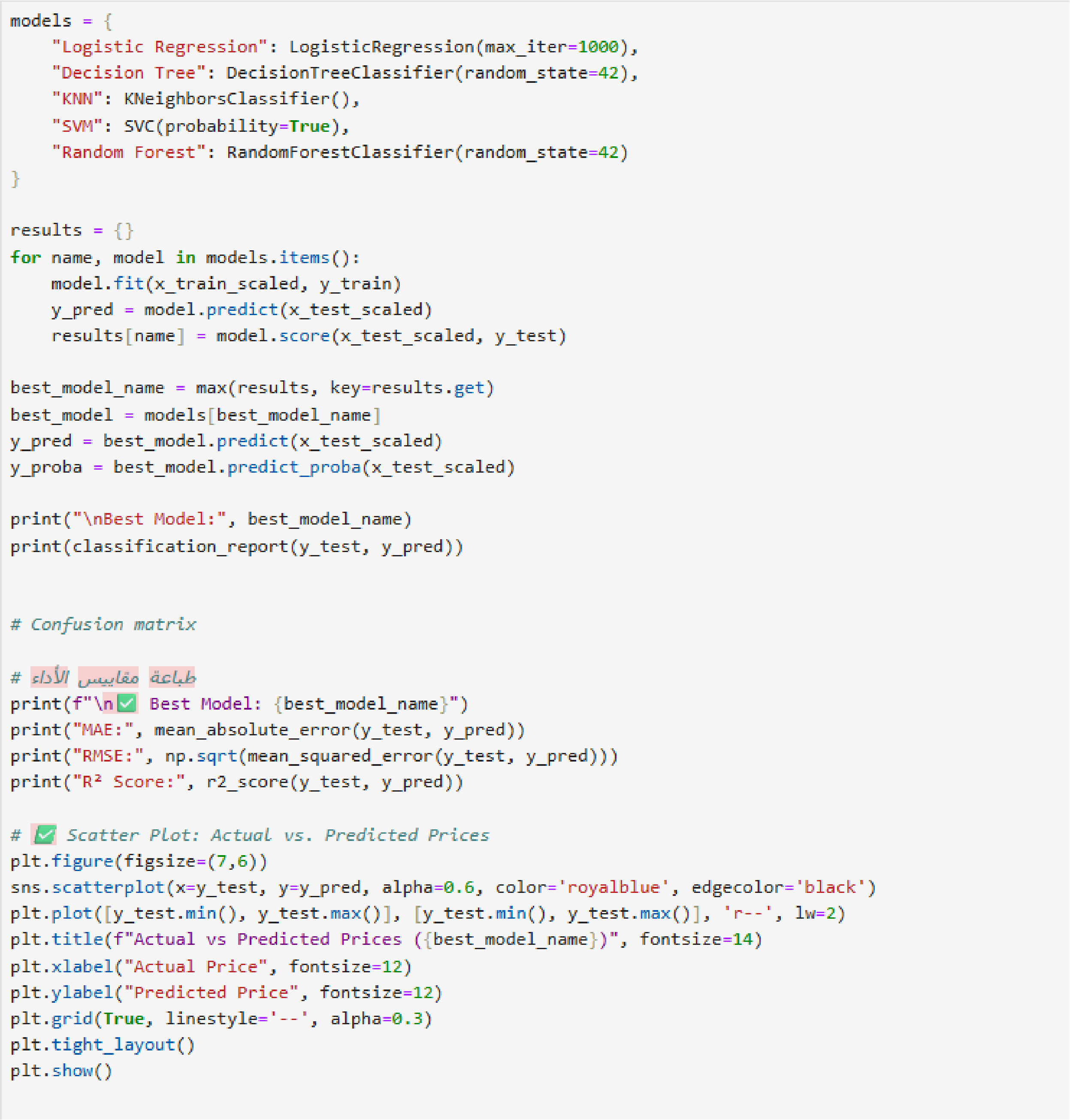
```
print(y_train.value_counts())
```

```
price
0        34
16500    21
15000    18
25       18
25000    16
         ..
