

Team No : PNT2022TMID16853

1. INTRODUCTION

1.1. Project Overview :

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. We implement and evaluate various learning methods on a dataset consisting of the sale prices of different makes and models . We will compare the performance of various machine learning algorithms like Linear Regression, Ridge Regression, Lasso Regression, Elastic Net, Decision Tree Regression and choose the best out of it. Depending on various parameters we will determine the price of the car. Regression Algorithms are used because they provide us with continuous value as an output and not a categorized 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.

1.2. Purpose :

With difficult economic conditions, it is likely that sales of second-hand imported (reconditioned) cars and used cars will increase. In many developed countries, it is common to lease a car rather than buying it outright. After the lease period is over, the buyer has the possibility to buy the car at its residual value, i.e. its expected resale value. Thus, it is of

commercial interest to sellers/financiers to be able to predict the salvage value (residual value) of cars with accuracy.

In order to predict the resale value of the car, we proposed an intelligent, flexible, and effective system that is based on using regression algorithms. Considering the main factors which would affect the resale value of a vehicle a regression model is to be built that would give the nearest resale value of the vehicle. We will be using various regression algorithms and algorithm with the best accuracy will be taken as a solution, then it will be integrated to the web-based application where the user is notified with the status of his product.

2. LITERATURE SURVEY

2.1. Existing Problem:

In existing problem, the solution is not good to predict the car prize. To predict the used car value , we need to concentrate in more accuracy by using algorithms to give accuracy. In this solution does not predict correct value of the used car.

2.2. References:

[1] Sameerchand Pudaruth, "Predicting the Price of Used Cars using Machine Learning Techniques";(IJICT 2014)

[2] Enis gegic, Becir Isakovic, Dino Keco, Zerina Masetic, Jasmin Kevric, "Car Price Prediction Using Machine Learning"; (TEM Journal 2019)

[3] Ning sun, Hongxi Bai, Yuxia Geng, Huizhu Shi, "Price Evaluation Model In Second Hand Car System Based On BP Neural Network Theory"; (Hohai University Changzhou, China)

[4] Nitis Monburinon, Prajak Chertchom, Thongchai Kaewkiriya, Suwat Rungpheung, Sabir Buya, Pitchayakit Boonpou, "Prediction of Prices for Used Car by using Regression Models" (ICBIR 2018) [5] Doan Van Thai, Luong Ngoc Son, Pham Vu Tien, Nguyen Nhat Anh, Nguyen Thi Ngoc Anh, "Prediction car prices using qualify qualitative data and knowledge-based system" (Hanoi National University).

2.3. Problem Statement:

The main aim of this project is to predict the price of used cars using the various Machine Learning (ML) models. This can enable the customers to make decisions based on different inputs or factors namely

- Brand or Type of the car one prefers like Ford, Hyundai
- Model of the car namely Ford Figo, Hyundai Creta
- Location like Delhi, Chennai, Mumbai
- Year of manufacturing like 2020, 2021
- Type of fuel namely Petrol, Diesel
- Price range or Budget
- Type of transmission which the customer prefers like Automatic or Manual

- Mileage

to name a few characteristic features required by the customer. The project Car Price Prediction deals with providing the solution to these problems. Through this project, we will get to know which of the factors are significant and tell us how they affect the car's worth in the market

3.Ideation and Proposed Solution

3.1. Empathy Map Canvas:



3.2. Ideation And Brainstorming:

The image displays a digital workspace for brainstorming and idea prioritization, organized into seven main panels. The first panel on the left is titled "Brainstorm & idea prioritization" and includes a list of ideas. The second panel shows a flowchart with a central node and four sub-nodes. The third panel displays a grid of sticky notes, each containing a number and a brief description. The fourth panel shows a grid of sticky notes, each containing a number and a brief description. The fifth panel shows a grid of sticky notes, each containing a number and a brief description. The sixth panel shows a grid of sticky notes, each containing a number and a brief description. The seventh panel on the right shows a grid of sticky notes, each containing a number and a brief description. The bottom of the workspace features a series of icons representing different stages or types of ideas.

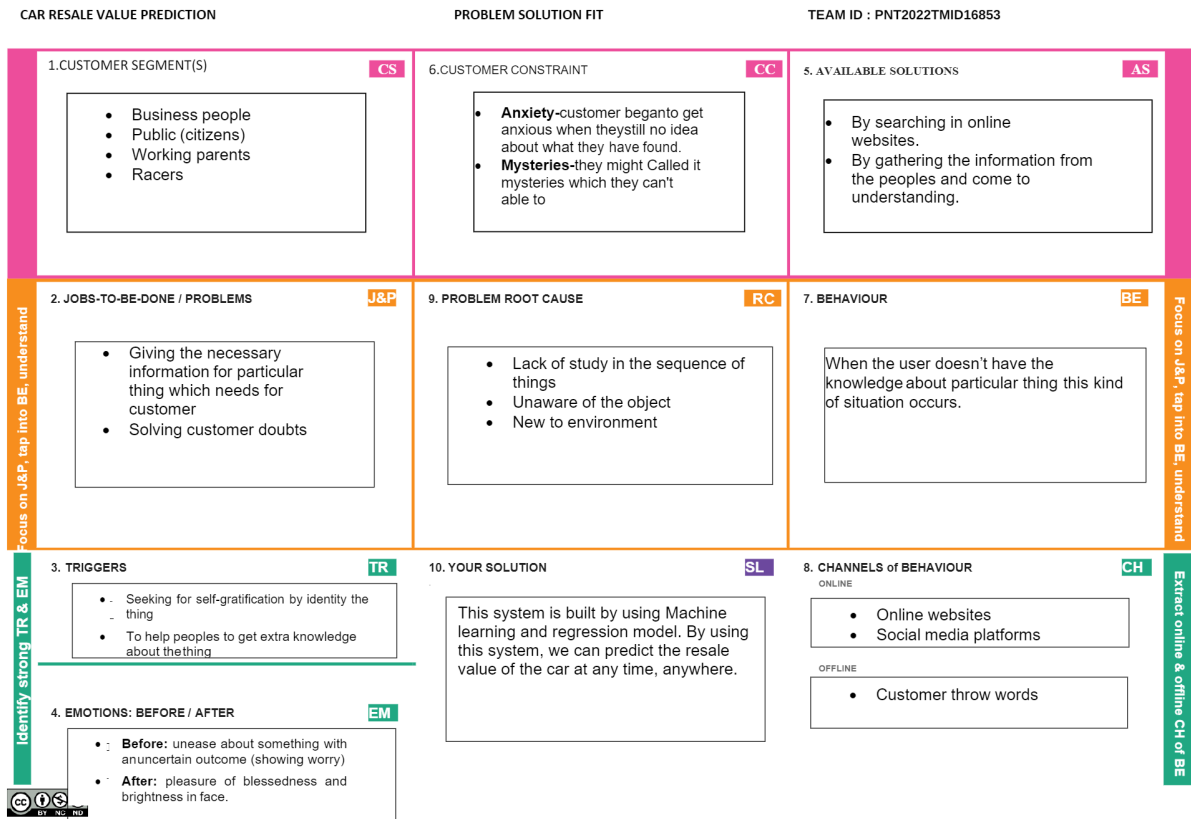
3.3. Proposed Solution:

Proposed Solution Template:

Project team shall fill the following information in proposed solution template.

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	With Difficult economic conditions, it is likely that sales of second-hand imported cars and used cars will increase in many developed countries, it is common to lease a car rather than buying it outright. After the lease a period is over, the buyer has the possibility to buy the car at its residual value, i.e. its expected resale value. Thus, it is of commercial interest to sellers/financers to be able to predict the salvage value of cars with accuracy.
2.	Idea / Solution description	In order to predict the resale value of the car, we proposed an intelligent, flexible, and effective system that is based on using regression algorithms. Considering the main factors which would affect the resale of a vehicle a regression model is to be built that would give the nearest resale value of the vehicle. We will be using various regression algorithms and algorithm with best accuracy will be taken as a solution, then it will be integrated to the web-based application where the user is notified with the status of his product.
3.	Novelty / Uniqueness	<ul style="list-style-type: none">• A loss function to be optimized• A weak learner to make predictions• An additive model to add weak learners to make the loss functions.• Easy to predict by using regression model.
4.	Social Impact / Customer Satisfaction	To be able to predict resale cars market value can help both layers and sellers. Used car sellers: They are one of the biggest target groups that can be interested in results of this study. If used sellers better understand what makes a car desirable, what the important features are for a used car, then they may consider this knowledge and offer a better service.

3.4. Problem Solution Fit:



4. Requirements Analysis:

4.1. Functional Requirements:

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Website
FR-2	User Confirmation	Confirmation via website
FR-3	Car Registration	Registering the car details
FR-4	Value Prediction	Predicting the car resale value

4.2. Non Functional Requirements:

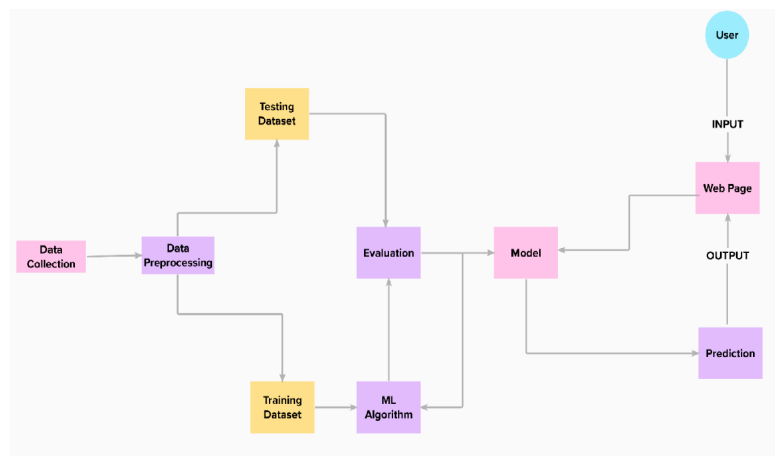
Non-functional Requirements:

Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	Usability	Predicting the resale value
NFR-2	Security	Providing security to the website
NFR-3	Reliability	Providing high reliability by predicting values for different types of cars
NFR-4	Performance	Providing high performance by using some machine learning techniques
NFR-5	Availability	It is used for all types of cars
NFR-6	Scalability	Predicting values for different types of cars

5. Project Design:

5.1. Data Flow Diagram:



5.2. Solution and Technical Architecture:

Technical Architecture:

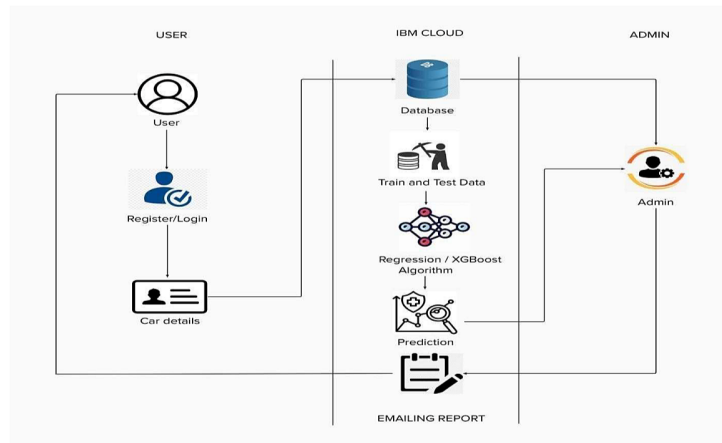


Table-1 : Components & Technologies:

S.No	Component	Description	Technology
1.	User Interface	The user interacts with application using Web UI.	HTML, CSS, JavaScript , ReactJS etc.
2.	Database	The dataset containing car details is used for training the model to predict the rate.	Python libraries like NumPy, Pandas etc.
3.	Cloud Database	The dataset is stored in the IBM cloud	IBM Cloud
4.	Machine Learning algorithms	The machine learning algorithms are used to predict the used cars rate.	XGBoost or Regression algorithm
5.	Chart	The user will receive the prediction chart	SMTP

Table-2: Application Characteristics:

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	Open-source frameworks used	Python Flask, Python, IBM Cloud
2.	Security Implementations	Authentication process implementation	Encryptions.
3.	Scalable Architecture	Scalability of architecture consists of 3 tiers	Web server-HTML, CSS, Java script Application server-Python Flask Database server-IBM Cloud
4.	Availability	The user can access through cloud	IBM Cloud hosting
5.	Performance	Multiple users can access the web application	IBM Load Balance

5.3. User Stories:

User Stories

Use the below template to list all the user stories for the product.

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Mobile user)	Data Entry	USN-1	As a user, I can enter the car details in the application.	I can enter the car details	Medium	Sprint-1
Customer (Mobile user)	Obtain output	USN-2	As a user, I will receive car resale value in the application.	I can receive my car resale value	High	Sprint-1
Customer (Mobile user)	Data Entry	USN-1	As a user, I can enter the car details in the application.	I can enter the car details	Medium	Sprint-1
Customer (Mobile user)	Obtain output	USN-2	As a user, I will receive car resale value in the application.	I can receive my car resale value	High	Sprint-1

6. Project planning and scheduling:

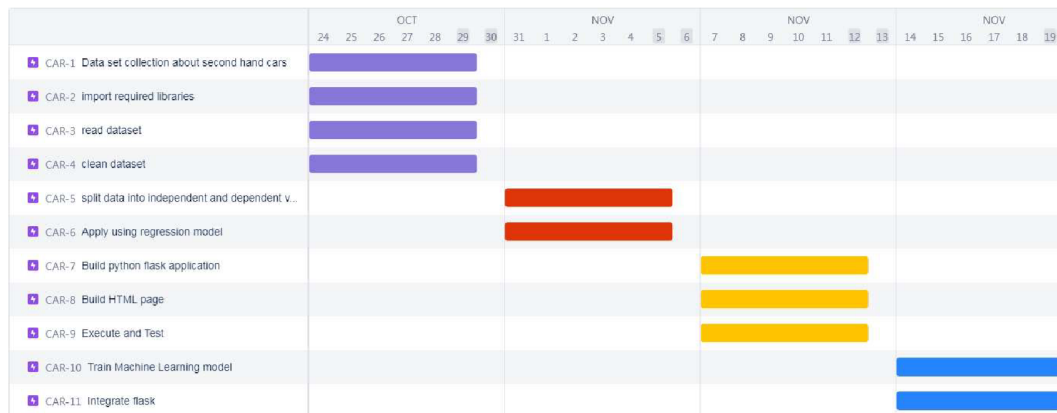
6.1. Sprint Planning and estimation:

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Pre-process data	USN-1	Collect Dataset	1	Low	Ishwarya S N
Sprint-1		USN-2	Import required libraries	1	Low	Deepthi Sharon P
Sprint-1		USN-3	Read and clean data sets	2	Low	Hilkia Lourdes G
Sprint-2	Model building	USN-1	Split data into independent and dependent variables	3	Medium	Jaya Gowry M
Sprint-2		USN-2	Apply using regression model	3	Medium	Ishwarya S N, Deepthi Sharon
Sprint-3	Application building	USN-1	Build python flask application and HTML page	5	High	Jaya Gowry M, Hilkia Lourdes G
Sprint-3		USN-2	Execute and test	5	High	Ishwarya S N, Hilkia Lourdes G
Sprint-4	Training the model	USN-1	Train machine learning model	5	High	Jaya Gowry M, Deepthi Sharon P
Sprint-4		USN-2	Integrate flask	5	High	Jaya Gowry M

6.2.Sprint Delivery Schedule:

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

Burndown Chart:



7. Coding and Solutioning:

CSS CODE for predict

```
.header{
  min-height: 100vh;
  width: 100%;
  background-image: linear-
gradient(rgba(25,30,30,0.7),rgba(25,30,30,0.7)),url(../Images/car6.png);
  background-position: center;
  background-size: cover;
  position: relative;
}
```

```
.text-box{
  text-align: center;
  position: relative;
  color: #FFE4C4;
```

```

    top:50%;
}
.text-box h1{
    margin-top: 50px;
    font-size: 55px;
}

.text-box p{
    margin: 10px 0 40px;
    font-size: 15px;
}

body{
    margin: 0;
}

nav{
    display:flex;
    padding: 2% 6%;
    justify-content: space-between;
    align-items: center;
}

```

CSS code for style

```

*{
    margin: 0;
    padding: 0;
}

.header{
    min-height: 100vh;
    width: 100%;
    background-image: linear-

```

```

gradient(rgba(25,30,30,0.7),rgba(25,30,30,0.7)),url(../Images/car1.png);
background-position: center;
background-size: cover;
position: relative;
}
nav{
display: flex;
padding: 2% 6%;
justify-content: space-between;
align-items: center;
}
.nav-links{
flex: 1;
text-align: right;
}
.nav-links ul li{
list-style: none;
display: inline-block;
padding: 8px 12px;
position: relative;
}
.nav-links ul li a{
color: white;
text-decoration: none;
font-size: 13px;
}
.text-box{
text-align: center;
position: relative;
color: #FFE4C4;
top: 50%;
}

```

```
.text-box h1{
  margin-top: 50px;
  font-size: 55px;
}
.text-box p{
  margin: 10px 0 40px;
  font-size: 15px;
}
.visit-btn{
  display: inline;
  border: 3px solid #fff;
  padding: 10px 14px;
  font-size: 15px;
  background: transparent;
  color: white;
  text-decoration: none;
}
```

CSS code for value

```
.header{
  width: 100%;
  text-align: center;
  //padding-top: 20px;
  font-size: 20px;
  font-family: "Lucida Console";
  background-color: #43FFB6;
  border: 0%;
  top: 0px;
  bottom: 0px;
  right: 0px;
  left: 0px;
  overflow-y: auto;
}
```

```

body{
    margin: 0;
}
.form{
background-image: linear-
gradient(rgba(25,30,30,0.7),rgba(25,30,30,0.7)),url(../Images/car4.jpg);
background-position: center;
background-size: cover;
position: relative;
}
.form{
text-align: center;
padding:20px;
text-top:10px;
display: flex;
flex-direction: column;
align-items: center;
}
.form{
font-size:22px;
}
textarea {
width: 100%;
height: 150px;
padding: 12px 20px;
box-sizing: border-box;
border: 2px solid #ccc;
border-radius: 4px;
background-color: #f8f8f8;
resize: none;
}

```

```
input[type=text] {  
  transition: width 0.4s ease-in-out;  
}
```

```
input[type=text] {  
  width: 70%;  
  height: 10%;  
  padding: 10px 10px;  
  margin: 5px 0;  
}  
#model{  
  width: 70%;  
}  
#brand{  
width:70%;  
}  
#vehicle{  
width:70%;  
}  
*{  
color:black;  
}
```

```
#button{  
  padding: 10px 10px;  
  margin: 0;  
  
  text-align:center;  
  width:100px;  
}
```

Build an Html Page
car.html


```

<!DOCTYPE html>
<html lang="en" dir="ltr">
  <head>
    <meta charset="utf-8">
    <title>Car resale value </title>
    <link rel="stylesheet" href="../static/css/style.css">
    <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-
awesome/4.7.0/css/font-awesome.min.css">
  </head>
  <body>
    <section class="header">
      <nav>
        <a href="/"></a>

      </nav>
      <div class="text-box">
        <h1>Car resale value Predictor</h1>
        <p>Best system to predict the amount of resale value based on the
parameters provided by the user .</p>
        <a href="/predict_page" class="visit-btn ">Check price</a>
      </div>
    </section>

  </body>
</html>

```

Predict.html

```

<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta http-equiv="X-UA-Compatible" content="IE=edge">

```

```

<meta name="viewport" content="width=device-width, initial-scale=1.0">
<link rel="stylesheet" href="../static/css/predict.css">
<title>Car Resale Predicted Value</title>
</head>
<body>
    <section class="header">
        <nav>
            <a href="/"></a>
        </nav>
        <div class="text-box">
            <h1>The Predicted Car Resale Value is </h1>
                <h1>{{predict}}</h1>
            </div>
        </section>

</body>
</html>

```

Build a python flask app:

Import Libraries

import pandas as pd

import numpy as np

from flask import Flask, render_template, Response, request

import pickle

from sklearn.preprocessing import LabelEncoder

import requests

NOTE: you must manually set API_KEY below using information retrieved from your IBM Cloud account.

API_KEY = "Qo9j8ni7qMJ8j1C8VFDRFHbuGRAhYWcTlkVqnYg1AGkE"

token_response = requests.post('https://iam.cloud.ibm.com/identity/token',

```
data={"apikey":API_KEY, "grant_type": 'urn:ibm:params:oauth:grant-  
type:apikey'})  
mltoken = token_response.json()["access_token"]  
header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' +  
mltoken}
```

```
app = Flask(__name__)#initiate flask app
```

```
def load_model(file='../Result/resale_model.sav'):#load the saved model  
    return pickle.load(open(file, 'rb'))
```

```
@app.route('/')  
def index():#main page  
    return render_template('car.html')
```

```
@app.route('/predict_page')  
def predict_page():#predicting page  
    return render_template('value.html')
```

```
@app.route('/predict', methods=['GET','POST'])  
def predict():  
    reg_year = int(request.args.get('regyear'))  
    powerps = float(request.args.get('powerps'))  
    kms= float(request.args.get('kms'))  
    reg_month = int(request.args.get('regmonth'))  
  
    gearbox = request.args.get('geartype')  
    damage = request.args.get('damage')  
    model = request.args.get('model')  
    brand = request.args.get('brand')  
    fuel_type = request.args.get('fuelType')
```

```

veh_type = request.args.get('vehicletype')

new_row = {'yearOfReg':reg_year, 'powerPS':powerps,
'kilometer':kms,
            'monthOfRegistration':reg_month,
'gearbox':gearbox,
            'notRepairedDamage':damage,
            'model':model, 'brand':brand,
'fuelType':fuel_type,
            'vehicletype':veh_type}

print(new_row)

new_df =
pd.DataFrame(columns=['vehicletype','yearOfReg','gearbox',

'powerPS','model','kilometer','monthOfRegistration','fuelType',
            'brand','notRepairedDamage'])
new_df = new_df.append(new_row, ignore_index=True)
labels =
['gearbox','notRepairedDamage','model','brand','fuelType','vehicletype']
mapper = {}

for i in labels:
    mapper[i] = LabelEncoder()
    mapper[i].classes =
np.load('../Result/'+str('classes'+i+'.npy'), allow_pickle=True)
    transform = mapper[i].fit_transform(new_df[i])
    new_df.loc[:,i+'_labels'] = pd.Series(transform,
index=new_df.index)

labeled =

```

```
new_df[['yearOfReg','powerPS','kilometer','monthOfRegistration'] +  
[x+'_labels' for x in labels]]
```

```
    X = labeled.values.tolist()  
    print('\n\n', X)  
    #predict = reg_model.predict(X)
```

```
    # NOTE: manually define and pass the array(s) of values to be  
    scored in the next line
```

```
    payload_scoring = {"input_data": [{"fields": [['yearOfReg',  
'powerPS', 'kilometer', 'monthOfRegistration','gearbox_labels',  
'notRepairedDamage_labels', 'model_labels','brand_labels', 'fuelType_labels',  
'vehicletype_labels']], "values": X}]}
```

```
    response_scoring = requests.post('https://us-  
south.ml.cloud.ibm.com/ml/v4/deployments/7f67cbcd-6222-413b-9901-  
b2a72807ac82/predictions?version=2022-10-30', json=payload_scoring,  
headers={'Authorization': 'Bearer ' + mltoken})
```

```
    predictions = response_scoring.json()  
    print(response_scoring.json())  
    predict = predictions['predictions'][0]['values'][0][0]  
    print("Final prediction :",predict)
```

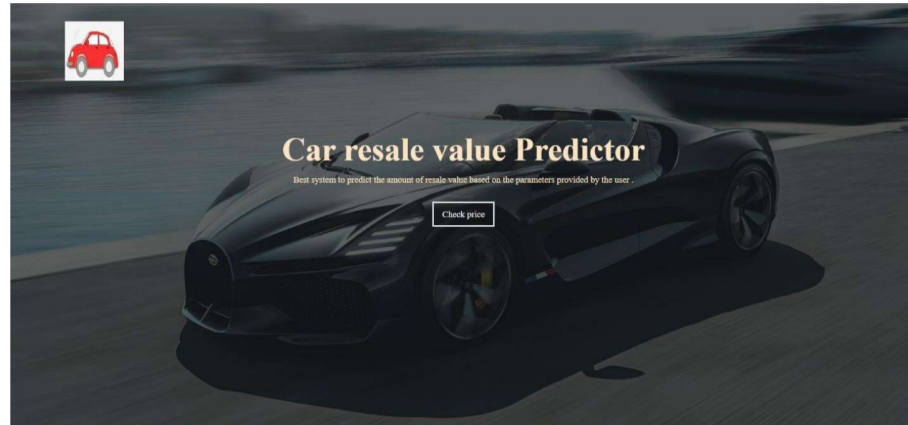
```
    return render_template('predict.html',predict=predict)
```

```
if __name__ == '__main__':
```

```
    reg_model = load_model()#load the saved model  
    app.run(host='localhost', debug=True, threaded=False)
```

8. Testing:

1) Home Page



2) Data Entry Page

The screenshot shows the data entry page of the web application. The title is "Get the Accurate Resale Value of Your Car". The form contains the following fields and options:

- Registration year :
- Registration Month :
- Power of car in PS:
- Kilometers that car have driven :
- Gear type : ☒ Manual ☐ Automatic ☐ Not declared
- Your car is repaired or damaged : ☒ Yes ☐ No ☐ Not declared
- Model type :
- Brand :
- Fuel type :
- Vehicle type :
-

9. RESULT

Car Resale Valur Display:



10. Advantages And disadvantages:

Advantages:

- Good at learning complex and non linear relationships
- highly explainable and easy to interpret
- Robust to outliers
- No features scaling is required
- Easy to predict the current rate of car

Disadvantages:

- consumes more time
- Require high computational power
- require more data to predict exact value and accuracy

11. Conclusion:

The increased prices of new cars and the financial incapability of the customers to buy them, Used Car sales are on a global increase. Therefore, there is an urgent need for a Used Car Price Prediction system which effectively determines the worthiness of the car using a variety of features. The proposed system will help to determine the accurate price of used car price prediction. This paper compares 3 different algorithms for machine

learning : Linear Regression, Lasso and Ridge Regression.

12. Future Scope:

In future this machine learning model may bind with various website which can provide real time data for price prediction. Also we may add large historical data of car price which can help to improve accuracy of the machine learning model. We can build an android app as user interface for interacting with user. For better performance, we plan to judiciously design deep learning network structures, use adaptive learning rates and train on clusters of data rather than the whole dataset.

13. Appendix:

Github Link:

<https://github.com/IBM-EPBL/IBM-Project-34693-1660271756>

Weights and basis link:

https://wandb.ai/jayagowry/car_resale_value?workspace=user-jayagowry

Google colab link for run the model:

https://colab.research.google.com/drive/10EHwGiA_KNKygUsjIA0G0Sr3YS9GAcXW?usp=sharing

https://colab.research.google.com/drive/1umCW77LeW3-srx_wW_0SVXIIWa0jDdLL?usp=sharing