Machine Learning based Vehicle Performance Analyzer

Technology: Applied Data Science

IBM-Project-11565-1659334799

Team ID: PNT2022TMID27752

A PROJECT REPORT

Submitted by

ABDULVAHITH.A.L	**(311419205001)**
HARANPRANAV.B.S	**(311419205011)**
NAVEENBALAJI.N.T	**(311419205023)**
SHYAM.K.S	**(311419205037)**

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

IN

INFORMATION TECHNOLOGY

MEENAKSHI COLLEGE OF ENGINEERING

CHENNAI - 600078

INTRODUCTION 1

1.1 Project Overview 1

1.2 Purpose 1

LITERATURE SURVEY 2

2.1 Existing Problem 2

2.2 Problem Definition 2

2.3 References 2

IDEATION AND PROPOSED SOLUTION 6

3.1 Empathy Map 6

3.2 Ideation and Brainstorming 7

3.3 Proposed Solution 8

3.4 Problem Solution Fit 10

REQUIREMENT ANALYSIS 11

4.1 Functional Requirements 11

4.2 Non-Functional Requirements 11

PROJECT DESIGN 12

5.1 Data Flow Diagram 12

5.2 Technical Architecture 13

5.3 User Stories 16

PROJECT PLANNING AND SCHEDULING 17

6.1 Sprint Planning & Estimation 17

6.2 Sprint Delivery Schedule 17

6.3 Reports for JIRA 18

CODING AND SOLUTION 19

TESTING 21

RESULTS 22

9.1 Performance Metrics 22

PROS AND CONS 24

CONCLUSION 25

FUTURE WORKS 26

APPENDIX 27

13.1 Source Code 35

13.2 GitHub & Project Demo Link 35

CHAPTER 1
INTRODUCTION

1.1 PROJECT OVERVIEW

Predicting a car's performance is a significant and intriguing challenge. The current study's main goal is to forecast automobile performance in order to improve specific vehicle behaviour. This can significantly reduce the system's fuel consumption and increase its effectiveness. Analysis of vehicle performance based on engine type, cylinder count, fuel type, and horsepower, among other factors. These variables can be used to forecast the health of the vehicle. It is a continuous process to collect, investigate, interpret, and document health data based on the three elements. Both prediction engines and engine management systems place a high value on performance metrics such as mileage, reliability, flexibility, and cost, which can be combined. To improve the vehicle's performance efficiency, it is critical to analyse the elements using a variety of well-known machine learning methodologies, such as linear regression, decision trees, and random forests. The power, lifespan, and range of automotive traction batteries are currently "hot topics" in automotive engineering. In this case, we also consider mileage performance. To solve this problem, we will build models using various techniques and neural networks. Then, we'll see which algorithm best predicts car performance (Mileage).

1.2 PURPOSE

The application of Machine Learning (supervised and unsupervised) techniques to automotive engine sensor data in order to discover driver usage patterns and perform classification via a distributed online sensing platform. These platforms can be used in a variety of domains, including fleet management, the insurance market, fuel consumption optimization, and CO_2 emission reduction. Thus, the project's main goal is to predict the performance of the car in order to improve certain vehicle behaviors using various machine learning algorithms.

CHAPTER 2
LITERATURE SURVEY

2.1 EXISTING PROBLEM

Since the development of new technologies, the potential for processing car sensing data has increased in recent years. This type of data is useful for analyzing how drivers behave behind the wheel, for example. Very little has been done to analyze car usage patterns based on car engine sensor data, and thus it has not been explored to its full potential by taking into account all sensors within a car engine. To bridge this gap, the use of Machine Learning techniques (supervised and unsupervised) on automotive engine sensor data to discover drivers' usage patterns, Such platforms can be used in a variety of domains, including fleet management, insurance markets, fuel consumption optimization, and CO2 emission reduction, among others

2.2 PROBLEM DEFINITION

As a result of going through the existing problem and learning from the various papers in the literature survey. The problem definition can be framed as follows:
"To predict the performance of the car in order to improve certain vehicle behaviors using various machine learning algorithms.

2.3 REFERENCE

2.3.1 ML Based Real-Time Vehicle Data Analysis for Safe Driving Modeling

In the paper "Machine Learning Based Real-Time Vehicle Data Analysis for Safe Driving Modeling" Machine learning approach to analyze and predict the vehicle performance in real time. The focus is on analyzing the data which is collected from the vehicle using the OBD-II scanner and eventually providing the driver's safety solutions The meta features of the vehicle are analyzed in the cloud and are then shared to the concerned parties. The proposed system consists of an OBD-II scanner and a mini dash cam which continuously send data to the cloud server where data analysis is done.

Multivariate Linear Regression Model:

It is used when we want to predict the value of a variable based on the value of two or more different variables. The variable we want to predict is called the Dependent Variable, while those used to calculate the dependent variable are termed as Independent Variables.

Features such as fuel efficiency, average speed value, maximum speed value, fourth section speed value, interval driving distance, driving time value during green zone, traveling time value, emergency accelerated value, emergency decelerated value, fourth rpm time value and fifth rpm time value are used for training the model.

The real time data obtained is normalized using Min-Max normalization technique and they hypothesize an outcome called Economic Driving Index (ECN_DRVG_INDX) and another outcome called Safe Driving Index (SFTY_DRVG_INDX). The results have proven to be approximately 80% fitting the given features.

2.3.2 Machine Learning Approach Based on Automotive Engine Data Clustering for Driver Usage Profiling Classification:

The paper "A Machine Learning Approach Based on Automotive Engine Data Clustering for Driver Usage Profiling Classification" proposes the use of Machine Learning techniques (supervised and unsupervised) on automotive engine sensor data to discover drivers' usage patterns, and to perform classification through a distributed online sensing platform and that such platform can be useful used in different domains, such as fleet management, insurance market, fuel consumption optimization, CO2 emission reduction, among others.

As automotive engine data has no class label, we use the following Machine Learning models used for clustering and class labels:

K means:

K-Means Clustering is an Unsupervised Learning algorithm, which groups the unlabeled dataset into different clusters. Here K defines the number of predefined clusters that need to be created in the process, as if K=2, there will be two clusters, and for K=3, there will be three clusters, and so on. It is a centroid-based algorithm, where each cluster is associated with a centroid. The main aim of this algorithm is to minimize the sum of distances between the data point and their corresponding clusters.

Expectation-Maximization:

The expectation-maximization algorithm is an approach for performing maximum likelihood estimation in the presence of latent variables. It does this by first estimating the values for the latent variables, then optimizing the model, then repeating these two steps until convergence. It is an effective and general approach and is most used for density estimation with missing data, such as clustering algorithms like the Gaussian Mixture Model.

Hierarchical Clustering:

Hierarchical clustering is another unsupervised machine learning algorithm, which is used to group the unlabeled datasets into a cluster. In this algorithm, we develop the hierarchy of clusters in the form of a tree, and this tree-shaped structure is known as the dendrogram.