18497     1
9210      1
4450      1
1400      1
4650      1
Name: count, Length: 693, dtype: int64
```

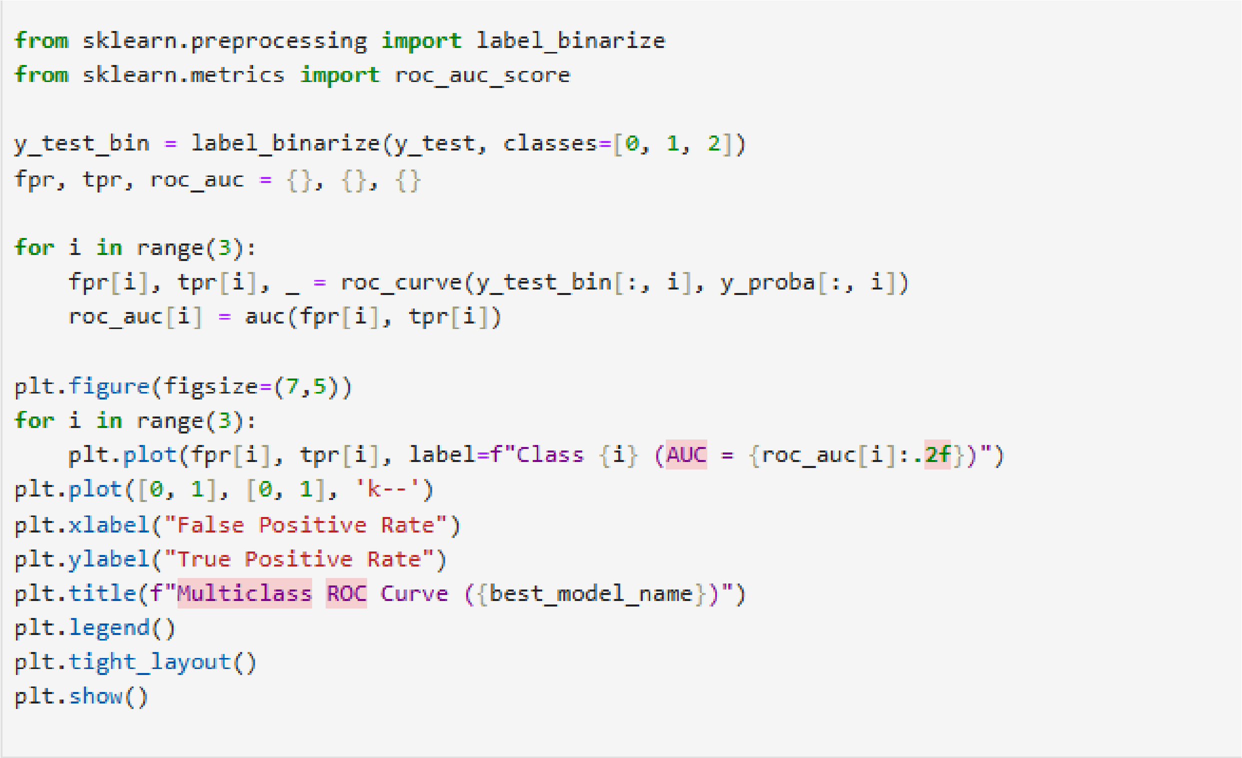


```python
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "SVM": SVC(probability=True),
    "Random Forest": RandomForestClassifier(),
    "KNN": KNeighborsClassifier()
}

results = {}
for name, model in models.items():
    model.fit(x_train_scaled, y_train)
    y_pred = model.predict(x_test_scaled)
    acc = accuracy_score(y_test, y_pred)
    results[name] = acc
    print(f"{name} Accuracy: {acc:.4f}")
```

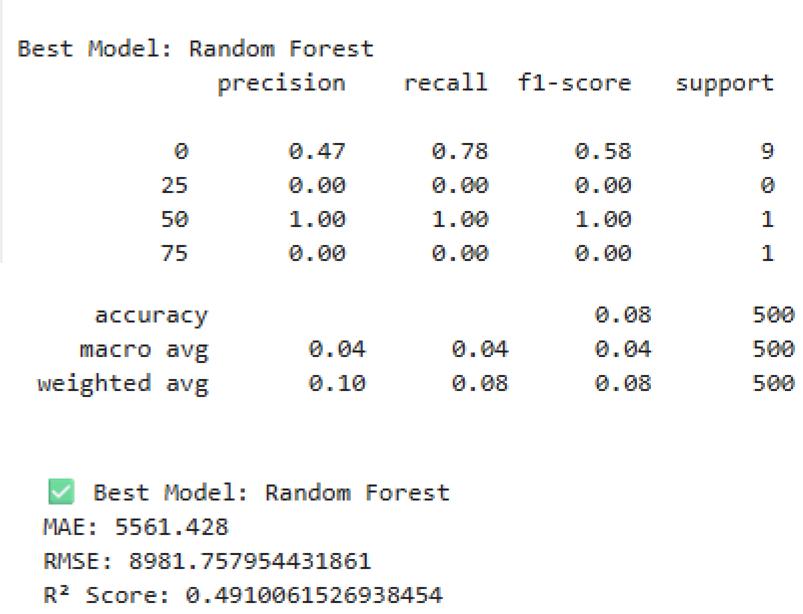
```
Logistic Regression Accuracy: 0.0380
Decision Tree Accuracy: 0.0640
SVM Accuracy: 0.0440
Random Forest Accuracy: 0.0800
KNN Accuracy: 0.0540
```



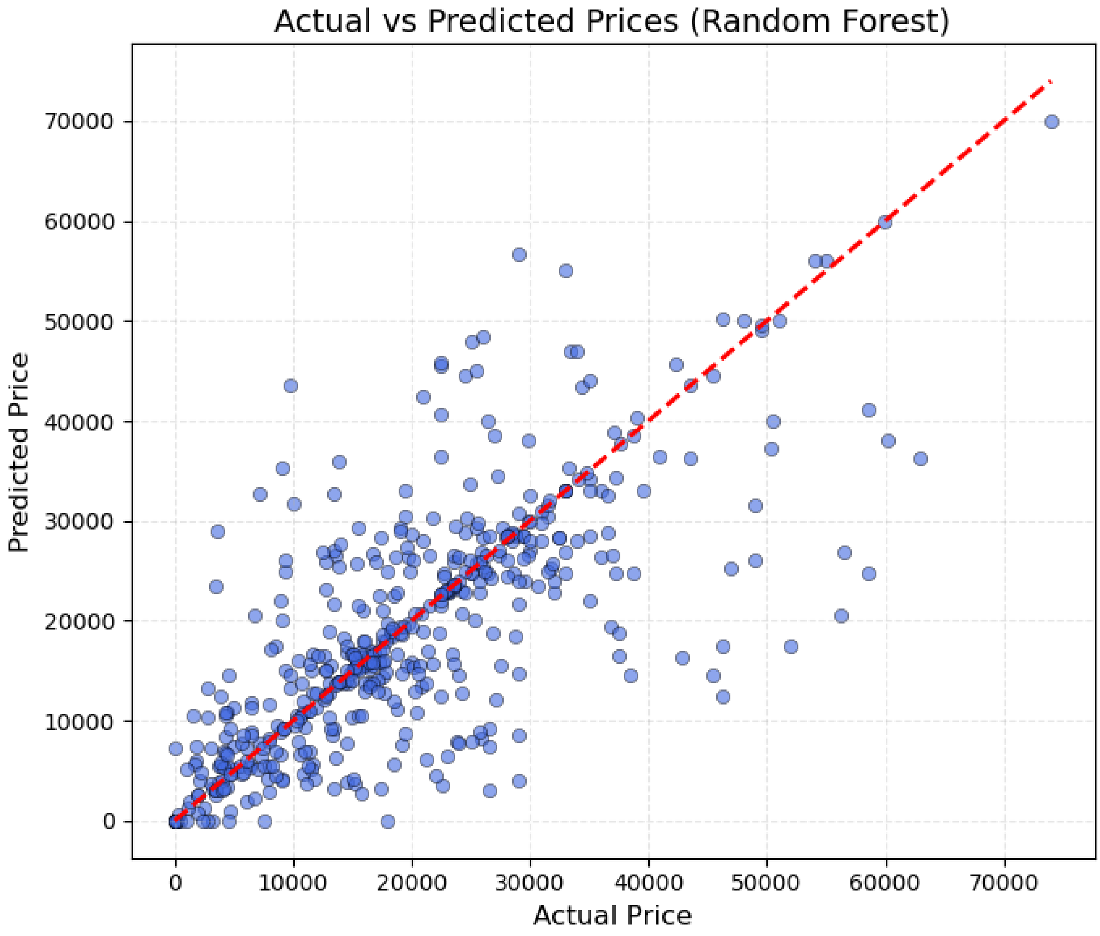
```
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC(probability=True),
    "Random Forest": RandomForestClassifier(random_state=42)
}

results = {}
for name, model in models.items():
    model.fit(x_train_scaled, y_train)
