1. Importing all the necessary dependencies

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import plotly.io as plio
plio.templates
import plotly.express as px
import plotly.graph_objects as go

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

from sklearn.metrics import accuracy_score, classification_report, confusion_ma

from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor

from xgboost import XGBRegressor

import joblib

from warnings import filterwarnings
filterwarnings(action='ignore')
```

2. Exploring the dataset

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

Out[2]:

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

301 rows × 9 columns

In [3]:
```
data.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
```

Finding any duplicates if present

In [4]:
```
duplicate_rows = data[data.duplicated(keep=False)]
duplicate_rows
```

Out[4]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmis
15	ertiga	2016	7.75	10.79	43000	Diesel	Dealer	Ma
17	ertiga	2016	7.75	10.79	43000	Diesel	Dealer	Ma
51	fortuner	2015	23.00	30.61	40000	Diesel	Dealer	Autor
93	fortuner	2015	23.00	30.61	40000	Diesel	Dealer	Autor

In [5]:
```
duplicated_rows = data[data.duplicated(keep='first')]
duplicated_rows
```

Out[5]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmis
17	ertiga	2016	7.75	10.79	43000	Diesel	Dealer	Ma
93	fortuner	2015	23.00	30.61	40000	Diesel	Dealer	Autor

Removing the duplicate rows from the dataset

In [6]:
```
data_cleaned = data.drop(duplicated_rows.index)
#data_cleaned.to_csv('car_data_cleaned.csv',index=False)
```

In [7]:
```
data = pd.read_csv('car_data_cleaned.csv')
```

In [8]:
```
data.Year.value_counts()
```

Out[8]:
```
2015    60
2016    49
2014    38
2017    35
2013    33
2012    23
2011    19
2010    15
2008     7
2009     6
2006     4
2005     4
2003     2
2007     2
2018     1
2004     1
Name: Year, dtype: int64
```

In [9]:
```
year = data.Year.value_counts().keys()
no_cars_sold = data.Year.value_counts().values
labels = [str(val) for val in no_cars_sold]

fig = px.bar(x=year, y=no_cars_sold, text=labels, title='Year vs No. of Cars S

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='no_cars_sold')
fig.update_xaxes(title_text='Year')

# Show the plot
fig.show()
```

In [10]:
```
car_name = data.Car_Name.value_counts().head(25).keys()
cars_sold = data.Car_Name.value_counts().head(25).values
labels = [str(val) for val in cars_sold]

fig = px.bar(x=car_name, y=cars_sold, text=labels, title='Top 25 Car Name vs N

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars Sold')
fig.update_xaxes(title_text='Car Name')

# Show the plot
fig.show()
```

In [11]:
```
data.Fuel_Type.value_counts().head(25)
```

Out[11]:
```
Petrol    239
Diesel     58
CNG         2
Name: Fuel_Type, dtype: int64
```

In [12]:
```
fuel_type = data.Fuel_Type.value_counts().keys()
cars_count = data.Fuel_Type.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=fuel_type, y=cars_count, text=labels, title='Fuel Type vs Cars

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars')
fig.update_xaxes(title_text='Fuel Type')

# Show the plot
fig.show()
```

In [13]:
```
selling_type = data.Selling_type.value_counts().keys()
cars_count = data.Selling_type.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=selling_type, y=cars_count, text=labels, title='Selling Type vs

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars')
fig.update_xaxes(title_text='Selling Type')

# Show the plot
fig.show()
```

In [14]:
```
transmission_type = data.Transmission.value_counts().keys()
cars_count = data.Transmission.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=transmission_type, y=cars_count, text=labels, title='Transmissi

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars')
fig.update_xaxes(title_text='Transmission Type')

# Show the plot
fig.show()
```

In [15]:
```
ownership_type = data.Owner.value_counts().keys()
cars_count = data.Owner.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=ownership_type, y=cars_count, text=labels, title='Ownership Typ

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars')
fig.update_xaxes(title_text='Ownership Type')

# Show the plot
fig.show()
```

Changing the catergorical columns Fuel_Type, Selling_Type, Transmission and Owner Type to Numerical columns

In [16]:
```
# Changing Fuel Type column : Petrol -> 0, Diesel -> 1 and CNG -> 2
category_mapping = {'Petrol': 0, 'Diesel': 1, 'CNG': 2}
data['Fuel_Type_encoded'] = data['Fuel_Type'].map(category_mapping)
```

In [17]:
```
data.Fuel_Type_encoded.value_counts()
```

Out[17]:
```
0    239
1     58
2      2
Name: Fuel_Type_encoded, dtype: int64
```

In [18]:
```
fuel_type = data.Fuel_Type_encoded.value_counts().keys()
cars_count = data.Fuel_Type_encoded.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=fuel_type, y=cars_count, text=labels, title='Fuel Type(encoded)

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars')
fig.update_xaxes(title_text='Fuel Type(encoded)')

# Show the plot
fig.show()
```

In [19]:
```
# Changing Selling_Type column : Dealer -> 0, Individual -> 1
category_mapping = {'Dealer': 0, 'Individual': 1}
data['Selling_type_encoded'] = data['Selling_type'].map(category_mapping)
```

In [20]:
```
data.Selling_type_encoded.value_counts()
```

Out[20]:
```
0    193
1    106
Name: Selling_type_encoded, dtype: int64
```

In [21]:
```
selling_type = data.Selling_type_encoded.value_counts().keys()
cars_count = data.Selling_type_encoded.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=selling_type, y=cars_count, text=labels, title='Selling Type(en

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars(encoded)')
fig.update_xaxes(title_text='Selling Type')

