

IBM PROJECT REPORT

| | |
|-------------------------|--|
| COLLEGE NAME | SRM EASWARI ENGINEERING COLLEGE |
| TEAM ID | PNT2022TMID54414 |
| PROJECT NAME | Machine Learning based Vehicle Performance Analyzer |

TEAM MEMBERS:

- Sachin Kumar Sahani
- Rosshan TC
- Sudev G
- Shyam M
- E Surya

Project Report **Format**

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INTRODUCTION

1.1 PROJECT OVERVIEW

Since the advent of the industrial revolution, transportation facilities have played a vital role in all areas of livelihood such as travel, trade, and exchange. Despite the invention of multiple transportation modes, roadways transportation is the most commonly preferred course by people to carry out day-to-day activities. Irrespective of the type of activity being carried out i.e., commercial or non-commercial purposes, roadways take up a major share in global transportation statistics. Although the growth of the automobile industry has contributed to the luxury of commuting to the communities and boosted economic growth, it certainly has had an unfavorable effect on the environment (Predić et al. 1 (2016)). The result of using fossil fuels as the primary source for the operation of these motor vehicles is already well known to man and extensive efforts are being carried out to at least subside them. Global temperature rise increased anthropogenic CO₂ emissions, depletion of fossil fuels and hazardous health risks are most concerning. Several legislative principles and policies are being drafted proactively by the government to help mitigate the emission of CO₂ emissions. Here it becomes important to understand that the levels of CO₂ emission by a particular motor vehicle are parallel to the amount of fuel being consumed by the same motor vehicle during operation. This in turn corresponds to the performance characteristics and the efficiency of the vehicle. Periodic maintenance of these motor vehicles becomes very essential in maintaining their fuel efficiency. Yet, with the assistance of the new and updated developments in technology, monitoring the fuel consumption of these motor vehicles can be achieved easily today. Several researchers have attempted to analyze the data to figure out the factors affecting the fuel efficiencies of these motor vehicles, which led to the formulation of another source of cause; the driving/driver behavior (C, abreast al. (2016)). The purpose of the study is to address the research question “How well does the machine learning technique XGBoost predict the fuel efficiency of a car by considering both vehicle characteristics and driving data like speed, throttle position, air intake temperature, and pressure?” Modern vehicles come with many sensors offering lot a of data to be analyzed to make maximum use of it and cottontail normation about engine characteristics as well as the behavior formation about vehicle characteristics inc including air flow, manifold absolute pressure, air intake temperature, and pressure and the driving data includes the throttle position. Machine learning techniques like Multiple Linear Regression, Artificial NeuralNetneural networks Vector Machine, and XGBoost are implemented, and models are developed to predict the fuel efficiency of a small passenger car. Speed and engine RPM are also considered to build the model. Objectives of this research are - • Analyse the correlation between n the fuel efficiency of a car and its characteristics and driving behavior. • Develop

machine learning models using Multiple Linear Regression, Support Vector Machine, Artificial Neural Networks, and XGBoost considering vehicle characteristics and driving behavior as input data to predict the fuel efficiency of a small passenger car. • Propose the optimum throttle position and other characteristics that would help in achieving better fuel efficiency and thereby reduce fuel consumption and emissions

Since the advent of the industrial revolution, transportation have played a vital role in all areas of livelihood such as travel, trade, and exchange. Despite the invention of multiple transportation modes, roadways transportation is the most commonly preferred course by people to carry out day-to-day activities. Irrespective of the type of activity being carried out i.e., commercial or non-commercial purposes, roadways take up a major share in global transportation statistics. Although the growth of the automobile industry has contributed to the luxury of commuting to the communities and boosted economic growth, it certainly has had an unfavorable effect on the environment (Predić et al. 1 (2016)). The result of using fossil fuels as the primary source for the operation of these motor vehicles is already well known to man and extensive efforts are being carried out to at least subside them. Global temperature rise increased anthropogenic CO₂ emissions, depletion of fossil fuels and hazardous health risks are most concerning. Several legislative principles and policies are being drafted proactively by the government to help mitigate the emission of CO₂ emissions. Here it becomes important to understand that the levels of CO₂ emission by a particular motor vehicle are parallel to the amount of fuel being consumed by the same motor vehicle during operation. This in turn corresponds to the performance characteristics and the efficiency of the vehicle. Periodic maintenance of these motor vehicles becomes very essential in maintaining their fuel efficiency. Yet, with the assistance of the new and updated developments in technology, monitoring the fuel consumption of these motor vehicles can be achieved easily today. Several researchers have attempted to analyze the data to figure out the factors affecting the fuel efficiencies of these motor vehicles, which led to the formulation of another source of cause; the driving/driver behavior (C, areas et al. (2016)). The purpose of the study is to address the research question “How well does the machine learning technique XGBoost predict the fuel efficiency of a car by considering both vehicle characteristics and driving data like speed, throttle position, air, and pressure?” Modern vehicles come equipped with many sensors offering a lot of data to be analyzed to make maximum use of it and contain information about engine characteristics as well as driving behavior.

The information about vehicle characteristics includes air flow, manifold absolute pressure, air intake temperature, and pressure, and the driving data includes the throttle position. Machine learning techniques like Multiple Linear Regression, Artificial Neural Networks, support Vector Machines, and XGBoost are implemented and, models are developed to predict the fuel efficiency of small passenger cars. Speed and engine RPM are also considered to build the model. Objectives of this research are -

- Analyse the correlation between the fuel efficiency of a car and its characteristics and driving behavior.
- Develop machine learning models using Multiple Linear Regression, Support Vector Machine, Artificial Neural Networks, and XGBoost considering vehicle characteristics and driving behavior as input data to predict the fuel efficiency of a small passenger car.
- Propose the optimum throttle position and other characteristics that would help in achieving better fuel efficiency and thereby reduce fuel consumption and emissions.

This document is structured as follows: Section 2 Critique of the literature highlighting the purpose, method, and limitations, section 3 Methodology this research follows and the steps involved, section 4 Design Specification and the architecture of the techniques used in this research, section 5 Implementation details of the techniques used to develop models, section 6 Results/Evaluation of the models developed, section 7 Conclusion and future scope, Acknowledgement, and Reference

LITERATURE SURVEY

REVIEW-1

Title Of The Paper:

Vehicle fuel economy and vehicle miles traveled

Name Of The Author:

Vinola Vincent Munyon, William M. Bowen, John Holcombe

Problem Description:

There has been, in recent decades, a concerted effort to promote energy efficiency as a means to reduce energy consumption. The general thesis is that in ceteris paribus, an increase in energy efficiency leads to a decrease in the consumption of the good or service rendered efficiently. This is in opposition to Jevons' Paradox which states that "It is wholly a confusion of ideas to suppose that the economical use of fuel is equivalent to a diminished consumption. The very contrary is the truth..." This study examines whether Jevons' Paradox holds when all available factors that could affect the consumption of an efficient good/service are controlled for. Using vehicle fuel economy as a measure of energy efficiency and vehicle miles traveled (VMT) as a measure of consumption, the study examines whether, other things being held equal, a more fuel-efficient vehicle accrues greater Vehicle Miles Traveled. The findings indicate that in this case, Jevons' Paradox does hold a 1% increase in fuel efficiency associated with a 1.2% increase in VMT.