Machine learning algorithms for Classification:

Decision Tree:

The decision tree and its variants are the other learning algorithms that divide the input space into regions and has separate parameters for each region. They are classified as a non- parametric supervised learning method which is widely used in classification and regression, as well as in representing decisions and decision making. The structure of a decision tree is a flowchart, in which each internal node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label. Besides, the paths from root to leaf represent classification rules

KNN:

K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.

Multilayer Perceptron:

A multilayer perceptron is a fully connected class of feedforward artificial neural network. it uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another.

Naive Bayes

Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

Random Forest

Random forests or random decision forests is an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training setRandom forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.

Support Vector Mechanism:

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called support vectors, and hence the algorithm is termed as Support Vector Machine.

2.3.3 Driving Behavior Analysis Using Machine and Deep Learning Methods for Continuous Streams of Vehicular Data:

The paper "Driving Behavior Analysis Using Machine and Deep Learning Methods for Continuous Streams of Vehicular Data" authored by Nikolaos Peppes, Theodoros Alexakis, Evgenia Adamopoulou, Konstantinos Demestichas aims to combine well-known machine and deep learning algorithms together with open-source-based tools to gather, store, process, analyze and correlate different data flows originating from vehicles

Machine Learning Algorithms for Classification:

Support Vector Mechanisms (SVM):

Support vector machines is a supervised machine learning algorithm used for both classification and regression. SVM classifies data points based on the hyperplane in an N – dimensional space. The separation function in support vector classification is a linear combination of kernels linked to the support vector.

Decision Tree-Based Algorithms:

The decision tree and its variants are the other learning algorithms that divide the input space into regions and have separate parameters for each region. They are classified as a nonparametric supervised learning method which is widely used in classification and regression, as well as in representing decisions and decision making. The structure of a decision tree is a treelike flowchart, in which each internal node represents a “test” on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label. Besides, the paths from root to leaf represent classification rules. Three decision tree-based models, including decision tree (DT), extra trees (ExT), and random forest, were evaluated in relation to various learning method

Random Forest

Random forests or random decision forests is an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.

Deep Learning Model:

RNN-based algorithms:

RNN-based models have been used widely nowadays due to its robustness and capability to handle nonlinear data even with its typically structured, single hidden layer, or advanced structured, multiple hidden layers. RNN includes three layers: input, hidden, and output layers. In case of increasing complexity of the problem, the number of layers will rise, and the computational resources will consequently also rise. Here, both the mentioned structures of the RNN-based models were utilized for predicting the Driving Behavioral Analysis.

Multilayer Perceptron:

A multilayer perceptron is a fully connected class of feedforward artificial neural network. it uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another.

CHAPTER 3 IDEATION & PROPOSED SOLUTION

3.1 EMPATHY MAP

The primary goal of the empathy map is to bridge the gap between the user and the developer. The empathy map for the machine learning-based vehicle performance analyzer is represented in Fig 3.1.

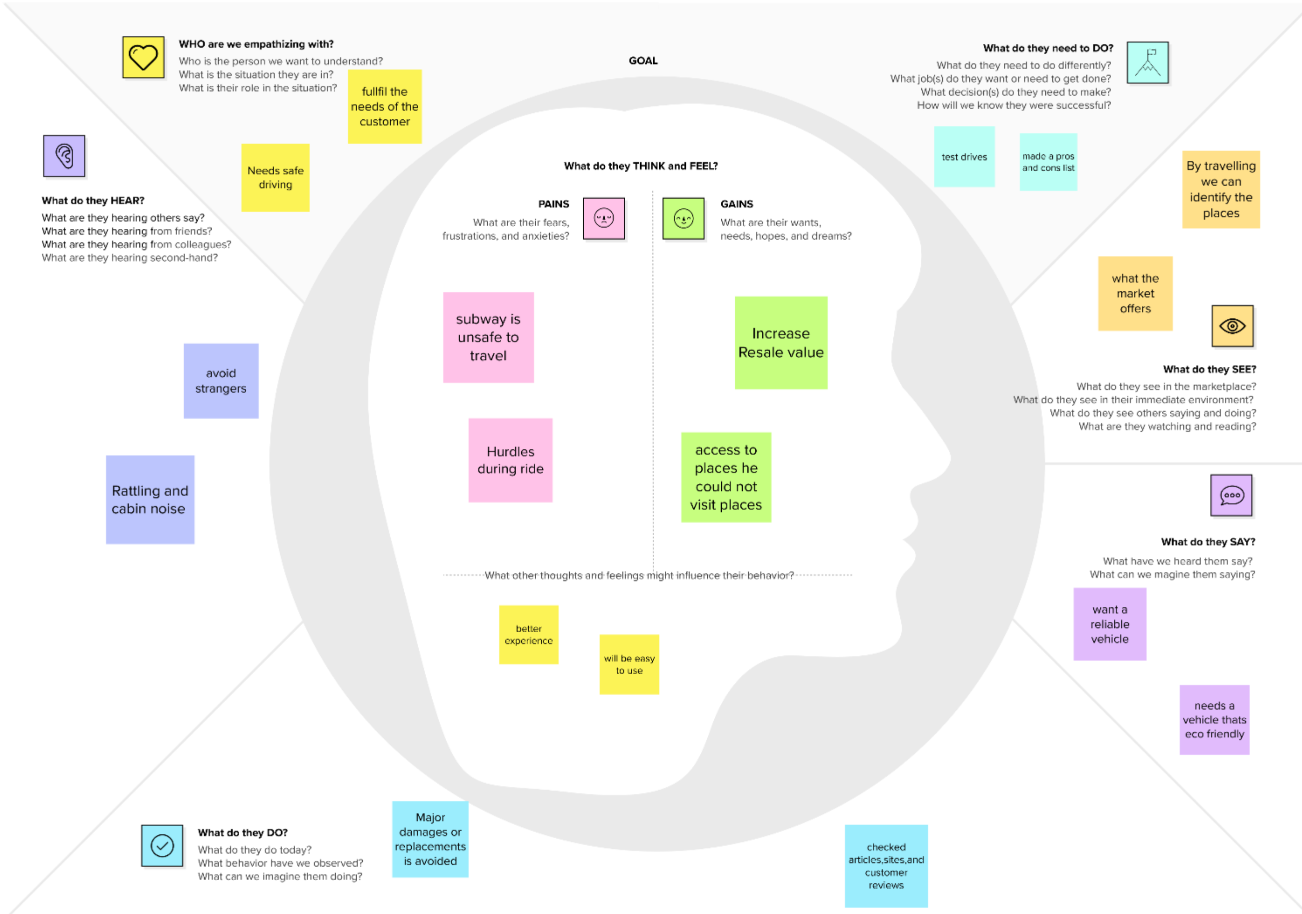


Figure 3.1 – Empathy Map

3.2 IDEATION & BRAINSTORMING

This is quite often the most exciting stage of a project because the goal of Ideation and brainstorming is to generate a large number of ideas that the team can then filter and cut down into the best, most practical, or most innovative ones to inspire new and better design solutions and products. The stages of ideation and brainstorming for the machine learning-based vehicle performance analyzer are shown in Figure 3.2.

