TRIP BASED MODELING OF FUEL CONSUMPTION IN MODERN FLEET VEHICLES USING MACHINE LEARNING

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NALAIYATHIRAN PROJECT BASED LEARNING ON PROFESSIONAL

READINESS FOR INNOVATION, EMPLOYING AND ENTERPRENEURSHIP

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1. INTRODUCTION

The fuel efficiency of heavy-duty trucks can be beneficial not only for the automotive and transportation industry but also for a country's economy and the global environment. The cost of fuel consumed contributes to approximately 30% of a heavy-duty truck's life cycle cost. Reduction in fuel consumption by just a few percent can significantly reduce costs for the transportation industry. The fuel economy of heavy-duty vehicles (HDV) is affected by several real-world parameters like road parameters, driver behavior, weather conditions, and vehicle parameters, etc. The model was further evaluated with data collected from a vehicle on-road trip .A simulation model was developed based on engine capacity, fuel injection, fuel specification, aerodynamic drag, grade resistance, rolling resistance, and atmospheric conditions, with simulated dynamic driving conditions to predict fuel consumption.
Machine learning techniques such as support vector machine (SVM) , random forest (RF) , and artificial neural networks (ANN) are widely applied to turn data into meaningful insights and solve complex problems .While the current approaches determine the fuel consumption of the vehicle, combining these techniques with data helps to identify parameters that may cause anomalies, such as malfunctions due to wear and tear of the engine, improper maintenance, engine failure, exhaust after-treatment system, and external factors like climate, traffic, road conditions, etc .
Several previous models for both instantaneous and average fuel consumption have been proposed. Physics-based models are best suited for predicting instantaneous fuel consumption because they can capture the dynamics of the behavior of the system at different time steps. Most states have now mandated that truck fleets update their vehicle inventory with modern vehicles due to air quality regulations. These techniques have been applied to estimate emissions and fuel consumption in motor vehicles, trucks, ships , and aircraft . A statistical model which is fast and simple compared to the physical load-based approach was developed to predict vehicle emissions and fuel consumption. However, these models are able to identify and learn trends in average fuel consumption with an adequate level of accuracy.

1.1. Project Overview

In the paper, we are enhancing the accuracy of the fuel consumption prediction model with Machine Learning to minimize Fuel Consumption. This will lead to an economic improvement for the business and satisfy the domain needs. We propose a machine learning model to predict vehicle fuel consumption. The proposed model is based on the Support Vector Machine algorithm. The Fuel Consumption estimation is given as a function of Mass Air Flow, Vehicle Speed, Revolutions Per Minute, and Throttle Position Sensor features. The proposed model is applied and tested on a vehicle's On-Board Diagnostics Dataset. These types of fleets exist in various sectors including, road transportation of goods, public transportation , construction trucks and refuse trucks .
The observations were conducted on 18 features. Results achieved a higher accuracy with an R-Squared metric value of 0.97 than other related work using the same Support Vector Machine regression algorithm. We concluded that the Support Vector Machine has a great

effect when used for fuel consumption prediction purposes. Data modeling can easily help to diagnose the reason behind fuel consumption with a knowledge of input parameters. Our model can compete with other machine learning algorithms for the same purpose which will help manufacturers find more choices for successful Fuel Consumption prediction models
Engines and Emissions (WVU CAFEE) using the portable emissions monitoring system (PEMS). The performance of the artificial neural network was evaluated using mean absolute error (MAE) and root mean square error (RMSE). The model was further evaluated with data collected from a vehicle on-road trip. The study shows that artificial neural networks performed slightly better than other machine learning techniques such as linear regression (LR), and random forest (RF), with high R-squared (R2) and lower root mean square error.

1.2. Purpose

Fuel economy is a measure of how far a vehicle will travel with a gallon of fuel; it is expressed in miles per gallon. As a metric, fuel economy actually measures distance traveled per unit of fuel. Before proceeding, it is necessary to define the terms fuel economy and fuel consumption; these two terms are widely used, but very often interchangeably and incorrectly, which can generate confusion and incorrect interpretations .Fuel consumption is the inverse of fuel economy. It is the amount of fuel consumed in driving a given distance. It is measured in the United States in gallons per 100 miles, and in liters per 100 kilometers in Europe and elsewhere throughout the world.
Fuel consumption is a fundamental engineering measure that is directly related to fuel consumed per 100 miles and is useful because it can be employed as a direct measure of volumetric fuel savings. It is actually as a fuel consumption. Because fuel economy and fuel consumption are reciprocal, each of the two metrics can be computed in a straight-forward manner if the other is known. In mathematical terms, if fuel economy is X and fuel consumption is Y, their relationship is expressed by XY = 1. This relationship is not linear, as illustrated by in which fuel consumption is shown in units of gallons per 100 miles, and fuel economy is shown in units of miles per gallon.
Also shown in the figure is the decreasing influence on fuel savings that accompanies increasing the fuel economy of high-mpg vehicles. Each bar represents an increase of fuel economy by 100 percent or the corresponding decrease in fuel consumption by 50 percent. The data on the graph show the resulting decrease in fuel consumption per 100 miles and the total fuel saved in driving 10,000 miles .The dramatic decrease in the impact of increasing miles per gallon by 100 percent for a high-mpg vehicle is most visible in the case of increasing the miles per gallon rating from 40 mpg to 80 mpg, where the total fuel saved in driving 10,000 miles is only 125 gallons, compared to 500 gallons for a change from 10 mpg to 20 mpg. Likewise, it is instructive to compare the same absolute value of fuel economy changes—for example, 10-20 mpg and 40-50 mpg.

2. LITERATURE SURVEY

2.1. Existing Problem

Fuel is one of a fleet operator’s biggest pain points. Being the second largest expense category, fuel seems to be an ever flowing source of stress and lost money. And if you don’t control it the fuel management is not a complex topic to dive into, if you’re already using a fleet management solution. This article will help you discover what other opportunities your software has in terms of fuel efficiency. And if you’re only considering getting or building an FMS, this will be your guide to the best features to ask your vendor about. A fuel management system is a subdivision of a fleet management system that uses telematics-based tools and analytical software to capture fuel consumption data and improve fuel economy.

Starting with the most extreme case that a car could be suffering through is a faulty engine. A damaged engine cannot work properly and in turn, can consume more fuel. Now you might be thinking that the engine itself can’t be faulty when the car has run only a few km. You are right. The engine may be fine but the crucial components that contribute to the combustion cycle could be faulty. For instance, a faulty spark plug or O2 sensor in a petrol engine and a dirty fuel injector in a diesel engine can cause more consumption of fuel resulting in low fuel mileage. Your engine may function normally for a while but the fuel won’t be burnt efficiently. This will eventually cause your car to consume more fuel than usual. They incorporate data about fuel transactions into analytics and learn what brands of fuel bring better economy, compare fuel usage across vehicles, break down fuel spend, and generally improve your fuel buying behavior.

Capture and prevent fuel theft and leakage. Fuel monitoring and anti-siphoning devices can update you on fuel amounts in trucks and on-site tanks and send alerts about fuel levels. Calculate and report fuel taxes. Integrated with your vehicle’s GPS, a fuel management system can automatically calculate traveled distance and purchased fuel to help file your IFTA tax reports. The ultimate benefit of fuel management systems is automation — operations that used to be done manually in spreadsheets can happen automatically in the background, providing analytics for you to base your decisions on. Now, let’s cover the main opportunities and how they work.