# Show the plot
fig.show()
```

In [22]:
```
# Changing Transmission column : Manual -> 0, Automatic -> 1
category_mapping = {'Manual': 0, 'Automatic': 1}
data['Transmission_encoded'] = data['Transmission'].map(category_mapping)
```

In [23]:
```
data.Transmission_encoded.value_counts()
```

Out[23]:
```
0    260
1     39
Name: Transmission_encoded, dtype: int64
```

In [24]:
```
transmission_type = data.Transmission_encoded.value_counts().keys()
cars_count = data.Transmission_encoded.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=transmission_type, y=cars_count, text=labels, title='Transmissi

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars')
fig.update_xaxes(title_text='Transmission Type(encoded)')

# Show the plot
fig.show()
```

In [25]:
```
# Changing Owner Type column : 0 -> 0, 1 -> 1 and 3 -> 2
category_mapping = {0: 0, 1: 1, 3: 2}
data['Owner_encoded'] = data['Owner'].map(category_mapping)
```

In [26]:
```
data.Owner_encoded.value_counts()
```

Out[26]:
```
0    288
1     10
2      1
Name: Owner_encoded, dtype: int64
```

In [27]:
```
ownership_type = data.Owner_encoded.value_counts().keys()
cars_count = data.Owner_encoded.value_counts().values
labels = [str(val) for val in cars_count]

fig = px.bar(x=ownership_type, y=cars_count, text=labels, title='Ownership Type

# Set the labels for the y-axis and x-axis
fig.update_yaxes(title_text='No. of Cars')
fig.update_xaxes(title_text='Ownership Type(encoded)')

# Show the plot
fig.show()
```

In [28]:
```
selected_columns = ['Car_Name','Year','Selling_Price','Present_Price','Driven_
```

In [29]:
```
new_data = data[selected_columns]
```

In [30]:
```
new_data
#new_data.to_csv('cars price encoded.csv', index=False)
```

Out[30]:

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

299 rows × 9 columns

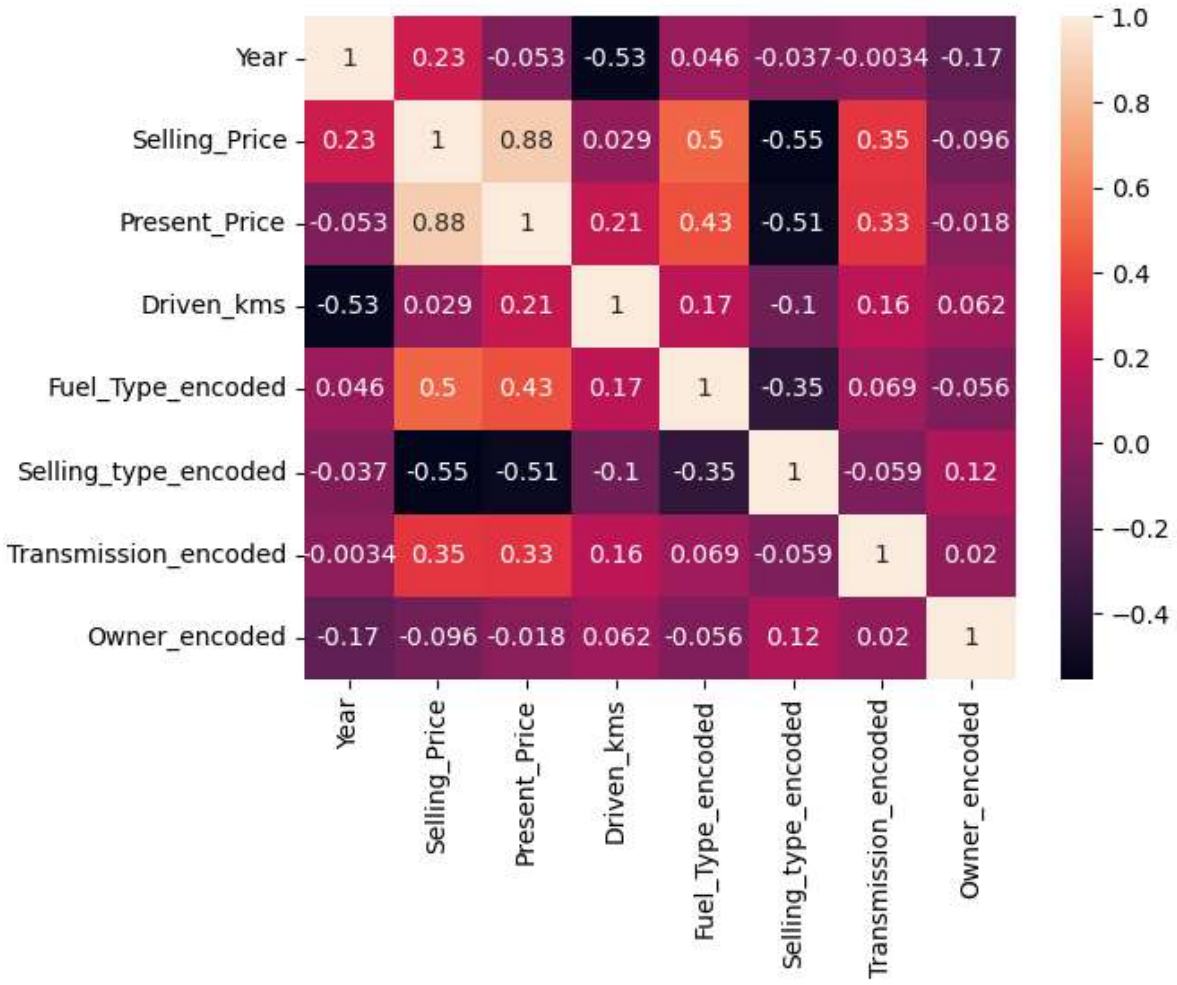
In [31]:
```
new_data.iloc[:,1:].corr()
```

Out[31]:

	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type_encoded
Year	1.000000	0.234369	-0.053167	-0.525714	0.046210
Selling_Price	0.234369	1.000000	0.876305	0.028566	0.500292
Present_Price	-0.053167	0.876305	1.000000	0.205224	0.431887
Driven_kms	-0.525714	0.028566	0.205224	1.000000	0.167287
Fuel_Type_encoded	0.046210	0.500292	0.431887	0.167287	1.000000
Selling_type_encoded	-0.036820	-0.553851	-0.511779	-0.101030	-0.347922
Transmission_encoded	-0.003434	0.348869	0.334326	0.163881	0.068618
Owner_encoded	-0.170694	-0.096019	-0.018158	0.061924	-0.055526

In [32]:
```
sns.heatmap(new_data.iloc[:,1:].corr(), annot=True)
```

Out[32]: <AxesSubplot:>



From the above correlation plot we can infer the following :-

A -> Selling_Price is influenced by :
(i) Present_price by a score of 0.88

(ii) Fuel_Type_encoded by a score of 0.5