Figure 3.2 – Ideation & Brainstorming

3.3 PROPOSED SOLUTION

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	The main goal is to predict the performance of the car to improve certain behaviours of the vehicle. This can significantly help to improve the system's fuel consumption and increase efficiency. The performance analysis of the car is based on the engine type, no of engine cylinders, fuel type, horsepower, etc. The performance objectives like mileage, dependability, flexibility and cost can be grouped together to play a vital role in the prediction engine and engine management system.
2.	Idea / Solution description	SENSOR BASED PREDICTION OF VEHICLE PERFORMANCE A sensor based vehicle information system (SVIS) is proposed to study vehicle environment perception in this paper. The different types of sensors are installed on the road side environment and wireless communication technology is used to realize the sense information between sensor, base stations and servers. The system considered the high speed characteristics of vehicles, when vehicles will be passing a road ahead that is prone to accidents; the vehicles driving states should be predicted to ensure drivers have advance information about road and safe from accidents. To evaluate the performance and stability the traditional sensor mounted system compared with SVIS system. The simulation results show the accuracy and efficiency of proposed system.

3.	Novelty / Uniqueness	The prediction of vehicle driving state in high speed environment. We tested the vehicle mounted system and compared the results of driving states. This sensor can ensure the system stability. Furthermore the system will provide accurate road information and efficient for warming applications. This sensor is cheaper than the other and estimates almost all attributes of the vehicle.

4.	Social Impact / Customer Satisfaction	• Reduce Costs • Expand Your Customer Base With the Localization • To Maintain a safer driving
5.	Business Model (Revenue Model)	**Informs the customer to check the car** The SVIS sensor will alert the user for the car requirement through your mobile phones. **Helps the customer** The office workers are busy and they are unable to take care of their car. So this sensor can make alert of the users by using smart phone connection. By this users will never find difficulties.
6.	Scalability of the Solution	With an sensor they can find the problems of the vehicle and will fixed it. This model are available in the Toyota company and thereby increasing its global reach and Ultimately growing usage.

3.4 PROBLEM SOLUTION FIT

The problem solution fit is the solution found to address the customer's problem.

The solution for the machine learning-based vehicle performance analyzer is depicted in Figure 3.4.

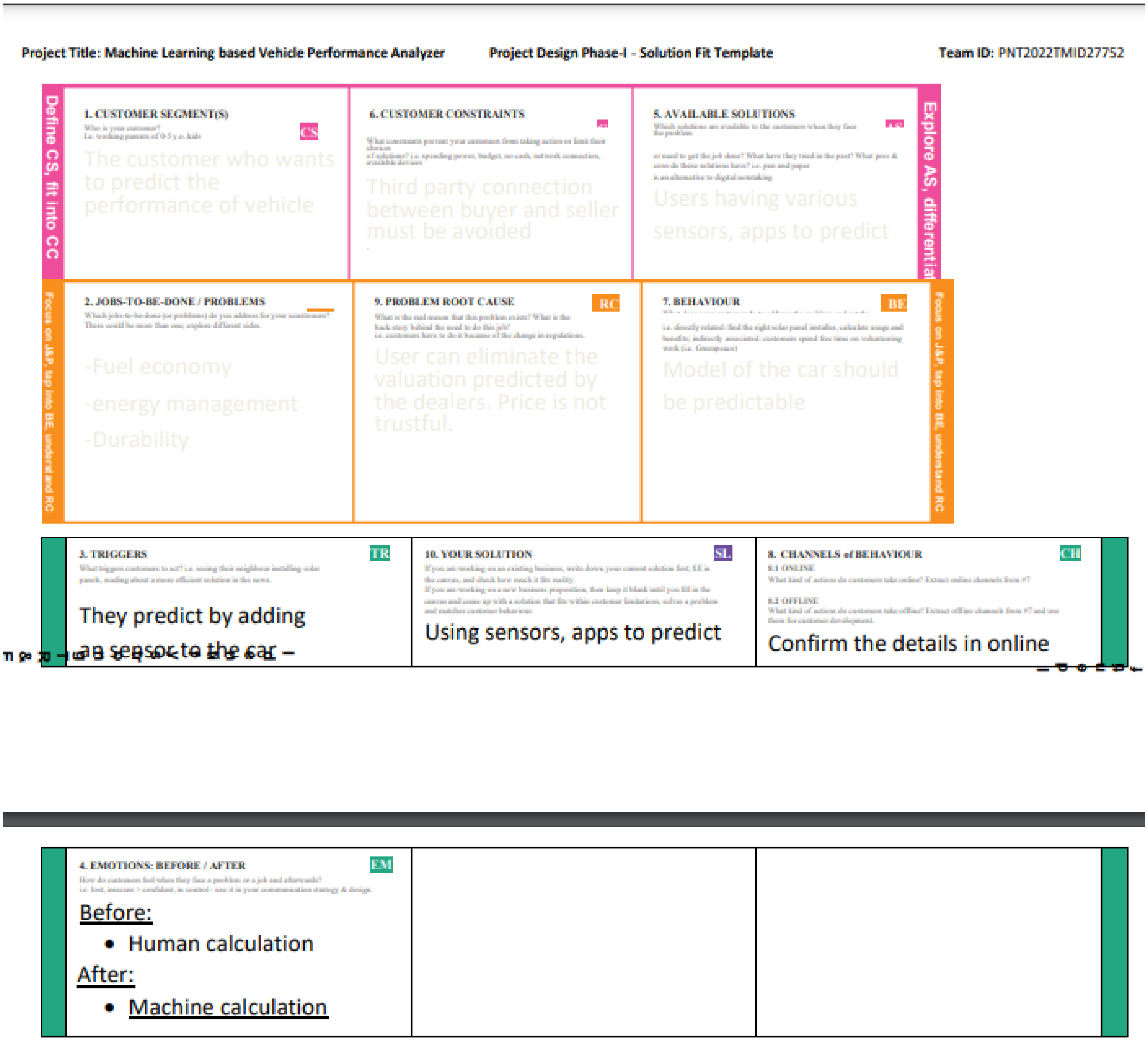


Figure 3.4 – Problem Solution Fit

CHAPTER 4
REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENTS

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	Enter the data	Get data through a form
FR-2	User Essential	Attributes of the vehicle
FR-3	Data Pre-processing	Form-based user input sending the data to the server
FR-4	User Input Evaluation	The ML model to forecast the vehicle behaviour. Search for more recent vehicles that resemble the current model.
FR-5	Report Generation	Display the problems of the vehicle and fix the requirements. Suggest related auto models based on the database.