REVIEW-2

Title Of The Paper:

Personalized assistance for fuel-efficient driving

Name Of The Author:

Ekaterina Gilman , Anja Keskinarkaus, Satu Tamminen, Susanna Pirttikangas, Juha Rönning, Jukka Riekk

Project Description:

Recently, keeping in mind that driving behavior affects fuel consumption significantly, car manufacturers have started to invest in the

development of onboard systems that provide drivers feedback about their driving (e.g., SmartGauge¹, ECO ASSIST²). These systems provide visual feedback about whether driving is fuel-efficient together with statistics about fuel consumption and possible savings. Another illustrative approach is ECO Pedal³ from Nissan, which provides physical feedback with a pedal push-back control mechanism when a driver accelerates too heavily. A more detailed analysis of trips is provided by the Fiat eco: Drive⁴ system. This solution gathers statistics about trips and provides explanatory feedback about how to drive more fuel-efficiently. On-board diagnostic scanners are becoming the most common tools for monitoring driving behavior, as they can be bought separately and plugged into onboard diagnostic ports. Kiwi Drive Green⁵ system serves as an example of such a tool. Kiwi device plugs into an onboard diagnostic port to obtain sensor information about the vehicle. The device analyses driving behavior and deliver it to the driver.

REVIEW-3

Title Of The Paper:

Analysis of Vehicle Fuel Efficiency And Survival Patterns For The Prediction of Total Energy Consumption From Ground Transportation In Korea.

Name of The Author:

H. LEE and H. CHOI*

Problem Description:

In this study, a correlation between vehicle fuel efficiency and the total fuel energy consumption is analyzed to support the energy consumption and greenhouse gas (GHG) emissions reduction master plan in Korea. The background and highlights of recently amended fuel economy regulations and fuel efficiency labeling standards in Korea are also introduced. 18 representative vehicle groups, classified by class, type, size, and fuel, are selected by investigating vehicle distribution statistics based on market penetration and registration data sets to reflect and predict total fuel energy consumption in the overall ground transportation sector in Korea. The validity of the vehicle survival patterns modeled and vehicle

classification rules are confirmed by comparing national fuel energy consumption statistics to the total amount of fuel consumed by each selected representative vehicle group. The latter figures are approximated from a representative number of registrations, weighted average fuel economy, and average annual distance traveled.

REVIEW-4

Title Of The Paper:

Impact of driver behavior on fuel consumption classification, evaluation, and prediction using machine learning

Name of The Author:

PENG PING¹, WENHU QIN¹, YANG XU¹, CHIYOMI MIYAJIMA², (Member, IEEE) and KAZUYA TAKEDA³, (Senior Member, IEEE).

Problem Description:

Driving behavior has a large impact on vehicle fuel consumption. A dedicated study on the relationship between driving behavior and fuel consumption can contribute to decreasing the energy cost of transportation and the development of behavior assessment technology for the ADAS system. So, it is vital to evaluate this relationship to develop more ecological driving assistance systems and improve vehicle fuel economy. However, modeling driving behavior under dynamic driving conditions is complex, making quantitative analysis of the relationship between driving behavior and fuel consumption difficult. In this paper, we introduce two kinds of machine learning methods for evaluating the fuel efficiency of driving behavior using naturalistic driving data. In the first stage, we use an unsupervised spectral clustering algorithm to study the macroscopic relationship between driving behavior and fuel consumption, using data collected during the natural driving process. In the second stage, dynamic information from the driving environment and natural driving data are integrated to generate a model of the relationship between various driving behaviors and the corresponding fuel consumption features. The dynamic environment factors are coded into a processible, digital form using a deep learning-based object detection method.

REVIEW-5

Title Of The Paper:

Driving Behavior Analysis through CAN Bus Data in an
Uncontrolled

Environment.

Name Of The Author:

Umberto Fugiglando , Emanuele Massaro, Paolo Santi, Sebastiano
Milardo

,Kacem Abida, Rainer Stahlmann, Florian Netter, and Carlo Ratti.

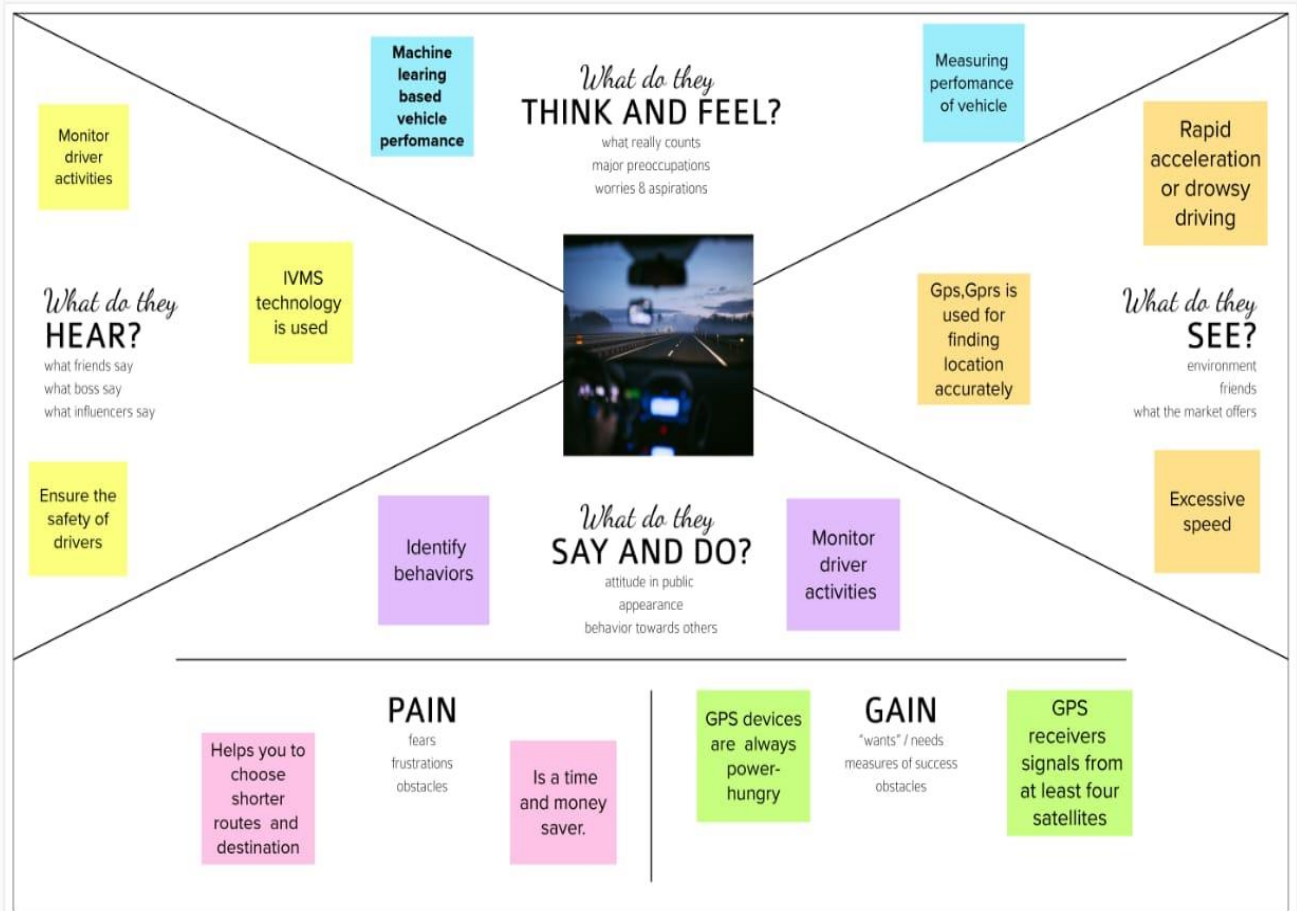
Problem Description:

Cars can nowadays record several thousands of signals through the controller area network (CAN) bus technology and potentially provide real-time information on the car, the driver, and the surrounding environment. This paper proposes a new methodology for near-real-time analysis and classification of driver behavior using a selected subset of CA bus signals, specifically gas pedal position, brake pedal pressure steering wheel angle, steering wheel momentum, velocity, RPM, and longitudinal and lateral acceleration. Data have been collected in a completely uncontrolled experiment involving 54 people, where over 2000 trips have been recorded without any type of predetermined driving instruction on a wide variety of road scenarios. While only a few works have analyzed the driving behavior of more than 50 drivers using CAN bus data, we propose an unsupervised learning technique that clusters drivers in different groups and offers a validation method to test the robustness of clustering in a wide range of experimental settings.

IDEATION & PROPOSED SOLUTION

Empathy Map Canvas

Machine Learning Based Vehicle Performance Analyzer



IDEATION AND BRAINSTORMING

IDEATION PHASE

Project Name: Machine Learning Based Vehicle Performance Analyse

Team Id : PNT2022TMD54414

| | | |
|---|--|---|
| <p>Vehicle's fuel consumption is influenced by external and internal factors. Road conditions, weather and traffic are considered as the external factors and vehicle characteristics, driving behavior and load are considered to be the internal factors.</p> | <p>The dataset consisted of a number of parameters of which few are speed, fuel level, fuel consumption and acceleration, the data was collected in the project requirements.</p> | <p>While both of them rely on on and off-board sensory data, the former aims to localize and classify the objects in the surrounding environment of the autonomous vehicle and the latter provides an understanding of the dynamics of surrounding objects and predicts their future behaviour.</p> |
| <p>Although engine and drive technology, vehicle type and condition influences vehicle's fuel consumption, personal driving style is an eminent factor and change in the style can minimize the fuel consumption.</p> | <p>The dataset consisted of a number of parameters of which few are speed, fuel level, fuel consumption and acceleration.</p> | <p>Several factors which directly influences the fuel consumption was considered in the study but other main factors like the engine RPM, traffic conditions and load were not considered in the study.</p> |
| <p>Driver is said to be aggressive when there is a higher VDI resulting in lower fuel economy.</p> | <p>Vehicle characteristics to build a model that predicts the fuel consumption either average consumption or on-the-go consumption, and the vehicle characteristics considered are the external characteristics like the weight, power and speed, not the sensor data of the engine or other factors like driving style or road condition combined with vehicle characteristics.</p> | <p>Research tries to use both driving behaviour and vehicle characteristics (sensor data) together to predict the fuel consumption.</p> |

PROPOSED SOLUTION

Proposed Solution:

| S.No | Parameter | Description |
|------|---------------------------------------|---|
| 1. | Problem Statement | As discussed in section 6 the models developed have promising results in predicting the fuel efficiency with the model outperforming all other models by constantly predicting better for all the experiments conducted with different train and test split ratio. |
| 2. | Idea/Solution Description | The dataset consisted of a number of parameters of which few are speed, fuel level, fuel consumption and acceleration the Random Forest outperformed the other two models built. Several factors which directly influences the fuel consumption was considered in the study but other main factors like the engine RPM, traffic conditions and load were not considered in the study. |
| 3. | Novelty/Uniqueness | Although this model was run on the data collected from small passenger car, the model is not limited only to that class and can be generalised for any vehicle with the driving data and vehicle characteristics available. |
| 4. | Social Impact / Customer Satisfaction | To analyze the relationship between driving behaviour and fuel economy of a car .Based on the acceleration. Driving behaviour was classified as moderate, aggressive and claim. |
| 5. | Business Model (Revenue Model) | The primary objective of the project was to develop a model using machine learning techniques which precisely predicts the fuel efficiency and to propose the optimum driving style and vehicle characteristics to achieve better fuel efficiency. |
| 6. | Scalability of the Solution | Analysis on mass air flow rate, intake air temperature and other vehicle characteristics with the predicted fuel efficiency is also carried out which gives deeper insight and better recommendations to mitigate fuel consumption. |

REQUIREMENT ANALYSIS

Functional Requirements:

| FR No. | Functional Requirement (Epic) | Sub Requirement (Story / Sub-Task) |
|--------|-------------------------------|---|
| FR-1 | Enter no of Cylinders | Based on the car |
| FR-2 | Enter Torque power | Based on the car engine |
| FR-3 | Enter Weight | weight based on the car |
| FR-4 | Enter Acceleration | acceleration depends upon the |
| FR-5 | Enter Model year | model year depends upon the car exact release |

Non-functional Requirements:

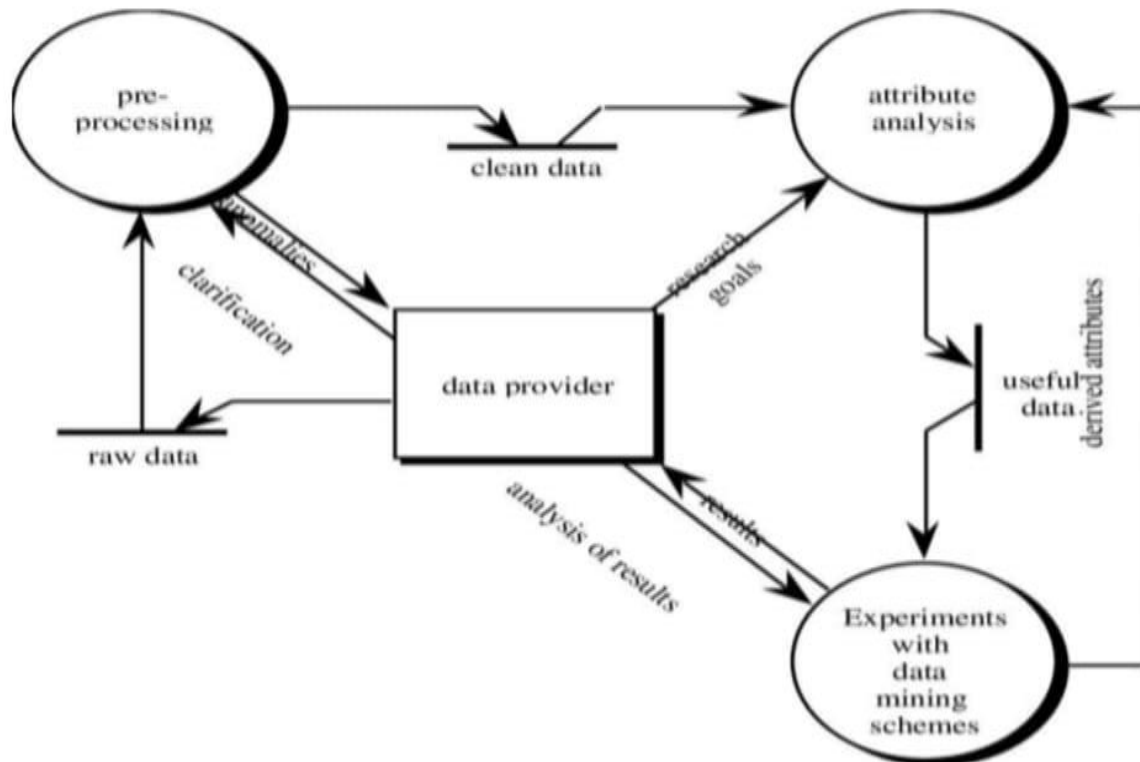
Following are the non-functional requirements of the proposed solution.

| FR No. | Non-Functional Requirement | Description |
|--------|----------------------------|--|
| NFR-1 | Usability | Vehicle's fuel consumption is influenced by external and internal factors. |
| | | |
| NFR-3 | Reliability | predicting the fuel efficiency with the XG Boost model outperforming all other models by constantly predicting |
| NFR-4 | Performance | performance is low only when there is low fuel efficiency repeatedly but in comparison with other models developed XGBoost model's performance is exceptional and the values obtained for RMSE, MAE and R2 is acceptable |
| NFR-5 | Availability | car, the model is not limited only to that class and can be generalized for any vehicle with the driving data and vehicle characteristics available |
| NFR-6 | Scalability | to improve the fuel economy by considering the characteristics that substantially influence the fuelefficiency |

Project design

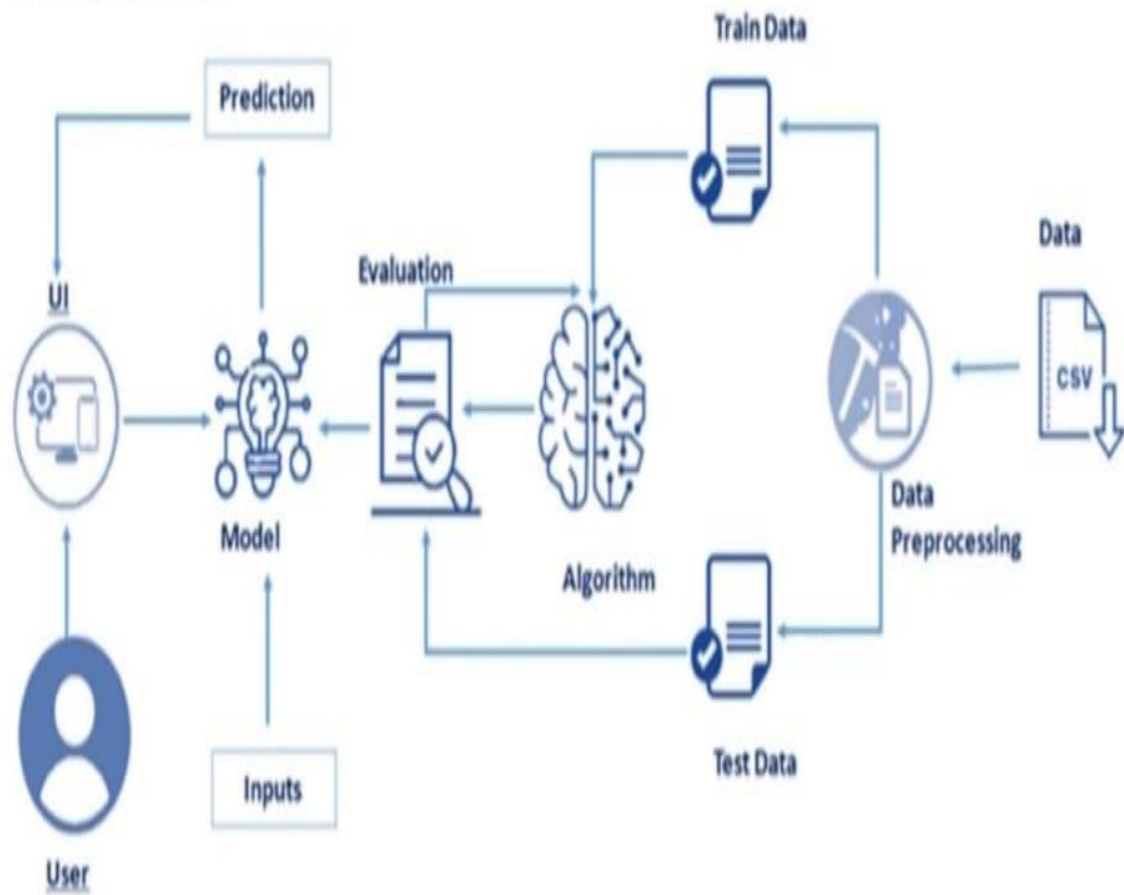
Data Flow Diagram

DataFlow Diagram:



SOLUTION AND TECHNICAL ARCHITECTURE

Technical architecture:



USER STORIES

User Stories:

| User Type | Functional Requirement (Epic) | User Story Number | User Story / Task | Acceptance criteria | Priority | Release |
|-----------|-------------------------------|-------------------|---|--|----------|----------|
| Developer | Data Preparation | USN-1 | Collecting car dataset and pre-processing it | Handle missing values, outliers, null values and so on | High | Sprint-1 |
| | Model Building | USN-2 | Create a ML model to predict car performance | Fitting data in perfect model | Medium | Sprint-1 |
| | Model Evaluation | USN-3 | Calculate the performance, error rate and complexity of ML model | Above 80% performance | Medium | Sprint-1 |
| | Model Deployment | USN-5 | Using flask and deploy model finally in IBM cloud using IBM storage and Watson Studio | Working in a proper manner | Medium | Sprint-2 |
| Customer | Enter the car cc | USN-5 | User enter the car cc power | Access to predict the performance | Medium | Sprint-3 |
| | Enter the car torque power | USN-6 | User enter the car torque power | Use to predict the performance | Low | Sprint-3 |
| | Enter the car model | USN-7 | User enter the car model | Car model to predicting the car life cycle | Medium | Sprint-3 |
| | Predict the car performance | USN-8 | As a user can analyzing the car performance | I am accessing my dashboard | High | Sprint-4 |