(iii) Transmission_type by a score of 0.35

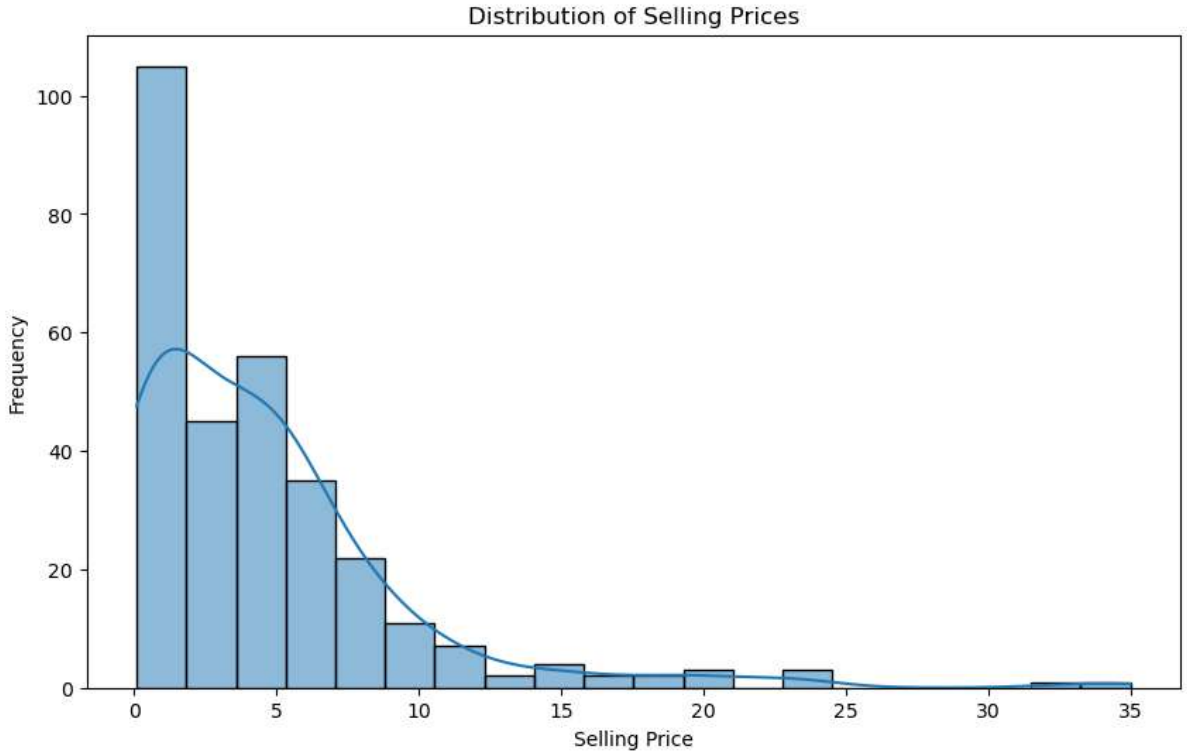
B -> Present_Price is influenced by :
(i) Selling_price by a score of 0.88

(ii) Fuel_Type_encoded by a score of 0.43

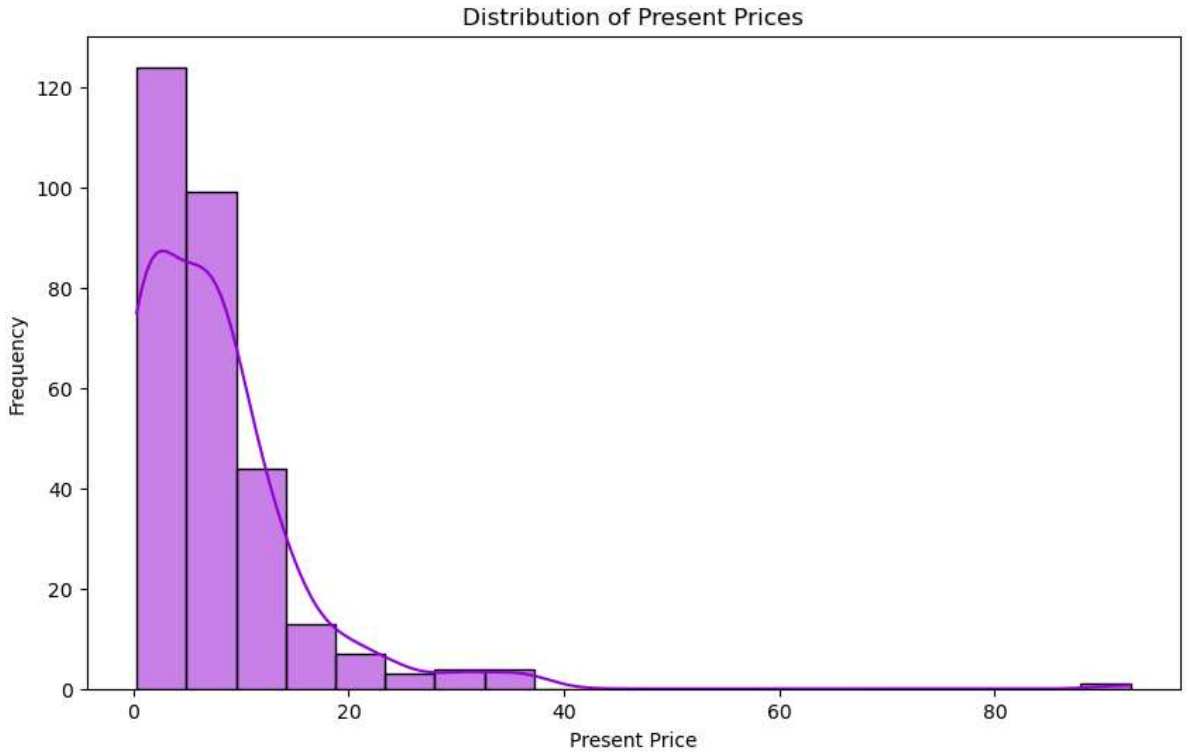
(iii) Transmission_type by a score of 0.33

3. Analyzing the distribution using histogram plots

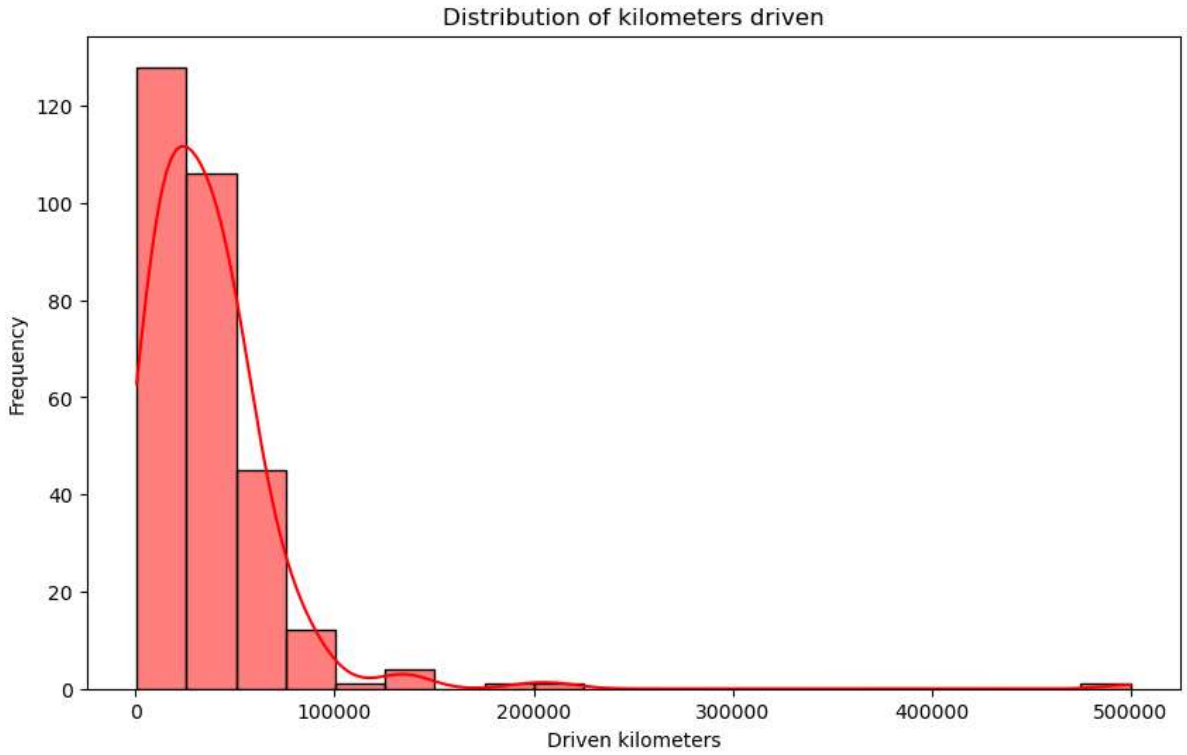
In [33]:
```
plt.figure(figsize=(10, 6))
sns.histplot(new_data['Selling_Price'], bins=20, kde=True)
plt.xlabel('Selling Price')
plt.ylabel('Frequency')
plt.title('Distribution of Selling Prices')
plt.show()
```



In [34]:
```
plt.figure(figsize=(10, 6))
sns.histplot(new_data['Present_Price'], bins=20, kde=True, color='darkviolet')
plt.xlabel('Present Price')
plt.ylabel('Frequency')
plt.title('Distribution of Present Prices')
plt.show()
```



In [35]:
```
plt.figure(figsize=(10, 6))
sns.histplot(new_data['Driven_kms'], bins=20, kde=True, color='red')
plt.xlabel('Driven kilometers')
plt.ylabel('Frequency')
plt.title('Distribution of kilometers driven')
plt.show()
```



4. Preparing the data for Modelling

Since, we need to predict the price(selling price) of the car using the features of the given dataset

In [36]:
```
x_data = new_data.drop(['Car_Name','Selling_Price'],axis=1)
y_data = new_data['Selling_Price']