4.2 NON-FUNCTIONAL REQUIREMENTS

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

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	To collect data, this programme need new, specialised sensor. Through data that the user can manually gather, it attempts to estimate the vehicle behaviour.
NFR-2	**Security**	Ensured Confidentiality, Integrity, and Availability while being protected from all types of obstacles threats.
NFR-3	**Reliability**	In terms of the efficiency and remaining life of the car, the programme will provide nearly perfect predictions, and it will be designed in such a way that false positives won't negatively impact users in anyway.
NFR-4	**Performance**	The performance of this application can handle a sizable number of concurrent users accessing the services with little to no apparent impact.
NFR-5	**Availability**	Minimizing service downtime by ensuring that the the programme is always accessible to all users.
NFR-6	**Scalability**	All the attributes of the vehicle can easily predicted.

CHAPTER 5
PROJECT DESIGN

5.1 DATA FLOW DIAGRAM

A Data Flow Diagram (DFD) is a classic visual representation of how data flows within a system. A neat and clear DFD can thus graphically depict the appropriate amount of system requirements. It demonstrates not only how data enters and exits the system, but also what changes the information and where it is stored. The DFD for the given project is depicted in Figure 5.1.

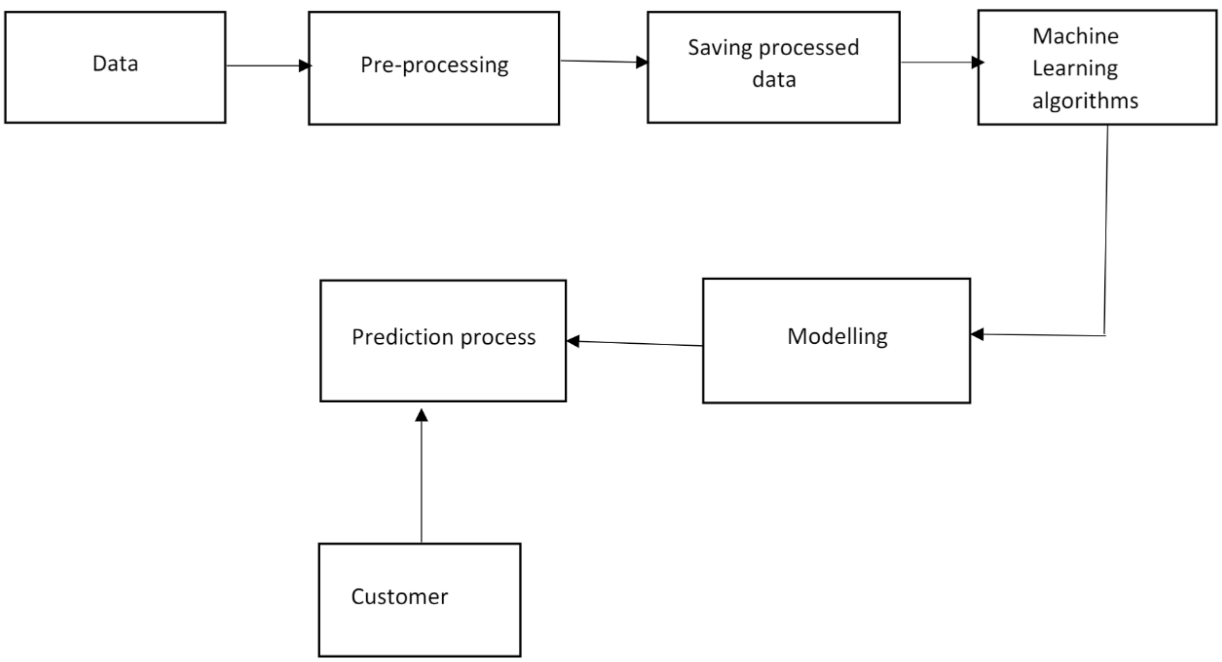


Figure 5.1 – Data Flow Diagram

5.2 SOLUTION & TECHNICAL ARCHITECTURE

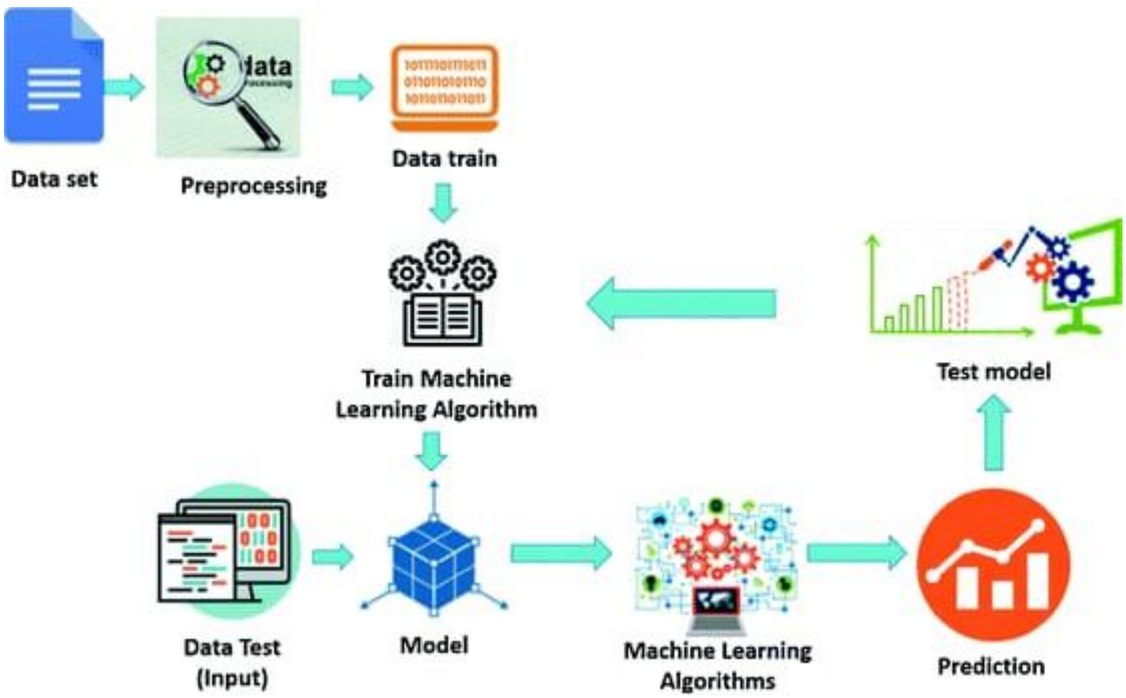


Figure 5.2 Technical Architecture

5.2.1 COMPONENTS AND TECHNOLOGIES

S.No	Component	Description	Technology
1.	Application	User interacts with the prediction of vehicle behavior	Python, Java, HTML, SQL, Android studio, JavaScript
2.	Database	Data Type, Configurations and data will be stored	MySQL, JavaScript
3.	Cloud Database	Database Service on Cloud	IBM DB2, IBM Cloudland, etc.
4.	Send User Report	Send the predictions to the users	REST API
5.	Machine Learning	Purpose of Machine Learning Model	ANN, CNN, RNN
6.	Database	Database contain user information such as name, email, vehicle information	MySQL
7.	File Storage	File storage requirements	IBM Block Storage or Other Storage Service or Local Filesystem
8.	External API	Vehicles details database	https://api.auto-data.net/
9.	Machine Learning Model	Purpose of Machine Learning Model	OpenCV, MATLAB

