CAR PRICE PREDICTION WITH MACHINE LEARNING

Problem Statement :

- Predicting the price of cars based on a wide range of attributes and features. Using a dataset containing car details such as driven kms, fuel type, transmission, and more, we aim to develop a machine learning model that accurately estimates the price of different car models.

!

In [1]:
```
# import libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

In [2]:
```
import warnings

# Set the warning filter to 'ignore'
warnings.filterwarnings('ignore')
```

In [3]:
```
# read data set

df=pd.read_csv("car data.csv")
```

In [4]:
```
# Top 5 rows

df.head(5)
```

Out[4]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	O
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	

In [5]:
```
df.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
```

In [6]:
```
# check Missing value
df.isnull().sum()
```

Out[6]:
```
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
```

In [7]:
```
# Check Duplication

df.duplicated().sum()
```

Out[7]:
```
2
```

In [8]:
```
#Check datatype

df.dtypes
```

Out[8]:
```
Car_Name          object
Year               int64
Selling_Price    float64
Present_Price    float64
Driven_kms         int64
Fuel_Type         object
Selling_type      object
Transmission      object
Owner              int64
dtype: object
```

In [9]:
```
# Check the number of unique values of each column

df.nunique()
```

Out[9]:
```
Car_Name          98
Year              16
Selling_Price    156
Present_Price    148
Driven_kms       206
Fuel_Type          3
Selling_type       2
Transmission       2
Owner              3
dtype: int64
```

In [10]:
```
#Check statistics of data set

df.describe()
```

Out[10]:

	Year	Selling_Price	Present_Price	Driven_kms	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.043189
std	2.891554	5.082812	8.642584	38886.883882	0.247915
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	15000.000000	0.000000
50%	2014.000000	3.600000	6.400000	32000.000000	0.000000
75%	2016.000000	6.000000	9.900000	48767.000000	0.000000
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

In [11]:
```
# checking the distribution of categorical data

print(df.Fuel_Type.value_counts())
```

```
Petrol    239
Diesel     60
CNG         2
Name: Fuel_Type, dtype: int64
```

In [12]:
```
print(df.Selling_type.value_counts())
```

```
Dealer        195
Individual    106
Name: Selling_type, dtype: int64
```

In [13]:
```
print(df.Transmission.value_counts())
```

```
Manual       261
Automatic     40
Name: Transmission, dtype: int64
```

In [14]:
```
# encoding "Fuel_Type" Column
df.replace({'Fuel_Type':{'Petrol':0,'Diesel':1,'CNG':2}},inplace=True)

# encoding "Seller_Type" Column
df.replace({'Selling_type':{'Dealer':0,'Individual':1}},inplace=True)

# encoding "Transmission" Column
df.replace({'Transmission':{'Manual':0,'Automatic':1}},inplace=True)
```

In [15]:
```
df.head()
```

Out[15]:

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

In [16]:
```
df['Selling_Price'] = df['Selling_Price'].astype(int)
```

In [17]:
```
df['Present_Price'] = df['Present_Price'].astype(int)
```

In [36]:
```
df.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    int32 
 3   Present_Price  301 non-null    int32 
 4   Driven_kms     301 non-null    int64 
 5   Fuel_Type      301 non-null    int64 
 6   Selling_type   301 non-null    int64 
 7   Transmission   301 non-null    int64 
 8   Owner          301 non-null    int64 
dtypes: int32(2), int64(6), object(1)
memory usage: 18.9+ KB
```

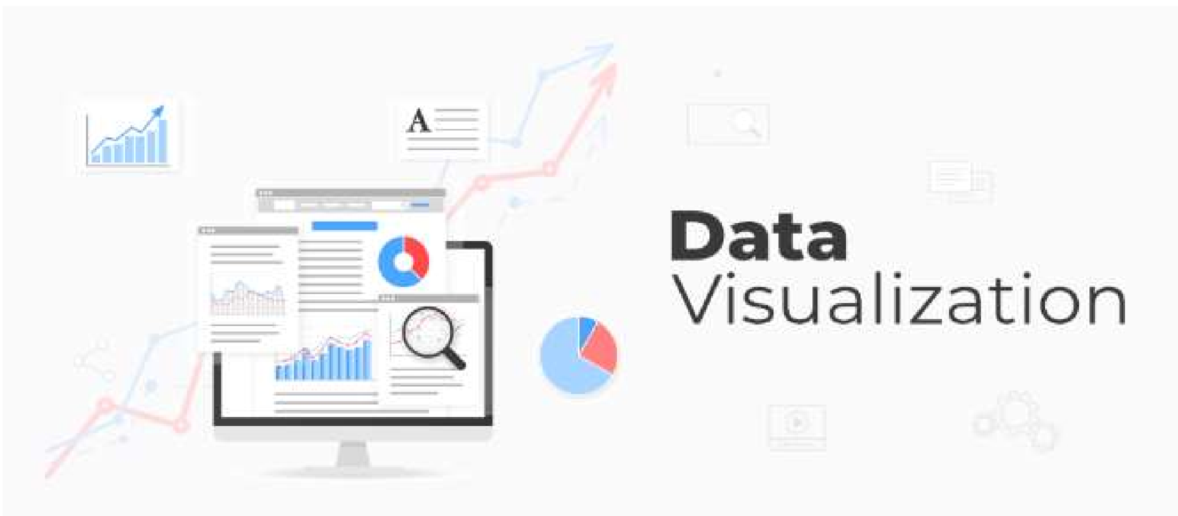
In [19]:
```
df.head()
```

Out[19]:

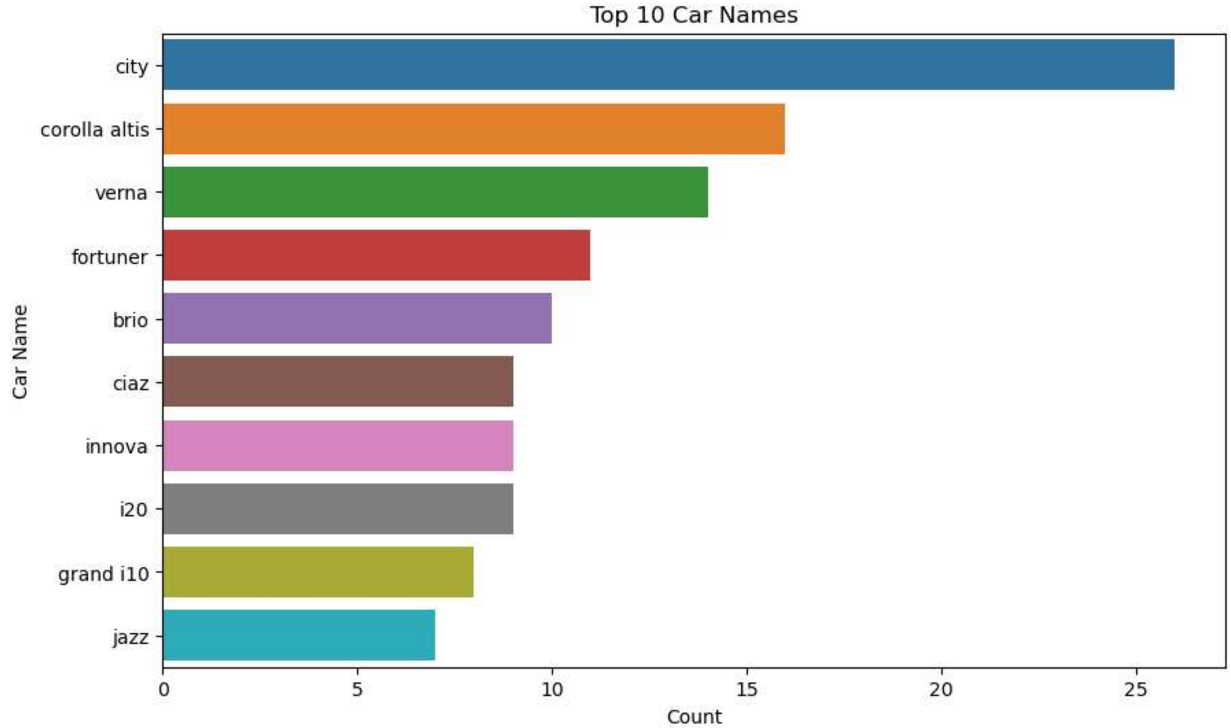
	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	O
0	ritz	2014	3	5	27000	0	0	0	
1	sx4	2013	4	9	43000	1	0	0	
2	ciaz	2017	7	9	6900	0	0	0	
3	wagon r	2011	2	4	5200	0	0	0	
4	swift	2014	4	6	42450	1	0	0	

Data Visualization

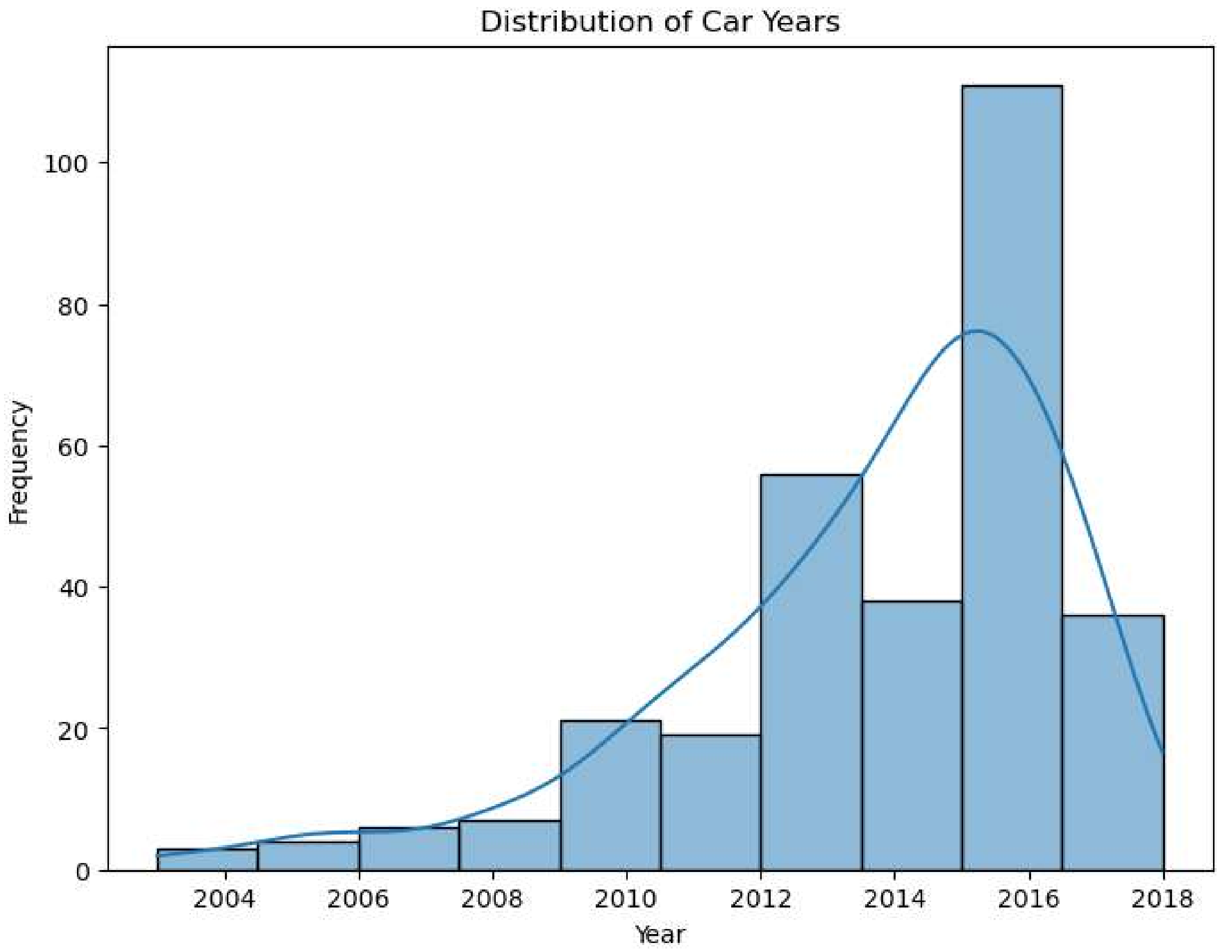
!



In [20]:
```
# Bar chart for Car_Name
plt.figure(figsize=(10, 6))
sns.countplot(y='Car_Name', data=df, order=df['Car_Name'].value_counts().index[:10])
plt.title('Top 10 Car Names')
plt.xlabel('Count')
plt.ylabel('Car Name')
plt.show()
```

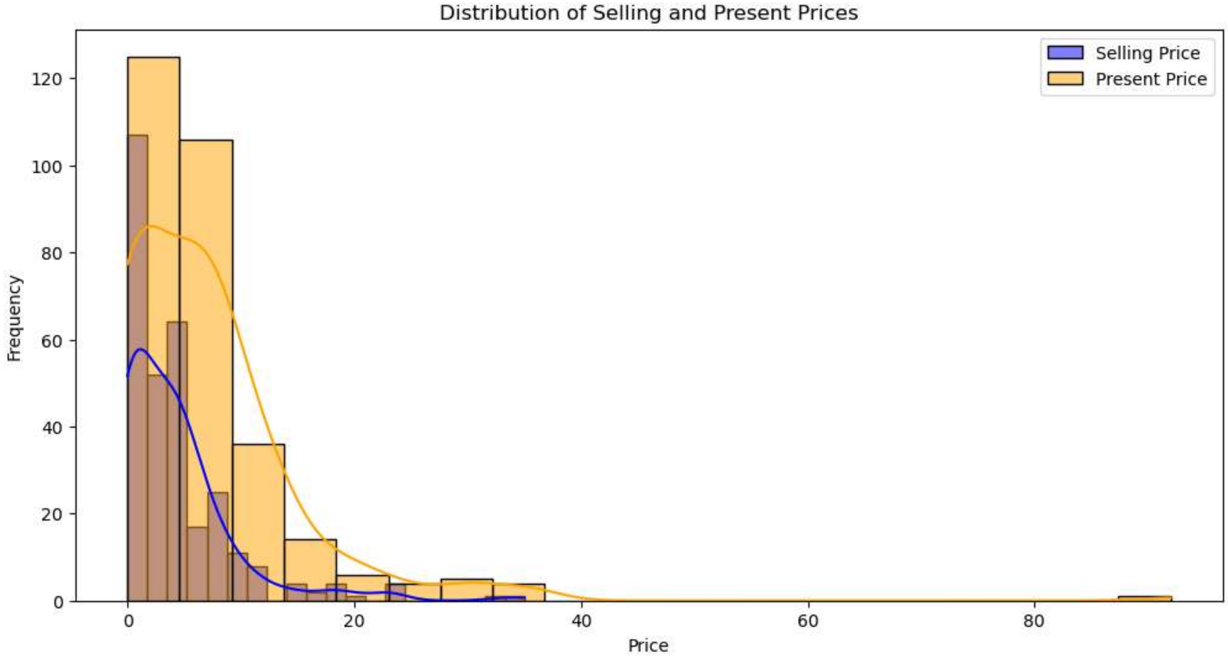


In [21]:
```
# Histogram for Year
plt.figure(figsize=(8, 6))
sns.histplot(df['Year'], bins=10, kde=True)
plt.title('Distribution of Car Years')
plt.xlabel('Year')
plt.ylabel('Frequency')
plt.show()
```

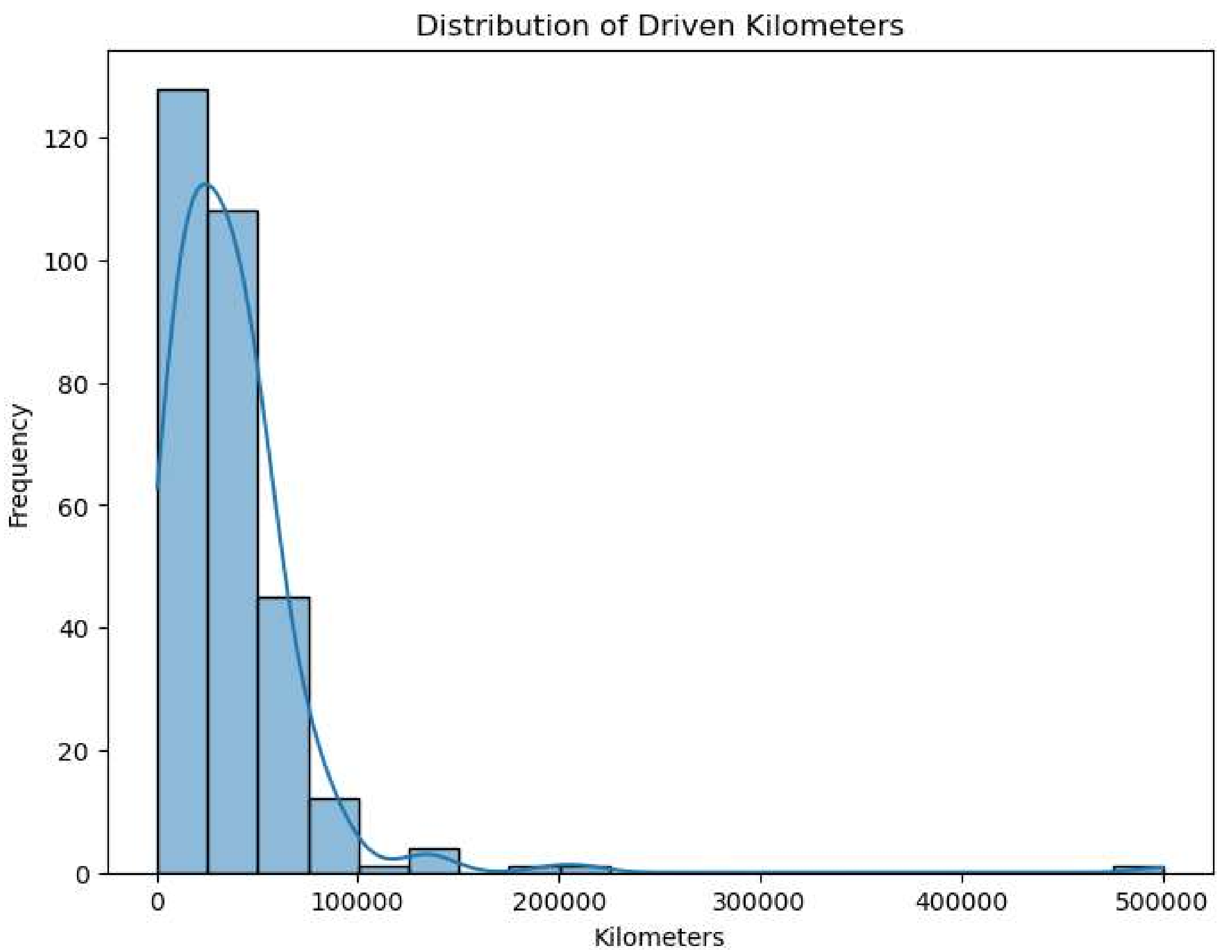


In [22]:

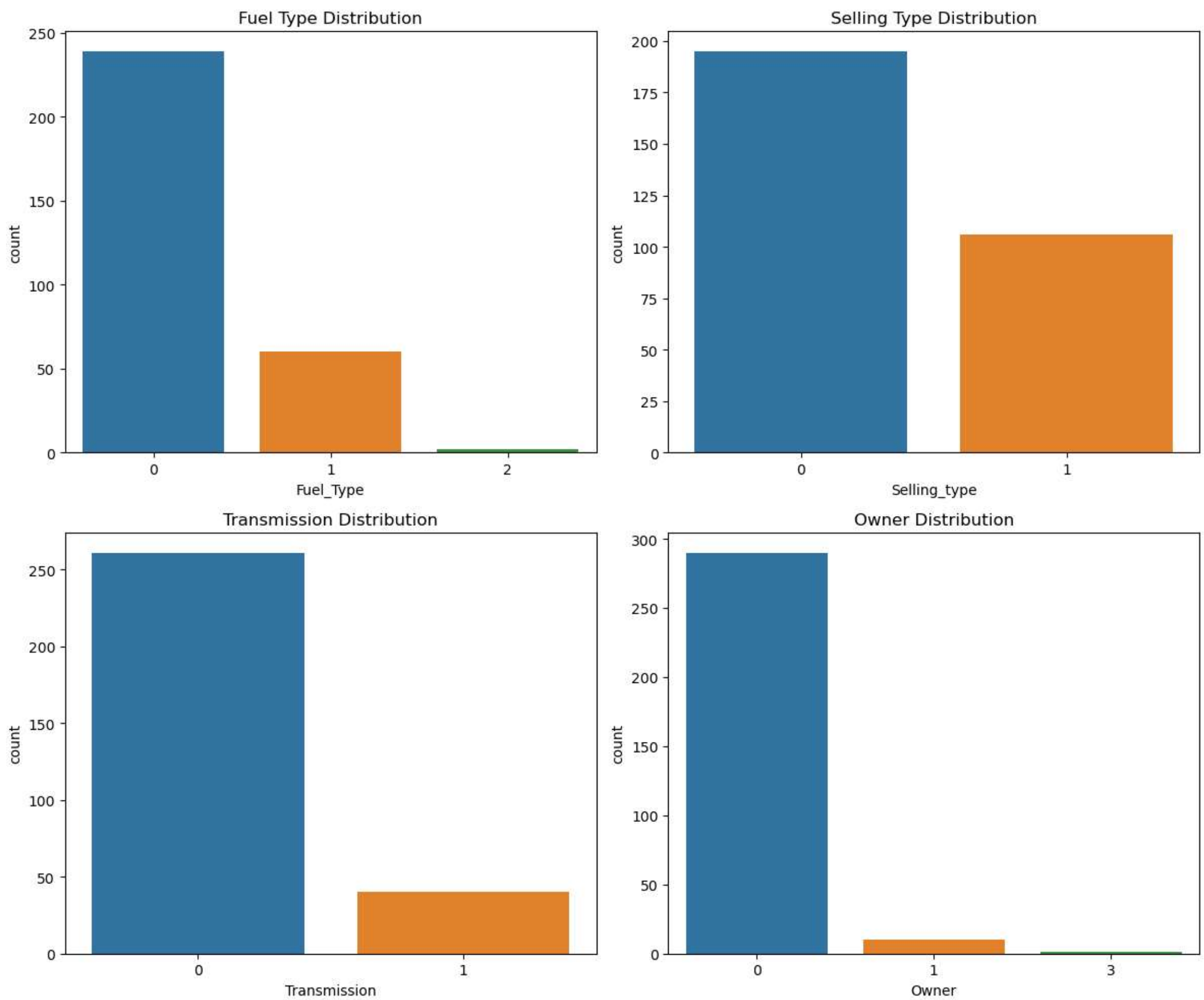
```
# Histogram for Selling_Price and Present_Price
plt.figure(figsize=(12, 6))
sns.histplot(df['Selling_Price'], bins=20, kde=True, color='blue', label='Selling Pric
sns.histplot(df['Present_Price'], bins=20, kde=True, color='orange', label='Present Pr
plt.title('Distribution of Selling and Present Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



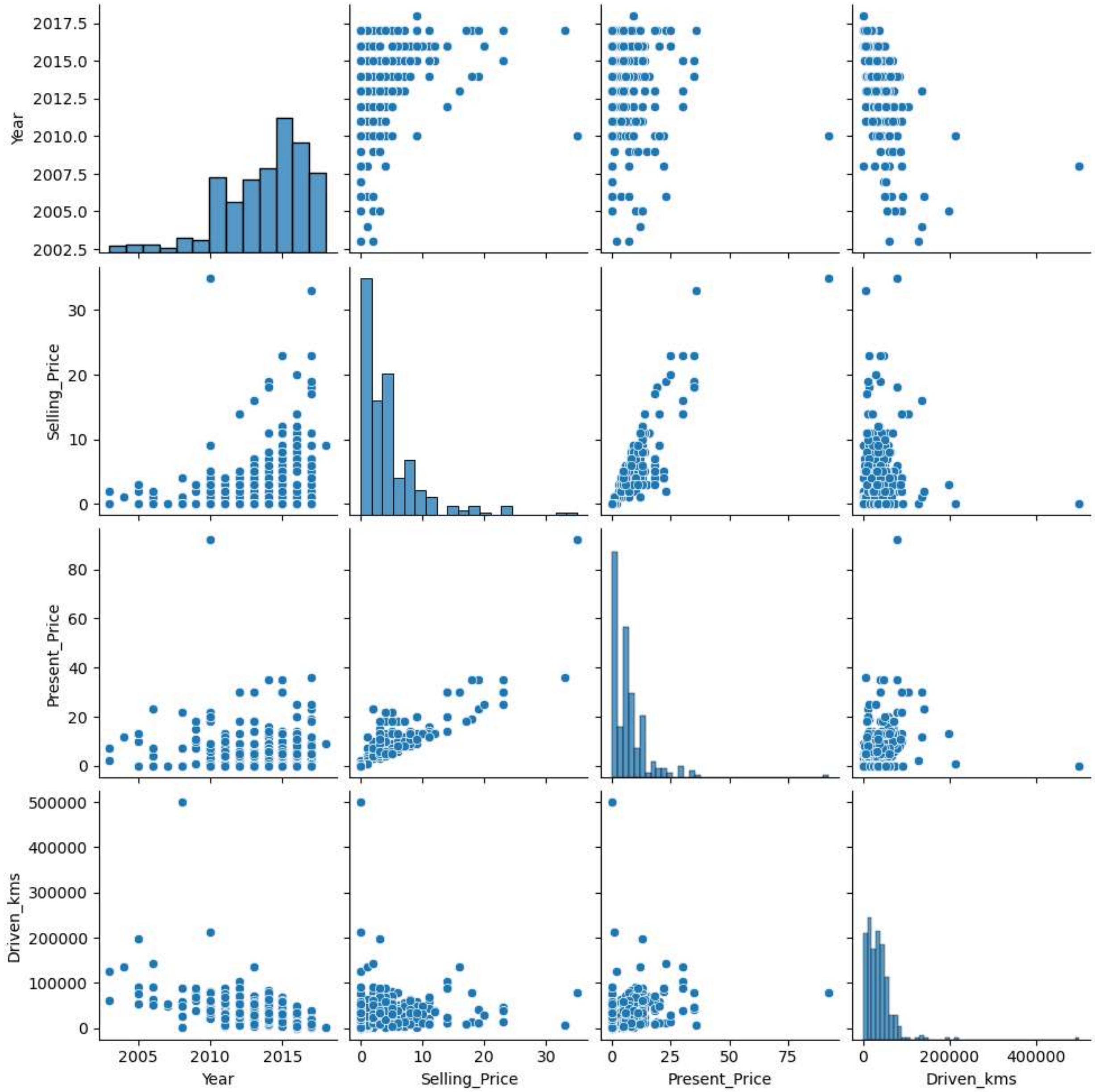
In [23]:
```python
# Histogram for Driven_kms
plt.figure(figsize=(8, 6))
sns.histplot(df['Driven_kms'], bins=20, kde=True)
plt.title('Distribution of Driven Kilometers')
plt.xlabel('Kilometers')
plt.ylabel('Frequency')
plt.show()
```



