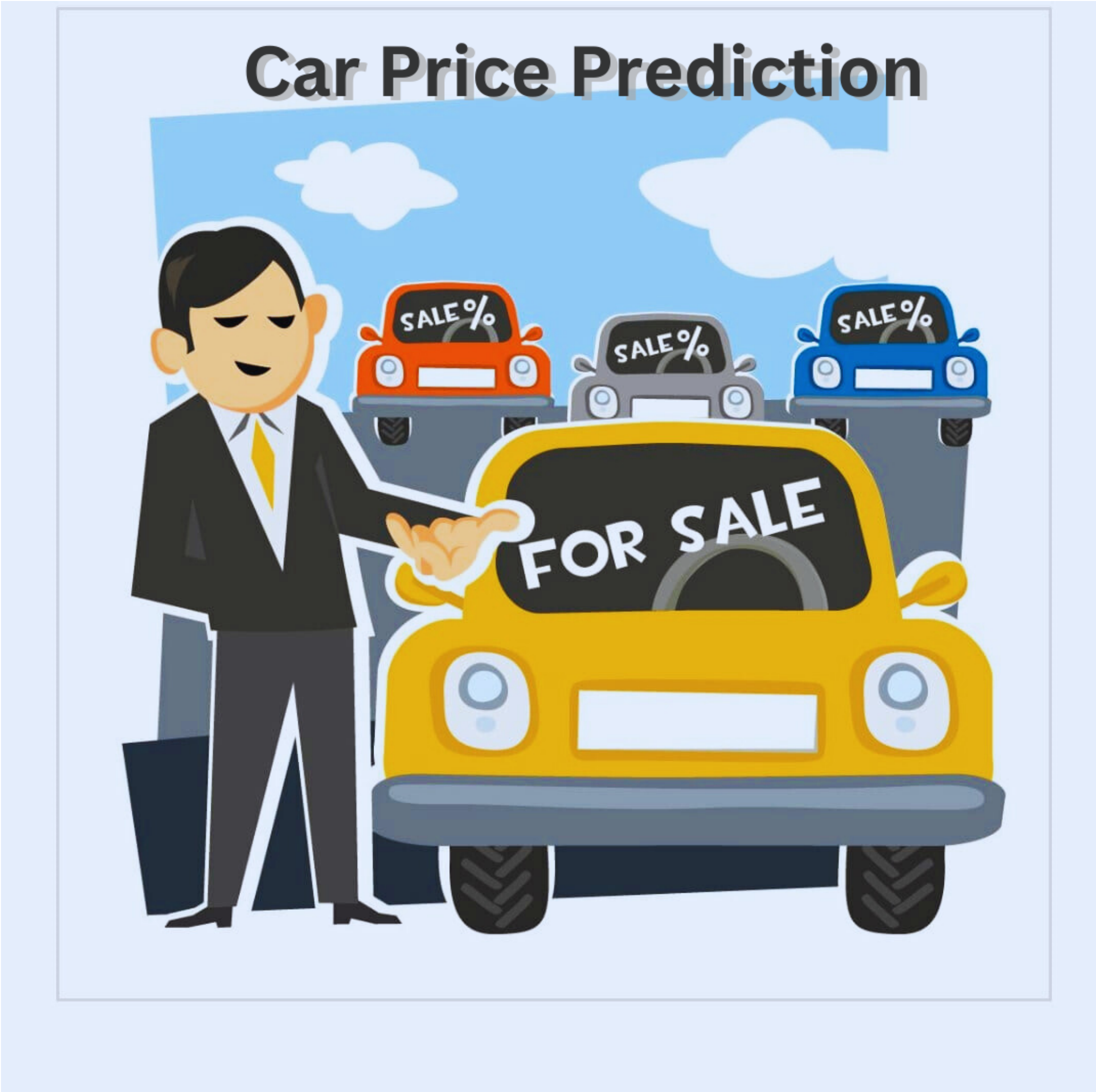


The columns in the given dataset are as follows:

The brief description of each columns in the dataset:

- 1. **Name**: The name of the car model.
- 2. **Year**: The manufacturing year of the car. This column indicates the year in which the car was originally produced.
- 3. **Selling Price**: The price at which the car is being sold. This is typically the amount the seller is asking for the vehicle.
- 4. **Kilometers Driven**: The total distance in kilometers that the car has been driven. This provides an insight into the usage and potential wear and tear of the vehicle.
- 5. **Fuel**: The type of fuel the car uses for propulsion. Common values could be "Petrol," "Diesel," "CNG" (Compressed Natural Gas), "Electric," etc.

- 6. **Seller Type**: This indicates the type of seller. It might include values like "Individual" (private seller) or "Dealer" (car dealership).
- 7. **Transmission**: The type of transmission the car has. It could be "Manual" or "Automatic," referring to the manual or automatic control of gears.
- 8. **Owner**: This column describes the number of previous owners the car has had. It's often represented as a number, such as 1st owner, 2nd owner, etc. It gives an idea of how extensively the car has been used.

These columns provide essential information about each car in the dataset and can be used for various analyses, such as predicting car prices, understanding market trends, and making recommendations to potential buyers or sellers.

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Import Dataset

In [2]:
```
car=pd.read_csv('car data.csv')
```

In [3]:
```
car.head()
```

Out[3]:

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

In [4]:
```
car.shape
```

Out[4]: (301, 9)

- 301 Rows and 9 Columns

In [5]:
```
car.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   Kms_Driven     301 non-null    int64
 5   Fuel_Type      301 non-null    object
 6   Seller_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
```

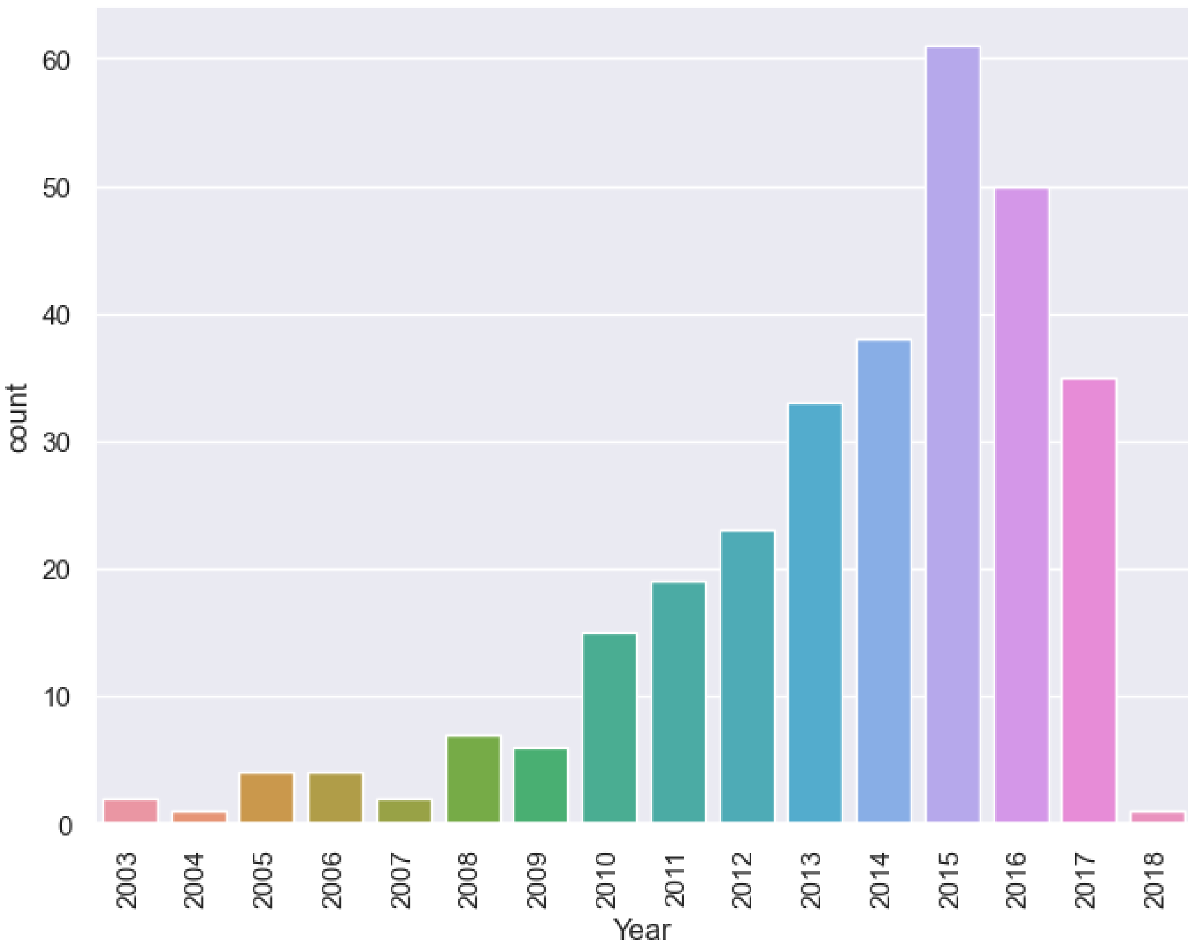
In [6]:
```
car.describe()
```

Out[6]:

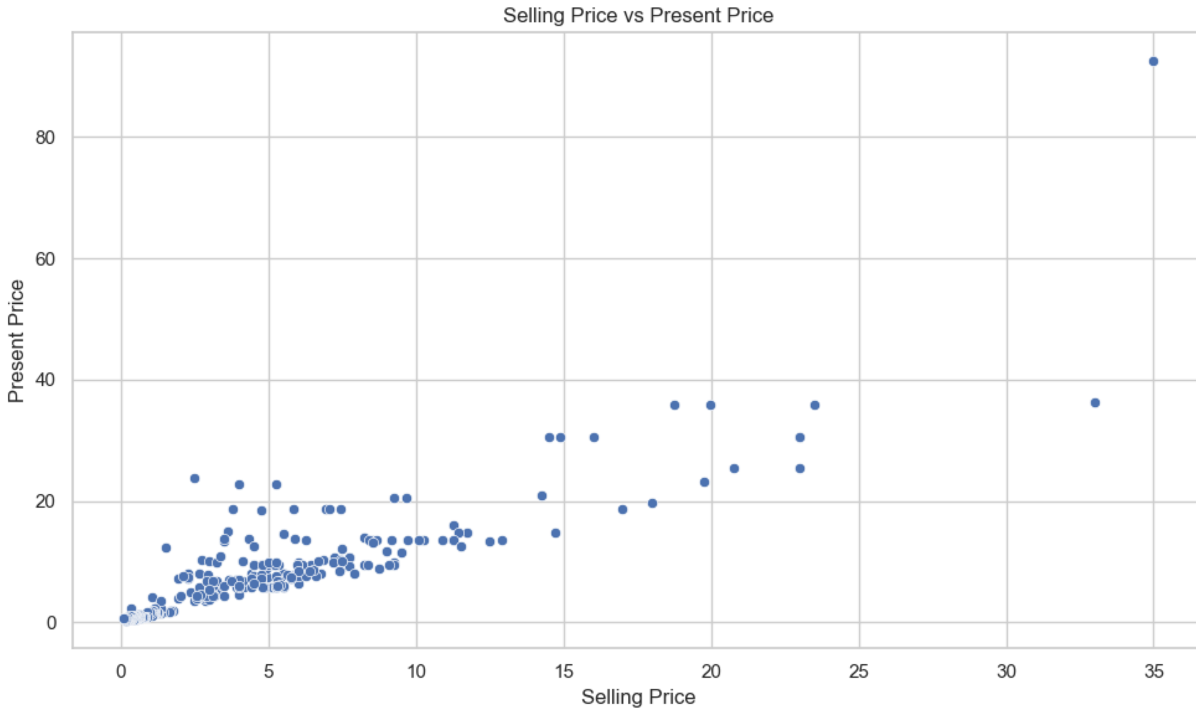
	Year	Selling_Price	Present_Price	Kms_Driven	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.043189
std	2.891554	5.082812	8.644115	38886.883882	0.247915
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	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

Data Visualization

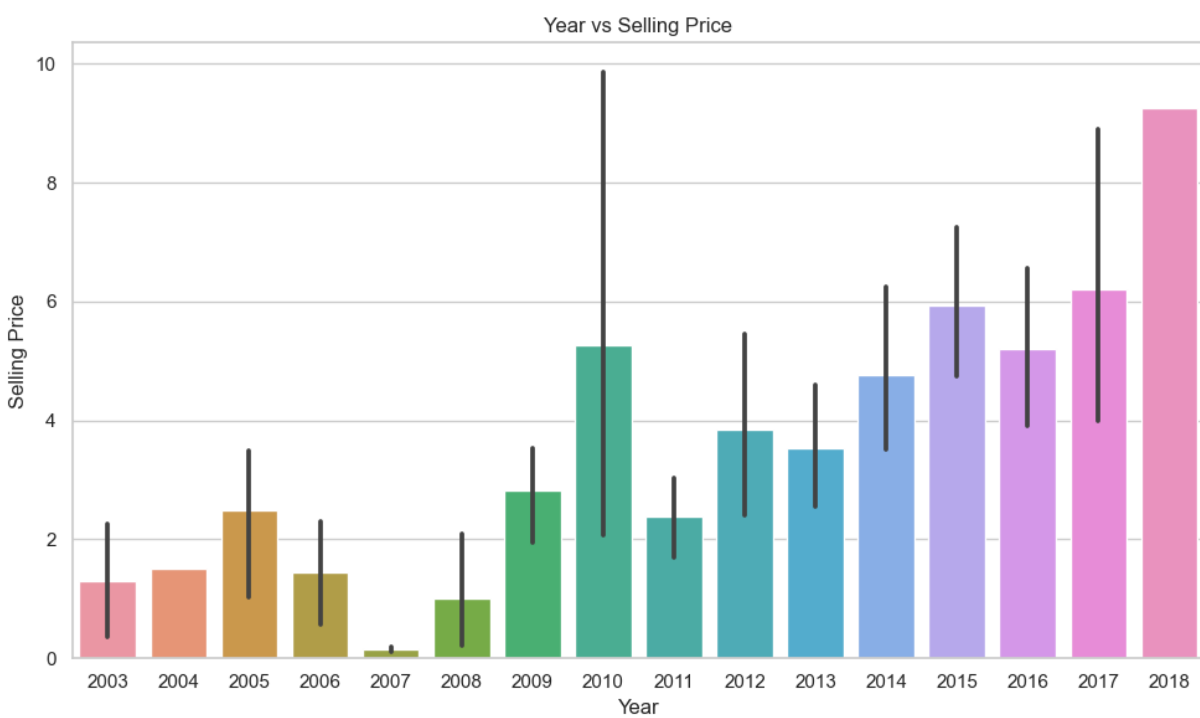
In [7]:
```
# car count based on year
plt.figure(figsize=(8, 6))
ax = sns.countplot(data=car, x=car['Year'])
ax.tick_params(axis='x', rotation=90)
```



In [8]:
```
sns.set(style="whitegrid")

# Selling Price vs Present Price
plt.figure(figsize=(10, 6))
sns.scatterplot(data=car, x='Selling_Price', y='Present_Price')
plt.title('Selling Price vs Present Price')
plt.xlabel('Selling Price')
plt.ylabel('Present Price')
plt.tight_layout()
plt.show()
```

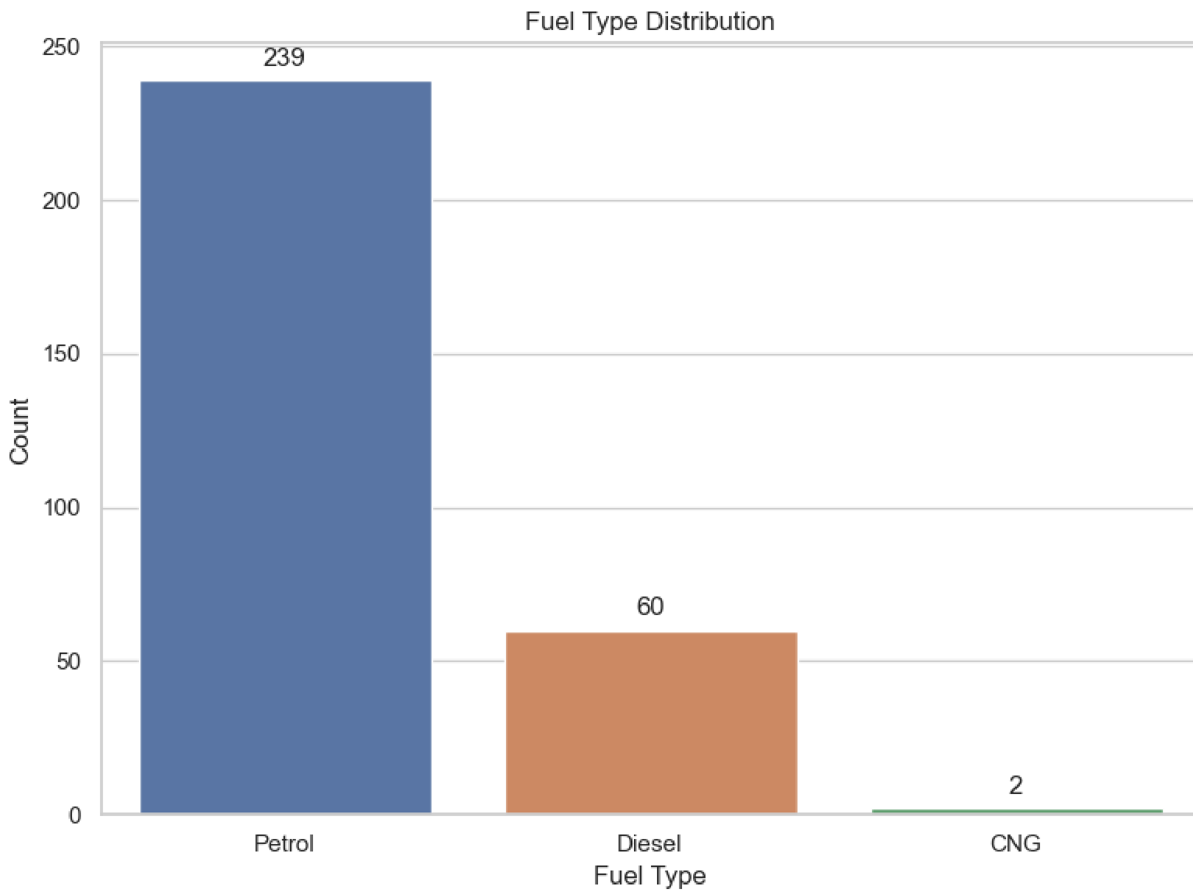


In [9]:
```
# Year vs Selling Price
plt.figure(figsize=(10, 6))
sns.barplot(data=car, x='Year', y='Selling_Price')
plt.title('Year vs Selling Price')
plt.xlabel('Year')
plt.ylabel('Selling Price')
plt.tight_layout()
plt.show()
```



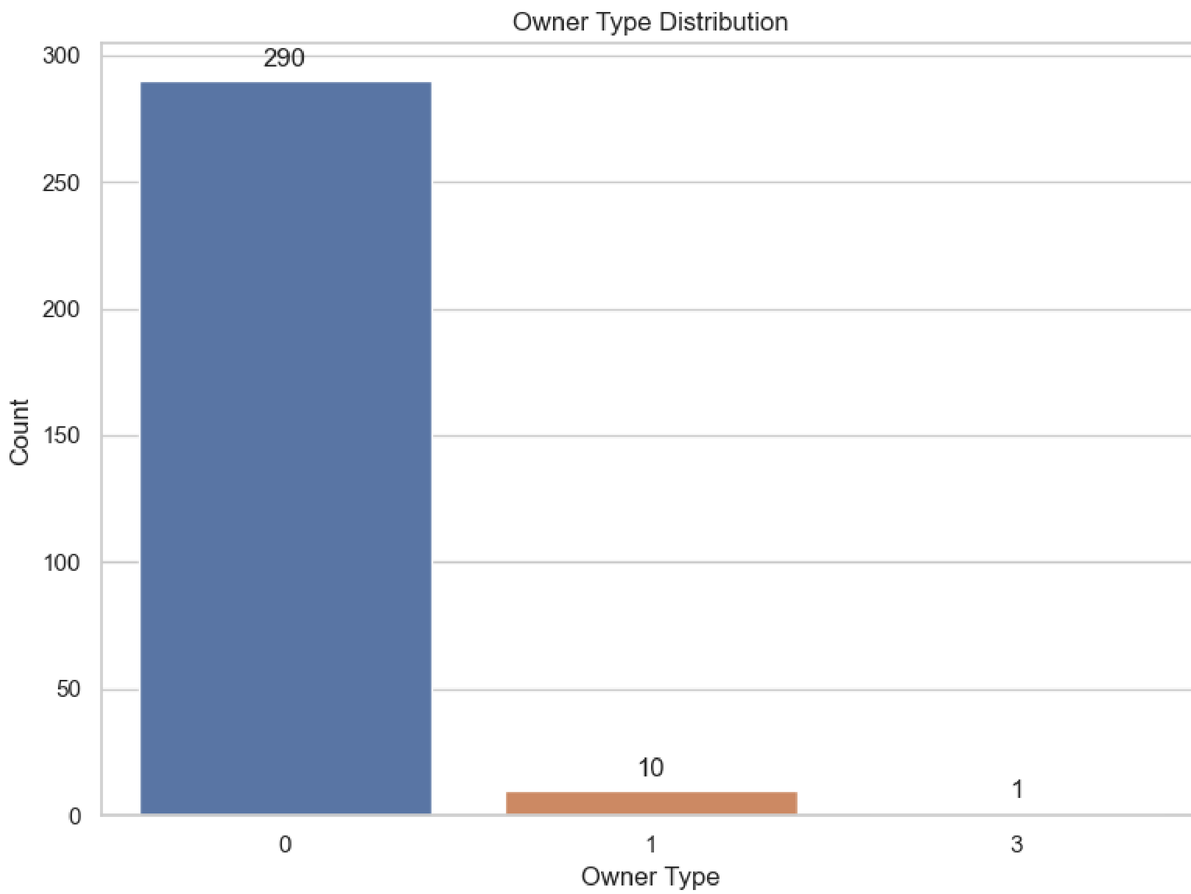
In [10]:
```
sns.set(style="whitegrid")
```

```
# Fuel Type Distribution
plt.figure(figsize=(8, 6))
ax = sns.countplot(data=car, x='Fuel_Type')
plt.title('Fuel Type Distribution')
plt.xlabel('Fuel Type')
plt.ylabel('Count')

# Add count numbers on top of the bars
for p in ax.patches:
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (0, 10),
                textcoords = 'offset points')

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



In [11]:
```
# Owner Type Distribution

plt.figure(figsize=(8, 6))
ax = sns.countplot(data=car, x='Owner')
plt.title('Owner Type Distribution')
plt.xlabel('Owner Type')
plt.ylabel('Count')

# Add count numbers on top of the bars
for p in ax.patches:
```

```
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                xytext=(0, 10),
                textcoords='offset points')

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



Data Preprocessing

1) Checking Missing Values

In [12]:
```
car.isnull().sum()
```

Out[12]:
```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
Owner            0
dtype: int64
```

- There is not any missing values

In [13]:
```
num_lst = []  # list of Numerical columns

for i in car:
    if car[i].dtype != object:
        num_lst.append(i)

num_lst.remove('Selling_Price')
```

In [14]:
```
num_lst
```

Out[14]:
```
['Year', 'Present_Price', 'Kms_Driven', 'Owner']
```

In [15]:
```
obj_lst=[]                          # list of Object Columns
for i in car:
    if car[i].dtype==object:
        obj_lst.append(i)
```

In [16]:
```
obj_lst
```

Out[16]:
```
['Car_Name', 'Fuel_Type', 'Seller_Type', 'Transmission']
```

In [17]:
```
car.duplicated().sum()              # Check Duplicate values
```

Out[17]:
```
2
```

In [18]:
```
car.drop_duplicates(keep=False, inplace=True)   # Drop the Duplicate values
```

