CAR RESALE VALUE PREDICTION

Project report

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ABSTRACT

To be able to predict used cars market value can help both buyers and sellers. There are lots of individuals who are interested in the used car market at some points in their life because they wanted to sell their car or buy a used car. In this process, it’s a big corner to pay too much or sell less then it’s market value. In this Project, we are going to predict the Price of Used Cars using various features like year, model type, brand, fuel type, kilo-meter. Existing System includes a process where a seller decides a price randomly and buyer has no idea about the car and it’s value in the present day scenario. In fact, seller also has no idea about the car’s existing value or the price he should be selling the car at. To overcome this problem we have developed a model which will be highly effective. Gradient boosting Regressor is used because calculates the difference between the current prediction and the known correct target value. Because of which it will be possible to predict the actual price a car rather than the price range of a car. User Interface has also been developed which acquires input from any user and displays the Price of a car according to user’s inputs.

Keyword: Gradient boosting regressor, Machine Learning, used car value predication

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CHAPTER 1

1. INTRODUCTION:

Almost everyone wants their own car these days, but because of factors like affordability or economic conditions, many prefer to opt for pre-owned cars. Accurately predicting used car prices requires expert knowledge due to the nature of their dependence on a variety of factors and features. Used car prices are not constant in the market, both buyers and sellers need an intelligent system that will allow them to predict the correct price efficiently. In this intelligent system, the most difficult problem is the collection of the dataset which contains all important elements like the manufacturing year of the car, its gas type, its condition, miles driven, horsepower, doors, number of times a car has been painted, customer reviews, the weight of the car, etc. It is necessary to pre-process and transform collected data in the proper format prior to feeding it directly to the data mining model. As a first step, the dataset was statistically analysed and plotted. Missing, duplicated, and null values were identified and dealt with. Features were chosen and extracted using correlation matrices. To build an efficient model, the most correlated features were retained, and others were discarded. This prediction problem can be considered a regression problem since it belongs to the supervised learning domain.

1.1 PROBLEM STATEMENT:

It is easy for any company to price their new cars based on the manufacturing and marketing cost it involves. But when it comes to a used car it is quite difficult to define a price because it involves it is influenced by various parameters like car brand, manufactured year and etc. The goal of our project is to predict the best price for a pre-owned car in the Indian market based on the previous data related to sold cars using machine learning.

1.2 PROJECT GOAL:

Cars are more than just a utility for many. We all have different tastes when it comes to owning a car or at least when thinking of owning one. Some fit in our budget and some luxury brands are heavy on our pockets. But that should not stop us from owning it, at least used ones. The goal of this project to predict the costs of used cars to enable the buyers to make informed purchase using the data collected from various sources and distributed across various locations in India.

1.3 MACHINE LEARNING:

The goal of machine learning (ML) is to help a computer learn without being explicitly instructed to do so by means of mathematical models of data. Artificial intelligence (AI) is a subset of machine learning. Data is analysed using algorithms to identify patterns, which are then used to create predictive models. Like humans, machine learning becomes more accurate with more data and experience. With machine learning, you can adapt to situations where data is constantly changing, the nature of the request or task is shifting, or coding a solution isn't feasible.

1.4 GRADIENT BOOSTING REGRESSOR:

Gradient boosting is one of the most popular machine learning algorithms for tabular datasets. It is powerful enough to find any nonlinear relationship between your model target and features and has great usability that can deal with missing values, outliers, and high cardinality categorical values on your features without any special treatment.

CHAPTER 2

2. LITERATURE SURVEY:

2.1 CAR RESALE PREDICTION SYSTEM

Author: Dhwani Nimbark, Akshat Patel, Sejal Thakkar - 2021

Used car resale market in India was marked at 24.2 billion US dollars in 2019. Due to the huge requirement of used cars and lack of experts who can determine the correct valuation, there is an utmost need of bridging this gap between sellers and buyers. This project focuses on building a system that can accurately predict a resale value of the car based on minimal features like kms driven, year of purchase etc. without manual or human interference and hence it remains unbiased.

2.2 VEHICLE RESALE PRICE PREDICTION USING MACHINE LEARNING

Author: B.Lavanya, Sk.Reshma, N.Nikitha, M.Namitha

The production of vehicles has been consistently expanding in the previous decade, with more than 70 million traveler's vehicles being delivered in the year 2016. This has brought about the trade-in vehicle market, which all alone has become a roaring industry. The new approach of online gateways has worked with the requirement for both the client and the merchant to be better educated about the patterns and examples that decide the worth of a pre-owned vehicle on the lookout. Utilizing Machine Learning Algorithms like Linear Regression, Multiple Regression. we will attempt to foster a factual model which will actually want to anticipate the cost of a pre-owned vehicle, in light of past shopper information and a given arrangement of highlights. We will likewise be contrasting the forecast precision of these models to decide the ideal one.

CHAPTER 3

3. MODULE DESCRIPTION:

3.1 COLLECT DATASET:

Machine Learning has become a tool used in almost every task that requires estimation. So we need to build a model to estimate the price of used cars. The model should take car-related parameters and output a selling price. On sprint-1 the selling price of a used car depends on certain features datasets are collected from different open sources like kaggle.com, data.gov, UCI machine learning repository, the dataset which contains a set of features through which the resale price of the car can be identified is to be collected as

- price
- vehicle Type
- year Of Registration
- gearbox
- model
- kilo meter
- month Of Registration
- fuel Type
- brand
- not Repaired Damage

ML is a data hunger technology, it depends heavily on data, without data, it is impossible. It is the most crucial aspect that makes algorithm training possible. Collects Data, Import necessary packages, Pre-process images, and passes on to Network Model and Saves Model Weights. The libraries can be imported,

[illegible]

Pre-Process The Data:

Pre-processing the dataset that includes:

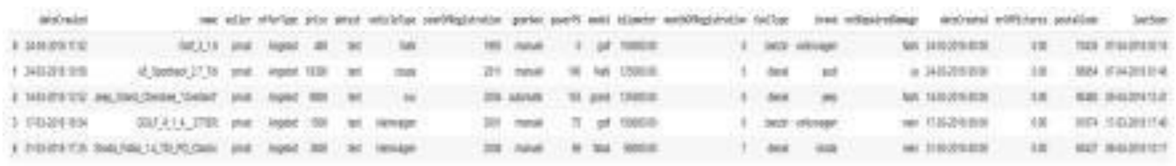
- Handling the null values.

- Handling the categorical values if any.

- Normalize the data if required.
- Identify the dependent and independent variables.

Data cleaning and wrangling methods are applied on the *used cars* data file. Before making data cleaning, some explorations and data visualizations were applied on data set. This gave some idea and guide about how to deal with missing values and extreme values. After data cleaning, data exploration was applied again in order to understand cleaned version of the data.

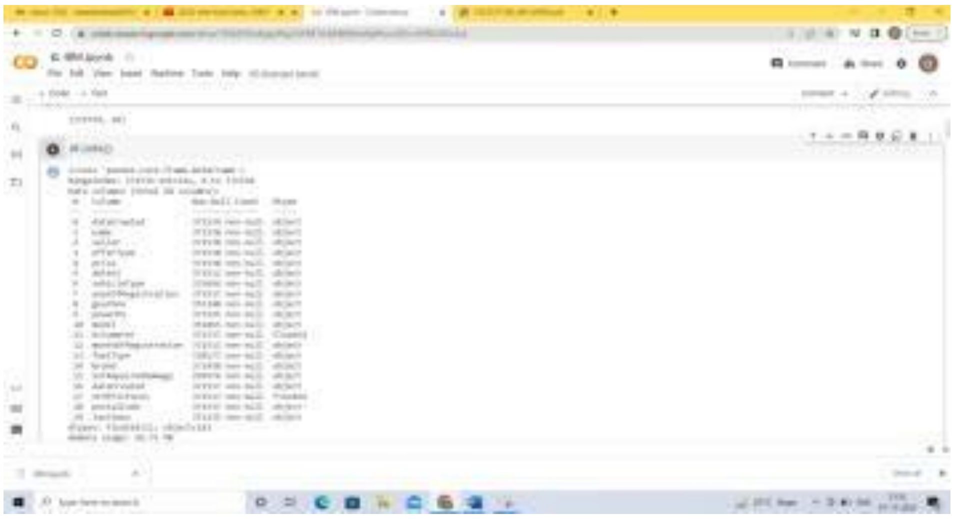
```
df = pd.read_csv("/content/drive/MyDrive/Colab
Notebooks/autos.csv") df.head()
```



	dateCrawled	name	seller	offerType	price	abtest	vehicleType	yearOfRegistration	gearbox	powerPS	model	kilometer	monthOfRegistration	fuelType	brand	notRepairedDamage	dateCreated	nrOfPictures	postalCode	lastSeen
0	24-03-2016 11:52	Golf_3_1.6	privat	Angebot	480	test	NaN	1993	manuell	0	golf	150000.0	0	benzin	volkswagen	NaN	24-03-2016 00:00	0.0	70435	07-04-2016 03:16
1	24-03-2016 10:58	A5_Sportback_2.7_Tdi	privat	Angebot	18300	test	coupe	2011	manuell	190	NaN	125000.0	5	diesel	audi	ja	24-03-2016 00:00	0.0	66954	07-04-2016 01:46
2	14-03-2016 12:52	Jeep_Grand_Cherokee_"Overland"	privat	Angebot	9800	test	suv	2004	automatik	163	grand	125000.0	8	diesel	jeep	NaN	14-03-2016 00:00	0.0	90480	05-04-2016 12:47
3	17-03-2016 16:54	GOLF_4_1_4__3TÜRER	privat	Angebot	1500	test	kleinwagen	2001	manuell	75	golf	150000.0	6	benzin	volkswagen	nein	17-03-2016 00:00	0.0	91074	17-03-2016 17:40
4	31-03-2016 17:25	Skoda_Fabia_1.4_TDI_PD_Classic	privat	Angebot	3600	test	kleinwagen	2008	manuell	69	fabia	90000.0	7	diesel	skoda	nein	31-03-2016 00:00	0.0	60437	06-04-2016 10:17