PROJECT PLANNING & SCHEDULING

SPRINT DELIVERY SCHEDULE

Project tracker:

| Sprint | Total story point | Duration | Sprint start date | Sprint end date | Story points completed | Sprint release date |
|----------|-------------------|----------|-------------------|-----------------|------------------------|---------------------|
| Sprint-1 | 20 | 6 days | 27-oct-2022 | 28-oct-2022 | 20 | 04-nov-2022 |
| Sprint-2 | 20 | 6 days | 02-nov-2022 | 05-nov-2022 | 20 | 07-nov-2022 |
| Sprint-3 | 20 | 6 days | 08-nov-2022 | 12-nov-2022 | 20 | 12-nov-2022 |
| Sprint-4 | 20 | 6 days | 14-nov-2022 | 19-nov-2022 | 20 | 19-nov-2022 |

Velocity:

average velocity = $80/20 = 4$ story points per day

Sprint Planning & Estimation

Product Backlog, Sprint Schedule, and Estimation:

| Sprint | Functional Requirement (Epic) | User Story Number | User Story / Task |
|----------|-------------------------------|-------------------|---|
| Sprint-1 | Data Preparation | USN-1 | Collecting water dataset and pre-processing it |
| Sprint-1 | Model Building | USN-2 | Create a ML model to predict water quality |
| Sprint-1 | Model Evaluation | USN-3 | Calculate the performance, error rate and complexity of ML model |
| Sprint-2 | Model Deployment | USN-5 | Using flask and deploy model finally in IBM cloud using IBM storage and Watson Studio |
| Sprint-3 | Registration | USN-5 | As a user, I can register for the application by entering email, password, and confirm password |
| Sprint-3 | Confirmation | USN-6 | As a user, I will receive confirmation email once I have registered for the application |
| Sprint-3 | Login | USN-7 | As a user, I can log into the application by entering email & password |
| Sprint-4 | Dashboard | USN-8 | As a user, I can use the application by entering water data |

CODING & SOLUTIONING

1. Feature 1

```
In [4]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
In [5]: ds=pd.read_csv("/content/car performance.csv")
```

```
In [6]: ds.head()
```

```
Out[6]:
```

| | mpg | cylinders | displacement | horsepower | weight | acceleration | model year | origin | car name |
|---|------|-----------|--------------|------------|--------|--------------|------------|--------|---------------------------|
| 0 | 18.0 | 8 | 307.0 | 130 | 3504 | 12.0 | 70 | 1 | chevrolet chevelle malibu |
| 1 | 15.0 | 8 | 350.0 | 165 | 3693 | 11.5 | 70 | 1 | buick skylark 320 |
| 2 | 18.0 | 8 | 318.0 | 150 | 3436 | 11.0 | 70 | 1 | plymouth satellite |
| 3 | 16.0 | 8 | 304.0 | 150 | 3433 | 12.0 | 70 | 1 | amc rebel sst |
| 4 | 17.0 | 8 | 302.0 | 140 | 3449 | 10.5 | 70 | 1 | ford torino |

```
In [7]: ds.tail()
```

```
Out[7]:
```

| | mpg | cylinders | displacement | horsepower | weight | acceleration | model year | origin | car name |
|-----|------|-----------|--------------|------------|--------|--------------|------------|--------|-----------------|
| 393 | 27.0 | 4 | 140.0 | 86 | 2790 | 15.6 | 82 | 1 | ford mustang gl |
| 394 | 44.0 | 4 | 97.0 | 52 | 2130 | 24.6 | 82 | 2 | vw pickup |
| 395 | 32.0 | 4 | 135.0 | 84 | 2295 | 11.6 | 82 | 1 | dodge rampage |
| 396 | 28.0 | 4 | 120.0 | 79 | 2625 | 18.6 | 82 | 1 | ford ranger |
| 397 | 31.0 | 4 | 119.0 | 82 | 2720 | 19.4 | 82 | 1 | chevy s-10 |

```
Out[41]: LinearRegression()
```

```
In [42]: pred = lin2.predict(poly.fit_transform(X_test))
pred[:5]
```

```
Out[42]: array([34.25303091, 32.80161339, 20.18258975, 21.79010672, 16.20953948])
```

```
In [43]: from sklearn.metrics import r2_score
r2_score(Y_test, pred)
```

```
Out[43]: 0.8730961035901238
```

```
In [44]: result = np.where(pred > 25, 1, 0)
result
```

```
Out[44]: array([1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1,
                0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0,
                1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0,
                0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1])
```

```
In [45]: import pickle
pickle.dump(ds,open('model.pkl','wb'))
```

```
Out[41]: LinearRegression()
```

```
In [42]: pred = lin2.predict(poly.fit_transform(X_test))
pred[:5]
```

```
Out[42]: array([34.25303091, 32.80161339, 20.18258975, 21.79010672, 16.20953948])
```

```
In [43]: from sklearn.metrics import r2_score
r2_score(Y_test, pred)
```

Out[43]: 0.8730961035901238

```
In [44]: result = np.where(pred > 25, 1, 0)
          result
```

```
Out[44]: array([[1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1,
                0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0,
                1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1])
```

```
In [45]: import pickle
pickle.dump(ds,open('model.pkl','wb'))
```

FEATURE 2

```
1 import numpy as np
2 from flask import Flask, request, jsonify, render_template
3 import pickle
4 #from joblib import load
5 app = Flask(__name__)
6 model = pickle.load(open('decision_model.pkl', 'rb'))
7
8 @app.route('/')
9 def home():
10     return render_template('index.html')
11
12 @app.route('/y_predict', methods=['POST'])
13 def y_predict():
14     '''
15     For rendering results on HTML GUI
16     '''
17     x_test = [[int(x) for x in request.form.values()]]
18     print(x_test)
19     #sc = load('scalar.save')
20     prediction = model.predict(x_test)
21     print(prediction)
22     output=prediction[0]
23     if(output<=9):
24         pred="Worst performance with mileage " + str(prediction[0]) + ". Carry extra fuel"
25     if(output>9 and output<=17.5):
26         pred="Low performance with mileage " +str(prediction[0]) + ". Don't go to long distance"
27     if(output>17.5 and output<=29):
28         pred="Medium performance with mileage " +str(prediction[0]) + ". Go for a ride nearby."
29     if(output>29 and output<=46):
30         pred="High performance with mileage " +str(prediction[0]) + ". Go for a healthy ride"
31     if(output>46):
32         pred="Very high performance with mileage " +str(prediction[0])+". You can plan for a Tour"
```

```
33
34
35     return render_template('index.html', prediction_text='{}'.format(pred))
36
37 @app.route('/predict_api', methods=['POST'])
38 def predict_api():
39     '''
40     For direct API calls through request
41     '''
42     data = request.get_json(force=True)
43     prediction = model.y_predict([np.array(list(data.values()))])
44
45     output = prediction[0]
46     return jsonify(output)
47
48 if __name__ == "__main__":
49     app.run(debug=True)
```

