Car Prediction Model(used cars)

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Problem Statement:

The price of a car is influenced by a multitude of factors, including brand reputation, features, horsepower, mileage, age, and market demand. Accurately predicting car prices is a challenging task due to the complex interplay of these variables. Traditional methods of price estimation often rely on subjective assessments or simplistic rules, which may not capture the nuanced relationships between car attributes and their market value. This project aims to address this challenge by leveraging machine learning techniques to build a predictive model that can accurately estimate car prices based on relevant features.

Objectives: Identify key drivers of car prices and provide actionable insights for sellers. Data Source: A dataset of 300 car sales records, including variables such as car name, year, selling price, present price, kilometers driven, fuel type, transmission type, and owner history. Scope: The analysis focuses on cars sold between 2003 and 2018.

Aim:

The aim of this project is to develop a machine learning model that can predict the price of a car based on its features.

Data Overview Car_Name: Categorical variable representing the model of the vehicle, including both cars and motorcycles. Year: indicates the manufacturing year, ranging from 2003 to 2018. Selling_Price:represents the price at which the vehicle is being sold.(target variable) Present_Price: indicates the current market value of the vehicle. Driven_kms:shows the kilometers driven. Fuel_Type: Categorical variable indicating the type of fuel used (e.g., Petrol, Diesel, CNG). ⚙Selling_type:denotes whether the vehicle is sold by a Dealer or an Individual. Transmission:indicates the type of transmission: Manual: The driver manually changes gears using a gear stick and clutch pedal. 😊Automatic: The car automatically changes gears without driver intervention. Owner:indicates the number of previous owners the vehicle has had.

Importing neccesary libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import ydata_profiling as pp
import warnings
%matplotlib inline
warnings.filterwarnings("ignore")

pip install xgboost

Requirement already satisfied: xgboost in c:\users\hp\anaconda3\lib\
site-packages (2.1.3)
Requirement already satisfied: numpy in c:\users\hp\anaconda3\lib\
site-packages (from xgboost) (1.26.4)
```

```
Requirement already satisfied: scipy in c:\users\hp\anaconda3\lib\
site-packages (from xgboost) (1.13.1)
Note: you may need to restart the kernel to use updated packages.
```

```
from sklearn.model_selection import train_test_split, GridSearchCV,
RandomizedSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler,
LabelEncoder
from sklearn.metrics import mean_squared_error, r2_score,
mean_absolute_error
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from xgboost import XGBRegressor
import shap
from sklearn.pipeline import make_pipeline
```

Data Loading

```
cars= pd.read_csv("C:\\Users\\HP\\Documents\\Code Alpha Tasks\\car
data.csv")
cars.head()
```

```
  Car_Name  Year  Selling_Price  Present_Price  Driven_kms
Fuel_Type  \
0     ritz  2014           3.35           5.59       27000    Petrol

1      sx4  2013           4.75           9.54       43000    Diesel

2     ciaz  2017           7.25           9.85        6900    Petrol

3  wagon r  2011           2.85           4.15        5200    Petrol

4    swift  2014           4.60           6.87       42450    Diesel


  Selling_type Transmission  Owner
0       Dealer       Manual      0
1       Dealer       Manual      0
2       Dealer       Manual      0
3       Dealer       Manual      0
4       Dealer       Manual      0
```

Data Exploration

```
cars.shape
```

```
(301, 9)
```

Our dataset has 301 observations and 9 columns

```
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       301 non-null    object 
 1   Year           301 non-null    int64  
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Driven_kms     301 non-null    int64  
 5   Fuel_Type      301 non-null    object 
 6   Selling_type   301 non-null    object 
 7   Transmission   301 non-null    object 
 8   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

```
cars_stats_summary=cars.describe()
palette = sns.color_palette('viridis', as_cmap=True)
cars_stats_summary.style.background_gradient(cmap=palette)
```

```
<pandas.io.formats.style.Styler at 0x1ec5ac3d970>
```

```
cars.columns
```

```
Index(['Car_Name', 'Year', 'Selling_Price', 'Present_Price',
'Driven_kms',
       'Fuel_Type', 'Selling_type', 'Transmission', 'Owner'],
      dtype='object')
```

```
cars["Car_Name"].unique()
```

```
array(['ritz', 'sx4', 'ciaz', 'wagon r', 'swift', 'vitara brezza',
       's cross', 'alto 800', 'ertiga', 'dzire', 'alto k10', 'ignis',
       '800', 'baleno', 'omni', 'fortuner', 'innova', 'corolla altis',
       'etios cross', 'etios g', 'etios liva', 'corolla', 'etios gd',
       'camry', 'land cruiser', 'Royal Enfield Thunder 500',
       'UM Renegade Mojave', 'KTM RC200', 'Bajaj Dominar 400',
       'Royal Enfield Classic 350', 'KTM RC390', 'Hyosung GT250R',
       'Royal Enfield Thunder 350', 'KTM 390 Duke ',
       'Mahindra Mojo XT300', 'Bajaj Pulsar RS200',
       'Royal Enfield Bullet 350', 'Royal Enfield Classic 500',
       'Bajaj Avenger 220', 'Bajaj Avenger 150', 'Honda CB Hornet
160R',
       'Yamaha FZ S V 2.0', 'Yamaha FZ 16', 'TVS Apache RTR 160',
       'Bajaj Pulsar 150', 'Honda CBR 150', 'Hero Extreme',
       'Bajaj Avenger 220 dtsi', 'Bajaj Avenger 150 street',
       'Yamaha FZ  v 2.0', 'Bajaj Pulsar  NS 200', 'Bajaj Pulsar 220
F',
       'TVS Apache RTR 180', 'Hero Passion X pro', 'Bajaj Pulsar NS
200',
       'Yamaha Fazer ', 'Honda Activa 4G', 'TVS Sport ',
       'Honda Dream Yuga ', 'Bajaj Avenger Street 220',
       'Hero Splender iSmart', 'Activa 3g', 'Hero Passion Pro',
       'Honda CB Trigger', 'Yamaha FZ S ', 'Bajaj Pulsar 135 LS',
       'Activa 4g', 'Honda CB Unicorn', 'Hero Honda CBZ extreme',
       'Honda Karizma', 'Honda Activa 125', 'TVS Jupyter',
       'Hero Honda Passion Pro', 'Hero Splender Plus', 'Honda CB
Shine',
       'Bajaj Discover 100', 'Suzuki Access 125', 'TVS Wego',
       'Honda CB twister', 'Hero Glamour', 'Hero Super Splendor',
       'Bajaj Discover 125', 'Hero Hunk', 'Hero  Ignitor Disc',
       'Hero  CBZ Xtreme', 'Bajaj  ct 100', 'i20', 'grand i10', 'i10',
       'eon', 'xcent', 'elantra', 'creta', 'verna', 'city', 'brio',
       'amaze', 'jazz'], dtype=object)

cars["Fuel_Type"].unique()

array(['Petrol', 'Diesel', 'CNG'], dtype=object)
```

Data Cleaning

```
#Checking for null values
missing = cars.isnull().sum()
print(missing)
print('\n There are no missing values in the dataset')

Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Driven_kms       0
Fuel_Type        0
Selling_type     0
Transmission     0
Owner            0
dtype: int64

 There are no missing values in the dataset

#Checking for duplicate values
duplicates=cars.duplicated().sum()
print(f"Number of duplicate rows = {duplicates}")

# drop duplicates
print("After dropping duplicates")
```

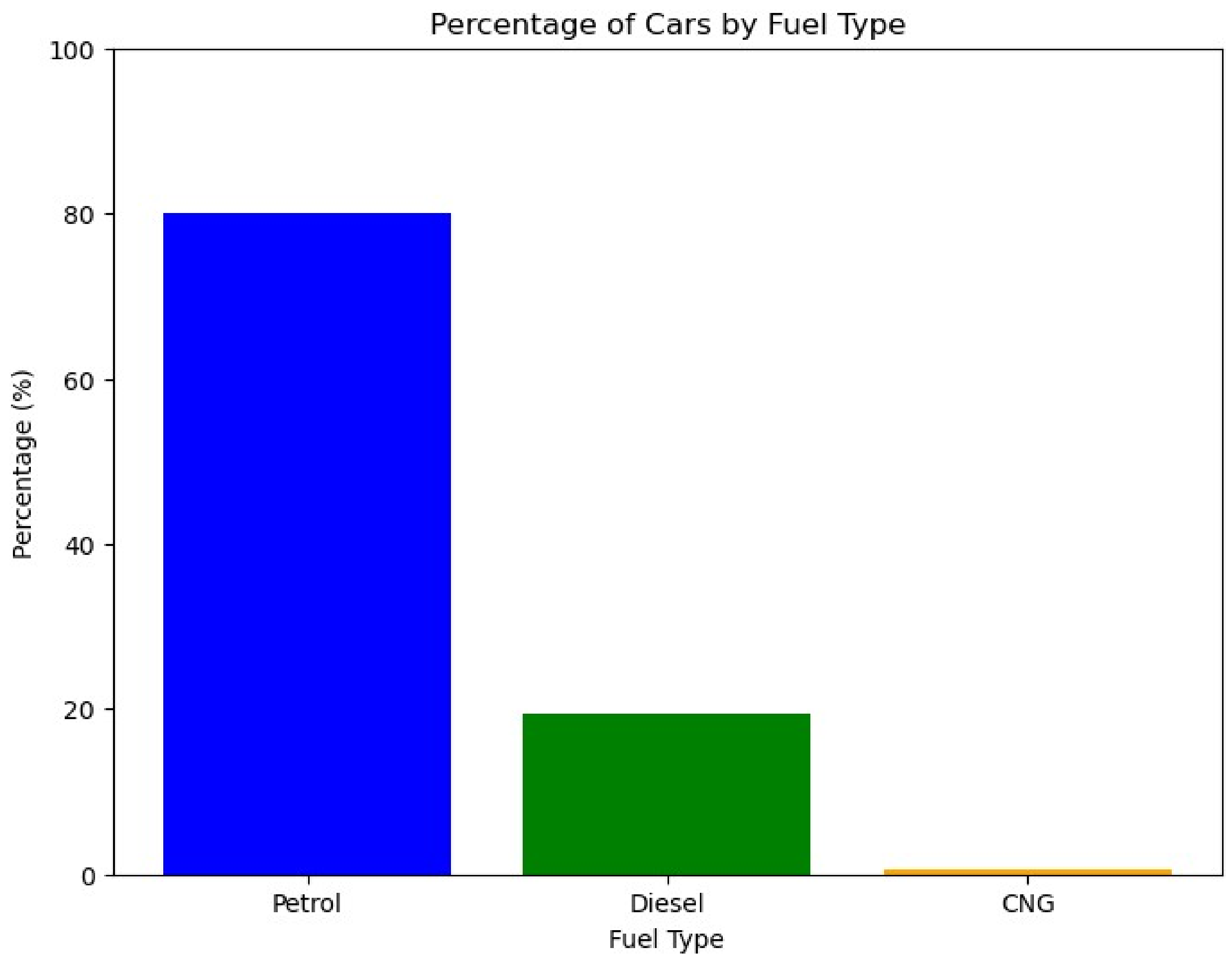
```
cars.drop_duplicates(inplace=True)
print(f"Number of duplicate rows = {cars.duplicated().sum()}")

Number of duplicate rows = 2
After dropping duplicates
Number of duplicate rows = 0

#Rename the "Year" column to "Manufacture Year"
cars.rename(columns={"Year": "Manufacturing_Year"}, inplace=True)
cars.head()

  Car_Name  Manufacturing_Year  Selling_Price  Present_Price
Driven_kms  \
0     ritz                2014           3.35           5.59
27000
1      sx4                2013           4.75           9.54
43000
2     ciaz                2017           7.25           9.85
6900
3  wagon r                2011           2.85           4.15
5200
4    swift                2014           4.60           6.87
42450

  Fuel_Type Selling_type Transmission  Owner
0    Petrol       Dealer       Manual      0
1    Diesel       Dealer       Manual      0
2    Petrol       Dealer       Manual      0
3    Petrol       Dealer       Manual      0
4    Diesel       Dealer       Manual      0

#What is the average selling price of cars in the dataset?
average_selling_price = cars['Selling_Price'].mean()
print(f"The average selling price of cars in the dataset is: $
{average_selling_price:.2f}")

The average selling price of cars in the dataset is: $4.59
```