```

In [37]:
```
x_data
```

Out[37]:

	Year	Present_Price	Driven_kms	Fuel_Type_encoded	Selling_type_encoded	Transmission_e
0	2014	5.59	27000	0	0	
1	2013	9.54	43000	1	0	
2	2017	9.85	6900	0	0	
3	2011	4.15	5200	0	0	
4	2014	6.87	42450	1	0	
...	...	...	...	...	...	
294	2016	11.60	33988	1	0	
295	2015	5.90	60000	0	0	
296	2009	11.00	87934	0	0	
297	2017	12.50	9000	1	0	
298	2016	5.90	5464	0	0	

299 rows × 7 columns

In [38]:
```
y_data
```

Out[38]:
```
0       3.35
1       4.75
2       7.25
3       2.85
4       4.60
       ...
294     9.50
295     4.00
296     3.35
297    11.50
298     5.30
Name: Selling_Price, Length: 299, dtype: float64
```

In [39]:
```
x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=
```

5. Training the Models using the above data

(A) -> (i) Training using Linear Regression Model

In [40]:
```
model_1 = LinearRegression()
model_1.fit(x_train, y_train)
```

Out[40]:
```
LinearRegression()
```

(ii) Predicting using Linear Regression Model

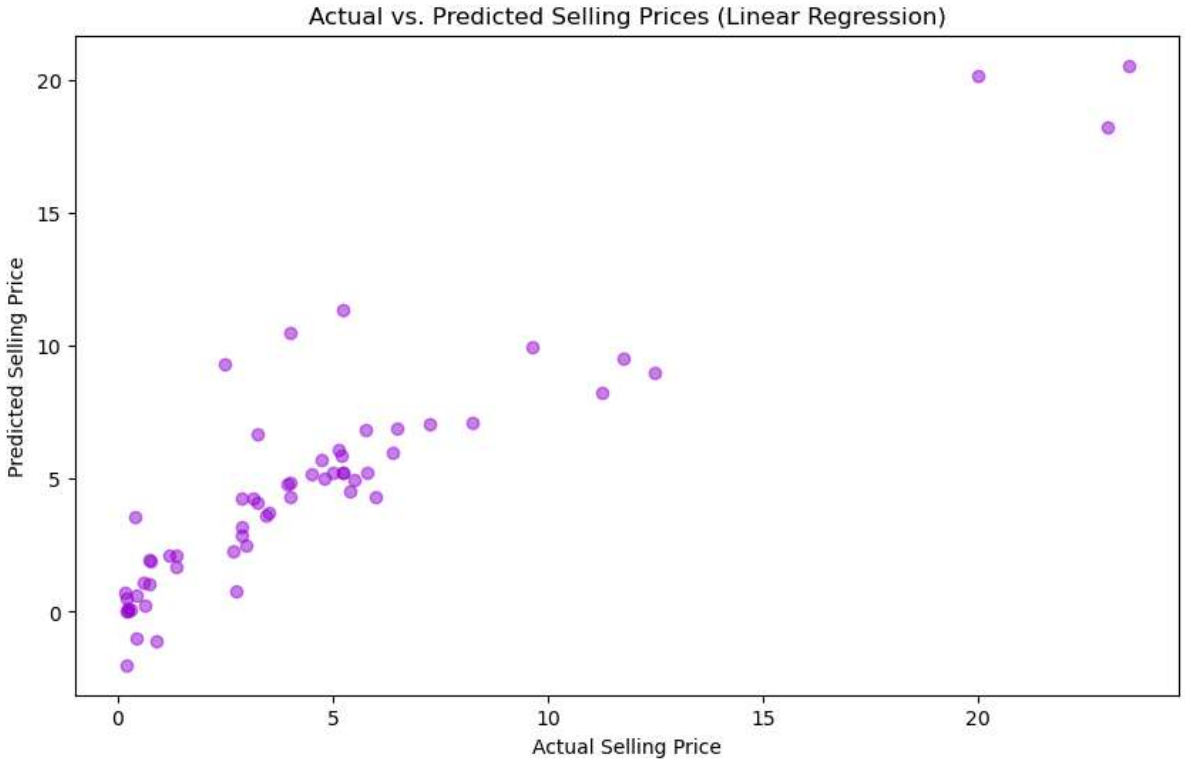
In [41]:
```
y_pred_1 = model_1.predict(x_test)
```

(iii) Evaluting the performance by Linear Regression Model

In [42]:
```
mse = mean_squared_error(y_test, y_pred_1)
r2 = r2_score(y_test, y_pred_1)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
```

