

CAR RESALE VALUE PREDICTION

TEAM ID: PNT2022TMID04349

Team Details

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1.INTRODUCTION

1.1 PROJECT OVERVIEW

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/financers 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.

1.2 PURPOSE

Predicting the price of used cars in both an important and interesting problem. According to data obtained from the National Transport Authority [1], the number of cars registered between 2003 and 2013 has witnessed a spectacular increase of 234%. From 68, 524 cars registered in 2003, this number has now reached 160, 701. With difficult economic conditions, it is likely that sales of second-hand imported (reconditioned) cars and used cars will increase. It is reported in [2] that the sales of new cars has registered a decrease of 8% in 2013. In many developed countries, it is common to lease a car rather than buying it outright. A lease is a binding contract between a buyer and a seller (or a third party – usually a bank, insurance firm or other financial institutions) in which the buyer must pay fixed instalments for a pre-defined number of months/years to the seller/financer. 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 make the predictions. Keywords-car; price; machine learning; artificial intelligence 754 Sameerchand Pudaruth seller/financers to be able to predict the salvage value (residual value) of cars with accuracy. If the residual value is under-estimated by the seller/financer at the beginning, the instalments will be higher for the clients who will certainly then opt for another

seller/financer. If the residual value is over-estimated, the instalments will be lower for the clients but then the seller/financer may have much difficulty at selling these high-priced used cars at this over-estimated residual value. Thus, we can see that estimating the price of used cars is of very high commercial importance as well. Manufacturers' from Germany made a loss of 1 billion Euros in their USA market because of mis-calculating the residual value of leased cars [3]. Most individuals in Mauritius who buy new cars are also very apprehensive about the resale value of their cars after certain number of years when they will possibly sell it in the used cars market. Predicting the resale value of a car is not a simple task. It is trite knowledge that the value of used cars depends on a number of factors. The most important ones are usually the age of the car, its make (and model), the origin of the car (the original country of the manufacturer), its mileage (the number of kilometers it has run) and its horsepower. Due to rising fuel prices, fuel economy is also of prime importance. Unfortunately, in practice, most people do not know exactly how much fuel their car consumes for each km driven. Other factors such as the type of fuel it uses, the interior style, the braking system, acceleration, the volume of its cylinders (measured in cc), safety index, its size, number of doors, paint colour, weight of the car, consumer reviews, prestigious awards won by the car manufacturer, its physical state, whether it is a sports car, whether it has cruise control, whether it is automatic or manual transmission, whether it belonged to an individual or a company and other options such as air conditioner, sound system, power steering, cosmic wheels, GPS navigator all may influence the price as well. Some special factors which buyers attach importance in Mauritius is the local of previous owners, whether the car had been involved in serious accidents and whether it is a lady-driven car. The look and feel of the car certainly contributes a lot to the price. As we can see, the price depends on a large number of factors. Unfortunately, information about all these factors are not always available and the buyer must make the decision to purchase at a certain price based on few factors only.

The main objective of this project is to predict the amount of resale and thereby eliminating the human intervention and biased valuation. So this project is made with the purpose of predicting the correct valuation of used cars that helps users to sell the car remotely with perfect valuation. It predicts the amount of resale value based on the parameters provided by the user. User enters the details of the car into the form given and accordingly the car resale value is predicted.

2. LITERATURE SURVEY

2.1 EXISTING PROBLEM

- Customers who want to purchase a used automobile are vulnerable to fraud since they do not have a thorough understanding of the vehicles.
- The cost of new automobiles might be expensive since the government must pay some additional expenses in the form of taxes. So, for those just starting out, purchasing a used automobile will be the best option.
- Customers run the risk of paying excessive prices for old-model or old-brand vehicles that aren't really worth the money.
- If buyers are uninformed about the models and brands of the used automobiles being sold, they risk being duped.
- Although there are websites that provide information on automobiles, they might not provide an estimate of the cost of the car.
- Customers need a reliable website or model to estimate the cost of a secondhand car.

2.2 REFERENCES

1. CAR RESALE PRICE FORECASTING[Stefan Lessmann, Stefan Vob, 2017]

Resale price forecasting is first done with Random Forest Regression. Then the same price forecast is done with externally generated residual value estimates and finally the two results are compared to determine the best approach.

2. PREDICTION OF RESALE VALUE OF THE CAR USING LINEAR REGRESSION ALGORITHM [Kiran S, 2020]

A correlation with each attribute to that of target attribute is found and linear regression curve with the target attribute is drawn. As a final step the total error and accuracy is measured

3. CAR PRICE PREDICTION IN THE USA BY USING LINEAR REGRESSION [Huseyn Mammadov, 2021]

They proposed a model using linear regression since the dependent variable price is linearly related to many independent variables and they have eliminated the irrelevant features by using the recursive feature elimination to reduce the dimensionality. Then R-square and root mean squared error is used to reduce the errors produced.

4. PREDICTING THE PRICE OF USED CARS USING MACHINE LEARNING TECHNIQUES [Sameerchand Pudaruth, 2013]

Different techniques like multiple linear regression analysis, k-nearest neighbors, naïve bayes and decision trees have been used to make the predictions. The predictions are then evaluated and compared in order to find those which provide the best performances.

5. USED CARS PRICE PREDICTION USING SUPERVISED LEARNING TECHNIQUES[Pattabiraman Venkatasubbu, Mukkesh Ganesh, 2019]

They proposed a model using multiple and lasso regression. Using Lasso regression on the training data set, we first select the subset of attributes that lead