In [19]:
```
car.shape
```

Out[19]:
```
(297, 9)
```

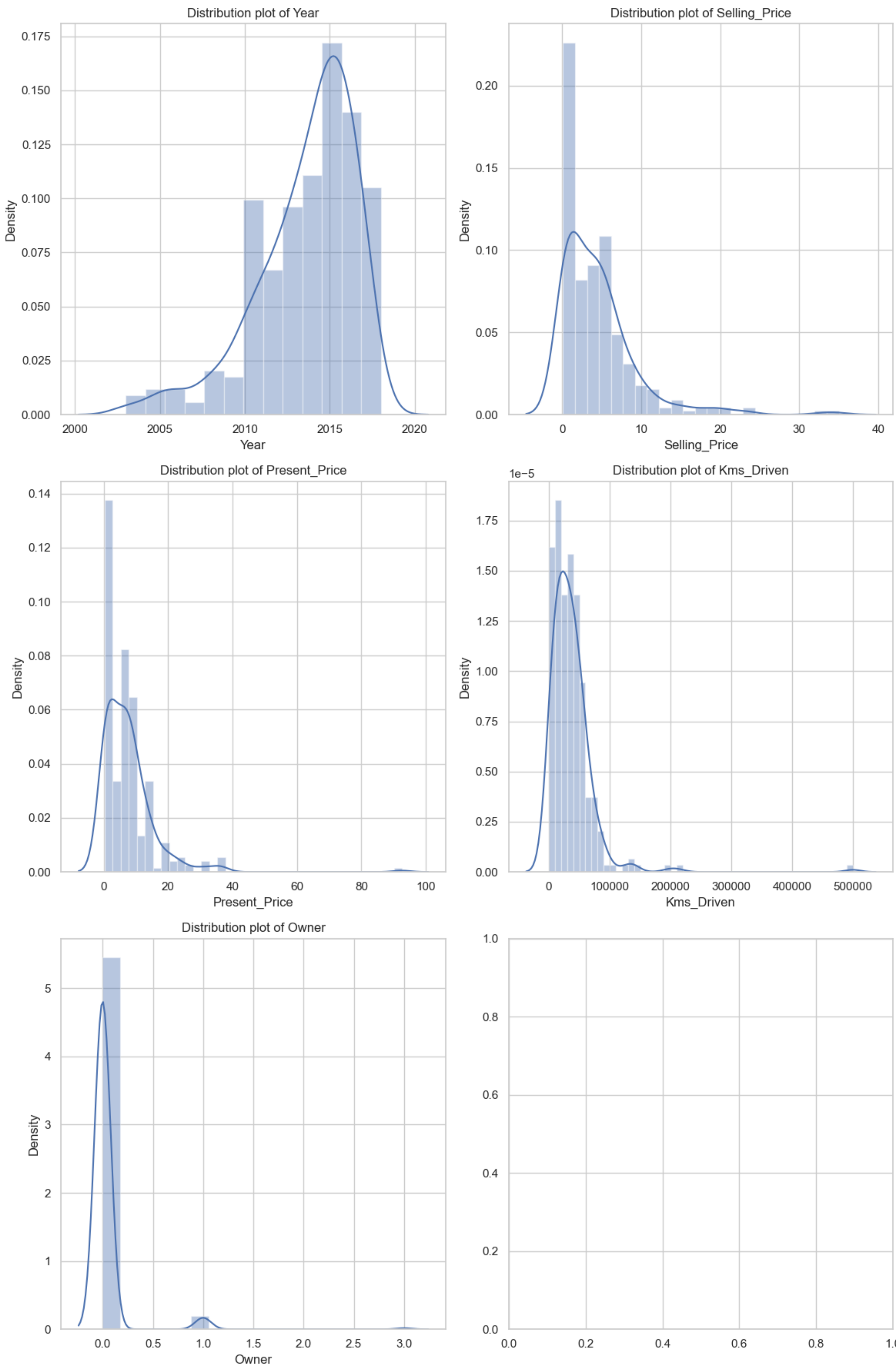
In [20]:
```
car['Year'].unique()
```

Out[20]:
```
array([2014, 2013, 2017, 2011, 2018, 2015, 2016, 2009, 2010, 2012, 2003,
       2008, 2006, 2005, 2004, 2007])
```

Handling Outlier

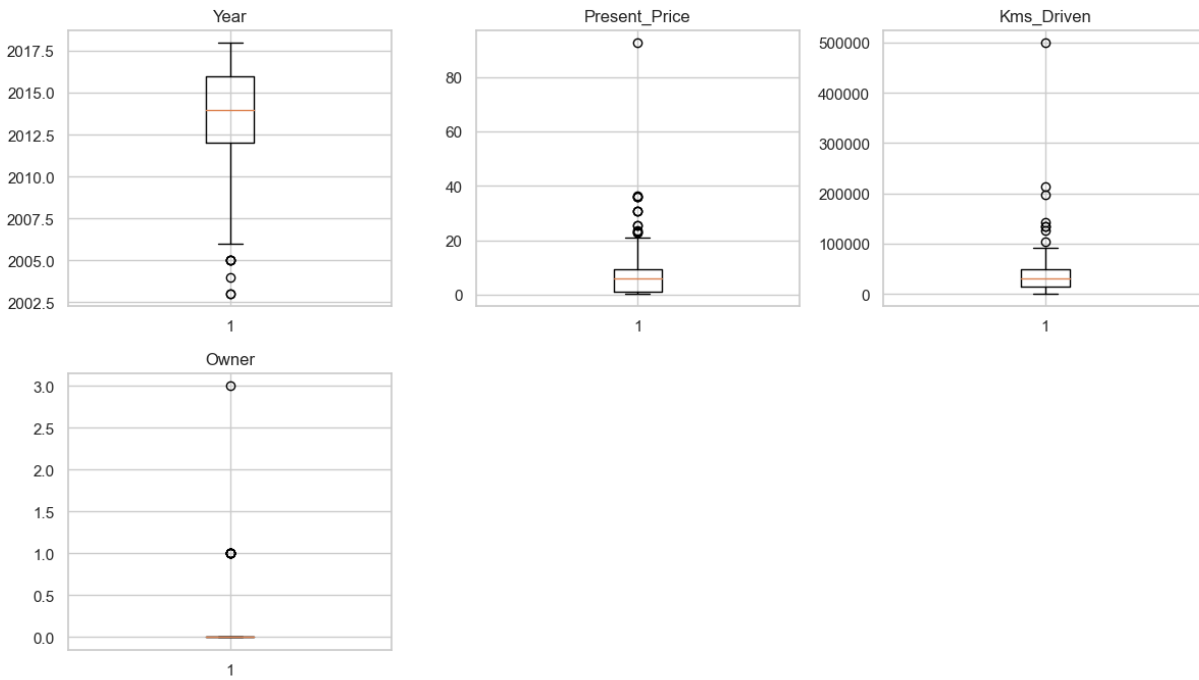
In [21]:
```
#Distribution plots

def distplot(car, col):
    if df[col].dtype in [int, float]:
        sns.distplot(car[col])
        plt.title(f'Distribution plot of {col}')
        plt.show()
    else:
        print(f"{col} is not a numeric column. Skipping...")

# Display distribution plots using subplots in two rows
num_columns = [col for col in car.columns if car[col].dtype in [int, float]]
```

```python
num_plots = len(num_columns)
num_rows = (num_plots + 1) // 2

fig, axes = plt.subplots(num_rows, 2, figsize=(12, 6 * num_rows))

for i, col in enumerate(num_columns):
    row = i // 2
    col = i % 2
    sns.distplot(car[num_columns[i]], ax=axes[row, col])
    axes[row, col].set_title(f'Distribution plot of {num_columns[i]}')

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



In [22]:
```
#boxplot
```