```
Mean Square Error is : 4.028076863760065
R-Squared score is : 0.8380235823890909
```

In [43]:
```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_1, alpha=0.5, color='darkviolet')
plt.xlabel('Actual Selling Price')
plt.ylabel('Predicted Selling Price')
plt.title('Actual vs. Predicted Selling Prices (Linear Regression)')
plt.show()
```



(B) -> (i) Training using the Random Forest Regression Model

In [44]:
```
model_2 = RandomForestRegressor()
model_2.fit(x_train, y_train)
```

Out[44]:
```
RandomForestRegressor()
```

(ii) Predicting using Random Forest Regression Model

In [45]:
```
y_pred_2 = model_2.predict(x_test)
```

(iii) Evaluting the performance by Random Forest Regression Model

In [46]:
```
mse = mean_squared_error(y_test, y_pred_2)
r2 = r2_score(y_test, y_pred_2)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
```

```
Mean Square Error is : 7.478897279166666
R-Squared score is : 0.6992597137710552
```

In [47]:
```
plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred_2, label=model_2, alpha=0.5, color='green')

plt.xlabel("Actual Selling Prices")
plt.ylabel("Predicted Selling Prices")
plt.title("Actual vs. Predicted Selling Prices")
plt.legend()
plt.show()
```

(C) -> (i) Training using the Ridge Regression Model

In [48]:
```
model_3 = Ridge()
model_3.fit(x_train, y_train)
```

Out[48]:
```
Ridge()
```

(ii) Predicting using Ridge Regression Model

In [49]:
```
y_pred_3 = model_3.predict(x_test)
```

(iii) Evaluating the performance by Ridge Regression Model

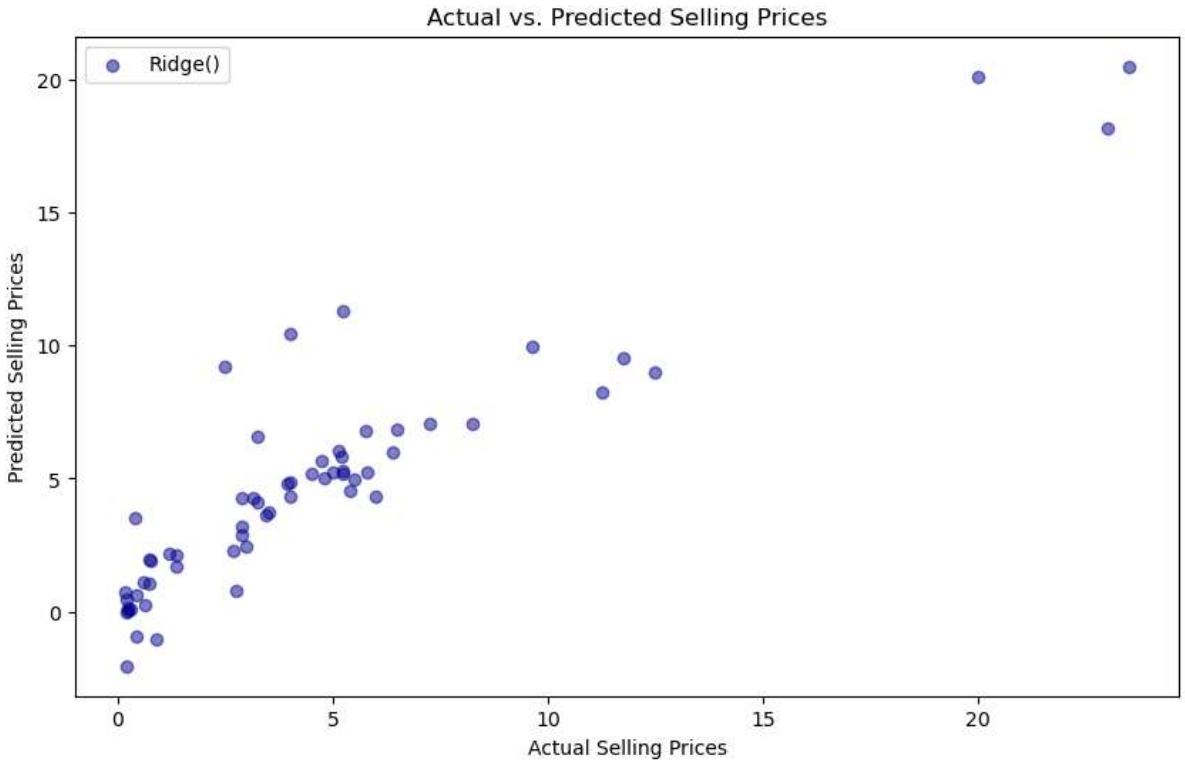
In [50]:
```
mse = mean_squared_error(y_test, y_pred_3)
r2 = r2_score(y_test, y_pred_3)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
```

```
Mean Square Error is : 3.9768973298980606
R-Squared score is : 0.840081606063998
```

In [51]:
```
plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred_3, label=model_3, alpha=0.5, color='darkblue')

plt.xlabel("Actual Selling Prices")
plt.ylabel("Predicted Selling Prices")
plt.title("Actual vs. Predicted Selling Prices")
plt.legend()
plt.show()
```



(D) -> (i) Training using the Lasso Regression Model

In [52]:
```
model_4 = Lasso()
model_4.fit(x_train, y_train)
```

Out[52]:
```
Lasso()
```

(ii) Predicting using the Lasso Regression Model

In [53]:
```
y_pred_4 = model_4.predict(x_test)
```

(iii) Evaluating the performance by Lasso Regression Model

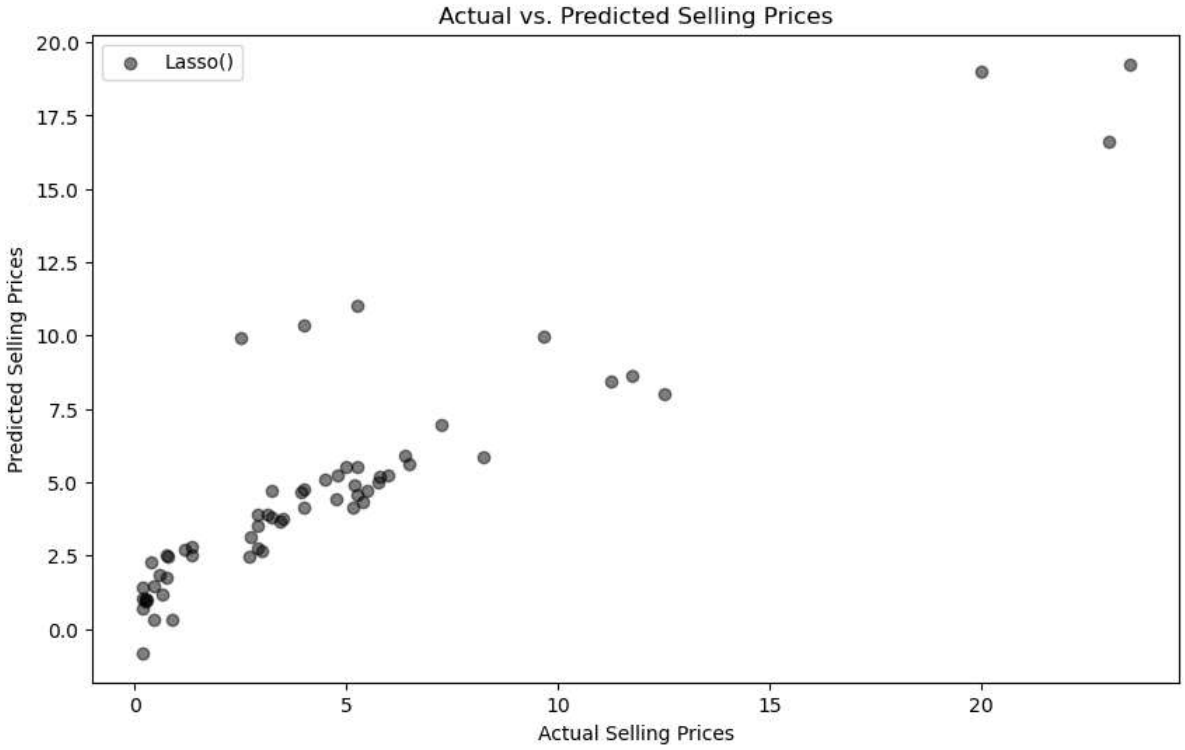
In [54]:
```
mse = mean_squared_error(y_test, y_pred_4)
r2 = r2_score(y_test, y_pred_4)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
```