2.2. References

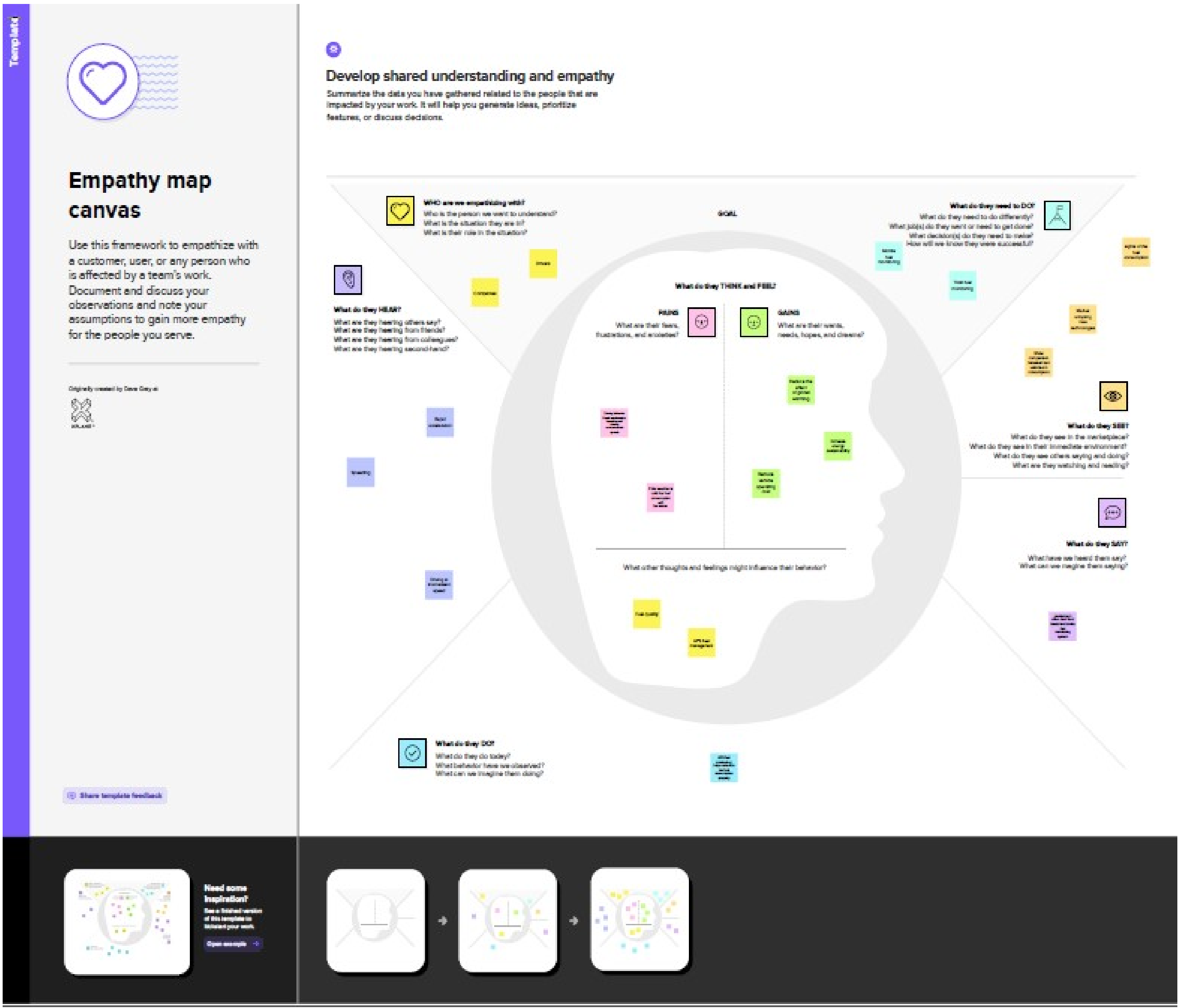
1.Sagnik Choudhury, Y.V. Mahesh Kumar and Ankit Aggarwal;Minimising fuel consumption of vehicles as a function of path parameters 2011.
2.Federico Perrottaa , Tony Parryaand Luis C. Neves;Application of Machine Learning for Fuel Consumption Modelling of Trucks 2017.
3.SasankaKatreddi and Arvind Thiruven;Trip Based Modeling of Fuel Consumption in Modern Heavy-Duty Vehicles Using Artificial Intelligence 2021.
4.Dr. B. Dhanalaxmi, M.Varsha, K. Roshan Chowdary and P. Mokshitha;An Enhanced Fuel Consumption Machine Learning Model Used in Vehicles 2021.

2.3. Problem Statement Definition

Reduction in fuel consumption by just a few percent can significantly reduce costs for the transportation industry. The effective and accurate estimation of fuel consumption (fuel consumed in L/km) can help to analyze emissions as well as prevent fuel-related fraud. While going for a long trip, it is quit tough to analyze the need fuel consumption.