    y_pred = model.predict(x_test_scaled)
    results[name] = model.score(x_test_scaled, y_test)

best_model_name = max(results, key=results.get)
best_model = models[best_model_name]
y_pred = best_model.predict(x_test_scaled)
y_proba = best_model.predict_proba(x_test_scaled)

print("\nBest Model:", best_model_name)
print(classification_report(y_test, y_pred))


# Confusion matrix

# طباعة مقاييس الأداء
print(f"\n✅ Best Model: {best_model_name}")
print("MAE:", mean_absolute_error(y_test, y_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
print("R² Score:", r2_score(y_test, y_pred))

# ✅ Scatter Plot: Actual vs. Predicted Prices
plt.figure(figsize=(7,6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.6, color='royalblue', edgecolor='black')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.title(f"Actual vs Predicted Prices ({best_model_name})", fontsize=14)
plt.xlabel("Actual Price", fontsize=12)
plt.ylabel("Predicted Price", fontsize=12)
plt.grid(True, linestyle='--', alpha=0.3)
plt.tight_layout()
plt.show()
```

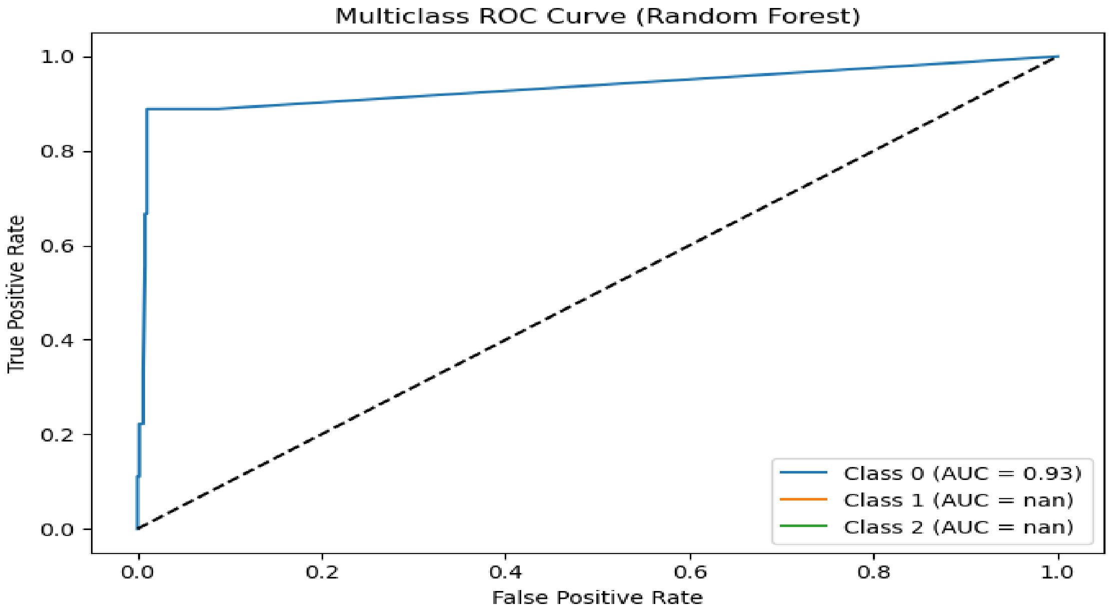


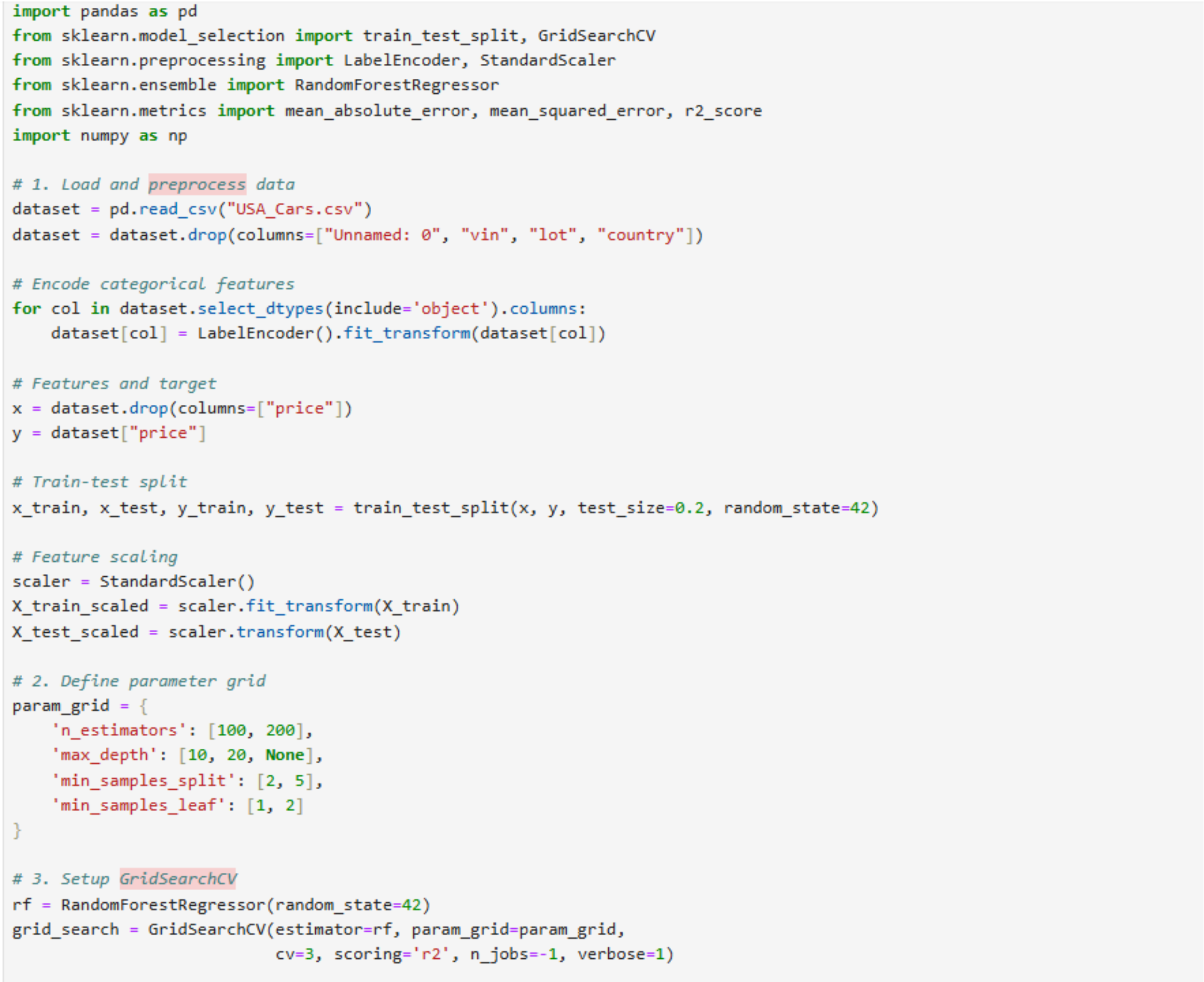
```python
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_auc_score

y_test_bin = label_binarize(y_test, classes=[0, 1, 2])
fpr, tpr, roc_auc = {}, {}, {}

for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(7,5))
for i in range(3):
    plt.plot(fpr[i], tpr[i], label=f"Class {i} (AUC = {roc_auc[i]:.2f})")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title(f"Multiclass ROC Curve ({best_model_name})")
plt.legend()
plt.tight_layout()
plt.show()
```



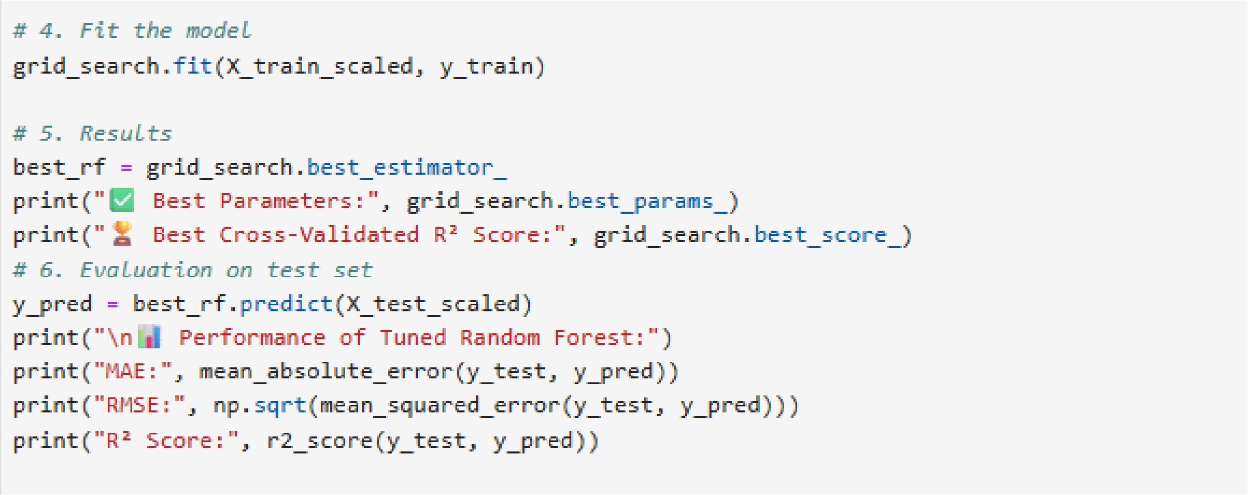
```
Best Model: Random Forest
              precision    recall  f1-score   support

           0       0.47      0.78      0.58         9
          25       0.00      0.00      0.00         0
          50       1.00      1.00      1.00         1
          75       0.00      0.00      0.00         1

    accuracy                           0.08       500
   macro avg       0.04      0.04      0.04       500