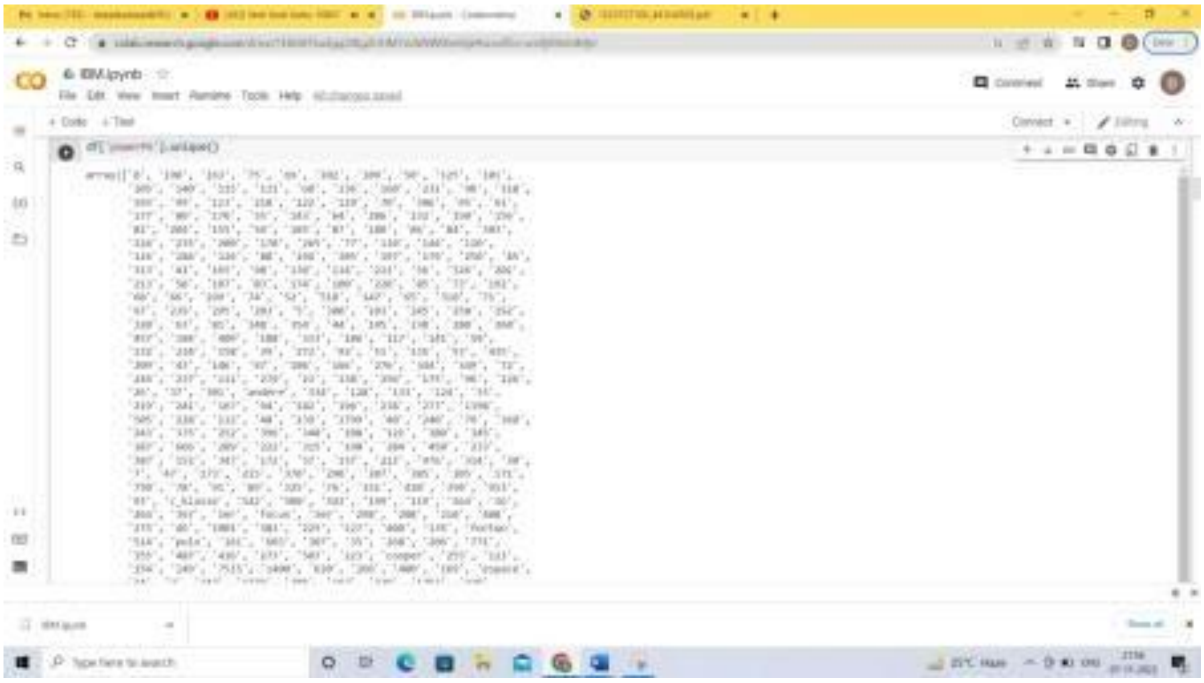
```
print(df.shape)
 (371539, 20)
```

```
df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 371539 entries, 0 to 371538
Data columns (total 20 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   dateCrawled          [illegible] non-null  object
 1   name                 [illegible] non-null  object
 2   seller               [illegible] non-null  object
 3   offerType            [illegible] non-null  object
 4   price                [illegible] non-null  object
 5   abtest               [illegible] non-null  object
 6   vehicleType          [illegible] non-null  object
 7   yearOfRegistration   [illegible] non-null  object
 8   gearbox              [illegible] non-null  object
 9   powerPS              [illegible] non-null  object
 10  model                [illegible] non-null  object
 11  kilometer            [illegible] non-null  float64
 12  monthOfRegistration  [illegible] non-null  object
 13  fuelType             [illegible] non-null  object
 14  brand                [illegible] non-null  object
 15  notRepairedDamage    [illegible] non-null  object
 16  dateCreated          [illegible] non-null  object
 17  nrOfPictures         [illegible] non-null  float64
 18  postalCode           [illegible] non-null  object
 19  lastSeen             [illegible] non-null  object
dtypes: float64(2), object(18)
memory usage: [illegible]
```

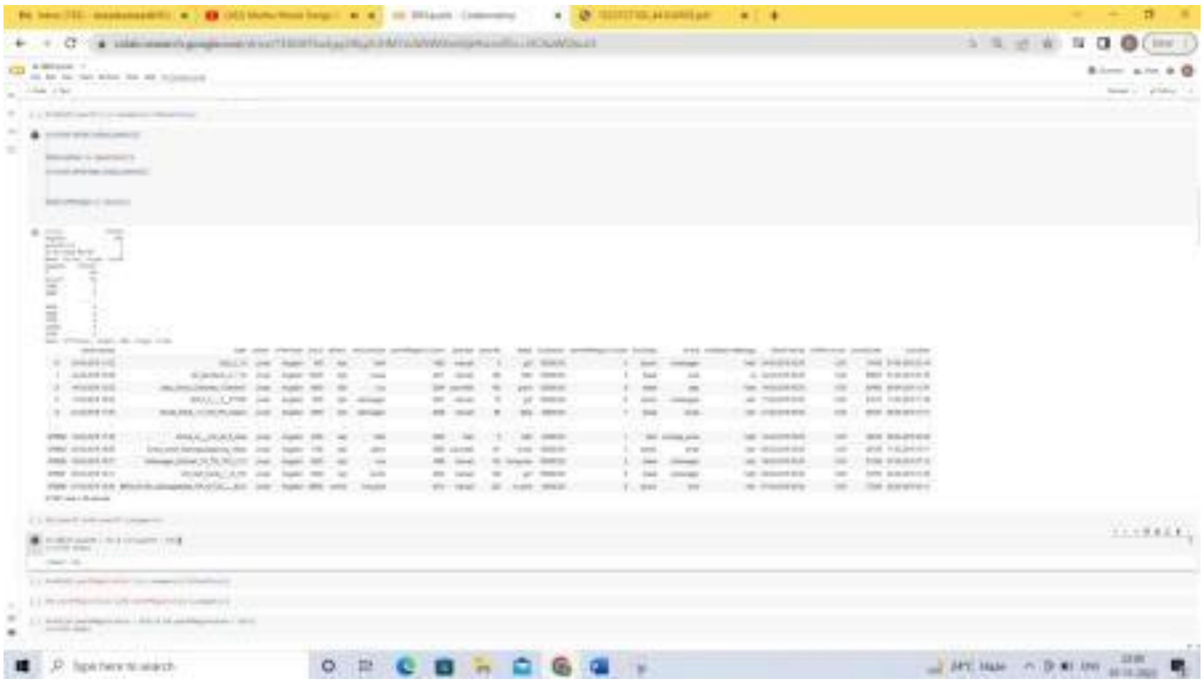
```
df['powerPS'].unique()
```



```
df['powerPS'].unique()
```

```
array(['0', '190', '163', '75', '69', '102', '109', '50', '125', '101',
[illegible]
```

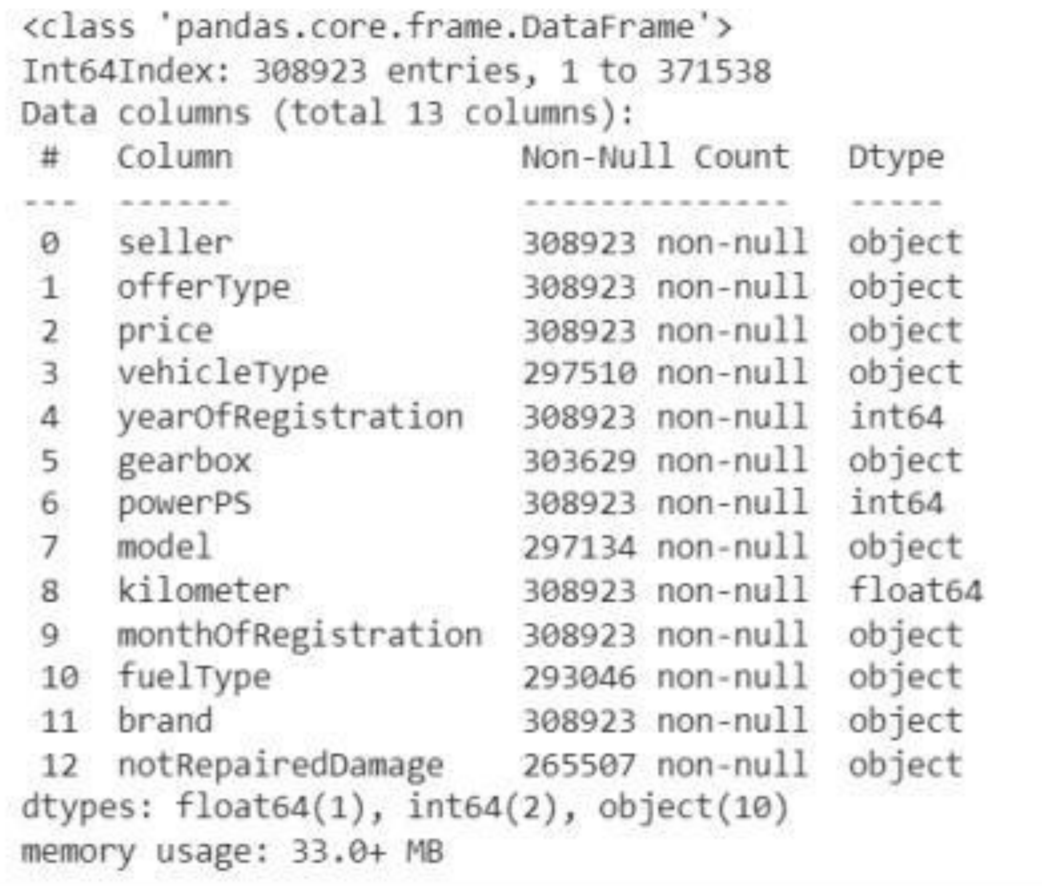
```
df=df[df['powerPS'].str.isnumeric().fillna(False)]
print(df.seller.value_counts())
df[df.seller != 'gewerblich']
print(df.offerType.value_counts())
df[df.offerType != 'Gesuch']
```