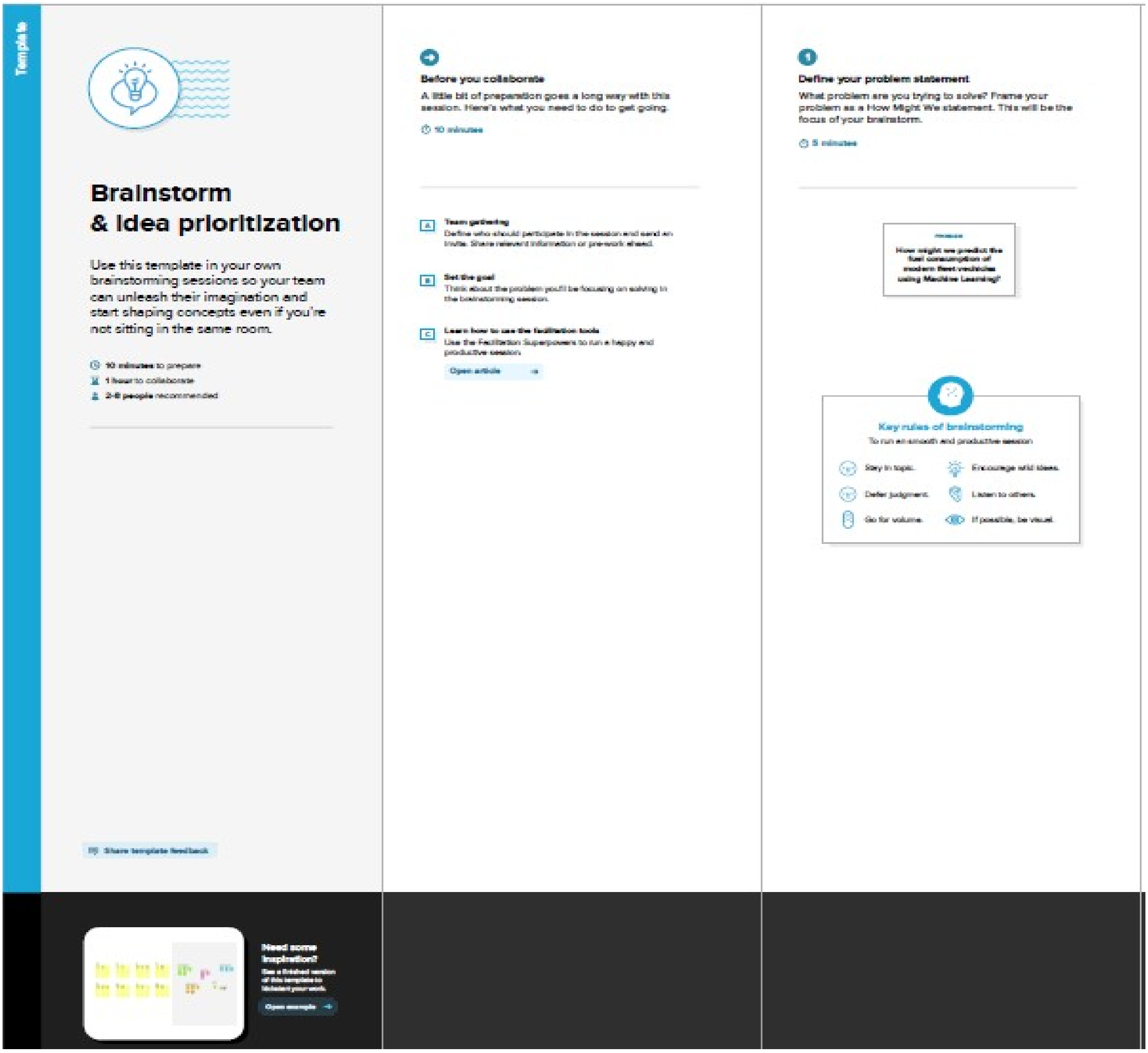
3.IDEATION & PROPOSED SOLUTION

3.1. Empathy Map Canvas

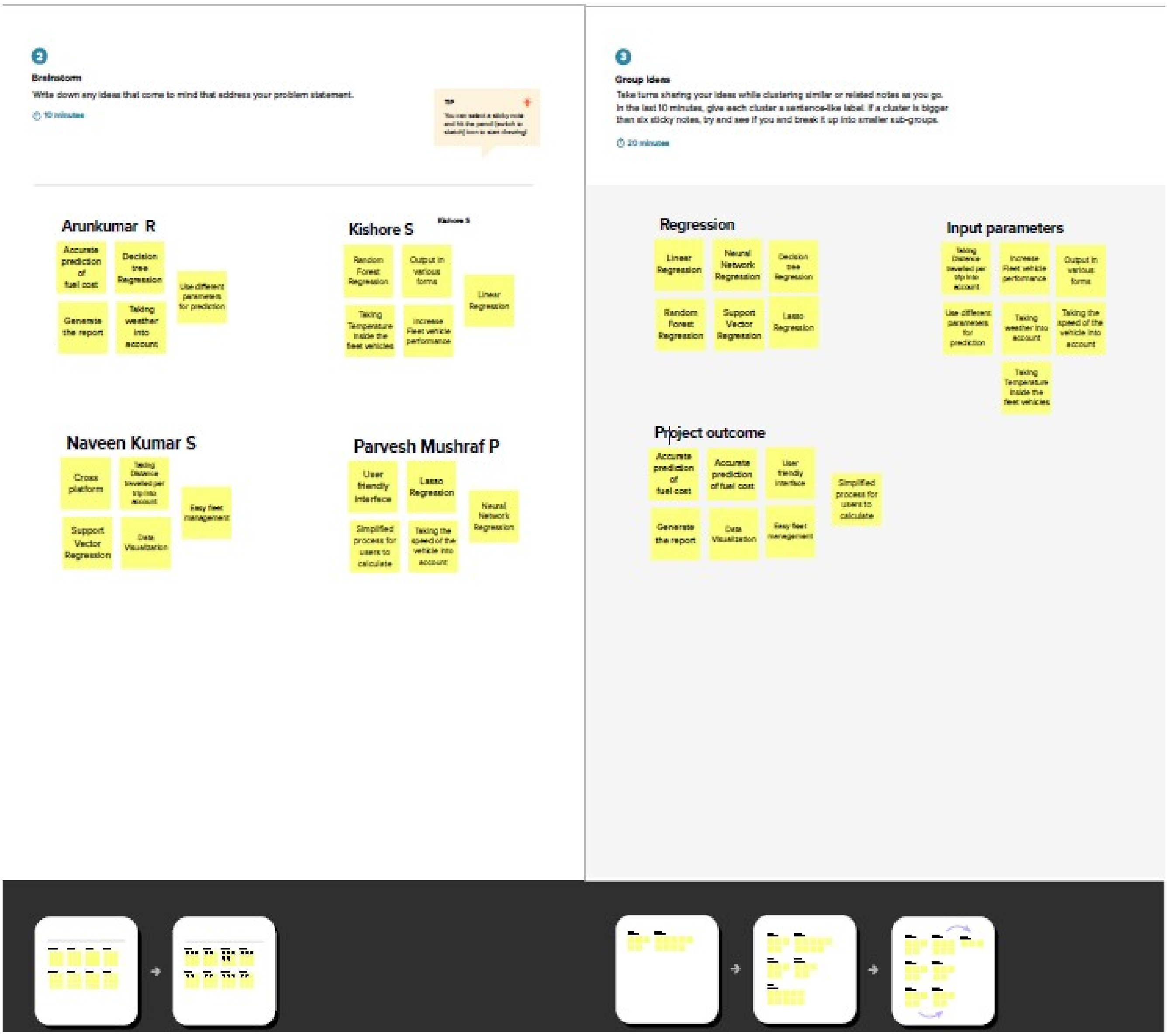


3.2. Ideation & Brainstorming

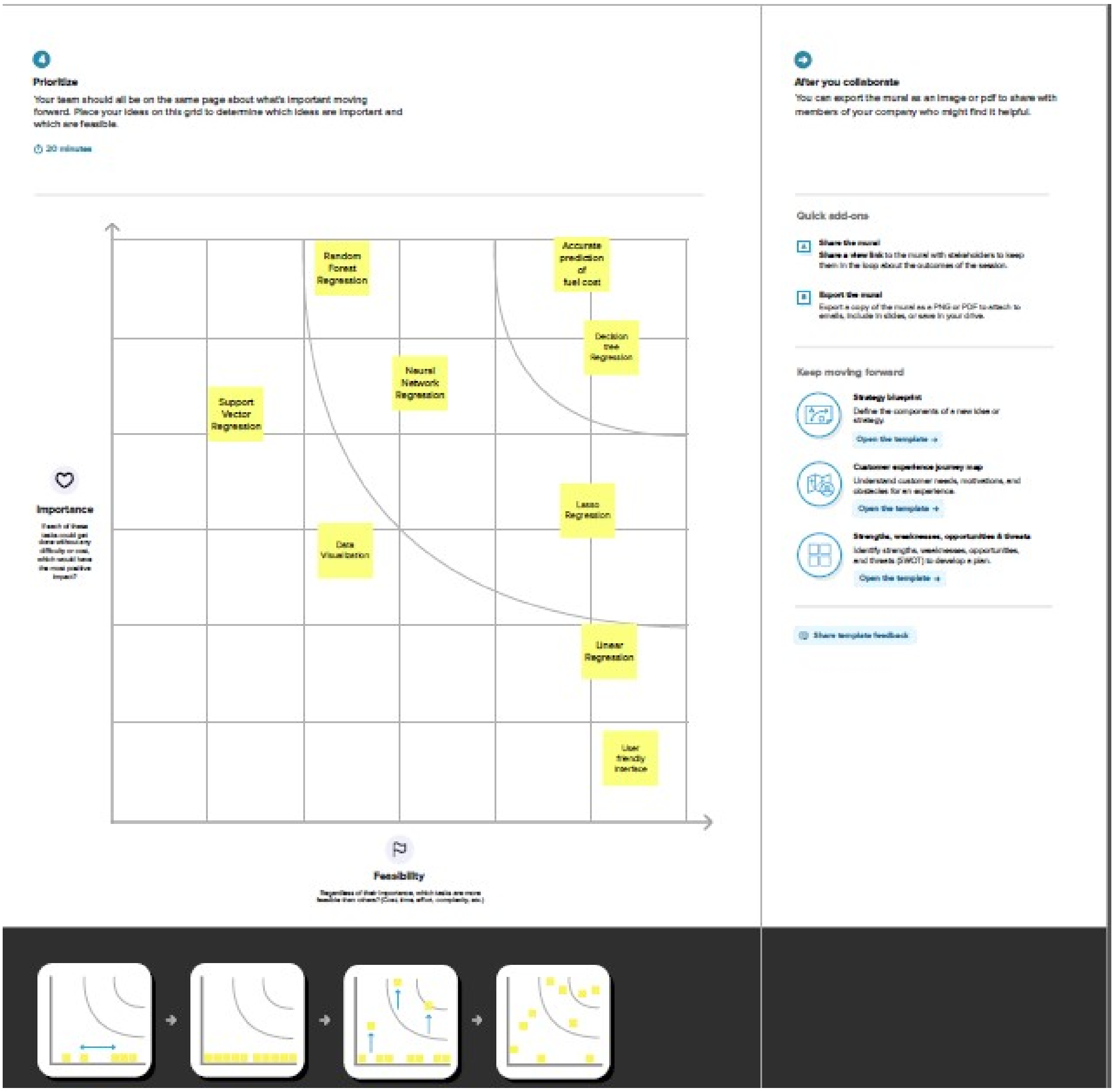
Step-1: Team Gathering, Collaboration and Select the Problem Statement