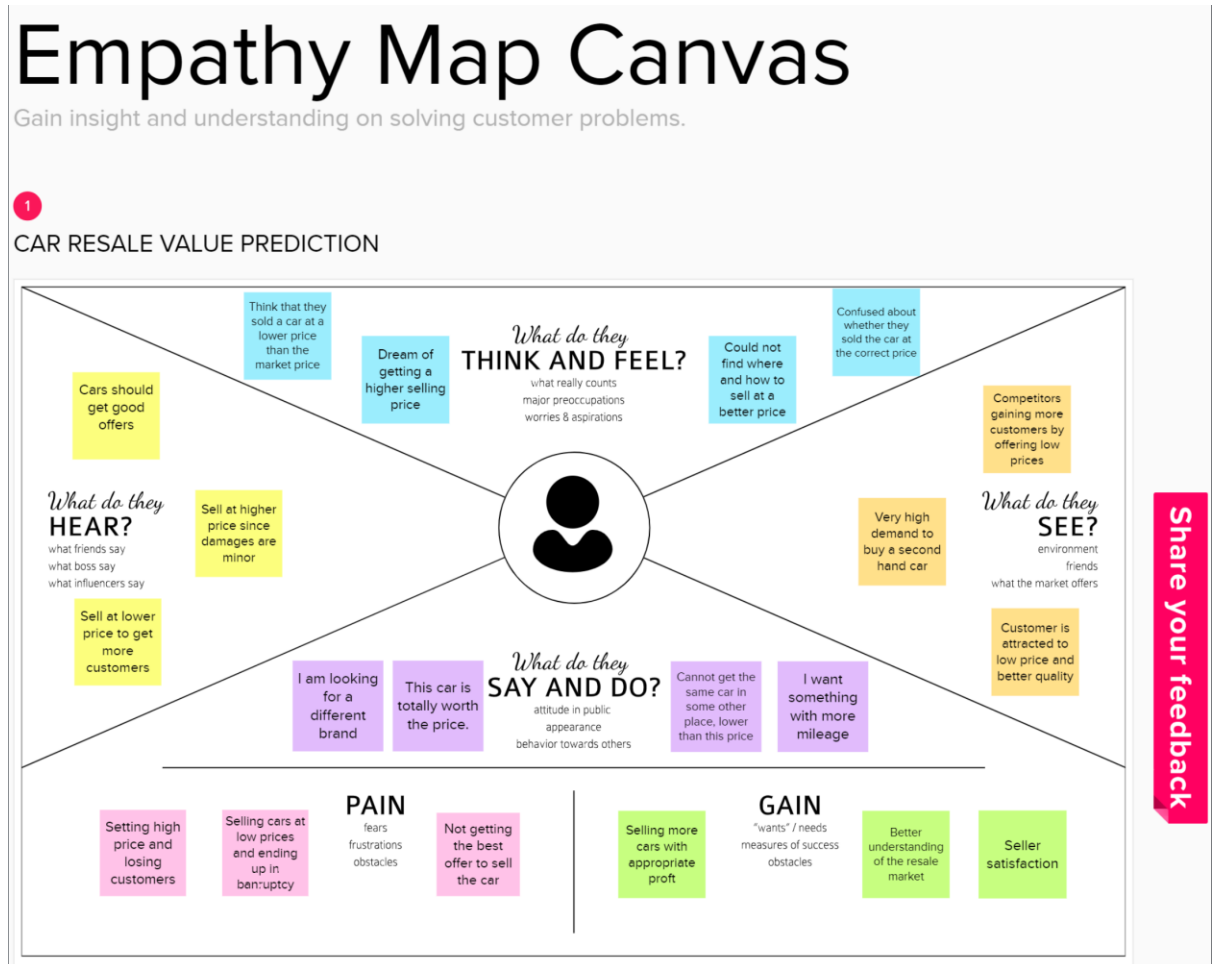
to less error while predicting the price. It makes use of 10-fold cross-validation and L1 regularization. A general linear model, which models price to the set of selected attributes from lasso regression is used for multiple regression training.

2.3 PROBLEM STATEMENT DEFINITION

| Problem Statement (PS) | I am (Customer) | I'm trying to | But | Because | Which makes me feel |
|-------------------------------|------------------------|------------------------------------|-------------------------------|---|---|
| PS-1 | Car dealer | sell used cars | Increasing price | rising interest rates, tariffs, and energy concerns, car dealerships are expected to have fewer sales, especially with newer vehicles | Sad and Worried |
| PS-2 | Common People | Buy 2 nd hand cars | Can't decide on cars | Too many car models & prices. Common man can't decide correct car. | Fear of making wrong choice |
| PS-3 | Budget Oriented People | Buy cheap cars | Price is not justified | Price is increased and cannot justify price | Paying more for cars |
| PS-4 | Seller | To sell my car at reasonable price | Deciding on the price is hard | Too many complications in calculating the correct price for selling cars | Unhappy for not selling car at correct price. |

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas



3.2 IDEATION & BRAINSTORMING

Cibikumar M V

| | | |
|-------------------------------|--------------------------------------|--|
| Using ML Model | Discuss with car dealers to get idea | Analyzing current condition of vehicle |
| Gathering similar car details | Collect the cost price of car | Measure mileage and performance |

Akash M


| | | |
|--|---|--------------------------------------|
| User Support/ Query Center | Online selling websites can be referred | Check current insurance policy |
| Show Current Vehicle Fitness Certificate | Analyze economic conditions of car | Provide results based on car mileage |

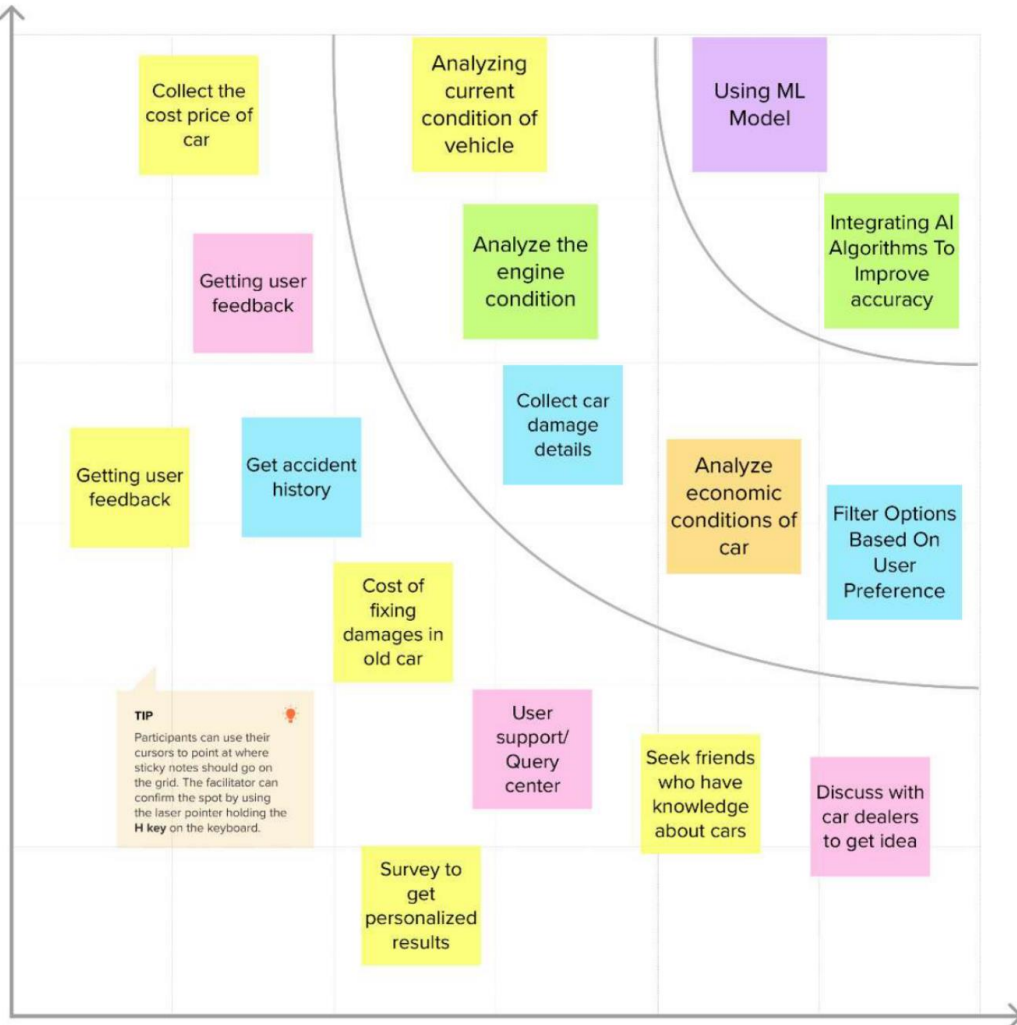
Charanraj T

| | | |
|---------------------------------|------------------------------------|---|
| Collect car damage details | Survey to get personalized results | Get accident history |
| Get idea from local car dealers | Analyze the engine condition | Integrating AI Algorithms To Improve accuracy |

Danushraj K S

| | | |
|---|--|---|
| Get performance of the car | Seek friends who have knowledge about cars | Analyze the quality of the car products |
| Filter Options Based On User Preference | Cost of fixing damages in old car | Getting user feedback |


Importance
If each of these tasks could get done without any difficulty or cost, which would have the most positive impact?



TIP
Participants can use their cursors to point at where sticky notes should go on the grid. The facilitator can confirm the spot by using the laser pointer holding the **H key** on the keyboard.


Feasibility
Regardless of their importance, which tasks are more feasible than others? (Cost, time, effort, complexity, etc.)

3.3 PROPOSED SOLUTION

| S.No. | Parameter | Description |
|-------|--|--|
| 1. | Problem Statement (Problem to be solved) | <ul style="list-style-type: none">• The main aim of this project is to predict the resale value of a used car using regression algorithms.• This could help the customers to find the best price of the used car that is going to be sold. |
| 2. | Idea / Solution description | <ul style="list-style-type: none">• The resale value of a car depends on factors such as price, vehicle type, gearbox, model, kilometres run, fuel type, etc.• The data is then pre-processed to handle missing values and outliers, to normalize the data and split it into dependent and independent variables.• After that the model is developed using regression algorithms to predict the resale price of the car. |
| 3. | Novelty / Uniqueness | <ul style="list-style-type: none">• This is a real-time problem which can benefit both customer and seller.• The novelty of this proposal is to predict the resale value as near as possible to the actual value. |
| 4. | Social Impact / Customer Satisfaction | <ul style="list-style-type: none">• Provided the current economic times, it is more likely that the usage of second-hand cars will increase.• This is a mutual commercial interest to both the customers and the sellers.• It predicts the resale values of the car based on all its features and prevents over-pricing or under-pricing.• This sets an understanding or trust between the seller and the customer. |
| 5. | Business Model (Revenue Model) | <ul style="list-style-type: none">• The proposed model could be sold to resellers so that they could use it to find the perfect price for bidding.• It could be developed into an application and get revenue from it if more no of users started to using it to find the best value of a second-hand car. |
| 6. | Scalability of the Solution | <ul style="list-style-type: none">• The primary model is targeted only for a lower number of audiences.• However, as the customer base increases for the model it can be extended to the cloud for effective services. |

3.4 PROBLEM SOLUTION FIT

| | | | | |
|---|---|---|--|---------------------------|
| Define CS, fit into CC | 1. CUSTOMER SEGMENT(S) Who is your customer? i.e. working parents of 0-5 y.o. Kids <div>CS</div> <ul style="list-style-type: none"> • Car dealer • Budget oriented people • Common people | 6. CUSTOMER CONSTRAINTS What constraints prevent your customers from taking action or limit their choices of solutions? i.e. spending power, budget, no cash, network connection, available devices. <div>CC</div> <ul style="list-style-type: none"> • No proper knowledge of internet • Fear of scammers • No big connection or trustable person for investigating | 5. AVAILABLE SOLUTIONS Which solutions are available to the customers when they face the problem or need to get the job done? What have they tried in the past? What pros & cons do these solutions have? i.e. pen and paper is an alternative to digital notetaking <div>AS</div> <ul style="list-style-type: none"> • Investigating in different places • Looking up in online • Using comparing tools for feature & price comparison | Explore AS, differentiate |
| | 2. JOBS-TO-BE-DONE / PROBLEMS Which jobs-to-be-done (or problems) do you address for your customers? There could be more than one; explore different sides <div>J&P</div> <ul style="list-style-type: none"> • Building ML model • Guide customer in buying resale cars • Helping customer with poor car knowledge • Providing best options for given criteria (fuel type, no. of owners, age of car) | 9. PROBLEM ROOT CAUSE What is the real reason that this problem exists? What is the back story behind the need to do his job? i.e. customers have to do it because of the change in regulations. <div>RC</div> <ul style="list-style-type: none"> • Many car types & features • Increased complexity in settling for justified price • Car dealer's & sellers not being honest in prices | 7. BEHAVIOUR What does your customer do to address the problem and get the job done? i.e. directly related: find the right solar panel installer, calculate usage and benefits; indirectly associated: customers spend free time on volunteering work (i.e. Greenpeace) <div>BE</div> <ul style="list-style-type: none"> • Ask known friends & relatives for car • Explore further options in resale websites • Advertise for need of car | |
| 3. TRIGGERS Why it triggers customers to act? i.e. seeing their neighbors selling old cars, finding about a more efficient solution in the news <div>TR</div> <ul style="list-style-type: none"> • In a court traveling • Cheap price of resale cars • Starting a business • As a means of transportation | 10. OUR SOLUTION If you're working on an existing business, write down your current solution first, fill in the canvas, and check how much it fits reality. If you are working on a new business proposition, then keep it blank until you fill in the canvas and come up with a solution that fits within customer limitations, solves a problem and matches customer behavior. <div>SL</div> <ul style="list-style-type: none"> • An ML model to predict justified price • Built with regression algorithms • Making parameters of used cars as inputs & making customers make decisions on their own. | 8. CHANNELS OF BEHAVIOR 8.1 ONLINE What kind of actions do customers take online? Extract online channels from #7 8.2 OFFLINE What kind of actions do customers take offline? Extract offline channels from #7 and use them for customer development. <div>CH</div> 8.1 Online: <ul style="list-style-type: none"> • Compare car price & features in online • Use online websites 8.2 Offline: <ul style="list-style-type: none"> • Ask local car dealers • Use help of friends knowledgeable in cars for price | Identify strong TR & EM | |
| 4. EMOTIONS: BEFORE / AFTER How do customers feel when they face a problem or a job and afterwards? i.e. lost, insecure > confident, in control - use it in your communication strategy & design. <div>EM</div> Before: <ul style="list-style-type: none"> • Doubt in price of car • Fear of making wrong choice After: <ul style="list-style-type: none"> • Satisfaction in price and choice • Happiness of owning a car | | | | |

4. REQUIREMENT ANALYSIS

4.1) FUNCTIONAL REQUIREMENT

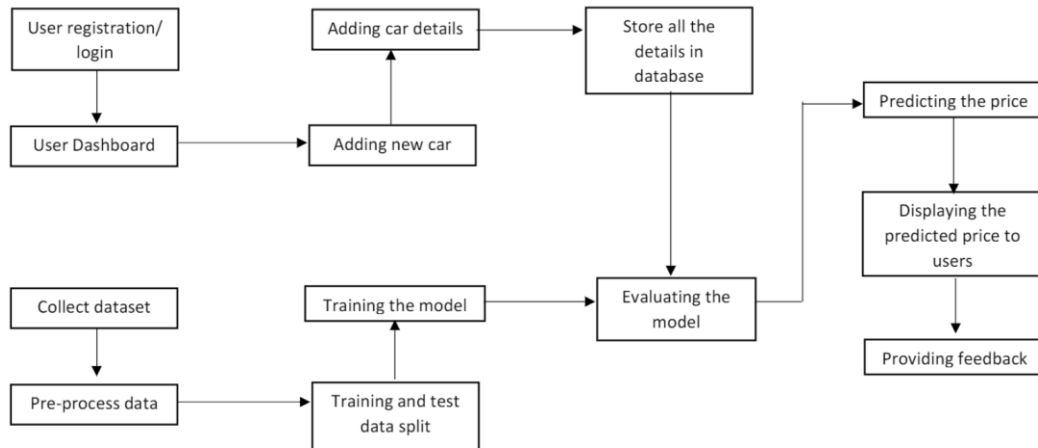
| FR No | Functional Requirement (Epic) | Sub Requirement (Story / Sub-Task) |
|-------|-------------------------------|--|
| FR-1 | User Registration | Registration through Form |
| FR-2 | User Confirmation | Confirmation via Email |
| FR-3 | User Profile | View account details |
| FR-4 | Car predictions | View the previous predicted prices along with model, brand and vehicle type |
| FR-5 | Maintain database | Maintain database to store user and their car details |
| FR-6 | Value prediction | Predict the value of the resale car using the regression model and details entered |
| FR-7 | Result display | Display the predicted value of the used car |

4.2) NON-FUNCTIONAL REQUIREMENTS

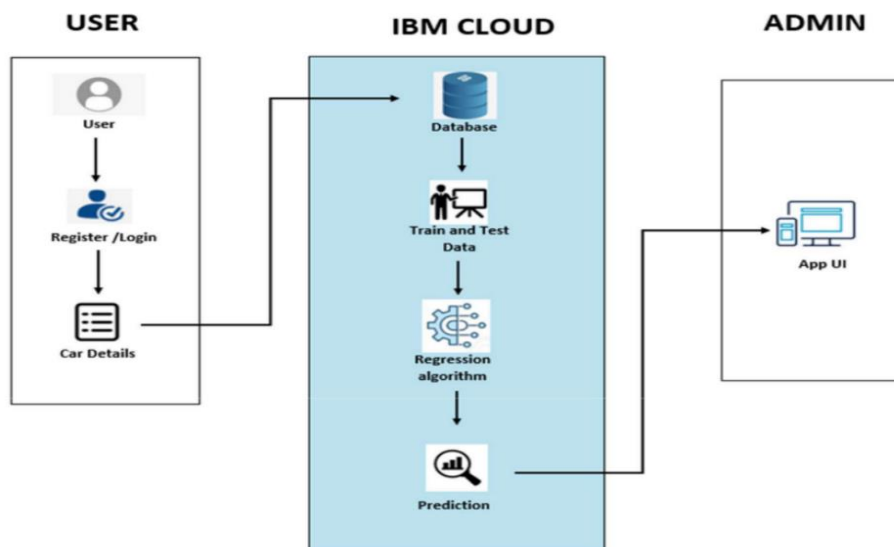
| FR No | Non-Functional Requirement | Description |
|-------|----------------------------|--|
| NFR-1 | Usability | <ul style="list-style-type: none">• User friendly UI• Easy process flow to predict value |
| NFR-2 | Security | <ul style="list-style-type: none">• User authentication while entering website• No information is shared with third party• User can see only his details |
| NFR-3 | Reliability | <ul style="list-style-type: none">• Data will be stored and replicated so that data loss can be avoided• Rate of occurrence of failure is very less |
| NFR-4 | Performance | <ul style="list-style-type: none">• Quick prediction results• Fast website loading• Efficient ML algorithm to provide accurate result with less time complexity |
| NFR-5 | Availability | <ul style="list-style-type: none">• Application can be accessed from both mobile and desktop• Single page failure does not affect the whole website• Uninterrupted user services |
| NFR-6 | Scalability | <ul style="list-style-type: none">• Able to handle large amount of data and traffic globally without failure• Database can be scaled according to the usage in a cost effective manner |

5) PROJECT DESIGN

5.1 DATA FLOW DIAGRAMS



5.2 SOLUTION & TECHNICAL ARCHITECTURE



5.3 USER STORIES

| User Type | Functional Requirement (Epic) | User Story Number | User Story / Task | Acceptance criteria | Priority | Release |
|-----------|--|-------------------|---|---|----------|----------|
| Admin | Dataset | USN-1 | Collect the required data for the Car resale prediction. | Enough data collected for training model | High | Sprint-1 |
| | Data preprocessing | USN-2 | Perform data cleaning to optimize the dataset | Clean Dataset enough to make correct predictions | High | Sprint-1 |
| | Training & Building Model | USN-3 | Build the model using regression algorithms to classify the data | Model should i.e predicting prices with acceptable accuracy | High | Sprint-1 |
| | Deploy the model | USN-4 | Deployment of ML model using IBM Cloud | Model should be working fine from the cloud | High | Sprint-2 |
| | Integrate the web app with the IBM model | USN-5 | Use flask for the integration purpose. | Model should be easy to use & working fine from the web app | High | Sprint-2 |
| Customer | Homepage | USN-6 | Details about the application and the car resale process | I can get an idea about the app | Medium | Sprint-2 |
| | Registration | USN-7 | As a user, I can register for the application by entering my email, password, and confirming my password. | I can access my account / dashboard | High | Sprint-3 |
| | | USN-8 | As a user, I will receive confirmation email once I have registered for the application | I can receive confirmation email | High | Sprint-3 |
| | Login | USN-9 | As a user, I can log into the application by entering email & password | I can login to my account | High | Sprint-3 |
| | Dashboard | USN-10 | As a user, I can add new cars and get access to insert and update their details | I can add new cars | Medium | Sprint-4 |
| | Car Details | USN-11 | As a user, I should give the car details like car model, engine and fuel type, etc... | Car details should be accepted & taken for further processing | High | Sprint-4 |
| | Car Price | USN-12 | As a user, I can view the current rate of the used car price | Car Prices must be shown based on the predicted result by the model | High | Sprint-4 |

6. PROJECT PLANNING & SCHEDULING

6.1 SPRINT PLANNING & ESTIMATION

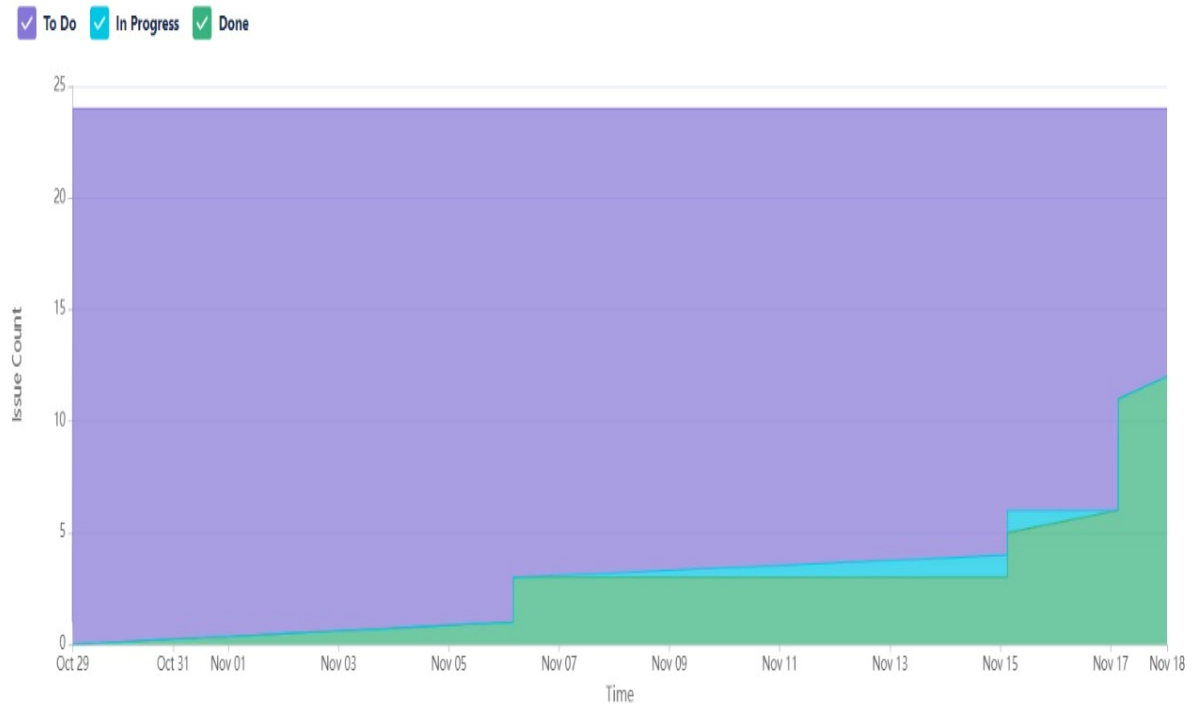
| TITLE | DESCRIPTION | DUE DATE |
|---|--|-------------------|
| Literature survey & Information gathering | Literature survey on the selected topic and collect information by referring to the related papers and research projects, journals etc. | 3 September 2022 |
| Prepare Empathy Map | Prepare empathy map canvas to understand about the user problems, pains and gains. From the empathised details, prepare the problem statements to be solved. | 10 September 2022 |
| Ideation | Conduct a brainstorming session with the teammates and discuss ideas to solve the problem. Prioritize the top 3 ideas based on feasibility. | 17 September 2022 |
| Proposed Solution | Prepare the proposed solution which includes the novelty, feasibility, revenue, social impact, scalability etc. | 24 September 2022 |
| Problem Solution Fit | Prepare the problem solution fit which includes the causes, problems and solutions of the problem. | 1 October 2022 |
| Solution Architecture | Prepare solution architecture that indicates the data flow from the user, model and the website. | 1 October 2022 |

| | | |
|--|--|------------------|
| Customer Journey | Prepare the customer journey map to understand the user needs and experience with the application. | 8 October 2022 |
| Functional Requirement | Prepare the functional requirement which includes all the features that will be available in the application. | 15 October 2022 |
| Technology Architecture | Prepare the technology architecture that defines about the technologies and the IBM cloud features used in the application. | 15 October 2022 |
| Data Flow Diagrams | Draw the data flow diagram to indicate the data flow from the user, during the model building and while predicting the result, | 15 October 2022 |
| Prepare Milestone & Activity List | Split the entire project into simpler tasks and prepare milestones and activity list of the project. | 22 October 2022 |
| Sprint Delivery Plan | Prepare a delivery plan of the project with specific due dates to complete each sprint consisting of a set of functional requirements. | 22 October 2022 |
| Project Development - Delivery of Sprint-1, 2, 3 & 4 | Develop, test and submit the code. | 19 November 2022 |

6.2 SPRINT DELIVERY SCHEDULE

| User | Sprint | Functional Requirement (Epic) | User Story Number | User Story / Task | Story Points | Priority | Team Members |
|----------|----------|-------------------------------|-------------------|---|--------------|----------|--|
| Admin | Sprint 1 | Dataset collection | USN-1 | Collect the required data for the Car resale prediction | 2 | High | Cibikumar, Charanraj, Akash, Danushraj |
| | Sprint 1 | Data pre-processing | USN-2 | Perform data cleaning to optimize the dataset | 4 | Medium | Charanraj, Cibikumar |
| | Sprint 1 | Training & Building Model | USN-3 | Build the model using regression algorithms to classify the data | 6 | High | Cibikumar, Charanraj, Akash, Danushraj |
| | Sprint 2 | Deploy the model | USN-4 | Deployment of ML model using IBM Cloud | 5 | High | Akash, Danushraj |
| | Sprint 4 | Integration | USN-5 | Integrate the web app developed using flask with IBM model | 5 | High | Charanraj, Cibikumar |
| Customer | Sprint 2 | Homepage | USN-6 | Details about the application and the car resale process | 2 | Low | Akash, Danushraj |
| | Sprint 2 | Registration | USN-7 | As a user, I can register for the application by entering my email, password, and confirming my password. | 5 | High | Cibikumar, Danushraj |
| | Sprint 3 | Confirmation | USN-8 | As a user, I will receive confirmation email once I have registered for the application | 3 | Medium | Charanraj, Akash |
| | Sprint 3 | Login | USN-9 | As a user, I can log into the application by entering email & password | 4 | High | Cibikumar, Danushraj |
| | Sprint 3 | Dashboard | USN-10 | As a user, I can add new cars and get access to insert and update their details | 5 | High | Cibikumar, Charanraj, Akash |
| | Sprint 4 | Car Details | USN-11 | As a user, I should give the car details like car model, engine and fuel type, etc... | 2 | Medium | Akash, Danushraj |
| | Sprint 4 | Car Price | USN-12 | As a user, I can view the current rate of the used car price | 5 | High | Charanraj, Akash, Danushraj |

6.3) REPORTS FROM JIRA



7. CODING & SOLUTIONING

7.1 FEATURE-1 (MODEL CREATION)

Importing the libraries

```
In [1]: # importing libraries

import pandas as pd
import numpy as np
import matplotlib as plt
from sklearn.preprocessing import LabelEncoder
import pickle
```

```
In [2]: #importing dataset

df=pd.read_csv("Data/autos.csv",header=0,sep=";",encoding="Latin1")
```

Cleaning the dataset

```
In [3]: df.dtypes
```

```
Out[3]: dateCrawled      object
name                  object
seller               object
offerType            object
price                int64
abtest               object
vehicleType          object
yearOfRegistration   int64
gearbox              object
powerPS              int64
model                object
kilometer            int64
monthOfRegistration   int64
fuelType             object
brand                object
notRepairedDamage    object
dateCreated          object
nrOfPictures         int64
postalCode           int64
lastSeen             object
dtype: object
```

```
In [4]: print(df.seller.value_counts())
df[df.seller!='gewerblich']
df=df.drop('seller',1)

print(df.offerType.value_counts())
df[df.offerType!='Gesuch']
df=df.drop('offerType',1)

privat      371525
gewerblich    3
Name: seller, dtype: int64
```

```
C:\Users\charan\AppData\Local\Temp\ipykernel_9104\587171588.py:3: FutureWarning: In a future version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only.
```

```
df=df.drop('seller',1)
```

```
Angebot      371516
```

```
Gesuch        12
```

```
Name: offerType, dtype: int64
```

```
C:\Users\charan\AppData\Local\Temp\ipykernel_9104\587171588.py:7: FutureWarning: In a future version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only.
```

```
df=df.drop('offerType',1)
```

```
In [5]: print(df.shape)
df=df[(df.powerPS>50) & (df.powerPS<900)]
print(df.shape)
df=df[(df.yearOfRegistration>=1950)&(df.yearOfRegistration<2017)]
print(df.shape)
```

```
(371528, 18)
```

```
(371528, 18)
```

```
(356559, 18)
```

```
In [6]: df.drop(['name', 'abtest', 'dateCrawled', 'nrOfPictures', 'lastSeen',
'postalCode', 'dateCreated'],axis='columns',inplace=True)
```

```
In [7]: new_df=df.copy()
new_df=new_df.drop_duplicates(['price', 'vehicleType', 'yearOfRegistration',
'gearbox', 'powerPS', 'model', 'kilometer', 'monthOfRegistration', 'fuelType',
'notRepairedDamage'])
```

```
In [8]: new_df.gearbox.replace(('manuell', 'automatik'),('manual', 'automatic'), inplace=True)
new_df.fuelType.replace(('benzin', 'andere', 'elektro'),('petrol', 'others', 'electric'),
new_df.vehicleType.replace(('kleinwagen', 'cabrio', 'kombi', 'andere'),('small car', 'conv
new_df.notRepairedDamage.replace(('ja', 'nein'),('Yes', 'No'),inplace=True)
```

```
In [9]: new_df = new_df[(new_df.price >= 100) & (new_df.price <= 150000)]

new_df['notRepairedDamage'].fillna(value='not-declared', inplace=True)
new_df['fuelType'].fillna(value='not-declared', inplace=True)
new_df['gearbox'].fillna(value='not-declared', inplace=True)
new_df['vehicleType'].fillna(value='not-declared', inplace=True)
new_df['model'].fillna(value='not-declared', inplace=True)
```

```
In [10]: new_df.to_csv('autos_preprocessed.csv')
```

```
In [11]: new_df
```


Out[11]:

| | price | vehicleType | yearOfRegistration | gearbox | powerPS | model | kilometer | monthOf |
|--------|-------|--------------|--------------------|--------------|---------|--------------|-----------|---------|
| 0 | 480 | not-declared | 1993 | manual | 0 | golf | 150000 | |
| 1 | 18300 | coupe | 2011 | manual | 190 | not-declared | 125000 | |
| 2 | 9800 | suv | 2004 | automatic | 163 | grand | 125000 | |
| 3 | 1500 | small car | 2001 | manual | 75 | golf | 150000 | |
| 4 | 3600 | small car | 2008 | manual | 69 | fabia | 90000 | |
| ... | ... | ... | ... | ... | ... | ... | ... | |
| 371523 | 2200 | not-declared | 2005 | not-declared | 0 | not-declared | 20000 | |
| 371524 | 1199 | convertible | 2000 | automatic | 101 | fortwo | 125000 | |
| 371525 | 9200 | bus | 1996 | manual | 102 | transporter | 150000 | |
| 371526 | 3400 | combination | 2002 | manual | 100 | golf | 150000 | |
| 371527 | 28990 | limousine | 2013 | manual | 320 | m_reihe | 50000 | |

317379 rows × 11 columns

```
In [12]: 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[['price', 'yearOfRegistration', 'powerPS', 'kilometer', 'monthOfRegistration']]
print(labeled.columns)

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

In []:

Splitting Data Into Independent And Dependent Variables

```
In [13]: Y = labeled.iloc[:,0].values
X = labeled.iloc[:,1:].values

Y = Y.reshape(-1,1)
```

```
In [14]: from sklearn.model_selection import cross_val_score, train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=
```

```
In [15]: X_train,X_test,Y_train,Y_test
```

```
Out[15]: (array([[ 2009,    101,  40000, ...,    36,     7,     4],
 [ 1998,    115, 150000, ...,    10,     5,     1],
 [ 2003,    109, 150000, ...,     1,     7,     7],
 ...,
 [ 2005,    209, 150000, ...,    39,     7,     8],
 [ 2007,    143, 150000, ...,     2,     7,     4],
 [ 1999,    136, 150000, ...,     2,     7,     4]], dtype=int64),
 array([[ 2006,    140, 100000, ...,    24,     7,     4],
 [ 2001,    179, 150000, ...,     1,     1,     1],
 [ 1999,    211, 150000, ...,    24,     7,     1],
 ...,
 [ 2003,    113, 150000, ...,    27,     4,     7],
 [ 1998,    140, 150000, ...,    39,     7,     4],
 [ 1994,     75, 150000, ...,    38,     7,     2]], dtype=int64),
 array([[ 7499],
 [  450],
 [ 2990],
 ...,
 [10500],
 [ 6995],
 [ 1899]], dtype=int64),
 array([[5990],
 [2999],
 [  89],
 ...,
 [2700],
 [  850],
 [1000]], dtype=int64))
```

Building the model

```
In [17]: from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score

rf_regressor = RandomForestRegressor(n_estimators=1000, max_depth=10, random_state=34)

rf_regressor.fit(X_train, np.ravel(Y_train, order='C'))
```

```
Out[17]: ▼ RandomForestRegressor
RandomForestRegressor(max_depth=10, n_estimators=1000, random_state=34)
```

```
In [18]: y_pred = rf_regressor.predict(X_test)

print(r2_score(Y_test, y_pred))

0.8191322832483275
```

```
In [20]: filename='resale_model.sav'
pickle.dump(rf_regressor, open(filename, 'wb'))
```

Accuracy metrics

```
In [21]: from sklearn.metrics import mean_absolute_error

print(mean_absolute_error(Y_test, y_pred))

1655.534681561534
```

```
In [22]: from sklearn.metrics import mean_squared_error

print(mean_squared_error(Y_test, y_pred))

11832644.335139675
```

```
In [23]: from sklearn.metrics import mean_squared_error

root_mean_squared_error = mean_squared_error(Y_test, y_pred, squared=False)
print(root_mean_squared_error)

3439.861092419238
```

```
In [24]: from sklearn.metrics import r2_score

print(r2_score(Y_test, y_pred))

0.8191322832483275
```

7.2 FEATURE-2 (FLASK)

```
import pandas as pd
import numpy as np
from datetime import timedelta
import matplotlib as plt
from flask import Flask, render_template, session, request, redirect
from sklearn.preprocessing import LabelEncoder
import pickle
import requests
import pyrebase

app = Flask(__name__)

firebaseConfig = {
    "apiKey": "FIREBASE_API_KEY",
    "authDomain": "carresale-fd630.firebaseio.com",
    "databaseURL": "https://carresale-fd630-default-rtdb.asia-southeast1.firebaseio.com",
    "projectId": "carresale-fd630",
    "storageBucket": "carresale-fd630.appspot.com",
    "messagingSenderId": "217742759498",
    "appId": "1:217742759498:web:8c55a5fa220ca091fa38b3",
    "measurementId": "G-VHBR6L69Q1"
}

firebase = pyrebase.initialize_app(firebaseConfig)
db = firebase.database()
app.secret_key = 'secret'
app.permanent_session_lifetime = timedelta(minutes=60)

@app.route("/")
def home():
    return render_template("home.html")

@app.route("/auth")
def auth():
    return render_template("login.html")

@app.route("/login", methods=['POST'])
def login():
    auth = firebase.auth()
    email = request.form['email']
    password = request.form.get('password')
    try:
        user = auth.sign_in_with_email_and_password(email, password)
        userDetails = auth.get_account_info(user['idToken'])
        if {userDetails['users'][0]['emailVerified']} == {True}:

```

```

        session['user'] = user
    else:
        return "Verify email"
except Exception as e:
    print(f'error:{e}')
    return redirect('/dashboard')

@app.route("/register", methods=['POST'])
def register():
    auth = firebase.auth()
    name = request.form['name']
    email = request.form['email']
    password = request.form.get('password')
    userDetails = {
        'name': name,
        'email': email,
        'history': False
    }
    try:
        user = auth.create_user_with_email_and_password(email, password)
        auth.update_profile(user['idToken'], display_name=name)
        db.child('users').child(user['localId']).set(userDetails, user['idToken'])
        auth.send_email_verification(user['idToken'])
    except Exception as e:
        print(f'error:{e}')
        return redirect('/dashboard')

@app.route('/logout')
def logout():
    if 'user' in session:
        session.pop('user',None)
        return redirect('/')
    else:
        return redirect('/')

@app.route("/dashboard")
def dashboard():
    if 'user' in session:
        user = dict(db.child('users').get().val())[session['user']['localId']]
        return render_template('history.html', name=session['user']['displayName'],history=user['history'])
    else:
        return redirect('/auth')

@app.route("/predict")
def predict():
    if 'user' in session:
        return render_template('predict.html', name=session['user']['displayName'],modelData=modelData,
fuelData=fuelData, vehicleData=vehicleData, brandData=brandData)

```

```

else:
    return redirect('/auth')

def predictFromDeploymentModel(userInput):
    API_KEY = "IBM_CLOUD_API_KEY"
    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}
    payload_scoring = {"input_data": [{"fields":
['yearOfRegistration' , 'powerPS' , 'kilometer' , 'monthOfRegistration' , 'gearbox_labels' , 'notRepairedDa
mage_labels' , 'model_labels' , 'brand_labels' , 'fuelType_labels' , 'vehicleType_labels'], "values":
[userInput]]}]
    response_scoring = requests.post('https://us-south.ml.cloud.ibm.com/ml/v4/deployments/b0df73c1-
d3dd-4e66-8f0d-90534cf3fe4a/predictions?version=2022-11-14', json=payload_scoring,
    headers={'Authorization': 'Bearer ' + mltoken})
    predictions = response_scoring.json()
    return predictions['predictions'][0]['values'][0][0]

@app.route("/y_predict", methods=['GET', 'POST'])
def y_predict():
    if 'user' not in session:
        return redirect('/auth')

    regyear = int(request.form['regyear'])
    powerps = float(request.form['powerps'])
    kms = float(request.form['kms'])
    regmonth = int(request.form.get('month'))
    gearbox = request.form['gearbox']
    damage = request.form['dam']
    model = request.form.get('modeltype')
    brand = request.form.get('brand')
    fuelType = request.form.get('fuel')
    vehicletype = request.form.get('vehicletype')

    new_row = {'yearOfRegistration': regyear, 'powerPS': powerps, 'kilometer': kms, 'monthOfRegistration':
regmonth,
               'gearbox': gearbox, 'notRepairedDamage': damage, 'model': model, 'brand': brand, 'fuelType':
fuelType, 'vehicleType': vehicletype}
    new_df = pd.DataFrame(columns=['vehicleType', 'yearOfRegistration', '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].fit(np.load(str('classes'+i+'.npy'), allow_pickle=True))
    tr = mapper[i].transform(new_df[i])
    new_df.loc[:, i+'_'+labels] = pd.Series(tr, index=new_df.index)

labeled = new_df[['yearOfRegistration', 'powerPS', 'kilometer',
                  'monthOfRegistration']+['x+'+_labels' for x in labels]]
X = labeled.values
res = predictFromDeploymentModel(list(X[0]))
# y_prediction = model_rand.predict(X)

data = [{
    'model': model,
    'brand': brand,
    'vehicle': vehicletype,
    'price': res
}]

user = dict(db.child('users').get().val())[session['user']]['localId']]
if(user['history']):
    user['history'].extend(data)
    db.child('users').child(session['user']]['localId']).child('history').set(user['history'],
session['user']]['idToken'])
else:
    db.child('users').child(session['user']]['localId']).child('history').set(data, session['user']]['idToken'])

return render_template('result.html', price="{:.2f}$".format(res))

if __name__ == '__main__':
    app.run(host='localhost', port=3001)

```

8. TESTING

8.1 TEST CASES

Sprint-1

MODEL USED = RANDOM FOREST REGRESSION MODEL

MAE (MEAN ABSOLUTE ERROR) – 1655.53

```
from sklearn.metrics import mean_absolute_error  
  
print(mean_absolute_error(Y_test, y_pred))  
  
1655.534681561534
```

MSE (MEAN SQUARED ERROR) –11832644.33

```
from sklearn.metrics import mean_squared_error  
  
print(mean_squared_error(Y_test, y_pred))  
  
11832644.335139675
```

RMSE (ROOT MEAN SQUARED ERROR) –3439.86

```
from sklearn.metrics import mean_squared_error  
  
root_mean_squared_error = mean_squared_error(Y_test, y_pred, squared=False)  
print(root_mean_squared_error)  
  
3439.861092419238
```

R2 SCORE – 0.82

```
from sklearn.metrics import r2_score  
  
print(r2_score(Y_test, y_pred))  
  
0.8191322832483275
```


Sprint-2

[illegible]

Sprint-3

[illegible]

Sprint-4

[illegible]

8.2 USER ACCEPTANCE TESTING

2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

| Resolution | Severity 1 | Severity 2 | Severity 3 | Severity 4 | Subtotal |
|----------------|------------|------------|------------|------------|----------|
| By Design | 6 | 3 | 2 | 2 | 13 |
| Duplicate | 1 | 0 | 3 | 0 | 4 |
| External | 2 | 2 | 0 | 1 | 5 |
| Fixed | 7 | 3 | 4 | 5 | 19 |
| Not Reproduced | 0 | 0 | 1 | 0 | 1 |
| Skipped | 0 | 0 | 1 | 1 | 2 |
| Won't Fix | 0 | 5 | 2 | 1 | 8 |
| Totals | 16 | 13 | 13 | 10 | 52 |

3. Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

| Section | Total Cases | Not Tested | Fail | Pass |
|---------------------|-------------|------------|------|------|
| Print Engine | 5 | 0 | 0 | 5 |
| Client Application | 9 | 0 | 0 | 9 |
| Security | 3 | 0 | 0 | 3 |
| Outsource Shipping | 1 | 0 | 0 | 1 |
| Exception Reporting | 2 | 0 | 0 | 2 |
| Final Report Output | 4 | 0 | 0 | 4 |
| Version Control | 2 | 0 | 0 | 2 |

9. RESULTS

9.1 PERFORMANCE METRICS

MODEL USED = RANDOM FOREST REGRESSION MODEL

MAE (MEAN ABSOLUTE ERROR) – 1655.53

```
from sklearn.metrics import mean_absolute_error  
  
print(mean_absolute_error(Y_test, y_pred))  
  
1655.534681561534
```

MSE (MEAN SQUARED ERROR) –11832644.33

```
from sklearn.metrics import mean_squared_error  
  
print(mean_squared_error(Y_test, y_pred))  
  
11832644.335139675
```

RMSE (ROOT MEAN SQUARED ERROR) –3439.86

```
from sklearn.metrics import mean_squared_error  
  
root_mean_squared_error = mean_squared_error(Y_test, y_pred, squared=False)  
print(root_mean_squared_error)  
  
3439.861092419238
```

R2 SCORE – 0.82

```
from sklearn.metrics import r2_score  
  
print(r2_score(Y_test, y_pred))  
  
0.8191322832483275
```

10. ADVANTAGES & DISADVANTAGES

ADVANTAGES:

- Common People will get the most use from this. Both people including those who want to sell their cars and also buy used cars can know the best price.
- Car Dealers are the next set of people who can benefit from it. They can use this service and will get to know proper pricing which will help them to set a competitive price for a car.
- All the online services used for selling and buying cars can use this service to give a fair price for a car.

DISADVANTAGES:

- The accuracy & speed of the performance limits the model. Although this can be improved overtime.
- Predicted price accuracy depends on the accuracy of dataset used.
- End user still have to verify with other sources and may use the predicted prices as only an estimation.

11. CONCLUSION

Car Resale Value Prediction is a useful project that has many advantages, especially to those who are looking to buy used cars or sell old cars for justified price. This can also help car dealers and also online services to better run their business with competitive prices.

Also, as an improvement, we can feed better and bigger dataset to improve its accuracy, test the model with different combinations of ML algorithms and find the one that best suits it and increase the speed of prediction with efficient solutions.

Since the model can be hosted online, it can be used by anyone, anywhere and at any time. This level of ease of access makes it even more useful. In conclusion, it is a useful project which will continue to evolve with future ML algorithms.

12. FUTURE SCOPE

The good thing about any ML models is, it can always be enhanced in a better way. As with CRVP model, we can use the next great ML algorithms for greater improvement in performance, use bigger and better datasets and make the model's prediction time lesser.

Instead of stopping with cars, we can also expand it to all vehicle types. The process remains the same with the exception of dataset. This will make it even more useful and won't be limited to just cars.

Another part that can be improved is its ease of access. Currently we can host it in separate website. Instead of it being separate, we can integrate it with existing online services where buying and selling old cars are provided. This saves the end users time immensely.

13. APPENDIX

GITHUB LINK:

<https://github.com/IBM-EPBL/IBM-Project-12077-1659369468>

PROJECT DEMO LINK:

<https://drive.google.com/file/d/14MJhLObGHL5Zrp6Gu-JZ421qjdAGLy36/view?usp=sharing>

APPLICATION HOSTED URL:

<https://crvp-anxious-fox-py.mybluemix.net/>