weighted avg       0.10      0.08      0.08       500


✅ Best Model: Random Forest
MAE: 5561.428
RMSE: 8981.757954431861
R² Score: 0.4910061526938454
```


Actual vs Predicted Prices (Random Forest)
Predicted Price
Actual Price
0
10000
20000
30000
40000
50000
60000
70000


Multiclass ROC Curve (Random Forest)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Class 0 (AUC = 0.93)
Class 1 (AUC = nan)
Class 2 (AUC = nan)



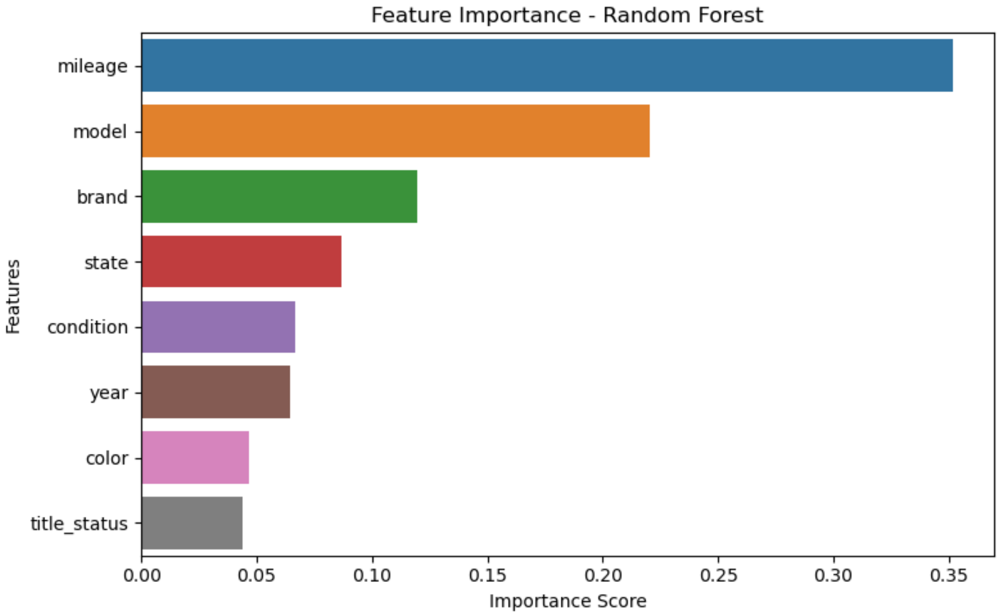
```python
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

# 1. Load and preprocess data
dataset = pd.read_csv("USA_Cars.csv")
dataset = dataset.drop(columns=["Unnamed: 0", "vin", "lot", "country"])

# Encode categorical features
for col in dataset.select_dtypes(include='object').columns:
    dataset[col] = LabelEncoder().fit_transform(dataset[col])

# Features and target
x = dataset.drop(columns=["price"])
y = dataset["price"]

# Train-test split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# 2. Define parameter grid
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