Table 5.2.1 – Components and Technologies

5.2.2 APPLICATION CHARACTERISTICS

S.No	Characteristics	Description	Technology
1	Open-Source Frameworks	Flask, Sci-kit learn	JavaScript, Python
2	Security Implementations	Identity and access management	IBM Cloud
3	Scalable Architecture	The scalability of architecture consists of 3 tiers Model-View-Controller Implementation	Web Server – HTML, CSS, JavaScript Application Server – Python Flask Database Server – IBM Cloud
4	Availability	Availability is increased by loads balancers in cloud VPS	IBM Cloud hosting
5	Performance	The application is expected to handle up to 4000 predictions per second	IBM Load Balance

Table 5.2.2 – Application Characters

5.3 USER STORIES

User Type	Functional Requirements	User Story Number	User Story/Task	Acceptance Criteria	Priority	Release
Customer	Access the app	USN -1	As a user, anyone can access the car specifications by connecting through bluetooh.	I can check my car attributes while in connection.	Medium	Sprint-1
Customer	Access the sensor	USN - 2	As per the usage of the sensor, the obstacles behind the car can be identified easily.	Sensing the objects can be easily done.	High	Sprint-2
Customer	Performance of the car	USN -3	As per the usage of the user, the performance of the vehicle should be predicted easily.	Prediction can be done in easy way.	High	Sprint-3

Table 5.3 – User Stories

CHAPTER 6 PROJECT PLANNING & SCHEDULING

6.1 Sprint Planning & Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Data Preparation	USN-1	Collecting Car dataset and create an Ml model to predict the car performance.	30	High	Abdulvahith.A.L Naveenbalaji.N.T Haranpranav.B.S Shyam.K.S
Sprint-2	Model Building	USN-2	As a user, I can get the predicted performance of the car using the Ml model	20	Medium	Abdulvahith.A.L Naveenbalaji.N.T Haranpranav.B.S Shyam.K.S
Sprint-3	Web Page Design	USN-3	As a user, I am able to view the website and I can get the predicted performance of the car using the given data.	30	High	Abdulvahith.A.L Naveenbalaji.N.T Haranpranav.B.S Shyam.K.S
Sprint-4	Expected Outcome	USN-4	As a user, I expect the prediction is highly accurate.	20	High	Abdulvahith.A.L Naveenbalaji.N.T Haranpranav.B.S Shyam.K.S

Table 6.1 – Sprint Planning

6.2 SPRINT DELIVERY SCHEDULE

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date(Actual)
Sprint-1	30	6 Days	01 Nov 2022	03 Nov 2022	30	13 Nov 2022
Sprint-2	20	6 Days	04 Oct 2022	06 Nov 2022	20	13 Nov 2022
Sprint-3	30	6 Days	07 Nov 2022	12 Nov 2022	30	15 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	18 Nov 2022	20	20 Nov 2022

Table 6.2 – Sprint Delivery Schedule

6.3 REPORT FOR JIRA

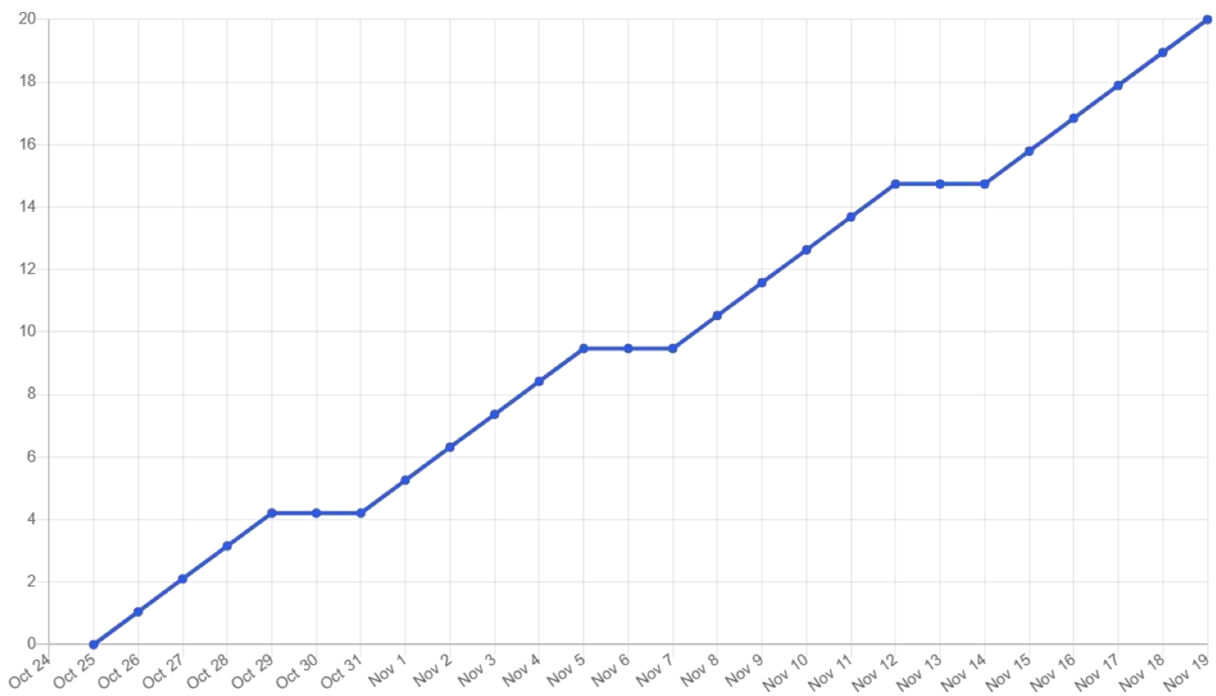
Velocity :

Imagine we have a 10-day sprint duration, and the velocity of the team is 20 (points per sprint). Let’s calculate the team’s average velocity (AV) per iteration unit (story points per day)

$$AV = \frac{sprint\ duration}{velocity} = \frac{20}{10} = 2$$

Burndown Chart:

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



CHAPTER 7 CODING AND SOLUTION

Feature 1:
Random Forest Regressor

Random Forest Regressor

```
In [49]: from sklearn.ensemble import RandomForestRegressor
```

```
In [50]: x11 = dataset.iloc[:,1:8].values
         y11 = dataset.iloc[:,0].values
```

```
In [51]: from sklearn.model_selection import train_test_split
         x_train1, x_test1, y_train1, y_test1 = train_test_split(x11,y11,test_size=0.2,random_state=0)
```

```
In [52]: rf= RandomForestRegressor(n_estimators=30,random_state=0)
         rf.fit(x_train1,y_train1)

Out[52]: RandomForestRegressor(n_estimators=30, random_state=0)
```

```
In [53]: y1_pred=rf.predict(x_test1)
         y1_pred

Out[53]: array([14.3       , 24.34333333, 14.18333333, 20.26666667, 18.43333333,
                30.21666667, 34.96     , 21.3       , 15.36666667, 26.22333333,
                36.01333333, 36.5      , 18.95666667, 27.22333333, 16.47666667,
                32.54333333, 27.89333333, 27.17      , 16.86666667, 34.64333333,
                15.88333333, 23.3      , 23.48333333, 20.71666667, 32.22      ,
                27.23333333, 34.40666667, 30.03      , 31.76333333, 15.93333333,
                19.07666667, 33.32333333, 18.55      , 32.66      , 20.35666667,
                24.2      , 18.92     , 16.40666667, 35.24      , 12.3       ,
                13.4      , 15.4      , 27.89666667, 32.61333333, 29.06666667,
                22.1      , 19.83     , 14.8      , 22.11333333, 29.86666667,
                34.04     , 25.36666667, 16.34     , 27.4      , 15.4       ,
                12.36666667, 18.56666667, 25.32666667, 31.78333333, 16.24      ,
                18.87     , 25.77666667, 18.96666667, 21.53333333, 13.26666667,
                15.11666667, 13.46666667, 17.26333333, 24.95666667, 14.        ,
                35.61333333, 13.3      , 23.01333333, 18.2      , 23.90333333,
                29.51666667, 27.1      , 30.97     , 29.67666667, 14.35      ])
```

Feature 2:
Accuracy

In [54]:
```
from sklearn.metrics import r2_score
accuracy = r2_score(y_test1, y1_pred)
accuracy
```

Out[54]: 0.8999792555413947

Dataset:

mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
18	8	307	130	3504	12	70	1	chevrolet chevelle malibu
15	8	350	165	3693	11.5	70	1	buick skylark 320
18	8	318	150	3436	11	70	1	plymouth satellite
16	8	304	150	3433	12	70	1	amc rebel sst
17	8	302	140	3449	10.5	70	1	ford torino
15	8	429	198	4341	10	70	1	ford galaxie 500
14	8	454	220	4354	9	70	1	chevrolet impala
14	8	440	215	4312	8.5	70	1	plymouth fury iii
14	8	455	225	4425	10	70	1	pontiac catalina
15	8	390	190	3850	8.5	70	1	amc ambassador dpl
15	8	383	170	3563	10	70	1	dodge challenger se
14	8	340	160	3609	8	70	1	plymouth 'cuda 340
15	8	400	150	3761	9.5	70	1	chevrolet monte carlo
14	8	455	225	3086	10	70	1	buick estate wagon (sw)
24	4	113	95	2372	15	70	3	toyota corona mark ii
22	6	198	95	2833	15.5	70	1	plymouth duster
18	6	199	97	2774	15.5	70	1	amc hornet
21	6	200	85	2587	16	70	1	ford maverick
27	4	97	88	2130	14.5	70	3	datsun pl510
26	4	97	46	1835	20.5	70	2	volkswagen 1131 deluxe sedan
25	4	110	87	2672	17.5	70	2	peugeot 504
24	4	107	90	2430	14.5	70	2	audi 100 ls
25	4	104	95	2375	17.5	70	2	saab 99e
26	4	121	113	2234	12.5	70	2	bmw 2002
21	6	199	90	2648	15	70	1	amc gremlin
10	8	360	215	4615	14	70	1	ford f250

CHAPTER 8
TESTING

3. Test Case Analysis

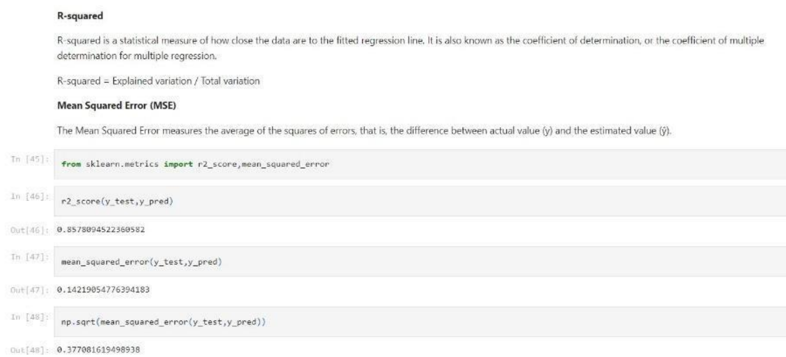
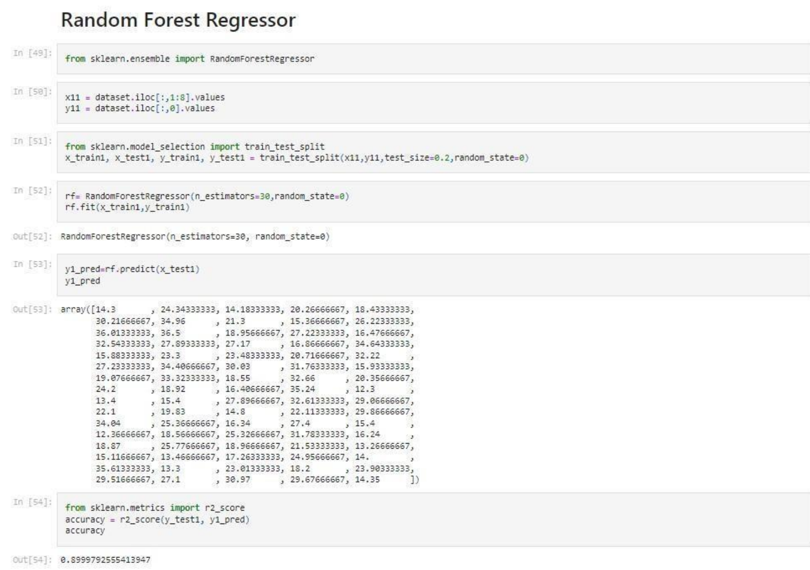
This report shows the number of test cases that have passed, failed, and untested

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

CHAPTER 9
RESULTS

9.1 PERFORMANCE METRICS

<table>
<tr><th>S. No.</th><th>PARAMETER</th><th>VALUES</th><th>SCREENSHOT</th></tr>
<tr><td>1.</td><td>Metrics</td><td>Regression Model:
MAE-,MSE-,RMSE-,R2 score-