[illegible]

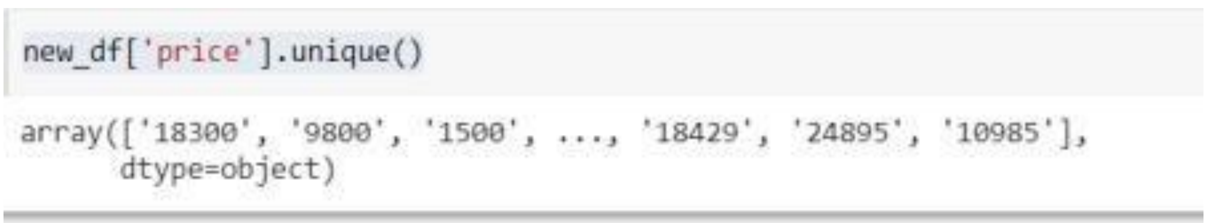
```
df['powerPS']=df['powerPS'].astype(int)
df=df[(df.powerPS > 50) & (df.powerPS < 900)]
print(df.shape)
df=df[df['yearOfRegistration'].str.isnumeric().fillna(False)]
df['yearOfRegistration']=df['yearOfRegistration'].astype(int)
df=df[(df.yearOfRegistration > 1950) & (df.yearOfRegistration <
2017)] print(df.shape)
```

```
df.drop(['name', 'abtest', 'dateCrawled', 'nrOfPictures', 'lastSeen',
' postalCode', 'dateCreated'], axis='columns', inplace=True)
df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 308923 entries, 1 to 371538
Data columns (total 13 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   seller               308923 non-null  object
 1   offerType            308923 non-null  object
 2   price                308923 non-null  object
 3   vehicleType          297510 non-null  object
 4   yearOfRegistration   308923 non-null  int64
 5   gearbox              303629 non-null  object
 6   powerPS              308923 non-null  int64
 7   model                297134 non-null  object
 8   kilometer            308923 non-null  float64
 9   monthOfRegistration  308923 non-null  object
 10  fuelType             293046 non-null  object
 11  brand                308923 non-null  object
 12  notRepairedDamage    265507 non-null  object
dtypes: float64(1), int64(2), object(10)
memory usage: 33.0+ MB
```

```
new_df=df.copy()
new_df = new_df.drop_duplicates(['price', 'vehicleType',
'yearOfRegistr ation',
 'gearbox', 'powerPS', 'model', 'kilometer', 'monthOfRegistration',
'fue lType',
 'notRepairedDamage'])
new_df.gearbox.replace(('manuell', 'automatik'), ('manual',
'automatic' ), inplace=True)
new_df.fuelType.replace(('benzin', 'andere', 'elektro'), ('petrol',
'ot hers', 'electric'), inplace=True)
new_df.notRepairedDamage.replace(('ja', 'nein'),('Yes', 'No'),
inplace= True)
    new_df.vehicleType.replace(('kleinwagen', 'cabrio', 'kombi',
  'andere'), ('small car','convertible', 'combination', 'others'),
                            inplace=True)
new_df['price'].unique()
```

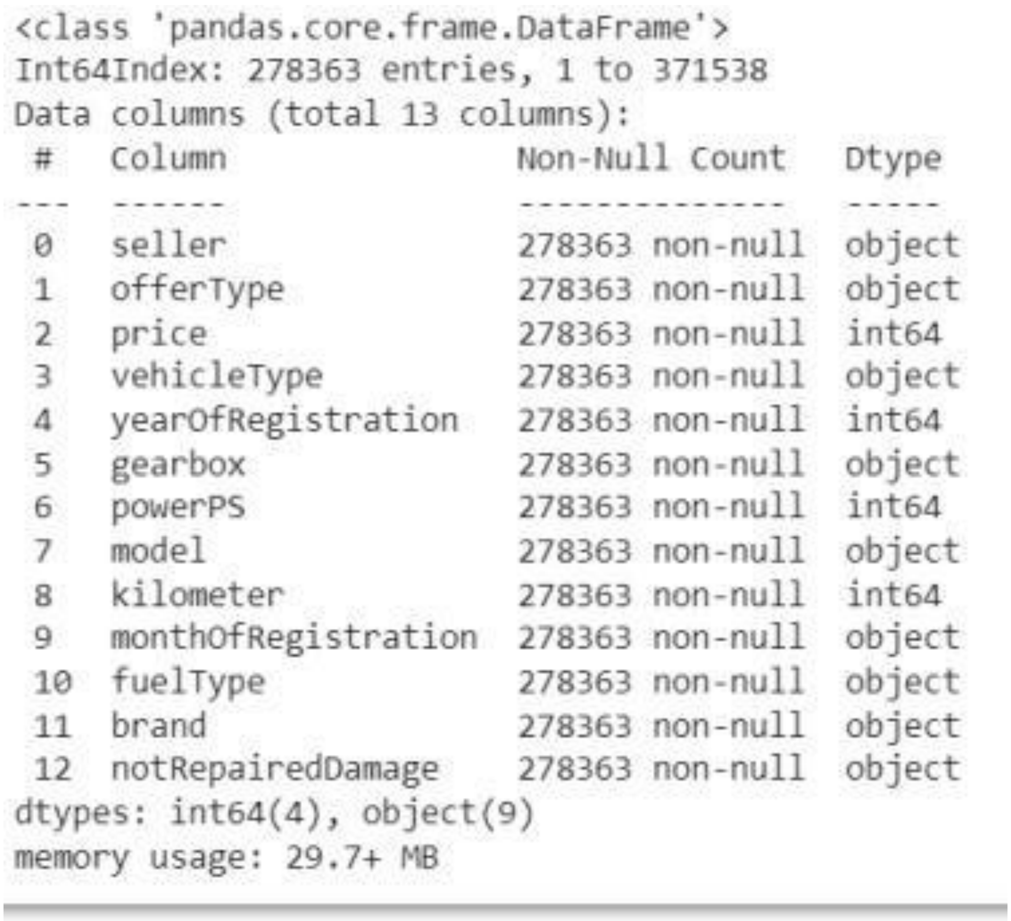


```
new_df['price'].unique()
```

```
array(['18300', '9800', '1500', ..., '18429', '24895', '10985'],
      dtype=object)
```

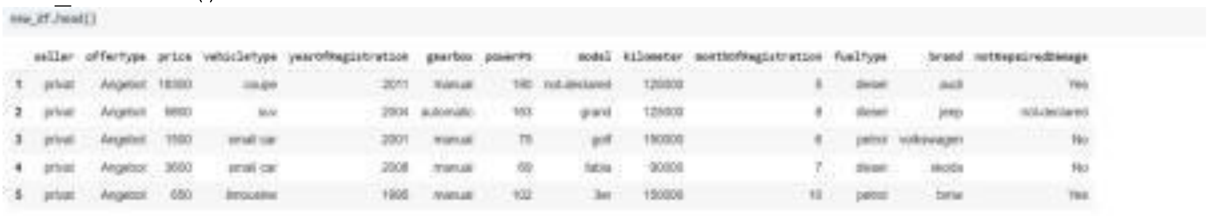
```
new_df['price']=new_df['price'].astype(int)
```

```
new_df = new_df[(new_df.price >= 100) & (new_df.price <=
150000)] new_df['fuelType'].fillna (value='not-declared',
inplace=True) new_df['gearbox'].fillna (value='not-declared',
inplace=True)

new_df['notRepairedDamage'].fillna (value='not-declared',
inplace=True)

new_df[ 'vehicleType'].fillna (value='not-declared',
inplace=True) new_df['model'].fillna (value='not-declared',
inplace=True)
new_df['kilometer']=new_df['kilometer'].astype(int)
new_df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 278363 entries, 1 to 371538
Data columns (total 13 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   seller               278363 non-null  object
 1   offerType            278363 non-null  object
 2   price                278363 non-null  int64
 3   vehicleType          278363 non-null  object
 4   yearOfRegistration   278363 non-null  int64
 5   gearbox              278363 non-null  object
 6   powerPS              278363 non-null  int64
 7   model                278363 non-null  object
 8   kilometer            278363 non-null  int64
 9   monthOfRegistration  278363 non-null  object
 10  fuelType             278363 non-null  object
 11  brand                278363 non-null  object
 12  notRepairedDamage    278363 non-null  object
dtypes: int64(4), object(9)
memory usage: 29.7+ MB
```

```
new_df.head()
```