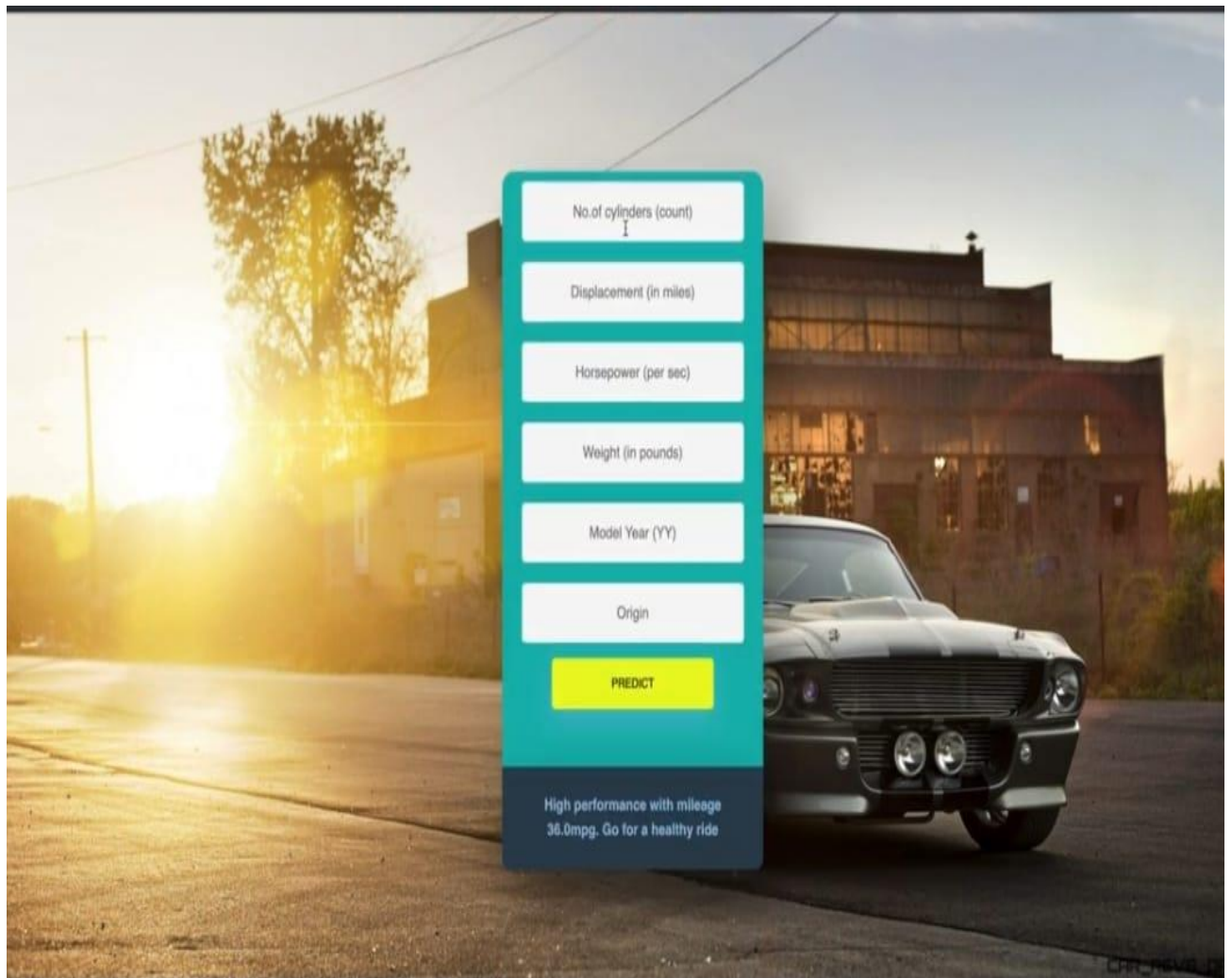
FRONT END

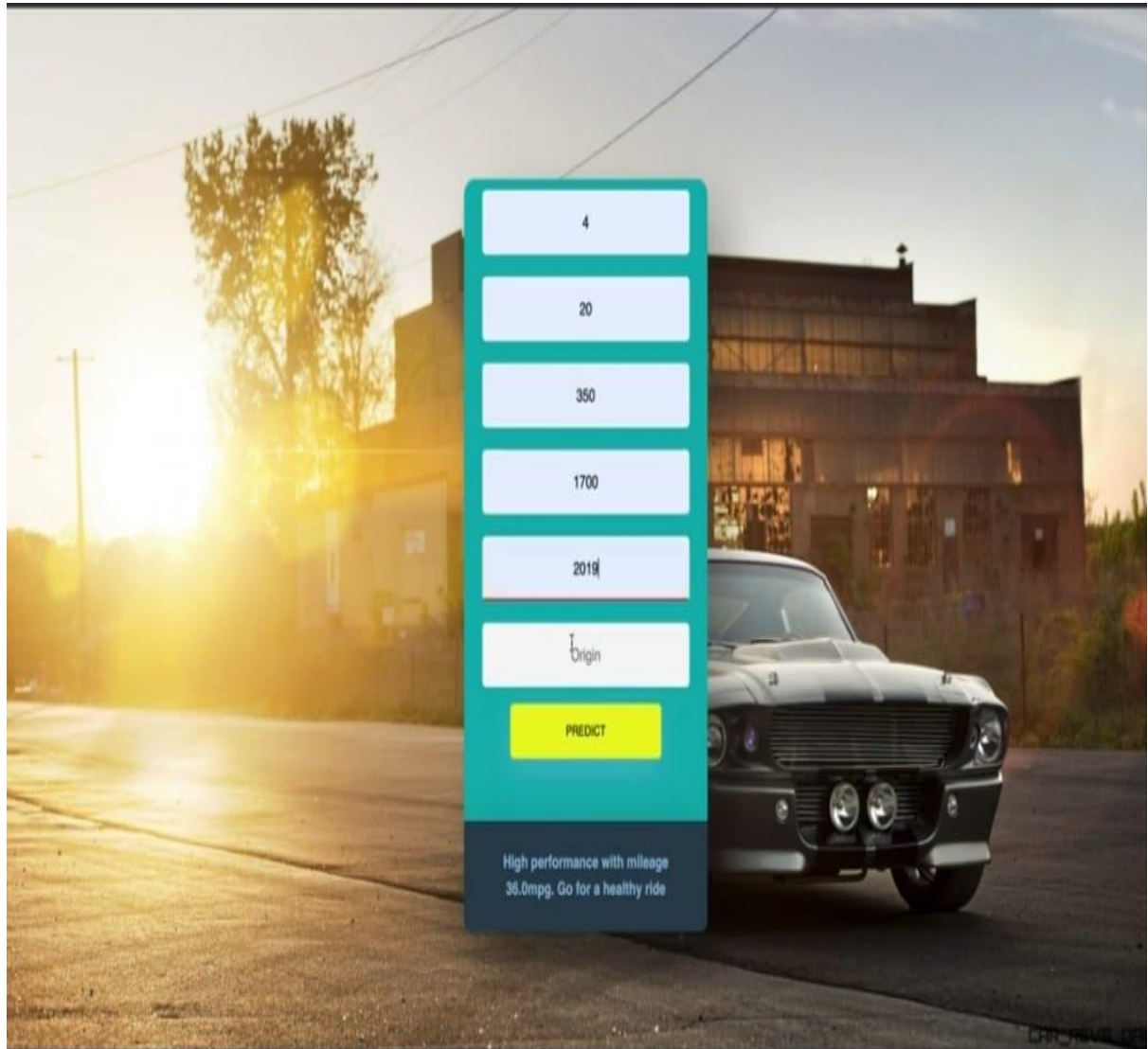
```
1 <html>
2 <link href="//maxcdn.bootstrapcdn.com/bootstrap/4.0.0/css/bootstrap.min.css" rel="stylesheet" id="bootstrap-css">
3 <link href="https://fonts.googleapis.com/css2?family=Girassol&display=swap" rel="stylesheet">
4 <script src="//maxcdn.bootstrapcdn.com/bootstrap/4.0.0/js/bootstrap.min.js"></script>
5 <script src="//cdnjs.cloudflare.com/ajax/libs/jquery/3.2.1/jquery.min.js"></script>
6 <link rel="stylesheet" href="{{ url_for('static', filename='css/style.css') }}">
7
8 <!-- <link rel="stylesheet" href="style.css"> -->
9
10 <div class="navbar">
11     <section class="title">
12         <h1>CAR PERFORMANCE PREDICTION</h1>
13     </section>
14 </div>
15
16 <div class="wrapper fadeInDown">
17     <div id="formContent">
18         <!-- Tabs Titles -->
19         <section class="date">
20             <!-- Icon -->
21             <div class="fadeIn first">
22
23
24         <form action="{{ url_for('y_predict') }}" method="post">
25             <input type="text" name="Cylinders" placeholder="No. of cylinders (count)" required="required" />
26             <input type="text" name="Displacement" placeholder="Displacement (in miles)" required="required" />
27             <input type="text" name="Horsepower" placeholder="Horsepower (per sec)" required="required" />
28             <input type="text" name="Weight" placeholder="Weight (in pounds)" required="required" />
29             <input type="text" name="Model Year" placeholder="Model Year (YY)" required="required" />
30             <input type="text" name="Origin" placeholder="Origin" required="required" />
31         </form>
32     </div>
33 </div>
```

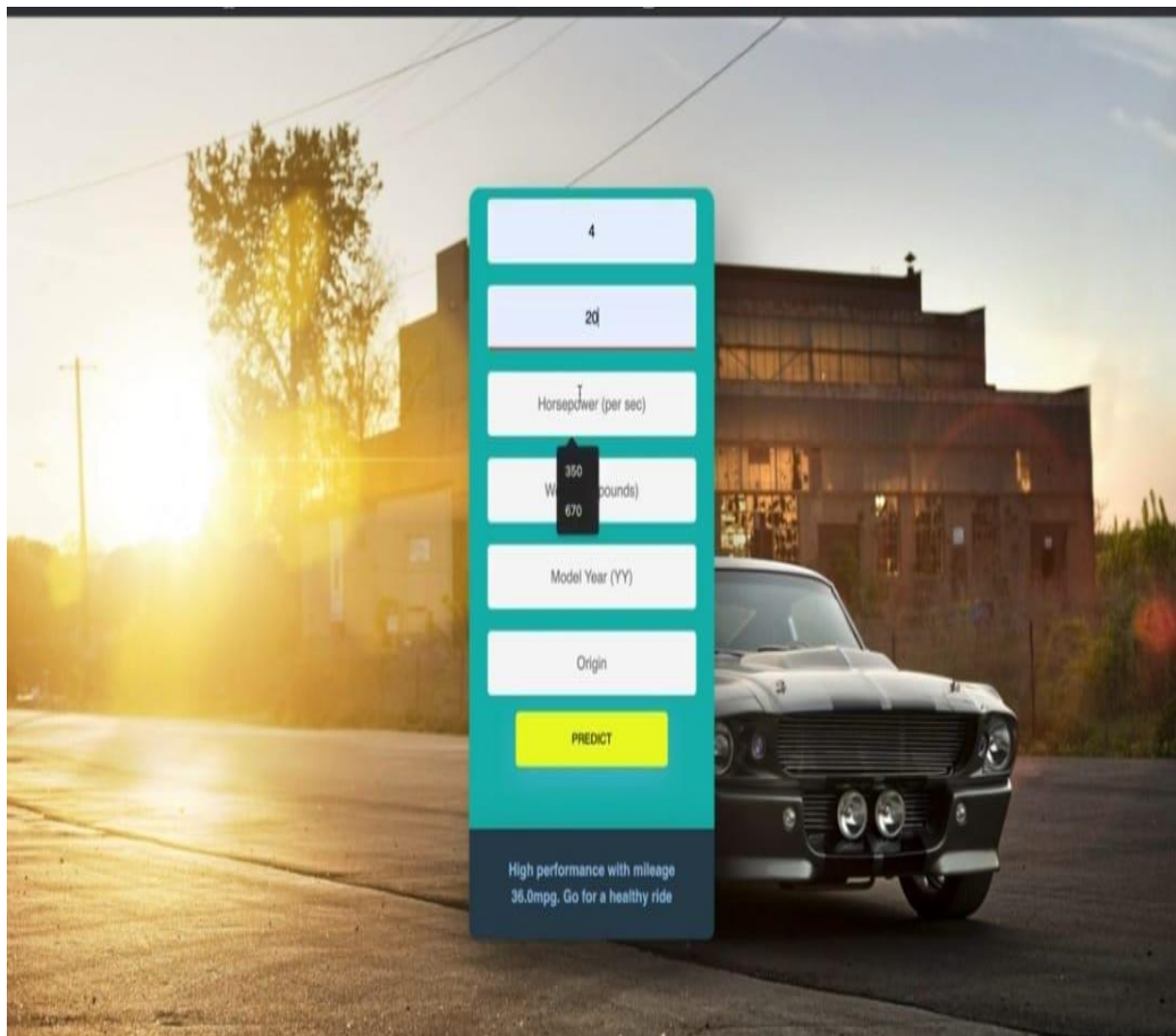
```
15
16 <div class="wrapper fadeInDown">
17   <div id="formContent">