Data Visualization

```
petrol_percentage = (len(cars[cars["Fuel_Type"] == 'Petrol']) /
len(cars)) * 100
print(f"Petrol percentage is {petrol_percentage:.2f}%")
diesel_percentage = (len(cars[cars["Fuel_Type"] == 'Diesel']) /
len(cars)) * 100
print(f"Diesel percentage is {diesel_percentage:.2f}%")
cng_percentage = (len(cars[cars["Fuel_Type"] == 'CNG']) / len(cars)) *
100
print(f"CNG percentage is {cng_percentage:.2f}%")
```

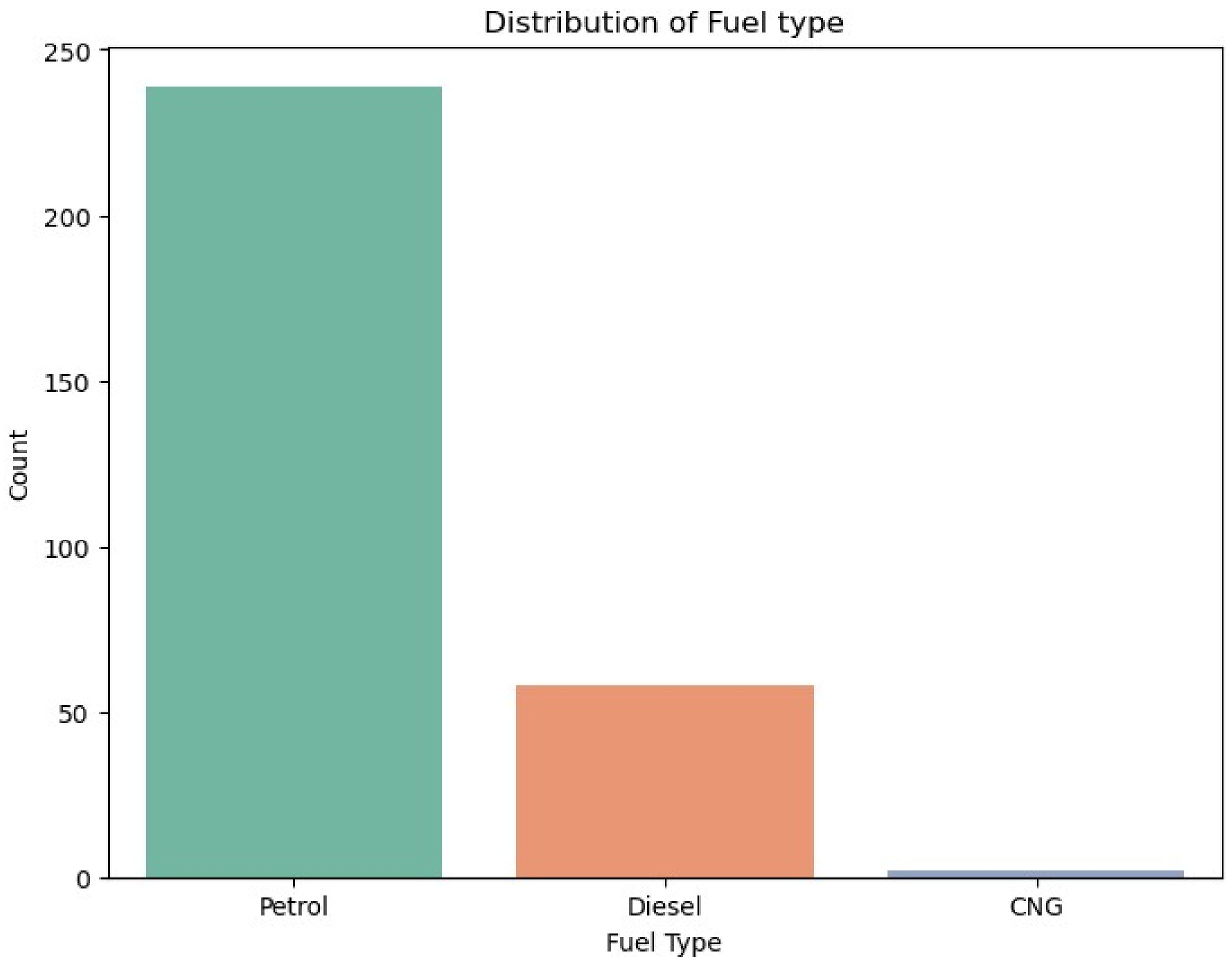
```
# Data for the bar plot
fuel_types = ['Petrol', 'Diesel', 'CNG']
percentages = [petrol_percentage, diesel_percentage, cng_percentage]

# Create the bar plot
plt.figure(figsize=(8, 6))
plt.bar(fuel_types, percentages, color=['blue', 'green', 'orange'])
plt.title('Percentage of Cars by Fuel Type')
plt.xlabel('Fuel Type')
plt.ylabel('Percentage (%)')
plt.ylim(0, 100)  # Set y-axis limit to 0-100%
plt.show()
```

```
Petrol percentage is 79.93%
Diesel percentage is 19.40%
CNG percentage is 0.67%
```

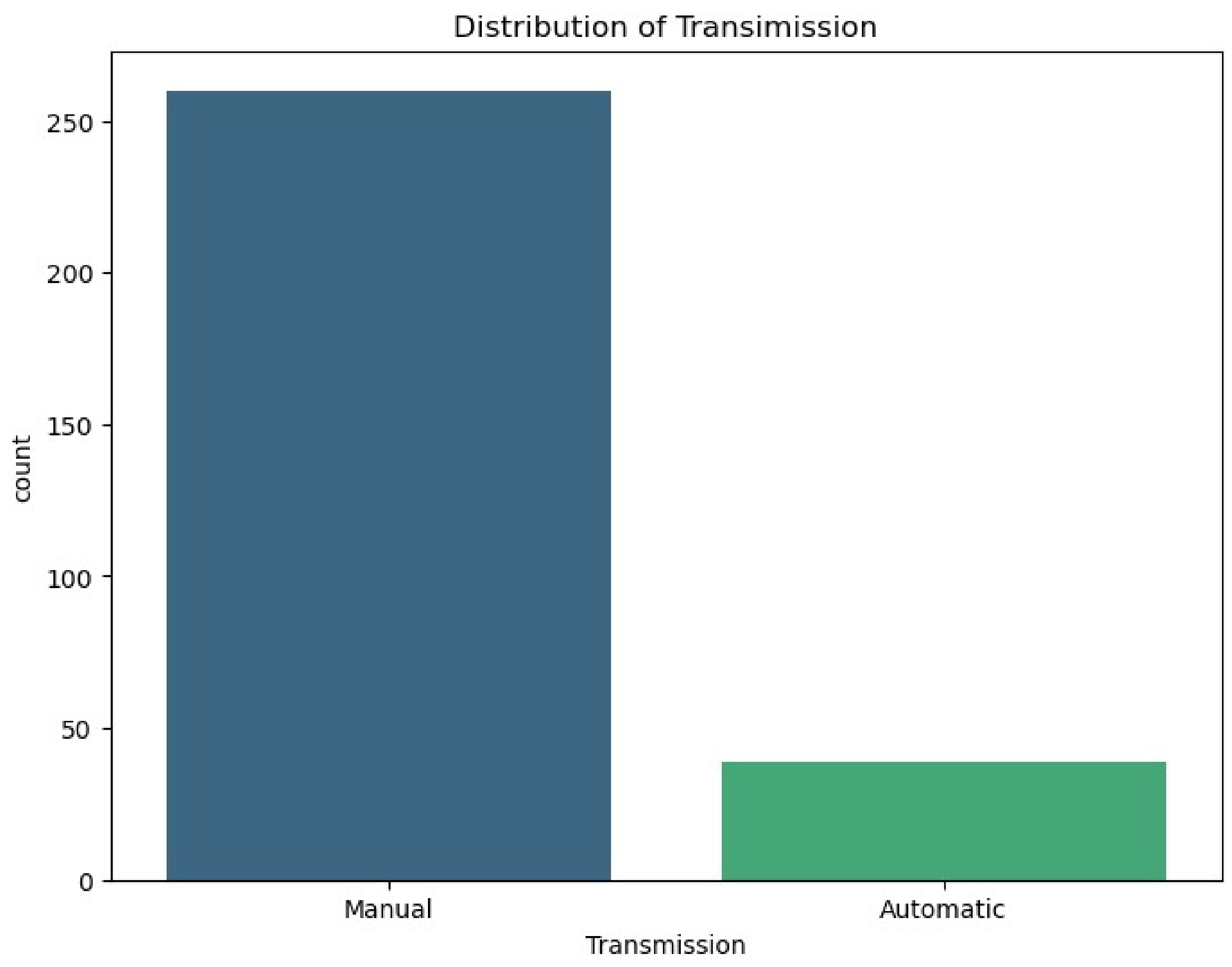


```
#distribution of fuel types (Petrol, Diesel, CNG)
plt.figure(figsize=(8,6))
```

```
sns.countplot(x= 'Fuel_Type', data= cars, palette='Set2')
plt.title("Distribution of Fuel type")
plt.xlabel("Fuel Type")
plt.ylabel("Count")

Text(0, 0.5, 'Count')
```