# 3. Setup GridSearchCV
rf = RandomForestRegressor(random_state=42)
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                           cv=3, scoring='r2', n_jobs=-1, verbose=1)
```



```python
# 4. Fit the model
grid_search.fit(X_train_scaled, y_train)

# 5. Results
best_rf = grid_search.best_estimator_
print("✅ Best Parameters:", grid_search.best_params_)
print("🏆 Best Cross-Validated R² Score:", grid_search.best_score_)
# 6. Evaluation on test set
y_pred = best_rf.predict(X_test_scaled)
print("\n📊 Performance of Tuned Random Forest:")
print("MAE:", mean_absolute_error(y_test, y_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
print("R² Score:", r2_score(y_test, y_pred))
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
✅ Best Parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
⏳ Best Cross-Validated R² Score: 0.6194780492869159

📊 Performance of Tuned Random Forest:
MAE: 4556.89337
RMSE: 6954.512725911367
R² Score: 0.6948430606086335
```

```
import seaborn as sns
import matplotlib.pyplot as plt
importances = best_rf.feature_importances_
feature_names = x.columns
feat_imp = pd.Series(importances, index=feature_names).sort_values(ascending=False)

plt.figure(figsize=(8,5))
sns.barplot(x=feat_imp, y=feat_imp.index)
plt.title("Feature Importance - Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.tight_layout()
plt.show()

import shap

# Create explainer using scaled data (because model was trained on it)
explainer = shap.Explainer(best_rf, x_train_scaled)

# Wrap test data in DataFrame to retain feature names
x_test_scaled_dataset = pd.DataFrame(x_test_scaled, columns=x.columns)

# Compute SHAP values (disable strict check)
shap_values = explainer(x_test_scaled_dataset, check_additivity=False)

# Global Explanation - Summary Bar Plot
shap.summary_plot(shap_values, x_test_scaled_dataset, plot_type="bar")
```


Feature Importance - Random Forest
mileage
model
brand
state
condition
year
color
title_status
Features
Importance Score