18     <!-- Tabs Titles -->
19     <section class="date">
20       <!-- Icon -->
21       <div class="fadeIn first">
22         </div>
23
24       <form action="{ { url_for('y_predict') }}" method="post">
25         <input type="text" name="Cylinders" placeholder="No.of cylinders (count)" required="required" />
26         <input type="text" name="Displacement" placeholder="Displacement (in miles)" required="required" />
27         <input type="text" name="Horsepower" placeholder="Horsepower (per sec)" required="required" />
28         <input type="text" name="Weight" placeholder="Weight (in pounds)" required="required" />
29         <input type="text" name="Model Year" placeholder="Model Year (YY)" required="required" />
30         <input type="text" name="Origin" placeholder="Origin" required="required" />
31         <br>
32         <input type="submit" class="fadeIn fourth" value="Predict">
33       </form>
34     </section>
35
36     <div id="formFooter">
37       <a class="underlineHover" href="#">
38         <strong>{{ prediction_text }}</strong></a>
39     </div>
40
41   </div>
42 </div>
43 </html>
```

```
1  html,body {
2      width: 100%;
3      height: 100%;
4      display: table;
5  }
6
7  body {
8      font-family: "Poppins", sans-serif;
9      display: table-cell;
10     min-height: 100%;
11     background-image: url('background.jpg');
12     background-position: center;
13     background-repeat: no-repeat;
14     background-attachment: fixed;
15     background-size: cover;
16     margin: 0;
17 }
18
19 a {
20     color: #92badd;
21     display:inline-block;
22     text-decoration: none;
23     font-weight: 400;
24 }
25 h1{
26     text-align:right;
27     font-size: 40px;
28     margin-left: 500px;
29     font-family: fantasy;
30     font-style: italic;
31     color: #f40909;
32 }
```

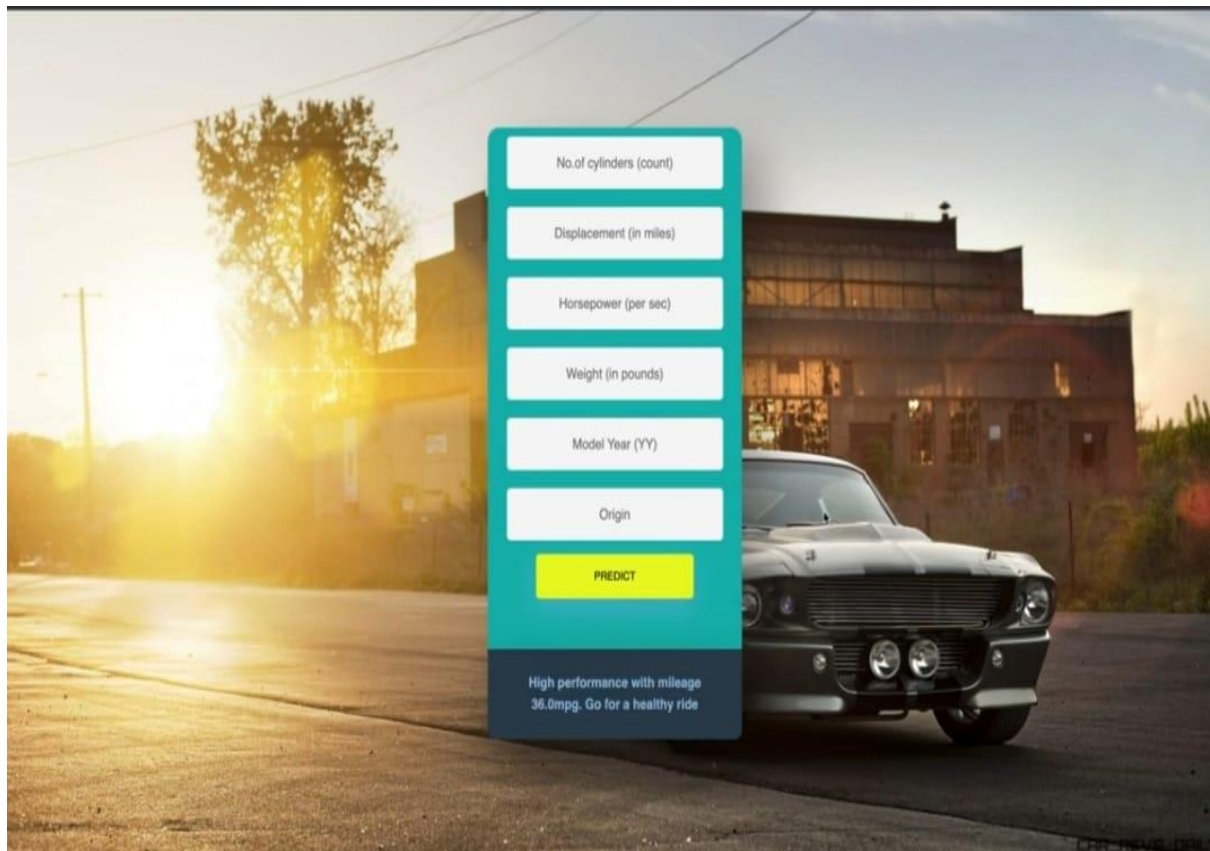
TESTING:







RESULTS



ADVANTAGES:

Vehicle performance is the study of the motion of a vehicle. The motion of any vehicle depends upon all the forces and moments that act upon it. These forces and moments, for the most part, are caused by the interaction of the vehicle with the surrounding medium(s) such as air or water (e.g. fluid static and dynamic forces), gravitational attraction (gravity forces), Earth's surface (support, ground, or landing gear forces), and on-board energy consuming devices such as rocket, turbojet, piston engine and propellers (propulsion forces). Consequently, to fully understand the performance problem, it is necessary to study and, in some way, characterize these interacting forces.

- Easy Implementation
- Low cost
- Can know and maintain the driver and car performance

DISADVANTAGES:

- Collection of the dataset is difficult.
- Should have great knowledge about the vehicles.

CONCLUSION:

As models developed have promising results in predicting fuel efficiency the model outperforms all other models by constantly predicting better for all the experiments conducted with different train and test split ratios. The model's performance is low only when there is low fuel efficiency repeatedly but in comparison with other models developed model's performance is exceptional and the values obtained for RMSE, MAE, and R2 are also acceptable. Although this model was run on the data collected from a small passenger car, the model is not limited only to that class and can be generalized for any vehicle with the driving data and vehicle characteristics available.

FUTURE SCOPE:

There is more scope in the future for research and analysis of fuel efficiency by including other factors like the road condition and real-time traffic with the help of google maps, this would help in analyzing much deeper. The knowledge discovered from the research and future work can be used by car manufacturing companies to improve fuel economy by considering the characteristics that substantially influence fuel efficiency.

APPENDIX:

Source Code

<https://github.com/IBM-EPBL/IBM-Project-42159-1660653299>

Demo Link:

https://drive.google.com/file/d/1Saxbi2brvGmoJCSkVlhdS0qJJv7M0wEb/view?usp=share_link