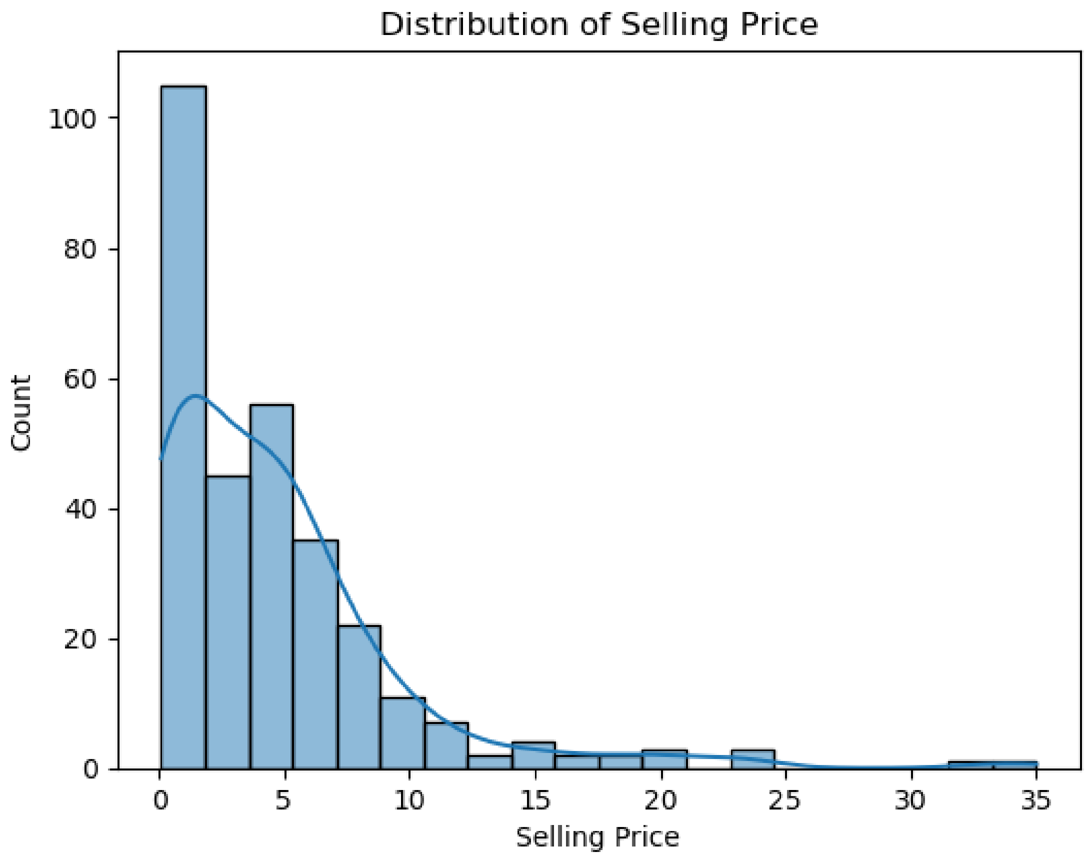
```
#Which transmission type (Manual or Automatic) is more common in the
dataset
plt.figure(figsize=(8, 6))
sns.countplot(x= 'Transmission', data= cars, palette='viridis')
plt.title("Distribution of Transimission")

Text(0.5, 1.0, 'Distribution of Transimission')
```



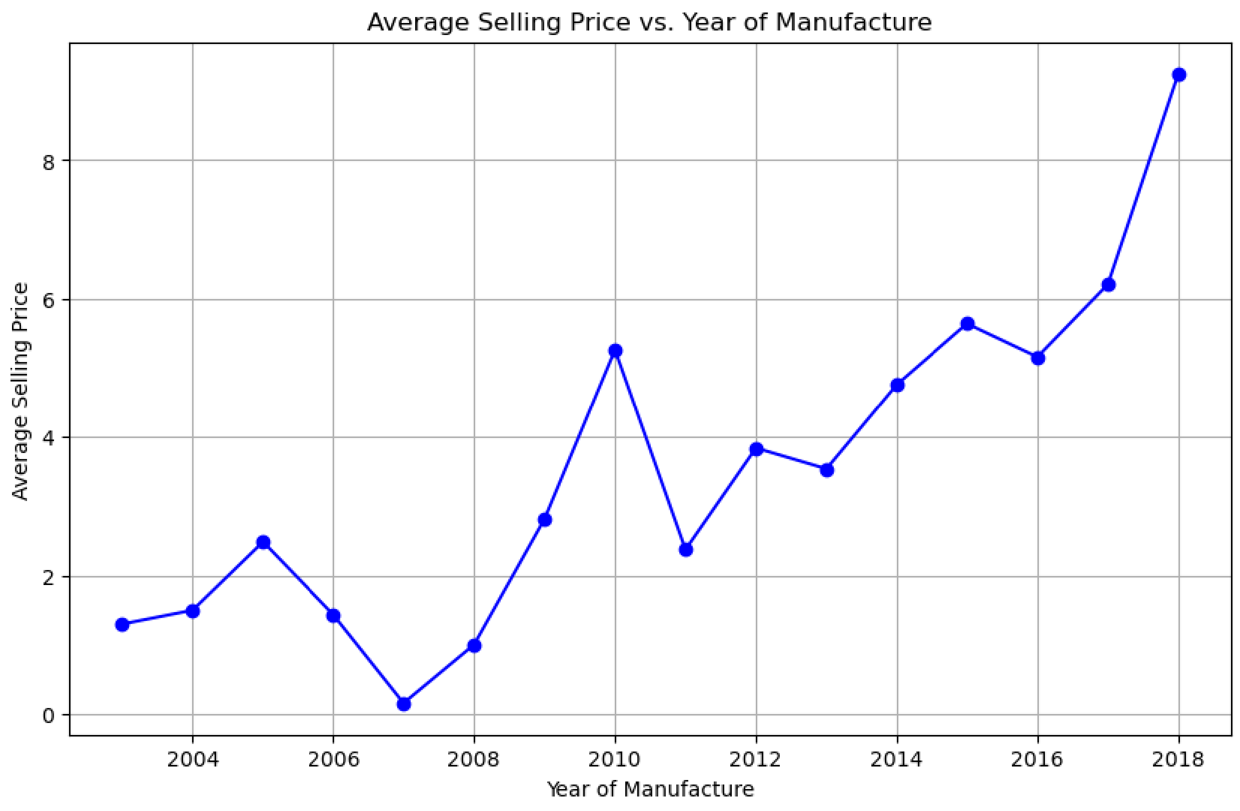
Most cars sold are manual transmissions

```
#Distribution of the target variable
sns.histplot(x= 'Selling_Price',kde= True,bins=20,data= cars)
plt.title("Distribution of Selling Price")
plt.xlabel("Selling Price")
```

```
Text(0.5, 0, 'Selling Price')
```



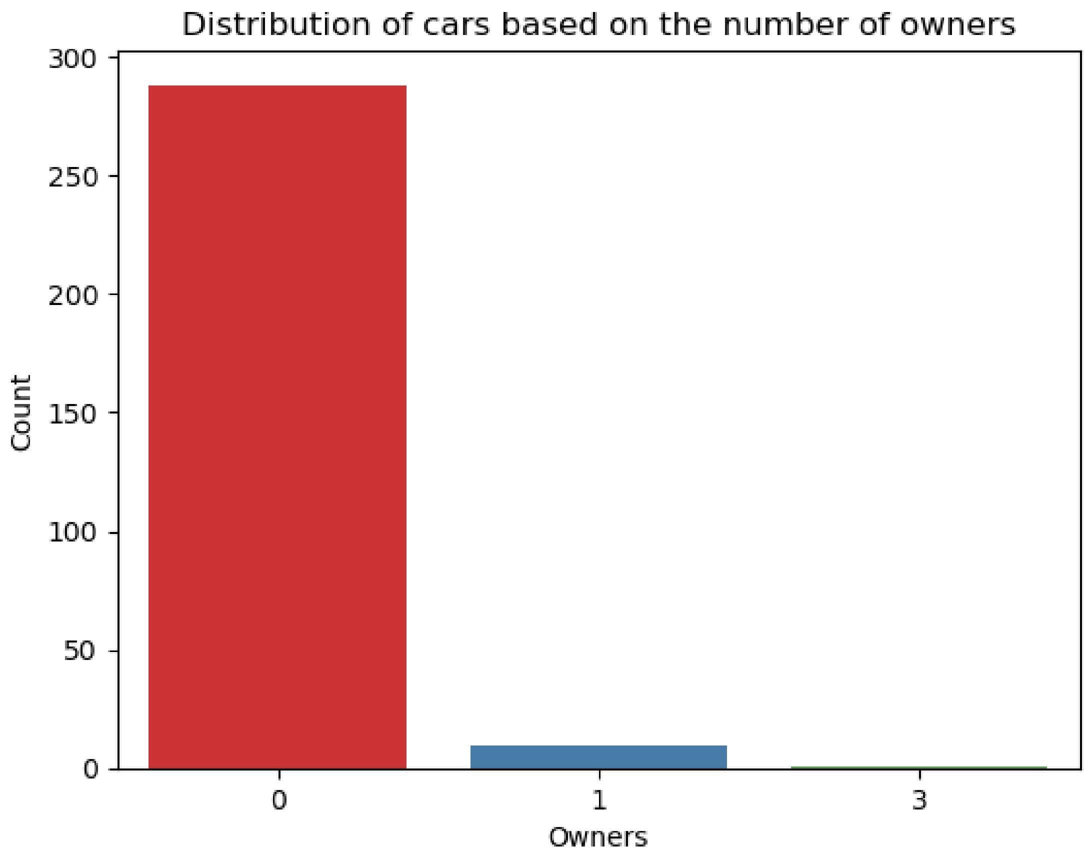
```
#selling price vary with the year of manufacture?
yearly_avg_price = cars.groupby('Manufacturing_Year')
['Selling_Price'].mean().reset_index()
#Visualization of Year vs Manufacturing Price
plt.figure(figsize=(10, 6))
plt.plot(yearly_avg_price['Manufacturing_Year'],
yearly_avg_price['Selling_Price'], marker='o', linestyle='-',
color='b')
plt.title('Average Selling Price vs. Year of Manufacture')
plt.xlabel('Year of Manufacture')
plt.ylabel('Average Selling Price')
plt.grid(True)
plt.show()
```



