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COLLEGE: TECHNO INTERNATIONAL NEW TOWN

BRANCH: ELECTRONICS AND COMMUNICATION ENGINEERING

YEAR: 3RD

GITHUB ACC.LINK: <https://github.com/HRISHAV18>

<https://github.com/HRISHAV18/RinexProject>

Heroku deployment link: <https://majorproject-rinex.herokuapp.com/>

1.MAJOR PROJECT 1

Machine learning-supervised learning-linear regression

Linear Regression

Dataset- Price Prediction

Heroku deployment

2.MAJOR PROJECT 2

Image Processing Projects using NumPy and OpenCV.

```
#30th AUGUST , 2022
```

```
#MACHINE LEARNING - SUPERVISED LEARNING -REGRESSION - LINEAR REGRESSION
# Linear Regression
#Dataset - Price Prediction
#Dataset - https://raw.githubusercontent.com/HRISHAV18/RinexProject/main/scrap%20price.csv
```

```
#1.Take the data and create dataframe
```

```
import pandas as pd
df = pd.read_csv('https://raw.githubusercontent.com/HRISHAV18/RinexProject/main/scrap%20price.csv')
df
```

	ID	symboling	name	fueltypes	aspiration	doornumbers	carbody	drive
0	1	3	alfa-romero giulia	gas	std	two	convertible	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	
3	4	2	audi 100 ls	gas	std	four	sedan	
4	5	2	audi 100ls	gas	std	four	sedan	
...
200	201	-1	volvo 145e (sw)	gas	std	four	sedan	
201	202	-1	volvo 144ea	gas	turbo	four	sedan	
202	203	-1	volvo 244dl	gas	std	four	sedan	
203	204	-1	volvo 246	diesel	turbo	four	sedan	
204	205	-1	volvo 264gl	gas	turbo	four	sedan	

205 rows × 26 columns



◀ ▶

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   ID               205 non-null    int64  
 1   symboling        205 non-null    int64  
 2   name             205 non-null    object  
 3   fueltypes        205 non-null    object  

```

```
4 aspiration          205 non-null    object
5 doornumbers        205 non-null    object
6 carbbody           205 non-null    object
7 drivewheels         205 non-null    object
8 enginelocation      205 non-null    object
9 wheelbase            205 non-null    float64
10 carlength           205 non-null    float64
11 carwidth            205 non-null    float64
12 carheight           205 non-null    float64
13 curbweight          205 non-null    int64
14 enginetype          205 non-null    object
15 cylindernumber      205 non-null    object
16 enginesize          205 non-null    int64
17 fuelsystem          205 non-null    object
18 boreratio            205 non-null    float64
19 stroke               205 non-null    float64
20 compressionratio     205 non-null    float64
21 horsepower           205 non-null    int64
22 peakrpm              205 non-null    int64
23 citympg              205 non-null    int64
24 highwaympg           205 non-null    int64
25 price                 205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```

```
df.shape
```

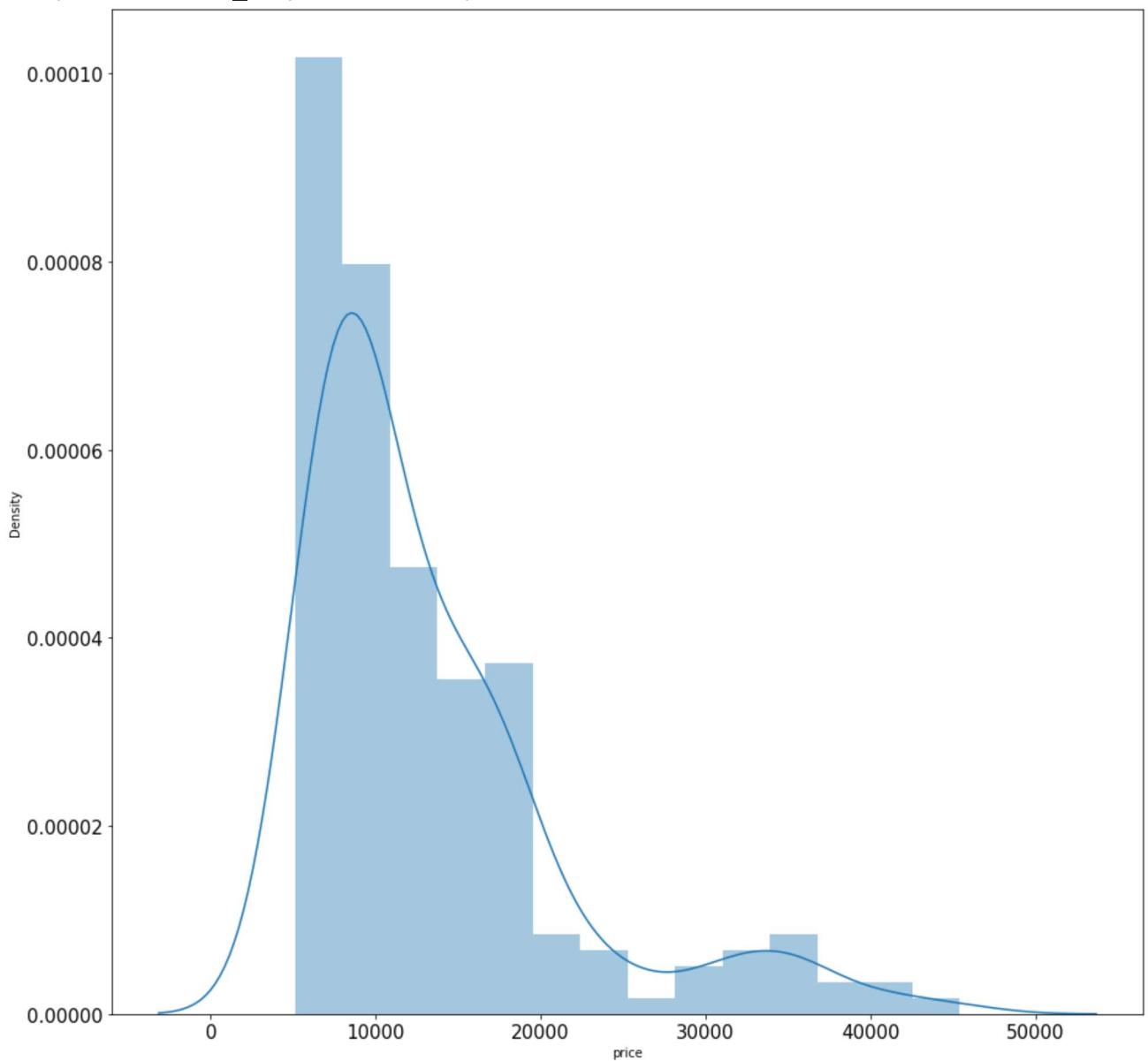
```
(205, 26)
```

```
df.size
```

```
5330
```

```
#VISUALISATION
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize = (15,15))
plt.xticks( fontsize=15)
plt.yticks( fontsize=15)
sns.distplot(df['price']) #distribution plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:  
    warnings.warn(msg, FutureWarning)  
<matplotlib.axes._subplots.AxesSubplot at 0x7f0b0d3b2190>
```



```
#Now we have to remove or drop the ID and Symboling column  
df = df.drop(columns=['ID', 'symboling'])
```

```
df.isna().sum()
```

name	0
fueltypes	0
aspiration	0
doornumbers	0
carbody	0
drivewheels	0
enginelocation	0
wheelbase	0
carlength	0
carwidth	0
carheight	0
curbweight	0

```

engine-type          0
cylinder-number     0
engine-size          0
fuel-system          0
bore-ratio           0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm              0
city-mpg              0
highway-mpg           0
price                 0
dtype: int64

```

df

		name	fuel-types	aspiration	door-numbers	car-body	drive-wheels	engine-lc
0	alfa-romero giulia		gas	std	two	convertible	rwd	
1	alfa-romero stelvio		gas	std	two	convertible	rwd	
2	alfa-romero Quadrifoglio		gas	std	two	hatchback	rwd	
3	audi 100 ls		gas	std	four	sedan	fwd	
4	audi 100ls		gas	std	four	sedan	4wd	
...
200	volvo 145e (sw)		gas	std	four	sedan	rwd	
201	volvo 144ea		gas	turbo	four	sedan	rwd	
202	volvo 244dl		gas	std	four	sedan	rwd	
203	volvo 246	diesel		turbo	four	sedan	rwd	
204	volvo 264gl		gas	turbo	four	sedan	rwd	

205 rows × 24 columns



df.info()

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 24 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   name              205 non-null    object 
 1   fuel-types        205 non-null    object 
 2   aspiration        205 non-null    object 

```

```

3 doornumbers      205 non-null    object
4 carbody          205 non-null    object
5 drivewheels      205 non-null    object
6 enginelocation   205 non-null    object
7 wheelbase         205 non-null    float64
8 carlength        205 non-null    float64
9 carwidth          205 non-null    float64
10 carheight        205 non-null    float64
11 curbweight       205 non-null    int64
12 enginetype       205 non-null    object
13 cylindernumber  205 non-null    object
14 enginesize       205 non-null    int64
15 fuelsystem       205 non-null    object
16 boreratio         205 non-null    float64
17 stroke           205 non-null    float64
18 compressionratio 205 non-null    float64
19 horsepower        205 non-null    int64
20 peakrpm          205 non-null    int64
21 citympg          205 non-null    int64
22 highwaympg       205 non-null    int64
23 price             205 non-null    float64
dtypes: float64(8), int64(6), object(10)
memory usage: 38.6+ KB

```

```

#We want to consider only the numeric data
#So we will create a new dataframe with only numeric data
df_numeric = df.select_dtypes(include = ['float64','int64'])
df_numeric

```

	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	s...
0	88.6	168.8	64.1	48.8	2548	130	3.47	
1	88.6	168.8	64.1	48.8	2548	130	3.47	
2	94.5	171.2	65.5	52.4	2823	152	2.68	
3	99.8	176.6	66.2	54.3	2337	109	3.19	
4	99.4	176.6	66.4	54.3	2824	136	3.19	
...
200	109.1	188.8	68.9	55.5	2952	141	3.78	
201	109.1	188.8	68.8	55.5	3049	141	3.78	
202	109.1	188.8	68.9	55.5	3012	173	3.58	
203	109.1	188.8	68.9	55.5	3217	145	3.01	
204	109.1	188.8	68.9	55.5	3062	141	3.78	

205 rows × 14 columns

```
df_numeric.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204

```

Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
0	wheelbase	205 non-null	float64
1	carlength	205 non-null	float64
2	carwidth	205 non-null	float64
3	carheight	205 non-null	float64
4	curbweight	205 non-null	int64
5	enginesize	205 non-null	int64
6	boreratio	205 non-null	float64
7	stroke	205 non-null	float64
8	compressionratio	205 non-null	float64
9	horsepower	205 non-null	int64
10	peakrpm	205 non-null	int64
11	citympg	205 non-null	int64
12	highwaympg	205 non-null	int64
13	price	205 non-null	float64

dtypes: float64(8), int64(6)

memory usage: 22.5 KB

```
#divide the data into i/p and o/p
#output - price
#input - All the columns except the price column
```

```
x = df_numeric.iloc[:,0:13].values
x
```

```
array([[ 88.6, 168.8, 64.1, ..., 5000. , 21. , 27. ],
       [ 88.6, 168.8, 64.1, ..., 5000. , 21. , 27. ],
       [ 94.5, 171.2, 65.5, ..., 5000. , 19. , 26. ],
       ...,
       [109.1, 188.8, 68.9, ..., 5500. , 18. , 23. ],
       [109.1, 188.8, 68.9, ..., 4800. , 26. , 27. ],
       [109.1, 188.8, 68.9, ..., 5400. , 19. , 25. ]])
```

```
y = df_numeric.iloc[:,13].values
y
```

```
array([13495. , 16500. , 16500. , 13950. , 17450. , 15250. ,
       17710. , 18920. , 23875. , 17859.167, 16430. , 16925. ,
       20970. , 21105. , 24565. , 30760. , 41315. , 36880. ,
       5151. , 6295. , 6575. , 5572. , 6377. , 7957. ,
       6229. , 6692. , 7609. , 8558. , 8921. , 12964. ,
       6479. , 6855. , 5399. , 6529. , 7129. , 7295. ,
       7295. , 7895. , 9095. , 8845. , 10295. , 12945. ,
       10345. , 6785. , 8916.5 , 8916.5 , 11048. , 32250. ,
       35550. , 36000. , 5195. , 6095. , 6795. , 6695. ,
       7395. , 10945. , 11845. , 13645. , 15645. , 8845. ,
       8495. , 10595. , 10245. , 10795. , 11245. , 18280. ,
       18344. , 25552. , 28248. , 28176. , 31600. , 34184. ,
       35056. , 40960. , 45400. , 16503. , 5389. , 6189. ,
       6669. , 7689. , 9959. , 8499. , 12629. , 14869. ,
       14489. , 6989. , 8189. , 9279. , 9279. , 5499. ,
       7099. , 6649. , 6849. , 7349. , 7299. , 7799. ,
       7499. , 7999. , 8249. , 8949. , 9549. , 13499. ,
       14399. , 13499. , 17199. , 19699. , 18399. , 11900. ,
       13200. , 12440. , 13860. , 15580. , 16900. , 16695. ,
```

```

17075. , 16630. , 17950. , 18150. , 5572. , 7957. ,
6229. , 6692. , 7609. , 8921. , 12764. , 22018. ,
32528. , 34028. , 37028. , 31400.5 , 9295. , 9895. ,
11850. , 12170. , 15040. , 15510. , 18150. , 18620. ,
5118. , 7053. , 7603. , 7126. , 7775. , 9960. ,
9233. , 11259. , 7463. , 10198. , 8013. , 11694. ,
5348. , 6338. , 6488. , 6918. , 7898. , 8778. ,
6938. , 7198. , 7898. , 7788. , 7738. , 8358. ,
9258. , 8058. , 8238. , 9298. , 9538. , 8449. ,
9639. , 9989. , 11199. , 11549. , 17669. , 8948. ,
10698. , 9988. , 10898. , 11248. , 16558. , 15998. ,
15690. , 15750. , 7775. , 7975. , 7995. , 8195. ,
8495. , 9495. , 9995. , 11595. , 9980. , 13295. ,
13845. , 12290. , 12940. , 13415. , 15985. , 16515. ,
18420. , 18950. , 16845. , 19045. , 21485. , 22470. ,
22625. ])

```

#5.TRAIN and TEST VARIABLES

```

#sklearn.model_selection - package , train_test_split - library
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 0)

```

```

print(x.shape) # 205 rows and 13 cols
print(x_train.shape) #153 rows and 13 cols (75%)
print(x_test.shape) # 52 rows and 13 cols (25%)

```

```

(205, 13)
(153, 13)
(52, 13)

```

```

print(y.shape) # 205 rows and 1 col
print(y_train.shape) # 153 rows and 1 cols(75 %)
print(y_test.shape) #52rows and 1 col(25%)

```

```

(205,)
(153,)
(52,)

```

```

#SCALING or NORMALISATION -DONE ONLY FOR INPUTS
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)

```

```

#7.RUN a CLASSIFIER/REGRESSOR/CLUSTERER
from sklearn.linear_model import LinearRegression
model = LinearRegression()

```

```

#8.MODEL FITTING
model.fit(x_train,y_train)

```

```

LinearRegression()

```

```
#9.PREDICT THE OUTPUT
```

```
y_pred = model.predict(x_test)#By taking the input testing data , we predict the output
y_pred #PREDICTED VALUES
```

```
array([ 7228.83749589, 21490.68704221, 16843.92578075, -408.88573459,
       12806.88877797, 14864.06930231, 6815.21828468, 7477.72764958,
       24370.76083649, 10122.57200019, 17227.20066046, 38255.87797552,
       11256.84858797, 15515.8531891 , 6862.33962216, 14495.22658006,
       12908.29759634, 20089.7360149 , 12112.9445916 , 7245.99470315,
       12180.32751173, 18941.52014488, 12446.19081036, 14964.92473417,
       22958.69376844, 8925.63443014, 7732.359849 , 18883.87938555,
       7815.43702522, 7137.47508384, 11136.70116598, 12703.41505146,
       22485.14049779, 8920.58002031, 7278.67268845, 28586.72492631,
       12234.13615858, 18290.11431538, 8085.5497993 , 38649.45073682,
       6761.48419029, 17525.36347714, 31858.57496193, 18698.70364197,
       12166.49554998, 8716.73070853, 8381.49914616, 17049.80445173,
       11020.16015803, 11326.88569464, 20247.44266236, 7818.27319638])
```

```
y_test #ACTUAL VALUES
```

```
array([ 6795. , 15750. , 15250. , 5151. , 9995. , 11199. , 5389. ,
       7898. , 17199. , 6529. , 20970. , 31400.5, 10945. , 18344. ,
       8916.5, 9989. , 9295. , 18920. , 7895. , 6488. , 9959. ,
       15580. , 9895. , 11549. , 15998. , 5118. , 6938. , 16695. ,
       8358. , 5499. , 7975. , 12290. , 22018. , 8948. , 6849. ,
       41315. , 11595. , 18150. , 6377. , 45400. , 8916.5, 17450. ,
       34184. , 15040. , 11259. , 7609. , 7609. , 14869. , 11694. ,
       8495. , 23875. , 7099. ])
```

```
#these are scaled/normalised values
print(x_train[10])
```

```
[0.28862974 0.48503937 0.07070707 0.525      0.280068  0.15625
 0.41964286 0.61437908 0.125      0.16190476 0.67346939 0.38888889
 0.44736842]
```

```
#INDIVIDUAL PREDICTION
```

```
model.predict([x_train[10]])# price of the car
```

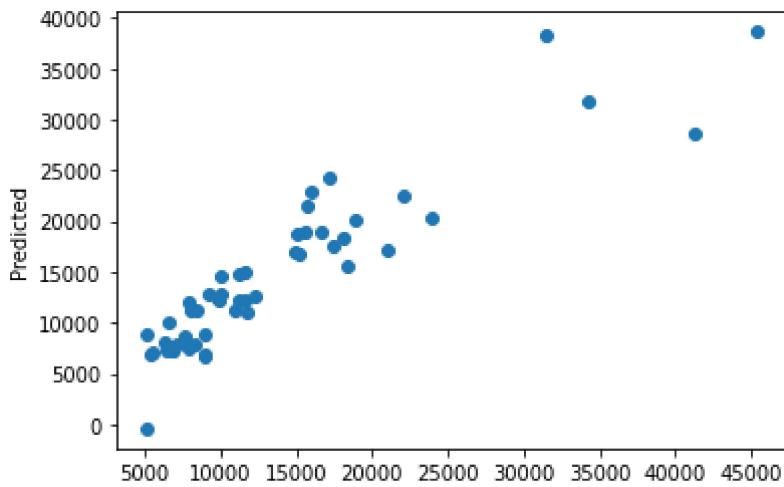
```
array([8070.06474751])
```

```
#INDIVIDUAL PREDICTION
```

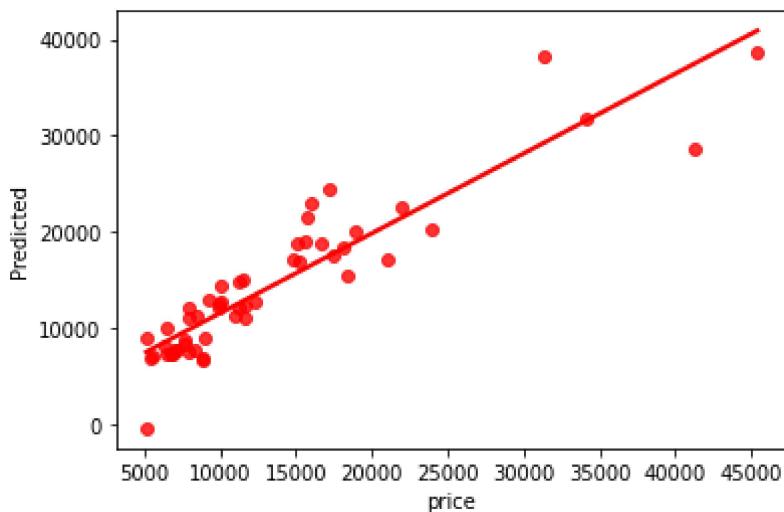
```
model.predict([x_train[5]])
```

```
array([17024.72437501])
```

```
plt.scatter(y_test,y_pred);
plt.xlabel('Actual');
plt.ylabel('Predicted');
```



```
sns.regplot(x=y_test,y=y_pred,ci=None,color = 'red');
plt.xlabel('price');
plt.ylabel('Predicted');
```



```
pred_df_numeric=pd.DataFrame({'Actual Value':y_test,'Predicted Value':y_pred,'Difference':
```

```
pred_df_numeric
```

	Actual Value	Predicted Value	Difference	
0	6795.0	7228.837496	-433.837496	
1	15750.0	21490.687042	-5740.687042	
2	15250.0	16843.925781	-1593.925781	
3	5151.0	-408.885735	5559.885735	
4	9995.0	12806.888778	-2811.888778	
5	11199.0	14864.069302	-3665.069302	
6	5389.0	6815.218285	-1426.218285	
7	7898.0	7477.727650	420.272350	
8	17199.0	24370.760836	-7171.760836	
9	6529.0	10122.572000	-3593.572000	
10	20970.0	17227.200660	3742.799340	
11	31400.5	38255.877976	-6855.377976	
12	10945.0	11256.848588	-311.848588	
13	18344.0	15515.853189	2828.146811	
14	8916.5	6862.339622	2054.160378	
15	9989.0	14495.226580	-4506.226580	
16	9295.0	12908.297596	-3613.297596	
17	18920.0	20089.736015	-1169.736015	
18	7895.0	12112.944592	-4217.944592	
19	6488.0	7245.994703	-757.994703	
20	9959.0	12180.327512	-2221.327512	
21	15580.0	18941.520145	-3361.520145	
22	9895.0	12446.190810	-2551.190810	
23	11549.0	14964.924734	-3415.924734	
24	15998.0	22958.693768	-6960.693768	
25	5118.0	8925.634430	-3807.634430	
26	6938.0	7732.359849	-794.359849	
27	16695.0	18883.879386	-2188.879386	
28	8358.0	7815.437025	542.562975	
29	5499.0	7137.475084	-1638.475084	
30	7975.0	11136.701166	-3161.701166	
31	12290.0	12703.415051	-413.415051	
32	22019.0	22195.110100	167.110100	

32	22010.0	22403.140490	-407.140490
33	8948.0	8920.580020	27.419980
34	6849.0	7278.672688	-429.672688
35	41315.0	28586.724926	12728.275074
36	11595.0	12234.136159	-639.136159
37	18150.0	18290.114315	-140.114315
38	6377.0	8085.549799	-1708.549799
39	45400.0	38649.450737	6750.549263
40	8916.5	6761.484190	2155.015810
41	17450.0	17525.363477	-75.363477
42	34184.0	31858.574962	2325.425038

```
# FOR HEROKU APP DEPLOY
# INPUT IS CAR'S NAME
# OUTPUT IS FUELTYPE
```

```
45    7600.0    8716.720700    1107.720700
```

```
df_object = df.select_dtypes(include = ['object'])
df_object
```

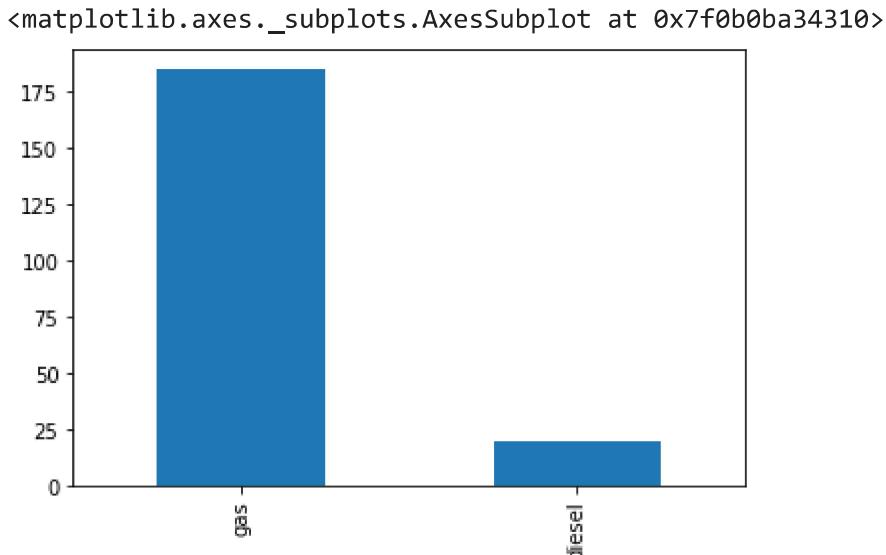
	name	fueltypes	aspiration	doornumbers	carbody	drivewheels	enginelc
0	alfa-romero giulia	gas	std	two	convertible	rwd	
1	alfa-romero stelvio	gas	std	two	convertible	rwd	
2	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	
3	audi 100 ls	gas	std	four	sedan	fwd	
4	audi 100ls	gas	std	four	sedan	4wd	
...
200	volvo 145e (sw)	gas	std	four	sedan	rwd	
201	volvo 144ea	gas	turbo	four	sedan	rwd	
202	volvo 244dl	gas	std	four	sedan	rwd	
203	volvo 240	diesel	std	four	sedan	rwd	

```
#I just want to know how many fueltypes are there
df['fueltypes'].value_counts()
```

```
gas      185
diesel     20
Name: fueltypes, dtype: int64
```

#VISUALISATION

```
df['fueltypes'].value_counts().plot(kind = 'bar')
```



```
#4.divide the data into input and output
```

```
x = df.iloc[:,0].values
y = df.iloc[:,1].values
print(x)
print(y)
```

```
'mazda glc' 'mazda rx-7 gs' 'buick electra 225 custom'
'buick century luxus (sw)' 'buick century' 'buick skyhawk'
'buick opel isuzu deluxe' 'buick skylark' 'buick century special'
'buick regal sport coupe (turbo)' 'mercury cougar' 'mitsubishi mirage'
'mitsubishi lancer' 'mitsubishi outlander' 'mitsubishi g4'
'mitsubishi mirage g4' 'mitsubishi g4' 'mitsubishi outlander'
'mitsubishi g4' 'mitsubishi mirage g4' 'mitsubishi montero'
'mitsubishi pajero' 'mitsubishi outlander' 'mitsubishi mirage g4'
'Nissan versa' 'nissan gt-r' 'nissan rogue' 'nissan latio' 'nissan titan'
'nissan leaf' 'nissan juke' 'nissan latio' 'nissan note' 'nissan clipper'
'nissan rogue' 'nissan nv200' 'nissan dayz' 'nissan fuga' 'nissan otti'
'nissan teana' 'nissan kicks' 'nissan clipper' 'peugeot 504'
'peugeot 304' 'peugeot 504 (sw)' 'peugeot 504' 'peugeot 504'
'peugeot 604sl' 'peugeot 504' 'peugeot 505s turbo diesel' 'peugeot 504'
'peugeot 504' 'peugeot 604sl' 'plymouth fury iii' 'plymouth cricket'

'plymouth fury iii' 'plymouth satellite custom (sw)'
'plymouth fury gran sedan' 'plymouth valiant' 'plymouth duster'
'porche macan' 'porcshce panamera' 'porche cayenne' 'porche boxter'
'porche cayenne' 'renault 12tl' 'renault 5 gtl' 'saab 99e' 'saab 99le'
'saab 99le' 'saab 99gle' 'saab 99gle' 'saab 99e' 'subaru' 'subaru dl'
'subaru dl' 'subaru' 'subaru brz' 'subaru baja' 'subaru r1' 'subaru r2'
'subaru trezia' 'subaru tribeca' 'subaru dl' 'subaru dl'
'toyota corona mark ii' 'toyota corona' 'toyota corolla 1200'
'toyota corona hardtop' 'toyota corolla 1600 (sw)' 'toyota carina'
'toyota mark ii' 'toyota corolla 1200' 'toyota corona' 'toyota corolla'
'toyota corona' 'toyota corolla' 'toyota mark ii'
'toyota corolla liftback' 'toyota corona' 'toyota celica gt liftback'
'toyota corolla tercel' 'toyota corona liftback' 'toyota corolla'
'toyota starlet' 'toyota tercel' 'toyota corolla' 'toyota cressida'
'toyota corolla' 'toyota celica gt' 'toyota corona' 'toyota corolla'
'toyota mark ii' 'toyota corolla liftback' 'toyota corona'
```

```
'toyota starlet' 'toyouta tercel' 'volkswagen rabbit'
'veolkswagen 1131 deluxe sedan' 'volkswagen model 111' 'volkswagen type 3'
'veolkswagen 411 (sw)' 'volkswagen super beetle' 'volkswagen dasher'
'vw dasher' 'vw rabbit' 'volkswagen rabbit' 'volkswagen rabbit custom'
'veolkswagen dasher' 'volvo 145e (sw)' 'volvo 144ea' 'volvo 244dl'
'volvo 245' 'volvo 264gl' 'volvo diesel' 'volvo 145e (sw)' 'volvo 144ea'
'volvo 244dl' 'volvo 246' 'volvo 264gl']
['gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'diesel' 'gas' 'gas' 'diesel' 'diesel' 'diesel' 'diesel'
'diesel' 'diesel' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'diesel'
'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'diesel' 'gas' 'diesel' 'gas' 'diesel' 'gas' 'gas'
'gas' 'diesel' 'gas' 'diesel' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'diesel' 'gas' 'gas'
'gas' 'gas' 'gas' 'gas' 'diesel' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'diesel' 'gas' 'diesel' 'gas' 'gas' 'diesel' 'gas' 'gas' 'gas' 'gas'
'gas' 'diesel' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas' 'gas'
'gas' 'diesel' 'gas']
```

```
#5.train_test_split
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 0)
```

```
#6.Apply TF-IDF vectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
vect = TfidfVectorizer()
x_train_v = vect.fit_transform(x_train)
x_test_v = vect.transform(x_test)
```

```
#7.Apply CLASSIFIER
from sklearn.svm import SVC
model = SVC()
```

```
#8.model fitting
model.fit(x_train_v,y_train)
```

```
SVC()
```

```
#9.Predictor variable/predict the output
y_pred = model.predict(x_test_v)
y_pred #Predicted values
```

```
array(['gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas'],
      dtype='|S5')
```

```
'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
'gas', 'gas', 'gas', 'gas', 'gas'], dtype=object)
```

```
y_test # actual values
```

```
array(['gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'diesel', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas'],
      dtype=object)
```

```
#Accuracy
```

```
from sklearn.metrics import accuracy_score
accuracy_score(y_pred,y_test)*100
```

```
96.15384615384616
```

```
#Evaluating a specific name (1st)
```

```
a = df['name'][10]
a
```

```
'bmw 320i'
```

```
a = vect.transform([a])
model.predict(a)
```

```
array(['gas'], dtype=object)
```

```
#Evaluating a specific name (2nd)
```

```
b = df['name'][12] #12th index from the message column
b
```

```
'bmw x1'
```

```
b = vect.transform([b])
model.predict(b)
```

```
array(['gas'], dtype=object)
```

```
#Evaluating by taking custom texts
```

```
c = 'audi'
c
```

```
'audi'
```

```
c = vect.transform([c])
model.predict(c)
```

```
array(['gas'], dtype=object)
```

```
#If ever I have to deploy my model,I will have to perform pipelining
```

```
#Pipelining
from sklearn.pipeline import make_pipeline
text_model = make_pipeline(TfidfVectorizer(),SVC())
text_model.fit(x_train,y_train)

Pipeline(steps=[('tfidfvectorizer', TfidfVectorizer()), ('svc', SVC())])
```

```
#predictor varibale
y_pred1 = text_model.predict(x_test)
y_pred1 # these are predicted outputs for pipelined model
```

```
array(['gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas'],
      dtype=object)
```

```
y_test #Actual output
```

```
array(['gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'diesel', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas',
       'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas', 'gas'],
      dtype=object)
```

```
#To check the accuracy of the pipelined model
accuracy_score(y_pred1,y_test)*100
```

```
96.15384615384616
```

```
#Individual Prediction/Evaluation of a specific name
```

```
a1 = df['name'][2]
a1
```

```
'alfa-romero Quadrifoglio'
```

```
text_model.predict([a1])
```

```
array(['gas'], dtype=object)
```

```
#JOBLIB - 2 different types - 1.Dump and 2.Load
```

```
import joblib
joblib.dump(text_model,'gas-diesel')
#We are creating a newfile called gas-diesel and we are dumping our pipelined model
#inside it.
```

```
['gas-diesel']
```

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✓ 0s completed at 8:12 PM



```
#We are creating a STREAMLIT WEB APPLICATION
```

```
#Temporary deployment - Local host
```

```
!pip install streamlit --quiet #Installing the streamlit library
```

```
|██████████| 9.1 MB 7.3 MB/s  
|██████████| 164 kB 56.5 MB/s  
|██████████| 4.7 MB 43.4 MB/s  
|██████████| 235 kB 37.7 MB/s  
|██████████| 181 kB 4.7 MB/s  
|██████████| 78 kB 4.8 MB/s  
|██████████| 63 kB 1.4 MB/s  
|██████████| 51 kB 5.3 MB/s  
Building wheel for validators (setup.py) ... done
```

```
%%writefile app.py  
# %%writefile is a magic command to create app.py file  
import streamlit as st  
import joblib  
model = joblib.load('gas-diesel')  
st.title('GAS-DIESEL CLASSIFIER') #creates a title in web app  
ip = st.text_input('Enter the message') #creates a text box in web app  
op = model.predict([ip])  
if st.button('Predict'): st.title(op[0]) # st.button will create a button with name Predict  
#st.title(op[0]) # the output will be displayed as a title
```

→ Writing app.py

```
#TEMPORARY DEPLOYMENT PART OF WEB APPLICATION  
!streamlit run app.py & npx localtunnel --port 8501  
#8501 is the default port number for local tunnel
```

```
2022-09-21 04:52:04.219 INFO     numexpr.utils: NumExpr defaulting to 2 threads.
```

You can now view your Streamlit app in your browser.

Network URL: <http://172.28.0.2:8501>

External URL: <http://34.145.107.186:8501>

```
npx: installed 22 in 5.583s
```

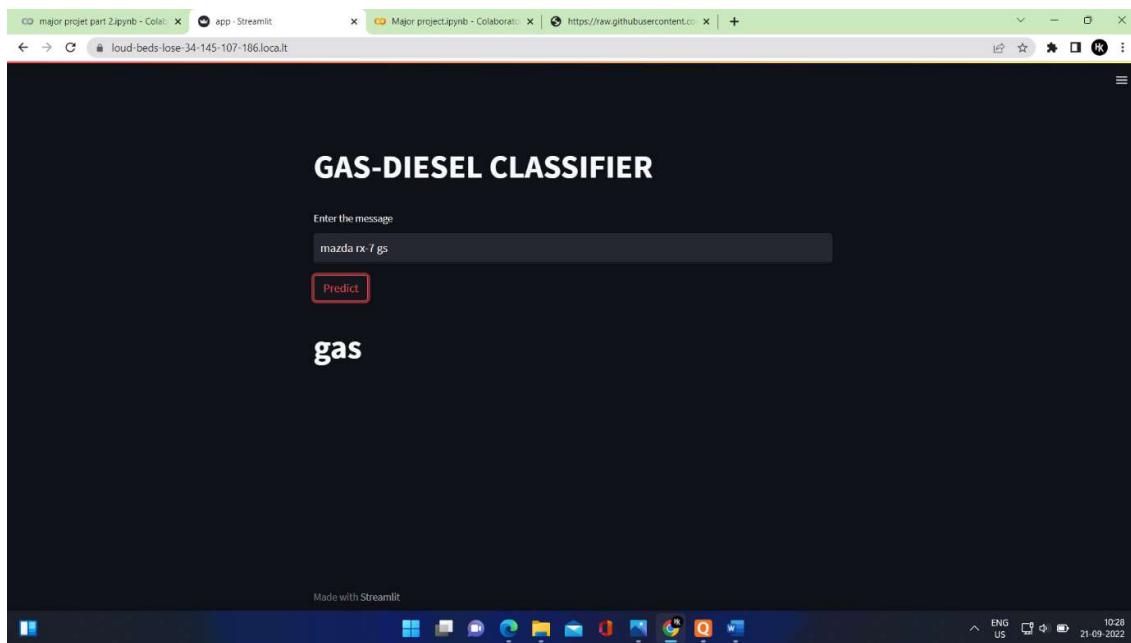
```
your url is: https://loud-beds-lose-34-145-107-186.localtunnel.me
```

[Colab paid products - Cancel contracts here](#)

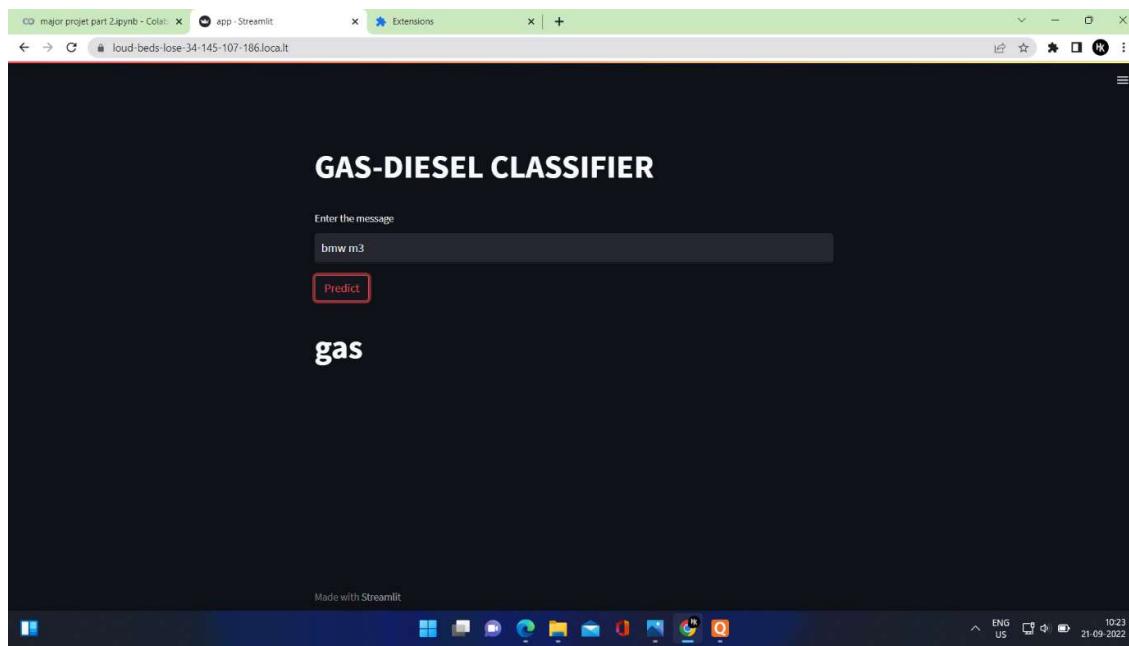


LOCAL APP DEPLOY

screenshots of local app 1:

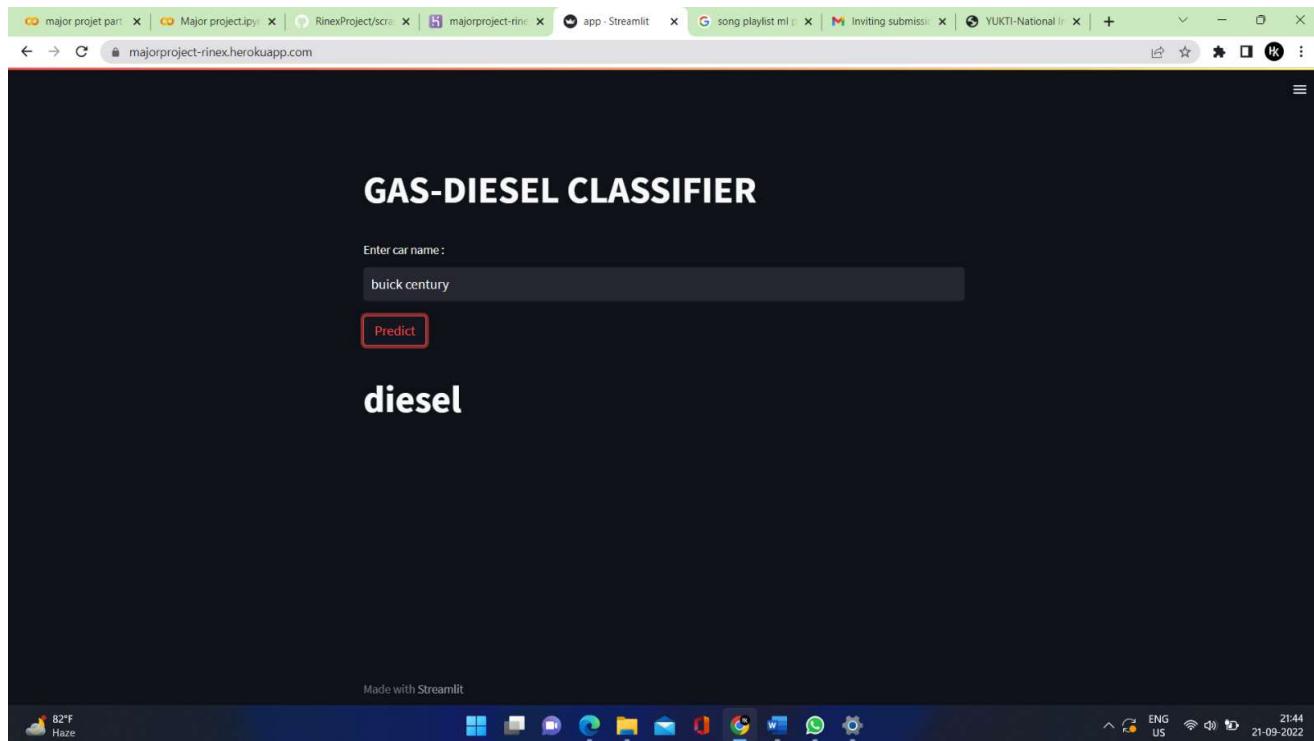


screenshots of local app 2:



Heroku deployment link: <https://majorproject-rinex.herokuapp.com/>

screenshots of web app 1:



screenshots of web app 2:

