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CAR RESALE VALUE PREDICTION

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1. INTRODUCTION

1.1 ABSTRACT

Predicting the price of used cars is one of the significant and interesting areas of analysis. As an increased demand in thesecond-hand car market, the business for both buyers and sellers has increased. For reliable and accurate prediction it requires expert knowledge about the field because of the price of the cars dependenton many important factors. This paper proposed a supervised machine learning model using KNN (K Nearest Neighbor) regression algorithm to analyze the price of used cars . Through this experiment, the data was examined with different trained and test ratios. As a result, the accuracy of the proposed model is around 85% and is fitted as the optimized model. The predictions are then evaluated and compared in order to find those which provide the best performances. A seemingly easy problem turned out to be indeed very difficult to resolve with high accuracy. All the four methodsprovided comparable performance. In the future, we intend to use more sophisticated algorithms to make the predictions . 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 across cities in the United States. Our results show that Random Forest model and K-Means clustering with linear regression yield the best results, but are compute heavy. Conventional linear regression also yielded satisfactory results, with the advantage of a significantly lower training time in comparison to the aforementioned methods

2. LITERATURE SURVEY

2.1 EXISTING PROBLEM

Several studies and related works have been done previously to predict used car prices around the world using different methodologies and approaches, with varying results of accuracy from 50% to 90%. In (Pudaruth, 2014) the researcher proposed to predict used car prices in Mauritius, where he applied different machine learning techniques to achieve his results like decision tree, K-nearest neighbours, Multiple Regression and Naive Bayes algorithms to predict the used cars prices, based on historical data gathered from the newspaper.

Achieved results ranged from accuracy of 60-70 percent, the author suggested using more sophisticated models and algorithms to make the evaluation, with the main weakness off the decision tree and naive Bayes that it is required to discretize the price and classify it which accrue to more inaccuracies. Moreover, he suggested a larger set of data of data to train the models hence the data gathered was not sufficient.

(Monburinon, et al., 2018) Gathered data from a German e-commerce site that totalled to 304,133 rows and 11 attributes to predict the prices of used car using different techniques and measured their results using Mean Absolute Error (MEA) to compare their results. Same training dataset and testing dataset was given to each model. Highest results achieved was by using gradient boosted regression tree with a MAE of 0.28, and MEA of 0.35 and 0.55 for mean absolute error and multiple linear regression respectively. Authors suggested adjusting the parameters in future works to yield better results, as well as using one hot encoding instead of label encoding for more realistic data interpretations on categorical data.

(Gegic, Isakovic, Keco, Masetic, & Kevric, 2019) from the International Burch University in Sarajevo, used three different machine learning techniques to predict used car prices. Using data scrapped from a local Bosnian website for used cars totalled at 797 car samples after pre-processing, and proposed using these methods: Support Vector Machine, Random Forest and Artificial Neural network. Results have shown using only one machine learning algorithm achieved results less than 50%, whereas after combing the algorithms with pre calcification of prices using Random Forest, results with accuracies up to 87.38% was recorded.

(Noor & Jan, 2017) were able to achieve high level of accuracy using Multiple linear regression models to predict the price of cars collected from used cars website in Pakistan called Pak Wheels that totalled to 1699 records after pre-processing, and where able to achieve accuracy of 98%, this was done after reducing the total amount of attributes using variable selection technique to include significant attributes only and to reduce the complexity of the model.

(K.Samruddhi & Kumar, 2020) Proposed using Supervised machine leaning model using K-Nearest Neighbour to predict used car prices from a data set obtained from Kaggle containing 14 different attributes, using this method accuracy reached up to 85% after different values of K as well as Changing the percent of training data to testing data, expectedly when increasing the percent of data that is tested better accuracy results are achieved. The model was also cross validated with 5 and 10 folds by using K fold method.

(Gongqi, Yansong, & Qiang, 2011) proposed using Artificial Neural Network (ANN) through a combined method of BP neural network and nonlinear curve fit and have achieved accurate value prediction with a feasible model.

(Listiani, 2009) used Support Vector Machines to evaluate leased cars prices, results have shown that SVM is far more accurate in large dataset with high dimensional data than Multiple linear regression. Whereas the computation Multiple linear regression can take several minutes and the SVM would take up to a day to compute the results. Multiple linear regression may be simple, but SVM is far more accurate. Moreover, the study includes Samples with up to 178 attributes which is far more than the proposed variable in our study, hence the use of multiple linear regression may be more suitable in our case.

(Kuiper, 2008) Collected data from General Motor of cars that are produced in 2005, where he as well used variable selection technique to include the most relevant attributes in his model to reduce the complexity of the data. He proposed used Multivariate regression model that would be more suitable for values with numeric format.

In order to predict the price of used cars, researchers (Nabarun Pal, 2018) used a supervised learning method known as Random Forest. Kaggle's dataset was used as a basis for predicting used car prices. In order to determine the price impact of each feature, careful exploratory data analysis was performed. 500 Decision Trees were trained with Random Forests. It is most commonly used for classification, but they turned it into a regression model by transforming the problem into an equivalent regression problem. Using experimental results, it was found that training accuracy was 95.82%, and testing accuracy was 83.63%. By selecting the most correlated features, the model can accurately predict the car price.

In light of the number of works that have been done in this field, another group of researchers (Jian Da Wu, 2017) conducted research on this topic and tried to develop a system that consists of three components: a data acquisition system, a price forecasting algorithm, and a performance analysis. Due to its adaptive learning capability, a conventional artificial neural network (ANN) with a back-propagation network is compared to the proposed ANFIS. In the ANFIS, qualitative fuzzy logic approximation as well as adaptive neural network capabilities are included. Using ANFIS as an expert system in predicting used car prices showed better results in the experiment. Using GUI, the consumer can get accurate and convenient

information about used cars' purchasing prices, and experiments proved that the proposed system could provide accurate and convenient price forecasting.

Hence, from all literature review it is concluded that used cars price prediction is an important topic which is the area of many researchers nowadays. So far, the best achieved accuracy is 83.63% on kaggle’s dataset using random forest technique. The researchers have tested multiple regressors and final model is regression model using linear regression.

Method :

The topic such as this can be assessed with mathematical models derived from quantitative data. A multiple variable regression can analyze the data by assessing the role each independent variable plays in determining the dependent variable (in this case, resale value). Significance can also be assessed by observing the p-values for each variable. The use of a statistical model will aide in making a claim on this, and to identify some of the major contributors to resale value in automobiles.

Data Collection :

The data used for this regression will be quantitative in nature. The sources of data are what someone would expect for used car information. Four sources that are used include Kelly Blue Book, Edmunds, a government fuel economy resource, and Car and Driver. Kelly Blue Book and Edmunds will both serve as data sources, with each source providing different aspects of the independent variables used. With the cooperation of these sources, data regarding price of a car-including new and used-with the respective age, mileage, make, condition, miles per gallon, safety ratings, and hybrid technology information will be obtained. These variables will allow for a regression to be run and an equation to be estimated.

Expected Outcomes :

Before I can make predictions regarding the influence each variable will have on resale value, a review of prior research and literature is appropriate. This will allow me to make a more confident prediction as well as confirm which variables are needed to produce a strong equation that explains much of the variations in vehicle depreciation. An expected equation could look like this:

Resale Value (DV) = Intercept- B3(Age) - B4(Mileage) + Bl(Make) + B2(MPG) + B5(Hybrid Tech)

2.2 REFERENCES

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[5] https://ieeexplore.ieee.org/Xplore/home.jsp

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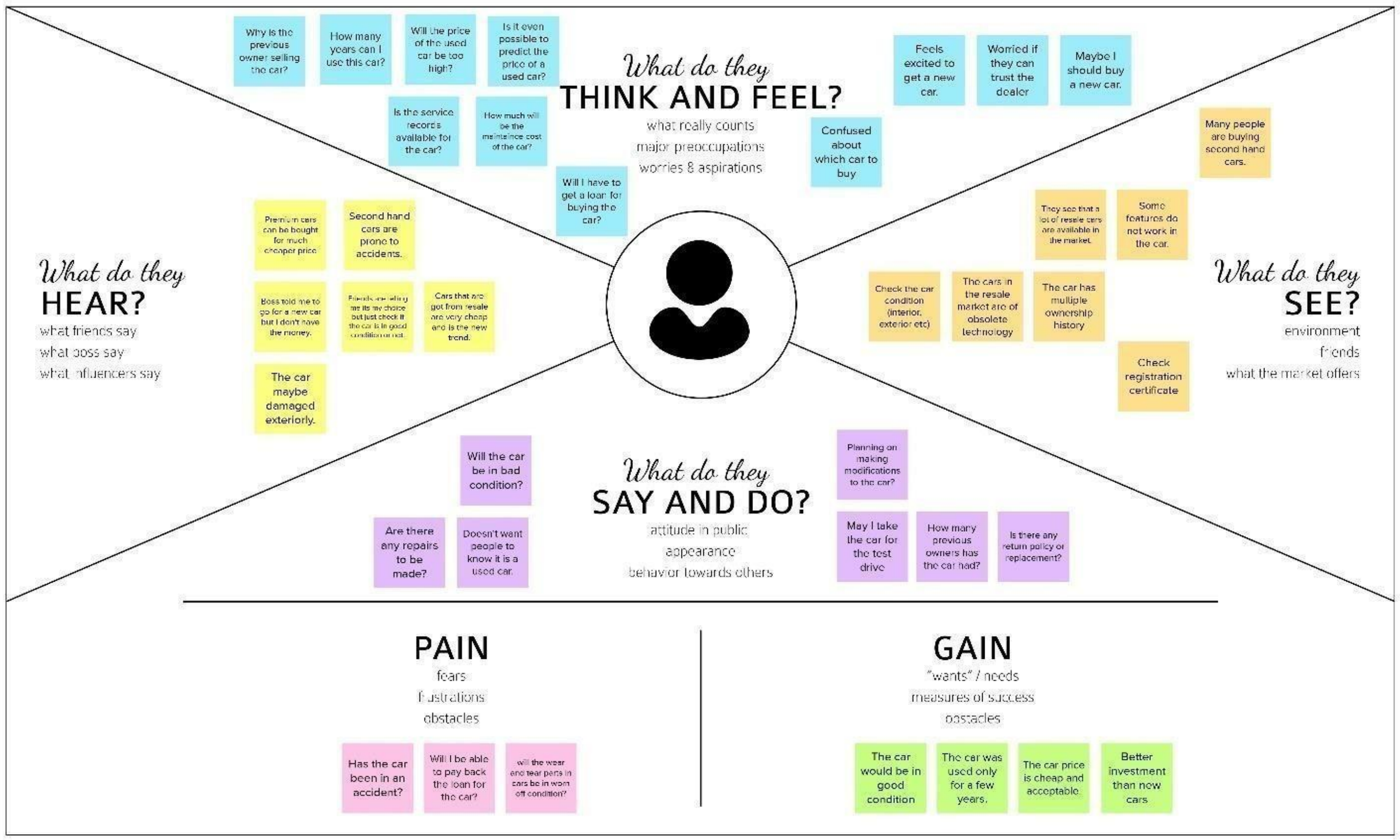
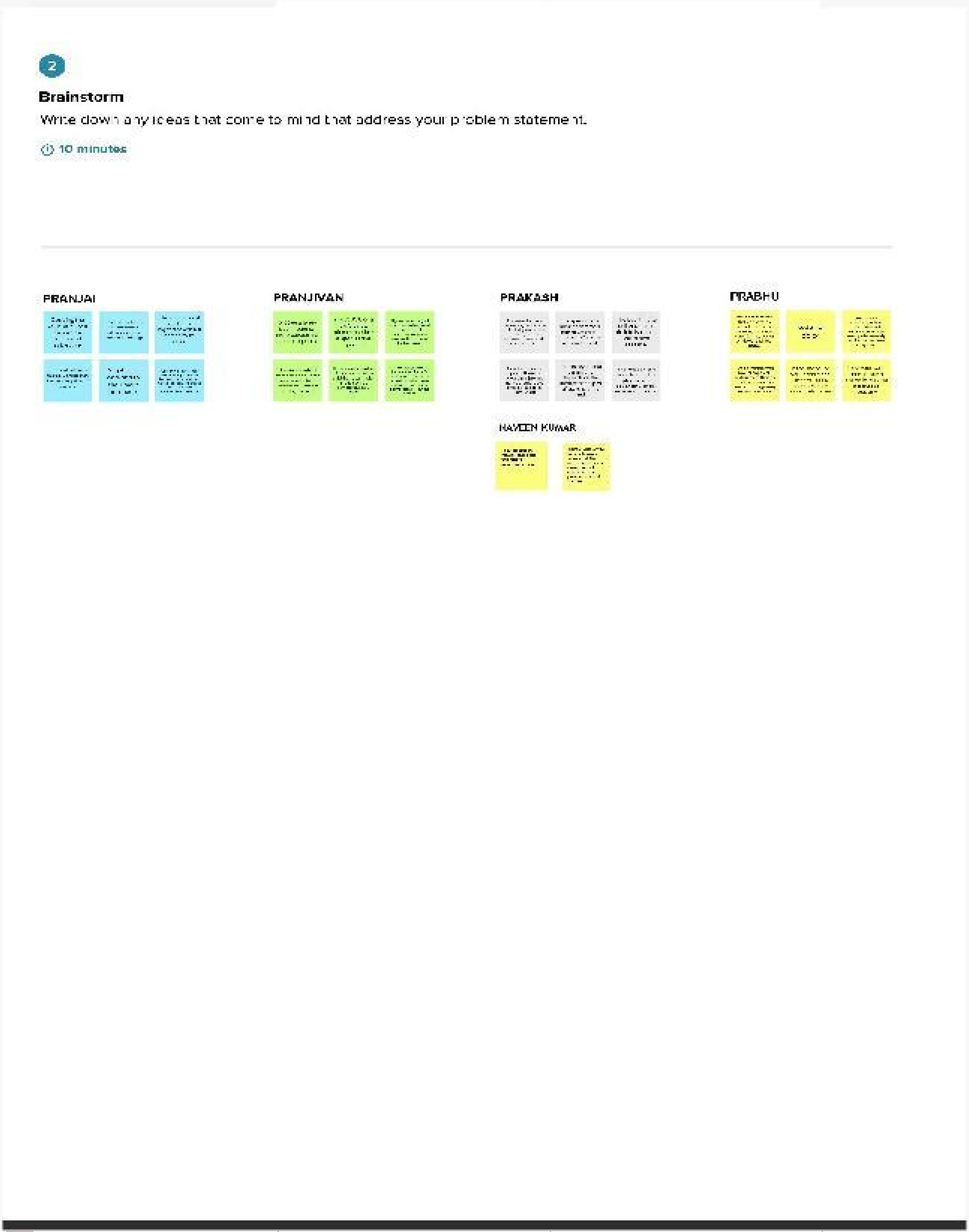
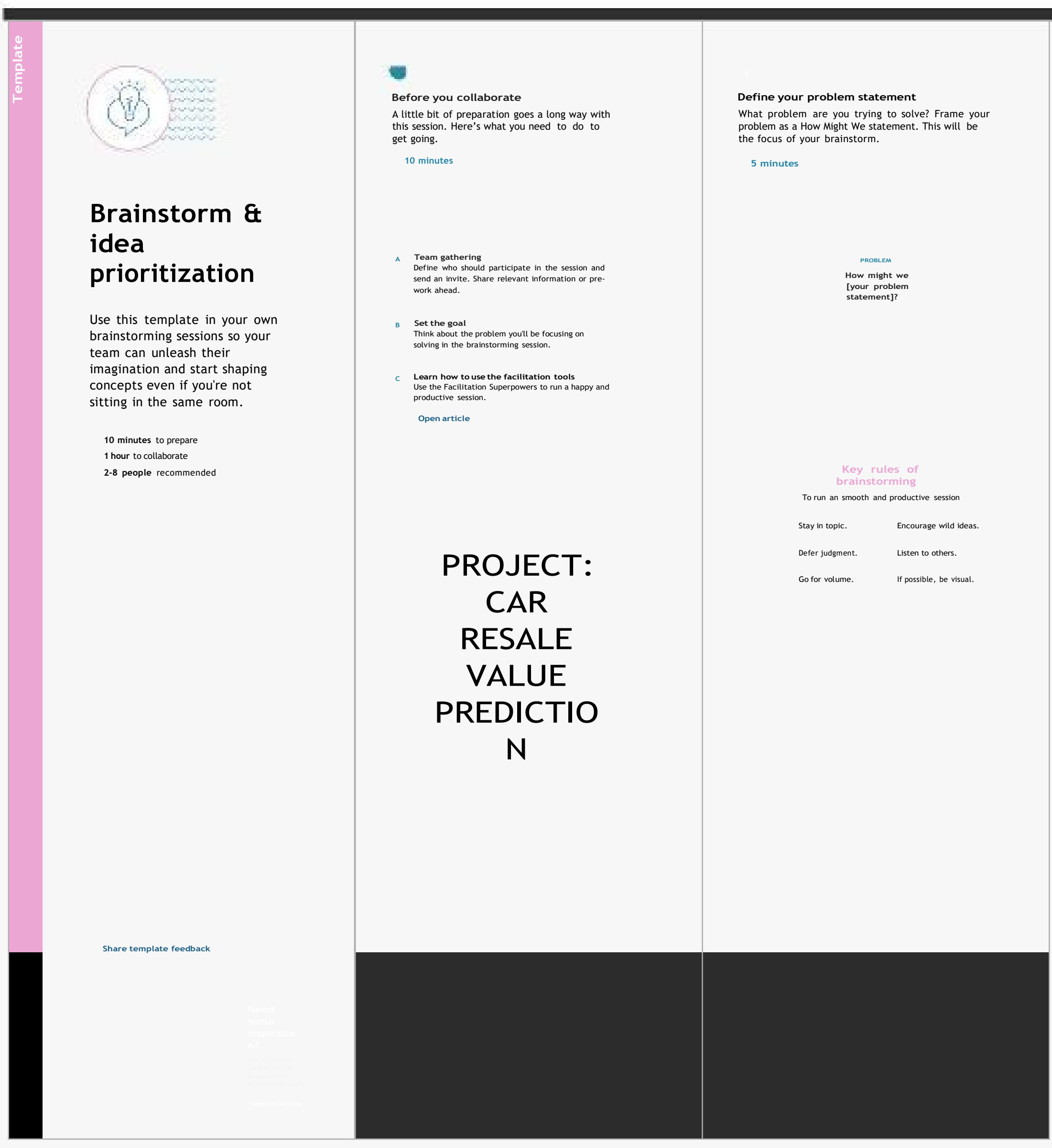
3. IDEATION PHASE

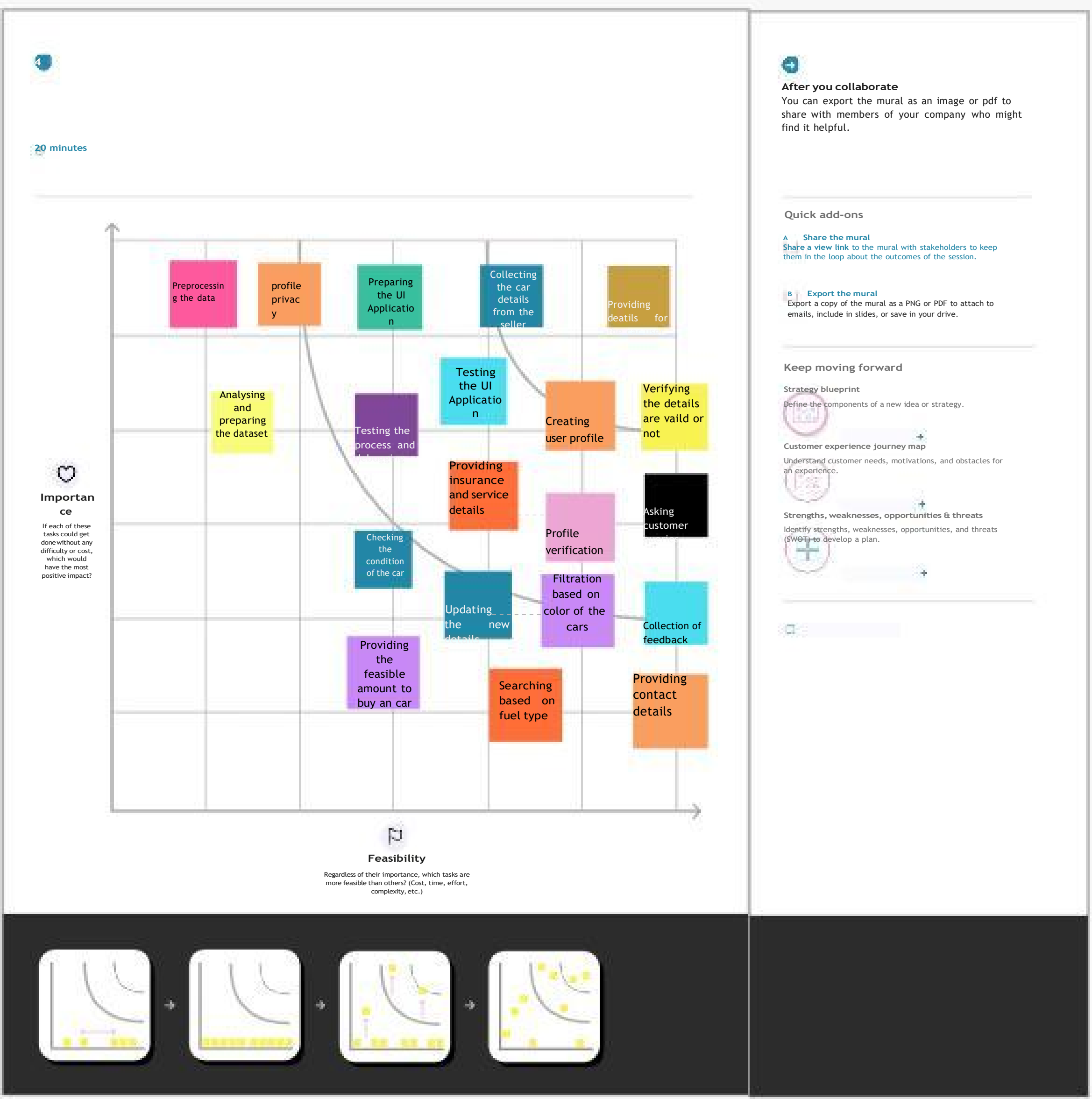
3.1 EMPATHY MAP



3.2 BRAINSTROMING







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)	I am a customer. I'm trying to buy a second hand car. But I cannot estimate the price of the car. Because I need a trustworthy platform to predict the price of the car. Which makes me feel Frustrated and Confused.
2.	Idea / Solution description	Deciding whether a used car is worth the posted price when you see listings online can be difficult. Several factors, including mileage, make, model, year, etc. can influence the actual worth of a car. From the perspective of a seller, it is also a dilemma to price a used car appropriately [2-3]. Based on existing data, the aim is to use machine learning algorithms to develop models for predicting used car prices.
3.	Novelty / Uniqueness	As there are so many ongoing experiments that use statistical approaches and some traditional methods to focus on predicting item sales. Most researches have experimented by taking single algorithm to predict sales. In this thesis Machine Learning algorithms such as Simple Linear Regression, Support Vector Regression, Gradient Boos4ng algorithm, and Random Forest Regression are considered for predict the most effective metrics such as accuracy, mean absolute error, and max error are considered for measuring algorithm efficiency. This method will be very beneficial in the future for advanced item sales forecasting.
4.	Social Impact / Customer Satisfaction	Predicting prices of a used car is a challenging task because of a high number of features and parameters that should be considered to generate accurate results. The first and foremost step is data gathering and pre-processing data. Therefore the results generated are highly accurate.so the customer was satisfied.
5.	Business Model (Revenue Model)	Deciding whether a used car is worth the posted price when you see listings online can be difficult. Several factors, including mileage,

		make, model, year, etc. can influence the actual worth of a car. From the perspective of a seller, it is also a dilemma to price a used car. Based on existing data, the aim is to use machine learning algorithms to develop models for predicting used car prices.
6.	Scalability of the Solution	We started with understanding the use case of machine learning in the Automotive industry and how machine learning has transformed the driving experience. Moving on, we looked at the various factors that affect the resale value of a used car and performed exploratory data analysis (EDA). Further, we build a Random Forest Regression model to predict the resale value of a used car. We could have also used simpler regression algorithms like Linear Regression and Lasso Regression. Still, we need to make sure there are no outliers in the dataset before implementing them. Pair plots and scatter plots help visualize the outliers

3.4 PROBLEM SOLUTION FIT

Project Title: Car Resale Value Prediction

Project Design Phase-I - Solution Fit Template

Team ID: PNT2022TMID00778

Define CS, fit into CC

1. CUSTOMER SEGMENT(S) CS

Who is your customer?
i.e. working parents of 0-5 y.o. kids

Dealers who sell used cars and customers who buy them.

6. CUSTOMER CONSTRAINTS CC

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.

Some constraints that the customers face may be worried about the condition of the car, is too expensive and so on.

5. AVAILABLE SOLUTIONS AS

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

Customers can be assured about the condition of the car and can be given a test drive, then the customer may be more inclined to buy the car.

Explore AS, differentiate

Focus on J&P, tap into BE, understand RC

2. JOBS-TO-BE-DONE / PROBLEMS J&P

Which jobs-to-be-done (or problems) do you address for your customers? There could be more than one; explore different sides.

We help dealers and customers predict the price of a used car.

9. PROBLEM ROOT CAUSE RC

What is the real reason that this problem exists?
What is the back story behind the need to do this job?
i.e. customers have to do it because of the change in regulations.

The root cause may be because the customer doesn't want to make a decision that he might regret later because he is the one using the car.

7. BEHAVIOUR BE

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)

The Customer may spend some time researching the prices of used cars and may also see if the dealer has any reviews.

Focus on J&P, tap into BE, understand RC

Identify strong TR & EM

3. TRIGGERS TR

What triggers customers to act? i.e. seeing their neighbour installing solar panels, reading about a more efficient solution in the news.

People around them buying used cars.

4. EMOTIONS: BEFORE / AFTER EM

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.

Customers feel frustrated because they don't how much a used car is worth.

10. YOUR SOLUTION SL

If you are 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 behaviour.

Our solution is that we will predict the ideal price for the car based on a lot of research and data and give the customer the most affordable approach.

8. CHANNELS of BEHAVIOUR CH

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.

1. The customer can talk see the car and compare it with other cars and offers

2. The customer can see if the car is really in good condition and if it suits their needs.

Identify strong TR & EM

3.REQUIREMENT ANALYSIS
3.1. Functional Requirements

Following are the functional requirements of the proposed solution.

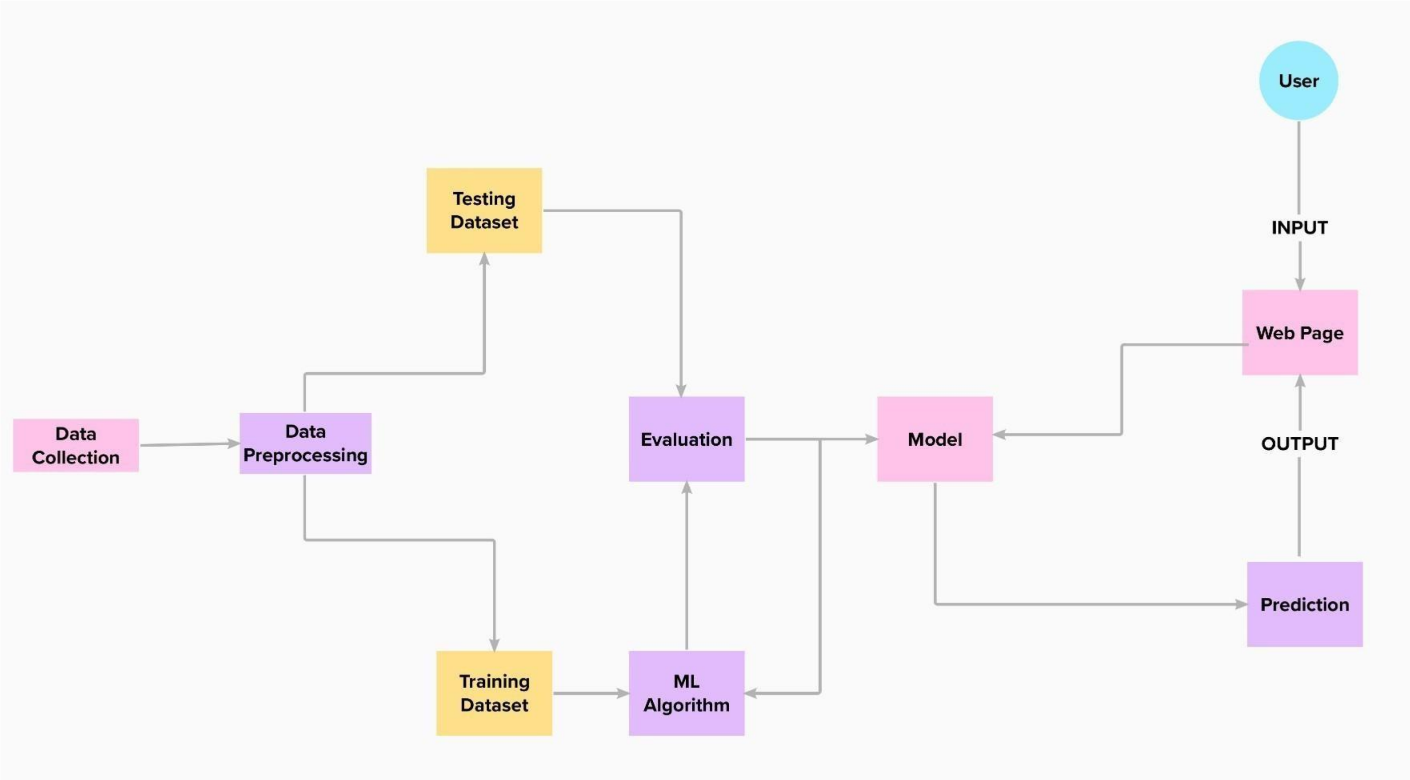
FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	User Profile	User information Bank details
FR-4	Database	Car database Customer database
FR-5	Features and Technology	Performance of the car Fuel capacity,mileage etc.
FR-6	Feedback	Feedback through Form Feedback through Gmail Feedback through LinkedIN

3.2. Non-functional Requirements

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

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	Great UI (user interface), Quick adaptation of user.
NFR-2	**Security**	Aware of fraud and scams, Protect your password and account personal details.
NFR-3	**Reliability**	Rate of occurrence of failure is less, Failure free.
NFR-4	**Performance**	Perform value and correct prediction value, The landing page must support several users must provide 5 second or less response time
NFR-5	**Availability**	Uninterrupted services must be available all time except the time of server updation.
NFR-6	**Scalability**	that can handle any amount of data and perform many computations in a cost-effective and timesaving way to instantly serve millions of users residing at global locations.

5.Project Design Phase-I
5.1.Data Flow Diagram & User Stories



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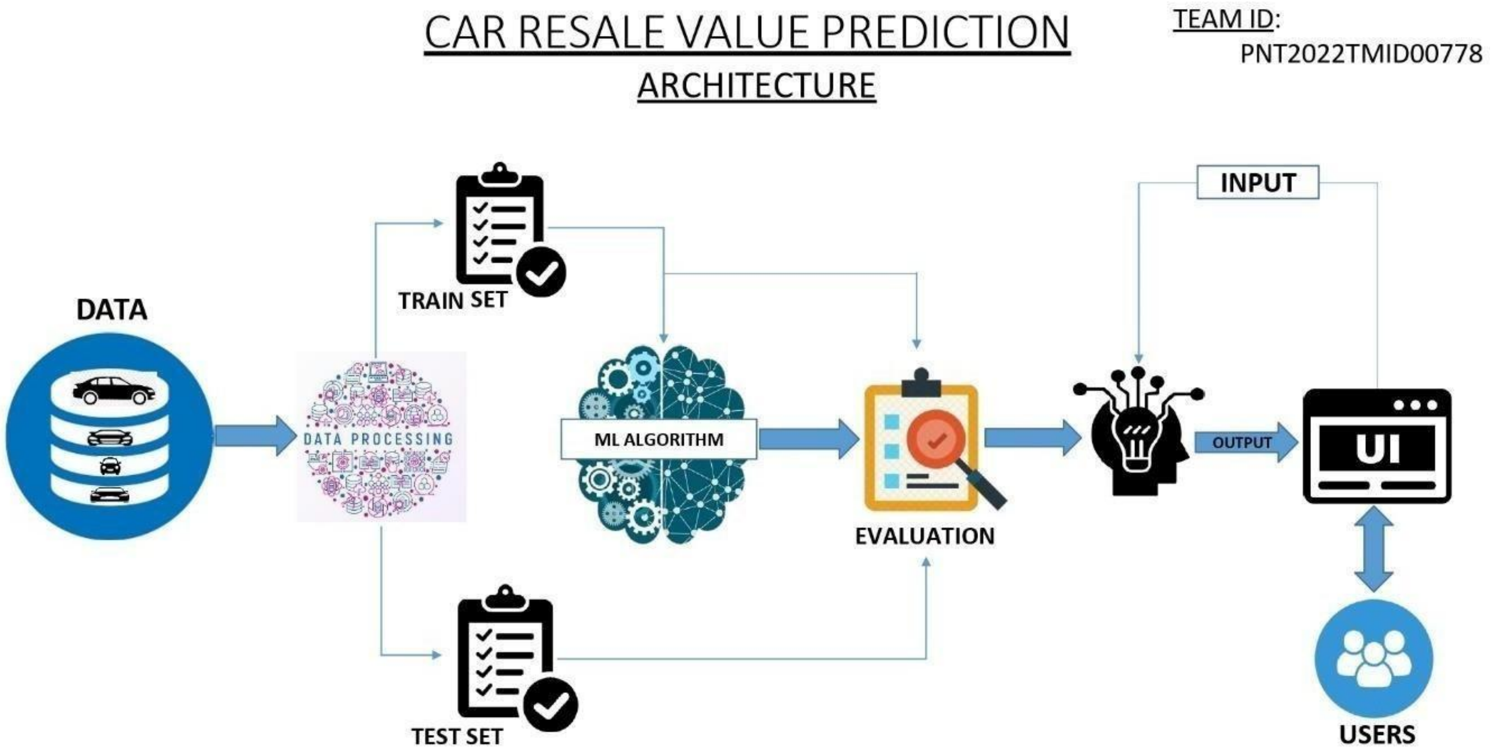
User Stories

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 theapplication.	I can receive my car resalevalue	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 theapplication.	I can receive my car resalevalue	High	Sprint-1

5.2. SOLUTION ARCHITECTURE



5.2.1. .Technology Architecture

Technical Architecture:

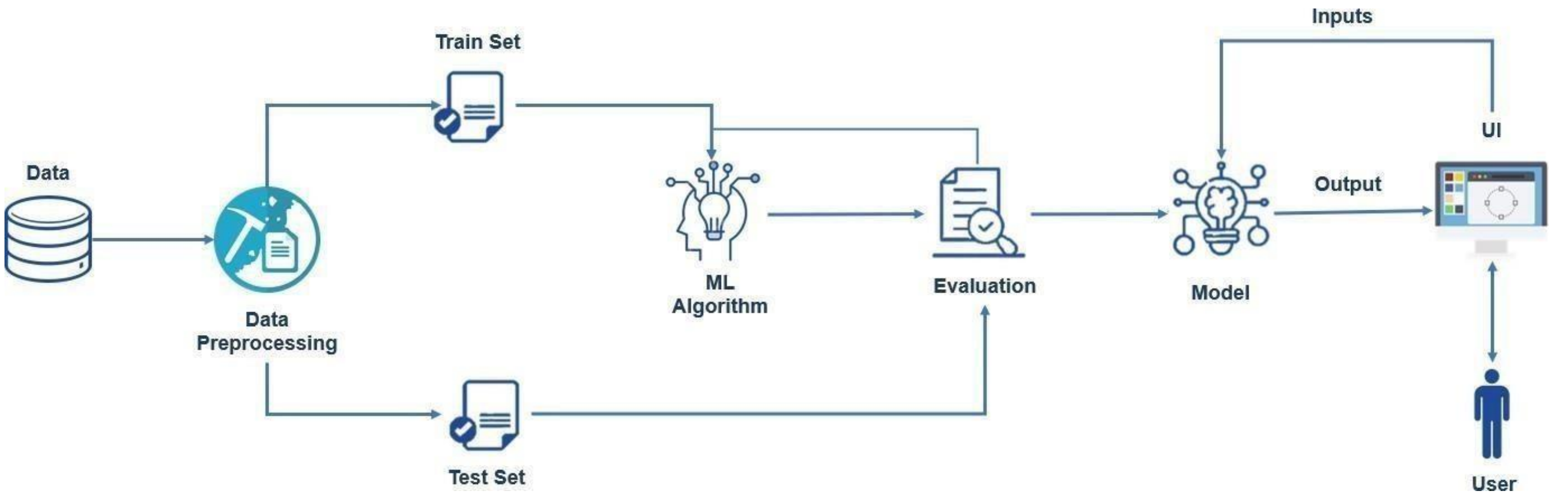


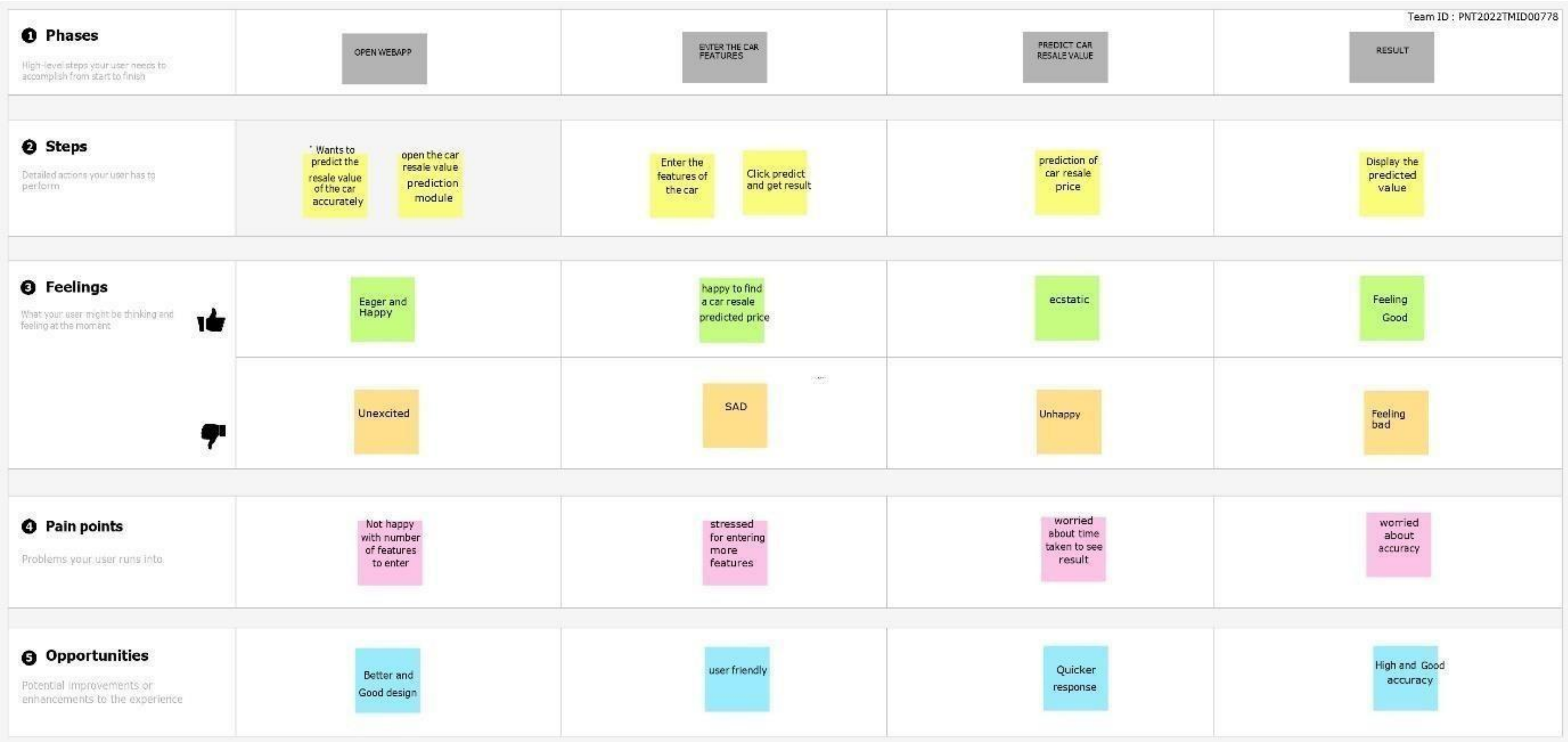
Table-1 : Components & Technologies:

S.NO	Component	Description	Technology
1.	User Interface	How user interacts with application e.g.Web UI, Mobile App, Chatbot etc.	HTML, CSS, JavaScript / Angular Js /React Js etc.
2.	Data Pre - Processing	Checking if the given data has any missing values,duplicate values, outliers and other noises that can affect the performance of the model.	Python, Pandas, Numpy, Matplotlib,Seaborn.
3.	Splitting the DataSet	The data set is split into test and train data for themodel.	Python, Sk – Learn
4.	Predicting the values	After the model is trained using various machine learning algorithms, some code is written to predict the value of a used car.	Python, Sk - Learn
5.	Database	The data is stored in the database.	MySQL, NoSQL, etc.
6.	Cloud Database	Database Service on Cloud	IBM DB2, IBM Cloudant etc.
7.	File Storage	File storage requirements	IBM Block Storage or Other StorageService or Local Filesystem
8.	Machine Learning Model	There are various Machine Learning Models that can be used like Linear Regression, Multi-Linear Regression, Decision Tree, Random Forest, SVMetc.	Python, Sk – Learn

Table-2: Application Characteristics:

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	Anaconda Navigator, Jupyter Notebook, Python,Flask.	Python
2.	Security Implementations	Aware of Fraud and Scams, Protection of password and account details.	e.g. SHA-256, Encryptions, IAM Controls, OWASP etc.
3.	Scalable Architecture	Whether demand increases gradually or abruptly, scalable web architecture can accommodate any load without compromising the application's integrity.	Microservies, Progressive Web Apps(PWA)
4.	Availability	Availability of application like load balancers,distributed servers etc	IBM Cloud
5.	Performance	Good Performance is expected.	IBM Cloud

5.3. CUSTOMER JOURNEY



6. PROJECT PLANNING PHASE

6.1. Sprint Planning &Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Dataset reading and Pre processing	USN-1	Cleaning the dataset and splitting to dependentand independent variables	2	High	Pranjai V
Sprint-2	Building the model	USN-2	Choosing the appropriate model for building and saving the model as pickle file	1	High	PranjivanV
Sprint-3	Application building	USN-3	Using flask deploying the ML model	2	Medium	Prakash R
Sprint-4	Train the model in IBM	USN-4	Finally train the model on IBM cloud and deploy the application	2	Medium	Prabhu sai D Naveen Kumar B

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	15	5 Days	24 Oct 2022	29 Oct 2022	15	29 Oct 2022
Sprint-2	15	5 Days	31 Oct 2022	05 Nov 2022	15	05 Nov 2022
Sprint-3	15	5 Days	07 Nov 2022	12 Nov 2022	15	12 Nov 2022
Sprint-4	15	5 Days	14 Nov 2022	19 Nov 2022	15	19 Nov 2022

Velocity:

We have a 5-day sprint duration, and the velocity of the team is 15 (points per sprint). The team’s average velocity (AV) per iteration unit (storypoints per day)

Actual Velocity = Sprint Duration/Velocity = 15/5 = 3

Burndown Chart:

A burn down chart is a graphical representation of work left to do versus time. It is often used in agile software development methodologies suchas Scrum. However, burn down charts can be applied to any project containing measurable progress over time

6.2. Sprint Delivery Schedule

Activity Number	Activity Name	Detailed Activity Description	Assigned To	Status / Comments
1	Preparation Phase	• Access the resources (courses) in projectdashboard • Access the guided project workspace • Create GitHub account & collaborate withProject Repository in project workspace • Set-up the Laptop / Computers based on the prerequisites for each technology track	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	It refers to done the listed activitiesi n the preparati on phase and done Prerequisi t es, Registrati o n, Environm e nt setup
2	Ideation Phase	• Literature survey on the selected project & Information Gathering • Preparation of Empathy Map Canvas to capture the user Pains & Gains Prepare listof problem statements • List the ideas by organizing thebrainstorming session and prioritize the top3 ideas based on the feasibility & importance	Pranjai Pranjivan Prakash Prabhu sai Naveen kumar ,	The activities in ideation phase refers to when gathering the ideafor project information and picturize in Empathy map
3	Project Design Phase -I			
3.1	Proposed Solution	Preparation of proposed solution document, which includes the novelty, feasibility of idea,business model, social impact, scalability of solution	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	The solution for the project is prepareda s a standard document structure

				from Team members

3.2	Problem SolutionFit	Prepared problem is analyzed and make effectivesolutions for the problem	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	
3.3	Solution Architecture	Prepare an architecture for solution	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	Suitable block diagram template used to prepare Solution architecture
4	Project Design Phase -II			
4.1	Requirement Analysis	Prepare the Functional Requirement and NonFunctional Document	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	Listing of functional and non-functional requirements of project.
4.2	Customer Journey	Preparation of customer journey maps tounderstand the user interactions & experiences with the application (entry to exit)	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	Customer journeymap prepared by suitable template by team members.
4.3	Data Flow Diagrams	Prepare a Data Flow Diagram for Project use level0(Industry Standard)	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	Use suitable data flow diagram rulesand standards to prepare level 0 DFD
4.4	Technology Architecture	Prepare Technology Architecture of the solution	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	

5	Project Planning Phase			
5.1	Milestones & Tasks	Prepare Milestone & Activity List	Pranjai, Pranjivan Prakash	

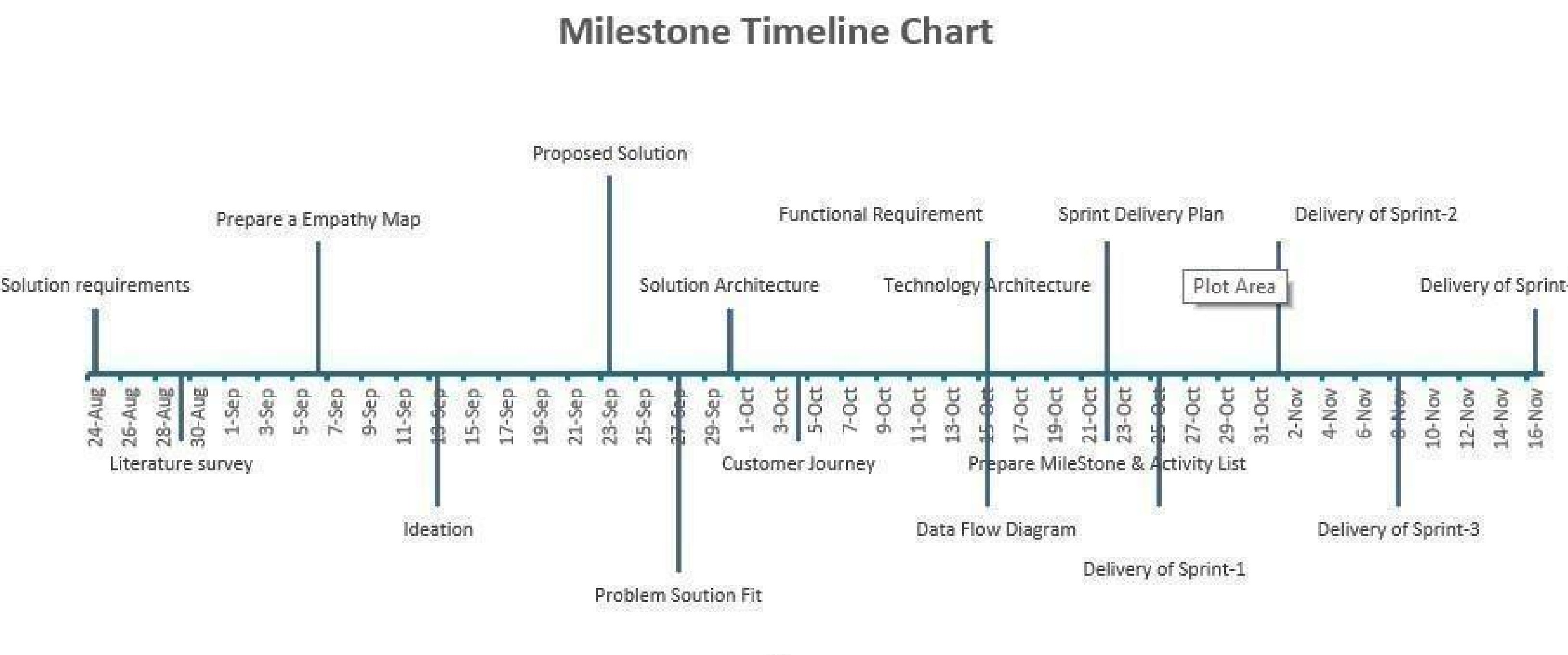
			Prabhu sai Naveen kumar	
5.2	Sprint Schedules	Prepare Sprint Delivery Plan	Pranjai Pranjivan Prakash Prabhusai Naveen kumar	
6	Project Development Phase			
6.1	Coding & Solutio ning	Sprint-1 Delivery: Develop the Code, Test andpush it to GitHub.	On Progress	
6.2	Acceptance Testing	• Sprint-2 Delivery: Develop the Code, Testand push it to GitHub. • Sprint-3 Delivery: Develop the Code, Testand push it to GitHub.	On Progress	
6.3	Perform ance Testing	Sprint-4 Delivery: Develop the Code, Test andpush it to GitHub.	On Progress	

Milestone:

When project begins then it is expected that project related activities must be initiated. In project planning, series of milestones must be established. Milestone can be defined as recognizable endpoint of software project activity. At each milestone, report must be generated.

Milestone is distinct and logical stage of the project. It is used as signal post for project start and end date,need for external review or input and for checking budget, submission of the deliverable, etc. It simply represents clear sequence of events that are incrementally developed or build until project gets successfully completed. It is generally referred to as task with zero-time duration because they are used tosymbolize an achievement or point of time in project. It helps in signifying change or stage in development.

6.3. Reports from JIRA



7. CODING & SOLUTIONING

7.1. FEATURE 1

Importing Required Libraries

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings warnings.filterwarnings('ignore')
```

Reading the Dataset

In [ ]:

```
df = pd.read_csv('autos.csv', parse_dates=['dateCrawled', 'dateCreated',
'lastSeen'], e
```

Cleaning the Dataset

In [ ]:

```
df.columns
```

Out[3]:

```
Index(['dateCrawled', 'name', 'seller', 'offerType', 'price',
       'abtest', 'vehicleType', 'yearOfRegistration', 'gearbox',
       'powerPS', 'model', 'kilometer', 'monthOfRegistration',
       'fuelType', 'brand', 'notRepairedDamage', 'dateCreated',
       'nrOfPictures', 'postalCode', 'lastSeen'],
      dtype='object')
```

In [ ]:

```
# Rearranging the Columns
df = df[['dateCrawled', 'name', 'seller', 'offerType', 'abtest', 'vehicleType',
'yearOfRegistration', 'gearbox', 'powerPS', 'model', 'kilometer',
'monthOfRegistration', 'fuelType', 'brand', 'notRepairedDamage', 'dateCreated',
'nrOfPictures', 'postalCode', 'lastSeen', 'price']]
```

In [ ]:

```
# Droping the Unwanted Columns
df.drop(columns= ['seller', 'offerType', 'nrOfPictures'], inplace = True)
```

In [ ]:

```
df.drop(columns= ['dateCrawled', 'dateCreated', 'lastSeen'], inplace = True)
```

Missing Values

In [ ]:

```
# Checking for Missing Values
df.isna().sum()
```

Out[6]:

```
name                     0
abtest                   0
vehicleType          37869
yearOfRegistration       0
gearbox              20209
powerPS                  0
model                20484
kilometer                0
monthOfRegistration      0
fuelType             33386
brand                    0
notRepairedDamage    72060
postalCode               0
price                    0
dtype: int64
```

In [ ]:

```
# Removing Missing Values df['vehicleType'].fillna(df['vehicleType'].mode()[0],
inplace = True) df['gearbox'].fillna(df['gearbox'].mode()[0], inplace = True)
df['model'].fillna(df['model'].mode()[0], inplace = True)
df['fuelType'].fillna(df['fuelType'].mode()[0], inplace = True)
df['notRepairedDamage'].fillna(df['notRepairedDamage'].mode()[0], inplace = True)
```

In [ ]:

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

Out[8]:

```
name                   0
abtest                 0
vehicleType            0
yearOfRegistration     0
gearbox                0
powerPS                0
model                  0
kilometer              0
monthOfRegistration    0
fuelType               0
brand                  0
notRepairedDamage      0
postalCode             0
price                  0
dtype: int64
```

Duplicate Values

In [

```
# Checking for Duplicates
df.duplicated().sum()
```

Out[9]:

```
4703
```

In [ ]:

```
# Removing Duplicates
df = df.drop_duplicates()
```

In [ ]:

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

Out[11]:

```
0
```

Label Encoding

In [ ]:

```
df.info()
```

```
<class
'pandas.core.frame.DataFrame'>
Int64Index: 366825 entries, 0 to
371527 Data columns (total 14
columns):
 #   Column              Non-Null  Count  Dtype
---  ------              --------------  -----
 0   name                366825 non-null object
 1   abtest              366825 non-null object
 2   vehicleType         366825 non-null object
 3   yearOfRegistration  366825 non-null  int64
 4   gearbox             366825 non-null  object
 5   powerPS             366825 non-null  int64
 6   model               366825 non-null  object
 7   kilometer           366825 non-null  int64
 8   monthOfRegistration 366825  non-null  int64
 9   fuelType            366825 non-null object
 10  brand               366825 non-null object
 11  notRepairedDamage   366825 non-null  object
 12  postalCode          366825 non-null  int64
 13  price               366825 non-null
int64 dtypes: int64(6),  object(8)
memory usage: 42.0+ MB
```

In [

```
from sklearn.preprocessing import LabelEncoder le = LabelEncoder()
df['name'] = le.fit_transform(df['name']) df['abtest'] =
le.fit_transform(df['abtest'])
df['vehicleType'] = le.fit_transform(df['vehicleType']) df['gearbox'] =
le.fit_transform(df['gearbox']) df['model'] = le.fit_transform(df['model'])
df['fuelType'] = le.fit_transform(df['fuelType']) df['brand'] =
le.fit_transform(df['brand'])
df['notRepairedDamage'] = df['notRepairedDamage'].replace({'nein' : 0, 'ja' : 1})
```

In [ ]:

```
df.info()
```

```
<class
'pandas.core.frame.DataFrame'>
Int64Index: 366825 entries, 0 to
371527 Data columns (total 14
columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   name                366825 non-null  int64
 1   abtest              366825 non-null  int64
 2   vehicleType         366825 non-null  int64
 3   yearOfRegistration  366825 non-null  int64
 4   gearbox             366825 non-null  int64
 5   powerPS             366825 non-null  int64
 6   model               366825 non-null  int64
 7   kilometer           366825 non-null  int64
 8   monthOfRegistration 366825  non-null int64
 9   fuelType            366825 non-null  int64
 10  brand               366825 non-null  int64
 11  notRepairedDamage   366825 non-null  int64
 12  postalCode          366825 non-null  int64
 13  price               366825 non-null
int64 dtypes: int64(14)
memory usage: 42.0 MB
```

Identifying and Handling Outliers

In [ ]:

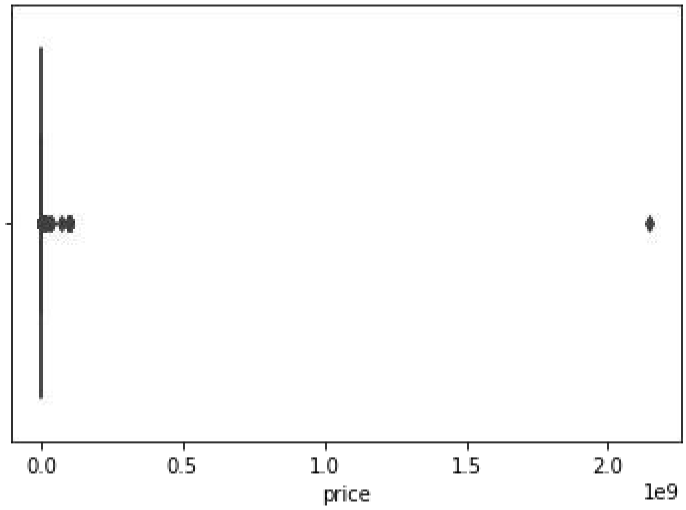
```
# Checking for outliers in 'price' column
```

In [

```
sns.boxplot(x = df['price'])
```

Out[16]:

```
<AxesSubplot:xlabel='price'>
```



In [ ]:

```
a =
df['price'].quantile(q=[0.75,0.25])
a
```

Out[17]:

```
0.75    7150.0
0.25    1150.0
Name: price, dtype: float64
```

In [ ]:

```
IQR = a.iloc[0] - a.iloc[1] IQR
```

Out[18]
:

```
6000.0
```

In [

```
upper = a.iloc[0]+(1.5*IQR) lower = a.iloc[0]-(1.5*IQR)
```

In [ ]:

```
upper
```

Out[20]:

```
16150.0
```

In [ ]:

```
lower
```

Out[21]:

```
-1850.0
```

In [ ]:

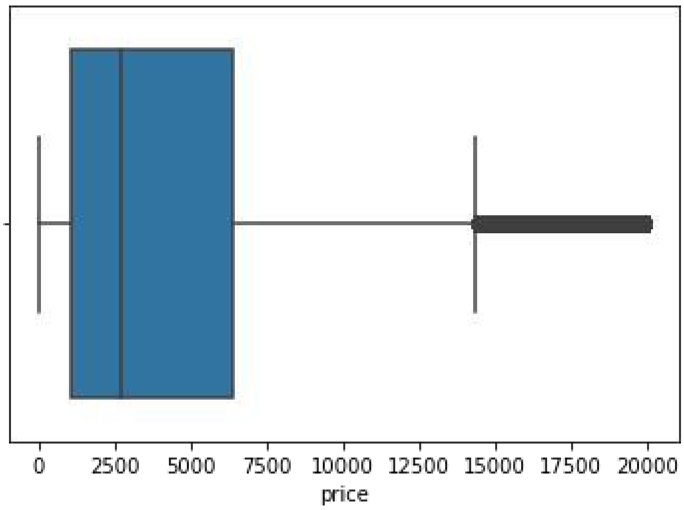
```
# Dropping outliers in price
a = df[df['price'] > 20000].index
df.drop(a, inplace = True)
```

In [ ]:

```
sns.boxplot(x = df['price'])
```

Out[23]:

```
<AxesSubplot:xlabel='price'>
```



In [ ]:

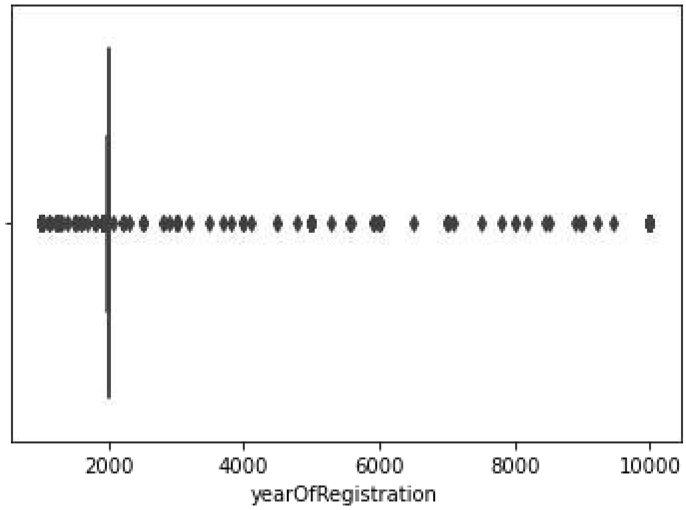
```
# Checking for outliers in 'yearOfRegistration' column
```

In [

```
sns.boxplot(x = df['yearOfRegistration'])
```

Out[25]:

```
<AxesSubplot:xlabel='yearOfRegistration'>
```



In [ ]:

```
a = df['yearOfRegistration'].quantile(q=[0.75,0.25]) a
```

Out[26]:

```
0.75    2008.0
0.25    1999.0
Name: yearOfRegistration, dtype: float64
```

In [ ]:

```
IQR = a.iloc[0] - a.iloc[1] IQR
```

Out[27]
:

```
9.0
```

In [ ]:

```
upper = a.iloc[0]+(1.5*IQR) lower = a.iloc[0]-(1.5*IQR)
```

In [

```
uppe
```

Out[29]:

2021.5

In [ ]:

```
lower
```

Out[30]:

1994.5

In [ ]:

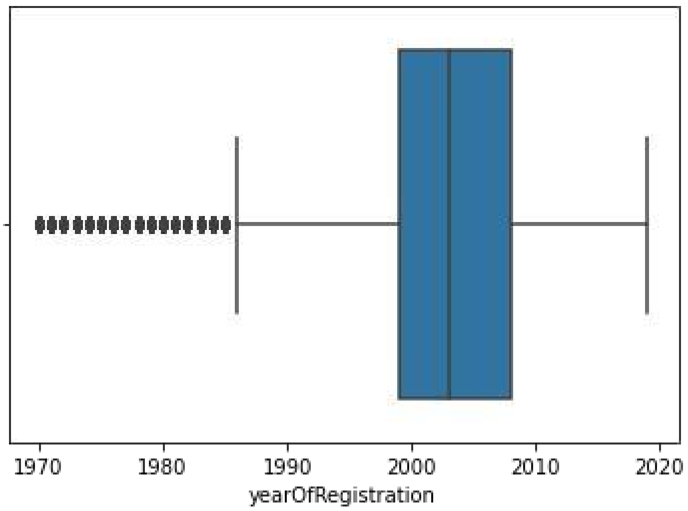
```
# Dropping outliers in yearOfRegistration
a = df[df['yearOfRegistration'] > 2019].index df.drop(a, inplace = True)
a = df[df['yearOfRegistration'] < 1970].index df.drop(a, inplace = True)
```

In [ ]:

```
sns.boxplot(x = df['yearOfRegistration'])
```

Out[32]:

<AxesSubplot:xlabel='yearOfRegistration'>



In [ ]:

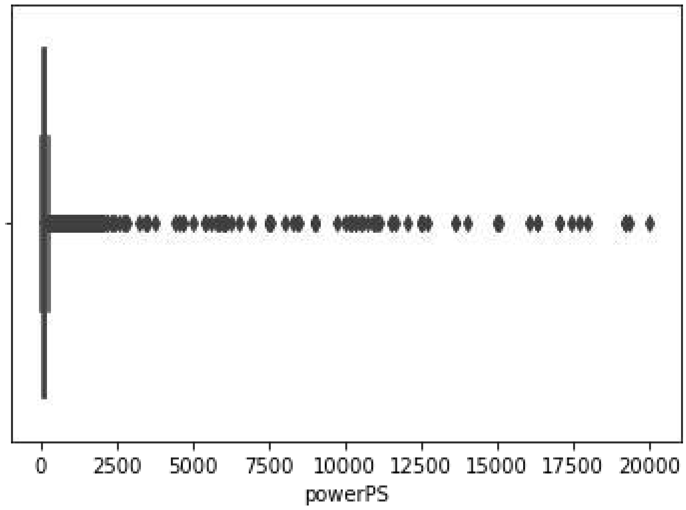
```
# Checking for outliers in 'powerPS' column
```

In [

```
sns.boxplot(x = df['powerPS'])
```

Out[34]:

```
<AxesSubplot:xlabel='powerPS'>
```



In [ ]:

```
a =
df['powerPS'].quantile(q=[0.75,0.25]) a
```

Out[35]:

```
0.75    141.0
0.25     69.0
Name: powerPS, dtype: float64
```

In [ ]:

```
IQR = a.iloc[0] -
a.iloc[1] IQR
```

Out[36]
:

```
72.0
```

In [ ]:

```
upper =
a.iloc[0]+(1.5*IQR) lower
= a.iloc[0]-(1.5*IQR)
```

In [

```
upper
```

Out[38]:

```
249.0
```

In [ ]:

```
lower
```

Out[39]:

```
33.0
```

In [ ]:

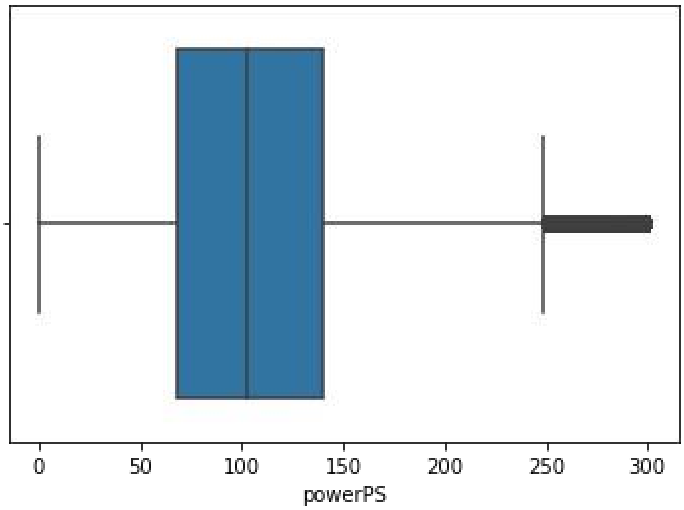
```
# Dropping outliers in powerPS
a = df[df['powerPS'] > 300].index
df.drop(a, inplace = True)
```

In [ ]:

```
sns.boxplot(x = df['powerPS'])
```

Out[41]:

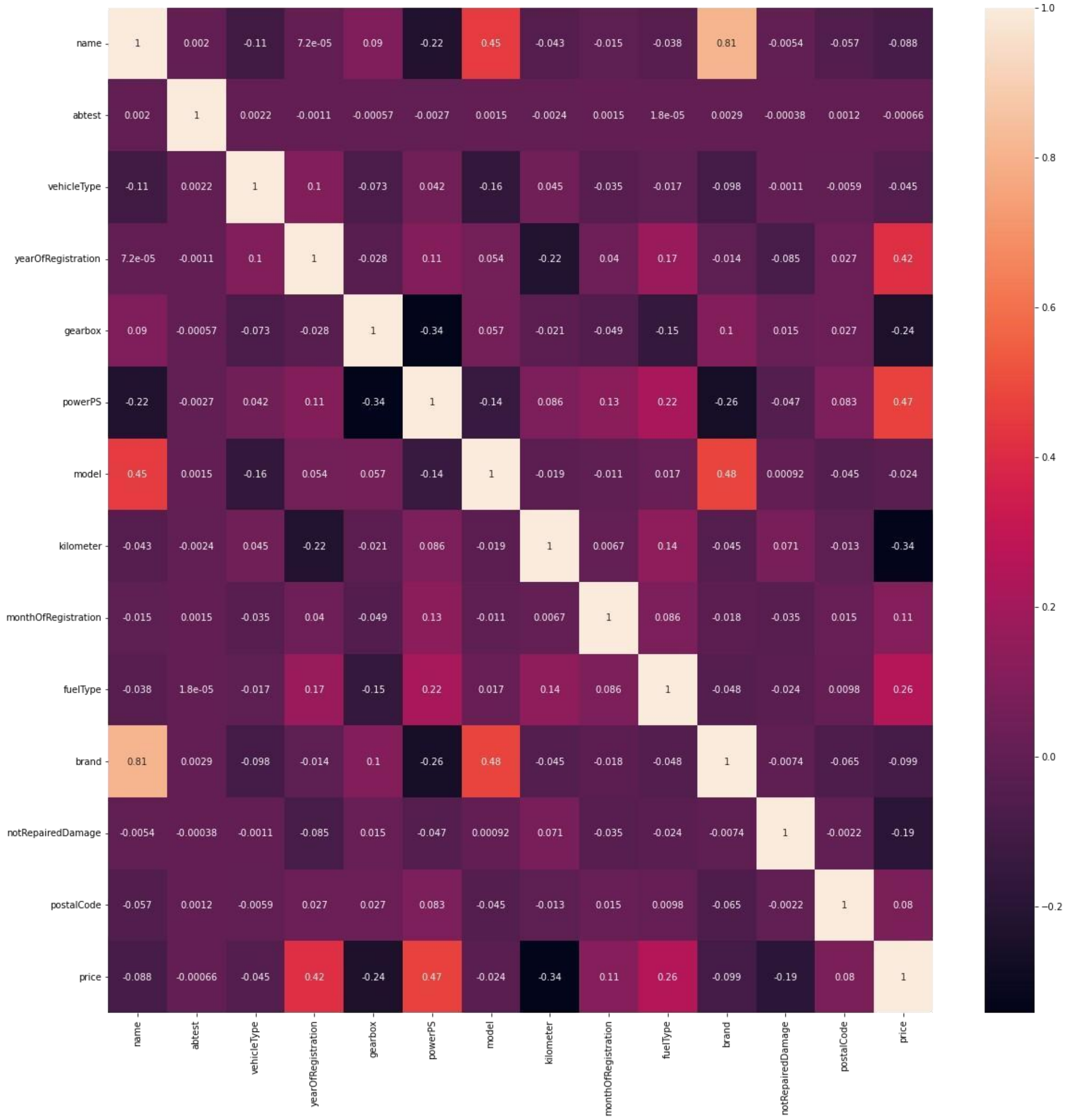
```
<AxesSubplot:xlabel='powerPS'>
```



Visualization

In [

```
plt.figure(figsize=(20,20)) sns.heatmap(df.corr(), annot = True) plt.show()
```

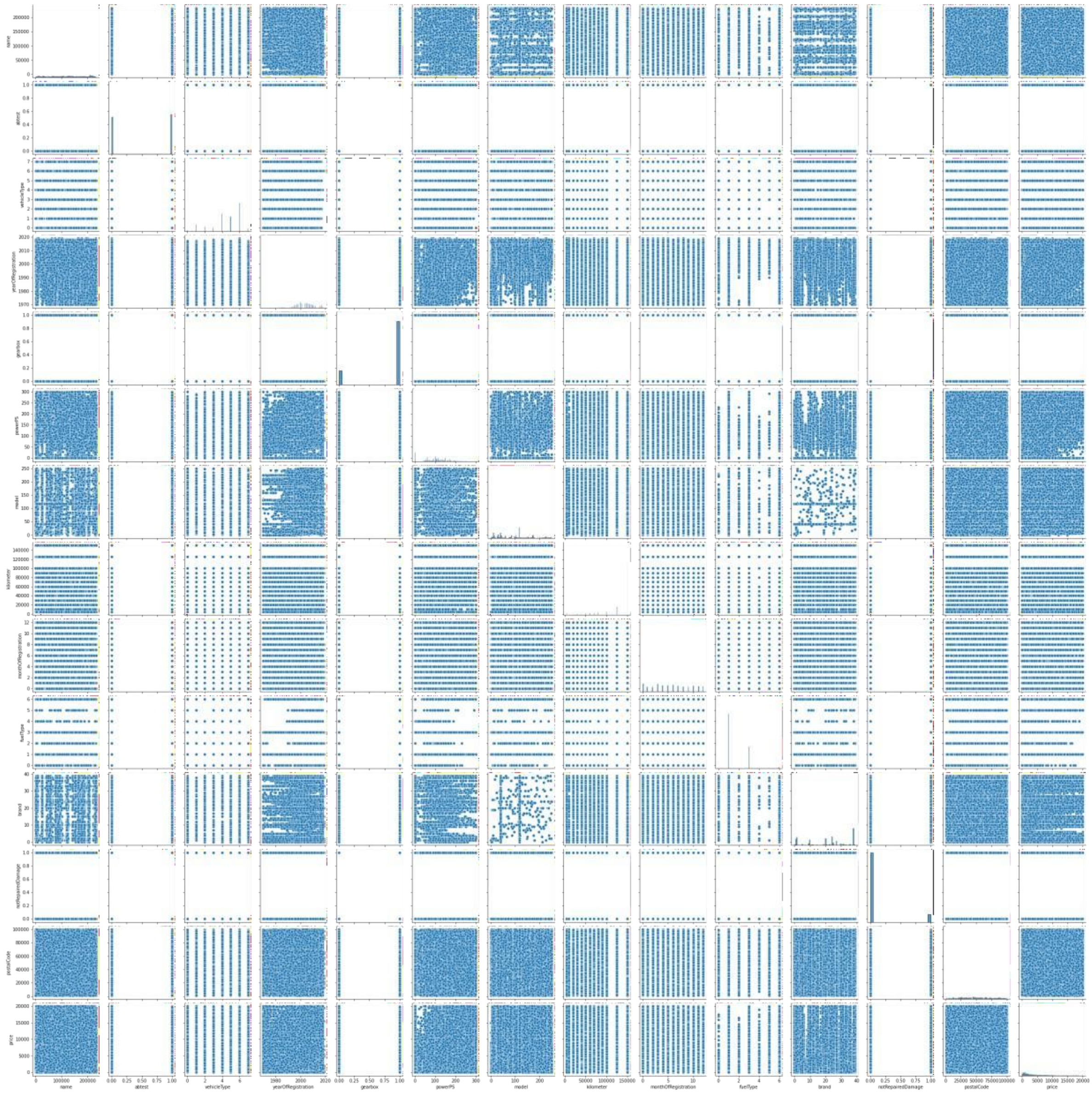


In [

```
sns.pairplot(df) plt.show()
```

Out[74]:

<seaborn.axisgrid.PairGrid at 0x7fc23cddbc40>



Descriptive Statistics

In [

```
df.nunique()
```

Out[80]:

```
name                   218805
abtest                      2
vehicleType                 8
yearOfRegistration         50
gearbox                     2
powerPS                   299
model                     250
kilometer                  13
monthOfRegistration        13
fuelType                    7
brand                      40
notRepairedDamage           2
postalCode               8140
price                    3708
dtype: int64
```

In [ ]:

```
df.describe()
```

Out[42]:

	name	abtest	vehicleType	yearOfRegistration	gearbox	
count	344985.000000	344985.000000	344985.000000	344985.000000	344985.000000	34498
mean	117904.585912	0.518202	4.565471	2003.229619	0.819265	10
std	67510.545516	0.499669	1.661815	6.980320	0.384799	5
min	0.000000	0.000000	0.000000	1970.000000	0.000000	
25%	60989.000000	0.000000	4.000000	1999.000000	1.000000	6
50%	119794.000000	1.000000	5.000000	2003.000000	1.000000	10
75%	175396.000000	1.000000	6.000000	2008.000000	1.000000	14
max	233530.000000	1.000000	7.000000	2019.000000	1.000000	30

In [

```
df.skew()
```

Out[43]:

```
name                 -0.022347
abtest               -0.072858
vehicleType          -0.917651
yearOfRegistration   -0.360852
gearbox              -1.659392
powerPS               0.189407
model                 0.395804
kilometer            -1.737954
monthOfRegistratio    0.082692
n
fuelType              1.542590
brand                -0.172770
notRepairedDamage     2.622955
postalCode            0.075437
price                 1.461433
dtype: float64
```

In [ ]:

```
df.kurt()
```

Out[44]:

```
name                 -1.200546
abtest               -1.994703
vehicleType          -0.028758
yearOfRegistration    1.432725
gearbox               0.753586
powerPS               0.085471
model                -0.883618
kilometer             1.984077
monthOfRegistratio   -1.147400
n
fuelType              2.400634
brand                -1.310623
notRepairedDamage     4.879922
postalCode           -0.962817
price                 1.547299
dtype: float64
```

Splitting the Data

In [ ]:

```
# Splitting x and y
variables x  =
df.drop(columns = 'price') y
= df['price']
```

In [

```
# Splitting into test and train
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
random_state=0
```

Building Models

In [ ]:

```
# Linear Regression
```

In [ ]:

```
from sklearn.linear_model import LinearRegression lr = LinearRegression()
lr.fit(x_train, y_train)
```

Out[48]:

```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:

```
# Lasso Regression
```

In [ ]:

```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.01,
normalize=True) lasso.fit(x_train,
y_train)
```

Out[72]:

```
Lasso(alpha=0.01, normalize=True)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:

```
# Ridge Regression
```

In [

```
from sklearn.linear_model import Ridge ridge = Ridge(alpha=0.01, normalize=True)
ridge.fit(x_train, y_train)
```

Out[73]:

```
Ridge(alpha=0.01, normalize=True)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:

```
# Decision Tree
```

In [ ]:

```
from sklearn.tree import
DecisionTreeRegressor DT =
DecisionTreeRegressor()
DT.fit(x_train, y_train)
```

Out[54]:

```
DecisionTreeRegressor()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:

```
# KNN
```

In [ ]:

```
from sklearn.neighbors import KNeighborsRegressor knn = KNeighborsRegressor()
knn.fit(x_train, y_train)
```

Out[56]:

```
KNeighborsRegressor()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:

```
# Random Forest
```

In [

```
from sklearn.ensemble import RandomForestRegressor RF = RandomForestRegressor()
RF.fit(x_train, y_train)
```

Out[58]:

```
RandomForestRegressor()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Checking the Metrics of the models

In [ ]:

```
# Linear Regression
lr.score(x_test, y_test)
```

Out[59]:

```
0.50461642931597
22
```

In [ ]:

```
from sklearn.metrics import mean_squared_error
np.sqrt(mean_squared_error(y_test,lr.predict(x_test)))
```

Out[60]:

```
3124.8392438160
01
```

In [ ]:

```
# Lasso Regression
lasso.score(x_test, y_test)
```

Out[61]:

```
0.50462790178427
87
```

In [ ]:

```
np.sqrt(mean_squared_error(y_test,lasso.predict(x_test)))
```

Out[62]:

```
3124.8030599083
48
```

In [

```
# Ridge Regression
ridge.score(x_test, y_test)
```

Out[63]:

```
0.50461321529664
06
```

In [ ]:

```
np.sqrt(mean_squared_error(y_test,ridge.predict(x_test)))
```

Out[64]:

```
3124.84938068573
36
```

In [ ]:

```
# K Nearest Neighbour
knn.score(x_test, y_test)
```

Out[65]:

```
0.36042646561748
47
```

In [ ]:

```
np.sqrt(mean_squared_error(y_test,knn.predict(x_test)))
```

Out[66]:

```
3550.6030573153
32
```

In [ ]:

```
# Decision Tree
DT.score(x_test, y_test)
```

Out[67]:

```
0.73518914589835
89
```

In [ ]:

```
np.sqrt(mean_squared_error(y_test,DT.predict(x_test)))
```

Out[68]:

```
2284.67679972225
64
```

In [ ]:

```
# Random Forest
RF.score(x_test, y_test)
```

In [
Out[69]:

```
0.86219410430520
54
```

In [

```
np.sqrt(mean_squared_error(y_test,RF.predict(x_test)))
```

Out[70]:

```
1648.12740037350
57
```

Saving the Model

In [ ]:

```
import pickle
pickle.dump(RF, open('Car Resale Value Prediction.pkl', 'wb'))
```

8. TESTING

8.1.USER ACCEPTANCE TESTING

1. Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the [ProductName] project at the time of the release to User Acceptance Testing (UAT).

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	10	4	2	3	20
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	11	2	4	20	37
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	24	14	13	26	77

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	7	0	0	7
Client Application	51	0	0	51
Security	2	0	0	2
Outsource Shipping	3	0	0	3

Exception Reporting	9	0	0	9
Final Report Output	4	0	0	4
Version Control	2	0	0	2

8.2.Model Performance Test

Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Values	Screenshot
1.	Metrics	**Regression Model:** MAE - 1232.3528089560773, MSE - 5063778.951720876, RMSE - 2250.2841935455344, R2 score - 0.87528399134989	from sklearn.metrics import r2_score r2_score(y_test, RF.predict(x_test)) 0.8752839913498982 from sklearn.metrics import mean_squared_error mean_squared_error(y_test, RF.predict(x_test)) 5063778.951720876 from sklearn.metrics import mean_squared_error np.sqrt(mean_squared_error(y_test, RF.predict(x_test))) 2250.2841935455344 from sklearn.metrics import mean_absolute_error mean_absolute_error(y_test, RF.predict(x_test)) 1232.3528089560773

2.	Tune the Model	**Validation Method** - train_test_split	# Splitting x and y variables
			x = df.drop(columns = 'price')
			y = df['price']
			# Splitting into test and train
			from sklearn.model_selection import train_test_split
			x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)

9. RESULT

The Car Resale Value is predicted by using Random Forest Algorithm .Proofs and Procedures are attached Above