```
plt.figure(figsize=(12,10),dpi=100)

if 'selling price' in num_lst:
    num_lst.remove('selling price')

for i,j in enumerate(num_lst):

    plt.subplot(3,3,i+1)
    plt.boxplot(car[j])
    plt.title(j)
    plt.tight_layout()
    #plt.show()
```

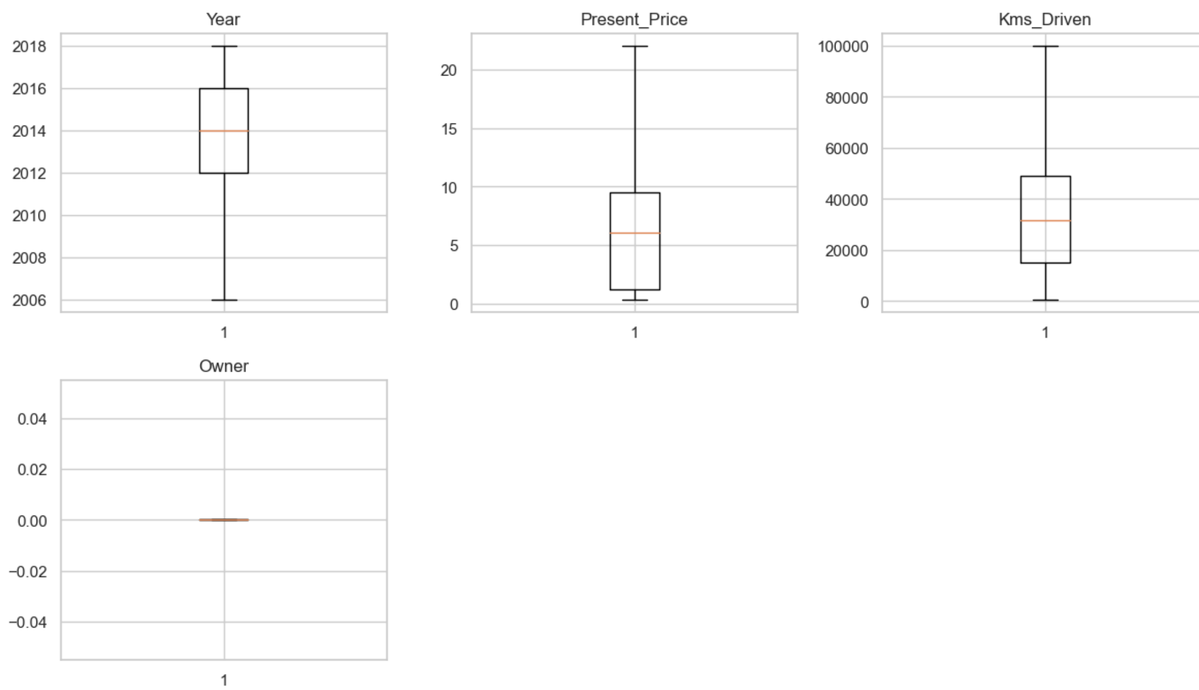


In [23]:
```
def cap_outlier(col):

    q3=car[col].quantile(0.75)
    q1=car[col].quantile(0.25)

    iqr=q3-q1

    lower=q1-1.5*iqr
    upper=q3+1.5*iqr

    car[col].clip(lower,upper,inplace=True)
```

In [24]:
```
for i in num_lst:
    cap_outlier(i)
```

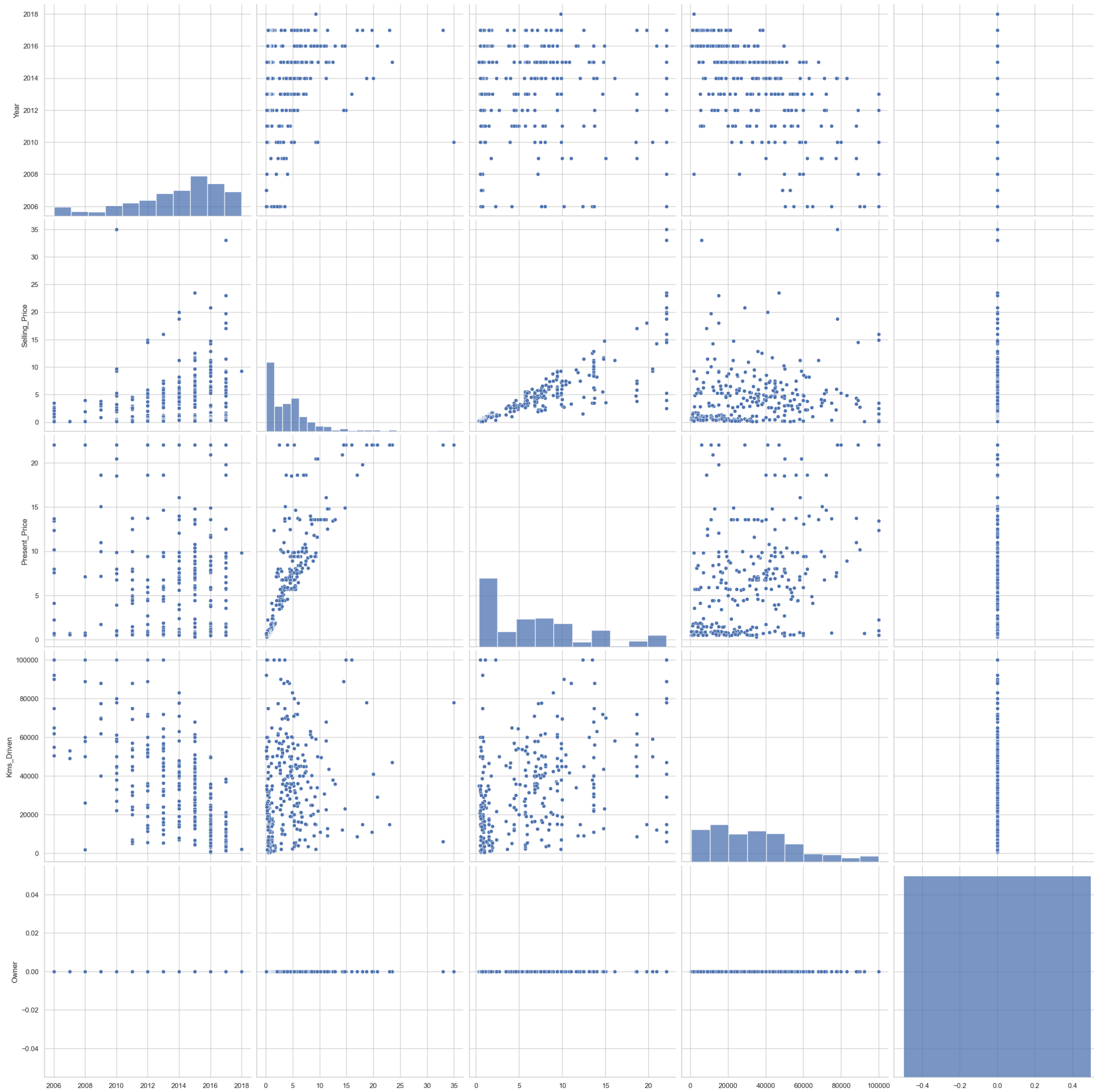
In [25]:
```
# after removing outliers

plt.figure(figsize=(12,10),dpi=100)

if 'selling price' in num_lst:
```

```
    num_lst.remove('selling price')

for i,j in enumerate(num_lst):

    plt.subplot(3,3,i+1)
    plt.boxplot(car[j])
    plt.title(j)
    plt.tight_layout()
    #plt.show()
```



In [26]:
```
#Pair plots

sns.pairplot(car, size = 5, kind = 'scatter')
```

Out[26]: <seaborn.axisgrid.PairGrid at 0x12923dc30>



Encoding

In [27]:
```
car.head()
```

Out[27]:

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

In [28]:
```
car['Fuel_Type'].value_counts()
```

Out[28]:
```
Petrol    239
Diesel     56
CNG         2
Name: Fuel_Type, dtype: int64
```

In [29]:
```
car['Transmission'].value_counts()
```

Out[29]:
```
Manual       259
Automatic     38
Name: Transmission, dtype: int64
```

In [30]:
```
car['Owner'].value_counts()
```

Out[30]:
```
0    297
Name: Owner, dtype: int64
```

In [31]:
```
# Label Encoder

car['Fuel_Type'] = car['Fuel_Type'].astype('category')
car['Fuel_Type'] = car['Fuel_Type'].cat.codes

car['Seller_Type'] = car['Seller_Type'].astype('category')
car['Seller_Type'] = car['Seller_Type'].cat.codes

# One Hot Encoder

car = pd.get_dummies(car, columns=['Seller_Type'])

car = pd.get_dummies(car, columns=['Transmission'])

car = pd.get_dummies(car, columns=['Owner'])
```

In [32]:
```
car = car.drop(['Transmission_Automatic','Owner_0','Seller_Type_0'], axis=1)
```

In [33]:
```
car.head()
```

Out[33]:

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

Feature Scaling

In [34]:
```
# split the data into independent variable and dependent variable
x = car.drop(['Car_Name','Selling_Price'],axis=1)
y = car['Selling_Price']
```

In [35]:
```
x.head()
```

Out[35]:

	Year	Present_Price	Kms_Driven	Fuel_Type	Seller_Type_1	Transmission_Manual
0	2014	5.59	27000	2	0	1
1	2013	9.54	43000	1	0	1
2	2017	9.85	6900	2	0	1
3	2011	4.15	5200	2	0	1
4	2014	6.87	42450	1	0	1

In [36]:
```
y.head()
```

Out[36]:
```
0    3.35
1    4.75
2    7.25
3    2.85
4    4.60
Name: Selling_Price, dtype: float64
```

In [37]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
sc_x = sc.fit_transform(x)
pd.DataFrame(sc_x)
```

Out[37]:

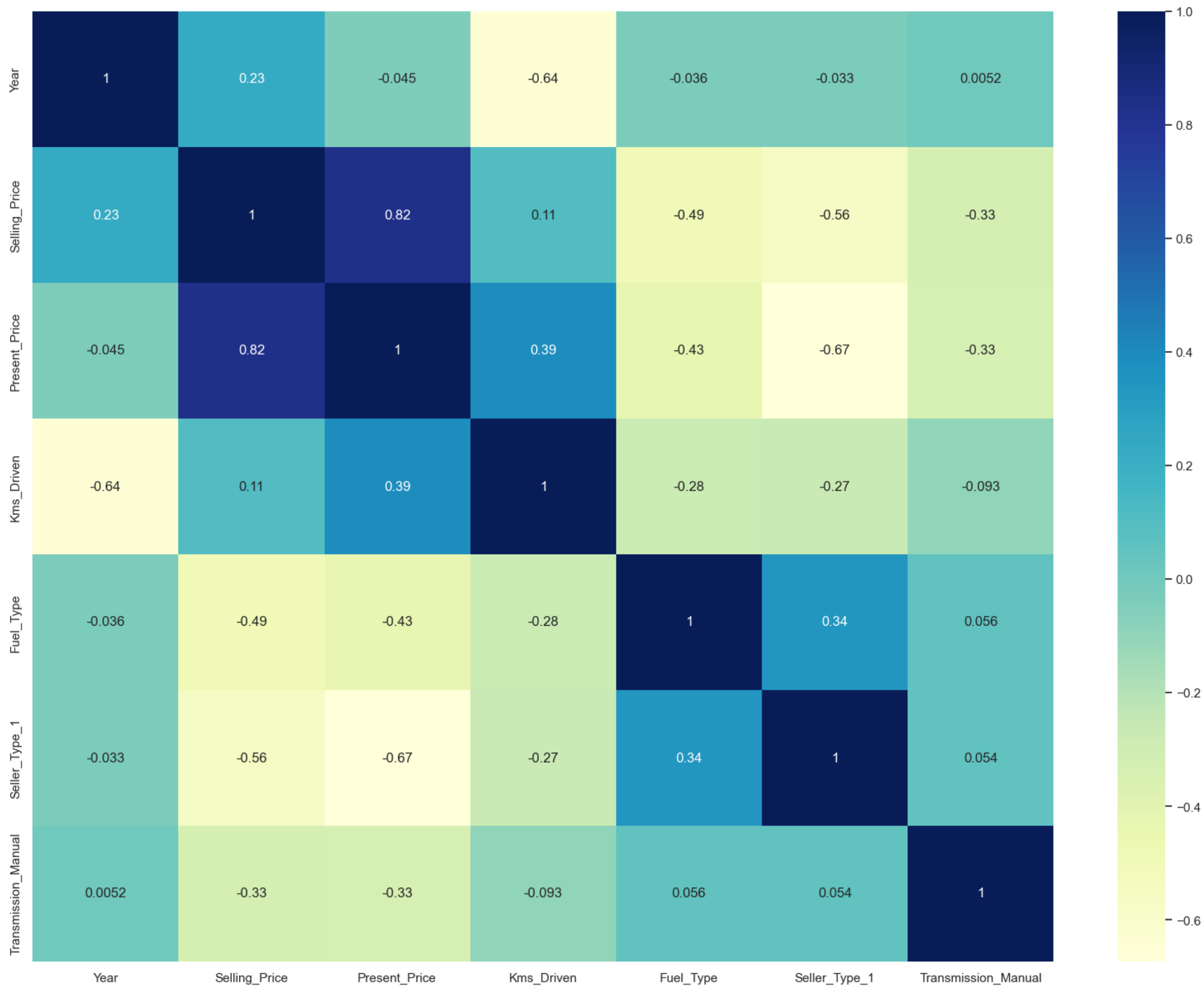
	0	1	2	3	4	5
0	0.128696	-0.221149	-0.307742	0.483368	-0.744966	0.383038
1	-0.231895	0.444033	0.362442	-1.909305	-0.744966	0.383038
2	1.210467	0.496237	-1.149662	0.483368	-0.744966	0.383038
3	-0.953076	-0.463645	-1.220869	0.483368	-0.744966	0.383038
4	0.128696	-0.005596	0.339405	-1.909305	-0.744966	0.383038
...	...	...	...	...	...	...
292	0.849876	0.790938	-0.015039	-1.909305	-0.744966	0.383038
293	0.489286	-0.168945	1.074514	0.483368	-0.744966	0.383038
294	-1.674256	0.689897	2.244573	0.483368	-0.744966	0.383038
295	1.210467	0.942498	-1.061700	-1.909305	-0.744966	0.383038
296	0.849876	-0.168945	-1.209811	0.483368	-0.744966	0.383038

297 rows × 6 columns

Finding correlation

In [38]:
```
plt.figure(figsize=(20,15))
corr = car.corr()
```

```
sns.heatmap(corr, annot=True, cmap='YlGnBu')
plt.show()
```



VIF - Variance Inflation Factor (to check multicollinearity)

In [39]:
```
variable = sc_x
variable.shape
```

Out[39]: (297, 6)

In [40]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
variable = sc_x

vif = pd.DataFrame()

vif['Variance Inflation Factor'] = [variance_inflation_factor(variable, i )

vif['Features'] = x.columns
```

In [41]:
```
vif
```

Out [41]:

	Variance Inflation Factor	Features
0	1.983920	Year
1	2.562714	Present_Price
2	2.351141	Kms_Driven
3	1.324415	Fuel_Type
4	1.975662	Seller_Type_1
5	1.207843	Transmission_Manual

Split the data into training and test for building the model and for prediction

In [42]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.1, rar

print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(267, 6) (30, 6) (267,) (30,)
```

Linear Regression

Approach no - 1

In [43]:
```
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
lm.fit(x_train, y_train)
```

Out [43]:
```
▾ LinearRegression
LinearRegression()
```

In [44]:
```
print(lm.intercept_)
print()
print(lm.coef_)
```

```
-551.785531223224

[ 2.77169715e-01  6.44982956e-01 -2.93641386e-05 -2.33346191e+00
  8.81285048e-02 -1.19395715e+00]
```

In [45]:
```
# Predict selling price by using lm model with test dataset

y_pred_price = lm.predict(x_test)
y_pred_price_train = lm.predict(x_train)
```

In [46]:
```
y_pred_price
```

Out[46]:
```
array([ 8.88822834,  4.4747697 , -0.25928022,  2.50491382,  1.33653492,
        6.19322049,  8.01518926,  1.09669301,  0.66031415,  4.70156723,
        8.43825228,  1.52629922,  6.09138103,  8.44415608,  5.62421714,
        6.76112816,  3.63707214,  6.43455481, -0.22264225,  8.91955305,
        1.54123831,  2.18013459,  2.7434277 ,  4.06052973,  5.05991459,
        0.59487513,  1.7689446 , 11.71279859, 17.11875745,  7.75802376])
```

In [47]:
```
# Validate the actual price of the test data and predicted price

from sklearn.metrics import r2_score
r2_score(y_test, y_pred_price)
```

Out[47]:
```
0.7564489097398766
```

In [48]:
```
r2_score(y_train, y_pred_price_train)
```

Out[48]:
```
0.7857015229799365
```

Approach no 2 - OLS Method

In [49]:
```
from statsmodels.regression.linear_model import OLS
import statsmodels.regression.linear_model as smf
```

In [50]:
```
reg_model = smf.OLS(endog = y_train, exog=x_train).fit()
```

In [51]:
```
reg_model.summary()
```

Out[51]:

OLS Regression Results

Dep. Variable:	Selling_Price	**R-squared (uncentered):**	0.877
Model:	OLS	**Adj. R-squared (uncentered):**	0.874
Method:	Least Squares	**F-statistic:**	309.6
Date:	Fri, 11 Aug 2023	**Prob (F-statistic):**	1.41e-115
Time:	20:04:37	**Log-Likelihood:**	-607.85
No. Observations:	267	**AIC:**	1228.
Df Residuals:	261	**BIC:**	1249.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Year	0.0039	0.001	7.125	0.000	0.003	0.005
Present_Price	0.6563	0.039	16.878	0.000	0.580	0.733
Kms_Driven	-5.363e-05	6.63e-06	-8.089	0.000	-6.67e-05	-4.06e-05
Fuel_Type	-2.6753	0.407	-6.574	0.000	-3.477	-1.874
Seller_Type_1	-0.1055	0.421	-0.251	0.802	-0.934	0.723
Transmission_Manual	-1.2727	0.477	-2.670	0.008	-2.211	-0.334

Omnibus:	214.194	**Durbin-Watson:**	2.169
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8238.353
Skew:	2.755	**Prob(JB):**	0.00
Kurtosis:	29.649	**Cond. No.**	1.46e+05

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 1.46e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Lasso Regularization (L1 - Regularization)

In [52]:

```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.1)
lasso.fit(x_train, y_train)
print("Lasso Model :", (lasso.coef_))
```

```
Lasso Model : [ 2.85799746e-01  6.79778301e-01 -2.69952914e-05 -1.47777073e+0
0
  0.00000000e+00 -1.36332863e-01]
```

In [53]:
```
y_pred_train_lasso = lasso.predict(x_train)
y_pred_test_lasso = lasso.predict(x_test)
```

In [54]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_lasso))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_lasso))
```

```
Training Accuracy : 0.777991797308078

Test Accuracy : 0.7886203090155269
```

Ridge Regression (L2 - Regularization)

In [55]:
```
from sklearn.linear_model import Ridge
ridge = Ridge(alpha=0.3)
ridge.fit(x_train, y_train)
print("Ridge Model :", (ridge.coef_))
```

```
Ridge Model : [ 2.77968481e-01  6.45856007e-01 -2.92536686e-05 -2.31132688e+0
0
  8.94330979e-02 -1.17803735e+00]
```

In [56]:
```
y_pred_train_ridge = ridge.predict(x_train)
y_pred_test_ridge = ridge.predict(x_test)
```

In [57]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_ridge))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_ridge))
```

```
Training Accuracy : 0.7856983656070035

Test Accuracy : 0.7574686092905991
```

ElasticNet

(L1- Regularization + L2- Regularization)

In [58]:
```
from sklearn.linear_model import ElasticNet
elastic = ElasticNet(alpha=0.3, l1_ratio=0.1)
elastic.fit(x_train, y_train)
```

Out[58]:
```
▾ ElasticNet
ElasticNet(alpha=0.3, l1_ratio=0.1)
```

In [59]:
```
y_pred_train_elastic = elastic.predict(x_train)
y_pred_test_elastic = elastic.predict(x_test)
```

In [60]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_elastic))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_elastic))
```

```
Training Accuracy : 0.7687033386771955

Test Accuracy : 0.7895248686762874
```

Performance Matrix

Mean Absolute Error (MAE)

In [61]:
```
from sklearn import metrics
```

In [62]:
```
print("MAE :", metrics.mean_absolute_error(y_test, y_pred_price))
```

```
MAE : 1.2843754119933342
```

Mean Absolute Percent Error (MAPE)

In [63]:
```
print("MAPE :", metrics.mean_absolute_error(y_test, y_pred_price)/100)
```

```
MAPE : 0.012843754119933342
```

Mean Squared Error (MSE)

In [64]:
```
print("MSE :", metrics.mean_squared_error(y_test, y_pred_price))
```

```
MSE : 4.014650600732763
```

Root Mean Squared Error (MSE)

In [65]:
```
print("RMSE :", np.sqrt(metrics.mean_squared_error(y_test, y_pred_price)))
```

```
RMSE : 2.0036593025593854
```

Gradient Descent

In [66]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(sc_x, y, test_size=0.25,

print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(222, 6) (75, 6) (222,) (75,)
```

In [67]:
```
from sklearn.linear_model import SGDRegressor
```

In [68]:
```
gd_model = SGDRegressor()
gd_model.fit(x_train, y_train)
```

Out[68]:

```
▾ SGDRegressor
SGDRegressor()
```

In [69]:

```python
y_pred_gd_train = gd_model.predict(x_train)

y_pred_gd_test = gd_model.predict(x_test)
```

In [70]:

```python
print("GD Trainging Accuracy :", r2_score(y_train, y_pred_gd_train))

print()

print("GD Test Accuracy :", r2_score(y_test, y_pred_gd_test))
```

```
GD Trainging Accuracy : 0.7880810276204224

GD Test Accuracy : 0.7167233857543006
```

Decision Tree

In [71]:

```python
from sklearn.tree import DecisionTreeRegressor
dtree = DecisionTreeRegressor()
dtree.fit(x_train, y_train)
```

Out[71]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

In [72]:

```python
y_pred_DT_train = dtree.predict(x_train)
y_pred_DT_test = dtree.predict(x_test)
```

In [73]:

```python
# Evaluate the model
from sklearn.metrics import r2_score
```

In [74]:

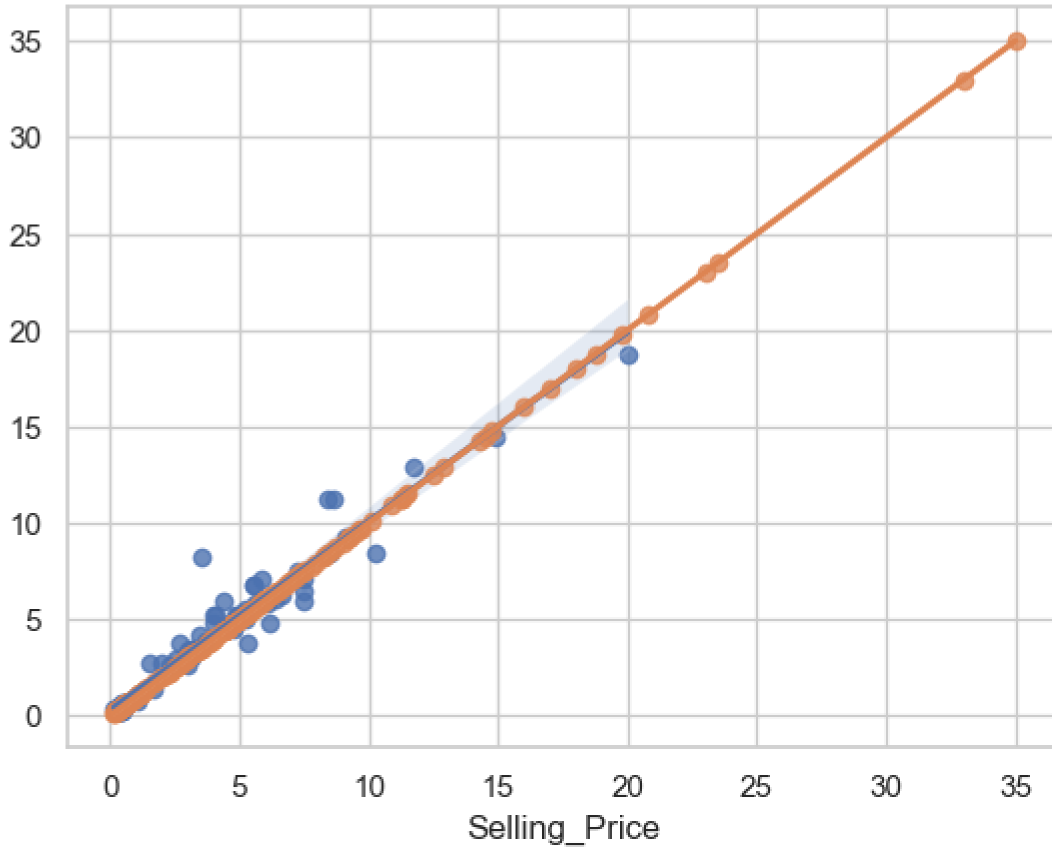
```python
print(r2_score(y_train, y_pred_DT_train))
print()
print(r2_score(y_test, y_pred_DT_test))
```

```
1.0

0.9298870446456924
```

In [75]:

```python
sns.regplot(x=y_test, y=y_pred_DT_test)
sns.regplot(x=y_train, y=y_pred_DT_train)
```

Out[75]: <Axes: xlabel='Selling_Price'>



Random Forest

In [76]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf.fit(x_train, y_train)
```

Out[76]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

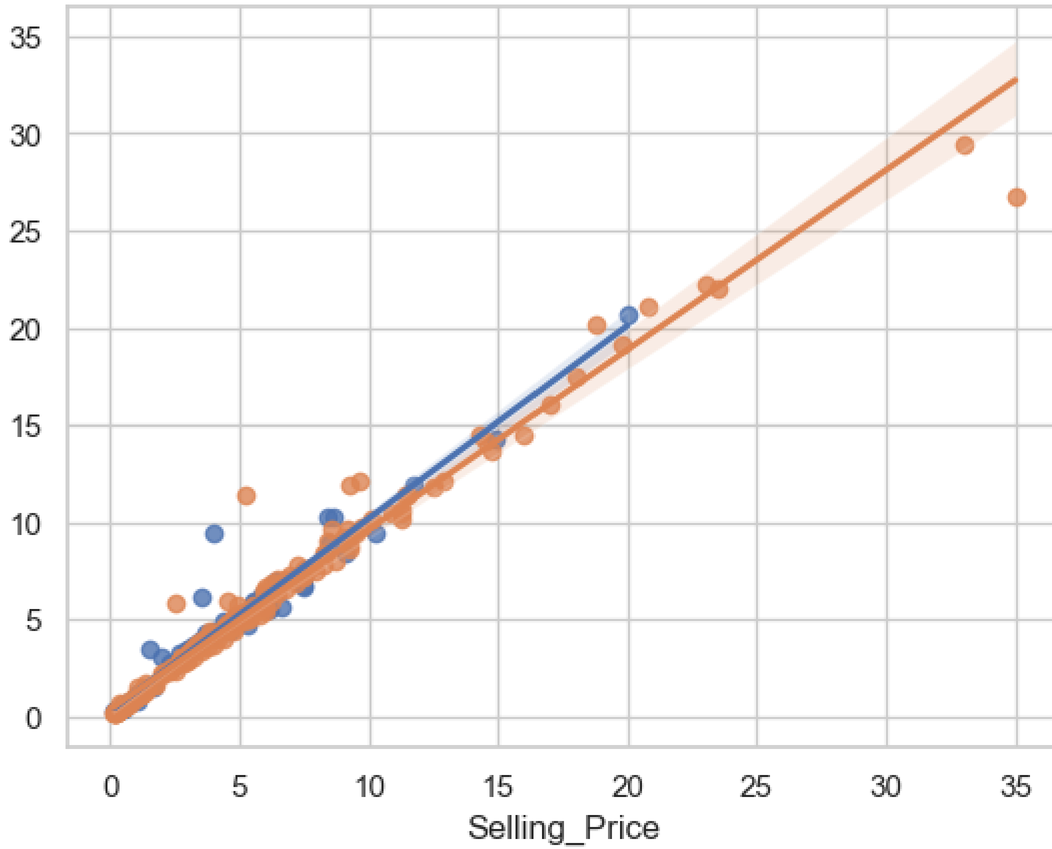
In [77]:
```
y_pred_RF_train = rf.predict(x_train)
y_pred_RF_test = rf.predict(x_test)
```

In [78]:
```
print(r2_score(y_train, y_pred_RF_train))
print()
print(r2_score(y_test, y_pred_RF_test))
```

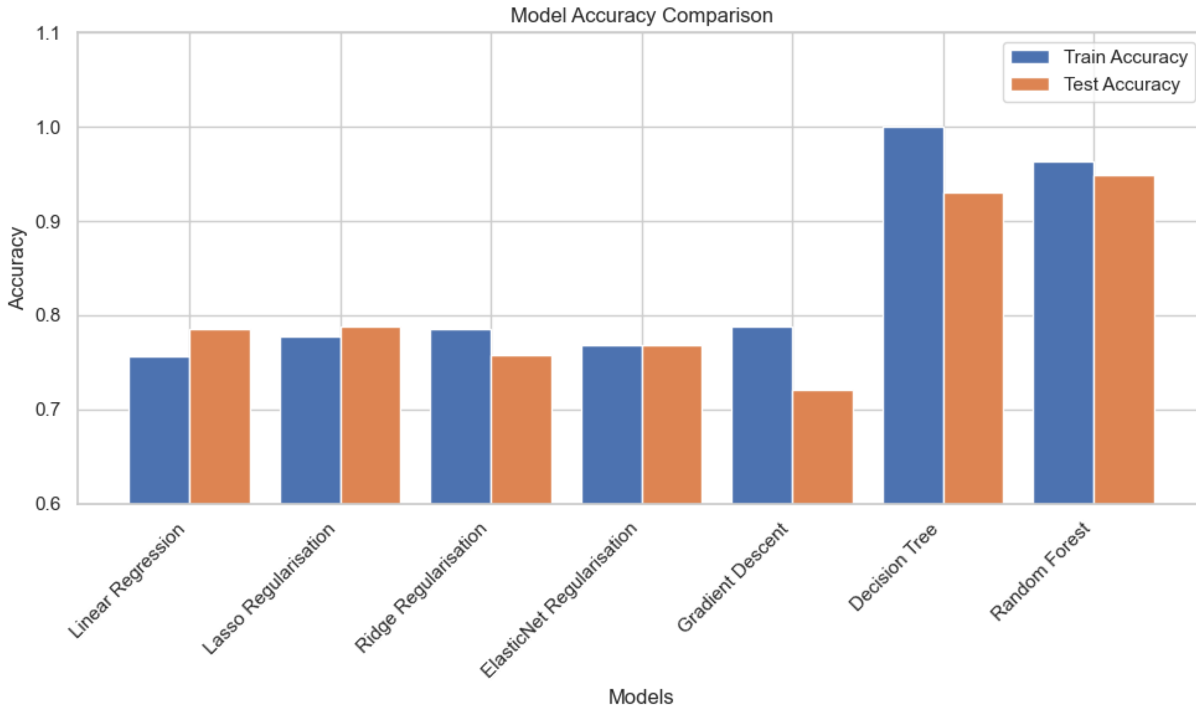
```
0.9718074632167586

0.9411645711757195
```

In [79]:
```
sns.regplot(x=y_test, y=y_pred_RF_test)
sns.regplot(x=y_train, y=y_pred_RF_train)
```

Out[79]:
```
<Axes: xlabel='Selling_Price'>
```



In [80]:
```
#Model Accuracy Comparison

model_names = ["Linear Regression", "Lasso Regularisation", "Ridge Regularis
accuracy_data = {
    'train_accuracies': [0.7564489097398766, 0.777991797308078, 0.7856983656
    'test_accuracies': [0.7857015229799365, 0.7886203090155269, 0.7574686092
}

x = list(range(len(model_names)))

plt.figure(figsize=(10, 6))
plt.bar(x, accuracy_data['train_accuracies'], width=0.4, label='Train Accura
plt.bar([i + 0.4 for i in x], accuracy_data['test_accuracies'], width=0.4, l
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.xticks([i + 0.2 for i in x], model_names, rotation=45, ha='right')
plt.ylim(0.6, 1.1)
plt.legend()
plt.tight_layout()

plt.show()
```



Conclusion

Here's a simplified conclusion with bullet points highlighting the performance of each model:

- **Linear Regression**: Shows steady accuracy on both training and testing.
- **Lasso Regularization**: Performs well with consistent accuracy scores.
- **Ridge Regularization**: Also does well with steady accuracy on both datasets.
- **ElasticNet Regularization**: Maintains similar accuracy on both training and testing.
- **Gradient Descent**: Has okay accuracy but not the highest.
- **Decision Tree**: Perfect on training but drops on testing (overfitting risk).
- **Random Forest**: Stands out with high accuracy on both training and testing.

In terms of the best performer, the **Random Forest** model demonstrates strong overall performance on both training and testing data.