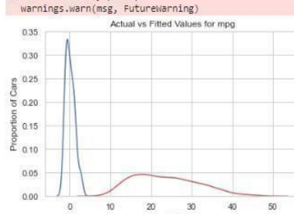
Classification Model:
Confusion Matrix,
Accuray Score-
&
Classification Report-</td><td>Decision tree regression

R-squared
R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression.
R-squared = Explained variation / Total variation
Mean Squared Error (MSE)
The Mean Squared Error measures the average of the squares of errors, that is, the difference between actual value (y) and the estimated value (ŷ).
In [45]: from sklearn.metrics import r2_score,mean_squared_error
In [46]: r2_score(y_test,y_pred)
Out[46]: 0.8578094522360582
In [47]: mean_squared_error(y_test,y_pred)
Out[47]: 0.14219054776394183
In [48]: np.sqrt(mean_squared_error(y_test,y_pred))
Out[48]: 0.377081619498938</td></tr>
<tr><td></td><td></td><td></td><td>
Random Forest Regressor
In [49]: from sklearn.ensemble import RandomForestRegressor
In [50]: x11 = dataset.iloc[:,1:8].values
y11 = dataset.iloc[:,0].values
In [51]: from sklearn.model_selection import train_test_split
x_train1, x_test1, y_train1, y_test1 = train_test_split(x11,y11,test_size=0.2,random_state=0)
In [52]: rf= RandomForestRegressor(n_estimators=30,random_state=0)
rf.fit(x_train1,y_train1)
Out[52]: RandomForestRegressor(n_estimators=30, random_state=0)
In [53]: y1_pred=rf.predict(x_test1)
y1_pred
Out[53]: array([14.3 , 24.34333333, 14.18333333, 20.26666667, 18.43333333,
30.21666667, 34.96 , 21.3 , 15.36666667, 26.22333333,
36.01333333, 36.5 , 18.95666667, 27.22333333, 16.47666667,
32.54333333, 27.89333333, 27.17 , 16.86666667, 34.64333333,
15.88333333, 23.3 , 23.48333333, 20.71666667, 32.22 ,
27.23333333, 34.40666667, 30.03 , 31.76333333, 15.93333333,
19.07666667, 33.32333333, 18.55 , 32.66 , 20.35666667,
24.2 , 18.92 , 16.40666667, 35.24 , 12.3 ,
13.4 , 15.4 , 27.89666667, 32.61333333, 29.06666667,
22.1 , 19.83 , 14.8 , 22.11333333, 29.86666667,
34.04 , 25.36666667, 16.34 , 27.4 , 15.4 ,
12.36666667, 18.56666667, 25.32666667, 31.78333333, 16.24 ,
18.87 , 25.77666667, 18.96666667, 21.53333333, 13.26666667,
15.11666667, 13.46666667, 17.26333333, 24.95666667, 14. ,
35.61333333, 13.3 , 23.01333333, 18.2 , 23.90333333,
29.51666667, 27.1 , 30.97 , 29.67666667, 14.35])
In [54]: from sklearn.metrics import r2_score
accuracy = r2_score(y_test1, y1_pred)
accuracy
Out[54]: 0.8999792555413947

Mean Squared error</td></tr>
</table>

```
In [60]: from sklearn.metrics import r2_score,mean_squared_error

In [61]: r2_score(y_test,y_pred2)

Out[61]: -0.04347826086956519

In [62]: mean_squared_error(y_test,y_pred2)

Out[62]: 0.6

In [63]: np.sqrt(mean_squared_error(y_test,y_pred2))

Out[63]: 0.7745966692414834
```

```
In [44]: ax1 = sns.distplot(dataset['mpg'], hist=False, color="r", label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" , ax=ax1)


plt.title('Actual vs Fitted Values for mpg')
plt.xlabel('mpg')
plt.ylabel('Proportion of Cars')

plt.show()
plt.close()
```

```
C:\Users\Max_l\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\Max_l\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



We can see that the fitted values are reasonably close to the actual values, since the two distributions overlap a bit. However, there is definitely some room for improvement.

Linear regression

	Accuracy	Training accuracy-0.8999792555413947	In [54]: `from sklearn.metrics import r2_score`
			`accuracy = r2_score(y_test1, y1_pred)`
			`accuracy`
			Out[54]: 0.8999792555413947

Figure 9.1 – Performance Metrics

CHAPTER 10
PROS AND CONS

Pros

- Using the Random Forest Algorithm in the model aids in classification and regression tasks.
- A random forest produces good predictions that are easy to understand
- It can easily handle large datasets
- The Random Forest Algorithm predicts outcomes with a higher level of accuracy.

Cons

- The main limitation of using random forest algorithm in the model is that a large number trees can make the algorithm too slow and ineffective for real-time predictions.
- The random forest algorithm is quite slow to create predictions once it is trained.

CHAPTER 11
CONCLUSION

Estimating a car's performance level is a significant and fascinating challenge. Our main goal was to forecast vehicle performance so that we could improve specific vehicle behavior. The car's performance is assessed based on factors such as horsepower, cylinder count, fuel type, and engine type, among others. The health of the car is forecasted based on factors such as horsepower, cylinder count, fuel type, and engine type. To optimize the vehicle's performance efficiency, we analyzed the components using a variety of well-known machine learning approaches such as linear regression, decision trees, and random forests. The power, longevity, and range of automobile traction batteries have recently become "hot topics" in automotive engineering. In this case, we also take mileage performance into account. We built the models to solve this problem using a variety of methods and neural networks. We then compared which algorithm is best at forecasting car performance (Mileage). A front-end web page was created to assist the user in presenting an appealing front while entering the values required by the developed machine learning model. The model was built on the IBM cloud platform.

CHAPTER 12
FUTURE WORKS

Since the dataset used for this model is an old vehicle dataset, the model's accuracy would suffer if the details of vehicles released recently were input. As a result, we propose that in the future, we use the most recent dataset set containing vehicle information to help train the model. We also intend to test other classification algorithms, such as SVM and Decision Tree, in place of Random Forest to see if any improvement in accuracy occurs. Finally, we propose that the machine learning model be scaled so that it can analyze the performance of a broader range of vehicles.

CHAPTER 13
APPENDIX

13.1 SOURCE CODE

13.1.1 car performance prediction.ipynb

Importing Libraries import
pandas as pd import numpy
as np import matplotlib.pyplot
as plt import seaborn as sns
import statsmodels.formula.api as smf

Importing Dataset
import os, types import
pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.
cos_client = ibm_boto3.client(service_name='s3',
ibm_api_key_id='xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx',
ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')

bucket = 'vehicleperformanceanalyserdeploym-donotdelete-pr-zcujqjsilptifi' object_key
= 'car performance.csv'

body = cos_client.get_object(Bucket=bucket,Key=object_key)['Body'] #
add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType(__iter__, body)

dataset = pd.read_csv(body)
dataset.head()

Splitting into train and test data.
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,random_state=0)
we are splitting as 90% train data and 10% test data

Normalisation
from sklearn.preprocessing import StandardScaler
sd = StandardScaler() x_train =
sd.fit_transform(x_train) x_test =
sd.fit_transform(x_test) y_train =
sd.fit_transform(y_train)
y_test = sd.fit_transform(y_test)

x_train
Decision tree regressor
from sklearn.tree import DecisionTreeRegressor
dt=DecisionTreeRegressor(random_state=0,criterion="mae") dt.fit(x_train,y_train)

import pickle
pickle.dump(dt,open('decision_model.pkl','wb'))

y_pred=dt.predict(x_test)
y_pred

y_test

ax1 = sns.distplot(dataset['mpg'], hist=False, color="r", label="Actual Value") sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" , ax=ax1)

plt.title('Actual vs Fitted Values for mpg')
plt.xlabel('mpg')
plt.ylabel('Proportion of Cars')

plt.show()
plt.close()

from sklearn.metrics import r2_score,mean_squared_error
r2_score(y_test,y_pred) 0.8578094522360582
mean_squared_error(y_test,y_pred)
0.14219054776394183
np.sqrt(mean_squared_error(y_test,y_pred))
0.377081619498938 Random
Forest Regressor
from sklearn.ensemble import RandomForestRegressor
x11 = dataset.iloc[:,1:8].values y11
= dataset.iloc[:,0].values
from sklearn.model_selection import train_test_split