```
Mean Square Error is : 4.489972829825654
R-Squared score is : 0.8194498916620485
```

In [55]:
```
plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred_4, label=model_4, alpha=0.5, color='black')

plt.xlabel("Actual Selling Prices")
plt.ylabel("Predicted Selling Prices")
plt.title("Actual vs. Predicted Selling Prices")
plt.legend()
plt.show()
```



(E) -> (i) Training using the ElasticNet Regression Model

In [56]:
```
model_5 = ElasticNet()
model_5.fit(x_train, y_train)
```

Out[56]:
```
ElasticNet()
```

(ii) Predicting using the ElasticNet Regression Model

In [57]:
```
y_pred_5 = model_5.predict(x_test)
```

(iii) Evaluating the performance by the ElasticNet Regression Model

In [58]:
```
mse = mean_squared_error(y_test, y_pred_5)
r2 = r2_score(y_test, y_pred_5)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
```

```
Mean Square Error is : 4.329718572290692
R-Squared score is : 0.825894011628066
```

In [59]:
```
plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred_5, label=model_5, alpha=0.5, color='gold')

plt.xlabel("Actual Selling Prices")
plt.ylabel("Predicted Selling Prices")
plt.title("Actual vs. Predicted Selling Prices")
plt.legend()
plt.show()
```

(F) -> (i) Training using the Gradient Boosting Regression Model

In [60]:
```
model_6 = GradientBoostingRegressor()
model_6.fit(x_train, y_train)
```

Out[60]:
```
GradientBoostingRegressor()
```

(ii) Predicting using the Gradient Boosting Regression Model

In [61]:
```
y_pred_6 = model_6.predict(x_test)
```

(iii) Evaluating the performance of Gradient Boosting Regression Model

In [62]:
```
mse = mean_squared_error(y_test, y_pred_6)
r2 = r2_score(y_test, y_pred_6)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
```

```
Mean Square Error is : 3.1284405404718694
R-Squared score is : 0.8741996221538454
```

In [63]:
```
plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred_6, label=model_6, alpha=0.5, color='red')

plt.xlabel("Actual Selling Prices")
plt.ylabel("Predicted Selling Prices")
plt.title("Actual vs. Predicted Selling Prices")
plt.legend()
plt.show()
```

(G) -> (i) Training using the XGBoost Regression Model

In [64]:
```
model_7 = XGBRegressor()
model_7.fit(x_train, y_train)
```

Out[64]:
```
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, ...)
```

(ii) Predicting using the XGBoost Regression Model

In [65]:
```
y_pred_7 = model_7.predict(x_test)
```

(iii) Evaluating the performance by XGBoost Regression Model

In [66]:
```
mse = mean_squared_error(y_test, y_pred_7)
r2 = r2_score(y_test, y_pred_7)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
```

```
Mean Square Error is : 2.4098547850320946
R-Squared score is : 0.9030952838676375
```

In [67]:
```
plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred_7, label='XGBoost Regression Model', alpha=0.5, col

plt.xlabel("Actual Selling Prices")
plt.ylabel("Predicted Selling Prices")
plt.title("Actual vs. Predicted Selling Prices")
plt.legend()
plt.show()
```

In [68]:
```
print("R-Squared score of each Model:- ")
print("\n Linear Regression Model: ",r2_score(y_test, y_pred_1))
print("\n Random Forest Regression Model: ",r2_score(y_test, y_pred_2))
print("\n Ridge Regression Model: ",r2_score(y_test, y_pred_3))
print("\n Lasso Regression Model: ",r2_score(y_test, y_pred_4))
print("\n ElasticNet Regression Model: ",r2_score(y_test, y_pred_5))
print("\n Gradient Boosting Regression Model: ",r2_score(y_test, y_pred_6))
print("\n XGBoost Regression Model: ",r2_score(y_test, y_pred_7))
```