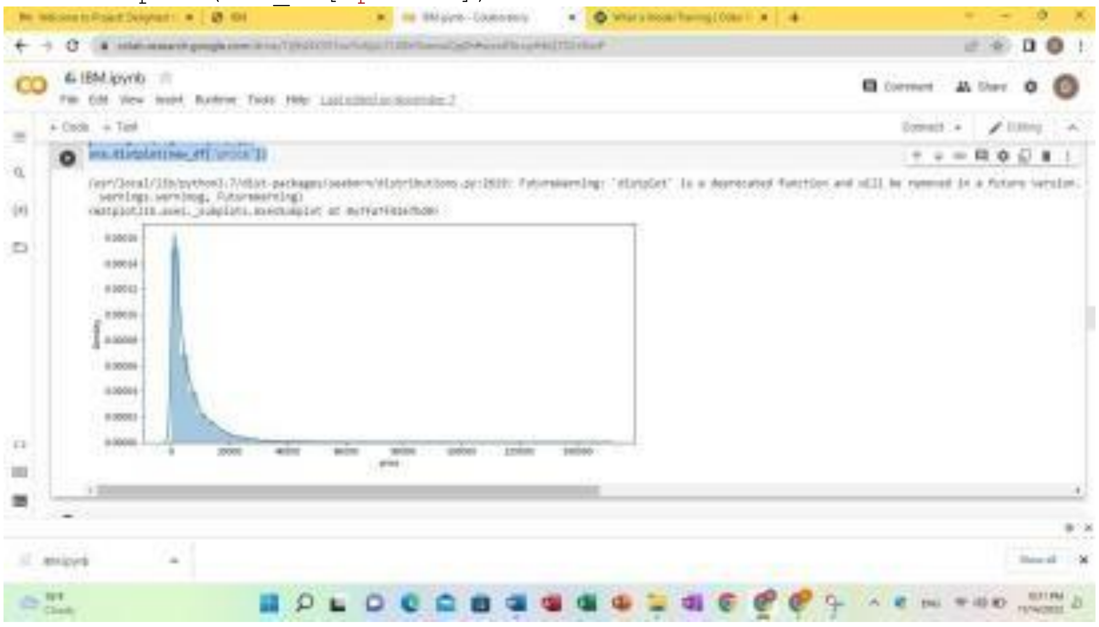
new_df.head()

	seller	offerType	price	vehicleType	yearOfRegistration	gearbox	powerPS	model	kilometer	monthOfRegistration	fuelType	brand	notRepairedDamage
1	privat	Angebot	18300	coupe	2011	manual	190	not-declared	125000	5	diesel	audi	Yes
2	privat	Angebot	9800	suv	2004	automatic	163	grand	125000	8	diesel	jeep	not-declared
3	privat	Angebot	1500	small car	2001	manual	75	golf	150000	6	petrol	volkswagen	No
4	privat	Angebot	3600	small car	2008	manual	69	fabia	90000	7	diesel	skoda	No
5	privat	Angebot	650	limousine	1995	manual	102	3er	150000	10	petrol	bmw	Yes

3.2 TRAINING AND TESTING PHASE:

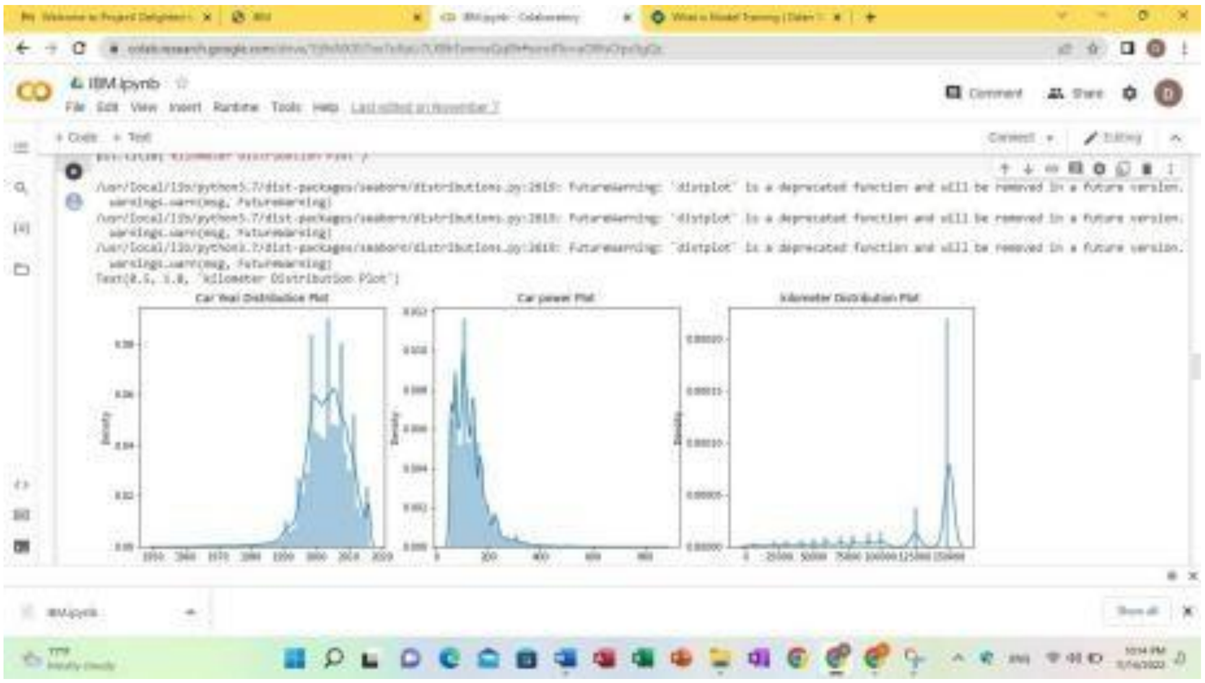
A training model is a dataset that is used to train an algorithm. It consists of the sample output data and the corresponding sets of input data that have an influence on the output. The training model is used to run the input data through the algorithm to correlate the processed output against the sample output. The result from this correlation is used to modify the model. This iterative process is called “model fitting”. The accuracy of the training dataset or the validation dataset is critical for the precision of the model. Model training is the process of feeding an algorithm with data to help identify and learn good values for all attributes involved.

```
import seaborn as sns
from matplotlib import *
import sys
from pylab import *
plt.figure(figsize=[11,5])
sns.distplot(new_df['price'])
```



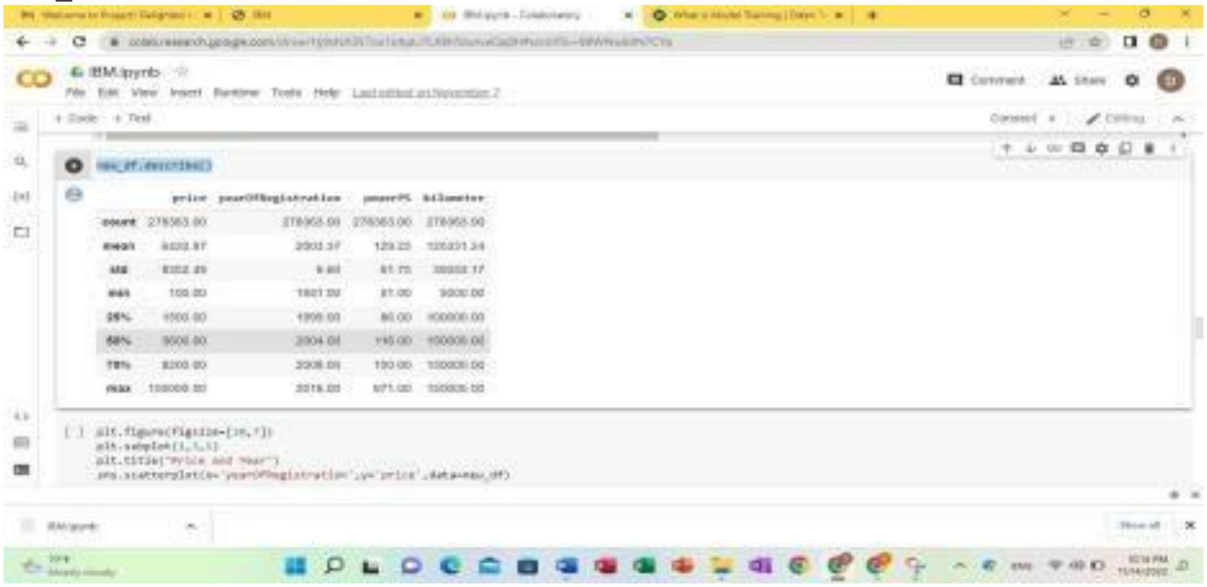
```
sns.distplot(new_df['price'])
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version.
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at [illegible]>
```

```
plt.figure(figsize=[17,5])
plt.subplot(1,3,1)
sns.distplot(new_df['yearOfRegistration'])
plt.title('Car Year Distribution Plot')

plt.subplot(1,3,2)
sns.distplot(new_df['powerPS'])
plt.title('Car power Plot')
```



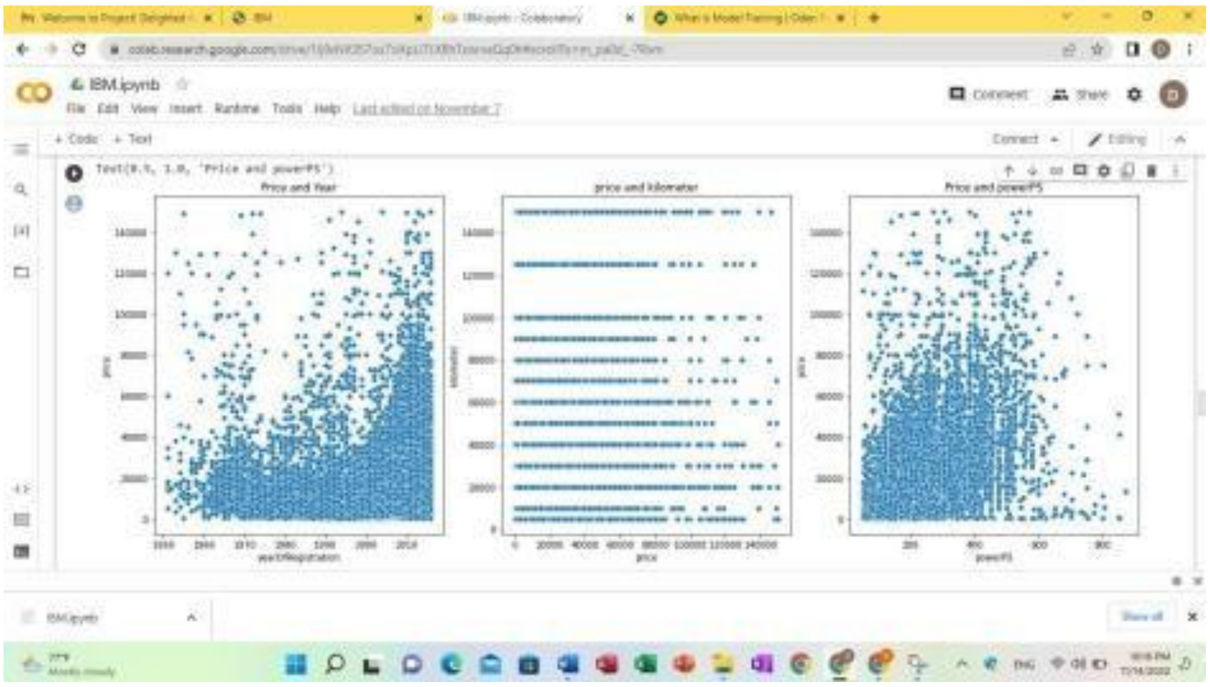
```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version.
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version.
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version.
  warnings.warn(msg, FutureWarning)
Text(0.5, 1.0, 'kilometer Distribution Plot')
```

```
new_df.describe()
```



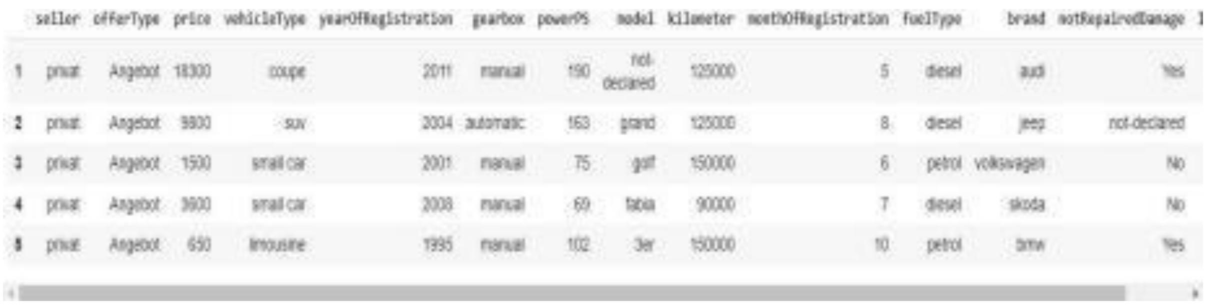
	price	yearOfRegistration	powerPS	kilometer
count	278363.00	278363.00	278363.00	278363.00
mean	6022.87	2003.37	129.23	125331.34
std	8352.25	6.60	61.75	38833.17
min	100.00	1901.00	51.00	5000.00
25%	1500.00	1999.00	80.00	100000.00
50%	3500.00	2004.00	116.00	150000.00
75%	8200.00	2008.00	150.00	150000.00
max	150000.00	2018.00	671.00	150000.00

```
plt.figure(figsize=[20,7])
plt.subplot(1,3,1)
plt.title("Price and Year")
sns.scatterplot(x='yearOfRegistration',y='price',data=new_df)

plt.subplot(1,3,2)
plt.title("price and kilometer")
sns.scatterplot(x='price',y='kilometer',data=new_df)

plt.subplot(1,3,3)
sns.scatterplot(y='price',x='powerPS',data=new_df)
plt.title("Price and powerPS")
```



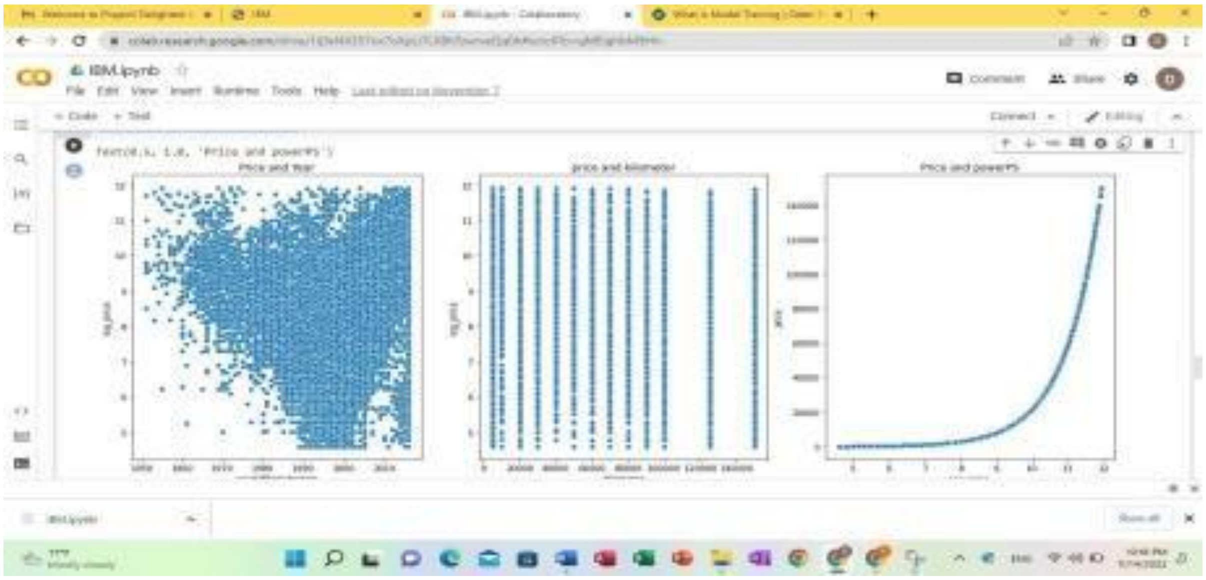
```
Text(0.5, 1.0, 'Price and powerPS')
```

```
log_price = np.log(new_df['price'])
new_df['log_price'] = log_price
new_df.head()
```



	seller	offerType	price	vehicleType	yearOfRegistration	gearbox	powerPS	model	kilometer	monthOfRegistration	fuelType	brand	notRepairedDamage
1	privat	Angebot	18300	coupe	2011	manual	190	not-declared	125000	5	diesel	audi	Yes
2	privat	Angebot	9800	suv	2004	automatic	163	grand	125000	8	diesel	jeep	not-declared
3	privat	Angebot	1500	small car	2001	manual	75	golf	150000	6	petrol	volkswagen	No
4	privat	Angebot	3600	small car	2008	manual	69	fabia	90000	7	diesel	skoda	No
5	privat	Angebot	650	limousine	1995	manual	102	3er	150000	10	petrol	bmw	Yes

```
plt.figure(figsize=[20,7])
plt.subplot(1,3,1)
plt.title("Price and Year")
sns.scatterplot(x='yearOfRegistration',y='log_price',data=new_df)

plt.subplot(1,3,2)
plt.title("price and kilometer")
sns.scatterplot(x='kilometer',y='log_price',data=new_df)

plt.subplot(1,3,3)
sns.scatterplot(y='price',x='log_price',data=new_df)
plt.title("Price and powerPS")
```

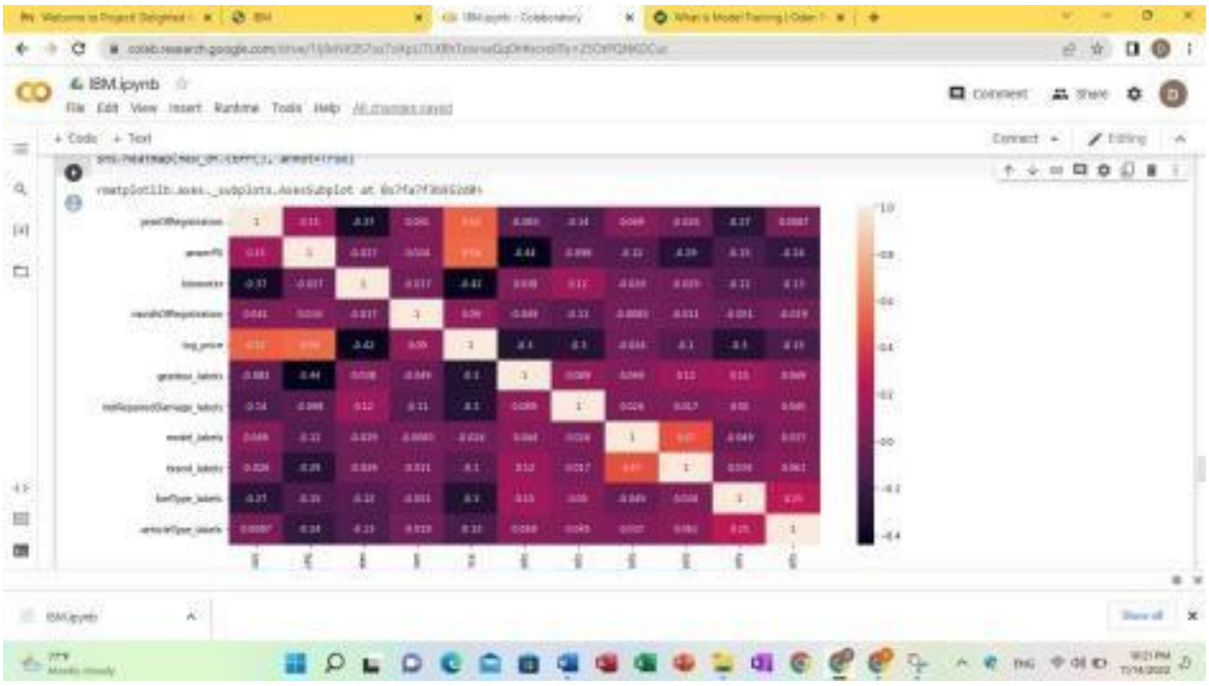


```
Text(0.5, 1.0, 'Price and powerPS')
```

```
new_df= new_df.drop(['price'],axis=1)
new_df['monthOfRegistration']=new_df['monthOfRegistration'].ast
ype(int)labels= ['gearbox', 'notRepairedDamage', 'model',
'brand', 'fuelType','vehicleType']
mapper={}
for i in labels:
  mapper[i] =LabelEncoder()
  mapper[i].fit(new_df[i])
  tr=mapper[i].transform(new_df[i])
  np.save(str('classes'+i+'.npy'), mapper[i].classes_)
  print(i, ":",mapper[i])
    new_df.loc[:, i+'_labels'] = pd.Series (tr, index=new_df.index)

labeled
=new_df[ ['log_price','yearOfRegistration','powerPS','kilom
eter','monthOfRegistration']
+ [x+"_labels" for x in labels]]
print(labeled.columns)
```

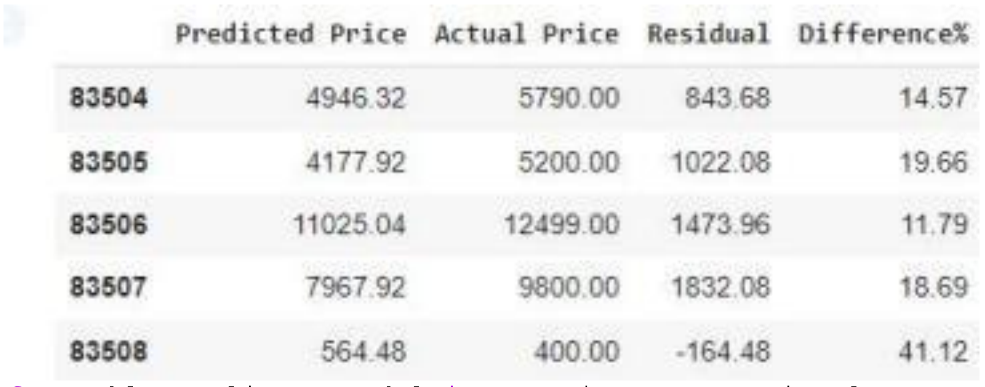
```
gearbox : LabelEncoder()
notRepairedDamage : LabelEncoder()
model : LabelEncoder()
brand : LabelEncoder()
fuelType : LabelEncoder()
vehicleType : LabelEncoder()
Index(['log_price', 'yearOfRegistration', 'powerPS', 'kilometer',
       'monthOfRegistration', 'gearbox_labels', 'notRepairedDamage_labels',
       'model_labels', 'brand_labels', 'fuelType_labels',
       'vehicleType_labels'],
      dtype='object')
```

```
plt.figure(figsize=[15,7])
sns.heatmap(new_df.corr(), annot=True)
```



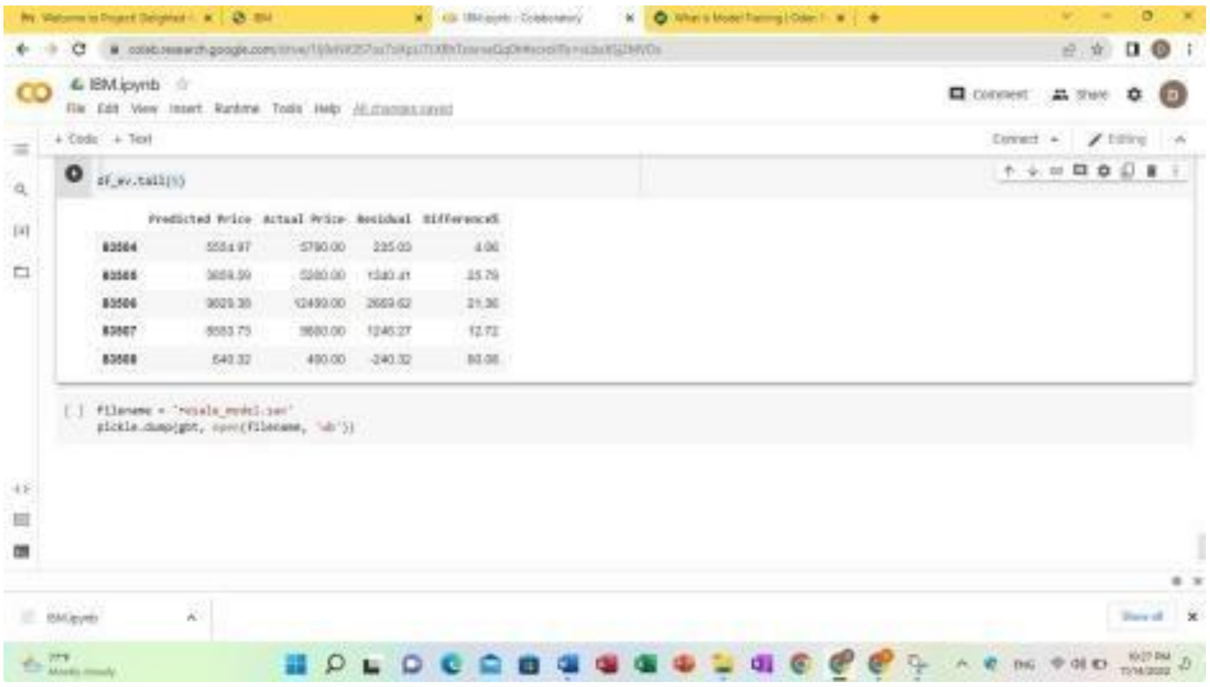
```
sns.heatmap(num_df.corr(), annot=True)
<matplotlib.axes._subplots.AxesSubplot at 0x7fa7f[illegible]>
```

```
Y =labeled.iloc[:,0].values
X = labeled.iloc[:,1:].values
Y = Y.reshape(-1,1)
from sklearn.model_selection import
train_test_split,cross_val_scoreX_train, X_test, Y_train,
Y_test = train_test_split(X,Y,test_size=0.3,random_state=3)

from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import r2_score
regressor= RandomForestRegressor (n_estimators=1000, max_depth=10,
random_state=34)

regressor.fit(X_train, np.ravel (Y_train, order='C'))
y_pred=regressor.predict(X_test)
print(r2_score (Y_test,y_pred))
y_pred=regressor.predict(X_test)
print(r2_score (Y_test,y_pred))
df_ev = pd.DataFrame(np.exp(y_pred), columns=['Predicted Price'])

# We can also include the Actual price column in that data frame
(sowecan manually compare them)
#Y_test=Y_test.reset_index(drop=True)
df_ev['Actual Price'] = np.exp(Y_test)

# we can calculate the difference between the targets and the
predictions
df_ev['Residual'] = df_ev['Actual Price'] - df_ev['Predicted
Price']df_ev['Difference%'] =
np.absolute(df_ev['Residual']/df_ev['Actual Price']*100)

pd.set_option('display.float_format', lambda x: '%.2f' % x)
df_ev.sort_values(by=['Difference%'])
df_ev.tail(5)
```



	Predicted Price	Actual Price	Residual	Difference%
83504	4946.32	5790.00	843.68	14.57
83505	4177.92	5200.00	1022.08	19.66
83506	11025.04	12499.00	1473.96	11.79
83507	7967.92	9800.00	1832.08	18.69
83508	564.48	400.00	-164.48	41.12

```
from sklearn.linear_model import LinearRegression lr =
LinearRegression()
lr.fit(X_train,Y_train)
y_pred_lr = lr.predict(X_test)
r_squared = r2_score(Y_test,y_pred_lr)
print("R_squared :",r_squared)

from sklearn.ensemble import GradientBoostingRegressor gbt
= GradientBoostingRegressor()
gbt.fit(X_train,Y_train)
y_pred_gbt = gbt.predict(X_test)
r_squared = r2_score(Y_test,y_pred_gbt)
print("R_squared :",r_squared)

df_ev = pd.DataFrame(np.exp(y_pred_gbt), columns=['Predicted
Price'])df_ev['Actual Price'] = np.exp(Y_test)
df_ev['Residual'] = df_ev['Actual Price'] - df_ev['Predicted
Price']df_ev['Difference%'] =
np.absolute(df_ev['Residual']/df_ev['Actual Price']*100)
pd.set_option('display.float_format', lambda x: '%.2f' % x)
df_ev.sort_values(by=['Difference%'])

df_ev.tail(5)
```



```
df_ev.tail(5)
```

	Predicted Price	Actual Price	Residual	Difference%
83504	5554.97	5790.00	235.03	4.06
83505	3859.59	5200.00	1340.41	25.78
83506	9829.38	12499.00	2669.62	21.36
83507	8553.73	9800.00	1246.27	12.72
83508	640.32	400.00	-240.32	60.08

```
filename = 'resale_model.sav'
pickle.dump(gbt, open(filename, 'wb'))
```

```
filename = 'resale_model.sav'
pickle.dump(gbt, open(filename, 'wb'))
```

CHAPTER 4

4. SYSTEM SPECIFICATION

4.1 HARDWARE SPECIFICATION

- Processors: Intel® Core™ i5 processor 4300M at 2.60 GHz or 2.59 GHz (1 socket, 2cores, 2 threads per core), 8 GB of RAM
- Disk space: 320 GB
- Operating systems: Windows® 10, macOS*, and Linux*

4.2 SOFTWARE SPECIFICATION

- Python 3.7.4(64-bit) or (32-bit)
- HTML, CSS, javascript
- Flask 1.1.1
- Jupyter Notebook
- Windows 10 64 –bit

4.3 SOFTWARE DESCRIPTION:

FLASK:

Flask is an open source web framework which offers us with the tools, library resources needed to create a web application. Flask is a microweb framework written in Python. It is classified as a microframework because it does not require particular tools or libraries. It has no database abstraction layer, form validation, or any other components where pre-existing third-party libraries provide common functions. However, Flask supports extensions that can add application features as if they were implemented in Flask itself. Extensions exist for object relational mappers, form validation, upload handling, various open authentication technologies and several common framework related tools.

PANDAS:

Data analysis and related manipulation of tabular data in Data frames are the major uses of Pandas. Data can be imported into Pandas from a variety of filetypes, including Microsoft Excel, JSON, Parquet, SQL database tables, and comma-separated values. Data wrangling, data cleaning, and other operations like merging, restructuring, and choosing are all possible with Pandas. Many of the R programming language's established functionality for working with data frames were brought into Python with the introduction of pandas. The NumPy library, which is focused on effectively working with arrays rather than the characteristics of working with Data frames, is the foundation upon which the Panda library is constructed.

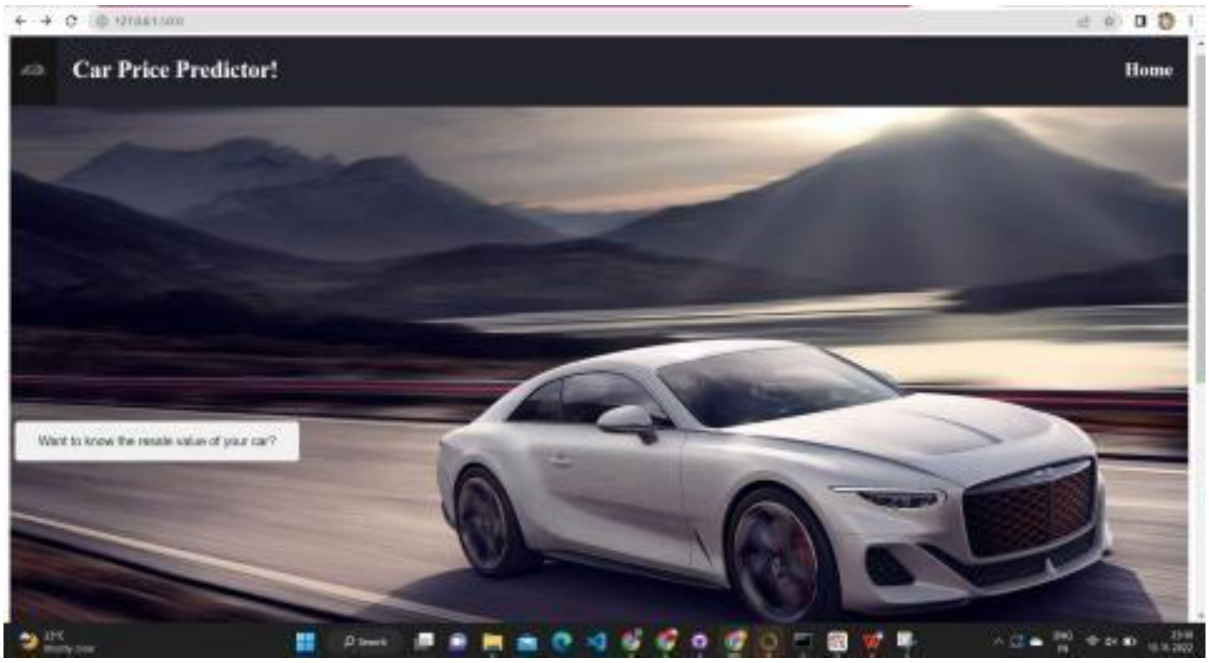
NumPy:

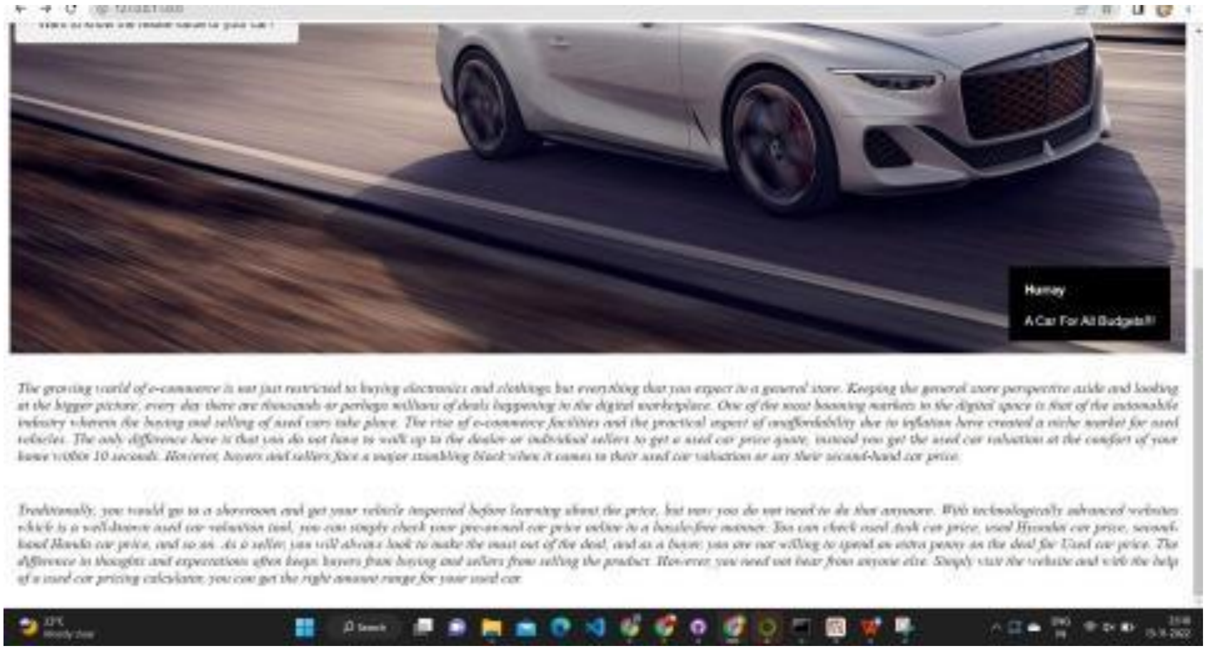
A collection of the multidimensional matrix that facilitates complex mathematical operations. NumPy can be used to execute operations on arrays that are related to mathematics, such as algebraic, statistical, and trigonometric patterns. The image is transformed into a matrix. The Convolutional Neural Network is utilized to understand and analyse the image in its matrix form. The image's annotations then adopted a NumPy array style. Finally, the dataset contains the precise labels for each image. On this, SciPy was also developed. It provides more noteworthy execution that utilizes NumPy arrays and is required for various logical and engineering tasks.

CHAPTER 5

5. OUTPUT:

Home page

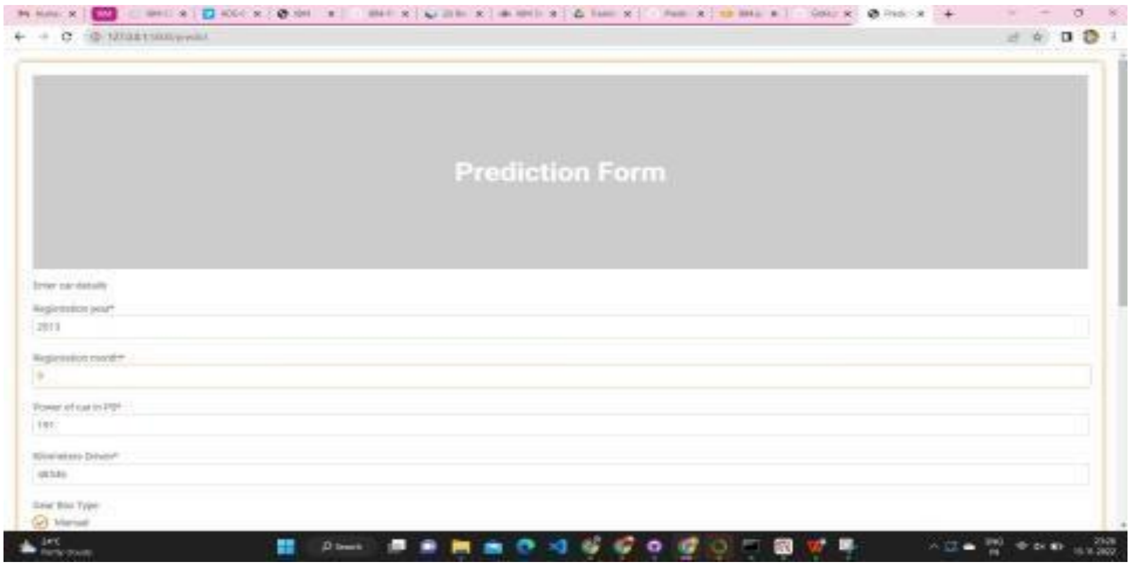




The growing world of e-commerce is not just restricted to buying electronics and clothings but everything that you expect in a general store. Keeping the general store perspective aside and looking at the bigger picture, every day there are thousands or perhaps millions of deals happening in the digital marketplace. One of the most booming markets in the digital space is that of the automobile industry wherein the buying and selling of used cars take place. The rise of e-commerce facilities and the practical aspect of unaffordability due to inflation have created a niche market for used vehicles. The only difference here is that you do not have to walk up to the dealer or individual sellers to get a used car price quote, instead you get the used car valuation at the comfort of your home within 10 seconds. However, buyers and sellers face a major stumbling block when it comes to their used car valuation or say their second-hand car price.

Traditionally, you would go to a showroom and get your vehicle inspected before learning about the price, but now you do not need to do that anymore. With technologically advanced websites which is a well-known used car valuation tool, you can simply check your pre-owned car price online in a hassle-free manner. You can check used Audi car price, used Hyundai car price, second-hand Honda car price, and so on. As a seller, you will always look to make the most out of the deal, and as a buyer, you are not willing to spend an extra penny on the deal for Used car price. The difference in thoughts and expectations often keeps buyers from buying and sellers from selling the product. However, you need not hear from anyone else. Simply visit the website and with the help of a used car pricing calculator, you can get the right amount range for your used car.

Prediction form page:



Prediction Form

Enter car details

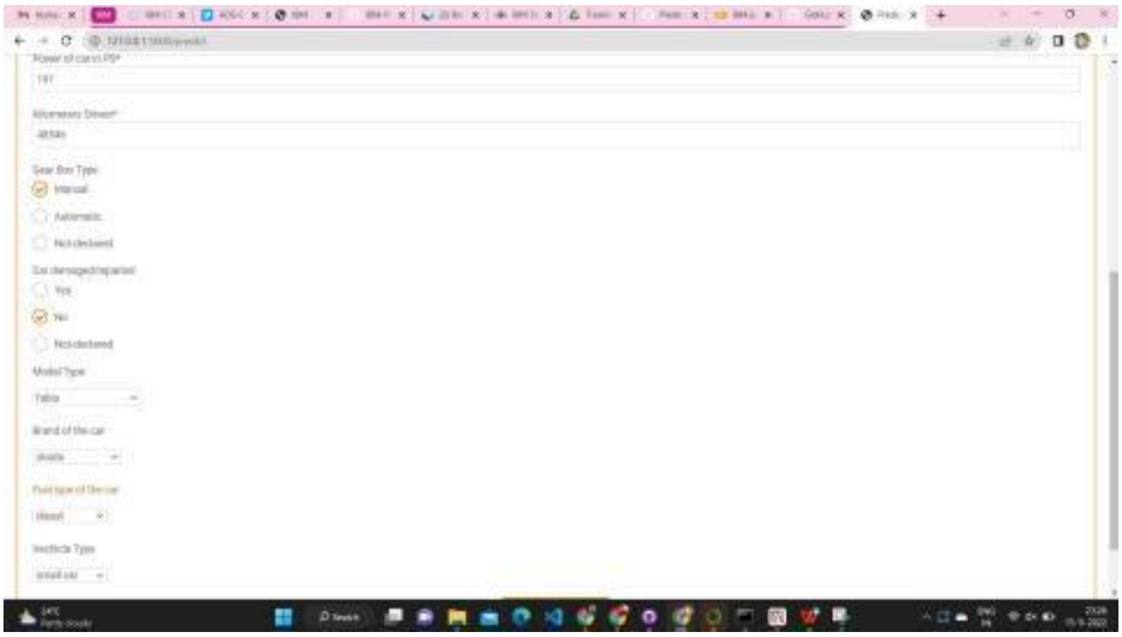
Registration year*
2013

Registration month*
9

Power of car in PS*
191

Kilometers Driven*
48546

Gear Box Type
[✓ Manual]



Power of car in PS*
191

Kilometers Driven*
48546

Gear Box Type
[✓ Manual]
Automatic
Not declared

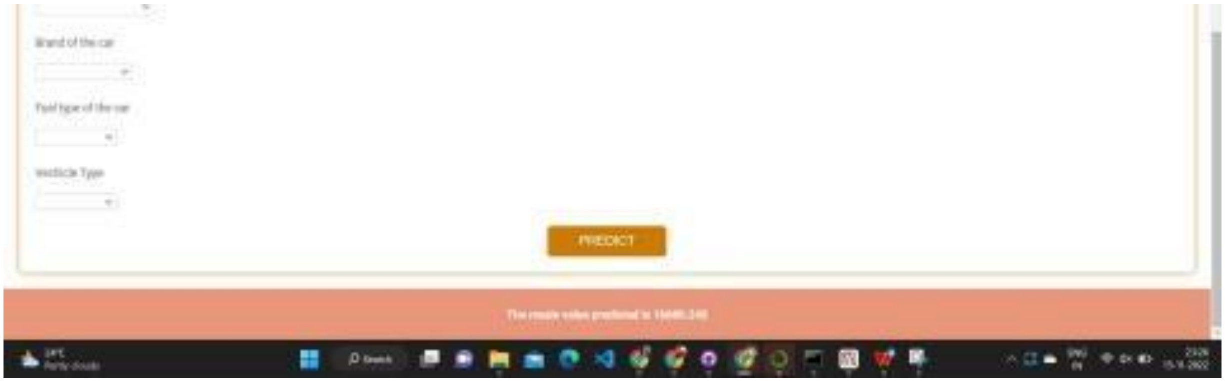
Car damaged/repaired
Yes
[✓ No]
Not declared

Model Type
fabia

Brand of the car
skoda

Fuel type of the car
diesel

Vehicle Type
small car



Brand of the car

Fuel type of the car

Vehicle Type

PREDICT

The resale value predicted is [illegible]

CHAPTER 6

6. CONCLUSION:

Determining whether the listed price of a used car is a challenging task, due to the many factors that drive a used vehicle's price on the market. The focus of this project is developing machine learning models that can accurately predict the price of a used car based on its features, in order to make informed purchases. By performing ML models, we aim to get a better result or less error with max accuracy to predict the value of the used car. Initially, data cleaning is performed to remove the null values and outliers from the dataset then ML models are implemented to predict the price of cars. Next, with the help of data visualization features were explored deeply. The relation between the features is examined. From the report, it can be said that gradient regression regressor is the best model for the prediction for used car prices.