```
x_train1, x_test1, y_train1, y_test1 = train_test_split(x11,y11,test_size=0.2,random_state=0) rf=
RandomForestRegressor(n_estimators=30,random_state=0)
rf.fit(x_train1,y_train1)
RandomForestRegressor(n_estimators=30, random_state=0) y1_pred=rf.predict(x_test1)
y1_pred

from sklearn.metrics import r2_score accuracy
= r2_score(y_test1, y1_pred) accuracy
0.8999792555413947 #save the model import pickle with
open('car_performance_regression_pkl', 'wb') as files:
   pickle.dump(rf, files)

from sklearn.metrics import r2_score,mean_squared_error
r2_score(y_test,y_pred2) -0.04347826086956519
mean_squared_error(y_test,y_pred2)
0.6 np.sqrt(mean_squared_error(y_test,y_pred2))
```

13.1.2 scoring end point.py

```
# -*- coding: utf-8 -*- """

import requests

# NOTE: you must manually set API_KEY below using information retrieved from your
IBM Cloud account.
API_KEY = "isS3P7auiIh4rzYJVtIMforGUPRhkBUhxz1GPVFJ_MbV"
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}

# NOTE: manually define and pass the array(s) of values to be scored in the next line
payload_scoring = {"input_data": [{"field":
[['cylinders','displacement','horsepower','weight','model year','origin']],
                              "values": [[8,307,130,3504,70,1]]}]}

response_scoring = requests.post('https://us-
south.ml.cloud.ibm.com/ml/v4/deployments/947e6ad9-2c7b-4002-
9bdf5e10aac95859/predictions?version=2022-11-17', json=payload_scoring,
```

```
 headers={'Authorization': 'Bearer ' + mltoken})
print("Scoring response") print(response_scoring.json())
```

13.1.3 app.py

```
import
numpy as np
from flask import Flask, request, jsonify, render_template import
pickle
#from joblib import load app
= Flask(__name__)
model = pickle.load(open('RandomForestRegressor.pkl', 'rb'))

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

@app.route('/y_predict',methods=['POST']) def
y_predict():
   '''
   For rendering results on HTML GUI
   '''
   x_test = [[int(x) for x in request.form.values()]]
print(x_test)
   #sc = load('scalar.save')
prediction = model.predict(x_test)
   print(prediction)
output=prediction[0]     if(output<=9):
      pred="Worst performance with mileage " + str(prediction[0]) +"mpg. Carry extra
fuel"     if(output>9 and output<=17.5):
      pred="Low performance with mileage " +str(prediction[0]) +"mpg. Don't go for long
distance"     if(output>17.5 and output<=29):
      pred="Medium performance with mileage " +str(prediction[0]) +"mpg. Go for a ride
nearby."     if(output>29 and output<=46):
      pred="High performance with mileage " +str(prediction[0]) +"mpg. Go for a healthy
ride"     if(output>46):
      pred="That's a very high performance with mileage " +str(prediction[0])+"mpg.
You can plan for a Tour"


   return render_template('index.html', prediction_text='{}'.format(pred))

@app.route('/predict_api',methods=['POST']) def
predict_api():
   '''
   For direct API calls trought request
   '''
   data = request.get_json(force=True)
```

```
    prediction = model.y_predict([np.array(list(data.values()))])

    output = prediction[0]
return jsonify(output)

if __name__ == "__main__":
    app.run(debug=True)
```

13.1.4 index.html

```
<!DOCTYPE html>
<html>
    <head>
        <title>Machine Learning Model</title>
        <meta charset="utf-8">
        <link rel="stylesheet" href="/static/css/main.css">
    </head>
    <body>
        <header>
            <h1>Car Performance prediction</h1>
        </header>
        <div class="form-container">
            <form action="" method="POST">
                <div class="field">
                    <label for="no_of_cylinders">
                        <p class="cylinders field-name">Number of Cylinders</p>
                    </label>
                    <input type="number" id="no_of_cylinders input"
name="no_of_cylinders">
                </div>

                <div class="field">
                    <label for="displacement">
                        <p class="displacement field-name">Displacement</p>
                    </label>
                    <input type="number" id="displacement input" name="displacement">
                </div>

                <div class="field">
                    <label for="horsepower">
                        <p class="horsepower field-name">Horse Power</p>
                    </label>
                    <input type="number" id="horsepower input" name="horsepower">
```

```
            </div>

            <div class="field">
                <label for="weight">
                    <p class="weight field-name">Weight</p>
                </label>
                <input type="number" id="weight input" name="weight">
            </div>

            <div class="field">
                <label for="acceleration">
                    <p class="acceleration field-name">Acceleration</p>
                </label>
                <input type="number" id="acceleration input" name="acceleration">
            </div>

            <div class="field">
                <label for="model_year">
                    <p class="model_year field-name">Model Year</p>
                </label>
                <input type="number" id="model_year input" name="model_year">
            </div>

            <div class="field">
                <label for="origin">
                    <p class="origin field-name">Origin</p>
                </label>
                <input type="number" id="origin input" name="origin">
            </div>

            <input type="submit" value="sumbit" class="submit-btn btn">
        </form>
    </div>
  </body>
</html>
```

13.2 GitHub & Project Demo Link

Source Code : **GitHub - IBM-EPBL/IBM-Project-11565-1659334799: Machine Learning based ...**

Project Demo Link : **GitHub - IBM-EPBL/IBM-Project-11565-1659334799: Machine Learning based ...**