Car Price Prediction Regression

Data Loading and Preprocessing:

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.simplefilter("ignore")
```

In [2]:
```
cp = pd.read_csv("C:\PGA32\MeriSkill\Oasis Infobyte\car data.csv")
```

In [3]:
```
cp
```

Out[3]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0
...	...	...	...	...	...	...	...	...	...
296	city	2016	9.50	11.60	33988	Diesel	Dealer	Manual	0
297	brio	2015	4.00	5.90	60000	Petrol	Dealer	Manual	0
298	city	2009	3.35	11.00	87934	Petrol	Dealer	Manual	0
299	city	2017	11.50	12.50	9000	Diesel	Dealer	Manual	0
300	brio	2016	5.30	5.90	5464	Petrol	Dealer	Manual	0

301 rows × 9 columns

In [4]:
```
cp.shape
```
Out[4]:
```
(301, 9)
```

In [5]:
```
cp.size
```
Out[5]:
```
2709
```

In [6]:
```
cp.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 [7]:
```
cp.dtypes
```

Out[7]:
```
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 [8]:
```
cp.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
Year	301.0	2013.627907	2.891554	2003.00	2012.0	2014.0	2016.0	2018.0
Selling_Price	301.0	4.661296	5.082812	0.10	0.9	3.6	6.0	35.0
Present_Price	301.0	7.628472	8.642584	0.32	1.2	6.4	9.9	92.6
Driven_kms	301.0	36947.205980	38886.883882	500.00	15000.0	32000.0	48767.0	500000.0
Owner	301.0	0.043189	0.247915	0.00	0.0	0.0	0.0	3.0

In [9]:
```
cp.corr()
```

Out[9]:

	Year	Selling_Price	Present_Price	Driven_kms	Owner
Year	1.000000	0.236141	-0.047192	-0.524342	-0.182104
Selling_Price	0.236141	1.000000	0.878914	0.029187	-0.088344
Present_Price	-0.047192	0.878914	1.000000	0.203618	0.008058
Driven_kms	-0.524342	0.029187	0.203618	1.000000	0.089216
Owner	-0.182104	-0.088344	0.008058	0.089216	1.000000

No Missing Value

In [10]:
```
cp.isnull().sum()
```

Out[10]:
```
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 [11]:
```
set(cp.duplicated())
```

Out[11]:
```
{False, True}
```

In [12]:
```
cp.duplicated().sum()
```

Out[12]:
```
2
```

In [13]:
```
# Check for duplicates across all columns
duplicated = cp.duplicated()

# Print the number of duplicated instances
print("Number of duplicated instances:", duplicated.sum())

# Print the duplicated instances
cp[duplicated]
```

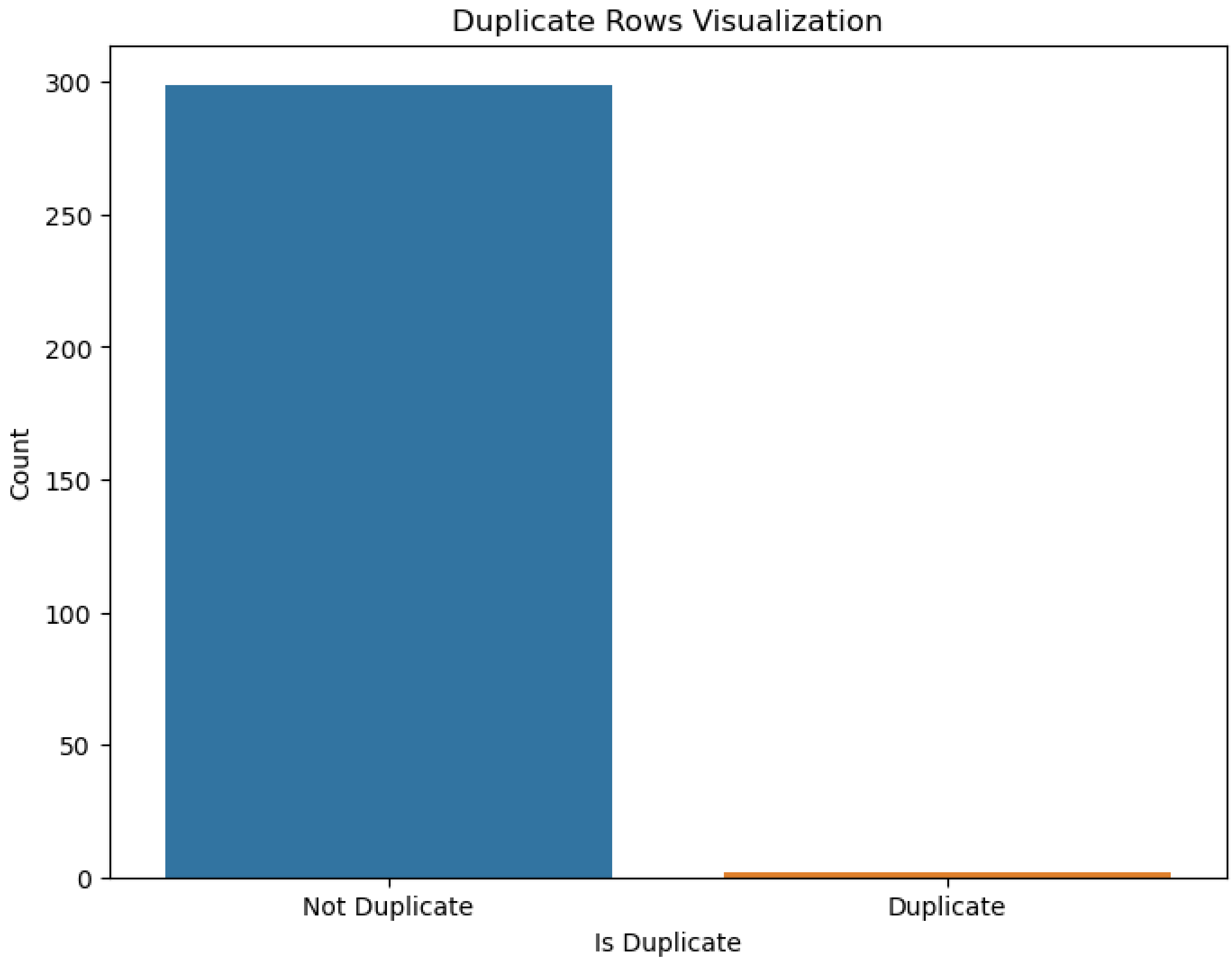
```
Number of duplicated instances: 2
```

Out[13]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner
17	ertiga	2016	7.75	10.79	43000	Diesel	Dealer	Manual	0
93	fortuner	2015	23.00	30.61	40000	Diesel	Dealer	Automatic	0

In [14]:

```
cp['Is_Duplicate'] = cp.duplicated()


# Create a count plot to visualize duplicates
plt.figure(figsize=(8, 6))
sns.countplot(x='Is_Duplicate', data=cp)
plt.xlabel('Is Duplicate')
plt.ylabel('Count')
plt.title('Duplicate Rows Visualization')
plt.xticks([0, 1], ['Not Duplicate', 'Duplicate'])
plt.show()

# Drop the "Is_Duplicate" column if not needed
cp.drop(columns=['Is_Duplicate'], inplace=True)
```



Duplicate Dropping

In [15]:
```
cp = cp.drop_duplicates(subset=['Car_Name', 'Year', 'Selling_Price', 'Present_Price', 'Driven_kms', 'Fuel_Type',
                                'Selling_type', 'Transmission', 'Owner'])
```

In [16]:
```
# Check for duplicates across all columns
duplicated = cp.duplicated()

# Print the number of duplicated instances
```

```
print("Number of duplicated instances:", duplicated.sum())

# Print the duplicated instances
cp[duplicated]
```

```
Number of duplicated instances: 0
```

Out[16]:

Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner

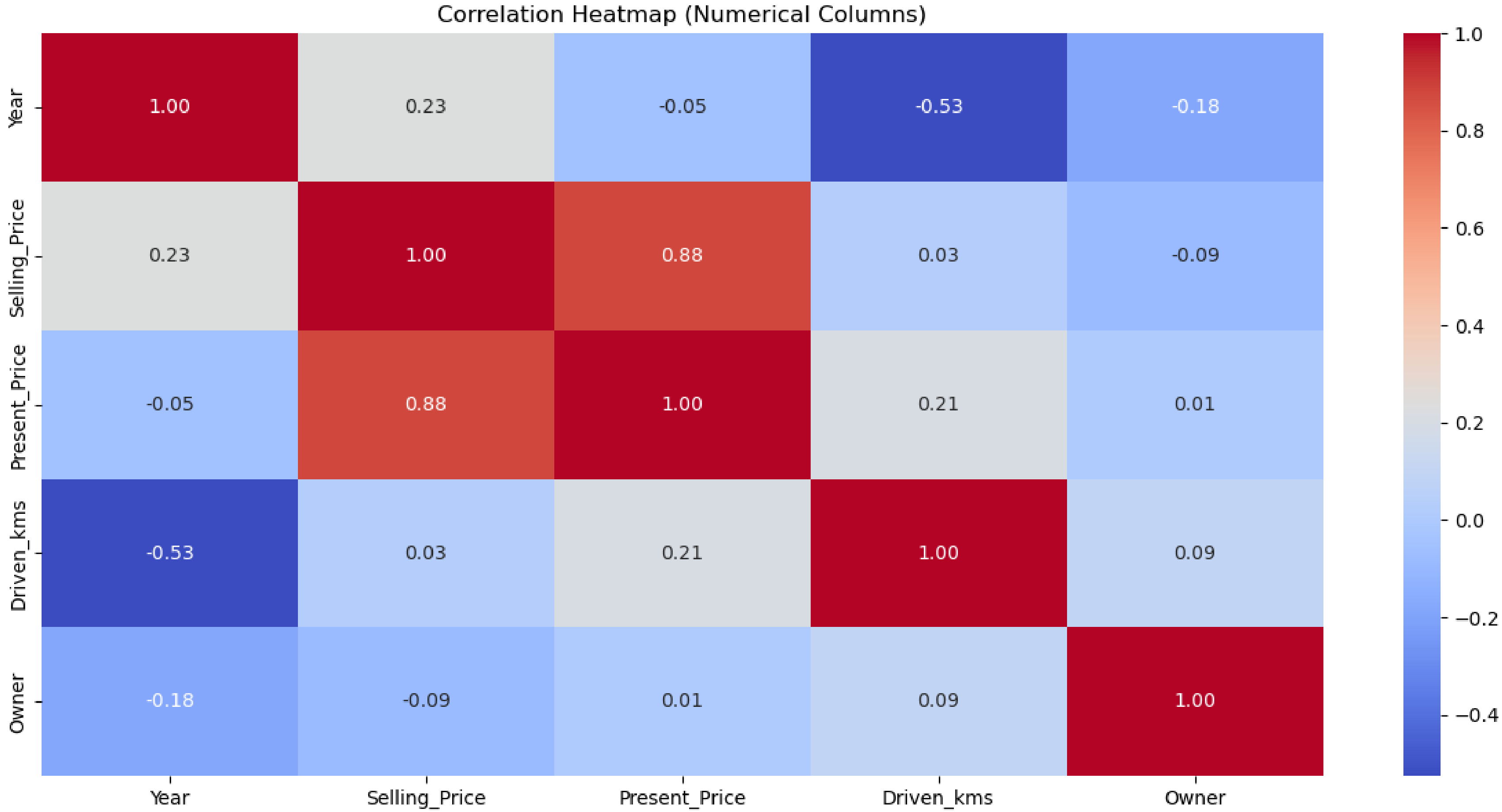
Numerical Columns

In [17]:
```
cp.dtypes[cp.dtypes!="object"]
```

Out[17]:
```
Year               int64
Selling_Price    float64
Present_Price    float64
Driven_kms         int64
Owner              int64
dtype: object
```

In [18]:
```
# Select numerical columns
numerical_columns = ['Year', 'Selling_Price', 'Present_Price', 'Driven_kms', 'Owner']

# Create a DataFrame containing only the numerical columns
numerical_df = cp[numerical_columns]
```

In [19]:
```
# Calculate the correlation matrix for numerical columns
correlation_matrix = numerical_df.corr()

# Create a heatmap
plt.figure(figsize=(15, 7))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap (Numerical Columns)')
plt.show()
```

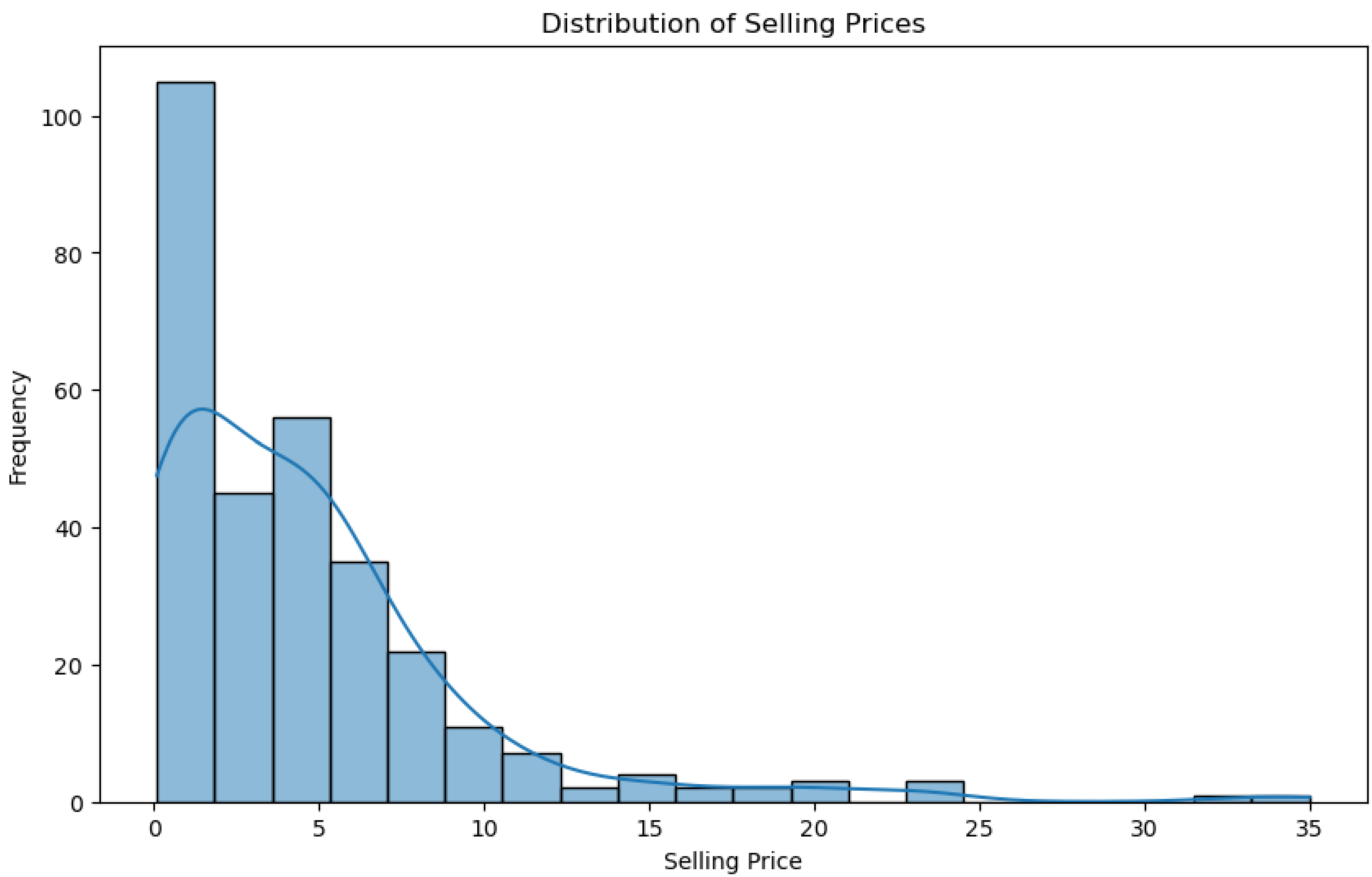


In [20]:
```
correlation_matrix.corr()
```

Out[20]:

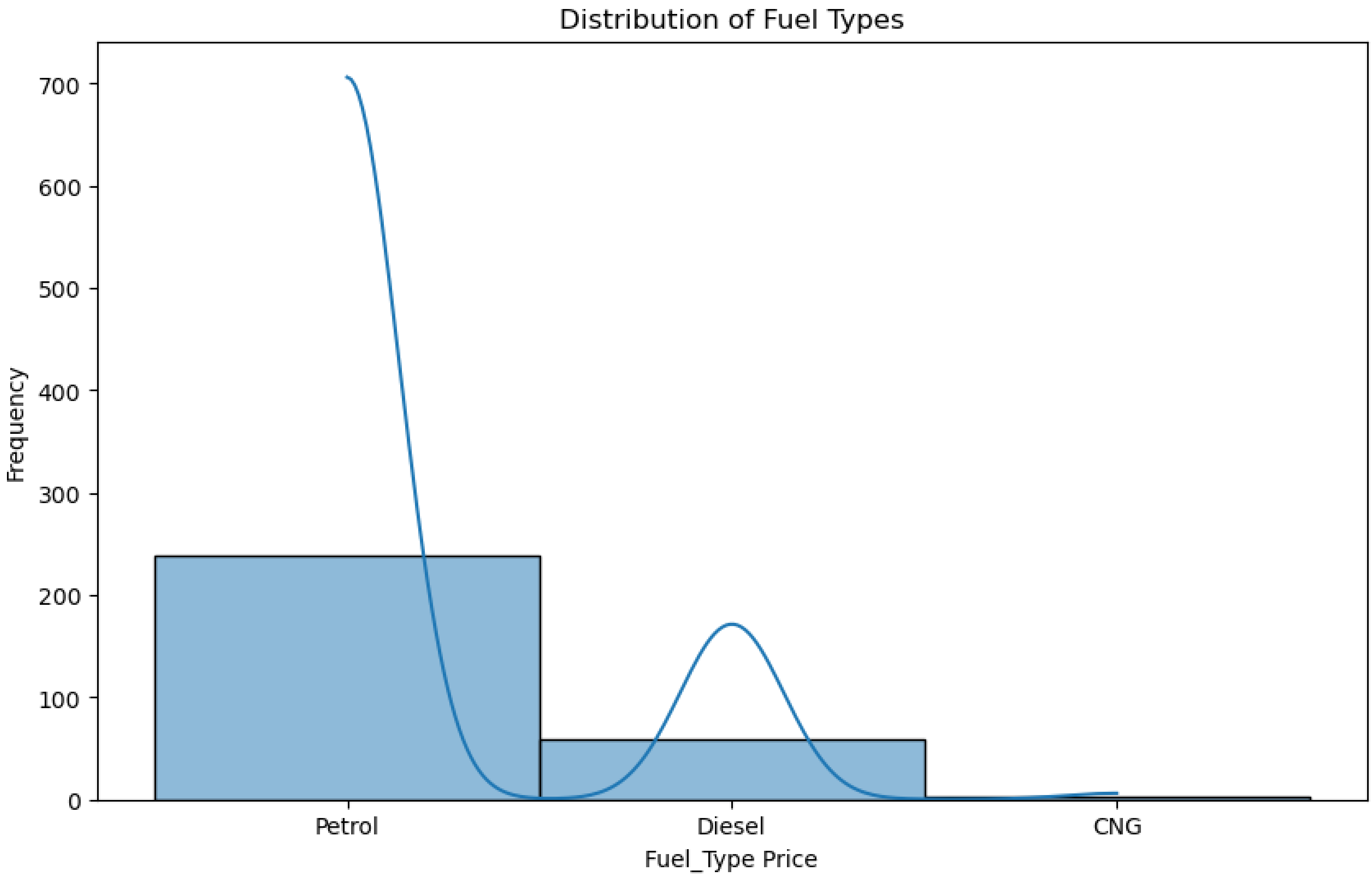
	Year	Selling_Price	Present_Price	Driven_kms	Owner
Year	1.000000	0.199905	-0.178871	-0.910902	-0.464685
Selling_Price	0.199905	1.000000	0.921894	-0.203017	-0.576554
Present_Price	-0.178871	0.921894	1.000000	0.128255	-0.388411
Driven_kms	-0.910902	-0.203017	0.128255	1.000000	0.135237
Owner	-0.464685	-0.576554	-0.388411	0.135237	1.000000

In [21]:
```
plt.figure(figsize=(10, 6))
sns.histplot(cp['Selling_Price'], bins=20, kde=True)
plt.xlabel('Selling Price')
plt.ylabel('Frequency')
plt.title('Distribution of Selling Prices')
plt.show()
```

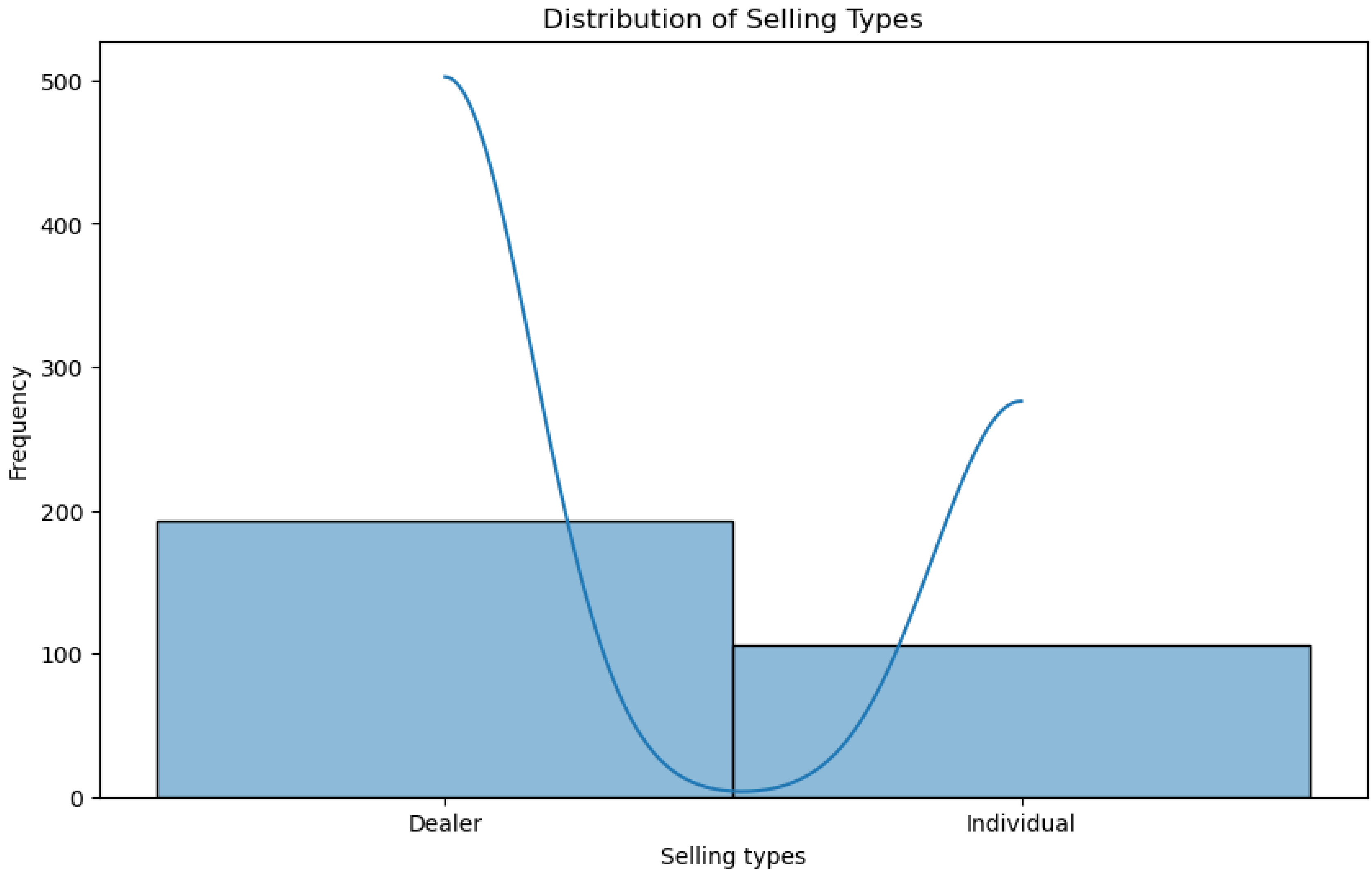


In [22]:
```
plt.figure(figsize=(10, 6))
sns.histplot(cp['Fuel_Type'], bins=20, kde=True)
plt.xlabel('Fuel_Type Price')
```

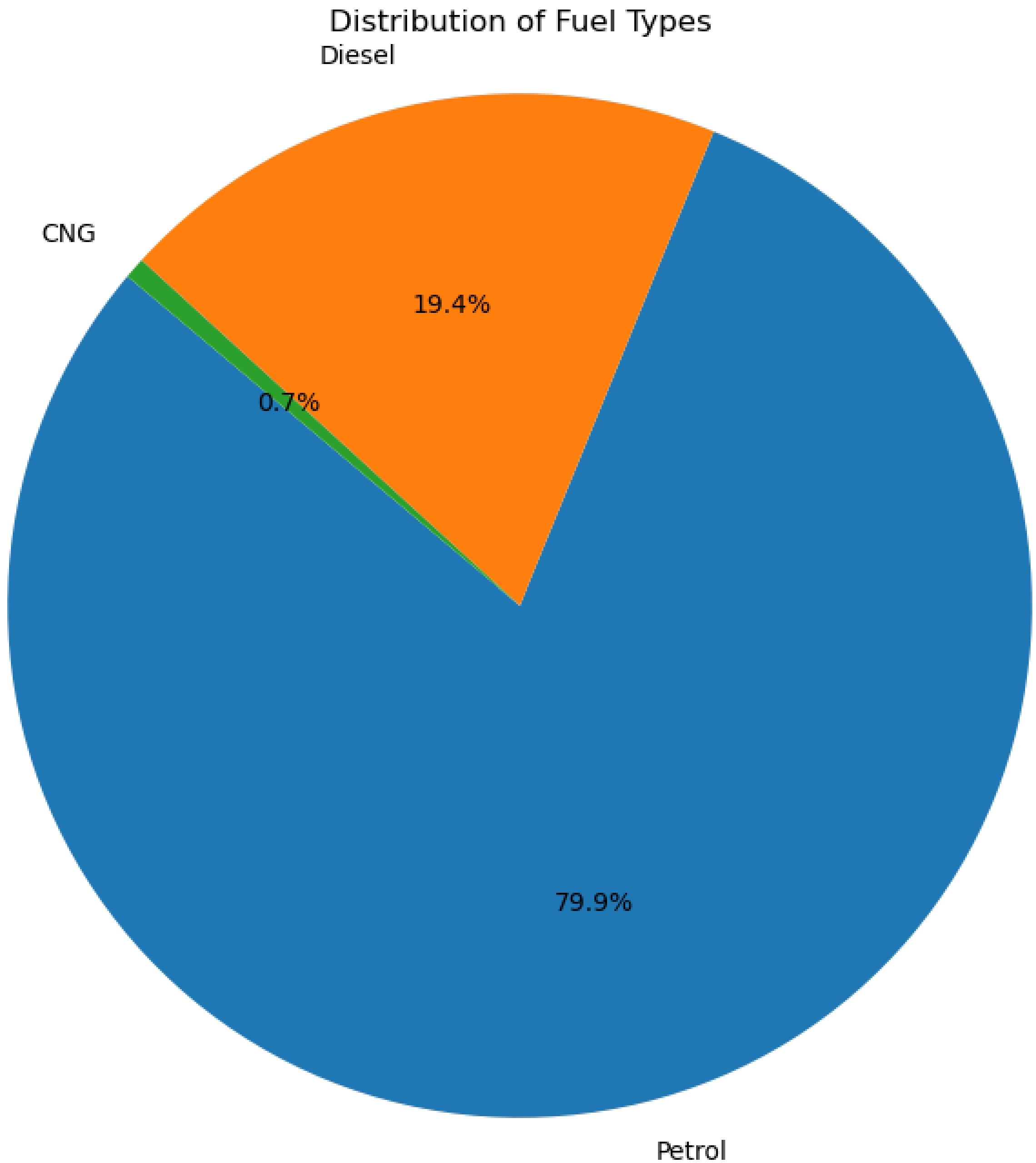
```
plt.ylabel('Frequency')
plt.title('Distribution of Fuel Types')
plt.show()
```



In [23]:
```
plt.figure(figsize=(10, 6))
sns.histplot(cp['Selling_type'], bins=20, kde=True)
plt.xlabel('Selling types')
plt.ylabel('Frequency')
plt.title('Distribution of Selling Types')
plt.show()
```

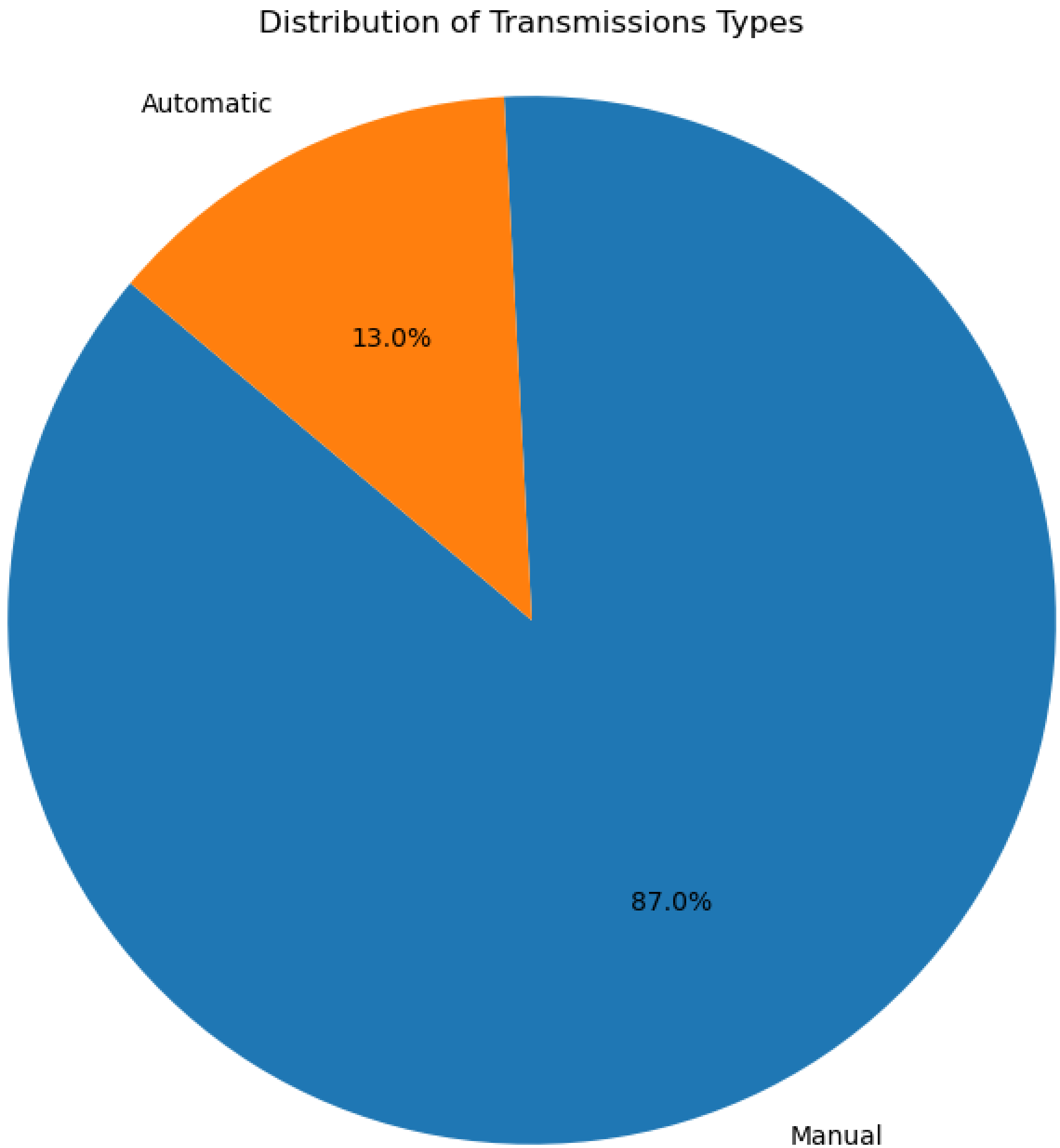


In [24]:
```
species_counts = cp['Fuel_Type'].value_counts()
plt.figure(figsize=(8, 8))
plt.title('Distribution of Fuel Types')
plt.pie(species_counts, labels=species_counts.index, autopct='%1.1f%%', startangle=140)
plt.axis('equal')
plt.show()
```



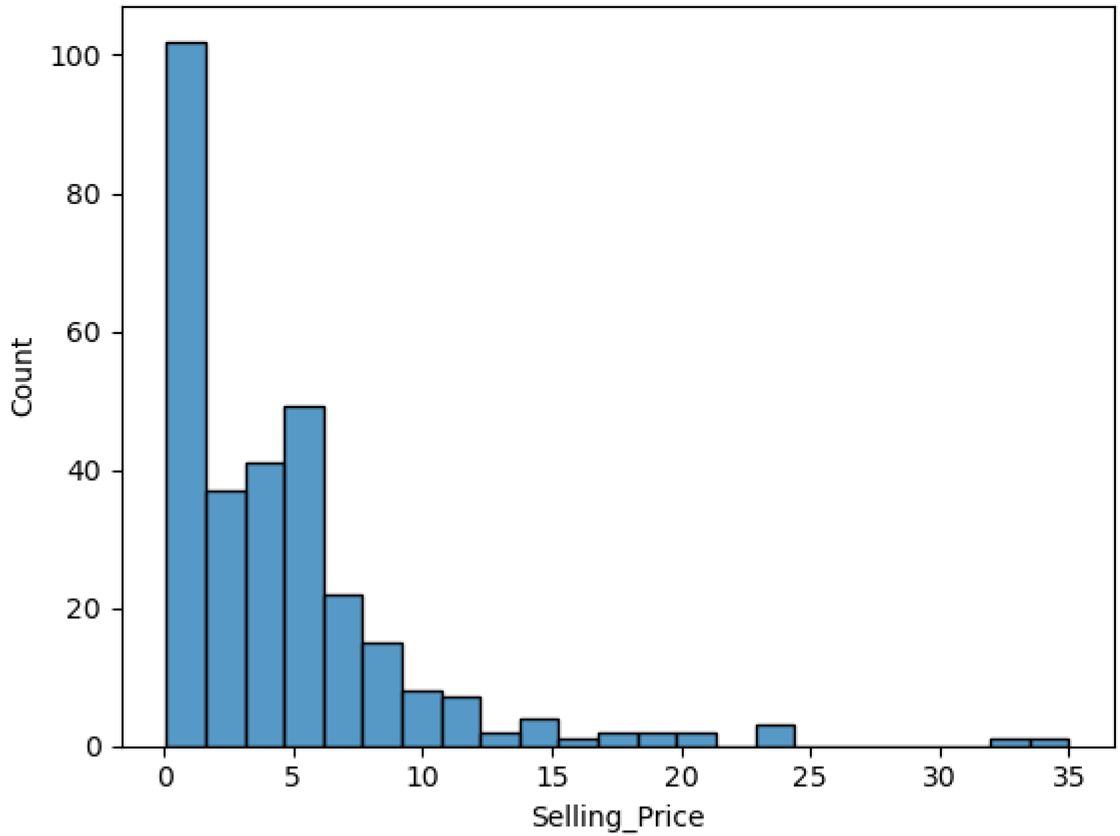
In [25]:
```
species_counts = cp['Transmission'].value_counts()
plt.figure(figsize=(8, 8))
plt.title('Distribution of Transmissions Types')
```

```
plt.pie(species_counts, labels=species_counts.index, autopct='%1.1f%%', startangle=140)
plt.axis('equal')
plt.show()
```

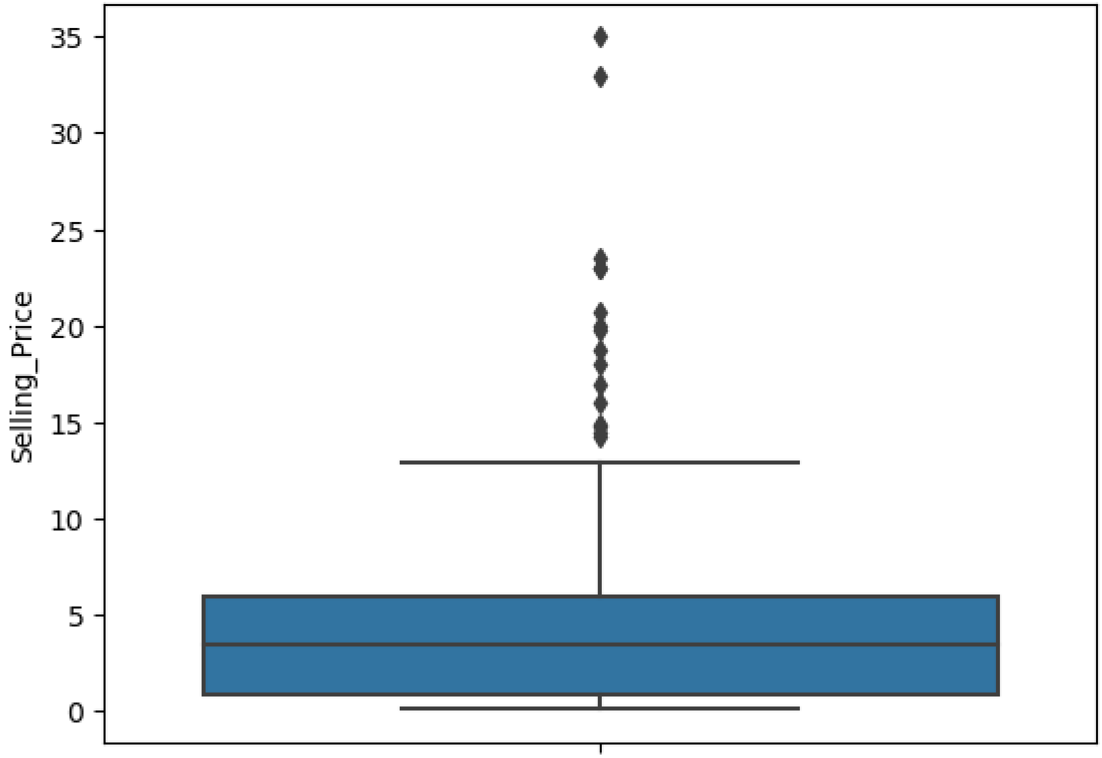


In [26]:
```
def univariate_numerical(data,var,graph_plot=True):
    missing=data[var].isnull().sum()
    min_n=data[var].min()
    max_n=data[var].max()
    var_n=data[var].var()
    std_n=data[var].std()
    p10=data[var].quantile(.1)
    p25=data[var].quantile(.25)
    p50=data[var].quantile(.5)
    p75=data[var].quantile(.75)
    p99=data[var].quantile(.99)
    iqr=p75-p25

    if graph_plot==True:
        sns.histplot(data[var])
        plt.show()
        sns.boxplot(y=data[var])
        plt.show()

    results={"missing":missing,"min":min_n,"max":max_n,"var":var_n,"std":std_n,
            "p10":p10,"p25":p25,"p50":p50,"p75":p75,"p99":p99,}
    return results
```

In [27]:
```
univariate_numerical(data=cp, var="Selling_Price")
```

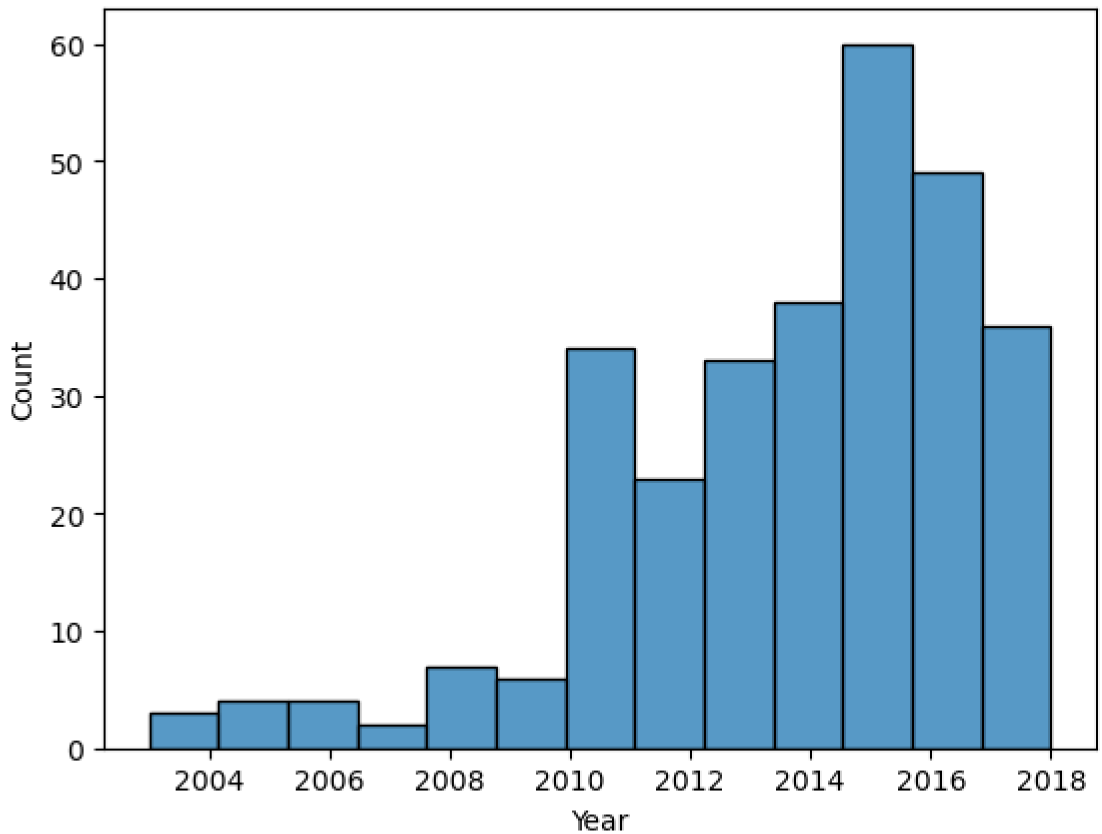


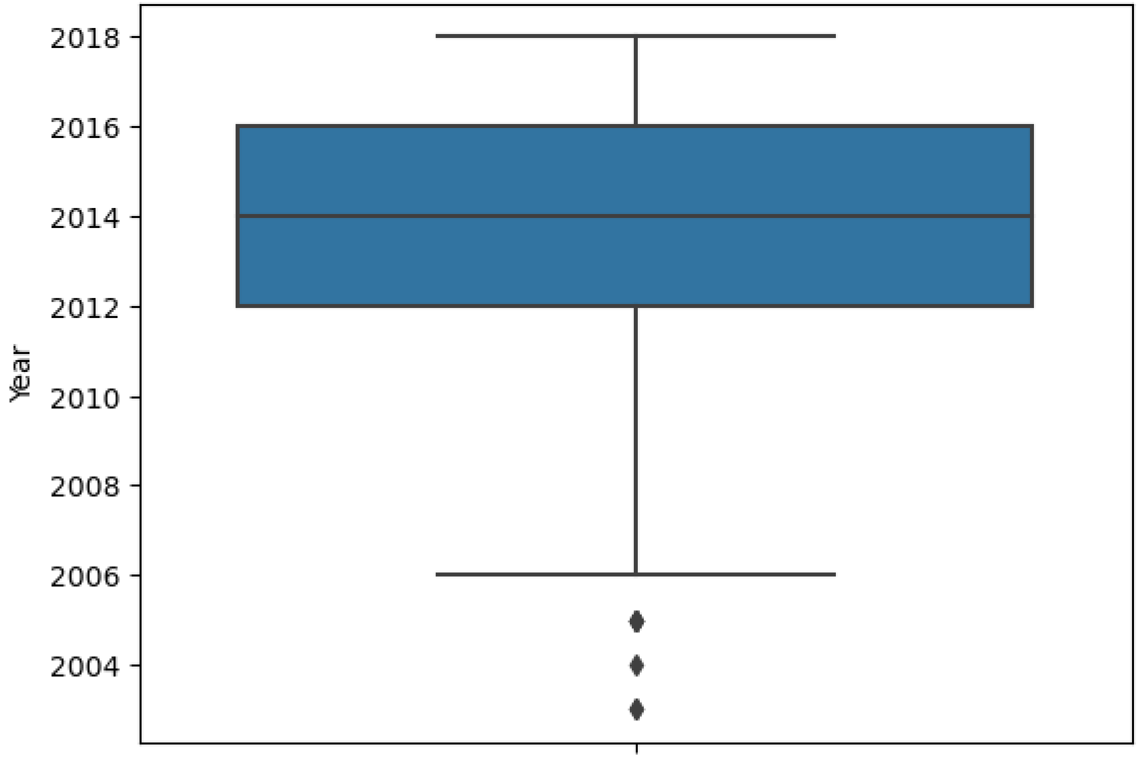
Count
Selling_Price
0
20
40
60
80
100
0
5
10
15
20
25
30
35



Out[27]:
```
{'missing': 0,
 'min': 0.1,
 'max': 35.0,
 'var': 24.842645166214016,
 'std': 4.984239677845962,
 'p10': 0.4,
 'p25': 0.8500000000000001,
 'p50': 3.51,
 'p75': 6.0,
 'p99': 23.00999999999999}
```

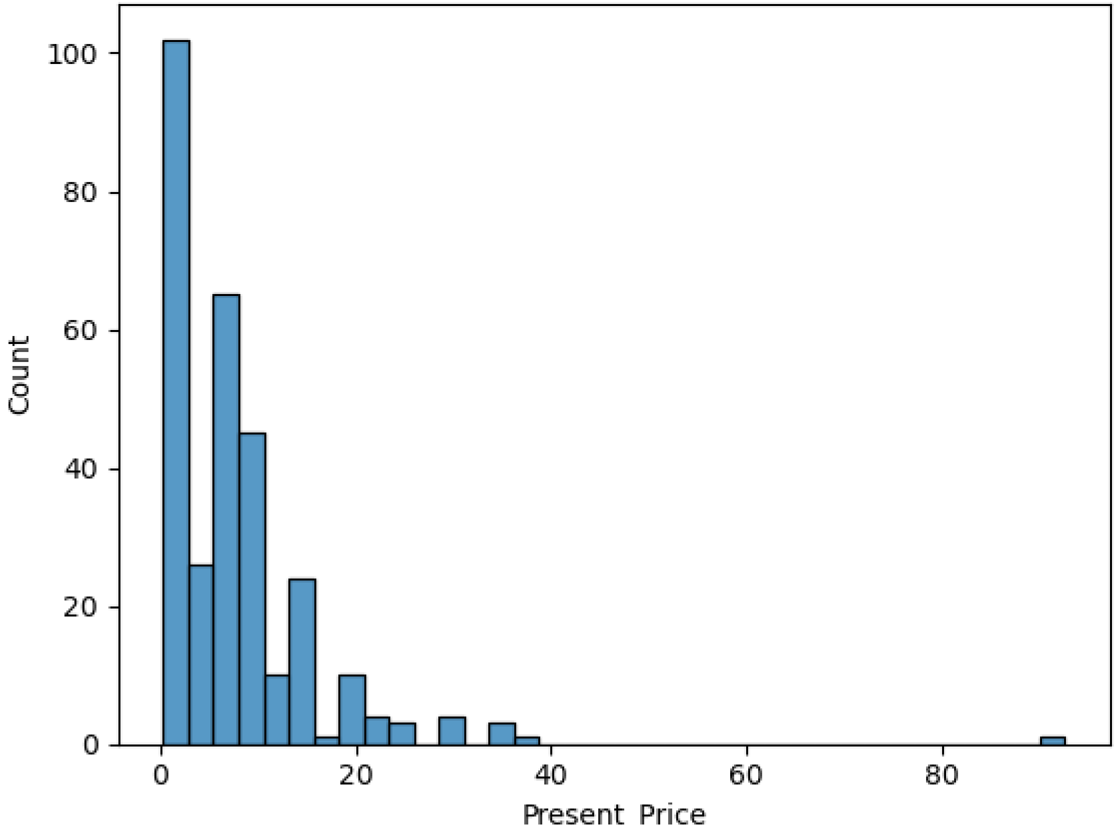
In [28]:
```
univariate_numerical(data=cp, var="Year")
```

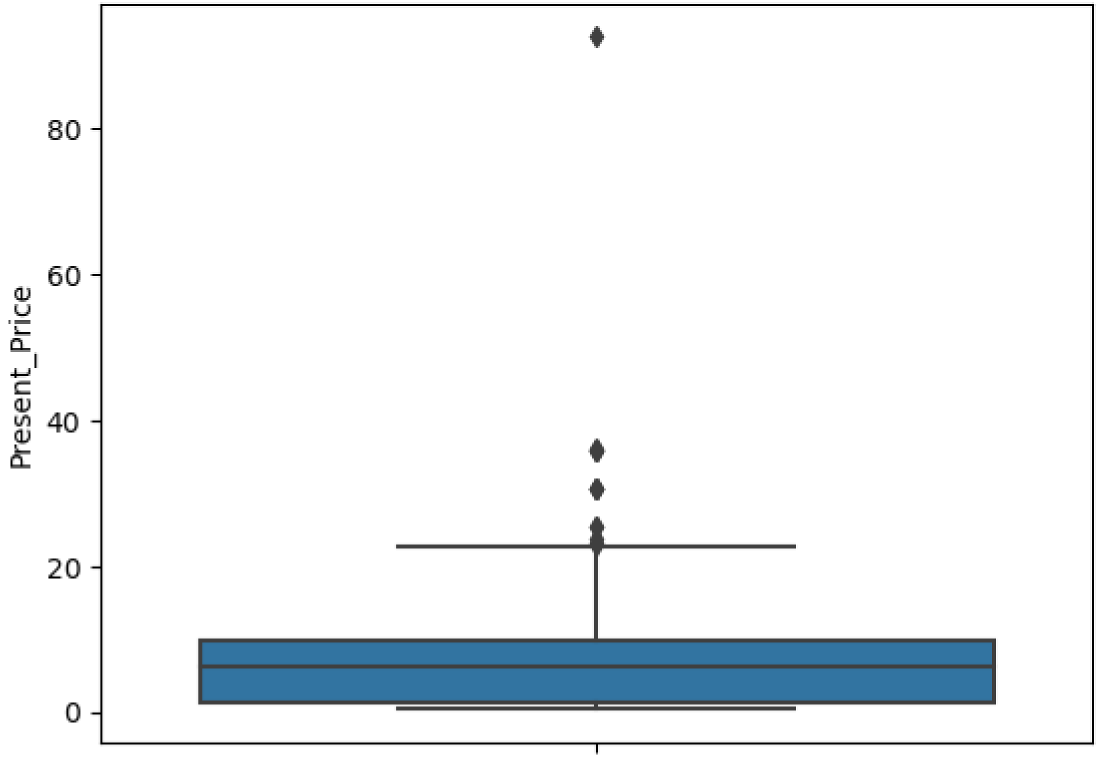

Count
Year
0
10
20
30
40
50
60
2004
2006
2008
2010
2012
2014
2016
2018



Out[28]:
```
{'missing': 0,
 'min': 2003,
 'max': 2018,
 'var': 8.391843056272588,
 'std': 2.8968678009658273,
 'p10': 2010.0,
 'p25': 2012.0,
 'p50': 2014.0,
 'p75': 2016.0,
 'p99': 2017.0}
```

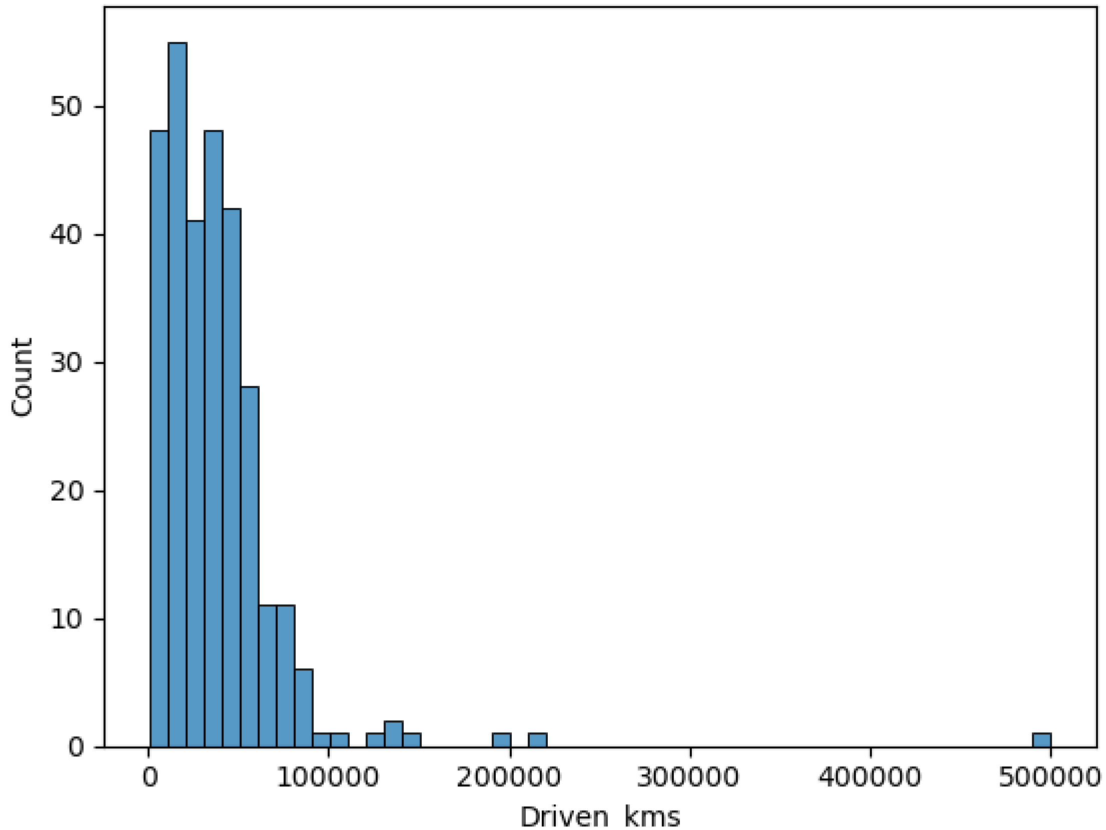
In [29]:
```
univariate_numerical(data=cp, var="Present_Price")
```

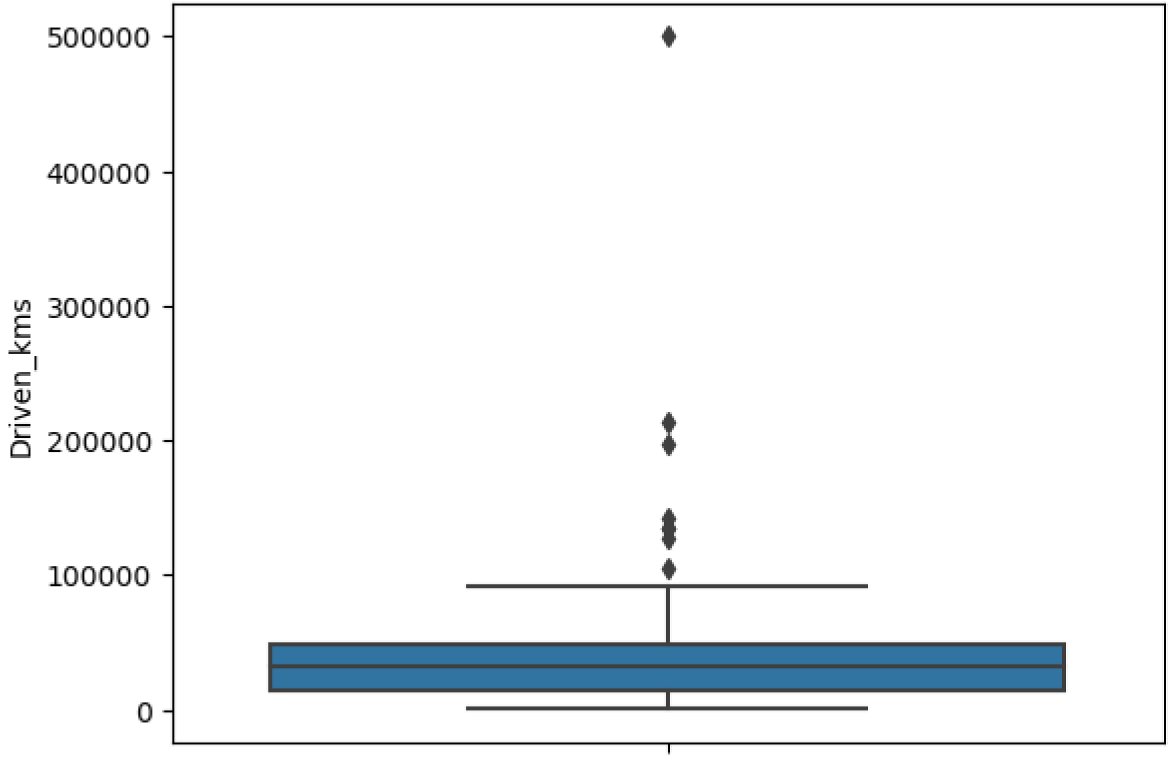

Count
Present_Price
0
20
40
60
80
100



Out[29]:
```
{'missing': 0,
 'min': 0.32,
 'max': 92.6,
 'var': 73.38203894830627,
 'std': 8.566331708981755,
 'p10': 0.7060000000000001,
 'p25': 1.2,
 'p50': 6.1,
 'p75': 9.84,
 'p99': 35.96}
```

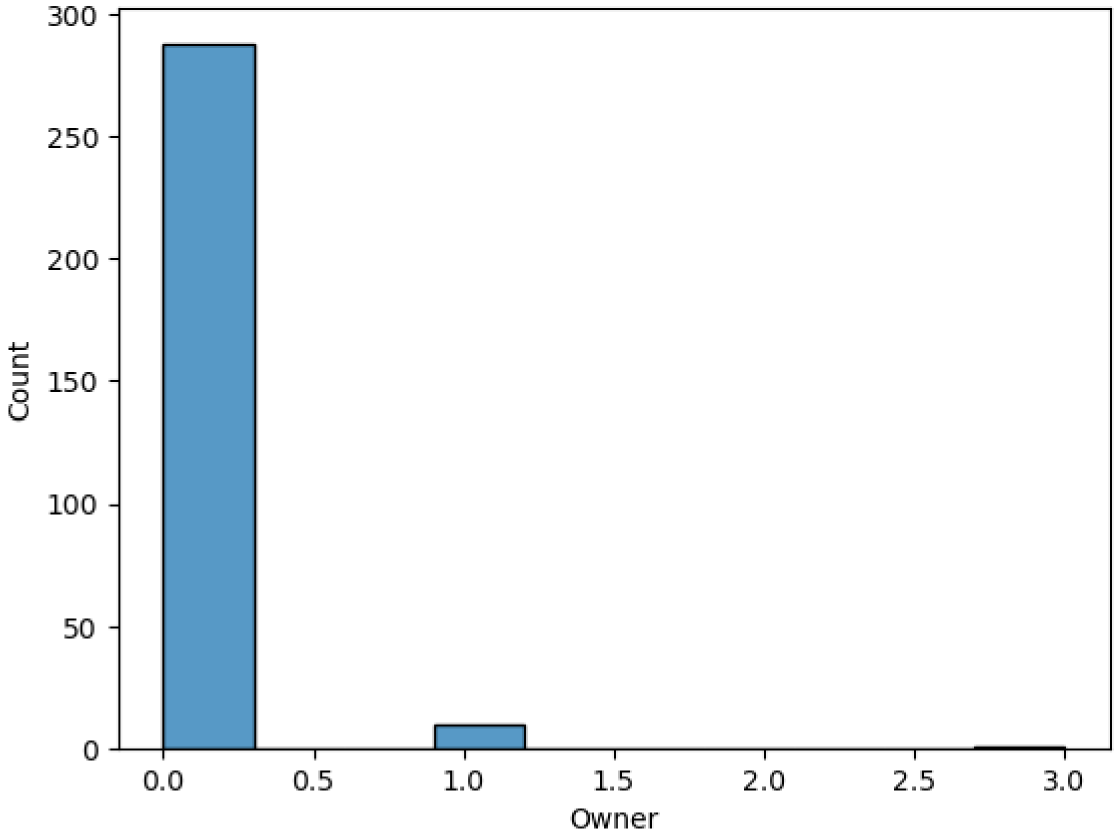
In [30]:
```
univariate_numerical(data=cp, var="Driven_kms")
```

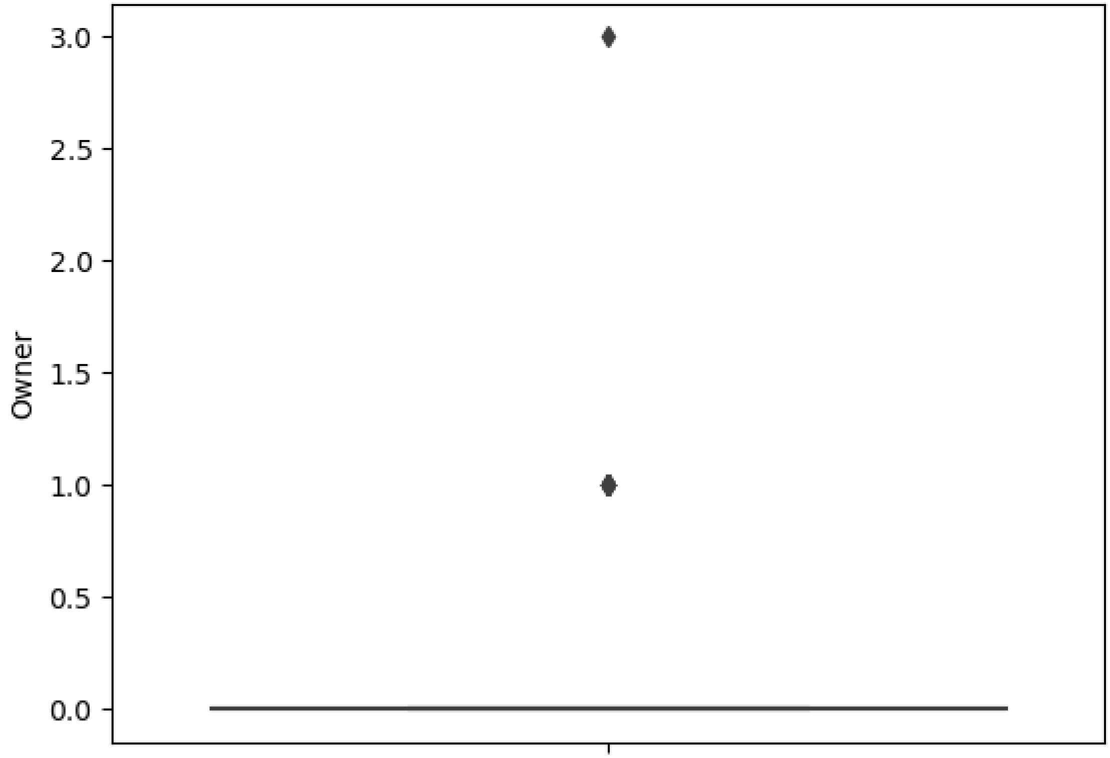

50
40
30
20
10
0
Count
0
100000
200000
300000
400000
500000
Driven_kms



Out[30]:
```
{'missing': 0,
 'min': 500,
 'max': 500000,
 'var': 1522183517.6298168,
 'std': 39015.17035243876,
 'p10': 5940.0,
 'p25': 15000.0,
 'p50': 32000.0,
 'p75': 48883.5,
 'p99': 143103.519999999}
```

In [31]:
```
univariate_numerical(data=cp, var="Owner")
```


300
250
200
150
100
50
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Owner

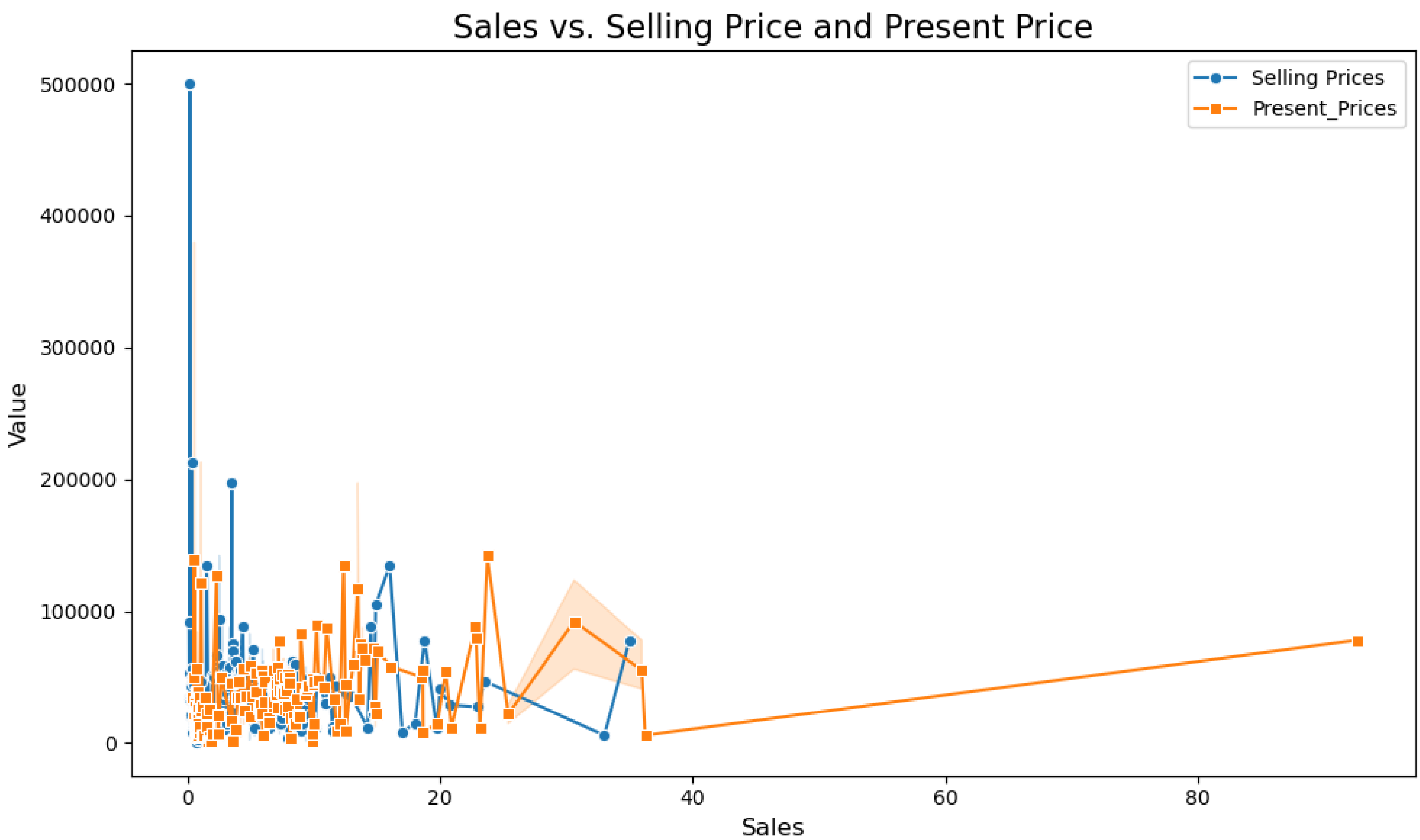


Out[31]:
```
{'missing': 0,
 'min': 0,
 'max': 3,
 'var': 0.061861686606361384,
 'std': 0.24872009690887745,
 'p10': 0.0,
 'p25': 0.0,
 'p50': 0.0,
 'p75': 0.0,
 'p99': 1.0}
```

Driven KMS Vs. Selling Price and Present Price

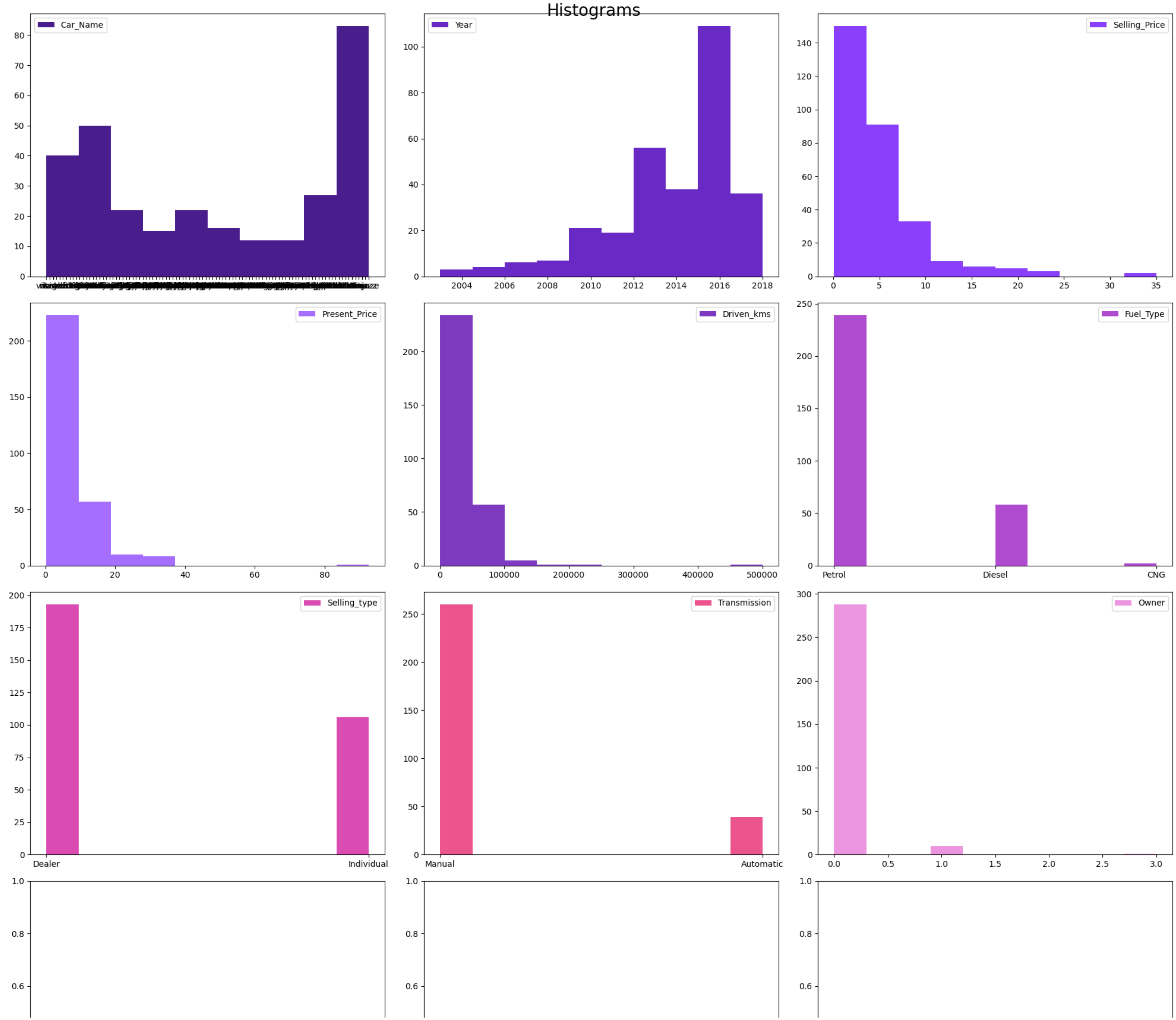
In [32]:
```
plt.figure(figsize=(10, 6))

