Vehicle Price Prediction

December 6, 2024

Introduction

- This project aims to analyze a dataset of used vehicles and build a predictive model to estimate the selling prices of cars.
- The dataset includes variables such as car features, mileage, fuel type, and engine specifications.
- Through exploratory data analysis, we uncover key relationships between the variables and implement machine learning techniques to create a reliable prediction model.
- The goal is to provide insights into the factors affecting car prices and to build a model that can accurately predict prices for unseen data.

[43]:
```python
# Importing necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
import re
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn import metrics
from sklearn.decomposition import PCA
from sklearn.model_selection import KFold, cross_val_score
```

[4]:
```python
#loading the dataset
df = pd.read_csv(r'C:\Users\PC\Desktop\Datasets\Car details.csv')
```

[5]:
```python
#viewing the first five entries
df.head()
```

[5]:
```
                          name  year  selling_price  km_driven    fuel  \
0       Maruti Swift Dzire VDI  2014         450000     145500  Diesel
1  Skoda Rapid 1.5 TDI Ambition  2014         370000     120000  Diesel
2      Honda City 2017-2020 EXi  2006         158000     140000  Petrol
3     Hyundai i20 Sportz Diesel  2010         225000     127000  Diesel
```

```
4        Maruti Swift VXI BSIII   2007        130000     120000   Petrol

  seller_type transmission         owner     mileage   engine   max_power  \
0  Individual       Manual   First Owner   23.4 kmpl  1248 CC      74 bhp
1  Individual       Manual  Second Owner  21.14 kmpl  1498 CC  103.52 bhp
2  Individual       Manual   Third Owner   17.7 kmpl  1497 CC      78 bhp
3  Individual       Manual   First Owner   23.0 kmpl  1396 CC      90 bhp
4  Individual       Manual   First Owner   16.1 kmpl  1298 CC    88.2 bhp

                    torque  seats
0           190Nm@ 2000rpm    5.0
1      250Nm@ 1500-2500rpm    5.0
2    12.7@ 2,700(kgm@ rpm)    5.0
3  22.4 kgm at 1750-2750rpm   5.0
4    11.5@ 4,500(kgm@ rpm)    5.0
```

[6]:
```
df.shape
```

[6]:
```
(8128, 13)
```

[7]:
```
df.isnull().sum()
```

[7]:
```
name              0
year              0
selling_price     0
km_driven         0
fuel              0
seller_type       0
transmission      0
owner             0
mileage         221
engine          221
max_power       215
torque          222
seats           221
dtype: int64
```

The data has some missing values in Mileage, Engine, max_power, torque and seats rows.

[8]:
```
df = df.dropna(how = 'any')

df.shape
```

[8]:
```
(7906, 13)
```

[9]:
```
# Function to extract the largest number (RPM) from a string
def extract_rpm(value):
    numbers = re.findall(r'\d+', str(value))  # Find all numbers
```

```
    return max(map(int, numbers)) if numbers else None  # Return the maximum␣
↪number

# Apply the function to the 'torque' column and create a new 'torque_rpm' column
df['torque_rpm'] = df['torque'].apply(extract_rpm)

# Display the first 2 rows to check the result
df.head(2)
```

[9]:
```
                         name  year  selling_price  km_driven    fuel  \
0       Maruti Swift Dzire VDI  2014         450000     145500  Diesel
1  Skoda Rapid 1.5 TDI Ambition  2014         370000     120000  Diesel

  seller_type transmission         owner     mileage   engine   max_power  \
0  Individual       Manual   First Owner   23.4 kmpl  1248 CC      74 bhp
1  Individual       Manual  Second Owner  21.14 kmpl  1498 CC  103.52 bhp

                  torque  seats  torque_rpm
0       190Nm@ 2000rpm    5.0        2000
1  250Nm@ 1500-2500rpm    5.0        2500
```

[10]:
```
# Function to extract numeric values from text (e.g. '190Nm @ 2000rpm' -> '190')
def extract_numeric(text):
    match = re.search(r'\d+', str(text))
    return float(match.group()) if match else None

# Apply the function to clean mileage, engine, max_power
df['mileage'] = df['mileage'].apply(extract_numeric)
df['engine'] = df['engine'].apply(extract_numeric)
df['max_power'] = df['max_power'].apply(extract_numeric)
df['torque'] = df['torque'].apply(extract_numeric)
```

[11]:
```
# Results after cleaning
df[['mileage', 'engine', 'max_power','torque']].head()
```

[11]:

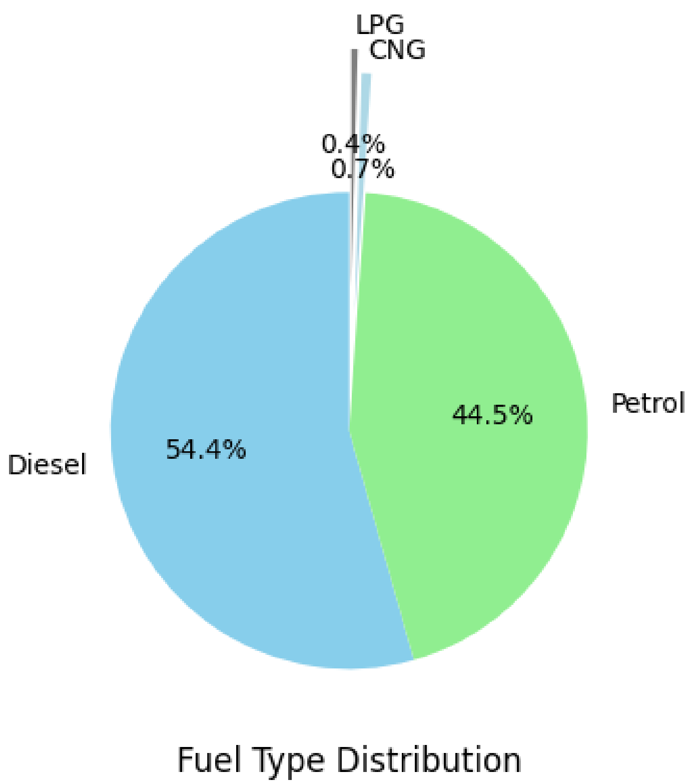
	mileage	engine	max_power	torque
0	23.0	1248.0	74.0	190.0
1	21.0	1498.0	103.0	250.0
2	17.0	1497.0	78.0	12.0
3	23.0	1396.0	90.0	22.0
4	16.0	1298.0	88.0	11.0