In [24]:
```
# Bar chart for Fuel_Type, Selling_type, Transmission, Owner
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

sns.countplot(x='Fuel_Type', data=df, ax=axes[0, 0])
axes[0, 0].set_title('Fuel Type Distribution')

sns.countplot(x='Selling_type', data=df, ax=axes[0, 1])
axes[0, 1].set_title('Selling Type Distribution')

sns.countplot(x='Transmission', data=df, ax=axes[1, 0])
axes[1, 0].set_title('Transmission Distribution')

sns.countplot(x='Owner', data=df, ax=axes[1, 1])
axes[1, 1].set_title('Owner Distribution')

plt.tight_layout()
plt.show()
```

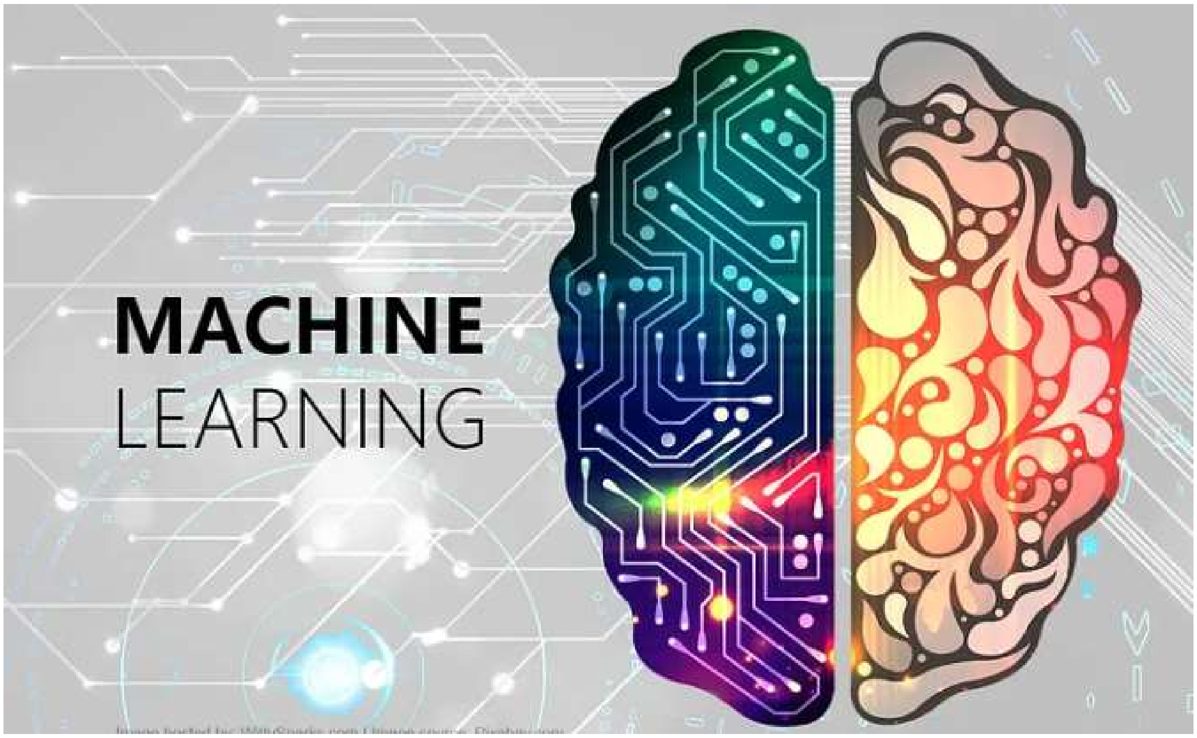


In [25]:
```
# Select columns for pairplot
columns_for_pairplot = ['Year', 'Selling_Price', 'Present_Price', 'Driven_kms']

# Create pairplot
sns.pairplot(df[columns_for_pairplot])
plt.show()
```



MACHINE LEARNING

!



In [26]:
```python
x = df.drop(['Car_Name','Selling_Price','Year'],axis=1)
y = df['Selling_Price']
```

In [27]:
```python
x.head()
```

Out[27]:

	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner
0	5	27000	0	0	0	0
1	9	43000	1	0	0	0
2	9	6900	0	0	0	0
3	4	5200	0	0	0	0
4	6	42450	1	0	0	0

In [28]:
```python
x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Present_Price  301 non-null    int32
 1   Driven_kms     301 non-null    int64
 2   Fuel_Type      301 non-null    int64
 3   Selling_type   301 non-null    int64
 4   Transmission   301 non-null    int64
 5   Owner          301 non-null    int64
dtypes: int32(1), int64(5)
memory usage: 13.1 KB
```

In [29]:
```python
y.head()
```

Out[29]:
```
0    3
1    4
2    7
3    2
4    4
Name: Selling_Price, dtype: int32
```

In [ ]:

In [30]:
```
### Importing the dependencies

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.metrics import accuracy_score,precision_score
```

In [31]:
```
### Machine Learning models Libraries:

from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import KFold,cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
```

In [32]:
```
#Splitting Training and Test data

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=3)
```

In [33]:
```
models = [LogisticRegression(max_iter=1000),DecisionTreeClassifier(),RandomForestClass
```

In [34]:
```
def compare_models_train_test():
    for model in models:
        model.fit(x_train, y_train)
        y_predicted = model.predict(x_test)

        # Calculate regression metrics
        mse = mean_squared_error(y_test, y_predicted)
        r2 = r2_score(y_test, y_predicted)
        mae = mean_absolute_error(y_test, y_predicted)
        accuracy = accuracy_score(y_test,y_predicted)
        precision = precision_score(y_test,y_predicted,average='macro')

        # Calculate cross-validation score
        cv_scores = cross_val_score(model, np.vstack((x_train, x_test)), np.hstack((y_

        print("Model:", model)
        print("Mean Squared Error (MSE):", mse)
        print("R-squared (R2):", r2)
        print("Mean Absolute Error (MAE):", mae)
        print("Cross-Validation Score:", -cv_scores.mean())
        print("Accuracy - ",accuracy)
        print("Precision - ",precision)
        print("="*50)
```

In [35]:
```
compare_models_train_test()
```

```
Model: LogisticRegression(max_iter=1000)
Mean Squared Error (MSE): 22.262295081967213
R-squared (R2): -0.0337692806868668
Mean Absolute Error (MAE): 2.0
Cross-Validation Score: 36.04754098360656
Accuracy -  0.5081967213114754
Precision -  0.221164891753127
==================================================
Model: DecisionTreeClassifier()
Mean Squared Error (MSE): 5.245901639344262
R-squared (R2): 0.7564019368042729
Mean Absolute Error (MAE): 0.9508196721311475
Cross-Validation Score: 6.854699453551912
Accuracy -  0.5573770491803278
Precision -  0.4219634460118889
==================================================
Model: RandomForestClassifier()
Mean Squared Error (MSE): 3.9672131147540983
R-squared (R2): 0.8157789647082314
Mean Absolute Error (MAE): 0.9508196721311475
Cross-Validation Score: 6.537595628415301
Accuracy -  0.5737704918032787
Precision -  0.4893465909090909
==================================================
Model: KNeighborsClassifier()
Mean Squared Error (MSE): 27.229508196721312
R-squared (R2): -0.26442619677532075
Mean Absolute Error (MAE): 3.3934426229508197
Cross-Validation Score: 35.22918032786886
Accuracy -  0.21311475409836064
Precision -  0.15120415982484947
==================================================
```

Conclusion :-

The RandomForestClassifier emerges as the best model for car price prediction. It exhibits the lowest Mean Squared Error (MSE) and Cross-Validation Score, indicating better predictive performance. Moreover, it achieves the highest Accuracy and Precision scores, indicating superior classification performance compared to other models.