# Create line plots for 'alcohol' and 'residual sugar' against 'density'
sns.lineplot(x="Selling_Price", y="Driven_kms", data=cp, label='Selling Prices', marker='o')
sns.lineplot(x="Present_Price", y="Driven_kms", data=cp, label='Present_Prices', marker='s')

plt.title("Sales vs. Selling Price and Present Price", fontsize=16)
```

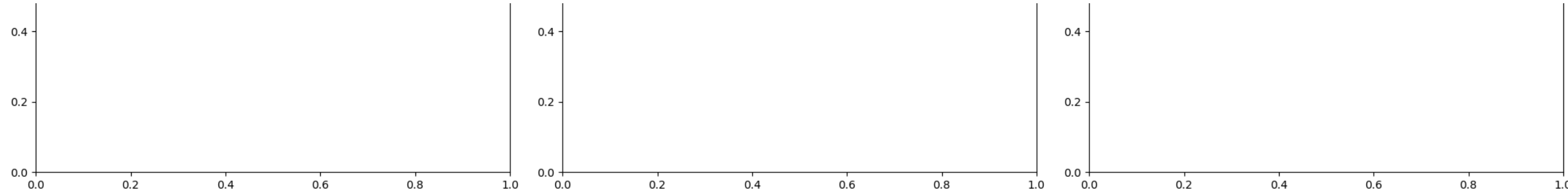
```
plt.xlabel("Sales", fontsize=12)
plt.ylabel("Value", fontsize=12)
plt.legend()
plt.tight_layout()
plt.show()
```



In [33]:
```
fig, axes = plt.subplots(nrows=4, ncols=3, figsize=(20, 20))

# Modify the color list to match the number of columns in your dataset
colors = ['#491D8B', '#6929C4', '#8A3FFC', '#A56EFF',
          '#7D3AC1', '#AF4BCE', '#DB4CB2', '#EB548C',
          '#EC96E0', '#A2128E', '#E8D9F3', '#641811']
```

```
# Loop through each column in your wine_df dataset
for index, column in enumerate(cp.columns):
    if index < 12:  # Limit the iteration to the number of subplots
        ax = axes.flatten()[index]
        ax.hist(cp[column], color=colors[index], label=column)
        ax.legend(loc="best")

plt.suptitle("Histograms", size=20)
plt.tight_layout()
plt.show()
```


Histograms
Car_Name
Year
Selling_Price
Present_Price
Driven_kms
Fuel_Type
Petrol
Diesel
CNG
Selling_type
Dealer
Individual
Transmission
Manual
Automatic
Owner



There is a statistically significant relationship between the "Selling_Price" and "Present_Price" & "Selling_Price" and "Year" variables

In [34]:

```python
from scipy import stats
figure=pd.crosstab(cp["Selling_Price"], cp["Present_Price"])
stats.chi2_contingency(figure)
```

Out[34]:

```
Chi2ContingencyResult(statistic=23320.2206292517, pvalue=0.006369652129717279, dof=22785, expected_freq=array([[0.00334
448, 0.00334448, 0.00334448, ..., 0.01003344, 0.00334448,
        0.00334448],
       [0.00334448, 0.00334448, 0.00334448, ..., 0.01003344, 0.00334448,
        0.00334448],
       [0.00334448, 0.00334448, 0.00334448, ..., 0.01003344, 0.00334448,
        0.00334448],
       ...,
       [0.00334448, 0.00334448, 0.00334448, ..., 0.01003344, 0.00334448,
        0.00334448],
       [0.00334448, 0.00334448, 0.00334448, ..., 0.01003344, 0.00334448,
        0.00334448],
       [0.00334448, 0.00334448, 0.00334448, ..., 0.01003344, 0.00334448,
        0.00334448]]))
```

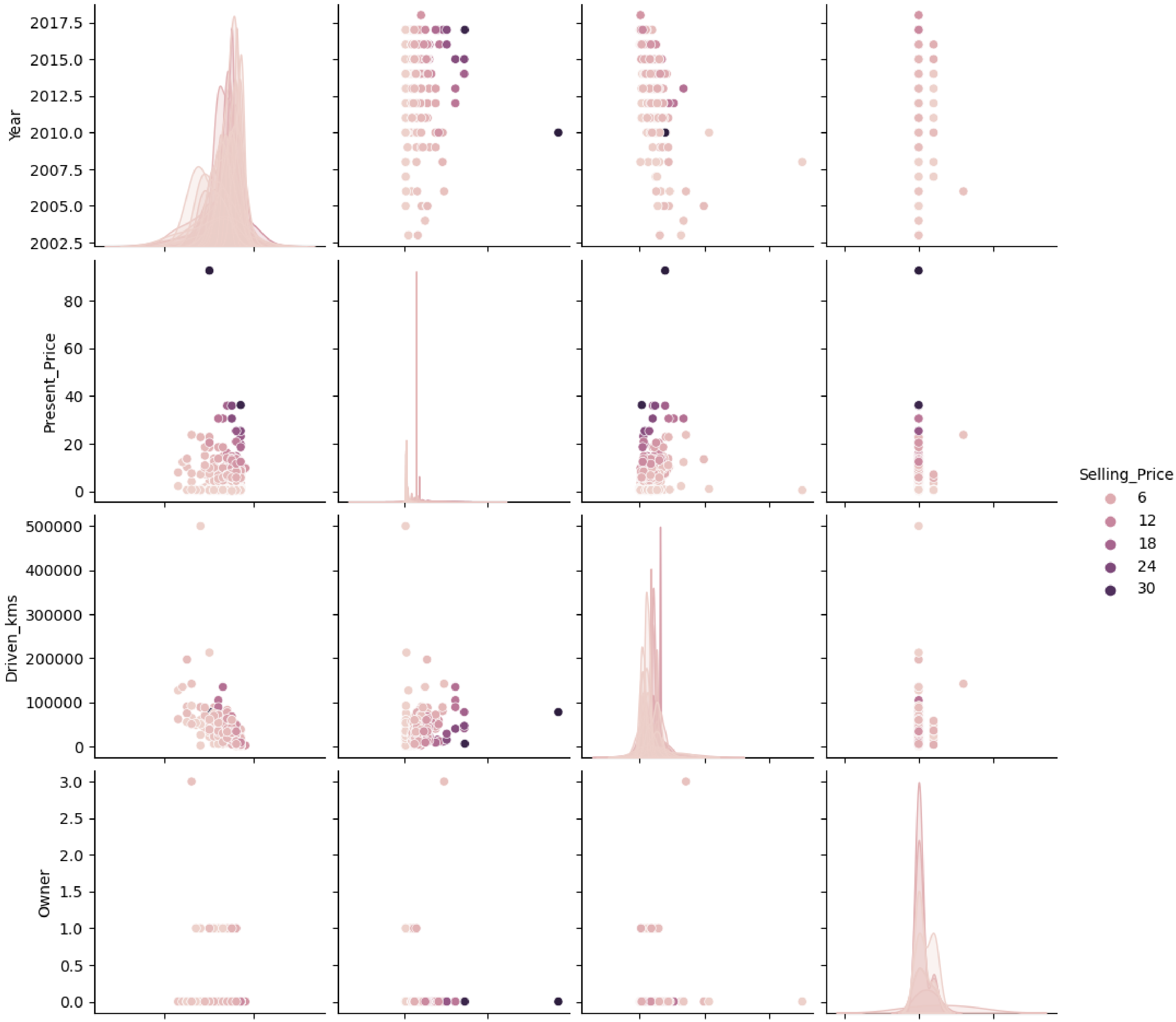
In [35]:

```python
from scipy import stats
figure=pd.crosstab(cp["Selling_Price"], cp["Year"])
stats.chi2_contingency(figure)
```

Out[35]:
```
Chi2ContingencyResult(statistic=2443.8008122656674, pvalue=0.04243557416005079, dof=2325, expected_freq=array([[0.00668
896, 0.00334448, 0.01337793, ..., 0.1638796 , 0.11705686,
        0.00334448],
       [0.00668896, 0.00334448, 0.01337793, ..., 0.1638796 , 0.11705686,
        0.00334448],
       [0.00668896, 0.00334448, 0.01337793, ..., 0.1638796 , 0.11705686,
        0.00334448],
       ...,
       [0.00668896, 0.00334448, 0.01337793, ..., 0.1638796 , 0.11705686,
        0.00334448],
       [0.00668896, 0.00334448, 0.01337793, ..., 0.1638796 , 0.11705686,
        0.00334448],
       [0.00668896, 0.00334448, 0.01337793, ..., 0.1638796 , 0.11705686,
        0.00334448]]))
```

I am visualizing the correlation of the dataset with the seaborn library.

In [36]:
```python
sns.pairplot(cp, hue = "Selling_Price")
plt.show()
```


Year
2017.5
2015.0
2012.5
2010.0
2007.5
2005.0
2002.5
Present_Price
80
60
40
20
0
Driven_kms
500000
400000
300000
200000
100000
0
Owner
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Selling_Price
6
12
18
24
30

Correlation Matrix

In [37]:
```
d=cp.corr()
def mylight(x):
    color="red" if abs(x)>=.6 else ""
    return "background-color: {}".format(color)
```

In [38]:
```
d.style.applymap(mylight)
```

Out[38]:

	Year	Selling_Price	Present_Price	Driven_kms	Owner
Year	1.000000	0.234369	-0.053167	-0.525714	-0.181639
Selling_Price	0.234369	1.000000	0.876305	0.028566	-0.087880
Present_Price	-0.053167	0.876305	1.000000	0.205224	0.009948
Driven_kms	-0.525714	0.028566	0.205224	1.000000	0.089367
Owner	-0.181639	-0.087880	0.009948	0.089367	1.000000

In [39]:
```
corrmat=cp.corr()
plt.figure(figsize=(15,8))
sns.heatmap(corrmat,cmap = 'plasma', annot=True)
plt.show()
```

There is a strong positive correlation (0.88) between "Selling_Price" and "Present_Price."

There is a strong negative correlation (-0.53) between "Driven_kms" and "Year."

Data Encoding:

In [40]:
```
# checking the distribution of categorical data
print(cp['Fuel_Type'].value_counts())
```

```
print(cp['Selling_type'].value_counts())
print(cp['Transmission'].value_counts())
```

```
Petrol    239
Diesel     58
CNG         2
Name: Fuel_Type, dtype: int64
Dealer        193
Individual    106
Name: Selling_type, dtype: int64
Manual       260
Automatic     39
Name: Transmission, dtype: int64
```

Label Encoding

In [41]:
```
# encoding "Fuel_Type" Column
cp.replace({'Fuel_Type':{'Petrol':0,'Diesel':1,'CNG':2}},inplace=True)

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

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

Out[41]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	0	0	0	0
1	sx4	2013	4.75	9.54	43000	1	0	0	0
2	ciaz	2017	7.25	9.85	6900	0	0	0	0
3	wagon r	2011	2.85	4.15	5200	0	0	0	0
4	swift	2014	4.60	6.87	42450	1	0	0	0
...	...	...	...	...	...	...	...	...	...
296	city	2016	9.50	11.60	33988	1	0	0	0
297	brio	2015	4.00	5.90	60000	0	0	0	0
298	city	2009	3.35	11.00	87934	0	0	0	0
299	city	2017	11.50	12.50	9000	1	0	0	0
300	brio	2016	5.30	5.90	5464	0	0	0	0

299 rows × 9 columns

Modeling: Feature Scaling

Pre-processing Steps for Machine Learning

In [42]:

```
X = cp.drop(['Car_Name','Selling_Price'],axis=1)
y = cp['Selling_Price']
```

In [43]:

```
X
```

Out[43]:

	Year	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner
0	2014	5.59	27000	0	0	0	0
1	2013	9.54	43000	1	0	0	0
2	2017	9.85	6900	0	0	0	0
3	2011	4.15	5200	0	0	0	0
4	2014	6.87	42450	1	0	0	0
...	...	...	...	...	...	...	...
296	2016	11.60	33988	1	0	0	0
297	2015	5.90	60000	0	0	0	0
298	2009	11.00	87934	0	0	0	0
299	2017	12.50	9000	1	0	0	0
300	2016	5.90	5464	0	0	0	0

299 rows × 7 columns

In [44]:

```
y
```

Out[44]:

```
0       3.35
1       4.75
2       7.25
3       2.85
4       4.60
       ...  
296     9.50
297     4.00
298     3.35
299    11.50
300     5.30
Name: Selling_Price, Length: 299, dtype: float64
```

Splitting the data

In [45]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=13)
```

Feature Scaling

In [46]:
```
from sklearn.preprocessing import StandardScaler
```

In [47]:
```
# Standardize the features
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Regression Models

Linear Regression

In [48]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

In [49]:
```
# Create and fit the linear regression model
lin_reg = LinearRegression()
```

In [50]:
```
lin_reg.fit(X_train, y_train)
```

Out[50]:
```
▾ LinearRegression
LinearRegression()
```

In [51]:
```
# Make predictions
y_pred = lin_reg.predict(X_test)
```

In [52]:
```
# Evaluate the model
mse_linear = mean_squared_error(y_test, y_pred)
print("Linear Regression Mean Squared Error:", mse_linear)
```

```
Linear Regression Mean Squared Error: 2.405203022617024
```

In [53]:
```
from sklearn.metrics import mean_squared_error, r2_score
```

In [54]:
```
r2 = r2_score(y_test, y_pred)
print("R-squared (R^2) Score:", r2)
```

```
R-squared (R^2) Score: 0.8915921588461179
```

In [55]:
```
# Optionally, you can print the model coefficients and intercept
print("Coefficients:", lin_reg.coef_)


print("Intercept:", lin_reg.intercept_)
```

```
Coefficients: [ 1.15565057  3.85889097 -0.23759324  0.53812924 -0.58201869  0.51898959
 -0.20249736]
Intercept: 4.456820083682
```

In [56]:
```
#Check the test score and train score to the RandomForestRegressor algorithm
print(f'The Test_accuracy: {lin_reg.score(X_test,y_test)*100:.2f}')

#Train score for the data
print(f'The Train_accuracy: {lin_reg.score(X_train,y_train)*100:.2f}')
```

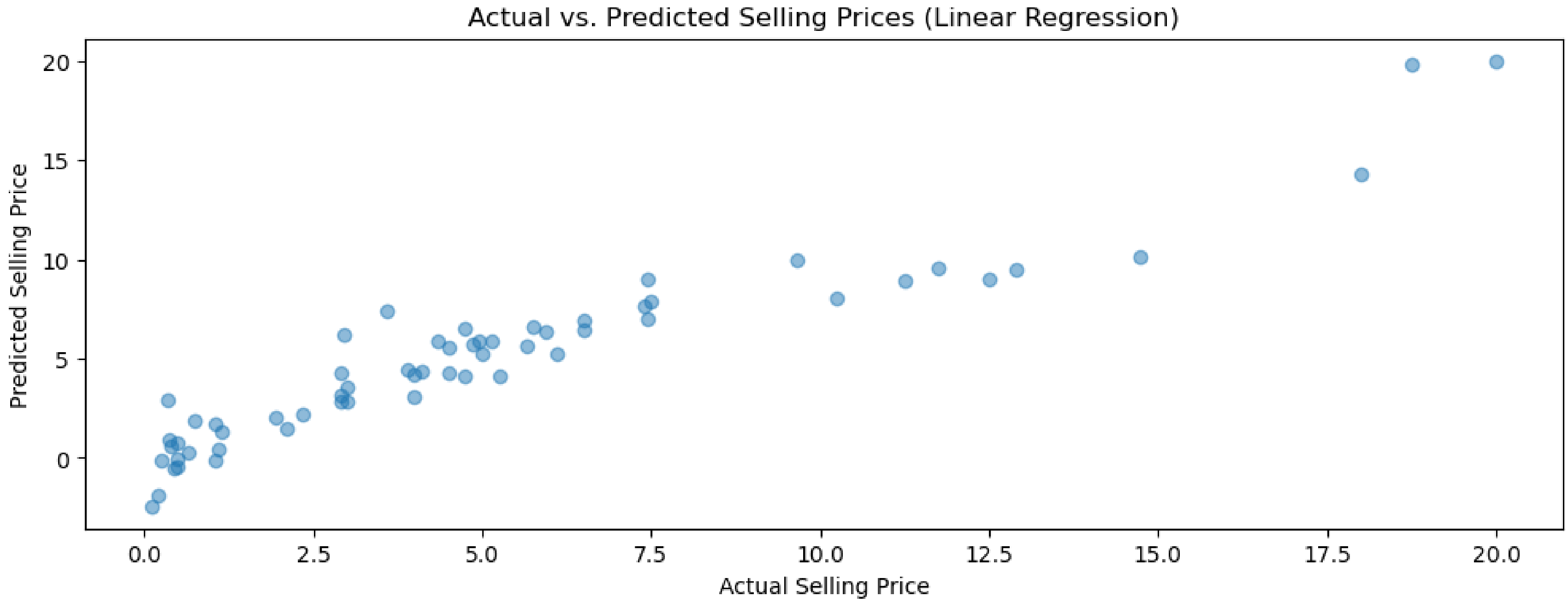
```
The Test_accuracy: 89.16
The Train_accuracy: 87.12
```

In [57]:
```
print(f"Linear Regression Mean Squared Error (MSE): {mse_linear:.2f}")
print(f"Linear Regression R-squared (R2): {r2:.2f}")
```

```
Linear Regression Mean Squared Error (MSE): 2.41
Linear Regression R-squared (R2): 0.89
```

Evaluation and Visualization:

In [58]:
```
plt.figure(figsize=(12,4))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel('Actual Selling Price')
plt.ylabel('Predicted Selling Price')
plt.title('Actual vs. Predicted Selling Prices (Linear Regression)')
plt.show()
```



Decision Tree Regression

In [59]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [60]:
```
Deci_Tree = DecisionTreeRegressor(random_state=17)
```

In [61]:
```
# Train the model on the training set
Deci_Tree.fit(X_train, y_train)
```

Out[61]:
```
▾ DecisionTreeRegressor
DecisionTreeRegressor(random_state=17)
```

In [62]:
```
# Make predictions on the test set
y_preds = Deci_Tree.predict(X_test)
```

In [63]:
```
#Check the test score and train score to the RandomForestRegressor algorithm
print(f'The Test_accuracy: {Deci_Tree.score(X_test,y_test)*100:.2f}')
```

```
#Train score for the data
print(f'The Train_accuracy: {Deci_Tree.score(X_train,y_train)*100:.2f}')
```

```
The Test_accuracy: 92.27
The Train_accuracy: 100.00
```

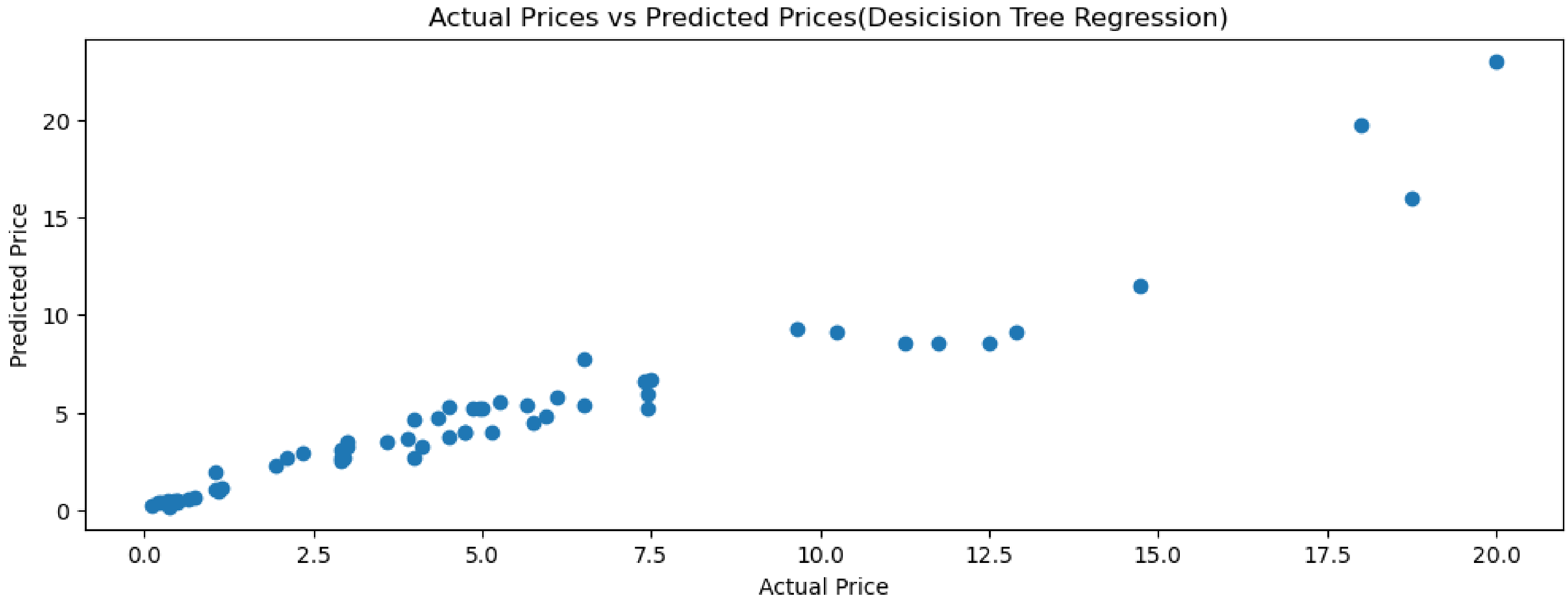
In [64]:
```
# Evaluate the model
mse = mean_squared_error(y_test, y_preds)
r2 = r2_score(y_test, y_preds)
```

In [65]:
```
print(f'Decision Tree Mean Squared Error: {mse:.2f}')
print(f'Decision Tree R-squared Score: {r2:.2f}')
```

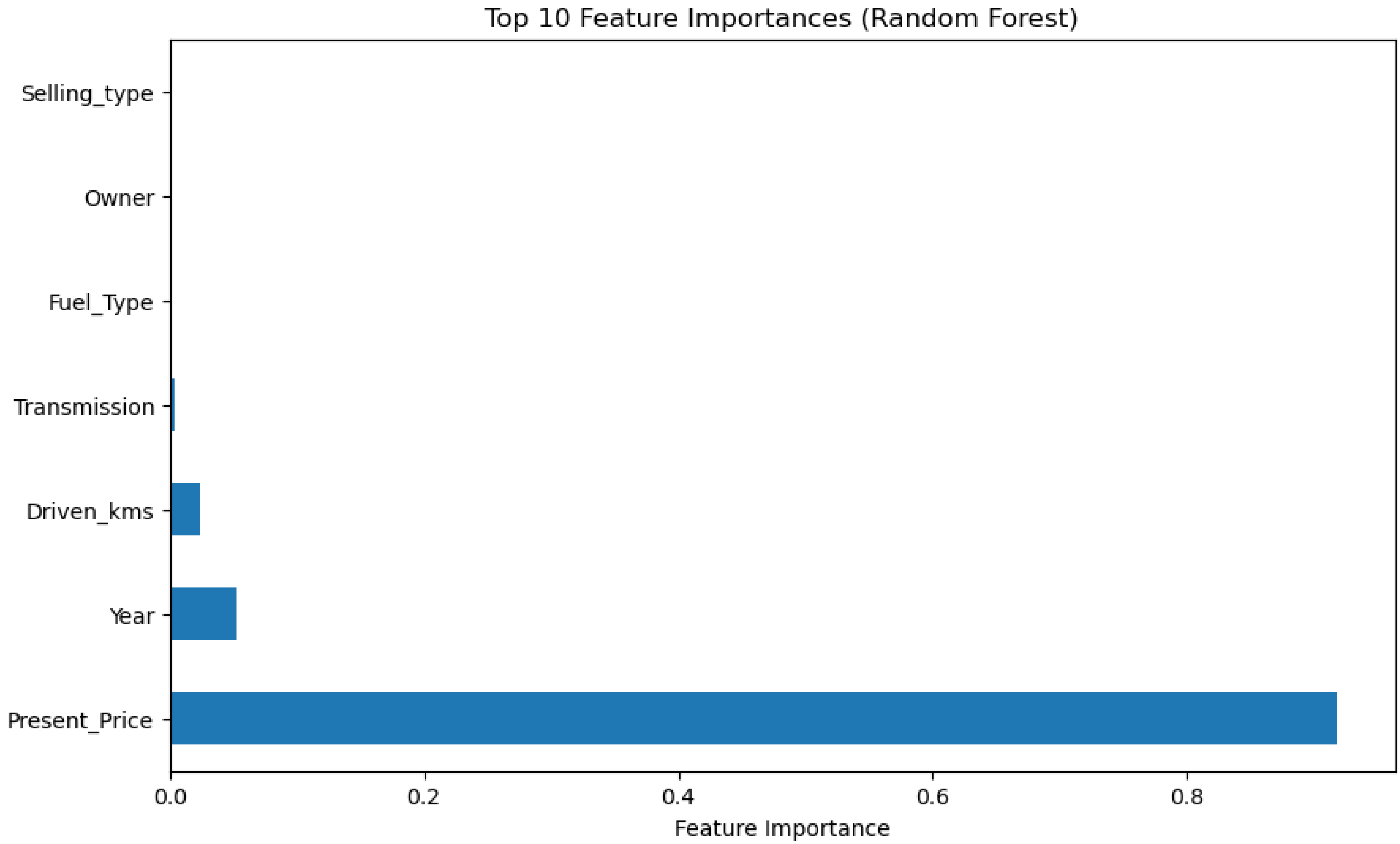
```
Decision Tree Mean Squared Error: 1.72
Decision Tree R-squared Score: 0.92
```

Evaluation and Visualization:

In [66]:
```
plt.figure(figsize=(12,4))


plt.scatter(y_test, y_preds)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices(Desicision Tree Regression)")
plt.show()
```



In [67]:
```
feature_importances = pd.Series(Deci_Tree.feature_importances_, index=X.columns)
plt.figure(figsize=(10, 6))
feature_importances.nlargest(10).plot(kind='barh')
plt.xlabel('Feature Importance')
plt.title('Top 10 Feature Importances (Random Forest)')
plt.show()
```



Support Vector Machine Regression Model

In [68]:
```
from sklearn.svm import SVR
```

In [69]:
```
# Initialize the Support Vector Regression model
Support_V = SVR(kernel='linear', C=5)
```

In [70]:
```
# Train the model on the scaled training set
Support_V.fit(X_train, y_train)
```

Out[70]:

```
SVR
SVR(C=5, kernel='linear')
```

In [71]:

```
# Make predictions on the scaled test set
y_pred_s = Support_V.predict(X_test)
```

In [72]:

```
#Check the test score and train score to the RandomForestRegressor algorithm
print(f'The Test_accuracy: {Support_V.score(X_test,y_test)*100:.2f}')

#Train score for the data
print(f'The Train_accuracy: {Support_V.score(X_train,y_train)*100:.2f}')
```

```
The Test_accuracy: 87.81
The Train_accuracy: 84.10
```

In [73]:

```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred_s)
r2 = r2_score(y_test, y_pred_s)
```

In [74]:

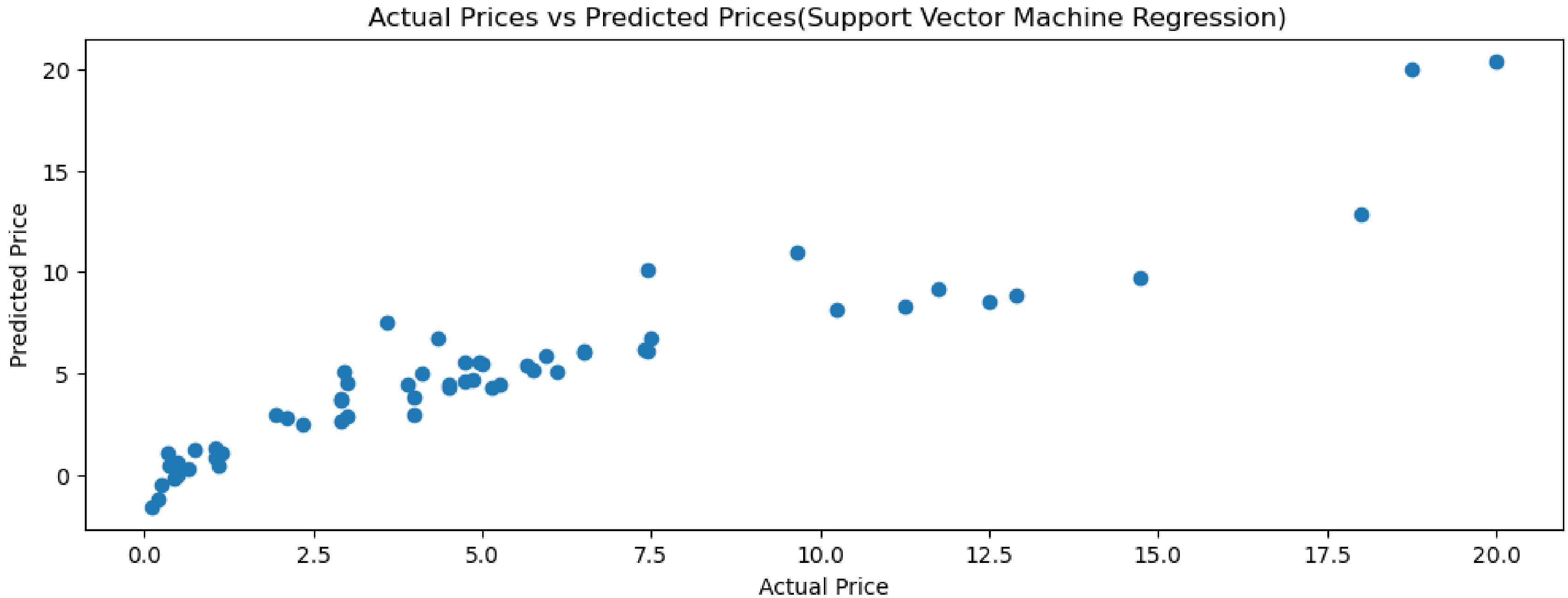
```
print(f'Support Vector Machine Mean Squared Error: {mse:.2f}')
print(f'Support Vector Machine R-squared Score: {r2:.2f}')
```

```
Support Vector Machine Mean Squared Error: 2.70
Support Vector Machine R-squared Score: 0.88
```

Evaluation and Visualization:

In [75]:

```
plt.figure(figsize=(12,4))


plt.scatter(y_test, y_pred_s)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices(Support Vector Machine Regression)")
plt.show()
```



Random Forest Regression Model

In [76]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [77]:
```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [78]:
```
# Initialize the Random Forest Regressor model
Random_Forest_model = RandomForestRegressor(n_estimators=100, random_state=17)
```

In [79]:
```
# Train the model on the training set
Random_Forest_model.fit(X_train, y_train)
```

Out[79]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=17)
```

In [80]:
```
# Make predictions on the test set
y_pred_ss = Random_Forest_model.predict(X_test)
```

In [81]:
```
#Check the test score and train score to the RandomForestRegressor algorithm
print(f'The Test_accuracy: {Random_Forest_model.score(X_test,y_test)*100:.2f}')

#Train score for the data
print(f'The Train_accuracy: {Random_Forest_model.score(X_train,y_train)*100:.2f}')
```

```
The Test_accuracy: 96.39
The Train_accuracy: 98.27
```

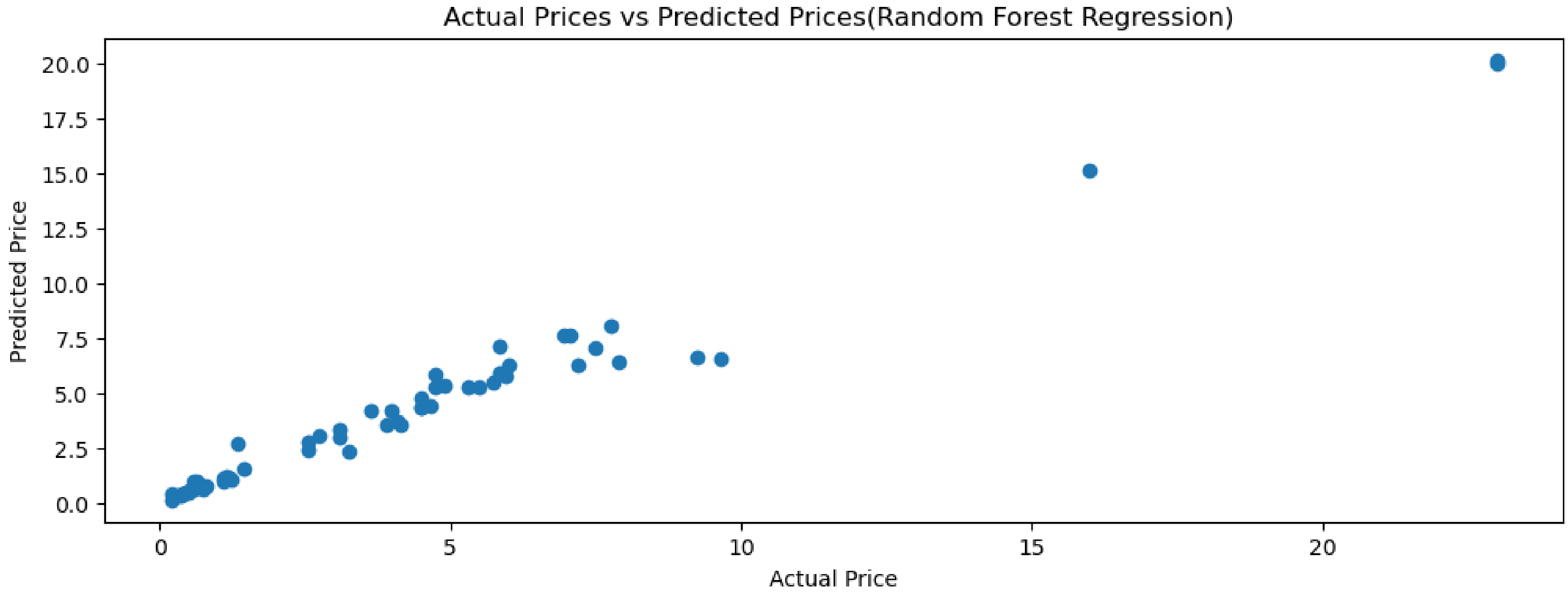
In [82]:
```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred_ss)
r2 = r2_score(y_test, y_pred_ss)
```

In [83]:
```
print(f'Random Forest Mean Squared Error: {mse:.2f}')
print(f'Random Forest R-squared Score: {r2:.2f}')
```

```
Random Forest Mean Squared Error: 0.77
Random Forest R-squared Score: 0.96
```

Evaluation and Visualization:

In [84]:
```
plt.figure(figsize=(12,4))


plt.scatter(y_test, y_pred_ss)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices(Random Forest Regression)")
plt.show()
```

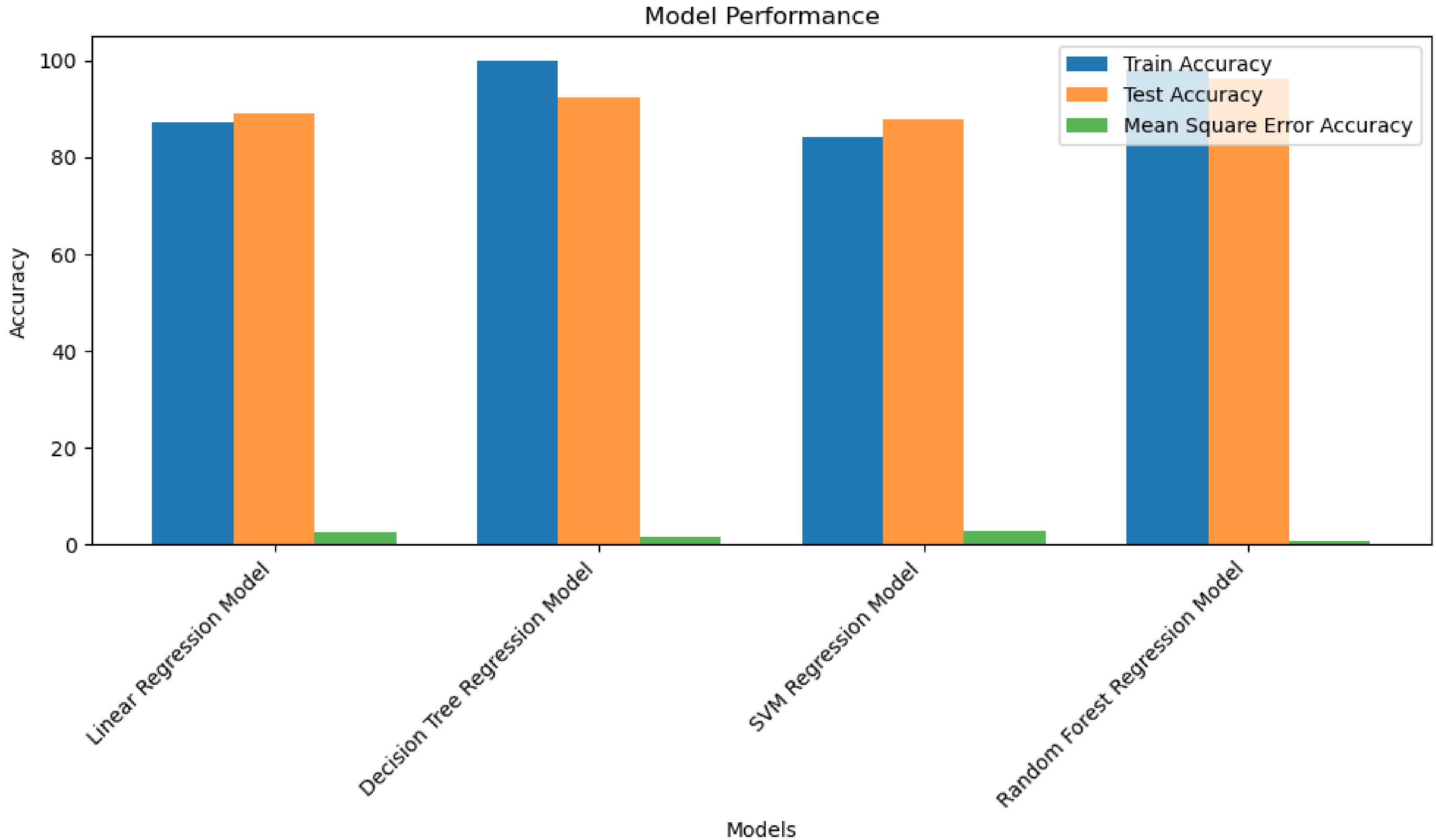


The model with the highest test accuracy is the "Random Forest Regression Model" with a test accuracy of 96.39

The model with the highest R-squared score is the Random Forest with a score of 0.96. The Random Forest regression model is considered to have the best goodness of fit to the data.

In [87]:
```
models = ["Linear Regression Model", "Decision Tree Regression Model", "SVM Regression Model", "Random Forest Regressio
train_accuracies = [87.12, 100.00, 84.10, 98.27]
test_accuracies = [89.16, 92.27, 87.81, 96.39]
mse_accuracies = [2.41, 1.72, 2.70, 0.77]

# Set the width of the bars
bar_width = 0.25  # Adjust the bar width as needed

# Create an array of equally spaced positions for the bars
x = np.arange(len(models))

plt.figure(figsize=(10, 6))
```

```
# Create a grouped bar chart
plt.bar(x - bar_width, train_accuracies, bar_width, label='Train Accuracy')
plt.bar(x, test_accuracies, bar_width, label='Test Accuracy', alpha=0.8)
plt.bar(x + bar_width, mse_accuracies, bar_width, label='Mean Square Error Accuracy', alpha=0.8)

# Set title and labels
plt.title("Model Performance")
plt.xlabel("Models")
plt.ylabel("Accuracy")
plt.legend()

# Rotate x-axis labels for better readability
plt.xticks(x, models, rotation=45, ha="right")

# Display the plot
plt.tight_layout()
plt.show()
```


Model Performance
Train Accuracy
Test Accuracy
Mean Square Error Accuracy
Accuracy
100
80
60
40
20
0
Linear Regression Model
Decision Tree Regression Model
SVM Regression Model
Random Forest Regression Model
Models

THANK YOU!