[12]:
```
df['fuel'].value_counts()
```

[12]:
```
fuel
Diesel    4299
Petrol    3520
```

```
CNG          52
LPG          35
Name: count, dtype: int64
```

[13]:
```python
Fuel_Type = df['fuel'].value_counts()

labels = Fuel_Type.index
explode = (0, 0, 0.5, 0.6)
colors = ['skyblue', 'lightgreen', 'lightblue', 'gray']

plt.figure(figsize=(4, 6))
plt.pie(Fuel_Type, labels=labels, autopct='%1.1f%%', startangle=90,␣
 ↪explode=explode, colors=colors)

# Add title and display the plot
plt.title('Fuel Type Distribution', loc='center', y=-0.1)
plt.show()
```



Observation - The pie chart titled “Fuel Type Distribution” shows the following:

Diesel: 54.4% Petrol: 44.5% CNG: 0.7% LPG: 0.4% Diesel is the most used fuel type, followed by Petrol. CNG and LPG have minimal usage.

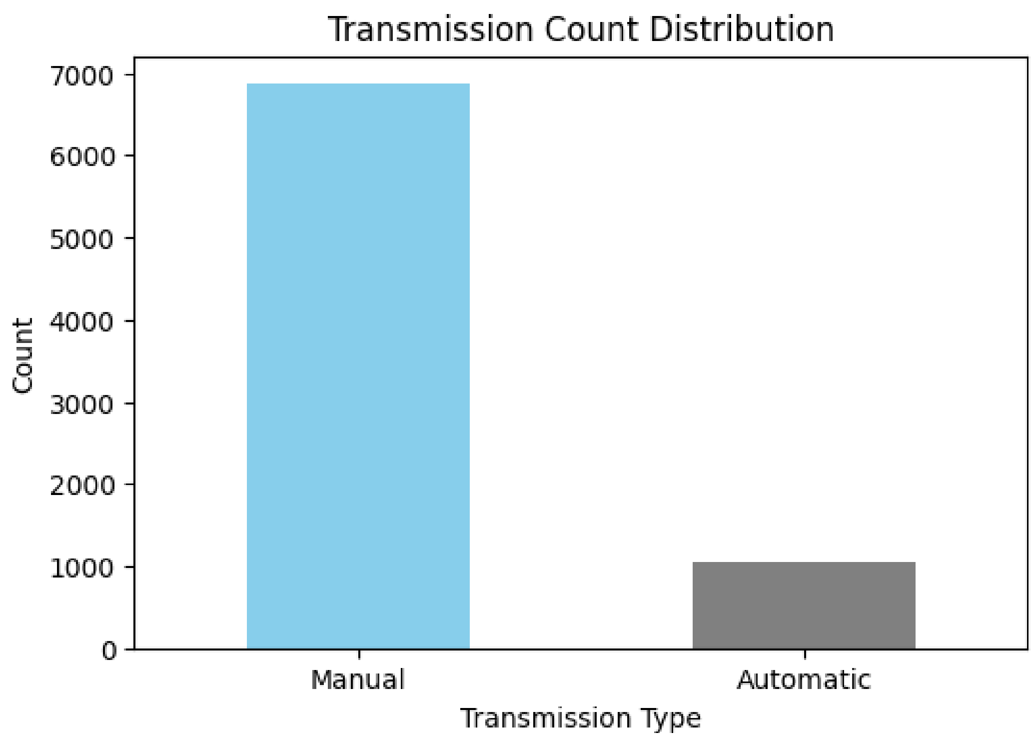
[14]:
```
df.head()
```

[14]:
```
                          name  year  selling_price  km_driven    fuel  \
0        Maruti Swift Dzire VDI  2014         450000     145500  Diesel
1  Skoda Rapid 1.5 TDI Ambition  2014         370000     120000  Diesel
2      Honda City 2017-2020 EXi  2006         158000     140000  Petrol
3     Hyundai i20 Sportz Diesel  2010         225000     127000  Diesel
4        Maruti Swift VXI BSIII  2007         130000     120000  Petrol

  seller_type transmission         owner  mileage  engine  max_power  torque  \
0  Individual       Manual   First Owner     23.0  1248.0       74.0   190.0
1  Individual       Manual  Second Owner     21.0  1498.0      103.0   250.0
2  Individual       Manual   Third Owner     17.0  1497.0       78.0    12.0
3  Individual       Manual   First Owner     23.0  1396.0       90.0    22.0
4  Individual       Manual   First Owner     16.0  1298.0       88.0    11.0

   seats  torque_rpm
0    5.0        2000
1    5.0        2500
2    5.0         700
3    5.0        2750
4    5.0         500
```

[15]:
```
df['transmission'].value_counts()
```

[15]:
```
transmission
Manual       6865
Automatic    1041
Name: count, dtype: int64
```

[16]:
```
Transmission_Type = df['transmission'].value_counts()

plt.figure(figsize=(6, 4))
Transmission_Type.plot(kind='bar', color=['skyblue', 'gray'])

plt.title('Transmission Count Distribution')
plt.xlabel('Transmission Type')
plt.ylabel('Count')

# Display the plot
plt.xticks(rotation=0)
plt.show()
```

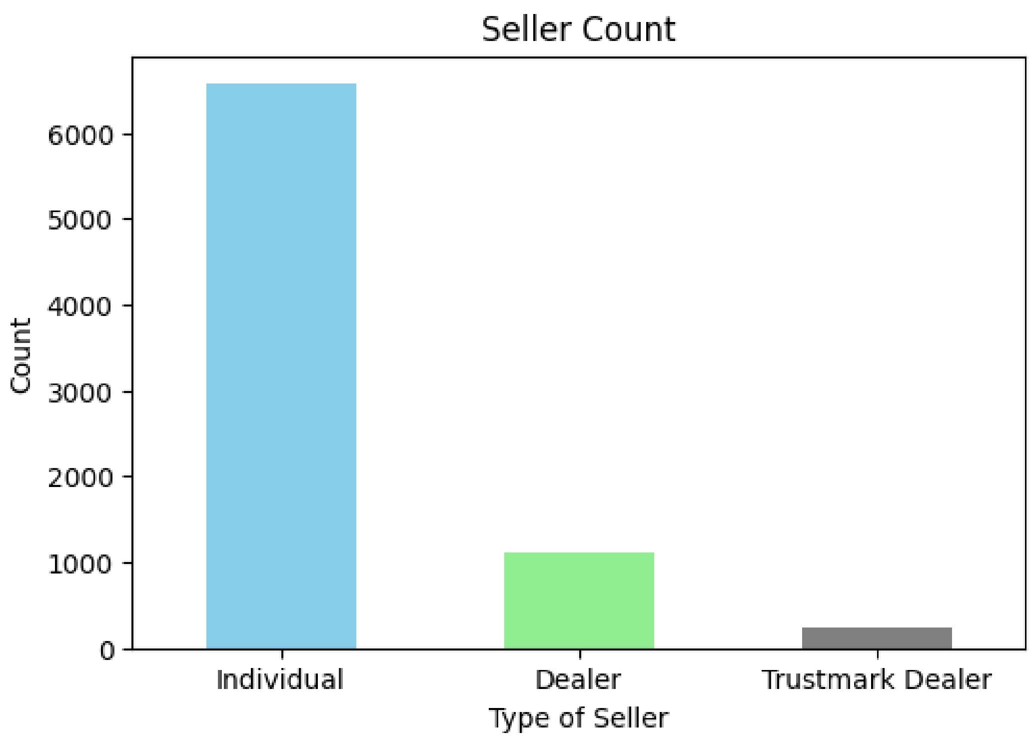


Observation - The bar chart titled "Transmission Count Distribution" shows that Manual transmissions have a significantly higher count compared to Automatic transmissions. This indicates a preference or higher availability of manual transmissions in the dataset.

[17]:
```
df['seller_type'].value_counts()
```

[17]:
```
seller_type
Individual          6563
Dealer              1107
Trustmark Dealer     236
Name: count, dtype: int64
```

[18]:
```
Seller_Type = df['seller_type'].value_counts()

plt.figure(figsize=(6, 4))
Seller_Type.plot(kind='bar', color=['skyblue', 'lightgreen','gray'])

plt.title('Seller Count')
plt.xlabel('Type of Seller')
plt.ylabel('Count')

plt.xticks(rotation=0)
plt.show()
```



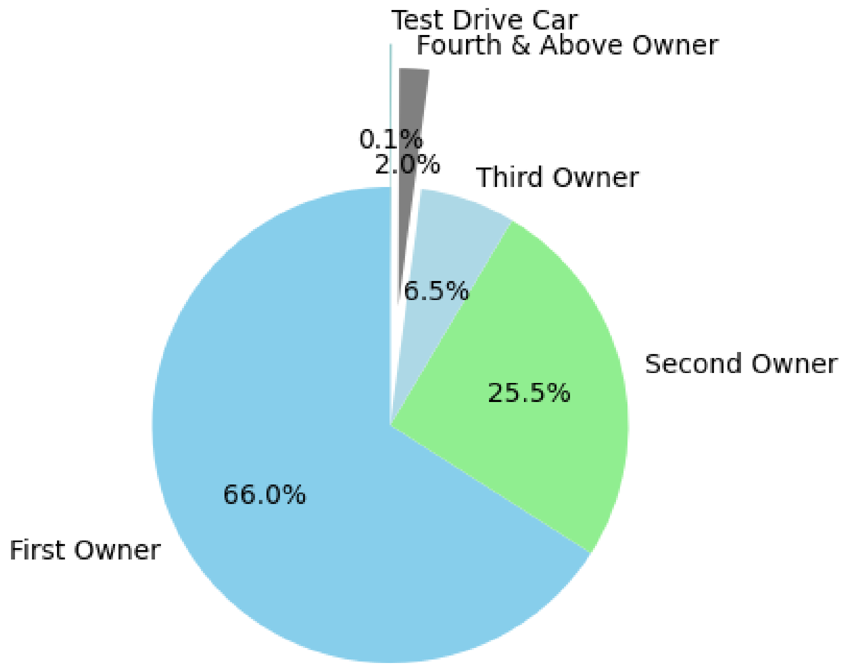
Observation - The bar chart titled "Seller Count" shows that Individual sellers have the highest count, followed by Dealers and Trustmark Dealers. This indicates that individual sellers dominate the market in the dataset

[21]:
```
df['owner'].value_counts()
```

[21]:
```
owner
First Owner             5215
Second Owner            2016
Third Owner              510
Fourth & Above Owner     160
Test Drive Car             5
Name: count, dtype: int64
```

[25]:
```
Owner_Type = df['owner'].value_counts()

labels = Owner_Type.index
explode = (0, 0, 0, 0.5, 0.6)
colors = ['skyblue', 'lightgreen', 'lightblue', 'gray','teal']

plt.figure(figsize=(4, 6))
plt.pie(Owner_Type, labels=labels, autopct='%1.1f%%', startangle=90,␣
 ↪explode=explode, colors=colors)
```

```
plt.show()
```

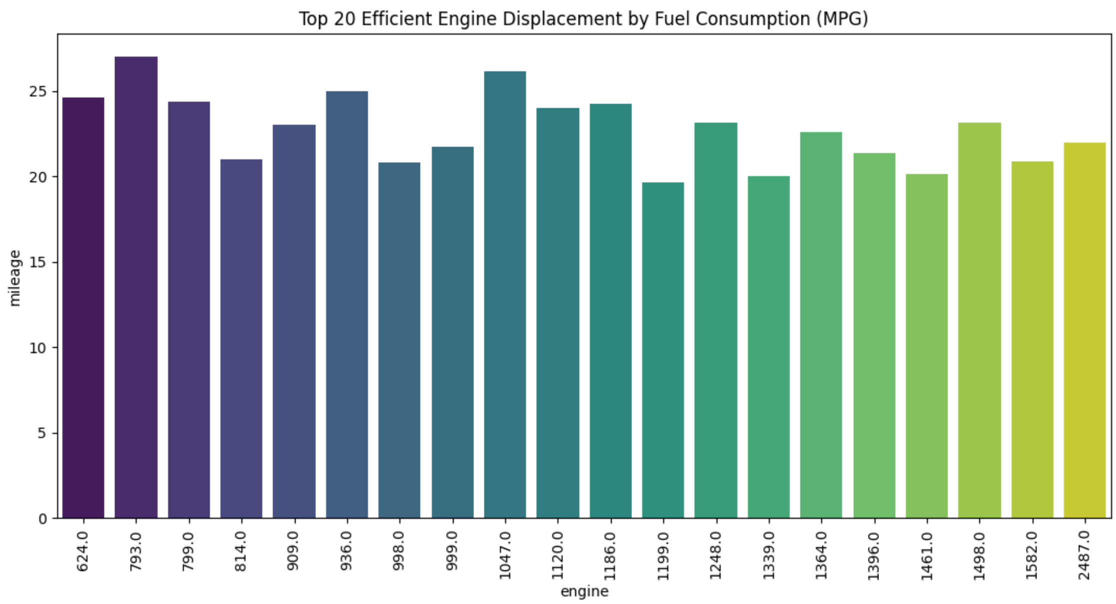


Observation - Distribution" shows:

First Owner: 66.0% Second Owner: 25.5% Third Owner: 6.5% Fourth & Above Owner: 2.0% Test Drive Car: 0.1% First owners dominate the distribution, indicating most test drive cars are from first-time owners.

Influence of Engine Displacement Size on Fuel Millage

[26]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Sort the DataFrame by mileage in descending order and select the top 20
top_engines = df.groupby('engine')['mileage'].mean().nlargest(20).reset_index()

# Create the bar chart
plt.figure(figsize=(13, 6))
sns.barplot(x='engine', y='mileage', data=top_engines, palette='viridis')  #␣
↪Using a color palette

plt.xticks(rotation=90)
plt.title("Top 20 Efficient Engine Displacement by Fuel Consumption (MPG)")
plt.show()
```



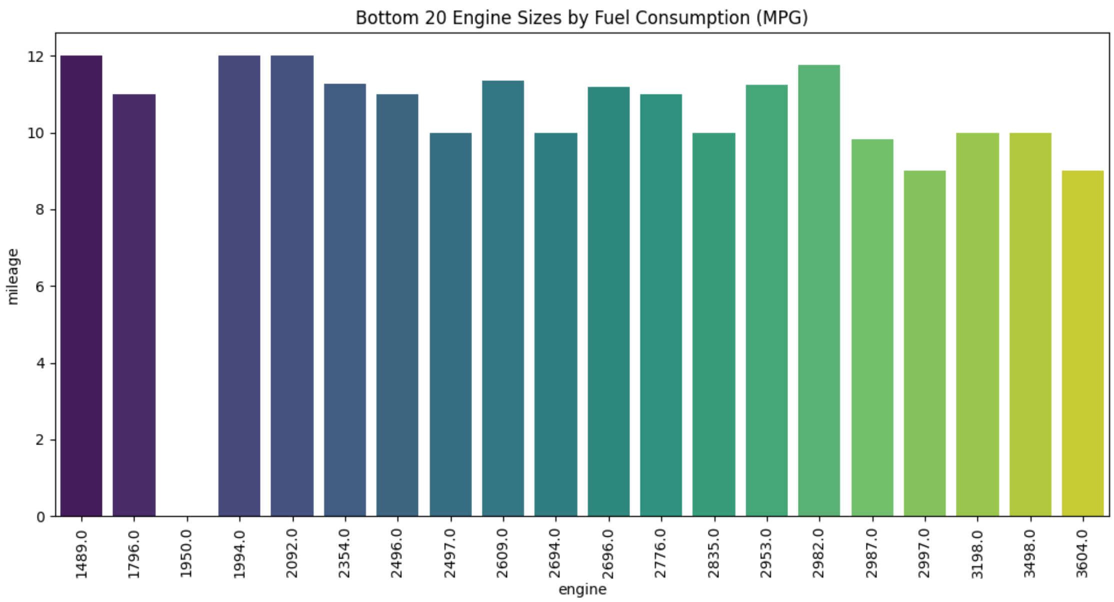
Observation - The bar chart titled "Top 20 Efficient Engine Displacement by Fuel Consumption (MPG)" shows the fuel efficiency (MPG) of different engine displacements. The bars are color-coded to indicate various MPG ranges, highlighting the most efficient engines.

[27]:
```
df['engine'].value_counts()
```

[27]:
```
engine
1248.0    1017
1197.0     832
998.0      453
796.0      443
2179.0     389
          …
2835.0       1
1489.0       1
1422.0       1
2496.0       1
1950.0       1
Name: count, Length: 121, dtype: int64
```

[28]:
```
# Sort the DataFrame by mileage in ascending order and select the lowest 20
bottom_engines = df.groupby('engine')['mileage'].mean().nsmallest(20).
 ↪reset_index()
plt.figure(figsize=(13, 6))
sns.barplot(x='engine', y='mileage', data=bottom_engines, palette='viridis')  #␣
 ↪Using a color palette
plt.xticks(rotation=90)
```

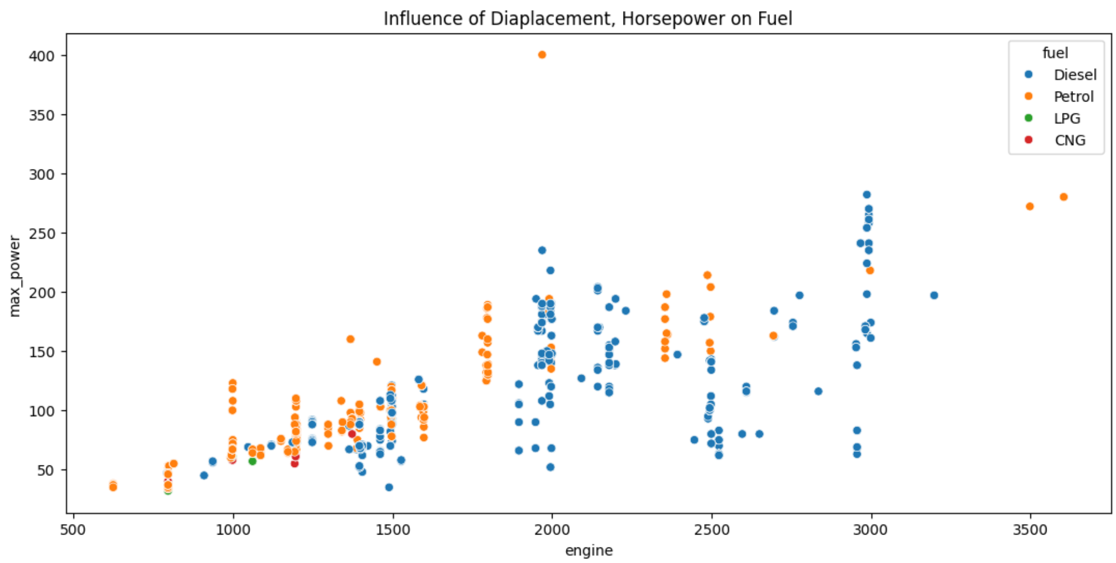
```
plt.title("Bottom 20 Engine Sizes by Fuel Consumption (MPG)")

plt.show()
```



Observation - The bar chart titled "Bottom 20 Engine Sizes by Fuel Consumption (MPG)" shows the least fuel-efficient engine sizes, with MPG values ranging from 0 to 12. The chart highlights the engine sizes that consume the most fuel, which is useful for identifying less efficient engines.

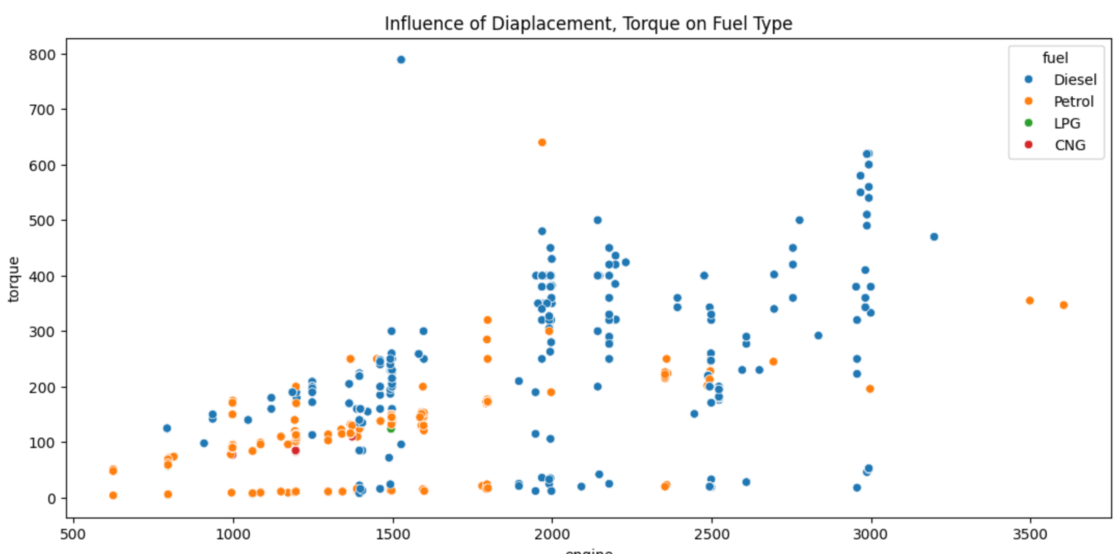
Influence of Engine Displacement, Max_Power(HORSEPOWER) on Fuel

[29]:
```
plt.figure(figsize=(13,6))
plt.title("Influence of Diaplacement, Horsepower on Fuel")
sns.scatterplot(x='engine', y='max_power',hue='fuel',data=df)
plt.show()
```



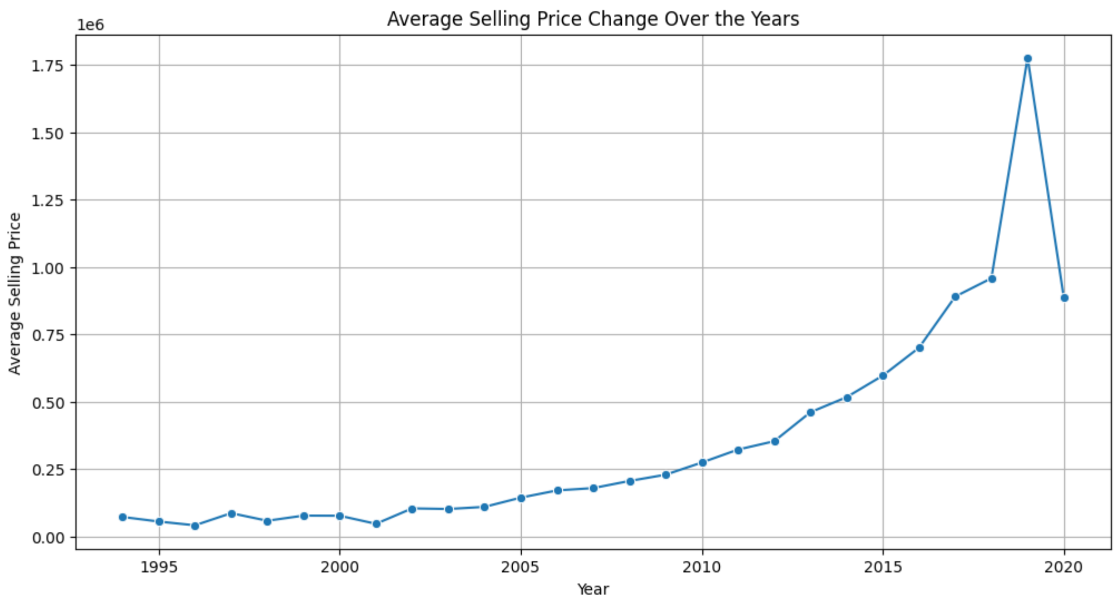
Observation - The scatter plot titled "Influence of Displacement, Horsepower on Fuel" shows the relationship between engine displacement and horsepower for different fuel types (Diesel, Petrol, LPG, CNG). Each point represents a specific fuel type, highlighting how engine size and power output vary across fuels.

[30]:
```
plt.figure(figsize=(13,6))
plt.title("Influence of Diaplacement, Torque on Fuel Type")
sns.scatterplot(x='engine', y='torque',hue='fuel',data=df)
plt.show()
```



Observation - The scatter plot titled "Influence of Displacement, Torque on Fuel Type" shows the relationship between engine displacement and torque for different fuel types (Diesel, Petrol, LPG, CNG). The data points indicate that as engine displacement increases, torque generally increases as well.

[31]:
```
price_trends = df.groupby('year')['selling_price'].mean().reset_index()

plt.figure(figsize=(12, 6))
sns.lineplot(x='year', y='selling_price', data=price_trends, marker='o')

# Add title and labels
plt.title("Average Selling Price Change Over the Years")
plt.xlabel("Year")
plt.ylabel("Average Selling Price")
plt.grid(True)
plt.show()
```



Observation - The line graph titled "Average Selling Price Change Over the Years" shows a general upward trend in average selling prices from 1990 to 2020, with a significant spike towards the end. This indicates increasing prices over time.

[32]:
```
df.describe()
```

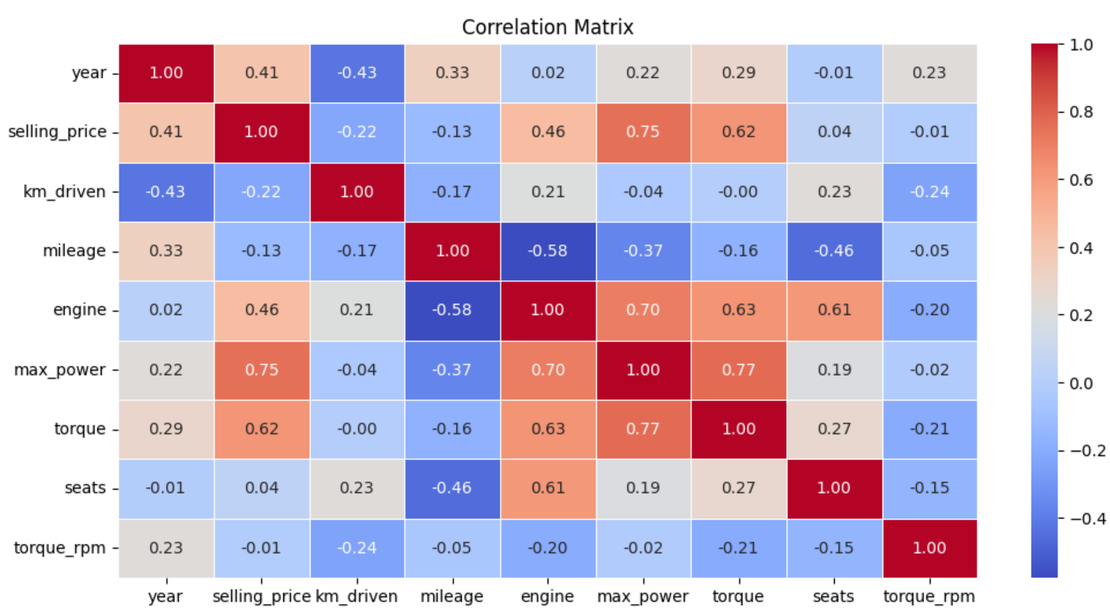
[32]:

	year	selling_price	km_driven	mileage	engine	\
count	7906.000000	7.906000e+03	7.906000e+03	7906.000000	7906.000000	
mean	2013.983936	6.498137e+05	6.918866e+04	18.981027	1458.708829	
std	3.863695	8.135827e+05	5.679230e+04	4.064364	503.893057	
min	1994.000000	2.999900e+04	1.000000e+00	0.000000	624.000000	

```
25%    2012.000000   2.700000e+05  3.500000e+04    16.000000  1197.000000
50%    2015.000000   4.500000e+05  6.000000e+04    19.000000  1248.000000
75%    2017.000000   6.900000e+05  9.542500e+04    22.000000  1582.000000
max    2020.000000   1.000000e+07  2.360457e+06    42.000000  3604.000000

         max_power       torque        seats   torque_rpm
count  7906.000000  7906.000000  7906.000000  7906.000000
mean     91.271060   168.187579     5.416393  2955.117253
std      35.732781    97.353926     0.959208  1052.997867
min      32.000000     4.000000     2.000000     6.000000
25%      68.000000   101.000000     5.000000  2200.000000
50%      82.000000   154.000000     5.000000  2800.000000
75%     102.000000   202.000000     5.000000  4000.000000
max     400.000000   789.000000    14.000000  5300.000000
```

[33]:

```python
# Correlation matrix
plt.figure(figsize=(12,6))
corr_matrix = df[['year', 'selling_price', 'km_driven', 'mileage', 'engine',␣
 ↪'max_power', 'torque', 'seats', 'torque_rpm' ]].corr()

sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```



Observation - Strong correlations:

Selling Price is positively correlated with max_power (0.75) and torque (0.62), indicating cars with higher power and torque have higher selling prices. Max Power and Torque are strongly correlated

(0.77), as they are mechanically related.

- Negative correlations:

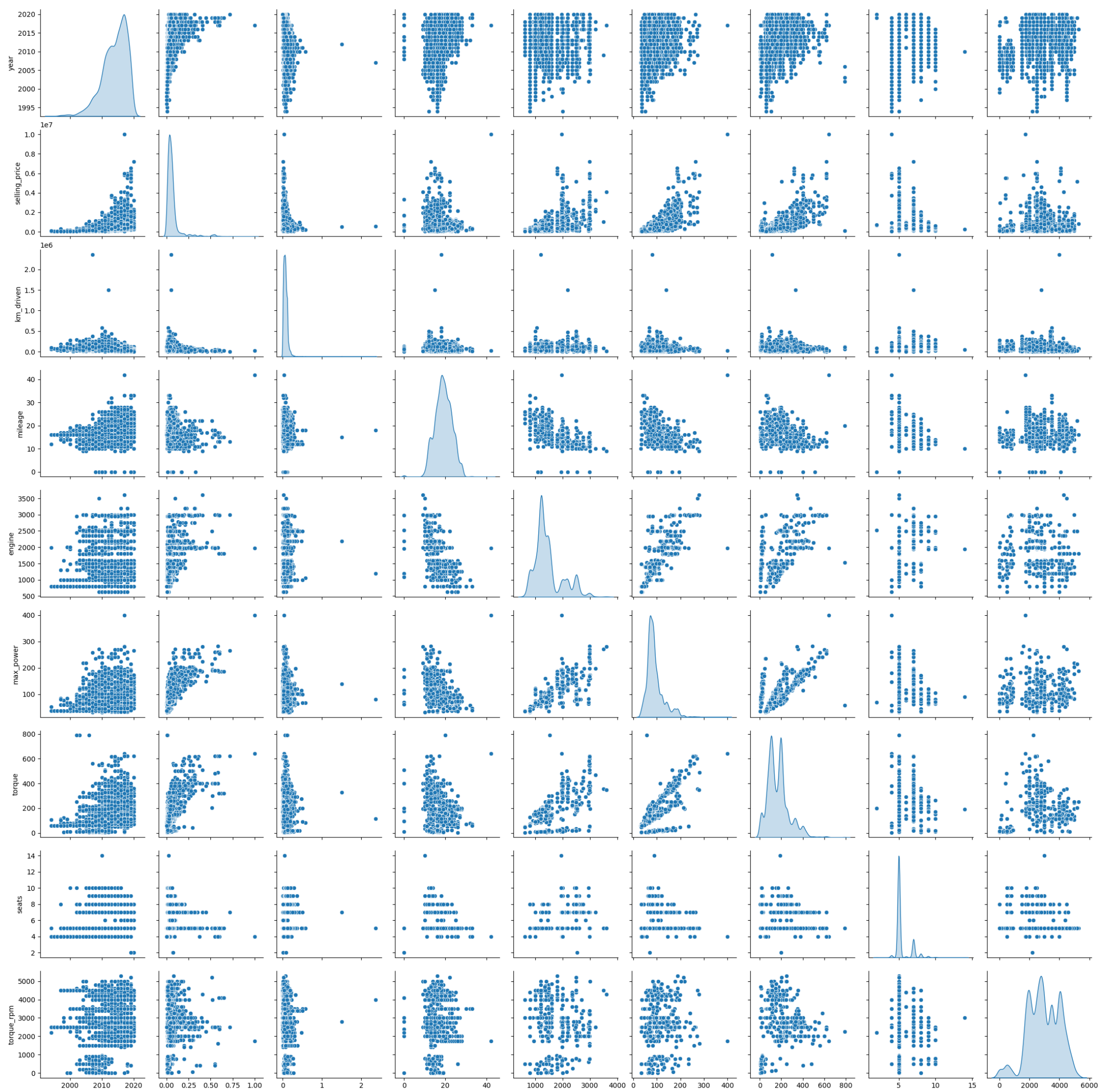
Selling Price is negatively correlated with km_driven (-0.22), meaning cars with more kilometers driven tend to have lower selling prices. Mileage and Engine size are negatively correlated (-0.58), indicating that larger engines tend to result in lower fuel efficiency.

- Low correlations:

Seats shows little to no correlation with other features, making it less influential in determining the selling price or other variables.

[34]:
```
# pairplot of variables
sns.pairplot(df, diag_kind='kde')
```

[34]: <seaborn.axisgrid.PairGrid at 0x1eb138ecaf0>



[35]:
```python
df = df.drop('name', axis=1)
```

[36]:
```python
# One-hot encode 'fuel', 'seller_type', 'transmission', 'owner'
encoded_data = pd.get_dummies(df, columns=['fuel', 'seller_type',␣
↪'transmission', 'owner'], drop_first=True)

# Ensure the encoded columns are of type int (0 and 1)
encoded_data[encoded_data.columns] = encoded_data[encoded_data.columns].
↪astype(int)

#Display the first few rows of the encoded DataFrame
encoded_data.head()
```

[36]:
```
   year  selling_price  km_driven  mileage  engine  max_power  torque  seats  \
0  2014         450000     145500       23    1248         74     190      5
1  2014         370000     120000       21    1498        103     250      5
2  2006         158000     140000       17    1497         78      12      5
3  2010         225000     127000       23    1396         90      22      5
4  2007         130000     120000       16    1298         88      11      5

   torque_rpm  fuel_Diesel  fuel_LPG  fuel_Petrol  seller_type_Individual  \
0        2000            1         0            0                       1
1        2500            1         0            0                       1
2         700            0         0            1                       1
3        2750            1         0            0                       1
4         500            0         0            1                       1

   seller_type_Trustmark Dealer  transmission_Manual  \
0                             0                    1
1                             0                    1
2                             0                    1
3                             0                    1
4                             0                    1

   owner_Fourth & Above Owner  owner_Second Owner  owner_Test Drive Car  \
0                           0                   0                     0
1                           0                   1                     0
2                           0                   0                     0
3                           0                   0                     0
4                           0                   0                     0

   owner_Third Owner
0                  0
1                  0
```

```
2                    1
3                    0
4                    0
```

[37]:
```
#mileage', 'engine', 'max_power', 'torque'
x = encoded_data.drop(columns=['selling_price','mileage'], inplace=False)
y = encoded_data['selling_price']
```

[38]:
```
xtrain, xtest, ytrain, ytest = train_test_split(x[:3000], y[:3000], test_size=0.
 ↪3)
```

[39]:
```
random_model = RandomForestRegressor(n_estimators=300, random_state = 42,␣
 ↪n_jobs = -1)
```

[40]:
```
random_model.fit(xtrain, ytrain)

y_pred = random_model.predict(xtest)

#Checking the accuracy
random_model_accuracy = round(random_model.score(xtrain, ytrain)*100,2)
print(round(random_model_accuracy, 2), '%')
```

```
99.05 %
```

[41]:
```
random_model_accuracy1 = round(random_model.score(xtest, ytest)*100,2)
print(round(random_model_accuracy1, 2), '%')
```

```
95.05 %
```

[44]:
```
#R2 Score
acc_R=metrics.r2_score(ytest, y_pred)
acc_R
```

[44]:
```
0.9504563834146211
```

[45]:
```
k = 20

# Initialize K-Fold with the specified number of splits
kfold = KFold(n_splits=k, shuffle=True, random_state=20)

# Perform cross-validation
K_results = cross_val_score(random_model, x, y, cv=kfold)

# Calculate the mean accuracy
accuracy = np.mean(K_results)  # Use K_results directly, not absolute values
print("Mean Cross-Validation Accuracy:", accuracy)
```

```
Mean Cross-Validation Accuracy: 0.9717099468929661
```

RESULT EVALUATION

(RANDOM FOREST)

Model Training Accuracy (99.05%):

This value indicates how well the model fits the training data. A high score (99.05%) shows that the model has learned the patterns in the training set very well.

Model Testing Accuracy (95.05%):

This accuracy is obtained when the model is tested on unseen data (xtest and ytest). A score of 95.05% shows that the model performs well on the test data but not as perfectly as on the training data, which is common and indicates the model generalizes well.

The R^2 score represents how well the model explains the variability of the target variable (y). An R^2 score of 0.9504 indicates that the model explains approximately 95% of the variance in the test data. This is a good score, suggesting that the model captures most of the data's underlying patterns.

K-Fold Cross-Validation (Mean Accuracy: 0.9717):

Cross-validation helps assess the model's performance across multiple subsets of the data. With 20 folds, the mean accuracy across all the splits is 97.17%, suggesting that the model consistently performs well on different subsets of the data. This high score provides confidence that the model is not just fitting a particular split of the data but generalizes well across the whole dataset.

Conclusion

The analysis and model development provide several important insights:

Strong Predictive Features: Features such as max_power (0.75 correlation with selling price) and torque (0.62 correlation) are highly indicative of a car's selling price, confirming the significant impact of engine performance. Moderate Predictors: Year of manufacture and kilometers driven show moderate correlations with selling price. Newer cars and those with fewer kilometers tend to sell for higher prices. Fuel Efficiency and Engine Size: Larger engines tend to reduce mileage, with a strong negative correlation between engine size and fuel efficiency (-0.58), reflecting their role in higher fuel consumption. Model Accuracy: The Random Forest model trained on this data achieves a training accuracy of 99.05% and a test accuracy of 95.05%, with an R^2 score of 0.9504, suggesting that the model explains a significant portion of the variance in selling price. Additionally, cross-validation yielded a mean accuracy of 97.17%, indicating robust generalization.

[48]:
```python
import pickle

# Save the trained model as a pickle file
with open('CarSelling.pickle', 'wb') as model_file:
    pickle.dump(random_model, model_file)
```

[ ]:
```python
```