```
R-Squared score of each Model:-

 Linear Regression Model:  0.8380235823890909

 Random Forest Regression Model:  0.6992597137710552

 Ridge Regression Model:  0.840081606063998

 Lasso Regression Model:  0.8194498916620485

 ElasticNet Regression Model:  0.825894011628066

 Gradient Boosting Regression Model:  0.8741996221538454

 XGBoost Regression Model:  0.9030952838676375
```

6. Saving the Model having the best fit

In our case it's XGBoost Regression Model with R^2 Score of 0.9031

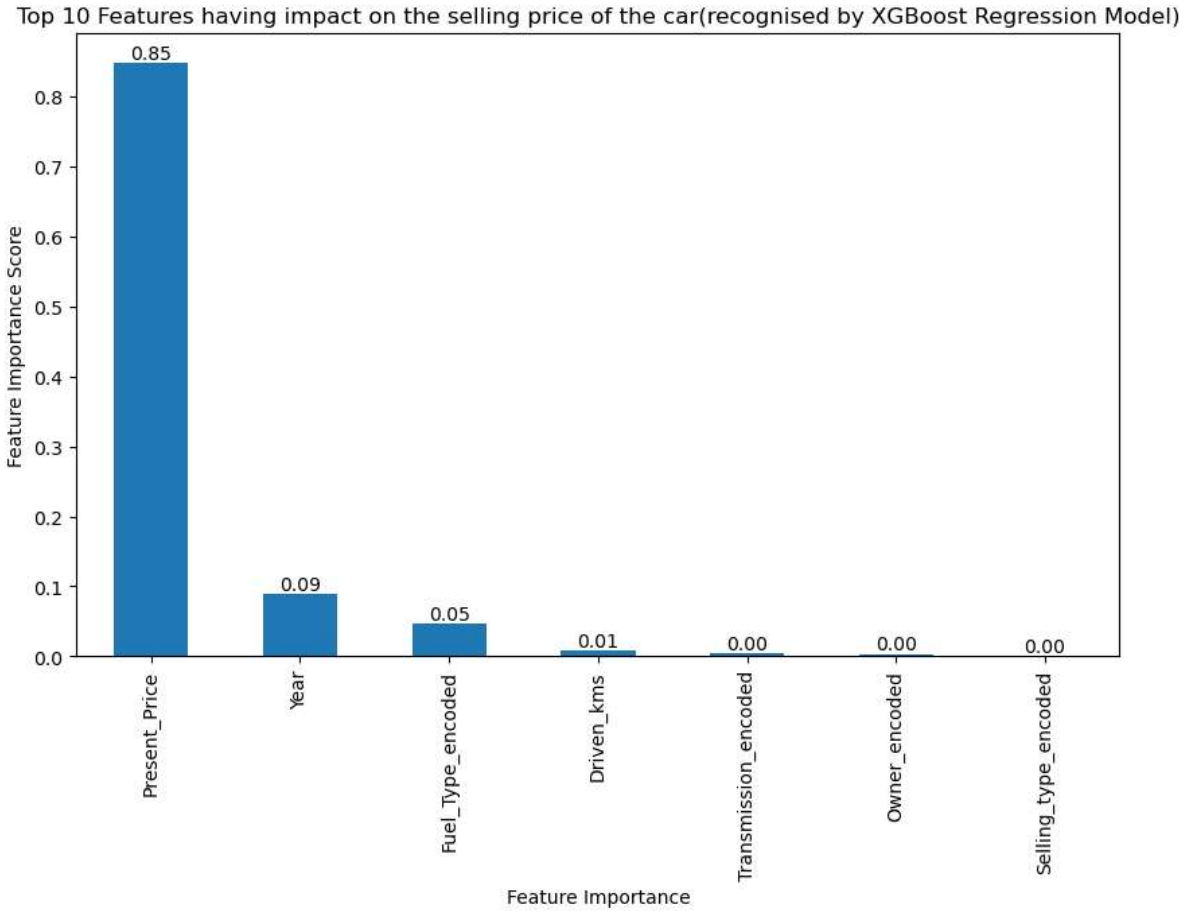
In [76]:
```
final_model =  XGBRegressor()
final_model.fit(x_train, y_train)
y_pred_final = final_model.predict(x_test)
mse = mean_squared_error(y_test, y_pred_final)
r2 = r2_score(y_test, y_pred_final)
print("Mean Square Error is :", mse)
print("R-Squared score is :",r2)
plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred_final, label='XGBoost Regression', alpha=0.5, color=

plt.xlabel("Actual Selling Prices")
plt.ylabel("Predicted Selling Prices")
plt.title("Actual vs. Predicted Selling Prices")
plt.legend()
plt.show()
```

```
Mean Square Error is : 2.4098547850320946
R-Squared score is : 0.9030952838676375
```

In [77]:
```
feature_importances = pd.Series(final_model.feature_importances_, index=x_data
plt.figure(figsize=(10, 6))
top_10_features = feature_importances.nlargest(10)
feature_importances.nlargest(10).plot(kind='bar')
plt.xlabel('Feature Importance')
plt.ylabel('Feature Importance Score')
plt.title('Top 10 Features having impact on the selling price of the car(recogr
for index, value in enumerate(top_10_features):
    plt.text(index, value, f'{value:.2f}', ha='center', va='bottom')
plt.show()
```



In [71]:
```
selling_price = new_data['Selling_Price']
present_price = new_data['Present_Price']
year = new_data['Year']


scatter_selling = go.Scatter(x=year, y=selling_price, mode='markers', name='Se
scatter_present = go.Scatter(x=year, y=present_price, mode='markers', name='Pr




fig = go.Figure(data=[scatter_selling, scatter_present])


fig.update_layout(
    xaxis_title='Year',
    yaxis_title='Price',
    title='Trivariate Plot of Selling Price and Present Price vs. Year'
)


fig.show()
```

In [72]:
```
selling_price = new_data['Selling_Price']
year = new_data['Year']


scatter_selling = go.Scatter(x=year, y=selling_price, mode='markers', name='Se



fig = go.Figure(data=[scatter_selling])


fig.update_layout(
    xaxis_title='Year',
    yaxis_title='Selling Price',
    title='Bivariate Plot of Selling Price vs. Year'
)


fig.show()
```

In [73]:
```
present_price = new_data['Present_Price']
year = new_data['Year']


scatter_present = go.Scatter(x=year, y=present_price, mode='markers', name='Pr



fig = go.Figure(data=[scatter_present])


fig.update_layout(
    xaxis_title='Year',
    yaxis_title='Present Price',
    title='Bivariate Plot of Present Price vs. Year'
)


fig.show()
```

In [78]:
```
model_filename = "final_car_prediction_model.h5"
joblib.dump(final_model, model_filename)
```

Out[78]:
```
['final_car_prediction_model.h5']
```

In [ ]: