Car Price Prediction using Random Forest Regressor

Project Overview

The aim of this Data Science Project to focuses on building a machine learning model to predict car price for a company in Poland. Identifying car price by their model, generation, year of production, mileage, localization, and type and volume of engine.

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

- **Variables:**

Price: Price variable shows the cost of car in Poland currency PLN (approx. 1USD=1PLN)
Unnamed: 0: It represent the serial number.
mark: Mark of the car.
model: Model of the car.
generation_name: Formatted Generation Name of the car.
year: Car Year of formatted.
mileage: Car Mileage in Kilometres.
vol_engine: Auto Engine Size.
fuel: Represent Engine Type according to their fuel type.
city: Locality in Poland.
province: Region of Poland.


```python
df = pd.read_csv("Car_Prices.csv")
df.head()
```

	Unnamed: 0	mark	model	generation_name	year	mileage	vol_engine	fuel	city	province	price
0	0	opel	combo	gen-d-2011	2015	139568	1248	Diesel	Janki	Mazowieckie	35900
1	1	opel	combo	gen-d-2011	2018	31991	1499	Diesel	Katowice	Śląskie	78501
2	2	opel	combo	gen-d-2011	2015	278437	1598	Diesel	Brzeg	Opolskie	27000
3	3	opel	combo	gen-d-2011	2016	47600	1248	Diesel	Korfantów	Opolskie	30800
4	4	opel	combo	gen-d-2011	2014	103000	1400	CNG	Tarnowskie Góry	Śląskie	35900

drop irralivant feature

```python
df.drop("Unnamed: 0",axis=1, inplace=True)
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 117927 entries, 0 to 117926
Data columns (total 10 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   mark             117927 non-null  object
 1   model            117927 non-null  object
 2   generation_name  87842 non-null   object
 3   year             117927 non-null  int64
```



```
3   year           117927 non-null  int64
4   mileage        117927 non-null  int64
5   vol_engine     117927 non-null  int64
6   fuel           117927 non-null  object
7   city           117927 non-null  object
8   province       117927 non-null  object
9   price          117927 non-null  int64
dtypes: int64(4), object(6)
memory usage: 9.0+ MB
```

drop all the null and duplicated values

```python
df.dropna(inplace=True)
```

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

5046

```python
#drop all the duplicatted values
df.drop_duplicates(inplace=True)
```

```python
df.describe().astype(int)
```

	year	mileage	vol_engine	price
count	82796	82796	82796	82796

mean	2012	152751	1842	62598
std	5	89996	613	75624
min	1978	0	0	900
25%	2008	86338	1498	19900
50%	2012	158700	1798	37900
75%	2017	212316	1995	73850
max	2022	2500000	6600	2399900

```
#for numaric colmuns
colmuns = df.select_dtypes(include='number')
```

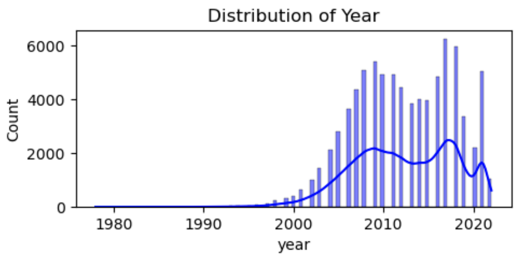
```
colmuns
```

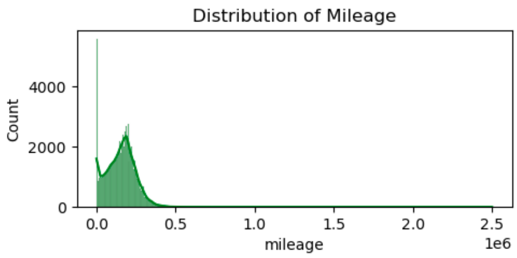
	year	mileage	vol_engine	price
0	2015	139568	1248	35900
1	2018	31991	1499	78501
2	2015	278437	1598	27000
3	2016	47600	1248	30800
4	2014	103000	1400	35900
...	...	...	...	...
117250	2017	51000	1969	229900
117251	2016	83500	1969	135000
117252	2017	174000	1969	154500
117253	2016	189020	1969	130000
117254	2016	95000	1969	126000

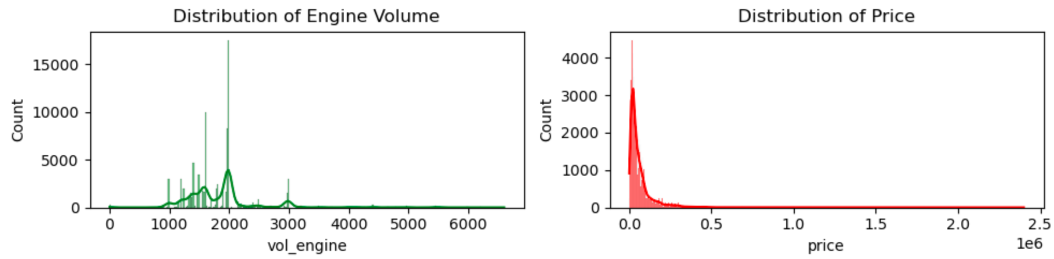
82796 rows × 4 columns

```
import seaborn as sns
```

```
fig, axes= plt.subplots(2,2, figsize=(10,5))

sns.histplot(data=df, x='year', kde=True, color="blue", edgecolor="black",ax=axes[0,0])
axes[0, 0].set_title('Distribution of Year')


sns.histplot(data=df, x='mileage', kde=True, color="green", edgecolor="black",ax=axes[0,1])
axes[0, 1].set_title('Distribution of Mileage')


sns.histplot(data=df, x='vol_engine', kde=True, color="green", edgecolor="black",ax=axes[1,0])
axes[1, 0].set_title('Distribution of Engine Volume')
sns.histplot(data=df, x='price', kde=True, color="red", edgecolor="black",ax=axes[1,1])
axes[1, 1].set_title('Distribution of Price')


plt.tight_layout()

plt.show()
```






```python
def remove_outliers(df, column):

    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)

    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    df_filtered = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

    num_outliers = len(df) - len(df_filtered)
    print(f"\n--- Outlier Removal Summary for '{column}' ---")
    print(f"Q1: {Q1:.2f}, Q3: {Q3:.2f}, IQR: {IQR:.2f}")
    print(f"Lower Bound: {lower_bound:.2f}, Upper Bound: {upper_bound:.2f}")
    print(f"Original rows: {len(df)}, Filtered rows: {len(df_filtered)}")
    print(f"Number of outliers removed: {num_outliers}")
```


```python
    print(f"Original rows: {len(df)}, Filtered rows: {len(df_filtered)}")
    print(f"Number of outliers removed: {num_outliers}")
```


```python
    return df_filtered
```

```python
for col in colmuns:
    df=remove_outliers(df, col)
```

```
--- Outlier Removal Summary for 'year' ---
Q1: 2008.00, Q3: 2017.00, IQR: 9.00
Lower Bound: 1994.50, Upper Bound: 2030.50
Original rows: 82796, Filtered rows: 82645
Number of outliers removed: 151

--- Outlier Removal Summary for 'mileage' ---
Q1: 86180.00, Q3: 212021.00, IQR: 125841.00
Lower Bound: -102581.50, Upper Bound: 400782.50
Original rows: 82645, Filtered rows: 82228
Number of outliers removed: 417

--- Outlier Removal Summary for 'vol_engine' ---
Q1: 1498.00, Q3: 1995.00, IQR: 497.00
Lower Bound: 752.50, Upper Bound: 2740.50
Original rows: 82228, Filtered rows: 75046
Number of outliers removed: 7182

--- Outlier Removal Summary for 'price' ---
Q1: 19500.00, Q3: 68899.00, IQR: 49399.00
Lower Bound: -54598.50, Upper Bound: 142997.50
Original rows: 75046, Filtered rows: 69488
```

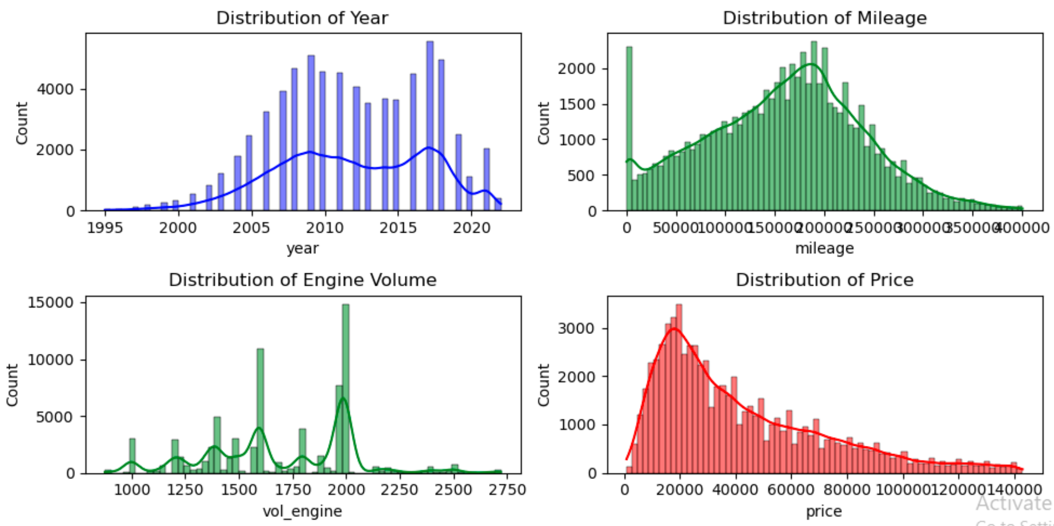

```
--- Outlier Removal Summary for 'price' ---
Q1: 19500.00, Q3: 68899.00, IQR: 49399.00
Lower Bound: -54598.50, Upper Bound: 142997.50
Original rows: 75046, Filtered rows: 69488
```


```
Number of outliers removed: 5558
```

After removed the outlier

[15]:

```python
fig, axes= plt.subplots(2,2, figsize=(10,5))

sns.histplot(data=df, x='year', kde=True, color="blue", edgecolor="black",ax=axes[0,0])
axes[0, 0].set_title('Distribution of Year')


sns.histplot(data=df, x='mileage', kde=True, color="green", edgecolor="black",ax=axes[0,1])
axes[0, 1].set_title('Distribution of Mileage')


sns.histplot(data=df, x='vol_engine', kde=True, color="green", edgecolor="black",ax=axes[1,0])
axes[1, 0].set_title('Distribution of Engine Volume')


sns.histplot(data=df, x='price', kde=True, color="red", edgecolor="black",ax=axes[1,1])
axes[1, 1].set_title('Distribution of Price')


plt.tight_layout()

plt.show()
```




```
df.describe()
```

	year	mileage	vol_engine	price
count	69488.000000	69488.000000	69488.000000	69488.000000
mean	2011.855961	159203.062716	1686.756131	42062.148788
std	5.141381	79948.075522	337.784631	30519.505297
min	1995.000000	1.000000	875.000000	900.000000
25%	2008.000000	102392.500000	1399.000000	18800.000000
50%	2012.000000	165000.000000	1598.000000	32900.000000
75%	2016.000000	212900.000000	1984.000000	59600.000000
max	2022.000000	400500.000000	2720.000000	142990.000000

```
# to getting text carring colmuns
text_columns = df.select_dtypes(include='object')
```

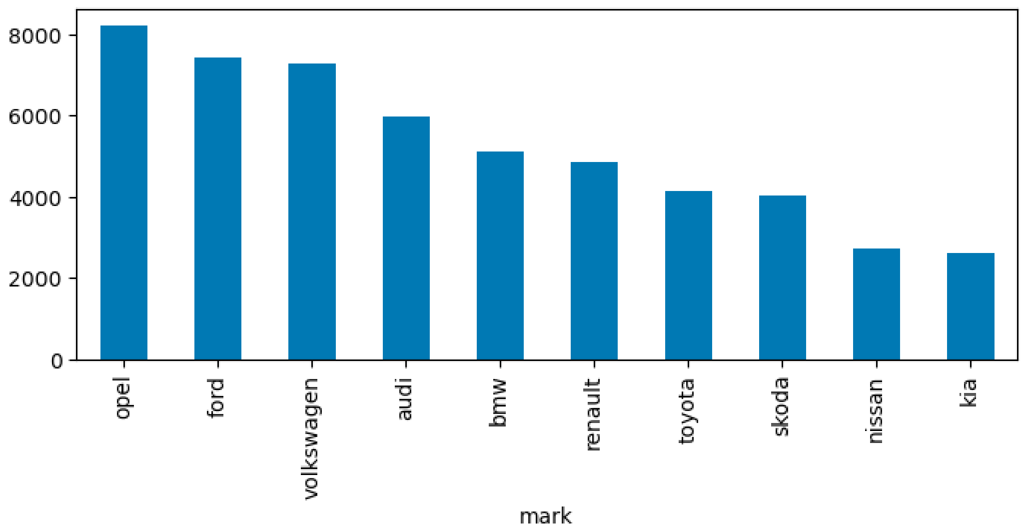
```
text_columns
```

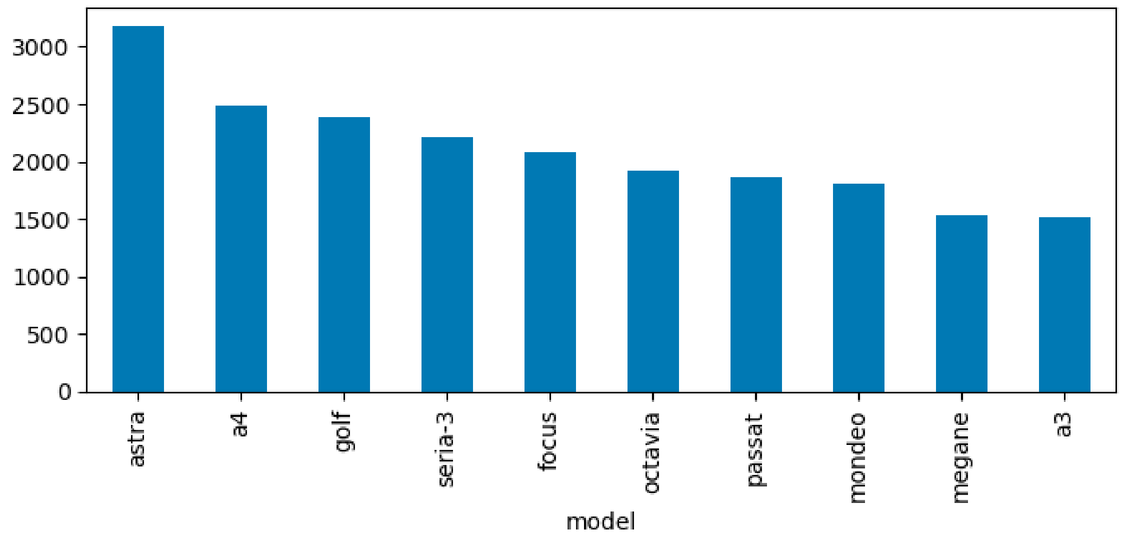
	mark	model	generation_name	fuel	city	province
0	opel	combo	gen-d-2011	Diesel	Janki	Mazowieckie
1	opel	combo	gen-d-2011	Diesel	Katowice	Śląskie
3	opel	combo	gen-d-2011	Diesel	Korfantów	Opolskie
4	opel	combo	gen-d-2011	CNG	Tarnowskie Góry	Śląskie
...	...	...	...	...	...	...
117230	volvo	xc-90	gen-ii-2014-xc-90	Diesel	Wrocław	Dolnośląskie
117237	volvo	xc-90	gen-ii-2014-xc-90	Gasoline	Warszawa	Mazowieckie
117251	volvo	xc-90	gen-ii-2014-xc-90	Gasoline	Pruszcz Gdański	Pomorskie
117253	volvo	xc-90	gen-ii-2014-xc-90	Gasoline	Sionna	Mazowieckie
117254	volvo	xc-90	gen-ii-2014-xc-90	Gasoline	Warszawa	Mazowieckie

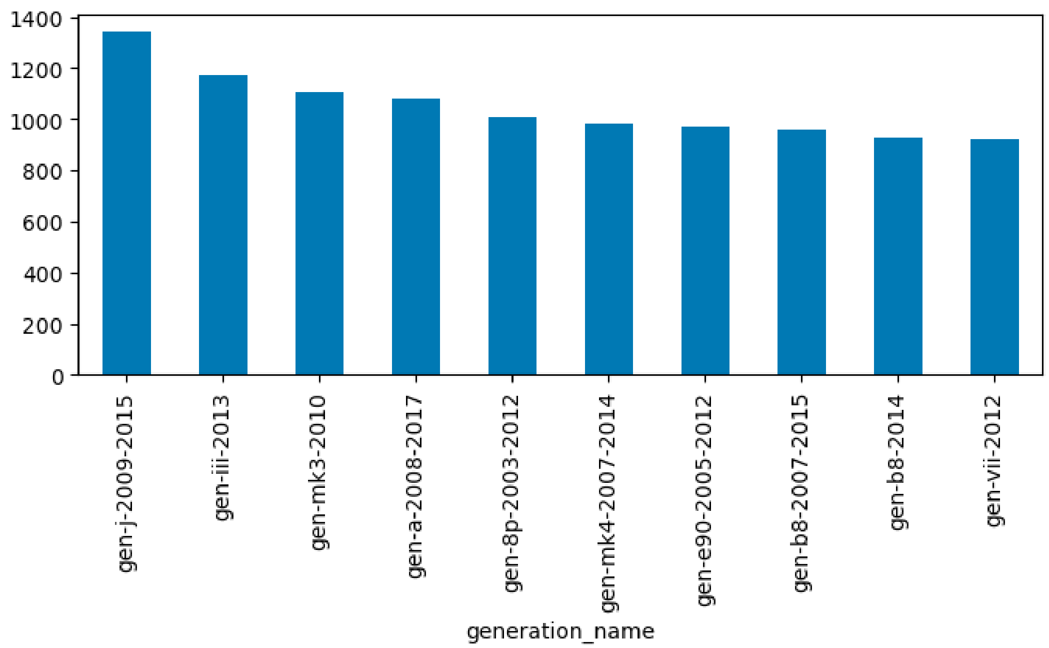
69488 rows × 6 columns

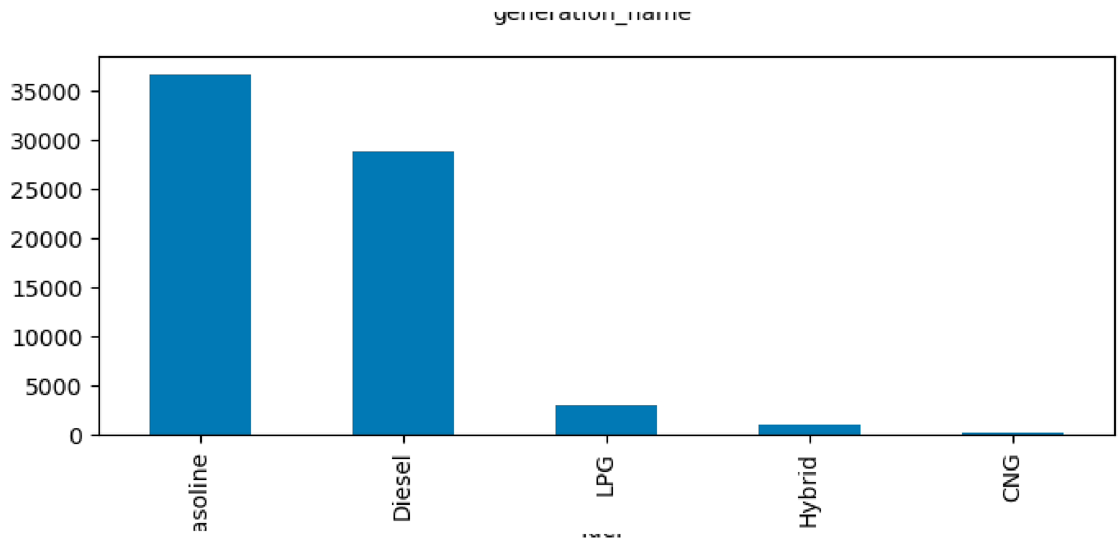
To know the Quantity of objects feature

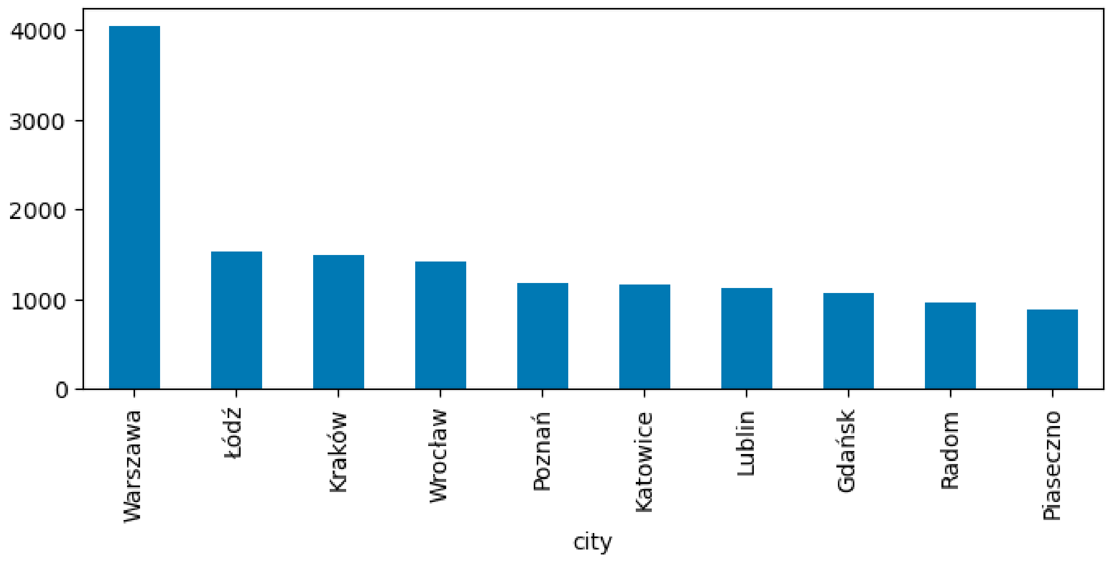
```
for col in text_columns:
    plt.figure(figsize = (8,3))
    df[col].value_counts(ascending=False).head(10).plot(kind="bar")
    plt.show()
```

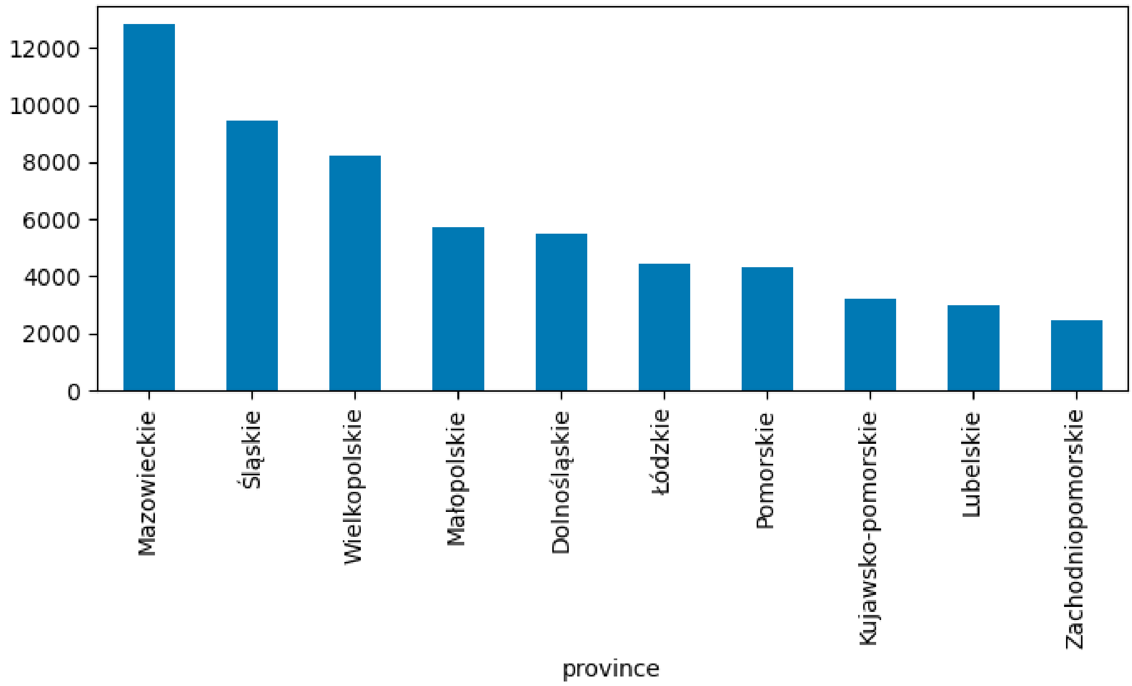

8000
6000
4000
2000
0
opel
ford
volkswagen
audi
bmw
renault
toyota
skoda
nissan
kia
mark


3000
2500
2000
1500
1000
500
0
astra
a4
golf
seria-3
focus
octavia
passat
mondeo
megane
a3
model


1400
1200
1000
800
600
400
200
0
gen-j-2009-2015
gen-iii-2013
gen-mk3-2010
gen-a-2008-2017
gen-8p-2003-2012
gen-mk4-2007-2014
gen-e90-2005-2012
gen-b8-2007-2015
gen-b8-2014
gen-vii-2012
generation_name


35000
30000
25000
20000
15000
10000
5000
0
asoline
Diesel
LPG
Hybrid
CNG

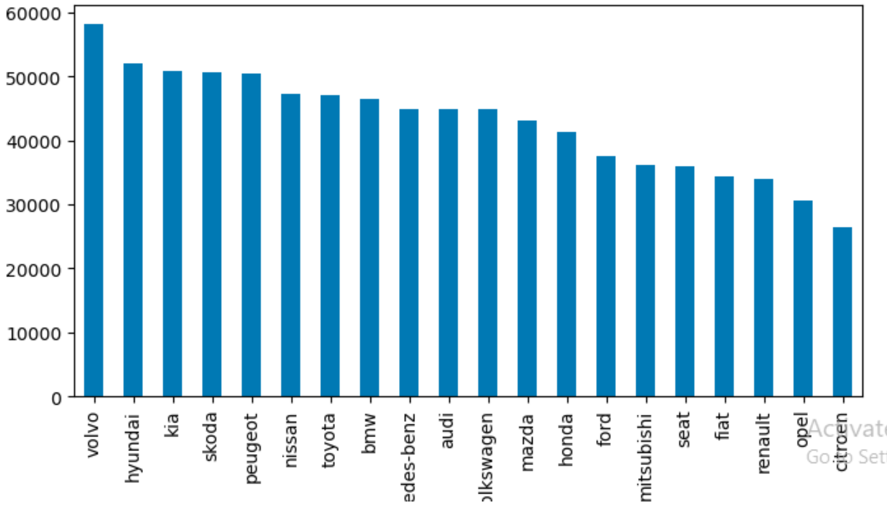

4000
3000
2000
1000
0
Warszawa
Łódź
Kraków
Wrocław
Poznań
Katowice
Lublin
Gdańsk
Radom
Piaseczno
city

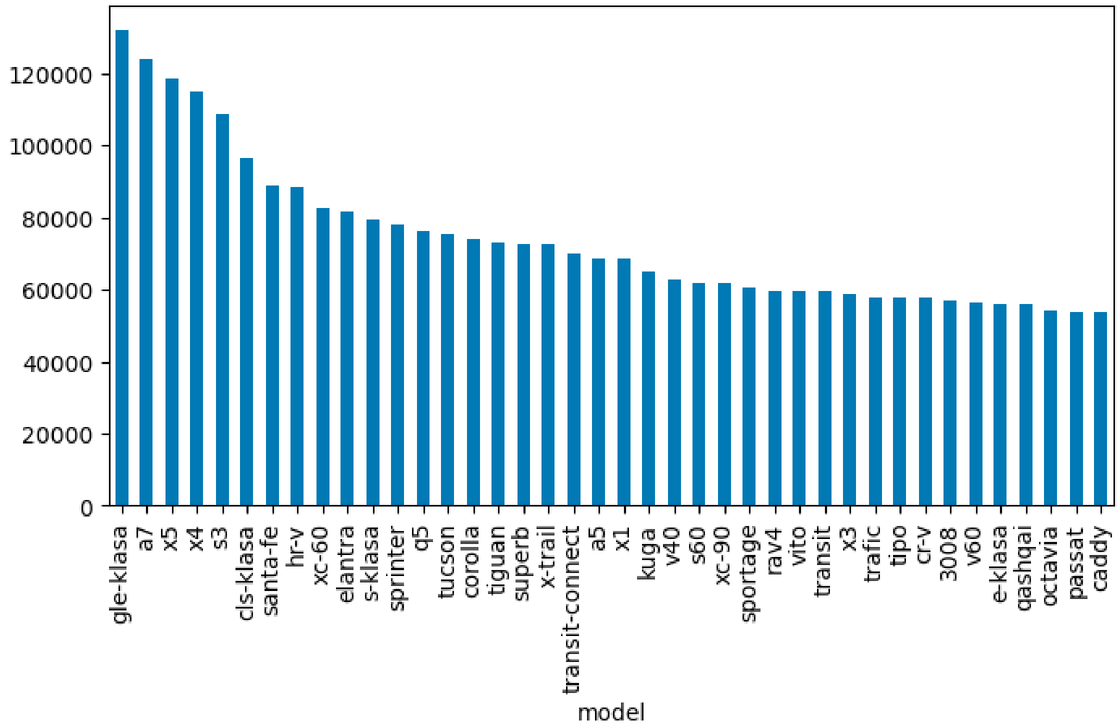

12000
10000
8000
6000
4000
2000
0
Mazowieckie
Śląskie
Wielkopolskie
Małopolskie
Dolnośląskie
Łódzkie
Pomorskie
Kujawsko-pomorskie
Lubelskie
Zachodniopomorskie
province

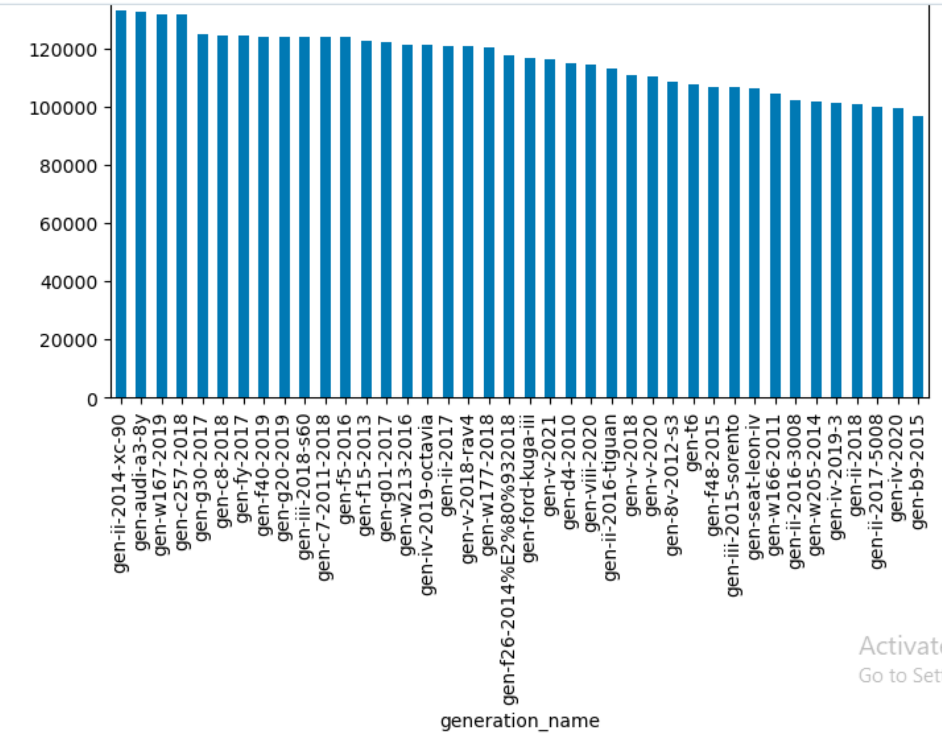
To check the relation of features with the price

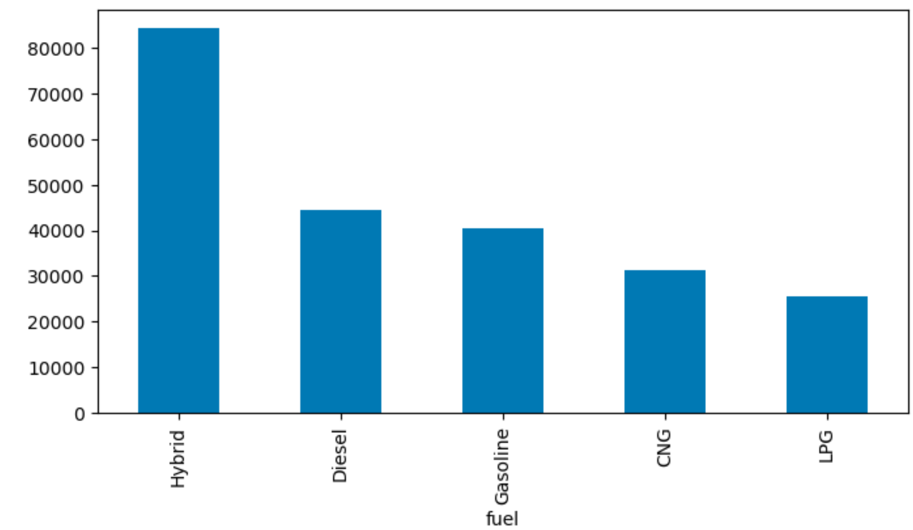
n [129…

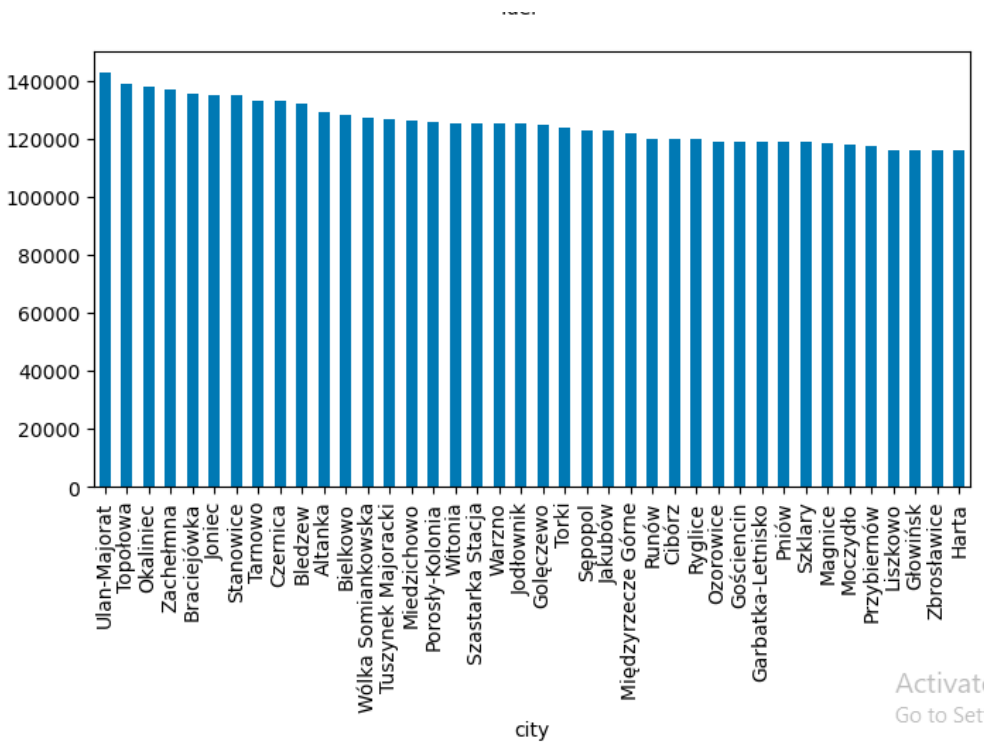
```python
for col in text_columns:
    plt.figure(figsize = (8,4))
    df.groupby(col)["price"].mean().sort_values(ascending=False).head(40).plot(kind="bar")
    plt.show()
```

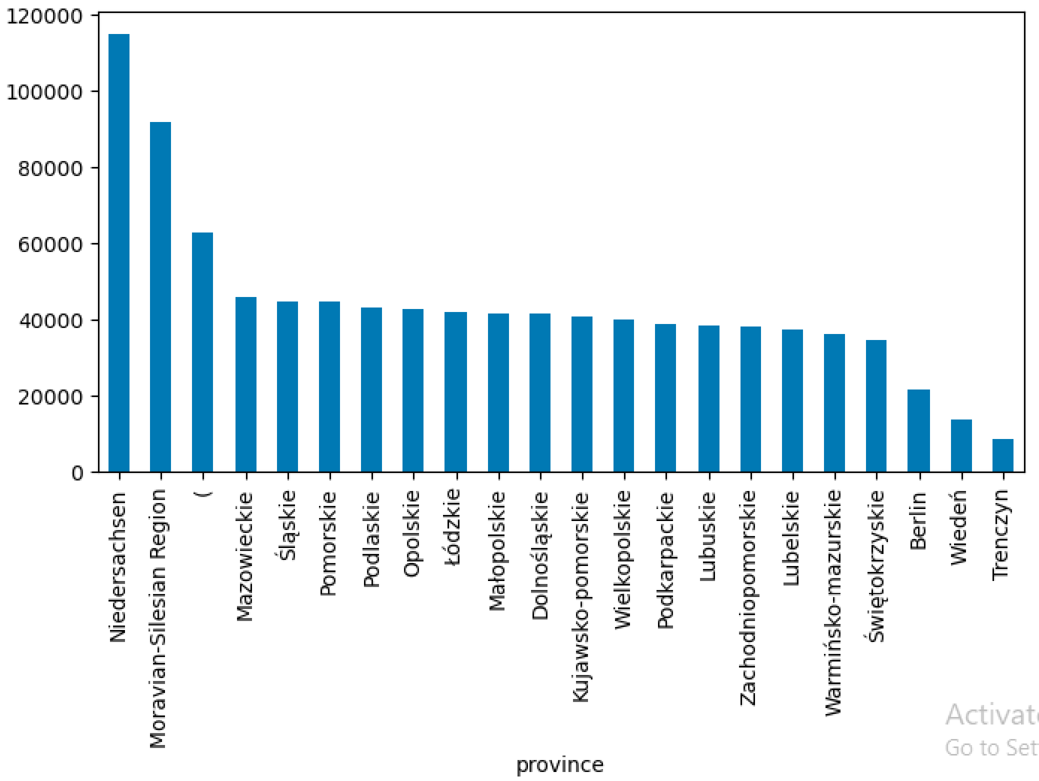





0
20000
40000
60000
80000
100000
120000
gen-ii-2014-xc-90
gen-audi-a3-8y
gen-w167-2019
gen-c257-2018
gen-g30-2017
gen-c8-2018
gen-fy-2017
gen-f40-2019
gen-g20-2019
gen-iii-2018-s60
gen-c7-2011-2018
gen-f5-2016
gen-f15-2013
gen-g01-2017
gen-w213-2016
gen-iv-2019-octavia
gen-ii-2017
gen-v-2018-rav4
gen-w177-2018
gen-f26-2014%E2%80%932018
gen-ford-kuga-iii
gen-v-2021
gen-d4-2010
gen-viii-2020
gen-ii-2016-tiguan
gen-v-2018
gen-v-2020
gen-8v-2012-s3
gen-t6
gen-f48-2015
gen-iii-2015-sorento
gen-seat-leon-iv
gen-w166-2011
gen-ii-2016-3008
gen-w205-2014
gen-iv-2019-3
gen-ii-2018
gen-ii-2017-5008
gen-iv-2020
gen-b9-2015
generation_name


0
10000
20000
30000
40000
50000
60000
70000
80000
Hybrid
Diesel
Gasoline
CNG
LPG
fuel


140000
120000
100000
80000
60000
40000
20000
0
Ulan-Majorat
Topołowa
Okaliniec
Zachełmna
Braciejówka
Joniec
Stanowice
Tarnowo
Czernica
Bledzew
Altanka
Bielkowo
Wólka Somiankowska
Tuszynek Majoracki
Miedzichowo
Porosły-Kolonia
Witonia
Szastarka Stacja
Warzno
Jodłownik
Golęczewo
Torki
Sępopol
Jakubów
Międzyrzecze Górne
Runów
Cibórz
Ryglice
Ozorowice
Gościencin
Garbatka-Letnisko
Pniów
Szklary
Magnice
Moczydło
Przybiernów
Liszkowo
Głowińsk
Zbrosławice
Harta
city


120000
100000
80000
60000
40000
20000
0
Niedersachsen
Moravian-Silesian Region
(
Mazowieckie
Śląskie
Pomorskie
Podlaskie
Opolskie
Łódzkie
Małopolskie
Dolnośląskie
Kujawsko-pomorskie
Wielkopolskie
Podkarpackie
Lubuskie
Zachodniopomorskie
Lubelskie
Warmińsko-mazurskie
Świętokrzyskie
Berlin
Wiedeń
Trenczyn
province

```python
from sklearn.preprocessing import LabelEncoder, StandardScaler
scaler = StandardScaler()
le = LabelEncoder()
```

to assign the numeric values to text columns

```python
for col in df.select_dtypes(include="object"):
    df[col] = le.fit_transform(df[col])
```

```python
df.corr()
```

	mark	model	generation_name	year	mileage	vol_engine	fuel	city	province	price
mark	1.000000	0.196819	0.246185	0.121745	-0.117552	-0.227961	0.052916	0.005299	0.001786	0.022738
model	0.196819	1.000000	-0.083408	0.071234	-0.018935	0.064960	-0.076213	-0.004996	-0.001162	0.123390
generation_name	0.246185	-0.083408	1.000000	0.240800	-0.239778	-0.253888	0.073241	0.007266	0.019613	0.100035
year	0.121745	0.071234	0.240800	1.000000	-0.671815	-0.250313	-0.077639	0.018455	0.004956	0.796587
mileage	-0.117552	-0.018935	-0.239778	-0.671815	1.000000	0.427870	-0.198991	-0.020707	-0.025703	-0.590134
vol_engine	-0.227961	0.064960	-0.253888	-0.250313	0.427870	1.000000	-0.300485	0.003427	-0.040087	0.077804
fuel	0.052916	-0.076213	0.073241	-0.077639	-0.198991	-0.300485	1.000000	0.008100	0.007001	-0.083026
city	0.005299	-0.004996	0.007266	0.018455	-0.020707	0.003427	0.008100	1.000000	-0.070049	0.026105
province	0.001786	-0.001162	0.019613	0.004956	-0.025703	-0.040087	0.007001	-0.070049	1.000000	-0.012935
price	0.022738	0.123390	0.100035	0.796587	-0.590134	0.077804	-0.083026	0.026105	-0.012935	1.000000


```python
df.columns
```

```
Index(['mark', 'model', 'generation_name', 'year', 'mileage', 'vol_engine',
       'fuel', 'city', 'province', 'price'],
      dtype='object')
```

select features for training the models

```python
x = df[['mark','model','generation_name','year','mileage','vol_engine','fuel']]
y = df['price']
```

```python
#convert the values in the standard form
x = scaler.fit_transform(x)
```

```python
from sklearn.model_selection import train_test_split,GridSearchCV
```

```python
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=42)
```

```python
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score,mean_absolute_percentage_error
```

```python
# write the function for predicting the result easily
def result(predict):
    print(f"mean_absolute_error is { mean_absolute_error(y_test,predict)}")
    print(f"mean_squared_error is { np.sqrt(mean_squared_error(y_test,predict))}")
    print(f"r2_score is {r2_score(y_test,predict)}")
    print(f"{mean_absolute_percentage_error(y_test,predict)}")
```



```python
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor()
```

```
dtr.fit(x_train, y_train)
```

```
DecisionTreeRegressor
DecisionTreeRegressor()
```

```
dtr_pred = dtr.predict(x_test)
```

```
result(dtr_pred)
```

```
mean_absolute_error is 6349.8935625805
mean_squared_error is 10303.527483857199
r2_score is 0.883536882477968
0.18629390851940947
```

```
from sklearn.neighbors import KNeighborsRegressor
knr = KNeighborsRegressor()
```

```
knr.fit(x_train,y_train)
```

```
KNeighborsRegressor
KNeighborsRegressor()
```

```
knr_pred = knr.predict(x_test)
```

```
result(knr_pred)
```

```
mean_absolute_error is 5352.348457287589
mean_squared_error is 8463.709915392914
r2_score is 0.9214152848250615
0.15901738520827738
```

```
from sklearn.ensemble import RandomForestRegressor
rfr = RandomForestRegressor()
```

```
grid_rfr = {

     'random_state': [None, 42],
    'n_estimators': [100,110,120],
}
```

```
gsv=GridSearchCV(rfr,grid_rfr, cv=5)
```

```
gsv.fit(x_train,y_train)
```

```
GridSearchCV
best_estimator_: RandomForestRegressor
RandomForestRegressor
```

```
grid_rfr_pred =gsv.predict(x_test)
```



```
result(grid_rfr_pred)
```

```
mean_absolute_error is 5040.714346060589
mean_squared_error is 8040.00448751887
r2_score is 0.9290864665432411
0.1485926172699571
```

```
gsv.best_params_
```

```
{'n_estimators': 120, 'random_state': 42}
```

```
import joblib
```

```
joblib.dump(scaler,"scaler")
```

```
['scaler']
```

```
joblib.dump(gsv,"rfr car price predictor model.pkl")
```

```
['rfr car price predictor model.pkl']
```