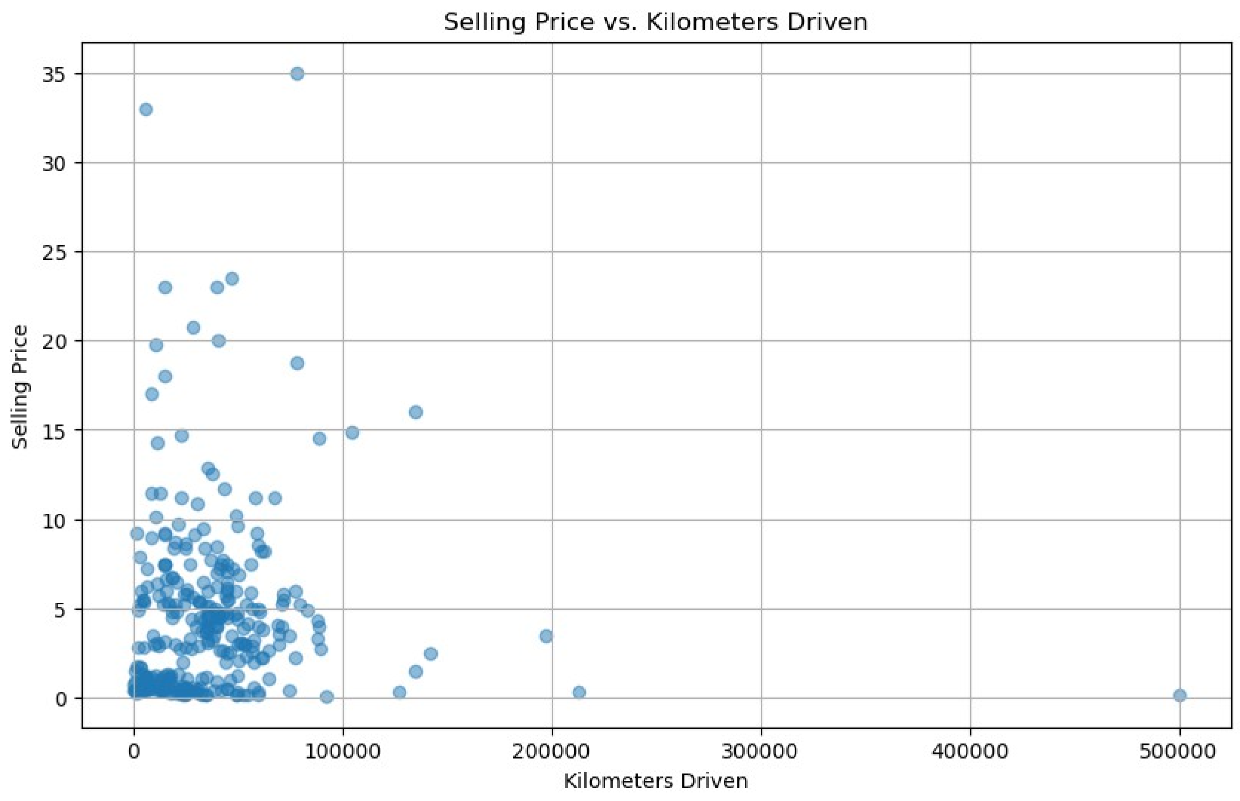
The graph shows that newer cars generally have higher selling prices, while older ones depreciate over time. Although the trend is upward, some years experience temporary dips due to market conditions or model demand. A sharp rise after 2015 suggests that newer models retain more value

```
#distribution of cars based on the number of owners (0, 1, or more)
sns.countplot(x="Owner", data= cars, palette="Set1")
plt.title("Distribution of cars based on the number of owners")
plt.xlabel("Owners")
plt.ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```



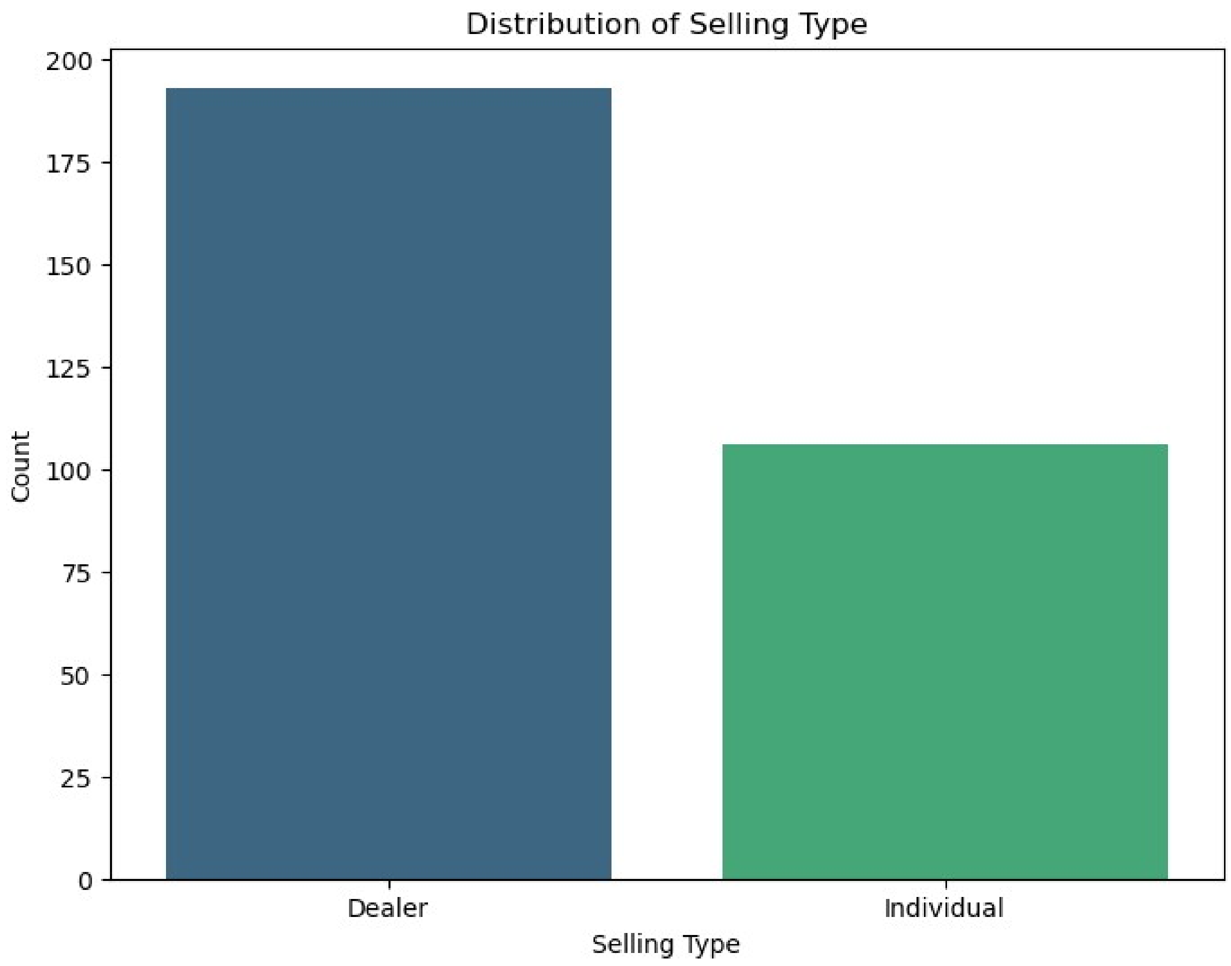
```
#Selling Price vs Kilometers driven
# Scatter plot: Kilometers Driven vs. Selling Price
plt.figure(figsize=(10, 6))
plt.scatter(cars['Driven_kms'], cars['Selling_Price'], alpha=0.5)
plt.title('Selling Price vs. Kilometers Driven')
plt.xlabel('Kilometers Driven')
plt.ylabel('Selling Price')
plt.grid(True)
plt.show()
```



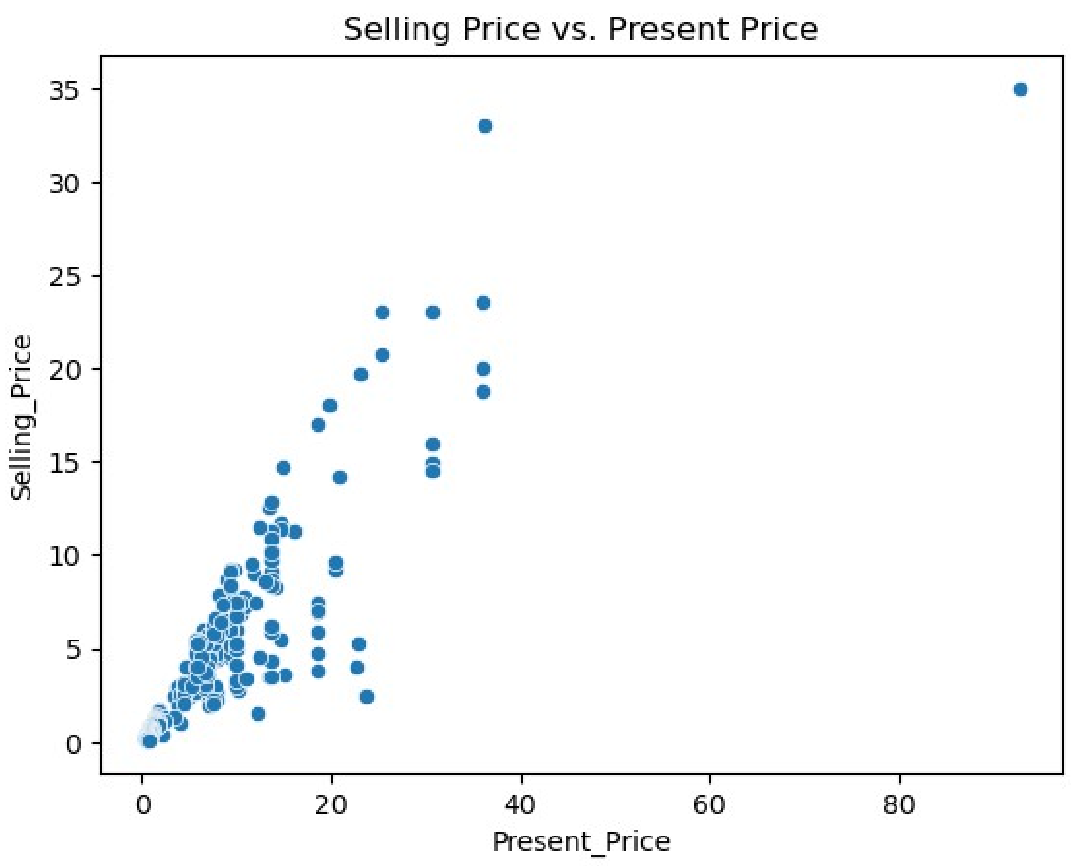
The scatter plot shows the relationship between kilometers driven and selling price of cars. In general, cars with lower kilometers driven tend to have higher selling prices, indicating that usage affects resale value. As kilometers driven increase, selling prices decrease, though some exceptions exist, possibly due to brand, model, or maintenance quality

```
#Distribution of selling type
plt.figure(figsize=(8, 6))
sns.countplot(x="Selling_type", data= cars, palette="viridis")
plt.title('Distribution of Selling Type')
plt.xlabel('Selling Type')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```

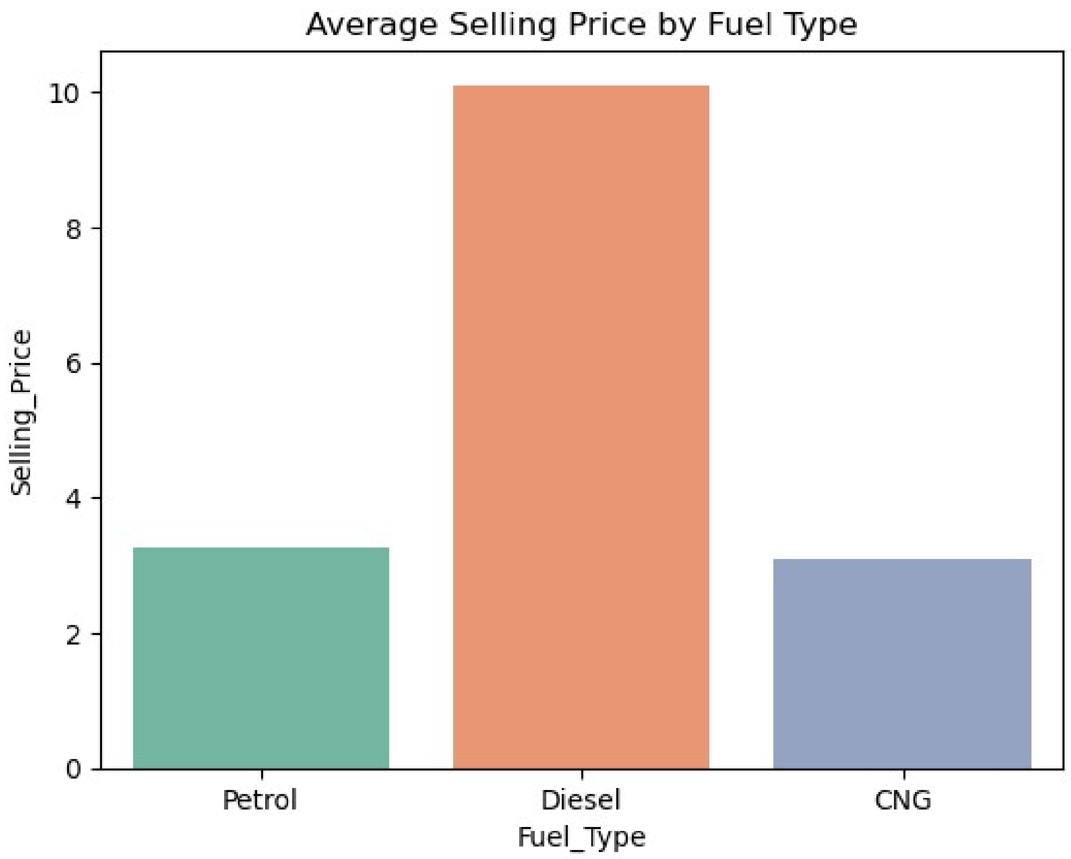


```
# Selling Price vs. Present Price (Scatter Plot)
sns.scatterplot(x='Present_Price', y='Selling_Price', data=cars)
plt.title('Selling Price vs. Present Price')
plt.show()
```



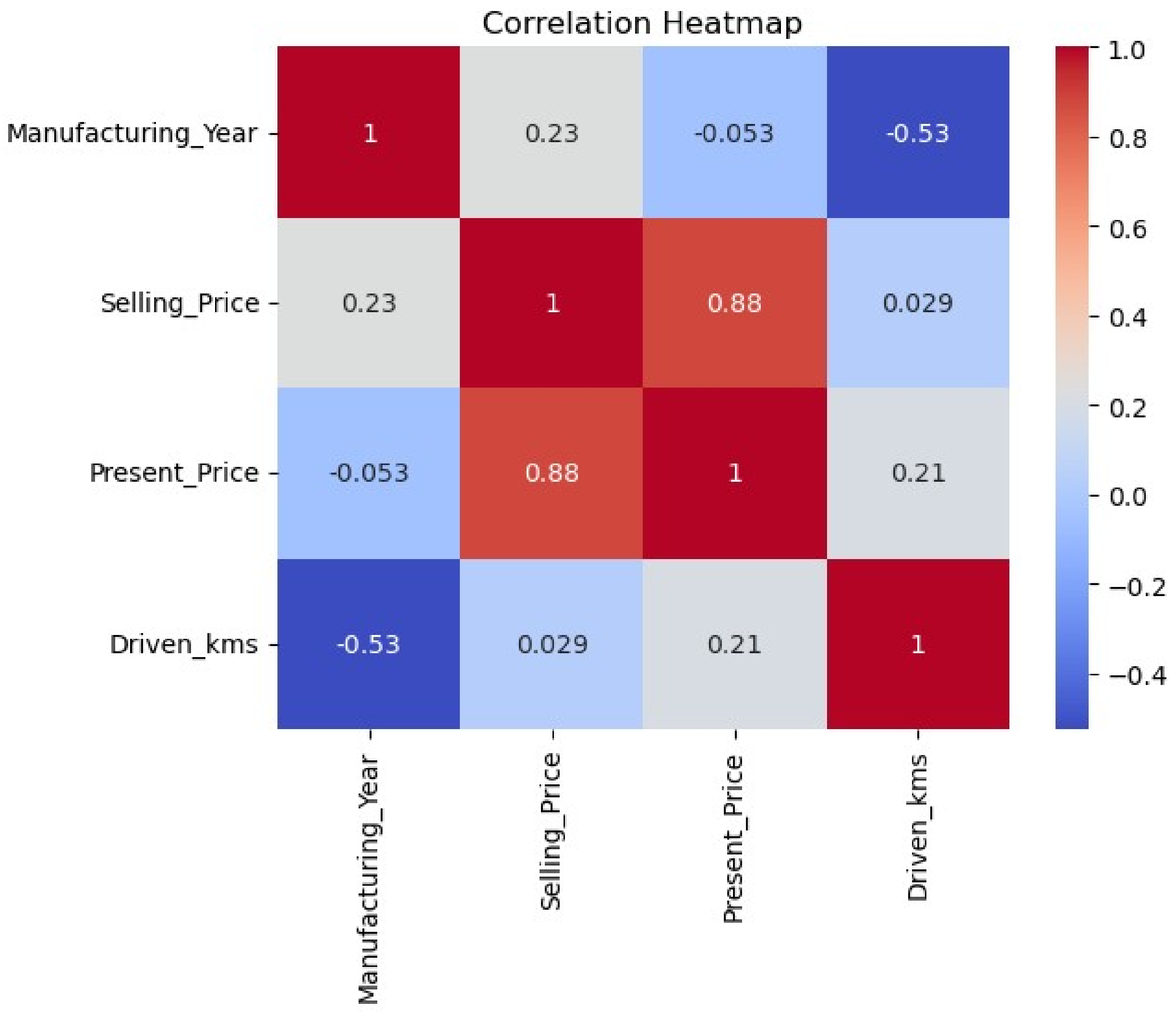
The plot visualizes the relationship between the present price and selling price There is a strong positive relationship between the present price and selling price, indicating that higher-priced cars tend to sell for more.

```
#Average Selling Price by Fuel Type (Bar Plot)
sns.barplot(x='Fuel_Type', y='Selling_Price', data=cars,
estimator='mean', ci= None, palette="Set2")
plt.title('Average Selling Price by Fuel Type')
plt.show()
```

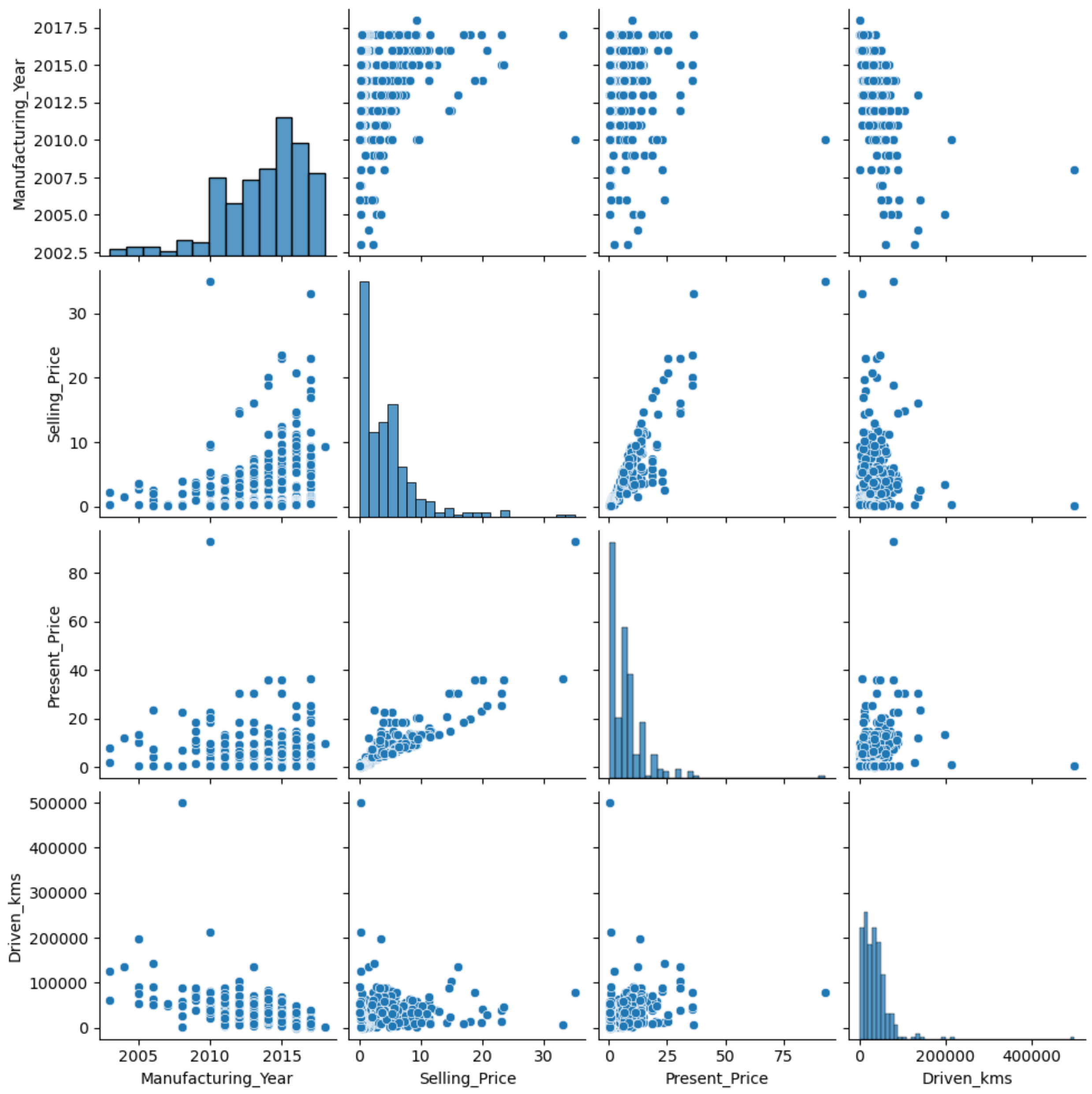


The barplot shows the average selling price by fuel type. Cars which use diesel are more expensive compared to cars which use other fuel types

```
#Correlation of numerical values
numerical_cols = ['Manufacturing_Year', 'Selling_Price',
'Present_Price', 'Driven_kms']
sns.heatmap(cars[numerical_cols].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

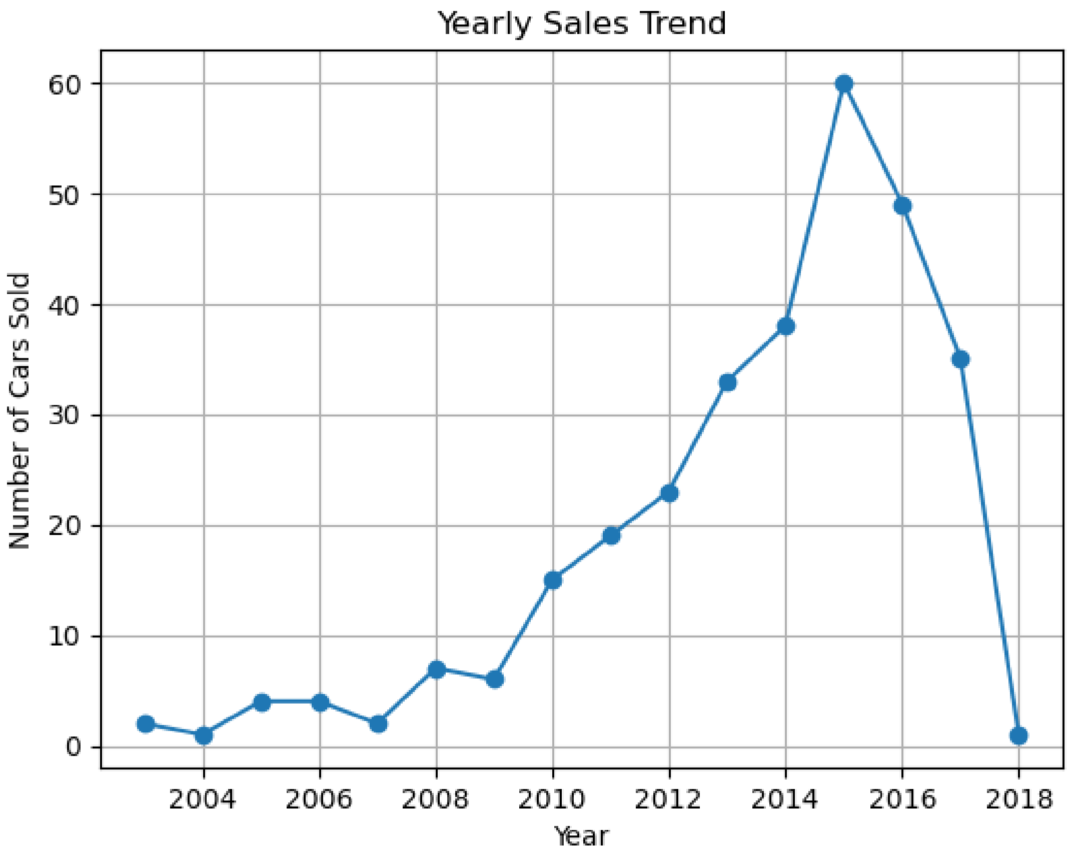


```
#Pairplot
sns.pairplot(cars[numerical_cols])
plt.show()
```



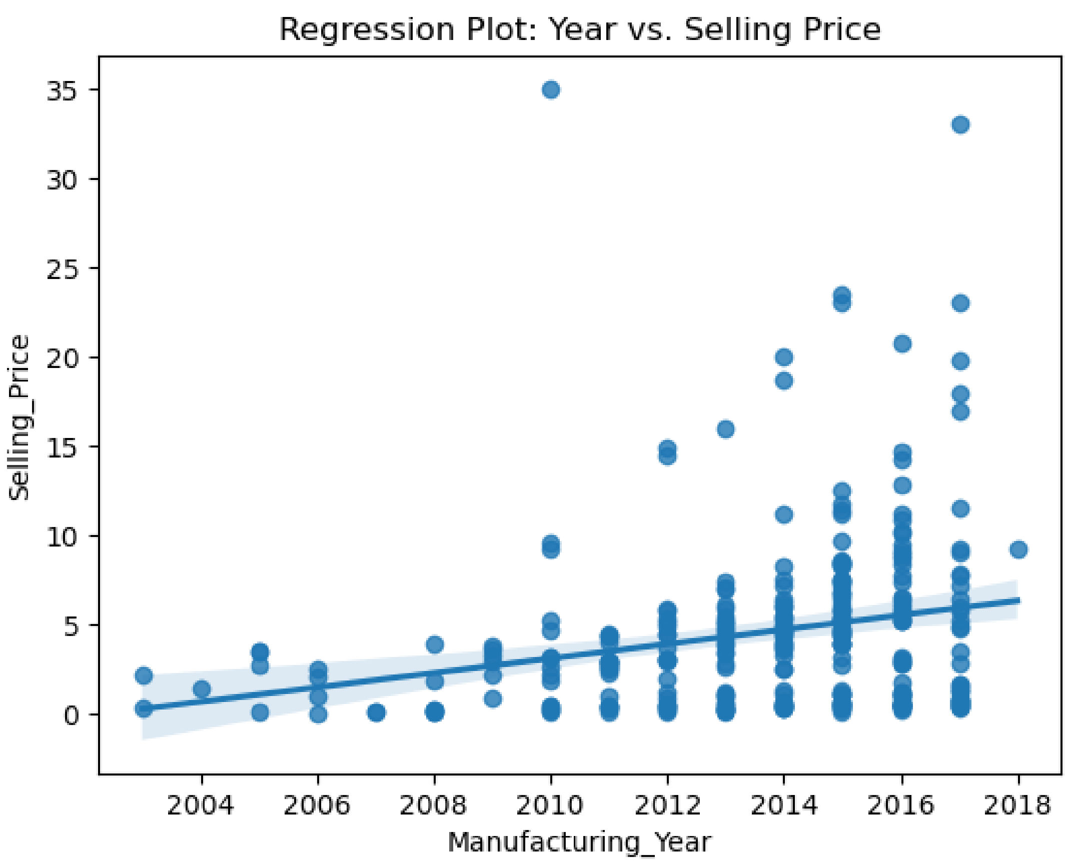
This pairplot visualizes relationships between numerical variables in the dataset. Selling_Price and Present_Price show a strong positive correlation, meaning higher present prices lead to higher selling prices. Manufacturing_Year negatively correlates with Driven_kms, indicating that older cars tend to have more kilometers driven.

```python
#Yearly sales trend
yearly_sales = cars['Manufacturing_Year'].value_counts().sort_index()
plt.plot(yearly_sales.index, yearly_sales.values, marker='o')
plt.title('Yearly Sales Trend')
plt.xlabel('Year')
plt.ylabel('Number of Cars Sold')
plt.grid()
plt.show()
```



The plot shows fluctuations in car sales over the years, with peaks and dips

```
#linear relationship between year and price.
sns.regplot(x='Manufacturing_Year', y='Selling_Price', data=cars)
plt.title('Regression Plot: Year vs. Selling Price')
plt.show()
```



This plot shows that newer cars (higher manufacturing year) tend to have higher selling prices.

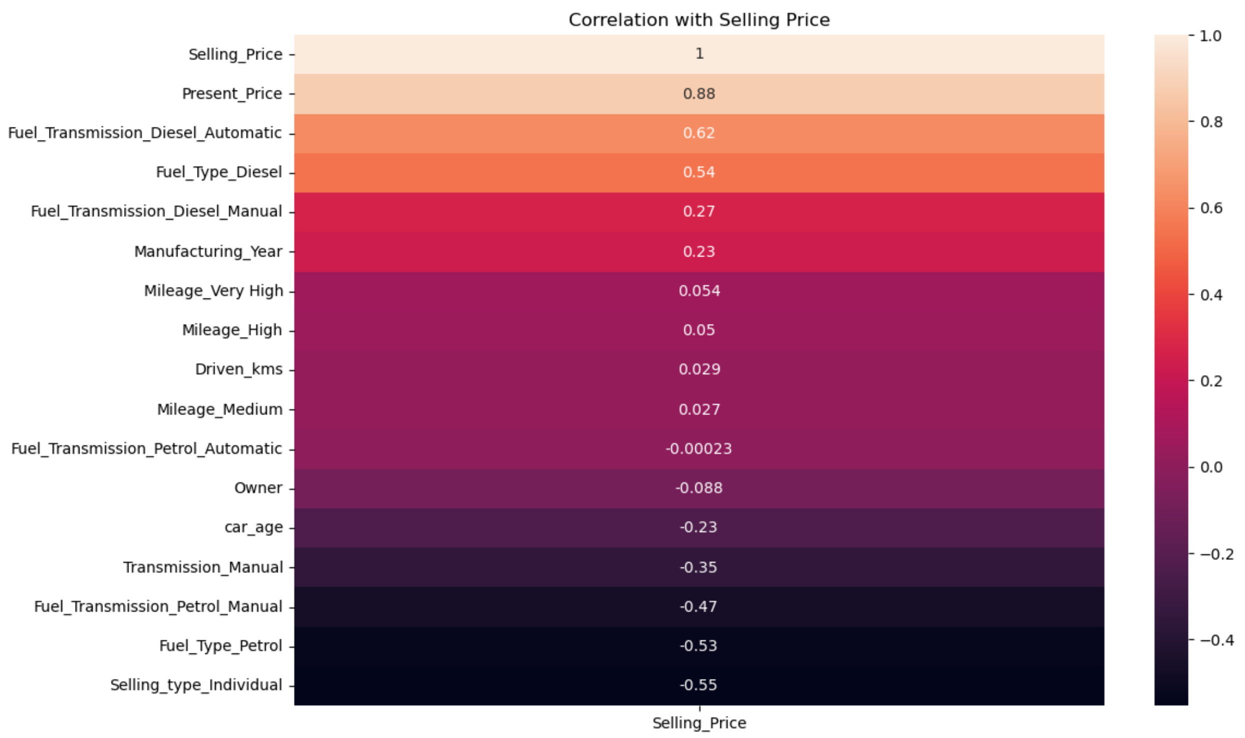
Feature engineering and selection

1.Create Age from Year. 2.Bin Driven_kms into categories. 3.Create interaction features (Fuel_Type * Transmission). 4.One-hot encode categorical variables.

```
#Create Age from Year
current_year= 2025
cars['car_age']= current_year- cars["Manufacturing_Year"]
cars.head()

  Car_Name  Manufacturing_Year  Selling_Price  Present_Price 
Driven_kms  \
0     ritz                2014           3.35           5.59 
27000
1      sx4                2013           4.75           9.54 
43000
2     ciaz                2017           7.25           9.85 
6900
3  wagon r                2011           2.85           4.15 
5200
4    swift                2014           4.60           6.87 
42450
```

```
  Fuel_Type Selling_type Transmission  Owner  car_age
0    Petrol       Dealer       Manual      0       11
1    Diesel       Dealer       Manual      0       12
2    Petrol       Dealer       Manual      0        8
3    Petrol       Dealer       Manual      0       14
4    Diesel       Dealer       Manual      0       11

#Bin Driven_kms into categories
bins = [0, 20000, 50000, 100000, 200000]
labels = ['Low', 'Medium', 'High', 'Very High']
cars['Mileage'] = pd.cut(cars['Driven_kms'], bins=bins, labels=labels)
cars.head()

  Car_Name  Manufacturing_Year  Selling_Price  Present_Price  
Driven_kms  \
0     ritz                2014           3.35           5.59  
27000
1      sx4                2013           4.75           9.54  
43000
2     ciaz                2017           7.25           9.85  
6900
3  wagon r                2011           2.85           4.15  
5200
4    swift                2014           4.60           6.87  
42450

  Fuel_Type Selling_type Transmission  Owner  car_age Mileage
0    Petrol       Dealer       Manual      0       11  Medium
1    Diesel       Dealer       Manual      0       12  Medium
2    Petrol       Dealer       Manual      0        8     Low
3    Petrol       Dealer       Manual      0       14     Low
4    Diesel       Dealer       Manual      0       11  Medium

#Create interaction features (Fuel_Type * Transmission)
cars['Fuel_Transmission'] = cars['Fuel_Type'] + '_' +
cars['Transmission']
cars.head()

  Car_Name  Manufacturing_Year  Selling_Price  Present_Price  
Driven_kms  \
0     ritz                2014           3.35           5.59  
27000
1      sx4                2013           4.75           9.54  
43000
2     ciaz                2017           7.25           9.85  
6900
3  wagon r                2011           2.85           4.15  
5200
4    swift                2014           4.60           6.87
```

```
42450

  Fuel_Type Selling_type Transmission  Owner  car_age Mileage  \
0    Petrol       Dealer       Manual      0       11  Medium
1    Diesel       Dealer       Manual      0       12  Medium
2    Petrol       Dealer       Manual      0        8     Low
3    Petrol       Dealer       Manual      0       14     Low
4    Diesel       Dealer       Manual      0       11  Medium

  Fuel_Transmission
0     Petrol_Manual
1     Diesel_Manual
2     Petrol_Manual
3     Petrol_Manual
4     Diesel_Manual

#Dropping Car_Name column
cars.drop('Car_Name', axis = 1, inplace=True)
cars.columns

Index(['Manufacturing_Year', 'Selling_Price', 'Present_Price',
'Driven_kms',
       'Fuel_Type', 'Selling_type', 'Transmission', 'Owner',
'car_age',
       'Mileage', 'Fuel_Transmission'],
      dtype='object')

#Encoding
cars_encoded = pd.get_dummies(cars,
columns=['Fuel_Type', 'Selling_type', 'Transmission', 'Mileage',
'Fuel_Transmission'],
    drop_first=True
)

#Correlation Analysis
correlation_matrix = cars_encoded.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix[['Selling_Price']].sort_values(by='Sell
ing_Price', ascending=False), annot=True)
plt.title('Correlation with Selling Price')
plt.show()
```



This plot shows the correlation between numerical features and the target variable (Selling_Price). Present_Price has a strong positive correlation with Selling_Price. Manufacturing_Year also shows a positive correlation. Features like Owner and car_age have a negative correlation with Selling_Price.

Model Training

```
#Features and target
X= cars.drop("Selling_Price", axis = 1)
y= cars["Selling_Price"]

#Splitting the data
X_train,X_test,y_train,y_test= train_test_split(X,y, test_size=0.2,
random_state=42)

label_encoder = LabelEncoder()
X_train['Fuel_Type'] =
label_encoder.fit_transform(X_train['Fuel_Type'])
X_test['Fuel_Type'] = label_encoder.transform(X_test['Fuel_Type'])

X_train['Selling_type'] =
label_encoder.fit_transform(X_train['Selling_type'])
X_test['Selling_type'] =
label_encoder.transform(X_test['Selling_type'])

X_train['Transmission'] =
label_encoder.fit_transform(X_train['Transmission'])
X_test['Transmission'] =
label_encoder.transform(X_test['Transmission'])

X_train['Mileage'] = label_encoder.fit_transform(X_train['Mileage'])
X_test['Mileage'] = label_encoder.transform(X_test['Mileage'])

X_train['Fuel_Transmission'] =
label_encoder.fit_transform(X_train['Fuel_Transmission'])
X_test['Fuel_Transmission'] =
label_encoder.transform(X_test['Fuel_Transmission'])
#label_encoder.fit_transform([['Fuel_Type', 'Selling_type',
'Transmission', 'Mileage', 'Fuel_Transmission']])

#Standardising data
scaler= StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

y_pred_baseline= [y_train.mean()]* len(y_train)
mae_baseline= mean_absolute_error(y_train,y_pred_baseline)
print(f"The MAE of the baseline model is {mae_baseline}")
```

```
The MAE of the baseline model is 3.3849918593862145
```

```
#Model training
lr= LinearRegression()
rf= RandomForestRegressor()
gb= GradientBoostingRegressor()
xr= XGBRegressor()

lr.fit(X_train,y_train)
print(f"{lr} \nmodel trained successfully!")
rf.fit(X_train,y_train)
print(f"{rf}\n model trained successfully!")
gb.fit(X_train,y_train)
print(f"{gb} \nmodel trained successfully!")
xr.fit(X_train,y_train)
print(f"{xr} \nmodel trained successfully!")
```

```
LinearRegression()
model trained successfully!
RandomForestRegressor()
 model trained successfully!
GradientBoostingRegressor()
model trained successfully!
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None,
early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None,
feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None,
max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan,
monotone_constraints=None,
             multi_strategy=None, n_estimators=None, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
model trained successfully!
```

```
#Accuracy
linear_score=lr.score(X_test,y_test)
print(f"Accuracy score LinearRegression is {linear_score:2f}")
random_score= rf.score(X_test,y_test)
print(f"Accuracy score Random Forest is {random_score:2f}")
gradient_score= gb.score(X_test,y_test)
print(f"Accuracy score GradientBoost is {gradient_score:2f}")
xgb_score= xr.score(X_test,y_test)
print(f"Accuracy score XGBRegressor is {xgb_score:2f}")
```

```
Accuracy score LinearRegression is 0.743422
Accuracy score Random Forest is 0.413490
Accuracy score GradientBoost is 0.693247
Accuracy score XGBRegressor is 0.798654
```

The best performing model is XGBRegressor with 79.86% accuracy score

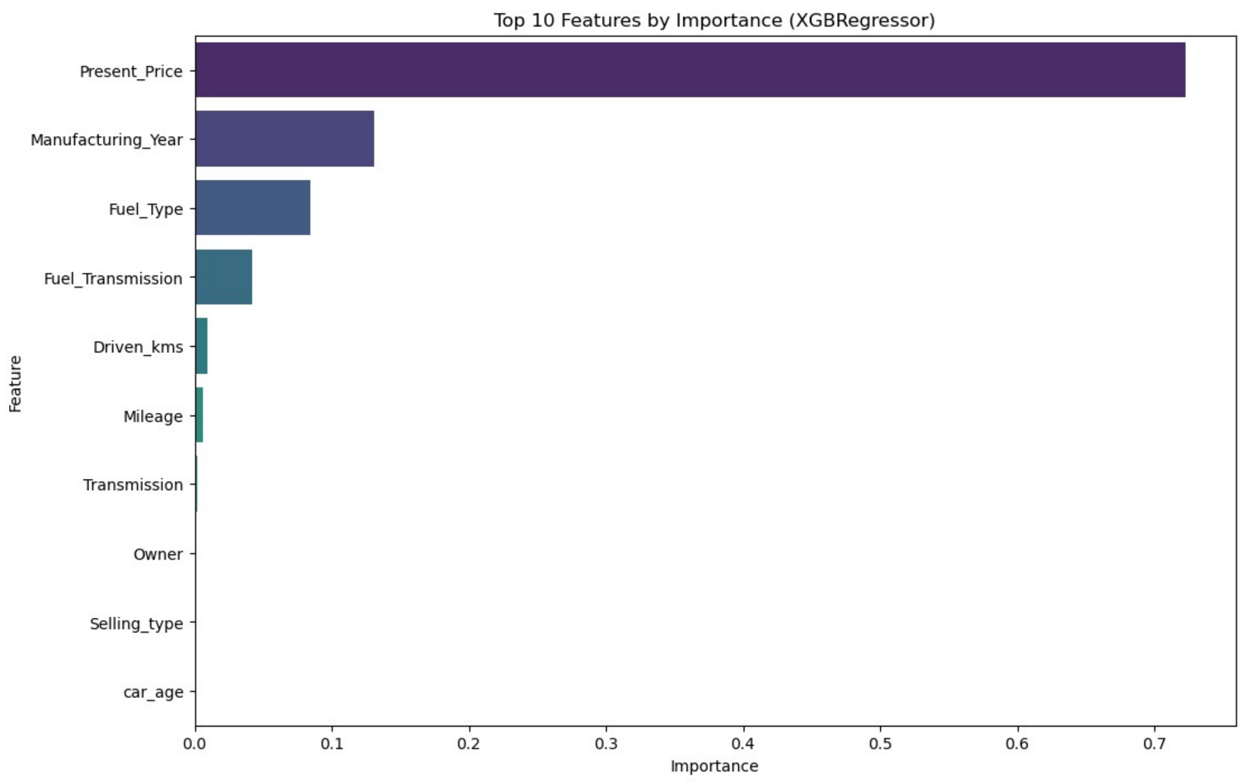
```
#Define parameter grids for each model
param_grids = {
    'Linear Regression': {},#Linear Regression doesn't have any
parameters to tune
    'Random Forest': {
        'n_estimators': [50, 100, 200],
        'max_depth': [None, 10, 20],
        'min_samples_split': [2, 5, 10]
    },
    'Gradient Boosting': {
        'n_estimators': [50, 100, 200],
        'learning_rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 5, 10]
    },
    'XGBRegressor': {
        'n_estimators': [50, 100, 200],
        'learning_rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 5, 10]
    }
}

# Define models
```

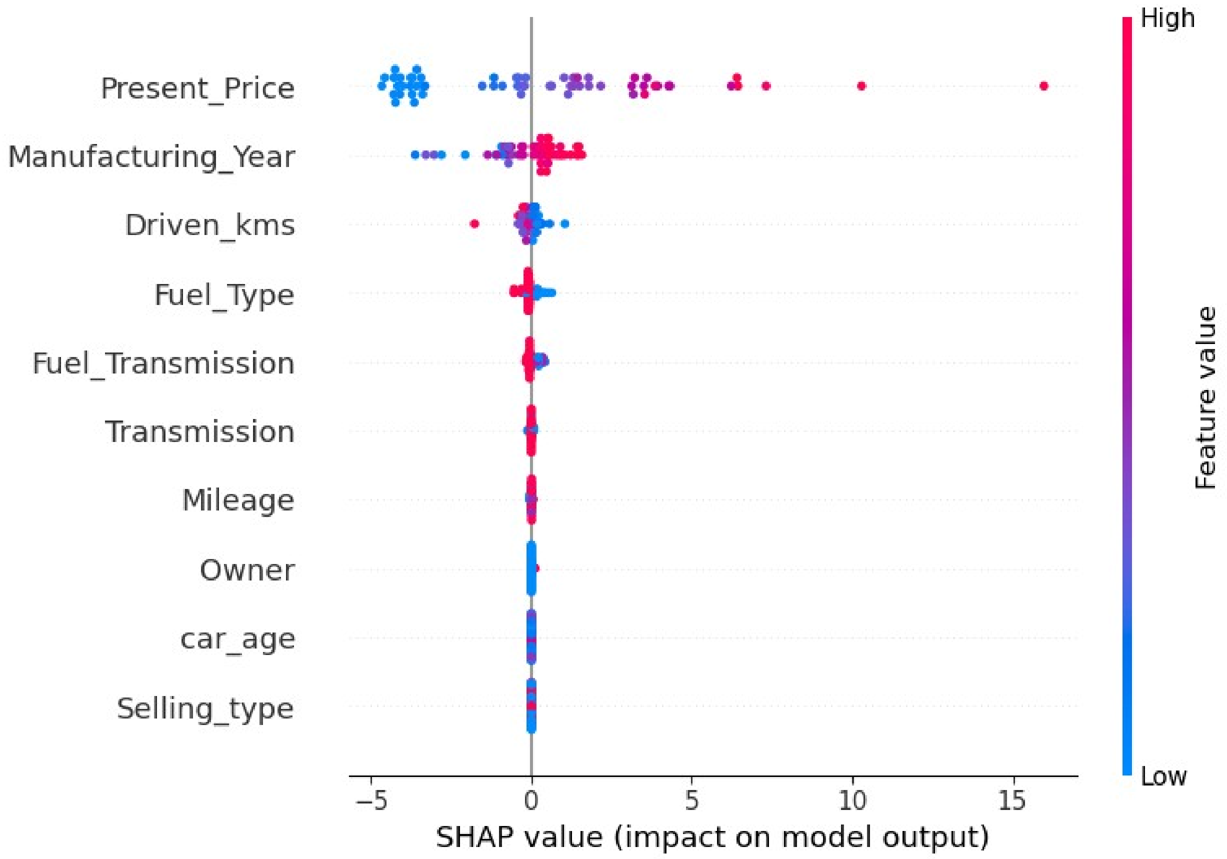
```
models = {
    'Linear Regression': make_pipeline(StandardScaler(),
LinearRegression()),
    'Random Forest': RandomForestRegressor(),
    'Gradient Boosting': GradientBoostingRegressor(),
    'XGBRegressor': XGBRegressor()
}

best_models = {}
results = {}

for model_name, model in models.items():
    print(f"Tuning {model_name}...")

    # Check if the model is a pipeline to avoid double scaling for
tree-based models
    if 'Linear Regression' in model_name:
        pipeline = model
        param_grid = param_grids[model_name]
    else:
        pipeline = model
        param_grid = param_grids[model_name]

    # Use GridSearchCV to find the best parameters
    grid_search = GridSearchCV(pipeline, param_grid, cv=5,
scoring='neg_mean_squared_error', n_jobs=-1)
    grid_search.fit(X_train, y_train)

    # Store the best model and results
    best_models[model_name] = grid_search.best_estimator_
    preds = grid_search.best_estimator_.predict(X_test)

    results[model_name] = {
        'Best Parameters': grid_search.best_params_,
        'MSE': mean_squared_error(y_test, preds),
        'R²': r2_score(y_test, preds),
        'MAE': mean_absolute_error(y_test,preds)
    }

# Print results
print("\nBest Model Results:")
for model_name, metrics in results.items():
    print(f"\n{model_name}")
    print(f"Best Parameters: {metrics['Best Parameters']}")
    print(f"MSE: {metrics['MSE']:.2f}")
    print(f"R²: {metrics['R²']:.4f}")
    print(f"MAE: {metrics['MAE']:.4f}")

# Identify the best model
best_model_name = min(results, key=lambda k: results[k]['MSE'])
```

```
print(f"\nThe best model is {best_model_name} with an MSE of
{results[best_model_name]['MSE']:.2f}")

Tuning Linear Regression...
Tuning Random Forest...
Tuning Gradient Boosting...
Tuning XGBRegressor...

Best Model Results:

Linear Regression
Best Parameters: {}
MSE: 6.61
R²: 0.7434
MAE: 1.5457

Random Forest
Best Parameters: {'max_depth': None, 'min_samples_split': 10,
'n_estimators': 50}
MSE: 16.64
R²: 0.3546
MAE: 1.6173

Gradient Boosting
Best Parameters: {'learning_rate': 0.2, 'max_depth': 3,
'n_estimators': 100}
MSE: 8.24
R²: 0.6803
MAE: 1.2982

XGBRegressor
Best Parameters: {'learning_rate': 0.2, 'max_depth': 3,
'n_estimators': 200}
MSE: 3.61
R²: 0.8600
MAE: 0.9248

The best model is XGBRegressor with an MSE of 3.61

#Feature importance
#the best model is XGBRegressor
best_model = best_models['XGBRegressor']

# Get feature importances
feature_importance = best_model.feature_importances_

# Map feature importance scores to feature names
feature_names = X_train.columns  # Ensure X_train contains the
original feature names
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importance
}).sort_values(by='Importance', ascending=False)

print("Top 10 Features by Importance:")
print(importance_df.head(10))
```

```
Top 10 Features by Importance:
              Feature  Importance
1       Present_Price    0.722966
0  Manufacturing_Year    0.131015
3           Fuel_Type    0.084633
9   Fuel_Transmission    0.042161
2          Driven_kms    0.009682
8             Mileage    0.006310
5        Transmission    0.002355
6               Owner    0.000878
4        Selling_type    0.000000
7             car_age    0.000000
```

```
#Visualize feature importance
# 1. Get feature importances
best_model = best_models[best_model_name]
feature_importance = best_model.feature_importances_
importance_df = pd.DataFrame({'Feature': X_train.columns,
'Importance': feature_importance})
importance_df = importance_df.sort_values(by='Importance',
ascending=False)

# 2. Plot feature importance
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=importance_df.head(10),
palette='viridis')
plt.title(f'Top 10 Features by Importance ({best_model_name})')
plt.show()

# 3. SHAP summary plot (for tree-based models)
if 'XGB' in best_model_name or 'Forest' in best_model_name:
    explainer = shap.TreeExplainer(best_model)
    shap_values = explainer.shap_values(X_test)
    shap.summary_plot(shap_values, X_test,
feature_names=feature_names)
```


Top 10 Features by Importance (XGBRegressor)
Present_Price
Manufacturing_Year
Fuel_Type
Fuel_Transmission
Driven_kms
Mileage
Transmission
Owner
Selling_type
car_age
Feature
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Importance


Present_Price
Manufacturing_Year
Driven_kms
Fuel_Type
Fuel_Transmission
Transmission
Mileage
Owner
car_age
Selling_type
−5
0
5
10
15
SHAP value (impact on model output)
High
Low
Feature value

Present_Price is the most important feature, followed by Manufacturing_Year and Driven_kms. Features like Transmission and Owner have lower importance.

Shows the impact of each feature on the model's predictions using SHAP (SHapley Additive exPlanations) values. X-axis (SHAP value): Represents the impact on the model output (positive or negative). Y-axis (Features): Lists the features ranked by their importance. Features like Present_Price and Manufacturing_Year have a strong positive impact on the predicted selling price. Features like Owner and Selling_type have a smaller or negative impact.

Summary of Insights

1.Key Drivers of Selling Price: 'Present_Price`and`Manufacturing_Year` are the most important features. Newer cars and higher-priced cars tend to have higher selling prices.

2.Correlation Analysis: Features like `Present_Price` and `Manufacturing_Year` are positively correlated with selling price. Features like `Owner` and `car_age` are negatively correlated.

3.Trends: Newer cars (higher manufacturing year) have higher selling prices. The number of cars sold fluctuates over the years.

1. Model Insights: The XGBRegressor model identifies `Present_Price`, `Manufacturing_Year`, and `Driven_kms` as the most important features. SHAP values provide detailed insights into how each feature impacts predictions.

The car price prediction project successfully identified the best model, XGBRegressor,which achieved the lowest Mean Squared Error (MSE) after hyperparameter tuning. Feature importance analysis revealed that Present_Price had the highest impact on Selling_Price, followed by Manufacturing_Year and Fuel_Type, while features like car_age and selling_type had a lesser influence. These insights can help car sellers set competitive prices and assist buyers in making informed decisions. The model can be leveraged by dealerships for automated price estimation, enhancing efficiency.

Future improvements could include incorporating additional features like brand name,brand reputation and service history and deploying the model for real-time pricing predictions.