Step-2: Brainstorm, Idea Listing and Grouping



Step-3: Idea Prioritization



3.3. Proposed Solution

A more detailed description of the Offer or understands of the TORFP scope of work, proposed methodology and solution. Even though we are aware that engines need fuel to run, that does not mean you can't make some small changes to help you gain some fuel savings. Keep tires pumped up tires that are underinflated have a higher rolling resistance on the road. This means that with every kilometer traveled, your tires generate more friction and rolling resistance, and hence, will increase fuel consumption. If all your tires are underinflated by 10 psi, this could reduce fuel efficiency by up to 10%.Lose the weight in your boot.

For those with a habit of keeping everything and anything in the boot, in addition to emergency spares, think twice when loading up next time. Every extra 50kg your car puts on increases fuel consumption by 2%.Driving with the windows down at speeds faster than 80km/h causes a lot of wind resistance, and costs you a lot more fuel. Contrary to what you may think, in this situation, it's simply more fuel efficient to drive with the air on. When cruising down a highway, your engine works hard to overcome wind resistance. You'll burn up to 15% more fuel at 100 km/h and 25% more at 110 km/h.

That might tempt you to drive slow, but if you drive slower than 50 km/h, your engine would drop to a lower gear, thus using up more fuel. In conclusion, a steady 50 – 90 km/h on the highway is best to achieve optimal fuel economy. Slamming on the brakes increases fuel consumption as you need to accelerate again later. This is especially true if you follow too closely behind the vehicle in front of you. Not to mention, tailgating is dangerous and something to avoid. If you're driving an automatic car, make use of cruise control to keep your speed constant. And if you're driving a manual car, maintain a higher gear when appropriate. In each of these instances, your engines go through less revolutions per minute (RPM) and will reduce your fuel consumption.

3.4. Problem Solution Fit

Define CS, fit into CL	**1. CUSTOMER SEGMENT(S)** CS Owners of vehicles/ Owners of fleet vehicles/ Managers	**6. CUSTOMER LIMITATIONS** EG. BUDGET, DEVICES CL They have tried to monitor their fuel consumptions but have failed to do so accurately. Fleet mangers are not able to track fraudulent activities.	**5. AVAILABLE SOLUTIONS** PROS & CONS AS Existing solutions provide only analysis. It is difficult for them to bring in a lot of parameters	Explore AS, differentiate
Focus on PR, tap into BE, understand RC	**2. PROBLEMS / PAINS** + ITS FREQUENCY PR We have to predict the fuel consumption of vehicles by using existing data and the type of gas they use. Customers often try to do rough average calculations to find the amount of fuel that they might consume. But they are not accurate,	**9. PROBLEM ROOT / CAUSE** RC The reason for not being able to predict the fuel consumption accurately is that there are a lot of parameters involved, and they vary depending on time. It is not easy to take into the variation in time. Also some parameters are not judgeable like Roasd conditions and traffic. For those we need hyper parameters.	**7. BEHAVIOR** + ITS INTENSITY BE When they are unable to solve this problem they try to find a way across to get an idea of the solution. They try to approximate the fuel prediction based on their own heuristics They try to find whether there are existing solutions for this issue and maybe try and hire a team that can develop a solution for this purpose .	Focus on PR, tap into BE, understand RC
Identify strong TR & EM	**3. TRIGGERS TO ACT** TR When they are unable to predict the fuel consumption. **4. EMOTIONS** BEFORE / AFTER EM They feel ignorant and less in control of their business. After the problem is solved, they feel empowered and confident.	**10. YOUR SOLUTION** SL -Interactive dashboard that provides insights about the vehicles and their fuel consumption. -We plan to collect data from various sensors in the fleet vehicles and store it in a database -Use that data to train the models to predict the fuel consumption. -Also plan to add real time mileage prediction using real time speed and other parameters.	**8. CHANNELS of BEHAVIOR** CH ONLINE Have to keep track of data from the vehicles to maintain statistics and also use them for further predictions.. OFFLINE For data to be collected hardware devices need to be installed and kept on the fleet. Devices need to be monitored and kept in proper conditions.	Extract online & offline CH of BE

4.REQUIREMENT ANALYSIS

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Dashboard	Single Sample Prediction Multiple Sample Prediction View user history
FR-2	Output Generation	Visual Representation Report Generation

Non-functional Requirements:

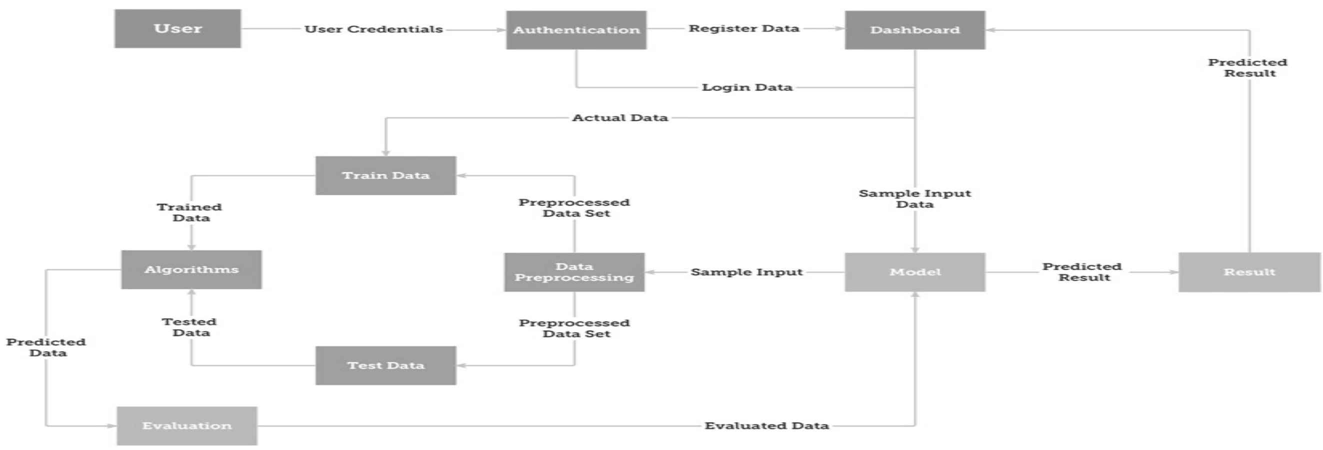
Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	User-friendly Interface to facilitate the user with easy processing. Model provides visual representation of predictions.
NFR-2	**Security**	Authentication - User can have his/her own private dashboard to have secured access.
NFR-3	**Reliability**	The model is capable enough to handle huge volume of data and run multiple samples simultaneously.
NFR-4	**Performance**	As the model is a combination of multiple ML algorithms, the accuracy is high.
NFR-5	**Availability**	The website is also mobile-responsive and is portable. It requires only basic configurations to run on any device.
NFR-6	**Scalability**	It can be extended further to provide API which can be used by third party organisations such as Automobile Manufacturers, Logistics companies,etc.

5. PROJECT DESIGN

5.1. Data Flow Diagrams:

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.



5.2. Solution & Technical Architecture

S. No	Component	Description	Technology
1.	Website	To predict fuel use, user interacts with prediction model via website.	HTML,CSS
2.	Cloud Database	The model receives information from an IBM cloud database.	IBM Cloud DB, ibm_db (python package)
3.	API	used to expand service to additional applications	Flask Application
4.	JWT &Sessions	It is employed to manage JSON web tokens (signing, verifying, decoding)	PyJWT, Flask-Sessions
5.	Machine Learning Model	This model was created using ML algorithms to forecast fuel use.	Sklearn, Algorithms- MLR
6.	Data processing	Data is pre-processed and used for training the model which is subsequently used for prediction.	Pandas, NumPy, Matplotlib

5.3. User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer	Registration/Login	USN-1	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
	Dashboard	USN-2	Once I enter the dashboard I can input values for a single sample prediction	I can predict for single sample	High	Sprint-1
Customer(Organization)		USN-3	Once I enter the dashboard I can input values via excel sheet for multiple sample prediction	I can perform multiple sample prediction	Medium	Sprint-2
		USN-4	As a user I can get visual representation of the prediction	I can have different forms of output	High	Sprint-1
		USN-5	As a user I can view the detailed report of my prediction	I can access details of my process and prediction	Medium	Sprint-1
	Documentation	USN-6	As a user I can refer the documentation for support and guidance	I can use user manual for guidance	Medium	Sprint-1,2,3,4
Developer	Settings	USN-7	As a developer I can access dashboard's settings and view the API token	I can view the API token for creating request such as predicting, downloading report, etc.,	Low	Sprint-4
		USN-8	As a developer I can use the API token to send request to server	I can send request to server along with token	Medium	Sprint-4

6. PROJECT PLANNING & SCHEDULING

6.1. Sprint Planning & Estimation

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	8	6 Days	24 Oct 2022	29 Oct 2022		
Sprint-2	10	6 Days	31 Oct 2022	05 Nov 2022		
Sprint-3	13	6 Days	07 Nov 2022	12 Nov 2022		
Sprint-4	13	6 Days	14 Nov 2022	19 Nov 2022		

6.2. Sprint Delivery Schedule

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN - 1	As a user, I can register using email and password	4	High	ARUNKUMAR R
Sprint-2		USN - 2	As a user, I can register using Gmail	2	Medium	KISHORE S
Sprint-1		USN - 3	As a user, I will receive confirmation email once I have registered for the application	1	Low	NAVEEN KUMAR S
	Login	USN - 4	As a user, I can login to my dashboard through emailid and password	2	High	PARVESH MUSHRAF P
	Dashboard	USN - 5	I can access my account details on dashboard	1	Low	ARUNKUMAR R
Sprint-2	Prediction Model	USN - 6	Once I enter the dashboard I can input values for a single sample prediction	8	High	KISHORE S
Sprint-3		USN - 7	I can input values via excel sheet for multiple sample prediction as per the template and perform prediction	6	Medium	ARUNKUMAR R
		USN - 8	As a user I can get visual representation of the prediction	4	Medium	KISHORE S
	Report Generation	USN - 9	As a user I can view the detailed report of my prediction	3	High	ARUNKUMAR R
Sprint-4	RestAPI	USN - 10	As a developer, I can use API Token to send request to the server	3	Low	ARUNKUMAR R
	Documentation	USN - 11	As a user I can refer to the documentation and user manual for support and guidance	4	High	KISHORE S
		USN - 12	As a developer, I can refer to technical Documentation for	6	Medium	ARUNKUMAR R

6.3. Reports from JIRA

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	8	6 Days	24 Oct 2022	29 Oct 2022		
Sprint-2	10	6 Days	31 Oct 2022	05 Nov 2022		
Sprint-3	13	6 Days	07 Nov 2022	12 Nov 2022		
Sprint-4	13	6 Days	14 Nov 2022	19 Nov 2022		

Velocity: Imagine we have a10-days print duration, and the velocity of the team is 20(points pers print). Let’s calculate the team’s average velocity (AV) per iteration unit (story points per day)

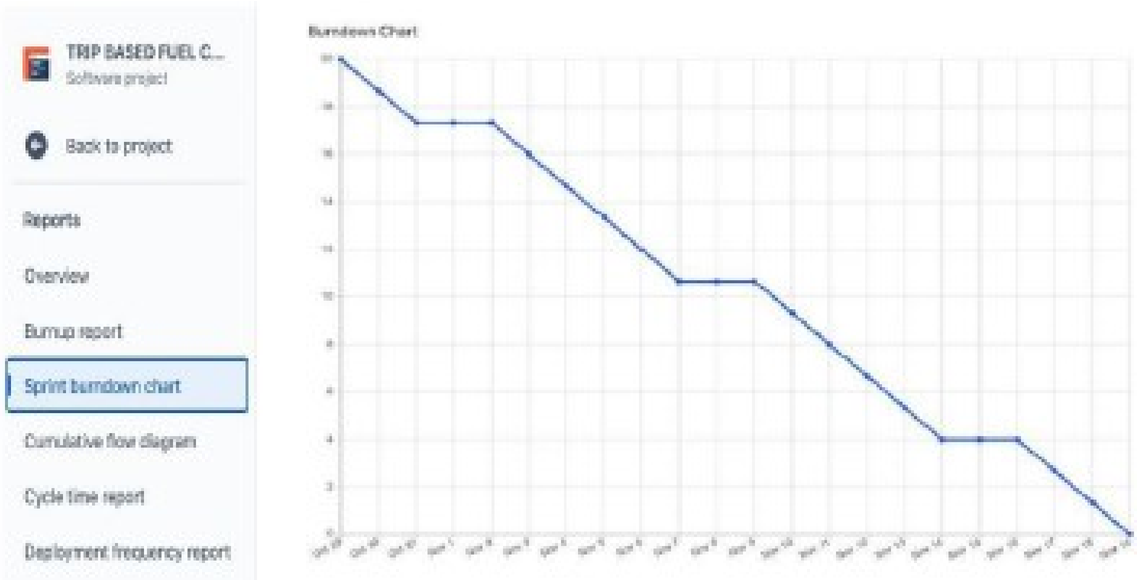
AV=Velocity/Sprint duration

Sprint	Average Velocity
Sprint1	1.33
Sprint2	1.67
Sprint3	2.17
Sprint4	2.17

Total Average Velocity = 1.83

Burn 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 such as Scrum. However, burn down charts can be applied to any project containing measurable progress over time.



7. CODING & SOLUTIONING

7.1. Feature 1

Have done building a web application that is integrated to the model we built. A UI is provided for the uses where user has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.

Building HTML Pages:

```
<html>
<head>
   <title>
      Prediction
   </title>
   <link href='https://fonts.googleapis.com/css?family=Montserrat' rel='stylesheet'>
   <style>
      * {
         box-sizing: border-box;
      }
      body {
         font-family: 'Montserrat';
      }
      .header {
         top: 0;
         margin: 0px;
         left: 0px;
         right: Opx;
         position: fixed;
         background-color: black;
         color: white;
         box-shadow: Opx 8px 4px grey;
         overflow: hidden;
         padding: 15px;
         font-size: 2vw;
         width: 100%;
         text-align: left;
         padding-left: 100px;
         opacity: 0.9;
      }
```

```
.header_text {
   font-size: 40px;
   text-align: center;
}
.content {
   margin-top: 100px;
}
.text {
   font-size: 20px;
   margin-top: 10px;
   text-align: center;
}
input[type=number],
select {
   width: 50%;
   padding: 12px 20px;
   margin: 8px 0;
   display: inline-block;
   border: 1px solid #ccc;
   border-radius: 4px;
   box-sizing: border-box;
}
input[type=submit] {
   width: 50%;
   background-color: #000000;
   color: white;
   padding: 14px 20px;
   margin: 8px 0;
   border: none;
   border-radius: 4px;
   cursor: pointer;
}
input[type=submit]:hover {
   background-color: #5d6568;
   color: #ffffff;
   border-color: black;
}
form {
   margin-top: 20px;
}
.results {
```

```
            color: black;
            margin-top: 30px;
            margin-bottom: 20px;
            font-size: 25px;
            color: red;
        }
    </style>
</head>
<body align=center>
    <div class="header">
        <div>Fuel Consumption </div>
    </div>
    <div class="content">
        <div class="header_text">Consumption Prediction</div>
        <div class="text">Fill in and below details to predict the consumption depending on the gas type. </div>
        <div class="result">
            {{ prediction_text }}
        </div>
        <form action="{{ url_for('y_predict') }}" method="POST">
            <input type="number" step="any" id="distance" name="distance" placeholder="distance(km)">
            <input type="number" id="speed" name="speed" placeholder="speed (km/h)">
            <input type="number" id="temp_inside" name="temp_insidet" placeholder="temp_inside(°C)">
            <input type="number" id="temp_outside" name="temp_outside" placeholder="temp_outside(°C)">
            <input type="number" id="AC" name="AC" placeholder="AC">
            <input type="number" id="rain" name="rain" placeholder="rain">
            <input type="number" id="sun" name="sun" placeholder="sun">
            <input type="number" id="E10" name="E10" placeholder="E10">
            <input type="number" id="SP98" name="SP98" placeholder="SP98">

            <input type="submit" value="Submit">
        </form>
    </div>
</body>

</html>
```

8. TESTING

8.1. Test Cases

The below mention chart conveys the user test cases and its details of the test cases.

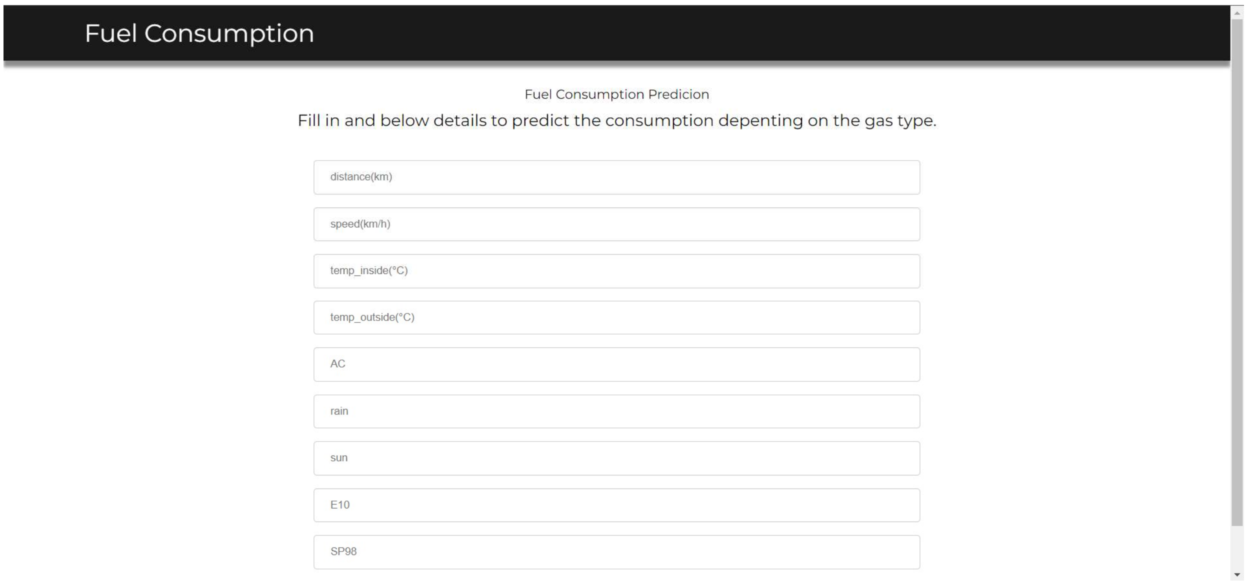
Steps To Execute	Test Data	Expected Result	Actual Result	Status
1)Run the Fuel Consumption Prediction page	http://127.0.0.1:5000	Local hosted the Web app Successfully	Working as expected	Pass
2)Enter the values to be predicted	Enter the values of distance, Speed, temp_inside, temp_outside, Gas type, rain and sun,E10,SP98.	Predicted Successfully	Working as expected	Pass
3)Predicted value displaying(output)	Value of fuel consumption litre (output) (L/100KM)	The value Fuel consumption came Successfully	Working as expected	Pass

8.2. User Acceptance Testing

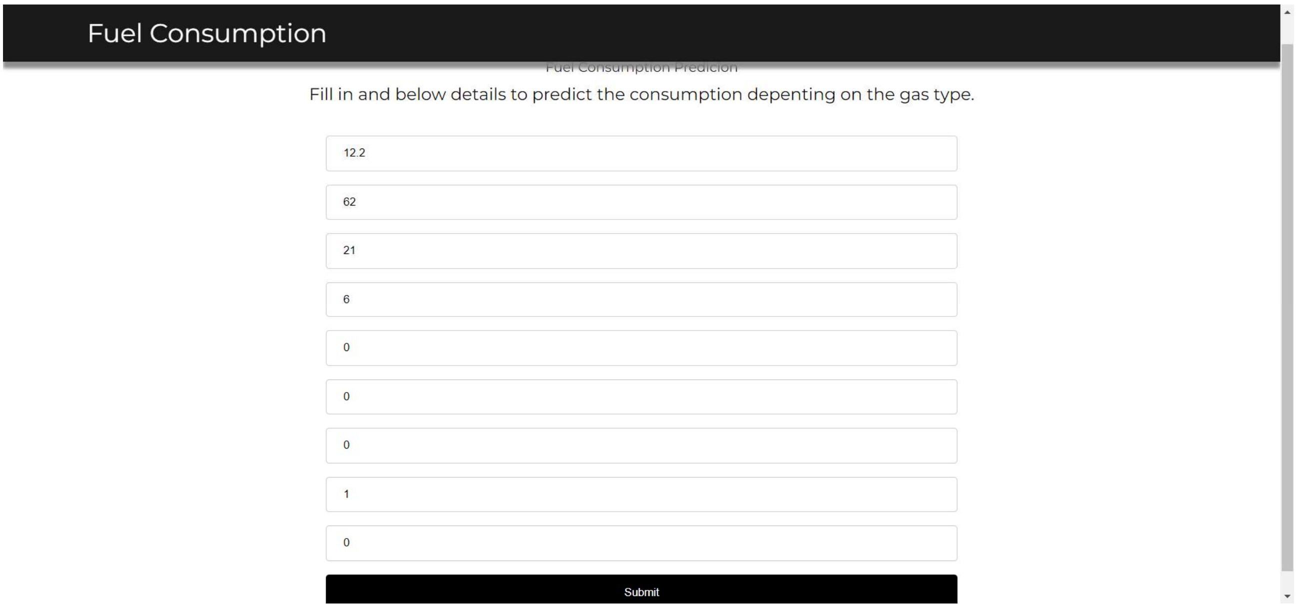
This report shows the number of resolved or closed bugs at each severity level, and how they were resolved. The following are the detail and description for user acceptance testing.

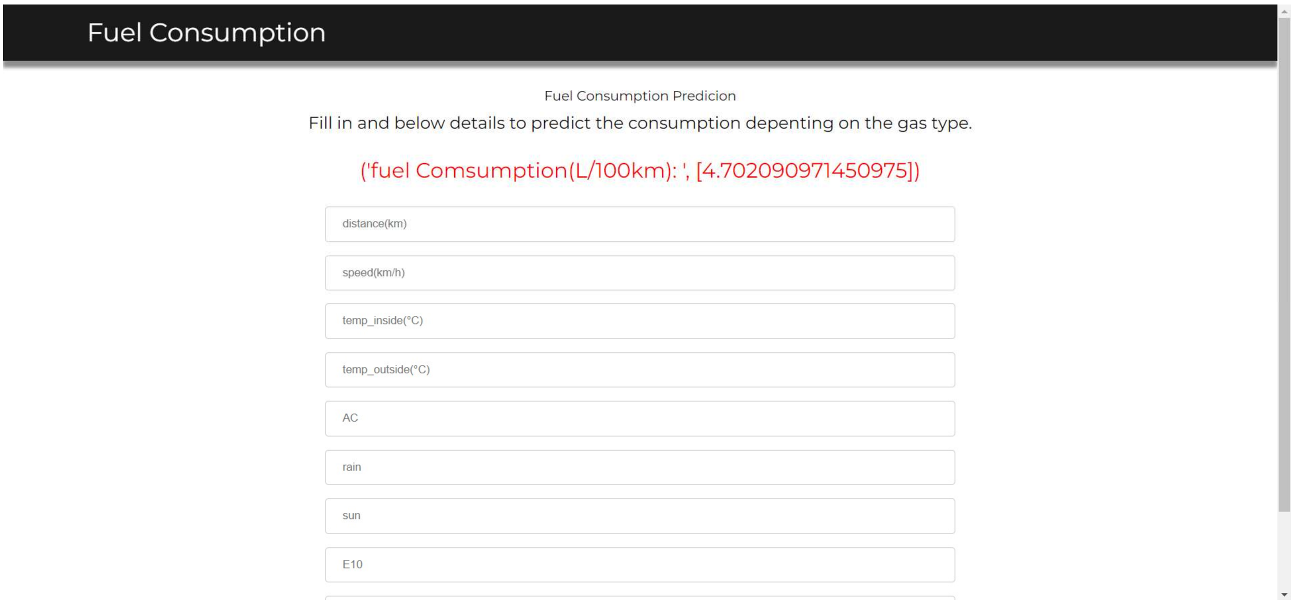
Satatistics

Current ratio:

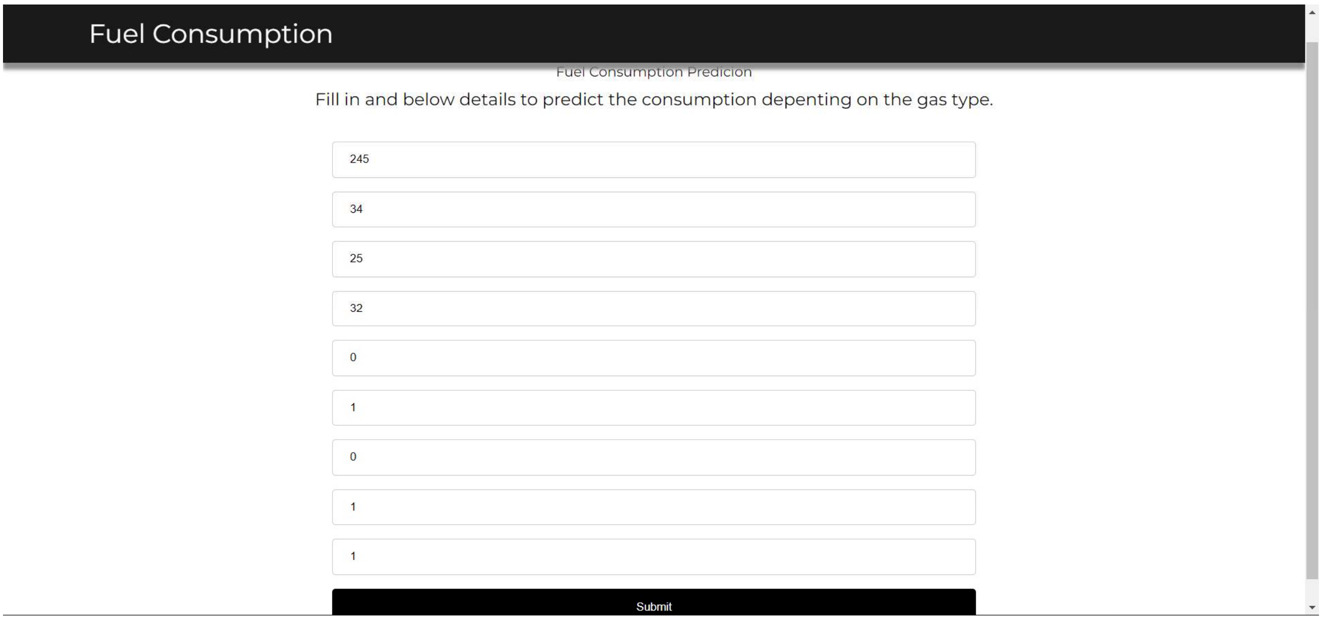


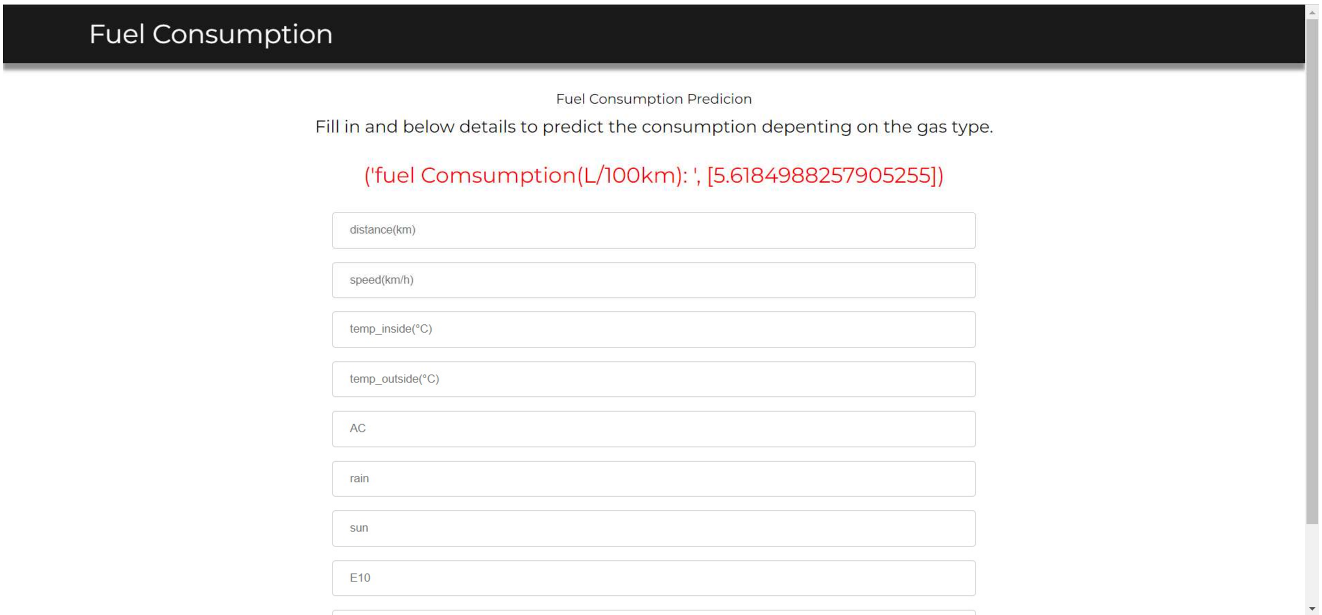
Example 1:


Fuel Consumption
Fuel Consumption Predicion
Fill in and below details to predict the consumption depenting on the gas type.
12.2
62
21
6
0
0
0
1
0
Submit


Fuel Consumption
Fuel Consumption Predicion
Fill in and below details to predict the consumption depenting on the gas type.
('fuel Comsumption(L/100km): ', [4.7020909714509751])
distance(km)
speed(km/h)
temp_inside(°C)
temp_outside(°C)
AC
rain
sun
E10

Example 2:


Fuel Consumption
Fuel Consumption Predicion
Fill in and below details to predict the consumption depenting on the gas type.
245
34
25
32
0
1
0
1
1
Submit


Fuel Consumption
Fuel Consumption Predicion
Fill in and below details to predict the consumption depenting on the gas type.
('fuel Comsumption(L/100km): ', [5.6184988257905255])
distance(km)
speed(km/h)
temp_inside(°C)
temp_outside(°C)
AC
rain
sun
E10

9. RESULTS

The Following passage which explains the end result of the overall development of the cloud application.

9.1. Performance Metrics

A	B	C	D	E
NFT - Risk Assessment				
Functional Changes	Hardware changes	Software Changes	Impact of Downtime	Load/Volume Change
Low	No Change	Moderate	no	>5-10%
NFT- Detailed Test Plan				
S. NO	Project Overview	NFT Test approach	Assumptions/Dependencie	Approvals/Sign OFF
1	Prediction Model App.py	1.Run the Fuel Consumption Prediction page and Locally hosted the Web app Success	No Risk	N/A
2	The values to be predicted	2.Enter the values of distance, Speed, Temp_out, Gas type, rain and sun	No Risk	N/A
3	Display the Output	3. Value of fuel consumption liter	No Risk	N/A
End of Test Report				
NFR - Met	Test Outcome	GO/NO-GO decision	Recommendation	Identified Error
Yes	Test Passed	GO	N/A	None

The accuracy of the technical side has accuracy 0.7309626842679302 rate of error where running model.

The three main metrics used to evaluate a classification model are accuracy, precision, and recall. Accuracy is defined as the percentage of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions.

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is best

The Mean Squared Error measures the average of the errors squared. It basically calculates the difference between the estimated and the actual value, squares these results and then computes their average.

• Mean Squared Error:

Mean Squared Error (MSE) represents the average of the squared difference between the original and predicted values in the data set. It measures the variance of the residuals.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE = mean squared error

n = number of data points

Y_i = observed values

$\hat{Y}_i$ = predicted values

Because the errors are squared, MSE can only assume non-negative values. Due to the intrinsic randomness and noise associated with most processes, MSE is usually positive and not zero. Mean Squared Error: 1.2565262554606385

10. ADVANTAGES & DISADVANTAGES

ADVANTAGES :

- Diesels get great mileage. They typically deliver 25 to 30 percent better fuel economy than similarly performing gasoline engines.
- Diesel fuel is one of the most efficient and energy dense fuels available today. Because it contains more usable energy than gasoline, it delivers better fuel economy.
- Diesels have no spark plugs or distributors. Therefore, they never need ignition tune-ups.
- Diesel engines are built to withstand the rigors of higher compression. Consequently, they usually last much longer than gas-powered vehicles before they require major repairs.
- Regression analysis is more versatile and has wide applicability.
- Regression Analysis is less of a black box and is easier to communicate.
- Learning Regression Analysis will give you a better understanding of statistical inference overall.
- Linear Regression is simple to implement. Less complexity compared to other algorithms.
- Linear Regression may lead to over-fitting but it can be avoided using some dimensionality reduction techniques, regularization techniques, and cross-validation.

DISADVANTAGES :

- Although diesel fuel is considered to be more efficient because it converts heat into energy rather than sending the heat out the tailpipe as gas-powered vehicles do, it doesn't result in flashy high-speed performance.
- Diesels still need regular maintenance to keep them running. You have to change the oil and the air, oil, and fuel filters.
- Although diesel fuel used to be cheaper than gasoline, it now often costs the same amount or more.

11. CONCLUSION

This paper presented a machine learning model that can be conveniently developed for each heavy vehicle in a fleet. The model relies on seven predictors: number of stops, stop time, average moving speed, characteristic acceleration, aerodynamic speed squared, change in kinetic energy and change in potential energy. The last two predictors are introduced in this paper to help capture the average dynamic behavior of the vehicle. All of the predictors of the model are derived from vehicle speed and road grade. These variables are readily available from telematics devices that are becoming an integral part of connected vehicles.
Moreover, the predictors can be easily computed on-board from these two variables. The model predictors are aggregated over a fixed distance traveled instead of a fixed time interval. This mapping of the input space to the distance domain aligns with the domain of the target output, and produced a machine learning model for fuel consumption with an RMSE. Different model configurations with 1, 2, and 5 km window sizes were evaluated. The results show that the 1 km window has the highest accuracy.

12. FUTURE SCOPE

The current vehicles that are powered by gasoline pollute, but as technologies improve and the human way of life changes alternatively powered vehicles enter the automotive industry. These vehicles developed to achieve better gas mileage and to help slow the production of the gasses that cause Global Warming. The hybrid vehicle is one of the newest and most popular alternatively powered vehicles. Air pollution is the term used to describe any harmful gases in the air we breathe. Pollution can be emitted from natural sources such as volcanoes, but humans are responsible for much of the pollution in our atmosphere. The problem of air pollution was first recognized about 500 years ago when the burning of coal in cities was is one of the newest and most popular alternatively powered vehicles. The Industrial Revolution was a fast growth in industry that was based around the use of fossil fuels.

13. APPENDIX

13.1. Source Codes

Building Server Side Script Code:

```
from flask import Flask, request,render_template
import joblib
import requests

# NOTE: you must manually set API_KEY below using information retrieved from your IBM Cloud account.
API_KEY = "QPrWDn2BZ7ubYvtx8nmiJ5LzmROuv-wxHLOl-WatJZmG"
token_response = requests.post('https://iam.cloud.ibm.com/identity/token', data={"apikey":
 API_KEY, "grant_type": 'urn:ibm:params:oauth:grant-type:apikey'})
mltoken = token_response.json()["access_token"]
header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' + mltoken}
app = Flask(__name__)
model = joblib.load("model.save")
app = Flask(__name__)
@app.route('/')
def predict():
    return render_template("manual_predict.html")
@app.route('/y_predict',methods=['POST'])
def y_predict():
    x_test = [[float(x) for x in request.form.values()]]
    payload_scoring = {"input_data": [{"field": [['distance', 'speed', 'temp_inside',
'temp_outside', 'AC', 'rain', 'sun','E10', 'SP98']], "values": x_test }]}
    response_scoring = requests.post('https://us-
south.ml.cloud.ibm.com/ml/v4/deployments/64d6e5d1-66b4-4d52-9ac1-
12c3731fcf11/predictions?version=2022-11-11',
json=payload_scoring,headers={'Authorization': 'Bearer ' + mltoken})
    pred = response_scoring.json()
    return render_template('manual_predict.html', prediction_text=('fuel
Comsumption(L/100km): ',pred['predictions'][0]['values'][0]))

if __name__ == "__main__":
    app.run(host='0.0.0.0',debug=True)
```

13.2. GITHUB AND PROJECT DEMO LINK:

1) GitHub link: https://github.com/IBM-EPBL/IBM-Project-53516-1661413635.git

2) Project Demo Link: https://drive.google.com/file/d/1JqIqblv31xKsKrQDoJhz12U34-F-Zwnd/view?usp=share_link